When Space Beats Time: decomposing and interpreting temporal and spatial components after hurricane events

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1. Introduction

GIS based predictive models have a long tradition of using both spatial and temporal structure. Temporal (e.g., past observations, moving averages, seasonal parameters), and spatial (neighboring pixel filters, moving windows, lags, distance and fragmentation variables) are typically used together. However, the nature of the contribution of each component and the interpretation of the shifts in each components importance is less understood (Griffith 2013).

Abrupt (shock or system reboot-inducing) events such as natural disasters or political crisis can dramatically disrupt the temporal autocorrelation of 'business as usual' inertia in a landscape or regional system so as to impair the predictive capability of temporal models based on past trends, especially in the immediate aftermath of such events. It is at these key temporal points when spatial autocorrelation (i.e., surrounding/neighboring observations) becomes better predictor, and when the opportunity to decouple spatial and temporal component arises (Griffith and Chun 2015).

In this paper, we seek focus on a few cases and examine the conditions by which spatial models become better predictors than temporal models in terms of model accuracy/performance. This paper seeks to 1) propose a framework to interpret the spatial and temporal components of phenomena and data; 2) analyze system disruptive events through the changing preponderance of predictive accuracy for temporal-only and spatial-only models 3) provide illustrative real world cases where and when the spatial structure of a variable trumps the predictive power of temporal structure.

We do this by applying the same framework to two case studies of system reboot/memory loss/scenarios of post hurricane recovery. One in southeastern Mexico, and the other, in New Orleans, Louisiana.

2. Data

For Case1 we model vegetation greenness as measured by the Normalized Vegetation Index -NDVI from before and after the impact of hurricane Dean in the Yucatan peninsula (August 21st 2007) using a MODIS 1km, 16-day time series (Figure 1). Vegetation indices have been used to proxy wind damage on vegetation before although the overall accuracy of such measures depends on the spatial resolution of the analysis and the landscape variability (Rogan et al. 2011).

