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Runoff estimation using radar and rain gage data

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Radar rainfall is an alternative input data to a rainfall-runoff model and potentially can improve the accuracy in runoff estimates. This study used daily gage rainfall (DGR) and 3 types of radar rainfall as the input data to the selected rainfall-runoff model (URBS) to find out the most appropriate rainfall dataset for the most accurate runoff hydrographs at 4 runoff stations in the upper Ping river basin, Northern Thailand. The DGR was approximated for each sub-catchment using the Thiessen polygon technique. The calibrated daily Z-R relationship for the Omkoi radar ($Z=74R^{1.6}$) and the mean field bias correction technique were applied to calculate the daily radar rainfall (DRR). The hourly radar rainfall (HRR) was estimated using the update daily Z-R relationship which was changed daily depending upon the mean field bias values. The scaling transformation equation ($A_t = (t/24)^{-0.055} A_{24}$) was applied to update the daily Z-R relationship for an estimation of hourly radar rainfall (HRRS). The results show that all radar rainfall input data tend to produce more accurate runoff hydrographs than the DGR. The HRRS dominates other rainfall datasets for producing the most accurate results in runoff estimation. The weather radar is therefore an effective measurement to estimate rainfall for improving runoff estimates especially in regions where continuous gage rainfall measurements are not available and rain gages are sparsely distributed.

Keywords: *Radar rainfall, rain gage rainfall, URBS model, runoff estimation, Z-R relationship, scaling logic*

1. INTRODUCTION

Measured rainfall is one of the most significant input data in applying the hydrological models for runoff and flood estimations. Unfortunately, the distribution of rainfall usually varies significantly in both space and time; therefore, the limited number of rainfall stations in the catchment can have a major impact on the accuracy of runoff and flood estimations (Bevan and Hornberger, 1982; Hamlin, 1983). The accurate estimation of the spatial distribution of rainfall therefore requires a very dense rainfall network, which involves high installation and operational costs. Radar rainfalls estimated from the weather radar are the alternative rainfall products which are spatially distributed over the catchment. The weather radar, which is a widely used basis for rainfall estimation at fine spatial and temporal resolutions (Collinge and Kirby, 1987; Sun et al., 2000; Uijlenhoet, 2001; Vieux, 2003), can better capture the spatial variation of rainfall fields than rain gage rainfall data in areas where rain gages are distributed sparsely (Yang et al., 2004; Segond et al., 2007). There are number of papers shown the improvements in flood estimation and flood forecasting using radar rainfall as the input data to hydrological models (Wyss et al., 1990; Pessoa et al., 1993; Borga et al., 2000; Sun et al., 2000).

In this study, radar rainfall at hourly and daily resolution was estimated to be used as different input data to the rainfall-runoff model. Since only daily gage rainfall (DGR) data is sufficiently available in the upper Ping river basin, a calibration process of the Z-R relationship proposed by Mapiam and Sriwongsitanon (2008) was therefore undertaken based on the daily basis. This calibrated daily Z-R relationship and mean field bias technique were applied here to estimate the daily radar rainfall (DRR) over the study area. For hourly radar rainfall estimation, there are two estimation approaches proposed in this study. Firstly, the daily Z-R relationship was directly used to estimate radar rainfall at hourly time scale (HRR). Secondly, the scaling equation introduced by Mapiam et al. (2009) was applied to the daily Z-R relationship for hourly rainfall (HRRS) estimation.

The DGR, DRR, HRR, and HRRS were later used as different input data to the rainfall-runoff model at particular runoff stations in the study area. Results of flow hydrograph estimated using these four types of rainfall data were compared for their accuracy and effectiveness.

2. STUDY AREA AND DATA COLLECTION

2.1. Study area

The study area is the upper Ping river basin, which is situated in northern Thailand (Figure. 1). It covers the area of approximately 25,370 km^2 across most of the land in Chiang Mai and Lam Phun Provinces. The average annual runoff and rainfall of the catchment are around 6,815 million m^3 and 1,174.1 mm, respectively.

