Optimizing flood mapping using multi-synthetic aperture radar images for regions of the lower mekong basin in Vietnam

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ABSTRACT
One major characteristic of floods is flood extent. Information on this characteristic is indispensable for flood monitoring. Recently, synthetic aperture radar (SAR) data have been increasing in quality and quantity. This allows more flood studies conducted over large areas regardless of cloud and weather conditions and provides advantages including clear surface water classification based on SAR scattering mechanisms for low values (open water) and high values (inundated vegetation, etc.). However, challenges remain due to sources of uncertainties, such as atmospheric disturbances and vegetation masking parts of water surfaces. Therefore, in this study, we aim to optimize flood mapping processes on flooded vegetation that generated high-value pixels based on a SAR scattering mechanism called double bounce that classifies vegetative flooded water in L-band SAR images. This optimization is nearly impossible using Sentinel-1 scenes. Backscattering of time-series Sentinel-1 and ALOS-2 images acquired for the 2018 and 2019 flood season was analysed, thresholded and hybridized for flood mapping of a study site in the Tam Nong district of the Dong Thap Province of Vietnam. We found that the accuracy of SAR flood maps was improved compared to ground truth data when the SAR-extracted vegetative-flooded plains were considered flooded.

INTRODUCTION

The number of flood monitoring applications using synthetic aperture radar (SAR) remote sensing (RS) has grown substantially due to increases in the quality and quantity of the available SAR data (Clement et al., 2018; Cohen et al., 2016). In addition, compared to optical remote sensing data, SAR data are less affected by weather conditions and are acquired during both day and night (Adam et al., 1998; Gan et al., 2012; Giustarini et al., 2015). Nonetheless, the applications of SAR RS data reveal limitations due to speckle effects (noise), topographic distortions greater than those in optical remote sensing scenes, such as SAR side acquisition mode, and vegetation covering sensed surfaces (Giustarini et al., 2015; Matgen et al., 2007). Despite these drawbacks, SAR RS technology is proving to be an effective and productive data source for an increasing number of flood studies (Schlaffer et al., 2017), particularly studies about rapid flood mapping due to the short revisit time and the all-weather and all-time imaging characteristics of SAR remote sensing (Amitrano et al., 2018).

Obviously, all SAR RS imagers are not designed for identical flood extraction or mapping applications; in particular, there are various types of sensors (regarding wavelength), acquisition modes, polarizations and spatial resolution (Sanyal & Lu, 2004). Therefore, we have more options for choosing or assimilating suitable SAR data for specific applications. For a particular region, SAR data should be chosen based on consideration of an understanding that the SAR scattering mechanism of the radar pulse reacts differently with different geographic surfaces, and that the penetration ability of the radar beams through the land surface cover, such as vegetation, varies with the wavelength (longer wavelengths correspond to better penetration ability (Ward et al., 2014)). Received SAR backscatters are also a function of the incidence angle (IA) (provided by production providers) and local incidence angle (LIA) variations due to target topography and the incidence angle (Escorihuela & Quintana-Segui, 2016; Wilusz et al., 2017). In regions with high slope values, the effects of LIA on the values of SAR scatters are significant and must be analysed. In some cases, the LIA information can be a source of data (Mason et al., 2016).

Increasing attention has been paid to flood responses in Vietnam’s Mekong Delta (Dang et al., 2018; Triet et al., 2017), as it has been increasingly altered for a decade, particularly with fresh water becoming more rare (Thu & Wehn, 2016). Hence, accurate flood extent may be critical. Vegetation cover, including melaleuca forest, lotus, and water grass, can cause uncertainty in flood extent mapping and is sometimes difficult to avoid. Although the dominant crop types in the study areas of the Dong
Thap Province are 2- and 3-season rice and fruit trees, there are normally large areas of flooded melaleuca forests and other spread water grasses and lotus lakes during the flood season (Bouvet & Le Toan, 2011). In contrast with rice fields, the water grass and lotus have little cover; however, it is important and related to local livelihoods and ecosystem conservation (Minh, 2019). When the flooded vegetation inundation areas are not accounted for in flood areas, we underestimate the flood extent and reduce the accuracy of flood mapping for this region. Moreover, the problem of floating water hyacinth (local name of Luc Binh) and floating rice (local name of Lua Ma), which appear sporadically, is extremely difficult to solve.

In a previous study by Quang et al. (2019), although the authors tried to map flood inundation using optimism Hammock Swing Thresholding (HST) algorithms of matching SAR-RS-based water masks with a well-calibrated hydraulic model output, the difference remained at a rate of 11.7% for the use of Sentinel-1 images. It is considered that the accuracy of the inundation map could be improved if the inundated vegetation areas were classified and accounted for in the flooded areas. To overcome this challenge, in this study, we analysed a SAR scattering mechanism called double bounce scattering to extract the inundated vegetation areas using ALOS2 images. Double bounce scattering occurs when the SAR electromagnetic (EM) beams penetrate the flooded vegetation and bounce twice, once on the water surface and once on the tree stands, before returning to the SAR sensors (Arnesen et al., 2013; Le Toan, 2009). Hence, the SAR sensors receive high values of scattered EM compared to single scattering on other surfaces. The double bounce will occur when SAR wavelengths penetrate the canopy cover alone (L band or longer) and will allow the detection of flooded vegetation areas (Chabani et al., 2018). This is reason we used L-band ALOS2 images for this study.

