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Hierarchical Spatially Varying Coefficient Process Regression for Modeling Net Anthropogenic Nitrogen Inputs (NANI) from the Watershed of the Yangtze River, China

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Abstract: The increasing discharge of nitrogen nutrients into watersheds calls for assessing and predicting nitrogen inputs, as an important basis for formulating management strategies. The traditional net anthropogenic nitrogen inputs (NANI) budgeting model relies on 45 predictor variables, for which data are sourced from local or national statistical yearbooks. The large number of predictor variables involved makes NANI accounting difficult, and the missingness of data reduces its accuracy. This study aimed to build a prediction model for NANI based on as few predictor variables as possible. We built a prediction model based on the last 30 years of NANI data from the watershed of the Yangtze River in China, with readily available and complete socio-economic predictor variables (per gross domestic product, population density) through a hierarchical spatially varying coefficient process model (HSVC), which exploits underlying spatial associations within 11 sub-basins and the spatially varying impacts of predictor variables to improve the accuracy of NANI prediction. The results showed that the hierarchical spatially varying coefficient model performed better than the Gaussian process model (GP) and the spatio-temporal dynamic linear model (DLM). The predicted NANIs within the entire catchment of the Yangtze River in 2025 and in 2030 were 11,522.87 kg N km⁻² to 12,760.65 kg N km⁻², respectively, showing an obvious increasing trend. Nitrogen fertilizer application was predicted to be 5755.1 kg N km⁻² in 2025, which was the most significant source of NANI. In addition, the point prediction and 95% interval prediction of NANI in the watershed of the Yangtze River for 2025 and 2030 were also provided. Our approach provides a simple and easy-to-use method for NANI prediction.

Keywords: nitrogen cycle; net anthropogenic nitrogen inputs (NANI); hierarchical spatially varying coefficient model; prediction



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1. Introduction

Nitrogen is a common element in nature, and controls the processes, functions, and diversity of ecosystems [1]. As a result of the industrial revolution and human activities, new sources of nitrogen, such as fertilizer application, crop cultivation, nitrogen deposition, and food inputs, have had a significant impact on nitrogen cycling at the global and the regional level [2–5]; in some cases, natural nitrogen fixation is exceeded [6]. However, when nitrogen inputs exceed the nitrogen uptake and storage capacity of regional ecosystems, the remaining nitrogen enters watersheds, with long-term negative impacts [7,8], such as groundwater contamination, soil acidification, biodiversity decline, water eutrophication, and hypoxia [9]. The increasing nitrogen concentrations and fluxes in watersheds have become major factors contributing to the eutrophication of lakeshores, estuaries, and coastal areas [4–9].

Driven by resource scarcity, population expansion, and economic growth, human activities greatly interfere with the natural nitrogen cycle [10], and it has been shown

that the nitrogen input from human activities has exceeded the natural nitrogen fixation in most river watersheds in China, such as the watershed of the Yangtze River and the watershed of the Pearl River [11]. For example, in 2010, 61.6% of the 26 state-controlled key lakes (reservoirs) in China had a water quality of V (the lowest grade), with total nitrogen being one of the main pollutants; in addition, inorganic nitrogen has become one of the common pollution indicators in the major sea areas of China [12]. Overall, excessive nitrogen input from human activities has become an important factor restricting environmental sustainability in China.

The high load of anthropogenic nitrogen input has attracted widespread attention from researchers, organizations, and the international scientific community, to study the anthropogenic biogeochemical cycling of nitrogen for sustainable development [13,14]. Quantitative source analysis of nitrogen in watershed ecosystems has become an international research hotspot, guiding studies on the optimization of nitrogen management in ecosystems at the watershed scale [15,16].

The most widely used model for accounting for anthropogenic nitrogen inputs into watersheds is the NANI model proposed by [17] and consisting of four components: atmospheric nitrogen deposition, nitrogen fertilizer consumption, crop nitrogen fixation, and food/feed imports, which represent the main types of nitrogen inputs due to human activities. The calculation results can be used to characterize the impacts of nitrogen produced by human activities on watersheds. The NANI model and its improved methods are widely used at various watershed and regional scales in the U.S., Europe, and Asia [18–21]. Han et al. estimated NANI for 99% of the world from 1961 to 2009 and suggested that the global NANI levels dramatically increased due to higher net nitrogen inputs in Asia; furthermore, the NANI values in Asia, Europe, and North America were above average [2]. To calculate NANI across United States watersheds, a consistent method was proposed and showed that yield-based estimation of NANI differed significantly from area-based estimation [18]. Hong et al. investigated regional variation parameters for the NANI Calculator Toolbox and observed significant regional variation in NANI across the Baltic Sea Basin, where the associated relationship with riverine nitrogen fluxes suggested that NANI contributed to a portion of the riverine nutrient fluxes [19]. Swaney et al. calculated NANI in Indian watersheds, showing that agricultural fertilizer is the main source of NANI, followed by crop nitrogen fixation, but the regression relationship between NANI and riverine nitrogen fluxes is problematic, due to the limited availability of river data [20]. A study about the spatiotemporal differences of NANI in mainland China from 1981 to 2009 revealed that the NANI had more than doubled [21].

To guide nitrogen management at the macroscopic scale, assessing the impacts of human activities on nitrogen inputs into watersheds is of great significance. The indicators involved in the NANI accounting model include the urban population, the rural population, the number of livestock, crop yield, nitrogen fertilizer consumption, compound fertilizer use, planting area, and energy consumption, among others, with a total of 45 indicators [22]. Data for these indicators are usually obtained from local or national statistical yearbooks. At longer time scales, the data usually have heavy missingness because of changes in the accounting of statistical yearbooks or omissions in data aggregation. The large number of indicators involved increases the difficulty of NANI accounting, and the missing data make NANI accounting less accurate. In this paper, we attempt to build a NANI prediction HSVC model based on as few predictor variables as possible for the Yangtze River Basin, China. The HSVC model is a generalization of the variable coefficient model, aiming to determine the spatial variations of data by allowing the coefficients to be functions of location. Since the model has obvious indigenous effects on analyzing spatial heterogeneity, and the coefficient function has a strong flexibility, it has been widely used in environmental science, ecology, and epidemiology [23–26].

In this study, a hierarchical spatially varying coefficient process regression (HSVC) model was built to elaborate the mechanisms of the predictor variables per gross domestic product (PGDP) and population density (PD) for NANI, and to forecast the annual values

of NANI within the watershed of the Yangtze River. The main objectives were as follows: (1) to analyze the spatiotemporal variations of NANI, PGDP, and PD; (2) to explore the relationship between watershed NANI, PGDP, and PD, and to compare the fitting and prediction accuracy of HSVC, GP, and DLM models; (3) to predict the values and 95% interval predictions of NANI for the years 2025 and 2030. This study not only provides a simple and easy-to-use method for NANI prediction but also provides a watershed nitrogen management strategy, which is useful for nitrogen pollution control.

2. Study Area and Data Sources

The Yangtze River Basin, displayed in Figure 1, is located between 90° – 122° E and 24° – 35° N, covering an area of approximately 1.8 million km^2 [27]. It originates southwest of the Tang-gu-la Mountains on the Qinghai-Tibet Plateau and flows through 11 provinces and autonomous regions, flowing into the East China Sea in Shanghai. According to the characteristics of the Yangtze River basin, the watershed of the Yangtze River is divided into 11 sub-basins; namely, Jinshajiang (JSJ), Mingtuojiang (MTJ), Wujiang (WJ), the Upper mainstream region (UM), Jialingjiang (JLJ), Dongtinghu (DTH), the Middle mainstream region (MM), Hanjiang (HJ), Poyanghu (PYH), the lower mainstream region (LM), and Taihu (TH) [22]. These sub-basins range in area from approximately 36,900 km^2 (TH) to 483,000 km^2 (JSJ). The map of the Yangtze River Basin and its subcatchments was created using ArcGIS 10.2.

