Report for 2005TX201B: Evaluation of Spatial Heterogeneity of Watershed through HRU Concept Using SWAT

Publications

- Conference Proceedings:
  - X. Zhang, and R. Srinivasan. 2006. Effect of Rainfall Field Estimated Using Different Interpolation Methods on Distributed Hydrologic Modeling, In AWRA 2006 GIS and Water Resources IV, Houston, TX
  - X. Zhang. December 2005. Hydrologic modeling of a macro-scale river basin: the headwater of Yellow River, AGU fall meeting, San Francisco, California.
- Other Publications:
  - X. Zhang. May 2006. Effect of rainfall field estimated using different interpolation methods on distributed hydrologic modeling, Houston, Texas.

Report Follows

Evaluation of spatial heterogeneity of watershed through HRU concept using SWAT

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Abstract

The accurate simulation of SWAT can assist the government in making correct decisions about water management practices, which are important for human health, agricultural management, industry development, environmental quality, flood risk assessment, and recreation. In this project, the PIs were trying to improve the simulation accuracy of the SWAT model through developing new algorithm to obtain accurate rainfall input. The PIs developed a GIS based automatic rainfall interpolation program which incorporates six interpolation methods to estimate rainfall field for the distributed hydrologic model – SWAT (Soil and Water Assessment Tool). The simulated results show that the areal mean rainfall depths estimated by different methods are similar to each other, while the spatial distribution of a rainfall field could exhibit great differences. The stream flow simulated by the SWAT model is sensitive to rainfall fields estimated by different methods, especially for the daily temporal scale, both hydrograph shape and flow volume could show big differences. The accuracy of rainfall field information is essential for distributed hydrologic modeling, and the tool developed in this study will be useful for accurately estimating rainfall fields. The tools developed in these studies are expected to be used in the HAWQS (Hydrologic and Water Quality System) project supported by the USEPA.

Developing a GIS tool for Accurately Estimating rainfall field for the SWAT model

1. Introduction

Numerous field experiments have revealed that hydrological processes and parameters can show considerable spatial variability (Merz and Bárdossy, 1998). Distributed hydrologic models offer the ability to simulate hydrologic processes using spatially distributed input data, which makes them preferable tools to predict water availability, sediments delivery and nutrients transport at a regional scale for sustainable water resource management, food security, human health and natural ecosystems (Chaplot et al. 2005). As rainfall is one of the primary hydrologic model inputs, it is essential to accurately represent rainfall in time and space for distributed rainfall-runoff modeling. Previous studies have shown that the spatial variability of rainfall fields can have a large influence on simulated runoff volume, time shift of hydrographs, sediment delivery and nutrient yield (Dawdy and Bergman, 1969; Wilson et al., 1979; Troutman, 1983; Duncan et al., 1993; Faurès et al., 1995; Shah et al., 1996a; Shah et al., 1996b; Lopes, 1996; Koren et al., 1999; Chaubey et al., 1999; Arnaud et al., 2002; Merz and Bárdossy, 1998; Smith et al., 2004; Chaplot et al. 2005). Generally, the methods used to study the sensitivity of hydrologic models to spatial rainfall variability are rain gauge network density and rainstorm displacement (Arnaud, et al., 2002). What needs to be noted is that in order to input spatially distributed rainfall into a distributed hydrologic model, the rainfall values at rain gauge points need to be interpolated to estimate rainfall value at the point without observed data. There are many interpolation methods that could be used for rainfall field estimation, and these methods will provide different rainfall fields. The tasks are to find how different the estimated rainfall fields will be and how much impact these differences could exert on distributed hydrologic modeling.

The general methods used by distributed hydrological models to estimate rainfall fields include Thiessen polygon and IDW (Inverse Distance Weighted). For example, SWAT and MIKE SHE use Thiessen Polygon, and VIC uses IDW. The theory of Thiessen polygon and IDW are simple and easy to be realized programmatically, but Goovaerts' (2000) work showed that the accuracy of these two methods is not as good as several other methods, including Linear Regression, Ordinary Kriging, and Simple Kriging with varying local means. Lloyd (2004) also showed that different interpolation methods could vary in accuracy of estimated rainfall distribution. In this work, six different interpolation methods were used: Thiessen polygon and IDW, which are widely used in distributed hydrologic modeling; Spline and Ordinary Kriging, which are widely used to interpolate spatially distributed environmental variables; and Linear Regression and Simple Kriging with varying local means, which incorporate elevation into spatial interpolation. Areal mean, coefficient of variability, and accuracy of rainfall fields predicted by different methods will be calculated and compared. The distributed rainfall fields interpreted by the various methods will be input into a physically based distributed hydrologic model – SWAT (Soil and Water Assessment Tool), and the simulation results will be compared and discussed at the annual, monthly, and daily temporal scales.

2. Materials and Methods

2.1 Study Area Description

The study site was selected at the downstream area of the Luohe River, which is the largest tributary of the downstream Yellow River (YR), whose area is about 5239 km^2. The study area covers the land of 12 cities and counties: Yiyang, Shanxian, Luoning, Ruyang, Yinchuan, Mianchi, Yima, Xinan, Luanchuan, Mengjin, Yanshi and Luoyang, which are characterized by flat alluvial and foothill plains. The average elevation of the Luohe basin is about 520 m. The Luohe River Basin belongs to the warm temperate climate zone with average annual rainfall depth 600 mm. Forty-one rain gauges, located within or around the study area, with daily rainfall records will be used in this study. As shown in Figure 1, the 31 solid circles denote the rain gauges will be used to interpolate rainfall spatial distribution, and the 10 solid triangles on the left denote the rain gauges used to test the accuracy of estimated rainfall field.

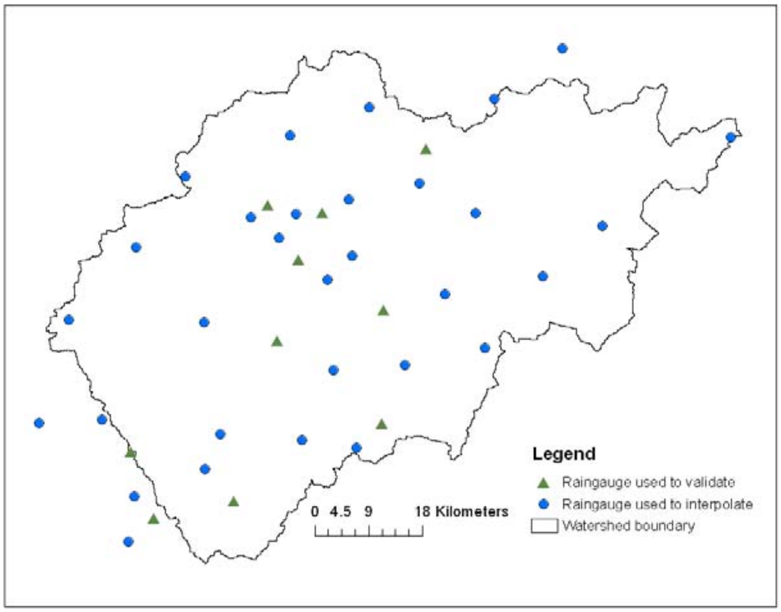

Figure 1. The rain gauges used for rainfall field interpolation and validation.