This study aims to increase the accuracy of water surface extraction from SAR data. Therefore, the flood extent mapping of the Tam Nong district of Dong Thap Province with the flooded vegetation extracted from ALOS-2 images added to the flood maps, which are not classified as flood areas in the Sentinel-1 (S1) images, is improved. In situ data on land cover and from Google Earth have been interpreted to identify major vegetation covering the water in the study site. We applied the thresholds for water extractions based on SAR scattering, incidence angle, and polarization statistics. By adding L-band SAR of ALOS-2 (AL2) information to S1 flood maps, the correlation between the flood extent and the field-updated land use and land cover (LULC) map has been improved by approximately 6%. Assimilation of multi-SAR data for flood monitoring is recommended particularly for regions with vegetation effects.

### Study site and data

#### Tam Nong district

The Tam Nong district of Dong Thap Province was chosen for the case study as a central area of the province whose representative flood response is directly linked to local livelihoods (Hung et al., 2012). As a typical flooding response of the Vietnam Mekong Delta, most flood water is based on the discharge from the Upper Mekong Basin while local rains contribute a small amount of total precipitation. The location of the district is shown in Figure 1 (highlighted by the red polygon) with a dense river and channel network. The district is home to 220,000 people (2019 statistics), who live in an area of 474 km². The average rainfall range varies from 1170 to 1520 mm, and 90–95% of the total annual rainfall is concentrated in the rainy season (May to November) (Quang et al., 2019). The typical crop is rice, which is divided into 2- (no irrigation) or 3-season rice (with irrigation and not flooded in the flooding season). There is a 7,500 ha UNESCO RAMSA, Tram Chim, recognized in 2000 and 2014 (Tran & Barzen, 2016). This site has large areas of melaleuca forest interlaced with water grass and lotus.

#### Field survey and google earth updates

A field survey was conducted in October 2018 to update the flood status on a LULC map generated in 2010 by the MONRE (Figure 2), with eight classes, including 2- and 3-season rice, aquaculture ponds, residence, river and channel, fruit trees, melaleuca, and water grass. Two global positioning systems (GPS) devices with integrated 5MP cameras were used to update inundation and to ground truth the LULC. The field work has been completed for the entire Dong Thap Province. However, in this study, we only used the information in the Tam Nong district. The LULC map was updated for inundated vegetation, including lotus (L), hyacinth (H), and aquaculture ponds (A), marked in Figure 2, by using Google Earth Pro software, which provides historical high-resolution images. The latest images of the study area were taken in March of 2019.

#### SAR remote sensing images

For this study, time-series Sentinel-1 and ALOS-2 images acquired in the 2018 flooding season were collected along with metadata from sensors, passing, incidence angle, and spatial resolution, which are summarized in Table 1. As projected by the AL2 images employed to update the S1-extracted water surfaces, the dates of acquisition were chosen in pairs as close to each other as possible and marked with the same lines as in Table 1. The images sensed in
July 2018 were used for flood reference data because July is at the end of the dry season, and the images sensed in August, September, October and November were used for surface water extractions.

Table 1: SAR data of Sentinel-1 and ALOS-2/PALSAR used for this research

Methodology

Study workflow

To achieve the study goals, the study procedures are described and shown in Figure 3. In the work flow, the pre-processing steps including radiometric, terrain correction, and speckle filter were completed first. These procedures are common SAR processes and are described in previous studies such as (Cian et al., 2018; Rejaur & Praveen, 2017). Hence, these steps are not explained in detail in this study. The core process was the thresholding calculation based on support from the zonal statistical information in order to extract water masks from the SAR images. The goal of the pixel resampling and segmentation task in the ASLO2 processing branch was to extract the inundated vegetation masks having a compatible spatial resolution of 10 m with the output of the Sentinel-1 (10 m). The important task, which is different from most previous flood mapping algorithms for SAR remote sensing data, is adding the inundated vegetation from the ALOS2 time-series images to the flood maps and analysing the final flood frequency and duration maps. The flood maps are generated by overlaying the permanent and flood water maps in time-series and accumulating for each month of the year 2018.

