

2-2018

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Recommended Citation

Mu, Jingru; Wang, Guannan; and Wang, Li, Estimation and inference in spatially varying coefficient models (2018). *Environmetrics*, 29(1).
10.1002/env.2485

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RESEARCH ARTICLE

Estimation and inference in spatially varying coefficient models

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College of William & Mary; National Science Foundation, Grant/Award Number: DMS-1542332

Spatially varying coefficient models are a classical tool to explore the spatial nonstationarity of a regression relationship for spatial data. In this paper, we study the estimation and inference in spatially varying coefficient models for data distributed over complex domains. We use bivariate splines over triangulations to represent the coefficient functions. The estimators of the coefficient functions are consistent, and rates of convergence of the proposed estimators are established. A penalized bivariate spline estimation method is also introduced, in which a roughness penalty is incorporated to balance the goodness of fit and smoothness. In addition, we propose hypothesis tests to examine if the coefficient function is really varying over space or admits a certain parametric form. The proposed method is much more computationally efficient than the well-known geographically weighted regression technique and thus usable for analyzing massive data sets. The performances of the estimators and the proposed tests are evaluated by simulation experiments. An environmental data example is used to illustrate the application of the proposed method.

KEYWORDS

bivariate splines, bootstrap test, penalized splines, permutation test, spatial data, triangulation

1 | INTRODUCTION

In spatial data analysis, a common problem is to identify the nature of the relationship that exists between variables. In many situations, a simple “global” model often cannot explain the relationships between some sets of variables, which is referred to as “spatial nonstationarity”. To handle such nonstationarity, the model needs to reflect the spatially varying structure within the data. In this paper, we investigate a class of spatially varying coefficient models (SVCMs) to explore the spatial nonstationarity of a regression relationship. The data in our study need not be evenly distributed; instead, we assume that the observations are randomly distributed over two-dimensional domain $\Omega \subseteq \mathbb{R}^2$ of arbitrary shape, for example, a polygonal domain with interior holes. Suppose there are n random selected locations, and let $\mathbf{U}_i = (U_{i1}, U_{i2})^\top$ be the location of i th point, $i = 1, \dots, n$, which ranges over Ω . Let Y_i be the response variable and $\mathbf{X}_i = (X_{i0}, X_{i1}, \dots, X_{ip})^\top$, with $X_{i0} \equiv 1$ being the explanatory variables. Suppose that $\{(\mathbf{U}_i, \mathbf{X}_i, Y_i)\}_{i=1}^n$ satisfies the following model (Brunsdon, Fotheringham, & Charlton, 1996; 1998; Fotheringham, Brunsdon, & Charlton, 2002; Shen, Mei, & Zhang, 2011):

$$Y_i = \mathbf{X}_i^\top \boldsymbol{\beta}(\mathbf{U}_i) + \epsilon_i = \sum_{k=0}^p X_{ik} \beta_k(\mathbf{U}_i) + \epsilon_i, \quad i = 1, \dots, n, \quad (1)$$

where $\beta_k(\cdot)$ are unknown varying-coefficient functions, and ϵ_i are independent and identically distributed random noises with $E(\epsilon_i) = 0$ and $\text{Var}(\epsilon_i) = \sigma^2$ and are independent of \mathbf{X}_i . Our primary interest is to estimate and make inferences for $\beta = (\beta_0, \beta_1, \dots, \beta_p)^\top$ based on the given observations $\{(\mathbf{U}_i, \mathbf{X}_i, Y_i)\}_{i=1}^n$.

When $\beta_k(\cdot)$ are univariate functions, model (1) is the typical varying-coefficient model that has been extensively studied in the literature (Fan & Zhang, 1999; Ferguson, Bowman, Scott, & Carvalho, 2009; Hastie & Tibshirani, 1993; Lian, 2012; Tang & Cheng, 2009; Xue & Yang, 2006). In this paper, $\beta_k(\cdot)$ are bivariate functions of locations, and model (1) allows the regression coefficients to vary over space and therefore can be used to explore the spatial nonstationarity of the regression relationship via the spatial variation patterns of the estimated coefficients.

In the past decade, SVCMS have been widely applied to a variety of fields including geography (Su, Lei, Li, Pi, & Cai, 2017), ecology (Finley, 2011), econometrics (Al-Sulami, Jiang, Lu, & Zhu, 2017; Bitter, Mulligan, & Dall'erba, 2007; Helbich & Griffith, 2016), epidemiology (Nakaya, Fotheringham, Brunson, & Charlton, 2005), meteorology (Lu, Steinskog, Tjøstheim, & Yao, 2009), and environmental science (Hu et al., 2013; Huang, Yuan, & Lu, 2017; Tang, 2014; Waller, Zhu, Gotway, Gorman, & Gruenewald, 2007).

There is a rich literature on how to estimate SVCMS. Two competing methods are the Bayesian approach (see Assunção, 2003; Gelfand, Kim, Sirmans, & Banerjee, 2003) and the local approach, such as the geographically weighted regression (GWR) technique (Brunson et al., 1996; 1998; Fotheringham et al., 2002). The Bayesian procedure is carried out by assuming a certain prior distribution of the coefficients and computing their posterior distribution on which the estimation and inference are performed. However, there is no correct way of choosing a prior. In practice, misleading results will be generated if one does not choose prior distributions with caution. In addition, for a large data set with many variables being estimated, the Bayesian method may be prohibitively computationally intensive. The GWR method estimates the coefficients in the traditional regression framework of kernel smoothing. It incorporates local spatial relationships into the regression framework in an intuitive and explicit manner. While this local kernel-based approach is very nice and useful, it becomes very computationally intensive for large data sets as it requires solving an optimization problem at every sample location. Typically, the GWR model fitting and spatial prediction require $O(n^2)$ operations for a data set of size n . Recent evolutions in technology provide increasing volumes of spatial data (Banerjee, Gelfand, Finley, & Sang, 2008; Zhang, Deng, Qian, & Wang, 2013), which are beyond the computing limit of the traditional Bayesian and GWR method. It is urgent to develop a more computationally expedient tool for analyzing spatial data.

Tang and Cheng (2009) and Lu, Tang, and Cheng (2014) proposed a B-spline approximation of the coefficient functions. The method is fast and efficient because it inherits many advantages of spline-based techniques. However, the data are required to be regularly spaced over a rectangular domain. In practice, spatial data are often collected over complex domains with irregular boundaries, peninsulas, and interior holes. Many smoothing methods, such as kernel smoothing, tensor product smoothing, and wavelet smoothing, suffer from the problem of “leakage” across the complex domains, which refers to the poor estimation over difficult regions by smoothing inappropriately across boundary features; see the discussions by Ramsay (2002); Sangalli, Ramsay, and Ramsay (2013); and Wood, Bravington, and Hedley (2008).

In this paper, we develop a powerful and efficient method to estimate SVCMS for data distributed over two-dimensional complex domains. Our method tackles the estimation problem differently from the local approach, and the coefficient functions $\beta_k(\cdot)$ are approximated using the bivariate splines over triangulations (BSTs) by Lai and Schumaker (2007) and Lai and Wang (2013). The proposed estimator solves the problem of “leakage” across the complex domains. Another advantage of this approach is that it can formulate a global penalized least-squares problem; thus, it is sufficiently fast and efficient for the user to analyze large data sets within seconds. In addition, under the independence error condition, which is not uncommon in the GWR literature (Brunson et al., 1996; 1998; Huang, Yuan, & Lu, 2017; Shen et al., 2011; Su et al., 2017), we show that the proposed coefficient estimators converge to the true coefficient functions.

An important statistical question in fitting SVCMS is whether the coefficient function is really varying over space (Brunson, Fotheringham, & Charlton, 1999; Leung, Mei, & Zhang, 2000), which amounts to testing if the coefficient functions are constant or in a certain parametric form. In the pioneering work of GWR by Brunson et al. (1996), two kinds of permutation test are proposed for global stationarity and individual stationarity, respectively. For the individual test, the variability of the estimated coefficient function is used to describe the plausibility of a constant coefficient. Brunson et al. (1999) developed a test via comparing the residual sum of squares (RSS) from the GWR estimation with that from the ordinary least-squares estimation for the null hypothesis of global spatial stationarity. Moreover, Leung et al. (2000) introduced another RSS-based statistics to test for the global stationarity of the regression relationship. Motivated by many sophisticated statistical inferential problems in a variety of areas and fueled by the power of modern computing techniques, bootstrap methods got increasingly popular in the past two decades. For example, Mei, Wang, and Zhang (2006) used the bootstrap test to investigate the zero

coefficients in a mixed GWR model, and Cai, Fan, and Yao (2000) proposed a new wild bootstrap test for the goodness of fit of the varying-coefficient models for nonlinear time series. In this work, we adopt the idea from Cai et al. (2000) and employ a bootstrap test for testing a globally stationary regression relationship in an SVCM. For individual stationarity test, we suggest the permutation test, which is an easily understandable and generally applicable approach to testing problems. Our simulation shows that the resulting testing procedure is indeed powerful and the bootstrap method does give the right null distribution.

The rest of the paper is organized as follows. In Section 2, we give a short review of the triangulations and propose our estimation method based on bivariate splines. Section 3 is devoted to the asymptotic analysis of the proposed estimators. Section 4 extends the bivariate splines to the penalized bivariate splines, in which smoothing parameters are used to balance the goodness of fit and smoothness. Section 5 describes the bootstrap goodness-of-fit test to examine the global stationarity, and the permutation test for each coefficient functions to check individual stationarity. Section 6 presents simulation results comparing our method with its competitors. An illustration of the proposed approach is provided in Section 7 by an analysis of the particle pollution data. Section 8 concludes the paper. Technical details, some Matlab codes, and more numerical studies are provided in Supporting Information.

2 | TRIANGULATIONS AND BIVARIATE SPLINE ESTIMATORS

Our estimation is based on BST. We briefly introduce below the techniques of triangulations and the bivariate spline smoothing for SVCMs.

2.1 | Triangulations

Triangulation is an effective tool to handle data distributed on irregular regions with complex boundaries and/or interior holes. In the following, we use τ to denote a triangle that is a convex hull of three points not located in one line. A collection $\Delta = \{\tau_1, \dots, \tau_K\}$ of K triangles is called a triangulation of $\Omega = \cup_{j=1}^K \tau_j$, provided that if a pair of triangles in Δ intersect, then their intersection is either a common vertex or a common edge. Without loss of generality, we assume that all \mathbf{U}_i are inside triangles of Δ , that is, they are not on edges or vertices of triangles in Δ . Otherwise, we can simply count them twice or multiple times if any observation is located on an edge or at a vertex of Δ .

