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Hydro-stochastic interpolation coupling with Budyko approach for spatial prediction of mean annual runoff

Ning Qiu[a,b], Xi Chen[a,b]*, Qi Hu[c], Jintao Liu[a,b], Richao Huang[a,b], Man Gao[a,b]

[a] *State Key Laboratory of Hydrology-Water Resources and Hydraulic Engineering Hohai University, Nanjing 210098, China*
[b] *College of Hydrology and Water Resources, Hohai University, Nanjing 210098, China*
[c] *School of Natural Resources, University of Nebraska-Lincoln, Lincoln NE 68583, U.S.*
**Corresponding author E-mail: xichen@hhu.edu.cn*

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Abstract

Hydro-stochastic interpolation method based on traditional block-kriging has often been used to predict mean annual runoff in river basins. A caveat in this method is that the statistic technique provides little physical insight on relationships of the external forcing of climate and landscape and basin runoff. In this study, the spatial runoff is decomposed into a deterministic trend and stochastic fluctuations around it. The former is described by the Budyko method (Fu's equation) and the latter by hydro-stochastic interpolation. The coupled method of stochastic interpolation and the Budyko method is applied to interpolate spatial runoff in the Huaihe River basin of China, based on outlet streamflow and climate data at 40 sub-basins. Results show that the coupled method significantly improves spatial interpolation accuracy of mean annual runoff. The prediction errors from the coupled method are much smaller than that from the respective predictions by the Budyko scheme and the hydro-stochastic interpolation. The cross-validation outcome of the determination efficient, $\mathrm{R}^2_{\mathrm{cv}}$, from the coupled method is 0.93, much larger than 0.81 and 0.54 from the Budyko method and the hydro-stochastic interpolation, respectively. The prediction from the coupled method describes accurately the runoff distribution in the Huaihe River basin. In comparison, predictions from the Budyko method and from the hydro-stochastic interpolation show substantial overestimate of low runoff and underestimate of high runoff. These comparison results support that the coupled hydro-stochastic interpolation with the Budyko method offers an effective and accurate way in spatial interpolation of mean annual runoff.

Keywords: coupled Budyko-Hydro-stochastic interpolation; Mean annual runoff;

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prediction accuracy, regional runoff

1. Introduction

Runoff at the outlet of a basin is a crucial element measuring the hydrological cycle in the basin. Estimating runoffs and associated distribution pattern of water resources in ungauged basins has been one of the key problems in hydrology (Sivapalan et al., 2003) and a thorny issue in water management and planning (Imbach, 2010; Greenwood et al., 2011). Among the existing methods for such estimation and prediction of water resources availability is the regional or global runoff mapping by spatial interpolation.

Geostatistical approaches are mostly used in spatial interpolation. It estimates the value at a given location as a weighted sum of data values at surrounding locations. The spatial interpolation, assuming similarity of a generalized stochastic field (Jones, 2009), uses secondary information often referred to as "multivariate" (Li and Heap, 2008). The variable of interest is represented as a random field of values. Spatial similarity is measured by the variance between pairs of points as a function of their Euclidian distance (such as in Ordinary Kriging). Kriging has been the popular linear unbiased estimator, i.e. an interpolation method in which the expected bias is zero and the expected kriging error is minimized (Skøien et al., 2006). Ordinary Kriging (OK) estimates the local constant mean and corresponding residuals which are regarded as random. Since the spatial mean could also tell the trend tendency or nonstationary variation in space, Kriging methods have been further developed into various geostatistical interpolators, such as Kriging with a trend by incorporating the local trend within the neighborhood search window as a smoothly varying function of the coordinates. Block Kriging (BK) is also suggested as an extension of OK for estimating a block value instead of a point value by replacing the point-to-point covariance with the point-to-block covariance (Wackernagel, 1995). Recently, the kriging with an external drift (KED) is introduced to incorporate the local trend within the neighborhood search window as a linear function of a smoothly varying secondary variable instead of as a function of the spatial coordinates (Goovaerts, 1997; Li and Heap, 2008).

Since streamflow discharge observed at the outlet represents the comprehensive outcome of both precipitation and land surface over a certain drainage basin, the nonstationary trend from spatial heterogeneity, regarded here as a “deterministic term” at locations, exists due to distinguishingly spatial variability in climate-landscape factors, such as higher or lower runoff corresponding to larger or smaller rainfall over space. The spatially nonstationary trend of runoff can be interpreted by hydrological regionalization in terms of hydro-climate and landscape data at various basins, e.g., developing empirical relationships between runoff and its controlling factors of climate, land use and topography (Qiao 1982; Arnell, 1992). Those empirical relationships obtain a consensus on the form of regression equation adopted. As a simple semi-empirical approach, the Budyko theory that partitions precipitation into evapotranspiration (E) and runoff in regional scales based on surface water and energy balance, has been frequently used (Milly, 1994; Koster and Suarez, 1999; Zhang et al., 2001; Donohue et al., 2007; Li et al., 2013; Greve et al., 2014). Because Budyko method describes hydro-climate relationship over a large area, its use in prediction of runoff and E in any specific basins/areas still comes with large errors (Potter and Zhang, 2009; Jiang et al., 2015).

Many efforts have been devoted to improving Budyko method in prediction of regional runoff. Improvements have been made by including land use/landcover, geomorphology and climate variability in deriving parameters in Budyko method (Han et al., 2011; Li et al., 2013; Yang et al., 2007; Han et al., 2011).

Unlike interpolating a field, such as precipitation and evaporation, to find its values at "points" in space (Lenton and RodriguezIturbe, 1977; Creutin and Obled, 1982; Tabios and Salas, 1985; Dingman et al, 1988; Barancourt et al, 1992 and Bloschl, 2005), spatial interpolation of runoff, which is an integrated spatial continuous process in basins consisting of nested sub-basins, must take into account of the river network structure that constraints water balance between upstream and downstream. Previous studies have indicated that without adequate spatial variation information of runoff, e.g., neglecting the lateral streamflow aspects or processing basin runoff behavior as "points" in space (Villeneuve et al, 1979, Hisdal and Tveito, 1993), the runoff interpolation may overestimate the actual runoff (Arnell, 1995). In hydro-stochastic interpolation of runoff, the upstream and downstream basin area has been treated differently from neighboring basins (Sauquet et al., 2000). It has been shown that the Euclidian distances used in conventional stochastic methods fail to measure the spatial distance of pairs of the connected (sub)-basins in most cases.

