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Extraction of water body information from high spatial resolution Sentinel-1 SAR images using Li's minimum cross entropy threshold method: a case study of Thac Ba Lake, Yen Bai Province, Vietnam

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ABSTRACT

The reliable and up-to-date information on the water resources is increasingly important, not only for the management scopes but also for farmers and urban planners. Microwave active remote sensing technology has the all-time and all-whether advantage for the earth observation. It is not affected by night and fog and has ability to penetrate through the cloud during the flood period. A new generation of synthetic aperture radar sensors, called Sentinel-1A, has a much improved spatial, temporal, and radiometric resolution. The Sentinel-1A, with four exclusive imaging modes of operations: Interferometric Wide Swath, Extra Wide Swath, Strip Map, and Wave, provides the obviousness for water and land boundary in the SAR images due to low backscatter value in the pixels of the water surface. As the results, analyzing images by using image thresholding techniques is often used to extract water surface from SAR images. In this study, an automatic method is presented to identify water body areas via using minimum cross entropy, which is also known as Li's minimum cross entropy method from Sentinel-1A IW images. The evaluation of the proposed method shows a high accuracy with 99.5% of the user accuracy, 98.8 % of the producer accuracy, and 97.9 % of the overall accuracy.

1. Introduction

Mapping the open surface freshwater (i.e. lakes, ponds, reservoirs) is an integral part of many hydrologic and agricultural models, wildlife management programs, and recreational and natural resource studies (Henderson, 1995). Concomitantly, the visibility and appearance of open surface water bodies should have supplemental value in radar geoscience research addressing the relationships among radar wavelength, specular reflectance, smooth/rough signal return criteria, and terrain features, especially

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when spatial variables are considered. Open surface water is a landscape feature that is generally regarded as easily detected on radar imagery; calm water surface acts as the specular reflector, which reflects the radar energy away from the sensor. As a result, the open surface water generally appears as a dark, no return area on the SAR image. However, this observation is an oversimplification. The radar signal is sensitive to surface roughness and water will not always appear as, or actually be, a smooth surface. Other surfaces can also appear smooth at radar wave-lengths and thus similar in appearance to the water body surface. Which surfaces appear smooth and under what conditions depends on the surface and the wavelength of the radar system, shadow effect for example. The appearance (radar response) of surface water may or may not be similar in appearance to its background as a function of the system wavelength.

Due to the cloud penetration capability, SAR satellites are almost independent from weather and daylight. Therefore, they are more suitable than optical sensors to reliably and timely map inundated areas in flood situations, which usually occur under overcast sky conditions, especially in tropical climate zones, as Vietnam for example. Thus, SAR has been paid more and more attention in the open water bodies mapping, flood monitoring, as well as disaster assessment (Brisco, 2009). Since nearly two decades operational space borne systems have been used to map water bodies and flood situations at C-Band (ERS-1/2, Envisat ASAR and Radarsat-1/2), L-Band (JERS1/2,ALOS PALSAR), and X-Band (TerraSAR-X). Those SAR sensors system are small coverage, medium spatial resolution, low frequency, and expensive. The most recently, space-borne radar system Sentinel-1 has a new breakthrough on the spatial resolution, polarization, incident angle and width. Sentinel-1A can gain horizontal, vertical and a variety of polarization combination information, which can provide products with different angles and a variety of spatial resolution products and provide greater coverage and shorter repeated observation because of its scanning and global monitoring. These SAR sensor properties make it become the most powerful space-borne radar system, which offer enormous potential in the domain of water bodies mapping as well as flood monitoring. However, the improved spatial resolution of the SAR data results in a large variety of very small-scaled image objects, which makes image processing and analysis even more challenging.

Surface water body extraction using intensity thresholding approaches on SAR image had been widely used (Brisco, 2009; Manjusree, 2012; Westerhoff, 2013). In these approaches, water is distinguished from other types of land cover in SAR backscatter images, but the final accuracy of the results relies on the ability to differentiate water versus non-water pixels in the backscatter domain, which becomes especially difficult when the response signal from water surface is affected by not only the weather condition (wind-induced roughness) but also the SAR geometry properties (e.g. wavelength, polarization and local incidence angle). Segmentation algorithms are quite successful but computationally expensive. More recently, Li’s minimum cross Entropy threshold method, has been widely used due to its simple, stable and effective (Mehmet and Bülent, 2004), and (Duaa, 2011).

The general aim of the ongoing research activities is applying the Li’s Minimum Cross Entropy Threshold Method for automated water body identification based on Sentinel-1 image, which does not require any ancillary data or a priori knowledge of the response signal from water bodies in SAR image. The method has been applied to extract water body information in the reservoir of Thac Ba hydroelectric, and achieved relatively good results.

