

Developing a decision tool to assist management of prescribed fires in the Flint Hills region to
reduce smoke impact on ambient ozone

by

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B.S., Ladoke Akintola University of Technology, 2004
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AN ABSTRACT OF A DISSERTATION

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Abstract

Prescribed burning is a long-standing practice to maintain the ecosystem in the Flint Hills region. Landowners use fires as economically efficient practices on rangeland to maintain ecosystem health and function, facilitate favorable grazing, and enhance livestock performance. Due to these benefits, prescribed fire is used to increase and maintain the diversity of tallgrass prairie species while suppressing the invasion of woody. However, the intensive burning impacts air quality and constitutes public health concerns. Smoke from the fires contributes to the violation of the ambient ozone (O_3) standard, formed through the reaction of nitrogen oxide (NO_x) and volatile organic compounds (VOCs) emitted from the fires.

The ultimate goal of this research is to establish practical forecasting models and decision tools for smoke and air quality management in the Flint Hills region, which will encourage and enable the continuous practice of prescribed rangeland burning and maintenance of the ecosystem in a manner that minimizes adverse air quality and social impacts. The specific research objectives of this dissertation include: (1) identify the spatial and temporal distributions and patterns of daily prescribed fire activities in the Flint Hills region using the combination of MODIS resolution imagery and standard active fire data; (2) characterize meteorological parameter sensitivities connected to daily fire activities and propose optimum weather conditions for mitigating smoke pollution associated with prescribed fires; and (3) develop regression models to simulate O_3 contributions from prescribed burning in order to assist collaborative management of prescribed fires and reduce smoke impact on ambient O_3 .

To map the daily burned area in the Flint Hills region from 2003 to 2019, correlations between the accumulated burned area from Moderate Resolution Imaging Spectroradiometer (MODIS) resolution imagery and standard active fire data from satellites were developed as a scale

model. Spatial and temporal distributions and patterns of daily fire activities were performed. The results showed that fire activity was concentrated on a few days in mid-April. The annual burned percentage (ranged from 11% to 52%) and average fire size (ranging from 160 to 400 ha) were higher in the Flint Hills region's center than in the south and at the edge. All ground-level O₃ concentrations exceeding 70 ppb were recorded in April, coinciding with intensive fires in the Flint Hills region and on days with high solar radiation. Overall, the results provided a solid foundation for the development of O₃ regression models using daily burned area and weather factors as predictor variables.

The relative importance of meteorological driving factors of prescribed burning in the Flint Hills region was evaluated with machine learning techniques using random forest (RF) with Shapley additive explanation (SHAP) values and Pearson correlation to identify weather impact on landowner burn decisions and optimum weather for prescribed burning based on historic data from 2003-2019. The three most important weather variables that affected the subjectivity of landowner decisions in prescribed burning were solar radiation, cloud cover, and relative humidity (RH). The data indicated that less cloud cover demonstrated superior predictive power in landowner decisions for prescribed burning and largely resulted in elevated O₃. About 62% of all the heavy-fire days had cloud cover less than 10⁺%, which was not in the Kansas Department of Health (KDHE) recommended range of optimum burning conditions (30~50%). Optimal weather conditions occurred on average six days per burning season when cloud cover varied from 10⁺ to 55%. Transitioning from current burning practices by landowners to the proposed optimal weather conditions could lead to a remarkable reduction in the occurrence of 70⁺ ppb O₃ levels, by reducing the probability from 35% to 9% on days characterized by heavy fires.

Finally, a practical burning decision tool to assist management of prescribed fires in the Flint Hills region was developed to reduce smoke impact on ambient O₃. Pearson correlation and machine learning techniques were used to evaluate predictor variables' influence on O₃ mixing ratios. Results show high sensitivity of daily O₃ mixing ratio to cloud cover, the previous day's O₃ mixing ratio, daily burned area and RH. Proposed optimal burning conditions demonstrate reduced O₃ sensitivity to fire activities, averaging six days per season. Further recommendations were offered about burning under second-class conditions (cloud cover = 10~30%) and marginal conditions (cloud cover = 0~10%).

The detailed findings from this research can assist land managers in planning burning activities for improved air quality, reducing smoke impacts, and enhancing land management capacity, thereby promoting safer, effective, and sustainable prescribed burning practices. These results highlight the rising concern about smoke impacts on air quality during the prescribed burning season in the Flint Hills region of the U.S. and suggest further research to address this challenge.

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The relative importance of meteorological driving factors of prescribed burning in the Flint Hills region was evaluated with machine learning techniques using random forest (RF) with Shapley additive explanation (SHAP) values and Pearson correlation to identify weather impact on landowner burn decisions and optimum weather for prescribed burning based on historic data from 2003-2019. The three most important weather variables that affected the subjectivity of landowner decisions in prescribed burning were solar radiation, cloud cover, and relative humidity (RH). The data indicated that less cloud cover demonstrated superior predictive power in landowner decisions for prescribed burning and largely resulted in elevated O₃. About 62% of all the heavy-fire days had cloud cover less than 10⁺%, which was not in the Kansas Department of Health (KDHE) recommended range of optimum burning conditions (30~50%). Optimal weather conditions occurred on average six days per burning season when cloud cover varied from 10⁺ to 55%. Transitioning from current burning practices by landowners to the proposed optimal weather conditions could lead to a remarkable reduction in the occurrence of 70⁺ ppb O₃ levels, by reducing the probability from 35% to 9% on days characterized by heavy fires.

Finally, a practical burning decision tool to assist management of prescribed fires in the Flint Hills region was developed to reduce smoke impact on ambient O₃. Pearson correlation and machine learning techniques were used to evaluate predictor variables' influence on O₃ mixing ratios. Results show high sensitivity of daily O₃ mixing ratio to cloud cover, the previous day's O₃ mixing ratio, daily burned area and RH. Proposed optimal burning conditions demonstrate reduced O₃ sensitivity to fire activities, averaging six days per season. Further recommendations were offered about burning under second-class conditions (cloud cover = 10~30%) and marginal conditions (cloud cover = 0~10%).

The detailed findings from this research can assist land managers in planning burning activities for improved air quality, reducing smoke impacts, and enhancing land management capacity, thereby promoting safer, effective, and sustainable prescribed burning practices. These results highlight the rising concern about smoke impacts on air quality during the prescribed burning season in the Flint Hills region of the U.S. and suggest further research to address this challenge.

Table of Contents

List of Figures	xiii
List of Tables	xv
Acknowledgements	xvii
Dedication	xviii
Chapter 1 – Introduction	1
1.1 Prescribed rangeland burning in the Flint Hills Region	1
1.2 Benefits of Grassland Ecosystems and Prescribed Burning	1
1.3 Impact of Smoke on Ambient O ₃	3
1.4 Ozone Monitoring Sites in Kansas	4
1.5 The current smoke management plan and modeling tools	5
1.6 Research Needs.....	6
1.7 Research Objectives.....	7
1.8 References.....	9
Chapter 2 - Daily Burned Area Mapping for Prescribed Rangeland Burning in the Flint Hills Region Using Modis Data	12
2.1 Introduction.....	13
2.2 Methods	14
2.2.1 Study Area	14
2.2.2 Modis Data Acquisition and Processing	15
2.2.3 Mapping Daily Burned Area.....	17
2.2.4 Classification Of Daily Burned Area	18
2.2.5 Normalized Daily Burned Area	19
2.3 Results.....	19
2.3.1 Annual Burned Area and Burned Percentage	19
2.3.2 Correlations Between Burned Area and Active Fire Count.....	20
2.3.3 Distribution Of Daily Burned Area.....	22
2.4 Discussion.....	24

2.4.4 Spatial And Temporal Distributions of Daily Burned Area	24
2.4.5 How Did Weather Conditions Affect Daily Burned Area	25
2.4.6 How Did Daily Burned Area Affect Ozone.....	27
2.5 Conclusion	28
2.6 Acknowledgments	29
2.7 References.....	29
Chapter 3 - Optimum Weather Conditions for Prescribed Burning in the Flint Hills Region.....	33
3.1 Introduction.....	34
3.2 Data and Methods	36
3.2.1 Fire Data.....	36
3.2.2 Weather Data.....	36
3.2.3 Data Analysis	37
3.2.4 Identifying the Preferred Weather Conditions for Burning by Landowners	39
3.2.5 Identifying the Optimum Weather Conditions for Prescribed Fires	39
3.3 Results.....	40
3.3.1 Prescribed Fire Driving Weather Variables	40
3.3.2 Weather Conditions for Different Fire Activity Levels	44
3.3.3 The Preferred Weather Conditions for Burning by Landowners	44
3.3.4 The Optimum Weather Conditions for Prescribed Fires	46
3.4 Discussion.....	47
3.4.1 How Weather Conditions Affected Landowner Burn Decisions.....	47
3.4.2 How the Proposed Optimum Conditions Can Reduce Ozone Impact	50
3.5 Conclusion	53
3.6 Acknowledgements.....	54
3.7 References.....	54
Chapter 4 – Regression models to reduce impact of prescribed burning on O ₃ in Flint Hills	
Region.....	58
4.1 Introduction.....	59
4.2 Data and Methods	61
4.2.1 Air Quality Data.....	61
4.2.2 Predictor Variables.....	63

4.2.3 Summary of Previous Results of Regression Analysis	65
4.2.4 Data Analysis	66
4.2.5 The Ozone Regression Models	67
4.3 Results.....	68
4.3.1 Contributions of Predictor Variables to Ozone Concentration	68
4.3.2 Ozone Regression Models	70
4.3.3 Identifying Weather Conditions for Burn Decision Tool	73
4.4 Discussion.....	74
4.4.4 Identifying How Predictor Variables Related to Elevated Ozone	74
4.4.5 The Burning Decision Tool	78
4.5 Conclusion	82
4.6 References.....	85
Chapter 5 - Conclusion and Future Research Directions.....	91
5.1 Conclusions.....	91
5.1.1 Key Conclusions and Limitations	92
5.2 Recommendations for future research directions	96
5.3 Practical Implications	98
5.4 References.....	99
Appendix A : Additional materials for Chapter 2.....	100
Appendix B : Additional materials for Chapter 4.....	121

List of Figures

Figure 1.1: The O ₃ and PM _{2.5} monitoring sites in Kansas and perimeter of the Flint Hills region (bold lines)	5
Figure 2.1.1: 17-county study area in Kansas and Oklahoma	15
Figure 2.2: Flowchart of the process for mapping daily burned area.	18
Figure 2.3: Area burned in each spring burning season in the 17 counties of the Flint Hills region.	19
Figure 2.4: Correlations between the annual burned areas (estimated from burn scars in satellite images) and the active fire count (based on the detection of the released elevated energy) in different counties.	22
Figure 2.5: Average and maximum daily burned area from 2003 to 2019 in the 17 counties of the Flint Hills region (The black bars represent the average daily burned area. Error bars represent the maximum daily burned area).....	23
Figure 2.6: Correlations between the acres burned in the whole spring burning seasons from 2001 to 2019 and the highest 8-hour O ₃ mixing ratios observed in the same period at any of the ten monitoring sites	27
Figure 2.7: The maximum 8-hour O ₃ concentrations in the Konza Prairie at different dates from 2003 to 2013 and the corresponding average daily burned area in the same period in the 17 counties of the Flint Hills region.....	28
Figure 3.1: Pearson correlation between daily burned area and meteorological factors.	42
Figure 3.2: Weather variables activity level in burning decisions by mean absolute SHAP values and their effect on daily burned area in (a) Flint Hills region (b) Wabaunsee County (c) Riley County and (d) Marion County	43
Figure 3.3: The SHAP dependence plots between SHAP values and (a) RH, (b) Air Temperature, (c) Wind speed and (d) Cloud cover	50
Figure 3.4: Distribution of weather variable (a) cloud cover; and air pollution (b) ozone under preferred condition and proposed optimum condition over the Flint Hills region. In the box plots, the solid black line represents the median; the black circle represents the mean; the	

bottom and top of the box plots represents the 25th percentile and 75th percentile, respectively.	53
Figure 4.1: Pearson correlation between the daily maximum 8-hour O ₃ mixing ratios and predictor variables.	70
Figure 4.2: Predictor variables contributions by mean absolute SHAP values and their effect on daily maximum 8-hour O ₃ mixing ratios	70
Figure 4.3: The SHAP dependence plots between SHAP values and (a) RH, (b) Cloud cover, (c) Daily burned area (d) Previous day maximum O ₃ level	77
Figure 4.4: Daily maximum 8-hour O ₃ mixing ratios vs daily burned area in the Flint Hills region from 2003 to 2019 under various weather conditions	80

List of Tables

Table 2.1: Annual average burned area and burned percentage from	20
Table 2.2: Classification of daily burned area of the 17 counties from March 8th to May 8th (Data are average values from 2003 to 2019).	23
Table 2.3: Preferred weather conditions for prescribed fires determined from days when daily burned area was larger than 50% of the maximum daily burned area in the county from 2003 to 2019.	26
Table 2.4: Median values of weather variables for different fire activity levels on all days with the preferred weather conditions for prescribed fires.	26
Table 3.1: Median values of weather variables for different fire activity levels in all days of spring burning seasons from 2003 to 2019	44
Table 3.2: The proposed optimum weather conditions in comparison with recommended weather conditions for prescribed burning from other regions in USA.	45
Table 3.3: Burned areas at different cloud covers in the spring burning seasons (March 8th to May 8th). The total burned area of the 17 counties were average values for the spring burning seasons from 2003 to 2019.	47
Table 3.4: Burned areas at different RH in the spring burning seasons (March 8th to May 8th) (The total burned area of the 17 counties were average values for the spring burning seasons from 2003 to 2019)	49
Table 3.5: Summary of the number of days when $O_3 > 70$ ppb under KDHE optimum weather conditions, preferred weather conditions and proposed optimum weather conditions from historical prescribed fires in terms of fire categories	51
Table 4.1: Kansas Ozone Monitor Network	62
Table 4.2: Modified Pasquill-Gifford stability classes	64
Table 4.3: Sensitivities of the predictor variables on O_3	71
Table 4.4: The O_3 regression models for Wichita, Kansas City, and Konza Prairie	72
Table 4.5: The acceptable burning conditions and proposed optimum conditions determined from all the heavy-fire days (The total burned area of the 17 counties were average values for the spring burning seasons from 2003 to 2019).....	73

Table 4.6: The maximum daily burned area in the Flint Hills region in to avoid $O_3 > 70$ ppb 78

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Dedication

To my beloved parents, and daughter.

Chapter 1 – Introduction

1.1 Prescribed rangeland burning in the Flint Hills Region

Wildfire plays a crucial role in shaping the ecological processes of North American ecosystems. In the United States, wildland fire, which includes both prescribed fire and wildfire, is a crucial component of ecosystems and land management (Afrin, 2021). Wildfires are unplanned fires in wildland areas that can encroach on populated regions, whereas prescribed burning is a controlled fire application primarily used to achieve specific land management goals (Kobziar et al., 2015; Zhao et al., 2019a). Prescribed burning has been used for a long time to preserve the ecosystem in the Flint Hills region, which covers a huge portion of eastern Kansas. Flint Hills grasslands are well known for their high pasture quality, which makes grazing cattle there an important economic activity. With about 2.4 million hectares of rangeland, the region contains the largest unplowed tallgrass prairie area in North America. Every year, approximately one-third of the rangeland is burned, primarily around April. According to Ratajczak et al. (2014), fires are necessary to maintain the grassland vegetation every 1-3 years and assist shape the tallgrass prairie. Smoke from the fires causes elevated ozone (O₃) and PM_{2.5} (Particulate matter less than 2.5 µm in equivalent aerodynamic diameter) in ambient air, contributing to O₃ exceedances, and affecting several states downwind of Kansas. The impact of burning in the Flint Hills region on human health first gained public awareness in 2003, and Kansas Department of Health and Environment (KDHE) received many dissatisfaction reports of high ambient O₃ concentrations in April. The smoke impact of the rangeland burning that helps maintain the health of grasslands has been subjected to intense discussion and regulatory issues.

1.2 Benefits of Grassland Ecosystems and Prescribed Burning

Grasslands are one of the largest terrestrial ecosystems and provide critical ecosystem goods and services at local, regional, and global scales (Blair & Briggs, 2014). They are highly biodiverse and productive terrestrial biomes, yet they receive limited protection (Pendall et al., 2018). Human welfare is dependent on ecosystem services and serve as a vital component of the ecosystem (Paudel et al., 2021). A

third of the Earth's surface is covered by grassland ecosystems, making them an important ecosystem of the planet (Lemaire & Chabbi, 2011). As a result of grassland ecosystems, humankind derives many benefits through livestock farming, as well as a variety of other overlooked services such as climate regulation, soil conservation, biodiversity, natural medicine, tourism, cultural and societal benefits (Franzluebbers & Steiner, 2014). Millennium Ecosystem Assessment (MEA, 2005) defines ecosystem services as benefits humans obtain from ecosystems that support survival and quality of life. Provisioning, regulating, and cultural services—which directly benefit people—as well as the supporting services necessary to sustain other services—are included in the category of benefits derive from grassland ecosystem services.

Grasslands provide regulating services, which are benefits derived from regulating ecosystem processes. These include climate regulation, pollination, disease, pest control, weed control, fresh and flood water, and fire regulation. The prescribed burning of grassland in the Great Plains region annually or every two years enhance the productivity cycle, which is necessary to sustain vegetative uniformity (Ratajczak et al., 2016). Consequently, applicability of fire to sustain grassland reduce the likelihood of woody incursions and large, intense fires that can significantly damage physical infrastructure, human health, and the environment ((Depietri & Orenstein, 2019). Grasslands such as Konza Prairie in the Flint Hills of northeastern Kansas, are protected nature reserves and national parks for local and national tourism. Large grasslands support a diversity of plants and animals that people can use for religious rituals, outdoor leisure, research, and education (Asbjrnsen et al., 2014). More importantly, research on grasslands has contributed immensely to understanding a large body of scientific knowledge, such as hydrological processes, succession theory, and the role of fire in ecosystems (Bengtsson et al., 2019).

The economic benefit of grass-based farming methods is forage production, which has global implications for raising animals. In the Flint Hills of the United States, the nutrient-rich palatable grassland provides food for the cattle when put on the grass and helps them to gain weight. Management of grasslands maintains a rich diversity of plants, provides habitat for birds and insects, supplies genetic resources, and promotes conservation efforts (Zografou et al. 2020). Across grassland, high diversity plant communities are reasonably resistant to insects, pests, and weeds and maintain constant soil quality and production in a range

of weather conditions (Paudel et al., 2021). Besides, grasslands are recognized for their ability to improve soil health, hold carbon, collect nitrogen and phosphorus, and support a variety of soil species, including microbial communities as part of the supporting services (Wilson et al., 2009).

Fires are the essential component to maintain grasslands (Gibson, 2009). The primary role of fires in grasslands is to curb the expansion of woody vegetation in grass-dominated ecosystems (Ratajczak et al., 2014). Prescribed burning has many benefits, including controlling weed and tree growth, releasing soil nutrients, revitalizing soil, eliminating pathogens that cause plant diseases, and preserving cattle grazing areas (Yang Liu, 2018). The frequency and severity of fires in preserving grasslands have been a contentious issue in the Flint Hills region of the Great Plains in the United States. The tallgrass prairie will transition toward a forest environment without fire as a control measure (Heisler et al., 2003). Grassland ecosystems provide many benefits against which the risks and damages to air quality associated with prescribed burning management practices must be considered. Despite prescribed burning's many benefits in maintaining tall grassland ecosystem, it also contributes to smoke emissions that can impact air quality, particularly elevated ambient O₃ levels. Prescribed burning near communities can exacerbate the effects on air quality, especially when conditions are conducive to incomplete combustion and poor atmospheric dispersion (Price et al., 2016). Thus, developing and using a decision tool to manage prescribed fires in the Flint Hills region to reduce smoke impacts on ambient O₃ will preserve grassland ecosystem, enhance human health, and stimulate local economic growth.

1.3 Impact of Smoke on Ambient O₃

Urban air quality is highly dependent on complex interactions involving numerous local and regional dispersed atmospheric pollutant. As the atmosphere rises, O₃ naturally accumulates from ground surface to stratosphere (Cirnu & Harrington, 2019). It is beneficial for the terrestrial life on earth that O₃ is present in the stratosphere and reduces the amount of ultraviolet (UV) radiation associated with O₃ chemical reactions. O₃ is a photochemical pollutant and greenhouse gas in the atmosphere, which is not directly emitted into the atmosphere but formed through the reactions between precursors such as nitrogen oxides (NO_x) and volatile organic compounds (VOCs) in presence of sunlight (Mueller & Mallard, 2011). O₃ has been one of the most

persistent and potentially harmful air pollutants in the United States for many years. Healthy people who are exposed to O₃ may experience breathing difficulties, headaches, chest pain, pulmonary edema, and an aggravation of their asthma and arrhythmias (Lippmann, 1989).

Rangeland fire smoke contains both NO_x and VOCs. O₃ is produced in the original smoke plume or through the interaction of the smoke plume with other pollutants in the atmosphere (Dokas et al., 2007). The national ambient air quality standards (NAAQ) 8-hour O₃ threshold was lowered from 75 to 70 parts per billion (ppb) in 2015. The requirement for smoke management is growing as air quality standards become more stringent and other anthropogenic emissions have been better controlled. The regulation of smoke management from fires that support the health of the Flint Hills grasslands has emerged as a problem. Urban communities nearby have experienced O₃ exceedances due to smoke plumes that have drifted downwind from prescribed fires in the Flint Hills region (Volland, 2015).

1.4 Ozone Monitoring Sites in Kansas

Kansas has monitoring network for O₃ and PM_{2.5} that includes nine sites throughout the state, with three sites around Wichita, one at Topeka, and one at Cedar Bluff as a background site. The Chanute monitoring site is new and began operations in 2014. Within the Flint Hills region, the Clean Air Status and Trends Network (CASTNET) has one site that reports O₃, and the Interagency Monitoring of Protected Visual Environments (IMPROVE) program has one site that reports speciated PM_{2.5}.

The current NAAQS for ozone is set at 70ppb for both the primary and secondary standards. Attainment of the standard is established by calculating the annual fourth-highest daily maximum 8-hour concentration, averaged over three years using Metropolitan Statistical Area (MSA) population. Location of the ten O₃ sites and the Tallgrass PM_{2.5} site are illustrated in Figure 1.1.

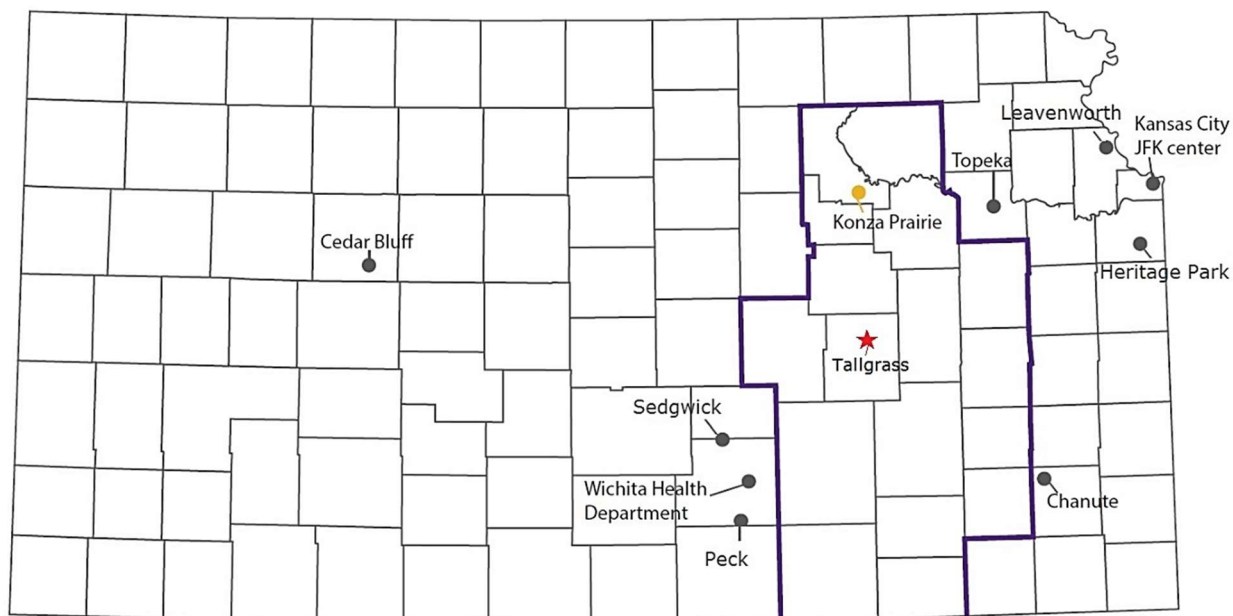


Figure 1.1. The O₃ and PM_{2.5} monitoring sites in Kansas and perimeter of the Flint Hills region (bold lines)

1.5 The current smoke management plan and modeling tools

Unlike many other pollutant sources, smoke from rangeland burning relies on management rather than control devices for impact reduction. The Flint Hills smoke management plan (SMP) was adopted by KDHE in late December 2010, and implementation began in 2011. Currently, smoke modeling tools rely on dispersion models, which include a cumulative impact model and a plume model to forecast smoke contributions to particulate matter (PM). The SMP modeling tool was included on www.ksfire.org for land managers and local fire officials to use when making burning decisions aimed at reducing air quality impacts. The model is based on projected meteorology and expected emissions. They can assist land managers to redistribute the emissions by burning when dispersion is good, and when wind direction is favorable, so that the smoke impact on sensitive locations such as major cities can be reduced.

However, the contributions of burning activities to ambient O₃ mixing ratios have not been well documented. The current modeling tools are not capable to forecast smoke impact on O₃, and therefore the current smoke management plan is not sufficient to prevent exceedance of the O₃ standard. The contributions of prescribed burning to ambient O₃ mixing ratios in the Flint Hills region have not been thoroughly characterized. Therefore, the current smoke management plan is not sufficient to prevent exceedance of the

O₃ standard. Current SMP prescribed fire mitigation efforts require improved measures to mitigate impact of smoke on ambient O₃.

1.6 Research Needs

Assessing the impact of smoke on ambient ozone is challenging due to the uncertainty in prescribed fire data. Post-burn circumstances are not typically recorded for burn permit, and there is variability in recordkeeping and data-reporting requirements across agencies. Analyzing the daily burned rangeland data and using air quality models are effective ways to quantify the impact of prescribed fires on air quality. Developing a more accurate method to estimate daily burned area is required to better understand and quantify prescribed fire impacts on air quality and improve related decision-making.

The prescribed burning season is constrained by the availability of suitable weather conditions essential to lower fire intensity and impact on urban air quality (Haikerwal et al., 2015). Analysis of previously daily prescribed burned areas and the weather conditions controlling them is critical for projecting future pollution control. While the optimum weather conditions recommended by KDHE are widely considered best practices in the Flint Hills region, the number of days available per burning season under these conditions are limited. The availability of optimum weather conditions to minimize smoke impacts from fire on the environment and air quality has been identified as the major constraint to achieving the desired levels and timings of prescribed burns (Chiodi et al., 2018). Given the short burn windows in the spring, it has become increasingly important to identify feasible burn conditions and the limiting weather conditions to prevent O₃ exceedance using long-term local weather data.

Complex photochemical air quality modeling is usually needed to simulate both chemical and physical processes to model O₃ formation. Results of several studies simulating impacts of prescribed fires suggested that the current module in photochemical models tend to underestimate O₃ production, indicating a lack of simulated photochemical production or a lack of precursors emitted from the burning (Hu et al., 2008). Accuracy of modeling results is affected by knowledge gaps in smoke evolution and photochemical mechanisms. The three-dimensional Eulerian grid modeling is used in most modern photochemical models. They solve a finite approximation by splitting the modeling region into many horizontal and vertical cells

that interact with one another to replicate the numerous mechanisms that affect pollutant concentration evolution. For each computational cell in the modeling domain, emission and meteorological data are typically specified at hourly intervals. The use of these photochemical models is often costly, with high demands on model inputs and computer resources. Additionally, accurate emission data with defined uncertainties for rangeland burning has not been available at the required space and time scales. Therefore, effort to apply photochemical modeling in smoke management is limited, and there is still a long way to go for a reliable and practical smoke management tool can be developed based on photochemical modeling. As air quality management is becomes more complex, higher level of competency in O₃ modeling is required to provide reliable, accurate results and practical tools to manage smoke-related air quality challenges.

1.7 Research Objectives

The goal of this project is to establish practical forecasting models and a decision support system for smoke and air quality management in the Flint Hills region, which will encourage and enable the continuous practice of prescribed rangeland burning and maintenance of the ecosystem in a manner that minimize adverse air quality and social impacts. Specific objectives include:

1. Identify the spatial and temporal distributions and patterns of daily prescribed fire activities in the Flint Hills region using the combination of MODIS resolution imagery and standard active fire data.
2. Characterize meteorological parameter sensitivities connected to daily fire activities and propose optimum weather conditions for mitigating smoke pollution associated with prescribed fires.
3. Develop regression models to simulate O₃ contributions from prescribed burning in order to assist collaborative management of prescribed fires and reduce smoke impact on ambient O₃.

Chapters 2 to 4 provide further elaboration on each objective, with concise descriptions of the chapters and the research goals that drive them.

Chapter 2: Daily Burned Area Mapping for Prescribed Rangeland Burning in the Flint Hills Region Using Modis Data.

To address Objective 1, method to map and retrieve the daily burned area in the Flint Hills region, covering 17 counties in Kansas and Oklahoma from 2003 to 2019 using the combination of MODIS imagery and standard active fire data was developed in this chapter. Correlations between the accumulated burned area and the active fire count observed at the same date are developed as a scale model for mapping daily burned area. The spatial and temporal distributions and patterns of daily fire activities in the Flint Hills region are identified from the resulting product. Additionally, analysis of the distribution of the daily burned area between March 8 to May 8 from 2003 to 2019 are studied to optimize the timing of the prescribed fire activities. The results show the preferred weather conditions for prescribed fires. How weather conditions affected the daily burned and effect of daily burned area on O₃ concentrations are also studied under this chapter.

Chapter 3 - Optimum Weather Conditions for Prescribed Burning in the Flint Hills Region

This chapter addresses Objective 2 by characterizing the sensitivities of meteorological parameters and identifying influential weather parameters linked to daily fire activities in the Flint Hills region. The Pearson correlation was used to analyze the relationship between daily burned area and meteorological driving factors. This chapter presents improvement on the current understanding of fire weather conditions and their effect on the timing of prescribed burning activities in the Flint Hills region with machine learning techniques using random forest (RF) with Shapley additive explanation (SHAP) values. The SHAP value are utilized to interpret the random forest algorithm and explain the impact of weather variables on daily burned areas. The weather conditions currently preferred by landowners based on county-level data are identified. In addition, the analysis assessed the main meteorological factors influencing the subjectivity of landowner decisions in prescribed burning and the optimum weather conditions for prescribed burning to reduce the impact of smoke on ambient air quality were identified.

Chapter 4: Regression Models to Reduce Impact of Prescribed Burning on Ozone in Flint Hills Region

Chapter 4 addresses objective 3 by developing regression models that assist to reduce smoke impact on ambient O₃. This chapter investigates key factors that influencing maximum 8-hour O₃ observations at

any of the O₃ monitoring sites in Kansa using Pearson correlation, machine learning technique (SHAP values with XGBoost), regression modeling and sensitivity analyses. The analysis was based on combined analysis of historical data including O₃, weather variables, and daily burned area that were obtained from satellite observations. Practical burning decision tool to assist management of prescribed fires in the Flint Hills region was developed using the predictors that are highly sensitive to O₃ level. Optimal burn conditions for heavy fire when O₃ level is not sensitive to fire were identified. Additional burning conditions were recommended under second-class condition and marginal conditions to supplement the optimal burning condition.

Chapter 5: Conclusions and Future Research Directions.

The final chapter of this dissertation highlights key conclusions, limitations and areas of research that need to be explored in the future.

1.8 References

- Afrin, S. (2021). Evaluating the Impacts of Prescribed Fire on Air Quality and Public Health in the Southeastern US. North Carolina State University.
- Asbjornsen, H., V. Hernandez-Santana, M. Liebman, J. Bayala, J. Chen, M. Helmers, C. K. Ong, and L. A. Schulte. 2014. Targeting perennial vegetation in agricultural landscapes for enhancing ecosystem services. *Renewable Agriculture and Food Systems* 29: 101– 125.
- Bengtsson, J., Bullock, J. M., Egoh, B., Everson, C., Everson, T., O'connor, T., ... & Lindborg, R. (2019). Grasslands—more important for ecosystem services than you might think. *Ecosphere*, 10(2), e02582.
- Blair, J., Nippert, J., & Briggs, J. (2014). *Grassland Ecology*. Monson RK editor. Ecology and the Environment.
- Chiodi, A. M., Larkin, N. S., & Varner, J. M. (2018). An analysis of Southeastern US prescribed burn weather windows: Seasonal variability and El Niño associations. *International Journal of Wildland Fire*, 27(3), 176-189.
- Depietri, Y., and D. E. Orenstein. 2019. Fire-regulating services and disservices with an application to the Haifa-Carmel region in Israel. *Frontiers in Environmental Science* 7:107.
- Cirnu, L., & Harrington Jr, J. (2019). Climatic Analysis of Ozone Data from the Konza Prairie Biological Station Sensor. *Transactions of the Kansas Academy of Science*, 122(1-2), 87-95.
- Dokas, I., Statheropoulos, M. and Karma, S. 2007. Integration of field chemical data in initial risk assessment of forest fire smoke. *Sci. Total Environ.* 376:72-85.

- Franzluebbers, A. J., and J. L. Steiner. 2016. Ecosystem services and grasslands in America. Pages 422– 425 in M. Potschin, R. Haines-Young, R. Fish, and K. Turner, editors. Routledge handbook of ecosystem services. Routledge/Informa UK Limited, Abingdon, UK.
- Gibson, D. J. (2009). Grasses and grassland ecology. Oxford University Press.
- Haikerwal, A., Reisen, F., Sim, M. R., Abramson, M. J., Meyer, C. P., Johnston, F. H., & Dennekamp, M. (2015). Impact of smoke from prescribed burning: Is it a public health concern? *Journal of the Air & Waste Management Association*, 65(5), 592-598.
- Heisler, J.L.; Briggs, J.M.; Knapp, K.A. 2003. Fire frequency and the dynamics of shrub cover and abundance. *American Journal of Botany* 90(3):423–28.
- Hu, Y., Odman, M.T., Chang, M.E., Jackson, W., Lee, S., Edgerton, E.S., Baumann, K., & Russell, A.G. 2008. Simulation of air quality impacts from prescribed fires on an urban area. *Environ. Sci. Technol.* 42:3676-3682.
- Kobziar, L., Godwin, D., Taylor, L., & Watts, A. (2015). Perspectives on Trends, Effectiveness, and Impediments to Prescribed Burning in the Southern U.S. *Forests*, 6(12), 561–580. <https://doi.org/10.3390/f6030561>
- KDHE. (2010). State of Kansas Flint Hills Smoke Management Plan. Kansas Department of Health and Environment. Division of Environment, Bureau of Air.
- Lemaire, G., Hodgson, J., & Chabbi, A. (Eds.). (2011). Grassland productivity and ecosystem services. Cabi.
- Lippmann, M. 1989. Health effects of ozone. A critical review. *JAPCA*. 39:672–695.
- Millennium Ecosystem Assessment (2005). Ecosystems and human well-being: wetlands and water. World Resources Institute.
- Mueller, S.F. & Mallard, J.W. 2011. Contributions of natural emissions to ozone and PM_{2.5} as simulated by the Community Multiscale Air Quality (CMAQ) model. *Environ. Sci. Technol.* 45:4817-4823.
- Paudel, S., Cobb, A. B., Boughton, E. H., Spiegel, S., Boughton, R. K., Silveira, M. L., ... & Steiner, J. L. (2021). A framework for sustainable management of ecosystem services and disservices in perennial grassland agroecosystems. *Ecosphere*, 12(11), e03837.
- Pendall, E., Bachelet, D., Conant, R.T., El Masri, B., Flanagan, L.B., Knapp, A.K., Liu, J., Liu, S. and Schaeffer, S.M. (2018). Grasslands (pp. 399-427). US global change research program.
- Price, O. F., Horsey, B., & Jiang, N. (2016). Local and regional smoke impacts from prescribed fires. *Natural Hazards and Earth System Sciences*, 16(10), 2247–2257.
- Ratajczak, Z., Nippert, J., Briggs, J. and Blair, J. 2014. Fire dynamics distinguish grasslands, shrublands and woodlands as alternative attractors in the Central Great Plains of North America. *Journal of Ecology* 102:1374-1385.
- Volland, C. 2015. Chapter calls for meaningful monitoring of the Flint Hills burning. *Planet Kansas* 39(4):45
- Wilson, G. W. T., C. W. Rice, M. C. Rillig, A. Springer, and D. C. Hartnett. 2009. Soil aggregation and carbon sequestration are tightly correlated with the abundance of arbuscular mycorrhizal fungi: results from long-term field experiments. *Ecology Letters* 12:452–461.

