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A Comparative Review of Wildfire Danger Rating Systems: Focus on Fuel Moisture Modeling Frameworks

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Abstract

As wildfires intensify globally due to climate change, accurate wildfire danger forecasting systems have become essential for effective disaster management and early warning. Fuel Moisture Content (*FMC*), defined as the ratio of water mass to dry fuel mass, plays a critical role in determining ignition probability and fire spread dynamics. This study conducts a comparative analysis of five major national wildfire danger rating systems: the National Fire Danger Rating System (NFDRS, USA), Canadian Forest Fire Danger Rating System (CFFDRS), European Forest Fire Information System (EFFIS), Australian Fire Danger Rating System (AFDRS), and the Korean Forest Fire Danger Rating System (KFDRS). Using a multi-criteria comparative framework, the systems were evaluated based on fuel classification structure, input variables, modeling approach, and spatiotemporal prediction resolution. The results reveal substantial disparities in spatial resolution (100 m to district-level), temporal resolution (hourly vs. daily), and fuel moisture modeling approaches (physics-based, index-based, and hybrid systems). Specifically, NFDRS and AFDRS provide high-frequency forecasting with hourly temporal resolution, operating at spatial resolutions of 1 km and 100 m, respectively, and incorporating dynamic fuel moisture modeling. In contrast, CFFDRS and KFDRS primarily rely on daily index-based predictions. Furthermore, while many global systems increasingly leverage remote sensing and machine learning for real-time *FMC* estimation, South Korea's KFDRS remains predominantly empirical and weather-driven. The analysis identifies critical limitations in the KFDRS, including coarse spatial resolution (district-level), limited integration of Live Fuel Moisture Content (*LFMC*) modeling, and the lack of AI-augmented hybrid approaches. Accordingly, this study proposes a phased three-stage policy roadmap (2026–2035), emphasizing sensor-network expansion, AI–physics fusion modeling, and high-resolution (10 m) *FMC* mapping to enhance forecasting accuracy in complex terrains. These findings provide strategic insights for improving wildfire risk management and supporting the transition from reactive response to predictive wildfire forecasting under increasing climate variability.

Keywords: forest fire prevention; early-warning systems; fuel management; machine learning models; fuel moisture content; wildfire danger rating

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1. Introduction

As climate change accelerates globally, wildfires have become increasingly frequent, intense, and widespread, resulting in severe ecological degradation and socio-economic disruption. Once limited to specific regions during dry seasons, wildfires are now a perennial global hazard. For instance, California's 2020 wildfires scorched vast tracts of land,

Australia's "Black Summer" (2019–2020) led to the loss of over 300 million wild animals, and Canada's 2023–2024 season recorded unprecedented burned areas. These megafires exacerbate climate feedback loops, accelerating soil erosion, degrading water and air quality, and releasing massive carbon emissions, including sharp surges in PM2.5. South Korea is no exception. While wildfires were previously seasonal, limited to spring coniferous forests, they now occur year-round—including in autumn deciduous forests and dry grasslands during winter. The 2022 Uljin–Samcheok wildfire typified this expansion. Contributing drivers include rising temperatures, prolonged droughts, intensified wind patterns, and an expanding wildland-urban interface. These factors underscore the need not just for accurate forecasting but for preemptive wildfire prevention, prioritization of response [1], and real-time resource allocation through scientific systems. Wildfire Danger Rating Systems (WFDRS) offer one such approach. These systems quantify ignition likelihood, spread rate, and fire intensity by integrating meteorological, topographic, and vegetation parameters [2]. Among the various inputs, Fuel Moisture Content (*FMC*), defined as the ratio of water to dry biomass, remains a pivotal variable. When *FMC* exceeds 30%, fire ignition is unlikely, whereas values below 10% are associated with sharply elevated risk [3]. A 10% decrease in *FMC* can raise ignition probability by over 60% due to the energy required for moisture evaporation [4,5]. Recent research has further emphasized that maintaining accurate *FMC* thresholds is critical for effective landscape-scale fire risk modeling [6]. However, overemphasis on *FMC* alone may neglect other critical indicators. Remote sensing variables such as *NDVI* (Normalized Difference Vegetation Index), LST (Land Surface Temperature), and *NDWI* (Normalized Difference Water Index) are increasingly used to monitor vegetation stress and ecosystem health [7,8]. Incorporating these indicators can complement *FMC* by providing spatially extensive, near-real-time insight into forest vulnerability, particularly through integrated global fuel moisture databases [9]. Global WFDRS reflects diverse modeling strategies tailored to regional ecosystems. The U.S. National Fire Danger Rating System (NFDRS) uses time-lag fuel classes; Canada's Canadian Forest Fire Danger Rating System (CFFDRS) implements a multi-layer model composed of *FFMC*, DMC, and DC for surface litter, intermediate duff, and deep organic layers, respectively [10]. The European Forest Fire Information System (EFFIS) integrates satellite-based indices, while Australia's Australian Fire Danger Rating System (AFDRS) incorporates equations adapted to eucalyptus-dominated landscapes. Yet most systems focus narrowly on short-term fire danger, with limited consideration for chronic drought stress or fuel accumulation trends. Moreover, the concept of forest monitoring systems, that is, dynamic surveillance of forest health and fuel load conditions, is often underrepresented. Particularly, fuel management (e.g., controlled burns, thinning, or vegetation removal) is treated separately from WFDRS in many frameworks, despite its importance for long-term risk mitigation. Despite the growing number of wildfire danger rating systems implemented worldwide, systematic comparative analyses focusing on their fuel moisture modeling frameworks and operational forecasting structures remain limited. Previous studies have primarily examined individual systems or specific modeling techniques, such as dead fuel moisture dynamics, remote sensing-based fuel moisture estimation, or machine learning-based wildfire prediction. However, comprehensive cross-system comparisons that evaluate the structural characteristics, modeling approaches, spatial and temporal resolutions, and data integration strategies of national wildfire danger forecasting systems are still scarce. In particular, significant differences exist among national systems in terms of fuel classification methods, input variables, prediction resolution, and technological integration, including the use of remote sensing data and artificial intelligence techniques. These differences make it difficult to systematically evaluate the strengths and limitations of each system and to identify potential development pathways for improving wildfire danger forecasting

capabilities. To address this research gap, this study conducts a comparative analysis of five representative national wildfire danger forecasting systems: The National Fire Danger Rating System (NFDRS), the Canadian Forest Fire Danger Rating System (CFFDRS), the European Forest Fire Information System (EFFIS), the Australian Fire Danger Rating System (AFDRS), and the Korean Forest Fire Danger Rating System (KFDRS). The comparison focuses on fuel moisture modeling structures, input variables, modeling approaches, and spatiotemporal prediction resolutions. The objectives of this study are threefold: (1) to analyze the structural characteristics of major global wildfire danger forecasting systems, (2) to identify technological differences and limitations among these systems, and (3) to propose future development pathways for improving wildfire danger forecasting systems, particularly for South Korea.

2. Methodology

2.1. Data Collection and Analysis Procedures

This study employed a dual approach—systematic literature review and analysis of official system documentation—to compare the structures and algorithms of national wildfire danger forecasting systems that utilize Fuel Moisture Content (*FMC*) as a core variable. The systems analyzed include those officially operated in the United States (NFDRS), Canada (CFFDRS), the European Union (EFFIS), Australia (AFDRS), and South Korea (National Wildfire Danger Forecasting System) [11–13].

These five systems were selected because they represent the most widely implemented operational wildfire danger forecasting frameworks across different climatic regions, including North America, Europe, Oceania, and East Asia. To understand the structural and operational frameworks of each system, official manuals, technical reports, and policy documents issued by national forest services and wildfire agencies were collected and reviewed. From an academic standpoint, research articles and technological development trends were identified using major scholarly databases such as Web of Science, Scopus, ScienceDirect, and Google Scholar. Relevant studies were selected based on their focus on wildfire danger rating systems, fuel moisture modeling techniques, and operational fire danger forecasting frameworks. Keywords such as "Wildfire danger rating system," "fuel moisture content (*FMC*)," and "fire danger index" were used to retrieve relevant literature published between 1990 and 2025.

The analysis was conducted across several dimensions. First, the structure of fuel classification was examined by assessing whether systems distinguished between Dead Fuel and Live Fuel, and further stratified fuel layers into surface, duff, and deep layers. Second, *FMC* estimation model types were classified as physics-based, satellite-based, or AI-based, and the algorithmic structure adopted by each country was analyzed accordingly [14]. Third, the composition of input data was assessed based on the inclusion of key variables such as meteorological data (temperature, humidity, precipitation, wind speed), topographical data (elevation, slope, aspect), vegetation, and soil information.

Fourth, prediction resolution was compared in terms of both spatial (meters to kilometers) and temporal (hourly to daily) scales, along with the geographic coverage (local, national, or continental level) and real-time forecasting capabilities. Fifth, the structure of the danger index calculation was evaluated by analyzing whether models used single or multiple indices and whether they were based on empirical or physical equations.

Based on these criteria, each national system was quantitatively compared within a unified framework. Quantitative comparisons involved measuring the number of input variables, resolution levels, and index calculation elements, while qualitative comparisons focused on structural features, operational strengths and limitations, and applicability of each system. This comparative approach was informed by recent methodologies, such as

the FIRER model framework proposed by [15], which enables multi-system comparison within a standardized structure.

The research procedure is illustrated in Figure 1, which outlines the five key steps of the study: (1) data collection, (2) trend analysis, (3) design of a comparative framework, (4) result interpretation, and (5) policy recommendations. Arrows indicate the research flow, and different colors represent distinct stages of the methodology. Each evaluation criterion was qualitatively assessed using a comparative scoring approach (high, medium, low) based on system capabilities, data integration level, and modeling complexity, enabling standardized cross-system comparison.

