

BUKTI KORESPONDENSI
ARTIKEL JURNAL INTERNASIONAL BEREPUTASI

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

Penulis : Syamani D. Ali, Hartono Hartono, Projo Danoedoro

DOI : <https://doi.org/10.22146/ijg.49914>

Jurnal : Indonesian Journal of Geography

ISSN : ISSN 2354-9114 (online), ISSN 0024-9521 (print)

Tautan Artikel : <https://journal.ugm.ac.id/ijg/article/view/49914>

Tautan Jurnal : <https://journal.ugm.ac.id/ijg>

Tautan Indeks : <https://www.scopus.com/sourceid/29186>

No.	Perihal	Tanggal
1.	Manuskrip yang Disubmit, Cover Letter, dan Bukti Konfirmasi Submit Manuskrip	23 September 2019
2.	Bukti Konfirmasi Review dan Hasil Review Pertama	14 Februari 2020
3.	Respon Kepada Reviewer dan Hasil Revisi Manuskrip Pertama	31 Maret 2020
4.	Bukti Konfirmasi Review dan dan Hasil Review Kedua, Manuskrip Diterima dengan syarat Revisi	8 November 2020
5.	Respon Kepada Reviewer dan Hasil Revisi Manuskrip Kedua	22 Desember 2020
6.	Bukti Konfirmasi Review Ketiga, Instruksi Editor untuk Mengimprovisasi Manuskrip	25 Juni 2021
7.	Respon Kepada Reviewer dan Hasil Improvisasi Manuskrip	25 Juni 2021
8.	Bukti Bahwa Manuskrip Diterima untuk Dipublikasikan di Indonesian Journal of Geography	30 Juli 2021
9.	Email permintaan koreksi dari Editor, dan permintaan kepada Editor untuk merubah penulisan nama Penulis Utama dari <i>Syam'ani</i> (nama asli Penulis Utama yang tertulis di ijazah) menjadi <i>Syamani Darmawi Ali</i> atau <i>Syamani D. Ali</i> (nama asli Penulis Utama ditambah nama Ayah Kandung)	29 September 2021 s/d 30 September 2021
10.	Bukti Historis Proses Review di Laman Indonesian Journal of Geography	-

**1. Manuskrip yang Disubmit, Cover Letter, dan
Bukti Konfirmasi Submit Manuskrip (23
September 2019)**

1 Comparison of Various Spectral Indices for Optimum Extraction 2 of Tropical Wetlands Using Landsat 8 OLI

3

4 **Syam'ani**

5 Faculty of Forestry, University of Lambung Mangkurat, Banjarbaru, Indonesia

6 syamani.fhut@ulm.ac.id

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8 **Abstract** This research specifically aims to investigate the most accurate spectral indices in extracting wetlands
9 geospatial information taking South Kalimantan, Indonesia, as an example of wetlands in tropical areas. Ten
10 spectral indices were selected for testing their ability to extract wetlands, those are NDVI, NDWI, MNDWI,
11 MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, and AWEIsh. Tests were performed on Landsat 8 OLI path/row
12 117/062 and 117/063. The threshold method which was used to separate the wetland features from the spectral
13 indices imagery is Otsu method. The results of this research showed that, generally MNDWIs2 was the most optimal
14 spectral indices in the wetlands extraction. Especially tropical wetlands that rich with green vegetation cover.
15 However, MNDWIs2 is very sensitive to dense vegetation, this feature has the potential to be detected as wetlands.
16 Furthermore, to improve the accuracy and prevent detection of the dryland vegetation as wetlands, the threshold
17 value should be determined carefully.

18

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

20

21 **Abstrak** Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
22 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
23 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
24 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
25 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
26 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
27 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
28 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
29 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
30 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

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

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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.

Tropical wetlands located in the South Kalimantan Province, especially in shallow waters, has a main characteristic, which 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. Besides NDWI or MNDWI, there are also a number of other spectral indices that can potentially be used to separate wetlands features from other features.

Of the many methods of optical digital imagery transformation that have been developed are, as a whole actually developed to separate water features from other features. Some research indicates that the spectral indices are very accurate in extracting the boundaries of water features. Xu (2006), for example, proved that MNDWI more accurate than NDWI when applied to the three water features, i.e. lakes, oceans, and rivers.

1 Li et al. (2013) also found that MNDWI more accurate than NDWI to the TM, ETM +,
2 and ALI imagery. Jiang et al. (2014) developed the Automated Method for Extracting Rivers
3 and Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM
4 +. It was found that in general MNDWI is the most excellent among the three other spectral
5 indices.

6 Interestingly, Ashraf and Nawaz (2015) when they detect changes in the wetlands of the
7 Baraila Lake (India) using four spectral indices, they found that in general NDWI is the most
8 accurate method when verified using the field data. Similar to Ashraf and Nawaz, Das and Pal
9 (2016) also found that NDWI was the most accurate spectral indices, when they compared six
10 spectral indices. While Zhai et al. (2015) when comparing surface water extraction
11 performances of four indices using Landsat TM and OLI, they found that Automated Water
12 Extraction Index (AWEI) has the highest overall accuracy.

13 Kwak and Iwami (2014) developed a Modified Land Surface Water Index (MLSWI),
14 and when they use it on flood inundation mapping using MODIS imagery, and test it using
15 ALOS AVNIR 2, they found that MLSWI more accurate than Normalized Difference
16 Vegetation Index (NDVI) and Land Surface Water Index (LSWI). Xie et al. (2016) used
17 MNDWI to separate the pure land pixel and pure water pixel in Spectral Mixture Analysis
18 (SMA), for mapping the surface of the water of lakes and rivers automatically at sub pixel level.

19 Yang et al. (2015) use a number of spectral indices on Landsat 8 OLI to extract the water
20 bodies. Those are, the single-band threshold in band 5, multiband spectral relationship b2, b3,
21 b4, b5, NDVI, NDWI, MNDWI, Normalized Difference Built-up Index (NDBI), TCT, and
22 Hue, Intensity and Saturation (HIS). Where all of the spectral indices are combined using deep
23 learning algorithm, called Stacked Sparse Autoencoder (SSAE).

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

28 Although the spectral indices are accurate to separate water with other features, we actually still
29 have one question, whether the spectral indices is quite optimal in extracting the wetlands

1 features from the drylands features? Because, most of the wetlands in tropical areas has a
2 spectral characteristic of water and green vegetation simultaneously. This research aimed to
3 compare the accuracy of some of the spectral indices for optimizing the extraction of wetlands,
4 by taking the case of the tropics area, that is, the South Kalimantan Province, Indonesia.

5

6 **2. The Methods**

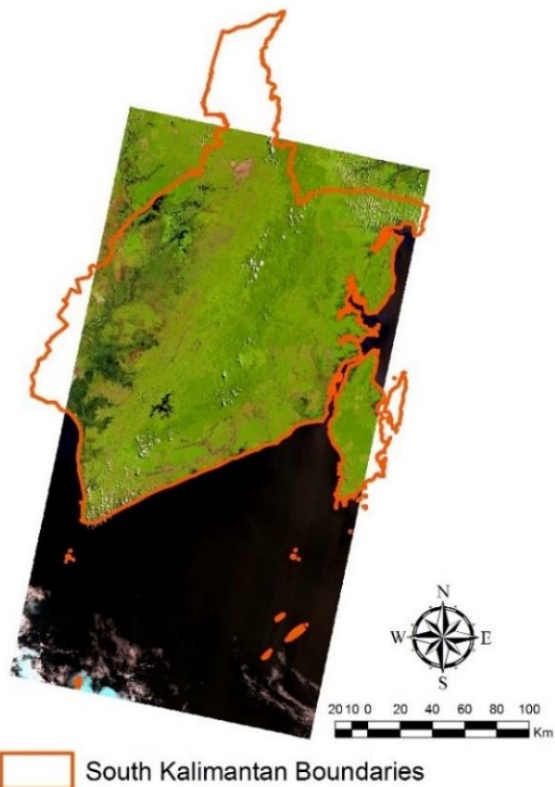
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8 2.1. Materials

9

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

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



 South Kalimantan Boundaries

Figure 1. Research location

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4 2.2. Water Indices

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

11

$$NDWI = \frac{\rho_g - \rho_n}{\rho_g + \rho_n}$$

12 Where:

13 ρ_g : green band

14 ρ_n : near infrared band

1 Due to lack of NDWI in error detection features of the building, Xu (2006) modifying
2 NDWI become MNDWI, by changing NIR band into SWIR. In this case, Xu (2006) using the
3 SWIR1.

$$4 \quad \text{MNDWI} = \frac{\rho_g - \rho_s}{\rho_g + \rho_s}$$

5 Where:

6 ρ_s : shortwave infrared band

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

$$10 \quad \text{MNDWI}_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$$

11 Where:

12 ρ_{s2} : shortwave infrared 2 band

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

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

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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 _{Insh} 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 _{Ish} 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)

4

5 Information:

6 ρ_{ca} : aerosol coastal bands (bands 1 Landsat 8)

7 ρ_b : blue band (band 2 Landsat 8)

8 ρ_g : green band (band 3 Landsat 8)

9 ρ_r : red band (band 4 Landsat 8)

- 1 ρ_n : near infrared band (band 5 Landsat 8)
- 2 ρ_s : shortwave infrared band (band 6 or 7 Landsat 8)
- 3 ρ_{s1} : shortwave infrared 1 band (band 6 Landsat 8)
- 4 ρ_{s2} : shortwave infrared 2 band (band 7 Landsat 8)

5

6 2.3. Wetlands Extraction

7

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

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

16

17 2.4. Accuracy Assessment

18

19 Accuracy assessment was conducted using the Confusion Matrix (Stehman and
20 Czaplewski, 1997), using a number of sample locations were selected purposively. In this case,
21 the location of the sample represents multiple characters wetlands in South Kalimantan.
22 Namely, mangroves, salt marshes, rivers, freshwater lakes, freshwater marshes, peatlands,
23 peat swamps, shrub-dominated wetlands, tree-dominated wetlands, fish pond, farm ponds,
24 swamp rice field, irrigated land, and deep water (reservoirs, canals, and coal open pits).

25 The sample locations were also chosen purposively on various dryland features that have
26 the potential to be detected as wetlands. Namely, built-up lands, barelands, grass, roads,
27 dryland forest, dryland farms, garden (include mix garden, rubber plants, palm oil), and shrub
28 and bushes. This is to assess the deeper capabilities of each spectral index. In the appointment
29 of the samples, the method used is knowledge-based.

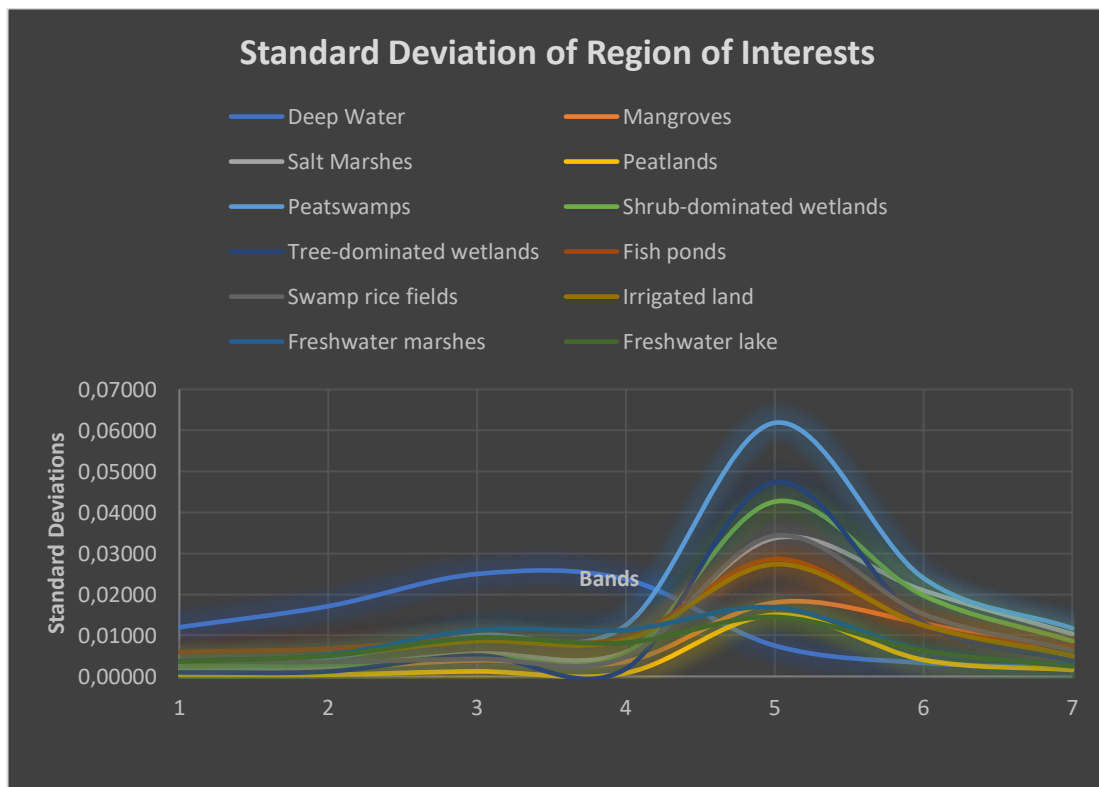
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2 3. Result and Discussion

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4 Visual appearance of wetlands in South Kalimantan varies in tone/colour. This shows
5 quite a high degree of variation in spectral value of each type of wetlands. In the accuracy
6 assessment, the samples were made for each type of wetlands. For the purpose to ensure that
7 variations in the class of all wetlands are represented as possible, Region of Interest (ROI) made
8 for every wetland types are distributed in several different locations. Figure 2 shows the
9 Standard Deviation (SD) ROI of all wetlands in each band Landsat 8 OLI.

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12 Figure 2. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

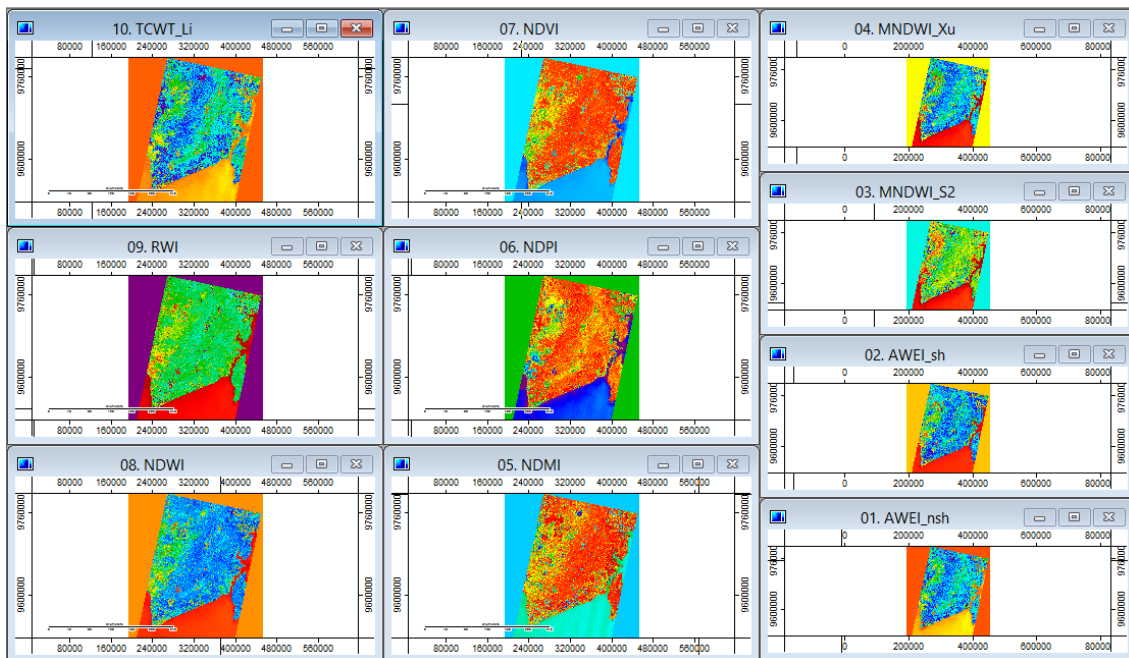
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14 Of course, spectral indices such as NDWI cannot distinguish between mangroves and
15 peatswamps, for example. In fact, the thresholding imageries results of spectral indices contains
16 only two classes, namely Wetlands and Non-wetlands. But for the sake of accuracy assessment,
17 the accuracy assessment ROI is made on every types of wetlands in the research locations. It is

1 intended that the spectral character of each wetland represented, and to provide an overview
 2 of each spectral indices extraction capabilities of each type of wetlands.

3 When the overall accuracy of the assessment is done, all types of wetland features are
 4 combined into a single class, namely the Wetlands. And all types of drylands features are
 5 combined into a single class, namely Non-wetlands. Figure 3 shows the results of the
 6 transformation of spectral indices were selected in this research. While Table 2 shows the
 7 results of Otsu thresholding and accuracy assessment results of each spectral index using the
 8 Confusion Matrix.

9



10

11 Figure 3. The result of the transformation of spectral indices on the SAGA application

12

13 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 _{hsh}	≥ -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

1

2 Information:

3 OA: Overall Accuracy

4 PA: Producer's Accuracy

5 UA: User's Accuracy

6 CE: Commission Error

7 OE: omission Error

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

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

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

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

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

No.	Spectral Indices	Producer's Accuracy (%)											
		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

6

7 Information:

8 Dw: Deep water (include river, reservoir, dam, and coal mining pits)

9 Mg: Mangroves

10 Sm: Salt marshes

11 Pl: Peatlands

12 Ps: Peatswamps

13 Sw: Shrub-dominated wetlands

14 Tw: Tree-dominated wetlands

15 Fp: Fish ponds

16 Sr: Swamp rice fields

17 Il: Irrigated land

18 Fm: Freshwater marshes

19 Fl: Freshwater lake

20

1 The entire spectral indices, except NDMI, do not have a problem when extracting the
2 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
3 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
4 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
5 2004).

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

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

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

25 The ability of a spectral indices for identifying wetlands (PA), is not directly indicated
26 its ability to extract the wetlands. Because when it comes to automatic feature extraction
27 method, the goal is not only whether the method is able to recognize the desired features, but
28 also how to be able to avoid such methods to recognize the other features. That is why, in this
29 research we also tested the CE. In this case, CE tested using dryland features in research

1 locations. These dryland features have been selected to investigate in which object the spectral
 2 indices encountered an error detection as wetlands.

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

6

7 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 _{Insh}	0	0	0	0	0.06	0	0	0
10.	AWEI _{Ish}	20.47	1.27	0	95.05	0.14	0	0	0

8

9 Information:

10 Bu: Built-up lands

11 Bl: Barelands

12 Gr: Grass

13 R: Roads

14 F: Dryland forest

15 Df: Dryland farms

16 Gd: Garden (mix garden, rubber plants, palm oil)

17 Sb: Shrub and bushes

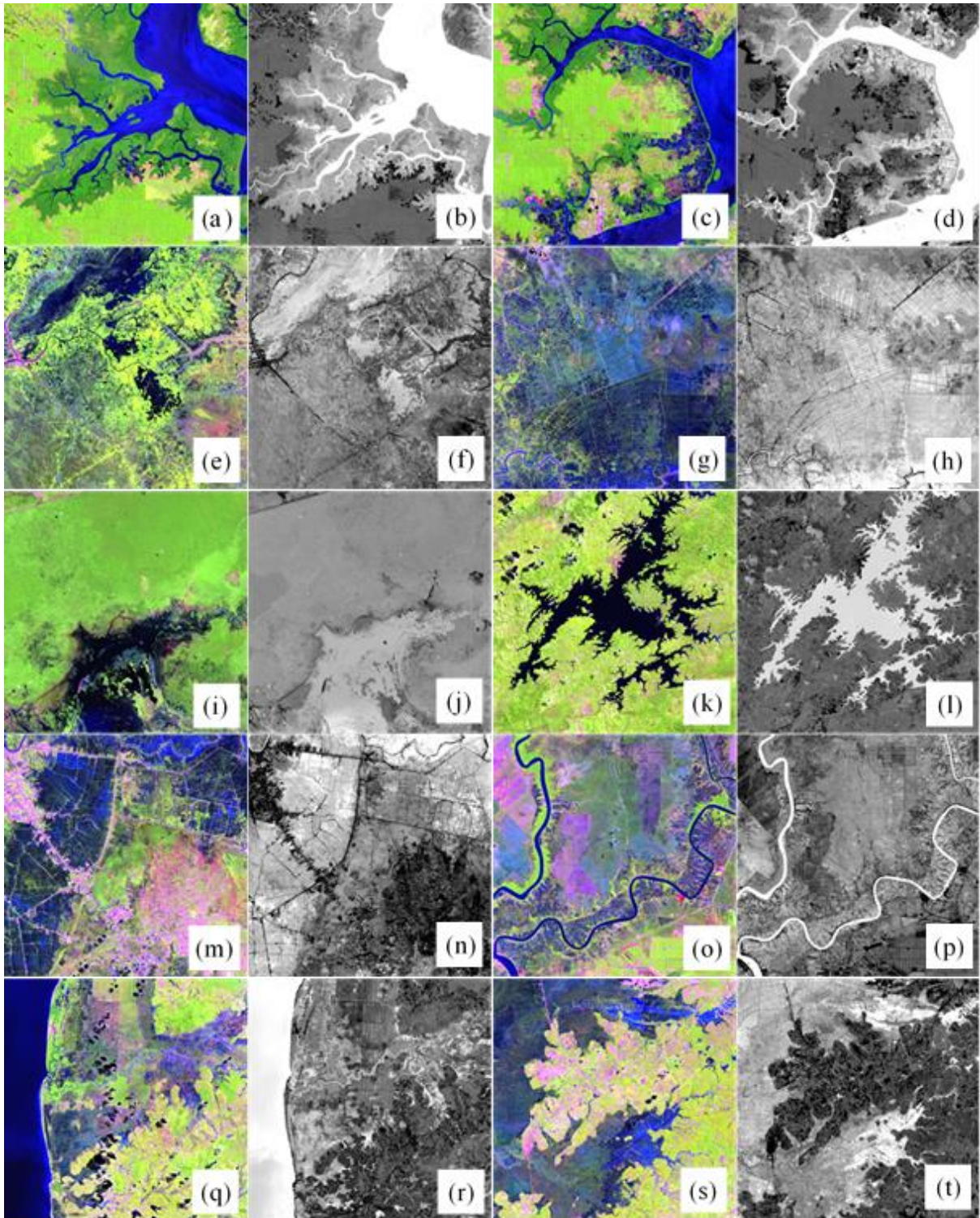
18

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

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

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

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



1

2

Figure 4. Comparison between Landsat 8 OLI composite 654 and MNDW_{s2}

3

(a) and (b) mangrove; (c) and (d) fishpond; (e) and (f) freshwater lake and freshwater

4

marshes; (g) and (h) irrigated land; (i) and (j) peatlands and peatswamps; (k) and (l) deep

5

clear water (reservoir); (m) and (n) swamp rice fields and tree-dominated wetlands; (o) and

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

3 MNDWI_{s2} can recognize deep water features as well as MNDWI, and MNDWI_{s2} still
4 able to capture the reflection of background water or soil moisture beneath the canopy. In the
5 MNDWI_{s2} imagery, built-up lands, road, and barelands, appear darker than MNDWI imagery.
6 It is an implication of the subtraction with SWIR₂. This can cause the dominant soil in wetlands
7 background features will bring potential OE to MNDWI_{s2}. Figure 4 shows the comparison
8 between Landsat 8 OLI composite 654 imageries and the MNDWI_{s2} imageries.

9 10 **4. Conclusion**

11
12 Based on this research, the spectral indices recorded the most accurate and optimal in
13 extracting wetlands is MNDWI_{s2}. But MNDWI_{s2} should be used wisely, given MNDWI_{s2} very
14 sensitive to dense vegetation. MNDWI_{s2} also has potential error in wetlands with dominant soil
15 background features. MNDWI_{s2} not only able to recognize the deep waters as well as MNDWI,
16 but still able to capture the wetlands with vegetation on it.

17 The ability of MNDWI_{s2} in detecting peatlands with dense canopy as wetlands was very
18 impressive. Given the peatlands actually not always saturated with water on the surface, most
19 of them just has a very high water content in the ground with very high moisture surfaces. Will
20 MNDWI_{s2} be considered as Normalized Difference Wetlands Index (NDWLI)? Well, of course,
21 more research needs to be done to investigate.

22 23 **Acknowledgement**

24
25 The author thank to the United States Geological Survey (USGS) for providing the
26 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
27 the Spatial Data Infrastructure Development Center (PPIDS), University of Lambung
28 Mangkurat. Digital image processing in this research was carried out at the Remote Sensing

1 and Geographic Information System Laboratory, Faculty of Forestry, University of Lambung
2 Mangkurat, Banjarbaru.

3

4

5

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Cover Letter

September 23, 2019

Editorial Team of Indonesian Journal of Geography, Faculty of Geography, Universitas Gadjah Mada, Indonesia

Dear Editor of IJG,

I am submitting a manuscript for consideration of publication in Indonesian Journal of Geography. The manuscript is entitled "Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI".

It has not been published elsewhere and that it has not been submitted simultaneously for publication elsewhere.

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, and AWEIsh.

Wetland-related researches are excellent research in University of Lambung Mangkurat. Because wetland problems are in harmony with the university's vision, that is, "*The realization of University of Lambung Mangkurat as a leading and competitive university in wetlands environment*".

For the purpose of reviewing my manuscript, I suggest the following reviewers:

1. Iswari Nur Hidayati, Faculty of Geography Universitas Gadjah Mada, Yogyakarta, Indonesia, email: iswari@ugm.ac.id
2. Muhammad Kamal, Faculty of, Geography, Universitas Gadjah Mada, Yogyakarta, Indonesia, email: m.kamal@ugm.ac.id
3. M. Pramono Hadi, Faculty of Geography, Universitas Gadjah Mada, Yogyakarta, Indonesia, email: mphadi@ugm.ac.id

Thank you very much for your consideration.

Yours Sincerely,

Syam'ani

Faculty of Forestry, University of Lambung Mangkurat

Jl. Ahmad Yani, km. 35, P.O. Box 19, Banjarbaru 70714, Kalimantan Selatan, Indonesia

Tel.: +62-511-4772290; Fax: +62-511-4772290

E-mail: syamani.fhut@ulm.ac.id

[IJG] Submission Acknowledgement

1 message

Dr. Eko Haryono, M.Si. <e.haryono@ugm.ac.id>
To: Syam'ani Syam'ani <syamani.fhut@ulm.ac.id>

Mon, Sep 23, 2019 at 2:41 PM

Dear Syam'ani Syam'ani,

Thank you for submitting the manuscript, "Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI" to Indonesian Journal of Geography. With the online journal management system that we are using, you will be able to track its progress through the editorial process by logging in to the journal web site:

Manuscript URL: <https://jurnal.ugm.ac.id/ijg/author/submission/49914>
Username: syamani

If you have any questions, please contact me. Thank you for considering this journal for publishing your work.

Best wishes,
Dr. Eko Haryono, M.Si.
Indonesian Journal of Geography

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Phone: +62 812-2711-480

**2. Bukti Konfirmasi Review dan Hasil Review
Pertama (14 Februari 2020)**

[IJG] Editor Decision: Decline and chance to resubmit the manuscript

3 messages

Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id>

Fri, Feb 14, 2020 at 8:00 AM

To: Syam'ani Syam'ani <syamani.fhut@ulm.ac.id>

Cc: Hartono Hartono <hartono@geo.ugm.ac.id>, Projo Danoedoro <projo.danoedoro@geo.ugm.ac.id>

Dear Mr. Syam'ani Syam'ani,

We have reached a decision regarding your submission to Indonesian Journal of Geography, "Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI". After thoroughly reading your manuscript, we decided to give you a chance to resubmit your manuscript. The quality of your manuscript at its current form did not meet our standard. However, you are allowed to resubmit your manuscript to our journal after major improvement by expanding the manuscript and rewriting of the content. We will wait for your resubmission no later than 31 March 2020.

Please carefully respond to reviewer's comments when resubmitting your manuscript, and please clearly indicate the changes that you made (or highlight them) to address reviewer's comments. Or, you can directly reply to reviewer's comments in the comments box written by the reviewer. You can also use the template attached below. We will not process any revised paper without a specific response to each reviewer's comments. See your OJS account for complete reviewer's comments.

I hope this decision does not discourage you to submit your paper to our journal in the future. Thank you.

Best wishes,

Dr. Pramaditya Wicaksono

Faculty of Geography Universitas Gadjah Mada, Yogyakarta

Phone +6281391179917

Fax +62274569595

prama.wicaksono@geo.ugm.ac.id

Section Editor

Indonesian Journal of Geography

Faculty of Geography, Universitas Gadjah Mada, Yogyakarta

Reviewer B:

General Comment

The manuscript of "Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI" has the potential to be published, however, a major and massive language editing is necessary. My main problem reading this manuscript lies on the grammatical errors, uncommon phrases and sentences used in texts, unnecessary complex sentences (which was hard to understand), lack of punctuation marks, and un-systematic paragraphs (no main ideas in the paragraphs). Those problems limit my ability to further assess the content of the manuscript, which in general, also needs to be revised.

I suggest to the author(s) to have their manuscript edited and proofreaded by professional so that the readability level can be increased. Due to the massive amounts of mistakes at this current state, I can not recommend this manuscript for publication at IJG.

See the example of errors in the review document attached.

1 Comparison of Various Spectral Indices for Optimum Extraction 2 of Tropical Wetlands Using Landsat 8 OLI

3

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

14

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

16

17 **Abstrak** Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
18 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
19 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
20 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
21 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
22 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
23 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
24 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
25 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
26 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

27

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

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1 **1. Introduction**

2

3 Wetlands are ecosystems saturated with water, either seasonally or permanently (EPA,
4 2004). According to ~~The~~ the Ramsar Convention on Wetlands 1993 (Matthews, 2013), based
5 on the habitat, wetlands classified into marine and coastal wetlands, inland wetlands, and man-
6 made wetlands. In the South Kalimantan Province, Indonesia, wetlands are one of the main
7 features of the landscape.

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

15 So far, various methods have been developed for the extraction of wetlands geospatial
16 data automatically. For example, the Normalized Difference Water Index (NDWI) (McFeeters,
17 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and so forth.
18 Besides NDWI or MNDWI, there are also a number of other spectral indices that can
19 potentially be used to separate wetlands features from other features.

20 Of the many methods of optical digital imagery transformation that have been developed are,
21 as a whole, actually developed to separate water features from other features. Some research
22 indicates that the spectral indices are very accurate in extracting the boundaries of water
23 features. Xu (2006), for example, proved that MNDWI more accurate than NDWI when
24 applied to the three water features, i.e. lakes, oceans, and rivers.

25 Li et al. (2013) also found that MNDWI more accurate than NDWI to the TM, ETM +,
26 and ALI imagery. Jiang et al. (2014) developed the Automated Method for Extracting Rivers
27 and Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM
28 +. It was found that in general, MNDWI is the most excellent among the three other spectral
29 indices.

Commented [A1]: Please give an explanation why using NDWI and MNDWI?

1 Interestingly, Ashraf and Nawaz (2015) when they detect changes in the wetlands of the
2 Baraila Lake (India) using four spectral indices, they found that in general NDWI is the most
3 accurate method when verified using the field data. Similar to Ashraf and Nawaz, Das and Pal
4 (2016) also found that NDWI was the most accurate spectral indices, when they compared six
5 spectral indices. While Zhai et al. (2015) when comparing surface water extraction
6 performances of four indices using Landsat TM and OLI, they found that Automated Water
7 Extraction Index (AWEI) has the highest overall accuracy.

Commented [A2]: Please re-write the sentence. Hard to read the sentence

8 Kwak and Iwami (2014) developed a Modified Land Surface Water Index (MLSWI),
9 and when they use it on flood inundation mapping using MODIS imagery, and test it using
10 ALOS AVNIR 2, they found that MLSWI more accurate than Normalized Difference
11 Vegetation Index (NDVI) and Land Surface Water Index (LSWI). Xie et al. (2016) used
12 MNDWI to separate the pure land pixel and pure water pixel in Spectral Mixture Analysis
13 (SMA), for mapping the surface of the water of lakes and rivers automatically at sub pixel level.

Commented [A3]: Hard to read the sentence. Give the limitations and strenght of every indices

14 Yang et al. (2015) use a number of spectral indices on Landsat 8 OLI to extract the water
15 bodies. Those are, the single-band threshold in band 5, multiband spectral relationship b2, b3,
16 b4, b5, NDVI, NDWI, MNDWI, Normalized Difference Built-up Index (NDBI), TCT, and
17 Hue, Intensity and Saturation (HIS). Where all of the spectral indices are combined using deep
18 learning algorithm, called Stacked Sparse Autoencoder (SSAE).

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

23 Although the spectral indices are accurate to separate water with other features, we actually still
24 have one question, whether the spectral indices is quite optimal in extracting the wetlands
25 features from the drylands features? Because, most of the wetlands in tropical areas has a
26 spectral characteristic of water and green vegetation simultaneously. This research aimed to
27 compare the accuracy of some of the spectral indices for optimizing the extraction of wetlands,
28 by taking the case of the tropics area, that is, the South Kalimantan Province, Indonesia.

Commented [A4]: Re-write in right sentence not interrogative sentence

29

1 **2.The Methods**

2

3 2.1.Materials

4

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

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



13
14 **Figure 1. Research location**

Commented [A5]: How did you analys that the research area is not full of landsat? Please explain.

15
16 2.2. Water Indices

17

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

$$6 \quad \text{NDWI} = \frac{\rho_g - \rho_n}{\rho_g + \rho_n}$$

7 Where:

8 ρ_g : green band

9 ρ_n : near infrared band

10 Due to lack of NDWI in error detection features of the building, Xu (2006) modifying
11 NDWI become MNDWI, by changing NIR band into SWIR. In this case, Xu (2006) using the
12 SWIR1.

$$13 \quad \text{MNDWI} = \frac{\rho_g - \rho_s}{\rho_g + \rho_s}$$

14 Where:

15 ρ_s : shortwave infrared band

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

$$19 \quad \text{MNDWI}_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$$

20 Where:

21 ρ_{s2} : shortwave infrared 2 band

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

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

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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 Transformation	Wetness	$0.1877\rho_{ca} + 0.2097\rho_b + 0.2038\rho_g + 0.1017\rho_r + 0.0685\rho_n - 0.7460\rho_{s1} - 0.5548\rho_{s2}$	-	Li et al. (2015)
9.	AWEI _{noh}	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)

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2 Information:

3 ρ_{ca} : aerosol coastal bands (bands 1 Landsat 8)

4 ρ_b : blue band (band 2 Landsat 8)

5 ρ_g : green band (band 3 Landsat 8)

6 ρ_r : red band (band 4 Landsat 8)

7 ρ_n : near infrared band (band 5 Landsat 8)

8 ρ_s : shortwave infrared band (band 6 or 7 Landsat 8)

9 ρ_{s1} : shortwave infrared 1 band (band 6 Landsat 8)

10 ρ_{s2} : shortwave infrared 2 band (band 7 Landsat 8)

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12 2.3. Wetlands Extraction

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

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

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23 2.4. Accuracy Assessment

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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, rivers, freshwater lakes, freshwater marshes, peatlands, peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish pond, farm ponds, swamp rice field, irrigated land, and deep water (reservoirs, canals, and coal open pits).

The sample locations were also chosen purposively on various dryland features that have the potential to be detected as wetlands. Namely, built-up lands, barelands, grass, roads, dryland forest, dryland farms, garden (include mix garden, rubber plants, palm oil), and shrub and bushes. This is to assess the deeper capabilities of each spectral index. In the appointment of the samples, the method used is knowledge-based.

3.Result and Discussion

Visual appearance of wetlands in South Kalimantan varies in tone/colour. 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 2 shows the Standard Deviation (SD) ROI of all wetlands in each band Landsat 8 OLI.

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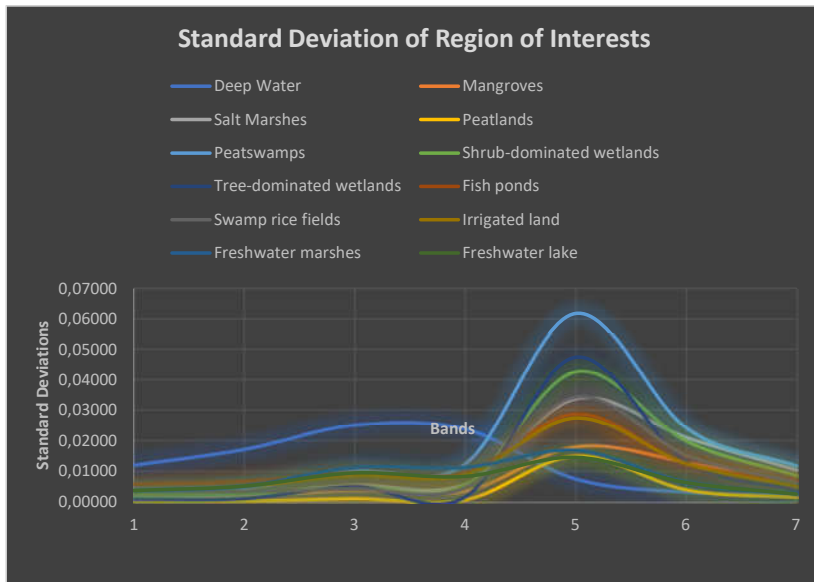


Figure 2. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

Of course, spectral indices such as NDWI cannot distinguish between mangroves and peatswamps, for example. 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 3 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.

