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Using GIS Buffer Technique to Improve Rainfall-Radar Reflectivity Relationship Estimation

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Abstract: - In Past decade, Thailand has regularly faced the problem of flash flood and landslides, especially over the lower Northern part of the country. This area is mountainous area where there is the problem of raingage scarcity and absence. In order to construct the effective warning system, the appropriate rainfall estimation should be first developed. Thus, this research was implemented based on the concept of using information from radar to detect rainfall in order to solve the problem of information lacking over ungaged area. This research was setup under the collaboration among Naresuan University, Thai Meteorological Department and Royal Irrigation Department. The objective of the research is to estimate the rainfall (R) from Z-R relationship by using the measured reflectivity (Z) from radar station located at the middle of flash flood risky area in Lower Northern Thailand. Coupling GIS technique with probability matching, the Spatial Probability Technique (SPT) and Buffer Probability Technique (BPT) were developed to evaluate the appropriate Z-R pair for Z-R relationship analysis. From both techniques, the obtained Z-R relationship can be expressed in form of $Z = aR^b$, where a, b are Function Parameters, as the previous studies. Comparing between these two techniques on rainfall detecting from reflectivity, the obtained R^2 from both processes are slightly difference, whereas, BPT provided less standard error of estimation. However, this study emphasized only on the Z-R relationship, the further study should be done with the other parameters to support the disaster warning system in the future

Key-Words: - Rainfall, Radar, Reflectivity, Z-R Relationship, Buffer, Spatial, Ungauged area

1 Introduction

In past decade, the flash flood and landslide have occurred more often over the Lower Northern Thailand which caused both losses in lives and properties. Thai government has been tried to develop appropriate warning system in order to prevent the losses from these disaster. The effective warning system needs the real time accuracy rainfall detection; however, these disasters usually occur over the mountainous area which there is the problem of rain gauge scarcity and absences. To consider the rainfall over these ungauged areas, the process of applying the radar reflectivity to detect the rainfall over the flash flood risky area is one of the attractive approaches. There are many attempts to develop the accuracy process of rainfall prediction using information obtained from radar [1],[2],[3],[4],[5]. Moreover, radar measured rainfall have been applied widely to several hydrological and environmental modeling, including real-time hydrological forecast. [6],[7],[8],[9].

In Thailand, the radar stations had been installed distributed over the country, of which the active radius covers the whole area, as shown in Fig.1. Table 1 show the Band type and active radius area for the radar network in Thailand. Even though, Thai Meteorological Department (TMD) provides the weather radar data via its website of www.tmd.go.th, the application of information from radar is very limited in Thailand. Most of the researches on radar application have been undertaken for Bangkok area and the pilot area where there is dense network of automatic rain gauges [10],[11]. This study, therefore, emphasizes on the process of detecting rainfall (R) from radar reflectivity (Z) by using the radar data from the Phitsanulok station (station 3 in Table 1) located in the middle of lower Northern Thailand where the highly flash flood risky area is. Unfortunately, the radar reflectivity obtained from this station is on hourly basis, whereas the rainfall obtained from rain gauged distributed over the area is on 15-minute basis. The rainfall data therefore need to be aggregated into hourly basis prior to analysis process. In this study, analysis techniques of Spatial Probability Technique (SPT) and Buffer Probability Technique (BPT) were developed based on GIS buffer technique and the concept of Probability Matching Method (PMM) to estimate Z-R relationship.

The project was set under the collaboration among Thai Meteorological Department (TMD), Royal Irrigation Department (RID) and Naresuan University (NU) obtained the financial support from National Research Council of Thailand (NRCT). The objective of the study is to process the corresponding radar reflectivity with the gauge measured rainfall and estimate Z-R relationship by using two techniques of SPT and BPT.

