Data-driven approach to evaluate fire risk for grassland prescribed burning management in the Great Plains Region

by

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Abstract

Prescribed burning is a critical land management practice in the Great Plains of North America, helping to maintain native rangelands, reduce wildfire risk, and to facilitate favorable grazing. However, the Great Plains experienced approximately 498,000 wildfires between 1992 and 2020 which raised concerns about the effectiveness and safety of prescribed fire as a land management tool. Barriers to prescribed burning practice remain due to concerns on potential fire escape and fire danger. A localized fire danger index can help address these concerns by providing clear, science-based guidance, encouraging safer and confident use of prescribed fire.

The Overall goal of this research is to develop a localized Grassland fire danger index through a data-driven modeling approach to support the planning and implementation of prescribed fire in the Great Plains. The specific research objectives of this dissertation include: (1) characterizing wildfire risks across the Great Plains using long-term historical records and climatic data to evaluate the spatial and temporal variability of fire activity and to identify key factors influencing wildfire occurrence; (2) developing user-friendly sub-models for dead fuel moisture content (DFMC) and grass curing, which serve as components of the proposed Grassland Fire Danger Index (GFDI), using localized meteorological and satellite data to represent mid-term and short-term drivers of fire potential.

To characterize risks for wildfires risk in the Great Plains, this study analyzes wildfire records from 1992 to 2020 across the Great Plains states to assess spatiotemporal patterns in wildfire risk and evaluate the role of prescribed fires through combined analysis of wildfire data. Results show a threefold increase in both wildfire frequency and area burned, with fire size increasing from east to west and frequency rising from north to south. Wildfire seasons have gradually shifted earlier due to climate change. Drought severity accounted for 51% of the

interannual variability in area burned, while grass curing accounted for 60% of the monthly variability of wildfires in grasslands.

To develop user-friendly sub-models for DFMC and grass curing, which serve as components of the proposed GFDI, this study uses Oklahoma Mesonet weather data and satellite observations in a data-driven statistical approach. DFMC reflects short-term fuel moisture that affects ignition and fire spread, while grass curing represents seasonal drying that controls fuel availability. Both are critical for fire prediction and safe burns. Lower DFMC and higher grass curing levels are strongly associated with wildfire risks. The DFMC sub-model improves the accuracy and sensitivity of existing models. The grass curing sub-model shows that 50% curing usually occurs around April 15–16, which matches the time for the most intensive prescribed fire activities in the region, indicating it as a safe and effective window for prescribed fire recognized by landowners.

The detailed findings from this research will lay a foundation for the development of a localized fire danger assessment tool that integrates long-term, mid-term, and short-term risk factors to improve prescribed fire planning and implementation in the Great Plains. The outcome of this study will assist land managers, fire professionals, and policymakers in making informed decisions for safer and more effective prescribed burning.

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I am grateful to my late father, whose memory continues to inspire me, and to my mother for her unwavering love, sacrifices, prayers, and moral support throughout my studies. I am also thankful to my siblings for their constant encouragement and belief in me.

I want to thank all my friends who have been helpful and supportive throughout my life's journey. I especially appreciate my roommate, Isaac Obembe, for creating a happy and peaceful home environment that made learning easier. Before I drop my acknowledgment pen, I would like to specially appreciate Ajayi John and Adebayo, who were both very supportive during my application process and have continued to show great encouragement ever since.

Dedication

This work is dedicated to my late father, whom I lost to cardiac arrest, and to everyone who has experienced a similar loss. May the souls of all who have passed from cardiac arrest rest in perfect peace.

Chapter 1 – Introduction

1.1 Grassland wildfires and Prescribed burning

Grassland wildfires are typically less severe and shorter-lived than forest fires but it continues to endanger lives and property throughout the Great Plains(Lindley et al., 2021) ; and predicting fire behavior has been challenging due to the vast expanses of grassland prairies, where fires can rapidly spread across large areas because of the abundance of fine fuels (Schreck et al., 2010). The Great Plains are characterized by extensive grasslands that support a large beef cattle industry, which produces a significant portion of the U.S. beef supply and serves as an important economic driver for the region(Steiner et al., 2020). These grasslands also frequently experience destructive wildfires, which pose a major regional hazard (Lindley et al., 2021). According to Liu et al.(Liu et al., 2025), the Great Plains experienced about 498,000 wildfires between 1992 and 2020 that burned roughly 18 million hectares, averaging 17,000 fires and 0.6 million hectares each year. Wildfire frequency and total burned area increased nearly threefold during this period, with the largest fires occurring in major drought years such as 2000, 2006, and 2011–2012.

Prescribed burning refers to the intentional use of fire under controlled conditions to accomplish management goals (D. Akinbile, 2024) ; and it also plays a vital role in maintaining grassland ecosystems around the world by limiting the spread of woody vegetation and invasive plant species (Bahm et al., 2011; Grace et al., 2001; Salesman & Thomsen, 2011). Prescribed burns also help in understanding the ecological consequences of both uncontrolled wildfires and intentionally set fires (Valkó et al., 2014). The implementation of prescribed fires depends on management decisions that consider fuel availability and weather conditions at ignition; and determining the optimal timing for burns is essential for achieving conservation goals(Yurkonis et al., 2019). In the northern Great Plains of North America, seasonal variations in burning generally have minimal influence on grassland productivity and plant composition (Clarke et al. 1943;

Biondini et al. 1989; Engle and Bidwell 2001; Vermeire et al. 2011; Russell et al. 2015). Roger and Carol (Roger & Carol, 2022) explains that a detailed burn plan is the best way to reduce risk and liability in prescribed fire operations. It should outline site preparation, confirm adequate staff and resources, ensure compliance with regulations, and verify suitable weather conditions.

1.2 Fire Danger Indexes

Fire danger refers to the likelihood of wildfire ignition, spread, and potential impact on valued assets (Sharples et al., 2009). It includes both static and dynamic components of the fire environment that influence ease of ignition, fire behavior, and suppression difficulty (Merrill & Alexander, 1987; Varela, 2015) . Fire danger indexes, which are calculated using meteorological and fuel variables, serve as critical tools for forecasting wildfire risk and supporting fire management decisions (Podschwit et al., 2022). They can be applied across a range of temporal and spatial scales (Andrews & Bradshaw, 1997).

1.2.1 Burning index

The Burning Index (BI) is a key component of the National Fire Danger Rating System (NFDRS) and is widely used for fire prevention and suppression planning (Andrews & Bradshaw, 1997). BI is derived from a combination of Spread Component (SC) , a relative index of rate of fire spread and Energy Release Component (ERC) , a relative index of the amount of heat released per unit area in the flaming zone of an initiating fire(Bradshaw et al., 1984).BI produce a scale that remains open-ended and accommodates a wide range of values to characterize fire potential, including during periods of low to moderate risk (Schoenberg et al., 2007). It serves as an indicator of fire behavior intensity, particularly flame length, and is extensively used by fire management agencies for resource allocation and operational planning (Schoenberg et al., 2007). BI, is linearly related to the length of flames at the head of the fire(Bradshaw et al., 1984). However, its reliance on coarse meteorological data and generalized fuel models limits its suitability for localized prescribed burning. BI lacks sensitivity to site-specific fuel and weather conditions, and validation efforts have shown weak correlations with observed fire behavior(Andrews & Bradshaw, 1997).

The BI is estimated from SC and ERC as follows:

$BI = 10 \times 0.45 \times [(SC/60) \times (25 \times ERC)]^{0.46}$ (Fang et al., 2025)

where SC (unit: ft/min) represents the fire spread rate, ERC (unit: $BTU/ft^2 \times 25$) indicates the fire heat per area.

1.2.2 Keetch-Byram Drought Index (KBDI)

The KBDI was developed in 1968 by the USDA Forest Service and it's a sluggish response measure of drought that enables sustained indication of seasonal soil drying initially designed for the southeastern USA (Keetch & Byram, 1968). It has been one of the most widely used drought indexes for wildfire monitoring and prediction throughout the past 50 years (Krueger et al., 2022; Kumar & Dharssi, 2017; Plucinski et al., 2023). It estimates cumulative soil moisture deficiency in the upper 0.2 meters. KBDI values range from 0 (saturated) to 800 (extreme drought), with values above 600 indicating elevated wildfire risk (Carlson et al., 2002; Sullivan, 2010; Taufik et al., 2015). Its simplicity and reliance on limited meteorological inputs have made it widely used in wildfire prediction for over five decades (Krueger et al., 2022; Plucinski et al., 2023). KBDI increases on dry days, decreases with rainfall, and reflects seasonal drying trends. High values are associated with low fuel moisture, increased fire intensity, and greater suppression difficulty (Finkele et al., 2006; Janis et al., 2002). KBDI is not designed to assess grassland fire danger directly, as it was developed to measure long-term soil moisture drought.

1.2.3 Australia GFDI

The Australia GFDI is originally developed in Australia and quantifies grassfire risk using environmental variables such as air temperature, relative humidity (RH), wind speed, and grass curing. The GFDI is a short-term, rapid-response index that utilizes high-resolution weather data to provide regional warnings of grassland fire danger, making it well-suited for operational decision-making during periods of elevated fire risk (Sullivan, 2010). For the GFDI, Wind speed is a sensitive factor; and wind stands out as the most pivotal meteorological factor that influences grassfire potential and determinant of the direction of spread of fire (Khastagir et al., 2018) . GFDI is also very sensitive to grass curing, which is the process of grass drying out and becoming more flammable (Hosking, 1990). The following two empirical equations have been used to calculate GFDI values.

$GFDI = 2\exp(-23.6 + 5.01\ln(C) + 0.038T - 0.226(RH)^{1/2} + 0.633(U)^{1/2})$ (Noble et al., 1980)

$GFDI = \exp(0.0217 - 0.009432(100-C)\ 1.536 + 0.02764T - 0.2205\ (RH)^{1/2} + 0.6422\ (U)^{1/2})$ (Purton, 1982)

where T is air temperature (°C); RH is relative humidity (%); C is grass curing (%); U is wind speed (km/h).

GFDI was operationalized through the McArthur Grassland Fire Danger Meter (Mark V), an analog tool that calculates the DFMC and combines it with weather inputs to produce a GFDI value. Under typical dry conditions (100% curing, 20°C, 20% RH), GFDI values ranged from 4 to 99, depending on wind speed. The meter integrates fuel and weather variables and has been proven effective for modeling fire behavior in grassland (P. Cheney & Sullivan, 2008).

