

Wildland fire risk quantification for prescribed fire management
in the Great Plains

by

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Abstract

Wildfire activity in the Great Plains has increased over the past three decades. As a fire-dependent ecosystem, the region relies on prescribed fire to sustain the grassland structure, improve forage quality, support biodiversity, and reduce wildfire risk posed by antecedent fuel accumulation. Despite its ecological importance, prescribed fire application remains constrained by safety concerns and lack of tools for accurate fire risk assessment. Existing fire danger indices often focus on forests or have coarse spatial resolution, limiting their use for operational-scale grassland fire planning. This study quantified and modeled wildland fire risk in the Great Plains using historical local weather, fine fuel, and wildfire data from 1992 to 2020. A composite fire risk framework was developed, defining wildland fire risk as the product of seasonal and daily fire risks.

The seasonal fire risk was estimated as the ratio of smoothed multi-year average daily burned area to the total land area and was modeled using multi-year average daily grass curing and multi-year average daily air temperature changes as predictors representing fuel phenology and climatic conditions, respectively. The seasonal fire risk model explained 97% of the variability in seasonal fire risk. Seasonal fire risk in the southern Flint Hills counties showed a bimodal pattern, with a primary peak in March and a secondary peak in October, covering 0.01% of the land area. In spring, seasonal fire risk decreases rapidly from its March peak of 0.034% of the land area. This decline coincides with the traditional April period for intensive prescribed burning, highlighting the importance of seasonal fire risk assessment. The daily fire risk was represented as the ratio of wildfire daily burned area to the smoothed multi-year average wildfire daily burned area, and was modeled using maximum sustained wind speed and dead fuel moisture as predictors.

The daily fire risk was estimated as the ratio of wildfire daily burned area to the smoothed multi-year average wildfire daily burned area, and was modeled using maximum sustained wind speed and dead fuel moisture as predictors. The model explained 15% of the variability in daily fire risk. Analysis of wildland fire risk during the spring burn window (March 8 - May 8) over 15 years in the Flint Hills reveals that the quantified risk ranged from 0.005% to 0.088%, representing an approximately 18-fold difference in burning potential. Eleven days were found within the defined low-risk level ($\leq 0.01\%$), during which optimal prescribed burning can be safely conducted, and 28 days were within the marginal range (0.01% - 0.18%), during which prescribed burning requires utmost caution. Spring's peak seasonal risk (0.034%) was three times more than the fall seasonal risk peak (0.01%), which lies within the defined safe range of wildland fire risk. This pattern indicates that the fall season offers opportunities to implement prescribed burns at lower daily fire risk. The consistent distribution of fire size, frequency, and fuel characteristics across the Flint Hills offers an opportunity to generalize the framework prospectively across the Great Plains.

These results provide a data-driven basis for selecting optimal prescribed burn days that consider fuel conditions and daily fire-weather variability. This approach establishes a foundation for continued efforts to develop localized decision-support tools for prescribed fire planning and wildfire management in the Great Plains.

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Dedication

To my beloved grandparents, in cherished memory.

Chapter 1– Introduction

Wildland fire is a defining ecological process across many of the world’s grassland and savanna biomes, where recurring fire shapes vegetation structure, nutrient cycles, and habitat patterns. In the central United States, the Great Plains are among the most fire-influenced landscapes, with natural ignitions and human-led burning shaping the prairie for centuries. The region’s fire activity reflects the combined influence of climate, fine-fuel dynamics, and land management practices, all of which have changed considerably over recent decades. As extreme weather, fuel accumulation, and expanding human settlement intensify the consequences of uncontrolled fire, prescribed burning has become increasingly important for sustaining ecological function and reducing wildfire hazards. This chapter explores the historical wildland fire regimes in the Great Plains, summarizes their ecological role, contemporary challenges, and the management context that motivates the need for improved fire-risk assessment tools in this fire-dependent region with wildland fire risk quantification as the initial steps.

1.1 Wildland Fire in the Great Plains Region

Wildland fire is an integral process in many fire-adapted ecosystems. In the grassland ecoregions of the Great Plains, prescribed burning regulates vegetation structure, promotes nutrient cycling, sustains biodiversity, and reduces wildfire potential by eliminating antecedent fine fuels (1-hour and 10-hour fuel types) buildup (Brodie et al., 2024; Jeffries et al., 2023; Kreuter et al., 2021; Rosen et al., 2023). The Flint Hills ecoregion is the largest remaining tract of tallgrass prairie in North America and depends on periodic burning for its long-term ecological stability (Akinbile et al., 2023; Baker et al., 2019; Towne & Craine, 2016). Natural ignitions from lightning also

sustain the pyric characteristics of the landscape. However, uncontrolled fires, whether natural or human-caused, can exhibit erratic behavior and cause severe ecological and economic impacts when extreme weather and cured fuel interact to ignite a fire (McClain et al., 2021).

The history of fire suppression, land-use change, and woody encroachment has altered historical fire regimes in the Great Plains. These changes increase the accumulation of fine fuels in wildlands, predisposing these areas to greater wildfire susceptibility (Bowman et al., 2017; Donovan et al., 2020; Liu et al., 2025). When prescribed fire is conducted within suitable weather and fuel conditions, it mitigates these risks by restoring natural fire functions and strengthening ecosystem resilience (Kreuter et al., 2021). The practice follows specific thresholds for temperature, humidity, wind speed, and fuel moisture to achieve ecological management and safety objectives (Higgins et al., 1989; Roos et al., 2018). Despite the known benefits of prescribed burning, prescribed fire remains underutilized due to social and regulatory concerns about potential fire escapes, liability, and air-quality impacts associated with smoke emission and ozone formation (Weir et al., 2017; Baker et al., 2016; Akinbile et al., 2023; El Asmar et al., 2025). Recent wildfire events in the Great Plains illustrate the limits of reactive suppression. The 2017 Starbuck Fire in Clark, Comanche, and Meade, Kansas, which burned more than 500,000 acres and caused extensive ecological and economic damage, remained a notable example (Legislative Division of Post Audit, 2018). Such extreme events typically occur under conditions of heavy fuel

accumulation, strong winds, and low humidity, indicating the need for proactive and science-based fire management.

Fire is an inevitable process in grassland ecosystems, and its exclusion leads to intense future extreme fires (Hiers et al., 2020; Huffman, 2014). The goal of fire management in the Great Plains is to maintain ecological function and improve forage quality for cattle grazing, thereby supporting the livestock industry while minimizing social, economic, and environmental losses. Achieving this goal requires substituting naturally induced fire for coordinated prescribed burning. The most limiting factor to conducting more prescribed fires is the limited number of suitable burn days within the traditional burn window due to climate change-induced weather extremes (Yurkonis et al., 2019; Akimbile et al., 2023). The issue imposes the difficult decision of selecting burn days that balance fire and environmental safety on fire managers on both private and public lands (Hiers et al., 2020; Kolden, 2019; Weir, 2011). Therefore, there is an existential need to support prescribed burn planning with quantitative, evidence-based tools that can improve burn day selection and scheduling and reduce over-reliance on traditional experience and the inherent biases.

1.2 Prescribed Burning Benefits in Grasslands

In fire-adapted ecoregions, prescribed fire sustains the resilience of the plant community. Common evidence is the role of prescribed burning in supporting the productivity of dominant C4 warm-season grasses such as big bluestem (*Andropogon gerardii*) and Indiangrass (*Sorghastrum*

nutans), which are predominant species in the tallgrass prairie biome (Chiodi et al., 2019; Twidwell et al., 2015) through nutrient cycling and suppression of invasive species. Periodic burning also prevents woody plant encroachment, promotes the regeneration of native herbaceous species, and maintains the open structure required for efficient grazing systems and diverse wildlife habitats (Augustine et al., 2010). From a rangeland management perspective, prescribed fire improves forage availability, supports livestock production, reduces invasive non-native grasses, and contributes to the stability of rural economies that depend on livestock grazing-based agriculture.

Compared with mechanical or chemical approaches to fuel treatments, prescribed burning offers an ecologically compatible and cost-effective approach for fuel management (Hyde & Strand, 2019). However, operational implementation is increasingly limited by variable fuel conditions, weather extremes, and policy constraints. Studies from the Northern Great Plains suggest that the number of suitable spring burn days has declined. However, late-summer and early-fall conditions may offer additional opportunities for safe and effective prescribed burning (Yurkonis et al., 2019). This observation raises two important management questions: how safe is burning outside the traditional spring window, and what are the ecological implications for native grass species and overall rangeland conservation? Addressing these questions will demand the recognition that any progressive expansion of the prescribed-burning window requires a quantitative understanding of how fire weather and fine-fuel moisture interact to determine ignition potential, spread rate, biological systems' modifying effect, and potential risk levels. McArthur (1966) acknowledged that such understanding should account for variable interactions across spatial and temporal scales. Quantifying these relationships is therefore central to improving the timing and reliability of prescribed burning while maintaining both ecological integrity and operational safety in fire-adapted ecoregions

1.3 Impact of Wildfire on the Great Plains

A regional analysis of the wildland fire regime in the Great Plains revealed an increase in frequency, areal extent, and severity over approximately three decades (Donovan et al., 2017; Liu et al., 2025). These surging wildfire activities were identified as caused by prolonged droughts, accumulation of fine dead fuel, and land-use changes, culminating in the expansion of the wildland-urban interface (Liu et al., 2025). Similar studies also identified fire exclusion and antecedent fuel as leading causes of large fires in the region, establishing that fire exclusion has increased fuel continuity and depth of cured fine fuels and shrub fuels, elevating flame lengths and fire spread rates across large rangeland areas (Bowman et al., 2017; Donovan et al., 2020; Hiers et al., 2020). The Anderson Creek and Starbuck fires of 2016 and 2017, respectively, burned more than 800,000 acres in southwest Kansas, demonstrating the scale of recent events and the ecological, economic, and infrastructure losses that can follow (Kansas Legislative Post Audit, 2018). The report also noted that these incidents occurred when heavy fine-fuel loads intersected hot, dry, and windy atmospheric conditions that favor rapid ignition, rapid spread, and long-range ember transport.

Similar trends are reported across U.S. grasslands and forests and at global scales, reflecting the influence of extreme weather on fire regimes (Abatzoglou et al., 2019). Since the mid-1980s, the United States has experienced a pronounced escalation in wildfire impacts, evidenced by steadily increasing burned area and rising federal suppression costs, indicating a growing national burden due to megafire activity (Fig. 1.1).

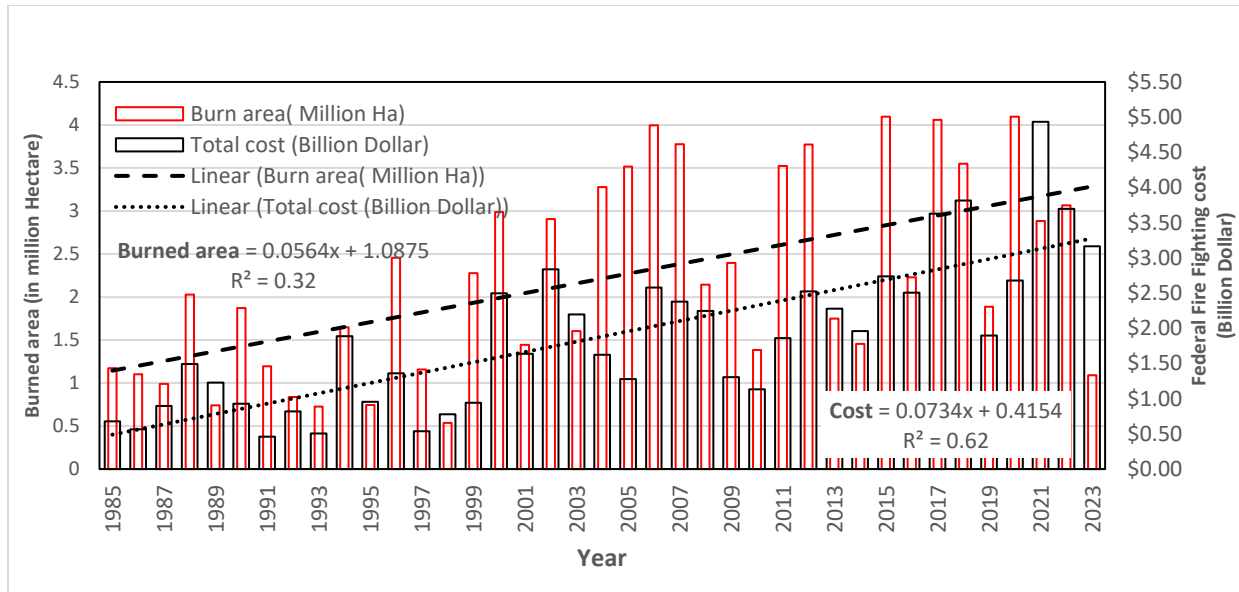


Figure 1.1: Annual U.S. wildfire burned area and federal firefighting expenditures (CPI-U adjusted), 1985-2025. Data: NIFC and U.S. BLS; figure prepared by the author.

Under dry fuel and high wind speed conditions, unburned rangelands become flammable, posing a wildfire threat to rural communities, grazing resources, and air quality. Precursors to Ozone formation, such as smoke plumes, particulate matter (PM_{2.5}), nitrous oxide (NO_x), and other volatile organic compounds from large fires, raise regional-scale concerns about ambient air quality (Baker et al., 2016; El Asmar et al., 2025).

Prescribed burning, when planned within safe fire risk thresholds, is the most effective landscape-scale strategy for reducing wildland exposure to extreme wildfire. Fire behavior in the Great Plains is highly responsive to meteorological conditions and fine-fuel moisture levels (Higgins et al., 1989). Local burn guidelines indicate that burn windows with approximate thresholds of 2- 43 °C for temperature, 25-80 % for relative humidity, and 6-24 km h⁻¹ for wind speed, recognizing that low humidity below about 25 % and higher wind velocities favor rapid growth, Spotfire when a fire spreads through burning embers carried by wind that ignite new, separate fires ahead of the main fire front, and control difficulty in fine-fuel complexes (Higgins et al., 1989b; Weir, 2011; Yurkonis et al., 2019). The operational use of these thresholds, combined

with fuel condition, which is not limited to availability, moisture content, and smoke-management planning, supports the safe application of prescribed fire and reduces the likelihood of large, destructive wildfires.

1.4 Wildland Fire Danger Modeling

Existing fire danger indices such as the Keetch-Byram Drought Index (KBDI), the Canadian Fire Weather Index (FWI), and McArthur's Forest Fire Danger Index (FDI) were originally developed for forested and shrubland environments. Although these systems remain valuable for assessing fire preparedness and suppression difficulties in those ecosystems, they do not provide the fine-scale, precise danger predictions required to support prescribed burning in grassland ecosystems (Cheney & Sullivan, 2008; McArthur, 1966). For example, the KBDI quantifies long-term soil moisture deficits but fails to capture the rapid fluctuations in fine-fuel moisture that strongly influence ignition and spread (Dolling et al., 2005; Garcia-Prats et al., 2015; Plucinski et al., 2023).

McArthur's pioneering research in the late 1960s resulted in the development of the early operational grassland fire danger meter for the southern tablelands of New South Wales and the Australian Capital Territory (McArthur, 1966). This instrument later evolved into an empirical formulation known as the Grassland Fire Danger Index (GFDI), which was adapted for ease of digital computation with the advent of computers (Noble et al., 1980). The original meter, designed as a circular slide rule, estimated expected fire intensity and suppression difficulty by aligning air temperature and relative humidity with empirical adjustments for grass curing and wind speed. The resulting GFDI scale ranges from 1 (low) to 100 (extreme) and provides estimates of fire rate of spread and behavior under defined pasture conditions (Sharples et al., 2009; Sullivan, 2010). Despite its conceptual clarity and operational simplicity, McArthur's model had limitations,

including the locale of design (Australian ecosystems) and variations in fuel structure (vegetation) and climate conditions, which limited its generalizability across diverse geographical locations (Purton, 1982). To retain the precise functional form of the model, which is one of its strengths, while using accessible inputs, it has undergone various transformations.

