“地理信息分析在公共卫生与健康中的应用”前沿论坛，
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时空变系数（STVC）模型:
探测健康地理现象的局域时空非平稳异质成因关系

Spatiotemporally Varying Coefficients (STVC) model

to detect nonstationary heterogeneous casual relationships at local spatiotemporal scales

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1. Background——1.1 Regression analysis

Regression analysis purposes

- (1) Explore relationships among variables. In restricted circumstances, regression analysis can be used to infer causal relationships between the independent (or 'predictors') and dependent variables.
  - Correlational relationship;
  - Intrinsic sequential logic;
  - Controlling other factors.
- (2) Prediction and forecasting, where its use has substantial overlap with the field of machine learning.

A regression model relates *Y* to a function of *X* and *β*.

$$Y \approx f(\mathrm{X}, \beta)$$

Where,
Y **is dependent (or response, outcome) variable.**
X **is independent (or covariate, explanatory) variables.**
β **are unknown parameters/regression coefficients, representing Y-X correlated or causal relationships.**

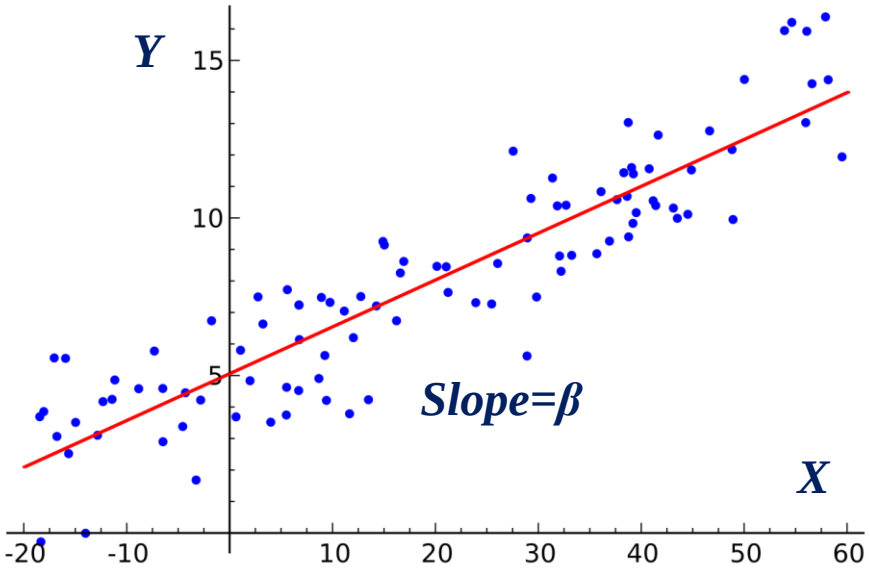
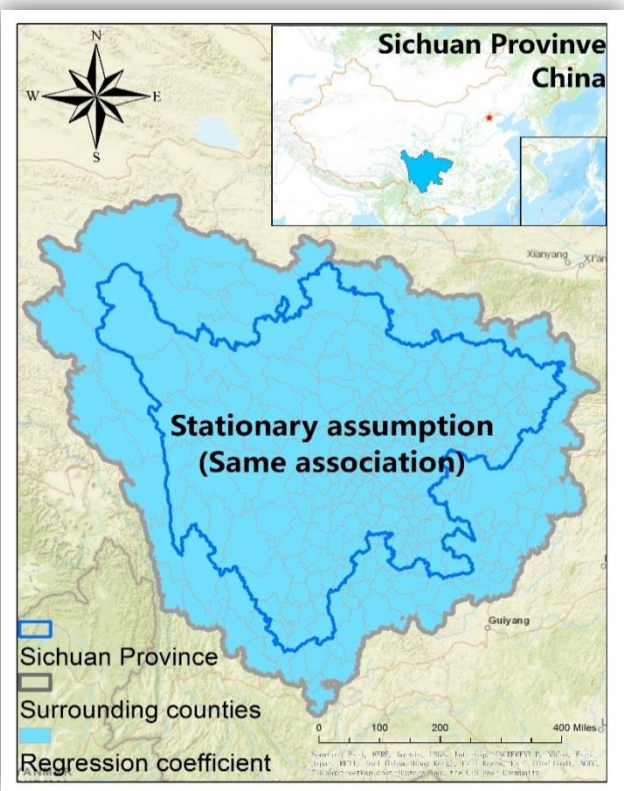


Illustration of linear regression on a data set

1. Background——1.2 Global and local regression

- **Global regression based on stationary assumption: *Y-X* variables relationships (i.e., regression coefficients) are homogeneous across the entire area and time period.**
- **Local regression based on non-stationary assumption: *Y-X* variables relationships (i.e., regression coefficients) vary among different spatial units and/or time frames.**

