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Assessing the Accuracy of Image Classification Algorithms Using During-Flood TerraSAR-X Imagery

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Abstract

Extracting and determining floods affected zones is one of the most crucial stages in floods hazard management to reduce damages caused by floods. Assessing and determining the accuracy of image classification algorithms is essential in producing accurate flood hazard maps. This study put forward the application of Remote Sensing and GIS computer programs to carry out a comparative analysis of three image classification algorithms: neural network, parallel-pipe and minimum distance to test which technique best classifies the 2010 during-flood TerraSAR-X image of Perlis, Malaysia. Confusion matrix was calculated to assess the accuracy of each algorithm.

The best result of the flood extent extraction model is from the network algorithm classification with an overall accuracy of 99.7661% and a kappa coefficient of 0.9862. These findings could be used to assist the Government to design appropriate measures to safeguard the lives and properties of the residents of Perlis.

Keywords: Classification algorithms, Flood mapping, GIS, RADARSAT, Remote sensing.

Introduction

Climate and weather are the key factors triggering the risks of natural disasters especially in the third world countries.[42,48,49] Natural disasters have caused a substantial amount of economic losses especially in the developing countries[42], along with irrecoverable damages to lives and properties worldwide[45]. In 1995, weather-related disasters have caused 606,000 deaths and 4.1 billion damages including injuries and homelessness[42]. Floods are among the natural disasters that always makes a headline.

Flood is one of the most recurrent natural catastrophes affecting people directly through their lives, properties and economic activities[32]. It exhibits serious calamities involving loss of lives, properties, and subjects inflicted people to ailments and starvations among others. Floods account for 47% of the overall weather-related disasters[47]. It injured about 2.3 billion lives and killed 157,000 from 1995-2015[42] and accounts for 40% of the total economic losses[10]. Flood disaster is the second most frequent and widespread of all natural catastrophes in the world[9]. According to the UN[42], the hardest-hit parts of flood disasters are low-income countries.

Recurring floods in Malaysia are caused by natural and anthropogenic activities which as a result account for 90% of damages originating from natural disasters[32]. Flood is the major natural catastrophe striking Malaysia[15,27] because historically, settlements in the Peninsula originated around the banks of the main estuaries and rivers[32]. In addition to natural flood triggering factors such as land cover types, intense monsoonal rainfall, inadequate drainages, geology types, slope, as well as other local factors among others, flood has turned to be a usual phenomenon in the day-to-day lives of a sizeable number of residents in Malaysia. It has caused damages to 29,800 km^2 (9%) of land and 4.82 million (22%) of the population[32] causing an average annual flood damages of approximately USD 0.3 billion[32].

In the Eastern coast of Peninsular Malaysia, monsoonal storms have an immense impact on the lives of the people[46]. The severely hit parts include the states of Kelantan, Johor Bahru, Pahang, and Terengganu. Similarly, more than a decade ago, floods hit the Northern part of the Western Peninsula. The hardest-hit parts include Perlis and Kedah. In 2005, Perlis and Kedah have witnessed the most severe floods in 30 years which have caused the relocation of over 16,000 residents to 113 relief centers[37]. This has caused the two-thirds of Perlis and major part of the Northern Kedah to be severely flooded by a three-day consecutive rainfall[37]. It similarly resulted in the destructions of approximately 25,000 ha of paddy lands in both states which have led to losses of nearly over RM 18 million[1,37] [USD $1 = RM4.09 (Malaysian Ringgit)].

Similarly, in 2010, heavy rainfall has triggered severe floods in Perlis and Kedah with a total number of evacuees reaching over 13,700 and 28,000 evacuees' respectively[25]. Moreover, in 2011, floods have again hit the State of Perlis with 4,761 people at the evacuation centers[26].

Thus, floods have cost millions of dollars as a result of damage to properties, economic activities, and lives. The magnitude of damages could have been lessened if an early warning system is in place. However, flood challenges continue to grow extensively[32]. Hence, there is a need to map the floods affected areas in order to lessen its catastrophic effects. Several factors are responsible for floods generation such as human and natural factors. These factors include haphazard development activities, major land-use changes, topography, geomorphology, climate, and natural drainage systems among others[32]. However, rainfall is the major factor triggering floods due to prolong intensive precipitation in an area.

