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A neural network method for the reconstruction of winter wheat yield series based on spatio-temporal heterogeneity

Li Jiang[1], Xiaohu Zhang[*,1], Wenjun Zuo, Hao Xu, Jianqing Zhao, Xiaolei Qiu, Yongchao Tian, Yan Zhu[*]

National Engineering and Technology Center for Information Agriculture, Key Laboratory for Crop System Analysis and Decision Making, Ministry of Agriculture and Rural Affairs, PRC, Jiangsu Key Laboratory for Information Agriculture, Jiangsu Collaborative Innovation Center for Modern Crop Production, Nanjing Agricultural University, 1 Weigang Road, Nanjing, Jiangsu 210095, PR China

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ABSTRACT

Crop growth conditions and meteorological environments are observed and recorded by agro-meteorological stations, which, however, may fail to record crop yield data in some specific years. In this context, incomplete yield series data constrain their application and result in inconvenience in information mining. Accordingly, this study improves the existing spatio-temporal interpolation method and succeeds in interpolating wheat yield data observed and recorded by 56 agro-meteorological stations on the Huang-Huai-Hai Plain of China. In this study, pre-interpolation is first implemented to improve the completion rate of interpolation and eliminate the effect of absent neighboring values on the positions to be interpolated. Then, data reconstruction is performed in spatial and temporal dimensions based on spatio-temporal heterogeneity. Finally, the reconstructed results are combined with the back propagation (BP) neural network model for spatio-temporal integration. Moreover, this study analyzes the settings of key parameters and compares them with traditional interpolation methods. Corresponding results demonstrate the superiority of the proposed method in this study over traditional interpolation methods in terms of interpolation precision and the completion rate. Meanwhile, individual interpolation precision in each step of the proposed method is effectively enhanced.

1. Introduction

Agro-meteorological stations are generally used to implement long-term observations and records on field-level wheat data such as main growth periods, main growth indicators, and yield structure as well as to provide other agricultural parameters such as soil types and meteorological data (Nilakanta et al., 2008). These observation records are used as data sources for comparison between models and baseline period analyses by the Agricultural Model Intercomparison and Improvement Project (AgMIP) (Rosenzweig et al., 2013). Moreover, such data are also included in studies on wheat growth model parameter settings (Lv et al., 2016), model simulation result validation (Zhang et al., 2017), model uncertainty analysis (Liu et al., 2018), temporal and spatial distribution characteristics of wheat yields (Chen et al., 2018), and the influence of meteorological conditions on wheat growth (Liu et al., 2014).

The original wheat growth report data are vulnerable to many quality issues due to record deviations and non-standard information preservation, and the incompleteness of the data hinders their application in various research. Existing studies have tried to select typical ecological points (Bai et al., 2016) to avoid meteorological stations with incomplete data or reconstruct missing data by spatial interpolation or time series interpolation. For spatial interpolation, commonly used methods include inverse distance weighted (IDW) interpolation, kriging interpolation, and geographic weighted regression (Vergni and Todisco, 2011). However, spatial interpolation precision can hardly meet the demand due to the large amount of data affecting crop yield as well as the large distances between agro-meteorological stations. Meanwhile, time series interpolation methods are mainly based on simple averages of neighboring data (Berhanu et al., 2015), linear interpolation (Feng et al., 2017) or neural network simulation (Prasomphan and Mase, 2013) to reconstruct the missing data. However, they fail to address conditions in which data are continuously or intermittently missing, which excludes those stations with long-term data missing from the research content (Asfaw et al., 2017) or results in the compromising use of the average value of the entire time series to represent the data from

* Corresponding authors.
E-mail addresses: zhangxiaohu@njau.edu.cn (X. Zhang), yanzhu@njau.edu.cn (Y. Zhu).
[1] Li Jiang and Xiaohu Zhang have contributed to the work equally.