SAR scattering mechanism pre-analysis for flooded vegetation

As the SAR scattering mechanism is complex and is a function of many variables, such as wavelength and frequency, polarizations, surfaces (roughness and volume), moisture (dielectric properties), incidence angle, etc., a thorough understanding of how each variable influences the SAR scattering is important. Thus, we may need intensive experiments. In this study, based on the literature and expert knowledge, we pre-analysed the SAR scattering mechanism and approximately predicted the backscatter values from
flooded vegetation, such as Tram forest (melaleuca), lotus, water hyacinth, water grass and water rice, which are typically present in the study site. The terrestrial natural colour pictures are presented in Table 2. To justify the mechanism of scattering of Sentinel-1 and ALOS-2 radar beams from each vegetation type, we refer to the SAR backscatter mechanism on natural surfaces described in the study of Richards (2009), vegetation penetration of spaceborne radar in Imhoff et al. (1986), explanation of double bounce effects in Arnesen et al. (2013) and expert knowledge as following:

- High-value backscatters (bright areas) on flooded melaleuca forest with L-band ALOS-2 images due to double bounce first occurred on the water surface and then on the melaleuca before returning to the sensor. In contrast, stable low backscatters (dark areas) appeared in the flooded melaleuca forest in the S1 images with no double-bounce effects.

- As the L-band SAR beams are able to penetrate the lotus leaves, but not their stems, which are too small and rough, most radar beams do not bounce twice on the lotus stems before returning to the sensor. Hence, the double bounce effect did not occur in S1 or AL2 for the case of lotuses. Based on this observation, we predicted low values of backscatters for both images.

- The water hyacinths gather in complex dimensions, with large leaves and stems that are normally not perpendicular to the water surface, which is not a favourable condition for bounce occurrence. However, we proposed that the backscatters received would have high values (bright) for both S1 and AL2 images, since the scattering mechanism would be similar to that for rough surfaces.

- We predict moderate values of the backscatters for water grass in the S1 and low values in the AL2 images based on the fact that water grass is highly heterogeneous, dense and affected by wind, waves and animals/birds (for example, we can see a large crane in the centre of the water grass picture). Therefore, the water grass is not perpendicular to the water surface and

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**Figure 2.** Map of land use land cover (LULC) updated in October 2018 with Google Earth to interpret inundated vegetation and aquaculture ponds.
does not meet the conditions for double bounce in flooded vegetation. As a result, the incoming C and L-band radar beams scatter moderately on the water grass surface and the sensors receive low values of backscatters.

We propose SAR backscatter mechanisms with no double bounce from the 3-season rice (with irrigated water but not flooded, and mid-term growth) in both S1 and AL2 images. In addition, the SAR scattering on the rice in different development stages could have different responses to the SAR pulses and the backscatter values could vary from low to high. How the SAR scatters on a surface is also a function of the wavelength (Richards, 2009). In the growing status of the 3-season rice in Table 2, it is shown that the rice reached approximately 30 cm in height compared to the 23.6 cm observed with the ALOS-2 wavelength. The rice was almost a smooth surface with the ALOS-2 sensor. In contrast, the rice was a very rough surface with the Sentinel-1 instrument using radar frequency of 5.405 GHz (corresponding to a wavelength of ~5.6 cm). Therefore, the S1 radar beams (brighter) scatter much more than those of AL2 (darker) from the 3-season rice. More SAR backscatter mechanism explanations for different rice-growing stages can be found in the previous studies of Lam-Dao et al. (2009), Bouvet and Le Toan (2011) and Lasko et al. (2018).

Table 2: Demonstrations of flooded vegetation SAR backscatters of Sentinel-1 (S1) and ALOS-2 (AL2); P-indicates predicted, H indicates high and L indicates low scattering value.

### Polarisations, local incidence angle and pass effects on SAR backscatter analyses

As the SAR images are acquired in different polarizations (single, double or a combination of these) and in side-looking modes, image pre-processing of different polarizations and local incidence angles (LIA), together with analyses of SAR scattering mechanisms, would support a better understanding of SAR scatters on various typical LULC types in the study area. However, few studies have currently completed such analyses. Accordingly, we calculate the backscatter statistics in decibel (dB) for each type of land use and compare this with predicted values from the previous section (3.2). Any contrasting results found in these two steps should be taken into account for reanalysis. The zonal statistics tool of the free QGIS software version 3.12.0 licensed under the GNU General Public License, developed by the QGIS Development Team, has been used to calculate the mean values and standard deviations of different polarizations and local incidence angles (LIA) of S1 and AL2. Local incidence angle (LIA) is crucial information (Schlaffer et al., 2017, 2015), and can sometimes be used for image classifications. The LIA is generated in the SAR geometric correction using the digital elevation model (DEM). In this study, we used the DEMs from the Shuttle Radar Topography Mission (SRTM) of the Jet Propulsion Laboratory (JPL) of the National Aeronautics and Space Administration (NASA), which are the SRTM1 (30 m resolution) and SRTM3 (90 m resolution).

As the SAR images are side-looking systems, the satellite passes (ascending and descending) may have different effects on the imaging geometry and distortions of the SAR images. Hence, we analyse the differences from satellite-passing effects on distinguishing land use land cover in the study area using a zonal statistical tool.