2. Study area and Data

2.1. Study area

Thac Ba reservoir is located in Yen Bai province, in the northwestern part of Vietnam between longitudes 104.6°E and 105.3°E, and latitudes 21.6°N and 22.1°N. It covers an area of about 235km^2 (19.05km^2 is water area and the remaining 4.35km^2 of islets on the reservoir) (Figure 1). The reservoir has altitudes approximate 150meters above sea level by the mountainous areas. There are hundreds of streams and canals, with small water source and low water flows, especially during the dry seasons. The flow of rivers and streams upstream is strong and the volume varies, sometimes causing sudden floods. During the dry season, the water level in Thac Ba lake is low and Ma people grow groundnut and a variety of vegetables to about 1.5ha to 2ha along the lake sides (Cos land). The Thac Ba lake of about 500ha of water surface is also managed and exploited by Ma people for aquaculture and fishing.

Thac Ba reservoir is the second largest dam-reservoirs in the Red River basin (Hoa Binh is the largest dam-reservoirs). It is also one of three Vietnam's largest artificial lakes which have been constructed as multi-purpose reservoirs: for power generation, flood control, agricultural irrigation, fishery and tourism. The Thac Ba dam, impounded in 1972 on the Chay River, with a storage volume of 2.94km^3, and provides 0.4billion KWh (Vu , 2002).

