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Contributed Paper

Adaptive Estimation of Local Rainfall from Radar Intensity using Rule-based Approach on Temporal and Spatial Data

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ABSTRACT

To achieve the highest accuracy of rainfall estimation using radar measurements, the parameters a and b in $Z=aR^b$ relation must be adaptively computed from the local relevant factors such as rain intensity, cloud types, duration of rain, etc. In this paper, a new and practical method to compute the values of a and b is introduced. The new method considered the effects of the following factors, i.e. cloud-rain type, ratio of gauge rain intensity(G) with radar rain intensity(R) for the computation of a and b. A rule-based classification concept was deployed to classify the relevant factors into seven cases and the technique of regression analysis was applied to derive the values of a and b. To evaluate the performance of the proposed method in terms of G/R ratio, the method was tested with data collected from S-band radar in the central areas of Thailand. Compared with the traditionally used formulas of $Z=200R^{1.6}$, $Z=300R^{1.4}$, and general probability matching method, the new Z-R relation achieved higher accuracy by approximately 10-30%. Furthermore, a new concept of similarity measure was introduced to select the appropriate rain gauge as the representative of any rain gauge with incomplete data.

Keywords: Z-R relation, rainfall estimation, rule-based classification, regression analysis, similarity measures

1. INTRODUCTION

Weather radar data have been widely used in rain measurement, forecasting, storm tracking, flood warning, and evaluating the result of hygroscopic flare seeding [1]. The relation between Z and R in a form of $Z=aR^b$ is one of the mostly used equation to estimate the amount of rainfall from the intensity of radar signal. Our focus is on estimating heavy rainfall in the tropics using weather radar. There were several studies concerning this relation in various aspects by many authors. Tropical rainfall using different types of data and approaches such as radar-based Quantitative Precipitation Estimation (QPE) were previously studied [2-21]. To estimate the parameters *a* and *b* in Z-R relation, several techniques using regression [18, 19, 20, 25], probability matching [6, 8, 21, 20], and neural network [7, 22] have been extensively utilized. In addition to the Z-R relation, rain type was also studied by [23-26].

Usually, the accuracy of $Z=aR^b$ relation with respect to the actual amount of rainfall strongly depends on the values of *a* and *b*, which can be easily computed from the values of Z and R by a linear regression analysis as follows:

$$\log (Z) = \log (a) + b \log (R) \tag{1}$$

However, the values of *a* and *b* can vary at each location and can be affected by various weather conditions. The study of Atlas [5] reported that using a single Z-R relation applied to all rain fields in rain drop size distributions can result in errors of radar rainfall estimation. Differences between raindrop size distributions of two rainfall types (e.g. convective vs. stratiform) conduct to different Z-R parameters [2, 5, 26]. The Z-R conversion error considerably reduced if the parameters of the Z-R relation are estimated by the studies of [2, 6, 21, 28, 35]. In previous studies, there were errors from the procedure used to convert radar reflectivity to rainfall rate (Z-R conversion error). When reflectivity data are used with no consideration of different rain types (e.g. convective vs. stratiform), the inaccuracy may occur due to a wrong Z-R relation. Although the previous studies reached some conclusive and practical results, it can be argued that one relation $Z=aR^b$ should not be generically used for all the locations because of different effecting weather factors. Some previous studies indicated that the accuracy of $Z=aR^b$ should be derived from various locations with the consideration of the variability of factors *a* and *b*.

Both radar reflectivity and rainfall rate depend on the drop size distribution (DSD) which may be varied spatially and temporally and also depends on weather systems. The frequently used DSDs is the exponential distribution $Z=200R^{1.6}$ proposed by Marshall and Palmer [27]. On the other hand, Battan [28] listed 69 different Z-R relations for different climatic conditions in various parts of the world. Additionally, the variability of DSDs in both time and space has a different effect on the accuracy of radar rainfall estimation as reported by [12, 13, 29]. [11, 28] established the storm-to-storm variability of Z-R relation and the variability within a storm as reported in [2, 23, 24]. [30] analyzed the uncertainty of Z-R relation and found that it was caused not only by the natural variability of the DSDs but also by the variations of radar measurements e.g. bright band contamination [31], attenuation [17], range degradation [9, 20]. [32] provided review of principal sources of errors affecting single polarization of radar-based rainfall estimation can not by itself eliminate the problems through the reflectivity measurement process such as radar mis-calibration, ground clutter, beam blocking, and anomalous propagation. Any factors concerning incomplete data of rain intensity, sparse distribution of rain-measuring stations, and types of rain can cause an error of Z-R relation.

Thailand is an agricultural country locating in the tropical region. The accurate weather forecast can help the farmers and agriculturists plan their activities more efficiently. Furthermore, due to the vast size of Thailand, applying a fixed Z-R relation based on the exact values of *a* and *b* to every agriculture areas is obviously inappropriate.

In the past, there were a few studies in Thailand concerning the values *a* and *b* for hydrological model in Northern [19, 33] and for different weather conditions in lower Northeastern [20]. However, those methods are not adaptive to the local atmospheric data at a particular time such as types of cloud and size of forecasting area. In this paper, a new approach to adaptively compute *a* and *b* from local atmospheric and temporal data is introduced. Our approach is based on rule-based classification and regression type analysis to estimate the best values of *a* and *b* in Z-R relation.

Rice is the major agricultural product of Thailand and it is mostly grown in the central part of Thailand. Therefore, we limited our study around the central area of Thailand centered at Nakornsawan province. The reason of selecting Nakornsawan province because there is a weather radar station located at Takhi district in Nakornsawan. The efficiency of our computing technique was validated with the experiments conducted with the data collected from Takhli radar site located in Nakornsawan province during August and September 2007 at 2.5-km height and 240-km range of Constant Altitude Plan Position Indicator (CAPPI) and compared with the other reported relations. In addition, the 2.5-km CAPPI height was set according to [34] and used for all radar sites in Thailand.

The rest of this paper is organized as follows. Section 2 proposes the computational process and data preparation. Determining and collecting computational factor are given in Section 3. Section 4 discusses experimental results and evaluation. Section 5 tests Z-R relation for various rain types. Section 6 estimates Z-R relation using selective stations and similarity measures and Section 7 concludes the paper.

2. PROPOSED CONCEPT AND DATA PREPARATION

2.1 Data Collecting

The experimental area of this research is located within 240 km radar range in Amphure Takhli, Nakornsawan province at an elevation of 254 m above Mean Sea Level (MSL), and latitude 15° 15′ N and longitude 100° 20′ 24″ E. The radar is an S-band METEOR-500S model of 2.78 GHz frequency and 10.8 cm wavelength. It measures rain in terms of radar reflectivity, position and movement of rain over the experimental area. This is a Doppler radar having single polarization capacities with clutter suppression. IIR Doppler filter was adopted to extract the corrected reflectivity (dBZ). The 3-dimensional raw radar data were obtained from 240-km radar range, 360-degree azimuth scan, and the following 13 antenna angle tilts: 0.5°, 1.1°, 1.8°, 2.6°, 3.6°, 4.7°, 6.0°, 7.6°, 9.4°, 11°, 13.9°, 16.7°, 20°. These raw data were composed of corrected reflectivity (dBZ), uncorrected reflectivity (dBuZ), radial velocity (V), and spectrum width (W) moments. The data can be stored the closest radius of 25 km with a height of 10 km and the outmost radius of 240 km with a height of 20 km. Radar and rain gauge observations were collected over Takhli radar site from August 22 to September 20, 2007. The 3D reflectivity data were collected with recording resolution of 6 minutes and rain gauge data were collected by using 33 tipping bucket rain gauges with recording resolution of 1 minute.

