EMERGENCY FLOOD MAPPING FROM SYNTHETIC APERTURE RADAR; A SIMPLE FUZZY LOGIC APPROACH

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ABSTRACT: Floods are common disasters causing economic and human losses all over the world and have accounted for more than 50% of all disasters in the Asia-Pacific region. Flood mapping has been done by several methodologies based on remote sensing satellite observations, both optical and microwave. Optical data usage is limited due to cloud cover in bad weather conditions during flood events. Microwave observations have been widely used due to its cloud penetrating capability and night time observations. However, the mapping accuracy is still an issue for emergency response mapping. Change detection and single thresholding is well known method used to detect open area floods quite accurately. However, the main challenge is water detection in vegetated and built-up areas. Flood detection in vegetated and built-up areas are possible with the increased backscatter change resulted from double bouncing radar returns. This study reveals a dual thresholding method applied for both decreased and increased backscatter change of L-band SAR obtained from PALSAR-2. The open area flood extent and digital elevation model was used to determine the maximum inundated level that employed to clean up the noises appeared due to complex radar returns from various land cover types. Finally, a fuzzy logic approach is proposed as a multi-criteria decision-making tool for emergency mapping, integrating the dual thresholds and flood potential elevation.

1. INTRODUCTION

Traditionally, flood mapping has been done quite accurately, based on ground surveys and aerial observations. When the flooding is widespread, this method is time consuming and extensive manpower is required. With the development of space technology, satellite data usage has become more popular, but the main obstacle of optical remote sensing data was the cloud cover although the spatial resolution was improved drastically. Microwave is commonly known as synthetic aperture radar (SAR), an active sensor permitted for day and night observations. The SAR sensors are capable of penetrating clouds and are useful for earth observation in bad weather conditions. Taking these advantages of SAR, flood mapping and the potential of SAR for large-scale flood detection has been demonstrated by several previous investigations (Horritt and Luckman 2001; Schumann and Pappenberger 2009; Smith 1997).

Water surfaces act as specular reflectors for SAR and the return signals back to the sensor are weak. Thus, the backscatter signals become weak from flooded area compared to a previous backscatter obtained in the same area. Therefore, the difference in backscatter have been used to detect floods using SAR data and the methodology is known as Change detection and thresholding. However, this method is detecting floods quite accurately in areas where water surfaces are open to the sky, but is not detecting the floods under vegetated and built-up land covers. SAR return signals are affected by land cover types as well as sensor characteristics such as the wavelength, polarization and incident angle (Pulvirenti and Guerriero 2011). Based on sensor operating wavelengths, SAR data are categorized into several classes as X-band (0.312 m), C-band (0.0567 m) and L-band (0.2423 m). Larger the wavelength is higher the radar penetration; thus, over-estimation of flooding can be expected due to backscatter enhancement from the soil moisture. On the other hand, a shorter wavelength enhances surface scattering that limits the flood detection in vegetated and built-up land covers. In this case the L-band is quite good at detecting water under vegetation compared to the X-band SAR. Specular reflection from water surfaces in vegetated and built-up structures causes an increase in radar returns due to the double bouncing effect in which inundation mapping becomes a difficult task with change detection and single thresholding techniques. Therefore, development of an algorithm considering double bouncing effect to extract floods in vegetated and built-up areas are important improve the accuracy of emergency flood mapping.

1.1 Fuzzy Logic

Fuzzy set theory, proposed by Zadeh 1965 and Zadeh 1975, aims to represent the knowledge of human experts in a set of fuzzy IF-THEN rules. Fuzzy logic is basically a multi-criteria decision-making tool and has emerged as a profitable tool for the controlling and steering of systems. Such systems are also capable of complex processes, as well as other expert systems and applications like the classification of remote sensing satellite data. Fuzzy classification has been applied in remote sensing as pixel-wise approaches by assigning gradual membership of pixels to classes. The degree of membership is based on the definition and interpretation of fussy set. An element of a fuzzy set can have different degree of membership which can be 0, 1 or any value in between the mathematical function. Simple membership functions are the standard S function and standard Z function those were used and described in the section 2.2.

