Examine the Association between Temperature Variation and Cardiovascular Disease Hospitalization

A Case Study in Shanxi, China

Miao Cai

Department of Epidemiology & Biostatistics,
Saint Louis University

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Introduction

Theoretical background

Global climate change

- Frequent heat shocks and cold spells[1,2]
- 12.6 M deaths attributable to climate change[3]

CVD

- Cardiovascular disease (CVD) is the leading cause of death worldwide and in China
- 15.2 M deaths, 26.7% of all deaths[4]

Aging China

- "Aging tsunami" <- Previous one-child policy
- 400 M (30%) older adults by 2050[5]

Research Question

Is **temperature variation** associated with **CVD hospitalizations**?

- biological association
- research gap

Data source

Shanxi Province, China

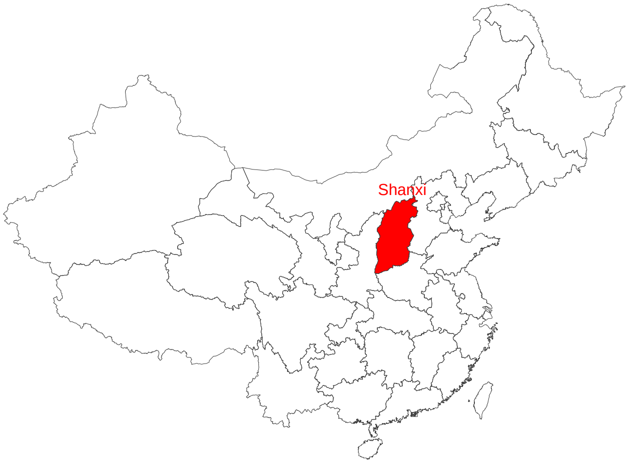


Figure 1: The location of Shanxi Province in China

Shanxi inpatient database

CVD inpatients

- 175 hospitals
- 112 out of 118 administrative districts (ADs)
- $\sim$ 1.2 million patients
- 2015 - 2017

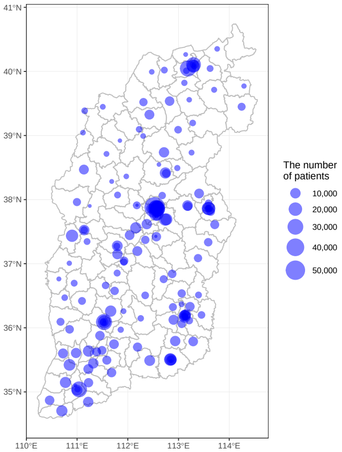


Figure 2: Geographic distribution of 175 hospitals in Shanxi, China

Shanxi Statistical Yearbook

County/city level

- 118 ADs

Variables available

- Population
- Gender
- Rural
- Education

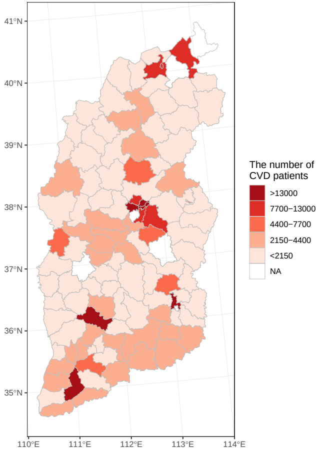


Figure 3: Choropleth map patient distribution in each county and city in Shanxi, China