2.2 Data Processing

The main objective of this work is to propose a computational algorithm for deriving Z-R relation between radar estimates at the rain gauge locations and the corresponding gauge rainfall amounts from 6-min temporal and 0.96 km/pixel spatial data. Since estimating a highly accurate Z-R relation concerns several factors, using only the data obtained from the observed radar reflectivity and rain gauges are not sufficient. The following factors have also been considered in our proposed technique: rain types, ratio of G/R, cloud types, and rain area. To classify types of rainfall, the criteria introduced by [2] were adopted. In addition, several studies [6, 21, 24, 36] related to convective-stratiform rain.

Tokay and Short [2] showed how DSD and Z-R relation geographically vary with rainfall rates from various types of storm. They presented stratiform-convective classification method based on raindrop spectra and rainfall rate using disdrometer data. The gamma rain DSDs were classified into six different rainfall rate categories including *extreme, very heavy, heavy, moderate, light,* and *very light*. In their study, they also observed a significant change in the gamma parameters during transition from convective to stratiform rain. Average raindrop spectra of convective-stratiform regimes and best-fitted estimate indicated that all three parameters: intercept - N_0 (m^{-3} mm^{-1}), slope - Λ (mm^{-1}), and shape - *m* of the gamma DSDs have lower values in stratiform spectra than in convective spectra for rainfall rate of approximately 5.0 mm/h. This is relevant to our proposed technique.

For cloud type classification, the study of Roger [35] was adapted to our process. Other relevant factors such as intensity, lifetime, and area of rain systems are typically controlled by vertical air motion. Thus it would be better to concentrate on two types of rain, i.e. convective and stratiform rain possibly caused by cumulonimbus, cumulus, and nimbostratus clouds for a better classification result, although the difference between convective and stratiform rain is not always clear. The study of Chumchean et al. [20] related to rain-cloud characteristics using weather radar. Radar measures rain but not cloud [35]. Thus three types of clouds, i.e. *cumulonimbus*, *cumulus*, and *nimbostratus* were considered in our study.

We defined a precipitation area of size larger than 1,200 km^2 as a *large* area and the other size as a *small* area as referred to the result of our experiment in sub-section 3.4. Different cloud types cover different sizes of rain area. Cumulonimbus cloud has the largest rain area compared to cumulus and nimbostratus clouds. Stratiform cloud usually rains in a larger area. In our study, we found that there were dissipating cumulus and orographic clouds producing rain in smaller areas. Furthermore, if the rainfall period is more than or equal to *one* hour, then it is considered as a *long* lifetime rainfall, otherwise it is a *short* lifetime rainfall as referred to the result of our experiment in sub-section 3.3 and stated in Algorithm 3 in Appendix A.

Rain gauges are conventionally used for rain measuring at ground level with high temporal resolution. We considered rain gauge measurement as the actual rain intensity measured in mm/h. However, the incorrect rain measurements could be caused due to the insufficient spatial coverage and gauge density, especially in the mountainous areas. Weather radar can overcome these disadvantages of rain gauges as it provides a rain field with high spatial (here is about 1 km^2) and 6-min temporal resolution as well as large areas coverage. Thus, the combination of weather radar and rain gauge are useful for rainfall measurement.

Let R and G be the radar and gauge rain intensities, respectively. Our computational process consists of the following five steps with their related parameters and attributes:

Step 1: Classifying rain types

The radar and gauge rainfall intensities were computed by Rainbow processing, a standard tool for operational Takhli radar system used to process the raw radar data, in order to compare the radar-derived and gauge rain intensities over the entire radar domain and gauge network. The relation of $Z=200R^{1.6}$ was used as default of Z-R relation in radar rainfall estimation. This relation which commonly describes stratiform rainfall is always used operationally at the Takhli radar site regardless of the rain characteristics even for convective events. The 1-hour time step was used to classify rain types. The radar and rain gauge intensities are obtained on numeric scale. In order to preliminarily classify convective and stratiform rain, the threshold was set to 5 mm/h, but for different rain types, the thresholds were set to 1, 2, 5, 10, 20, and > 20 mm/h for very light, light, moderate, heavy, very heavy, and extreme rain, respectively.

Step 2: Determining radar overestimates or underestimates

The G/R ratios were computed by using of the same set of the intensities as in step 1. This step is to categorize patterns of convective-stratiform rain on numeric scale into radar overestimates and underestimates, based on the justification of G/R ratio.

Step 3: Determining cloud types

The 6-min time step is used to determine cloud types based on lifetime and area of rainfall. The lifetime of rainfall was computed from the PRT output in 6-min consecutive time interval. Rain area was approximated from 6-min CAPPI image data.

Step 4: Computing *a* and *b* coefficients in $Z=aR^b$

The dBZ values were obtained from 6-min CAPPI output corresponding to rain gauge location. Coefficients *a* and *b* are computed from all possible seven cases of possible combinations of G/R ratio, cloud-rain type and rain area. There are seven cases consisting of three Z-R relations (Case 1: extreme, Case 2: very heavy, Case 3: heavy) of convective rain were radar-overestimated and another three Z-R relations (Case 4: extreme, Case 5: very heavy, Case 6: heavy) of convective rain were radar under-estimated. One Z-R relation (Case 7: moderate, light, and very light) of stratiform rain was fixed.

Step 5: Estimating Z-R relation of stations having incomplete data by using similarity measure

The detail of data collecting step will be discussed in the next sub-section and those of steps 1 to 4 are given in Appendix A. Step 5 was proposed to cope with the problem of incomplete data concerning the computation of constants *a* and *b* in Z-R relation and its details will be given in Section 6. Steps 1-4 are based on the assumption that the value of each parameter is available prior to the computational process. If this assumption is not true at some stations, the technique stated in the step 5 is applied. Figure 1 shows the input and output from each step when all of them are consecutively executed.

3. DETERMINING AND COLLECTING COMPUTATIONAL FACTORS

3.1 Amount of Convective and Stratiform Rain Data

With respect to radar detection and rain gauge measurements, there are three interesting event types concerning the reflectivity-based QPE detected by radar and amount of rain measured from rain gauge at each station as follows:

i. Event type 1: radar detected but rain gauge not registered.

ii. Event type 2: radar not detected but rain gauge registered.

iii. Event type 3: radar detected and rain gauge registered.

Each event was hourly recorded. Our study and experiments considered only the data in event type 3 which have only 1,222 events among all types of 22,077 events. The fixed $Z=200R^{1.6}$ relation referred to as the Marshall-Palmer Z-R relation was used to compare with our computational results.

