An Experiment to Model Spatial Diffusion Process with Nearest Neighbor Analysis and Regression Estimation

Jay Lee, Kent State University, Kent, OH, USA

Jinn-Guey Lay, National Taiwan University, Taipei, Taiwan

Wei Chien Benny Chin, National Taiwan University, Taipei, Taiwan

Yu-Lin Chi, National Taiwan University, Taipei, Taiwan

Ya-Hui Hsueh, National Taichung University of Education, Taichung, Taiwan

ABSTRACT

Spatial diffusion processes can be seen in many geographic phenomena that spread or migrate across space and over time. Studies of these processes were mostly done with verbal description until Hägerstrand (1966) started to approach it with quantitative models. A variety of attempts were made to continue this effort, but only with various degrees of success. Recognizing the critical role that distances between geographic objects or events play in a spatial diffusion process, we experimented with a new approach that uses these distances to detect and distinguish different types of spatial diffusion processes. Our approach is a two-step process that first calculates nearest neighbor ratios in a point process at each time step and then applies regression curve estimation to observe how these ratios change over time. We first report the results from applying this method to three spatio-temporal data sets which show the feasibility of our approach. We then report results of randomly simulated spatial diffusion processes to see if our approach is effective for the purpose of distinguishing different types of spatial diffusion processes. With only extreme cases as exceptions, our experiment found that using estimated regression curves of nearest neighbor ratios over time is usable in classifying spatial diffusion processes to either contagious/expansion or hierarchical/relocation diffusion processes.

Keywords: *Estimated Regression Curves, Nearest Neighbor Ratio, Regression Curve Estimation, Spatial Diffusion, Spatio-Temporal Data Sets*

DOI: 10.4018/ijagr.2014010101

INTRODUCTION

Spread of people, goods, information, or ideas can sometimes be more complex than what a simple wave-like diffusion model can describe. This is because the way such things are transported or transmitted is no longer confined to a localized geography or through a limited network of contacts. For example, a contagious influenza spreading in a place may become a complex diffusion process if virus carriers were dispersed over highway networks to faraway places. Such influenza may spread beyond a locality and even become international. Consequently, studies of spatial diffusion processes need to become more sophisticated and specialized than traditional approaches of fitting an infected population into a one-dimensional S-shape diffusion curve.

Rogers (1983) describes and discusses past efforts in modeling spatial diffusion processes that extend the one-dimensional S-shape diffusion curves by adding spatial terms into the diffusion models. Doing so required complex modifications of the S-shape models to approximate the diffusion processes. This makes the analysis of spatial diffusion processes difficult to understand. Furthermore, it also makes the resulting models difficult to apply to real world problems.

Given a geographic phenomenon that is spreading over space and time, let it be represented by a set of points where each point is defined by a pair of coordinates that gives its spatial attribute and a time stamp that gives its temporal attribute. First, we argue that the nearest neighbor distances at each stage of a spatial process over time are important in characterizing the spatial diffusion processes. Second, we suggest that the way nearest neighbor distances change at each diffusion stage is critical to the form of the spatial diffusion process.

Based on these two concepts, we describe our experiment that uses the nearest neighbor ratios and then regression curve estimation to model spatial diffusion processes so that main characteristics of diffusion processes can be detected and distinguished. We applied these methods to three spatio-temporal data sets. The results suggest that the methods discussed here provide a feasible way to quantitatively model and distinguish spatial diffusion processes. To validate the effectiveness of this approach, we tested it against randomly simulated spatial diffusion processes. The results of this experiment confirm our suggestion that nearest neighbor distances do play a critical role in the spatial structure of diffusion processes.

SPATIAL DIFFUSION PROCESSES

The most notable early effort in quantitative modeling of spatial diffusion was Hägerstrand (1966). He developed stochastic models using statistical techniques to simulate how a spatial diffusion process progresses over time. Using a mean information field (MIF), which is a matrix with cell values representing the likelihoods that cells may receive diffusing phenomenon from source cells, Hägerstrand (1967) illustrates how the spread of a geographic phenomenon can be modeled quantitatively by moving an MIF through source cells in the diffusing pattern and how other cells would be affected in subsequent steps. Essentially, a spatial diffusion process is decomposed into matrix cells that represent locations and an MIF that represents how cells are related.

Efforts of quantitative modeling of spatial diffusion processes since Hägerstrand had taken many forms, such as attempts with spatial interaction models, expansion methods and others. These were first reviewed by Brown (1968). Gregory and Urry (1985) provide a critique to Hägerstrand's models, noting that such models lack the ability to deal with spatial diffusion over intangible media such as social networks and the models' inability to deal with conflicts and resistance that may exist in the networks. Following this, Morrill, Gaile, and Thrall (1988) reviewed and discussed quantitative models of spatial diffusion processes by categorizing them as stochastic models or deterministic models.

A stochastic model is one in which the elements include probability. This means that an observed spatial pattern of diffusion phenomena may be the result of forces that have a random component. Alternatively, a deterministic model does not allow for chance. With a deterministic model, the way a geographic phenomenon diffuses is according to certain fixed forms in deterministic models. Several spatial diffusion models were discussed in Morrill, Gaile, and Thrall (1988) that include mathematical variants of the Hägerstrand's model (Pederson 1970; Berry, 1972; Webber, 1972), epidemiology model (Kendall, 1965), and spatial-temporal models (Casetti & Semple, 1969; Cliff & Ord, 1975; Haining, 1983).

A common trait in the aforementioned efforts is that they are mostly originating from simple linear diffusion models by adding spatial components to modify them. While some degree of success was achieved by these models, few were able to fully integrate spatial components in the modeling efforts. In the last two decades, there have been some attempts in incorporating spatial statistics to better detect and distinguish spatial diffusion processes.

