KSCE Journal of Civil Engineering (2015) 19(3):457-464

DOI 10.1007/s12205-013-1116-0

Coastal and Harbor Engineering

pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Spatial and Temporal Contours in Economic Losses from Natural Disasters: A Case Study of Florida

Hyun Kim*, Kyle M. Woosnam, and David W. Marcouiller*****

Received February 23, 2013/Revised January 17, 2014/Accepted March 26, 2014/Published Online October 3, 2014

Abstract

In this study, we addressed impacts of natural disasters on economic status in coastal and disaster-prone areas within the context of previous theoretical and empirical literature. Our spatio-temporal model accounted for nonlinear causality and spatial heterogeneity in assessment of unexpected disaster events employing a Matérn covariance structure, an empirical variogram, kriging, spatial regression, and spatial-temporal model. Empirically, we developed this model to estimate the natural disaster risk using county-level data in the U.S. State of Florida. Despite high prediction errors, empirical results suggest that both Atlantic and Gulf Coast counties experienced significant negative economic impacts of natural disasters.

Keywords: *natural disaster, stochastic process, spatio-temporal model*

1. Introduction

The damages and losses caused by unexpected disaster events (both natural and human-induced) have sudden and significant impacts on economic conditions and the environment (Alexander, 2000; Burton and Kates, 1964; Daniels *et al*., 2006; Drabek, 1989; Turner, 1976). In general economic terms, unexpected events may be viewed as a sudden loss of continuity in economic processes and as something that slows the pace of development. One of the critically important issues related to minimizing these losses is the temporal configuration for identifying economic conditions before and after the events (Alexander, 2000; Drabek, 1989). Prior research has focused mainly on identification of economic situations for a given study period using static and deterministic models (e.g., models constructed using input-output analysis and computable general equilibrium) (Ham *et al.*, 2005; Okuyama *et al.*, 2004).

However, previous studies of natural disasters effects (e.g., Alexander, 2000; Daniels *et al.*, 2006) tend not to accurately reflect the spatial-temporal characteristics of economic situations or social systems affected by unexpected disaster events. Furthermore, the results of previous research generally lack spatio-temporal changes even though the impacts of non-routine events have changed over time. Specifically, they generally do not consider non-linear phenomena, quality of uncertainty, spatial heterogeneity, randomness, unstable environmental characteristics, and stochastic processes. In order to overcome these issues, our contribution underscores the spatio-temporal characteristics and change brought about by unexpected events and deals with economies modified by theoretical and analytical frameworks or procedures.

In an attempt to estimate disaster damage to economies based on spatio-temporal statistical models, longitudinal data were collected on the economies and disaster losses at the county level during 20 years from 1990 through 2009 in the US State of Florida. Time series data was developed from a variety of databases including U.S. Census Bureau (USCB), National Ocean Economic Program Coastal Economy Data (NOEP), Spatial Hazard Events and Losses Database in U.S. (SHELDUS), National Hurricane Center (NHC), and the Beaches and Shores Center in Florida State University (BSC).

The counties in Florida are ideal for addressing the economic impacts of natural disasters due to the regularity of hurricanes during the study period (e.g., Hurricane Opal, 1995; Earl and George, 1998; Frances and Jeanne, 2004; Katrina, 2005). Economic data including unemployment rate and poverty levels used in this spatial-temporal modeling originates from USCB and NOEP in a similar fashion to previous research by Cutter *et al.* (2003) and Toya and Skidmore (2007). In addition, data on disaster damage including fatalities, injuries, property damage and crop damage at the county-level was obtained from the SHELDUS, BSC, and NHC databases. Whereas human damage refers to fatalities and injuries as a percentage of population in each county; physical damage indicates crop and property losses

*Ph.D. Candidate, Dept. of Urban and Regional Planning, University of Wisconsin-Madison, Wisconsin 53706, USA (Corresponding Author, E-mail: hkim525@wisc.edu)
**Associate Professor, Dept. of Recreation, Park and Tourism Sciences, Texas A&M University, College Station, Texas 77843, USA (E-mail: woosnam@tamu.edu)
***Professor, Dept. of Urban and Regional Planning, University of Wisconsin-Madison, Wisconsin 53706, USA (E-mail: dwmarcou@wisc.edu)

as a percentage of crops and property in each county in Florida.

With an integrative approach to social-ecological systems, our work rests on several research objectives. These involve outlining the analytical processes behind estimating economic impacts of natural disasters using spatio-temporal data using a case study region. Further, we estimate the risk of unexpected disaster events on county-level economic status during the last 20 years. Following this introduction, we present this spatio-temporal case in four subsequent sections. First, we summarize the extant knowledge to define economic loss from natural disaster events. Next, we develop our analytical model that incorporates both unique geographic space and time. The next section summarizes our empirical results. We conclude with a summary of our work and further research needs.

