DETERMINING THRESHOLDS OF WATER INDICES TO DETECT SMALL SURFACE WATER AREAS IN WETLANDS OF CHUONG MY DISTRICT, HANOI CITY

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SUMMARY

Developing indicators to monitor changes in surface water areas of wetlands is very crucial with the support of remotely sensing data, which offers to obtain spatial data that is not feasible with in situ measurements. This study aimed to test Sentinel- 2A image suitability for detecting small surface water areas in wetlands using previously published indices. To obtain this objective, the study used the medium spatial resoluton Sentinel-2A image, covering 32 townships and communes of Chuong My district. To validate the results, 460 GPS points in total (360 points in water areas, 100 points in land areas) were distributed randomly within a 10 m buffer around the border of each digitised water polygon. These polygons were mapped using as a base map Goolge Earth image. As a result, the best performing index was the NDWI with accuracy of 90.0%, followed by 89.7% and 89.4% for MNDWI and B_BLUE, respectively. Overall accuracy and Kappa index results were optimal for -0.35 threshold for NDWI (0.80 for Kappa coefficient) and MNDWI (0.79 for Kappa coefficient) in Chuong My district. Therefore, using Sentinel-2A image to calculate the NDWI and other indices to monitor flooded areas and changes in surface water areas is suitable in Chuong My district.

Keywords: Kappa index, NDWI, overall accuracy, remote sensing, surface water, wetlands.

1. INTRODUCTION

Wetlands, especially surface water areas, are known as among the most ecosystems suffereing from human activities. These ecosystems offer a wide range of ecosystem services, including provision of freshwater reserve, a source for groundwater recharge, regulation of farming irrigation system, and hydrologic cycle regulation. The important role of flooding extent to wetland functioning and carbon storage has been confirmed by several previous studies (Jin et al., 2017). The spatial and temporal variation in flooded areas are high due to hydrological processes, such as precipitation and evapotranspiration, but also to anthropogenic activities (Jin et al., 2017). Effects of hydrological processes are more likely to affect other ecosystems functions, such as groundwater recharge and nutrient cycling, species distribution and composition (Leibowitz, 2003). Therefore, monitoring spatial and temporal changes of surface water areas is both crucial for water management and biodiversity conservation.

In recent decades, monitoring surface water areas has been relied on in situ detectors to gather data used by regulatory agencies and research institutions. However, gauge measurements provide little information about spatial patterns (Huang et al., 2014; Li et al., 2015). On the other side, remote sensing technology has already provided a useful and powerful tool to obtain spatial and temporal information about surfave water areas, it also offers the potential information needed for accurate surface water inventory, assessment and monitoring (Glasgow et al., 2004; Guo et al., 2016). Detection and analysis of surface water by satellite images are primarily based on supervised and unsupervised classification; and definition of water indices and their subsequent classification using thresholds (Fisher et al., 2016; Zhou et al., 2017).

For the approach based water indices, a simple threshold can be used to classify water pixels using atmostpherically corrected satellite images of different data. Images from satellite sensors of low spatial resolution, such AVHRR and MODIS have been applied to monitor flood extent by distinguishing flooded and non-flooded or mixed pixels. Other sensors with higher spatial, such as Landsat MSS/TM/ETM+ and SPOT have been employed for smaller surface water areas or wetland monitoring. The coarser spatial resolution sensors offer the advantage of a higher temporal resolution and more frequent observations than higher spatial resolution sensors. From 2015 onward, Sentinel-2A/B images are freely available, offering highly temporal resolution and bands of 10 m that enable to explore and extract small-sized surface water areas that are unlikely to be mapped by Landsat and MODIS images. There has been a growing interest in developing indicators to monitor environmental dynamics in surface water areas by using remote sensing technology over the last decades (Tiner, 2004). Some of the original constraints have been overcome with the recent satellites launching. However, there are still remaining constraints of developing indicators that can be global, non-specific for a type of surface water areas and wetland or location (Pena-Regueiro et al., 2020). The aim of this study is to test Sentinel-2A image suitability for detecting small water areas in wetlands characterised by diversity of temporal and spatial patterns in Chuong My district, Hanoi city using previously published remote sensing indices. Thresholds of water indices are then determined and suggested to use for surface water areas monitoring in study site.

2. RESEARCH METHODOLOGY

2.1. Study site

This study was conducted in all communes of Chuong My district, Hanoi city, which is located in 20.924 N and 105.704 E (Fig. 1). Chuong My is a district of Hanoi in the Red Delta region of Vietnam, which is bordered by Ha Dong county; Thanh Oai to the east; Hoa Binh to the west; My Duc and Ung Hoa districts to the south; and Quoc Oai district to the north. Chuong My is subdivided to 32 townships and communes, including two townships named as Chuc Son and Xuan; and the rural communes, namely Dai Yen, Dong Phuong Yen, Dong Son, Dong Lac, Dong Phu, Hoa Chinh, Hoang Dieu, Hoang Van Thu, Hong Phong, Hop Dong, Huu Van, Lam Dien, My Luong, Nam Phuong Tien, Ngoc Hoa, Phu Nam An, Phu Nghia, Phung Chau, Quang Bi, Tan Tien, Thanh Binh, Thuy Huong, Thuy Xuan Tien, Thuong Vuc, Tien Phuong, Tot Dong, Tran Phu, Trung Hoa, Truong Yen, Van Vo. This district is well-known due to an abundance of surface water resources, including a network of rivers and streams, which play a very important role in regulation of farming irrigation system and hydrologic cycles. However, agricultural and urban land use conversion have been main drivers for water crisis and droughts in particular in a dry season; and flooding in a rainy season.