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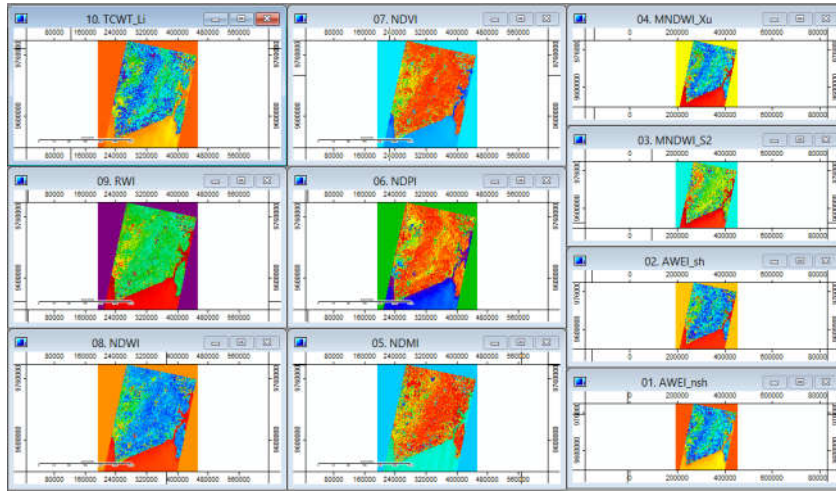


Figure 3. The result of the transformation of spectral indices on the SAGA application

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 ₂	≥ 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

1 OE: omission Error

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

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

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

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

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

No.	Spectral Indices	Producer's Accuracy (%)											
		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 ₂	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 _{hsh}	100	69.97	88.46	0	95.87	25.47	5.92	99.88	96.38	100	100	100
10.	AWEI _h	100	5.81	99.95	0	97.92	88.55	15.45	100	99.83	100	100	100

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2 Information:

3 Dw: Deep water (include river, reservoir, dam, and coal mining pits)

4 Mg: Mangroves

5 Sm: Salt marshes

6 Pl: Peatlands

7 Ps: Peatswamps

8 Sw: Shrub-dominated wetlands

9 Tw: Tree-dominated wetlands

10 Fp: Fish ponds

11 Sr: Swamp rice fields

12 Il: Irrigated land

13 Fm: Freshwater marshes

14 Fl: Freshwater lake

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16 The entire spectral indices, except NDMI, do not have a problem when extracting the
 17 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
 18 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
 19 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
 20 2004).

21 NDVI and NDWI have the same character in separating wetland features from other
 22 features. Both can be said to be successful wetlands extracting, especially wetlands with high
 23 concentration of water. However, they completely fail in identifying wetlands with dense

1 vegetation, such as mangrove or peatlands. This is because NDVI and NDWI using the same
2 NIR band, where vegetation will have a contrasting difference with water in NIR.

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

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

17 The ability of a spectral indices for identifying wetlands (PA), is not directly indicated
18 its ability to extract the wetlands. Because when it comes to automatic feature extraction
19 method, the goal is not only whether the method is able to recognize the desired features, but
20 also how to be able to avoid such methods to recognize the other features. That is why, in this
21 research we also tested the CE. In this case, CE tested using dryland features in research
22 locations. These dryland features have been selected to investigate in which object the spectral
23 indices encountered an error detection as wetlands.

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

27

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

Commented [A9]: What is the accuracy assessment method and field sampling method?

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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.	AWEL _{sh}	0	0	0	0	0.06	0	0	0
10.	AWEL _{sh}	20.47	1.27	0	95.05	0.14	0	0	0

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2 Information:

3 Bu: Built-up lands

4 Bl: Barelands

5 Gr: Grass

6 R: Roads

7 F: Dryland forest

8 Df: Dryland farms

9 Gd: Garden (mixgarden, rubber plants, palm oil)

10 Sb: Shrub and bushes

11

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

17 NDVI and NDWI that have the same character, they are also sensitive to built-up lands,
18 roads, and barelands. NDPI better than NDVI and NDWI in distinguishing between built-up
19 lands or barelands and wetlands. However, NDPI also slightly failed in distinguishing the paved

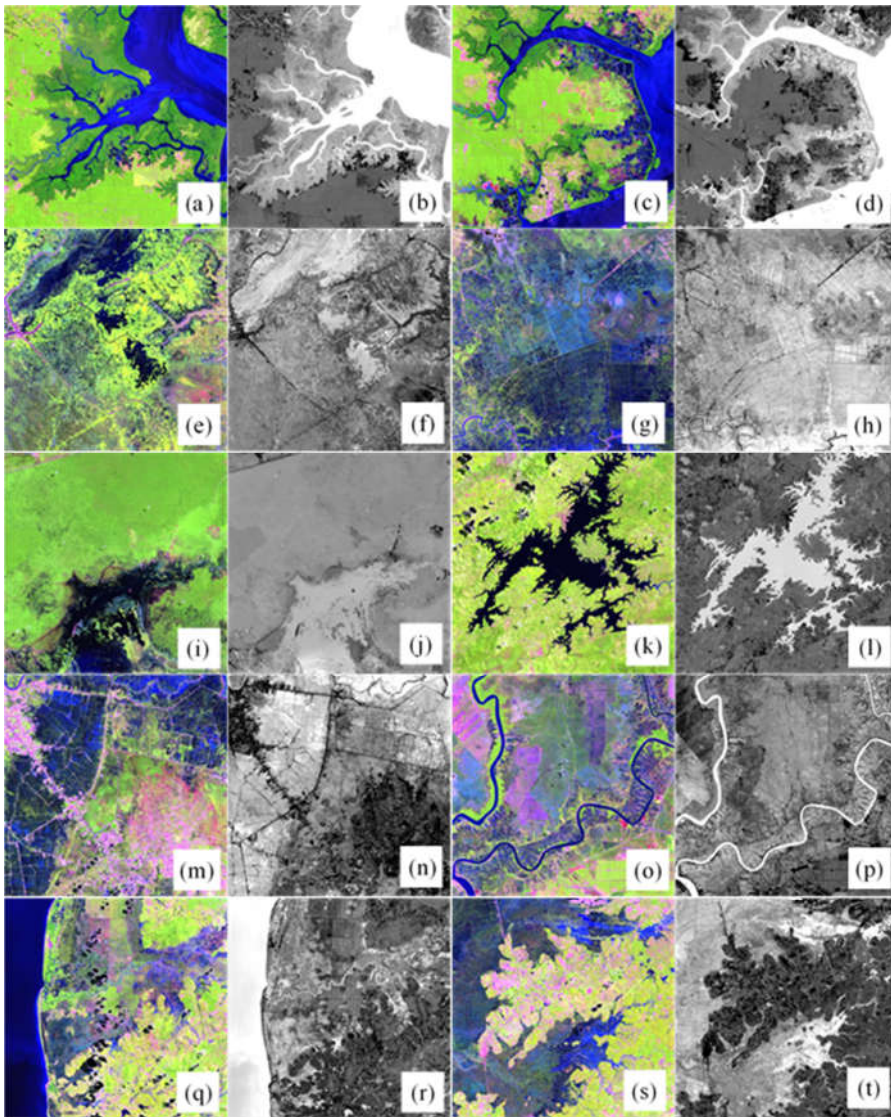
1 roads to the wetlands. TCWT and AWEInsh are two spectral indices of the nicest in minimizing
2 error detection wetlands. Since both spectral indices have the lowest CE. Different from
3 AWEInsh, AWEIsh disadvantaged in distinguishing between the paved roads to the wetlands.

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

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

14

Commented [A11]: Give the explanation about relationship between MNDWI and the spectral characteristics



1
 2 Figure 4. Comparison between Landsat 8 OLI composite 654 and MNDW_{s2}
 3 (a) and (b) mangrove; (c) and (d) fishpond; (e) and (f) freshwater lake and freshwater
 4 marshes; (g) and (h) irrigated land; (i) and (j) peatlands and peatswamps; (k) and (l) deep
 5 clear water (reservoir); (m) and (n) swamp rice fields and tree-dominated wetlands; (o) and

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

3 MNDWI_{s2} can recognize deep water features as well as MNDWI, and MNDWI_{s2} still
4 able to capture the reflection of background water or soil moisture beneath the canopy. In the
5 MNDWI_{s2} imagery, built-up lands, road, and barelands, appear darker than MNDWI imagery.
6 It is an implication of the subtraction with SWIR₂. This can cause the dominant soil in wetlands
7 background features will bring potential OE to MNDWI_{s2}. Figure 4 shows the comparison
8 between Landsat 8 OLI composite 654 imageries and the MNDWI_{s2} imageries.
9

10 4. Conclusion

11
12 Based on this research, the spectral indices recorded the most accurate and optimal in
13 extracting wetlands is MNDWI_{s2}. But MNDWI_{s2} should be used wisely, given MNDWI_{s2} very
14 sensitive to dense vegetation. MNDWI_{s2} also has potential error in wetlands with dominant soil
15 background features. MNDWI_{s2} not only able to recognize the deep waters as well as MNDWI,
16 but still able to capture the wetlands with vegetation on it.

17 The ability of MNDWI_{s2} in detecting peatlands with dense canopy as wetlands was very
18 impressive. Given the peatlands actually not always saturated with water on the surface, most
19 of them just has a very high water content in the ground with very high moisture surfaces. Will
20 MNDWI_{s2} be considered as Normalized Difference Wetlands Index (NDWLI)? Well, of course,
21 more research needs to be done to investigate.
22

23 Acknowledgement

24
25 The author thank to the United States Geological Survey (USGS) for providing the
26 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
27 the Spatial Data Infrastructure Development Center (PPIDS), University of
28 Lambung Mangkurat. Digital image processing in this research was carried out at the Remote

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1 Sensing and Geographic Information System Laboratory, Faculty of Forestry, University of
2 Lambung Mangkurat, Banjarbaru.

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General Comment

The manuscript of “Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI” has the potential to be published, however, a major and massive language editing is necessary. My main problem reading this manuscript lies on the grammatical errors, uncommon phrases and sentences used in texts, unnecessary complex sentences (which was hard to understand), lack of punctuation marks, and un-systematic paragraphs (no main ideas in the paragraphs). Those problems limit my ability to further assess the content of the manuscript, which in general, also needs to be revised.

I suggest to the author(s) to have their manuscript edited and proofreaded by professional so that the readability level can be increased. Due to the massive amounts of mistakes at this current state, I can not recommend this manuscript for publication at IJG.

Example of the errors (not limited to the one listed below) found on the text:

1. Grammatical error:

- “One of them is quite popular is Otsu thresholding” (using two IS?)

2. Uncommon phrases and sentences:

- “**we actually still have one question**, whether the spectral indices is quite optimal in extracting the wetlands features from the drylands features?”

Should be rephrased because the research problem should be of interest of other people.

By using “we actually still have one question”, it feels subjective.

3. unnecessary complex sentences (which was hard to understand):

- Of the many methods of optical digital imagery transformation that have been developed are, as a whole actually developed to separate water features from other features.

Give this to your colleagues to see whether they could understand the meaning. This type of unnecessary complex (and wrong) sentences are common on the text.

4. Lack of punctuation marks

- In South Kalimantan there are also quite a lot of open pit coal mining activities.

Comma?

5. Unsystematic paragraphs

- The sample locations were also chosen purposively on various dryland features that have the potential to be detected as wetlands. Namely, built-up lands, barelands, grass, roads, dryland forest, dryland farms, garden (include mix garden, rubber plants, palm oil), and shrub and bushes. This is to assess the deeper capabilities of each spectral index. In the appointment of the samples, the method used is knowledge-based.

Which one is the main idea?

**3. Respon Kepada Reviewer dan Hasil Revisi
Manuskrip Pertama (31 Maret 2020)**

1 Comparison of Various Spectral Indices for Optimum Extraction 2 of Tropical Wetlands Using Landsat 8 OLI

3

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

14

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

16

17 **Abstrak** Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
18 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
19 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
20 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
21 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
22 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
23 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
24 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
25 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
26 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

27

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

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33

1. Introduction

2

3 Wetlands are ecosystems saturated with water, either seasonally or permanently (EPA,
4 2004). According to the Ramsar Convention on Wetlands 1993 (Matthews, 2013), based on the
5 habitat, wetlands classified into marine and coastal wetlands, inland wetlands, and man-made
6 wetlands. In the South Kalimantan Province, Indonesia, wetlands are one of the main features
7 of the landscape.

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

16 So far, various methods have been developed for the extraction of wetlands geospatial
17 data automatically. For example, the Normalized Difference Water Index (NDWI) (McFeeters,
18 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and so forth.
19 ~~NDWI and MNDWI are the two most popular spectral indices for the extraction of water~~
20 ~~features or wetland features. Their ability to extract open water features or wetland features has~~
21 ~~been tested from several research results.~~ Besides NDWI or MNDWI, there are also a number
22 of other spectral indices that can potentially be used to separate wetlands features from other
23 features.

24 ~~Of the many methods of optical digital imagery transformation that have been~~
25 ~~developed are, as a whole, actually developed to separate water features from other features. In~~
26 ~~general, spectral indices such as NDWI or MNDWI are actually developed to separate open~~
27 ~~water features from other features.~~ Some research indicates that the spectral indices are very
28 accurate in extracting the boundaries of water features. For example, Xu (2006), ~~for example,~~

Commented [A1]: Response to Reviewer B. Adding the main idea of the paragraph.

Commented [A2]: Response to Reviewer B. Adding punctuation (comma).

Commented [A3]: Please give an explanation why using NDWI and MNDWI?

Commented [A4]: Response to Reviewer A. The explanation why using NDWI and MNDWI.

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Commented [A5]: Response to Reviewer B. Simplification of complex sentences.

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1 proved that MNDWI more accurate than NDWI when applied to the three water features, i.e.
2 lakes, oceans, and rivers.

3 ~~Similar to Xu (2006),~~ Li et al. (2013) also found that MNDWI more accurate than
4 NDWI to the TM, ETM +, and ALI imagery. ~~To further test MNDWI's capabilities,~~ Jiang et al.
5 (2014) developed the Automated Method for Extracting Rivers and Lakes (AMERL) for the
6 extraction of rivers and lakes automatically from Landsat TM/ETM +. It was found that in
7 general, ~~MNDWI is the most excellent among the three other spectral indices MNDWI remains~~
8 ~~the best among the three other spectral indices.~~

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

13 ~~In other cases, other spectral indices have proven to be more accurate in extracting open~~
14 ~~water or wetlands features. InterestinglyFor example, when~~ Ashraf and Nawaz (2015) ~~when~~
15 ~~they~~ detect changes in the wetlands of the Baraila Lake (India) using four spectral indices, they
16 found that in general NDWI is the most accurate method when verified using the field data.

17 Similar to Ashraf and Nawaz, Das and Pal (2016) also found that NDWI was the most accurate
18 spectral indices, when they compared six spectral indices. While Zhai et al. (2015) when
19 comparing surface water extraction performances of four indices using Landsat TM and OLI,
20 they found that Automated Water Extraction Index (AWEI) has the highest overall accuracy.

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

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

Commented [A7]: Response to Reviewer B. Improved paragraph structure to clarify the main idea of the paragraph.

Commented [A8]: Revision (move a paragraph) on our own initiative to improve the writing systematics.

Commented [A9]: Response to Reviewer B. Adding the main idea of the paragraph.

Commented [A10]: Please re-write the sentence. Hard to read the sentence

Commented [A11]: Response to Reviewer A. Rewriting the sentence.

Commented [A12]: Hard to read the sentence. Give the limitations and strenght of every indices

Commented [A13]: Response to Reviewer A. Rewriting the sentence.

Commented [A14]: Response to Reviewer B. Improved paragraph structure to clarify the main idea of the paragraph.

1 ~~Other researchers, such as Yang et al. (2015) combined several spectral indices and~~
2 ~~single band multispectral imagery simultaneously to extract water bodies water features. They~~
3 use a number of spectral indices ~~and single band~~ on Landsat 8 OLI to extract the water bodies.
4 Those are, the single-band threshold in band 5, multiband spectral relationship b2, b3, b4, b5,
5 NDVI, NDWI, MNDWI, Normalized Difference Built-up Index (NDBI), TCT, and Hue,
6 Intensity and Saturation (HIS). Where all of the spectral indices ~~and bands~~ are combined using
7 deep learning algorithm, called Stacked Sparse Autoencoder (SSAE).

Commented [A15]: Response to Reviewer B. Improved paragraph structure to clarify the main idea of the paragraph.

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

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12 Although the spectral indices ~~such as NDWI, MNDWI, NDVI, or others~~ are accurate
13 to separate ~~open water features with from~~ other features, ~~but it still needs to be studied further,~~
14 ~~whether these spectral indices are also accurate when used to separate wetland features from~~
15 ~~dryland features. we actually still have one question, whether the spectral indices is quite~~
16 ~~optimal in extracting the wetlands features from the drylands features? we still need to test~~
17 ~~whether the spectral indices are also accurate when used to separate wetland features from~~
18 ~~dryland features.~~ Because, most of the wetlands in tropical areas has a spectral characteristic of
19 water and green vegetation simultaneously. This research aimed to compare the accuracy of
20 some of the spectral indices for optimizing the extraction of wetlands, by taking the case of the
21 tropics area, that is, the South Kalimantan Province, Indonesia.

Commented [A17]: Response to Reviewer A and Reviewer B. Rewriting the sentences.

23 2.The Methods

25 2.1.Materials

27 This research used two scenes of Landsat 8 OLI, the path/row 117/062 and 117/063, the
28 acquisition on April 22, 2015. Most of the wetlands in South Kalimantan to be in these two

1 scenes. Imageries acquiring date selected on April because it was the rainy season. Therefore,
2 the condition of wetlands is at the maximum extends.

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



7
8 **Figure 1. Research location**

9
10 **2.2. Water Indices**

11
12 Water indices is a generic term for all of the spectral indices intended to sharpen the water
13 features. One of the water indices which is most extensively used is NDWI (McFeeters, 1996).
14 According to McFeeters (1996), if the pixel values of NDWI are positive means the water
15 features. Thus, the value of 0 by McFeeters (1996) is set as the threshold value. NDWI
16 formulated by McFeeters (1996) as follows:

Commented [A18]: How did you analys that the research area is not full of landsat? Please explain.

Commented [A19R18]: Response to Reviewer A. This research does not focus on producing maps of wetlands in a particular area. But it focuses on evaluating the ability of spectral indices to extract wetlands. So regional boundaries are not so important. What is important is that in the imagery used there are quite varied features of tropical wetlands. This study sampled a portion of South Kalimantan (Indonesia) province, using two Landsat 8 scenes. Where most of the tropical wetlands in South Kalimantan are found in both Landsat 8 scenes. And this is quite satisfying as a location to test spectral indices in extracting tropical wetland features.

1
$$NDWI = \frac{\rho_g - \rho_n}{\rho_g + \rho_n}$$

2 Where:

3 ρ_g : green band

4 ρ_n : near infrared band

5 Due to lack of NDWI in error detection features of the building, Xu (2006) modifying
6 NDWI become MNDWI, by changing NIR band into SWIR. In this case, Xu (2006) using the
7 SWIR1.

8
$$MNDWI = \frac{\rho_g - \rho_s}{\rho_g + \rho_s}$$

9 Where:

10 ρ_s : shortwave infrared band

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

14
$$MNDWI_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$$

15 Where:

16 ρ_{s2} : shortwave infrared 2 band

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

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

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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 Transformation Wetness	$0.1877\rho_{ca} + 0.2097\rho_b + 0.2038\rho_g + 0.1017\rho_r + 0.0685\rho_n - 0.7460\rho_{s1} - 0.5548\rho_{s2}$	-	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)

9

1 Information:

2 ρ_{ca} : aerosol coastal bands (bands 1 Landsat 8)

3 ρ_b : blue band (band 2 Landsat 8)

4 ρ_g : green band (band 3 Landsat 8)

5 ρ_r : red band (band 4 Landsat 8)

6 ρ_n : near infrared band (band 5 Landsat 8)

7 ρ_s : shortwave infrared band (band 6 or 7 Landsat 8)

8 ρ_{s1} : shortwave infrared 1 band (band 6 Landsat 8)

9 ρ_{s2} : shortwave infrared 2 band (band 7 Landsat 8)

10

11 2.3. Wetlands Extraction

12

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

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

22

23 2.4. Accuracy Assessment

24

25 Accuracy assessment was conducted using the Confusion Matrix (Stehman and
26 Czaplewski, 1997), using a number of sample locations were selected purposively. In this case,
27 the location of the sample represents multiple characters wetlands in South Kalimantan.
28 Namely, mangroves, salt marshes, rivers, freshwater lakes, freshwater marshes, peatlands,
29 peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish pond, farm ponds,

Commented [A20]: Response to Reviewer B. Fixing the grammatical error.

1 swamp rice field, irrigated land, and deep water (reservoirs, canals, and coal open pits). ~~So,~~
2 ~~there are a total of 15 samples for wetland classes.~~

Commented [A21]: Response to Reviewer A. Number of wetland class samples.

3 ~~For the purpose of assessing the deeper capabilities of each spectral index, The the sample~~
4 ~~locations were also chosen purposively on various dryland features that have the potential to~~
5 ~~be detected as wetlands. This is to assess the deeper capabilities of each spectral index. In the~~
6 ~~appointment of the samples, the method used is knowledge-based. There are a total of 10~~
7 ~~samples for dryland classes.~~ Namely, built-up lands, barelands, grass, roads, dryland forest,
8 dryland farms, garden (include mix garden, rubber plants, palm oil), and shrub and bushes. ~~So,~~
9 ~~there are a total of 10 samples for dryland classes. This is to assess the deeper capabilities of~~
10 ~~each spectral index. In the appointment of the samples, the method used is knowledge-based.~~

Commented [A22]: Response to Reviewer B. This is the main idea of this paragraph.

Commented [A23]: What the stepp and how to measure the accuracy assessment? How many sample do you have? How about the method?

Commented [A24]: Response to Reviewer A. Number of dryland class samples.

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

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19 ~~Furthermore, to test the ability of each spectral index to recognize each wetland class, a~~
20 ~~confusion matrix was constructed for each spectral index in each wetland class. For example,~~
21 ~~for NDWI in the Mangroves class, a confusion matrix will be constructed. Furthermore, from~~
22 ~~the resulting confusion matrix the Producer's Accuracy value will be taken, to obtain a~~
23 ~~quantitative description of the ability of the spectral index to recognize one type of wetland. So~~
24 ~~we will get an overview of NDWI's ability to recognize Mangroves for example. Recapitulation~~
25 ~~of producer's accuracy values for each spectral index in each wetland class can be seen in Table~~
26 ~~3.~~

27 ~~The final step, to test the ability of each spectral index to avoid the detection of dryland~~
28 ~~features, a confusion matrix is constructed for each spectral index in each dryland class. For~~
29 ~~example, for NDWI in the Dryland Forest class, a confusion matrix will be constructed.~~

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

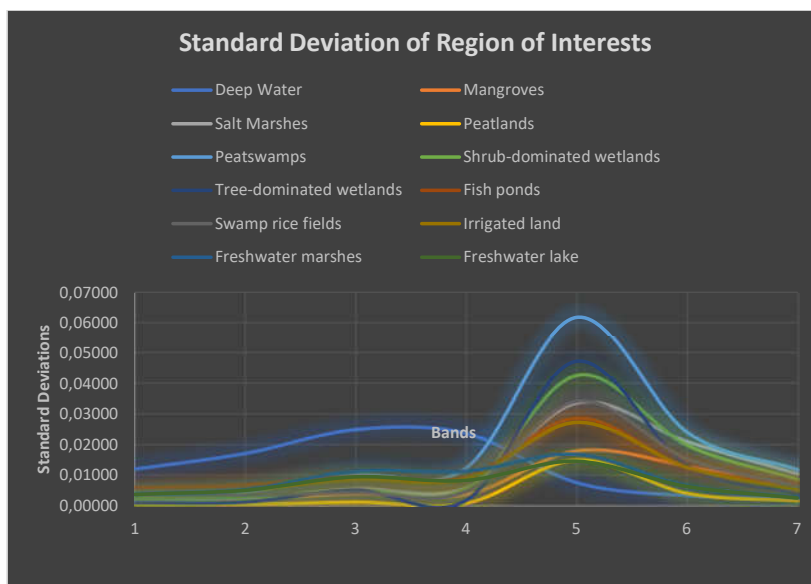
Commented [A25]: Response to Reviewer A. The step and how to measure the accuracy.

7 3.Result and Discussion

9 Visual appearance of wetlands in South Kalimantan varies in tone/colour on
10 multispectral satellite imageries such as Landsat 8. This shows quite a high degree of variation
11 in spectral value of each type of wetlands. In the accuracy assessment, the samples were made
12 for each type of wetlands. For the purpose to ensure that variations in the class of all wetlands
13 are represented as possible, Region of Interest (ROI) made for every wetland types are
14 distributed in several different locations. Figure 2 shows the Standard Deviation (SD) ROI of
15 all wetlands in each band Landsat 8 OLI.

Commented [A26]: What the meaning of this sentence?

Commented [A27]: Response to Reviewer A. It means visual appearance on multispectral imageries.



17

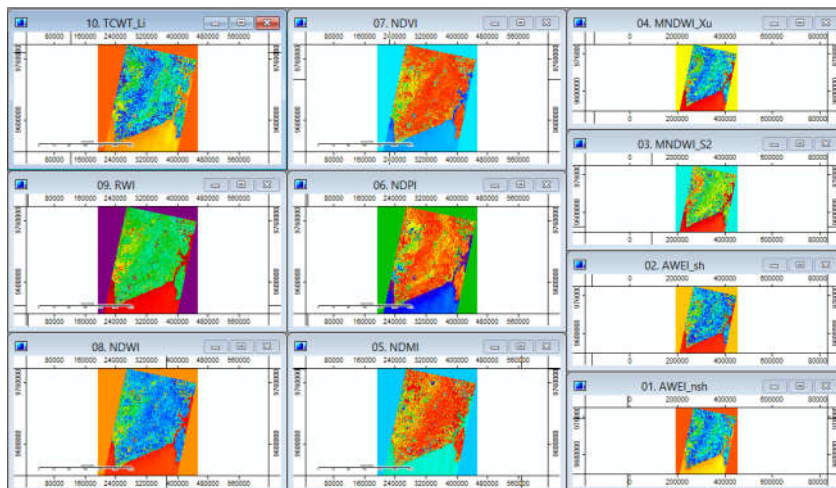
1 Figure 2. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

2
3 Of course, spectral indices such as NDWI cannot distinguish between mangroves and
4 peatswamps, for example. Because spectral indices such as NDWI are only designed to
5 recognize and separate water/wetlands from dryland features. While mangroves and
6 peatswamps are both wetland features. In fact, the thresholding imageries results of spectral
7 indices contains only two classes, namely Wetlands and Non-wetlands. But for the sake of
8 accuracy assessment, the accuracy assessment ROI is made on every types of wetlands in the
9 research locations. It is intended that the spectral character of each wetland represented, and
10 to provide an overview of each spectral indices extraction capabilities of each type of wetlands.

11 When the overall accuracy of the assessment is done, all types of wetland features are
12 combined into a single class, namely the Wetlands. And all types of drylands features are
13 combined into a single class, namely Non-wetlands. Figure 3 shows the results of the
14 transformation of spectral indices were selected in this research. While Table 2 shows the
15 results of Otsu thresholding and accuracy assessment results of each spectral index using the
16 Confusion Matrix.

Commented [A28]: Why?

Commented [A29]: Response to Reviewer A. Why spectral indices such as NDWI cannot distinguish between mangroves and peatswamps, for example.



18
19 Figure 3. The result of the transformation of spectral indices on the SAGA application

1

2 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 ₁₂	≥ 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 _{nh}	≥ -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

3

4 Information:

5 OA: Overall Accuracy

6 PA: Producer's Accuracy

7 UA: User's Accuracy

8 CE: Commission Error

9 OE: Omission Error

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

16 Although in this research was found the spectral indices which has overall accuracy
 17 above 70%, but when seen from the small Kappa coefficient, it seems overall accuracy was more
 18 to conditionally. However, this study is sufficient to provide an overview comparison of the

1 relative accuracy of each spectral index, if used specifically for the delineation of wetland
 2 features.

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

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

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

No.	Spectral Indices	Producer's Accuracy (%)											
		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 _{mh}	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

16

17 Information:

18 Dw: Deep water (include river, reservoir, dam, and coal mining pits)

19 Mg: Mangroves

20 Sm: Salt marshes

Commented [A30]: Response to Reviewer B. Fixing grammatical error.

- 1 Pl: Peatlands
- 2 Ps: Peatswamps
- 3 Sw: Shrub-dominated wetlands
- 4 Tw: Tree-dominated wetlands
- 5 Fp: Fish ponds
- 6 Sr: Swamp rice fields
- 7 Il: Irrigated land
- 8 Fm: Freshwater marshes
- 9 Fl: Freshwater lake

10

11 The entire spectral indices, except NDMI, do not have a problem when extracting the
12 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
13 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
14 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
15 2004).

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

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

28 MNDWI and $MNDWI_{s2}$ quite successful in identifying wetlands. Except MNDWI
29 failed to recognize the peatlands and tree-dominated wetlands. Where these two features are

Commented [A31]: Response to Reviewer B. Fixing the grammatical error.

1 wetlands with dense canopy. Not so with MNDWI_{s2} capable of recognizing peatlands and tree-
 2 dominated wetlands with almost 100% accuracy. Based on this fact, our assumption when
 3 shifting SWIR1 into SWIR2 on MNDWI has been proven. MNDWI_{s2} able to recognize the
 4 characteristic spectral features that have water and vegetation spectral characteristics as well
 5 with better.

6 The ability of a spectral indices for identifying wetlands (PA), is not directly indicated
 7 its ability to extract the wetlands. Because when it comes to in automatic features extraction
 8 method, the goal is not only whether that the method is able to recognize the desired features,
 9 but also how to be able to avoid such methods to recognize the other features but also how the
 10 method avoids recognizing other features. That is why, in this research we also tested the CE.
 11 In this case, CE tested using dryland features in research locations. These dryland features have
 12 been selected to investigate in which object the spectral indices encountered an error detection
 13 as wetlands.

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

18 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.	AWEL _{nsh}	0	0	0	0	0.06	0	0	0
10.	AWEL _{sh}	20.47	1.27	0	95.05	0.14	0	0	0

Commented [A32]: What is the accuracy assessment method and field sampling method?

Commented [A33R32]: Reponse to Reviewer A. The accuracy assessment method is using confusion matrix. There is no field sampling in this research, the method of determining the sample of each wetland class is to use a knowledge-based approach. Because the research location is the area of origin and residence of the main researcher (the project leader), so the main researcher are able to recognize each feature in Landsat 8 imagery properly without having to verify the field.

Commented [A34]: Hard to read sentence

Commented [A35]: Response to Reviewer A. Rewriting the sentence.

- 1 Information:
- 2 Bu: Built-up lands
- 3 Bl: Barelands
- 4 Gr: Grass
- 5 R: Roads
- 6 F: Dryland forest
- 7 Df: Dryland farms
- 8 Gd: Garden (mixgarden, rubber plants, palm oil)
- 9 Sb: Shrub and bushes

10

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

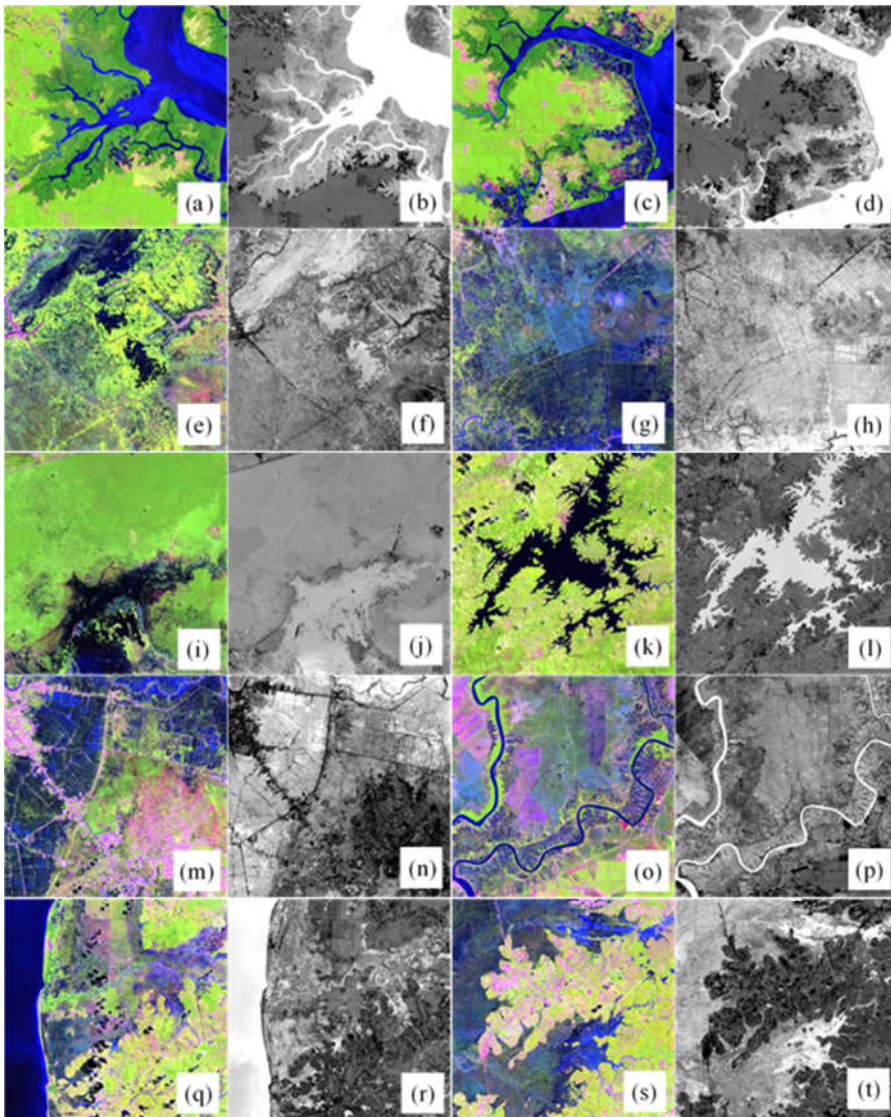
16 NDVI and NDWI that have the same character, they are also sensitive to built-up lands,
17 roads, and barelands. NDPI better than NDVI and NDWI in distinguishing between built-up
18 lands or barelands and wetlands. However, NDPI also slightly failed in distinguishing the paved
19 roads to the wetlands.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

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

Commented [A36]: Response to Reviewer B. Fixing the grammatical error.

1 Based on the results of the accuracy assessment, it appears that MNDWI_{s2} is most
2 optimal spectral indices for the extraction of wetlands. Some experts previously also been
3 modified MNDWI using SWIR₂. Among them was Chen et al. (2005), Ji et al. (2009), Boschetti
4 et al. (2014), and Islam et al. (2014).

Commented [A37]: Give the explanation about relationship between MNDWI and the spectral characteristics
Commented [A38R37]: Response to Reviewer A. The explanations are in the next paragraph.



1 Figure 4. Comparison between Landsat 8 OLI composite 654 and MNDW_{s2}

2 (a) and (b) mangrove; (c) and (d) fishpond; (e) and (f) freshwater lake and freshwater
3 marshes; (g) and (h) irrigated land; (i) and (j) peatlands and peatswamps; (k) and (l) deep
4 clear water (reservoir); (m) and (n) swamp rice fields and tree-dominated wetlands; (o) and
5 (p) deep turbid water (river); (q) and (r) salt marshes; and (s) and (t) shrub-dominated
6 wetlands.