1.3 Research Objectives

The overarching goal of this study is to develop a localized Grassland fire danger index through a data-driven modeling approach to support the planning and implementation of prescribed fire in the Great Plains. This goal is pursued through a sequence of interrelated objectives designed to quantify wildfire and prescribed fire risks and to model key fuel-moisture components that together contribute to a unified framework suitable for grassland ecosystems.

The specific objectives of the study are to:

1. Characterize wildfire risk across the Great Plains using long-term historical records and climatic data to evaluate the spatial and temporal variability of fire activity and to identify key factors influencing wildfire occurrence.

2. Develop user-friendly sub-models for DFMC and grass curing, which serve as components of the proposed Grassland Fire Danger Index GFDI, using localized meteorological and satellite data to represent mid-term and short-term drivers of fire potential.

Chapters 2 and 3 provide further elaboration on each objective, with concise descriptions of the chapters and the research goals that drive them.

To address Objective 1, chapter 2 analyzes wildfire data to quantify spatiotemporal variations in fire activity and identify key environmental factors influencing wildfire occurrence in the Great Plains. Historical wildfire records (1992–2020) were obtained from the U.S. Forest Service Fire Program Analysis Database.

Relationships among fire frequency, drought severity (KBDI), and grass curing were established to represent long- and mid-term fire risk drivers. Results show a threefold increase in wildfire frequency and area burned, with a gradual shift in fire season toward earlier months. Wildfire frequency generally increases from north to south, while average fire size increases from east to west.

Drought severity explained about 51% of interannual wildfire variability, and grass curing explained nearly 60% of monthly variability, emphasizing the influence of moisture dynamics on fire potential. These findings form the scientific foundation for developing a localized fire danger framework and for optimizing prescribed burning seasons in the Great Plains.

To address Objective 2, chapter three develops empirical sub-models for DFMC and grass curing as components of the proposed GFDI. Meteorological and remote-sensing data from the Oklahoma Mesonet network were used to represent localized temperature, relative humidity, and drought conditions affecting short- and mid-term fire risk.

The DFMC sub-model was developed using an exponential regression with logarithmic transformation, capturing the nonlinear effects of temperature and relative humidity on fuel moisture dynamics. The grass-curing sub-model was developed using a logistic regression, incorporating the Day of Year (DOY) as the predictor variable and the previous year's KBDI category as a grouping factor to quantify the effects of seasonal progression and long-term drought carryover on grass-curing levels.

Both models showed strong predictive performance and statistical validity. DFMC values below 15% were associated with large wildfire occurrences, while increasing grass-curing rates indicated greater fuel availability and ignition potential. Together, these user-friendly, data-driven sub-models enable land managers to monitor both short-term fuel moisture variability and seasonal vegetation curing. This integration provides a practical basis for identifying safe prescribed burning windows and supports the development of a localized GFDI that enhances fire danger assessment and prescribed fire planning across the Great Plains.

Chapter four of this thesis highlights key conclusions, limitations and areas of research that need to be explored in the future.

Chapter 2 – Characterizing risks for wildfires in the Great Plains

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Increasing wildfire activities across the Great Plains raised concerns about the effectiveness and safety of prescribed fire as a land management tool. This study analyzes wildfire records from 1992 to 2020 from the 10 states that form the Great Plains (figure2.1) to assess spatiotemporal patterns in wildfire risk. Results show a threefold increase in both wildfire frequency and area burned, with fire size increasing from east to west and frequency rising from north to south. Wildfire seasons have gradually shifted earlier due to climate change. Drought severity accounted for 51% of the interannual variability in area burned, while grass curing accounted for 60% of monthly variability of wildfires in grasslands. The results will lay a foundation for the development of a localized fire risk assessment tool that integrates various long-term, mid-term, and short-term risk factors, and supports more effective fire management in this region.

2.1 Introduction

Fire represents an inherent ecological process within the prairie-grassland ecosystems characterizing the United States Great Plains. The region's semi-arid climatic regime creates conditions where ecosystems exhibit heightened fire susceptibility, with wildfire events typically manifesting during extended drought periods (Stubbendieck et al., 2007) . Lightning is responsible for the majority (60-90%) of these wildfires, followed by human activities such as negligence and accidents (Reid, 2009). While fire can play a beneficial ecological role, unplanned wildfires often result in adverse impacts and are among the most destructive natural hazards to human communities (Russell et al., 2024). These risks are particularly pronounced in the wildland-urban interface (WUI), the transitional zone between undeveloped natural areas and human-built environments, where homes are increasingly built near flammable vegetation. As WUI areas continue to expand and the climate becomes hotter and drier (Ojima et al., 2021), the frequency and severity of catastrophic wildfires are projected to rise, posing greater threats to livelihoods in these regions (Brunson, 2023). Understanding wildfire risk is essential for guiding the strategic allocation of resources to mitigate wildfire hazards (Yu et al., 2023).

Given that eliminating fire from fire-prone ecosystems is not realistic, prescribed fire has been used as a tool for maximizing socio-ecological benefits while minimizing the harmful impacts of uncontrolled wildfire (Russell et al., 2024). Historically, Indigenous peoples frequently used deliberate fire to manage prairie landscapes, with such practices often exceeding the frequency of lightning-induced wildfires (Higgins, 1989). Unlike unplanned wildfires, prescribed fires are intentionally planned and conducted under controlled conditions to achieve specific land management objectives. They offer a cost-effective and indispensable method for reducing fuel loads, mitigating wildfire risk (Clark et al., 2022; Hanberry et al., 2019), and dealing with a fire deficit (Watts et al., 2024). Amid rising wildfire threats, there is increasing advocacy for the expanded use of prescribed fire (Twidwell et al., 2013). However, perceived risks and concerns about legal liability continue to hinder its widespread adoption, particularly among private landowners (Clark et al., 2022; Hanberry et al., 2019).

Most existing modeling efforts in the U.S. focused on the forested ecosystems, often overlooking key fire weather variables relevant to grasslands, while the Grassland Fire Danger Index (GFDI) was developed for temperate grassland systems in Australia and does not align with the climate and fuel characteristics of the Great Plains (Schreck et al., 2010). Our overarching goal is to develop a localized fire risk index through a data-driven modeling approach to support the planning and implementation of prescribed fire in the Great Plains. The first step of the data-driven approach is to characterize and quantify wildland fire risks using local historical data. The specific objective of this study is to identify and evaluate the long-term, mid-term, and short-term risk factors by synthesizing data from various sources, including both wildfire data from standardized reporting systems and prescribed fire data from satellite observations. Combined analysis of wildfire and prescribed fire data is innovative, and it enables better understandings of wildland fire risks and the relationship between wildfires and prescribed fires. The results will lay a foundation for the development of a fire risk quantification tool that assists wildfire and prescribed fire management in this region.

2.2 Materials and Methods

2.2.1 Wildfire data

Wildfire information was sourced from the Fire Program Analysis Fire Occurrence Database maintained by the U.S. Forest Service. This database compiles wildfire reports from federal, state, and local agencies and follows the standardized procedures of the National Wildfire Coordinating Group, including updated classifications for wildfire causes. For this analysis, we selected all geo-referenced wildfire events recorded across the ten states that make up the United States Great Plains region. For this study, we extracted all geo-referenced wildfire records across the ten states comprising the U.S. Great Plains (Figure 2.1) from 1992 to 2020. Although the source dataset had undergone basic error-checking, we conducted an additional round of data cleaning to improve data reliability. Duplicate records were identified and removed, resulting in a refined dataset of 497,749 wildfire incidents spanning a total burned area of over 18 million hectares across 29 years. From the more than fifty available variables, we focused on key attributes including the fire start date (reported as the discovery date), final fire size in hectares (ha), and geospatial location, accurate to at least the Public Land Survey System section level, approximately one square mile. Geospatial processing was performed using the tigris and sf packages in R (Pebesma, 2018;

Walker, 2016)This included reading spatial location data, importing county shapefiles, and sub-setting fire records based on geographic coordinates to improve spatial precision for subsequent analysis.

Figure 2.1.The Great Plains includes portions of 10 states (Montana, North Dakota, Wyoming, South Dakota, Nebraska, Colorado, Kansas, New Mexico, Oklahoma, and Texas). Map credit: The Great Plains Fire Science Exchange.

2.2.2 Prescribed fire data

Prescribed fire is a long-established land management practice in the Flint Hills region (Figure 2.2), which spans much of eastern Kansas and northern Oklahoma. On average, approximately 0.8 million hectares are intentionally burned in the region each year, with most prescribed fires occurring during April. To quantify prescribed fire activities, we used a remotely sensed burned area dataset derived from the Moderate Resolution Imaging Spectroradiometer (MODIS) onboard National Aeronautics and Space Administration (NASA)'s Terra and Aqua satellites (D. S. Akinbile et al., 2023). This dataset, which covers the 17 Flint Hills counties from 2003 to 2019, was generated using a supervised minimum distance classification of bi-spectral MODIS imagery. MODIS on these satellites is making daily observations of the earth with 36 channels spanning the spectral range from 0.41 to 15 μm and representing three spatial resolutions: 250 m (2 channels), 500 m (5 channels), and 1 km (29 channels) (Remer et al., 2005). Combination of band 1-red (620-

670 nm) and band 2- near-infrared (841-876 nm) at a spatial resolution of 250m was used in our study because it offers the optimal combination of spatial, temporal, and spectral properties for this application. The MODIS-based daily burned area captures both prescribed and unplanned fire events across the region. For our analysis, we integrated this dataset with reported wildfire burned area data in the Flint Hill region to enable comparative assessments of prescribed fires and wildfires.

