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Areal rainfall estimation using spatial interpolation techniques

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ABSTRACT: Accuracy in runoff and flood estimation is important for mitigating water related problems. The accuracy depends on the methods used for areal rainfall approximation. The thin plate spline (TPS) technique was introduced in this study for daily areal rainfall approximation in the Upper Ping river basin and was compared with the areal rainfall estimated from two conventional techniques, the isohyetal and Thiessen polygon techniques. Two data sets of maximum rainfall registered in August 2001 and September 2003 at 68 non-automatic rainfall stations located in the basin and nearby areas were used in the analysis. The TPS technique was carried out in conjunction with two separate sources of digital elevation model (DEM), namely, GLOBE-DEM and SRTM-DEM, which were downloaded from the NOAA and NASA websites and have horizontal resolutions of 1 km and 90 m, respectively. The TPS technique proved to provide more accurate results of rainfall estimation than the other two techniques. The coarser DEM resolution (GLOBE-DEM) performed marginally better in rainfall estimation than the finer DEM resolution (SRTM-DEM).

KEYWORDS: ANUSPLIN software, digital elevation model, Upper Ping river basin

INTRODUCTION

Rainfall plays an important role in the hydrologic cycle which controls our water supplies and water disasters. Knowing the nature and characteristics of rainfall, we can conceptualize and predict its effects in runoff, infiltration, evapotranspiration, and water yield[1]. Many rainfall-runoff models have been developed over the last few decades to estimate runoff characteristics, mainly using rainfall data as well as other catchment area and meteorological parameters. Acquiring more accurate rainfall data is therefore crucial to improve the hydrograph prediction results. Since rainfall is never evenly distributed over the area of study due to the topographic variability of the catchment areas, it is preferable to have as many rainfall stations as possible to estimate the areal rainfalls which represents the actual rainfalls over the basin. Unfortunately, it is not possible to install rainfall stations in as many locations as were hoped due to limiting factors such as budget constraints, inaccessibility of certain areas, or lack of available staff.

Several areal rainfall estimation techniques are currently used for averaging rainfall depths collected at ground stations. The isohyetal and Thiessen polygon techniques are conventional techniques that are usually applied to estimate the areal rainfall over the entire basin[2]. However, the fundamental principles of applying these techniques may produce inaccurate results because of the effects of topographical variation and the limited number of available rainfall stations. Alternative techniques are therefore needed to improve the accuracy of areal rainfall estimation. Two of the most well-known alternative techniques that have been generally applied are the geostatistics and the thin plate splines (TPS) techniques. Geostatistics, which is based on the theory of regionalized variables, has been accepted because it is able to assess spatial correlation among neighbouring observations to predict attribute values at unsampled locations[3]. Several authors including Tabios and Salas[4], and Phillips et al[5] concluded that the geostatistical prediction technique (kriging) provides better estimates of rainfall than conventional techniques such as the Thiessen polygon and inverse distance weighting (IDW) techniques. However, Dirks et al[6] found that the kriging method does not significantly improve predictions compared to the simpler techniques such as IDW in the area with high-resolution networks (e.g., 13 raingauges over a 35 km^2 area).

The TPS technique, which was introduced by Hutchinson[7,8], can also be used to interpolate spatial rainfalls more accurately than the conventional techniques, especially for mountainous areas. This technique can generate meteorological surfaces using a trivariate function of latitude, longitude, and elevation of meteorological stations together with the terrain elevation. It was proved to be a robust technique for dealing with noisy multivariate data and was applied in many countries such as Australia[9,10], Canada[11], and Thailand[12]. Price[11] revealed that the TPS technique produced better results for elevation-dependent spatial interpolation of monthly climatic data from sparse weather station networks than did the statistical method termed gradient plus inverse-distance-squared. Ekasingh[12] applied four spatial interpolation techniques comprising (Thiessen polygon, IDW, kriging, and TPS) to monthly meteorological data of 305 daily rainfall stations, 73 air temperature stations, and 12 sunlight radiation stations in Chiang Mai and Pitsanulok Provinces. The results showed that the TPS technique gave the lowest RMSE values for climate spatial interpolation. Boer et al[13] applied four forms of kriging and three forms of TPS to predict monthly maximum temperature and monthly mean precipitation in Jalisco State of Mexico. The trivariate regression-kriging and trivariate TPS showed the best performance. The authors also pointed that TPS is simpler than kriging, which can be very significant from a practical point of view.