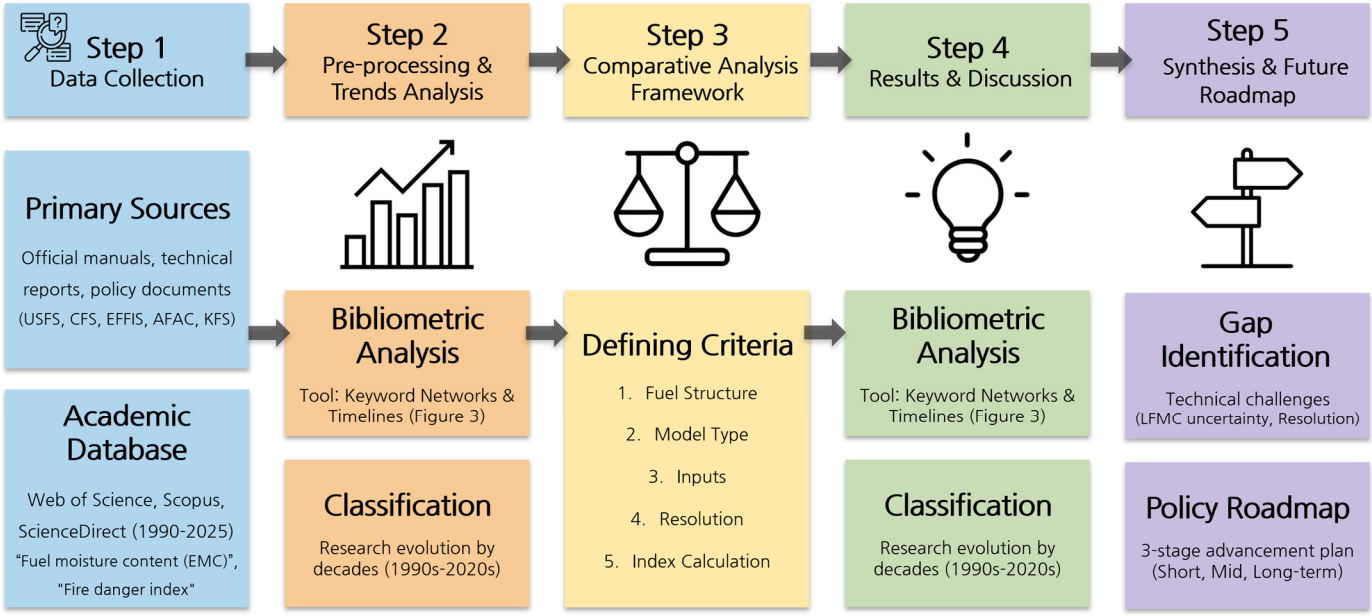


Figure 1. Flowchart of the research procedure. Arrows indicate the research flow, and different colors represent distinct stages of the methodology.

2.2. Historical Context of Fuel Moisture Content Research

To systematically analyze the evolution of wildfire danger forecasting systems related to fuel moisture content (*FMC*), this study conducted a literature review of scholarly articles published between 1989 and 2025. Using the Web of Science database, representative core studies were selected by applying key terms such as "fire danger rating system," "fuel moisture," and "fire danger index".

Analysis of research trends over the past 35 years reveals a clear shift in the technological paradigm. Research in the 1990s primarily focused on laboratory-based investigations into fuel combustion characteristics and the physical impacts of moisture content, which provided the foundational data for developing basic combustion models. In the 2000s, the utilization of satellite remote sensing data—such as MODIS and Landsat—became widespread, and index-based models within the Canadian Forest Fire Danger Rating System (CFFDRS) were standardized and adopted in operational settings. The 2010s marked the emergence of predictive models integrating meteorological reanalysis data with machine learning algorithms like Random Forest and Artificial Neural Networks (ANN), significantly enhancing *FMC* estimation accuracy. Currently, in the 2020s, research is dominated by integrated wildfire forecasting systems that fuse deep learning models—such as LSTM and CNN—with real-time sensor data and high-resolution satellite observations [16–19].

This study performs a multifaceted visualization analysis to present these technological advancements and key milestones over the last three decades. First, the keyword-based text mining results in Figures 2 and 3 identify shifts in research topics and core materials. Figure 4, titled "Bibliometric timeline of wildfire danger research," presents a roadmap of key milestones by arranging influential studies chronologically. Finally, the Cite Space-based cluster analysis in Figure 5 demonstrates how these studies are structured within the actual reference network. This visualization confirms the knowledge evolution process, transitioning from early physical modeling through remote sensing to current AI-based smart defense systems [20,21]. As shown in Figures 2 and 3, recent research trends are increasingly centered on fuel moisture estimation, remote sensing technologies, and machine learning-based wildfire prediction, indicating a shift toward data-driven wildfire forecasting approaches. Figure 4 further illustrates a chronological transition from early laboratory-based combustion studies to modern integrated forecasting systems combining meteorological data and artificial intelligence. In addition, Figure 5 reveals that recent studies form densely connected clusters around AI-based modeling and satellite-driven monitoring, highlighting the convergence of remote sensing and data-driven methodologies in wildfire research.

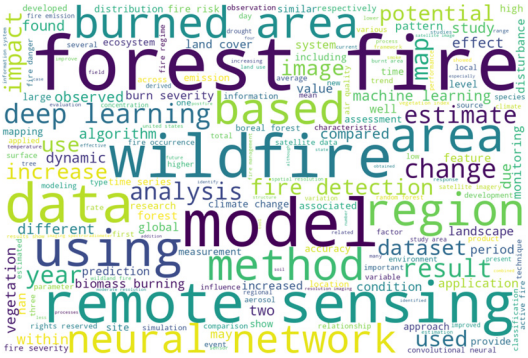


Figure 2. Keyword text mining visualization for wildfire danger forecasting system research. The different colors are used for visual differentiation of keywords and denote thematic clustering, while font sizes represent the relative frequency and research importance of each term within the analyzed literature.

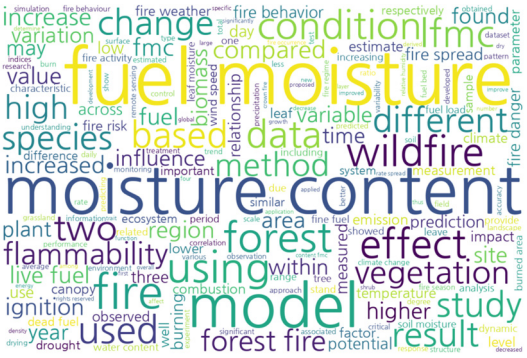


Figure 3. Keyword text mining visualization for Fuel Moisture Content (*FMC*) research. The various colors facilitate visual distinction between individual terms and signify categorical relevance, while the text dimensions illustrate the occurrence frequency and prominence of each keyword.

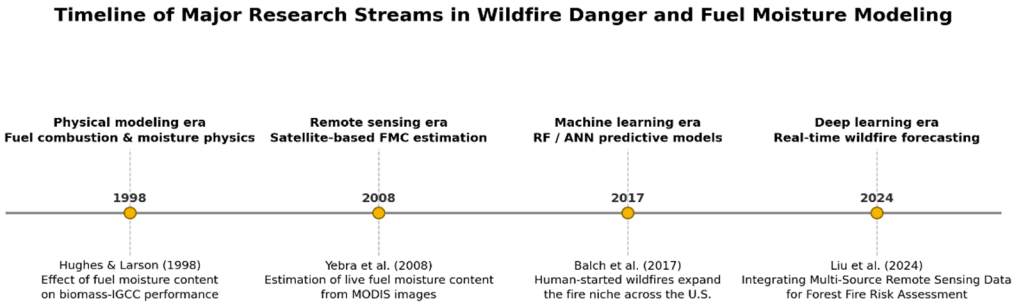


Figure 4. Trends in Wildfire Danger Forecasting and Fuel Moisture Research [22–25].

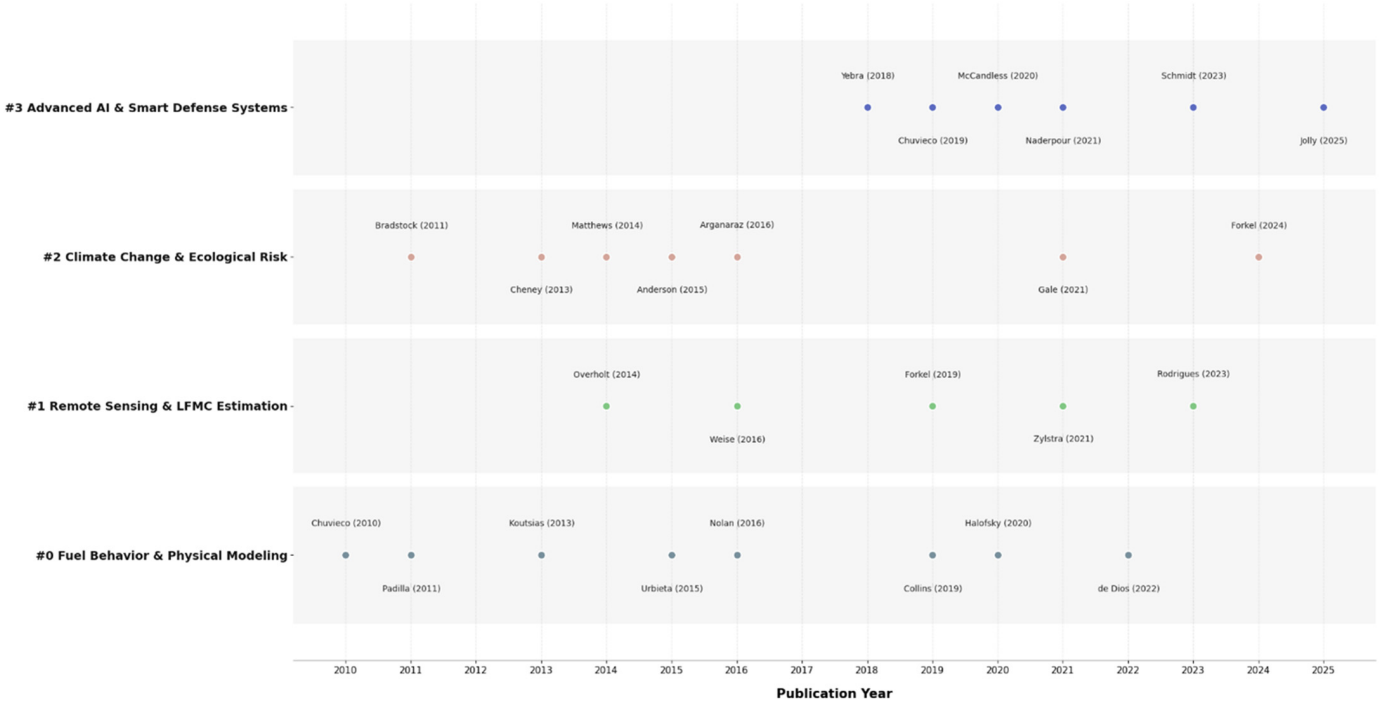


Figure 5. Master Roadmap: A chronological bibliometric analysis of global wildfire danger forecasting trends [6,16,26–51].