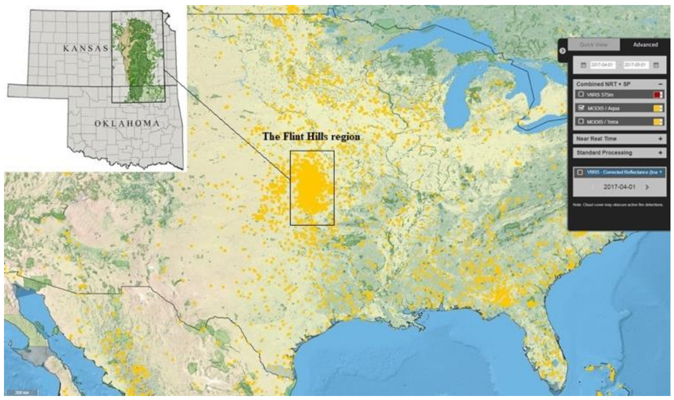


Figure 2.2. Prescribed fires in the Flint Hills region (Map shows NASA satellite image of fire activities in April 2017)

2.2.3 Long-term and mid-term risk factors

To characterize long-term and mid-term fire risk factors, we obtained data from the Keetch–Byram Drought Index (KBDI) and grassland curing data from the Oklahoma Mesonet network for the years 2006 to 2019. The KBDI is a slow-response drought index developed by the USDA Forest Service to quantify seasonal soil moisture depletion, particularly in forested ecosystems (Keetch & Byram, 1968). The index ranges from zero, the point of saturation, to 800, the maximum soil moisture deficiency, and represents the amounts of rainfall required (from 0 to 8 inches) to return the soil to saturation. Over the past five decades, KBDI has become one of the most widely used indicators for wildfire monitoring and prediction (Krueger et al., 2022; Plucinski et al., 2023). However, given that it was originally designed for forest landscapes, its applicability to grassland ecosystems, such as those in the Great Plains, requires further evaluation. Grassland curing, defined as the proportion of dead material within a grassland fuel complex, is a critical factor in grassland fire behavior. Curing levels range from 0 to 100%, with 0% representing premature, green grass, and 100% representing fully cured, dry grass. Cured grasses are prone to fire ignition because it is more flammable than green grasses. The levels of grassland curing affects moisture content of fuel and directly affect fire behavior and potential fire spread. Fires can barely spread at curing levels below 50%, but can spread rapidly when curing exceeds 90% (Sullivan, 2010). Therefore, it is an important factor for determining fire danger levels in grasslands (Anderson et al., 2011). Grassland curing can be estimated from satellite-derived vegetation greenness metrics, particularly the Normalized Difference Vegetation Index (NDVI) (Newnham et al., 2011)KBDI and grassland curing levels were included in our analysis as proxies for long-term and mid-term fire risk, respectively.

2.3 Results

2.3.1 Wildfire statistics

Wildfire activity throughout the Great Plains from 1992 to 2020 encompassed roughly 498,000 separate incidents, impacting a combined area approaching 18 million hectares. Per-year calculations yield averages of approximately 17,000 wildfire events and 600,000 hectares of affected territory. Mean fire size in the ten Great Plains states measured about 36 hectares per occurrence (Table 2.1).

Table 2.1. Wildfire summary in the Great Plains by state (1992-2020)

State	**Total fire count**	**Total burned area (ha)**	**Area burned per year (Thousand ha)**	**Average fire size per count (ha)**	**Average fire count per year**
Colorado	68313	1379834	48	20	2356
Kansas	18275	562291	19	31	630
Montana	51804	3312605	114	64	1786
North Dakota	19834	198103	7	10	684
Nebraska	11625	441661	15	38	401
New Mexico	43466	2994334	103	69	1499
Oklahoma	48495	2339363	81	48	1672
South Dakota	36165	718740	25	20	1247
Texas	179791	4818406	166	27	6200
Wyoming	19981	1353126	47	68	689
Total	**497749**	**18118463**	**625**	**36**	**17164**

Results show that both the total number of wildfires and the annual burned area in the Great Plains increased approximately threefold from 1992 to 2020 (Figure 2.3). Substantial increases in maximum fire size were observed during major drought years, including 2000, 2006, and 2011-2012.

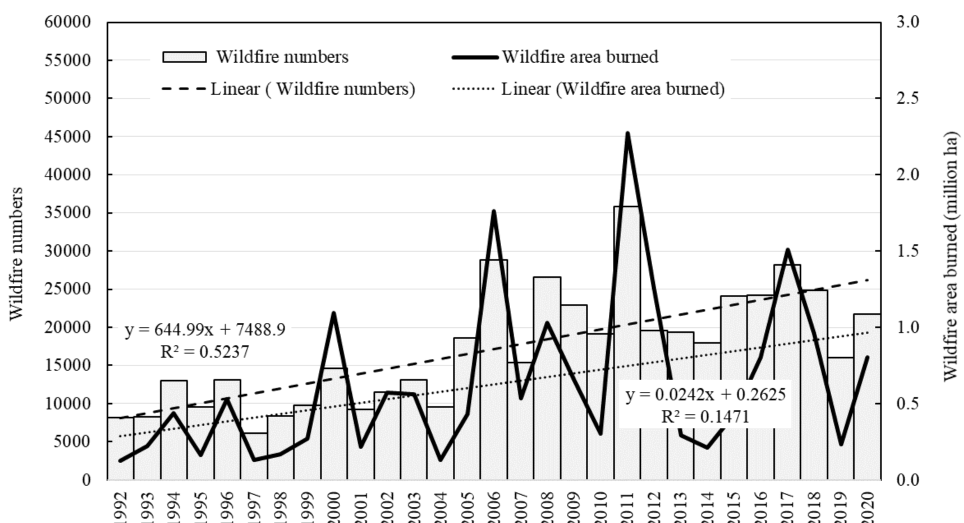


Figure 2.3.Trends in wildfire frequency and burned area in the Great Plains, 1992–2020.

2.3.2 KBDI vs. annual wildfire in the Great Plains

Figure 2.4 shows a clear positive relationship between the annual average KBDI and wildfire activity in the Great Plains. As drought severity increases, both the number of wildfires and the area they burn also rise. However, wildfire size responds more strongly to increases in KBDI than wildfire frequency. For instance, when the annual average KBDI increases from 150 to 350, wildfire occurrences grow by about 25 percent, yet the average fire size increases from roughly 30 hectares to 60 hectares. As a result, the total area burned at a KBDI of 350 becomes about two and a half times larger than the area burned at a KBDI of 150.

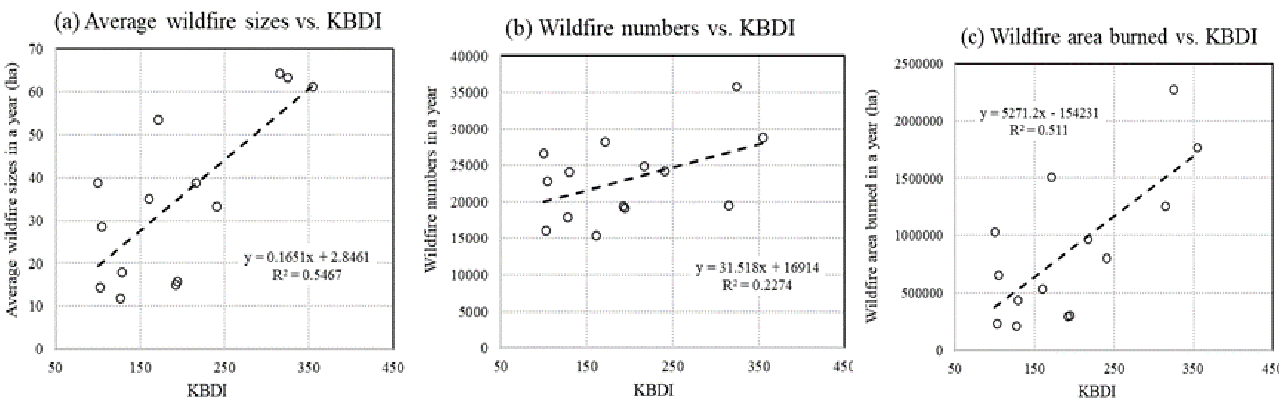


Figure 2.4. Annual wildfires vs. annual average KBDI, 2006-2019 (Wildfire numbers, area burned, and average sizes are for the 10 Great Plains states. The annual average KBDI was from Oklahoma Mesonet stations)

2.3.3 Grass curing vs. monthly wildfire in Oklahoma

Figure 2.5 shows the multi-year average monthly wildfire numbers (1992-2020) in Oklahoma were aligned with multi-year average grass curing levels. Regression analysis indicates that grass curing explains approximately 60% of the variability in monthly wildfire occurrences, highlighting its role as a significant mid-term fire risk factor in grassland ecosystems.

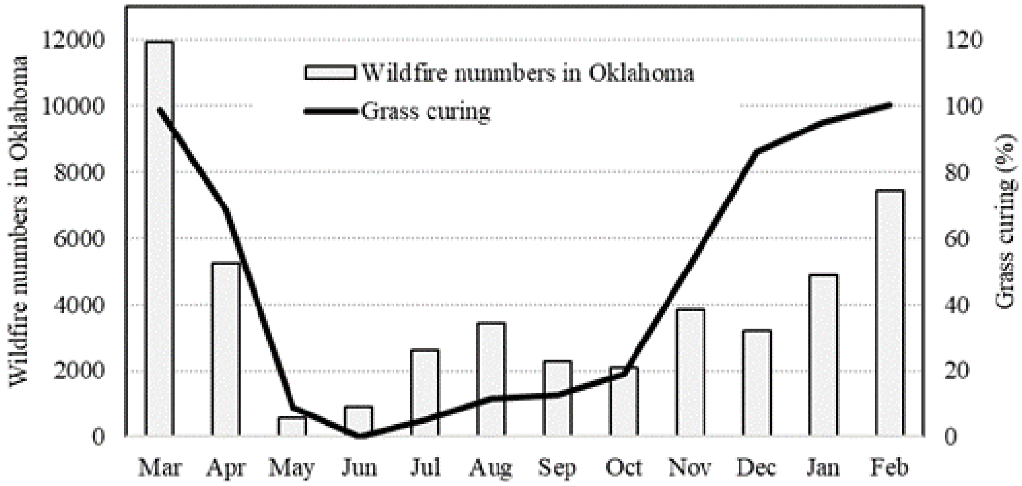


Figure 2.5. Grass curing vs Wildfire Frequency

2.4 Discussion

2.4.1 General trends of wildfires in the Great Plains

This study analyzed historical wildfire data from 1992 to 2020 to characterize wildfire risk across the Great Plains. The results show that wildfire frequency generally increases from north to south, likely driven by increasing temperature, while average wildfire size increases from east to west due to differences in dominant land cover types. The average wildfire size per burn was notably larger in Montana, Wyoming, and New Mexico (Figure 2.6a). This pattern is likely due to the greater prevalence of woody vegetation in these mountainous western states, which is more conducive to extreme wildfire behavior compared to other land-use types in the region (Donovan et al., 2017). The distribution of land-use types in the Great Plains is shown in Figure 2.7. As also reported by Scasta et al. (Scasta et al., 2016), wildfire frequency generally increases from north to south, driven by rising temperatures. Texas exhibits the highest wildfire frequency. As a result, both the western and southern Great Plains states tend to have larger annual burned areas (Figure 2.6b).