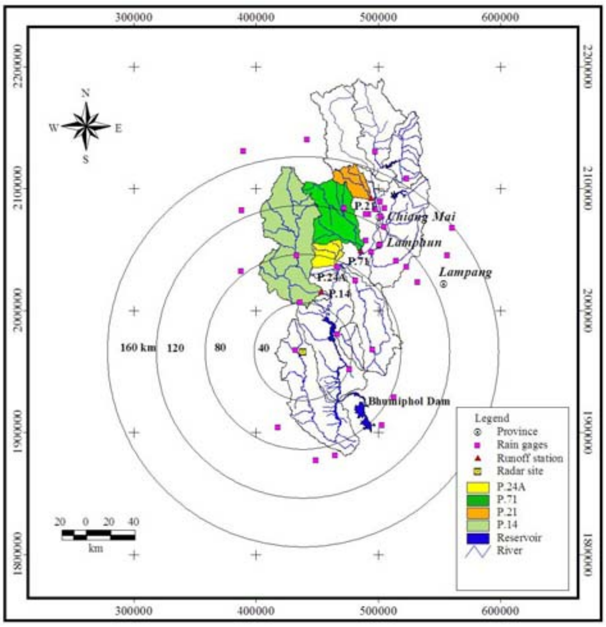

Figure 1. The upper Ping river basin and the locations of rainfall and runoff station.

2.2. Radar reflectivity data

Radar reflectivity data recorded from the Omkoi radar, which is own and operated by the Bureau of Royal Rainmaking and Agricultural Aviation (BRRAA), was used for daily and hourly radar rainfall estimation in some sub-catchments of the upper Ping river basin. The Omkoi radar is a S-band Doppler radar which transmits radiation with a wave length of 10.7 cm and produces a beam width of 1.2^o. The radar reflectivity data are in Cartesian grid with 480 km $\times$ 480 km extent with 1 km^2 spatial resolution and 6 minutes temporal resolution. Because of the accuracy of the recorded reflectivity data and their suitability to the gauge rainfall and runoff data within the same periods, three periods of data in rainy season (May – October) of the 2.5-km CAPPI reflectivity data at the Omkoi radar during June – October 2003, May – September 2004, and May – July 2005 were used for the analysis. Since the reflectivity data used in this study was ascertained from the S-band radar, beam attenuation effect was considered to be insignificant in this study. To avoid the effects of bright band, the reflectivity data lying within the radar range of 160 km that causes the height of the upper beam to be below the climatological freezing level of Chaing Mai (around 4.9 km) was therefore used in the analysis. To avoid the effect of noise and hail in the measured radar reflectivity, the reflectivity values that are less than 15 dBZ were excluded from the analysis, and the reflectivity values that are greater than 53 dBZ were assumed to be 53 dBZ. Additionally, the errors due to the effect of ground clutter were also removed from the reflectivity data by finding the strong persistent radar reflectivity from the radar map to denote the clutter locations. Thereafter the reflectivity data in these clutter areas were eliminated from the analysis.

2.3. Rain gage rainfall data

Since most of gages in and around the project are daily rain gages, three periods of rain gage rainfall data obtained from the networks of 35 rain gages (see Figure 1) at the same period of the reflectivity data were used in this study. These rain gages are owned and operated by the Royal Irrigation Department (RID) and the Thai Meteorological Department (TMD).

2.4. Runoff data

As the reflectivity data lying within a range of 160 km from the Omkoi radar were used in this study, runoff data obtained from the 4 stations namely P.21, P.71, P.14, and P.24A (see Figure 1), which have sufficient data available and located in the upper Ping river basin within that range, were used for the analysis. Catchment characteristics for each station comprising catchment area (A), main channel length (L), main channel length from the centroid (L_c), and channel slope (S) are presented in Table 1. These runoff stations are owned and operated by the RID. In the analysis, we used three periods of hourly runoff hydrograph data for these 4 runoff stations at the same period of reflectivity and rain gage rainfall data.

Table 1 Catchment characteristics for each runoff station

Runoff station	A (km^2)	L (km)	L_c (km)	S
P.21	515	47	27	0.0121
P.71	1,771	112	53	0.0067
P.14	3,853	194	100	0.0044
P.24A	460	42	25	0.0351

3. URBS MODEL

The URBS model developed by Carroll (2004) has been chosen for runoff estimation using four different rainfall data sets. It is a semi-distributed non-linear rainfall runoff routing model that can account for the spatial and temporal variation of rainfall. The URBS model has been used extensively for flood forecasting by the Australian Bureau of Meteorology and by the Chiangjiang (Yangtze) Water Resources Commission in China (Pengel et al., 2007). Mapiam and Sriwongsitanon (2009) also used the URBS model for flood estimation on the gaged catchments in the upper Ping river basin and later formulated the ungaged relationships for being applied on the ungaged catchments of the basin. The Split module - the sub-runoff routing module of the URBS model - was used for runoff estimation for the 4 runoff stations in this study. To implement the URBS model for runoff estimation, the catchment of the runoff stations P.21, P.71, P.14, and P.24A were divided into a number of sub-catchments of 5, 15, 25, and 5, respectively.

