DETERMINANTS OF FIRE INTENSITY IN A MESIC WEST AFRICA SAVANNA:

A STATISTICAL ANALYSIS OF FIRE CHARACTERISTICS

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ABSTRACT

DETERMINANTS OF FIRE INTENSITY IN A MESIC WEST AFRICA SAVANNA: A STATISTICAL ANALYSIS OF FIRE CHARACTERISTICS

By

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A fundamental premise of savanna fire ecology is that late dry season fires burn more intensely than early dry season fires. Late dry season fires are considered a major determinant of savanna woody vegetation as they are thought to be more damaging to trees, thus shaping the grass/tree dynamic of savannas. Most savanna fire experiments have adopted the early/late fire convention in their experimental design, based on the pioneering work of Aubréville. Recent research suggests that numerous factors determine fire intensity, and that the widely accepted dichotomous view of fire intensity as driven by early/late seasonal timing greatly oversimplifies a complex phenomenon. In particular, wind direction may be a significant factor in determining fire intensity.

To determine the factors that influence fire intensity, experimental fires were conducted in the mesic savanna of Mali. Data were collected for fire season, biomass consumed, grass type, scorch height, speed of fire front, fire type, and ambient air conditions for each burn. Multiple regression analyses were used to determine the key factors affecting the fire intensity and severity. Results suggest there are fundamental differences in fire behavior and intensity depending on wind direction relative to the fire. Intensity is not explained by any tested variables in head fires. Intensity of back fires is determined primarily by seasonal timing and, to a lesser extent, grass characteristics.

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CHAPTER 1

INTRODUCTION

Savannas

Savannas, defined as ecosystems with a continuous layer of grasses and a discontinuous layer of trees and/or shrubs, are a unique and important biome (Solbrig 1996). The savanna vegetation type exists as a continuum of varying amounts of grasses and trees bracketed on one side by dense tree canopies that exclude grasses and on the other by open grasslands lacking any trees (Hill, Roman, and Schaaf 2011). However, this simplistic description belies the complexity and “diversity in both biotic and abiotic characteristics, in floristic composition and in vegetation history” of savanna landscapes (Solbrig 1996, 1). In addition, the coexistence/codominance of grasses and trees has long puzzled biologists, earning the title "the savanna conundrum" (House et al. 2003, 1763). Confounding matters more is that savanna ecosystems can support a greater or lesser amount of tree cover depending on a variety of human and natural factors with critical consequences for carbon storage and ecosystem services.

Globally, savanna ecosystems cover over 20 percent of the world's land area, contain much of its rangelands, generate approximately 30 percent of global net primary productivity, and provide directly or indirectly for millions of people (Scholes and Archer 1997; Lehmann et al. 2008; Smit et al. 2016). Given their significance, it is crucial to understand savanna systems and their drivers. Savanna ecosystems face a number of threats, including woody encroachment, landscape degradation, drought, and land use changes (Campbell 2013; Smit et al. 2016). Fire is one of the most important drivers of savanna given that the “association between fire and savannas is as old as savannas themselves, since it follows inevitably from their climate and fuel characteristics" (Scholes and Walker 1993, 10). In environments capable of supporting one of several life forms, such as savannas, fire can be a selective process driving the survival of one species over another, restructuring the habitat, or directing the energy flows of an ecosystem (Pyne 1991).

Intensity is thought to determine tree survival and growth rates in savannas because of its importance to the tree/grass dynamic, and significant research has focused on identifying the drivers of fire intensity. Fire timing, i.e., early, middle, or late dry season, appears to be a critical factor determining fire intensity (Williams, Gill, and Moore 1998; Higgins, Bond, and Trollope 2000; Govender, Trollope, and Van Wilgen 2006; Laris et al. 2016). Seasonal timing is associated with dryness of fuels as well as fire-facilitating weather conditions. Determination of the fire seasonality at regional and global scales is important for characterizing fire regimes, variation in biomass burning emissions, and fire climate impacts (Le Page et al. 2010; Zhang, Kondragunta, and Roy 2014).

Found in both temperate and tropical regions, one climatic constant of savanna areas is rainfall seasonality (Solbrig, Medina, and Silva 1996). This seasonality of precipitation produces a wet growing period followed by a period of progressive drying until the next growing season's rains arrive. These conditions broadly frame the general requirements necessary for savanna landscapes to form, however they do not reveal the causative factors behind the "savanna conundrum." Several ecological theories have been suggested to explain the coexistence of trees and grasses in savanna landscapes (Laris 2008). Early models were based on resource partitioning theories where trees and grasses utilized distinct subsurface levels, allowing them to grow together without competition, and the savanna landscape was seen as existing in a stable, equilibrium state (Walter 1971). Later models recognized the inherent instability of savanna systems. These disequilibrium models are based on disturbance regimes where some disrupting force favors either grasses or trees and prevents one from excluding the other (Scholes and Archer 1997; Laris 2008).

However, even these disequilibrium models fall short of creating a general theory to explain grass-tree regulation in all savannas. As in most cases, the reality of what maintains savannas's grass/tree codominance becomes more nuanced as one looks more closely at it. The best way to understand savanna dynamics may be a geographic perspective, one which recognizes that different determining forces may create and maintain savanna landscapes in different places. As Sankaran, Ratnam, and Hanan (2008) found, a number of different woody cover drivers interact with varying levels of importance to shape the savanna landscape. In addition, results by Vaughn et al. (2015) suggest that large-scale environmental factors may be less important than commonly assumed in understanding vegetation structure in southern African savanna systems.

Savannas are considered climate determined in areas below 750 mm of precipitation per year as too little rain falls to form a closed canopy forest (Furley 2010). Above 750 mm of annual precipitation, savannas are termed mesic and are considered disturbance driven. The disturbance driving savanna dynamics may be biotic or abiotic. In southern and eastern Africa, herbivory by grazers and browsers appears to be a primary determinant (Sankaran, Ratnam, and Hanan 2008; Holdo, Holt, and Fryxell 2009) while in Australia and sub-Sahalian western Africa, fire is believed to be the primary driver (Lehmann et al. 2008; Laris et al. 2016). Thus, outside of climatic restraints, savanna landscapes can be created by different forces in different locations.

In addition to being shaped by different drivers in different places, savanna ecosystems exhibit noteworthy botanical and floristic differences. For example, in the Brazilian savannas, the *cerrados*, the phylogenetic affinities of the flora are with the nearby Amazonian flora;

however, the *cerrado* savanna vegetation physiognomically resembles that of the savannas of West Africa more than it does the Amazonian forest (Solbrig, Medina, and Silva 1996). Similarly, the plants in African savannas are more floristically related among themselves than to savanna vegetation on other continents. In other words, vegetation in the major savanna regions evolved separately while resulting in similar structural features. This can make it more difficult to understand one savanna based on research from other, geographically separated savannas (Solbrig, Medina, and Silva 1996).

Fire in Savannas

Savanna landscapes have been the focus of scientific inquiry for over 100 years, and the motivation behind that research has varied widely, often reflecting contemporary priorities and biases as well as a geographic predilection (House et al. 2003; Laris et al. 2017). In Africa, historical savanna research has frequently been driven by anti-fire policy goals underlain by the belief that local peoples were degrading the land, turning forests into less desirable savannas (Aubréville 1953; Laris and Wardell 2006). "While it is true that scientific writers have endeavoured to inform the public of the manifold evils following the wake of fire, it is equally true that but little scientific experimentation has been brought to bear upon the problems connected with the periodic fires that sweep through vast areas of Africa" (Phillips, cited in Scott 1984, 54). This quote by Phillips from the early twentieth century illustrates the colonial mindset regarding fire in Africa. On the other hand, historic Australian fire research focused more on avoiding dangerous and uncontrollable wildfires, usually by prescribing "controlled" burning to reduce fuel loads (Pyne 1991). Despite differences in their stated goals, researchers in both Africa and Australia saw fire on the landscape as something to ideally be prevented or at worst managed to reduce the damage it could cause (Laris and Wardell 2006; Furley et al. 2008).

More recent scholarly work has begun to question these scientific legacies, acknowledging the importance and even necessity of fire in savanna systems (Fairhead and Leach 1998; Laris et al. 2017). Anthropogenic fire originated in Africa and has existed there longer than anywhere else in the world (Pyne et al. 2004). The African savannas are the Earth's most extensively and frequently burned regions, accounting for approximately 64 percent of the global burned area annually (Giglio et al. 2010). This hotspot of savanna systems and fire has sparked a wealth of research on the drivers of changes in woody cover.

In the 1930s, Andre Aubréville started what became the longest running burning experiment in West Africa (Furley et al. 2008). His study in the Ivory Coast was intentionally designed to show dramatic differences between early and late dry season fire treatments in order to garner support for his anti-fire forestry policies (Laris et al. 2017). The results of his experiments demonstrated that late dry season fires were much more damaging to trees than fires set earlier in the dry season. Aubréville's research was highly influential and many later studies continued to use his early/late dry season dichotomy (Laris and Wardell 2006). However, Aubréville's experimental setup does not reflect the actual burning practices of people in that area since most fires occur during the middle of the dry season (Laris et al. 2017). As Furley et al. (2008) note, burning experiments have been plagued by concerns with artificiality, as illustrated above, and scale, as described below.

Most of the burning experiments conducted in southern Africa have been large-scale, hundreds of times larger than fires typical of other areas, and often at the same geographic location (Govender, Trollope, and Van Wilgen 2006; Higgins et al. 2007; Higgins et al. 2012). While this may be highly beneficial from a logistics perspective, it could also skew the scientific discussion, biasing it towards large fires in this specific area. Many of the Australian fire studies have also been large-scale (Williams, Woinarski, and Anderson 2003). In addition, the majority of modern savanna fire research has been conducted in South African and Australian savannas, often in areas where indigenous and local populations have been removed and excluded from the landscape or remain in limited numbers (see Higgins et al. 2007 in Kruger National Park, South Africa; Williams, Gill, and Moore 1998 in Kakadu National Park, Australia for examples).

In contrast, the mesic savannas of West Africa, of which 25 to 80 percent burns annually, are well populated by the very people who are setting nearly all of these fires (Laris 2011). This is a highly humanized system where climate, culture, and environment have interacted for millennia (Duvall 2011). A humanized fire regime is one where human practices are the primarily determining factor rather than the climate or ecological factors that tend to dictate most fire regimes globally (Krawchuk et al. 2009). The regularity of the fire regime in the West African savanna suggests that humans play a strong role in governing the regime of burning (Archibald, Staver, and Levin 2012). Further, research suggests that it is often the number of fires, rather than the size of individual large fires, that affects how much of the landscape burns and when (Archibald et al. 2010) The fire regime of the mesic West African savanna is dominated by numerous small fires (Laris 2005).

Fire Research

Understanding the characteristics of fires is important to understanding their landscape effects. The frequency, seasonality, intensity, severity, type, and spread patterns of fires that prevail in a particular location are known as its regime (Bond and Keeley 2005). Terminology used here follows Keeley's (2009) definitions of fire intensity as the physical process of energy released by combustion and of fire severity as the loss of organic matter resulting from the fire. Fire severity describes how fire intensity affects ecosystems and had been used following wildfires where direct information on fire intensity was absent (Keeley 2009). Measures of fire intensity and severity have been linked to a number of landscape and ecosystem variables, and studies show fire intensity may have a more profound impact than fire frequency on tree survival in some savanna types (Higgins et al. 2007; Laris et al. 2016). Thus, assessing fire intensity allows for the quantification of a fire's landscape disturbance and the prediction of subsequent ecological responses.

Byram (1959) defined fireline intensity as the rate of energy or heat release per unit time per unit length of fire front, regardless of its depth. Fireline intensity uses kilowatts per meter (kWm^{-1}) as the unit of measure and can be mathematically derived from commonly collected fire data. Intensity values factor in the heat of combustion of the fuel, the amount of biomass consumed, and how quickly the fire travelled. As Van Wagner (1977) notes ". . . fire intensity thus conceived contains about as much information about a fire's behavior as can be crammed into one number" (24). Weather conditions, fuel load, and fuel moisture are the principle determinants of fire intensity (Cheney, Gould, and Catchpole 1998).

