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GIS-BASED SPATIAL PRECIPITATION ESTIMATION: A COMPARISON OF GEOSTATISTICAL APPROACHES[1]

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ABSTRACT: As one of the primary inputs that drive watershed dynamics, the estimation of spatial variability of precipitation has been shown to be crucial for accurate distributed hydrologic modeling. In this study, a Geographic Information System program, which incorporates Nearest Neighborhood (NN), Inverse Distance Weighted (IDW), Simple Kriging (SK), Ordinary Kriging (OK), Simple Kriging with Local Means (SKlm), and Kriging with External Drift (KED), was developed to facilitate automatic spatial precipitation estimation. Elevation and spatial coordinate information were used as auxiliary variables in SKlm and KED methods. The above spatial interpolation methods were applied in the Luohe watershed with an area of 5,239 km^2, which is located downstream of the Yellow River basin, for estimating 10 years' (1991-2000) daily spatial precipitation using 41 rain gauges. The results obtained in this study show that the spatial precipitation maps estimated by different interpolation methods have similar areal mean precipitation depth, but significantly different values of maximum precipitation, minimum precipitation, and coefficient of variation. The accuracy of the spatial precipitation estimated by different interpolation methods was evaluated using a correlation coefficient, Nash-Sutcliffe efficiency, and relative mean absolute error. Compared with NN and IDW methods that are widely used in distributed hydrologic modeling systems, the geostatistical methods incorporated in this GIS program can provide more accurate spatial precipitation estimation. Overall, the SKlm_EL_X and KED_EL_X, which incorporate both elevation and spatial coordinate as auxiliary into SKlm and KED, respectively, obtained higher correlation coefficient and Nash-Sutcliffe efficiency, and lower relative mean absolute error than other methods tested. The GIS program developed in this study can serve as an effective and efficient tool to implement advanced geostatistics methods that incorporate auxiliary information to improve spatial precipitation estimation for hydrologic models.

(KEY TERMS: Geographic Information System; geostatistics; interpolation; Kriging; spatial precipitation.)

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INTRODUCTION

Numerous studies have revealed that climatological variables and hydrological processes can show considerable spatial variability (Merz and Bárdossy, 1998). As one of the primary inputs that drive distributed hydrologic models, previous studies have shown that the spatial variability of precipitation fields can translate into influence on simulated runoff volume,

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time shift of hydrographs, sediment delivery, and nutrient yield (e.g., Dawdy and Bergman, 1969; Wilson *et al.*, 1979; Lopes, 1996; Chaubey *et al.*, 1999; Arnaud *et al.*, 2002; Hossain *et al.*, 2004; Chaplot *et al.*, 2005). With the popularity of applying distributed hydrologic model for simulating spatially variable hydrologic processes and assessment of land use/climate change, and management practices, accurate spatial precipitation estimation is becoming more and more important for reliable decision making in real world water resources management problems.

The popular methods used to estimate rainfall fields by distributed hydrologic models include the Nearest Neighborhood (NN) and Inverse Distance Weighted (IDW) methods. For example, The Soil and Water Assessment Tool (SWAT) and Systeme Hydrologique European (SHE) use the NN method (Arnold *et al.*, 1998; El-Nasr *et al.*, 2005), and the Variable Infiltration Capacity (VIC) model uses IDW (O'Donnell *et al.*, 2006). Recent studies have shown that spatial precipitation estimated using different interpolation methods can be substantially different from each other. Several recent examples are introduced as follows. Goovaerts (2000) compared Thiessen Polygon, Linear Regression, IDW, Ordinary Kriging (OK), Simple Kriging with varying local means (SKlm), Kriging with an External Drift (KED) and co-Kriging for monthly and annual rainfall interpolation using 36 climatic stations in a 5,000 km^2 region of Portugal; Lloyd (2005) used Moving Window Regression, IDW, OK, SKlm, and KED to interpolate monthly precipitation values in England for 1999. Carrera-Hernández and Gaskin (2007) used OK, KED, and Block Kriging with External Drift (BKED) to analyze spatial and temporal characteristics of daily precipitation and temperature in the Basin of Mexico, and the accuracy of different interpolation methods was evaluated using accumulated monthly data. Results presented in the studies described above have shown that the accuracy of spatial precipitation estimated using different methods exhibit evident differences, and advanced geostatistical methods performed better than simple interpolation algorithms (i.e., IDW and Thiessen Polygon) that are widely used in distributed hydrologic modeling system. Their results also show that the interpolation of spatial precipitation is improved by the use of elevation as a secondary variable even when these variables show a low correlation with precipitation. Several other studies (e.g., Zhang and Srinivasan, 2006; Schuurmans and Bierkens, 2007) used the spatial precipitation estimated by different interpolation methods as input into distributed hydrologic models, and showed that the modeling results are sensitive to the difference between spatial precipitation estimated using different interpolation methods. But, to the best of the authors' knowledge, few studies that applied distributed hydrologic model with rain-gauge precipitation input have used the advanced geostatistical methods introduced above. One major reason is that there lacks an effective and efficient tool to facilitate the use of these advanced geostatistical methods to interpolate rain-gauge precipitation data for a long period. Therefore, the major objective of this study is to develop and evaluate a Geographic Information System (GIS) based spatial precipitation estimation tool for easing the spatial interpolation of long period daily precipitation data. Different interpolation methods were incorporated into this GIS tool, and their performances were compared in a test watershed. The remainder of this paper is organized as follows. Meterials and Methods section provides a brief description of the study area and precipitation data, methods used to conduct spatial precipitation interpolation, functions of the GIS-based spatial precipitation estimation tool, and the statistics used to compare the performances of different interpolation methods. Results and Discussion section, presents and discusses the application of different methods for interpolating long-term daily precipitation data. Finally, a Summary with conclusions is provided in section four.