These research trends clearly demonstrate a paradigm shift from simplistic index-based estimations toward high-precision wildfire danger forecasting frameworks centered on *FMC*, leveraging diverse remote sensing data sources and advanced AI algorithms.

2.3. Field-Based Measurement Methods: Oven-Drying Method, Fuel Moisture Sticks, Electrical Resistance Method

The most accurate way to measure fuel moisture is through direct sampling from the field, followed by laboratory analysis using the oven-drying method. This method is recognized as the reference technique globally. In this process, fresh fuel samples (weighing between 10–50 g) are collected and placed in an oven at temperatures ranging from 95 °C to 105 °C for 16 to 24 h. After drying, the moisture content (*FMC*) is calculated by measuring the difference in weight between the wet (M_wet) and dry (M_dry) samples. The accuracy of this method is typically ±1%–2%.

The advantage of the oven-drying method is its ability to clearly distinguish between dead and live fuels, as well as to quantify the moisture content in biologically active tissues. However, the method is labor-intensive, and the time lag between sample collection and analysis makes it impractical for real-time large-scale forecasting systems. Moreover, it lacks spatial representativeness, limiting its applicability in wide-area fire prediction.

To overcome these limitations, fuel moisture sticks were developed as a practical field-based tool. Standardized by the U.S. National Fire Danger Rating System (NFDRS), these sticks are typically made of wood (with a 10-h time-lag classification) and are fixed at observation stations in the field [52]. The sticks automatically measure weight at intervals of 15 to 30 min, tracking moisture fluctuations in response to local weather conditions. This method allows real-time tracking of moisture changes, and it is widely used in automated systems such as Remote Automated Weather Stations (RAWS).

Fuel moisture sticks are advantageous for continuous monitoring and long-term observations. However, the moisture absorption properties of the wood may not perfectly replicate those of actual forest fuels, requiring calibration factors. Moreover, they are unsuitable for measuring live fuels, as these involve more complex physiological processes.

The electrical resistance method is another portable and quick method for measuring *FMC* in the field. It works by inserting two electrodes into a fuel sample and measuring changes in electrical resistance, which vary with moisture content. Moisture increases the ion conductivity of the fuel, reducing its resistance. This method is particularly useful for rapid, on-site assessments, such as during emergency situations or nighttime operations.

The primary advantage of the electrical resistance method is its speed, providing near-instantaneous readings. However, it has some limitations. Measurement accuracy can vary depending on the ion content of the sample (e.g., potassium and calcium in live fuels), leading to potential errors of ±5%–10%. Additionally, the method is less reliable for coarse dead fuels or highly decomposed fuels, such as those found in coastal or marshy areas.

2.4. Remote Sensing-Based Estimation Methods: Satellite Vegetation Indices (NDVI, NDWI) and Thermal Infrared Utilization

Recent advancements in remote sensing technologies, particularly satellite-based systems, have enabled significant progress in estimating Fuel Moisture Content (*FMC*) across large areas. The ability to estimate *FMC* remotely is a critical development, as it allows for the monitoring of vast and inaccessible areas that would otherwise be difficult to assess using traditional ground-based methods.

Satellite imagery from platforms like MODIS (1 km resolution), Landsat (30 m), and Sentinel-2 (10 m) provides multispectral data that can be used to indirectly estimate the moisture and biochemical state of vegetation. Among the most commonly used vegetation indices is the Normalized Difference Vegetation Index (*NDVI*), which uses the difference in reflectance between near-infrared (NIR) and red bands to evaluate vegetation health and biomass. The formula for *NDVI* is as follows:

$$NDVI = \frac{\text{NIR} - \text{Red}}{\text{NIR} + \text{Red}} \quad (1)$$

NDVI values range from 0 to 1, with higher values (0.6–0.9) indicating healthy, well-watered vegetation, while lower values (0.2–0.4) suggest water stress or drought conditions. *NDVI* is widely used to estimate vegetation conditions in fire danger models, although it does not directly measure moisture content, as it primarily reflects vegetation density and photosynthetic activity.

Another important index is the Normalized Difference Water Index (*NDWI*), which is more directly related to moisture content in vegetation [23]. *NDWI* utilizes the green and NIR bands to estimate the water content of leaves, providing a more direct measure of moisture content in vegetation:

$$NDWI = \frac{\text{Green} - \text{NIR}}{\text{Green} + \text{NIR}} \quad (2)$$

NDWI is strongly correlated with Live Fuel Moisture Content (*LFMC*), with a typical coefficient of determination R^2 ranging from 0.65 to 0.85. *NDWI* is particularly effective in monitoring drought conditions and has been shown to be a valuable tool for assessing live fuel moisture. European systems like EFFIS (European Forest Fire Information System) use *NDWI*, combined with other satellite indices, to generate daily *LFMC* maps for Europe. This approach provides a spatially continuous and near-real-time overview of fuel moisture, which is essential for early wildfire detection and risk prediction.

In addition to vegetation indices, thermal infrared (TIR) imagery is another effective tool for monitoring fuel moisture. TIR uses surface temperature (LST) data to indirectly estimate the moisture content of vegetation, as moist vegetation tends to have lower surface temperatures due to evaporative cooling. By analyzing the relationship between LST and vegetation moisture content, thermal infrared data can help identify areas of moisture stress.

One of the main advantages of TIR-based methods is their ability to penetrate cloud cover, making them more reliable in regions with frequent cloud cover. However, challenges remain in atmospheric correction and the mixed pixel effect, where surface heterogeneity (such as the presence of bare soil or rock) complicates moisture estimations.

While remote sensing methods provide valuable data for monitoring large areas, they do have limitations. The spatial resolution of satellite images often ranges from 10 m to 1 km, meaning fine-scale variability in fuel moisture—particularly in dead fuels—may not be captured accurately. Additionally, cloud cover, varying revisit periods (typically 5 to 16 days), and resolution-accuracy trade-offs pose challenges for real-time forecasting, especially in fast-developing fire situations.

2.5. Meteorological Data and AI-Based Modeling: VPD-Based Regression Models and Machine Learning (Random Forest, LSTM, Etc.)

Meteorological-based estimation is one of the most widely used real-time methods in wildfire danger forecasting systems. The Vapor Pressure Deficit (*VPD*) is a key atmospheric variable used to quantify the drying power of the air. *VPD* is the difference between the saturated vapor pressure (e_s) and the actual vapor pressure (e), and is calculated using the following formula:

$$VPD = e_s(T)\left(1 - \frac{RH}{100}\right),\ e_s(T) = 0.6108\exp\left(\frac{17.27T}{T + 237.3}\right) \quad (3)$$

where $e_s(T)$ is the saturated vapor pressure at temperature T, and e is the actual vapor pressure. *VPD* is a direct indicator of the atmospheric demand for moisture, and it is inversely correlated with *FMC* (Fuel Moisture Content). As *VPD* increases, the rate of evaporation accelerates, leading to a reduction in *FMC*, which, in turn, increases fire danger.

Both the NFDRS (National Fire Danger Rating System) in the U.S. and the CFFDRS (Canadian Forest Fire Danger Rating System) utilize this relationship between *VPD* and *FMC*. They calculate Equilibrium Moisture Content (*EMC*) using meteorological data, and then use time-lag models to predict changes in *FMC* over time. This approach is straightforward and well-suited to real-time operational forecasting, as it primarily relies on meteorological inputs like temperature, humidity, wind speed, and precipitation.

However, this method has its limitations. It cannot adequately account for differences in fuel types, soil properties, or vegetation structure. It is also less effective at predicting the moisture content of live fuels, which are subject to complex physiological moisture regulation mechanisms such as transpiration, water uptake, and drought stress.

To overcome these limitations, AI-based models have been increasingly incorporated into wildfire forecasting systems. These models leverage machine learning algorithms to

analyze vast amounts of input data from multiple sources, including meteorological data, satellite indices (e.g., *NDVI*, *NDWI*), soil moisture, and topographic information, in order to predict *FMC* more accurately.

Random Forests (RF), XGBoost, Long Short-Term Memory (LSTM) networks, and Convolutional Neural Networks (CNN) are among the most common machine learning models being applied to *FMC* prediction. These AI models have shown improvements over traditional regression-based methods, offering better performance in terms of R^2 (coefficient of determination) values (typically between 0.85–0.92) and a reduction in Root Mean Square Error (RMSE) by 20%–40%.

For instance, Random Forest is a popular algorithm due to its ability to handle complex, non-linear relationships between multiple input variables without requiring explicit feature selection. LSTM networks, a type of recurrent neural network, are particularly effective for time-series forecasting tasks, such as predicting *FMC* trends over time based on historical meteorological data. CNNs, which are commonly used in image processing, have been applied to *FMC* prediction by extracting spatial features from remotely sensed images, such as those from MODIS or Landsat, to improve model accuracy.

One of the key advantages of machine learning models is their ability to integrate diverse data types and learn complex relationships automatically. These models do not require explicit physical relationships between variables, allowing them to adapt to diverse environmental conditions and fuel types. They also offer the potential for continuous learning and improvement as more data becomes available.

However, machine learning models also have some drawbacks. They require large, high-quality datasets for training and are prone to overfitting if not properly managed. Moreover, their interpretability is often limited, meaning that it can be challenging to understand how the model is making predictions or which features are most influential in the decision-making process. Additionally, for real-time operational use, these models can be computationally intensive and require substantial processing power, which may be a limiting factor for certain applications.

As such, the trend in wildfire forecasting systems is to integrate AI-based models with traditional meteorological methods, combining their strengths to create hybrid models. This integration can enhance the accuracy of *FMC* predictions while reducing the computational cost and maintaining operational feasibility for real-time use. These hybrid models are particularly promising for incorporating both dead and live fuel moisture content predictions, as well as for handling data from heterogeneous sources such as weather stations, satellite imagery, and sensor networks.