Lam et al. (1996) used spatial autocorrelation calculated from temporal sequences of spatial patterns of AIDS in the Northeastern US, California, Florida and Louisiana to construct a spatial correlogram. The spatial correlogram is a curve with distance intervals as the horizontal axis and the spatial autocorrelation coefficients as the vertical axis. When spatial autocorrelation calculated from spatial distribution of AIDS decreases gently over time, the spatial diffusion processes that these coefficient values represent are said to be contagious. If the correlogram shows a V-shape curve with first a decreasing trend then an upward change, the spatial diffusion pattern is said to have been hierarchical (Lam et al., 1996, pp. 97-101).

Using localized spatial autocorrelation coefficients, Cohen and Tita (1999) and Tita and Cohen (2004) suggest a method for detecting a spatial diffusion process to be expansion, relocation, or hierarchical. With local indicators of spatial association, or known as LISA (Anselin, 1995), it was proposed that an expansion diffusion pattern of homicides could be observed when neighborhoods show changes from not being in spatial clusters of high homicides areas to being in such clusters over time. Whether a neighborhood falls inside any spatial cluster is measured by LISA. In very similar way, Schutte and Weidman (2011) examined the diffusion patterns of violence in civil wars.

Also using nearest neighbor ratios as we suggest in this article, Rogerson and Sun (2001) proposed a combination of nearest neighbor ratios and cumulative sum methods to detect changes in spatial patterns when new locations were added to a point pattern. This approach was discussed with an application to crime analysis which had already seen much use of nearest neighbor analysis because of its simplicity. Although the objective of their paper is not to distinguish spatial diffusion processes, the observation of how nearest neighbor ratios change over time is similar to the conceptual framework we describe here.

Besides adding spatial terms to classic statistics and using them to help detect and distinguish contagious and hierarchical diffusion processes, Allaway et al. (1994, 2003) added spatial and temporal lag as variables in event history analysis to describe contagious diffusion processes for how retail market areas evolved over time. Knoke (1982) applied event history analysis by incorporating the population size and spatial lag to illustrate the spread of local governing policies as hierarchical and expansion diffusion processes. Similar approaches can be seen in studies in racial riots (Myers 1997, 2010), diffusion of union formation (Hedström 1994) and formation of political parties (Hedstrom et al., 2000), same-sex marriage bans (Halder-Markel, 2001), spread of changes in income tax policies (Aidt & Jensen, 2009), and ethnic violence (Braun & Koopmans, 2010).

As a geographic phenomenon spreads or migrates spatially and temporally, a spatial pattern can be observed at each time or temporal stage. A spatial process is formed by linking up these spatial patterns temporally. As a point pattern receives additional points, the dynamics of how nearest neighbor distances change defines the spatial structure of the diffusion processes. In other words, distance between sources (first points) and adopters (added points) in a spatial pattern influences the number and rate of spatial diffusion processes. Capturing the role nearest neighbor distances play in a spatial diffusion process enables spatial diffusion processes to be distinguished.

We suggest that nearest neighbor ratios be used to measure how the nearest neighbor distances change in a spatial diffusion process over time. The average nearest neighbor distances measured for different time periods describe the form and structure of the point pattern's spatial diffusion process. We suggest that we can then use regression curve estimation to mathematically differentiate spatial diffusion processes.

In the following sections, we first report the initial but encouraging results of applying three spatio-temporal datasets. We then use simulated spatial diffusion processes to validate the applicability of the methods.

METHODS

Classic Spatial Diffusion Patterns

Spatial diffusion processes have been classified into a number of classic schemes: contagious, expansion, hierarchical, and relocation diffusion processes (Brown, 1968; Gould, 1969, 1975; Ord, 1981; Brown, 1981). Expansion diffusion processes and contagious diffusion processes are sometimes grouped together as Gould (1969) suggested. This may be due to the very similar nature of how these two processes progress. Furthermore, relocation and hierarchical diffusion processes are in fact similar in that they both contain a distance-jumping element in the processes, except that hierarchical processes tend to have pre-defined structures of where these jumps are. Essentially, the four classic spatial diffusion processes are often grouped into two schemes: contagious/expansion and hierarchical/relocation processes as suggested in Saint-Julien (2007).

It should be noted that spatial diffusion process in reality may have more than one source that begins the diffusion processes and may be followed by a mix of all classic spatial diffusion processes. As the first step, our experiment aims at testing the feasibility of our approach to detect and distinguish different spatial diffusion processes between the two aforementioned schemes. We hope to build on this understanding with future development for additional ways that can be effective when modeling complex mixes of spatial diffusion processes.

Nearest Neighbor Analysis

Nearest neighbor analysis is a well-established method for analyzing spatial patterns of geographic phenomena. Discussion and usage of this method can be found in Lee and Wong (2001). In general, a nearest neighbor ratio, or R, is calculated by taking the average of nearest neighbor distances in a point pattern and dividing it with a theoretically derived such average distance given the same number of points is randomly distributed in the same area.

The value of R ranges from 0 for a totally clustered point pattern, to 1 for a spatially random point pattern and to approximately 2.15 for a regularly distributed point pattern (Rossbacher, 1986). A Z-score can be calculated for each R to test if the point pattern is significantly different from a spatially random one. It should be noted that correction factors can be applied to account for the boundary effect when needed (Donnelly, 1978). In addition, extensions of this simple nearest neighbor analysis to K-nearest neighbor analysis can be easily found in most GIS software. Finally, it should be noted that nearest neighbor ratios account for only locations of the points, not any attribute values associated with the points.