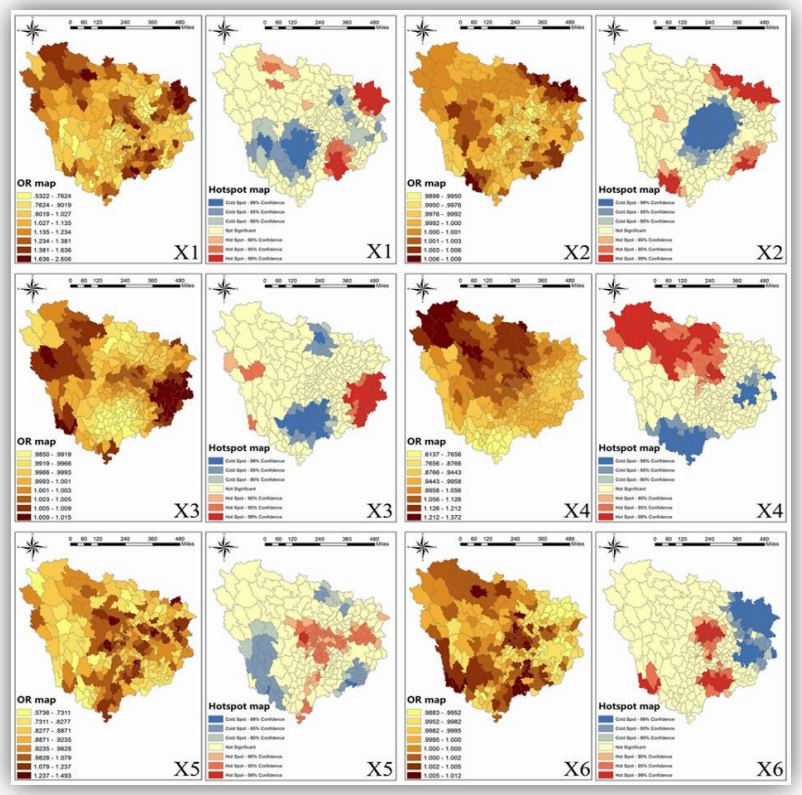
Stationary assumption



Disease-climate relationship

Global regression

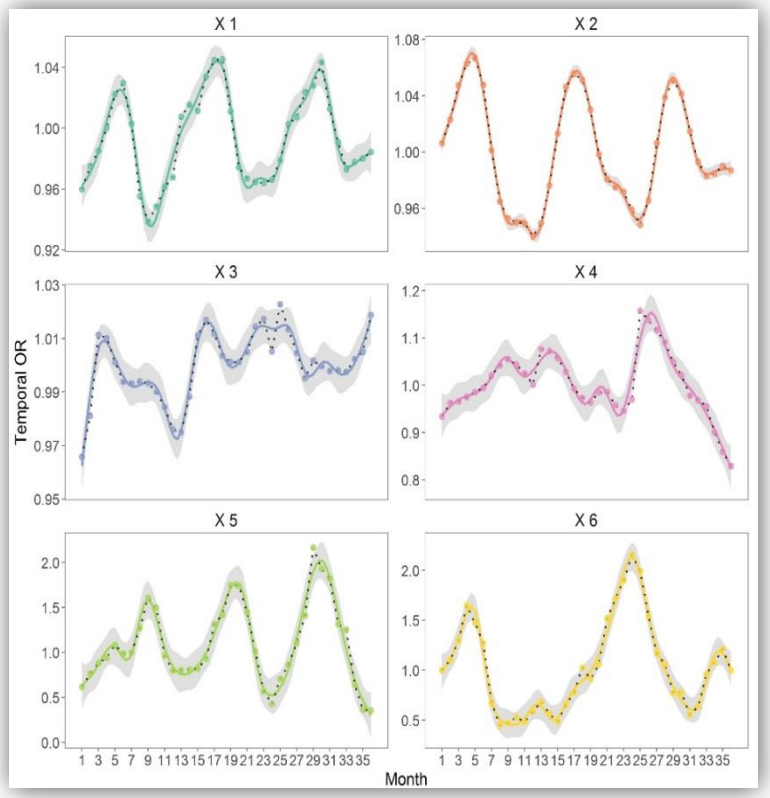
Spatial non-stationary assumption



Spatially varying disease-climate relationships

Local spatial regression

Temporal non-stationary assumption

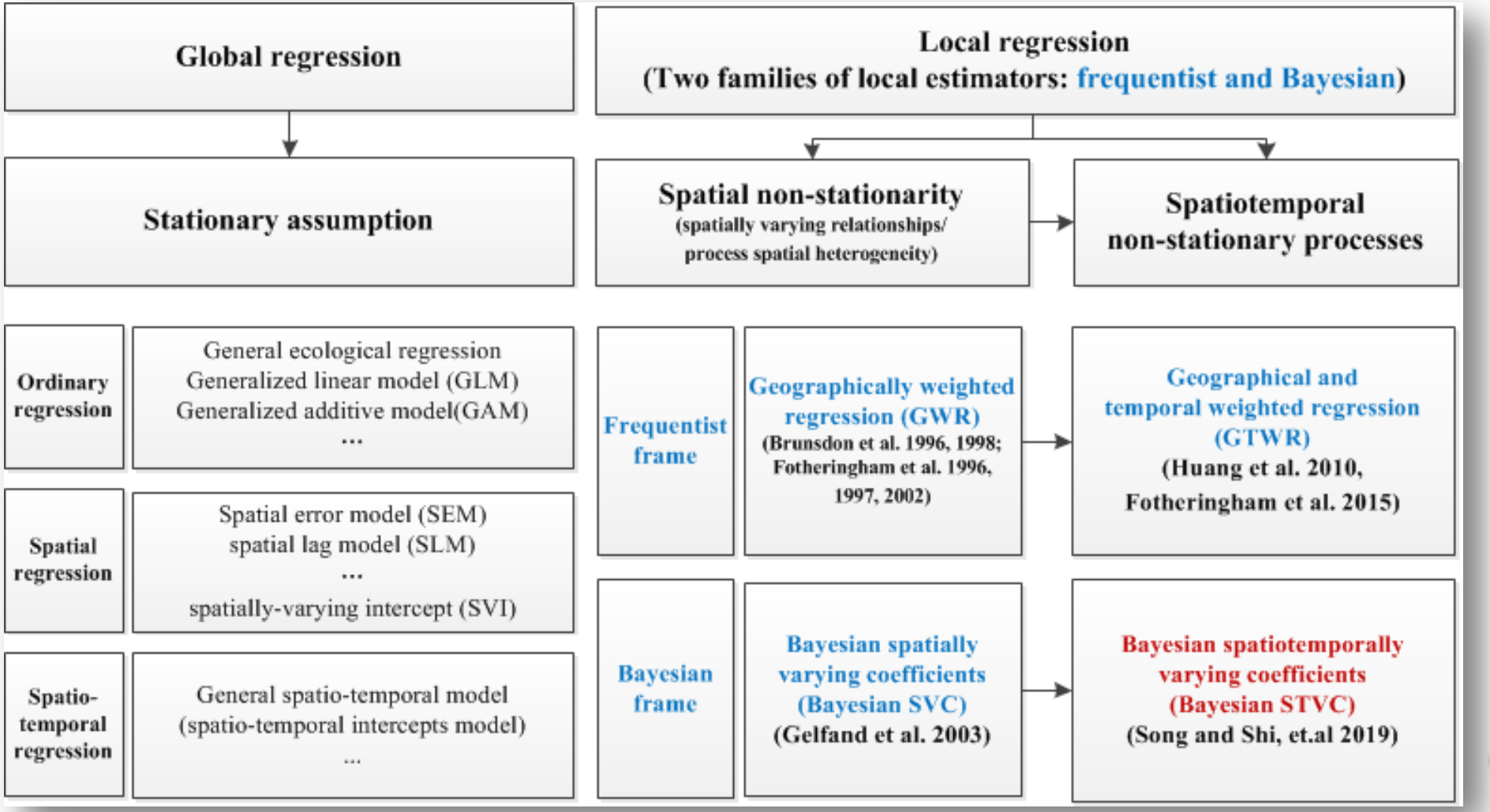


Temporally varying disease-climate relationships

