A Spatio-temporal Analysis of Wildland Fires in North Carolina's National Forests

By

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Contents

Abstract

Previous research suggests that humans are responsible for a significant majority of wildland fires, and that those fires are not randomly distributed on the landscape. Nearly 98% of all fire starts on North Carolina private lands are human caused and almost 90% of fire starts across the country are human related. A data set was compiled of daily fire and weather observations from 1970 to 2008, as well as four decades of county level census information. The number of fires per year for North Carolina's Nantahala, Pisgah and Croatan National Forests range from 42 to 425 (mean: 106; standard deviation: 74). These fires burn an average of 2,800 acres (standard deviation: 1,700). These data were used in order to assess the hypothesis that fires are most likely to occur during drier months and near forest roads.

Several methodologies were used in order to understand the occurrence of fires and the results of this research are to inform fire managers about places in space and time that are particularly prone to fire. It was found that wildland fires in North Carolina have a bi-modal distribution during the year, with a local maximum in November and a global maximum in April. A time-series analysis of the data indicated that fires are correlated in time and confirmed this seasonality. Regression analysis showed that specific climate variables were significant in explaining the number of fires. The climate variables that were found to be most significant were temperature, which had a positive correlation with the number of fires and relative humidity, which had a negative correlation. Precipitation and wind speed were found significant in some, but not all cases. In addition, certain counties had higher incidence of wildland fire. In contrast, Buncombe county had the fewest and Graham the most wildland fires; Buncombe county has the largest population and most development, while Graham had the smallest population and highest amount acreage under National Forest control. A spatial analysis found that approximately half of human started wildland fires were within 100m of a road or trail, and nearly all fires were within 1000m.

Keywords: Wildland fire

Introduction

An estimated 176,100 intentionally set outdoor fires occur annually in the United States and result in approximately 20 deaths, 250 injuries, and $23 million in damages to property (USFA 2009). And over the past 40 years across the United States, the number of wildland fires have ranged from 18,229 to 249,370 (mean: 108,176; standard deviation: 58,232) and the number of acres impacted from 1,148,409 to 9,873,745 (mean: 2,127,602; standard deviation: 2,518,176) (NIFC, 2010). In addition, billions of dollars are spent to suppress fires. These burdens fall on natural resource agencies and the costs are ultimately borne by citizens. Outdoor fires can include a variety of fires; wildland fires, crop fires and rubbish fires to name but a few. These can be further divided by the cause of the fire; intentionally set fires include those of a malicious or incendiary nature (arson), controlled fires, and prescribed fires.

From the historical fire records, the strict definition of arson--starting a fire with malicious intent--accounts for half of fire starts in the North Carolina's National Forests. Nearly 98% of all fire starts on North Carolina private lands are human caused and almost 90% of fire starts across the country are human related. The number of fires per year for North Carolina's Nantahala, Pisgah and Croatan National Forests range from 42 to 425 (mean: 106; standard deviation: 74). These fires burn an average of 2,800 acres (standard deviation: 1,700).

In an economic approach to understanding arson, decisions are weighed by cost and perceived benefits. Such costs would be those related to the opportunity costs of the arsonist--wage, employment status--and are things that could be captured by socioeconomic variables of the surrounding community. Mercer and Prestemon (2002) found correlations between population, poverty and number of police on the amount of area burned and ignitions. In addition, a person must have access to the area to start a fire. Fires are likely in areas that are publicly owned, near municipalities and within 500m of roads (Yang et al. 2007). Consequently, it is hypothesized that the greatest incidences of fires occur in poor counties with a large network of forest roads.

The basic fire triangle is made up of three parts: fuel, weather and topography, and each has a significant effect on the success of fire on a landscape. Consequently, in this analysis and for explanatory purposes, a statistical model will be built to identify critical places in space and time that are fire prone. In doing so, the goal is to inform fire managers so that they are able to anticipate resource needs. The second stage of the analysis will be to explain why some communities and months of the year are at a greater risk than others.

Methods

Data used in the construction of this model were collected from a number of federal, state and academic databases. A list of fires in that occurred in North Carolina's National Forests was compiled through the program FireFamilyPlus4 developed by the USFS Missoula Fire Sciences Laboratory. These data back to 1970, and this date was used as a bound for the analysis. Weather observations were compiled through the NC CRONOS database made available through the State Climate Office. Daily observations were taken from three different locations within the state. The only continuous observations dating back to 1970 were available through the recorded measurements taken at airports, so the closest locations to each National Forest were Boone Municipal Airport for the Pisgah National Forest, Asheville Regional Airport for the Nantahala National Forest and Craven County Airport for the Croatan National Forest. Having only three sources of weather information is not ideal; it is enough to provide a difference between the general weather patterns in the different parts of the state. Scale does remain an issue however as.for example, topography can influence climate at the smallest of scales. A spot-weather forecast at the location of each fire would provide the best information for determining the necessary conditions for fire. However, for dealing with wildland fires at this large of scale, keeping climate data at the larger scale is still suitable for this analysis. Because these data are averaged over a monthly time frame, it can be expected that small differences as a result of topography would be averaged out as well. County socio-economic variables were compiled through the National Historic Geographic Information System operated through the University of Minnesota. As only census data were available, the frequency of information was limited to ten years. In addition, with every different census, different information was available. For example, the years of education by population were grouped into four-year increments, no education for people with less than 4 years of education, elementary for people with 4 to 8 years of education, high school for those people with between 8 and 12 years education, college for those with more than 12 years of education.

Exploratory data analysis was performed to better understand the frequency of fires and to determine how large of correlation there might be between fire events and between seasons. All data were processed in the statistical package R and Excel. Figures 1 and 2 are dedicated to identifying basic trends. Figure 1 shows a bi-modal distribution to the number of fires, indicating two fire seasons, one in the late fall and another in the early spring. Figure 2 shows the average number of fires by year by county. Both figures include standard deviation for error bars. There is one apparent outlier—McDowell County—and is a result of three years of above average fire activity. In Figure 3, time series plots were constructed at day, month and year frequencies. The frequencies of the peaks at day and month intervals indicate seasonality to the data. Consequently, in order to further explore the strength of that seasonality, a method to decompose seasonal trends through loess curves was used at the day and month intervals in Figure 4. The seasonal trend is found through using loess smoothing through the seasonal subseries, for example all the January 1st (daily) or January (monthly) values and such seasonal values are removed and the remaining values smoothed to find the trend. The remainders are the residuals from the seasonal and trend fits. Even after seasonal decomposition at the day level, the residuals were still correlated, and so additional work is needed to explain why.

For the spatial analysis, ArcGIS 10 was used. The fire data included spatial coordinates of those fires, which were combined with additional layers from the landfire.gov website, and roads data provided by the US Forest Service to form maps. Because of the spatial data did not include information on the perimeter of the fire, there were a number of steps taken to convert the locations into representations on the map. These steps were: 1) assume that the fire could be represented by a circle; 2) use the acreage of the fire and calculated the radius of that circle; 3) assume that the spatial coordinates could represent the center of the fire; 4) buffer the center points to create a circle that reflected the size and location of the fire and; 5) use the intersect and distance command to determine the proximity of arson fires to roads. The assumption that a fire can be represented by a circle is the best alternative available to represent fire size on the map. Any wind driven fire—ignoring the effects of topography—will form an ellipse with the semi-major axis determined by wind direction. (Rothermel 1972). Inclusion of topography to recreate fire boundaries using Flammap after the fire would only further complicate the analysis and not necessarily improve it, as there is no guarantee that the extent of each fire can be perfectly recreated.

