

# EXTRACTING FLOOD EXTENT FROM RADARSAT SAR DATA USING NEURAL NETWORK

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**KEY WORDS:** Flood, RADARSAT SAR Data, Neural Network

**ABSTRACT:** Flood is one of the most severe nature disaster. It is taken place very year in the Northeastern part of Thailand. It is impractical to explore the flooded area through field investigating. The methods to extract flood extent from passive remotely sensed data such as LANDSAT TM , SPOT data are hardly carried out because flooded area is usually covered by cloud. Microwave remotes sensing is very useful for monitoring flood because it can obtain a good image especially in bad weather. Flood extent is mostly extracted from SAR images by visual interpretation. It is accurate but very labor intensive. The purpose of this study is to extract flood extent using Neural Network method in order to enhance flood analysis. The RADARSAT SAR data acquired in 2001, 2002 and 2003 were used to monitor flood extent in the lower Songkhram river basin, Northeast Thailand. The back propagation of Neural Network Classifier was used to identify flooded area. The Kappa analysis was used to measure an accuracy of the flooded area from the classifier. The result shows that the overall accuracy of flood extent in 2001, 2002 and 2003 were 86.01 %, 91.68 and 87.74 % respectively when the reference data were the flooded area obtained from visual interpretation. Therefore, the Neural Network technique plays effectively role to extract the flood extent from SAR data.

## 1. INTRODUCTION

Flood is one of the most severe nature disaster. It is taken place very year in the Northeastern part of Thailand. It is impractical to explore the flooded area through field investigating. The methods to extract flood extent from passive remotely sensed data such as LANDSAT TM, SPOT data are hardly carried out because flooded area is usually covered by cloud. Microwave remotes sensing is very useful for monitoring flood because it can obtain a good image especially in bad weather. Flood extent is mostly extracted from SAR images by visual interpretation. It is accurate but very labor intensive. For analyzing flood event from SAR images by digital image processing, it is critical to accurately and efficiently identify water area extent because the topographic effects by terrain relief may cause a large effect on image quality and mislead the classification results in the rugged areas. Therefore, this study investigates an efficient water area detection method based on Neural Network Model with back propagation algorithm.

## 2. OBJECTIVE

The objective of this study is to extract flood extent using Neural Network method in order to enhance flood analysis.

### 3. STUDY AREA

The study area, the lower Songkhram river basin, is located in parts of Nakhon Phanom, Sakhon Nakhon, Udon Thani and Nong Khai provinces, Northeast Thailand (Figure 1). It experiences heavier annual rainfall than most other parts of Central, Northern and Northeast Thailand. The annual average precipitation varies between 1,600 – 2,400 mm/year, 90 % of which falls in the six month rainy season (May – October). As a result of the highly seasonal rainfall pattern, there is a distinct peak in the Songkhram River’s hydrograph during the months of August and September with prolonged overtopping of the riverbanks occurring at any time between July – October. A second factor leading to annual flooding, which is perhaps more important than in-basin run-off, is the influence of the Mekong River’s level in inducing a backwater effect in the lower Songkhram basin, when river levels rise above a certain critical level, the Mekong River actually flows back into the Nam Songkhram river. The lower 250 kilometers of the 420 km long Songkhram river has a very low gradient of just 3-4 cm fall every kilometer, so flows are naturally quite slow and the river is typified by large meanders and oxbow lakes. Due to the low-lying nature of the landscape and extensive floodplain, the floodwater’s reach far inland from the riverbanks, once they are breached, covering broad areas of seasonally-flooded forest, water resources like reservoirs and natural ponds and paddy field landscape. At the peak of floods the landscape of the lower Songkhram river basin resembles one large shallow lake, no deeper than 1 – 2 meters at most points (Figure 2). The floods may extend up to nearly 2,000 km<sup>2</sup> in a particularly “wet” year, although are more typically around 1,000 km<sup>2</sup> (MWBP, 2006 ).