### Thresholding

An optimal thresholding algorithm called Hammock Swing Thresholding (HST) was developed, which was applied in Quang et al. (2019) for both Sentinel-1 and ALOS-2 images because it has shown its high accuracy and consistency with different SAR inputs. The concept of HST is simple: it minimizes the total absolute values of the difference layer between the SAR and reference water extent in order to obtain an optimal
Figure 3. Study workflow. LIA is local incidence angle, Po is polarizations, and dB is SAR backscatters in decibel. FF and FD are flood frequency and flood duration, respectively.

Table 2. Demonstrations of flooded vegetation SAR backscatters of Sentinel-1 (S1) and ALOS-2 (AL2); P indicates predicted, H indicates high and L indicates low scattering value.

| Vegetation type | S1 | AL2 | S1 Scatters | AL2 Scatters | P-Value |
|-----------------|----|-----|-------------|--------------|---------|
| Malva           | ![Image](image1.jpg) | ![Image](image2.jpg) | ![Image](image3.jpg) | ![Image](image4.jpg) | S1-L AL2-H |
| Lotus           | ![Image](image5.jpg) | ![Image](image6.jpg) | ![Image](image7.jpg) | ![Image](image8.jpg) | S1-H AL2-L |
| Hyacinth        | ![Image](image9.jpg) | ![Image](image10.jpg) | ![Image](image11.jpg) | ![Image](image12.jpg) | S1 and AL2-H |
| Water grass     | ![Image](image13.jpg) | ![Image](image14.jpg) | ![Image](image15.jpg) | ![Image](image16.jpg) | S1-H AL2-L |
| 3 season rice   | ![Image](image17.jpg) | ![Image](image18.jpg) | ![Image](image19.jpg) | ![Image](image20.jpg) | S1-H AL2-L |

The vegetation pictures were taken during our field survey trip.
threshold. The reference water extent should be more accurate than that in the target images, such as that obtained from finer-calibrated remote sensing extractions or from field survey maps. In this application, we used a field survey with Google Earth updates for the reference. The map was converted to a 10 m × 10 m grid for the S1 thresholding and a 25 m × 25 m grid for the AL2 thresholding. Graphical presentation of the HST is depicted in Figure 4 with the differentials equal to the SAR-based layer minus the reference layer (A). Hence, when the threshold is adjusted from the left to the right of the graph, (B) will result in changes of the differentials. The optimal threshold will be determined by the minimal differential or the number of pixels with values of 1 (orange) and −1 (grey) in the differentials that are minimized.

The minimum or optimal absolute value of the differential (VD\(_{\text{opt}}\)) is mathematically defined in equation 1.

\[
VD_{\text{opt}} = \min \left( \sum_{Ti=1}^{n} |DN_{\text{SARij}} - DN_{\text{REij}}| \right)
\]

where \(VD_{\text{opt}}\) is the optimal absolute differential value between the two compared raster layers, and \(DN_{\text{SARij}}\) and \(DN_{\text{REij}}\) are pixel values of the SAR and reference water masks, respectively. \(n\) is the number of threshold adjustments (Ti) for the SAR images. The \(DN_{\text{SARij}}\) at threshold \(i\) is calculated from the sigma nought decibel band (\(\sigma_{\text{dB}}^0\)). The \(\sigma_{\text{dB}}^0\) values are solved with equation 2.

\[
\sigma_{\text{dB}}^0 = 10.\log_{10} \sigma^0
\]

\[
\sigma^0 = \frac{DN^2}{A_{\text{en}}^2} \times \frac{1}{G_{\text{cap}}} \times \left( \frac{R}{R_{\text{ref}}} \right)^3 \times \sin(\varphi)
\]

The sigma nought decibel values of AL2 images are calibrated by solving equation 4.

\[
AL2\sigma_{dB}^0 = 10.\log_{10} \sigma^0 - 83
\]

where \(\frac{1}{G_{\text{cap}}}\) is the elevation antenna pattern correction (2-way), \(\left( \frac{R}{R_{\text{ref}}} \right)^3\) is the range of the spreading loss correction, \(A_{\text{en}}^2\) is the product final scaling from internal SLC to final SLC or GRD, \(\varphi\) is the local incidence angle and \(DN^2\) is the average product intensity and has a value of 22,142.71.

In the graphical evaluation phase, we present the relationship for the different residual \(RE_{\text{SAR–RE}}\) solved in the equation 5.

\[
RE_{\text{SAR–RE}} = \sum_{i=1}^{n} |DN_{\text{SARij}} - DN_{\text{REij}}|
\]

Percentages of the mutual flooded pixel values \(P_{\text{SAR&RE}}\) are solved in equation 6 for both SAR and the reference flood grid layer, and the SAR decibel value \(\sigma_{dB}^0\) is solved with equation 2.

\[
P_{\text{SAR amp:RE}} = \frac{\sum_{i} |DN_{\text{SARij}} - RE_{\text{SAR–RE}}|}{\sum_{i} DN_{\text{SARij}}} \times 100
\]

**Flood mapping and flood frequency and duration analysis**

Flood maps are generated from flooded vegetation water masks (see Figure 3) before and during floods using the raster calculator tool in the QGIS software version 3.12.0. The water mask pixels were numbered 1 for wet pixels and 0 for dry pixels and accumulated for monthly maps of August, September, October and November.