2. Economic Losses from Natural Disasters

Damage from natural disasters relates to the ability of an affected region/county to deal with the impact of natural hazards and withstand potential negative consequences while coping with the resulting damage in a timely manner (Cutter *et al.*, 2003; Mileti, 1991). Furthermore, impacts are the outcome of the interaction between exogenous factors determined by the incidence (i.e., frequency) and intensity (i.e., severity) of disasters and the ability of a country/region to deal with the impact of endogenous elements or factors (Sadowski and Sutter, 2005).

The association between the impacts of natural disasters and economies includes both broad and specific damage in accordance with spatial areas such as a region or country. Broad damage in regional areas is related to economic losses to diverse industrial sectors. Natural disaster damage involves economic loss to personal property and commercial and industrial businesses (Ewing *et al.*, 2009). As one would predict, greater losses from disasters lead to weaker economies than before the disaster occurred (Sadowski and Sutter, 2005).

Similarly, natural disaster exposure has been found to be negatively correlated with initial per capita gross domestic product (Kahn, 2005; Yang, 2008). In essence, richer nations experience fewer or weaker disaster results than those experienced by poorer nations (Kahn, 2005; Kellenberg and Mobarak, 2008). In the case of an equal quantity and intensity of disaster shocks, people in rich nations suffer fewer deaths from natural disasters than those in poor nations. As might be expected, hurricanes and accompanying disasters have had a negative impact on the labor market.

Based on the differences between economic losses and natural disaster damage, a conceptual framework has been developed to provide the theoretical basis and applications for a spatial-temporal statistical model. This framework illustrates the socio-economic impacts and consequences of natural disasters, particularly hurricanes in Florida. The natural disasters factor ($T+\alpha$, T means time and α, β, and γ indicate time order), as a part of the exogenous shocks, was examined to determine which factors contributed to the increase or decrease in disaster losses (Raddatz, 2007) in accordance with spatial configuration of existing area (T) before natural disasters (e.g., populated coastal area, developed areas). The disaster losses factor after a disaster ($T+\beta$) involves human losses (i.e., fatalities and injuries) and physical damage (i.e., property and crop damage). The disaster losses contribute to the increase or decrease in economic status before a natural disaster ($T+\gamma$). In the empirical evidence, the economic factor includes the unemployment rate and poverty rate as noted by previous studies (Cutter *et al.*, 2003; Ewing *et al.*, 2009).

3. Analytical Framework and Model Specification

Based on the theoretical basis, an analytical framework or procedure has been formulated as illustrated in Fig. 1. First, to estimate parameters and develop a variogram in spatial-temporal

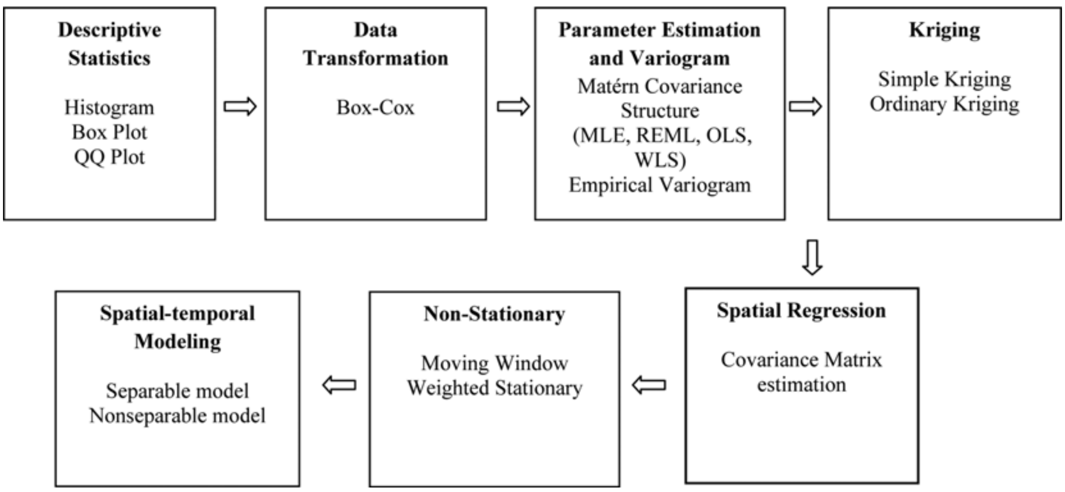

Fig. 1. Analytical Procedure

Note, MLE: Maximum Likelihood Estimation, OLS: Ordinary Least Square, WLS: Weighted Least Square, REML: Restricted Maximum Likelihood data, a covariance matrix, $M'(x)$ using a Matérn covariance structure was employed as in the following equation (Gneiting and Sasvari, 1999; Matérn, 1986; Schabenberger and Gotway, 2005; Stein, 2005):

$$M'(x) = \alpha\left(\frac{x}{\beta}\right)v \ \ M'_v\left(\frac{x}{\beta}\right) \tag{1}$$

There are four parameters that need to be estimated: α represents sill; β means range; v indicates smoothness, and ε is nugget effect. Furthermore, an empirical variogram to assess spatial autocorrelation was plotted. Based on the Matérn covariance matrix, the variogram parameters were estimated using maximum likelihood estimation (hereafter MLE), restricted maximum likelihood (hereafter REML) methods, ordinary least squares (hereafter OLS), and weighted least squares (hereafter WLS) (Christakos, 1992; Corbeil and Searle, 1976; Cressie, 1993; Gneiting and Sasvari, 1999; Matérn, 1986; Schabenberger and Gotway, 2005). Fitted lines based on the variogram plot were added to determine how well the lines fit the data.