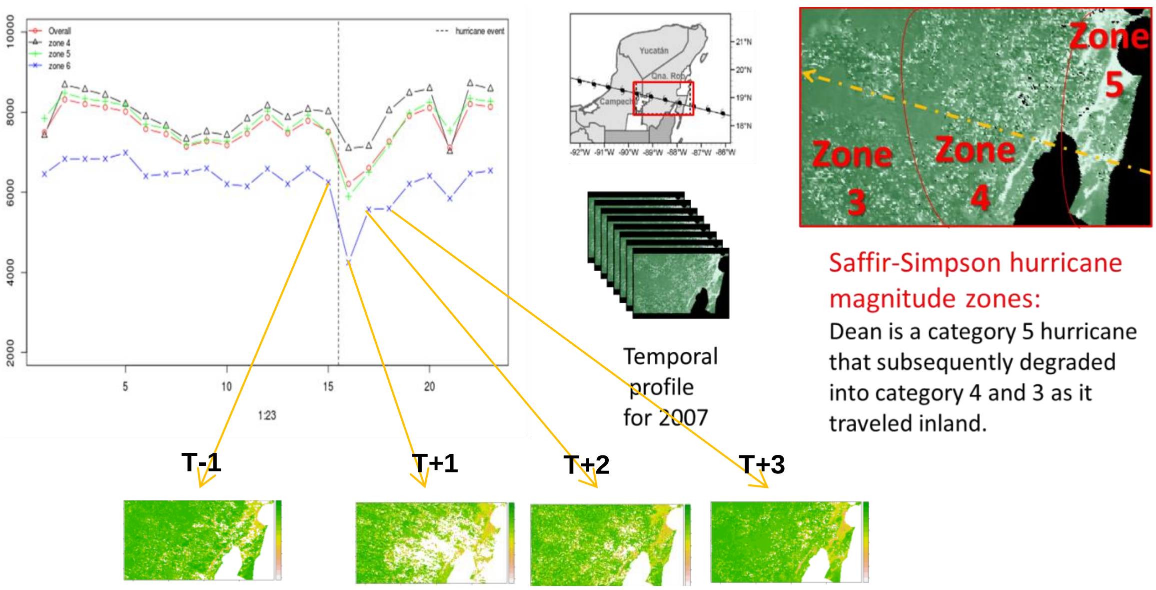

Figure 1. NDVI MODIS time series data: a) top center= study area identifying the hurricane path and the study area delimitation; b) top right= Magnitude zones (5 = strongest winds); c) bottom center= NDVI images of dates before (T-1), and after (T+1, T+2, T+3) the hurricane hit (T0), darker green= higher NDVI; and, d) top left =temporal profile of the mean NDVI for the whole study area (red circles), hurricane zone 5 (blue Xs), zone 4 (green plus signs), and zone 3 (black triangles).

For Case 2 we utilize the flooding of New Orleans following the levee breaches associated with Hurricane Katrina (2005). The data utilized is the Version 4 of the Defense Meteorological Satellite Program - Operational Linescan System) (DMSP-OLS) Nighttime Lights Time Series provided by the Earth Observation Group within the National Geophysical Data Center of NOAA. These data provides average annual measures of light emissions in W/cm^2 and are corrected for sunlight, glare, moonlight, cloud cover, and lightning features. DMSP-OLS Nighttime Lights have been used in a wide variety of scientific application (Elvidge et al. 2000) including providing a useful measurement of regional economic activity (Doll et al. 2006; Elvidge et al 1997; Ghosh 2010; Sutton and Costanza 2002). We not only run the temporal and spatial models across the entire dataset but also in areas that had high levels of flooding and areas that had little or no flooding.

