Environmental Modelling and Software 181 (2024) 106181

Contents lists available at ScienceDirect

Environmental Modelling and Software

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

Position Paper

Modernizing the US National Fire Danger Rating System (version 4): Simplified fuel models and improved live and dead fuel moisture calculations

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ARTICLE INFO

Keywords:
Fire danger
Model
NFDRS
Weather
Climate
Fuel moisture
Fuel models

ABSTRACT

The US National Fire Danger Rating System (USNFDRS) supports wildfire management decisions nationwide, but it has not been updated since 1988. Here we implement new fuel moisture models, and we simplify the fuel models while maintaining the overall USNFDRS structure. Modeled and measured live fuel moisture content values were highly correlated ($r^2 = 0.629$ with defaults and $r^2 = 0.693$ when species and location optimized). We also consolidated fuel models to five fuel types that eliminated significant index cross-correlation. Index seasonality compared between old (V2) and new USNFDRS models (v4) across six US National Forests was very similar ($\rho = 0.97$). V4 was as good or better than V2 at predicting fire days in 92% of the cases tested and V4 effectively predicted wildfire days and large fire ignition days (AUCs 0.647 to 0.915). USNFDRS V4 can adequately depict spatial and temporal wildland fire potential and it can be adapted for worldwide use.

1. Introduction

Wildland fires are common global disturbances, recently burning between 360 and 380 Mha per year (Chuvieco et al., 2016). As populations grow and urban development expands into the wildlands, the socio-economic impacts of wildfire continues to mount (Bowman et al., 2017). Because extreme wildfires are becoming more common, there is a need to transform how society views wildland fire and there is also a need to develop better systems to expand decision space and help society better coexist with fire (Moritz et al., 2014). Such decision support systems would include tools that effectively characterize when and where wildfires start and how they might burn over time. This information could be used to manage wildfires more effectively by promoting the ecological role of wildfires while reducing risks to responders and society.

Wildland fires occur when an ignition source strikes an available fuel under suitable weather conditions and subsequent fire behavior is often enhanced by terrain. 'Fire Danger Rating Systems' characterize these interactions between fuel, weather and terrain to predict spatio-temporal variations in wildland fire potential. These systems produce collections of indices that are related to a variety of wildfire characteristics such as ignition probability, spread rates and heat release/fire intensities. The 'fire danger indices' are used to inform operational decision making at local, regional, national and sometimes international scales. In the United States, the National Fire Danger Rating System (USNFDRS) has been used to support operational decision making for the last 50 years (Deeming, 1972; Deeming et al., 1977; Bradshaw et al., 1984). Observed and forecast outputs from the USNFDRS are monitored daily and used to maintain wildland fire situational awareness and appropriately staff for and respond to wildfires (National Wildfire Coordinating Group (NWCG), 2023). These indices are also used to plan for and safely conduct prescribed fires (Andrews and Williams, 1998) as well as to inform the public about wildfire potential. This potential is commonly communicated through signage commonly seen on US National Forests (Fig. 1).

The USNFDRS was first created in 1972 (Version 1) in an effort to standardize fire potential estimates across the country from an assemblage of research efforts that started as early as 1916 (Deeming, 1972; Hardy and Hardy, 2007). In 1978 (Version 2), the system was revised to address a number of issues that arose in the original system such as its poor response to long-term drought and its inability to depict live fuel dynamics (Deeming et al., 1977), and in 1988 (Version 3), the system was revised to address concerns of fire managers primarily in the Southeastern United States that the original model was performing poorly in humid environments (Burgan, 1988). Until recently, either USNFDRS Version 2 or Version 3 has been used operationally throughout the United States, serving as the basis for many local, regional

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https://doi.org/10.1016/j.envsoft.2024.106181
Received 29 May 2024; Received in revised form 5 August 2024; Accepted 8 August 2024
Available online 13 August 2024
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Fig. 1. Example fire danger sign commonly displayed on public lands throughout the United States. Fire danger categories, sometimes referred to as Adjective Fire Danger Ratings (Schlobohm and Brain, 2002), are one of the outputs of USNFDRS.
Source: (US Department of Agriculture, 2014).

Table 1
Versions of the US National Fire Danger Rating System.

Year	NFDRS Version	Reference
1972	Version 1	Deeming (1972)
1978	Version 2	Deeming et al. (1977)
1988	Version 3	Burgan (1988)
2024	Version 4	Jolly et. al. (This Pub)

and national fire management decisions but predominately Version 2 was used everywhere except a few isolated fire management units the Southeastern US. No further revisions or modifications to the system had been made for over thirty years (Table 1). Even early during the development of the USNFDRS, the system developers recognized the need for the underpinning science to evolve and for improvements to these systems to be made over time. One of the original USNFDRS developers once said:

> “A technical revision of the National Fire Danger Rating System alone will not cure all the problems with the fire danger rating programs. What is needed is a national program that will emphasize research in NFDRS application, management, and validation, and that will revise the System as required”. John Deeming (1984)

The USNFDRS is primarily a weather-based system and it is structurally similar to other fire danger rating models in use throughout the world such as the Canadian Forest Fire Danger Rating System (CFFDRS) (Stocks et al., 1989) and the McArthur Forest Fire Danger Index (FFDI) (Noble et al., 1980). However, in contrast to many other fire danger models, the USNFDRS has enabled fire danger estimation across multiple fuel types since its inception. Early version of other systems, like the Australia Fire Danger Rating System (AFDRS), created different fire danger systems or meters for grasslands and forests and the CFFDRS was integrated with Canadian Fire Behavior Prediction System to provide more detailed, fuel type-dependent assessments of burning conditions but neither these systems were not harmonized into a single system that varies by fuel type like USNFDRS. Recently, other national systems, such as the AFDRS (Hollis et al., 2024) and the CFFDRS (Boucher et al., 2021), have also started expanding to multiple fuel types to better reflect local fire behavior potential. Independently, research teams in the US, Canada and Australia have recognized the need to modernize their systems, further emphasizing the importance of these system to support fire management decisions as multiple scales. The USNFDRS uses weather observations to first estimate fuel moistures of various size classes of dead and various categories of live fuels. These fuel moistures are then combined with surface fuel loadings and site characteristics to estimate fire danger metrics that relate to the rate of spread, energy release and flame length of an initiating fire (Schlobohm and Brain, 2002; Chuvieco et al., 2023).

Through decades of use, fire managers and scientists have developed an in-depth understanding of the USNFDRS and through these insights have identified clear deficiencies in some system components while also noting clear benefits of other system components. Early during its development, it was decided that control of some of the key elements of the system, such as the calculation of live and fine dead fuel moistures, would require manual inputs. Users were thus required to enter values such as green-up dates annually and daily state-of-the-weather (a proxy for sky cover) (Bradshaw et al., 1984). With over 2200 weather stations providing the input to calculate fire danger each day, these manual entries are very costly and are often subjective. If these entries are not made, fire danger estimates are not available to decision makers at various local, regional and national levels. Extensive human input also precluded the system from leveraging gridded weather datasets to map and forecast fire danger where weather stations are absent, thus foregoing the opportunity to provide fire danger estimates at any point in the country (Jolly et al., 2019).

The USNFDRS was created as a collection of modules that interact to estimate fire potential. These modules, or sub-models, can be improved in isolation while maintaining the overall structure and continuity of the system (Bradshaw et al., 1984). For example, the live and dead fuel moisture models can be replaced without interrupting the fuel model module, and fuel models can be replaced to reflect different fuel types without interrupting the fire danger index module. New research exists to improve the various sub-models and these advances can overcome specific limitations of Versions 2 and 3 such as its inability to depict live fuel seasonal dynamics or the need to fully automate the fire danger calculations. Specifically, a physically-based dead fuel moisture model (Nelson, 2000; Carlson et al., 2007) and a physiologically-based phenology model (Jolly et al., 2005; Daham et al., 2019) can serve as the foundation for the next generation of USNFDRS fuel moisture models. Further, the abundance of fuel models included in Versions 2 and 3 adds unneeded system complexity that warrants exploration and simplification as long as the efficacy to predict fire potential can be retained. By replacing the dead and live fuel moisture models and simplifying the fuel models, these combined changes could yield a system that is fully automated, sensitive to vegetation type, responsive to drought and robust enough to assess historical and forecast fire potential throughout the country. Fire danger indices can be produced using historical weather data but indices can also be calculated using short- or medium-range weather forecasts or even climate change scenarios. This new fire danger rating system can provide critical fuel moisture and fire danger inputs to decision support systems at every spatial scale of interest and it could substantially improve the ability to plan for and respond to wildland fires across the United States. Further, it is sufficiently generalized to be applied anywhere in the world where wildfires are common.

Here we leverage the USNFDRS modularity to implement new dead and live fuel moisture models and to implement a simpler set of existing surface fuel models that represent broad, globally applicable fuel types. We also demonstrate how local calibration of the new live fuel moisture model can significantly improve seasonal predictions of live fuel dynamics. We evaluate these changes across six US National Forests System. We apply these sub-models in the existing USNFDRS framework and produce a revised fire danger model that is as good, or better, than the current USNFDRS while ensuring the new model is fully automated, produces the same fire danger indices as previous versions and is simpler. Finally, we discuss how this model is better equipped to meet the expanding availability of gridded weather observations and forecasts.

Table 2
Hourly weather inputs to the USNFDRS Version 4.

Parameter	Units
Temperature	°C or °F
Relative Humidity	%
Rainfall	mm or inches
Windspeed	KPH or MPH
Downward Shortwave Solar Radiation	W/m^2
Snow cover	(Yes or No)

Table 3
Fuel model parameters in the USNFDRS. Fuel load and fuel particle surface area-to-volume ratio are specified for each of the six fuel classes and categories.

Parameter	Units
Fuel Loads	tons acre^{-1}
Fuel Surface Area-to-Volume Ratios	ft^{-1}
Fuel Heat Content	BTU lb^{-1}
Dead Fuel Moisture of Extinction	% dry wt
Wind Adjustment Factor	DIM
Maximum Spread Component	DIM
Drought Fuel Loading	tons acre^{-1}

2. US National Fire Danger Rating System (USNFDRS) structure

The USNFDRS is composed of four primary modules: Inputs, Fuel Moisture Models, Fuel Models and Fire Danger Index Models (Fig. 2). Inputs include measured weather data and local fuels and terrain characterizations. Operationally, weather inputs (Table 2) for USNFDRS come from a network of over 2200 Remote Automated Weather Stations (RAWS) that are situated throughout the contiguous United States (CONUS), Alaska, Hawaii, Guam and Puerto Rico. Historically, these stations have recorded hourly air temperature, relative humidity, rainfall, wind speed measured 20 ft above ground level and averaged over a 10 min period, wind direction and instantaneous peak wind gusts. Hourly measurements were summarized to daily extremes of temperature and relative humidity and summations of rainfall duration for use in USNFDRS Versions 1–3. Installation of solar radiation sensors began in 2001 and currently all operational fire weather stations now measure hourly solar radiation in addition to the suite of aforementioned variables. All weather data are ingested into the Weather Information Management System (WIMS) which maintains the data archive for all weather stations and also performs all fire danger calculations for operational use. Local fuel descriptions defined numerically as a 'fuel model', historical weather climatology and terrain characteristics, such as slope, at the estimation site round out the required set of USNFDRS inputs. While the operational system currently uses RAWS weather data, the system can operate on any input weather data sources as long as the required variables are provided or can be estimated.

The second module is a collection of dead and live fuel moisture models. Dead fuel moisture contents are calculated for four size classes based on their response times, or timelags (Byram and Nelson, 2015), to changing environmental conditions. Small diameter dead fuels are represented by the One Hour (1-h) and Ten Hour (10-h) fuel moisture classes and generally correspond to fuel diameter classes of < 6 mm (1/4 inch) and 6 mm up to 25.4 mm (1/4 to 1 inch) in diameter. Large diameter dead fuels are represented by One Hundred Hour (100-h) and One Thousand Hour (1000-h) fuel moisture classes and they correspond to fuel diameter classes of 25.4 mm (1 inch) up to 76.2 mm (3 inches) inches and 76.2 mm (3 inches) or greater. Fine dead fuel moistures vary rapidly both diurnally and daily, while heavy dead fuel moistures are generally stable day to day but show more variability from week to week. In USNFDRS Version 2, these fuel moistures are calculated using two separate models, one for fine dead fuels (Fosberg, 1971) and one for heavy dead fuels (Fosberg et al., 1981). Moisture contents for two live fuel categories, herbaceous (grasses and forbs) and woody shrub (twigs and foliage) surface fuels, are estimated using another two models separate from, but linked to 1000-h fuel moistures (Burgan, 1979). Modifications in 1988 (Version 3) provided more control over live fuel moistures by including climatological and phenological parameters such as Season Codes and Greenness Factors (Burgan, 1988). Together the dead and live fuel moisture models form the foundation of the USNFDRS and the outputs from these models are combined and weighted with Fuel Models to calculate fire danger metrics. All of these models were built modularly to allow them to easily be improved as new science and technologies became available (Deeming et al., 1977). Yet, despite these early intentions, no significant modifications or improvements have been made to the system for 37 years.