In this study, we applied three different techniques (TPS, isohyetal and Thiessen polygon) for interpolating the areal rainfall over the study site (the Upper Ping river basin, Northern Thailand).

BASIN OVERVIEW

The Upper Ping river basin covers an area of approximately 25 370 km^2 in the provinces of Chiang Mai and Lamphun, Northern Thailand. The Bhumibol Dam is the downstream end of the Upper Ping river basin and separates the Ping river basin into the upper and lower parts[14]. The Upper Ping river basin can be separated into 14 sub-basins (Fig. 1). The Upper Ping river basin is mostly covered by forest and steep mountains, which form a line from the northern to the southern parts of the basin. The weather is monsoon type, with a rainy season from May to October and supplementary rains from occasional westward storm depressions originating in the Pacific. Mean temperatures for a 30 year period, recorded at the Chiang Mai meteorological station, varied from 14 °C in January to 36 °C in April.

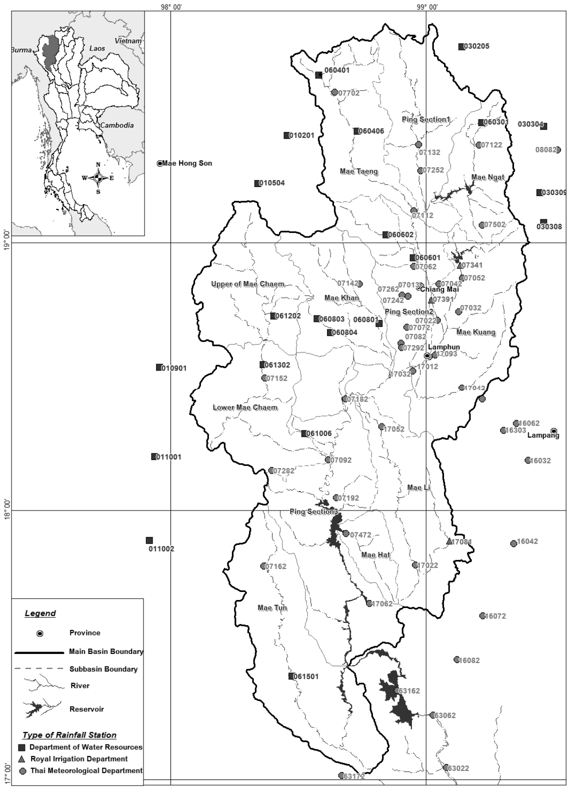

Fig. 1 Upper Ping river basin map showing the location of rain gauges.

DATA COLLECTION

Rainfall data

Daily rainfall data were collected from 81 rainfall stations located within and around the Upper Ping river basin between 1988 and 2006. The consistency of the rainfall data was investigated using the double mass curve technique. Rainfall data at 68 rainfall stations were shown to be reliable and were therefore used for further analysis. To be able to distinguish the effectiveness of each technique for areal rainfall interpolation, large amounts of rainfall give better results than small amounts[7,8].

Two periods of rainfall registered in August 2001 and September 2003, which had average rainfall depths over the data network of around 252.11 and 220.96 mm, respectively, were then chosen for further analysis. The number of rainfall stations located within the 15 sub-basin areas of the Upper Ping river basin and nearby area is shown in Table 1. The average rainfall registered in August 2001 and September 2003 over each sub-basin is also presented.

Table 1 Number of rainfall stations (N) in each sub-catchment area in the Upper Ping river basin and their average rainfall in August 2001 and September 2003.