For the purpose of modeling spatial diffusion processes, a nearest neighbor ratio is calculated after each additional point is added to the point set over time. With the nearest neighbor ratios calculated over time, they can be plotted against time steps to describe the unique characteristics of that spatial diffusion process. This curve of nearest neighbor ratios over time can be fitted with a regression curve mathematically.

Regression Curve Estimation

When the distribution of data points does not form a linear pattern, regression curve estimation is a widely used method for modeling sequential changes of numeric values (Härdle 1990). Various implementations of this method are available in most statistical software, such as SAS or SPSS. Essentially, a series of paired values are plotted in a chart with one variable as the X-axis and the other as the Y-axis. The distribution of paired values in the chart is fitted with a set of mathematically constructed curves to find one that best approximates the distribution. The best fit, often called the best goodness-of-fit, is determined by the highest coefficient of determination, or R^2, (Glantz & Slinker 1990). Table 1 lists 11 models that most statistical packages include for regression curve estimation.

In the next section, we discuss the outcome of estimating regression curves for nearest neighbor ratios from three spatio-temporal data sets to empirically assess the feasibility of this approach for modeling spatial diffusion processes. The locations of the data points in these three example data sets are defined by their latitude and longitude coordinates without any other attribute values associated with them.

EMPIRICAL SPACE-TIME DATA AND MODELING

Three sets of space-time data were used to test the method outlines above. The first data set contains all daily reported dengue fever cases in Kaoshiung City in south Taiwan from 2003 to 2008. The home addresses of reported dengue fever cases were geocoded to latitude/longitude coordinates. Figure 1a provides a reference for the location of Kaoshiung City in Taiwan. All reported cases have time stamps which enable the analysis of how those cases spread spatially over time. Since dengue fever is a contagious disease, we expect its spatial diffusion processes to be closely in line with contagious or expansion diffusion processes.

The second data set is the locations of mushroom farms in Xinshe, a mountainous village in central Taiwan. A total of 176 mushroom farms were surveyed with GPS to record their latitude and longitude coordinates. Figure 1b provides a reference for the location of Xinshe Village. In Xinshe, the success of initial mushroom farms was observed by nearby farmers which prompted followers to convert their rice fields to mushroom farms with the hope of duplicating their success. As this process requires the spread of this idea via close contacts, the spatial diffusion process of mushroom farms could also be a contagious or expansion diffusion. For the purpose of modeling the diffusion process, we calculated nearest neighbor ratios and fitted regression curves for all stages and the overall process.

Finally, the third data set is the locations and opening years of two major chain department stores in the U.S., Target and Walmart stores from their first stores untill 2006. Over time, as demonstrated in Figure 2, they took very different business strategies in expanding their retail networks.

In studying the spatial strategies that retail chains took in expanding their store networks, Laulajainen (1987, 1988) suggested that a retailer's basic approach could be of contagious diffusion with hierarchical elements. He further pointed out that discount merchandisers and grocers are more likely to expand with a hierarchical flavor if they favor large markets. The evolution of spatial diffusion processes of these two chains can be clearly seen in Figure 2, which shows the spatial patterns of stores for their first 100 stores, first 500 stores and all stores by 2006.

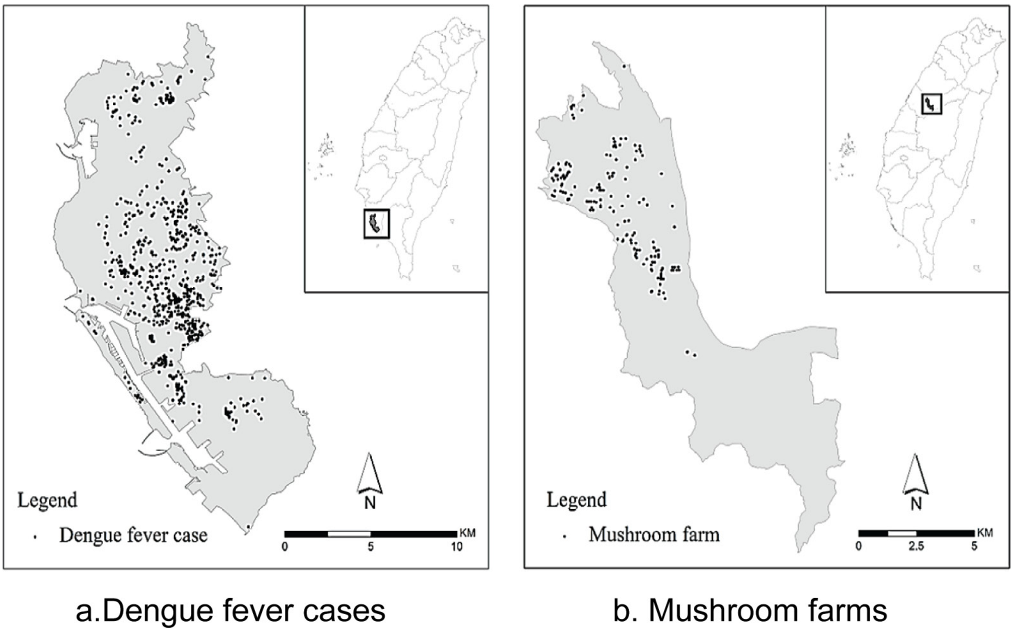
Table 1. Models for regression curve estimation