Given the obvious nested structure of basins, Gottschalk (1993a, b) developed a hydro-stochastic approach for runoff interpolation. It takes full account of the concept that runoff is an integrated course in the hierarchical structure of the river basin system. Distance between a pair of basins is measured along the river network by sub-basin distance instead of Euclidian distance. A drainage basin covariogram is replacing the covariogram among "points" in conventional spatial interpolation. However, in this concept, spatial runoff was considered as the spatial homogeneity (Sauquet, 2006) or stationarity in the "deterministic term" of the regional average runoff over basins.

The inclusion of the deterministic term in the original geostatistical models has been shown to increase interpolation accuracy of the basin variables, e.g., mean annual runoff (Sauquet, 2006) and stream temperature (Laaha et al., 2013). Nevertheless, the deterministic term is mostly described by an empirical formula linking the spatial features, e.g. variability of mean annual runoff with elevation (Sauquet, 2006) and relationship between the mean annual stream temperature and altitude of the gauge (Laaha et al., 2013). The aims of this study are to incorporate the stochastic interpolation method with semi-empirical approach in quantifying the deterministic trend for spatial interpolation of runoff in Huaihe River, China. In this study, the spatial runoff at sub-basins is separated into the deterministic trend and its residuals, which are estimated by the Budyko framework and the errors between the observed runoff and the Budyko estimation. The residuals or errors were used in the hydro-stochastic interpolation proposed by Gottschalk (1993a, b, 2000). After that, the runoff prediction of any specific sub-basins is calculated as the total of the interpolated residual and the Budyko estimation. The improved method is tested in the Huaihe River basin, China. For comparison, the leave-one-out cross validation approach was applied to evaluate performance of the three interpolation methods: Budyko equation, hydro-stochastic interpolation, and hydro-stochastics coupling with the Budyko equation.

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2. Methodology

2.1 Spatial estimation of mean annual runoff by Budyko approach

Budyko approach explains the variability of mean annual water balance on terrestrial scale. It describes dependence of actual evapotranspiration (*E*) on precipitation (*P*) and potential evapotranspiration (E_0) (Williams et al., 2012). The original relationship ($E/P{\sim}E_0/P$) derived by Budyko (1974) is deterministic and nonparametric. After the Budyko curve was applied in various basins and climate conditions, it was found also dependent on local conditions, e.g., land use/cover (Donohue et al., 2007; Li et al., 2013), soil properties (Porporato et al., 2004; Donohue et al., 2012), topography (Shao et al., 2012; Xu et al., 2013), hydro-climatic variations of seasonality (Milly, 1994; Gentine et al., 2012; Berghuijs et al., 2014) and groundwater levels (Istanbulluoglu et al., 2012). Consequently, the Budyko curve has been extended to include those effects. Some of such effects were included in parametric forms (Fu, 1981; Choudhury, 1999; Yang et al., 2008; Gerrits et al., 2009; Wang and Tang, 2014). Among all revised Budyko curves, the one-parameter equation derived by Fu (Fu, 1981, Zhang et al. 2004) has been popularly used. This equation is as follows:

$$\frac{E}{P} = 1 + \frac{E_0}{P} - \left(1 + \left(\frac{E_0}{P}\right)^{\omega}\right)^{\frac{1}{\omega}} \quad (1)$$

or

$$R = \left(1 + \left(\frac{E_0}{P}\right)^{\omega}\right)^{\frac{1}{\omega}} - E_0 \quad (2)$$

where P, E, E_0 and R are mean annual precipitation, actual evapotranspiration, potential evapotranspiration, and runoff (unit: mm), respectively, and ω is a dimensionless model parameter within the range $(1, \infty)$. In this formula, the

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larger the ω is, the less the partitioning of precipitation into runoff.

The parameter ω can be calibrated by observed runoff at gauged basins or sub-basins in the study area. With known ω, Eq. (2) can be used for prediction of ungauged basin runoff or interpolation of spatial variation of runoff by using meteorological data in the target sub basins (Parajka and Szolgay, 1998).

2.2 Hydro-stochastic interpolation method

Gottschalk (1993a) proposed the hydro-stochastic interpolation method for spatial prediction of runoff based on Kriging interpolation. The Gottschalk's interpolation method redefined a relevant distance between drainage basins to identify the river system structure and supplement water balance constraints as follows.

As a spatial integrated continuous process, the predicted runoff in the specific unit $r^*(A_0)$ in a basin can be expressed as

$$r^*(A_0) = \sum_{i=1}^{n} \lambda_i r(A_i) = \Lambda^T R \quad (3)$$

where A_0 is the area of the specific unit, e.g. the basin area in this study, $r^*(A_0)$ is the predicted runoff from that basin area, $r(A_i)$ is the observed runoff in a gauged basin i with an area A_i ($i = 1, \dots n$, n is the total number of gauged basins), λ_i is the weights of a gauged basin i, and Λ is the transposed column vector of the weights and R is the column vector of runoff $r(A_i)$.