4. CATCHMENT RAINFALL ESTIMATION

There are four types of catchment rainfall that have been calculated to be used as the input data for the URBS model for runoff estimation at the 4 runoff stations in the upper Ping river basin during three period of the datasets. Catchment rainfall estimation methods for different rainfall types are explained as follows.

4.1. Daily gage rainfall (DGR) estimation

Rainfall data measured from rain gages installed on the ground has generally been used to estimate the areal rainfall and then used as the input data to a rainfall-runoff model for runoff and flood estimation. In this study, the catchment rainfall for the sub-catchments of each runoff station was calculated using the Thiessen polygon technique - which is a spatial interpolation technique and usually applied in the area with non-uniform distribution of the rain gages. Thirty five daily rain gages located in and around the upper Ping river basin were used to construct the Thiessen polygons. Daily catchment rainfall for each sub-catchment was calculated by the multiplication between the daily gage rainfall and its corresponding weighting factor estimated from the generated polygons.

4.2. Daily radar rainfall (DRR) estimation

In this study, the daily Z-R relationship $Z=74R^{1.6}$ for the upper Ping river basin proposed by Mapiam and Sriwongsitanon (2008) was used for DRR estimation. This equation was used to convert three data sets of instantaneous radar reflectivity data recorded at the Omkoi radar at the pixel located in the target area into the instantaneous radar rainfall intensity. The instantaneous radar rainfall was thereafter accumulated into 24-hour rainfall resolution using the accumulation algorithm proposed by Fabry et al. (1994).

Although the errors caused by reflectivity measurement process were corrected (see details in section 2.2) and the Z-R relationship suitable for the study area were used in radar rainfall estimation, there remain errors in the radar rainfall estimates (Chumchean et al., 2006). A mean field bias correction technique can be used to eliminate these residual errors for improving the accuracy on radar rainfall estimation. An adjustment factor - computed as the ratio of the mean areal gage rainfall to the corresponding radar rainfall (Anagnostou et al., 1998; Borga et al., 2000) - was first assessed, and the radar rainfall estimated by the Z-R relationship $Z=74R^{1.6}$ was thereafter adjusted by multiplying the adjustment factor to the initial radar rainfall.

As most of gages in and around the project area are daily rain gages, the mean field bias was computed at the daily time scale in this study. The recorded daily gage rainfall and initial daily radar rainfall (estimated using the relationship $Z=74R^{1.6}$) during the three dataset of 2003, 2004, and 2005 were used in the mean field bias analysis. An adjustment factor for day t (B_t) was calculated as:

$$B_t = \frac{\text{Mean areal gage rainfall}}{\text{Mean areal radar rainfall}} \tag{1}$$

Mean areal gage rainfall was calculated using the Thiessen polygon technique. All 35 rain gages in the Upper Ping River Basin located within the range of 160 km from the Omkoi radar were used in the analysis. Mean areal gage and radar rainfall can be written as:

$$\text{Mean areal gage rainfall} = \frac{1}{A}\sum_{i=1}^{N_{G,t}} A_{i,t} G_{i,t} \tag{2}$$

where A is the catchment area of the upper Ping river basin located within 160 km range from the Omkoi radar, $A_{i,t}$ is the sub-area of Thiessen polygon corresponding to the i^{th} rain gage for day t, $G_{i,t}$ is the corresponding DGR (mm) for day t, and $N_{G,t}$ is the number of sub-area of the polygon over the basin for day t.

$$\text{Mean areal radar rainfall} = \frac{1}{N_P}\sum_{i=1}^{N_P} R_{i,t} \tag{3}$$

where, R_i is the initial DRR (mm) at the i^{th} pixel for day t, N_P is the number of radar pixels in the upper Ping river basin situated within the 160 km range.

In this study, the mean filed bias for the previous day (t-1) was therefore used for radar rainfall correction at day t, under the assumption that the mean field bias will be the same between yesterday and today. The initial DRR for day t at all pixels located in the 4 gaged catchments was multiplied by B_{t-1} to obtain adjusted DRR. For sub-catchment rainfall estimation in each gaged catchment, the corrected DRR at all pixels located in the sub-catchment was averaged using the simple arithmetic averaging method to ascertain the total daily rainfall input for the URBS model.