Figure 1—Average Number of Fires per Year by Month

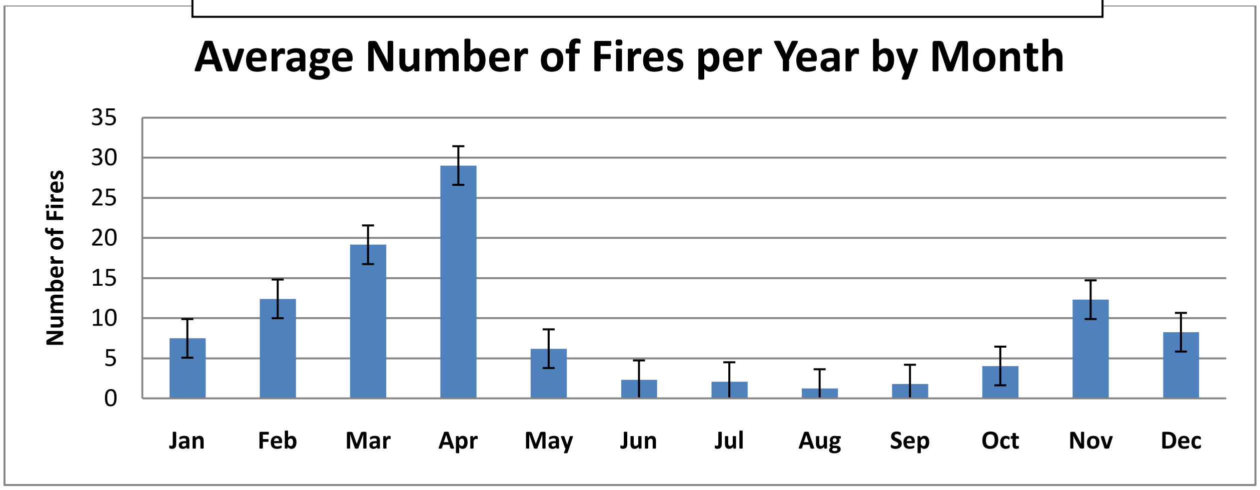


Figure 2—Average Number of Fires per Year by County

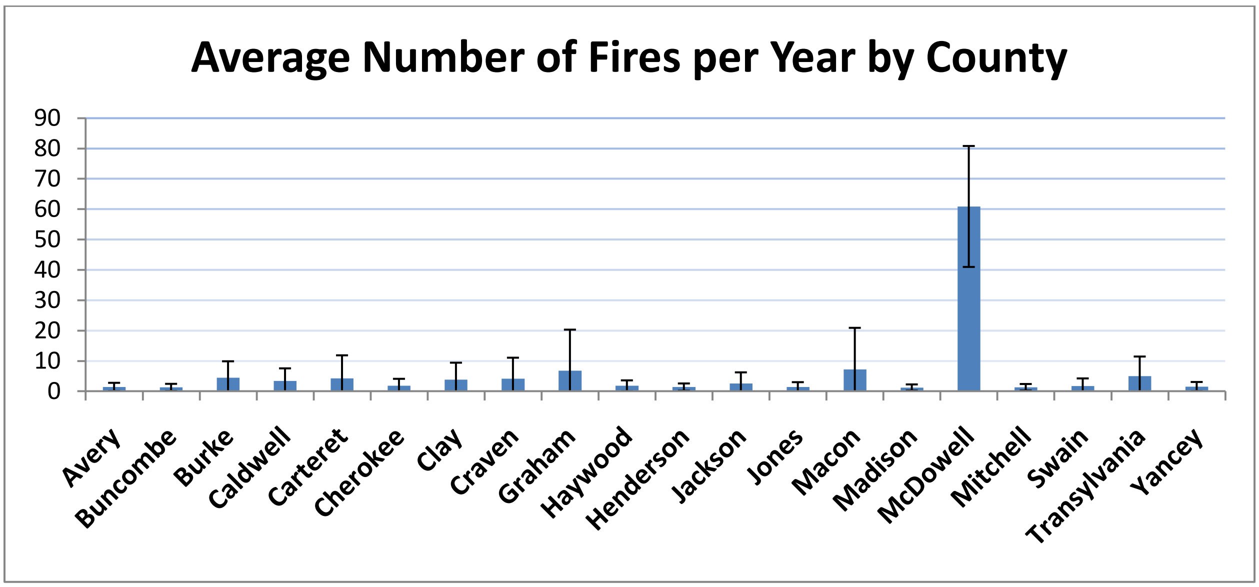


Figure 3—Time series plots of fire occurrence by different frequencies

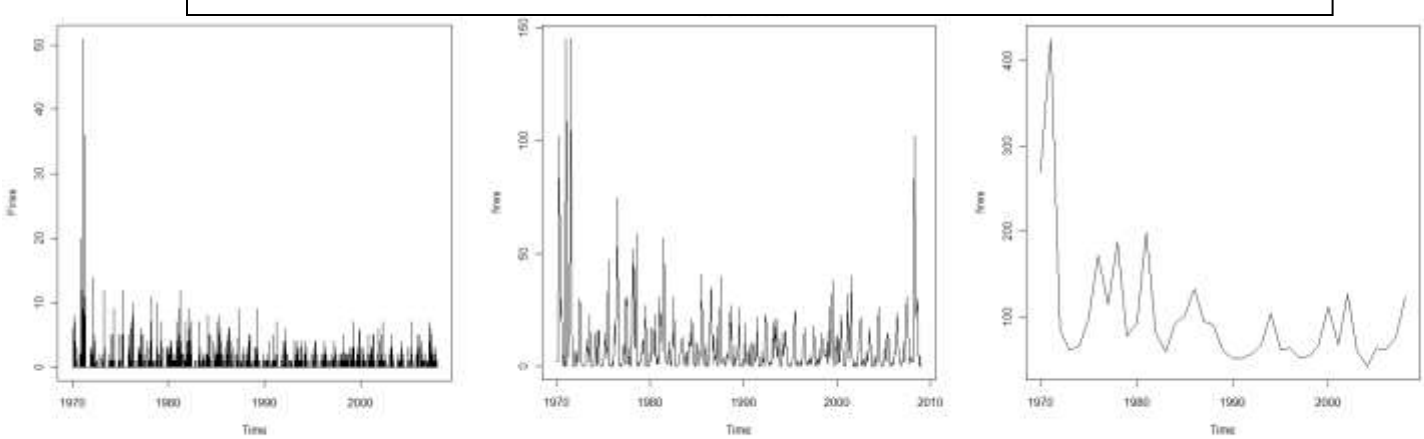


Figure 3—time series plots of fire occurrence by different frequencies, starting from the left: day, month and year