2.6. Synthesis of FMC Estimation Methodologies: A Comparative Analysis

The three core methodologies for estimating Fuel Moisture Content (*FMC*) exhibit distinct and complementary characteristics in terms of precision, spatial coverage, and operational latency. The oven-drying method, a representative field-based approach, remains the global reference standard due to its superior accuracy, typically within ±1%–2%. It allows for a clear distinction between dead and live fuels and provides high-fidelity data on biologically active tissues. However, the labor-intensive nature of sample collection and the 16–24 h laboratory processing time create a significant time lag, making it impractical for real-time, large-scale forecasting. Furthermore, its lack of spatial representativeness limits its utility in predicting fire behavior across broad, heterogeneous landscapes. In contrast, remote sensing-based methods utilizing satellite indices, such as *NDVI* and *NDWI*, offer the unique advantage of continuous monitoring over vast and inaccessible areas at spatial resolutions ranging from 10 m to 1 km. Specifically, *NDWI* has demonstrated a strong correlation with Live Fuel Moisture Content (*LFMC*), with R^2 values typically

between 0.65 and 0.85. Despite these strengths, remote sensing approaches are susceptible to cloud contamination and "mixed-pixel" effects—where spectral signatures from soil and rock interfere with vegetation data—reducing the reliability of moisture estimations in complex or sparse forest strata. Finally, AI-based modeling using modern machine learning algorithms, such as Random Forest and LSTM, has significantly enhanced *FMC* prediction by integrating multi-source data including meteorology, satellite indices, and topography. These models outperform traditional regression techniques, often reducing Root Mean Square Error (RMSE) by 20%–40% and achieving R^2 values between 0.85 and 0.92. While AI models excel at capturing complex, non-linear environmental relationships without requiring explicit physical equations, they demand large, high-quality training datasets and often suffer from limited interpretability, commonly referred to as the "black-box" problem, which can be a constraint for operational transparency.

3. Research Results

3.1. Theoretical Background of Fuel Moisture Content (FMC)

Fuel Moisture Content (*FMC*) is one of the most fundamental physical factors determining wildfire ignition and spread. *FMC* refers to the percentage of water mass in fuel relative to its dry mass, and is calculated using the following formula:

$$FMC\ (\%) = \frac{M_{wet} - M_{dry}}{M_{dry}} \times 100 \quad (4)$$

The higher the *FMC* value, the more moisture the fuel contains, which increases the energy required for ignition and makes flame spread more difficult. In contrast, when *FMC* drops below 10%, even small ignition sources like cigarette butts can easily start fires, and combustion reactions accelerate rapidly. Studies have shown that when *FMC* decreases from 15% to 5%, the ignition probability can increase by a factor of 3 to 5 under the same weather conditions. For this reason, *FMC* is considered one of the most important input variables in wildfire forecasting systems, and the accuracy of its estimation is directly tied to the system's overall reliability. Based on their physical and biological properties, forest fuels are generally classified into dead fuels and live fuels [53]. Dead fuels consist of physiologically inactive materials such as fallen leaves, twigs, deadwood, and decomposed organic matter. These are directly exposed to external environmental conditions such as temperature, humidity, wind, and precipitation, and their moisture content can change rapidly. Because these fuels lack biological mechanisms to retain moisture, they respond sensitively to atmospheric conditions and serve as the primary fuel source for ignition and rapid surface fire spread [54]. Live fuels, in contrast, include green leaves, grasses, shrubs, and new shoots—plant tissues that remain physiologically active. The moisture content of live fuels, referred to as Live Fuel Moisture Content (*LFMC*), varies dynamically depending on plant transpiration, water absorption and transport, and seasonal growth cycles. *LFMC* typically ranges from 60% to 150%, but may sharply decline during drought stress or at the end of the growing season, acting as a critical factor in triggering crown fires. In Mediterranean or arid climates, accurate *LFMC* estimation is essential for long-term wildfire risk prediction. These fundamental differences between dead and live fuels are directly reflected in the design of national wildfire danger forecasting systems. For instance, the U.S. NFDRS and Canadian CFFDRS place greater emphasis on the physical response of dead fuels and have developed precise time-lag models [55], while the European EFFIS and Australian AFDRS systems have recently advanced toward capturing ecological variability in live fuels through satellite remote sensing.

3.2. Time-Lag Concept in Dead Fuels

The rate of moisture change in dead fuels is influenced by fuel particle size, density, and the surface-area-to-volume (A/V) ratio. To quantify these differences, the concept of time lag is introduced. Time lag refers to the characteristic time it takes for a fuel to reach equilibrium with the surrounding Equilibrium Moisture Content (*EMC*). Physically, it reflects the processes of moisture diffusion and heat transfer, and is mathematically expressed as:

$$\tau = \frac{\rho C_v L^2}{4\pi^2 k D} \quad (5)$$

where ρ is the fuel density, C is the specific heat capacity, L is the characteristic length of the fuel particle, k is the thermal conductivity, D is the moisture diffusion coefficient. As the particle size increases (i.e., larger L), the time lag also increases. This means that fine fuels respond more quickly to environmental changes, while coarse fuels respond more slowly. Based on this principle, the U.S. National Fire Danger Rating System (NFDRS) categorizes dead fuels into four time-lag classes. 1-h fuels (diameter < 0.64 cm), such as leaves, grasses, and fine twigs, have a high surface-area-to-volume ratio and respond to environmental changes within a few hours, playing a critical role in ignition. 10-h fuels (0.64–2.54 cm), such as small branches, are sensitive to daily variations in temperature and humidity, and determine the sustainability and early spread of fire. 100-h fuels (2.54–7.62 cm), including larger branches and small logs, reflect multi-day cumulative drying and are important for assessing fire intensity and sustained combustion. 1000-h fuels (diameter > 7.62 cm), such as large logs and dead trunks, reflect long-term drying over weeks to months and serve as long-duration fuel sources and smoldering risks during large-scale wildfires. These time-lag classifications are not based on empirical estimations alone, but on the thermodynamic and moisture-diffusion properties of fuel particles. For example, 1-h fuels can reach 90% of *EMC* within 2–3 h, while 1000-h fuels may require over three weeks under the same conditions. This distinction allows fire behavior models to simulate fuel layer responses with much higher accuracy than single-value *FMC* models, enabling more precise danger assessments Figure 6.

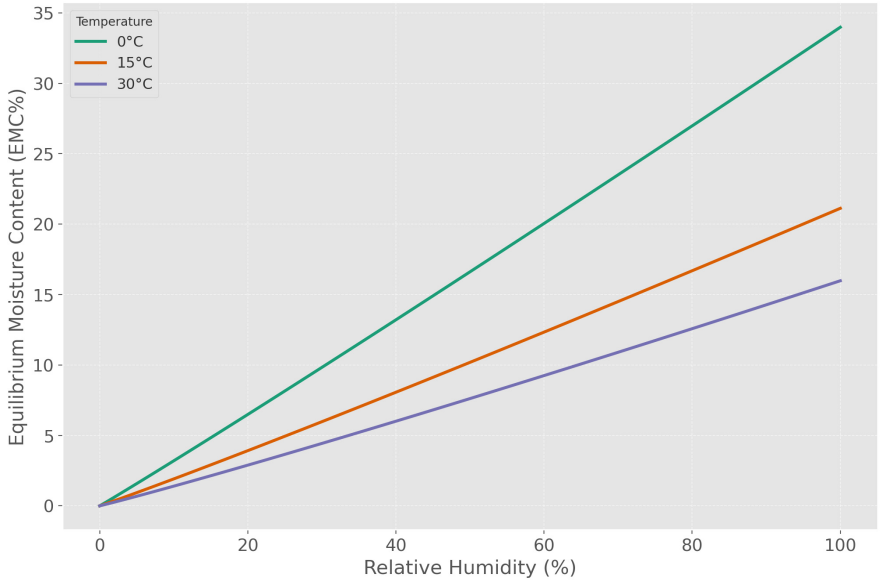


Figure 6. Predicted Drying and Moistening Response of Fuel Based on *EMC* and Time Lag Model.

3.3. Equilibrium Moisture Content (EMC) and Moisture Dynamics

The dynamic moisture changes in dead fuels are driven by the tendency toward equilibrium with external atmospheric conditions, where equilibrium moisture content

(*EMC*) is defined as the moisture level a fuel reaches after prolonged exposure to a given temperature and relative humidity [56]. *EMC* provides the theoretical foundation for all dead fuel modeling and is calculated using Fosberg's widely applied empirical formula.

$$EMC = a + bIn(RH) + cT + dIn(RH)T \quad (6)$$

Here a, b, c, d are coefficients representing the hygroscopic and desorption properties of different fuel types, with relative humidity (RH, %) and temperature (T, °C) as the primary input variables. The convergence of current fuel moisture content (*FMC*) toward *EMC* is governed by time lag and the difference between *FMC* and *EMC*, driven by four key mechanisms: evaporation, condensation, absorption, and physiological water transport [57]. Under hot and dry conditions (high vapor pressure deficit, *VPD*), surface moisture evaporates, causing *FMC* to fall below *EMC*, while vapor condensation during humid nights raises *FMC* above *EMC*. Moisture absorption into capillaries or adsorption onto cell walls proceeds rapidly as a function of RH, and in live fuels, root uptake and transpiration induce seasonal *LFMC* variations [58]. These mechanisms are modulated by external factors, including weather (±1% RH change can alter *FMC* by ±2%–3%), topography (faster drying on south-facing slopes), fuel characteristics (particle size, surface-to-volume ratio, cellulose content), and ecological variables (soil moisture, canopy microclimate). These nonlinear interactions result in substantial spatiotemporal variability in *FMC*, which modern wildfire forecasting systems address through the *EMC*-time lag framework to simplify complexity and enable real-time operations. As single observation stations cannot capture local variability, spatial interpolation combined with remote sensing and reanalysis data integration is essential. These theoretical principles of fuel moisture dynamics provide the foundation for understanding how different national wildfire danger forecasting systems model fuel moisture processes. The following section presents a comparative analysis of major global wildfire danger forecasting systems. These theoretical and methodological insights provide the foundation for the following comparative analysis of national wildfire danger forecasting systems.