Successive refinements of McArthur's work aimed to enhance accuracy and accommodate greater environmental variability. Noble et al. (1980) presented McArthur's 3rd version (MK3) of the GFDI as: $GFDI_{Mk3} = 2.0 \times \exp [-23.6 + (-5.01 \ln(C) + 0.0281T - 0.226\sqrt{RH} + 0.633\sqrt{U})]$ where, T is air temperature ($^{\circ}C$), RH is relative humidity (%), U is wind speed ($km\ h^{-1}$), and C is grass curing (%) with a $4.5\ t\ ha^{-1}$ fuel load assumption. The Mk 4 version introduced a nonlinear interaction between humidity and curing (Purton, 1982):

$$\log_{10}(GFDI_{Mk4}) = 0.009254 - 0.004096 (100-C)^{1.536} + 0.01201T + 0.2789\sqrt{U} - 0.09577\sqrt{RH}$$

A subsequent refinement included variable fuel load (Q , $t\ ha^{-1}$):

$$GFDI_{Mk4} = Q^{1.027} \times \exp [(-0.009432 (100-C)^{1.536} + 0.02764T - 0.2205\sqrt{RH} + 0.6422\sqrt{U})]$$

The Mk 5 model incorporated explicit fuel load (Q) and fuel moisture content (m , %), allowing the model to account for nonlinear moisture load interactions (Noble et al., 1980):

$$\text{for } m < 18.8: GFDI_{Mk5} = 3.35Q \times \exp(-0.0897m + 0.0403U)$$

$$\text{for } 18.8 \leq m < 30: GFDI_{Mk5} = 0.299Q \times \exp[(-1.686 + 0.0403U)(30-m)]$$

Fuel moisture (m) was estimated empirically as:

$$M = \frac{(97.7 + 4.06RH)}{(T + 6)} - 0.00854 RH + \frac{(3000)}{(C)} - 30$$

In the Great Plains, the U.S. National Weather Service station in Wichita, Kansas, attempted adaptation of McArthur's Mk 4 GFDI model for the central Great Plains, producing the calibrated grassland fire danger index (cGFDI), which allowed for hourly forecasting and improved situational awareness during Kansas fire events (Schreck et al., 2010). The equation is given as:

$$\text{cGFDI} = 10^{(0.009254 - 0.00409 \times (100 - C)^{1.536} + 0.01201 \times T + 0.2789 \times \sqrt{V} - 0.09577 \times \sqrt{RH})},$$

where C = curing (%), T = temperature (°C), V = sustained wind (km h⁻¹), and RH = relative humidity (%). However, the index's limited sensitivity to relative humidity and inconsistencies in wind speed parameterization could account for the cGFDI's inability to predict some extreme wildfire days on validation (Schreck et al., 2010). These shortcomings highlighted the generalizability challenges of Australian-based fire danger systems in North American prairie ecosystems, despite the identified shared similarities in burn windows between the regions.

The catastrophic 2009 Victorian “Black Saturday” fires further exposed weaknesses in the Mk 4 framework and prompted the development of the Australian Fire Danger Rating System (AFDRS), officially adopted in 2022 (Gregory et al., 2024; Kenny et al., 2024). The AFDRS integrates multiple empirical sub-models that account for differences in fuel type, structure, and load, recognizing that a single index cannot describe all vegetation classes. Although the Mk 5 version was never fully operationalized due to uncertainty in estimating live and dead fuel moisture, McArthur’s core structure of linking meteorological conditions to fire behavior remained informative for quantifying grassland fire risk (Kenny et al., 2024). This conceptual framework continues to guide the development of locally calibrated fire danger indices for grassland ecosystems.

For instance, the RING (Rate of Spread in Northern Grasslands) model represents a more recent step in fire danger assessment for northern ecosystems (Sjöström & Granström, 2023). RING integrated grass phenology by using cumulative temperature, expressed as growing degree-days, to approximate the seasonal progression of live grass growth and curing within a rate-of-spread model that also included wind and moisture variables. The model shows that as live grass biomass increases through the growing season, fire spread potential declines exponentially,

representing the transition from high post-snowmelt flammability to negligible spread potential during green-up. RING relies on empirical relationships derived from wildfire records and experimental burns and can be calculated from standard meteorological data. Although RING performs well under boreal conditions, its underlying assumptions differ from conditions in the Great Plains. For example, complete winter curing, short post-snowmelt burn windows, and single-peak fire seasons in northern regions contrast with the dual-season fire activity and prescribed burning practices of prairies. The differing patterns of curing, drought, and fuel continuity in the Great Plains demonstrate the need for a regionally calibrated fire danger index that captures the local relationships between meteorological conditions, fuel dynamics, and observed fire activity. The present study addresses this need by quantifying a wildland fire risk using a local data formulation specific to the Great Plains.

1.5 Research Needs

The increasing frequency and intensity of wildfires worldwide reflect a complex interaction of climatic conditions, behavioral dynamics towards land-use in relation to wildland urban interface expansion, and shifting fire regimes across regions. In the Great Plains, a long-standing culture of burning has preserved the use of prescribed fire as an essential tool for maintaining grassland structure, controlling woody encroachment, and enhancing forage quality. However, maximizing the benefits of prescribed fire is limited by fire safety and environmental safety concerns, narrowing burn windows, and the absence of localized tools that support evidence-based planning and real-time fire-based decision-making. The fine precision required to predict prescribed fire danger, hazards, and risk renders existing legacy indexes inadequate as standalone metrics for quantifying grassland prescribed fire behaviors. As a result, land managers often rely on experience and traditional ecological knowledge to determine when and how to conduct

controlled burns. While these practices have cultural and ecological value, they also introduce uncertainty and subjectivity, which can lead to unpredictable burn outcomes or missed burn opportunities amidst a limited available meteorologically defined burn window each spring (Akinbile et al., 2023; Chiodi et al., 2019; Kolden, 2019; Weir, Coffey et al. 2017; Yurkonis et al., 2019). There are also social barriers, such as the unavailability of enough manpower to support planned burns.

The cost of lost burn opportunities poses cascading consequences, including antecedent fuel accumulation, greater fire suppression costs, and heightened likelihood of wildfire incidents. Beyond ecological management, public safety and air quality concerns are increasingly shaping prescribed fire policy and practice. The spatial and temporal overlap between the peak prescribed burning window and the peak wildfire window in the region poses a serious concern for making the case for more burning when permitted. It also poses an air quality risk by potentially amplifying regional smoke exposure and ozone formation, which may negatively affect the health of people with preexisting conditions.

Therefore, expanding the prescribed burning window through improved fire risk quantification would not only reduce seasonal smoke plumes from marginal, clustered burning within a narrow burn window, but also aid in distributing emissions and reduce the lag effect of ozone precursors. A comprehensive, locally calibrated risk framework is therefore necessary to inform decisions that balance ecological benefits with community safety and atmospheric considerations. Recent regional analyses provide a quantitative basis for developing such a framework.

In Oklahoma, within the Great Plains, drought severity accounts for approximately 51% of the interannual variability in burned area, while grass curing explains around 60% of the

monthly variability in wildfire occurrence (Liu et al., 2025). These findings underscore the interconnected roles of mid-term fuel readiness and short-term fire weather in determining fire potential and the need to account for wildland fire risk at diverse scales.

1.6 Research Objectives

This research aims to quantify and model wildland fire risk in the Flint Hills region of the Great Plains to support prescribed burn planning, enhance operational wildland fire safety, and lay the foundation for developing an optimized grassland fire risk and environmental risk assessment index. The overarching goal is to provide a localized framework for assessing wildland fire risk that captures the dynamic interactions among fuel, weather, and climate conditions influencing wildland fires in grassland ecosystems. The specific objectives of this thesis are to:

1. characterize the occurrence and behavior of wildfires in the Great Plains to understand the broader ecological and climatic context of fire activity.
2. quantify wildland fire risk as a function of seasonal and daily grassland fire risk.
3. model quantified fire risk using ecologically relevant and accessible explanatory factors that align with the temporal scales of fire behavior.

Chapters 2 and 3 expanded on these research objectives, each focusing on an interconnected aspect of wildland fire risk. The progression of analysis involves characterizing regional fire occurrence in Chapter 2, creating a quantitative risk metric, and exploring management implications in Chapter 3. Using long-term wildfire data, meteorological datasets, and fine fuel condition variables in the short and midterm, a localized quantitative risk metric for the Flint Hills ecoregion is developed. The modeling examines the relationship between dead fuel moisture and wind speed as key factors in short-term risk. In the midterm, it considers grass curing and

temperature changes as important influences on relative fire risk. The distribution of overall wildland fire risks within the traditional spring burning window was studied to offer insights into operationally relevant wildland risk periods that can aid in developing a localized fire risk index for prescribed burning. Chapter 4 integrates findings from chapters 2 and 3, emphasizing the operational implications of quantified wildfire risk for regional fire management and prescribed burn safety. It demonstrates how combining seasonal and daily risk factors can enhance decision-making and support adaptive fire management in the face of changing climate conditions. This chapter also discusses future research directions, such as local model calibration and developing a comprehensive ground-level ozone model to estimate the impact of wildland fire smoke and particulate matter on regional air quality. Overall, these outputs aim to generate a set of indices that balance fire safety, air quality, and ecological goals in planning and decision-making for prescribed burns across the Great Plains.

Chapter 2– **Characterizing risks for wildfires and prescribed fires regimes in the Great Plains**

*Part of this chapter has been published by MDPI Fire chapter

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Introduction

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 to assess spatiotemporal patterns in wildfire risk and evaluate the role of prescribed fires through a combined analysis of wildfire and prescribed fire data. Results show a threefold increase in both wildfire frequency and area burned in the Great Plains, 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. Negative correlation between prescribed fires in spring and wildfires in summer indicated the effectiveness of prescribed fire in mitigating wildfire risk. 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. The ratio of wildfire area burned to total area burned (dominated by prescribed fires) declined from over 20% in early March to below 1% by early April. The result laid the foundation for quantifying wildland fire risk in the Great Plains with the overall goal of developing a localized fire risk assessment tool that integrates various long-term, mid-term, and short-term risk factors, thereby supporting more effective fire management in this region.

2.1 Background

Fire is an intrinsic ecological process in the prairie ecosystems of the U.S. Great Plains. These semi-arid landscapes are naturally fire-prone, with most wildfires occurring during extended droughts and being triggered primarily by lightning, followed by human activities such as negligence and accidents (Ojima et al., 2021; Reid, 2007; Stubbendieck et al., 2007). Although fire plays a vital ecological role, unplanned wildfires remain among the most destructive natural hazards, particularly in expanding wildland-urban interfaces, where human settlements border flammable vegetation (Russell et al., 2024). As this interface expands and regional climates become hotter and drier, the frequency and severity of catastrophic wildfires are expected to increase, intensifying risks to life, property, and air quality (Brunson, 2023; Yu et al., 2023). Understanding wildfire risk and its driving factors in the Great Plains based on historical records is therefore essential for informed resource allocation and proactive mitigation.

Since fire exclusion is not ecologically sustainable in fire-adapted ecosystems, prescribed fire has emerged as a critical tool for maintaining grassland ecosystems. Indigenous peoples historically applied deliberate burning at frequencies often exceeding those of lightning ignitions, shaping the ecological balance of the prairies (Higgins et al., 1989). Modern prescribed fires are intentionally planned to reduce hazardous fuels, restore habitat, protect native plant species from non-native species invasion, and mitigate wildfire risk under controlled conditions (Leis, 2013; Watts et al., 2024). Despite their proven ecological and economic benefits, prescribed fires remain underutilized due to public safety concerns, liability fears, and limited access to science-based decision-support tools (Clark et al., 2022; Hanberry et al., 2019; Russell et al., 2024).

To address these barriers, it is essential to develop region-specific fire risk assessment frameworks that help land managers identify safe and effective burn opportunities. Existing

indices, such as the Keetch-Byram Drought Index and the Grassland Fire Danger Index, were developed for forested or Australian systems and do not represent the fine-fuel and climatic characteristics of the Great Plains (Schreck et al., 2010).

This study aims to characterize and quantify wildland fire risk in the Great Plains as a foundation for developing a localized, data-driven fire risk index to support prescribed burn planning. Using historical wildfire and prescribed fire data, combined with meteorological and fine-fuel variables, we identify and evaluate long-term, mid-term, and short-term fire risk factors. The integrated analysis of wildfire and prescribed fire activity represents a novel approach that enhances understanding of the dynamic relationship between managed and unmanaged fires. The results will inform the development of a quantitative fire risk assessment tool that supports both prescribed fire implementation and wildfire preparedness across the Great Plains.

2.2 Data and Methods

2.2.1 Wildfire data

Historical wildfire data analyzed in this study were sourced from the Fire Program Analysis Fire Occurrence Database (FPA-FOD) maintained by the U.S. Forest Service. FPA-FOD consolidates incident reports from federal, state, and local agencies under National Wildfire Coordinating Group standards, including updated cause classifications and metadata fields (Short, 2022). For this study, all georeferenced wildfire incidents across the ten Great Plains states from 1992 to 2020 were extracted. Figure 2.1 shows the map of the United States with all the regions. Although FPA-FOD undergoes baseline quality control, additional screening was conducted to improve reliability. Duplicate events were identified and removed, yielding 497,749 unique wildfire incidents and a cumulative burned area exceeding 18 million ha over 29 years (1992-2020).

The analysis utilized the discovery date, final fire size (in hectares), and geospatial coordinates accurate to at least the Public Land Survey System section scale, approximately one square mile in area. Spatial processing was performed in R using the `sf` and `tigris` packages (Pebesma, 2018; Walker, 2016). Procedures included importing county boundaries, validating and projecting coordinates to a uniform CRS, removing records with invalid or out-of-domain locations, and subsetting events to the defined study area. These steps produced a standardized, spatially consistent wildfire dataset suitable for subsequent modeling and risk analysis.



Figure 2.1: Map of the United States with regions (Furian, 2022)

2.2.2 Prescribed fire data

Prescribed fire is a core management tool in many fire-adapted ecosystems and is particularly important in the Flint Hills region (Figure 3.1), where regular burning is needed to maintain the tallgrass prairie that extends across much of eastern Kansas and northern Oklahoma. In this region, an estimated 0.8 million hectares are intentionally burned each year, with most burns concentrated in April. Prescribed-fire activity was quantified using a remotely sensed burned-area product developed from Moderate Resolution Imaging Spectroradiometer (MODIS) data collected by NASA's Terra and Aqua satellites (Akinbile et al., 2023). The product covers 17 Flint Hills counties from 2003 to 2019 and was produced via supervised minimum-distance classification of bi-spectral MODIS imagery. MODIS provides daily global observations in 36 spectral bands spanning 0.41–15 μm at spatial resolutions of 250 m (2 bands), 500 m (5 bands), and 1 km (29 bands) (Remer et al., 2005). For this study, we used the 250 m bands 1 (red, 620–670 nm) and 2 (near-infrared, 841–876 nm), which offer a suitable balance of spatial, temporal, and spectral resolution for mapping fire activity. The MODIS-derived daily burned area includes both prescribed and unplanned fires; we combined these data with reported wildfire burned area for the Flint Hills to compare prescribed fire and wildfire patterns across the region, long-term and mid-term risk factors.

Seasonal variability in the fire regime was characterized using two complementary indicators obtained from the Oklahoma Mesonet station at Skiatook: the Keetch–Byram Drought Index (KBDI) and grassland curing, available for 2006–2019. The KBDI is a slow-responding drought metric developed by the USDA Forest Service to describe cumulative soil moisture deficit, originally for forested settings (Keetch & Byram, 1968). The KBDI values range from 0 (saturated soils) to 800 (maximum modeled deficit) and can be interpreted as the rainfall (0–8 in) needed to

return the profile to saturation. It is widely applied for wildfire monitoring and forecasting (Krueger et al., 2022; Plucinski et al., 2023), although its suitability for grassland systems, such as the Great Plains, remains an open question. Grassland curing, defined as the percentage of dead material in the grass fuel complex, ranges from 0% (fully green) to 100% (fully cured) and strongly influences dead fuel moisture and flammability. Cured grasses ignite more readily and support faster spread than green grasses, with limited propagation below about 50 % curing (Chaivaranont et al., 2018), and rapid fire growth once curing exceeds roughly 90 % (Sullivan, 2010). The critical nature of fine fuel condition and there rapid response to meteorological changes validates the need for quantifying levels of potential extreme fire behaviors in grassland ecosystems (Anderson et al., 2011).

The difficulties associated with grass curing estimation at the field scale have been a limiting factor in exploring this scientific gap. In contemporary times, grass curing can be estimated from satellite-derived vegetation greenness metrics, especially exploring established relationships between relative greenness and the normalized difference vegetation index (NDVI) (Newnham et al., 2011). Therefore, in characterizing the fire dynamic regimes in the Great Plains, the focus is on the driving factor of dynamic fire behaviors in different temporal scales.