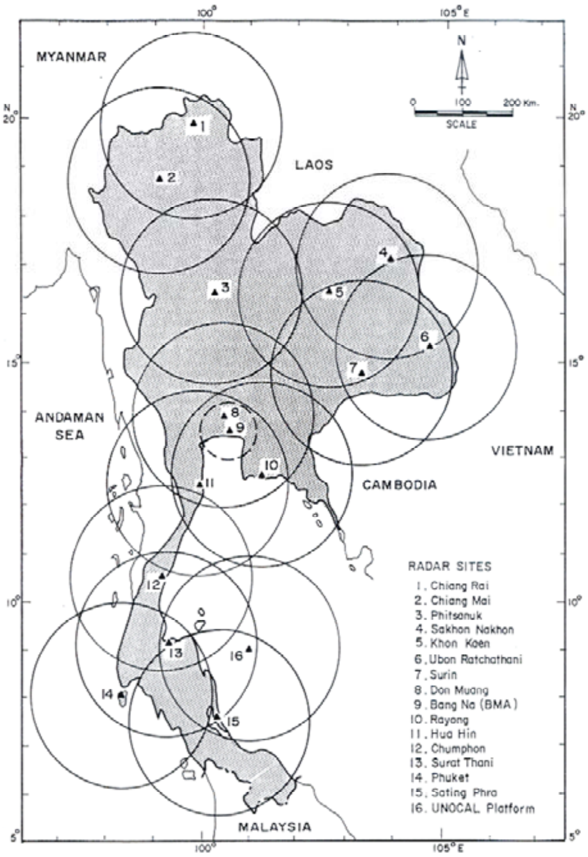


Fig. 1 Radar Network in Thailand

Source: TMD

2 Used Data and Study Process

2.1 Study Area and Used Data

The selected study area is the flash flood risky area in the Lower Northern Thailand. This area comprises of 8 provinces of which the spatial rainfall characteristics of average annual rainfall over the area are shown in Fig.2.

Table 1 Radar Stations in Thailand

Station	Band	Maximum Range (km)	Installed
1. Chiang Rai	C	460	1994
2. Chiang Mai	C	450	1982
3. Phitsanulok	C	450	1991
4. Sakon Nakhon	C	460	1977
5. Khon Kaen	S	460	1993
6. Ubon Ratchathani	C	460	1993
7. Surin	S	450	1992
8. Don Muang	S	460	1992
9. Bangna	X	120	1995
10. Rayong	C	450	1992
11. Hua Hin	S	460	1995
12. Chumphon	C	450	1985
13. Surat Thani	S	460	1993
14. Phuket	S	450	1990
15. Sating Phra	C	450	1991
16. UNOCAL	C	480	1990
17. Phasri Charoen	C	-	2005

Source: TMD

In last couple year, there were several flash flood and landslides occurred over mountainous part of the area which caused severe losses for both lives and properties. Thus, Phitsanulok Radar station that located in the middle of the area and 27 rain gauge stations distributed over the area were selected to study. The installed radar at this station is C-type Doppler radar of DWSR-74C; of which active radius is 240 km. Fig.3 shows the active measured area with the locations of studied rain gauge stations. As the radar reflectivity, Z (mm^6/mm^3) commonly varies across many orders of magnitude, therefore Z used in this study is the reflectivity expressed in term of dBz as Equation (1). The radar reflectivity has been measured in hourly basis, whereas the obtained rainfall from automatic gauge stations is in 15-minute basis. Thus, the normalized process to aggregate 15-minute rainfall into hourly rainfall has been done before analyzing process. The rainfall events occurred during August and September 2007 were analyzed in this study.