MATERIALS AND METHODS

Study Area Description

The study site was selected at the downstream area of the Luohe River – the largest tributary of the downstream Yellow River – with an area of 5,239 km^2 and characterized by flat alluvial and foothill plains. Figure 1 shows the location and terrain of the study area. The horizontal and vertical resolutions of topography data, which were obtained from the National Geomatics Center of China, are 90 and 1 m, respectively. The elevation data derived from the topography of the study area were used as auxiliary variable in SKlm and KED methods. The average elevation of Luohe basin is about 520 m. While a large part of the study area is flat with low relief, a relatively abrupt relief exists in the south, north, and west part of the study area. The highest elevation of Luohe basin is 1,901 m, while the lowest is 136 m. Luohe River basin is within a warm temperate climate zone. Precipitation in this area is mainly influenced by East Asia monsoon. The average annual precipitation is about 520 mm. The precipitation amount during flood season (May-September) accounts for about 80% of the annual total. For this study, 41 rain gauges (Figure 1) recording daily

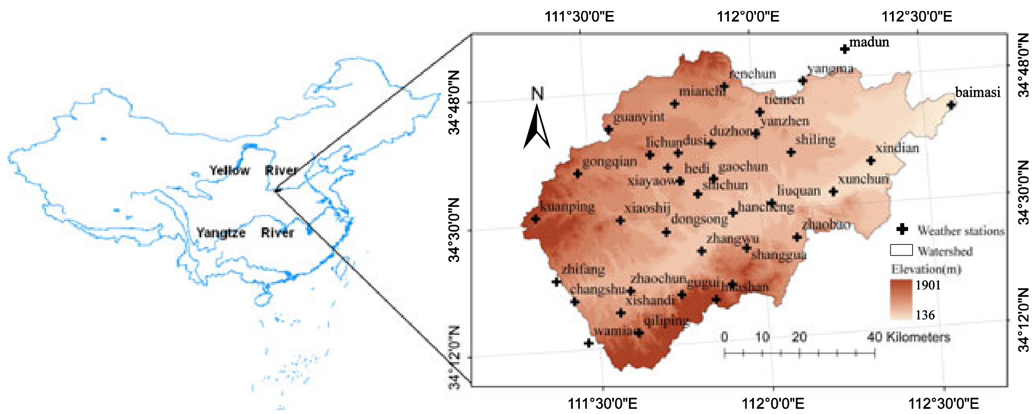

FIGURE 1. Location and Digital Terrain Map of the Study Area and 41 Rain Gauges Used to Estimate Spatial Precipitation. (Modified from Zhang *et al.*, 2007.)

precipitation provided by Water Resources Conservancy Committee of the Yellow River Basin were used to test the accuracy of the performance of different spatial precipitation interpolation methods. All the 41 recorded daily precipitation from 1991 to 2000. Because a small amount of precipitation has relatively insignificant effect on hydrologic modeling (Neitsch *et al.*, 2005; Westcott *et al.*, 2008), only those days with areal mean precipitation depth larger than 3 mm (calculated using Thiessen polygon) were used to evaluate the interpolation methods in this study.

Interpolation Methods

Eight interpolation methods were selected in this study, which include NN (i.e., Thiessen polygon), IDW, OK, SK, KED, SKlm, and several extensions of KED and SKlm. The aim of spatial interpolation methods is to estimate the value of a random variable, Z, at one or more unsampled points from a set of sample data $(Z(\mathbf{x}_1), Z(\mathbf{x}_2), \ldots, Z(\mathbf{x}_n)$ at points $(\mathbf{x}_1, \mathbf{x}_2, \ldots, \mathbf{x}_N)$ within a spatial domain, where N is the number of sample data. The basic forms of the six interpolation methods and two variants are introduced as follows.

Thiessen Polygon. Thiessen polygon assigns the precipitation of each unsampled point to the value observed by the closest rain gauge (Thiessen, 1911). The precipitation value at an unsampled location (u) is estimated using the function below,

$$Z(u) = Z(\mathbf{x}_i), \quad h_{ui} < h_{uj} \text{ for all } i \neq j, \tag{1}$$

where $Z(u)$ is the interpolated value, $Z(\mathbf{x}_i)$ is the sampled data value at location $\mathbf{x}_i$, h_{ui} denotes the distance between unsampled location u and sampled location $\mathbf{x}_i$, h_{uj} denotes the distance between unsampled location u and sampled location $\mathbf{x}_j$.

Inverse Distance Weighted. The IDW method explicitly implements the assumption that observations closer to one another are more alike than those farther apart, weighting the points closer to the prediction location greater than those farther away. With inverse distance weighting (Equation 2), data points are weighted during interpolation so that the influence of one data point relative to another declines with distance from the interpolation point,

$$Z(u) = \frac{1}{\sum_{i=1}^{n} \lambda_{ui}} \sum_{i=1}^{n} \lambda_{ui} Z(\mathbf{x}_i), \qquad \lambda_{ui} = \frac{1}{h_{ui}{}^{p}} \tag{2}$$

where n represents the number of sample data values around the unsampled location to be used in interpolation, λ_{ui} denotes the weight of the sampled data at location $\mathbf{x}_i$, p is the power of the h_{ui}. $Z(u)$, h_{ui}, and $Z(\mathbf{x}_i)$ have been defined above. In the following sections, variables defined in previous sections will not be introduced again. In this study, n and p were set to 5 and 2 respectively based on preliminary trial and error analysis.

Kriging. Kriging is a category of advanced geostatistical techniques that provides the best linear unbiased estimation of the variable of interest at an unobserved location from observations of the random field at nearby locations. In Kriging methods, the random variable Z is decomposed into a trend (m) and a residual (ε), where $Z(\mathbf{x}) = m(\mathbf{x}) + \varepsilon(\mathbf{x})$. The Kriging estimator is given by a linear combination of the surrounding observations (Goovaerts, 1997). The weights of the points that surround the predicted points are calculated based on the spatial dependence (i.e., semivariogram or covariance) of the random field. Of the different Kriging techniques, the SK, OK, KED, and SKlm are introduced as follows.

Ordinary Kriging. OK is a common type of Kriging in practice. In the OK, the trend is considered as unknown and constant. OK estimates the unknown precipitation depth at the unsampled location u as a linear combination of neighboring observations, that is, $Z(u) = \sum_{i=1}^{n} \lambda_{ui} Z(\mathbf{x}_i)$. The optimal weights are obtained through solving a series of linear functions known as the "Ordinary Kriging System" (Goovaerts, 2000),

$$\begin{cases} \sum_{j=1}^{n} \lambda_{uj}\gamma(h_{ij}) + \mu(u) = \gamma(h_{ui}) & i = 1,\ldots,n \\ \sum_{j=1}^{n} \lambda_{uj} = 1 \end{cases} \tag{3}$$

where $\mu(u)$ is the Lagrange parameter accounting for the constraint on the weights, h_{ij} denotes the separation distance between sampled location x_i and x_j. The semivariance $\gamma(h)$ is computed using the equation below,

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i}^{N(h)} \left(z(\mathbf{x}_i) - z(\mathbf{x}_i + h)\right)^2, \tag{4}$$

where h is the difference between two point locations, $N(h)$ is the number of pairs of points separated by h, $z(\mathbf{x}_i)$ - $z(\mathbf{x}_i + h)$ is the value difference between point $\mathbf{x}_i$ and another point separated by distance h.

