THE IMPACT OF CONSECUTIVE DRY DAY EVOLUTION ON THE FREQUENCY AND MAGNITUDE OF LARGE-SCALE FIRES IN SOUTHERN APPALACHIA

by

MATTHEW DANIEL WARREN

Under the Direction of Marshall Shepherd

ABSTRACT

Over the past few years, the frequency and severity of forest fires throughout Southern Appalachia have been on the rise. This area, until recently, had experienced a prolonged period of relatively low wildfire activity. This leads one to scientific questions about what is driving the increase in activity. The climate of the study region has been fairly stable for several decades, but there could be a shift occurring, particularly related to precipitation frequency and intensity. This study is motivated by the notion that there is a relationship between consecutive "dry days" and fire frequency/magnitude. While drought has been a central focus, recent studies suggest that fuel load and consecutive "dry days" could be significant identifiers of an impending large-scale fire event. Using a climate division framework, we identify key co-relationships between precipitation and large-scale wildfire activity in the region.

INDEX WORDS: Consecutive dry days, fire, ignition, precipitation, wildfire, fire, Appalachia

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DEDICATION

This research is dedicated first and foremost to the 14 people who lost their lives in the Great Smoky Mountain Wildfire of 2016. May their memory live on. It is dedicated to the men and women who sustained injuries, lost their businesses, and lost their homes. It is dedicated to the first responders who fought bravely to put out the fire and the local authorities who did their best to alert the public and help the communities cope with the aftermath. It is also dedicated to the scientists who work tirelessly to help better understand tragedies such as this fire, and help to create improved warning systems, fire prevention, and community preparedness. May this work be a critical contribution towards a greater understanding of wildfire in the Southeastern United States and help its communities to be better prepared for future events. Finally, this is dedicated to the good people of Southern Appalachia and all those affected by the wildfire outbreak of 2016.

ACKNOWLEDGEMENTS

I would like to acknowledge my committee for their assistance in my research: Dr. Marshall Shepherd, Dr. Marcus Williams, and Dr. Andrew Grundstein. I would like to thank NOAA, the U.S. Forest Service, and ORNL DAAC for providing all necessary data for this research. I would also like to acknowledge Dr. Gabe Kooperman for his assistance in using MATLAB 2017 to parse the original Daymet data. I would like to thank Dr. Lynne Seymour for her help in conducting statistical analysis with JMP software. I would also like to acknowledge Dr. Jacob M. McDonald for his assistance in developing the R code used to geographically reference the data points. Finally, I would like to thank my colleague Stephen Cooper for his assistance in producing the maps seen in this presentation.

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CHAPTER 1

INTRODUCTION

Fire activity is an integral element of the forest ecosystems in the Southern Appalachian region of the United States. It is a determining factor governing spatial forest structure (Kane et al. 2014) and also influences soil-nutrient composition (Morris et al. 2015, Schlesinger et al. 2016) and biotic community structure (Johnstone et al. 2016). Fire is not only responsible for shaping the vegetative composition of the landscape but also influences the structure and composition of biotic communities, soil quality and composition, watershed quality, and nutrient availability (Johnstone et al. 2016; Morris et al. 2015; Schlesinger et al. 2016). In addition, small increases in pollution episodes, including those associated with forest fires, can negatively affect the outstanding visibility and air quality that characterize Southern Appalachia (Hyslop, 2009, Liu, 2004). Some forest ecosystems of the Appalachian Mountains are pyrogenic (Lafon et al. 2017), meaning that the composition of these ecosystems is determined by and influenced by fire. Southern Appalachia has an extensive history as a pyrogenic ecosystem, and still has its landscape significantly altered by fire activity despite the increase in population and human-environmental interaction (Van Lear et al. 1989).

In the Appalachian Region of the United States, fire poses a major economic threat to natural resources and communities, making wildfire occurrence of great importance to managing agencies (Lynch & Hessl, 2010). This area of the United States is often synonymous with higher levels of poverty and vulnerability than the rest of the country (Lynch & Hessl, 2010). This means that the surrounding communities are more susceptible to changes in climate and fire activity (Lynch & Hessl, 2010). The area is also characterized by similar topography and current climate characteristic. Southern Appalachia contains the Appalachian Mountains, which has formed a system of ridges and valleys within the area. Several ridges and valleys indicate significant topographic variability, creating an additional challenge for dealing with fire activity. The organic matter of the area provides other significant challenges for dealing with the ignition and spread of wildfire.

Dry days have a direct impact on detritus that has collected on the forest floor (Chen et al. 2014). This detritus serves as fuel to be ignited by either anthropogenic sources or lightning. Research shows that consecutive dry days in the Appalachian region are a key factor in wildfire ignition (Lafon et al. 2017). It has been shown that consecutive dry-days leading up to a fire event have a statistically significant relationship pertaining to the amount of burned area for each specific fire (Chen et al. 2014). Current fire-suppression strategies (i.e. controlled-burns) implemented by management agencies in the Appalachians support the fuel-loading of forest understories. This allows for the continued build-up of biomass fuels in the Appalachian forest. This continued build-up could influence fire severity and burned area of current and future wildfires specifically in areas with prolonged dry periods. Southern Appalachia is characterized by current changes in precipitation behavior, a large amount of fuel-loading compared to other forested areas, and a statistical relationship shown between consecutive dry-days and area burned (Lafon, 2017). There is emerging evidence that research is needed on the relationships between consecutive dry days and fire behavior in Southern Appalachia, particularly after the catastrophic fire season of 2016. Research will examine the relationship between the two factors to see the scale of the impact consecutive dry-days have on Southern Appalachian fire activity.

1.1 Motivation

In late November to early December of 2016, a series of wildfires devastated much of the Great Smoky Mountains National Park. The largest fire was brought on by anthropogenic ignition, but prime conditions for a disastrous fire event, including an extended period of low precipitation and record high daily maximum temperatures throughout Southern Appalachia, caused the fire to impact the area at such a large scale. Anomalous ridging over the central United States reduced south-southwesterly moisture transports into the southeastern region of the country by around 75% (Park Williams et al. 2018). The United States Drought Monitor index characterized the Southeastern United States as in a state of "severe drought" or worse around late November (Svoboda et al., 2002). The fire burned nearly 18,000 acres, destroyed over 2,400 buildings, and caused millions of dollars' worth of damage. The large scale of the fire was the result of optimal climatic conditions for expansion. The Smoky Mountain fires came on the tail-end of unseasonably dry weather for the late autumn in Southern Appalachia. This fact, accompanied by leaf litter accumulation, provided ample fuel for fires to ignite. Finally, a cold front moving through the area aided the expansion of already ignited fires with sustained winds of over 40 mph in some areas, with gusts exceeding 70 mph. The event created a demand for research examining the relationships between the dynamic climate of Southern Appalachia, specifically precipitation, and recent fire activity.

Similar research has been carried out previously in other areas of the globe such as Dr. Feng Chen's paper examining the influence of consecutive dry-days on burned area in the Yunnan Province of Southwestern China (Chen et al., 2014). The unique organic and physiological characteristics of Southern Appalachia with the recently observed changes in both fire behavior and climate, specifically regarding intra-annual precipitation variability, suggest further research is needed.

Current methods of predicting the potential for large scale fire activity currently exist using numerous parameters as determinants. One example of a method for predicting the fire activity is the National Fire Danger Rating System. The system consists of spread and ignition components, the Keetch-Byrum Drought Index, and a burning index to classify conditions as one of five severities of risk for fire activity (Bradshaw et al. 1984; Cohen & Deeming, 1985). The system is weighted towards specific regions at a national scale to indicate optimal conditions for wild fire activity. However, current analysis of such rating systems shows blanket coverage of the Southern Appalachian region having the same climatic characteristics as areas of the Northeast and the Mid-Atlantic (Schlobaum & Brain, 2002). This is not necessarily the case as it pertains to variables such as precipitation and humidity (Rice et al. 2018). This research is more interested in looking at the specific relationship between precipitation and fire, rather than considering numerous, more complex variables.

With the support of the United States Forest Service, an investigation is conducted on the climatological processes potentially responsible for the increase in fire frequency and magnitude in Southern Appalachia. The goal is to ultimately aid first responders, policy makers, and citizens of the region to be better prepared for fire events such as the 2016 season. The conclusions drawn from investigating the relationship between dry-days and fire magnitude frequency may yield results that will aid the United States Forest Service in areas outside of simply Southern Appalachia and may also help the organization gain a greater understanding of the dynamic climate's impact on fire behavior.

1.2 Research Objectives

The main research objective is to determine if there is a statistically significant relationship between dry days, specifically consecutive dry days, leading up to major fire events and the area burned as a result of the fire. This may determine the role consecutive dry days have leading up to fire events in the Southern Appalachian region, specifically catastrophic and large-scale fire events. Historic fire data will be used to observe how fire behavior has progressed within the region. Historic daily precipitation data will then coincide with the fire data to analyze the existing relationships and how they impact the scale and severity of Southern Appalachian fire events. These relationships will be analyzed at the scale of the entire region of study, individual climate divisions within the southeastern United States, and each fire individually. Individual threshold values of precipitation will also be compared with fire data to identify relationships between consecutive dry days and fire severity. This statistical analysis should identify relationships among consecutive dry days, fire frequency, and severity. The analysis used to explain the relationships between fire and precipitation will consist of generalized correlation and regression modeling such as Poisson regression modeling and negative binomial regression modeling. The aim of the research is to identify relationships in order to aid the communities of Southern Appalachia in being better prepared to identify, prevent, and respond to the potential for future large-scale fires and the potential of their occurrence.

CHAPTER 2

LITERATURE REVIEW

2.1 Southern Appalachian Larger-Scale Climate Themes

Fire in regions as humid as Southern Appalachia rely on specific conditions in order for the organic matter to be flammable enough for ignition. Dry periods must occur in order for the organic matter, brought on by precipitation events, to burn (Lafon, 2017). Williams et al.'s assessment of the 2016 Southeastern fire season details climatological and teleconnection patterns surrounding the anomalous event (Williams et al., 2017). Teleconnections such as the El Niño Southern Oscillation (ENSO), Pacific-North American (PNA), Pacific Decadal Oscillation (PDO), and North Atlantic Oscillation (NAO) have explicit relationships with increased fire activity in the Southern United States (Dixon et al. 2008). Fire activity in the winter months is shown to be related to strong ENSO and NAO values during the late summer and autumn (Dixon et al. 2008). Late winter month fires show some correlation with the PDO and PNA anomalies just a few months prior to them in the Southeastern United States (Dixon et al. 2008). Late summer fires can be predicted by ENSO anomalies in the prior six months, and late summer/early autumn fires can be indicated by PNA variation in July (Dixon et al. 2008). Teleconnections, however, work as more broad, large scale indicators of an increase in fire activity during certain months.

Large-scale synoptic patterns can have a profound impact on setting up the necessary conditions for fire activity in Southern Appalachia. Pacific surface highs characterized by dry weather and strong winds hinder moisture transport east towards the Appalachian Mountains (Lafon, 2017). The air masses are also characterized by gusty weather along the edge of dry cold fronts that provide optimal conditions for fire activity. Perhaps the synoptic indicator with the greatest impact on the region is the Bermuda High (Diem, 2013; Doublin & Grundstein, 2008). This subtropical high has a tendency to linger over the region for extended periods of time (Lafon, 2017). When this particular high extends westward towards Texas, moisture from the Gulf of Mexico cannot reach Southern Appalachia, which results in extended periods of drought within the region (Lafon, 2017).

Interannual climatic variability strongly influences the spatio-temporal variability of burning. For example, the location of high and low-pressure centers has a direct impact on the precipitation patterns that indicate whether a certain area at a specific time of the year may be prone to fire activity. This control may extend to fire regimes dominated by anthropogenic ignitions and those altered by modern fire management strategies (Swetnam & Betancourt, 1990; Swetnam et al., 1999; Veblen, 2000; Roman-Cuesta et al. 2003; Westerling et al., 2006). While there has been significant research into linkages between fire and climate in areas such as the Southwestern United States, China, and on a global scale (Lynch & Hessl, 2010; Crimmins, 2005; Holden et al., 2007; Chen et al. 2014), much less research has investigated the role of climate in controlling wildfire occurrence and severity in the humid regions of Southern Appalachia, or the Southeastern United States in general. Modern climate and precipitation regimes are changing in the Southeastern United States, specifically in areas with significant topographic variability, such as the Appalachian Mountains (Burt et al., 2017; Wang et al., 2010). Prior research shows a recent trend of increasing intra-annual variability of summer precipitation in the Southeastern United States, leading up to the autumn fire season (Wang et al., 2010). The same research indicated that summer rainfall variability was not addressed by a difference in the amount of summer rainfall, rather the intensity of the rainfall dropped at one time (Wang et al., 2010).

Similar trends were found in the fall months as well, with research showing an increase in the frequency and intensity of rainfall events characterized as heavy events in Appalachia (Burt et al. 2017). The same research claims that an increase in the percentage of precipitation derived from heavy rainfall events must mean that there is also an increase in the number of "dry days" (Burt et al. 2017). This precipitation variability pattern provides ample fuel to stage fire events throughout the region (Haines, 1983). Annual precipitation is not shown to have as large of an impact on Southeastern wildfire behavior as the differences in intra-annual precipitation variability (Lafon & Quiring, 2012).

2.2 Southern Appalachian Smaller-Scale Climate Themes

Smaller scale indicators, such as precipitation, can be used to identify prime conditions for potential fire activity. The spring and autumn fire seasons of 2016 had similar behaviors to previous fire events, but was one of the most, if not the most severe, based on the amount of area burned (Williams et al. 2017). There was also an increase in the number of fires considered to be large-scale fires (> 500 acres burned) as opposed to previous years (Williams et al. 2017). Several sites throughout the Southeastern United States had some of their driest months of record, but what was specifically different about 2016 from other events was the number on consecutive days without precipitation, otherwise known as dry days (Konrad II & Knox, 2016). Dry days are used as a metric for indicating the potential for fire activity (Chen, 2014). They play a major role in drying out organic matter to provide the conditions for ignition to take place (Chen, 2014).

Other factors that must be considered when observing fire behavior in the Southeastern United States include wind, temperature, means of ignition, and topography. Studies point out that the increasing trend in intense rainfall events is amplified in areas characterized by major topographic variability, specifically at higher elevations (Burt et al. 2017). The Southeastern United States is also characterized by higher temperatures that coincide with previously stated precipitation patterns. Higher temperatures create a rapid drying effect following precipitation events, which cause organic material to be in the optimal state for ignition (Pyne, 2017). This is not ideal considering the organic build-up in Appalachia (Pyne, 2017). Finally, wind can play a considerable role in Southern fire activity by unsettling organic matter and allowing more oxygen to reach the fires (Park Williams et al., 2017). This aids the spread of fires as observed in the 2016 Smoky Mountain fire (Park Williams et al., 2017). These and other climatological-geographical factors directly impact the Southern Appalachian region in regard to fuel loading and burning.

2.3 Fire Activity Themes

In an area with limited controlled burning, more intense rainfall events can cause a greater fuel loading than previously observed (Lafon & Quiring, 2012). The combination of large fuel loading with extended periods of dry weather due to more intense, less frequent precipitation events results in an increase in Southeastern fire activity (Lafon & Quiring, 2012). Current general circulation models (GCMs) suggest an increase in the seasonal severity ratings of fire seasons moving forward, especially in the southeast (Flanning et al. 2000). Worldwide, mean annual precipitation values are expected to increase, while the number of rainfall events are projected to decrease (Polade et al. 2014). Considering the known importance of the number of dry days to both fire frequency and burned area (Chen et al. 2014) in parts of the world, it is necessary to investigate what impact this increase in dry-days may have on fires at a more local scale.

The means of ignition is also important to consider when observing fire activity in Southern Appalachia. According to the United States Forest Service, the two main instigators of fire activity are anthropogenic causes, or human involvement, and lighting strikes, specifically in the spring (Short 2015). Human caused fires vary from an out of control bonfires to arson (Hawbaker et al. 2013). Human-induced fires make up around 85% of annual wildfires in the United States (Short 2015). The other 15% consists of other instigators, but the largest of these is lightning. Especially in months with active severe weather, such as the spring and summer, lighting can be responsible for wildfire ignition when organic matter is dry enough (Barden 1974). When considering the means of ignition however, it is important to address that human and lightning-induced fires are not simply the result of an acting igniter, but the result of certain fire conditions as well.

It is also important to consider the regeneration of organic matter following previously occurring fires (Coppoletta et al. 2016). In areas such as the southeastern United States, this occurs more rapidly due to greater humidity and frequent precipitation throughout the year, providing ample fuel for fire ignition (Coppoletta et al. 2016). Dry conditions and low humidity are necessary in order for the fire produced from the listed actors to ignite and spread (Lafon et al. 2017). Recent measures such as an increase in prescribed burns have been implemented in the Southeastern United States (Elliot et al. 1999). Prescribed fires in the Southeastern United States require specific conditions in order for them to occur (Fowler & Konopik, 2007). Nearly 70% of prescribed burning, by area, takes place in the Southeast (Chiodi et al. 2018).

In the Appalachian Region of the United States, fire poses a major economic threat to natural resources and communities, making wildfire occurrence of great importance to managing agencies (Lynch & Hessl, 2010). Dry days have a direct impact on detritus that has collected on the forest floor (Chen et al. 2014). This detritus serves as fuel to be ignited by either anthropogenic forces or lightning. Research shows that consecutive dry days in the Appalachian region is a key factor in wildfire ignition as shown in Figure 2.1.1 (Lafon et al. 2017). It has been shown that consecutive dry days leading up to a fire event have a statistically significant relationship pertaining to the amount of burned area for each specific fire as shown in Figure 2.1.2 (Chen et al. 2014). Current fire-suppression strategies (i.e. controlled-burns) implemented by management agencies in the Appalachians aim to prevent the fuel-loading of forest understories, but not all areas can be targeted, and ideal conditions are necessary for implementation (Chiodi et al. 2018). In fact, the National Prescribed Fire Use Survey Report shows that significant prescribed burn activity takes place in Southern Appalachian states such as Georgia, South Carolina, and Alabama (Melvin, 2012). However, even with significant steps taken to prevent large-scale fire activity, it still occurs.

The areas with a significant build-up of biomass influence the fire severity and burned area of current and future wildfires specifically in areas with prolonged dry periods. Southern Appalachia is characterized by current changes in precipitation behavior, a large amount of fuel-loading compared to other forested areas, and a statistical relationship shown between consecutive dry days and area burned (Lafon, et al. 2017).

Research has been carried out pertaining to the factors that indicate the potential for fire activity in the United States such as the Keetch-Byram drought index, which quantifies drought conditions throughout the country (Keetch & Byram 1968, Janis et al. 2002). Much of the research focuses on the western United States as opposed to the eastern or southern part of the country. Research has also studied the relationship between dry days and fire magnitude in other areas of the world but not in Southern Appalachia (Chen et al. 2014). There is the demand to conduct research on the relationship pertaining to consecutive dry days and fire behavior in Southern Appalachia, following the catastrophic fire season of 2016. Research will examine the correlation between the two factors to see the scale of the impact consecutive dry days have on Southern Appalachian fire activity.

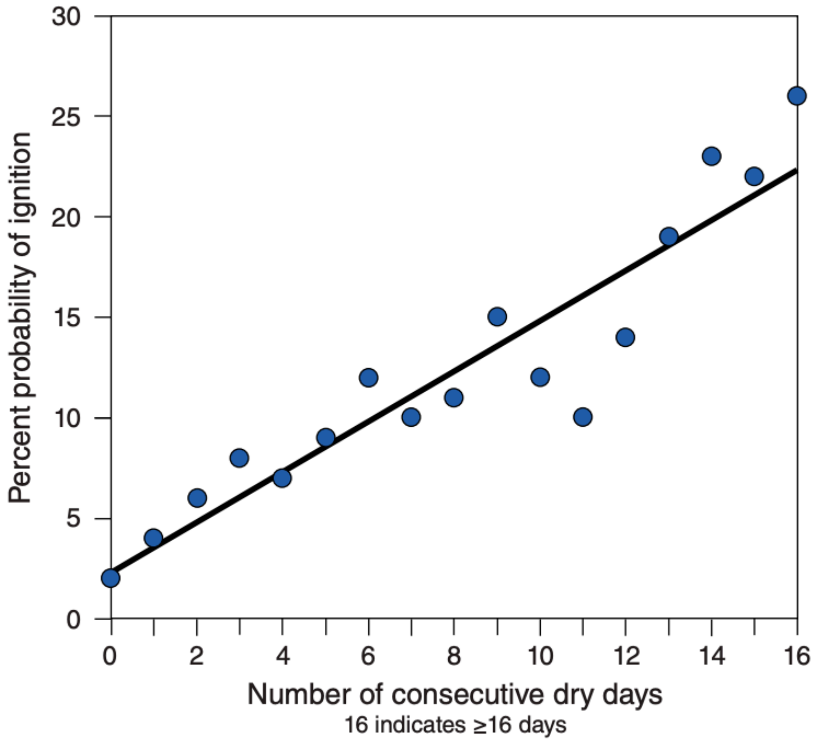

Figure 2.03—Probability of ignition in the National forests in the Ridge and Valley province, West Virginia and Virginia, 1970–2001. Model $R^2 = 0.89$, $F = 115.0$ (df = 1), $P < 0.001$. Probability of ignition increases with the number of consecutive dry days.

Figure 2.1.1: The Relationship between consecutive rain free days (< 0.001mm precipitation) and the probability of wildfire ignition

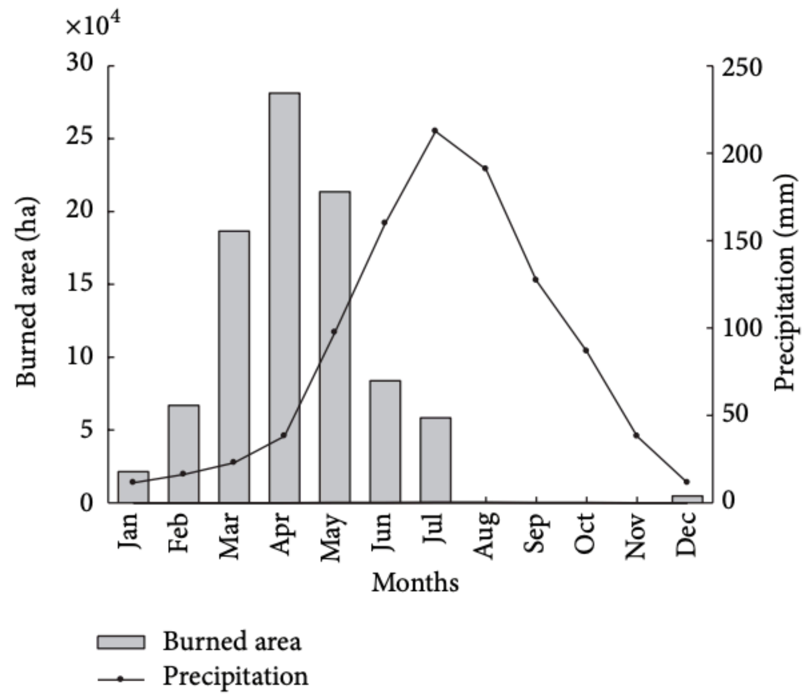

FIGURE 2: The mean annual burned area (ha) and precipitation (mm) during 1996–2008 by month in Yunnan province.

Figure 2.1.2: The Relationship between precipitation and area burned on a monthly basis in Yunnan Province, China

CHAPTER 3

RESEARCH DESIGN AND METHODS

3.1 Study Area

The area chosen to represent Southern Appalachia was based on NOAA's current United States climate division dataset (Figure 3.1.1), which subdivides by states and specific climatological parameters (Vose et al. 2014). The current "nClimDiv" dataset is based on the past Global Historical Climatological Network (GHCN) dataset with improvements made in the accuracy of the data collected at regional, state, and divisional scales from the hundreds of land surface weather stations used (Menne et al., 2012). The climate divisions chosen for this research consist of parts of Alabama, Georgia, North Carolina, South Carolina, and Tennessee (Table 3.1.1). The zones span an elevation gradient of 91 to 1965 meters above sea level. The divisions chosen to represent Southern Appalachia were selected based on similarities in topography, temperature patterns, and precipitation trends. They also contain similar organic composition, which is important while considering the fuel being provided for the ignition and spread of fire. Based on data provided, the divisions used should be fairly consistent topographically, climatologically, and organically.

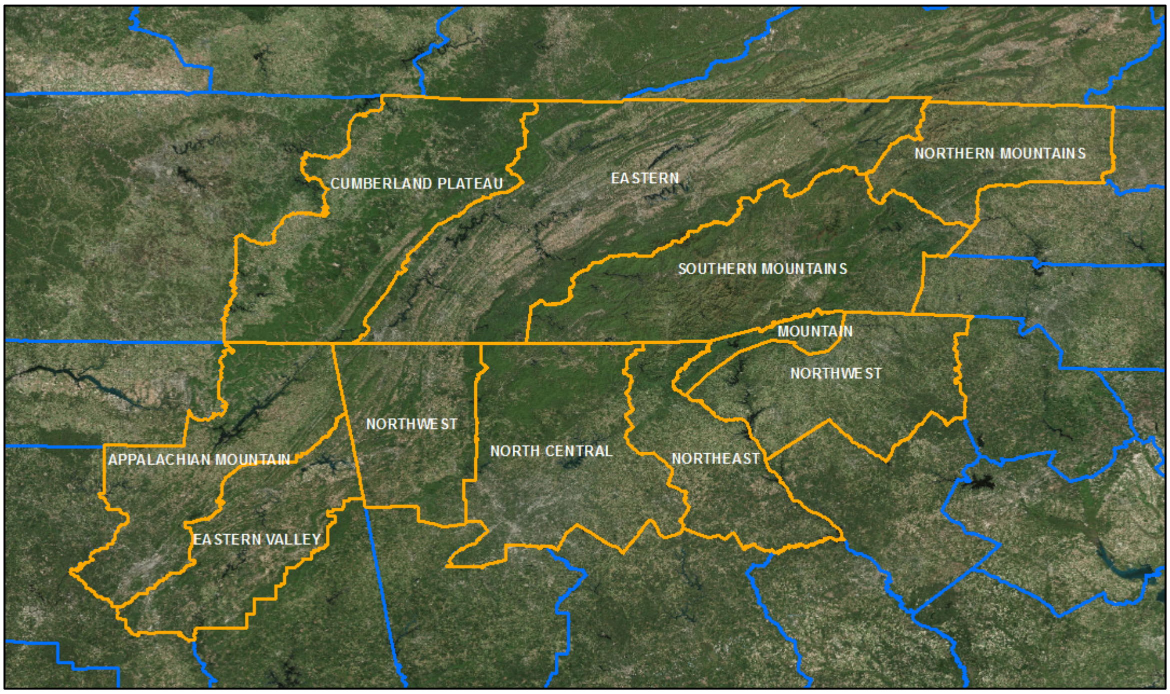

Figure 3.1.1: Southern Appalachia Area of Study and Global Historical Climatological Network's (GHCN) nClimDiv Climate Divisions

nClimDiv (State)	Elevation min (m)	Elevation max (m)	Gradient (m)	Area (US acres)
Appalachian Mountain (AL)	122	558	436	2896040.59
Eastern Valley (AL)	122	594	472	2286239.03
Northwest (GA)	180	1033	853	2121501.78
North Central (GA)	152	1213	1061	3513832.76
Northeast (GA)	91	1338	1247	1964118.79
Southern Mountains (NC)	233	1965	1732	4141111.94
Northern Mountains (NC)	215	1667	1452	1894434.19
Mountain (SC)	230	1002	772	422655.91
Northwest (SC)	94	498	404	2544954.05
Cumberland Plateau (TN)	177	908	731	3925987.54
Eastern (TN)	239	1965	1726	6277979.60

Table 3.1.1: Southern Appalachia Global Historical Climatological Network's (GHCN) nClimDiv Climate Divisions with Area in Acres and Elevation

3.2 Data

3.2.1 Precipitation Data

Precipitation data used for observations and calculations in the area of study were gathered from Daily Surface Weather and Climatological Summaries (Daymet) data, created by Oak Ridge National Laboratory's Distributed Active Archive Center for Biogeochemical Dynamics (DAAC) (Figure 3.2.1) (Thornton, 2014). Daymet provides daily gridded weather estimates for North America including daily precipitation occurrences and accumulation, minimum and maximum temperature, shortwave radiation, humidity, day length, and snow water equivalent. The spatial resolution of the data is very high at 1 km x 1 km. Daymet is able to achieve this resolution due to the availability of a large number of weather stations. The dataset extends from 1980 to the present. Using the THREDDS open-source data server, NetCDF formatted daily precipitation data will be gathered for the area of study from 1980-2017. It should also be noted that Daymet data is topographically adjusted, which is necessary for dealing with areas of significant elevation variance, such as Southern Appalachia. The specific dataset used for this study has detailed information on latitude, longitude, daily precipitation, and time.