The third module is the Fuel Model (Table 3). Fuel Models are used to weight the relative influence of each of the six fuel moisture contents on the final Fire Danger Index calculations. For each of the 4 dead fuel size classes and 2 live fuel categories, loadings and surface-area-to-volume (SAV) ratios are specified and these are used in the Fire Danger Index Calculations. Originally there were 9 fuel models in Version 1 (Deeming and Brown, 1975). This expanded to 20 in Version 2, which were then modified to generate an additional 20 more in Version 3. Most of the fuel models in Version 3 were identical to the Version 2 fuel models but some parameters were changed for a few of the fuel models. Many of these fuel models are similar, if not completely redundant, presenting a potential source of simplification for a future version of the system.

The final module is the Fire Danger Index Calculation. The original USNFDRS produces four primary metrics related to various aspects of the management and / or control of a wildland fire: Energy Release Component (ERC), Spread Component (SC), Burning Index (BI) and Ignition Component (IC). Later, the Severe Fire Danger Index (SFDI), a combination of the ERC and BI percentiles, was added to improve UNFDRS' ability to assess extreme events (Jolly et al., 2019). Components are individual, stand-alone values and Indices are a combination of two or more Components. All Components and Indices are meant to represent conditions at the head of an initiating surface fire. Energy Release Component represents the total potential energy release per unit ground area of the flaming front of a wildfire. Spread Component is proportional to the fire's forward rate of spread. Burning Index is proportional to the fire's flame lengths and Ignition Component is a measure of how likely a fire will start and will require some sort of suppression action (Schlobohm and Brain, 2002). Components and Indices are calculated daily using midday fuel moistures and the results are published and stored in WIMS to support operational fire management decisions. These components and indices are generally derived from a surface fire spread model developed by Rothermel in 1972 (Bradshaw et al., 1984). Selection of a particular Component or Index to characterize and communicate daily fire potential in a given area is a local decision, with ERC and BI selected by over 95% of users nationwide.

3. Software availability

Source code for the NFDRS Version 4.0 Command Line Interface (CLI) is available on Github (https://github.com/firelab/NFDRS4 (Brittain and Jolly, 2024)). Included in the code are SWIG wrappers to allow users to build a Python library that exposes the CLI for use in other modeling frameworks. The calculator is also implemented in a Windows-based desktop application called FireFamily+ (FireFamily+, 2022) that can import weather data, calculate USNFDRS Version 4 fuel moistures and indices and perform statistically comparisons of NFDRS V4 outputs to wildfire occurrence data. Additionally, all model simulations and analyses performed for this manuscript are provided as Jupyter Notebooks on Github (https://github.com/firelab/NFDRS4-TechDoc) to ensure transparency and reproducibility of all analyses.

Name: FireFamily Plus (FireFamily+, FF+)

Developer: USFS, RMRS, Missoula Fire Sciences Laboratory in collaboration with Altura Solutions.

Year first officially released: 1999

Hardware required: PC

Operating Systems Supported: MS Windows for FF+ and Both MS Windows and Linux for the Command Line Interface

Availability: https://www.firelab.org/project/firefamilyplus

Cost: Free

4. Methods

4.1. Updates for the US national fire danger rating system (USNFDRS version 4)

Over the last four decades, the US National Fire Danger Rating System has been used extensively to support fire management decisions nationwide. During that time, several system deficiencies have been identified and many lessons have been learned. In order to address these identified needs, three major changes are being implemented in the USNFDRS: replacing the dead fuel moisture models, replacing the live fuel moisture models and simplifying the number of fuel models.

4.2. A new dead fuel moisture model

The fine and heavy dead fuel moisture models used in USNFDRS Versions 2 and 3 are based on simple equilibrium moisture content equations developed by the USDA Forest Products Laboratory (Bradshaw et al., 1984; Fosberg et al., 1981). In conjunction with empirically derived diffusivity coefficients for each of the four timelag fuels, these equations are solely based on temperature and relative humidity for the fine fuels. Rain events that fully saturate fine fuels are handled by a rule that simply sets the fuel moisture content (FMC) to 35%, and changes in fuel surface temperature and relative humidity are set by a rule based on cloud cover. Heavier fuels are influenced by 24 h precipitation duration. However, generally these models do not include key inputs that are known to influence fuel moisture, such as precipitation amount and insolation and they do not attempt to simulate the underlying physical processes that drive moisture exchanges between the fuel and the atmosphere (Fosberg et al., 1981).

In previous USNFDRS versions, users are required to manually enter a daily 'State-of-the-Weather' (SOW) code that describes the sky cover at observation time. Categorical values specifically entered at each of the 2200+ weather stations across the network are used to estimate the influence of cloud cover on fuel surface temperature and relative humidity. The fuel moisture model developed by Nelson (2000) circumvents SOW codes by using measured solar radiation to resolve the fuel stick surface energy balance. This physically-based model has been adapted to scale to any fuel size class and it is driven by hourly measurements of temperature, relative humidity, precipitation and solar radiation. It is considerably more robust than the fine dead fuel moisture models used in Versions 2 and 3 because it includes daily antecedent conditions in all calculations. One of the primary benefits of this change is that the model can run completely automated without the need for any subjective, daily SOW inputs. This has already significantly reduced workloads and increased system reliability, while also concurrently improving the accuracy of the underlying dead fuel moisture model.

Version 4 directly uses the fuel moisture model presented by Nelson (Nelson, 2000), which was only developed for dead fuels between 6 mm to 25.4 mm (1/4 to 1 inch) in diameter (10-h timelag fuels).

Table 4
Timelag dead fuel size classes and simulated fuel stick diameters used by USNFDRS to parameterize the Nelson–Carlson dead fuel moisture model.

Timelag	Stick Diameter (ϕ) (cm/in)
1 h	0.4/0.16
10 h	1.28/0.5
100 h	4.0/1.57
1000 h	7.62/3.0

However since FMCs are required for all four dead fuel size classes, the model was extended to allow the direct application of the fuel moisture model to any diameter of fuel by Carlson et al. (2007). To accommodate these changes, six functions were derived to allow the automatic derivation of model parameters as a function of fuel diameter. Version 4 uses four 'fuel sticks' within the Nelson–Carlson model to represent the four timelag dead fuel classes and these diameters are given in Table 4.

4.2.1. Nelson–Carlson dead fuel moisture evaluation

In the early 1990s, a new dead fuel moisture model was developed by Nelson 2000 and field tested using standard arrays 10-h fuel sticks with diameters of about 1.27 cm (0.5 inches). The model was developed with the express intention to replace existing dead fuel moisture models used for both Fire Danger and Fire Behavior prediction systems used in the US and worldwide. It is driven by easily measured hourly surface weather parameters: temperature, relative humidity, total rainfall and solar radiation. While this model showed great improvements over existing dead fuel moisture models, it still was not useful for replacing the timelag fuel moistures in NFDRS because it was only developed for 10-h fuels.

Over subsequent years, the fuel stick parameter set for the original Nelson model was expanded, allowing for the simultaneous simulation of dead fuel moisture in each of the four timelag dead fuel classes (Carlson et al., 2007). After field testing, this model was implemented into the Weather Information Management System (WIMS) for operational use and it was compared to traditional USNFDRS dead fuel moistures for a decade but it never officially replaced the existing dead fuel moisture models in previous USNFDRS versions. Here we leverage this flexible dead fuel moisture model, hereafter referred to as the Nelson–Carlson model, as a one-for-one replacement for the extant dead fuel moisture models in NFDRS for each dead fuel size class. Given that the model has already been developed, tested and peer-reviewed, we will not offer further evaluation here. For more information about the model implementation and testing, refer to Carlson et al. (2007).

4.3. A new live fuel moisture model

The live fuel moisture model in USNFDRS Versions 2 and 3 has long been known to be the weakest module of the entire system. While it performs adequately in some of the semi-arid Western United States where it was developed, it lacks sufficient generality to be applicable to a wide range of ecosystems and it has no actual physiological foundations. Additionally, it requires human intervention through manual system inputs throughout the season to operate. In Version 2, the user must define the green-up date, the live fuel dormant date and other transition dates each season. In Version 3, users must define Season Codes each year and Greenness Factors roughly weekly to maximize system performance. Ultimately, this high degree of human interaction limits the ability of NFDRS to be used across broad spatial and temporal scales and even with these manual inputs, feedback from field users has suggested that the system rarely tracks live fuel variations sufficiently across the country.

The generalized vegetation phenology model that was developed by Jolly et al. (2005) and extended by Daham et al. (2019) can solve these deficiencies. This model, called the Growing Season Index (GSI), operates on daily surface weather observations of minimum temperature, vapor pressure deficit, photoperiod and rainfall, all of which can

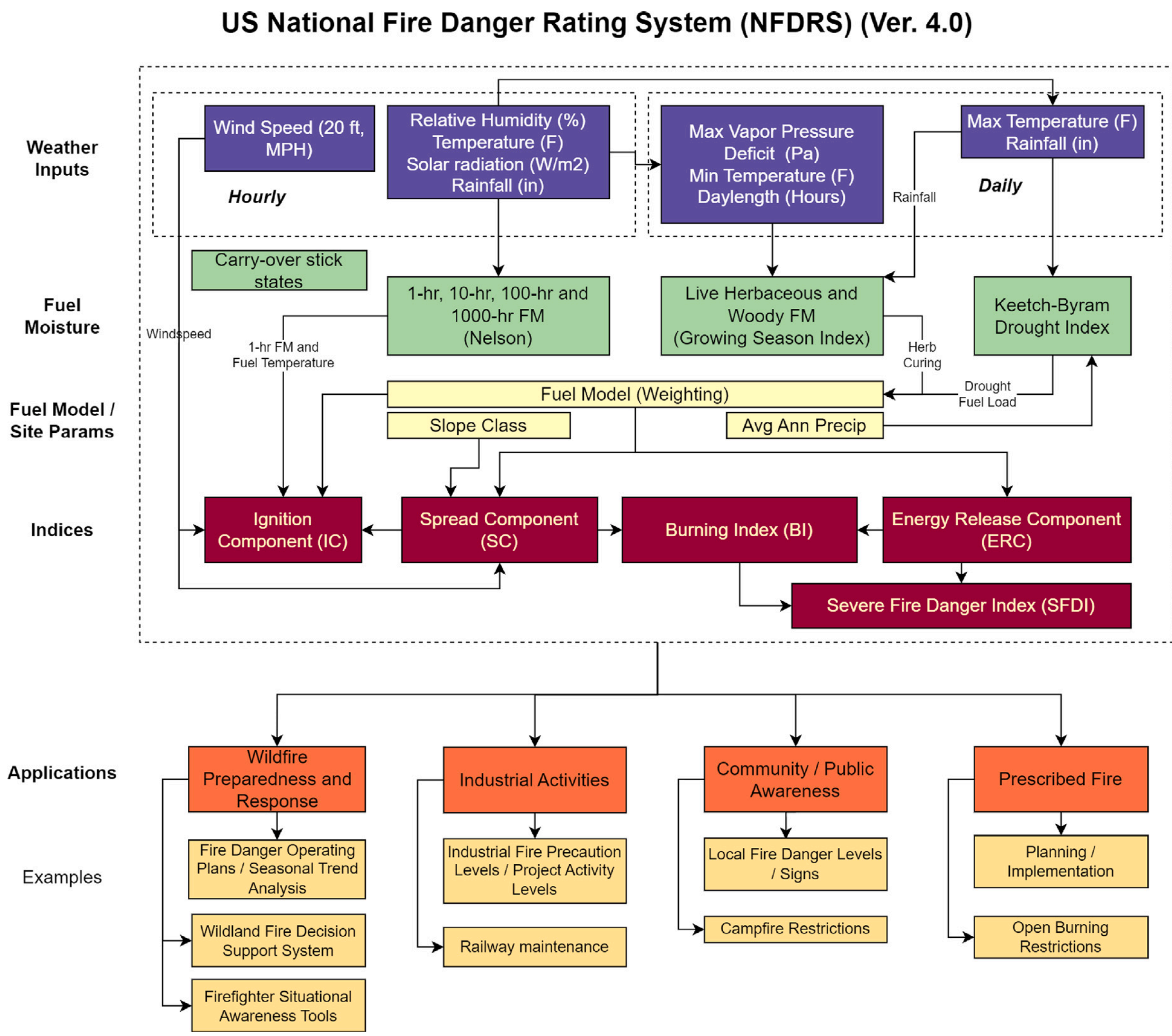

Fig. 2. Structure of the US National Fire Danger Rating System Version 4. Weather inputs are divided into hourly or daily values where daily values are simple sums or extrema of the hourly inputs.

be obtained from point-source and gridded weather observations and forecast. The original model only used minimum temperature, vapor pressure deficit and photoperiod but it was extended by Daham et al. (2019) to include a direct influence of precipitation. This modification greatly improved the prediction of live fuel dynamics in arid and semi-arid climates. The model has been tested and it has proven sufficiently general to predict seasonal changes in leaf cover and productivity across a wide range of global biomes (Jolly et al., 2005; Daham et al., 2019). It automatically predicts transitions from dormancy to growth throughout the season and it also depicts periods of water stress when herbaceous fuels begin to cure or when woody plants begin to shed leaves. Automated predictions of live fuel conditions will eliminate the need for USNFDRS users to manually 'manage' live fuel model states throughout the year. It will also facilitate historical comparisons between fire danger and fire activity, especially when green-up dates were not recorded. Finally, this model can also be forecast using available numerical weather predictions or climate change scenarios, thus providing a more robust solution for future applications of US-NFDRS. Ultimately, this simple model can substantially strengthen the linkage between live fuel dynamics and fire danger and it is sufficiently generalized to allow global application.