Model	Regression Curve Estimation Equation
Linear	$Y = b_0 + b_1 \times t$
Logarithmic	$Y = b_0 + b_1 \times \ln\left(t\right)$
Inverse	$Y = b_0 + \frac{b_1}{t}$
Quadratic	$Y = b_0 + b_1 \times t + b_2 \times t^2$
Cubic	$Y = b_0 + b_1 \times t + b_2 \times t^2 + b_3 \times t^3$
Power	$Y = b_0 \times t^{b_1}$ or $\ln\left(Y\right) = \ln\left(b_0\right) + b_1 \times \ln\left(t\right)$
Compound	$Y = b_0 \times b_1^{\,t}$ or $\ln\left(Y\right) = \ln\left(b_0\right) + \ln\left(b_1\right) \times t$
S-curve	$Y = e^{b_0 + \frac{b_1}{t}}$ or $\ln\left(Y\right) = b_0 + \frac{b_1}{t}$
Logistic	$Y = \frac{1}{\left[\frac{1}{u} + \left(b_0 \times b_1^{\,t}\right)\right]}$ or $\ln\left(\frac{1}{y} - \frac{1}{u}\right) = \ln\left(b_0\right) + \left(\ln\left(b_1\right) \times t\right)$
Growth	$Y = e^{b_0 + b_1 t}$ or $\ln\left(Y\right) = b_0 + b_1 \times t$
Exponential	$Y = b_0 \times e^{b_1 t}$ or $\ln\left(Y\right) = \ln\left(b_0\right) + b_1 \times t$

Note: u in the Logistic model is the upper boundary value which must be a positive number that is greater than the largest dependent variable value.

Target expanded over larger areas in the US since the early stages of their growth. They opened new stores in larger cities, bypassing locations close to their headquarters in Minneapolis. Conversely, Walmart expanded over time with a more geographically compact form than Target. While Walmart exhibited a diffusion process closely related to the expansion/contagious diffusion process, an examination of Target stores shows that they diffused in a hierarchical manner through the urban hierarchy. Graff and Ashton (1994) report that, with about 1,600 stores, Walmart chain expanded with a mixed form of contagious and hierarchical diffusion processes. In our dataset, with over 3,000 stores modeled by nearest neighbor ratios and regression curve estimation, Walmart stores seem to lean more toward an expansion/contagious spatial diffusion process overall.

Figure 1. Locations of data points in Kaohsiung City and Xinshe Village in Taiwan



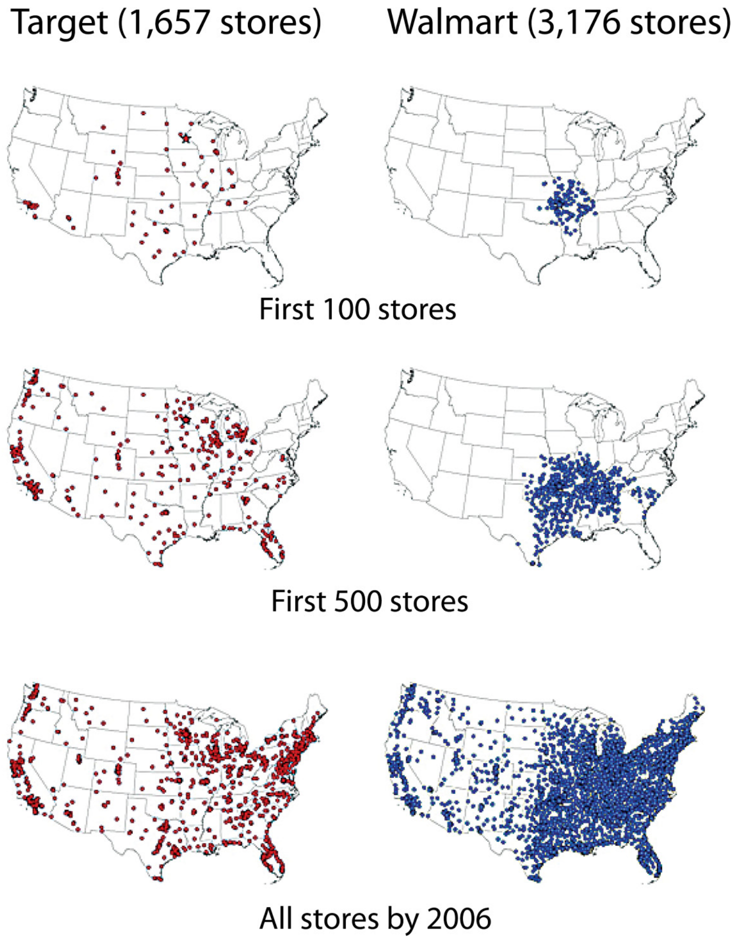
REGRESSION CURVE ESTIMATION

The results of regression curve estimation for nearest neighbor ratios calculated from the annual cycles of dengue fever are shown in the first part of Table 2. It is apparent that the spread of dengue fever in Kaoshiung City between 2003 and 2008 followed what can be described as contagious/expansion diffusion processes. The best-fit models for these are all inverse regression curves, similar to the inverse curve fitted for the hypothetic contagious/expansion diffusion process. For the spatial diffusion processes of converting rice farms to mushroom farms in Xinshe Village, contagious diffusion/expansion process again seems to be what the resulting regression curves suggest. The way Target stores expanded their retail network can be characterized as a hierarchical/relocation diffusion process while Walmart stores maintained a contagious/expansion diffusion process when opening new stores.

All dengue fever cases spread in processes similar to contagious/expansion diffusion for reasons discussed in Wolfe, Dunavan and Diamond (2007) and Hsueh, Lee and Beltz (2012). For mushroom farms, we assume that farmers converted their rice fields to planting mushroom only after they observed others' success in close vicinity, similar to what was described in Bhatia, Chaughan, and Chahal (2012). As shown in Table 2, the best fitted curves for these processes were inverse curves, with R^2 values ranging from a low of 0.815 to a high of 0.988. Results from the third data set, Target stores and Walmart stores, seem to have expanded in hierarchical/relocation process (Target: $R^2 = 0.888$) and in expansion/contagious process (Walmart: $R^2 = 0.889$). Their respective curves are shown in Figure 3.