There are quite a few packages available that can be used to construct a triangulation. For example, one can use the ‘‘Delaunay’’ algorithm to find a triangulation; see MATLAB program *delaunay.m* or MATHEMATICA function *DelaunayTriangulation*. ‘‘DistMesh’’ is another method to generate unstructured triangular and tetrahedral meshes; see the *DistMesh* generator at <http://persson.berkeley.edu/distmesh/>. A detailed description of the program is provided by Persson and Strang (2004). In all the simulation studies and real data analysis below, we used the ‘‘DistMesh’’ to generate the triangulations.

2.2 | Bivariate spline estimators

For a nonnegative integer r , let $\mathbb{C}^r(\Omega)$ be the collection of all r th continuously differentiable functions over Ω . Given a triangulation Δ , let $S_d^r(\Delta) = \{s \in \mathbb{C}^r(\Omega) : s|_\tau \in \mathbb{P}_d(\tau), \tau \in \Delta\}$ be a spline space of degree d and smoothness r over triangulation Δ , where $s|_\tau$ is the polynomial piece of spline s restricted on triangle τ , and \mathbb{P}_d is the space of all polynomials of degree less than or equal to d . Given $\{(\mathbf{U}_i, \mathbf{X}_i, Y_i)\}_{i=1}^n$, we consider the following minimization problem:

$$\min_{s_k \in S_d^r(\Delta), k=0, \dots, p} \sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} s_k(\mathbf{u}_i) \right\}^2.$$

We use Bernstein basis polynomials to represent the bivariate splines. For any $k = 0, \dots, p$, let $\{B_j\}_{j \in \mathcal{J}_k}$ be the set of degree- d bivariate Bernstein basis polynomials for $S_d^r(\Delta)$ constructed by Lai and Schumaker (2007), where \mathcal{J}_k denotes the index set of the basis functions. Then, we can write the function $s_k(\mathbf{u}) = \sum_{j \in \mathcal{J}_k} B_{kj}(\mathbf{u}) \gamma_{kj} = \mathbf{B}_k(\mathbf{u})^\top \boldsymbol{\gamma}_k$, where $\boldsymbol{\gamma}_k = (\gamma_{kj}, j \in \mathcal{J}_k)^\top$ is the spline coefficient vector. Using the above approximation, we have the following minimization:

$$\sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} \mathbf{B}_k(\mathbf{U}_i)^\top \boldsymbol{\gamma}_k \right\}^2. \tag{2}$$

To meet the smoothness requirement of the bivariate splines, we need to impose some linear constraints on the spline coefficients to enforce smoothness across shared edges of triangles. Denote by \mathbf{H}_k the constraint matrix on the coefficients $\boldsymbol{\gamma}_k$. Here \mathbf{H}_k depends on the smoothness r and the structure of the triangulation. Putting all smoothness conditions together yields $\mathbf{H}_k \boldsymbol{\gamma}_k = \mathbf{0}$. We first remove the constraint via the following QR decomposition: $\mathbf{H}_k^\top = (\mathbf{Q}_{1,k} \ \mathbf{Q}_{2,k}) \begin{pmatrix} \mathbf{R}_{1,k} \\ \mathbf{0} \end{pmatrix}$, where $(\mathbf{Q}_{1,k} \ \mathbf{Q}_{2,k})$ is an orthogonal matrix, and $\mathbf{R}_{1,k}$ is an upper triangle matrix. We then reparametrize using $\boldsymbol{\gamma}_k = \mathbf{Q}_{2,k} \boldsymbol{\theta}_k$ for some $\boldsymbol{\theta}_k$; it is then guaranteed that $\mathbf{H}_k \boldsymbol{\gamma}_k = \mathbf{0}$. Thus, the minimization problem in (2) is now converted to a conventional regression problem without any restriction, as follows:

$$\sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} \mathbf{B}_k^\top(\mathbf{U}_i) \mathbf{Q}_{2,k} \boldsymbol{\theta}_k \right\}^2. \quad (3)$$

For simplicity, we assume $\mathbf{B}(\mathbf{u}) = \mathbf{B}_0(\mathbf{u}) = \mathbf{B}_1(\mathbf{u}) = \cdots = \mathbf{B}_p(\mathbf{u}) = \{B_j(\mathbf{u})\}_{j \in \mathcal{J}}$, then $\mathbf{H}_0 = \mathbf{H}_1 = \cdots = \mathbf{H}_p$ and $\mathbf{Q}_2 = \mathbf{Q}_{2,0} = \mathbf{Q}_{2,1} = \cdots = \mathbf{Q}_{2,p}$. In practice, if the coefficients are of very different degrees of smoothness, one can choose different bivariate spline basis functions with variable triangulations for different coefficient functions to guarantee sufficient smoothness. Denote $\boldsymbol{\theta} = (\boldsymbol{\theta}_0^\top, \boldsymbol{\theta}_1^\top, \dots, \boldsymbol{\theta}_p^\top)^\top$ and let $\mathbf{X}_i = (1, X_{i1}, \dots, X_{ip})^\top$. Let $\mathbf{B}^*(\mathbf{U}_i) = \mathbf{Q}_2^\top \mathbf{B}(\mathbf{U}_i)$. Then the minimization problem in (3) can be written as follows:

$$\sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} \mathbf{B}^*(\mathbf{U}_i)^\top \boldsymbol{\theta}_k \right\}^2. \quad (4)$$

Let “ \otimes ” denote the Kronecker product. Solving the least-squares problem in (4), we obtain the following:

$$\hat{\boldsymbol{\theta}} = \left[\sum_{i=1}^n \{ \mathbf{X}_i \otimes \mathbf{B}^*(\mathbf{U}_i) \} \{ \mathbf{X}_i \otimes \mathbf{B}^*(\mathbf{U}_i) \}^\top \right]^{-1} \sum_{i=1}^n \{ \mathbf{X}_i \otimes \mathbf{B}^*(\mathbf{U}_i) \} Y_i. \quad (5)$$

The BST estimator of $\beta_k(\mathbf{u})$ is $\hat{\beta}_k(\mathbf{u}) = \mathbf{B}(\mathbf{u})^\top \hat{\boldsymbol{\gamma}}_k$, where $\hat{\boldsymbol{\gamma}}_k = \mathbf{Q}_2 \hat{\boldsymbol{\theta}}_k$, for $k = 0, \dots, p$.

3 | ASYMPTOTIC RESULTS

This section studies the asymptotic properties of the proposed estimators. To discuss these properties, we introduce some notation of norms. For any function g over the closure of domain Ω , denote by $\|g\|_{L^2(\Omega)}^2 = \int_{\mathbf{u} \in \Omega} g^2(\mathbf{u}) d\mathbf{u}_1 d\mathbf{u}_2$ the regular L_2 norm of g , and $\|g\|_{\infty, \Omega} = \sup_{\mathbf{u} \in \Omega} |g(\mathbf{u})|$ the supremum norm of g . For directions $u_j, j = 1, 2$, let $D_{u_j}^q g(\mathbf{u})$ denote the q th order derivative in the direction u_j at the point \mathbf{u} . Let $\|g\|_{v, \infty, \Omega} = \max_{i+j=v} \|D_{u_1}^i D_{u_2}^j g(\mathbf{u})\|_{\infty, \Omega}$ be the maximum norms of all the v th order derivatives of g over Ω .

Let $W^{\ell, \infty}(\Omega) = \{g : \|g\|_{k, \infty, \Omega} < \infty, 0 \leq k \leq \ell\}$ be the standard Sobolev space. Given random variables T_n for $n \geq 1$, we write $T_n = o_P(b_n)$ if $\lim_{c \rightarrow \infty} \limsup_n P(|T_n| \geq cb_n) = 0$. Similarly, we write $T_n = O_P(b_n)$ if $\lim_n P(|T_n| \geq cb_n) = 0$, for any constant $c > 0$. Also, we write $a_n \asymp b_n$ if there exist two positive constants c_1, c_2 such that $c_1 |a_n| \leq |b_n| \leq c_2 |a_n|$, for all $n \geq 1$.

For a triangle $\tau \in \Delta$ defined in Section 2.1, let $|\tau|$ be its longest edge length, and ρ_τ be the radius of the largest disk, which can be inscribed in τ . Define the shape parameter of τ as the ratio $\pi_\tau = |\tau|/\rho_\tau$. When π_τ is small, the triangles are relatively uniform in the sense that all angles of triangles in the triangulation τ are relatively the same. Denote the size of Δ by $|\Delta| := \max\{|\tau|, \tau \in \Delta\}$, that is, the length of the longest edge of Δ .

In the following, we introduce some technical conditions.

- (C1) The joint density function of $\mathbf{U} = (U_1, U_2)$, $f_{\mathbf{U}}(\cdot)$ is bounded away from 0 and infinity.
- (C2) For any $k = 0, \dots, p$, there exists a positive constant C_k such that $|X_k| \leq C_k$. The eigenvalues $\phi_0(\mathbf{u}) \leq \phi_1(\mathbf{u}) \leq \cdots \leq \phi_p(\mathbf{u})$ of $\boldsymbol{\Sigma}(\mathbf{u}) = E(\mathbf{X}\mathbf{X}^\top | \mathbf{U} = \mathbf{u})$ are bounded away from 0 and infinity uniformly for all $\mathbf{u} \in \Omega$, that is, there are positive constants C_1 and C_2 such that $C_1 \leq \phi_0(\mathbf{u}) \leq \phi_1(\mathbf{u}) \leq \cdots \leq \phi_p(\mathbf{u}) \leq C_2$ for all $\mathbf{u} \in \Omega$.
- (C3) For any $k = 0, \dots, p$, the bivariate function β_k belongs to the Sobolev space $W^{\ell+1, \infty}(\Omega)$ for an integer $\ell \geq 1$.
- (C4) For every $s \in S_d^r(\Delta)$ and every $\tau \in \Delta$, there exists a positive constant F_1 , independent of s and τ , such that $F_1 \|s\|_{\infty, \tau} \leq \left\{ \sum_{\mathbf{U}_i \in \tau, i=1, \dots, n} s(\mathbf{U}_i)^2 \right\}^{1/2}$, for all $\tau \in \Delta$.

- (C5) Let F_2 be the largest among the numbers of observations in triangles $\tau \in \Delta$, that is, $\{\sum_{\mathbf{U}_i \in \tau, i=1, \dots, n} s(\mathbf{U}_i)^2\}^{1/2} \leq F_2 \|s\|_{\infty, \tau}$, for all $\tau \in \Delta$, where $\|s\|_{\infty, \tau}$ denotes the supremum norm of s over triangle τ . The constants F_1 and F_2 satisfy $F_2/F_1 = O(1)$.
- (C6) The triangulation Δ is π -quasi-uniform, that is, there exists a positive constant π such that the triangulation Δ satisfies $|\Delta|/\rho_\tau \leq \pi$, for all $\tau \in \Delta$.