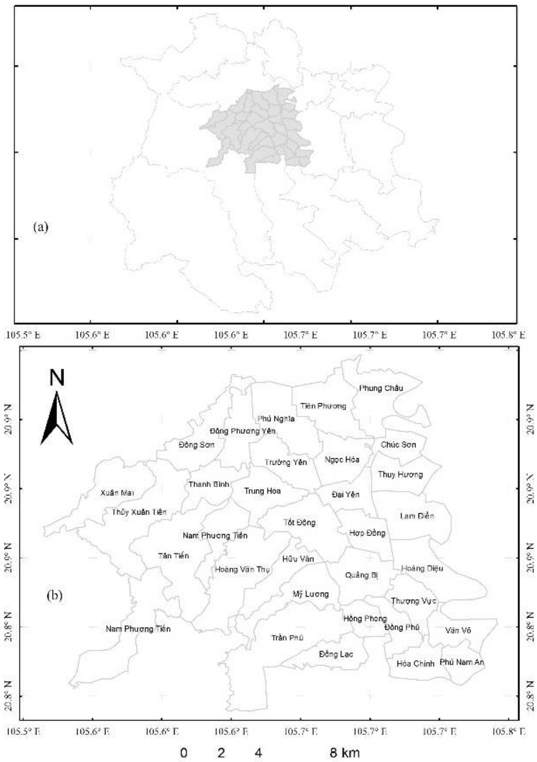

Figure 1. Geographic location of study site: (a) Hanoi city, (b) Studied communes in Chuong My district

2.2. Remote sensing data

In this study, the available Sentinel-2A image in 2020 processed at Level 1C (already an orthorectified and top-of-atmosphere reflectance), covering Chuong My district, Hanoi city, were downloaded from Sentinel Scientific Data Hub (ESA, https://scihub.copernicus) and EarthExplorer (https://eartexplorer.usgs.gov) as shown in Table 1. The acquired Level- 1C orthorectified, top-of-atmosphere optical Sentinel-2 images were atmosphererically corrected and further processed to Level- 2A product to obtain bottom-of-atmosphere corrected reflectance image (Castillo et al., 2017) by using the Semi-Automatic Classification Plugin in QGIS version 3.10.2 (Congedo, 2020). In addition, the pre-processed Sentinel Level 2A were geo-referenced to UTM WGS 1984 Zone 48N projection and datum. Sentinel-2 Level 2A image was then resampled to a 10m pixel size using the nearest neighbour algorithm. Bands of Sentinel-2 (Bands 2 - 12) were stacked into composite image.

Table 1. Remotely sensed imageries used in this study

ID	Image code	Date	Spatial resolution (m)	Note
1	L1C_T48QWJ_A025326_20200428T033028	28/04/2020	10	Provided by USGS

The Google Earth image in May 2020 was used to delimitate water areas (Fig. 2). The methodology was applied to the polygons classified as natural areas. In fact, this study delimited the water and non-water polygons. Water polygons smaller than 100 m^2 were excluded. The water and non-water polygons were delineated through visual examination using as a base map high-resolution Google earth image and was conducted with the ArcGIS 10.4.1.

The spectral information was extracted from Sentinel 2A image to calculate 4 spectral indices indicated in Table 2. The selection of spectral indices was selected based on literature review. These indices were classified as water/non-water according to a threshold values, although various authors have proposed different thresholds for the same indices. This study aimed to define a unique threshold that could be possibly optimal to detect small water areas in study site. This study tested all thresholds from 0 ÷ -0.50 with a 0.05 step. The step was detailed in the results section.

