Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI

Abstract*This research specifically aims to investigate the most accurate spectral indices in extracting wetlands geospatial information taking South Kalimantan, Indonesia, as an example of wetlands in tropical areas. Ten spectral indices were selected for testing their ability to extract wetlands, those are NDVI, NDWI, MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, andAWEIsh. Tests were performed on Landsat 8 OLI path/row 117/062 and 117/063. The threshold method which was used to separate the wetland features from the spectral indices imagery is Otsu method. The results of this research showed that generally MNDWIs2 was the most optimal spectral indices in wetlands extraction. Especially tropical wetlands that rich with green vegetation cover. However, MNDWIs2 is very sensitive to dense vegetation, this feature has the potential to be detected as wetlands. Furthermore, to improve the accuracy and prevent detection of the dryland vegetation as wetlands, the threshold value should be determined carefully.*

Key words: wetlands; spectral indices; Landsat 8 OLI; South Kalimantan

Abstrak*Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis. Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI, MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat, fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.*

Kata kunci *: lahan basah; indeks spektral; Landsat 8 OLI; Kalimantan Selatan*

1. Introduction

Wetlands are ecosystems saturated with water, either seasonally or permanently (EPA, 2004). According to the Ramsar Convention on Wetlands 1993 (Matthews, 2013), based on the habitat, wetlands classified into marine and coastal wetlands, inland wetlands, and man-made wetlands. In the South Kalimantan Province, Indonesia, wetlands are one of the main features of the landscape.

The characteristics of tropical wetlands located in South Kalimantan Province are quite varied. For example, shallow water has a main characteristic, that is rich with green vegetation cover. On the deep water bodies (rivers) in this area, the waters have high enough levels of turbidity. In South Kalimantan, there are also quite a lot of open pit coal mining activities. The water inside the pits the rest of the coal mine will be mixed with the toxic minerals out of the mine. Hence, on the ground the pits look green. The green colour was formed distinct spectral signatures in multispectral optical imagery.

So far, various methods have been developed for the extraction of wetlands geospatial data automatically. For example, the Normalized Difference Water Index (NDWI) (McFeeters, 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and so forth. NDWI and MNDWI are the two most popular spectral indices for the extraction of water features or wetland features. Their ability to extract open water features or wetland features has been tested from several research results (McFeeters, 1996; Xu, 2006; Li et al., 2013; Jiang et al., 2014; Ashraf and Nawaz, 2015; Das and Pal, 2016; Du et al., 2016). Besides NDWI or MNDWI, there are also a number of other spectral indices that can potentially be used to separate wetland features from other features.

In general, spectral indices such as NDWI or MNDWI are actually developed to separate open water features from other features. Some research indicates that the spectral indices are very accurate in extracting the boundaries of water features. For example, Xu (2006) proved that MNDWI more accurate than NDWI when applied to the three water features, i.e. lakes, oceans, and rivers. Similar to Xu (2006), Li et al. (2013) also found that MNDWI more accurate than NDWI to the TM, ETM +, and ALI imagery. To further test MNDWI's capabilities, Jiang et al. (2014) developed the Automated Method for Extracting Rivers and Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM +. It was found that in general, MNDWI remains the best among the three other spectral indices.

Du et al. (2016) used MNDWI on the Sentinel-2 imagery, where the SWIR band of Sentinel-2 sharpened to 10 meters by a number of pan-sharpening method. Du et al. (2016) found that MNDWI with a combination of Principle Component Analysis (PCA) is more accurate than the NDWI and MNDWI with a combination of other pan-sharpening.

In other cases, other spectral indices have proven to be more accurate in extracting open water or wetlands features. For example, when Ashraf and Nawaz (2015) detect changes in the wetlands of the Baraila Lake (India) using four spectral indices, they found that in general NDWI is the most accurate method when verified using the field data. Similar to Ashraf and Nawaz, Das and Pal (2016) also found that NDWI was the most accurate spectral indices, when they compared six spectral indices. While Zhai et al. (2015) when comparing surface water extraction performances of four indices using Landsat TM and OLI, they found that Automated Water Extraction Index (AWEI) has the highest overall accuracy.

Kwak and Iwami (2014) developed a Modified Land Surface Water Index (MLSWI), they use it on flood inundation mapping using MODIS imagery and they test its accuracy using ALOS AVNIR 2. They found that MLSWI more accurate than Normalized Difference Vegetation Index (NDVI) and Land Surface Water Index (LSWI).

Several other researchers, such as Xie et al. (2016), they make further use of the spectral index to extract water features at the sub pixel level. They used MNDWI to separate the pure land pixel and pure water pixel in Spectral Mixture Analysis (SMA), for mapping the surface of the water of lakes and rivers automatically at sub pixel level.

Other researchers, such as Yang et al. (2015) combined spectral indices and single band multispectral imagery simultaneously to extractwater features. They use a number of spectral indices and single band on Landsat 8 OLI to extract the water bodies. Those are, the single-band threshold in band 5, multiband spectral relationship b2, b3, b4, b5, NDVI, NDWI, MNDWI, Normalized Difference Built-up Index (NDBI), TCT, and Hue, Intensity and

Saturation (HIS). Where all of the spectral indices and bands are combined using deep learning algorithm, called Stacked Sparse Autoencoder (SSAE).

Although the spectral indices such as NDWI, MNDWI, NDVI, or others are accurate to separate open water features from other features, but it still needs to be studied further, whether these spectral indices are also accurate when used to separate wetland features from dryland features. Because, most of the wetlands in tropical areas has a spectral characteristic of water and green vegetation simultaneously. This research aimed to compare the accuracy of some of the spectral indices for optimizing the extraction of wetlands, by taking the case of the tropics area, that is, the South Kalimantan Province, Indonesia.

2.The Methods

2.1. Materials

This research used two scenes of Landsat 8 OLI, the path/row 117/062 and 117/063, the acquisition on April 22, 2015. Most of the wetlands in South Kalimantan to be in these two scenes. Imageries acquiring date selected on April because it was the rainy season. Therefore, the condition of wetlands is at the maximum extends.

Overall spectral indices in this study applied to Landsat 8 Operational Land Imager (OLI) surface reflectance imageries. Atmospheric correction methods used in this research was the Dark Object Subtraction 4 (DOS4) (Chavez, 1988; Chavez, 1996; Zhang et al., 2010; Hong et al., 2014).

