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

Adam Terando[1,2], Alexa McKerrow[1]
[1]Biodiversity and Spatial Information Center, NC State University, Raleigh, NC
[2]Doctoral Student, Dept. of Geography, Penn State University, University Park, PA
adam_terando@ncsu.edu

Introduction

Fire regimes are dependent on the local biotic and abiotic factors that regulate the probability and frequency of fire 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, geological, and climatic circumstances. For example, in the Southeast United States, 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 intra- and inter-annual variability of the fire season is thus a critical step in gauging how current 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 depicting the pre-European settlement fire season across the entire known range of longleaf pine. The model uses the US Forest Service’s Fire Potential Index (FPI; Burgan et al. 1998) and ignition probabilities to calculate a daily probability of fire occurrence. Daily probabilities are a function of three variables:

$$\text{fire probability} = f\begin{pmatrix}\text{live fuel}\\ \text{fine dead fuels}\\ \text{ignitions}\end{pmatrix}$$

1) Live Fuel:

Live fuel values are a measure of the ratio of live fuel to dead fuel in vegetation. The FPI estimates this value using satellite derived Normalized Difference Vegetation Index (NDVI) values. Values are scaled from 0 to 1 in such a way so as to match periods of high and low relative ‘greenness’ at each pixel. We apply the same method however a major difficulty arises since we are interested in the pre-settlement fire regime and by extension the live fuel ratios 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:

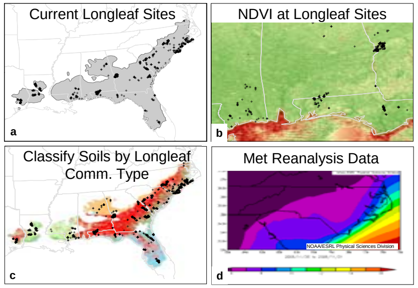
We utilized data from current high-quality longleaf pine stands, soil layers, NDVI, and meteorological data to predict historic NDVI values for 26 years.[1] We first classified the longleaf sites into six community types as determined by soil fertility and soil moisture gradients as outlined in Peet (2006). We were able to identify over 800 high quality sites whose acreage matched or exceeded the resolution of the satellite data (250 m^2). Once classified, regression analyses were performed to estimate relationships between the six years of NDVI data at the longleaf sites 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 soil 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 soil types. The output Kriged values represent our estimate of 26 years of pre-settlement NDVI values across a longleaf pine dominated landscape. With these data were able to estimate historic live fuel ratios for use in the fire probability model.

2) Fine Dead Fuels:

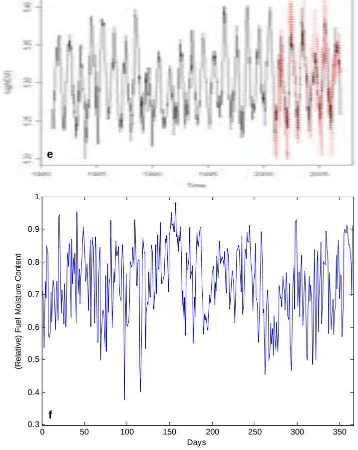
Fine dead fuels refers to the moisture content of fuels that are most likely to carry a fire (e.g twigs, leaves, needles, etc.). Typically moisture values above 35% of mass of the object will not carry a fire. Fuel moisture is determined by estimated the equilibrium moisture content (i.e. the moisture content of the fuel particle at a steady-state with the atmosphere) according to a model developed by Nelson (1984). The model requires knowledge of humidity, precipitation, and fuel temperature which were obtained from the same meteorological data (for 1981 – 2006) used in the live fuel ratio calculations. Fuel moisture content was scaled in a similar way as the live fuel ratios so as to capture periods of relative wetness and dryness at each analysis location.

---

[1] **Data Sources:**
1. Fedor, et al. 2004. North American Regional Reanalysis. Bulletin of the American Meteorological Society 87: 343 – 360. (Meteorological Data)
2. Global Land Cover Facility, www.landcover.org. (NDVI Data)
3. Soil Survey Staff, Natural Resources Conservation service, USDA, Soil Survey Geographic (SSURGO) Database. (Soils Data)
4. NCDC TD3210 U.S. First Order Summary of the Day. (Thunderstorm Data).
5. Global Hydrology Resource Center (GHRC) at the Global Hydrology and Climate Center, Huntsville, AL. (Lightning Data).
6. Southeast Gap Analysis Project (SEGAP), www.basic.ncsu.edu. (Longleaf pine site data).



Site Predictions by Longleaf Community Type	Met Data as NDVI Proxy
	$NDVI_1 = \beta_0^1 + \beta_1^1 x_1^1 + \beta_2^1 x_2^1 + \beta_n^1 x_n^1$
	$NDVI_2 = \beta_0^2 + \beta_1^2 x_1^2 + \beta_2^2 x_2^2 + \beta_n^2 x_n^2$
	....
	....
	$NDVI_i = \beta_0^i + \beta_1^i x_1^i + \beta_2^i x_2^i + \beta_n^i x_n^i$



Field (a), satellite (b), soil (c), and meteorological (d) data were used as predictors of historical seasonal vegetation health (e) and fuel moisture (f). Six longleaf community types were delineated by soil moisture holding capacity and fertility. These six community types were extrapolated across the historic range. Predicted NDVI values at individual sites for each community were then interpolated to all locations in the longleaf range with community soil types. Twenty-six years of re-analysis data were used to drive the NDVI predictions as well the fuel moisture calculations.