Sub-catchment	Area (km^2)	N	Average rainfall (mm) Aug 2001	Average rainfall (mm) Sep 2003
Ping Section 1	1972	2	309.55	291.85
Mae Ngat	1282	3	223.97	237.70
Mae Taeng	1956	4	293.38	257.20
Ping Section 2	1723	10	291.46	291.74
Mae Rim	566	2	228.70	186.15
Mae Kuang	2680	7	349.10	194.44
Mae Khan	1732	4	310.35	271.50
Mae Li	2080	3	222.43	186.10
Mae Klang	616	2	176.15	200.10
Ping Section 3	3180	3	176.80	151.05
Upper Mae Chaem	1965	1	435.40	273.70
Lower Mae Chaem	1930	3	248.93	197.70
Mae Hat	521	1	192.90	156.50
Mae Tun	3167	2	129.50	191.65
Nearby Area	-	21	193.07	226.99
Total Area	25 370	68	252.11	220.96

Digital elevation model

Two sources of digital elevation model (DEM) data covering an area of 53 100 km^2 in the Upper Ping river basin and some parts of Myanmar between longitude 97.8° to 99.6° and latitude 16.9° to 19.85° were downloaded from NOAA-GLOBE[15] and NASA-SRTM[16]. The DEM data provided by these two organizations have horizontal resolutions of around 1 km and 90 m, respectively. Hastings and Dunbar[15] and Gorokhovich and Voustianiouk[17] applied the DEM data from NOAA-GLOBE and NASA-SRTM, respectively, and they concluded that the vertical accuracy provided by these two data sources are around 20 and 16 m, respectively, which are not much different. By using these two sources of DEM data in the analysis, we can investigate whether the horizontal resolution of DEM data would have any impact on the accuracy of areal rainfall interpolation.

RAINFALL INTERPOLATION TECHNIQUES

Thin plate spline technique

The TPS technique is a general technique for smoothing a continuous surface by minimizing the curvature of the surface[23]. In this study, the TPS technique was applied to interpolate daily rainfall data over the study area. To equilibrate the variance of the noise across the rainfall data network and to reduce the skew in the raw data, the square root transformation was applied to the observed rainfall values using[24]

$$r_i^{(1/2)} = f(x_i, y_i, h_i) + \varepsilon_i \quad i = 1, 2, \dots n, \tag{1}$$

where f is a smooth function of the longitude (x_i), latitude (y_i), and elevation (h_i), r_i is the rainfall recorded at the location i, n is the number of locations, and ε_i are random error terms (assumed to be normally distributed with zero mean and variance σ^2) associated with rainfall data measurement and the model deficiency. The unit of the observed rainfall is mm and varies according to the longitude and latitude coordinates (in degrees), whereas the unit of elevation is km. As a result, the elevation scale is around 100 times larger than horizontal coordinates[9].

The general thin-plate smoothing spline estimate of the function g is obtained by minimizing

$$\frac{1}{n}\sum_{i=1}^{n}\left[r_i^{(1/2)} - f(x_i, y_i, h_i)\right]^2 + \lambda J_m(f)$$

over a class of suitably smooth functions[25]. The first term is the average squared Euclidean distance between the observed data and fitted values, and the $J_m(f)$ term is the mth order roughness penalty consisting of the integral of squared mth spatial derivatives of f. In this study we use $m = 2$ and $J_2(f)$ equals

$$\iiint f_{xx}^2 + f_{yy}^2 + f_{hh}^2 + 2f_{xh}^2 + 2f_{xy}^2 + 2f_{yh}^2 \,\mathrm{d}x\,\mathrm{d}y\,\mathrm{d}h.$$

The smoothing parameter λ determines a balance between the fidelity to the data and the degree of smoothness of the fitted spline function f. This parameter is usually determined by minimizing the generalized cross validation (GCV). The GCV is an estimate of predictive error of the spline surface. It is calculated by removing each data point and summing the square of the difference of each point from a surface fitted by all other data points[26].