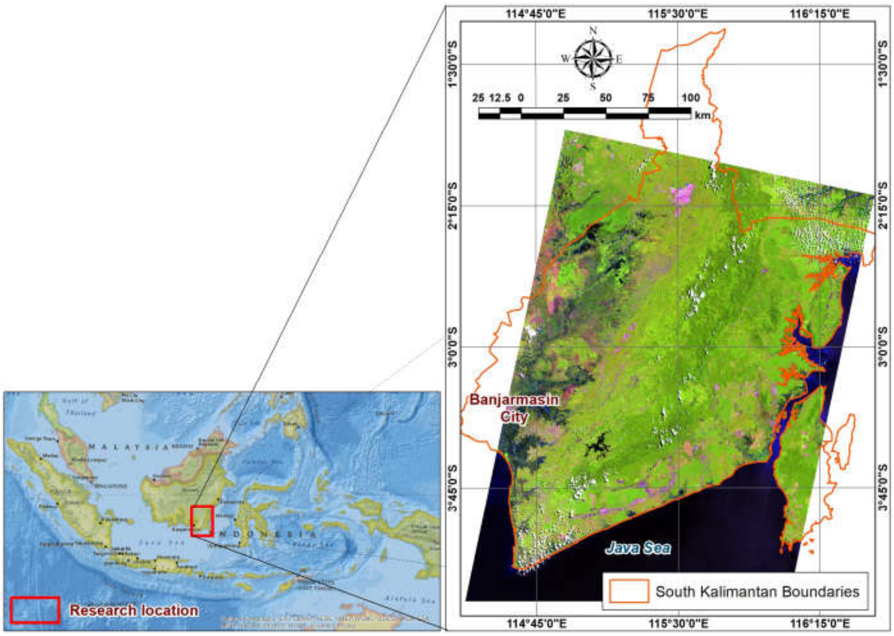

Figure 1. Research location

2.2. Water Indices

Water indices is a generic term for all of the spectral indices intended to sharpen the water features. One of the water indices which is most extensively used is NDWI (McFeeters, 1996). According to McFeeters (1996), if the pixel values of NDWI are positive means the water features. Thus, the value of 0 by McFeeters (1996) is set as the threshold value. NDWI formulated by McFeeters (1996) as follows:

$$\mathrm{NDWI} = \frac{\rho_g - \rho_n}{\rho_g + \rho_n} \qquad (1)$$

Where:

- ρ_g: green band
- ρ_n: near infrared band

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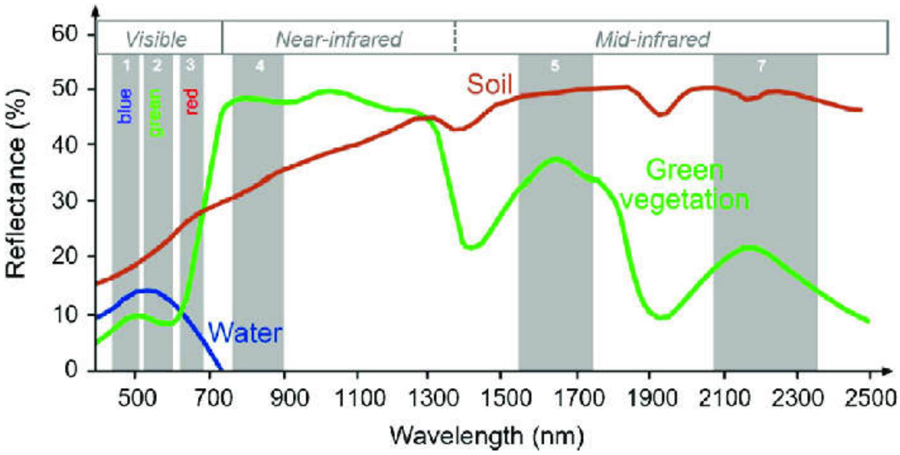

Figure 2. Spectral value curves on three base surface features (Chen et al., 2019)

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Due to lack of NDWI in error detection features of the building, Xu (2006) modifying NDWI become MNDWI, by changing NIR band into SWIR. In this case, Xu (2006) using the SWIR1. The replacement of NIR with SWIR1 aims to suppress soil features (including buildings) in McFeeters's NDWI, because in the SWIR1 soil reflectances are higher than NIR. As seen in the spectral value curves in Figure 2.

$$\mathrm{MNDWI} = \frac{\rho_g - \rho_s}{\rho_g + \rho_s} \qquad (2)$$

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Where:

- ρ_s: shortwave infrared band

In this research, we were also adding a water index modified from MNDWI, by replacing the SWIR1 in MNDWI with SWIR2. Thus, the MNDWI_{s2} formula that we modified in this research is as follows:

$$\mathrm{MNDWI}_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}} \qquad (3)$$

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Where:

- ρ_{s2}: shortwave infrared 2 band

Xu (2006) replaces NIR with SWIR1 in NDWI (McFeeters, 1996) with the aim to suppress building features, because in the SWIR1, soil and building reflectance higher than NIR. In this research, we replace SWIR1 into SWIR2, with the aim to capture the spectral vegetation located above the wetlands. Because vegetation reflectance in SWIR2 is not as high as SWIR1 and NIR.

Besides NDWI, MNDWI and $MNDWI_{s2}$, there are various other spectral indices to be tested in this research. Table 1 shows the full list of spectral indices which are capabilities will be compared in this study.