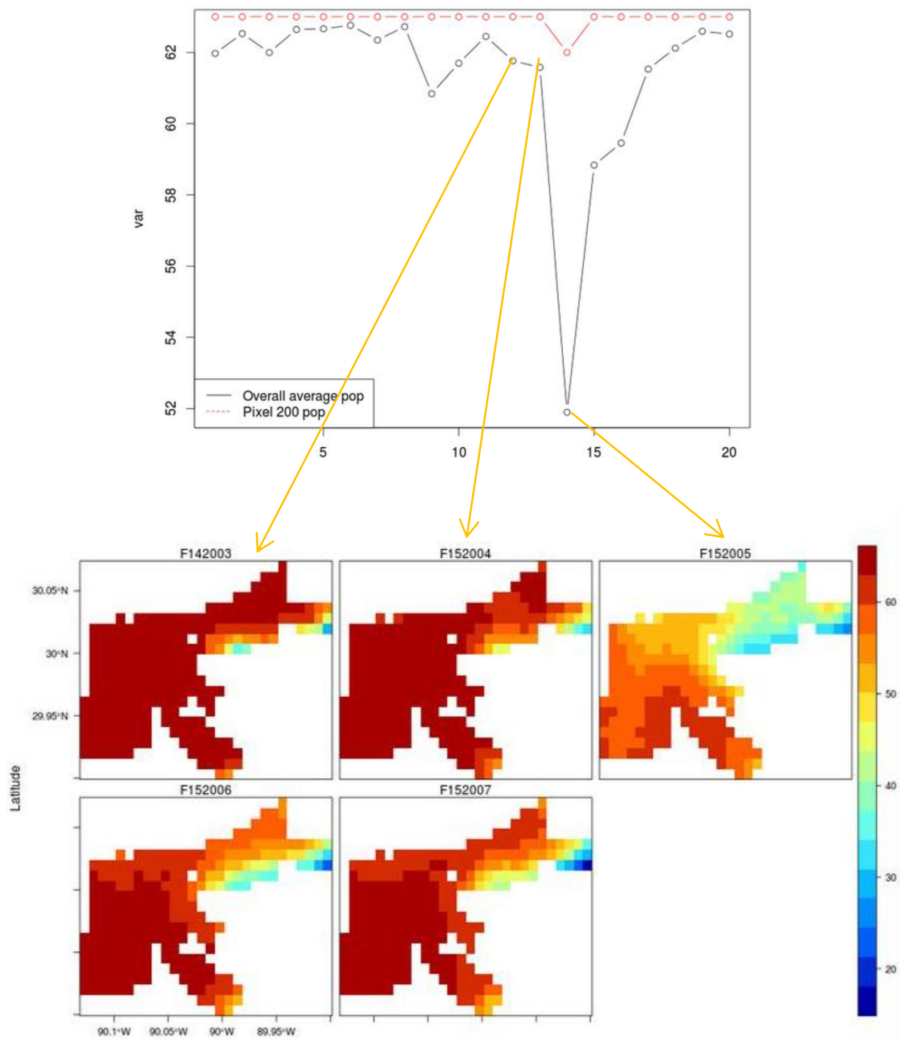

Figure2. a) Top Panel: Profile Nightlights intensity average for affected area in New Orleans (black circles); and, b) Bottom Panel: light intensity maps of New Orleans before (2003, 2004) and after Hurricane Katrina (2005, 2006, 2007)

3. Methods

For Case1, an Autoregressive Integrated Moving Average model (ARIMA) with self-selection of parameters based on AIC scores at every image cell location is utilized to estimate a temporal-only model prediction (equation 1). Spatial Lag models are calculated to estimate spatial-only model (equation 2). For Case2, temporal prediction was based on the previous year (2004) nightlights intensity values via a standard OLS regression model. Model performance was measured by mean absolute error (MAE). Models were run in the R Sped package and SAS for confirmation. Processing and Codes will be made available after publication

$$y_{t+1} = \alpha\, y_t + \mathrm{e} \quad (1),$$

where y is NDVI (Case1) or population density (Case2), t is a time index, and e is error.

$$y = \alpha x + \lambda W y + e \quad (2),$$

where y is NDVI (Case1) or nightlights intensity (Case2), W is the spatial weight matrix, x are factors, and e is error.

4. Results and Discussion

Results for Case1 show that the spatial patterns of the prediction models (spatial and temporal) are relatively similar up until the hurricane event after which they differ noticeably (Figure 2 and Figure 3).

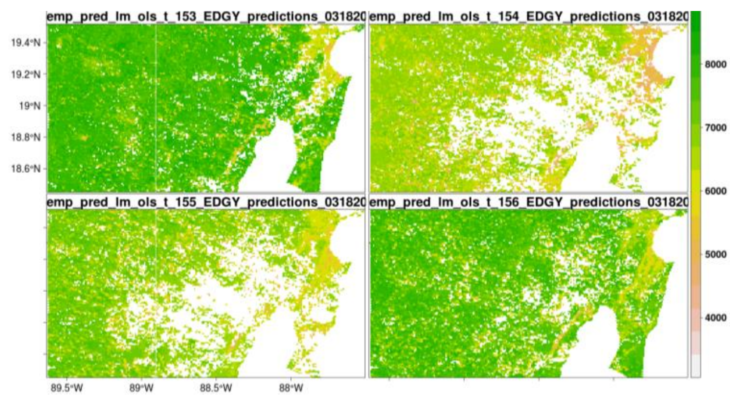

Figure 2. Temporal Prediction Maps for NDVI based on ARIMA: a) top left=T-1; b) top right= T+1; c) bottom left=T+2; d) bottom right=T+3.

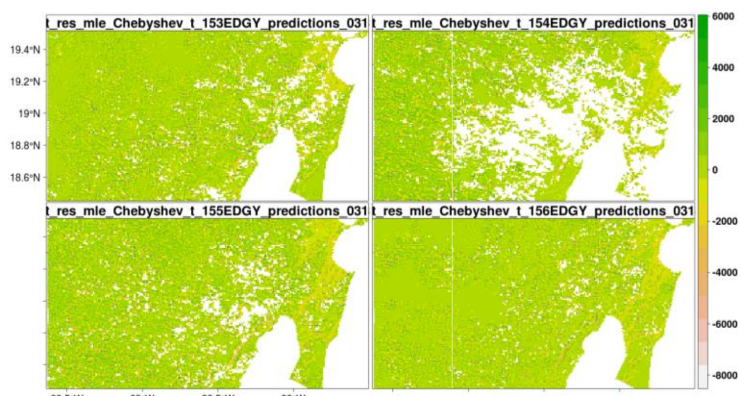

Figure 3. Spatial Prediction Maps for NDVI based on Spatial Lag using Chebyshev estimation: a) top left=T-1; b) top right= T+1; c) bottom left=T+2; d) bottom right=T+3.