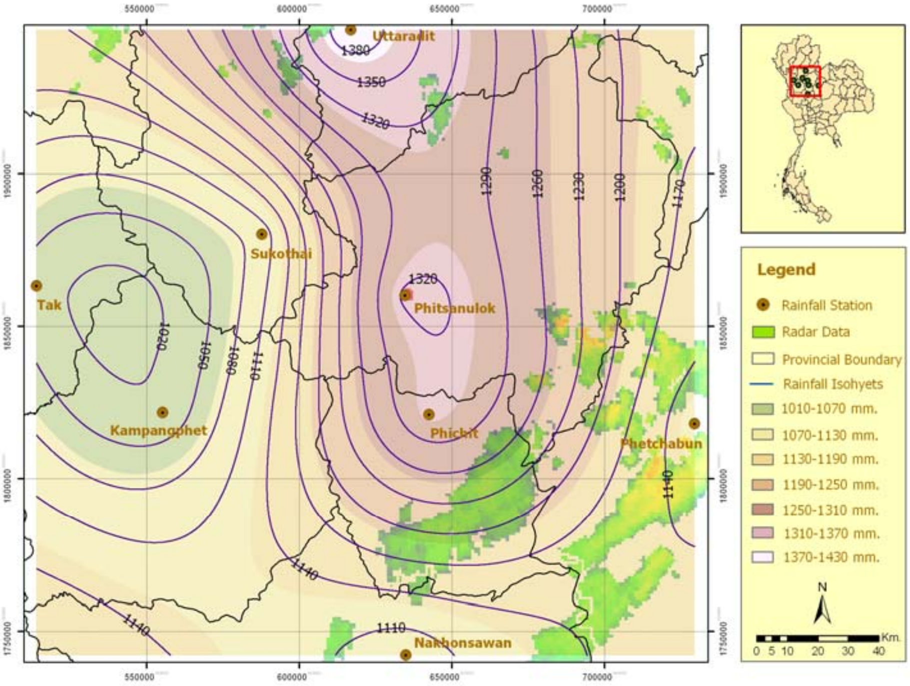


Fig. 2 The spatial Distribution of Annual Rainfall over the Study Area

$$Z(dBz) = 10 \times \log_{10} Z(mm^6 / mm^3) \qquad (1)$$

2.2 Z-R Matching

As Z-R relationships have been widely applied for rainfall estimation, the significant point is the accuracy of the estimation process [2], [3], [12]. There are several Z-R matching techniques have been proposed such as Traditional Matching Method (TMM), Probability Matching Method (PMM), Window Probability Matching Method (WPMM) and Window Correlation Matching Method (WCMM). TMM is the approach that matches the radar reflectivity value on the space vertically with the rainfall from gauge station at the corresponding time of measurement [13]. In this method, it is assumed that there is no effect of the different altitude between radar and rainfall measurement. PMM is the process that the sampling volume, timing and location problems are not taken into account [2]. The matching is done between the Cumulative Distribution Functions (CDFs) of Z values and R from rain gauge measurement as described in Equation (2).

$$\int_{R_i}^{\infty} P(R)dR = \int_{Z_i}^{\infty} P(Z)dZ \qquad (2)$$

where *P(R)* is the probability density function of rainfall from gauge measurement and *P(Z)* is the probability density function of radar reflectivity. The matching of Z and R is done at the same probability level. According that the analysis is done on frequency domain, the timing errors are then eliminated in this method.

WPMM is the process that reduces the error of geometrical mismatch and synchronization in matching [11]. In this process, the obtained Z from space window and the obtained R from time window are processed to contribute to *P(Z)* and *P(R)*. The space window of n × n provides number of Z values as n^2 and the time window of t ± i provides number of R values as 2i+1. This process can increase the number of both Z and R values. The Z-R matching is also done at the same percentile. WCMM is the process that had been further developed from the process of WPMM by extension the possible matching area of Z and optimizing Z for the best corresponding R [11]. WCPP processes Z values from both space and time window, these Z values are then analyzed to find the best corresponding R at time t. The optimal Z-R pair can be evaluated from the maximum correlation coefficient (r) as shown in Equation (3) and (4).

$$r = \frac{\operatorname{cov} ZR}{S_Z S_R} \qquad (3)$$

$$\operatorname{cov} ZR = \frac{\sum_{i=1}^{n}((Z_i - \overline{Z}) \times (R_i - \overline{R}))}{(n-1)} \qquad (4)$$

where Z_i is Z value of non-zero Z-R pair i, R_i is R value of non-zero Z-R pair i, n is the number of non-zero Z-R pair, $\overline{Z}$ and $\overline{R}$ are mean value of *Z* and *R*,

S_Z and S_R are the standard deviation of Z and R, respectively. It can conclude that the matching process is based on the probability matching for all methods except TMM.

2.3 Z-R Relationship

The Z-R relationship can be described by the empirical power law relationship [14],[15] which can be expressed in form of:

$$Z = aR^b \qquad (4)$$

where a and b are coefficients that depend on location and difference in climatology such as season, type of rain. These coefficients are independent on rainfall itself. For equilibrium rainfall condition as steady tropical rain, the linear Z-R relationship was proposed, as well [16].

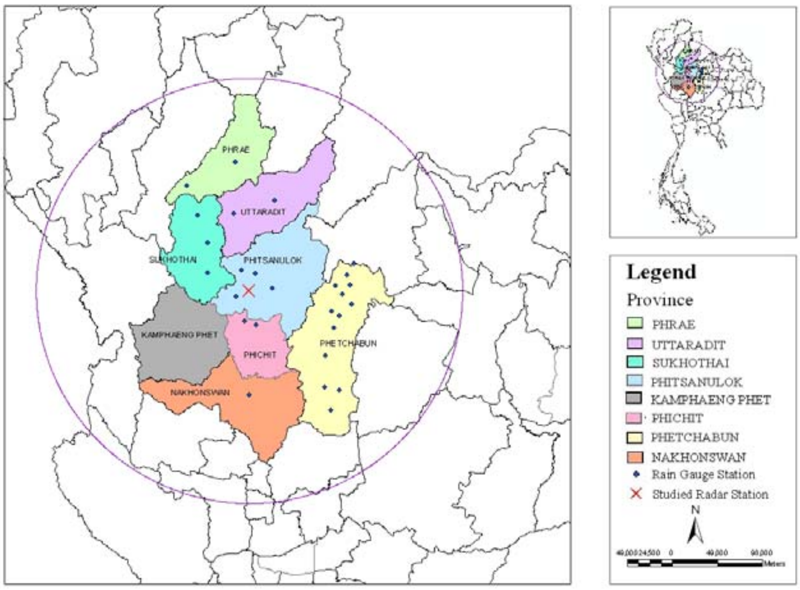


Fig.3 The Active Measured Area with the Locations of Rain Gauge Stations.