- Yang Liu, 2018. Comparative analysis of Unmix/PMF modeling for PM_{2.5} source apportionment in rural and urban Kansas and a review of life cycle assessment on carbon footprint of beef production. Abstract of PhD. Dissertation. Department of Biological and Agricultural Engineering College of Engineering, Kansas State University Manhattan, Kansas.
- Zhao, F., Liu, Y., Goodrick, S., Hornsby, B., & Schardt, J. (2019). The contribution of duff consumption to fire emissions and air pollution of the Rough Ridge Fire. *International Journal of Wildland Fire*, 28(12), 993–1004. <https://doi.org/10.1071/WF18205>
- Zografou, K., Swartz, M. T., Tilden, V. P., McKinney, E. N., Eckenrode, J. A., & Sewall, B. J. (2020). Stable generalist species anchor a dynamic pollination network. *Ecosphere* 11, e03225.

Chapter 2 - Daily Burned Area Mapping for Prescribed Rangeland Burning in the Flint Hills Region Using Modis Data

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Abstract

Smoke from prescribed burning in the Flint Hills region impacts air quality and contributes to the exceedances of ozone (O_3). The objectives of this study were 1) to map the daily burned area in this region from 2003 to 2019 using the combination of Moderate Resolution Imaging Spectroradiometer (MODIS) resolution imagery and standard active fire data from satellite, and 2) to identify the spatial and temporal distributions and patterns of daily fire activities. Red and near-infrared images were combined, and supervised minimum distance classification of the bi-spectral images was applied to map the daily burned area. Results showed that fire activities were highly concentrated in a few days in mid-April. The annual burned percentage (ranged from 11% to 52%) and the average fire size (ranged from 160 to 400 ha) were larger in the central part of the Flint Hills region than in the Southern part and at the edge. On average, the preferred weather conditions by landowners only occurred in around 10 days in one spring burning season. The maximum daily burned area in the Flint Hills study region was as high as 0.2 million ha, about 1/6 of the total burned area in the whole spring burning season. Based on historical daily burned area analysis and weather data, most fires occurred on days with high solar radiation, favoring O_3 production. Changing this pattern or more evenly distributed fires can reduce the smoke impact on daily O_3 . The results of this study provided a solid foundation for the development of O_3 regression models using daily burned area and meteorological factors as predictor variables.

2.1 Introduction

The Flint Hills region is the home to the largest remaining area of unplowed tallgrass prairie in North America, which has been preserved for biophysical and socioeconomic reasons. Prescribed burning is a long-standing practice to maintain the structure and functionalities of the tallgrass ecosystem, as it enhances nutritional value of native grasses and reduces weeds/brush and wildfire risk (Towne and Craine, 2016). However, the intensive fires impact air quality due to the particulate matter in the smoke and the elevated ozone (O_3) formed through the reaction of nitrogen oxide (NO_x) and volatile organic compounds (VOCs) emitted from the fires (Liu, 2017; McClure and Jaffe, 2018). In Kansas, the number of days with O_3 exceedance above the air quality standard increased with increasing burned area in the Flint Hills region (Liu et al., 2018). Smoke can transport thousands of kilometers downwind, affecting regional air quality (Vakkari et al., 2020).

Responsible smoke management relies on modeling tools that can quantify the contributions of burning activities to daily air quality, which requires quantification of burned area and smoke emissions at defined space and time scales (Odman et al., 2013). This is essential for collaborative smoke management that allows regulators and land managers to plan a burn's timing and size to avoid air quality problems. Satellite remote sensing is available for the detection of fire activities. Fire emission inventories are often based on burned area data from satellites accompanied by biogeochemical modeling of fuel load (Ito and Penner, 2004; Lentile et al., 2006; Langmann et al., 2009). Land managers have used satellite data to supplement existing fire data and assist with fire management initiatives (Morgan et al., 2001). Terrestrial imagery from the National Aeronautics and Space Administration (NASA)'s Moderate Resolution Imaging Spectroradiometer (MODIS) instrument has been used for mapping accumulated burned area of the tallgrass prairie in a whole burning season (Mohler and Goodin, 2010, 2012a, b). Managers can keep track of fire activities using satellite products through an annual reporting system. However, few can track them on a daily basis (Ferguson et al., 2001). The method developed by Mohler and Goodin (2010) could only estimate accumulated burned area but not daily burned area due to cloudy satellite imagery and the quickly changing nature of burned and unburned areas amid rapid vegetation regeneration. Satellite active fire data provides

information on the spatial and temporal distribution of fires. The active fire data had been used to quantify the effects of agricultural fires on air quality (Zha et al., 2013). Freeborn et al. (2009) claimed that combining and fusing satellite imagery and active fire data from various satellite platforms could improve the satellite-derived estimation of burned area. The algorithm to detect both day and nighttime active fires and other thermal anomalies was often based on the detection of the released elevated energy relative to the non-burning surroundings. And it could be obtained at middle-infrared to thermal wavelengths through MODIS Fire and Thermal Anomalies product (Schroeder et al., 2014; Chen et al., 2017). The new R-Series of Geostationary Operational Environmental Satellite (GOES-R), launched in November 2016, could detect active fire activity with higher temporal resolution but had lower spatial resolution (Barmpoutis et al., 2020; Xu et al., 2021). Urbanski et al. (2009) suggested that the combination of active fire data and burn scar detection algorithm be used to produce daily burned area.

Daily variation of ambient O_3 is significantly affected by variations in weather conditions and emissions of O_3 precursors (Liu et al., 2018). Estimating daily burned area is essential for quantifying the actual contributions of fire activities on daily ambient O_3 , and understanding fire patterns can assist land management in controlling smoke impact (Scholtz et al., 2020). Our goal was to establish a regression model to simulate the smoke impact on O_3 by using daily burned area and meteorological factors as predictor variables and develop a practical burning decision tool based on the model. The specific objectives of this study were: 1) to map the daily burned area in the Flint Hills region from 2003 to 2019 using the combination of MODIS highest resolution imagery and standard active fire data; 2) to identify the spatial and temporal distributions and patterns of daily fire activities in the Flint Hills region.

2.2 Methods

2.2.1 Study Area

The Flint Hills region extends throughout much of eastern Kansas and northern Oklahoma and contains over 2.4 million ha of rangeland. Almost half of the rangeland is burned yearly, and burning is done almost exclusively in the spring season due to economic and cultural factors (Baker et al., 2019; Weir and

Scasta, 2017). A land use distribution map can be found in Scholtz et al. (2020) or Mohler and Goodin (2012a, b). Our study area covers 17 counties in Kansas and Oklahoma (fig. 2.1), as they represent a significant portion of the Flint Hills region, and we have access to consistent data in these counties from 2003 to 2019.

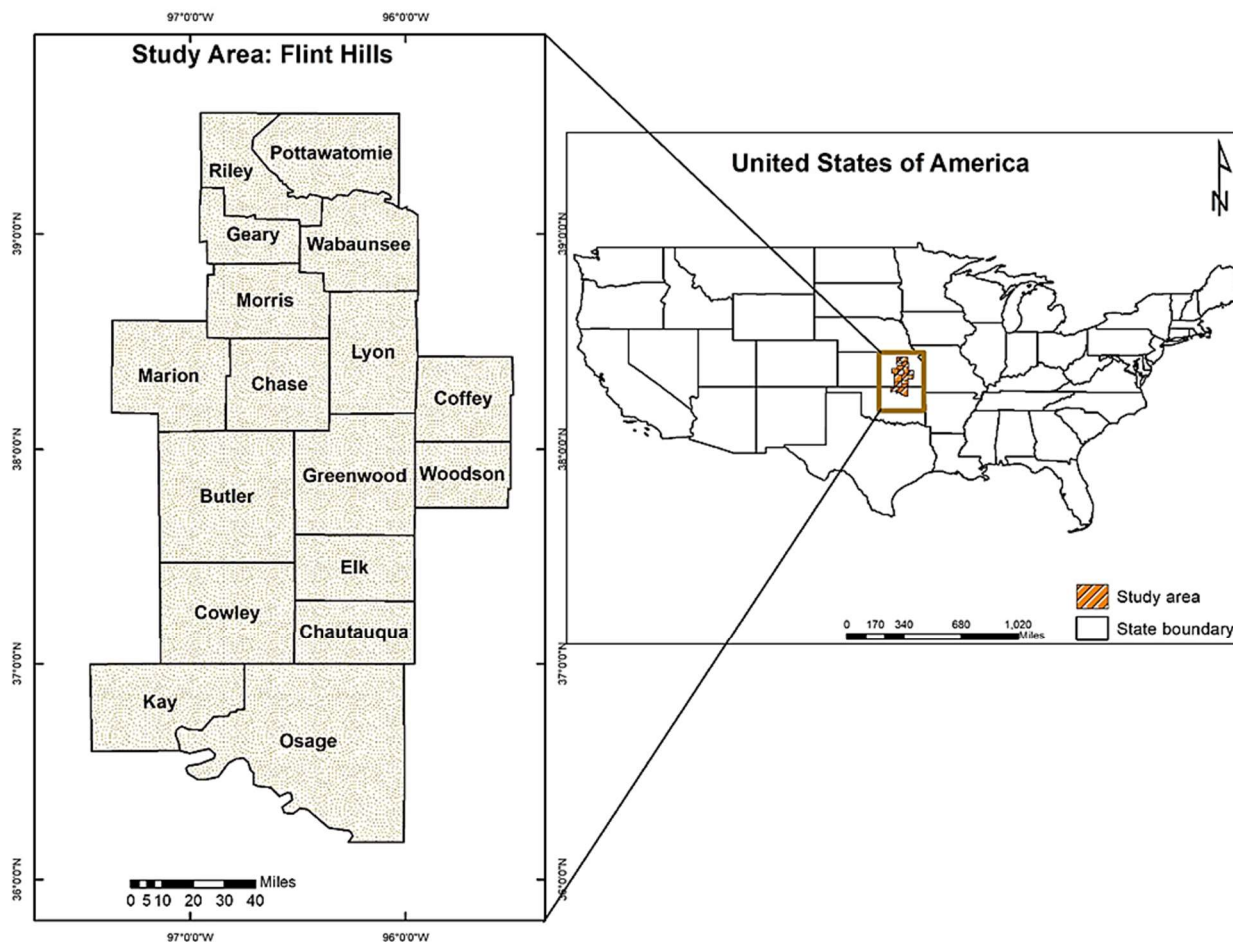


Figure 2.1.1: 17-county study area in Kansas and Oklahoma

2.2.2 Modis Data Acquisition and Processing

MODIS on NASA's Terra and Aqua satellites is making daily observations of the earth with 36 channels spanning the spectral range from 0.41 to 15 μm and representing three spatial resolutions: 250 m (2 channels), 500 m (5 channels), and 1 km (29 channels) (Remer et al., 2005). Combination of band 1-red (620 – 670nm) and band 2- near-infrared (NIR) (841 – 876nm) at a spatial resolution of 250m was used because it offers the optimal combination of spatial, temporal, and spectral properties for this application as suggested by Mohler and Goodin (2012a). All 250m red and NIR Terra (MOD09GQ) and Aqua (MYD09GQ) images in March, April, and May in each of the 17 years (2003 to 2019) were acquired from the Warehouse Inventory

Search Tool of NASA. MODISTsp, an R package source code with a graphical user interface (Busetto and Ranghetti., 2016), was used to perform downloading, mosaicking, reprojection, and resizing of raster derived from MODIS land products data. The downloaded images were converted from their native hierarchical data format (HDF) to tagged image file format (TIFF) using HDF-EOS to GeoTIFF conversion tool (HEG).

The TIFF format images were imported into ArcMap 10.7 to check for cloud or shadow cover through image metadata and visual examination. Images acquired on cloud-free days generally had lower reflectance with a smaller standard deviation over a county. When clear images without cloud cover from both the Terra and Aqua platforms were available on the same date, the Aqua platform image was selected. This is because Aqua images could represent more burned areas from that day since the images were acquired during the evening pass. From 2000 to 2002, only one MODIS sensor on the Terra platform was in orbit, and these data were not included in our analysis.

The cloud cover was checked by visual examination of the downloaded MODIS images. Only the best cloud-free images with a classification accuracy of 90% and above were selected for mapping. Other images were considered cloudy to minimize false positives. The burns in cloudy images did not go unmapped because they were visible in images from other dates close to the dates with the cloudy image.

Masked layers that contain the ground truth data from 2008 and 2010 (Mohler, 2011) were used to map out non-grassland from the selected cloudy free bi-spectral images using the ENVI 5.2 software. The stacked image masked files were obtained from the Kansas Department of Health and Environment (KDHE). These layers were prepared to permit the majority of each non-grassland land cover type, such as actively growing crops, water, and evergreen vegetation, to be excluded from consideration.

Supervised minimum distance classification of the bi-spectral images was applied. The freshest burn scars were the darkest in color, and they fade to a lighter color as they get older (Mohler, 2011). Therefore, pixels from the most recent burned areas were selected as the training data to sustain the burned area estimation. Each day, different training data were used to prevent cloudy areas from being classified as burned areas. It was necessary to get good results due to the quickly changing nature of the burned areas and

other variables like clouds and cloud shadows. The accuracy of classifications using this method has been estimated to be 90% or better by Mohler (2011).

2.2.3 Mapping Daily Burned Area

The daily active fire data (2013-2019) in a point format at a 1 km resolution was collected from the MODIS Global Monthly Fire Location Product (MCD14ML), Collection 6 product through the NASA's FIRMS website (<https://firms.modaps.eosdis.nasa.gov/download/create.php>). Each active fire count data point included coordinate location (latitude and longitude), date, time, confidence level, and satellite type (Terra or Aqua). The acquired raw active fire points with a vegetation fire type and a non-zero confidence level were subset to the 17-county study area.

Correlations between the accumulated burned area and the active fire count observed at the same date were developed as a scale model. The scale model incorporates knowledge of the point spread function when the acquired burn scar images are cloudy. Figure 2 presents a flowchart of the process for mapping daily burned area.

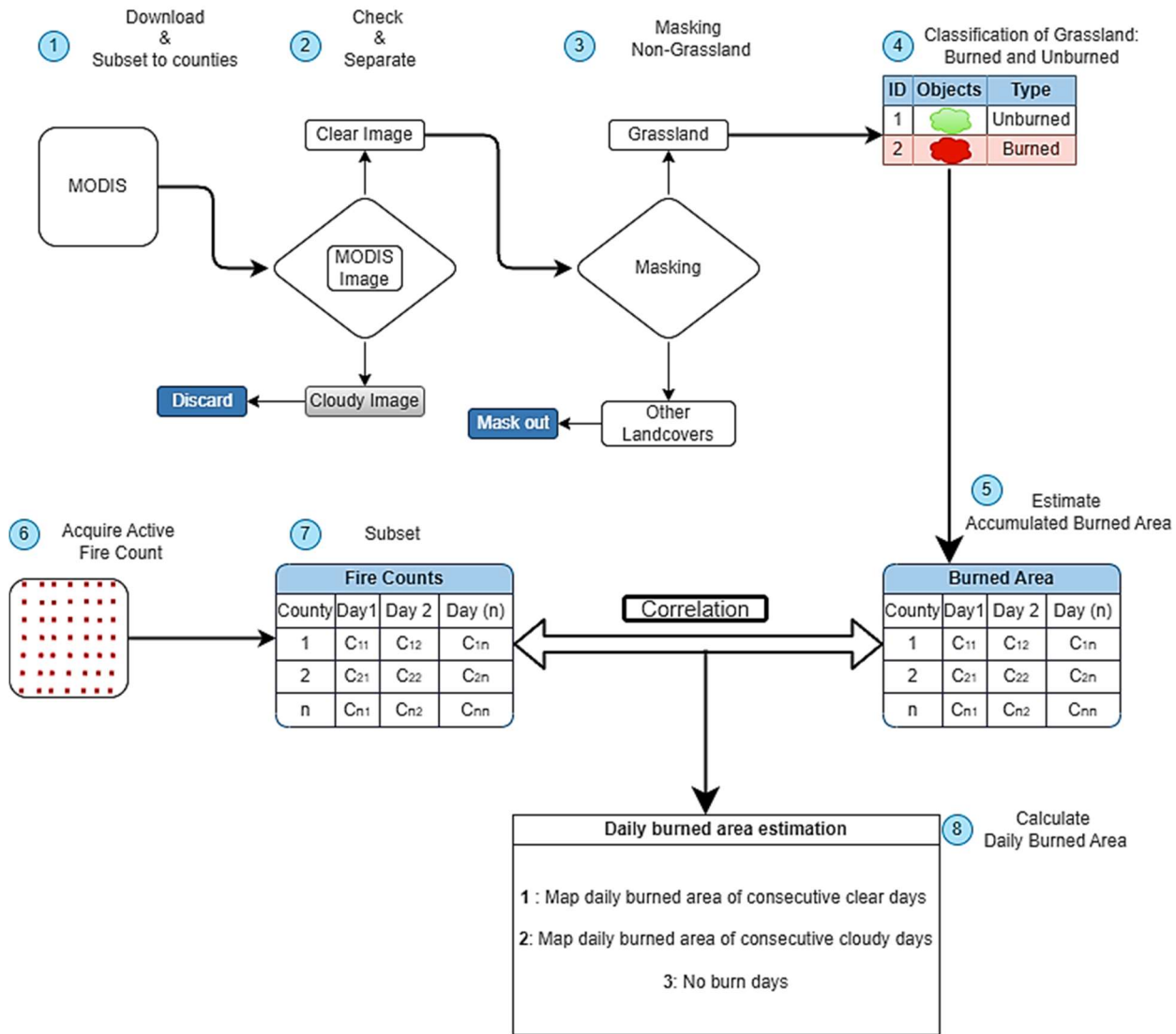


Figure 2.2: Flowchart of the process for mapping daily burned area.

2.2.4 Classification Of Daily Burned Area

Clustering analysis was used to classify daily burned area into different categories by minimizing the distance between points in a cluster and maximizing the distance between clusters. A list for the within-cluster sum of square (WCSS) was appended to the clusters using all the initial clusters. K-means algorithm is sensitive to the centroids' initialization or the mean points. A poor initialization of centroids could result in poor clustering. To overcome this drawback, K-means++ was used to ensure a smarter initialization of the centroids and improve the clustering quality (Kapoor and Singhal, 2017). The optimal number of clusters was determined to be 4 using the elbow method on the plot of WCSS against the number of clusters.

2.2.5 Normalized Daily Burned Area

Historical weather data for 4 counties (Riley and Geary in Kansas, Kay, and Osage in Oklahoma) were obtained from Kansas State University weather data library and the Mesonet website (<http://mesonet.k-state.edu/weather/historical>). The daily burned area in these counties was normalized by dividing the maximum daily burned area in the county so that data from counties with different sizes become comparable. The weather conditions when the normalized daily burned area in a county was larger than 0.5 are considered the preferred weather conditions for prescribed fires.

2.3 Results

2.3.1 Annual Burned Area and Burned Percentage

The area burned in the 17 counties of the Flint Hills region in each spring burning season is presented in figure 2.3. On average, around 30% of the rangeland was burned annually in spring. Due to different weather conditions, the annual burned percentage ranged from 3% to 48%. The drought in 2012 and 2013 resulted in extremely small, burned area in these two years.

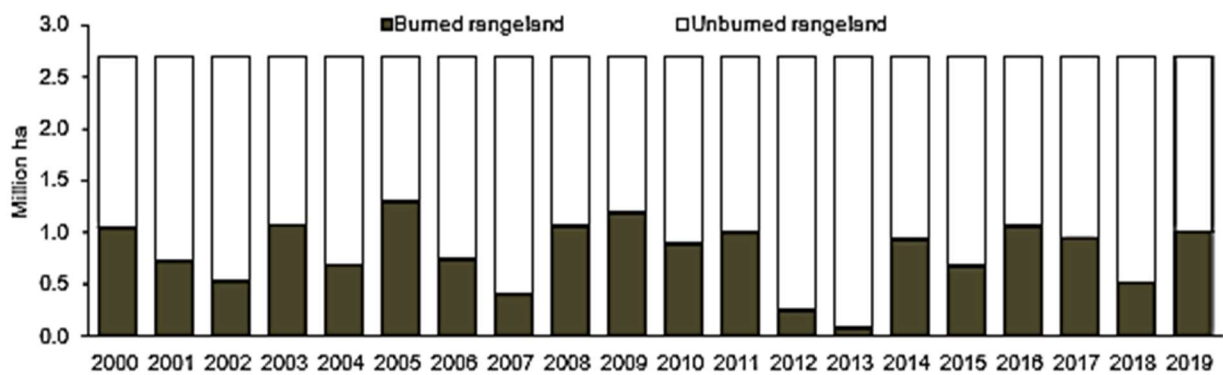


Figure 2.3: Area burned in each spring burning season in the 17 counties of the Flint Hills region.

The annual burned percentage also varied in different parts of the Flint Hills region. As shown in table 2.1, in the central part of the Flint Hills region (Chase, Wabaunsee, Greenwood, Lyon, Elk, and Woodson counties), the annual average burned percentage ranged from 33% to 52%. In contrast, in the

Southern part and at the edge of the Flint Hills region (Cowley, Chautauqua, Osage, Kay, Pottawatomie, and Marion counties), the annual average burned percentage ranged from 11% to 25%.

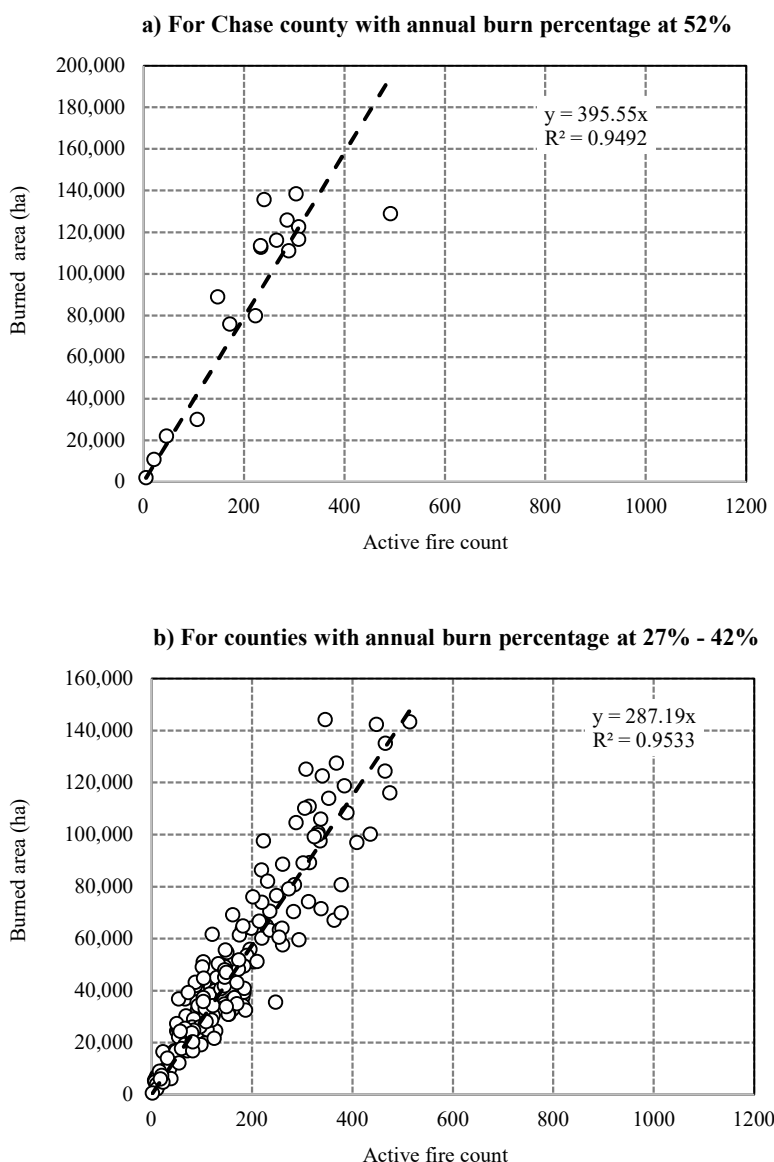
Table 2.1: Annual average burned area and burned percentage from 2000 to 2019 in each of the 17 counties.

County	Total rangeland hectares	Annual average burned hectares	Annual average burned percentage
Kansas, Chase	172,125	90,237	52%
Kansas, Wabaunsee	165,158	69,274	42%
Kansas, Greenwood	252,350	94,607	37%
Kansas, Lyon	149,516	55,163	37%
Kansas, Elk	138,168	46,127	33%
Kansas, Woodson	85,771	28,133	33%
Kansas, Riley	101,513	32,309	32%
Kansas, Coffey	96,819	28,373	29%
Kansas, Morris	132,196	38,449	29%
Kansas, Butler	269,738	72,879	27%
Kansas, Geary	71,258	19,096	27%
Oklahoma, Osage	369,590	92,872	25%
Kansas, Pottawatomie	154,833	38,640	25%
Kansas, Cowley	193,545	44,314	23%
Kansas, Chautauqua	132,102	29,385	22%
Kansas, Marion	116,513	16,457	14%
Oklahoma, Kay	96,338	10,360	11%
Total	2,697,533	806,674	30%

2.3.2 Correlations Between Burned Area and Active Fire Count

The annual burned area and the active fire count demonstrated strong correlations (R^2 ranged from 0.74 to 0.85 in different counties). The slope of the annual burned area over the active fire count indicates the average size of one active fire count, and it was higher for counties with a higher annual average burned

percentage (fig. 2.4). In Chase County, the annual average burned percentage was as high as 52%, and the average size of one active fire count was 400 ha. In the counties with the annual average burned percentages between 27% and 42%, the average size of one active fire count was 280 ha. Most of these counties are in the central part of the Flint Hills region. For the counties in the Southern part and at the edge of the Flint Hills region (Cowley, Chautauqua, Osage, Kay, Pottawatomie, and Marion counties), the annual average burned percentage was less than 25%, and the average size of one active fire count was only 160 ha. As a comparison, the average burned area in the Flint Hills region in U.S. EPA's National Emission Inventory was only 80 ha, with many fires exceeding 200 ha (Baker et al., 2019).



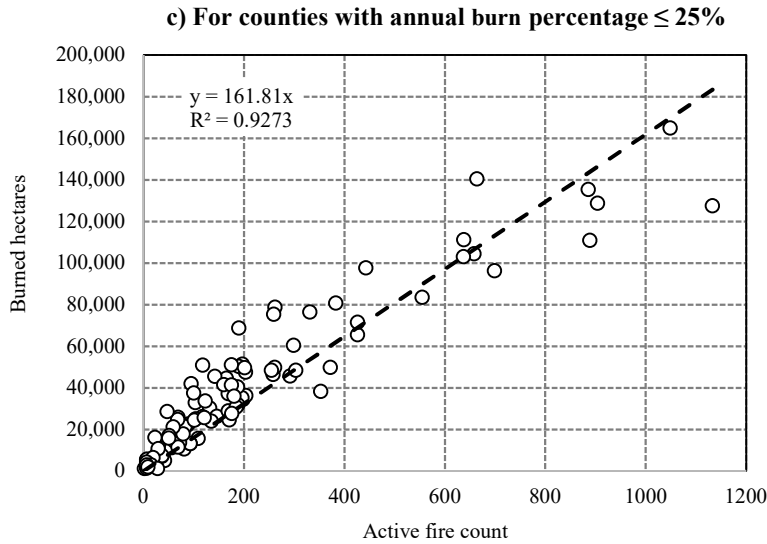


Figure 2.4: Correlations between the annual burned areas (estimated from burn scars in satellite images) and the active fire count (based on the detection of the released elevated energy) in different counties.

2.3.3 Distribution Of Daily Burned Area

The average and maximum daily burned area from 2003 to 2019 in the 17 counties of the Flint Hills region are plotted in figure 2.5. The daily burned area generally started to increase rapidly since the end of March and peaked on April 14th. On average, the burned area from fires between March 31st and April 30th accounted for 86% of the total burned area in the whole burning season. The maximum daily burned area was around 0.2 million ha, which occurred on April 14th, 2005, and was about 1/6 of the total burned area in the 2005 burning season.

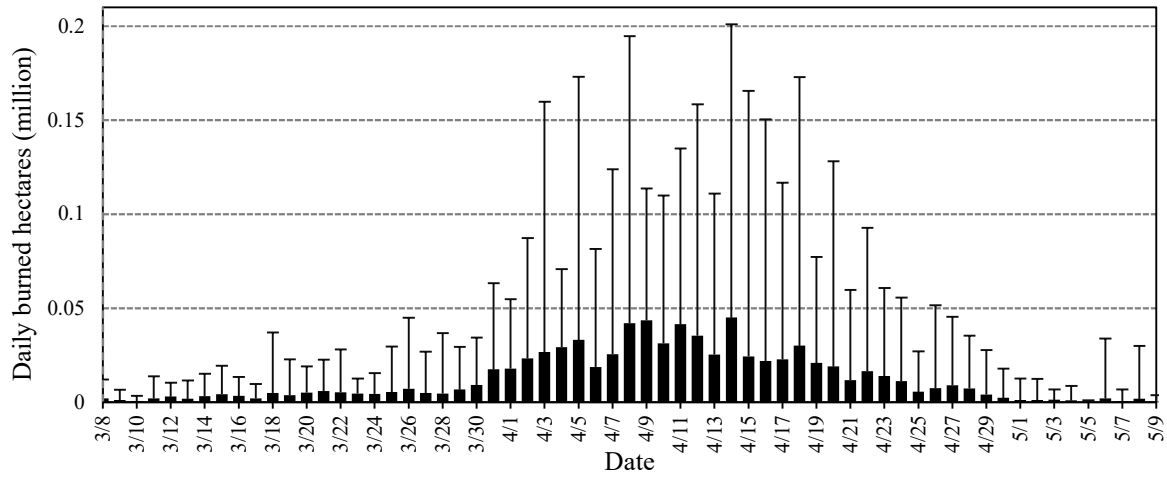


Figure 2.5: Average and maximum daily burned area from 2003 to 2019 in the 17 counties of the Flint Hills region (The black bars represent the average daily burned area. Error bars represent the maximum daily burned area).

All the days in the spring burning seasons from 2003 to 2019 were classified into 4 categories based on daily burned area, as shown in table 2.2. On average, in the 62 days between March 8 and May 8, 44 days were no-fire days or light-fire days with daily burned area in the 17 counties less than 0.01 million ha, likely due to limited weather or fuel conditions; 12 days were medium-fire days with a daily burned area between 0.01 and 0.04 million ha; only 6 days were heavy-fire days with a daily burned area larger than 0.04 million ha. Fire activities were largely concentrated in a few days with desired weather and fuel conditions. On average, 58% of the total burned area in the spring burning season occurred on 6 heavy-fire days. The total burned area in the medium-fire days (12 days) and the heavy-fire days (6 days) accounted for 91% of the total burned area.

Table 2.2: Classification of daily burned area of the 17 counties from March 8th to May 8th (Data are average values from 2003 to 2019).

Category	Range of daily burned area (million ha)	Average daily burned area (million ha)	Days	Total burned area (million ha)	Percentage of Burned area
No-fire	0	0	23	0	0%
Light-fire	0 ⁺ to 0.01	0.003±0.003	21	0.07	9%
Medium-fire	0.01 ⁺ to 0.04	0.021±0.009	12	0.26	33%
Heavy-fire	0.04 ⁺ to 0.20	0.083±0.037	6	0.45	58%
Total			62	0.78	100%

2.4 Discussion

2.4.4 Spatial And Temporal Distributions of Daily Burned Area

The Great Plains of the United States have a clear fire frequency relationship. Fire frequency generally increases from west to east due to precipitation and north to south due to temperature (Stambaugh et al., 2011). The frequency and size of wildfires also depend on fuel production and the ability of fires to spread (Scasta et al., 2016). Our results showed both the burn frequency and the average sizes of prescribed fires varied at different parts of the Flint Hills region. In the central part of the Flint Hills region, landowners tend to burn more frequently, and the fire sizes are generally larger. In the Southern part and at the edge of the Flint Hills region, they burn less frequently, and the fire sizes are generally smaller. This spatial variation agrees with the 2000-2010 data in Mohler and Goodin (2012b) and the observation that small fires are more frequent at the edge and periphery of the Flint Hills region. It reflected different fire management practices in different counties due to variations in weather, fuel, topography, and land use management. The six counties (Chase, Wabaunsee, Greenwood, Lyon, Elk, and Woodson counties) in the central part of the Flint Hills region had an annual average burned percentage ranging from 33% to 52%, and they represented almost half of the total burned area in the 17 counties of the study area. A well-recognized hypothesis was that burning annually or biennially could maximize productivity (Anderson et al., 1970; Towne and Owensby, 1984), and burning on a 3-year (or less) cycle is needed to maintain vegetative homogenization (Ratajczak et al., 2016). However, many other counties had much lower burn frequencies. In Oklahoma, at a minimum, a four-year fire return interval or 25% of the burnable area each year had been recommended (Weir, 2011). The different burn frequencies in different counties provided a research opportunity to optimize burn frequency for maximum productivity by closely examining the historical burn area data.

To analyze the spatial and temporal distributions of burned area in the Flint Hills region, Baker et al. (2019) used three data sources to estimate burned area: the Fire INventory from NCAR (FINN; Wiedinmyer et al., 2011), the Global Fire Emission Database (GFED; Van Der Werf et al., 2017) and the U.S. EPA's National Emission Inventory (NEI; USEPA, 2018), and the burned area assigned to

detected prescribed fires were based on default field size assumptions. With the combination of active fire data and burn scar detection algorithm, our method reduced missing daily fire detections. Therefore, our estimation of the burned area was more accurate and much larger than the estimations from FINN, GFED, and NEI.

Results of daily burned area in our study showed that fire activities were highly concentrated in a few days that had desired weather and fuel conditions. The daily burned area generally started to increase at the end of March and peaked in mid-April. A large daily burned area often resulted in the exceedance of air quality standards in daily O_3 . If fire activities can be more evenly distributed, smoke impact could be reduced. Recent research suggested a longer spring burning season or burning outside of spring should be considered (Towne and Craine, 2016; Weir and Scasta, 2017). It would provide more days with acceptable weather conditions for burning, thus reducing daily burned areas and the smoke impact on daily O_3 . To optimize the timing of fire activities, it is necessary to study how weather conditions affect fire activities, and a clear guideline for better timing may be generated with precisely defined weather conditions.

