

Simulating spatial and temporally related fire weather

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Abstract

Use of fire behavior models has assumed an increasingly important role for managers of wildfire incidents to make strategic decisions. For fire risk assessments and danger rating at very large spatial scales, these models depend on fire weather variables or fire danger indices. Here, we describe a method to simulate fire weather at a national scale that captures the same patterns of seasonality, spatial correlation and temporal correlation as the observed inputs. This method incorporates daily surface weather observations, which are incorporated into large scale models that give a grid of modeled weather values across a landscape. We use those observations to obtain estimates of the seasonal trend, the pixel-by-pixel temporal autocorrelation, and the spatial autocorrelation of the remaining residuals. We then use these three sub-models to simulate artificial seasons of weather data. Finally, we verify the results to ensure that the simulated seasons are indistinguishable from the input observations, from a statistical standpoint.

Keywords: Spatial temporal simulation, Energy Release Component, Gridded weather

1. Introduction

Weather observations used for fire behavior calculations and fire danger rating often come from a single weather station that is located nearby to an active fire or an area of concern. As long as the land area is small or mostly homogeneous, neglect of spatial variation of fuel moisture or winds may be acceptable. At very large scales used in fire risk simulation assessments, say 100's or 1000's of km across (Ager et al. 2010, Calkin et al. 2010, Parisien et al. 2005, Parisien and Moritz 2009), fire weather and climate is determined by synoptic weather trends and major geographic features (mountain ranges and coastal proximity). Khalili (2009) presented a method for simulating fire weather at multiple specific sites. However, for our purposes it is necessary to have simulated values covering the entirety of the landscape. Fire risk assessments for such large domains would be greatly improved if the spatial influence of weather patterns could be incorporated. To better represent variation at these large scales, we investigated a method which would statistically analyze historical gridded weather observations for the purpose of generating spatial and temporal weather sequences.

2. Data

The source of gridded weather data was produced at 8 km resolution following the methods used for the North American Regional Reanalysis (NARR) which has a resolution of 32 km (<http://www.emc.ncep.noaa.gov/mmb/rrean/>) (Mesinger et al. 2006). This data set provided daily temperature and humidity extremes and precipitation duration every three hours at an 8 km resolution. Next, daily grids were derived for the period of 1980 – 2008 for the purpose of calculating the Energy Release Component (ERC). ERC is an index of the U.S. National Fire Danger Rating System (Deeming et al. 1977) which reflects the energy available per unit area of the flaming front of a spreading fire. ERC for a given fuel type is only sensitive to the moisture content of the dead and live fuels. It is highly predictive of fire occurrence and fire behavior potential (Andrews *et al.* 2003) and depicts well seasonal and regional variations in moisture contentment and fire danger. ERC was calculated using fuel model G for all cells facilitate inter-comparison between geographic locations.

Our general methods for using the gridded historical weather dataset were to:

- i. Systematically obtain the seasonal trend and the temporal autocorrelation function at each pixel
- ii. Estimate the spatial autocorrelation of the deviations from the seasonal trend over the domain in question, for each day of the year.
- iii. Then reverse the process, simulating grids of spatially autocorrelated errors, filtering those errors through the temporal autocorrelation function, and adding in the seasonal trend, to obtain independent sets of simulated seasons.

3. Statistical Methods

In accounting for the correlation structure of interest, we assume that fire weather can be approximated using the following model:

$$ERC(x, y, t, yr) = \alpha(x, y, t) + \epsilon(x, y, t) \quad (1)$$

Where α is the the seasonal trend (a simple average of the daily ERC values at each location over the 10 years), and ϵ is a matrix of the residuals. We account for the correlation structure in ϵ using the following model:

$$\epsilon(x, y, t) = \phi_{x,y}\epsilon(x, y, t - k) + \gamma(x, y, t) \quad (2)$$

Where $\phi_{x,y}$ is a vector of autocorrelation coefficients at each location, (x, y) , and $\gamma(x, y, t)$ is a temporally independent grid of spatially correlated residuals. For the purposes of modelling, we assume that $\gamma(x, y, t)$ can be modelled using an exponential variogram, with a different sill for each day of the year.

We estimate these models using the statistical package R. Once the estimates for the seasonal average, the autocorrelation coefficients, and the range for the spatial residual grids are obtained, we used the method for spatial simulation described in (1) to produce

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the necessary grids of the residuals, pass those grids through the filter $\phi_{x,y}$, and add that result to the estimated trend function, resulting in simulated seasons of *ERC* streams, as desired.