2.3 Results

2.3.1 Wildfire statistics

From 1992 to 2020, approximately 498,000 wildfires in the Great Plains burned about 18 million ha, averaging nearly 17,000 fires and 0.6 million ha of burned area per year, with a mean

fire size of about 36 ha across the ten Great Plains states. Table 2.1 presents the detailed distribution of wildfires across the Great Plains.

Table 2.1: Synopsis of wildfires across the 10 states in the Great Plains from 1992 to 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

2.3.2 Grass curing relationship with wildfire in Oklahoma state

Analysis of the multi-year average monthly wildfire numbers from 1992 to 2020 in the state of Oklahoma, aligned with the multi-year average grass curing levels (Fig. 2.2). While this relationship is non linear, a least square regression analysis shows that grass curing explains approximately 60% variability of the wildfire frequency across the monthly temporal scale. This further reflects the influential role of grass curing as a mid-term fire risk factor in grassland ecosystems.

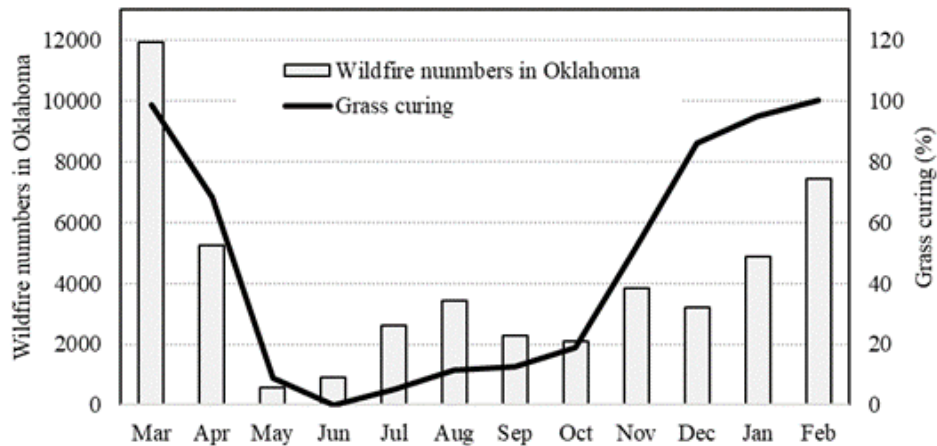


Figure 2.2: Wildfire frequency and grass curing in the state of Oklahoma

2.3.3 Prescribed fires and wildfire dynamics in the Flint Hills region.

Between 2003 and 2019, an average of approximately 0.8 million hectares of rangeland were treated with more than 2,000 prescribed fires each spring across the 17 Flint Hills counties. Figure 2.3 a, b, and c compare the total area burned and the wildfire area burned in the Flint Hills region. Figure 2.3a shows that spring wildfires accounted for only about 1% of the total burned area from March through May, and the correlation between spring wildfire area and total burned area was weak ($R^2 = 0.08$). Figure 2.3b presents a comparison of the total spring burned area with the wildfire area burned in the subsequent summer (June to August). In most years, increased spring burning, primarily due to prescribed fire, corresponded with a reduction in summer wildfire area, resulting in a negative relationship ($R^2 = 0.26$). The primary exceptions occurred in 2007 and 2013, when limited burning in both seasons was likely due to reduced fine-fuel continuity following severe antecedent droughts. Figure 2.3c describes the ration of wildfire to total fire which is hypothesized to be dominated by prescribed fire in the spring season due to intensive prescribed burn activities in the region with the spring season. The results showed that from 2003 to 2019, there was an increasing trend, potentially indicating increased wildfire risk in the region. This is expected amid heightened public fear over perceived fire risk and burn bans.

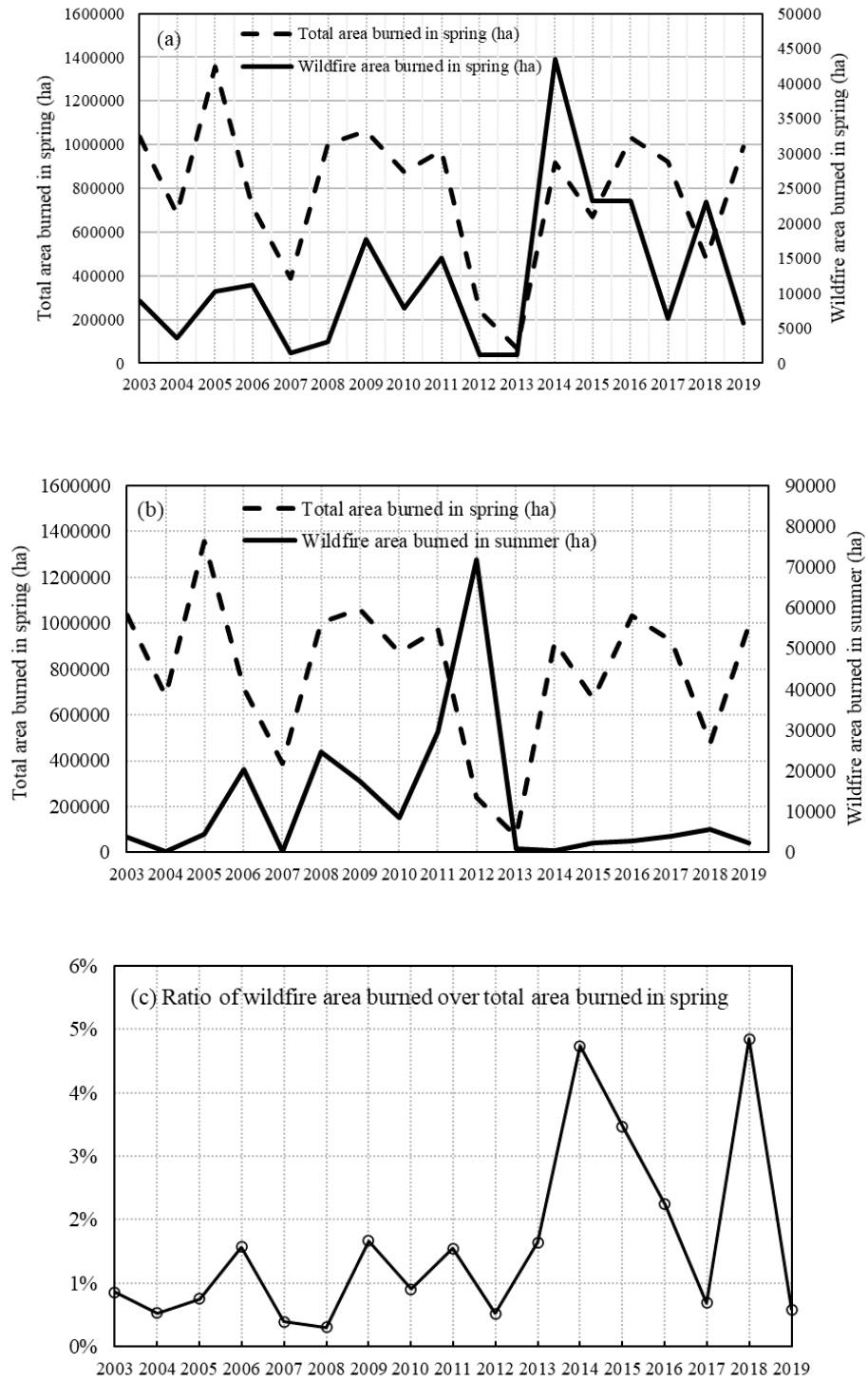


Figure 2.3: Wildfire burned area and total burned area comparison in the Flint Hills from 2003 to 2019

Figure 2.4 presents the multi-year average of daily wildfire and total area burned. Both metrics followed a bell-shaped distribution, with wildfire activity peaking around March 22 and total burn area peaking around April 10. Typically, more prescribed fires indicate weather and fuel conditions with lower fire risk, while more wildfires indicate conditions with higher fire risk. The ratio of wildfire area burned to total area burned varied by the day of the year. Figure 2.4 shows the ratio of daily wildfire area burned to total area burned throughout the spring season. The ratio declines steadily over time, from more than 20% in early March to less than 1% by early April, highlighting a sharp decrease in fire risk as spring progresses.

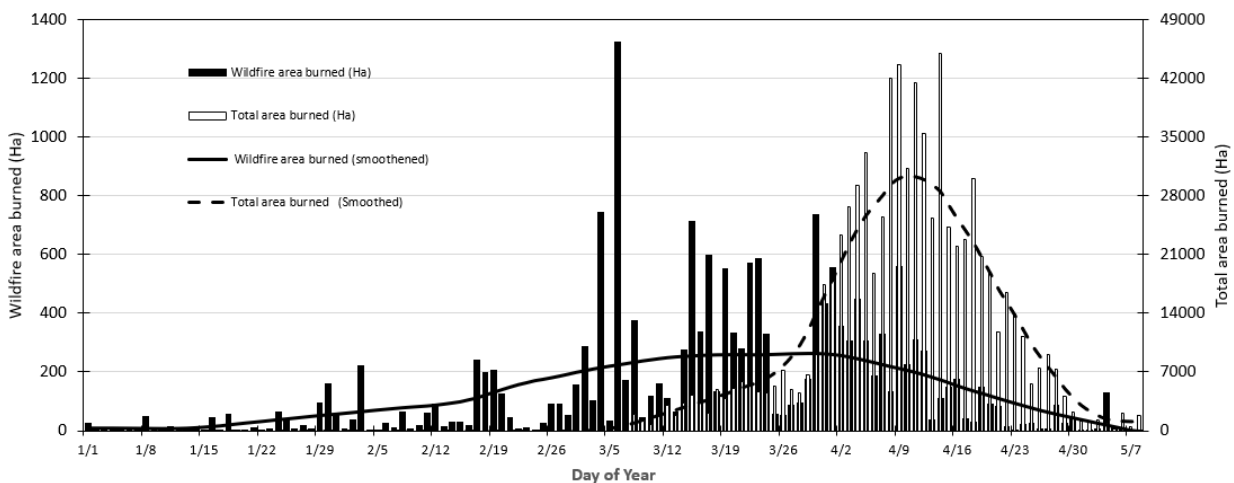


Figure 2.4: Multiple year average daily wildfire area burned and total area burned on different dates in the Flint Hills region (2003-2019)

2.4 Discussion

2.4.1 General trends of wildfires in the Great Plains

This study evaluated Great Plains wildfire patterns from 1992 to 2020 to describe broad-scale gradients in fire risk and explore the fire range in the region. Across the region, the number of recorded wildfires tended to increase toward the southern states, consistent with warmer conditions and stronger drying at lower latitudes, whereas mean fire size generally increased from

east to west, tracking a transition from predominantly herbaceous fuels to more extensive woody and mixed fuel types. The two potential driving factors of this fire regime change are increasing summer daily temperatures and increasing vapor pressure deficit (Gutierrez et al., 2021), which are responsible for the increased rate of dry fuel. As the grassland ecosystem transitions into an ecotone from east to western woodlands, the resulting burn areas expand due to varying fuel types(Gutierrez et al., 2021).

Average burned area per wildfire was especially high in Montana, Wyoming, and New Mexico (Fig. 2.5), where rugged topography and greater woody fuel loads favor large, high-intensity events compared with the mostly grassland and cropland settings elsewhere in the Great Plains (Donovan et al., 2020). Scasta et al. (2016) also documented a north–south increase in wildfire occurrence associated with rising temperatures. Texas recorded the most significant number of fires, and, collectively, the western and southern portions of the Great Plains accounted for the largest annual areas burned (Fig. 3.6).

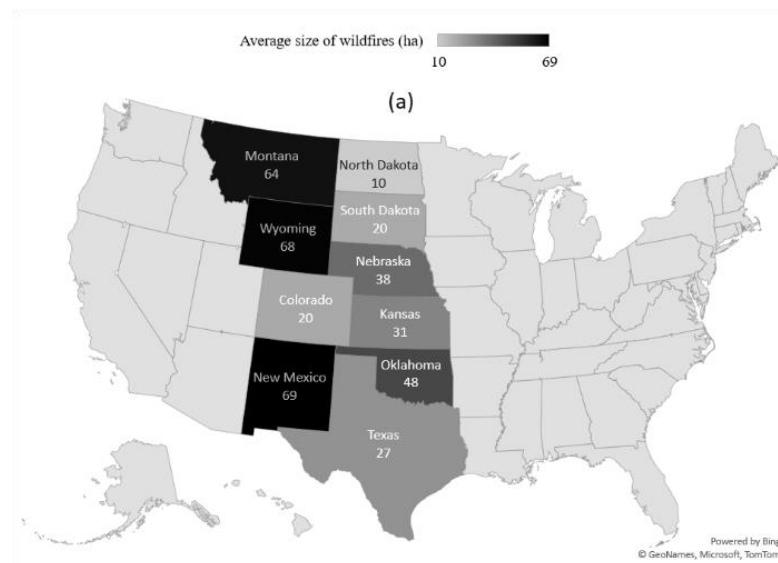


Figure 2.5: Average wildfire size per incident across the Great Plains, 1992-2020.

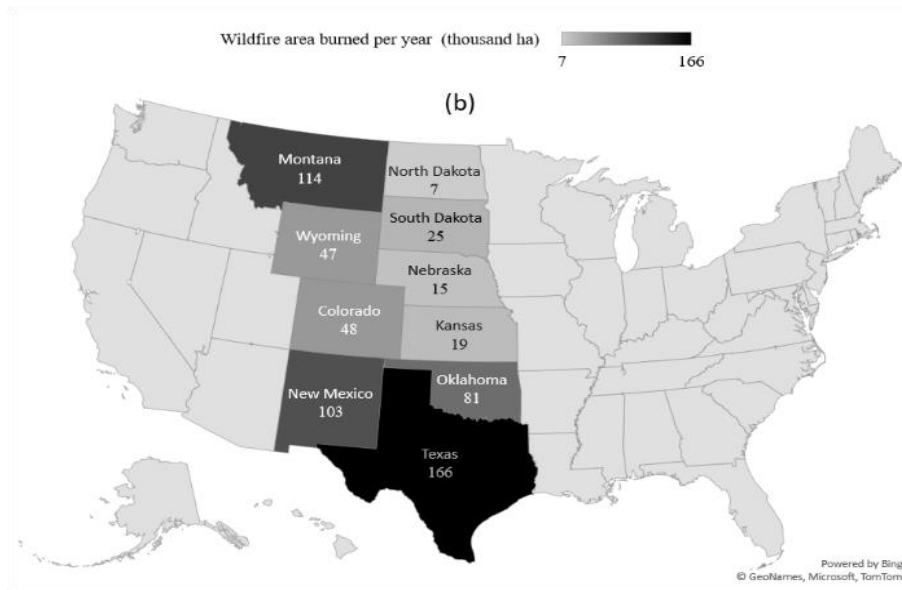


Figure 2.6: Average annual burned area across the Great Plains, 1992-2020.

During the study period, wildfire activity in the Great Plains increased overall, consistent with patterns reported in other parts of the western United States (Boisramé et al., 2022; Donovan et al., 2017). Donovan et al. (2020) documented a roughly fourfold increase in area burned by large wildfires (>400 ha) between 1985 and 2014 using hurdle models, and similar upward trends have been inferred from satellite products (Dennison et al., 2014; Iglesias et al., 2022), fire records (Westerling, 2016), and simulation studies (Boisramé et al., 2022). Yu et al. (2023) further reported that, at broader western U.S. scales, growth in total burned area has exceeded the rise in fire counts, implying larger mean fire sizes. In contrast, our Great Plains analysis did not detect a significant increase in average wildfire size over time, indicating a regionally distinct response of fire behavior despite increasing activity.

A combination of climatic and human drivers likely shapes the observed increase in wildfire occurrence in the Great Plains. Warmer and drier conditions, longer fire seasons, and more frequent or intense droughts promote lower fuel moisture and greater flammability, contributing

to higher fire activity and larger extreme events (Dennison et al., 2014; Gamelin et al., 2022; Lang & Moeinni-Meybodi, 2021; Russell et al., 2024). Anthropogenic pressures, including expanding populations in and near wildland areas (Cooke et al., 2016) and long-term fire exclusion that allows fuels to accumulate (Brotons et al., 2013), likely compound these climatic effects and further elevate wildfire risk.