2.4 Proposed Studied Techniques

During the study period of August-September 2007, there are very few of the reflectivity-rainfall pairs over the same location at the corresponding time of measurement. In addition, the wind records over the radar station are unavailable. In order to enhance the number of data to be sufficient for analysis, therefore, two techniques of Spatial Probability Technique (SPT) and Buffer Probability Technique had been developed.

SPT is based on the interpolation basic function of GIS to generate radar reflectivity over the rain gauge station at the corresponding time of measurement. In this process, it is assumed that raindrops vertically fall downward. As rainfall (R) is the measured rainfall at time t for a rain gauge location, the reflectivity (Z) can be calculated by GIS Kriging interpolation from the surrounding measured reflectivity data at time t. Then, for any time t, the corresponding data of Z – R can be obtained. However, the wind effect was not taken into account in this process. Thus, the second technique of BPT was developed in order to decrease the error from wind effect.

BPT is based on the buffer basic function of GIS to estimate the radar reflectivity over the rain gauge station at the same time. BPT was developed with the assumption that raindrops may not vertically fall into the rain gauge because of wind effect. To decrease this error, the Z value which corresponds to R value at time t can be calculated from the arithmetic mean of Z values detected at time t within 1 km buffer area above the rain gauge. Fig. 4 shows the buffer constructed over the rain gauge stations. Fig. 5 illustrates the simplified diagram for SPT and BPT over the rain gauge location.

The probability matching as PMM was selected to use for both SPT and BPT in order to avoid the timing error, as well. Therefore, the Cumulative Density Function (CDF) of R and Z were constructed to consider Z-R matching at the same percentile. Both SPT and BPT also match the Z-R pair at the same percentile, as Fig. 6.

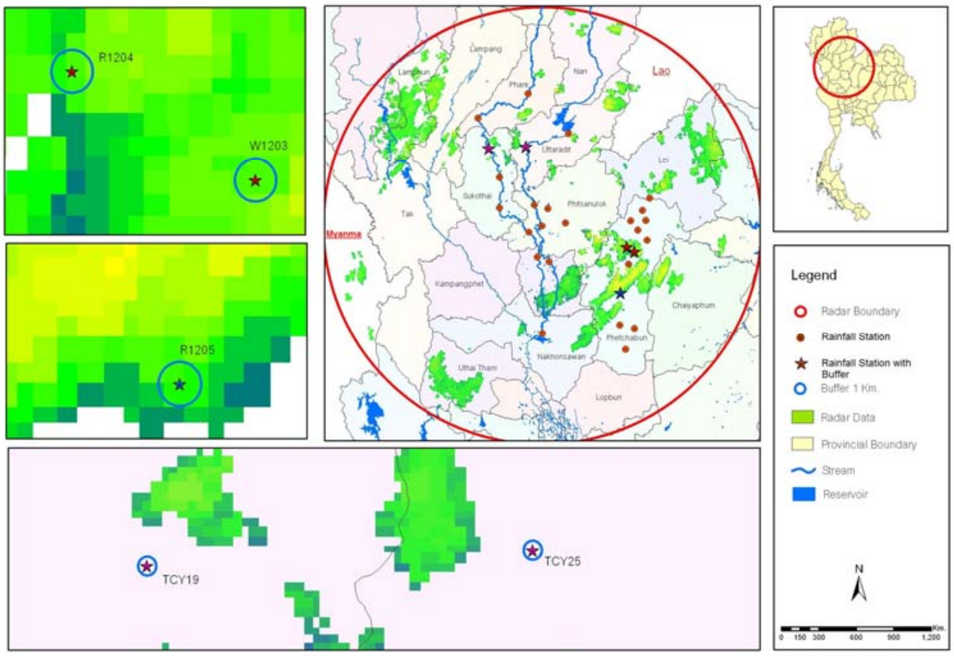
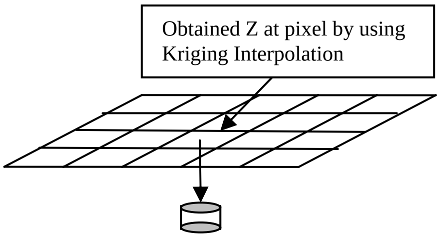
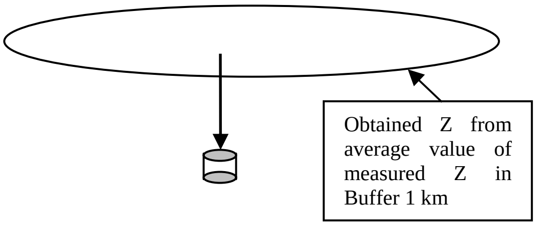


Fig. 4 The Buffer Constructed over the Studied Rain Gauge Stations



(a) Spatial Probability Technique (SPT)



(a) Buffer Probability Technique (BPT)