Table 1. List of the spectral indices used in the research

No.	Spectral Indices		Formula	Value of Water	Reference
1.	NDVI	Normalized Difference Vegetation Index	$\frac{\rho_n - \rho_r}{\rho_n + \rho_r}$	Negative	Rouse et al. (1973)
2.	NDWI	Normalized Difference Water Index	$\frac{\rho_g - \rho_n}{\rho_g + \rho_n}$	Positive	McFeeters (1996)
3.	MNDWI	Modified Normalized Difference Water Index	$\frac{\rho_g - \rho_{s1}}{\rho_g + \rho_{s1}}$	Positive	Xu (2006)
4.	$MNDWI_{s2}$	Modified Normalized Difference Water Index with SWIR2	$\frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$	Positive	This research
5.	NDMI	Normalized Difference Moisture Index	$\frac{\rho_n - \rho_s}{\rho_n + \rho_s}$	Positive	Gao (1996); Wilson and Sader (2002); Xiao et al. (2002); Lacaux et al. (2007)
6.	WRI	Water Ratio Index	$\frac{\rho_g + \rho_r}{\rho_n + \rho_s}$	Greater than 1	Shen (2010)
7.	NDPI	Normalized Difference Pond Index	$\frac{\rho_s - \rho_g}{\rho_s + \rho_g}$	Negative	Lacaux et al. (2007)
8.	TCWT	Tasseled-Cap Wetness Transformation	$0.1877\rho_{ca} + 0.2097\rho_b + 0.2038\rho_g + 0.1017\rho_r + 0.0685\rho_n - 0.7460\rho_{s1} - 0.5548\rho_{s2}$	-	Li et al. (2015)
9.	$AWEI_{nsh}$	Automated Water Extraction Index with no shadow	$4(\rho_g - \rho_{s1}) - (0.25\rho_n + 2.75\rho_{s2})$	-	Feyisa et al. (2014)
10.	$AWEI_{sh}$	Automated Water Extraction Index with shadow	$\rho_b + 2.5\rho_g - 1.5(\rho_n + \rho_{s1}) - 0.25\rho_{s2}$	-	Feyisa et al. (2014)

Information:

- ρ_{ca}: aerosol coastal bands (bands 1 Landsat 8)
- ρ_b: blue band (band 2 Landsat 8)
- ρ_g: green band (band 3 Landsat 8)
- ρ_r: red band (band 4 Landsat 8)
- ρ_n: near infrared band (band 5 Landsat 8)
- ρ_s: shortwave infrared band (band 6 or 7 Landsat 8)
- ρ_{s1}: shortwave infrared 1 band (band 6 Landsat 8)
- ρ_{s2}: shortwave infrared 2 band (band 7 Landsat 8)

2.3. Wetlands Extraction

For the purpose of separating wetland features and non-wetland features from spectral indices imageries, some literature recommends a specific threshold value. However, in certain cases, the threshold value is often not optimal. According to Ji et al. (2009), the NDWI threshold is not a constant value, an appropriate NDWI threshold needs to be determined.

There are several methods of automatic thresholding used to classify digital imageries. One of the most popular automatic thresholding methods is Otsu thresholding (Otsu, 1979). In this research, the Otsu thresholding process is done using free open source public domain software, namely ImageJ (Schneider et al., 2012; Schindelin et al., 2015).

2.4. Accuracy Accuracy Assessment

Accuracy assessment was conducted using the Confusion Matrix (Stehman and Czaplewski, 1997), using a number of sample locations were selected purposively. In this case, the location of the sample represents multiple characters wetlands in South Kalimantan. Namely, mangroves, salt marshes, deep water (include reservoirs, canals, and coal open pits), peatlands, peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish ponds, swamp rice fields, irrigated land, freshwater marshes, and freshwater lake.Therefore, there are a total of 12 samples for wetland classes. Meanwhile, the number of sample pixels for each wetlands class are 4,495, 4,245, 10,904, 2,309, 6,739, 14,396, 2,265, 3,217, 6,597, 2,307, 5,020 and 2,330 pixels respectively.

For the purpose of assessing the deeper capabilities of each spectral index, the sample locations were also chosen purposively on various dryland features that have the potential to be detected as wetlands. In the appointment of the samples, the method used is knowledge-based. There are a total of 10 samples for dryland classes. Namely, built-up lands, barelands, grass, roads, dryland forest, dryland farms, garden (include mix garden, rubber plants, palm oil), and shrub and bushes. The number of sample pixels for each of these drylands classes are 1,236, 4,003, 2,377, 323, 6,445, 2,169, 4,694, and 8,075 pixels, respectively.

A confusion matrix is constructed for each spectral index, for example for NDWI a confusion matrix will be constructed, as well as for other spectral indices. The first accuracy assessment is done in general, where each spectral index is tested for its ability to separate wetlands and drylands. From the resulting confusion matrix, the overall accuracy, kappa coefficient, producer's accuracy, user's accuracy, commission error, and omission error are calculated to obtain quantitative descriptions of the capabilities of each spectral index. The recapitulation results of overall accuracy, kappa coefficient, producer's accuracy, user's accuracy, commission error, and omission errors can be seen in Table 2.

Furthermore, to test the ability of each spectral index to recognize each wetland class, a confusion matrix was constructed for each spectral index in each wetland class. For example, for NDWI in the Mangroves class, a confusion matrix will be constructed. Furthermore, from the resulting confusion matrix the Producer's Accuracy value will be taken, to obtain a quantitative description of the ability of the spectral index to recognize one type of wetland. So we will get an overview of NDWI's ability to recognize Mangroves for example. Recapitulation of producer's accuracy values for each spectral index in each wetland class can be seen in Table 3.

The final step, to test the ability of each spectral index to avoid the detection of dryland features, a confusion matrix is constructed for each spectral index in each dryland class. For example, for NDWI in the Dryland Forest class, a confusion matrix will be constructed. Furthermore, from the resulting confusion matrix the Commission Error value will be taken, to obtain a quantitative description of the ability of the spectral index to avoid the detection of one type of dryland. So that a description of NDWI's ability to avoid detecting Dryland Forest as a wetland will be obtained, for example. Recapitulation of commission error values for each spectral index in each dryland class can be seen in Table 4.

3.Result and Discussion

Visual appearance of wetlands in South Kalimantan varies in tone/colour on multispectral satellite imageries such as Landsat 8. This shows quite a high degree of variation in spectral value of each type of wetlands. In the accuracy assessment, the samples were made for each type of wetlands. For the purpose to ensure that variations in the class of all wetlands are represented as possible, Region of Interest (ROI) made for every wetland types are distributed in several different locations. Figure 3 shows the Standard Deviation (SD) ROI of all wetlands in each band Landsat 8 OLI.

