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Statistical Downscaling and Evaluation of Summer Temperature in Jianghuai Region based on the FPCA

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Abstract: Based on the monthly temperature data of 34 stations in Jianghuai region of China from 1961 to 2005, we proposed a functional downscaling model of summer temperature, which taking into consideration the related optimal regional climate factors. The sample independence test is used to verify the robustness of the model. The ability in simulating summer temperatures in Jianghuai region is evaluated. The main results show: (1) The best selected predictors and their regions are 850hPa air temperature (27.5-37.5°N, 107.5-125°E) and sea level pressure (25-35°N, 102.5-125°E). (2) The first four principal components of the two factors can account for more than 85% of the original information after downscaling. (3) The independent sample test proves that the functional downscaling model has a good ability to simulate the spatial and temporal structure and the changes of summer temperature in Jianghuai region during the period of 1991-2005, especially for the northeast coastal part.

Keywords: Jianghuai region; Summer temperature; FPCA; Statistical downscaling model.

1. Introduction

Since the 20th century, the global climate has changed dramatically compared to the previous period, with significant warming as its main characteristic. Intergovernmental Panel on Climate Change (IPCC) has also pointed out that the global surface temperature has shown a linear increase. Climate change will have far-reaching implications for life on earth and the development of human society. Given the specificity of China's geographical location, summer temperatures in China show more complex characteristics both in terms of spatial distribution and temporal variability, which are challenging to study. In particular, the climate situation in the Jianghuai region, which lies between the subtropical and warm temperate zones, is even more complex and variable, coupled with its population concentration and economically developed characteristics, the development and improvement of temperature prediction and forecasting capabilities in this region will provide an important reference basis for enhancing the response to climate change and formulating long-term development plans in the region and in China.

A number of researchers have already made excellent contributions to the study of improving the modelling capabilities of climate models. An important practical tool for modelling future climate change scenarios is the Global Climate Models (GCMs). These models are useful to help simulate large-scale mean modes and better characterize local climate at the global scale [1,2]. However, it has difficulty to provide accurate regional climate information to meet the assessment needs of researchers. Statistical downscaling methods stand out among the many methods due to their fast simulation speed and are widely used in various fields [3, 4]. Some scholars in China have also applied downscaling models to the study of climate change in China, verifying their superiority for short-term prediction in local regions [5, 6].

Ramsay and Silverman [7] firstly propose the concept of functional data. They have made an invaluable contribution to the advancement of functional data analysis. The relationship between temperature and precipitation in Canada is discussed based on the theory of functional principal component analysis. The use of functional principal component models for forecasting was first proposed by Hyndman and Ullah [8] and applied to mortality and fertility forecasting problems. Maity [9] and Ivanescu et al.[10] have conducted research on functional principal component regression. The research on functional regression problems is mainly divided into parametric models and nonparametric methods. Wang Bo et al. [11, 12] conducted research on the Gaussian process of nonparametric functional regression for nonparametric methods. In the study of parametric models, in order to estimate the functional slope of the model, the standard functional principal component regression estimation method is proposed to regress the response of the principal component score associated with the largest eigenvalue of the function prediction covariance operator, Since this estimation method may have great uncertainty for large samples, in order to obtain a more stable slope estimation, Hall and Horowitz [13] and Ferraty et al. [14] proposed a regularization function from different perspectives.

In view of the potential continuous generation process of climate factor data, this paper introduces a functional data analysis method and constructs a downscaling model. Based on the observed month-by-month summer temperatures and NCEP reanalysis data, downscaling simulations are carried out for 34 stations in the Jianghuai region, and the robustness of the model is tested. The rest of the article is organized as follows: Section 2 gives a brief description of the relevant data sources the relevant methods. In Section 3, we select climate influencing factors and related regions with strong correlation with air temperature. In Section 4, we test the optimal combination of climate influence factors, constructs a functional downscaling model for the month-by-month temperature in the Jianghuai region, and evaluate the model based on independent validation. Some discussions are given in Section 5.

2. Data and Methodology

2.1 Data

The surface observations of temperature used in this paper are the monthly mean temperatures for the year1961-2005, provided by the climate system of the National Climate Centre of the China Meteorological Administration. The relevant climate factor observations were selected from the National Oceanic and Atmospheric Administration's CDC derivation of the NCEP reanalysis. The climate factor fields selected include air temperature, which is directly related to surface temperature, and geopotential height, which is negatively correlated, as well as relative humidity, specific humidity, sea level pressure and longitudinal/latitudinal winds. The climate factor fields are available for a time span of 1961-2005, all at monthly intervals, and at a spatial resolution of 2.5℃×2.5℃. The specific area of Jianghuai is 27.5-35°N, 107.5-122.5°E, which contains 34 of the first-class stations.

2.2 Two-dimensional Functional Principal Components Analysis

Climate change can be considered as a random process on a space-time domain defined on the space of square-producible functions S^2. For $L \subset R^{d_1}$, $B \subset R^{d_2}$, consider the stochastic process $X : B \to S^2(L)$, where $X(\cdot,b)$ denotes the value of this stochastic process on $b \in B$.

Define the climate function as

$$X^{(t)} = X^{(t)}(l,b) = (X^{(1)}(l,b), X^{(2)}(l,b),..., X^{(n)}(l,b)) \qquad (2.1)$$

$X^{(t)}$ is a matrix of $n \times m$, where $X^{(t)}(l,b): t = 1,...,n; l = 1,...,i; b = 1,...j; i \times j = m$, t is the year of observation, l is the longitude of the observation grid and b is the latitude of the observation grid. Then the two-dimensional Karhunen-Loève expansion of the *t*-th subject can be represented as

$$X^{(t)}(b|l) = \mu(b|l) + \sum_{q=1}^{\infty} \xi_q(l)\varphi_q(b|l) = \mu(b|l) + \sum_{q=1}^{\infty}\sum_{p=1}^{\infty} \chi_{pq}\psi_{pq}(l)\varphi_p(b|l) \qquad (2.2)$$

where $\{\psi_{pq}(l): p \ge 1\}$ is the eigenfunction operator on the space $S^2(L)$, $\{\xi_q(l): q \ge 1\}$ represents the coefficients of the centralized expansion process $X^c(\cdot,b)$, $\xi_q(l) = \sum_{q=1}^{+\infty} \chi_{pq}\phi_p(b|l)$ is the Karhunen-Loève expansion of the random function $\xi_q(l)$ on the space $S^2(B)$ which has the functional principal component χ_{pq} .

3. Selection of main influential factors

In the process of using downscaling methods for projections, the selection of appropriate climate impact factors is a matter of concern. Climate impact factors are supposed to determine the feature of future climate projection scenarios for the region under study. Therefore, when selecting factors, it is important to confirm that they have a significant physical link to the climate under study. That is to say they are supposed to be strongly correlated with the local climate and can be more accurately by the model, and weakly correlated with each other.