Conditions (C1) and (C2) are common in the nonparametric regression literature; specifically, they are similar to Conditions (C1) and (C2) in Xue and Yang (2006) and Conditions (C1)–(C3) in Huang, Wu, and Zhou (2004). Condition (C3) describes the requirement for the coefficient functions usually used in the literature of nonparametric estimation. Condition (C4) ensures the existence of a discrete least-squares spline. In practice, it requires that within each triangle, the number of data points should not be too small. Condition (C5) suggests that we should not put too many observations in one triangle. In Section 4, we describe the penalized least-squares spline fitting so that Conditions (C4) and (C5) can be relaxed in the application, for example, F_1 can be zero for some triangles. Condition (C6) suggests the use of more uniform triangulations with smaller shape parameters, and this condition can be automatically handled via Delaunay and DistMesh triangulation program in MATLAB/MATHEMATICA.

The following theorem provides the convergence rate of $\hat{\beta}_k(\cdot)$. The detailed proofs of this theorem are given in Supporting Information.

Theorem 1. *Suppose Conditions (C1)–(C6) hold, then for any $k = 0, \dots, p$, the spline estimator $\hat{\beta}_k(\cdot)$ is consistent and satisfies that $\|\hat{\beta}_k - \beta_k\|_{L^2(\Omega)} = O_P\left(\frac{F_2}{F_1} |\Delta|^{\ell+1} + \frac{1}{\sqrt{n}|\Delta|}\right)$.*

Theorem 1 implies that if $F_2/F_1 = O(1)$, and the number of triangles K_n and the sample size n satisfy that $K_n \asymp n^{1/(\ell+2)}$, then the BST estimator $\hat{\beta}_k$ has the convergence rate $\|\hat{\beta}_k - \beta_k\|_{L^2(\Omega)}^2 = O_P(n^{-(\ell+1)/(\ell+2)})$, which is the optimal convergence rate in Stone (1982).

4 | BIVARIATE PENALIZED SPLINE ESTIMATORS

When we have regions of sparse data, bivariate penalized splines, as a direct ridge regression shrinkage-type global smoothing method, provide a more convenient tool for data fitting than the BST approach presented in Section 2.2. In this section, we introduce a computationally efficient and stable method to estimate the regression coefficients based on the bivariate penalized splines over triangulations (BPSTs). In this approach, roughness penalty parameters are used to balance the goodness of fit and smoothness. The number and shape of the triangles in triangulation are no longer crucial, compared with the BST in Section 2.2, as long as the minimum number of triangles is reached. To define the BPST method, let

$$\mathcal{E}(g) = \int_{\Omega} \{ (D_{u_1}^2 g)^2 + 2(D_{u_1} D_{u_2} g)^2 + (D_{u_2}^2 g)^2 \} du_1 du_2, \tag{6}$$

which is similar to the thin-plate spline penalty (Green & Silverman, 1994), except that the latter is integrated over the entire plane \mathbb{R}^2 . An advantage of this penalty is that it is invariant with respect to Euclidean transformations of spatial coordinates; thus, the bivariate smoothing does not depend on the choice of the coordinate system.

Let $\lambda_k \geq 0$ be the penalty parameter for coefficient function β_k , $k = 0, 1, \dots, p$. Given $\{(\mathbf{U}_i, \mathbf{X}_i, Y_i)\}_{i=1}^n$, we consider the following regularized minimization problem:

$$\min_{s_k \in S_d^r(\Delta), k=0, \dots, p} \sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} s_k(\mathbf{u}_i) \right\}^2 + \sum_{k=0}^p \lambda_k \mathcal{E}(s_k),$$

where separate penalty parameters are used to allow different smoothness for different coefficient functions. Using the bivariate splines approximation, we have the following minimization:

$$\sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} \mathbf{B}_k(\mathbf{U}_i)^\top \boldsymbol{\gamma}_k \right\}^2 + \sum_{k=0}^p \lambda_k \boldsymbol{\gamma}_k^\top \mathbf{P}_k \boldsymbol{\gamma}_k. \tag{7}$$

where \mathbf{P}_k is the diagonally block penalty matrix satisfying that $\boldsymbol{\gamma}_k^\top \mathbf{P}_k \boldsymbol{\gamma}_k = \mathcal{E}(\mathbf{B}_k^\top \boldsymbol{\gamma}_k)$.

Similar to what has been done in Section 2.2, we remove the constraint via QR decomposition of \mathbf{H}_k^\top ; then, the minimization problem in (7) is converted to the following:

$$\sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} \mathbf{B}_k(\mathbf{U}_i)^\top \mathbf{Q}_{2,k} \boldsymbol{\theta}_k \right\}^2 + \sum_{k=0}^p \lambda_k \boldsymbol{\theta}_k^\top \mathbf{Q}_{2,k}^\top \mathbf{P}_k \mathbf{Q}_{2,k} \boldsymbol{\theta}_k. \quad (8)$$

Assuming $\mathbf{B}(\mathbf{u}) = \mathbf{B}_0(\mathbf{u}) = \mathbf{B}_1(\mathbf{u}) = \cdots = \mathbf{B}_p(\mathbf{u}) = \{B_j(\mathbf{u})\}_{j \in J}$, the minimization problem in (8) can be written as follows:

$$\sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} \mathbf{B}(\mathbf{U}_i)^\top \mathbf{Q}_2 \boldsymbol{\theta}_k \right\}^2 + \sum_{k=0}^p \lambda_k \boldsymbol{\theta}_k^\top \mathbf{Q}_2^\top \mathbf{P} \mathbf{Q}_2 \boldsymbol{\theta}_k. \quad (9)$$

Let $\boldsymbol{\Lambda} = \text{diag}(\lambda_0, \lambda_1, \dots, \lambda_p)$ and $\mathbf{D}_\Lambda = \boldsymbol{\Lambda} \otimes (\mathbf{Q}_2^\top \mathbf{P} \mathbf{Q}_2)$. Solving the penalized least-squares problem in (9), we obtain the following:

$$\hat{\boldsymbol{\theta}}^* = \left[\sum_{i=1}^n \{ \mathbf{X}_i \otimes \mathbf{B}^*(\mathbf{U}_i) \} \{ \mathbf{X}_i \otimes \mathbf{B}^*(\mathbf{U}_i) \}^\top + \mathbf{D}_\Lambda \right]^{-1} \sum_{i=1}^n \{ \mathbf{X}_i \otimes \mathbf{B}^*(\mathbf{U}_i) \} Y_i.$$

Therefore, the bivariate penalized spline estimators of β_k is $\hat{\beta}_k^*(\mathbf{u}) = \mathbf{B}(\mathbf{u})^\top \hat{\boldsymbol{\gamma}}_k^*$, where $\hat{\boldsymbol{\gamma}}_k^* = \mathbf{Q}_2 \hat{\boldsymbol{\theta}}_k^*$, $k = 0, \dots, p$.

A crucial issue for the implementation of penalized smoothing above is the selection of the penalty parameters λ_k , which control the trade-off between the goodness of fit and smoothness. A standard possibility is to select the penalty parameters using the cross-validation approach, for example, multi-fold cross-validation and generalized cross-validation. Based on our simulation studies and real data applications, we find that multi-fold cross-validation and generalized cross-validation usually yield similar results. In this work, we choose a common λ for all coefficient functions; nevertheless, separate smoothing parameters for coefficient functions can be adopted with heavier computing; see the discussion by Ruppert (2002).

5 | TESTS FOR NONSTATIONARITY

5.1 | Goodness-of-fit test

Statistical tests for examining if some of the coefficients vary over space are fundamental in achieving a valid interpretation of spatial nonstationarity of the regression relationship. To test whether model (1) holds with a specified parametric form such as linear regression models, we propose a bootstrap goodness-of-fit test based on the comparison of the RSS from both parametric and nonparametric fittings.

Consider the following null hypothesis:

$$H_0 : \beta_k(\mathbf{u}) = \beta_k(\mathbf{u}; \boldsymbol{\rho}), \quad 0 \leq k \leq p, \quad (10)$$

where $\beta_k(\cdot; \boldsymbol{\rho})$ is a given family of functions indexed by unknown parameter vector $\boldsymbol{\rho}$. Let $\hat{\boldsymbol{\rho}}$ be an estimator of $\boldsymbol{\rho}$. The RSS under H_0 (RSS₀) and the RSS corresponding to model (1) (RSS₁) are as follows:

$$\text{RSS}_0 = \sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} \beta_k(\mathbf{U}_i; \hat{\boldsymbol{\rho}}) \right\}^2, \quad \text{RSS}_1 = \sum_{i=1}^n \left\{ Y_i - \sum_{k=0}^p X_{ik} \hat{\beta}_k(\mathbf{U}_i) \right\}^2.$$

The test statistics is defined as follows:

$$T_n = (\text{RSS}_0 - \text{RSS}_1) / \text{RSS}_1 = \text{RSS}_0 / \text{RSS}_1 - 1, \quad (11)$$

and we reject the null hypothesis (10) for large values of T_n . Due to the feature of less assumption on the distribution of the error term of the model, bootstrap is a good technique for testing the nonstationarity for the SVCMS. We use the following nonparametric bootstrap approach (Cai et al., 2000) to evaluate the p value of the test.

Step 1. Based on the data $\{(\mathbf{U}_i, \mathbf{X}_i, Y_i)\}_{i=1}^n$, obtain the following residuals $\hat{\varepsilon}_i = Y_i - \sum_{k=0}^p X_{ik} \hat{\beta}_k(\mathbf{U}_i)$, $i = 1, \dots, n$, and calculate the centered residuals $\hat{\varepsilon}_i - \hat{\bar{\varepsilon}}$, where $\hat{\bar{\varepsilon}} = \frac{1}{n} \sum_{i=1}^n \hat{\varepsilon}_i$;

- Step 2. Generate the bootstrap residuals $\{\varepsilon_i^*\}_{i=1}^n$ from the empirical distribution function of the centered residuals $\hat{\varepsilon}_i - \bar{\varepsilon}$ in Step 1, and define $Y_i^* = \sum_{k=0}^p X_{ik} \beta_k(\mathbf{U}_i; \hat{\rho}) + \varepsilon_i^*$;
- Step 3. Calculate the bootstrap test statistic T_n^* based on the sample $\{(\mathbf{U}_i, \mathbf{X}_i, Y_i^*)\}_{i=1}^n$;
- Step 4. Repeat Steps 2 and 3 B times and obtain a bootstrap sample of the test statistics T_n as $\{T_{nb}^*\}_{b=1}^B$, and the p value is estimated by $\hat{p} = \sum_{b=1}^B I(T_{nb}^* \geq T_{obs})/B$, where $I(\cdot)$ is the indicator function, and T_{obs} is the observed value of the test statistics T_n by (11), or reject the null hypothesis H_0 when T_n is greater than the upper- α quantile of $\{T_{nb}^*\}_{b=1}^B$.