Local temporal regression

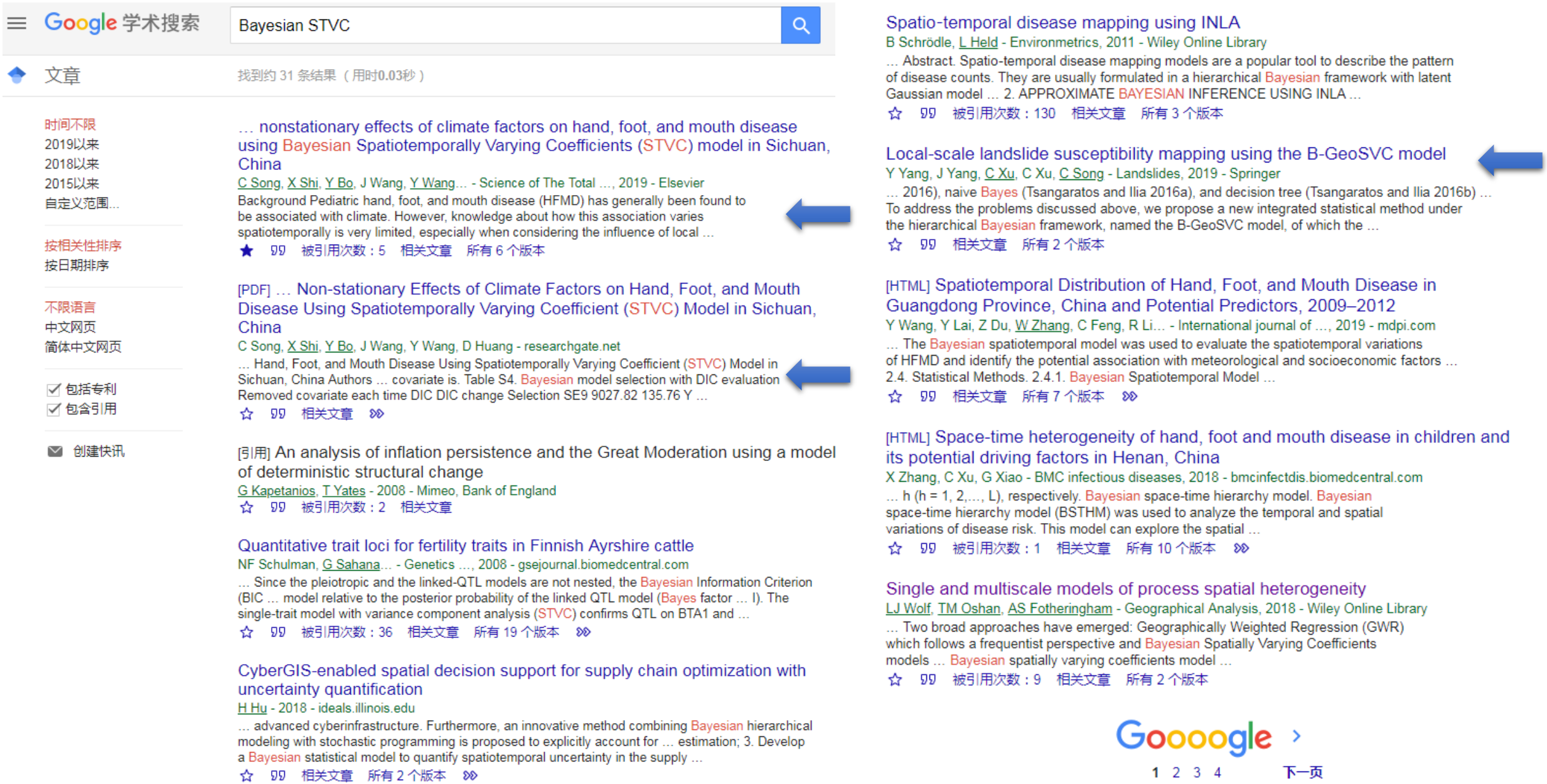
1. Background——1.3 Why proposing Bayesian STVC model?

- **Note that the core difference between global and local regression is whether consider nonstationary effects for regression coefficients which represent dependent-independent relations, not for intercepts which represent residuals or random errors.**



STVC model fills this GAP!