The importance of combating floods has been declared by the UN in order to improve the socio-economic well-being of the people. For instance, the Sustainable Development Goal15.3 aims to end flood, desertification and drought by 2030. Goal 15.3 called for global efforts to fight desertification, restore degraded land and soil affected by floods, drought and desertification, and struggle to realize a degradation free world. In recent years, RS and GIS have been employed in natural disasters monitoring. These tools have received growing attention by researchers and international organizations. RS is used to examine the vulnerability of the environment to develop floods risk and potential damage maps, to examine the likely risk areas, and to manage post-disaster situations[44]. Several studies have employed RS and GIS as the major sources of information and analytical tools in assessing flood disasters.[2,6-8,11,12,16-18,20,21,23,28-30,32-35,38,39,46]

Moreover, many studies have extensively utilized radar RS in flood monitoring, mapping, and forecasting worldwide. In spite of this plethora of studies in the area under consideration, none in the study area seems to have developed and utilized the tool of a flood extent mapping employed in this study. For example, in a recent study, Dano et al[3] employed different image classification algorithms on RADARSAT imagery to aid in accurate flood vulnerable areas forecasting for Perlis, Malaysia. Their findings show a greater agreement between the employed flood forecasting model and the extracted flood extent map.

Another study by Horritt and Bates[13] utilized radar remote sensing in calibrating flood hydraulic models (TELEMAC-2D, HEC-RAS, and LISFLOOD-FP) against flood extent model at River Severn, UK. Horritt and Bates[13] findings proved the calibration of HEC-RAS and TELEMAC-2D models against flood areas and flood flow data to be more efficient than the LISFLOOD-FP model. In Kelantan, Malaysia, Pradhan[31] utilized RADARSAT-1 images in extracting flood extent areas. The author found that the flood susceptibility map revealed the areas that have the likelihood of being inundated in the future.

Pirasteh et al[30] used ERS-1 SAR data in carrying out a flood delineating management in Gujarat, India. The data was found to be highly efficient in delineating flood-related catastrophes. Similarly, around the Maghna River Basin, Bangladesh, Hoque et al[12] employed LANDSAT and RADARSAT images to explore large flooded areas using supervised classification method. The result of the maximum flood extent produced by RADARSAT image highly corresponded with the heavy rainfall that fell around the area. Pradhan et al[33] used a TerraSAR-X imagery to perform a texture analysis in Terengganu area, Malaysia. The study revealed that the texture analysis program proved its capability of producing high classification accuracy on TerraSAR-X imagery.

Another study conducted by Lawal et al[17] utilized RADARSAT and SPOT images of Perlis, Malaysia in developing flood extent map using minimum distance classification algorithm. The result of the flood extent model revealed a high correlation with certain flood causative factors investigated in the area. Similarly, Matori and Lawal[20] employed RADARSAT during-flood image in extracting flood extent zones. Their findings correspond with the model created. A similar study by Lawal et al[18] employed RADARSAT SPOT images in predicting flood vulnerable areas in Perlis, Malaysia. The extracted flood extent superimposed over the flood vulnerability map shows great correlation between the two.

In Perlis, Malaysia, Dutsenwai et al[7] employed radar satellite-1 imageries and a TerraSAR-X image in obtaining accurate flood disaster information using Principal Component Spectral Sharpening (PCSS), Hue Saturation and Value (HSV), Gram Schmidt (GS), and Brovey Transformation (BT). The outcome from BT produced a more accurate output with an overall accuracy of 70.9615% and kappa coefficient of 0.3418. Dutsenwai et al[8] used radar satellite-1 imageries and a TerraSAR-X in mapping the flood extent areas in Perlis, Malaysia using Brovey Transformation (BT) and Principal Component Analysis (PCA). The findings signify that the image classification of BT using support vector machine yielded better accuracy of 70.97%.

In Kelantan and Kuala Terengganu, Malaysia, Pradhan et al[35] employed multi-temporal RADARSAT-2, single Terra-SAR-X and Landsat images in identifying inundated areas. The images were classified using rule-based object-oriented method. The authors found that the classification results from RADARSAT-2 present a better result with an overall accuracy of 86.16%. As far as we know, there is no study conducted in the study area that develops a flood extent map using neural network, parallel-pipe, and minimum distance classification algorithms.