Table 2. Equations of spectral water indices used in Chuong My district

Indices	Equation	Sentinel- 2 Bands	Sources
NDWI	(GREEN-NIR)/(GREEN+NIR)	(B03-B08)/(B03+B08)	Mcfeeters (1996)
MNDWI	(GREEN-SWIR)/(GREEN+SWIR)	(B03-B11)/(B03+B11)	Xu (2006)
RE-NDWI	(GREEN-NIR)/(GREEN+NIR)	(B03-B05)/(B03+B05)	Klemenjak et al., (2012)
B_BLUE	(BLUE-NIR)/(BLUE+NIR)	(B02-B08)/(B02+B08)	Pena-Regueiro et al., (2020)

To validate the results obtained from the Sentinel 2A image, this study designed a random sampling of 360 points of wetland and water areas across Chuong My district, evenly distributed all 30 communes and two townships of Chuong My distict. The ground control points were randomly distributed within a 10 m buffer around the border of each digitised water polygon. These features were mapped using as a base map Google Earth of high spatial resolution. A number of both water points near shore (360 points in total) and surrounding non-water points (100 points in total) were selected in study site, which makes a total of 460 points for validation. The number of points were selected according to the general guideline by Congalton and Green (1999) that suggested a minimum of 50 samples for each map class for maps of less than 0.5 ha in size and fewer than 12 classes. For all these points, the study compared the classification of each index (4 indices presented in Table 2) and each threshold, with the ground-truth image, to evaluate correct classifications.

Overall accuracy and Kappa index were calculated for each random sampling. Overall accuracy was obtained by dividing the number of pixels correctly classified by the total number sampled (Congalton and Green, 1999). Kappa index was calculated according Congalton's equation (Congalton, 1991). The best index and threshold were selected according to overall accuracy and Kappa index results.

Figure 2. Water areas and wetland areas according to the official delimitation of study site. Spatial reference system: UTM coordinates Zone 48N

3. RESULTS AND DISCUSSION

Calculation of water indices:

As a result of water indices calculated, the values of NDWI, MNDWI, RENDWI and B_BLUE range from -0.9303 ÷ 0.4618, -0.9561 ÷ 0.8958, -0.8835 ÷ 0.6736, and -0.8968 ÷ 0.3526, respectively. These ranges show different types of land use and land covers in the study site. However, recent studies confirm that negative values of these water indices tend to be surface water bodies, but exact values (thresholds) for certain areas are various (Mcfeeters, 1996; Xu, 2006). The important statistics of these water indices are summarised in Table 3.

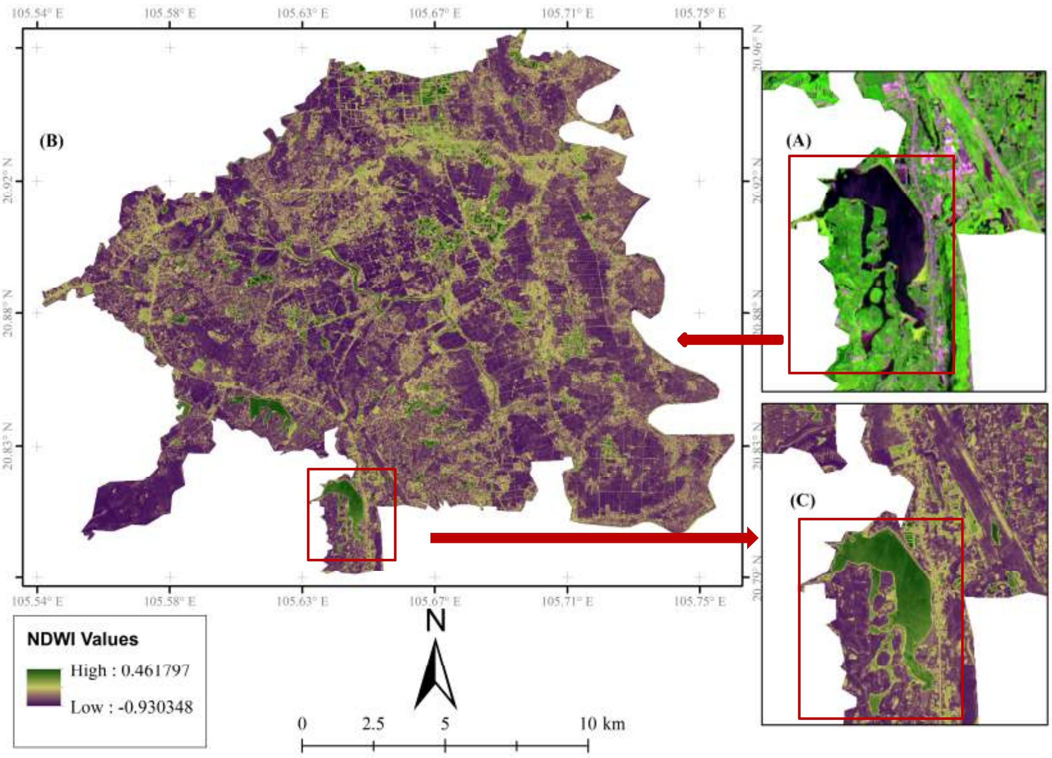

Figure 3. Values of NDWI (Normalised Difference Water Index) calculated from Sentinel-2A 28 April 2020: (A) Band combination (RGB- 584) showing Dong Xuong lake in Tran Phu commune; (B) The NDWI values in Chuong My district; (C) Dong Xuong lake in Tran Phu commune calculated by NDWI

Table 3. Summary of important statistics of the water indices in Chuong My district

Statistics	NDWI	MNDWI	RENDWI	B_BLUE
Mean	-0.5695	-0.4701	-0.1742	-0.6347
Min	-0.9303	-0.9561	-0.8835	-0.8968
Max	0.4618	0.8958	0.6736	0.3526
Standard Deviation	0.1794	0.1831	0.0786	0.1712

Accuracy assessments of the water indices:

Overall accuracy and Kappa index results are represented in Table 4 and 5. Shaded in yellow appears the indices and thresholds with poorest performance. It is suggested that the classification system from the Sentinel- 2A image fails to meet the reality confirmed by the ground- truth image. Shaded in red appear the indices and thresholds with the best performance, closely approached to 1, thus meaning that the classification system from the Sentinel-2A image matches the reality determined from the ground-truth image.