4.3. Hourly radar rainfall (HRR) estimation

Because of the limitation in obtaining continuous rain gage rainfall data for the upper Ping river basin, the mean filed bias correction was undertaken based on daily basis. The DRR adjusted by the mean field bias values was also applied for HRR estimation in this study. When the DRR were adjusted by the mean field bias, as a result, the original 24-hour A parameter (A=74) was changed daily depending upon the mean field bias used for correcting DRR. The update 24-hour A parameter for day t $(A_{24new})_t$ was therefore computed using the following equation.

$$(A_{24new})_t = \frac{A_{old}}{B_{t-1}^{b}} \tag{4}$$

where A_{old} is the 24-hour A parameter used in DRR estimation before applying mean field bias correction (A_{old} =74), B_{t-1} is the adjustment factor for day *t-1*, and b is the radar parameter which was fixed as 1.6. For HRR estimation at day *t* covering the project area, three datasets of the recorded instantaneous radar reflectivity at the pixel located in the target area were converted into radar rainfall using the updated 24-hour Z-R relationship, which A parameter was calculated using Eq. (4). The calculated instantaneous radar rainfall was thereafter accumulated into 1-hour rainfall resolution using the accumulation algorithm proposed by Fabry et al. (1994). For sub-catchment rainfall estimation in each gaged catchment, the estimated HRR at all pixels located in the sub-catchment was averaged using the simple arithmetic averaging method to ascertain the HRR as the input data for the URBS model.

4.4. Hourly radar rainfall estimation using the scaling transformation equation (HRRS)

Since Mapiam et al. (2009) found that an application of the 24-hour Z-R relationship to estimate radar rainfall at finer temporal resolution, especially at hourly time resolution, gives significant error on extreme rainfall estimates. For the situations where only DGR data is available for Z-R calibration, Mapiam et al. (2009) proposed a climatological scaling transformation equation for converting the A parameter to finer resolutions as presented below:

$$A_t = (\frac{t}{24})^{-0.055} A_{24} \tag{5}$$

where *t/24* is a scale factor, *t* (hr) is the temporal resolution at which the rainfall needs to be estimated, 24 (hr) is the reference temporal resolution of the radar rainfall, 0.055 is a scaling exponent, and A_{24} and A_t represent the parameter A in Z-R relationship at temporal resolutions 24 and *t*, respectively.

To estimate hourly radar rainfall in this study, the *t* as presented in Eq. (5) was substituted as 1 hour. If there is no mean field bias correction in DRR estimation, the A_{24} was fixed as 74 and constant with day. However, the mean field bias correction based on daily time scale was applied in this study, the A_{24} was therefore changed daily depending upon the mean field bias used for correcting DRR. The 1-hour *A* parameter for day *t*, $(A_1)_t$, was derived using the following equation.

$$(A_1)_t = (\frac{1}{24})^{-0.055} (A_{24new})_t \tag{6}$$

For hourly radar rainfall estimation at day *t* covering the project area, the calculated $(A_1)_t$ parameter and the b parameter fixed at 1.6 will be applied to the three datasets of the recorded instantaneous radar reflectivity for the pixel located in the target area.

5. EVALUATION OF MODEL PERFORMANCE IN RUNOFF ESTIMATION

Model calibration and verification processes were first carried out to define the most suitable set of control parameters of the URBS model for each rainfall dataset and each runoff station. For each runoff station, the 4 estimated catchment rainfall fields for the first dataset (June – October 2003) and the last 2 datasets (May – September 2004, and May – July 2005) were used separately as the input data to the URBS model for model calibration and verification, respectively. The individual set of model parameters for each rainfall input type that produced the goodness of fit between the hourly observed and the simulated flow hydrographs for both in calibration and verification processes were identified as the most suitable set. Four statistical measures: the correlation coefficient (r), the efficiency index (EI), overall root mean square error (RMSE), and RMSE of peak flow events ($RMSE_{peak}$) (Madsen, 2000) were considered to provide a general guide in the assessment of the overall performance in hydrograph simulation.

The result shows that control parameters of each runoff station are different for each rainfall type. By using these parameters for the model calibration and verification, the average statistical values within 3 flow periods (2003-2005) show that the URBS model can reasonably simulate the hydrographs at these 4 runoff stations with the average r and EI values of around 0.70 and 59.89 %, respectively as presented in Table 1. Using these two statistical indicators (r and EI), the DRR seems to produce runoff hydrographs closer to the observed data than those produced by the DGR. The HRR and HRRS can further improve the accuracy of runoff hydrographs over the DRR, respectively.