Since $r^*(A_0)$ is the estimator of the true value $\mathrm{r}(A_0)$, the best linear unbiased estimator requires: $E[\, r^*(A_0) - \mathrm{r}(A_0)\,] = 0$. To achieve the goal of minimizing the estimate error, the following set of equations was developed to solve for the optimal weights given that hydrologic variables satisfy the second order stationary assumption

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(Ripley, 1976)

$$\begin{cases} \sum_{j=1}^{n} \lambda_i C\left(u_i, u_j\right) - \mu = C_0(u_i, u_0), \quad i = 1,2,\dots n \\ \sum_{i=1}^{n} \lambda_i = 1 \end{cases} \tag{4}$$

where $C\left(u_i, u_j\right)$ is the fitted covariance function value between each pair of gauged basins (i=1,…n), and $C_0(u_i, u_0)$ is the fitted covariance value between the location of interest u_0 and each of the samples u_i, μ is the Lagrange multiplier. After calculating the weights, λ_i, and substituting them into Eq. (3), the runoff prediction in the region of interest is solved by the linear combination of the weights and the observed runoff.

To calculate the weights, we write Eq. (4) into a matrix form: $C\Lambda = C_0$, and the weights matrix as

$$\Lambda = C^{-1}C_0 \tag{5}$$

where

$$C = \begin{bmatrix} Cov(u_1, u_1) & Cov(u_1, u_2) & \cdots & Cov(u_1, u_n) & 1 \\ Cov(u_2, u_1) & Cov(u_2, u_2) & \cdots & Cov(u_2, u_n) & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ Cov(u_n, u_1) & Cov(u_n, u_2) & \cdots & Cov(u_n, u_n) & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{6}$$

$$C_0 = \begin{bmatrix} Cov(u_1, u_0) \\ Cov(u_2, u_0) \\ \vdots \\ Cov(u_n, u_0) \\ 1 \end{bmatrix} \tag{7}$$

$$\Lambda = \begin{bmatrix} \lambda_1 \\ \lambda_2 \\ \vdots \\ \lambda_n \\ \mu \end{bmatrix} \tag{8}$$

Eq. (4) is the main equation set of the stochastic interpolation approach. In the runoff interpolation procedure, the fundamental unit is the block instead of point, thus matrix C represents covariance function value of the pair blocks, and matrix C_0 is the

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covariance of block and the location of interest. The covariance values are function of block, not spatial location. Eqs. (3) and (4) only present one location to be predicted. If the interpolation procedure is multiple M non-overlapping sub-basins, Eq. (5) will be the same, but the optimal weights must be solved using the following set of equations (Sauquet and Gottschalk, 2000):

$$\Lambda = \begin{bmatrix} L_1 \\ L_2 \\ \vdots \\ L_M \\ \mu^* \end{bmatrix} \text{ and } L_i = \begin{bmatrix} \lambda_1^i \\ \lambda_2^i \\ \vdots \\ \lambda_n^i \\ \mu^i \end{bmatrix} \tag{9}$$

where L_i is the weights of all the sample observations with respect to the $i-th$ sub-basin. The matrixes C and C_0 in Eqs. (6) and (7) are

$$\mathrm{C} = \begin{bmatrix} K & 0 & \cdots & 0 & V_1 \\ 0 & K & 0 & \vdots & V_2 \\ \vdots & 0 & \ddots & 0 & \vdots \\ 0 & \cdots & 0 & K & V_M \\ V_1^T & V_2^T & \cdots & V_M^T & 0 \end{bmatrix} \text{ and } \mathrm{C}_0 = \begin{bmatrix} G_1 \\ G_2 \\ \vdots \\ G_M \\ n_T q_T \end{bmatrix} \tag{10}$$

In Eq. (10)

$$K = \begin{bmatrix} Cov(A_1, A_1) & Cov(A_1, A_2) & \cdots & Cov(A_1, A_n) & 1 \\ Cov(A_2, A_1) & Cov(A_2, A_2) & \vdots & Cov(A_2, A_n) & 1 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ Cov(A_n, A_1) & Cov(A_n, A_2) & \cdots & Cov(A_n, A_n) & 1 \\ 1 & 1 & 1 & 1 & 0 \end{bmatrix} \tag{11}$$

and

$$\mathrm{V}_i = \begin{bmatrix} n_i r(A_1) \\ n_i r(A_2) \\ \vdots \\ n_i r(A_n) \\ 0 \end{bmatrix} \tag{12}$$

$$\mathrm{G}_i = \begin{bmatrix} Cov(A_1, \Delta A_i) \\ Cov(A_2, \Delta A_i) \\ \vdots \\ Cov(A_n, \Delta A_i) \\ \mu^i \end{bmatrix} \tag{13}$$

where ΔA_i is the non-overlapping area for sub-basin i $(i = 1, \dots M)$.

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Unlike the random point interpolation, the above set of matrix equations should be constrained by water balance, i.e., the sum of the interpolated discharge for each sub-basin should equal to the observed discharge in its river outlet. This constraint equation can be expressed specifically as

$$R_T = \sum_{i=1}^{M} \Delta A_i \, r(\Delta A_i) \tag{14}$$

where R_T is total streamflow observed at outlet of the basin.

On grid estimation of runoff (Sauquet and Gottschalk, 2000), each of the non-overlapping areas ΔA_i is further subdivided into n_i grids surrounded by an area of a. The runoff prediction of each ΔA_i is the linear combination of weights and runoff observations presented as Eq. (15). Rearrange Eq. (14) yields

$$\mathrm{R}_T = \sum_{i=1}^{M}\left(\sum_{j=1}^{n} n_i \, \lambda_j^i r(A_j)\right) = \mathrm{n}_T \mathrm{r}_T \tag{15}$$

where n_T is the number of fundamental grids; and r_T is the runoff depth in outlet of the basin.

To develop the theoretical covariance function C and then the matrixes C_0 and G_0, the fundamental step is to define the distance between a pair of sub-basins from the identified runoff hierarchical structure in the river system. The appropriate geostatistical distance between sub-basins A and B defined by Gottschalk (1993b) is expressed as the expectation of distances of all the possible sub-basin pairs:

$$d(A,B) = \frac{1}{A_1 A_2} \int\int_{A_1 A_2} ||u_1 - u_2|| du_1 du_2 \tag{16}$$

where A_1 and A_2 are the areas of sub-basin A and B.