2.4.2 Wildfire seasonality in the Great Plains

Seasonal wildfire patterns in the Great Plains differ by region and reflect underlying land cover. In the western Great Plains, wildfire activity generally peaks in summer, whereas in the eastern portion of the region, it peaks in spring, particularly in Kansas and Oklahoma, as shown in Figure 2.7a. This is likely due to the dominance of woody fuels in the west and grassland fuels in the east. Yu et al. (2023) reported a bimodal fire season across the United States, with a primary maximum in August and a secondary maximum in April, which is consistent with the pattern observed here. The summer peak is often associated with convective storms and frequent lightning ignitions (Balch et al., 2017). In grassland systems, wildfire activity commonly peaks in spring, before green-up, when cured grasses are more flammable than actively growing vegetation.

Wildfire size demonstrates pronounced seasonal and regional differences. In the southern Great Plains, including Texas, New Mexico, Oklahoma, and Kansas, fires are generally peak in spring, with mean sizes approximately one to two times greater than in other seasons as shown in Figure 2.7b. Conversely, in the northern states, such as Wyoming and Montana, they experience their peak fires during the summer. In Oklahoma and Kansas, both wildfire frequency and mean fire size reach their highest levels in spring, indicating that this season poses the most significant wildfire risk. In Texas, although most ignitions occur in summer, the largest total burned area is observed in spring.

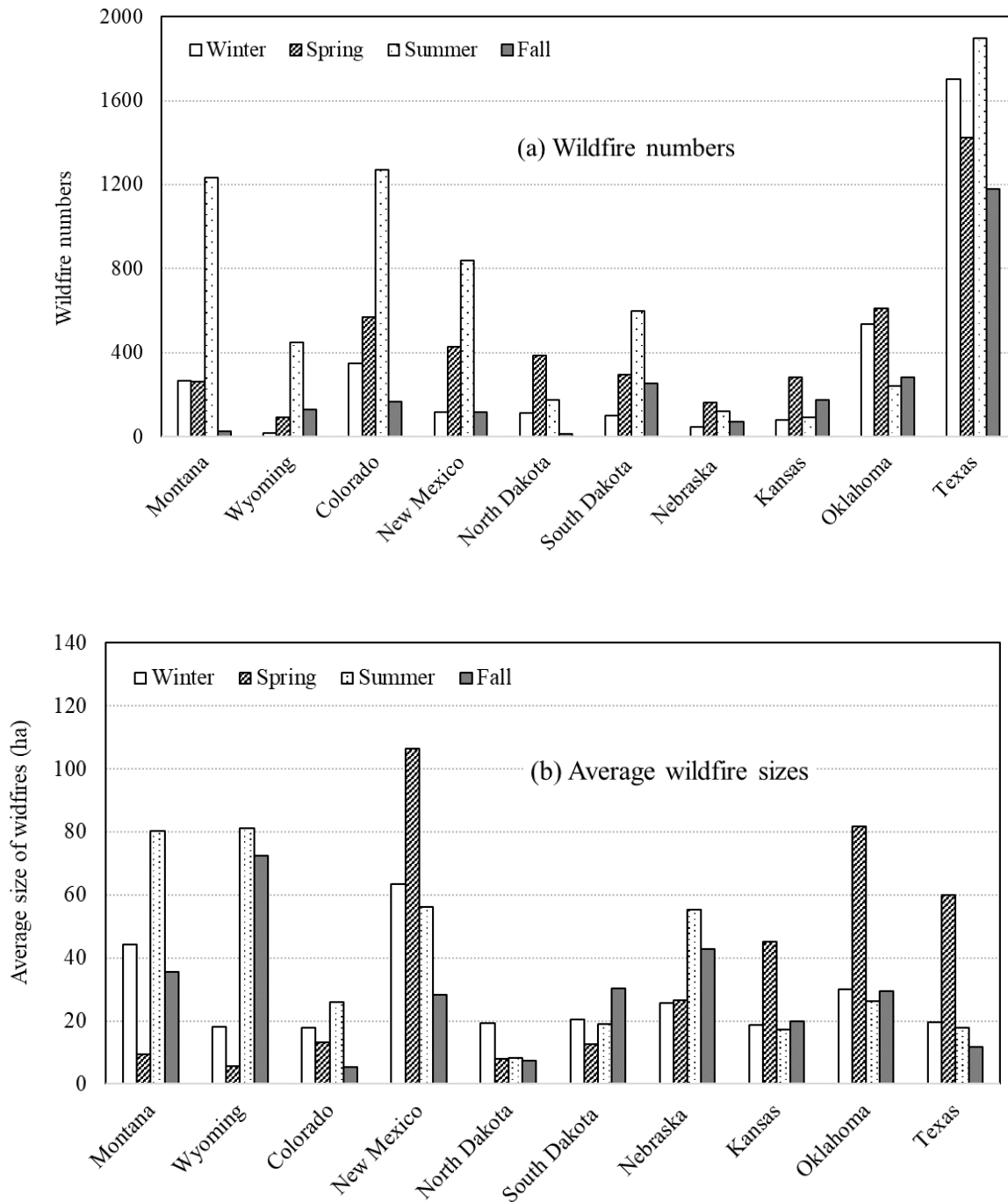


Figure 2.7: Seasonal analysis of wildfire number and average wildfire sizes Great Plains from 1992 to 2020

A key indicator of extreme weather in the Great Plains is the gradual advancement of the wildfire season. In northern states such as Montana and Wyoming, the month with the largest burned area has shifted from August to July, as evidenced by increased July activity and decreased August activity. This trend is also observed farther south. In New Mexico and Colorado, the seasonal maximum has shifted from July to June due to the earlier onset of warmer, drier conditions. Grassland ecosystems exhibit a similar pattern. In the Flint Hills, spring fire peaks have progressively advanced, and in both Oklahoma and Kansas, wildfire activity has increased in February and March while remaining relatively stable in April.

These observations collectively indicate a gradual but persistent shift of the fire season toward earlier months. They are consistent with Figures 2.3a and 2.3b, which demonstrate that, after 2013, the Flint Hills region experienced more wildfires in spring than in summer, reinforcing the broader regional shift toward earlier-season fire activity. These changes align with the ecological impacts of climate change, which have led to the earlier onset of hot, dry conditions and an extended period during which fuels remain susceptible to ignition. Scasta et al. (2016) further reported that these seasonal advances are most pronounced in cooler, higher-latitude, and higher-elevation regions such as Montana and Wyoming. This shift in seasonality has significant implications for wildfire management. Earlier fire peaks affect preparedness timelines, seasonal staffing, resource allocation, and the determination of safe and ecologically appropriate windows for prescribed burns.

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

Wildfire activity in the Great Plains is influenced by risk factors operating across multiple temporal scales. Over the long term, interannual variability in burned area is closely associated with drought severity. The Keetch–Byram Drought Index (KBDI), which quantifies cumulative

soil moisture deficit, serves as a widely recognized indicator of drought stress and wildfire risk (Brown et al., 2021; Dolling et al., 2005). In the present study, the annual average KBDI accounted for 51% of the interannual variation in total burned area, underscoring its role as a primary long-term driver of wildfire activity (Liu et al., 2025). Abatzoglou and Williams (2016) reported even stronger associations between KBDI and burned area in southwestern forests, with coefficients of determination ranging from 0.6 to 0.8. However, fuel accumulation influenced by earlier-season rainfall can also modulate wildfire patterns on an annual basis. For example, Scasta et al. (2016) observed that severe wildfire years in Oklahoma and Wyoming frequently followed periods of average or above-average growing-season rainfall, while in Nevada, wildfire activity was more strongly linked to precipitation in the preceding year.

These interactions help explain the stronger relationship between KBDI and burned area observed at broader spatial scales (Yu et al., 2023). Across the entire Great Plains, the correlation between KBDI and burned area is substantially higher than within individual states, where local fuel conditions and varying land uses introduce greater uncertainty.

At the mid-term scale, grass curing serves as a significant predictor of monthly wildfire activity. In grassland regions, curing explained 60% of the variation in monthly wildfire counts. However, grass curing alone does not fully account for seasonal fire patterns. For example, July and August experience substantially more wildfires than May and June, despite all four months exhibiting similarly low curing levels below 20%. This discrepancy is likely attributable to higher midsummer temperatures and increased lightning frequency. Conversely, December through February record far fewer wildfires than March, even though curing levels remain similarly high above 80 percent. Cold winter temperatures likely inhibit ignition, even when fuels are dry. These

observations indicate that seasonal wildfire behavior in grasslands is best explained by the combined influence of grass curing and temperature.

Short-term risk factors, including wind speed and dead-fuel moisture, are critical in determining the likelihood of fire ignition and early spread. These variables fluctuate rapidly in response to changes in temperature and humidity (Wade, 2013), positioning them as primary drivers of daily fire danger. The ongoing research aims to integrate long-term, mid-term, and short-term factors into a unified, practical fire-risk framework to inform both wildfire response and prescribed fire planning.

The pronounced increase in wildfire occurrences during March prompts an investigation into the potential influence of early-spring prescribed fire operations. Further research is required to assess whether these activities significantly affect wildfire statistics during this period.

2.4.4 Wildland fire relationships in the Great Plains

Prescribed fire has historically been employed in the Great Plains to reduce fuel loads, maintain grassland structure, and mitigate wildfire risk. Its significance is increasing as wildfires become more frequent and as the expansion of the wildland-urban interface places additional communities at risk. The Flint Hills region, encompassing eastern Kansas and northern Oklahoma, represents one of the most active prescribed fire areas in North America, with the majority of burns occurring during the spring.

The association between spring prescribed fires and wildfires was found to be weak. Only 8 percent of the variation in spring wildfire area was attributable to the total spring burned area, which predominantly results from prescribed burns. This finding is consistent with Reid (2009), who reported that prescribed fire ignitions constituted the smallest proportion of wildfire ignition

sources, ranging from 0 to 13.2 percent. Similarly, Toledo et al. (2014) observed that wildfire risk was only weakly associated with prescribed fire in their model. Furthermore, wildfire incidence was substantially higher in March than in April, despite prescribed fire activity peaking in April. These results suggest that wildfire occurrence is more strongly influenced by grass curing than by prescribed fire activity.

Although spring prescribed fire activity did not strongly predict spring wildfire area, it demonstrated a clear negative association with summer wildfire activity. The total area burned in spring accounted for 26% of the variation in summer burned area, indicating that extensive spring prescribed burning may contribute to reduced fuel loads and lower summer wildfire risk. This finding corroborates earlier research by Wade (2013), who concluded that prescribed fire can effectively reduce wildfire risk when implemented under appropriate conditions.

Prescribed fires are typically conducted under lower fire danger conditions, whereas wildfires generally occur during periods of elevated weather and fuel risk. To assess fire risk in spring, this study calculated the ratio of wildfire area burned to total area burned. Between 2003 and 2019, this ratio declined from over 20 % in early March to less than 1 percent by early April, reflecting a rapid seasonal decrease in wildfire risk as spring advanced. This trend parallels the seasonal reduction in grass curing, which typically decreases from nearly 100 percent in winter to almost zero in summer.

A secondary increase in the wildfire-to-prescribed-fire ratio was observed in early May (Figure 2.2), during a period when grass curing remained low and stable. This rise is likely attributable to short-term weather events, such as increased thunderstorms, lightning, and stronger winds, which are prevalent in late spring. These findings underscore the importance of accounting

for multiple temporal scales of risk in planning and decision-making for both prescribed fire and wildfire management.

2.5 Conclusions

Concerns about fire risk continue to be a major barrier to landowners adopting prescribed fire, as noted by Hanberry et al. (2019). Effective risk management requires precise wildland fire risk quantification to reduce uncertainty and facilitate informed decision-making. In the Great Plains, the limited application of prescribed fire is frequently attributed to resource limitations and insufficient confidence among landowners, especially those with limited experience. Expanding the safe use of prescribed fire will necessitate the development of practical, science-based tools that enable land managers to assess fire risk under local conditions. This study establishes a foundation for the development of such tools by identifying and quantifying long-term, mid-term, and short-term factors that influence wildfire activity in the region. Improved understanding of the interactions among drought, fuel conditions, weather, and daily fire behavior facilitates more effective planning. Determining optimal times and locations for prescribed fire may promote broader adoption and enhance landowner confidence in grassland management. Proactive, evidence-based application of prescribed fire can enhance landscape resilience and mitigate future wildfire risk throughout the Great Plains. The results of this study support the creation of a localized fire risk assessment framework to inform prescribed fire planning and strengthen wildfire preparedness in this fire-dependent region.

2.6 Acknowledgments

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Chapter 3— **Quantifying and modeling wildland fire risk for prescribed fire management in the Great Plains**

A modified version of this chapter is being prepared for submission to the *Fire Ecology Journal*

3.1 Introduction

In North America, wildfires pose a natural hazard, threatening human life, infrastructure, air quality, and altering fire regimes in both forest and grassland ecosystems (Yu et al., 2023). Over the past three decades, the region has experienced an increase in wildfire activity, reportedly due to recurrent droughts, reduced fire use, and urban land expansion into fire-prone areas (Bowman et al., 2017; Donovan et al., 2020; Liu et al., 2025). Prescribed fires are relevant for delivering ecologically sustainable benefits to grasslands such as improved forage quality for livestock grazing, reducing woody plant encroachment, enhancing biodiversity, and mitigating elevated wildfire risk (Knapp et al., 2009; Williams et al., 2024). Despite these benefits, prescribed fire application remains constrained due to safety concerns and a lack of tools for accurate fire risk assessment (Kolden, 2019; Weir, 2011; Yurkonis et al., 2019; Hiers et al., 2020; Akinbile et al., 2023), particularly for grassland and savanna ecosystems.

Fire behavior in grasslands reflects the combined influence of meteorological and climatological conditions, fuel properties, and topography. Among weather variables, wind speed, air temperature, and relative humidity (RH) are the primary controls on ignition and spread (Cruz et al., 2022). Dead fuel moisture content (DFMC) responds rapidly to RH and air temperature, and directly affects ignition probability, rate of spread, and flame intensity. In the Great Plains, grassland prescribed burns are commonly conducted in spring under the following recommended conditions to balance ecological benefits and safety: air temperature 2 - 43 °C (35-110 °F), RH 25

- 80%, and wind speed 6.4 - 24.1 km h⁻¹ (4 -5 mph) (Higgins et al., 1989; Weir, 2011; Yurkonis et al., 2019). DFMC at 7-20% is considered optimal for conducting prescribed fire with minimal risks of spotfires and escape fires, whereas DFMC below 5% substantially increases the likelihood of erratic fire behavior (Sullivan, 2010; Weir, 2011). Since only a few spring days meet the optimum burn conditions (Akinbile et al., 2023; Swain et al., 2023; Yurkonis et al., 2019), burn managers need a more precise delineation of suitable burn conditions thresholds and a stronger evidence base for expanding the traditional burn window.

Fire danger indices are used to quantify fire hazard profiles into explainable categories. Fire danger indices are used to represent the likelihood of ignition, spread, or difficulty in suppression (Sharpley et al., 2009). The most widely used indices include the Keetch-Byram Drought Index (KBDI), the Burning Index (BI), and the Grassland Fire Danger Index (GFDI). The KBDI estimates soil moisture deficit from temperature and adequate rainfall (Keetch & Byram, 1968; Plucinski et al., 2023) but assumes a fixed soil-water capacity, which makes it insensitive to the rapid fine-fuel moisture changes typical of grasslands, where fuel moisture can change rapidly with slight variations in RH (Banerjee et al., 2020; Weir et al., 2021). Because this capacity is fixed and tied to slowly changing deep soil moisture, KBDI does not capture the rapid fine-fuel moisture changes typical of grasses, which respond to short-term humidity rather than deep soil drying. As a result, it is better suited to representing long-term soil moisture conditions in larger fuel layers than fast fuel-moisture dynamics in grasslands. The BI, developed under the U.S. National Fire Danger Rating System (Deeming, 1974), quantifies fireline intensity and suppression difficulty (Wildland Fire Application Information Portal, 2025). However, it relies on daily, coarse spatial conditions modeled at 1-km resolution weather inputs and standardized fuel models that

struggle to account for sub-daily meteorological variation or site-level fuel heterogeneity characteristic of tallgrass and mixed-grass prairies (Jolly et al., 2019; Schmidt et al., 2002).