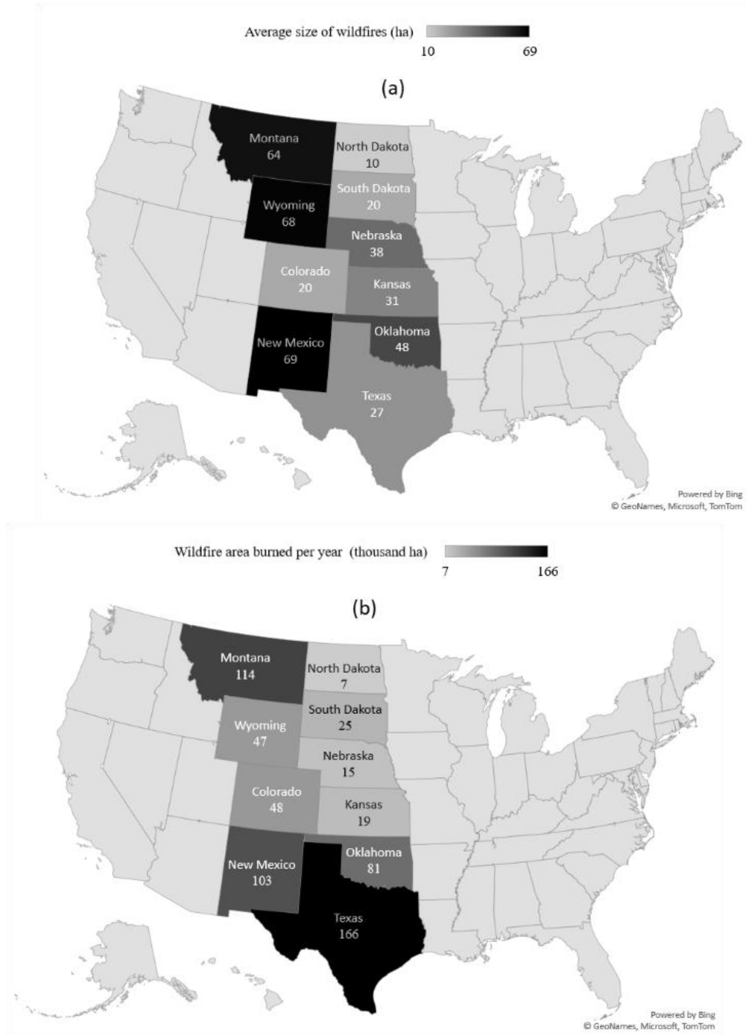


Figure 2.6. Average wildfire size per incident (a) and average annual burned area (b) across the Great Plains, 1992–2020.

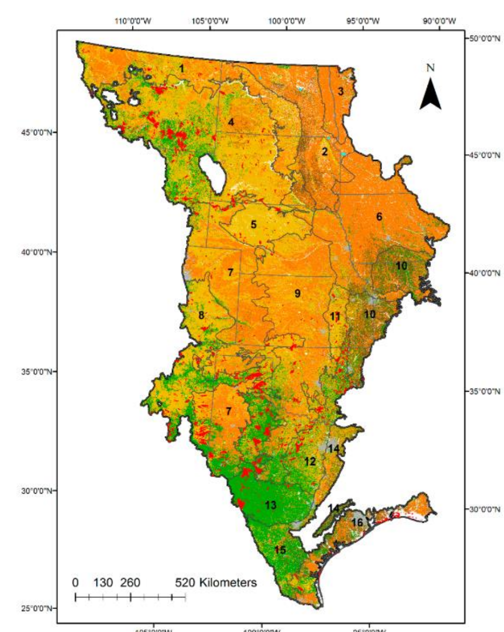


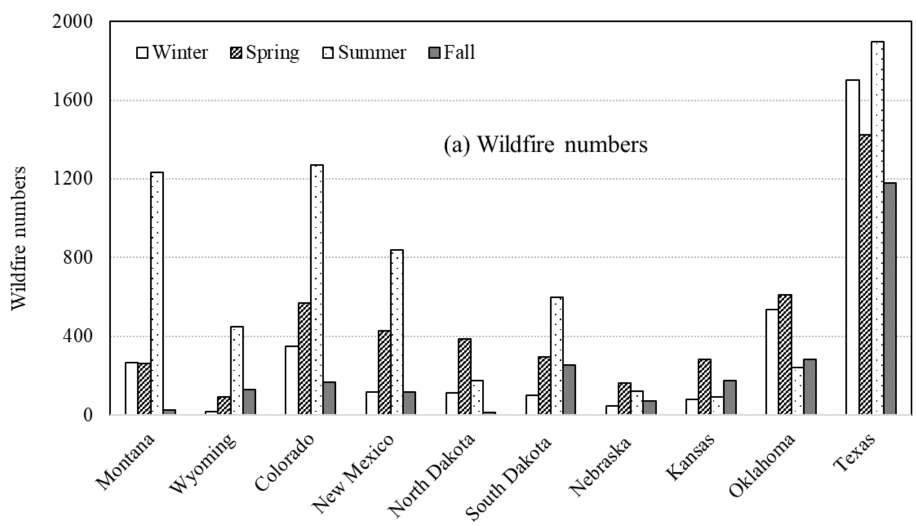
Figure 2.7. Land-use types in the Great Plains (1993-2014). (Grassland in yellow, woody vegetation in green, crops in orange, pasture/hay fields in brown, and developed areas in grey; large wildfires (>400 ha) are in red

Both wildfire frequency and total area burned exhibited clear upward trends during the study period, consistent with findings from other regions in the western United States (Boisramé et al., 2022; Dennison et al., 2014; Iglesias et al., 2022; Westerling, 2016). The observed increasing trend of wildfires in the Great Plains is consistent with Donovan et al. (Donovan et al., 2017), who reported a fourfold increase in the area burned by large wildfires (>400 ha) between 1985 and 2014 using hurdle models. These results also align with recent findings based on satellite observations (Dennison et al., 2014; Iglesias et al., 2022), wildfire reports (Westerling, 2016), and simulation models (Boisramé et al., 2022), all of which suggest an upward trend in wildfire activity across the western United States. While Yu et al. (Yu et al., 2023) noted that the increase in total burned area has outpaced the rise in wildfire frequency, implying larger average fire sizes, the data for the Great Plains do not show a significant increase in mean fire size.

The increasing trend in wildfire activities is likely driven by multiple factors, including climate change, particularly warmer and drier conditions that lead to drier vegetation and extended fire seasons (Dennison et al., 2014; Gamelin et al., 2022; Lang & Hossein, 2021; Russell et al., 2024). The increasing frequency and size of large wildfires have been linked to intensifying drought severity (Dennison et al., 2014; Gamelin et al., 2022). Our correlation analysis further revealed that severe droughts had a stronger effect on increasing fire size than fire frequency (Figure 2.4). Human factors, such as population growth near wildland areas (Cooke et al., 2016) and fire suppression policies that lead to fuel accumulation (Brotons et al., 2013), may also play a role in escalating wildfire risks.

2.4.2 Pattern of wildfires in the Great Plains across different seasons

Seasonal wildfire patterns in the Great Plains show distinct geographic variation driven largely by differences in land cover. In the Great Plains western, wildfire activity generally peaks during the summer months, while in the eastern portion of the region, peak wildfire occurrences are most common in the spring (Figure 2.8a). This contrast likely reflects differences in dominant vegetation types, woody vegetation in the west versus grasslands in the east. Yu et al. (Yu et al., 2023) identified a bimodal seasonal distribution of wildfires across the U.S., with a primary peak in August and a secondary peak in April, a pattern consistent with findings from this study. The summer wildfire peak is likely driven by convective storms and frequent lightning strikes (Balch et al., 2017). In contrast, in grassland regions, the wildfire peak often occurs in spring before grass green up, as dormant grasses are more flammable than actively growing grasses. Wildfire size also exhibits distinct seasonal patterns by region. In the southern Great Plains states (Texas, New Mexico, Oklahoma, and Kansas), wildfires are largest in spring, about 1 to 2 times larger than in other seasons (Figure 2.8b). In contrast, northern states such as Wyoming and Montana see peak wildfire sizes in summer. Notably, in Oklahoma and Kansas, both wildfire numbers and sizes peak in spring, indicating that wildfire risk is highest during that season. In Texas, while most wildfires occur in summer, the largest total area burned is recorded in spring.



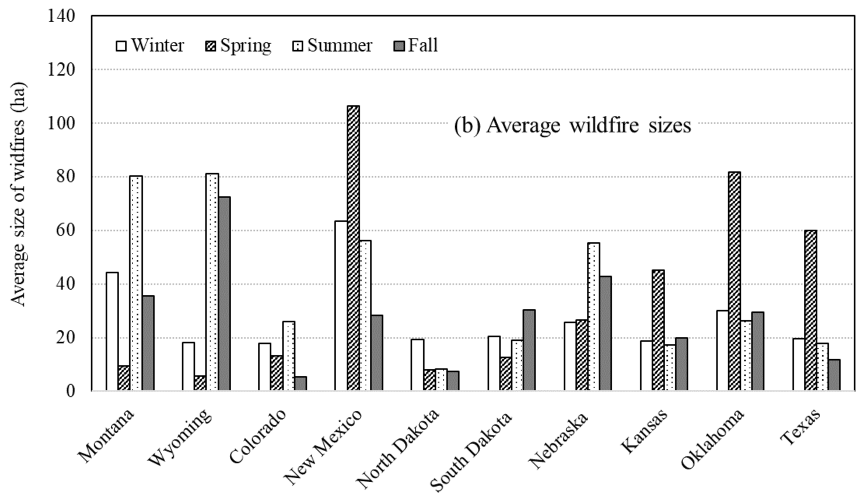


Figure 2.8. Seasonal pattern of wildfire numbers and average wildfire sizes per incident in the Great Plains, 1992-2020

From figure 2.8, One notable effect of climate change is the gradual shift in the timing of the wildfire season across the Great Plains. In northern states such as Montana and Wyoming, the peak month for area burned have advanced from August to July, evidenced by increasing burned area in July and declining activity in August. A similar pattern is observed in southern states such as New Mexico and Colorado, where the seasonal peak shifted from July to June. Grassland regions, including the Flint Hills, also show earlier spring fire peaks. In Oklahoma and Kansas, wildfire activity has increased in February and March while remaining relatively stable in April, indicating a progressive shift of the fire season toward earlier months. Furthermore, Figures 2.8a and 2.8b show that wildfire activity in the Flint Hills shifted after 2013, with more fires occurring in spring rather than summer. These patterns are consistent with broader regional trends suggesting that wildfire activity is moving earlier in the calendar year, likely due to climate-driven changes that promote earlier onset of warm and dry conditions. As also noted by Scasta et al. (Scasta et al., 2016), such seasonal shifts are especially apparent in cooler, high-latitude and high-elevation regions like Montana and Wyoming. This evolving pattern is important for strategic wildfire preparedness, resource allocation, and planning prescribed fire windows.