Thus, to bridge this research gap, the current study presents a different approach of developing flood extent maps of Perlis based on neural network, parallel-pipe and minimum distance classification algorithms from the 2010 during-flood TerraSAR-X image. This is to see which of the classification algorithms corresponds with the results produced by previous studies conducted in the area.

Material and Methods

Study setting: Perlis, the smallest state in Peninsular Malaysia (Figure 1), has a population size of 227,025 as per the 2010 census[6]. Its major economic activities include agriculture: oil palm, fruit farms, sugarcane farms, paddy, and rubber. These made up approximately 54.5% of the entire city while rivers, bushes, forest, and shrubs covered around 32.7% of the city. The paddy fields are found to dominate the flat terrain zones of South Perlis, while the rubber and sugarcane farms are scattered in the areas of the higher elevation of the Northern part of the city. The city lies at latitude 6º 43’ 19” N and longitude 100º 07’ 59” E and has an altitude of 6m (19ft) above sea-level with two separate raining seasons typified by intense rainstorm and a drought.

It suffers a monsoonal hot weather and cold breezes originating from the Gulf of Thailand. The drought period lasting from December-March is coupled with the Northeastern monsoonal rainfall. The rainy seasons are coupled with fluctuating monsoon of the Southwestern between April-May and September-October and the end period generates larger depths of precipitation. The city has an annual temperature that varies from 21ºC to 32ºC and a mean annual rainfall of 2000-3000 mm.

The peaks of the period of rainfall occur during the periods of the post-equinoctial transition between the monsoons. Rainfall data analysis reveals that the high and less mean monthly rainfall takes place between the months of May-November, and December-March respectively.

In 2010 and 2011, serious flood catastrophes were recorded which resulted in causing injuries and damages to people and their properties. The flood disaster in 2010 was the most severe one and referred to as the worst flood catastrophe in the study area in thirty years[22]. The disaster caused a loss worth more than RM 50 million (USD 11.8 million) with 13,711 people evacuated[40].

Data Collection

Creation of Spatial Database: The present study is based on secondary analysis of radar and SPOT (Systeme Pour l'Observation de la Terre) satellite images obtained from Malaysian Agency for Remote Sensing. The study investigates the use of RS data from SPOT and radar satellite images for flood extent mapping in Perlis. The two key types of data used are spatial and attribute data. These data were initially identified and obtained from various sources (Table 1).

The SPOT satellite imagery was employed in developing the land use map of the study area (Figure 2) and the precipitation map (Figure 3) was developed from the rainfall data obtained from the Department of Irrigation and Drainage, Malaysia. The flood extent areas were extracted from the 2010 during flood TeraSAR-X image (Figure 4B).