Table 4. Overall accuracy of tested remote sensing indices at different thresholds (%)

No	Thresholds	Indices			
		NDWI	MNDWI	RENDWI	B_BLUE
1	0.00	19.7	59.4	17.5	4.2
2	-0.05	31.1	66.4	39.2	10.8
3	-0.10	45.3	70.3	66.9	22.2
4	-0.15	61.9	76.9	86.1	44.7
5	-0.20	73.9	80.8	**88.6**	62.5
6	-0.25	82.2	83.9	86.1	75.3
7	-0.30	87.5	87.2	84.4	83.6
8	-0.35	**90.0**	**89.7**	80.3	86.9
9	-0.40	89.2	86.7	77.2	88.6
10	-0.45	87.8	85.3	75.3	**89.4**
11	-0.50	86.7	84.2	73.1	86.4
12	-0.55	84.4	80.6	70.3	82.2
13	-0.60	80.5	77.8	69.7	80.6

	0.50 ÷ 0.60
	0.60 ÷ 0.70
	0.70 ÷ 0.80
	0.80 ÷ 0.90

Table 5. Kappa index of tested remote sensing indices at different thresholds

No	Thresholds	Indices			
		NDWI	MNDWI	RENDWI	B_BLUE
1	0.00	0.10	0.39	0.08	0.02
2	-0.05	0.16	0.46	0.22	0.05
3	-0.10	0.26	0.51	0.47	0.11
4	-0.15	0.41	0.59	0.73	0.26
5	-0.20	0.55	0.65	**0.77**	0.42
6	-0.25	0.67	0.69	0.73	0.57
7	-0.30	0.75	0.75	0.70	0.69
8	-0.35	**0.80**	**0.79**	0.64	0.74
9	-0.40	0.78	0.74	0.60	0.76
10	-0.45	0.76	0.72	0.57	**0.79**
11	-0.50	0.74	0.70	0.54	0.73
12	-0.55	0.70	0.64	0.51	0.67
13	-0.60	0.64	0.60	0.50	0.64

	0.00 ÷ 0.10
	0.10 ÷ 0.20
	0.20 ÷ 0.30
	0.30 ÷ 0.40
	0.40 ÷ 0.50
	0.50 ÷ 0.60
	0.60 ÷ 0.70
	0.70 ÷ 0.80

In Table 4, the overall accuracy assessments are presented for the four tested indices. The tested threshold ranged are detailed in the methodology section. The best overall accuracy assessment (0.90) is for NDWI index with thresholds of -0.35. The other indices indicated lower overall accuracy results in all other tested thresholds (≤0.90).

In Table 5, the Kappa index assessments are presented in for the four tested indices. The tested thresholds are the same that for overall accuracy assessments. The best Kappa index results (0.80) is for NDWI with -0.35 threshold, 0.79 for MNDWI with threshold of -0.35, 0.77 for RENDWI with threshold of -0.20, and 0.79 for B_BLUE with threshold of -0.45.

The performance of the indices is more likely to graphically observe in detail in Table 4. This table indicates a compilation of image of indices for their optimal thresholds in the outlined water areas and wetland areas. As results, the NDWI index has the best performance for identifying water areas and wetland areas. One of the factors may explain the different performance of four indices is that the lower spatial resolution (20 m) for the bands B5 and B11 used for the indices MNDWI and RE-NDWI has been attributed (Pena-Regueiro et al., 2020). In addition, the reflectance value of Band 11 on water areas and wetland areas were more variable than B3 and B8 used in NDWI index (Pena-Regueiro et al., 2020).

Overall accuracy results are optimal for -0.35 threshold, with mean of 0.74, 0.64 of minimum values and maximum values of 0.80. Kappa index results show the highest average value (0.80) for -0.35 threshold. Considering that the objective of study is to provide a methodology to detect surface water areas in wetland areas, this study has confirmed the NDWI index with -0.35 threshold is the best index for surface water detection in Chuong My district. These findings have found the areas with highest variability, that is the water areas' borders, and are likely to more accurate central areas of land/water covers with less variation in reflectance values.