Fig.5 The Buffer Area over the Rain Gauge

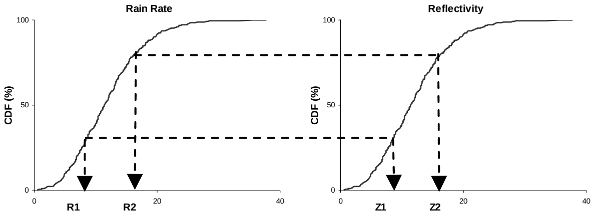


Fig.6 Z-R Probability Matching

The rainfall from automatic rain gauges was measured every 15-min, whereas the reflectivity from radar was measured once an hour. Thus, the normalized process for rainfall should be done prior to SPT and BPT process. The 15-min rainfall was normalized by aggregating into hourly rainfall with the same time interval as radar measurement. The process of SPT and BPT are summarized in the schematic diagram of Fig. 7

3 Results

From rainfall events occurred during August-September 2007, there are 664 non-zero Z-R pairs obtained from SPT, whereas, 448 non-zero Z-R pairs are obtained from BPT. The statistical characteristics are shown in Table 2.

With these non-zero Z-R pairs, the primary investigate for relationship between dBz and Rain Rate was then determined for both techniques. Fig. 8 shows the scattering plots of data set with the linear and empirical power function estimation. The obtained R^2 from linear function analysis are 0.0195 and 0.0177 for SPT and BPT, respectively. The obtained R^2 from empirical power function analysis are 0.0374 and 0.0272 for SPT and BPT, respectively. It is obviously that the relationship can not describe with these 2 functions directly. Thus, the further step of Probability Matching was processed by generating CDFs of dBz and R for both SPT and BPT to define the matching Z-R pairs as shown in Fig. 9.

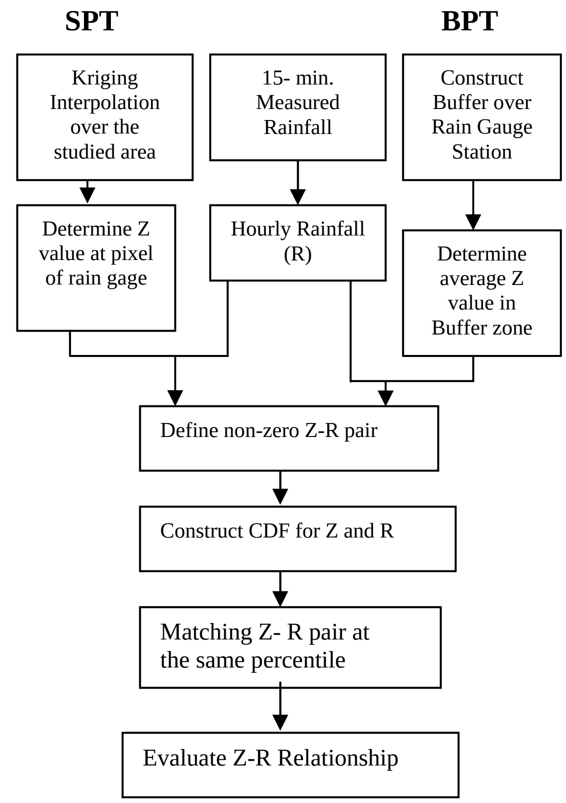
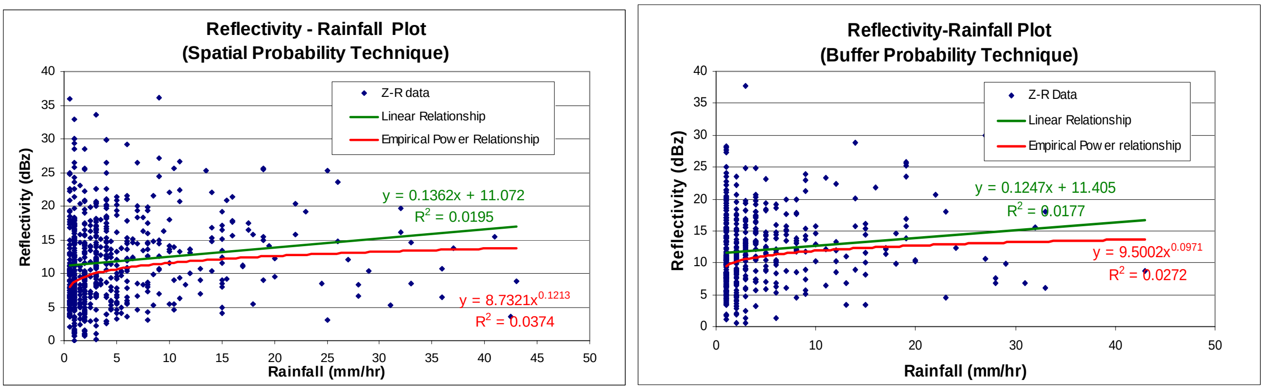