7 MNDWI uses the green band and SWIR1 band. In SWIR1, vegetation features have a
8 much higher reflectance value than in green. As a result, green subtraction with SWIR1 in
9 MNDWI causes vegetation features to be depressed. So that wetlands with dense vegetation are
10 not detected as wetland features in MNDWI. Not so with MNDWIs2 which uses green bands
11 and SWIR2 bands. Where in SWIR2, the reflectance value of vegetation features is not as high
12 as in SWIR1. Even the spectral value tends to be similar to green. Thus, green subtraction
13 using SWIR2 will not suppress vegetation features as in MNDWI. As a result, wetlands with
14 dense vegetation can still be detected in MNDWIs2. This makes MNDWIs2 the most optimal
15 spectral index in extracting vegetation-rich wetlands such as tropical wetlands. Figure 4 shows
16 the comparison between Landsat 8 OLI composite 654 imageries and the MNDWIs2 imageries.

17 MNDWIs2 can recognize deep water features as well as MNDWI. [This is the
18 implication of the use of green band that is able to capture reflections of open water features
19 with high intensity, which is subtracted using SWIR1/SWIR2 band that do not capture
20 reflections of open water features. and Compared to MNDWI, MNDWIs2 still able to capture
21 the reflection of background water or soil moisture beneath the canopy. In the MNDWIs2
22 imagery, built-up lands, road, and barelands, appear darker than MNDWI imagery. It is an
23 implication of the subtraction with SWIR2. This can cause the dominant soil in wetlands
24 background features will bring potential OE to MNDWIs2. ~~Figure 4 shows the comparison~~
25 ~~between Landsat 8 OLI composite 654 imageries and the MNDWIs2 imageries.~~

Commented [A39]: Response to Reviewer A. The explanation about relationship between MNDWI and the spectral characteristics.

Commented [A40]: Response to Reviewer A. The explanation about relationship between MNDWI and the spectral characteristics.

27 **4. Conclusion**

1 Based on this research, the spectral indices recorded the most accurate and optimal in
2 extracting wetlands is MNDWI_{s2}. But MNDWI_{s2} should be used wisely, given MNDWI_{s2} very
3 sensitive to dense vegetation_s. MNDWI_{s2} also has potential error in wetlands with dominant
4 soil background features. MNDWI_{s2} not only able to recognize the deep waters as well as
5 MNDWI, but still able to capture the wetlands with vegetation_s on it.

6 Like MNDWI, MNDWI_{s2} also uses a green band. In spectral library, that green band
7 has the highest reflectance value of water features among all spectral bands. So that open or
8 deep-water features can be detected properly by MNDWI_{s2}. The advantage of MNDWI_{s2} is
9 the use of SWIR2, which where in spectral library SWIR2 band has a lower reflectance value of
10 vegetation. So that subtraction green with SWIR2 will not cause vegetation features to
11 become depressed as in MNDWI.

12 The ability of MNDWI_{s2} in detecting peatlands with dense canopy as wetlands was very
13 impressive. Given the peatlands actually not always saturated with water on the surface, most
14 of them just has a very high water content in the ground with very high moisture surfaces. Will
15 MNDWI_{s2} be considered as Normalized Difference Wetlands Index (NDWLI)? Well, of course,
16 more research needs to be done to investigate.

18 Acknowledgement

19
20 The author thank to the United States Geological Survey (USGS) for providing the
21 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
22 the Spatial Data Infrastructure Development Center (PPIDS), University of
23 LambungMangkurat. Digital image processing in this research was carried out at the Remote
24 Sensing and Geographic Information System Laboratory, Faculty of Forestry, University of
25 LambungMangkurat, Banjarbaru.

Commented [A41]: Response to Reviewer A. The explanation of the relationship between the spectral library and the indices that we use.

Formatted: English (Indonesia)

Commented [A42]: Add the explanation of The relationship between the spectral library and the indeks that you use

Commented [A43R42]: Response to Reviewer A. The explanations are in the next paragraph.

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4. Bukti Konfirmasi Review dan dan Hasil Review

Kedua, Manuskrip Diterima dengan syarat Revisi

(8 November 2020)

***Catatan:* Pada tahap ini, Penulis Kedua, yaitu Prof. Dr. H. Hartono, DEA, DESS, sudah meninggal dunia pada Hari Senin, tanggal 31 Agustus 2020.**

[IJG] Editor Decision: Revision Required

2 messages

Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id>

Sun, Nov 8, 2020 at 9:28 AM

To: Syam'ani Syam'ani <syamani.fhut@ulm.ac.id>

Cc: Hartono Hartono <hartono@geo.ugm.ac.id>, Projo Danoedoro <projo.danoedoro@geo.ugm.ac.id>

Dear Mr. Syam'ani,

After considering the reviewer's comments (see the attachment in your OJS account), We have reached the decision to Accept your manuscript with revision regarding your submission to the Indonesian Journal of Geography, "Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI".

You should improve the quality of your manuscript by revising your manuscript according to the reviewer's comments. See attached files. Please carefully respond to the reviewer's comments when submitting the revision and please clearly indicate the changes that you made (or highlight them) to address the reviewer's comments. Or, you can directly reply to the reviewer's comments in the comments box written by the reviewer. You should also use the template attached below. We will not process any revised paper without a specific response to each reviewer's comments

Once again, thank you for submitting your manuscript to the Indonesian Journal of Geography and I look forward to receiving your revision no later than 45 days from now. If you failed to meet the deadline, we may have to consider your paper rejected.

NB: Please use the follow the guideline in the attached template for your revision.

Best wishes,

Dr. Pramaditya Wicaksono

Faculty of Geography Universitas Gadjah Mada, Yogyakarta

Phone +6281391179917

Fax +62274569595

prama.wicaksono@geo.ugm.ac.id

Section Editor

Indonesian Journal of Geography

Faculty of Geography, Universitas Gadjah Mada, Yogyakarta

Chief Editor

Indonesian Journal of Geography

<http://jurnal.ugm.ac.id/index.php/ijg>

0024-9521 (print),2354-9114 (online)

Phone: +62 812-2711-480

2 attachments**49914-165181-1-ED.docx**

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**Template for Respond for Reviewer's comments.docx**

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Syam'ani <syamani.fhut@ulm.ac.id>

Tue, Dec 22, 2020 at 10:23 PM

To: Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id>

Dear Dr. Pramaditya Wicaksono

We have revised the manuscript, and we have resubmitted the revised results of our manuscript along with responses to reviewer comments through OJS Indonesian Journal of Geography. For additional information, I also changed my name. Now I use my family name, Syamani D. Ali or Syamani Darmawi Ali. My name is no longer written in single quotation marks, because in database systems this often creates problems.

Thank you for your attention,

Syamani D. Ali

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2 attachments



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1 Comparison of Various Spectral Indices for Optimum Extraction 2 of Tropical Wetlands Using Landsat 8 OLI

3

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

14

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

16

17 **Abstrak** Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
18 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
19 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
20 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
21 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
22 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
23 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
24 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
25 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
26 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

27

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

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1 **1. Introduction**

2

3 Wetlands are ecosystems saturated with water, either seasonally or permanently (EPA,
4 2004). According to the Ramsar Convention on Wetlands 1993 (Matthews, 2013), based on the
5 habitat, wetlands classified into marine and coastal wetlands, inland wetlands, and man-made
6 wetlands. In the South Kalimantan Province, Indonesia, wetlands are one of the main features
7 of the landscape.

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

15 So far, various methods have been developed for the extraction of wetlands geospatial
16 data automatically. For example, the Normalized Difference Water Index (NDWI) (McFeeters,
17 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and so forth.
18 NDWI and MNDWI are the two most popular spectral indices for the extraction of water
19 features or wetland features. Their ability to extract open water features or wetland features has
20 been tested from several research results. Besides NDWI or MNDWI, there are also a number
21 of other spectral indices that can potentially be used to separate wetland features from other
22 features.

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

Commented [A1]: Provide references here all the several research results you mentioned

1 Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM +.
2 It was found that in general, MNDWI remains the best among the three other spectral indices.

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

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

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

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

23 Other researchers, such as Yang et al. (2015) combined spectral indices and single band
24 multispectral imagery simultaneously to extract water features. They use a number of spectral
25 indices and single band on Landsat 8 OLI to extract the water bodies. Those are, the single-
26 band threshold in band 5, multiband spectral relationship b2, b3, b4, b5, NDVI, NDWI,
27 MNDWI, Normalized Difference Built-up Index (NDBI), TCT, and Hue, Intensity and
28 Saturation (HIS). Where all of the spectral indices and bands are combined using deep learning
29 algorithm, called Stacked Sparse Autoencoder (SSAE).

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

8

9 **2.The Methods**

10

11 2.1.Materials

12

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

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



Figure 1. Research location

Commented [A2]: Provide coordinate to the image and also an inset. Some toponym will also be useful

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:

$$NDWI = \frac{\rho_g - \rho_n}{\rho_g + \rho_n}$$

Where:

- ρ_g : green band
- ρ_n : near infrared band

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1 Due to lack of NDWI in error detection features of the building, Xu (2006) modifying
2 NDWI become MNDWI, by changing NIR band into SWIR. In this case, Xu (2006) using the
3 SWIR1.

$$4 \quad \text{MNDWI} = \frac{\rho_g - \rho_s}{\rho_g + \rho_s}$$

5 Where:

6 • ρ_s : shortwave infrared band

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

$$10 \quad \text{MNDWI}_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$$

11 Where:

12 • ρ_{s2} : shortwave infrared 2 band

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

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

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

Commented [A3]: NDWI, MNDWI, and MNDWI_{s2} were explained in more detail. Why other indices are not?

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 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)

4

5 Information:

- 6 • ρ_{ca} : aerosol coastal bands (bands 1 Landsat 8)
- 7 • ρ_b : blue band (band 2 Landsat 8)
- 8 • ρ_g : green band (band 3 Landsat 8)
- 9 • ρ_r : red band (band 4 Landsat 8)

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- 1 • ρ_n : near infrared band (band 5 Landsat 8)
- 2 • ρ_s : shortwave infrared band (band 6 or 7 Landsat 8)
- 3 • ρ_{s1} : shortwave infrared 1 band (band 6 Landsat 8)
- 4 • ρ_{s2} : shortwave infrared 2 band (band 7 Landsat 8)

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6 2.3. Wetlands Extraction

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

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

16

17 2.4. Accuracy Assessment

18

19 Accuracy assessment was conducted using the Confusion Matrix (Stehman and
20 Czaplewski, 1997), using a number of sample locations were selected purposively. In this case,
21 the location of the sample represents multiple characters wetlands in South Kalimantan.
22 Namely, mangroves, salt marshes, rivers, freshwater lakes, freshwater marshes, peatlands,
23 peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish pond, farm ponds,
24 swamp rice field, irrigated land, and deep water (reservoirs, canals, and coal open pits). So,
25 there are a total of 15 samples for wetland classes.

26 For the purpose of assessing the deeper capabilities of each spectral index, the sample
27 locations were also chosen purposively on various dryland features that have the potential to
28 be detected as wetlands. In the appointment of the samples, the method used is knowledge-
29 based. There are a total of 10 samples for dryland classes. Namely, built-up lands, barelands,

1 grass, roads, dryland forest, dryland farms, garden (include mix garden, rubber plants, palm
2 oil), and shrub and bushes.

Commented [A4]: How many samples are for each of this class?

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

11 Furthermore, to test the ability of each spectral index to recognize each wetland class, a
12 confusion matrix was constructed for each spectral index in each wetland class. For example,
13 for NDWI in the Mangroves class, a confusion matrix will be constructed. Furthermore, from
14 the resulting confusion matrix the Producer's Accuracy value will be taken, to obtain a
15 quantitative description of the ability of the spectral index to recognize one type of wetland. So
16 we will get an overview of NDWI's ability to recognize Mangroves for example. Recapitulation
17 of producer's accuracy values for each spectral index in each wetland class can be seen in Table
18 3.

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

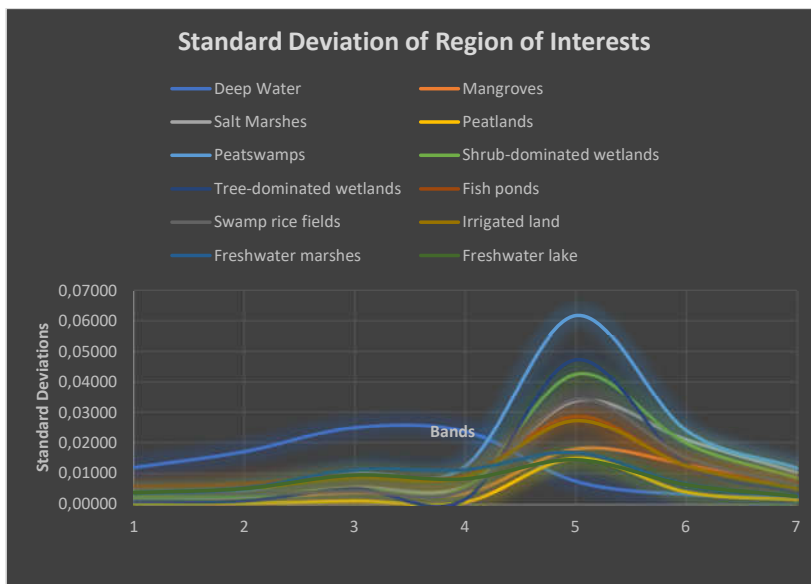
Commented [A5]: Why do you need to create confusion matrix for each wetland class and dryland class? One confusion matrix can involve all the class altogether.

28 3.Result and Discussion

29

1 Visual appearance of wetlands in South Kalimantan varies in tone/colour on
2 multispectral satellite imageries such as Landsat 8. This shows quite a high degree of variation
3 in spectral value of each type of wetlands. In the accuracy assessment, the samples were made
4 for each type of wetlands. For the purpose to ensure that variations in the class of all wetlands
5 are represented as possible, Region of Interest (ROI) made for every wetland types are
6 distributed in several different locations. Figure 2 shows the Standard Deviation (SD) ROI of
7 all wetlands in each band Landsat 8 OLI.

8



9

10 Figure 2. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

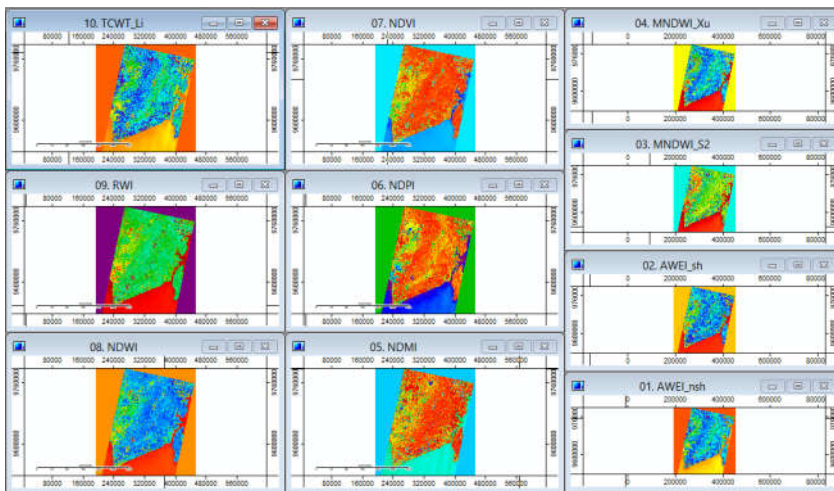
11

12 Of course, spectral indices such as NDWI cannot distinguish between mangroves and
13 peatswamps, for example. Because spectral indices such as NDWI are only designed to
14 recognize and separate water/wetlands from dryland features. While mangroves and
15 peatswamps are both wetland features. In fact, the thresholding imageries results of spectral
16 indices contains only two classes, namely Wetlands and Non-wetlands. But for the sake of
17 accuracy assessment, the accuracy assessment ROI is made on every types of wetlands in the

1 research locations. It is intended that the spectral character of each wetland represented, and
 2 to provide an overview of each spectral indices extraction capabilities of each type of wetlands.

3 When the overall accuracy of the assessment is done, all types of wetland features are
 4 combined into a single class, namely the Wetlands. And all types of drylands features are
 5 combined into a single class, namely Non-wetlands. Figure 3 shows the results of the
 6 transformation of spectral indices were selected in this research. While Table 2 shows the
 7 results of Otsu thresholding and accuracy assessment results of each spectral index using the
 8 Confusion Matrix.

9



10
 11 Figure 3. The result of the transformation of spectral indices on the SAGA application

12

13 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 ₂	≥ 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

Commented [A6]: Explain the abbreviation in the caption

Commented [A7]: Explain the abbreviation in the caption

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 _{sh}	≥ -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

1

2 Information:

- 3 • OA: Overall Accuracy
- 4 • PA: Producer's Accuracy
- 5 • UA: User's Accuracy
- 6 • CE: Commission Error
- 7 • OE: Omission Error

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

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

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

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

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

Commented [A8]: What about the user's accuracy analysis?

No.	Spectral Indices	Producer's Accuracy (%)											
		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 ₂	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.	AWEl _{nh}	100	69.97	88.46	0	95.87	25.47	5.92	99.88	96.38	100	100	100
10.	AWEl _{sh}	100	5.81	99.95	0	97.92	88.55	15.45	100	99.83	100	100	100

6

7 **Information:**

- 8 • Dw: Deep water (include river, reservoir, dam, and coal mining pits)
- 9 • Mg: Mangroves
- 10 • Sm: Salt marshes
- 11 • Pl: Peatlands
- 12 • Ps: Peatswamps
- 13 • Sw: Shrub-dominated wetlands
- 14 • Tw: Tree-dominated wetlands
- 15 • Fp: Fish ponds
- 16 • Sr: Swamp rice fields
- 17 • Il: Irrigated land
- 18 • Fm: Freshwater marshes
- 19 • Fl: Freshwater lake

20

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1 The entire spectral indices, except NDMI, do not have a problem when extracting the
2 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
3 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
4 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
5 2004).

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

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

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

25 The ability of spectral indices for identifying wetlands (PA), is not directly indicated its
26 ability to extract the wetlands. Because in automatic features extraction, the goal is not only
27 that the method is able to recognize the desired features, but also how the method avoids
28 recognizing other features. That is why, in this research we also tested the CE. In this case, CE

1 tested using dryland features in research locations. These dryland features have been selected
2 to investigate in which object the spectral indices encountered an error detection as wetlands.

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

6

7 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 _{k2}	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 _{sh}	0	0	0	0	0.06	0	0	0
10.	AWEI _{sh}	20.47	1.27	0	95.05	0.14	0	0	0

8

9 Information:

- 10 • Bu: Built-up lands
- 11 • Bl: Barelands
- 12 • Gr: Grass
- 13 • R: Roads
- 14 • F: Dryland forest
- 15 • Df: Dryland farms
- 16 • Gd: Garden (mixgarden, rubber plants, palm oil)
- 17 • Sb: Shrub and bushes

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

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

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

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

22

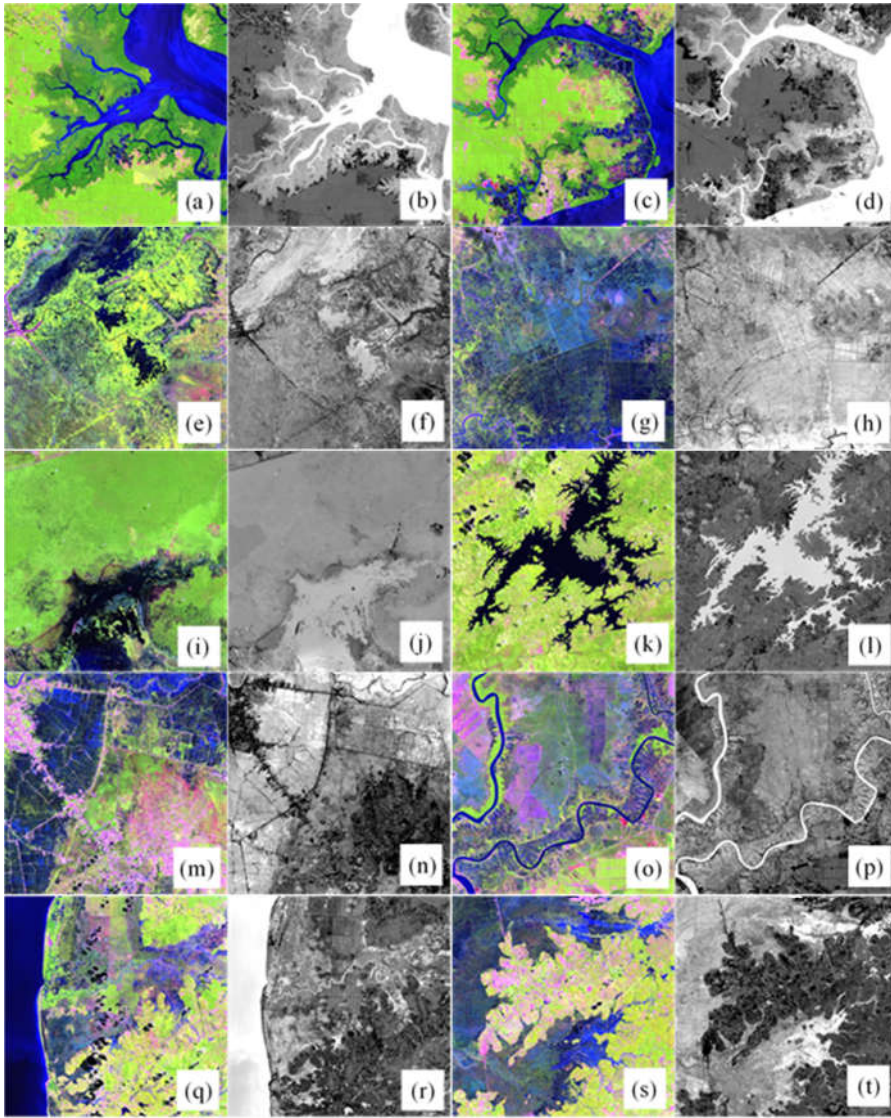


Figure 4. Comparison between Landsat 8 OLI composite 654 and MNDW_{s2}

(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

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

3 MNDWI uses the green band and SWIR1 band. In SWIR1, vegetation features have a
4 much higher reflectance value than in green. As a result, green subtraction with SWIR1 in
5 MNDWI causes vegetation features to be depressed. So that wetlands with dense vegetation are
6 not detected as wetland features in MNDWI. Not so with MNDWI_{s2} which uses green bands
7 and SWIR2 bands. Where in SWIR2, the reflectance value of vegetation features is not as high
8 as in SWIR1. Even the spectral value tends to be similar to green. Thus, green subtraction
9 using SWIR2 will not suppress vegetation features as in MNDWI. As a result, wetlands with
10 dense vegetation can still be detected in MNDWI_{s2}. This makes MNDWI_{s2} the most optimal
11 spectral index in extracting vegetation-rich wetlands such as tropical wetlands. Figure 4 shows
12 the comparison between Landsat 8 OLI composite 654 imageries and the MNDWI_{s2} imageries.

13 MNDWI_{s2} can recognize deep water features as well as MNDWI. This is the
14 implication of the use of green band that is able to capture reflections of open water features
15 with high intensity, which is subtracted using SWIR1/SWIR2 band that do not capture
16 reflections of open water features. Compared to MNDWI, MNDWI_{s2} still able to capture the
17 reflection of background water or soil moisture beneath the canopy. In the MNDWI_{s2} imagery,
18 built-up lands, road, and barelands, appear darker than MNDWI imagery. It is an implication
19 of the subtraction with SWIR2. This can cause the dominant soil in wetlands background
20 features will bring potential OE to MNDWI_{s2}.

21

22 4. Conclusion

23

24 Based on this research, the spectral indices recorded the most accurate and optimal in
25 extracting wetlands is MNDWI_{s2}. But MNDWI_{s2} should be used wisely, given MNDWI_{s2} very
26 sensitive to dense vegetations. MNDWI_{s2} also has potential error in wetlands with dominant
27 soil background features. MNDWI_{s2} not only able to recognize the deep waters as well as
28 MNDWI, but still able to capture the wetlands with vegetations on it.

Commented [A9]: I don't really get it. To my knowledge, healthy vegetation with high leaf moisture content should have a low reflectance on SWIR 1 and SWIR 2. This is especially true in wetlands such as mangrove. So, why did you mention that SWIR 1 reflectance is much higher than green? Can you please provide the figure showing the spectral response of the objects you classified.

Commented [A10]: SWIR 1 or SWIR 2? It should be SWIR 2 right?

Commented [A11]: What is OE?

1 Like MNDWI, MNDWI_{s2} also uses a green band. In spectral library, green band has
2 the highest reflectance value of water features among all spectral bands. So that open water
3 features can be detected properly by MNDWI_{s2}. The advantage of MNDWI_{s2} is the use of
4 SWIR₂, where in spectral library SWIR₂ band has a lower reflectance value of vegetation. So
5 that subtraction green with SWIR₂ will not cause vegetation features to become depressed as
6 in MNDWI.

7 The ability of MNDWI_{s2} in detecting peatlands with dense canopy as wetlands was very
8 impressive. Given the peatlands actually not always saturated with water on the surface, most
9 of them just has a very high water content in the ground with very high moisture surfaces. Will
10 MNDWI_{s2} be considered as Normalized Difference Wetlands Index (NDWLI)? Well, of course,
11 more research needs to be done to investigate.

Commented [A12]: Why not blue band?
Also, which spectral library? You did not discuss anything about
spectral library in the manuscript before.

Commented [A13]: But this condition is enough to make SWIR₁
and SWIR₂ to reflect very lowly

Commented [A14]: Don't use such sentence

13 Acknowledgement

14
15 The author thank to the United States Geological Survey (USGS) for providing the
16 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
17 the Spatial Data Infrastructure Development Center (PPIDS), University of
18 LambungMangkurat. Digital image processing in this research was carried out at the Remote
19 Sensing and Geographic Information System Laboratory, Faculty of Forestry, University of
20 LambungMangkurat, Banjarbaru.

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**5. Respon Kepada Reviewer dan Hasil Revisi
Manuskrip Kedua (22 Desember 2020)**

1 Comparison of Various Spectral Indices for Optimum Extraction 2 of Tropical Wetlands Using Landsat 8 OLI

3

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

14

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

16

17 **Abstrak** Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
18 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
19 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
20 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
21 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
22 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
23 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
24 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
25 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
26 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

27

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

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1 **1. Introduction**

2

3 Wetlands are ecosystems saturated with water, either seasonally or permanently (EPA,
4 2004). According to the Ramsar Convention on Wetlands 1993 (Matthews, 2013), based on the
5 habitat, wetlands classified into marine and coastal wetlands, inland wetlands, and man-made
6 wetlands. In the South Kalimantan Province, Indonesia, wetlands are one of the main features
7 of the landscape.

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

15 So far, various methods have been developed for the extraction of wetlands geospatial
16 data automatically. For example, the Normalized Difference Water Index (NDWI) (McFeeters,
17 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and so forth.
18 NDWI and MNDWI are the two most popular spectral indices for the extraction of water
19 features or wetland features. Their ability to extract open water features or wetland features has
20 been tested from several research results (McFeeters, 1996; Xu, 2006; Li et al., 2013; Jiang et al.,
21 2014; Ashraf and Nawaz, 2015; Das and Pal, 2016; Du et al., 2016). Besides NDWI or MNDWI,
22 there are also a number of other spectral indices that can potentially be used to separate wetland
23 features from other features.

24 In general, spectral indices such as NDWI or MNDWI are actually developed to
25 separate open water features from other features. Some research indicates that the spectral
26 indices are very accurate in extracting the boundaries of water features. For example, Xu (2006)
27 proved that MNDWI more accurate than NDWI when applied to the three water features, i.e.
28 lakes, oceans, and rivers. Similar to Xu (2006), Li et al. (2013) also found that MNDWI more
29 accurate than NDWI to the TM, ETM +, and ALI imagery. To further test MNDWI's

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1 capabilities, Jiang et al. (2014) developed the Automated Method for Extracting Rivers and
2 Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM +.
3 It was found that in general, MNDWI remains the best among the three other spectral indices.

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

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

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

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

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

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

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

10

11 **2.The Methods**

12

13 2.1.Materials

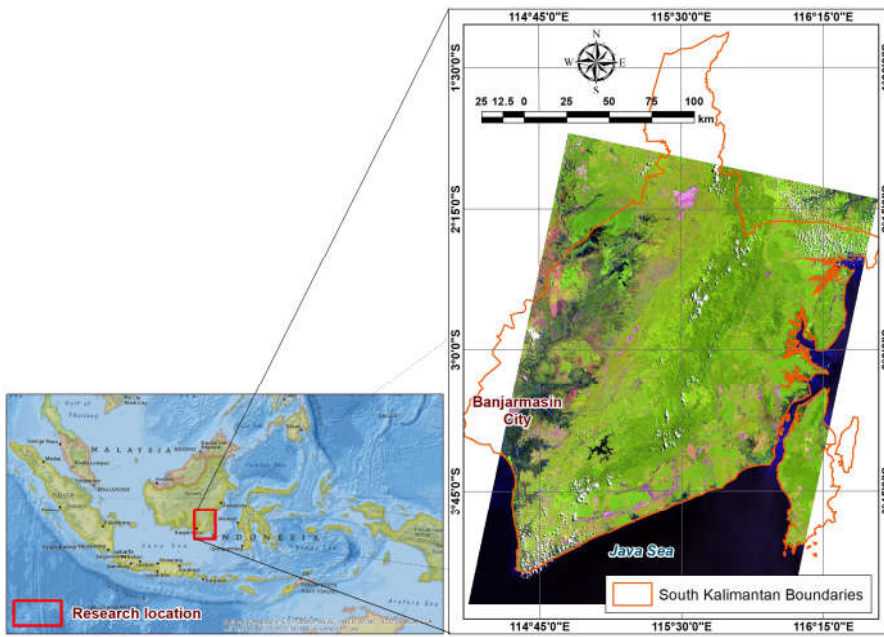
14

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

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



1



2

3

4

Figure 1. Research location

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1 2.2. Water Indices

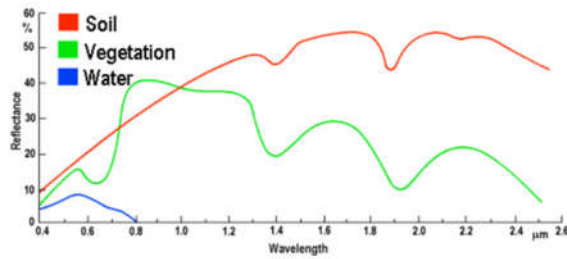
2

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

8
$$NDWI = \frac{\rho_g - \rho_n}{\rho_g + \rho_n}$$

9 Where:

- 10 • ρ_g : green band
11 • ρ_n : near infrared band



12 Figure 2. Spectral value curves on three base surface features

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14 Due to lack of NDWI in error detection features of the building, Xu (2006) modifying
15 NDWI become MNDWI, by changing NIR band into SWIR. In this case, Xu (2006) using the
16 SWIR1. The replacement of NIR with SWIR1 aims to suppress soil features (including
17 buildings) in McFeeters's NDWI, because in the SWIR-1 soil reflectances are higher than NIR.
18 As seen in the spectral value curves in Figure 2.

19
$$MNDWI = \frac{\rho_g - \rho_s}{\rho_g + \rho_s}$$

20 Where:

- 21 • ρ_s : shortwave infrared band

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

$$4 \quad \text{MNDWI}_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$$

5 Where:

- 6 • ρ_{s2} : shortwave infrared 2 band

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

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

15
16
17
18
19
20
21
22
23
24
25 **Table 1. List of the spectral indices used in the research**

No.	Spectral Indices	Formula		Value of Water	Reference
1.	NDVI Vegetation Index	Normalized Difference	$\frac{\rho_n - \rho_r}{\rho_n + \rho_r}$	Negative	Rouse et al. (1973)

Commented [A5]: NDWI, MNDWI, and MNDWI_{s2} were explained in more detail. Why other indices are not?

Commented [A6R5]: In the methods, NDWI is a formula that is the basis for Xu (2006) in developing MNDWI, while MNDWI itself is a formula that is used as the basis for developing a new formula in this research, namely MNDWI_{s2}. Of course, MNDWI_{s2} is a formula specifically developed in this research. Meanwhile, other indices are only cited from a number of literature, without any further development and not directly related to the development of a new formula in this research. These are the reasons why only NDWI, MNDWI, and MNDWI_{s2} are discussed in detail in the Methods section.

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 _{noh}	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)

1

2 Information:

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

11

12 2.3. Wetlands Extraction

1

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

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

10

11 2.4. Accuracy Assessment

12

13 Accuracy assessment was conducted using the Confusion Matrix (Stehman and
14 Czaplewski, 1997), using a number of sample locations were selected purposively. In this case,
15 the location of the sample represents multiple characters wetlands in South Kalimantan.

16 Namely, ~~mangroves, salt marshes, rivers, freshwater lakes, freshwater marshes, peatlands,~~
17 ~~peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish pond, farm ponds,~~
18 ~~swamp rice field, irrigated land, and deep water (reservoirs, canals, and coal open pits)~~
19 mangroves, salt marshes, deep water (include reservoirs, canals, and coal open pits), peatlands,
20 peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish ponds, swamp rice
21 fields, irrigated land, freshwater marshes, and freshwater lake. ~~So~~Therefore, there are a total of
22 1512 samples for wetland classes. Meanwhile, the number of sample pixels for each wetlands
23 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
24 pixels respectively.

25 For the purpose of assessing the deeper capabilities of each spectral index, the sample
26 locations were also chosen purposively on various dryland features that have the potential to
27 be detected as wetlands. In the appointment of the samples, the method used is knowledge-
28 based. There are a total of 10 samples for dryland classes. Namely, built-up lands, barelands,
29 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 is are 1,236, 4,003, 2,377, 323, 6,445, 2,169, 4,694, and 8,075 pixels, respectively.

Commented [A7]: How many samples are for each of this class?

Commented [A8R7]: We've provided information on the number of sample pixels for each wetlands and drylands class.

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.

Commented [A9]: Why do you need to create confusion matrix for each wetland class and dryland class? One confusion matrix can involve all the class altogether.

Commented [A10R9]: One confusion matrix can involve all the class altogether, this applies for example in the case of multispectral classification. However, in this research, spectral indices such as NDWI or others, are relatively difficult, or even completely unable to distinguish between Wetland classes. Given the spectral indices such as NDWI are only one band, not a multispectral imagery.

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.

One NDWI band is difficult to distinguish between Mangroves and Peatlands, for example. While Peatlands in the case of this research are overgrown with dense forests whose spectral characters are similar to mangroves. We can confirm that the range of values between Mangroves and Peatlands in NDWI will be similar.

Like the Normalized Difference Vegetation Index (NDVI) which can only separate between vegetation and non-vegetation, so in the context of this research, spectral indices such as NDWI are only considered to be able to separate between Wetlands and Drylands. This also underlies the use of Otsu thresholding as a method of separating the features in this research. Where Otsu thresholding can only produce 2 classes in one classification process.

So when testing Mangroves on NDWI, for example, Mangroves will be tested with Non mangroves (the Drylands). When testing Peatlands on NDWI, Peatlands will be tested with Non peatlands (the Drylands). It is not possible to test Mangroves and Peatlands simultaneously on a single NDWI index, if such a test were forced the error would be very large.

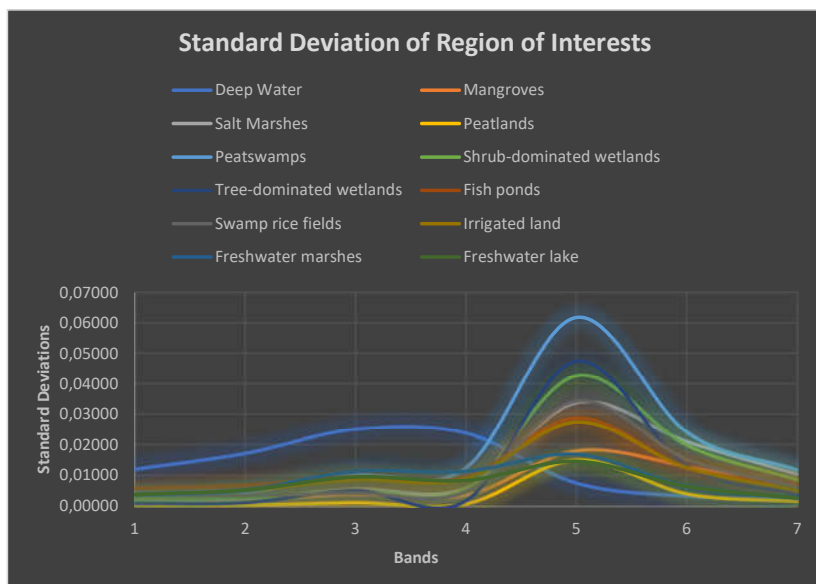
The same is true of Dryland classes. NDWI certainly cannot distinguish between Built-up lands and Barelands for example.

A brief explanation of this has been provided in the Results and Discussion section. See page 12 line 1 to 9.