Figure 4—Seasonal Decomposition through Loess (STL) at day and month frequencies

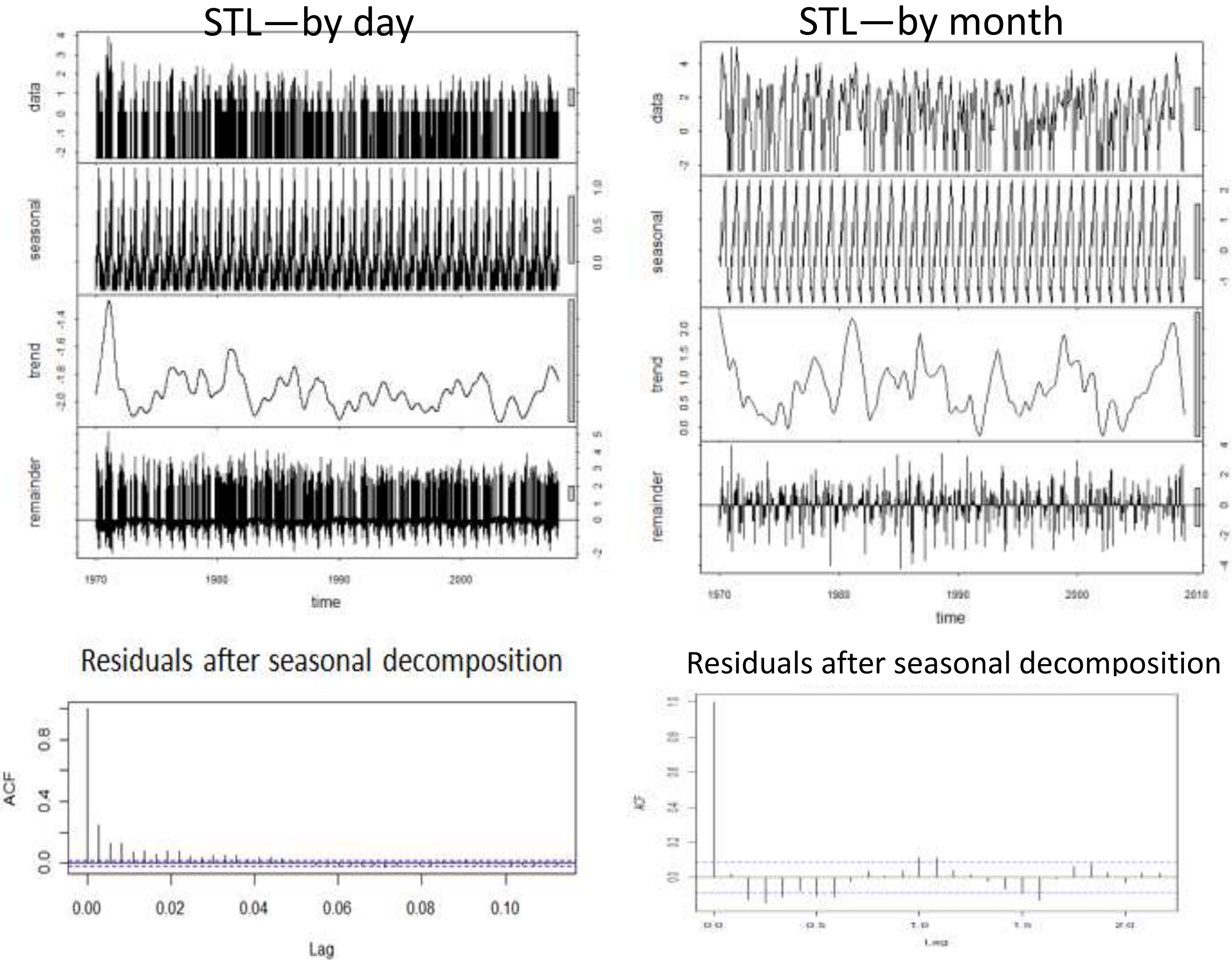


Figure 4 Note that at the day frequency, even after seasonal decomposition, the residuals are still autocorrelated

Because of seasonality, an autocorrelation function (ACF) was used to determine when and in what way the fires are related to themselves. Again, following the previous analyses an ACF was used at different frequencies. As seen from Figure 3, at the day frequency, fires were autocorrelated, in that the number of fires yesterday influences the number of fires today. The x-axis on the graph is by year, and so at the day frequency, fires were found to be autocorrelated up to a month and a half in time. At the month frequency, the fires displayed autocorrelation at each year. This is to be expected as the number of fires peak in April of each and every year, and is reflective of North Carolina's fire season that runs from mid-March to mid-April. At the year frequency, the number of fires each year was not correlated to itself. This is most likely determined by long term trends, for example climate and urbanization.

Figure 5—Autocorrelation Functions of fires at different frequencies

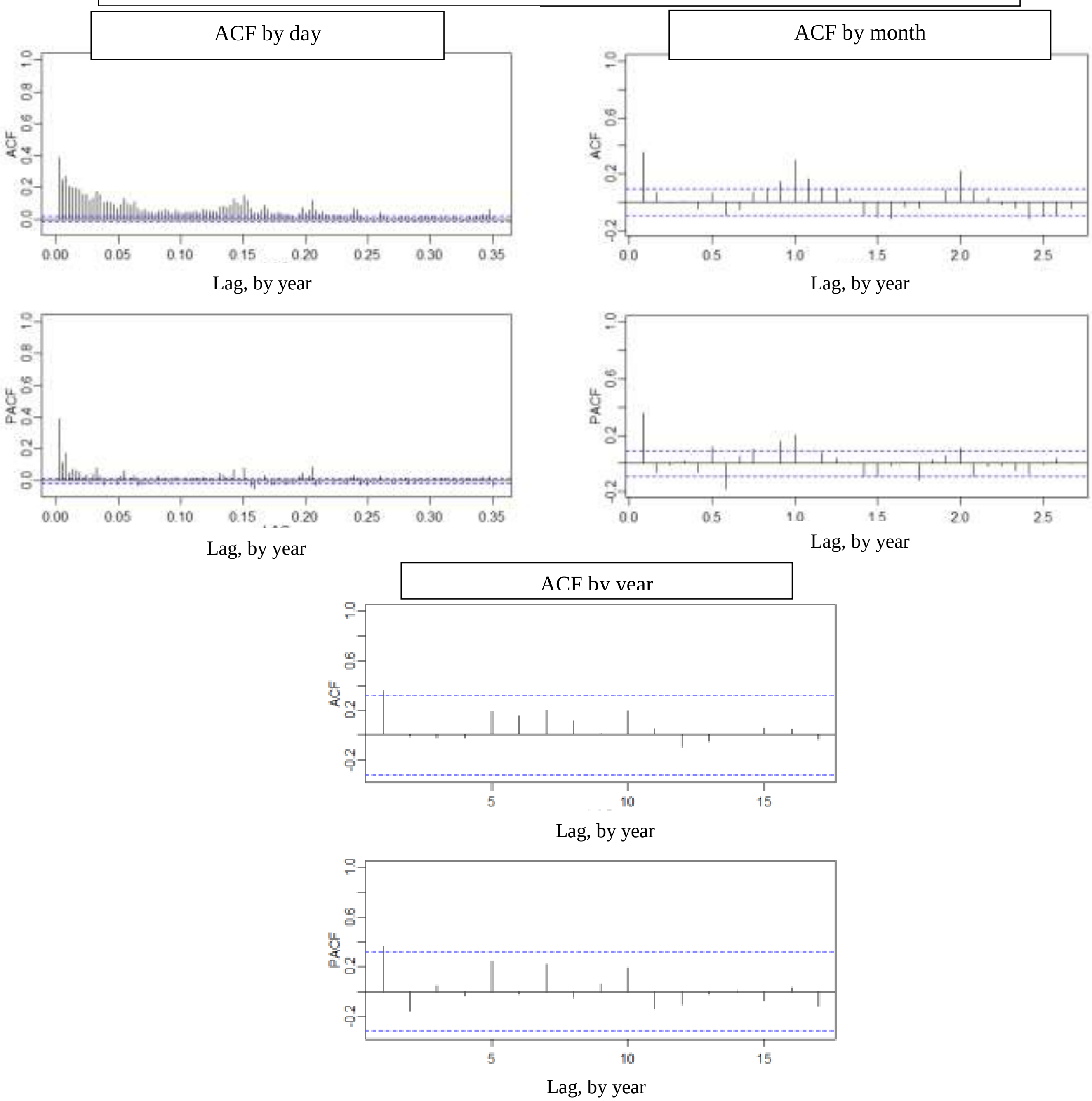


Figure 5. ACF's for differnet time intervals. Note the autocorrelation in the day and month frequencies.

Because of the predictability of the behavior of the monthly frequency, and the fact that the corresponding weather variables make sense as a monthly average that can reflect the effects of seasonality, the chosen unit of time for the analysis was by month. A Poisson regression was used because the data were discrete events. The count of the number of fires was taken to be relative to an "exposure" of the total population, and hence, the use of the offset in the model used in R. As most fires are human caused, this link allowed for a consistent metric between counties with different population sizes. In order to best determine how counties themselves vary, a multilevel model was chosen. Letting the counties vary by slope and intercept can determine trends in specific counties, which is something that policy makers can use in determining the allocation of resources to fight wildland fires. In addition, because the frequency of observations was at the monthly level, month was included so that the intercept and slope would vary for each month as well to reflect the importance of seasonal effects. The end equation chosen was:

$$Fires = Population \times e^{(\beta_{0jk} + \beta_{1jk}(TEMP) + \beta_{2jk}(WIND) + \beta_{3jk}(PRECIP) + \beta_{4jk}(RH) + \varepsilon_{jk})}$$

for $j = 1, \ldots, J$, and $k = 1, \ldots, K$, where j is for each county and k is for each month

A list of the variables used in the model along with the number of observations and respective units can be seen in Table 1. An equation was chosen that utilized all four weather variables. It is recognized that minimum relative humidity and maximum temperature are used in determining probability of ignition, a measure of likelihood that a firebrand will start a fire in a receptive fuel bed. The coefficients, their standard errors and significance at the 5% level for each individual county can be seen below in Table 2 and for each month in Table 3.

