COMPARISON BETWEEN PIXEL-BASED AND OBJECT-BASED CLASSIFICATIONS USING RADAR SATELLITE IMAGE IN EXTRACTING MASSIVE FLOOD EXTENT AT NORTHERN REGION OF PENINSULAR MALAYSIA

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ABSTRACT. Year 2010 massive flood hit the northern region of Peninsular Malaysia particularly Perlis and Kedah involved several districts and destroyed many agricultural areas and the infrastructure. This study focuses on the comparison between pixel-based classification and object-based classification of five machine learning algorithms including Parallelepiped (PP), Minimum Distance (MD), Maximum Likelihood (ML), Mahalanobis Distance (MH) and Neural Network (NN) using radar satellite image in extracting that flood extent. TerraSAR-X image was used to map the flood extent of the study area. In object-based approach, there were three simple machine learning algorithms such as PP, MD, MH together with NN performed with high accuracy while in pixel based approach, NN was the highest accuracy of all machine learning algorithms. The best output was chosen to be converted to vector format for mapping the flood extent. The result showed clearly through the map output that Kubang Pasu, Kota Setar and Kangar districts were highly affected by the flood. From the flood extent information, the collaboration of government, private sector, Non Governmental Organization (NGO) and community are needed to play the appropriate role in managing flood damage especially at the highly affected area and thus prevent loss of human live. Besides that, the authority could take action plan for pre-disaster, during and post-disaster caused by flooding.

Keywords: object-based classification, pixel-based classification, machine learning, radar satellite image, massive flood

INTRODUCTION

Flooding is one of the weather phenomenon that kills more people than the other natural hazards. People and the environment are increasingly suffering from the effects of flooding. Flooding happens when water level rises caused by a combination of factors such as overflow of river banks and low lying channels, broken dams, heavy and continuous rain, high ocean waters washed over the coast, etc. The northern region of Peninsular Malaysia's massive flood occurred in the year 2010 and was considered the worst flood in decades. Most floods that occur in Malaysia are caused by the Southwest (late May to September) and Northeast

Monsoons (November to March) that are characterised by heavy and regular rainfall. The Northeast Monsoon brings heavy rainfall, particularly to the east coast states of Peninsular Malaysia and western Sarawak, whereas the Southwest Monsoon normally signifies relatively drier weather.

Earth-observation remote sensing satellites such as radar and optical sensors with high spatial resolution and suitable coverage area are useful in monitoring the extent of the inundation area. The information will be useful for post flood analysis. With remote sensing and GIS technologies, mapping and assessment have become reliable, more accurate and much less time consuming compared to the conventional aerial based technique. Although Earth observation techniques by using satellites can contribute toward efficient flood detection and mapping at minimum time lag, optical satellites cannot be used to detect flood because of the cloudy weather during the floods (Takeuchi et al., 1998). Radar satellites can provide image during the cloudy weather because of the active ways of providing its own energy (Hahmann et al., 2010). Thus, radar satellites such as RADARSAT, ERS-SAR, ASAR and TerraSAR can be used separately to map the flood or as an adjunct to optical satellites.

RELATED RESEARCH

Much of the recent work has been a growing interest in applying radar image characteristics approaches rather than focusing on machine learning techniques for the analysis of single or multi-temporal Synthetic Aperture Radar (SAR) imagery. This interest stems from the wide range of applications in which the techniques can be used such as land cover detection, urban and rural area monitoring, disaster management and flood extraction as this study is focusing on. For the machine learning techniques, Selvi & Sathya (2014) attempted to improve the classification accuracy of single TerraSAR-X image by object-based classification using SVM method to identify the flood extent. For the case of multi-temporal SAR images, Aghababaee et al. (2013) improved change detection methods by using a new fractal change measure. However, Li et al. (2015) proposed sub-pixel flood inundation mapping using discrete particle swarm optimization on Landsat multispectral images. While Frate et al. (2000) studied the potentialities of neural network method for the detection of oil spills in ERS-SAR image. The neural network could correctly discriminate over a set of independent examples between oil spills and look-alikes with a largely acceptable rate of success. For the researches on radar image characteristics on flood detection, Long et al. (2014) utilized statistical thresholding techniques after the images was subtracted using change detection technique where it eliminated the need for detailed floodplain delineations which may change over time. Han et al. (2005) proposed a method to detect flood boundary based on texture information. Giustarini et al. (2013) introduced a hybrid methodology combining backscatter thresholding, region growing, and change detection (CD) to overcome the difficulty of detecting flooded areas in a built-up environment that needs a high-resolution Digital Elevation Model (DEM) and a SAR simulator for determining shadow regions that are not visible to the satellite. While Hahmann et al. (2010) demonstrates the potentials and limitations of two active contour models, namely Parametric Active Contour (PAC) model and Geometric Active Contour (GAC) model for mapping both smooth and rough water bodies in high-resolution SAR data. For the case of Heremans et al. (2003), they identified flooded area on ENVISAT ASAR images by distinguishing object-based classification technique and the active contour technique where it was based on the subtraction of the existing water bodies obtained from the non-flooded reference image with the image recorded during the flooded period.