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those stations (Osman and Sauerborn, 2002). Recently developed spatio-temporal integration interpolation schemes have been widely used in the interpolation of meteorological observation data. However, they are rarely reported in direct reconstructions of crop yield observation data. As an improved linear interpolation method based on traditional spatial interpolation models, spatio-temporal integration interpolation mainly includes spatio-temporal inverse distance weighting (ST-IDW), spatio-temporal kriging (ST-kriging), and geographical and temporal weighted regression (GTWR) (Fotheringham et al., 2015; Snepvangers et al., 2003). It is an extension of the traditional methods in the temporal dimension but fails to solve the problems in the traditional methods (Deng et al., 2016).

Spatio-temporal heterogeneity has been applied by some recent studies in reconstructing the missing data. Specifically, an interpolation method, referred to as the point estimation model of the Biased Sentinel Hospitals-Based Area Disease Estimation (P-Bshade), is used in the construction of temperature data from meteorological stations through establishment of a heterogeneous covariance function that is able to address spatial heterogeneity (Xu et al., 2013). Some studies further extend the P-Bshade method in the temporal dimension and combine the spatio-temporal interpolation results by linear fitting, which results in higher precision than previous interpolation methods (Zide et al., 2016). However, this method is of high computational complexity and fails to cope with the continuously missing data. Accordingly, a two-step interpolation method for spatio-temporal missing data reconstruction (ST-2SMR) is proposed to improve the interpolation of urban atmospheric environmental monitoring data (Cheng and Lu, 2017). This method consists of the rough spatio-temporal interpolation of all the data, subsequent fine interpolation using a dynamic window, and final spatio-temporal nonlinear combination using the back propagation (BP) neural network model. Two key issues should be noted in using ST-2SMR to interpolate wheat yield per unit area: (1) the time granularity is too coarse for the dynamic window construction since the time scale of crop yield is annual, and (2) it is not reasonable and proper to interpolate all the data for the entire area since yield data are not relevant for two distant meteorological stations. Based on an improvement in the window setting of the ST-2SMR method as well as analysis of key parameter settings, this study finally succeeds in implementing a complete interpolation of all the wheat yield data from agro-meteorological stations.

2. Methodology and experiment

2.1. Improved ST-2SMR (IST2SMR)

Based on ST-2SMR, this study proposes an improved method for interpolating wheat yield data from agro-meteorological stations, which includes five steps, namely, screening sample data for interpolation, pre-interpolation for missing values, fine interpolation considering spatio-temporal heterogeneity, spatio-temporal integration interpolation modeling, and reconstruction of the wheat yield data from the stations (Fig. 1).

Step 1. Screening sample data for interpolation

The interpolation dataset in this study is denoted *DS_Ini*, which consists of spatial (S) and temporal (T) dimensions. Specifically, S = $\{S_0, S_1, S_2, \ldots, S_{ns}\}$, where S_0 is the station to be interpolated, and $S_1, S_2, \ldots, S_{ns}$ are *ns* nearest stations to S_0; T = $\{T_{n-nt}, \ldots, T_{n-1}, T_n, T_{n+1}, \ldots, T_{n+nt}\}$, where T_n is the year to be interpolated, and $T_{n-nt}, \ldots, T_{n-1}, T_{n+1}, \ldots, T_{n+nt}$ are *nt* years before and after T_n (Fig. 1A). y_i^s is denoted by the yield time series from years T_{n-nt} to T_{n+nt} at the ith station, and y_j^t is the yield dataset of all stations at year j.