Simple Kriging. The SK estimator is $Z(u) - m(u) = \sum_{i=1}^{n} \lambda_{ui}[Z(\mathbf{x}_i) - m(\mathbf{x}_i)]$. SK assumes the trend of the random variable is known and constant. The equation system used to estimate the weights is,

$$\sum_{j=1}^{n} \lambda_{uj} C(h_{ij}) = C(h_{ui}) \quad i = 1, \ldots, n \tag{5}$$

where $C(h)$ is the spatial covariance between two points separated by distance h.

Kriging with External Drift. In OK and SK, the trend of the random variable is constant. While in real world problems some spatial processes include varying trend or "drift" (Webster and Oliver, 2007). In KED, the trend $m(\mathbf{x})$ of the random variable is not stationary, which can take into account both the spatial dependence of the variable and its linear relation to one or more additional variables (Ahmed and de Marsily, 1987). The basic form of $m(\mathbf{x})$ can be expressed as $\sum_{k=0}^{K} \beta_k y_k(\mathbf{x})$, where $y_1(\mathbf{x}), y_2(\mathbf{x}), \ldots, y_K(\mathbf{x})$ are known "external" variables and the β_k are unknown coefficients to be determined (Webster and Oliver, 2007). The usual expression for the KED estimate is the same as that of OK, but the equation system used to obtain the optimal weights of KED is different. These equations are expressed as,

$$\begin{cases} \sum_{j=1}^{n} \lambda_{uj}\gamma_{\varepsilon}(h_{ij}) + u_0 + \sum_{k=1}^{K} u_k y_k(\mathbf{x}_i) = \gamma_{\varepsilon}(h_{ui}) & \text{for } \mathrm{i} = 1,2,\ldots,\mathrm{n}, \\ \sum_{i=1}^{n} \lambda_{ui} = 1, \\ \sum_{i=1}^{n} \lambda_{ui} y_k(\mathbf{x}_i) = y_k(\mathbf{x}_i) & \text{for } \mathrm{k} = 1,2,\ldots,\mathrm{K}, \end{cases} \tag{6}$$

where $\gamma_{\varepsilon}(h_{ij})$ is the semivariances of the residuals between the data at $\mathbf{x}_i$ and $\mathbf{x}_j$; u_k, k = 0, 1, 2, …, K, are Lagrange multipliers. The number of equations needing to be solved depends on the number of additional variables that are used to estimate the trend. In this study, the spatial coordinate and elevation at point $\mathbf{x}$ are taken as the external variables to estimate the trend of the primary variable (precipitation). Two types of KED are applied in this study: the first one takes the elevation at point $\mathbf{x}$ as external variable with $m(\mathbf{x}) = \beta_0 + \beta_1\mathrm{EL}$, where EL is the elevaton; the second type of KED incorporates information from both the spatial coordinate at point $\mathbf{x}$ and elevation to estimate the trend with $m(\mathbf{x}) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3\mathrm{EL}$, where x_1 and x_2 are the spatial coordinates. The first type of KED is represented as KED_EL, and the second one is denoted as KED_EL_X. For a more thorough introduction of KED, please refer to Webster and Oliver (2007). It is worth noting that the semivariance function $\gamma_{\varepsilon}(h_{ij})$ is estimated from the residuals but not the original observed data. It is a difficult task to obtain such a task, because often we do not have direct observation of the residuals. Different methods have been proposed to estimate $\gamma_{\varepsilon}(h_{ij})$. One way of dealing with drift is to use trend surface analysis, and remove it from the data to obtain the residuals, then the variogram is computed and modeled (Webster and Oliver, 2007). The generalized least squares method was suggested to estimate the trend through an iterative means. The ordinary least square (OLS) estimates are obtained, and the variogram is fitted to the residuals. This variogram is then used in the generalized least squares method to re-estimate the trend, and the procedures are repeated until the estimates stabilize (e.g., Hengl *et al.*, 2004).

Simple Kriging with Varying Local Means. Goovaerts (2000) presents another type of Kriging, which replaces the known stationary mean in the SK with known varying means [$m(\mathbf{x})$] derived from secondary information, to improve spatial prediction of precipitation. The basic procedures of implementing the SKlm are described as follows: first, the OLS method is used to estimate the known varying means using secondary information; second the residuals from subtracting the original data from the varying means are taken as the random variable and to be estimated using the SK method; finally, the estimated residuals are added back to the varying means to get the SKlm estimates. The form of the equations used by the SKlm is similar to those used by SK. The estimated precipitation is expressed as $Z(u) = m(u) + \sum_{i=1}^{n} \lambda_{ui}^{\varepsilon}(\varepsilon_i)$, where $\lambda_{ui}^{\varepsilon}$ is the weight of residual at point $\mathbf{x}_i$, which is obtained through solving the following equations,

$$\sum_{j=1}^{n} \lambda_{uj}^{\varepsilon} C_{\varepsilon}(h_{ji}) = C_{\varepsilon}(h_{ui}) \qquad i = 1, \ldots, n \tag{7}$$

where $C_R(h)$ is the covariance function of the residual ε. Other variables denote the same meaning as stated above. In this study, the trend surface used by SKlm was obtained using two forms of $m(\mathbf{x})$. The first one uses elevation (denoted as SKlm_EL), and the second one uses both elevation and spatial coordinate (denoted as SKlm_EL_X). For more detailed information on SKlm, please refer to Goovaerts (1997).

Semivariogram Model

The Kriging methods require semivariogram models to be fitted to the experimental semivariogram values. In this study, two types of semivariogram models (i.e., Spherical and Cubic models) were applied,

Spherical model:

$$\gamma(h) = \begin{cases} c\left[1.5\frac{h}{a} - 0.5\left(\frac{h}{a}\right)^3\right] & \text{for } h \le a \\ \text{c} & \text{for } h > a \end{cases} \tag{8}$$

Cubic model:

$$\gamma(h) = \begin{cases} c\left[7\left(\frac{h}{a}\right)^2 - 8.75\left(\frac{h}{a}\right)^3 + 3.5\left(\frac{h}{a}\right)^5 - 0.75\left(\frac{h}{a}\right)^7\right] & \text{for } h \le a \\ c & \text{h} > \text{a} \end{cases} \tag{9}$$

These two different types of semivariogram models were combined with a nugget-effect model (c_0) for the fitting of the experimental semivariogram of daily precipitation. Following Goovaerts (2000) methods, the two models were fitted using regression and such that the weighted sum of squares (WSS) of differences between experimental $\hat{\gamma}(h_k)$ and model $\gamma(h_k)$ semivariogram values is minimum,

$$\text{WSS} = \sum_{k=1}^{K} \omega(h_k)[\hat{\gamma}(h_k) - \gamma(h_k)]^2 \tag{10}$$

The weights $\omega(h_k)$ were taken as $N(h_k)/[\gamma(h_k)]^2$ in order to give more importance to the first lags and the ones computed from more data pairs. For each day, the two semivariogram models were trained to fit the empirical semivariogram values, and the model with smaller WSS value was used in the Kriging interpolation.