2.2 Interpolation Methods

2.2.1 *Thiessen Polygon*

Thiessen polygons, also referred to as Voronoi Diagrams, are polygons whose boundaries define the area that is closer to that polygon's centroid point than all other points. Then the point without observed rainfall value will be assigned the closest rain gauge's record (Thiessen, 1911). Let (Z_i, i = 1, … , n) be the set of rainfall data measured at n rain gauges, and here $n = 31$. The rainfall depth Z at an unsampled location *u* is estimated using function below:

$$Z_u = Z_i \quad h_{ui} < h_{uj} \forall i \neq j . \qquad (1)$$

where Z_u is the interpolated value, Z_i is the data value of i th sampled location, h_{ui} denotes the distance between unsampled location u and the sampled location i, h_{uj} denotes the distance between unsampled location u and the sampled location j.

2.2.2 Spline

The Spline method uses a basic minimum-curvature technique to interpolate a spatial surface, which 1) passes exactly through the data points, 2) has minimal curvature (ESRI, 2005). The Spline function uses the following formula for the surface interpolation:

$$Z_u = T_u + \sum_{i=1}^{n} \lambda_{ui} R(h_{ui}) \qquad (2)$$

Where, Z_u is the interpolated value, n is the number sampled location points, λ_{ui} are coefficients found by the solution of a system of linear equations, h_{ui} is the distance between the unsampled point *u* to the sampled location i. Trend function T_u and generating function $R(h_{ui})$ are determined by the REGULARIZED or TENSION option of Spline. In this work, we use REGULARIZED Spline, which incorporate third derivatives into the smooth seminorm (Mitas and Mitasova, 1988). For detailed introduction to Spline method, please reference to Franke (1982), and Mitas and Mitasova (1988).

2.2.3 IDW

The IDW interpolation method explicitly implements the assumption that things that are close to one another are more alike than those that are farther apart. It weights the points closer to the prediction location greater than those farther away. With inverse distance weighting, data points are weighted during interpolation so that the influence of one data point relative to another declines with distance from the interpolation point:

$$Z_u = \frac{1}{\sum_{i=1}^{n} \lambda_{ui}} \sum_{i=1}^{n} \lambda_{ui} Z_i \qquad \lambda_{ui} = \frac{1}{h_{ui}} \tag{3}$$

where Z_u is the interpolated value, n represents the total number of sample data values around the unsampled location that will be used in interpolation, Z_i is the ith rain gauge value, h_{ui} denotes the separation distance between unsampled location u and the measured data value location i, and λ_{ui} denotes the weight of the ith measured data value.

2.2.4 Kriging

Kriging is an advanced geostatistical procedure that provides a best linear unbiased estimation model. The unknown rainfall depth Z at the unsampled location u is estimated by a linear combination of observed neighboring rain gauge values:

$$Z_u = \sum_{i=1}^{n} \lambda_{ui} Z_i \tag{4}$$

where Z_u and Z_i have the same meaning as described above. Instead of weighting nearby data points by some power of their inverted distance, the Ordinary Kriging relies on the spatial correlation structure of the data to determine the weighting values. Ordinary Kriging determines the weights λ_{ui} under two assumptions: 1) ensuring the unbiased nature of the estimator, $E\{Z_u - Z_u{}^*\} = 0$; 2) minimizing the estimation variance, $Var\{Z_u - Z_u{}^*\}$, where $Z_u{}^*$ denotes the measurement value. Kriging uses semi-variogram to identify the weights of the points that surround the predicted points through solving a series of linear function known as the "Ordinary Kriging system" (Goovaerts, 2000):

$$\sum_{j=1}^{n} \lambda_{uj} \gamma(h_{ij}) - \mu(u) = \gamma(h_{ui}) \quad i = 1,\dots,n \tag{5}$$

$$\sum_{j=1}^{n} \lambda_{uj} = 1 \tag{6}$$

where $\mu(u)$ is the Lagrange parameter accounting for the constraint on the weights. h_{ui} denotes the separation distance between unsampled location u and sampled location i, h_{ij} denotes the separation distance between sampled location i and j. The semi-variogram $\gamma(h)$ is computed using the equation below:

$$\gamma(h) = \frac{1}{2N(h)} \sum_{i}^{N(h)} (z_i - z_{i+h})^2 \qquad (7)$$

where h is the difference between two point location, $N(h)$ is the number of pairs of points separated by h , $z_i - z_{i+h}$ is the value difference between point i and another point separated by distance h. For more information on Kriging, please refer to Edward and Srivastava (1989).

2.2.5 Linear Regression

With the orographic effect, rainfall tends to increase with increasing elevation. Hevesi et al. (1992) and Goovaerts (2000) both reported a significant correlation between average annual precipitation and elevation in Nevada and southeastern California, and Aogarve (the most southern region of Portugal) respectively. Goovaerts (2000) also reported average monthly rainfall has close correlation with elevation for most months except for July and August. A simple method to incorporate elevation into rainfall distribution estimation is to develope the linear regression function:

$$Z_u = f(y_u) = a0 + a1 \times y_u \qquad (8)$$

where y_u is the elevation at prediction point u, the $a0$ and $a1$ are regression coefficients estimated with a set of collocated rainfall and elevation data $\{(Z_i, y_i),\ i = 1, \cdots, n)\}$.

2.2.6 Simple Kriging with varying local means

Goovaerts (2000) presented the basic form of Simple Kriging with varying local means (SKlm), which replaces the known stationary mean in the simple Kriging estimate by known varying means m_u derived from the secondary information:

$$Z_u - m_u = \sum_{i=1}^{n} \lambda_{ui} (R_i) \qquad (9)$$

where $R_i = Z_i - m_i$. In this work the local means are derived using linear regression function (8). Then the estimated rainfall at unsampled point u can be expressed as:

$$Z_u = f(y_u) + \sum_{i=1}^{n} \lambda_{ui} (R_i) \qquad (10)$$

where the weights λ_{ui} are obtained by solving the simple Kriging system:

$$\sum_{j=1}^{n} \lambda_{uj} C_R(h_{ji}) = C_R(h_{ui}) \quad i = 1, \cdots, n \qquad (11)$$

where $C_R(h\ )$ is the covariance function of the residual R_i, not that of Z_i itself (Goovaerts, 2000). And other variables denote the same meaning as stated above. For more detailed information on SKlm, please refer to Goovaerts (1997).

2.3 Distributed hydrologic model

SWAT is a continuous-time, long-term, distributed-parameter model (Arnold et al., 1998). SWAT subdivides a watershed into sub-basins, and further delineates Hyrologic Response Unit

(HRU) consisting of unique combinations of land cover and soils in each sub-basin. HRU delineation can minimize computational costs of simulations by lumping similar soil and land use areas into a single unit (Neitsch et al., 2000). The hydrologic routines within SWAT account for snow fall and snow melt, vadose zone processes (*i.e.*, infiltration, evaporation, plant uptake, lateral flows and percolation), and ground water flows. Surface runoff volume is estimated using a modified version of the SCS CN method (USDA-SCS, 1972). A kinematic storage model (Sloan et al., 1983) is used to predict lateral flow. And return flow is simulated by creating a shallow aquifer (Arnold et al. 1993; Arnold et al., 1998). Channel flood routing uses the Muskingum method. Outflow from a channel is also adjusted for transmission losses, evaporation, diversions, and return flow.