4. Comparative Analysis of Global Wildfire Danger Forecasting Systems

To provide a comprehensive understanding of the diverse strategies employed globally for wildfire risk management, this study first outlines the basic operational profiles of leading national wildfire danger forecasting systems. Table 1 summarizes the institutional context of each system, including the operating agencies, primary modeling targets, and geographic application scales. To enable a more analytical comparison, Table 2 presents a quantitative overview of the key technical characteristics of each system, including spatial resolution, temporal resolution, and modeling approach. This comparison highlights clear technological differences among systems. For example, the NFDRS and AFDRS provide high-frequency predictions with hourly temporal resolution, whereas systems such as CFFDRS and KFDRS operate primarily on daily forecasting cycles. In terms of modeling architecture, systems range from physics-based time-lag models (NFDRS) and index-based models (CFFDRS) to satellite-driven and hybrid approaches (EFFIS and AFDRS). To enhance analytical rigor, this study applies a multi-criteria evaluation framework based on four key dimensions: (1) fuel structure representation, (2) modeling approach, (3) data integration level, and (4) spatiotemporal resolution. Each system is comparatively assessed across these dimensions to identify relative strengths and limitations in wildfire danger forecasting performance. As illustrated in Figure 7, the comparative analysis framework is structured around a hierarchical process linking input variables, core modeling parameters, and prediction outputs. Meteorological factors such as temperature, humidity, wind speed, and rainfall serve as primary driving inputs, which are translated into fuel moisture content

(*FMC*) as the central controlling variable. Based on this, the systems can be categorized into three main modeling pathways: (i) physical time-lag models, (ii) index-based models, and (iii) satellite-driven or data-integrated approaches. This framework provides a unified conceptual basis for comparing heterogeneous wildfire danger forecasting systems and highlights the evolution from traditional empirical models toward integrated, data-driven forecasting architectures.

Table 1. Overview and Operational Context of Global Wildfire Forecasting Systems.

System	Operating Agency	Primary Modeling Target	Application Scale
NFDRS	U.S. Forest Service (USFS)	Dead + Live Fuels	Continental USA
CFFDRS	Canadian Forest Service (CFS)	Primarily Dead Fuels	National (Canada)
EFFIS	European Commission (JRC)	Satellite-derived Greenness	Pan-Europe
AFDRS	Bureau of Meteorology (BoM)	Dead + Live Fuels	National (Australia)
KFDRS	Korea Forest Service (KFS)	Primarily Dead Fuels	Korean Peninsula

Table 2. Quantitative comparison of spatial resolution, temporal resolution, and modeling approaches among major wildfire danger rating systems.

System	Spatial Resolution	Temporal Resolution	Model Type
NFDRS	1 km	hourly	physics
CFFDRS	10 km	daily	index
EFFIS	500 m	daily	satellite
AFDRS	100 m	hourly	hybrid
KFDRS	district	daily	empirical

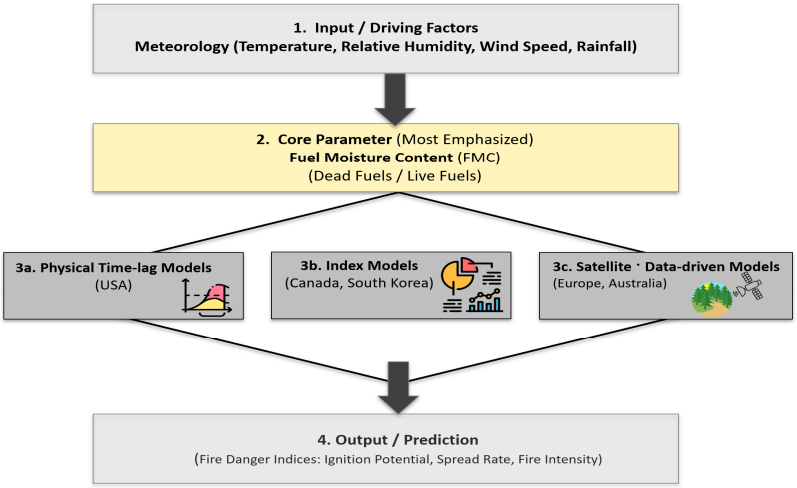


Figure 7. Comparative Analysis Framework. Arrows indicate the logical flow from input data to predictive outputs, while distinct colors are used to categorize different modeling pathways, including physical, index-based, and satellite-driven approaches.

4.1. United States (NFDRS): Time-Lag-Based Dead Fuel Segmentation and Real-Time Forecasting System

The National Fire Danger Rating System (NFDRS) of the United States, developed by the USDA Forest Service in 1972, is one of the most systematic and widely used wildfire forecasting systems in the world. It has evolved over more than five decades and serves as the primary operational model in the U.S. The core of NFDRS is the classification of dead fuels into four time-lag categories: 1-h, 10-h, 100-h, and 1000-h fuels, as illustrated in Figure 8. This classification is based on the time it takes for these fuels to reach moisture equilibrium with the surrounding environment. The NFDRS incorporates these classifications alongside live herbaceous and shrub fuels, generating a comprehensive fuel model through the Behave fire behavior prediction and fuel modeling system [59]. Tis framework effectively evaluates the likelihood of fire starts, including ignition from specific human-caused sources such as cigarettes in grassland environments [60]. Furthermore, previous research has analyzed the dead fuel moisture content across various fire danger rating systems, highlighting the importance of standardized modeling approaches. The effectiveness of these moisture models has been further validated through empirical field sampling and modeling in diverse forest plantations, confirming the relationship between fuel moisture and varying weather conditions [61]. The system is used in conjunction with data collected from Remote Automated Weather Stations (RAWS) for real-time forecasting. The key indicators produced by the NFDRS are the Ignition Component (IC), which assesses the likelihood of ignition, the Burning Index (BI), which measures flame length and intensity, and the Energy Release Component (ERC), which estimates the total energy release during combustion. Additionally, the system includes Fire Behavior Fuel Models (FBFM), which customize fuel characteristics based on regional data. One of the strengths of the NFDRS is its practical implementation of physical time-lag models and its long-standing operational experience across the U.S. The system has recently incorporated grid-based weather forecasts (WFAS), offering hourly forecasts at 1 km resolution since the 2016 version, further enhancing the spatial and temporal accuracy of the fire danger predictions. Overall, NFDRS demonstrates strong performance in real-time forecasting and physical interpretability; however, its reliance on station-based inputs limits its ability to capture fine-scale spatial variability compared to satellite-driven systems.

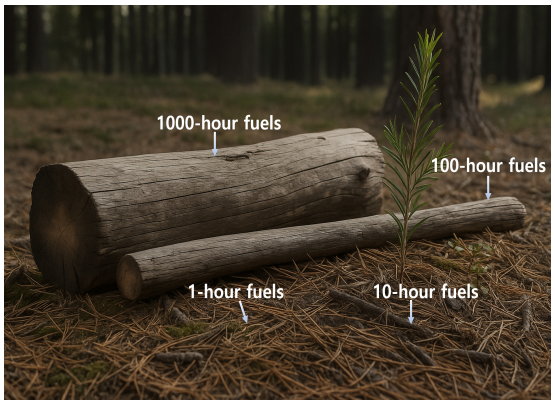


Figure 8. Fuel Classification for the U.S. Wildfire Danger Forecasting System (NFDRS).

4.2. Canada (CFFDRS): Layered Fuel Moisture Codes (FFMC, DMC, DC) Modeling

The Canadian Forest Fire Danger Rating System (CFFDRS) is one of the most rigorously documented and internationally adopted wildfire danger forecasting systems. It consists of two primary modules: The Fire Weather Index (FWI) and the Fire Behavior Prediction (FBP) module [62–64]. The FWI module is based on fuel moisture codes that model the moisture response of different fuel layers, categorized into three main layers: fine fuels, duff, and

deep fuels Figure 9. The Fine Fuel Moisture Code (*FFMC*) reflects the moisture content of surface fuels (e.g., leaves, grass, small twigs), which have a 1–2day time-lag response. The Duff Moisture Code (DMC) is designed for the moisture response of the duff layer (surface organic material), which has a 2-week cumulative response time. The Drought Code (DC) estimates the moisture content of deep organic layers, which have a long-term drying cycle of several weeks to months. These layers provide a clear advantage over single *FMC* values by quantifying the hierarchical moisture response of different fuel types. The CFFDRS uses daily meteorological observations (temperature, relative humidity, wind speed, and 24-h precipitation) as input, producing indices such as the Initial Spread Index (ISI), Buildup Index (BUI), and final Fire Weather Index (FWI), which together represent the overall fire danger. The CFFDRS is well-regarded for its mathematical documentation and its role as an international benchmark, with applications in more than 50 countries. It is one of the most robust systems globally due to its comprehensive modeling of fuel layers and its wide adoption for regional calibrations. While CFFDRS provides a well-structured multi-layer fuel moisture framework, its daily temporal resolution and limited integration of real-time remote sensing data constrain its responsiveness to rapidly evolving fire conditions.

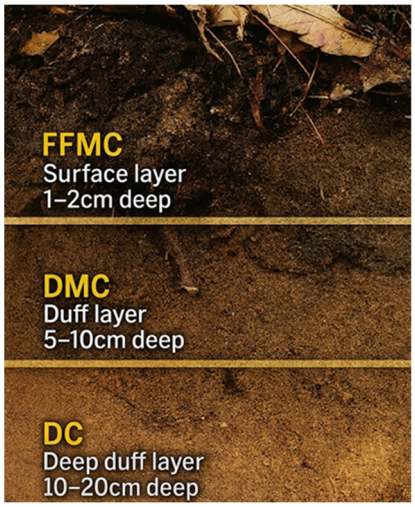


Figure 9. Fuel Classification for the Canadian Fire Danger Rating System (CFFDRS).

4.3. Europe (EFFIS): Satellite-Based Pan-European Monitoring

The European Forest Fire Information System (EFFIS), operated by the European Joint Research Centre (JRC), is a pan-European platform that provides real-time wildfire monitoring using satellite remote sensing data. Unlike traditional systems that focus on dead fuels, EFFIS aims to track Live Fuel Moisture Content (*LFMC*), which is crucial for detecting large-scale crown fire risks, particularly in Mediterranean climates.

EFFIS utilizes satellite imagery from MODIS (1 km resolution), Sentinel-2 (10–250 m), and other platforms to generate daily *LFMC* maps. These maps are based on vegetation indices such as *NDVI* (Normalized Difference Vegetation Index) and *NDWI* (Normalized Difference Water Index), as well as thermal infrared data. The combination of these indices helps monitor vegetation health and water content, providing timely information on wildfire risks across Europe.

The EFFIS system also integrates meteorological data and numerical weather predictions (ECMWF) for enhanced forecasting [65]. The system produces 1–6day forecasts of fire risk, along with risk maps that are accessible to EU member states. EFFIS's main strength lies in its ability to monitor large areas continuously, combining satellite and weather data to offer real-time insights into wildfire dangers.