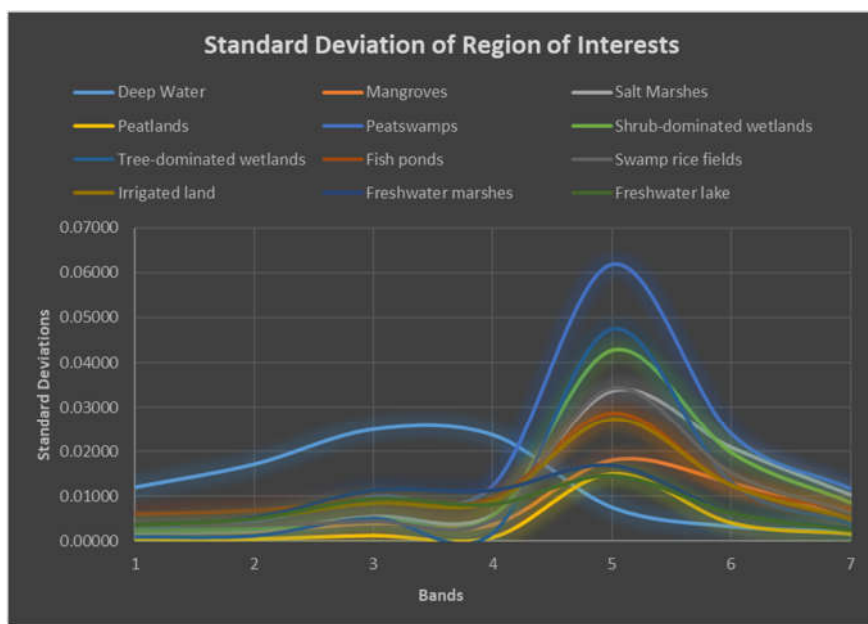
3.Result and Discussion

1 Visual appearance of wetlands in South Kalimantan varies in tone/colour on
2 multispectral satellite imageries such as Landsat 8. This shows quite a high degree of variation
3 in spectral value of each type of wetlands. In the accuracy assessment, the samples were made
4 for each type of wetlands. For the purpose to ensure that variations in the class of all wetlands
5 are represented as possible, Region of Interest (ROI) made for every wetland types are
6 distributed in several different locations. Figure 32 shows the Standard Deviation (SD) ROI of
7 all wetlands in each band Landsat 8 OLI.

8



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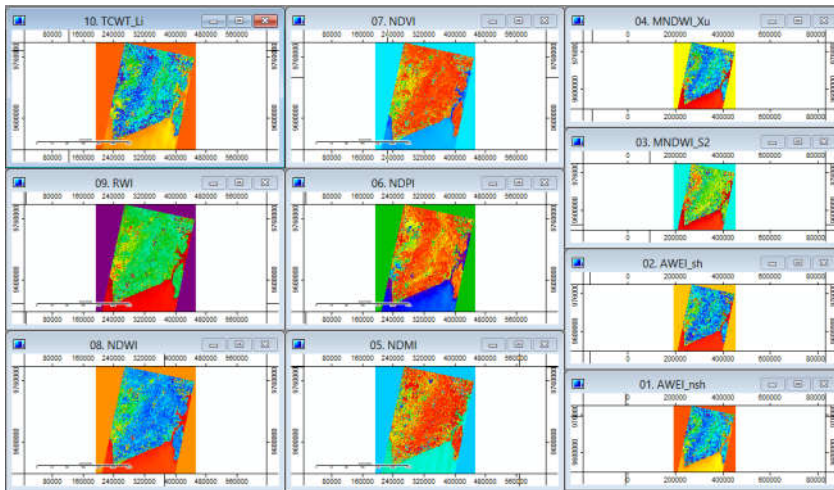
Figure 23. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

4

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

9 When the overall accuracy of the assessment is done, all types of wetland features are
 10 combined into a single class, namely the Wetlands. And all types of drylands features are
 11 combined into a single class, namely Non-wetlands. Figure 43 shows the results of the
 12 transformation of spectral indices were selected in this research. While Table 2 shows the
 13 results of Otsu thresholding and accuracy assessment results of each spectral index using the
 14 Confusion Matrix.

15



16 Figure 34. The result of the transformation of spectral indices on the SAGA application
 17

18
 19 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 _{k2}	≥ 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 _{nah}	≥ -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

Commented [A11]: Explain the abbreviation in the caption

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Commented [A13]: Explain the abbreviation in the caption

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1

2 Information:

- 3
- 4 • OA: Overall Accuracy
 - 5 • PA: Producer's Accuracy
 - 6 • UA: User's Accuracy
 - 7 • CE: Commission Error
 - 8 • OE: Omission Error

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

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

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

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

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

No.	Spectral Indices	Producer's Accuracy (%)											
		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 _{mh}	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

Commented [A15]: What about the user's accuracy analysis?

Commented [A16R15]: User's Accuracy (UA) analyzes are represented by Commission Error (CE) in Table 4.

CE + UA = 100%, so if there is a CE of 15% for example, it means that the UA is 85%.

14

15 Information:

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

- 1 • Sw: Shrub-dominated wetlands
- 2 • Tw: Tree-dominated wetlands
- 3 • Fp: Fish ponds
- 4 • Sr: Swamp rice fields
- 5 • Il: Irrigated land
- 6 • Fm: Freshwater marshes
- 7 • Fl: Freshwater lake

8

9 The entire spectral indices, except NDMI, do not have a problem when extracting the
10 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
11 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
12 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
13 2004).

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

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

26 MNDWI and MNDWI_{s2} quite successful in identifying wetlands. Except MNDWI
27 failed to recognize the peatlands and tree-dominated wetlands. Where these two features are
28 wetlands with dense canopy. Not so with MNDWI_{s2} capable of recognizing peatlands and tree-
29 dominated wetlands with almost 100% accuracy. Based on this fact, our assumption when

1 shifting SWIR1 into SWIR2 on MNDWI has been proven. MNDWI_{s2} able to recognize the
 2 characteristic spectral features that have water and vegetation spectral characteristics as well
 3 with better.

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

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

14 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

15

16 Information:

- 17 • Bu: Built-up lands
- 18 • Bl: Barelands
- 19 • Gr: Grass

- 1 • R: Roads
- 2 • F: Dryland forest
- 3 • Df: Dryland farms
- 4 • Gd: Garden (mixgarden, rubber plants, palm oil)
- 5 • Sb: Shrub and bushes

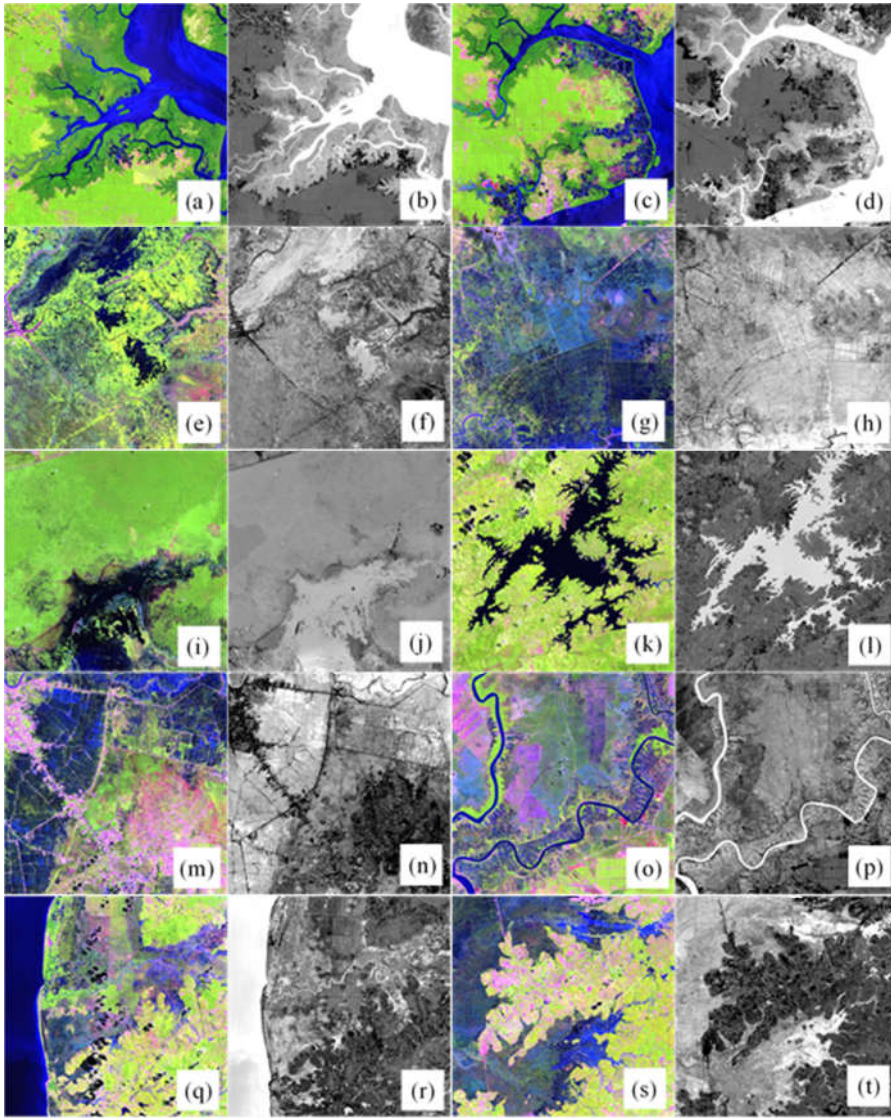
6
7 Based on Table 3 and Table 4, it appears that NDMI cannot distinguish between dryland
8 forest and wetlands forest. Likewise, the overall WRI has high accuracy, and as if it is able to
9 recognize all types of wetlands with good, it fails on a number of dryland features and take it as
10 wetlands. This translates into an overall accuracy WRI does not mean anything, because in fact
11 it could not distinguish well between wetland features and some dryland features.

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

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

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

28



1
 2 Figure 45. Comparison between Landsat 8 OLI composite 654 and $MNDW_{s2}$
 3 (a) and (b) mangrove; (c) and (d) fishpond; (e) and (f) freshwater lake and freshwater
 4 marshes; (g) and (h) irrigated land; (i) and (j) peatlands and peatswamps; (k) and (l) deep
 5 clear water (reservoir); (m) and (n) swamp rice fields and tree-dominated wetlands; (o) and

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

3 MNDWI uses the green band and SWIR1 band. In SWIR1, vegetation features have a
 4 much higher reflectance value than in green. We can see this fact in wetlands which are
 5 dominated by dense vegetation, as seen in Table 5 and Figure 65. Table 5 and Figure 65 are
 6 constructed using the mangroves, peatlands, and tree-dominated wetlands samples from this
 7 research. Where in the wetlands which are dominated by dense vegetation, such as mangroves,
 8 peatlands, and tree-dominated wetlands, reflectance values for SWIR1 are higher than
 9 reflectance values for green. As a result, green subtraction with SWIR1 in MNDWI causes
 10 vegetation features to be depressed. So that wetlands with dense vegetation are not detected as
 11 wetland features in MNDWI.

12 Not so with MNDWI2 which uses green bands and SWIR2 bands. Where in SWIR2,
 13 the reflectance value of vegetation features is not as high as in SWIR1. Even the spectral value
 14 tends to be similar to lower than green. We can also see this fact in Table 5 and Figure 65.
 15 Where in the wetlands which are dominated by dense vegetation, the reflectance values for
 16 SWIR2 are lower than reflectance values for SWIR1 or green. Thus, green subtraction using
 17 SWIR2 will not suppress vegetation features as in MNDWI. As a result, wetlands with dense
 18 vegetation can still be detected in MNDWI2. This makes MNDWI2 the most optimal spectral
 19 index in extracting vegetation-rich wetlands such as tropical wetlands. Figure 54 shows the
 20 comparison between Landsat 8 OLI composite 654 imageries and the MNDWI2 imageries.

21 Table 5. Average reflectance values on each Landsat 8 band on three types of dense vegetation
 22 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

Commented [A17]: I don't really get it. To my knowledge, healthy vegetation with high leaf moisture content should have a low reflectance on SWIR 1 and SWIR 2. This is especially true in wetlands such as mangrove. So, why did you mention that SWIR 1 reflectance is much higher than green? Can you please provide the figure showing the spectral response of the objects you classified.

Commented [A18R17]: The data are in Table 5 and Figure 6. Where Table 5 and Figure 6 are constructed using the Mangroves, Peatlands, and Tree-dominated wetlands samples from this research. From Table 5 it can be seen that for the three types of wetlands with dense vegetation, the spectral values for SWIR1 were higher than for Green.

23

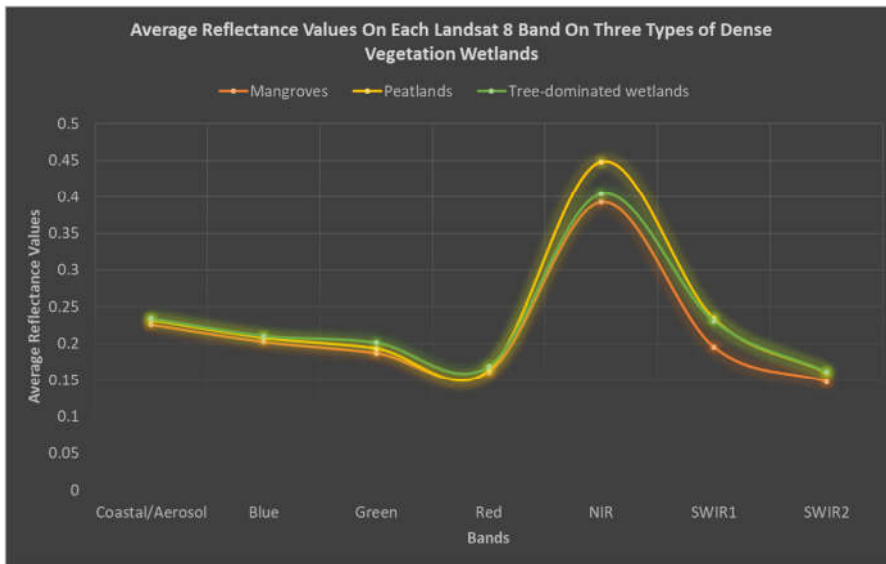


Figure 56. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

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MNDWI_{s2} 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 ~~SWIR1/SWIR2~~ band that do not capture reflections of open water features. Compared to MNDWI, MNDWI_{s2} still able to capture the reflection of background water or soil moisture beneath the canopy. In the MNDWI_{s2} 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 ~~OE~~ omission error to MNDWI_{s2}.

Commented [A19]: SWIR 1 or SWIR 2? It should be SWIR 2 right?

Commented [A20R19]: Yes, the correct one is SWIR2, we made a typo in this term.

Commented [A21]: What is OE?

Commented [A22R21]: OE is Omission Error. We've replaced the acronym with the abbreviation.

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

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

3 Like MNDWI, MNDWI_{s2} also uses a green band. In ~~spectral library spectral value~~
4 ~~curves~~, green band has the highest reflectance value of water features among all spectral bands.
5 So that open water features can be detected properly by MNDWI_{s2}. The advantage of
6 MNDWI_{s2} is the use of SWIR2, where in ~~spectral library spectral value curves~~ SWIR2 band has
7 a lower reflectance value of vegetation. So that subtraction green with SWIR2 will not cause
8 vegetation features to become depressed as in MNDWI.

9 The ability of MNDWI_{s2} in detecting peatlands with dense canopy as wetlands was very
10 impressive. ~~Given the peatlands actually not always saturated with water on the surface, most~~
11 ~~of them just has a very high water content in the ground with very high moisture surfaces.~~
12 ~~However, this condition is enough to make SWIR2 have very low reflections, so that green~~
13 ~~subtraction using SWIR2 will enhance moist surfaces such as peatlands.~~ ~~Will MNDWI_{s2} be~~
14 ~~considered as Normalized Difference Wetlands Index (NDWLI)? Well, of course, more~~
15 ~~research needs to be done to investigate.~~

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

21 Acknowledgement

22
23 The author_s thank to the United States Geological Survey (USGS) for providing the
24 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
25 the Spatial Data Infrastructure Development Center (PPIDS), University of Lambung
26 Mangkurat. Digital image processing in this research was carried out at the Remote Sensing
27 and Geographic Information System Laboratory, Faculty of Forestry, University of Lambung
28 Mangkurat, Banjarbaru.

29

Commented [A23]: Why not blue band?
Also, which spectral library? You did not discuss anything about spectral library in the manuscript before.

Commented [A24R23]: The green band has the highest reflectance value of water features, as seen in the spectral value curves in Figure 2 (The Methods section).

Commented [A25]: But this condition is enough to make SWIR1 and SWIR2 to reflect very lowly

Commented [A26R25]: Yes, it is true. We have added the statement in the paragraph. However, since in this paragraph we only discuss MNDWI_{s2} that use SWIR2, so we only include SWIR2 in our statement in this paragraph.

Commented [A27]: Don't use such sentence

Commented [A28R27]: We've refined the sentence, and tried to propose new sentence forms in the next paragraph without changing the information.

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RESPOND TO REVIEWER'S COMMENTS

Paper ID : #49914

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

No.	Page	Reviewer's comments	Author's responses
1	2	Provide references here all the several research results you mentioned	We've provided all the necessary references, as you suggest.
2	5	Provide coordinate to the image and also an inset. Some toponym will also be useful	We've fixed the image, and added some information according to your suggestions.
3	7	NDWI, MNDWI, and MNDWIs2 were explained in more detail. Why other indices are not?	In the methods, NDWI is a formula that is the basis for Xu (2006) in developing MNDWI, while MNDWI itself is a formula that is used as the basis for developing a new formula in this research, namely MNDWIs2. Of course, MNDWIs2 is a formula specifically developed in this research. Meanwhile, other indices are only cited from a number of literature, without any further development and not directly related to the development of a new formula in this research. These are the reasons why only NDWI, MNDWI, and MNDWIs2 are discussed in detail in the Methods section.
4	9	How many samples are for each of this class?	We've provided information on the number of sample pixels for each wetlands and drylands class.
5	9	Why do you need to create confusion matrix for each wetland class and dryland class? One confusion matrix can involve all the class altogether.	One confusion matrix can involve all the class altogether, this applies for example in the case of multispectral classification. However, in this research, spectral indices such as NDWI or others, are relatively difficult, or even completely unable to distinguish between Wetland classes. Given the spectral indices such as NDWI are only one band, not a multispectral imagery. One NDWI band is difficult to distinguish between Mangroves and

		<p>Peatlands, for example. While Peatlands in the case of this research are overgrown with dense forests whose spectral characters are similar to mangroves. We can confirm that the range of values between Mangroves and Peatlands in NDWI will be similar.</p> <p>Like the Normalized Difference Vegetation Index (NDVI) which can only separate between vegetation and non-vegetation, so in the context of this research, spectral indices such as NDWI are only considered to be able to separate between Wetlands and Drylands. This also underlies the use of Otsu thresholding as a method of separating the features in this research. Where Otsu thresholding can only produce 2 classes in one classification process.</p> <p>So when testing Mangroves on NDWI, for example, Mangroves will be tested with Non mangroves (the Drylands). When testing Peatlands on NDWI, Peatlands will be tested with Non peatlands (the Drylands). It is not possible to test Mangroves and Peatlands simultaneously on a single NDWI index, if such a test were forced the error would be very large.</p> <p>The same is true of Dryland classes. NDWI certainly cannot distinguish between Built-up lands and Barelands for example.</p> <p>A brief explanation of this has been provided in the Results and Discussion section. See page 12 line 1 to 9.</p>
--	--	--

6	14	What about the user's accuracy analysis?	<p>User's Accuracy (UA) analyzes are represented by Commission Error (CE) in Table 4.</p> <p>CE + UA = 100%, so if there is a CE of 15% for example, it means that the UA is 85%.</p>
7	19	<p>I don't really get it. To my knowledge, healthy vegetation with high leaf moisture content should have a low reflectance on SWIR 1 and SWIR 2. This is especially true in wetlands such as mangrove. So, why did you mention that SWIR 1 reflectance is much higher than green?</p> <p>Can you please provide the figure showing the spectral response of the objects you classified.</p>	<p>The data are in Table 5 and Figure 6. Where Table 5 and Figure 6 are constructed using the Mangroves, Peatlands, and Tree-dominated wetlands samples from this research. From Table 5 it can be seen that for the three types of wetlands with dense vegetation, the spectral values for SWIR1 were higher than for Green.</p>
8	21	<p>Why not blue band?</p> <p>Also, which spectral library? You did not discuss anything about spectral library in the manuscript before.</p>	<p>We've change the phrase spectral library into spectral value curves.</p> <p>The green band has the highest reflectance value of water features, as seen in the spectral value curves in Figure 2 (The Methods section).</p>
9	21	But this condition is enough to make SWIR1 and SWIR2 to reflect very lowly	<p>Yes, it is true. We have added the statement in the paragraph. However, since in the paragraph we only discuss MNDWIs2 that use SWIR2, so we only include SWIR2 in our statement in the paragraph.</p>
10	21	Don't use such sentence	<p>We've refined the sentence, and tried to propose new sentence forms in the next paragraph without changing the information.</p>

Important!

Please also indicate your changes in the revised manuscript using track changes or highlighted text.

**6. Bukti Konfirmasi Review Ketiga, Instruksi Editor
untuk Mengimprovisasi Manuskrip (25 Juni 2021)**

[IJG] Editor Decision: Revision Required

5 messages

Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id>

Fri, Jun 25, 2021 at 10:06 AM

To: Syamani Darmawi Ali <syamani.fhut@ulm.ac.id>

Cc: Hartono Hartono <hartono@geo.ugm.ac.id>, Projo Danoedoro <projo.danoedoro@geo.ugm.ac.id>

Dear Dr. Syamani Darmawi Ali,

We are generally happy with the revised version of your manuscript. However, before we can recommend your manuscript for publication, I want you to improve your manuscript based on my comment. See attached file.

Once again, thank you for submitting your manuscript to the Indonesian Journal of Geography and I look forward to receiving your revision no later than 30 days from now. If you failed to meet the deadline, we may have to consider your paper rejected.

NB: Please use the follow the guideline in the attached template for your revision.

Best wishes,
Dr. Pramaditya Wicaksono
Faculty of Geography Universitas Gadjah Mada, Yogyakarta
Phone +6281391179917
Fax +62274569595
prama.wicaksono@geo.ugm.ac.id
Section Editor
Indonesian Journal of Geography
Faculty of Geography, Universitas Gadjah Mada, Yogyakarta

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Syam'ani <syamani.fhut@ulm.ac.id>

Fri, Jun 25, 2021 at 10:13 AM

To: Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id>

Cc: Hartono Hartono <hartono@geo.ugm.ac.id>, Projo Danoedoro <projo.danoedoro@geo.ugm.ac.id>

Thank you, I will do that.

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From: "Syam'ani" <syamani.fhut@ulm.ac.id>

To: Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id>

Cc: Hartono Hartono <hartono@geo.ugm.ac.id>, Projo Danoedoro <projo.danoedoro@geo.ugm.ac.id>

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Date: Fri, 25 Jun 2021 10:13:07 +0800

Subject: Re: [IJG] Editor Decision: Revision Required

Thank you, I will do that.

Pada tanggal Jum, 25 Jun 2021 10.07, Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id> menulis:

Dear Dr. Syamani Darmawi Ali,

We are generally happy with the revised version of your manuscript. However, before we can recommend your manuscript for publication, I want you to improve your manuscript based on my comment. See attached file.

Once again, thank you for submitting your manuscript to the Indonesian Journal of Geography and I look forward to receiving your revision no later than 30 days from now. If you failed to meet the deadline, we may have to consider your paper rejected.

NB: Please use the follow the guideline in the attached template for your revision.

Best wishes,

Dr. Pramaditya Wicaksono

Faculty of Geography Universitas Gadjah Mada, Yogyakarta

Phone +6281391179917

Fax +62274569595

prama.wicaksono@geo.ugm.ac.id

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<http://jurnal.ugm.ac.id/index.php/ijg>
0024-9521 (print), 2354-9114 (online)
Phone: +62 812-2711-480

Syam'ani <syamani.fhut@ulm.ac.id>
Draft To: Mail Delivery Subsystem <mailer-daemon@googlemail.com>

Fri, Jun 25, 2021 at 5:15 PM

Dear Dr. Pramaditya Wicaksono

We have revised the manuscript, and we have resubmitted the revised results of our manuscript along with responses to reviewer comments through OJS Indonesian Journal of Geography.

Thank you for your attention,

Syamani D. Ali

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

3

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

14

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

16

17 **Abstrak**Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
18 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
19 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
20 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
21 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
22 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
23 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
24 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
25 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
26 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

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

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34 **1. Introduction**

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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

1 Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM +.
2 It was found that in general, MNDWI remains the best among the three other spectral indices.

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

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

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

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

23 Other researchers, such as Yang et al. (2015) combined spectral indices and single band
24 multispectral imagery simultaneously to extract water features. They use a number of spectral
25 indices and single band on Landsat 8 OLI to extract the water bodies. Those are, the single-
26 band threshold in band 5, multiband spectral relationship b2, b3, b4, b5, NDVI, NDWI,
27 MNDWI, Normalized Difference Built-up Index (NDBI), TCT, and Hue, Intensity and
28 Saturation (HIS). Where all of the spectral indices and bands are combined using deep learning
29 algorithm, called Stacked Sparse Autoencoder (SSAE).

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

8

9 **2.The Methods**

10

11 2.1.Materials

12

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

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

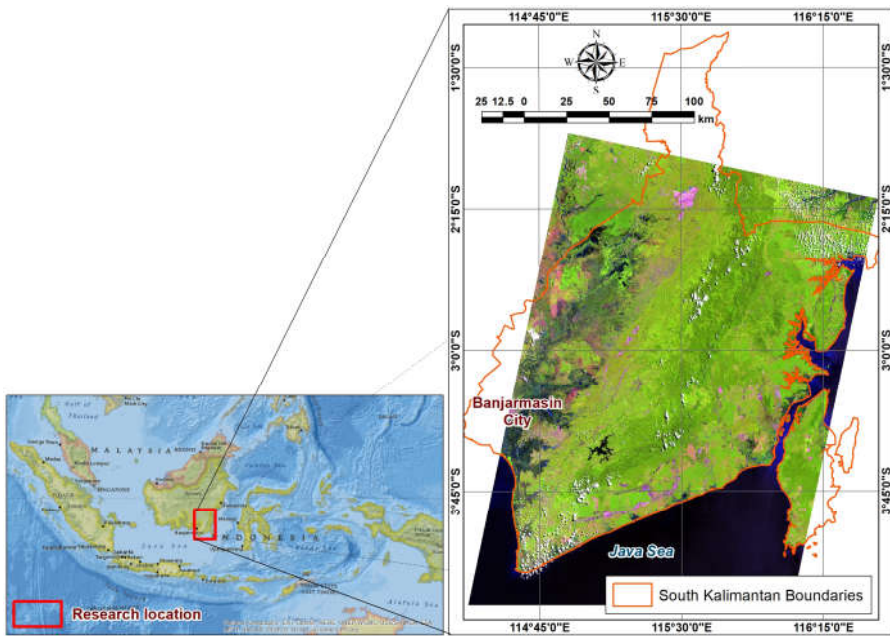


Figure 1. Research location

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:

$$NDWI = \frac{\rho_g - \rho_n}{\rho_g + \rho_n}$$

Where:

- ρ_g : green band
- ρ_n : near infrared band

Commented [A1]: Please number the formula

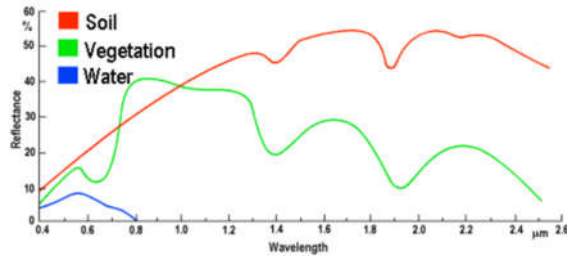


Figure 2. Spectral value curves on three base surface features

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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.

$$MNDWI = \frac{\rho_g - \rho_s}{\rho_g + \rho_s}$$

Commented [A3]: Please number the formula

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:

$$MNDWI_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$$

Commented [A4]: Please number the formula

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.

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

4
 5 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 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)

6
 7 Information:

- 8 • ρ_{ca} : aerosol coastal bands (bands 1 Landsat 8)
 9 • ρ_b : blue band (band 2 Landsat 8)

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

7

8 2.3. Wetlands Extraction

9

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

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

18

19 2.4. Accuracy Assessment

20

21 Accuracy assessment was conducted using the Confusion Matrix (Stehman and
22 Czaplewski, 1997), using a number of sample locations were selected purposively. In this case,
23 the location of the sample represents multiple characters wetlands in South Kalimantan.
24 Namely, mangroves, salt marshes, deep water (include reservoirs, canals, and coal open pits),
25 peatlands, peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish ponds,
26 swamp rice fields, irrigated land, freshwater marshes, and freshwater lake. Therefore, there are
27 a total of 12 samples for wetland classes. Meanwhile, the number of sample pixels for each
28 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
29 2,330 pixels respectively.

1 For the purpose of assessing the deeper capabilities of each spectral index, the sample
2 locations were also chosen purposively on various dryland features that have the potential to
3 be detected as wetlands. In the appointment of the samples, the method used is knowledge-
4 based. There are a total of 10 samples for dryland classes. Namely, built-up lands, barelands,
5 grass, roads, dryland forest, dryland farms, garden (include mix garden, rubber plants, palm
6 oil), and shrub and bushes. The number of sample pixels for each of these drylands classes are
7 1,236, 4,003, 2,377, 323, 6,445, 2,169, 4,694, and 8,075 pixels, respectively.

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

16 Furthermore, to test the ability of each spectral index to recognize each wetland class, a
17 confusion matrix was constructed for each spectral index in each wetland class. For example,
18 for NDWI in the Mangroves class, a confusion matrix will be constructed. Furthermore, from
19 the resulting confusion matrix the Producer's Accuracy value will be taken, to obtain a
20 quantitative description of the ability of the spectral index to recognize one type of wetland. So
21 we will get an overview of NDWI's ability to recognize Mangroves for example. Recapitulation
22 of producer's accuracy values for each spectral index in each wetland class can be seen in Table
23 3.

24 The final step, to test the ability of each spectral index to avoid the detection of dryland
25 features, a confusion matrix is constructed for each spectral index in each dryland class. For
26 example, for NDWI in the Dryland Forest class, a confusion matrix will be constructed.
27 Furthermore, from the resulting confusion matrix the Commission Error value will be taken,
28 to obtain a quantitative description of the ability of the spectral index to avoid the detection of
29 one type of dryland. So that a description of NDWI's ability to avoid detecting Dryland Forest

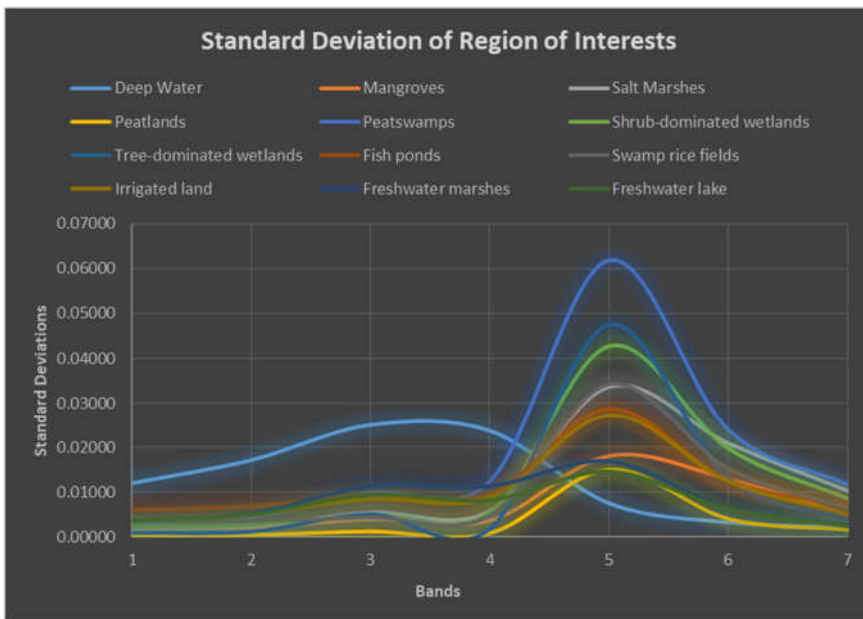
1 as a wetland will be obtained, for example. Recapitulation of commission error values for each
2 spectral index in each dryland class can be seen in Table 4.

3

4 3.Result and Discussion

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

12



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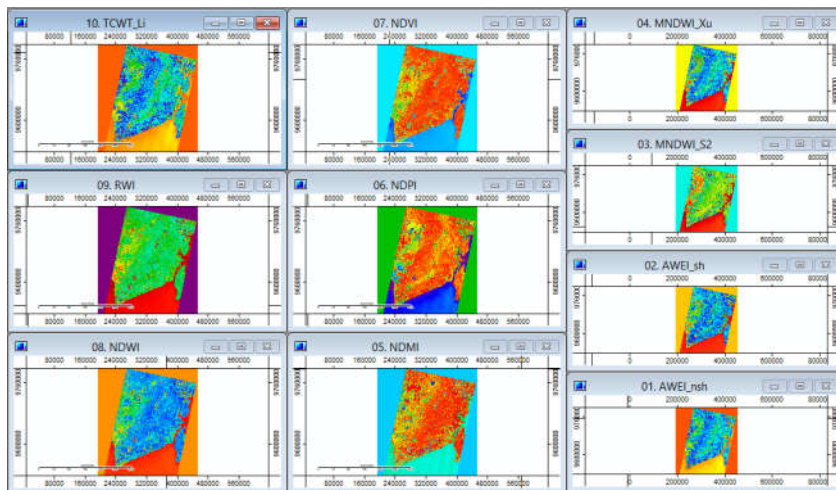
14 Figure 3. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

15

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

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

15



16
 17 Figure 4. The result of the transformation of spectral indices on the SAGA application

18
 19 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 _{k2}	≥ 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 _{nsb}	≥ -0.55	54.15	0.31	57.11	99.99	0.01	42.89
10.	AWEI _{sb}	≥ -0.20	62.46	0.41	72.53	98.87	1.13	27.47

1

2 Information:

- 3
- 4 • OA: Overall Accuracy
 - 5 • PA: Producer's Accuracy
 - 6 • UA: User's Accuracy
 - 7 • CE: Commission Error
 - 8 • OE: Omission Error

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

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

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

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

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

No.	Spectral Indices	Producer's Accuracy (%)											
		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 _{mh}	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

14

15 Information:

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

- 1 • Sw: Shrub-dominated wetlands
- 2 • Tw: Tree-dominated wetlands
- 3 • Fp: Fish ponds
- 4 • Sr: Swamp rice fields
- 5 • Il: Irrigated land
- 6 • Fm: Freshwater marshes
- 7 • Fl: Freshwater lake

8
9 The entire spectral indices, except NDMI, do not have a problem when extracting the
10 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
11 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
12 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
13 2004).

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

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

26 MNDWI and $MNDWI_{s2}$ quite successful in identifying wetlands. Except MNDWI
27 failed to recognize the peatlands and tree-dominated wetlands. Where these two features are
28 wetlands with dense canopy. Not so with $MNDWI_{s2}$ capable of recognizing peatlands and tree-
29 dominated wetlands with almost 100% accuracy. Based on this fact, our assumption when

1 shifting SWIR1 into SWIR2 on MNDWI has been proven. MNDWI_{s2} able to recognize the
 2 characteristic spectral features that have water and vegetation spectral characteristics as well
 3 with better.