McArthur's GFDI, developed in Australia (McArthur, 1966; Noble et al., 1980), provided a seminal approach to quantify grassland fire danger through a simple functional form and interpretable parameters. While the interpretability of the model is one of its strengths, the fixed fuel load assumption limits its use outside Australia (Purton, 1982; Cheney & Sullivan, 2010) and other continuous fuel landscapes. An attempted calibration of the Mk 4 GFDI in the central Great Plains showed a tendency to underestimate fire danger under low RH, and wind conditions were challenging to parameterize (Schreck et al., 2010). Recent advances, such as the Australian Fire Danger Rating System (AFDRS) introduced in 2022, have replaced the GFDI with fuel-specific empirical models (Gregory et al., 2024; Kenny et al., 2024), acknowledging that practical fire danger assessment must be at the scale of local fuel-driven systems. Wildland fire management in the Great Plains is constrained by the lack of locally calibrated, quantitative fire danger metrics designed for grassland ecosystems. This limitation exacerbates the difficulties faced by fire managers in developing burn plans that effectively anticipate ignition potential and fire spread under region-specific fuel and weather conditions. Persistent socioecological barriers and the ecological complexity of grassland fire regimes point to the need for adaptive, regionally calibrated fire danger tools that represent fine-scale fuel and microclimate variability and improve operational planning and stakeholder engagement.

The objective of this study was to quantify and model wildland fire risk in the Great Plains using historic local weather, wildfire, and fine fuel data from 1992 to 2020. We developed a composite fire risk framework that incorporated two temporal dimensions: seasonal fire risk and daily fire risk. The overall wildland fire risk was estimated as a product of seasonal fire risk and

daily fire risk, each modeled by ecologically relevant explanatory factors. The seasonal fire risk was represented as the ratio of smoothed multi-year average wildfire daily burned area to the total land area and was modeled using grass curing and seasonal air temperature changes as predictors.

The daily fire risk was represented as the ratio of wildfire daily burned area to the smoothed multi-year average wildfire daily burned area and was modeled using wind speed and dead fuel moisture as predictors. The combined model offers a region-specific and interpretable approach for quantifying wildland fire risk at an ecologically relevant scale. The formulation is premised on the theory that seasonal fire risk is influenced by cumulative fuel phenology and climatic factors, while transient weather and short-term fuel moisture dynamics primarily influence daily fire risk.

To strengthen this framework, we incorporated region-specific grass curing and DFMC sub-models (George et al. 2025, in press) as complementary input. This formulation enhances ecological understanding of grassland fire risk and provides a transparent and operationally adaptable decision-support tool for prescribed burning and wildfire management in the Great Plains. The study provides a foundation for developing adaptive fire-danger tools for grassland ecosystems.

3.2 Data and Methods

3.2.1 Study Area

The Flint Hills ecoregion of the Great Plains spans approximately 2.4 million hectares, extending from eastern Kansas into the Osage Hills of northern Oklahoma, centered near 37.3°N, 96.7°W (Akinbile & Liu, 2022). The region's elevation ranges from 320 to 512 m, with shallow, rocky soils that have limited agricultural potential and have preserved extensive native grasslands (Anderson, 1953). The region has a continental climate characterized by hot, humid summers, cold

winters, and an average annual precipitation of approximately 800 mm, with most precipitation occurring in late spring and early summer (McKane et al., 2025). The Flint Hills ecoregion contains the largest remaining tract of tallgrass prairie in North America, holding global conservation significance. Vegetation is dominated by warm-season perennial grasses, including big bluestem (*Andropogon gerardii*), little bluestem (*Schizachyrium scoparium*), Indian grass (*Sorghastrum nutans*), and switchgrass (*Panicum virgatum*), along with a diverse community of forbs (Anderson, 1953). Prescribed fire and grazing are the primary ecological practices used to sustain the ecosystem. These prescribed burns are conducted in the spring to sustain rangeland productivity and limit woody encroachment in grasslands (Akinbile et al., 2023; Baker et al., 2019; Weir, 2011). Our wildland fire risk quantification considered 17 counties within this ecoregion (Fig. 3.1), selected for their extensive historical wildfire and high-quality fuel data, which are suitable for regional-scale modeling.

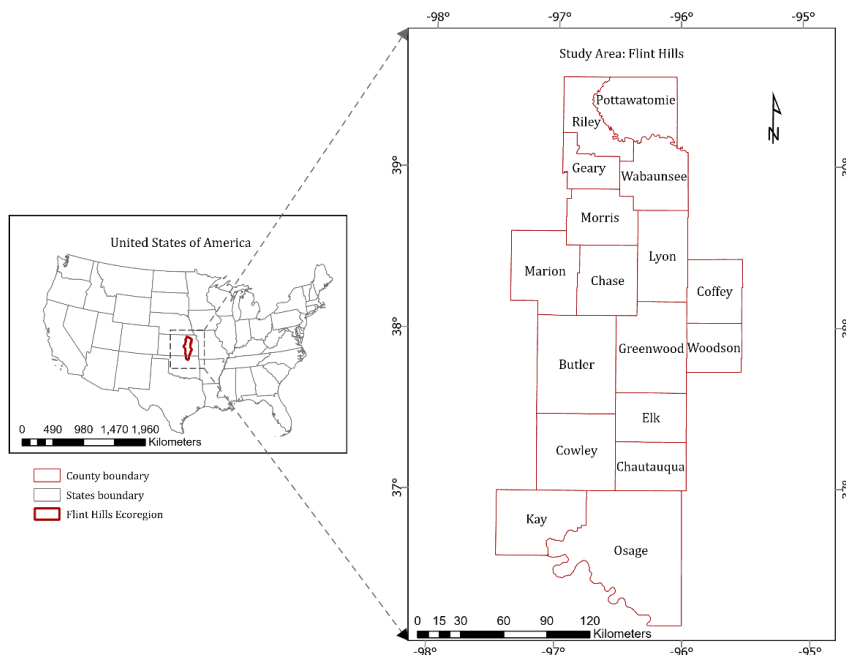


Figure 3.1: Map of the study area

3.2.2 Wildfire Data

Wildfire data of the study area were obtained from the U.S. Forest Service Fire Program Analysis Fire-Occurrence Database (USFS-FOD) available from 1992 to 2020. This national standardized archive documented consolidated wildfire incident reports from multiple sources, including federal, state, local, and private agencies, in accordance with National Wildfire Coordinating Group (NWCG) protocols. Each record was georeferenced to at least the public land survey system section, allowing for spatially consistent regional analysis (Short, 2022). To enhance data quality beyond initial quality checks, duplicate entries were removed, while missing county names of each wildfire event were added by spatially joining fire areal coordinates to U.S. county boundaries shapefile retrieved utilizing `tigris` (Walker, 2016) and processed with the `sf` package (Pebesma, 2018) in R (4.3.1). After data cleaning, 6,126 wildfire entries from the 17 Flint Hills counties, totaling 439,380 hectares of burned area, were retained for the analysis. The attributes retained from the original dataset include wildfire size (hectares, ha), fire discovery date and time, fire county, and categorical fire size class, due to their relevance to the defined risk formulation. Fire sizes considered for the analysis were classified according to hectare equivalent of the NWCG standards as follows: A (< 0.1 ha), B (0.1 to < 4 ha), C (4 to <40 ha), D (40 to <120 ha), E (120 to < 400 ha), F (400 to < 2,000 ha), and G ($\geq$ 2000 ha) (NWCG. 2025).

3.2.3 Weather Data

Hourly weather data for Osage County was gathered from the Oklahoma Mesonet station at Skiatook, available from 2006 to 2020. Historical weather data for the preceding years (1992-2005) and for the other 16 Flint Hills counties were supplemented using Visual Crossing weather data to match the span of the wildfire data. Visual Crossing provides meteorological data for climatological and environmental studies by combining outputs from multiple numerical weather

prediction models to generate hourly and daily weather fields with broad spatial coverage, relevant for regional analyses (Visual Crossing Corporation, 2025; Topnani, 2021; Akimbile et al., 2023). A correlation analysis of the Mesonet data of Osage County and the corresponding Visual Crossing data showed a strong positive correlation. The obtained meteorological variables included hourly air temperature ($^{\circ}\text{C}$), relative humidity (RH, %), and sustained 10-m wind speed (km h^{-1}), along with daily minima, means, and maxima derived from the hourly observations based on the fire discovery time, latitude, and longitude. In the data query, each reported wildfire's geographic coordinates, ignition start time, and the nearest fire discovery time in hours or midday hours as a proxy in cases of missing fire discovery time and fire date were considered. The noon-time imputation for missing fire discovery times is consistent with prior studies (Liu et al., 2024; Matteo et al., 2025; Prestemon et al., 2013). Exact ignition times were unavailable, so discovery time was used as a proxy. In the FPA-FOD, discovery time is the time at which a fire is first observed, which often follows ignition closely. At the regional and daily scales of this study, this proxy consistently represents fire timing, and slight differences between ignition and discovery are unlikely to affect the modeled quantified fire risks.

The discovery time was converted from local time to Coordinated Universal Time (UTC) and rounded to the nearest hour to match the API's temporal resolution for available data. Following the conversion, the weather variables were extracted for the ignition hour and the preceding hour to capture fire-time weather and the meteorological conditions prior to fire ignition. These records were combined with the wildfire dataset by fire date, start time, county, and geographic coordinates for exploratory analysis before selecting candidate predictors.

3.2.4 Fuel moisture data

The fine fuel condition for this study was represented at short- and seasonal scales: 1-hour dead fuel moisture content (DFMC, %) captured short-term variability due to changes in atmospheric conditions, and grass curing captured mid-term seasonal moisture and grass phenological cycles. The following hourly variables were obtained from the Oklahoma Mesonet: air temperature, relative humidity (RH), and 1-hour DFMC, as a representative of the tallgrass prairie complex, were obtained from the Oklahoma Mesonet station at Skiatook, Osage County, which was available from 2006 to 2020. For the years before this period, 1992-2005, and for other counties, DFMC was estimated as a function of the mean hourly RH and mean hourly temperature using a regional empirical DFMC sub-model as explained in George et al. (2025, in press). The equation is given as: $DFMC (\%) = \exp(1.313 + 0.02 \times RH - 0.009 \times T)$, where RH is relative humidity (%), and T is the mean daily air temperature at hourly resolution.

Grass curing is defined as the proportion of dead material in the grass sward. This quantity reflects burnable fine-fuel biomass when fully cured and was estimated using the approach by Newnham et al. (2011) for estimating grass curing from relative greenness: $C = (1 - RG) \times 100$, where C = grass curing (%), RG = relative greenness. Grass curing was estimated from relative greenness, an NDVI-based metric scaled to 0 -100% mapped at a 500 m resolution, with higher greenness indicating lower curing (Carlson et al., 2002). For years without relative greenness coverage, grass curing was estimated using an empirical logistic regression based on the day of the year. The sub-model is given as: $Grass\ curing (\%) = 100 / (1 + \exp(-B \times (DOY - C)))$ for Flint Hills, where DOY is day of year and B and C are regression-derived model parameters, B controls the rate of change in curing and thus the steepness of the transition, whereas C is the inflection point, corresponding to the DOY at 50% curing. Under normal pre-season moisture

(previous-year mean KBDI < 280), curing parameters were $C = 111$ (95% CI: 111–112) and $B = -0.0527$ (95% CI: -0.0539 to -0.0516), indicating consistent timing and slope of curing across years. Under extreme drought (previous-year mean KBDI > 280), curing shifted earlier and became steeper, with $C = 89$ (95% CI: 88–90) and $B = -0.057$ (95% CI: -0.058 to -0.0566). The details of this model are available in George et al. (2025, in press). This NDVI-based grass-curing approach is well established in the remote-sensing literature (Newnham et al., 2011; Chaivaranont et al., 2018; Sharma et al., 2021).

3.2.5 Quantified wildland risk framework

A wildland fire risk framework was formulated to quantify grassland fire risk as the product of two dimensionless risk metrics at seasonal and daily temporal scales. In this study, fire risks were considered a normalized measure of realized fire activity that integrates both the likelihood and the extent of burning, consistent with a broader risk assessment perspective rather than a probability-only approach (Hardy, 2005). Seasonal fire risk reflects long-term influences of fuel availability and climate fluctuations, while daily fire risk reflects short-term variability driven by changes in meteorological conditions and the rapid response of fine fuels to them. Seasonal fire risk was represented as the ratio of the smoothed multi-year average daily wildfire burned area to the total land area. Daily fire risk was represented as the ratio of wildfire daily burned area to the smoothed multi-year average daily burned area.

This grassland-specific dual-scale framework directly relates fire risk to observed burned areas and separates seasonal fine-fuel phenology and climatic influences from daily weather influences. It supports the shift toward modular, locally calibrated fire danger systems and is aligned with the Australian Fire Danger Rating System in a local fuel-centric approach (Gregory et al., 2024; Kenny et al., 2024; Grootemaat et al., 2024). This framework offers the prospect of

complementing legacy Indices, such as the BI, by supplying localized fuel-based risk metrics. The work flow is as presented in Fig 3.2

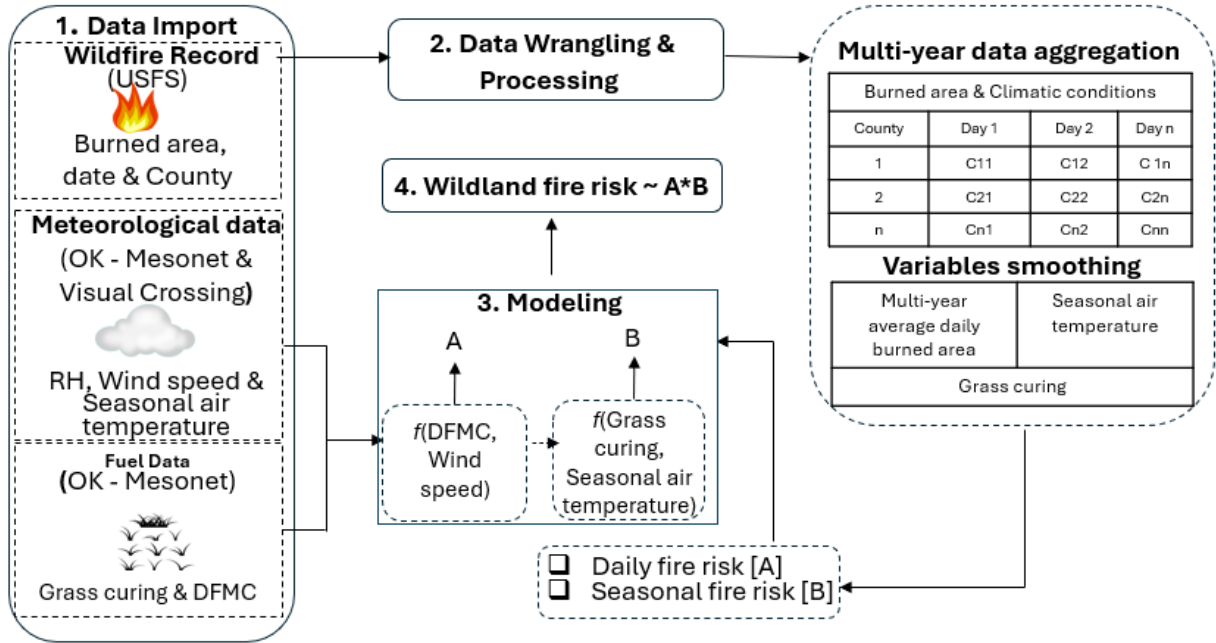


Figure 3.2: Workflow for estimating grassland wildland fire risk.

3.2.6 Modeling of the Seasonal Fire Risk

Osage and Kay counties in Oklahoma were selected as representative locations for Flint Hills seasonal fire risk modeling because of the availability of high-quality fuel data, including relative greenness for grass curing estimation and DFMC from the Oklahoma Mesonet. During the 26-year study period, these two counties accounted for 37.5% of all reported wildfires and 52.7% of the total burned area in the Flint Hills. Osage contributed the largest burned area, while Kay contributed the least. The combined burned-area record from these counties, which demonstrates consistent fire size and frequency distributions with other counties in the Flint Hills ecoregion, formed the basis for deriving seasonal fire risk estimates that are applicable across the Flint Hills (Appendix A). Fire counts were less reliable than burned area estimates, which could be due to

underreporting of historical fire events prior to 1995, as noted by Short (2022). The analysis focuses on burned area, which offered a more consistent pattern with prior studies in the region.

Although wildfire records for Kansas and Oklahoma span from 1992 to 2020, in Osage and Kay counties, prior to 1995, there were fewer reports, which could be attributed to underreporting of incidents, as Short (2022) explained. Therefore, the seasonal fire risk analysis for these counties was limited to 26 years (1995-2020). Osage County alone accounted for approximately 99% of the combined wildfire activity in the Osage-Kay region. Including Kay wildfire records ensured the analysis covered the entire Oklahoma portion of the Flint Hills ecoregion.