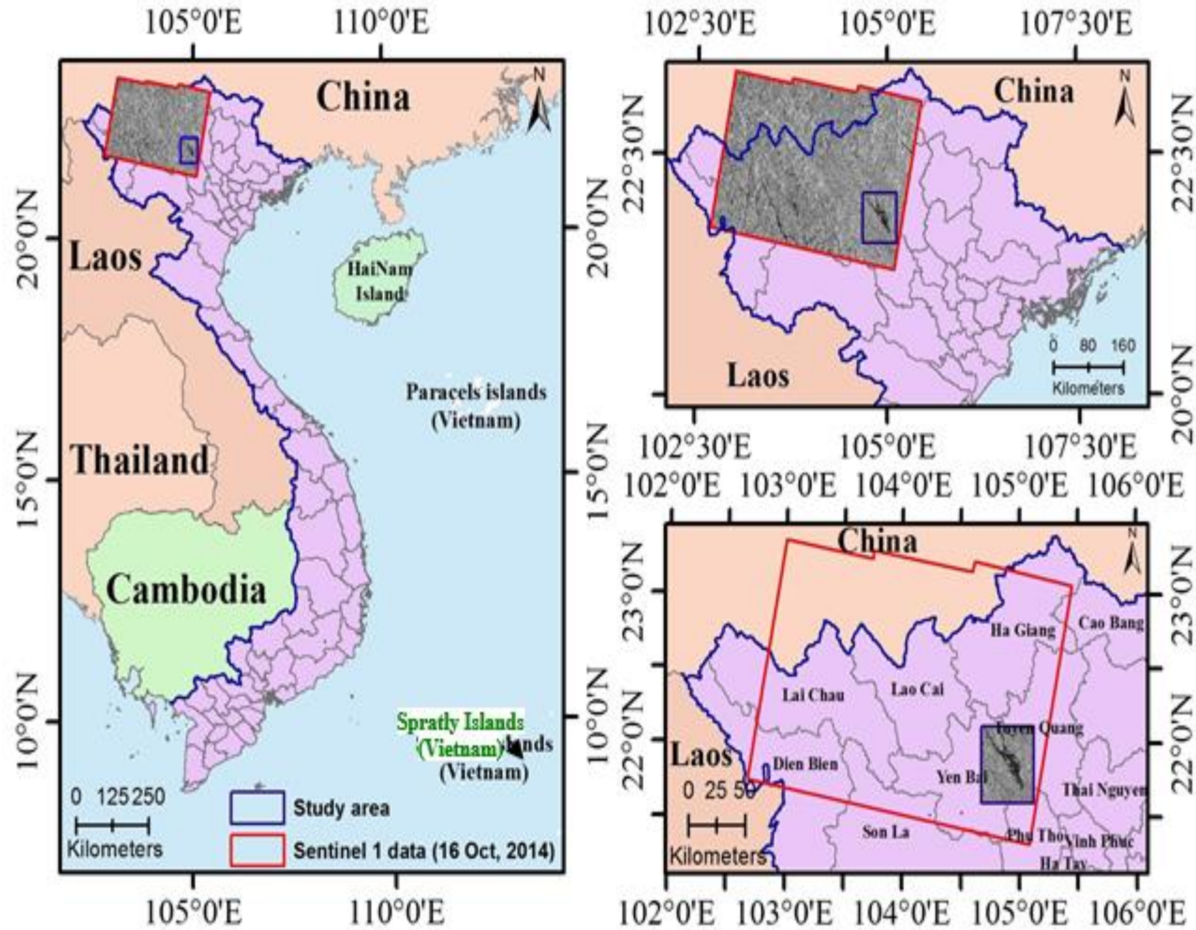

Figure 1. Study area and data location

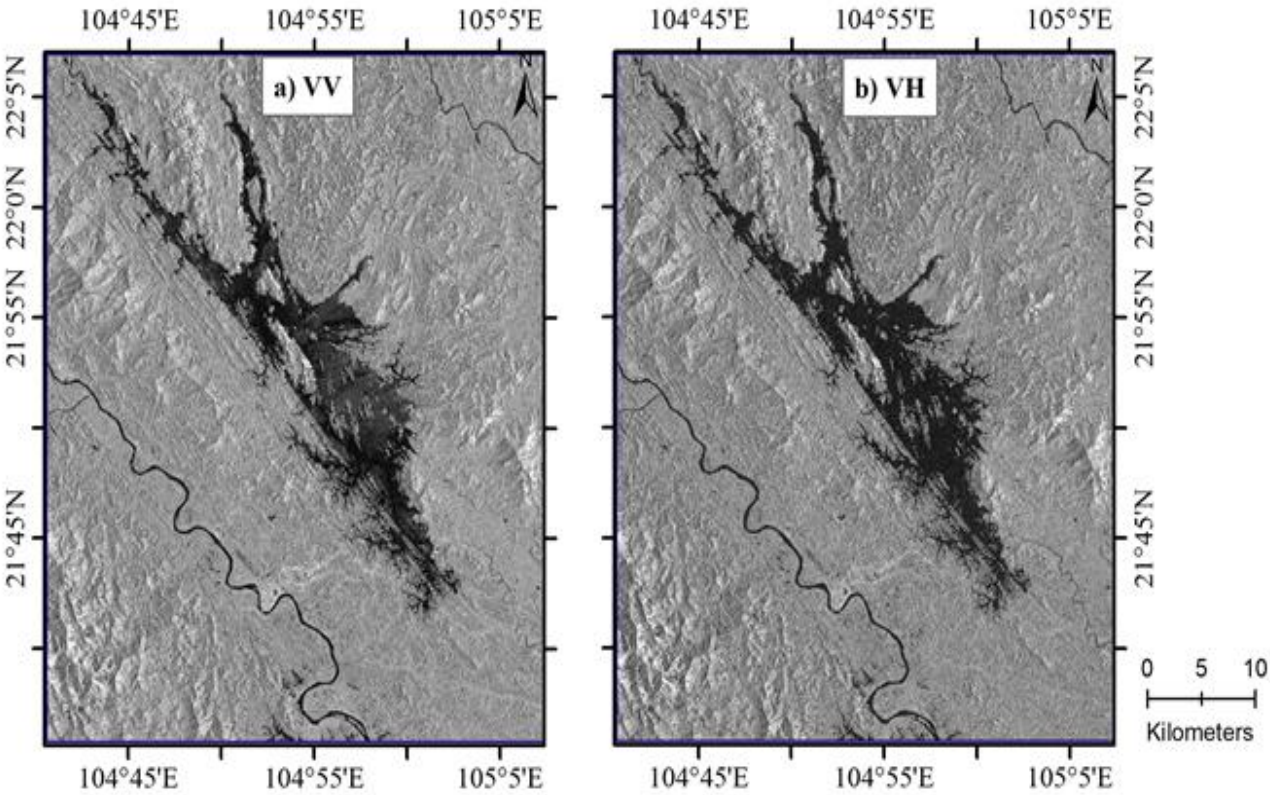

Figure 2. Sentinel 1A SAR data acquired in October 16, 2014 (a) VV image, (b) VH image