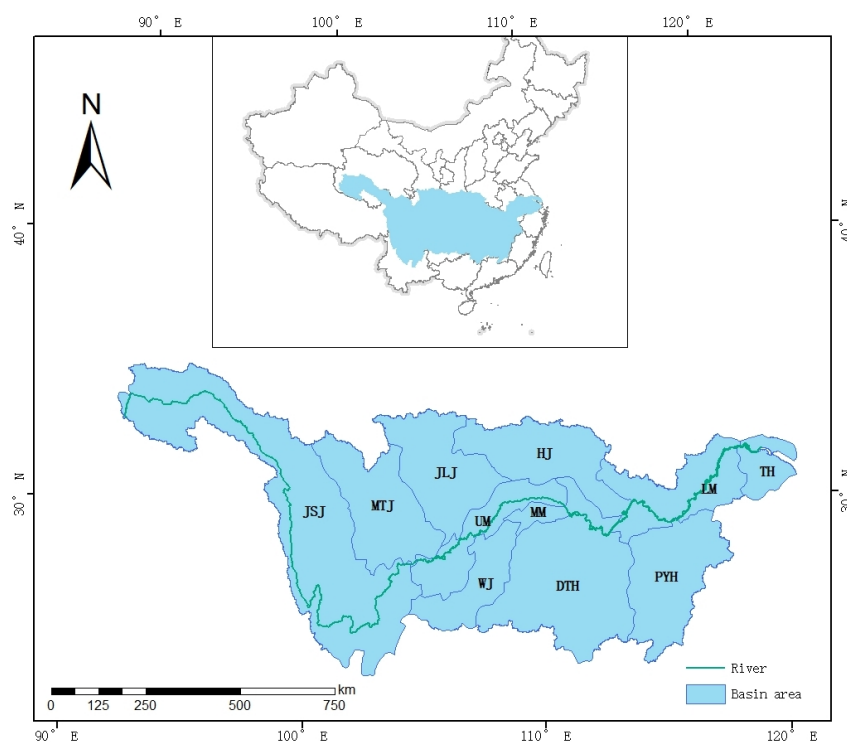


Figure 1. Map of the Yangtze River watershed and its subcatchments. JSJ—Jinshajiang, MTJ—Mingtuojiang, WJ—Wujiang, UM—the Upper mainstream region, JLJ—Jialingjiang, DTH—Dongtinghu, MM—the Middle mainstream region, HJ—Hanjiang, PYH—Poyanghu, LM—the lower mainstream region, and TH—Taihu.

In previous research, Cui et al. [28], studied the linear relationship between NANI, per capita GDP (PGDP), and population density (PD). In addition, the correlation coefficients between PGDP and PD were below 0.7, and we did not consider collinearity, as per reference [29]. Therefore, we directly adopted PGDP and PD as explanatory variables. The data for modeling were derived from a published master's thesis [22], including the response variable NANI and its four components; the predictor variables GDP; and the population

in each subcatchment for the years 1980, 1985, 1990, 1995, 2000, 2005, 2010, and 2012, with a total of 88 samples. To ensure normality, NANI was modeled on the square root scale, PGDP and PD were centralized. Model fitting was performed using data between 1980 and 2010; for validation, data from 2012 were used.

3. Methods

3.1. Hierarchical Spatially Varying Coefficient Process Regression

In the Bayesian hierarchical setting, the hierarchical spatially varying coefficient model is specified, as follows [30,31]: Let $Y(\mathbf{u}_i, t)$, $i = 1, \dots, N$, $t = 1, \dots, T$ be the response variable of the observed data at site $\mathbf{u}_i$ for time t , $X_j(\mathbf{u}_i, t)$, $j = 1, \dots, p$ denote the predictor variables. The HSVC model has three stages, with the first stage equation given by

$$Y(\mathbf{u}_i, t) = \mu(\mathbf{u}_i, t) + \varepsilon(\mathbf{u}_i, t), \quad (1)$$

where $\mu(\mathbf{u}_i, t)$ is the underlying mean process, $\varepsilon(\mathbf{u}_i, t)$ is an independent error term of the model, assumed to follow a normal distribution $\varepsilon(\mathbf{u}_i, t) \sim N(0, \sigma_\varepsilon^2)$. In the second stage, specifying the underlying mean process $\mu(\mathbf{u}_i, t)$ as

$$\mu(\mathbf{u}_i, t) = \gamma(\mathbf{u}_i, t) + \eta(\mathbf{u}_i, t), \quad (2)$$

where $\gamma(\mathbf{u}_i, t)$ is the mean surface modeled by the following equation:

$$\gamma(\mathbf{u}_i, t) = \alpha + \sum_{j=1}^p X_j(\mathbf{u}_i, t) \tilde{\beta}_j, \quad (3)$$

here, α is the global intercept, $\tilde{\beta}_j = \beta_{j0} + \beta_j(\mathbf{u}_i)$ and β_{j0} , $\beta_j(\mathbf{u}_i)$ are the fixed coefficient and the spatially varying coefficient at site $\mathbf{u}_i$, respectively. $\eta(\mathbf{u}_i, t)$ is a spatially correlated random effect assumed to follow a Gaussian process with mean 0 and spatial correlated covariance $\Sigma_\eta = \sigma_\eta^2 H_\eta(\phi)$. In particular, for any t , the covariance of $\eta(\mathbf{u}_i, t)$ and $\eta(\mathbf{u}_j, t)$ is

$$\begin{aligned} (\Sigma_\eta)_{ij} &= \sigma_\eta^2 H_\eta(\phi)_{ij} \\ &= \sigma_\eta^2 \exp(-\phi \|\mathbf{u}_i - \mathbf{u}_j\|), \end{aligned}$$

where σ_η^2 is an unknown invariant variance parameter, $H_\eta(\phi)$ is an exponential covariance function, which depends on the distance $\|\mathbf{u}_i - \mathbf{u}_j\|$ between sites $\mathbf{u}_i$ and $\mathbf{u}_j$, ϕ is the parameter of correlation, controlling the decay rate, so the larger ϕ is, the faster $(\Sigma_\eta)_{ij}$ decrease.

Let $\mathbf{Y}_t = (Y(\mathbf{u}_1, t), \dots, Y(\mathbf{u}_N, t))^\top$, $\boldsymbol{\mu}_t = (\mu(\mathbf{u}_1, t), \dots, \mu(\mathbf{u}_N, t))^\top$, $\boldsymbol{\varepsilon}_t = (\varepsilon(\mathbf{u}_1, t), \dots, \varepsilon(\mathbf{u}_N, t))^\top$, and $\boldsymbol{\eta}_t = (\eta(\mathbf{u}_1, t), \dots, \eta(\mathbf{u}_N, t))^\top$, (1)–(3) are therefore written in vector and matrix notations:

$$\begin{aligned} \mathbf{Y}_t &= \boldsymbol{\mu}_t + \boldsymbol{\varepsilon}_t, \\ \boldsymbol{\mu}_t &= \mathbf{X}_t \boldsymbol{\beta}_0 + \sum_{j=1}^p \mathbf{Z}_{jt} \boldsymbol{\beta}_j(\mathbf{u}) + \boldsymbol{\eta}_t, \end{aligned} \quad (4)$$

where $\boldsymbol{\beta}_0 = (\alpha, \beta_{10}, \dots, \beta_{p0})^\top$ is an unknown $p+1$ dimensional vector of fixed parameters, $\boldsymbol{\beta}_j(\mathbf{u}) = (\beta_j(\mathbf{u}_1), \dots, \beta_j(\mathbf{u}_N))^\top$ is an unknown N dimensional spatially varying parameter vector. In this study, we assume $\boldsymbol{\beta}_j(\mathbf{u}) \sim N(\mathbf{0}, \Sigma_\beta)$, $\Sigma_\beta = \sigma_\beta^2 H_\eta(\phi)$ with σ_β^2 as an unknown hyper-parameter and $\boldsymbol{\beta}_0 \sim N(\boldsymbol{\mu}_0, \Sigma_0)$ in the last stage [26,32]. The term $\mathbf{X}_t$ is the $N \times (p+1)$ matrix and defined as

$$\mathbf{X}_t = \begin{pmatrix} 1 & X_1(\mathbf{u}_1, t) & X_2(\mathbf{u}_1, t) & \cdots & X_p(\mathbf{u}_1, t) \\ \vdots & \vdots & \vdots & \cdots & \vdots \\ 1 & X_1(\mathbf{u}_N, t) & X_2(\mathbf{u}_N, t) & \cdots & X_p(\mathbf{u}_N, t) \end{pmatrix},$$

the term $\mathbf{Z}_{jt}$ is an $N \times N$ diagonal matrix and defined as

$$\mathbf{Z}_{jt} = \begin{pmatrix} X_j(\mathbf{u}_1, t) & 0 & \cdots & 0 \\ 0 & X_j(\mathbf{u}_2, t) & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & X_j(\mathbf{u}_N, t) \end{pmatrix},$$

and $\boldsymbol{\eta}_t = (\eta(\mathbf{u}_1, t), \dots, \eta(\mathbf{u}_N, t))^\top$.