1. Background——1.4 First official named model as Bayesian STVC



1. Background——1.5 Comparisons between GWR and Bayesian SVC

- **Key literature review:**
  - **(1) Bayesian SVC produced more accurate estimates of the regression coefficients than GWR, in the presence of moderate and strong collinearity, using point-referenced public health data (Wheeler & Calder 2007, Wheeler & Waller 2009).**
  - **(2) GWR models were inferior to the SVC models, and GWR might be not robust to collinearity among the covariates, supported by two ecological data sets (Finley, 2011).**
  - **(3) GWR has been shown to be more robust in larger samples (Paez, Farber, and Wheeler 2011; Fotheringham and Oshan 2016).**
  - **(4) However, the interpretation of the bandwidth parameter is not transferrable between the two frameworks because the correlation kernel used to specify spatial mixed effects in the SVC simply behaves differently from the data-borrowing kernel of a GWR (Wolf et.al, 2017).**
- **Conclusion: ultimately, the choice of which local model to employ to study spatial nonstationary process might come down to personal preference, access to software and familiarity with the broad statistical framework in which each model sits (Wolf et.al, 2017).**

2. Bayesian STVC——2.1 Theory of a general STVC model

- The **Spatiotemporally Varying Coefficients (STVC)** model is a recent proposed Bayesian local regression approach for detecting both spatial and temporal nonstationary relationships between the dependent and various independent variables (process heterogeneity) , which is an essential development and extension of the local analysis methods (Song and Shi, et.al. 2019).

$$\eta_{it} = g(y_{it} \in Y) = \beta_0 + f(\mu_i^0) + f(\gamma_t^0) + \sum_k^K f(\mu_i^k X_{k,it}) + \sum_k^K f(\gamma_t^k X_{k,it}) + \sum_h^H \beta_h C_{h,it}$$

1 2 3 4 5

Prior data distribution of response variable	Intercepts: spatial random effects	Intercepts: temporal random effects	Covariates Xs: spatial non-stationery random effects	Covariates Xs: temporal non-stationery random effects	Control covariates Cs: fixed effects

Estimated parameters → **SVI** μ_i^0 **TVI** γ_t^0 **SVC** μ_i^k **TVC** γ_t^k **Fixed effects** β_h

η_{it} Structured additive predictor; Y: target dependent variable;
$g()$ Likelihood function; $f()$ Latent Gaussian model function;
X_k Main/core independent variables (1-K) with spatiotemporal nonstationary assumption;
C_h Other control independent variables (1-H) with stationary assumption.

SVI: spatial varying intercepts
TVI: temporal varying intercepts
SVC: spatial varying coefficients
TVC: temporal varying coefficients

2. Bayesian STVC——2.1 Theory of a general STVC model

- **For spatial autocorrelation sub-level model, conditional autoregressive *f* (CAR) prior is considered for all the spatial random effects, i.e., components 1 and 3.**
- **For temporal autocorrelation sub-level model, random walk *f* (RW) prior is considered for all the temporal random effects, i.e., components 2 and 4 .**

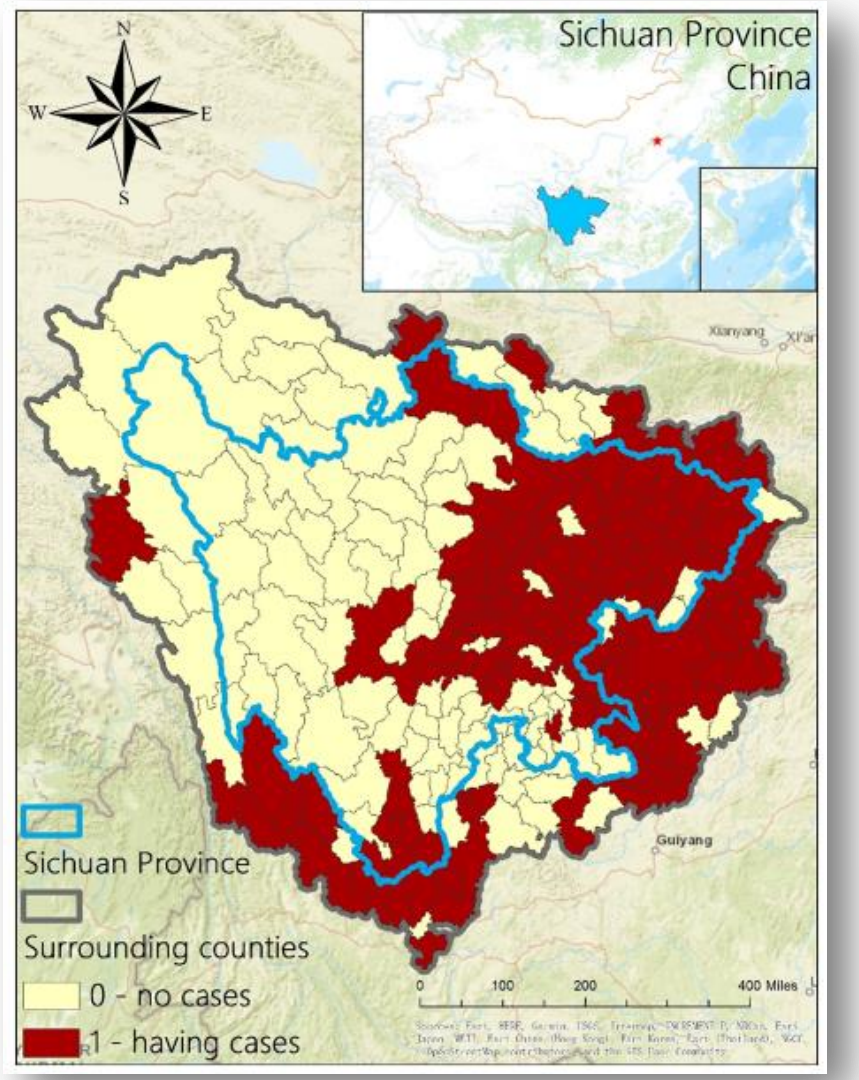
- **The CAR prior model assumes that the disease occurrence risk in a spatial area is derived from nearby geographical neighbors (spatial autocorrelation). *That is, everything is related to everything else, but near things are more related than distant things -Tobler*.**

$$\mu_i^0, \mu_i^k \sim CAR \qquad \mu_i \Big| \ \mu_{j\neq i} \sim N(\frac{1}{m_i}\sum_{i\sim j}\mu_i, \frac{\sigma^2}{m_i})$$