However, there are challenges related to the heterogeneity of vegetation and climate across Europe. For instance, the system has struggled with *LFMC* calibration in regions with complex forest types, such as boreal forests in the North and Mediterranean scrublands in the South. These challenges highlight the ongoing need for regional *LFMC* calibration to improve accuracy. EFFIS excels in large-scale monitoring and *LFMC* estimation through satellite integration; however, its dependence on remote sensing introduces uncertainties related to cloud cover and spatial heterogeneity.

4.4. Australia (AFDRS): Customized Multivariate Prediction Models for Fuel Types

Australia's Australian Fire Danger Rating System (AFDRS), introduced in 2022, replaced the previous McArthur Fire Danger Index and was redesigned following the extensive damage caused by the Black Summer fires (2019–2020) [66]. The AFDRS integrates various fuel types across the country, using a multivariate model to estimate Dead Fuel Moisture Content (*DFMC*) and Live Fuel Moisture Content (*LFMC*) independently for each fuel type.

The AFDRS model applies specific equations to eucalyptus forests, scrublands, and savannas, customizing fire behavior predictions based on fuel type characteristics. It also integrates high-resolution fuel maps (up to 100 m grid), real-time meteorological data, and satellite imagery (MODIS, Landsat). Some machine learning techniques, such as Random Forest, are also incorporated to improve prediction accuracy.

AFDRS is particularly effective in capturing regional variations in fuel types and adapting predictions accordingly. The system visually represents fire risk on a 4-level scale ranging from Moderate to Catastrophic and provides actionable fire behavior and suppression difficulty indicators. The AFDRS also integrates government data-sharing platforms and national mobile alert systems, making it highly effective for real-time fire risk management. AFDRS represents a next-generation system with strong integration of multi-source data and hybrid modeling approaches, although its complexity may limit operational transparency and computational efficiency.

4.5. South Korea: National Wildfire Danger Forecasting System

South Korea's National Wildfire Danger Forecasting System is the only official wildfire forecasting system in the country, developed and operated by the Korea Forest Service [67]. The system primarily uses real-time meteorological data from ASOS (Automated Surface Observing Systems) and AWS (Automatic Weather Stations), and generates daily fire danger indices at the administrative district level (Si-Gun-Gu).

The system relies heavily on an empirical regression model based on 10-h time-lag dead fuel moisture content (*DFMC*), combining weather variables such as temperature, relative humidity, precipitation, and wind speed with vegetation and topographic data. However, the system is still in the early stages of incorporating more advanced methods, such as Live Fuel Moisture Content (*LFMC*) or satellite-based remote sensing data (e.g., *NDVI*, *NDWI*).

One of the system's main strengths is its efficient operation at a national level, utilizing real-time weather data for rapid response. However, there are limitations related to its spatial resolution, which is based on administrative districts (approximately 300–500 km^2), and its inability to capture local variations in fuel distribution and moisture content [68]. Additionally, the system has yet to integrate AI or satellite-based data fully, making it necessary to upgrade with modern technologies to enhance prediction accuracy and real-time monitoring. A granular comparison of the modeling architectures reveals significant technological disparities in how each system estimates fuel moisture dynamics. As detailed in Table 3, the advancement of these systems varies from traditional empirical

regression models to high-precision physics–AI hybrid frameworks. Notably, the integration of live fuel moisture content (*LFMC*) and high-resolution gridded data distinguishes next-generation systems like AFDRS from more conventional frameworks. Compared to global systems, KFDRS remains limited in spatial resolution, modeling sophistication, and integration of *LFMC* and AI-based approaches, highlighting the need for systematic technological advancement.

Table 3. Structural and Functional Comparison of Modeling Architectures.

Category	NFDRS (USA)	CFFDRS (Canada)	AFDRS (Australia)	KFDRS (Korea)
Core Algorithm	Nelson Model (Physics)	Van Wagner's *EMC*	Biophysical Balance	Simple *EMC* (Stat)
Moisture Response	1, 10, 100, 1000-h Classes	1-h Class (*FFMC*) Focus	Real-time Dynamic	24-h (Daily Average)
Live Fuel (*LFMC*)	Physiological (GSI)	Seasonal Constant	Integrated Canopy Model	Not Modeled (Indirect)
Spatial Framework	Station-based (10–30 km)	Station-based (10–50 km)	Gridded Hybrid	Station + *NDVI* Proxy
Framework Type	Physics-Stat Hybrid	Empirical/ Regression	Physics-AI Hybrid	Simple Statistical

5. Technical Limitations

Currently, global wildfire danger forecasting systems face significant technical limitations in handling Fuel Moisture Content (*FMC*). First, the lack of spatiotemporal resolution is the most critical issue. Ground-based systems, such as those using AWS/ASOS (Automatic Weather Stations/Automated Surface Observing Stations), have an average station spacing of 10–50 km, which is insufficient to capture local microclimate phenomena—such as changes in wind direction, thermal updrafts, and humidity gradients—especially in mountainous terrain. As a result, these systems apply the same meteorological input values across large regions using simple interpolation, failing to detect fine-scale variations. Despite technological progress, several systemic bottlenecks continue to hinder the predictive reliability of current wildfire danger rating systems. Table 4 synthesizes these critical limitations, categorizing them into spatiotemporal resolution gaps, physiological modeling deficiencies, and the lack of standardized validation protocols. These identified challenges serve as the primary motivation for the phased technology roadmap proposed in the following section.

On the other hand, satellite-based approaches like *NDVI*/*NDWI* (Normalized Difference Vegetation Index/Normalized Difference Water Index) have spatial resolutions ranging from 250 m to 1 km. These systems suffer from the mixed-pixel effect of vegetation, soil, and exposed rocks, and frequent cloud contamination during the summer, leading to a significant reduction in the accuracy of Live Fuel Moisture Content (*LFMC*) estimates. This resolution mismatch results in systematic overestimation or underestimation of fire risk in wildfire spread paths, which are inherently continuous. As shown in Table 2, the NFDRS (National Fire Danger Rating System) performs hourly forecasting based on time-lag models, whereas the KFDRS (Korea Forest Service) system predicts on a daily basis, and EFFIS (European Forest Fire Information System) relies on lower-resolution, large-area *NDVI*-based *LFMC* maps. Thus, there are inherent gaps in resolution and spatial coverage between these systems. Second, the structural incompleteness of *LFMC* prediction is a serious issue. Most traditional systems, including CFFDRS (Canadian Forest Fire Danger Rating System) and South Korea's National Wildfire Danger Forecasting System, rely on

equilibrium moisture content (*EMC*)-time-lag models that focus on dead fuels. However, the physiological moisture regulation mechanisms in live tissues—such as transpiration, water conduction, and drought stress responses—are not modeled separately. This becomes a significant limitation, especially in Mediterranean and subtropical climates, where the transition to high-intensity crown fires occurs when *LFMC* drops below 60%. As seen in Table 2, while the U.S. (NFDRS) and Australia (AFDRS) have adopted integrated or multivariate fuel structures, Canada (CFFDRS) and South Korea (KFDRS) still rely on simple index-based models centered on dead fuels. Third, prediction discrepancies among models and the lack of a quantitative verification system continue to be persistent issues. Even under the same regional and meteorological conditions, NFDRS, CFFDRS, and EFFIS produce different *FMC* values, which arise due to structural differences in input data resolution, time-lag classification criteria, moisture exchange equations, and regional calibration factors. However, without standardized quantitative metrics for cross-validation, such as RMSE (Root Mean Square Error), ROC-AUC (Receiver Operating Characteristic Area Under the Curve), and Brier Score, objective comparisons and performance improvements among systems remain limited [69,70]. As seen in Table 3, differences in input variable composition, model types, and spatial coverage across systems inherently lead to result discrepancies.

Table 4. Identified Technical Bottlenecks and Systemic Limitations in *FMC* Forecasting.

Bottleneck	Technical Description	Impact on Wildfire Management
Resolution Mismatch	Gap between AWS station density (10–50 km) and local microclimate variations.	Failure to detect localized ignition risks in complex terrain.
Physiological Gap	Lack of modeling for plant transpiration and drought stress responses.	Inaccurate forecasting of high-intensity crown fire transitions.
Satellite Dependency	Cloud contamination in optical sensors (*NDVI*) and mixed-pixel errors.	Discontinuity in real-time monitoring of wildfire spread paths.
Validation Scarcity	Lack of standardized quantitative metrics (e.g., RMSE, ROC-AUC) for cross-system comparison.	Absence of objective evidence for model performance enhancement.
Latency Issues	1–2 day delay in satellite data processing and revisit cycles.	Reduced situational awareness for rapid field-level response.

6. Policy Implications and Future Research

At the international level, there is an urgent need to establish a cross-system Fuel Moisture Content (*FMC*) validation protocol among leading wildfire danger rating systems, including the NFDRS (USA), CFFDRS (Canada), EFFIS (EU), and AFDRS (Australia). Utilizing standardized evaluation metrics such as RMSE, ROC-AUC, and Brier Score will help identify system-specific calibration requirements and performance disparities. South Korea's pine forest-centered model should be actively integrated into the Asia-Oceania Fire Forecasting Network as a globally deployable asset. Furthermore, the development of harmonized climate scenarios using Representative Concentration Pathways (RCPs) and Shared Socioeconomic Pathways (SSPs) is essential for aligning long-term forecasting efforts. A technology roadmap for 2026–2035 is proposed to guide this phased development

- Phase 1 (2026–2028): The focus will be on developing high-resolution *FMC* maps (10 m scale) by fusing data from Sentinel-1 Synthetic Aperture Radar (SAR)—noted for its cloud-penetrating capabilities—with UAV-based LiDAR systems. Concurrently, the national meteorological infrastructure will be bolstered by expanding the ASOS and AWS networks. Real-time integration of Sentinel-2 *NDVI* data will further enhance the spatial resolution necessary for precise wildfire danger forecasting.
- Phase 2 (2028–2030): The objective shifts toward establishing a physiological modeling module for Leaf Fuel Moisture Content (*LFMC*). This module will integrate critical variables such as Vapor Pressure Deficit (*VPD*), Normalized Difference Water Index (*NDWI*), and soil moisture into Long Short-Term Memory (LSTM) networks for time-series forecasting. Additionally, fuel layer segmentation will be refined based on the Fine Fuel Moisture Code (*FFMC*) structure from the Canadian CFFDRS to better model moisture dynamics across forest strata.
- Phase 3 (2030–2035): The final phase aims to build a next-generation *FMC* forecasting platform leveraging Physics-Informed Neural Networks (PINNs). Operating on a 100-m spatial grid, this system will incorporate physical constraints for superior predictive reliability. Real-time edge computing will enable ultra-fast, hourly updates transmitted directly to field-level response units, significantly enhancing situational awareness and tactical decision-making.