1.2 Sentinel Asia

Sentinel Asia (SA) promotes cooperation amongst the space community, the disaster management community, and the international community in using spaced based technologies for Disaster Risk Reduction (DRR). SA was established as an initiative of APRSAF in a step-by-step and was expanded introducing satellite communication systems and fully operationalize emergency support system in 2008. In the case of a regional disasters, several space agencies and related institutions act as Data Provider Nodes (DPN), providing satellite data from their own satellites to the Data Analysis Node (DAN). The data observed by these satellites are provided to the requester of a given disaster to use for emergency response as well as other disaster risk reduction activities.

The radar sensor PALSAR-2 on board ALOS-2, JAXAs L-SAR satellite mission, was launched in late 2014. The main purpose was to provide data to be used for cartography, regional observation, disaster monitoring, and environmental monitoring. ALOS-2/PALSAR-2 dual polarized (HH, HV) L-band data are freely available for the Asia-Pacific region at the time of a disaster. Recent flood occurred in Colombo during May 2016, was severe and similar to an event that occurred in 1986, about 30 years before. SAR data from several sensors were processed to access the flood affected area. The complete flood detection by single thresholding method was hampered by different land use and land-cover types. Colombo being the capital of Sri Lanka, SAR data usage for flood mapping was limited due to the built-up areas and the mixture of buildings and vegetation along the river banks. Therefore, this event was selected as a case study to investigate a suitable methodology to improve the accuracy of emergency mapping of SA. Based on the analyses, a fuzzy logic approach is proposed for emergency response mapping using L-band SAR. This study reveals a simple flood extent mapping methodology to detect floods in vegetated and built-up areas, integrating double bouncing effect of SAR in those areas.

2. DATA AND METHODS

L-band (14 MHz), dual polarized (HH, HV) and level 1.5 SAR data were obtained for the flood event occurred in Colombo. The pre-disaster image was acquired on 19.12.2014, a gap of nearly 1.5 years compared to the post-disaster image which was taken on 20.05.2016. Dual polarized (HH, HV) SAR data were obtained in 2.5 m spatial resolution from the JAXA, through the Sentinel Asia initiative. The elevation data were obtained from the USGS archived data of the Shuttle Radar Topography Mission (SRTM) in 30 m resolution. The mapping accuracy was tested using the flood extent data produced by the Survey Department of Sri Lanka. Figure 1 shows the backscatter strengths of the two polarized bands (HH and HV). The backscatter strength of the HH is higher and shows a clear difference in both specular and double bounced scattering compared to the HV. Thus, the HH polarization band is more suitable for flood detection.

2.1 Change Detection and Thresholding

Change detection and thresholding is the most commonly used method for flood mapping. Several studies have been done taking the double bouncing effect into consideration (Pulvirenti and Guerriero 2011). However, those methods are developed for particular wavelength bands, incident angles and polarizations. SAR image pairs before and after the event were filtered (3×3) to remove the speckle noise and were co-registered to overlap the corresponding pixels. A subset is required to remove the non-overlapping parts of the image pair. Then the two images were normalized prior to obtain the backscatter difference which will bring the image values between -1 and $+1$ (Figure 2). Denoting the flooded image as F and the non-flooded pre-image as reference image R, the image difference, D, was taken in the normalized form as,

$$R_n = \frac{\sum_{i=1}^{n} R_i}{max(R)} \tag{1}$$

$$F_n = \frac{\sum_{i=1}^{n} F_i}{max(F)} \tag{2}$$

$$D_n = F_n - R_n \tag{3}$$

where D_n is the normalized difference, and R_n and F_n are the normalized images before and after the flood event, respectively.