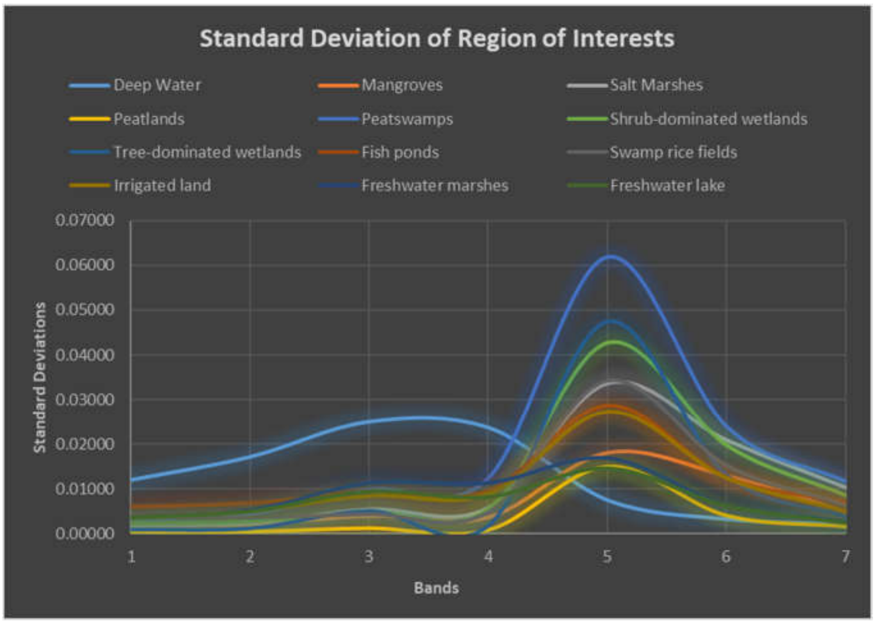


Figure 3. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

Of course, spectral indices such as NDWI cannot distinguish between mangroves and peatswamps, for example. Because spectral indices such as NDWI are only designed to recognize and separate water/wetlands from dryland features. While mangroves and peatswamps are both wetland features. In fact, the thresholding imageries results of spectral indices contains only two classes, namely Wetlands and Non-wetlands. But for the sake of accuracy assessment, the accuracy assessment ROI is made on every types of wetlands in the research locations. It is intended that the spectral character of each wetland represented, and to provide an overview of each spectral indices extraction capabilities of each type of wetlands.

When the overall accuracy of the assessment is done, all types of wetland features are combined into a single class, namely the Wetlands. And all types of drylands features are combined into a single class, namely Non-wetlands. Figure 4 shows the results of the transformation of spectral indices were selected in this research. While Table 2 shows the results of Otsu thresholding and accuracy assessment results of each spectral index using the Confusion Matrix.

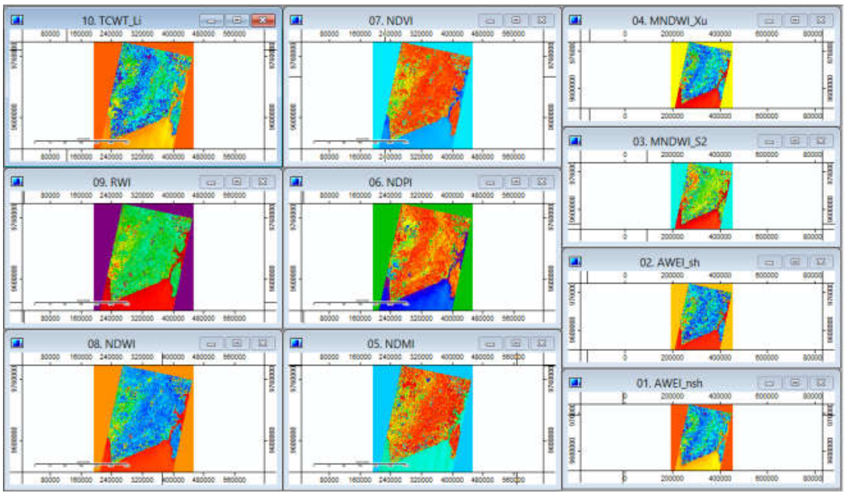


Figure 4. The result of the transformation of spectral indices on the SAGA application

Table 2. The Otsu thresholding and accuracy assessment results using the Confusion Matrix

No.	Spectral Indices	Otsu Threshold	OA (%)	Kappa	PA (%)	UA (%)	CE (%)	OE (%)
1.	NDVI	≤ 0.21	44.20	0.18	43.59	88.49	11.51	56.41
2.	NDWI	≥ -0.17	45.19	0.19	44.84	89.73	10.27	55.16
3.	MNDWI	≥ -0.06	68.59	0.50	84.22	99.74	0.26	15.78
4.	$MNDWI_{s2}$	≥ 0.07	74.82	0.59	97.54	98.13	1.87	2.46
5.	NDMI	≥ 0.13	32.68	-0.14	38.86	60.48	39.52	61.14
6.	WRI	≥ 0.51	73.02	0.50	98.61	84.61	15.39	1.39
7.	NDPI	≤ 0.05	65.02	0.45	77.15	99.85	0.15	22.85
8.	TCWT	≤ 0.45	59.32	0.37	66.37	99.95	0.05	33.63
9.	$AWEI_{nsh}$	≥ -0.55	54.15	0.31	57.11	99.99	0.01	42.89
10.	$AWEI_{sh}$	≥ -0.20	62.46	0.41	72.53	98.87	1.13	27.47

Information:

- OA: Overall Accuracy
- PA: Producer's Accuracy
- UA: User's Accuracy
- CE: Commission Error
- OE: Omission Error

The use of a single method based on the spectral indices looks like it is not so qualified in the extraction of wetlands, as well as the extraction of the open water features. Because somehow wetlands are the composite features, which are mainly composed of water and vegetation. Islam et al. (2014) research results are not much different from the results of this research. Islam et al. (2014) found the spectral indices for mapping wetlands have the highest overall accuracy of 78%.

Although in this research was found the spectral indices which has overall accuracy above 70%, but when seen from the small Kappa coefficient, it seems overall accuracy was more to conditionally. However, this study is sufficient to provide an overview comparison of the relative accuracy of each spectral index, if used specifically for the delineation of wetland features.