Based on the sub-basin distance, an empirical covariogram versus geostatistical distance can be drawn in a scatter diagram. The theoretical covariogram $Cov(A,B)$ is derived in the same way as geostatistical distance

$$Cov(A,B) = \frac{1}{A_1 A_2} \int\int_{A_1 A_2} Cov_p(||u_1 - u_2||) du_1 du_2 \tag{17}$$

In the above, Cov_p is the point covariance function and can be calibrated by trial-and-error fitting method. Only independent drainage basins are used to calculate the covariance function to avoid spatial correlation of the nested drainage basins.

2.3 Hydro-stochastic interpolation scheme with Budyko approach

The above stochastic interpolation procedure assumes a stationary stochastic variation of runoff among sub-basins or spatial homogeneity in runoff features (Sauquet, 2006) despite consideration of the river network structure. However, nonstationary variation of runoff from spatial heterogeneity in the river system often exists due to distinguishing spatial variability in climate-landscape factors, such as regional distribution of rainfall, evapotranspiration, topography and soils, particularly in large basins. Thus, the spatial runoff can be decomposed into nonstationary deterministic and stochastic components:

$$R(x) = R_d(x) + R_s(x). \tag{18}$$

In (18), $R(x)$ is runoff at location *x*, $R_d(x)$ is the deterministic component of the spatial trend and/or the external drift (Wackernagel, 1995) that results in nonstationary variability, $R_s(x)$ is the stochastic component regarded as a stationary variable.

In this study, Fu's equation (Eq. (1)) is used as an external drift function, $R_d(x)$ in (18), accounting for the deterministic variation of mean runoff in space. The residual $R_s(x)$ [the sub-basin runoff $R(x)$ minus the external drift $R_d(x)$] is used for executing

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the hydro-stochastic interpolation scheme known as "residual kriging" (Sauquet, 2006). The sum of $R_s(x)$ and $R_d(x)$, i.e., $R(x)$ predict of runoff at ungauged sub-basins.

2.4 Cross validation

The validation procedure for (18) is conducted using leave-one-out cross-validation method (Kearns, 1999) in order to examine and compare quantitatively the performances of three prediction models (Budyko approach, hydro-stochastic interpolation, and coupling). The performance of each model is evaluated by the same metrics (Laaha and Bloschl, 2006):

$$\mathrm{MAE} = \frac{1}{n}\sum_{j=1}^{n}[R(x_i) - R^*(x_i)\,] \tag{19}$$

$$\mathrm{MSE} = \frac{1}{n}\sum_{j=1}^{n}[R(x_i) - R^*(x_i)\,]^2 \tag{20}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{j=1}^{n}[R(x_i) - R^*(x_i)\,]^2} \tag{21}$$

where $R^*(x)$ is the prediction of spatial variable $R(x)$. *MAE* is mean absolute error, *MSE* is mean square error, *RMSE* is root-mean-square error between prediction values and observation data.

The coefficient of determination for cross-validation is

$$\mathrm{R}_{cv}^2 = 1 - \frac{V_{cv}}{V_{NK}} \tag{22}$$

where V_{cv} is mean square error (*MSE*); and V_{NK} is the spatial variance of the runoff over all the tested sub-basins.

The prediction result can be illustrated by regression analysis of the observation vs. prediction in addition to the evaluation metrics and R_{cv}^2.

3. Study catchment and data

Huaihe River Basin (HRB), the sixth largest basin in China, was selected for the validation of the spatial interpolation of runoff. HRB is of particular interest because of its situation in China's transition terrain from north to south, and the transition climate from the warm temperate monsoonal climate in the east to sub-humid climate on the west (Hu, 2008). The basin has the most human population density, and is one of the major agricultural areas in China. Millions of tons of water are consumed each year to sustain the population and agriculture. Water resources per capita and per unit area is less than one-fifth of the national average. Moreover, more than 50% of the water resources is overexploited, much higher than the recommended rate for international inland rivers (30%) (Yan et al, 2011). Higher precipitation concentration, represented by large percentages of the annual precipitation in a few very rainy months, makes the region vulnerable for severe floods as well as droughts. The frequent droughts and floods increase difficulty in water resources utilization and flood prevention (Zhang et al., 2015).

The selected study area is located upstream of Bengbu Sluice in HRB with an area of 121,000 km^2 (Fig. 1). The river network system is derived from data packages of National Fundamental Geographic Information System issued by National Geomatics Center of China. The area in the upstream is divided into 40 sub-basins, in terms of available hydrological stations with records within the period 1961-2000 (Fig. 2). The sub-basin area varies from the smallest of 17.9 km^2 (at PH station) to the largest of 30630 km^2 (WJB station). Among the 40 sub-basins, there are 27 independent sub-basins and 13 nested sub-basins of the observation network.

Annual precipitation data from 1961-2000 are obtained from monthly mean climatological dataset at 0.5° spatial resolution constructed by China Meteorological Administration (available at: http://data.cma.cn/data/detail/dataCode/SURF_CLI_CHN _PRE_MON_GRID_0.5/keywords/0.5.html). Pan evaporation data at 21 meteorological stations in HRB are used to interpolate spatial potential evapotranspiration via ArcGIS, and then the annual potential evapotranspiration of each sub-basin in HRB is obtained. The statistical features of mean annual precipitation, potential evapotranspiration and runoff during the period from 1961-2000 are listed in Table 1. During 1961-2000, the mean annual precipitation P varied from 638~1629 mm; mean annual temperature was 11~16℃, and the mean annual potential evaporation E_0 varied between 900~1200 mm. The sub-basins in the north are relatively dry with the dryness index (E_0/P) higher than 1.3 for the sub-basins of ZM, ZQ, XY and ZK. Sub-basins in the south are wet with the dryness index (E_0/P) lower than 0.8 for the sub-basins of MS, HBT and HC. The average mean annual runoff depth R is about 400 mm, but fluctuating from a minimum of 90 mm in the northern region near the Yellow River to a maximum of 1000mm in the south mountainous areas. The temporal and spatial variation of runoff of HRB is relatively small in the south but large in the north.