To further compared the model performance using four different datasets, the average values of RMSE and $RMSE_{peak}$ for each rainfall type at each runoff station were calculated as shown in Table 2. It shows that the average $RMSE_{peak}$ calculated using the three types of radar rainfall are much lower than using the DGR at all runoff stations. The percent improvements in the accuracy of runoff estimation using each rainfall type compared with other types were then calculated. The average value of percent improvement in $RMSE_{peak}$ for all events at all stations varies between 4.21% and 44.74% with the average of around 23.50%. Average values of percent improvement in $RMSE_{peak}$ of using DRR, HRR, and HRRS instead of DGR for all 4 stations are around 19.65%, 25.50%, and 25.37%, respectively. RMSE calculated using three types of radar rainfall are also lower than using DGR for all stations. The average value of percent improvement in RMSE for all stations varies between 5.91% and 31.46% with the average of around 20.14%. Average values of percent improvement in RMSE of using DRR, HRR, and HRRS instead of DGR for all stations are around 18.38%, 18.77%, and 23.28%, respectively. These results confirm that all radar rainfall data (DRR, HRR, and HRRS) tends to produce more accurate runoff hydrographs (both overall hydrograph and peak flow) than the DGR.

The comparison between DRR and HRRS can be seen by the average values of percent improvement in RMSE of using HRRS instead of DRR for all 4 stations varying between 2.78% and 11.19% with the average of around 5.73%. However, $RMSE_{peak}$ of using HRRS instead of DRR reduced at 3 stations except for P.24A. The average value of percent improvement in $RMSE_{peak}$ within 3 stations varies between 11.24% and 12.36% with the average of around 11.68%. The HRRS therefore tends to improve the accuracy of the overall hydrograph and the peak flow compared to the DRR.

The comparison between DRR and HRR can be seen by the average values of percent improvement in $RMSE_{peak}$ of using HRR instead of DRR for 3 stations except for P.24A varying between 0.99% and 17.15% with the average of around 11.05%. On the other hand, the use of HRR can improve the accuracy of overall hydrograph compared to the use of DRR for only at P.24A with the percent improvement of around 10.90%. By using these two statistical parameters (RMSE and $RMSE_{peak}$), it can be concluded that we rather use DRR instead of HRR and use HRRS instead of DRR for runoff estimation.

The comparison between HRR and HRRS can be seen by the average values of percent improvement in RMSE of using HRRS instead of HRR for all 4 stations varying between 0.33% and 9.91% with the average of around 5.63%. On the other hand, the HRRS does not have any consistency in improving the accuracy of peak flow compared to the HRR, because there are both the percent improvement and percent reduction of $RMSE_{peak}$ within those 4 stations. The results confirm that using HRRS instead of using the HRR can improve the accuracy in overall hydrograph more consistency than the peak flow. The scaling logic is therefore an effective algorithm to be useful for preparing the HRRS and can be applied for improving the accuracy of the overall hydrograph better than the peak flow.

Table 1 Comparison of average r and EI (%) using four different rainfall datasets at each runoff station.

Rainfall type	R				EI (%)			
	P.21	P.71	P.14	P.24A	P.21	P.71	P.14	P.24A
DGR	0.684	0.649	0.654	0.637	46.744	53.272	25.195	53.746
DRR	0.766	0.779	0.586	0.679	65.781	61.907	70.821	60.040
HRR	0.787	0.787	0.622	0.697	60.813	58.085	69.997	66.679
HRRS	0.787	0.790	0.629	0.700	67.819	57.951	72.047	67.337

Table 2 Comparison of average RMSE and $RMSE_{peak}$ using four different rainfall datasets at each runoff station.

Rainfall type	Average RMSE (m^3/s)				Average $RMSE_{peak}$ (m^3/s)			
	P.21	P.71	P.14	P.24A	P.21	P.71	P.14	P.24A
DGR	4.42	10.17	27.97	3.19	7.04	14.02	47.56	7.41
DRR	3.54	8.18	20.07	3.00	5.61	8.84	45.56	6.14
HRR	3.73	8.21	21.28	2.67	4.77	8.75	37.74	6.55
HRRS	3.45	7.82	19.17	2.67	4.97	7.75	40.43	6.49

6. CONCLUSIONS

The study shows that the accuracy of overall hydrograph and peak flow estimated using all radar rainfall data (DRR, HRR, and HRRS) are generally higher than that of estimated using the DGR data, respectively. The results have therefore confirmed an ability of the weather radar rainfall to be used as the input data for improving the accuracy of runoff estimation in the upper Ping river basin, where continuous gage rainfall measurement is unavailable and the available daily rain gages are sparsely distributed. However, the use of HRR cannot produce better results of runoff hydrograph than the use of DRR. On the other hand, the HRRS has already proved its ability to be used to improve the accuracy of runoff estimates, especially the overall hydrographs. The scaling logic is therefore necessary to be applied to prepare the HRRS for the situation like the upper Ping river basin, where daily Z-R relationship is only available.

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