Note that the nonparametric estimate is always consistent, no matter the null or whether the alternative hypothesis is correct. Therefore, here, we bootstrap the centralized residuals from the nonparametric fit instead of the parametric fit, and this should provide a consistent estimator of the null hypothesis even when the null hypothesis does not hold. As proved by Kreiss, Neumann, and Yao (2008), which considered the nonparametric bootstrap tests in a general nonparametric regression setting, asymptotically, the conditional distribution of the bootstrap test statistics is indeed the distribution of the test statistics under the null hypothesis, as long as $\hat{\rho}$ converges to ρ at the root- n rate.

5.2 | Testing individual function stationarity

One important question arose in varying-coefficient literature: “Does a particular set of local parameter estimates exhibit significant spatial variation?”. To answer this question, we focus on testing the following null hypothesis:

$$H_{0k} : \beta_k(\mathbf{u}) = \beta_k, \quad \text{versus} \quad H_{1k} : \beta_k(\mathbf{u}) \neq \beta_k, \quad \text{for a fixed } k = 0, \dots, p. \tag{12}$$

To conduct a hypothesis test, we can use the variability of the local estimates to examine the plausibility of the stationarity assumption held in traditional regression (Brunsdon et al., 1996; 1999). Specifically, for a given covariate function β_k at location i , suppose $\hat{\beta}_k(\mathbf{u}_i)$ is the BST or BPST estimate of $\beta_k(\mathbf{u}_i)$. If we take n values of this parameter estimate (one for each location point within the region), an estimate of variability of the parameter is given by the variance of the n parameter estimates.

The test statistics is defined as follows:

$$V_{nk} = \frac{1}{n-1} \sum_{i=1}^n \left(\hat{\beta}_k(\mathbf{U}_i) - \bar{\beta}_k \right)^2, \tag{13}$$

and we reject the null hypothesis (12) for large values of V_{nk} .

The next stage is to determine the sampling distribution of V_{nk} under the null hypothesis. Under H_{0k} , any permutation of \mathbf{U}_i among the data points is equally likely. Thus, the observed value of V_{nk} could be compared with the values obtained from randomly rearranging the data in space and repeating the BPST procedure. The comparison between the observed V_{nk} value and those obtained from a large number of randomized distributions can then form the basis of the significance test.

- Step 1. Randomly shuffle the n locations and obtain $\{\mathbf{U}_i^*\}_{i=1}^n$;
- Step 2. Calculate the test statistics V_{nk}^* based on the sample $\{(\mathbf{U}_i^*, \mathbf{X}_i, Y_i)\}_{i=1}^n$;
- Step 3. Repeat Steps 1 and 2 B times and obtain a sample of the test statistics V_{nk}^* as $\{V_{nk,b}^*\}_{b=1}^B$, and the p value is estimated by $\hat{p} = \sum_{b=1}^B I(V_{nk,b}^* \geq V_{k,obs})/B$, where $V_{k,obs}$ is the observed value of the test statistics V_{nk} by (13), or reject the null hypothesis when V_{nk} is greater than the upper- α quantile of $\{V_{nk,b}^*\}_{b=1}^B$.

6 | SIMULATION

In this section, we analyze synthetic data generated from the model to assess the validity of the proposed estimation and inference procedure based on BST and BPST smoothing methods. We also implement the GWR method to each of these artificial data and compare the estimator with our proposed ones.

To obtain the BST and BPST estimators, we set degree $d = 2$ and smoothness $r = 1$ when generating the bivariate spline basis functions. Supporting Information provides more simulation results with different values of d and different triangulations. For BPST, a common penalty λ for all coefficient functions is selected using 5-fold cross-validation from a

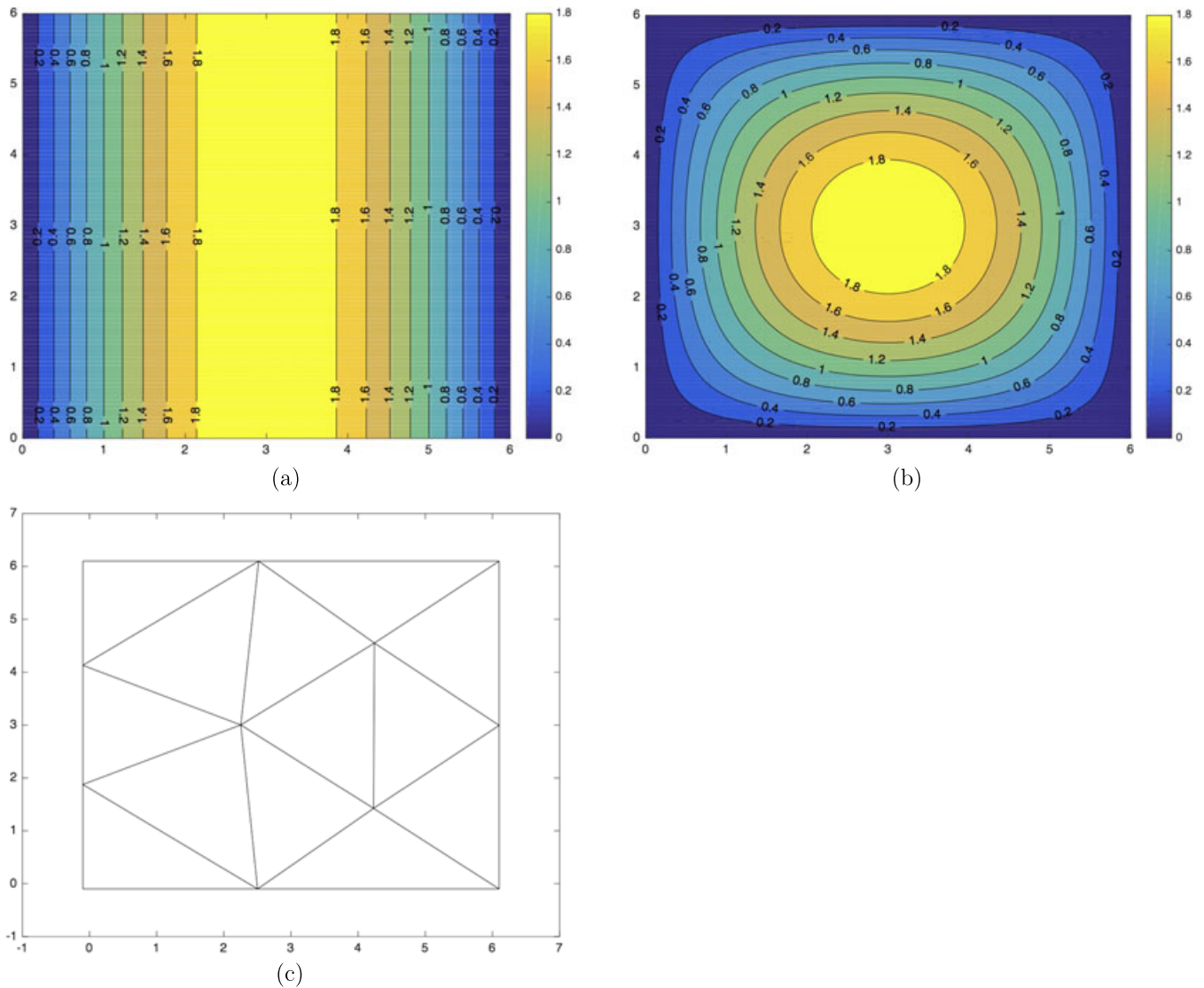


FIGURE 1 Simulation study 1: plots of (a) true β_0 , (b) true β_1 , (c) triangulation

9-point grid, where the values of $\log_{10}(\lambda)$ are equally spaced between -2 and 2 . For the GWR method, we use the “spgwr” R package to obtain the GWR estimator. In all simulation studies, the total number of replications is 500.

6.1 | Simulation study 1

Following Shen et al. (2011), the spatial layout in this example is designated as a $[0, 6]^2$ domain, and the population is collected at $N = 100 \times 100$ lattice points with equal distance between any two neighboring points along the horizontal and vertical directions. At each location, the response variable is generated by $Y_i = \beta_0(\mathbf{U}_i) + X_i\beta_1(\mathbf{U}_i) + \varepsilon_i$, $i = 1, \dots, N$, where X_i is generated randomly from a Uniform(0,2) distribution. The random error, ε_i , $i = 1, \dots, N$, are generated independently from $N(0, 1)$, and the coefficient functions are as follows:

$$\beta_0(u_1, u_2) = 2 \sin\left(\frac{\pi u_1}{6}\right), \quad \beta_1(u_1, u_2) = \frac{2}{81} \{9 - (3 - u_1)^2\} \{9 - (3 - u_2)^2\}. \quad (14)$$

See Figure 1 (a) and (b) for the contour plots of the two true coefficient functions. We randomly sample $n = 500, 1000$, and 2000 points from the 100×100 points in each Monte Carlo experiment.

Figure 1 (c) shows the triangulation used to obtain the BST and BPST estimators, and there are 13 triangles and 12 vertices in this triangulation. The mean squared estimation error (MSE) and mean squared prediction error (MSPE) for the

TABLE 1 Estimation and prediction results for Simulation study 1

<i>n</i>	Method	β_0		β_1		σ^2	<i>Y</i>	Time
		MSE	MSPE	MSE	MSPE	BIAS	MSPE	
500	BST	0.1046	0.1128	0.0840	0.0904	0.0642	1.0345	0.087
	BPST	0.0628	0.0637	0.0548	0.0559	0.0527	1.0165	1.102
	GWR	0.1708	0.1763	0.1379	0.1434	0.1439	1.1063	28.152
1000	BST	0.0479	0.0496	0.0410	0.0421	0.0427	1.0030	0.121
	BPST	0.0340	0.0345	0.0326	0.0331	0.0381	0.9984	2.138
	GWR	0.1127	0.1144	0.0889	0.0907	0.1097	1.0505	102.666
2000	BST	0.0241	0.0244	0.0219	0.0222	0.0300	0.9897	0.186
	BPST	0.0204	0.0205	0.0205	0.0207	0.0266	0.9888	4.902
	GWR	0.0726	0.0733	0.0564	0.0571	0.0798	1.0122	441.230

estimators of the coefficient functions, as well as the MSPE of the response variable *Y*, are computed using the following:

$$\text{MSE}(\hat{\beta}_k) = \frac{1}{n} \sum_{i=1}^n \left\{ \hat{\beta}_k(\mathbf{U}_i) - \beta_k(\mathbf{U}_i) \right\}^2, \quad \text{MSPE}(\hat{\beta}_k) = \frac{1}{N} \sum_{i=1}^N \left\{ \hat{\beta}_k(\mathbf{U}_i) - \beta_k(\mathbf{U}_i) \right\}^2, \quad k = 0, 1,$$

$$\text{MSPE}(\hat{Y}) = \frac{1}{N} \sum_{i=1}^N (\hat{Y}_i - Y_i)^2.$$

In addition, we report the bias (BIAS) of $\hat{\sigma}^2 = \frac{1}{n} \sum_{i=1}^n (Y_i - \hat{Y}_i)^2$ in estimating the true variance of errors σ^2 . All the results are summarized in Table 1.