As a physically based distributed model, SWAT needs many input data:

1. Topography: the 1:250,000 DEM obtained from National Geomatics Center of China will be used to provide terrain characteristics of Luohe basin.
2. Soil: the soil map at 1:4,000,000 scale obtained from Institute of Soil Science, Chinese Academy of Sciences (CAS), provides the soil spatial distribution and physical properties like bulk density, texture, saturated conductivity, etc.
3. Land use: Land-use classifications such as cropland, pasture, forest, etc were obtained from Institute of Geographical Sciences and Natural Resources Research, CAS at 1: 1,000,000 scale.
4. Weather: Water Resources Conservancy Committee of the YR basin provided precipitation, air temperature, relative humidity, solar radiation and wind speed, etc.

2.4 GIS based rainfall field interpolation program

GIS is a very powerful tool to facilitate geospatial related research, including spatially interpolated climate data and analysis of storm kinematics (Jeffrey et al., 2001; Tsanis and Gad, 2001). In this work, we wanted to interpolate the daily rainfall in 1991 and output the spatially distributed rainfall into the distributed hydrologic model, which required much manual work. An automatic interpolation program developed as an extension of ArcGIS 9.0 was used to facilitate rainfall field estimation and output job. The function of this GIS based program includes: automaticaly and continuously estimating rainfall distribution using the six interpolation methods described above; calculating each day's areal mean rainfall depth and coefficient of variability (CV) of estimated rainfall fields; validating the accuracy of estimated rainfall fields using Mean Absolute Error (MAE); calculating each hydrologic unit's mean rainfall, which will be input into distributed hydrologic model. Since ArcObject doesn't provide the Simple Kriging estimator, in order to use the SKlm method, the user still has to manually perform the Simple Kriging interpolation procedure using the Geostatistical Analyst extension of ArcGIS. This shortcoming of the program is expected to be overcome when ArcObject provides the Simple Kriging estimator. The general work flow chart of this program is shown in Figure 2. The equations for calculating CV and MAE are:

$$MAE = \frac{1}{n}\sum_{l-1}^{n}\left|Z_i^{\,o} - Z_i^{\,p}\right| \qquad (11)$$

$$CV = \frac{\partial}{z_{ave}} \qquad (12)$$

where Z_i^o is the true rainfall depth value, Z_i^p is estimated value, n is the number of rain gauges used to validate the accuracy of estimated rainfall fields, ∂ is standard deviation of rainfall field and z_{ave} is areal mean rainfall.

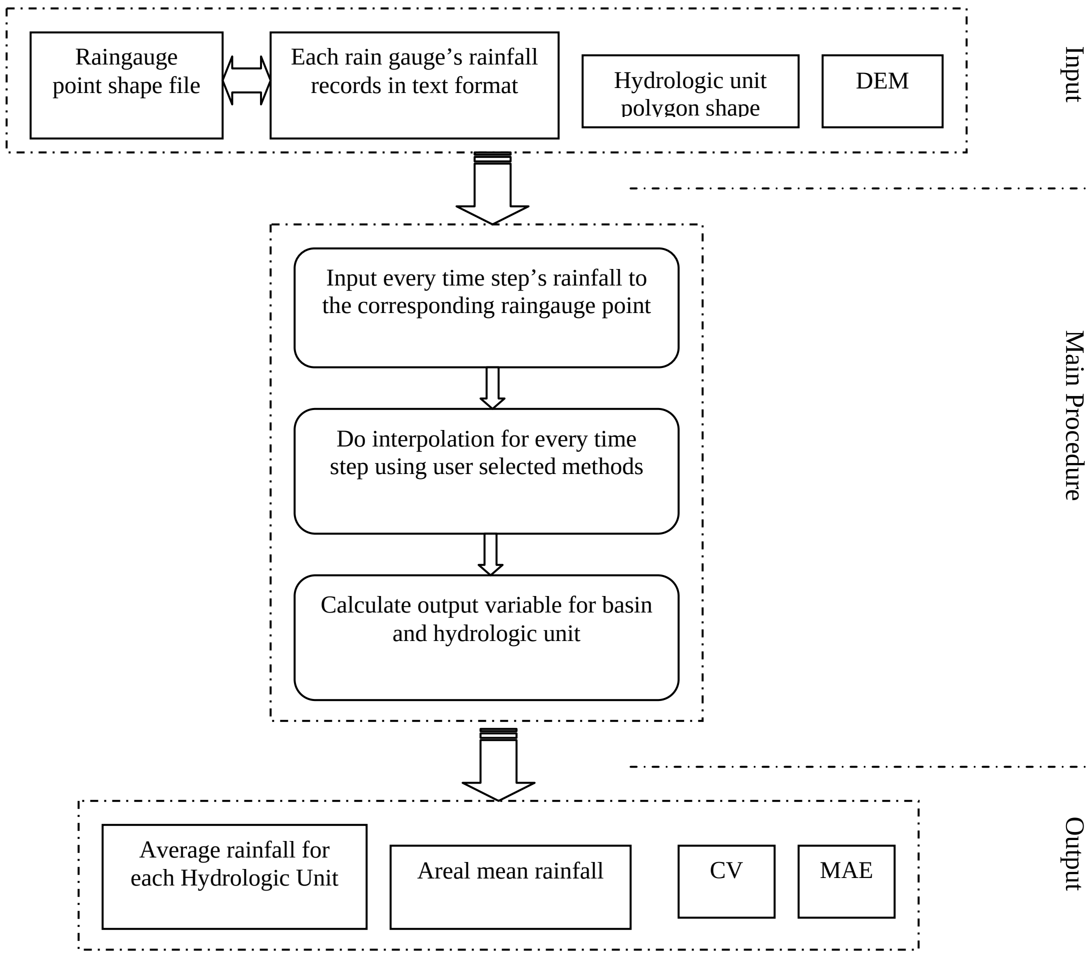

Figure 2. Work flowchart of GIS based interpolation program.

3. Results and Discussion

3.1 Difference between rainfall fields estimated by different methods

The daily rainfall data from the 31 rain gauges in 1991 were used to test the differences between rainfall fields estimated by different methods discussed in section 2.1. The parameters of different methods are listed in Table 1. There were 52 total storms whose rainfall depth was larger than 2 mm, and the accuracy, areal mean and spatial variability of these 52 storms will be compared and discussed.

Table 1. Parameters used by different methods for rainfall field estimation.

Parameters / Methods	Search radius setting (Number of points)	Out put cell size (m)	Others
Thiessen polygon	-	100	-
IDW	12	100	Distance Porwer: 2
Spline	12	100	Spline type: Regularized Weight: 0.1
Linear regression	-	100	-
Kriging	12	100	Semi-variogram model: Spherical
SKlm	12	100	Covariance model: Spherical

3.1.1 Accuracy comparison of different methods

Figure 3 shows the accuracy for rainfall fields estimated by six different interpolation methods. There is no one method that can always predict better results than the other methods. For example, for storm No. 4 Spline gives the worst result, while for storm No.35 it is the best predictor. It's hard to say which method is the best, and different methods may be applicable to predict different types of storms. In order to give a general idea about which method is more reliable, the average MAE for the 52 storms was used to assess performance of different methods. SKlm predicted the smallest average MAE (2.65). Kriging and IDW give similar results (2.77 and 2.80 respectively). Thiessen polygon gives the largest average MAE (3.80). Linear regression and Spline predict 3.23 and 3.75 respectively. This result is similar to Goovaerts' (2000), but the complex geostatistical method SKlm doesn't show much advantage over other methods. The reason maybe that the topography of the study area is not complex, elevation does not change much and has no great impact on rainfall distribution. Since we can't get the actual rainfall field, in the following analysis, we will choose the rainfall field estimated by SKlm as a standard for comparison purposes.

