Seizing the Forest Fire through the Trees: Modeling the historic longleaf pine fire season

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Introduction

Fire regimes are dependent on the local biotic and abiotic factors that regulate the probability and frequency of the ignition and spread. The anthropogenic effects on these fire regimes can be large and variable through time. Anthropogenic influences may therefore mask or decouple drivers of an area’s historical fire regime that developed through unique ecological, geologic, and climatic circumstances. For example, in the Southeastern USA, prior to large-scale fire suppression efforts, the longleaf pine (Pinus palustris) ecosystem was characterized by high-frequency, low-intensity fires that impeded woody vegetation encroachment, replenished soil nutrients, and facilitated seed germination and growth (Noss et al. 1995). Understanding how the abiotic and biotic (absent anthropogenic) factors influence the inter- and inter-annual variability of the fire season is thus a critical step in quantifying how fire regimes differ from pre- suppression conditions and for modeling future scenarios (e.g. anthropogenic climate change).

Methods

To address this we present a spatio-temporal model describing the pre-European settlement fire season across the entire longleaf range of longleaf. The model uses the US Forest Service's Fire Potential Index (FFI; Burgan et al. 1989) and ignition probabilities to calculate a daily probability of fire occurrence. Daily probabilities are a function of three variables:

\[ \text{fire probability} = \text{five fuel} \times \text{dead fuel} \times \text{ignitions} \]

1) Five Fuel:

Five fuel values are a measure of the ratio of live fuel to dead fuel in vegetation. The FFI estimates this value using satellite derived Normalized Difference Vegetation Index (NDVI) values. Values are scaled from 0 to 1 in such a way that as fuel loads transition from high to low relative greenness at each year. We apply the same method however to a major difficulty arise since we are interested in the pre-settlement fire regime and by extension the basin that accompanied a southeastern coastal plain landscape dominated by longleaf pine. Given that only 3% of the original longleaf pine acreage remains another method was required to make predictions of historic NDVI values across the region.

Proxy Methods:

We allowed data from current high-quality longleaf stands, solid layers, NDVI, and meteorological data to predict historic NDVI values for 26 years. We first classified the longleaf sites into six community types as determined by soil fertility and soil moisture gradients as outlined in Peet (2006). We were able to identify over 800 high quality sites whose acreage exceeds the potential of the satellite data (200 m). Once classified, regression analyses were performed to estimate relationships between the six years of NDVI data and the longleaf site with meteorological variables. Model performance was measured through comparison of AIC values. In the end two models were selected to represent NDVI values for the six longleaf pine communities. Both models used similar meteorological variables in their prediction (e.g. temperature, accumulated winter precipitation, previous month's precipitation, evapotranspiration, and daylight hours). Using these six years of predicted NDVI values, we then backcasted the NDVI values at the longleaf sites for the previous 26 years (1981 – 2006) using the meteorological data. These 26 years of predicted NDVI values were then interpolated across the historic longleaf range using universal Kriging at locations that match the site type of the six longleaf community types. Thus each set of longleaf community predicted NDVI values is interpolated across the landscape to all points that share the same site type. The output grid objects are used for predicting 26 years of post-settlement NDVI values across a longleaf pine dominated landscape. With these data were able to estimate historic five fuel ratios for use in the fire probability model.

2) Dead Fuels:

Five dead fuels refers to the moisture content of fuels that are most likely to carry a fire (e.g. large, leaves, needles, etc.). Typically maximum values above 25% of mass of the object will not carry a fire. Fuel moisture is determined by estimating the equilibrium moisture content (i.e. the moisture content of the fuel particle at a steady-state with the atmosphere) according to a model developed by Nelson (1982). The model requires knowledge of humidity, precipitation, and fuel temperature which were obtained from the NCDC Thunderstorm Data. The model runs for each fire month across the summer into the fall months. Most studies do not view this as the peak of summer-time ignitions from frequent thunderstorms.

3) Ignitions:

Ignition probabilities were estimated from (1) a 12 year global lightning flash dataset available from NASA, (2) daily thunderstorm occurrence as reported by local climatological stations from the National Climatic Data Center (NCDC), and (3) mean seasonal thunderstorm counts, also reported by NCDC. The lightning climatology was combined with the mean thunderstorm frequency to estimate lightning flash density per area (Flashstorms / thunderstorms + flash/season). This however creates a static mean lightning frequency/ignition potential value that corresponds with the mean flash density and Thunderstorm frequency for a given period. To better reflect reality we fit Gamma distributions to each grid point’s seasonal lightning data in order to create random flash counts at each location for each day. Daily lightning flash densities were randomly sampled from the fitted distribution and then transformed to storm flash densities.

Once the daily flash densities were obtained, NCDC station reports of thunderstorm activity were used to estimate the spatial extent of possible thunderstorms per month across the same period as the reanalysis dataset (1981 – 2006). The station reports were re-classed to binary presence/absence values and then these polygons were calculated. Areas days within these polygons (i.e. potential thunderstorm activity) received daily corresponding lightning flash density. Thus this process provides for an estimate of lightning activity for any given storm day that follows the distribution of the actual data. The final ignition value standardized for each grid cell to produce a relative ignition potential/probability scaled from 0 to 1.

4) Results

Initial results indicate that the model is able to detect the generally acknowledged spring fire season. However, as seen in the average daily time series (Figure 2 in results box), the model tends to predict a gradually more severe fire season throughout the summer into the fall months. Most studies do not view this as the peak fire season because of preponderance of still moist, green vegetation. Most likely, the model underestimated the importance of fuels in determining a probable ignition and at the same time overestimates the influence of summer-time ignitions from frequent thunderstorms.

Future Goals

We would like to further test and refine the model to understand the source and magnitude the hypothesized storm result. Improvements will be made so as to retain the process-based and probabilistic elements of the model without resorting to tuning and other potentially ad-hoc measures. Once completed, the model will be a high quality, high resolution depiction of the pre-settlement fire season for this highly endangered ecosystem. The results can then be used in conjunction with restoration activities or other modeling efforts such as landscape or climate change scenario comparisons.

References


Examples of types of model output. Times series of fire potential (a) can be used in change detection studies to understand how the historic fire regime is changing due to external perturbations such as climate change. Time series analysis can also be used to identify dominant frequencies or auto-regressive moving average (ARMA) processes that efficiently characterize the data. Summary time series (b) depict the seasonal cycle of the model. The model is important for understanding the dynamics of the ecosystem and for restoration purposes. Summary maps of monthly fire potential (c) establish the spatial variation in the fire season and indicate the important role that climate plays in shaping the fire season.