Fire intensity is strongly related to wind direction. Of the studies that compare fires in similar fuels under similar conditions, head fires on average have higher intensity values than back fires (Trollope et al. 1996). Head fires are believed to have a greater effect on trees than on grasses while back fires have the potential to have a greater effect on grasses than on trees (Trollope, Trollope, and Hartnett 2002). However, many studies on fire intensity and ecological response fail to note the wind direction relative to the fire direction (Brookman-Amissah et al. 1980; Higgins et al. 2007; Levick et al. 2009; Smit et al. 2010; Werner and Prior 2013; Smit et al. 2016). Other studies were conducted only as head fires, which may be a more efficient method but may also have unintended and/or unidentified effects on their results (Govender et al. 2006; Rissi et al. 2017).

Significant modern research has focused on combating woody encroachment, a progressively more frequent phenomenon in dry lands globally (Smit et al. 2016). Woody encroachment is decreasing grass cover and increasing woody cover, which reduces the usefulness of rangelands and diminishes biodiversity. Research in southern and eastern Africa shows that Byram's fireline intensity is significantly correlated to post-fire vegetation response (Trollope, de Ronde, and Geldenhuys 2004). Higher intensity fires rather than more frequent fires may be the most effective tool for combating woody encroachment (Smit et al. 2016). In other areas, parts of Australia and western Africa for instance, tree loss is a greater concern than woody encroachment, and a number of studies have attempted to quantify the relationship between fire intensity and tree survival (Prior, Williams, and Bowman 2010; Werner and Prior 2013) Fire intensity does have some important limitations, particularly in how it is measured and the ability to make cross-ecosystem comparisons (Keeley 2009). In addition, post-fire effects such as tree mortality may be a function of residence time or seasonal timing rather than fire intensity.

The Chandler Burning Index (CBI) is a fire risk index based on temperature and relative humidity, originally designed for application at a monthly time-scale (Chandler et al. 1983). Primarily climatic, the CBI integrates the role of vegetation moisture in this fire risk index through the incorporation of relative humidity (Le Page et al. 2010). The CBI has been used to illustrate eco-climatic fire seasonality both at the regional and global levels (Le Page et al. 2010; Zhang, Kondragunta, and Roy 2014). Chandler et al. (1983) define fire risk as the result of constant and variable factors that affect the inception, spread, difficulty of control, and the damage fires may cause. In savannas, areas with high seasonal climatic variability, the CBI is closely aligned with the dry season as it reflects the conditions under which fire is likely to occur (Le Page et al. 2010).

Study Questions

The relationship between seasonal timing and fire intensity has been demonstrated by large-scale burning experiments in two of the most studied savanna landscapes, the southern African and the northern Australian. However, data are lacking for smaller fires and for more humanized savanna systems. Using measurements from burning experiments in southwestern Mali in West Africa, this statistical analysis will evaluate if seasonal timing controls the intensity and severity of fires.

The primary goals of this study are to determine the driver(s) of fire intensity and severity for burning experiments in an area of mesic Sudanian savanna in Mali, West Africa.

There are three specific objectives:

1. To investigate seasonal variation in fire behavior
2. To explore the effect of wind direction on fire behavior
3. To use multiple regression analysis to determine the key factors effecting the fire intensity

CHAPTER 2

METHODS

Study Area

The study area is located in the southwestern region of Mali within the southern Sudanian savanna belt (White 1983). In general, the climate of this area can be divided into three seasons: a relatively cooler dry phase from October to February, a hot and dry season from February to June, and a warm and rainy period from June to October (Laris et al. 2016). With average annual precipitation of approximately 900 to 1200 mm, this region is categorized as a mesic savanna. The rainy season extends over a five month period; however, precipitation is sporadic and typically concentrated over seventy to eighty days during that season (Laris 2013). As sufficient rain falls to support a closed forest canopy (Staver, Archibald, and Levin 2011), disturbances such as grazing, browsing, rotational agriculture, or fire maintain this landscape as a savanna (Laris et al. 2017).

The two study sites for this research, Tabou and Faradiele, both exist within the humanized southern Sudanian savanna. The Tabou area is slightly more populous than Faradiele, but in both areas the population is mostly smallholder farmers of the Bambara and Malinke ethnic groups (Laris, Foltz, and Voorhees 2015). Faradiele receives more precipitation than Tabou, 1200 mm and 1000 mm per year respectively (Henry 2011). In Tabou, about 43 percent of the land is under annual cropping while in Faradiele about 33 percent is cropped annually (Laris, Foltz, and Voorhees 2015). Significant amounts of land remain fallow annually due to the shifting agricultural patterns.

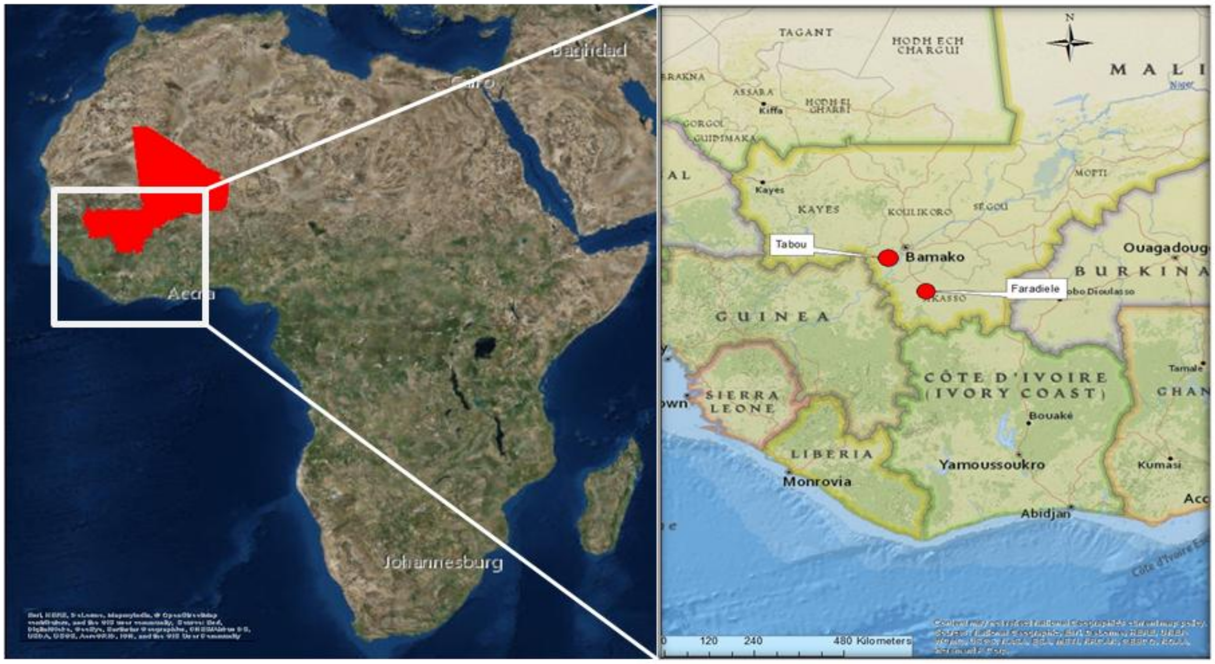

FIGURE 1. Locations of experimental burning sites. Country of Mali is in red on the left and the study sites, Tabou and Faradiele, are marked as red circles on the right.

The southern Sudanian savanna landscape exhibits high heterogeneity due to soil, hydrology, and anthropogenic land uses (Duvall 2011). Spatially, this creates a mosaic pattern of annual-dominated short grass savannas in areas of hard pan or poor, gravelly soils while more fertile soils are covered in a near-continuous layer of tall perennial grasses with a widely varying mixture of trees and shrubs (Laris, Foltz, and Voorhees 2015). In very moist areas, thickly forested savanna woodlands can form as well as closed canopy gallery forests along stream channels (Laris et al. 2017). In addition, traditional land rotation patterns result in a patchwork of actively farmed plots and fallow fields of various ages (Duvall 2011).

The annual fire season begins shortly after the rains end and typically runs from November through March with the majority of fires occurring in late December and early January (Laris et al. 2017). The fire regime is bounded by climatic limitation, but the timing of burning is significantly influenced by people within that period (Laris 2002). Most fires in this region are set intentionally by farmers, herders, and other resource user groups for a variety of user-specific reasons, such as preparing fields for agriculture, improving pasture and hunting grounds, and preventing destructive fires (Laris and Wardell 2006).

Field Collection

The fire experiment data were collected as part of the field campaign of Dr. Paul Laris and Dr. Moussa Koné for their ongoing research on savanna fire emissions and ecological impacts in West Africa. Experimental burns during three different fire seasons, early dry season (November and December), middle dry season (January) and late dry season (February and March), were set on 10 m x 10 m plots at several locations in the Tabou and Faradiele areas of southern Mali. The designation of early, middle, and late fire timing was selected for two reasons. First, the selection of early (November and December) and late (February and March) allow for comparison with numerous historical and modern savanna fire experiments that used only early and late dry season dates for their fires (e.g., Aubréville 1953; Swaine 1992; Govender, Trollope, and Van Wilgen 2006; Russell-Smith and Edwards 2006; Prior, Bowman, and Williams 2010; Werner and Prior 2013). Second, the middle fire season of January reflects the actual fire practices of this region; most burning occurs during the middle of the dry season (Laris 2011; Laris et al. 2016). Studies that mention a middle season often state that middle dry season fires are uncommon, with more fires occurring in the early dry season and more extensive fires occurring in the late dry season (Werner and Prior 2013). While that may be true in other locations, fire frequency peaks in the middle of the dry season in the study area. The decision to divide the dry season into three distinct periods also reflects recent studies that separate the fire season into early, middle, and late (see Rissi et al. 2017 for an example).

For the 2014 - 2015 fire season, twenty-two middle dry season plots were burned in January and twenty-eight late dry season plots were burned in February. No plots were burned during the 2014 - 2015 early dry season due to logistical constraints. During the 2015 - 2016 fire season, thirty-five early dry season plots were burned in November and December, twenty-seven middle dry season plots were burned in January, and twenty-five late dry season plots were burned in March.

TABLE 1. Experimental Fires by Location, Year, and Timing Within the Dry Season

Location	**Number of fires**		
Fire season	Early	Middle	Late
Tabou			
2014 - 2015	0	13	15
2015 - 2016	15	12	13
Faradiele			
2014 - 2015	0	9	13
2015 - 2016	20	15	12

Fuel load (plot biomass) was measured in each of the experimental plots by delineating three pre-fire quadrats of 1 x 1 m. Quadrat 1 was located in the area determined qualitatively to have the highest grass biomass, Quadrat 2 the average grass biomass, and Quadrat 3 the lowest grass biomass. Quadrat boundaries were marked with fire-proof material, grasses were cut at the base, and an electronic balance was used to weigh the biomass. The average biomass of the three quadrats was recorded as the plot biomass. When present, leaf litter was weighed separately from grass biomass. For fires conducted in the early and middle dry seasons when grasses were not fully cured, the grasses from one of the 1 m quadrats were weighed wet and left to dry in a protected area for one week, after which they were weighed again and the percent moisture content taken as the average for the plot. Small uncertainties and inaccuracies may affect these measurements due to field conditions including changing relative humidities over the course of the sample drying period, but they are not expected to affect outcomes significantly.

Vegetation characteristics including grass type (annual or perennial), grass species, and their height classification were recorded for each site. A Kestrel 5500 Weather Meter portable weather station was used to collect wind speed, ambient humidity, and temperature during the burning of each plot, and values were averaged for each burn. The weather station was placed near each experimental plot approximately 2 m off the ground in an open area. Wind direction relative to the direction of each fire was recorded as head, where the fire and the wind are traveling in the same direction; back, where the fire and the wind are traveling in opposing directions; and mixed, where the wind switches between head and back during the course of the fire. Whenever possible, pairs of head and back fires were conducted on adjacent plots.