A global optimization algorithm, Particle Swarm Optimization (PSO) (Kennedy and Eberhart, 2001), was used to calibrate the nonlinear semivariogram models. PSO is a population-based stochastic optimization technique inspired by social behavior of bird flocking or fish schooling (Kennedy and Eberhart, 2001). During the optimization process, in order to find global optimum each particle in the population adjusts its “flying” according to its own flying experience and its companions’ flying experience (Eberhart and Shi, 1998). The basic PSO algorithm consists of three steps: (1) generating particles’ positions (coordinate in the parameter space) and velocities (“flying” direction and speed), (2) update the velocity of each particle using the information from the best solution it has achieved so far (personal best) and another particle with the best fitness value that has been obtained so far by all the particles in the population (global best), (3) the new position of each particle is calculated by adding the updated velocity to the current position. Steps 2 and 3 are referred to as velocity update and position update operators, respectively. For further information about PSO, please refer to Kennedy and Eberhart (2001). Three parameters (i.e., c_0, c, and a) of semivariogram models need to be optimized using the PSO algorithm with objective function of WSS. First, a population of particles (50) composed of the three parameters and the moving directions of these particles are randomly generated. Second, these particles are evolved by the velocity and position update operators 10,000 iterations. Finally, the parameters with the smallest WSS value are used to calculate the semivariogram model.

GIS-Based Spatial Precipitation Interpolation Program

GIS is a powerful tool for facilitating geospatial-related research including spatial interpolation of climate data and analysis of storm kinematics (Tsanis and Gad, 2001). An automatic interpolation program developed as an extension of ArcGIS 9.x was used to facilitate spatial precipitation estimation in this study. The workflow chart of this GIS program is shown in Figure 2. The basic input data include a point shapefile that contains the geographic location of the rain gauges, and daily precipitation records for each rain gauge in text format, and a Digital Elevation Model to provide elevation information. The GIS program automatically reads in each day's precipitation value for each rain gauge, and the interpolation method selected by the user will be implemented to estimate the spatial distribution of precipitation. The interpolated spatial precipitation data are output in raster format, which can be used for further analysis. Finally, several statistics that evaluate the characteristics and accuracy of the estimated spatial precipitation are calculated.

Evaluation of the Performance of Different Interpolation Methods

Several evaluation coefficients were calculated to compare the characteristics of the spatial precipitation estimated by different interpolation methods, which include areal mean precipitation depth (AMPD), maximum precipitation depth (MaxP), minimum precipitation depth (MinP), and coefficient of variation (CV). CV is calculated as the ratio between the standard deviation and areal mean depth of the spatial precipitation.

Cross-validation is a popular method that has been used to compare the prediction performances of spatial interpolation methods (Isaaks and Srivastava, 1989). In cross-validation, each of the rain gauge data is temporarily removed at a time and the remaining data are used to estimate the value of the deleted datum. The difference between the observed and estimated values is used to evaluate the accuracy of interpolation methods. The evaluation coefficients used in this study are coefficient of correlation (ρ), Nash-Sutcliffe efficiency (E_{ns}), and relative mean absolute error (RMAE). The formula for calculating coefficient ρ is,

$$\rho = \left\{ \frac{\sum_{i=1}^{N} \left(Z_i^{\mathrm{o}} - \bar{Z}^{\mathrm{o}}\right)\left(Z_i^{\mathrm{p}} - \bar{Z}^{\mathrm{p}}\right)}{\left[\sum_{i=1}^{N} \left(Z_i^{\mathrm{o}} - \bar{Z}^{\mathrm{o}}\right)^2\right]^{0.5} \left[\sum_{i=1}^{N} \left(Z_i^{\mathrm{p}} - \bar{Z}^{\mathrm{p}}\right)^2\right]^{0.5}} \right\}, \tag{11}$$

where Z_i^p is the estimated value, Z_i^o is the observed data, the over bar represents the areal mean of the spatial precipitation, and $i = 1, 2, ..., N$, where N is the total number of simulated and observed data pairs. ρ is an indicator of the

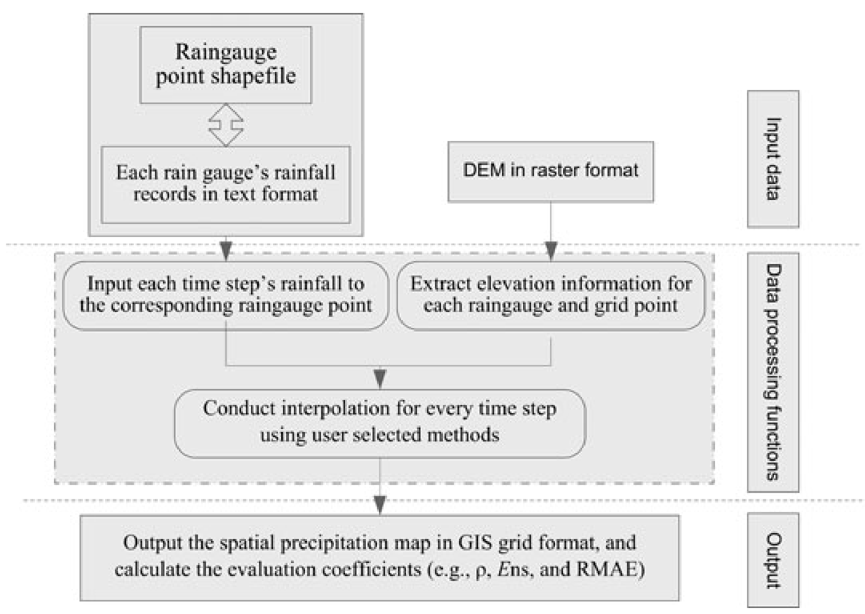

FIGURE 2. Workflow Chart of GIS-Based Interpolation Program.

strength of the relationship between the observed and simulated values. The formula to calculate E_{ns} is (Nash and Sutcliffe, 1970),

$$E_{\mathrm{ns}} = 1.0 - \frac{\sum_{i=1}^{N}\left(Z_i^{\mathrm{o}} - Z_i^{\mathrm{p}}\right)^2}{\sum_{i=1}^{N}\left(Z_i^{\mathrm{o}} - \bar{Z}^{\mathrm{o}}\right)^2}, \qquad (12)$$

where the symbols are the same as described above. E_{ns} indicates how well the plot of the observed *vs.* the simulated values fits the 1:1 line, and ranges from - ∞ to 1. When the values for E_{ns} and R^2 are equal to one, the model prediction is considered to be "perfect." The formula for calculation of RMAE is,

$$\mathrm{RMAE} = \frac{\frac{1}{N}\sum_{i-1}^{N}\left|Z_i^{\mathrm{o}} - Z_i^{\mathrm{p}}\right|}{\bar{Z}^{\mathrm{o}}} \qquad (13)$$

The variables used for calculation of RMAE have been defined in previous sections. The smaller value of RMAE means that the simulated value is closer to the observed one.