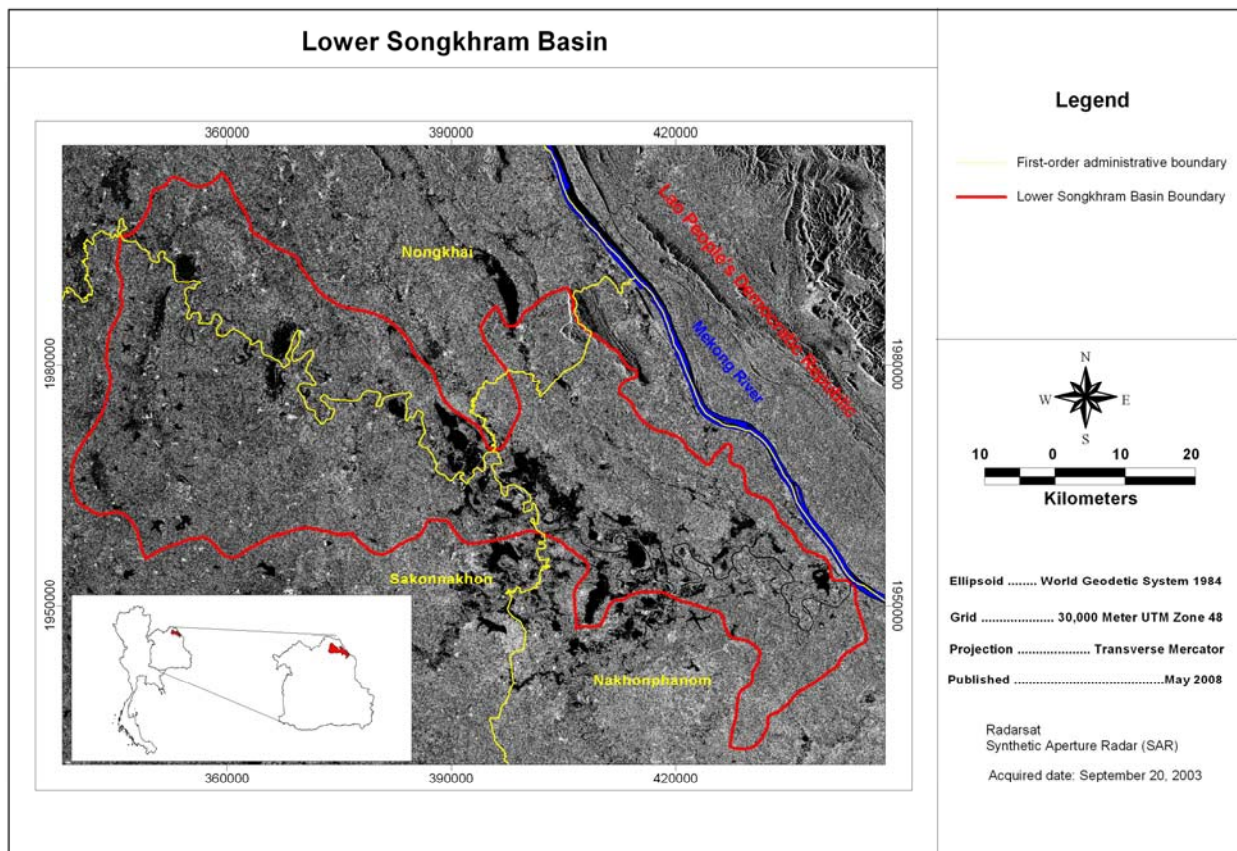


Figure 1 Location of the study area.



Figure 2 The false color composite image of Landsat 5 in the Songkhram River Basin during flood event.

## 4. METHODOLOGY

### 4.1 Data Use

RADARSAT SAR data acquired in 2001, 2002, and 2003 were used to identify the extent of flood by Neural Network classifier and visual interpretation. The flooded area maps obtained from visual interpretation and field observation were used to be reference for accuracy assessment of the flood extent maps obtained from Neural Network classifier.

### 4.2 The Procedures of Image Processing

The digital image processing was performed using Geometricas software. The neural network programs NNCREAT (create neural net), NNTRAIN(train neural net), and NNCLASS process for multispectral image classification based on training sites. The neural network classifier provides an alternative to using the maximum likelihood classifier program (MLC) and other classifiers from the PACE Multispectral Analysis package. Neural network classifiers process imagery by pattern recognition. The programs use a back-propagation network that learns using the Generalized Delta Rule. The procedures of image processing shown in Figure 3, are as follows:

Geometric correction of SAR data was carried out using stream vector to be reference map. The corrected SAR Images were filtered using KUAN Filter in order to eliminate speckle noise. Then the filtered SAR images were used to define training area to be trained the Neural Network classifier. Eight training set of flooded area and three training set of non-flooded area shown in Figure 4, were input to classifier.



