# Spatial Analysis of Social Vulnerability to Environmental Risks:
# A Study for China Prefecture Regions between 2000 and 2010

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## 1. Introduction

Human beings are at the center of the environmental system, both as the driver of and as the unit being affected by climate change. The recently observed increasing environmental risks appear to be having serious effects on the livelihoods and the well-being of people. The new Sustainable Development Goals (SDGs) recognized climate action as one of the priorities to promote sustainable development. Therefore, promote social resilience to environmental risks is very important in the long run. Risk identification through the assessment of vulnerability can facilitate the emergence of a common understanding of responses to risk among stakeholders and actors, and thus represents one of the initial stages in the processes of risk reduction, prevention, transfer, and climate adaptation in the context of climate extremes.

Environmental risk is universally acknowledged to be a function of hazard, exposure, and vulnerability. In both the short and long term future, environmental risks can have devastating economic and social consequences for affected areas and their inhabitants. Exposure can be evaluated by capturing natural disaster events including temperature and precipitation extremes, floods, storms and droughts. While the risks may change across regions, people in the same area tend to be differentially vulnerable according to their age, gender, level of education, occupation, and other social and economic characteristics. Social vulnerability emphasizes the inherent properties of human systems that make individuals or groups susceptible to damage from external hazards. There is growing interest among researchers and policy-makers in the social vulnerability studies as the climate changes.

China has already been identified as one of the most vulnerable countries to environmental risks in the world, which experienced very large changes in its social fabrics over the past few decades. Thus, the recognition of regional heterogeneity of the vulnerable groups exposed to environmental risks is crucial for future disaster reduction planning and risk management. Although many efforts to perform social vulnerability assessment to environmental risks in China have been made in recent years, there has not been a consensus on the selection of variables for constructing social vulnerability index due to different research interest. Also, little research has focused on combining spatial patterns of social vulnerability and exposure to test that whether populations with higher levels of social vulnerability generally suffer greater impacts from climate-related hazards.

The objective of this research is to investigate the prefectural-level spatial changes of social vulnerability in China between 2000 and 2010. In this study, social vulnerability index (SVI) will be constructed based on the hazards-of-place model of vulnerability developed by Cutter et al. By applying several measurable variables, each of which indicates a facet of prefecture region's vulnerability to environmental risks. By using factor analysis (FA), the underlying factors which make a location socially vulnerable to environmental risks are identified. Next, the Standardized Precipitation-Evapotranspiration Index (SPEI) are used to examine the relations and impacts of changing SVI. Then, we further utilize exploratory spatial data analysis (ESDA) to explore the spatial patterns of social vulnerability in China based on the constructed SVI for each prefecture region and their relationship with SPEI during the same period.

## 2. Materials and Methods

2.1 Data

To examine the social vulnerability, socioeconomic data were collected from population censuses of China, China Statistical Yearbook for Regional Economy and China City Statistical Yearbook between 2000 and 2010. The prefectural-level administrative map was obtained from Global Administrative Areas (GADM), Geospatial Centre of University of Waterloo. Because the prefectural administrative boundaries of China have changed between 2000 and 2010, to ensure that the results are comparable, they were merged based on the 2010 Chinese prefectural boundaries. Therefore, the units of analysis are the 344 Chinese prefectural regions (excluding Taiwan, Hong Kong and Macao). Climatic factors are measured using the Standardized Precipitation-Evapotranspiration Index (SPEI), which are obtained from the Global SPEI database.

## 2.2 Social vulnerability indicators

Many factors influence social vulnerability including lack of access to resources and services, limited social capital etc. There always has been disagreement concerning the selection of variables that represent and measure these broad concepts. Among which the generally accepted contributors are age, gender, and socioeconomic status. Based on the Social Vulnerability Index (SVI) constructed by the Hazards & Vulnerability Research Institute, College of Arts & Sciences, University of South Carolina in 2000, 32 variables were reduced and altered to 22 considering China's social context and data availability. This study examined the social vulnerability of China from the perspective of demographic characteristics, education, economic status, occupations, infrastructure dependence and development. The sources and description for these variables including in this study are shown in Table I.

Table I

| No. | VARIABLE | DESCRIPTION | SOURCE |
|---|---|---|---|
| 1 | QMINOR | Percent Ethnic Minority | Census |
| 2 | CDR | Children Dependency Ratio | Census |
| 3 | EDR | Elderly Dependency Ratio | Census |
| 4 | GDP | GDP Per Capita | CSYRE |
| 5 | AVEWAGE | Average Wage | CSYRE |
| 6 | QFEMALE | Percent Female | Census |
| 7 | HOSPTPER | Hospitals Per Capita | CCSY |
| 8 | PHYSIPER | Number of Physicians Per Capita | CCSY |
| 9 | QED9LES | Percent with Less than Nine Years of Education | Census |
| 10 | QINTERP | Percent migrants from other provinces | Census |
| 11 | QEMP | Percent Employment | Census |
| 12 | QURBAN | Percent Urban Population | Census |
| 13 | PPHH | Person per household | Census |
| 14 | QRENTER | Percent Renters | Census |
| 15 | QWLHR | Percent Population in Local Household Registration | Census |
| 16 | QAGRI | Percent Employment in Extractive Industries | Census |
| 17 | QSERV | Percent Employment in Service Industry | Census |
| 18 | QTRAN | Percent Employment in Transportation & Public Utilities | Census |
| 19 | QFEMLBR | Percent Female Participation in Labor Force | Census |
| 20 | QACL | Percent Area Cultivated Land | CSYRE |
| 21 | ELG | Expenditure of Local Governments | CSYRE |
| 22 | QSCH | Percent Self-constructed Homes | Census |