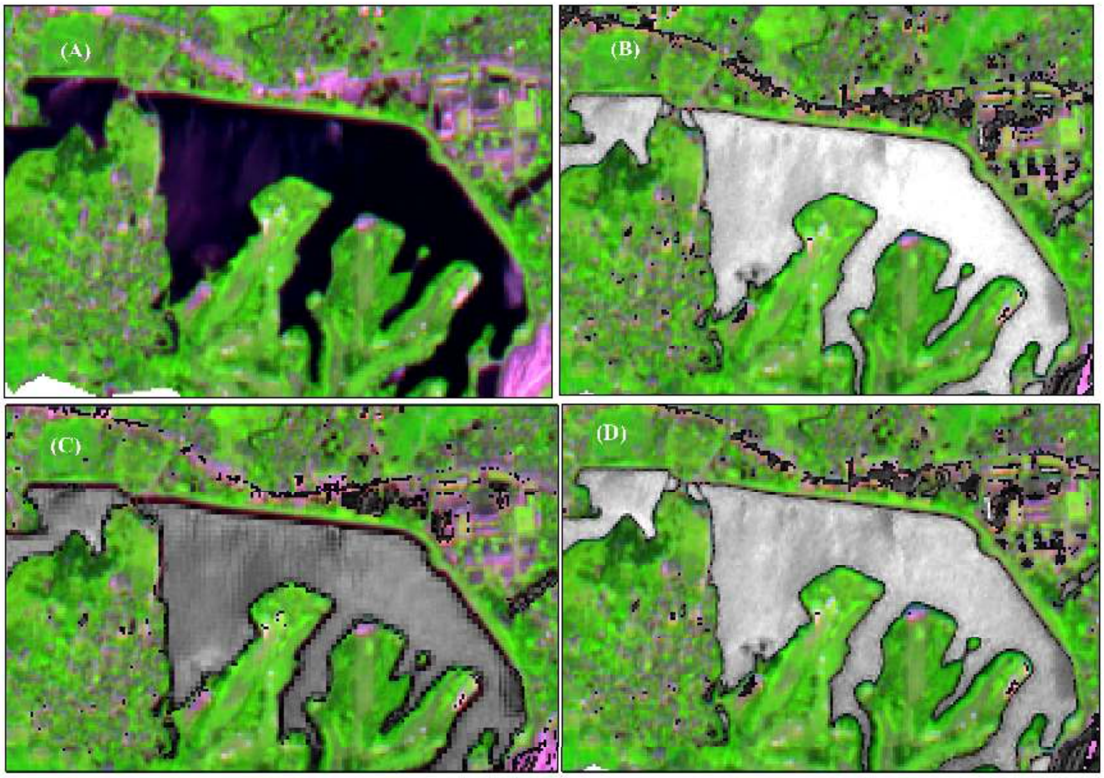

Figure 4. Delimited water areas in Tan Tien commune of Chuong My district are represented in 28 April 2020 (A): Sentinel-2A 28 April 2020, (B) NDWI index (threshold -0.35), (C): MNDWI index (threshold -0.35), (D): B_BLUE index (threshold -0.45)

Sentinel- 2A image offered to detect smaller water areas than previously published studies (Li et al., 2015; Jin et al., 2017). The minimum water body surface detected was 100 m^2. Precipitation is one of the main variables that is more likely to determine the extent of the flooded areas in wetland areas (Pena-Regueiro et al., 2020), in particular in the rainy season. The flooded surface is not neccesarily a continuum, but the addition of water areas that is connected or not (Pena-Regueiro et al., 2020). Pena-Regueiro et al. (2020) argue that the average size of flooded areas is nearly 1500 m^2, thus using Sentinel-2A image is suitable for detecting water areas and avoid underestimating the water surface. It also suggests that the NDWI index is unlikely to detect the water layer underlying marsh vegetation, but free water layers (Pena-Regueiro et al., 2020). The main free water layers are coastal lagoons, natural eutrophic lakes, and natural dystrophic lake and ponds. Natural lakes have a permanent water surface along the year, but grasslands are vegetation only periodically inundated. Large variability of wetlands may make difficult to monitor the status of these wetlands, mainly due to the small size of some surfaces that results in difficult detection and quantification (Gallant, 2015). This study has been able to detect all these water surface under different inundation conditions in Chuong My district.

In this study, the best performing index was the NDWI index (Mcfeeters, 1996). This finding is confirmed by previous studies showing the high performance of this index for extracting water surfaces (Wilson et al., 2016; Kaplan and Avdan, 2017; Zhou et al., 2017). This study the higher spatial resolution of the Sentinel-2A Bands (10m band 3, Green; band 8, NIR) allowed to define with more accuracy the boundary of water surface avoiding pixels with a mixture of covers (soil, vegetation and water). The minimum surface water areas detected this study may not be extracted using moderate spatial resolution images, such as Landsat (Sun et al., 2012; Pena-Regueiro et al., 2020). Similarly, other studies also have confirmed that a better performance with Sentinel-2A/B images than Landsat images is observed in surface water detection (Jara et al., 2012).