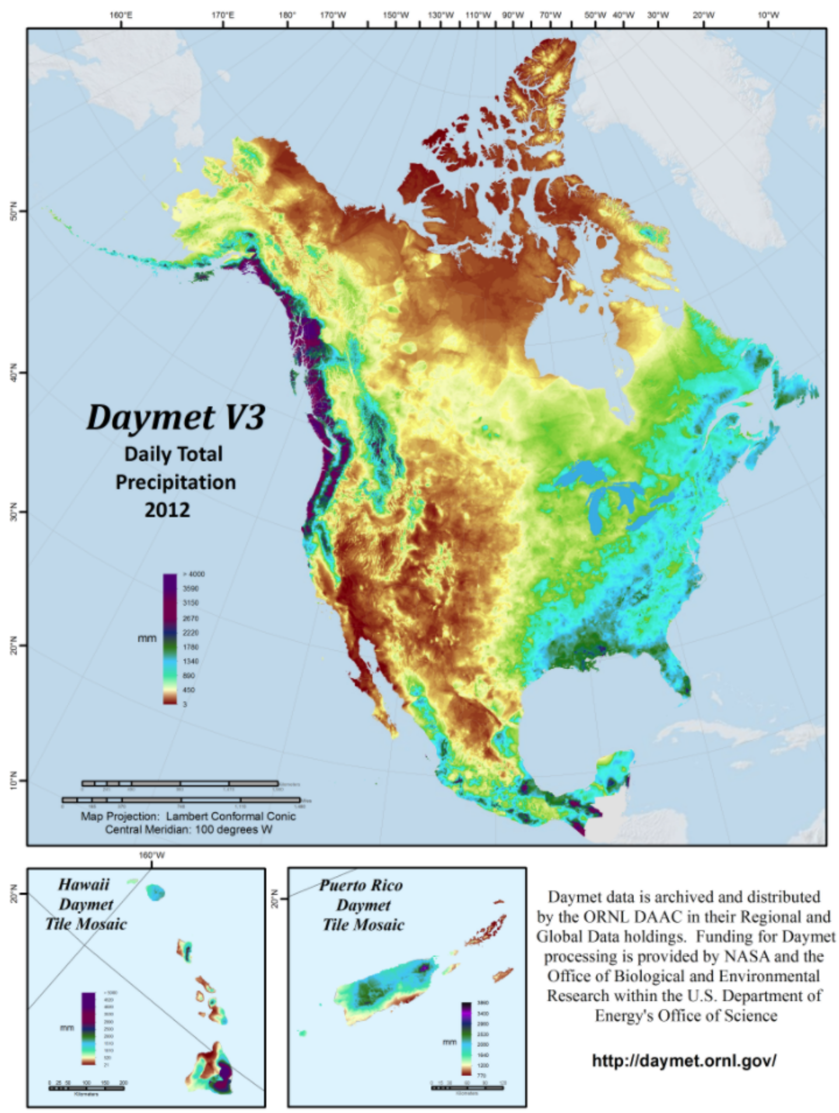

Figure 3.2.1: ORNL DAAC Daymet Daily Precipitation Data example

3.2.2 Fire Data

Fire data used for this study was gathered from the United States Forest Service's Monitoring Trends in Burn Severity Fire Occurrence Locations (MTBS) feature layer projects (Eidenshink et al., 2007; Finco et al., 2012). This project tabulates all large wildland fires in the continental US, Alaska, Hawaii, and Puerto Rico for the years 1984-2016, with updates currently being made. Fires reported in the dataset are greater than 1,000 acres burned in the Western United States and greater than 500 acres burned in the Eastern United States. The MTBS project by its own acknowledgement is used to study fire frequency, extent, and magnitude based on the data collected. For this research, point shapefiles locating the centroid of fire occurrences were used as well as polygon shapefiles displaying acres burned area for fire events, with some overlap (Figures 3.2.2 & 3.2.3). From table data and spatial representation, several attributes for fires were considered within the study. Among these were: number of fires, starting month, day, and duration of each fire, acres burned, year, and perimeter.

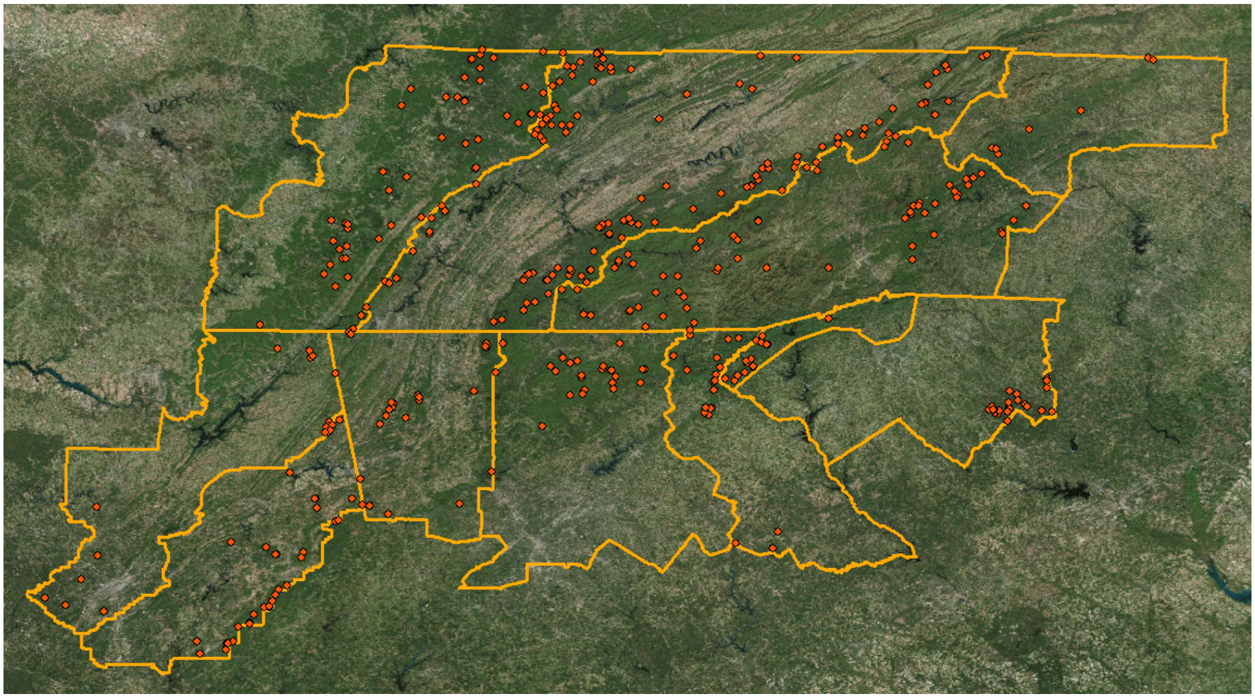

Figure 3.2.2: United States Forest Service (USFS) Monitoring Trends in Burn Severity (MTBS) Fire Occurrence Feature Layer 1985-2016

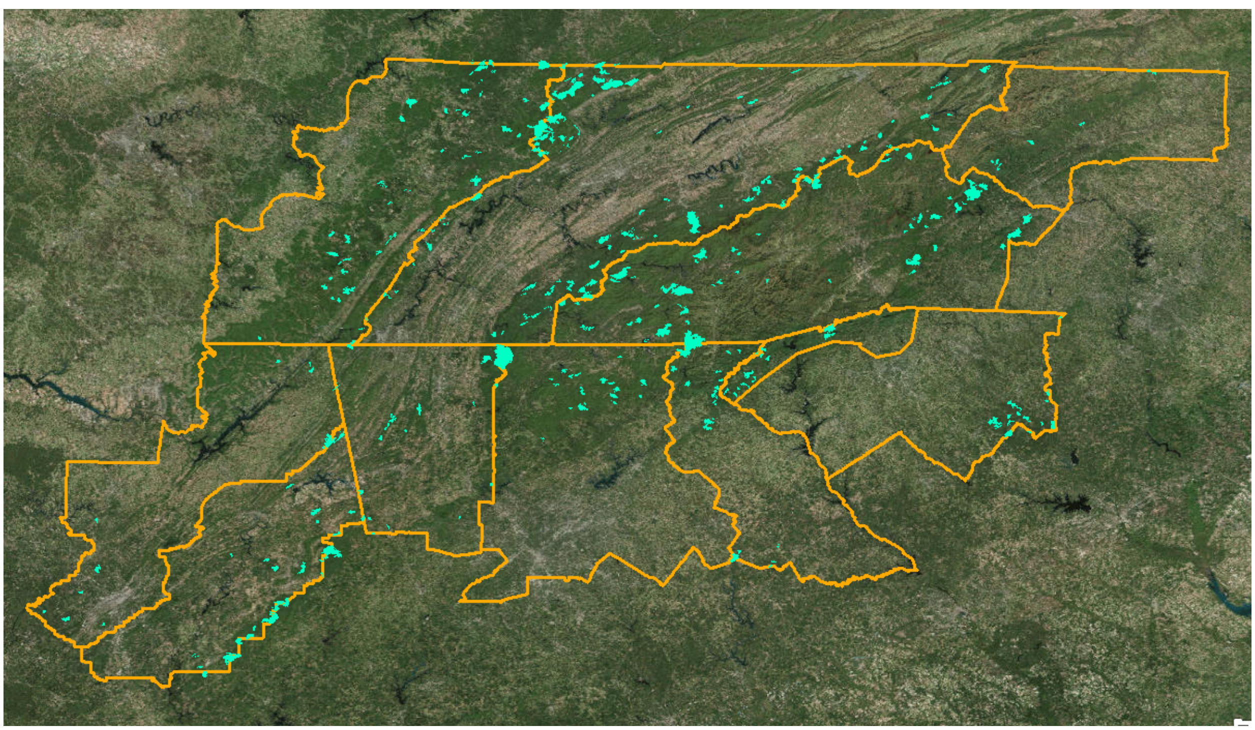

Figure 3.2.3: United States Forest Service (USFS) Monitoring Trends in Burn Severity (MTBS) Burned Area in Acres Feature Layer 1985-2016

3.3 Methodology

Basic linear correlation and regression modeling were conducted in R, Python, and Statdisk software to identify the relationship between mean annual dry days and acres burned. The temporal range set for the calculations is currently between 1985 and 2016 with the potential to cover a longer timespan as updated precipitation and fire datasets become readily available. This form of modelling allowed the user to easily update datasets as needed for the system to process and can be used to run similar correlation and regression models on other proxies, which may become necessary to better understanding the relationships between climatic processes and fire frequency/magnitude. However, this form of statistical analysis proved rudimentary and was expanded to provide analysis that better fits the dataset.

Daymet daily precipitation data was downloaded from Oak Ridge National Laboratory's Distributed Active Archive Center (ORNL DAAC) (Thornton, 2014). These 1 km x 1 km data were obtained in NetCDF format, containing an array of daily precipitation values for each study year. MATLAB 2017 was employed to parse the NetCDF data arrays into .csv files containing latitude, longitude, and annual dry days (defined as precipitation < 1 mm). The coding sequence produced a single .csv containing latitude data for all data points, another .csv containing longitude data for all points, and 32 .csv files containing annual number of dry days (one for each study year). R x64 3.4.3 coding interface was then used to assign appropriate x, y locations to each data point in the dry day data. The coding procedure resulted in 32 .csv files, which each contained 454,370 annual dry-day values with geographic reference.

Geographically referenced annual dry day data files, representing 1985-2016, were then imported into ArcMap 10.6 (Esri). The data were displayed in x, y coordinate space then converted to individual point shapefiles. This resulted in 32-point shapefiles, each containing

454,370 data points. Using ArcMap 10.5's Spatial Analyst toolkit, these point shapefiles were each converted to raster format. The result was 32 geographically-referenced raster datasets, with each grid cell containing a single annual dry day value for that particular location.

Grid cells which fell within the study area were then extracted for analysis using ArcMap's "Model Builder." Mean annual dry day (MADD) values were obtained with 32 raster datasets, representing the entirety of the study area. The 32 raster datasets were then separated into each of the 11 climate regions using Model Builder. The minimum, maximum, mean, and standard deviation of the annual DD values contained within the resulting 360 raster files were computed and exported into a spreadsheet for analysis. Initial analysis was conducted to identify the relationship between MADD and both the number of fires and area burned using correlation and linear regression modelling. Early results showed no linear statistical relationship between the two variables, as no linear relationship is evident. More strenuous statistical analysis was necessary to identify the relationship between precipitation and fire activity.

The same methods used above for the initial analysis on the basis of MADD were used and applied to calculate and analyze consecutive dry days leading up to fire events in the region. Consecutive dry days might act as a more satisfactory indication of fire frequency and magnitude, as previously shown by Chen et al. 2014. The suggestion to use consecutive dry days instead of MADD is mentioned in Lafon's 2017 paper. Initial research into areas of Northern Appalachia shows increases in fire probability as the number of consecutive dry days increases (Lafon, 2017).

Dry days were previously defined only as days with precipitation less than 1mm of total accumulation in the preliminary analysis conducted. For further analysis, other precipitation thresholds were considered to define dry days due to the possibility of instrument error, as well as variation caused by Appalachia's significant topographic variability. Chen et al. 2014 lays out a means of using different daily precipitation thresholds to define dry days in an analysis in southwestern China. Chen et al. (2014) defined dry days as ≤ 0, 1, 2, 3, 4, 5, 6 mm of daily precipitation. The author then used these values as the basis for running a Spearman's rank correlation test to find the correlation between the number of consecutive dry days (based on the specified value) and the log-transformed burned area of forest fires for each individual region (Chen et al., 2014). This statistical analysis was used as a guide for conducting similar statistical analysis based on the precipitation and fire data collected for the Southern Appalachian region as a whole, and the individual climate divisions within the region.

However, rather than using the threshold values identified by Chen et al. (2014), the threshold values of ≤ 1, 5, 10, 25, and 50 mm were used to cover a larger range of consecutive dry day threshold values. Originally, the same threshold values used in Chen's study were to be used to account for instrument error, but early findings prompted new values to cover a greater range of dry day thresholds. This will be done because little to no instrumentation error was found and a minimal amount of difference in the number of consecutive dry days per threshold was discovered. Expanding the range of threshold values provides a greater understanding of how consecutive dry day thresholds and fire activity are related. This is especially important considering the climatic trends and topographic variability experienced in Southern Appalachia. Threshold values will not be the only difference from prior research.

Originally, linear correlation and regression analysis, as well as Spearman's rank correlation analysis were proposed to observe relationships between precipitation and fire data. After careful research and discussion with Dr. Lynne Seymour of the University of Georgia's Department of Statistics, it was determined that the relationships between the two attributes would most likely be non-linear nature. Non-linear analyses were conducted to provide more accurate insight into how the data are related. Specifically, Poisson regression and negative binomial analysis were conducted to provide a more detailed analysis of the fire and precipitation relationship.

Poisson regression is a generalized linear model (GLM) that is often referred to as a log-linear model (Gardner et al. 1968, Dixon et al. 2008). It is specifically used to model count data and contingency tables, such as the fire and precipitation data collected (Figure 3.2.1) (Gardner et al. 1968, Dixon et al. 2008). A Poisson regression model assumes that the Y variable has a Poisson distribution and assumes that the logarithm of its expected value can be modeled using a linear combination of unknown characters (Gardner et al. 1968, Dixon et al. 2008). In the case of the data being used, the Y variable is acres burned or number of fires and the X value would be the number of consecutive dry days for each threshold value (Gardner et al. 1968, Dixon et al. 2008). Poisson regression models are considered to be generalized linear models. Within the models the logarithm is the link function, and the Poisson distribution function is the assumed probability distribution of the response.

Poisson Distribution

$$f(y|\lambda) = \frac{\lambda^y}{y!}\exp(-\lambda)\text{ , } y = 0, 1, 2, \ldots$$

$$E(Y) = \lambda$$

$$Var(Y) = \lambda$$

Figure 3.3.1: Poisson Regression Model used in the analysis of precipitation and fire data from SAS JMP statistical analysis software

Negative binomial regression is also used to determine the relationship between the provided fire and precipitation data. It is a generalization of the previously mentioned Poisson regression model (Gardner et al. 1968, Dixon et al. 2008). This model is considered a generalization because it loosens the restrictive assumption that the variance is equal to the mean made by the Poisson regression model (Gardner et al. 1968, Dixon et al. 2008). It is a popularly used model due to the fact that it models the Poisson heterogeneity with a gamma distribution, allowing for less restriction (Gardner et al. 1968, Dixon et al. 2008). In this case, the Y variable and the X value will be the same as in the Poisson regression model. The forms of regression analysis used in this case are much more ideal for the data used than those previously proposed.

Negative Binomial Distribution

$$f(y|\mu, \sigma) = \frac{\Gamma[y + (1/\sigma)]}{\Gamma[y+1]\Gamma[1/\sigma]}\left[\frac{(\mu\sigma)^y}{(1+\mu\sigma)^{y+(1/\sigma)}}\right], y = 0, 1, 2, \ldots$$

$$E(Y) = \mu$$

$$Var(Y) = \mu + \sigma\mu^2$$

Figure 3.3.2: Negative Binomial Regression Model used in the analysis of precipitation and fire data from SAS JMP statistical analysis software

The Akaike information criterion (AICc), Bayesian information criterion (BIc), and negative log-likelihood aid in determining which models are the best fit at different threshold values. Other analyses were also conducted based on the interactions between fire and precipitation data. A few of the trends observed were based on monthly, annual, and seasonal behavior, considering all five threshold values and overarching themes. Time series analysis were graphed and charted to provide a visual representation of the data. Visual aids of both fire and precipitation over time were documented, including daily precipitation and fire activity across the entire designated time period of study. The analysis provides a greater understanding of the existing relationships between precipitation activity, specifically consecutive dry day thresholds, and the behavior of large-scale forest fires in Southern Appalachia.

CHAPTER 4

RESULTS

4.1 Breakdown of Fire Activity

4.1.1 Main Observations

Figures 4.1.1 and 4.1.2 show the spatial variability and magnitude of each individual fire during the study period. It is important to remember that all fires in the dataset are considered to be large-scale fires, as they each burned a minimum of 500 acres of land. Table 4.1.1 breaks down each fire and the amount of area burned based on the climate division location of the point of ignition. Divisions stretching along the Appalachian Mountains, such as the Eastern Valley of Alabama, Eastern Tennessee, and the Southern Mountains of North Carolina tend to experience a greater number of fires and coinciding acres burned than surrounding areas. Figures 4.1.1 and 4.1.2 indicate that areas of high elevation in Southern Appalachia tend to be more prone to fire activity than lower lying areas. From 1985-2016 the number of fires has significantly increased as shown in Figure 4.1.3. There are several years during the earlier section of the period of study without any large-scale fires at all. However, towards the middle and latter part of the period, large-scale fire occurrences happen more frequently. This confirms the hypothesis regarding recent fire trends in Southern Appalachia. However, the amount of area burn per fire season only slightly increased over time. This is largely due to the lack of fire activity at the beginning of the study period. It is also important to consider that the upward trajectory shown in Figure 4.1.4 is largely due to the outlying amount of area burned in the year 2016. The year 2016 is an outlier both in the number of fires and the area burned. The final tally of fires across the dataset is 409 fires with over 711,000 acres burned. Identifying fire behavior on an annual basis, instead of simply looking at individual fires, will also provide a greater insight into how fire is dispersed temporally.

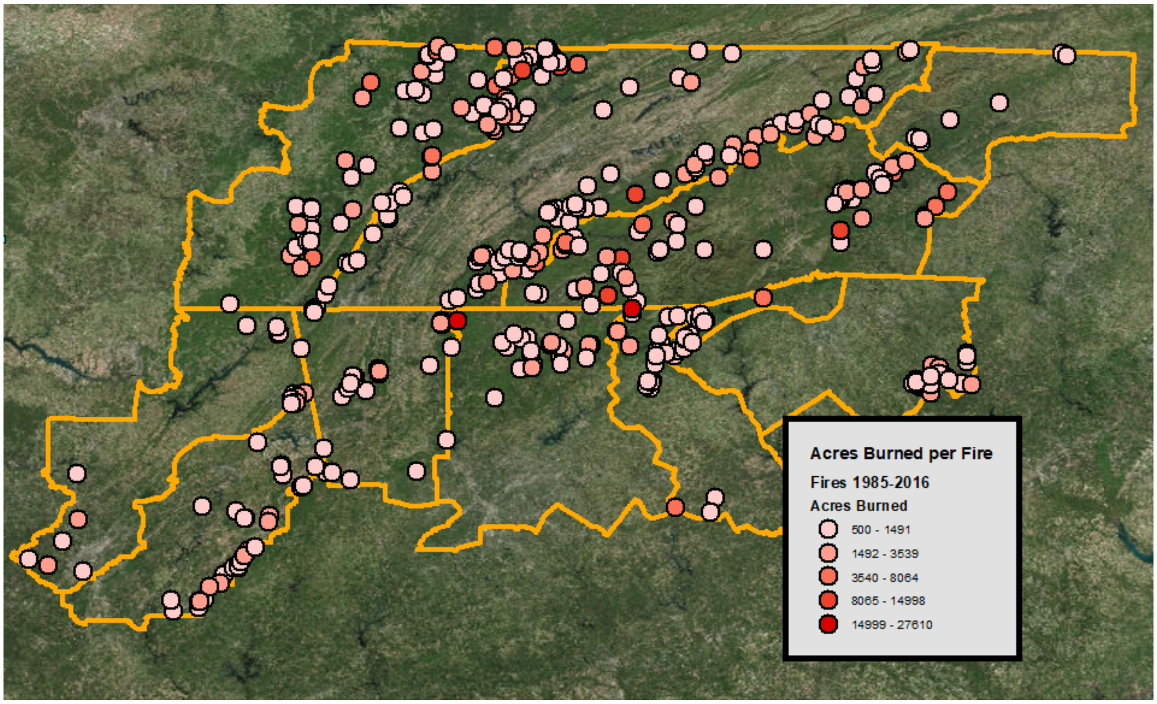

Figure 4.1.1: Spatially-referenced Map of Individual Fire Occurrences weighted by the number of acres burned per fire event

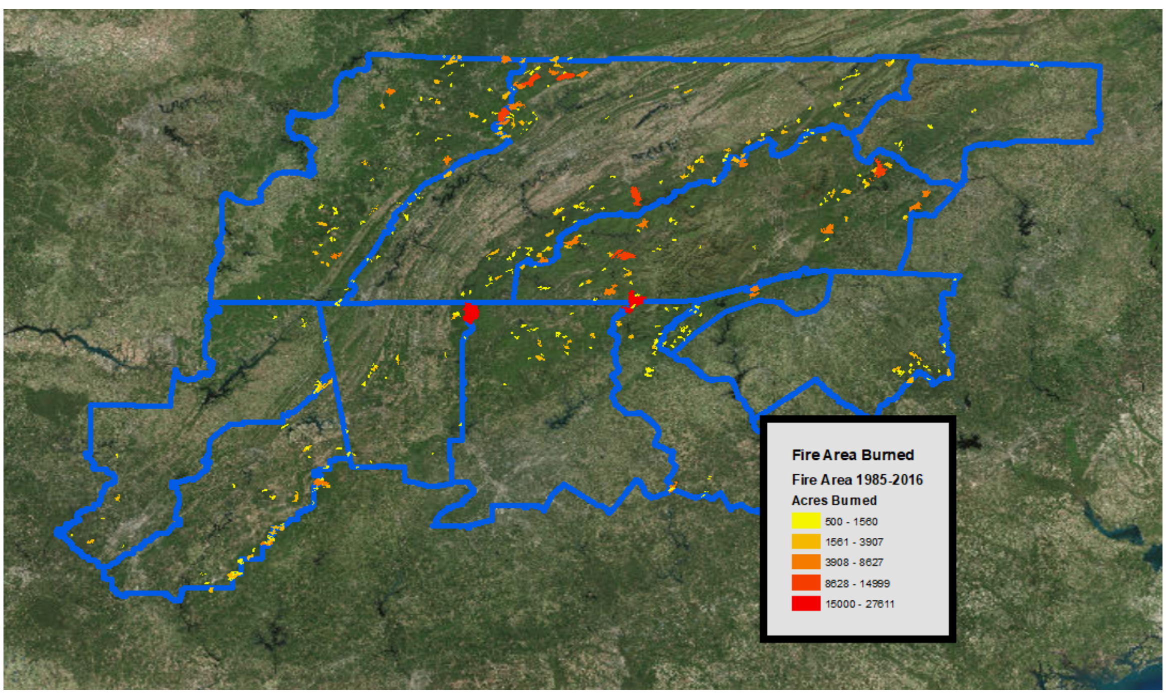

Figure 4.1.2: Spatially-referenced Map of Area Burned polygons weighted by the number of acres burned per fire event

DIVISION	TOTAL FIRES	ACRES BURNED
Appalachian Mountains AL	19	19594
Cumberland Plateau TN	49	88343
Eastern TN	125	211802
Eastern Valley AL	36	55304
Mountain SC	15	21207
North Central GA	25	53156
Northeast GA	25	58713
Northern Mountains NC	7	6614
Northwest GA	22	22345
Northwest SC	23	26051
Southern Mountains NC	63	148789
TOTAL	**409**	**711918**

Table 4.1.1: List of total number of fires and acres burned within each individual Southern Appalachian climate division

4.1.2 Annual Observations

Looking at the fire data on an annual basis, a gradual increase from 1985-2016 in the number of fires per year is apparent. With the mean set at roughly 12.7 fires per year, 7 of the last 10 years within the dataset have experienced a fire total greater than that of the annual average as shown in Figure 4.1.3. The number of acres burned has slightly increased throughout the study. However, this is skewed by the massive amount of area burned in the year 2016, which also skews the area burned time series in Figure 4.1.4. Figure 4.1.5 is a scatterplot showing the relationship between the number of fires and acres burned on an annual basis. There is a slight exponential relationship between the two, but this is due in part to the outlying fire activity of 2016. Figure 4.1.6 shows the annual distribution of both the number fires and acres burned per fire. From this graph, it is apparent that a few massive outlying fires can have a significant impact on skewing the dataset as a whole, such as in the years 1987, 2001, and 2016. It can also be determined that the years with the greatest number of fires will often produce the largest-scale fires on average. A major uptick in fire activity, both in the number of fires and the amount of area burned, has been seen since around 1999 and 2000, however there is no major evidence to support that fire practices have changed over the period of study, especially as it relates to prescribed burning (Elliott & Vose, 2005).

