Modeling Forest Wildfire Risks with Non-structural Correction for Spatio-temporal Autocorrelation: A Block Bootstrapping Approach

Xuan Chen
PhD candidate, Department of Agricultural and Resource Economics, North Carolina State University, Raleigh, NC 27695, e-mail: xchen8@ncsu.edu

Barry K. Goodwin
William Neal Reynolds Distinguished Professor, Department of Agricultural and Resource Economics, North Carolina State University, Raleigh, NC 27695

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Abstract

Our study focuses on modeling wildfire damage in the State of Florida. The approach is to evaluate wildfire risks in a spatio-temporal framework. A block bootstrapping method has been proposed to construct a statistical model accounting for explanatory variables while adjusting for spatial and temporal autocorrelation. Although the bootstrap (Efron 1979) method can handle independent observations well, the strong autocorrelation of wildfire risks brings about a major challenge. Motivated by bootstrapping overlapped blocks methods in an autoregressive time series scenario (Kunsch 1989) and block bootstrapping method of dependent data from a spatial map (Hall 1985), we have developed a method to bootstrap overlapping spatio-temporal blocks. By selecting an appropriate block size, the spatial-temporal correlation can be eliminated. With our saptio-temporal block bootstrapping approach, impacts of environmental factors on SPB outbreaks and implications of pine forest management are assessed. Almost all the explanatory variables, including climate factors, forest ecosystem and socio-economic conditions have been detected to have significant impacts. Consequently, our method offers a way to forecast the future burning risks, given the current influential information of a county.

Introduction

Wildfires cause huge losses for landowners every year and have recently become a major threat to the U.S. forest industry. An understanding of these risks is essential to efficient management of these risks through public and private solutions. There is an extensive literature evaluating this subject, focusing on both individual wildfire behavior(e.g. Butry 2009; Holmes et al. 2004)) and broadscale wildfire risks (e.g. Prestemon et al. 2002; Prestemon and Butry 2005). Research that addresses widespread, aggregate fire risks provided insightful suggestions for government wildfire management. Our research, built upon a comprehensive survey of county level wildfire loss records in Florida, is used to empirically evaluate wildfire risks and to develop a tool to forecast wildfire occurrences. This line of inquiry has important policy implications. We discuss implications within the context of wildfire risk management.

In the existing literature, to account for wildfires' spatio-temporal dependence, a variety of structural regression models were proposed. A convenient approach is to include temporal lags of the dependent variable and to average neighboring observations of the lagged dependent variable. One of the implications underlying such models, though, is that spatial transmissions do not occur simultaneously with fire occurrences. While a wildfire rarely lasts longer than a month, the assumption that spatial interaction happens across years may be questionable.

Compared with conventional methods that build spaio-temporal dependence into structural models, a block bootstrapping method has several advantages in correcting for spaio-temporal autocorrelation. The first benefit stems from the fact that the block bootstrapping method is convenient to implement. The second benefit stems from its flexibility with data. In our experiments, the estimation of parameters remained very robust when some observations were randomly deleted. In addition, predictions of the future wildfire risks in a county now only rely on that county's own prior information and therefore the presence of missing information of other spatial units is irrelevant.