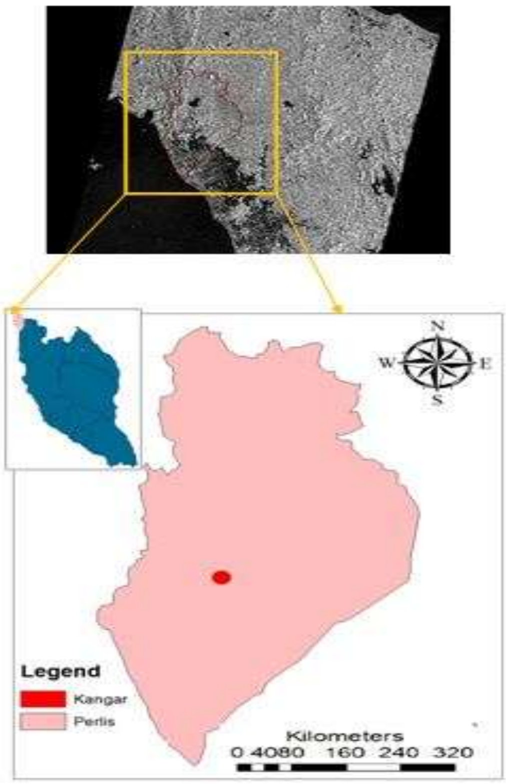

Figure 1: Perlis and its capital city

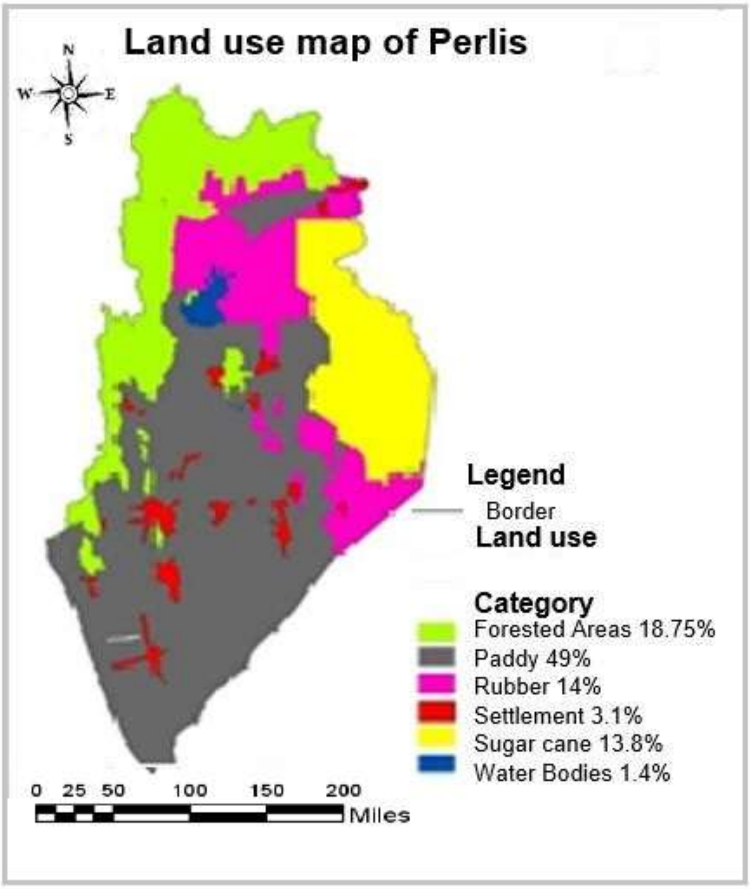

Figure 2: Land use map of Perlis[3]

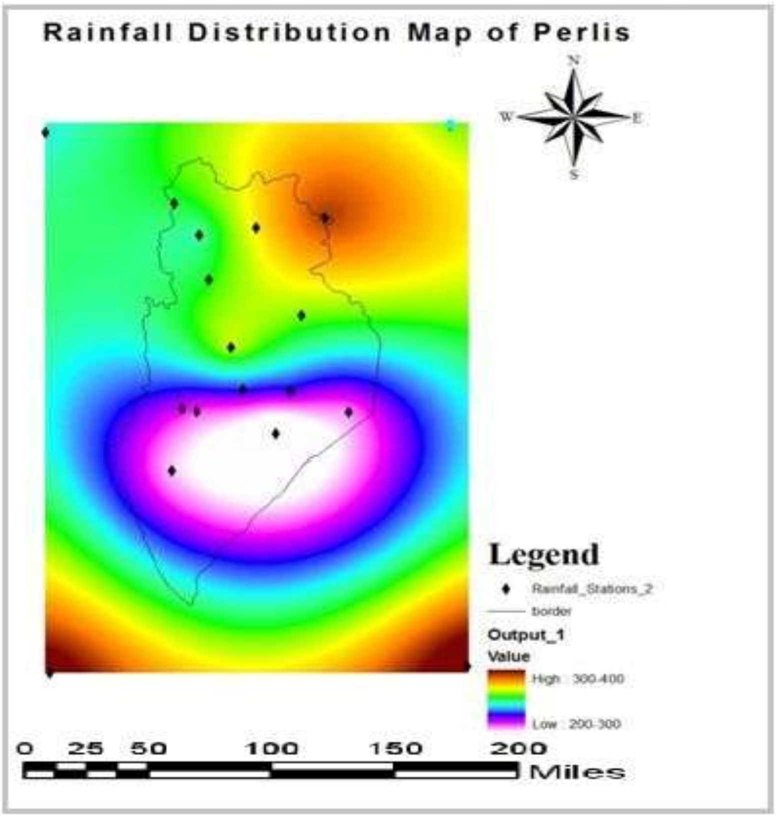

Figure 3: Precipitation map of Perlis[3]