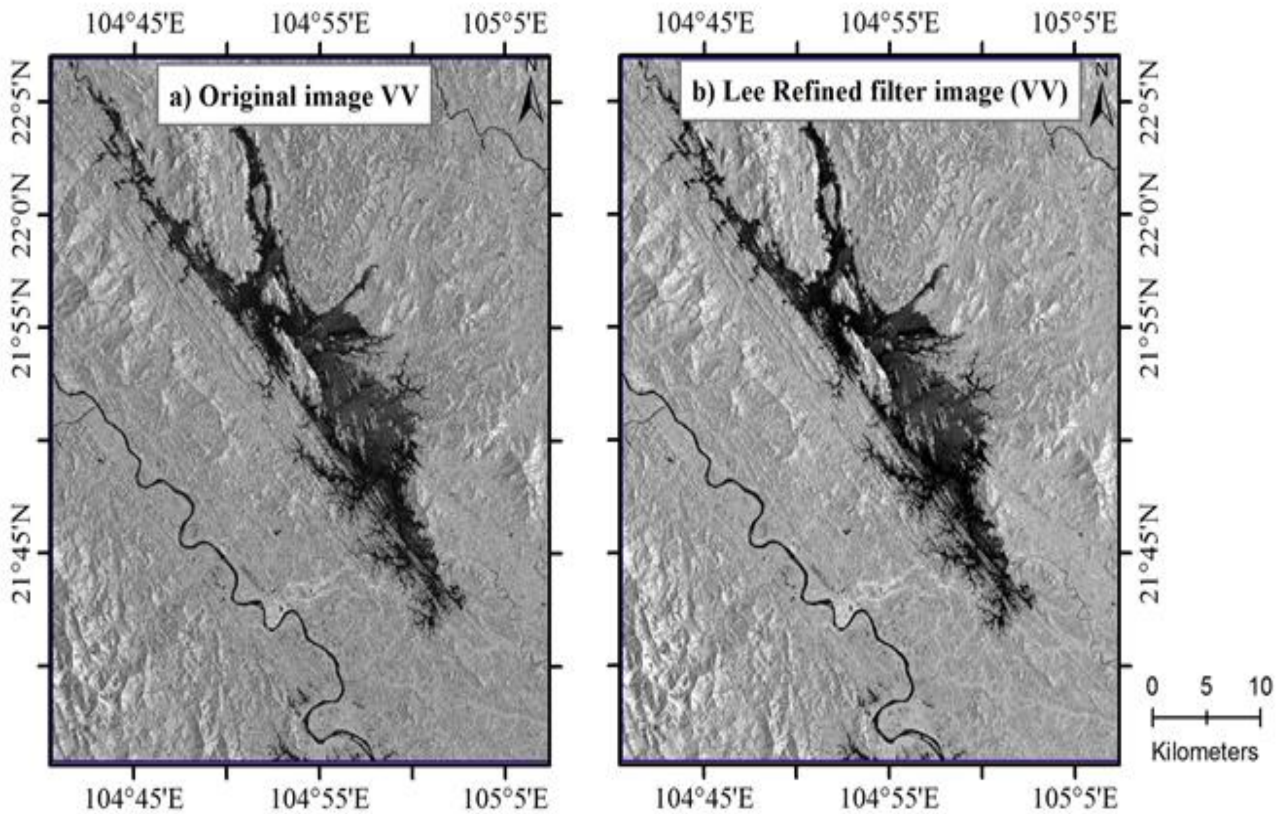

Figure 3. The backscattering coefficient map before and after filtering

2.2. Satellite data

The study has used the satellite imagery of Sentinel 1A (dual polarization VV and VH) with 10m spatial resolution in October 16, 2014. The satellite data used in the present study are showed in the Figure 2

3. Methodology

3.1. Satellite image processing

According to the Rayleigh criterion, the incidence angle decreases that the roughness of target surface increases, which will make the range of target scattering energy distribution expanded. When the surface of the water generated waves due to strong winds, that is similar to the increase in surface roughness, then the radar echo energy increases, and the rate weakened with the increase of the incident angle. When the incident angle decreased, the scattering coefficient of wavy surface increased, and it is very difficult to distinguish with build-up areas, therefore, we should do local incident angle normalization for the water body identification. In this paper, we applied flattening gamma for radiometric terrain correction for Sentinel-1A SAR data (Small, 2011). When the surface is rough, echo has nothing to do with the incident angle and polarization. But when the surface is smooth, echo is related to the polarization in a certain extent. For the same surface, the measured value of cross-polarization (VH) is smaller than co-polarization (VV). In this study we observed that VH image still provides useful information for water extraction. Therefore, for the Sentinel-1A data used to disaster evaluation, we can use both VH and VV images products. Based on the above discussion, in this paper, the input data is Sentinel-1A data in the October 16, 2014 for Thac Ba reservoir (Figure 1).

3.1.1. Calculating the Backscattering Coefficient (Gamma nought - γ^o)

For water body mapping as well as flood disaster assessment, we must accurately identify the water body pixel. And for the water body extraction from Sentinel-1A images mainly based on that water has lower backscattering characteristics in the microwave range. Using the Sentinel-1 Toolbox software provided by ESA to calculate backscattering coefficient, the main contents include: original data extraction, clip image, backscattering image generation. Processing Sentinel-1A data according the following steps: import data, subset data, data calibration, backscattering image generation, then the backscattering coefficient (gamma nought - γ^o) of each pixel will be obtained, data speckle filtering, data terrain correction (Small, 2011).

3.1.2. Removing the Noise

Since SAR is a coherent-imaging system. So the speckle noise inevitably exists in the images. Removal of the speckle noise is very important to obtain high-quality radar images. Previous studies confirmed that SAR images comply with the multiplicative noise model from theoretical deduction and test., and used the multiplicative noise model filtering algorithm with different filters and different window sizes to filter the ASAR images. The results showed that with 7 x 7 window Enhanced Lee had the best effect (Figure 3). Therefore, this paper uses 7 x 7 window Enhanced Lee filtering method provided with Sentinel-1 Toolbox version 1.1 for the Sentinel-1A image filter processing (Gonzalez and Woods, 2002), (Ye, 2008) .