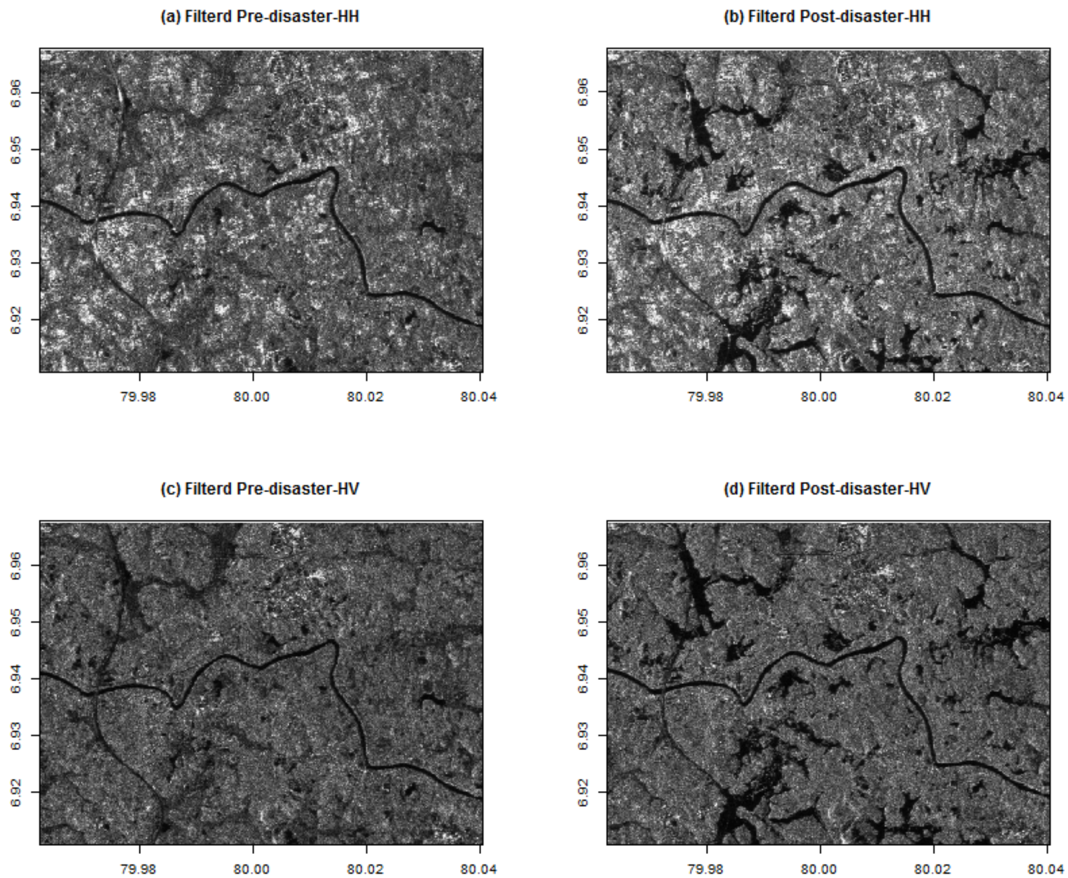

Figure 1: ALOS-2/PALSAR-2 datasets before and after the disaster event in Colombo's Kaduwela area showing the higher backscatter strengths of HH compared to HV.

In the histogram of backscatter difference (Figure 2), negative values belong to the flooded pixels in open waters while positive values represent the increased backscatter due to double bouncing in vegetated and built-up areas. According to the thresholding techniques, all pixels in an intensity image whose backscattering coefficient is smaller than a given threshold value are classified as flooded (Hess and Simonett 1990). But, for the water surfaces in vegetated or built-up areas, the enhanced backscattering due to double bouncing are appeared in the right tail of the histogram are not classified as flooded. Thus, a second threshold was obtained by considerable iterations to extract the flooded pixels in the vegetated and built-up areas. The two thresholds on the left and right tails were determined after a considerable number of iterations with visual comparison of the ground data. The percentiles at 30 and 70 were given adequate limits to extract the flooded pixels in the normalized backscatter difference of the L-band SAR.

As the negative change detects the open flood waters more accurately, the output of the 30 percentile thresholded flood extent was used to estimate the maximum flood elevation. In this case, 14 m was the maximum elevation which was achieved by overlaying the flood extent of open area floods. The elevation data were classified using the 14 m threshold to obtain the lowland which has more potential for flooding. This flood prone area was used as a mask to clean up the classified pixels as floods in higher elevated areas due to radar shadows.

2.2 Fuzzy Logic Approach

Fuzzy logic approach is proposed in this study and the membership functions are basically standard S (Eq: 4) and Z (Eq: 5) function as shown in the Figure 3. For the S function values greater than b belongs definitely to the set (membership degree equal to 1) while values less than a do not belongs to the set (membership degree equal to 0) and for the Z function occurs the opposite way. (Pulvirenti and Guerriero 2011). The parameters a and b denotes the fuzzy thresholds. The S and Z functions are suitable for representing the set of flooded pixels in normalized difference of SAR images for which extracting the positive and negative change thresholds. The difference between a and b determines the mix region in between the two classes, flooded or non-flooded. In contrast the two classes are divided sharply, if this gap is zero. Similarly, Z function was used to demarcate lowland which was used to mask out the pixels classified as flooded in higher elevations for which inundation is not permitted to the particular flood.