7. Conclusions

This study performed a structural comparison of global wildfire danger rating systems with an emphasis on fuel moisture modeling, identifying critical gaps in South Korea's current framework. Notably, advanced systems provide up to 10–100 times higher spatial resolution and transition from daily to hourly forecasting cycles compared to conventional systems. While the United States, Canada, and Australia have developed mature and technologically integrated models tailored to their specific ecosystems, South Korea's system remains limited in terms of physiological modeling, multi-source data integration, and spatial resolution.

By analyzing international best practices and performance characteristics, this study proposes a strategic policy and technology roadmap encompassing high-resolution *FMC* mapping, *LFMC* modeling, and AI–physics fusion platforms. These advancements are essential for improving forecasting accuracy and enabling real-time, data-driven wildfire risk assessment.

Ultimately, the findings highlight a clear technological gap between traditional empirical systems and next-generation hybrid frameworks. The systematic and comparative approach presented in this study provides both a technical foundation and a strategic roadmap for transitioning South Korea's wildfire management from a reactive system to a predictive and preventive paradigm under increasing climate variability. This study contributes to the literature by providing a standardized comparative framework for evaluating wildfire danger rating systems and offering actionable insights for next-generation system development.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

FMC	Fuel Moisture Content
LFMC	Live Fuel Moisture Content
NFDRS	National Fire Danger Rating System
CFFDRS	Canadian Forest Fire Danger Rating System
EFFIS	European Forest Fire Information System
AFDRS	Australian Fire Danger Rating System
KFDRS	Korean Forest Fire Danger Rating System
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
VPD	Vapor Pressure Deficit
EMC	Equilibrium Moisture Content
AWS	Automatic Weather Station
ASOS	Automated Surface Observing System
RAWS	Remote Automated Weather Stations

References

1. Quan, X.; Xie, Q.; He, B.; Luo, K.; Liu, X. Integrating remotely sensed fuel variables into wildfire danger assessment for China. *Int. J. Wildland Fire* **2021**, *30*, 822. [CrossRef]
2. Field, R.D.; Spessa, A.C.; Aziz, N.A.; Camia, A.; Cantin, A.; Carr, R.; de Groot, W.J.; Dowdy, A.J.; Flannigan, M.D.; Manomaiphiboon, K.; et al. Development of a global fire weather database. *Nat. Hazards Earth Syst. Sci.* **2015**, *15*, 1407–1423. [CrossRef]
3. Davies, G.M.; Legg, C.J. Fuel Moisture Thresholds in the Flammability of Calluna Vulgaris. *Fire Technol.* **2011**, *47*, 421–436. [CrossRef]
4. Chuvieco, E.; Cocero, D.; Riano, D.; Martin, P.; Martınez-Vega, J.; De La Riva, J.; Pérez, F. Combining *NDVI* and surface temperature for the estimation of live fuel moisture content in forest fire danger rating. *Remote Sens. Environ.* **2004**, *92*, 322–331. [CrossRef]
5. Yebra, M.; Dennison, P.E.; Chuvieco, E.; Riaño, D.; Zylstra, P.; Hunt, E.R., Jr.; Danson, F.M.; Qi, Y.; Jurdao, S. A global review of remote sensing of live fuel moisture content for fire danger assessment: Moving towards operational products. *Remote Sens. Environ.* **2013**, *136*, 455–468. [CrossRef]
6. Perello, N.; Trucchia, A.; D'aNdrea, M.; Degli Esposti, S.; Fiorucci, P.; Gollini, A.; Negro, D. An adaptable dead fuel moisture model for various fuel types and temporal scales tailored for wildfire danger assessment. *Environ. Model. Softw.* **2025**, *183*, 106254. [CrossRef]
7. Watt, M.S.; Gross, S.; Difuntorum, J.K.; McCarty, J.L.; Pearce, H.G.; Shuman, J.K.; Yebra, M. Monitoring Wildfire Risk with a Near-Real-Time Live Fuel Moisture Content System: A Review and Roadmap for Operational Application in New Zealand. *Remote Sens.* **2025**, *17*, 3580. [CrossRef]
8. Ivison, K.; Little, K.; Orpin, A.; Lewis, C.H.M.; Dyer, N.; Keyzor, L.; Everett, L.; Stoll, E.; Andersen, R.; Graham, L.J.; et al. A national-scale sampled temperate fuel moisture database. *Sci. Data* **2024**, *11*, 973. [CrossRef]

9. Jain, P.; Coogan, S.C.P.; Subramanian, S.G.; Crowley, M.; Taylor, S.W.; Flannigan, M.D. A review of machine learning applications in wildfire science and management. *Environ. Rev.* **2020**, *28*, 478–505. [CrossRef]
10. Fan, J.; Hu, T.; Ren, J.; Liu, Q.; Sun, L. A comparison of five models in predicting surface dead fine fuel moisture content of typical forests in Northeast China. *Front. For. Glob. Chang.* **2023**, *6*, 1122087. [CrossRef]
11. Stocks, B.J.; Lynham, T.J.; Lawson, B.D.; Alexander, M.E.; Wagner, C.V.; McAlpine, R.S.; Dube, D.E. Canadian Forest Fire Danger Rating System: An Overview. *For. Chron.* **1989**, *65*, 258–265. [CrossRef]
12. Bradshaw, L.S.; Deeming, J.E.; Burgan, R.E.; Cohen, J.D. *The 1978 National Fire-Danger Rating System: Technical Documentation*; General Technical Report INT-39; USDA Forest Service: Ogden, UT, USA, 1984. [CrossRef]
13. Noble, I.R.; Gill, A.M.; Bary, G.A.V. McArthur's fire danger meters expressed as equations. *Aust. J. Ecol.* **1980**, *5*, 201–203. [CrossRef]
14. Masinda, M.M.; Li, F.; Liu, Q.; Sun, L.; Hu, T. Prediction model of moisture content of dead fine fuel in forest plantations on Maoer Mountain, Northeast China. *J. For. Res.* **2021**, *32*, 2023–2035. [CrossRef]
15. Ning, J.; Liu, H.; Yu, W.; Deng, J.; Sun, L.; Yang, G.; Wang, M.; Yu, H. Comparison of Different Models to Simulate Forest Fire Spread: A Case Study. *Forests* **2024**, *15*, 563. [CrossRef]
16. Yebra, M.; Scortechini, G.; Badi, A.; Beget, M.E.; Boer, M.M.; Bradstock, R.; Chuvieco, E.; Danson, F.M.; Dennison, P.; de Dios, V.R.; et al. Globe-*LFMC*, a global plant water status database for vegetation ecophysiology and wildfire applications. *Sci. Data* **2019**, *6*, 155. [CrossRef]
17. Rao, K.; Williams, A.P.; Flefil, J.F.; Konings, A.G. SAR-enhanced mapping of live fuel moisture content. *Remote Sens. Environ.* **2020**, *245*, 111797. [CrossRef]
18. Quan, X.; Chen, R.; Yebra, M.; Riaño, D.; de Dios, V.R.; Li, X.; He, B.; Nolan, R.H.; Griebel, A.; Boer, M.M.; et al. Sub-daily live fuel moisture content estimation from Himawari-8 data. *Remote Sens. Environ.* **2024**, *308*, 114170. [CrossRef]
19. Cho, K.; Abraham, S.; Kumar, S.V.; Wang, J. Remote sensing of live fuel moisture for wildfires using SMAP satellite observations. *Geophys. Res. Lett.* **2025**, *52*, e2025GL117025. [CrossRef]
20. Lai, G.; Quan, X.; Yebra, M.; He, B. Model-driven estimation of closed and open shrublands live fuel moisture content. *GIScience Remote Sens.* **2022**, *59*, 1837–1856. [CrossRef]
21. Yebra, M.; Scortechini, G.; Adeline, K.; Aktepe, N.; Almoustafa, T.; Bar-Massada, A.; Beget, M.E.; Boer, M.; Bradstock, R.; Brown, T.; et al. Globe-*LFMC* 2.0, an enhanced and updated dataset for live fuel moisture content research. *Sci. Data* **2024**, *11*, 332. [CrossRef]
22. Hughes, W.E.M.; Larson, E.D. Effect of fuel moisture content on biomass-IGCC performance. *J. Eng. Gas Turbines Power* **1998**, *120*, 455–459. [CrossRef]
23. Yebra, M.; Chuvieco, E.; Riano, D. Estimation of live fuel moisture content from MODIS images for fire risk assessment. *Agric. For. Meteorol.* **2008**, *148*, 523–536. [CrossRef]
24. Balch, J.K.; Bradley, B.A.; Abatzoglou, J.T.; Nagy, R.C.; Fusco, E.J.; Mahood, A.L. Human-started wildfires expand the fire niche across the United States. *Proc. Natl. Acad. Sci. USA* **2017**, *114*, 2946–2951. [CrossRef] [PubMed]
25. Liu, X.; Zheng, C.; Wang, G.; Zhao, F.; Tian, Y.; Li, H. Integrating Multi-Source Remote Sensing Data for Forest Fire Risk Assessment. *Forests* **2024**, *15*, 2028. [CrossRef]
26. Chuvieco, E.; Aguado, I.; Yebra, M.; Nieto, H.; Salas, J.; Martín, M.P.; Vilar, L.; Martínez, J.; Martín, S.; Ibarra, P.; et al. Development of a framework for fire risk assessment using remote sensing and geographic information system technologies. *Ecol. Model.* **2010**, *221*, 46–58. [CrossRef]
27. Padilla, M.; Vega-García, C. On the comparative importance of fire danger rating indices and their integration with spatial and temporal variables for predicting daily human-caused fire occurrences in Spain. *Int. J. Wildland Fire* **2011**, *20*, 46–58. [CrossRef]
28. Koutsias, N.; Xanthopoulos, G.; Founda, D.; Xystrakis, F.; Nioti, F.; Pleniou, M.; Mallinis, G.; Arianoutsou, M. On the relationships between forest fires and weather conditions in Greece from long-term national observations (1894–2010). *Int. J. Wildland Fire* **2013**, *22*, 493–507. [CrossRef]
29. Urbieta, I.R.; Zavala, G.; Bedia, J.; Gutiérrez, J.M.; San Miguel-Ayanz, J.; Camia, A.; Keeley, J.E.; Moreno, J.M. Fire activity as a function of fire-weather seasonal severity and antecedent climate across spatial scales in southern Europe and Pacific western USA. *Environ. Res. Lett.* **2015**, *10*, 114013. [CrossRef]
30. Nolan, R.H.; Boer, M.M.; Resco De Dios, V.; Caccamo, G.; Bradstock, R.A. Large-scale, dynamic transformations in fuel moisture drive wildfire activity across southeastern Australia. *Geophys. Res. Lett.* **2016**, *43*, 4229–4238. [CrossRef]
31. Collins, L.; Penman, T.D.; Price, O.F. Some wildfire ignition causes pose more risk of destroying houses than others. *PLoS ONE* **2019**, *14*, e0212220. [CrossRef]
32. Halofsky, J.E.; Peterson, D.L.; Harvey, B.J. Changing wildfire, changing forests: The effects of climate change on fire regimes and vegetation in the Pacific Northwest, USA. *Fire Ecol.* **2020**, *16*, 4. [CrossRef]
33. Resco de Dios, V.; Fellows, A.W.; Nolan, R.H.; Boer, M.M.; Bradstock, R.A.; Domingo, F.; Goulden, M.L. A semi-mechanistic model for predicting the moisture content of fine litter. *Agric. For. Meteorol.* **2015**, *203*, 64–73. [CrossRef]