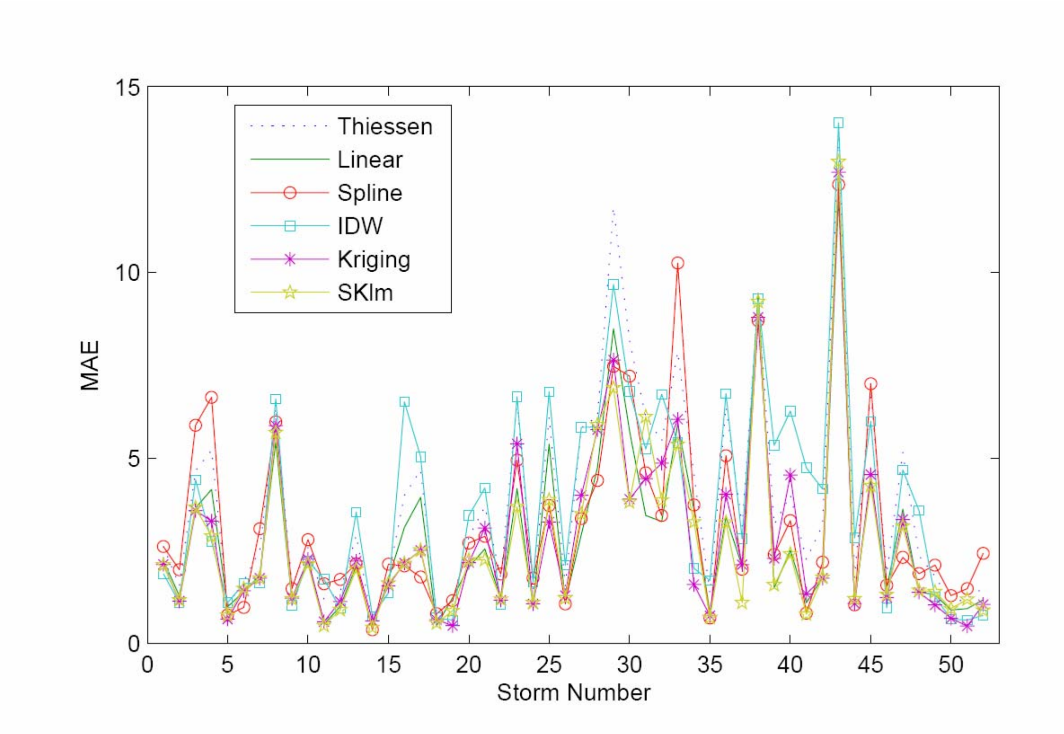

Figure 3. Accuracy of rainfall estimated using different methods for 52 storm events.

3.1.2 Areal mean rainfall

Figure 4 reveals that the areal mean rainfall depths interpreted by different methods are closely related, except for storm No. 31, 32 and 34. Using the areal mean estimated by SKlm as a standard, the relative error of areal mean rainfall for the other five methods was calculated. The absolute relative error for IDW and Kriging is no more than 20%, and for most cases was within 10%. For the Thiessen polygon, Spline and Linear methods, the absolute relative error was always with 25%, and for most cases was within 15%. Generally, there was little variation among areal mean rainfall depths for the different interpolation methods.

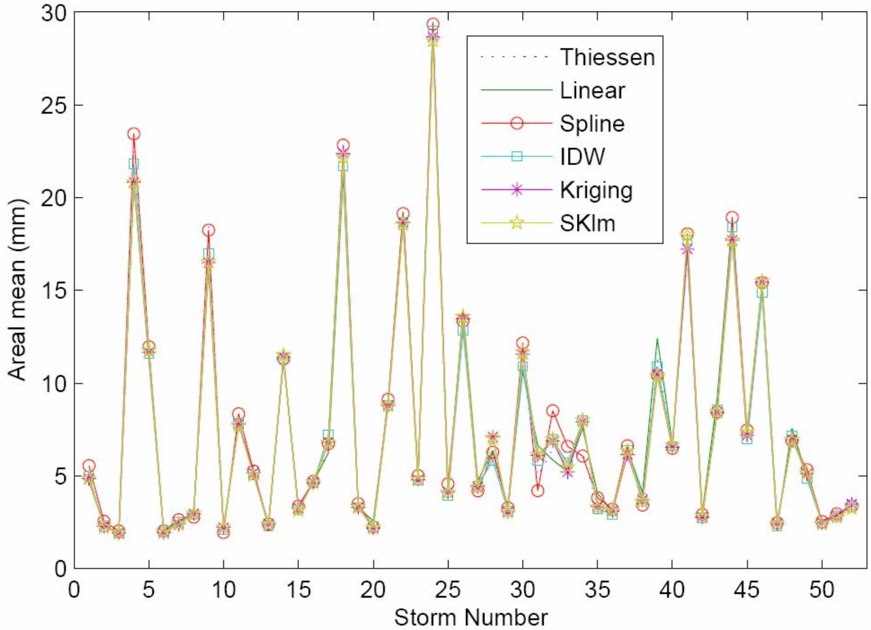

Figure 4. Areal mean rainfall estimated using different methods for 52 storm events.

3.1.3 Spatial distribution of rainfall

The coefficient of variability of the rainfall fields estimated by different methods in Figure 5 shows that different methods can predict different rainfall distribution. Spline predicted the largest rainfall distribution variability for almost all the 52 storms (average CV for 52 storms is 0.93), while Linear regression predicted the lowest average CV value 0.25. Thiessen polygon, IDW, Kriging and SKlm predicted similar CV, 0.71, 0.63, 0.55 and 0.59 respectively. The No. 1 storm event was used as an example to visually show the difference among six interpolated rainfall fields by different methods in Figure 6, and the statistical characteristics of different rainfall fields are listed in Table 2. It's obvious that there is big visual and statistical differences among the rainfall fields estimated by the various methods. Spline even predicted negative value input into hydrologic model, which is set to zero to avoid negative rainfall when input into the SWAT model. And as rainfall has no significant relationship with elevation ($R^2 = 0.06$) for this storm, the spatial pattern predicted by SKlm is different than that of Linear regression. The big difference in spatial patterns of rainfall fields will exert impact on the processes that route a rain drop through the basin.