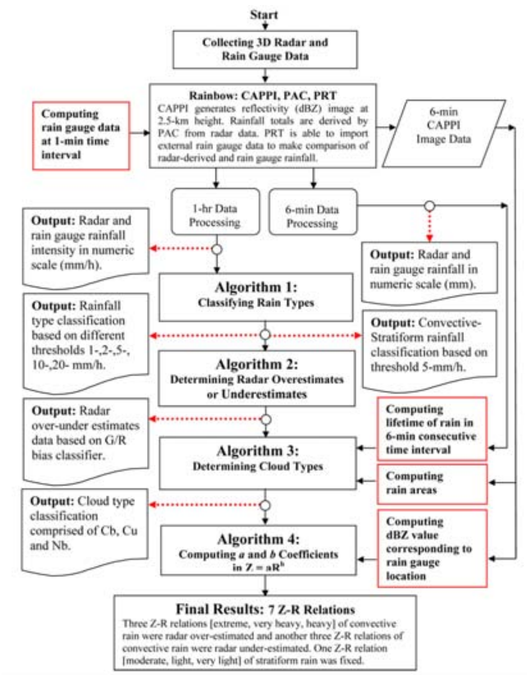

Figure 1. Algorithmic steps of our proposed technique. The thick lines denote the procedural flow and the dotted lines denote the outcomes of each step. The thick arrow denotes the flow of data to the next process and the dotted arrow denotes the flow of data to the reporting process.

At the k^{th} hour, let $R_{k,j}$ be the 1-hour radar-derived rainfall totals (mm) and $G_{k,j}$ be the 1-hour gauge rainfall totals (mm) measured at the j^{th} gauge. Supposing there were N gauges being collected at the k^{th} hour, the ratio G/R factor at the k^{th} hour is defined as:

$$G/R\ ratio = \frac{G_k}{R_k} = \frac{\sum_{j=1}^{N} G_{k,j}}{\sum_{j=1}^{N} R_{k,j}} \qquad (2)$$

The experimental events in convective rain type consisted of 31 extreme (2.5%), 60 very heavy (4.9%), and 109 heavy (8.9%). But in case of stratiform rain type, the events were 217 moderate (17.8%), 223 light (18.2%), and 582 very light (47.6%). A threshold value of 5 mm/h gauge rainfall intensity as suggested by [2] was used to distinguish convective and stratiform rain types as stated in Step 1 (Algorithm 1 in Appendix A).

However, Steiner et al. [23] and Sempere-Torres et al. [36] identified the type of precipitation of different precipitation systems over the radar domain at a pixel scale. Their method tends to overestimate the area identified as convective precipitation. The difference is our presented method tends to underestimate the area identified as convective precipitation. From the collected data, we justify the average G/R ratios of 1.61, 1.32, and 1.43 as the results of extreme, very heavy, and heavy rainfalls for convective rain type. But the G/R ratios of 1.15, 0.73, and 0.44 were justified as the results of moderate, light, and very light rainfalls for stratiform rain type. Table 1 summarizes the intervals of R values and different G/R.

3.2 Determining Radar Overestimates and Underestimates Based on G/R

Krajewski and Smith [37] defined "bias" as the systematic departure from the true, and unknown rainfall. A systematic difference between gauge rainfall and radar-derived rainfall can be removed using information determined by rain gauges [3, 4, 23, 26, 37, 38]. This is an adjustment factor that is estimated as the ratio of the accumulated gauge rainfall and the accumulated radar-derived rainfall (G/R). Based on the systematic difference between radar and gauge measurements at the same location, it is possible to determine whether the radar overestimates or underestimates the amount of rain. The G/R ratio was deployed in our algorithm to preliminarily justify the overestimate from underestimate for convective rain. In this study, the radar overestimates the amount of rain if G/R ratio is less than 1, otherwise, underestimate occurs when G/R ratio is larger than 1. However, there may be some outlier data in overestimate and underestimate groups that should be eliminated before proceeding to the other steps. To detect these outlier data in each group, the following steps for measuring the correlation of hourly G and R data from the total experimental events are executed. In this study, 42 cycles of the iterative optimization procedure were performed by the justification. The process for G/R justification and outlier elimination is to:

1. compute hourly G/R ratio from all experimental events,

2. preliminarily classify the data in to radar-overestimate group *if* G/R<1 and radar-underestimate group *if* G/R>1,

3. make a scattered plot between hourly radar and gauge rain intensity data set,

4.fit a trend line of regression type with intercept = 0 so as to know the determination of correlation coefficient (r^2) between the data set,

5. *if* there is a less the r^2 of the data (empirically, r^2 is 0.15) *then* filter out each pair of the radar-gauge rain data as outlier data, and

6. repeat step 5 *until* the value of the r^2 is steady so that the justification is completed.

Table 1. The convective-stratiform rain and the ratio of G/R for different rainfall intensity categories.

Rainfall Classification	Category of Rainfall	Rainfall Intensity *R* (mm/h)	No. of Events	% of Events	Radar R(mm)	Gauge G(mm)	G/R Ratio	Avg G/R
Convective	Extreme	20 < R	31	2.5	572.1	923.5	1.61	1.45
	Very Heavy	10 < R ≤ 20	60	4.9	633.9	839.2	1.32	
	Heavy	5 < R ≤ 10	100	8.9	527.2	752.3	1.43	
		R > 5	200	16.4	1,733.2	2,515.0	1.45	
Stratiform	Moderate	2 < R ≤ 5	217	17.8	578.1	662.4	1.15	0.78
	Light	1 < R ≤ 2	223	18.2	403.4	293.4	0.73	
	Very Light	0 < R ≤ 1	582	47.6	548.6	242.6	0.44	
		0 < R ≤ 5	1,022	83.6	1,530.1	1,198.4	0.78	

Figure 2 shows an example of hourly scattered plot between radar and gauge rain intensity dataset in a case of convective rain. There are 200 events for convective rain comprising 50 events of radar overestimate and 150 events of radar underestimate. The x-axis represents radar rain intensity (mm/h) while the y-axis represents gauge rain intensity (mm/h) over the gauge network. Figure 2(a) is the result after step 2 (Algorithm 2 in Appendix A). After eliminating all outlier data, the remaining data of 50 radar overestimate events and 108 radar underestimate events are shown in Figure 2(b). Approximately 21% (42 out of 200 events) were filtered out from all convective rain dataset. The maximum of the r^2 for radar underestimate is 0.75 and for radar overestimate is 0.76. In this study, based on rain intensity 0 < R ≤ 5 mm/h, the G/R bias classifier was not focused in the classification of stratiform rain.

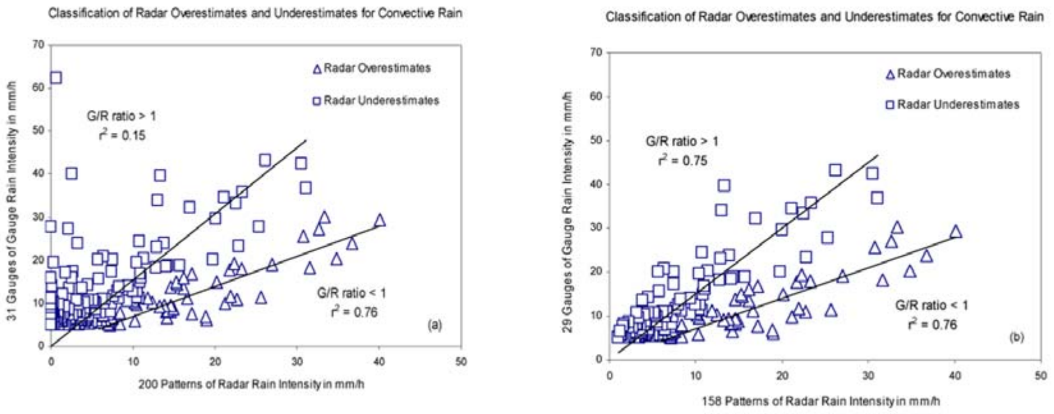

Figure 2. An example of G/R ratio for classifying radar overestimates and radar underestimates of convective rain. (a) The result after preliminarily justifying overestimates and underestimates. (b) The result after outlier elimination by the determination of correlation coefficient (r^2) measure.