4 Results

4.1 Prediction of runoff by Fu's equation

Actual evapotranspiration E (Table 1) is estimated according to long-term mean of annual water balance ($E=P-R$). On the basis of Eq. (1) and long-term mean of annual water balance components during 1961–2000 at the 40 sub-basins (Table 1), we plot the E/P vs. E_0/P in Fig. 3. In Fig. 3, we also include the water limit line of the arid edge at which E = P and the energy limit line of the wet edge at which E = E_0. The curve shape in Fig. 3 is determined by the parameter ω. Its value in each sub-basin is calculated directly using Eq. (1) and is listed in Table 1. The range of ω is from the smallest 1.43 at HWH to the largest 3.16 at JJJ, the average of ω is 2.32 over the 40 sub-basins.

The sub-basin averaged ω can be fitted by minimizing the mean absolute error (*MAE*) (Legates and McCabe, 1999) between the predicted and the estimated annual evapotranspiration E from the long-term water balance (Fig. 3). The fitted value of ω for the 40 sub-basins determined from this process is 2.213, very close to the average directly from the 40 individual sub-basins.

Using ω=*2.213* in our study basin, Fu's Eq. (2) is written

$$R = \left(1 + \left(\frac{E_0}{P}\right)^{2.213}\right)^{\frac{1}{2.213}} - E_0. \quad (23)$$

Eq. (23) and Fig. 3 clearly show the deterministic trend of runoff in space. The smaller the index $\frac{E_0}{P}$ is, the larger the runoff is over the sub-basins in HRB. In Fig. 3, the larger R in the sub-basins in the north indicates drier conditions in those sub-basins.

Using Eq. (23) and the mean annual precipitation P and potential evapotranspiration E_0 at the 40 sub-basins given in Table 1, the predicted runoff depth by Fu's equation and deviation, or prediction error, between prediction and observation are calculated. The results are also summarized in Table 1 and 2. The *MAE* of Budyko runoff prediction is 94 mm, and the *RMSE* is 112 mm. The largest absolute error is at HWH (328.03 mm) and the smallest at XX (23.77 mm) (Table 1 and 2). The largest relative error is 91 mm at XZ station, about 81.6% of the observed runoff at the site, and the smallest is 36.94 mm at XHD, 4.99% of the observed runoff.

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4.2 Hydro-stochastic interpolation of runoff

For comparison, direct use of the observed runoff in the hydro-stochastic interpolation is executed based on the procedure detailed in Section 2.2. The covariance was firstly calculated by

$$C(d) = E[\, r(x_i) \cdot r(x_i + d)] - \bar{r}^{\,2} \tag{24}$$

where $\bar{r}$ is the average of the observed runoff among the sub-basins, d is the geostatistical distance between pairs of the sub-basins.

In order to obtain the distance d between the sub-basin pairs, HRB is divided into grids of 40 row × 50 column resolution. According to Eq. (16), the geostatistical distances of all the possible sub-basin pairs (820 in this study) were calculated to obtain the average distance of each pair of grid points in sub-basins A and B. According to the estimated distance for pairs of sub-basins and the observed runoff at 40 sub-basins (Table 1), the empirical covariance $C(d)$ is estimated for each pair of sub-basins. From plots of the mean estimated $C(d)$ of the independent sub-basin pairs versus the corresponding distances d with an interval of 50 km, we get an empirical covariogram shown in Fig. 4. The best fit to this empirical covariogram is

$$C(d) = 600000 \times \exp(-d/28.62). \tag{25}$$

The fitted exponential function in (25) is used to calculate the theoretical covariance matrix $Cov(A, B)$ in Eq. (17). Then the matrices of C, C_0, K, V and G are subsequently generated by MATLAB programs, and the weight coefficient matrix is calculated consequently.

The interpolation results over 40 sub-basins are conducted, and the prediction error is shown in Table 1. The *MAE* and *RMSE* are 134 mm and 176mm, respectively. The largest absolute error is at HWH (448 mm) and the smallest at XHD (3 mm) (Table 2). The interpolation errors are larger than those from the Budyko curve, a result indicating that the observed runoff is controlled by the deterministic trend in space, which markedly affects spatial interpolation accuracy.

4.3 Hydro-stochastic interpolation with Fu's equation

Because of the significant deterministic trend of runoff in space, the trend removal can help justify assumptions of spatially-autocorrelated random error for the hydro-stochastic interpolation. Following Section 2.3, we use Fu's equation (Eq. (2)) to estimate the deterministic trend or the external drift function $R_d^*(x)$, and departures of the trend, or the residual/errors, between the prediction and observation. The residual $R_s^*(x)$ is used for hydro-stochastic interpolation. The results are given in Table 1.

The empirical covariogram of $R_s^*(x)$ for each pair of sub-basins versus sub-basin distances is plotted in Fig. 5. The following exponential function is obtained from the best fitting the empirical covariogram

$$C(d) = 3000 \times \exp(-d/48.34). \tag{26}$$

From (26), matrices C, C_0, K, V and G in Eqs. (9) ~ (13) are calculated using MATLAB, and the weight coefficient matrix of runoff deviation is then calculated to predict runoff deviation. Since this interpolation scheme represents the spatial runoff deviation, the sum of the interpolated runoff deviation and the simulated runoff by Fu's equation is regarded as the total interpolated runoff in sub-basins.

Prediction outcome of runoff is listed in Table 1, with the *MAE* of 47 mm and *RMSE* of 69mm over the 40 sub-basins. The largest absolute error is at HWH (236 mm) and the smallest at JJJ (1.5 mm) (Table 2).

4.4 Comparison of spatial runoff perdition by the three approaches

As listed in Table 2, our method coupling the deterministic and stochastic processes described in this study significantly reduces the prediction errors in space. *MAE* and *RMSE* from the coupled method are much smaller than those from the Budyko and the hydro-stochastic interpolation methods. The maximum error at HWH is significantly reduced as well; 236 mm from the coupled method is much smaller than 328 mm from the Budyko method and 448 mm from the hydro-stochastic interpolation. In terms of the cross-validation outcome in Table 2, the cross-validation outcome R_{cv}^2 from our coupled method is as large as 0.93, much larger than 0.81 and 0.54 from the Budyko method and the hydro-stochastic interpolation, respectively.