In general, MNDWI, $MNDWI_{s2}$, and WRI, are three spectral indices overall most accurately. However, the value of OA and Kappa both is not enough to describe the accuracy or optimality a digital imagery transformation method in extracting particular features. From OA has been seen that $MNDW_{s2}$ implemented in this study is more accurate than MNDWI. However, when seen from the CE, map of wetlands resulting from MNDWI a little more accurate. For the next, we want to see, in which object successes and failures of each spectral indices located. Based on this, we examine the PA on each of the spectral indices, for each type of wetlands.

In testing the PA, each ROI at each wetland type tested separately on each thresholding results imagery of spectral indices. This is because, each thresholding results imagery of spectral indices does not distinguish among types of wetlands. Table 3 shows the PA for each spectral index and each wetland type.

Table 3. Producer's accuracy for each spectral index and each wetlands type

No.	Spectral	Producer's Accuracy (%)											
	Indices	Dw	Mg	Sm	Pl	Ps	Sw	Tw	Fp	Sr	Il	Fm	Fl
1.	NDVI	100	0	72.16	0	87.10	6.29	0	98.91	89.77	99.13	99.94	99.87
2.	NDWI	100	0	77.93	0	87.02	8.4	0	99.25	92.92	99.61	99.96	99.91
3.	MNDWI	100	92.77	98.87	0	98.71	90.28	41.41	99.97	99.94	100	100	100
4.	$MNDWI_{s2}$	100	100	96.11	99.52	97.91	97.19	99.65	99.81	99.97	100	100	100
5.	NDMI	0	100	89.61	100	24.69	99.89	100	20.14	80.39	45.69	6.99	2.40
6.	WRI	100	100	100	89.39	100	98.81	98.41	100	100	100	100	100
7.	NDPI	100	86.01	97.17	0	97.95	77.71	18.23	99.94	99.58	100	100	100
8.	TCWT	100	89.39	91.24	0	96.96	47.97	11.79	99.84	98.38	100	99.98	100
9.	$AWEI_{nsh}$	100	69.97	88.46	0	95.87	25.47	5.92	99.88	96.38	100	100	100
10.	$AWEI_{sh}$	100	5.81	99.95	0	97.92	88.55	15.45	100	99.83	100	100	100

Information:

- Dw: Deep water (include river, reservoir, dam, and coal mining pits)
- Mg: Mangroves
- Sm: Salt marshes
- Pl: Peatlands
- Ps: Peatswamps

- Sw: Shrub-dominated wetlands
- Tw: Tree-dominated wetlands
- Fp: Fish ponds
- Sr: Swamp rice fields
- Il: Irrigated land
- Fm: Freshwater marshes
- Fl: Freshwater lake

The entire spectral indices, except NDMI, do not have a problem when extracting the deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open water features. NDMI successfully on lands that are quite dense vegetation cover. This is because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al., 2004).

NDVI and NDWI have the same character in separating wetland features from other features. Both can be said to be successful wetlands extracting, especially wetlands with high concentration of water. However, they completely fail in identifying wetlands with dense vegetation, such as mangrove or peatlands. This is because NDVI and NDWI using the same NIR band, where vegetation will have a contrasting difference with water in NIR.

NDPI and TCWT ability in recognizing wetlands is almost similar to NDVI and NDWI. Only NDPI more successful in recognizing wetlands with dense canopy. Compared to NDPI, TCWT worse at recognizing wetlands topped with vegetations with a bright hue, which are commonly found in shrub-dominated wetlands and freshwater marshes. $AWEI_{nsh}$ ability in recognizing wetlands also similar to NDPI and TCWT. However, $AWEI_{nsh}$ failures in identifying wetlands with dense canopy worse than TCWT. $AWEI_{sh}$ even worse at recognizing wetlands with dense canopy. Although overall, $AWEI_{sh}$ better than $AWEI_{nsh}$.

MNDWI and $MNDWI_{s2}$ quite successful in identifying wetlands. Except MNDWI failed to recognize the peatlands and tree-dominated wetlands. Where these two features are wetlands with dense canopy. Not so with $MNDWI_{s2}$ capable of recognizing peatlands and tree-dominated wetlands with almost 100% accuracy. Based on this fact, our assumption when shifting SWIR1 into SWIR2 on MNDWI has been proven. $MNDWI_{s2}$ able to recognize the characteristic spectral features that have water and vegetation spectral characteristics as well with better.

The ability of spectral indices for identifying wetlands (PA), is not directly indicated its ability to extract the wetlands. Because in automatic features extraction, the goal is not only that the method is able to recognize the desired features, but also how the method avoids recognizing other features. That is why, in this research we also tested the CE. In this case, CE tested using dryland features in research locations. These dryland features have been selected to investigate in which object the spectral indices encountered an error detection as wetlands.

Technical testing of CE is similar to the PA, which is any ROI dryland features tested separately on each thresholding results imagery of spectral indices. Table 4 shows the CE for each spectral index and each wetland type.

Table 4. Commission error for each spectral index and each drylands feature

No.	Spectral Indices	Commission Error (%)							
		Bu	Bl	Gr	R	F	Df	Gd	Sb
1.	NDVI	71.76	98.13	0	87.62	0	0	0	0
2.	NDWI	55.10	90.43	0	85.14	0	0	0	0
3.	MNDWI	0	0.05	0	37.15	0.47	0	0	0
4.	$MNDWI_{s2}$	0	0	0	0	18.65	0.05	0	0.15
5.	NDMI	1.70	0.10	100	5.57	100	91.47	100	100
6.	WRI	99.92	99.83	0	100	69.84	33.38	0.64	10.58
7.	NDPI	0	0.05	0	21.98	0.16	0	0	0
8.	TCWT	0	0	0	0	0.39	0	0	0
9.	$AWEI_{nsh}$	0	0	0	0	0.06	0	0	0
10.	$AWEI_{sh}$	20.47	1.27	0	95.05	0.14	0	0	0

Information:

- Bu: Built-up lands
- Bl: Barelands
- Gr: Grass

- R: Roads
- F: Dryland forest
- Df: Dryland farms
- Gd: Garden (mixgarden, rubber plants, palm oil)
- Sb: Shrub and bushes

Based on Table 3 and Table 4, it appears that NDMI cannot distinguish between dryland forest and wetlands forest. Likewise, the overall WRI has high accuracy, and as if it is able to recognize all types of wetlands with good, it fails on a number of dryland features and take it as wetlands. This translates into an overall accuracy WRI does not mean anything, because in fact it could not distinguish well between wetland features and some dryland features.