We compare the proposed BST and BPST with GWR by evaluating the estimation accuracy and their predictive accuracy of the spatial pattern. As the sample size increases, all three estimators tend to result in better performance in terms of MSE, MSPE, and BIAS. Moreover, regardless of the sample size, both the BST and BPST estimators outperform the GWR estimator. Compared with the BST estimators, the BPST estimators are more stable, especially when the sample size is small, and the difference between the BST and the BPST estimators is getting smaller as the sample size increases. Supporting Information provides more simulation results with different triangulations, which suggest that the number of triangles or the number of basis functions only has a little effect on the BPST estimator, especially when there is a sufficient number of triangles.

Figure 2 visualizes the estimated surfaces of $\beta_0(\cdot)$ and $\beta_1(\cdot)$ using BST, BPST, and GWR, which are based on one typical replication with $n = 2000$. These plots suggest that the BPST method is able to estimate the spatial pattern with the greatest accuracy, followed by the BST method, and the GWR is not able to capture the spatial pattern very accurately.

In terms of the computing, because the GWR technique is largely based on kernel regression, a locally weighted regression is required at every single point in the data set, which results in great computational complexity. In contrast, both BST and BPST can be formulated as one single least-squares problem; thus, the computing is very easy and fast. The last column (Time) in Table 1 summarizes the average computing time per iteration in seconds for each method. All the methods are implemented using a personal computer with Intel(R) Core(TM) i5 CPU dual core @ 2.90 GHz and 8.00 GB RAM. Specifically, one can see that as the sample size increases, the computational time for GWR method increases dramatically, whereas BST and BPST almost provide a linear complexity of the sample size when the number of triangles is much less than the sample size.

As one of the most important inferences in the GWR literature, the test for a globally stationary regression relationship can provide the information that a SVCMM is really necessary for the given data. Next, we investigate the performance of the proposed bootstrap test described in Section 5.1. We consider the following hypothesis:

$$H_0 : \beta_k(\mathbf{u}) = \beta_k, k = 0, 1 \quad \text{versus} \quad H_1 : \beta_k(\mathbf{u}) \neq \beta_k, \quad \text{for at least one } k.$$

Note that H_0 corresponds to the ordinary linear regression model. The power function is evaluated under a sequence of the alternative models indexed by δ , as follows:

$$H_1 : \beta_k(\mathbf{u}) = \bar{\beta}_k^0 + \delta (\beta_k^0(\mathbf{u}) - \bar{\beta}_k^0), \quad k = 0, 1, \quad (0 \leq \delta \leq 1), \quad (15)$$

where $\beta_k^0(\mathbf{u})$, $k = 0, 1$, are given in (14), and $\bar{\beta}_k^0$ is the average height of $\beta_k^0(\mathbf{u})$, and in our simulation, $\bar{\beta}_0^0 = 1.2604$, $\bar{\beta}_1^0 = 0.8710$. The parameter δ is designated different values to evaluate the power of the test. The null hypothesis corresponds to $\delta = 0$ in the coefficients.

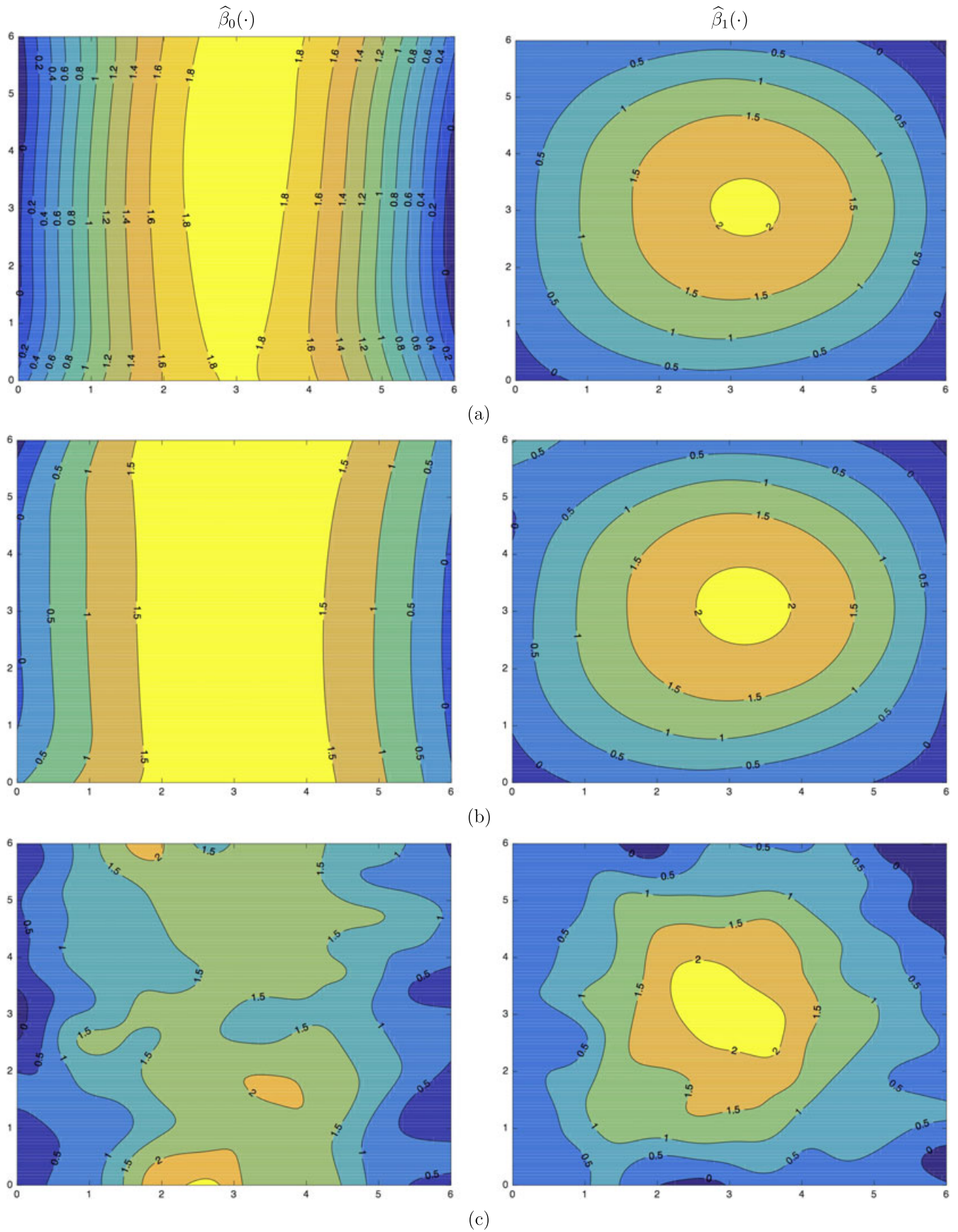


FIGURE 2 Simulation study 1: estimated surface via (a) BPST, (b) BST, and (c) GWR based on sample size $n = 2000$. BPST = bivariate penalized splines over triangulation; BST = bivariate splines over triangulation; GWR = geographically weighted regression