Given the outcome of applying the method of using nearest neighbor ratios and regression curve estimation, it seems possible to analyze spatio-temporal data for detecting their types

Figure 2. Spatial diffusion processes of Target stores and Walmart stores



of spatial diffusion processes. The empirical runs with these three data sets may not provide perfect matches; they nevertheless suggest that the use of nearest neighbor ratios and regression curve estimate is a viable approach to detecting and distinguishing spatial diffusion processes.

SIMULATIONS OF SPATIAL DIFFUSION PROCESSES

To explore how effective the nearest neighbor ratios may be for detecting the different types of spatial diffusion processes, we developed a simulator using NetLogo (http://ccl.northwestern.edu/netlogo/). The simulator allows users to select if the simulated process is to follow contagious, expansion, hierarchical or relocation processes. Figure 4a is an example for expansion diffusion and Figure 4b is an example for relocation diffusion.

Using randomly generated parameters that define the probability of spreading the diffusion, the simulator creates contagious and expansion diffusion processes. With user-defined parameters for the levels and the numbers of hierarchy of locations and the manual relocation function, the simulator enables simulation of hierarchical diffusion and relocation diffusion processes. In developing the simulator, we set up a simulation parameter of the probability of

Table 2. Estimated regression curves for dengue fever, mushroom farms, and Target and Walmart stores diffusion processes

	Model Summary					Parameter Estimates			
The Best-Fit Model	**R^2**	**F**	**df1**	**df2**	**Sig.**	**Constant**	**b1**	**b2**	**b3**
Dengue Fever									
2003-2004 (Inverse)	0.891	219.862	1	27	0.000	0.225	6.260		
2004-2005 (Inverse)	0.941	554.040	1	35	0.000	0.821	3.619		
2005-2006 (Inverse)	0.983	5492.296	1	95	0.000	2.312	4.745		
2006-2007 (Inverse)	0.828	3506.166	1	729	0.000	0.267	10.767		
2007-2008 (Inverse)	0.988	9794.961	1	119	0.000	0.399	6.027		
Mushroom Farms									
All stages (Inverse)	0.815	775.934	1	176	0.000	0.360	3.039		
Target-Walmart Stores									
Targets (Cubic)	0.888	113.519	3	43	0.000	6.423	-0.709	0.026	0.000
Walmarts (Inverse)	0.889	343.332	1	43	0.000	-0.444	6.960		

spread. The higher value this parameter is set to, the faster the spread of the diffusion is. In this manner, critiques by Gregory and Urry (1985) regarding how Hägerstrand's model lacking consideration for conflicts and resistance to diffusion is corrected in the simulations.

With the simulator, each of contagious, expansion, hierarchical, and relocation diffusion processes was simulated 100 times. Each simulation is then fitted with a regression curve. Table 3 shows the number of times that a particular type of regression curve is found to be the best fitted curve. With small number of exceptions, contagious and expansion diffusion processes are best described by inverse curves and hierarchical and relocation diffusion processes are most closely modeled by cubic curves. These two outcomes compliment what we found from applying the three real-world data sets. The small numbers of exceptions are likely due to extreme parametric values generated by random numbers.

Table 4 summarizes the distributions of R^2 values for the simulations of four classic diffusion types. Again, contagious and expansion diffusion processes are best described by inverse curves but the fitness is better for expansion than for contagious diffusion processes. Note that S-curves also yield very good fitness for expansion diffusion processes, though with a wider range of R^2 (i.e., slightly higher standard deviation). This may be a useful property to use if further distinction is needed between contagious and expansion diffusion. Alternatively, hierarchical and relocation diffusion processes are best approximated by cubic curves as the R^2 values indicating their best fitness.

Simulations of diffusion processes allow various spatial structures to be employed. Between relocation and hierarchical diffusion processes, relocation processes are implemented in the simulator by spreading with fewer jumps to distant locations than jumps by hierarchical processes. Contagious and expansion diffusion processes share a property of spreading to neighboring locations but differ in whether spreading to one neighbor in each time step or spreading to multiple neighbors at a time.

The results of the simulations suggested that estimated regression curves of nearest neighbor ratios are indeed useful in helping to detect the distinctive characteristics of a spatial diffusion process. Simulations indicate that inverse curves often fit well to the nearest neigh-

Figure 3. Estimated regression curves for diffusion processes of dengue fever cases, mushroom farms, and Target and Walmart stores