To estimate the parameters of HSVC model in Equation (4), it is necessary to obtain the posterior distribution of the parameters conditional on the observed data based on Bayes rule, which is as follows:

$$\pi(\boldsymbol{\theta}|Y(\mathbf{u}, t)) \propto \pi(Y(\mathbf{u}, t)|\boldsymbol{\theta})\pi(\boldsymbol{\theta}),$$

where $\boldsymbol{\theta} = (\beta_0, \sigma_\varepsilon^2, \sigma_\eta^2, \sigma_\beta^2, \phi)$ denotes all unknown parameters, $\pi(\boldsymbol{\theta})$ is the prior distribution of the parameters $\boldsymbol{\theta}$. Let $n = NT$, $\mathbf{Y} = \{Y_1, \dots, Y_T\}$ denote the observed data, the posterior distribution of the parameters $\boldsymbol{\theta}$ given by the observed data $\mathbf{Y}$ can be written as follows:

$$\begin{aligned} \pi(\boldsymbol{\theta}|\mathbf{Y}) &\propto (\sigma_\varepsilon^2)^{-N/2} \exp\left[-\frac{1}{2\sigma_\varepsilon^2} \sum_{t=1}^T (\mathbf{Y}_t - \boldsymbol{\mu}_t)^\top (\mathbf{Y}_t - \boldsymbol{\mu}_t)\right] \\ &\quad \times |\Sigma_\eta|^{-N/2} \exp\left[-\frac{1}{2\sigma_\eta^2} \sum_{t=1}^T ((\boldsymbol{\mu}_t - \mathbf{v}_t)^\top H_\eta(\phi)^{-1} (\boldsymbol{\mu}_t - \mathbf{v}_t))\right] \\ &\quad \times \prod_{j=1}^p |\Sigma_\beta|^{-N/2} \exp\left[-\frac{1}{2\sigma_\beta^2} (\boldsymbol{\beta}_j(\mathbf{u}))^\top H_\eta(\phi)^{-1} (\boldsymbol{\beta}_j(\mathbf{u}))\right] \\ &\quad \times \pi(\sigma_\varepsilon^2) \times \pi(\sigma_\eta^2) \times \pi(\sigma_\beta^2) \times \pi(\beta_0) \times \pi(\phi), \end{aligned} \quad (5)$$

where $\mathbf{v}_t = \mathbf{X}_t \beta_0 + \sum_{j=1}^p \mathbf{Z}_{jt} \boldsymbol{\beta}_j(\mathbf{u})$; $\pi(\sigma_\varepsilon^2)$, $\pi(\sigma_\eta^2)$, $\pi(\sigma_\beta^2)$, $\pi(\beta_0)$, and $\pi(\phi)$ are the prior distribution.

3.2. Temporal Forecasting and Model Assessment

Suppose we forecast $Y(\mathbf{u}_i, T+1)$, the value at location $\mathbf{u}_i$ for time point $T+1$. In terms of (1) and (2), $Y(\mathbf{u}_i, T+1)$ has a normal distribution

$$Y(\mathbf{u}_i, T+1) \sim N(\mu(\mathbf{u}_i, T+1), \sigma_\varepsilon^2).$$

Subsequently, $\mu(\mathbf{u}_i, T+1)$ was obtained sequentially as

$$\mu(\mathbf{u}_i, T+1) = \alpha + \sum_{j=1}^p X_j(\mathbf{u}_i, T+1)(\beta_{j0} + \boldsymbol{\beta}_j(\mathbf{u}_i)) + \eta(\mathbf{u}_i, T+1).$$

As a result, the posterior predictive distribution of $Y(\mathbf{u}_i, T+1)$ conditional on $\mathbf{Y}$ is followed by

$$\begin{aligned} \pi(Y(\mathbf{u}_i, T+1)|\mathbf{Y}) &= \int \pi(Y(\mathbf{u}_i, T+1)|\mu(\mathbf{u}_i, T+1), \sigma_\varepsilon^2) \\ &\quad \times \pi(\mu(\mathbf{u}_i, T+1)|\boldsymbol{\beta}_j(\mathbf{u}_i), \boldsymbol{\theta}) \\ &\quad \times \pi(\boldsymbol{\beta}_j(\mathbf{u}_i)|\boldsymbol{\theta}) \pi(\boldsymbol{\theta}|\mathbf{Y}) d\mu(\mathbf{u}_i, T+1) d\boldsymbol{\beta}_j(\mathbf{u}_i) d\boldsymbol{\theta}, \end{aligned} \quad (6)$$

To derive the distribution $\pi(Y(\mathbf{u}_i, T+1)|\mathbf{Y})$, some assumptions need to be made for the terms on the right-hand side of (6). The terms $\mu(\mathbf{u}_i, T+1)$ and μ_{T+1} follow a multivariate normal distribution,

$$\begin{pmatrix} \mu(\mathbf{u}_i, T+1) \\ \mu_{T+1} \end{pmatrix} \sim N \left[\begin{pmatrix} \alpha + \sum_{j=1}^p X_j(\mathbf{u}_i, T+1)(\beta_{j0} + \beta_j(\mathbf{u}_i)) \\ \mathbf{X}_{T+1}\beta_0 + \sum_{j=1}^p \mathbf{Z}_{j,T+1}\beta_j(\mathbf{u}) \end{pmatrix}, \sigma_\beta^2 \begin{pmatrix} 1 & S_{12} \\ S_{21} & H_\eta(\phi) \end{pmatrix} \right],$$

where $\mathbf{X}_{T+1}$ and μ_{T+1} are $\mathbf{X}_t$ and μ_t with t being replaced by $T+1$. Subsequently, the conditional distribution $\pi(\mu(\mathbf{u}_i, T+1)|\beta_j(\mathbf{u}_i), \theta)$ is

$$\mu(\mathbf{u}_i, T+1)|\beta_j(\mathbf{u}_i), \theta \sim N(\zeta, \sigma_\eta^2(1 - S_{12}H_\eta(\phi)^{-1}S_{21})),$$

where $\zeta = \alpha + \sum_{j=1}^p X_j(\mathbf{u}_i, T+1)(\beta_{j0} + \beta_j(\mathbf{u}_i)) + S_{12}H_\eta(\phi)^{-1}(\mu_{T+1} - \mathbf{X}_{T+1}\beta_0 + \sum_{j=1}^p \mathbf{Z}_{j,T+1}\beta_j(\mathbf{u}))$, S_{12} is the $1 \times N$ vector with the i th entry as $\exp(-\phi\|\mathbf{u}_i - \mathbf{u}_j\|)$ and $S_{12} = S_{21}$. Furthermore, the coefficients $\beta_j(\mathbf{u}_i)$ and $\beta_j(\mathbf{u})$ have the following joint distribution,

$$\begin{pmatrix} \beta_j(\mathbf{u}_i) \\ \beta_j(\mathbf{u}) \end{pmatrix} \sim N \left[\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \sigma_\beta^2 \begin{pmatrix} 1 & S_{12} \\ S_{21} & H_\eta(\phi) \end{pmatrix} \right], \quad j = 1, \dots, p.$$

Hence, we obtain the conditional distribution $\beta_j(\mathbf{u}_i)|\theta$:

$$\beta_j(\mathbf{u}_i)|\theta \sim N(S_{12}H_\eta(\phi)^{-1}\beta_j(\mathbf{u}), \sigma_\beta^2(1 - S_{12}H_\eta(\phi)^{-1}S_{21})).$$

The conditional distribution $\pi(\theta|\mathbf{Y})$ is provided in (5), where the parameters of the posterior distribution are not tractable, but sampling from the posterior predictive distribution $\pi(Y(\mathbf{u}_i, T+1)|\mathbf{Y})$ using the Markov chain Monte Carlo (MCMC) algorithm is straightforward [33–35].