4.3.1. The Growing Season Index (GSI)

GSI is the product of four daily ramp functions that are derived from surface weather conditions and that are proxies for physiological mechanisms that limit plant functions: low temperatures (daily minimum temperature), evaporative demand (vapor pressure deficit), photoperiod (daylength) and water stress/low soil moisture (precipitation). Upper and lower thresholds were referenced from the literature, assuming that phenological activity varied linearly from inactive (0) to unconstrained (1) between a pair of well-defined environmental limits (Jolly et al., 2005; Daham et al., 2019). The generalized form of the ramp function is given in Eq. (1) and their parameter-specific (α and β) variants are described in detail below for each of the four daily input weather variables.

Ramp functions use the following generalized equation and are parameterized for each daily GSI input variable:

$$iX_t = \begin{cases} 0, & \text{if } X_t \leq \alpha \\ \dfrac{X_t - \alpha}{\beta - \alpha} & \text{if } \alpha < X_t < \beta \\ 1, & \text{if } X_t \geq \beta \end{cases} \tag{1}$$

where X_t is the weather variable input on day t, α and β are the lower and upper ramp function limits and iX_t is the daily, derived ramp function value bounded between 0 and 1 inclusive. GSI uses four weather-based ramp functions, each with their own default lower and upper limits. These lower and upper limits can be adjusted to better reflect local conditions when necessary. The four ramp function descriptions are given below.

Table 5
Default GSI input variable ramp function limits used for NFDRS Version 4.

Variable	Units	Lower Limit (α)	Upper Limit (β)
$iVPD_t$	Pa	900	4100
$iTmin_t$	°C (°F)	−2° (28.4°)	5° (41°)
$iDayl_t$	Seconds (Hours)	36,000 (10)	39,600 (11)
$iPrcp_t$	mm (in)	0 (0)	10 (0.394)

4.3.2. Daily minimum temperature

$$iTmin_t = iX_t(X_t = Tmin_t, \alpha = -2.0, \beta = 5.0) \quad (2)$$

where $Tmin_t$ is the daily minimum temperature (° C) and $iTmin_t$ is the daily minimum temperature ramp value.

4.3.3. Daily maximum vapor pressure deficit (VPD)

$$iVPD_t = 1 - iX_t(X_t = VPD_t, \alpha = 900, \beta = 4100) \quad (3)$$

where VPD_t is the daily maximum vapor pressure deficit (VPD) in Pascals, and $iVPD_t$ is the daily VPD ramp value. VPD is computed using the daily maximum temperature and minimum relative humidity using saturation vapor pressure calculations presented by Murray (1967).

4.3.4. Photoperiod/daylength

$$iDayl_t = iX_t(X_t = Dayl_t, \alpha = 36000, \beta = 39600) \quad (4)$$

where $Dayl_t$ is the daily photoperiod, or daylength, (seconds) and $iDayl_t$ is the daily daylength ramp value.

4.3.5. Daily precipitation

Precipitation is included using a short-term running total with a user-defined temporal window (in days) as follows:

$$Prcp_t = \sum_{n=0}^{PrcpNDays-1} DailyPrcp_{t-n} \quad (5)$$

where $DailyPrcp_t$ is the total daily precipitation at time t in millimeters and *PrcpNDays* is the number of lag days to include in the running total. *PrcpNDays* is 28 days by default but it can be adjusted. $Prcp_t$ is the daily running sum of the last *PrcpNDays* and is updated daily. The daily running total precipitation is then used in an ramp function to calculate the daily running total precipitation ramp value as follows:

$$iPrcp_t = iX_t(X_t = Prcp_t, \alpha = 0, \beta = 0.394) \quad (6)$$

where $Prcp_t$ is the running daily sum of precipitation for the past N days calculated from Eq. (5) on day t.

Default upper and lower limits for each of the four ramp functions are summarized in Table 5 but these parameters can be locally calibrated to better reflect local physiological constraints to plant activity.

The final GSI value is calculated as the product of the four, daily ramp function values for minimum temperature, maximum VPD, photoperiod and running total precipitation. The unsmoothed, daily GSI (iGSI) is calculated as follows:

$$iGSI_t = iTmin_t * iVPD_t * iDayl_t * iPrcp_t \quad (7)$$

Where $iGSI_t$ is the daily product of the ramp function values for the 4 inputs (Eqs. (2)–(4) and (6)). The final daily GSI is then calculated as the n-day lagged moving average of the daily indicator (iGSI):

$$GSI_t = \frac{1}{GSINDays} \sum_{n=0}^{GSINDays-1} iGSI_{t-n} \quad (8)$$

Where *GSINDays* is 28 days by default but can be modified as part of model calibration (see Fig. 3).

4.3.6. Conversion of GSI to live fuel moisture

To make daily GSI values useful for USNFDRS, it must be transformed into a live fuel moisture content value for both herbaceous (grasses and forbs) and woody live fuels(shrubs and small seedlings or saplings). To facilitate this inclusion and transformation, a separate GSI calculations is performed daily for herbaceous and woody live fuels (live fuel categories are denoted by subscript f). Daily Herbaceous and Woody GSI values are then used to calculate daily live herbaceous LFMC and live woody LFMC, respectively. The ramp functions for the live herbaceous and live woody fuel categories are identical by default (hence $GSI_h = GSI_w$ by default). However, the lower and upper limits presented in Table 5 can be modified independently for herbaceous and woody fuels to better capture phenological and physiological differences between the two functional types. GSI values below a specified green-up (GU) threshold are assigned either a fully cured value for herbaceous fuels or a dormant fuel moisture value for woody plants, consistent with the live fuel moisture model in USNFDRS Version 2/3 (Burgan, 1979). Minimum and maximum live herbaceous and woody fuel moisture ranges were carried over from USNFDRS Version 2 (Bradshaw et al., 1984) with the exception of a single dormant woody fuel moisture value rather than four separate values previously set according to Climate Class, as shown in Table 6.

To calculate live fuel moistures from GSI, daily woody or herbaceous GSI values (GSI_f) are first rescaled based on the local, historical maximum GSI for each live fuel type as follows:

$$GSI'_f = \frac{GSI_f}{MaxGSI_f} \quad (9)$$

where GSI_f is the daily running average GSI, the subscript f specifies the live fuel type, $MaxGSI_f$ is historical maximum GSI_f used for scaling (1.0 by default indicates no scaling), and GSI'_f is the rescaled GSI_f value ($0 \leq GSI'_f \leq 1$). GSI'_f is only scaled over the max historical GSI value for each fuel type because GSI values generally reach 0 at most sites tested but in wet sites, GSI only reaches 0 for a few days each year (Jolly et al., 2005; Daham et al., 2019).

This rescaled value was found to be more robust than raw GSI values because in some regions not all ramp function values simultaneously exceeded their upper limits anytime during the observation record. For example, GSI ranges may only vary from 0 to 0.75 but the timing of the onset and offset of the growing season were appropriate if they were simply rescaled. It also ensures that a generalized green-up threshold of 0.2 has the same meaning everywhere. Using the rescaled GSI values, live fuel moistures are then calculated for either herbaceous or woody fuels based on a linear transform above the green-up GU_f threshold as follows:

$$LFMC_f = \begin{cases} Min_f & \text{if } GSI'_f < GU_f \\ m_f * GSI'_f + b_f & \text{if } GSI'_f \geq GU_f \end{cases} \quad (10)$$

Where the parameters m_f and b_f are defined by appropriate values in by the following equations:

$$m_f = \frac{Max_f - Min_f}{1.0 - GU_f} \quad (11)$$

$$b_f = Max_f - m_f \quad (12)$$

where Max_f, Min_f and GU_f are the upper and lower fuel moisture limits and green-up threshold, respectively, defined for both live fuel types in Table 6. Rescaling the GSI to GSI' generally ensures that LFMC values reach the maximum values for each fuel type. However, in some areas GSI values will not drop the green-up threshold and thus will never reach minimum values. Additionally, local calibration of minimum and maximum values by fuel type is allowed in the model if sufficient field measurements are available for calibration.

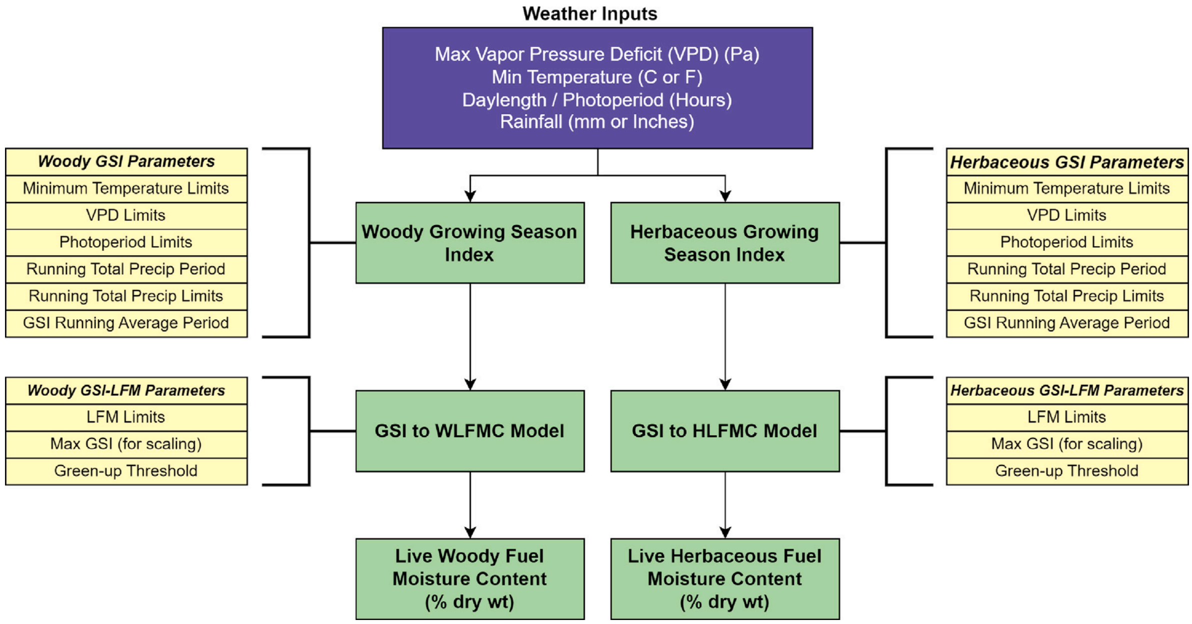

Fig. 3. Flow diagram of GSI-based Live Fuel Moisture Content calculations for herbaceous and woody fuels.

Table 6
Lower and upper fuel moisture limits and green-up thresholds used to calculate live herbaceous and live woody fuel moisture content from the Growing Season Index. Model parameter names are given in parenthesis.

Live Fuel Category [f]	Min LFMC (% dry wt) [Min_f]	Max LFMC (% dry wt) [Max_f]	Green-up Threshold [GU_f]
Woody	60	200	0.2
Herbaceous	30	250	0.2

4.3.7. GSI live fuel moisture evaluation

GSI-based live fuel moisture estimates were compared to field-measurements across six species measured in five US states (Table 7). Field measured live fuel moisture content data were extracted from the US National Fuel Moisture Database (US National Fuel Moisture Database, 2023, 2024). This database tracks, stores and displays real-time fuel moisture measurements across the United States and it makes those data available for use in both fire management and research applications. These data are also available as part of the GlobeLFMC Version 2.0 database (Yebra et al., 2024).