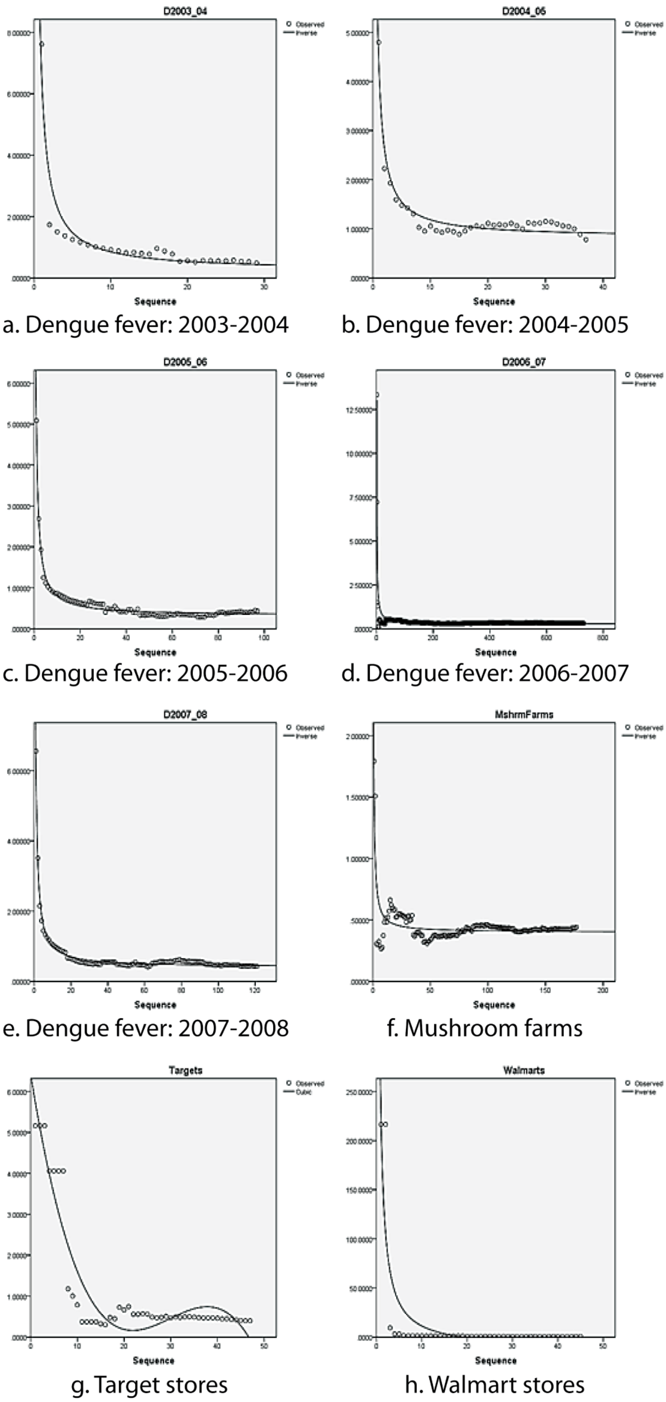


Figure 4. Simulations of spatial diffusion processes

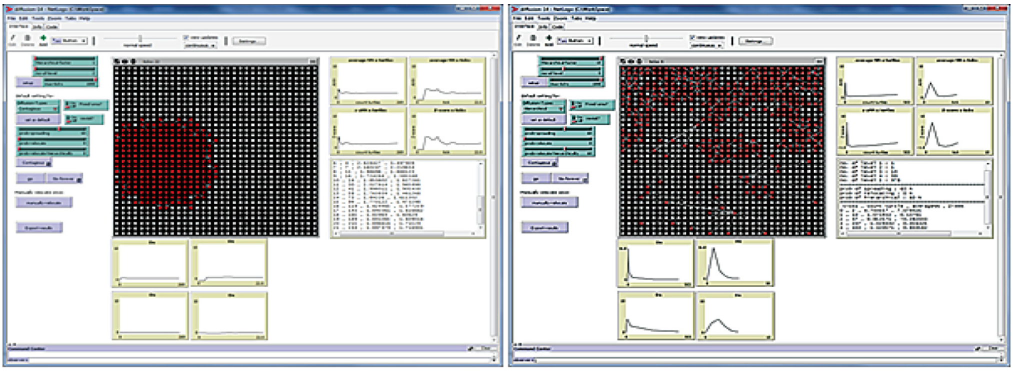


Table 3. Numbers of best fitted curves for 100 simulations for each type of spatial diffusion processes

Curve	Contagious	Expansion	Hierarchical[a]	Relocation
Linear	0	0	0	0
Logarithmic	0	0	0	0
Inverse	77	75	10	12
Quadratic	0	0	0	1
Cubic	21	4	80	86
Compound	0	0	0	0
Power	0	0	0	0
S	2	21	0	1
Growth	0	0	0	0
Exponential	0	0	0	0
Logistic	0	0	2	0

[a]8 out of 100 simulations have ties for the highest R^2 values so the total number of reported simulation is 92.

bor ratios calculated from expansion diffusion processes with S-curves also getting significant goodness-of-fit. Furthermore, hierarchical diffusion processes often have more spatial jumps at a time step than those of relocation diffusion processes. Based on our simulations, cubic curves fit better to the nearest neighbor ratios calculated from hierarchical processes than those from relocation processes.

CONCLUDING REMARKS

Conventional approaches to analyzing spatial clustering in a point pattern are useful for helping to focus on areas with high densities or low densities of the events. However, they do have limits when considering how a point pattern changes over space and time. This is especially the case when different point patterns may

Table 4. Distributions of R^2 from regression curve estimations for 100 simulations for each type of spatial diffusion processes

	Contagious		Expansion		Hierarchical		Relocation	
Curve	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**	**Mean**	**Std Dev**
Linear	0.05	0.04	0.45	0.05	0.49	0.26	0.17	0.10
Logarithmic	0.26	0.12	0.79	0.05	0.33	0.23	0.41	0.13
Inverse	0.65	0.14	0.99	0.01	0.12	0.16	0.68	0.13
Quadratic	0.34	0.13	0.72	0.05	0.53	0.26	0.73	0.12
Cubic	0.51	0.17	0.87	0.04	0.65	0.22	0.85	0.08
Compound	0.04	0.04	0.49	0.05	0.53	0.18	0.15	0.10
Power	0.23	0.13	0.83	0.04	0.37	0.20	0.34	0.14
S	0.60	0.15	0.99	0.02	0.07	0.09	0.57	0.13
Growth	0.04	0.04	0.49	0.05	0.53	0.18	0.12	0.10
Exponential	0.04	0.04	0.49	0.05	0.53	0.18	0.12	0.10
Logistic	0.04	0.04	0.49	0.05	0.53	0.18	0.12	0.10

be similar spatially but different in how they develop over time. To fully understand how a particular spatial pattern evolves over time so to explore and understand the underlying factors, it would be necessary to distinguish its spatio-temporal process. For example, studies and planning for containment strategies for an infectious disease such as dengue fever during an outbreak can be assisted by knowing how the disease spreads over time and space. The increases of mushroom farms in Xinshe indicate the spatial structure of expansion diffusion processes. This may be due to the close distances and direct contacts between farmers in the village that promote the spread of the idea. For local governments wishing to disseminate new policies or encouraging new agricultural practices, such knowledge has a great value.