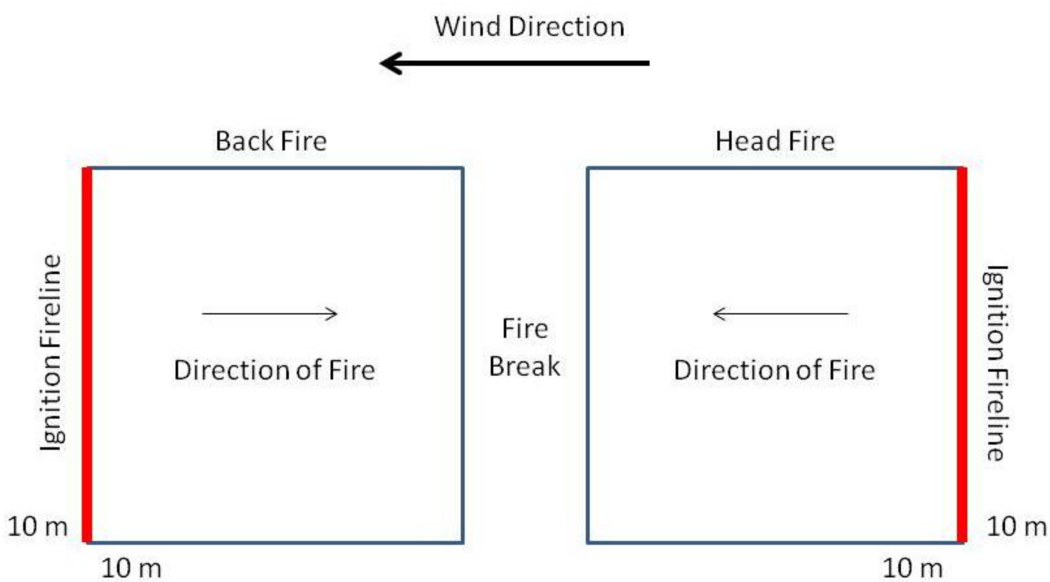

FIGURE 2. Diagram of typical experimental burn plots. Back fires are conducted first to reduce risk posed by head fires.

Ignition time was noted and each fire was timed from start to when the flaming front reached the end of the 10 meter plot. Flame height and fire behavior were observed during the fire. Post-fire, ash and any unburned material were weighed for three 1 m x 1 m quadrats adjacent to and of similar composition to the three 1 m x 1 m pre-fire quadrats to determine the amount of biomass consumed. Scorch height was averaged for each plot by measuring the height of scorch marks on several shrubs and small trees with a tape measure. Visual efficiency, the completeness or patchiness of each burn, was estimated by two observers.

In summary, data on the following variables were collected in the field: timing/season (early, middle or late), average plot biomass, grass percentage of biomass, biomass consumed (fire severity), grass type (annual or perennial), grass species and their height classification, wind speed, ambient humidity, temperature, fire direction (head or back), time of day, fire duration, scorch height, and visual efficiency (patchiness). Field observations were entered into spreadsheets and any discrepancies between values collected by different researchers were addressed and resolved.

Statistical Analysis

To quantify fire intensity, Byram's Fireline Intensity, which combines the heat of combustion, the amount of fuel consumed, and the rate of spread, is commonly used (Bryam 1959). The formula to compute Byram's fireline intensity is:

$$I = Hwr$$

where I is Byram’s fireline intensity (kWm^{-1}), H is the net low heat of combustion ($kJ\ kg^{-1}$), w is the fuel consumed in the active flaming front ($kg\ m^{-2}$), and r is the linear rate of fire spread ($m\ sec^{-1}$). The net low heat of combustion (H) was selected following Williams, Gill, and Moore (1998) with 20,000 $kJ\ kg^{-1}$ as an appropriate value for savanna fires. The amount of fuel consumed in the flaming front was calculated by subtracting the average ash remaining post-fire in three quadrats per plot from the pre-fire dry biomass. Variable r was derived from the plot dimensions (10 m x 10 m) and the time it took for the first flaming front to reach the end of the plot. Byram's I, calculated for each of the experimental fires, is the dependent variable for all analyses.

Additional variables also were calculated for the analysis. Time of day of the fires, called "day timing," was determined by dividing the range of fire start times into four groups: 10:00 a.m. to 12:00 p.m., 12:00 p.m. to 2:00 p.m., 2:00 p.m. to 4:00 p.m., and 4:00 p.m. to 6:00 p.m. All experimental fires were within this time range and any fires spanning more than one group were assigned the group with the majority of the duration of the fire. While this is an ordinal variable, older studies have used that type of variable in multiple regression (Winship and Mare 1984), and it is discussed further at the end of this chapter. Fire severity was calculated by dividing the biomass consumed, determined by post-fire weighing of ash, by the pre-fire biomass.

The Chandler Burning Index (CBI) is a fire risk index and was selected for use in this analysis as a proxy for seasonality as it is most suitable for monthly time scales (Carlson and Burgan 2003), and it has been used to illustrate eco-climatic fire seasonality both at the regional and global levels (Roads et al. 2008; Le Page et al. 2010; Zhang, Kondragunta, and Roy 2014). The formula, modified following Le Page et al. (2010), uses monthly mean high temperatures and relative humidity from early (November and December), middle (January), and late (February and March) periods over the 2005 - 2015 time period. Weather data from Bamako, Mali (approximately 70 km from the Tabou study site) were accessed online from CustomWeather with permission.

The modified Chandler Burning Index is:

$$\text{CBI} = \frac{(110-1.373 * (\text{RH}) - 0.54*(10.20 - \text{T})) * (124 * 10^{-0.0142 * \text{RH}})}{60}$$

where RH is the relative humidity and T is the temperature in Celsius.

Values for the CBI index range from zero, no fire danger, to over 100, extreme fire danger and can be interpreted in terms of the fire's likely behavior or of the danger posed by a fire staring during those conditions. Tables 2 and 3 below define the CBI value range and illustrate the meanings of the values as they relate to fire behavior and to fire risk.

TABLE 2. Interpretation of Chandler Burning Index Values as Fire Behavior from Chandler et al. (1983)

Calculated Values	**Fire Behavior**
0 - 19	Creeping fire only
20 - 39	Surface fire only
40 - 59	Running fire, occasional torching of tree crowns
60 - 79	Hot running fire, spot fires, and torching common
80 +	Crown fire likely

While Chandler's original value classification system refers to the behavior of forest fires, it retains its usefulness in this application to savanna fires. High intensity savanna fires may behave more like traditional forest fires given the right conditions of strong winds, low humidity, and high temperatures with similarly severe impacts to tree cover. In addition, the interpretation of the CBI as fire danger levels aligns with this study's investigation of the role of season as a driver of fire intensity.

TABLE 3. Interpretation of Chandler Burning Index Values as Fire Danger Levels from the National Wildland Fire Coordinating Group (Schlobohm and Brain 2002)

Calculated Values	Fire Danger Level	Description
0 - 50	Low	Fuels do not readily ignite from small firebrands. Wood fires spread slowly by creeping or smoldering and fires in open cured grasslands may burn easily. Little danger of spotting and control generally easy.
50 - 75	Moderate	Fires may start from most accidental causes but the number of starts is low. In open cured grasslands, fires burn briskly and spread rapidly. Timber fires spread slowly to moderately fast and short-distance spotting may occur. Fires of moderate intensity and unlikely to become serious. Control is relatively easy.
75 - 90	High	Fine, dead fuels ignite readily and fires start easily from most causes. Fires spread rapidly and short-distance spotting is common. High intensity burning may develop in areas of concentrated fine fuels and on slopes. Fires may become serious and difficult to control as they grow.
90 - 97.5	Very High	Fires will start easily, spread rapidly, and quickly increase in intensity. Long-distance spotting and fire whirls possible. Can be difficult to control and often become much larger and longer-lasting fires.
97.5 +	Extreme	All fires potentially serious and will start quickly, spread vigorously, and burn intensely. Small fires increase in size much faster than at lower danger levels and long-distance spotting likely. Fires may be unmanageable and control action impossible until danger level declines.

Intensity was calculated for 137 fires, and of those, eighty-three plots possessed all of the necessary variables after being cleaned and prepared in Microsoft Excel. The dataset was saved as an .xls file and opened in IBM Statistical Package for Social Science Statistics 24 software. A correlation matrix was created and relationships between variables were identified. Using information from the correlation matrix, the most relevant independent variables were chosen for the multiple regression analysis. Given the known Y variable, the fairly normal distribution of X variables, and the records:variables ratio, a multiple regression analysis is appropriate. With the goal of determining which factor(s) best explain intensity, the multiple regression analysis sorts through the possible explanatory variables to find the most economical X variable(s) in light of their interactions with one another. Since this is the first analysis of the drivers of fire intensity in West Africa, a high level of significance is called for and a rigorous alpha of $p = 0.05$ shall be set.

Enter, Forward, and Backward multiple regression models were run on the entire dataset. Byram's fireline intensity was the dependent variable for all models. Independent variables were CBI of the season, time of day, wind speed, ambient humidity, temperature, grass type (annual or perennial), grass species (classified by height), and grass percentage of biomass.

Field observations of the fire team identified wind direction as the most meaningful bifurcation of the dataset. Data were separated into head (fire and wind traveling the same direction) and back (fire and wind traveling in opposing directions) fires and analyzed as distinct datasets. Separate correlation matrices were created for head and back fires. Three types of multiple regression models, Enter, Forward, and Backward, were run on both datasets. The Y variable for all regressions was Byram's fireline intensity. The independent variables for the head and back regressions were the same as for the complete dataset: CBI of the season, time of day, wind speed, ambient humidity, temperature, grass type (annual or perennial), grass species (classified by height), and grass percentage of biomass.

Removal of plots with missing values reduced the number of records to eighty-three, and separating the data into head (forty) and back (forty-three) decreased it further. The records: variables ratio of this dataset is at the cusp of what is recommended for multiple regression models, 5:1. This could limit the robustness the analysis. Another possible issue with this analysis is the inclusion of an ordinal independent variable, day timing. Most current statistical theory does not endorse using ordinal variables as predictors in multiple regressions. However, older studies in psychology and sociology have done so (see Winship and Mare 1984). As this analysis is an exploratory study, the variable will be used and any possible complications resulting from this decision will be addressed in the discussion. A final potential limitation of these data is the possibility for imprecision in the measurements. Chaotic fire behavior may make precise observations challenging. However, standardization among observers should work to limit any potential variation.

CHAPTER 3

RESULTS

Fire Characteristics

Intensity was able to be calculated for 137 fires over the 2014-2015 and 2015-2016 fire seasons, and of those, eighty-three plots possessed all of the necessary variables for multiple regression analysis. Dividing the plot data into early, middle, and late shows general trends over the dry season. Average temperature increases while average humidity decreases as the dry season progresses and wind speed peaks mid-season. The percent grass of the total plot biomass is greatest in the early season, reflecting an increase in the amount of leaf litter in the middle and late dry seasons due to drought senescence.

TABLE 4. Mean Plot Characteristics by Season

Mean plot characteristics	Early	Middle	Late
Dry biomass (tons/hectare)	3.90	4.48	4.53
Grass biomass (percent)	90	71	77
Temperature (Celsius)	32.5	31.8	37.0
Relative humidity (percent)	29.6	21.2	19.4
Wind speed (meters/second)	1.1	1.4	0.85

The characteristics of the experimental fires also vary by season. The average visual efficiency (i.e., the completeness of a burn) and the average severity (i.e., the percent biomass consumed) both increase as the dry season progresses from early through middle to late. Scorch height and burn time show a slightly different pattern where the middle season has the lowest average values followed by early and late, respectively. Both visual efficiency and severity are positively correlated to CBI, with severity having a higher and more significant correlation.

TABLE 5. Mean Fire Characteristics by Season

Mean fire characteristics	Early	Middle	Late
Burn time (meters/second)	0.030	0.024	0.034
Scorch height (meters)	1.39	1.35	1.71
Visual efficiency (completeness of burn in percentage)	85	92	99
Severity (percent biomass consumed)	85	86	93

Calculated intensity values for early, middle, and late are shown in Table 6. While the minimum intensity increases over the fire season, the maximum intensity decreases. The standard deviation of the seasonal intensity values indicates high variability in these fires, especially in early season fires. Calculated intensity values ranged from 24.69 to 1395.36 kWm^{-1} for all plots. Intensity is positively correlated to scorch height and visual efficiency but not correlated to fire severity (percent biomass consumed). Complete correlation matrix for all fires is found in Appendix A.