3.2. Li's Minimum Cross Entropy Threshold Method for Water body Extraction

For the flood disaster assessment, the main issue is the water area information extraction; the process is actually "Binarization" process in the image segmentation. Therefore, the threshold method is often used in water body extraction.

Currently, there are experience method, test method, two-peak method and mathematical statics method for the threshold determination. Among them, the experience method is affected by the subjective judgment influence. The two-peak method is easily to get a false bottom. Moreover, these methods are time and effort consuming. While the maximum variance between clusters, the maximum entropy and the minimum error method are often used. In particular, the maximum variance between clusters, due to its simple, stable and effective, has been widely used. And in the actual application, some scholars improved this method, so that it might obtain better segmentation results.

There are different methods for generating image objects. Some are fully automated (unsupervised methods) while the others are semi-automatic (supervised methods, Zhang, 2010). In an unsupervised segmentation method, pixels are grouped automatically according to some criteria, while in a supervised one; the user has an influence on the segmentation by interventions made through the process by the user in order to guide the segmentation. Image thresholding is considered one of the main approaches of segmentation and entropy based thresholding is one broad type of thresholding techniques. In the following subsection 3.3.1, a brief introduction on the cross entropy thresholding technique is presented; while sub-section 3.3.2 present the principle of the Li's minimum cross-entropic thresholding technique.

3.2.1. Cross-Entropic Thresholding

Cross entropy (or Relative Entropy, Kullback-Leibler Divergence) thresholding approach was proposed by Kullback (David, 2009), (Chang, 2006). The approach measures a theoretic information distance between two distributions: the smaller the cross entropy, the more similar the distribution of the two variables, and conversely (Ramaca and Varshney, 1997). (Mehmet and Bülent, 2004) have given the basic definition of the cross entropy as below formula:

$$D(q,p)=\sum_{i=1}^{L} q(i)\log\left(\frac{q(i)}{p(i)}\right) \qquad (1)$$

Where, *q* and *p* are two different sources of input information, *q(i)* and *p(i)* are the two statistical distributions of the corresponding two sources while *L* presents the range of input information values. In image thresholding, cross entropy is used as a constraint to force the total intensity in the threshold image to be identical to that of the original image by minimization of relative entropy between input image and output binary image. There are several thresholding techniques based on the concept of cross entropy; some of the most popular methods in this category are Entropy-Li, Entropy-Brink, and Entropy-Pal. Since the scope of this study is to automatically identify water body in an efficient way from Sentinel-1 backscatter coefficient image, Entropy-Li was chosen over the others because its simple, stable, effective and appropriate with a log-normal distribution of the input data.

3.2.2. The Minimum Cross Entropy Thresholding technique

The Minimum Cross Entropy Thresholding technique is used for finding the optimal threshold t^* by minimizing the cross entropy between the original Sentinel-1 backscatter image (σ^o) and the resulting thresholded backscatter image ($\sigma_t^{\ o}$) which is defined as:

$$\sigma_t^{\ o}(r,c)=\begin{cases}\mu(1,t)=\mu_{a(t)}, \sigma^o(r,c)<t \\ \mu(t,L+1)=\mu_{b(t)}, \sigma^o(r,c)\geq t\end{cases} \qquad (2)$$

Where (σ^o) is the input backscatter image, $\mu_{a(t)}$ is the mean value of the region A in the thresholded image and $\mu_{b(t)}$ is the mean value of region B, where regions A and B are the background (non-water) and object (water), respectively. In Entropy-Li algorithm, the optimal threshold is estimated by minimizing the relative entropy between the input image (σ^o) and the thresholded image $\sigma_t^{\,o}$). The optimal threshold can be estimated as the below formula:

$$t^* = \min\left[\sum_{I=0}^{T} I\sigma^o(I)\log\frac{I}{\mu_{a(T)}} + \sum_{g=T+1}^{L} I\sigma^o(I)\log\frac{I}{\mu_{b(T)}} + \right] \qquad (3)$$

Where t^* is the optimal threshold image; L is the maximum grey level which represent the number of information values in an image; $\mu_{a(t)}$ and $\mu_{b(t)}$ are the means the foreground (water) and background (non-water) regions. The detail of the algorithm was very well presented in (Mehmet and Bülent, 2004), (Duaa, 2011).

4. Results & Discussion

It is possible to get the backscattering coefficient image after pretreatment on Sentinel-1 SAR data. In the ENVI/IDL programming environment to achieve the optimal threshold search, the Li's Minimum Cross Entropy Threshold algorithm was performed. The principle of water body defining can be stated that if the pixel value is less than the threshold, the pixel is the water, inversely, if the pixel value is more than the threshold, the pixel is not the water, as can be seen in the Figure 4.