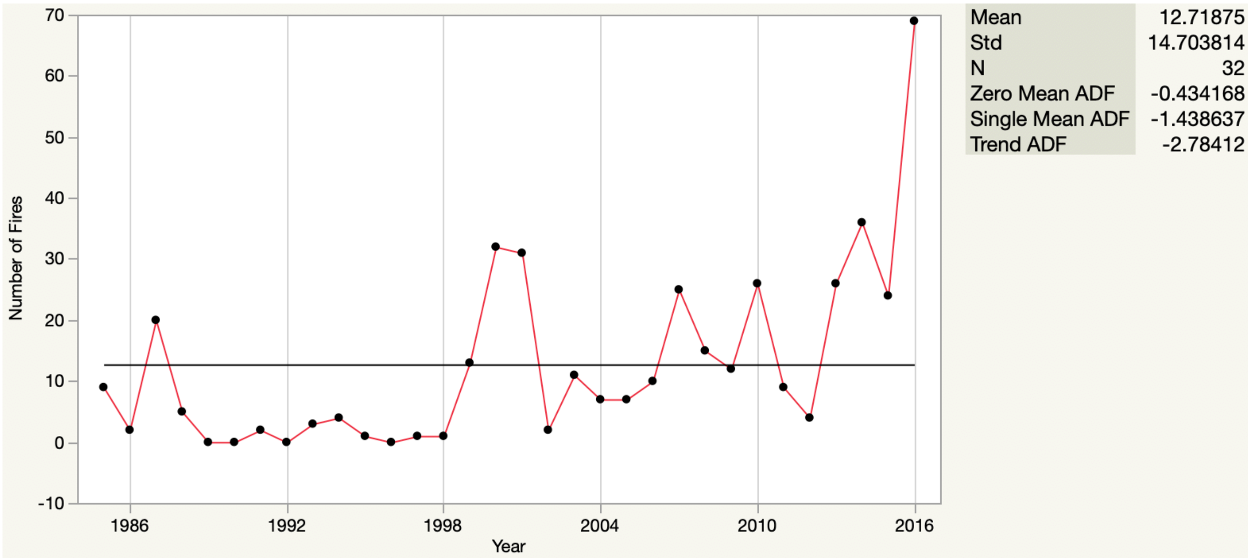

Figure 4.1.3: Annual time series plot of the number of fires per year from 1985-2016 with a line showing the mean number of fires per year

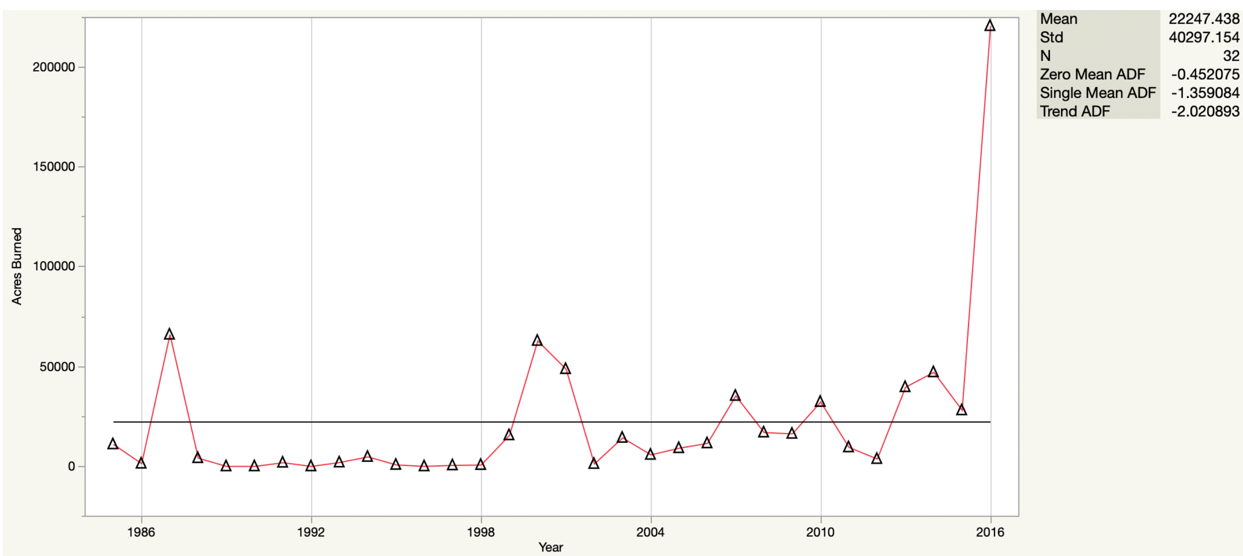

Figure 4.1.4: Annual time series plot of the amount of area burned per year in acres from 1985-2016 with a line showing the mean area burned per year

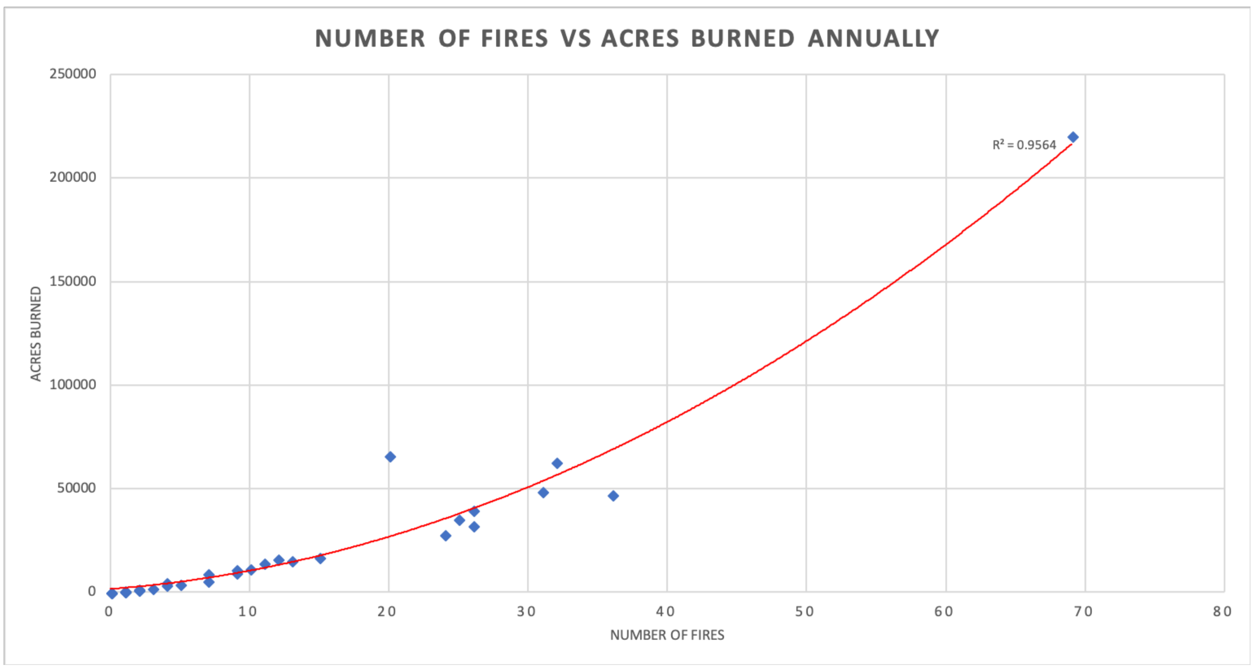

Figure 4.1.5: Scatterplot showing the relationship between the number of fires and area burned in acres on an annual basis

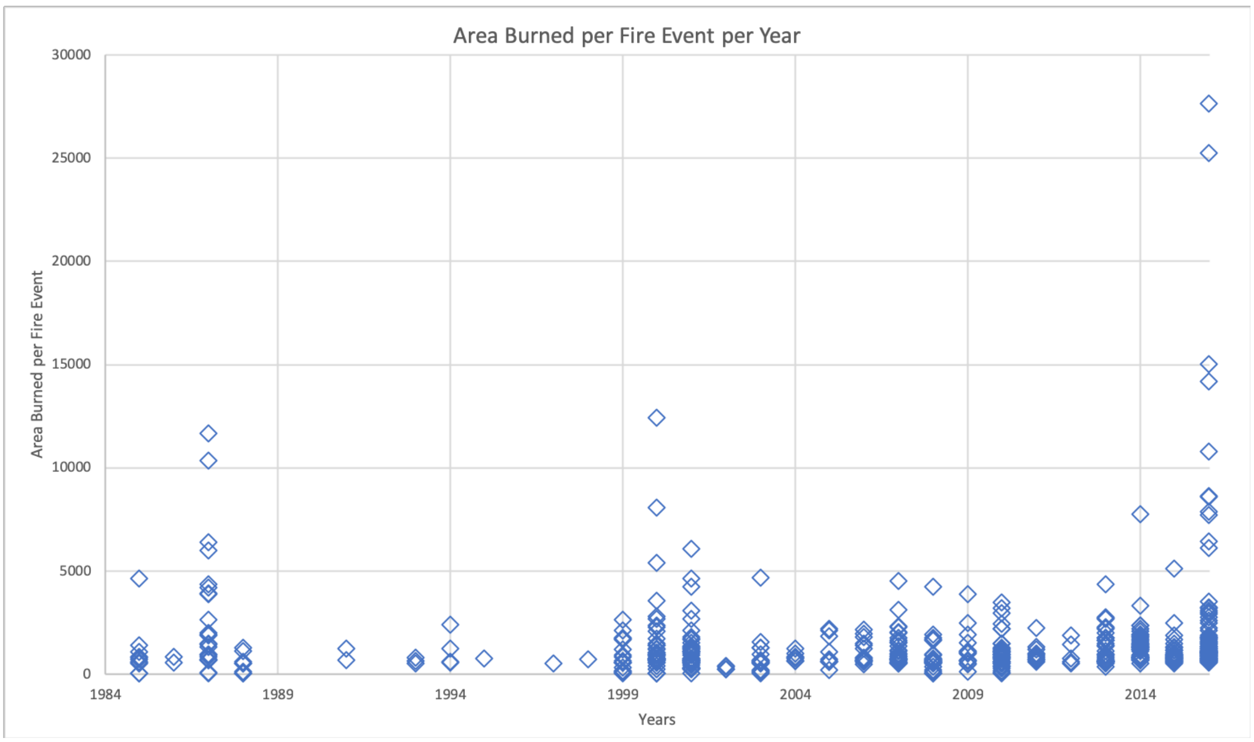

Figure 4.1.6: Time series scatterplot showing the distribution of both number of fires and area burned in acres on an annual basis

4.1.3 Monthly Observations

Fire activity trends within Southern Appalachia were also observed on a monthly basis. Figure 4.1.7 shows the monthly progression of fires for the entire study period (1985-2016). The figure indicates that there are two discrete fire seasons within the region. The spring fire season consists of fires between March and April mainly, while the fall fire season mainly takes place in November. Based on the climatic profile of Southern Appalachia, this would indicate that there are periods of wet weather followed by extremely dry weather leading up to the two individual fire seasons. Consecutive dry day periods, based on the graph, should be very pronounced prior to the months of March and November. Figure 4.1.8 shows a similar monthly trend for the number of acres burned per month. Based on the months above the mean acres burned, February, October, and December are also capable of having increased fire activity. Table 4.1.2 shows that fire activity was previously more prevalent in the fall months prior to the 2000s but has recently become more frequent in the spring months. The year of 2016 is fairly even with major fire activity both in the spring and fall seasons. This observation reaffirms 2016 as an outlier from normal southern fire activity. Figure 4.1.9 provides insight into the temporal variability of fire activity. It shows the number of fire ignitions occurring on a daily basis throughout all climate divisions used. It also confirms previously stated trends but provides a helpful visual aid for identifying discreet fire seasons.

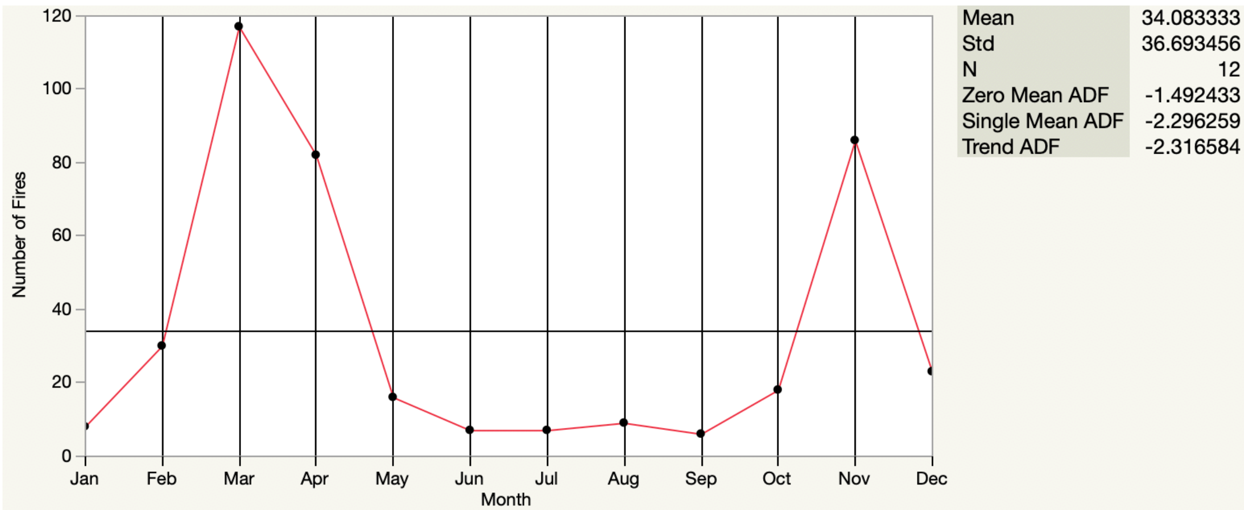

Figure 4.1.7: Time series scatterplot showing the distribution of fires on a monthly basis with a line representing the mean number of fires per month

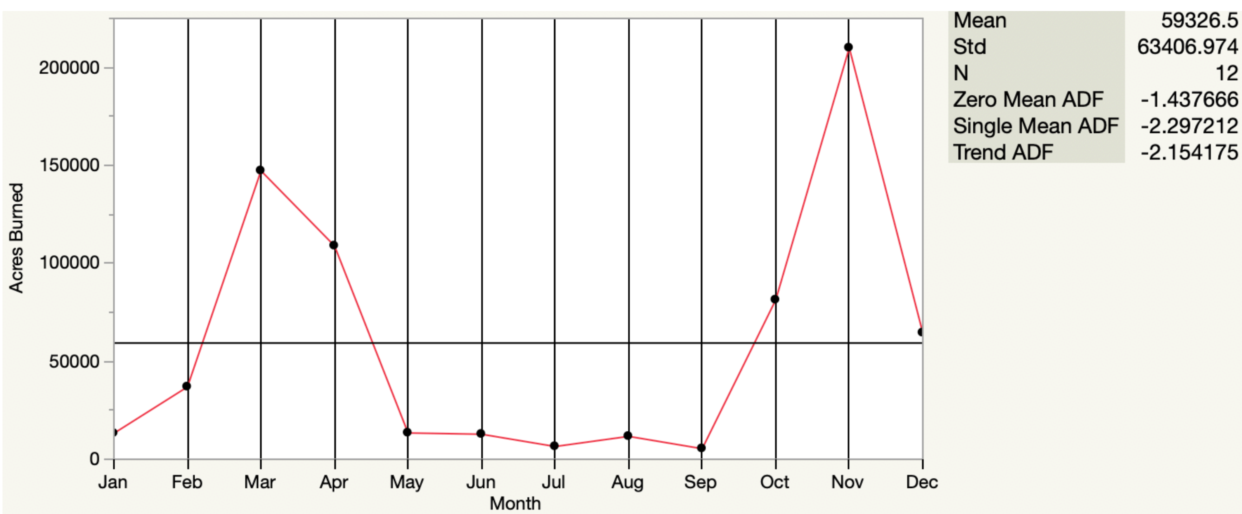

Figure 4.1.8: Time series scatterplot showing the distribution of both number of fires and area burned in acres on an annual basis with a line representing the mean area burned per month

Year	MODE Month	Predominant	Spring	Fall	Outliers
1985	April	Spring	9	0	0
1986	April	Spring	2	0	0
1987	December	Fall	0	20	0
1988	March	Spring	3	0	2
1989	None	None	0	0	0
1990	None	None	0	0	0
1991	October	Fall	0	2	0
1992	None	None	0	0	0
1993	None	None	1	1	1
1994	None	None	2	2	0
1995	August	Fall	0	1	0
1996	None	None	0	0	0
1997	April	Spring	1	0	0
1998	October	Fall	0	1	0
1999	November	Fall	2	11	0
2000	November	Fall	9	22	1
2001	November	Fall	2	28	1
2002	None	Outliers	0	0	2
2003	August	Fall	2	7	2
2004	April	Spring	5	0	2
2005	April	Spring	3	2	2
2006	March	Spring	9	1	0
2007	March	Spring	21	1	4
2008	March	Spring	12	1	2
2009	March	Spring	12	0	0
2010	March	Spring	23	2	1
2011	February	Spring	7	1	1
2012	November	Fall	0	3	1
2013	April	Spring	25	1	2
2014	March	Spring	33	0	3
2015	March	Spring	15	1	8
2016	November	None/Fall	31	34	4

Table 4.1.2: Table shows seasonal and monthly trends of fire activity from 1985 (top) to 2016 (bottom)

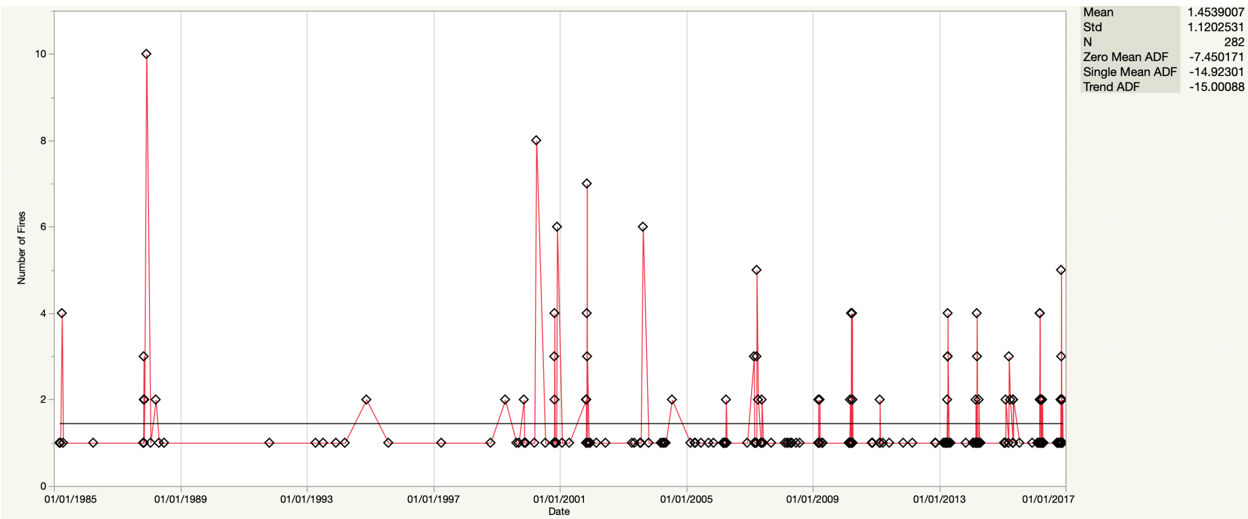

Figure 4.1.9: Time series scatterplot showing the distribution of fires on a daily basis with a line representing the mean number of fires per day

4.2 Breakdown of Precipitation

4.2.1 Main Observations

Using the Daymet gridded daily precipitation dataset, several precipitation trends can be identified before comparing it against fire data. Table 4.2.1 shows the distribution of average threshold values for all five used. It shows how they are distributed by individual climate division and averaged out for the entire Southern Appalachian region. The average thresholds can act as initial indicators of the potential for fire activity within the region based on past fire data. The 1mm threshold has an average of less than 6 days prior to fire activity. The 5mm threshold has a threshold of a little more than 8 days before fire activity. The 10mm threshold also provides a fairly small increment before fire environment indication at an average of 12.5 days. After this threshold however, there is a major jump in the average number of days before reaching the precipitation threshold of 25mm. On average slightly less than 37 days occur after the 25mm threshold before fire activity is present. Finally, the 50mm thresholds occurs on average 218 days before wildfire ignition. This information is useful for knowing how many days out from a certain precipitation threshold one might expect to see fire ignition.

DIVISION	1mm THRESHOLD	5mm THRESHOLD	10mm THRESHOLD	25mm THRESHOLD	50mm THRESHOLD
Appalachian Mountains AL	5.32	7.32	12.05	30.42	193.32
Cumberland Plateau TN	7.51	10.92	13.57	40.98	233.71
Eastern TN	6.672	10.30	15.62	54.22	417.10
Eastern Valley AL	5.06	6.56	10.33	26.31	222.03
Mountain SC	3.20	4.47	8.87	28.60	158.40
North Central GA	6.16	6.60	9.76	19.56	180.60
Northeast GA	4.92	6.52	9.48	30.40	86.16
Northern Mountains NC	7.57	15.14	22.57	58.57	174.00
Northwest GA	4.91	7.50	11.91	38.27	243.86
Northwest SC	3.83	4.57	6.96	31.65	282.13
Southern Mountains NC	8.57	12.08	15.73	44.41	213.30
AVERAGE	**5.79**	**8.36**	**12.44**	**36.67**	**218.60**

Table 4.2.1: Table identifies individual average thresholds for all climate divisions and the average threshold values for Southern Appalachia as a whole

4.2.2 Annual Observations

Prior research showed the precipitation trends concerning mean annual dry days throughout Southern Appalachia such as in Figure 4.2.1. The spatial distribution of mean annual dry days was thought to give insight into how to predict fire behavior, but after careful research it was determined that observing consecutive dry day trends is a much better indicator of the potential for fire activity. Annual analysis of the behavior of the different threshold values can provide insight into how they have progressed over the period of study and how they behave in regard to active fire years. Figures 4.2.2 through 4.2.6 show the average number of consecutive dry days since the 5 main precipitation threshold values (1, 5, 10, 25, 50mm) occurred on an annual basis. When comparing the results with Table 4.1.2 from the fire data, there seems to be only a slight relationship between the number of fires per year and the consecutive number for dry days at each threshold value. However, years with a greater amount of fall wildfire activity seem to also have a greater number of consecutive dry days leading up to an event. This relationship is more apparent at the lower threshold values than the higher threshold values, but it is evident nonetheless. It is also more apparent with recent fire activity such as 1999-2001 and the 2016 fire season. Over time, at all major thresholds, the number of consecutive dry days prior to fire events has slightly decreased over time. It is also important to consider the sample size of fires when identifying the relationships between precipitation and wildfire frequency. Annual precipitation threshold results fluctuate greatly throughout the entire period of study, so these relationships may be loose at best. However, with the use of proper statistical analysis, it is easy to identify whether relationships between fire frequency and magnitude and the number of consecutive dry days does exist.

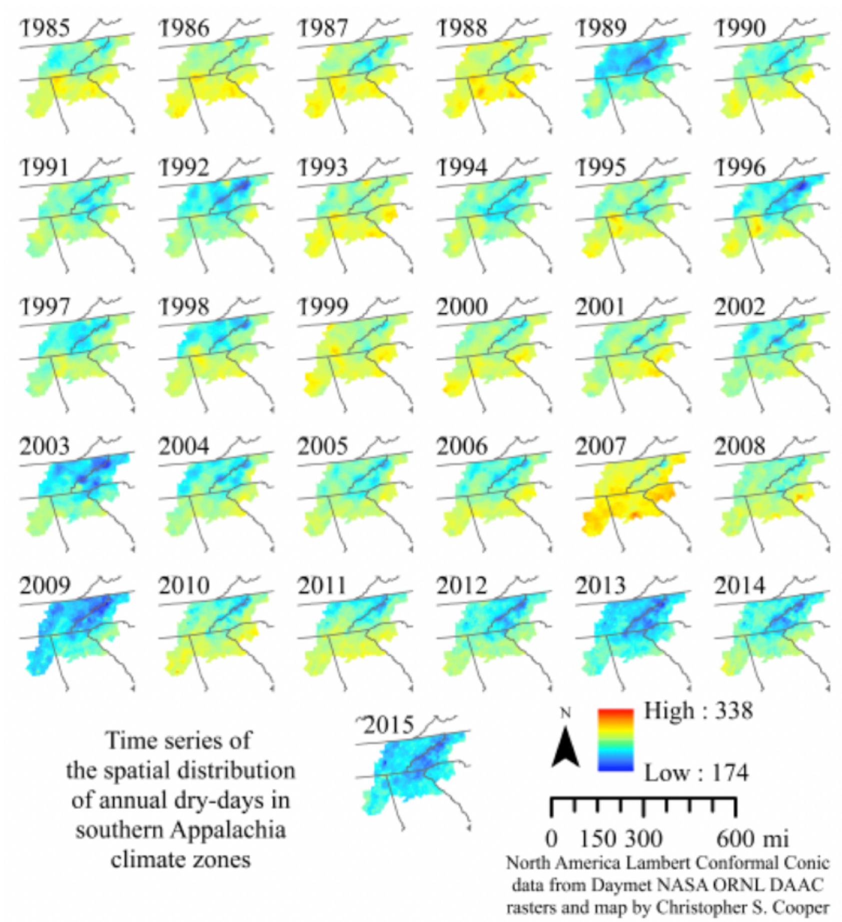

Figure 4.2.1: Raster data showing the average number of rain free (< 1mm precipitation) days per year for all of Southern Appalachia

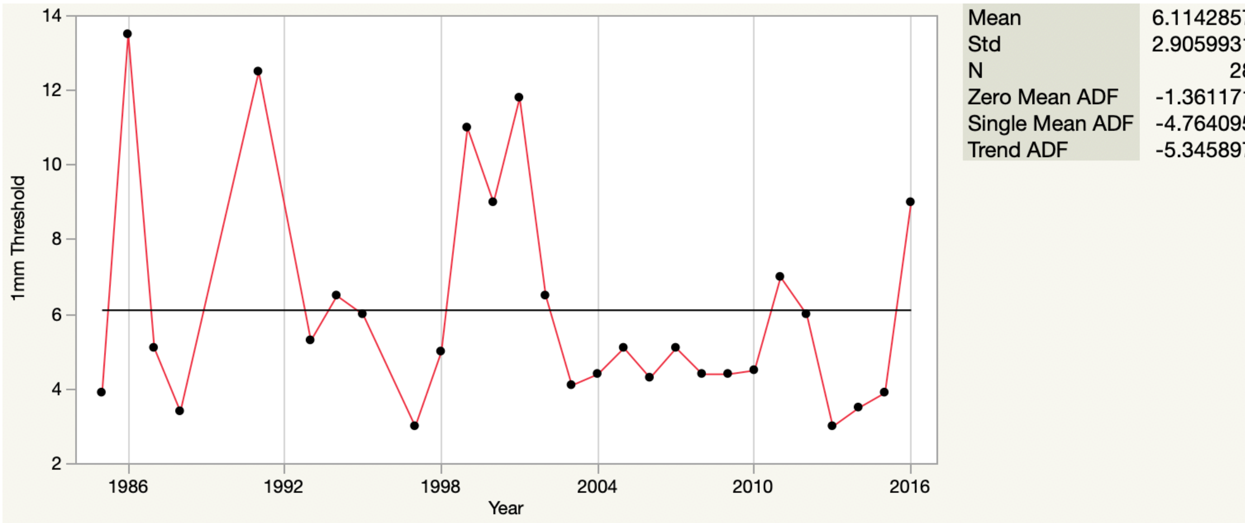

Figure 4.2.2: Time series scatterplot showing the days since the 1mm precipitation threshold was reached on an annual basis with a line showing the average number of consecutive dry days per year