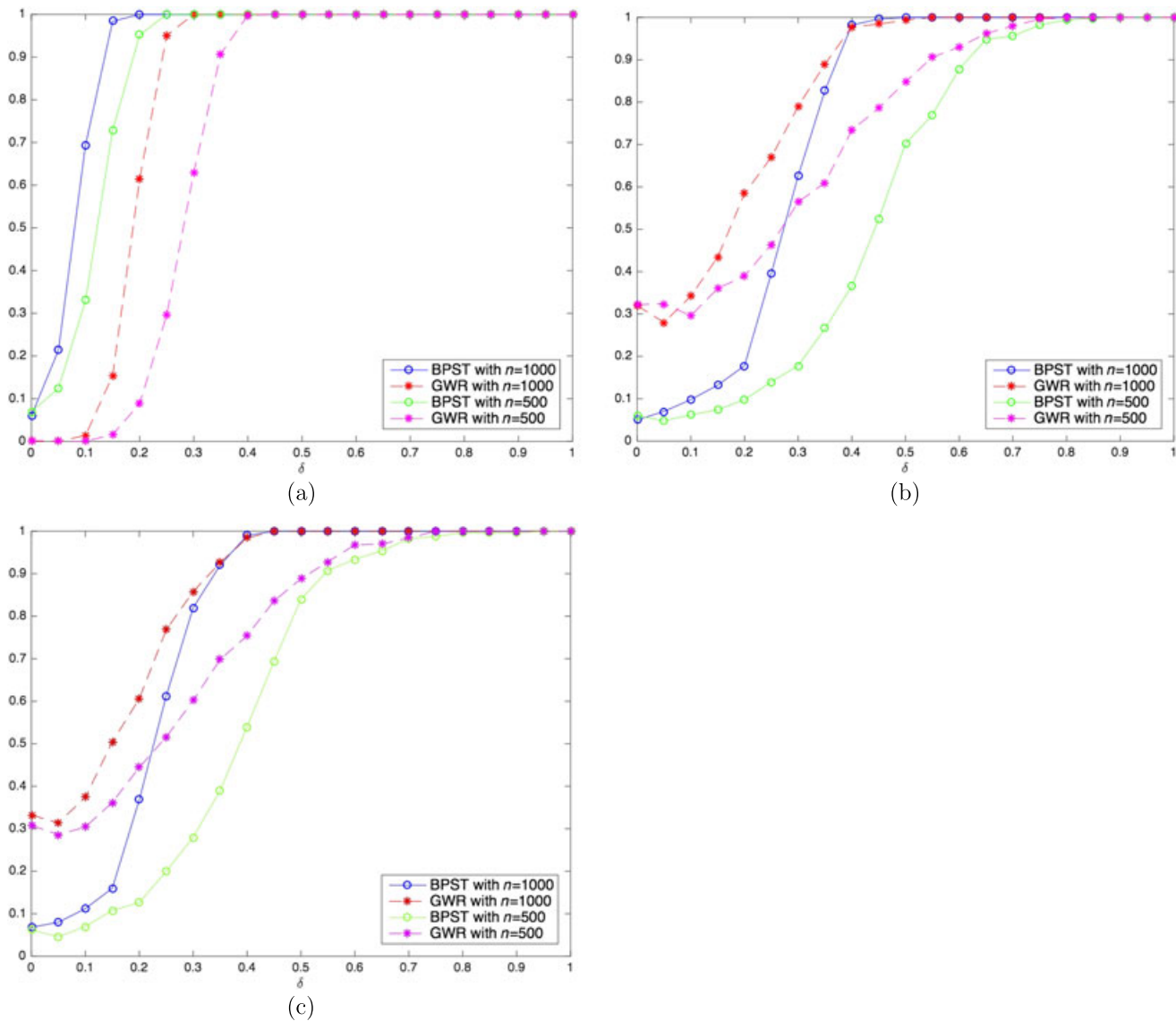


FIGURE 3 Type I errors and power for bootstrap tests in Simulation study 1: (a) $H_0 : \beta_k(\mathbf{u}) = \beta_k, k = 1, 2$ versus $H_1 : \beta_k(\mathbf{u}) = \beta_k^0 + \delta(\beta_k^0(\mathbf{u}) - \beta_k^0), k = 1, 2$; (b) $H_0 : \beta_0(\mathbf{u}) = \beta_0$ versus $H_1 : \beta_0(\mathbf{u}) = \beta_0^0 + \delta(\beta_0^0(\mathbf{u}) - \beta_0^0)$; (c) $H_0 : \beta_1(\mathbf{u}) = \beta_1$ versus $H_1 : \beta_1(\mathbf{u}) = \beta_1^0 + \delta(\beta_1^0(\mathbf{u}) - \beta_1^0)$. BPST = bivariate penalized splines over triangulation; GWR = geographically weighted regression

We apply the bootstrap goodness-of-fit test in a simulation with 500 replications of sample size $n = 500$ and 1000 , and we record the relative frequencies of rejecting H_0 under the significance level $\alpha = 0.05$. For each realization, we repeat bootstrap sampling 100 times. Figure 3 illustrates the empirical frequencies of rejecting H_0 against δ using BPST and GWR methods. For GWR, we use the “`BFC02.gwr.test`” function within the “`spgwr`” package in R, where the test result is obtained by test statistics based on the RSS described by Fotheringham et al. (2002). When $\delta = 0$, these relative frequencies represent the size of the test. For BPST, the relative frequency is 0.060, which is fairly close to the given significant level 5%. This demonstrates that the bootstrap estimate of the null distribution is approximately correct. However, the GWR gives 0.000, which is much smaller than the significant level. For our BPST-based bootstrap test, regardless of the sample size, the power increases rapidly to one when $\delta = 0.2$, suggesting that the proposed test is quite powerful. Overall, the proposed test is of a higher power in identifying the varying coefficients than the GWR based test.

Next, we conduct an individual stationarity test with $H_{0k} : \beta_k(\mathbf{u}) = \beta_k$ versus $H_{1k} : \beta_k(\mathbf{u}) \neq \beta_k$, for $k = 0, 1$. Similar to (15), the power function is evaluated under a sequence of the alternative models indexed by δ , specifically, $H_{1k} : \beta_k(\mathbf{u}) = \beta_k^0 + \delta(\beta_k^0(\mathbf{u}) - \beta_k^0), (0 \leq \delta \leq 1)$.

We apply the individual stationarity test described in Section 5.2 at significant level $\alpha = 0.05$ with $n = 500$ and 1000 , respectively. Similar as in the global stationarity, 500 replications with $B = 100$ bootstrap samples in each replication

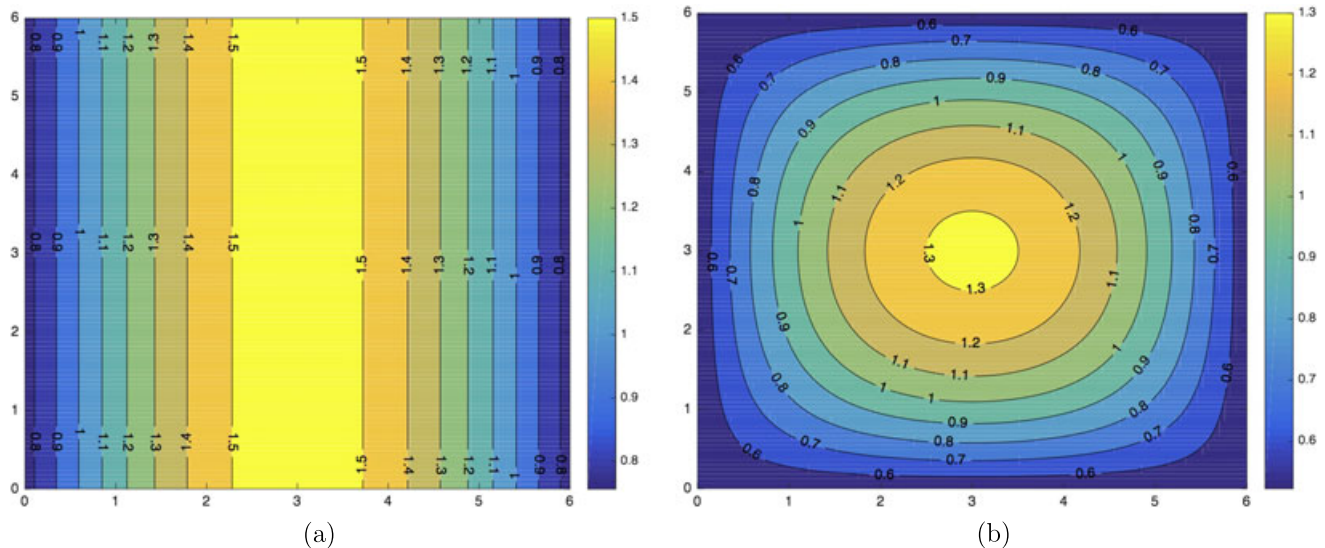


FIGURE 4 Simulation study 1: coefficient functions under H_1 when $\delta = 0.4$. (a) β_0 (b) β_1

are conducted to compute the p value. The individual test for the GWR is based on the test statistics proposed by Leung et al. (2000) and implemented using the R function “`LMZ.F3GWR.test`”.

When $\delta = 0$, the rejection frequencies of BPST are reasonably close to the given significance level for both coefficient functions. Consider the specific alternative with $\delta = 0.4$, where the functions $\{\beta_k(\mathbf{u})\}$ under H_{1k} are shown in Figure 4. Even with such a small difference, we can correctly detect the alternative over 80% of the 500 simulations. With the value of δ increasing, the rejection frequencies increase rapidly, and thus, the rejection frequency of BPST is definitely high if the coefficient functions are indeed spatially varying. However, for GWR, the rejection frequencies are much higher than the given significance level, which indicates a much larger Type I error. Although the results improve with the sample size increasing, the rejection rates are still two or three times higher than the significance level.

In summary, the simulation study demonstrates that the proposed bootstrap tests can well approximate the null distribution of the test statistics even for a moderate sample size.

6.2 | Simulation study 2

In this simulation study, we consider a modified horseshoe domain constructed by Wood et al. (2008). In particular, we divide the entire horseshoe domain evenly into $N = 401 \times 901$ grid points, which are considered as the population. We adopt the coefficient functions shown in Figure 5 (a) and (b), where $\beta_0(\cdot)$ is the same function used by Wood (2003) and $\beta_1(u_1, u_2) = 4 \sin \{0.05\pi(u_1^2 + u_2^2)\}$. The response variable Y_i are generated from the following model: $Y_i = \beta_0(\mathbf{u}_i) + X_i \beta_1(\mathbf{u}_i) + \varepsilon_i$, $i = 1, \dots, N$, where X_i is generated randomly from a Uniform(0,2) distribution. The random errors, ε_i , $i = 1, \dots, N$, are generated independently from the $N(0, 0.5^2)$ distribution. For each of the 500 Monte Carlo experiments, we randomly sample $n = 2000$ and 5000 locations uniformly on the domain.

Figure 5 (c) shows the triangulation used to obtain the BST and BPST estimators, and there are 77 triangles and 65 vertices in this triangulation. The results of MSE, MSPE, and BIAS based on 500 replications are summarized in Table 2, and the predicted surfaces from one iteration when $n = 2000$ are demonstrated in Figure 6. These results highlight, on the irregular domain, that both BST and BPST methods can provide more accurate and efficient estimation than the GWR method.

Another computational issue worth mentioning is that when GWR is used for prediction, a locally weighted regression is also required at every single point in the predicting data set. In this example, the prediction is conducted over the entire $401 \times 901 = 361301$ grid points. Therefore, the entire process cannot be completed using personal computers; instead, the GWR algorithm is conducted via cluster using a parallel computing of 24 general-purpose compute nodes with 128 GB RAM associated to each node, in which, on average, each iteration takes more than 5 hr to complete for $n = 2000$. Unfortunately, when $n = 5000$, we are not able to obtain any results using the same cluster with the same setting within 1 week. On the other hand, for BST and BPST, the prediction can be done with one simple matrix multiplication, and thus,