4. Results

To evaluate the validity of this method, we used 10 years of the NARR data taken from the the Pacific Northwest region of the United States. We then examine the autocorrelation functions for the simulated seasons, as well as the spatial variability of the residuals, and verify that they approximate the same patterns as the original input data. For this initial study, we used a maximum lag time of 6 days for the autoregressive component of the model.

A graphical visualization of several days from a simulated season is shown in Figure 1a for the northwest U.S. The maps of *ERC* show clearly the spatial patterns and variability that is important to large-scale fire danger dynamics. Figure 1b shows that for individual cells, there is a time-series of *ERC* with its own distinct seasonal pattern.

A reasonable degree of agreement was found in the autocorrelation functions from both the simulated and observed seasons, as well as the observed and simulated variograms of the deviations from the seasonal trend (Figure 2). Using a spherical variogram model, we obtain an estimated range of 15.27715 pixels (approx. 122 km), a nugget effect of 12.893062, and a sill of 4.368459. This compares to the values for the simulated grid, yielding a range of 4.476583 pixels (approx. 36 km), a nugget of 6.603975, and a sill of 3.948523. The difference in the estimates of the range may be due to the sensitivity of the fitting algorithm in R, as visual inspection of the two variograms lends itself to an interpretation that the two are satisfactory in their similarity.

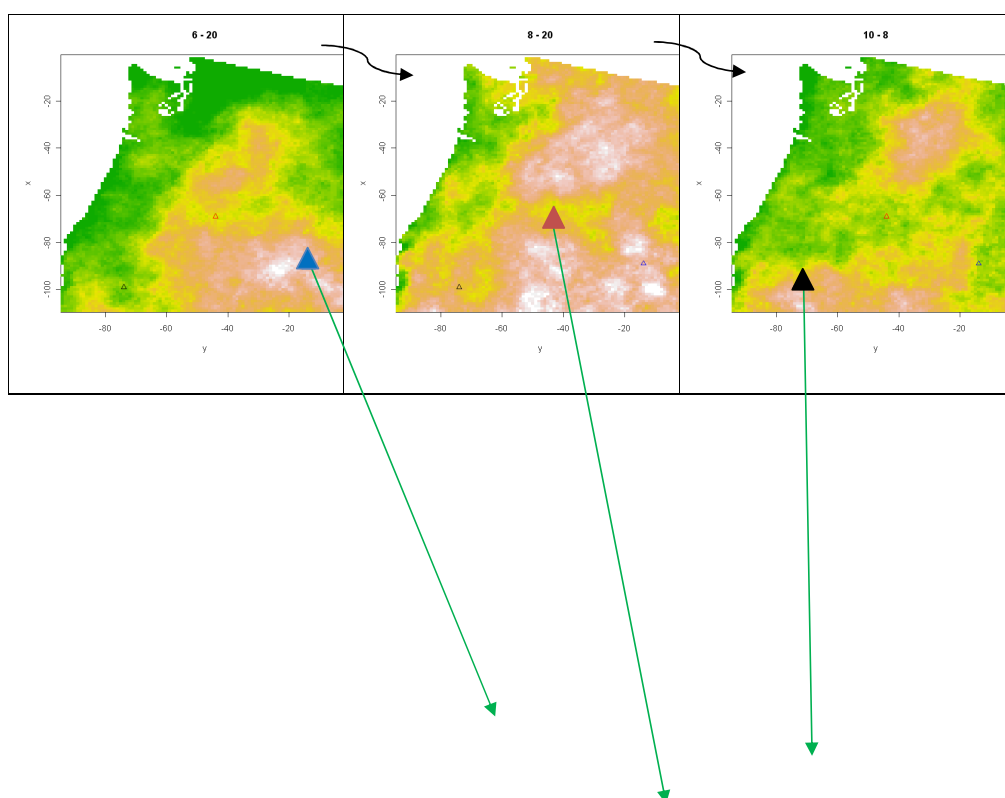
As an example of the scalability of the process, *ERC* simulations were performed for the entire Continental U.S. (Figure 3). Similar to the results for the northwest region (Figure 2) we found that the autocorrelations were very comparable between the simulated and input data. The variograms showed little of the expected increase in variance with distance however, as expected from the regional example in Figure 1.

5. Discussion

We have developed a method for simulating fire weather that incorporates the spatial and temporal characteristics explicitly, and thus presents an improvement over currently used methods. By virtue of allowing for simulation across entire landscapes, this method allows for the potential to simulate many fire incidents simultaneously, while using a cohesive set of simulated weather scenarios. This method would lend itself naturally to further development in climatological wind simulation, as well as improvements in fuel models that more realistically incorporated live fuel moisture.