Earlier studies have defined a threshold of 0 for the water indices NDWI and MNDWI (Mcfeeters, 1996; Xu, 2006). Values greater than 0 are classified as water pixels, whereas values lower than 0 are defined as non-water pixels (Mcfeeters, 1996; Xu, 2006). However, this study has showed that the best performing thresholds were negative values. This result is consistent with other studies where values lower than 0 were set for extracting water areas (Ji et al., 2009; Kaplan and Avdan, 2017; Pena-Regueiro et al., 2020). Ji et al. (2009) concluded that the mixture of land covers distributed in the same pixel had a strong influence on the NDWI values with negative and variable thresholds according to the relative proportions of soil and vegetation. The negative values for extracting water surfaces may be due to the spectral response of the analysed wetlands. Water quality also significantly influences on reflectance, high values of chlorophyll a generate higher reflectance values for NIR band (B3) than for the Green band (B8) (Pena-Regueiro et al., 2020). Therefore, the negative values of the selected threshold are in agreement with the spectral response of the water in the studied wetlands.

A number of studies conducted in wetlands have emphasised calculating global gain or loss of wetland area and indicated that agricultural and urban land use conversion are the main drivers of wetland loss (Fickas et al., 2016). In the studied area, agricultural and urban use have been coexisting with natural use and strongly related to condition water management. Therefore, using Sentinel-2A imagery to monitor flooded area changes through the NDWI index will be very important to analyse the consequence of these management actions. This data can be used to assist both wetland managers and farming practitioners to make decisions about priority management interventions to maintain the ecological character of wetlands and surface water areas.

Mapping suface water areas in Chuong My district:

With the optimal threshold of NDWI greater than -0.35, the study have spatially mapped the surface water areas in Chuong My district. The results of surface water mapping are illustrated in Fig. 5.