Table 1. List of variables

Name:	Description:	Variable type:	Type:	Units:	# of obs.:
Fire Count	Number of fires per county per month per year	Dependent	Discrete	fires	3989
Total Population	Census data of total population by county	Dependent	Discrete	persons	80
County	County of North Carolina with National Forest land	Independent	Discrete	county	20
Month	Calendar month	Independent	Discrete	month	468
TEMP	Average maximum monthly temperature	Independent	Continuous	degrees Fahrenheit	3067
WIND	Average monthly wind speed	Independent	Continuous	miles per hour	1416
PRECIP	Average monthly precipitation	Independent	Continuous	inches	3067
RH	Average minimum monthly relative humidity	Independent	Continuous	percent	1416

Again, such a multilevel model was chosen because it is well suited for dealing with a hierarchical data, where hierarchical data are individual items that also can be classed as a group. In this instance, the list of counties from Avery to Yancey still fall under the 'county' group and the list of months are under the 'month' group. One approach to the analysis would be to use the group level variables only; an approach known as complete pooling. This approach assumes that all counties and months would share the same regression coefficients. Because the counties are in different corners of the state, and each has their own unique characteristics--number of people, miles of roads, amount of development, etc.--the complete pooling approach is dubious.

With partial pooling, each county and month could be included in a single regression using the group level indicators, but would prevent the use of group level predictors due to collinearity (Gelman and Hill, 2007). It was because of this collinearity that the group level predictors obtained, like county level statistics, were not used. Using county as a dummy variable alongside the countywide unemployment, poverty and education rates would produce insignificant coefficients. As the goal of this paper was to anticipate resource needs in space and time, only the county level dummy variable was left in. Further research could be done to use the collected county statistics to explain the variation within counties. Problems still exist with regards to scale of each variable. Even though socio-economic statistics are likely to be different between counties, such things like species composition and weather likely vary on smaller or wider spatial scales. When data are combined under complete pooling, the model ignores the variation in the average response variable between counties. With the partial pooling method, the data are likely to be over-fit (Gelman and Hill, 2007). However, it the multi-level model with partial pooling was the best choice in maximizing the explanatory power of the regression in order to identify significant counties and months that are prone to fires.

Results

At the county level, weather variables were significant and their signs were as expected. The coefficients and standard errors can be seen in Table 2 below. High daily maximum temperatures contribute to the number of fires, while total precipitation decreases the number of fires. Increasing the relative humidity also decreases the number of fires. In the reverse, lowering the minimum relative humidity contributes to fires. The effect of wind speed on fire was mixed. Higher wind speeds are increases the rate of fire spread, and so wind speed would be expected to contribute to the number of fires. However, weather fronts link winds and precipitation and so windy days may not be correlated to dry weather. Consequently, any impacts of wind towards increasing the number of fires during dry spells could be counterbalanced by winds in weather fronts bringing precipitation. Additionally, the impact of winds might be more of a result of localized topography.

In order to start a fire, a stretch of dry weather is required. This explains why there is autocorrelation at the day frequency, as it is those stretches of days when fires are likely to start that fires will occur. Prestemon and Butry (2005) found autocorrelation at the daily level extending up to 12 days at a time. At the month level, the coefficients on the weather variables become less significant and reflect the seasonal trend in fires. From Figures 1 above, on a yearly basis, the numbers of fires peak twice, once in the late fall and then again in the early spring. This coincides with the significance of the coefficient for daily the monthly maximum average temperature. Higher temperatures during the months of February, March, April, October and November correlates to higher numbers of fires. The role of monthly precipitation changes during those months. For the late fall fire season, the coefficients for monthly precipitation remain significant, and for the month of October the value especially large. It is the early spring fire season that fires are the most numerous and severe, which is when the coefficients on precipitation where either insignificant at the 5% level or no different than zero.

This story is paralleled below in Figure 6, where monthly relative humidity values are at their lowest in April and precipitation in April and October. The spring leaf out date for North Carolina is at the beginning of March, and full bloom in later March. It is possible that rain in February and March contributes to fuel load and fires in April. In addition to the local minimums for relative humidity and precipitation for the fire seasons, changes in solar radiation likely contribute to the number of fires. Deciduous trees shed their leaves in the autumn and regain them in the spring. Pines shed cohorts of needles during that time as well. While this number is for a mixed hardwood species canopy and can vary by species composition and location, the difference between leaf senescence and peak leaf area can be more than 30% of net solar radiation reaching the forest floor (Baldocchi et al., 1984). Shading, alongside temperature and relative humidity, is another factor in calculating the probability of ignition.

Table 2. Coefficients of a GL-MLM by Month

	(Intercept)		TEMP		WIND		PRECIP		RH	
January	-10.04007	*	0.02883	*	0.03669		-5.49966	*	-0.08013	*
	0.53993		0.00644		0.04749		1.18296		0.01234	
February	-10.04007	*	0.02892	*	-0.10940	*	2.49462		-0.04961	*
	0.53993		0.00646		0.04846		1.90056		0.01300	
March	-10.04007	*	0.02937	*	-0.13215	*	-1.86154		-0.02659	*
	0.53993		0.00646		0.04874		1.78091		0.01256	
April	-10.04007	*	0.02874	*	-0.14917	*	-2.42665	*	-0.01844	
	0.53993		0.00645		0.04780		1.42629		0.01266	
May	-10.04007	*	0.02855	*	-0.01035		-0.88619		-0.07697	*
	0.53993		0.00646		0.05076		1.93454		0.01334	
June	-10.04007	*	0.02885	*	0.04497		-3.71036		-0.08912	*
	0.53993		0.00646		0.04912		1.90122		0.01322	
July	-10.04007	*	0.02894	*	0.07338		-1.62428		-0.10674	*
	0.53993		0.00646		0.04843		1.73891		0.01285	
August	-10.04007	*	0.02898	*	0.04882		-1.47386		-0.09776	*
	0.53993		0.00645		0.04772		1.24819		0.01245	
September	-10.04007	*	0.02900	*	0.02923		-1.72607		-0.08939	*
	0.53993		0.00646		0.04800		1.56897		0.01252	
October	-10.04007	*	0.02906	*	0.01914		-4.31119	*	-0.07722	*
	0.53993		0.00645		0.04741		1.37609		0.01203	
November	-10.04007	*	0.02933	*	-0.10543	*	-3.32731		-0.03233	*
	0.53993		0.00646		0.04878		1.73163		0.01239	
December	-10.04007	*	0.02919	*	-0.02247		-3.62519	*	-0.06325	*
	0.53993		0.00646		0.04842		1.77588		0.01259	