2.4.5 How Did Weather Conditions Affect Daily Burned Area

The preferred weather conditions by landowners for prescribed fires were determined from the days when the daily burned area was larger than 50% of the maximum daily burned area in the county from 2003 to 2019 (table 2.3). These preferred weather conditions generally agreed with the weather conditions recommended by KDHE (2010) but had a slightly higher relative humidity (RH). Burning in higher RH may result in more smoke. More importantly, our data showed most fires occurred on days with high solar radiation when cloud cover is close to 0. Many landowners prefer to burn in a day with strong sunshine and moderate temperature. The preferred weather conditions by landowners had a narrow window for high solar radiation. The larger differences between the maximum and minimum temperatures also showed that the preferred weather conditions had relatively high daytime and low night temperatures, indicating a warm and clear day without much cloud cover. KDHE recommended burning when cloud cover is 30-50% to reduce photochemical reactions that form O_3 (KDHE, 2010). Based on the above reasons, we believe there is more

room to reduce smoke generation and its impact on O₃ if landowners can burn at lower solar radiation. More analysis will generate a clear guideline for better timing of fire activities considering solar radiation and cloud cover in order to reduce smoke impact.

Table 2.3: Preferred weather conditions for prescribed fires determined from days when daily burned area was larger than 50% of the maximum daily burned area in the county from 2003 to 2019.

	Wind speed (m/s)	Relative humidity (%)	Solar radiation (Langley)	Precipitation (mm)	Maximum temperature (°C)	Minimum temperature (°C)	Average Days per season
Preferred conditions for prescribed fires	1.9 ~ 7.5	34 ~ 82	536 ~ 633	0 ~ 0.5	8 ~ 31	-5 ~ 2	10
In the whole season	0.2 ~ 12.2	25 ~ 98	19 ~ 760	0 ~ 131	-6 ~ 38	-11 ~ 22	62
Conditions recommended by KDHE	2.2 ~ 6.7	30 ~ 50					

On average, the preferred weather conditions determined from the prescribed fire practices of landowners only occurred in around 10 days in one spring burning season. However, not all of these days had significant fire activities. Table 2.4 presents the fire activity levels in these 10 days and the corresponding median values of weather variables for each level. As shown in table 2.4, when all the preferred weather conditions had been met, most landowners chose to burn at relatively lower wind velocity, higher RH, higher temperature, and higher solar radiation, which is likely mainly due to safety considerations or convenience. However, lower wind speed may reduce smoke dispersion, and higher RH may result in more smoke, while higher temperature and higher solar radiation favor O₃ production. If fire activities could be more evenly distributed in all the 10 days that had the preferred weather conditions, the smoke impact could be reduced. Expanding burning to other days with acceptable weather conditions could further increase the burning capacity of landowners. Weir (2011) estimated an average of 18.5 days per month with acceptable weather conditions for burning, which only considered temperature, RH, wind velocity, and precipitation, but not solar radiation.

Table 2.4: Median values of weather variables for different fire activity levels on all days with the preferred weather conditions for prescribed fires.

	Wind speed (m/s)	Relative humidity (%)	Solar radiation (Langley)	Precipitation (mm)	Maximum temperature (°C)	Minimum temperature (°C)	Average days per season
A* > 0.5	3.2	59	595	0	23	4	1
A = 0.10* to 0.50	3.6	54	581	0	21	3	3
A = 0 + to 0.10	3.9	55	572	0	21	3	4
No fire	4.1	55	583	0	21	5	2

* A is normalized daily burned area, which was calculated as the ratio of the daily burned area in the county to the maximum daily burned area in the county.

2.4.6 How Did Daily Burned Area Affect Ozone

The overall R^2 between the total acres burned in the whole spring burning seasons and the highest 8-hour O_3 mixing ratios observed in the same period at any of the ten monitoring sites in Kansas was as high as 0.62 (Figure 2.6). Generally, for one million increments of burned acres in the whole spring burning season, the highest 8-hour O_3 mixing ratios increased around 10ppb.

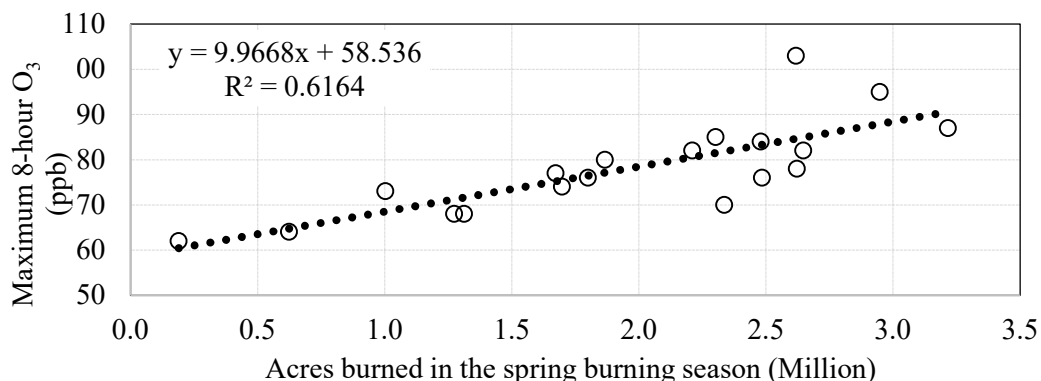


Figure 2.6: Correlations between the acres burned in the whole spring burning seasons from 2001 to 2019 and the highest 8-hour O_3 mixing ratios observed in the same period at any of the ten monitoring sites

The maximum 8-hour O_3 concentrations at different dates in the spring burning seasons from 2003 to 2013 and the corresponding average daily burned area in the same period in the 17 counties of the Flint Hills region are plotted in figure 2.6. The O_3 data was from the Konza Prairie CASTNET (Clean Air Status and Trends Network) research monitoring site located at the center of the Flint Hills region. As shown in figure 2.7, the O_3 concentration generally increased from March 8th to May 8th due to increasing temperature. However, all the O_3 exceedances than 70 ppb were in April, when intensive fires occurred in the Flint Hills region. The O_3 concentrations were affected by daily burned area and temperature, solar radiation, RH, and wind speed (Liu et al., 2018; Baker et al., 2016). Previously, O_3 regression models have been developed in this region using weather factors as predictor variables (Liu et al., 2018). More analysis will add daily burn area as an additional predictor variable in the models to quantify the actual contributions of fire smoke to O_3 under different weather conditions and develop a practical burning decision tool based on the models.

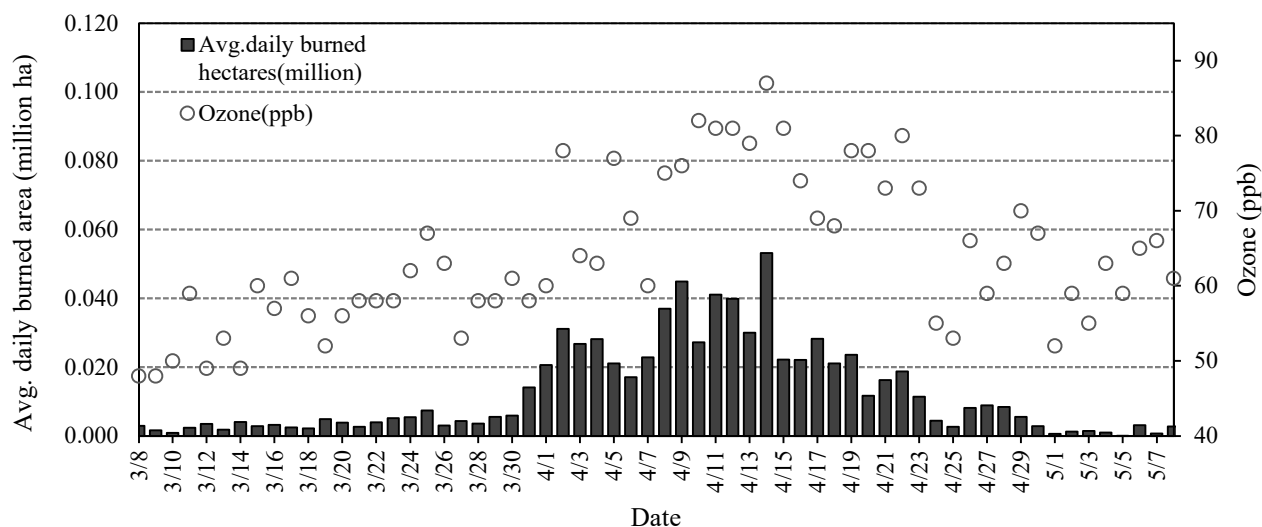


Figure 2.7: The maximum 8-hour O₃ concentrations in the Konza Prairie at different dates from 2003 to 2013 and the corresponding average daily burned area in the same period in the 17 counties of the Flint Hills region.

2.5 Conclusion

Daily burned area in 17 counties of the Flint Hills region in the spring seasons from 2003 to 2019 were retrieved through a combined analysis of burn images and active fire data from MODIS. The resulting product was used to analyze the temporal and spatial variability of fire activities and will facilitate further studies on the smoke impact on daily O₃. Results showed that fire activities were highly concentrated in a few days in mid-April. Both the annual burned percentage and the average fire size were larger in the central part of the Flint Hills region compared with the Southern part and at the edge. More importantly, based on analysis of historical daily burned area and weather data, it was found that landowners preferred to burn on warm and clear days with high solar radiation. High solar radiations favor O₃ production. If landowners can choose to burn at lower solar radiation, and if fire activities can be more evenly distributed, smoke impact can be reduced. The results of this study provided a solid foundation for the development of O₃ regression models using daily burned area and weather factors as predictor variables. More analysis will be conducted to quantify the actual contributions of the daily burned area to O₃ and to generate a clear guideline with precisely defined weather conditions for better timing of fire activities to reduce smoke impact.

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2.7 References

- Anderson, K. L., Smith, E. F., & Owensby, C. E. (1970). Burning bluestem range. *Rangel. Ecol. Manag./J. Range Manag.*, 23(2), 81-92. <https://doi.org/10.2307/3896105>
- Baker, K. R., Koplitz, S. N., Foley, K. M., Avey, L., & Hawkins, A. (2019). Characterizing grassland fire activity in the Flint Hills region and air quality using satellite and routine surface monitor data. *Sci. Total Environ.*, 659, 1555-1566. <https://doi.org/10.1016/j.scitotenv.2018.12.427>
- Baker, K. R., Woody, M. C., Tonnesen, G. S., Hutzell, W., Pye, H. O., Beaver, M. R., Pierce, T. (2016). Contribution of regional-scale fire events to ozone and PM2.5 air quality estimated by photochemical modeling approaches. *Atmos. Environ.*, 140, 539-554. <https://doi.org/10.1016/j.atmosenv.2016.06.032>
- Barnpoutis, P., Papaioannou, P., Dimitropoulos, K., & Grammalidis, N. (2020). A review on early forest fire detection systems using optical remote sensing. *Sensors*, 20(22), 6442. <https://doi.org/10.3390/s20226442>
- Busetto, L., & Ranghetti, L. (2016). MODISr: An R package for automatic preprocessing of MODIS Land Products time series. *Comput. Geosci.*, 97, 40-48. <https://doi.org/10.1016/j.cageo.2016.08.020>
- Chen, D., Pereira, J. M., Masiero, A., & Pirotti, F. (2017). Mapping fire regimes in China using MODIS active fire and burned area data. *Apl. Geogr.*, 85, 14-26. <https://doi.org/10.1016/j.apgeog.2017.05.013>
- Ferguson, S. A., Peterson, J., & Acheson, A. (2001). Automated, real-time predictions of cumulative smoke impacts from prescribed forest and agricultural fires. 4th Symposium on Fire and Forest Meteorology (pp. 168-175). American Meteorological Society.
- Freeborn, P. H., Wooster, M. J., Roberts, G., Malamud, B. D., & Xu, W. (2009). Development of a virtual active fire product for Africa through a synthesis of geostationary and polar orbiting satellite data. *Remote Sens. Environ.*, 113(8), 1700-1711. <https://doi.org/10.1016/j.rse.2009.03.013>
- Ito, A., & Penner, J. E. (2004). Global estimates of biomass burning emissions based on satellite imagery for the year 2000. *J. Geophys. Res.: Atmospheres*, 109(D14). <https://doi.org/10.1029/2003JD004423>
- Kapoor, A., & Singhal, A. (2017). A comparative study of K-Means, K-Means++ and Fuzzy C-Means clustering algorithms. Proc. 3rd Intl. Conf. Computational Intelligence Communication Technol. (CICT) (pp. 1-6). IEEE. <https://doi.org/10.1109/CICT.2017.7977272>
- KDHE. (2010). State of Kansas Flint Hills smoke management plan. Kansas Department of Health and Environment. Division of Environment, Bureau of Air.

- Langmann, B., Duncan, B., Textor, C., Trentmann, J., & van der Werf, G. R. (2009). Vegetation fire emissions and their impact on air pollution and climate. *Atmos. Environ.*, 43(1), 107-116. <https://doi.org/10.1016/j.atmosenv.2008.09.047>
- Lentile, L. B., Holden, Z. A., Smith, A. M., Falkowski, M. J., Hudak, A. T., Morgan, P., Benson, N. C. (2006). Remote sensing techniques to assess active fire characteristics and post-fire effects. *Intl. J. Wildland Fire*, 15(3), 319-345. <https://doi.org/10.1071/WF05097>
- Liu, Z. (2017). How much does Kansas rangeland burning contribute to ambient ozone? MF3357. Kansas State University.
- Liu, Z., Liu, Y., Murphy, J. P., & Maghirang, R. (2018). Contributions of Kansas rangeland burning to ambient O₃: Analysis of data from 2001 to 2016. *Sci. Total Environ.*, 618, 1024-1031. <https://doi.org/10.1016/j.scitotenv.2017.09.075>
- McClure, C. D., & Jaffe, D. A. (2018). Investigation of high ozone events due to wildfire smoke in an urban area. *Atmos. Environ.*, 194, 146-157. <https://doi.org/10.1016/j.atmosenv.2018.09.021>
- Mohler, R. L. (2011). Multi-scale burned area mapping in tallgrass prairie using in situ spectrometry and satellite imagery. Doctor of Philosophy Dissertation. Kansas State University, Department of Geography College of Arts and Sciences.
- Mohler, R. L., & Goodin, D. G. (2010). A comparison of red, NIR, and NDVI for monitoring temporal burn signature change in tallgrass prairie. *Remote Sens. Lett.*, 1(1), 3-9. <https://doi.org/10.1080/01431160903154291>
- Mohler, R. L., & Goodin, D. G. (2012a). Identifying a suitable combination of classification technique and bandwidth(s) for burned area mapping in tallgrass prairie with MODIS imagery. *Int. J. Appl. Earth Obs. Geoinf.*, 14(1), 103-111. <https://doi.org/10.1016/j.jag.2011.08.008>
- Mohler, R. L., & Goodin, D. G. (2012b). Mapping burned areas in the Flint Hills of Kansas and Oklahoma, 2000-2010. *Gt. Plains Res*, 15- 25.
- Morgan, P., Hardy, C. C., Swetnam, T. W., Rollins, M. G., & Long, D. G. (2001). Mapping fire regimes across time and space: Understanding coarse and fine-scale fire patterns. *Intl. J. Wildland Fire*, 10(4), 329-342. <https://doi.org/10.1071/WF01032>
- Odman, M. T., Hu, Y., Garcia-Menendez, F., Davis, A., & Russell, A. G. (2013). Fires and air quality forecasts: Past, present, and future. *Environ. Manag.*, 1, 12-21.
- Ratajczak, Z., Briggs, J. M., Goodin, D. G., Luo, L., Mohler, R. L., Nippert, J. B., & Obermeyer, B. (2016). Assessing the potential for transitions from tallgrass prairie to woodlands: Are we operating beyond critical fire thresholds? *Rangeland Ecol. Manage.*, 69(4), 280- 287. <https://doi.org/10.1016/j.rama.2016.03.004>
- Remer, L. A., Kaufman, Y. J., Tanre, D., Mattoo, S., Chu, D. A., Martins, J. V., Holben, B. N. (2005). The MODIS aerosol algorithm, products, and validation. *J. Atmos. Sci.*, 62(4), 947-973. <https://doi.org/10.1175/jas3385.1>
- Scasta, J. D., Weir, J. R., & Stambaugh, M. C. (2016). Droughts and wildfires in western U.S. rangelands. *Rangelands*, 38(4), 197-203. <https://doi.org/10.1016/j.rala.2016.06.003>

- Scholtz, R., Prentice, J., Tang, Y., & Twidwell, D. (2020). Improving on MODIS MCD64A1 burned area estimates in grassland systems: A case study in Kansas Flint Hills tall grass prairie. *Remote Sens.*, 12(13), 2168. <https://doi.org/10.3390/rs1213216>
- Schroeder, W., Oliva, P., Giglio, L., & Csiszar, I. A. (2014). The New VIIRS 375m active fire detection data product: Algorithm description and initial assessment. *Remote Sens. Environ.*, 143, 85-96. <https://doi.org/10.1016/j.rse.2013.12.008>
- Stambaugh, M. C., Guyette, R. P., McMurtry, E. R., Cook, E. R., Meko, D. M., & Lupo, A. R. (2011). Drought duration and frequency in the U.S. Corn Belt during the last millennium (AD 992–2004). *Agric. For. Meteorol.*, 151(2), 154-162. <https://doi.org/10.1016/j.agrformet.2010.09.010>
- Towne, E. G., & Craine, J. M. (2016). A critical examination of timing of burning in the Kansas Flint Hills. *Rangeland Ecol. Manage.*, 69(1), 28-34. <https://doi.org/10.1016/j.rama.2015.10.008>
- Towne, G., & Owensby, C. (1984). Long-term effects of annual burning at different dates in ungrazed Kansas tallgrass prairie. *Rangeland Ecol. Manag./J. Range Manag.*, 37(5), 392-397. <https://doi.org/10.2307/3899622>
- Urbanski, S. P., Salmon, J. M., Nordgren, B. L., & Hao, W. M. (2009). A MODIS direct broadcast algorithm for mapping wildfire burned area in the western United States. *Remote Sens. Environ.*, 113(11), 2511-2526. <https://doi.org/10.1016/j.rse.2009.07.007>
- USEPA. (2018). 2014 National emissions inventory, Version 2 technical support document. U.S. Environmental Protection Agency. Retrieved from https://www.epa.gov/sites/production/files/2018-07/documents/nei2014v2_tsd_05jul2018.pdf
- Vakkari, V., Beukes, J. P., Josipovic, M., & van Zyl, P. G. (2020). Observations of ozone formation in southern African savanna and grassland fire plumes. *Atmos. Environ.*, 223, 117256. <https://doi.org/10.1016/j.atmosenv.2019.117256>
- van der Werf, G. R., Randerson, J. T., Giglio, L., van Leeuwen, T. T., Chen, Y., Rogers, B. M., Kasibhatla, P. S. (2017). Global fire emissions estimates during 1997–2016. *Earth Syst. Sci. Data*, 9(2), 697-720. <https://doi.org/10.5194/essd-9-697-2017>
- Weir, J. R. (2011). Are weather and tradition reducing our ability to conduct prescribed burns? *Rangelands*, 33(1), 25-30. <https://doi.org/10.2111/RANGELANDS-D-10-00050.1>
- Weir, J. R., & Scasta, J. D. (2017). Vegetation responses to season of fire in tallgrass prairie: A 13-year case study. *Fire Ecol.*, 13(2), 137- 142. <https://doi.org/10.4996/fireecology.130290241>
- Wiedinmyer, C., Akagi, S. K., Yokelson, R. J., Emmons, L. K., Al-Saadi, J. A., Orlando, J. J., & Soja, A. J. (2011). The Fire INventory from NCAR (FINN): A high resolution global model to estimate the emissions from open burning. *Geosci. Model Dev.*, 4(3), 625-641. <https://doi.org/10.5194/gmd-4-625-2011>
- Xu, W., Wooster, M. J., He, J., & Zhang, T. (2021). Improvements in high-temporal resolution active fire detection and FRP retrieval over the Americas using GOES-16 ABI with the geostationary Fire Thermal Anomaly (FTA) algorithm. *Sci. Remote Sens.*, 3, 100016. <https://doi.org/10.1016/j.srs.2021.100016>

Zha, S., Zhang, S., Cheng, T., Chen, J., Huang, G., Li, X., & Wang, Q. (2013). Agricultural fires and their potential impacts on regional air quality over China. *Aerosol Air Qual. Res.*, 13(3), 992-1001. <https://doi.org/10.4209/aaqr.201>

Chapter 3 - Optimum Weather Conditions for Prescribed Burning in the Flint Hills Region

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Abstract

Land managers use weather conditions to determine when meteorological and fuel conditions are suitable for prescribed burning. The objectives of this study were: 1) to characterize meteorological parameters' sensitivities and identify the influential weather parameters connected to daily fire activities and, 2) to identify optimum weather conditions that are practical for mitigating smoke impact associated with prescribed fires in the Flint Hills region. Machine learning techniques using random forest (RF) with the Shapley additive explanation (SHAP) values and Pearson correlation were used to identify the relative importance of weather variables and their impact on the landowner burn decisions in the Flint Hills region based on historic data in 2003-2019. Results showed that less cloud cover demonstrated superior predictive power in landowner decisions for prescribed burning and largely resulted in elevated ambient ozone(O_3). We found out that six days per burning season on average provided the proposed optimum weather conditions, which cloud cover ranged from 10⁺ to 55%. However, 62% of the total burned area occurred when the cloud cover was less than 10⁺% during 2003-2019. By changing the current burning occurrence to the proposed optimum weather conditions in our study, the probability of 70⁺ppb O_3 occurrence could be reduced from 35% to 9% on heavy fire days.

3.1 Introduction

The history of the rangeland is intertwined with the importance of grasslands for maintaining biodiversity at the landscape level. Grasslands cover one-third of the Earth's surface, making them an important global ecosystem (Lemaire et al., 2011). Humankind benefits from grassland ecosystems through livestock farming, soil conservation, biodiversity, cultural and social benefits, and climate regulation. The area and species richness of grasslands have constantly declined in many parts of the world. Landowners use prescribed fires as economically efficient practices for long-term resource management and the sustenance of grassland ecosystems. Despite the crucial role fire plays in the sustainability of grassland ecosystems (Bowman et al., 2009), smoke plumes from prescribed burning can contribute to exceeding the National Ambient Air Quality Standards (NAAQS) for ground-level ozone (Wilkins et al., 2020). The prescribed burning season is constrained by the availability of suitable weather conditions essential to lower fire intensity and impact on air quality (Haikerwal et al., 2015). Therefore, identifying the essential meteorological drivers of prescribed burning is important for rangeland management to limit their risks and promote ecosystem health.

Several studies have used statistical methods to examine the relationships between prescribed fires and their environmental drivers in the United States (Chiodi et al., 2018; Kupfer et al., 2020; Striplin et al., 2020; Yurkonis et al., 2019). Weather is considered the dominant environmental factor for controlling prescribed fire (Hong et al., 2019) and for landowners burning decisions (Agastra, 2022). The correlations between weather variables and observed fire burn area are an important step in understanding burning and smoke management decisions by landowners. The application of machine learning approaches to mapping environmental data across heterogeneous environments has demonstrated tremendous potential (Belgiu and Drăguț, 2016).

Machine learning methods have been applied to predict wildfire burn areas and analyze environmental drivers of fire (Wang et al., 2021), and the role of weather in prescribed burning decisions (Agastra, 2022). Machine learning models such as random forest (RF) can automatically select important variables and evaluate complex interactions, but they are regarded as black boxes due to their limited interpretability. Wang et al. (2021) suggested the Shapley additive explanation (SHAP), a novel game-theory-based approach to open the black box and interpret the machine learning model used to predict prescribed burned area.

Prescribed burning is the primary rangeland management tool employed to maintain the tallgrass prairie ecosystem in the Flint Hills region (Towne and Craine, 2016; Liu et al., 2017). The climate of the Flint Hills region is sub-humid, temperate, and mid-continental, and is characterized by warm, moist air masses from the Gulf of Mexico that produce moderate to heavy rainfall (Goodin, 1995). The map of the study area is provided by Akinbile and Liu (2022). While previous studies have examined the synoptic analysis of ozone (O_3) exceedance days during the prescribed burning season (Cirnu and Harrington, 2019), the analysis of weather variables and conditions influencing prescribed burning decisions in the region is still sparse. Consequently, we seek to improve the current understanding of fire weather conditions and their effect on the timing of prescribed burning activities in the Flint Hills region using machine learning techniques.

In our study, we employed the Pearson correlation to analyze the relationship between daily burned area and meteorological driving factors. Furthermore, we used SHAP value to interpret the random forest algorithm and explain the impact of weather variables on daily burned areas. Our specific objectives were to: 1) characterize the sensitivities of meteorological parameters and identify influential weather parameters linked to daily fire activities; and 2) identify optimal

weather conditions that are practical for mitigating the smoke impact associated with prescribed fires in the Flint Hills region.

Previous studies have evaluated weather conditions favorable for prescribed fires (Yurkonis et al., 2019; Weir, 2011a); however, our approach using machine learning techniques to identify and interpret influential weather parameters can provide more insight and aid in the development of better management strategies for the region.

3.2 Data and Methods

3.2.1 Fire Data

An inventory of data from historic fire events was prepared to perform statistical analysis of weather conditions associated with prescribed fire. The prescribed fire records include the county, detection dates, and estimated daily burned rangeland (ha) in the Flint Hills region during the spring-prescribed burn season, which were developed by Akinbile & Liu (2022). To ensure the consistency of the data, we analyzed the period from March 8 to May 8 for the years 2003-2019.

3.2.2 Weather Data

The average value of the weather variables largely indicates the conditions that affect fires after ignition and the ultimate outcomes of burned area (Littell et al., 2016). Since it is uncommon to start prescribed fire after 18:00 h, and almost all the prescribed burnings were conducted in the daytime (Yurkonis et al., 2019), the average hourly values of weather variables from 8 am to 6 pm were used.

The weather variables included in our analysis are air temperature ($^{\circ}\text{C}$), relative humidity (RH, %), wind speed (m/s), solar radiation (W/m^2), cloud percentage cover (%), and precipitation (mm). Hourly weather data in the Flint Hills region were obtained from Kansas State University

Mesonet (Kansas Mesonet, 2022). Cloud cover data were obtained from the Visual Crossing Weather (Visualcrossing, 2022). To identify the fire weather pattern trend across the whole Flint Hills region, we used historical meteorological data from Riley County because it has the longest records of weather observations in our study domain. To identify preferred weather conditions by landowners, weather data in specific counties were used, including Wabaunsee, Riley, and Marion counties. These stations were selected based on data availability in terms of longer observation years and fewer interrupted observations.

3.2.3 Data Analysis

The importance of different weather variables as related to daily burned area were evaluated by the Pearson correlation with Pandas library in Python. The relative importance of weather variables was evaluated with SHAP values for a RF algorithm. Data analysis using RF models and Pearson correlation are restricted to the month of April because Flint Hills landowners have a tradition of burning intensively in April (Akinbile & Liu, 2022). In March and May, the favorable weather condition is not clearly defined. There were days in March and May with favorable weather conditions, but landowners choose not to burn.

RF is an ensemble machine-learning technique that is non-parametric and nonlinear (Breiman, 2001). It builds a forest out of numerous mutually independent decision trees by using a random algorithm to select important variables and estimate each variable's relative importance (Breiman et al., 2017). With high prediction performance and low overfitting, it grows each tree from the training dataset using bagging or bootstrap sampling (Hapfelmeier & Ulm, 2013). The method reduces the variance in the dataset by de-correlating individual trees because they are not all dependent on the same data or variables (James et al., 2013).

SHAP is a technique of assigning impact to features that do not have an equal impact on the prediction outcome using an additive feature attribution method to explain the output of any machine learning model (Lundberg & Lee, 2017). The method can be compared to a game in which each input variable is a player, and the final prediction is the result of the game. The goal of the game is to understand how each input variable contributes to the final prediction by ranking according to variable importance (Wang et al., 2021). Optimizing weather conditions for prescribed burning can be considered a game as it involves making decisions to achieve the desired outcome.

The independent variables are RH, air temperature, cloud cover, solar radiation, wind speed, and precipitation. The dependent variable is the estimated daily burned area. Approximately three-quarters of the samples in the dataset are used for training, and the remaining one-quarter are used for model validation. We tuned the model parameters using grid search and ten-fold cross-validation to avoid overfitting. The RF models produce the best performance with n -estimators, maximum depth, maximum features, and criterion equal to 100, 6, square root, and mean absolute error, respectively. The relative importance of the independent variables was identified with the SHAP value to determine which of these variables most predicted the dependent variable in descending order. Two types of models and rankings were trained: a regional model for the whole Flint Hills and county specific models. We used the county-level models to verify the performance of the weather variable importance ranking of the regional model. The disadvantage of RF is that it might only select the most significant features when correlated features exist and neglect the importance of other features. Therefore, we evaluated the findings of RF feature importance in conjunction with the Pearson correlation method.

3.2.4 Identifying the Preferred Weather Conditions for Burning by Landowners

Landowners may apply their intuitive judgments to choose whether to burn or not (Kupfer et al., 2020). To identify the preferred weather conditions, the weather conditions of three counties were analyzed. At the county level, all the days were classified into four categories based on daily burned area according to heavy-fire day ($> 4,000$ ha, definition from Weir & Scasta, 2022), medium-fire day (1,000-4,000 ha), light-fire day ($<1,000$ ha) and no-fire day. The preferred weather conditions were screened for weather conditions that were not safe or practical for the prescribed burn. These include very low RH ($<20\%$) and very high wind speeds ($> 9\text{m/s}$) informed by Chiodi et al. (2018) and daily precipitation (>6.35 mm/day) that make burns ineffective, as in Chiodi et al. (2016). The weather conditions on the medium-fire and heavy-fire days at county-level were used to define the preferred conditions and compared to the optimum burning conditions recommended in the Flint Hills smoke management plan (KDHE, 2010; RH = 30-55%; wind speed = 5-15 mph, or 2-7 m/s; cloud cover = 30-50%) to identify the potential areas for improvement. We applied the preferred weather conditions determined from the county-level to the whole Flint Hills region. The preferred weather conditions are compared with the other regions' recommended weather conditions in United States outside Flint Hills region (Weir, 2011b; Yurkonis et al., 2019; Kupfer et al., 2020; Baijnath-Rodino et al., 2020; Waldrop et al., 2018). Given the burden of conducting all desired burns within a short window in the spring, we identified all possible burn windows using preferred weather conditions as the yardstick.

3.2.5 Identifying the Optimum Weather Conditions for Prescribed Fires

By improving the current understanding of the prescribed burn decision pattern, we proposed optimum weather conditions for burning from historical data. Daily ozone (O_3) concentrations from 2003 to 2019 at nine Kansas regulatory monitoring stations around Flint Hills

and the Clean Air Status and Trends Network (CASTNET) in Konza Prairie were obtained. The air quality was deemed unsatisfactory on days with O₃ exceedances over 70ppb (McCarthy & Shouse, 2018). Optimum weather conditions are determined using actual available days within preferred weather conditions that minimize the O₃ exceedance occurrence.

3.3 Results

3.3.1 Prescribed Fire Driving Weather Variables

Figure 3.1 illustrates the results of the Pearson correlation analysis between the daily burned area and the weather variables. As it can be seen, cloud cover, RH and solar radiation have the highest correlation with daily burned area. The same trend can be seen in the RF model output using SHAP values (Fig. 3.2). The SHAP values are the absolute mean over the counties to illustrate the intricate relationships between the weather variables and daily burned area. The SHAP values on the x-axis represent the contribution of each weather variable on the daily burned area, which could be negative or positive. Color gradient of each point represents the feature value of the weather variables (red high, blue low). The negative SHAP values indicate decreased daily burned area; positive SHAP values show an increased daily burned area. It reveals, for example, that high solar radiation increases the daily burned area while low solar radiation lowers the daily burned area. In contrast, high RH (red) decreases the daily burned area with a negative SHAP value, while low RH increases the daily burned area (blue) with a positive SHAP value.

Unlike Pearson correlation, RF feature importance does not account for positive and negative correlations and only reports factor significance. Figure 3.1 shows wind speed and air temperature as the least correlated with daily burned area. As noted by Ahmadi et al. (2022), RF feature importance is prone to choose only the most important input variable and undervalue the effect of others. The SHAP values (Fig. 3.2) ranked precipitation as the least predictor of daily

burned area, however, it is more correlated with daily burned than both air temperature and wind speed.

The significance of weather variables and burn decision patterns vary by county. The relationships between the weather variables and daily burned area (Figs. 3.2b-d) at Wabaunsee, Riley and Marion counties are illustrated. With a few minor exceptions, the results from Wabaunsee and Riley counties, with annual average burned percentage range of 42% and 32%, respectively (Akinbile & Liu, 2022), are substantially identical within the whole Flint Hills region. However, the model output based on weather variables of Marion County, with annual average burned percentage of 14%, was entirely different from other counties. The variations in model output were largely due to the fact that smaller fires tend to be more common in counties with lower annual burned percentages, occurring under variable weather conditions. Light fires dominated the prescribed burning days in Marion County, and RH is considered to have a greater impact than other weather variables. The spatial disparity agrees with Parks et al. (2012), who established that local weather conditions control fire decisions at a larger spatial scale.