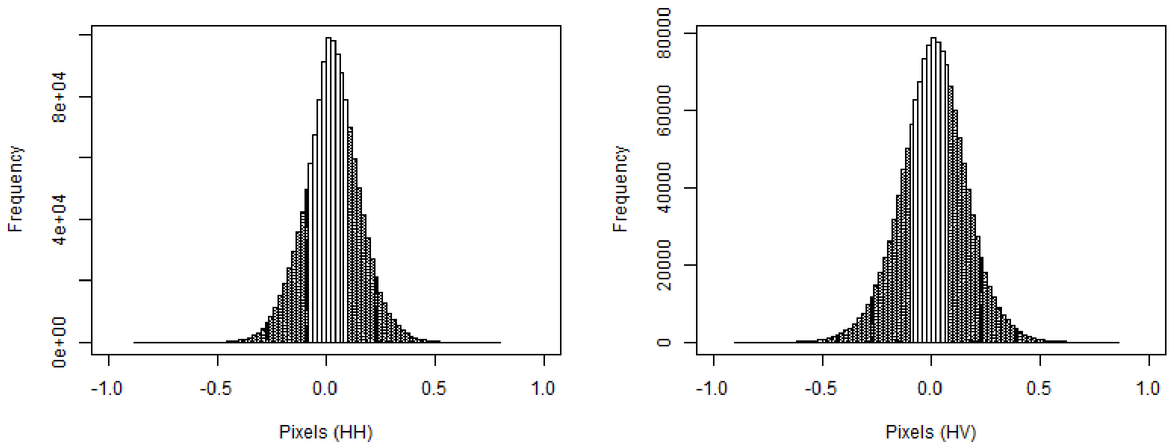

Figure 2: Histograms of the change image of the HH (left) and HV (right) bands showing the data distribution. The pixel values of the normalized difference fall in between -1 and +1. The dark color tails indicate the negative (< 30 percentile) and positive (> 70 percentile) thresholded pixels.

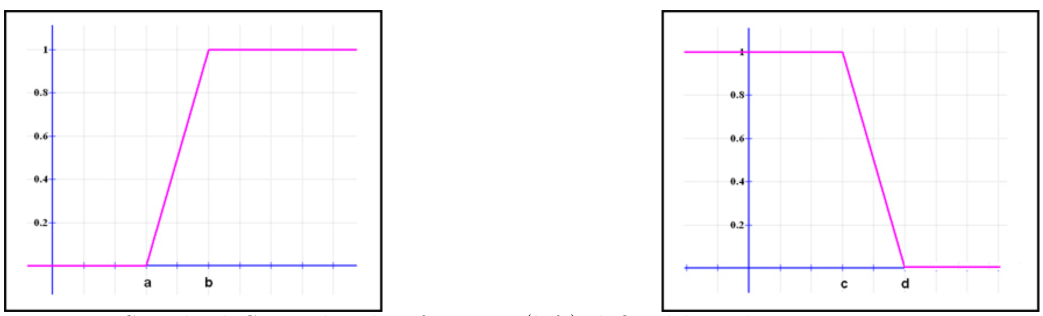

Figure 3: Standard S membership function (left) defined by a lower support a, an upper limit b and the standard Z function (right) defined by an upper limit c and lower support d.