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

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

14 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

15

16 Information:

- 17 • Bu: Built-up lands
- 18 • Bl: Barelands
- 19 • Gr: Grass

- 1 • R: Roads
- 2 • F: Dryland forest
- 3 • Df: Dryland farms
- 4 • Gd: Garden (mixgarden, rubber plants, palm oil)
- 5 • Sb: Shrub and bushes

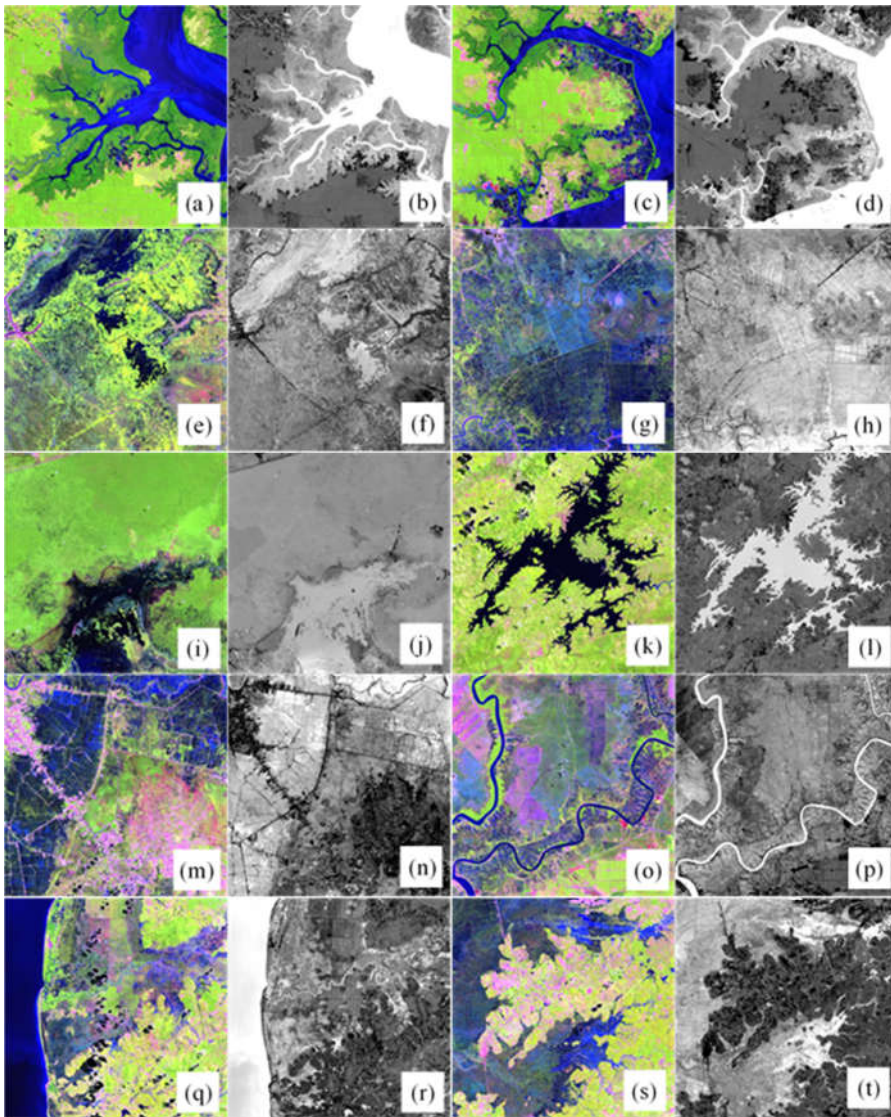
6
7 Based on Table 3 and Table 4, it appears that NDMI cannot distinguish between dryland
8 forest and wetlands forest. Likewise, the overall WRI has high accuracy, and as if it is able to
9 recognize all types of wetlands with good, it fails on a number of dryland features and take it as
10 wetlands. This translates into an overall accuracy WRI does not mean anything, because in fact
11 it could not distinguish well between wetland features and some dryland features.

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

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

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

28



1

2

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

3

(a) and (b) mangrove; (c) and (d) fishpond; (e) and (f) freshwater lake and freshwater

4

marshes; (g) and (h) irrigated land; (i) and (j) peatlands and peatswamps; (k) and (l) deep

5

clear water (reservoir); (m) and (n) swamp rice fields and tree-dominated wetlands; (o) and

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

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

12 Not so with MNDWI₂ which uses green bands and SWIR2 bands. Where in SWIR2,
 13 the reflectance value of vegetation features is not as high as in SWIR1. Even the spectral value
 14 tends to be lower than green. We can also see this fact in Table 5 and Figure 6. Where in the
 15 wetlands which are dominated by dense vegetation, the reflectance values for SWIR2 are lower
 16 than reflectance values for SWIR1 or green. Thus, green subtraction using SWIR2 will not
 17 suppress vegetation features as in MNDWI. As a result, wetlands with dense vegetation can still
 18 be detected in MNDWI₂. This makes MNDWI₂ the most optimal spectral index in extracting
 19 vegetation-rich wetlands such as tropical wetlands. Figure 5 shows the comparison between
 20 Landsat 8 OLI composite 654 imageries and the MNDWI₂ imageries.

21 Table 5. Average reflectance values on each Landsat 8 band on three types of dense vegetation
 22 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

23

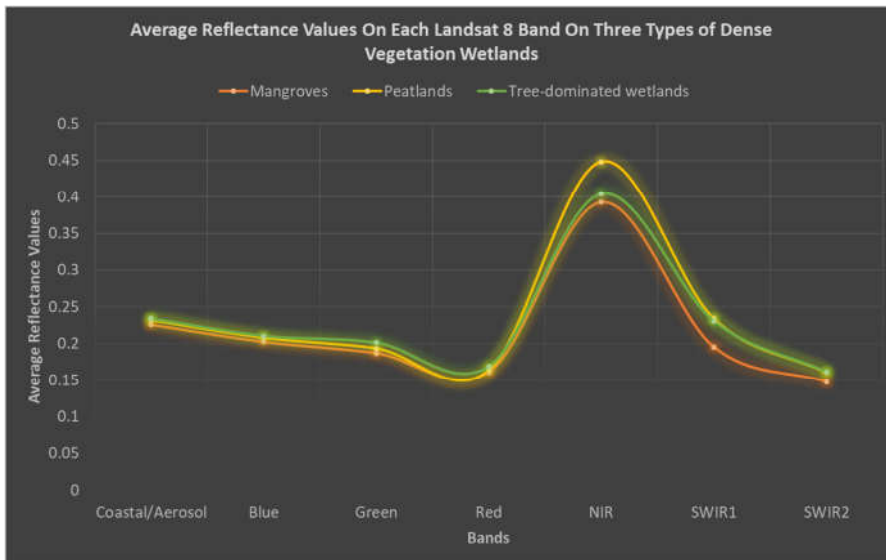


Figure 6. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

MNDWI_{s2} 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, MNDWI_{s2} still able to capture the reflection of background water or soil moisture beneath the canopy. In the MNDWI_{s2} 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 MNDWI_{s2}.

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 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.

Commented [A5]: 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

1 Like MNDWI, MNDWI_{s2} also uses a green band. In spectral value curves, green band
2 has the highest reflectance value of water features among all spectral bands. So that open water
3 features can be detected properly by MNDWI_{s2}. The advantage of MNDWI_{s2} is the use of
4 SWIR₂, where in spectral value curves SWIR₂ band has a lower reflectance value of vegetation.
5 So that subtraction green with SWIR₂ will not cause vegetation features to become depressed
6 as in MNDWI.

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

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

16

17 **Acknowledgement**

18 The authors thank to the United States Geological Survey (USGS) for providing the
19 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
20 the Spatial Data Infrastructure Development Center (PPIDS), University of Lambung
21 Mangkurat. Digital image processing in this research was carried out at the Remote Sensing
22 and Geographic Information System Laboratory, Faculty of Forestry, University of Lambung
23 Mangkurat, Banjarbaru.

24

25

26

27 **References**

28

Commented [A6]: Please make sure that all your cited references are listed here and vice versa

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**7. Respon Kepada Reviewer dan Hasil Improvisasi
Manuskrip (25 Juni 2021)**

1 Comparison of Various Spectral Indices for Optimum Extraction 2 of Tropical Wetlands Using Landsat 8 OLI

3

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

14

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

16

17 **Abstrak** Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
18 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
19 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
20 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
21 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
22 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
23 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
24 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
25 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
26 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

27

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

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1 1. Introduction

2

3 Wetlands are ecosystems saturated with water, either seasonally or permanently (EPA,
4 2004). According to the Ramsar Convention on Wetlands 1993 (Matthews, 2013), based on the
5 habitat, wetlands classified into marine and coastal wetlands, inland wetlands, and man-made
6 wetlands. In the South Kalimantan Province, Indonesia, wetlands are one of the main features
7 of the landscape.

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

15 So far, various methods have been developed for the extraction of wetlands geospatial
16 data automatically. For example, the Normalized Difference Water Index (NDWI) (McFeeters,
17 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and so forth.
18 NDWI and MNDWI are the two most popular spectral indices for the extraction of water
19 features or wetland features. Their ability to extract open water features or wetland features has
20 been tested from several research results (McFeeters, 1996; Xu, 2006; Li et al., 2013; Jiang et al.,
21 2014; Ashraf and Nawaz, 2015; Das and Pal, 2016; Du et al., 2016). Besides NDWI or MNDWI,
22 there are also a number of other spectral indices that can potentially be used to separate wetland
23 features from other features.

24 In general, spectral indices such as NDWI or MNDWI are actually developed to
25 separate open water features from other features. Some research indicates that the spectral
26 indices are very accurate in extracting the boundaries of water features. For example, Xu (2006)
27 proved that MNDWI more accurate than NDWI when applied to the three water features, i.e.
28 lakes, oceans, and rivers. Similar to Xu (2006), Li et al. (2013) also found that MNDWI more
29 accurate than NDWI to the TM, ETM +, and ALI imagery. To further test MNDWI's

1 capabilities, Jiang et al. (2014) developed the Automated Method for Extracting Rivers and
2 Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM +.
3 It was found that in general, MNDWI remains the best among the three other spectral indices.

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

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

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

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

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

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

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

10

11 **2.The Methods**

12

13 2.1.Materials

14

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

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

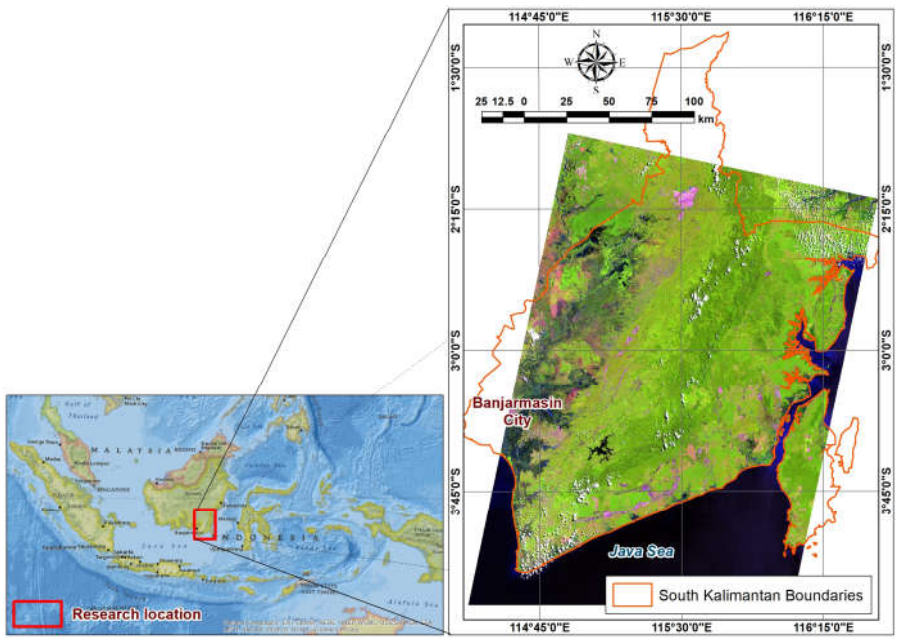


Figure 1. Research location

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:

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

Where:

- ρ_g : green band
- ρ_n : near infrared band

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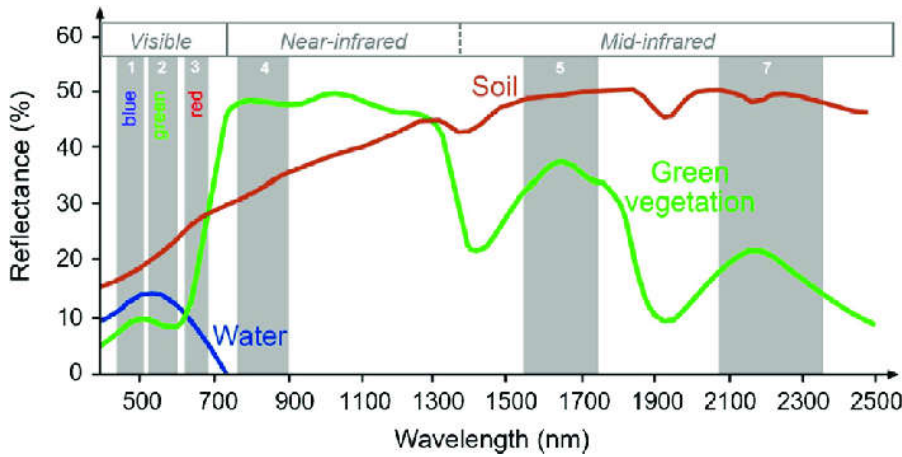


Figure 2. Spectral value curves on three base surface features (Chen et al., 2019)

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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.

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

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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:

$$MNDWI_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}} \quad (3)$$

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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

1 vegetation located above the wetlands. Because vegetation reflectance in SWIR2 is not as high
 2 as SWIR1 and NIR.

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

6

7

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 Gao (1996); Wilson and Sader (2002); Xiao et al. (2002); Lacaux et al. (2007)
5.	NDMI Normalized Difference Moisture Index	$\frac{\rho_n - \rho_s}{\rho_n + \rho_s}$	Positive	
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 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)

8

9 Information:

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

9

10 2.3. Wetlands Extraction

11

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

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

20

21 2.4. Accuracy Assessment

22

23 Accuracy assessment was conducted using the Confusion Matrix (Stehman and
24 Czaplewski, 1997), using a number of sample locations were selected purposively. In this case,
25 the location of the sample represents multiple characters wetlands in South Kalimantan.
26 Namely, mangroves, salt marshes, deep water (include reservoirs, canals, and coal open pits),
27 peatlands, peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish ponds,
28 swamp rice fields, irrigated land, freshwater marshes, and freshwater lake. Therefore, there are
29 a total of 12 samples for wetland classes. Meanwhile, the number of sample pixels for each

1 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 2,330 pixels respectively.

3 For the purpose of assessing the deeper capabilities of each spectral index, the sample
4 locations were also chosen purposively on various dryland features that have the potential to
5 be detected as wetlands. In the appointment of the samples, the method used is knowledge-
6 based. There are a total of 10 samples for dryland classes. Namely, built-up lands, barelands,
7 grass, roads, dryland forest, dryland farms, garden (include mix garden, rubber plants, palm
8 oil), and shrub and bushes. The number of sample pixels for each of these drylands classes are
9 1,236, 4,003, 2,377, 323, 6,445, 2,169, 4,694, and 8,075 pixels, respectively.

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

18 Furthermore, to test the ability of each spectral index to recognize each wetland class, a
19 confusion matrix was constructed for each spectral index in each wetland class. For example,
20 for NDWI in the Mangroves class, a confusion matrix will be constructed. Furthermore, from
21 the resulting confusion matrix the Producer's Accuracy value will be taken, to obtain a
22 quantitative description of the ability of the spectral index to recognize one type of wetland. So
23 we will get an overview of NDWI's ability to recognize Mangroves for example. Recapitulation
24 of producer's accuracy values for each spectral index in each wetland class can be seen in Table
25 3.

26 The final step, to test the ability of each spectral index to avoid the detection of dryland
27 features, a confusion matrix is constructed for each spectral index in each dryland class. For
28 example, for NDWI in the Dryland Forest class, a confusion matrix will be constructed.
29 Furthermore, from the resulting confusion matrix the Commission Error value will be taken,

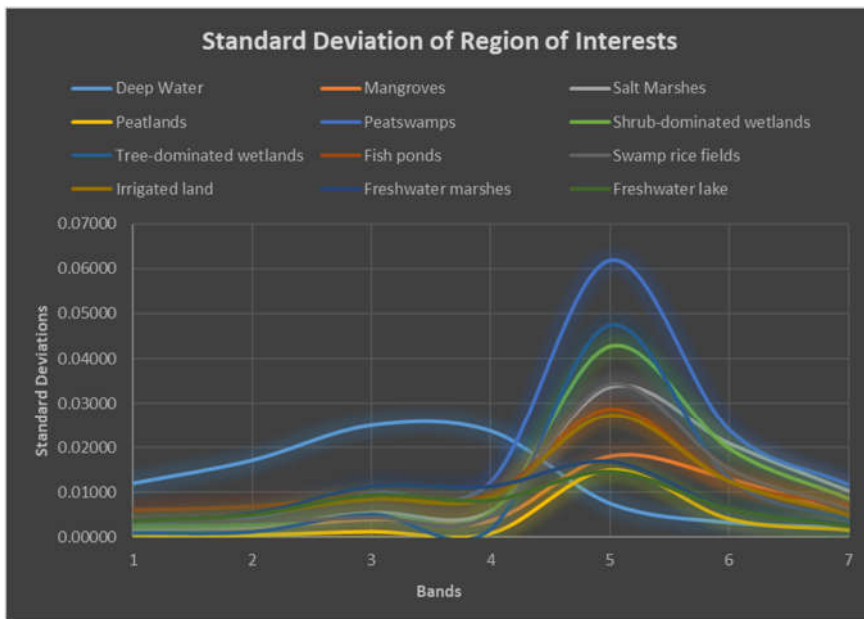
1 to obtain a quantitative description of the ability of the spectral index to avoid the detection of
2 one type of dryland. So that a description of NDWI's ability to avoid detecting Dryland Forest
3 as a wetland will be obtained, for example. Recapitulation of commission error values for each
4 spectral index in each dryland class can be seen in Table 4.

5

6 **3.Result and Discussion**

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

14



15

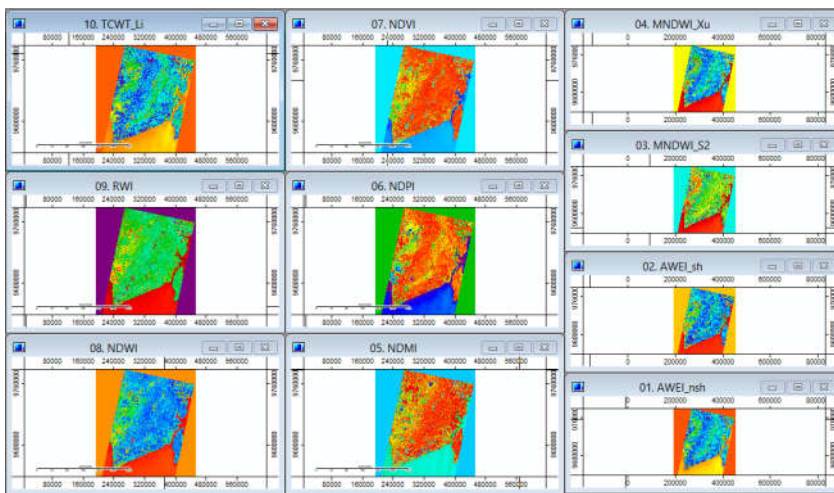
16 Figure 3. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

1

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

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

16



17

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

19

1 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 ₁₂	≥ 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 _{nh}	≥ -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

2

3 Information:

- 4 • OA: Overall Accuracy
- 5 • PA: Producer's Accuracy
- 6 • UA: User's Accuracy
- 7 • CE: Commission Error
- 8 • OE: Omission Error

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

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

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

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

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

No.	Spectral Indices	Producer's Accuracy (%)											
		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 _{mh}	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

14

15 Information:

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

- 1 • Sw: Shrub-dominated wetlands
- 2 • Tw: Tree-dominated wetlands
- 3 • Fp: Fish ponds
- 4 • Sr: Swamp rice fields
- 5 • Il: Irrigated land
- 6 • Fm: Freshwater marshes
- 7 • Fl: Freshwater lake

8
9 The entire spectral indices, except NDMI, do not have a problem when extracting the
10 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
11 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
12 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
13 2004).

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

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

26 MNDWI and $MNDWI_{s2}$ quite successful in identifying wetlands. Except MNDWI
27 failed to recognize the peatlands and tree-dominated wetlands. Where these two features are
28 wetlands with dense canopy. Not so with $MNDWI_{s2}$ capable of recognizing peatlands and tree-
29 dominated wetlands with almost 100% accuracy. Based on this fact, our assumption when

1 shifting SWIR1 into SWIR2 on MNDWI has been proven. MNDWI_{s2} able to recognize the
 2 characteristic spectral features that have water and vegetation spectral characteristics as well
 3 with better.

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

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

14 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 _{nh}	0	0	0	0	0.06	0	0	0
10.	AWEI _{sh}	20.47	1.27	0	95.05	0.14	0	0	0

15

16 Information:

- 17 • Bu: Built-up lands
- 18 • Bl: Barelands
- 19 • Gr: Grass

- 1 • R: Roads
- 2 • F: Dryland forest
- 3 • Df: Dryland farms
- 4 • Gd: Garden (mixgarden, rubber plants, palm oil)
- 5 • Sb: Shrub and bushes

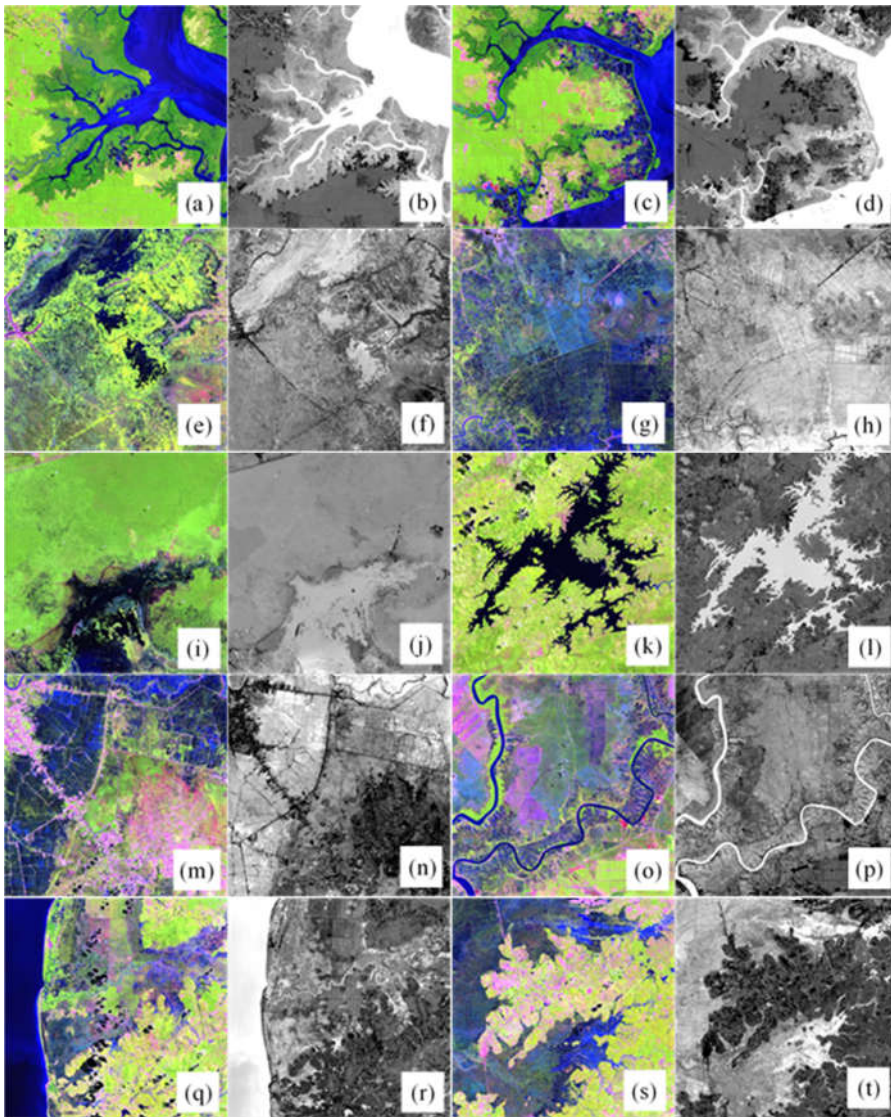
6
7 Based on Table 3 and Table 4, it appears that NDMI cannot distinguish between dryland
8 forest and wetlands forest. Likewise, the overall WRI has high accuracy, and as if it is able to
9 recognize all types of wetlands with good, it fails on a number of dryland features and take it as
10 wetlands. This translates into an overall accuracy WRI does not mean anything, because in fact
11 it could not distinguish well between wetland features and some dryland features.

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

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

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

28



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4
5

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

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

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

12 Not so with MNDWI₂ which uses green bands and SWIR2 bands. Where in SWIR2,
 13 the reflectance value of vegetation features is not as high as in SWIR1. Even the spectral value
 14 tends to be lower than green. We can also see this fact in Table 5 and Figure 6. Where in the
 15 wetlands which are dominated by dense vegetation, the reflectance values for SWIR2 are lower
 16 than reflectance values for SWIR1 or green. Thus, green subtraction using SWIR2 will not
 17 suppress vegetation features as in MNDWI. As a result, wetlands with dense vegetation can still
 18 be detected in MNDWI₂. This makes MNDWI₂ the most optimal spectral index in extracting
 19 vegetation-rich wetlands such as tropical wetlands. Figure 5 shows the comparison between
 20 Landsat 8 OLI composite 654 imageries and the MNDWI₂ imageries.

21 Table 5. Average reflectance values on each Landsat 8 band on three types of dense vegetation
 22 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

23

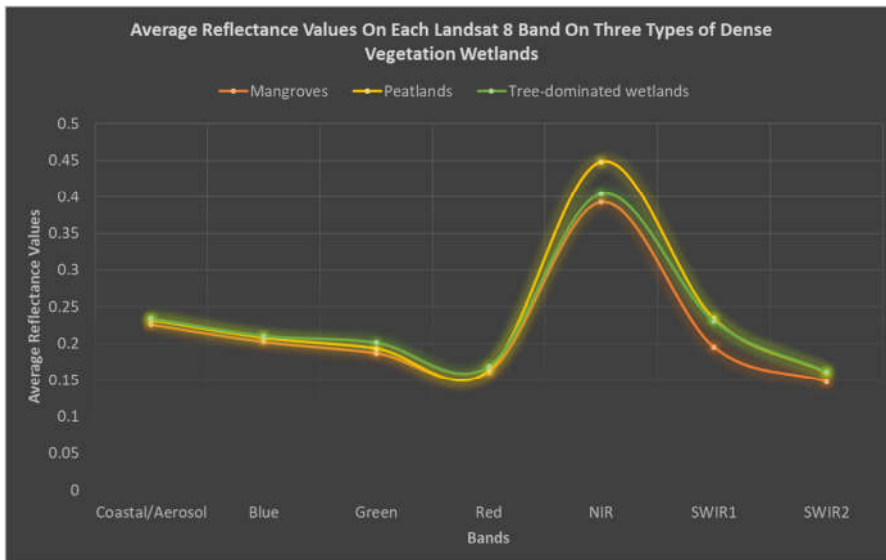


Figure 6. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

MNDWI_{s2} 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, MNDWI_{s2} still able to capture the reflection of background water or soil moisture beneath the canopy. In the MNDWI_{s2} 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 MNDWI_{s2}.

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 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.

Commented [A9]: 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 [A10R9]: 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.

1 Like MNDWI, MNDWI_{s2} also uses a green band. In spectral value curves, green band
2 has the highest reflectance value of water features among all spectral bands. So that open water
3 features can be detected properly by MNDWI_{s2}. The advantage of MNDWI_{s2} is the use of
4 SWIR2, where in spectral value curves SWIR2 band has a lower reflectance value of vegetation.
5 So that subtraction green with SWIR2 will not cause vegetation features to become depressed
6 as in MNDWI.

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

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

16

17 **Acknowledgement**

18 The authors thank to the United States Geological Survey (USGS) for providing the
19 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
20 the Spatial Data Infrastructure Development Center (PPIDS), University of Lambung
21 Mangkurat. Digital image processing in this research was carried out at the Remote Sensing
22 and Geographic Information System Laboratory, Faculty of Forestry, University of Lambung
23 Mangkurat, Banjarbaru.

24

25

26

27 **References**

28

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Paper ID : #49914

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

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2	9	Provide reference for this figure	I've provided a reference for this figure
3	9	Please number the formula	I've given the number for the formula
4	9	Please number the formula	I've given the number for the formula
5	21	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	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.
6	22	Please make sure that all your cited references are listed here and vice versa	I've made sure that all the references I cite are listed here, and vice versa

Important!

Please also indicate your changes in the revised manuscript using track changes or highlighted text.

1 Comparison of Various Spectral Indices for Optimum Extraction 2 of Tropical Wetlands Using Landsat 8 OLI

3

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

14

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

16

17 **Abstrak** Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
18 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
19 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
20 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
21 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
22 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
23 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
24 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
25 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
26 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

27

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

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1 1. Introduction

2

3 Wetlands are ecosystems saturated with water, either seasonally or permanently (EPA,
4 2004). According to the Ramsar Convention on Wetlands 1993 (Matthews, 2013), based on the
5 habitat, wetlands classified into marine and coastal wetlands, inland wetlands, and man-made
6 wetlands. In the South Kalimantan Province, Indonesia, wetlands are one of the main features
7 of the landscape.

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

15 So far, various methods have been developed for the extraction of wetlands geospatial
16 data automatically. For example, the Normalized Difference Water Index (NDWI) (McFeeters,
17 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and so forth.
18 NDWI and MNDWI are the two most popular spectral indices for the extraction of water
19 features or wetland features. Their ability to extract open water features or wetland features has
20 been tested from several research results (McFeeters, 1996; Xu, 2006; Li et al., 2013; Jiang et al.,
21 2014; Ashraf and Nawaz, 2015; Das and Pal, 2016; Du et al., 2016). Besides NDWI or MNDWI,
22 there are also a number of other spectral indices that can potentially be used to separate wetland
23 features from other features.

24 In general, spectral indices such as NDWI or MNDWI are actually developed to
25 separate open water features from other features. Some research indicates that the spectral
26 indices are very accurate in extracting the boundaries of water features. For example, Xu (2006)
27 proved that MNDWI more accurate than NDWI when applied to the three water features, i.e.
28 lakes, oceans, and rivers. Similar to Xu (2006), Li et al. (2013) also found that MNDWI more
29 accurate than NDWI to the TM, ETM +, and ALI imagery. To further test MNDWI's

1 capabilities, Jiang et al. (2014) developed the Automated Method for Extracting Rivers and
2 Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM +.
3 It was found that in general, MNDWI remains the best among the three other spectral indices.

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

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

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

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

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

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

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

10

11 **2.The Methods**

12

13 2.1.Materials

14

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

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

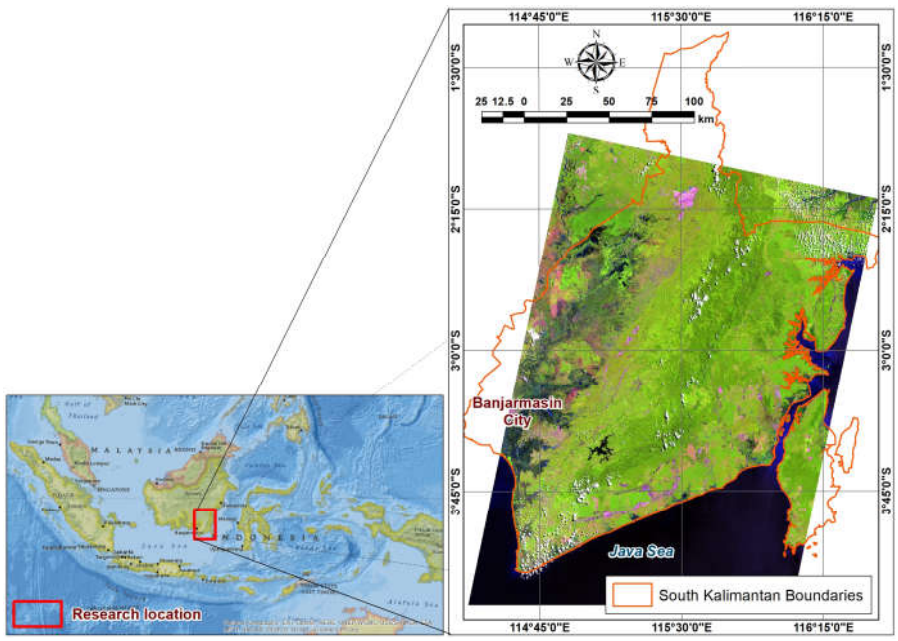


Figure 1. Research location

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:

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

Where:

- ρ_g : green band
- ρ_n : near infrared band

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Commented [A2R1]: I've given the number for the formula

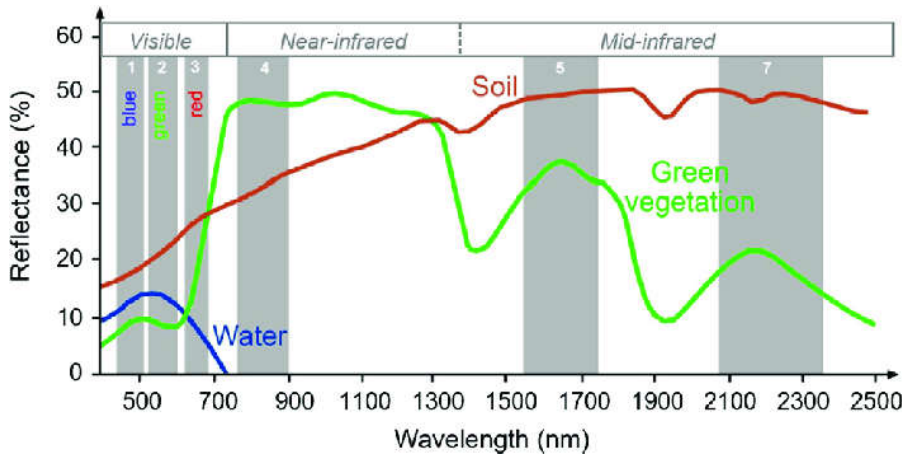


Figure 2. Spectral value curves on three base surface features (Chen et al., 2019)

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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.

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

Commented [A5]: Please number the formula

Commented [A6R5]: I've given the number for the formula

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:

$$MNDWI_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}} \quad (3)$$

Commented [A7]: Please number the formula

Commented [A8R7]: I've given the number for the formula

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

1 vegetation located above the wetlands. Because vegetation reflectance in SWIR2 is not as high
 2 as SWIR1 and NIR.

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

6

7

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 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)

8

9 Information:

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

9

10 2.3. Wetlands Extraction

11

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

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

20

21 2.4. Accuracy Accuracy Assessment

22

23 Accuracy assessment was conducted using the Confusion Matrix (Stehman and
24 Czaplewski, 1997), using a number of sample locations were selected purposively. In this case,
25 the location of the sample represents multiple characters wetlands in South Kalimantan.
26 Namely, mangroves, salt marshes, deep water (include reservoirs, canals, and coal open pits),
27 peatlands, peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish ponds,
28 swamp rice fields, irrigated land, freshwater marshes, and freshwater lake. Therefore, there are
29 a total of 12 samples for wetland classes. Meanwhile, the number of sample pixels for each

1 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 2,330 pixels respectively.

3 For the purpose of assessing the deeper capabilities of each spectral index, the sample
4 locations were also chosen purposively on various dryland features that have the potential to
5 be detected as wetlands. In the appointment of the samples, the method used is knowledge-
6 based. There are a total of 10 samples for dryland classes. Namely, built-up lands, barelands,
7 grass, roads, dryland forest, dryland farms, garden (include mix garden, rubber plants, palm
8 oil), and shrub and bushes. The number of sample pixels for each of these drylands classes are
9 1,236, 4,003, 2,377, 323, 6,445, 2,169, 4,694, and 8,075 pixels, respectively.

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

18 Furthermore, to test the ability of each spectral index to recognize each wetland class, a
19 confusion matrix was constructed for each spectral index in each wetland class. For example,
20 for NDWI in the Mangroves class, a confusion matrix will be constructed. Furthermore, from
21 the resulting confusion matrix the Producer's Accuracy value will be taken, to obtain a
22 quantitative description of the ability of the spectral index to recognize one type of wetland. So
23 we will get an overview of NDWI's ability to recognize Mangroves for example. Recapitulation
24 of producer's accuracy values for each spectral index in each wetland class can be seen in Table
25 3.

26 The final step, to test the ability of each spectral index to avoid the detection of dryland
27 features, a confusion matrix is constructed for each spectral index in each dryland class. For
28 example, for NDWI in the Dryland Forest class, a confusion matrix will be constructed.
29 Furthermore, from the resulting confusion matrix the Commission Error value will be taken,

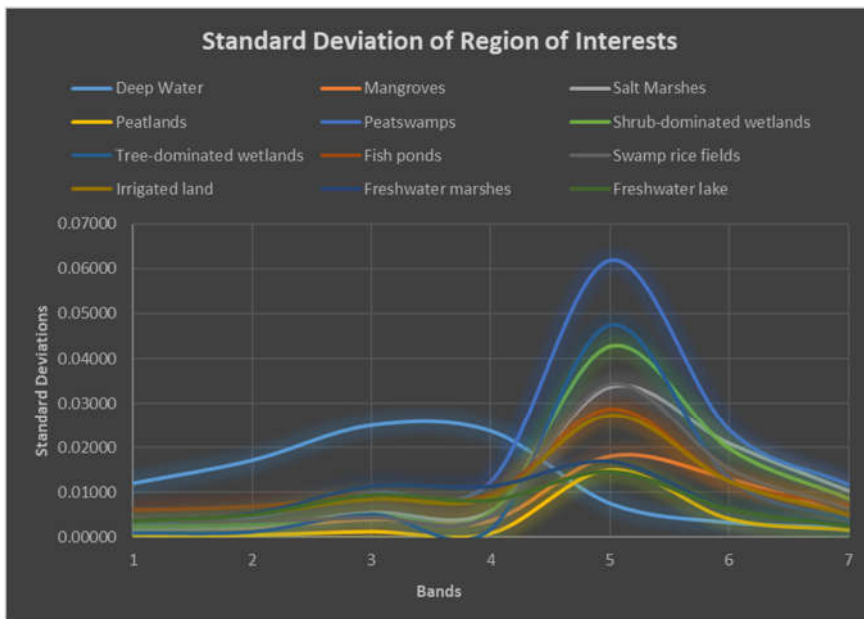
1 to obtain a quantitative description of the ability of the spectral index to avoid the detection of
2 one type of dryland. So that a description of NDWI's ability to avoid detecting Dryland Forest
3 as a wetland will be obtained, for example. Recapitulation of commission error values for each
4 spectral index in each dryland class can be seen in Table 4.

