CHAPTER IV

PROBLEM DEFINITION

4.1 Problem Definition

For at least five decades, radar has been utilized as a useful remote sensing tool for precipitation estimation on the ground. At Omkoi, Thailand, for the past ten years, the WSR-88D radar, as shown in Figure 4.1, has monitored and recorded the 3-D structure of the cloud while scanning the whole troposphere over 40 automatic rain gauges network at every 5 minute. The inaccuracy of radar observation process such as incomplete beam filling and bright band can result in no precipitating echoes. In fact, incompatibility between radar and ground rainfall observation can result in zero rainfall observation on rain gauge. It has been found that several factors such as the human and equipment factors, and physical mechanism environments can result in inaccurate data or no rain as in [17, 18]. Solutions to this problem are needed.

Due to spatial and temporal variability of rainfall intensity, the measured reflectivities corresponding to the centered and neighboring gauges are applied. Neighboring gauges with topography are considered for clustered time series. For an example of rain gauge location of gauge no. 071 and 081, not only the neighboring gauges but also the topography whose the altitude in feet of gauges no. 071 and 081 are 2400 and 2850, respectively are considered as illustrated in Figure 4.2.

Ground rainfall estimation can be viewed to solve a complex functional approximation problem. Therefore, the window probability matching method is used for rainfall measurement with radar [10] and neural networks are well suited for this problem [12, 13].