## 2.3. SVI for China

Utilizing the original methodology pioneered by Cutter et al. in 2003, the SVI for China is created at prefecture-level in 2000 and 2010 respectively. First, a correlation analysis was used to determine whether the input variables were highly collinear. After excluding potentially relevant variables, the input variables were normalized to z-scores. Next, factor analysis was applied to identify the factors that make Chinese prefectural regions socially vulnerable to environmental risks. A positive sign was assigned to variables increase the total vulnerability, and a negative score was assigned when it decreases the vulnerability. Then, the SVI was created by summing the value of all variables for each prefecture regions. Because of the lack of a theoretical basis for assuming the relative importance of one factor over another in the construction of the index, following Cutter et al., the factors were equally weighted to produce the composite SVI score for every decade. Last, SPEI is used to examine the relations and impacts of changing SVI which is measured on an intensity scale with negative values, indicating drought conditions, and positive values, indicating wet conditions.

2.4 Spatial Autocorrelation

Global and/or local Moran's I can be used to investigate the spatial autocorrelation among the prefecture regions by characterizing the relative distribution of social vulnerability index in different regions with the objective of finding spatial patterns or verifying if the data are randomly distributed. This paper uses local spatial autocorrelation to specify where the agglomerations (clusters) or extreme cases occur, which is defined as follows:

$$I_i = c \cdot z_i \sum_j w_{ij} z_j$$

where $z_i$ and $z_j$ are deviations from the mean; the value $w_{ij}$ is the weight assigned to areas i and j; the scalar c is the same for all locations. Using GeoDa software, the cluster maps and Moran scatter plots are produced by *LISA* (Local Indicators of Spatial Association) statistics. The cluster maps present sites with local statistical significance of Moran with the significant locations color coded by type of spatial autocorrelation.

There are four different types of spatial clusters for social vulnerability at the prefectural-level as high–high (HH), low–low (LL), high–low (HL), low–high (LH). For example, HH means a prefecture region with a high SVI value (above the mean of SVI in a given time period) surrounded by counties with high values. Both high–high and low–low are considered spatial clusters, thus defined as positive local spatial autocorrelation, other two are regarded as spatial outliers, defined as negative local spatial autocorrelation. In Geoda, a neighborhood structure between the prefecture regions called Queen was also defined. This criterion correlates the prefecture regions with their neighbor independent of their direction. The level of significance used in this paper was 5%. In other words, this is the percentage of error likely to say that the spatial distribution is not random.

**3. Preliminary results**

First, the change of the extracted dominant components using Kaiser's criterion between 2000 and 2010 are observed, also the percentage of the variation explained by the SVI among Chinese prefecture regions. Using factor analysis is helpful for understanding Chinese social-economic context by recognizing the major contributors to social vulnerability. Spatial changes of SVI in China as geographic patterns of social vulnerability to environmental risks are found from 2000 to 2010. In 2000, the most socially vulnerable prefecture regions were mainly concentrated in the northeastern, southwestern, also some provinces located in the middle of China. For 2010, the southwestern area like Sichuan, Yunnan, Guangxi, Guizhou became more vulnerable compared with they were in 2000. Anhui, also the middle area of Heilongjiang remained vulnerable during this period. In general, the social vulnerability of the coastal regions of China were relatively lower, which may be influenced by the implementation of China's reform and opening-up policy since 1978. Since then, larger numbers of people migrated to eastern China, which changed the demographic structure and exacerbated the process of urbanization.

As Figure 1 showed, in Moran scatter plot, SVIs are on the horizontal axis, and their spatially lagged counterparts on the vertical axis. Note that the SVIs have been standardized, where the mean is 0 and the standard deviation is 1. Similarly, the spatial lag is computed for those standardized values. Then, in order to test for regional clustering, and *Lisa* Cluster maps (Figure 1) show the presence of significant spatial clusters or outliers by prefecture regions. In 2000, the prefecture regions with HH patterns were mainly concentrated in southwestern China (Tibet, Xinjiang;

Inner Mongolia, Shanxi, Shan'xi; Jiangxi, Anhui, Fujian), whereas the LL patterns were more dispersed as found in Ningxia, Sichuan, Heilongjiang and Guangdong). By 2010, there was a relatively strong spatial clustering in the SVI. The prefecture regions with HH patterns tend to concentrate in southwestern China like Sichuan, Tibet, Qinghai, Guizhou and Guangxi. During this decade, Shanghai and Shenzhen remain surrounded by regions with low social vulnerability. The variations in spatial patterns of Chinese prefecture regions' social vulnerability reflected the changes in its population distribution over the decade, which are closely linked to its resource endowment, economic levels, and national policies.

Figure 1

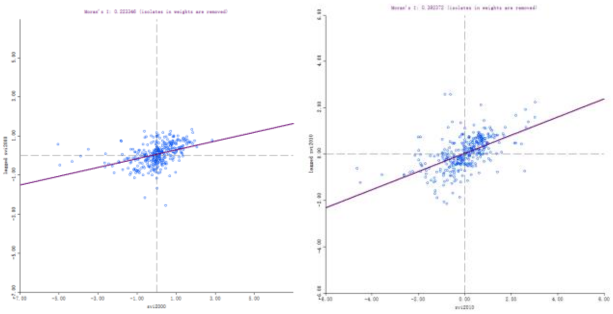

Figure 2