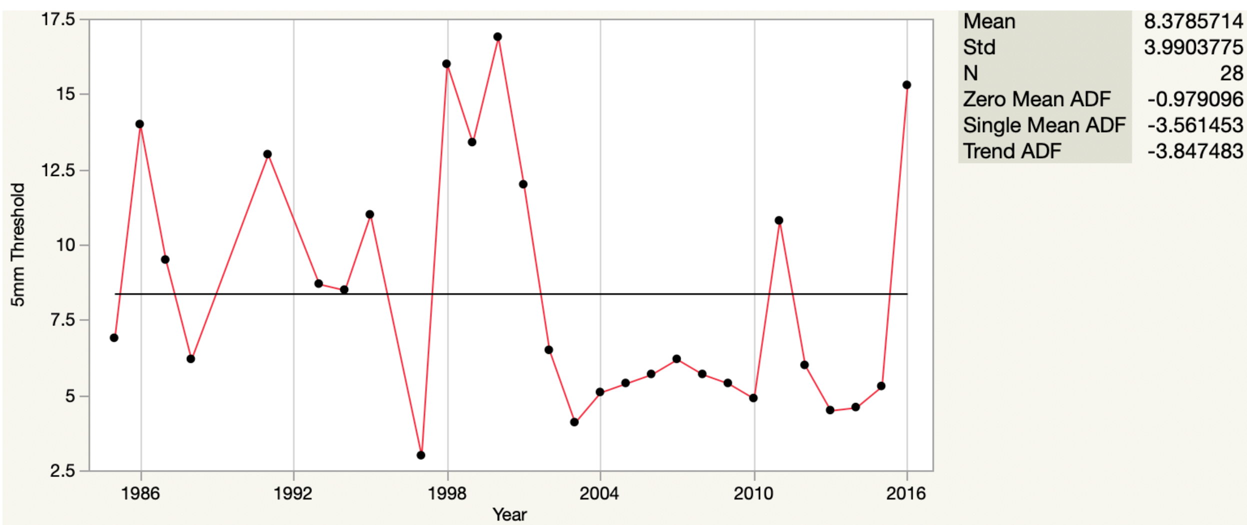

Figure 4.2.3: Time series scatterplot showing the days since the 5mm precipitation threshold was reached on an annual basis with a line showing the average number of consecutive dry days per year

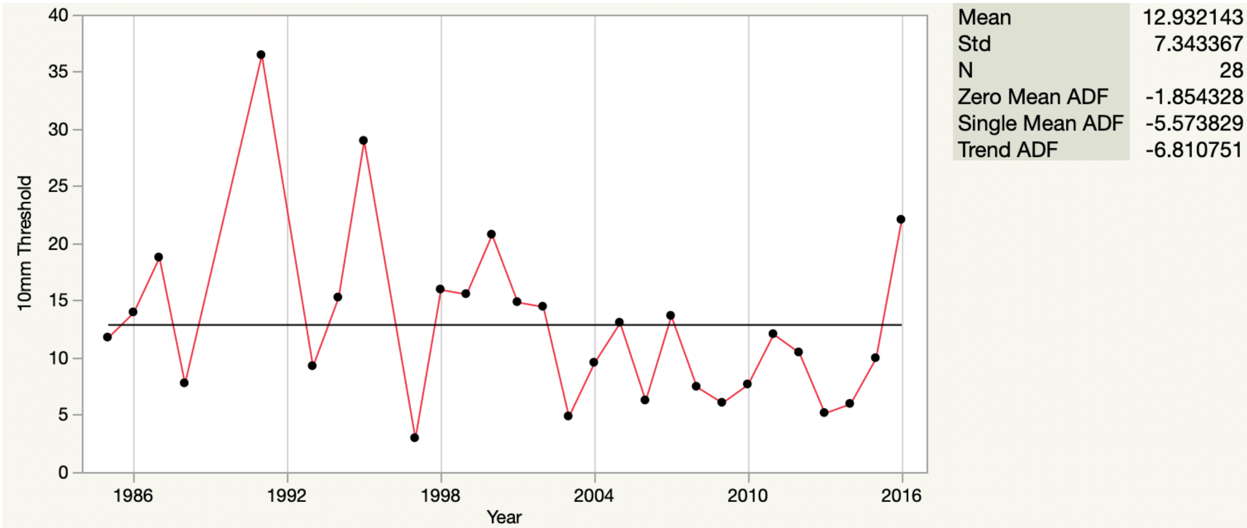

Figure 4.2.4: Time series scatterplot showing the days since the 10mm precipitation threshold was reached on an annual basis with a line showing the average number of consecutive dry days per year

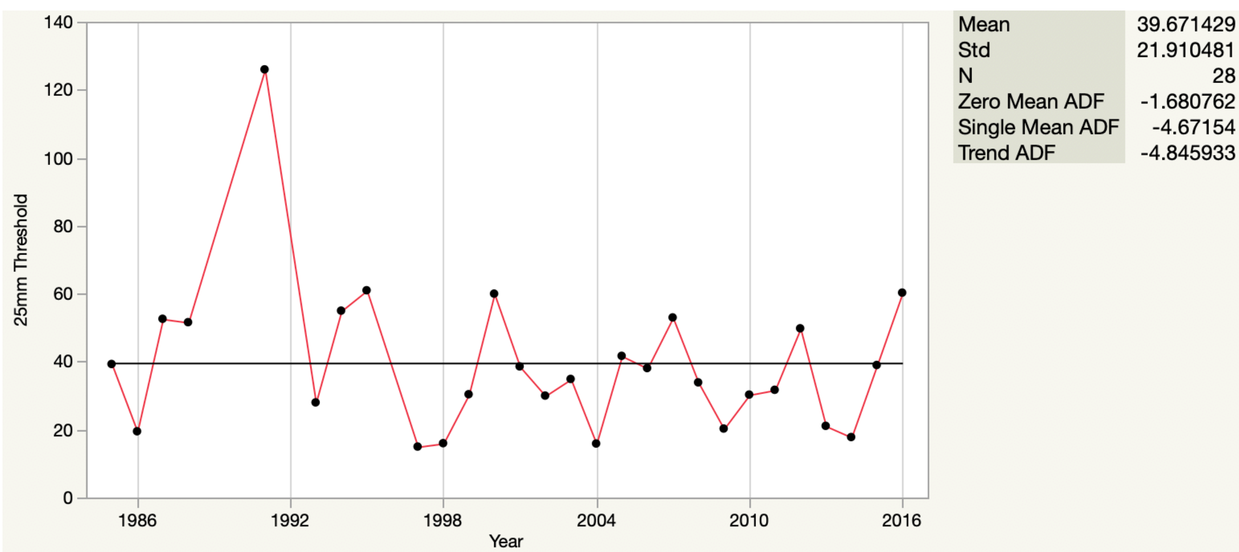

Figure 4.2.5: Time series scatterplot showing the days since the 25mm precipitation threshold was reached on an annual basis with a line showing the average number of consecutive dry days per year

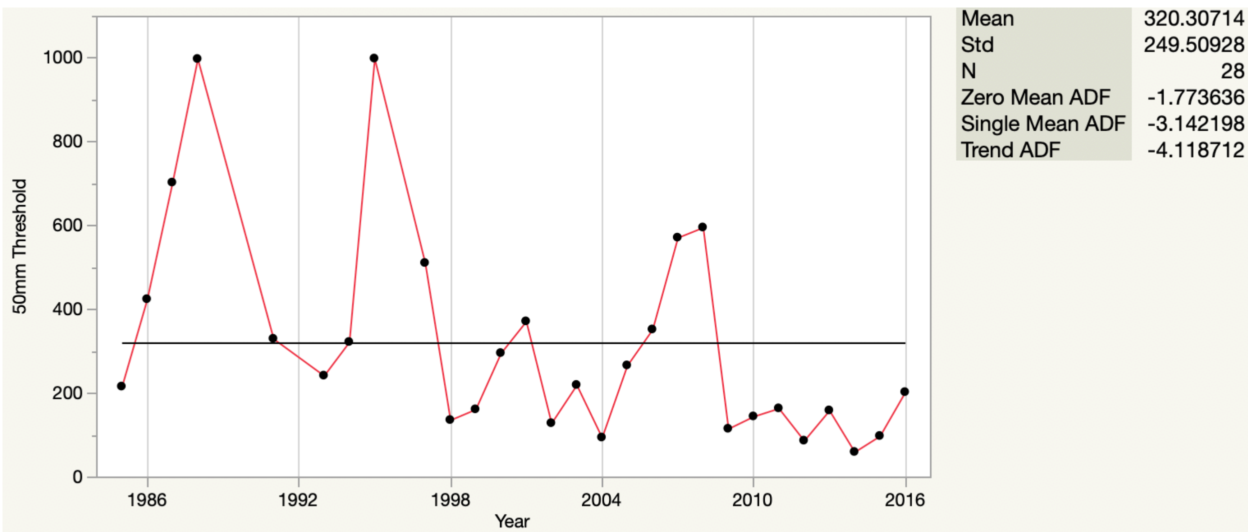

Figure 4.2.6: Time series scatterplot showing the days since the 50mm precipitation threshold was reached on an annual basis with a line showing the average number of consecutive dry days per year

4.2.3 Monthly Observations

Monthly analysis of the patterns of consecutive dry days following individual precipitation threshold values provides a greater understanding of its relationship with fire behavior. Similar to the patterns seen when analyzing the thresholds on an annual basis, monthly analysis identifies a greater number of consecutive dry days leading up to fire activity in the fall fire season. This is especially prevalent at lower threshold values such as 1, 5, and 10mm of precipitation. As the thresholds increase, however, the greatest number of consecutive dry days prior to fire events can be seen at the larger threshold values. Thresholds such as 10, 25, and 50mm have a greater number of consecutive dry days in June as well as the aforementioned fall months. One explanation as to why this may be the pattern in autumn months and not the spring is the seasonality of precipitation. Late summer and autumn months are more prone to drought than the spring in the Southeastern United States. Something else to consider is that the major proponents of fire ignition are anthropogenic causes and lightning. Lightning could be the cause of more springtime fire activity as opposed to fall activity depending on its seasonal variability. Storms containing lightning also bring precipitation events as well, which could be a key reason for a difference in the threshold values for the two seasons. The topography of Appalachia also plays a role. Steeper landscape hinders the ability of precipitation to saturate organic life, even during dry spells.

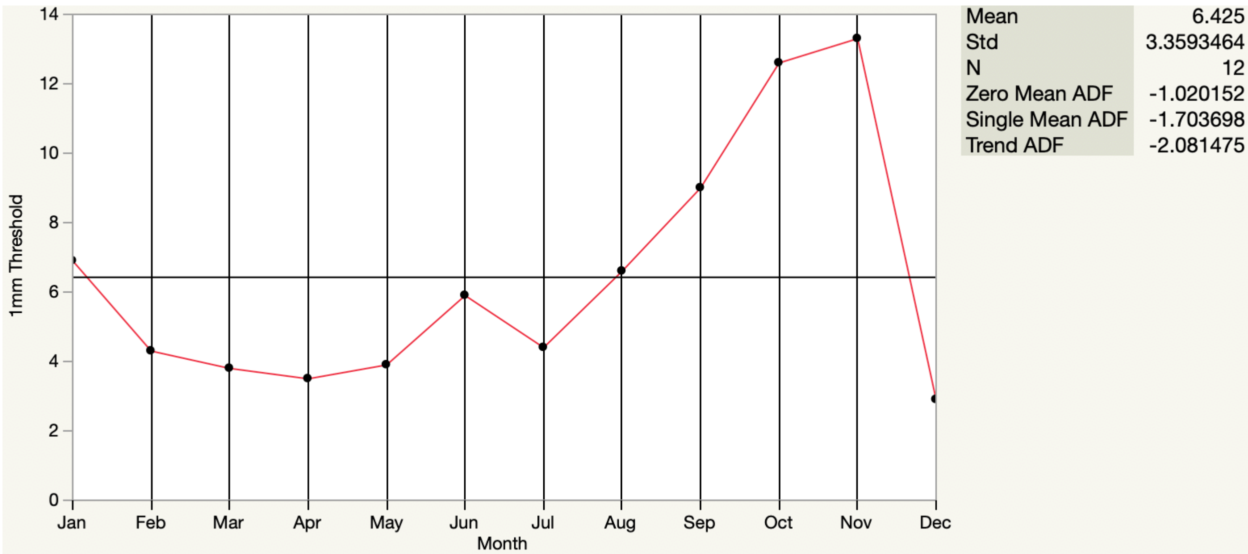

Figure 4.2.7: Time series scatterplot showing the average days since the 1mm precipitation threshold was reached on a monthly basis with a line showing the average number of consecutive dry days per month

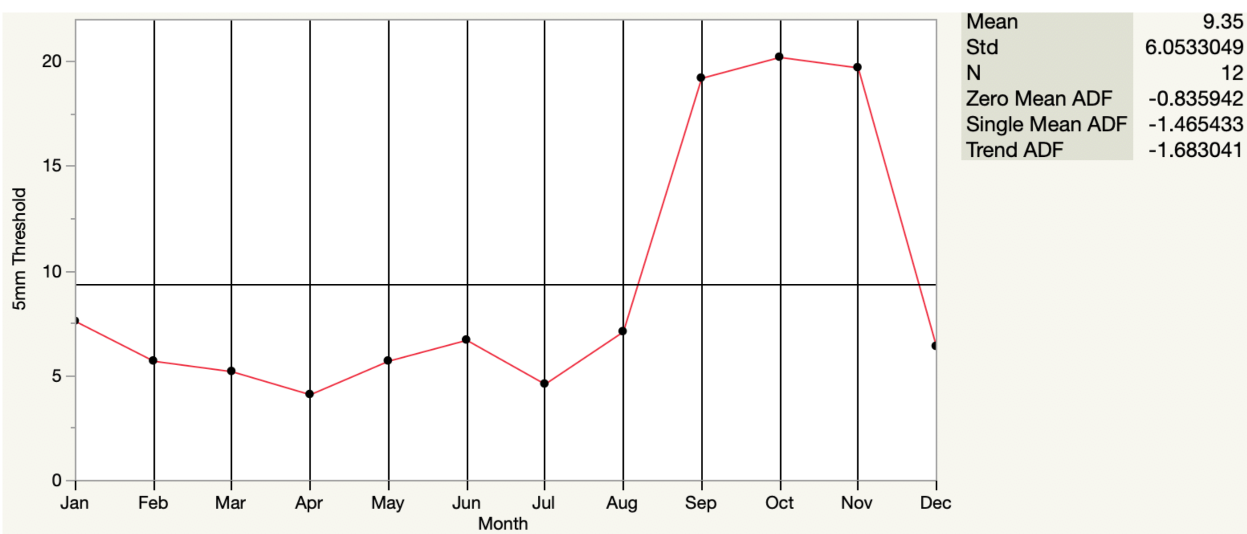

Figure 4.2.8: Time series scatterplot showing the average days since the 5mm precipitation threshold was reached on a monthly basis with a line showing the average number of consecutive dry days per month

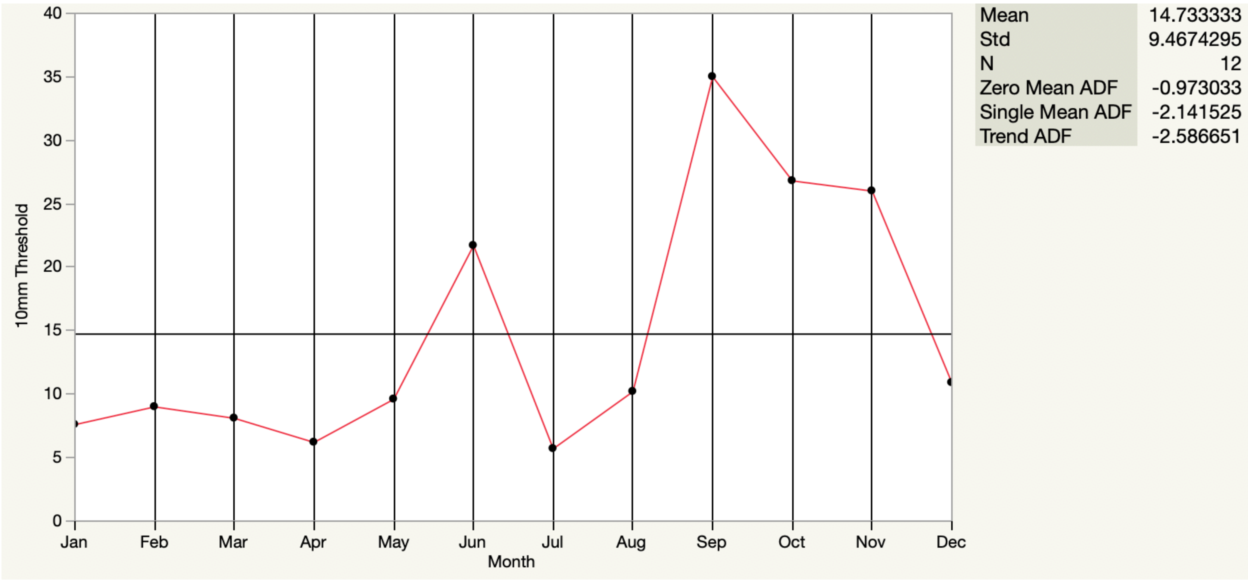

Figure 4.2.9: Time series scatterplot showing the average days since the 10mm precipitation threshold was reached on a monthly basis with a line showing the average number of consecutive dry days per month

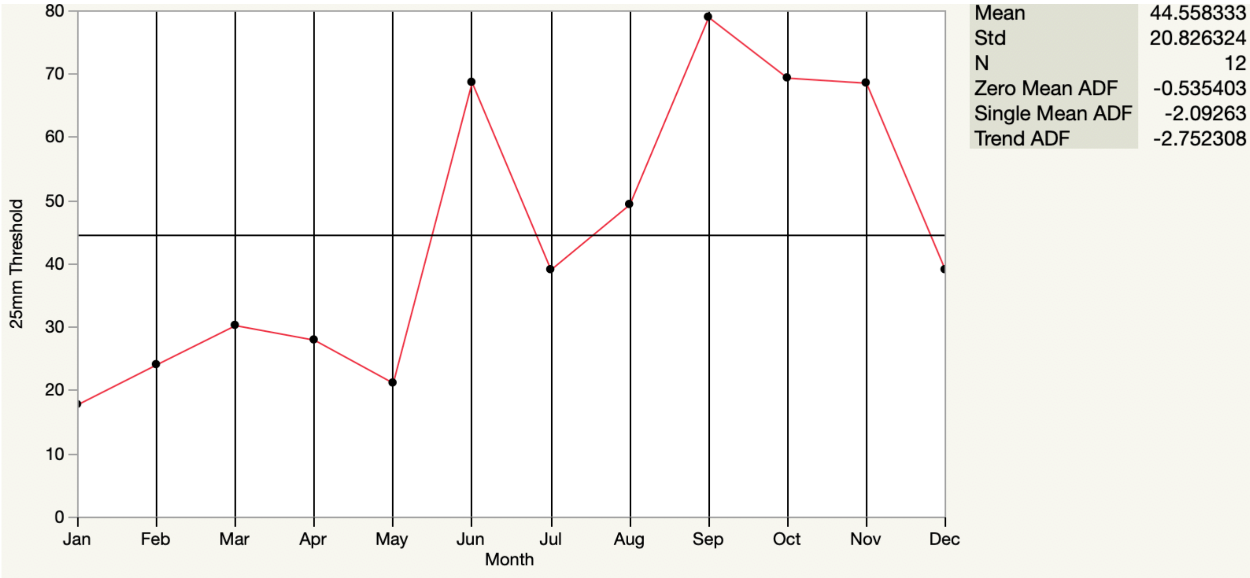

Figure 4.2.10: Time series scatterplot showing the average days since the 25mm precipitation threshold was reached on a monthly basis with a line showing the average number of consecutive dry days per month

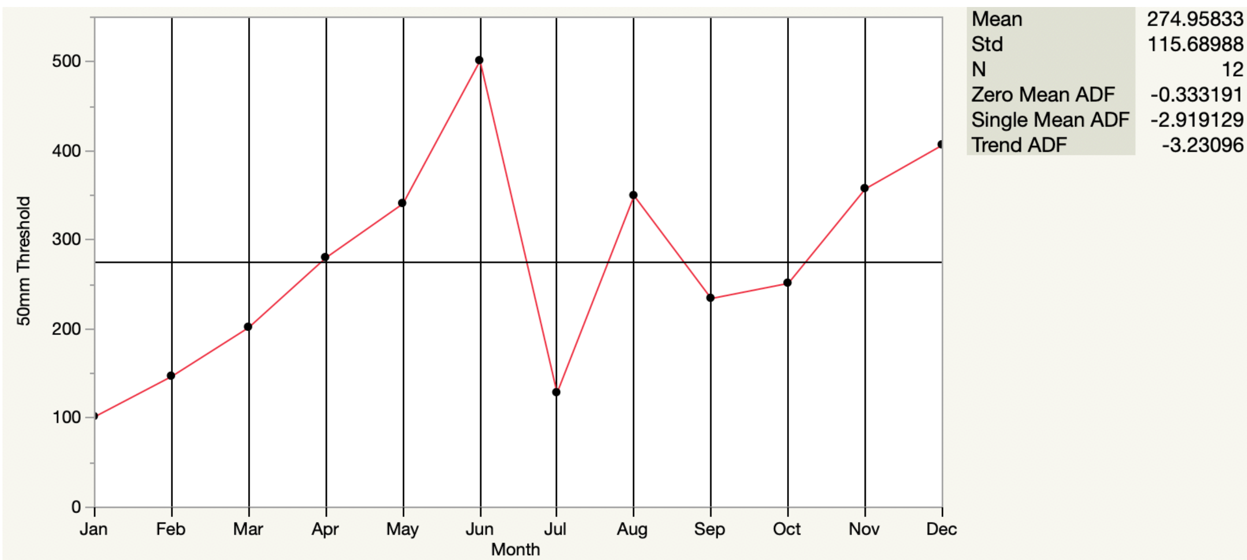

Figure 4.2.11: Time series scatterplot showing the average days since the 50mm precipitation threshold was reached on a monthly basis with a line showing the average number of consecutive dry days per month

4.3 Statistical Analysis

4.3.1 Poisson Regression Analysis

Poisson regression analysis was used to identify the relationship between the number of consecutive dry days between specific precipitation thresholds being reached and wildfire ignition. The threshold values of 1, 5, 10, 25, and 50mm were used both individually and together against all individual fires from the MTBS dataset, to see if there is a statistically significant relationship between consecutive dry days and fire activity in Southern Appalachia. P-values and standard error values act as indicators for the existence of a relationship. According to the values, when the tests are run individually at thresholds 1, 5, 10, 25, 50mm, there is a very strong log-link relationship between the number of acres burned and days since the given threshold value as shown in Figures 4.3.1-4.3.5 and Tables 4.3.1-4.3.5. This is indicated by strong p-values and a small standard error. R-squared values should be ignored when conducting both Poisson and negative binomial regression analysis. Figure 4.3.2 is an example plot of how dry days were distributed on the basis of area burned. The plot shows a gradual increase in the number of consecutive dry days leading up to fire events as the events cause a larger amount of area burned. Table 4.3.6 shows a strong relationship between dry day threshold values and acres burned per fire when all thresholds are used. The -log likelihood, AICc, and Bic, show that the 5mm threshold has the best fit of the models, followed by the 1mm and 10mm threshold values. Poisson regression modeling analysis indicates a very strong log-link relationship between consecutive dry days, at multiple thresholds, and the amount of area burned per fire for the entire period and area of study.

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	312159.01
Number of Parameters	2
BIC	624330.05
AICc	624322.05
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.1579837	0.0016831	18087763	<.0001*	7.1546849	7.1612824
1mm Threshold	0.0413472	0.0001393	88107.21	<.0001*	0.0410742	0.0416202

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
1mm Threshold	1	1	88107.21	<.0001*

Table 4.3.1: Poisson regression model of acres burned vs consecutive dry days since the 1mm threshold value was reached

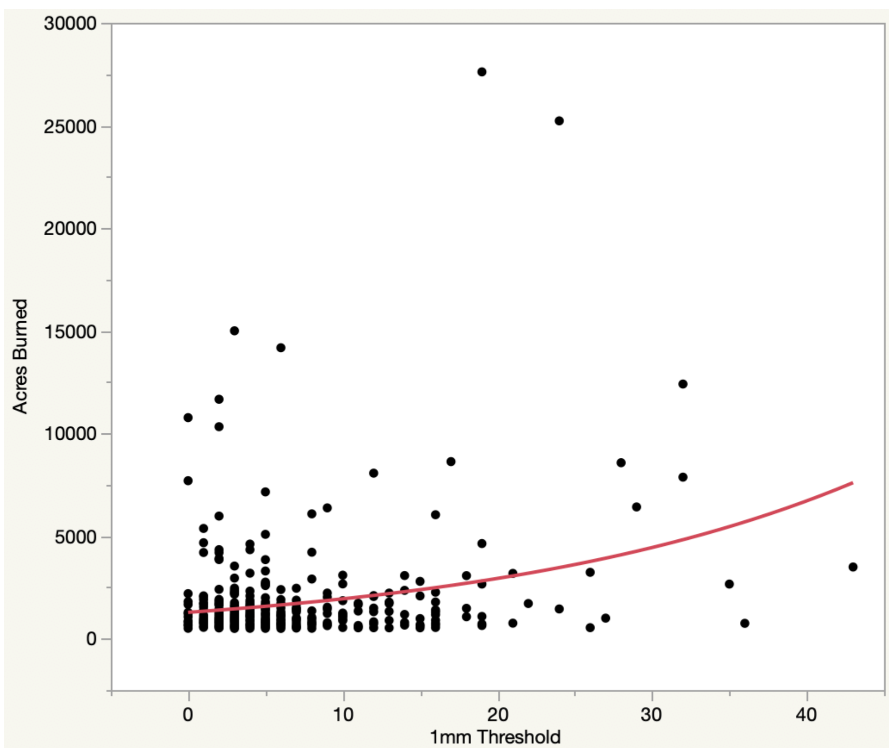

Figure 4.3.1: Poisson regression plot of acres burned vs consecutive dry days since the 1mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	307334.37
Number of Parameters	2
BIC	614680.78
AICc	614672.78
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.1371973	0.0017117	17386692	<.0001*	7.1338425	7.1405521
5mm Threshold	0.0303199	9.7951e-5	95815.232	<.0001*	0.0301279	0.0305119

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
5mm Threshold	1	1	95815.232	<.0001*

Table 4.3.2: Poisson regression model of acres burned vs consecutive dry days since the 5mm threshold value was reached

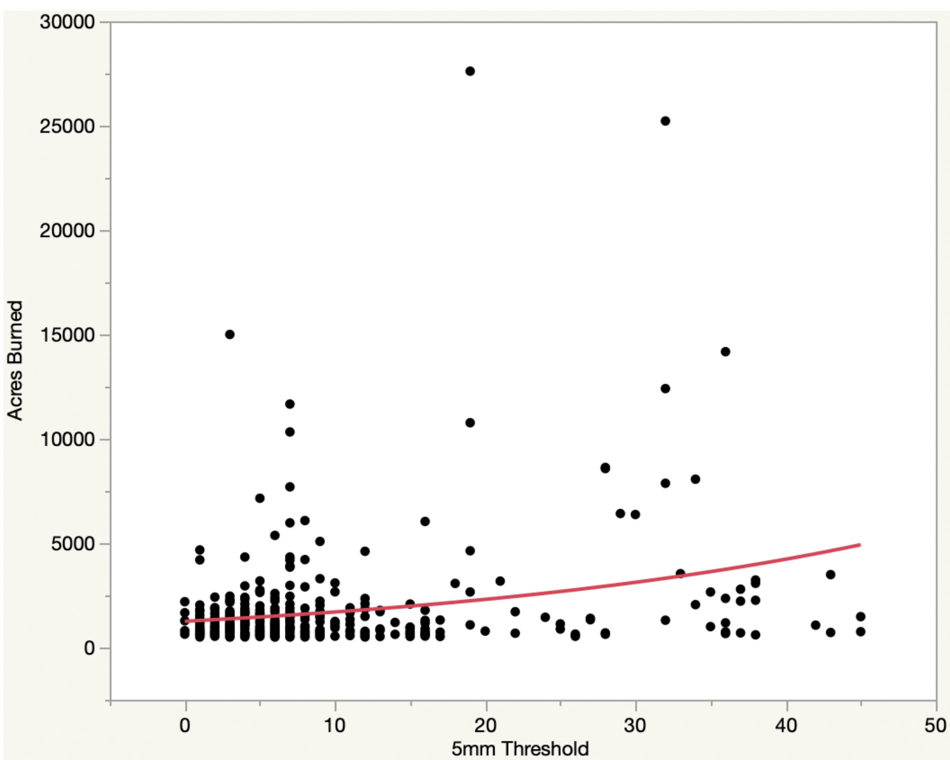

Figure 4.3.2: Poisson regression plot of acres burned vs consecutive dry days since the 5mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	320394.4
Number of Parameters	2
BIC	640800.82
AICc	640792.83
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.1608979	0.0018087	15674698	<.0001*	7.1573529	7.1644429
10mm Threshold	0.0201525	8.0929e-5	62008.24	<.0001*	0.0199939	0.0203112