Burned areas were aggregated when both counties recorded fires on the same day. Fire day weather and fuel conditions were represented using Osage in joint fire days, as it was observed to have larger fire sizes in most of those days. Individual, unique fire-weather data were used for each county fire day. The seasonal fire risk was estimated as the ratio of the smoothed multi-year average daily burned area to the combined land area of the two counties. The estimated areas of the two counties are approximately 841,333 ha, calculated from U.S. Census TIGER/Line shapefiles (EPSG:5070). The following multiple-year average data were computed for fire days throughout the data span as the representation of baseline seasonal conditions: burned area, grass curing, and seasonal temperature, and were smoothed using generalized additive models with basis function ($K=7$) and cyclic cubic splines to capture the periodicity as a function of day of year (DOY). The multi-year average daily burned area across DOY. The resulting risk metric was bimodal. The minimum seasonal fire risk marked the transition between the first and second halves of the fire year, designated as H1 and H2, respectively. H1 ($\text{DOY} \leq 200$) is the primary peak fire season in early spring, marked by rising fire wildfires from January to March, and subsequent decline. H2 ($\text{DOY} > 200$) is the secondary fire season in the fall, characterized by resurging

wildfire activity and decreasing wildfire activity toward the beginning of winter. The seasonal risk pattern was consistent with seasonal phenomena associated with fine fuel with an annual lifecycle under varying climatic conditions.

Following this preliminary observation, we modeled seasonal fire risk as a power function of grass curing and seasonal air temperature, two biophysical variables identified as primary drivers of grassland fire behavior on a seasonal scale (Chaivaranont et al., 2018; Prestemon et al., 2013). Separate nonlinear power-law seasonal fire risk models were fit to H1 and H2 using nonlinear least-squares to capture their distinct distributions. Model performance was assessed using 10-fold cross-validation, and predictive accuracy was measured by the root mean square error (RMSE). Parameter uncertainties were quantified using a nonparametric bootstrap to generate confidence intervals for the estimated model parameters.

3.2.7 Modeling of the Daily Fire Risk

The relationship between wildfire size, estimated daily risk and fine fuel variables was explored in considering sustained 10-m fire hour wind speed, air temperature, RH, and DFMC. It was observed that fires greater than or equal to 100 ha showed consistent non-linear relationships with maximum fire day hourly wind speed and fire hour DFMC while no noticeable pattern was observed small fire sizes are include in the analysis. The identified relationship informed the decision to select fires ≥ 100 ha in size for our daily fire risk modeling data across all 17 counties. Fire day was therefore defined as a day with reported fire size equal to or greater than the 100ha cutoff.

The daily fire risk was estimated as the ratio of the reported fire daily burned area to the smoothed multi-year county average. To ensure smooth convergence, we excluded counties with fewer than 10 fire days before applying smoothing, thereby isolating Kay and Woodson counties.

Exploratory analysis of the data revealed that the maximum daily 10 m sustained wind speed and fire hour-based DFMC were candidate predictors for modeling the quantified daily risk. These variables aligned with those identified in prior studies to affect fire behavior in the short term (Sullivan, 2009; Fernandes, 2001; Cheney et al., 1998; Ellis et al., 2022; Matthews, 2014). Hence, the candidate explanatory variables were used to fit a least squares regression model ($n = 410$).

To stabilize variance in the daily fire risk metric, a logarithmic transformation was applied; a square root transformation for maximum daily sustained 10 m wind speed; and a reciprocal transformation for DFMC, respectively, based on the predictors' observed relationships with the target variable. The wind speed transformation was necessary to capture the effect of increasing wind speed, which McArthur (1966) and Sharples et al. (2009) noted to be nonlinear. Modeling was restricted to the first half of the year, which coincides with the spring prescribed fire season when daily fire risk estimates are most relevant for prescribed fire planning and management. A multiple linear regression model was fitted, and its goodness fit was evaluated using the 10-fold cross-validation coefficient of determination and root mean square error. The estimated parameter uncertainty was assessed using a nonparametric bootstrap with 1,000 resamples.

3.3 Results

3.3.1 Seasonal fire risk as a function of grass curing and seasonal air temperature

The seasonal fire risk showed a bimodal pattern in Osage and Kay Counties (1995-2020) with a primary peak in late March at 0.034% of land area, and a secondary peak in early October (Fig. 3.3). It was modeled as a power-law function of grass curing (C, %) and seasonal air temperature (T, °C) as:

$$\text{Seasonal fire risk} = \alpha \times C^{\beta_1} \times T^{\beta_2}$$

Model **parameter estimates (mean $\pm$ SE)** were:

in H1, $\alpha = 8.28 \times 10^{-9} \pm 1.34 \times 10^{-9}$, $\beta_1 = 1.27 \pm 0.02$, $\beta_2 = 1.75 \pm 0.03$.

in H2, $\alpha = 6.40 \times 10^{-9} \pm 1.26 \times 10^{-9}$, $\beta_1 = 0.89 \pm 0.02$, $\beta_2 = 2.20 \pm 0.04$.

In the model, the multi-year daily average grass curing ranges from 0 -100%, and the multi-year daily average air temperatures range from 8.5 °C to 33.1 °C, averaged over 26 years. It can be seen that the seasonal fire risk was affected by fuel availability, as indicated by the grass-curing exponent in H1(DOY $\leq$ 200) compared with H2 (DOY $>$ 200). The multi-year daily-average air temperature effect was more pronounced in H2 than in H1. The modelled values closely matched the observed seasonal risk pattern ($R^2 = 0.97$, cross-validated RMSE = 0.001%). Figures 3.3, 3.4, 3.5, and 3.6 represent the modeled seasonal risk, multi-year average daily curing, and multi-year average daily air temperature changes across the fire seasons. The predictors reflect the contributions of the fuel life cycle to the dead fuel load. Similarly, changes in air temperature reflect climatic conditions throughout the fire year in the southern Flint Hills, with prospective extrapolation across other Flint Hills counties due to similarities in fire distribution and climatic conditions.

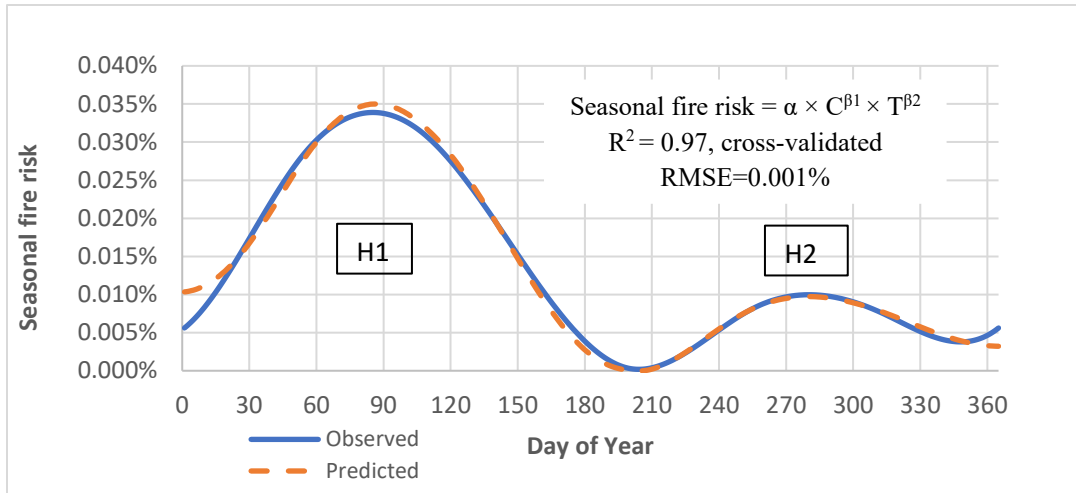


Figure 3.3: Modeled seasonal variation in fire risk in Osage and Kay counties, Oklahoma

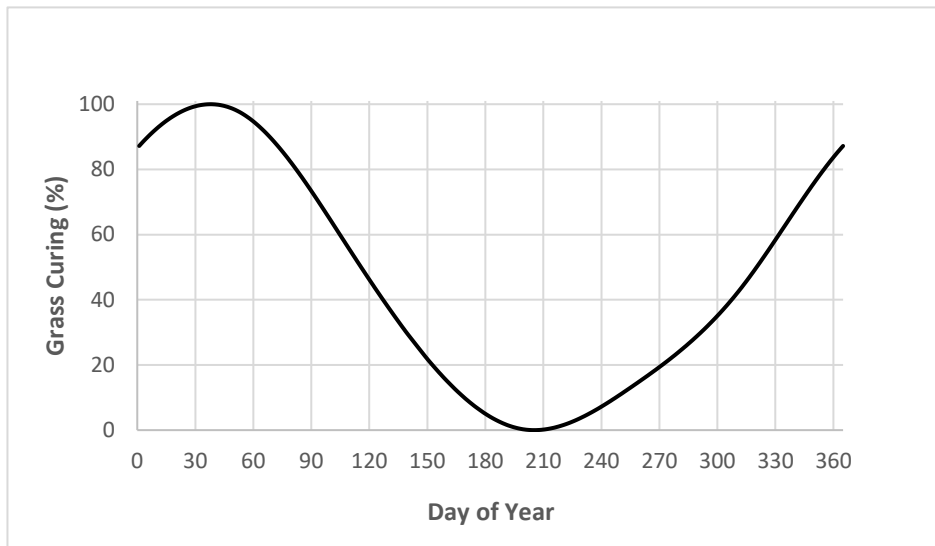


Figure 3.4: Multiple year average daily grass curing in Osage County, Oklahoma

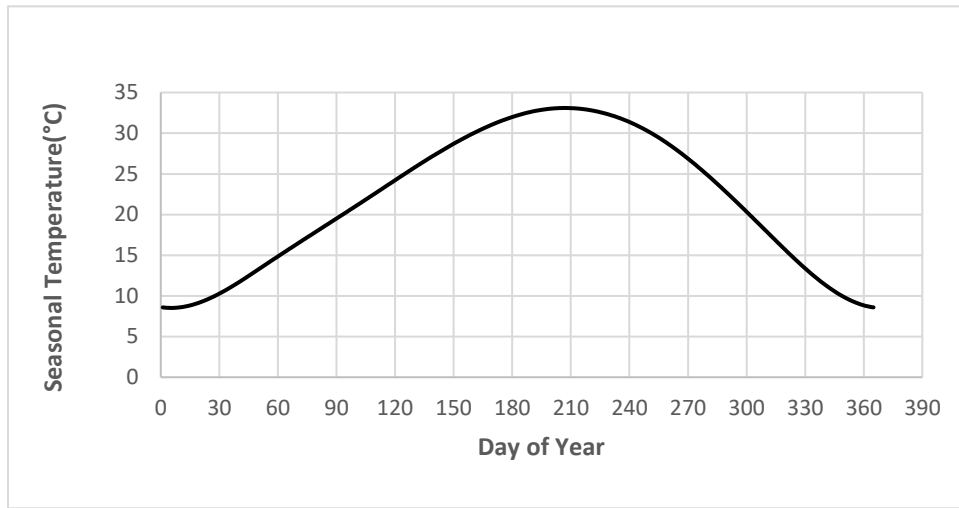


Figure 3.5: Multiple year average daily air temperature in Osage County, Oklahoma

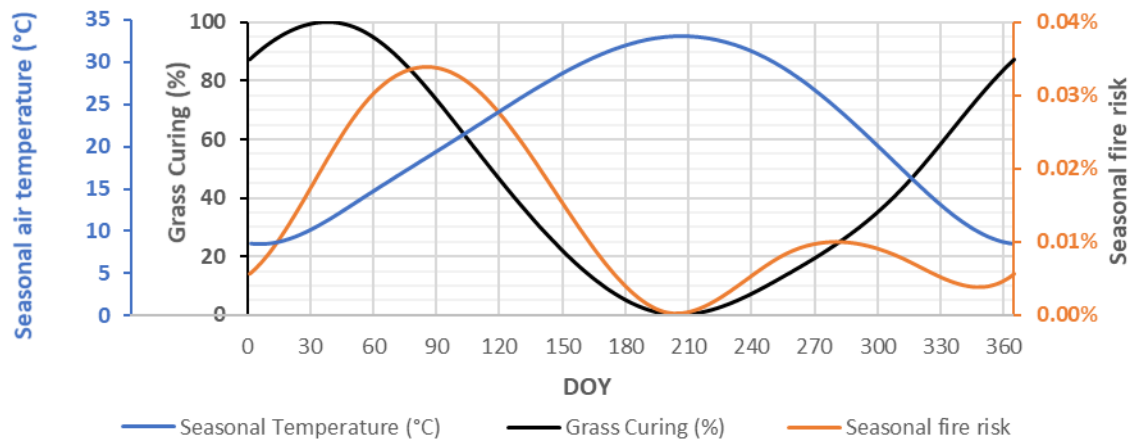


Figure 3.6: Seasonal risk, multiple year average daily grass curing, multi-year average, and temperature

3.3.2 Daily fire risk as a function of DFMC and maximum sustained wind speed

The daily fire risk in the Flint Hills was modeled as an exponential function of DFMC (%) and maximum sustained wind speed (U , km h^{-1}) as:

$$\text{Daily fire risk} = \exp \left(\alpha + \frac{\beta_1}{\text{DFMC}} + \beta_2 \sqrt{U} \right)$$

$$\text{in H1, } \alpha = -2.773 \pm 0.376, \beta_1 = 5.653 \pm 1.020, \beta_2 = 0.211 \pm 0.061$$

$$\text{in H2, } \alpha = -3.529 \pm 1.061, \beta_1 = 4.362 \pm 2.417, \beta_2 = 0.417 \pm 0.158$$

Both 1-hour DFMC and maximum sustained 10 m wind speed are statistically significant ($p < 0.001$) in the Spring-dominated model (H1). In the fall-dominated model (H2), only wind speed was statistically significant, with DFMC marginally contributing to the explained variability in daily risk, but must be retained due to its important role in influencing fire spread. The Spring model explained 15% of the variance in daily fire risk, while the fall model explained 13% of the variance in daily risk, indicating that daily fire risk during the fall season is primarily wind-driven, with fuel moisture exerting only a secondary effect. In the models, DFMC ranged from 3.78% to 24.55%, and the maximum sustained wind speed ranged from 15.1 to 62.6 km h^{-1} (9.4 to 38.9 mph). DFMC contributed most significantly to explaining daily risk, as lower values increased the potential for fire ignition and spread in the spring. Wind speed played a role in accelerating fire spread once ignition occurred in a large fire area across the year.

3.4 Discussion

3.4.1 Seasonal Fire Risk Factors

Variations in grass curing and seasonal temperature explain the bimodal pattern of the quantified wildland fire risk in Osage and Kay counties. In late winter and early spring, progressive

fine fuel curing and rising air temperatures increase dead fuel continuity and fine-fuel flammability, resulting in the primary seasonal fire risk peak in late March (Sullivan, 2010; Cruz et al., 2022). After summer, renewed curing process contributes to the secondary seasonal fire risk peak in early October, when temperature has a more influence than curing (Fig. 2.4). Similar dual-season fire risk patterns have been reported for savanna ecosystems during periods of prolonged dryness, which aligns with the bimodal wildfire activity characteristic of the Great Plains (Donovan et al., 2017; Trollope et al., 1996). The subdued secondary seasonal fire risk peak in early October may also be affected by reduced fine-fuel loads and disrupted continuity following extensive spring burning and grazing (Bond & Keeley, 2005; Roos et al., 2018; Wilcox et al., 2022).

Prior studies have shown that sustained spread in grasslands generally requires at least 50% curing, with the propagation probability increasing nonlinearly as fuels become thoroughly dried (Cruz et al., 2015; Kidnie et al., 2015). In grass-dominated systems, the spread potential depends mainly on the continuity and curing of fine fuels. The predominance of grassy fuels, rather than microclimate alone, explains the higher flammability of savannas and prairies compared to forests (Archibald et al., 2010; Hoffmann et al., 2012). In addition to seasonal climate, fuel characteristics control the likelihood and behavior of wildfires.