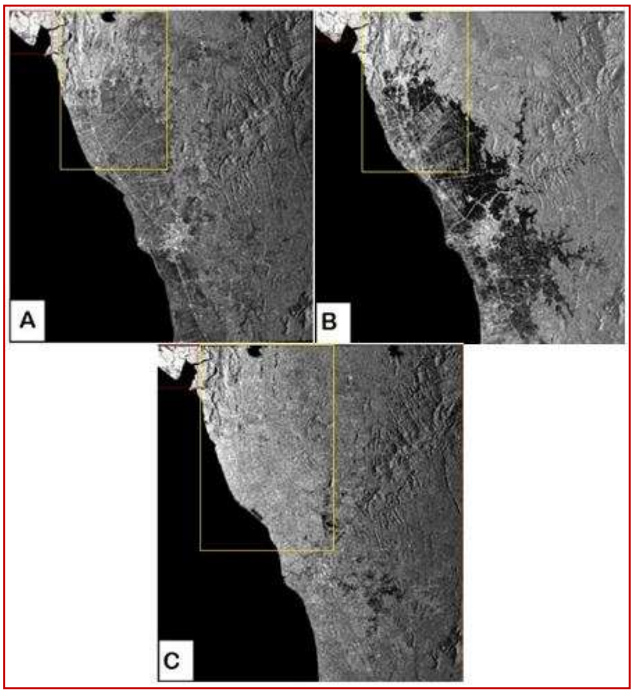

Figure 4: (A) Before flood RADARSAT 1 image, (B) During flood TeraSAR-X image, (C) After flood RADARSAT 1 image

Table 1
Type and data sources used for the study

Data	Year	Information obtained	Source
SPOT imagery	2005	Land use classes	Malaysian Agency for Remote Sensing
Precipitation data	2001-2011	Amount of rainfall from 2001 to 2011	Department of Irrigation and Drainage
RADARSAT imagery	2010	Extraction of flooded zones	Malaysian Agency for Remote Sensing

Extraction of Flood Areas

The flooded areas were extracted from a level-3 2010 during-flood TerraSAR-X image. Post-processing of the data was performed using an appropriate filter to prepare it for analysis. This includes rasterization, vectorization, vector overlay, classification, and accuracy assessment. A Lee filter, with 3x3 filter size and noise variance of 0.2500 was used to filter and smoothen the image. ENVI 4.8 and ArcGIS 9.3 software were used in extracting the maximum flood extent from the 2010 during-flood TerraSAR-X image of Perlis. In developing the maximum extent of the flooded areas, the actual water extent, mountain shadows, and non-flooded paddy areas were extracted whilst the flooded paddy fields were included to form part of the maximum flood extent model so as not to under-estimate the flood disastrous effects.

Thus, the technique employed in developing the maximum flood extent model involved two distinct modeling procedures: the extraction of actual water bodies and flooded paddy fields. Though paddy fields are naturally waterlogged because of irrigation activities, but they happen to be more inundated in the events of flooding, where water remains stagnant in the paddy areas for sometimes before the river level dwindles to allow the flow of flooded water into the sea[24].

The methodology followed in developing the maximum flood extent model is illustrated in figure 5. Parallel-pipe, neural network, and minimum distance classification algorithms were employed in classifying the 2010 during-flood TeraSAR-X image to see which of them is going to yield an optimum result. Accuracy assessment is essential so as to realize the objective of the analysis. Accuracy is measured by empirically comparing a sample of pixels from the classified image to the ground truth data. The percentage of pixels classified and corrected were calculated as well as the percentage of pixels classified by mistake.

The rationale for using the aforesaid classification algorithms are:

(i) The neural network classification algorithm uses normal back-propagation algorithm used for supervised learning. Thus, several hidden layers can be selected and chosen between logistic or hyperbolic activation function of a neural network. In the neural network classification, learning takes place by altering the weights in the node to reduce the variation between the node activation outputs. The error is back-propagated via the network and weight alteration is performed using a recursive technique. Neural network classification algorithm can as well be used in carrying out a non-linear classification.

(ii) Parallelepiped classification algorithm employs an easy decision rule in classifying multispectral data. Within the image data space, an *n*-dimensional parallelepiped classification is created by the decision boundaries. The parallelepiped classification dimensions are defined according to a standard deviation threshold from the mean of every chosen category. For instance, if a pixel value falls above or below the low and high threshold for all *n* bands under classification, it is allotted to that particular class. If the pixel value lies within various classes, the pixel is automatically allotted to the last class. Thus, the unclassified zones are those outside the parallelepiped classes.