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
10mm Threshold	1	1	62008.24	<.0001*

Table 4.3.3: Poisson regression model of acres burned vs consecutive dry days since the 10mm threshold value was reached

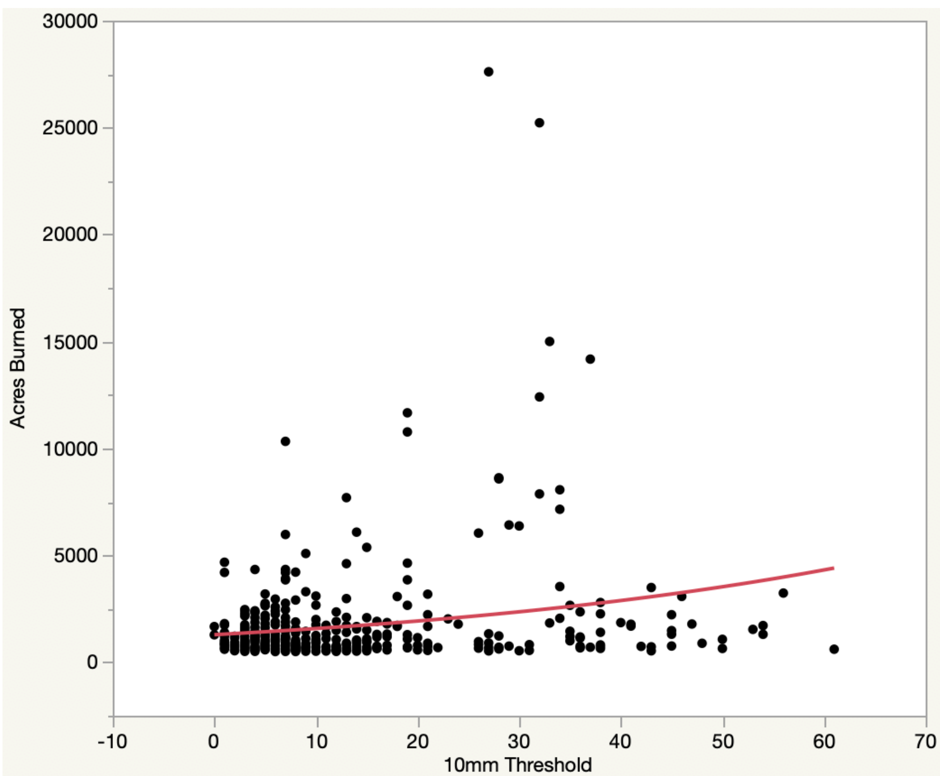

Figure 4.3.3: Poisson regression plot of acres burned vs consecutive dry days since the 10mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	341625.82
Number of Parameters	2
BIC	683263.68
AICc	683255.68
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.3213367	0.0017293	17925190	<.0001*	7.3179474	7.324726
25mm Threshold	0.0032201	2.7038e-5	14183.143	<.0001*	0.0031671	0.0032731

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
25mm Threshold	1	1	14183.143	<.0001*

Table 4.3.4: Poisson regression model of acres burned vs consecutive dry days since the 25mm threshold value was reached

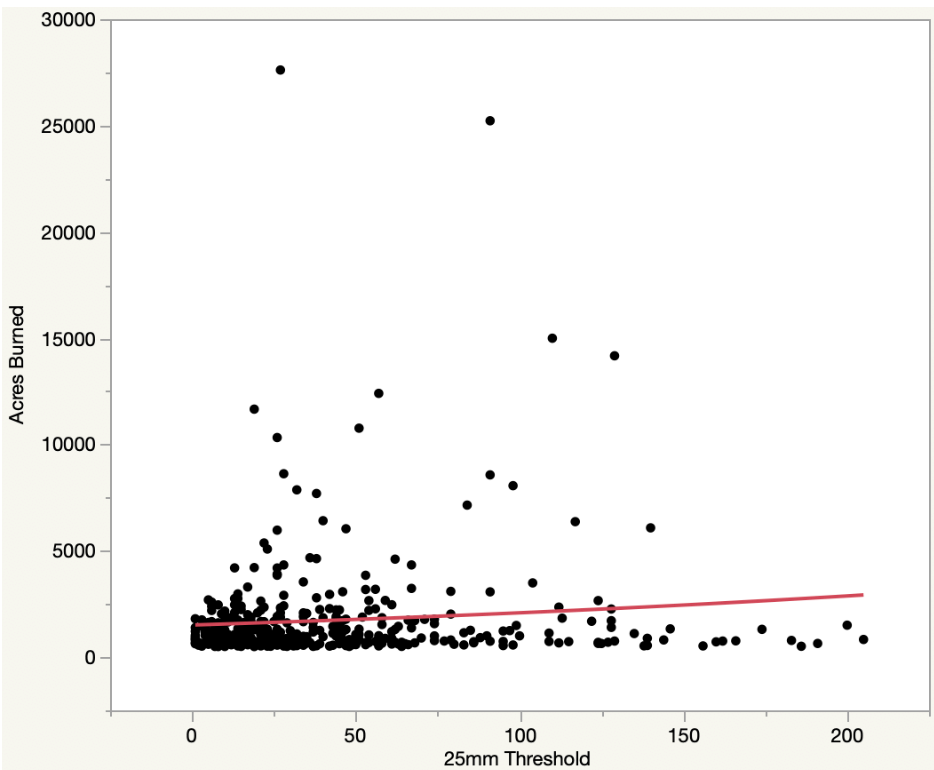

Figure 4.3.4: Poisson regression plot of acres burned vs consecutive dry days since the 25mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	348130.46
Number of Parameters	2
BIC	696272.95
AICc	696264.95
Generalized RSquare	0.4320558

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.4468902	0.0015492	23107248	<.0001*	7.4438539	7.4499266
50mm Threshold	5.5189e-5	3.6045e-6	234.4332	<.0001*	4.8124e-5	6.2253e-5

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
50mm Threshold	1	1	234.4332	<.0001*

Table 4.3.5: Poisson regression model of acres burned vs consecutive dry days since the 50mm threshold value was reached

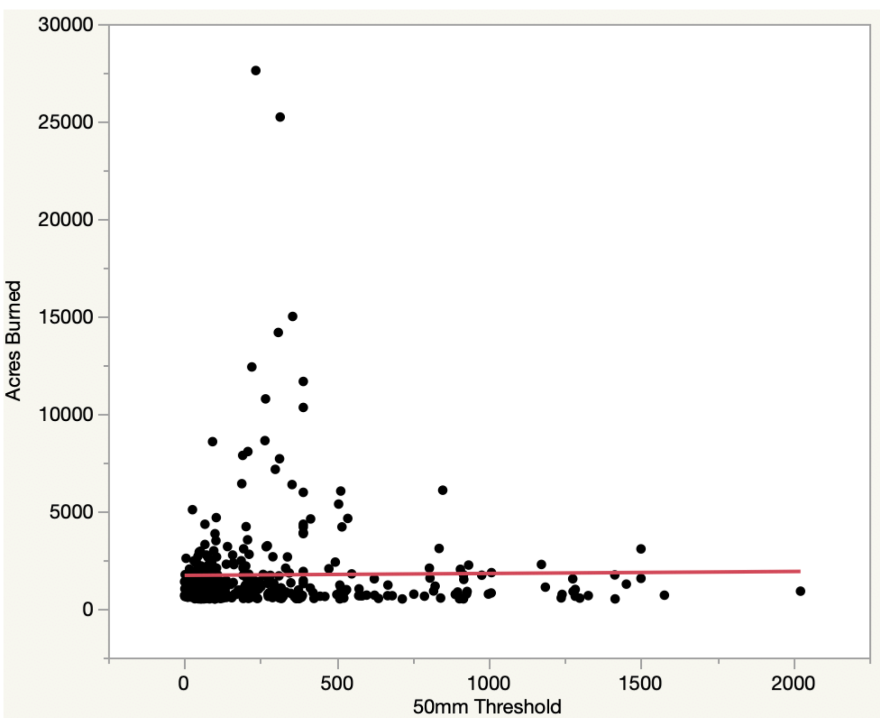

Figure 4.3.5: Poisson regression plot of acres burned vs consecutive dry days since the 50mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	305552.76
Number of Parameters	6
BIC	611141.61
AICc	611117.74
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.1527782	0.0021363	11210568	<.0001*	7.1485912	7.1569653
< 1mm Threshold	0.0007093	0.0002297	9.5376338	0.0020*	0.0002592	0.0011595
< 5mm Threshold	0.0193568	0.0002086	8608.9166	<.0001*	0.0189479	0.0197657
< 10mm Threshold	0.0129825	0.0001498	7511.6159	<.0001*	0.0126889	0.0132761
< 25mm Threshold	-0.001694	3.6387e-5	2168.1214	<.0001*	-0.001766	-0.001623
< 50mm Threshold	-9.267e-5	4.1042e-6	509.7624	<.0001*	-0.000101	-8.462e-5

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 5mm Threshold	1	1	8608.9166	<.0001*
< 10mm Threshold	1	1	7511.6159	<.0001*
< 25mm Threshold	1	1	2168.1214	<.0001*
< 50mm Threshold	1	1	509.7624	<.0001*
< 1mm Threshold	1	1	9.5376338	0.0020*

Table 4.3.6: Poisson regression model of acres burned vs consecutive dry days at all threshold values reached

4.3.2 Negative Binomial Regression Analysis

Negative binomial regression analysis was used in a similar way to Poisson regression analysis. It was used to determine the relationship between consecutive dry days from different precipitation thresholds and the amount of area burned. Much like Poisson regression, the relationship between the two variables within the negative binomial regression model can be observed by looking at the p-value and the standard error. Based on the results of each threshold value, Tables 4.3.7-4.3.11 and Figures 4.3.6-4.3.10 show a strong relationship between consecutive dry days and area burned at all 5 major precipitation thresholds except for the 50mm threshold value. Very low p-values and standard error indicate a strong log-link relationship between the two variables at all threshold values. Figure 4.3.7 is an example plot of how dry days were distributed on the basis of area burned. The plot shows a gradual increase in the number of consecutive dry days leading up to fire events as the events cause a larger amount of area burned. Table 4.3.12 shows the results for the relationship between area burned and consecutive dry days at all 5 precipitation threshold values. Assessing this table p-values indicate that strong relationships between the consecutive dry day threshold values and area burned exist at the 5mm and 10mm threshold values. However, according to negative binomial regression analysis the same relationships do not exist at the 1, 25, and 50mm threshold values. Based on the AICc, Bic, and – log likelihood values for the individual tests, the 5mm threshold value has the best fit followed by the 10 then 1mm threshold value. The fits for the 25 and 50mm threshold values are not near as good as the other 3 values.

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	3416.8605
Number of Parameters	3
BIC	6851.7621
AICc	6839.7802
Generalized RSquare	0.1136501

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.1900281	0.0520374	19091.073	<.0001*	7.0880368	7.2920195
1mm Threshold	0.0368735	0.0055784	43.692599	<.0001*	0.02594	0.0478069

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.5927515	0.010975	2916.9878	<.0001*	0.5712408	0.6142621

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
1mm Threshold	1	1	43.692599	<.0001*

Table 4.3.7: Negative binomial regression model of acres burned vs consecutive dry days since the 1mm threshold value was reached

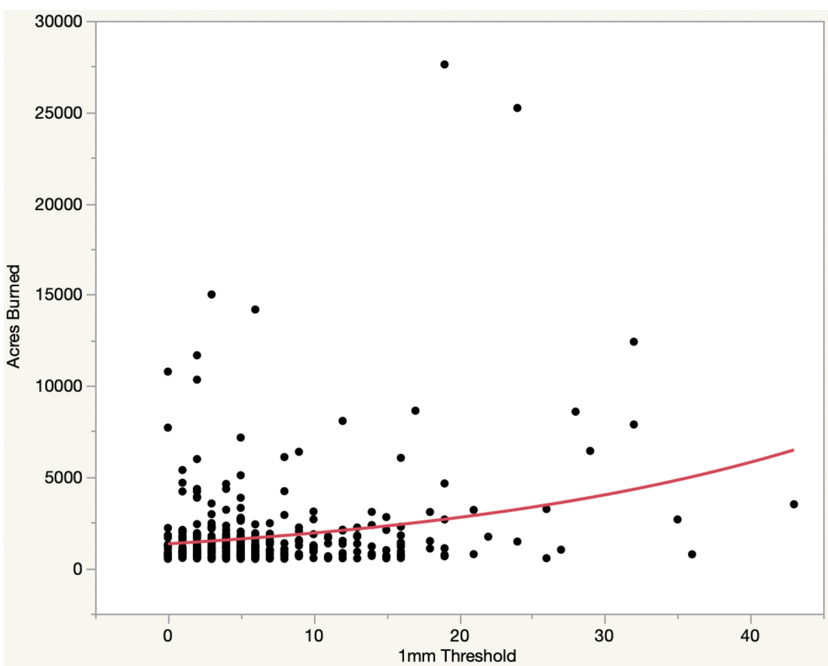

Figure 4.3.6: Negative binomial regression plot of acres burned vs consecutive dry days since the 1mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	3405.8531
Number of Parameters	3
BIC	6829.7474
AICc	6817.7655
Generalized RSquare	0.1600973

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.1060774	0.0530052	17973.127	<.0001*	7.0021892	7.2099656
5mm Threshold	0.0331865	0.0041357	64.391707	<.0001*	0.0250808	0.0412923

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.5663625	0.0103112	3016.9874	<.0001*	0.546153	0.586572

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
5mm Threshold	1	1	64.391707	<.0001*

Table 4.3.8: Negative binomial regression model of acres burned vs consecutive dry days since the 5mm threshold value was reached

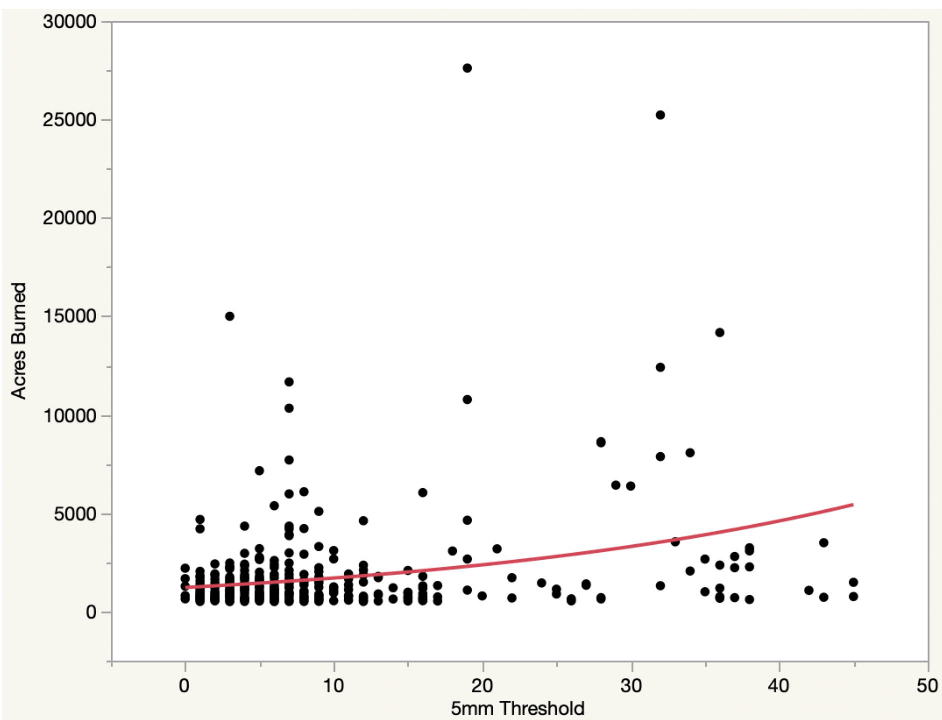

Figure 4.3.7: Negative binomial regression model of acres burned vs consecutive dry days since the 5mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	3413.3648
Number of Parameters	3
BIC	6844.7707
AICc	6832.7888
Generalized RSquare	0.1286725

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.0969433	0.0579449	15000.711	<.0001*	6.9833734	7.2105133
10mm Threshold	0.0243978	0.0033221	53.934421	<.0001*	0.0178866	0.0309091

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.584271	0.0107606	2948.2191	<.0001*	0.5631808	0.6053613

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
10mm Threshold	1	1	53.934421	<.0001*

Table 4.3.9: Negative binomial regression model of acres burned vs consecutive dry days since the 10mm threshold value was reached

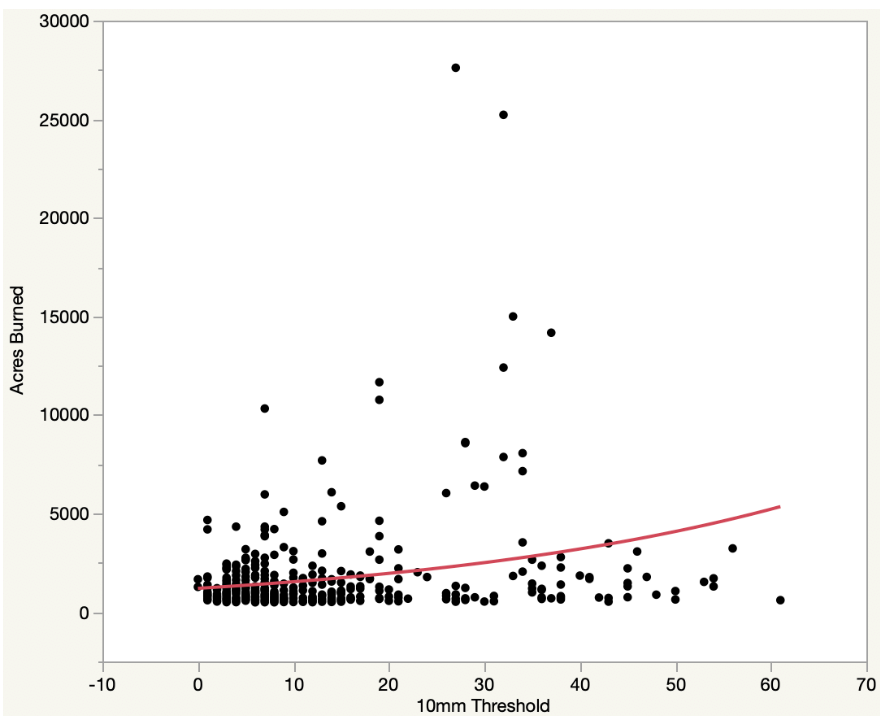

Figure 4.3.8: Negative binomial regression model of acres burned vs consecutive dry days since the 10m threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	3434.4749
Number of Parameters	3
BIC	6886.9909
AICc	6875.009
Generalized RSquare	0.0339209

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.2811967	0.0609138	14288.105	<.0001*	7.1618079	7.4005855
25mm Threshold	0.0041384	0.0011313	13.381492	0.0003*	0.0019211	0.0063556

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.6372212	0.012116	2766.0644	<.0001*	0.6134743	0.6609681

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
25mm Threshold	1	1	13.381492	0.0003*

Table 4.3.10: Negative binomial regression model of acres burned vs consecutive dry days since the 25mm threshold value was reached

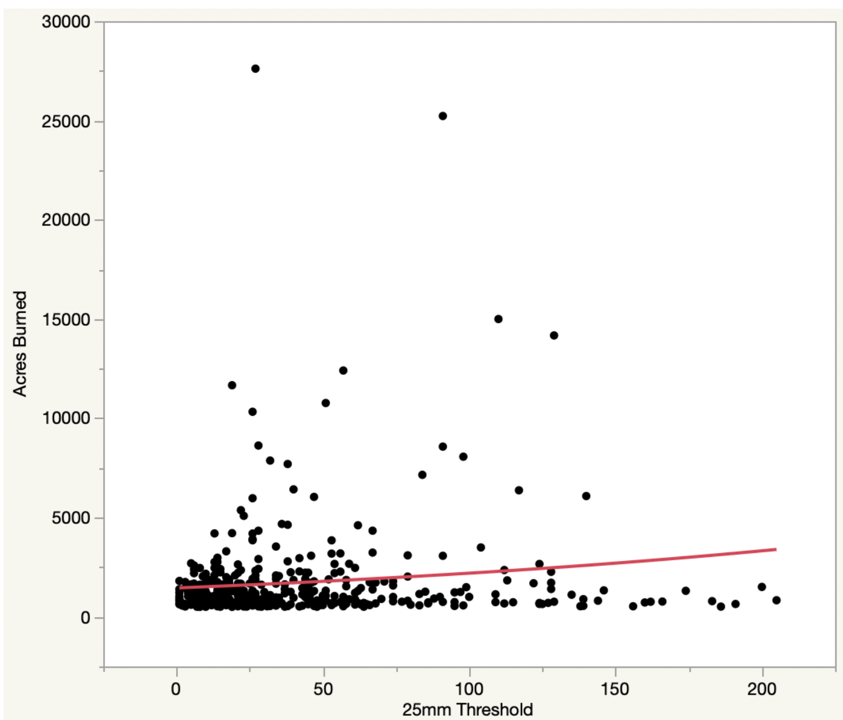

Figure 4.3.9: Poisson regression model of acres burned vs consecutive dry days since the 25mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	517
Sum of Frequencies	409
-LogLikelihood	3441.4954
Number of Parameters	3
BIC	6901.0319
AICc	6889.0501
Generalized RSquare	0.0001793

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.4724441	0.0556312	18042.141	<.0001*	7.3634089	7.5814793
50mm Threshold	-3.876e-5	0.0001425	0.0739815	0.7856	-0.000318	0.0002405

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.6557094	0.0125982	2708.9683	<.0001*	0.6310174	0.6804015

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
50mm Threshold	1	1	0.0739815	0.7856

Table 4.3.11: Negative binomial regression model of acres burned vs consecutive dry days since the 50mm threshold value was reached

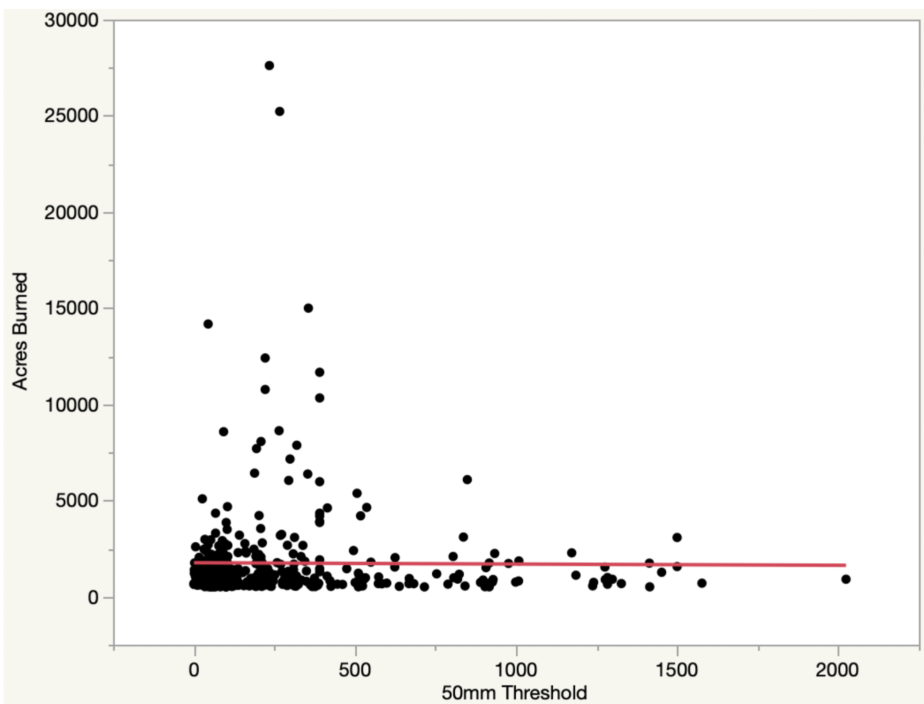

Figure 4.3.10: Negative binomial regression model of acres burned vs consecutive dry days since the 50mm threshold value was reached

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	409
Sum of Frequencies	409
-LogLikelihood	3402.7335
Number of Parameters	7
BIC	6847.563
AICc	6819.7463
Generalized RSquare	0.1728126

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.1007989	0.0663581	11450.545	<.0001*	6.9707394	7.2308585
< 1mm Threshold	-0.009026	0.008474	1.1343984	0.2868	-0.025634	0.0075833
< 5mm Threshold	0.0244331	0.007797	9.8198737	0.0017*	0.0091513	0.0397149
< 10mm Threshold	0.0162383	0.0052677	9.5024253	0.0021*	0.0059138	0.0265629
< 25mm Threshold	-0.001703	0.0012655	1.8104066	0.1785	-0.004183	0.0007776
< 50mm Threshold	-2.431e-5	0.000132	0.0339387	0.8538	-0.000283	0.0002344

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.559072	0.0101296	3046.1686	<.0001*	0.5392184	0.5789256

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 5mm Threshold	1	1	9.8198737	0.0017*
< 10mm Threshold	1	1	9.5024253	0.0021*
< 25mm Threshold	1	1	1.8104066	0.1785
< 1mm Threshold	1	1	1.1343984	0.2868
< 50mm Threshold	1	1	0.0339387	0.8538

Table 4.3.12: Negative binomial regression model of acres burned vs consecutive dry days at all threshold values

4.4 Case Study of Eastern Tennessee

4.4.1 Fire Trends

Fire activity in the Eastern Tennessee climate division was chosen as a case study because this individual division contained the greatest number of fires as well as the greatest number of acres burned throughout the entire period of study. It made up roughly 25% of all Southern Appalachian fire activity. Preliminary research indicated weak correlation and linear regression relationships between mean annual dry days under 1mm of precipitation and both fire frequency and area burned in the division, which is worth following up on. This area also has the highest elevation point in the fire dataset and the greatest amount of topographic variability. With a landscape defined by ridges and valleys and climatic characteristics that mimic those of Southern Appalachia as a whole, Eastern Tennessee stood out as an ideal case study for which to observe the relationships between consecutive dry days and fire at a more localized scale. By looking at the annual fire activity in Eastern Tennessee in Table 4.4.1, one can observe that there are years with a large number of fires and area burned, but the normal behavior is less than 10 fires or none at all. The data for the division seems to be fairly sporadic. Figures 4.4.1 and 4.4.2 show spikes in the years 1987, 2000, 2001, 2007, and 2016. This is important to consider when the precipitation data is studied during the years mentioned specifically. Monthly patterns of fire data provide an understanding of the seasonality of fire behavior within Eastern Tennessee. Table 4.4.2 shows the distribution of the number of fires and acres burned on a monthly basis throughout the entire period of study. Figures 4.4.3 and 4.4.4 plot the distribution and identify two major peak fire seasons. March and April are the peak of the spring fire season. November is the peak of the fall fire season with an increase in the number of fires and acres burned in December. Figures 4.4.5 and 4.4.6 show the daily distribution of the number of fires and acres burned for entire study period. The figures show that large portions of the acres burned are due to individual extremely large-scale fire episodes. A few individual fires from the years 1987, 2000, and 2016 are responsible for a significant portion of the area burned for the whole dataset. Precipitation trends can be an indication of the environment's susceptibility for producing events such as the extreme fires within the dataset.