2.4.3 Long-term, mid-term, and short-term risk factors

Wildfire activity is influenced by risk factors operating on multiple timescales. The interannual variability in wildfires can be linked to the severity of drought conditions in a given year. The KBDI, which reflects soil moisture deficit, serves as a strong indicator of drought severity. A higher annual average KBDI generally corresponds to larger average wildfire sizes and greater wildfire frequency, and therefore a greater total area burned. In this study, the annual average KBDI explains 51% of the interannual variability in total area burned, making it a critical long-term risk factor for wildfires. KBDI has been widely used to model wildfire potential (Brown et al., 2021; Dolling et al., 2005). Abatzoglou and Williams (Abatzoglou & Williams, 2016) reported R^2 values ranging from 0.6 to 0.8 between KBDI and area burned across southwestern U.S. forests, compared to 0.51 in this study of the Great Plains. However, other factors, such as fuel accumulation, also contribute to interannual variability in wildfires. Fuel accumulation is influenced by the timing and amount of precipitation during the growing season, regardless of the current drought severity. Scasta et al. (Scasta et al., 2016) found that in Oklahoma and Wyoming, the most severe wildfire seasons often followed years with average or above-average precipitation, while in Nevada, wildfire activity was linked to precipitation from the previous year. These dynamics may explain why the relationship between KBDI and area burned tends to be more robust at broader spatial scales (Yu et al., 2023). The R^2 between KBDI and area burned across the entire Great Plains is stronger than the correlations found within individual states, suggesting that localized differences in fuel conditions and other factors introduce uncertainty in smaller-scale assessments.

Grass curing, a mid-term risk factor, explained 60% of monthly wildfire variability in grasslands. However, curing grass alone does not fully explain seasonal wildfire patterns. For instance, as shown in Figure 2.5, wildfire numbers in July and August are substantially higher than in May and June, despite all four months exhibiting similarly low grass curing levels (<20%). This discrepancy is likely due to higher temperatures and increased lightning activity during midsummer. Conversely, December through February experiences significantly fewer wildfires than March, even though all these months exhibit similarly high grass curing levels (>80%). This is likely due to lower winter temperatures, which reduce ignition potential despite high fuel dryness. The variation of seasonal fire risk could be simulated using grass curing and temperature as two predictors.

Short-term risk factors, such as wind speed and dead fuel moisture, largely determined by daily relative humidity and temperature fluctuations, also play a critical role in fire ignition and spread (Wade, 2013). Ongoing research aims to integrate all the long-term, mid-term, and short-term risk factors into a comprehensive fire risk assessment tool for both wildfire response and prescribed fire planning.

2.5 Conclusions

This study provides a comprehensive assessment of wildfire patterns and drivers across the Great Plains states from 1992 to 2020. The outcome shows a clear upward trend in both wildfire frequency and total area burned, with activity intensifying during major drought years and shifting toward earlier months in the fire season. Long-term drought severity, represented by the annual average KBDI, emerged as a major determinant of interannual wildfire variability, especially influencing fire size. Mid-term factors such as grass curing strongly shaped monthly fire activity in grassland ecosystems, while short-term conditions include daily temperature, relative humidity, and wind speed-controlled ignition potential and fire spread. Together, these findings show that wildfire risk in the Great Plains is driven by the combined effects of long-term drying trends, fuel conditions, and immediate weather variability. By identifying how these factors interact across multiple temporal scales, this study establishes a strong scientific foundation for developing a localized, data-driven fire risk assessment tool tailored to the Great Plains. Such a tool will support fire managers, policymakers, and communities in anticipating high-risk periods, improving resource allocation, and reducing the impacts of increasingly frequent and severe wildfires in the region.

Chapter 3 – Modeling moisture factors in grassland fire danger index for prescribed fire management in the Great Plains

*A modified version of this chapter has been submitted to MDPI- Fire Journal and it's under review.

Prescribed burning is a critical land management practice in the Great Plains of North America, helping to maintain native rangelands and reduce wildfire risk. Barriers to prescribed burning practice remain due to concerns on potential fire escape and fire danger. A localized fire danger index can help address these concerns by providing clear, science-based guidance, encouraging safer and confident use of prescribed fire. Our goal is to support the development of a localized Grassland Fire Danger Index (GFDI) for prescribed burning management in the Great Plains. The specific objective of this study is to develop user-friendly sub-models for dead fuel moisture content (DFMC) and grass curing, which serve as components of the proposed GFDI. DFMC reflects short-term fuel moisture that affects ignition and fire spread, while grass curing represents seasonal drying that controls fuel availability. Both are critical for fire prediction and safe burns. Lower DFMC and higher grass curing levels are strongly associated with wildfire risks. Using Oklahoma Mesonet weather data, the DFMC sub-model improves the accuracy and sensitivity of existing models. The grass curing sub-model shows that 50% curing usually occurs around April 15–16, which matches the time for the most intensive prescribed fire activities in the region, indicating it as a safe and effective window for prescribed fire recognized by landowners. Our sub-models lay the foundation for development of GFDI in the region.

3.1 Introduction

Prescribed burning of grasslands is a crucial element of rangeland management in the Great Plains, effectively managing the destructive effects of woody plant germination. It supports the structure and function of the tallgrass ecosystem by enhancing the nutritional quality of native grasses, suppressing weeds and invasive shrubs, and reducing the risk of large-scale wildfires (Liu et al., 2025; Roger & Carol, 2022; Steiner et al., 2020). Prescribed burning, as a fuel management strategy, mitigates risks to human life and ecological assets by altering fire behavior dynamics (Penman et al., 2020). However, when inadequately implemented, it can result in escape fires, posing significant threats to surrounding environments. Consequently, a comprehensive understanding of the interactions among meteorological conditions, fuel characteristics, and topographic variables is essential for the safe and effective planning of prescribed burns (Volesky et al., 2010).

The grasslands of the Great Plains are critical to the U.S. beef industry, contributing significantly to national production while supporting regional economies (Steiner et al., 2020). These ecosystems also provide essential services, including biodiversity conservation, climate regulation, and hydrologic stability. Predicting fire behavior remains a major management challenge due to the dominance of fine fuels and the potential for rapid fire spread across expansive prairie landscapes (Schreck et al., 2010).

3.1.1 Our Proposed GFDI for the Great Plains

The Australian GFDI was previously adapted for the U.S. Central Plains, showing initial promise (Schreck et al., 2010). It generates hourly forecasts several days in advance at a spatial resolution of a few kilometers and can potentially provide timely guidance for determining safe burn windows. However, the Australian GFDI exhibited limited sensitivity to RH, occasionally reporting low danger ratings under low-RH conditions that are known to enhance fuel drying and fire spread. This limitation indicates that the Australian GFDI model does not fully capture RH influence in the Central Plains. To improve accuracy and operational relevance, region-specific historical weather and fuel data should be incorporated.

The proposed GFDI for the Great Plains builds on the core structure of the Australian model, incorporating wind speed, temperature, grass curing, and DFMC as key predictors, as illustrated in Figure 3.1.

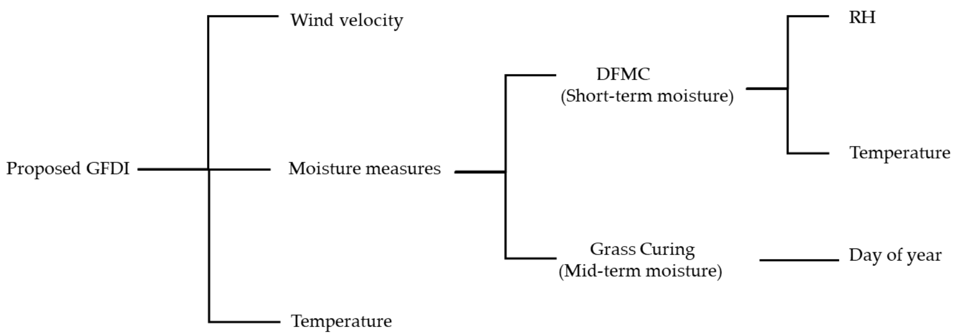


Figure 3.1. Structure of the proposed GFDI for the Great Plains

3.1.2 DFMC

DFMC, expressed as a percentage of the fuel's dry weight, is a critical variable influencing fire behavior, ignition potential, and wildfire risk. Lower DFMC values increase the probability of ignition and fire spread, thereby intensifying fire exposure and suppression difficulty (Cruz et al., 2012; Nolan et al., 2016). For prescribed burning, DFMC levels between 8% and 15% are generally considered optimal. Moisture levels below 8% substantially increase the likelihood of spot fires and erratic fire behavior, while levels above 15% may inhibit ignition and reduce burn consistency (Weir et al., 2021). DFMC is highly responsive to meteorological conditions, particularly temperature, RH, and surface moisture, which are in turn influenced by solar radiation, precipitation, and heat and vapor exchange processes (Viney, 1991). DFMC can fluctuate rapidly in response to weather changes (Nelson, 2001), making it an effective indicator of short-term fire danger. This sensitivity is particularly important in grass-dominated systems, where fine fuels respond quickly to drying conditions (Yebra et al., 2008). However, regional variability in vegetation structure, microclimate, and exposure can result in substantial differences in DFMC, limiting the effectiveness of generalized models. Incorporating localized meteorological and fuel data is therefore essential for improving DFMC estimation and ensuring reliable fire behavior predictions in operational contexts.

Nelson (Nelson, 2001) developed a mechanical model to simulate DFMC based on a complex set of partial differential equations that represent the movement of liquid water and vapor through porous materials, such as conifer needles or grass leaves. This physically based framework was designed to capture fuel moisture dynamics in detail, accounting for evaporation, absorption, and internal moisture transport within fuel particles (Jolly et al., 2019). It was originally developed for 10-hour fuels and was later adapted to simulate other dead fuel classes using weather-based fuel stick parameters. It requires inputs such as air temperature, RH, solar radiation, and rainfall to simulate moisture transfer processes within fuels (Carlson et al., 2005).