TABLE 6. Intensity Values by Fire Season Timing for All Fires, kWm^{-1}

Fire season	Minimum	Maximum	Mean + standard deviation
Early	24.69	1395.36	223.29 + 273.51
Middle	31.73	1273.28	189.23 + 232.80
Late	58.46	835.03	294.34 + 225.83

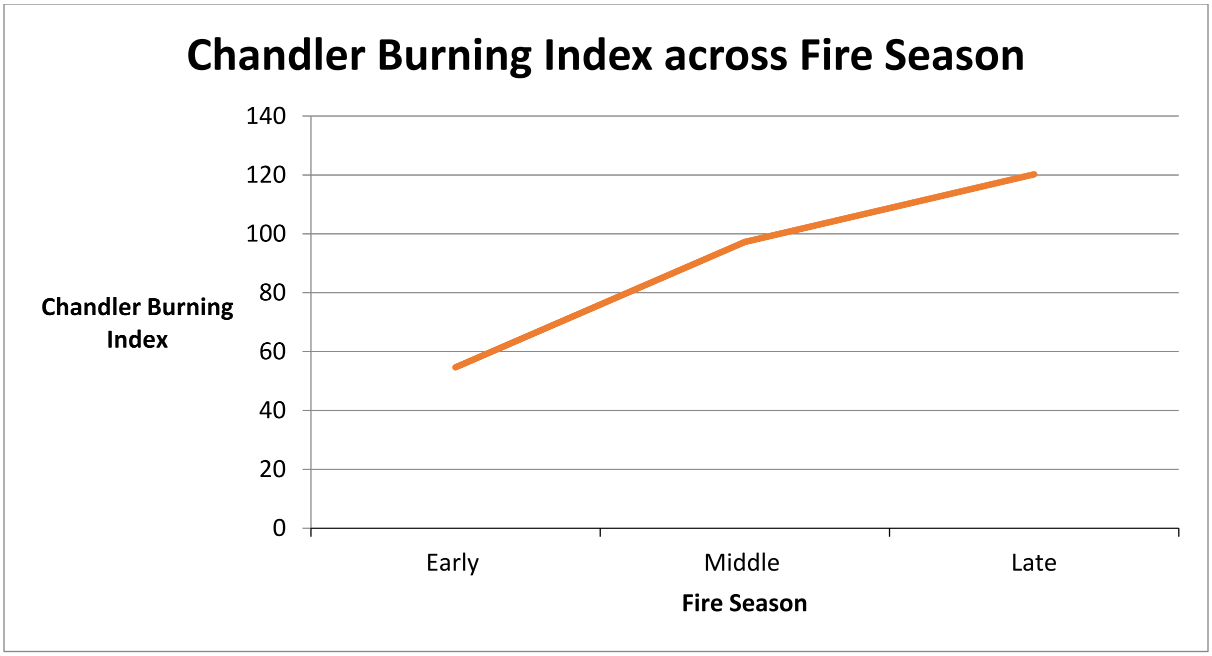

FIGURE 3. Changes in the Chandler Burning Index across the fire season. Weather data from Bamako, Mali over the time span of 2005 - 2015.

The Chandler Burning Index (CBI) was calculated at 54.667 for the early dry season, 97.226 for the middle dry season, and 120.202 for the late dry season. The corresponding fire risk classifications are Moderate, Very High, and Extreme, respectively (see Table 3).

Running the three multiple regression types on the entire dataset results in three very different models. In the Enter method, wind speed at 0.052 is the closest variable to reaching significance, however the entire model is not significant, $p = 0.300$. The Forward method fails to create a model; no variables fit well enough to begin the regression. The Backwards regression analysis created seven models, removing variables with each iteration. The final Backwards model is significant at $p = 0.033$ with wind speed and temperature as the explanatory variables. For this model, the adjusted $R^2 = 0.059$, indicating a poor fit of variables in the Backwards regression.

Analysis by Wind Direction

FIGURE 4. Back fire with low flame heights and slow rate of spread. Note the wind pushing the flames back over the previously burned area.

FIGURE 5. Head fire with high flame heights and fast rate of spread. Note the wind pushing the flames forward toward the unburnt area.

The data were divided into two separate datasets based on wind direction at the time of the fire: head fires when the wind and the fire are traveling in the same direction and back fires when the wind and the fire are traveling in opposite directions. Figures 4 and 5 illustrate the visual differences between head and back fires under similar weather conditions and in similar fuels. The mean head fire intensity is 336.26 kWm^{-1}, more than double the back fire mean intensity of 124.24 kWm^{-1}. Head fires also display far more variation in intensity values, indicated by the standard deviations shown in Table 7.

Intensity is not correlated to CBI in head fires but is significantly correlated in back fires. Scorch height, an accepted metric for estimating fire intensity, is significantly correlated with intensity in both head and back fires, but it is more strongly correlated in back fires than in head fires. CBI is correlated to scorch height in back fires only. In both head and back fires, CBI was positively correlated to the visual efficiency but not to the severity. Complete correlation matrices can be found at the beginning of Appendix B for head fires and Appendix C for back fires.

TABLE 7. Intensity of Head and Back Fires for All Plots, kWm^{-1}

Fire type	Number	Minimum	Maximum	Mean + standard deviation
Head fire	40	48.5170	1395.362	336.262 + 312.76
Back fire	43	24.6907	476.937	124.241 + 84.93

All of the multiple regression analyses of the head fires dataset were unsuccessful. The Enter and Backward regressions failed to create significant models, their *p* value did not reach the level of significance of $p = 0.05$ (details in Table 8). Running the Forward model results in an error warning that no model can be created. Since none of the variables have adequate explanatory power, none are selected to begin the model.

TABLE 8. Head Fire Regression Model Statistics

Model	R	R^2adj	F	Sig F	Valid
Enter	0.545	0.297	1.640	0.154	No
Backward	0.421	0.177	2.589	0.068	No
Forward	N/A	N/A	N/A	N/A	No

Note: No significant models were created. Model details in Appendix B.

All back fire multiple regression models were significant at *p* = 0.05 or less. CBI and the two grass variables emerged as the explanatory variables in the Backward and Forward models. The Forward regression ran twice and the Backward regression ran five times. Excluded variables in both final models were humidity, day timing, annual/perennial, wind speed, temperature, and grass type by height. CBI was the only significant variable in the Enter regression model.

TABLE 9. Back Fire Regression Model Statistics

Model	R	R^2adj	F	Sig f	Valid	Explanatory variable
Enter	0.641	0.272	2.963	0.013	Yes	CBI
Backward	0.623	0.323	6.019	0.001	Yes	CBI, grass by height
Forward	0.518	0.232	7.334	0.002	Yes	CBI, grass biomass percent

Note: Model details in Appendix C.

CHAPTER 4

DISCUSSION

Seasonal Differences in All Fires

The primary goal of this study was to determine the driver(s) of fire intensity in an area of mesic Sudanian savanna. Using measurements from burning experiments in southwestern Mali in West Africa, this statistical analysis evaluated the role of seasonal timing in determining the intensity and severity of fires and explored the effect of wind direction on fire behavior. As noted, determination of the fire seasonality at regional and global scales is important for characterizing fire regimes, variation in biomass burning emissions, and fire climate impacts (Le Page et al. 2010; Zhang, Kondragunta, and Roy 2014).

Seasonal timing is associated with dryness of fuels as well as fire-facilitating weather conditions. The calculated CBI values of 54.667 for the early dry season, 97.226 for the middle dry season, and 120.202 for the late dry season correspond to the fire risk classifications of Moderate, Very High, and Extreme (described in Table 3). These risk classifications align with assumed seasonal fire behavior (Smit et al. 2016). Although these risk classifications were originally based on North American forest fires, the CBI been used to indicate eco-climatic fire seasonality on both local and global scales (Roads et al. 2008; Le Page et al. 2010). While less sophisticated than other fire risk metrics that incorporate fuel structure, slope, or wind speed, the CBI's value lies in its simplicity. It is particularly well suited for application in areas lacking the detailed data other fire risk indices require.

The measured bio-physical characteristics of the experimental plots accurately reflect conditions across the fire season. As the dry season progresses, this study found that average temperature increases while average humidity decreases. The percent grass biomass is greatest in the early season, indicating an increase in the amount of leaf litter in the middle and late seasons. The characteristics of the experimental fires also vary by season. Mean visual efficiency (the completeness of a burn) and mean severity (the percent biomass consumed) both increase as the dry season progresses from early to middle to late. These observations fit well with how savanna landscapes and fires are believed to be effected by seasonal timing. Studies by Smit et al. (2010) in southern Africa, Werner and Prior (2013) in Australia, and Laris et al. (2016) in West Africa show similar seasonal changes. The significance of these seasonal changes lies in how they may affect the behavior of fires occurring in that season.

It is fairly well accepted that fires in different seasons behave differently with differences in flame height, fire intensity, and severity (Werner and Prior 2013), and that late dry season fires will burn more intensity and thus are more damaging to trees (Govender, Trollope, and Van Wilgen 2006; Smit et al. 2016; Laris et al. 2017). Fire timing, i.e., early, middle, or late dry season, appears to be a critical factor in determining fire intensity (Williams, Gill, and Moore 1998; Higgins, Bond and Trollope 2000; Govender, Trollope, and Van Wilgen 2006; Laris et al. 2016). Smit et al. (2016) found in their study that late dry season fires were more intense, had a higher scorch height, and consumed more fuel than early dry season fires. As noted, the selection of the three fires seasons reflects the actual fire practices of this region as most burning occurs during the middle of the dry season while also allowing for comparison with the values for early and late season fires of other studies (Laris et al. 2017).

In this study, the highest intensity fire occurred in the early dry season, and the early season fires also exhibited the greatest variation in intensity values (shown in Table 6). While the minimum intensity value increases as over the course of the dry season, the maximum intensity value decreases. Fires tend to become more intense as the dry season progresses, but they also become more uniform with less variation in intensity. The middle dry season had the lowest mean intensity value, 189 kWm^{-1}, and the late dry season had the highest mean intensity, 294 kWm^{-1}, with the early season mean intensity between them at 223 kWm^{-1}. Interestingly, intensity was not correlated to fire severity, although intensity was correlated to scorch height and visual efficiency. This could indicate that some fires had a high rate of spread but a lower amount of biomass consumption, or inversely that slower fires were able to consume a greater amount of biomass due to their longer residence time. The potentially problematic ordinal variable, day timing, was significantly correlated only to temperature (positively) and wind speed (negatively). This accurately reflects increasing temperatures and decreasing wind speed over the duration of a typical day at that time of year. Day timing was dropped by all multiple regression analyses so is unlikely to affect the results. Future analysis will not require this variable.

Fire intensity values calculated here were considerably less than those found by other studies. The mean intensity found by Williams, Gill, and Moore (1998) in their Australian savanna fire experiments was 4900 kWm^{-1}, while Govender, Trollope, and Van Wilgen (2006) studying fire in South Africa calculated a mean intensity of 1775 kWm^{-1}. Both of these values are considerably larger than 235.62 kWm^{-1}, the mean calculated from this dataset. This is likely due to the greater fuel loads of their experimental sites, which in turn is strongly influenced by fire return interval. More rapid rates of spread may also contribute to the higher values found by other studies. Further, wind direction relative to fire direction is another likely factor explaining their higher intensity values and is addressed in detail in the section below.

The results of the three multiple regression analyses of all fires, while all different, converge on a single meaningful conclusion. The Enter regression model failed to reach an acceptable level of significance, the Forward model failed to create any model at all, and the

Backwards model, although significant, is highly penalized as shown by the very low adjusted R^2. Taken together, the results of these three regressions do not indicate that any of the tested variables clearly drive fire intensity. When looking at the entire experimental burn dataset, season, represented by CBI, does not determine a fire's intensity.

Seasonal Differences by Fire Direction

To explore the impact of wind direction on fire behavior and intensity, the data was divided into head and back fire datasets, and analyses were run on them separately. The mean head fire intensity is 336.26 kWm^{-1}, more than double the back fire mean intensity of 124.24 kWm^{-1}. Intensity is not correlated to CBI, the seasonal timing proxy, in head fires, but is significantly correlated in back fires. Intensity was correlated to fire severity only in back fires. Scorch height, an accepted metric for estimating fire intensity, is significantly correlated with intensity in both head and back fires, but more strongly correlated in back fires than in head fires. CBI is correlated to scorch height in back fires only. In both head and back fires, CBI was positively correlated to visual efficiency but not to severity.