The correlation analysis between predicted and observed runoff depth is shown in Fig. 6. The prediction from our coupled method is highly correlated with the prediction (R^2=0.95) and small deviation from the 1:1 line. In contrast, correlation between the prediction and observation from the Budyko method and the hydro-stochastic interpolation is low (R^2=0.58 and 0.82, respectively). Particularly, they markedly overestimate low runoff and underestimate high runoff (strong departures to 1:1 line in Fig. 6). The systematic deviation of the runoff prediction by the hydro-stochastic interpolation has also been reported in the previous work by Sauquet et al. (2000), Laaha and Bloschl (2006) and Yan et al. (2011).

Mapping spatial distribution of runoff in HRB by the three approaches of Budyko equation, hydro-stochastic interpolation and our coupled method is shown in Fig. 7. There are significant differences in mapped runoff distribution in HRB by the three-spatial interpolation methods. Compared with our coupled method, the Budyko method and hydro-stochastic interpolation markedly underestimate sub-basin runoff in the north where climate is relatively dry and runoff is small. Among the predicted runoff in the largest non-overlapping area above BB, the one made by our coupled method is 125mm, and the ones made by the Budyko method and the hydro-stochastic interpolation are 264 and 179 mm, respectively.

5. Discussion and conclusions

Investigating the underlying patterns of hydrological variables is important in our effort to obtain good knowledge of spatial variation of the hydrological variables in a region of interest. Because of existence of some degree of natural organization or connection of water basins (Dooge, 1986; Sivapalan, 2005), e.g., rivers that connect sub-basins, and hydro-climate similarity, we can describe the hydrological variables of interest in deterministic forms of functions, curves or distributions and construct conceptual and mathematical models to predict hydro-climate variability (Wagener et al, 2007). However, the deterministic method in describing complex patterns suffers inevitable loss of information (Wagener et al, 2007) because of existence of uncertainty in many hydrological processes and data. Thus, hydrological variables also contain information of stochastic nature, and should be treated as outcomes of both deterministic and stochastic processes. Use of combined or coupled deterministic and statistical hydrological models to predict hydrological processes has been recommended and proven to be effective in improving accuracy of various aspects of hydrology, such as hydrological forecast (Cheng et al., 2014; Ly et al., 2013) and groundwater table interpolation (Holman et al., 2009).

In this study, we use the Budyko's deterministic method to describe mean annual runoff as an integrated spatial continuous process determined by both the hydro-climate elements and the hierarchical river system networks. A deviation from the Budyko estimation is our use of the hydro-stochastic interpolation that assumes spatially-autocorrelated random error. The predicted runoff is the coupling of predictions by the Budyko method and the hydro-stochastic interpolation. The deterministic aspects of runoff described by Budyko method reflect regional trends at positions (sub-basins) and their deviations caused by stochastic processes are determined by the weights as a function of physical distance. Weights are higher for near points/basins and are smaller for distant points/basins.

We tested our coupled method in the Huaihe River basin in China. Our results show that the coupled method outperformed both the Budyko method and the stochastic interpolation by significantly increasing the spatial interpolation and prediction accuracy. The interpolation errors in terms of *MAE* and *RMSE* from our coupled method are 47 and 69mm over the 40 sub-basins, respectively, much smaller than 94 and 112 mm from the Budyko, and 134 and 176mm from the hydro-stochastic interpolation. The maximum error at HWH is significantly reduced as well. It is 236 mm from our coupled method much smaller than 328 mm from the Budyko method and 448 mm from the hydro-stochastic interpolation. The cross-validation outcome of the deterministic coefficient R_{cv}^2 from our coupled method is 0.93, much larger than 0.81 and 0.54 from the Budyko method and the hydro-stochastic interpolation, respectively. The prediction from the coupled method captures most accurately among the three methods the regional high and low runoff in the HRB.

Because our coupled method incorporates climate conditions, e.g., precipitation and evapotranspiration, it provides a useful tool to estimate climate change impacts on long-term water availability in large-scale river basins and to assess potential consequences of climate change in environment and water and food security.

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Captions of figures:

1. Figure 1 Topography and river network of HRB above Bengbu;
2. Figure 2 Sub-basins and hydrological stations of HRB above Bengbu;
3. Figure 3 Plot of E/P ~E0/P for 40 sub-basins and Budyko curve of HRB
4. Figure 4 Empirical covariogram from sub-basin runoff data and fitted covariogram of HRB;
5. Figure 5 Empirical covariogram from sub-basin runoff deviation and fitted covariogram of HRB
6. Figure 6 Cross validation of runoff prediction vs. observation by (a) Fu's equation, (b) hydro-stochastic interpolation, and (c) coupled method. The dotted line is 1:1;
7. Figure 7 Spatial distribution of mean annul runoff: (a) Budyko; (b) hydro-stochastic interpolation; (c) coupled method

Table 1 Summary of hydro-meteorological data and predicted runoff of sub-basins in HRB