For quick estimation of DFMC in the field, two empirical DFMC models were also developed. McArthur (McArthur, 1966) developed a simple empirical DFMC model as part of the Australian GFDI system to provide rapid, field-ready estimates of 1-hour DFMC from standard meteorological observations. Derived from empirical measurements in open grasslands, the model uses a simple linear relationship between RH (%), and air temperature T (°C), expressed as:

$$\mathrm{DFMC} = 12.5 + 0.111\ \mathrm{RH} - 0.279\ \mathrm{T}$$

Marsden-Smedley (Marsden-Smedley & Catchpole, 2001) developed a simple empirical model to estimate 1-hour DFMC in the button grass moorlands of western Tasmania, where fine, surface-level dead fuels are intermixed with live vegetation under cool, moist, maritime conditions. Using gravimetric sampling of near-surface fuels and 1-hour fuel stick measurements across a wide range of weather conditions, the researchers identified RH and dew point temperature as the most effective predictors. Dew point temperature was chosen in place of air temperature to reduce multicollinearity, as RH and air temperature were strongly negatively correlated (r = –0.80) in the study area. The model is expressed as:

$$DFMC = \exp(1.660 + 0.0214\ RH - 0.0292\ T_{Dew})$$

where T_{Dew} is dew point temperature (°C). These empirical models' simplicity and reliance on widely available weather data have made it operationally valuable for fire danger assessment. However, because they were developed under the climatic and fuel conditions of its original study area, their predictive accuracy can decline in regions with different vegetation structures, humidity–temperature correlations, and diurnal drying patterns. Adjustments would be needed before applying them to environments with very different weather–fuel relationships.

3.1.3 Grass Curing

Grass curing refers to the physiological drying and senescence of grasses, during which live fuel transitions to dead fuel, and is defined as the percentage of dead material in the grass fuel bed, reaching 100% when all fuels are dead and dry (Duff et al., 2018). It is controlled by species genetics and influenced by environmental factors such as temperature, photoperiod, evapotranspiration, soil type, water availability, competition, and disturbance. Annual grasses typically cure completely at the end of the growing season, generally about six weeks after the onset of yellowing, while many perennial grasses retain live material and can reshoot after rainfall (P. Cheney & Sullivan, 2008).

Grass curing is a critical variable influencing fire behavior in grassland ecosystems, as it simultaneously increases the proportion of dead fuel while reducing live fuel moisture content. These changes enhance ignition potential and elevate fire intensity and spread rates as curing progresses (Garvey & Millie, 2001). The degree of curing directly affects fire propagation by altering fuel continuity and flammability, thereby influencing fire danger assessments and fire behavior prediction (Anderson et al., 2011). Fires rarely sustain when curing is below 20% but spread rate and flame height increase progressively between 20% and 60%, and fire spread potential rises sharply above 60 to 70%, reaching near-maximum levels at full curing (Cruz et al., 2012). Grasslands with less than 50% curing typically do not sustain fire spread due to insufficient dead fuel, whereas curing levels between 75% and 90% result in a marked increase in fire spread potential (Anderson et al., 2011). Cured grasses are significantly more flammable than green vegetation and are more likely to ignite under dry and windy conditions (N. Cheney et al., 1993), with increased combustibility accelerating spread rates (Catchpole & Wheeler, 1992). Fuel continuity is also important, as patchy curing caused by uneven grazing or variable soil moisture can limit fire spread despite high average curing.

Accurate measurement of grass curing is essential for reliable fire danger assessment, yet each available method has distinct advantages and limitations. Direct sampling, which involves physically harvesting and drying plant material is labor-intensive and impractical for frequent or large-scale monitoring. Visual assessments are faster and widely applied in operational contexts, although they are subjective; though consistency can be improved by linking observations to clearly defined phenological stages, such as flowering, seed head emergence, and browning (P. Cheney & Sullivan, 2008). Remote sensing techniques, particularly those based on vegetation indices such as the Normalized Difference Vegetation Index (NDVI), enable broad-scale and repeatable monitoring but require site-specific calibration for vegetation type and seasonal variation (Roberts et al., 2009). In heterogeneous landscapes, mixed pixels containing bare soil or evergreen vegetation can lead to significant under- or overestimation of curing (Chuvieco et al., 2003; Peterson et al., 2008). More recently, advances in high-resolution satellite imagery, such as Sentinel-2 with red-edge spectral bands and MODIS-derived indices, have improved both the spatial and temporal accuracy of curing estimates (Duff et al., 2018; Martin et al., 2009). The

GRAZPLAN pasture simulation model was incorporated into the GFDI for Canberra, Australia, using simulated pasture growth, and curing dynamics from different grass functional types (annual, exotic perennial, and native perennial) to estimate curing as a driver of fire danger (Gill et al., 2010). This demonstrates that process-based models can represent grass curing in ways that reflect ecological processes, complementing empirical field assessments and remote sensing approaches; however, curing is difficult to represent consistently because it varies among functional types, is strongly influenced by climatic variability, and shows considerable spatial heterogeneity across landscapes (Gill et al., 2010).

3.1.4 Objective of the Study

This study aims to develop region-specific, user-friendly sub-models for DFMC and grass curing, which function as components of the proposed GFDI for the Great Plains. These tailored components are intended to enhance predictive accuracy and more effectively support prescribed fire management decisions in grassland ecosystems.

3.2 Materials and Methods

3.2.1 Weather and Fuel Data

Weather and fuel data (2006 to 2019) from four Oklahoma Mesonet (Brock et al., 1995; McPherson et al., 2007) stations Bixby, Forza, Wyno, and Skiatook in Oklahoma state were used to develop the DFMC and grass curing sub-models. Environmental variables collected included 1-hour DFMC, air temperature, and RH. The dataset encompassed a wide range of environmental conditions across the four stations and are characterized by tallgrass vegetation. The 1-hour DFMC reflects the moisture content of fine dead fuels, such as grasses and small twigs less than 0.25 inches in diameter, which respond rapidly to atmospheric conditions. The Nelson DFMC model was used by the Oklahoma Mesonet system to calibrate DFMC values. Originally developed for

10-hour fuels, the Nelson model was later adapted to simulate other dead fuel classes using weather-based fuel stick parameters. For the development of the DFMC sub-model, observations were filtered to include only non-rainy days during 08:00 to 17:00 hours, corresponding to operational burning hours for prescribed fires.

Grass curing was estimated using relative greenness derived from satellite-based NDVI (Peterson et al., 2008) and reported by the Oklahoma Mesonet. Daily relative greenness values were smoothed using locally estimated scatterplot smoothing (LOESS), a non-parametric regression method that fits locally weighted polynomials to subsets of the data to reduce short-term fluctuations while preserving seasonal trends. The smoothed series was then rescaled using min–max normalization, with the annual maximum set to 0% curing (completely green) and the annual minimum set to 100% curing (fully cured).

3.2.2 Wildfire Data

Wildfire records were obtained from the Fire Program Analysis Fire Occurrence Database, maintained by the U.S. Forest Service. This database consolidates fire reports from federal, state, and local agencies and is standardized according to National Wildfire Coordinating Group protocols, including updated wildfire cause classifications. For this study, all geo-referenced wildfire records within the Great Plains from 1992 to 2020 were extracted.

Although the source dataset had undergone initial error-checking, additional data cleaning was conducted to improve accuracy. Duplicate entries were removed, resulting in a refined dataset of 497,749 wildfire incidents spanning approximately 18 million hectares over 30 years. Of the more than 50 available variables, this study focused on key attributes: fire discovery date, final fire size (in hectares), and geospatial location, which was recorded to at least the Public Land Survey System section level.

Geospatial processing was conducted using the tigris and sf packages in R (v 4.3.1). This involved reading spatial coordinates, importing county-level shapefiles, and subsetting fire records by geographic location to enhance spatial precision for subsequent analysis.

3.2.3 Development of the Sub-models

For the development of the DFMC sub-model, an exponential model was developed through regression using daily air temperature and RH as predictors. Air temperature and RH were selected due to their relatively weaker correlation in the dataset (r = -0.11), comparing with the correlation between dew point temperature and RH (r = 0.16). This selection minimizes multicollinearity concerns. This contrasts with prior study of Marsden-Smedley (Marsden-Smedley & Catchpole, 2001), who avoided using air temperature and RH together as predictors due to their high negative correlation (r = -0.80) in their dataset, and used dew point temperature and RH instead. To benchmark model performance, the two existing empirical DFMC models McArthur (McArthur, 1966) and Marsden-Smedley (Marsden-Smedley & Catchpole, 2001) were compared with our proposed DFMC sub-model under the Great Plains conditions.

For the development of the grass curing sub-model, a logistic regression model was fitted using data from January 1 to June 30, aligning with the early growing season and primary window for prescribed burning. The KBDI estimates the moisture deficit in the upper soil layer that influences vegetation dryness and fire potential. In this study, annual average KBDI in the previous year was used as a categorical grouping factor to differentiate between normal pre-season moisture conditions (annual average KBDI ≤ 280) and severe drought conditions (annual average KBDI > 280). Across the 14 years of data used in this study, extreme drought conditions (annual average KBDI > 280) occurred only twice (2012 and 2013). Model parameters were estimated respectively for normal pre-season moisture conditions and severe drought conditions, using nonlinear least squares (nls) in R (v 4.3.1). This stratification enabled the model to capture distinct curing dynamics under contrasting moisture regimes.

3.3 Results

3.3.1 The DFMC Sub-model

The DFMC sub-model model takes the following form:

$$DFMC=\exp(1.313+0.020RH-0.009T)$$

where RH is relative humidity (%) and T is air temperature (°C).

The model accounted for 88% of the variance in DFMC, with both predictors statistically significant ($p < 0.001$). As expected, DFMC increases with increasing RH and decreases with increasing temperatures.

Figure 3.2 compares the performance of the three DFMC empirical models using the weather and fuel data from Oklahoma Mesonet stations. It shows that the proposed DFMC sub-model reproduces reported values with high accuracy, particularly within the operationally critical range of DFMC (8-15%). The Marsden-Smedley model (Marsden-Smedley & Catchpole, 2001) progressively overestimates DFMC at higher values, whereas the McArthur model (McArthur, 1966) exhibits greater deviations, characterized by overestimation at lower DFMC and underestimation at higher DFMC.

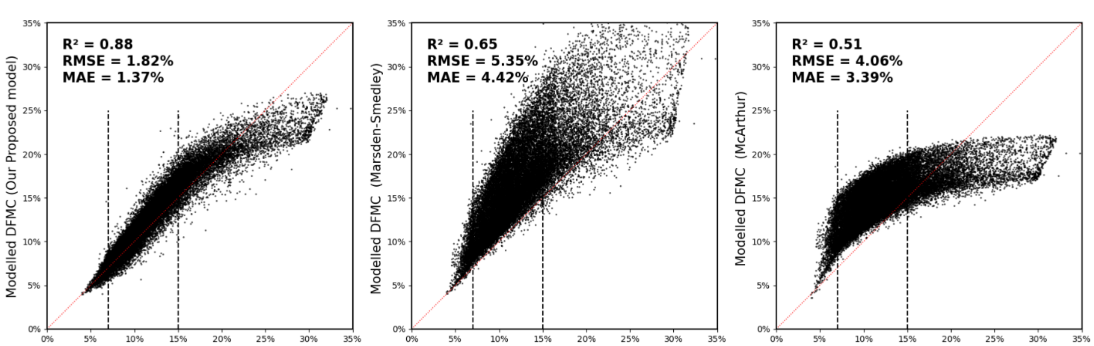


Figure 3.2. Performance of the three empirical DFMC models using the weather and fuel data from Oklahoma Mesonet stations.