To interpolate values in a random field at unobserved locations from neighboring locations, kriging was employed (Haining, 2003; Schabenberger and Gotway, 2005). Kriging, in a basic sense, is the best linear unbiased prediction. Based on the stochastic properties of the random fields, three different types exist (i.e., simple kriging, ordinary kriging, and universal kriging). Each type determines the linear constraint on the weights implied by the unbiasedness (Schabenberger and Gotway, 2005). The method for calibrating the weights depends on the type of kriging.

In accordance with basic assumption in kriging, simple kriging has a known constant mean. While ordinary kriging assumes an unknown constant mean, universal kriging employs a general linear model for mean. To apply simple kriging to this study, 63% of the locations (42 among 67 total counties in Florida) were selected in that property damage rates were originally available during study period. As a result, it was possible to compare selected data to the interpolated values. The property damage rate, $P(S_0)$ with the overall mean was subtracted from the data with a mean of zero as follows:

$$P(S_0) = C^{-1}cP \tag{2}$$

where, $P=[P(S_1)\ldots P(S_{42})]$, $C=Cov(P,P)$, $c=Cov[P,P(S_0)]$, $(S_1)\ldots(S_{42})$ means the number of selected study areas (i.e., counties affected by natural disasters). In an effort to fit a Matérn covariance and estimate the parameters such as sill (α), range (β), smoothness (v), and nugget (ε), the training data (i.e., 63% of the locations) was used in the model. The difference between the interpolated values and original ones at each location is employed to assess the kriging. When it comes to ordinary kriging, data for property damage rates was used without subtracting the overall mean. The linear specification, $L(s)$ is fitted to the training data with the remaining 37% of locations:

$$L(s) = \alpha_0 + \alpha_1 Latitude + \alpha_2 Longitude + \alpha_3 Poverty\ rate \tag{3}$$

where, α_0, α_1, α_2, and α_3 indicate coefficients for intercept, latitude, longitude, and poverty rate, respectively. Using the training data to estimate covariance parameters and fit those parameters to locations, the differences between interpolated values and original ones can be obtained.

With an emphasis on spatial characteristics, a spatial regression model of property damage rates, $P'(s)$ with covariates was employed with a fitting variogram as the following specification:

$$P'(s) = \gamma_0 + \gamma_1 Latitude + \gamma_2 Longitude + \gamma_3 Poverty\ rate(s) + \varepsilon(s) \tag{4}$$

where, $\varepsilon(s)$ is Gaussian random error, $\varepsilon(s) \sim N(0,\Sigma)$, where Σ is the covariance structure, γ_0, γ_1, γ_2, and γ_3 are coefficients for intercept, latitude, longitude, and poverty rate, respectively. By employing the Matérn covariance matrix estimation, we attempted to fit the covariance function of the regression residuals assumed as isotropic. The covariance function was fitted with different analytical methods, including MLE and REML.

Prior to spatial-temporal analysis, identifying whether or not the data is stationary should be taken into account for the minimization of biases. As employed in numerous research (Finkenstädt *et al.*, 2007; Haining, 2003; Harris *et al.*, 2010; Lloyd, 2010; Ma, 2005; Schabenberger and Gotway, 2005), both moving windows and weighted stationary approaches were used to detect whether or not the data was stationary in different locations. The moving window approach divides the whole random field into sub-regions and assumes that the processes in the sub-regions are stationary or isotropic. This approach contributes to fit a variogram in each sub-region. On the other hand, the weighted stationary approach, $P(s)$ is used in a non-stationary process as the following equation:

$$P(s) = \sum_{i=1} w_i(s) P_i(s) \tag{5}$$

$P_i(s)$ is uncorrelated, and has the same covariance function with different parameter. In line with time lag effects as well as distance in space, a spatial-temporal model can be divided into a separable and a non-separable (Iaco *et al.*, 2002; Ma, 2005).

4. Empirical Findings

4.1 Descriptive Statistics

On the basis of the analytical framework or procedure, an empirical approach was developed to provide an application for economic loss estimation as a result of hurricanes damage. Florida (comprised of 67 counties) as a study area is a long and narrow state and can be divided into eight regions. Table 1 shows descriptive statistics of the property damage rate in eight areas during the last 20 years. The rate indicates property damage (adjusted to 2009 US dollars) divided by each area (square miles). The total damage rate in 67 counties is about 288,200. The hurricanes ruined a great deal of property in the central east area resulting in a damage rate of 1,033,200, which is four times the total average. The central west and south west area also had huge property losses, with 658,095 and 635,137 damage rates,