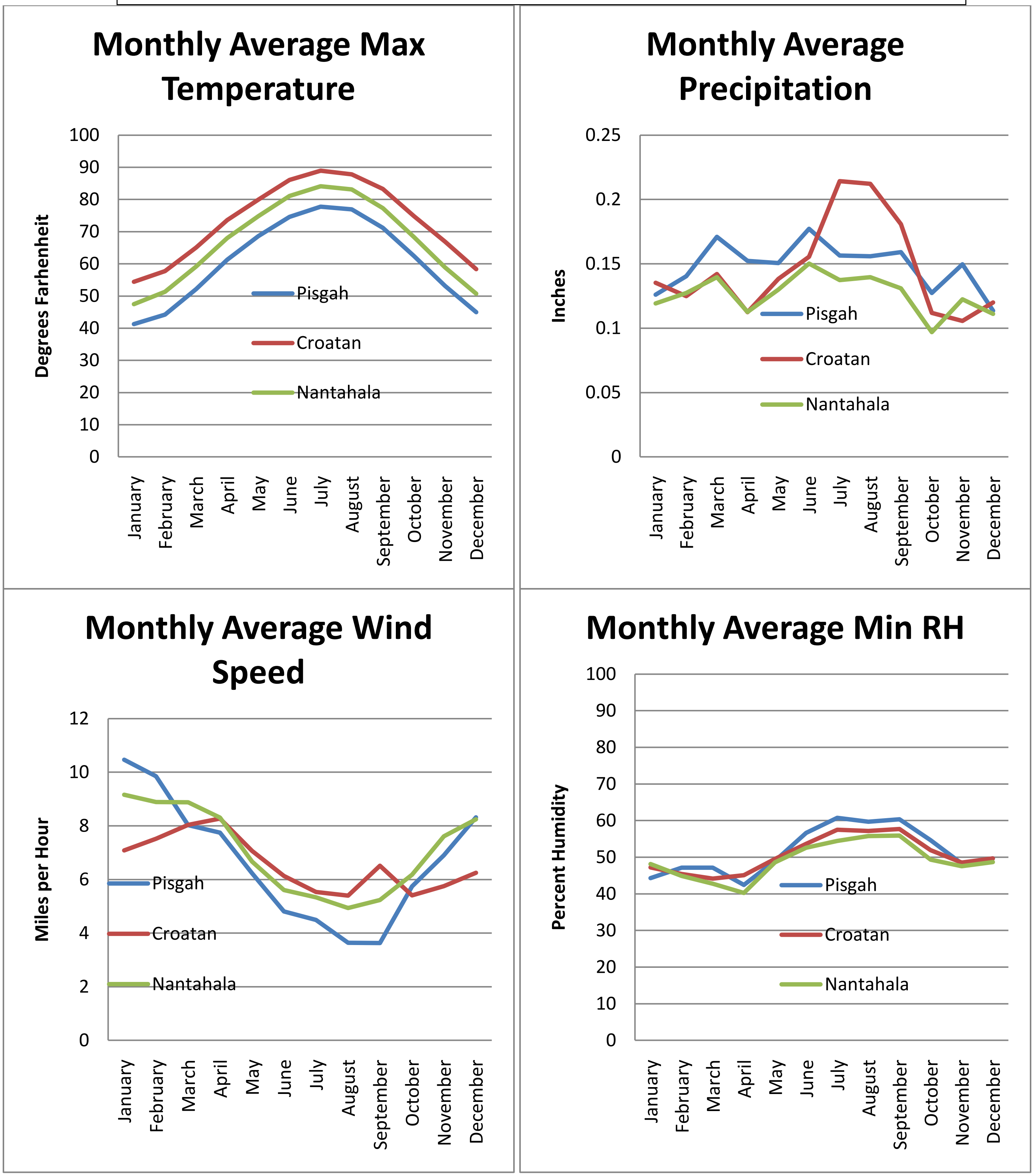
Note: standard errors are in parentheses below the coefficient, and significance at the 5% level is denoted by the asterisk next to the coefficient.

Table 3. Coefficients of a GL-MLM by County

	(Intercept)		TEMP		WIND		PRECIP		RH	
Avery	-10.06425	*	0.02861	*	-0.17824		-2.77867	*	-0.04928	*
	0.57702		0.00710		0.09526		1.27185		0.01765	
Buncombe	-10.71009	*	0.01869	*	-0.15545		-0.43247		-0.07674	*
	0.57457		0.00706		0.09031		1.27344		0.01746	
Burke	-10.16699	*	0.02703	*	-0.13852		-2.26013		-0.05837	*
	0.56802		0.00693		0.07417		1.20241		0.01558	
Caldwell	-10.07801	*	0.02840	*	-0.14458	*	-2.96454	*	-0.05011	*
	0.56636		0.00690		0.07015		1.17887		0.01504	
Carteret	-9.95650	*	0.03026	*	-0.10977		-2.07722		-0.06305	*
	0.56734		0.00692		0.07543		1.18735		0.01518	
Cherokee	-10.23341	*	0.02601	*	0.08088		-2.21047		-0.07779	*
	0.56534		0.00688		0.06465		1.17475		0.01470	
Clay	-9.72554	*	0.03381	*	0.22633	*	-3.07111	*	-0.08120	*
	0.55968		0.00677		0.05713		1.11377		0.01362	
Craven	-10.29188	*	0.02511	*	-0.06731		-1.90282		-0.06838	*
	0.56823		0.00693		0.07761		1.19860		0.01548	
Graham	-9.20086	*	0.04187	*	0.15902	*	-3.32561	*	-0.07299	*
	0.55312		0.00664		0.05215		1.04698		0.01266	
Haywood	-10.27332	*	0.02540	*	-0.11656		-2.06825		-0.06231	*
	0.57359		0.00704		0.08666		1.25713		0.01705	
Henderson	-10.42038	*	0.02314	*	-0.15144		-1.88186		-0.06125	*
	0.57517		0.00707		0.09058		1.26771		0.01738	
Jackson	-9.89735	*	0.03117	*	0.02432		-1.45771		-0.08152	*
	0.56192		0.00681		0.06023		1.14144		0.01403	
Jones	-10.02984	*	0.02914	*	-0.01156		-2.42238		-0.06763	*
	0.57322		0.00703		0.09386		1.26709		0.01757	
Macon	-9.40748	*	0.03869	*	0.19565	*	-1.30960		-0.09833	*
	0.55329		0.00664		0.05225		1.05034		0.01271	
Madison	-10.03835	*	0.02901	*	0.02333		-1.56662		-0.08012	*
	0.57606		0.00708		0.08757		1.28455		0.01755	
McDowell	-10.28315	*	0.02525	*	0.03987		-1.62084		-0.08075	*
	0.57266		0.00702		0.08032		1.25830		0.01684	
Mitchell	-10.03329	*	0.02908	*	-0.08697		-2.33676		-0.06207	*
	0.57673		0.00710		0.09254		1.27962		0.01768	
Swain	-9.94822	*	0.03039	*	0.06688		-2.64028	*	-0.07205	*
	0.56480		0.00687		0.06349		1.16805		0.01453	
Transylvania	-9.99353	*	0.02969	*	0.06697		-3.65869	*	-0.06073	*
	0.56832		0.00693		0.06968		1.20543		0.01556	
Yancey	-10.08253	*	0.02833	*	-0.11026		-2.54241		-0.05775	*
	0.57641		0.00709		0.09243		1.27466		0.01760	

Note: standard errors are in parentheses below the coefficient, and significance at the 5% level is denoted by the asterisk next to the coefficient.

Figure 6—Monthly averages of the climate variables by forest



There were a wide range of values for the coefficients found with the weather variables regressed by county. Maximum temperatures and minimum relative humidity were found to be significant for nearly all the counties. However, counties responded differently to monthly precipitation and wind speeds. Possible explanations and additional county level information are included in the Discussion section.

Because so many fires are human caused, spatial location is a function of proximity to roads and development. Maps including the spatial location of the fire as well as size calculated as a circle are located below (Figures 7-9). Note that the size of the wildland fire on these maps are proportional to the acreage burned by the fire and do not represent the extent of the fire. Within the National Forests, a majority of fires are accessible from the road, and 71% of fires are within 100 meters of a road or trail, and 87% are within 300 meters. This finding coincides with other work done by Yang et al. (2007). Figure 10 shows the distribution of fires by distance bin, the cumulative number of fires by distance, and cumulative number of fires weighted by the amount of area affected by roads. A majority of all fires occur within 100m of a road or trail, and nearly all fires occur within 1000m of road or trail. When the cumulative distribution is divided by the percentage area of National Forest within a distance of a road the result is reaffirms that a disproportionate number of fires occur within 100m of a road or trail; nearly all land is within 1000m, but only 20% or so is within 100m.