- **Similar to CAR, the RW prior model assumes that the temporal variation of disease occurrence risk is influenced by adjacent time points (temporal autocorrelation), which is expressed as a smoothly varying nonlinear curve.**

$$\gamma_t^0, \gamma_t^k \sim RW \qquad \pi(\gamma_t \Big| \sigma_\gamma^2) \propto \exp(-\frac{1}{2\sigma_\gamma^2}\sum_{t=2}^{T}(\gamma_t - \gamma_{t-1})^2)$$

3. Case study I : explore HFMD-climate nonstationary relationships at local spatiotemporal scales



Geographical distribution of reported HFMD cases in Sichuan Province of China in June 2009

- Pediatric hand, foot, and mouth disease (HFMD) has generally been found to be associated with climate.
- However, knowledge about how this association varies spatiotemporally is very limited, especially when considering the influence of local socioeconomic conditions.
- We use data of monthly county-level HFMD occurrence and data of related climate and socioeconomic variables in Sichuan, China from 2009 to 2011 for our experiments.

Dependent variable
HFMD occurrence

Space dimension

Bayesian STVC

Time dimension

Independent variables
various climate variables

3.1 Disease relative risk assessment indicator OR

- **Odds ratio (*OR*) is widely used to identify risk factors for a binary disease outcome variable in classical epidemiology.**
- **Generally, *OR* indicator can be obtained directly by a logistic regression model.**

$$OR_x = e^{\beta} \qquad In(\frac{P_i}{1-P_i}) = \beta_0 + \beta_1 x_{1,i} + \cdots + \beta_n x_{n,i}$$

***OR* >1 , *OR* <1, *OR* =1**

- **where β is the regression coefficient of the potential risk factor *x*.**

Global *OR* (stationery assumption)

Original covariates maps to show fake risks

Spatialization/ Downscaling issue

GWR, SVC

Local spatial *OR*s (non-stationery assumption)

True covariate-disease risk associations maps

Q: How to obtain local *OR*s to represent local risk at both spatial and temporal scales?

3.2 Spatiotemporal local ORs estimated by STVC model

$$\eta_{it} = In(\frac{P_{it}}{1-P_{it}}) = \beta_0 + f(\mu_i^0) + f(\gamma_t^0) + \sum_k^K f(\mu_i^k X_{k,it}) + \sum_k^K f(\gamma_t^k X_{k,it}) + \sum_h^H \beta_h C_{h,it}$$

Varying coefficients

$\mu_{k,i}$ is the **spatial varying coefficients (SVC)** that represents the spatial covariate-disease risk associations.

$\gamma_{k,t}$ is the **temporal varying coefficients (TVC)** that represents the temporal covariate-disease risk associations.

The **local spatial $OR_{k,i}$ value** of each risk factor is obtained by

$$OR_{k,i} = e^{\mu_{k,i}}$$

The **local temporal $OR_{k,t}$ value** of each risk factor is obtained by

$$OR_{k,t} = e^{\gamma_{k,t}}$$

Local spatial and temporal ORs

3.3 Model implementation

- **To evaluate the performance of the STVC model, we compared it with the other four regression models.**

Model 1: Ordinary ecological logistic regression model

$$\eta_{it} = \beta_0 + \sum_k^m \beta_k C_k + \sum_j^n \beta_j SE_j$$

Model 2: Temporal ecological logistic regression model

$$\eta_{it} = \beta_0 + \sum_k^m \beta_k C_k + \sum_j^n \beta_j SE_j + \gamma_t + \varphi_t$$

Model 3: Spatial ecological logistic regression model

$$\eta_{it} = \beta_0 + \sum_k^m \beta_k C_k + \sum_j^n \beta_j SE_j + \mu_i + \nu_i$$

Model 4: Spatiotemporal ecological logistic regression model

$$\eta_{it} = \beta_0 + \sum_k^m \beta_k C_k + \sum_j^n \beta_j SE_j + \mu_i + \nu_i + \gamma_t + \varphi_t$$

Model 5: STVC model

$$\eta_{it} = In(\frac{P_i}{1-P_i}) = \beta_0 + \xi_i + \psi_t + \sum_k^m f(\mu_{k,i} X_{k,it}) + \sum_k^m f(\gamma_{k,t} X_{k,it}) + \sum_j^n \beta_j SE_j$$

3.4 Model evaluation results under three cross-validation experiments

- **The STVC model outperformed these models in the Bayesian model evaluation.**

Table 1
Model evaluation results of the five alternative Bayesian models in three cross-validation experiments.