There have been studies carried out to differentiate the growth patterns of Target and Walmart stores, including those focused on locations, trade areas, profile of customers, and overall value platforms of these two department store chains (Graff 2006; Joseph, 2009, 2010). The approach reported in this article allows us to quantitatively distinguish the two very different schemes of spatial diffusion processes that are likely the result of different business practices adopted by the two chains.

The three real-world data sets further verified the usefulness of these methods. The simulations we did provide good indications of how well these methods performed. Overall, we suggest that nearest neighbor ratios and regression curve estimation can be used to do initial assessment of how geographic phenomena diffuse across space and over time before applying other means of more in-depth analysis.

REFERENCES

Aidt, T. S., & Jensen, P. S. (2009). The taxman tools up: An event history study of the introduction of the personal income tax. *Journal of Public Economics*, *93*(1-2), 160–175. doi:10.1016/j.jpubeco.2008.07.006

Allaway, A. W., Berkowitz, D., & D'Souza, G. (2003). Spatial diffusion of a new loyalty program through a retail market. *Journal of Retailing*, *79*(3), 137–151. doi:10.1016/S0022-4359(03)00037-X

Allaway, A. W., Black, W. C., Richard, M. D., & Mason, J. B. (1994). Evolution of a retail market area: An event history model of spatial diffusion. *Economic Geography*, *70*(1), 23–40. doi:10.2307/143576

Anselin, L. (1995). Local indicators of spatial association – LISA. *Geographical Analysis*, *27*(2), 93–115. doi:10.1111/j.1538-4632.1995.tb00338.x

Berry, B. J. L. (1972). Hierarchical diffusion: The basis of developmental filtering and spread in a system of growth centers. In N. M. Hansen (Ed.), *Growth centers in regional economic development* (pp. 103–138). New York, NY: Free Press.

Bhatia, J. N., Chauhan, R. S., & Chahal, D. (2012). Transfer of mushroom fanning technology as one of the livelihoods generating activity identified in rural Haryana. *Agricultural Update*, *7*(1/2), 80–84.

Braun, R., & Koopmans, R. (2010). The diffusion of ethnic violence in Germany: The role of social similarity. *European Sociological Review*, *26*(1), 111–123. doi:10.1093/esr/jcp056

Brown, L. (1968). *Diffusion dynamics: A review and revision of the quantitative theory of the spatial diffusion of innovation*. Lund, Sweden: The Royal University of Lund.

Brown, L. (1981). *Innovation diffusion: A new perspective*. London, UK: Methuen.

Casetti, E., & Semple, R. K. (1969). Concerning the testing of spatial diffusion hypothesis. *Geographical Analysis*, *1*(3), 254–259. doi:10.1111/j.1538-4632.1969.tb00622.x

Cliff, A. D., Haggett, P., Ord, J. K., & Versey, G. R. (1981). *Spatial diffusion: A historical geography of epidemics in an island community*. Cambridge, UK: Cambridge University Press.

Cliff, A. D., & Ord, J. K. (1975). Space time modeling with an application to regional forecasting. *Transactions of the Institute of British Geographers*, *64*, 119–128. doi:10.2307/621469

Cohen, J., & Tita, G. (1999). Diffusion in homicide: Exploring a general method for detecting spatial diffusion processes. *Journal of Quantitative Criminology*, *15*(4), 451–493. doi:10.1023/A:1007596225550

Donnelly, K. (1978). Simulations to determine the variance and edge-effect of total nearest neighbor distance. In I. Hodder (Ed.), *Simulation methods in archaeology* (pp. 91–95). Cambridge University Press.

Glantz, S. A., & Slinker, B. K. (1990). *Primer of applied regression and analysis of variance*. New York, NY: McGraw-Hill.

Gould, P. (1969). *Spatial diffusion*. Washington, DC: Association of American Geographers.

Gould, P. (1975). *Spatial diffusion: The spread of ideas and innovations in geographic space*. Learning Resources in International Studies.

Graff, T. O. Z., & Ashton, D. (1994). Spatial diffusion of Wal-Mart: Contagious and reverse hierarchical elements. *The Professional Geographer*, *46*(1), 19–29. doi:10.1111/j.0033-0124.1994.00019.x

Gregory, D., & Urry, J. (1985). Suspended animation: The stasis of diffusion theory. In D. Gregory, & J. Urry (Eds.), *Social relations and spatial structures* (pp. 296–336). New York, NY: St. Martin's Press.

Hägerstrand, T. (1966). Aspects of the spatial structure of social, communication and the diffusion of information. *Papers in Regional Science*, *16*(1), 27–42. doi:10.1007/BF01888934

Hägerstrand, T. (1967). *Innovation diffusion as a spatial process* (A. Pred, Trans.). Chicago, IL: University of Chicago Press.