RESULTS AND DISCUSSION

Visual Inspection of Spatial Precipitation Estimated by Different Methods

Although daily interpolations were undertaken for all the 443 days between 1991 and 2000, the visual inspection of figures showing the difference between precipitation distribution maps estimated by different interpolation methods was conducted for two dates in order to save space. March 13, 1997 was selected to show that different methods can produce precipitation maps with different distribution patterns. June 6, 1994 was selected to reveal that precipitation maps estimated by different methods can have very different accuracy evaluation coefficients even if their distribution patterns are similar.

Figure 3 shows the interpolated spatial precipitation distribution estimated by different interpolation

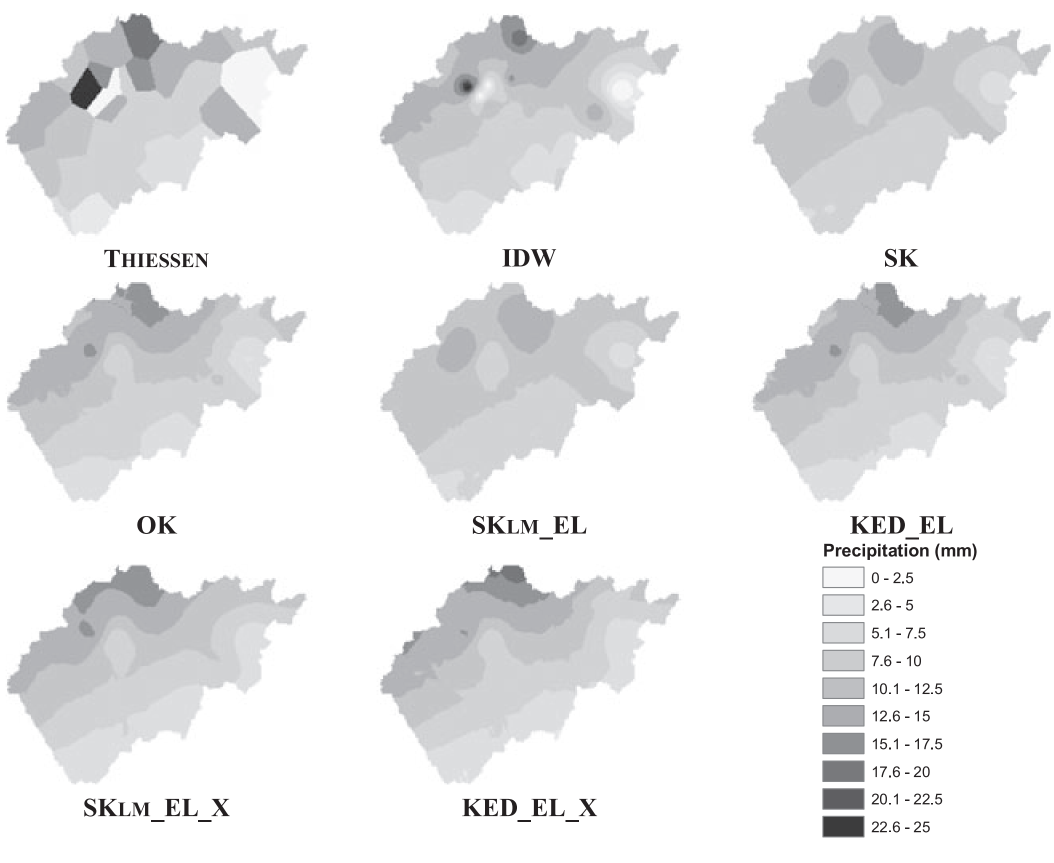

FIGURE 3. The Spatial Precipitation Estimated by Different Interpolation Methods on March 13, 1997.

methods on March 13, 1997. Visually, the patterns of precipitation maps obtained by different methods can be substantially different from each other. For example, Thiessen polygon method produced largest precipitation at some place southwest to the uppermost part where KED_EL_X predicted largest precipitation. Table 1 lists the evaluation coefficients, which quantitatively show that the spatial variation of the maps produced by the eight methods is pronouncedly different. The CV values range between 0.162 and 0.476. Thiessen polygon methods produced the largest CV value (0.476). SK and SKlm_EL produced the smallest CV values (0.16). The CV values obtained by the other methods are between 0.247 and 0.29. Thiessen and IDW produced larger MaxP and lower MinP values than the other six methods. The MaxP values obtained by Thiessen and IDW are larger than 24, while the MaxP values obtained by the other methods are < 20. The MinP values obtained by Thiessen and IDW are < 0.1, while the MinP values obtained by the other methods are larger than 4.5. Although the precipitation maps in Figure 3 show substantially different spatial variation, the areal mean precipitation values obtained by all the eight methods are very close to each other, which range between 10.2 and 10.4. Accuracy evaluation coefficients (Table 1) also show the varied performance of the eight interpolation methods. SKlm_EL_X performed the best (with $\rho = 0.41$, $E_{ns} = 0.15$ and RMAE = 0.26). Thiessen polygon performed the least in terms of RMAE (0.38) and E_{ns} (−0.49), while SK performed the least in terms of ρ (0.11).