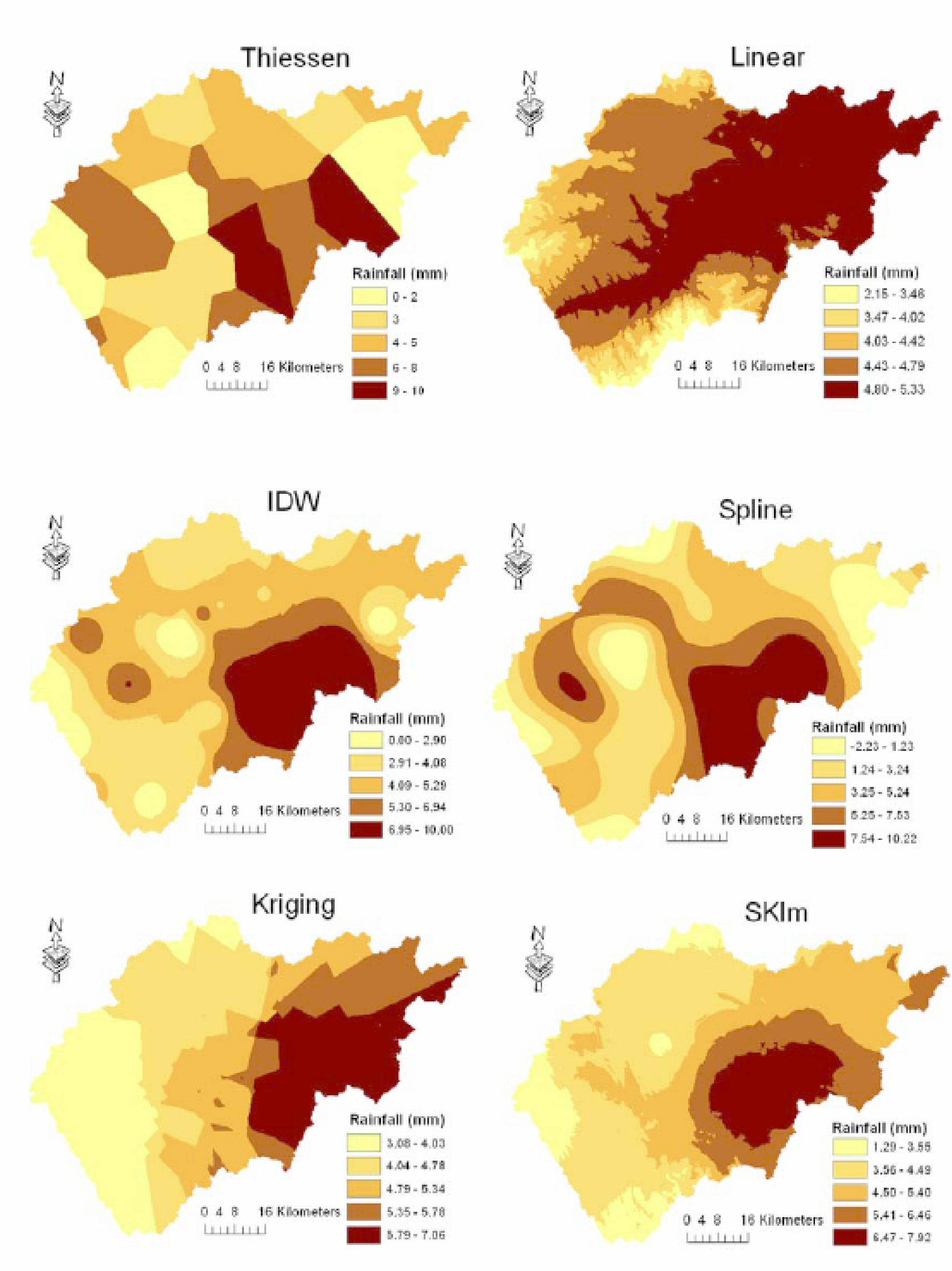

Figure 6. Rainfall fields estimated using different methods.

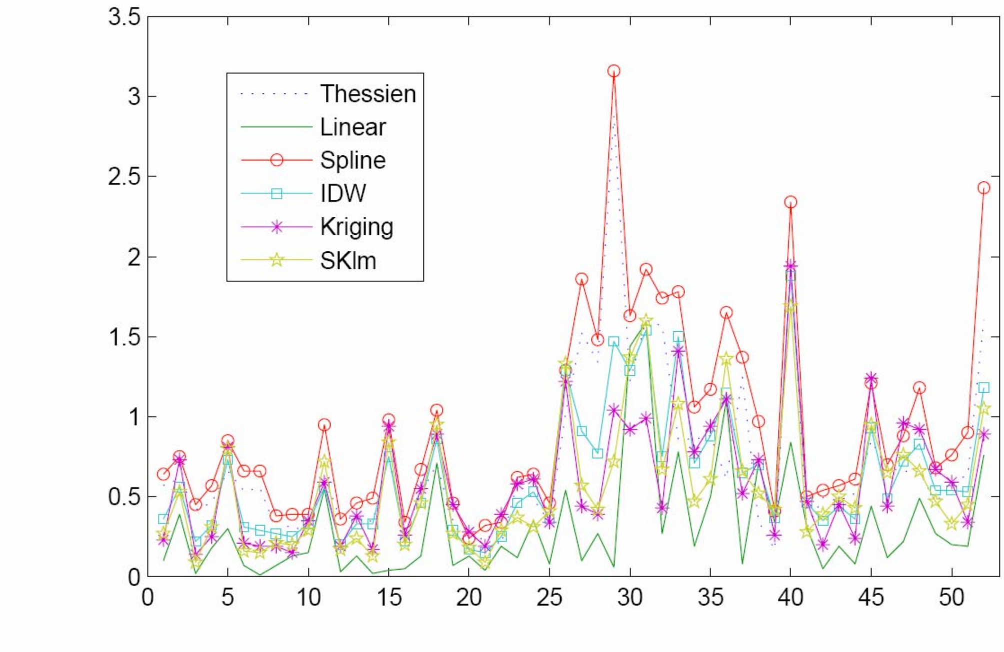

Figure 5. Spatial variability of rainfall filed estimated using different methods for 52 storm events.

Table 2. Statistical characteristic of rainfall field estimated by different methods.

Variable / Methods	Areal mean	CV	Highest value	Lowest value
Thiessen polygon	4.77	0.57	10	0
IDW	4.99	0.36	9.99	0.001
Spline	5.54	0.64	10.2	-2.23
Linear regression	4.63	0.10	5.33	2.15
Kriging	4.85	0.23	7.06	3.08
SKlm	4.87	0.27	7.92	1.28

3.2 Impact of estimated rainfall fields on distributed hydrologic modeling

The outputs from the GIS based interpolation program were input into the SWAT model. Hydrologic modeling of flow at the outlet of the Luohe River was conducted at a daily time scale using daily rainfall data in 1991. In order to reflect differences of estimated rainfall fields on the water yield in the study area, the upstream inflow was not input into model. The parameters used here were the default values in SWAT. The differences of simulated flow were discussed at the annual, monthly and daily temporal scale, and we took the simulated flow with rainfall input interpreted by SKlm as the standard for comparison purpose.

Figure 7 shows the annual flow simulated according to different interpolation methods. The Spline method predicted highest flow volume with relative difference of 25% compared to SKlm. The Thiesen polygon predicted a relative difference of 16%. Linear regression, IDW and Kriging predicted a relative difference within 10%. At the annual temporal scale, the simulated flow volume difference is small.