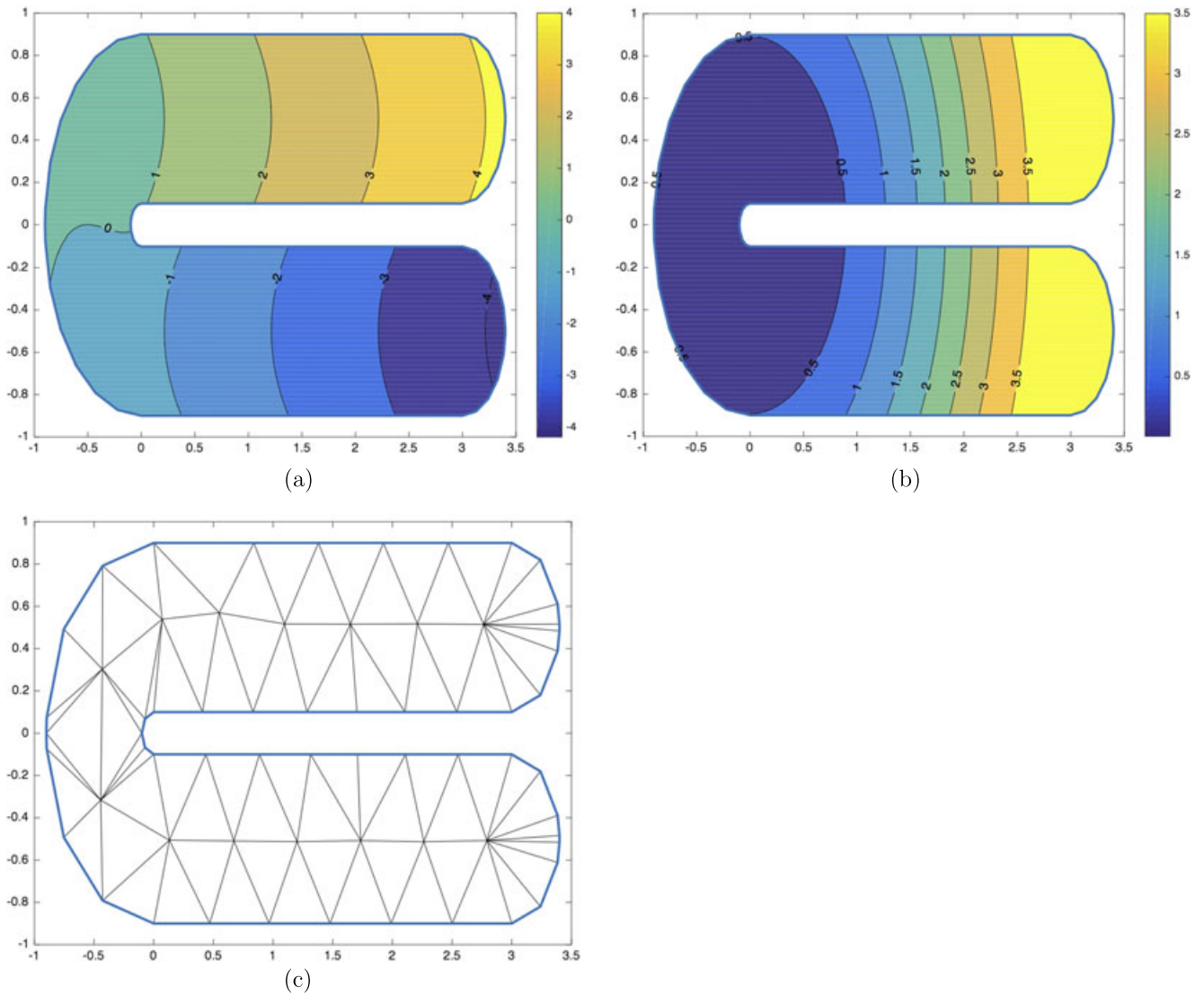


FIGURE 5 Simulation study 2: plots of (a) true β_0 , (b) true β_1 , and (c) triangulation

TABLE 2 Estimation and prediction results for Simulation study 2

n	Method	β_0		β_1		σ^2	Y	Time
		MSE	MSPE	MSE	MSPE	BIAS	MSPE	
2000	BST	0.0312	0.0348	0.0237	0.0269	0.0129	0.2647	12.376 [#]
	BPST	0.0130	0.0132	0.0080	0.0081	0.0060	0.2588	29.589 [#]
	GWR	0.0325	0.0337	0.0240	0.0248	0.0306	0.2697	18280.320 ^a
5000	BST	0.0117	0.0120	0.0085	0.0088	0.0051	0.2560	14.033 [#]
	BPST	0.0070	0.0070	0.0042	0.0042	0.0028	0.2545	64.016 [#]
	GWR	_b	_b	_b	_b	_b	_b	_b

Note. The average computational time is measured using a personal computer with Intel(R) Core(TM) i5 CPU dual core @ 2.90 GHz and 8.00 GB RAM. ^aThe average computational time is measured by cluster using a parallel computing of 24 general-purpose compute nodes with 128 GB RAM associated to each node. ^bWe do not have the results here because the computing time for 500 iterations in total is more than 168 hr even using a cluster with 24 cores in parallel. MSE = mean squared estimation error; MSPE = mean squared prediction error.

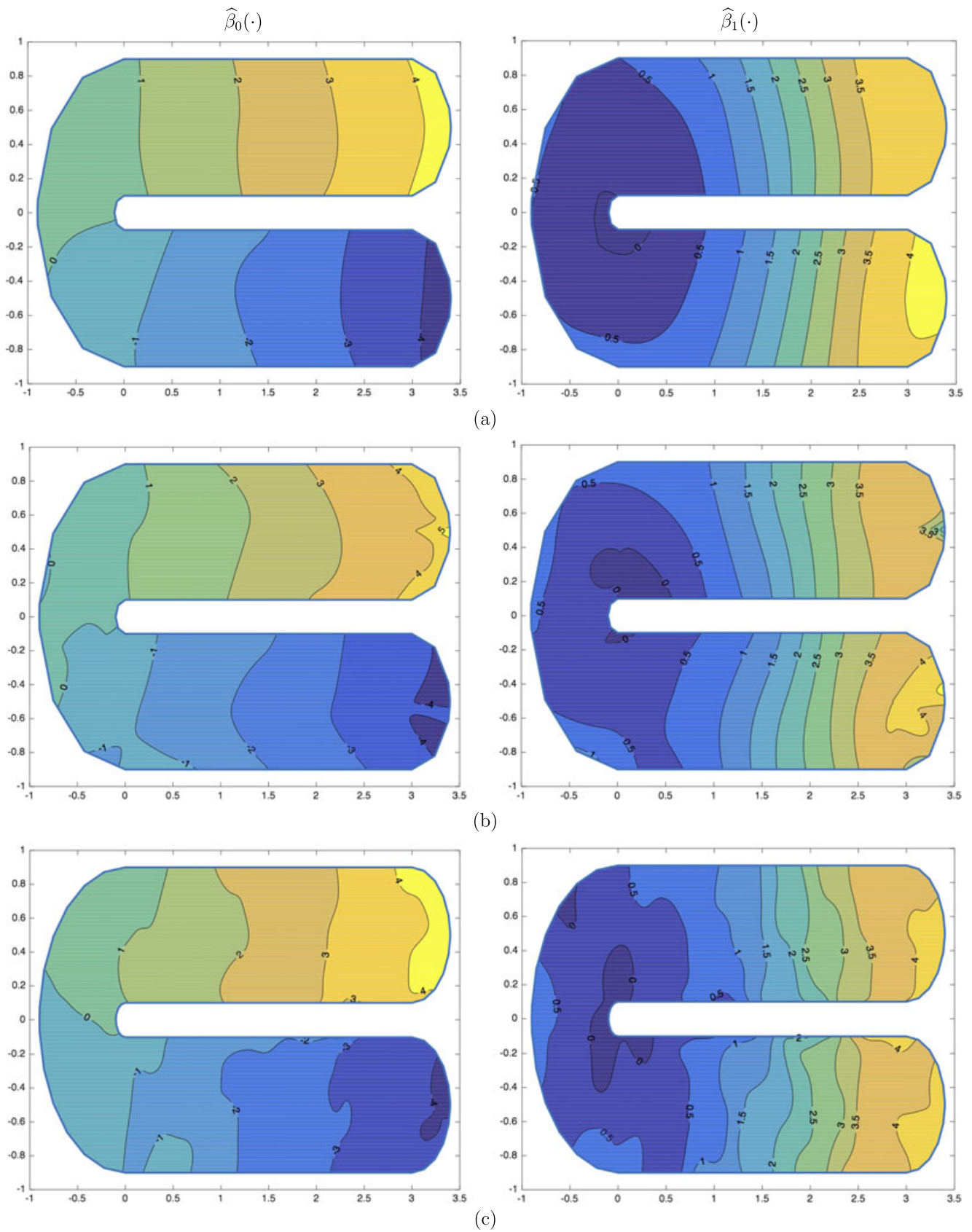


FIGURE 6 Simulation study 2: estimated surface via (a) BPST; (b) BST; (c) GWR based on sample size $n = 2000$. BPST = bivariate penalized splines over triangulation; BST = bivariate splines over triangulation; GWR = geographically weighted regression

TABLE 3 Meteorological parameters

Variable	Meteorological Parameter
PPTN	Daily total precipitation (mm)
RH	Air relative humidity at 2m (%)
T_{\min}	Surface daily minimum air temperature ($^{\circ}\text{C}$)
T_{\max}	Surface daily maximum air temperature ($^{\circ}\text{C}$)
WS	Surface wind speed (m/s)
TCDC	Total column cloud cover (%)

TABLE 4 Estimation and prediction accuracy for air pollution data

	OLS	GWR	BPST
MSE	18.68	8.44	7.03
MSPE	18.95	13.20	12.30

Note. OLS = ordinary linear least squares; GWR = geographically weighted regression; BPST = bivariate penalized splines over triangulation; MSE = mean squared estimation error; MSPE = mean squared prediction error.

it is very fast even when the data set is huge. For example, one BPST-based iteration of size 5000 only takes about 1 min on a personal computer with Intel(R) Core(TM) i5 CPU dual core @ 2.90 GHz and 8.00 GB RAM.

7 | APPLICATION TO AIR POLLUTION DATA ANALYSIS

Recently, fine particles ($\text{PM}_{2.5}$, which is a particulate matter with a diameter of 2.5 μm or less) has become a major air quality concern because it poses significant risks to human health, such as asthma, chronic bronchitis, lung cancer, and atherosclerosis. Many recent research works (Hu et al., 2013; Russell, Wang, & McMahan, 2017; Tai, Mickley, & Jacob, 2010) suggest that $\text{PM}_{2.5}$ concentrations depend on meteorological conditions. To improve current pollution control strategies, there is an urgent need for a more comprehensive understanding of $\text{PM}_{2.5}$ and a more accurate quantification between the meteorological drivers and the levels of $\text{PM}_{2.5}$.

In this section, we show the applicability of the proposed SVCMM on a meteorological data set to study the effects of meteorological characteristics on air quality. In our study, daily mean surface concentrations of total $\text{PM}_{2.5}$ for the year 2011 are obtained from the United States Environmental Protection Agency; meteorological drivers are provided by the National Oceanic and Atmospheric Administration (<http://www.esrl.noaa.gov/psd/>); daily total gridded precipitation (PPTN), surface wind speed (WS), surface daily minimum air temperature (T_{\min}), and surface daily maximum air temperature (T_{\max}) are acquired from Livneh et al. (2013); air relative humidity (RH) and total column cloud cover (TCDC) are obtained from North American Regional Reanalysis. See Table 3 for details.