In this paper, model performance was assessed using predictive model choice criteria (PMCC) [36], which are expressed as follows:

$$\text{PMCC} = \sum_{i=1}^N \sum_{t=1}^T E\{Y(\mathbf{u}_i, t)_{\text{new}} - Y(\mathbf{u}_i, t)\}^2 + \text{Var}\{Y(\mathbf{u}_i, t)_{\text{new}}\},$$

where $Y(\mathbf{u}_i, t)_{\text{new}}$ is a new observation, sampled from the distribution $\pi(Y(\mathbf{u}_i, t)_{\text{new}}|\mathbf{Y})$ for the given data $Y(\mathbf{u}_i, t)$. The smaller the value of PMCC, the better the model fitting performance. Model prediction capability was assessed using the root mean square error (RMSE), mean absolute error (MAE), and relative bias (RB) [37], which are defined as follows:

$$\begin{aligned} \text{RMSE} &= \sqrt{\frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T (\hat{Y}(\mathbf{u}_i, t) - Y(\mathbf{u}_i, t))^2}, \\ \text{MAE} &= \frac{1}{NT} \sum_{i=1}^N \sum_{t=1}^T |\hat{Y}(\mathbf{u}_i, t) - Y(\mathbf{u}_i, t)|, \\ \text{RB} &= \frac{1}{NTY} \sum_{i=1}^N \sum_{t=1}^T (\hat{Y}(\mathbf{u}_i, t) - Y(\mathbf{u}_i, t)), \end{aligned}$$

where $\hat{Y}(\mathbf{u}_i, t)$ is the prediction value, which could be the mean of the posterior distribution $\pi(Y(\mathbf{u}_i, t)|\mathbf{Y})$, and $\bar{Y}$ is the mean of the observations, a model with a lower value is preferred for prediction.

3.3. Spatial Correlation Test

Global Moran's I index was determined, to examine the spatial correlation of NANI across the Yangtze River Basin. Based on the locations and values of each sub-basin simultaneously, global Moran's I measures spatial autocorrelation and evaluates whether the Yangtze River Basin shows a positive correlation, negative correlation, or random

correlation [38]. The global Moran's I for spatial autocorrelation across the Yangtze River Basin of the t year is given as follows:

$$I_t = \frac{\sum_{i=1}^N \sum_{j=1}^N w_{ij} (Y(\mathbf{u}_i, t) - \bar{Y}_t)(Y(\mathbf{u}_j, t) - \bar{Y}_t)}{s^2 \sum_{i=1}^N \sum_{j=1}^N w_{ij}},$$

where w_{ij} is the spatial weight between sub-basin i and j , if i and j are adjacent, $w_{ij} = 1$; otherwise, $w_{ij} = 0$, $Y(\mathbf{u}_i, t)$ is the NANI value for sub-basin i in the year t , $\bar{Y}_t = \sum_{i=1}^N Y(\mathbf{u}_i, t) / N$, $s^2 = \sum_{i=1}^N (Y(\mathbf{u}_i, t) - \bar{Y}_t)^2 / N$. The z-score is computed as follows:

$$z_t = \frac{I_t - E(I_t)}{\sqrt{\text{Var}(I_t)}}.$$

According to [39], $E(I_t) = -\frac{1}{N-1}$ and $\lim_{N \rightarrow \infty} \text{Var}(I_t) = 2 / \sum_{i=1}^N \sum_{j=1}^N w_{ij}$.

4. Results

4.1. Exploratory Analysis of Spatiotemporal Availability and Variability of the Observations

Figure 2a shows the year-by-year changes in the overall spatial pattern of NANI in the Yangtze River Basin. To ensure the clarity of the standard deviation ellipse trajectory, only the elliptical trajectories of NANI in 1980, 1990, 2000, and 2010 are shown. The dynamic feature is that the average center of NANI moved from east to west during 1980–2010. To analyze the spatial variations of NANI, PGDP, and PD, the average NANI, PGDP, and PD values in each subcatchment were calculated. Figure 2b shows that NANI, PGDP, and PD had significant spatial variations in 11 subcatchments. The spatial differences in the PDGP and PD distributions were highly influenced by the NANI distribution across the catchment of the Yangtze River. The TH subcatchment had the highest PDGP/PD and the highest NANI values, and the JSJ subcatchment had the lowest PGDP/PD and the lowest NANI values.

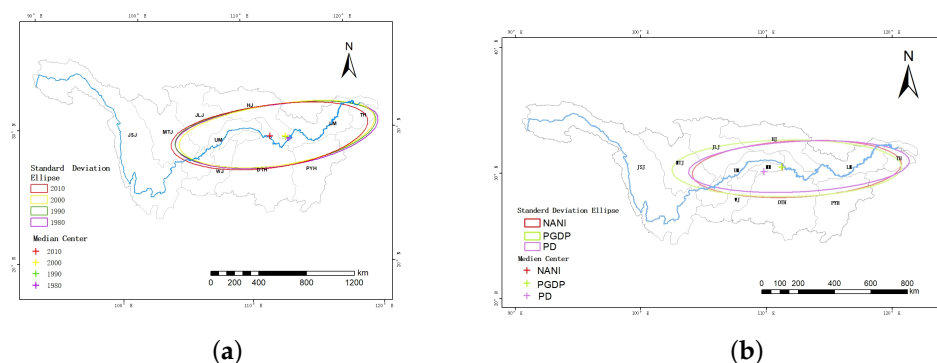


Figure 2. Temporal variation map of NANI (a) and spatial variation map of average NANI, PGDP (per gross domestic product), and PD (population density) (b) based on the standard deviation ellipse across the Yangtze River Basin.

The results of Global Moran's I for NANI across the catchment of the Yangtze River from 1980 to 2012 are listed in Table 1.

Table 1. Global Moran's I of NANI across the Yangtze River Basin 1980–2012.

Year	1980	1985	1990	1995	2000	2005	2010	2012
Moran's I	0.237	0.304	0.257	0.272	0.253	0.250	0.211	0.211
z_t	2.671	2.769	2.563	2.570	2.398	2.317	2.052	2.018
p-value	0.004	0.003	0.005	0.005	0.008	0.01	0.02	0.022

The values of global Moran's I ranged between 0.211 and 0.304, and all p -values were below 0.05, indicating that the NANI of the basin was significantly positively spatially correlated at a 5% significance level.

In the watershed of the Yangtze River, the total NANI gradually increased from 3514.7 kg N km⁻² in 1980 to 8138.2 kg N km⁻² in 2012. However, in the same period, the mean values of NANI were 2360 kg N km⁻² in 1980 and 5013 kg N km⁻² in 2009 in mainland China [21], lower than those for the Yangtze River Basin. At the same time, the temporal variations in NANI, PGDP, and PD are shown in Figure 3, illustrating that they steadily increased from 1980 to 2012. The PGDP grew at a rate of approximate 2.5 times per year, which was the highest, whereas PD increased at a rate of approximate 5% each year, which was the lowest.