Daily weather data from each RAWS station was collected from the Western Region Climate Center RAWS archive (Western Region Climate Center, 2024). These data were imported into the FireFamily+ software package (FireFamily+, 2022) and used to calculate daily maximum vapor pressure deficit and estimate herbaceous and woody live fuel moistures from NFDRS Version 2. GSI-LFMC was modeled in a Python 3.9 environment inside Jupyter notebooks and this workflow is available here (Jolly et al., 2024). Modeled fuel moisture values were compared to field-measured fuel moistures. Initially, GSI-LFMC are estimated using default parameters from Tables 5 and 6 using a 28 day period for both the total precipitation and GSI smoothing and a green-up threshold of 0.2.

In addition to testing the GSI-LFMC default parameters, we performed a second analysis to assess model calibration ability using local live fuel moisture content field measurements. We performed a simple Grid Search Optimization (GSO) where random samples of parameter combinations were computed and compared against field-measured live fuel moistures to determine a set of parameters that minimized the mean absolute error (MAE) between modeled and predicted herbaceous and woody live fuel moistures. The GSO iterated through 10,000 random combinations of parameters from the variable ranges shown in Table 8 and returned the model parameters with the highest correlation between measured and modeled LFMC. All GSO code and simulation results are also provided in the Jupyter notebook available on Github (Jolly et al., 2024).

In addition to varying the upper and lower limits of the ramp functions, we allowed the smoothing period length (*GSINDays* in Eq. (8)) and the precipitation summarizing period (*PrcpNDays* to vary from 21 to 60 days, in Eq. (5)) and the green-up threshold (GU_f in Eqs. 10 and 11) to vary from 0 to 0.8. Finally, rather than using the minimum and maximum fuel moisture ranges carried over from Version 2, we set Min_f and Max_f to the 5th percentile and 95th percentile of the live fuel moistures measured at each location. All source code for the GSI calculations and the Grid Search Optimization is provided in a Python-based Jupyter notebook (Jolly et al., 2024).

4.4. Reducing the number of fuel models

The USNFDRS uses 20 fuel models in Version 2 and 20 similar, but not identical, fuel models in Version 3 to represent a range of fuel types across the country. However, over many years of experience, fire managers have recognized that fire danger components and indexes calculated with these fuel models exhibit very similar seasonal patterns, even though the absolute magnitude of the values may differ. Multiple fuel models that are not truly independent from one another adds unnecessary complexity to the system for very little gain and since USNFDRS components and indexes are most commonly applied as percentiles (Heinsch et al., 2009), their absolute magnitudes are less relevant. Further, fuel models used for fire danger rating are different from the fuel models used for fire behavior simulation modeling, thus adding complexity to training and operational use. Therefore, if Version 2 fuel model groups are better understood, a simpler, more general set of fire danger fuel models that are anchored to fire behavior fuel models may be derived to reduce complexity while ensuring independent seasonal responses across a range of fuel types.

4.4.1. Fuel model evaluation

To identify fuel model similarities and explore existing groupings, we simulated dead and live fuel moisture scenarios to compute ERC across all 20 NFDRS Version 2 fuel models. We randomly simulated 50,000 1-h, 10-h, 100-h and 1000-h dead fuel moistures from 1% to

Table 7
Live fuel moisture sampling sites used for comparison to and optimization of the GSI-based live fuel moisture model.

Site Name	Measuring Agency	State	Species	Weather Station (RAWS ID)	Lat/Long (DD)
Sevier Reservoir	Filemore Field Office (BLM)	UT	Basin Big Sagebrush (*Artemesia tridentata*) Cheatgrass (*Bromus techtorum*)	Sevier Reservoir (421501)	39.58°/−112.0°
Laurel Canyon	LA County Fire	CA	Chamise (*Adenostoma fasciculatum*)	Beverly Hill (045442)	34.12°/−118.37°
Angelina (SE-TX-ANG)	Texas A&M Forest Service	TX	Yaupon (*Ilex vomitoria*)	Lufkin (413509)	31.31°/−94.83°
Hearst-Lead	State of South Dakota	SD	Smooth brome (*Bromus inermis*)	Spearfish (SSFS)	44.349°/−103.8°
Humbug	Salmon–Challis NF	ID	Pacific Ninebark (*Physiocarpus capitatus*)	Idianola (101303)	45.54°/−114.03°

Table 8
GSI input variables and ramp function ranges used for Grid Search Optimization of GSI-derived Live Fuel Moisture Content.

Variable	Units	LowerLimit	UpperLimit	Steps
$iVPD_t$	Pa	500	9000	500
$iTmin_t$	°C	−5	10	1
$iDayl_t$	s	32,400	46,800	3600
$iPrcp_t$	mm	0	127	1

35% and live woody from 60% to 200% and herbaceous fuel moistures from 30% to 250%. We then performed a cross-correlation analysis to assess the similarities of ERC between Version 2 fire danger fuel models. Correlations were further used in a cluster analysis to group similar fuel models into distinct fuel types. Once established, these fuel type groups served as the basis for the Version 4 fire danger fuel models and were assigned a new, unique alphabetical code. Physical parameters for the reduced fire danger fuel models (i.e., loading by size class and category, SAV ratio, bed depth, etc.,) were taken directly from existing fuels models used for fire behavior modeling in the United States (Scott, 2005). Finally, the Version 4 fuel model behavior was also assessed and compared to the Version 2 models. These one-for-one match-ups align fire danger and fire behavior fuel models and eliminates the need to train firefighters on two separate sets of fuel models for fire danger and fire behavior applications. All source code for the fuel model comparisons and subsequent publication figures is provided in a Python-based Jupyter notebook (Jolly et al., 2024).

4.5. USNFDRS versions 2 and 4 comparisons

Individual fire danger rating systems are typically evaluated separately by assessing the capability of each to predict the location and timing of fire activity (Andrews et al., 2003; Viegas et al., 1999). Here we first compared USNFDRS Version 2 and Version 4 directly to assess similarities and differences in their seasonality and their efficacy to predict wildfire occurrence. Since part of the rationale for revising the USNFDRS is to simplify and automate the system, the standard for assessing Version 4 is based on whether the updates resulted in any loss of predictive capability. Additionally, we explore how Version 4 performs when used to differentiate between days with wildfires (Fire Days), days when large wildfires (fire greater than the local 97%ile fire size), or distinguishing the conditional probability of a large fire given a fire day and we explore the best indices and fuel models for prediction of each wildfire event. All comparison dates between fire danger indices and fire activity are the dates the fires were reported, regardless of how many days the fires burned to reach their final fire size (Andrews et al., 2003).

4.5.1. Site selection and data processing

Six evaluation sites spanning a range of climate, fuels and topography were selected from National Forest System lands across CONUS: the Okanogan–Wenatchee National Forest (NF), the Lolo NF, the Little Missouri National Grassland (part of the Dakota Prairie Grasslands), the Angeles NF, the Prescott NF, and the Apalachicola NF. Administrative boundaries were used to select weather stations and to spatially clip historical fire activity records. Weather station catalogs containing metadata about the RAWS location were downloaded from the National Fire and Aviation Management Web Applications website (FAMWEB) and hourly weather data was downloaded from the Wildland Fire Assessment System (WFAS) fire weather data file interface. Federal, state and local fire records containing information about the discovery date, origin location and final size of reported wildland fires were obtained from the Fire Program Analysis Fire Occurrence Database, FPA FOD (Short, 2014). All years from 2003–2017 and all days from Jan–Dec were included in the analysis.

Station catalogs, hourly weather data, and historical fire records were loaded into the latest version of FireFamily Plus (FF+5.0) to generate a synchronized daily time series of fire danger and fire activity for each evaluation site. Both USNFDRS Versions 2 and 4 were used to calculate all fire danger metrics (i.e., ERC, BI, SC and IC) at every RAWS location once daily at the standard observation hour (typically either 1200 or 1300 local time). All Version 4 calculations use the default GSI-to-LFMC conversion parameters discussed above. Moreover, whilst Version 2 was limited to fuel model G, Version 4 was run using all five updated fuel models (i.e., V through Z). Spatially averaging the RAWS-based calculations yielded four daily time series for Version 2 (i.e., four metrics × one fuel model) and 20 daily time series for Version 4 (i.e., four metrics × five fuel models) for every evaluation site. Since climate varies between evaluation sites, and since Version 2 and Version 4 produce fire danger ratings on different absolute scales, all daily time series were converted to percentiles to facilitate comparisons (Heinsch et al., 2009). For each evaluation site, the 100th and 0th percentiles indicate the locally highest and lowest daily fire danger recorded between 2003 and 2017.

Fire activity records from the FPA FOD (Short, 2014) were distilled into binary time series of fire-days (FD) and non-fire-days (NFD). A fire-day is a standard measure of fire activity (Haines et al., 1983) and is defined as a 24-h period during which at least one new wildland fire was reported within an evaluation site. The largest, individual, final fire size reported on a fire-day was also retained. This enabled the construction of binary time series of large-fire-days (LFD), where a LFD is defined as a 24-h period during which at least one new wildland fire was reported and eventually exceeded a certain size threshold. Final fire size thresholds used to define a LFD were unique for every evaluation site and were set to the 97th percentile of the historical fire size distribution.

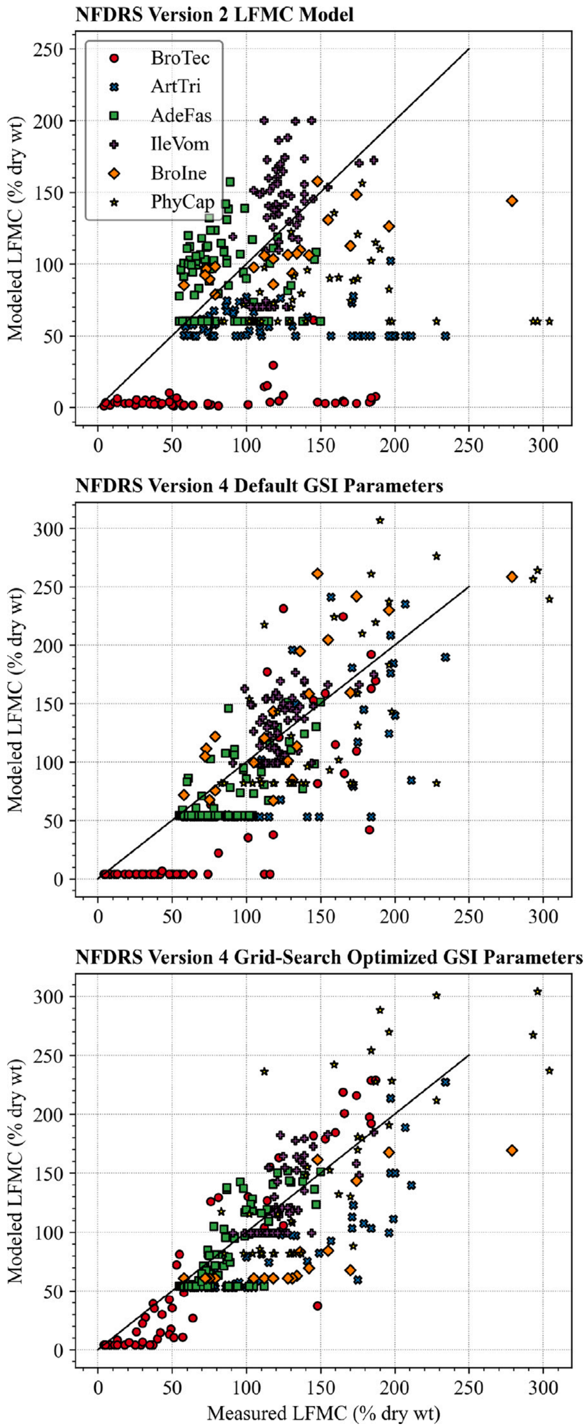

Fig. 4. Comparisons of modeled and measured live fuel moisture content across three species for five years (2015–2019). Top panel shows comparison of old NFDRS V2 modeled LFMC to observations, middle panel compares new GSI-based LFMC using default or out-of-the-box parameters, bottom panel shows the final results of Grid Search Optimized (GSO) GSI-based LFMC compared to field measurements. Correlations between measured and modeled LFMC for NFDRS Version 2 were 0.33 (Top) and correlations for NFDRS Version 4 LFMC values using default parameters (Middle) were 0.78 and were 0.84 when parameters were optimized by species and site using the GSO.