Table 1. Descriptive Statistics on Property Losses

	Model 1		Model 2	
	Mean	SD	Mean	SD
Region I	67,559	202,677	608,033	-
Region II	1,033,228	776,297	1,291,536	598,915
Region III	658,094	854,761	658,094	854,761
Region IV	5,134	5,162	9,127	2,996
Region V	5	15	41	-
Region VI	401,861	730,187	401,861	730,187
Region VII	38,301	37,483	63,835	19,105
Region VIII	635,136	748,697	635,136	748,697
Number of observations	67		42	

Note: SD is standard deviation, Model 1 is property damage rate and Model 2 is damage rate without zero, Region I : central Florida, Region II: central east in Florida, Region III: central west in Florida, Region IV: north central in Florida, Region V: north east in Florida, Region VI: north west in Florida, Region VII: south east in Florida, Region VII: south west in Florida

respectively. Due to hurricanes coming from the Atlantic Ocean and making land fall on the eastern coast of Florida (crossing over to the Gulf of Mexico), the central east, central west, and south west areas had greater damage than other areas.

In light of spatial configuration, some counties were not affected by such hurricanes, and revealed no property damage at all. Therefore, we re-analyzed the data to exclude the non-damaged areas (see Model 2 in Table 1). There were 42 counties affected by hurricanes and the average damage rate was about 456,592. This result indicates a 1.5 times higher property damage rate over the other counties. Hurricanes were most destructive in the central east, resulting in a 1,291,536 damage rate. The central west and south west also had huge property losses, at 658,094 and 635,136, respectively. It is important to note that damage rates have not changed that much for the 67 counties in general or the 42 counties specifically. This finding indicates that whereas all the counties in the central west and southwest were affected by hurricanes, the central area, in particular Marion county, shows an increase in property damage rate.

In order to examine the data distribution, a histogram and box plot regarding property damage rates before and after transformation were addressed. Half of the data were within the 500,000 damage rate, with minimal outliers on the box plot. After removing the counties not affected by hurricanes, no outliers remained for the 42 counties in the box plot. The histogram did not look like a classic bell-shaped (i.e., symmetric histogram) with most of the frequency counts bunched in the middle. This shape indicated that the data used in this study did not follow a normal distribution. Further, to examine the normality of the data, a Q-Q plot was utilized and revealed property damage rates in all the counties (67 counties) and hurricane-affected counties (42 counties). None had a normal distribution and most fell far from the 45-degree line. The point pattern was curved with the slope increasing from left to right and was skewed to the right. To transform the data into a normal distribution, a Box-Cox method was conducted (Nelson and Granger, 1979; Spitzer, 1984; Velilla, 1993).

Table 2. Comparison of Variogram Estimation

	α	β	v	δ
MLE	0.089	26.297	2.999	0.044
OLS	0.413	1.000	2.999	0.000
WLS	0.524	25.956	1.546	0.000

Note: MLE: maximum likelihood estimation, OLS: ordinary least square, WLS: weighted least square

4.2 Variogram

As illustrated in Table 1, since the property damage rate value was quite large, the variable was scaled down by 1,000,000. An empirical variogram cloud and box plots showed a spatial dependency among variables and the transformed data were not isotropic. Based on the direction variogram, whether or not the data was geometrically anisotropic was taken into account (Ecker and Gelfand, 1999; Schabenberger and Gotway, 2005). Given the distance is above 6, covariance rapidly increases in 135 degrees and 45 degrees. On the other hand, if the distance is below 6, there is no similar pattern at all. Therefore, it is difficult to determine that the data is geometrically anisotropic.

In an effort to estimate the covariance parameter and maximize the likelihood, the nlm ( ) function in *R* statistical software was employed as suggested by Paciorek and Schervish (2006) and Jun and Stein (2007). The findings indicated a non-positive definite or infinite value. Given that the nlm ( ) function is to iterate new parameter values, the parameters of the Matérn covariance function can be too extreme. The covariance cannot be positive definite and produce some infinite values. Accordingly, the optim ( ) function in *R* was used to search for an appropriate initial point (Cressie, 1993; Ribeiro and Diggle, 2001). In line with the optim ( ) function, the parameters were transformed in an effort to determine the most efficient method among MLE, OLS, and WLS (see Table 2). Since MLE shows better parameter estimation rather than WLS and OLS, it was employed to estimate kriging.

4.3 Kriging

As mentioned earlier, due to the estimated covariance structure and the zero-mean process, we employed a simple kriging method. As such, the data used in this study was divided into training data and predicted data. While the training data means the observed data with latitude ranging from 27 and 30.5 degree (i.e., 27 data points), predicted data indicates the other 15 data points (except for 27 data points). Furthermore, whereas training data was used to estimate the parameter in the Matérn covariance function, predicted data was employed to predict the value at the prediction data points.

In the context of spatial configuration, the simple kriging shows that there is a bigger difference for the southwest counties (e.g., Escambia, Santa Rosa, and Okaloosa) near the Gulf of

Table 3. Spatial Regression Results

	Parameter	SD	t value
Intercept	-2.797	5.299	-0.528
Longitude	-0.161*	0.092	-1.743
Latitude	-0.349**	0.122	-2.847
Poverty rate	-3.19e-06*	1.68e-06	-1.898

Note: * : significant at 10%, **: significant at 5%

Mexico. In addition, Palm Beach, Broward, and Miami-Dade counties which border the Atlantic Ocean show higher prediction error than other counties. Similarly, ordinary kriging was conducted based on REML. Southwest counties (e.g., Palm Beach, Broward, and Miami-Dade) in the study area, show higher prediction errors than other counties.