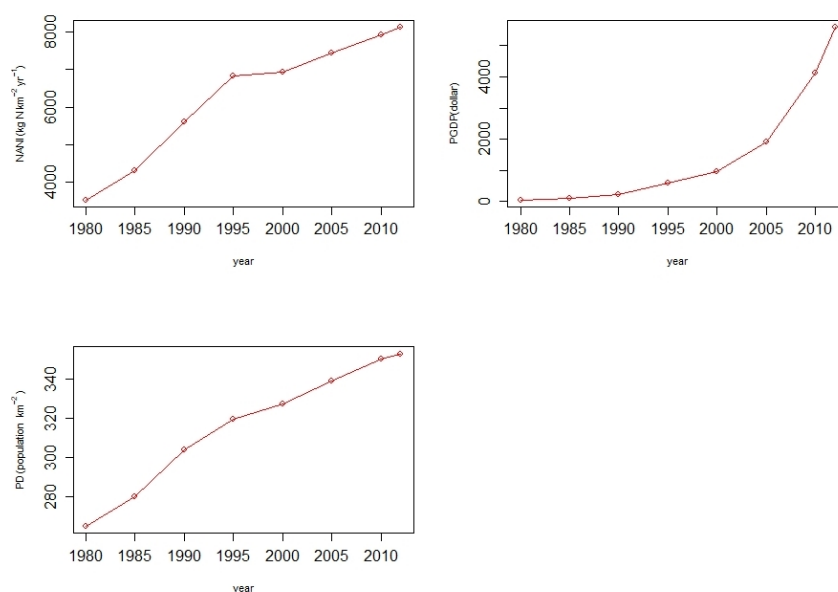


Figure 3. Temporal variations in NANI, PGDP, and PD across the watershed of the Yangtze River.

4.2. Model Fitting Based on Hierarchical Spatially Varying Coefficient Process Model

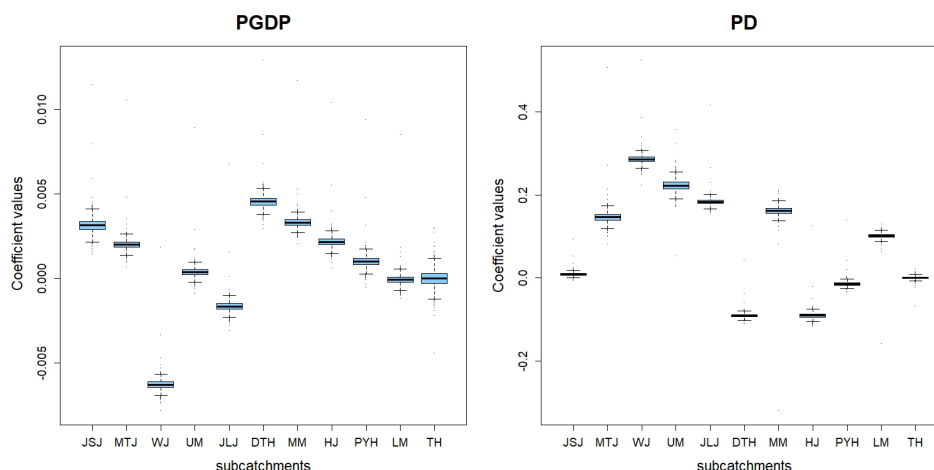
To complete the estimation of model parameters, for the parameters σ_ϵ^2 , σ_η^2 , and σ_β^2 , we assigned an inverse Gamma prior with hyperparameters 1 and 2. Considering a normal distribution with hyperparameters $\Sigma_0 = 10^4 I_3$ and $\mu_0 = \mathbf{0}$ for parameter β_0 . For the parameter ϕ , assuming a Gamma distribution, the location parameter and scale parameter were set to 2 and 1, respectively [26,40]. The calculations were performed using the software R and the package spTDyn proposed by [32]. The MCMC chain was run for 5000 iterations, with the first 1000 as burn-in iterations. Satisfactory convergence of the chain was obtained in 5000 iterations.

The estimated results of the parameters based on fitting data for the HSVC model are displayed in Table 2, which shows that the predictor variables PD and PGDP had a significant and positive effect on NANI. The variance estimators of the random error term σ_ϵ^2 and the spatially correlated error term σ_η^2 were 0.0302 and 61.2185, respectively. Thus, the variability in NANI could be attributed to the spatially correlated error term. This indicates the necessity of using the HSCV modeling approach for NANI. The estimated spatial decay parameter ϕ was 0.4079, implying that the effective spatial correlation distance in NANI among sub-basins was 8 km, determined by $\exp(-\phi d_0) \approx 0.05$ [41].

Table 2. Parameters estimated based on fitting data for the HSVC Model.

Parameter	Posterior Mean	95% Credible Intervals
Intercept	93.6702	(89.8597, 97.3934)
PGDP	0.0014	(0.0003, 0.0025)
PD	0.0513	(0.0460, 0.0566)
σ_{ε}^2	0.0302	(0.0221, 0.0418)
σ_{η}^2	61.2185	(34.4768, 68.1783)
σ_{β}^2	0.1006	(0.0531, 0.1725)
ϕ	0.4079	(0.0110, 0.9469)

Figure 4 shows the spatially varying coefficient values for PGDP and PD by sub-basin. As expected, the coefficient estimators varied by location, which also validated the HSVC model. The positive effect of PGDP on NANI was significant across sub-basins JSJ, DTH, and MM, and the negative effect of PGDP on NANI was seen across sub-basins WJ and JLJ. PD had a positive effect on NANI and was significant across sub-basins WJ, UM, and JLJ, and in the DTH and HJ sub-basins, PD had a significant positive effect on NANI.

**Figure 4.** Boxplot of the spatially varying coefficient values for PGDP (per gross domestic product) and PD (population density).

4.3. Forecasting Based on the Hierarchical Spatially Varying Coefficient Process Model

A fitted HSVC model was applied for the temporal prediction of NANI. For the purpose of comparison among prediction models, we also fitted a GP model and a DLM with the same response and predictor variables. For more details of these two models, see previous studies [34,42]. Based on Table 3, the PMCC for the HSVC model was 4952.56, and those for the other two models were 23,125.30 and 1,762,757.79, indicating a better performance of the HSVC model in model fitting. To access the performance in prediction, we predicted the NANI for the 11 sub-basins in 2012 based on the HSVC model. In Table 4, the results show that the RMSE, MAE, and RB values were lower for the HSVC model. Thus, the HSVC model had a better prediction than the other two models.

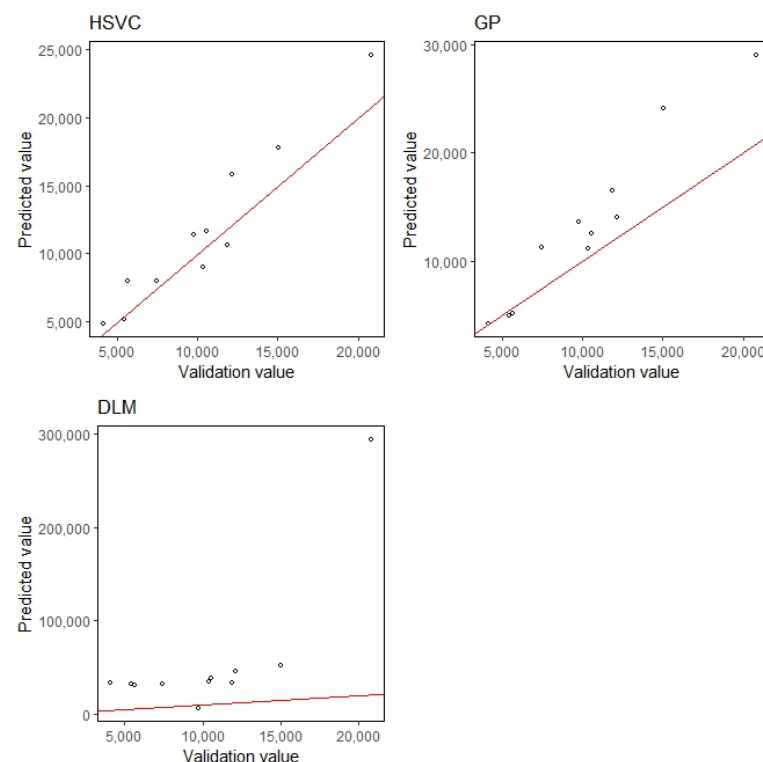
Table 3. PMCC for HSVC, GP, and DLM.