Year	Number of Fires	Area Burned
1985	0	0
1986	1	530
1987	13	38822
1988	4	3604
1989	0	0
1990	0	0
1991	2	1848
1992	0	0
1993	0	0
1994	2	1776
1995	0	0
1996	0	0
1997	0	0
1998	0	0
1999	3	1704
2000	19	35002
2001	12	13577
2002	0	0
2003	4	4102
2004	1	729
2005	3	4650
2006	4	3514
2007	11	13908
2008	5	4182
2009	1	501
2010	6	9319
2011	0	0
2012	1	1856
2013	8	13158
2014	7	10060
2015	0	0
2016	18	48960

Table 4.4.1: Time series table showing the total number of fires and area burned in acres on an annual basis for the Eastern Tennessee climate division from 1985-2016

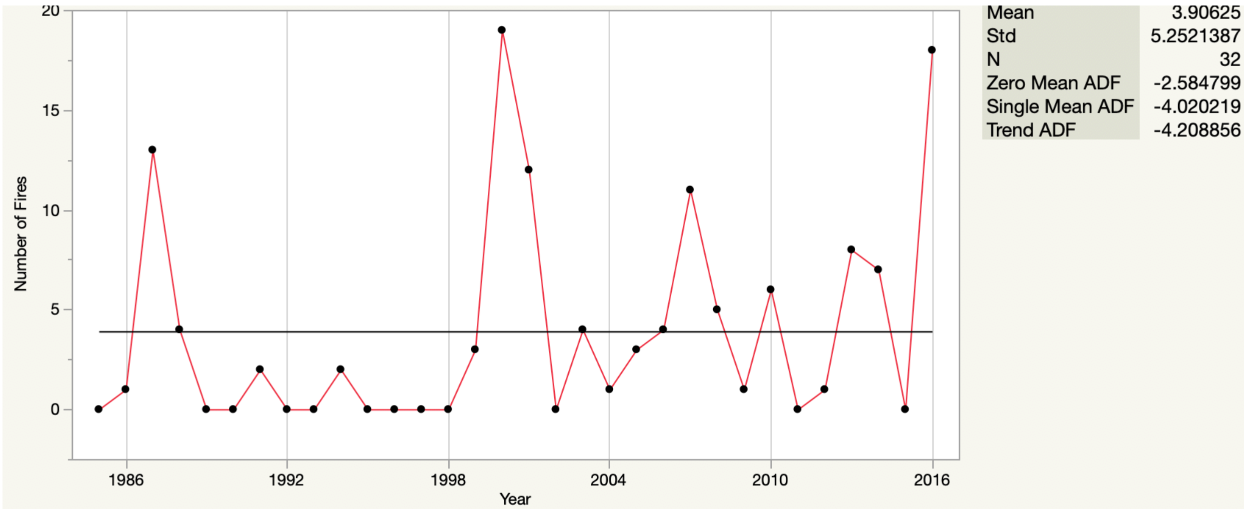

Figure 4.4.1: Time series plot showing the total number of fires on an annual basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the average number of fires per year

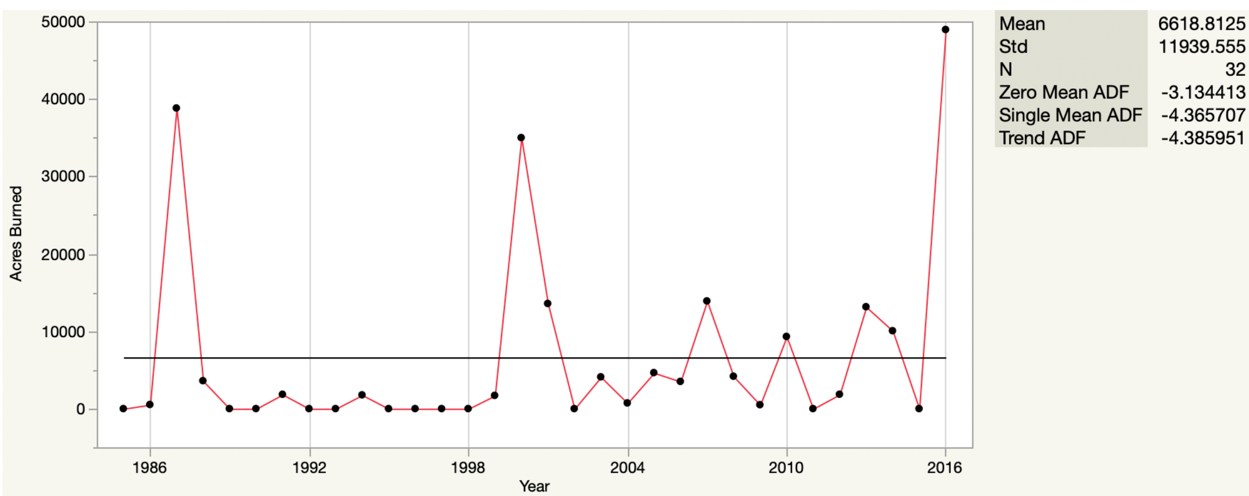

Figure 4.4.2: Time series plot showing the total area burned in acres on an annual basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the average area burned per year

Month	Number of Fires	Area Burned
January	0	0
February	0	0
March	45	83790
April	25	27743
May	8	10511
June	2	2279
July	0	0
August	3	1887
September	1	1738
October	4	5586
November	31	59018
December	6	19250

Table 4.4.2: Time series table showing the total number of fires and area burned in acres on a monthly basis for the Eastern Tennessee climate division

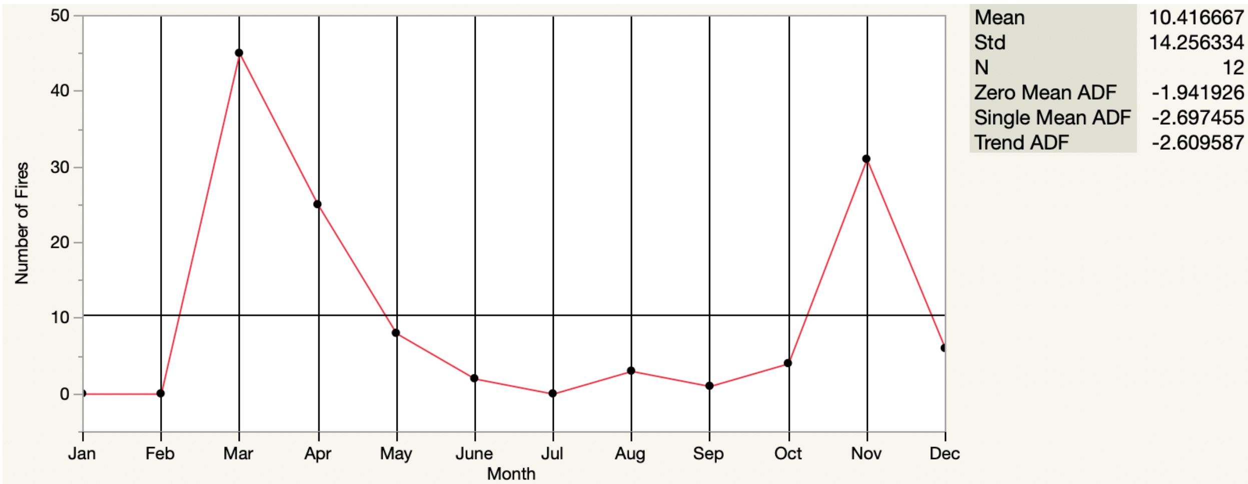

Figure 4.4.3: Time series plot showing the total number of fires on a monthly basis for the Eastern Tennessee climate division with a line showing the average number of fires per month

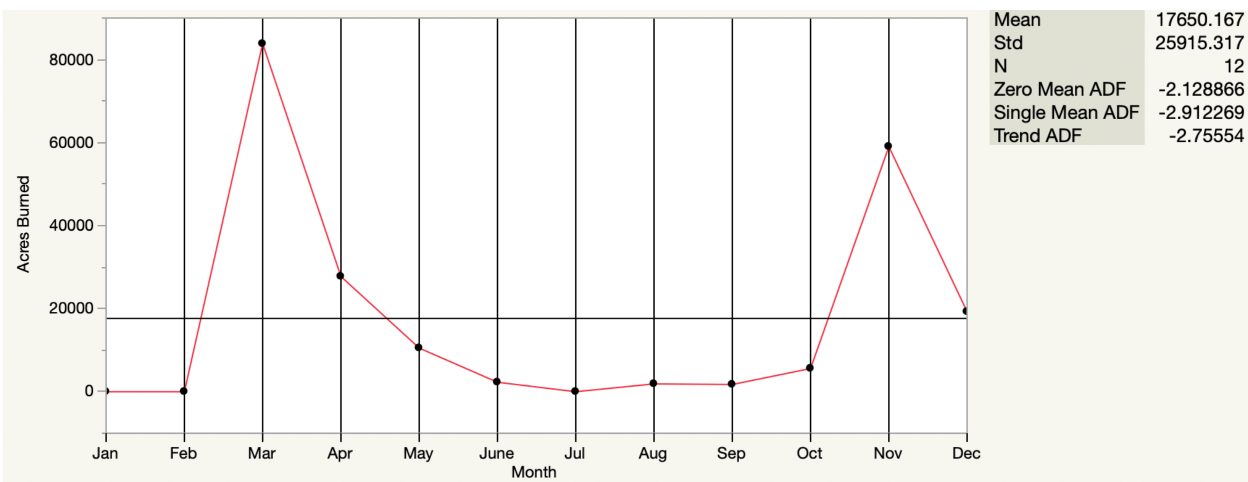

Figure 4.4.4: Time series plot showing the total area burned in acres on a monthly basis for the Eastern Tennessee climate division with a line showing the average area burned per month

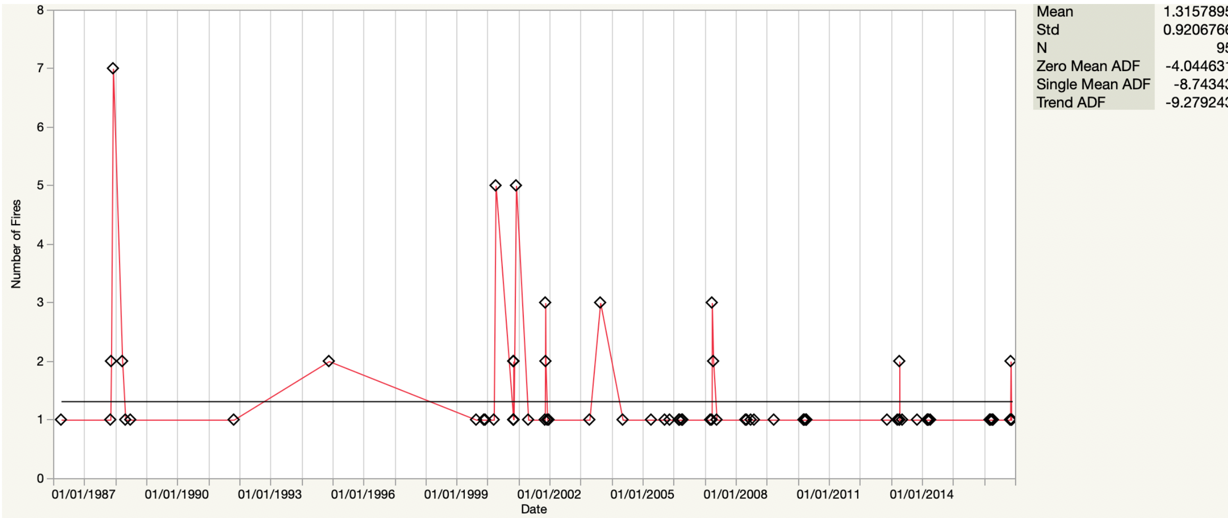

Figure 4.4.5: Time series plot showing the total number of fires on a daily basis for the Eastern Tennessee climate division from 1/1/1985-12/31/2016 with a line showing the mean number of fires per day

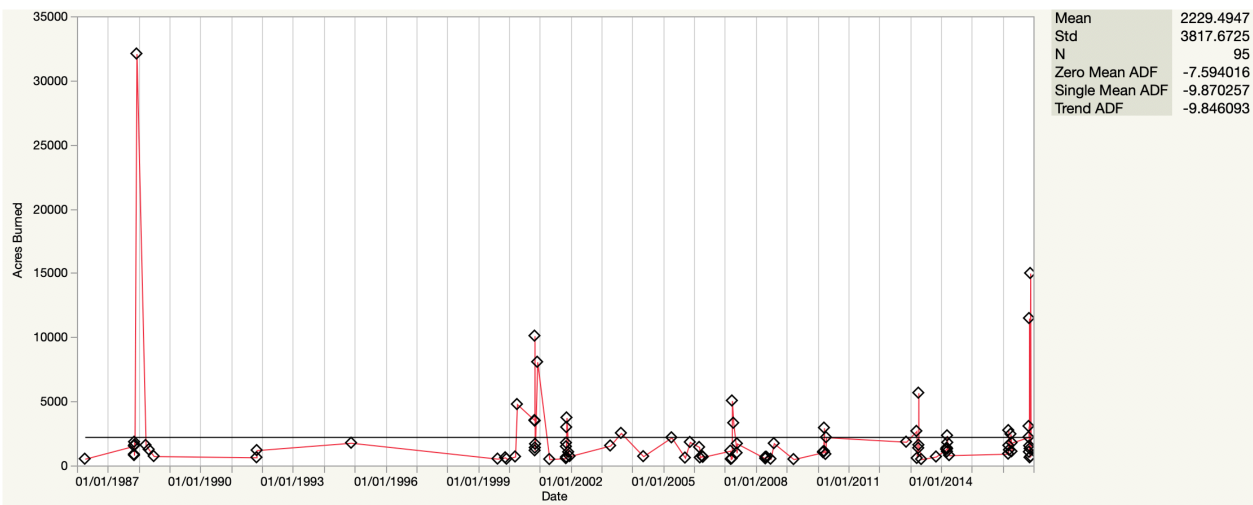

Figure 4.4.6: Time series plot showing the total area burned in acres on a daily basis for the Eastern Tennessee climate division from 1/1/1985-12/31/2016 with a line showing the mean area burned per day

4.4.2 Precipitation Trends

Precipitation trends within the Eastern Tennessee climate division are similar to those in the Southern Appalachia area of study as a whole. However, a major difference is the sample size of fires from which to run analysis on. This is especially true when looking at fire activity on an annual basis. Prior to analyzing precipitation trends by the consecutive number of dry days since a precipitation threshold has been reached, preliminary research observed the mean annual dry days with precipitation under 1mm in Figure 4.4.7. This provided limited insight into how dry days impact fire frequency and magnitude. Table 4.4.3 provides a greater understanding of dry day trends within the Eastern Tennessee climate division by displaying the average number of dry days since each of the major 5 precipitation thresholds was reached on an annual basis. Figures 4.4.8-4.4.12 plot the data showing how it is distributed in a time series format. The time series threshold analysis for Eastern Tennessee shows how during the years with the greatest number of fires and the largest area burned the number of consecutive dry days, for the most part, is greater for all 5 thresholds than when there is limited fire activity. It is important to consider, however, that the understanding of the time series annual distribution of the data is limited due to several years not containing fires greater than 500 acres burned. Table 4.4.4 looks at the same threshold values on a monthly basis rather than annually for the entire period of study. Figures 4.4.13-4.4.17 plot the monthly results to identify any existing patterns for each threshold value. Understanding is limited due to some months lacking any fires at all such as January, February, and July. The months that do contain fires, however, identify a greater number of dry days for the months with the most fire activity at lower threshold values such as 1, 5, and 10mm. At the larger threshold values such as 25 and 50mm, there seems to be no distinct pattern between the months, especially when comparing them to the monthly fire data. Figure

4.4.18 is a plot of daily precipitation from the National Weather Service station in Morristown, Tennessee within the Eastern Tennessee climate division. The plot shows that thresholds such as 1, 5, and 10mm are reached on a fairly regular basis throughout the period of study. However, the 25mm threshold is not reached near as frequently, and the 50mm threshold is rarely reached since the beginning of the time series in January 1, 1985.

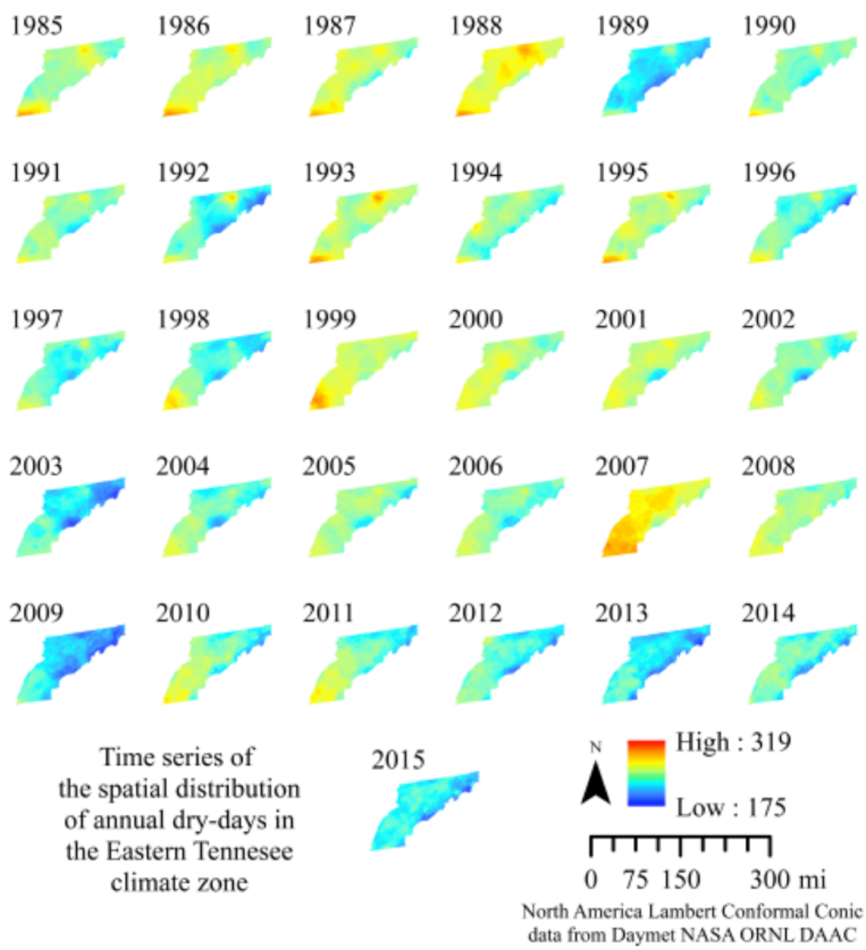

Figure 4.4.7: Time series rasters showing the mean annual dry days without 1mm of precipitation for the Eastern Tennessee climate division from 1985-2015

Year	1mm	5mm	10mm	25mm	50mm
1985	0.00	0.00	0.00	0.00	0.00
1986	15.00	15.00	15.00	21.00	426.00
1987	7.00	11.17	31.50	61.83	1040.83
1988	3.33	6.00	8.67	80.67	1369.33
1989	0.00	0.00	0.00	0.00	0.00
1990	0.00	0.00	0.00	0.00	0.00
1991	12.50	13.00	36.50	126.00	330.00
1992	0.00	0.00	0.00	0.00	0.00
1993	0.00	0.00	0.00	0.00	0.00
1994	9.00	9.00	28.00	95.00	237.00
1995	0.00	0.00	0.00	0.00	0.00
1996	0.00	0.00	0.00	0.00	0.00
1997	0.00	0.00	0.00	0.00	0.00
1998	0.00	0.00	0.00	0.00	0.00
1999	15.67	15.67	17.33	28.33	148.33
2000	9.67	20.78	28.00	89.33	340.44
2001	10.78	11.00	15.67	47.44	303.11
2002	0.00	0.00	0.00	0.00	0.00
2003	4.00	4.00	4.50	26.00	802.00
2004	6.00	6.00	7.00	7.00	64.00
2005	5.67	6.00	22.00	60.67	303.00
2006	4.50	7.25	7.75	62.75	396.00
2007	5.13	5.50	9.25	42.50	591.38
2008	4.40	6.80	10.60	40.20	1038.80
2009	6.00	6.00	8.00	8.00	100.00
2010	4.67	5.17	9.83	39.83	382.17
2011	0.00	0.00	0.00	0.00	0.00
2012	2.00	2.00	17.00	58.00	58.00
2013	3.00	6.86	7.57	31.86	105.71
2014	2.86	4.57	4.71	13.71	47.43
2015	0.00	0.00	0.00	0.00	0.00
2016	6.69	15.31	23.19	89.69	325.44

Table 4.4.3: Time series table showing the average number of dry days prior to fire activity for all major thresholds on an annual basis for the Eastern Tennessee climate division from 1985-2016

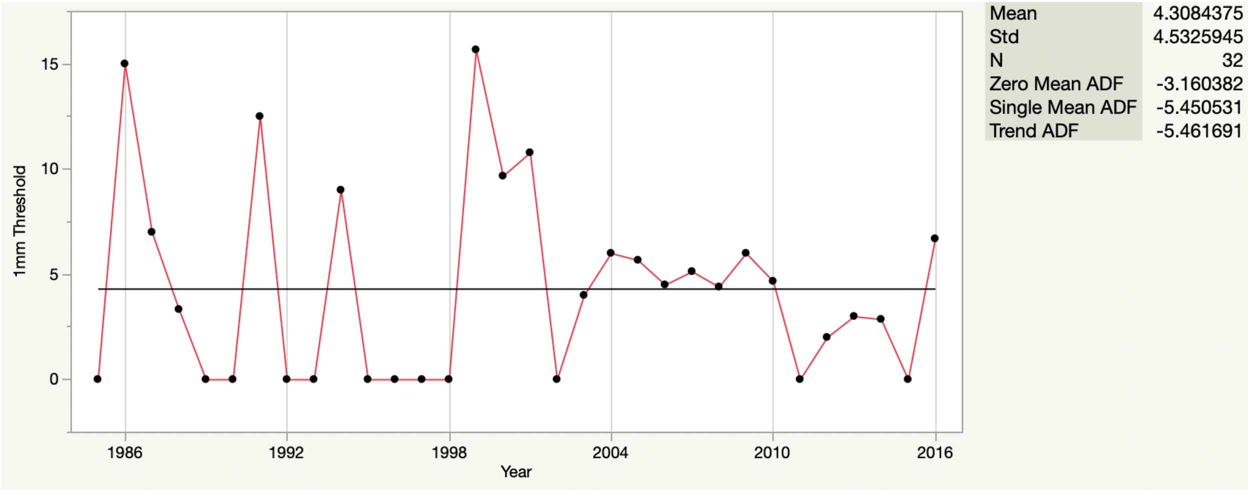

Figure 4.4.8: Time series plot showing the average number of dry days prior to fire activity for the 1mm threshold value on an annual basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per year

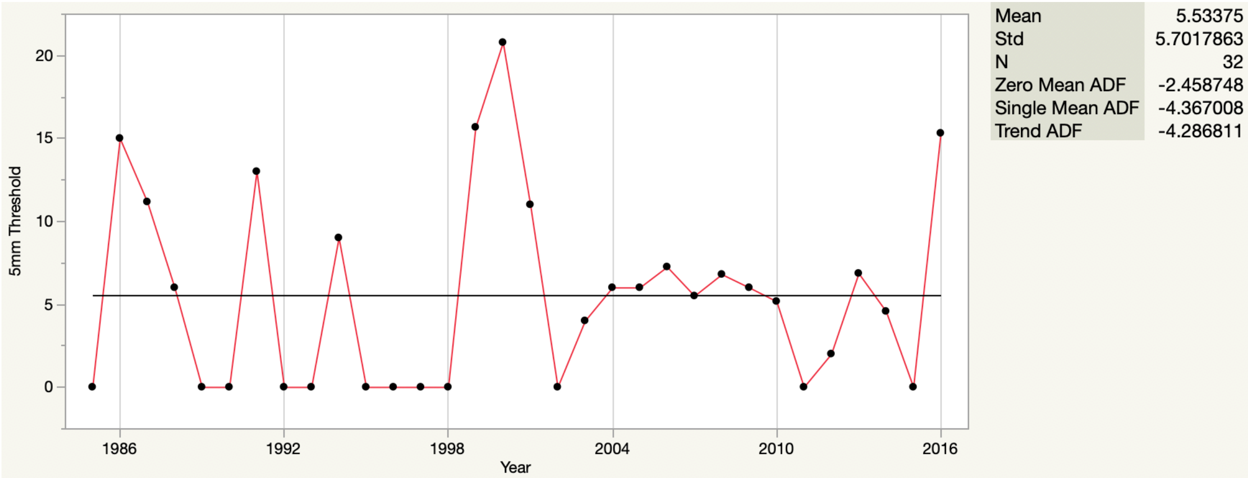

Figure 4.4.9: Time series plot showing the average number of dry days prior to fire activity for the 5mm threshold value on an annual basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per year

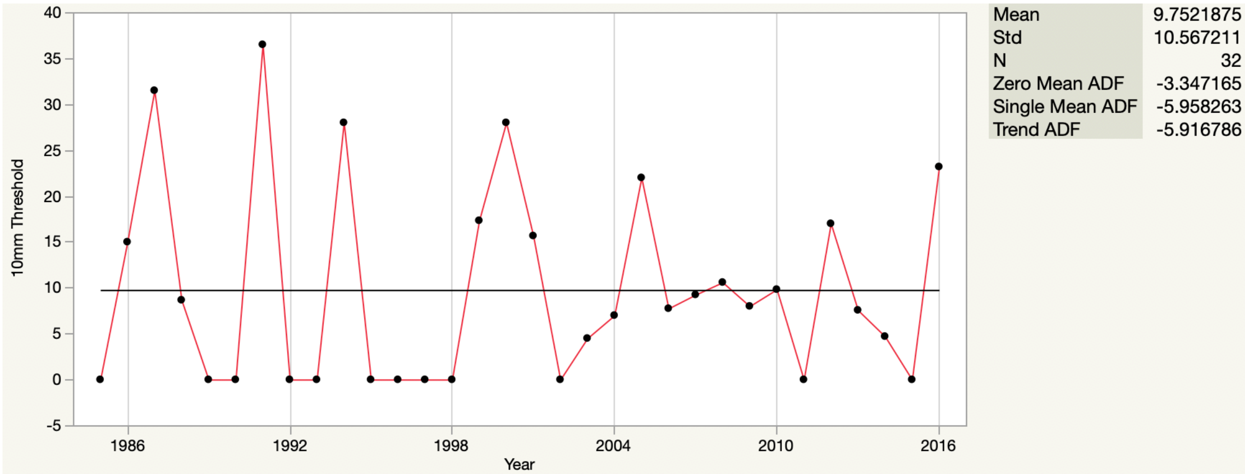

Figure 4.4.10: Time series plot showing the average number of dry days prior to fire activity for the 10mm threshold value on an annual basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per year

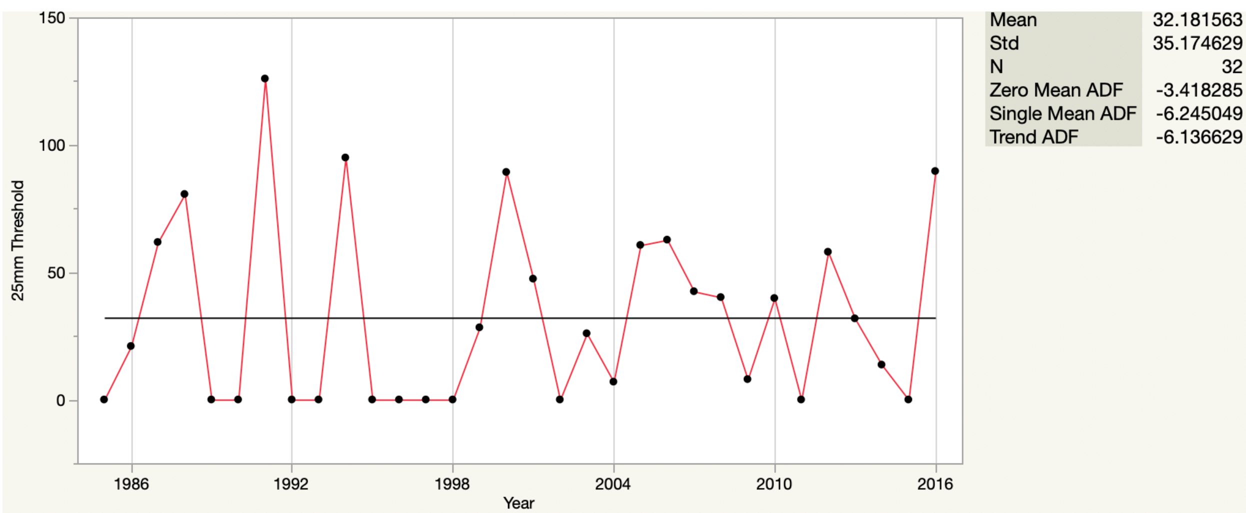

Figure 4.4.11: Time series plot showing the average number of dry days prior to fire activity for the 25mm threshold value on an annual basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per year