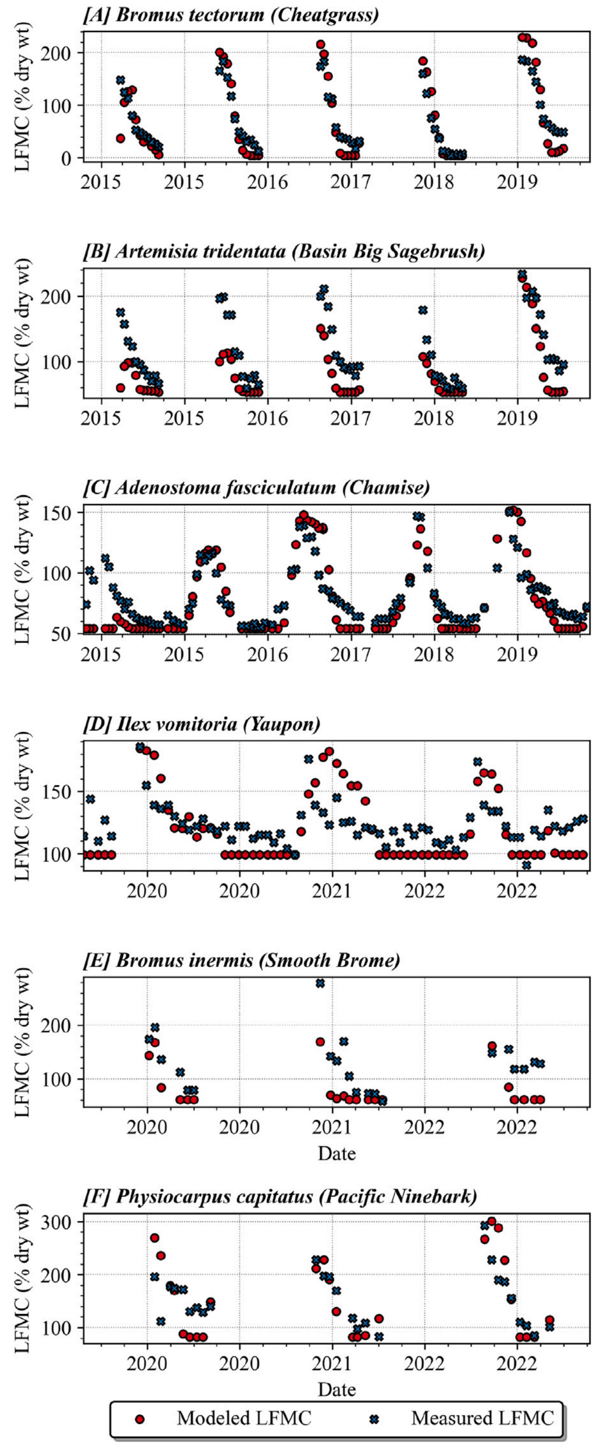

Fig. 5. Seasonal plots of Grid Search Optimized GSI-based live fuel moisture contents compared to field measured values for *Bromus tectorum* (Top), *Artemisia tridentata* (Middle) and *Adenostoma fasciculatum* (Bottom). Overall, we see good agreement between the seasonality of modeled and measured live fuel moistures for both an herbaceous and two woody species.

4.5.2. Evaluation

The USNFDRS is often used to convey the local seasonality of fire danger to outside incident management teams and firefighters (Andrews et al., 1998). To avoid large day-to-day fluctuations, seasonal profiles are typically generated using fire danger metrics less influenced by wind and fuel models less influenced by fine dead fuels. Hence ERCs were selected here as the seasonal fire danger metric, and since only fuel model G was used in Version 2, its counterpart fuel model Y was selected here for Version 4. Daily time series of ERC(G) and ERC(Y) at each evaluation site were converted to seasonal profiles of 15-yr, monthly mean percentiles and compared between Versions 2 and 4.

Given the influence of wind and fine dead fuel moisture content on new wildfire ignitions and their initial spread, associations between fire danger and fire activity are also performed on a daily basis. Several analytical techniques have been developed to evaluate the ability of fire danger rating systems to predict fire activity (Viegas et al., 1999; Andrews et al., 2003). Here we select the receiver operating characteristic (ROC) curve, a tool commonly used to assess the performance of fire occurrence models (Vilar et al., 2010; Zhang et al., 2016; Barreto and Armenteras, 2020). The ROC curve and the Area Under the ROC Curve (AUC) objectively quantify whether a fire danger metric is any better at making predictions compared to random guessing. This requires two synchronized time series: one for the fire danger metric and one for the binary indicator of fire activity (i.e.,"1" versus "0"). The ROC and its integral the AUC were used to assess the ability of fire danger metrics calculated from Versions 2 and 4 to distinguish (i) fire-days from non-fire-days (FD = 1 | NFD = 0), (ii) large-fire-days from non-fire-days (LFD = 1 | NFD = 0), and (iii) large-fire-days from fire-days (LFD = 1 | FD = 0).

In the analysis, the continuous fire danger rating is used as a classifier such that setting a single fire danger threshold splits the predictions into two classes. Days when fire danger is below the threshold are predicted as zeros, and days when fire danger is above the threshold are predicted as ones. At each threshold there exists a true positive rate (TPR) and a false positive rate (FPR). Calculating TPR and FPR over all possible thresholds along the fire danger continuum and plotting them against each other yields the ROC curve. Integrating the ROC curve yields the AUC. Values for the AUC near 0.5 indicate the fire danger metric is no more useful at making predictions than random guessing. Higher values for the AUC indicate improved prediction performance, and values of AUC=1.0 indicate perfect predictions (i.e., distributions of fire danger on fire-days and non-fire-days do not overlap and are completely separated). When comparing fire danger ratings generated from Version 2 and Version 4, the one with the higher AUC is considered to have better predictive capability.

5. Results

5.1. Live fuel moisture modeling

Of the six species tested, only cheatgrass, yaupon and smooth brome showed a significant correlation between NFDRS Version 2 modeled LFMC and the field-measured values (Table 10). For all species tested, the LFMC modeled with Version 2 generally undepredicted the field measurements (Fig. 4) and overall the Version 2 live fuel moisture model failed to capture the LFMC dynamics for these species.

In contrast, the Version 4 GSI-LFMCs showed better correlations and lower MAE than the Version 2 values. GSI-LFMC calculated using the default parameters from Tables 5 and 6 were all significantly correlated with LFMC measured for the six test species ($p < 0.01$). Correlations between modeled and measured LFMC ranged from a low of 0.381 ($r^2 = 0.205$) in Yaupon to a high of 0.789 ($r^2 = 0.638$) for Cheatgrass. Additionally, MAE was as much as three times lower between Version 2 and Version 4 (default) LFM contents where MAE was lowest for Chamise (17.9%) and highest for Pacific ninebark (64.3%).

Correlations also improved dramatically when GSI-LFMC parameters were calibrated with a Grid Search Optimization (GSO). Final optimized GSI-LFMC parameters are given in Table 9. Correlations ranged from 0.727 ($r^2 = 0.461$) for Yaupon to 0.924 for cheatgrass ($p < 0.01$) and MAE were reduced and ranged from 13.3% for Chamise to 46.3% for cheatgrass. Optimized GSI-LFMC values showed very good agreement with the seasonal dynamics of each of the six species over multiple measurement years (Fig. 5.

When pooled across all six species (N = 346), NFDRS Version 2 LFMC were poorly related to field-measured LFMC ($r^2 = 0.076$, $p < 0.01$)(Fig. 4, Top Panel). In contrast, NFDRS Version 4 GSI-LFMC, calculated using the default parameters, showed a strong correlation with field measured values ($r^2 = 0.629$, $p < 0.01$) (Fig. 4, Middle Panel) and when each species response was optimized using GSO before being pooled, overall correlations were even higher ($r^2 = 0.693$, $p < 0.01$ (Fig. 4, Bottom Panel). Overall, this suggests that default GSI parameters should be a good starting point for modeling site-specific LFMC and if field measurements are available, model dynamics can be improved through a simple parameter optimization.

5.2. Fuel model reductions

ERC values from 50,000 simulated live and dead fuel moisture scenarios showed that Version 2 fuel models (A - U) are strongly cross-correlated across fuel type groups. A summary of the cross-correlations between USNFDRS Versions 2 and 4 fuel models is shown in Fig. 6. Eighteen of the 20 NFDRS Version 2 fuel models showed at least one correlation with another fuel model that was greater than 0.85. Moreover, fuel models I, J and K (slash) were nearly perfectly correlated with each other (r > 0.999) and showed cross-correlations greater than 0.85 with as many as 7 other fuel models.

Cross-correlations between fuel model-specific ERC values shown in Fig. 6 revealed some unique groupings amongst Version 2 fuel models. Simulated ERC values based on the LFMC for annual and perennial grass fuel models such as A and L were similar to one another but different from other fuel models. Timber models such as G and H also clustered together while grass/shrub and brush based models formed a large cluster. Ultimately, Version 2 fuel models clustered into five fuel type groups, which were then assigned their own fuel model parameters and a new NFDRS Version 4 alphabetical code: grass (V), grasses/shrubs (W), brush (X), timber (Y) and slash (Z). Correlations between Version 4 and Version 2 fuel models, as well cross-correlations between Version 4 fuel models themselves, are shown in Fig. 6. Finally, based on the NFDRS Version 4 fuel type groups, we identified the closest matching fire behavior fuel model, as summarized in Table 11 and a cross-walk between Version 2/3 and Version 4 fuel models in Table 12 based on the hierarchical clustering of the Version 2 and Version 4 fuel models. Cross-correlations between the five new Version 4 fuel models showed that none of the models had a correlation greater than 0.85 with any of the other Version 4 fuel models (Fig. 6), suggesting that condensing fuel models into fuel type groups yields a set of five fuel models that are unique.

5.3. USNFDRS versions 2 and 4 comparisons

Maps of the administrative boundaries and RAWS locations within the six evaluation sites are shown in Fig. 7. As desired, the broad geographic selection of evaluation sites captured the diverse seasonality of fire danger across CONUS. Based on long-term (15-yr) minimum and maximum monthly mean ERC percentiles, respectively, the lowest fire danger was identified by Version 2 fuel model G or Version 4 fuel model Y in at least one evaluation site every month from December to March, whilst the highest fire danger was identified in at least one evaluation site every month from May through August. A specific example for the Lolo NF demonstrates good seasonal agreement where both Versions 2 and 4 identified February has having the lowest fire danger and August as having the highest fire danger (Fig. 8a). Good seasonal agreement extended beyond the Lolo NF where long-term, monthly mean percentiles generated by Versions 2 and 4 were strongly correlated ($r^2 = 0.94$) across all six evaluation sites (Fig. 8b)

Even during a single month the range of daily fire danger components and indexes can vary greatly. For example, in the Lolo NF during April, daily mean values for Version 2 ERC(G) and Version 4 ERC(Y) ranged from the 29th to the 53rd percentile, and from the 27th to the 59th percentile, respectively (Fig. 8a). The range of values for any single, individual day varied even more. These high frequency day-to-day fluctuations are the reason why daily fire danger metrics are associated with daily occurrences of new wildland fires. For Version 2 ERC(G)

Table 9
Grid Search Optimized GSI-LFMC parameters for six common, fire-prone live fuels. Parameters were fit by simulating 10,000 combinations of parameters and minimizing the MAE between modeled and predicted values.

Variable	Minimum Temp	Vapor Pressure Deficit	Daylength	Running Total Precip	PrcpNDays	Greenup Threshold	GSINDays
Units	(°C)	(Pa)	(s)	(inches)	(days)		(days)
Lower/Upper Limits	(α/β)	(α/β)	(α/β)	(α/β)			
Cheatgrass *(Bromus tectorum)*	−4/−1	2000/5500	32400 /43200	0.2/0.8	50	0.2	50
Basin Big Sagebrush *(Artemesia tridentata)*	−5/−1	2000/4000	32400 /43200	0.1/0.4	59	0.2	59
Chamise *(Adenostoma fasciculatum)*	−4/0	2500/4000	32400/36000	1.5/3.0	55	0.0	55
Yaupon *(Ilex vomitoria)*	−3/7	1000/6000	39600/43200	1.2/4.4	49	0.5	49
Smooth brome *(Bromus inermis)*	−1/8	1000/2000	32400/43200	0.5/1.9	21	0.1	21
Pacific Ninebark *(Physocarpus capitatus)*	−5/−1	2000/4000	32400/43200	0.1/0.4	42	0.2	42

Table 10
Results of comparisons between modeled and measured live fuel moisture content (LFMC) for six fire prone plant species in the United States. Spearmans' rank order correlations (ρ_S), the r^2 from an Ordinary Least Squares regression and Mean Absolute Error (MAE) are reported for each comparison.