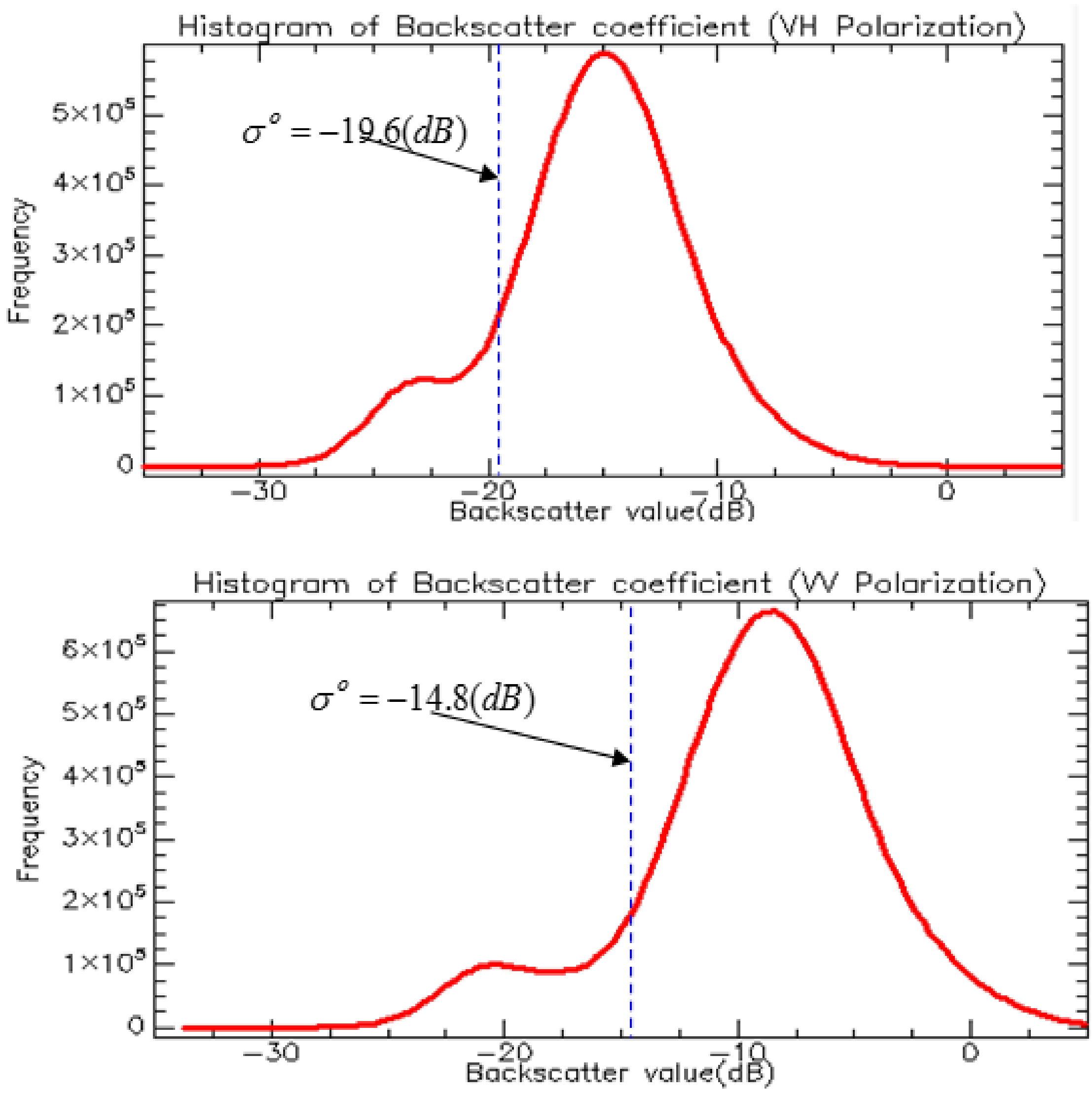

Figure 4. Automatic threshold value extraction based on Li's Minimum Cross Entropy