Figure 7—Fires by location, Croatan National Forest

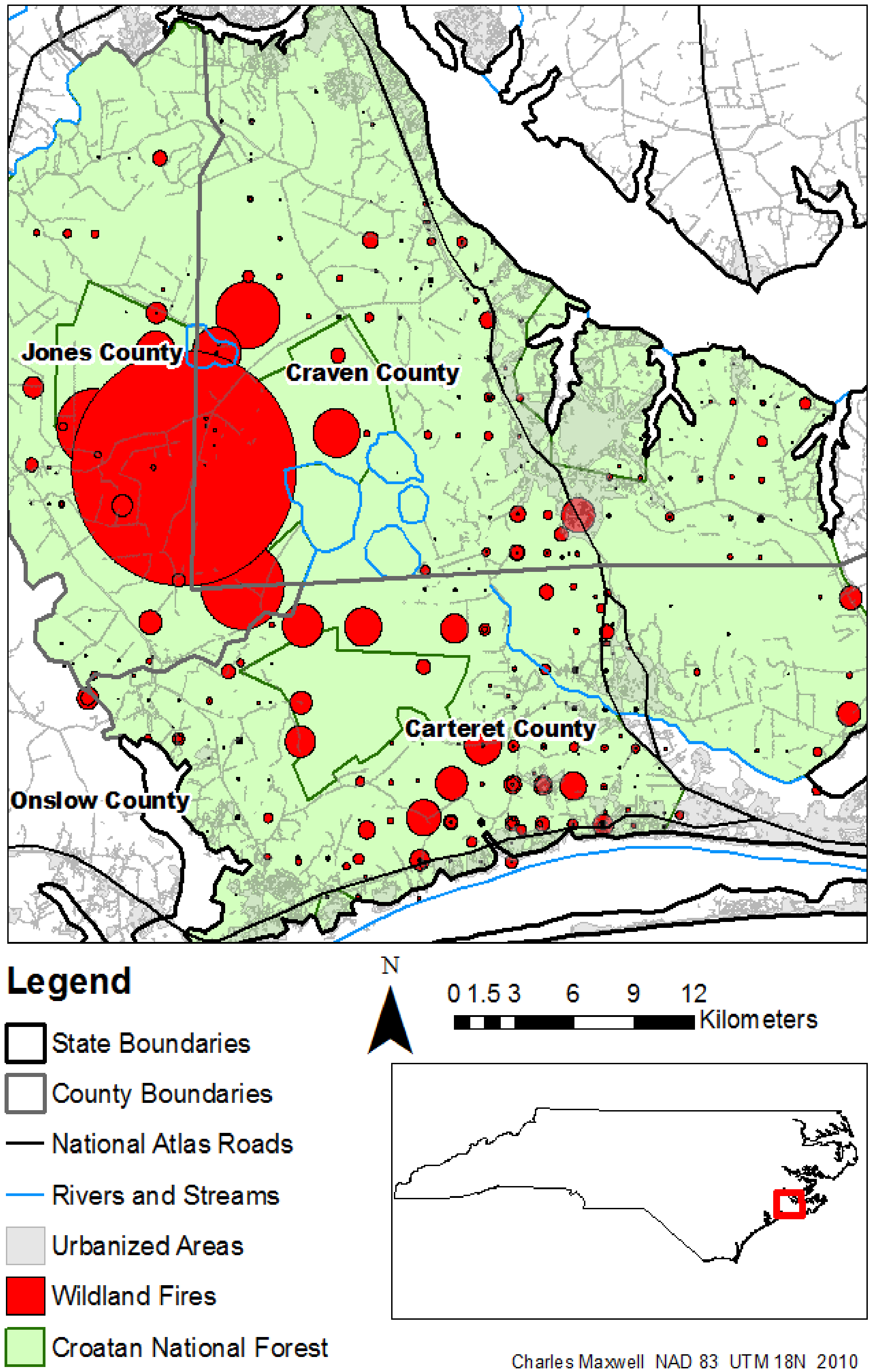


Figure 8—Fires by location, Nantahala National Forest

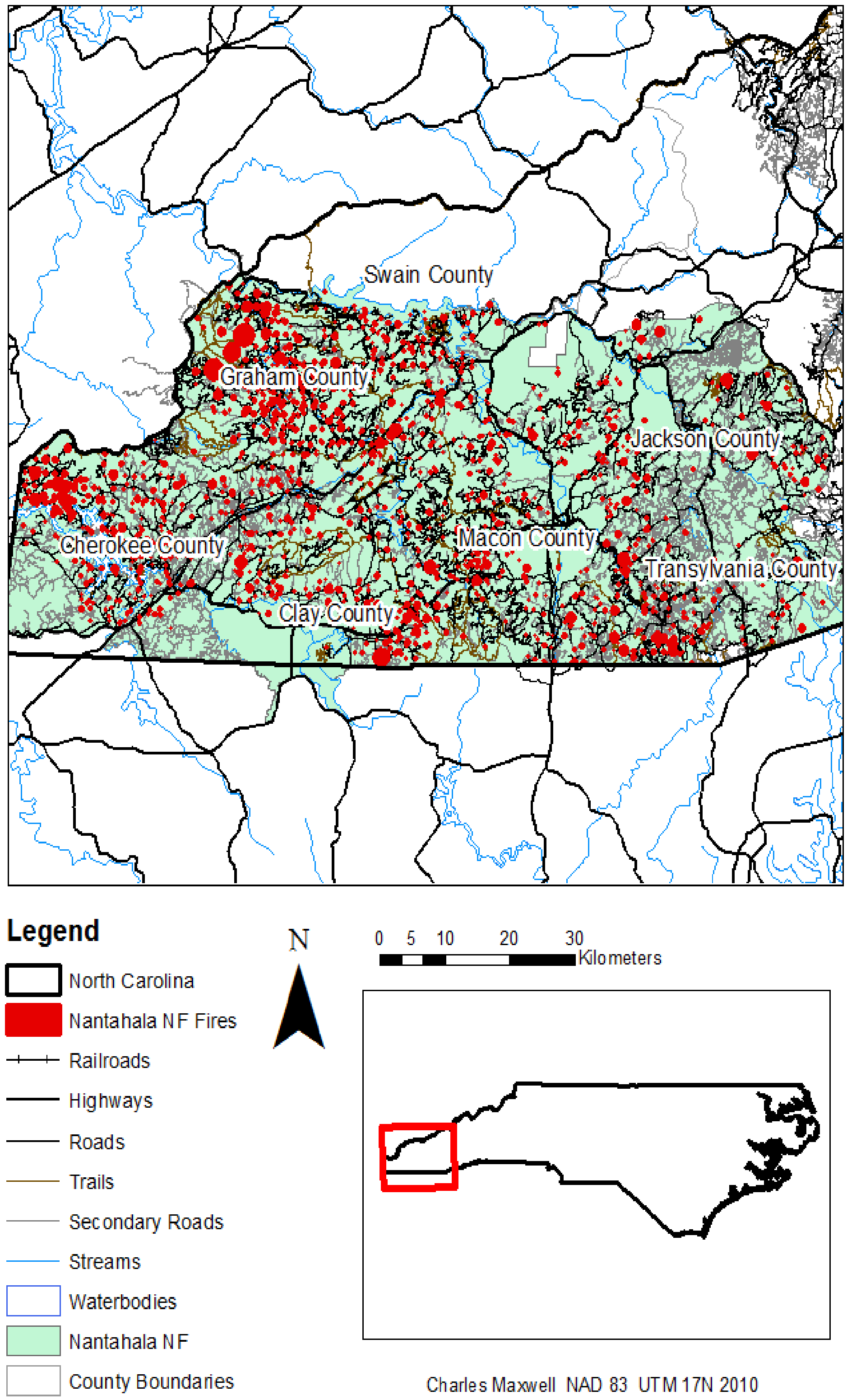


Figure 9—Fires by Location, Pisgah National Forest

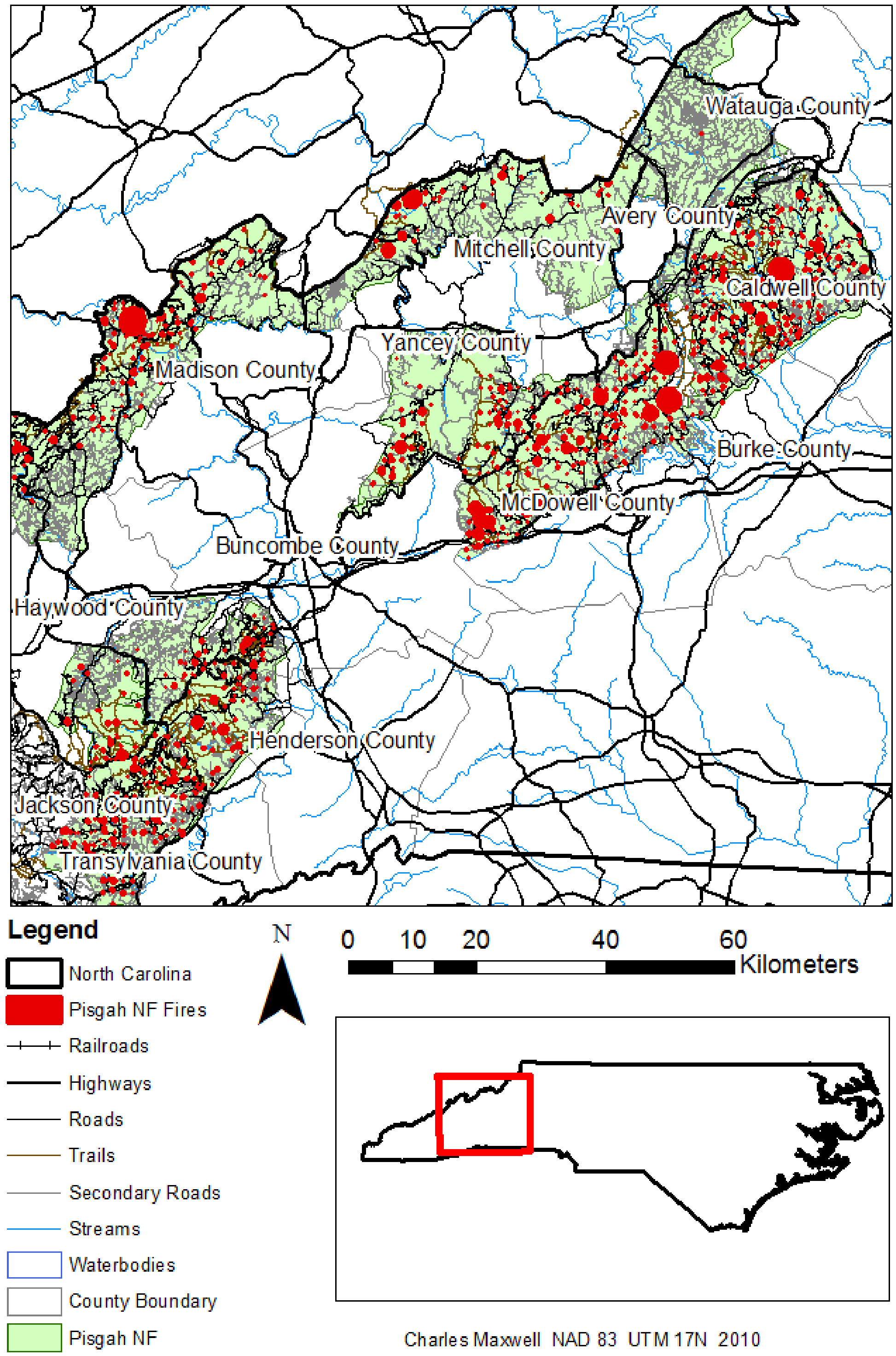
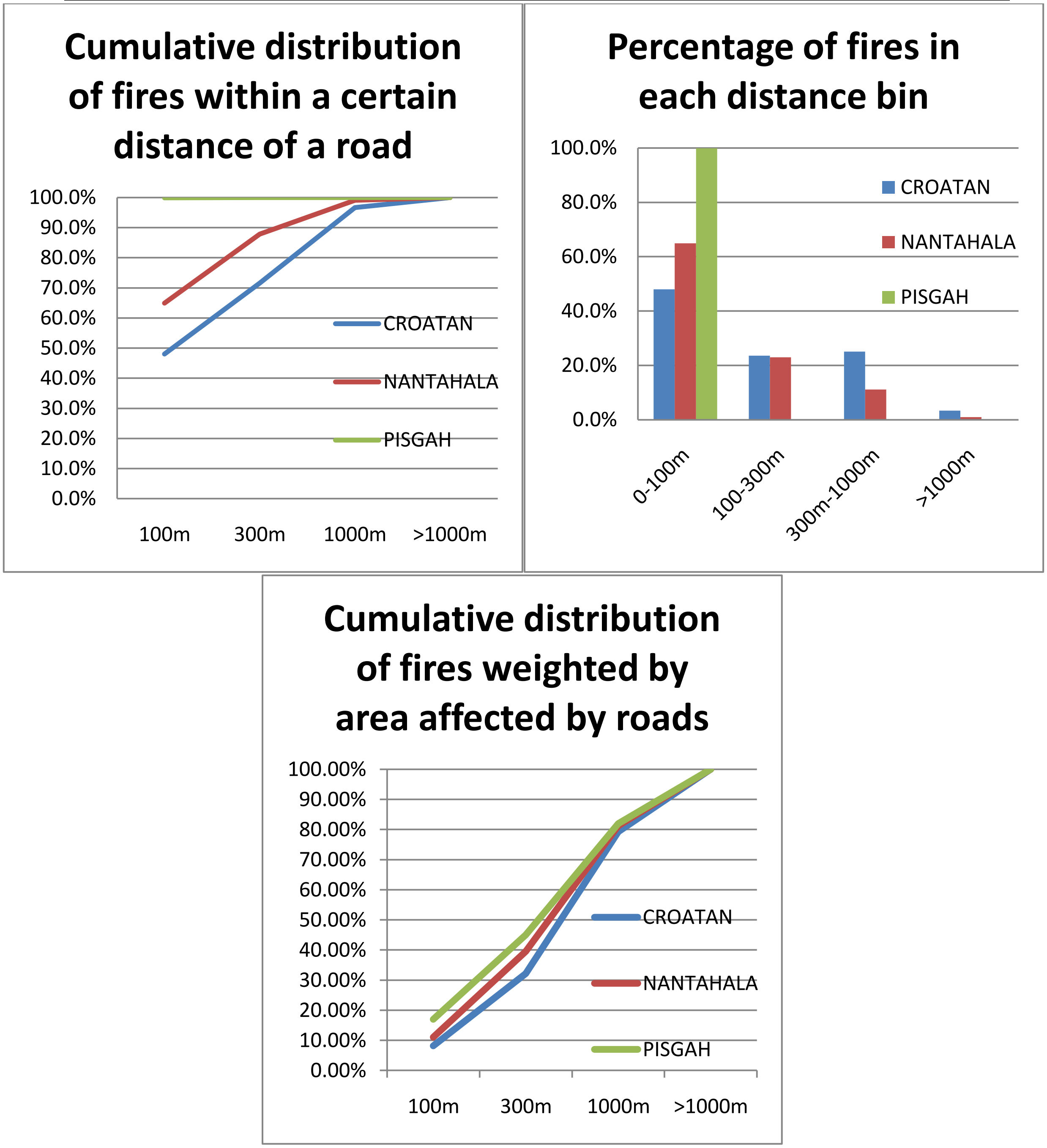


Figure 10—Fires by distance from road or trail



Discussion

In order to interpret the coefficients from Tables 2 and 3, an incidence rate ratio (IRR) was calculated. Poisson regression coefficients can be interpreted as the difference between the log of expected counts. When the predictor variable is evaluated at k and $k+1$, holding everything else constant, the difference of the two log counts is equal to the log of their quotient whose result is a ratio of the impact of a unit change on the number of fires. These IRR values were calculated from the fixed effects, the value of the coefficients of the model before being adjusted by the county and month factors, of the multi-level model and can be seen in Table 4. As a ratio, the IRR coefficients show the return of one additional unit of the predictor variables and so values greater than one have a positive effect on the number of fires, and values less than one have a negative effect on the number of fires. Increasing temperature and wind speed increase the predicted number of fires, while precipitation and relative humidity decrease the number of predicted fires, holding everything else constant. All but WIND were found to be significant at the 5% level.