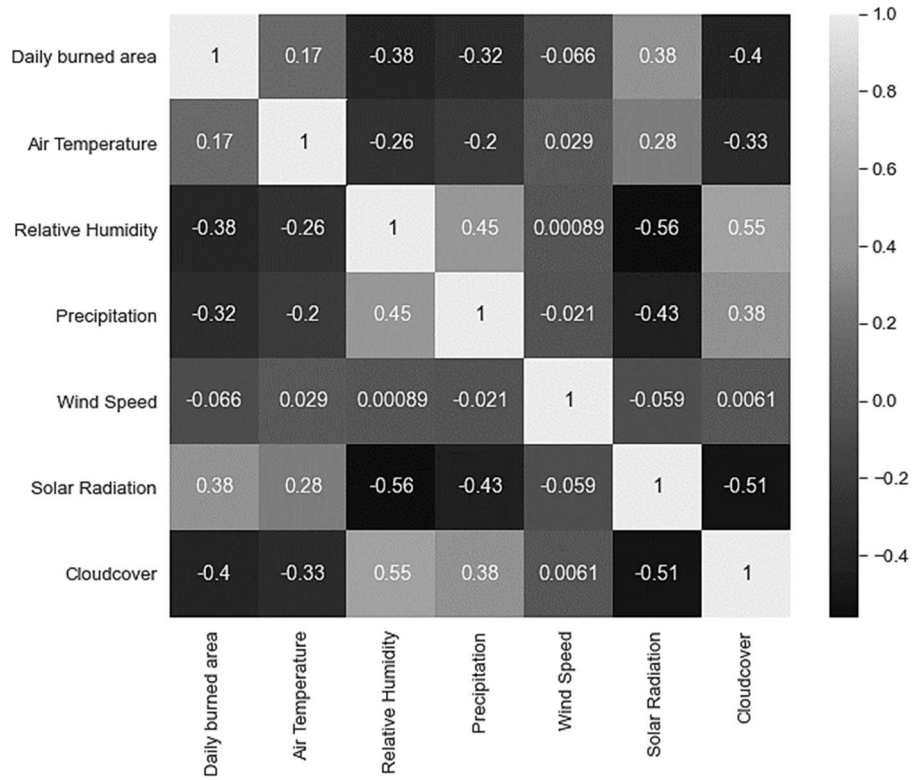
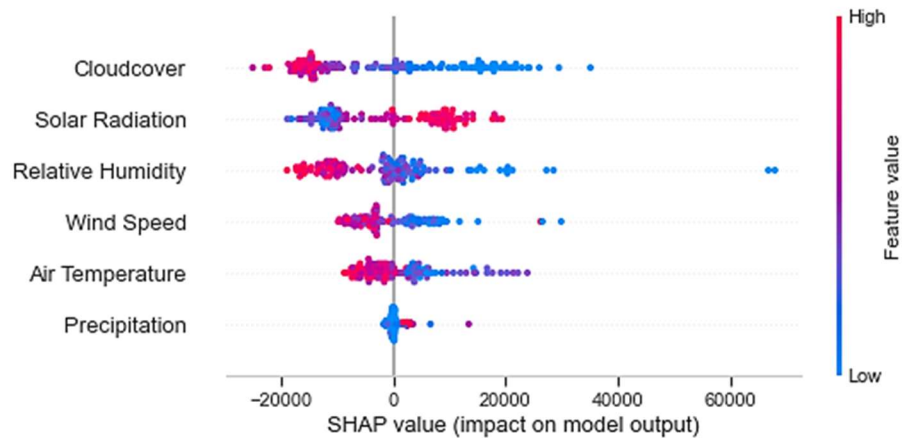
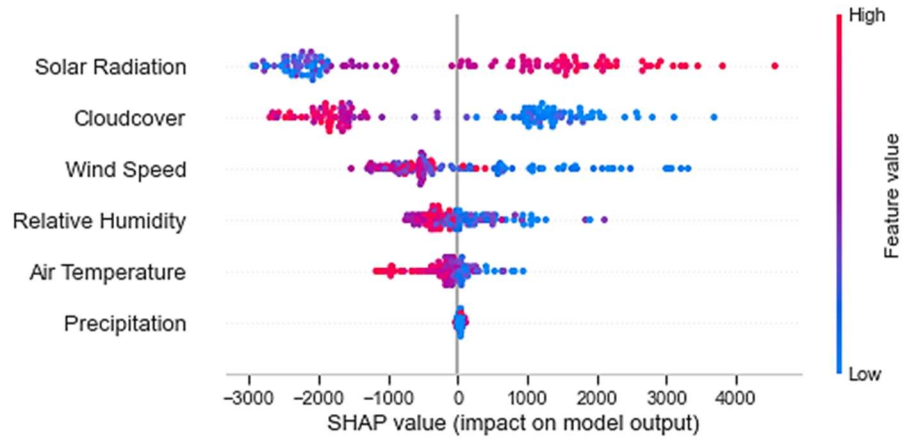


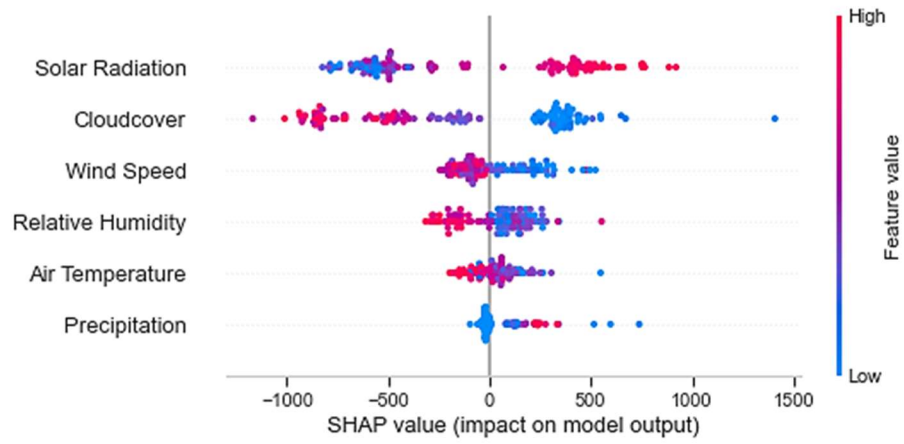
Figure 3.1: Pearson correlation between daily burned area and meteorological factors.



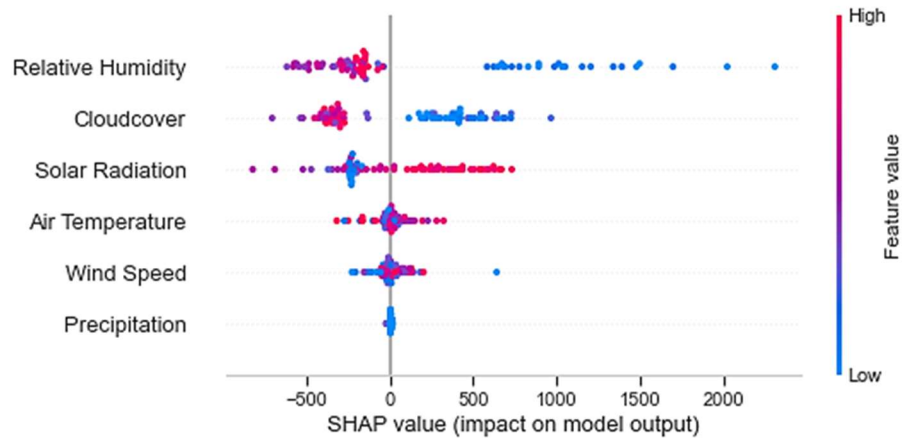
(a)



(b)



(c)



(d)

Figure 3.2: Weather variables activity level in burning decisions by mean absolute SHAP values and their effect on daily burned area in (a) Flint Hills region (b) Wabaunsee County (c) Riley County and (d) Marion County

3.3.2 Weather Conditions for Different Fire Activity Levels

Table 3.1 presents the fire activity levels on all days (1054 days) during spring burning seasons from March 8 to May 8 and the corresponding median values of weather variables for each fire activity level. The heavy fire days occurred averagely on 6 days per spring burning season. A total of 91% of the burned acres in spring burning seasons (12.18 out of 13.40 million ha) were burned on medium-fire and heavy-fire days. Many landowners chose to burn at less cloud cover, higher solar radiation, a wide range of RH, moderate temperature, and lower wind velocity. Simultaneous low RH, high temperature, high solar radiation, less cloud cover and moderate wind speeds intensify prescribed fires and can ultimately lead to more burn area of rangeland (Nguyen et al., 2022).

Table 3.1: Median values of weather variables for different fire activity levels in all days of spring burning seasons from 2003 to 2019

	Wind speed (m/s)	Relative humidity (%)	Solar radiation (W/m ²)	Cloud cover (%)	Precipitation (mm)	Temperature (°C)	Average days per season	Total burned area (million ha)
No-fire	4.1	71	260	39	0	13.9	23	0
Light-fire	4.2	52	418	16	0	14.4	21	1.22
Medium-fire	4.2	47	486	9	0	16.7	12	4.43
Heavy-fire	3.7	42	520	3	0	17.4	6	7.75
Total								13.40

3.3.3 The Preferred Weather Conditions for Burning by Landowners

On average, the preferred weather conditions have 39 days per burning season. For cloud cover and RH, the preferred weather conditions had a larger range than the optimum burning conditions recommended by KDHE (2010). Landowners sometimes chose to burn when cloud cover and RH were much less or more than the recommended ranges of optimum conditions. More importantly, KDHE (2010) recommended burning when cloud cover is 30-50% to reduce photochemical reactions that form O₃ and RH between 30-55% to reduce smoke production. Our data show that most fires in preferred weather conditions occurred on days with high solar

radiations when cloud cover was lesser than 30%. Many landowners did not choose to burn when the air temperature was too low or too high but burned when there was strong sunshine and moderate temperature.

On average, 90% of the burned acres in the spring burning seasons (12.0 out of 13.4 million ha) were burned within the preferred weather conditions. In all the 39 days per burning season with the preferred weather conditions, there were only 5.5 days with 30- 50% cloud cover, which was within the KDHE recommended range of optimum burning conditions. The preferred weather conditions defined in our data generally agreed with the weather conditions recommended in other regions (Table 3.2) from the previous studies. Evidence suggests that tallgrass prairies may be able to burn under more favorable conditions outside spring season than commonly believed (Weir, 2011a). Neighbors helping neighbors is a well-known idea, which frequently results in combining numerous burn units (Weir & Scasta, 2022) on a single day under preferred weather conditions. For safety, time management and labor reasons, landowners typically take advantage of the preferred weather conditions for large burns.

Table 3.2: The proposed optimum weather conditions in comparison with recommended weather conditions for prescribed burning from other regions in USA.

	Wind speed (m/s)	RH (%)	Solar radiation (W/m ²)	Cloud cover (%)	Precipitation (mm)	Air temperature (°C)
Preferred weather conditions from historic prescribed fires	1.0 ~ 7.8	20 ~ 82	278 ~ 693	0 ~ 55	0 ~ 5.33	2.6 ~ 30.5
Conditions recommended by Weir (2011b) in Oklahoma	1.01~ 4.02	25 ~ 80			0	1.7 ~ 43.3
Conditions recommended by Yurkonis et al., (2019) in Northern Great Plains	1.8 ~ 6.7	25 ~ 80			0	2 ~ 43
Conditions recommended by Kupfer et. al (2020) in Georgia and Florida	2.25 ~ 8.0	>30				0 ~ 32.5
Conditions recommended by Wade & Lunsford (1989) in Southern region	2 ~ 10	30 ~ 55				0 ~ 32
Conditions recommended by KDHE (2010,2017)	2 ~ 7	30 ~ 55		30 ~ 50		10 ~ 27
Proposed optimum conditions	2 ~ 7	30 ~ 55	279 ~ 669	10 ⁺ ~ 55	0 ~ 1.27	10 ~ 27

3.3.4 The Optimum Weather Conditions for Prescribed Fires

The preferred weather condition datasets were used to analyze the weather patterns under the current conditions and explore the potential improvement to KDHE optimum conditions. To ensure that the set of weather variables was representative of the preferred conditions used by the landowners, we analyzed each weather variable by descriptive statistics. An assessment of the temperature and wind speed showed that a significant portion of the preferred conditions falls within the KDHE optimum conditions. There was a large variance for RH ranged 20-82%. However, about 65% of the preferred weather condition days were actually within the 30-55% KDHE optimum RH. There were only 14% (93 out of 667 days) of the preferred condition days within the 30-50% KDHE optimum cloud cover. The number of days that simultaneously met KDHE optimum weather conditions was limited by cloud cover and was less than 1 day per burning season.

To obtain the proposed optimum weather conditions, we ranked all the 667 days within the preferred weather conditions according to cloud cover percentage from highest (55%) to lowest (0%), while other weather variables are within the KDHE recommended range. Our results show that in all the days in the spring burning season from 2003 to 2019, 77% of O₃ exceedance days have cloud cover below or at 10%. We choose cloud cover at 10% as cut off for optimum weather condition. Cloud cover percentage between 10+ and 55% provided average of 6 days of optimum weather conditions per burning season.

3.4 Discussion

3.4.1 How Weather Conditions Affected Landowner Burn Decisions

Weather conditions can render a fire ineffectual, challenging to manage, or erratic. As Zhao & Liu (2021) observed, the weather conditions in the spring are unpredictable and extremely dynamic. The interpretation of Pearson correlation and RF results show that burning decisions by grassland managers are mainly affected by three weather variables (cloud cover, solar radiation, and RH). Understanding how weather influences burn decisions improve knowledge of optimum weather condition for prescribed fires and pollution control.

Cloud cover was the most consistent meteorological predictor of burned area with significant impact at county level. Based on the review of worldwide variation and meteorological influences, Nguyen et al. (2022) reported that more cloud cover influences the amount of solar radiation reaching the earth's surface, keeping temperatures lower and slowing ignition. Their results were consistent with the results of this study which show that 2% of the total burned area per season occurred when the cloud cover exceeded 50% (Table 3.3). Within the past two decades, 62% of the total burned area occurred with a cloud cover of less than 10⁺%. Landowners chose to burn with significantly less cloud cover than the KDHE advised optimum conditions. The result of elevated ozone exceedances in our findings suggests that reduced cloudiness plays substantial role in increasing O₃ concentrations, according to Waiaszek et. al. (2018), by altering the photochemical partitioning between NO₂ and O₂ toward greater O₃ in the atmosphere. Large areas of concurrent burn when the sky was clear with high solar radiation are more likely to impact air quality.

Table 3.3: Burned areas at different cloud covers in the spring burning seasons (March 8th to May 8th). The total burned area of the 17 counties were average values for the spring burning seasons from 2003 to 2019.

Total burned area per spring burning season (million ha)	Percentage of burned area	Average days per spring burning season
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Cloud cover 0 ~ 10%	0.49	62%	23
Cloud cover 10 ⁺ ~ 30%	0.20	25%	15
Cloud cover 30 ⁺ ~ 50%	0.08	11%	13
Cloud cover > 50%	0.02	2%	11
Total	0.79	100%	62

Landowners prefer to conduct fewer prescribed burns during cloudy conditions in anticipation of impending rain. The result of RF with SHAP values shows that precipitation is the least considered weather factor for prescribed burning. This is not the case for Pearson correlation; thus, the significance can be attributed to a nonlinear correlation. Precipitation moistens the fuel and dampens the soil surface, which can reduce the intensity of the fire and make it easier to control. Landowners burn often on non-rainy days. However, it was particularly observed from our data analysis that landowners prefer to burn one or two days after rainfall. Therefore, it could be inferred that precipitation is used as safety measure to reduce the risk of the prescribed burn getting out of control.

The SHAP dependence plots (Fig. 3.3) show how RH, temperature, wind speed and cloud cover impacted the daily burned area. The RF model shows that landowners prefer to burn heavily within the KDHE recommended RH (30%-55%). The RH between 30⁺ - 50% contributed most positively to the daily burned area and accounted for 58% of the daily burned area (Table 3.4). While wind speed and temperature were mostly within the KDHE recommended optimum limit, further analysis established landowner can sometimes choose a larger window (20 - 82%) for RH than the recommended range. When the RH value exceeded 65%, the daily burned area decreased abruptly. Air temperature has a narrow window from about 10°C to 26°C, contributing positively to the model's prediction. It is evident from our analysis that landowners prefer to burn mostly in the temperature range recommended by KDHE for optimal smoke management. According to Skvarenina et al. (2003), RH combines information about temperature, air moisture, and

biophysical processes in the environment to determine fire occurrence. The moderate inverse correlation between solar radiation and RH suggests that a change in RH will have impact on other weather variables. Our results indicate that landowners preferred to burn on days with not too high RH and strong solar radiation. These findings complement prior research findings that warm and dry weather condition promoted more burned area (Higuera & Abatzoglou, 2021; Abolafia-Rosenzweig, 2022).

Table 3.4: Burned areas at different RH in the spring burning seasons (March 8th to May 8th) (The total burned area of the 17 counties were average values for the spring burning seasons from 2003 to 2019)

	Total burned area per spring burning season (million ha)	Percentage of burned area	Average days per spring burning season
RH 20 ~ 30%	0.06	8%	3
RH 30+ ~ 50%	0.46	58%	22
RH 50+ ~ 70%	0.23	29%	20
RH > 70%	0.04	5%	17
Total	0.79	100%	62

Wind speed defines spread of fires and drives oxygen delivery in the combustion process (Rothermel, 1983). The RF model segments the wind speed into three different categories. Low wind speed (1.2m/s to <4.5m/s) has most positive impact on the model prediction with positive SHAP value. At high wind speed conditions (>6.5 m/s), there are some positive SHAP values that captured large episodic fire events. Analysis of the wind frequencies affirmed that stronger wind under hot conditions speeds up the fire spread leading to larger fires. Negative SHAP values generally related to wind speed between ~4.5m/s to 6.5m/s. More importantly, landowners do not burn at low relative humidity and high wind speed that could increase the spread and intensity of the fire. Results of the preferred weather conditions by the landowners reveal they are more concerned about prescribed burning's safety than its environmental impact.

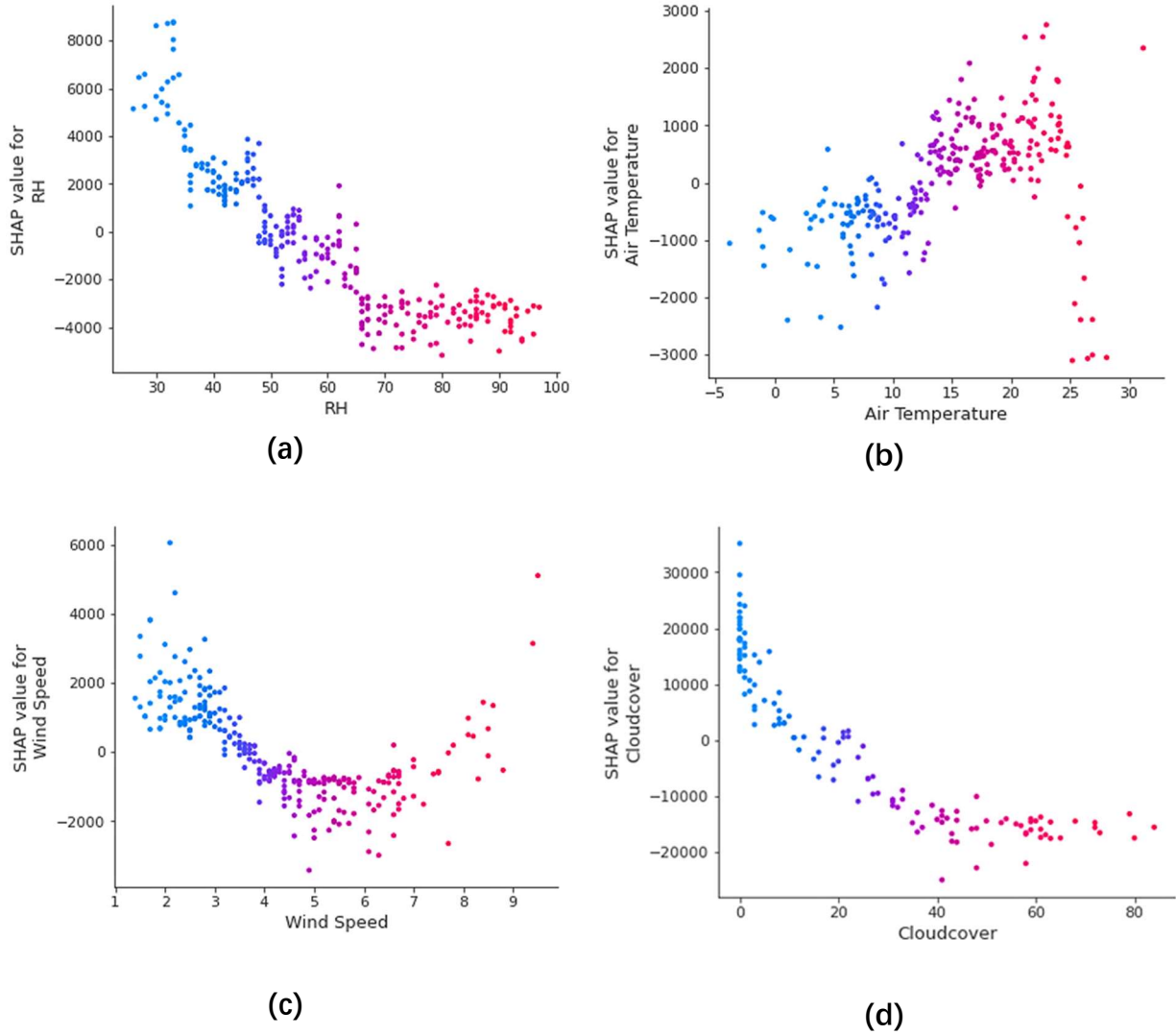


Figure 3.3: The SHAP dependence plots between SHAP values and (a) RH, (b) Air Temperature, (c) Wind speed and (d) Cloud cover

3.4.2 How the Proposed Optimum Conditions Can Reduce Ozone Impact

Finding KDHE optimum weather conditions for prescribed burns during the burning season has become a challenge. There were only 16 days that satisfied the KDHE optimum conditions during the whole 17 years of study. In contrast, our proposed optimum weather condition averages 6 days per burning season and recommends cloud cover ranging from 10⁺ to 55%. Heavy fire characteristically occurs when the cloud cover is less. As a result, cloud cover

demonstrated a superior predictive power for daily burned area and largely impacted O₃ concentration. Our proposed optimum weather conditions reduced the probability of O₃>70ppb exceedance occurrence from 35% to 9% on heavy fire days (Table 3.5). If the landowner could choose to burn under the proposed optimum weather condition, it would decrease O₃ exceedance frequency. A more detailed analysis is underway to quantify the maximum daily burned area in the Flint Hills region to avoid O₃ >70ppb exceedance under different weather conditions.

Table 3.5: Summary of the number of days when O₃>70ppb under KDHE optimum weather conditions, preferred weather conditions and proposed optimum weather conditions from historical prescribed fires in terms of fire categories

Fire category	Number of days in the 17 study year	KDHE optimum weather condition	Preferred weather condition	Proposed optimum weather condition
Heavy fire	Number of actual days	2	88	11
	Number of days O ₃ >70ppb	0	28	1
	Probability of O ₃ >70ppb exceedance occurrence	0%	32%	9%
Medium fire	Number of actual days	7	176	25
	Number of days O ₃ >70ppb	0	16	1
	Probability of O ₃ >70ppb exceedance occurrence	0%	9%	4%
Light fire	Number of actual days	4	252	37
	Number of days O ₃ >70ppb	0	2	0
	Probability of O ₃ >70ppb exceedance occurrence	0%	~1%	0%
Overall	Number of actual days	13	516	73
	Number of days O ₃ >70ppb	0	46	2
	Probability of O ₃ >70ppb exceedance occurrence	0%	9%	3%
Average days per burning season		~1	39	~6

The proposed optimum weather conditions reduce the overall probability of O₃ exceedance days from 9% to 3%. Our data show that the remaining O₃ exceedance days were associated with high previous day O₃ concentration (>60ppb). In addition to proposed optimum weather conditions, further improvement could be achieved by modeling of daily O₃ under impact of prescribed burning considering input from previous day's O₃. As a result of this study, the ongoing research project will develop O₃ regression models based on daily burned area, previous-day O₃ concentration and weather variables to simulate the smoke impact on O₃.

The boxplot interpretation of cloud cover patterns and maximum 8-hour O₃ concentrations under the proposed optimum and preferred weather conditions are shown in Figure 3.4. From the figure, the proposed weather conditions had significantly better performance in reducing O₃ exceedance days. Significant differences (p-value < 0.05) between the groups are found in cloud cover. The means of the cloud covers were generally higher than the medians in all categories, indicating that few more cloud covers skewed the distribution to the high side. The first quartile of the proposed optimum weather conditions is a higher percentage of cloud cover than both the median and mean values for the preferred condition. The proposed optimum weather conditions had fewer O₃ exceedance days than the preferred weather condition. Higher O₃ in the region tend to coincide with heavier burning and lesser cloud cover; 80% of burn season O₃ exceedance days were recorded when cloud cover was less than 10⁺%.

The boxplot distribution of O₃ for the preferred weather conditions shows elevated O₃ outliers. In contrast, the proposed optimum weather condition has no outliers with less O₃ exceedance. As compared to the inter-quartile range of the cloud cover for the proposed optimum weather conditions, the cloud cover inter-quartile range for the preferred weather conditions were larger, indicating more variation in cloud cover on the day of O₃ exceedances. Therefore, our recommendation has higher mean and median values and higher percent cloud cover, lowering O₃ production from fire emissions.

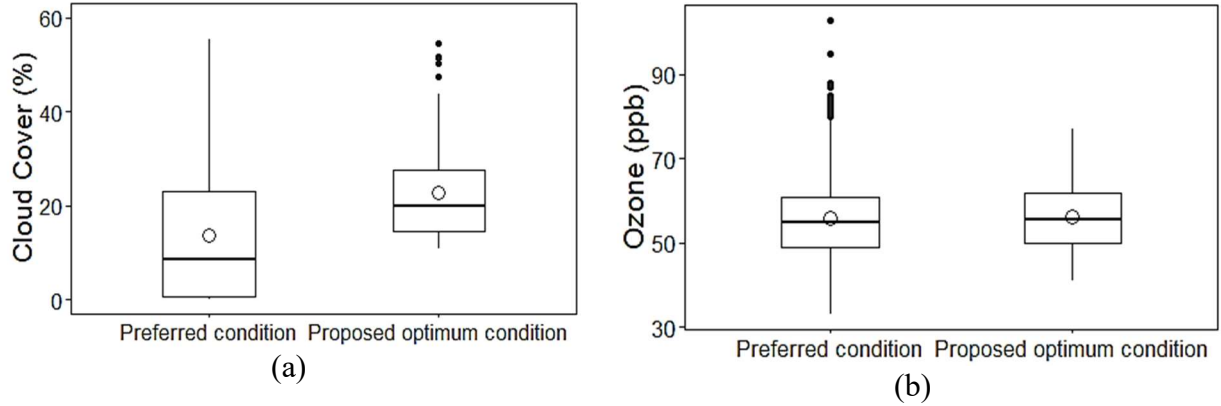


Figure 3.4: Distribution of weather variable (a) cloud cover; and air pollution (b) ozone under preferred condition and proposed optimum condition over the Flint Hills region. In the box plots, the solid black line represents the median; the black circle represents the mean; the bottom and top of the box plots represents the 25th percentile and 75th percentile, respectively.

3.5 Conclusion

Our study evaluated the relative importance of meteorological driving factors of prescribed burning in the Flint Hills regions. Machine learning methodology (SHAP values using RF) was applied to rank weather variables' importance in prescribed burning and Pearson correlation was employed to explain their relationship with daily burned area. Weather conditions currently preferred by the landowners were determined from the county-level weather conditions. We proposed the optimum weather conditions for prescribed burning to mitigate smoke impact on ambient air quality. Current key findings include:

- Prescribed burning decisions by landowners is mainly influenced by cloud cover, solar radiation, and RH.
- Cloud cover demonstrates a superior predictive power for the daily burned area and largely impacts ambient O₃ concentration.
- The safety of the prescribed burning procedure is more importance to landowners than environmental impact of smoke pollution.

- The proposed optimum weather condition has an estimated 6 days per burning season and recommends cloud cover ranging from 10⁺ to 55%. If the landowners could choose to burn under the proposed optimum condition, the probability of O₃ exceedance frequency could be reduced from 35% to 9% on heavy fire days.

More analyses are ongoing to quantify the maximum daily burned area in the Flint Hills region to avoid O₃ exceedance under different weather conditions.

3.6 Acknowledgements

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3.7 References

- Abolafia-Rosenzweig, R., He, C., & Chen, F. (2022). Winter and spring climate explains a large portion of interannual variability and trend in western US summer fire burned area. *Environmental Research Letters*, 17(5), 054030.
- Agastra, A. (2022). Forecasting Prescribed Fires Using Weather Forecasts, Satellite Data, and Machine Learning.
- Ahmadi, A., Daccache, A., Snyder, R. L., & Suvočarev, K. (2022). Meteorological driving forces of reference evapotranspiration and their trends in California. *Science of The Total Environment*, 849, 157823.
- Akinbile, D. S., & Liu, Z. (2022). Daily Burned Area Mapping for Prescribed Rangeland Burning in the Flint Hills Region Using MODIS Data. *Journal of the ASABE*, 0.
- Bajinath-Rodino, J. A., Li, S., Martinez, A., Kumar, M., Quinn-Davidson, L. N., York, R. A., & Banerjee, T. (2022). Historical seasonal changes in prescribed burn windows in California. *Science of the total environment*, 836, 155723.
- Belgiu, M., & Drăguț, L. (2016). Random forest in remote sensing: A review of applications and future directions. *ISPRS journal of photogrammetry and remote sensing*, 114, 24-31.
- Bowman, D. M., Balch, J. K., Artaxo, P., Bond, W. J., Carlson, J. M., Cochrane, M. A., ... & Pyne, S. J. (2009). Fire in the Earth system. *science*, 324(5926), 481-484.
- Breiman, L. (2001). Random forests. *Machine learning*, 45(1), 5-32.

- Breiman, L., Friedman, J. H., Olshen, R. A., & Stone, C. J. (2017). Classification and regression trees. Routledge.
- Castellnou, M., Kraus, D., & Miralles, M. (2010). 1.1 Prescribed Burning and Suppression Fire Techniques: from Fuel to Landscape Management. *Best Practices of Fire Use Prescribed Burning and Suppression Fire Programmes in Selected Case-Study Regions in Europe*, 1.
- Chiodi AM, Bond NA, Larkin NK, Barbour RJ (2016) Summertime rainfall events in eastern Oregon and Washington. *Weather and Forecasting* 31, 1465–1480. doi:10.1175/WAF-D-16-0024.1
- Chiodi, A. M., Larkin, N. S., & Varner, J. M. (2018). An analysis of Southeastern US prescribed burn weather windows: Seasonal variability and El Niño associations. *International Journal of Wildland Fire*, 27(3), 176-189.
- Cirnu, L., & Harrington Jr, J. (2019). Climatic Analysis of Ozone Data from the Konza Prairie Biological Station Sensor. *Transactions of the Kansas Academy of Science*, 122(1-2), 87-95.
- Goodin, D. G. (1995). Climate and weather atlas of Kansas: an introduction. Kansas geological survey, University of Kansas.
- Haikerwal, A., Reisen, F., Sim, M. R., Abramson, M. J., Meyer, C. P., Johnston, F. H., & Dennekamp, M. (2015). Impact of smoke from prescribed burning: Is it a public health concern? *Journal of the Air & Waste Management Association*, 65(5), 592-598.
- Hapfelmeier, A., & Ulm, K. (2013). A new variable selection approach using random forests. *Computational Statistics & Data Analysis*, 60, 50-69.
- Higuera, P. E., & Abatzoglou, J. T. (2021). Record-setting climate enabled the extraordinary 2020 fire season in the western United States. *Global change biology*, 27(1).
- Hong, H., Jaafari, A., & Zenner, E. K. (2019). Predicting spatial patterns of wildfire susceptibility in the Huichang County, China: An integrated model to analysis of landscape indicators. *Ecological Indicators*, 101, 878-891.
- James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013). An introduction to statistical learning (Vol. 112, p. 18). New York: springer.
- Kadiyala, A., & Kumar, A. (2018). Applications of python to evaluate the performance of decision tree-based boosting algorithms. *Environmental Progress & Sustainable Energy*, 37(2), 618-623.
- Kansas Mesonet. (2022). Historical weather. Kansas Mesonet. <https://mesonet.k-state.edu/weather/historical/>
- KDHE. (2010). State of Kansas Flint Hills Smoke Management Plan. Kansas Department of Health and Environment. Division of Environment, Bureau of Air.

- KDHE. (2017). State of Kansas Flint Hills Smoke Management Plan. Kansas Department of Health and Environment. Division of Environment, Bureau of Air.
- Kupfer, J. A., Terando, A. J., Gao, P., Teske, C., & Hiers, J. K. (2020). Climate change projected to reduce prescribed burning opportunities in the south-eastern United States. *International Journal of Wildland Fire*, 29(9), 764-778.
- Lemaire G., Hodgson J., and Chabbi A., editors. 2011. *Grassland productivity and ecosystem services*. CABI, Wallingford, UK.
- Littell, J. S., Peterson, D. L., Riley, K. L., Liu, Y., & Luce, C. H. (2016). A review of the relationships between drought and forest fire in the United States. *Global change biology*, 22(7), 2353-2369.
- Liu, Z., Liu, Y., Murphy, J. P., & Maghirang, R. (2017). Estimating Ambient Ozone Effect of Kansas Rangeland Burning with Receptor Modeling and Regression Analysis. *Environments*, 4(1), 14.
- Lundberg, S. M., & Lee, S. I. (2017). A unified approach to interpreting model predictions. *Advances in neural information processing systems*, 30.
- McCarthy, J. E., & Shouse, K. C. (2018). Implementing EPA's 2015 Ozone Air Quality Standards. CRS Report, 43092.
- Nguyen, D.H., Lin, C., Vu, C.T., Cheruiyot, N.K., Nguyen, M.K., Le, T.H., Lukkhasorn, W. and Bui, X.T., (2022). Tropospheric ozone and NO_x: A review of worldwide variation and meteorological influences. *Environmental Technology & Innovation*, p.102809.
- Parks, S. A., Parisien, M. A., & Miller, C. (2012). Spatial bottom-up controls on fire likelihood vary across western North America. *Ecosphere*, 3(1), 1-20.
- Rothermel, R. C. (1983). How to predict the spread and intensity of forest and range fires (Vol. 143). US Department of Agriculture, Forest Service, Intermountain Forest and Range Experiment Station.
- Skvarenina, J., Mindas, J., Holec, J., & Tucek, J. (2003). Analysis of the natural and meteorological conditions during two largest forest fire events in the Slovak Paradise National Park. Forest fire in the wildland-urban interface and rural areas in Europe: an integral planning and management challenge. Athens.
- Striplin, R., McAfee, S. A., Safford, H. D., & Papa, M. J. (2020). Retrospective analysis of burn windows for fire and fuels management: an example from the Lake Tahoe Basin, California, USA. *Fire Ecology*, 16(1), 1-16.
- Towne, E. G., & Craine, J. M. (2016). A critical examination of timing of burning in the Kansas Flint Hills. *Rangeland Ecology & Management*, 69(1), 28-34.

- Visualcrossing.(2022). Total Weather Data. Retrieved from <https://www.visualcrossing.com/weather-data>.
- Wade, D. D., Lunsford, J.D., (1989). A guide for prescribed fire in southern forests. US Department of Agriculture, Forest Service, Southern Region. Technical Publication R8-TP-11.
- Waiaszek, K. I. N. G. A., Kryza, M., Szymanowski, M., Werner, M., & Ojrzyńska, H. (2018). Sensitivity study of cloud cover and ozone modeling to microphysics parameterization. *Geoinformatics and Atmospheric Science* (pp. 33-52). Birkhäuser, Cham
- Waldrop, T. A., Goodrick, S. L., Harper, C. A., & Towne, G. (2018). Introduction to Prescribed Fire in Southern Ecosystems.
- Wang, S. S. C., & Wang, Y. (2020). Quantifying the effects of environmental factors on wildfire burned area in the south-central US using integrated machine learning techniques. *Atmospheric Chemistry and Physics*, 20(18), 11065-11087.
- Weir, J. R. (2011a). Are weather and tradition reducing our ability to conduct prescribed burns?. *Rangelands*, 33(1), 25-30.
- Weir, J. R. (2011b). Best Time of the Year to Conduct Prescribed Burns. Oklahoma State University. Division of Agricultural Sciences and Natural Resources. Cooperative Extension Service.
- Weir, J. R., & Scasta, J. D. (Eds.). (2022). Global Application of Prescribed Fire. CSIRO PUBLISHING.
- Wilkins, J. L., de Foy, B., Thompson, A. M., Peterson, D. A., Hyer, E. J., Graves, C., ... & Morris, G. A. (2020). Evaluation of stratospheric intrusions and biomass burning plumes on the vertical distribution of tropospheric ozone over the midwestern United States. *Journal of Geophysical Research: Atmospheres*, 125(18), e2020JD032454.
- Xiao, H., Zhang, F., Shen, Z., Wu, K., & Zhang, J. (2021). Classification of weather phenomenon from images by using deep convolutional neural network. *Earth and Space Science*, 8(5), e2020EA001604.
- York, R. A., Levine, J., Russell, K., & Restaino, J. (2021). Opportunities for winter prescribed burning in mixed conifer plantations of the Sierra Nevada. *Fire Ecology*, 17(1), 1-16.
- Yurkonis, K. A., Dillon, J., McGranahan, D. A., Toledo, D., & Goodwin, B. J. (2019). Seasonality of prescribed fire weather windows and predicted fire behavior in the northern Great Plains, USA. *Fire Ecology*, 15(1), 1-15.
- Zhao, F., & Liu, Y. (2021). Important meteorological predictors for long-range wildfires in China. *Forest Ecology and Management*, 499, 119638.