Haider-Markel, D. P. (2001). Policy diffusion as a geographical expansion of the scope of political conflict: Same-sex marriage bans in the 1990s. *State Politics & Policy Quarterly*, *1*(1), 5–26. doi:10.1177/153244000100100102

Haining, R. (1983). Spatial and spatial-temporal interaction models, and the analysis of patterns of diffusion. *Transactions of the Institute of British Geographers*, *8*(2), 158–169. doi:10.2307/622109

Härdle, W. (1990). *Applied nonparametric regression*. Cambridge University Press. doi:10.1017/CCOL0521382483

Hedström, P. (1994). Contagious collectives: On the Spatial Diffusion of Swedish Trade Unions, 1890-1940. *American Journal of Sociology*, *99*(5), 1157–1179. doi:10.1086/230408

Hedström, P., Sandell, R., & Stern, C. (2000). Mesolevel networks and the diffusion of social movements: The case of the Swedish social democratic party. *American Journal of Sociology*, *106*(1), 145–172. doi:10.1086/303109

Hsueh, Y.-H., Lee, J., & Beltz, L. (2012). Spatio-temporal patterns of dengue fever cases in Kaoshiung City, Taiwan, 2003-2008. *Applied Geography (Sevenoaks, England)*, *34*, 587–594. doi:10.1016/j.apgeog.2012.03.003

Joseph, L. (2009). The effects of big-box stores on a specialty retailer. *Papers of the Applied Geography Conferences, 32,* 30-39.

Joseph, L. (2010). National level analysis of major US domestic retailers. *Papers of the Applied Geography Conferences, 33,* 343-352.

Kendall, D. G. (1965). Mathematical models of the spread of infection. In Medical Research Council (Ed.), Mathematics and computer sciences in biology and medicine (pp. 213-55). London, UK: Her Majesty's Stationary Office.

Knoke, D. (1982). The spread of municipal reform: Temporal, spatial, and social dynamics. *American Journal of Sociology*, *87*(6), 1314–1339. doi:10.1086/227595

Lam, N. S. N., Fan, M., & Liu, K. (1996). Spatial-temporal spread of the AIDS epidemic, 1982-1990: A correlogram analysis of four regions of the United States. *Geographical Analysis*, *28*(2), 93–107. doi:10.1111/j.1538-4632.1996.tb00923.x

Laulajainen, R. (1987). *Spatial strategies in retailing*. Dordrecht, Germany: D. Reidel. doi:10.1007/978-94-009-3983-7

Laulajainen, R. (1988). Chain store expansion in national space. *Geografiska Annaler. Series B, Human Geography*, *70*(2), 293–299. doi:10.2307/490955

Lee, J., & Wong, D. W. S. (2001). *Statistical analysis with ArcView GIS*. New York, NY: John Wiley & Sons.

Morrill, R., Gaile, G. L., & Thrall, G. I. (1988). *Spatial diffusion. SAGE scientific geography series 10*. Newbury Park, CA: SAGE Publications, Inc.

Myers, D. J. (1997). Racial rioting in the 1960s: An event history analysis of local conditions. *American Sociological Review*, *62*(1), 94–112. doi:10.2307/2657454

Myers, D. J. (2010). Violent protest and heterogeneous diffusion processes: The spread of US racial rioting from 1964 to 1971. *Mobilization: An International Quarterly*, *15*(3), 289–321.

Pederson, P. (1970). Innovation diffusion within and between national urban systems. *Geographical Analysis*, *2*(3), 203–254. doi:10.1111/j.1538-4632.1970.tb00858.x

Rogers, E. M. (1983). *Diffusion of innovations* (3rd ed.). New York, NY: Free Press.

Rogerson, P., & Sun, Y. (2001). Spatial monitoring of geographic patterns: An application to crime analysis. *Computers, Environment and Urban Systems*, *25*(6), 539–556. doi:10.1016/S0198-9715(00)00030-2

Rossbacher, L. A. (1986). Nearest-neighbour analysis: A technique for quantitative evaluation of polygonal ground patterns. *Geografiska Annaler. Series A. Physical Geography*, *68*(1/2), 101–105. doi:10.2307/521180

Saint-Julien, T. (2007). The process of spatial diffusion and modeling change. In L. Sanders (Ed.), *Models in spatial analysis* (pp. 127–157). Newport Beach, CA: ISTE. doi:10.1002/9780470612255.ch5

Schutte, S., & Weidmann, N. B. (2011). Diffusion patterns of violence in civil wars. *Political Geography*, *30*(3), 143–152. doi:10.1016/j.polgeo.2011.03.005

Tita, G., & Cohen, J. (2004). Measuring spatial diffusion of shots fired activity across city neighborhoods. In M. F. Goodchild, & D. G. Janelle (Eds.), *Spatially Integrated social science* (pp. 171–204). Oxford University Press.

Webber, M. (1972). *The impact of uncertainty on location*. Cambridge, MA: MIT Press.

Wolfe, N. D., Dunavan, C. P., & Diamond, J. (2007). Origins of major human infectious disease. *Nature*, *447*, 279–283. doi:10.1038/nature05775 PMID:17507975

Jay Lee is Professor of Geography at Kent State University in Ohio. His research interests include geographic information sciences, geospatial analysis, and Geosimulations.

Jinn-Guey Lay is Professor of Geography at National Taiwan University in Taiwan. His research interests include geographic information sciences, geographic education, and cartography.

Wei Chien Chin is a research assistant in the Department of Geography at National Taiwan University, Taiwan. His research interests include agent-based simulation in spatial analysis, and geographical information science.

Yu-Lin Chi is a research assistant in the Department of Geography at National Taiwan University in Taiwan. His research interests include health geography, population geography, and quantitative methods.

Ya-Hui Hsueh is a professor of Department of Regional and Social development at National Taichung University of Education in Taiwan. Her research interests include geographic information sciences, and tourism geography.