The time-series water masks extracted from S1 images and added areas of flooded vegetation from the ALOS-2 images of the entire 2018 flood season were combined and spatially analysed for flood frequency and duration classification. Flood frequency
here is defined in five flood frequency levels of rare, occasionally, often, frequently, and permanent, where water that is present most the time is considered as a permanent water body, such as rivers or ponds.

**Accuracy improvement evaluation**

Improvement of flood mapping was assessed for each land use type by calculating the percentage of agreement between the field investigation flood status map and the original S1-based map (using the backscattering assessment threshold), HST thresholds and HST with updates from AL2 images. The total performance improvement assumes an increased percentages of flooded areas and reduced percentages of dry areas in the flood maps. The total improvement of the entire district is also calculated by summarizing all the land use classes with weightings of percentages for each area. In addition, we confirmed the accuracy of the flood maps by calculating the producer and user, overall accuracy, and Kappa coefficient from the four confusion matrices developed based on comparisons of the field survey and the Google Earth updated data and results of SAR flood extraction.

**Results**

**Local incidence angle analysis**

Figure 5 shows slightly different mean local incidence angle analysis (LIA) values (approximately 0.1 degree)
using the 30 m SRTM1 (SRTM 1 second DEM) and 90 m SRTM3 (SRTM 3 second DEM) based on the zonal statistics for the different land cover types in both S1 and AL2 data. Furthermore, the standard deviations (STD) of the LIA using the finer DEM (30 m) (black light caps) were nearly double the STD of the LIA using the rougher DEM (90 m) (grey thick caps) in all S1 and AL2 images. This indicates that using the finer DEM generated wider STD ranges for LIA than using the lower resolution DEM. Interestingly, lower LIA of under 40 degrees were calculated for the dry areas (barren, shrub, road and residence), while estimated values for the wet areas were above 40 degrees in the S1 ascending data. In contrast, in the representation shown in the descending (AL2), the dry areas (black and grey rectangles) were over 37.3 degrees for both SRTM1 and SRTM3, while the wet LULC classes were estimated with a lower LIA of under 37.2 degrees. Uses of LIA for masking the water surface could be worth discussing in some cases, particularly where the land use type depends strongly on the presence of water and the terrain. The results of this study showed distinguishable dry and wet LIA values. However, as the STDs were wide, there will be various mixed wet and dry pixels. These mixed pixels are source of uncertainty if we base water classification on the LIA. Therefore, limitations of using LIA information in flat regions such as the Mekong Delta to classify SAR images remain.

**Radar polarization effects on SAR backscatters**

The mean backscatter values (dB) were calculated for the 12 LULC classes (Figure 6), showing clear differences between the S1 VH and VV polarization with VV values larger than VH by approximately 5 dB, and AL2 HH higher than HV polarizations by approximately 9 dB. In addition, low backscatter values were received in the wet areas as the SAR beams scattered more weakly than on dry areas in both S1 and AL2 images in general (see the wet and dry mean lines), except for the high backscatters in inundated vegetative areas of lotus, water grass, and melaleucas in the S1 graph and hyacinth and melaleuca in the AL2 graph. The high dB values of the wet vegetation areas in the S1 images were considered in the uncertainty for extracting water surface information when we use thresholding methods. To reduce this uncertainty, lotus, water grass, and melaleucas should not be considered water, otherwise the wet mean values of S1 would be overestimated when we average to determine the water threshold. Similarly, hyacinth and melaleuca should not be included when averaging the wet mean value in the AL2 images. The mean values used as water thresholds of the water for the S1 images and AL2 data included the melaleuca areas. However, these were rough thresholding estimates. As the double bounce affected the backscatters of the inundated melaleuca in the AL2 images, the mean backscatters of this forest were highest among all classes. Moreover, despite the fact that these were rough zonal statistics, we could find good agreement between the dB distribution for the LULC classes and the pre-analysis for flooded vegetation (compared to the predicted values in Table 2).