Thiessen polygon technique

The Thiessen polygon technique was introduced to estimate equivalent uniform depth[27]. This technique assumes that an average value over the same area of a Thiessen polygon is taken to be equivalent to the point value located at the centroid of this polygon. A hypothetical basin with three rainfall stations is shown in Fig. 2 For this basin, encompassing n Thiessen polygons, the areal rainfall over the basin (P_{T}) is computed from

$$P_{\mathrm{T}} = \sum_{i=1}^{n} T_i P_i,$$

where P_i is the observed rainfall at the centroid of the ith polygon, and the weighting factor T_i is given by

$$T_i = \frac{A_i}{A_{\mathrm{T}}},$$

where A_{T} is the total area of the basin, and A_i is the area defined by the intersection of the Thiessen polygon and the basin boundary.

The Thiessen polygon technique is suitable for application over relatively flat and expansive areas. However, this technique assumes that precipitation varies linearly between stations and is therefore unsuitable for use in mountainous regions which have an effect on the precipitation amount[29].

Isohyetal technique

An isohyetal map shows lines of equal precipitation. A sample of isohyetal lines is shown in Fig. 2. The fitted isohyets were generated using the bivariate TPS technique by considering only two independent variables namely the longitude (x_i) and latitude (y_i) coordinates. Using this technique, (1) is replaced by

$$r_i^{(1/2)} = f(x_i, y_i) + \varepsilon_i \quad i = 1, 2, \ldots, n,$$

The second order derivative for the smoothing parameter and minimization of the GCV are also applied for interpolating the isohyetal lines.

METHOD

DEM generation

To assist with comparisons, the DEM resolutions were transformed into 100 m using a nearest neighbour method in the ARCVIEW GIS software (version 3.2)[19]. Ground elevation of those 68 selected rainfall stations can be later defined using these generated DEM data. The generated DEM data, rainfall locations, and their ground elevations were later used as the input data for ANUSPLIN[18].

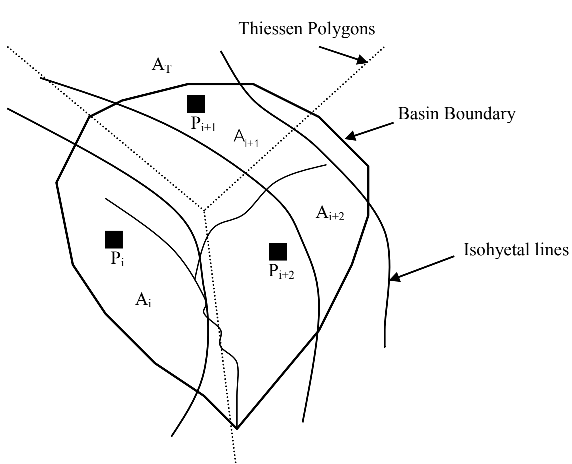

Fig. 2 Hypothetical basin with three point rainfall stations and associated Thiessen polygons and Isohyetal defined[28].

Investigation of topographical effect on rainfall depths

Rainfall depths generally vary with space and time and tend to increase with increasing elevations because of the orographic effect of mountainous terrain, which causes the air to be lifted vertically, and the condensation occurs due to adiabatic cooling[3,20]. Hevesi et al[21,22] revealed that there is a significant correlation of around 0.75 between average annual precipitation and their elevation recorded at 62 rainfall stations in Nevada and southeastern California. To investigate whether this occurred here, the average annual rainfall of each rainfall station between 1988 and 2006 were plotted against its elevation in the Upper Ping river basin. A linkage between the two parameters would mean that it is therefore possible to increase the accuracy of areal rainfall interpolation by applying a topographic parameter (ground elevation of rainfall station) as proposed in this study.

Areal rainfall estimation

In this study, the interpolation methods described above were carried out by applying ANUSPLIN, developed by Hutchinson[23], to generate a surface of interpolated daily rainfalls in conjunction with observed elevations in the Upper Ping river basin. Input data consisted of the generated DEM data covering the Upper Ping river basin, daily rainfall at 68 stations as well as their observed locations and elevations. The outputs from ANUSPLIN were areal rainfall surfaces which correspond to point rainfalls and DEM data. A summary of the statistical indicators can be printed to show the accuracy of point rainfall estimation using the cross-validation technique. The output of areal rainfall surfaces in the text file can be later imported to generate a grid format in the GIS environment. This software was also used to generate the isohyetal map.