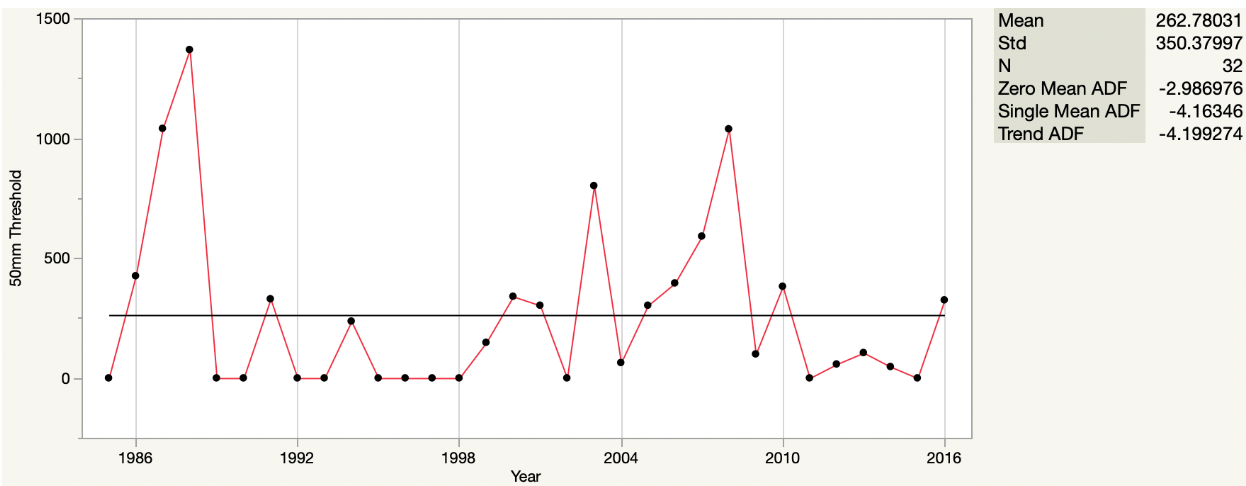

Figure 4.4.12: Time series plot showing the average number of dry days prior to fire activity for the 50mm threshold value on an annual basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per year

Month	1mm	5mm	10mm	25mm	50mm
January	0.00	0.00	0.00	0.00	0.00
February	0.00	0.00	0.00	0.00	0.00
March	9.23	14.46	24.69	72.31	611.58
April	7.65	8.30	13.00	54.95	395.05
May	4.60	5.00	8.60	16.40	405.20
June	4.50	4.50	14.50	43.50	1107.50
July	0.00	0.00	0.00	0.00	0.00
August	6.00	10.00	13.67	38.67	847.33
September	1.00	1.00	1.00	66.00	1414.00
October	5.00	5.25	10.75	28.25	59.50
November	3.83	7.93	11.38	43.69	228.90
December	10.60	22.60	33.60	135.80	370.80

Table 4.4.4: Time series table showing the average number of dry days prior to fire activity for all major thresholds on a monthly basis for the Eastern Tennessee climate division from 1985-2016

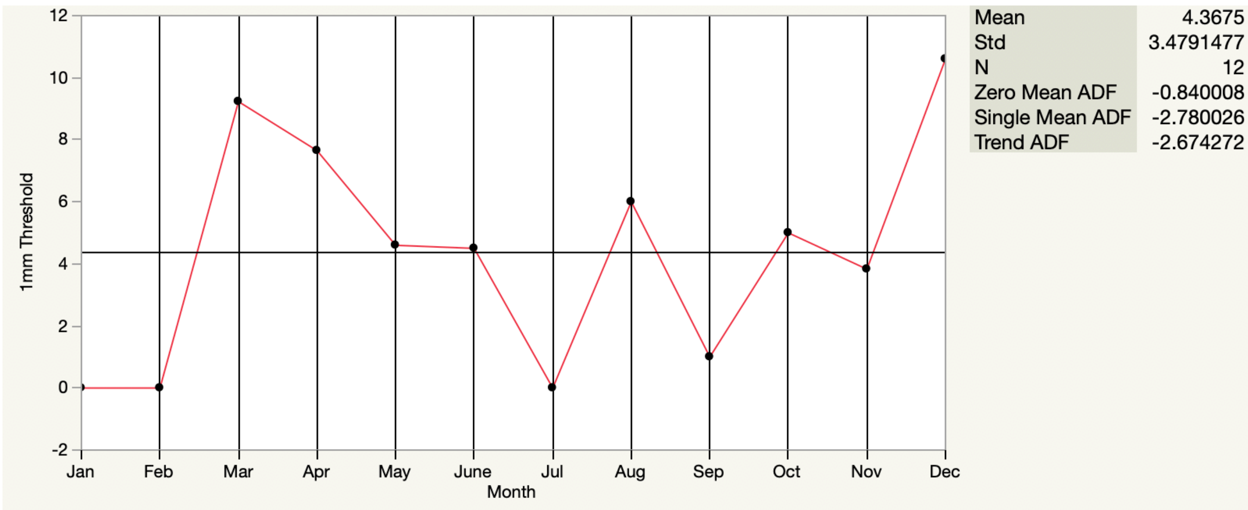

Figure 4.4.13: Time series plot showing the average number of dry days prior to fire activity for the 1mm threshold value on a monthly basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per month

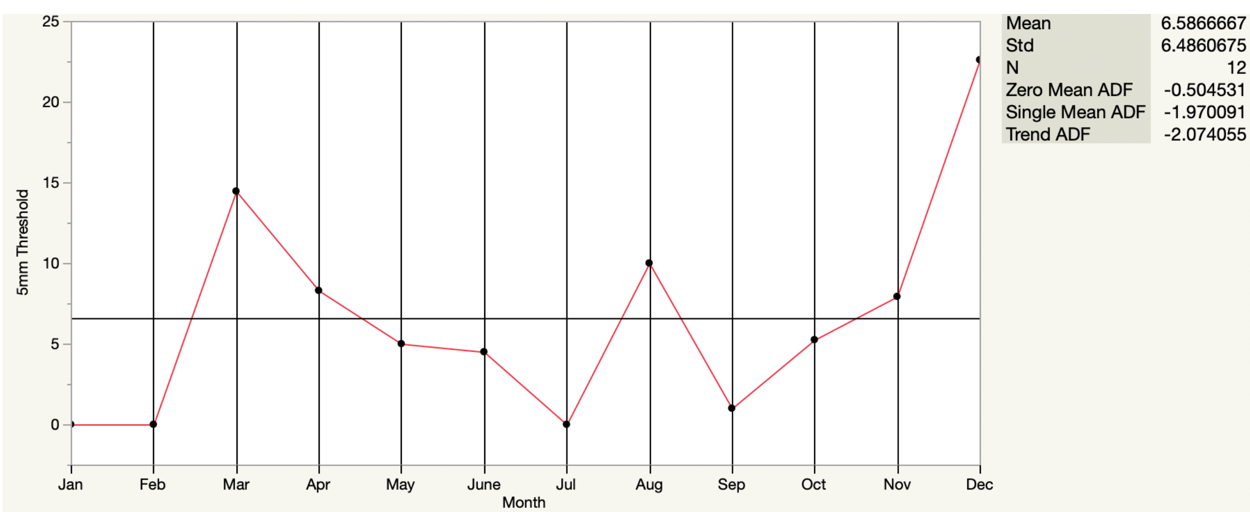

Figure 4.4.14: Time series plot showing the average number of dry days prior to fire activity for the 5mm threshold value on a monthly basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per month

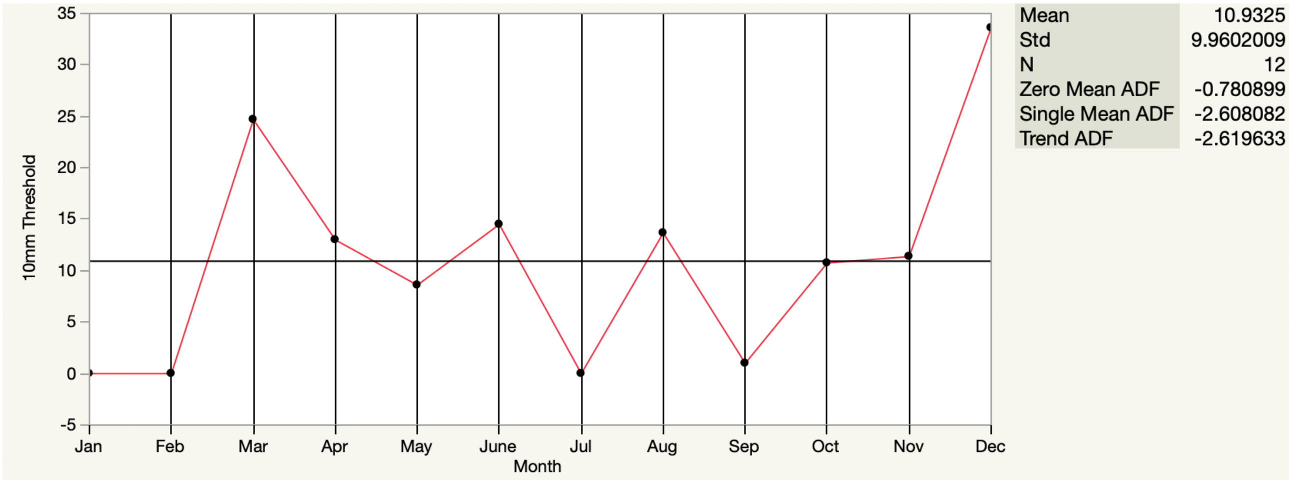

Figure 4.4.15: Time series plot showing the average number of dry days prior to fire activity for the 10mm threshold value on a monthly basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per month

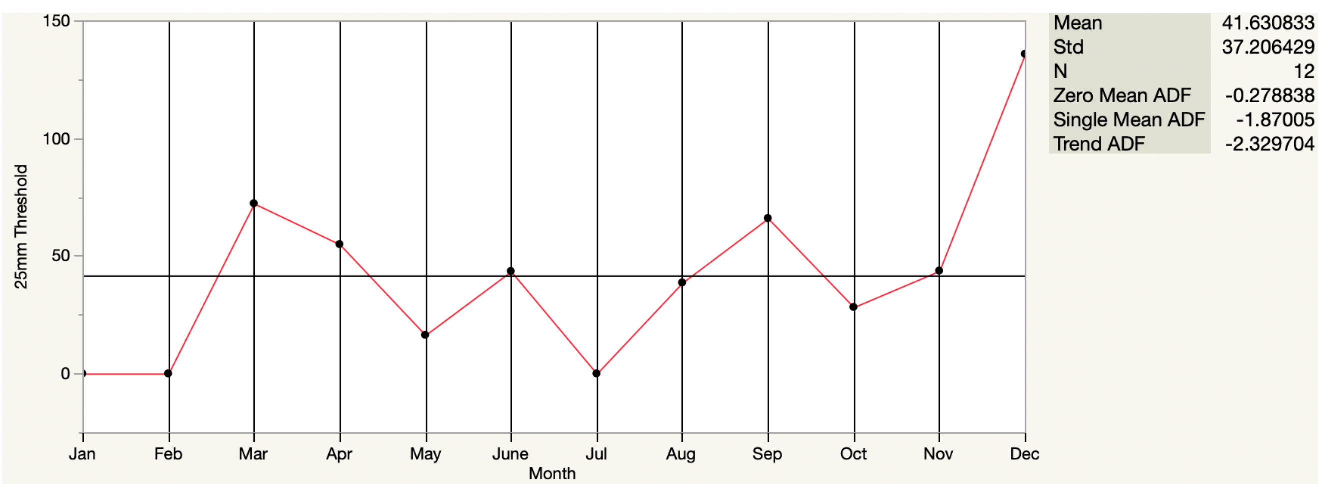

Figure 4.4.16: Time series plot showing the average number of dry days prior to fire activity for the 25mm threshold value on a monthly basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per month

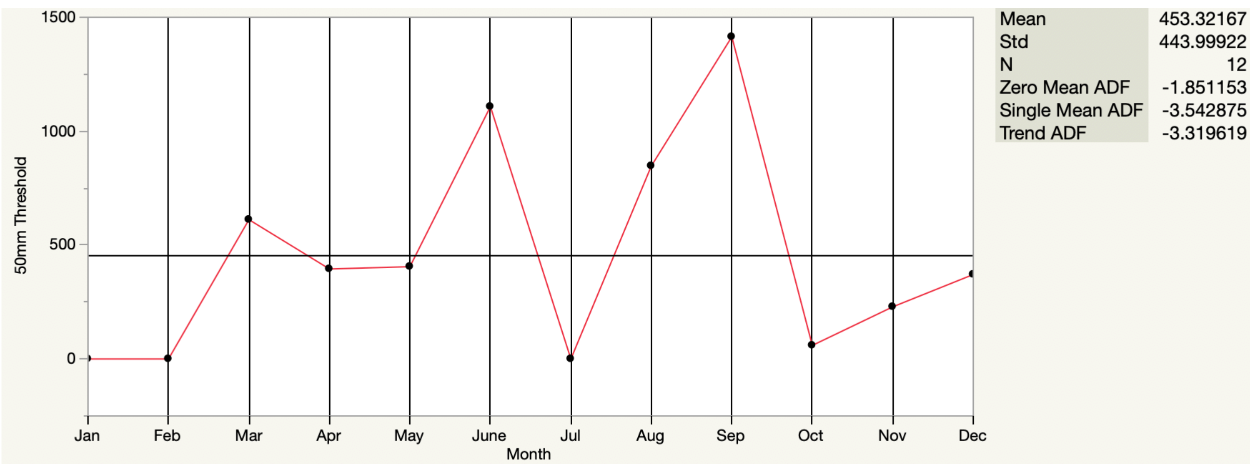

Figure 4.4.17: Time series plot showing the average number of dry days prior to fire activity for the 50mm threshold value on a monthly basis for the Eastern Tennessee climate division from 1985-2016 with a line showing the mean consecutive dry days per month

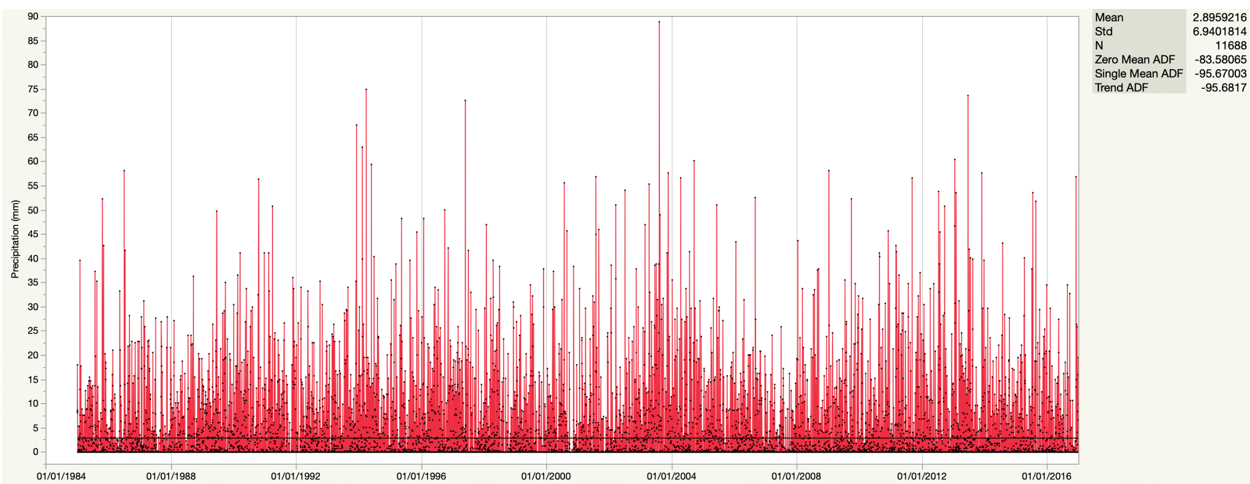

Figure 4.4.18: Time series plot showing the daily total precipitation gathered from the National Weather Service station in Morristown, TN for the Eastern Tennessee climate division from 1/1/1985-12/31/2016

4.4.3 Poisson Regression Analysis

Similar to the statistical analysis used on Southern Appalachia as a whole, Poisson regression modeling analysis was conducted on the Eastern Tennessee climate division. Tables 4.4.5-4.4.9 show the results of the model and can be used to identify whether a relationship exists between consecutive dry days since each precipitation threshold was reached and the area burned. Results show that a strong statistical relationship exists between the two variables at all 5 major precipitation thresholds. The conclusion can be made based off of the p-values and standard error for each Poisson regression model. Figures 4.4.19-4.4.23 plot the results and identify the log-link relationship existing between both variables. Table 4.4.10 also shows that when the same Poisson regression model is run using all 5 major precipitation thresholds, the results are very similar. Extremely low p-values and standard present the conclusion that a statistically significant relationship exists between all threshold values and the number of acres burned per fire. AICc, Bic, and negative log likelihood show that the 10mm threshold has the best fit followed by the 5 and 1mm threshold values. Of the Poisson regression models, the 25mm threshold had the worst fit.

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	85434.315
Number of Parameters	2
BIC	170878.29
AICc	170872.73
Generalized RSquare	0.9983297

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.4990287	0.0031158	5792408.1	<.0001*	7.4929218	7.5051357
< 1mm Threshold	-0.009875	0.0003554	771.99268	<.0001*	-0.010572	-0.009179

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 1mm Threshold	1	1	771.99268	<.0001*

Table 4.4.5: Poisson regression model of acres burned vs consecutive dry days since the 1mm threshold value was reached for the Eastern Tennessee climate division

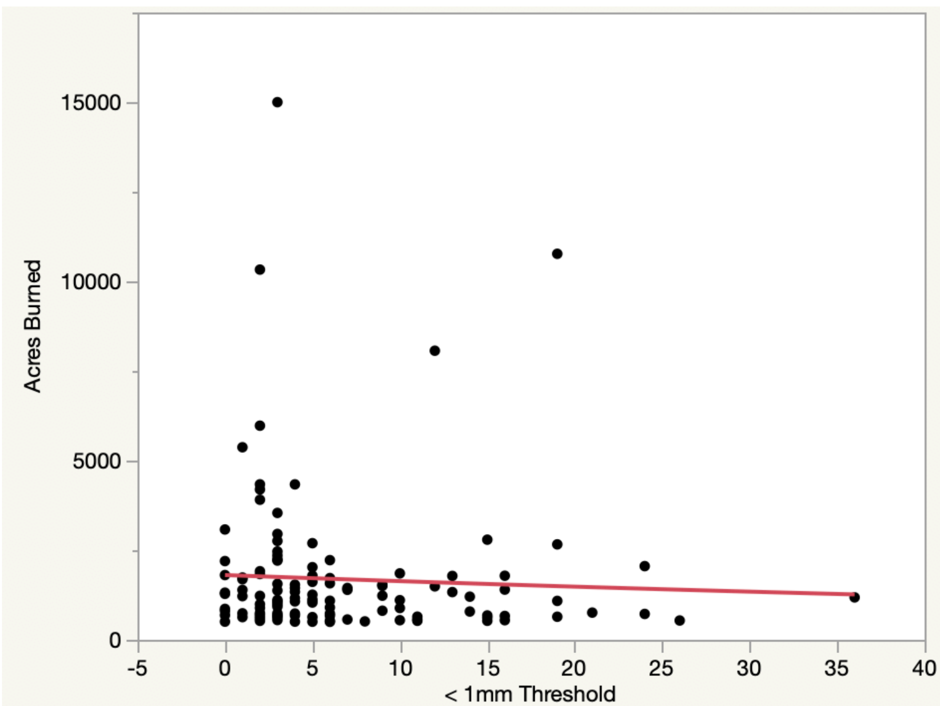

Figure 4.4.19: Poisson regression plot of acres burned vs consecutive dry days since the 1mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	83955.294
Number of Parameters	2
BIC	167920.24
AICc	167914.69
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.3002113	0.0031447	5389210.9	<.0001*	7.2940479	7.3063747
< 5mm Threshold	0.0122833	0.0001942	3999.0082	<.0001*	0.0119026	0.012664

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 5mm Threshold	1	1	3999.0082	<.0001*

Table 4.4.6: Poisson regression model of acres burned vs consecutive dry days since the 5mm threshold value was reached for the Eastern Tennessee climate division

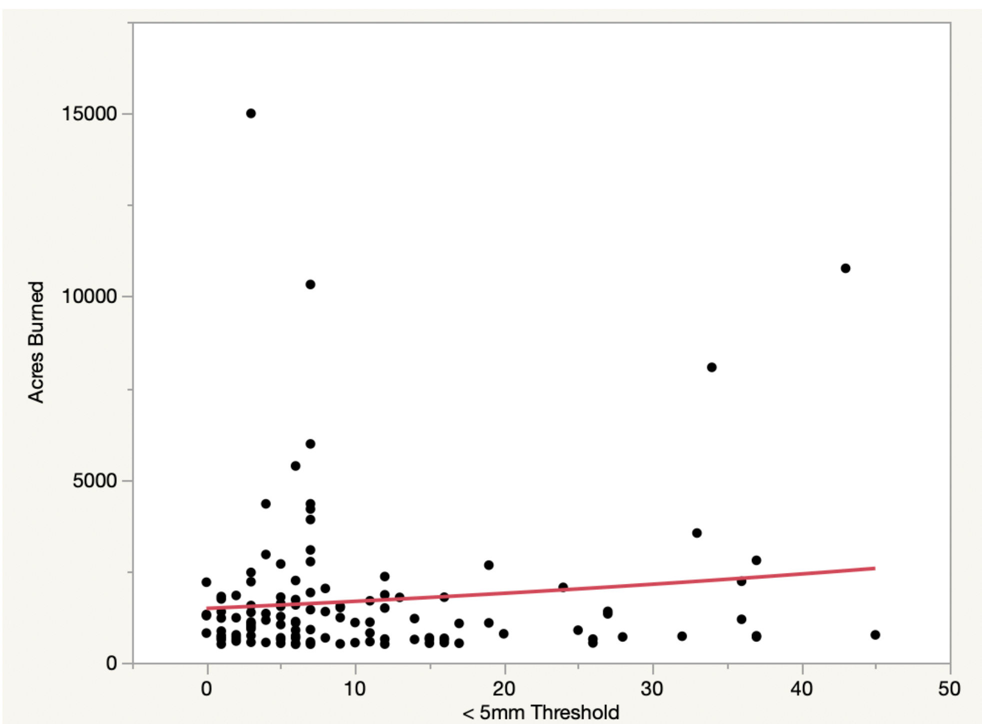

Figure 4.4.20: Poisson regression plot of acres burned vs consecutive dry days since the 5mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	83232.744
Number of Parameters	2
BIC	166475.14
AICc	166469.59
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.2512131	0.0034384	4447493.8	<.0001*	7.244474	7.2579522
< 10mm Threshold	0.0110166	0.0001497	5418.8674	<.0001*	0.0107233	0.0113099

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 10mm Threshold	1	1	5418.8674	<.0001*

Table 4.4.7: Poisson regression model of acres burned vs consecutive dry days since the 10mm threshold value was reached for the Eastern Tennessee climate division

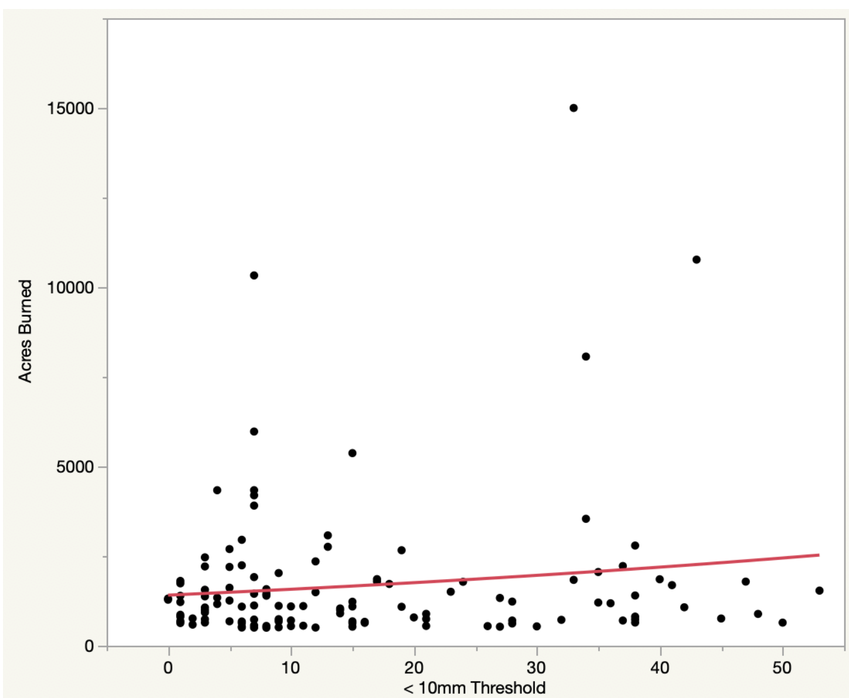

Figure 4.4.21: Poisson regression plot of acres burned vs consecutive dry days since the 10mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	85168.797
Number of Parameters	2
BIC	170347.25
AICc	170341.69
Generalized RSquare	0.9999761

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.3421014	0.0033901	4690442	<.0001*	7.3354569	7.3487459
< 25mm Threshold	0.0016588	0.0000449	1364.7747	<.0001*	0.0015708	0.0017468

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 25mm Threshold	1	1	1364.7747	<.0001*

Table 4.4.8: Poisson regression model of acres burned vs consecutive dry days since the 25mm threshold value was reached for the Eastern Tennessee climate division

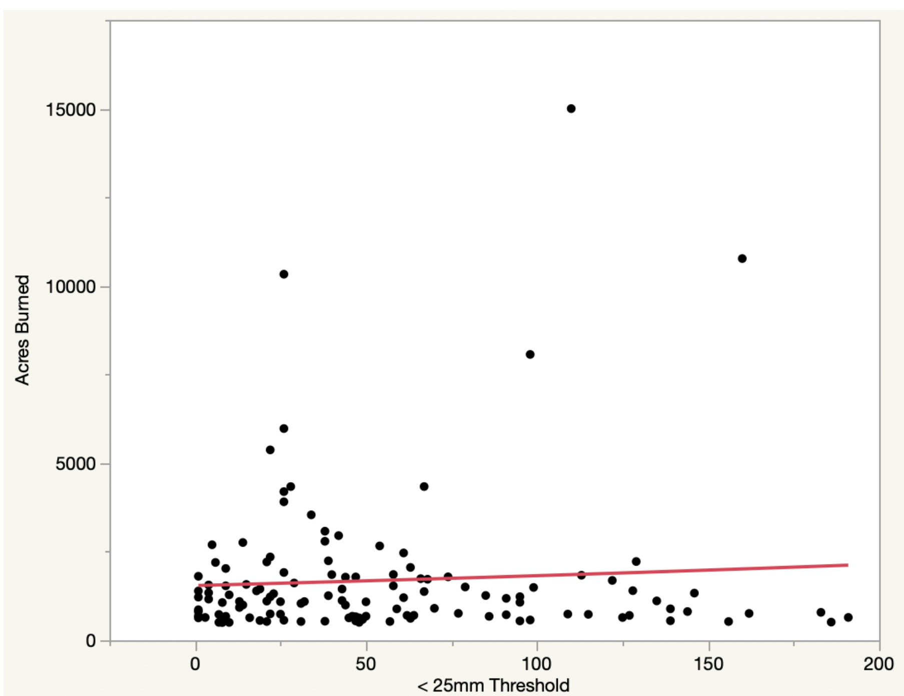

Figure 4.4.22: Poisson regression plot of acres burned vs consecutive dry days since the 25mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	84124.711
Number of Parameters	2
BIC	168259.08
AICc	168253.52
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.5621479	0.0030251	6248918.4	<.0001*	7.5562188	7.5680771
< 50mm Threshold	-0.000325	5.7539e-6	3195.7978	<.0001*	-0.000337	-0.000314