No	Stations	Basin area\km^2	P (mm)	R (mm)	E_0 (mm)	E_0/P	E (mm)	ω	Fu's Equation		Hydro-stochastic interpolation		Coupling method	
									Predicted R (mm)	Error (mm)	Predicted R (mm)	Error (mm)	Predicted R (mm)	Error (mm)
1	CTG	3090	1012	366	932	0.92	646	2.41	399	32.85	371	4.90	348	17.84
2	XHD	1431	1517	740	974	0.64	776	2.41	777	36.94	737	2.70	692	47.82
3	SQ	3094	822	168	1024	1.25	653	2.83	248	79.29	285	116.77	178	10.10
4	MS	1970	1517	672	957	0.63	845	3.06	786	114.28	584	88.45	662	10.13
5	BGS	2730	877	225	1029	1.17	651	2.57	279	53.93	247	22.39	181	44.01
6	XC	4110	945	225	997	1.06	720	3.02	332	106.82	272	46.77	212	13.11
7	BT	11280	910	223	993	1.09	687	2.85	310	86.94	275	52.25	219	3.74
8	ZK	25800	678	123	1061	1.56	555	2.54	163	39.96	228	104.65	61	61.70
9	JJJ	5930	1347	513	969	0.72	834	3.16	640	127.27	520	7.49	512	1.49
10	HB	16005	1092	335	937	0.86	757	3.15	455	120.48	334	1.02	360	25.01
11	ZQ	3410	739	118	1083	1.47	621	2.83	190	71.71	219	101.07	141	23.40
12	HPT	4370	1629	764	984	0.60	865	2.92	868	103.53	755	9.22	712	51.64
13	XX	10190	987	367	1053	1.07	620	2.10	343	23.77	381	13.73	424	56.96
14	BB	121330	850	215	1024	1.20	635	2.54	264	49.48	394	179.16	125	90.46
15	WJB	30630	1003	294	957	0.95	709	2.85	384	90.29	304	9.65	287	6.90
16	LZ	390	963	345	1078	1.12	618	2.09	320	24.96	320	25.08	399	53.75
17	NLD	1500	1019	439	1101	1.08	581	1.86	351	88.30	309	129.64	401	37.56
18	ZMD	109	690	212	1093	1.58	478	1.94	163	48.65	281	68.78	235	22.53
19	BLY	737	1504	868	1126	0.75	635	1.69	695	173.27	639	229.05	794	74.23
20	HWH	292	1560	1068	1127	0.72	492	1.43	740	328.03	619	448.83	832	236.16
21	ZC	493	1512	838	1112	0.74	674	1.79	708	130.23	695	142.77	777	61.19
22	BQY	284	1268	693	1094	0.86	575	1.68	527	166.21	349	344.06	604	89.35
23	QL	178	1559	970	1090	0.70	589	1.60	756	214.17	646	324.06	840	130.17
24	HNZ	805	1480	640	1114	0.75	840	2.41	681	41.37	577	63.05	585	55.20
25	TJH	152	1305	699	1090	0.84	605	1.74	556	143.66	262	437.02	589	110.18
26	LX	77.8	1025	484	1079	1.05	540	1.75	361	123.77	241	242.88	436	48.01
27	ZLS	1880	755	253	1104	1.46	502	1.91	194	58.45	169	84.28	233	19.94
28	ZT	501	1021	437	1101	1.08	583	1.87	351	85.87	242	195.10	411	26.08
29	XGS	375	830	302	1088	1.31	528	1.91	238	63.74	243	58.60	297	5.46

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30	JZ	46	1103	583	1107	1.00	520	1.63	404	178.81	200	382.51	455	127.50
31	GC	620	638	111	1055	1.65	528	2.51	145	34.18	139	28.42	103	8.08
32	ZM	2106	645	97	1039	1.61	548	2.72	150	53.48	141	43.80	105	7.58
33	YZ	814	979	235	1083	1.11	743	2.85	329	94.07	277	42.13	246	11.24
34	XZ	1120	746	111	1040	1.39	636	3.06	202	90.66	167	56.30	152	40.95
35	GZ	1030	855	342	1098	1.28	513	1.81	250	92.10	255	86.54	307	35.14
36	DPL	1770	1067	331	1066	1.00	736	2.57	393	61.62	339	8.02	342	11.39
37	XX2	256	1301	606	1092	0.84	695	2.00	552	53.68	705	99.36	552	53.82
38	PH	17.9	1248	708	1094	0.88	540	1.61	512	196.04	604	104.35	512	195.9 0
39	HC	2050	1255	454	1095	0.87	802	2.54	517	63.36	363	91.02	409	44.52
40	HK	2141	871	227	1077	1.24	644	2.44	264	37.28	309	82.40	186	41.22

Table 2 Interpolation and cross-validation errors between the predicted and observed runoff at 40 sub-basins for the three methods

Evaluation indicators	Budyko	Hydro-stochastic interpolation	Coupling method
MAE (mm)	94	134	47
RMSE (mm)	112	176	69
Max error (mm)	328	448	236
Min error (mm)	24	3	1.5
R^2_{cv}	0.81	0.54	0.93