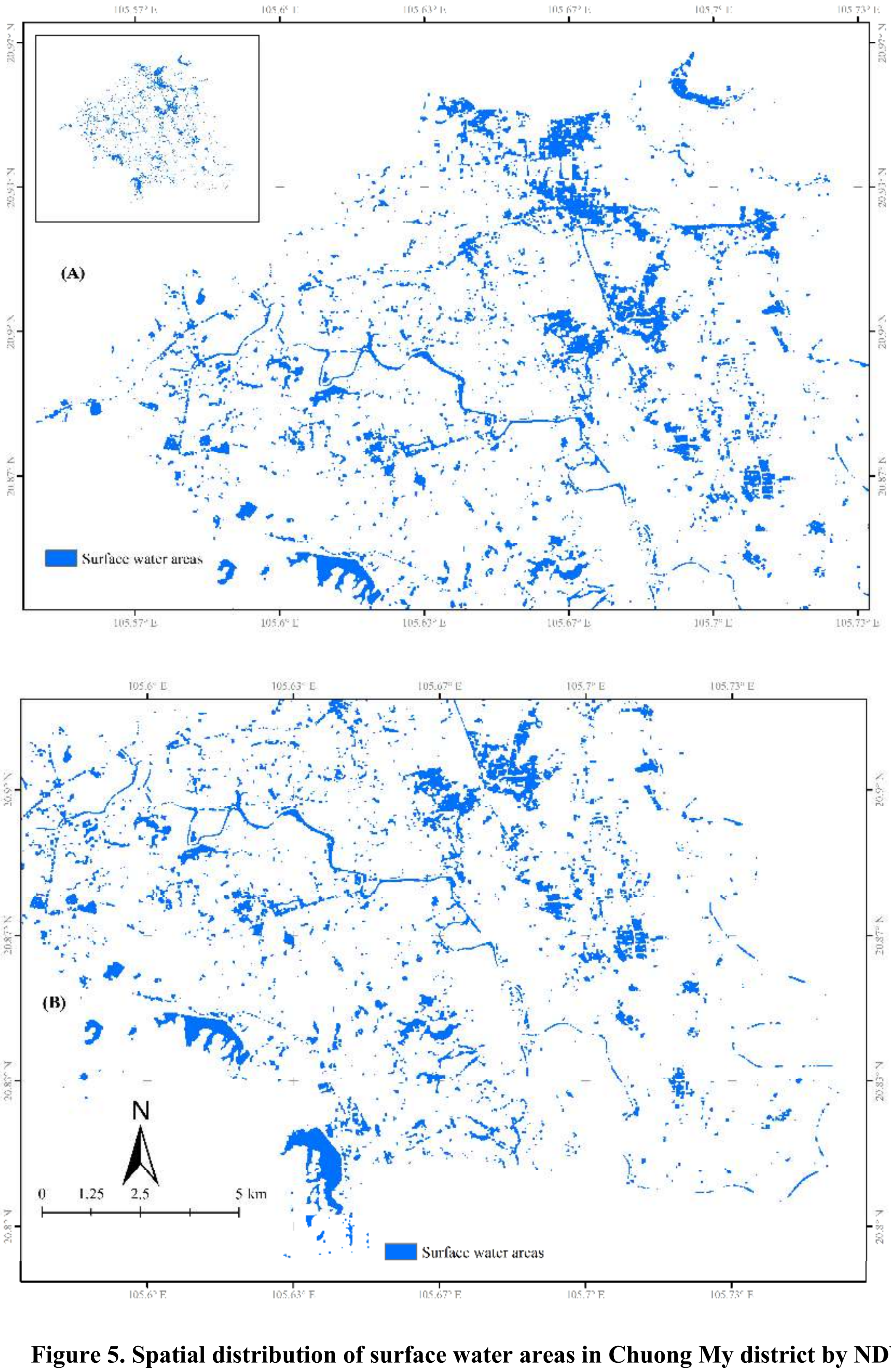

Figure 5. Spatial distribution of surface water areas in Chuong My district by NDWI with threshold greater than -0.35 (Sentinel-2A 28 April 2020)

As indicated in Fig. 5, it is seen that surface water bodies have distributed across all of the communes in Chuong My district in 2020. The results of surface water areas and its ratio compared to total natural areas of each commune in Chuong My district are calculated and summarised in Table 6 and Fig. 5.

As can be seen from Table 5 and Fig. 5, Phu Nghia and Ngoc Hoa communes have the largest areas covered by the surface water, estimated at 25.38% and 24.43%, respectively, followed by Chuc Son, Dai Yen, Hop Dong, Tan Tien, Tien Phuong, Tran Phu, and Truong Yen, valued at about 15.58%, 16.7%, 17.02%, 13.04%, 15.17%, 15.38%, and 13.53%, respectively. The remaining communes have a percentage of areas covered by the surface water ranging from 1.97% to 10.9%. These findings imply that the surface water resources are quite abundant in most of communes in Chuong My district, while some communes have been facing with a shortage of the surface water in a dry season.

Table 6. Areas of surface water distributing in each commune of Chuong My district by NDWI with threshold greater than -0.35

TT	Commune, township	Areas of surface water calculated from Sentinel-2A (ha)	Total natural areas each commune	Ratio of water coverage (%)	Remarks
1	**Chuc Son**	**55.56**	**356.53**	**15.58**	**Township**
2	Dai Yen	73.69	441.34	16.70	
3	Dong Lac	37.70	502.17	7.51	
4	Dong Phu	23.57	412.81	5.71	
5	Dong Phuong Yen	38.59	598.92	6.44	
6	Dong Son	54.58	798.30	6.84	
7	Hoa Chinh	14.84	460.47	3.22	
8	Hoang Dieu	43.27	813.23	5.32	
9	Hoang Van Thu	95.42	1280.8	7.45	
10	Hong Phong	6.20	314.18	1.97	
11	Hop Dong	82.61	485.28	17.02	
12	Huu Van	45.24	550.56	5.22	
13	Lam Dien	40.22	804.61	5.00	
14	My Luong	59.94	735.51	8.15	
15	Nam Phuong Tien	98.17	1635.19	6.00	
16	Ngoc Hoa	147.22	602.51	24.43	
17	Phu Nam An	14.04	327.21	4.29	
18	Phu Nghia	210.47	829.14	25.38	
19	Phung Chau	69.77	892.41	7.820	
20	Quang Bi	54.54	717.04	7.61	
21	TanTien	179.49	1376.26	13.04	
22	Thanh Binh	43.45	512.30	8.48	
23	Thuong Vuc	32.11	478.40	6.71	
24	Thuy Huong	20.32	535.03	3.80	
25	Thuy Xuan Tien	141.82	1385.06	10.24	
26	Tien Phuong	124.48	820.49	15.17	
27	Tot Dong	98.46	905.36	10.88	
28	Tran Phu	255.23	1660.02	15.38	
29	Trung Hoa	63.09	633.99	9.95	
30	Truong Yen	81.82	604.77	13.53	
31	Van Vo	12.54	480.23	2.61	
32	**Xuan Mai**	**74.50**	**883.33**	**8.43**	**Township**