3.3 Determining Lifetime of Each Rain Type

Depending on vertical air motion, the lifetime of rain, called *duration of precipitation,* is the time during developing, maturing, and dissipating stages. Although this definition is rather simple, the problem is how to determine the duration of each rain type from the radar and rain gauge measurements. Our algorithm considered the types of cloud as determining factors. Cloud type can be changed according to the course of 6-min time resolution. Here, only the situation when the values of radar and gauge rainfall are non-zero was focused over the entire radar domain for all rain gauge stations. The question is what detection criteria should be used to detect the beginning and ending of each event. Our algorithm of step 3 (Algorithm 3) extracted the occurrences of both radar and rain gauge having continuous rain in different time periods. It was found that the average gauge rainfall intensity produced by cumulonimbus clouds of extreme and very heavy rain were 33 and 15 mm/h. For cumulus cloud, it was 8 mm/h. But the average of moderate, light, and very light rain were 4, 2, and 1 mm/h for nimbostratus clouds. Based on the rain rate, the average lifetime of extreme and very heavy rain were 1 hour 6 minutes and 1 hour for cumulonimbus cloud but the averages of moderate, light, and very light were 30, 24, and 12 minutes for nimbostratus cloud. For cumulus cloud, it is around 42 minutes. Some statistic values of rainfall intensity and lifetime of each rain type are presented in Table 2. The results of this study showed that the lifetimes of rainfall were justified by determining the lifetime of each cloud type. As the result shown in the last column of Table 2, the maximum lifetime of rain is 2 hours 12 minutes for extreme, very heavy, and heavy rain. This is because there is some rainfall events caused a long lifetime of rain due to the present of cumulonimbus clouds which were composed of several large rain cells.

Table 2. Some statistics of rainfall intensity and lifetime of each cloud-rain type.

Classification Criteria		Rainfall Intensity		No. of	Lifetime of Rain (h:mm)			
Cloud Types	Rain Types	R (mm/h)	Avg	Events	Min	Med	Avg	Max
Cumulonimbus	Extreme	$20 < R \leq 54$	33	41	0:24	1:06	1:06	2:12
Cumulonimbus	Very Heavy	$10 < R \leq 20$	15	55	0:18	0:54	1:00	2:12
Cumulus	Heavy	$5 < R \leq 10$	8	67	0:06	0:36	0:42	2:12
Nimbostratus	Moderate	$2 < R \leq 5$	4	116	0:06	0:30	0:30	1:18
Nimbostratus	Light	$1 < R \leq 2$	2	86	0:06	0:24	0:24	0:48
Nimbostratus	Very Light	$0 < R \leq 1$	1	233	0:06	0:12	0:12	0:30

3.4 Determining Rain Area of Each Rain Type

Rain area of each rain type is different. Rain areas based on Algorithm 3 were evaluated by using 144 rainfall events out of 200 events for convective and stratiform rain. This is because, at some gauge stations, there were many rainfall events caused by the same type of cloud. We found that there were 33 events for extreme rain, 33 events for very heavy rain, 39 events for heavy rain, 13 events for moderate rain, 11 events for light rain, and 15 events for very light rain. The average rain areas of extreme, very heavy, heavy, moderate, light, and very light rain were 2, 204, 1,799, 502, 1,139, 102, and 114 km^2, respectively. On the average, rain areas of cumulonimbus, cumulus, and nimbostratus clouds were 2, 067, 502, and 452 km^2, respectively. The average area of all rainfall events was 1,206 km^2. Some examples of the rain types and areas of rain of each event are plotted in Figure 3.

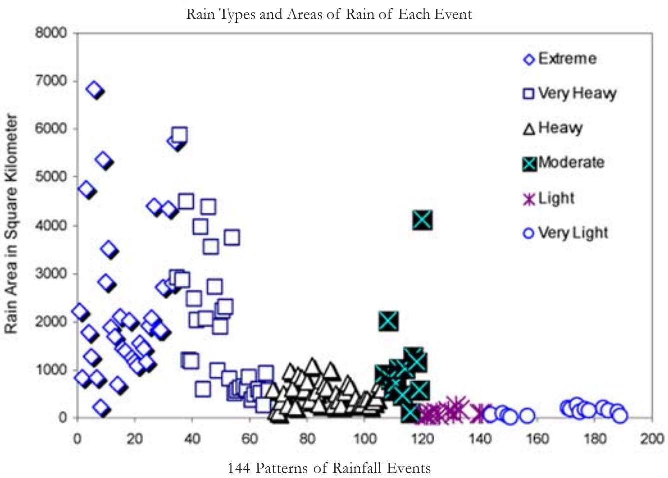

Figure 3. Rain types and areas of rain of each event.

4. EXPERIMENTAL RESULTS AND EVALUATION

4.1 Experimental Sites and Course of Times

To test our algorithm, the data collected from rain gauge stations c30, c11, c13, c12, c26, c33 were selected as the experimental data due to their completeness. A minimum threshold for radar reflectivity and rain gauge dataset is 8 dBZ and 0.254 mm, respectively. The consecutive detecting duration was defined as the period of time when both radar and rain gauge detect the amount of rain.

4.2 Horizontal Characteristics of Each Rain Type

Physical characteristics of horizontal average of each rain type can be explained using the CAPPI radar product. Radar CAPPI volume data can provide information on spatial variables of rain measurement. An example of horizontal characteristics of this radar map from the S-band Takhli radar (at center of circle) and range rings correspond to 60, 120, 180, 240 km was labeled as a cumulonimbus (Cb) cloud situation on August 24, 2007 of station c30 which is located in longitude 99.7958° E and latitude 13.4914° N at an elevation of 22 m above MSL as illustrated in Figure 4(a). An hourly comparison of radar-derived rainfall (R) and rain gauge rainfall (G) of station c30 during 9:01-9:55 UTC, G/R ratio is 0.65, with extreme rainfall type (rainfall intensity = 24 mm/h). Whereas during 10:01-10:55 UTC, G/R ratio is 0.89, with very heavy rainfall type (rainfall intensity = 15 mm/h). The G/R ratio which is less than 1 means that the radar is over-estimated. A problem is zero rainfall on rain gauge during hourly time interval. Here, we optimize them in form of integration of extreme and very heavy rainfall type during 9:43-10:43 UTC, and G/R ratio is equal to 0.74 (G = 43.3 mm/R= 58.6 mm) as illustrated in Figure 4(b). The lifetime of a Cb cloud beginning with developing to mature until dissipating states for radar-derived and gauge rainfall were 1 hour 6 minutes. The question is how to determine Z-R relation which will be described in the next subsection.