A membership function for a fuzzy set A on the universe of discourse x is defined as $\mu_A : x \longrightarrow [0, 1]$, where each element of x is mapped to a value between 0 and 1. This value, called membership value or degree of membership, quantifies the grade of membership of the element in x to the fuzzy set A.

$$\mu_A(x) = \begin{cases} 0, & \text{for} \quad x < a \\ \frac{x-a}{b-a}, & \text{for} \quad a \leq x \leq b \\ 1, & \text{for} \quad x > b \end{cases} \tag{4}$$

$$\mu_A(x) = \begin{cases} 0, & \text{for} \quad x > d \\ \frac{d-x}{d-c}, & \text{for} \quad c \leq x \leq d \\ 1, & \text{for} \quad x < c \end{cases} \tag{5}$$

The fuzzy thresholds for the three membership functions of negative-change, positive-change and elevation were obtained in a sequential process. First, the pixel values less than 30 percentiles used as a default fuzzy threshold to extract open flood waters and that flood extent was used to estimate the maximum flooded elevation which is a fuzzy threshold for generate lowland mask. Then, the pixel values greater than 70 percentiles was taken as default fuzzy threshold to extract flood waters in vegetated and built-up areas. The above thresholds were used as inputs to formulate the membership functions in a fuzzy system, as shown in Figure 5, and the fuzzy rules base defined as follows:

IF the pixel value is LESS THAN 30 percentile AND the elevation is GREATER THAN 14 m, THEN the pixel is classified as non-flooded

IF the pixel value LESS THAN 30 percentile AND the elevation is LESS THAN 14 m, THEN the pixel is classified as flooded

IF the pixel value is GREATER THAN 70 percentile AND the elevation is LESS THAN 14 m, THEN pixel is classified as flooded

IF the pixel value is GREATER THAN 70 percentile AND the elevation is GREATER THAN 14 m, THEN pixel is classified as non-flooded

All the three thresholds were used to construct the membership functions in a system as shown in Figure 5 to generate the final flood map.

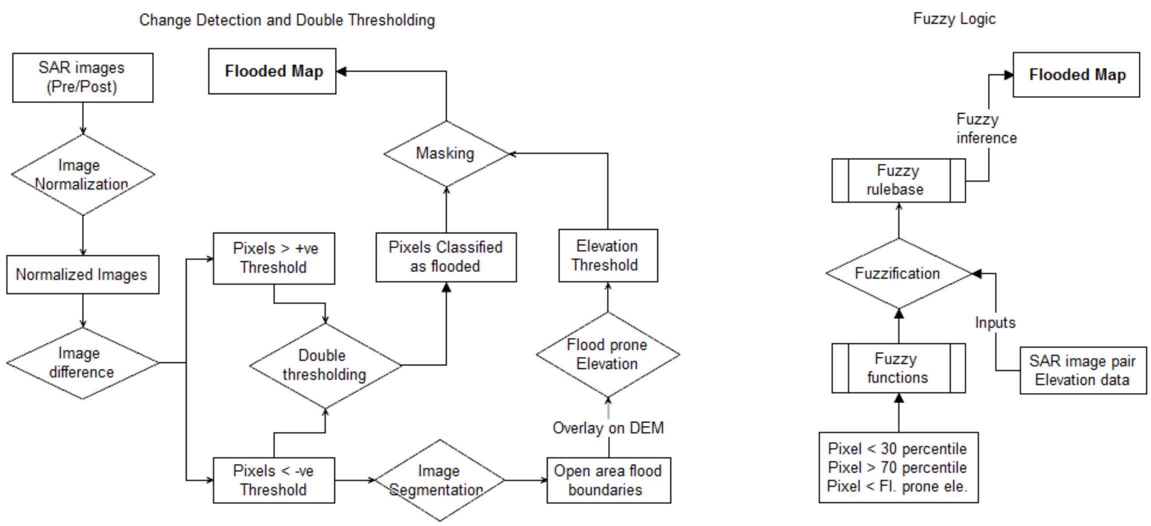

Figure 4: Flow diagram of the process showing the inputs, thresholding and fuzzy inference with pre-defined rule base that generates final flood map.

3. RESULTS AND DISCUSSIONS

The normalized difference of the pre- and post-flood images shows different textural features (Figure 6); water boundaries are sharp in the HV and the shadow of the river bank is also detected as a flood. On the other hand, water boundaries are blurred in the HH difference image, but the shadow effect is not speared. The double bouncing is more enhanced (bright green) in the HH which can be used to detect flood water in vegetated and built-up areas.