The multiple regression analysis of head fires failed to create successful models to determine the driver(s) of fire intensity. When the fire and the wind are traveling in the same direction, that fire characteristic overpowers the influence of all other potentially important variables. None of the tested variables have the power to explain fire intensity in head fires. In contrast, the three multiple regression analyses of back fires created three valid models with CBI, the seasonality proxy, the most significant driver in each model. For back fires, seasonal timing does drive fire intensity. The other explanatory variables, grass height in the Backward regression and percent grass biomass in the Forward regression, likely drive fire intensity by the amount of fuel available. These results show similarities with some previous work on fire intensity but also significant divergence from others.

The study by Trollope et al. (1996) found that back fires tended to be relatively uniform slow, cool fires with lower flame heights. The head fires in their study showed significant variation from slow moving, very low intensity fires (93 kWm^{-1}) to rapidly moving, high intensity fires (3644 kWm^{-1}) with tall flames. Comparing two sets of fire experiments in the same national park, Russell-Smith and Edwards (2006) describe how more significant effects were found on trees in the experiments conducted as head fires than in the experiments conducted as back fires. Even early season fires can be quite intense if burned with a head wind as noted by Cook, Liedloff, and Murphy (2015) in the Kapalga fire experiment in Australia. The highest calculated intensity in this study was in an early season head fire. Additionally, two of the explanatory variables for back fire intensity, CBI and percent grass biomass, are in opposition; the relative percentage of grass biomass available for combustion will decrease as the fire season progresses and leaf litter builds up. If intensity is moderated by the presence of leaf litter, fires occurring later in the season will be less intense despite seasonal factors promoting intensity.

Fire intensity is strongly related to wind direction. Of the studies that compare fires in similar fuels under similar conditions, head fires on average have higher intensity values than back fires (Trollope et al. 1996) Head fires are believed to have a greater effect on trees than on grasses while back fires have the potential to have a greater effect on grasses than on trees (Trollope, Trollope, and Hartnett 2002). However, many studies on fire intensity and ecological response fail to note the wind direction relative to the fires (Biggs et al. 2003; Smit et al. 2010; Smit et al. 2016). Other studies simply state that their goal was to achieve as high a burn temperature as possible by setting late dry season fires (like the Marondera fire trials in Zimbabwe (Furley et al. 2008)) or to prove the damaging impacts of fire (like the Experimental Burn Plot fire trials in South Africa (Biggs et al. 2003)). Given the value-laden, anti-fire agenda of some of the longest running burning experiments, it would be plausible to assume that their fires were likely set as head fires, thus designed to be as damaging as possible. Descriptions of the behavior of the some of these historic fires provides support for this supposition (Aubréville 1953).

Govender, Trollope, and Van Wilgen's (2006) study in South Africa estimated fire intensity for twenty-one years of experimental burns. Their lowest mean intensity was 1225 kWm^{-1} in the early season, supporting the position that early season fires tend to be less intense than those occurring later in the dry season. However, in comparison to the fire intensity values calculated in this study, that number is quite large. Govender, Trollope, and Van Wilgen's lowest seasonal mean intensity is close to the maximum intensity values found in this study. The maximum intensity values calculated in this study are in the early and middle dry seasons, 1395 and 1273 kWm^{-1} respectively. Govender, Trollope, and Van Wilgen's highest intensities, 11,000 to 17,500 kWm^{-1}, are about an order of magnitude greater than the highest intensities of this analysis. One important thing to note about Govender, Trollope, and Van Wilgen's fire study; all of their fires were set as head fires. A recent study in the *cerrado* savanna of South America found that the amount of dead fuel best explains fire intensity and flame height (Rissi et al. 2017). They did not find significant differences in intensity or flame height across the early, middle, and late fire seasons. However, again, all of their experimental fires were set as head fires.

In addition, both of these studies were conducted in areas, either reserves or experimental stations, where indigenous and local populations have been removed and people are excluded from the landscape. In contrast, the mesic West African savanna of this study is well populated by people who may be grazing cattle and setting annual fires, reducing the potential burnable biomass and subsequent intensity (Laris 2011). This is a highly humanized system, and experiments in this "lived-in" savanna will help to more realistically explain fire behavior and ecological effects across other populated savanna landscapes.

While research indicates higher intensity fires are more damaging to woody growth (Govender, Trollope, and Van Wilgen 2006; Higgins et al. 2012; Werner and Prior 2013; Smit et al. 2016), the applicability of their results to the West Africa humanized savanna landscape is called into question by this study. Intensity values found in this analysis are more than an order of magnitude less than those reported in other studies. It is unknown if tree survival also varies from previous work in different savanna systems. More research is need to establish the relationship between fire intensity and ecological response in this landscape. Given the inconsistencies between intensity values found in prior research and in this analysis, it would be reasonable to postulate that ecological effects would also diverge from previous studies.

Conclusions

The variation in fire intensities found in this study reflect fundamental differences in the savanna landscapes found in across continents and regions, as well as potential experimental bias. Fires in sparsely populated and fairly homogenous landscapes like those found in the most frequently studied savannas possess distinct characteristics from those in more populous and patchier landscapes (Laris 2011). For the West African humanized savanna landscapes, fire behavior is dependent on wind direction. The results of this analysis show that head fires have a higher average intensity and much greater variation than back fires. In head fires, none of the evaluated variables explains intensity. When the fire and the wind are traveling in the same direction, that fire characteristic overpowers the influence of all other potentially important variables. This is possibly due to the radiant heat of the head fire pre-heating the standing vegetation, thus moisture content (roughly dictated by seasonality) is a less significant factor. For back fires, timing within the fire season, as represented by CBI, does emerge as the explanatory variable. However, few studies note the wind direction of their experimental burns so it may be challenging to evaluate the influence of that factor on their intensity values. The commonly accepted relationship between timing within the fire season and intensity should be called into question if the impact of wind direction is not accounted for.

In this study, wind direction determines the primary drivers of fire intensity. The statistically significant relationship between seasonal timing, grass variables, and back fire intensity aligns with previous savanna research. For head fires, an absence of explanatory variables indicates that the dynamics of these fires are significantly different from that of back fires. There have been few efforts to determine the amount of the African landscape burned by head or back fires. Given the impact of fire direction on fire intensity, it is likely that this variable is also a determinant of fire emissions and, in particular, greenhouse gas emissions. Future efforts could focus on estimating the amount of area fire burned as head or back fire using remotely sensed imagery and models. Certainly, additional research is needed to evaluate the role of wind direction in fire intensity in different savanna systems.

APPENDICES

APPENDIX A

MODEL DETAILS FOR ALL FIRES

Correlations

		CBI	day_timing	Wind_speed	grass_percent	humidity	temp	Grass by Ht	An_Peren	Flam_height (m)	Eff_Visual	Biom_cons %	Intensity
CBI	Pearson Correlation	1	0.103	-0.092	-.302**	-.596**	.317**	.248*	.228*	0.142	.467**	.265*	0.063
	Sig. (2-tailed)		0.353	0.408	0.006	0.000	0.003	0.024	0.038	0.202	0.000	0.016	0.573
	N	83	83	83	83	83	83	83	83	83	83	83	83
day_timing	Pearson Correlation	0.103	1	-.402**	-0.127	-0.076	.238*	-0.031	0.075	0.117	0.188	0.112	0.020
	Sig. (2-tailed)	0.353		0.000	0.251	0.493	0.030	0.783	0.503	0.294	0.089	0.312	0.856
	N	83	83	83	83	83	83	83	83	83	83	83	83
Wind_speed	Pearson Correlation	-0.092	-.402**	1	0.092	.229*	-.482**	-0.031	-0.083	-0.016	-0.048	-0.018	0.105
	Sig. (2-tailed)	0.408	0.000		0.408	0.037	0.000	0.784	0.456	0.884	0.668	0.874	0.346
	N	83	83	83	83	83	83	83	83	83	83	83	83
grass_percent	Pearson Correlation	-.302**	-0.127	0.092	1	.238*	-0.043	-.264*	-.227*	-0.036	0.006	-0.051	0.121
	Sig. (2-tailed)	0.006	0.251	0.408		0.030	0.700	0.016	0.039	0.747	0.956	0.646	0.277
	N	83	83	83	83	83	83	83	83	83	83	83	83
humidity	Pearson Correlation	-.596**	-0.076	.229*	.238*	1	-.538**	-.450**	-.495**	-0.203	-0.201	-0.075	-0.121
	Sig. (2-tailed)	0.000	0.493	0.037	0.030		0.000	0.000	0.000	0.065	0.068	0.499	0.274
	N	83	83	83	83	83	83	83	83	83	83	83	83
temp	Pearson Correlation	.317**	.238*	-.482**	-0.043	-.538**	1	0.117	0.039	0.203	.321**	.225*	0.183
	Sig. (2-tailed)	0.003	0.030	0.000	0.700	0.000		0.292	0.727	0.066	0.003	0.041	0.098
	N	83	83	83	83	83	83	83	83	83	83	83	83
Grass by Ht	Pearson Correlation	.248*	-0.031	-0.031	-.264*	-.450**	0.117	1	.676**	-0.027	-0.057	-0.201	-0.089
	Sig. (2-tailed)	0.024	0.783	0.784	0.016	0.000	0.292		0.000	0.812	0.608	0.069	0.423
	N	83	83	83	83	83	83	83	83	83	83	83	83
An_Peren	Pearson Correlation	.228*	0.075	-0.083	-.227*	-.495**	0.039	.676**	1	0.080	-0.028	-.221*	-0.074
	Sig. (2-tailed)	0.038	0.503	0.456	0.039	0.000	0.727	0.000		0.471	0.804	0.045	0.508
	N	83	83	83	83	83	83	83	83	83	83	83	83
Flam_height (m)	Pearson Correlation	0.142	0.117	-0.016	-0.036	-0.203	0.203	-0.027	0.080	1	.363**	0.065	.541**
	Sig. (2-tailed)	0.202	0.294	0.884	0.747	0.065	0.066	0.812	0.471		0.001	0.562	0.000
	N	83	83	83	83	83	83	83	83	83	83	83	83
Eff_Visual	Pearson Correlation	.467**	0.188	-0.048	0.006	-0.201	.321**	-0.057	-0.028	.363**	1	.393**	.306**
	Sig. (2-tailed)	0.000	0.089	0.668	0.956	0.068	0.003	0.608	0.804	0.001		0.000	0.005
	N	83	83	83	83	83	83	83	83	83	83	83	83
Biom_cons %	Pearson Correlation	.265*	0.112	-0.018	-0.051	-0.075	.225*	-0.201	-.221*	0.065	.393**	1	0.134
	Sig. (2-tailed)	0.016	0.312	0.874	0.646	0.499	0.041	0.069	0.045	0.562	0.000		0.226
	N	83	83	83	83	83	83	83	83	83	83	83	83
Intensity	Pearson Correlation	0.063	0.020	0.105	0.121	-0.121	0.183	-0.089	-0.074	.541**	.306**	0.134	1
	Sig. (2-tailed)	0.573	0.856	0.346	0.277	0.274	0.098	0.423	0.508	0.000	0.005	0.226	
	N	83	83	83	83	83	83	83	83	83	83	83	83

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

Enter Regression

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI, Wind_speed (m/s), Grass by Ht, humidity[b]		Enter
a. Dependent Variable: Intensity_act_dry			
b. All requested variables entered.			