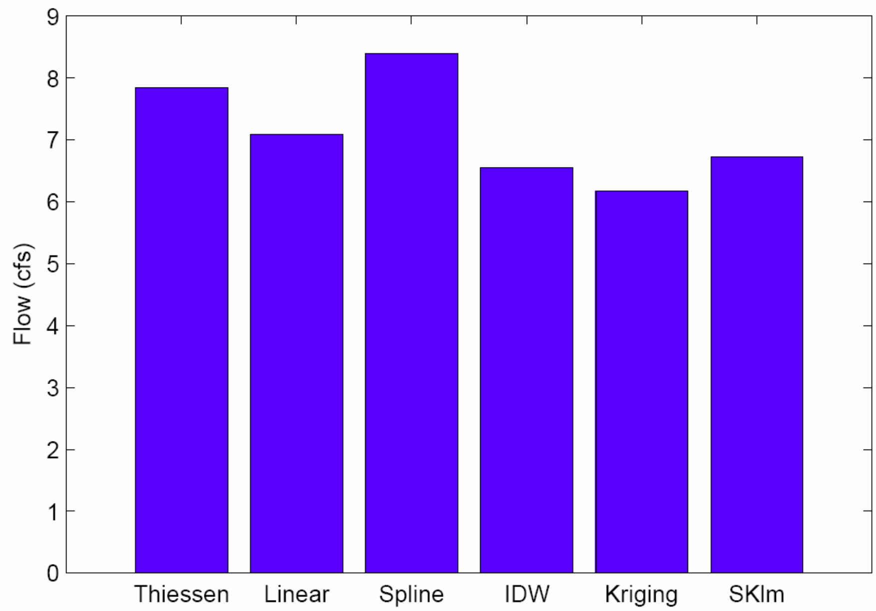

Figure 7. Simulated annual flow volume in 1991 using different interpolation methods.

The simulate monthly flows are shown in Figure 8. The general hydrograph shape simulated according to different rainfall field estimation methods is similar, and the peaks appear at the same month (September). But for each individual month, the simulated flow volume shows obvious differences. For example, in April, the relative difference is 116% for Thiessen polygon, 65% for IDW, 85% for Spline, 33% for Linear regression and -3% for Kriging. The highest flow interpreted by Thiessen polygon reached 4.28m^3/s, while the lowest flow interpreted by Kriging is only 1.9m^3/s in April. And in July, the relative difference is 31% for Thiessen polygon, 7.6% for IDW, 46% for Spline, -7.7% for Linear regression and -15% for Kriging. The difference between Spline and Kriging is 4 m^3/s, which accounts for 50% of the flow volume simulated by Kriging. At the monthly temporal scale, the difference between simulated flows interpreted by different methods is much more appreciable than at annual scale.

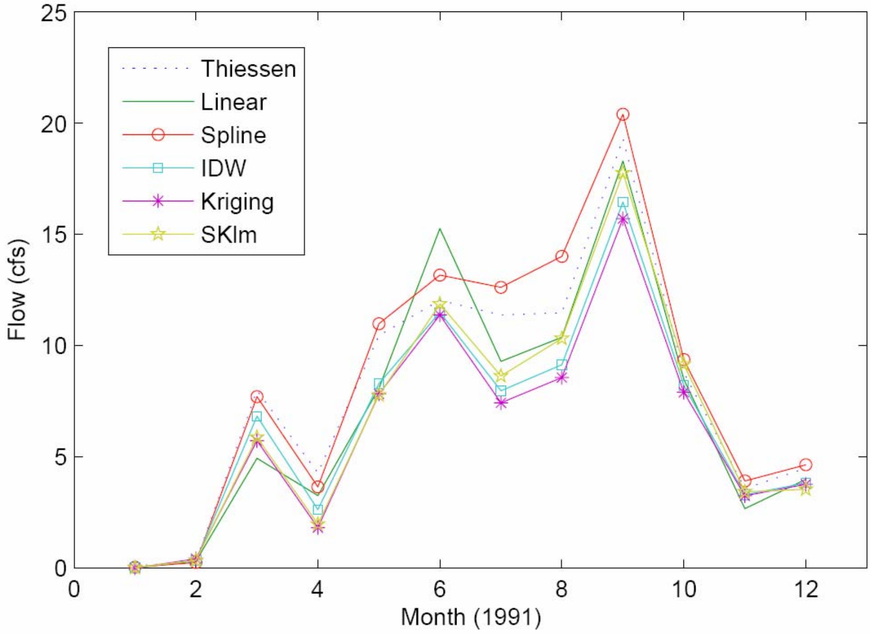

Figure 8. Simulated monthly flow volume in 1991 using different interpolation methods.

Finally, we wanted to examine the simulated daily flow difference. Figure 9 shows the daily flow discharge hydrograph simulated by the SWAT model based on rainfall fields estimated by the different methods. Generally, the hydrographs have similar shape during low flow period, while predicted peak flows show big difference during a flood event. Here we selected daily flows during July as an example to analyze, Figure10. This figure shows that the hydrograph shape estimated by the different methods doesn't correlate well. The peak flow simulated by Thiessen polygon appears on July 23, Linear regression on July 24, Spline on July 19, IDW on July 24, Kriging on July 24, and SKlm on July 23. The flow volume simulated by different methods also shows dramatic differences. For example, on July 19 the Thiessen polygon predicted 32.4 m^3/s, Linear regression 10.7 m^3/s, Spline 46.1 m^3/s, IDW 19.9 m^3/s, Kriging 8.9 m^3/s, and SKlm 10.8 m^3/s. Also significant is that the hydrographs during the flood recession period (July 1 to 14) generally have a similar trend and flow volume, but for the period with a large rainfall storm (July 15 to 20 and July 23 to 28), the hydrographs' shapes and flow volumes have obvious differences. To some extent, we can infer that the hydrograph shape and flow volume difference is mainly caused by surface flow routing during a storm event, while the ground water flow simulated based on different methods doesn't show dramatic differences. In addition, although the accuracy, areal mean rainfall and CV for rainfall field estimated by IDW, Kriging, SKlm are close, we can still see differences in the hydrographs during July 15 to 20 and July 22 to 26.

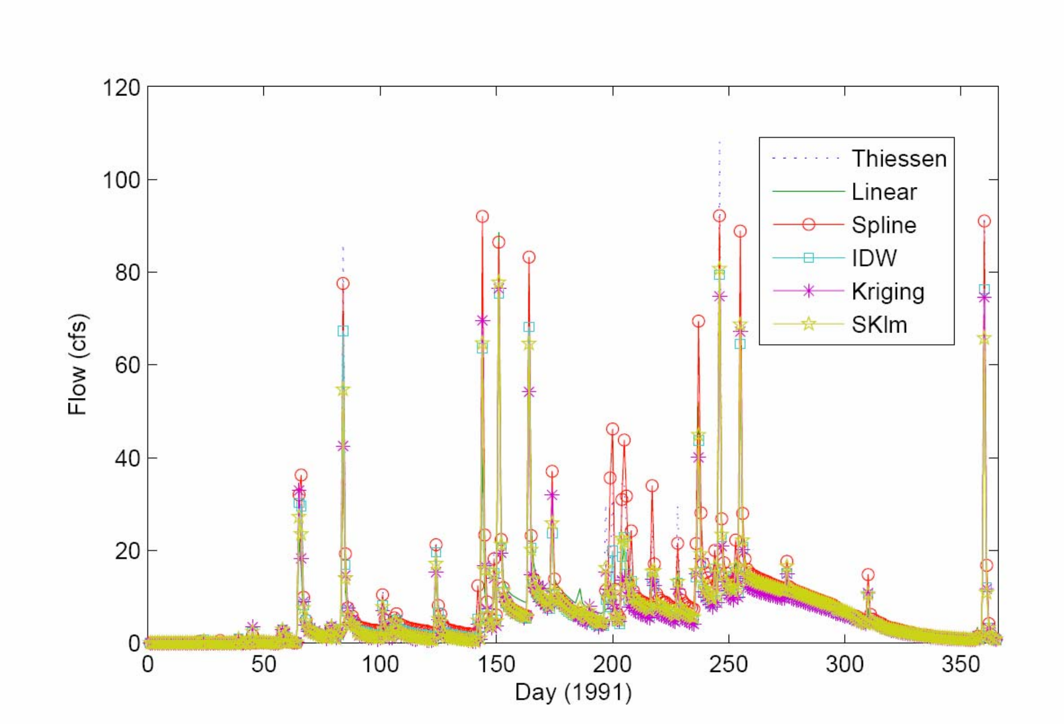

Figure 9. Simulated daily flow volume in 1991 using different interpolation methods.