NDVI and NDWI that have the same character, they are also sensitive to built-up lands, roads, and barelands. NDPI better than NDVI and NDWI in distinguishing between built-up lands or barelands and wetlands. However, NDPI also slightly failed in distinguishing the paved roads to the wetlands. TCWT and AWEInsh are two spectral indices of the best in minimizing error detection wetlands. Since both spectral indices have the lowest CE. Different from AWEInsh, AWEIsh disadvantaged in distinguishing between the paved roads to the wetlands.

MNDWI turned out to be problematic with paved roads in the wetlands. However, MNDWI failure to distinguish between wetlands and paved roads here occurs only as a result of Otsu thresholding is negative. MNDWIs2 was almost no problems with all the dryland features, except dryland forests. Furthermore, MNDWIs2 troubled with all the dense and dark vegetation features. As with all other spectral indices, MNDWIs2 also failed to recognize the wetlands on which there are very bright vegetation features.

Based on the results of the accuracy assessment, it appears that MNDWIs2 is the most optimal spectral indices for the extraction of wetlands. Some experts previously also been modified MNDWI using SWIR2. Among them was Chen et al. (2005), Ji et al. (2009), Boschetti et al. (2014), and Islam et al. (2014).

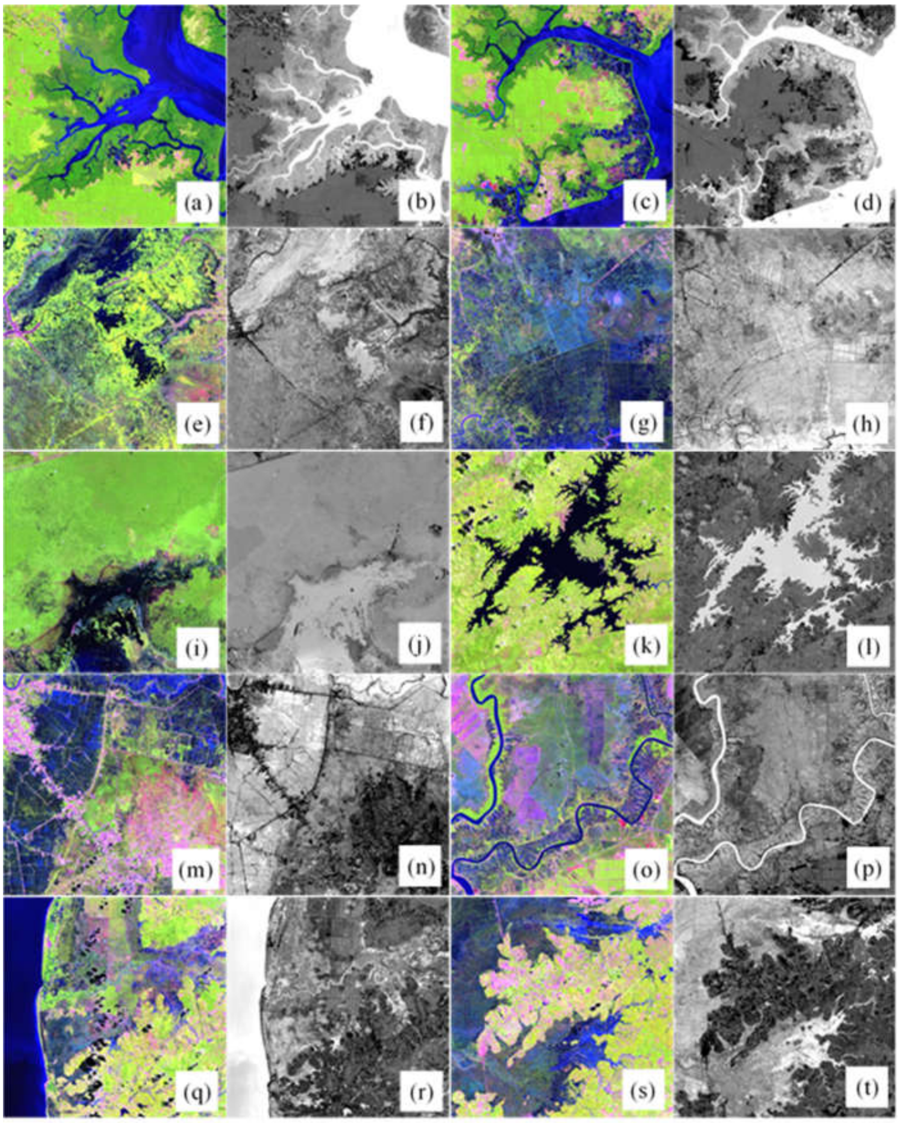


Figure 5. Comparison between Landsat 8 OLI composite 654 and $MNDW_{s2}$

(a) and (b) mangrove; (c) and (d) fishpond; (e) and (f) freshwater lake and freshwater marshes; (g) and (h) irrigated land; (i) and (j) peatlands and peatswamps; (k) and (l) deep clear water (reservoir); (m) and (n) swamp rice fields and tree-dominated wetlands; (o) and

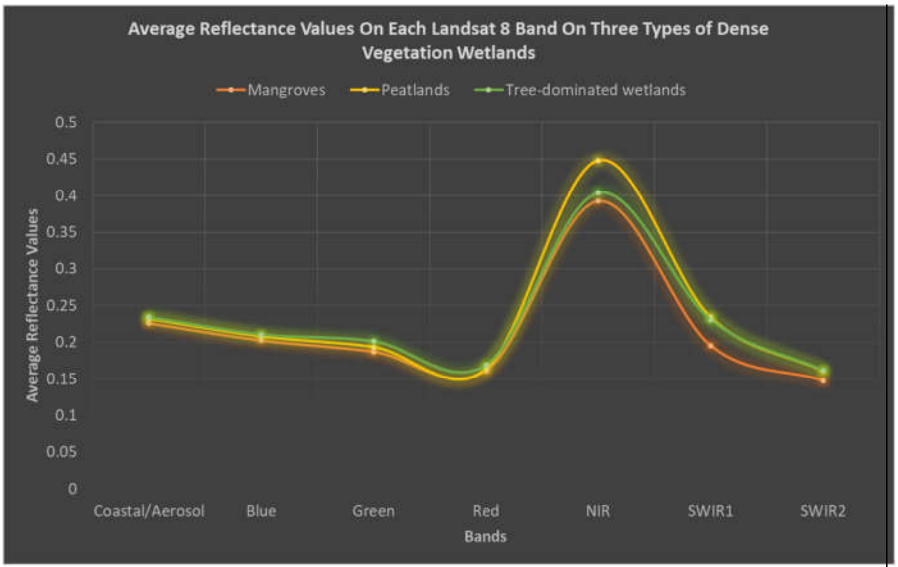
(p) deep turbid water (river); (q) and (r) salt marshes; and (s) and (t) shrub-dominated wetlands.