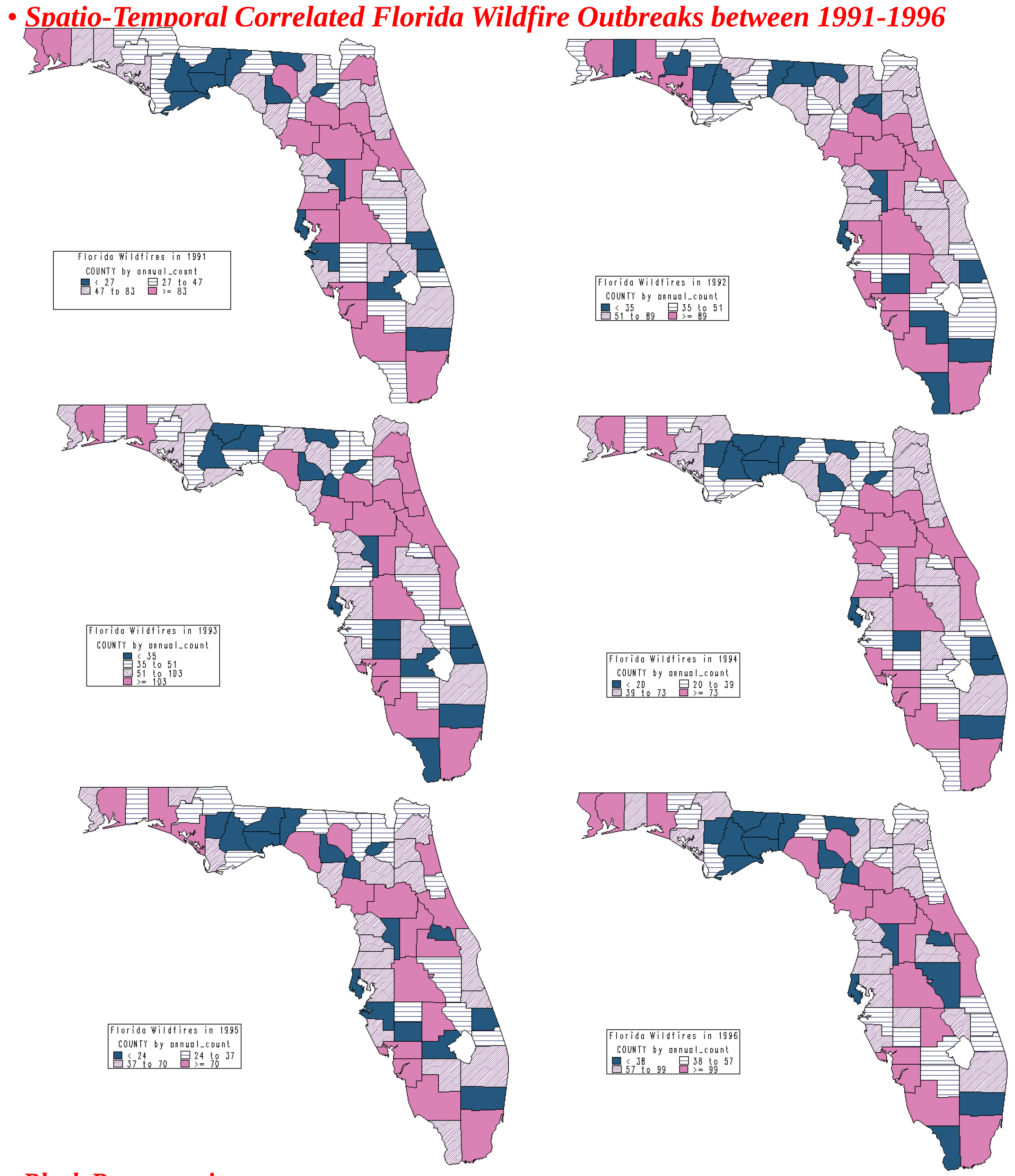
Methods

• ***Bootstrapping (Efron 1979)***

Suppose that $\hat{\theta}_n$ *is* an estimate of a parameter vector θ based on a sample $X = (x_1, x_2 \ldots x_n)$. An approximation to the statistical properties of $\hat{\theta}_n$ can be obtained by studying a sample of bootstrap estimators $\hat{\theta}(b)_m$, $b=1, 2, \ldots.B$, obtained by sampling m observations, with replacement, from X and re-computing $\hat{\theta}$ with each sample. After a total of B times, the desired sampling characteristic is computed from $\Theta = [\hat{\theta}(1)_m \ldots \hat{\theta}(B)_m]$

For example, if it were known that the estimator were consistent and if B were reasonably large, then one might approximate the asymptotic covariance matrix of the estimator $\text{Est.Asy.Var}\,[\hat{\theta}] = \frac{1}{B}\sum_{b=1}^{B}(\hat{\theta}(b)_m - \hat{\theta}_n)(\hat{\theta}(b)_m - \hat{\theta}_n)'$. Basic Assumptions: Independence

• ***Spatio-Temporal Correlated Florida Wildfire Outbreaks between 1991-1996***



• ***Block Bootstrapping***

Hall (1995) discussed techniques to deal with dependent data on a spatial map in the bootstrapping context. Motivated by this method, we derived a spatio-temporal block bootstrapping method in the hope to eliminate the spatio-temporal autocorrelation.