	10% Cross-validation			15% Cross-validation			20% Cross-validation		
	DIC	*pD*	*LS*	*DIC*	*pD*	*LS*	*DIC*	*pD*	*LS*
Model 1	8010.98	6.02	0.5750	7597.18	6.02	0.5774	7203.89	6.01	0.5817
Model 2	7324.76	35.86	0.5258	6936.34	35.77	0.5272	6584.97	35.52	0.5318
Model 3	6523.59	190.52	0.4673	6225.77	188.67	0.4722	5896.36	187.99	0.4752
Model 4	6125.04	196.21	0.4394	5840.08	195.11	0.4436	5537.17	194.02	0.4469
Model 5	5191.31	408.24	0.3741	4962.17	301.11	0.3779	4761.72	321.22	0.3848
	PA(1)	*PA(0)*	*PA(1,0)*	*PA(1)*	*PA(0)*	*PA(1,0)*	*PA(1)*	*PA(0)*	*PA(1,0)*
Model 1	55.18%	75.77%	64.73%	70.33%	67.70%	69.08%	70.33%	71.65%	70.99%
Model 2	61.45%	81.06%	70.54%	73.44%	70.42%	72.01%	73.46%	75.48%	74.48%
Model 3	76.14%	71.87%	74.16%	80.82%	72.23%	76.74%	79.48%	74.71%	77.07%
Model 4	78.55%	73.26%	76.10%	80.82%	75.32%	78.21%	79.22%	77.78%	78.49%
Model 5	80.48%	81.06%	80.75%	83.93%	79.67%	81.91%	83.66%	82.89%	83.27%

Note: (model 1: ordinary; model 2: temporal; model 3: spatial; model 4: spatiotemporal; model 5: STVC). *DIC*: deviance information criterion; *pD*: effective number of parameters; *LS*: logarithmic score; *PA(1)*: prediction accuracy for have-cases regions; *PA(0)*: prediction accuracy for no-cases regions; *PA(1,0)*: prediction accuracy for all-cases regions.

- **Cross-validation experiments showed that the STVC model achieved the best average prediction accuracy (81.98%), compared with ordinary (68.27%), temporal (72.34%), spatial (75.99%) and spatiotemporal (77.60%) ecological models.**

3.5 Global scale risk indicator (traditional epidemiologic OR)

- **Both climate and socioeconomic factors were found to be associated with HFMD occurrence in the study area.**

Climate factors

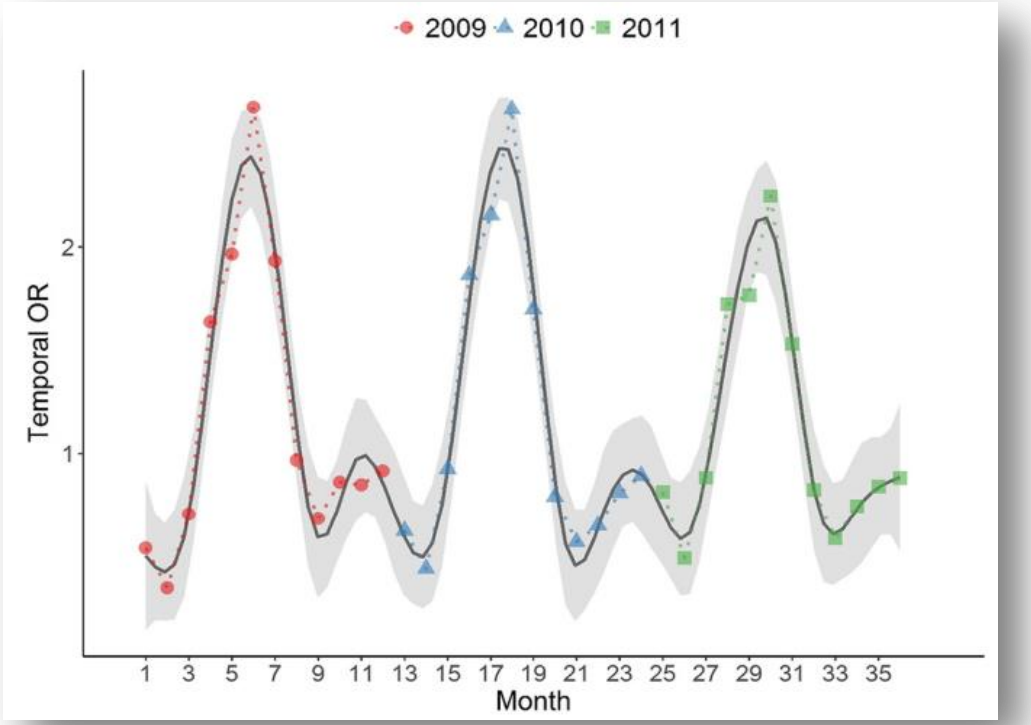
Socioeconomic factors

Table 2

Odds ratio (OR) values and estimated posterior parameters of the climate and socioeconomic factors on HFMD occurrence.