STUDY AREA

The chosen study area of this research is the northern region of Peninsular Malaysia which is known as the Rice Bowl of Malaysia because the largest paddy field in this country is in this region. Generally it covers six districts for Perlis and Kedah states including Kangar, Kubang Pasu, Padang Terap, Kota Setar, Pendang and Yan districts as shown in Figure 1. It has mainly a flat terrain in the West area while a high terrain in the East area. In 2010, the mean monthly temperature was 22.92 °C and the mean monthly rainfall was 176.43 mm. Paddy field is the main land use, while others include forest, rubber, orchard and oil palm are also present as in Figure 2.

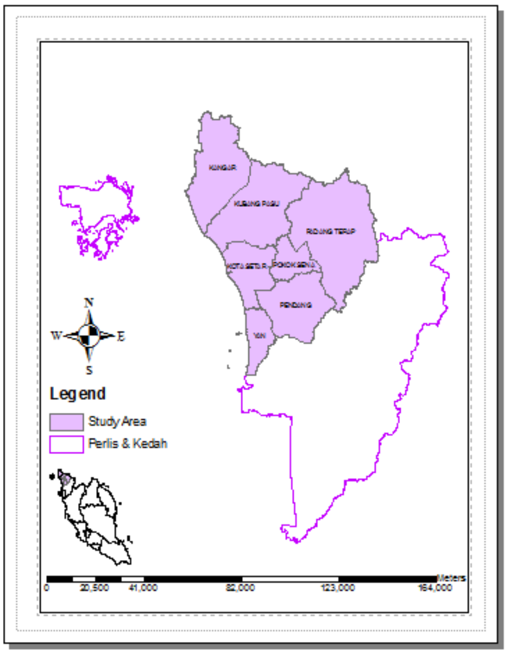

Figure 1. Study Area

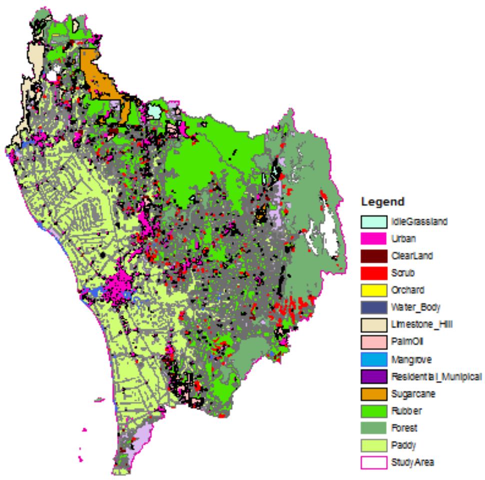

Figure 2. Ground Truth Land Use

MATERIALS AND METHODS

A simple representation of the methodology which are applied in this study and their sequence of use are illustrated in Figure 3. Radar image is processed until the final flood extent map is produced. After getting the radar satellite image, it cannot be processed straight away as it needs to be preprocessed because it is subjected to different errors according to the condition the images were acquired. According to Jensen (2005), before any classification method can be applied to satellite images, they need to be preprocessed for geometric and atmospheric correction.

According to Figure 3, pre-processing radar satellite image involved geo-referencing & geometric correction, atmospheric correction, data transformation (subset) and speckle filtering processes while additional process is required for object-based approach, feature extraction or segmentation after performing data transformation process. For geo-referencing process, image registration of image to image geometric correction was chosen to recover the transformation parameters that describe how one image maps to another. There were 30 ground control points (GCPs) with average Root Mean Square (RMS) error was 0.267219. Geometric correction was applied with the registration process. It used polynomial method whereby higher order transforms require a greater number of GCPs in order to produce the transform model. After that, speckle filtering was applied in order to achieve a smoothing effect and the visual appearance of the speckle reduced. Lastly for pixel-based pre-processing stage, it involved image subset process which created small portion of a larger image to determine a study area. Additionally for object based classification, feature extraction process was applied. In this stage, it divided an image into segments that have similar spectral, spatial and/or texture characteristics. The segments in the image ideally correspond to real-world features.