5

6 **3.Result and Discussion**

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

14



15

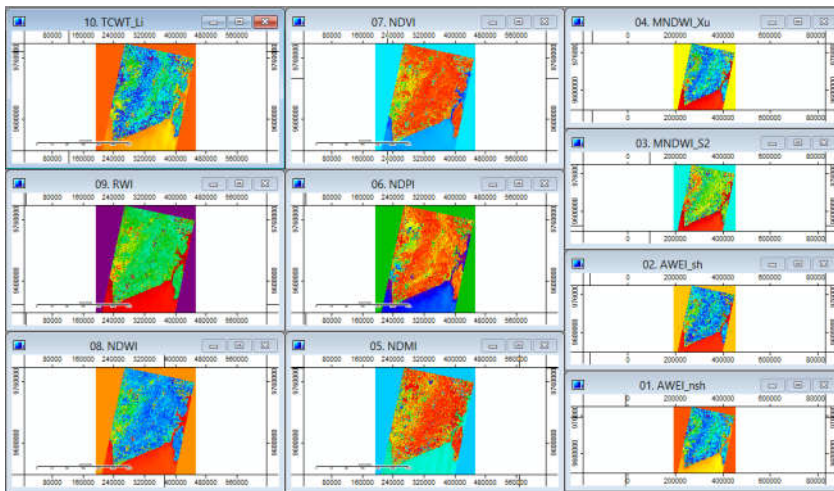
16 Figure 3. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

1

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

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

16



17

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

19

1 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 ₁₂	≥ 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 _{nh}	≥ -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

2

3 Information:

- 4 • OA: Overall Accuracy
- 5 • PA: Producer's Accuracy
- 6 • UA: User's Accuracy
- 7 • CE: Commission Error
- 8 • OE: Omission Error

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

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

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

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

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

No.	Spectral Indices	Producer's Accuracy (%)											
		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 _{mh}	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

14

15 Information:

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

- 1 • Sw: Shrub-dominated wetlands
- 2 • Tw: Tree-dominated wetlands
- 3 • Fp: Fish ponds
- 4 • Sr: Swamp rice fields
- 5 • Il: Irrigated land
- 6 • Fm: Freshwater marshes
- 7 • Fl: Freshwater lake

8

9 The entire spectral indices, except NDMI, do not have a problem when extracting the
10 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
11 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
12 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
13 2004).

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

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

26 MNDWI and $MNDWI_{s2}$ quite successful in identifying wetlands. Except MNDWI
27 failed to recognize the peatlands and tree-dominated wetlands. Where these two features are
28 wetlands with dense canopy. Not so with $MNDWI_{s2}$ capable of recognizing peatlands and tree-
29 dominated wetlands with almost 100% accuracy. Based on this fact, our assumption when

1 shifting SWIR1 into SWIR2 on MNDWI has been proven. MNDWI_{s2} able to recognize the
 2 characteristic spectral features that have water and vegetation spectral characteristics as well
 3 with better.

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

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

14 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

15

16 Information:

- 17 • Bu: Built-up lands
- 18 • Bl: Barelands
- 19 • Gr: Grass

- 1 • R: Roads
- 2 • F: Dryland forest
- 3 • Df: Dryland farms
- 4 • Gd: Garden (mixgarden, rubber plants, palm oil)
- 5 • Sb: Shrub and bushes

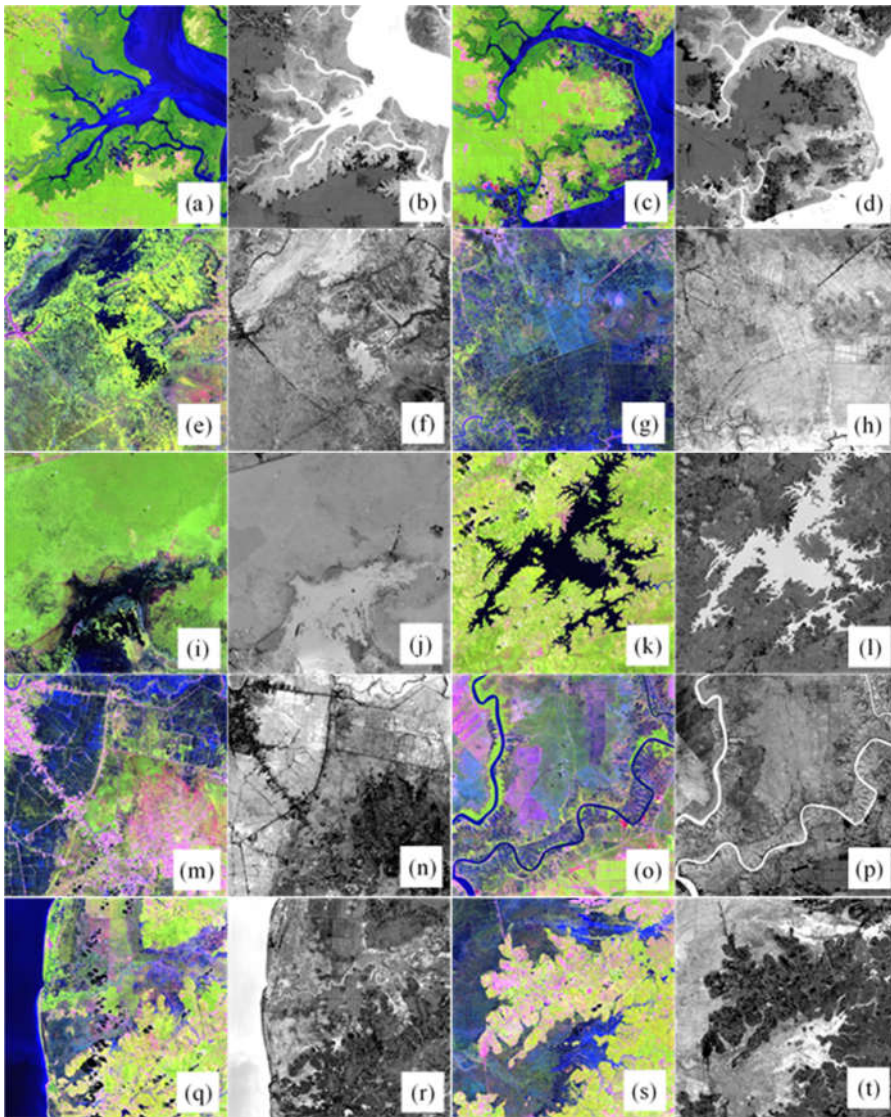
6
7 Based on Table 3 and Table 4, it appears that NDMI cannot distinguish between dryland
8 forest and wetlands forest. Likewise, the overall WRI has high accuracy, and as if it is able to
9 recognize all types of wetlands with good, it fails on a number of dryland features and take it as
10 wetlands. This translates into an overall accuracy WRI does not mean anything, because in fact
11 it could not distinguish well between wetland features and some dryland features.

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

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

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

28



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2
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4
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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

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

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

12 Not so with MNDWI₂ which uses green bands and SWIR2 bands. Where in SWIR2,
 13 the reflectance value of vegetation features is not as high as in SWIR1. Even the spectral value
 14 tends to be lower than green. We can also see this fact in Table 5 and Figure 6. Where in the
 15 wetlands which are dominated by dense vegetation, the reflectance values for SWIR2 are lower
 16 than reflectance values for SWIR1 or green. Thus, green subtraction using SWIR2 will not
 17 suppress vegetation features as in MNDWI. As a result, wetlands with dense vegetation can still
 18 be detected in MNDWI₂. This makes MNDWI₂ the most optimal spectral index in extracting
 19 vegetation-rich wetlands such as tropical wetlands. Figure 5 shows the comparison between
 20 Landsat 8 OLI composite 654 imageries and the MNDWI₂ imageries.

21 Table 5. Average reflectance values on each Landsat 8 band on three types of dense vegetation
 22 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

23

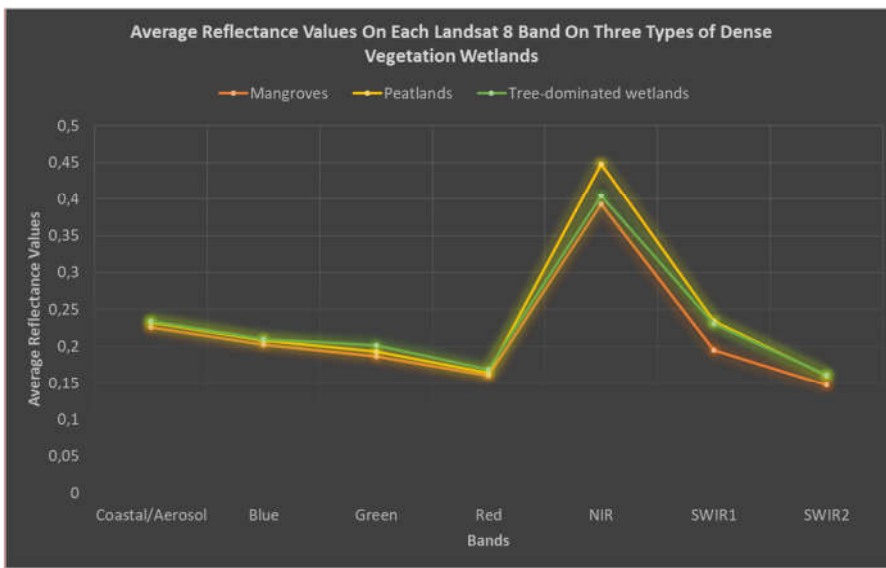
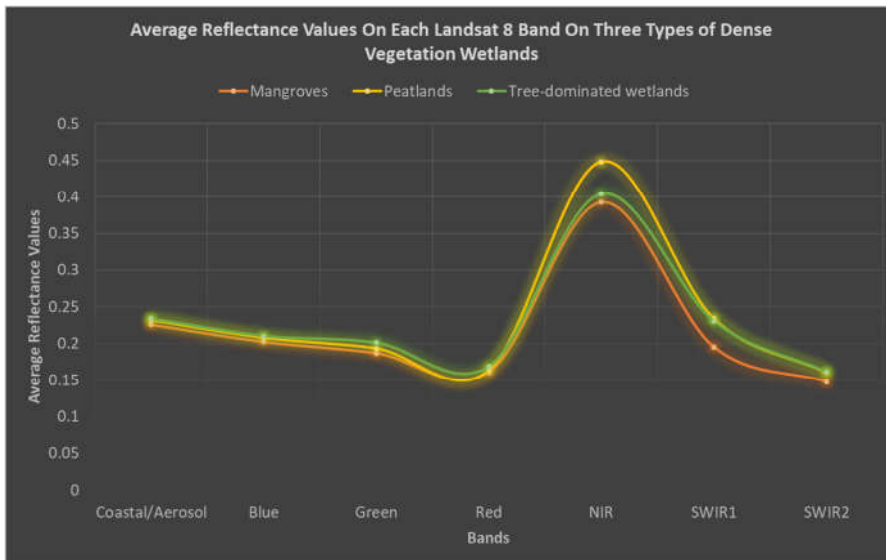


Figure 6. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

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.

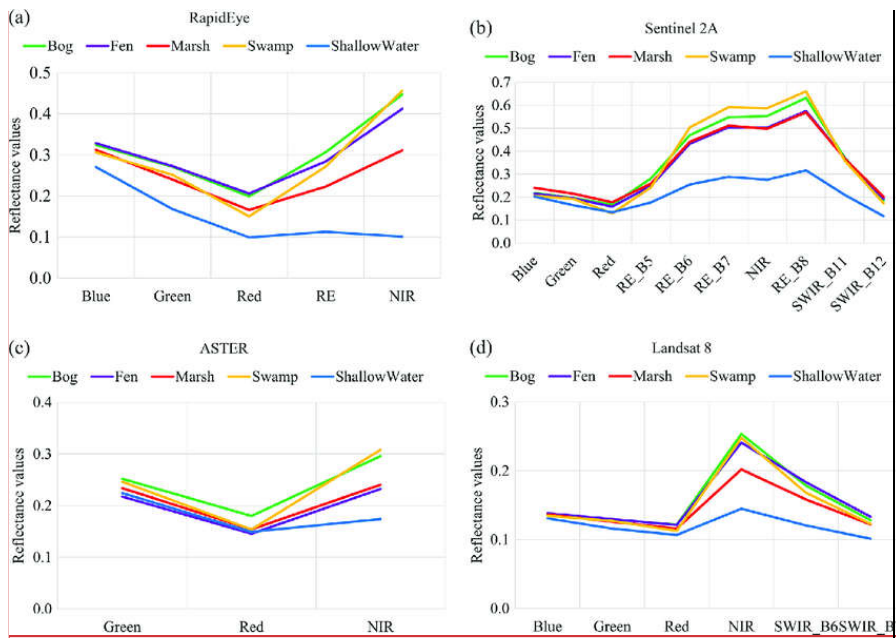
For further explanation, we have provided in two paragraphs and a figure (Figure 7) which we've just added.

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

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

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Commented [A16]: We've just added this Figure 7.

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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 MNDWIs2. But MNDWIs2 should be used wisely, given MNDWIs2 very sensitive to dense vegetations. MNDWIs2 also has potential error in wetlands with dominant

1 soil background features. $MNDWI_{s2}$ not only able to recognize the deep waters as well as
2 $MNDWI$, but still able to capture the wetlands with vegetations on it.

3 Like $MNDWI$, $MNDWI_{s2}$ also uses a green band. In spectral value curves, green band
4 has the highest reflectance value of water features among all spectral bands. So that open water
5 features can be detected properly by $MNDWI_{s2}$. The advantage of $MNDWI_{s2}$ is the use of
6 $SWIR2$, where in spectral value curves $SWIR2$ band has a lower reflectance value of vegetation.
7 So that subtraction green with $SWIR2$ will not cause vegetation features to become depressed
8 as in $MNDWI$.

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

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

18

19 **Acknowledgement**

20 The authors thank to the United States Geological Survey (USGS) for providing the
21 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
22 the Spatial Data Infrastructure Development Center (PPIDS), University of Lambung
23 Mangkurat. Digital image processing in this research was carried out at the Remote Sensing
24 and Geographic Information System Laboratory, Faculty of Forestry, University of Lambung
25 Mangkurat, Banjarbaru.

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**8. Bukti Bahwa Manuskrip Diterima untuk
Dipublikasikan di Indonesian Journal of
Geography (30 Juli 2021)**

[IJG] Editor Decision: Manuscript Accepted for Publication

3 messages

Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id> Fri, Jul 30, 2021 at 3:32 PM
To: Syamani Darmawi Ali <syamani.fhut@ulm.ac.id>
Cc: Hartono Hartono <hartono@geo.ugm.ac.id>, Projo Danoedoro <projo.danoedoro@geo.ugm.ac.id>

Dear Dr. Syamani Darmawi Ali,

Congratulations! After considering your responses to the editor's and reviewer's comments, We have reached the decision regarding your submission to the Indonesian Journal of Geography, "Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI" to Accept your manuscript to be published in Indonesian Journal of Geography.

You will receive emails regarding the details of your publication. We may also request a technical edit of your manuscript if necessary.

Thank you for submitting it to the Indonesian Journal of Geography and we look forward to receiving your manuscript in the future.

Best wishes,
Dr. Pramaditya Wicaksono
Faculty of Geography Universitas Gadjah Mada, Yogyakarta
Phone +6281391179917
Fax +62274569595
prama.wicaksono@geo.ugm.ac.id
Section Editor
Indonesian Journal of Geography
Faculty of Geography, Universitas Gadjah Mada, Yogyakarta

Chief Editor
Indonesian Journal of Geography
<http://jurnal.ugm.ac.id/index.php/ijg>
0024-9521 (print),2354-9114 (online)
Phone: +62 812-2711-480

Syam'ani <syamani.fhut@ulm.ac.id> Fri, Jul 30, 2021 at 3:49 PM
To: Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id>
Cc: Hartono Hartono <hartono@geo.ugm.ac.id>, Projo Danoedoro <projo.danoedoro@geo.ugm.ac.id>

Thank you for the great news!

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Mail Delivery Subsystem <mailer-daemon@googlemail.com> Fri, Jul 30, 2021 at 3:50 PM
To: syamani.fhut@ulm.ac.id



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Your message wasn't delivered to **hartono@geo.ugm.ac.id** because the address couldn't be found, or is unable to receive mail.

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Final-Recipient: rfc822; hartono@geo.ugm.ac.id

Action: failed

Status: 5.1.1

Remote-MTA: dns; alt1.aspmx.l.google.com. (2607:f8b0:4023:401::1b, the server for the domain geo.ugm.ac.id.)

Diagnostic-Code: smtp; 550-5.1.1 The email account that you tried to reach does not exist. Please try 550-5.1.1 double-checking the recipient's email address for typos or 550-5.1.1 unnecessary spaces. Learn more at

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Last-Attempt-Date: Fri, 30 Jul 2021 00:50:07 -0700 (PDT)

----- Forwarded message -----

From: "Syam'ani" <syamani.fhut@ulm.ac.id>

To: Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id>

Cc: Hartono Hartono <hartono@geo.ugm.ac.id>, Projo Danoedoro <projo.danoedoro@geo.ugm.ac.id>

Bcc:

Date: Fri, 30 Jul 2021 15:49:55 +0800

Subject: Re: [JG] Editor Decision: Manuscript Accepted for Publication

Thank you for the great news!

Pada tanggal Jum, 30 Jul 2021 15.32, Pramaditya Wicaksono <prama.wicaksono@geo.ugm.ac.id> menulis:
Dear Dr. Syamani Darmawi Ali,

Congratulations! After considering your responses to the editor's and reviewer's comments, We have reached the decision regarding your submission to the Indonesian Journal of Geography, "Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI" to Accept your manuscript to be published in Indonesian Journal of Geography.

You will receive emails regarding the details of your publication. We may also request a technical edit of your manuscript if necessary.

Thank you for submitting it to the Indonesian Journal of Geography and we look forward to receiving your manuscript in the future.

Best wishes,
Dr. Pramaditya Wicaksono
Faculty of Geography Universitas Gadjah Mada, Yogyakarta
Phone +6281391179917
Fax +62274569595
prama.wicaksono@geo.ugm.ac.id
Section Editor
Indonesian Journal of Geography
Faculty of Geography, Universitas Gadjah Mada, Yogyakarta

Chief Editor
Indonesian Journal of Geography
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Phone: +62 812-2711-480

1 Comparison of Various Spectral Indices for Optimum Extraction 2 of Tropical Wetlands Using Landsat 8 OLI

3
4 **Abstract** This research specifically aims to investigate the most accurate spectral indices in extracting wetlands
5 geospatial information taking South Kalimantan, Indonesia, as an example of wetlands in tropical areas. Ten
6 spectral indices were selected for testing their ability to extract wetlands, those are NDVI, NDWI, MNDWI,
7 MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, and AWEIsh. Tests were performed on Landsat 8 OLI path/row
8 117/062 and 117/063. The threshold method which was used to separate the wetland features from the spectral
9 indices imagery is Otsu method. The results of this research showed that generally MNDWIs2 was the most optimal
10 spectral indices in wetlands extraction. Especially tropical wetlands that rich with green vegetation cover. However,
11 MNDWIs2 is very sensitive to dense vegetation, this feature has the potential to be detected as wetlands. Furthermore,
12 to improve the accuracy and prevent detection of the dryland vegetation as wetlands, the threshold value should be
13 determined carefully.

14
15 **Key words:** wetlands; spectral indices; Landsat 8 OLI; South Kalimantan

16
17 **Abstrak** Penelitian ini bertujuan untuk menginvestigasi indeks spektral yang paling akurat dalam ekstraksi
18 informasi geospasial lahan basah di Kalimantan Selatan, Indonesia, sebagai sampel lahan basah di daerah tropis.
19 Sepuluh indeks spektral dipilih untuk diuji kemampuannya dalam mengekstrak lahan basah, yaitu NDVI, NDWI,
20 MNDWI, MNDWIs2, NDMI, WRI, NDPI, TCWT, AWEInsh, dan AWEIsh. Uji coba dilakukan pada Citra Landsat
21 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur lahan
22 basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara umum
23 MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstaksi lahan basah. Khususnya lahan basah
24 tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi rapat,
25 fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan mencegah
26 vegetasi lahan kering terdeteksi sebagai lahan basah, nilai threshold harus ditentukan secara hati-hati.

27
28 **Kata kunci :** lahan basah; indeks spektral; Landsat 8 OLI; Kalimantan Selatan

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1 **1. Introduction**

2

3 Wetlands are ecosystems saturated with water, either seasonally or permanently (EPA,
4 2004). According to the Ramsar Convention on Wetlands 1993 (Matthews, 2013), based on the
5 habitat, wetlands classified into marine and coastal wetlands, inland wetlands, and man-made
6 wetlands. In the South Kalimantan Province, Indonesia, wetlands are one of the main features
7 of the landscape.

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

15 So far, various methods have been developed for the extraction of wetlands geospatial
16 data automatically. For example, the Normalized Difference Water Index (NDWI) (McFeeters,
17 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and so forth.
18 NDWI and MNDWI are the two most popular spectral indices for the extraction of water
19 features or wetland features. Their ability to extract open water features or wetland features has
20 been tested from several research results (McFeeters, 1996; Xu, 2006; Li et al., 2013; Jiang et al.,
21 2014; Ashraf and Nawaz, 2015; Das and Pal, 2016; Du et al., 2016). Besides NDWI or MNDWI,
22 there are also a number of other spectral indices that can potentially be used to separate wetland
23 features from other features.

24 In general, spectral indices such as NDWI or MNDWI are actually developed to
25 separate open water features from other features. Some research indicates that the spectral
26 indices are very accurate in extracting the boundaries of water features. For example, Xu (2006)
27 proved that MNDWI more accurate than NDWI when applied to the three water features, i.e.
28 lakes, oceans, and rivers. Similar to Xu (2006), Li et al. (2013) also found that MNDWI more
29 accurate than NDWI to the TM, ETM +, and ALI imagery. To further test MNDWI's

1 capabilities, Jiang et al. (2014) developed the Automated Method for Extracting Rivers and
2 Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat TM/ETM +.
3 It was found that in general, MNDWI remains the best among the three other spectral indices.

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

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

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

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

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

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

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

10

11 **2.The Methods**

12

13 2.1.Materials

14

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

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

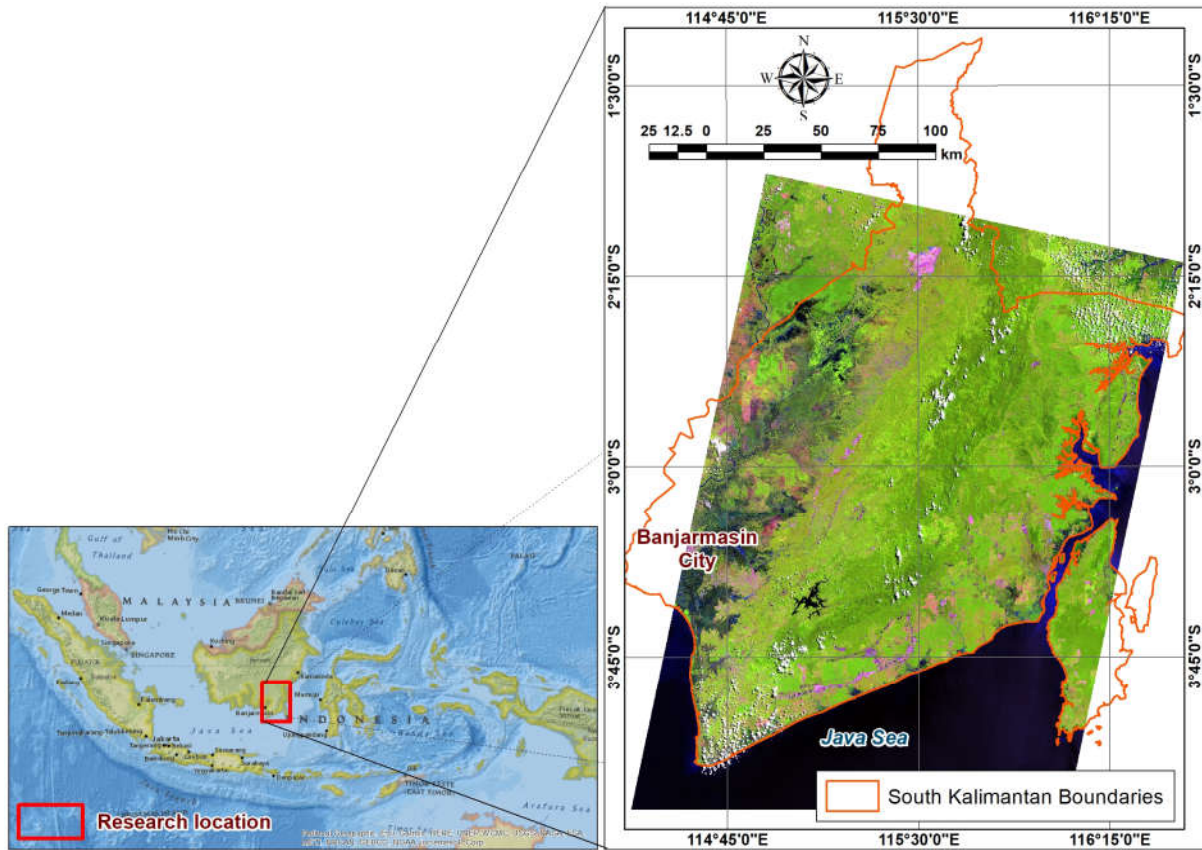


Figure 1. Research location

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:

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

Where:

- ρ_g : green band
- ρ_n : near infrared band

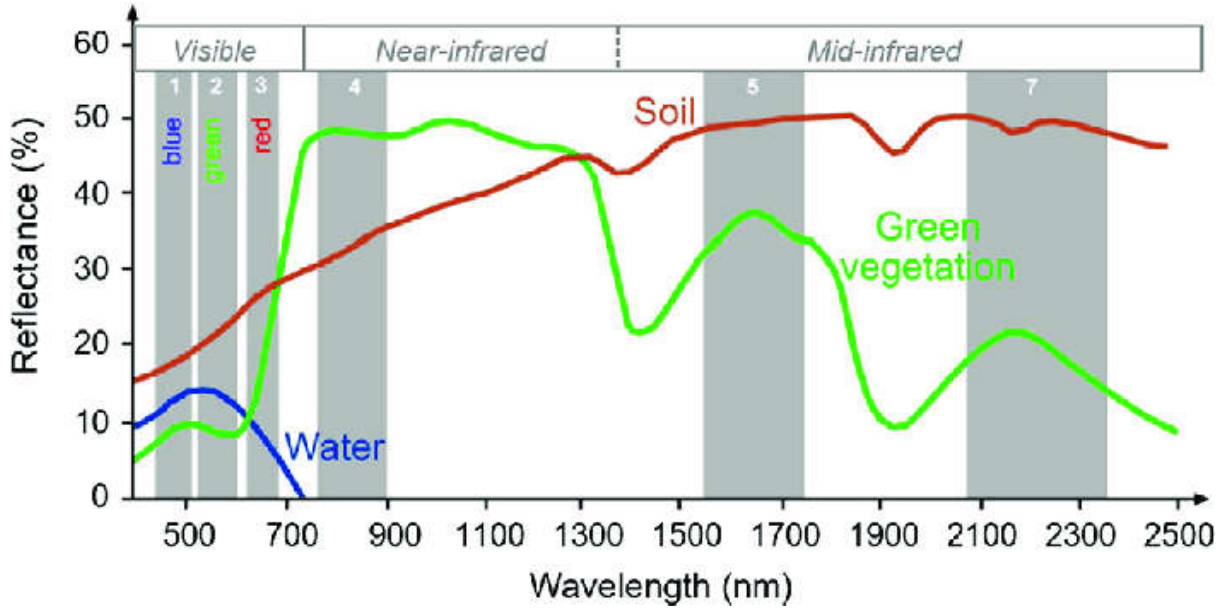


Figure 2. Spectral value curves on three base surface features (Chen et al., 2019)

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.

$$\text{MNDWI} = \frac{\rho_g - \rho_s}{\rho_g + \rho_s} \quad (2)$$

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:

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

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

1 vegetation located above the wetlands. Because vegetation reflectance in SWIR2 is not as high
 2 as SWIR1 and NIR.

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

6
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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 _{insh} 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)

8

9 Information:

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

9

10 2.3. Wetlands Extraction

11

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

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

20

21 2.4. Accuracy Assessment

22

23 Accuracy assessment was conducted using the Confusion Matrix (Stehman and
24 Czaplewski, 1997), using a number of sample locations were selected purposively. In this case,
25 the location of the sample represents multiple characters wetlands in South Kalimantan.
26 Namely, mangroves, salt marshes, deep water (include reservoirs, canals, and coal open pits),
27 peatlands, peatswamps, shrub-dominated wetlands, tree-dominated wetlands, fish ponds,
28 swamp rice fields, irrigated land, freshwater marshes, and freshwater lake. Therefore, there are
29 a total of 12 samples for wetland classes. Meanwhile, the number of sample pixels for each

1 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 2,330 pixels respectively.

3 For the purpose of assessing the deeper capabilities of each spectral index, the sample
4 locations were also chosen purposively on various dryland features that have the potential to
5 be detected as wetlands. In the appointment of the samples, the method used is knowledge-
6 based. There are a total of 10 samples for dryland classes. Namely, built-up lands, barelands,
7 grass, roads, dryland forest, dryland farms, garden (include mix garden, rubber plants, palm
8 oil), and shrub and bushes. The number of sample pixels for each of these drylands classes are
9 1,236, 4,003, 2,377, 323, 6,445, 2,169, 4,694, and 8,075 pixels, respectively.

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

18 Furthermore, to test the ability of each spectral index to recognize each wetland class, a
19 confusion matrix was constructed for each spectral index in each wetland class. For example,
20 for NDWI in the Mangroves class, a confusion matrix will be constructed. Furthermore, from
21 the resulting confusion matrix the Producer's Accuracy value will be taken, to obtain a
22 quantitative description of the ability of the spectral index to recognize one type of wetland. So
23 we will get an overview of NDWI's ability to recognize Mangroves for example. Recapitulation
24 of producer's accuracy values for each spectral index in each wetland class can be seen in Table
25 3.

26 The final step, to test the ability of each spectral index to avoid the detection of dryland
27 features, a confusion matrix is constructed for each spectral index in each dryland class. For
28 example, for NDWI in the Dryland Forest class, a confusion matrix will be constructed.
29 Furthermore, from the resulting confusion matrix the Commission Error value will be taken,

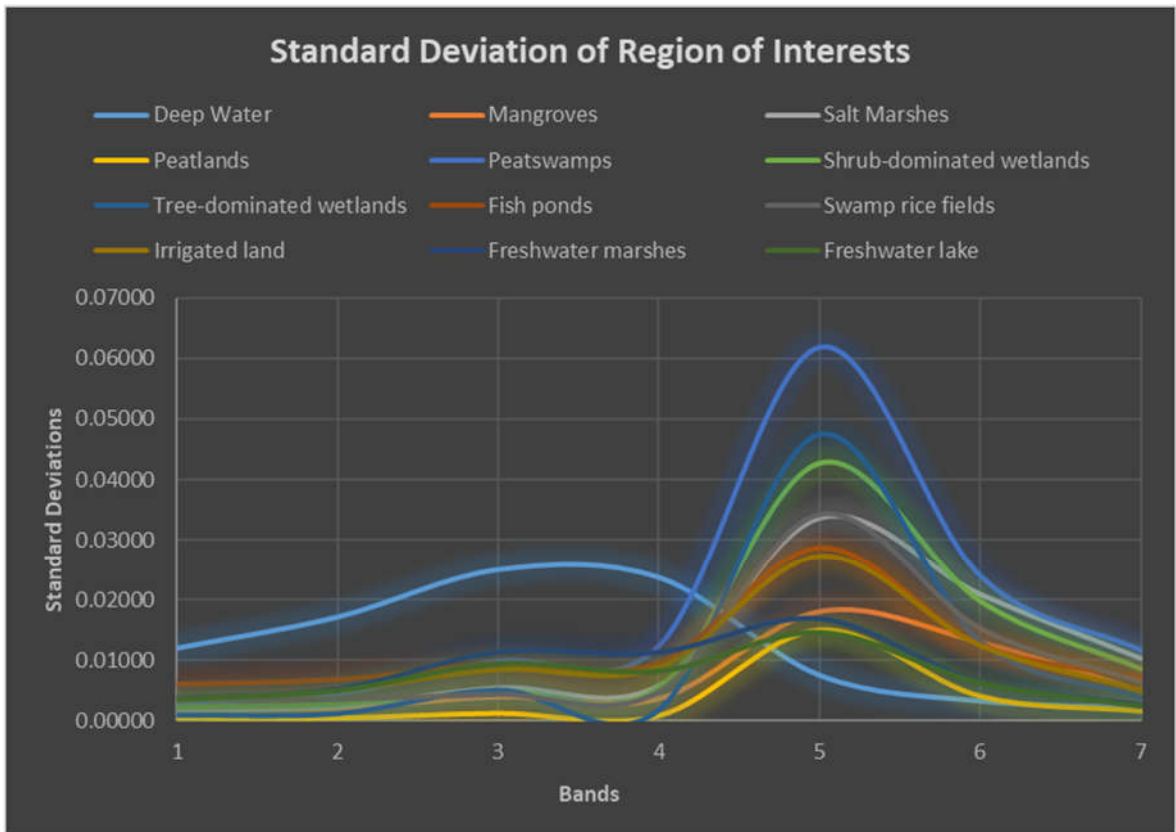
1 to obtain a quantitative description of the ability of the spectral index to avoid the detection of
2 one type of dryland. So that a description of NDWI's ability to avoid detecting Dryland Forest
3 as a wetland will be obtained, for example. Recapitulation of commission error values for each
4 spectral index in each dryland class can be seen in Table 4.

5

6 3.Result and Discussion

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

14



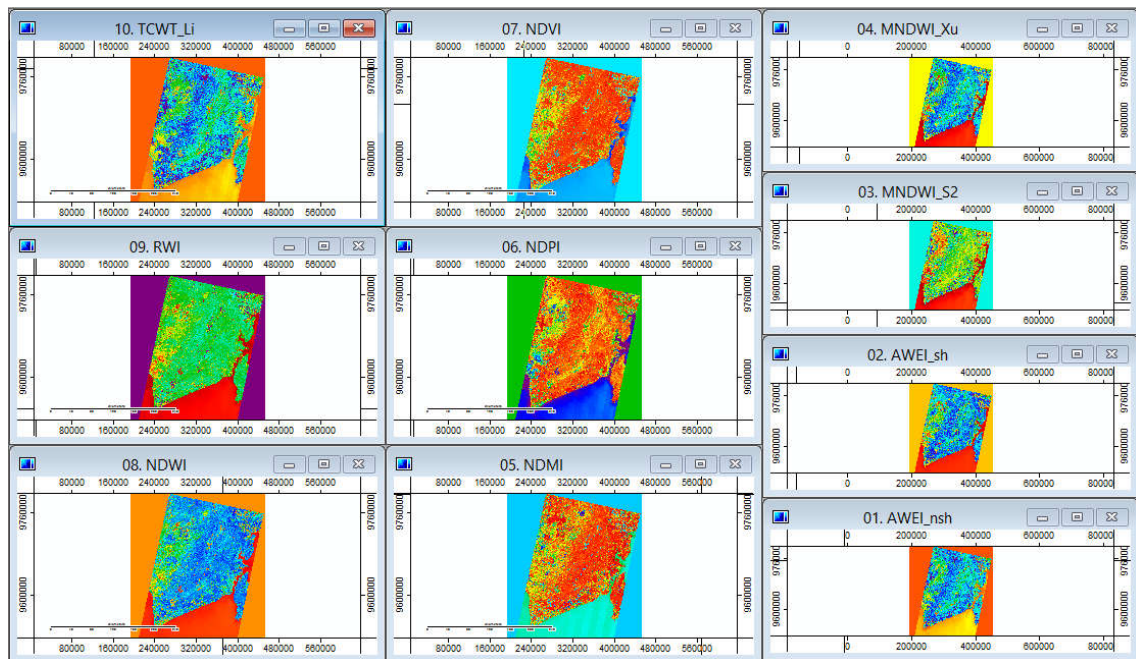
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16 Figure 3. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

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Of course, spectral indices such as NDWI cannot distinguish between mangroves and peat swamps, for example. Because spectral indices such as NDWI are only designed to recognize and separate water/wetlands from dryland features. While mangroves and peat swamps 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.