The detected flood from the two polarization bands and the HV shows less flooding although the river is classified as a flood. Thus, the HH polarization of ALOS2/PALSAR-2 data is more appropriate for flood detection using the change detection and thresholding method. Traditionally in the change detection algorithm, negative thresholding which detects open waters was used. Some studies have also shown that positive change thresholding can detect flood water in vegetated land cover Pulvirenti and Guerriero (2011). However, positive change can also appear due to long term land cover changes such as crops. Thus, the time gap between the image pair must be as short as possible.

The larger the wavelength is higher the radar penetration; thus, over-estimation of flooding can be expected due to backscatter enhancement from the soil moisture. On the other hand, a shorter wavelength enhances surface

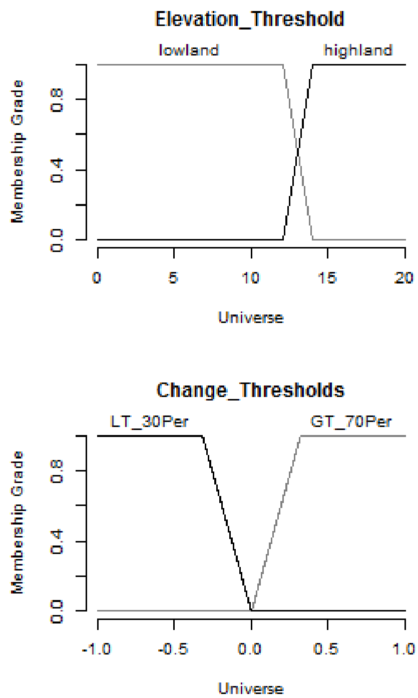

Figure 5: Fuzzy logic system showing membership functions for the elevation threshold to classify the elevation image to lowland and highland the flood threshold to classify image pixels based on the rule base; and the change threshold to classify the normalized difference image to extract negative and positive change membership grade into the fuzzy inference of the system.

scattering that limits the flood detection in vegetated areas. In this case the L band is quite good at detecting water under vegetation compared to the X band SAR. HV polarization overestimates the flood and its double bouncing effect is also low compared to the HH polarization. The low double bouncing leads to hampering the flood detection over vegetation.

Comparing the out puts of the two polarization, HH was selected to generate the flood map as shown in Figure 7. However, the positive thresholded output is consisting more noise due to complex backscatter returns from the vegetated and built-up land covers. The noises of this type as well as radar shadows which was classified as floods by the negative thresholding can be removed by elevation mask generated in the process.

The fuzzy logic system is capable of adding more parameters, such as land use, that maximize mapping accuracy depending on the variable double bouncing backscatter from land cover types. Fuzzy thresholding techniques need to be developed depending on the frequency band, polarization and incident angle. Fuzzy functions were developed based on the results and run as a human intelligence decision-making platform for emergency mapping. The thresholds (percentiles) used in this study can be used as defaults for the L-band SAR.

Spatial resolution and the accuracy of elevation data is important to determine the area where flood extent is permitted. Extracting flood potential elevation (FPE) is tricky, and is based on the assumption that the FPE is same for the mapping area concerned. This is based on the water-surface gradient depending on the terrain condition and the river discharge rates at the time of SAR data acquired. The mapping extent must be selected to meet this condition by splitting the area into several domains along the river as the flooded water-surface is not follow a contour as it goes towards upstream.