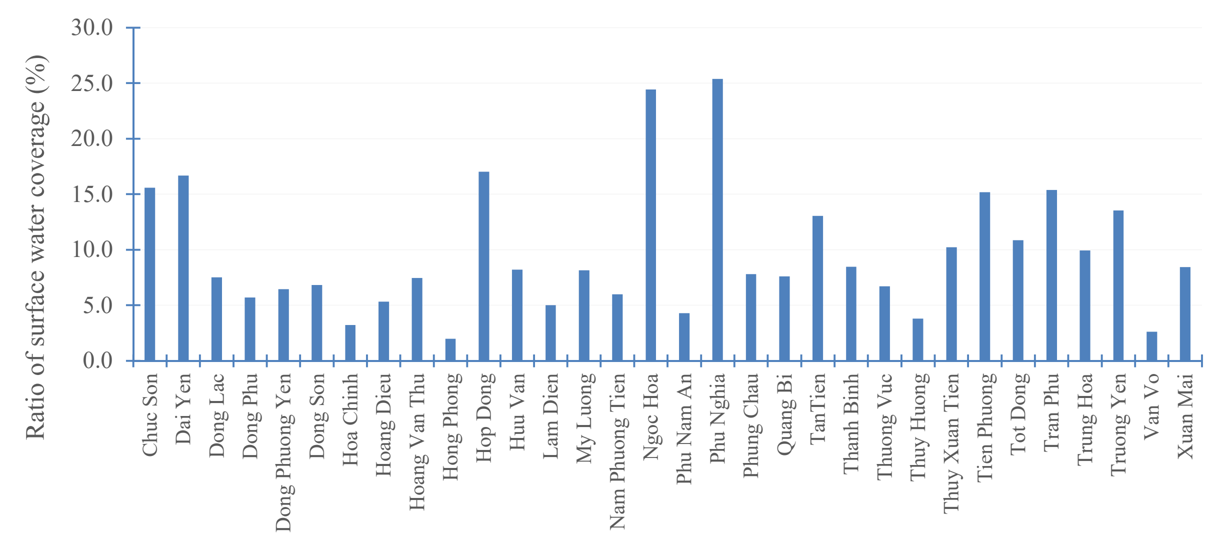

Figure 6. Ratio of areas covered by the surface water in comparison with total natural areas each commune in Chuong My district

3. CONCLUSION

The spatial resolution of Sentinel-2A image has enabled to detect the small surface water areas compared to previously spatial medium and low resolution studies. The findings of this study showed that the potential of NDWI index calculated from Sentinel-2A image (Bands 3 and 8) is suitable to extract open water areas in delimited wetlands. It was confirmed that a -0.35 threshold generated is acceptable to classify the surface water bodies in Chuong My district. With the selected threshold of NDWI, the study calculated the surface water areas each commune in Chuong My district. As a result, Phu Nghia and Ngoc Hoa communes have the largest areas covered by the surface water, estimated at 25.38% and 24.43%, respectively, followed by Chuc Son, Dai Yen, Hop Dong, Tan Tien, Tien Phuong, Tran Phu, and Truong Yen, valued at about 15.58%, 16.7%, 17.02%, 13.04%, 15.17%, 15.38%, and 13.53%, respectively. The remaining communes have a percentage of areas covered by the surface water ranging from 1.97% to 10.9%. Therefore, the information derived from Sentinel-2A bands can be useful to monitor these ecosystems, providing valuable information for managers of these areas, especially to study the effect of hydrologic cycle manipulation.

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XÁC ĐỊNH NGƯỠNG CHỈ SỐ NƯỚC ĐỂ PHÁT HIỆN NƯỚC BỀ MẶT QUI MÔ NHỎ TẠI HUYỆN CHƯƠNG MỸ, THÀNH PHỐ HÀ NỘI

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SUMMARY

Việc xây dựng các chỉ số để giám sát sự thay đổi tài nguyên nước bề mặt phân bố ở vùng đất ngập nước có ý nghĩa rất quan trọng với sự hỗ trợ của dữ liệu viễn thám, việc này đã giúp chúng ta có được nguồn dữ liệu không gian khả thi so với các phương pháp điều tra truyền thống. Nghiên cứu sử dụng dữ liệu ảnh Sentinel-2A để phát hiện phân bố nước bề mặt với diện tích nhỏ tại các vùng đất ngập thông qua các chỉ số về nước đã được công bố trước đây. Để đạt được mục tiêu này, nghiên cứu đã sử dụng ảnh Sentinel-2A độ phân giải không gian trung bình, che phủ 32 thị trấn và xã của huyện Chương Mỹ. Để đánh giá độ tin cậy kết quả nghiên cứu, 460 điểm GPS, trong đó 360 điểm GPS tại các vùng có tài nguyên nước bề mặt, 100 điểm ở vùng đất, các điểm GPS được lựa chọn ngẫu nhiên với bán kính 10 m xung quanh các vùng có phân bố nước bề mặt được số hoá. Các vùng số hoá phân bố nước bề mặt được số hoá trên ảnh Goolge Earth có độ phân giải cao. Kết quả nghiên cứu cho thấy chỉ số NDWI có độ chính xác 90,0%, tiếp theo là 89,7% và 89,4% đối với chỉ số MNDWI và B_BLUE. Độ chính xác tổng thể và kết quả chỉ số Kappa là tối ưu cho ngưỡng -0,35 giá chí đối với chỉ số NDWI (hệ số Kappa là 0,80) và MNDWI (hệ số Kappa là 0,79) tại huyện Chương Mỹ. Do vậy, việc sử dụng ảnh Sentinel-2A để tính toán NDWI và các chỉ số khác để theo dõi diện tích ngập lụt và biến động nước mặt là phù hợp ở huyện Chương Mỹ.

Từ khóa: chỉ số Kappa, đất ngập nước, độ chính xác tổng thể, NDWI, nước mặt, viễn thám.

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