In Figure 4, the general patterns of precipitation distribution maps obtained by different interpolation methods are similar. All the methods predicted larger precipitation in the south than in the north. Further analysis shows that there is difference between the precipitation maps in Figure 4 at local scale. For example, the KED_EL and SKlm predicted precipitation larger than 11 mm at the north of the maps, while the other methods obtained precipitation <8 mm for the same area. Quantitative evaluation coefficients of the spatial precipitation estimated by different methods for June 6, 1994 are listed in Table 2, which show the variation. The AMPDs range between 12.3 and 12.4. The MaxP values range between 26 and 33.4, and MinP values range between 2.5 and 4. The CVs range between 0.44 and 0.48. Compared with Figure 3, the difference between the precipitation maps produced by different methods in Figure 4 is relatively small. Among these eight interpolation methods, SKlm_EL_X (with $\rho = 0.95$, $E_{ns} = 0.9$, and RMAE = 0.12) performed better than the other algorithms. The Thiessen polygon method, which obtained the lowest ρ and E_{ns} and highest RMAE, performed the least.

From Figures 3 and 4 and Tables 1 and 2, it is shown that different interpolation methods produced precipitation maps with varied spatial properties (i.e., AMPD, MaxP, MinP, and CV) and accuracy (i.e., ρ and E_{ns}, and RMAE). It is worth noting that the performances of different methods are not constant for different storm events, which is consistent with the findings in previous studies (e.g., Goovaerts, 2000; Carrera-Hernández and Gaskin, 2007). For example, the performance rank KED_EL_X is less than IDW on March 13, 1997, but its performance is better than IDW on June 6, 1994. In order to obtain overall evaluation of the performance of different interpolation methods, the eight interpolation methods were applied to estimate spatial precipitation of 443 days with average precipitation depth larger than 3 mm. The results are discussed in the following sections.

The Overall Performance of Different Interpolation Methods

In Figures 5a-d and 6a-c, the box-and-whisker plot was used to plot the evaluation coefficients for the 443 days precipitation fields obtained by different interpolation methods. The meanings of the symbols in Figures 5a-d and 6a-c are described as follows. Lower and upper lines of the “box” are the 25th and 75th percentiles of the sample. The distance between top and bottom of the box is the interquartile range. The line in the middle of the box is the sample median.

TABLE 1. Evaluation Coefficients for Spatial Precipitation Estimated by Different Interpolation Methods on March 13, 1997.

	Thiessen	**IDW**	**SK**	**OK**	**SKlm_EL**	**KED_EL**	**SKlm_EL_X**	**KED_EL_X**
AMPD	10.3	10.2	10.3	10.4	10.3	10.3	10.3	10.3
MaxP	25	24.4	15	16.7	14.8	16.6	17	19.3
MinP	0	0.02	5.37	4.71	5.73	4.76	4.77	4.5
CV	0.48	0.29	0.16	0.25	0.16	0.25	0.28	0.29
ρ	0.36	0.3	0.11	0.27	0.11	0.27	0.41	0.33
RMAE	0.38	0.29	0.32	0.29	0.31	0.30	0.26	0.29
E_{ns}	−0.49	0.06	−0.01	0.03	−0.02	0.02	0.15	0.05

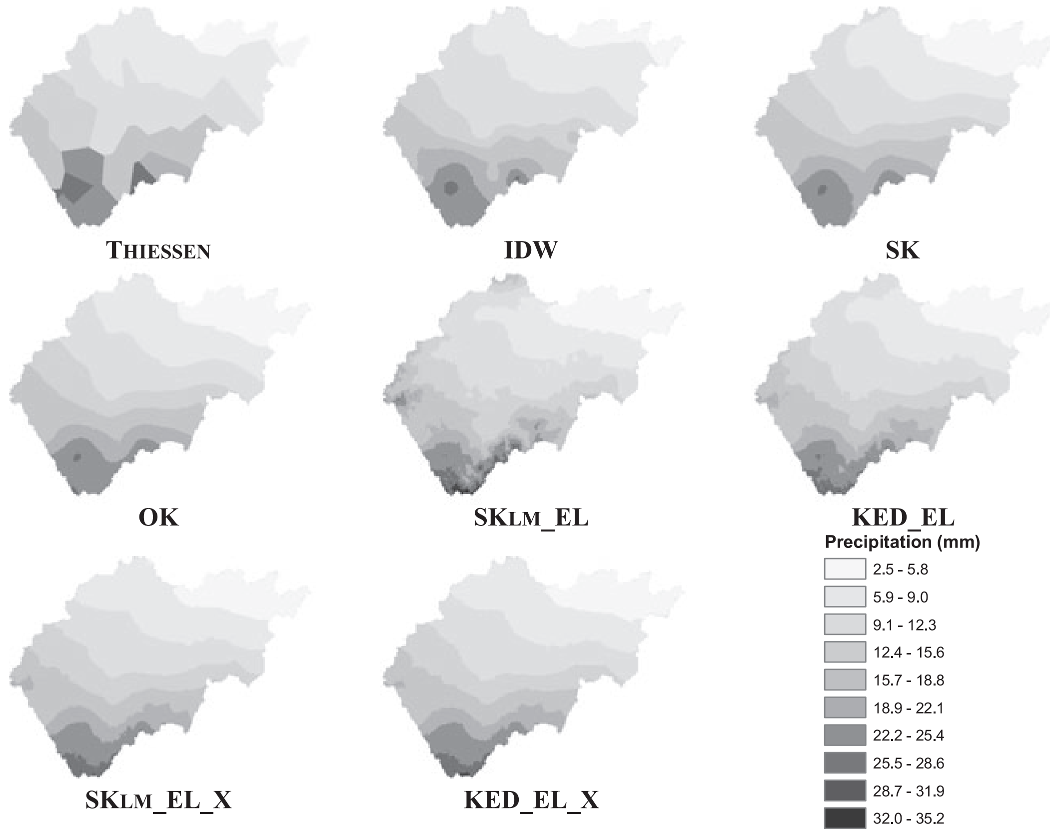

FIGURE 4. The Spatial Precipitation Estimated by Different Interpolation Methods on June 6, 1994.

TABLE 2. Evaluation Coefficients for Spatial Precipitation Estimated by Different Interpolation Methods on June 6, 1994.

	Thiessen	IDW	SK	OK	SKlm_EL	KED_EL	SKlm_EL_X	KED_EL_X
AMPD	12.3	12.5	12.4	12.3	12.6	12.4	12.4	12.4
MaxP	27	26.9	26	26	33.4	29.2	29.2	29.9
MinP	4	4	3.9	3.9	3.3	3.6	2.5	2.5
CV	0.48	0.44	0.47	0.46	0.46	0.46	0.47	0.47
ρ	0.86	0.93	0.92	0.94	0.94	0.94	0.95	0.95
RMAE	0.22	0.14	0.15	0.14	0.13	0.12	0.12	0.13
E_{ns}	0.72	0.86	0.84	0.88	0.88	0.89	0.9	0.89

The "whiskers" are lines extending above and below the box. The plus signs are values that are more than 1.5 times the interquartile range away from the top or bottom of the box. The notches in the box represent a robust estimate of the uncertainty about the medians for box-to-box comparison. Boxes whose notches do not overlap indicate that the medians of the two groups differ at the 5% significance level (Matlab, 2007).