MNDWI uses the green band and SWIR1 band. In SWIR1, vegetation features have a much higher reflectance value than in green. We can see this fact in wetlands which are dominated by dense vegetation, as seen in Table 5 and Figure 6. Table 5 and Figure 6 are constructed using the mangroves, peatlands, and tree-dominated wetlands samples from this research. Where in the wetlands which are dominated by dense vegetation, such as mangroves, peatlands, and tree-dominated wetlands, reflectance values for SWIR1 are higher than reflectance values for green. As a result, green substraction with SWIR1 in MNDWI causes vegetation features to be depressed. So that wetlands with dense vegetation are not detected as wetland features in MNDWI.

Not so with MNDWIs2 which uses green bands and SWIR2 bands. Where in SWIR2, the reflectance value of vegetation features is not as high as in SWIR1. Even the spectral value tends to be lower than green. We can also see this fact in Table 5 and Figure 6. Where in the wetlands which are dominated by dense vegetation, the reflectance values for SWIR2 are lower than reflectance values for SWIR1 or green. Thus, green substraction using SWIR2 will not suppress vegetation features as in MNDWI. As a result, wetlands with dense vegetation can still be detected in MNDWIs2. This makes MNDWIs2 the most optimal spectral index in extracting vegetation-rich wetlands such as tropical wetlands. Figure 5 shows the comparison between Landsat 8 OLI composite 654 imageries and the MNDWIs2 imageries.

Table 5. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

	Average reflectance values on each Landsat 8 band						
	Coastal/Aerosol	Blue	Green	Red	NIR	SWIR1	SWIR2
Mangroves	0.2259	0.2024	0.187	0.1609	0.393	0.1953	0.1476
Peatlands	0.2324	0.2082	0.1938	0.1639	0.4483	0.2341	0.1608
Tree-dominated wetlands	0.2342	0.2106	0.2014	0.1688	0.4041	0.2308	0.1614
Average	0.2308	0.2071	0.1941	0.1645	0.4151	0.2201	0.1566



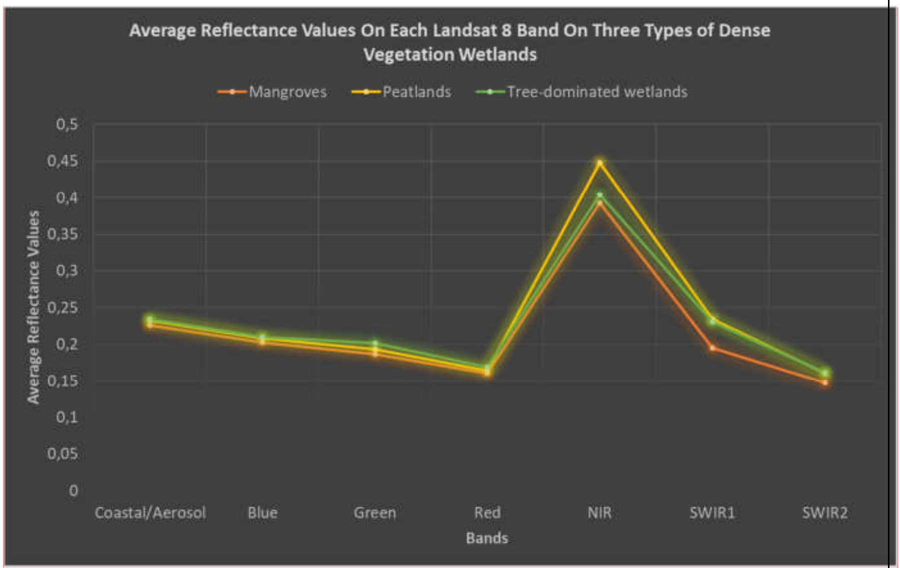


Figure 6. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

Figure 6 shows a slightly unusual spectral values pattern, at least from two aspects. First, theoretically, vegetation features generally have low reflectance values in the blue band and coastal/aerosol. However, in Figure 6, the average reflectance of dense vegetation wetlands has

Commented [A9]: We've changed the format of the curves in this figure, because the previous curves weren't very precise.

Commented [A10]: Did you really perform atmospheric correction or not? Because the reflectance spectra of the vegetation you put on Figure 6 resemble the TOA reflectance only, not surface reflectance.
Vegetation reflectance on atmospherically corrected images should have been low in coastal and blue band

Commented [A11R10]: Yes, I've done atmospheric correction using the DOS4 method, as I explained in the manuscript. The reflectance spectra of the vegetation that I put in Figure 6 are TOC or surface reflectance.

It is true that the reflectance of vegetation should have been low in the coastal and blue band. But it applies to pure vegetation features. While the vegetation listed in Figure 6 are wetland vegetations. Wetland vegetations are composite features between vegetation (chlorophyll) and water. Where the water feature itself has a high reflectance on the coastal and blue band. This fact makes the reflectance curve pattern of wetland vegetations unique, which is high in the NIR band and still quite high in the coastal and blue band.

Commented [A12R10]: TOC or surface reflectance? What does TOC mean? If you mean TOA, then it is still not atmospherically corrected

Please explain how did you select the dark target for your DOS correction. This way I can judge if the atmospheric correction was conducted properly

Previously you mention that water has high reflectance in green band. Now you mentioned that blue is higher. This is contradictory. Please explain this inconsistency of your statement.

Commented [A13R10]: What we mean is Top of Canopy (TOC) reflectance or in other words is surface reflectance.