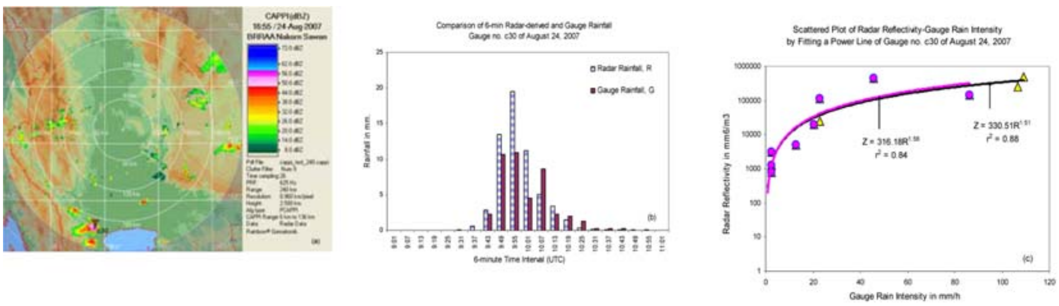

Figure 4. The Z-R relation of very heavy rain type for radar underestimates of convective rain. (a) An example of horizontal characteristics of this radar map was labeled as a Cb cloud situation at gauge no. c30. (b) Comparison of 6-min radar-derived and gauge rainfall of extreme and very heavy rain types. (c) The Z-R relations of a Cb cloud are $Z=330.51R^{1.51}$ and $Z=316.18R^{1.56}$ denoted by triangles and circles symbols.

4.3 Computing Z-R Relation of Each Rain Type

In this paper, our results were compared with the $Z=200R^{1.6}$ relation of [20]. To distinguish between linear and logarithmic expressions for reflectivity, Z was used for the linear value (in mm^6/m^3) and dBZ for the logarithmic value. Therefore, $Z=10^{(dBZ/10)}$ is in unit of mm^6/m^3 and $R=(Z/a)^{(1/b)}$ is in unit of mm/h. The question here is how to determine Z-R relation of 6-min comparison of radar-derived and rain gauge rainfall of station c30. Here is an example of parameters analysis of Z-R relation of a Cb cloud by fitting a power line of extreme rain type; $Z=330.51R^{1.51}$ (black line) denoted by triangles symbol with the r^2 of 0.88 and that of very heavy rain type; $Z=316.18R^{1.56}$ (pink line) denoted by circles symbol with the r^2 of 0.84 as illustrated in Figure 4(c).

Table 3 gives examples of Z values for several rainfall rates, rainfall types and proposed Z-R relation variables. For stratiform rain, there are three reflectivity values, i.e. 24, 28, and 34 dBZ. Each of these values was used to compute Z values shown in the second line under column *Stratiform rain*. Similarly, for convective rain, the reflectivity values are 39, 43.9, and 50.2 dBZ. The Z values were computed from these reflectivity values as shown in the second line under column *Convective rain*. The Z values of both stratiform and convective rain were used further to compute R values based on $Z=200^{1.6}$ relation as denoted in the third line. The fourth line, the values of R was computed by using the values of Z from the second line with selective stations: $Z=195R^{1.61}$ relation as described in Section 6. From the fifth to the last lines, the values of R were computed by using the values of Z from the second line with different Z-R relations. For example, in the fifth line, the values of R were computed under the condition defined in Algorithm 4. Unless the values of R were computed by using the values of Z from the second line based on WSR-88D radar: $Z=300R^{1.4}$ relation as denoted in the eighth line.

Table 3. Reflectivity as a function of rainfall rates, rainfall type and proposed Z-R relation variables.

Topics of Z-R relations	Parameters and Z-R Relations	*Stratiform rain*			*Convective rain*		
		Very Light	Light	Moderate	Heavy	Very Heavy	Extreme
stratified by rain intensity and rain type	Reflectivity, dBZ	24	28	34	39	43.9	50.2
	$Z = 10^{(dBZ/10)}$	251	631	2,512	7,943	24,547	104,713
	$R = (Z/200)^{(1/1.6)}$	1	2	5	10	20	50
Selective station	$R = (Z/195)^{(1/1.61)}$	1	2	5	10	20	50
Case 1	$R = (Z/330)^{(1/1.51)}$	1	2	4	8	17	45
Case 2	$R = (Z/316)^{(1/1.56)}$	1	2	4	8	16	41
Case 3	$R = (Z/163)^{(1/1.76)}$	1	2	5	9	17	39
WSR-88D radar	$R = (Z/300)^{(1/1.4)}$	1	2	5	10	23	66
Case 4	$R = (Z/255)^{(1/1.40)}$	1	2	5	12	26	74
Case 5	$R = (Z/250)^{(1/1.31)}$	1	2	6	14	33	100
Case 6	$R = (Z/226)^{(1/1.26)}$	1	2	7	17	41	131
Case 7	$R = (Z/305)^{(1/1.52)}$	1	2	4	9	18	47

4.4 Error Evaluation of Proposed Z-R Relations

Cross validation was performed in order to avoid biased experiments in a generic situation. Six rain gauges were used to adjust the final radar-derived rainfall. Different Z-R relations were used to estimate radar rainfall of the Takhli radar. The accuracy of each Z-R relation was evaluated by comparing the radar-derived rainfall with the corresponding rain gauge data. The errors of radar rainfall estimates were presented in terms of Mean Absolute Error (MAE) between radar-derived rainfall and rain gauge rainfall. The MAE is defined as follows:

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|f_i - y_i| \quad (3)$$

f_i is the prediction (radar rainfall estimation) and y_i is the true value (rain gauge rainfall). Moreover, the mean field biases (G/R ratio) of each rain type were also evaluated. Hence, the percentage of error produced by the Z-R relation will be measured in terms of G/R with respect to G/R=1. The evaluation will be separately discussed for convective and stratiform rain as follows.

4.4.1 Accuracy of Z-R relation in convective rain case

The accuracy of our proposed Z-R relation of each rain type based on criteria of radar overestimate and radar underestimate was evaluated, and the details are presented in Table 4. For convective rain in case of radar overestimate, the last column indicates the percentage error between radar-derived rainfall and rain gauge rainfall in terms of MAE. The Z-R relations proposed in this study in rows 2 to 4 in Table 4 give G/R ratios closer to one than the G/R ratio from Takhli radar (1st row). In case of radar underestimate for convective rain, it can be seen again that our proposed Z-R relations in rows 8 to 10 give less error than Z-R relation from both Takhli (7th row) and WSR-88D radars (13th row).

Table 4. The accuracy of proposed Z-R relations in case of radar overestimates (G/R<1) and radar underestimates (G/R>1) for convective rain. The accuracy of proposed Z-R relation for stratiform rain.