The water extraction thresholds of −20.84 dB for S1 (the VH mean value) for the VH polarization and of −16.02 dB (the VV mean value) for the VV polarization are estimated and marked by the blue line and the broken blue line in Figure 6, respectively. Similarly, the water extraction thresholds were calculated for the

**Figure 7.** Comparison of the effects of satellite passes on SAR backscatter values with different polarizations from different land use land covers. S1 stands for Sentinel-1, and AL2 stands for ALOS/PALSAR-2. The letters V and H indicate vertical and horizontal, respectively, and the coupled letters VV, VH, HV and HH indicate SAR cross-polarized polarizations.
AL2 HH polarization marked at \(-14.44\) dB for water surface (we avoided the double bounce effect on the melaleuca areas) as depicted by the continuous blue line and the averaged backscattering values for the HV wet classes at \(-24.1\) dB (the melaleuca class was again not included), marked by the broken blue line. Applying these thresholds and comparing to the water extraction from the optimal HST method of Quang et al. (2019), we find that both approaches underestimated the water extent. For this reason, the melaleuca forest should be included in the water surface. It was remarkable that these thresholds, calibrated with field data and updated using Google Earth information, were crucial for extracting accurate water surfaces, which are fundamental for flood mapping.

**Descending versus ascending**

Figure 7 shows the differences in the mean SAR backscatter values from the 12 LULC classes acquired by Sentinel-1 (left) and ALOS PALSAR-2 (right) instruments travelling in the descending and ascending directions, and polarized VH and VV for S1 and HH and HV for AL2. In general, the S1 descending pass generated higher backscatter values than the S1 ascending pass for most layers, except for similar values for open water from both passes. In addition, all the dry layers including barren, road, residence and shrub measured in the descending pass were approximately four dB higher than those in the ascending pass. Minor differences of less than one dB have been found between AL2 ascending and descending passes, with almost identical graphs having higher sigma nought values for the first four wet classes of 2- and 3-season rice, river, channel and lotus during the ascending pass. The rest of the layers during the ascending pass were slightly lower than during the descending pass. Similar to the results of polarization effects, the standard deviations (STD) of S1 (divided by 2 for better visualization) were higher than those of AL2. We assume these differences were driven by the input data resolutions of 10 m for S1 and 25 m for AL2 because we used the same intersected LULC polygons.

![Figure 8](image_url)

**Figure 8.** Hammock Swing Thresholding (HST) estimated optimal flood thresholds for the ascending and descending Sentinel-1 (S1) and ALOS PALSAR-2 (AL2) data. P is the percentages of common pixels between the SAR water layers and reference layers; RE is residuals of differences between the SAR water layers and reference layers.
Meanwhile, Sentinel-1 was the Optimal - and Figure 9 in undesated of coloured Flood AL2. The optimal agreement differences acquisition a presented flood AL2, −14.1 dB was the (filled ascending estimated blue) and shorter durations (lighter blue) in the middle of the district (where Tram Chim is located). Comparing the flood duration map (FDM) using S1 data and updates from AL2 images, a large area of the melaleuca forest assigned as a short flooded duration in the S1 was updated as a long flooded duration (dark blue) in the Tram Chim National Park and other areas in the east near the park (indicated by the red M). This information on flooded vegetation is considered to improve the accuracy of flood mapping, particularly in sites that have large areas of melaleuca forest.

The maps in Figure 9C and D showed different areas with the frequency of flood inundation varying from very often (longer than 120 days/season) to rare (once or twice/season) as accumulated from the time-series Sentinel-1 images acquired from the dry season to the end of flood season in 2018, and updated for the inundated vegetation areas extracted from the series of AL2 images. The frequency of flood occurrences indicated by the colours varies from brown to blue (presented in the legend of the Figure 9C and D). The dry areas were represented by the darkest brown colour. Similar to maps of flood duration, the melaleuca forest

**Optimal thresholds**

The Hammock Swing Thresholding (HST) method was applied to the ascending and descending Sentinel-1 images and resulted in the optimal thresholds of −15.0 dB and −13.69 dB, respectively. Meanwhile, the P_{SARRE} was calculated at 88.26% for the ascending S1 and 88.30% for the descending S1 (filled by blue colour in Figure 8A and C). Similarly, the best match (optimal) for SAR and reference layers was estimated at P of 86.01% and a backscatter value of −14.1 dB for the ascending AL2, and P of 85.91% and a backscatter value of −15.0 dB for the descending AL2. The optimal thresholds of S1 were used for the flood water extraction. The AL2 optimal thresholds presented in Figure 8B and D were employed for a comparison between ascending and descending acquisition satellite direction. We found no significant differences between the two passes (the percentage of agreement (P) and the residuals (RE)).

**Flood duration and frequency maps**

Flood duration maps, divided into six levels and coloured in darker blue, were generated from series of the Sentinel-1 (S1) images and the S1 updated inundated vegetation areas from the paired ALOS-2 scenes (Figure 9A and B). Figure 9 shows different lengths of inundation time accumulated in the 2018 flood season and spatial variations of flood duration, with longer durations in the east and west (darker blue) and shorter durations (lighter blue) in the middle of the district (where Tram Chim is located). Comparing the flood duration map (FDM) using S1 data and updates from AL2 images, a large area of the melaleuca forest assigned as a short flooded duration in the S1 was updated as a long flooded duration (dark blue) in the Tram Chim National Park and other areas in the east near the park (indicated by the red M). This information on flooded vegetation is considered to improve the accuracy of flood mapping, particularly in sites that have large areas of melaleuca forest.
and water grass in the middle of the Tam Nong District from the Sentinel-1 (S1) were mapped as dry season. However, based on our field survey data, these areas were flooded and were therefore classified as inundated areas (in blue) using AL2 images as shown in Figure 9D. This information is considered extremely useful for flood management and control in the National Park. Other areas of lotus and hyacinth were also updated in the S1 + AL2 map. However, these areas were too small to be clearly depicted in the flood frequency maps.