Fig. 7 Study Process

Table 2 Statistical characteristic of dBz and R

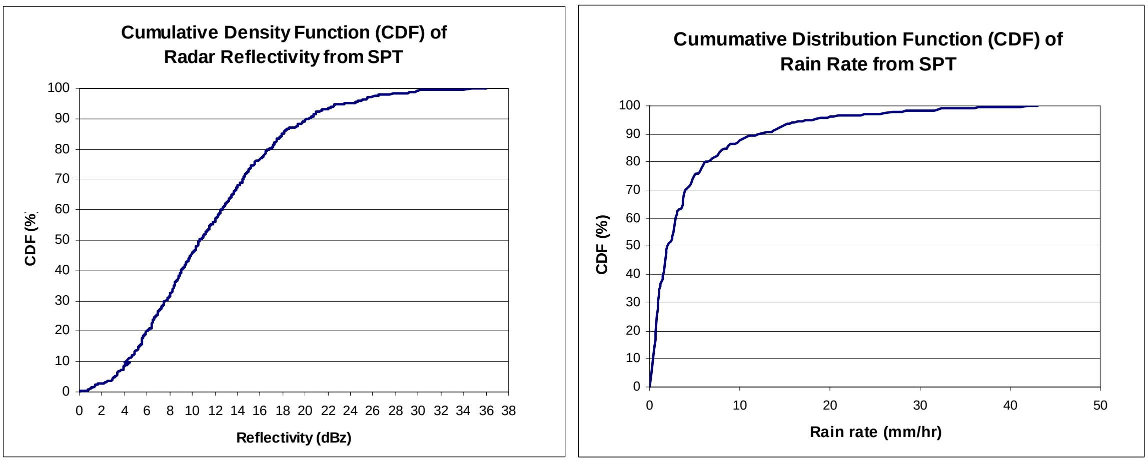
Parameter	Average Reflectivity, dBz		Rainfall, R	
	SPT	BPT	SPT	BPT
Mean	11.72	12.00	4.74	4.74
Standard Deviation	0.25	5.68	6.53	6.07
Sample Variance	40.52	32.30	42.58	36.85
Skewness	0.77	0.69	2.89	2.73
Range	36.00	37.17	42.5	42.00
Minimum	0.05	0.5	0.5	1
Maximum	36.05	37.67	43	43.00
Number of Data	664	448	664	448

From these CDFs, the dBz and R at the same percentile can be obtained. These matching pairs were then used for Z-R relationship evaluation. Considering these matching pairs with two functions of Linear and Empirical Power, it shows high correlation between Z and R for both SPT and BPT process. Using linear function, the obtained R^2 are 0.821 and 0.806 for SPT and BPT process, respectively. Whereas, using empirical power function, the obtained R^2 are 0.9424 and 0.9655 for SPT and BPT process, respectively. Fig. 10 shows how good these functions can explain Z-R relationship. In order to determine the residual and standard error of estimation from these functions, the process of regression analysis was applied. To alternate the empirical power to linear function , it is needed to transform Z and R from matching pairs to logarithm prior to calculate for the residual and standard error of estimation. Table 3 shows the regression statistics output of linear and empirical power function of both SPT and BPT process. It is shown that linear function provides less R^2, higher residual sum of squares and higher standard error than empirical power function in both processes. Therefore, it can summarize that empirical power function is more appropriate to describe Z-R relationship than linear function. The results also agree with the previous study of Z-R relationship that common form of Z-R relationship can be expressed as $Z = aR^b$, where a, b function parameters.