4.4 Spatial Regression and Non-stationary

On the ground of the kriging estimation, scatter plots of property damage rates versus various covariates were checked in accordance with longitude, latitude, and poverty rate. From this plot, we conclude that it seems reasonable to fit longitude, latitude and poverty rate in the mean model. As shown in Table 3, the estimated value with the coefficients of longitude, latitude, and poverty rate indicates significance at the 0.05 and 0.01 alpha levels. The spatial regression of property damage (P) equation can be addressed as follows:

$$P = -2.797[5.299] - 0.349[0.092]Latitude - 0.16[0.122]Longitude + 3.19e{-06}[1.68e-06]Poverty\ rate \tag{6}$$

The residuals are approximately normal. In an attempt to estimate Matérn covariance parameters using MLE and REML, the normalized residuals are used. The positive association between poverty rate and property damage rate is supported by the works of Ewing *et al.* (2009) and Sadowski and Sutter (2005).

Given the data have a longitudinal property, it is essential to identify whether or not the data are stationary in order to decrease bias in the process of analysis. The first method for non-stationary covariance model is moving window (Finkenstädt *et al.*, 2007; Lloyd, 2010; Ma, 2005). Our domain in this study was divided into nine sub-domains: groups A, B, C, and D (non-affected counties from hurricanes) and groups E, F, G, H, and I (hurricane-affected counties). The basic assumptions for the data using the moving window method indicate that each region has a Matérn covariance model structure and the data from different regions are uncorrelated.

As shown in Table 4, the estimated parameters are quite different from each other. Since the data have clustering points, property damage rates from hurricanes are quite different in accordance with location. This finding would be clearer on the variogram plot (see Fig. 2). However, there are problems that the estimated α is too small (almost 0) and v is close to the boundary value. The result was similar to the old data with prior to transformation, scaling, and having few data points (see Table 4). Since v is quite close to the boundary value, the variogram was shown as flat. The finding indicates that the data used in this study is non-stationary.

4.5 Spatial-Temporal Model

Natural disasters do not happen every year and result in different impacts each time they occur. Even though certain counties or regions have been damaged in distinct years, the possibility to predict damage in subsequent years exists. Among the study periods and areas, two consecutive years (2004 to 2005) with severe two hurricanes (i.e., Frances and Jeanne) and 35 counties affected hurricane were selected.

Both space and time with a separable influence on the data was assumed in the separable exponential model (O'connell and Wolfinger, 1997). Based on spatial distance (d) and time lag (T), the result of MLE estimators and equations, $S(T, d)$ is as follows:

$$S(T, d) = \alpha \exp\left(-\frac{T}{\delta_1}\right) exp\left(-\frac{d}{\delta_2}\right), \tag{7}$$

$\alpha = 0.719$ [0.398], $\delta_1 = 0.050$ [22.548], $\delta_2 = 222.170$ [133.926]

In this equation, both time and space distance with an exponential covariance were assumed. Given the model is difficult to estimate, another separable model (e.g., separable Matérn model) can be employed.

Table 4. MLE and Moving Window Estimation in Disaster-affected Areas

		α	β	v	δ	Mean	Nugget	Function value
Group E	MLE	5.149e-13	13.650	2.999	2.557e-12	-4.415e-06		-518.368
	MW	775.768	3.574	3.000		9.075e-119	87.467	51.242
Group F	MLE	4.887e-13	10.020	3.000	2.595e-12	-5.927e-06		-542.501
	MW	606.112	1.828	3.000		3.887e-05	68.018	41.787
Group G	MLE	1.263e-12	0.031	3.000	2.074e-12	-5.021e-06		-580.413
	MW	85.801	11.137	3.000		1.110e-16	94.038	30.117
Group H	MLE	5.197e-11	4.366e+08	0.135	6.156e-12	-5.625e-06		-781.610
	MW	6.768e-11	2.815e+15	2.732		2.123e-02	0.854	-12.833
Group I	MLE	3.943e-12	5.297e+01	0.106	4.467e-27	-8.09e-06		-225.792
	MW	79.635	14.885	3.000		3.3501e-09	11.851	20.997