Row No.	Rainfall Classification	Z-R Relations	No. /Out of Events	% Correct Estimates	Radar R(mm)	Gauge G(mm)	G/R Ratio	% Error (MAE)
1.	Takhli radar	$Z = 200R^{1.6}$	50/50	-	17.2	12.2	0.71	26
2.	Extreme	$Z = 330R^{1.51}$	5/6	83	31.7	27.3	0.86	13
3.	Very Heavy	$Z = 316R^{1.56}$	14/19	74	17.1	14.6	0.86	11
4.	Heavy	$Z = 163R^{1.76}$	21/25	84	9.6	7.4	0.77	19
5.	All Events	$Z = 163R^{1.76}$	40/50	80	14.5	11.8	0.82	18
6.	G/R<1	$Z = 200R^{1.6}$	10/50	20	14.6	13.9	0.95	4
7.	Takhli radar	$Z = 200R^{1.6}$	101/101	-	8.2	13.3	1.62	79
8.	Extreme	$Z = 255R^{1.40}$	17/20	85	24.6	29.3	1.19	26
9.	Very Heavy	$Z = 250R^{1.31}$	23/30	77	12.6	14.0	1.11	16
10.	Heavy	$Z = 226R^{1.26}$	41/51	80	6.3	6.9	1.09	22
11.	All Events	$Z = 250R^{1.31}$	82/101	81	12.0	13.4	1.11	35
12.	G/R>1	$Z = 200R^{1.6}$	5/101	5	17.8	18.5	1.04	4
13.	WSR-88D radar	$Z = 300R^{1.4}$	73/101	72	10.3	14.8	1.44	63
14.	Takhli radar	$Z = 200R^{1.6}$	1,022/1,022	-	1,537.1	1,198.4	0.76	24
15.	Proposed Z-R	$Z = 305R^{1.52}$	1,022/1,022	-	1,314.0	1,198.4	0.91	9
16.	Reference Z-R	$Z = 316R^{1.5}$	1,022/1,022	-	1,313.5	1,198.4	0.91	9
17.	WSR-88D radar	$Z = 200R^{1.6}$	1,022/1,022	-	1,559.1	1,198.4	0.77	23

4.4.2 Accuracy of Z-R relation in stratiform rain case

Steiner and Smith [11] computed the parameters of $Z=aR^b$ using several years of disdrometer data. They concluded that the parameter b=1.5 was appropriate. From [10, 22], the Z-R relation of stratiform rain was set to $Z=316R^{1.5}$. In this analysis, the Z-R relation was used for converting radar reflectivity into rainfall intensity with a=305 and b=1.52 for stratiform rain as shown in Table 4. The results in the last column gave less error than Z-R relation from both Takhli radar (14th row) and WSR-88D radar (in the last row) and at least equal to the reference Z-R relation (16th row).

4.5 Selecting Suitable Z-R Relations

The optimal Z-R relation for each rain type was chosen to minimize MAE. It is clear from Table 4 that G/R ratio varies with rain types. The G/R ratios obtained from our proposed Z-R relations were closer to 1 than the others' obtained by using $Z=200R^{1.6}$ of [27] and $Z=300R^{1.4}$ of [39]. Therefore, we can conclude that radar rainfall estimate of the experimental area based on our proposed Z-R relations gave more accurate rainfall amount than the amount estimated from the above mentioned two equations.

To signify our result, we compared our results with others' Z-R relations. We considered the data of 24-hour rainfall on entire experimental days. The accuracy can be easily measured by using the ratio of G/R. The MAE obtained from the proposed Z-R relations gave more accurate than the $Z=200R^{1.6}$ and $Z=300R^{1.4}$ relations by approximately 18% and 15%, respectively.

5. TESTING Z-R RELATION IN DIFFERENT RAIN TYPES

We used rain intensity classification and distinguished between stratiform (moderate, light, and very light) and convective (extreme, very heavy, and heavy) rain. In this section, we derived the Z-R relation without considering the rain type. In addition, our computation of Z-R relation is statistics-based, implying that the more available data are collected, the higher accuracy of the Z-R relation can be achieved. Therefore, to resolve the effect of small amount available data, we conducted another experiment by combining all data from every rain rate of each rain type. The probability matching method (PMM) was developed to match non-synchronous dataset of Z and R using cumulative density function (CDF) [40]. Rosenfeld et al. [21] applied the PMM using synchronous time series of radar and rain gauge measurements. The timing errors were eliminated because the PMM did not use the actual time at which each count of R or Z intensity occurred. The calculations of Z-R relation with PMM became simple by the unconditional cumulative probabilities of Z and R matching. In practice, the two datasets of Z and R were sorted and a given of Z value was associated with the R at the same percentile. However, Krajewski and Smith [18] found that the regression method was still significantly superior, providing higher rainfall-estimates accuracy as compared to the PMM. The advantage of regression technique is that this method represents the real physical process of rainfall.

Our Z-R relation was computed by using regression analysis technique and compared with the *PMM*, $Z=200R^{1.6}$, and $Z=300R^{1.4}$. All the data were collected from rainfall events during August 22 to September 20, 2007 in an hourly time interval. There were 14 rainfall events for radar overestimate of *convective rain* and 28 rainfall events for radar underestimate of *convective rain*. But there were 11 *stratiform rain* rainfall events in which the rainfall was over-underestimated. It is obvious from Table 5 that the average reflectivities of convective and stratiform rain were 40 and 34 dBZ. The average rain intensities for convective and stratiform rain were 20 and 5 mm/h, respectively.

Table 5 summarizes statistical Z-R relations based on each cloud-rain type and ensemble of all rain rates. The Z-R relations of *convective rain* for radar overestimate was $Z=243.08R^{1.60}$ and that for radar underestimate was $Z=184.06R^{1.42}$ with the r^2 of 0.74. The Z-R relations of *stratiform rain* for radar over-underestimate was $Z=247.87R^{1.53}$ with the r^2 of 0.72.

Table 5. Separate statistical Z-R relations based on each cloud-rain type and ensemble of all rain intensities.

Rainfall Classification	Cloud Types	Rain Types	No. of Events (Data points)	Reflectivity (dBZ)	Rain Intensity (mm/h)	Z-R Relations	r^2 Values
Convective (G/R<1)	Cb	Extreme	5 (40)	44.9	33	$Z = 328R^{1.52}$	0.79
	Cb	Very Heavy	6 (69)	40.3	15	$Z = 241R^{1.60}$	0.65
	Cu	Heavy	3 (21)	36.1	7	$Z = 176R^{1.71}$	0.63
		Ensemble	14 (130)	41.1	20	$Z = 243R^{1.60}$	0.74
Convective (G/R>1)	Cb	Extreme	10 (84)	41.1	32	$Z = 328R^{1.52}$	0.79
	Cb	Very Heavy	9 (64)	37.7	17	$Z = 241R^{1.60}$	0.65
	Cu	Heavy	9 (104)	34.7	10	$Z = 176R^{1.71}$	0.63
		Ensemble	28 (252)	37.6	20	$Z = 184R^{1.42}$	0.74
Stratiform	Nb	Ensemble	11 (71)	33.8	5	$Z = 248R^{1.53}$	0.72

The comparison of radar-derived rainfall and gauge rainfall data for different Z-R relations and different methods was conducted and shown in Table 6. The last column of the table indicates that our proposed method gave G/R ratios closer to one and achieved the MAE among four Z-R relations. When compared with $Z=200R^{1.6}$ and $Z=300R^{1.4}$, our results for ensemble of convective (radar overestimate) rain data, convective (radar underestimate) rain data, and stratiform rain data achieved more improvement by approximately 14%, 48%, and 12%, respectively. In addition, when compared with the PMM, our results for ensemble of radar overestimated convective rain data, radar underestimated convective rain data, and stratiform rain achieved more improvement by approximately 29%, 3%, and 8%, respectively.

To signify our experiments on ensemble of all rain rates for Z-R relation, we applied this technique to the data of 24-hour rainfall on entire experimental days. The MAE obtained from the ensemble Z-R relation gave more precise than the $Z=200R^{1.6}$ and $Z=300R^{1.4}$ relations by approximately 21% and 18%.

Table 6. Comparison of G/R ratio (% MAE) of our proposed Z-R relations for ensemble convective and stratiform rain data.