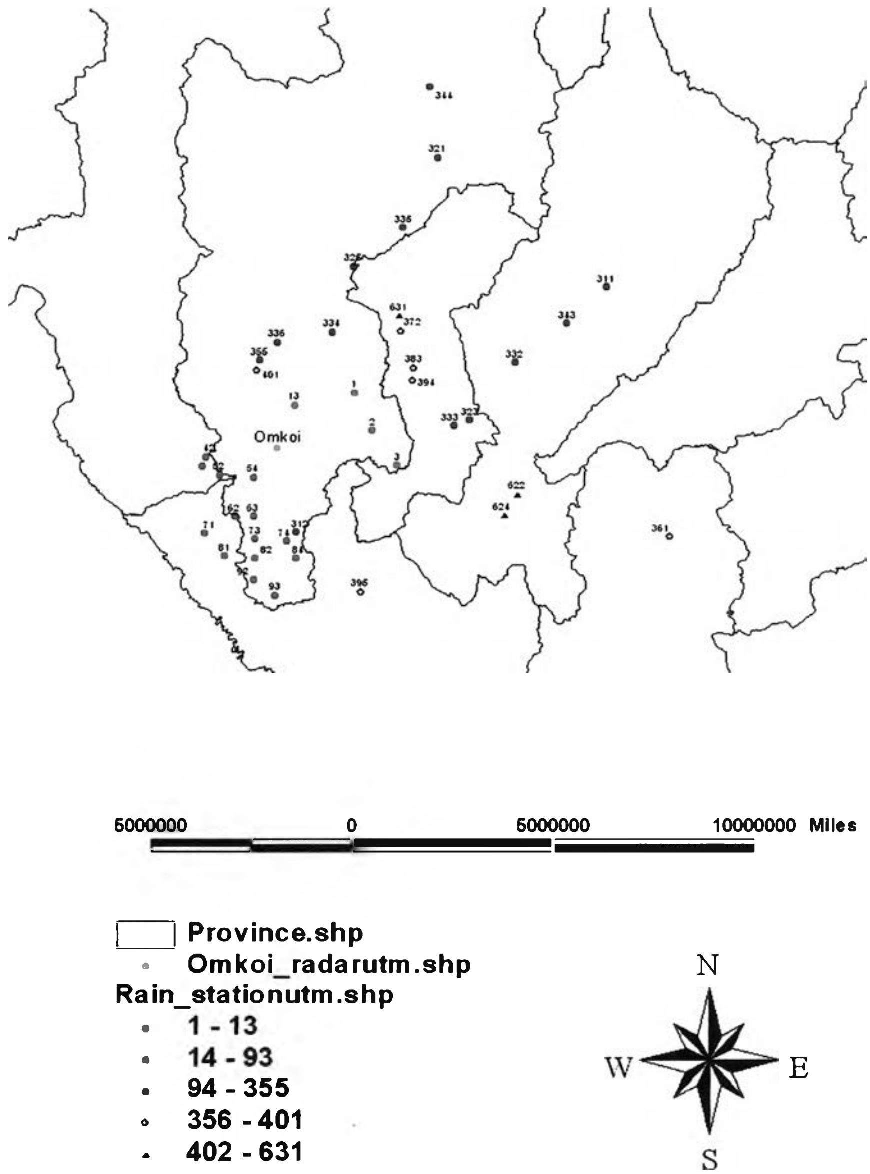

Figure 4.1: The WSR-88D radar site in Omkoi Chiangmai, Thailand corresponding to rain gauge location.

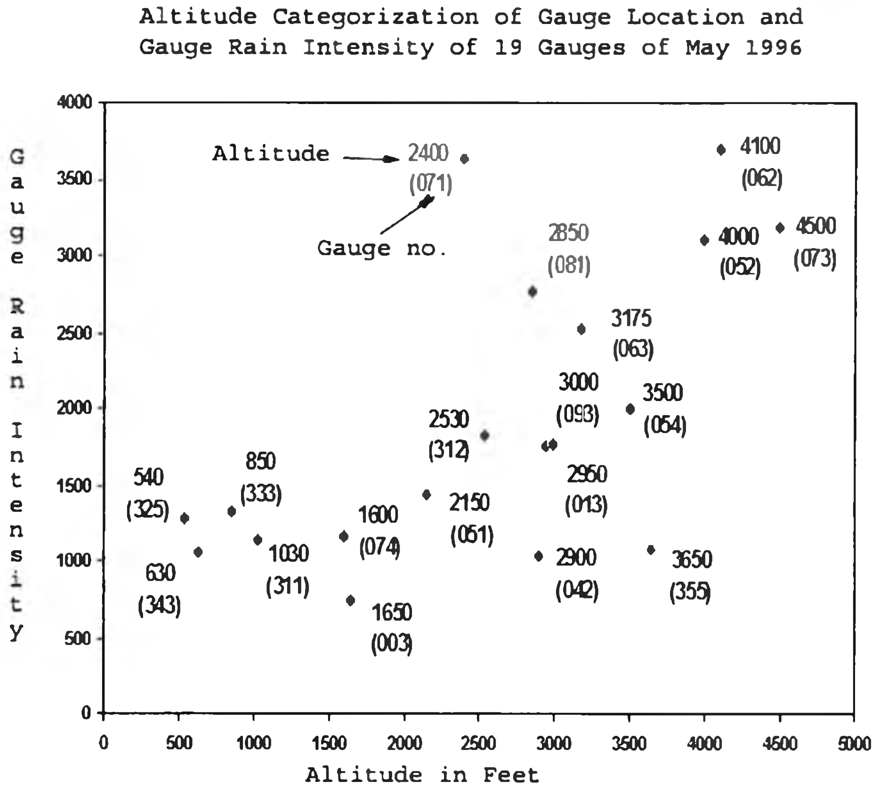

Figure 4.2: The altitude categorization of a difference of rain gauge location corresponding to monthly total gauge rain intensity.

The model is $G_i = f(Z_1, Z_2, ..., Z_n)$ where G_i is the gauge rain intensity at centered gauge which is maximum value of total i, Z_i is the radar reflectivity at cloud base corresponding to the centered and neighboring gauges, i is the number of gauge locations, and n is the maximum number of neighboring gauges. Unfortunately, these two methods do not seem to succeed because the findings derived from the two researches appeared unclear. The data collected for these two methods; the probability matching method and neural network method, seemed to be invalid because of the excessiveness of the missing data.