The seasonal fire risk model explained much of the variation in the quantified fire risk, yet several contributing factors were likely only partially represented. Fuel load and arrangement, land-use change and wildland-urban expansion, bison and cattle grazing (Roos et al., 2018), suppression response, and interannual drought can influence fine fuel continuity and burned extent (Addington et al., 2015), but these variables are difficult to measure or quantify consistently at regional scales (Abatzoglou & Williams, 2016; Bond & Keeley, 2005; Gannon & Steinberg, 2021;

Wilcox et al., 2022). Grass curing was introduced into the model as a biophysical mid-term indicator of seasonal fuel dryness and phenology, capturing dominant variation in fine fuel availability and reducing dependence on indirect drought metrics. It was applied as an annual variable to represent broad phenological trends across the study region. This necessary simplification may introduce uncertainty in areas with mixed vegetation or expanding woody cover, where curing may not accurately reflect the actual continuity of fine fuels. Nonetheless, this approach provides a consistent and interpretable framework for assessing large-scale seasonal fire patterns, even when fine-scale fuel and vegetation data are not readily available.

The seasonal fire risk model revealed the precise pattern in seasonal fire potential, supporting early resource allocations, mobilization, and smoke management before the primary seasonal fire risk peak in late March. From a fire management standpoint, the primary seasonal fire risk peak marks elevated dormant-season wildfire potential when suppression is most difficult. Shifting prescribed burning away from the peak, when green-up improves control despite narrower operational windows and tighter smoke limits, can reduce the risk of escape. The late-season window, preceding the secondary seasonal fire risk peak in early October, provides an additional opportunity to conduct prescribed fires when meteorological and regulatory conditions permit (Twidwell et al., 2015; Wonkka et al., 2015; Yurkonis et al., 2019). Evidence from the Great Plains and other grassland systems indicates that fall burns can meet ecological objectives and distribute fire activity more evenly throughout the year (Twidwell et al., 2015; Yurkonis et al., 2019). Quantification of seasonal fire risk helps to identify conditional opportunities for potential prescribed burning in the fall.

3.4.2 Daily Fire Risk Factors

Preliminary analysis of wildfire discovery times showed that 77.8 % of recorded fires (4,775 of 6,138) were reported between 10:00 and 17:00 local time, with the highest concentration near midday from 1992 to 2020. This pattern corresponds to the period of increased solar heating, minimum dead fuel moisture content (DFMC), and potentially increasing wind speed, conditions that jointly promote ignition success and fire spread. In the USFS-FOD database, discovery time refers to the hour a fire was first detected or confirmed rather than the precise ignition time; however, at regional scales, it provides a consistent and ecologically meaningful proxy for diurnal fire activity because most ignitions are detected shortly after onset during daytime burning conditions (Short 2022; Prestemon et al., 2013; Matteo et al., 2025).

To represent the upper bound of daily spread potential, the daily fire-risk model used the maximum daily wind speed rather than an intraday or burn-window average. Although prescribed fires are commonly conducted between 08:00 and 17:00, wildfires may ignite or intensify outside these hours when winds remain elevated or residual heat sustains combustion. Using the daily maximum captures the strongest convective and advective influences on fire behavior, providing a conservative, operationally relevant predictor of spread potential. This approach follows established fire-danger modeling principles that emphasize peak meteorological drivers, particularly wind speed, as dominant determinants of daily risk (Cheney & Sullivan, 2008; Cruz et al., 2022) and allows for potential flexible adaptation of the resulting risk metric for all wildland fires.

The quantified daily fire risk was significantly affected by DFMC and maximum sustained wind speed. DFMC integrates atmospheric and vegetation responses to environmental variability (Cheney et al., 1998; Matthews et al., 2010) and remains the dominant predictor of ignition

likelihood and flame persistence. Higher wind speeds amplified daily fire risk by enhancing convective heating and maintaining flame attachment to fuel surfaces, thereby promoting rapid spread and larger burned areas (Archibald et al., 2010; Marsden-Smedley & Catchpole, 2001). Together, DFMC and wind speed govern short-term fire behavior in grassland ecosystems. Figures 3.7 and 3.7 show how DFMC and wind speed in the Flint Hills are related to large wildfire size (≥ 100 ha). As DFMC increased, the mean fire size on defined fire days decreased, highlighting the role of dried grass in wildland fires in response to short-term atmospheric conditions. Also, the mean large-fire burn area increased with increasing wind. To ensure that the model accounted for these relationships, reciprocal and square-root transformations of DFMC and wind speed, respectively, stabilized the variances. These transformations are necessary and consistent with established fire-spread theory, in which wind-speed effects on fire behavior are best captured as an exponential component (Sharples et al., 2009). Cross-validation and bootstrap resampling verified parameter stability (Guisan & Zimmermann, 2000), quantitatively confirming thresholds long recognized by fire managers but seldom formalized through regionally calibrated models.

Fire-ignition clustering, suppression timing, and variable fuel continuity all contribute to the high uncertainty inherent in short-term fire-risk estimation (Cheney & Sullivan, 2008). Some unexplained variability in the model is likely a reflection of ecological and anthropogenic processes that influence fire activity at the regional scale, which are difficult to measure. Grazing intensity, variable vegetation structure, and management decisions regarding fire suppression and fire-fighting resources deployment affect fine-fuel continuity, modify the effect of DFMC and wind speed on fire behavior (Archibald et al., 2010; Davies et al., 2017; Donovan et al., 2017) and ultimately influence the areal spread. Grazing reduces fuel loads and increases the proportion of live to dead fuels, thereby lowering ignition likelihood in herbaceous systems (Davies et al., 2017;

Starrs et al., 2024), whereas clustered ignitions during narrow burn windows can intensify wind-driven spread (Coogan et al., 2022). Since DFMC was derived primarily from meteorological rather than in-situ measurements, which makes it difficult to achieve consistency over a large area, it could account for some of the unexplained variables. This is expected given that in the short term, fuel induced uncertainty persists in areas with complex topography or mixed canopy cover (Aguado et al., 2007; Matthews et al., 2010). This variability is expected in regional modeling and is best interpreted as probabilistic variation consistent with modern risk frameworks that incorporate fuel-moisture dynamics to approximate realistic predictions at landscape scales.

From a management perspective, the daily fire-risk model provides a practical means of assessing short-term fire potential effects within the fire seasons. Incorporating DFMC as an integrative predictor that consolidates multiple atmospheric variables improves the interpretability of the quantified risk fire-danger metric and improves model transparency and operational transferability. Real-time monitoring of DFMC and wind speed can guide ignition timing and identify periods when suppression is most challenging. A sub-model that estimates DFMC from relative humidity (RH) and air temperature (George et al., 2025) offers a practical alternative to field-measured fuel moisture, which is rarely feasible across large regions but highly recommended as an input when available. Previous efforts in Mediterranean and eucalypt ecosystems have also estimated DFMC from meteorological variables (Aguado et al., 2007; Matthews et al., 2010). In Tasmania, Marsden-Smedley and Catchpole (2001) used dew-point temperature and RH as a better indicator of fuel moisture in the area, citing multicollinearity between humidity and air temperature in the region as the motivation. Climatic conditions in the continental Great Plains differ from those of cool, moist, and topographically different regions.

George et al. (2025, in press) demonstrated that RH and air temperature are superior predictors of DFMC in the Flint Hills.

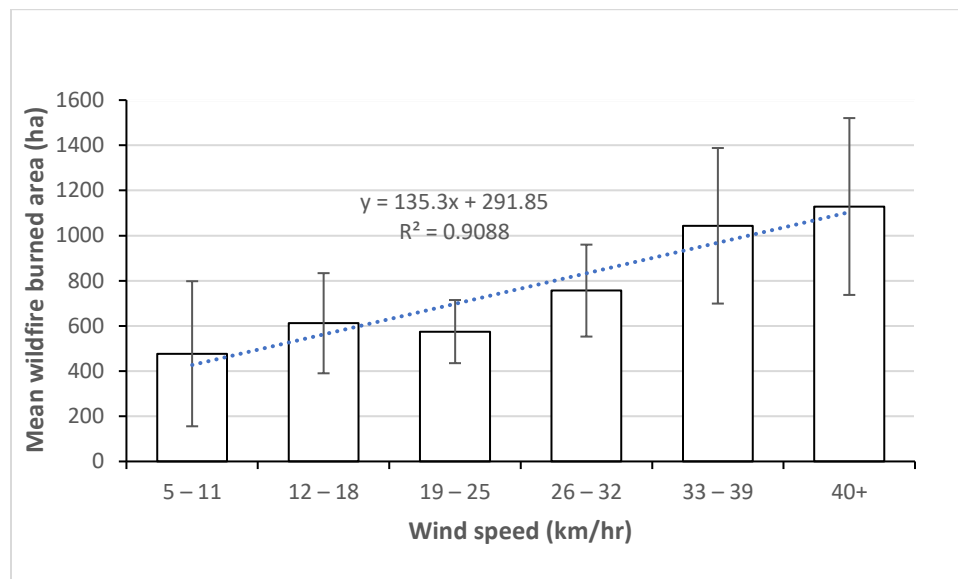


Figure 3.7: Large wildfire (≥ 100 ha) distributed across wind speed levels in the Flint Hills (1992-2020).

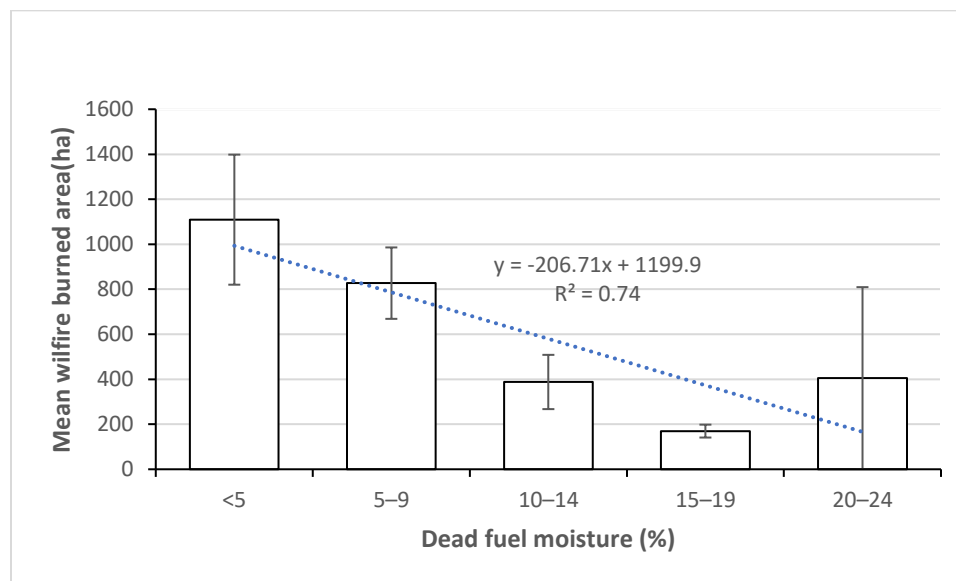


Figure 3.8: Large Wildfire (≥ 100 ha) distribution across DFMC levels in Flint Hills (1992-2020).

3.4.3 Overall wildland fire risk

The 15-year normalized record for the spring prescribed-burn window in the Flint Hills (March 8–May 8, 2006–2020; 0800–1700 h) shows substantial variability in quantified wildland fire risk across the 62-day period. Risk values, computed from daytime maximum sustained windspeed and daytime DFMC, ranged from 0.004 % to 0.088 %, reflecting an approximately 18-fold difference in potential fire behavior across the spring season (Fig. 2.8). This dynamic range indicates that even within a fixed seasonal window, atmospheric and fuel conditions fluctuate sharply, reinforcing the need for quantitative, day-specific guidance to complement experiential calendar-based burn scheduling.

Prescribed burn planning benefits from identifying days when fire can be used with confidence. Within the analyzed record, 11 days fell below the low-risk threshold (≤ 0.01 %), representing the most reliable opportunities for safe and well-controlled burning. An additional 28 days occurred within the marginal range (>0.01 % - 0.018 %), when prescribed fire remains feasible but requires strict operational control, experienced crews, and real-time monitoring due to elevated spread potential. Beyond this range lie extreme-risk conditions, characterized by high winds, low humidity, and desiccated fuels, under which prescribed burning should be prohibited.

The distribution of quantified risk values (Fig. 3.9) is strongly right-skewed, demonstrating that low-to-moderate risk conditions dominate the burn window while extreme-risk days are rare. This asymmetry underscores the practicality of the quantified-risk framework: it provides an empirical foundation for defining operational thresholds that separate safe, marginal, and prohibitive fire-weather conditions. While the spring peak risk exceeded the fall peak by more than threefold, the fall maximum (~ 0.01 %) still lies within the low-risk band. This finding suggests that fall burning can achieve ecological objectives under comparably safe conditions,

supporting expanded seasonal flexibility in prescribed-fire programs. The prospect of shifting burning into the late summer to fall season is consistent with contemporary studies. Our results show that although spring wildland fire risk peaks at approximately three times the fall maximum, the fall peak remains within the low-risk band, indicating that late-summer and autumn prescribed fires can meet management objectives under comparably safe operational conditions.

This interpretation is supported by empirical work in the Flint Hills, where Duncan et al. (2021) demonstrated that summer and autumn prescribed fires maintained forage biomass, root carbohydrate reserves, and native plant community structure at levels comparable to conventional spring burns, while summer fire provided additional benefits for suppressing sericea lespedeza without reducing grazing performance. At a broader regional scale, Yurkonis et al. (2019) documented a climatological shift in acceptable prescribed-fire weather windows across the northern Great Plains, with declining spring opportunities but a clear increase in suitable burn days during late summer and early fall. Together, these studies corroborate our conclusion that extending prescribed-fire operations into the late-summer-fall period is both ecologically realistic and operationally feasible, offering land managers additional flexibility to meet fuel, vegetation, and conservation objectives while reducing reliance on the increasingly constrained spring window.

Typical P20 - P90 marginal fire risk range conditions were DFMC 9.5%, wind 20.6 km h⁻¹, grass curing 68%, and seasonal temperature 18.5 °C. Low-risk range ($\leq$ P20) occurred with DFMC 13.4%, wind 13.8 km h⁻¹, and curing 51%, whereas high-risk days ($\geq$ P90) aligned with DFMC 6%, wind 31.1 km h⁻¹, and curing 73%.

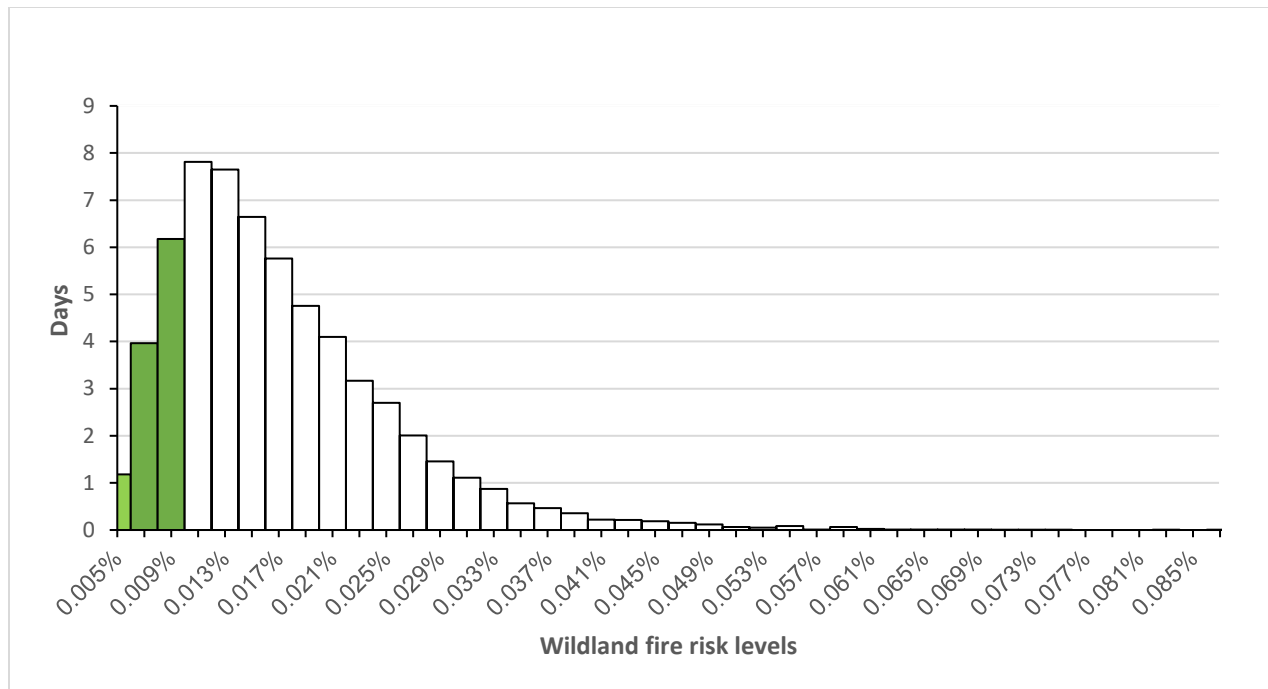


Figure 3.9: Wildland fire risk distribution in the Flint Hills within the spring burn window (March 8-May 8) 2006-2020, with the bars(green) denoting available safe conditions defined by the lower 20th percentile of risk

3.5 Conclusion

This study quantified and modeled wildland fire risk in the Flint Hill ecosystem of the Great using a composite framework that combined seasonal and daily fire risk potentials. Utilizing local data, including long-term wildfire records, weather, and fuel data, the risk formulation demonstrated that seasonal fire risk is primarily governed by grass curing and multi-year average daily air temperature, while daily fire risk is driven by change in meteorological conditions, explained by maximum wind speed and dead fuel moisture content. The seasonal model explained most of the observed variability. This shows the deterministic influence of phenological and climatic processes on fire potential, while the daily model captured short-term variability linked to ignition and spread. Together, these components provide a mechanistic understanding of grassland fire behavior, linking broad-scale fuel dynamics with fine-scale atmospheric conditions that control daily fire danger.