(iii) In minimum distance classification algorithm, mean vectors of every end-member is used and Euclidean distance of every unknown pixel to the mean vector for every class is calculated. Every pixel is classified to its closest class except a standard deviation or distance threshold is defined. The degree of accuracy of the classification outputs was determined using accuracy assessment via a confusion matrix.

Results and Discussion

The classification results of the 2010 during-flood TeraSAR-X image are shown. The entire parts of Perlis were classified so as not to underestimate the flood impacts. As can be seen in figure 6, the result of the neural network classification algorithm generated concordant output with an overall accuracy and kappa coefficient of 99.77% and 0.99 respectively. This is then followed by parallel-pipe classification algorithm (Figure 7) with 98.64% accuracy and 0.92 coefficients and finally the minimum distance classification algorithm (Figure 8) with 96.77% accuracy and 0.83 coefficients. The kappa coefficient used in image classification accuracy assessment serves as an accuracy indicator with 0 implying zero concordance between the ground truth image and the classified image and 1 implying absolute concordance.

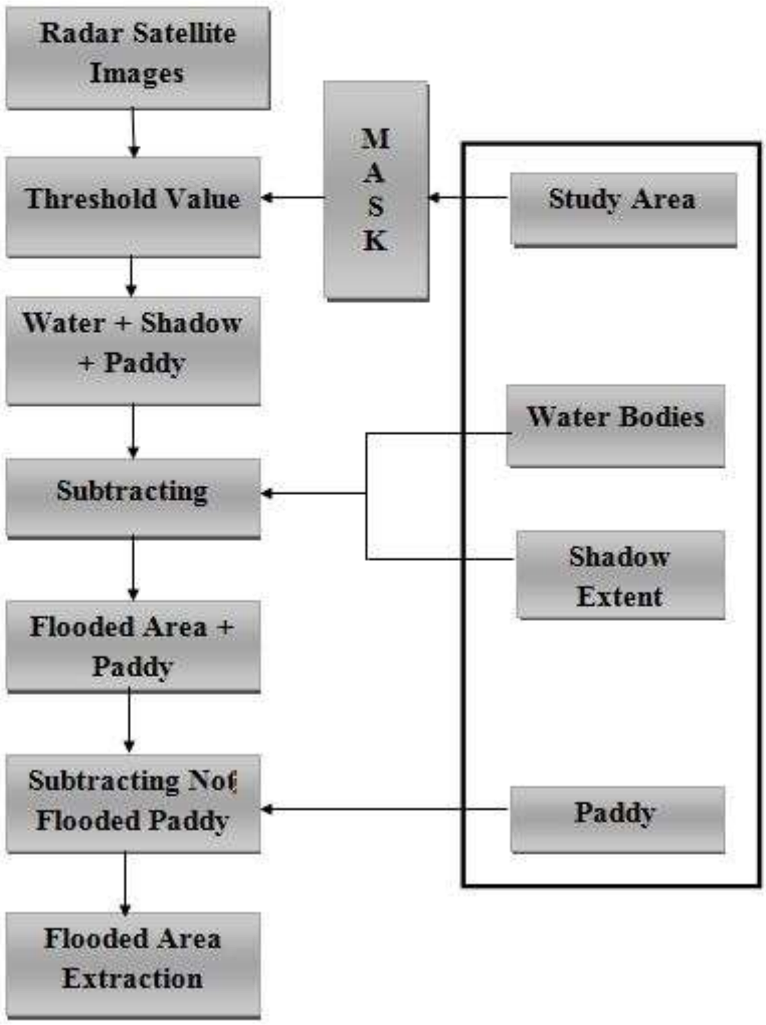

Figure 5: Flood extent extraction flowchart

Therefore, the aforementioned algorithms were used in order to see which of them produces the best result. The results of these three classification algorithms are presented in a tabular form called a confusion or error matrix. The results indicated that the neural network classification algorithm generated a suitable producer and user accuracies for all the flooded areas with an overall accuracy of 99.7661% and kappa coefficient 0.9862. Tables 2, 3 and 4 present the accuracy assessment results.

Thus, the findings of the current study concur well with earlier studies conducted in the area and areas bordering the study area that found the South of Perlis to be the most flood vulnerable area due to its low lying terrain, paddy fields, and so forth. For instance, in Keddah State, bordering the Southern part of the study, Adiat et al[1] carried out a similar study and their findings concurred well with the findings of this study.