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.341[a]	0.116	0.021	245.53
a. Predictors: (Constant), An_Peren, ambient_temp,				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	588261.08	8	73532.635	1.220	.300[b]
	Residual	4461209.58	74	60286.616		
	Total	5049470.66	82			
a. Dependent Variable: Intensity_act_dry						
b. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI,						

Coefficients[a]						
		Unstandardized Coefficients		Standardized Coefficients		
Model		B	Std. Error	Beta	t	Sig.
1	(Constant)	-349.531	530.993		-0.658	0.512
	CBI	-0.177	1.321	-0.019	-0.134	0.894
	day_timing	21.151	35.190	0.074	0.601	0.550
	Wind_speed (m/s)	111.211	56.216	0.265	1.978	0.052
	grass_biomass_%	115.238	126.304	0.108	0.912	0.365
	humidity	-5.366	6.187	-0.160	-0.867	0.389
	ambient_temp	15.254	10.141	0.233	1.504	0.137
	Grass by Ht	-12.585	15.973	-0.121	-0.788	0.433
	An_Peren	-13.092	62.976	-0.034	-0.208	0.836
a. Dependent Variable: Intensity_act_dry						

Backward Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI, Wind_speed (m/s), Grass by Ht, humidity[b]		Enter
2		CBI	Backward (criterion: Probability of F-to-remove >= .100).
3		An_Peren	Backward (criterion: Probability of F-to-remove >= .100).
4		day_timing	Backward (criterion: Probability of F-to-remove >= .100).
5		humidity	Backward (criterion: Probability of F-to-remove >= .100).
6		grass_biomass_%	Backward (criterion: Probability of F-to-remove >= .100).
7		Grass by Ht	Backward (criterion: Probability of F-to-remove >= .100).

a. Dependent Variable: Intensity_act_dry

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.341[a]	0.116	0.021	245.53
2	.341[b]	0.116	0.034	243.92
3	.340[c]	0.116	0.046	242.37
4	.335[d]	0.112	0.054	241.32
5	.320[e]	0.103	0.057	241.03
6	.309[f]	0.096	0.061	240.42
7	.286[g]	0.082	0.059	240.74

a. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI,

b. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, Wind_speed

c. Predictors: (Constant), ambient_temp, grass_biomass_%, day_timing, Wind_speed (m/s),

d. Predictors: (Constant), ambient_temp, grass_biomass_%, Wind_speed (m/s), Grass by Ht,

e. Predictors: (Constant), ambient_temp, grass_biomass_%, Wind_speed (m/s), Grass by Ht

f. Predictors: (Constant), ambient_temp, Wind_speed (m/s), Grass by Ht

g. Predictors: (Constant), ambient_temp, Wind_speed (m/s)

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	588261.08	8	73532.635	1.220	.300[b]
	Residual	4461209.58	74	60286.616		
	Total	5049470.66	82			
2	Regression	587176.39	7	83882.342	1.410	.214[c]
	Residual	4462294.27	75	59497.257		
	Total	5049470.66	82			
3	Regression	584900.82	6	97483.470	1.659	.143[d]
	Residual	4464569.84	76	58744.340		
	Total	5049470.66	82			
4	Regression	565311.09	5	113062.218	1.941	.097[e]
	Residual	4484159.58	77	58235.839		
	Total	5049470.66	82			
5	Regression	518124.92	4	129531.230	2.230	.073[f]
	Residual	4531345.74	78	58094.176		
	Total	5049470.66	82			
6	Regression	483274.10	3	161091.365	2.787	.046[g]
	Residual	4566196.57	79	57799.957		
	Total	5049470.66	82			
7	Regression	413115.12	2	206557.561	3.564	.033[h]
	Residual	4636355.54	80	57954.444		
	Total	5049470.66	82			

a. Dependent Variable: Intensity_act_dry

b. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI, Wind_speed

c. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, Wind_speed

d. Predictors: (Constant), ambient_temp, grass_biomass_%, day_timing, Wind_speed (m/s), Grass by

e. Predictors: (Constant), ambient_temp, grass_biomass_%, Wind_speed (m/s), Grass by Ht, humidity

f. Predictors: (Constant), ambient_temp, grass_biomass_%, Wind_speed (m/s), Grass by Ht

g. Predictors: (Constant), ambient_temp, Wind_speed (m/s), Grass by Ht

h. Predictors: (Constant), ambient_temp, Wind_speed (m/s)

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-349.531	530.993		-0.658	0.512
	CBI	-0.177	1.321	-0.019	-0.134	0.894
	day_timing	21.151	35.190	0.074	0.601	0.550
	Wind_speed (m/s)	111.211	56.216	0.265	1.978	0.052
	grass_biomass_%	115.238	126.304	0.108	0.912	0.365
	humidity	-5.366	6.187	-0.160	-0.867	0.389
	ambient_temp	15.254	10.141	0.233	1.504	0.137
	Grass by Ht	-12.585	15.973	-0.121	-0.788	0.433
	An_Peren	-13.092	62.976	-0.034	-0.208	0.836
2	(Constant)	-376.538	488.111		-0.771	0.443
	day_timing	20.722	34.814	0.072	0.595	0.553
	Wind_speed (m/s)	110.502	55.599	0.263	1.987	0.051
	grass_biomass_%	118.785	122.693	0.112	0.968	0.336
	humidity	-4.967	5.389	-0.148	-0.922	0.360
	ambient_temp	15.255	10.074	0.233	1.514	0.134
	Grass by Ht	-12.608	15.867	-0.122	-0.795	0.429
	An_Peren	-12.161	62.181	-0.032	-0.196	0.845
3	(Constant)	-417.122	438.997		-0.950	0.345
	day_timing	19.788	34.266	0.069	0.577	0.565
	Wind_speed (m/s)	111.579	54.975	0.266	2.030	0.046
	grass_biomass_%	118.236	121.882	0.111	0.970	0.335
	humidity	-4.550	4.919	-0.136	-0.925	0.358
	ambient_temp	15.874	9.504	0.243	1.670	0.099
	Grass by Ht	-14.394	12.894	-0.139	-1.116	0.268
4	(Constant)	-361.537	426.457		-0.848	0.399
	Wind_speed (m/s)	101.223	51.742	0.241	1.956	0.054
	grass_biomass_%	109.440	120.402	0.103	0.909	0.366
	humidity	-4.402	4.891	-0.131	-0.900	0.371
	ambient_temp	16.332	9.430	0.250	1.732	0.087
	Grass by Ht	-14.797	12.819	-0.143	-1.154	0.252
5	(Constant)	-619.712	315.215		-1.966	0.053
	Wind_speed (m/s)	103.344	51.626	0.246	2.002	0.049
	grass_biomass_%	91.916	118.673	0.087	0.775	0.441
	ambient_temp	20.707	8.071	0.316	2.566	0.012
	Grass by Ht	-9.933	11.610	-0.096	-0.855	0.395
6	(Constant)	-548.852	300.881		-1.824	0.072
	Wind_speed (m/s)	107.040	51.274	0.255	2.088	0.040
	ambient_temp	20.916	8.046	0.320	2.600	0.011
	Grass by Ht	-12.306	11.170	-0.119	-1.102	0.274
7	(Constant)	-558.989	301.142		-1.856	0.067
	Wind_speed (m/s)	105.361	51.320	0.251	2.053	0.043
	ambient_temp	19.881	8.001	0.304	2.485	0.015

a. Dependent Variable: Intensity_act_dry

Excluded Variables[a]						
Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics
						Tolerance
2	CBI	-.019[b]	-0.134	0.894	-0.016	0.599
3	CBI	-.016[c]	-0.113	0.911	-0.013	0.607
	An_Peren	-.032[c]	-0.196	0.845	-0.023	0.443
4	CBI	-.010[d]	-0.069	0.945	-0.008	0.610
	An_Peren	-.019[d]	-0.115	0.908	-0.013	0.452
	day_timing	.069[d]	0.577	0.565	0.066	0.819
5	CBI	.044[e]	0.366	0.716	0.042	0.789
	An_Peren	.036[e]	0.240	0.811	0.027	0.531
	day_timing	.063[e]	0.531	0.597	0.060	0.822
	humidity	-.131[e]	-0.900	0.371	-0.102	0.543
6	CBI	.017[f]	0.145	0.885	0.016	0.850
	An_Peren	.029[f]	0.195	0.846	0.022	0.533
	day_timing	.051[f]	0.437	0.664	0.049	0.833
	humidity	-.110[f]	-0.764	0.447	-0.086	0.558
	grass_biomass_%	.087[f]	0.775	0.441	0.087	0.922
7	CBI	-.012[g]	-0.102	0.919	-0.011	0.895
	An_Peren	-.065[g]	-0.603	0.549	-0.068	0.993
	day_timing	.058[g]	0.495	0.622	0.056	0.836
	humidity	-.022[g]	-0.170	0.865	-0.019	0.709
	grass_biomass_%	.112[g]	1.039	0.302	0.116	0.992
	Grass by Ht	-.119[g]	-1.102	0.274	-0.123	0.985

a. Dependent Variable: Intensity_act_dry

b. Predictors in the Model: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing,

c. Predictors in the Model: (Constant), ambient_temp, grass_biomass_%, day_timing, Wind_speed

d. Predictors in the Model: (Constant), ambient_temp, grass_biomass_%, Wind_speed (m/s), Grass by

e. Predictors in the Model: (Constant), ambient_temp, grass_biomass_%, Wind_speed (m/s), Grass by

f. Predictors in the Model: (Constant), ambient_temp, Wind_speed (m/s), Grass by Ht

g. Predictors in the Model: (Constant), ambient_temp, Wind_speed (m/s)

APPENDIX B

MODEL DETAILS FOR HEAD FIRES

Correlations

		CBI	day_timing	Wind_speed	grass_percent	humidity	temp	Grass by Ht	An_Peren	Flam_height (m)	Eff_Visual	Biom_cons %	Intensity
CBI	Pearson Correlation	1	0.221	-0.216	-.412**	-.604**	.383*	.369*	.334*	0.141	.523**	0.267	0.070
	Sig. (2-tailed)		0.171	0.181	0.008	0.000	0.015	0.019	0.035	0.384	0.001	0.096	0.668
	N	40	40	40	40	40	40	40	40	40	40	40	40
day_timing	Pearson Correlation	0.221	1	-.621**	-0.053	-0.088	0.151	-0.038	0.124	0.135	0.198	0.210	0.005
	Sig. (2-tailed)	0.171		0.000	0.747	0.591	0.354	0.818	0.444	0.407	0.220	0.193	0.978
	N	40	40	40	40	40	40	40	40	40	40	40	40
Wind_speed	Pearson Correlation	-0.216	-.621**	1	0.079	0.275	-.463**	-0.065	-0.209	0.052	-0.036	-0.123	0.222
	Sig. (2-tailed)	0.181	0.000		0.628	0.086	0.003	0.690	0.196	0.751	0.825	0.449	0.169
	N	40	40	40	40	40	40	40	40	40	40	40	40
grass_percent	Pearson Correlation	-.412**	-0.053	0.079	1	0.248	-0.007	-0.308	-0.201	0.145	0.062	-0.139	0.243
	Sig. (2-tailed)	0.008	0.747	0.628		0.122	0.964	0.053	0.214	0.372	0.706	0.393	0.131
	N	40	40	40	40	40	40	40	40	40	40	40	40
humidity	Pearson Correlation	-.604**	-0.088	0.275	0.248	1	-.502**	-.524**	-.568**	-0.207	-0.254	-0.050	-0.131
	Sig. (2-tailed)	0.000	0.591	0.086	0.122		0.001	0.001	0.000	0.201	0.114	0.761	0.420
	N	40	40	40	40	40	40	40	40	40	40	40	40
temp	Pearson Correlation	.383*	0.151	-.463**	-0.007	-.502**	1	0.109	0.069	0.152	0.304	.324*	0.128
	Sig. (2-tailed)	0.015	0.354	0.003	0.964	0.001		0.503	0.674	0.348	0.057	0.041	0.432
	N	40	40	40	40	40	40	40	40	40	40	40	40
Grass by Ht	Pearson Correlation	.369*	-0.038	-0.065	-0.308	-.524**	0.109	1	.665**	0.018	-0.026	-0.152	-0.162
	Sig. (2-tailed)	0.019	0.818	0.690	0.053	0.001	0.503		0.000	0.914	0.873	0.348	0.319
	N	40	40	40	40	40	40	40	40	40	40	40	40
An_Peren	Pearson Correlation	.334*	0.124	-0.209	-0.201	-.568**	0.069	.665**	1	0.201	0.117	-.342*	-0.134
	Sig. (2-tailed)	0.035	0.444	0.196	0.214	0.000	0.674	0.000		0.214	0.474	0.031	0.408
	N	40	40	40	40	40	40	40	40	40	40	40	40
Flam_height (m)	Pearson Correlation	0.141	0.135	0.052	0.145	-0.207	0.152	0.018	0.201	1	.369*	0.083	.420**
	Sig. (2-tailed)	0.384	0.407	0.751	0.372	0.201	0.348	0.914	0.214		0.019	0.612	0.007
	N	40	40	40	40	40	40	40	40	40	40	40	40
Eff_Visual	Pearson Correlation	.523**	0.198	-0.036	0.062	-0.254	0.304	-0.026	0.117	.369*	1	.449**	.367*
	Sig. (2-tailed)	0.001	0.220	0.825	0.706	0.114	0.057	0.873	0.474	0.019		0.004	0.020
	N	40	40	40	40	40	40	40	40	40	40	40	40
Biom_cons %	Pearson Correlation	0.267	0.210	-0.123	-0.139	-0.050	.324*	-0.152	-.342*	0.083	.449**	1	0.231
	Sig. (2-tailed)	0.096	0.193	0.449	0.393	0.761	0.041	0.348	0.031	0.612	0.004		0.152
	N	40	40	40	40	40	40	40	40	40	40	40	40
Intensity	Pearson Correlation	0.070	0.005	0.222	0.243	-0.131	0.128	-0.162	-0.134	.420**	.367*	0.231	1
	Sig. (2-tailed)	0.668	0.978	0.169	0.131	0.420	0.432	0.319	0.408	0.007	0.020	0.152	
	N	40	40	40	40	40	40	40	40	40	40	40	40

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

c. Cannot be computed because at least one of the variables is constant.