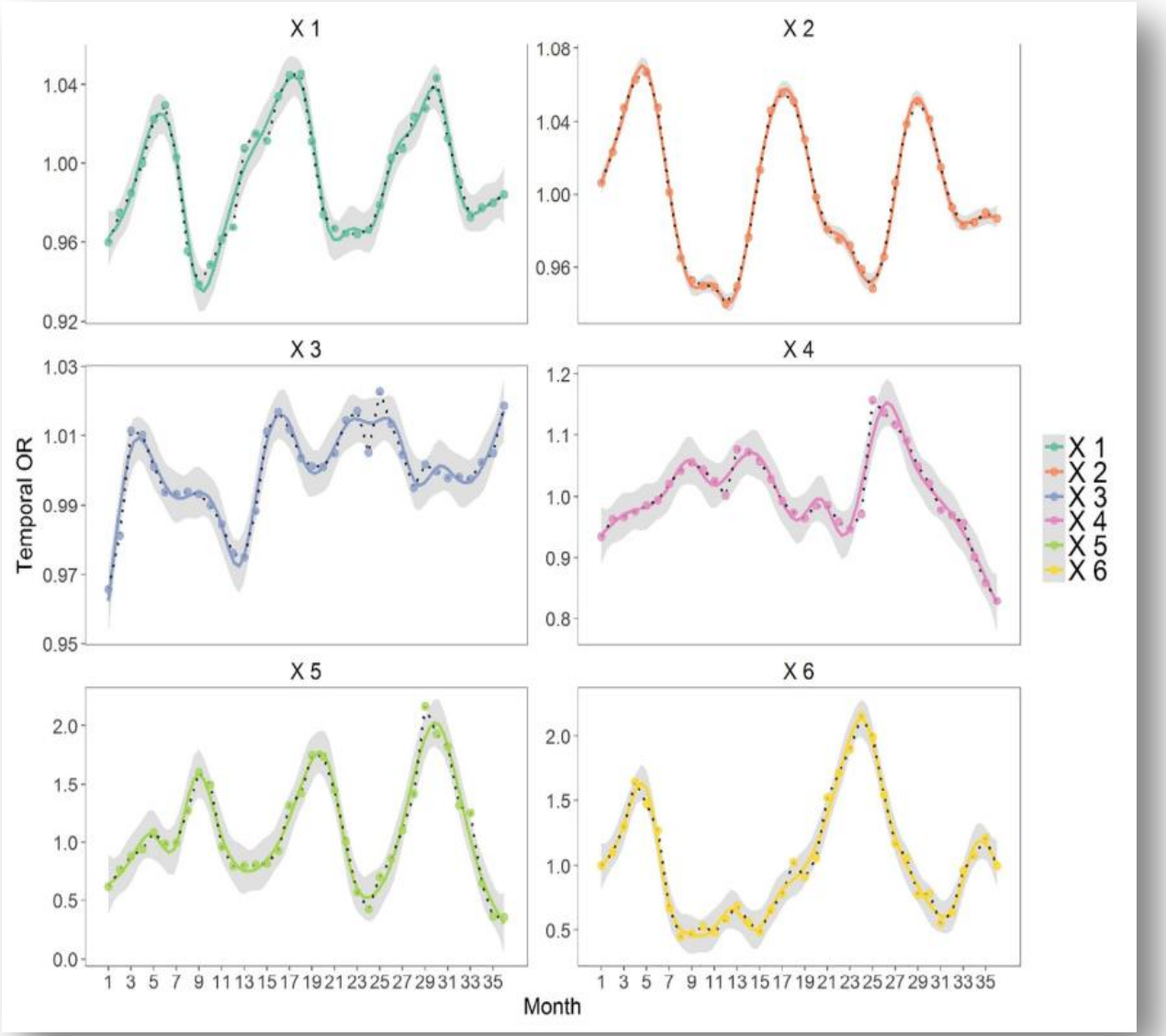
Covariates	OR	Mean	SD	0.025 CI	0.975 CI
Temperature	2.59	0.9508	0.2858	0.3980	1.5201
Relative humidity	1.35	0.2978	0.1401	0.0232	0.5729
Sunshine hours	1.06	0.0621	0.1207	−0.1749	0.2988
Air pressure	0.95	−0.0423	0.2439	−0.5203	0.4374
Wind speed	0.65	−0.4259	0.1250	−0.6720	−0.1812
Precipitation	0.99	−0.0010	0.0007	−0.0023	0.0004
Enterprise number density	3.43	1.2326	0.2641	0.7166	1.7532
Per capita household savings	2.44	0.8921	0.2068	0.4850	1.2971
Per capita gross domestic product (GDP)	1.41	0.3465	0.1672	0.0183	0.6748
Children gender ratio	1.35	0.3015	0.1152	0.0761	0.5281
Per capita industrial output values	0.71	−0.3486	0.2210	−0.7832	0.0844

3.6 Temporal disease distribution and disease-climate relations (temporally local ORs)



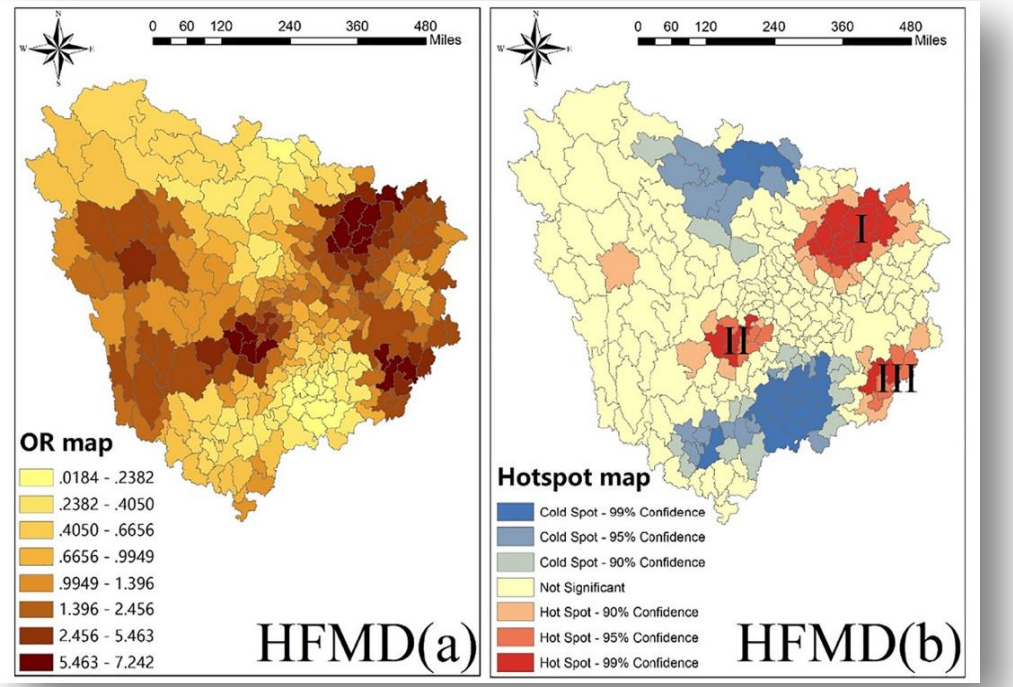
Temporal local ORs of disease itself

X1 temperature
X2 relative humidity
X3 precipitation
X4 air pressure
X5 wind speed
X6 sunshine hours