The number of CVD patients by month

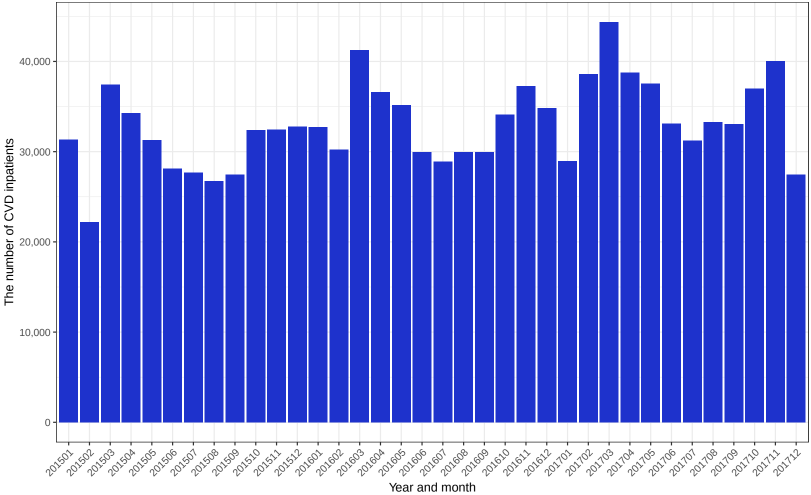
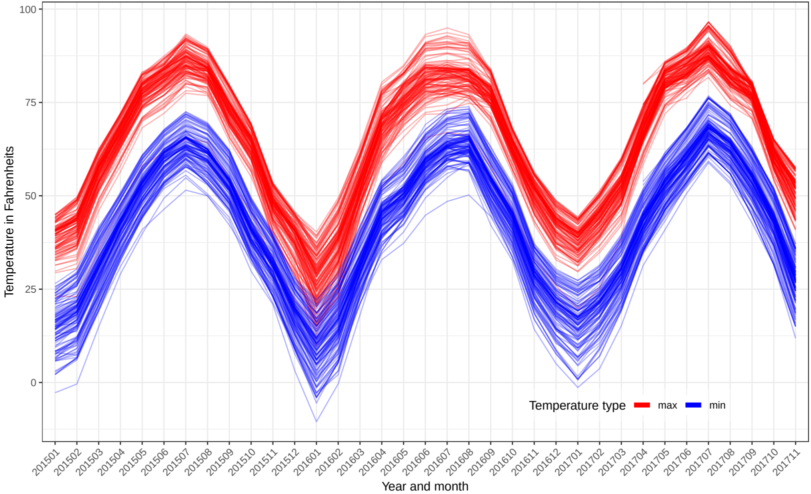


Figure 4: The number of CVD patients by year and month

Temperature variation definition

- Vertical variation: $V_v = T_{max} - T_{min}$
- Horizontal variation: $V_h = \sum_{i=\mathrm{d}-7}^{\mathrm{d}} \left| T_i - T_{i-1} \right|$



Temperature variation trend

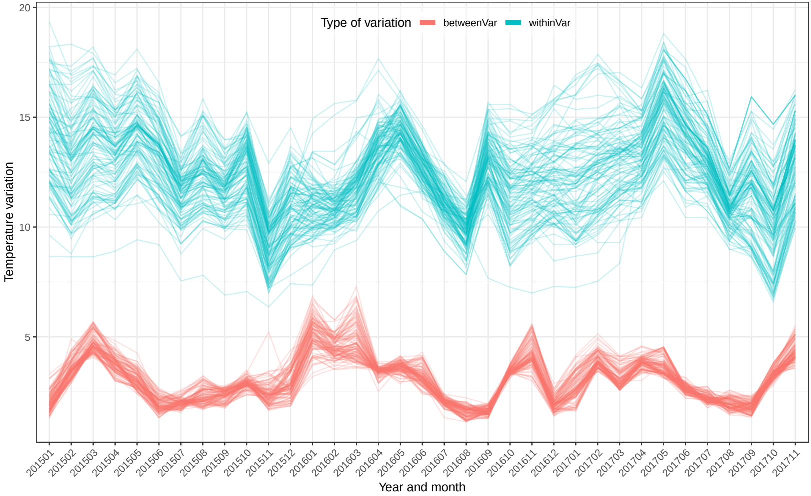


Figure 6: Temperature variation trend in 118 ADs in Shanxi, 2015 - 2017

Final sample

- 109 ADs
- 12 months in 3 years
- $109 * 12 * 3 = 3,924$ rows

Data cleaning, visualization, statistical models, and reporting in R 3.6.0.

Statistical models

Model selection

The outcome is the count of CVD patients:

- Must be non-negative,
- integers,
- highly righ-skewed.

OLS assumpts are **not met**!