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18
19

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

1 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

2

3 Information:

- 4 • OA: Overall Accuracy
- 5 • PA: Producer's Accuracy
- 6 • UA: User's Accuracy
- 7 • CE: Commission Error
- 8 • OE: Omission Error

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

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

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

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

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

No.	Spectral Indices	Producer's Accuracy (%)											
		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.	AWEL _{nsh}	100	69.97	88.46	0	95.87	25.47	5.92	99.88	96.38	100	100	100
10.	AWEL _{sh}	100	5.81	99.95	0	97.92	88.55	15.45	100	99.83	100	100	100

14

15 Information:

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

- 1 • Sw: Shrub-dominated wetlands
- 2 • Tw: Tree-dominated wetlands
- 3 • Fp: Fish ponds
- 4 • Sr: Swamp rice fields
- 5 • Il: Irrigated land
- 6 • Fm: Freshwater marshes
- 7 • Fl: Freshwater lake

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9 The entire spectral indices, except NDMI, do not have a problem when extracting the
10 deep water features. Exclusively for NDMI, it looks like it is not appropriate to extract the open
11 water features. NDMI successfully on lands that are quite dense vegetation cover. This is
12 because NDMI is designed to detect moisture vegetation canopy (Gao, 1996; Jackson et al.,
13 2004).

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

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

26 MNDWI and $MNDWI_{s2}$ quite successful in identifying wetlands. Except MNDWI
27 failed to recognize the peatlands and tree-dominated wetlands. Where these two features are
28 wetlands with dense canopy. Not so with $MNDWI_{s2}$ capable of recognizing peatlands and tree-
29 dominated wetlands with almost 100% accuracy. Based on this fact, our assumption when

1 shifting SWIR1 into SWIR2 on MNDWI has been proven. MNDWI_{s2} able to recognize the
 2 characteristic spectral features that have water and vegetation spectral characteristics as well
 3 with better.

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

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

13

14 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

15

16 Information:

- 17 • Bu: Built-up lands
- 18 • Bl: Barelands
- 19 • Gr: Grass

- 1 • R: Roads
- 2 • F: Dryland forest
- 3 • Df: Dryland farms
- 4 • Gd: Garden (mixgarden, rubber plants, palm oil)
- 5 • Sb: Shrub and bushes

6

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

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

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

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

28

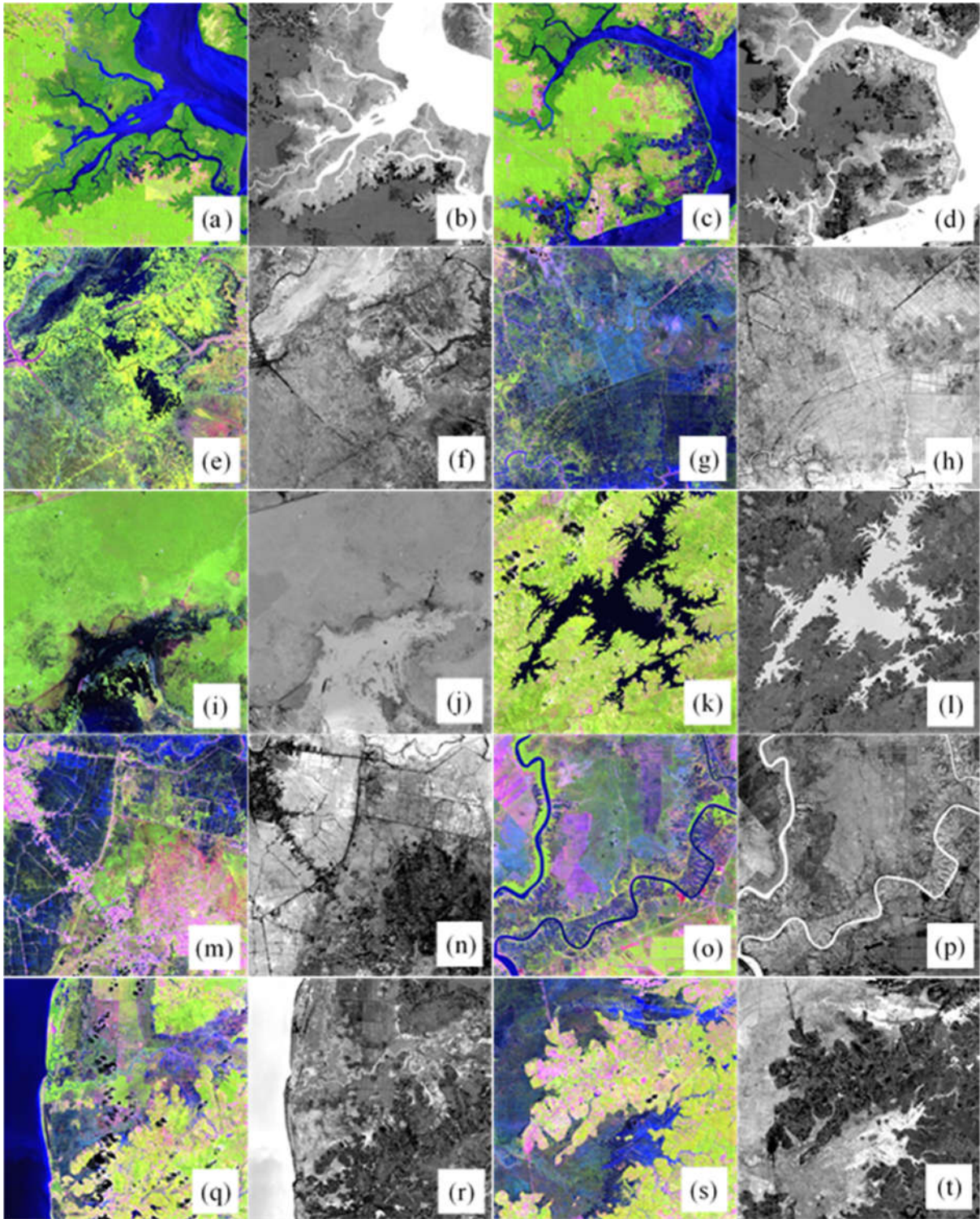


Figure 5. Comparison between Landsat 8 OLI composite 654 and MNDW_{s2}

(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

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(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 subtraction 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 subtraction 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

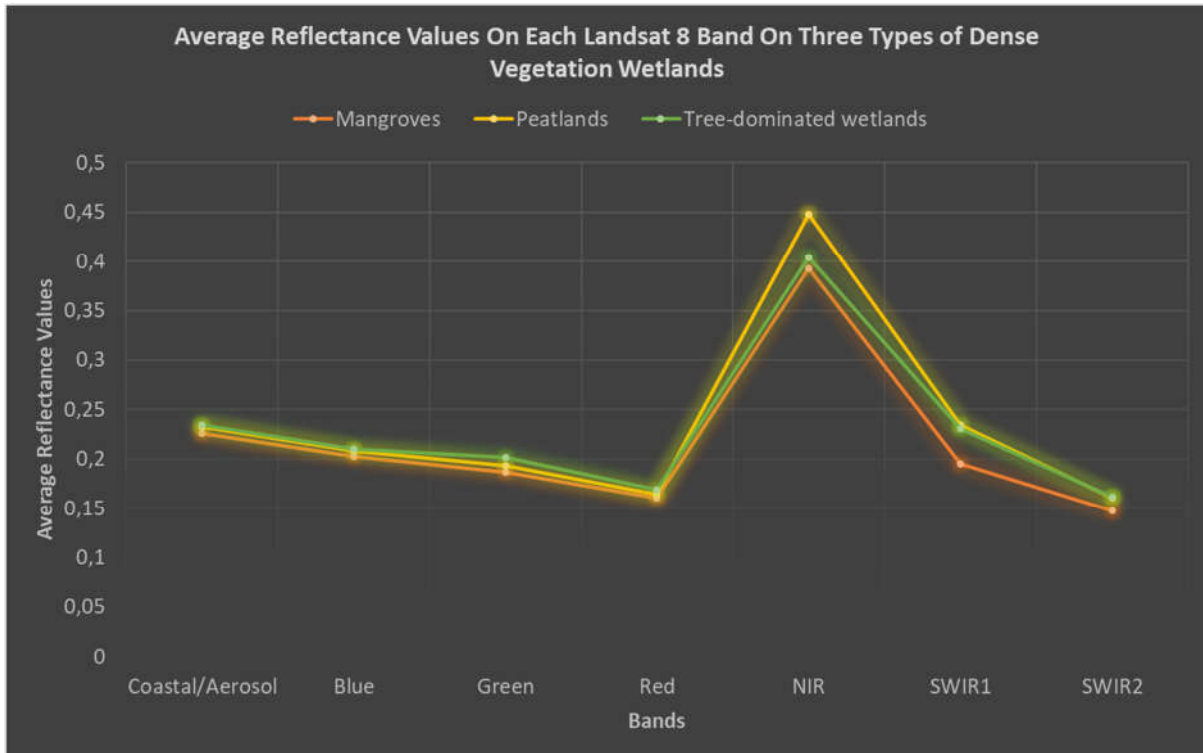
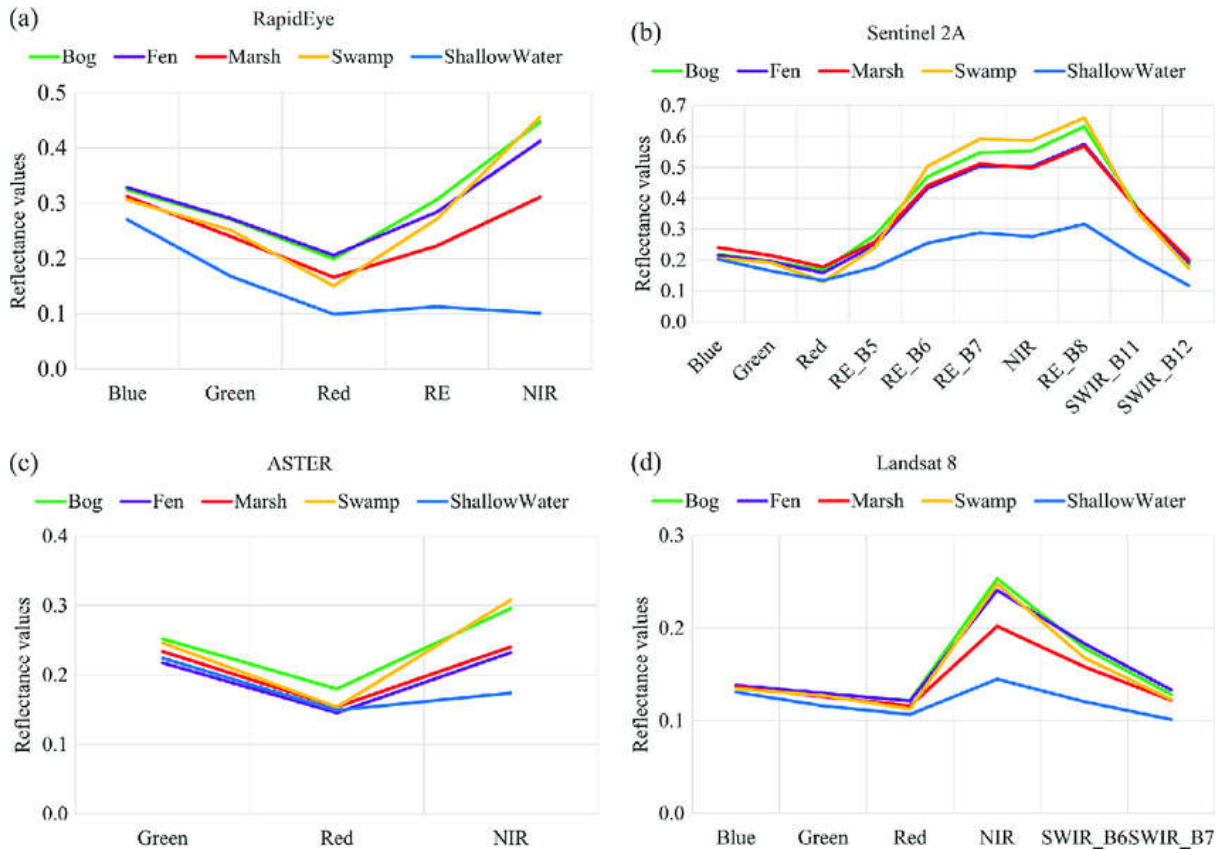


Figure 6. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

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 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.

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

1 features which have the highest reflectance in green, shadow reflectance is higher in blue and
 2 lower in green (Li et al., 2009). Second, the spectral response of broadleaf forests shows low
 3 reflectance in the green band, and higher in blue and coastal/aerosols (Osgouei et al., 2019). In
 4 accordance with the facts, the dense vegetation wetlands in this research location are broadleaf
 5 forests.



6
 7 Figure 7. The spectral signature of wetlands, obtained from (a) RapidEye, (b) Sentinel 2A, (c)
 8 ASTER, and (d) Landsat 8 (Amani et al., 2018)

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

1

2 **4.Conclusion**

3 Based on this research, the spectral indices recorded the most accurate and optimal in
4 extracting wetlands is $MNDWI_{s2}$. But $MNDWI_{s2}$ should be used wisely, given $MNDWI_{s2}$ very
5 sensitive to dense vegetations. $MNDWI_{s2}$ also has potential error in wetlands with dominant
6 soil background features. $MNDWI_{s2}$ not only able to recognize the deep waters as well as
7 $MNDWI$, but still able to capture the wetlands with vegetations on it.

8 Like $MNDWI$, $MNDWI_{s2}$ also uses a green band. In spectral value curves, green band
9 has the highest reflectance value of water features among all spectral bands. So that open water
10 features can be detected properly by $MNDWI_{s2}$. The advantage of $MNDWI_{s2}$ is the use of
11 $SWIR2$, where in spectral value curves $SWIR2$ band has a lower reflectance value of vegetation.
12 So that subtraction green with $SWIR2$ will not cause vegetation features to become depressed
13 as in $MNDWI$.

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

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

23

24 **Acknowledgement**

25 The authors thank to the United States Geological Survey (USGS) for providing the
26 Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by
27 the Spatial Data Infrastructure Development Center (PPIDS), University of Lambung
28 Mangkurat. Digital image processing in this research was carried out at the Remote Sensing

1 and Geographic Information System Laboratory, Faculty of Forestry, University of Lambung
2 Mangkurat, Banjarbaru.

3

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9. Email permintaan koreksi dari Editor, dan permintaan kepada Editor untuk merubah penulisan nama Penulis Utama dari Syam'ani (*nama asli Penulis Utama yang tertulis di ijazah*) menjadi Syamani Darmawi Ali atau Syamani D. Ali (*nama asli Penulis Utama ditambah nama Ayah Kandung*) (29 September 2021 s/d 30 September 2021)

[IJG] Proofreading Request (Author)

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

Syam'ani¹, Hartono² and Projo Danoedoro³

¹Faculty of Forestry, University of Lambung Mangkurat, Banjarbaru, Indonesia

^{2,3}Faculty of Geography, Universitas Gadjah Mada, Yogyakarta, Indonesia

Received: 2019-10-11

Accepted: 2021-07-30

Keywords:

wetlands;
spectral indices;
Landsat 8 OLI;
South Kalimantan

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, MNDWI_{s2}, NDMI, WRI, NDPI, TCWT, AWEInsh, and AWEIsh. 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 MNDWI_{s2} was the most optimal spectral indices in wetlands extraction. Especially tropical wetlands that rich with green vegetation cover. However, MNDWI_{s2} 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.

Correspondent email:
syamani.fhut@ulm.ac.id

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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 extract water 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. Methods

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).

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:

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

Where:

ρ_g : green band

ρ_n : near infrared band

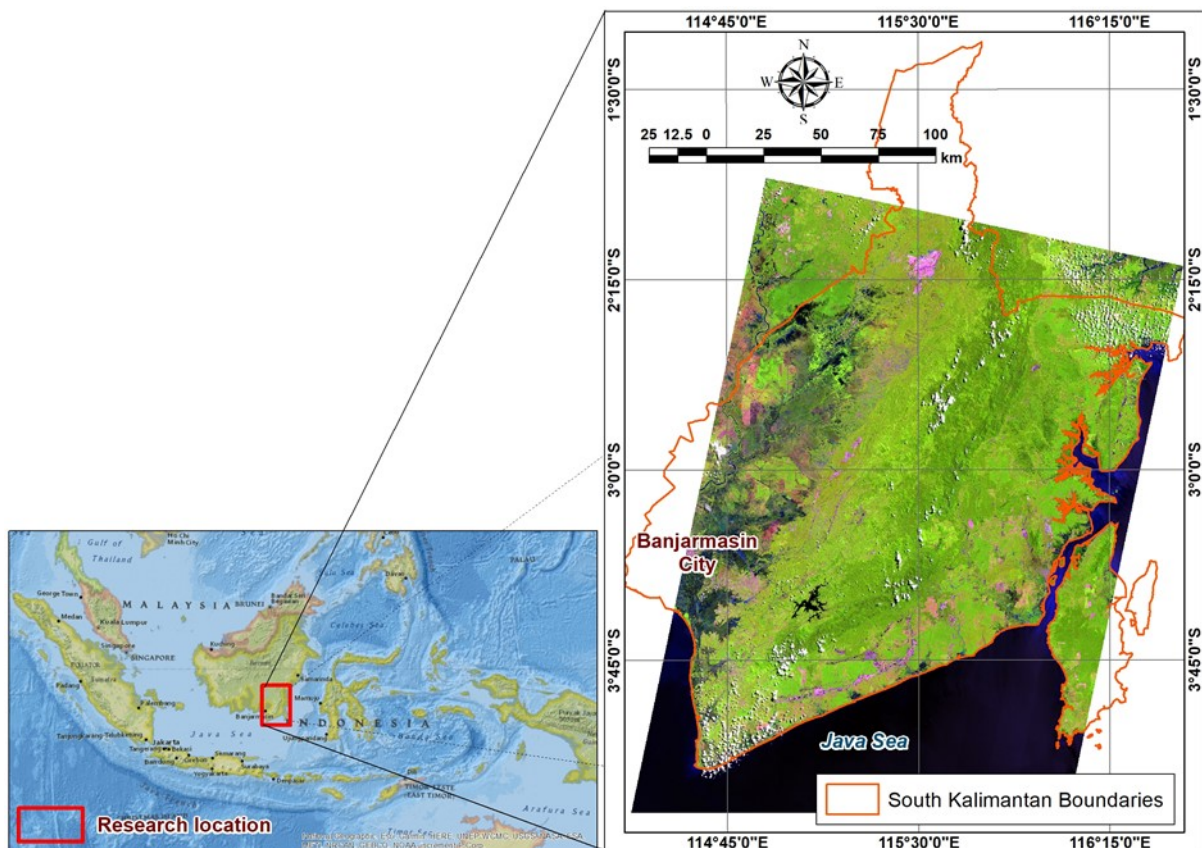


Figure 1. Research location

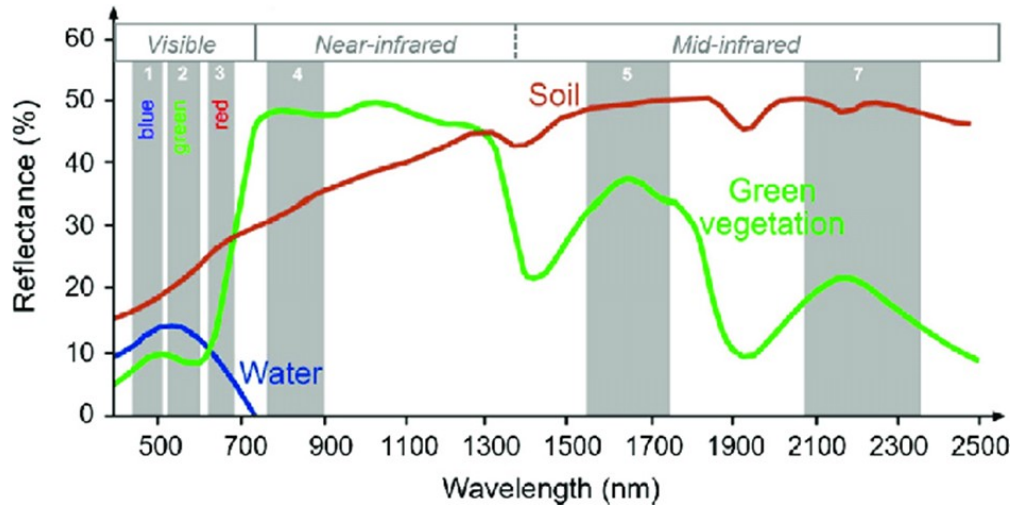


Figure 2. Spectral value curves on three base surface features (Chen et al., 2019)

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.

$$MNDWI = \frac{\rho_g - \rho_s}{\rho_g + \rho_s} \tag{2}$$

Where:

r_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:

$$MNDWI_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}} \tag{3}$$

Where:

r_{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.

Information:

- r_{ca} : aerosol coastal bands (bands 1 Landsat 8)
- r_b : blue band (band 2 Landsat 8)
- r_g : green band (band 3 Landsat 8)
- r_r : red band (band 4 Landsat 8)
- r_{nir} : near infrared band (band 5 Landsat 8)
- r_s : shortwave infrared band (band 6 or 7 Landsat 8)
- r_{s1} : shortwave infrared 1 band (band 6 Landsat 8)
- r_{s2} : shortwave infrared 2 band (band 7 Landsat 8)

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).

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

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

Spectral Indices		Formula	Value of Water	Reference
NDVI	Normalized Difference Vegetation Index	$\frac{\rho_n - \rho_r}{\rho_n + \rho_r}$	Negative	Rouse et al. (1973)
NDWI	Normalized Difference Water Index	$\frac{\rho_g - \rho_n}{\rho_g + \rho_n}$	Positive	McFeeters (1996)
MNDWI	Modified Normalized Difference Water Index	$\frac{\rho_g - \rho_{s1}}{\rho_g + \rho_{s1}}$	Positive	Xu (2006)
MNDWI _{s2}	Modified Normalized Difference Water Index with SWIR2	$\frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$	Positive	This research
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)
WRI	Water Ratio Index	$\frac{\rho_g + \rho_r}{\rho_n + \rho_s}$	Greater than 1	Shen (2010)
NDPI	Normalized Difference Pond Index	$\frac{\rho_s - \rho_g}{\rho_s + \rho_g}$	Negative	Lacaux et al. (2007)
TCWT	Tasseled-Cap Wetness Transformation	$0.1877r_{ca} + 0.2097r_b + 0.2038r_g + 0.1017r_r + 0.0685r_n - 0.7460r_{s1} - 0.5548r_{s2}$	-	Li et al. (2015)
AWEI _{nsh}	Automated Water Extraction Index with no shadow	$4(r_g - r_{s1}) - (0.25r_n + 2.75r_{s2})$	-	Feyisa et al. (2014)
AWEI _{sh}	Automated Water Extraction Index with shadow	$r_b + 2.5r_g - 1.5(r_n + r_{s1}) - 0.25r_{s2}$	-	Feyisa et al. (2014)

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.

Of course, spectral indices such as NDWI cannot distinguish between mangroves and peat swamps, for example. Because spectral indices such as NDWI are only designed to recognize and separate water/wetlands from

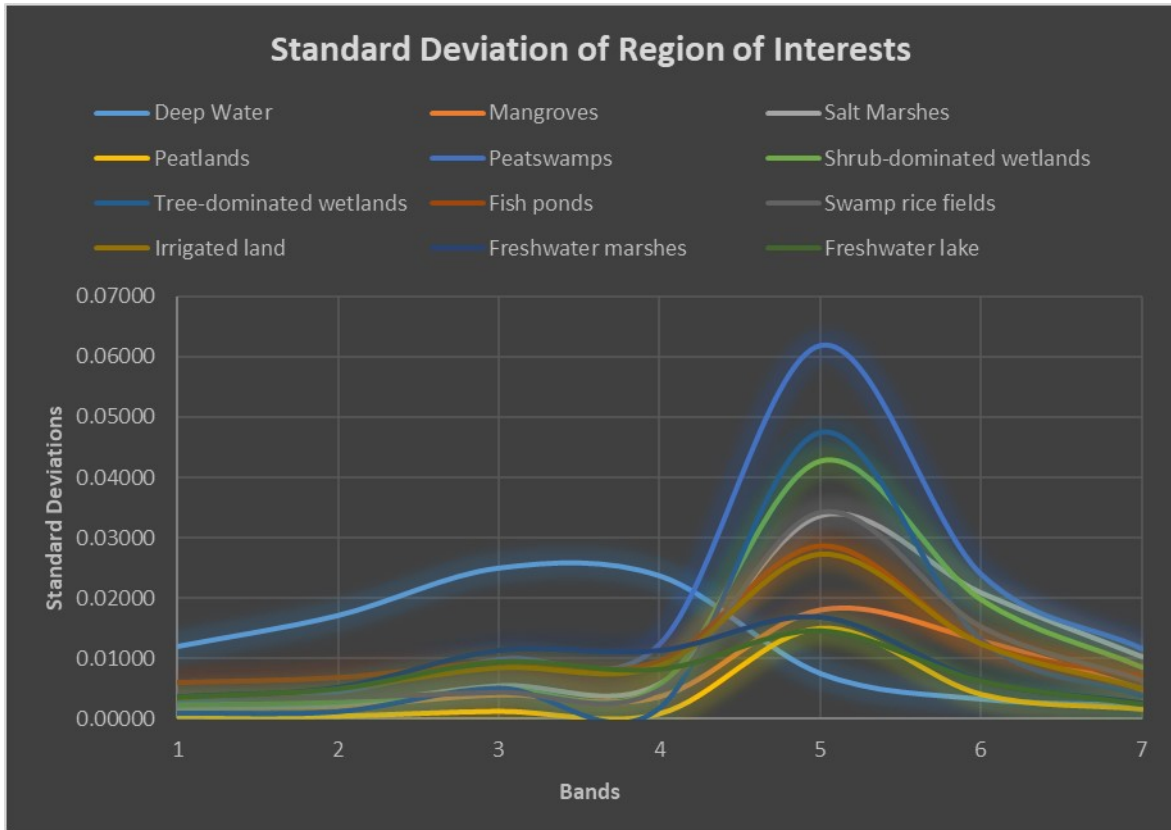


Figure 3. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

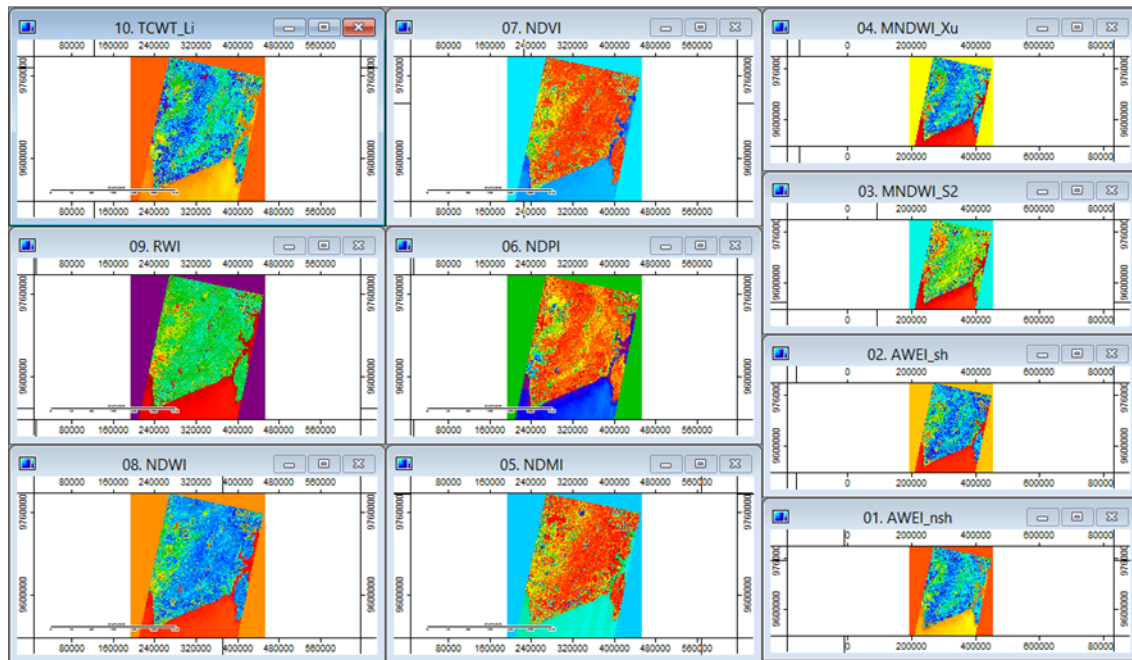


Figure 4. The result of the transformation of spectral indices on the SAGA application

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. Information:

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

Spectral Indices	Otsu Threshold	OA (%)	Kappa	PA (%)	UA (%)	CE (%)	OE (%)
NDVI	≤ 0.21	44.20	0.18	43.59	88.49	11.51	56.41
NDWI	≥ -0.17	45.19	0.19	44.84	89.73	10.27	55.16
MNDWI	≥ -0.06	68.59	0.50	84.22	99.74	0.26	15.78
MNDWI _{s2}	≥ 0.07	74.82	0.59	97.54	98.13	1.87	2.46
NDMI	≥ 0.13	32.68	-0.14	38.86	60.48	39.52	61.14
WRI	≥ 0.51	73.02	0.50	98.61	84.61	15.39	1.39
NDPI	≤ 0.05	65.02	0.45	77.15	99.85	0.15	22.85
TCWT	≤ 0.45	59.32	0.37	66.37	99.95	0.05	33.63
AWEI _{nsh}	≥ -0.55	54.15	0.31	57.11	99.99	0.01	42.89
AWEI _{sh}	≥ -0.20	62.46	0.41	72.53	98.87	1.13	27.47

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

Spectral Indices	Commission Error (%)							
	Bu	Bl	Gr	R	F	Df	Gd	Sb
NDVI	71.76	98.13	0	87.62	0	0	0	0
NDWI	55.10	90.43	0	85.14	0	0	0	0
MNDWI	0	0.05	0	37.15	0.47	0	0	0
MNDWI _{s2}	0	0	0	0	18.65	0.05	0	0.15
NDMI	1.70	0.10	100	5.57	100	91.47	100	100
WRI	99.92	99.83	0	100	69.84	33.38	0.64	10.58
NDPI	0	0.05	0	21.98	0.16	0	0	0
TCWT	0	0	0	0	0.39	0	0	0
AWEI _{nsh}	0	0	0	0	0.06	0	0	0
AWEI _{sh}	20.47	1.27	0	95.05	0.14	0	0	0

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 MNDWI_{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.

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. MNDWI_{s2} was almost no problems with all the dryland features, except dryland forests. Furthermore, MNDWI_{s2} troubled with all the dense and dark vegetation features. As with all other spectral indices, MNDWI_{s2} also failed to recognize the

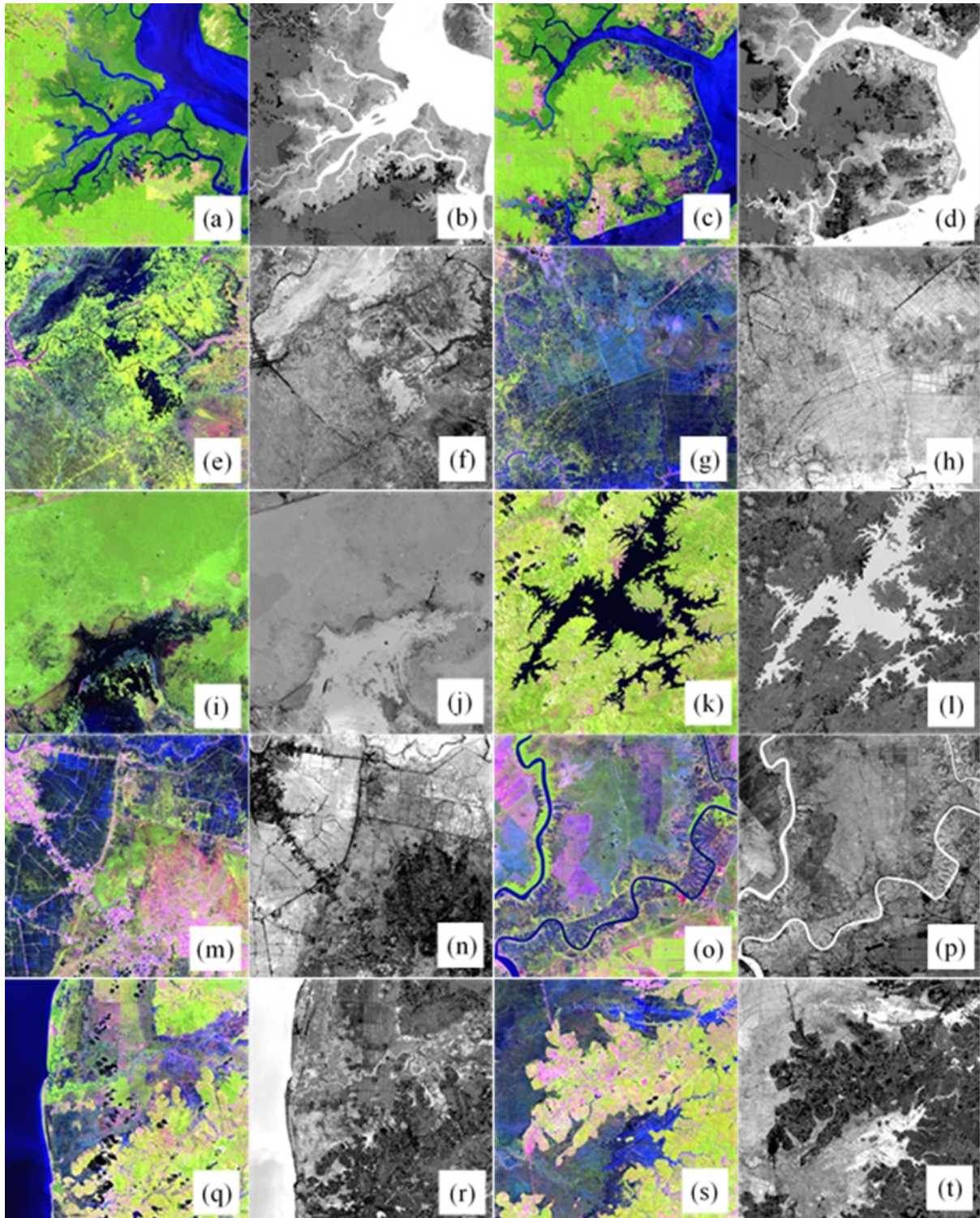


Figure 5. Comparison between Landsat 8 OLI composite 654 and MNDW_{s2} (a) and (b) mangrove; (c) and (d) fishpond; (e) and (f) freshwater lake and freshwater marshes; (g) and (h) irrigated land; (i) and (j) peatlands and peatswamps; (k) and (l) deep clear water (reservoir); (m) and (n) swamp rice fields and tree-dominated wetlands; (o) and (p) deep turbid water (river); (q) and (r) salt marshes; and (s) and (t) shrub-dominated wetlands.

wetlands on which there are very bright vegetation features.

Based on the results of the accuracy assessment, it appears that MNDWI₂ 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).

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 subtraction 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 MNDWI₂ 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 subtraction using SWIR₂ will not suppress vegetation features as in MNDWI. As a result, wetlands with dense vegetation can still be detected in MNDWI₂. This makes MNDWI₂ 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 MNDWI₂ imageries.