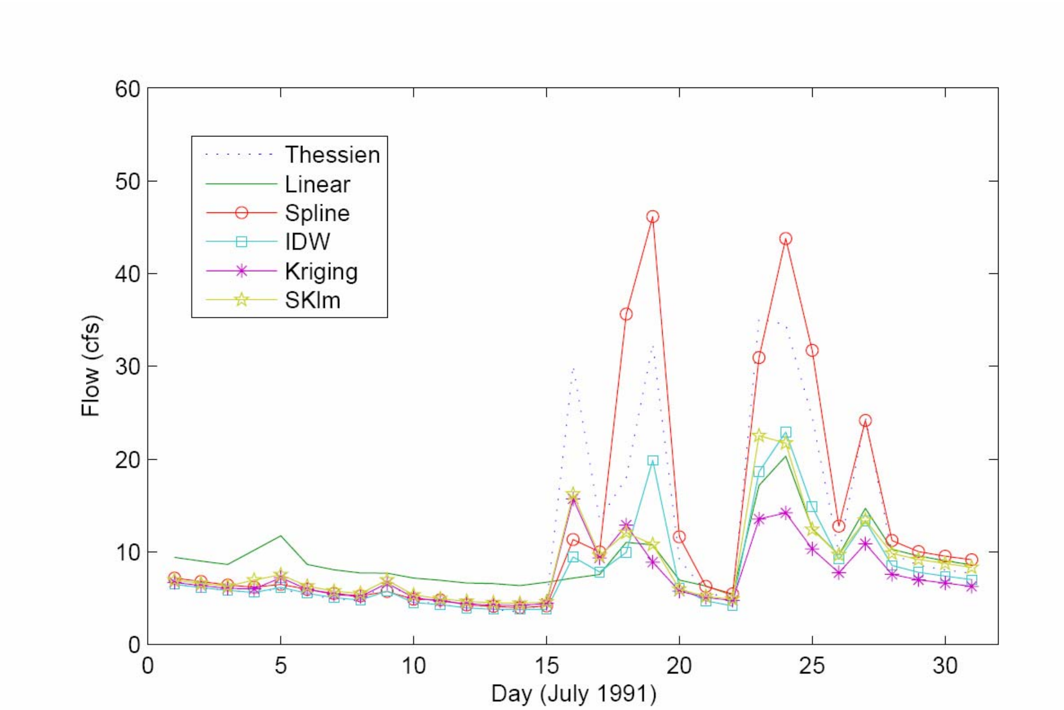

Figure 10. Simulated daily flow volume in July, 1991 using different interpolation methods.

3.3 Discussion

Intuitively, the results described above show that different interpolation method will predict obviously different rainfall field. Based on previous reported results that the spatial variability of rainfall could exert great impact on rainfall-runoff simulation, and combined with the obvious difference of spatial variability of rainfall fields and little difference of areal mean rainfall depth estimated by different interpolation methods (Figure5), it seems that spatial distribution is the major reason explaining the difference of simulated flow. But at same time we should note that distributed hydrologic model describing the basin's dynamic behavior is a nonlinear system, small difference in input data may cause dramatic output change. So according to the results got in this work, we can't exclude the possibility that the small difference of areal mean rainfall may generate greatly different flow. More detailed process based analysis of soil water, evapotranspiration, plant growth, flood routing (overland and channel), and interaction between surface and subsurface water may provide us deeper insight into the mechanism how rainfall depth and spatial distribution impact rainfall-runoff process. Also we should not extrapolate the results got in this work directly to other watershed and distributed hydrologic model. Different types of rainfall-runoff conversion models, characteristic of basin and storm, density of rain gauge network (Arnaud, 2002; Koren, 1999; Smith, 2004) are also the factors need to be considered for explaining hydrologic response.

As we can't get the accurate rainfall field, it's impossible to assess the exact difference between interpolated rainfall field and actual rainfall field. But the average MAE for 52 selected storms show that the difference between the estimated rainfall field and actual one is relatively large, the reason maybe the sparse rain gauge network (31 rain gauges though a 5239 km^2 watershed) used to interpolated rainfall fields. The difference between the highest and lowest average MAE of all interpolation methods is 1.15 mm, which is less than half of the lowest average MAE 2.65 mm. And given the significant difference between flow simulated using different interpolation methods, the difference between the flow simulated using interpolated rainfall field and the flow simulated using actual rainfall field may be more significant.

Since rainfall is a driving force behind many kinds of pollutant release and subsequent transport and spread mechanisms, ignoring this property of rainfall in the application of distributed hydrologic modeling limits the accuracy of the model results (Chaubey et al., 1999). O'Cornell and Todini (1996) suggested using radar and dense network of rain gauge data to gain better capturing of rainfall filed, which seems necessary for model developers and users to reduce rainfall inputs error. As radar and dense network of rain gauge data are difficult to collect, choosing the best interpolation method according to accuracy evaluation maybe an acceptable compromise.

4. Conclusions

In this work, the authors reported the difference of rainfall field estimated by different interpolation methods and to how extent this difference could impact distributed hydrologic simulation in a meso-scale watershed. The objective of this work was realized by combining a GIS based automatic rainfall field interpolation program and distributed hydrologic model – SWAT. The results got in this paper were generalized below.

The estimated 52 storms' rainfall field by six different interpolation methods reveal: 1) The accuracy of rainfall fields estimated by different interpolation could show big difference. Complex geo-statistical methods can provide more accurate results. 2) Areal mean rainfall depth doesn't show big difference between different methods. Compared with the value predicted by SKlm, the relative differences of areal mean rainfall for the other methods are all within 25%. 3) Spatial distribution of rainfall field estimated by different interpolation methods show obvious difference. The highest average CV for 52 storms is 0.93 for Spline method while lowest CV is 0.25 for Linear regression method.

Daily flow simulation using distributed rainfall input estimated by the six interpolation methods were conducted, and the results were analyzed at annual, monthly and daily temporal scale. With the temporal scale decrease from annual to monthly and daily, the variation between simulated flow volumes became more and more obvious, and hydrograph shape simulated at daily time step could show dramatic difference for different methods.

Generally, different interpolation methods could yield obviously different rainfall field, and distributed hydrologic model could be very sensitive to the methods used to interpolate rainfall field. Also it should be noted, the results got in this paper are sensitive to many factors, such as types of distributed hydrologic models, state or parameters of hydrologic model, characteristic of basin, storm property and density of rain gauge network and so on. Much care should be taken when conclusions generalized here be used to different situations.