Model	Gof	Penalty	PMCC
HSVC	30.34	4922.13	4952.56
GP	73.41	23,051.89	23,125.30
DLM	473.68	1,762,284.12	1,762,757.79

Table 4. Validation statistics for temporal predictions.

Model	RMSE	MAE	RB
HSVC	2125.95	1771.33	0.12
GP	4367.85	3214.07	0.30
DLM	86,377.89	48,133.13	4.64

Plotting the validation values against predicted values based on validation data is another way to validate the prediction accuracy. As shown in Figure 5, for the HSVC model, most of the validation values ranged between 4000 and 21,000. The predicted values in this interval had a higher accuracy. Based on the results, the HSVC model had a better prediction performance.

**Figure 5.** Predicted values of the validation data for the HSVC, GP, and DLM models.

We also predicted the future NANI in 2025 and 2030 using GDP and the natural rate of population growth as base conditions. In this study, GDP growth was 5.35%, the natural growth rate of the population continued to decline to 1.76 per 1000 per year, and 2021 was the peak year of China's population [43,44]. For simplicity, we set the population size in 2030 at the same level as in 2025. The predicted PGDP and PD values in each sub-basin are given in Table 5.

By plugging the predicted PGDP and PD values for 2025 and 2030 into the fitted HSVC model, the future NANI values in each sub-basin were predicted (Table 6 and Figure 6). As shown in Figure 6, the spatial variability was well captured by the spatial distribution of the predicted NANI. High NANIs appeared in almost all eastern and northern sub-basins, indicating that economically developed and densely populated areas tended to form agglomerations of high NANIs.

The NANI within the catchment of the Yangtze River was calculated as follows:

$$\text{NANI} = \sum_{i=1}^{11} (\text{area}_i \times \text{NANI}_i) / \text{area},$$

where area denotes the entire area of the watershed of the Yangtze River, $area_i$ denotes the area of the i th subcatchment, and $NANI_i$ denotes the predicted NANI of the i th subcatchment. As a result, the predicted NANIs within the entire catchment of the Yangtze River in 2025 and in 2030 were $11,522.87 \text{ kg N km}^{-2}$ and $12,760.65 \text{ kg N km}^{-2}$, respectively. By mimicking the above procedure of the prediction, the NANI values of four components was also predicted, namely the atmospheric nitrogen deposition, nitrogen fertilizer application, crop nitrogen fixation, and food/feed imports in 2025 (Figure 7). Based on this, NANI from atmospheric nitrogen deposition was the main source, whereas that from crop nitrogen fixation was the most insignificant.

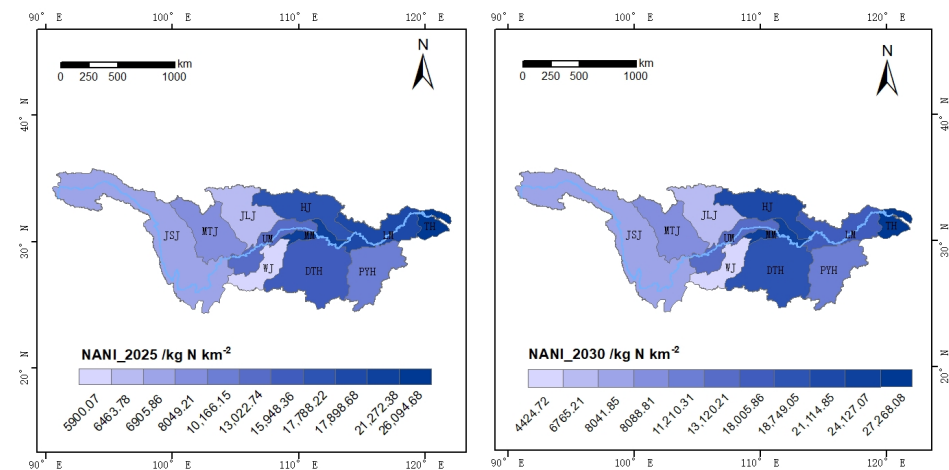


Figure 6. Spatial distribution of the predicted NANI in 2025 (left) and 2030 (right).

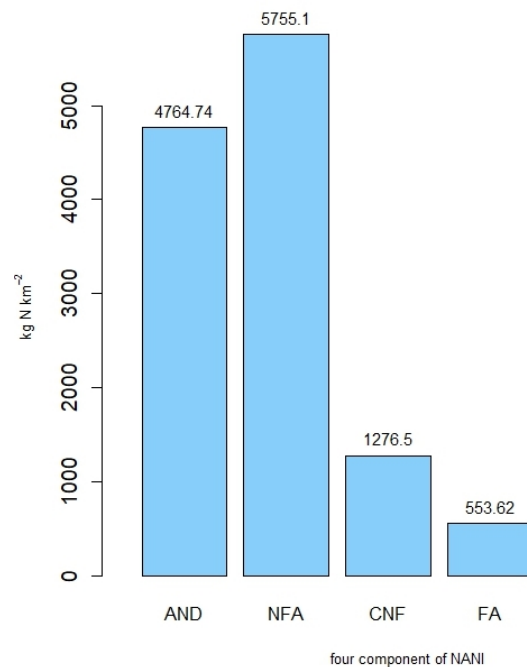


Figure 7. Predicted value of AND (atmospheric nitrogen deposition), NFA(nitrogen fertilizer application), CNF (crop nitrogen fixation), and FA (food/feed imports) in 2025.

Although these predictions were affected by the uncertainty of the predicted values of PGDP and PD in each sub-basin in 2025 and 2030, these predicted results roughly reflect the potential impact of PGDP and PD on NANI in the Yangtze River Basin. The response of the NANI yield can provide a reference for protecting the estuarine and coastal environment.

Table 5. Predicted values of PGDP (per gross domestic product) and PD (population density) in each sub-basin in 2025 and 2030.

Sub-Basins	PGDP (Dollars) 2025	PGDP (Dollars) 2025/2030	PD (Population/km ²) 2030
JSJ	8760.68	10,658.71	101.60
MTJ	9029.65	10,985.95	489.51
WJ	6785.13	8255.14	500.80
UM	9679.47	11,776.55	562.88
JLJ	9007.11	10,958.53	412.88
DTH	10,352.04	12,594.84	269.93
MM	13,083.11	15,917.60	624.39
HJ	11,568.40	14,074.73	381.75
PYH	11,020.25	14,074.73	312.14
LM	12,382.57	15,065.29	768.59
TH	24,586.34	29,913.04	1587.02

Table 6. Point prediction and 95% interval prediction of NANI in each sub-basin in 2025 and 2030.

Sub-Basins	NANI (kg N km ⁻²) 2025	NANI (kg N km ⁻²) 2030
JSJ	6905.86 (4568.95, 9453.57)	8041.85 (5464.00, 11,136.07)
MTJ	8049.21 (5577.38, 610,984.13)	8088.81 (5549.45, 10,982.74)
WJ	5900.07 (3844.00, 8157.66)	4424.72 (2673.50, 6533.14)
UM	13,022.74 (9987.85, 16,427.58)	13,120.21 (9849.54, 16,771.60)
JLJ	6463.78 (4273.25, 9001.23)	6765.21 (4334.47, 9424.51)
DTH	15,948.36 (14,391.56, 17,609.91)	18,749.05 (16,595.49, 21,051.63)
MM	21,272.38 (17,059.94, 25,753.51)	24,127.07 (19,596.08, 28,939.42)
HJ	17,788.22 (13,748.97, 21,978.56)	21,114.85 (16,681.13, 26,004.13)
PYH	10,166.15 (7284.77, 13,316.57)	11,210.31 (8091.63, 14,810.84)
LM	17,898.68 (14,225.23, 22,057.67)	18,005.86 (14,140.37, 22,067.98)
TH	26,094.68 (21,804.81, 30,773.32)	27,268.08 (22,856.46, 31,876.56)

5. Discussion

5.1. Characteristics of the Predictor Variables

In this study, we modeled NANI based on as few predictor variables as possible, i.e., PGDP and DP across the Yangtze River Basin for 1980–2012 through a HSVC model. The NANI, PGDP, and PD in the Basin showed remarkable spatiotemporal variations.