Evaluation of the accuracy of spatial interpolation techniques

The cross-validation technique was achieved by removing data from one observation point at a time (j), taken from all of the available observation points in the data set and then estimating the value of the removed observation point data using the data from the remaining $(n-1)$ observation points. This technique is used to evaluate how well the neighbouring stations estimate the missing value[30].

The accuracy of spatial interpolation techniques was evaluated by using the following three statistical indicators. The mean error (ME) is given by

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}(R_{\mathrm{o}i} - R_{\mathrm{e}i}), \qquad (2)$$

where n is the number of rain events, $R_{\mathrm{o}i}$ is the observed rainfall depth at a time (i), and $R_{\mathrm{e}i}$ is the estimated rainfall depth at a time (i). A positive ME shows that the estimated rainfall is generally underestimated, while a negative sign shows it is generally overestimated. The mean absolute error (MAE) is given by

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|R_{\mathrm{o}i} - R_{\mathrm{e}i}|.$$

The root mean square error (RMSE) is given by

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left[R_{\mathrm{o}i} - R_{\mathrm{e}i}\right]^2}.$$

The MAE and RMSE are used as indicators of the magnitude of extreme errors. Lower MAE and RMSE values indicate greater central tendencies and generally smaller extreme errors.

RESULTS AND DISCUSSION

DEM Generation

The elevations generated using the SRTM-DEM and GLOBE-DEM covering the selected area are between 26 to 2520 m, and 33 to 2487 m above mean sea level, respectively. The elevation of each rainfall station can be specified from these two generated maps. Fig. 3 shows a scatter plot of the elevations of each rainfall station derived from SRTM-DEM and GLOBE-DEM. The accumulated different value of ground elevations generated from SRTM-DEM and GLOBE-DEM at the same rainfall stations presented by the mean errors (ME) is shown to be approximately −0.58 m. This different value is not so great when compared to the resolution differences of these two data sources that are quite large (90 m for SRTM-DEM and 1 km for GLOBE-DEM). It can be concluded that two different horizontal resolutions of DEM data used in this study did not have much impact on the vertical accuracy.

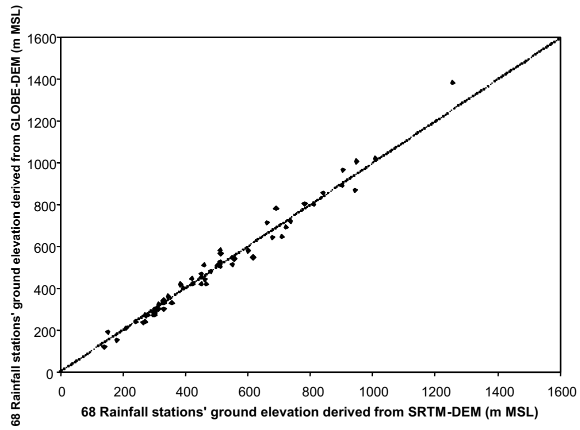

Fig. 3 Ground elevations of each rainfall station derived from SRTM-DEM and GLOBE-DEM.

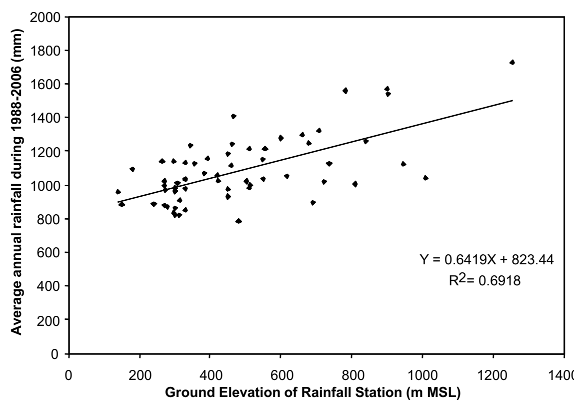

Fig. 4 Relationship between the average annual rainfall of each rainfall station and its elevation in the Upper Ping river basin.