Analysis of the 62-day spring burn window in Flint Hills showed a 15-year quantified wildland fire range of 0.005% to 0.088%, an approximately 18-fold variation in burning potential. The distribution is right-skewed, with a modal band near 0.011- 0.028%, indicating that low-to-marginal conditions are common but not uniformly optimal. Within the record, 11 days met the low-risk threshold ($\leq 0.01\%$), representing the most promising opportunities for safe, well-controlled burning and occurring under relatively low levels of moist fine fuels and optimal sustained wind speeds. Although the spring peak exceeded the fall peak by about threefold, the fall risk peak (0.01%) lies within the defined safe-risk band, indicating additional opportunities for optimal prescribed burns in the fall provided daily conditions align with ecological objectives that balance fire safety and air quality expectations.

The management implications of these findings are substantial. The quantified risk thresholds provide a practical and science-based foundation for classifying safe, moderate, and extreme burning conditions across the prescribed fire window. Integrating real-time monitoring of fuel moisture and wind speed into burn decision frameworks can strengthen the issuance of prompt advisories, provide guidance to mitigate escape risk, improve smoke management, and enhance wildfire preparedness. Overall, the localized fire risk models developed in this study established a foundation for our proposed adaptive, grassland-specific fire-danger systems that can enhance prescribed fire governance, promote ecological resilience, and reduce wildfire risk across the Great Plains and support existing legacy indices like the Burning Index for better adaptation for prescribed fire management.

Availability of data and materials

The wildfire datasets analyzed for this study are available in the USDA/Forest Service research data archive, <https://www.fs.usda.gov/rds/archive/catalog/RDS-2013-0009.6/>.

Chapter 4– Conclusion and Future Work

4.1 Conclusions

This research quantified and modeled wildland fire risk across the Flint Hills ecoregion of the Great Plains using a composite framework that integrates seasonal and daily dimensions of grassland fire ignition and the areal extent of fire spread. Based on approximately three decades of wildfire, weather, and fuel data, the study developed a localized and ecologically based representation of wildfire risk that advances both scientific understanding and management practice in the ecoregion. The overarching goal to provide a localized, operationally interpretable framework that captures the dynamic interactions among fuel, weather, and climate was achieved through a dual-scale modeling approach that distinguishes the slow phenological controls on fire readiness from the fast meteorological controls on ignition and spread.

The quantification of wildland fire risk as a function of seasonal and daily fire risks demonstrated that these scales interact to define the temporal structure of fire potential in fine-fuel ecosystems. Seasonal fire risk, driven primarily by grass curing and seasonal air temperature, explained 97 % of the observed variability in multi-year burned areas, confirming that fuel availability and thermal conditions jointly determine when grasslands become receptive to fire in the long term. The identified bimodal pattern, with a dominant spring maximum in late March and a secondary Fall peak in early October, captures the characteristic fire-activity regime across the Flint Hills and reflects shifts in phenological and climatic conditions. These findings provide a quantitative basis for understanding the ecological seasonality of grassland fire and offer a predictive range within which prescribed burning could be safely and effectively planned.

At the daily scale, fire risk in the tallgrass prairie-dominated area was influenced significantly by maximum sustained wind speed and DFMC, which together accounted for 15%

of the variance in daily fire activity in the spring fire season. Although the daily model expressed greater uncertainty, consistent with the stochastic nature of ignition and spread, it successfully represented the mechanistic link between fine-fuel dryness, wind forcing, and fire behavior, as consistently reported in the fire ecology domain. The exponential relationships derived from observed data captured how rapidly atmospheric fluctuations amplify or constrain the potential for fire ignition and spread, emphasizing the value of short-response variables for operational fire danger assessment. The inclusion of locally derived DFMC addressed limitations of traditional forest-based indices and provided a framework explicitly tuned to the fine-fuel dynamics of Great Plains grasslands.

This study demonstrated that wildland fire risk in the Great Plains can be effectively quantified using a composite framework that integrates long-term fuel phenology with short-term fire-weather drivers, providing a mechanistic understanding of grassland fire danger across both seasonal and daily timescales. Seasonal fire potential was primarily governed by grass curing and air temperature, reflecting the deterministic influence of fuel condition and climate, whereas daily variability in fire danger emerged from rapid changes in wind and dead fuel moisture, the key drivers of ignition success and spread. Applied to the 62-day spring burn window in the Flint Hills, the model revealed an eighteen-fold range in quantified risk (0.005-0.088%), a right-skewed distribution, and a limited but clearly identifiable set of low-risk days ($\leq 0.01\%$) that offer the safest opportunities for prescribed burning. The spring season produced the dominant peak in quantified fire risk. In contrast, the fall peak remained within the low fire risk band, highlighting additional operational flexibility for meeting ecological objectives outside the traditional burn season. These findings provide a science-based foundation for operational risk thresholds, support the integration of real-time weather-fuel monitoring into burn planning, and establish the basis for an adaptive,

grassland-specific fire-danger system capable of improving prescribed-fire governance, ecological resilience, and wildfire preparedness across the Great Plains.

Overall, the findings contribute new knowledge by translating complex ecological and meteorological processes into a measurable and operationally interpretable fire-danger metric. It fills a critical gap between national forest-oriented systems and the unique fuel-climate interactions of prairie ecosystems. For operational utility of the quantified risks, the simple functional form can potentially facilitate ease of use by non-technical, prescribed-fire-focused groups, support adaptive prescribed-fire management, resource prioritization, and environmental-risk assessment across multiple temporal and spatial scales.

Continuing work will include validation with field-measured DFMC and grass curing across representative areas in the Flint Hills counties to strengthen model transferability and refine parameter responses to local fuel and climate characteristics. Also, the model's performance against local fire activity data will be analyzed. Integration with ozone impact index and air-quality modules will further ensure that prescribed-fire operations are consistent with environmental regulations and community health objectives.

4.2 Study Limitations

This study quantified wildfire risk across the 17 counties of the Flint Hills ecoregion, where grasslands dominate fuel composition but occur alongside shrublands, riparian timber, and croplands. While the model appropriately reflects the ecological reality of the Flint Hills, it may not capture localized variations in fire behavior where non-grass fuels exert stronger control. Consequently, model performance is expected to be highest in grass-dominated areas and moderately reduced in mixed-fuel landscapes. This limitation does not undermine the integrity of

the analysis but confines the framework's direct applicability to ecosystems with similar fine-fuel characteristics.

Also, the wildfire activity data, although comprehensive, has known uncertainties related to uneven jurisdictional coverage and underreporting of small fires, especially before 1995 (Short 2022). Aggregating data to the county-day scale and applying multi-year smoothing and minimizing these inconsistencies by emphasizing persistent temporal and spatial patterns over event-level variability. This approach enhances the robustness of trend detection but may obscure the influence of isolated and extreme days. The resulting trade-off favors reliability in regional-scale interpretation over precision at individual fire events.

one-hour DFMC was estimated from RH and air temperature, which served as a suitable predictor of short-response fine fuels characteristic of the Flint Hills. However, a one-hour DFMC may not fully represent the moisture dynamics of all fuel strata, particularly in areas with more complex vegetation or topographic variability. Similarly, modeled grass curing values, while empirically strong, were partially calibrated using Oklahoma Mesonet data and may not perfectly capture within-region differences in phenology or fuel condition. These factors may introduce uncertainty in localized predictions of fire potential, but do not compromise the overall explanatory relationships identified. The use of physically meaningful, ecologically relevant variables ensures that the model remains operationally feasible.

The validation phase of the quantified wildland fire-risk framework will directly address these sources of uncertainty by comparing model performance with field-measured DFMC and curing data across representative counties where such measurements are available. This will allow evaluation of model predictions under observed fuel and weather conditions, refine parameter

sensitivity to local variation, and strengthen the framework's generalizability for broader application across the Great Plains.

4.3 Continuing Study

Quantifying how wildland fires contribute to ground-level ozone (O₃) formation during the ozone season is the next step in this research. This continued study seeks to integrate the quantified wildland fire risk established in this study with the air-quality effect during peak wildland fire seasons across the region to create a unified decision-support framework for prescribed-fire management. Central to this effort is the development of an Ozone Impact Index (OII) that captures how prescribed-burning activity affects daily and seasonal variability in O₃ concentrations. Although the quantified fire-risk framework describes the conditions that govern ignition and spread, it does not include the photochemical mechanisms responsible for secondary pollutant formation. Regional exceedances of established statutory O₃ levels often coincide with the peak burning period in March and April (Akinbile & Liu, 2022), expressing the need for an integrated framework that balances ecological fire safety and ambient air quality standards.

Building on the quantified wildland fire risk, the ongoing study will use statistical modeling to quantify the fire-attributable portion of O₃ variability across the Flint Hills and the wider Great Plains. The OII will be developed using a combined regression and time-series modeling framework that integrates meteorological, photochemical, and fire-activity indicators to identify conditions that support both safe burning and acceptable air quality, while also delineating extreme-event days that are critical for estimating maximum average daily eight-hour ozone (MAD8) concentrations for regulatory applications. Candidate predictor variables reported in previous studies, such as temperature, solar radiation, relative humidity, wind speed, and cloud cover, will be considered to represent the key atmospheric drivers of O₃ formation and dispersion

based on available knowledge on the subject (Cisneros et al., 2020; El Asmar et al., 2025). Fire activity will be expressed as daily burned area derived from MODIS satellite observations for prescribed burns and wildfire data from the USFS Fire Occurrence Database. Background O₃ and meteorological data will be drawn from the EPA Air Quality System (AQS), Clean Air Status and Trends Network (CASTNET), and Mesonet records. Through time-series analysis, multivariate regression, and machine learning for feature selection, the modeling will effectively isolate fire-related O₃ variability from meteorological background and regional transport effects. This structure will adopt the dual temporal design of the quantified fire-risk framework by linking seasonal fuel and climate patterns with short-term atmospheric sensitivity to fire emissions.

Advancing beyond traditional fire-danger models and large-scale chemical-transport systems, the proposed OII will prioritize a locally calibrated, computationally efficient, and easy-to-use alternative simple functional form. Studies such as Baker et al. (2016) used the Community Multiscale Air Quality (CMAQ) model to investigate the effects of prescribed burning on O₃ and PM_{2.5} in the Flint Hills but identified challenges that limit operational application, including uncertain emission inventories, overprediction near sources, and insufficient mesoscale calibration. More recent deterministic models (El Asmar et al., 2025; Lee & Jaffe, 2024) have similarly shown that physics-based systems, while valuable for regional analysis, remain too computationally demanding and coarse to support daily prescribed-burn decisions. A statistical approach grounded in observed local relationships offers a practical improvement by producing regionally specific predictions of fire-related O₃ fluctuations that can be easily validated and operationalized.

Combining the OII with quantified wildland fire risk will yield a combined fire-safety and ozone-safety tool structured to identify optimal burn opportunities. Identifying the intersection

between moderate fire-risk conditions and low O₃ formation potential will be the primary purpose of the proposed suite of indexes. The indices will collectively identify periods that are both ecologically favorable and environmentally safe to conduct prescribed burning. Such integration will enhance the ability of land managers, burn associations, and regional agencies to plan and schedule prescribed burns that achieve fuel management objectives while minimizing the risk of O₃ exceedances.

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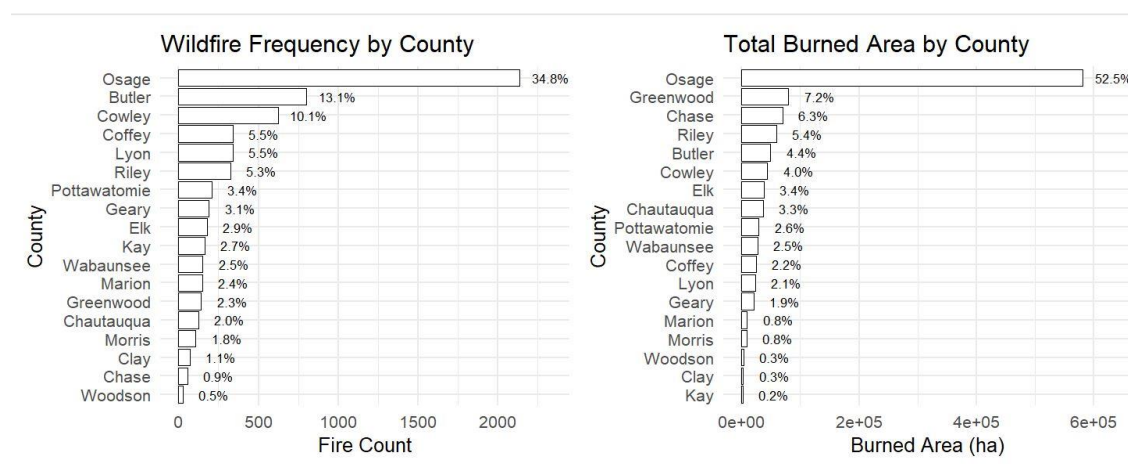
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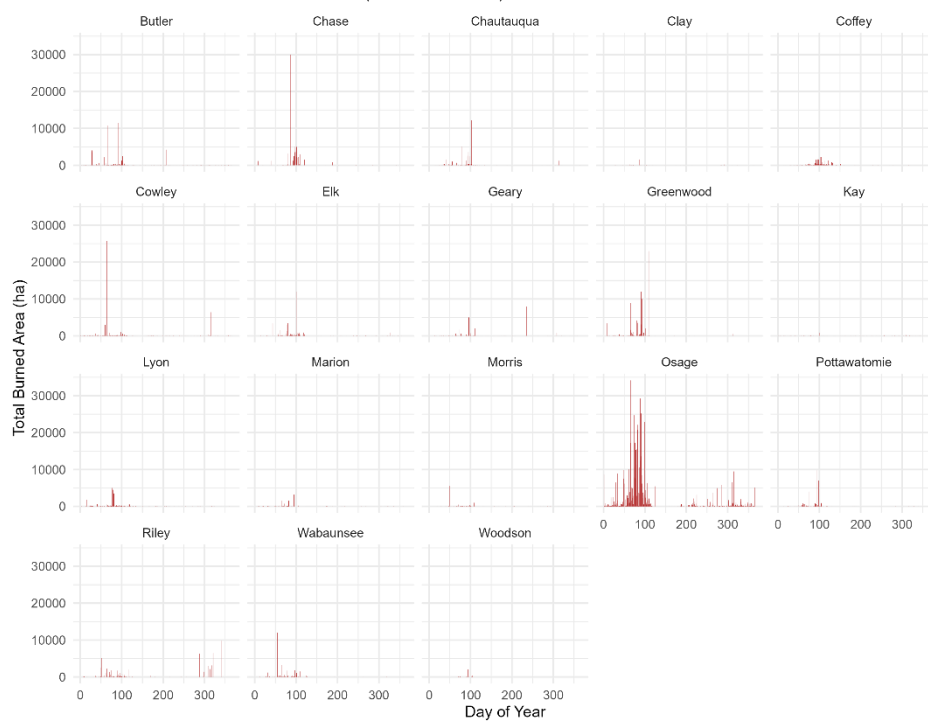
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Appendix A: Additional materials for Chapter 3

Appendix A: wildfire distribution in the Flint Hills



Total Burned Area Across the Year (Common Scale)



Wildfire Frequency Across the Year (Common Scale)