Note: MLE: maximum likelihood estimation, MW : moving window

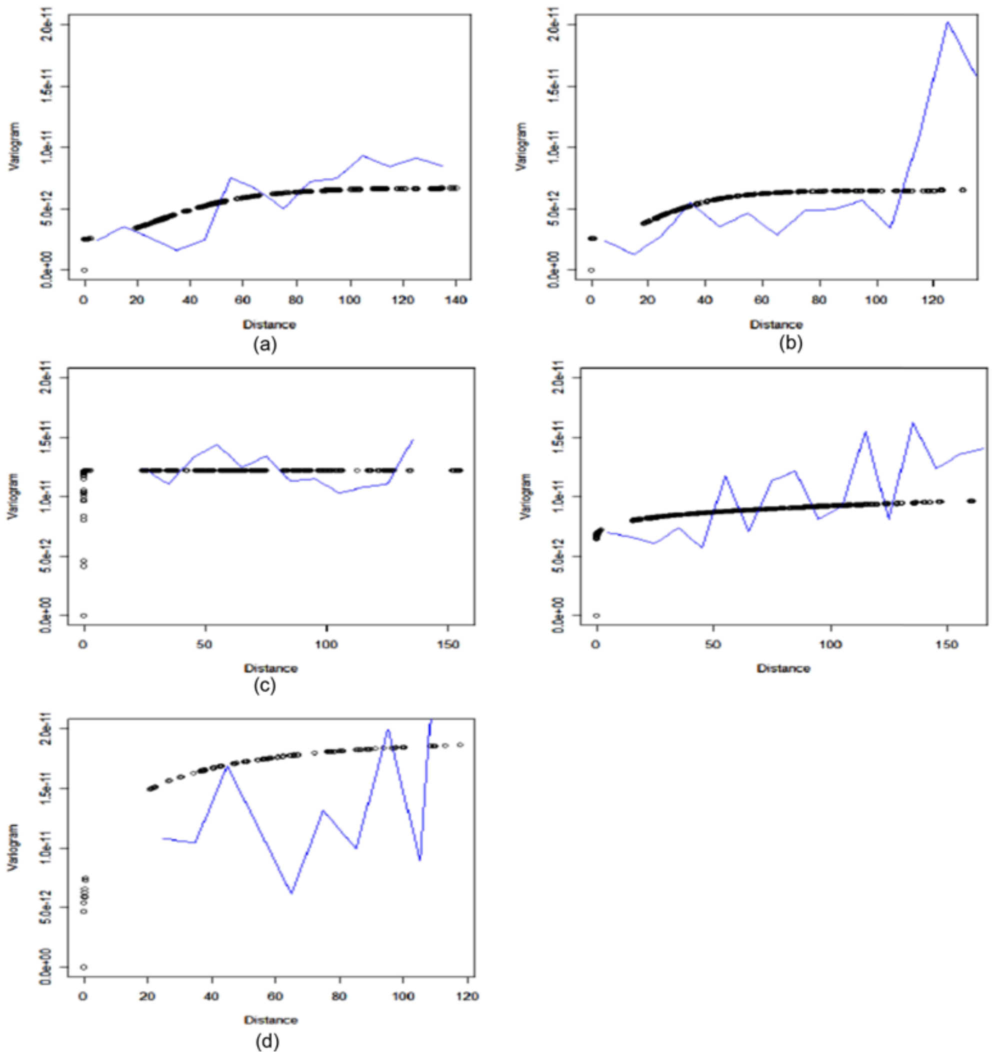

Fig. 2. Empirical vs. Estimated Variogram of: (a) Group E, (b) Group F, (c) Group G, (d) Group H, (e) Group I

Similar to the separable exponential model, both space and time with a separable influence on the data were assumed in the separable Matérn model. In general, Matérn covariance structure is more flexible than this model (Finkenstädt *et al.*, 2007; Haas, 2002). Based on the covariance structure, the result of MLE estimators and specification is as follows:

$$S(T,d) = \alpha\left(\frac{|d|}{\delta_1}\right)^{v1} K_{v1}\left(\frac{|d|}{\delta_1}\right)\left(\frac{|T|}{\delta_2}\right)^{v2} K_{v2}\left(\frac{|T|}{\delta_2}\right) + nugget \qquad (8)$$

$\alpha = 0.706$ [0.349], $\delta_1 = 8.820$ [2.060], $v_1 = 0.895$ [0.293],
$\delta_2 = 0.044$ [4.770],
$v_2 = 2.590$ [0.004], $nugget = 2.360$ [0.870]

Since spatial-temporal data cannot be separated into distinct time and space, it is crucial to take into consideration a more comprehensive and flexible model. In this case, non-separable models can be used to address this restriction (Finkenstädt *et al.*, 2007; Haas, 2002). In terms of the covariance structure used in the non-separable exponential model, the MLE estimators and quation $S(T,d)$ are as follows:

$$S(T,d) = \frac{\alpha}{aT^2+1} exp \frac{-sd^2}{aT^2+1} \qquad (9)$$

$\alpha = 0.529$ [0.089], $\alpha = 17.659$ [58.703], s = 0.891

On the other hand, based on the covariance structure used in the non-separable Matérn model, the finding of MLE equation $S(T,d)$ and estimators is as follows:

$$S(T,d) = \alpha|D|vKv(D) + nugget \qquad (10)$$

where, $D = \sqrt{\left(\frac{d}{\delta_1}\right)^2 + \left(\frac{T}{\delta_2}\right)^2}$, α = 6.72e-2 [0.021], δ_1 = 28.800 [4.080], $\delta_2 = 0.013$ [0.001], v = 3 [1.180], nugget = 0.002 [0.007]

In accordance with two different time points, fitted lines within spatial-temporal models versus the empirical variogram were estimated. Based on the above statistical finding, the separable model was more easily conducted than the non-separable model. That is why the data used in this study is annual and the time effect points are independent.