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 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

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	SWIR ₁	SWIR ₂
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

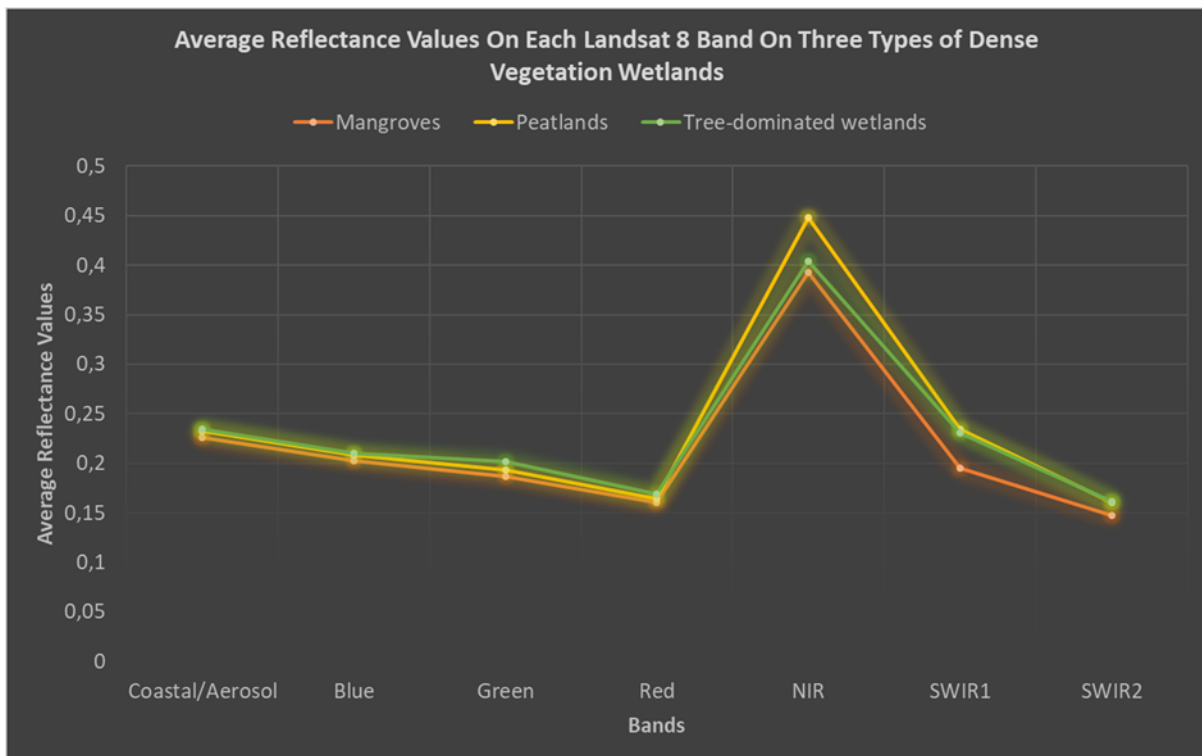


Figure 6. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

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.

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.

MNDWI_{s2} 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, MNDWI_{s2} still able to capture the reflection of background water or soil moisture beneath the canopy. In the MNDWI_{s2} 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 MNDWI_{s2}.

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 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, MNDWI_{s2} 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 MNDWI_{s2}. The advantage of MNDWI_{s2} is the use of SWIR2, where in spectral value curves SWIR2 band has a lower reflectance value of vegetation. So that subtraction 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 subtraction 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

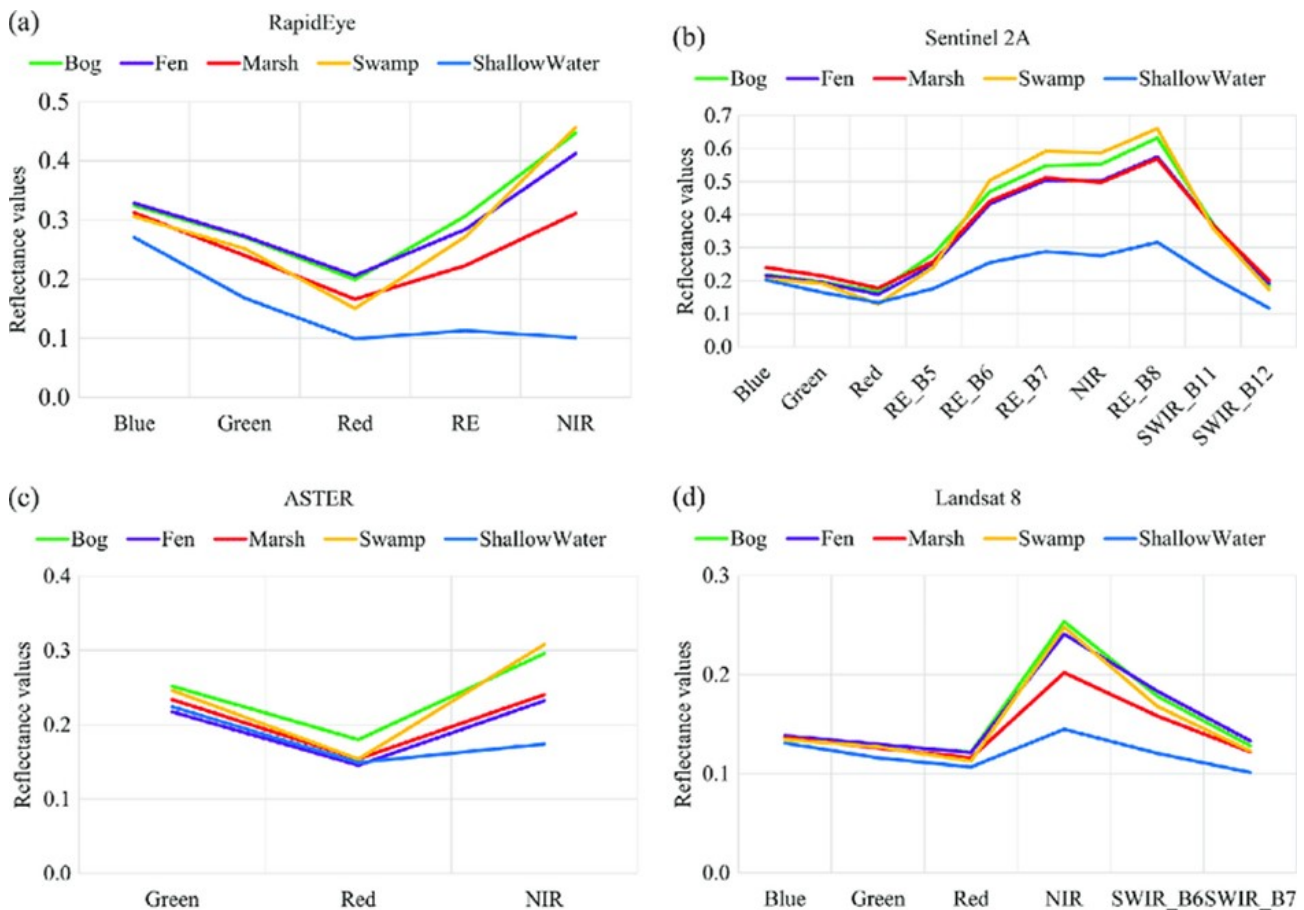


Figure 7. The spectral signature of wetlands, obtained from (a) RapidEye, (b) Sentinel 2A, (c) ASTER, and (d) Landsat 8 (Amani et al., 2018)

the accuracy of the NDWI formula. Especially if the formula be examined in other regions with different conditions, or be examined on other multispectral imageries.

Acknowledgement

The authors thank to the United States Geological Survey (USGS) for providing the Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by the Spatial Data Infrastructure Development Center (PPIDS), University of Lambung Mangkurat. Digital image processing in this research was carried out at the Remote Sensing and Geographic Information System Laboratory, Faculty of Forestry, University of Lambung Mangkurat, Banjarbaru.

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

Syamani D. Ali¹, Hartono² and Projo Danoedoro³

¹Faculty of Forestry, University of Lambung Mangkurat, Banjarbaru, Indonesia

^{2,3}Faculty of Geography, Universitas Gadjah Mada, Yogyakarta, Indonesia

Received: 2019-10-11

Accepted: 2021-07-30

Keywords:

wetlands;
spectral indices;
Landsat 8 OLI;
South Kalimantan

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, MNDWI_{s2}, NDMI, WRI, NDPI, TCWT, AWEInsh, and AWEIsh. 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 MNDWI_{s2} was the most optimal spectral indices in wetlands extraction. Especially tropical wetlands that rich with green vegetation cover. However, MNDWI_{s2} 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.

Correspondent email:

syamani.fhut@ulm.ac.id

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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 extract water 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. Methods

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).

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:

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

Where:

ρ_g : green band

ρ_n : near infrared band

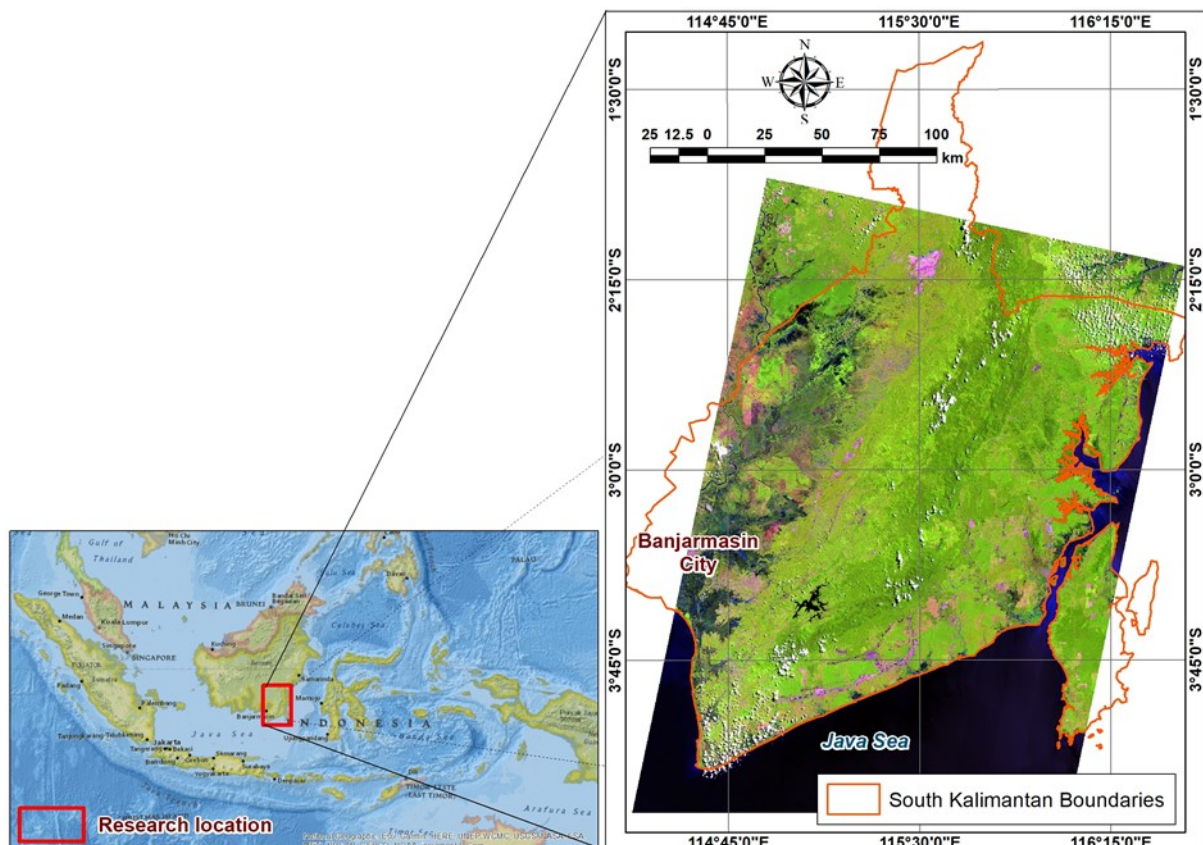


Figure 1. Research location

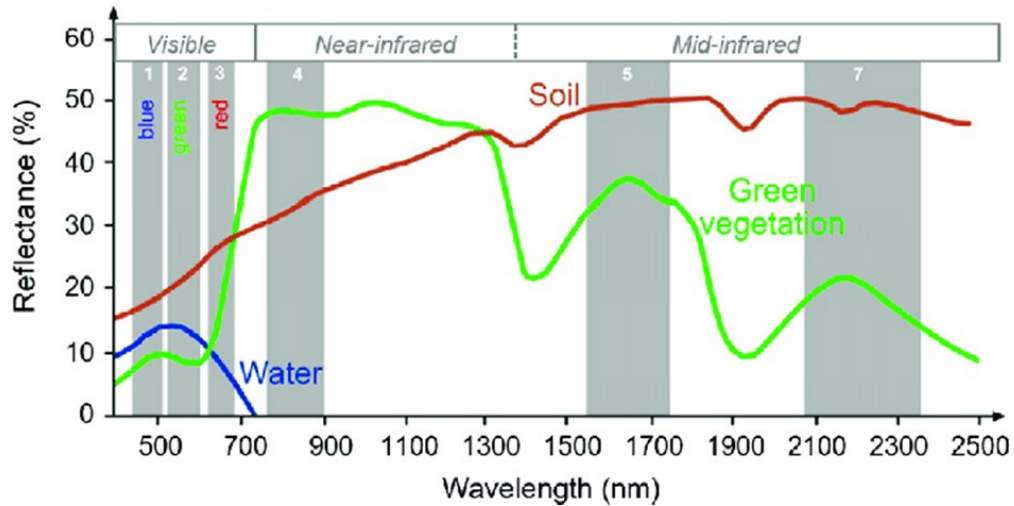


Figure 2. Spectral value curves on three base surface features (Chen et al., 2019)

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.

$$MNDWI = \frac{\rho_g - \rho_s}{\rho_g + \rho_s} \tag{2}$$

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:

$$MNDWI_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}} \tag{3}$$

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.

Information:

- r_{ca} : aerosol coastal bands (bands 1 Landsat 8)
- r_b : blue band (band 2 Landsat 8)
- r_g : green band (band 3 Landsat 8)
- r_r : red band (band 4 Landsat 8)
- r_{nir} : near infrared band (band 5 Landsat 8)
- r_s : shortwave infrared band (band 6 or 7 Landsat 8)
- r_{s1} : shortwave infrared 1 band (band 6 Landsat 8)
- r_{s2} : shortwave infrared 2 band (band 7 Landsat 8)

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).

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

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

Spectral Indices		Formula	Value of Water	Reference
NDVI	Normalized Difference Vegetation Index	$\frac{\rho_n - \rho_r}{\rho_n + \rho_r}$	Negative	Rouse et al. (1973)
NDWI	Normalized Difference Water Index	$\frac{\rho_g - \rho_n}{\rho_g + \rho_n}$	Positive	McFeeters (1996)
MNDWI	Modified Normalized Difference Water Index	$\frac{\rho_g - \rho_{s1}}{\rho_g + \rho_{s1}}$	Positive	Xu (2006)
MNDWI _{s2}	Modified Normalized Difference Water Index with SWIR2	$\frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$	Positive	This research
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)
WRI	Water Ratio Index	$\frac{\rho_g + \rho_r}{\rho_n + \rho_s}$	Greater than 1	Shen (2010)
NDPI	Normalized Difference Pond Index	$\frac{\rho_s - \rho_g}{\rho_s + \rho_g}$	Negative	Lacaux et al. (2007)
TCWT	Tasseled-Cap Wetness Transformation	$0.1877r_{ca} + 0.2097r_b + 0.2038r_g + 0.1017r_r + 0.0685r_n - 0.7460r_{s1} - 0.5548r_{s2}$	-	Li et al. (2015)
AWEI _{nsh}	Automated Water Extraction Index with no shadow	$4(r_g - r_{s1}) - (0.25r_n + 2.75r_{s2})$	-	Feyisa et al. (2014)
AWEI _{sh}	Automated Water Extraction Index with shadow	$r_b + 2.5r_g - 1.5(r_n + r_{s1}) - 0.25r_{s2}$	-	Feyisa et al. (2014)

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.

Of course, spectral indices such as NDWI cannot distinguish between mangroves and peat swamps, for example. Because spectral indices such as NDWI are only designed to recognize and separate water/wetlands from

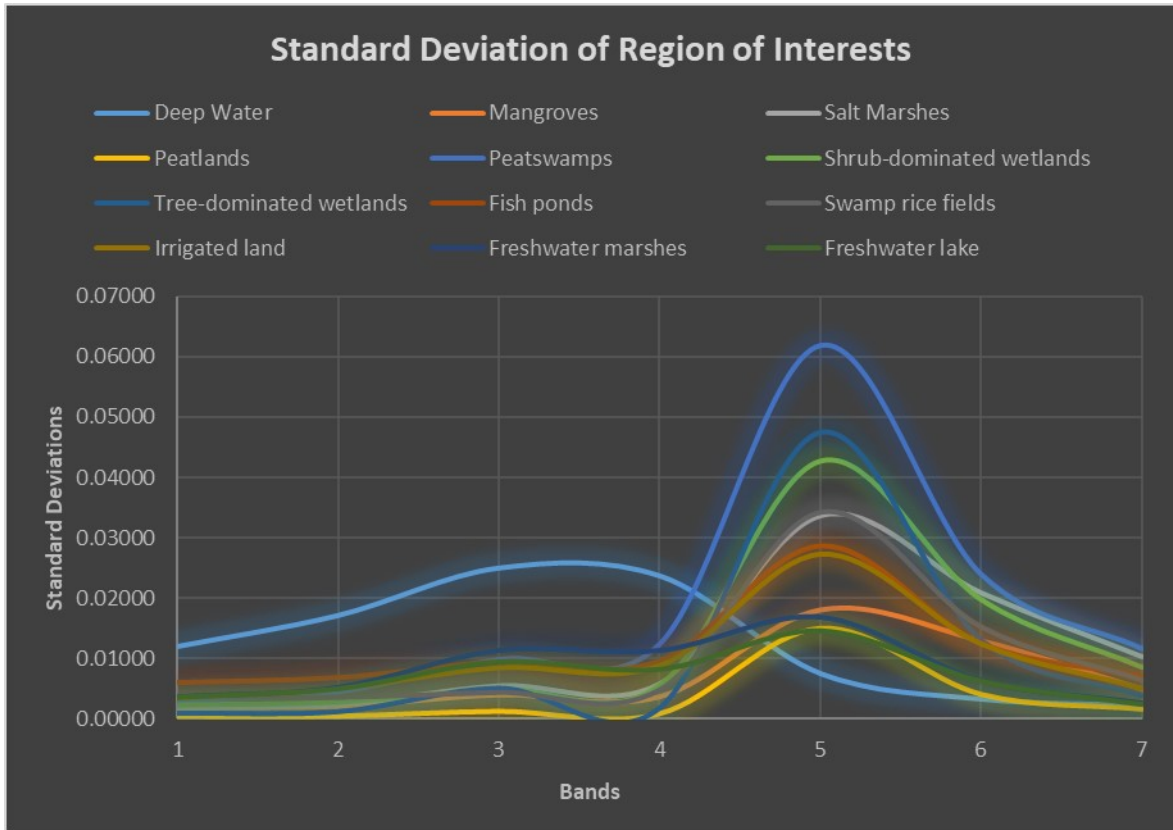


Figure 3. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

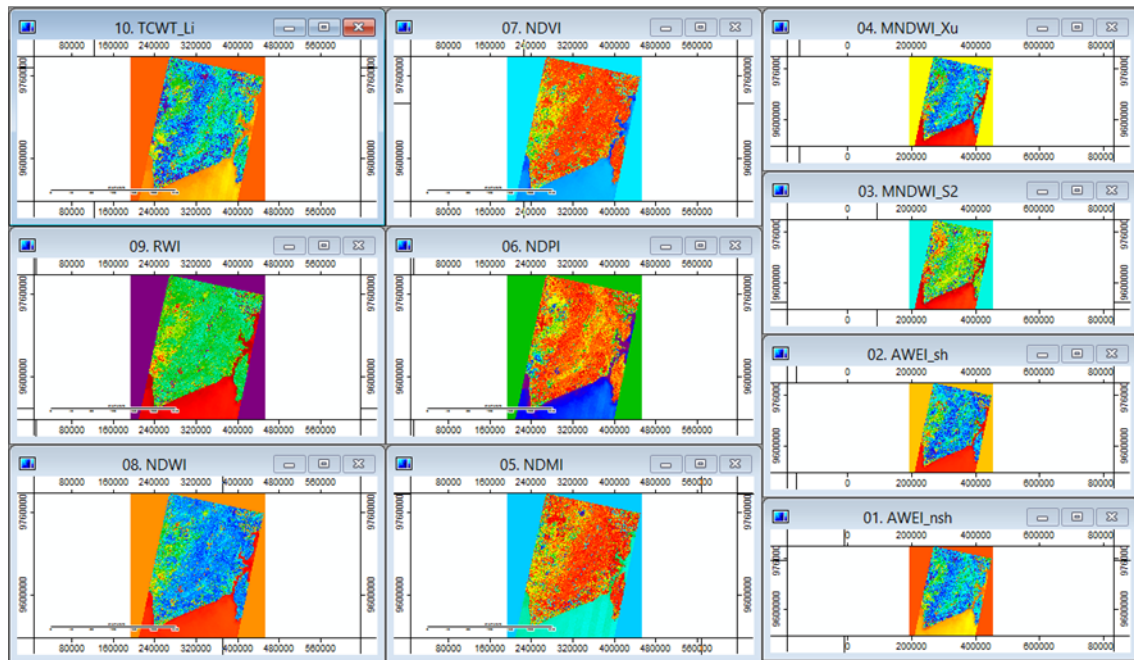


Figure 4. The result of the transformation of spectral indices on the SAGA application

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. Information:

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

Spectral Indices	Otsu Threshold	OA (%)	Kappa	PA (%)	UA (%)	CE (%)	OE (%)
NDVI	≤ 0.21	44.20	0.18	43.59	88.49	11.51	56.41
NDWI	≥ -0.17	45.19	0.19	44.84	89.73	10.27	55.16
MNDWI	≥ -0.06	68.59	0.50	84.22	99.74	0.26	15.78
MNDWI _{s2}	≥ 0.07	74.82	0.59	97.54	98.13	1.87	2.46
NDMI	≥ 0.13	32.68	-0.14	38.86	60.48	39.52	61.14
WRI	≥ 0.51	73.02	0.50	98.61	84.61	15.39	1.39
NDPI	≤ 0.05	65.02	0.45	77.15	99.85	0.15	22.85
TCWT	≤ 0.45	59.32	0.37	66.37	99.95	0.05	33.63
AWEI _{nsh}	≥ -0.55	54.15	0.31	57.11	99.99	0.01	42.89
AWEI _{sh}	≥ -0.20	62.46	0.41	72.53	98.87	1.13	27.47

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

Spectral Indices	Commission Error (%)							
	Bu	Bl	Gr	R	F	Df	Gd	Sb
NDVI	71.76	98.13	0	87.62	0	0	0	0
NDWI	55.10	90.43	0	85.14	0	0	0	0
MNDWI	0	0.05	0	37.15	0.47	0	0	0
MNDWI _{s2}	0	0	0	0	18.65	0.05	0	0.15
NDMI	1.70	0.10	100	5.57	100	91.47	100	100
WRI	99.92	99.83	0	100	69.84	33.38	0.64	10.58
NDPI	0	0.05	0	21.98	0.16	0	0	0
TCWT	0	0	0	0	0.39	0	0	0
AWEI _{nsh}	0	0	0	0	0.06	0	0	0
AWEI _{sh}	20.47	1.27	0	95.05	0.14	0	0	0

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 MNDWI_{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.

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. MNDWI_{s2} was almost no problems with all the dryland features, except dryland forests. Furthermore, MNDWI_{s2} troubled with all the dense and dark vegetation features. As with all other spectral indices, MNDWI_{s2} also failed to recognize the

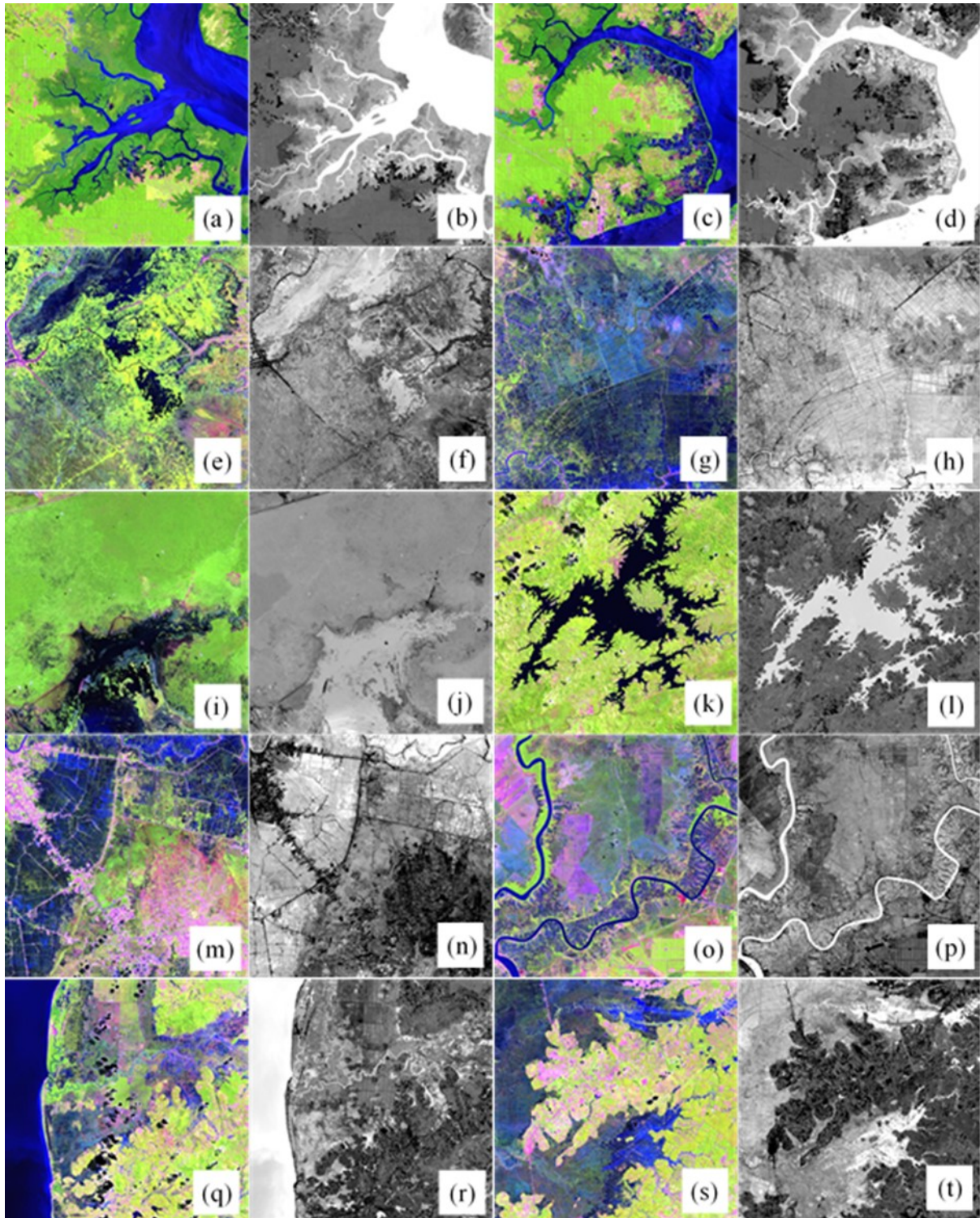


Figure 5. Comparison between Landsat 8 OLI composite 654 and MNDW_{s2} (a) and (b) mangrove; (c) and (d) fishpond; (e) and (f) freshwater lake and freshwater marshes; (g) and (h) irrigated land; (i) and (j) peatlands and peatswamps; (k) and (l) deep clear water (reservoir); (m) and (n) swamp rice fields and tree-dominated wetlands; (o) and (p) deep turbid water (river); (q) and (r) salt marshes; and (s) and (t) shrub-dominated wetlands.

wetlands on which there are very bright vegetation features.

Based on the results of the accuracy assessment, it appears that MNDWI₂ 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).

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 subtraction 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 MNDWI₂ 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 subtraction using SWIR₂ will not suppress vegetation features as in MNDWI. As a result, wetlands with dense vegetation can still be detected in MNDWI₂. This makes MNDWI₂ 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 MNDWI₂ imageries.

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 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

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	SWIR ₁	SWIR ₂
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

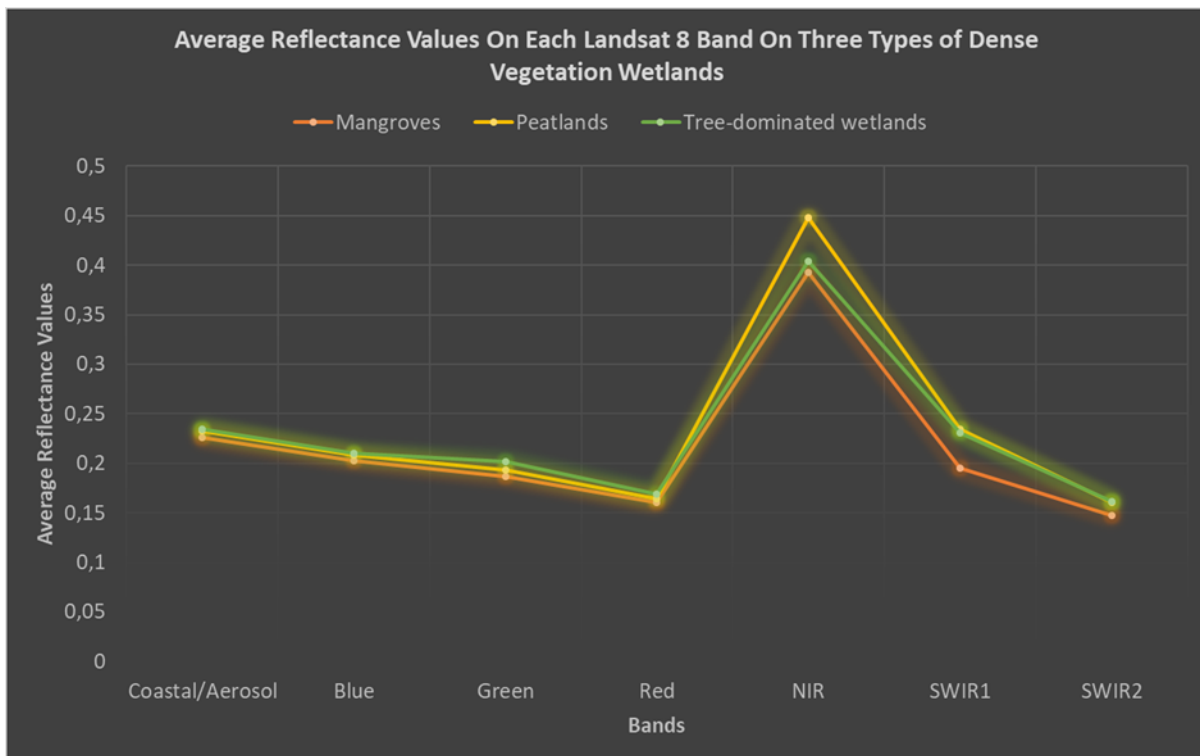


Figure 6. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

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.

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.

MNDWI_{s2} 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, MNDWI_{s2} still able to capture the reflection of background water or soil moisture beneath the canopy. In the MNDWI_{s2} 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 MNDWI_{s2}.

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 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, MNDWI_{s2} 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 MNDWI_{s2}. The advantage of MNDWI_{s2} is the use of SWIR2, where in spectral value curves SWIR2 band has a lower reflectance value of vegetation. So that subtraction 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 subtraction 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

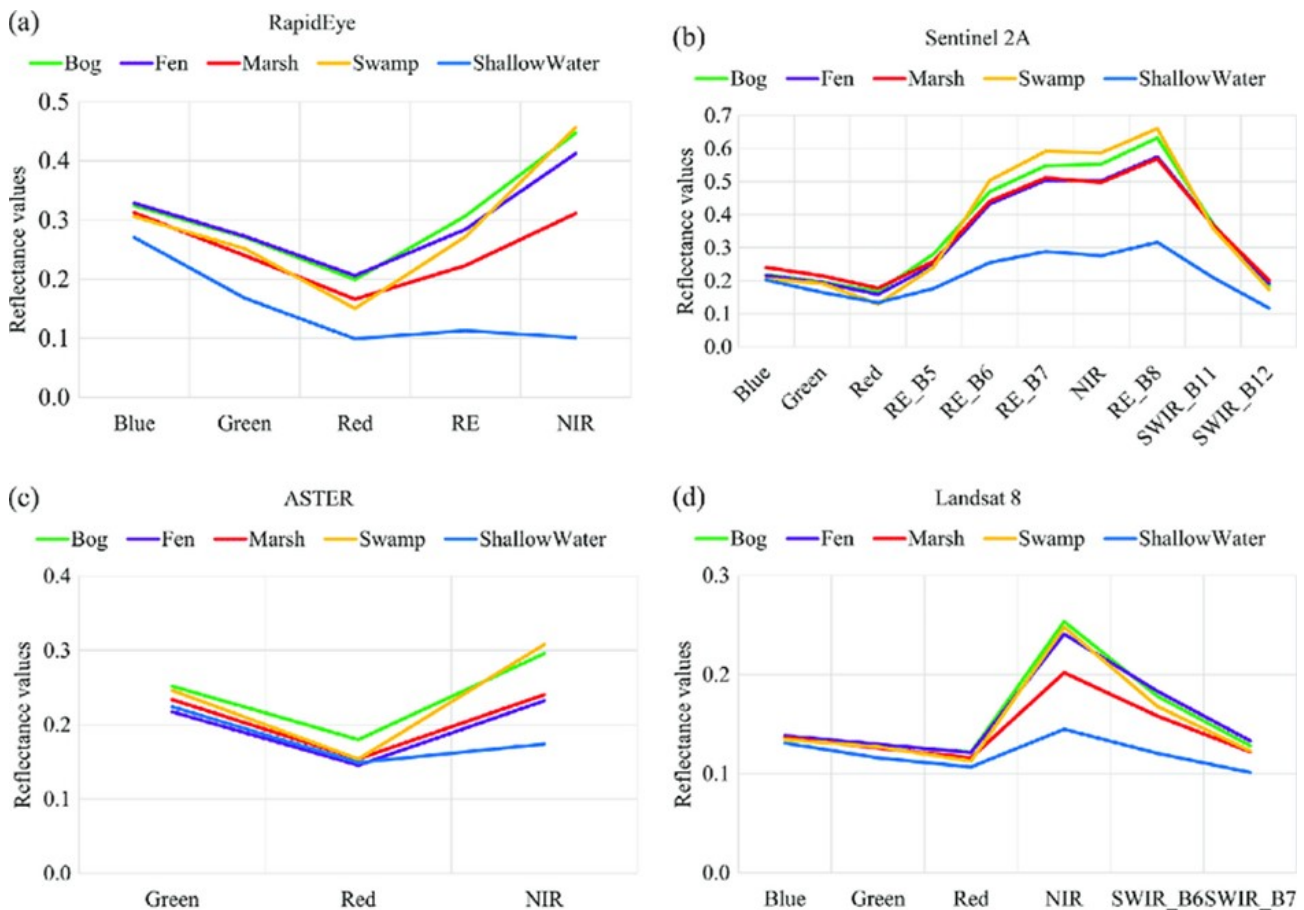


Figure 7. The spectral signature of wetlands, obtained from (a) RapidEye, (b) Sentinel 2A, (c) ASTER, and (d) Landsat 8 (Amani et al., 2018)

the accuracy of the NDWI formula. Especially if the formula be examined in other regions with different conditions, or be examined on other multispectral imageries.

Acknowledgement

The authors thank to the United States Geological Survey (USGS) for providing the Landsat 8 OLI imageries for free, as a main data of this research. This research was funded by the Spatial Data Infrastructure Development Center (PPIDS), University of Lambung Mangkurat. Digital image processing in this research was carried out at the Remote Sensing and Geographic Information System Laboratory, Faculty of Forestry, University of Lambung Mangkurat, Banjarbaru.

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Title	Comparison of Various Spectral Indices for Optimum Extraction of Tropical Wetlands Using Landsat 8 OLI
Section	Research Articles
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Review Version	49914-143927-2-RV.DOCX 2019-10-18
Initiated	2019-10-18
Last modified	2020-02-14
Uploaded file	Reviewer A 49914-148916-1-RV.DOCX 2019-11-06 Reviewer B 49914-155347-1-RV.DOCX 2019-12-28

Editor Decision

Decision	Accept Submission 2021-07-30
Notify Editor	Editor/Author Email Record 2021-07-30
Editor Version	49914-146716-1-ED.DOCX 2019-10-18 49914-146716-2-ED.DOCX 2020-11-08 49914-146716-3-ED.DOCX 2021-06-25 49914-146716-4-ED.DOCX 2021-06-27 49914-146716-5-ED.DOCX 2021-07-30
Author Version	49914-165181-1-ED.DOCX 2020-03-31 DELETE 49914-165181-2-ED.DOCX 2020-12-22 DELETE 49914-165181-3-ED.DOCX 2020-12-22 DELETE 49914-165181-4-ED.DOCX 2021-06-25 DELETE 49914-165181-5-ED.DOCX 2021-06-25 DELETE 49914-165181-6-ED.DOCX 2021-07-26 DELETE

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