34. Overholt, K.J.; Cabrera, J.; Kurzawski, A.; Koopersmith, M.; Linn, R.R. PyroSim: A simulation tool for wildland fire behavior. *Fire Saf. J.* **2014**, *68*, 37–46. [CrossRef]
35. Weise, D.R.; Coen, J.L.; Mahalingam, S. Fire spread in chaparral—'Go or no-go'. *Int. J. Wildland Fire* **2016**, *25*, 163–184. [CrossRef]
36. Forkel, M.; Dorigo, W.; Lasslop, G.; Teubner, I.; Chuvieco, E.; Thonicke, K. A data-driven approach to identify controls on global fire activity from satellite and climate observations. *Geosci. Model Dev.* **2017**, *10*, 4443–4476. [CrossRef]
37. Zylstra, P.; Bradstock, R.A.; Bedward, M.; Penman, T.D.; Doherty, M.D.; Weber, R.O.; Cary, G.J. Biophysical mechanistic modelling quantifies the effects of plant traits on fire severity: Species, not surface fuel loads, determine flame dimensions in eucalypt forests. *PloS ONE* **2016**, *11*, e0160715. [CrossRef]
38. Rodrigues, M.; de Dios, V.R.; Sil, Â.; Camprubí, À.C.; Fernandes, P.M. VPD-based models of dead fine fuel moisture provide best estimates in a global dataset. *Agric. For. Meteorol.* **2024**, *346*, 109868. [CrossRef]
39. Bradstock, R.A. A biogeographic model of fire regimes in Australia: Current and future implications. *Glob. Ecol. Biogeogr.* **2010**, *19*, 145–158. [CrossRef]
40. Cheney, P.; Gould, J.; Catchpole, W. The influence of fuel, weather and fire shape variables on fire spread in grasslands. *Int. J. Wildland Fire* **2012**, *21*, 721–735. [CrossRef]
41. Matthews, S. Dead fuel moisture research: 1991–2012. *Int. J. Wildland Fire* **2014**, *23*, 78–92. [CrossRef]
42. Anderson, W.R.; Cruz, M.G.; Fernandes, P.M.; McCaw, L.; Vega, J.A.; Bradstock, R.A.; Fogarty, L.; Gould, J.; McCarthy, G.; Marsden-Smedley, J.B. A generic, empirical-based model for predicting rate of fire spread. *Int. J. Wildland Fire* **2015**, *24*, 443–460. [CrossRef]
43. Argañaraz, J.P.; Radeloff, V.C.; Bar-Massada, A.; Gavier-Pizarro, G.I.; Scavuzzo, C.M.; Bellis, L.M. Assessing wildfire exposure in the wildland–urban interface. *Land Use Policy* **2016**, *55*, 254–263. [CrossRef]
44. Gale, M.G.; Cary, G.J.; Van Dijk, A.I.; Yebra, M. Forest fire fuel through the lens of remote sensing: Review of approaches, challenges and future directions in the remote sensing of biotic determinants of fire behaviour. *Remote Sens. Environ.* **2021**, *255*, 112282. [CrossRef]
45. Ellis, T.M.; Bowman, D.M.J.S.; Jain, P.; Flannigan, M.D.; Williamson, G.J. Global increase in wildfire risk due to climate-driven declines in fuel moisture. *Glob. Change Biol.* **2022**, *28*, 1544–1559. [CrossRef]
46. Yebra, M.; Quan, X.; Riaño, D.; Larraondo, P.R.; Van Dijk, A.I.; Cary, G.J. A fuel moisture content and flammability monitoring methodology for continental Australia based on optical remote sensing. *Remote Sens. Environ.* **2018**, *212*, 260–272. [CrossRef]
47. Chuvieco, E.; Aguado, I.; Jurdao, S.; Pettinari, M.L.; Yebra, M.; Salas, J.; Martínez-Vega, F.J. Integrating geospatial information into fire risk assessment. *Int. J. Wildland Fire* **2014**, *23*, 606–619. [CrossRef]
48. McCandless, T.C.; Kosovic, B.; Petzke, W. Enhancing wildfire spread modelling by building a gridded fuel moisture content product with machine learning. *Mach. Learn. Sci. Technol.* **2020**, *1*, 035010. [CrossRef]
49. Naderpour, M.; Rizeei, H.M.; Ramezani, F. Forest fire risk prediction: A spatial deep neural network-based framework. *Remote Sens.* **2021**, *13*, 2513. [CrossRef]
50. Schmidt, L.; Forkel, M.; Zotta, R.-M.; Scherrer, S.; Dorigo, W.A.; Kuhn-Régnier, A.; van der Schalie, R.; Yebra, M. Assessing the sensitivity of multi-frequency passive microwave vegetation optical depth to vegetation properties. *Biogeosciences* **2023**, *20*, 1027–1046. [CrossRef]
51. Jolly, W.M.; Freeborn, P.H.; Bradshaw, L.S.; Wallace, J.; Brittain, S. Modernizing Wildfire Hazard Prediction: An Update to the US National Fire Danger Rating System. *Environ. Softw.* **2024**, *181*, 106181. [CrossRef]
52. Yeom, C.H.; Lee, S.Y.; Park, H.S.; Won, M.S. A Study on a Development of Automated Measurement Sensor for Forest Fire Surface Fuel Moistures. *J. Korean Wood Sci. Technol.* **2020**, *48*, 917–935. [CrossRef]
53. McNorton, J.R.; Di Giuseppe, F. A global fuel characteristic model and dataset for wildfire prediction. *Biogeosciences* **2024**, *21*, 279–300. [CrossRef]
54. Nelson, R.M., Jr. Water relations of forest fuels. In *Forest Fires*; Academic Press: Cambridge, MA, USA, 2001; pp. 79–149. [CrossRef]
55. Cohen, J.D.; Deeming, J.E. *The National Fire-Danger Rating System: Basic Equations*; US Department of Agriculture, Forest Service, Pacific Southwest Forest and Range Experiment Station: Albany, CA, USA, 1985; Volume 82.
56. Fosberg, M.A. Climatological influences on moisture characteristics of dead fuel: Theoretical analysis. *For. Sci.* **1971**, *17*, 64–72. [CrossRef]
57. Viney, N.R. A Review of Fine Fuel Moisture Modelling. *Int. J. Wildland Fire* **1991**, *1*, 215–234. [CrossRef]
58. Nelson, R.M. A method for describing equilibrium moisture content of forest fuels. *Can. J. For. Res.* **1984**, *14*, 597–600. [CrossRef]
59. Burgan, R.E.; Rothermel, R.C. *Behave: Fire Behavior Prediction and Fuel Modeling System, Fuel Subsystem*; USDA Forest Service: Ogden, UT, USA, 1984; Volume 167.
60. Countryman, C.M. Ignition of grass fuels by cigarettes. *Fire Manag. Notes* **1983**, *44*, 3–7.
61. Alves, M.V.G.; Batista, A.; Soares, R.; Ottaviano, M.; Marchetti, M. Fuel moisture sampling and modeling in Pinus elliottii Engelm. plantations based on weather conditions in Paraná, Brazil. *iForest* **2009**, *2*, 99–103. [CrossRef]

62. Van Wagner, C.E. *Development and Structure of the Canadian Forest Fire Weather Index System*; Forestry Technical Report 35; Canadian Forestry Service: Ottawa, ON, Canada, 1987.
63. Alexander, M.E. *Diurnal Adjustment Table for the Fine Fuel Moisture Code*; Northern Forest Research Centre: Edmonton, AB, Canada, 1982.
64. Lawson, B.D.; Armitage, O.B. *Weather Guide for the Canadian Forest Fire Danger Rating System*; Northern Forestry Centre: Edmonton, AB, Canada, 2008.
65. Amatulli, G.; Camia, A.; San-Miguel-Ayanz, J. Estimating future burned areas under changing climate in the EU-Mediterranean countries. *Sci. Total Environ.* **2013**, *450*, 209–222. [CrossRef]
66. Ahmed, I.; Ledger, K. Lessons from the 2019/2020 'black summer bushfires' in Australia. *Int. J. Disaster Risk Reduct.* **2023**, *96*, 103947. [CrossRef]
67. Korea Forest Service (KFS). *National Wildfire Danger Forecasting System Operation Manual*; National Institute of Forest Science: Seoul, Republic of Korea, 2022.
68. Lee, H.; Won, M.S.; Yoon, S.H.; Jang, K.C. Modeling and mapping fuel moisture content using equilibrium moisture content computed from weather data of the AMOS. *J. Korean Assoc. Geogr. Inf. Stud.* **2019**, *22*, 21–36. [CrossRef]
69. Mölders, N. Comparison of Canadian Forest Fire Danger Rating System and National Fire Danger Rating System fire indices derived from WRF model data. *Atmos. Res.* **2010**, *95*, 290–306. [CrossRef]
70. Júnior, J.S.S.; Paulo, J.R.; Mendes, J.; Alves, D.; Ribeiro, L.M.; Viegas, C. Automatic forest fire danger rating calibration: Exploring clustering techniques for regionally customizable fire danger classification. *Expert Syst. Appl.* **2022**, *193*, 116380. [CrossRef]

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