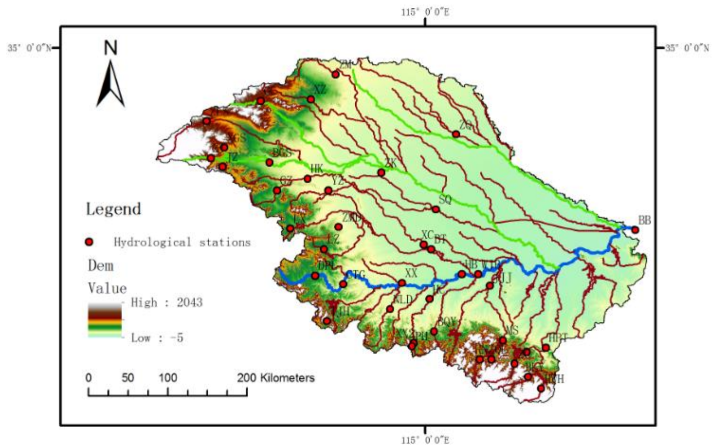


Figure 1 Topography and river network of HRB above Bengbu

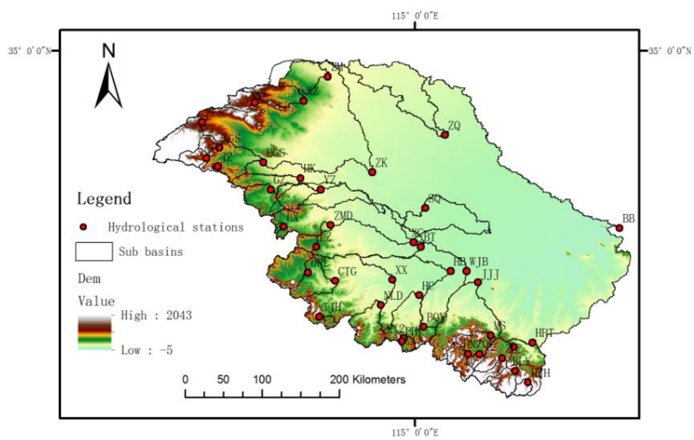


Figure 2 Sub-basins and hydrological stations of HRB above Bengbu

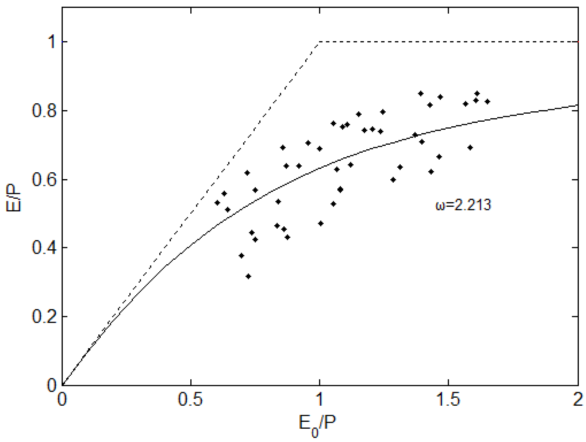


Figure 3 Plot of $E/P \sim E_0/P$ for 40 sub-basins and Budyko curve of HRB

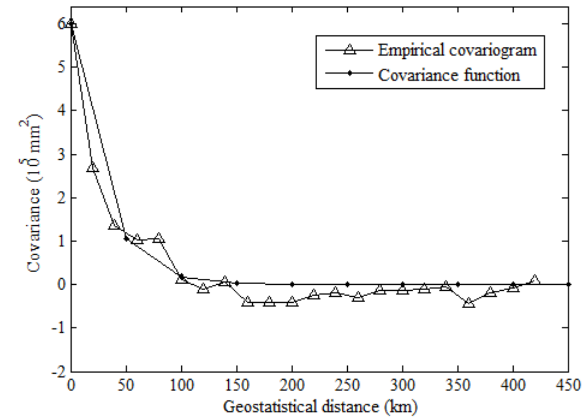


Figure 4 Empirical covariogram from sub-basin runoff data and fitted covariogram of HRB

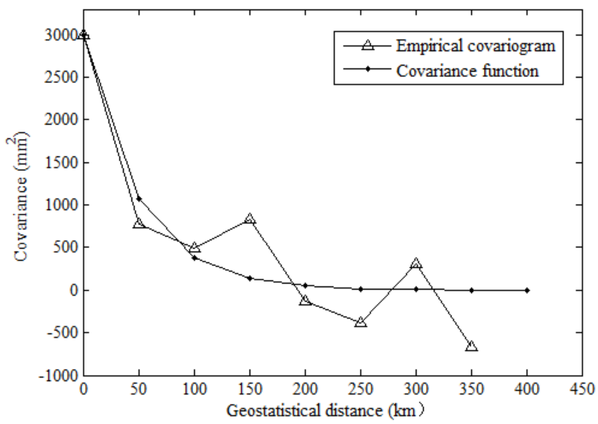
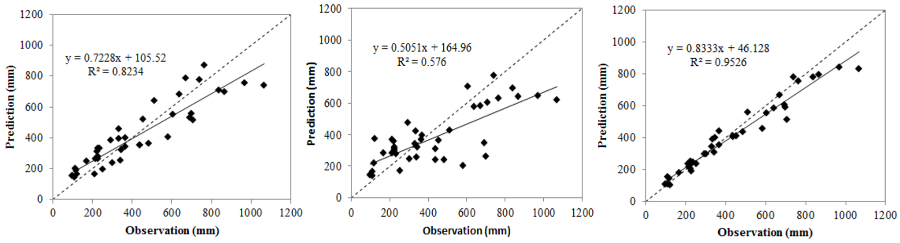


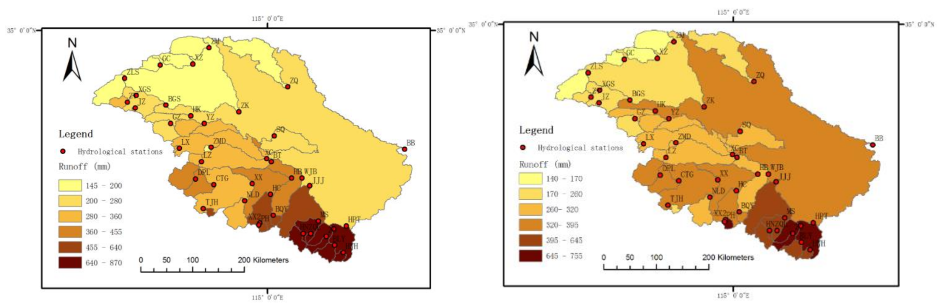
Figure 5 Empirical covariogram from sub-basin runoff deviation and fitted covariogram of HRB



(a) (b) (c)

Figure 6 Cross validation of runoff prediction vs. observation by (a) Fu's equation, (b) hydro-stochastic interpolation, and (c) coupled method. The dotted line is 1:1

(a) (b)



(c)

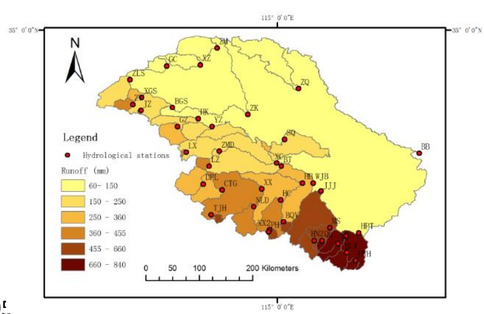


Figure 7 Spatial distribution of mean annul runoff: (a) Budyko; (b) hydro-stochastic interpolation; (c) coupled method