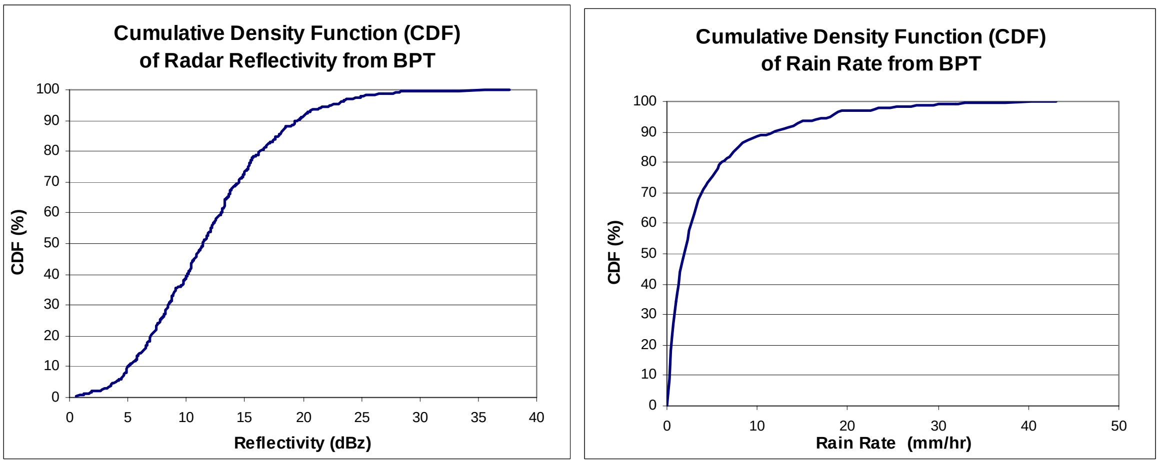


(a) Reflectivity and Rain rate from SPT (b) Reflectivity and Rain rate from BPT

Fig. 9 Primary Relationship Investigation between dBz and R

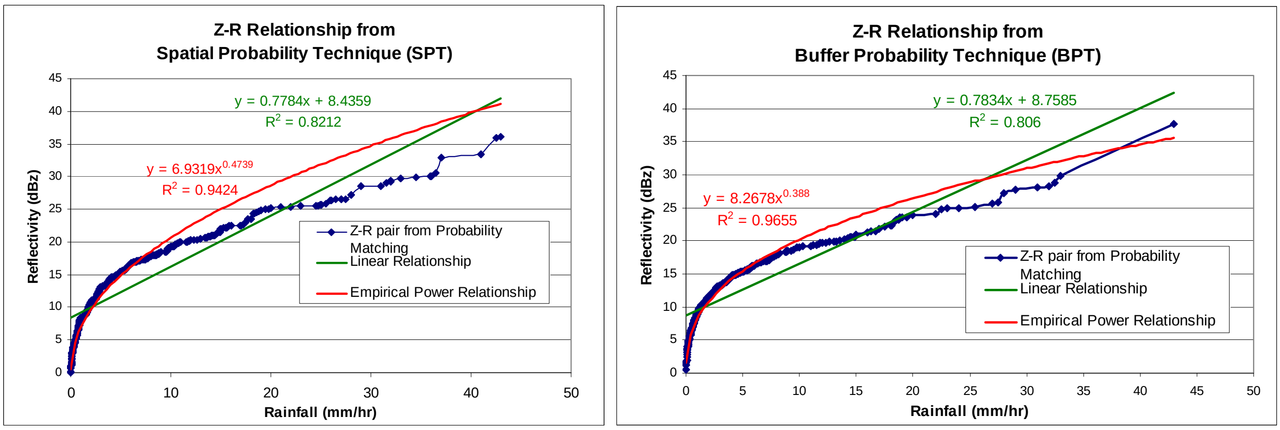


(a) CDF of Reflectivity from SPT (b) CDF of Rainfall from SPT



(c) CDF of Reflectivity from BPT (d) CDF of Rainfall from BPT

Fig. 9 Cumulative Distribution Function (CDF)



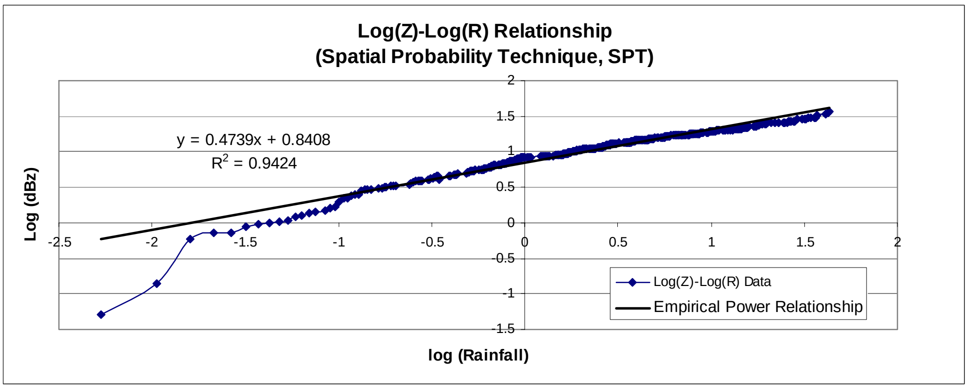
(a) Matching pairs from SPT (b) Matching pairs from BPT