Enter Regression

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	An_Peren, ambient_temp, day_timing, grass_biomass_%, CBI, Grass by Ht, Wind_speed (m/s), humidity[b]		Enter

a. Dependent Variable: Intensity_act_dry

b. All requested variables entered.

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.545[a]	0.297	0.116	294.07

a. Predictors: (Constant), An_Peren, ambient_temp, day_timing,

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1134243.61	8	141780.45	1.640	.154[b]
	Residual	2680737.59	31	86475.406		
	Total	3814981.19	39			

a. Dependent Variable: Intensity_act_dry

b. Predictors: (Constant), An_Peren, ambient_temp, day_timing, grass_biomass_%, CBI, Grass by

Coefficients[a]						
Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-445.030	957.312		-0.465	0.645
	CBI	0.555	2.453	0.048	0.226	0.822
	day_timing	106.575	76.026	0.286	1.402	0.171
	Wind_speed (m/s)	294.789	126.661	0.525	2.327	0.027
	grass_biomass_%	291.973	203.092	0.248	1.438	0.161
	humidity	-15.524	10.248	-0.378	-1.515	0.140
	ambient_temp	13.087	18.330	0.151	0.714	0.481
	Grass by Ht	-22.246	25.611	-0.188	-0.869	0.392
	An_Peren	-58.600	106.428	-0.126	-0.551	0.586

a. Dependent Variable: Intensity_act_dry

Backward Regression

Variables Entered/Removed[a]

Model	Variables Entered	Variables Removed	Method
1	An_Peren, ambient_temp, day_timing, grass_biomass_%, CBI, Grass by Ht, Wind_speed (m/s), humidity[b]		Enter
2		CBI	Backward (criterion: Probability of F-to-remove >= .100).
3		An_Peren	Backward (criterion: Probability of F-to-remove >= .100).
4		temp	Backward (criterion: Probability of F-to-remove >= .100).
5		day_timing	Backward (criterion: Probability of F-to-remove >= .100).
6		grass_percent	Backward (criterion: Probability of F-to-remove >= .100).

a. Dependent Variable: Intensity_act_dry

b. All requested variables entered.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.545[a]	0.297	0.116	294.07
2	.544[b]	0.296	0.142	289.67
3	.538[c]	0.289	0.160	286.67
4	.516[d]	0.267	0.159	286.84
5	.476[e]	0.227	0.138	290.35
6	.421[f]	0.177	0.109	295.24

a. Predictors: (Constant), An_Peren, ambient_temp, day_timing, grass_biomass_%,

b. Predictors: (Constant), An_Peren, ambient_temp, day_timing, grass_biomass_%,

c. Predictors: (Constant), ambient_temp, day_timing, grass_biomass_%, Grass by Ht,

d. Predictors: (Constant), day_timing, grass_biomass_%, Grass by Ht, Wind_speed

e. Predictors: (Constant), grass_biomass_%, Grass by Ht, Wind_speed (m/s), humidity

f. Predictors: (Constant), Grass by Ht, Wind_speed (m/s), humidity

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	1134243.606	8	141780.451	1.640	.154[b]
	Residual	2680737.588	31	86475.406		
	Total	3814981.194	39			
2	Regression	1129810.212	7	161401.459	1.923	.098[c]
	Residual	2685170.982	32	83911.593		
	Total	3814981.194	39			
3	Regression	1103028.152	6	183838.025	2.237	.064[d]
	Residual	2711953.042	33	82180.395		
	Total	3814981.194	39			
4	Regression	1017466.017	5	203493.203	2.473	.052[e]
	Residual	2797515.177	34	82279.858		
	Total	3814981.194	39			
5	Regression	864464.023	4	216116.006	2.564	.055[f]
	Residual	2950517.170	35	84300.491		
	Total	3814981.194	39			
6	Regression	677066.843	3	225688.948	2.589	.068[g]
	Residual	3137914.351	36	87164.288		
	Total	3814981.194	39			

a. Dependent Variable: Intensity_act_dry

b. Predictors: (Constant), An_Peren, ambient_temp, day_timing, grass_biomass_%, CBI, Grass by

c. Predictors: (Constant), An_Peren, ambient_temp, day_timing, grass_biomass_%, Grass by Ht,

d. Predictors: (Constant), ambient_temp, day_timing, grass_biomass_%, Grass by Ht, Wind_speed

e. Predictors: (Constant), day_timing, grass_biomass_%, Grass by Ht, Wind_speed (m/s), humidity

f. Predictors: (Constant), grass_biomass_%, Grass by Ht, Wind_speed (m/s), humidity

g. Predictors: (Constant), Grass by Ht, Wind_speed (m/s), humidity

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-445.030	957.312		-0.465	0.645
	CBI	0.555	2.453	0.048	0.226	0.822
	day_timing	106.575	76.026	0.286	1.402	0.171
	Wind_speed (m/s)	294.789	126.661	0.525	2.327	0.027
	grass_biomass_%	291.973	203.092	0.248	1.438	0.161
	humidity	-15.524	10.248	-0.378	-1.515	0.140
	ambient_temp	13.087	18.330	0.151	0.714	0.481
	Grass by Ht	-22.246	25.611	-0.188	-0.869	0.392
	An_Peren	-58.600	106.428	-0.126	-0.551	0.586
2	(Constant)	-411.763	931.842		-0.442	0.662
	day_timing	111.055	72.311	0.298	1.536	0.134
	Wind_speed (m/s)	299.452	123.109	0.534	2.432	0.021
	grass_biomass_%	275.809	187.292	0.234	1.473	0.151
	humidity	-16.391	9.364	-0.399	-1.750	0.090
	ambient_temp	13.904	17.703	0.160	0.785	0.438
	Grass by Ht	-21.864	25.173	-0.185	-0.869	0.392
	An_Peren	-59.210	104.805	-0.128	-0.565	0.576
3	(Constant)	-632.218	837.427		-0.755	0.456
	day_timing	108.764	71.448	0.292	1.522	0.137
	Wind_speed (m/s)	311.371	120.030	0.555	2.594	0.014
	grass_biomass_%	265.708	184.504	0.225	1.440	0.159
	humidity	-14.183	8.421	-0.345	-1.684	0.102
	ambient_temp	16.999	16.660	0.196	1.020	0.315
	Grass by Ht	-29.219	21.322	-0.247	-1.370	0.180
4	(Constant)	128.215	382.174		0.335	0.739
	day_timing	95.978	70.383	0.258	1.364	0.182
	Wind_speed (m/s)	261.659	109.764	0.466	2.384	0.023
	grass_biomass_%	287.417	183.384	0.244	1.567	0.126
	humidity	-18.213	7.442	-0.443	-2.447	0.020
	Grass by Ht	-32.924	21.023	-0.278	-1.566	0.127
5	(Constant)	495.676	274.312		1.807	0.079
	Wind_speed (m/s)	168.961	87.232	0.301	1.937	0.061
	grass_biomass_%	276.491	185.445	0.234	1.491	0.145
	humidity	-17.478	7.513	-0.425	-2.326	0.026
	Grass by Ht	-34.569	21.245	-0.292	-1.627	0.113
6	(Constant)	702.776	240.528		2.922	0.006
	Wind_speed (m/s)	173.278	88.653	0.309	1.955	0.058
	humidity	-16.431	7.606	-0.400	-2.160	0.037
	Grass by Ht	-41.487	21.081	-0.351	-1.968	0.057

a. Dependent Variable: Intensity_act_dry

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
2	CBI	.048[b]	0.226	0.822	0.041	0.507
3	CBI	.051[c]	0.243	0.809	0.043	0.507
	An_Peren	-.128[c]	-0.565	0.576	-0.099	0.430
4	CBI	.093[d]	0.454	0.653	0.079	0.532
	An_Peren	-.183[d]	-0.855	0.399	-0.147	0.475
	ambient_temp	.196[d]	1.020	0.315	0.175	0.584
5	CBI	.147[e]	0.737	0.466	0.125	0.559
	An_Peren	-.149[e]	-0.691	0.494	-0.118	0.481
	ambient_temp	.145[e]	0.751	0.458	0.128	0.603
	day_timing	.258[e]	1.364	0.182	0.228	0.604
6	CBI	.039[f]	0.202	0.841	0.034	0.628
	An_Peren	-.133[f]	-0.604	0.550	-0.102	0.482
	ambient_temp	.177[f]	0.913	0.367	0.153	0.612
	day_timing	.245[f]	1.270	0.212	0.210	0.605
	grass_biomass_%	.234[f]	1.491	0.145	0.244	0.893

a. Dependent Variable: Intensity_act_dry

b. Predictors in the Model: (Constant), An_Peren, ambient_temp, day_timing, grass_biomass_%, Grass by

c. Predictors in the Model: (Constant), ambient_temp, day_timing, grass_biomass_%, Grass by Ht,

d. Predictors in the Model: (Constant), day_timing, grass_biomass_%, Grass by Ht, Wind_speed (m/s),

e. Predictors in the Model: (Constant), grass_biomass_%, Grass by Ht, Wind_speed (m/s), humidity

f. Predictors in the Model: (Constant), Grass by Ht, Wind_speed (m/s), humidity

APPENDIX C

MODEL DETAILS FOR BACK FIRES

Correlations

		CBI	day_timing	Wind_speed	grass_percent	humidity	temp	Grass by Ht	An_Peren	Flam_height (m)	Eff_Visual	Biom_cons %	Intensity
CBI	Pearson Correlation	1	0.009	0.000	-0.229	-.595**	0.294	0.147	0.146	.317*	.491**	0.228	.429**
	Sig. (2-tailed)		0.952	0.999	0.140	0.000	0.056	0.347	0.349	0.039	0.001	0.141	0.004
	N	43	43	43	43	43	43	43	43	43	43	43	43
day_timing	Pearson Correlation	0.009	1	-0.230	-0.209	-0.067	.303*	-0.036	0.022	0.081	0.182	0.028	-0.008
	Sig. (2-tailed)	0.952		0.139	0.179	0.668	0.048	0.821	0.890	0.607	0.243	0.858	0.962
	N	43	43	43	43	43	43	43	43	43	43	43	43
Wind_speed	Pearson Correlation	0.000	-0.230	1	0.095	0.193	-.492**	0.016	0.035	-0.042	-0.046	0.072	0.011
	Sig. (2-tailed)	0.999	0.139		0.545	0.215	0.001	0.917	0.822	0.791	0.770	0.648	0.944
	N	43	43	43	43	43	43	43	43	43	43	43	43
grass_percent	Pearson Correlation	-0.229	-0.209	0.095	1	0.243	-0.048	-0.157	-0.240	-0.136	0.001	0.003	0.185
	Sig. (2-tailed)	0.140	0.179	0.545		0.116	0.760	0.315	0.120	0.385	0.993	0.986	0.236
	N	43	43	43	43	43	43	43	43	43	43	43	43
humidity	Pearson Correlation	-.595**	-0.067	0.193	0.243	1	-.581**	-.374*	-.425**	-0.265	-0.184	-0.106	-0.266
	Sig. (2-tailed)	0.000	0.668	0.215	0.116		0.000	0.013	0.005	0.086	0.237	0.500	0.085
	N	43	43	43	43	43	43	43	43	43	43	43	43
temp	Pearson Correlation	0.294	.303*	-.492**	-0.048	-.581**	1	0.105	-0.005	0.206	.325*	0.179	.351*
	Sig. (2-tailed)	0.056	0.048	0.001	0.760	0.000		0.503	0.976	0.185	0.033	0.251	0.021
	N	43	43	43	43	43	43	43	43	43	43	43	43
Grass by Ht	Pearson Correlation	0.147	-0.036	0.016	-0.157	-.374*	0.105	1	.687**	-0.243	-0.112	-0.229	-0.211
	Sig. (2-tailed)	0.347	0.821	0.917	0.315	0.013	0.503		0.000	0.117	0.475	0.140	0.174
	N	43	43	43	43	43	43	43	43	43	43	43	43
An_Peren	Pearson Correlation	0.146	0.022	0.035	-0.240	-.425**	-0.005	.687**	1	-0.150	-0.137	-0.043	-0.156
	Sig. (2-tailed)	0.349	0.890	0.822	0.120	0.005	0.976	0.000		0.337	0.382	0.782	0.319
	N	43	43	43	43	43	43	43	43	43	43	43	43
Flam_height (m)	Pearson Correlation	.317*	0.081	-0.042	-0.136	-0.265	0.206	-0.243	-0.150	1	.377*	0.283	.716**
	Sig. (2-tailed)	0.039	0.607	0.791	0.385	0.086	0.185	0.117	0.337		0.013	0.066	0.000
	N	43	43	43	43	43	43	43	43	43	43	43	43
Eff_Visual	Pearson Correlation	.491**	0.182	-0.046	0.001	-0.184	.325*	-0.112	-0.137	.377*	1	.453**	.439**
	Sig. (2-tailed)	0.001	0.243	0.770	0.993	0.237	0.033	0.475	0.382	0.013		0.002	0.003
	N	43	43	43	43	43	43	43	43	43	43	43	43
Biom_cons %	Pearson Correlation	0.228	0.028	0.072	0.003	-0.106	0.179	-0.229	-0.043	0.283	.453**	1	.398**
	Sig. (2-tailed)	0.141	0.858	0.648	0.986	0.500	0.251	0.140	0.782	0.066	0.002		0.008
	N	43	43	43	43	43	43	43	43	43	43	43	43
Intensity	Pearson Correlation	.429**	-0.008	0.011	0.185	-0.266	.351*	-0.211	-0.156	.716**	.439**	.398**	1
	Sig. (2-tailed)	0.004	0.962	0.944	0.236	0.085	0.021	0.174	0.319	0.000	0.003	0.008	
	N	43	43	43	43	43	43	43	43	43	43	43	43