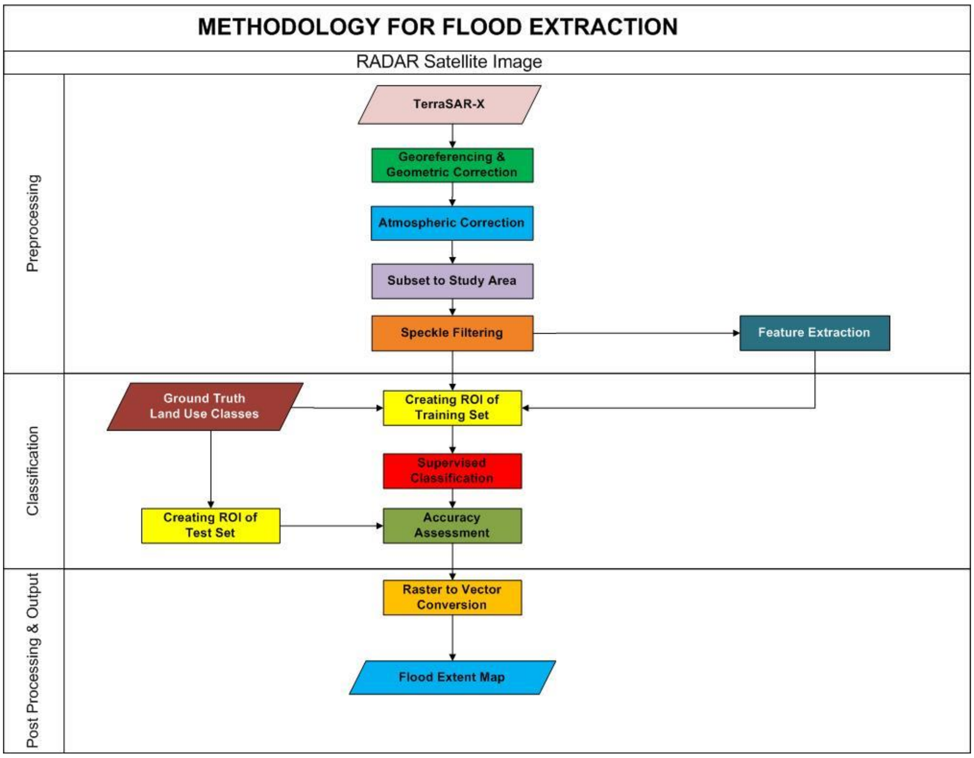

Figure 3. Methodology

Satellite image classification is to produce a thematic representation by grouping image pixels into categories or spectral classes. It can be performed on single or multiple image channels to separate areas according to their different scattering or spectral characteristics (Giordano et al., 2005). However, before the classifying process can be performed, region of interest (ROI) is determined by collecting training and testing set of data to make sure the correct spectral classes on the map are assigned to their dedicated land use classes. ROI data is collected from ground truth data related to a pixel on a satellite image which is compared to what is there in reality in order to verify the content of the pixel on the image. In classification of remotely sense image, suitable machine learning algorithm is chosen. However, for object based classification, the same machine learning algorithm is used but the classification of image objects was assigned according to class descriptions after performing feature extraction process.

Post-processing stages in this study include refining and preparing data towards the flood extent of inundated area mapping. These cover accuracy assessment, raster and vector conversion and vector overlaying. Accuracy is determined empirically by comparing a sample of pixels (testing pixels) from the classified image to a ground truth data. The percentage of pixels from each class classified correctly can be calculated and also the percentage of pixels that are mistakenly classified into other classes. The results are expressed in tabular forms (confusion or error matrix). Errors of omission and commission are calculated, in particular when the number of land cover types is small. The result of classified remote sensing image raster data is to be converted into vector format prior to mapping the inundated area as shown in Figure 4.