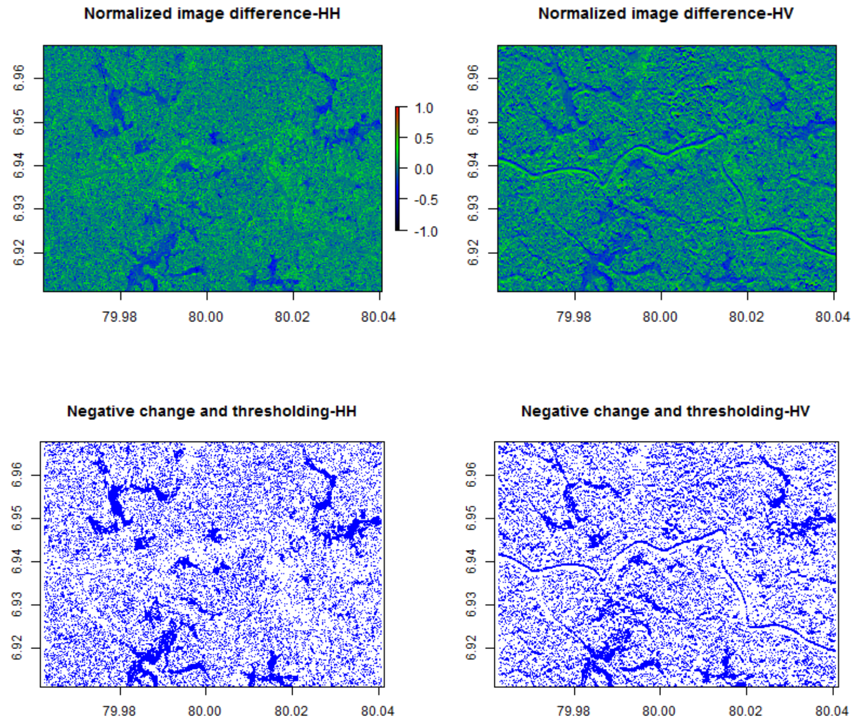

Figure 6: Normalized difference images for HH and HV (top) showing open water surfaces in blue and corresponding floods detected by the negative change single-thresholding method.

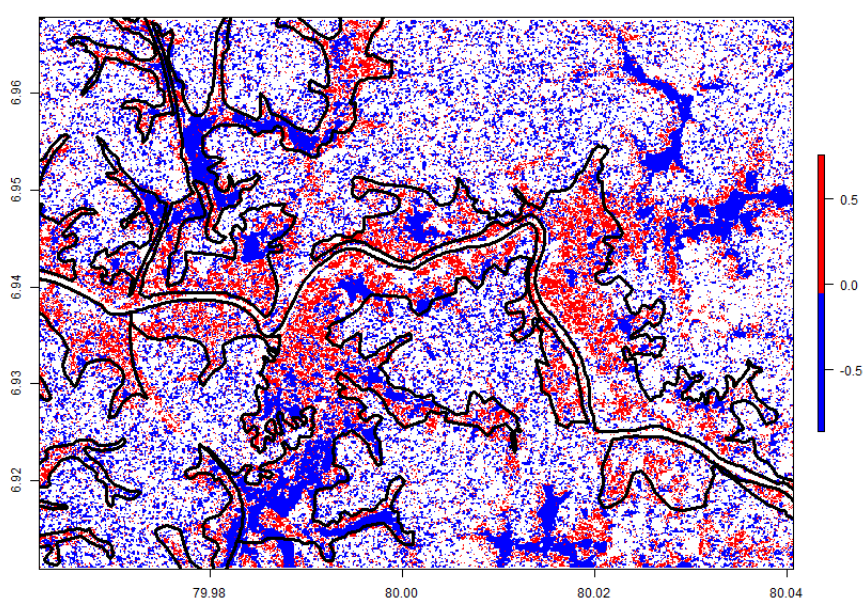

Figure 7: Flood map generated from the HH polarized band by double thresholding negative change (blue) and positive change (red) while the dark black line shows the flood extent of the ground surveyed.

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References

Melack J.M. Hess, L.L. and D.S. Simonett. Radar detection of flooding beneath the forest canopy: a review. *International Journal of Remote Sensing*, 11(7):1313–1325, 1990.

Mason D.C. Horritt, M.S. and A.J. Luckman. Flood boundary delineation from synthetic aperture radar imagery using a statistical active contour model. *International Journal of Remote Sensing*, 22(13):2489–2507, 2001.

Pierdicca N. Chini M. Pulvirenti, L. and L. Guerriero. An algorithm for operational flood mapping from synthetic aperture radar (sar) data based on the fuzzy logic. *Natural Hazard and Earth System Sciences*, 2011.

Bates P.D. Horritt M.S. Matgen P. Schumann, G. and F. Pappenberger. Progress in integration of remote sensing–derived flood extent and stage data and hydraulic models. *Reviews of Geophysics*, 47(4), 2009.

L.C. Smith. Satellite remote sensing of river inundation area, stage, and discharge: A review. *Hydrological Processes*, 11(10):1427–1439, 1997.

L.A. Zadeh. Fuzzy sets. *Information and Control*, 8(3):338–353, 1965.

L.A. Zadeh. The concept of a linguistic variable and its application to approximate reasoning - part i. *Information and Control*, 8(3):199–249, 1975.