6. Acknowledgements

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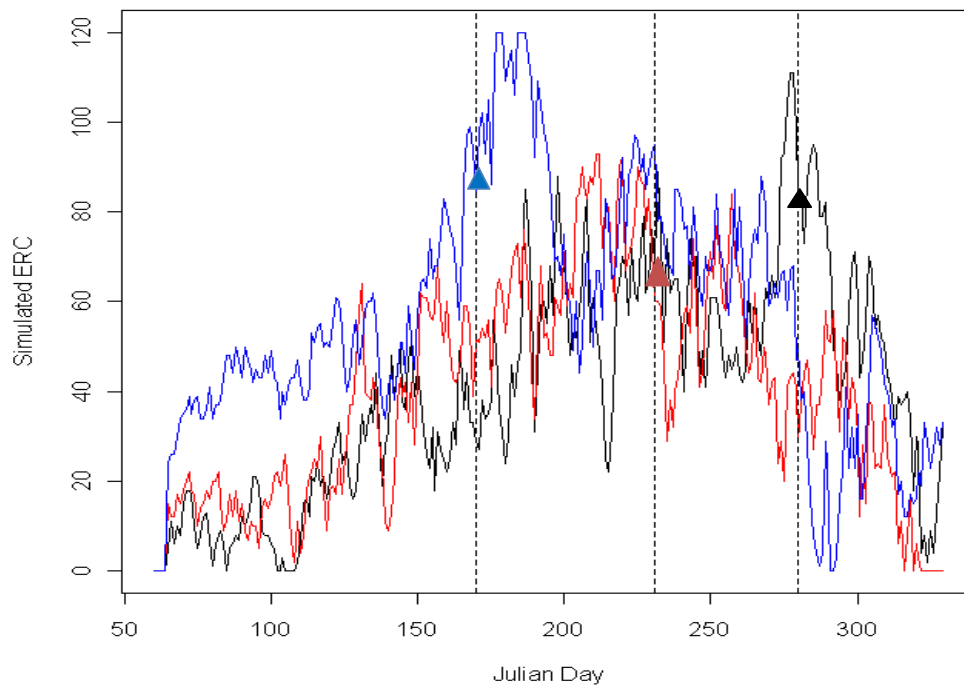


Figure 1. *Visualization of a simulated season across the Northwestern portion of the United States. The spatial grids are shown for 3 days of the simulated season (June 20, August 20, and October 20). Below, we show 3 time series plots for the selected locations for the entirety of the season, with the locations of these selected observations indicated.*