		NFDRS Version 2.0 Live Fuel Moisture Model	NFDRS Version 4.0 Live Fuel Moisture Model	
	LFMC Model Version	Burgan (1979)	GSI LFMC	
	Parameters	N/A	Default	Grid Search Opt
Cheatgrass *(Bromus tectorum)*	ρ_S/r^2 **MAE**	0.289/0.078* (68.6%)	0.789/0.638*** (27.6%)	0.924/0.854*** (23.9%)
Basin Big Sagebrush *(Artemesia tridentata)*	ρ_S/r^2 **MAE**	−0.165/0.00NS (59.6%)	0.749/0.561*** (37.9%)	0.880/0.774*** (38%)
Chamise *(Adenostoma fasciculatum)*	ρ_S/r^2 **MAE**	0.180/0.0007NS (25.9%)	0.586/0.343*** (17.9%)	0.821/0.716*** (13.3%)
Yaupon *(Ilex vomitoria)*	ρ_S/r^2 **MAE**	0.467/0.195*** (30.2%)	0.381/0.205*** (34.2%)	0.727/0.461*** (17.8%)
Smooth Brome *(Bromus inermis)*	ρ_S/r^2 **MAE**	0.865/0.653*** (70.0%)	0.781/0.620*** (34.3%)	0.881/0.583*** (46.3%)
Pacific Ninebark *(Physiocarpus capitatus)*	ρ_S/r^2 **MAE**	0.065/0.000NS (78.7%)	0.643/0.441*** (64.3%)	0.792/0.60*** (36.0%)

Significance indicators are as follows: $*= p < 0.05$, $**= p < 0.01$, $***= p < 0.001$, NS = Not Significant.

Table 11
New fire danger fuel models for NFDRS Version 4 and their mappings to fire behavior fuel models (FBFMs) from Scott and Burgan (2005). Full parameter listings are given in Andrews (2018).

NFDRS Version 4: Code	Fuel Type	Fire Behavior Fuel Model: Equivalent	Code
V	Grass	Grass 2	GR2 (102)
W	Grass-Shrub	Grs-Shrub 2	GS2 (122)
X	Brush	Shrub 9	SH9 (149)
Y	Timber	Timber litter 1	TL1 (181)
Z	Slash	Slash-Blowdown 2	SB2 (202)

Table 12
Fuel model cross-walk table between new NFDRS V4 and old NFDRS V2/V3 fuel models based on the correlogram in Fig. 6 and a correlation threshold of 0.8. Note: Fuel models W and X have similar balances of live and dead loading, so care should be chosen when selecting a cross-walk fuel model.

Fuel Type	V4 FM	V2/3 FM
Grass	V	A,L
Grass-Shrub/Brush	W/X	B,F,C,R,U,T,N,E,D
Timber	Y	H,P,G
Slash	Z	O,Q,S,I,K,J

and Version 4 ERC(Y), results of the ROC analysis revealed AUC values of 0.78 and 0.85 in the Lolo NF, respectively, indicating that updates have improved the ability of the USNFDRS to distinguish fire-days from non-fire-days. In general, these improvements are widespread. All AUC values reported for Version 4 fuel model Y are above 0.6 regardless of fire danger metric or evaluation site (Fig. 9), indicating better than random predictions when using the new timber fuel model. Of the 24 comparisons generated from the combination of six evaluation sites and four fire danger metrics (i.e., ERC, BI, SC and IC), AUC values from Version 2 fuel model G and Version 4 fuel model Y were significantly different on 10 occasions, leaving 14 comparisons where predictions from Version 2 and Version 4 were not distinguishable from one another. Of the 10 occasions that were significantly different, Version 4 outperformed Version 2 for 8 of them, leaving just 2 out of 24 occasions where Version 4 under-performed Version 2.

Results for all combinations of evaluation sites, fire danger metrics and Version 4 fuel models revealed that ERC(Y) emerged as the best at distinguishing fire-days from non-fire days (Table 13), reflecting the synchronized seasonality of new wild fire occurrences and

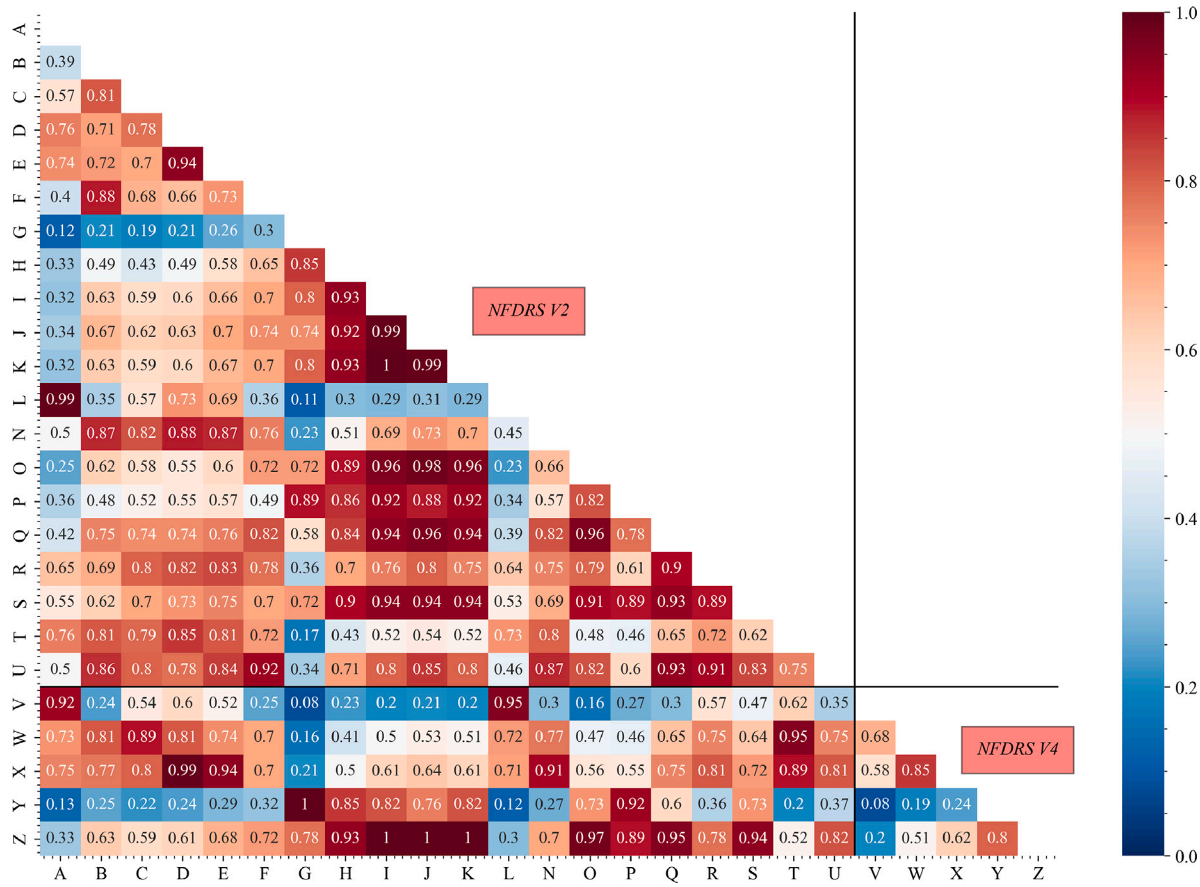

Fig. 6. Correlogram comparing 50,000 simulated Energy Release Component (ERC) values computed from combinations of dead and live fuel moisture scenarios applied to NFDRS Version 2 (A - U) and Version 4 (V - Z) fuel models. Numbers and colors indicate the strength of the correlations between fuel models.

fire danger primarily driven by large dead fuel moistures. Values for AUCs universally increased for each evaluation site when distinguishing large-fire-days from non-fire-days. New wildfires that escape initial attack are often started when conditions are more conducive to large fire growth; hence the better separation in the fire danger distributions and the higher AUCs. Also note the emergence of BI and thus the role of wind on large fire growth. Compared to non-fire-days which occur mostly outside of the fire weather season, large-fire days and fire-days generally coincide at the same time of year. The lower AUCs when distinguishing large-fire-days from fire-days is likely due to such similar fire danger conditions. Nevertheless, large-fire-days can be better differentiated from fire-days by using metrics that capture the influence of wind (e.g., BI and SC) as well as the fine fuels (e.g., fuel models V and W) on the rapid growth of initiating wildfires.

6. Discussion

6.1. NFDRS version 4 updates

Fire danger rating systems are a critical component of any wildland fire preparedness and response decision support system but they must be maintained to keep pace with scientific and technological advancements in order to meet the evolving needs of wildland fire decision makers. The Version 4 updates to USNFDRS incorporate the latest research in fire environment modeling while also positioning developers to continually improve the system over future decades. The methods used to perform these updates retain the same components and indices output by Versions 1 through 3 while leveraging the modular design to seamlessly replace antiquated dead and live fuel moisture models and simplify the fuels representation within the system. Despite these changes and simplifications, this new system reproduces or exceeds the predictive power of the old system while eliminating the need for daily and seasonal intervention. Ultimately, these system changes pave the way for more robust future applications of USNFDRS.

6.1.1. Dead fuel moisture model updates

This USNFDRS revision has many improvement over the previous versions but there are still challenges for future development. For example, the Nelson–Carlson dead fuel moisture model provides a simpler implementation for modeling timelag fuel moistures but the model does pose some computation challenges for fine dead fuel moistures. Internally, the frequency of moisture computation time steps is inversely proportional radius of the fuel. This means that model speed increases with decreasing stick/fuel diameters. Ultimately, future work should focus in part on optimizing these radius-dependent model parameters to maximize dead fuel moisture model performance.

6.1.2. Live fuel moisture model updates

The GSI-based live fuel moisture model implemented in Version 4 is a significant improvement over the old USNFDRS live fuel moisture model but it is still a simplification/generalization of the live fuels present on a given site. USNFDRS live fuel moistures are meant to capture the average change in growing conditions and will not likely represent every species at every site. As such, these modeled fuel moistures will not always compare well to seasonal measured live fuel moistures. The analysis of GSI-based live fuel moisture content values presented here is meant to be illustrative and is by no means exhaustive. Future work should focus on understanding how GSI behaves in different climate and for different plant functional types. Preliminary explorations revealed that leveraging local climatologies to

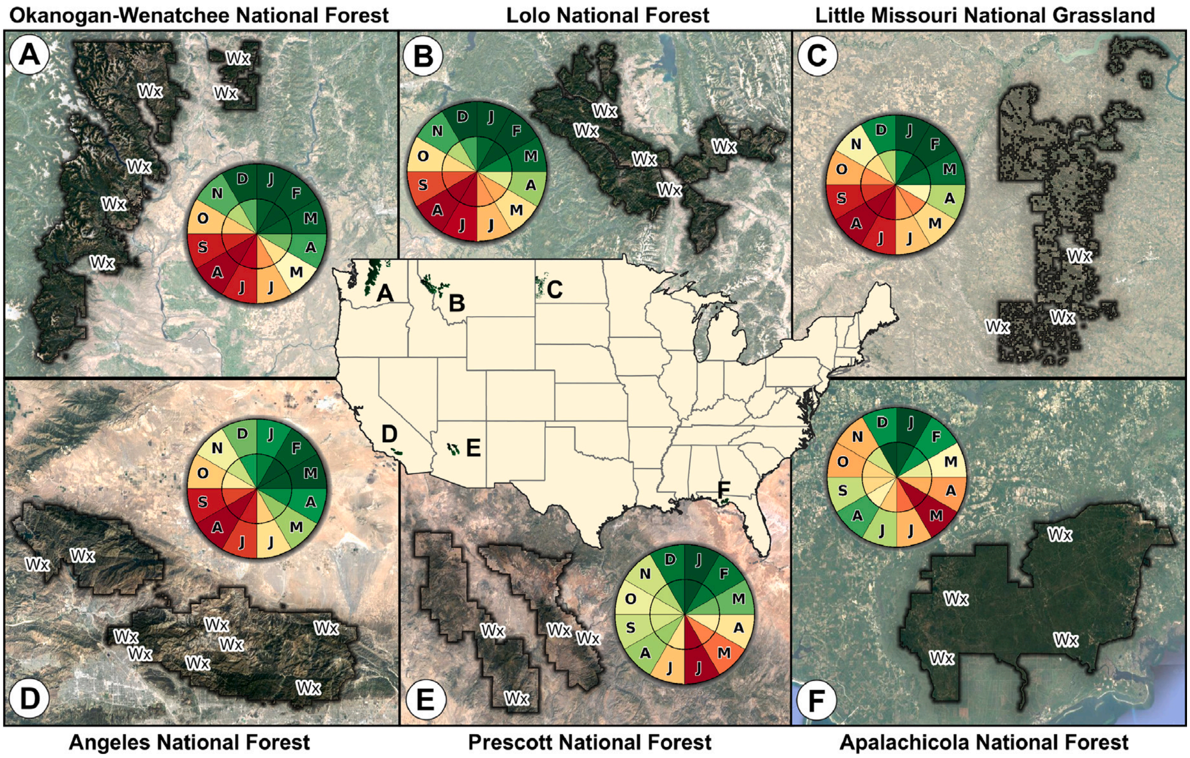

Fig. 7. Six evaluation sites used to compare USNFDRS Version 2 and Version 4. (A) the Okanogan–Wenatchee National Forest (NF), (B) the Lolo NF, (C) the Little Missouri National Grassland, (D) the Angeles NF, (E) the Prescott NF, and (F) the Apalachicola NF. Remote Automated Weather Stations (RAWS) are labeled "Wx". The wheels qualitatively illustrate the seasonality of fire danger characterized by the long-term (15-yr) monthly mean Energy Release Component (ERC) percentile. The inner wheel corresponds to Version 4 fuel model Y, and the outer wheel corresponds to Version 2 fuel model G. Color wheels are scaled from the minimum (green) to the maximum (red). Long-term, monthly mean percentiles of ERC(G) and ERC(Y) are quantitatively compared in Fig. 8b.