Relationship between rainfall depths and observed locations

The relationships between the average annual rainfall of each rainfall station between 1988 and 2006 and its elevation are plotted as shown in Fig. 4. The figure shows that the average annual rainfalls tend to increase with increasing observed elevations with a coefficient of determination of 0.7. It can be seen that rainfall stations located in the Upper Ping river basin and nearby area, show the same tendency between rainfall depths and their station locations.

Areal rainfall estimations using three spatial interpolation techniques

Daily areal rainfall depth estimates in the Upper Ping river basin that occurred in August 2001 and September 2003 were created and shown as histograms in Fig. 5 and Fig. 6, respectively. In addition, maps of maximum areal rainfalls that occurred on 11 August 2001 and 13 September 2003 were generated using three different techniques and are illustrated in Fig. 7 and Fig. 8, respectively.

Table 2 Differences of areal rainfall depths (in mm) using various techniques for rainfall events in 2001 and 2003.

	TPS-SRTM		TPS-GLOBE		Isohyetal		Thiessen polygon	
	2001	2003	2001	2003	2001	2003	2001	2003
TPS-SRTM	-	-	0.01	0.23	−1.01	0.82	−1.38	1.01
TPS-GLOBE	−0.01	−0.23	-	-	−1.02	0.58	−1.39	0.78
Isohyetal	1.01	−0.82	1.02	−0.58	-	-	−0.37	0.19
Thiessen polygon	1.38	−1.01	1.39	−0.78	0.37	−0.19	-	-

TPS-SRTM = TPS technique with SRTM-DEM; TPS-GLOBE = TPS technique with GLOBE-DEM

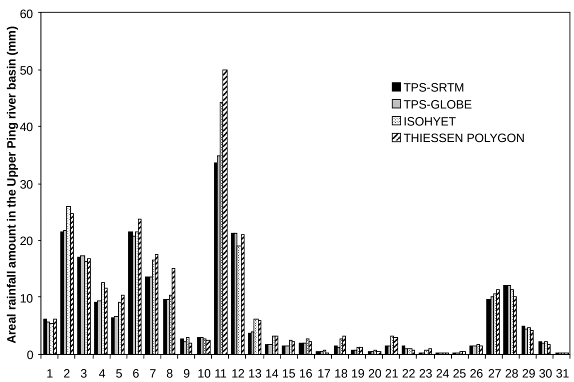

Fig. 5 Histograms of daily areal rainfall depths in August 2001.

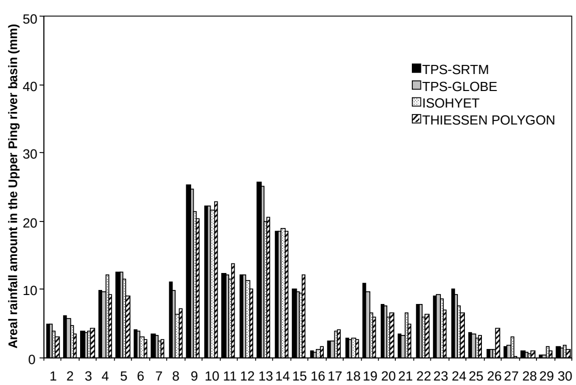

Fig. 6 Histograms of daily areal rainfall depths in September 2003.

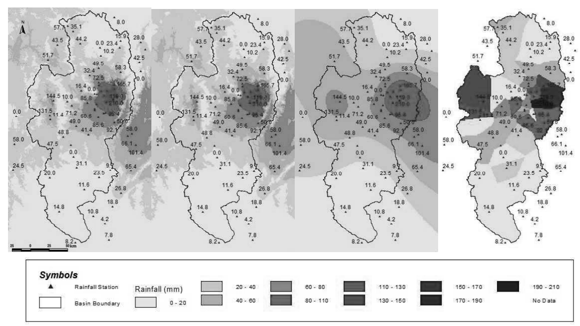

Fig. 7 Maps of areal rainfall depths in the Upper Ping river basin on 11 August 2001 generated by (a) TPS-SRTM (b) TPS-GLOBE (c) Isohyetal technique (d) Thiessen polygon.