Model Performance analysis of Case1 shows that temporal-only models perform better (lower MAE) than spatial models (spatial lag) *before* the hurricane event. However, immediately *after* the event, they perform worse (higher MAE) than the spatial models (Figure 6). After a period of time, however, temporal models recover and outperform spatial models again. Thus illustrating that in, for short window of time, space can beat time. Note that a higher MAE means more error and therefore a poorer model performance. The space-beasts-time pattern described is stronger in areas where the event effects were expected to be stronger like eastern most areas (hurricane wind magnitude zones 5 and 4) closer to the coast (Figure 4).

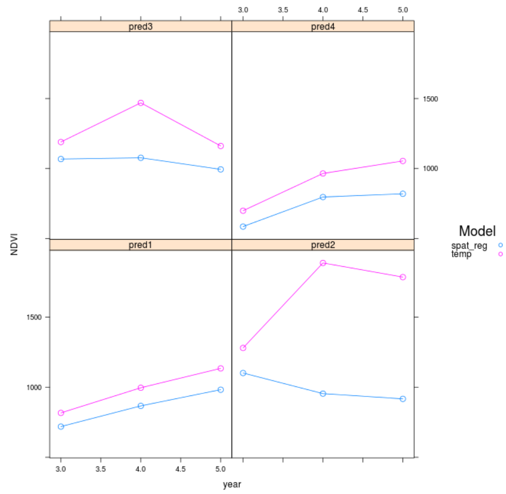

Figure 4 . MAE performance (vertical axis) by Spatial Lag (light blue line) and ARIMA predictions (pink line) by different wind magnitude zones and time steps. Each quadrant represents one of the four dates for each hurricane zone (horizontal axis, zones 3 through 5). Clockwise: T-1=upper left, T+1=upper right, T+2= lower right, and T+3= lower left.

In Case2, a similar effect is shown, especially. in lower elevation areas that were flooded in the south city during the hurricane event. In addition we also see that the spatial pattern of the prediction maps for 2005 from the spatial lag model produce better results than the temporal prediction model when compared to the observed data (Figures 5, 6 and 7).

Figure5. Temporal Prediction maps of light intensity for Case2.

Figure 6. Spatial Prediction maps of light intensity for Case2.

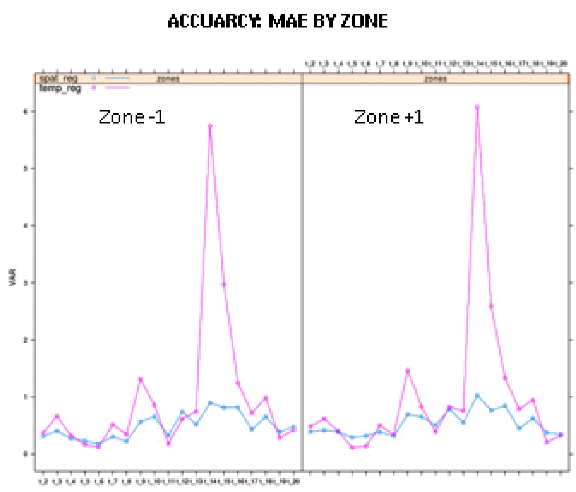

Figure 7.. MAE performance over time (1993-2013) for nightlight intensity. Spatial prediction (pink line) and previous date temporal prediction (light blue line) by different elevation zones: Zone-1=Low (left) and Zone+1= High (right). In time steps around the hurricane (2005) spatial predictions have less error (lower MAE) than temporal predictions.

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