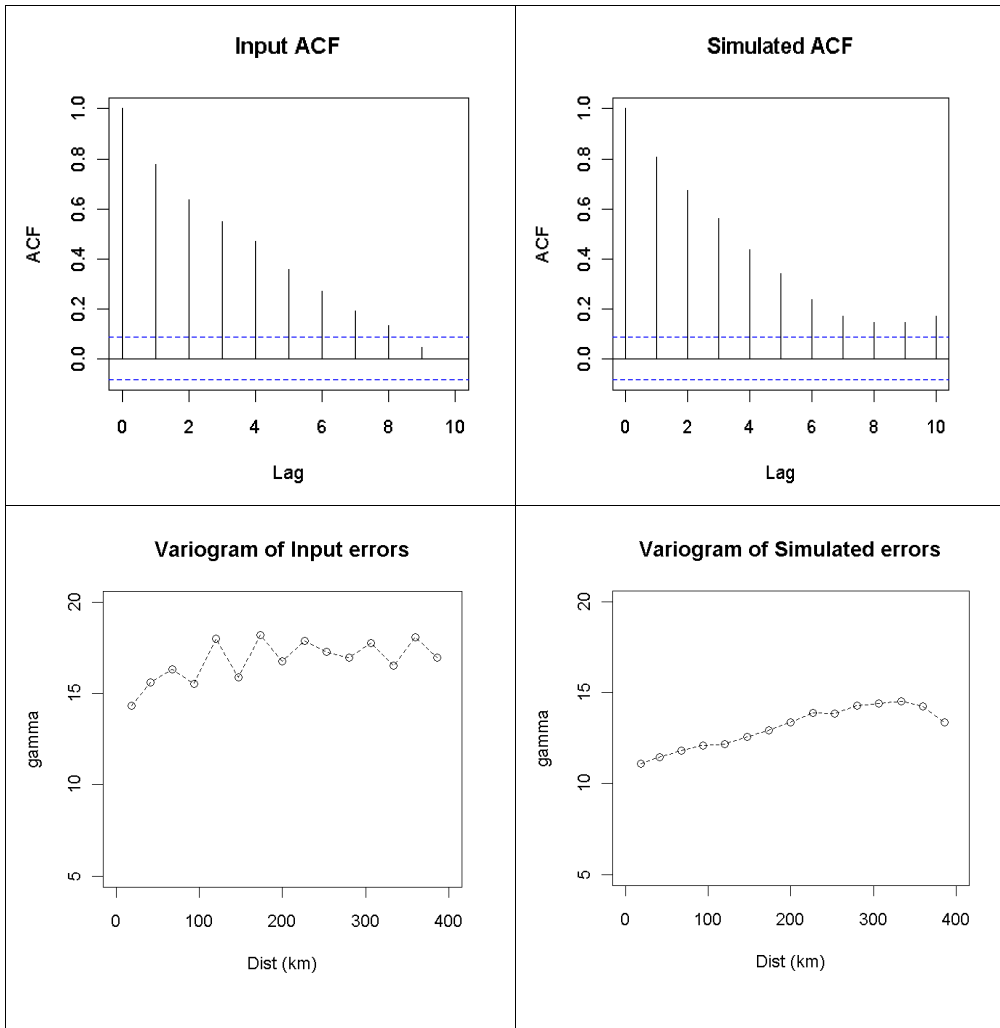


Figure 2. Above left, we have the autocorrelation function of the deviations from the seasonal trend of the observed ERC values for the rightmost site of the Pacific Northwest data from figure 1. Above right, the same function for the simulated values. Below left, the estimated variogram for a specific day (June 20) of the grid of deviations from the seasonal trend, and below right, the variogram for the simulated values. In the autocorrelation plots, we note that both simulated and input variabes appear to have a similar correlation structure, remaining autocorrelated out to a time interval of approximately 7 days. For the variograms, we note that both grids appear to be spatially correlated out to a distance of approximately 100 km.