Poisson regression is a natural model for count data. We consider:

1. non-spatial Poisson regression
2. random effects Poisson regression
3. spatial Poisson regressions

Non-spatial Poisson model

$$Y_i \sim \text{Poisson}(\text{Pop}_i * \lambda_i)$$
$$\log(\lambda_i) = \beta_0 + \sum_k \beta \mathbf{X}$$

- Y_i: The number of CVD inpatients
- Pop_i: The total population as an offset
- λ_i: The rate parameter of Poisson distribution, both the mean and vaiance
- Predictor variables: temperature variation (horizontal and vertical), average temperature, log of GDP per capita, the percent of female, and the percent of rural population

Hierarchical Poisson model

Assuming that each ADs have its own characteristics, and observations are **conditionally independent**.

$$
\begin{aligned}
Y_{ij} &\sim \mathrm{Poisson}(\mathrm{Pop}_{ij} * \lambda_{ij}) \\
\log(\lambda_{ij}) &= \beta_{0j} + \beta_{1j} HV_{ij} + \beta_{2j} VV_{ij} + \sum_{k-2} \beta \mathbf{X} + u_{0j} \\
\beta_{0j} &\sim N(\mu_0, \sigma_0^2) \\
\beta_{01} &\sim N(\mu_1, \sigma_1^2) \\
\beta_{02} &\sim N(\mu_2, \sigma_2^2)
\end{aligned}
$$

- Random intercepts: β_{0j} for each AD j
- Random slopes: β_{1j} and β_{2j} for each AD j

Spatial Poisson models

Spatial lag Poisson model

- An autoregressive parameter ρ
- A weighting matrix $\mathbf{W}$

$$Y_i \sim \text{Poisson}(\text{Pop}_i * \lambda_i)$$
$$\log(\lambda_i) = \beta_0 + \sum_k \beta \mathbf{X} + \rho \mathbf{W} y$$

Geographically weighted Poisson model

Still at the initial proof of concept stage. It can be conducted in the `R` package `spgwr` by Roger Bivand (2017).

Results

Moran's I

```
##
##  Moran I test under randomisation
##
## data:  hloca$N
## weights: nb2listw(nb, style = "W")
##
## Moran I statistic standard deviate = 2.4915, p-value = (
## alternative hypothesis: greater
## sample estimates:
## Moran I statistic       Expectation          Variance
##       0.075114045      -0.006896552       0.001083440
```

non-spatial Poisson models

Table 1: Parameter estimates of non-spatial Poisson models

	Dependent variable:	
	Poisson	Mixed-effects Poisson
	(1)	(2)
Between variance	0.072^{***} (0.001)	0.065^{***} (0.006)
Within variance	-0.0003 (0.001)	0.015^{***} (0.004)
Mean temperature	-0.001^{***} (0.0001)	-0.002^{***} (0.0001)
Log GDP	0.237^{***} (0.002)	0.425^{***} (0.016)
Rural	-1.022^{***} (0.007)	-1.037^{***} (0.141)
Female	0.129^{***} (0.001)	0.011^{***} (0.004)
Constant	-13.347^{***} (0.065)	-8.114^{***} (0.224)
Log Likelihood	-141,512.000	-29,727.990
Akaike Inf. Crit.	283,038.000	59,481.970
Note:		$^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Spatial Poisson models

To be added

- Spatial lag Poisson model
- Geographically weighted Poisson model

Discussion

Limitations

- Assumptions: the patients did not seek care in other ADs
- Omitted variable bias: air pollution, older population
- Hospitalization database: inpatients are not included
- Different weights for different severity of CVD hospitalization?

Future directions

- Add time series analysis in several major cities?
- Mortality?
- Different effects in cold and hot days?
- Hierarchical spatial Poisson regression?

References

1 Ryti NR, Guo Y, Jaakkola JJ. Global association of cold spells and adverse health effects: A systematic review and meta-analysis. *Environmental health perspectives* 2015; **124**: 12–22.

2 Huber D, Gulledge J. The global links between extreme weather and climate change. *Extreme Weather Events* 2017;: 17.

3 Watts N, Adger WN, Ayeb-Karlsson S *et al.* The lancet countdown: Tracking progress on health and climate change. *The Lancet* 2017; **389**: 1151–64.

4 The World Health Organization. The top 10 causes of death. 2018.

5 Chen Z, Yu J, Song Y, Chui D. Aging beijing: Challenges and strategies of health care for the elderly. *Ageing research reviews* 2010; **9**: S2–5.