To solve the sparse data, or excessively incomplete data problem, first, the determination of "missing" or "no rain" condition has to be revealed prior to the data imputation. Then, the similarity-based techniques including similarity measures (a time series measuring tool) is required to recognize and classify patterns according to similar features of the data collected. Here, the similarity measures are to correct the problem by classifying the similar patterns of the radar reflectivity and the ground rainfall. Then, the incomplete data remaining are further processed using the similarity measures and the expectation maximization (EM) for incomplete data imputation.

4.2 Determination of "Missing" or "No Rain" Condition

In principle, a functional approximation can be obtained between rainfall on the ground and the 3-D radar observation above the observation point. However, determination of "missing" or "no rain" condition can be viewed as a complex classification problem. Therefore, the determination can be easily modeled by this classification concept and the selection of targets designed by the user which "missing" is 0 whereas "no rain" is +1.

4.2.1 Problem Formulation

There are four possible criteria for rainfall classification. The first criterion called "no rain" is no rain for both radar and rain gauge observation. The second criterion called "negative fault" is the values of radar measurement missing while the values of rain gauge measurement are not missing. The third criterion called "positive fault" is the values of rain gauge measurement missing while the values of radar measurement are not missing. The forth criterion called "both rain" is the values of rain gauge and radar measurement not missing. A supervised network with three layers configuration is used. Each training pattern consists of two inputs; one is the amount of gauge rain intensity in mm/hr, and another is the amount of radar reflectivity in dBZ from each gauge, and one target which is 0, +1. Here, each weight is adjusted by using Levenberg-Marquardt algorithm [19]. The learning is based on two simple concepts, gradient descent learning when the solution is far from the minimum and Newton's method when the solution is near the minimum.

4.2.2 Designing Threshold

The radar reflectivity threshold applied for filling in missing data of gauge rain intensity is summarized in Table 4.1. Two aspects, $Z_e - R$ relationship and correlation coefficient are considered. The threshold of effective radar reflectivity factor is filtered by gradually increasing the number of effective radar reflectivity data and measuring the correlation coefficient between radar reflectivity factor and gauge rain intensity. The $Z_e - R$ relationships between effective radar reflectivity factor (Z_e) and rainfall rate (R) is developed for rainfall measurement by using basic power empirical equation: $Z = a * R^b$. The power $Z_e - R$ relationship can be transformed to standard linear equation: $\log(Z_e) = b\log(R) + \log(a)$. Therefore, least-square regression method can be used to estimate a and b parameters. The minimum of effective radar reflectivity factor of rain gauge no. 071 and 081 is 13.5 and 12.5 dBZ, respectively. Consider our experiment, the lower and upper bounds of effective radar reflectivity threshold is set to 24 and 30 dBZ for both rain gauges having highest correlation coefficient for gauge no. 071 is equal to 0.9261 and equal to 0.9755 for gauge no. 081.

Table 4.1: A result of a difference of radar reflectivity thresholds

Radar Reflectivity in dBZ	Rain Gauge No. 071		Rain Gauge No. 081	
	$Z_e - R$ Relations	Correlation Coefficient	$Z_e - R$ Relations	Correlation Coefficient
Minimum	$Z_e = 53R^{1.92}$	0.8868	$Z_e = 100R^{1.74}$	0.9033
18	$Z_e = 81R^{1.81}$	0.9118	$Z_e = 154R^{1.63}$	0.9510
24	$\mathbf{Z_e = 114R^{1.72}}$	**0.9261**	$Z_e = 184R^{1.59}$	0.9582
27	$Z_e = 169R^{1.62}$	0.9256	$Z_e = 223R^{1.54}$	0.9655
30	$Z_e = 252R^{1.51}$	0.9004	$\mathbf{Z_e = 424R^{1.39}}$	**0.9755**
33	$Z_e = 403R^{1.40}$	0.8711	$Z_e = 594R^{1.31}$	0.9732
36	$Z_e = 12305R^{0.58}$	0.4458	$Z_e = 533R^{1.33}$	0.9558
42	$Z_e = 12305R^{0.58}$	0.4458	$Z_e = 8R^{2.24}$	0.8850