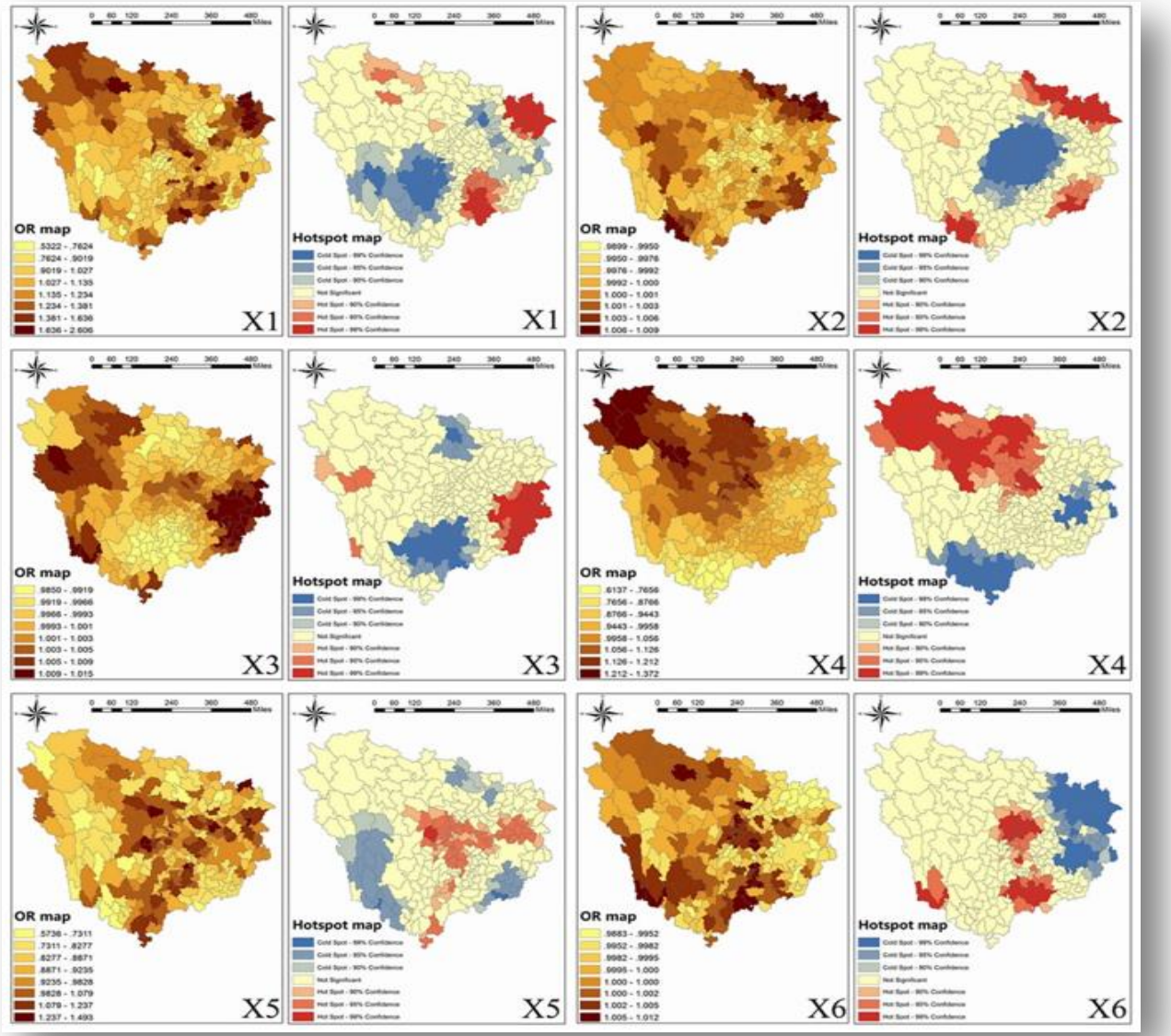
Temporal local ORs of disease-climate relationships

3.7 Spatial disease distribution and disease-climate relations (spatially local ORs)



Spatial local ORs of disease itself

X1 temperature
X2 relative humidity
X3 precipitation
X4 air pressure
X5 wind speed
X6 sunshine hours



Spatial local ORs of disease-climate relationships

3.8 Conclusion and innovation

I. Regarding space-time analysis methods development:

- **The Bayesian STVC model is firstly and officially proposed for exploring the local-scale spatiotemporal nonstationary dependent-independent variables relationships, as well as to further improve model fitness and prediction accuracy.**

II. Regarding local-scale epidemiologic risk assessment:

- **The STVC model with logistic prior distribution was able to spatialize the risk indicator odds ratio (OR) into local ORs to represent spatial and temporal varying disease-climate relationships.**

III. Regarding hand, foot and mouth disease (HFMD) propagation:

- **We detected local temporal nonlinear seasonal trends and spatial hot spots for both disease occurrence and disease-climate associations over 36 months in Sichuan, China.**
- **Among the six representative climate variables, temperature (OR = 2.59), relative humidity (OR = 1.35), and wind speed (OR = 0.65) were not only overall related to the increase of HFMD occurrence, but also demonstrated spatiotemporal variations in their local associations with HFMD.**

5. Further studies of Bayesian STVC-family modeling

Limitations of Bayesian STVC:

Overfitting, extreme parameter problem.

High computational burden, high model complexity for large sample size.

No off-the-shelf software for Bayesian STVC modeling.

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Thanks.

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