Fig. 10 Z-R Relationship of matching pairs

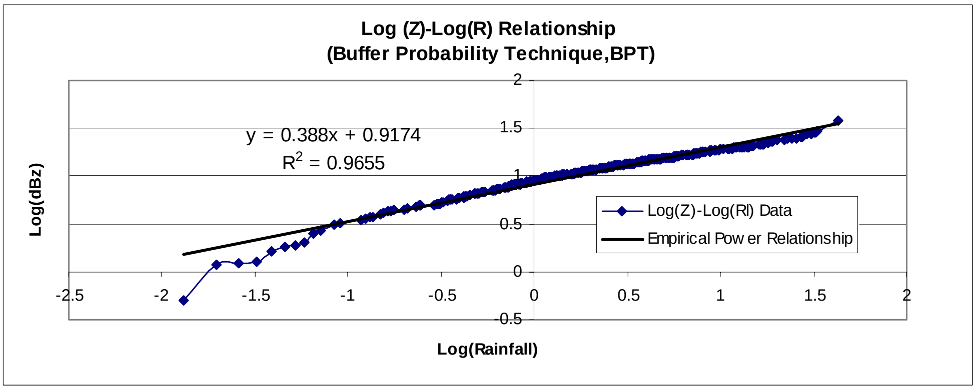
Table 3 Regression Statistics Output

Regression Statistic Parameter	Z-R Linear Relationship		Log(Z) – Log (R) Linear Relationship (Z-R empirical power function)	
	SPT	BPT	SPT	BPT
Regression Sum of Squares	22870.266	9260.563	53.658	20.142
Residual Sum of Squares	4977.943	2229.189	3.278	0.719
R Square	0.821	0.806	0.9424	0.965
Standard Error	2.984	2.660	0.0765	0.0478

The further consideration was undertaken only for empirical power function to compare between process of SPT and BPT. Fig.11 shows the Z-R relationship of log (Z) and log (R), whereas Fig.12 shows the residual of estimation for both processes. Although, R^2 obtained from both processes are slightly different, the residual graph illustrates larger error of estimation of SPT process. In addition, the BPT provides less standard error on estimation, as shown in Table 3 above. The obtained Z-R relationship from SPT is $Z = 0.8404R^{0.4739}$ while using BPT the obtained relationship is $Z = 0.9174R^{0.388}$, as shown in Fig. 11.

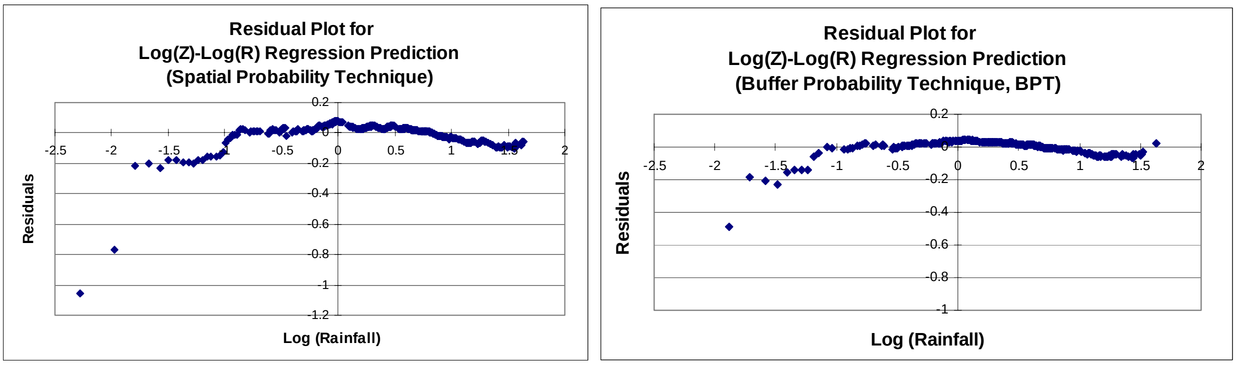


(a) Relationship between Log (Z) and Log(R) from SPT



(b) Relationship between Log (Z) and Log(R) from BPT

Fig.11 Transformation of Empirical Power Function to Linear Function



(a) Residual of Estimation from SPT (b) Residual of Estimation from BPT

Fig.12 Residual plot of Estimation

4 Conclusion

Under the collaboration among Thai Meteorological Department, Royal Irrigation Department and Naresuan University, the primary work on attempting to utilize the measured reflectivity from radar station at the flash flood risky area to estimate the Z-R relationship in Thailand was undertaken. According to insufficient of Z-R data that can be detected at same time and same location, and unavailable of wind data, the simplified GIS based technique of Spatial Probability Technique (SPT) and Buffer Probability Technique (BPT) were developed. Both techniques couple GIS function with Probability Matching Method to match appropriate Z-R pairs. The techniques were also used to increase the number of Z-R data to analyze. The results shows that the obtained Z-R relationship from both proposed technique can described in empirical power form of $Z = aR^b$, where a, b function parameters as same as the common concept of Z-R relationship. Comparing between these 2 techniques, BPT provides less error on estimation. However, this study emphasized only on the Z-R relationship, the further study should be done with the other parameters and applied the obtained Z-R relationship to develop the disaster warning system in the future.

Acknowledgement

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