Noting that there are some missing values in RH, TCDC, and total $\text{PM}_{2.5}$, we aggregate the data by season and focus on the most severely polluted season in a year—winter (December, January, February). We predict the $\text{PM}_{2.5}$ for winter season using the proposed SVCMM, as follows:

$$\text{PM}_{2.5} = \beta_0(\mathbf{u}) + \beta_1(\mathbf{u})\text{PPTN} + \beta_2(\mathbf{u})\text{RH} + \beta_3(\mathbf{u})T_{\min} + \beta_4(\mathbf{u})T_{\max} + \beta_5(\mathbf{u})\text{WS} + \beta_6(\mathbf{u})\text{TCDC} + \varepsilon. \quad (16)$$

We also consider the multiple linear regression without using the spatial information, as follows:

$$\text{PM}_{2.5} = \beta_0 + \beta_1\text{PPTN} + \beta_2\text{RH} + \beta_3T_{\min} + \beta_4T_{\max} + \beta_5\text{WS} + \beta_6\text{TCDC} + \varepsilon. \quad (17)$$

To evaluate different methods, we examine both the estimation accuracy and the prediction accuracy of the multiple linear regression in (17) and the GWR and the BPST in (16). The out-of-sample prediction errors of each method are calculated by 10-fold cross-validation. The MSE and MSPE of the three methods are summarized in Table 4. It is obvious that the BPST estimator provides a much more accurate estimation and prediction. Figure 7 (b)–(h) summarizes the coefficient estimation results via BPST.

A natural question is if the coefficients are really varying over space in model (16). We now use our proposed test procedure in Section 5 to answer this question. The p values of these tests are listed in Table 5. For the global stationary test, the p value is smaller than 0.001, so under the significance level $\alpha = 0.05$, we conclude that at least one of the coefficients is nonstationary over the entire United States. For the individual stationarity test, the resulting p values for the intercept,

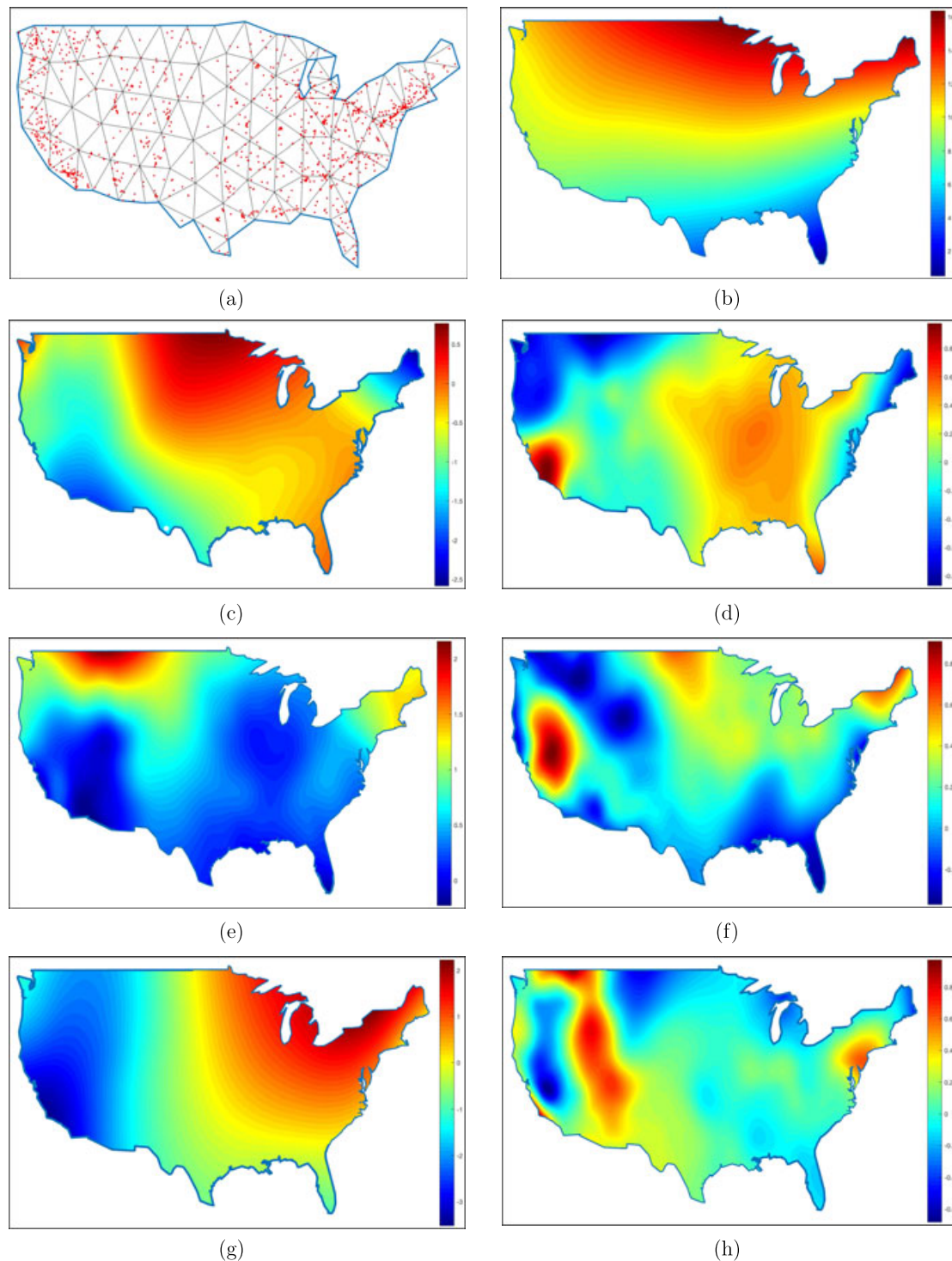


FIGURE 7 Estimates of the coefficient functions of the spatially varying coefficient model for $PM_{2.5}$ data. PPTN = daily total precipitation; RH = relative humidity; T_{\min} = surface daily minimum air temperature; T_{\max} = surface daily maximum air temperature; WS = wind speed; TCDC = total column cloud cover. (a) Triangulation with Data Points (b) β_0 (Intercept) (c) β_1 (PPTN) (d) β_2 (RH) (e) β_3 (T_{\min}) (f) β_4 (T_{\max}) (g) β_5 (WS) (h) β_6 (TCDC)

TABLE 5 Hypothesis tests with their p values of the tests for $PM_{2.5}$ data

Null hypothesis	Corresponding variables	p value
$\beta_0(\mathbf{u}) = \beta_0$	Intercept	< 0.001
$\beta_1(\mathbf{u}) = \beta_1$	PPTN	0.406
$\beta_2(\mathbf{u}) = \beta_2$	RH	0.688
$\beta_3(\mathbf{u}) = \beta_3$	T_{\min}	0.430
$\beta_4(\mathbf{u}) = \beta_4$	T_{\max}	0.020
$\beta_5(\mathbf{u}) = \beta_5$	WS	< 0.001
$\beta_6(\mathbf{u}) = \beta_6$	TCDC	< 0.001
$\beta_k(\mathbf{u}) = \beta_k, k = 0, 1, \dots, 6$		< 0.001

Note. PPTN = daily total precipitation; RH = relative humidity; T_{\min} = surface daily minimum air temperature; T_{\max} = surface daily maximum air temperature; WS = wind speed; TCDC = total column cloud cover.

T_{\max} , WS, and TCDC are all smaller than the significant level $\alpha = 0.05$, indicating that the coefficients $\beta_0(\mathbf{u})$, $\beta_4(\mathbf{u})$, $\beta_5(\mathbf{u})$, and $\beta_6(\mathbf{u})$ are really varying over space. However, for PPTN, RH, and T_{\min} , the p value $\gg \alpha$, so we do not have enough evidence to reject the null hypothesis. The estimated coefficient function plots in Figure 7 confirm the conclusion of the proposed tests.

8 | CONCLUDING REMARKS

In summary, the proposed method has the following advantages in analyzing the spatial nonstationarity of a regression relationship for spatial data. First, compared with GWR, the proposed method is much more computationally efficient to deal with large data sets. Specifically, the computational complexity of BST and BPST is $O(nK_n^2)$, which indicates that it is almost linear in terms of the sample size. In addition, as a global estimation with an explicit model expression, the proposed spline approach enables easy-to-implement prediction compared with the local approaches. Second, the proposed method can overcome the problem of “leakage” across the complex domains that many conventional tools suffer. Third, by introducing the roughness penalty into the BST, the BPST can alleviate the adverse effect of the collinearity problem in GWR (Wheeler & Tiefelsdorf, 2005) and provide more accurate estimators of the coefficient functions. By assigning different penalty parameters, the BPST also easily allows different smoothness for different functional coefficients. Finally, with increasing volumes of data being collected on the environment through remote sensing platforms, complex sensor networks, and Global Positioning System (GPS) movement, this work provides one feasible approach to study large-scale environmental spatial data.

The proposed method in this article can be easily extended to semiparametric varying-coefficient partially linear models (Brunsdon et al., 1999; Fan & Huang, 2005; Fotheringham et al., 2002), where some coefficients in the model are assumed to be constant and the remaining coefficients are allowed to spatially vary across the studied region.

In spatial data analysis, there are mainly two issues: spatial dependence and spatial heterogeneity, and our paper focuses on the latter. To understand the theoretical behavior of the estimators, we assume that the errors are independent. Although this assumption is not uncommon in the GWR literature, it is more realistic to relax the independence assumption. The spatial dependence can be alleviated by choosing the optimal triangulation; it may not fully vanish, and certainly, there is more future work ahead to investigate this issue. Lu and Tjøstheim (2014) proposed nonparametric kernel estimators for probability density functions for irregularly observed spatial data and established a new framework of expanding-domain infill asymptotics, which might be useful in defining the “mixing” condition for the errors in our model and in studying the asymptotics of our estimators. Sun, Yan, Zhang, and Lu (2014) proposed the following semiparametric spatial autoregressive varying-coefficient model:

$$Y_i = \alpha \sum_{j \neq i} w_{ij} Y_j + \mathbf{X}_i^\top \boldsymbol{\beta}(\mathbf{U}_i) + \epsilon_i, \quad i = 1, \dots, n, \quad (18)$$

where w_{ij} is the impact of Y_j on Y_i , for example, a specified physical or economic distance. This model considers the neighboring effect and is thus able to take care of the spatial dependence issue. We are interested in extending our work to this class of models for irregularly spaced data over complex domains. However, it is challenging to define w_{ij} (distance) for our method due to the “leakage” problem across complex boundary features. Another interesting future work is the

spatiotemporal extension to analyze data collected across time and space. We might be able to establish some promising theoretical results under some dependent error assumptions if we let the number of time points go to infinity. We believe that more careful and intensive future work is necessary in these directions.

ACKNOWLEDGEMENTS

Guannan Wang's research was partially supported by the Faculty Summer Research Grant from the College of William & Mary. Li Wang's research was partially supported by the National Science Foundation under Grant No. DMS-1542332. We are very grateful to Ming-Jun Lai for providing us with the Matlab code on bivariate spline basis constructions. The authors would also like to thank the editor, associate editor, and two reviewers for their valuable comments and suggestions to improve the quality of the paper.

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How to cite this article: Mu J, Wang G, Wang L. Estimation and inference in spatially varying coefficient models. *Environmetrics*. 2018;29:e2485. <https://doi.org/10.1002/env.2485>