Figure 3.3 compares the responses of the three DFMC models to changes in RH at air temperature of 30 °C. The proposed sub-model exhibits a strong nonlinear increase beyond 70% RH, indicating higher effects in moisture accumulation under humid conditions. The McArthur model follows a nearly linear trend across the RH range, showing limited responsiveness to increasing humidity. The Marsden-Smedley model displays moderate curvature, with intermediate effectiveness between the proposed and McArthur models.

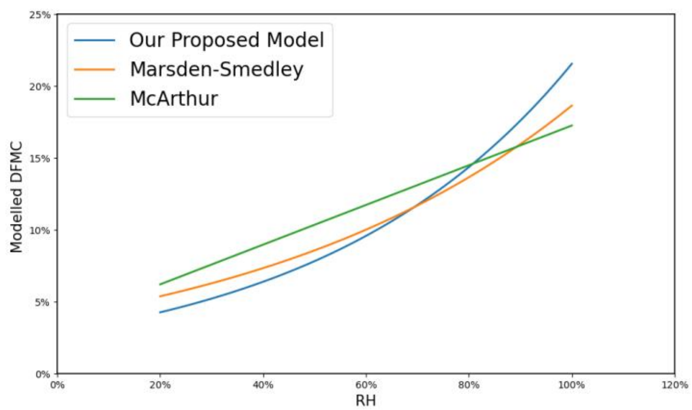


Figure 3.3.Effects of the three empirical DFMC models to RH at air temperature of 30 °C.

3.3.2 The Grass Curing Sub-model

The grass curing sub-model model takes the following form:

Grass curing (%) = 100 / [1 + exp (-B × (DOY-C))]

where DOY is the day of year; B and C are model parameters determined by regression. The B value represents the rate of change in curing levels, determining the steepness of the transition. The C value represents the inflection point of the model and the DOY at 50% curing.

Under normal pre-season moisture conditions, when the annual average KBDI in the previous year was less than 280, C = 111 (95% CI: 111-112) and B = -0.0527 (95% CI: -0.0539 to -0.0516). The narrow 95% confidence interval for C demonstrates high precision in the timing of 50% curing, while the tight confidence bounds for B indicate consistent rate of change in curing levels across years with moderate drought influence.

During extreme drought years, when the annual average KBDI in the previous year was more than 280, C = 89 (95% CI: 88-90), B = -0.057 (95% CI: -0.058 to -0.0566), which indicated an earlier and more rapid rate of change in curing levels. Curing levels decreased more quickly and reached key thresholds earlier in the season, highlighting interannual variability in vegetation response (Marsden-Smedley & Catchpole, 2001).

Seasonal patterns of reported and modeled grass curing and associated wildfire risk are shown in Figure 3.4. Wildfire risk was quantified as the ratio of daily wildfire burned area to total land area in Osage county, OK, averaged across 1994-2020. Variations in grass curing and seasonal temperature explain the bimodal pattern of the quantified wildfire risks. Figure 3.4 demonstrated the close relationship of grass curing and seasonal change of wildfire risks in the Great Plains. While winter represents close to 100% curing and the driest fuel conditions, wildfire risk is constrained by cold temperatures, or snow cover. In early March, when curing is still above 70%, wildfire risk is at highest level, peaking near 0.043%. During spring green-up, both grass curing and wildfire risk decreases sharply with time. In the transition phase, when curing decreases from 70% to 30%, wildfire risk correspondingly decreases from 0.039% to 0.027%. In end of July, wildfire risk is at lowest level and close to 0%. From late summer to fall, wildfire risk increases again to about 0.012% as late-season curing progress under favorable thermal conditions. The lower peak of wildfire risk in the fall transition phase reflects reduced fine fuel loads and disrupted continuity following extensive spring burning and grazing. For this study, modeling was focused on the first half of the year because this period encompasses the prescribed burning season in the Great Plains, when curing dynamics most strongly influence fire planning.

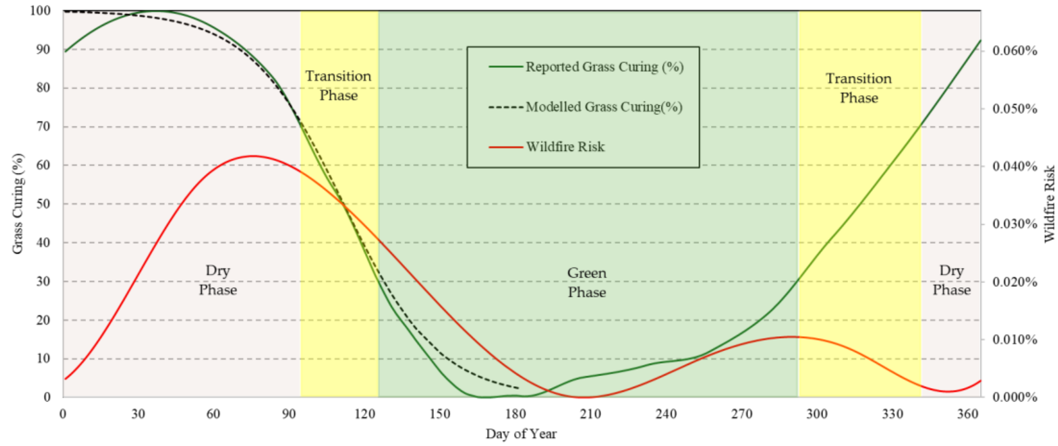


Figure 3.4. Seasonal trends in observed and modeled grass curing (%) and wildfire risk throughout the year. Wildfire risk was quantified as the ratio of daily wildfire burned area to total land area in Osage county, OK, averaged across 1994-2020, and the data was smoothed using LOESS

3.4 Discussion

3.4.1 DFMC as a Daily Fire Risk Factor

DFMC is a daily fire risk factor because it directly controls fuel ignitability and flame sustainability. Reductions in DFMC substantially increase ignition likelihood and accelerate fire spread, a relationship well documented in grassland and savanna ecosystems(Schreck et al., 2010). The mean wildfire size under different reported DFMC levels in Osage county, OK, is shown in Figure 3.5. It shows that the mean wildfire size linearly increased with decreasing DFMC levels. About 99% of the total burned area from wildfires ≥100 ha occurred when DFMC was less than 15%. This observation underscores the importance of DFMC as a daily fire risk factor. Incorporating DFMC as a daily fire risk factor within the proposed GFDI enables explicit representation of short-term variability in wildfire danger, thereby improving the operational utility of fire danger assessments in the Great Plains.

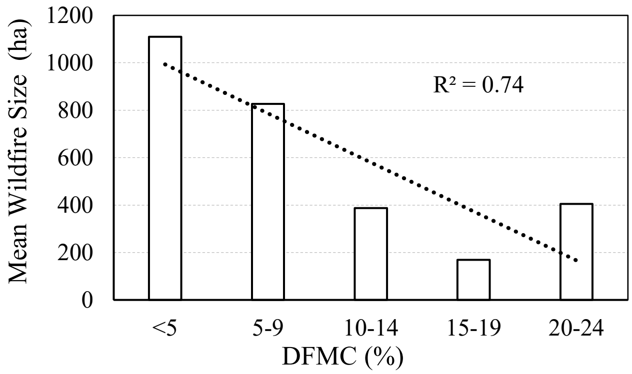


Figure 0.1. The mean wildfire size (from 1994 to 2020) under different reported DFMC levels in Osage County, OK, for wildfires ≥100 ha.

The Great Plains dataset used in this study encompassed a broad and variable range, with temperatures from 5.0°C to 32.3°C, RH from 18% to 100%, and DFMC from 4.6% to 31.7%. These gradients reflect the region's continental climate, characterized by strong seasonal contrasts and frequent weather extremes, and the dominance of tallgrass prairie fuels, which differ markedly from Australian fuel types in structure, curing dynamics, and moisture retention. By contrast, McArthur's (McArthur, 1966) and Marsden-Smedley (Marsden-Smedley & Catchpole, 2001) DFMC models were developed using datasets with relatively narrower temperature and RH ranges suited to temperate or Mediterranean climates. Marsden-Smedley (Marsden-Smedley & Catchpole, 2001)derived their model from button grass moorland fuels in Tasmania, where temperatures ranged from 10.3°C to 34.4°C, RH from 24.6% to 99%, and DFMC from 6.1% to 31.7%. McArthur's (McArthur, 1966) dataset covered temperatures from 10°C to 38°C, RH from 5% to 80%, and DFMC from 2% to 18%. These narrower environmental conditions limit the direct applicability of such models to the Great Plains. The proposed DFMC sub-model for the Great Plains demonstrates superior predictive performance compared to both McArthur's and Marsden-Smedley's models when applied to this region.

As shown in Figure 3.2, the proposed DFMC exhibits the highest overall accuracy and the lowest error, particularly within the ignition-relevant DFMC range of 8% to 15%. This DFMC range corresponds to fire behavior thresholds where fuels burn well yet remain controllable (Brock et al., 1995; McPherson et al., 2007) and thus is common for prescribed fires in grasslands. The alignment with local grassland fuel dynamics and meteorological conditions makes the DFMC sub-model a robust tool for operational fire danger assessments, prescribed burn planning, and ecological forecasting in the Great Plain.

The empirical model developed in this study is based on only two variables, RH and temperature, yet explains 88% of the variance in DFMC. This high performance, combined with a simpler structure, makes the model not only statistically robust but also more accessible and easier to implement for real-time fire danger assessments in the Great Plains. The model's simplicity supports its practical utility in fire management, particularly in regions with limited meteorological inputs or rapid decision-making needs. Our approach follows the principle of keeping the model as simple as possible while still maintaining strong agreement with the calibrated values produced by the Nelson model.