Figure 5a shows the box-and-whisker plot of AMPD values obtained for the 443 days. Through visual inspection, the shapes of the whiskers boxes for different interpolation methods are very similar to each other. The notches in these boxes are overlapping with each other. This indicates that the AMPD values obtained by different methods are not significantly different from each other. In Figures 5b and 5c, the maximum and minimum precipitation values obtained by different interpolation methods are evidently different from each other. For example, the median of maximum precipitation values obtained by Thiessen polygon and IDW are significantly higher than those obtained by the other methods, while the median of minimum precipitation values obtained by Thiessen polygon and IDW are significantly higher than those obtained by the other methods. In Figure 5d, the median of CV values obtained by Thiessen polygon is much higher than those of the other methods. IDW obtained CV values close to those estimated by the six Kriging-based

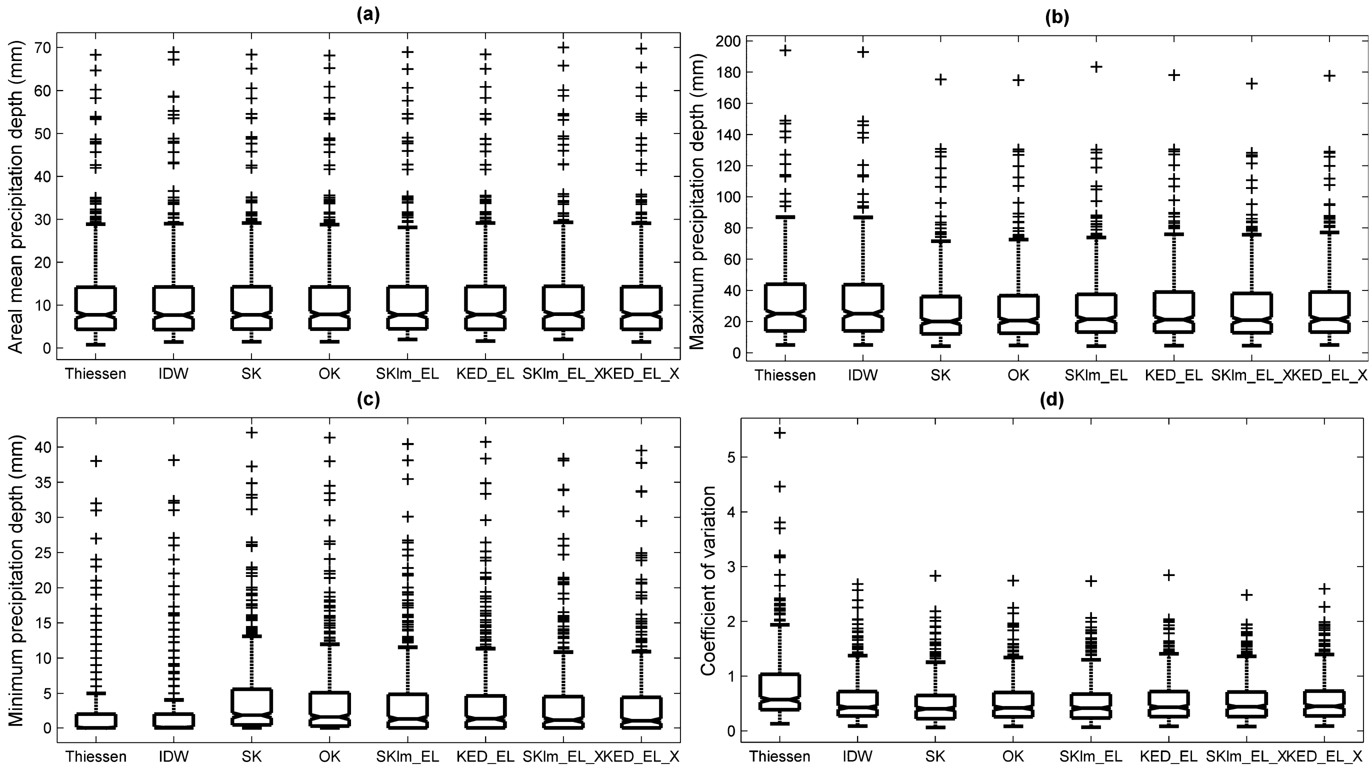

FIGURE 5. Box-and-Whisker Plots of (a) Areal Mean Precipitation Depth, (b) Maximum Precipitation Depth, (c) Minimum Precipitation Depth, and (d) Coefficient of Variation Values Obtained by Different Interpolation Methods for 443 Days.

methods. Overall, although the AMPDs estimated by different interpolation methods are close to each other, the MaxP, MinP, and CV values can be significantly different from each other. Among these different spatial precipitation maps obtained by different interpolation methods, determining which one should be selected and used in distributed hydrologic modeling and agriculture and hydrology-related analysis is important.

The accuracy assessment coefficients are plotted in Figures 6a-c. In Figure 6a, the median of ρ-values obtained by Thiessen polygon is significantly lower than the other seven methods at a significance level of 0.05. SKlm_EL_X and KED_EL_X obtained significantly higher ρ-values than IDW. Similar to correlation coefficients, the E_{ns} values obtained by Thiessen polygon is significantly lower than the other seven methods (Figure 6b). SKlm_EL_X and KED_EL_X also obtained significantly higher E_{ns} values than IDW. For the RMAE values plotted in Figure 6c, Thiessen polygon performed significantly less than the other methods, while IDW obtained RMAE values close to the six Kriging-based methods. Overall, SKlm_EL_X obtained higher median of ρ and E_{ns} and lower median of RMAE than the other seven methods. The performance of KED_EL_X is comparable to that of SKlm_EL_X. In addition to median comparison, the mean values obtained by different interpolation methods were also compared (Table 3). The results obtained through comparing mean values are similar to those from comparing median values. The mean AMPDs obtained by different methods are very close to each other, while mean MaxP, MinP, and CV values can be evidently different from each other. SKlm_EL_X obtained higher mean ρ and E_{ns} values and lower mean RMAE than other methods. The performance of KED_EL_X is comparable to SKlm_EL_X in terms of mean evaluation coefficients. The overall accuracy assessment of the eight interpolation methods shows that SKlm_EL_X performed better than the other methods, while the Thiessen polygon method performed the least. But it is also worth noting that no one method can consistently outperform other methods for all days. Table 4 lists the number of days that different interpolation methods performed the best among all methods for evaluation coefficients ρ, E_{ns}, and RMAE, respectively. It was found that SKlm_EL_X outperformed other methods for about 45% of the 443 days, while other methods can provide better results for the remaining days (also about 55%). Implementing multiple methods to interpolate spatial precipitation maps and choosing the one with better evaluation coefficients is a practical way to provide more accurate estimation of spatial precipitation.