Specifically, PGDP and PD had a positive effect on NANI. This is consistent with the results of Cui et al. [28], where PGDP and PD contributed to the increase in NANI in the watershed of the Pearl River. However, in some sub-basins such as WJ and DTH, the spatially varying coefficient values for PGDP and PD were negatively related to NANI, respectively. As a result, the predicted NANIs within the WJ sub-basin decreased from 2025 to 2030, this conclusion contradicts the fact that NANI increases over time.

5.2. Limitations and Future Research

The limitations of this research are as follows: (1) Due to the data available for analysis being eight years, we only used one year of data from 2012 for model validation. Therefore, the validation measures, RMSE, MAE, and RB were calculated for a fixed time, which may have caused the prediction to be inaccurate. (2) When predicting the future NANI in 2025 and 2030, the GDP growth and the natural rate of population growth were based on previous expert evaluations [43,44]. However, GDP growth and the natural rate of population growth can be divided into various scenarios, and we only used one of them for prediction, which is an approximate way to achieve this. NANI can be influenced by

various factors, such as land-use factors and social factors [15], which still need further investigation. Further research could explore the explanatory variables of NANI, to gain a deeper understanding of the factors influencing NANI and to make more accurate predictions. Additionally, exploring more scientific model and research methods, such as geographically and temporally weighted regression, could provide a more comprehensive and profound understanding of modeling NANI.

5.3. Implications for Watershed Nitrogen Management

With the ongoing development of globalization in China, the Yangtze River Basin will play an increasing role in the future of the regional economy. The prediction of NANI is of great significance for nitrogen management in watersheds, since nitrogen concentrations in watersheds have become an indicator of ecological restoration and eutrophication mitigation. Based on the results of this study, watershed nitrogen management strategies could be implemented. First, partially organic alternatives to nitrogen fertilizer should be explored, given the high predicted value of nitrogen fertilizer application. Second, more attention should be given to atmospheric nitrogen deposition and reducing the amount of nitrogen emissions. Finally, from the perspective of nitrogen pollution control, effective riparian buffer strips and wetland treatment techniques could be built downstream of NANI hotspot areas, to intercept nitrogen pollution [45].

6. Conclusions

The purpose of this study was to use a hierarchical spatially varying coefficient process regression (HSVC) model to elaborate the mechanisms of the predictor variables per gross domestic product (PGDP) and population density (PD) for NANI, as well as to forecast the annual values of NANI within the watershed of the Yangtze River. First, we analyzed the spatiotemporal availability and variability of NANI, PGDP, and PD, and a significant ($p < 0.05$) spatial autocorrelation of NANI was diagnosed using global Moran's I from 1980 to 2012 in the watershed of the Yangtze River. Then, through a case study of NANI within the watershed of the Yangtze River, the performance of the proposed NANI prediction model was compared with those of the Gaussian process (GP) model and the spatiotemporal dynamic linear model (DLM). It was found that the HSVC model could extract more information on the relationships among NANI and predictor variables, thus improving the fitting and prediction accuracy. Finally, we predicted the NANI values for the years 2025 and 2030, and the values increased from $11,522.87 \text{ kg N km}^{-2}$ to $12,760.65 \text{ kg N km}^{-2}$. In addition, the point predictions and 95% interval predictions of NANI within the watershed of the Yangtze River for the years 2025 and 2030 were provided. This paper provides a simple and easy-to-use method for NANI prediction.

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References

1. Yu, C.; Huang, X.; Chen, H.; Godfray, H.C.J.; Wright, J.S.; Hall, J.W.; Gong, P.; Ni, S.; Qiao, S.; Huang, G.; et al. Managing nitrogen to restore water quality in China. *Nature* **2019**, *567*, 516–520. [[CrossRef](#)] [[PubMed](#)]
2. Han, Y.; Feng, G.; Swaney, D.; Dentener, F.; Koeble, R.; Ouyang, Y.; Gao, W. Global and regional estimation of net anthropogenic nitrogen inputs (NANI). *Geoderma* **2020**, *361*, 114066. [[CrossRef](#)]
3. Pei, W.; Yan, T.; Lei, Q.; Zhang, T.; Fan, B.; Du, X.; Luo, J.; Stuart, L.; Liu, H. Spatio-temporal variation of net anthropogenic nitrogen inputs (NANI) from 1991 to 2019 and its impacts analysis from parameters in Northwest China. *J. Environ. Manag.* **2022**, *321*, 115996. [[CrossRef](#)] [[PubMed](#)]
4. Wang, H.; Wu, Z.; Guo, X.; Di, D.; Jiang, M. Management implications of spatial–temporal variations of net anthropogenic nitrogen inputs (NANI) in the Yellow River Basin. *Environ. Sci. Pollut. Res.* **2022**, *29*, 52317–52335. [[CrossRef](#)]
5. Yan, T.; Bai, J.; Bao, H.; Lei, Q.; Du, X.; Zhai, L.; Liu, H. Net Anthropogenic Nitrogen Input and Its Relationship with Riverine Nitrogen Flux in a Typical Irrigated Area of China Based on an Improved NANI Budgeting Model. *Water* **2023**, *15*, 276. [[CrossRef](#)]
6. Gao, W.; Duan, Z.; Yan, C.; Liu, C. Influence of nutrient mitigation measures on the fractional export of watershed inputs in an urban watershed. *Environ. Sci. Pollut. Res.* **2020**, *27*, 1–9. [[CrossRef](#)] [[PubMed](#)]
7. Liu, X.; Duan, L.; Mo, J.; Du, E.; Shen, J.; Lu, X.; Zhang, Y.; Zhou, X.; He, C.; Zhang, F. Nitrogen deposition and its ecological impact in China: An overview. *Environ. Pollut.* **2011**, *159*, 2251–2264. [[CrossRef](#)] [[PubMed](#)]
8. Chen, F.; Hou, L.; Liu, M.; Zheng, Y.; Yin, G.; Lin, X.; Li, X.; Zong, H.; Deng, F.; Gao, J.; Jiang, X. Net anthropogenic nitrogen inputs (NANI) into the Yangtze River basin and the relationship with riverine nitrogen export. *J. Geophys. Res. Biogeosci.* **2016**, *121*, 451–465. [[CrossRef](#)]
9. Gao, W.; Howarth, R.W.; Swaney, D.; Hong, B.; Guo, H. Enhanced N input to Lake Dianchi Basin from 1980 to 2010: Drivers and consequences. *Sci. Total Environ.* **2015**, *505*, 376–384. [[CrossRef](#)]
10. Ti, C.; Pan, J.; Xia, Y.; Yan, X. A nitrogen budget of mainland China with spatial and temporal variation. *Biogeochemistry* **2012**, *108*, 381–394. [[CrossRef](#)]
11. Yang, Y.; Gao, B.; Hao, H.; Zhou, H.; Lu, J. Nitrogen and phosphorus in sediments in China: A national-scale assessment and review. *Sci. Total Environ.* **2017**, *576*, 840–849. [[CrossRef](#)] [[PubMed](#)]
12. Huang, H.; Chen, D.; Zhang, B.; Zeng, L.; Dahlgren, R.A. Modeling and forecasting riverine dissolved inorganic nitrogen export using anthropogenic nitrogen inputs, hydroclimate, and land-use change. *J. Hydrol.* **2014**, *517*, 95–104. [[CrossRef](#)]
13. Chen, F.; Jia, G.; Chen, J. Nitrate sources and watershed denitrification inferred from nitrate dual isotopes in the Beijiang River, south China. *Biogeochemistry* **2009**, *94*, 163–174. [[CrossRef](#)]
14. Gu, B.; Ge, Y.; Ren, Y.; Xu, B.; Luo, W.; Jiang, H.; Gu, B.; Chang, J. Atmospheric reactive nitrogen in China: Sources, recent trends, and damage costs. *Environ. Sci. Technol.* **2012**, *46*, 9420–9427. [[CrossRef](#)] [[PubMed](#)]
15. Deng, C.; Liu, L.; Peng, D.; Li, H.; Zhao, Z.; Lyu, C.; Zhang, Z. Net anthropogenic nitrogen and phosphorus inputs in the Yangtze River economic belt: Spatiotemporal dynamics, attribution analysis, and diversity management. *J. Hydrol.* **2021**, *597*, 126221. [[CrossRef](#)]
16. Zhang, W.; Su, J.; Du, X.; Li, X. Net anthropogenic nitrogen input to Huaihe River Basin, China during 1990–2010. *Chin. J. Appl. Ecol.* **2015**, *26*, 1831–1839. [[CrossRef](#)]
17. Howarth, R.W.; Billen, G.; Swaney, D.; Townsend, A.; Zhu, Z. Regional nitrogen budgets and riverine N & P fluxes for the drainages to the North Atlantic Ocean: Natural and human influences. *Biogeochemistry* **1996**, *35*, 75–139. [[CrossRef](#)]
18. Hong, B.; Swaney, D.; Howarth, R.W. Estimating net anthropogenic nitrogen inputs to US watersheds: Comparison of methodologies. *Environ. Sci. Technol.* **2013**, *47*, 5199–5207. [[CrossRef](#)]
19. Hong, B.; Swaney, D.; Mörtz, C.M.; Smedberg, E.; Hägg, H.E.; Humborg, C.; Howarth, R.W.; Bouraoui, F. Evaluating regional variation of net anthropogenic nitrogen and phosphorus inputs (NANI/NAPI), major drivers, nutrient retention pattern and management implications in the multinational areas of Baltic Sea basin. *Ecol. Model.* **2012**, *227*, 117–135. [[CrossRef](#)]
20. Swaney, D.; Hong, B.; Selvam, A.; Howarth, R.W.; Ramesh, R.; Purvaja, R. Net anthropogenic nitrogen inputs and nitrogen fluxes from Indian watersheds: An initial assessment. *J. Mar. Syst.* **2015**, *141*, 45–58. [[CrossRef](#)]
21. Han, Y.; Fan, Y.; Yang, P.; Wang, X.; Wang, Y.; Tian, J.; Xu, L.; Wang, C. Net anthropogenic nitrogen inputs (NANI) index application in Mainland China. *Geoderma* **2014**, *213*, 87–94. [[CrossRef](#)]
22. Chen, F. Net Anthropogenic Nitrogen Inputs (NANI) into the Yangtze River Basin and Analysis on Eco-Environmental Impacts. Master’s Thesis, East China Normal University, Shanghai, China, 2016.
23. Cai, B.; Lawson, A.B.; Hossain, M.M.; Choi, J.; Kirby, R.S.; Liu, J. Bayesian semiparametric model with spatially–temporally varying coefficients selection. *Stat. Med.* **2013**, *32*, 3670–3685. [[CrossRef](#)] [[PubMed](#)]
24. Jensen, S.T.; Park, J.; Braunstein, A.F.; Mcauliffe, J. Bayesian hierarchical modeling of the HIV evolutionary response to therapy. *J. Am. Stat. Assoc.* **2013**, *108*, 1230–1242. [[CrossRef](#)]
25. Manga, E.; Awang, N. Bayesian autoregressive spatiotemporal model of PM 10 concentrations across Peninsular Malaysia. *Stoch. Environ. Res. Risk Assess.* **2018**, *32*, 3409–3419. [[CrossRef](#)]
26. Kim, H.; Lee, J. Hierarchical spatially varying coefficient process model. *Technometrics* **2017**, *59*, 521–527. [[CrossRef](#)]
27. Hu, M.; Liu, Y.; Zhang, Y.; Shen, H.; Yao, M.; Dahlgren, R.A.; Chen, D. Long-term (1980–2015) changes in net anthropogenic phosphorus inputs and riverine phosphorus export in the Yangtze River basin. *Water Res.* **2020**, *177*, 115779. [[CrossRef](#)]