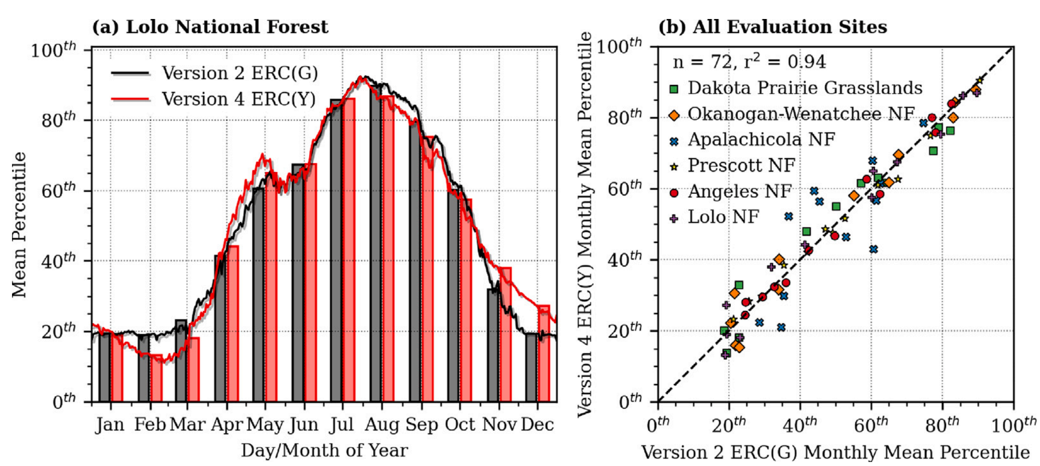

Fig. 8. Demonstration of the seasonal agreement between USNFDRS Version 2 and Version 4. (a) Long-term (15-yr) mean daily (lines) and mean monthly (bars) time series of Energy Release Component (ERC) percentiles for Version 2 fuel model G and Version 4 fuel model Y on the Lolo National Forest. (b) Correlation between long-term, monthly mean ERC percentiles for Version 2 fuel model G (x-axis) and Version 4 fuel model Y (y-axis) for all evaluation sites (n = 72 = 6 evaluation sites x 12 months per year). Long-term mean monthly comparisons are also illustrated qualitatively as seasonal wheels in Fig. 7.

calibrate ramp function ranges for variables such as VPD could provide a simple way to spatially calibrate GSI either by weather station or using gridded weather inputs. Additionally, the lower and upper limits for both herbaceous and woody fuel moisture contents are very general and we found that relationships were improved when species-specific, local ranges were used. It is possible that the model could be designed to self-calibrate when provided with local field measurements of both dead and/or live fuel moisture. Ultimately, more work is needed to provide better, more localized baseline calibration of the GSI-LFMC model as well as better representations of the differences between leaf life spans such as evergreen and deciduous plants.

The GSI-LFMC method incorporates elements of previous NFDRS LFMC modeling (V3 and earlier), including assigning minimum and maximum LFMC values based on fuel type. While default minimum and maximum LFMC values for herbaceous and woody fuels are 30%/250% and 60%/200% respectively, our research indicates that using locally determined ranges for these values improves model accuracy. However, species in wetter climates, such as the Southeast Texas Yaupon we tested, might not attain these lower default values. Minimum woody LFMC values across all four of our woody fuel evaluation sites was 55%, which is close to the default of 60%, but Yaupon only reached a historic minimum of 91%. Maximum values across all species were 279% for

Table 13
Results of the evaluation distilled into the combination of fire danger metric and fuel model (FM) that provides the best discrimination (i.e., the highest AUC) between (i) fire-days (FDs) and non-fire days (NFDs), (ii) large-fire-days (LFD's) and NFD's, and (iii) LFD's and FD's. From 2003–2017 there were a total of 5479 days, of which the number of fire-days (# FD) and large-fire-days (# LFD) for each evaluation site are presented in the left most column along with the size threshold (97th percentile) used to identify large fires.

Evaluation Site	FD | NFD		LFD | NFD		LFD | FD	
# FD, # LFD and Large Fire Threshold	*AUCmax*	*Metric(FM)*	*AUCmax*	*Metric(FM)*	*AUCmax*	*Metric(FM)*
Angeles NF 1936, 78 and 27 ha	0.685	ERC(Y)	0.786	BI(Y)	0.701	BI(Z)
Apalachicola NF 482, 16 and 179 ha	0.696	ERC(Y)	0.789	SC(W)	0.647	SC(V)
Little Missouri National Grassland 213, 9 and 127 ha	0.742	ERC(Z)	0.915	ERC(Y)	0.772	BI(W)
Lolo NF 1204, 71 and 10 ha	0.853	ERC(Y)	0.897	ERC(Y)	0.802	ERC(W)
Okanogan–Wenatchee NF 1081, 76 and 110 ha	0.853	ERC(Y)	0.900	ERC(Y)	0.719	ERC(Y)
Prescott NF 697, 29 and 28 ha	0.676	ERC(Y)	0.790	ERC(Y)	0.679	ERC(X)

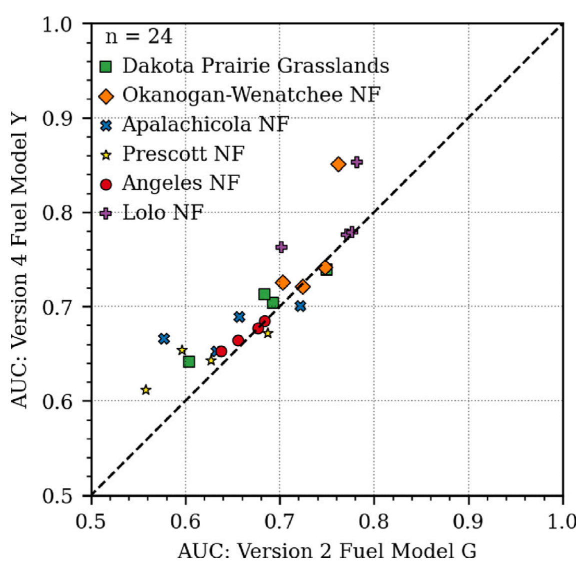

Fig. 9. Comparisons between the Area Under the Receiver Operating Characteristic (ROC) Curve (AUC) determined from historical associations between fire occurrence data and fire danger metrics output from NFDRS Version 2 fuel model G (x-axis) and Version 4 fuel model Y (y-axis). All six evaluation sites are included (Fig. 7) and each has four comparisons (i.e., one per fire danger metric: ERC, BI, SC, and IC) to provide $n = 24$ observations.

herbaceous and 304% for woody fuels. Our findings highlight the need for further research to establish regional seasonal limits and extremes for herbaceous and woody LFMC values by fuel type.

6.1.3. Fuel model simplifications

Simplifying the fuel models in the USNFDRS is helpful for training system users but it can also provide more robust ways to assess fire danger changes across regions. Landcover maps exist that can easily distinguish between grasses, shrubs, brush and timber and these fuels maps could be used to assess the local impacts of climatic changes on fire potential. Historically, applications of USNFDRS to assess regional fire potential changes have ignored fuel type differences and constrained analyses to a single fuel type. This new, simple fuel type description could allow future studies to contrast the differential response of fire potential across plant functional types both historical and into the future. An example NFDRS V4 fuel model map is presented in Fig. 10. This map was derived from the LANDFIRE fire behavior fuel models map that was aggregated by fuel types (https://www.landfire.gov/lf_230.php). These maps could be the foundation of a fully gridded fire danger forecast system in the future.

Historically, many studies have emphasized the use of a fixed index and fuel model for NFDRS, such as the Energy Release Component for Fuel Model G, to standardize model behavior across large regions (Andrews et al., 2003; Riley et al., 2013; Abatzoglou, 2013; Jolly et al., 2015). Our results suggest that explorations of the relationships between fire weather and fire activity may be strengthened by exploring the interaction and local sensitivity of fire danger indices to fine and coarse dead fuel moisture as well as live herbaceous and woody fuel moisture. Large fire activity for each region tested in this study was best characterized by different fuel models and indices (Table 13). Fuel model V is only a mixture of fine dead fuel (1 h) and herbaceous fuels, while fuel models W and X are a mixture fine dead fuels (1 and 10 h) and both live woody and herbaceous fuels. Fuel models Y and Z do are not sensitive to live fuels but each have different distributions of fine and coarse dead fuel loadings. Large fire probabilities at four of the six USNFDRS V4 model evaluation sites were best predicted using fuel models with live fuels (LFD|FD column in Table 13). In contrast, Fire Days (which are analogous to predicting ignition probability) were best predicted at each evaluation site using just the Energy Release Component and fuel models that only have dead fine and coarse fuels. Those fuel models, Y and Z, are essentially similar or equivalent to the old Fuel Model G. Overall, this suggests that USNFDRS Version 4 could improve our understanding of the factors that influence the times and places of new wildfire ignitions as well as the contrasting factors that lead to the development of large fires.

6.2. System user feedback

Components of this revised USNFDRS have been implemented in operational tools for the last 12 years. For example, the Nelson–Carlson model was built into the Weather Information Management System and the values have been monitored and locally compared to fire activity and this dead fuel moisture model was built into fire behavior simulators such as FlamMap to provide spatio-temporally variant fine fuel moistures (Finney, 2006). Additionally, the GSI-LFMC models have been built into the Wildland Fire Decision Support System since 2010 as an optional way to determine live fuel moisture contents for probabilistic fire behavior simulations (Noonan-Wright et al., 2011) and the Growing Season Index has been incorporated into FireFamily+ since 2010. These field tests of the sub-models have allowed us to understand their behavior across a variety of ecosystems and socialize their implementation into USNFDRS over time.

Our updates to the US National Fire Danger Rating System started in 2016 and the final model version was accepted for operational, nationwide use in March 2023. Feedback was captured both from

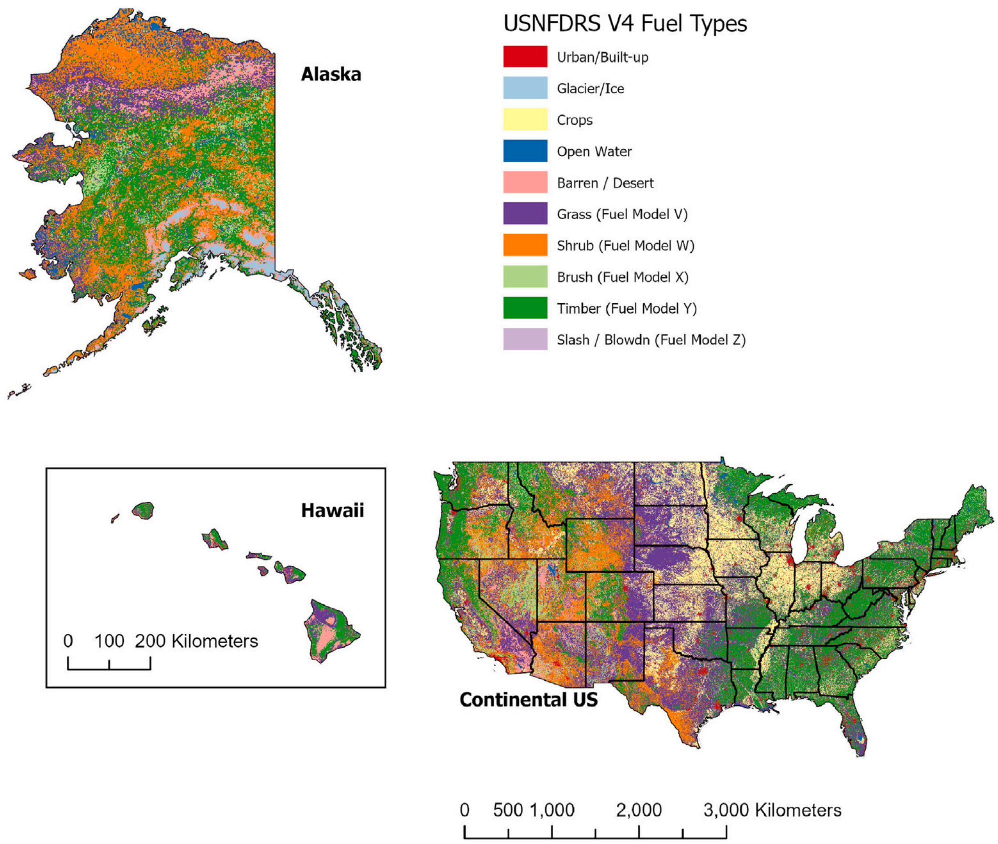

Fig. 10. Example NFDRS Version 4 fuel model maps derived from the Scott and Burgan 40 fuel models from LANDFIRE (Rollins, 2009) (Version 2.3.0 (2022)). Fuel type maps like this may help expand the way that NFDRS4 is implemented across large landscapes with highly varying vegetation types.

the initial integration of the models into the Weather Information Management System (WIMS) starting in 2017 and from field users over the 2023 fire season. Some critical observations were made of the full Version 4 implementation. Generally, users observed that the Version 4 model performs as well or better than Version 2 with a few caveats. First, the lack of live fuel loading in Fuel Model Y means that fire danger is sometimes over-rated during unusually hot/dry periods even if the live fuels are not available to burn. Additionally, the lack of moderate and heavy dead fuel loading in Fuel Model X leads to an index that is very responsive to live fuel conditions and day-to-day variations in weather but that is not equally responsive to longer-term dryness over weeks or months. We also observed some challenges implementing GSI locally but many of these challenges were mitigated when the final precipitation control was added. Local calibration procedures documented here will help provide better system outputs for live fuel dominated systems. Our intent is to leverage these lessons learned to guide the development of future improvements to the fuel moisture models and fuel models as part of USNFDRS Version 5.