We divided all the county-year observations into a number of blocks. First of all, if an observation for the county *i* at the time *t*, is selected as the center of a block. Second, all the counties bordering county *i*'s centroid should be thought as spatial neighbors. Third, the observations of same county in consecutive time periods are deemed as temporal neighbors. Finally, the observation (*i*,*t*), along with all the records of its spatial neighbors and temporal neighbors forms a block. In this way, we grouped the space-time records into *n* overlapping blocks. Each iteration, we resampled the blocks, with replacement *m* times.

Estimation

• ***Dependent Variable: Logarithm of Wildfire***

Lagged Independent Variable	OLS Model	Conventional Spatio-temporal Model	Spatio-temporal Block Bootstrapping Method
Spatial Dependence		-0.0292 (0.0349)	
Temporal Dependence		0.2643*** (0.0264)	
Intercept	-4.4674*** (0.2875)	-3.6629*** (0.3189)	-4.6037*** (0.1278)
Forestland ratio	-3.5721*** (0.2802)	-2.6151*** (0.2946)	-3.4148 *** (0.1004)
Private share	1.4833*** (0.2392)	0.9049*** (0.2384)	1.2581*** (0.09003)
Longleaf /slash & loblolly /shortleaf	3.2207*** (0.3878)	2.9126*** (0.3939)	3.5071*** (0.1722)
Oak/pine & oak/hickory	-1.7279*** (0.3834)	-0.7750** (0.3789)	-1.4182*** (0.1750)
Oak/gum/cypress	2.0596*** (0.4157)	1.7687*** (0.4151	-1.41828*** (0.1750)
Daily average of HDD index (Coldness)	-0.3193*** (0.0532)	-0.3094*** (0.0540)	-0.3793*** (0.0225)
December SP12 index (Humidity)	-0.2757*** (0.0413)	-0.1121** (0.0448)	-0.2614 *** (0.0182)
Hurricane incidences	-0.1118 (0.2069)	-0.1649 (0.1988)	-0.1309 *** (0.0437)
Log(population density)	0.3627*** (0.0442)	0.2650*** (0.0449)	0.3801*** (0.02177)
Employment Ratio	-2.2862*** (0.4367)	-1.5802*** (0.4350)	-1.9498*** (0.15020)
R2	0.4091	0.4446	0.6086
	Autocorrelation Test		
Percentage of Years when Spatial Autocorrelation found in Residuals	24.00%	29.17%	12%
Percentage of Counties where Temporal Autocorrelation found in Residuals	5.97%	10.45%	8.96%

Note: Iteration=100. Single (*), double (**), and triple (***) denote significance at 0.10, 0.05, and 0.01 levels, respectively.

Conclusion

Our results suggest that all of the conditioning explanatory variables, except the hurricane frequency measure, have statistically significant impacts on wildfire risks. Climate factors, such as temperature and drought, affect wildfires in the expected ways. Both cold (HDD index) and humidity (SP12 index) appear to significantly reduce wildfire risks. At the same time, the significant impact of population density verifies that human intervention is an important causal element of wildfires. Regional factors related to the economic welfare of the population in a given county may also reflect other aspects of behavior. In particular, economic stresses may be related to deliberate acts of arson and other criminal activities. A high employment ratio could significantly mitigate wildfire risks, since employed persons have higher opportunity costs to commit criminal acts of arson.

Forest land characteristics affect wildfires through a number of ways. A high private ownership share of forest lands always implies a significantly higher wildfire risk. As rangers and forest police work actively on public forest lands, private lands are expected to be more vulnerable to wildfire threats. The group of longleaf/slash pine forest lands and loblolly/shortleaf pine forest lands appear to significantly enhance fire risks while the combination of oak/pine forest lands and oak/hickory forest lands significantly lessen wildfire risks. The oak/gum/cypress forest land group also appears to have significantly higher burning risks. This reflects the fact that most swamp fires can be easily spread in this type of ecosystem.

Most importantly, our proposed block bootstrapping method has outperformed both conventional models. Not only does the bootstrapping method produce significant estimates for all the parameters, but also it has substantially lessened spatial autocorrelation among residuals.