Table 4—Incidence Rate Ratio of the Fixed Effects

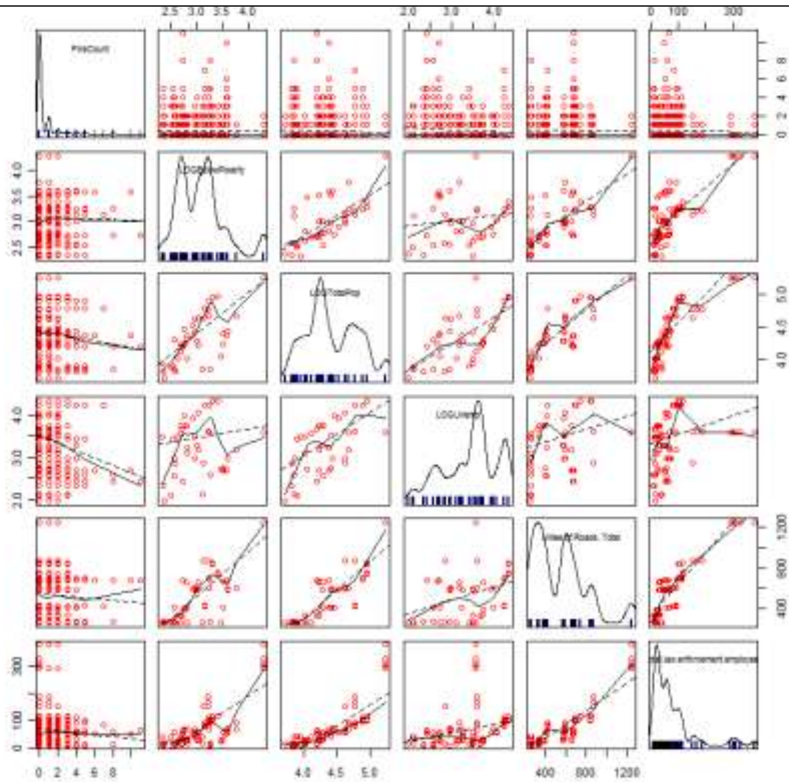
	IRR	Std. Err.	z	P>|z|	[95% Conf.	Interval]
TEMP	1.0148	0.0056	2.6300	0.0080	1.0038	1.0259
PRECIP	0.1319	0.0582	-4.5900	0.0000	0.0555	0.3134
WIND	1.0374	0.0229	1.6600	0.0960	0.9935	1.0833
RH	0.9400	0.0042	-13.990	0.0000	0.9318	0.9481

From the coefficients from Table 2, several counties are noticeable like Buncombe and Graham. Buncombe has the largest negative intercept and Graham the smallest; this means that for same weather conditions, Buncombe would have fewer fires than Graham. Additionally, the precipitation coefficients largely differ and the wind speed coefficients have different signs. While there can be a number of different factors influencing these results, these counties are opposite in a number of ways. Buncombe has the largest population while Graham has the smallest. Graham has three times as many acres of National Forest than Buncombe.

Additionally, Graham has higher than state average unemployment, Buncombe less than average unemployment (U.S Census, 2000). Consequently, the difference in the number of fires between the two counties (481) is likely due to the differences in the characteristics of the counties themselves beyond just differences in total population.

Linking socio-economic factors directly to the number of fires has proved difficult. Exploratory data plots showed no obvious trends, see Figure 11 below,

Figure 11—Scatterplot matrix of socio-economic data



and models constructed replacing the county dummy variable with the county specific socio-economic factors yielded entirely insignificant coefficients (see the Appendix for the explicit models). Further research would be needed to isolate the important socio-economic drivers in the number of fires per county. In regards to future research, obtaining finer scale socio-economic data would allow for better explanatory power. In addition, from the monthly observations, it might be possible to interpolate the socio-economic data to a daily scale and in conjunction with daily weather observations, it might allow for forecasting.

While the county coefficients are informative, they do not display the variation that the monthly coefficients do. The range of variation is largest with the influence of month on monthly average precipitation. The influence of precipitation is most limited during the early spring months, coinciding with fire season. Moreover, for the month of February the coefficient on precipitation is zero to positive. A possible explanation is that precipitation at this point in the spring season might cause a flush of green materials that would dry out by March or April, potentially adding to the fuel bed. There is also a seasonal effect in terms of the temperature coefficient by month; values for the coefficient peaks in the spring, coinciding with fire season, and falls to the lowest in the summer, when higher temperatures are offset by higher humidity and precipitation.

Conclusions

Progress was made in terms of gaining understanding the coarse time and space scales of fires North Carolina's National Forests. Additional work will be necessary to isolate the socio-economic drivers of wildfires. And so while it is people who start fires, the model developed here confirmed the importance of weather in regards to fires. Consequently, even though there were an increasing number of people in these areas over this time frame, climate was still the most important factor in determining the number of fires. An avenue for additional work would be to explain the influence of long term climatic trends on fires on a per year basis.

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Appendix

```
Generalized linear mixed model fit by the Laplace approximation
Formula: FireCount ~ Percent.Unemployed + Total.Officers +
Total.Population +      Miles.of.Roads..Total + (1
+mPercent.Unemployed + Total.Officers + Total.Population +
Miles.of.Roads..Total | County)
   Data: FireCount
 AIC BIC logLik deviance
 NaN NaN    NaN      NaN
Random effects:
 Groups Name                  Variance   Std.Dev.   Corr
 County (Intercept)           2.9630e-02 1.7213e-01
        Percent.Unemployed    7.0952e-01 8.4233e-01 0.000
        Total.Officers        6.4224e-06 2.5342e-03 0.000 0.000
        Total.Population      9.0225e-12 3.0037e-06 0.000 0.000 0.000
        Miles.of.Roads..Total 8.2621e-08 2.8744e-04 0.000 0.000 0.000
0.000
Number of obs: 1800, groups: County, 20

Fixed effects:
                        Estimate Std. Error z value Pr(>|z|)
(Intercept)           -4.674e-01  6.674e+06  -1e-07    1.000
Percent.Unemployed    -3.659e+00  1.625e+07  -2e-07    1.000
Total.Officers        -1.735e-02  1.005e+05  -2e-07    1.000
Total.Population      -2.281e-01  1.119e+02  -0.002    0.998
Miles.of.Roads..Total -4.576e-03  1.538e+04  -3e-07    1.000

Correlation of Fixed Effects:
            (Intr) Prcn.U Ttl.Of Ttl.Pp
Prcnt.Unmpl -0.614
Totl.Offcrs  0.083  0.396
Total.Ppltn  0.412 -0.487 -0.667
Mls.f.Rd..T -0.825  0.206 -0.400 -0.335

glm(formula = FireCount ~ Below.Poverty.Line.Percent +
Percent.Unemployed +
    Total.law.enforcement.employees + Total.Population +
Miles.of.Roads..Total +
    County, family = poisson(log), data = FireCount)

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-1.8055  -0.8084  -0.5407  -0.3841   5.1927

Coefficients:
                                  Estimate Std. Error z value Pr(>|z|)
(Intercept)                     -8.157e+00  8.134e+00  -1.003   0.3159
Below.Poverty.Line.Percent       6.718e-01  9.427e-01   0.713   0.4761
Percent.Unemployed              -3.791e-01  9.409e-01  -0.403   0.6870
```

```
Total.law.enforcement.employees  2.281e-02  5.380e-03   4.240 2.23e-05
***
Total.Population                -1.980e-05  2.713e-05  -0.730   0.4655
Miles.of.Roads..Total            1.650e-02  2.423e-02   0.681   0.4960
County[T.Buncombe]              -1.900e+01  2.135e+01  -0.890   0.3734
County[T.Burke]                 -7.264e+00  1.194e+01  -0.608   0.5429
County[T.Caldwell]              -4.816e+00  8.435e+00  -0.571   0.5681
County[T.Carteret]              -7.023e-02  2.220e+00  -0.032   0.9748
County[T.Cherokee]              -3.389e+00  5.840e+00  -0.580   0.5618
County[T.Clay]                   2.443e+00  2.000e+00   1.222   0.2218
County[T.Craven]                -5.390e+00  9.623e+00  -0.560   0.5754
County[T.Graham]                 3.560e+00  1.712e+00   2.080   0.0375
*
County[T.Haywood]               -4.481e+00  6.149e+00  -0.729   0.4662
County[T.Henderson]             -1.110e+01  1.255e+01  -0.885   0.3761
County[T.Jackson]               -3.188e+00  5.943e+00  -0.536   0.5917
County[T.Jones]                  4.254e-01  4.833e-01   0.880   0.3787
County[T.Macon]                 -3.737e+00  8.099e+00  -0.461   0.6445
County[T.Madison]               -4.804e+00  7.806e+00  -0.615   0.5383
County[T.McDowell]              -3.733e+00  6.118e+00  -0.610   0.5417
County[T.Mitchell]               6.280e-01  5.696e-01   1.102   0.2703
County[T.Swain]                  1.752e+00  1.966e+00   0.891   0.3730
County[T.Transylvania]          -2.794e-01  1.673e+00  -0.167   0.8673
County[T.Yancey]                -4.978e-01  1.263e+00  -0.394   0.6935
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for poisson family taken to be 1)

    Null deviance: 2255.1  on 1799  degrees of freedom
Residual deviance: 1825.8  on 1775  degrees of freedom
  (7565 observations deleted due to missingness)
AIC: 2733.3

Number of Fisher Scoring iterations: 6
```