Similarly, the findings correspond with the findings of Dano et al[3] and Lawal et al[19] where they both found the most flood susceptible area to be in the Southern part of the study area characterized by a flat slope terrain, low-humid clay soil, alluvium deposits, and paddy fields. This is also in agreement with the findings of Toriman et al[14] that revealed the hard hit victims of flood disasters to be the dwellers of the low lying terrains and riverbanks as shown in figure 9.

The study also proves the view of Dano et al[4] that the use of radar imageries in flood mapping produces more accurate results because of its capability to penetrate clouded sky and captures during flood events. Moreover, the study is in agreement with De Oliveira Duarte et al[5] that neural network classification algorithm produces outputs which are in consistent with the reality.

Table 2
Confusion matrix for neural network algorithm (overall accuracy = 99.7661% and kappa coefficient = 0.9862)

	Non-flooded Areas	Flooded Areas	Total	User's Accuracy
Unclassified	0 (0.00%)	0 (0.00%)	0 (0.00%)	
Non-flooded Areas	28651 (99.77%)	9 (0.31%)	28660 (90.58%)	28651/28660 (99.97%)
Flooded Areas	65 (0.23%)	2917 (99.69%)	2982 (9.42%)	2917/2982 (97.82%)
Total	28716 (100.00%)	2926 (100.00%)	31642 (100.00%)	
Producer's Accuracy	28651/28716 (99.77%)	2917/2926 (99.69%)		

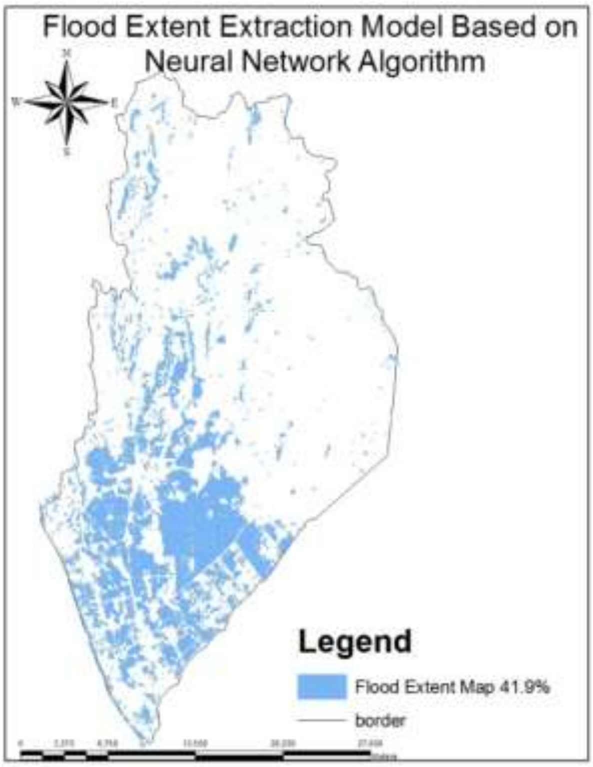

Figure 6: Neural network flood extent model

Table 3
Confusion matrix for parallel-pipe algorithm (overall accuracy = 98.6410% and kappa coefficient = 0.9243)

	Flooded Areas	**Non-flooded Areas**	**Total**	**User's Accuracy**
Unclassified	0 (0.00%)	345 (1.20%)	345 (1.09%)	
Flooded Areas	2919 (99.76%)	78 (0.27%)	2997 (9.47%)	2919/2997 (97.40%)
Non-flooded Areas	7 (0.24%)	28293 (98.53%)	28300 (89.44%)	28293/28300 (99.98%)
Total	2926 (100.00%)	28716 (100.00%)	31642 (100.00%)	
Producer's Accuracy	2919/2926 (97.40%)	28293/28716 (99.98%)		