**. Correlation is significant at the 0.01 level (2-tailed).

*. Correlation is significant at the 0.05 level (2-tailed).

c. Cannot be computed because at least one of the variables is constant.

Enter Regression

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI, Wind_speed (m/s), Grass by Ht, humidity[b]		Enter

a. Dependent Variable: Intensity_act_dry

b. All requested variables entered.

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.641[a]	0.411	0.272	72.45

a. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing,

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	124451.38	8	15556.422	2.963	.013[b]
	Residual	178490.53	34	5249.722		
	Total	302941.91	42			

a. Dependent Variable: Intensity_act_dry

b. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI,

Coefficients[a]						
Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	-341.632	226.765		-1.507	0.141
	CBI	1.378	0.555	0.422	2.482	0.018
	day_timing	-4.960	13.881	-0.052	-0.357	0.723
	Wind_speed (m/s)	22.168	21.105	0.163	1.050	0.301
	grass_biomass_%	101.276	62.650	0.233	1.617	0.115
	humidity	0.290	2.715	0.025	0.107	0.915
	ambient_temp	8.204	4.453	0.382	1.843	0.074
	Grass by Ht	-12.554	7.369	-0.315	-1.704	0.098
	An_Peren	8.432	27.394	0.063	0.308	0.760

a. Dependent Variable: Intensity_act_dry

Forward Regression

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	CBI		Forward (Criterion: Probability-of-F-to-enter <= .050)
2	grass_biomass_%		Forward (Criterion: Probability-of-F-to-enter <= .050)
a. Dependent Variable: Intensity_act_dry			

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.429[a]	0.184	0.164	77.66
2	.518[b]	0.268	0.232	74.44
a. Predictors: (Constant), CBI				
b. Predictors: (Constant), CBI, grass_biomass_%				

ANOVA[a]						
Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	55681.089	1	55681.089	9.233	.004[b]
	Residual	247260.82	41	6030.752		
	Total	302941.91	42			
2	Regression	81278.452	2	40639.226	7.334	.002[c]
	Residual	221663.46	40	5541.587		
	Total	302941.91	42			
a. Dependent Variable: Intensity_act_dry						
b. Predictors: (Constant), CBI						
c. Predictors: (Constant), CBI, grass_biomass_%						

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-0.663	42.778		-0.015	0.988
	CBI	1.400	0.461	0.429	3.039	0.004
2	(Constant)	-128.783	72.355		-1.780	0.083
	CBI	1.623	0.454	0.497	3.578	0.001
	grass_biomass_%	129.776	60.383	0.299	2.149	0.038

a. Dependent Variable: Intensity_act_dry

Excluded Variables[a]

Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
1	day_timing	-.012[b]	-0.081	0.936	-0.013	1.000
	Wind_speed (m/s)	.011[b]	0.078	0.938	0.012	1.000
	grass_biomass_%	.299[b]	2.149	0.038	0.322	0.948
	humidity	-.016[b]	-0.092	0.927	-0.015	0.646
	ambient_temp	.247[b]	1.710	0.095	0.261	0.914
	Grass by Ht	-.280[b]	-2.039	0.048	-0.307	0.978
	An_Peren	-.223[b]	-1.595	0.119	-0.244	0.979
2	day_timing	.052[c]	0.375	0.710	0.060	0.955
	Wind_speed (m/s)	-.017[c]	-0.125	0.901	-0.020	0.991
	humidity	-.067[c]	-0.390	0.699	-0.062	0.634
	ambient_temp	.240[c]	1.742	0.089	0.269	0.913
	Grass by Ht	-.247[c]	-1.842	0.073	-0.283	0.962
	An_Peren	-.168[c]	-1.206	0.235	-0.190	0.933

a. Dependent Variable: Intensity_act_dry

b. Predictors in the Model: (Constant), CBI

c. Predictors in the Model: (Constant), CBI, grass_biomass_%

Backward Regression

Variables Entered/Removed[a]			
Model	Variables Entered	Variables Removed	Method
1	An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI, Wind_speed (m/s), Grass by Ht, humidity[b]		Enter
2		humidity	Backward (criterion: Probability of F-to-remove >= .100).
3		An_Peren	Backward (criterion: Probability of F-to-remove >= .100).
4		day_timing	Backward (criterion: Probability of F-to-remove >= .100).
5		Wind_speed (m/s)	Backward (criterion: Probability of F-to-remove >= .100).
a. Dependent Variable: Intensity_act_dry			
b. All requested variables entered.			

Model Summary				
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	.641[a]	0.411	0.272	72.45
2	.641[b]	0.411	0.293	71.42
3	.640[c]	0.409	0.311	70.51
4	.638[d]	0.407	0.327	69.66
5	.623[e]	0.388	0.323	69.86
a. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI,				
b. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI,				
c. Predictors: (Constant), ambient_temp, grass_biomass_%, day_timing, CBI, Wind_speed				
d. Predictors: (Constant), ambient_temp, grass_biomass_%, CBI, Wind_speed (m/s), Grass				
e. Predictors: (Constant), ambient_temp, grass_biomass_%, CBI, Grass by Ht				

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	124451.38	8	15556.422	2.963	.013[b]
	Residual	178490.53	34	5249.722		
	Total	302941.91	42			
2	Regression	124391.26	7	17770.180	3.483	.006[c]
	Residual	178550.65	35	5101.447		
	Total	302941.91	42			
3	Regression	123952.39	6	20658.732	4.155	.003[d]
	Residual	178989.52	36	4971.931		
	Total	302941.91	42			
4	Regression	123400.07	5	24680.014	5.086	.001[e]
	Residual	179541.84	37	4852.482		
	Total	302941.91	42			
5	Regression	117497.41	4	29374.353	6.019	.001[f]
	Residual	185444.50	38	4880.118		
	Total	302941.91	42			

a. Dependent Variable: Intensity_act_dry

b. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI,

c. Predictors: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI,

d. Predictors: (Constant), ambient_temp, grass_biomass_%, day_timing, CBI, Wind_speed (m/s),

e. Predictors: (Constant), ambient_temp, grass_biomass_%, CBI, Wind_speed (m/s), Grass by Ht

f. Predictors: (Constant), ambient_temp, grass_biomass_%, CBI, Grass by Ht

Coefficients[a]

Model		Unstandardized Coefficients B	Unstandardized Coefficients Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	-341.632	226.765		-1.507	0.141
	CBI	1.378	0.555	0.422	2.482	0.018
	day_timing	-4.960	13.881	-0.052	-0.357	0.723
	Wind_speed (m/s)	22.168	21.105	0.163	1.050	0.301
	grass_biomass_%	101.276	62.650	0.233	1.617	0.115
	humidity	0.290	2.715	0.025	0.107	0.915
	ambient_temp	8.204	4.453	0.382	1.843	0.074
	Grass by Ht	-12.554	7.369	-0.315	-1.704	0.098
	An_Peren	8.432	27.394	0.063	0.308	0.760
2	(Constant)	-322.373	135.995		-2.370	0.023
	CBI	1.348	0.470	0.413	2.868	0.007
	day_timing	-4.705	13.479	-0.049	-0.349	0.729
	Wind_speed (m/s)	22.066	20.784	0.163	1.062	0.296
	grass_biomass_%	102.056	61.340	0.235	1.664	0.105
	ambient_temp	7.929	3.582	0.370	2.213	0.033
	Grass by Ht	-12.563	7.264	-0.315	-1.729	0.093
	An_Peren	7.258	24.746	0.054	0.293	0.771
3	(Constant)	-311.578	129.247		-2.411	0.021
	CBI	1.357	0.463	0.416	2.933	0.006
	day_timing	-4.424	13.274	-0.046	-0.333	0.741
	Wind_speed (m/s)	21.987	20.516	0.162	1.072	0.291
	grass_biomass_%	99.357	59.871	0.229	1.660	0.106
	ambient_temp	7.791	3.506	0.363	2.222	0.033
	Grass by Ht	-11.112	5.253	-0.279	-2.115	0.041
4	(Constant)	-319.730	125.378		-2.550	0.015
	CBI	1.376	0.454	0.421	3.032	0.004
	Wind_speed (m/s)	22.327	20.244	0.165	1.103	0.277
	grass_biomass_%	104.002	57.523	0.239	1.808	0.079
	ambient_temp	7.482	3.340	0.349	2.240	0.031
	Grass by Ht	-10.954	5.169	-0.275	-2.119	0.041
5	(Constant)	-246.659	106.746		-2.311	0.026
	CBI	1.471	0.447	0.451	3.293	0.002
	grass_biomass_%	112.569	57.158	0.259	1.969	0.056
	ambient_temp	5.557	2.856	0.259	1.946	0.059
	Grass by Ht	-10.520	5.168	-0.264	-2.036	0.049

a. Dependent Variable: Intensity_act_dry

Excluded Variables[a]						
Model		Beta In	t	Sig.	Partial Correlation	Collinearity Statistics Tolerance
2	humidity	.025[b]	0.107	0.915	0.018	0.321
3	humidity	-.004[c]	-0.018	0.986	-0.003	0.382
	An_Peren	.054[c]	0.293	0.771	0.050	0.499
4	humidity	-.013[d]	-0.062	0.951	-0.010	0.388
	An_Peren	.049[d]	0.273	0.787	0.045	0.501
	day_timing	-.046[d]	-0.333	0.741	-0.055	0.844
5	humidity	-.022[e]	-0.107	0.915	-0.018	0.389
	An_Peren	.046[e]	0.254	0.801	0.042	0.502
	day_timing	-.054[e]	-0.386	0.702	-0.063	0.846
	Wind_speed (m/s)	.165[e]	1.103	0.277	0.178	0.719

a. Dependent Variable: Intensity_act_dry

b. Predictors in the Model: (Constant), An_Peren, ambient_temp, grass_biomass_%, day_timing, CBI,

c. Predictors in the Model: (Constant), ambient_temp, grass_biomass_%, day_timing, CBI, Wind_speed

d. Predictors in the Model: (Constant), ambient_temp, grass_biomass_%, CBI, Wind_speed (m/s), Grass

e. Predictors in the Model: (Constant), ambient_temp, grass_biomass_%, CBI, Grass by Ht

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