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 50mm Threshold	1	1	3195.7978	<.0001*

Table 4.4.9: Poisson regression model of acres burned vs consecutive dry days since the 50mm threshold value was reached for the Eastern Tennessee climate division

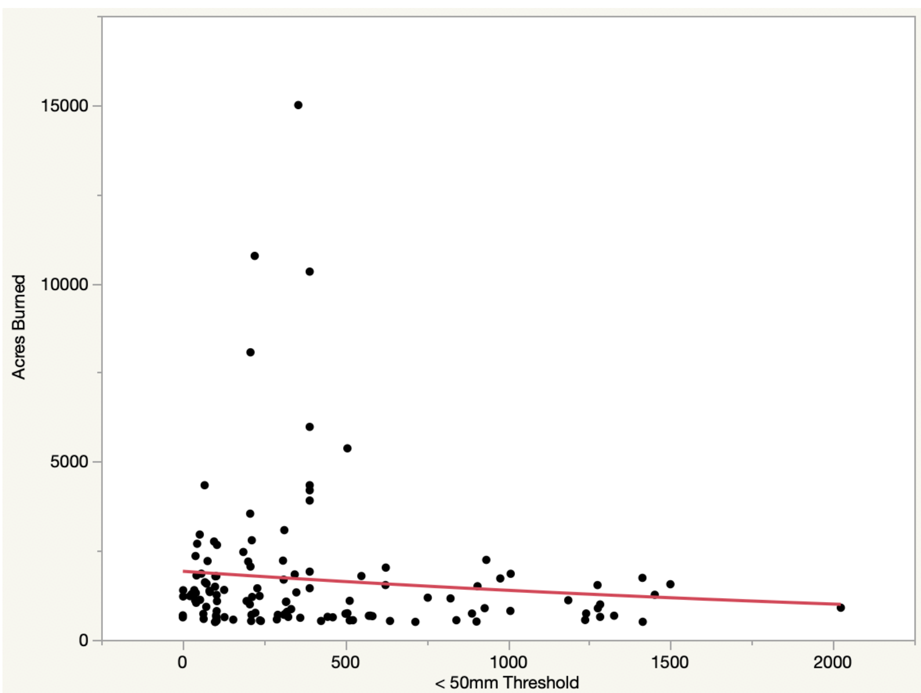

Figure 4.4.23: Poisson regression plot of acres burned vs consecutive dry days since the 50mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Poisson
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	75203.59
Number of Parameters	6
BIC	150436.15
AICc	150419.89
Generalized RSquare	1

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.4889897	0.0042172	3153585.4	<.0001*	7.4807242	7.4972552
1mm Threshold	-0.050961	0.0004768	11424.172	<.0001*	-0.051896	-0.050027
5mm Threshold	0.0150406	0.0003173	2246.5357	<.0001*	0.0144186	0.0156625
10mm Threshold	0.0158418	0.0002511	3980.8673	<.0001*	0.0153497	0.016334
25mm Threshold	0.0002133	5.7886e-5	13.578095	0.0002*	9.9846e-5	0.0003268
50mm Threshold	-0.000421	6.2076e-6	4598.1271	<.0001*	-0.000433	-0.000409

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
1mm Threshold	1	1	11424.172	<.0001*
5mm Threshold	1	1	2246.5357	<.0001*
10mm Threshold	1	1	3980.8673	<.0001*
50mm Threshold	1	1	4598.1271	<.0001*
25mm Threshold	1	1	13.578095	0.0002*

Table 4.4.10: Poisson regression model of acres burned vs consecutive dry days for all threshold values were reached for the Eastern Tennessee climate division

4.4.4 Negative Binomial Regression Analysis

Negative binomial regression modeling was used to analyze the Eastern Tennessee climate division in the same way that Poisson regression was used. Tables 4.4.11-4.4.15 show how the models were used to identify relationships between all 5 individual consecutive dry day threshold values and the area burned for all fires within the Eastern Tennessee climate division. Results show statistically significant relationships based on the p-value and standard error values within the 10 and 50mm threshold negative binomial regression models. The 10mm and 50mm threshold values also had the best fit according to the AICc, BIC, and negative log likelihood, with 10mm having the best fit. A loose relationship is seen in the 5mm threshold model. No statistically significant relationship is observed at the 1 or 25mm model when comparing each threshold individually against the acres burned per fire. Figures 4.4.24-4.4.28 show plots for all of the negative binomial regression models, including those without statistically significant relationships. For the ones that are significant, a log-link relationship can be seen within the plot’s data points. Table 4.4.16 shows the model run with all 5 consecutive dry day precipitation thresholds run against the number of acres burned for each fire. The results of the model show a statistically significant relationship between all major threshold values and the area burned except for the 25mm threshold value, which has no statistical significance. Based on the results of the negative binomial regression modeling, it can be determined that at certain thresholds there is significance between the two variables. However, it is always important to consider the sample size when running forms of analysis such as the negative binomial.

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	1045.2314
Number of Parameters	3
BIC	2104.9478
AICc	2096.6612
Generalized RSquare	0.0061346

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.4947986	0.097376	5924.008	<.0001*	7.303945	7.6856521
< 1mm Threshold	-0.009222	0.0103411	0.795199	0.3725	-0.02949	0.0110466

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.5896967	0.019015	961.75709	<.0001*	0.552428	0.6269654

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 1mm Threshold	1	1	0.795199	0.3725

Table 4.4.11: Negative binomial regression model of acres burned vs consecutive dry days since the 1mm threshold value was reached for the Eastern Tennessee climate division

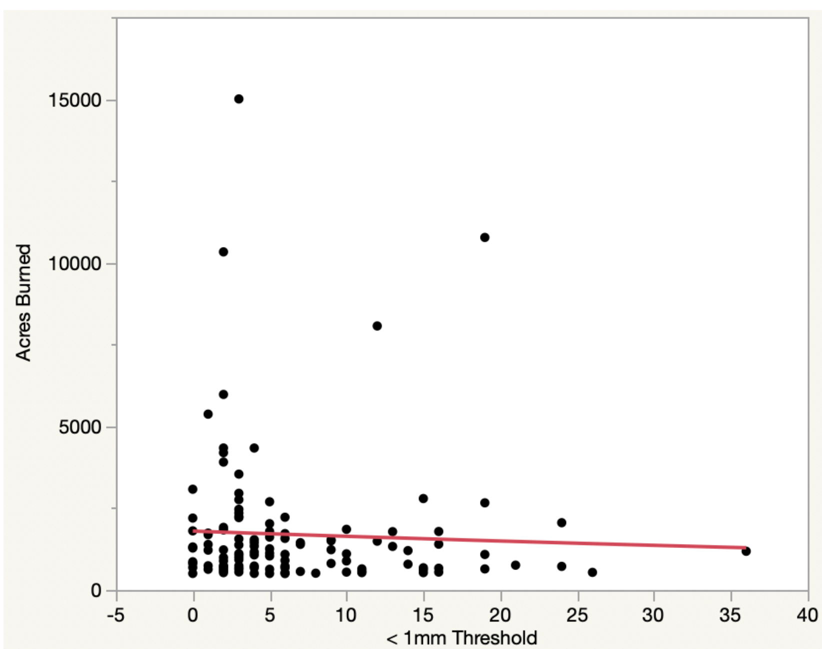

Figure 4.4.24: Negative binomial regression plot of acres burned vs consecutive dry days since the 1mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	1044.1308
Number of Parameters	3
BIC	2102.7465
AICc	2094.4599
Generalized RSquare	0.0234834

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.3218693	0.0931511	6178.2883	<.0001*	7.1392965	7.5044421
< 5mm Threshold	0.010311	0.006156	2.8054427	0.0939	-0.001755	0.0223766

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.5809808	0.0186305	972.47113	<.0001*	0.5444658	0.6174958

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 5mm Threshold	1	1	2.8054427	0.0939

Table 4.4.12: Negative binomial regression model of acres burned vs consecutive dry days since the 5mm threshold value was reached for the Eastern Tennessee climate division

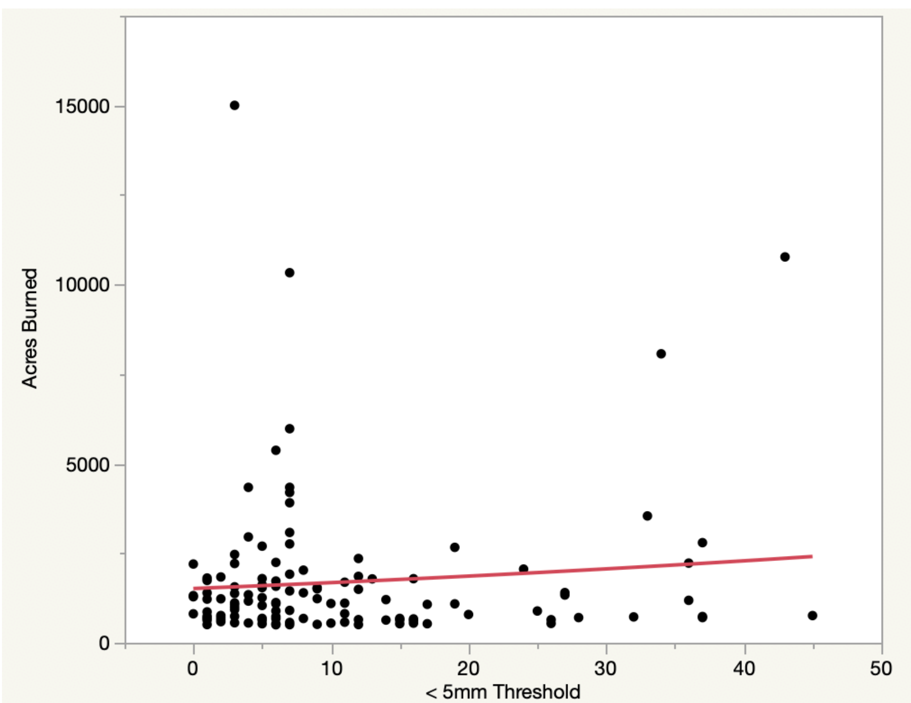

Figure 4.4.25: Negative binomial regression plot of acres burned vs consecutive dry days since the 5mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	1043.0683
Number of Parameters	3
BIC	2100.6216
AICc	2092.335
Generalized RSquare	0.0399429

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.2495311	0.1032507	4929.8498	<.0001*	7.0471634	7.4518988
< 10mm Threshold	0.0111159	0.0049878	4.9668187	0.0258*	0.0013401	0.0208918

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.5726762	0.0182659	982.9629	<.0001*	0.5368758	0.6084767

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 10mm Threshold	1	1	4.9668187	0.0258*

Table 4.4.13: Negative binomial regression model of acres burned vs consecutive dry days since the 10mm threshold value was reached for the Eastern Tennessee climate division

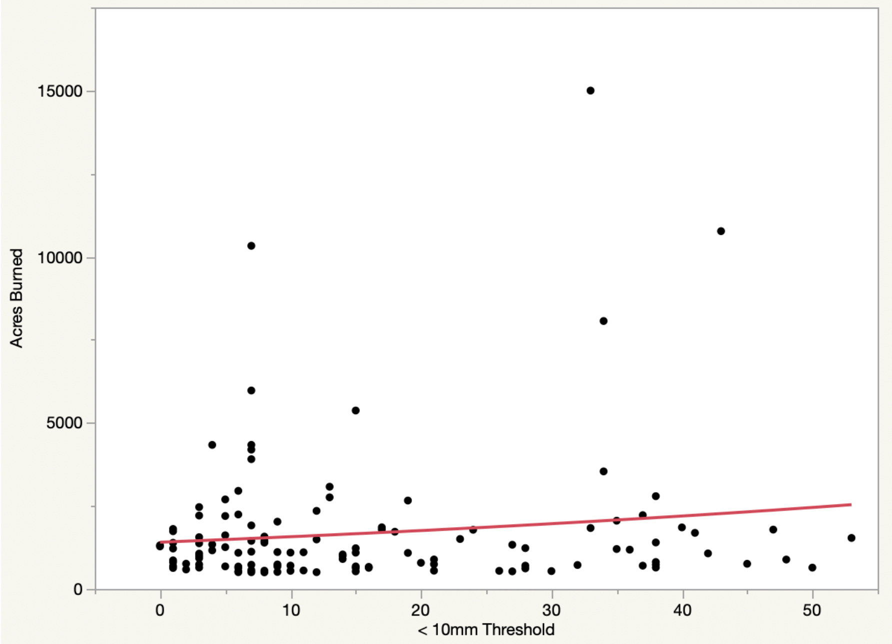

Figure 4.4.26: Negative binomial regression model of acres burned vs consecutive dry days since the 10mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	1044.9149
Number of Parameters	3
BIC	2104.3148
AICc	2096.0282
Generalized RSquare	0.0111547

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.3344631	0.1077165	4636.3078	<.0001*	7.1233427	7.5455836
< 25mm Threshold	0.001795	0.0015321	1.3726285	0.2414	-0.001208	0.0047979

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.5871799	0.0189037	964.82062	<.0001*	0.5501293	0.6242306

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 25mm Threshold	1	1	1.3726285	0.2414

Table 4.4.14: Negative binomial regression model of acres burned vs consecutive dry days since the 25mm threshold value was reached for the Eastern Tennessee climate division

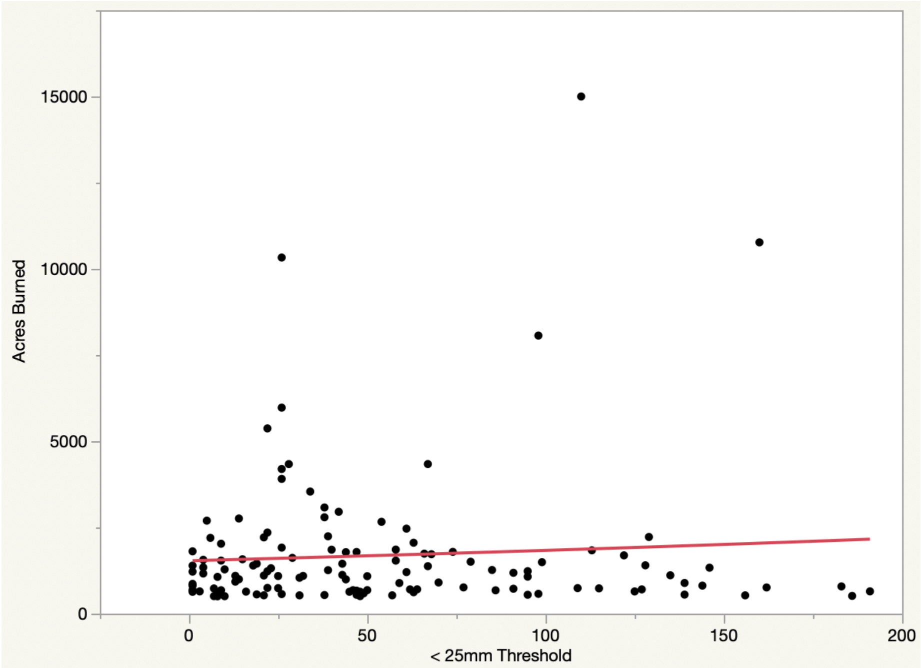

Figure 4.4.27: Negative binomial regression plot of acres burned vs consecutive dry days since the 25mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	1043.4561
Number of Parameters	3
BIC	2101.3972
AICc	2093.1106
Generalized RSquare	0.0339679

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.582816	0.0992641	5835.4817	<.0001*	7.3882619	7.77737
< 50mm Threshold	-0.000378	0.0001736	4.7495528	0.0293*	-0.000719	-0.000038

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.575701	0.0183984	979.11029	<.0001*	0.5396407	0.6117613

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
< 50mm Threshold	1	1	4.7495528	0.0293*

Table 4.4.15: Negative binomial regression model of acres burned vs consecutive dry days since the 50mm threshold value was reached for the Eastern Tennessee climate division

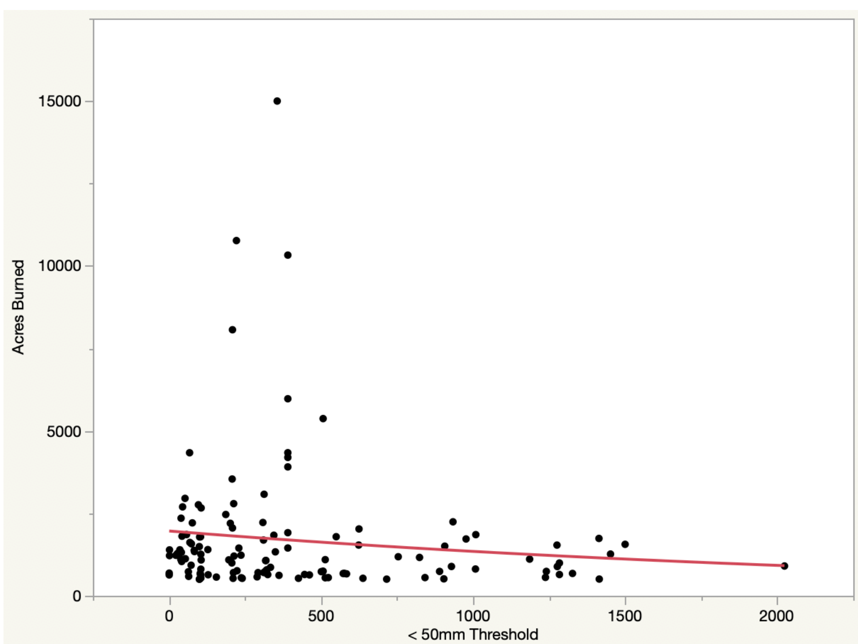

Figure 4.4.28: Negative binomial regression plot of acres burned vs consecutive dry days since the 50mm threshold value was reached for the Eastern Tennessee climate division

Model Summary

Response	Acres Burned
Distribution	Negative Binomial
Estimation Method	Maximum Likelihood
Validation Method	None
Mean Model Link	Log
Dispersion Model Link	Identity

Measure	
Number of rows	125
Sum of Frequencies	125
-LogLikelihood	1032.997
Number of Parameters	7
BIC	2099.7923
AICc	2080.9514
Generalized RSquare	0.1828259

Parameter Estimates for Original Predictors

Term	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Intercept	7.4700853	0.1237019	3646.6877	<.0001*	7.2276341	7.7125365
1mm Threshold	-0.063058	0.0150032	17.665116	<.0001*	-0.092464	-0.033653
5mm Threshold	0.024274	0.0111666	4.7254586	0.0297*	0.0023879	0.04616
10mm Threshold	0.0171411	0.0076745	4.9885813	0.0255*	0.0020993	0.0321828
25mm Threshold	-0.000683	0.0019349	0.1245819	0.7241	-0.004475	0.0031094
50mm Threshold	-0.00036	0.0001606	5.03007	0.0249*	-0.000675	-4.542e-5

Negative Binomial Distribution Parameters	Estimate	Std Error	Wald ChiSquare	Prob > ChiSquare	Lower 95%	Upper 95%
Dispersion	0.4989025	0.015109	1090.3284	<.0001*	0.4692893	0.5285157

Effect Tests

Source	Nparm	DF	Wald ChiSquare	Prob > ChiSquare
1mm Threshold	1	1	17.665116	<.0001*
50mm Threshold	1	1	5.03007	0.0249*
10mm Threshold	1	1	4.9885813	0.0255*
5mm Threshold	1	1	4.7254586	0.0297*
25mm Threshold	1	1	0.1245819	0.7241

Table 4.4.16: Negative binomial regression model of acres burned vs consecutive dry days for all threshold values were reached for the Eastern Tennessee climate division

CHAPTER 5

CONCLUSIONS

The main goal of this research was to use statistical analysis to identify the relationship between consecutive dry days and fire frequency and magnitude within the Southeastern United States so that policy makers, first responders, residents, and scientists will be better equipped to prepare for future events similar to those in the fall of 2016. The relationship between consecutive dry days and both fire frequency and magnitude for large-scale fires in Southern Appalachia was determined using time-scale, Poisson regression, and negative binomial regression modeling. By identifying statistically significant relationships between consecutive dry days and area burned at specific threshold values, precipitation can be used as a standalone variable to identify the potential for large-scale fire activity. By having a single variable indicator, such as the 5 or 10mm threshold value for consecutive dry days, scientists may be able to identify the potential for catastrophic fires earlier than in more complex models. The 10mm model, based on analysis would be the best indication for this potential as it fit all Poisson and negative binomial regression models for Southern Appalachia as a whole and the individual climate division case study.

The aim of the research was to quantify the relationship in order to better predict future large-scale fire events within a region of the country with a recent increase in fire activity, that is often neglected where wildfire research is concerned. By conducting this analysis, warning signs of potential fire activity will hopefully become more identifiable, allowing for the communities most affected by such disasters to be better equipped to prevent loss of life, property, well-being. If this research can improve the quality of life for the people of Southern Appalachia, then it has accomplished its core goals set-out. With the findings of the relationship between consecutive dry day impact on large-scale frequency and magnitude and further research into other climatic variables, the scientific community edges closer to painting a fire indication profile of Southern Appalachia allowing for greater understanding of past events and better preparation for future events.

Fire Analysis 5.1

Fire activity was analyzed on the basis of spatial distribution, temporal variability at an annual, monthly, and daily scale, and based on frequency and magnitude. The spatial distribution shows that areas of higher elevation and greater topographic variability were more susceptible to fire than lower elevations or consistent topography. The Eastern Tennessee and Southern Mountains (NC) and Cumberland Plateau (TN) were the climate divisions with both the greatest acres burned for the entire period of study and the greatest number of fires. A statistically significant exponential relationship between fire frequency and magnitude was discovered throughout the dataset both spatial and temporally. Annual analysis showed that years with the greatest number of fires were synonymous with years with the largest amount of area burned. The years that stuck out the most in this respect were 1987, 2000, 2001, and 2016. Much of this was due to one or two individual fires from each year that burned a significantly larger area than the rest of the fires for the given year. It could be determined from this finding that years with a greater number of fires increases the likelihood of a catastrophic fire as opposed to years with less large-scale fire activity. Monthly analysis indicates two distinct fire seasons in which the vast majority of fire activity occurs in Southern Appalachia. There is a spring season which takes place in March and April and a fall fire season which mainly takes place in the month of November. This is important to consider when observing the behavior of precipitation and organic matter preceding each season. The case study for Eastern Tennessee concerned the finding for the area of study as a whole, showing that it is a microcosm of the behaviors seen in all of Southern Appalachia, with the greatest sample size for both fire frequency and magnitude for the region.

Precipitation Analysis 5.2

Precipitation was initially observed on the basis of mean annual dry days (MADD) with a dry day considered to be days with total precipitation under 1mm, but early findings altered the definition of what was considered to be a dry day. To obtain a greater understanding of how precipitation impacts fire frequency and magnitude, dry days were observed based on how many consecutive dry days had occurred since a specific precipitation threshold was reached prior to a fire event. The thresholds used to locate the consecutive dry day values were 1, 5, 10, 25, and 50mm of precipitation per day. Spatially, there is a slight relationship between consecutive dry days and fire activity. Climate divisions with a greater number of fires and acres burned had a slightly higher amount of consecutive dry days leading up to fire events than regions with less fire frequency and magnitude. This was especially true at lower threshold values such as 1, 5, and 10mm. Annual analysis showed that at lower threshold values such as 1, 5, and 10mm there was a greater number of consecutive dry days preluding fire events in years with a greater number of fires and more area burned. Monthly analysis confirms the findings of the annual time series observations. Years with more fire activity in the fall were shown to have a greater number of consecutive dry days leading up to fires than years with a more pronounced spring fire season. This is especially apparent at lower threshold values such as 1, 5, and 10mm. Based on the findings, seasonality of the fire events plays a major role in the expectations for how many consecutive dry days will lead up to a major fire event. The same results experienced in the entire area of study were experienced in Eastern Tennessee for the annual time series analysis. However, monthly analysis showed a less apparent relationship between consecutive dry days and fire activity in the spring season vs the fall. Part of this may be due to the fact that the sample size is smaller, but slight variation can be observed that matches with that of all of Southern Appalachia.

Poisson Regression Analysis 5.3

Poisson regression modeling was used to identify relationships between consecutive dry days since reaching the threshold value, for all 5 major precipitation thresholds, and the area burned per fire. Using the p-value and standard error as major indicators of whether a relationship exists, it was determined that there is a strong statistical relationship between all major precipitation thresholds individually and the area burned per fire. The models run in JMP software also provided scatterplots showing the distribution of the data. From the scatterplots, a log-link relationship is indicated for the entire area of study throughout the period of study with a few outlying fires. The same analysis was run using all threshold values in the same Poisson regression model instead of each one individually. The results were the same with all p-values and standard error values indicating a strong relationship between the variables. The same tests were run for each threshold individually and all at the same time for the Eastern Tennessee case study. The results were very similar to those of the whole Southern Appalachia area of study. All individual dry day threshold values showed strong relationships with the area burned for their respective fires. Results were the same when running the Poisson regression model with all threshold values. P-values and standard error indicated strong relationships between the variables. AICc, BIc, and the negative log likelihood also indicated the 5mm threshold value provided the best fit for the data, with 10 and 1mm values providing good fits as well. Based on results, it can be determined that using Poisson regression modelling, analysis concludes the existence of a strong log-link relationship between the number of consecutive dry days, at all thresholds, and the amount of area burned per fire. Based on the model results, the 5mm and 10mm threshold values act as the best indication for predicting the potential for large-scale fire activity, using Poisson regression analysis.

Negative Binomial Regression Analysis 5.4

Negative binomial regression modelling was used similarly to Poisson regression modelling to determine if relationships between consecutive dry days prior to precipitation threshold values and area burned in acres exists. Running the model at each individual threshold suggests that there is a strong log-link relationship between the two variables, as each contained very small p-values and standard error. However, running all threshold values in the model at the same time only provided strong statistically significant relationships and model fits at the 5mm and 10mm threshold. The 1, 25, and 50mm thresholds did not have a strong relationship with the amount of area burned when the negative binomial model was run containing all threshold values simultaneously. The same models were run for the Eastern Tennessee case study. The negative binomial model comparing the number of consecutive dry days for each individual threshold value against the number of acres burned provided results different than the ones from the entire area of study. The 1mm and 25mm threshold values showed no statistically significant relationship with the area burned per fire. The 5mm threshold value showed a loose relationship with a p-value of roughly .09, which may be considered significant depending on the significance limit (.05 vs .1). The consecutive dry days since the 10mm and 50mm thresholds were reached showed a statistically significant relationship with the amount of area burned during the entire period of study. The negative binomial regression model was then run containing all 5 major thresholds vs the number of acres burned vs fire for Eastern Tennessee, similar to the model run for all of Southern Appalachia. Results showed strong statistically significant relationships between all major thresholds except the 25mm threshold. The relationships are displayed in the form of a log-link relationship between the two variables. Based on the model results, the 5mm and 10mm threshold values act as the best indication for predicting the potential for large-scale fire activity, using negative binomial regression analysis.

Future Analysis 5.5

The results of the research conducted analyzing the relationship between consecutive dry days and both fire frequency and magnitude in Southern Appalachia provides detailed insight into the behavior of fire and precipitation in the Southeastern United States as a whole. Consecutive dry days; and precipitation analysis are just a fraction of the numerous climatological processes affecting fire activity in the Southern and Eastern United States. Several other atmospheric characteristics within the region are capable of providing greater understanding of what climatological factors impact fire activity in this area of the country the most. Elements such as relative humidity, soil moisture, organic fuel, wind, insolation angle, anthropogenic forcing, and evapotranspiration rates, to name a few also contribute to the multiple processes impact fire ignition, frequency, and magnitude in Southern Appalachia. Based on the results collected from this research, it is believed that the number of consecutive dry days prior to fire activity, since reaching precipitation threshold values at multiple levels, have a strong relationship with the chance for fire ignition, fire frequency, and more specifically, fire magnitude. The hope is that this research will be seen as a major contribution to greater understanding how the climatic characteristics, specifically precipitation, helps provide a greater understanding and critical indication of fire ignition, frequency, and magnitude in Southern Appalachia and the Southeastern United States as a whole.

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