Rainfall Classification	PMM Rosenfeld (1993)	G/R Ratio (% MAE)	$Z = 200R^{1.6}$ M-P Relation	$Z = 300R^{1.4}$ WSR-88D	Proposed Z-R Relations	G/R Ratio (% MAE)
Ensemble Convective (G/R<1)	$Z = 56R^{1.81}$	0.53 (47)	0.74 (26)	0.62 (38)	$Z = 243R^{1.60}$	0.82 (18)
Ensemble Convective (G/R>1)	$Z = 63R^{1.82}$	1.22 (22)	1.71 (71)	1.62 (62)	$Z = 184R^{1.42}$	1.19 (19)
Ensemble Stratiform (G/R>1 or G/R<1)	$Z = 192R^{1.78}$	0.82 (18)	0.75 (25)	0.74 (26)	$Z = 248R^{1.53}$	0.90 (10)

6. Estimating Z-R Relation Using Selective Stations and Similarity Measures

Suppose station α has incomplete data which cannot be used in our Z-R computational process. Some neighboring stations having similar radar reflectivity pattern and gauge rainfall intensity to station α will be considered as candidate stations for assisting the computational process of Z-R relation. The Z-R relation of each candidate station is used to estimate the Z value based on the existing R value of station. The Z-R relation of any candidate station providing the minimum error of Z values will be used as the Z-R relation for station. However, the problem is how to measure the similarity of radar reflectivity and gauge rain intensity.

Let $X_i = [x_{i,1}\ x_{i,2}\ \ldots\ x_{i,n}]^T$ be radar reflectivity pattern of rainfall collected during *n* unit times at station *i*. $x_{i,1}$ is the amount of rainfall measured at the beginning of collection and is the amount of rainfall measured at the end of collection. The radar reflectivity pattern X_i can be viewed as a vector in *n* dimensions. Thus, the similarity of two radar reflectivity vectors X_1 and X_k, denoted by $S_{i,k}$, can be measured in terms of *cosine* values between vectors X_i and X_k as follows.

$$S_{i,k} = \frac{X_i \cdot X_k}{||X_i||\,||X_k||} \tag{4}$$

The use of $Z=200R^{1.6}$ to the hourly comparison of radar-derived and gauge rainfall at central gauge no. c21 gave a G/R ratio of 0.92 (G= 9.7 mm/R=10.4 mm). At the same time, the G/R ratio of neighboring gauge no. c18 was 0.94 (G=7.9 mm and R=8.4 mm) and gauge no. c17 was 0.76 (G=5.3 mm and R=7.0 mm). All three stations had heavy rainfall type. Other neighboring gauges c02, c16, c23 had no radar rainfall and c06 had no rain gauge and radar rainfall. Also, neighboring gauge no. c20 had very heavy rainfall type with separate Z-R relation $Z=270.91R^{1.52}$.

An example of central gauge and neighboring gauges are shown in Figure 5 and the following is the result of similarity measures of radar reflectivity pattern of central and neighboring gauges and the corresponding rain gauge rainfall pattern are illustrated in Figure 6. The Z-R relations of c21 was defined by $Z=194.64R^{1.61}$ with the r^2 of 0.74. But the Z-R relations of c18 and c17 were defined by $Z=182.89R^{1.77}$ and $Z=189.0R^{1.60}$ with the r^2 of 0.53 and 0.57. The values of similarity measures (SM) of pair c18-c21 and c17-c21 were 0.86 and 0.72. For example, the *vector* values which stand for normalized values of radar reflectivity (mm^6/m^3), and gauge rain intensity (mm/h) of gauge c18 is $[0.1\ 0.2, 0.1\ 0.2, 0.4\ 0.7, 1.0\ 1.0, 0.6\ 0.8, 0.1\ 0.7, 0\ 0.5, 0\ 0.3, 0\ 0.2, 0\ 0.2, 0\ 0.2, 0\ 0, 0\ 0]^T$ and that of gauge c21 is $[0\ 0, 0\ 0, 0.7\ 0.6, 1.0\ 1.0, 0.2\ 0.4, 0.1\ 0.4, 0\ 0.1, 0\ 0.1, 0.1\ 0.3, 0.1\ 0.3, 0.1\ 0.5, 0.1\ 0.3, 0.2\ 0.4]^T$. Their similarity measure is $\frac{3.66}{\sqrt{4.67}\cdot\sqrt{3.88}} = 0.86$

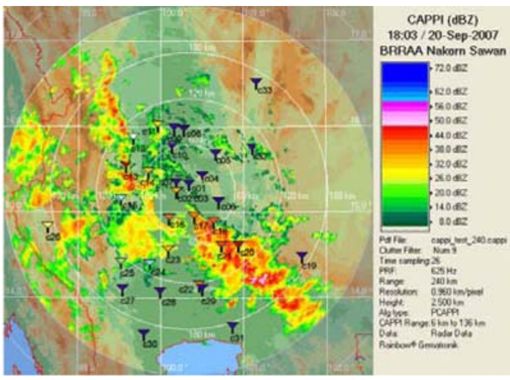

Figure 5. An example of the CAPPI and PRT Rainbow product comprised of central gauge no. c21 and its neighboring gauges within radar domain.

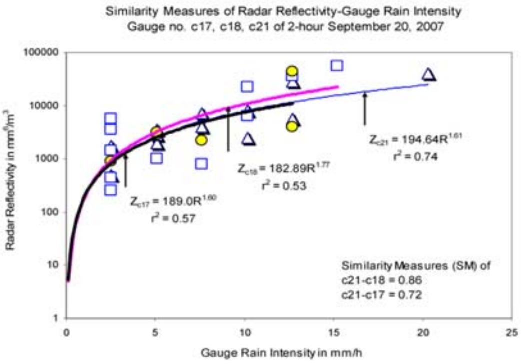

Figure 6. Similarity Measure (SM) of radar reectivity and gauge rain intensity of central gauge no. c21 and its neighboring gauges no. c18, c17 with SM of 0.86, 0.72. The Z-R relations are Z_{c21}= 194.64$R^{1.61}$, Z_{c18}= 182.89$R^{1.77}$ and Z_{c17}= 189.0$R^{1.60}$ denoted by triangles, squares and circles symbols, respectively.

After testing the use of Z=194.64$R^{1.61}$ based on the hourly comparison of radar-derived and gauge rainfall for center gauge c21 and its neighboring c18 and c17, the G/R ratios of the gauges were 0.92, 0.94 and 0.76, respectively. While the use of Z=182.89$R^{1.77}$ gave G/R ratio of 1.18, 1.13 and 0.96, the use of Z=189.00$R^{1.60}$ gave G/R ratio of 0.89, 0.92 and 0.74. The Z-R relation was measured in terms of G/R ratio with respect to G/R=1. Therefore, the suitable Z-R relations of Z=194.64$R^{1.61}$ can be used as the representative of our experiment.

7. CONCLUSIONS

Two new concepts for adaptively estimating the coefficients *a* and *b* of Z-R relations according to the present weather conditions were proposed. In the first concept, a new feasible computational process to derive Z-R relation based on parameters obtained from radar reflectivity and rain gauge data, rain intensity, cloud-rain type, lifetime of rain, and rain area, was proposed. The process was tested with the data obtained from Takhli radar station in Nakornsawan, Thailand. The adaptive Z-R relations derived by our proposed computation process achieved higher accuracy than the fixed Z-R relations previously suggested by others' in terms of G/R ratio. The following results were obtained.