Step 2. Pre-interpolation for missing values

The pre-interpolation method is used in this study to reduce the impact of continuously missing data. For all the missing data in *DS_Ini*, the IDW (Eq. (1)) interpolation method and the weighted moving average (Eq. (2)) time series interpolation method are used for interpolation, resulting in $\hat{y}^{spa}$ and $\hat{y}^{tem}$, respectively.

$$\hat{y}^{spa} = \frac{\sum_i y_i^{spa} d_i^{-\alpha}}{\sum_i d_i^{-\alpha}} \tag{1}$$

y_i^{spa} is the observation data at observation point *i*; d_i is the distance between interpolated point and observation point *i*; α is the power parameter, and a larger α assigns greater influence to values closest to the interpolated point.

$$\hat{y}^{tem} = \frac{\sum_j y_j^{tem} w_j}{\sum_j w_j} \tag{2}$$

y_j^{tem} is the observation data at time *j* and w_j is the weight of y_j^{tem} (Eq. (3)).

$$w_j = n - th_j + 1 \tag{3}$$

th_j is the time interval between interpolation time and observation time *j*; *n* is half of the size of the moving window.

If the number of sample data involved in the interpolation is less than 3, then the interpolation result is null. If both $\hat{y}^{spa}$ and $\hat{y}^{tem}$ are not null, then the average of $\hat{y}^{spa}$ and $\hat{y}^{tem}$ is regarded as the pre-interpolation result, denoted by $\hat{y}^{coarse}$. If one of $\hat{y}^{spa}$ and $\hat{y}^{tem}$ is null, then $\hat{y}^{coarse}$ is set to the non-null one of the two. Meanwhile, if both $\hat{y}^{spa}$ and $\hat{y}^{tem}$ are null, then $\hat{y}^{coarse}$ is null, which means interpolation failure. Accordingly, dataset *DS_COARSE* is obtained (Fig. 1B).

Step 3. Fine reconstruction based on spatio-temporal heterogeneity

All the data in *DS_COARSE* are reconstructed in spatial and temporal dimensions. In the spatial dimension, the data from *ns* stations constitute the time series $\{y_1^s \ldots y_{ns}^s\}$, which are correlated with the time series at the station to be interpolated (y_0^s). Then, the *nbr* stations with the highest correlation coefficients are selected, and their spatial interpolation contribution weights ($\theta_1 \ldots \theta_{nbr}$) are calculated using the P-Bshade method (Eq. (4)) (Xu et al., 2013).

$$\begin{bmatrix} C(y_1^s, y_1^s) & \cdots & C(y_1^s, y_{nbr}^s) & b_1 \\ \vdots & \ddots & \vdots & \vdots \\ C(y_{nbr}^s, y_1^s) & \cdots & C(y_{nbr}^s, y_{nbr}^s) & b_{nbr} \\ b_1 & \cdots & b_{nbr} & 0 \end{bmatrix} \begin{bmatrix} \theta_1 \\ \vdots \\ \theta_{nbr} \\ \mu \end{bmatrix} = \begin{bmatrix} C(y_1^s, y_0^s) \\ \vdots \\ C(y_{nbr}^s, y_0^s) \\ 1 \end{bmatrix} \tag{4}$$

μ is the Lagrange factor; $C(y_i^s, y_{i'}^s)$ is the covariance between the yield time series at the ith station and that at the i′th station; and b_i is the ratio of the time series expectation at the ith station over that at the station to be interpolated (Eq. (5)), which can be used to evaluate the spatial distribution heterogeneity of the data to be interpolated, and its value is influenced by and increases with the difference between the yield at the sample station and that at the station to be interpolated.

$$b_i = E(y_i^s)/E(y_0^s) \tag{5}$$

$E(y_i^s)$ represents the expectation of the yield data at the ith station. $E(y_0^s)$ represents the expectation of the yield series at the interpolated station without the data to be interpolated.

Based on the spatial contribution weights of the *nbr* most relevant stations at the year of T_n as well as the corresponding yield ($y_i^s[T_n]$), the fine reconstruction in the spatial dimension is achieved, resulting in $\hat{y}^{FineS}$ (Eq. (6)).

$$\hat{y}^{FineS} = \sum_{i=1}^{nbr} \theta_i y_i^s [T_n] \tag{6}$$