Chapter 4 – Regression models to reduce impact of prescribed burning on O₃ in Flint Hills Region

Abstract

The tallgrass prairie of the Flint Hills region is a fire-dependent ecosystem. Ground-level ozone (O₃) exposure is unusually high in the Flint Hills region during the prescribed burning spring season. The objectives of this study were: 1) to model and quantify the impact of prescribed burning on daily O₃ mixing ratio using regression models; 2) to develop a practical burning decision to assist collaborative management of prescribed fires for mitigating smoke impact on ambient O₃. Pearson correlation and machine learning technique using extreme gradient boosting algorithm (XGBoost) with Shapley additive explanation (SHAP) values feature importance were used to evaluate the relevance and influence of predictor variables driving forces on O₃ mixing ratio. Burn decision tool were developed based on O₃ regression models to reduce smoke impact on ambient O₃. Results showed the daily O₃ mixing ratio is highly sensitive to the O₃ mixing ratio on the previous day, daily burned area, RH, and cloud cover. On average, for every 0.1 million increase in daily burned hectares, the maximum O₃ level increased by around 9 ppb. Proposed optimum weather conditions for burning demonstrate reduced O₃ sensitivity to fire activities, averaging six days per season. Further recommendations were offered about burning under second-class conditions (cloud cover = 10~30%) and marginal conditions (cloud cover =0~10%). The detailed findings of this analysis can assist land managers in planning their burning activities better and enable the continuous practice of land management in a manner that minimizes adverse air quality.

4.1 Introduction

Prescribed rangeland burning is essential for maintaining the ecological balance and enhancing agricultural productivity in the tallgrass land ecosystem (Whitehill et al., 2019). Over the past two decades, approximately one-third of the total rangeland has been burned annually in the Flint Hills region of Kansas, United States (Akinbile & Liu, 2022). The smoke plume emanating from these burnings emits primary pollutants such as particulate matter (PM), carbon monoxide (CO), nitrogen oxides (NO_x), and volatile organic compounds (VOCs) (Liu et al., 2017; McClure & Jaffe, 2018). The generation of ozone (O₃) is significantly influenced by emissions from fires, as nitrogen oxides (NO_x) and volatile organic compounds (VOCs) act as their precursors (Buysse et al., 2019). Ground-level O₃ is one of the criteria pollutants regulated by the U.S. Clean Air Act (USEPA, 2012) and World Health Organization air quality guidelines (WHO, 2005). The pollutant impacts regional air quality, leading to numerous adverse effects on human health, including impaired respiratory and cardiovascular functions (Baker et al., 2016; Reid et al., 2016; WHO, 2014). Environmental Protection Agency (EPA) revised the ground-level O₃ standard from 75 parts per billion (ppb) to 70 ppb in October 2015 (Mervis, 2015). Over the past several years, historically recorded population exposure to O₃ by the Kansas Ambient Air Monitoring Network (KAAMN) had many days exceeded the daily maximum 8-hour O₃ mixing ratios above 70 ppb during the prescribed burning season downwind of the Flint Hills region. With the projected increase of prescribed fire events in rangelands, the adverse impacts of prescribed fires due to O₃ exceedance above air quality standards and human health have been increased in recent years (Liu et al., 2018; Langford et al., 2023). Recently, efforts have been made for developing modeling tools that enhanced smoke management for prescribed fires (Heilman et al., 2014; Hu et al., 2008;

Liu et al., 2017; KDHE, 2010). However, air quality management requires improved O₃ modeling for accurate and reliable results, along with practical tools to mitigate the impact of smoke on O₃.

The production of O₃ from fires is influenced by several factors, including the type of fuel, moisture content, photochemical reaction rates, the prevailing weather conditions, and smoke transportation (Jaffe et al., 2008; Zhang et al., 2014). O₃ is a photochemical pollutant formed by the oxidation of emitted VOCs and elevated NO_x concentrations in the presence of sunlight, especially when meteorological conditions are in favor of this oxidation process (Whitehill et al., 2019). The generation of O₃ occurs either in the original smoke plume or by the reaction of the smoke plume with existing atmospheric pollutants (Dokas et al., 2007). On a regional scale, close to the source area, prescribed fires with increased burning can contribute a significantly stronger impact on the formation of O₃ in ambient air (Marufu et al., 2000; McKeen et al., 2002). The impact of grassland burning on O₃ formation requires understanding the relationships between burned rangeland and atmospheric conditions to develop effective strategies for mitigating the detrimental effects on air quality.

Synoptic spring weather conditions influence O₃ by transporting and accumulating O₃ and its precursors (Pope et al., 2016). Temporal variations in O₃ in ambient air are influenced by meteorological factors and atmospheric boundary layer height (Yan et al., 2018). The strong seasonal and daily cycle of O₃ concentrations can be attributed to the influence of meteorological conditions on the physical and chemical processes involved in O₃ formation. Studies have indicated that large fires and smoke plumes are responsible for a portion of the increased tropospheric O₃ reported at the regional scale (Kondo et al., 2004; Forster et al., 2001; Duncan et al., 2003a, 2003b). Large fires can result in elevated O₃ being transported downwind over long distances and persist in the atmosphere for several days (Baker et al., 2016; VanCuren & Gustin,

2015). Unlike other pollution sources, smoke from rangeland burning cannot be mitigated by control devices. The contributions of rangeland burning activities to ambient O₃ mixing ratios have received limited research attention. Current available smoke management tools are inadequate to prevent ambient O₃ levels from exceeding the air quality standard.

Modeling O₃ formation and impact requires complex photochemical air quality modeling that simulates chemical and physical processes. Modeling typically requires hourly inputs of meteorological and emission data. The application of photochemical models is expensive, highly sensitive to dynamics of atmospheric conditions, difficult to capture heterogeneous chemical processes, and requires significant inputs and computational power (Jaffe et al., 2008; Lawson et al., 2017; Mason et al., 2006). The most frequently used alternative statistical models are based on regression models (Thompson et al., 2001). The regression models of ozone pollution are based on one or more input variables between weather data that are potentially correlated with ozone concentrations and other pollution-related variables (Feister & Balzer, 1991; Robeson & Steyn, 1990). In this study, we based on the work of Liu et al. (2018) and Akinbile et al. (2023) and constructed modeling through addition of daily burned area, daily mixing height, and daily maximum 8-hour O₃ mixing ratios from the previous day as predictor variables. The specific objectives of this study are: 1) to model and quantify the impact of prescribed burning on daily O₃ using regression models; and 2) to develop a practical burning decision to assist collaborative management of prescribed fires for mitigating smoke impact on ambient O₃.

4.2 Data and Methods

4.2.1 Air Quality Data

Mixing ratio, commonly expressed in parts per million (ppm) or parts per billion (ppb), signifies the ratio of number of O₃ molecules to number of dry air molecules in a given volume

(Seinfeld & Pandis, 2016). The O₃ mixing ratio is pivotal in atmospheric science, enabling quantification of O₃ concentration under atmospheric conditions, which is a key factor for comprehending atmospheric dynamics and its impacts on climate and air quality. Hourly O₃ mixing ratios (ppb) are measured at air monitoring stations. Kansas' O₃ monitoring network encompasses nine sites, with three located near Kansas City, three near Wichita, one in Topeka, and a background site at Cedar Bluff, including the newly established Chanute monitoring site initiated in 2014 (Liu et al., 2018). The O₃ mixing ratio data from the nine regulatory monitoring sites were obtained via <https://www.epa.gov/outdoor-air-quality-data/download-daily-data>. Also, the O₃ data from the Konza Prairie CASTNET (Clean Air Status and Trends Network) research monitoring site located in the Flint Hills region center was included. The locations of the O₃ monitoring sites are provided (Table 4.1) and shown in Fig. 1.1. The daily maximum 8-hour O₃ concentrations at the 10 sites in the spring-burning seasons from 2003 to 2019 were collected. The response variable in our regression models is the daily maximum 8-hour O₃ mixing ratio.

Table 4.1: Kansas Ozone Monitor Network

Ozone Site Location	Latitude	Longitude	Air Quality System Site ID	Spatial Scale
Heritage Park	38.84	-94.75	20-091-0010	Neighborhood
Leavenworth	39.33	-94.95	20-103-0003	Neighborhood
Chanute	37.68	-95.48	20-133-0003	Regional
Sedgwick	37.90	-97.49	20-173-0018	Neighborhood
Wichita	37.70	-97.31	20-173-0010	Urban
Topeka KNI	39.70	-95.71	20-177-0013	Urban
Peck	37.48	-97.37	20-191-0002	Neighborhood
Cedar Bluff	38.77	-99.76	20-195-0001	Regional
JFK/NCore	39.12	-94.64	20-209-0021	Urban
Konza Prairie	39.10	-96.61	20-161-9991	Regional

4.2.2 Predictor Variables

We included the mixing height (MH), fire data, weather variables, and maximum 8-hour O_3 concentration on the previous day as predictor variables in our regression models to explain the variation of daily maximum 8-hour O_3 concentrations. The weather variables included in our analysis are air temperature ($^{\circ}C$), relative humidity (RH) (%), wind speed (m/s), solar radiation (W/m^2), cloud percentage cover (%), and precipitation (mm). Weather data is the average hourly values of weather variables from 8 a.m. to 6 p.m. based on Riley County's historical meteorological data. This location was chosen because it has the longest uninterrupted record of weather data measurements in the Flint Hills region. Hourly weather data were obtained from Kansas State University Mesonet (Kansas Mesonet, 2022). Data on cloud cover were obtained from the Visual Crossing Weather (Visualcrossing, 2022).

The fire data represents the estimated daily burned rangeland (ha) in the Flint Hills region during the spring-prescribed burn season, developed by Akinbile & Liu (2022) and spanning from March 8 to May 8 for the years 2003 to 2019.

One of the key metrics for describing the structure of the atmospheric boundary layer is mixing height (MH), which also plays a significant role in determining the tropospheric O_3 concentration and the atmospheric dispersion of air pollution (Al-Hemoud et al., 2019; Doll, 1991). Seibert et al. (2002) defines MH as the vertical extent of the atmospheric boundary layer near the ground, wherein pollutants or emitted constituents disperse vertically due to convection or mechanical turbulence. We included MH as one of the predictor variables due to its role in the turbulent transfer of air pollutants. Previously, the planetary boundary layer height was derived using observational meteorological data by Du et al. (2013) and Lai (2015). Di Virgilio et al. (2018) used this technique in their study and found it an effective approximation. Direct MH

measurements would be preferable but are not available for the Flint Hills region at appropriate spatial and temporal resolutions. The daytime MH estimate is derived from the planetary boundary layer height estimate in the Flint Hills region from a subset of the meteorological data from Riley County's weather monitoring station using equations 1 and 2 (Di Virgilio et al., 2018):

$$MH = \left(\frac{121}{6}\right)(6 - s)(t - t_d) + \left(\frac{0.169s(V+0.257)}{12f \ln(\frac{h}{l})}\right) \dots\dots\dots (1)$$

$$f = 2\Omega \sin\theta \dots\dots\dots (2)$$

where s is a stability class that estimates lateral and vertical dispersion, t is daytime average air temperature and t_d is daytime average dew point temperature, V is daytime average wind speed, h is measured wind speed's height in m, l is the weather station's estimated surface roughness index of the Flint Hills region from Hansen (1993) and Businger et al. (1971), f is the Coriolis parameter in s⁻¹, Ω is the earth's rotational speed (rad/s) and θ is the station latitude. The daytime average dew point temperature t_d is calculated using the simplified conversion method by Lawrence (2005). Air stability classes were determined using the modified Pasquill-Gifford method (EPA Australia, 2012; Manju and Siddiqui, 1998) based on solar radiation and daytime wind speed as in Table 4.2.

**Table 4.2: Modified Pasquill-Gifford stability classes
(EPA Australia, 2012; Manju and Siddiqui, 1998)**

Wind Speed (m/s)	Day-time incoming solar radiation (W/m ²)			
	Strong (>600)	Moderate (300-600)	Slight (175-300)	Overcast (<175)
<2	A	A	B	D
2 - 3	A	B	C	D
3 - 5	B	B	C	D
5 - 6	C	C	D	D
>6	C	D	D	D

Note: Very unstable = A, Moderately unstable = B, Slightly unstable= C, Neutral = D. For overcast conditions, regardless of wind speed, Class D is assumed. In equation 1, the stability class (s) is assigned the value of 1 if it corresponds to class A, 2 for class B, 3 for class C, and 4 for class D.

4.2.3 Summary of Previous Results of Regression Analysis

Previously, regression models have been developed to simulate background daily O_3 at each of the ten O_3 monitoring sites around the Flint Hills region using year-round O_3 and weather data (Liu et al., 2018). In these O_3 models, seasonal cycle was described using the sine term that takes into account the day of the year (Gardner & Dorling, 2000), and influence of O_3 from the previous day was described using the persistent term (Liu et al., 2018).

The O_3 regression models at the ten monitoring sites was expressed using the equation 3 (Liu et al., 2018):

$$O_3(d) = c_1 + c_2 O_{3pre} + c_3 \sin\left(\frac{2\pi(d+2)}{365}\right) + c_4(T_{max} - T_{min}) + c_5 T_{max} - c_6 RH - c_7 V \dots (3)$$

In which, $O_3(d)$ is 8-hour daily maximum O_3 concentration in ppb; O_{3pre} is 8-hour daily maximum O_3 concentration on the previous day in ppb; d corresponds to the day of the year; T_{max} is the daily maximum air temperature in $^{\circ}C$; T_{min} is the daily minimum air temperature in $^{\circ}C$; RH is daily average relative humidity (%); V is daily average wind speed in ms^{-1} ; c_1 to c_7 are coefficients estimated at different sites.

The results showed higher solar radiation, temperature, lower relative humidity, and wind speed corresponded to higher O_3 mixing ratios. Solar radiation lost significance as a predictor variable when the difference between the daily maximum and minimum air temperature was incorporated into the models. In the models, the effect of solar radiation was likely reflected by the difference between the daily maximum and minimum air temperature since air was heated by solar radiation. The regression models could explain 62 to 76 percent of day-to-day O_3 variation at various sites. April had the largest positive residuals at all ten sites compared with other months. In most other months, the average O_3 model residuals were either negative or very close to zero. The high positive residuals in April represented the O_3 daily variations that the regression models

did not explain, and they were likely associated with the impact of the smoke emissions from burning. Details on the regression modeling results can be found in Liu et al. (2018).

4.2.4 Data Analysis

Pearson correlation and extreme gradient boosting algorithm (XGBoost) for feature importance are used to evaluate the relevance and influence of driving forces of changes of O₃ concentration, which captured both linear and nonlinear relationships. In addition, we used XGBoost feature importance to determine the importance of input variables as identified by a machine learning tool.

XGBoost is a boosting-based extreme learning method designed to prevent over-fitting (Chen & Guestrin, 2016). It is an improvement of the gradient descent tree-based boosting algorithm, featuring multiple decision tree iterations that are first built as CART (Classification and Regression Trees) models to predict the dataset and then integrated into a new tree model (Liu et al., 2021). The feature's importance of independent variables can be determined by XGBoost using the weighting coefficients, which describes the number of times the feature has been used to split the data (Ma et al., 2020). The SHapley Additive ExPlanation (SHAP) values were used to quantify the individual contributions of each predictor variable to the daily maximum 8-hour O₃ mixing ratios. SHAP values quantitatively measure the individual feature contributions to the model's output. The contribution of each feature is determined by calculating the discrepancy between the model's outputs when the feature is included or excluded (Stirnberg et al., 2021).

The dataset consists of independent variables, including RH, air temperature, cloud cover, wind speed, precipitation, MH, daily burned area in the Flint Hills region, and maximum 8-hour O₃ mixing ratio on the previous day, while the dependent variable is the daily maximum 8-hour O₃ mixing ratio. For model development, approximately three-quarters of the samples are allocated

for training, with the remaining one-quarter reserved for model validation. We fine-tuned the model parameters to prevent overfitting through grid search and ten-fold cross-validation. Combination of XGBoost and Pearson correlation methods was used to identify the important factors influencing O₃ concentrations.

4.2.5 The Ozone Regression Models

Updated O₃ regression models were developed to simulate the daily maximum 8-hour O₃ mixing ratios in the spring burning seasons at any of the ten monitoring sites in Kansas, using optimal predictor variables as in the equation 4:

$$O_3(d) = c_1 + c_2 O_{3pre} + c_3 \sin\left(\frac{2\pi(d+2)}{365}\right) + c_4 A + c_5 T - c_6 RH - c_7 C - c_8 V \dots\dots\dots (4)$$

In the equation 4, O₃(d) is maximum 8-hour O₃ concentration in ppb; O_{3pre} is maximum 8-hour O₃ concentration on the previous day in ppb; d corresponds to the day of the year; A is the daily burned area in the Flint Hills region, in million hectares; C is the day-time average cloud cover, ranging from 0 to 100%; RH is the day-time average RH, ranging from 0 to 100%; T is the day-time average air temperature in °C; and V is the day-time average wind speed in m·s⁻¹. The regression model was developed based on 1054 daily observations in the spring burning seasons from 2003 to 2019.

Regression models were developed for the whole Flint Hills and co-located monitoring O₃ stations. O₃ regression models for co-located monitoring O₃ stations were developed using the daily maximum 8-hour O₃ mixing ratios from monitoring sites at Wichita (three sites), Kansas City (three sites), and Konza Prairie.

Sensitivity analysis and the feature importance results were used to produce O₃ models that maximize accuracy with an optimally reduced number of predictor variables. Simplified regression

O₃ models are developed from predictor variables most sensitive to O₃ level to estimate the maximum daily burned area in the Flint Hills region to avoid O₃ >70 ppb.

4.3 Results

4.3.1 Contributions of Predictor Variables to Ozone Concentration

The Pearson correlation and XGboost algorithm were applied to analyze the relationship between predictor variables and O₃ concentrations. The analysis specifically focused on the time period from March 8 to May 8, spanning from 2003 to 2019. It can be seen from Figure 4.1 that wind speed is the least correlated with the O₃ concentration. Wind speed can affect the dispersion and mixing of pollutants in the atmosphere, and O₃ concentration is determined by the balance between its production and dilution processes (Neu et al., 1994). The processes can be influenced by weather factors such as sunlight, temperature, relative humidity, and other pollutants in the atmosphere. As observed, it is evident that cloud cover, air temperature, solar radiation, mixing height, daily burned area, and the previous day's maximum O₃ mixing ratio exhibit the highest correlation with the daily maximum 8-hour O₃ mixing ratios. Positive correlations were found between the daily burned area, solar radiation, mixing height, and the previous day's maximum and daily maximum O₃ ratio, suggesting that the increase in these predictor variables contributed to the enhancement of O₃ production in the ambient air. On the other hand, relative humidity, precipitation, wind speed, and cloud cover percentage negatively correlate with O₃. The XGBoost model output utilizing SHAP values (Fig. 4.2) shows a similar pattern. The x-axis of the SHAP values represents the impact of each predictor variable on the O₃ concentration, with the potential for both positive and negative contributions. The color gradient shown by each point indicates the feature value associated with the predictor variables, with red representing high values and blue representing low values.

The XGBoost algorithm with SHAP results revealed that, in general, cloud cover percentage, previous day maximum O₃, daily burned area, air temperature, solar radiation, wind speed, and relative humidity have the highest impacts and contributions to the O₃ mixing ratio. While Pearson correlation shows wind speed and precipitation as the least correlated variables with the daily maximum O₃ mixing ratio, the SHAP ranked precipitation and mixing height as the least predictive of the daily maximum O₃ mixing ratio. As Stevens & Treadwell (2022) suggested, excessive rainfall reduces application of prescribed fire on rangeland. Our data showed that from 2003 to 2019, fewer than 10% (65 days) of prescribed burning occurred on rainy days, with just one day having O₃ levels > 70 ppb. Although the SHAP value showed that mixing height has a small contribution, the Pearson correlation indicated that it is moderately correlated with the maximum daily O₃ level.

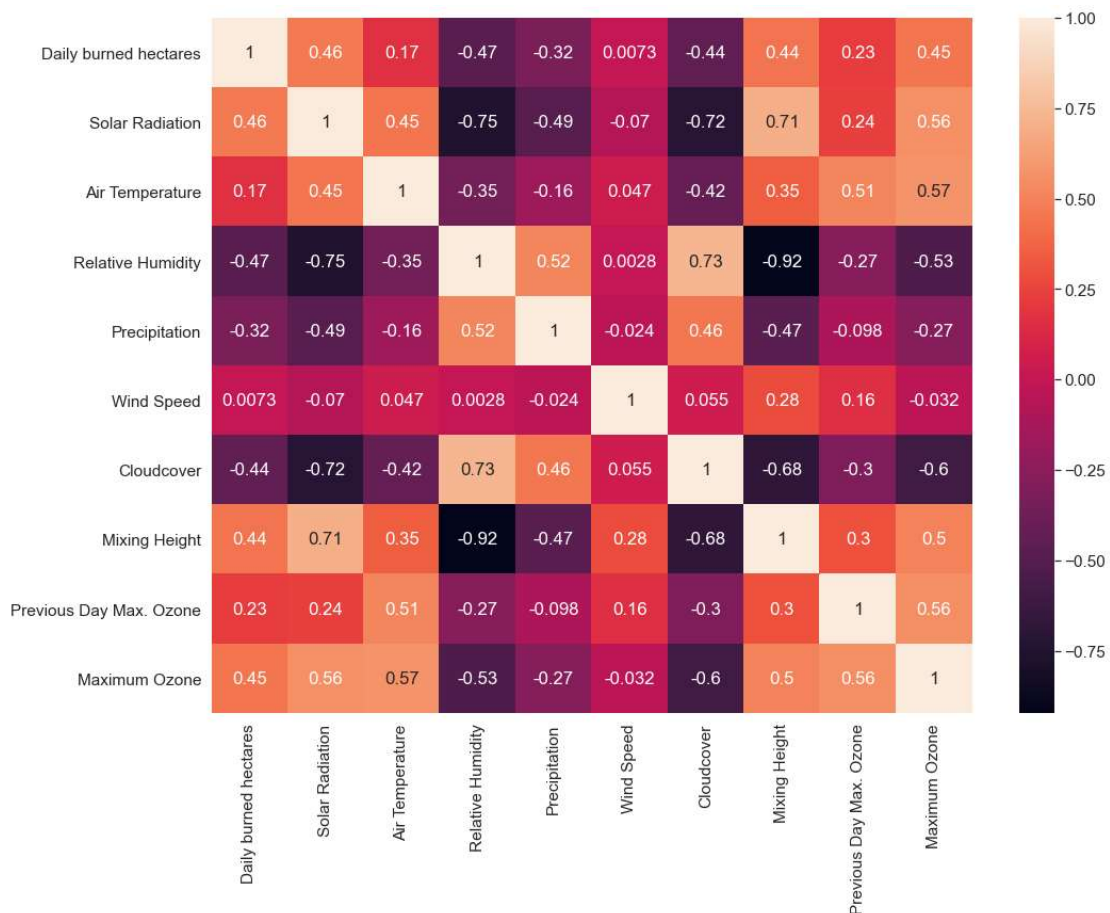


Figure 4.1: Pearson correlation between the daily maximum 8-hour O₃ mixing ratios and predictor variables.

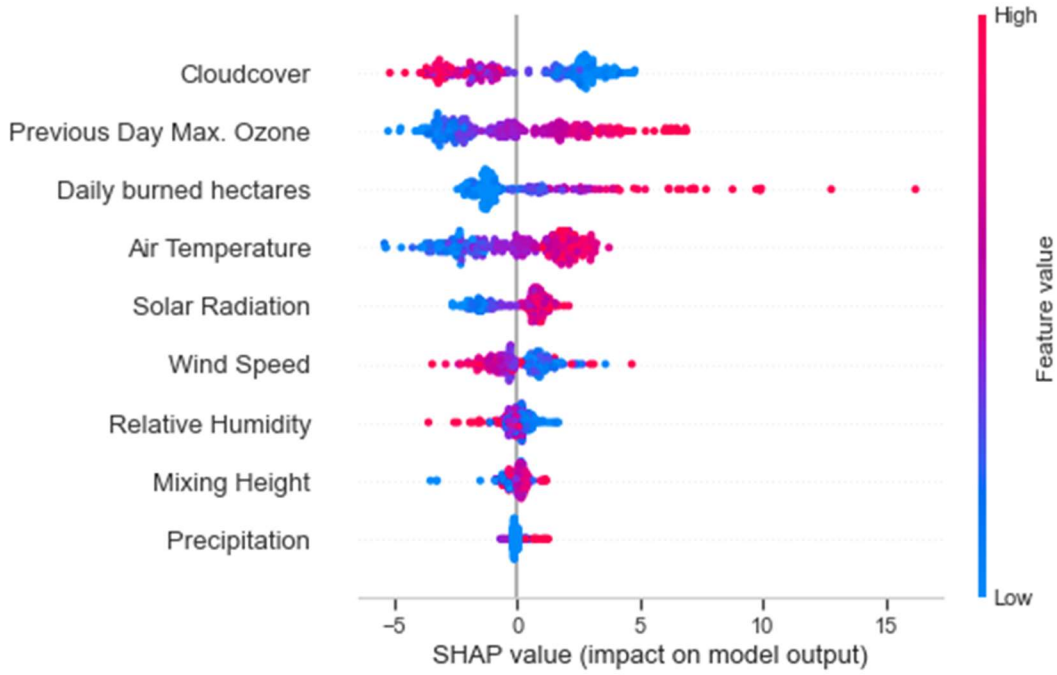


Figure 4.2: Predictor variables contributions by mean absolute SHAP values and their effect on daily maximum 8-hour O₃ mixing ratios

4.3.2 Ozone Regression Models

Using the results of Pearson correlation and XGBoost algorithm, we started with all the predictor variable to build a model. We used a combination of multicollinearity tests and the XGBoost algorithm feature importance results to build O₃ models that maximizes accuracy with an optimally reduced number of predictor variables. Following this process, we excluded solar radiation, precipitation and mixing height from predictor variables as these variables are not statistically significant ($p\text{-value} > 0.05$).

An O₃ regression model was developed to simulate the daily maximum 8-hour O₃ mixing ratios in the spring burning seasons at any of the ten monitoring sites in Kansas, using chosen predictor variables, as in the equation (5):

$$O_3(d) = 39.99 + 0.30O_{3_{pre}} + 3.86 \sin\left(\frac{2\pi(d + 283)}{365}\right) + 92.89A + 0.22T - 0.07RH - 0.11C - 0.36V$$

$$n = 1054, R^2 = 0.62, p - value < 0.05 \quad \dots\dots\dots (5)$$

The regression model was developed using R^2 value of 0.60. On average, for every 0.1 million increments of daily burned hectares, the maximum O_3 mixing ratios increased about 9 ppb. Levels of sensitivity of the predictor variables in the model were presented in Table 4.3 to know the percentage change in O_3 when the predictor variables increase by one standard variation. The analysis reveals that the maximum O_3 level in the region is highly sensitive to the previous day's maximum O_3 mixing ratio, with a 5.9% increase in O_3 levels if the predictor variable is increased by one standard deviation. The daily burned area, cloud cover and RH also showed a high sensitivity level, with 4.8%, 4.6% and 4.5% increase respectively in O_3 levels if the predictor variable is increased by one standard deviation. Air temperature showed a medium level of sensitivity while wind speed had low sensitivity level. These findings demonstrate that cloud cover, RH, daily burned area and previous day maximum O_3 are crucial factors to consider in developing burn decision tool for prescribed burning in the Flint Hills region. Thus, simplified regression models are developed using O_3 mixing ratio on the previous day and daily burned area under different ranges of cloud cover and RH that need to be considered when making burn decisions to mitigate smoke impact on O_3 .

Table 4.3: Sensitivities of the predictor variables on O_3

Variables	Average values $\pm$ standard deviation (std) in the spring burning seasons	Percent change of O_3 if the predictor variable increases by one std	Sensitivity level
Maximum O_3 (ppb)	50.5 $\pm$ 10.9		
Previous day maximum O_3 (ppb)	50.5 $\pm$ 10.9	+5.9%	Very High
Daily burned area (million hectares)	0.03 $\pm$ 0.06	+4.8%	High
RH (%)	58 $\pm$ 19	+4.6%	High
Cloud cover (%)	26 $\pm$ 24	-4.5%	High
Air temperature ($^{\circ}$ C)	14.7 $\pm$ 6.8	+3.8%	Medium
Wind speed (m/s)	4.4 $\pm$ 1.8	-1.9%	Low

Additional O₃ regression models were developed using the daily maximum 8-hour O₃ mixing ratios from monitoring sites at Wichita (three sites), Kansas City (three sites), and Konza Prairie, respectively (Table 4.4). The O₃ regression model for Konza Prairie had the highest R² (0.62), although much less data was available at this site for the development of the regression model. This was likely due to the fact that Konza Prairie is located at the center of the Flint Hills region and is therefore less affected by urban emissions. As expected, at the three sites around the Wichita area (Sedgwick, Wichita Health Department, Peck) and the Konza Prairie site, O₃ was found to be more sensitive to daily burned area in the Flint Hills region. At the three sites around the Kansas City area (Leavenworth, Kansas City JFK center, Heritage Park), O₃ was found to be less sensitive to daily burned area, likely due to the further distances from the Flint Hills region. The O₃ regression model for Wichita had a relatively lower R², which may be attributed to the presence of more complex factors that could contribute to the O₃ level in Wichita. Heavy burn on days with high wind speed could impact a larger population if the wind direction is toward major cities.

Table 4.4: The O₃ regression models for Wichita, Kansas City, and Konza Prairie

For Konza Prairie: $O_3(d) = 44.77 + 0.22O_{3_{pre}} + 3.74 \sin\left(\frac{2\pi(d + 283)}{365}\right) + 112.71A + 0.25T - 0.06C - 0.16RH - 0.42V$ n = 648, R² = 0.62, p-value < 0.05
For Wichita: $O_3(d) = 43.65 + 0.27O_{3_{pre}} + 5.18 \sin\left(\frac{2\pi(d + 283)}{365}\right) + 61.64A + 0.09T - 0.09C - 0.15RH - 0.41V$ n = 1054, R² = 0.52, p-value < 0.05
For Kansas City: $O_3(d) = 39.61 + 0.23O_{3_{pre}} + 2.47 \sin\left(\frac{2\pi(d + 283)}{365}\right) + 36.53A + 0.38T - 0.10C - 0.14RH - 0.21V$ n = 1054, R² = 0.60, p-value < 0.05

4.3.3 Identifying Weather Conditions for Burn Decision Tool

We considered the recommended optimum weather conditions in Chapter 3 (wind speed: 2 ~ 7m/s; RH: 30 ~ 55%; solar radiation: 279 ~ 669W/m²; cloudcover:10⁺~55; precipitation: 0 ~ 1.27 mm; temperature: 10 ~ 27°C) and explore the area of improvement to avoid O₃ mixing ratio >70ppb. The conditions in all the heavy-fire days (daily burned area greater than 0.04 million hectares) from 2003 to 2019 were considered acceptable burning conditions by the landowners (Table 4.5). We applied the acceptable conditions to the 17-year study period, and the days that met acceptable burning conditions were extracted. The Pearson correlation analysis and XGBoost algorithm results show that combination of daily burned area, maximum previous day's O₃ mixing ratio, RH and cloud cover have the most significant impact on the O₃ levels in the ambient air. Our analysis recommended the optimal weather conditions in which O₃ is not sensitive for prescribed burning. We applied the acceptable weather conditions to cloud cover and relative humidity to build regression models associated with the O₃ mixing ratio levels < 70 ppb.

Table 4.5: The acceptable burning conditions and proposed optimum conditions determined from all the heavy-fire days (The total burned area of the 17 counties were average values for the spring burning seasons from 2003 to 2019)

	Wind speed (m/s)	RH (%)	Solar radiation (W/m ²)	Cloud cover (%)	Precipitation (mm)	Air temperature (°C)	Mixing Height (m)	Average days per burn season	Total burned area (million ha)
Acceptable conditions for prescribed fires	1.3 ~ 8.0	20 ~ 80	312 ~ 639	0 ~ 43	0 ~ 2.38	4.2 ~ 25.8	≥ 490	30	0.66
In the whole spring burn season	1.0 ~ 14.7	20 ~ 100	38 ~ 735	0 ~ 100	0 ~ 94.48	-4.6 ~ 31.2	194 ~ 1727	62	0.79
Conditions recommended by KDHE (2010)	2.2 ~ 6.7	30 ~ 50		30 ~ 50		10 ~ 27	>550	~1	0.02
Proposed Optimum Conditions (Akinbile &Liu, 2023)	2 ~ 7.0	30 ~ 55		10 ⁺ ~ 55	0 ~ 1.27	10 ~ 27		~6	

4.4 Discussion

4.4.4 Identifying How Predictor Variables Related to Elevated Ozone

Each predictor variable contributes to O₃ level variation by eliciting a distinct reaction and impact. The Pearson correlation results show that cloud cover percentage, air temperature, previous day maximum O₃ mixing ratio, solar radiation and relative humidity have highest correlation with the daily maximum O₃ mixing ratio. The SHAP dependence plot (Fig. 4.3) demonstrates the impact of a particular predictor variable on O₃ after accounting for the effects of all the other variables (Lunberg et al., 2019). As a result, the SHAP dependence plot accounts for both non-linear predictor variables with O₃ level and any possible intercorrelation between the predictor variables. From the SHAP value result analysis of the predictor variables, the interaction between cloud cover percentage, previous day maximum O₃ and daily burned area largely controls variability in the maximum daily O₃ ratio. These three predictor variables emerged as pivotal, collectively contributing to 70% of the feature importance in the XGBoost algorithm.

The moderate inverse correlation between RH and O₃ (correlation coefficient of -0.53) suggests that decreasing RH is associated with increasing O₃ in Flint Hills region during prescribed burning season. As Camalier et al. (2007) observed, our result from XGBoost algorithm using SHAP value agreed with their finding that higher levels of RH >40% are often correlated with increased cloud cover percentage and atmospheric instability, resulting in slowing down of the photochemical process and a reduction in ground-level O₃. The Figure 4.3a displays non-linear relationship between RH and O₃ according to the XGBoost model. Low RH between 20 ~ 40% has most positive impact on the model prediction with positive SHAP values. This finding complements the previous research by Li et al. (2021) that increased O₃ levels with temperature

were more pronounced at $RH \leq 40\%$. The O_3 response to RH has some degrees of non-linearity, indicating that changes in RH will influence other predictor variables.

The SHAP dependence plots and Pearson association generally agree that elevated levels of O_3 in ambient air during spring burning season are attributed to a combination of increasing air temperature, O_3 from the previous day, daily burned area, and solar radiation. Warmer temperatures and high solar radiation accelerate the photochemical reaction of O_3 precursors, such as NO_x and VOCs, contributing to O_3 formation (Finlayson-Pitts & Pitts, 1999). The importance of previous day's O_3 concentration and daily burned area in smoke management is evident from our sensitivity analysis (Table 4.3). The variable showing the highest sensitivity and second most important variable according to the XGBoost algorithm was the maximum O_3 concentration from the previous day, indicating autocorrelation. The previous day's O_3 concentration has been utilized frequently in similar research works (Davis & Speckman, 1999; Jorquera et al., 1998). Air pollution concentrations generally follow this pattern, which indicates that it is more likely that O_3 concentrations will be similar to the previous day than to be different (Barrero et al., 2006). Identification of previous day O_3 as an important variable suggests saturation effects, wherein its impact diminishes beyond a certain threshold. Another important and highly correlated predictor variable is daily burned rangeland. Previous studies have demonstrated that biomass burning emissions can contribute to elevated O_3 levels at regions far from the sources. (Boian & Kirchhoff, 2005; Shan et al., 2009). Burning biomass emits O_3 precursors, however the magnitude of its impact varies depending on the amount of burned rangeland and the interaction of smoke emission with other predictor variables. The intricate interaction between predictor variables highlights the need for region-specific burn decision tool aimed at reducing ground-level O_3 impact during prescribed burning season.