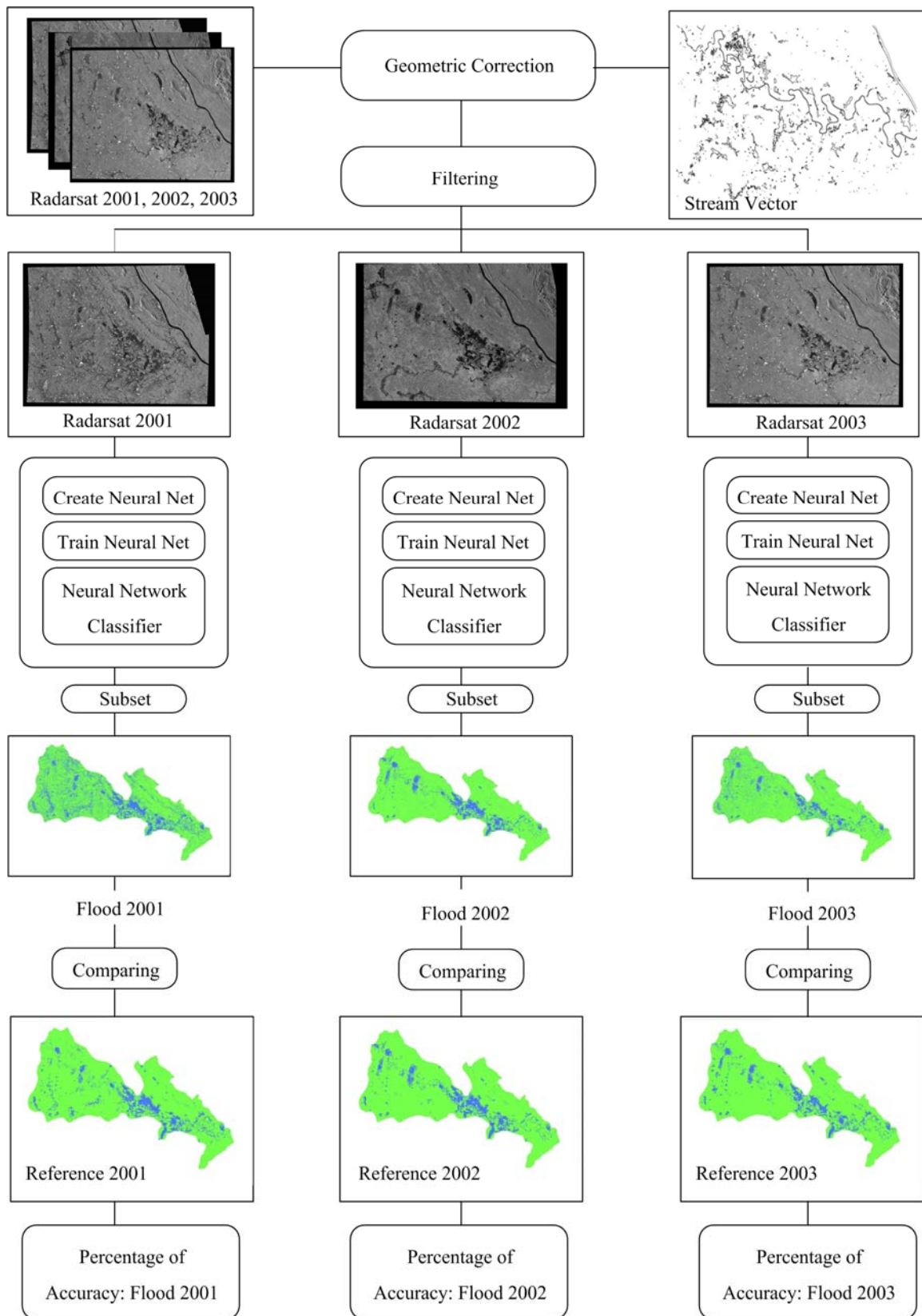


Figure 3 The Procedures of Image Processing.