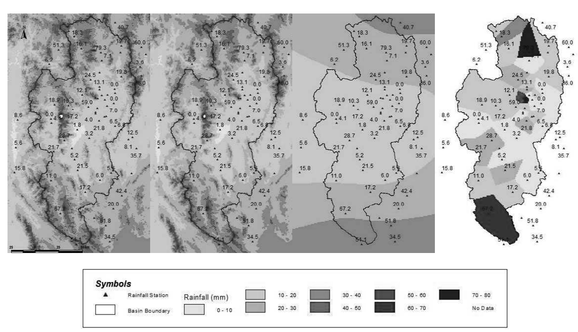

Fig. 8 Maps of areal rainfall depths in the Upper Ping river basin on 13 September 2003 generated by (a) TPS-SRTM (b) TPS-GLOBE (c) Isohyetal technique (d) Thiessen polygon.

The differences of areal rainfall depths generated by three different techniques for rainfall events in August 2001 and September 2003 are presented in Table 2. The rainfall depths calculated by the techniques presented in the first row were used as $R_{\mathrm{o}i}$ in (2), whereas the techniques presented in the first column were used as $R_{\mathrm{e}i}$. Areal rainfall depths calculated by the TPS-SRTM and TPS-GLOBE are close with mean errors of around $\pm\,0.01$ and $\pm\,0.23$ mm, respectively (Table 2). Areal rainfall depths calculated by the conventional techniques (Isohyetal and Thiessen polygon) are also close to each other with mean errors of $\pm\,0.37$ and $\pm\,0.19$ mm, respectively. However, rainfall depths produced by TPS and conventional techniques are much more different.

Table 3 Values of the statistical indicators for three spatial interpolation techniques.

Indicator	TPS-SRTM	TPS-GLOBE	Iso	Th poly
ME (mm)	0.53	0.50	0.94	−1.98
MAE (mm)	3.94	3.81	5.16	15.61
RMSE (mm)	8.50	8.42	9.70	28.15
α	0.59	0.61	0.48	0.37
r	0.70	0.71	0.56	0.06

Evaluation of the accuracy of spatial interpolation techniques

Daily rainfall data at each station was removed at each time and the remaining data were used to estimate the missing one by applying three spatial interpolation techniques. Table 3 shows that the TPS technique produced smaller values of ME, MAE, and RMSE than the isohyetal and Thiessen polygon techniques. The TPS-GLOBE produced an insignificant improvement in daily rainfall estimation compared to the TPS-SRTM. The TPS and isohyetal techniques provided an underestimate of areal rainfall depths (positive ME) whereas the Thiessen polygon technique overestimated areal rainfall depths.

The correlation between point rainfall estimation using three different techniques and the observed data were tested by fitting lines between estimated and observed rainfalls. The slope (α) of the linear regression line and its correlation coefficient (r) of each technique are given in Table 3. The TPS-GLOBE and TPS-SRTM give values of α closer to 1 than the other techniques. The values of r from the TPS techniques are also higher. The results show that the TPS technique is better for rainfall estimation better than the isohyetal technique and much better than the Thiessen polygon technique. The coarser DEM resolution (GLOBE-DEM) performed slightly better than the finer DEM resolution (SRTM-DEM). Although the difference was not significant in our case, this result is consistent with that from the studies of Hutchinson[7,8], who found that the 10 km DEM resolution gave the least values of RMSE in rainfall estimation among the range of DEM resolutions between 2.5 and 20 km. Moreover, Sharples et al[24] also found that the optimum scale of the resolution of DEM data is around 5–10 km among the range between 250 m and 90 km.

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