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 storm (flashes/month **/** thunderstorms/month = flashes/storm). 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 randomized 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 thunderstorm activity for over the same period as the reanalysis dataset (1981 – 2006). The station reports were re-classed to binary presence/absence values and thiessen polygons were calculated. Areas on days within thiessen polygons (i.e. potential thunderstorm activity) received that day’s 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 b in results box), the model tends to depict a gradually more severe fire season through the summer into the fall months. Most studies do not view this as the peak historical fire season because of preponderance of still moist, green live vegetation. Most likely, the model underestimates the importance live 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 spurious results. 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.

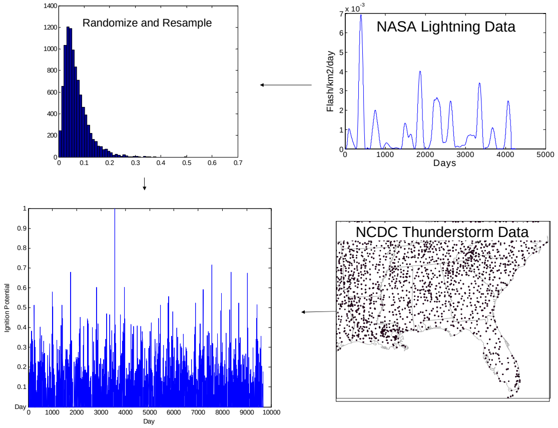
References

Burgan, R.E., R.W. Klaver, and J.M. Klaver. 1998. Fuel models and fire potential from satellite and surface observations. International Journal of Wildland Fire **8**: 159-170.

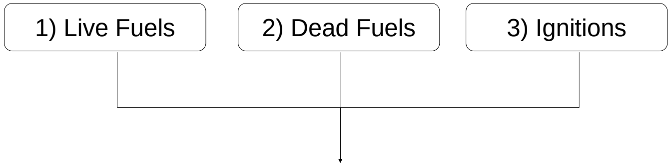
Nelson, R.M., Jr. 1984. A method for describing equilibrium moisture content of forest fuels. Canadian Journal of Forestry Research **14**: 597-600.

Noss, R.F., E.T. LaRoe III, and J.M. Scott. 1995. Endangered Ecosystems of the United States: A preliminary assessment of loss and degradation. Biological Report 28, National Biological Service, U.S. Department of the Interior, Washington, D.C.

Peet, R.K. 2006. Ecological classification of longleaf pine woodlands. In *The Longleaf Pine Ecosystem*, ed. S. Jose, E.J. Jokela, and D.L. Miller, pp. 51-93. New York: Springer.



Lightning flash data were obtained from NASA. These data were pre-processed and spatially and temporal smoothed. To obtain an estimate of ignition probabilities on a daily basis gamma distributions were fit to the lightning data at each grid point in the study area. From these estimated pdfs, daily flash counts were sampled to obtain a randomized daily flash rate. We then combined mean monthly thunderstorm counts with the mean flash rate to estimate the mean flash rate per thunderstorm. Finally, daily thunderstorm presence/absence data were used to select the resampled lightning days used in the final analysis.

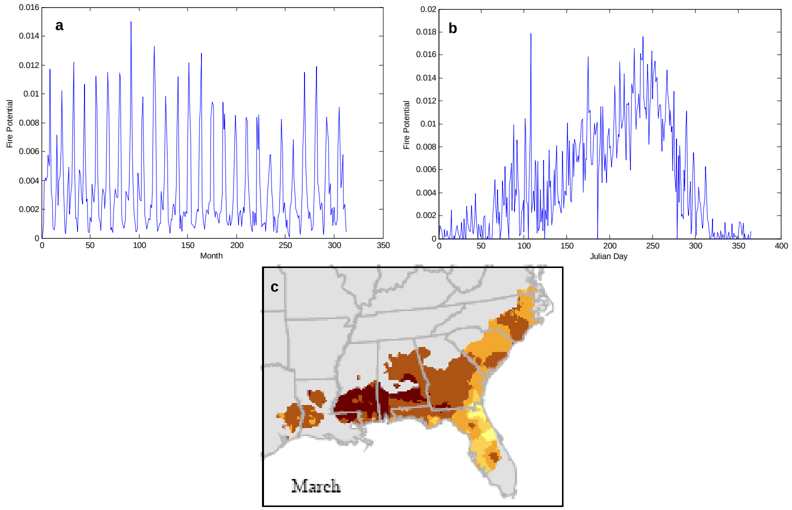


1) Live Fuels

2) Dead Fuels

3) Ignitions

Predicted Historic Longleaf Fire Regime



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 fire season and are 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.