5. Conclusions

In this study we demonstrated the risk and estimated the impact of natural disasters on county-level economic status in coastal and disaster-prone areas using spatio-temporal statistical models. These models were developed to account for nonlinear causality and spatial heterogeneity to assess chance of unexpected events. A variety of analytical procedures to estimate the natural disaster risk in this study area were employed. This work is different from prior research in that it encompasses a conceptual framework and an analytical procedure including a Matérn covariance structure, an empirical variogram, kriging, spatial regression based on covariance estimation, and a spatial-temporal model. In terms of the empirical variogram along with the Matérn covariance structure, whereas the plot of the variogram looked reasonable and was a best fit using the MLE, the variogram parameters using the OLS were not reasonable. Similar to previous studies (e.g., Cutter and Finch, 2008), the reason for this result is that the data (i.e., property damage rate, poverty rate) has a non-stationary and a spatial autocorrelation in accordance with the spatial domain.

The analytical procedure for addressing diverse risk estimation modeling was implemented and tested using spatial-temporal characteristics. It found appropriate modeling for risk estimation after unexpected events considering the spatial-temporal variation in relation to economic aspects. The challenge of implementation was integrating the different components (e.g., hurricane wind speed, track, intensity, pressure) that have been developed by other fields (e.g., geophysics, meteorology, ecology).

Certainly, limitations of this work lead to further research to improve the robustness of our results. Statistical procedures are likely not efficient with large data sets developed to address fatality and injury from natural disasters at the sub-county level. In order to overcome this drawback, it is necessary to employ various computing systems (e.g., GeoDa, Geographically Weighted Regression, Remote sensing, Geographical Information System), primarily have been applied in environmental assessment studies (Kumar and Pandey, 2013). Furthermore, in an effort to search out initial settings or damage to the property, this research needs to adopt a method to simulate natural disasters such as floods as has been done in previous studies (Sohn *et al*., 2003). Despite these limitations, this work addresses an overview of natural disaster risk estimation from spatial-temporal statistical perspectives in hazard-prone areas. Such a theoretical and practical approach can help remove the limitations of previous related studies (i.e., consideration of nonlinear causality regarding unexpected events). Furthermore, this study can suggest fundamental applications useful in risk analysis in relation to spatial and temporal situations.

References

Alexander, D. E. (2000). *Confronting catastrophe: New perspectives on natural disasters*, Oxford University Press.

Burton, I. and Kates, R. W. (1964). "The perception of natural hazards in resource management." *Natural Resources Journal*, Vol. 3, No. 3, pp. 412-441.

Christakos, G. (1992). *Random field models in earth sciences*, Academic Press, San Diego.

Corbeil, R. and Searle, S. (1976). "Restricted Maximum Likelihood (REML) estimation of variance components in the mixed model." *Technometrics*, Vol. 18, No. 1, pp. 31-38.

Cressie, N. A. C. (1993). *Statistics for spatial data,* 2nd Ed., John Wiley, New York.

Cutter, S. L., Boruff, B. J., and Shirley, W. L. (2003). "Social vulnerability to environmental hazards." *Social Science Quarterly*, Vol. 84, No. 2, pp. 242-261.

Cutter, S. L. and Finch, C. (2008). "Temporal and spatial changes in social vulnerability to natural hazards." *Proceedings of the National Academy of Science of the United States of America*, Vol. 105, No. 7, pp. 2301-2306.

Daniels, R. J., Kettl, D. F., and Kunreuther, H. (2006). *On risk and disaster: Lessons from Hurricane Katrina*, University of Pennsylvania Press, Philadelphia, U.S.

Drabek, T. E. (1989). "Disasters as nonroutine social problems." *International Journal of Mass Emergencies and Disasters*, Vol. 7, No. 3, pp. 253-264.

Ecker, M. D. and Gelfand, A. E. (1999). "Bayesian modeling and inference for geometrically anisotropic spatial data." *Mathematical Geology*, Vol. 31, No. 1, pp. 67-83.

Ewing, B. T., Kruse, J. B., and Thompson, M. A. (2009). "Twister! Employment responses to the 3 May 1999 Oklahoma City tornado." *Applied Economics*, Vol. 41, No. 6, pp. 691-702.

Finkenstädt, B., Held, L., and Isham, V. (2007). *Statistical methods for spatio-temporal systems*, Chapman & Hall/CRC.

Gneiting, T. and Sasvari, Z. (1999). "The characterization problem for isotropic covariance functions." *Mathematical Geology*, Vol. 31, No. 1, pp. 105-111.

Haas, T. C. (2002). "New systems for modeling, estimating, and predicting a multivariate spatio-temporal process." *Environmetrics*, Vol. 13, No. 4, pp. 311-332.

Haining, R. P. (2003). *Spatial data analysis: Theory and practice*, Cambridge University Press.