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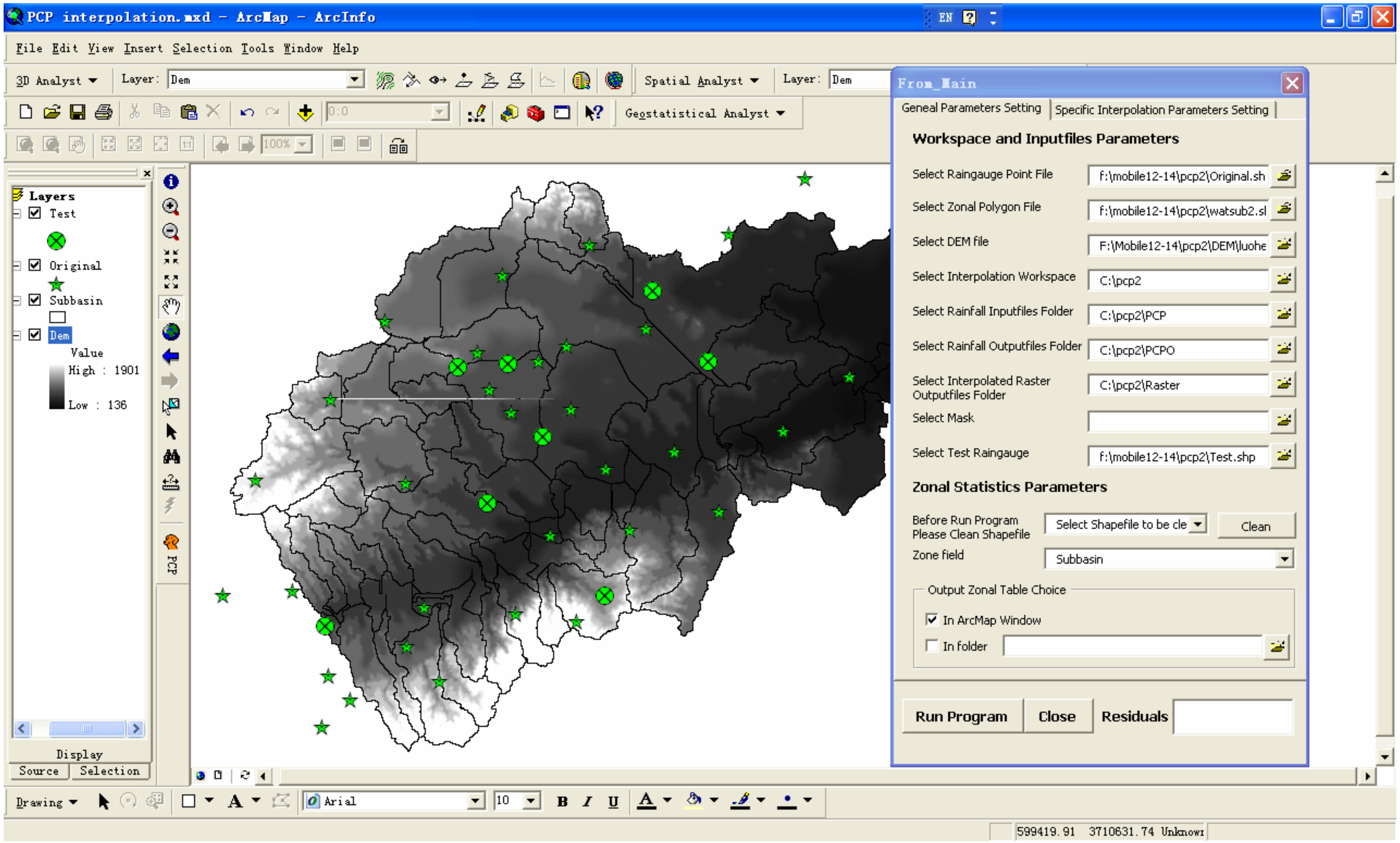
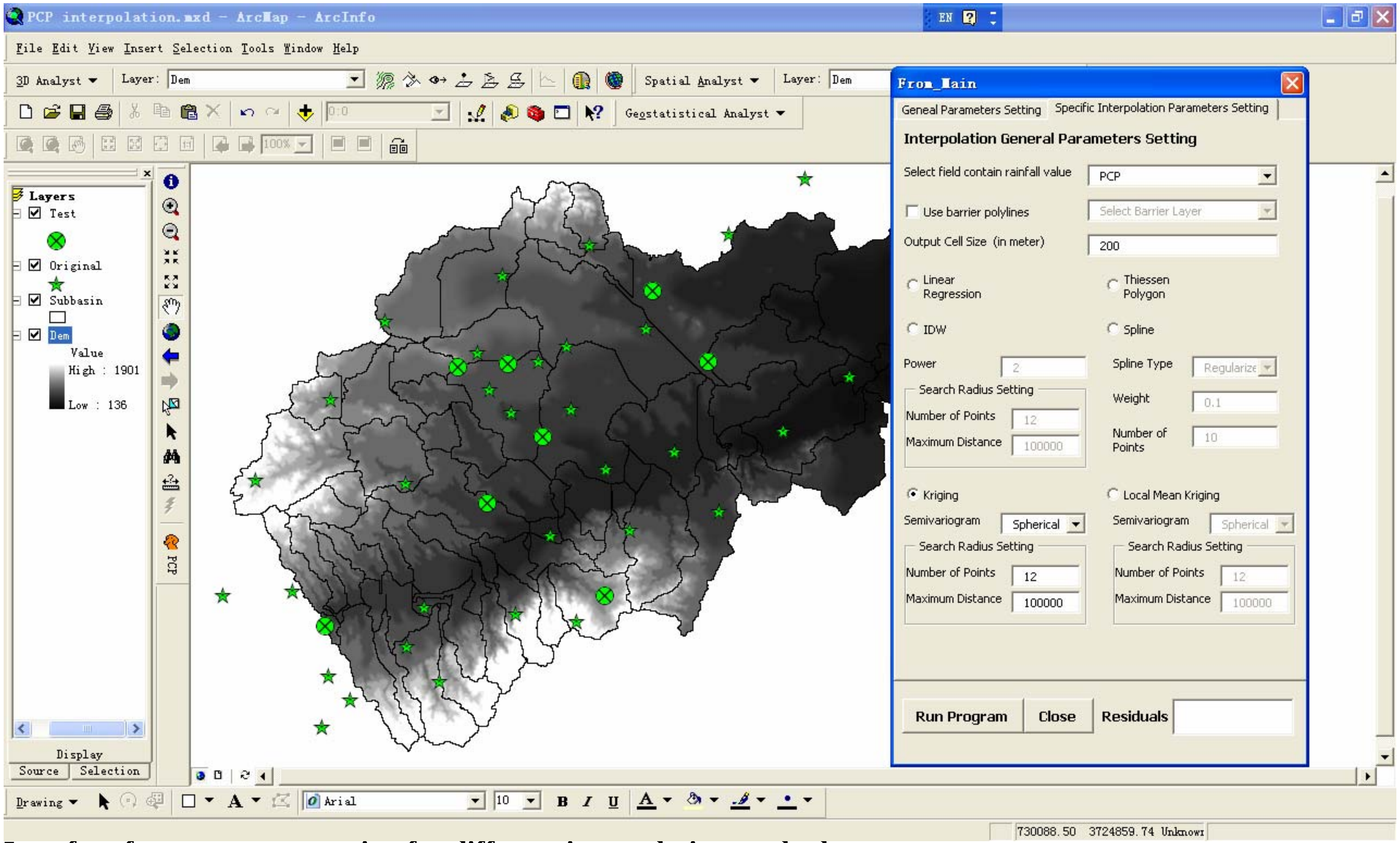
APPENDIX I – GIS INTERFACE FOR AUTOMATIC RAINFALL FIELD ESTIMATION PROGRAM



Interface for workspace and input data setting



Interface for parameters setting for different interpolation methods