**Monthly flood maps**

Figure 10 indicates the results of monthly flood maps generated for the 2018 flood season (from August to November) with spatial changes in flood status from dry (light red) to semi-flooded and flooded areas. The term "semi-flooded" refers the situation when flooding occurs during half of the month, while the other half of the month is dry. The “dry area” indicates no water covering the area for entire the month, in contrast to the flooded status (flooded the whole month). In Tam Nong, October of 2018 was the peak time for flooding with most areas flooded (in blue). The beginning of the flood season occurred in August, which had the lowest level of flooding. The rise and recession of the flood were recorded in September and November, respectively, with medium flooding levels. Permanent water was present in the Tien river and some small areas in the district and is coloured dark blue. Comparing to the LULC map, the flooded areas were mostly the 2-season rice, in contrast to the dry areas which were mostly the 3-season rice.

**Evaluation of improvements**

Flooding percentages for the 12 classes using the thresholds from the polarization effects on the SAR backscattering assessment (Section 4.2 (S1) column) and applying HST (HST column) and HST with updated inundated vegetation (S1 + AL2 column) in Table 3 compared to the field investigation of flood status on 10 October 2018 (the same data as S1 acquisition) showed a general improvement in flood mapping accuracy. The field map is considered as having no error or a total accuracy of 100%, where classes with 100% indicate fully flooded areas and classes with 0% indicate dry areas. It was clear that employing the HST method gradually improved the flood map for every LULC classes compared to the S1, and the total accuracy improved from 78.2% to 83.3%. In the S1 + AL2 results, the percentages of flooding areas were dramatically increased compared to the S1 and HST (primarily due to the melaleuca and water grass, indicated by numbers in bold). The total accuracy of the map was improved by approximately 5% compared to HST and nearly 15% compared to the rough threshold of S1. It is noted that although the improvement for lotus and hyacinth was significant, these areas were
Table 3. Statistics of accuracy improvement evaluated for the 12 LULC classes. PW is permanent water; HST is the use of the Hammock Swing Thresholding method; ¥ is the note of averaged values; the numbers in bold highlight water bodies and flooded vegetation.

| LULC type       | Field investigation (flood percentage) | Area (ha) | Area % | S1 (%) | HST (%) | S1 + AL2 (%) |
|-----------------|----------------------------------------|-----------|--------|---------|---------|--------------|
| 3 season rice   | 0                                      | 4320.1    | 9.1    | 6.0     | 4.4     | 4.4          |
| Mangroves       | 90                                     | 4101.2    | 8.7    | 8.1     | 15.7    | 97.2         |
| Water grass     | 100                                    | 3450.4    | 7.3    | 13.0    | 15.8    | 89.3         |
| Road            | 0                                      | 176.0     | 0.4    | 17.8    | 16.2    | 16.2         |
| Residence       | 0                                      | 2030.1    | 4.3    | 18.3    | 15.6    | 15.6         |
| River and channel | 0 (PW)                            | 2462.0    | 5.2    | 56.5    | 55.5    | 55.5         |
| Barren          | 0                                      | 176.6     | 0.4    | 31.7    | 28.5    | 28.5         |
| Shrub           | 0                                      | 92.6      | 0.2    | 16.0    | 15.2    | 15.2         |
| Aquaculture ponds | 0 (PW)                      | 795.1     | 1.7    | 66.1    | 65.7    | 5.1          |
| Lotus           | 85                                     | 10.0      | 0.001  | 33.3    | 34.2    | 86.7         |
| Hyacinth        | 100                                    | 12.4      | 0.002  | 34.8    | 35.7    | 98.1         |
| 2 season rice   | 100                                    | 29,768.4  | 62.8   | 79.6    | 90.7    | 90.7         |
| Total           | 96.7                                   | 47,394.7  | 100    | 78.2    | 88.3    | 93.1         |

very small (0.001 and 0.002) and the contribution to the total accuracy was negligible. The statistics also showed that the accuracy of long and narrow geographic feature such as rivers or roads was lower due to effects of image spatial resolutions (10 m in S1 and 25 m in AL2) on the final results.

Table 3: Statistics of accuracy improvement evaluated for the 12 LULC classes. PW is permanent water; HST is the use of the Hammock Swing Thresholding method; ¥ is the note of averaged values; the numbers in bold highlight water bodies and flooded vegetation.