1.For convective rain, the value of *b* parameter is in between 1.5 to 1.8 when radar overestimates and between 1.2 to 1.4 when radar underestimates.

2. For cumulonimbus and cumulus clouds, the value of *b* parameter increased if the value of *a* tended to decrease when radar overestimates. But in case of radar underestimates, the values of *a* and *b* parameters were slightly decreased.

3.The Z-R relation of stratiform rain is fixed, i.e. Z=305$R^{1.52}$ obtained from this research. Additionally, the Marshall-Palmer relation can be used.

4.The use of seven Z-R relations for cross-over validation of each rain type to estimate radar rainfall gave more accurate rainfall than that estimated from Z=200$R^{1.6}$ and Z=300$R^{1.4}$ by approximately 20% in terms of mean average error measure.

5.The use of ensemble Z-R relations to estimate radar rainfall gave more accurate rainfall than that estimated from Z=200$R^{1.6}$ and Z=300$R^{1.4}$, and the probability matching method by approximately 10-30%.

In the second concept, the problem of incomplete data was studied and solved by using a newly proposed rainfall similarity measure. At any station, the computation process of Z-R relation may not be efficient if the collected data are incomplete. In this situation, a feasible technique of similarity measure of radar reflectivity and rainfall between two neighboring stations was introduced. The similarity value is used to select the appropriate gauge to represent a gauge with incomplete data.

The proposed method helped to achieve the higher accuracy for estimating amount of rain from radar reflectivity corresponding to spatial and temporal variability of rain intensity. It is also possible to temporally run the algorithm with new data in real time since the problem is not a time series prediction.

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REFERENCES

[1] Yin Y., Levin Z., Reisin T.G. and Tzivion S., *J. Appl. Meteor.*, 2001; **40**: 1654-1661.

[2] Tokay A. and Short D.A., *J. Appl. Meteor.*, 1996; **35**: 355-371.

[3] Baeck M.L. and Smith J.A., *Weather and Forecasting*, 1998; **13**: 416-436.

[4] Anagnostou E.N. and Krajewski W.F., *Weather and Forecasting*, 1998; **13**: 396-406.

[5] Atlas D., Ulbrich C.W., Marks F.D., Amitai E. and Williams C.R., *J. Geophys. Res.*, 1999; **104**: 6155-6169.

[6] Amitai E., *J. Appl. Meteor.*, 2000; **39**: 2198-2208.

[7] Liu H., Chandrasekar V. and Xu G., *J. Appl. Meteor.*, 2001; **40**: 2038-2050.

[8] Wol D.B., Marks D.A., Amitai E., Silberstein D.S., Fisher B.L., Tokay A., Wang J. and Pippitt J.L., *J. Atmos. Ocean Technol.*, 2005; **22**: 365-379.

[9] Xu X., Howard K. and Zhang J., *J. Hydrometeorol.*, 2008; **9**: 885-902.

[10] Doelling I.G., Joss J. and Reidl J., *Atmos. Res.*, 1998; **48**: 635-649.

[11] Steiner M. and Smith J. A., *J. Appl. Meteor.*, 2000; **39**: 1923-1940.

[12] Lee G.W. and Zawadzki I., *J. Appl. Meteor.*, 2005; **44**: 241-255.

[13] Lee G.W., Seed A.W. and Zawadzki I., *J. Hydrol.*, 2006; **328**: 83-97.

[14] Kumar L.S., Lee Y.H., Yeo J.X. and Ong J.T., *Prog. Electromag. Res. B*, 2011; **32**: 107-127.

[15] Chen B., Yang J. and Pu J., *J. Meteorol. Soc. Japan*, 2013; **91**: 215-227.

[16] Vanaja S.J., Mudgal B.V. and Thampi S.B., *MAUSAM*, 2014; **65**: 49-56.

[17] Yeo J.X., Lee Y.H. and Ong J.T., *Int. J. Electron. Commun. (AEU)*, 2015; **69**: 458-461.

[18] Krajewski W.F. and Smith J.A., *J. Appl. Meteor.*, 1991; **30**: 1436-1445.

[19] Mapiam P.P. and Sriwongsitanon N., *ScienceAsia*, 2008; **34**: 215-222.

[20] Chumchean S., Aungsuratana P., Khommuang A. and Hanchoowong R., *18th World IMACS/MODSIM Congress, Cairns, Australia*, 13-17 July 2009, http://mssanz.org.au/modsim09.

[21] Rosenfeld D., Wol D.B. and Atlas D., *J. Appl. Meteor.*, 1993; **32**: 50-72.

[22] Christodoulou C.I. and Michaelides S.C., *Adv. Geosci.*, 2007; **10**: 111-115.

[23] Steiner M., House R.A. and Yuter S.E., *J. Appl. Meteor.*, 1995; **34**: 1978-2007.

[24] Uijlenhoet R., Steiner M. and Smith J.A., *J. Hydrometeorol.*, 2003; **4**: 43-61.

[25] Wesson S.M. and Pegram G.G.S., *Nat. Hazards Earth Syst. Sci.*, 2006; **6**: 323-342.

[26] Chumchean S., Sharma A. and Seed A., *J. Atmos. Ocean Technol.*, 2006; **23**: 67-79.

[27] Marshall J.S. and Palmer W.M., *J. Meteor.*, 1948; **5**: 165-166.

[28] Battan L.J., *Radar Observation of The Atmosphere*, University of Chicago Press, Chicago, 1973.

[29] Zawadzki I., *The 22nd Conference on Radar Meteorology*, Zurich, Switzerland, 1984.

[30] Tapiador F.J., Checa R. and Castro de M., *Geophys. Res. Lett.*, 2010. DOI 10.1029/2010GL044120.

[31] Leary A. and Houze A., *J. Appl. Meteor.*, 1978; **36**: 437-457.

[32] Villarini G. and Krajewski W.F., *Serv. Geophys.*, 2010; **31**: 107-129.

[33] Piman T., Babel M.S., Gupta A.D. and Weesakul S., *Hydrol. Earth Syst. Sci.*, 2007; **11**: 1361-1372.

[34] Silverman B.A., Hartzell C.L., Woodley W.L. and Rosenfeld D., Thailand applied atmospheric resource research program, Demonstration project design, *Bureau of Reclamation, U.S. Dept. of the Interior*, Denver, CO, **2**, 183 p., 1994.

[35] Rogers R.R., *A Short Course in Cloud Physics*, 2nd Edn., International Series in Natural Philosophy, **96**, 235 p., 1979.

[36] Sempere-Torres D., Sanchez-Diezma R., Zawadzki I. and Creutin J. D., *Phys. Chem. Earth Pt B*, 2000; **25**: 985-990.

[37] Krajewski W.F. and Smith J.A., *Adv. Water Resour.*, 2002; **25**: 1387-1394.

[38] Steiner M., Smith J.A., Burger S.J., Alonso C.V. and Darden R.W., *Water Resour. Res.*, 1999; **35**: 2487-2503.

[39] Fulton R.A., Breidenbach J.P., Seo D.J. and Miller D.A., *J. Weather and Forecasting*, 1998; **13**: 377-395.

[40] Calheiros R.V. and Zawadzki I., *J. Climate Appl. Meteor.*, 1987; **26**: 118-132.