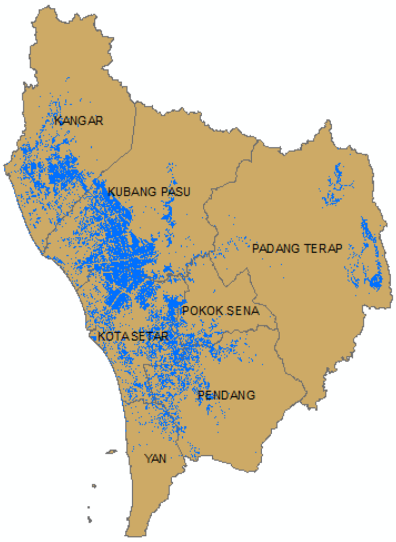

Figure 4. Flood Extent Map of Inundated Area

RESULT AND DISCUSSION

For the pixel based classification, it can be shown that Neural Network method outperformed other machine learning methods with overall accuracy of 99.7863% and Kappa Coefficient of 0.9955 while the lowest was Maximum Likelihood with overall accuracy of 37.1989% and Kappa Coefficient of 0.0000. Other machine learning methods achieved a high accuracy nearest to Neural Network algorithm performance as shown in Table 1. However, for object-based classification, the output of the four algorithms have the same results but with a very high accuracy (overall accuracy: 99.9998%, Kappa Coefficient: 1.000). Maximum Likelihood algorithm was the worst accuracy where overall accuracy was 68.3368% and Kappa Coefficient was 0.000.

The result can be shown clearly that for all five algorithms, object-based classification result outperformed pixel-based classification with higher accuracy and Kappa Coefficient equal 1.00 except for the Kappa Coefficient for Maximum Likelihood was 0.00. In pixel-based classification, only spectral signature of a pixel was considered and thus resulted 'salt and pepper' appearance such as fragmented flood feature class. In contrast to pixel-based classification, object-based classification used spatial context around a pixel, produced a flood feature class that was much more homogeneous compared to the pixel-based classification.

Table 6. Overall Accuracy and Kappa Coefficient of Pixel-based (PB) and Object-based (OB) TerraSAR-X Classification for 5 Algorithms

Machine Learning Algorithm	Overall Accuracy PB (%)	Overall Accuracy OB (%)	Kappa Coefficient PB	Kappa Coefficient OB
Parallelepiped	98.8666	99.9998	0.9760	1.0000
Minimum Distance	97.2982	99.9998	0.9433	1.0000
Maximum Likelihood	37.1989	68.3368	0.0000	0.0000
Mahalanobis Distance	97.2982	99.9998	0.9433	1.0000
Neural Network	99.7863	99.9998	0.9955	1.0000

In neural network classification, instead of calculating discriminant functions as in other machine learning approaches, class selection for each pixel using a feed-forward mode network make it more suitable quantitatively and better reflects the actual distribution of classes in the image. However, for Maximum Likelihood with the lowest accuracy compared to others because of some land cover area also producing spectral signatures different from each other if grouped as one big class compared to the flood area as a result of different reflective land cover types. In Maximum Likelihood, if the assumption of a normal distribution for each class is not correct, then the classification has a maximum overall probability of error and the maximum-likelihood classifier is not a good choice.

CONCLUSION

In this study, a flood extent of massive flood disaster for the northern region of Peninsular Malaysia could be mapped using radar satellite image. The flood extend can be seen clearly and covers a large area of those districts. From the result, it showed that it involved Perlis and some districts of Kedah including Kubang Pasu, Kota Setar, Pokok Sena, Padang Terap, Pendang and Yan. Kota Setar district was the worst affected by the flood with 25.89% while Padang Terap was the least affected by the flood with 0.14%. Moreover, Kota Setar was the biggest contributor for paddy because of the geographical position as a low land area that is more suitable for paddy farming. That is considered a very big area and impacted many public and private wealth. Object-based approach was found to be the most appropriate technique in extracting flood area compared to pixel-based approach. In this approach, there were four algorithms including Parallelepiped, Minimum Distance, Mahalanobis Distance and Neural Network performed very high accuracy. However in pixel-based approach, Neural Network outperformed other 4 machine learning algorithms. As a summary, in object-based approach, it is sufficient enough to use simple machine learning algorithms such as Parallelpiped, Minimum Distance and Mahalanobis Distance in extracting flood extent from radar satellite image while in pixel-based approach, advanced machine learning algorithm such as Neural Network is more precise than simple machine learning algorithms but it requires more time and computer resources to process the similar task.

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