In addition to the daily burned area and previous day's O₃ mixing ratio, the importance of cloud cover in smoke management is evident from our Pearson correlation and XGBoost algorithm with SHAP analysis. Figure 4.3b highlights the importance of cloud cover in smoke management. Lower cloud cover < 20+% mainly contributed to the high concentration of O₃ and accounted for 92% of days with O₃ ≥ 70ppb. As clouds modulate solar radiation, less cloud cover increases photochemical reactions involving CO₂ and NO_x formation, therefore increasing O₃ production (Erickson et al., 2015). Our analysis shows that during high pollution days (O₃ ≥ 70ppb), the MH is on average 600m higher than MH recommended by KDHE (MH > 550m). MH tend to diminish with the sunset, while clouds inhibit sun from heating the ground. The O₃ concentrations are < 70ppb on days with MH < 550m, as landowners rarely burn due to high RH and low cloud cover percentage. This can explain the main reason why MH is not statistically significant and not included as predictor variable in O₃ regression model. These results contradict Di Virgilio et al. (2018), who see higher MH during low pollution days (attributed to stable atmospheric air condition). Our results suggest that land managers screen most days conducive to fire related safety by following acceptable burn conditions. Overall, these findings indicate that exposure to fire related O₃ can be mitigated by burning under optimum conditions recommended in chapter 3.

The O₃ concentrations ≥ 70ppb were observed in 61 days from 2003 to 2019 during spring prescribed burning season in Flint Hills region, with maximum of 103ppb on April 4, 2016. High O₃ days were associated with high solar radiation, less cloud cover, high previous day O₃ concentration, heavy daily burned rangeland, high temperature, and little or no rainfall. On the contrary, it is less associated with low RH (≤ 40%), which is in agreement with the findings of Shan et al. (2009). However, accumulating effects of low wind speed (< 4m/s) were frequently attributed to high O₃ levels, while certain episode days are influenced by high wind speed (> 8m/s).

Generally, wind speed correlates negatively with O_3 levels, with lower wind speeds allowing for O_3 accumulation due to stable boundary layer and higher wind speeds facilitating dispersion and lower O_3 concentrations (Tu et al., 2007). Our analysis suggests that wind speed is not the dominant factor influencing O_3 levels which align with findings reported by Gorai et al. (2017).

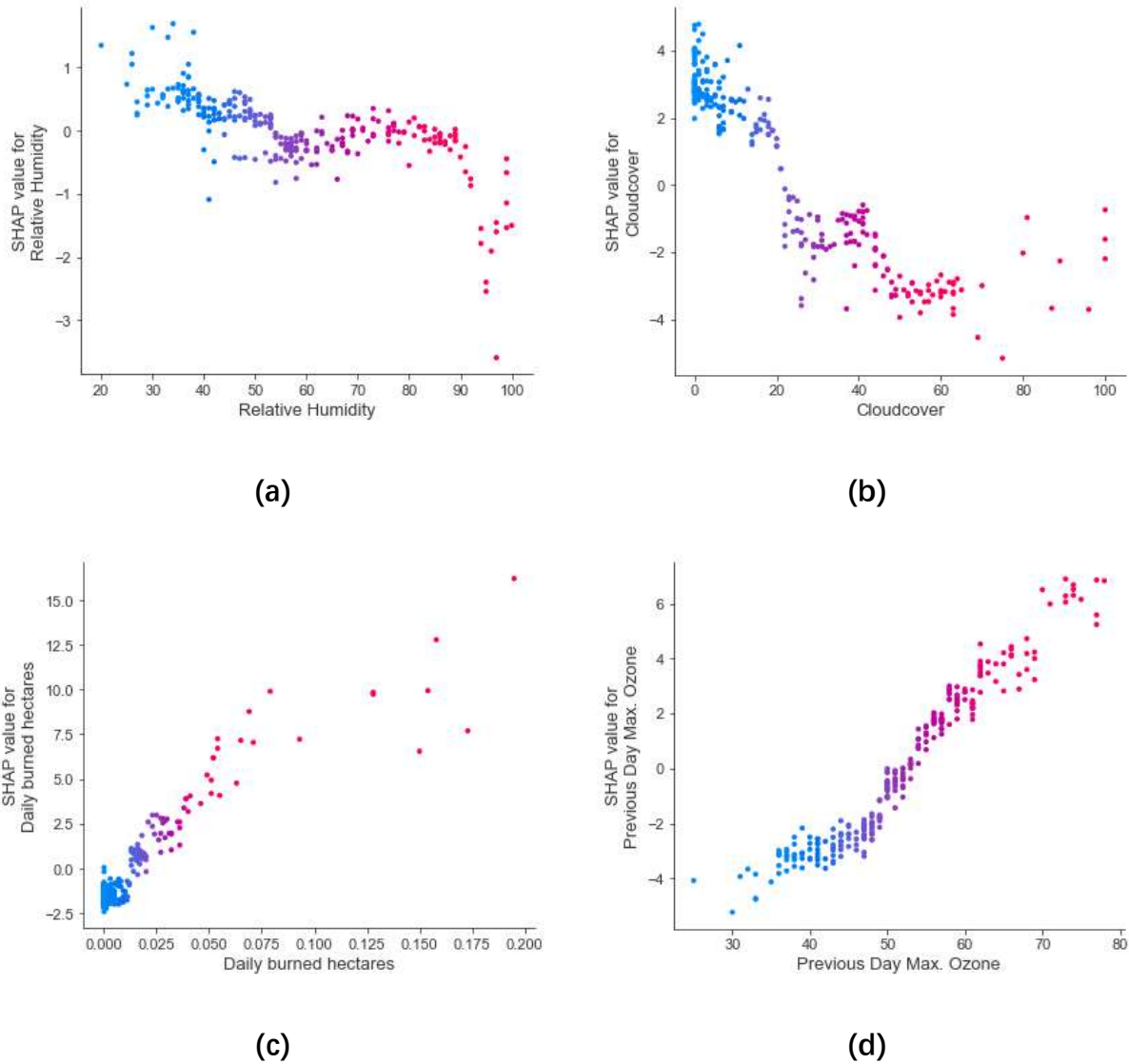


Figure 4.3: The SHAP dependence plots between SHAP values and (a) RH, (b) Cloud cover, (c) Daily burned area (d) Previous day maximum O_3 level

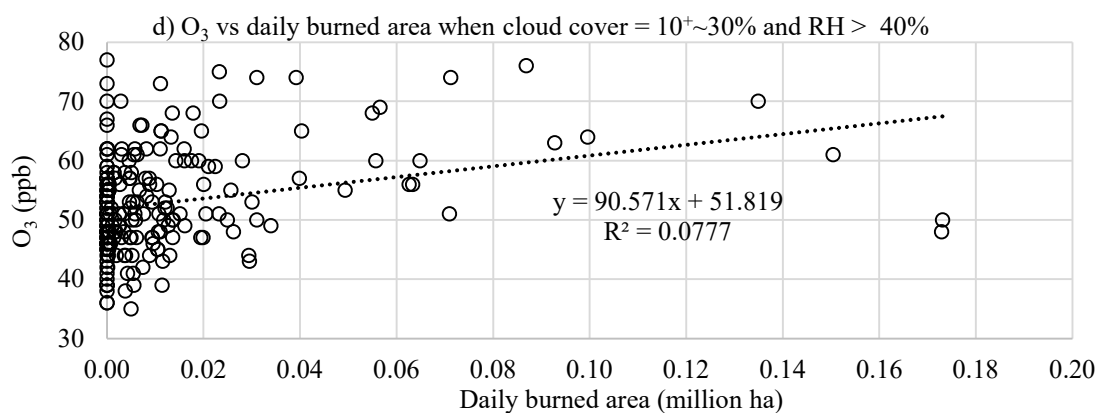
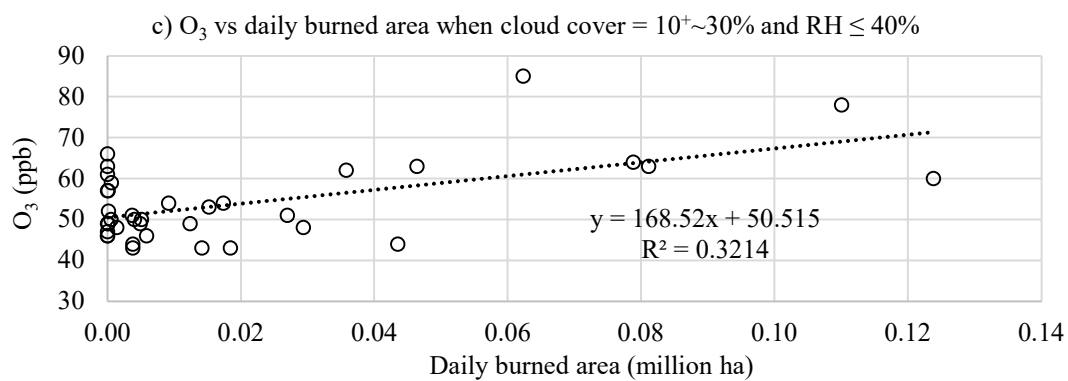
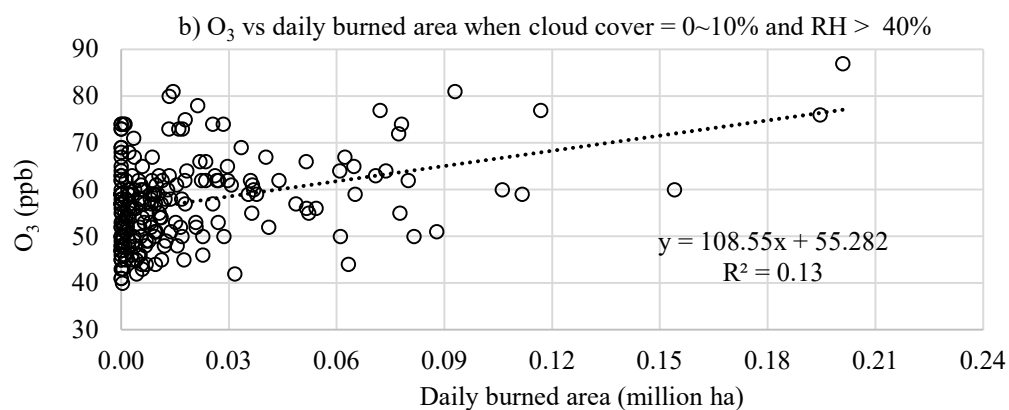
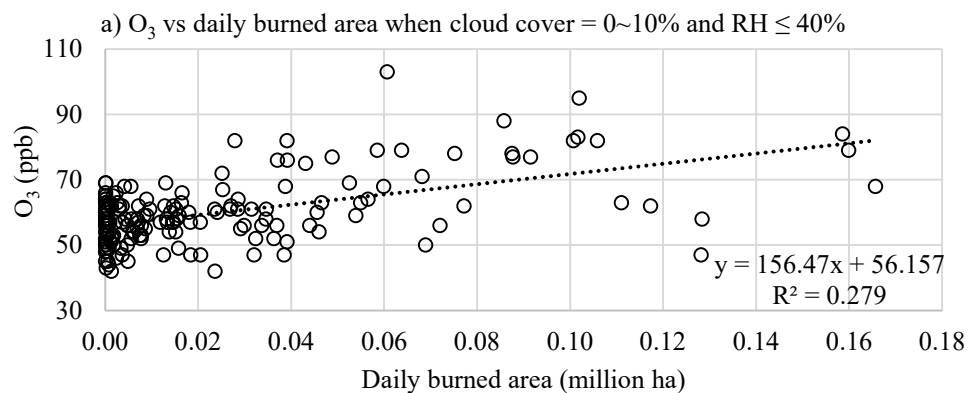
4.4.5 The Burning Decision Tool

Our analysis shows that seasonal variations in O₃ concentration exhibited a substantial susceptibility to daily burned area, maximum previous day's O₃ mixing ratio, RH and cloud cover. The maximum daily burned area in the Flint Hills region to prevent O₃ >70 ppb was estimated under different weather and previous day's O₃ conditions, based on simple O₃ regression models (Table 4.6). The daily burned area in the Flint Hills region and the corresponding maximum 8-hour O₃ mixing ratio under various weather conditions were plotted in Figure 4.4.

Table 4.6: The maximum daily burned area in the Flint Hills region in to avoid O₃ >70 ppb

Cloud cover	RH	Simplified O ₃ models	A _{max} in order to avoid O ₃ >70 ppb	Recommendations
0~10%	≤ 40%	O ₃ = 35.1+0.39O _{3pre} +124.3A R ² = 0.40, n = 167	If O _{3pre} =50, A _{max} = 0.12 If O _{3pre} =60, A _{max} = 0.09 If O _{3pre} =70, A _{max} = 0.06 O₃ is most sensitive to fire	Marginal conditions for burning. Burn with constraints considering O _{3pre} .
	> 40%	O ₃ = 30.6+0.45O _{3pre} +105.6A R ² = 0.38, n = 223	If O _{3pre} =50, A _{max} = 0.16 If O _{3pre} =60, A _{max} = 0.12 If O _{3pre} =70, A _{max} = 0.07 O₃ is sensitive to fire	
10 ⁺ ~30%	≤ 40%	O ₃ = 39.5+0.22O _{3pre} +114.9A R ² = 0.39, n = 37	If O _{3pre} =50, A _{max} = 0.17 If O _{3pre} =60, A _{max} = 0.15 If O _{3pre} =70, A _{max} = 0.13 O₃ is sensitive to fire	Second-class conditions for burning. Burning is permissible but heavy fire is not recommended.
	> 40%	O ₃ = 25.6+0.51O _{3pre} +67.9A R ² = 0.40, n = 222	If O _{3pre} =50, A _{max} = 0.28 If O _{3pre} =60, A _{max} = 0.21 If O _{3pre} =70, A _{max} = 0.13 O₃ is less sensitive to fire	
10 ⁺ ~50%	30 ⁺ ~ 55%	O ₃ = 29.7+0.47O _{3pre} +60.9A R ² = 0.44, n = 98	If O _{3pre} =50, A _{max} = 0.27 If O _{3pre} =60, A _{max} = 0.19 If O _{3pre} =70, A _{max} = 0.12 O₃ is less sensitive to fire	Proposed Optimum conditions. Heavy fire is permissible if O _{3pre} ≤60 ppb.
30 ⁺ ~50%	30 ⁺ ~ 50%	O ₃ = 0.005-0.00001RH+0.0009O _{3pre} R ² = 0.52, n = 16	O₃ is not sensitive to fire	KDHE Optimum conditions for burning.

Notes: O_{3pre} is maximum 8-hour O₃ mixing ratio on the previous day in ppb; A is the daily burned area in the Flint Hills region, in million hectares; A_{max} is the maximum daily burned area in the Flint Hills region, in million hectares, in to avoid O₃ >70 ppb; RH is the day-time average RH, ranging from 0 to 100%; n is number of days used in the models.



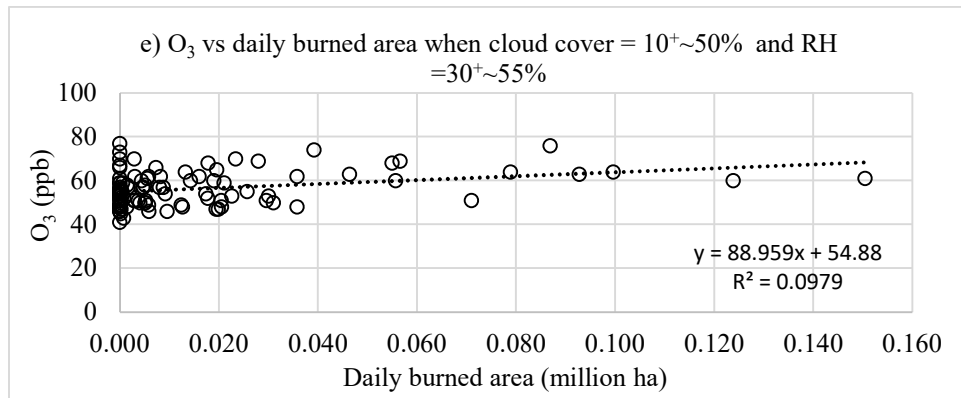


Figure 4.4: Daily maximum 8-hour O₃ mixing ratios vs daily burned area in the Flint Hills region from 2003 to 2019 under various weather conditions

Based on the data presented in Table 4.6 and Figure 4.4, it is evident that O₃ level is not highly sensitive to fire activities when cloud cover percentage is between 30% and 50%. Our data analysis indicates that KDHE optimum weather conditions are the most favorable weather conditions for prescribed burning in the Flint Hills region, ensuring that the maximum O₃ mixing ratio < 70 ppb. Although O₃ is not sensitive to fire, the KDHE optimum conditions occur less than 1 day per burning season. Our proposed optimum conditions provide an average of 6 days per burning season, during which the O₃ level shows reduced sensitivity to its previous day's maximum mixing ratio but becomes more responsive to heavy fire activities. Under the proposed optimum conditions, for every 0.1 million increase in daily burned hectares, the maximum O₃ mixing ratios increase by approximately 6 ppb. However, it is advisable to avoid heavy fire activities if the previous day's O₃ mixing ratio exceeds 60 ppb to prevent O₃ levels > 70 ppb. Since six days may not be sufficient to complete all the necessary burning in one season, landowner may also need to consider burning in other days with lower cloud cover.

Additional recommended conditions that are suitable for burning are when cloud cover = 10~30%, and RH > 40%. Under these conditions, the background O₃ mixing ratio tends to be lower

than those observed under reduced cloud cover, and O_3 is less sensitive to fire activities. On average, for every 0.1 million hectares increase of daily burned acres, the maximum O_3 mixing ratios increased by around 6.8 ppb. Nevertheless, O_3 is more sensitive to the O_3 level on the previous day, likely due to the higher RH. Generally, if the O_3 level on the previous day is at the average level (50.5 ± 10.9 ppb in the spring burning season) or less, burning under these conditions will not likely result in $O_3 > 70$ ppb. From 2003 to 2019, there were 16 days with heavy fire activities (daily burned area > 0.04 million hectares) under these conditions, and only 2 days (12% chance) had $O_3 > 70$ ppb mostly due to higher O_3 level on the previous day (Fig.4.4-d). The whole set of this recommended conditions for prescribed burning are cloud cover = 10~30%; RH = 40⁺~80%; wind speed = 1.3~8.0 m/s; air temperature = 4.2~25.8 °C, MH $\geq$ 490m; precipitation < 2.38 mm. On average, there were about 11 days with these conditions in one spring burning season from March 8th to May 8th, based on the data from 2003 to 2019.

It is observed that when the percentage of cloud cover ranges from 10 to 30%, and the RH is $\leq 40\%$, the sensitivity of O_3 to its previous day's level decreases. However, the O_3 mixing ratio becomes more sensitive to fire activities. On average, there was an increase of around 11.5 ppb in maximum O_3 mixing ratios for every 0.1 million daily burned hectares. Between 2003 and 2019, a total of 7 days were identified as having heavy fire activity (daily burned area > 0.04 million hectares). Among these days, it was observed that 2 days, representing a 28% probability, had $O_3 > 70$ ppb (Fig. 4.4-c). These requirements may be regarded as second-class conditions for implementing prescribed burning. Under these conditions, prescribed burning is permitted, but heavy fire should be avoided. The whole range of prescribed burning weather conditions classified as second-class are as follows: cloud cover = 10~30%; RH = 20~40%; wind speed = 1.3~8.0 m/s;

air temperature = 4.2~25.8 °C; MH $\geq$ 490m; precipitation < 2.38 mm. On average, there are total of 2 days per spring burning season under these burn conditions.

The O₃ background is often greater when cloud cover is between 0 and 10%. O₃ is also very susceptible to fire activity, particularly when RH is low. The maximum O₃ mixing ratios increase by an average of 10.5 to 12.4 ppb for every 0.1 million increase in daily burned hectares. Under cloud cover of 0–10% from 2003 to 2019, 34 days had heavy fire activity (daily burned area > 0.04 million hectares) when RH was less than $\leq$ 40%, and 16 days (47% probability) had O₃ levels over 70 ppb (Fig. 4.4-a). Further analysis revealed there were 29 days with heavy fire activity with RH >40% and 7 days (24% probability) with O₃ >70 pp (Fig. 4.4-b). Therefore, cloud cover percentage between 0~10% could be regarded as marginal conditions for prescribed burning. As a result, burning should not exceed the maximum daily burned area which can be determined by the O₃ level on the previous day and the RH under these conditions. For instance, if the previous day's average O₃ level was about 50 ppb and the relative humidity was less than 40%, the maximum daily burnt area would have been around 0.12 million hectares. To prevent O₃ >70 ppb, the maximum daily burnt area must be lowered when the O₃ level was greater the day before.

4.5 Conclusion

The air pollution associated with O₃ from prescribed burning is likely to increase in coming years in the Flint Hills regions as rangeland treated with prescribed fire are increasing. Burning is ecologically and financially important to the rangeland communities. Our work examines ways in which smoke management can be conducted to efficiently mitigate O₃ impacts on air quality. We considered nine predictor variables: air temperature (°C), relative humidity (RH) (%), wind speed (m/s), solar radiation (W/m²), cloud percentage cover (%), and precipitation (mm), mixing height (m), daily burned rangeland (hectares) and maximum 8-hour O₃ mixing ratio on the previous; to

simulate background daily O₃ ten O₃ monitoring sites around the Flint Hills region using data from 2003 to 2019. Pearson correlation and machine learning technique (SHAP values with XGBoost) feature importance used to evaluate the relevance and influence of predictor variables driving forces on O₃ concentration. O₃ regression models were developed to simulate the daily maximum O₃ mixing ratios in the spring burning seasons using optimally reduced number of predictor variables to maximize accuracy. We proposed decision burning tool for prescribed burning to mitigate smoke impact on ambient air quality based on simplified O₃ regression models. The results of this study demonstrate the following key findings:

- The Flint Hills region experienced 61 days of O₃ mixing ratio ≥ 70 ppb during the spring prescribed burning season from 2003 to 2019, with a maximum of 103 ppb on April 4, 2016. High O₃ days were generally associated with high solar radiation, less cloud cover, high previous day's O₃ concentration, high temperature, and little or no rainfall.
- The daily maximum O₃ mixing ratio was most sensitive to the O₃ level on the previous day, followed by the daily burned area, RH, and cloud cover. On average, for every 0.1 million increments of daily burned hectares, the maximum O₃ level increased around 9 ppb.
- The daily O₃ mixing ratio is less sensitive to fire activities under proposed optimum weather conditions for burning, averaging six days per burning season. To mitigate exposure to O₃ associated with prescribed fire, land managers could avoid unfavorable weather conditions by following the burn decision recommendations for the proposed optimal weather conditions.

- Further recommendations were offered about burning under second-class condition since proposed optimal weather conditions six days per burning season is not sufficient to conduct seasonal burns. When cloud cover = 10~30%, RH >40% and O₃ level on the previous day is at the average level (50.5 ± 10.9 ppb) or less, burning under these conditions will not likely result in O₃ exceedance. On average, there were 11 days available in one spring burning season from March 8th to May 8th, with these conditions. When cloud cover = 10~30%, and RH = 20~40%, it is permissible to burn but heavy fire is not recommended.
- Additionally, recommendations were made for burning under marginal conditions (cloud cover = 0~10%), with the caveat that burning activities should be carried out with constraints, considering limitations to previous day maximum mixing O₃ ratio. Under these conditions, the O₃ background is generally higher, and O₃ is also most sensitive to fire activities. As such, burning should be properly managed to not exceed the maximum daily burned area, which was determined by the O₃ level on the previous day and the RH.

Overall, the results of this study support smoke mitigation methods that take land management and public health concerns into account. The findings offered may boost confidence in land management programs' capacity to reduce smoke impact on ambient O₃. We uncover important factors that have a significant impact on prescribed fire air pollution, which might assist burn practitioners in developing ways to limit smoke exposure while expanding the rangeland treated with prescribed burning.

4.6 References

- Ahmadi, A., Daccache, A., Snyder, R. L., & Suvočarev, K. (2022). Meteorological driving forces of reference evapotranspiration and their trends in California. *Science of The Total Environment*, 849, 157823.
- Akinbile, D. S., & Liu, Z. (2022). Daily Burned Area Mapping for Prescribed Rangeland Burning in the Flint Hills Region Using MODIS Data. *Journal of the ASABE*, 0.
- Al-Hemoud, A., Al-Sudairawi, M., Al-Rashidi, M., Behbehani, W., & Al-Khayat, A. (2019). Temperature inversion and mixing height: Critical indicators for air pollution in hot arid climate. *Natural Hazards*, 97, 139-155.
- Baker, K. R., Woody, M. C., Tonnesen, G. S., Hutzell, W., Pye, H. O. T., Beaver, M. R., ... & Pierce, T. (2016). Contribution of regional-scale fire events to ozone and PM_{2.5} air quality estimated by photochemical modeling approaches. *Atmospheric Environment*, 140, 539-554.
- Barrero, M. A., Grimalt, J. O., & Cantón, L. (2006). Prediction of daily ozone concentration maxima in the urban atmosphere. *Chemometrics and intelligent laboratory systems*, 80(1), 67-76.
- Boian, C., & Kirchhoff, V. W. (2005). Surface ozone enhancements in the south of Brazil owing to large-scale air mass transport. *Atmospheric Environment*, 39(33), 6140-6146.
- Burling, I. R., Yokelson, R. J., Akagi, S. K., Urbanski, S. P., Wold, C. E., Griffith, D. W., ... & Weise, D. R. (2011). Airborne and ground-based measurements of the trace gases and particles emitted by prescribed fires in the United States. *Atmospheric Chemistry and Physics*, 11(23), 12197-12216.
- Businger, J. A., J. C. Wingard, Y. Isumi, and E. F. Bradley (1971). Flux-Profile Relationships in the Atmospheric Surface Layer. *J Atmos Sci*, 28:181-189.
- Buyse, C. E., Kaulfus, A., Nair, U., & Jaffe, D. A. (2019). Relationships between particulate matter, ozone, and nitrogen oxides during urban smoke events in the western US. *Environmental science & technology*, 53(21), 12519-12528.
- Camalier, L., Cox, W., & Dolwick, P. (2007). The effects of meteorology on ozone in urban areas and their use in assessing ozone trends. *Atmospheric environment*, 41(33), 7127-7137.
- Chen, T., & Guestrin, C. (2016). Xgboost: A scalable tree boosting system. In *Proceedings of the 22nd acm sigkdd international conference on knowledge discovery and data mining* (pp. 785-794).
- Davis, J. M., & Speckman, P. (1999). A model for predicting maximum and 8 h average ozone in Houston. *Atmospheric Environment*, 33(16), 2487-2500.
- Di Virgilio, G., Hart, M. A., & Jiang, N. (2018). Meteorological controls on atmospheric particulate pollution during hazard reduction burns. *Atmospheric Chemistry and Physics*, 18(9), 6585-6599.

Dokas, I., Statheropoulos, M. and Karma, S. 2007. Integration of field chemical data in initial risk assessment of forest fire smoke. *Sci. Total Environ.* 376:72-85.

Doll, D. C. (1991). Guideline for regulatory application of the Urban Airshed Model (No. PB-92-108760/XAB). Environmental Protection Agency, Research Triangle Park, NC (United States). Office of Air Quality Planning and Standards.

Duncan, B. N., Bey, I., Chin, M., Mickley, L. J., Fairlie, T. D., Martin, R. V., & Matsueda, H. (2003a). Indonesian wildfires of 1997: Impact on tropospheric chemistry. *Journal of Geophysical Research: Atmospheres*, 108(D15).

Duncan, B. N., Martin, R. V., Staudt, A. C., Yevich, R., & Logan, J. A. (2003b). Interannual and seasonal variability of biomass burning emissions constrained by satellite observations. *Journal of Geophysical Research: Atmospheres*, 108(D2), ACH-1.

Du, C., Liu, S., Yu, X., Li, X., Chen, C., Peng, Y., ... & Wang, F. (2013). Urban boundary layer height characteristics and relationship with particulate matter mass concentrations in Xi'an, central China. *Aerosol and Air Quality Research*, 13(5), 1598-1607.

EPA Victoria, Australia. 2012. Construction of input meteorological data files for AUSPLUME: Publication 1459.

Erickson III, D. J., Sulzberger, B., Zepp, R. G., & Austin, A. T. (2015). Effects of stratospheric ozone depletion, solar UV radiation, and climate change on biogeochemical cycling: interactions and feedbacks. *Photochemical & Photobiological Sciences*, 14(1), 127-148.

Feister, U., & Balzer, K. (1991). Surface ozone and meteorological predictors on a subregional scale. *Atmospheric Environment. Part A. General Topics*, 25(9), 1781-1790.

Finlayson-Pitts, B. J., & Pitts Jr, J. N. (1999). Chemistry of the upper and lower atmosphere: theory, experiments, and applications. Elsevier.

Forster, C., Wandering, U., Wotawa, G., James, P., Mattis, I., Althausen, D., ... & Stohl, A. (2001). Transport of boreal forest fire emissions from Canada to Europe. *Journal of Geophysical Research: Atmospheres*, 106(D19), 22887-22906.

Gardner, M. W., & Dorling, S. R. (2000). Statistical surface ozone models: an improved methodology to account for non-linear behaviour. *Atmospheric Environment*, 34(1), 21-34.

Gorai, A. K., Tchounwou, P. B., & Mitra, G. (2017). Spatial variation of ground level ozone concentrations and its health impacts in an urban area in India. *Aerosol and air quality research*, 17(4), 951.

Hansen, F. V. (1993). Surface roughness lengths. Adelphi, MD, USA: US Army Research Laboratory.

Heilman, W. E., Liu, Y., Urbanski, S., Kovalev, V., & Mickler, R. (2014). Wildland fire emissions, carbon, and climate: Plume rise, atmospheric transport, and chemistry processes. *Forest Ecology and Management*, 317, 70-79.

Hu, Y., Odman, M. T., Chang, M. E., Jackson, W., Lee, S., Edgerton, E. S., Baumann, K., & Russell, A. G. (2008). Simulation of air quality impacts from prescribed fires on an urban area. *Environmental Science & Technology*, 42(10), 3676-3682.

Jaffe, D., Chand, D., Hafner, W., Westerling, A., & Spracklen, D. (2008). Influence of fires on O₃ concentrations in the western US. *Environmental science & technology*, 42(16), 5885-5891.

Jorquera, H., Pérez, R., Cipriano, A., Espejo, A., Letelier, M. V., & Acuña, G. (1998). Forecasting ozone daily maximum levels at Santiago, Chile. *Atmospheric Environment*, 32(20), 3415-3424.

Kansas Mesonet. (2022). Historical weather. Kansas Mesonet. Retrieved from <https://mesonet.k-state.edu/weather/historical/>

KDHE. (2010). State of Kansas Flint Hills Smoke Management Plan. Kansas Department of Health and Environment. Division of Environment, Bureau of Air.

Kondo, Y., Morino, Y., Takegawa, N., Koike, M., Kita, K., Miyazaki, Y., Sachse, G.W., Vay, S.A., Avery, M.A., Flocke, F. and Weinheimer, A.J. (2004). Impacts of biomass burning in Southeast Asia on ozone and reactive nitrogen over the western Pacific in spring. *Journal of Geophysical Research: Atmospheres*, 109(D15).

Lai, L. W. (2015). Fine particulate matter events associated with synoptic weather patterns, long-range transport paths and mixing height in the Taipei Basin, Taiwan. *Atmospheric Environment*, 113, 50-62.

Langford, A. O., Senff, C. J., Alvarez, R. J., Aikin, K. C., Ahmadov, R., Angevine, W. M., ... & Zucker, M. L. (2023). Were Wildfires Responsible for the Unusually High Surface Ozone in Colorado During 2021?. *Journal of Geophysical Research: Atmospheres*, 128(12), e2022JD037700.

Lawrence, M. G. (2005). The relationship between relative humidity and the dewpoint temperature in moist air: A simple conversion and applications. *Bulletin of the American Meteorological Society*, 86(2), 225-234.

Lawson, S. J., Cope, M., Lee, S., Galbally, I. E., Ristovski, Z., & Keywood, M. D. (2017). Biomass burning at Cape Grim: exploring photochemistry using multi-scale modelling. *Atmospheric Chemistry and Physics*, 17(19), 11707-11726.

Li, M., Wang, T., Xie, M., Li, S., Zhuang, B., Chen, P., ... & Han, Y. (2018). Agricultural fire impacts on ozone photochemistry over the Yangtze River Delta region, East China. *Journal of Geophysical Research: Atmospheres*, 123(12), 6605-6623.

Li, M., Yu, S., Chen, X., Li, Z., Zhang, Y., Wang, L., Liu, W., Li, P., Lichtfouse, E., Rosenfeld, D. and Seinfeld, J.H.(2021). Large scale control of surface ozone by relative humidity observed during warm seasons in China. *Environmental Chemistry Letters*, 19, 3981-3989.

Liu, B., Tan, X., Jin, Y., Yu, W., & Li, C. (2021). Application of RR-XGBoost combined model in data calibration of micro air quality detector. *Scientific Reports*, 11(1), 15662.

Liu, Z., Liu, Y., Murphy, J. P., & Maghirang, R. (2017). Estimating Ambient Ozone Effect of Kansas Rangeland Burning with Receptor Modeling and Regression Analysis. *Environments*, 4(1), 14.

Liu, Z., Liu, Y., Murphy, J. P., & Maghirang, R. (2018). Contributions of Kansas rangeland burning to ambient O₃: Analysis of data from 2001 to 2016. *Science of the Total Environment*, 618, 1024-1031.

Lundberg, S.M., Erion, G., Chen, H., DeGrave, A., Prutkin, J.M., Nair, B., Katz, R., Himmelfarb, J., Bansal, N. and Lee, S.I. (2019). Explainable AI for trees: From local explanations to global understanding. *arXiv preprint arXiv:1905.04610*.

Ma, J., Cheng, J. C., Xu, Z., Chen, K., Lin, C., & Jiang, F. (2020). Identification of the most influential areas for air pollution control using XGBoost and Grid Importance Rank. *Journal of Cleaner Production*, 274, 122835.

Manju Mohan, T.A. Siddiqui. 1998. Analysis of various schemes for the estimation of atmospheric stability classification. *Atmospheric Environment*, Volume 32, Issue 21.

Marufu, L., Dentener, F., Lelieveld, J., Andreae, M. O., & Helas, G. (2000). Photochemistry of the African troposphere: Influence of biomass-burning emissions. *Journal of Geophysical Research: Atmospheres*, 105(D11), 14513-14530.

Mason, S.A., Trentmann, J., Winterrath, T., Yokelson, R.J., Christian, T.J., Carlson, L.J., Warner, T.R., Wolfe, L.C. and Andreae, M.O., 2006. Intercomparison of two box models of the chemical evolution in biomass-burning smoke plumes. *Journal of atmospheric chemistry*, 55, pp.273-297.

McClure, C. D., & Jaffe, D. A. (2018). Investigation of high ozone events due to wildfire smoke in an urban area. *Atmospheric Environment*, 194, 146-157.

McKeen, S. A., Wotawa, G., Parrish, D. D., Holloway, J. S., Buhr, M. P., Hübler, G., ... & Meagher, J. F. (2002). Ozone production from Canadian wildfires during June and July of 1995. *Journal of Geophysical Research: Atmospheres*, 107(D14), ACH-7.

Mervis, J. (2015). GOP legislators choke on ozone standards. *Science* 349(6254):1268.

Neu, U., Künzle, T., & Wanner, H. (1994). On the relation between ozone storage in the residual layer and daily variation in near-surface ozone concentration—A case study. *Boundary-Layer Meteorology*, 69, 221-247.

Nikolov, N. Impact of Wildland Fires and Prescribed Burns on Ground Level Ozone Concentration.

Pope, R. J., Butt, E. W., Chipperfield, M. P., Doherty, R. M., Fenech, S., Schmidt, A., Arnold, S.R. & Savage, N. H. (2016). The impact of synoptic weather on UK surface ozone and implications for premature mortality. *Environmental Research Letters*, 11(12), 124004.

Reid, C. E., Brauer, M., Johnston, F. H., Jerrett, M., Balme, J. R., & Elliott, C. T. (2016). Critical review of health impacts of wildfire smoke exposure. *Environmental health perspectives*, 124(9), 1334-1343.