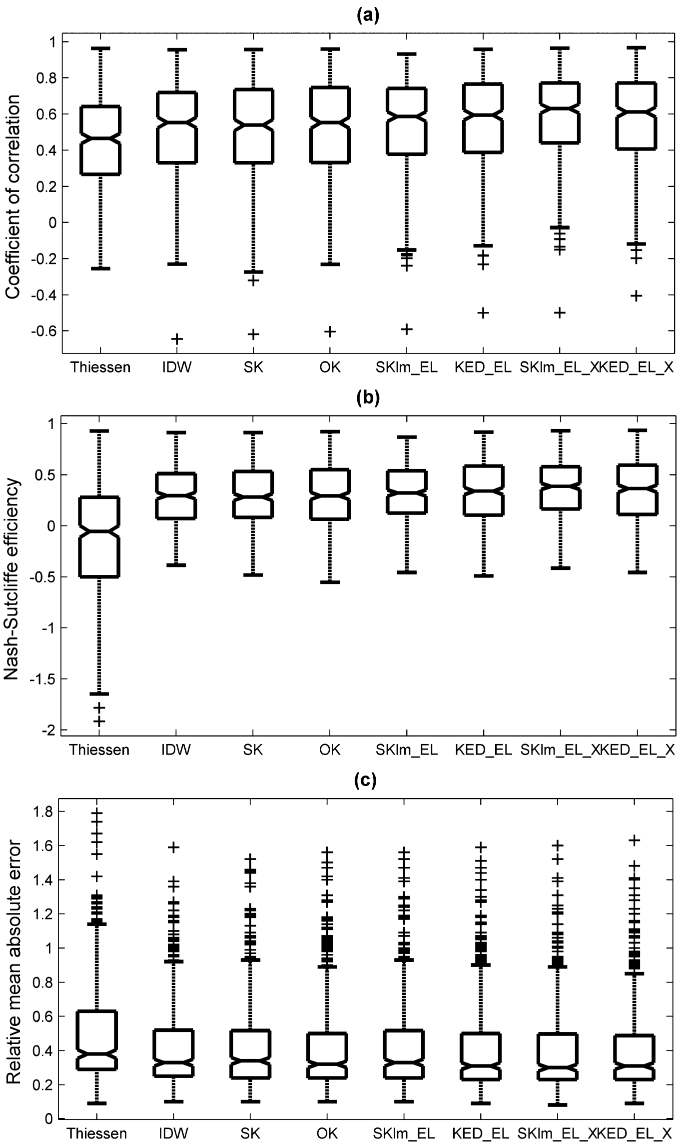

FIGURE 6. Box-and-Whisker Plots of (a) Coefficient of Correlation, (b) Nash-Sutcliffe Efficiency, and (c) Relative Mean Absolute Error Values Obtained by Different Interpolation Methods for 443 Days.

SUMMARY

In this study, a GIS tool was developed to facilitate the application of advanced geostatistical methods for automatic spatial precipitation estimation. The methods incorporated into this tool include Thiessen polygon, IDW, SK OK, SKlm, and KED. These methods were applied for spatial precipitation interpolation of 443 days between 1991 and 2000 in the Luohe watershed, downstream from the Yellow River basin. The results obtained in this study show that different interpolation methods can obtain similar areal mean precipitation depth, but significantly different values of maximum precipitation, minimum precipitation, and CV. The accuracy of the spatial precipitation estimated by different interpolation methods was evaluated using a correlation coefficient, Nash-Sutcliffe efficiency and relative mean absolute error. The evaluation results show that use of elevation and spatial coordinate as secondary variable improved the accuracy of spatial precipitation estimation. The SKlm_EL_X and KED_EL_X methods, which incorporate elevation and spatial coordinates into SKlm and KED, respectively, produced significantly better results than Thiessen polygon and IDW in terms of coefficient of correlation and Nash-Suttcliffe coefficient. Overall, the SKlm_EL_X and KED_EL_X methods obtained higher average correlation coefficient and Nash-Sutcliffe efficiency, and lower average relative mean absolute error than other methods. It is also worth noting that no one interpolation method can consistently perform better than the other methods. SKlm_EL_X outperformed other methods for about 45% of the 443 days, while the other methods provided more accurate spatial precipitation than SKlm_EL_X for the remaining 55%. In order to provide accurate spatial precipitation, it is suggested to implement multiple spatial interpolation methods and select the one with better evaluation coefficients. The GIS program developed in this study can serve as an effective and efficient tool to implement advanced geostatistics methods that incorporate auxiliary information to improve spatial precipitation estima-

TABLE 3. The Mean Evaluation Coefficients Obtained by Different Interpolation Methods.

	Thiessen	IDW	SK	OK	SKlm_EL	KED_EL	SKlm_EL_X	KED_EL_X
AMPD	11.27	11.28	11.34	11.37	11.38	11.37	11.41	11.40
MaxP	33.10	32.24	27.22	27.61	28.57	28.77	28.47	29.11
MinP	2.07	2.19	4.20	3.96	3.70	3.63	3.48	3.37
CV	0.80	0.56	0.51	0.55	0.52	0.56	0.55	0.57
ρ	0.45	0.51	0.50	0.52	0.53	0.55	0.59	0.57
E_{ns}	−0.13	0.29	0.30	0.30	0.32	0.33	0.38	0.35
RMAE	0.51	0.43	0.43	0.42	0.43	0.42	0.41	0.41

TABLE 4. The Number of Days That Different Interpolation Methods Outperform the Other Methods for Evaluation Coefficients ρ, E_{ns}, and RMAE, Respectively.

	Thiessen	IDW	SK	OK	SKlm_EL	KED_EL	SKlm_EL_X	KED_EL_X
ρ	38	28	27	20	19	35	202	96
E_{ns}	3	40	31	24	23	38	208	95
RMAE	14	47	27	33	22	43	181	79

tion. Currently, this GIS tool has been combined with the SWAT model system, which is sensitive to spatial precipitation estimated by different interpolation methods (Zhang and Srinivasan, 2006). It is recommended that this GIS tool be used for hydrologic modeling using SWAT and other distributed hydrologic models.

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