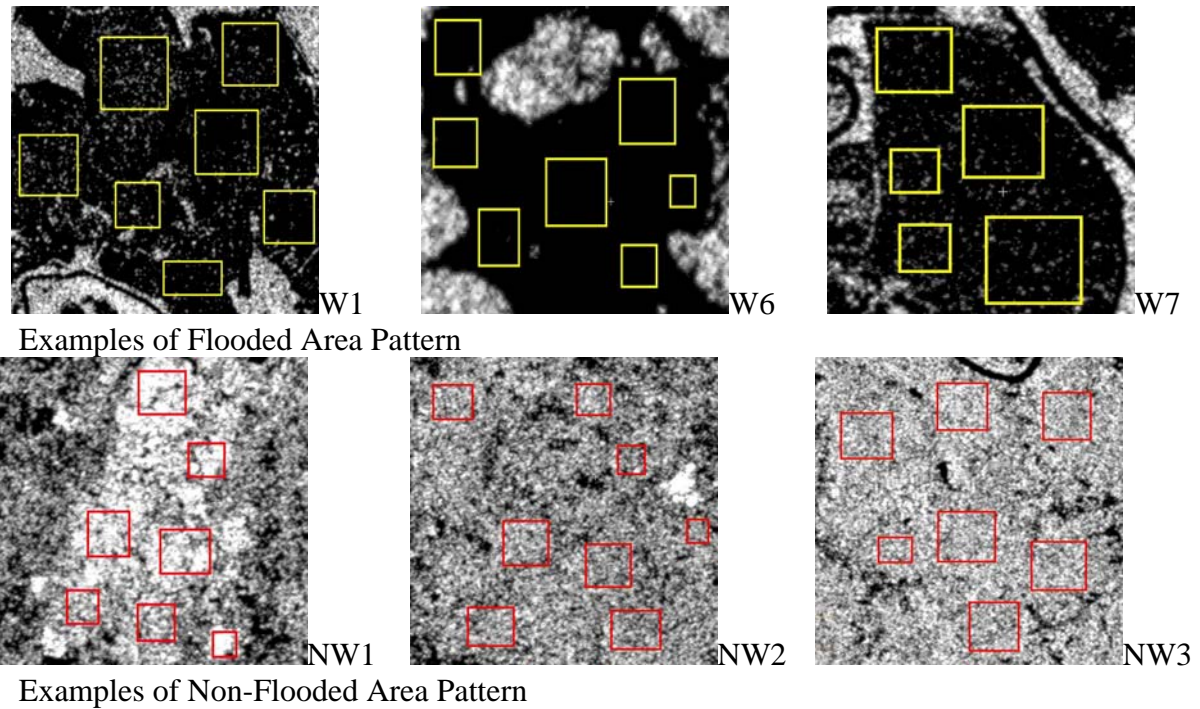


Figure 4 Examples of training data.

## 5. RELIABILITY ASSESSMENT

Kappa analysis was utilized to measure the output accuracy. Therefore, the output maps obtained from the neural network classifier were compared to the reference maps obtained from visual interpretation and field observation (Figure 3 and Table 1). The accuracy report is shown in Table 2.

Table 1 The comparison of flooded are obtained from the neural network classifier and the flooded area obtained from visual interpretation.

Reference Map (square kilometers)	Output Map (square kilometers)								
	2001			2002			2003		
	Flooded Area	Non-Flooded Area	Total	Flooded Area	Non-Flooded Area	Total	Flooded Area	Non-Flooded Area	Total
Flooded Area	303.14	26.46	329.60	275.62	41.89	317.50	245.00	55.94	300.94
Non-Flooded Area	400.33	2321.21	2721.54	94.20	2639.43	2733.63	163.09	2587.10	2750.19
Total	703.47	2347.67	3051.14	369.82	2681.32	3051.14	408.09	2643.04	3051.13

Table 2 The Accuracy Report from Kappa Analysis.

Accuracy Report	Output Map (square kilometers)					
	2001		2002		2003	
	Flooded Area	Non-Flooded Area	Flooded Area	Non-Flooded Area	Flooded Area	Non-Flooded Area
User Accuracy (%)	43.09	98.87	74.53	98.44	60.04	97.88
Producer Accuracy (%)	91.97	85.29	86.81	96.55	81.41	94.07
Average Accuracy (%)	88.63		95.54		92.82	
Overall Accuracy (%)	86.01		91.68		87.74	
Kappa Coefficient	0.5156		0.7770		0.6515	

## 5. RESULT

The result from the neural network model (Table 1) shows that the flooded area in 2001, 2002, and 2003 covering 703.47 square kilometers, 369.82 square kilometers, and 408.09 square kilometers respectively. It is found that in 2001 and 2003, the flooded area obtained from the model are quite greater than the reference data especially the flood in 2001. However, the overall accuracy of flood extent in 2001, 2002 and 2003 were 86.01 %, 91.68 and 87.74 % respectively.

## 6. CONCLUSION AND RECOMMENDATION

The neural network model with back propagation algorithm carried out in the lower Songkhram river basin, plays effectively role to extract the flood extent from SAR data. The efficiency index of the model results is found to range from 86-91 %. The neural network model is however still dominated by trial and error process in many aspects. It is important to mention that the selection of training area significantly influences the output performance of the model. More studies are encouraged to apply neural network models for extracting flood extent in other river basins in Northeast Thailand such as Chi and Mun river basin.

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