3.4.2 Grass Curing as a Seasonal Fire Risk Factor

Grass distribution and seasonal dynamics across the United States are shaped by physiological differences among species and regional climate. In the Great Plains, C_3 grasses are more common in northern areas, where they begin growing early in the season, while C_4 grasses dominate in the south, reaching peak productivity later in summer (Tieszen et al., 1997). This regional pattern is also reflected in species composition. The tallgrass prairie in the east is dominated by C_4 species such as big bluestem (*Andropogon gerardii*), little bluestem (*Schizachyrium scoparium*), Indiangrass (*Sorghastrum nutans*), and switchgrass (*Panicum virgatum*). The mixed-grass prairie contains both C_4 species, including sand bluestem (*Andropogon hallii*) and blue grama (*Bouteloua gracilis*), and C_3 species such as needlegrass (*Stipa* spp.) and western wheatgrass (*Pascopyrum smithii*) (Barnes & Harrison, 1982; Schacht et al., 2000). In the shortgrass prairie of the High Plains, C_4 species like blue grama are dominant, though farther north C_3 shortgrasses, including needlegrass and wheatgrass, become more prevalent (Tieszen et al., 1997). In the western United States, C_3 grasses are associated with cooler conditions and variable precipitation, whereas C_4 grasses are favored in warmer regions with summer rainfall and distinct soil types. Climate projections suggest that continued warming will reduce the distribution of C_3 grasses across much of the West while expanding C_4 dominance (Havrilla et al., 2023). At the continental scale, latitudinal gradients are clear: C_4 grasses dominate central and southern grasslands, while northern states remain primarily C_3 (Luo et al., 2024; Still et al., 2003). Phenological studies confirm this trend, showing that C_4 grasses account for up to 80% of cover in southern Texas but decline sharply toward the north, where C_3 species predominate (Wang et al., 2013). These geographic and climatic patterns shape ecosystem productivity and determine seasonal fuel dynamics, with C_4 systems in the south retaining green tissue later into the season compared with C_3 systems in the north, leading to slower curing rates.

The grass curing sub-model provides landowners and fire managers with a practical tool to estimate seasonal fuel availability, identify safe and effective burn windows, and anticipate wildfire potential under varying drought conditions, thereby improving both prescribed fire implementation and wildfire preparedness. Visual field assessments remain essential for operational decision-making. Aligning model predictions with visual indicators such as seed maturity and stalk color improves site-specific fire planning, especially in areas with limited real-time data access. Grass curing is influenced by interannual variability in temperature and precipitation, site-specific soil moisture conditions, species composition, grazing pressure, and microclimatic differences (Anderson et al., 2011). These factors create fine-scale heterogeneity that may not be fully captured by regional greenness indices or weather-station data. Localized rainfall or differences in dominant grass species can accelerate or delay curing relative to modeled averages, while heavy grazing can make pastures appear more cured than they are physiologically.

Table 3.1 outlines characteristic changes in grass color and landscape appearance associated with key curing thresholds. The table highlights observable transitions from fully cured to fully green vegetation. The driest conditions occur before January 3rd, when curing is close to 100%. In early March, curing levels are around 90%, representing peak dryness but with early signs of green-up beginning to appear. Around March 15th-16th, the landscape remains mostly dry and straw-colored, but some stalks begin to show green at the base (70% cured). Around April 15th-16th, the green-up process is at the midpoint (50% cured). Many landowners perceive this stage as a time for safe and effective prescribed fire, since partial greenness reduces fire intensity, though fuel conditions can still support active fire spread. By June 23rd, the landscape is fully green and dominated by live vegetation (less than 10% cured).

Table 0.1.Change of grass curing levels from January to June in the Great Plains

	Date[1]	Grass curing	Landscape Features	Photo[2]
Dry phase	Before Jan 3rd	Close to 100%	Grass is fully cured. Stalks are dry and bleached, seed heads are empty, and stems are brittle with no moisture.	
	Mar 1st - 2nd	90%	The landscape is still largely dry and straw-colored, with early signs of green-up.	
	Mar 15th - 16th	70%	The landscape remains mostly dry and straw-colored.	
Transition phase	Apr 15th – 16th	50%	Green-up is at the midpoint. The landscape has a mix of cured and uncured grasses.	
Green phase	May 10th - 11th	30%	All grasses are almost green.	
	After Jun 23rd	Less than 10%	All the grass is fully green.	

1. Dates are based on normal conditions in Osage county, OK.

2. Photo credit: Mark Garvey.

Landowners, fire managers, and prescribed burn planners should integrate visual field observations with model outputs when planning burns. While the alignment between modeled and observed curing values supports the use of curing percentages as an operational guide, acknowledging these uncertainties ensures more cautious and effective application in practice. Integrating model outputs with visual cues such as seed maturity and stalk coloration can enhance site-specific burn planning, particularly in areas with limited real-time fuel moisture data.

3.5 Conclusions

This study developed region-specific sub-models for DFMC and grass curing as foundational components of a proposed Great Plains GFDI. DFMC is a daily fire risk factor because it regulates ignition probability and fire spread. Grass curing represents seasonal fuel availability and readiness to burn. However, the grass-curing model was developed using only Oklahoma data, which limits its use across the wider Great Plains. By explicitly modeling both processes, the proposed framework captures short-term weather-driven variability and mid-term seasonal dynamics. Our results show that tailoring sub-models to Great Plains conditions improves the reliability of fire danger assessment, strengthens operational planning, and provides landowners and fire managers with ecologically meaningful metrics for prescribed burning. The unique strength of this approach lies in its ability to separate daily and seasonal risks while integrating them into a single index that is both interpretable and operationally relevant. This work provides practical tools for safer prescribed fire implementation, improved wildfire preparation, and more informed decision-making across Great Plains landscapes, while laying the foundation for a fully localized and operationally relevant fire danger index system for the region.

Chapter 4 – -Conclusion and On-going work.

Key Conclusions for Research Objective 1

- Wildfire occurrence and wildfire burned areas have increased tremendously over the past three decades, with a threefold rise in both fire frequency and total area burned between 1992 and 2020.
- The spatial distribution of fires revealed that larger wildfire sizes occurred in the western Great Plains, while higher fire frequency was observed in the southern and central portions of the region.
- A seasonal shift toward earlier wildfire activity was detected, indicating that climatic warming and extended drought periods are influencing fire timing and intensity.
- KBDI explained about 51% of the interannual variability in total area burned, explaining its role as a key long-term indicator of wildfire potential in the Great Plains. However, its relationship with fire activity weakens at smaller spatial scales due to local variations in fuel accumulation and precipitation patterns.
- Grass curing explained about 60% of monthly wildfire variability, confirming its importance as a mid-term fire risk factor. However, it does not fully capture seasonal wildfire patterns, as temperature and ignition factors such as lightning also play critical roles.

Key Conclusions for Research Objective 2

- The DFMC sub-model accurately captured the nonlinear relationship between temperature, relative humidity, and short-term moisture variation.
- DFMC values between 8% and 15% were identified as optimal for prescribed burning, ensuring safe ignition while minimizing the likelihood of escape fires.
- The grass-curing sub-model effectively represented the seasonal progression of fuel readiness influenced by temperature.

- Results indicated that 50% grass curing typically occurs around mid-April, aligning with the peak prescribed burning period and confirming its operational relevance.
- Our approach separates daily and seasonal fire risks and will integrate them into one clear, operationally useful index.
- This work establishes a foundation for a fully localized fire danger index tailored to Great Plains landscapes.

General Limitations

Data Coverage and Spatial Resolution: The study utilized weather data from Oklahoma Mesonet stations, wildfire occurrence data across the Great Plains, and MODIS burned-area products for the Flint Hills. While these datasets are robust, differences in spatial coverage and resolution may not fully capture local variations in microclimate, vegetation structure, or topography. This could lead to spatial uncertainty, and some results may be less accurate in areas with different local conditions.

Lack of Field Validation: The sub-models were validated using observational and satellite-derived datasets rather than direct field measurements. Field-based validation of fuel moisture and curing levels under real-time prescribed burning or wildfire conditions would provide stronger operational reliability.

Ongoing Work

Current efforts are focused on integrating the developed sub-models (DFMC and grass curing) into a unified framework for the development of a localized GFDI for the Great Plains. This integrated model will combine short-term, mid-term, and long-term fire risk components to provide a comprehensive and regionally tailored GFDI and rating system. The framework aims to enhance prescribed burning safety, improve daily fire risk monitoring, and strengthen wildfire preparedness and decision making among land managers across the region.

The ongoing work focuses on validating the proposed GFDI across multiple states in the Great Plains by applying an established evaluation framework for fire danger assessment (Andrews et al., 2003). This framework uses percentile analysis and logistic regression to examine how effectively an index represents observed fire activity across different environments. Applying these methods will make it possible to assess the reliability, consistency, and transferability of GFDI across the diverse climatic and fuel conditions found throughout the region.

A key component of the validation is a direct comparison between GFDI and BI. BI is widely used in operational fire management and including it in the evaluation provides a clear reference for determining whether GFDI offers improved sensitivity or predictive accuracy in grassland settings. Both indexes will be evaluated using the same analytical procedures to ensure methodological consistency and scientific credibility (Andrews et al., 2003) .

Percentile analysis will be conducted for both GFDI and BI across all-days, fire-days, large-fire-days, and days with prescribed burning. This approach follows established fire danger evaluation practices for determining index sensitivity and discriminatory ability (Andrews et al., 2003; Sirca et al., 2018)The analysis will show whether index values shift toward higher levels on days with fire activity or planned burn operations. A strong upward shift indicates better sensitivity to fire danger conditions. Comparing the percentile distributions for GFDI and BI will help identify which index more effectively distinguishes periods of low and high fire potential across the Great Plains.

Logistic regression will be used to model the probability of a fire-day, a large-fire-day, or a prescribed-burn-day as a function of each index. This method is widely used in fire danger index evaluation to generate probability curves, model fit statistics, and R-squared values that quantify the relationship between index values and real fire activity (Andrews et al., 2003). Applying logistic regression to both GFDI and BI will allow a rigorous comparison of their predictive performance. Higher R-squared values or broader probability transitions for GFDI would indicate stronger operational value for grassland fire management.

Prescribed burning data from multiple states will also be used to evaluate operational relevance. Prescribed fire planning requires accurate assessments of fire behavior potential, and incorporating days with planned burns provides an opportunity to test index performance under real management conditions. Evaluating how well each index aligns with the timing of prescribed burns will show whether GFDI or BI better reflects the environmental conditions considered suitable for planned fire operations. Including both wildfire and prescribed burning records ensures that the validation represents actual management practices rather than relying solely on unplanned fire occurrence.

By applying this complete evaluation framework, the study aims to determine whether GFDI provides measurable advantages over BI in predicting fire danger and supporting management decisions across the Great Plains.

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