Ham, H., Kim, T. J., and Boyce, D. E. (2005). "Assessment of economic impacts from unexpected events using an interregional commodity flow and multimodal transportation network model." *Transportation Research A*, Vol. 39, No. 10, pp. 849-860.

Harris, P., Charlton, M., and Fotheringham, A. S. (2010). "Moving window kriging with geographically weighted variograms." *Stochastic Environmental Research Risk Assessment*, Vol. 24, No. 8, pp. 1193-1209.

Iaco, S. D., Myers, D. E., and Posa, D. (2002). "Nonseparable space-time covariance models: some parametric families." *Mathematical Geology*, Vol. 34, No. 1, pp. 23-42.

Jun, M. and Stein, M. L. (2007). "An approach to producing space-time covariance functions on spheres." *Technometrics*, Vol. 49, No. 4, pp. 468-479.

Kahn, M. E. (2005). "The death toll from disasters: The role of income, geography and institution." *The Review of Economics and Statistics*, Vol. 87, No. 2, pp. 271-284.

Kellenberg, D. K. and Mobarak, A. M. (2008). "Does rising income increase or decrease damage risk from natural disasters?." *Journal of Urban Economics*, Vol. 63, No. 3, pp.778-802.

Kumar, A. and Pandey, A. C. (2013). "Spatio-temporal assessment of urban environmental conditions in Ranchi Township, India using remote sensing and geographical information system techniques." *International Journal of Urban Sciences*, Vol. 17, No. 1, pp. 117-141.

Lloyd, C. D. (2010). "Nonstationary models for exploring and mapping monthly precipitation in the United Kingdom." *International Journal of Climatology*, Vol. 30, No. 3, pp. 390-405.

Ma, C. (2005). "Spatio-temporal variograms and covariance models." *Advances in Applied Probability*, Vol. 37, No. 3, pp. 706-725.

Matérn, B. (1986). *Spatial variation 2nd ed.: Lecture notes in statistics 36 and Ed.*, Springer, Berlin.

Mileti, D. S. (1991). *Disasters by design: A reassessment of natural hazards in the United States*, Joseph Henry Press, Washington, D.C.

Nelson, H. L. and Granger, C. W. J. (1979). "Experience with using the box-cox transformation when forecasting economic time series." *Journal of Econometrics*, Vol. 10, No. 1, pp. 57-69.

O'connell, M. and Wolfinger, R. D. (1997). "Spatial regression models, response surface, and process optimization." *Journal of Computational and Graphical Statistics*, Vol. 6, No. 2, pp. 224-241.

Okuyama, Y., Hewings, G. J. D., and Sonis, M. (2004). "Measuring economic impacts of disasters: Interregional input-output analysis using sequential interindustry model. In Okuyama, Y., Chang, S.E. (eds)." *Modeling spatial and economic impacts of disasters*, Springer, pp. 77-101.

Paciorek, C. J. and Schervish, M. J. (2006). "Spatial modeling using a new class of nonstationary covariance functions." *Environmetrics*, Vol. 17, No. 5, pp. 483-526.

Raddatz, C. (2007). "Are external shocks responsible for the instability of output in low-income countries?." *Journal of Development Economics*, Vol. 84, No. 1, pp. 155-187.

Ribeiro, P. J. and Diggle, P. J. (2001) "GeoR: A package for geostatistical analysis." *R News*, Vol. 1, No. 2, pp. 15-18.

Sadowski, N. C. and Sutter, D. (2005). "Hurricane fatalities and hurricane damages: Are safer hurricanes more damaging?." *Southern Economic Journal*, Vol. 72, No. 2, pp. 422-432.

Schabenberger, O. and Gotway, C. A. (2005). *Statistical methods for spatial data analysis,* CRC press.

Sohn, J., Kim, T. J., and Hewings, G. J. D., Lee, J. S., and Jang, S. G. (2003). "Retrofit priority of transport network links under an earthquake." *ASCE Journal of Urban Planning and Development*, Vol. 129, No. 4, pp. 195-210.

Spitzer, J. J. (1984). "Variance estimates in models with the box-cox transformation: Implication for estimation and hypothesis testing." *The Review of Economics and Statistics*, Vol. 66, No. 4, pp. 645-652.

Stein, M. L. (2005). "Space-time covariance functions." *Journal of the American Statistical Association*, Vol. 100, No. 469, pp. 310-321.

Toya, H. and Skidmore, M. (2007). "Economic development and the impacts of natural disasters." *Economics Letters*, Vol. 94, No. 1, pp. 20-25.

Turner, B. A. (1976). "The development of disasters: A sequence model for the analysis of the origin of disasters." *Sociological Review*, Vol. 24, No. 4, pp. 753-774.

Velilla, S. (1993). "A note on the multivariate box-cox transformation to normality." *Statistics & Probability Letters*, Vol. 17, No. 4, pp. 259-263.

Yang, D. (2008). "Coping with disaster: The impact of hurricanes on international financial flows." *Journal of Economic Analysis and Policy*, Vol. 8, No. 1, pp. 1-14.