6.3. Other limitations and future needs

6.3.1. Needs for better drought metrics/indices

Drought is an important component of wildland fire potential but historically, with the exception of the McArthur Forest Fire Danger Index and the Drought Code of the Canadian Forest Fire Danger Rating System, most fire danger rating systems do not include any long-term drought metrics that quantify water deficits over monthly scales or longer. While the Keetch–Byram Drought Index is included in the USNFDRS, its performance across a wide range of biomes is varied (Krueger et al., 2022). The simplified water balance of KBDI heavily focuses on water loss through transpiration but mainly ignore losses through evaporation. As such, future NFDRS versions must be built to use new or emerging drought indices that implement a more complete representation of the site water balance. Within USNFDRS, the Drought Fuel Loading variations (from USNFDRS Version 3) are driven by KBDI (Burgan, 1988) and they can affect the seasonal ranges of fire danger indices during drought conditions by adding more available fuel across the dead fuel size classes proportional to their initial loadings. Therefore, KBDI alone can impact the dynamics of computed indices independent of live and dead fuel moisture. If KBDI does not perform equally across the country it could lead to inconsistencies in regional fire danger. Thus it is desirable to have a more robust and generalized drought index that is tested globally for use as a replace to KBDI in USNFDRS.

6.3.2. Needs for better fire danger components and indices

The core fire danger components and indices models, such as the Energy Release Component, Spread Component, Ignition Component and the Burning Index, used in USNFDRS are based on the fire spread model is based on Rothermel (1972). This model has been staple in fire operations and research for over 50 years but it is antiquated. New three-dimensional computational fluid dynamics-based fire behavior models, such as FIRETEC (Linn et al., 2002) and the Wildland-Urban Interface Fire Dynamics Simulation (WFDS) (Mell et al., 2007), have emerged to assess relationships between fuels, weather, terrain and fire behavior characteristics such as rate-of-spread and intensity. Future work should explore ways to leverage these models in numerical experiments to create simplified equations to replace the core fire danger component/index models with more robust and modern fire behavior assessment tools.

6.3.3. Needs for higher resolution fire danger observations and forecast

This new USNFDRS revision also paves the way to leverage geospatial analysis and forecast weather data to transform how we deliver fire hazard/danger information in the future. Previous version of USNFDRS required manual user inputs such as the State-of-the-Weather and Green-up dates (Deeming et al., 1977) that were difficult to derive spatially but the implementation of the Nelson–Carlson dead fuel moisture model the GSI-based live fuel moisture model have made the USNFDRS V4 fully automated and able to characterize dead and live fuel dynamics, and subsequent fire danger components and indices, spatially using gridded weather, fuels and terrain information. Future work can also include the integration of forest canopy densities to better characterize 'Wind Adjustment Factors (WAFs)' used to estimate near-surface windspeeds (Massman et al., 2017) and to better scale these WAFs over space and time (Sutherland et al., 2023). Additionally, linking canopy fuel dynamics from biogeochemical cycling models to characterize dynamic surface fuel loads may further improve geospatial predictions of fire danger, especially in areas with deciduous overstories (Eastaugh and Hasenauer, 2014). Finally, even with these spatio-temporal assessments of fire hazard (danger), future systems should consider the integration of socio-economic factors and responder exposure to better prepare for and mitigate risk to communities and firefighter (Chuvieco et al., 2023).

6.3.4. Needs for improved fire danger metric evaluation

Comparing USNFDRS Versions 2 and 4 has reinforced the simplicity and utility of the ROC and AUC for assessing the ability of fire danger components and indices to capture the weather and fuels conditions conducive to new wildfire occurrences. Future work should consider incorporating these techniques and metrics into FireFamily Plus where they can be used in more practical applications, such as developing Fire Danger Operating Plans (FDOPs). Fire danger rating systems – and particularly the USNFDRS – have traditionally been used to predict new fire activity. This has partly been due to the original intent of the USNFDRS (i.e., representing conditions at the head of an initiating surface fire) and the availability of historical fire occurrence data that only contains a record of the origin location and discovery date of newly reported wildfires. However with daily fire observations obtained from incident status summary (ICS-209) forms (St. Denis et al., 2023) or from satellite based active fire products (Schroeder et al., 2014; Giglio et al., 2016), recent efforts have demonstrated that beyond the ability to predict new fire activity, fire danger has the potential to predict fire activity after ignition (Freeborn et al., 2015). Future work should consider developing a streamlined process for loading daily fire observations (e.g., active fire pixel counts and/or fire radiative power) into FireFamily Plus for evaluating the capability of the USNFDRS to predict ongoing fire activity beyond the discovery date. Together, relationships between fire danger, new fire-days and active-fire-days offer an opportunity to cover the full spectrum of fire management scenarios, from planning prescribed fires, to preparing for initial and extended attack, to monitoring fires for resource benefit.

6.4. Components of a fire danger rating system

The term 'Fire Danger Rating System' is often a misnomer because the term is often used to describe a numerical model and not the full system required to support its use. In reality, the system needed to actually use the fire danger information to support decision making is much broader. A well-formed Decision Support System (DSS) has five components (Stanescu and Filip, 2011): 1.) Model base, 2.) Database, 3.) Knowledge engine, 4.) User Interface/User Experience (UI/UX) and 5.) Users/Stakeholders (Fig. 11). Model bases, like the fire danger model presented in this paper, form the backbone of the system but the model base alone is insufficient to provide realtime decision support tools to users. It must be supported by a real-time database of fuels, weather and terrain information. Additionally, Decision support plans (Knowledge Engines) must be created that link fire danger levels to appropriate decisions such as when and where to staff firefighters, what types and how many resources are deployed during an initial wildfire response or when open burning restrictions implemented. Finally, a User Interface must make the information readily accessible and usable by the User and/or Stakeholders. Throughout the process of designing these decision support system, it is important to consider the needs of various user communities to better enable these systems for polycentric decision making (Zulkafli et al., 2017) and also to engage these user communities in the design of the final user interface (Díez and McIntosh, 2009; Newman et al., 2017). NFDRS users span from firefighters and fire managers to private industry and the public. The work presented here forms from the foundation of the Model Base but the rest of the system must be implemented if fire danger information can be leveraged to make sound decisions. Further, USNFDRS outputs must be translated into critical breakpoints to guide the development and implementation of decision support plans (Andrews et al., 1998). In the United States, the Weather Information Management System (WIMS) provides the foundational database and user interface, while Knowledge bases are created locally in the form of Fire Danger Operating Plans or Seasonal Trend Analyses which are mandated by policy for all firefighting units (National Wildfire Coordinating Group (NWCG), 2023). It is important to keep these components in context when designing fire danger rating systems for operational use and to continue to engage the diverse user communities in the design of the final user interfaces to the system to ensure effective use.

7. Conclusions

Here we have presented the development and implementation of the first revisions to the US National Fire Danger Rating System model in more than three decades. We have detailed the implementation of a physically-based, scalable dead fuel moisture model and we have evaluated a new physiologically-based live fuel moisture model. We have shown that reducing the number of fuel models and focusing on five broad fuel types ensures that fuel models are truly unique. Finally, we assessed the impact of these USNFDRS revisions across six US National Forests that span a range of climate, fuels and topography. Both versions demonstrated similar seasonality despite differences in absolute index values. Moreover, good agreement between AUC values demonstrated that despite the largely streamlined and automated nature of the USNFDRS revisions, in most cases Version 4 either outperformed or was indistinguishable from the Version 2 when compare to historical wildfire occurrence. The iterative process of research, development, implementation and evaluation provided invaluable insights into the steps necessary to update the USNFDRS without interrupting user access, thus establishing a working framework for performing future revisions. This next-generation fire danger model paves the way for a nationally-relevant, fully-automated fire danger rating system that can adequately depict fire danger across a range of climates and fuel types but that is simpler to understand and communicate. This new model could be easily adapted for use worldwide.

CRediT authorship contribution statement

W. Matt Jolly: Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Patrick H. Freeborn:** Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis. **Larry S. Bradshaw:** Writing – review & editing, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Jon Wallace:** Writing – review & editing, Validation, Project administration. **Stuart Brittain:** Writing – review & editing, Visualization, Validation, Software, Methodology, Investigation, Conceptualization.

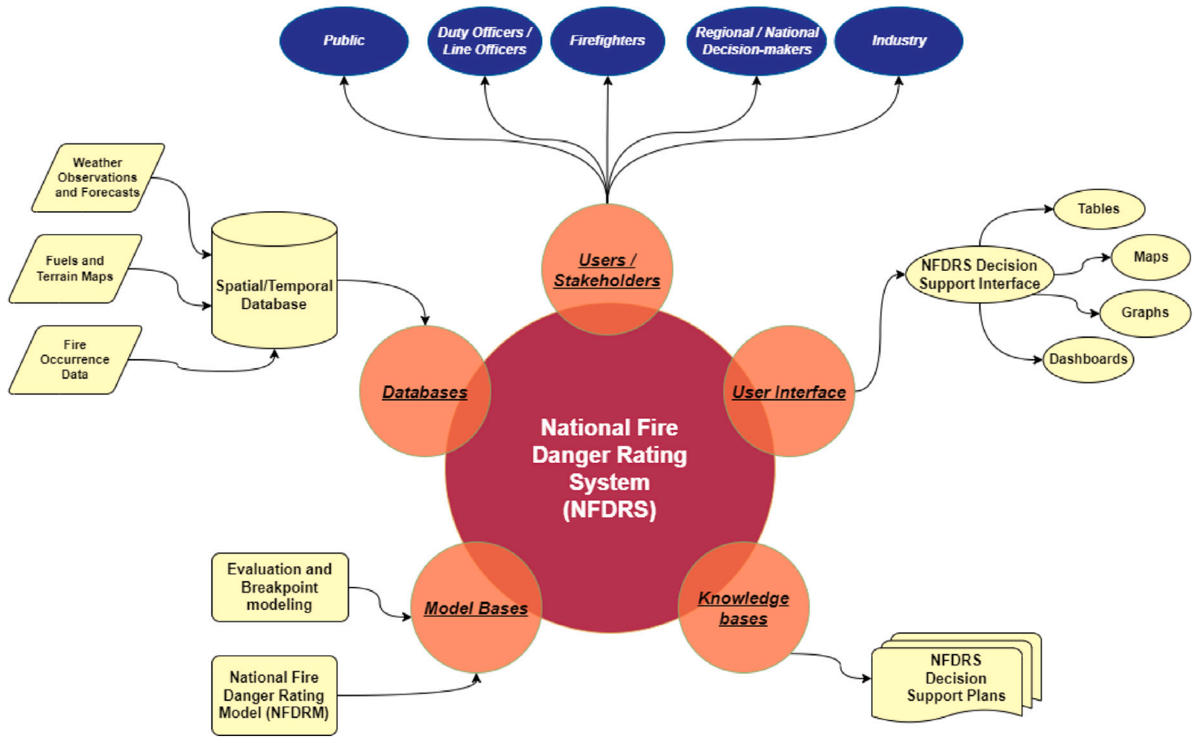

Fig. 11. The five components of a Fire Danger Rating System based on the decision support system characterization of Stanesc and Filip (Stanescu and Filip, 2011). Each of the five components is vital to ensuring that a fire danger rating model like the one presented here is made available in real-time to support wildland fire management tactical and strategic decisions.

Declaration of competing interest

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

Data availability

Data used are shared as an openly downloadable Jupyter Notebook on Github. The link is in the paper.

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