The atmospheric correction method we use is Dark Object Subtraction 4 (DOS4). In this research, we run DOS4 using SAGA software (http://www.saga-gis.org). The DOS4 tool in SAGA software does not ask us to select a dark target, but only asks us to input the number of pixels that are considered as dark objects. In this case, we chose to use the default pixel count provided by SAGA's DOS4 tool, which is 1,000 pixels.

Theoretically, pure water features have the highest reflectance in the green band, but are actually also high in blue and coastal/aerosols, although blue and coastal/aerosols are not as high in green. What we previously meant blue higher was to explain that wetland vegetation still has a high reflectance in blue, unlike pure vegetation in general which should be low in the blue band. This is because wetland vegetation is a composite feature between vegetation and water.

For further explanation, we have provided in two paragraphs and a figure (Figure 7) which we've just added.

a high reflectance value in blue and coastal/aerosol. This is because wetland vegetations are composite features between vegetation (chlorophyll) and water. Where the water feature itself has a high reflectance on the coastal and blue band. This fact makes the reflectance curve pattern of wetland vegetations unique, which is high in the NIR band and still quite high in the coastal and blue band. Second, theoretically, the highest reflectance value of pure water features is in the green band. However, in Figure 6, it can be seen that the highest reflectance values are in the coastal/aerosol and blue bands. The results of this research are similar (though not exactly the same due to different features) with the research results of Amani et al. (2018), as shown in Figure 7. Especially for vegetated wetlands such as bog, fen, and marsh.

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Phenomena as shown in Figure 6 can occur due to various possibilities. The first possibility, the shadow of the tree crowns, or also called the sunlit crown. Sometimes the tree canopy forms a dark blue color, so they can appear like water features. Unlike pure water features which have the highest reflectance in green, shadow reflectance is higher in blue and lower in green (Li et al., 2009). Second, the spectral response of broadleaf forests shows low reflectance in the green band, and higher in blue and coastal/aerosols (Osgouei et al., 2019). In accordance with the facts, the dense vegetation wetlands in this research location are broadleaf forests.

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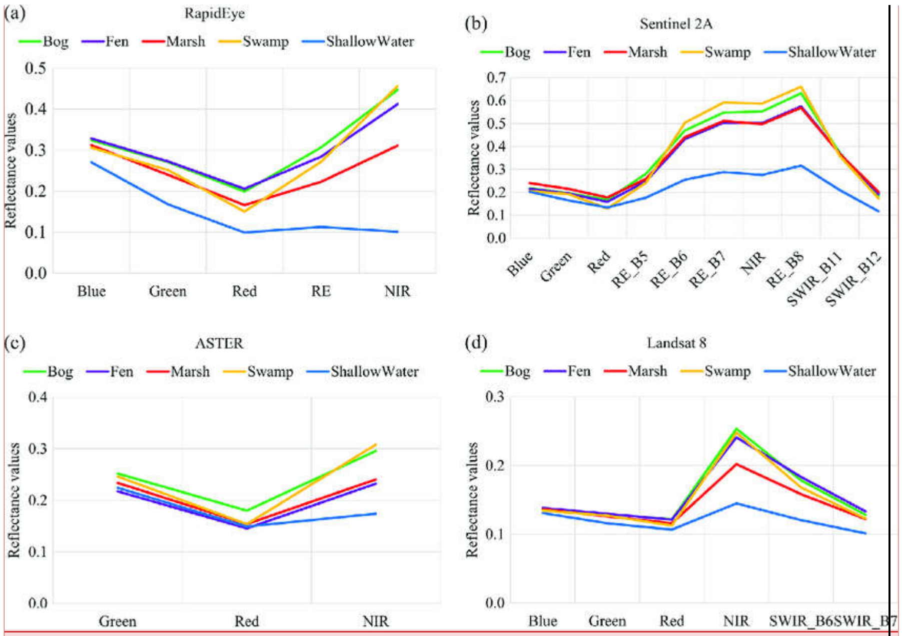

Figure 7. The spectral signature of wetlands, obtained from (a) RapidEye, (b) Sentinel 2A, (c) ASTER, and (d) Landsat 8 (Amani et al., 2018)

MNDWIs2 can recognize deep water features as well as MNDWI. This is the implication of the use of green band that is able to capture reflections of open water features with high intensity, which is subtracted using SWIR2 band that do not capture reflections of open water features. Compared to MNDWI, MNDWIs2 still able to capture the reflection of background water or soil moisture beneath the canopy. In the MNDWIs2 imagery, built-up lands, road, and barelands, appear darker than MNDWI imagery. It is an implication of the subtraction with SWIR2. This can cause the dominant soil in wetlands background features will bring potential omission error to MNDWIs2.

4.Conclusion

Based on this research, the spectral indices recorded the most accurate and optimal in extracting wetlands is $MNDWI_{s2}$. But $MNDWI_{s2}$ should be used wisely, given $MNDWI_{s2}$ very sensitive to dense vegetations. $MNDWI_{s2}$ also has potential error in wetlands with dominant

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soil background features. $MNDWI_{s2}$ not only able to recognize the deep waters as well as MNDWI, but still able to capture the wetlands with vegetations on it.

Like MNDWI, MNDWIs2 also uses a green band. In spectral value curves, green band has the highest reflectance value of water features among all spectral bands. So that open water features can be detected properly by MNDWIs2. The advantage of MNDWIs2 is the use of SWIR2, where in spectral value curves SWIR2 band has a lower reflectance value of vegetation. So that substraction green with SWIR2 will not cause vegetation features to become depressed as in MNDWI.

The ability of $MNDWI_{s2}$ in detecting peatlands with dense canopy as wetlands was very impressive. Given the peatlands actually not always saturated with water on the surface, most of them just has a very high water content in the ground with very high moisture surfaces. However, this condition is enough to make SWIR2 have very low reflections, so that green substraction using SWIR2 will enhance moist surfaces such as peatlands.

Based on the results of this research, $MNDWI_{s2}$ can be considered as the Normalized Difference Wetlands Index (NDWLI). Of course, further research are needed to verify the accuracy of the NDWLI formula. Especially if the formula be examined in other regions with different conditions, or be examined on other multispectral imageries.

Acknowledgement

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