Robeson, S. M., & Steyn, D. G. (1990). Evaluation and comparison of statistical forecast models for daily maximum ozone concentrations. *Atmospheric Environment. Part B. Urban Atmosphere*, 24(2), 303-312.

Seibert, P., Beyrich, F., Gryning, S. E., Joffre, S., Rasmussen, A., & Tercier, P. (2000). Review and intercomparison of operational methods for the determination of the mixing height. *Atmospheric environment*, 34(7), 1001-1027.

Seinfeld, J. H., & Pandis, S. N. (2016). *Atmospheric chemistry and physics: from air pollution to climate change*. John Wiley & Sons.

Shan, W., Yin, Y., Lu, H., & Liang, S. (2009). A meteorological analysis of ozone episodes using HYSPLIT model and surface data. *Atmospheric Research*, 93(4), 767-776.

Stevens, R., & Treadwell, M. (2022). Prescribed burn associations: US landowners getting fire on the ground. *Global Application of Prescribed Fire*, 176.

Stirnberg, R., Cermak, J., Kotthaus, S., Haeffelin, M., Andersen, H., Fuchs, J., Kim, M., Petit, J.E., Favez, O., 2021. Meteorology-driven variability of air pollution PM1 revealed with explainable machine learning. *Atmos. Chem. Phys.* 21, 3919–3948. <https://doi.org/10.5194/acp-21-3919-2021>.

Thompson, M. L., Reynolds, J., Cox, L. H., Guttorp, P., & Sampson, P. D. (2001). A review of statistical methods for the meteorological adjustment of tropospheric ozone. *Atmospheric environment*, 35(3), 617-630.

Tu, J., Xia, Z. G., Wang, H., & Li, W. (2007). Temporal variations in surface ozone and its precursors and meteorological effects at an urban site in China. *Atmospheric Research*, 85(3-4), 310-337.

United States Environmental Protection Agency (2012). Clean air act: Title I—Air pollution prevention and control. Available at <http://epa.gov/oar/caa/title1.html>.

VanCuren, R. T., & Gustin, M. S. (2015). Identification of sources contributing to PM2.5 and ozone at elevated sites in the western US by receptor analysis: Lassen Volcanic National Park, California, and Great Basin National Park, Nevada. *Science of the Total Environment*, 530, 505-518.

Visualcrossing. (2022). Total Weather Data. Retrieved from <https://www.visualcrossing.com/weather-data>

Whitehill, A. R., George, I., Long, R., Baker, K. R., & Landis, M. (2019). Volatile organic compound emissions from prescribed burning in tallgrass prairie ecosystems. *Atmosphere*, 10(8), 464.

World Health Organization. (2005). Who air quality guidelines for particulate matter, ozone, nitrogen dioxide and sulfur dioxide—global update (who/sde/phe/oeh/06.02), World Health Organization. Air Quality Guidelines-Global Update.

WHO 2014 Ambient (outdoor) air quality and health (www.who.int/mediacentre/factsheets/fs313/en/)

Yan, Y., Pozzer, A., Ojha, N., Lin, J., & Lelieveld, J. (2018). Analysis of European ozone trends in the period 1995–2014. *Atmospheric Chemistry and Physics*, 18(8), 5589-5605.

Zhang, L., Jacob, D. J., Yue, X., Downey, N. V., Wood, D. A., & Blewitt, D. (2014). Sources contributing to background surface ozone in the US Intermountain West. *Atmospheric Chemistry and Physics*, 14(11), 5295-5309.

Chapter 5 - Conclusion and Future Research Directions

5.1 Conclusions

This chapter includes a summary of key conclusions and recommendations for future research directions.

This dissertation examines the impact and implications of prescribed fires in the Flint Hills region. Focusing on the 17-county in the Kansas and Oklahoma, this dissertation applied machine learning techniques and regression models to identify optimum weather conditions and develop decision tool to reduce smoke impact on ambient ozone for better management of prescribed burning in the region. The research objectives of this dissertation are:

1. Identify the spatial and temporal distributions and patterns of daily prescribed fire activities in the Flint Hills region using the combination of MODIS resolution imagery and standard active fire data.
2. Characterize meteorological parameter sensitivities connected to daily fire activities and propose optimum weather conditions for mitigating smoke pollution associated with prescribed fires.
3. Develop regression models to simulate O₃ contributions from prescribed burning in order to assist collaborative management of prescribed fires and reduce smoke impact on ambient O₃.

5.1.1 Key Conclusions and Limitations

Key Conclusions and Limitations for Research Objective 1

- Both the annual burned percentage and the average sizes of one active fire varied at different part of the Flint Hills region. In the central part of the Flint Hills region, landowners tend to burn more frequently, and the fire sizes were generally larger. In the central part of the Flint Hills region, the annual average burned percentage ranged from 33% to 52%; while in the Southern part and at the edge of the Flint Hills region the annual average burned percentage ranged from 11% to 25%.
- The daily burned area generally started to increase rapidly since the end of March and peaked on April 14th. Fire activities were highly concentrated in a few days in April that had desired weather and fuel conditions. In average, the burned area from fires between March 31st and April 30th accounted for 86% of the total burned area in the whole burning season. The maximum daily burned area in the Flint Hills region was around 0.5 million acres.
- Landowners prefer days with strong sunshine and moderate temperatures for prescribed burning. On average, preferred weather conditions by landowners occur only around 10 days during one spring burning season. Despite this, not all these days witness significant fire activities. If efforts were made to evenly distribute fire activities across all 10 days with preferred weather conditions, it could help mitigate smoke impact.
- O₃ concentrations typically increases between March 8th and May 8th, in response to rising temperatures. All O₃ levels exceeding 70 ppb were recorded in April, coinciding with intensive fires in the Flint Hills region. The concentration of O₃ was influenced by

factors such as daily burned area, temperature, solar radiation, relative humidity (RH), and wind speed.

- Correlation between MODIS and active fire products may not accurately estimate daily burned areas when the satellite images were cloudy. Mohler (2011) reported that active fire products detected only up to 63% of burned areas. The new GOES-R satellite series, launched in November 2016, could revolutionize burn scar monitoring (Weidong et al., 2021), but its data are available only from 2017 onwards, limiting coverage for this study's 17-year period. Future research should focus on satellite monitoring product that can detect burned area mapping in tallgrass prairie with improve accuracy.
- The classification technique used in this study employed different training data for each day to prevent cloudy areas from being classified as burned areas which make the process tedious and time consuming. Future research should investigate automating this classification technique to produce timely burned area maps and minimize human labor costs.

Key Conclusions and Limitations for Research Objective 2

- The three most important weather variables that affected the daily burned area were solar radiation, cloud cover, and relative humidity (RH). The data indicated that, when weather conditions were preferred for burning, many landowners chose to burn at lower cloud cover, higher solar radiation, lower RH, higher temperature, and lower wind velocity. About 94% of all the heavy-fire days had cloud cover <30%, which were not in the KDHE recommended range of optimum burning conditions (30~50%).

- Results showed that less cloud cover demonstrated superior predictive power in landowner decisions for prescribed burning and largely resulted in elevated ambient ozone (O_3). The analysis's results revealed that 62% of the total burned area occurred with a cloud cover of less than 10⁺%. Conducting burns with a cloud cover of less than 10⁺% can lead to higher fire related O_3 concentrations.
- Land management programs can play an important role in mitigating smoke pollution in the Flint Hills region. However, the safety of the prescribed burning procedure is more important to landowners than the environmental impact of smoke pollution. Landowners typically conduct fewer prescribed burns on cloudy days with anticipated rain. This preference may be due to the beneficial effects of moisture on fuel and soil, which can reduce fire intensity and enhance control, to mitigate the risk of uncontrolled burns.
- The proposed optimum weather conditions, which are estimated to occur around six days per burning season, suggest a range of cloud cover from 10⁺% to 55%. This is a significant improvement to one day associated with current KDHE guidelines. If landowners were to opt for burning under these proposed optimal weather conditions, it has the potential to decrease the probability of O_3 exceedance from 35% to as low as 9% on days with intensive fire activity.
- Historical meteorological data from Riley County due to availability of long record of observations, were used to determine the fire weather pattern trend in the Flint Hills region. Additional meteorological data from Marion and Wabaunsee were analyzed at county level. We could not access long term meteorological data for other counties. Future work should focus on using accurate long term meteorological data from other

counties in the Flint Hills regions to identify preferred weather patterns for prescribed burning at county level.

- Additional work should also focus on identifying key management factors that affect the timing and frequency of prescribed rangeland burning in the Flint Hills region through survey and interviews among land managers and extension agents. The results from such addition effort will be used to compare the historical daily burned area retrieved from satellite data for potential discrepancy and explanations.

-

Key Conclusions and Limitations for Research Objective 3

- The O₃ levels were very sensitive to the previous day's O₃, daily burned area, RH, and cloud cover. For every 0.1 million increase in daily burned hectares, maximum O₃ level rose by 9 ppb on average. The daily O₃ mixing ratio is less sensitive to fire activities under proposed optimum weather conditions for burning averaging 6 days in one spring burning season from March 8th to May 8th.
- Another recommended weather conditions that are suitable for burning are when cloud cover = 10~30%, and RH = 40~80%. Burning under these conditions will not likely result in O₃ exceedance if the O₃ level on the previous day is at the average level (50.5 ± 10.9 ppb) or less. On average, there were 11 days available in one spring burning season from March 8th to May 8th, with these conditions and other weather variables also in the acceptable ranges for burning. However, when cloud cover = 10~30%, and RH = 20~40%, it is permissible to burn but heavy fire is not recommended.
- When cloud cover = 0~10%, the O₃ background is generally higher, and O₃ is also most sensitive to fire activities, especially when RH is also low. Under these conditions,

burning should be managed not to exceed the maximum daily burned area, which can be determined by the O₃ level on the previous day and the RH.

- Future work should prioritize enhancing modeling analysis of the total daily burned area within a specified radius from O₃ monitoring sites and its effect on daily O₃ mixing ratios. By improving model performance, accurate estimate of the maximum allowable daily burned area within a certain distance from O₃ monitoring sites can be achieved with greater confidence and reduced uncertainties to prevent O₃ exceedance.
- Mixing height plays crucial in determining both tropospheric O₃ mixing ratio and the dispersion of air pollution in the atmosphere. It could be calculated by employing various meteorological data and atmospheric modeling techniques. Future work should focus on accurate calculations of mixing height in Flint Hills region as the method applied in this work might not accurate.

5.2 Recommendations for future research directions

Complete prescribed burn data and modeling

Prescribed burns are typically conducted on a small scale to maintain control, and the use of satellite-derived data can have considerable uncertainty to estimate the burned area (Moulliot, 2014). Estimation of biomass burning emissions for air quality forecast and development of land and air shed management policies requires burned area data (Burling et al., 2011). Improved prescribed daily burned data in the Flint Hills region would enhance the management of prescribed fires and understanding of how to reduce the smoke pollution impact on ambient air quality. It is important to obtain complete daily data on prescribed burning activities through burn permit and updated ground truth data from field research to develop accurate regression models to simulate

O₃ contributions from prescribed burning. Current satellite-derived products are limited in their ability to estimate the burned areas of prescribed fires (Huang et al., 2018). The availability of accurate daily prescribed burn permit record data will play a pivotal role in improving the mapping of daily burned area in the Flint Hills region. According to Huang et al. (2018), higher confidence is placed in permit records due to the limitations of satellite-derived products and the data gaps caused by cloudy days. However, high spatial and temporal resolution satellite-derived products to improve accuracy in detecting prescribed fires is needed to address the deficiencies and performance of current fire detecting satellite products. Satellite data can supplement existing fire data and assist with fire management initiatives (Morgan et al., 2001). The new GOES-R satellite, launched in November 2016, was designed to improve the detection of active fire activity by providing higher temporal resolution; therefore, it could be a better-quality product for monitoring prescribed fire burn scars after fire event (Xu et al., 2021). In addition, to improve and evaluate the performance of the O₃ regression model, further accurate measurements of weather variables, soil properties, mixing heights, and pollutant concentrations are also needed. The integration of modeling and measurement endeavors would prove valuable in evaluating the capacity of emerging high-resolution satellite products to detect low-intensity and short-duration prescribed fires (Afrin, 2021).

Development of risk index to assist planning of prescribed fires

Current practices of prescribed burning are mainly based on experience. Landowners need more tools to identify possible improvements in prescription parameters to burn with optimal conditions and timing for improved burn efficiency and reduced smoke emissions. Burning at the right day with appropriate conditions is not only critical for fire safety but also the most practical way for reducing smoke impact. An innovative data-driven strategy to evaluating fire and

environmental risks under varied weather and fuel conditions should be developed to help landowners make sensible decisions about when to burn. An indexing method can help simplify complex scientific principles of theoretical and empirical models during the development of a tool to aid decision making (Koutsomarkos et al., 2021). Fire and environmental risk index should be developed to assist planning of prescribed fires to improve fire safety and minimize fire-associated risks through synthesis analysis fire danger indices from methods in the literature (Sharpley et al., 2009; Howard et al., 2020; Fujioka et al., 2008). Analyses focused on the associations between prescribed fire risk index and pollutants are a pressing research need, particularly for region like Flint Hills with intense prescribed burning activity.

5.3 Practical Implications

Prescribed burning is the dominant rangeland management tool used to sustain the tallgrass prairie ecosystem in the Flint Hills region. Rangeland prescribed fires are conducted during the spring season comprising of short-duration prescribed fires with low intensity fires to consume surface fuels. Landowners use fires as economically efficient practices on rangeland to maintain favorable grazing and enhance livestock performance. Despite the crucial role fire plays in the sustainability of the environmental system, the Flint Hills residents experience local smoke impacts during prescribed fire season by contributing to contributing to O₃ exceedances and have affected several states downwind of Kansas. Continuous public acceptance of prescribed burning relies on following best practices to manage smoke impact of rangeland burning.

The O₃ exceedance may have been prevented if most of the prescribed burning had occurred on the right timing. Prescribed fire management and timing are hindered by the dearth of scientific knowledge among many landowners on the effects of smoke and how weather and fire behavior interact. To prevent ambient O₃ standard exceedance, further smoke management

measures are required. Land managers can benefit from the comprehensive guidelines produced by this research by using them to better plan their burning operations and to continue burning in a way that minimize adverse air quality. The goal of this initiative is to mitigate smoke effects as well as expand land management capabilities by enabling more burning under favorable conditions. Ultimately, this will result in safer, more efficient, and more sustainable prescribed burning.

The impact of smoke on air quality has been connected to prescribed rangeland fire. This research will increase public and land managers' understanding of smoke's impact from prescribed rangeland burning, promoting confidence in engaging in conversations and effectively collaborating to reduce smoke's social impact.

5.4 References

- Afrin, S. (2021). Evaluating the Impacts of Prescribed Fire on Air Quality and Public Health in the Southeastern US. North Carolina State University.
- Fujioka, F. M., Gill, A. M., Viegas, D. X., & Wotton, B. M. (2008). Fire danger and fire behavior modeling systems in Australia, Europe, and North America. *Developments in Environmental Science*, 8, 471-497.
- Howard, T., Burrows, N., Smith, T., Daniel, G., & McCaw, L. (2020). A framework for prioritising prescribed burning on public land in Western Australia. *International journal of wildland fire*, 29(5), 314-325.
- Huang, R., Zhang, X., Chan, D., Kondragunta, S., Russell, A. G., & Odman, M. T. (2018). Burned area comparisons between prescribed burning permits in southeastern United States and two satellite-derived products. *Journal of Geophysical Research: Atmospheres*, 123(9), 4746-4757.
- Koutsomarkos, V., Rush, D., Jomaas, G., & Law, A. (2021). Tactics, objectives, and choices: Building a fire risk index. *Fire safety journal*, 119, 103241.
- Mohler, R. L. (2011). Multi-scale burned area mapping in tallgrass prairie using in SITU spectrometry and satellite imagery (Doctoral dissertation, Kansas State University).

- Morgan, P.; Hardy, C.C.; Swetnam, T.W.; Rollins, M.G.; Long, D.G. 2001. Mapping fire regimes across time and space: Understanding coarse and fine-scale fire patterns. *Int. J. Wildl. Fire*, 10, 329–342.
- Mouillot, F., Schultz, M. G., Yue, C., Cadule, P., Tansey, K., Ciais, P., & Chuvieco, E. (2014). Ten years of global burned area products from spaceborne remote sensing—A review: Analysis of user needs and recommendations for future developments. *International Journal of Applied Earth Observation and Geoinformation*, 26, 64-79.
- Sharples, J. J., McRae, R. H., Weber, R. O., & Gill, A. M. (2009). A simple index for assessing fire danger rating. *Environmental Modelling & Software*, 24(6), 764-774.
- Xu, W., Wooster, M. J., He, J., & Zhang, T. (2021). Improvements in high-temporal resolution active fire detection and FRP retrieval over the Americas using GOES-16 ABI with the geostationary Fire Thermal Anomaly (FTA) algorithm. *Science of Remote Sensing*, 3, 100016.
- Weidong Xu, Martin J. Wooster, Jiangping He, Tianran Zhang. 2021.Improvements in high-temporal resolution active fire detection and FRP retrieval over the Americas using GOES-16 ABI with the geostationary Fire Thermal Anomaly (FTA) algorithm, *Science of Remote Sensing*, Volume 3, 100016, ISSN 2666-0172.<https://doi.org/10.1016/j.srs.2021.100016>.

Appendix A : Additional materials for Chapter 2

Appendix A: Analysis Procedures for MODIS Image on ENVI, R and ArcGIS

Step 1: Download MODIS data

a.) First Method:

(i) Download MODIS images:

Download the two files for Aqua (MYD) and Terra (MOD) for each day through:

<https://e4ftl01.cr.usgs.gov/MOLT/MOD09GQ.006/>

<https://e4ftl01.cr.usgs.gov/MOLA/MYD09GQ.006/>

Aqua: MYD09GQ.A2012037.h10v05.006.2012039051533.hdf

Terra: MOD09GQ.A2012037.h10v05.006.2012039053119.hdf

(ii) Reprojection of MODIS data for Flint Hills, Kansas

Download “MODIS Reprojection Tool” through:

<https://lpdaac.usgs.gov/tools>

In the MODIS reprojection tool, enter the following information and run the tool:

- Latitude and longitude (for Flint Hills):
UL: 40.124 (latitude), -97.516 (longitude)
LR: 36.05 (latitude), -95.259 (longitude)
- Output File: MYDxx.tif
- Output File Type: GEOTIFF
- Resampling Type: Nearest Neighbor
- Output Projection Type: UTM
- Datum: WGS84
- UTM Zone: 14
- Output Pixel Size: 250m
- Click “Run”
- Save the file in a folder for step 2

Hdf-Eos to GIS Conversion Tool (HEG) - Version 2.15

File Tool Help

Input File: sktop\MOD09GQ.A2000093.h10v05

Objects: MODIS_Grid_2D

Fields:

- num_observations
- QC_250m_1
- obscov_1
- iobs_res_1
- orbit_pnt_1
- granule_pnt_1

Selected:

- sur_refl_b01_1
- sur_refl_b02_1

Band: Dim 4: Dim 5: Dim 6:

Spatial Subset: Lat-Long

Field Image for Subset Selection

Default Corners

	Latitude	Longitude
UL Corner:	40.124	-97.516
LR Corner:	36.05	-95.259

View geolocation

Object Info:

Field Name: num_observations
Data Type: INT8
Num Dims: 2

Field Name: sur_refl_b01_1
Data Type: INT16
Num Dims: 2

Field Name: sur_refl_b02_1

Output File Name:

ilade\Documents\MODIS_TIF

Browse...

Output File Type: GeoTIFF

Resampling Type: Nearest Neighbor

Projection: UTM

Subsample? ☐ Yes ☒ No

Ellipsoid/Proj Params

SP Zone

Pixel Sizes Unit: Meters

Pixel Size X: 250

Pixel Size Y: 250

Accept

Accepted List

Remove Save Clear

Run Batch Run

HEG Projection Parameters

Lon/Z	Lat/Z	
0.0	0.0	disabled
disabled	disabled	disabled
0.0	0.0	0.0
disabled	disabled	disabled
0.0	0.0	0.0
disabled	disabled	disabled
0.0	0.0	0.0
disabled	disabled	disabled
0.0	0.0	0.0

NOTE: All lats/lons must be in DecDeg format

UTM Zone: 14 Ellipsoid: WG S84

OK Cancel

b.) Second Method:

Download and Reprojection of MODIS data using MODISStp

MODISStp specifically developed in the R language was used to download acquired MODIS images. We installed an open source the third-party tool, Geospatial Data Abstraction Library (GDAL) as part of the requirement. The source code was downloaded at the GitHub repository <https://github.com/lbusett/MODISStp> .

In the MODISStp Graphical User Interface (GUI), enter the following information and run the tool:

- Product: 250m MYD09GQ(Terra) or MOD09GQ(Aqua)
- Starting date (choose) and Ending date (choose)
- Required MODIS Tiles:
Horizontal: Start (10), End (10)
Vertical: Start (5), End (5)
- Output Projection: Native
- Output Resolution: Native
- Resampling Method: near
- Output Options:
Output Format: GTiff
Compression: No
Save Time Series as: tick R rasterStack
- Original MODIS Layers:
Tick: 250m Surface Reflectance Band 1 (620 – 670nm) and 250m Surface Reflectance Band 2 (841 – 876nm)
- Quality Indicators:
Tick: band 1 data quality four-bit range and band 1 data quality four-bit range
- Click OK and save the data in separate folder

Select Processing Layers - Surf_Ref_Daily_250m (M*D09GQ) vers. 6

Original MODIS Layers	Quality Indicators	Indices
☐ Number of observations within the pixel ☒ 250m Surface Reflectance Band 1 (620-670 nm) ☒ 250m Surface Reflectance Band 2 (841-876 nm) ☐ 250m Reflectance Band Quality ☐ percentage of the grid cell area covered by the observation ☐ Observation number ☐ Orbit pointer ☐ Granule pointer	☐ MODLAND QA bits ☐ cloud state ☒ band 1 data quality four bit range ☒ band 2 data quality four bit range ☐ atmospheric correction performed ☐ adjacency correction performed	☐ NDVI (NIR-Red)/(NIR+Red) ☐ Simple Ratio (NIR/Red) ☐ SAVI (NIR-Red)/(NIR+Red+0.5)*(1+0.5)
?	?	?

Product Info - [www \(Surf_Ref_Daily_250m \(M*D09GQ\) vers. 6\)](#)

OK Cancel

Select Processing Layers - Surf_Ref_Daily_250m (M*D09GQ) vers. 6

Original MODIS Layers	Quality Indicators	Indices
☐ Number of observations within the pixel ☒ 250m Surface Reflectance Band 1 (620-670 nm) ☒ 250m Surface Reflectance Band 2 (841-876 nm) ☐ 250m Reflectance Band Quality ☐ percentage of the grid cell area covered by the observation ☐ Observation number ☐ Orbit pointer ☐ Granule pointer	☐ MODLAND QA bits ☐ cloud state ☒ band 1 data quality four bit range ☒ band 2 data quality four bit range ☐ atmospheric correction performed ☐ adjacency correction performed	☐ NDVI (NIR-Red)/(NIR+Red) ☐ Simple Ratio (NIR/Red) ☐ SAVI (NIR-Red)/(NIR+Red+0.5)*(1+0.5)
?	?	?

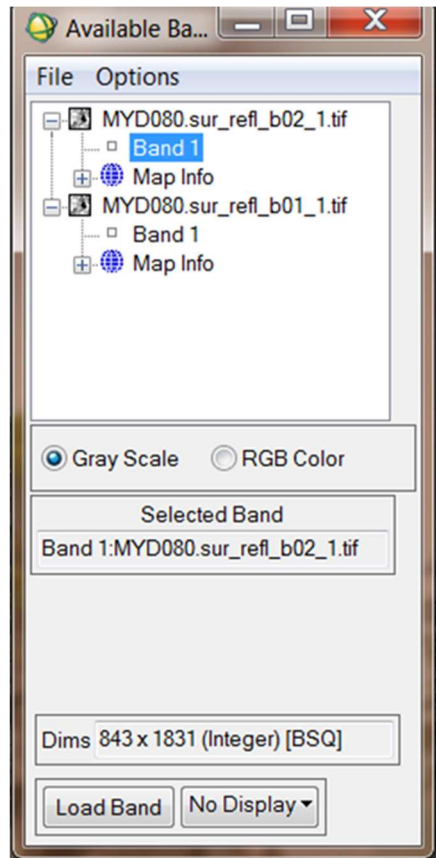
Product Info - [www \(Surf_Ref_Daily_250m \(M*D09GQ\) vers. 6\)](#)

OK Cancel

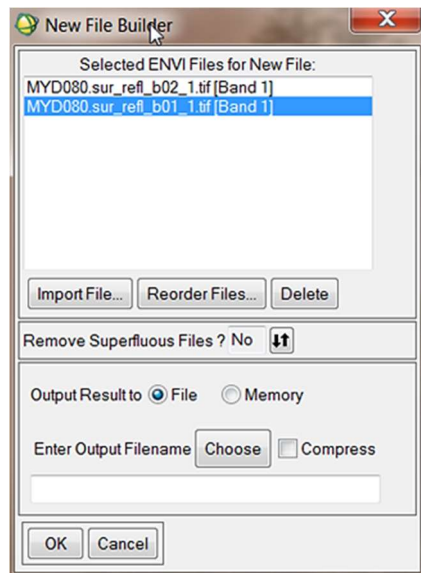
Note: The two methods could be applied for downloading MODIS data, but we opted for the second method as it is automated, faster, and minimizes human labor costs.

Step 2: Image processing on ENVI Classic 5.4 (64-bit)

- a.) Load and combine two TIFF files (MODIS data downloaded) on ENVI
 - File > Open Image Files to load two TIFF files

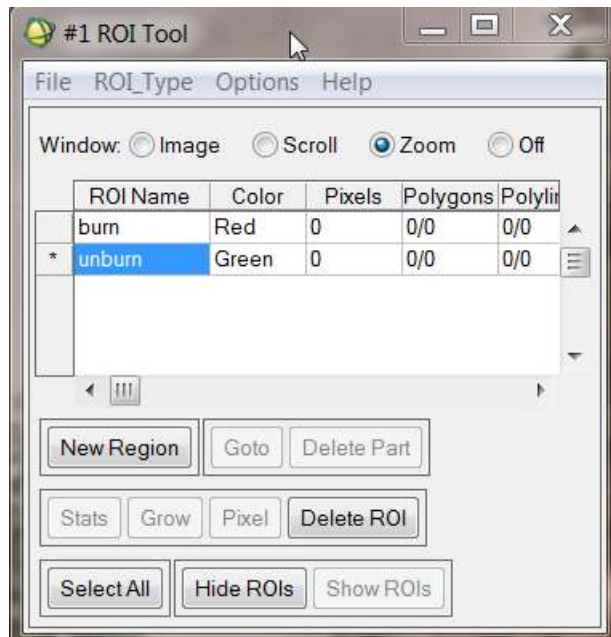


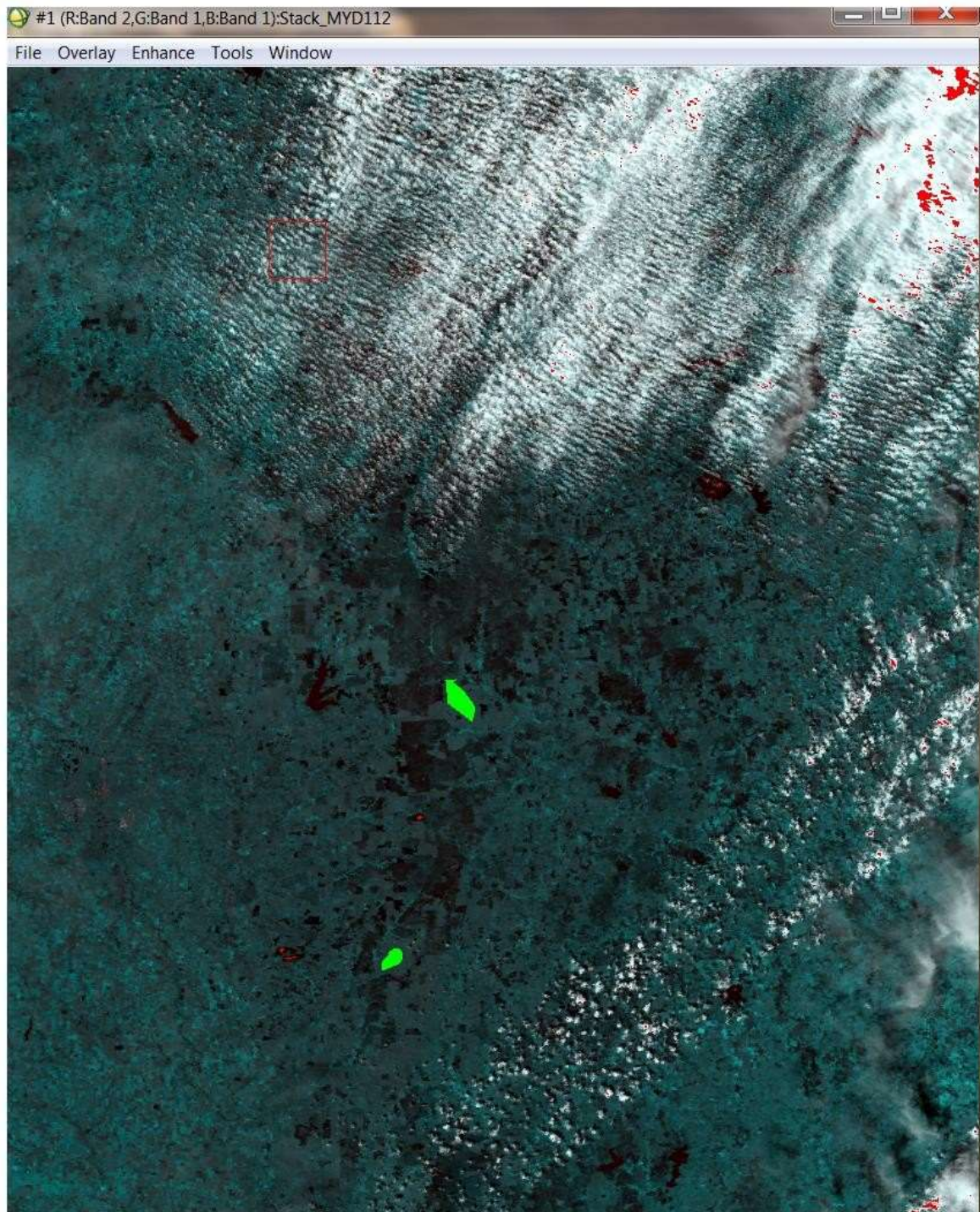
- Combine two bands on Envi: File > Save File As > ENVI Standard > Import file > Choose



- b.) Load stacked image by selecting RGB: R (2), G (1), B (1)

- d.) Pick training data for classification
- Tools > Region of Interest > ROI Tool
 - Pick burned (dark) and unburned (pink) pixels in Zoom Window

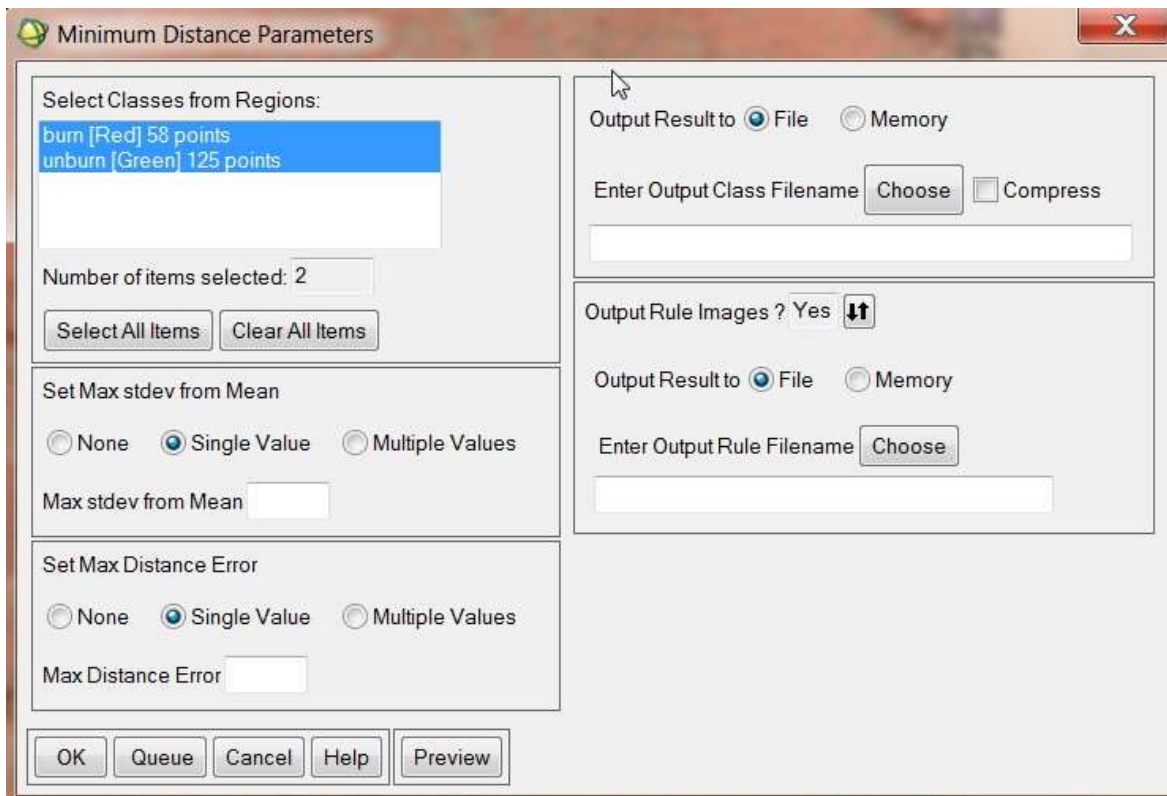
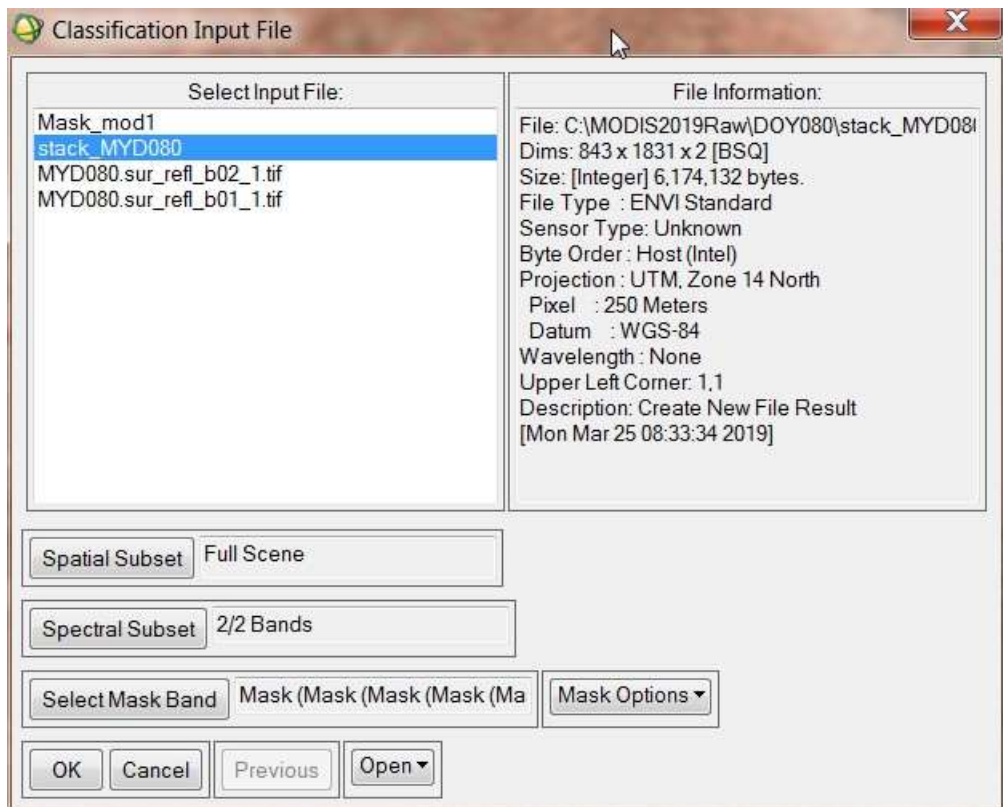