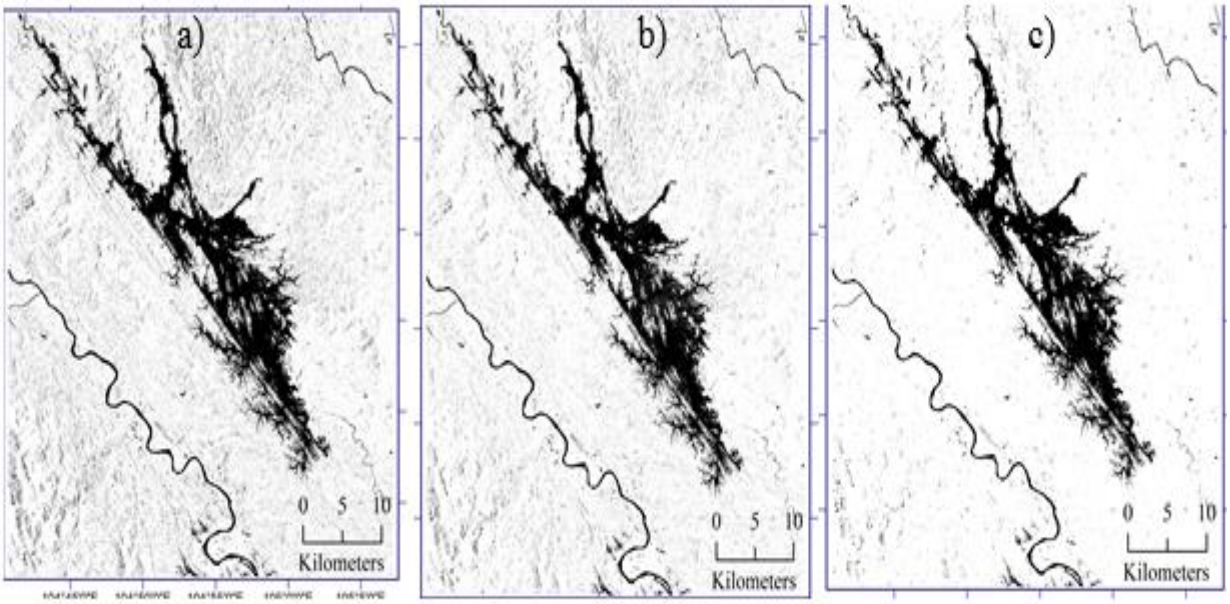

Figure 5. Water body extraction based on Li's Minimum Cross Entropy Threshold algorithm: a) Water body extraction from VH image; b) Water body extraction from VV image; c) Water body extraction from intersection of VH image and VV image