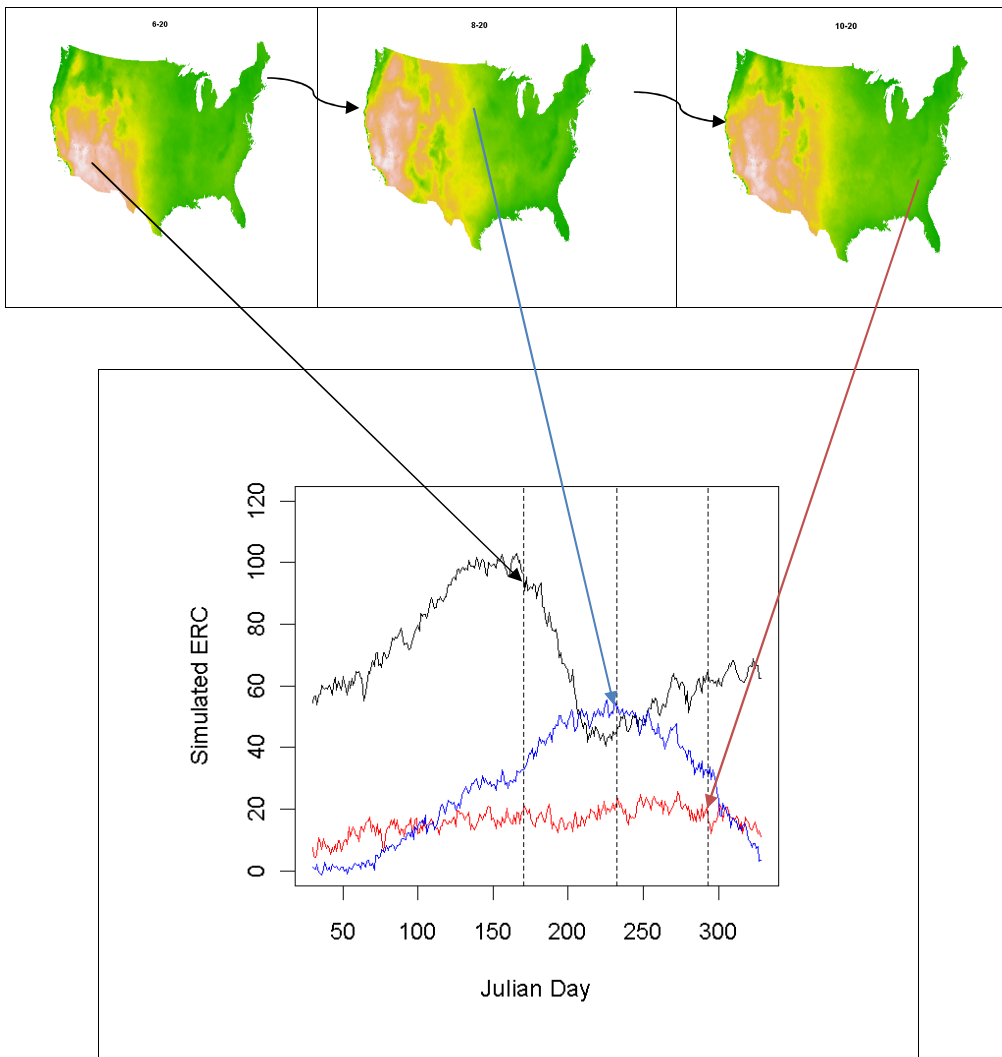


Figure 3. A demonstration of 3 simulated days of ERC with the seasonal traces at each location, as indicated on the grids. Above, we have the grids for June 20, August 20, and October 20 of the simulated season.

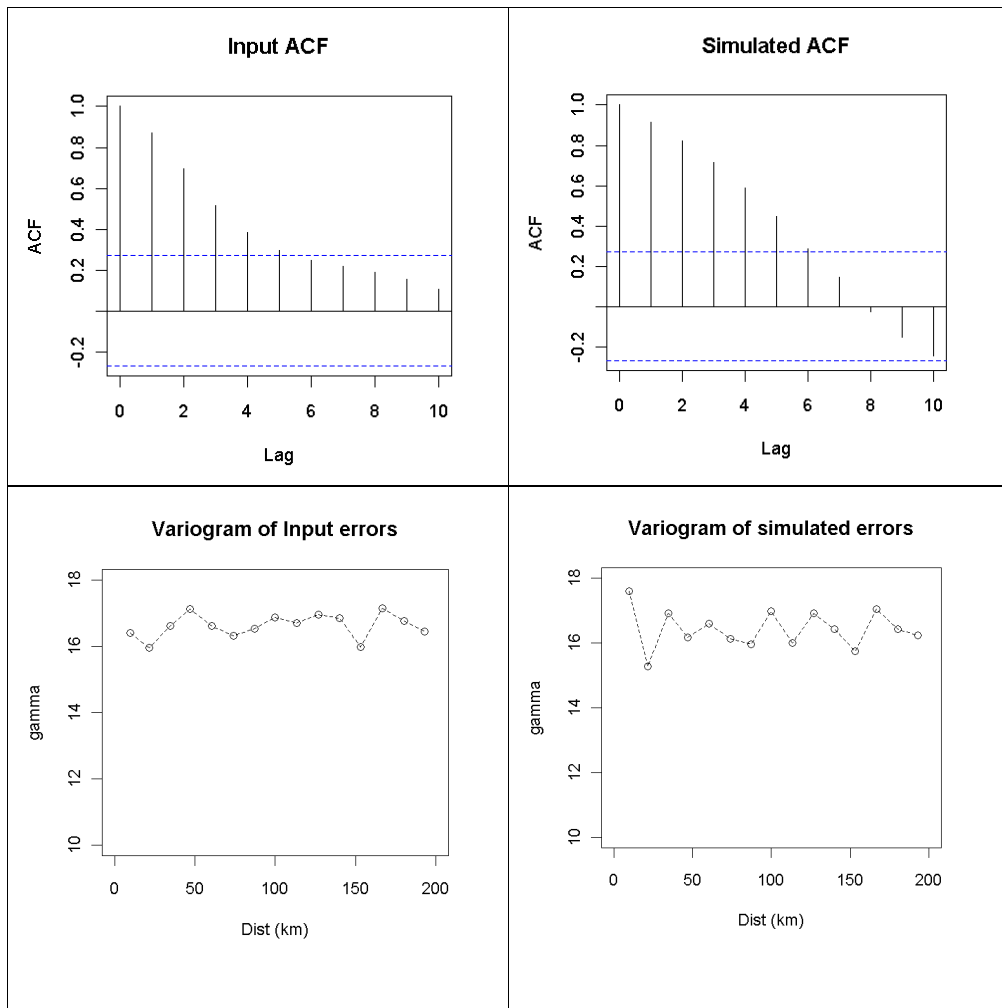


Figure 4. Above left, the autocorrelation function of the deviations from the seasonal trend of the observed ERC values for the rightmost site of the continental U.S. data shown in Figure 3). Above right, the same function for the simulated values. Below left, the estimated variogram for a specific day (June 20) of the grid of deviations from the seasonal trend, and below right, the variogram for the simulated values. In the autocorrelation plots, we note that the simulated data appear to be autocorrelated out to about 5 days, while the input data are correlated out to about 4 days. For the variograms, both variograms appear similar, but yield ambiguous results, suggesting a correlation structure that is not as well defined as on the smaller regional domain shown in Figure 1.

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