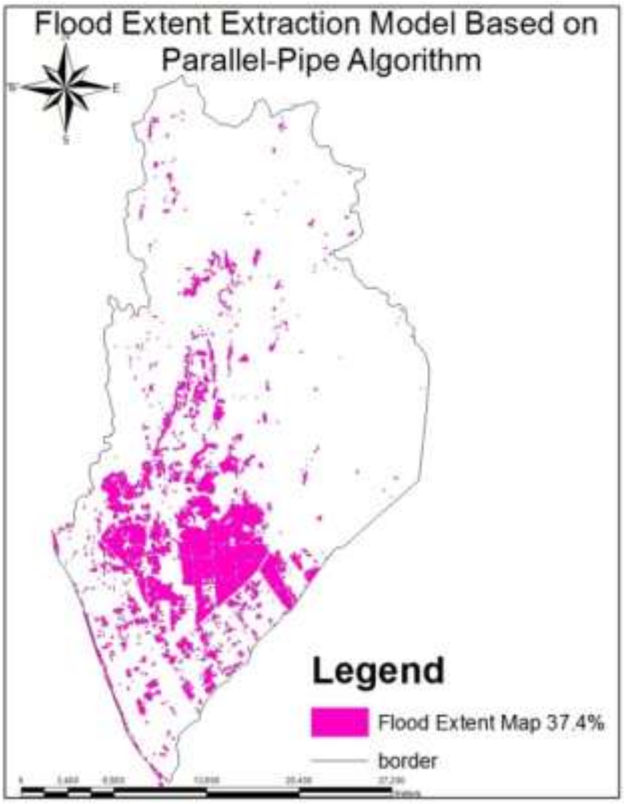

Figure 7: Parallel-pipe flood extent model

Table 4
Confusion matrix for minimum distance algorithm (overall accuracy = 96.7670% and kappa coefficient = 0.8335

	Flooded Areas	**Non-flooded Areas**	**Total**	**User's Accuracy**
Unclassified	0 (0.00%)	0 (0.00%)	0 (0.00%)	
Flooded Areas	2925 (99.97%)	1022 (3.56%)	3947 (12.47%)	2925/3947 (74.11%)
Non-flooded Areas	1 (0.03%)	27694 (96.44%)	27695 (89.53%)	27694/27695 (100.00%)
Total	2926 (100.00%)	28716 (100.00%)	31642 (100.00%)	
Producer's Accuracy	2925/2926 (99.97%)	27694/28716 (96.44%)		

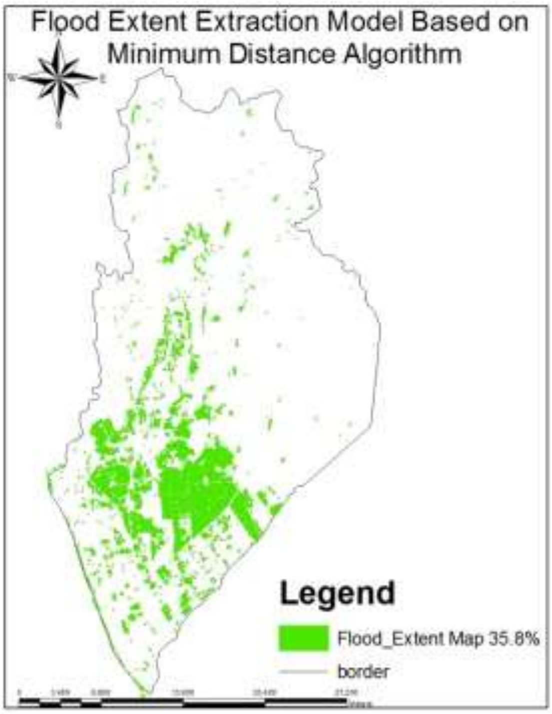

Figure 8: Minimum distance flood extent model

The results were further validated using previous studies conducted in the study area and its neighboring state. For instance, the extracted flood extent maps classify the southern part of Perlis as high-risk flood zones. This has concurred well with previous studies[1, 3, 19].

Conclusion

The analysis has empirically confirmed the efficacy of neural-network classification algorithm in analyzing the 2010 during-flood TerraSAR-X imagery better than the other two approaches. This is further validated by all the past research works and literature in the study area. What remains is for the policymakers and other stakeholders to direct their actions and efforts towards providing better measures of reducing the impacts of flood disaster in the Southern part of Perlis extracted and mapped as high-risk flood zones.

Besides, the approach due to its efficiency and effectiveness can be deployed in several earth observation analyses such as change detection, natural disasters mapping, land use/land cover mapping among others. This, to our mind, will prevent the loss of lives and properties experienced during a flood, minimize the cost expended on the provision of relief packages as well as a guide against various health hazards and challenges which are the aftermath of flooding.

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