Discussion and conclusion

SAR remote sensing data are widely used for flood studies and range from the regional to the local scale (Escorihuela & Quintana-Segui, 2016); however, backscatters on flood surfaces are not fully understood, as the surfaces are not homogenous (Stephens et al., 2012). Hence, understanding the backscattering mechanism of different SAR wavelengths on different LULC types is crucial for particular uses. For example, we can foresee limitations of C-band SAR and advantages of L-band SAR images for flood mapping due to the SAR backscatter analyses. Therefore, a solution of integration with other SAR sensors (e.g. L or P band SAR) could be the multi-sensor integration of ALOS-2 images (25 m) and Sentinel-1 images, freely provided with finer spatial resolution of 10 m, to detect water under vegetation canopies and other flooded vegetation; thus, we could optimize the flood mapping processes, as supported by (Webby et al., 2007; Zhang & Xu, 2018).

Data acquisition in SAR sensors and sensor configurations can be complicated in terms of the wide ranges of modes, polarizations, and incidence angles (Martinis et al., 2015). Therefore, selection of suitable data for particular uses is a remaining challenge and should be completed with consideration. Information on polarizations and local incidence angle (LIA) effect analyses could guide users to the best SAR data types for certain study areas (Martinis et al., 2015; Schumann et al., 2009). A combination of different SAR polarizations or ratios such as HH/VV of S1 are sometimes useful (Phan et al., 2018) as well. However, LIAs are defended on used DEMs, and in the case of flat areas, this information is only for reference.

We found that even the HST optimizes the fit of S1 and the reference field survey data. The errors still remained at approximately 17% due to large areas of flooded melaleuca and grass water accounted as dry areas in the S1 images. The coupling C-band (Sentinel-1) using the threshold of HST and L-band (ALOS-2) SAR images could improve the accuracy of flood mapping of regions with problems of vegetation cover, as supported by (Martinez & Letoan, 2007). It was also found that the double bounce backscatters could apply for some types of inundated vegetation (for example, melaleuca). However, not all kinds of flooded vegetation (for example, hyacinth and lotus) could be detected. Nonetheless, the contribution of AL2 extraction and the HST method to the accuracy of the flood maps has been proved by the producer and user accuracy and the Kappa statistics. All ratios were greater than 90% (Table 4). The improvements from the HST and the AL2 updates compared to the S1 averaged threshold were approximately 11% and 5%, respectively, which while small, is nevertheless significant as the accuracy of the S1 averaged threshold method was already high (76%).

Table 4: Final flood map accuracy assessment calculated from fusion matrix comparing S1 water extraction and the reference field survey data. S1 stands for Sentinel-1; HST stands for Hammock Swing Thresholding; AL2 stands for ALOS PALSAR 2.

| Methods and accuracy improvement | S1 averaged threshold | HST method | HST + AL2 updates | S1-HST improvement | HST-AL2 improvement |
|---------------------------------|-----------------------|------------|-------------------|--------------------|--------------------|
| Producer accuracy (%)           | 75.6                  | 87.2       | 92.3              | 11.6               | 5.1                |
| User accuracy (%)               | 76.2                  | 88.1       | 93.4              | 11.9               | 5.3                |
| Kappa statistics                | 0.74                  | 0.86       | 0.92              | 0.12               | 0.06               |


stands for Sentinel-1; HST stands for Hammock Swing Thresholding; AL2 stands for ALOS PALSAR 2.

Although the flood maps of the final results exhibited improved accuracy, it is worthwhile to discuss the sources of uncertainty. Some improvement assessments showed that the effects of image spatial resolution on thin and long geographic objects (rivers and channels) were great and are a challenge to solve (errors of 55% remaining). In addition, as the roads and residences in the Mekong Delta are typically found along the rivers and channels, a number of mixed pixels (approximately 16%, Table 3) were misclassified to water using the 10 m S1 images. (Młezko & Mróz, 2018) also pointed out a disadvantageous feature of the S1 dataset, which is that it is too coarse to detect small areas. These authors suggested that an integration of Sentinel-1 and TerraSAR-X images with the same polarisation would enhance the classification accuracy. Finally, scales are important for topics such as mage flood assessments or forest studies (Martone et al., 2018) and coarse images would be acceptable.

The final point to discuss is the water extraction thresholding method, which is a simple but robust method particularly when automatic flood services are established (big data or data cube for example) in order to provide timely flood extent information for a quick flood response (Martinis et al., 2015). However, a thresholding method normally combines all pixels values under the threshold into a target group, so results contain errors even with an optimally determined threshold (Quang et al., 2019a); in many cases, we still need more accurate flood information generated from an integration of multi-temporal remote sensing data sources (Tong et al., 2018).

Acknowledgments
This research was funded by the Space Science and Technology Program, supported by Vietnam Academy of Science and Technology (VAST), project number: VT-UD.12/17-20.

Disclosure statement
No potential conflict of interest was reported by the authors.

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