28. Cui, X.; Huang, C.Z.; Wu, J.P.; Liu, X.H.; Hong, Y.G. Temporal and spatial variations of net anthropogenic nitrogen inputs (NANI) in the Pearl River Basin of China from 1986 to 2015. *PLoS ONE* **2020**, *15*, e0228683. [[CrossRef](#)] [[PubMed](#)]
29. Zhang, X.; Huang, B.; Zhu, S. Spatiotemporal Influence of Urban Environment on Taxi Ridership Using Geographically and Temporally Weighted Regression. *ISPRS Int. J. Geo-inf.* **2019**, *8*, 23. [[CrossRef](#)]
30. Gelfand, A.E. Hierarchical modeling for spatial data problems. *Spat. Stat.* **2012**, *1*, 30–39. [[CrossRef](#)]
31. Cressie, N.; Wikle, C.K. *Statistics for Spatio-Temporal Data*; John Wiley & Sons: Hoboken, NJ, USA, 2015. [[CrossRef](#)]
32. Bakar, K.S.; Kokic, P.; Jin, H.D. Hierarchical spatially varying coefficient and temporal dynamic process models using spTDyn. *J. Stat. Comput. Simul.* **2016**, *86*, 820–840. [[CrossRef](#)]
33. Gelman, A. Parameterization and Bayesian modeling. *J. Am. Stat. Assoc.* **2004**, *99*, 537–545. [[CrossRef](#)]
34. Bakar, K.S.; Sahu, S.K. spTimer: Spatio-temporal bayesian modelling using R. *J. Stat. Softw.* **2015**, *63*, 1–32. [[CrossRef](#)]
35. Dou, Y.P.; Le, N.D.; Zidek, J.V. Modeling hourly ozone concentration fields. *Ann. Appl. Stat.* **2010**, *4*, 1183–1213. [[CrossRef](#)]
36. Gelfand, A.E.; Ghosh, S.K. Model choice: A minimum posterior predictive loss approach. *Biometrika* **1998**, *85*, 1–11. [[CrossRef](#)]
37. Yip, C.Y. Bayesian Spatio-Temporal Modelling for Forecasting Ground Level Ozone Concentration Levels. Ph.D. Thesis, University of Southampton, Southampton, UK, 2010.
38. Anselin, L. Local indicators of spatial association—LISA. *Geogr. Anal.* **1995**, *27*, 93–115. [[CrossRef](#)]
39. Griffith, D.A. The Moran coefficient for non-normal data. *J. Stat. Plan. Inference* **2010**, *140*, 2980–2990. [[CrossRef](#)]
40. Bakar, K.S.; Kokic, P.; Jin, H.D. A spatiodynamic model for assessing frost risk in south-eastern Australia. *J. R. Stat. Soc. Ser. C Appl. Stats.* **2015**, *64*, 755–778. [[CrossRef](#)]
41. Finley, A.O.; Banerjee, S.; Carlin, B.P. Bayesian spatially varying coefficient models in the spBayes R package *Environ. Model. Softw.* **2020**, *125*, 104608. [[CrossRef](#)]
42. Sahu, Sujit K and Bakar, KS. A comparison of Bayesian models for daily ozone concentration levels. *Stat. Methodol.* **2012**, *9*, 144–157. [[CrossRef](#)]
43. Chen, W. Forecasting negative Population Growth and Population Ageing in China. *Soc. Sci. J.* **2020**, *05*, 133–144.
44. Chen, X.K.; Yang, C.H.; Zhu, K.F.; Wang, H.J.; Li, X.R.; Jiang, Q.Y. Forecast of China's Economic Growth Rate in 2023 and Policy Suggestions. *Bull. Chin. Acad. Sci.* **2022**, *5*, 133–144. [[CrossRef](#)]
45. Lyu, C.; Li, X.; Yuan, P.; Song, Y.; Gao, H.; Liu, X.; Liu, R.; Yu, H. Nitrogen retention effect of riparian zones in agricultural areas: A meta-analysis. *J. Clean. Prod.* **2021**, *315*, 128143. [[CrossRef](#)]

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