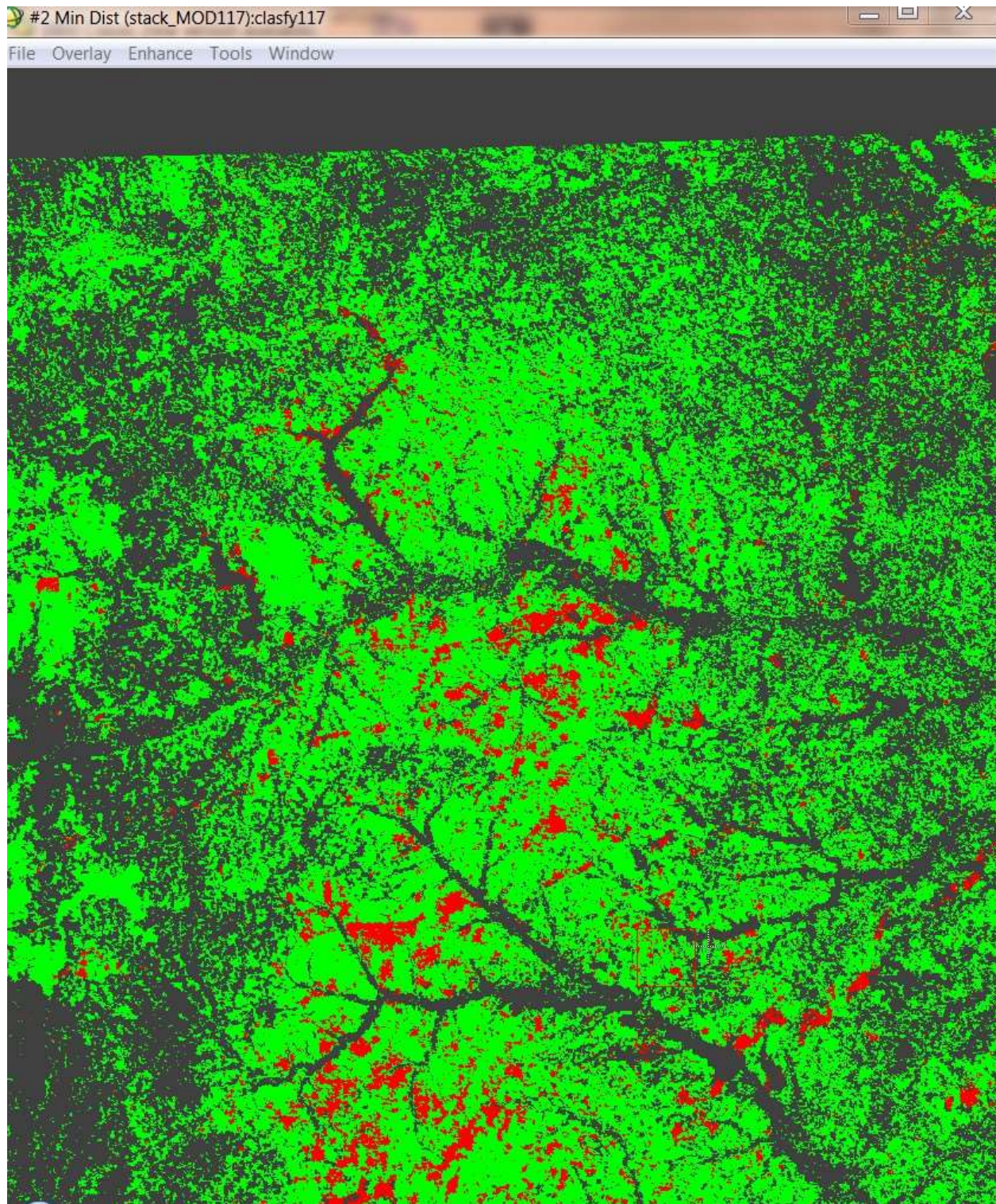


Training data picking. Red (burn scar) and green (unburn areas)

e.) Classification

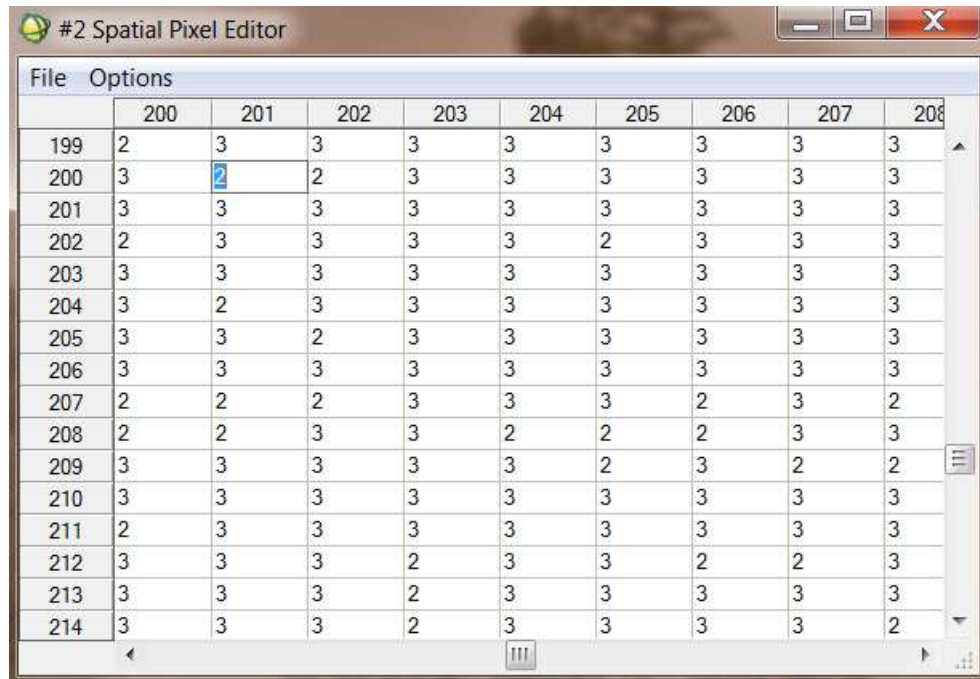
- Classification> Supervised> Minimum Distance





Classified image. Red is burned areas.

- f.) Edit classified image for wrongly classified pixels through “Spatial Pixel Editor” tool
- Tools > Spatial Pixel Editor



The screenshot shows the "#2 Spatial Pixel Editor" window. It contains a grid with 10 columns labeled 200 through 208 and 10 rows labeled 199 through 214. The grid contains numerical values representing pixel classifications. The value '2' is highlighted in the cell at row 200, column 201.

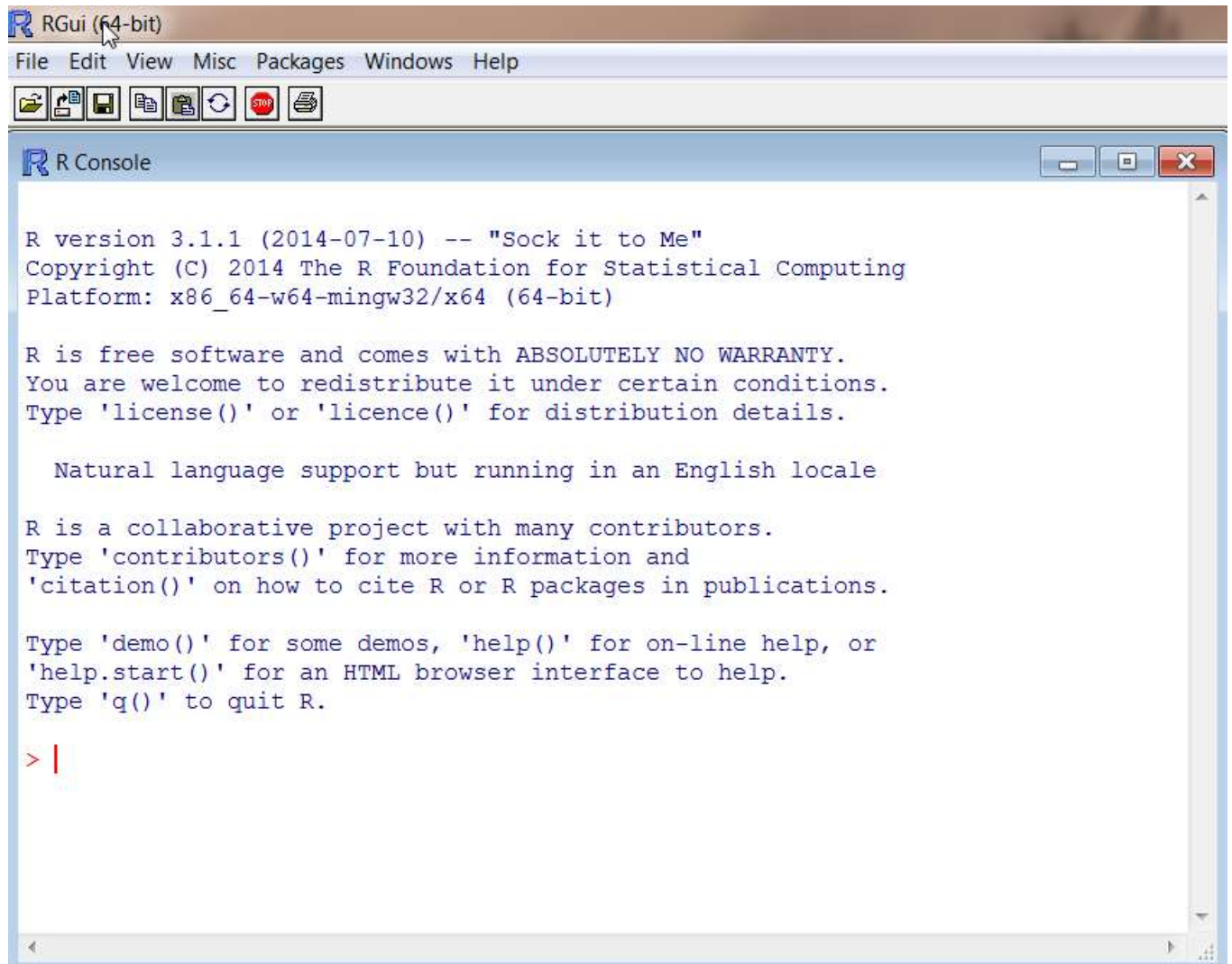
	200	201	202	203	204	205	206	207	208
199	2	3	3	3	3	3	3	3	3
200	3	2	2	3	3	3	3	3	3
201	3	3	3	3	3	3	3	3	3
202	2	3	3	3	3	2	3	3	3
203	3	3	3	3	3	3	3	3	3
204	3	2	3	3	3	3	3	3	3
205	3	3	2	3	3	3	3	3	3
206	3	3	3	3	3	3	3	3	3
207	2	2	2	3	3	3	2	3	2
208	2	2	3	3	2	2	2	3	3
209	3	3	3	3	3	2	3	2	2
210	3	3	3	3	3	3	3	3	3
211	2	3	3	3	3	3	3	3	3
212	3	3	3	2	3	3	2	2	3
213	3	3	3	2	3	3	3	3	3
214	3	3	3	2	3	3	3	3	2

- g.) After editing, export classified image to TIFF file
- File > Save File As > TIFF/Geo TIFF

Step 3: Work on R program (this step also can be done with ArcGIS)

- Install R program in a folder “r_modis”
- Save Flint Hills shape file (Kansas county shp file) to the folder “r_modis”
- Save exported TIFF files from step 2 to the folder “r_modis”

d.) Open R GUI window



e.) Open the word document below with R code “modis.r”. Copy the code and paste it to R GUI window

```

library(raster)
library(rgdal)
library(date)
#library(gplots)

cnty <- c
("kansas,butler","kansas,chase","kansas,chautauqua","kansas,coffe
y","kansas,cowley","kansas,elk","kansas,geary","kansas,greenwood"
,"kansas,lyon","kansas,marion","kansas,morris","kansas,osage","ka
nsas,pottawatomie","kansas,riley","kansas,wabaunsee","kansas,wils
on","kansas,woodson","oklahoma,nowata","oklahoma,osage","oklahoma
,washington","oklahoma,kay")
#cnty <- sort(cnty) #a sort for yao
.simpleCap <- function(x) {
  s <- strsplit(x, ",")[[1]]
  paste(toupper(substring(s, 1, 1)), substring(s, 2),
        sep = "", collapse = " ")
}
shape_cnty <- readOGR("C:\\r_modis","cnty_new")
shape_cnty <- spTransform(shape_cnty,CRS("+proj=utm +zone=14
+datum=WGS84"))

#pdf(paste("C:/r_modis/out/acres.pdf",sep=""), width=8.5, height=
11)

```

f.) After the running of R program, the individual TIFF files for Flint Hills counties will be saved in the folder “r_modis”>”out”>“rasters”

g.) The burning acreage for individual counties is saved in a spreadsheet “acres.csv” which is in “out” folder

The script to calculate burned acres using R:

```

library(raster)
library(rgdal)
library(date)
#library(gplots)

cnty <-
c("kansas,butler","kansas,chase","kansas,chautauqua","kansas,coffey","kansas,cowley","kansas,
elk","kansas,geary","kansas,greenwood","kansas,lyon","kansas,marion","kansas,morris","kansas,

```

```

,osage","kansas,pottawatomie","kansas,riley","kansas,wabaunsee","kansas,wilson","kansas,wood
son","oklahoma,nowata","oklahoma,osage","oklahoma,washington","oklahoma,kay")
#cnty <- sort(cnty) #a sort for yao
.simpleCap <- function(x) {
  s <- strsplit(x, ",")[[1]]
  paste(toupper(substring(s, 1, 1)), substring(s, 2),
    sep = "", collapse = " ")
}
shape_cnty <- readOGR("C:\\r_modis","cnty_new")
shape_cnty <- spTransform(shape_cnty,CRS("+proj=utm +zone=14 +datum=WGS84"))

#pdf(paste("C:/r_modis/out/acres.pdf",sep=""), width=8.5, height=11)
files <- list.files(path=paste("C:\\r_modis",sep=""), pattern="tif")
ans <- matrix(nrow=length(cnty), ncol=length(files))
rownames(ans) <- cnty
colnames(ans) <- files

### this code does the entire area and creates tif files
pdf(paste("C:/r_modis/out/acres.pdf",sep=""), width=8.5, height=11)
i <- 1
mask3 <- raster(paste("C:\\r_modis\\",files[i],sep=""))
tmp1 <- mask3
tmp1[tmp1!=1] <- 0
tmp1 <- mask(tmp1,shape_cnty)
writeRaster(tmp1, filename=paste("C:/r_modis/out/rasters/",files[i],".tif",sep=""),
format="GTiff",datatype='INT1U',overwrite=TRUE)
plot(tmp1,zlim=c(1,1),col='red',legend=FALSE,main=paste("Burns as
of",date.mmddyy(as.numeric(substr(files[i],4,6))+2008)))
plot(shape_cnty, add=TRUE)
for (j in 1:length(cnty)) {

```

```

ks_poly_utm <- shape_cnty[paste(shape_cnty$STATE_NAME,shape_cnty$NAME)==
.simpleCap(cnty[j]),]
text(mean(c(extent(ks_poly_utm)[1],extent(ks_poly_utm)[2])),mean(c(extent(ks_poly_utm)[3],e
xtent(ks_poly_utm)[4])),ks_poly_utm$NAME,cex=0.6)
}
for (i in 2:length(files)) {
mask3 <- raster(paste("C:\\r_modis\\",files[i],sep=""))
tmp <- mask3
tmp[tmp!=1] <- 0
tmp <- mask(tmp,shape_cnty)
tmp1 <- tmp+tmp1
tmp1[tmp1!=0] <- 1
writeRaster(tmp1, filename=paste("C:/r_modis/out/rasters/",files[i],".tif",sep=""),
format="GTiff",datatype='INT1U',overwrite=TRUE)
plot(tmp1,zlim=c(1,1),col='red',legend=FALSE,main=paste("Burns as
of",date.mmddyy(as.numeric(substr(files[i],4,6))+2008)))
plot(shape_cnty, add=TRUE)
for (j in 1:length(cnty)) {
ks_poly_utm <- shape_cnty[paste(shape_cnty$STATE_NAME,shape_cnty$NAME)==
.simpleCap(cnty[j]),]
text(mean(c(extent(ks_poly_utm)[1],extent(ks_poly_utm)[2])),mean(c(extent(ks_poly_utm)[3],e
xtent(ks_poly_utm)[4])),ks_poly_utm$NAME,cex=0.6)
}
}
dev.off()
### end of entire area code... county by county next

for (j in 1:length(cnty)) {
i=1
mask3 <- raster(paste("C:\\r_modis\\",files[i],sep=""))

```

```

ks_poly_utm <- shape_cnty[paste(shape_cnty$STATE_NAME,shape_cnty$NAME)==
.simpleCap(cnty[j]),]
tmp <- crop(mask3,ks_poly_utm)
tmp <- mask(tmp,ks_poly_utm)
tmp1 <- tmp
tmp2 <- tmp
tmp1[tmp1!=1] <- 0
tmp1[is.na(tmp1)] <- 20
ifelse(((freq(tmp1)[2,1])==1),(ans[j,i]=format(round(freq(tmp1)[2,2]*res(tmp1)[1]**2*0.000247
11,0),big.mark=","scientific=F)),(ans[j,i]=0))
#plot(tmp,legend=FALSE,main=paste(files[i],.simpleCap(cnty[j]),ans[j,i],"acres burned"))
#plot(tmp,legend=FALSE,zlim=c(1,1),col='red',add=TRUE)
#plot(ks_poly_utm,add=TRUE)
writeRaster(tmp1, filename=paste("C:/r_modis/out/rasters/",cnty[j],"_",files[i],".tif",sep=""),
format="GTiff",datatype='INT1U',overwrite=TRUE)
#text(mean(c(xmin(tmp),xmax(tmp))),mean(c(ymin(tmp),ymax(tmp))),paste(format(round(freq(t
mp)[1,2]*res(tmp)[1]**2*0.00024711,0),big.mark=","scientific=F),"acres burned"))
for (i in 2:length(files)) {
mask3 <- raster(paste("C:\\r_modis\\",files[i],sep=""))
ks_poly_utm <- shape_cnty[paste(shape_cnty$STATE_NAME,shape_cnty$NAME)==
.simpleCap(cnty[j]),]
tmp <- crop(mask3,ks_poly_utm)
tmp <- mask(tmp,ks_poly_utm)
tmp[tmp!=1] <- 0
tmp1 <- tmp1+tmp
tmp1[tmp1!=0] <- 1
tmp1[is.na(tmp1)] <- 20
ifelse(((freq(tmp1)[2,1])==1),(ans[j,i]=format(round(freq(tmp1)[2,2]*res(tmp1)[1]**2*0.000247
11,0),big.mark=","scientific=F)),(ans[j,i]=0))
#plot(tmp2,legend=FALSE,main=paste(files[i],.simpleCap(cnty[j]),ans[j,i],"acres burned"))
#plot(tmp1,legend=FALSE,zlim=c(1,1),col='red',add=TRUE)

```

```
writeRaster(tmp1, filename=paste("C:/r_modis/out/rasters/",cnty[j],"_",files[i],".tif",sep=""),
format="GTiff",datatype='INT1U',overwrite=TRUE)

#plot(ks_poly_utm,add=TRUE)

#text(mean(c(xmin(tmp),xmax(tmp))),mean(c(ymin(tmp),ymax(tmp))),paste(format(round(freq(t
mp)[1,2]*res(tmp)[1]**2*0.00024711,0),big.mark=","scientific=F),"acres burned"))

}}

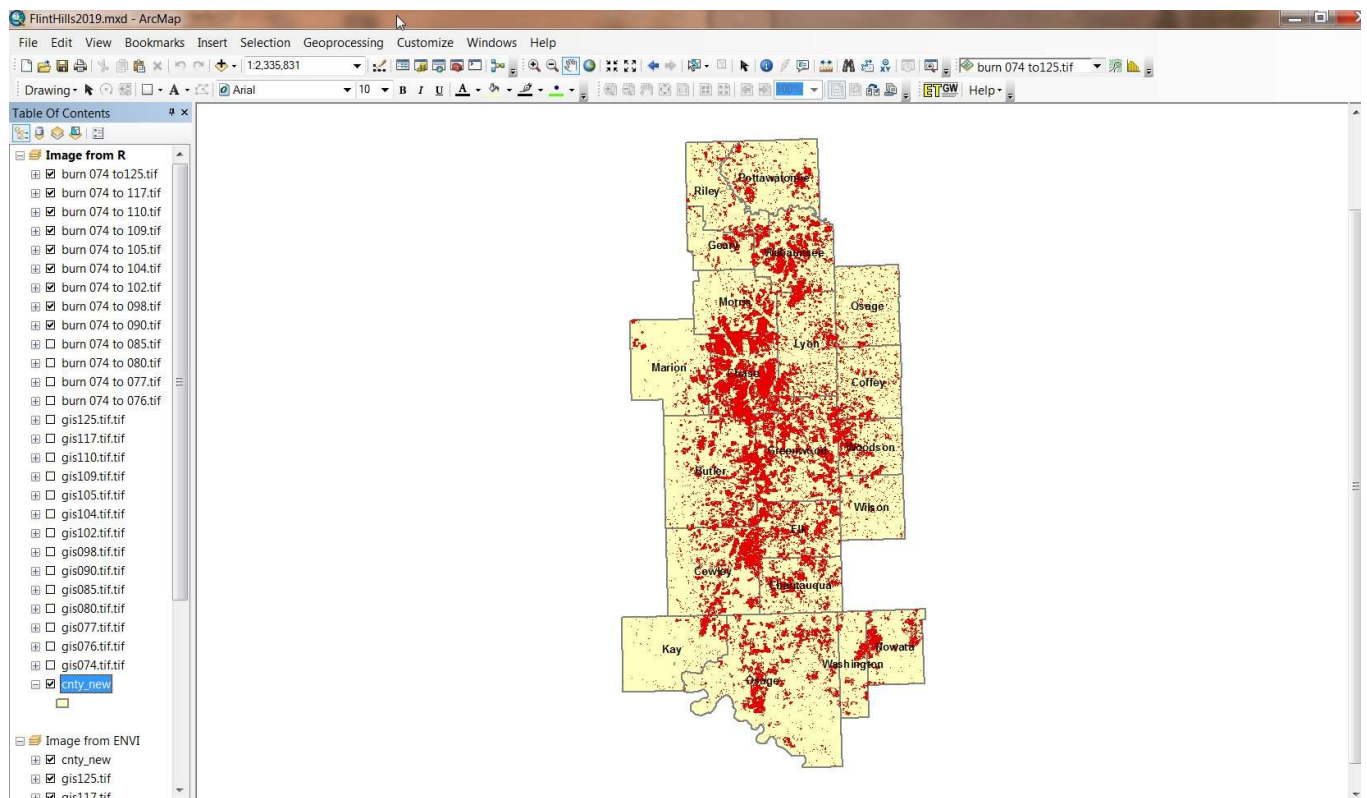
#textplot(ans)

write.table(ans,file="C:/r_modis/out/acres.csv",sep=","")

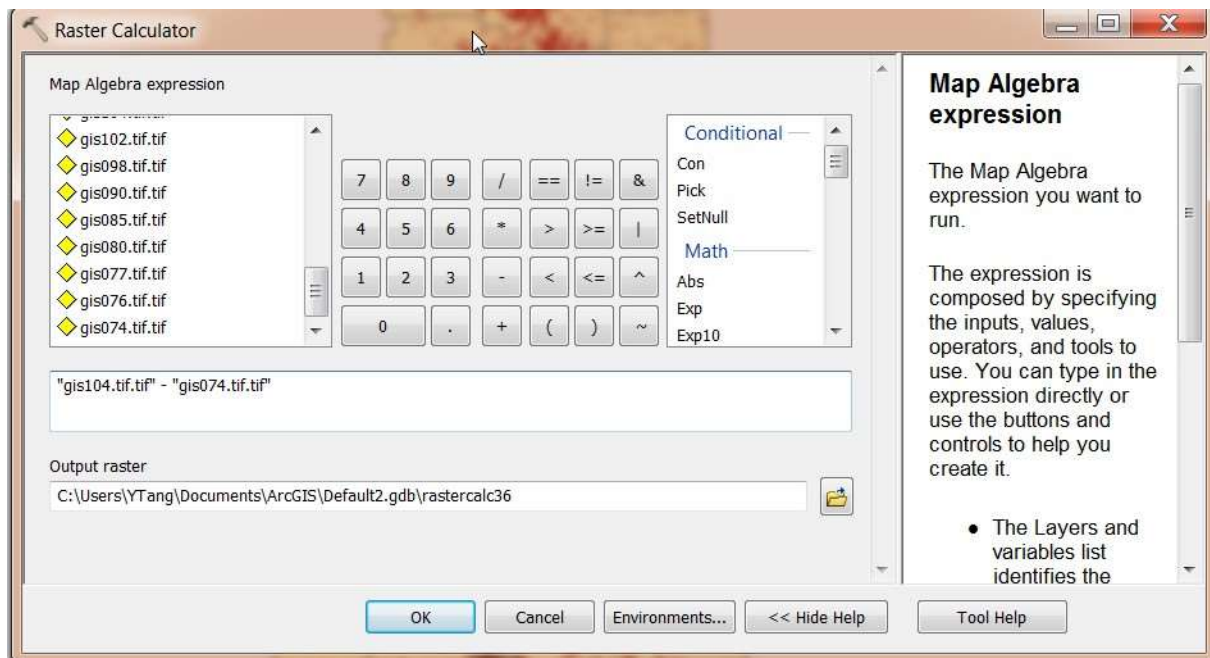
#dev.off()
```

Step 4: Work on ArcGIS

- a.)** Load all TIFF files obtained from R program in step 3 for individual counties into ArcGIS



b.) Calculate new accumulated burned area by “Spatial Analysis Tools”>” Map Algebra”>” Raster Calculator”. The base image (the first image) is subtracted from a new image



c.) The accumulated burn acreage for individual images can be calculated from spreadsheet which is saved in “r_modis” folder

FlintHills Burn Sum2019.xlsx - Excel

Yao Tang [KDHE]

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	A	B	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U
1																					
2	The acreages is from table through R program																				
3																					
4	Counties		DOY074 (3/15)	DOY076 (3/17)	DOY077(3/18)	DOY080 (3/21)	DOY085 (3/26)	DOY090 (3/31)	DOY098 (4/8)	DOY102 (4/12)	DOY104 (4/14)	DOY105									
5																					
6	Butler		5,251	7,120	12,325	26,564	42,657	58,133	169,255	195,773	211,264	2									
7	Chase		2,440	2,533	9,298	35,924	97,099 *	146,706	272,655	287,065	306,478	3									
8	Chautauqua		0	31	494	1,467	3,274 *	7,908	68,357	85,222	90,921										
9	Coffey		0	0	216	1,189	3,043 *	6,579	49,283	57,546	60,959										
10	Cowley		0	31	973	2,687	8,865	18,116	120,744	152,590	165,919	1									
11	Elk		2,780	2,888	4,711	5,313	9,174 *	14,271	114,335	136,744	143,216	1									
12	Geary		2,965	3,135	3,135	3,645	3,645 *	5,158	23,692	28,479	32,356										
13	Greenwood		3,784	5,807	6,409	14,240	34,796 *	60,357	195,340	249,751	262,801	2									
14	Lyon		0	0	0	417	6,255	13,267	79,183	100,466	108,420	1									
15	Marion		0	0	185	973	5,483	13,622	39,553	45,453	46,472										
16	Morris		0	0	0	1,884	1,946 *	8,278	57,098	86,195	95,230										
17	Osage (KS)		0	0	154	432	803 *	4,077	24,294	30,225	32,449										
18	Pottawatomie		0	0	0	386	386 *	6,008	49,499	62,333	69,870										
19	Riley		12,124	13,437	13,437	15,336	15,336 *	20,263	42,657	51,661 *	56,032										
20	Wabaunsee		0	0	0	139	139 *	3,212	94,010	128,652	148,390	1									
21	Wilson		0	0	154	525	525 *	4,433	20,665	22,688	23,568										
22	Woodson		0	0	31	556	1,035 *	5,622	45,221	60,696	65,839										
23	Nowata (OK)		0	0	93	247	386 *	803	43,043	53,190	54,750										
24	Osage (OK)		13,236	15,676	17,792	29,066	39,568 *	53,793	157,270	206,599	225,627	2									
25	Washington (OK)		0	0	216	340	1,112 *	2,085	26,410	32,449	33,082										
26	Kay (OK)		0	0	309	1,776	2,517	2,965	11,552	25,900	31,043										
27																					
28	Total		42,580	50,658	69,932	143,106	278,044	455,656	1,704,116	2,099,677	2,264,686	2,3									
29	accumulated from R reporting accumulated acre daily acre burn percentage																				

FlintHills Burn Sum2019.xlsx - Excel

Yao Tang (KDHE)

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M13

=accumulated from R1013-accumulated from R1C13

	A	C	D	E	F	G	H	I	J	K	L	M	N	O	P	Q	R	S	T	U	V
1																					
2																					
3																					
4																					
5																					
6																					
7	Chase	93 *	6,858	33,484	94,659 *	144,266	270,215	284,625	304,038	311,019	314,201										
8	Chautauqua	31	494	1,467	3,274 *	7,908	68,357	85,222	90,921	95,230	96,141 *										
9	Coffey	0	216	1,189	3,043 *	6,579	49,283	57,546	60,959	64,805	64,820 *										
10	Cowley	31	973	2,687	8,865	18,116	120,744	152,590	165,919	174,938	180,746										
11	Elk	108	1,931	2,533	6,394 *	11,491	111,555	133,964	140,436	146,552	148,034 *										
12	Geary	170	170	680	680 *	2,193	20,727	25,514	29,391	31,630	36,603										
13	Greenwood	2,023	2,625	10,456	31,012 *	56,573	191,556	245,967	259,017	271,713	279,960 *										
14	Lyon	0	0	417	6,255	13,267	79,183	100,466	108,420	115,122	118,675 *										
15	Marion	0 *	185	973	5,483	13,622	39,553	45,453	46,472	49,499	50,565										
16	Morris	0	0	1,884	1,946 *	8,278	57,098	86,195	95,230	99,647	104,605										
17	Osage (KS)	0	154	432	803 *	4,077	24,294	30,225	32,449	35,290	37,931										
18	Pottawatomie	0 *	0	386	386 *	6,008	49,499	62,333	69,870	75,338	79,708										
19	Riley	1,313 *	1,313	3,212	3,212 *	8,139	30,533	39,537 *	43,908	46,750	52,001 *										
20	Wabaunsee	0	0	139	139 *	3,212	94,010	128,652	148,390	160,127	178,676										
21	Wilson	0	154	525	525 *	4,433	20,665	22,688	23,568	24,170	24,170 *										
22	Woodson	0	31	556	1,035 *	5,622	45,221	60,696	65,839	68,805	68,805 *										
23	Nowata (OK)	0	93	247	386 *	803	43,043	53,190	54,750	57,021	57,021 *										
24	Osage (OK)	2,440	4,556	15,830	26,332 *	40,557	144,034	193,363	212,391	226,862	230,940 *										
25	Washington (OK)	0	216	340	1,112 *	2,085	26,410	32,449	33,082	34,024	34,024 *										
26	Kay (OK)	0	309	1,776	2,517	2,965	11,552	25,900	31,043	33,653	34,812										
27																					
28	Total	8,078	27,352	100,526	235,464	413,076	1,661,536	2,057,097	2,222,106	2,337,273	2,418,868										
29																					
30																					
31																					

accumulated from R reporting accumulated acre daily acre burn percentage

Acknowledgment

I would like to acknowledge Ms. Yao Tang from the Kansas Department of Health and Environment's Bureau of Air for generously sharing essential materials crucial to the mapping of daily burns in this dissertation. Yao Tang's valuable contributions significantly enriched the research methodology and outcomes, enhancing the overall quality of this work.

Appendix B : Additional materials for Chapter 4

Appendix B: Derivation of Mixing Height

We calculated mixing height from equation (1) in section 4.2.2. The method involves incorporation of angular velocity of the Earth, Coriolis parameter and dew point temperature into the equation which are described in detail below:

The angular velocity of the Earth can be used to determine its rotational speed in radians per second (rad/s). The Earth undergoes a complete revolution in a time span of about 24 hours, corresponding to a total angular displacement of 2π radians.

The angular velocity may be determined by use the following mathematical expression:

The angular velocity (Ω) = 2π radians / (24 hours * 3600 seconds per hour)

To begin, the conversion from hours to seconds may be achieved by multiplying it by 3600.

Therefore, angular velocity can be calculated as:

The angular velocity (ω) = 2π radians / (24 * 3600 seconds).

$\Omega = 7.272 \times 10^{-5}$ radians per second.

The Earth's rotational velocity is estimated to be roughly 7.272×10^{-5} radians per second.

The Coriolis parameter, denoted as "f," is defined by:

$$f = 2 \Omega \sin(\phi).$$

The Coriolis parameter, denoted as f, is measured in units of s^{-1} (per second).

The Earth's angular velocity, denoted by the symbol Ω , is estimated to be roughly 7.272×10^{-5} radians per second.

The symbol ϕ represents the latitude measured in radians.

In order to determine the Coriolis parameter of the Flint Hills region, it is necessary to convert the latitude from degree to radians.

The latitude of Flint Hills region is approximately 38° (degrees)

Therefore, to determine the Coriolis parameter at a latitude of 38 degrees, we converted the latitude into radians first:

$$\varphi = 38 \text{ degrees} * (\pi/180) \approx 0.663 \text{ radians, where } \pi = 3.142$$

Next, compute the Coriolis parameter:

$$f = 2\Omega \sin(\varphi) = 2 * 7.292 \times 10^{-5} \text{ s}^{-1} * \sin(0.663) \approx 0.0001223 \text{ s}^{-1}$$

At the Flint Hills region, latitude of 38 degrees, the Coriolis parameter is estimated to be roughly 0.0001223 s⁻¹.

Dew point temperature was derived from:

$$t_d = t - \left(\frac{100 - RH}{5} \right) \quad (\text{Lawrence, 2005}).$$

Where t_d is daytime average dew point temperature, t is daytime average air temperature and RH is the average day time relative humidity.

Finally, **mixing height (MH)** is derived from:

$$MH = \left(\frac{121}{6} \right) (6 - s)(t - t_d) + \left(\frac{0.169s(V+0.257)}{12f \ln(\frac{h}{l})} \right) \quad (\text{Di Virgilio et al., 2018})$$

$$f = 2\Omega \sin \theta \quad (\text{Di Virgilio et al., 2018})$$

where s is a stability class that estimates lateral and vertical dispersion, t is daytime average air temperature and t_d is daytime average dew point temperature, V is daytime average wind speed, h is wind speed altitude in m, l is the weather monitoring station's estimated surface roughness index, f is the Coriolis parameter in s⁻¹, Ω is the earth's rotational speed (rad/s) and θ is the station latitude.

References

Di Virgilio, G., Hart, M. A., & Jiang, N. (2018). Meteorological controls on atmospheric particulate pollution during hazard reduction burns. *Atmospheric Chemistry and Physics*, 18(9), 6585-6599.

Lawrence, M. G. (2005). The relationship between relative humidity and the dewpoint temperature in moist air: A simple conversion and applications. *Bulletin of the American Meteorological Society*, 86(2), 225-234.