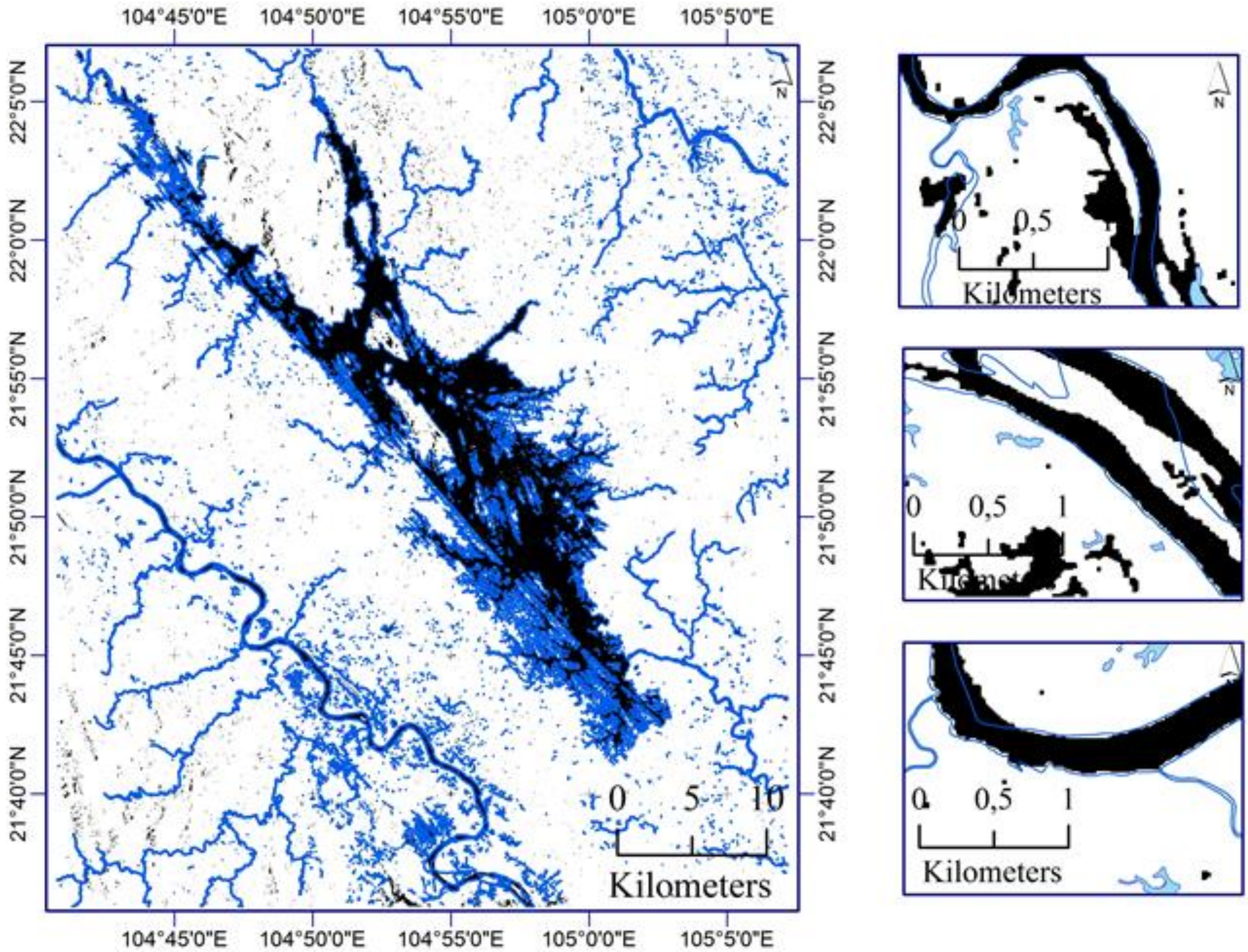

Figure 6. Water body extraction based on Li's Minimum Cross Entropy Threshold algorithm from Sentinel-1 SAR image overlay with water body layer from GIS

Table 1. Accuracy assessment of the results Threshold algorithm

Thresholding method	Completeness (%)	Correctness (%)	Quality (%)
Otsu	93.7	61.5	59.1
Li's Minimum Cross Entropy	99.5	98.8	97.9

From the image, the water body extraction result is good. However, there are a number of islands in the river, which is in the lower left corner of the image. These islands influenced the backscattering coefficient of the water, so this part of water body is not extracted. And due to the effect of noise and shadow of the mountain, some error inevitably exits in the extraction result.

The goal of object detection (or image classification) is usually a distinction between two classes (or object and background). Comparing the results of the automated extraction to reference data, an entity classified as an object as a True Positive (TP). A False Negative (FN) is an entity corresponding to an object in the reference that is classified as background, and a False Positive (FP) is an entity classified as an object that does not correspond to an object in the reference. A True Negative (TN) is an entity belonging to the background both in the classification and in the reference (Heipke, 1997), (Zhan, 2005). The confusion matrix has a very simple structure. It consists of the number of entities assigned to these four classes (denoted by ||.||). Two metrics for the quality of the results, the Completeness (Comp) and the Correctness (Corr), can be derived:

$$Comp = \frac{\|TP\|}{\|TP\| + \|FN\|} \quad (4)$$

$$Corr = \frac{\|TP\|}{\|TP\| + \|FP\|} \quad (5)$$

$$Quality = \frac{\|TP\|}{\|TP\| + \|FP\| + \|FN\|} \quad (6)$$

For validating the accuracy of the classification result, a number of shape files of water body was generated based on the land use map of the year 2010 and Landsat 8 data, it is also called knowledge-based digitizing datasets. Theses shape files are then converted into binary raster format and used to evaluate the quality of former classification results (Figure 6).

True positive pixels are all the pixels in both datasets have the value of 1. False Negative pixels are the pixels have value of 1 in knowledge-based digitizing dataset and value of 0 in classification results and the pixels have value of 0 in knowledge-based digitizing dataset and value of 1 in classification results. In this study, the well-know thresholding Otsu method (Otsu, 1979) was also performed to compare with Li's Minimum Cross Entropy thresholding method. The accuracy assessment of the results presented in the Table 1.As could be expected, Li's Minimum Cross Entropy thresholding method shows the better result, which the Completeness (Comp-user's accuracy), Correctness (Corr-producer's accuracy) and Quality (Over all accuracy) were 99.5%, 98.8% and 97.8% respectively.

5. Conclusion

Comparing with the visible and multi-spectral remote sensing data, Sentinel-1A SAR has more broad application prospects in the flood disaster assessment, due to its all-time, all- weather data acquisition capability, and it is not impacted by rainy and cloudy. So this paper selects the test data is Sentinel-1A SAR image in the October 16, 2014 for Thac Ba reservoir.

Li's Minimum Cross Entropy Threshold algorithm was applied to the water body extraction from Sentinel-1A SAR images. The method is simple, is easy to implement. It improves the automatic identification level of computer water body identification to a large extent. The pixel in the shadow of the mountain also has low scattering coefficient, therefore, the results of water body extraction often include the shadow of the mountain. Although several errors causes-notably SAR imagery properties ,topography issues, as well as mixed-pixel issues, between the classification result and the reference data contributed to the accuracy level of classification results, the Correctness (Corr) and Quality achieved by comparing the classification map and the reference data were approximately 99% and 98% for water body surface, respectively.

Despite its limitations, the presented procedure is a fully automated method to identify water body surface from Sentinel-1A Interferometric Wide mode, based on backscatter values, which is, in terms of processing time, much faster than running more complex segmentation procedures. Processing time becomes a key factor when the information on the land surface needs to be derived to flood monitoring.

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