

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.

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

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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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1 **1. Introduction**

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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

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.

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9 **2.The Methods**

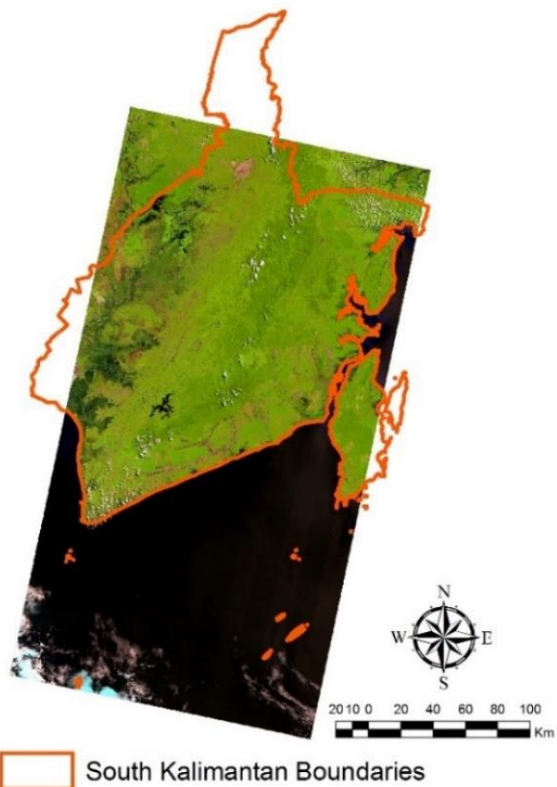
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11 2.1.Materials

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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).



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.	AWE _{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.	AWE _{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)

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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)

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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).

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17 2.4. Accuracy Assessment

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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). 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.

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.

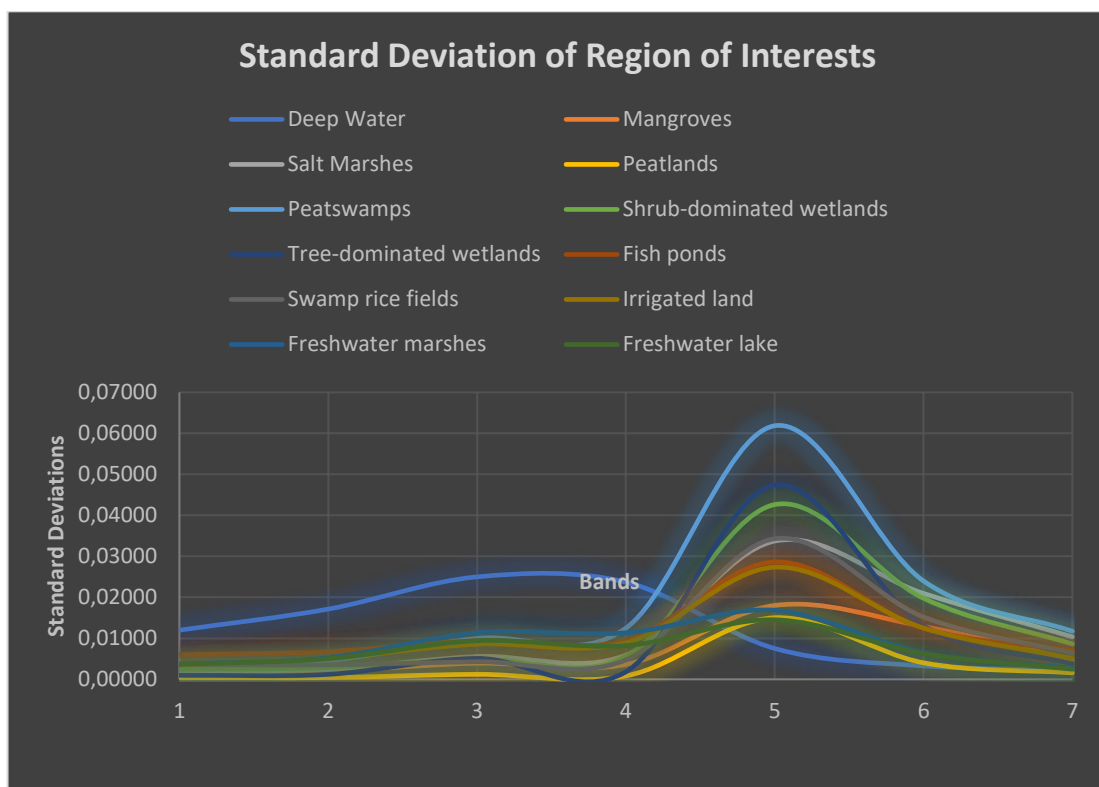
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28 **3.Result and Discussion**

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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.

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

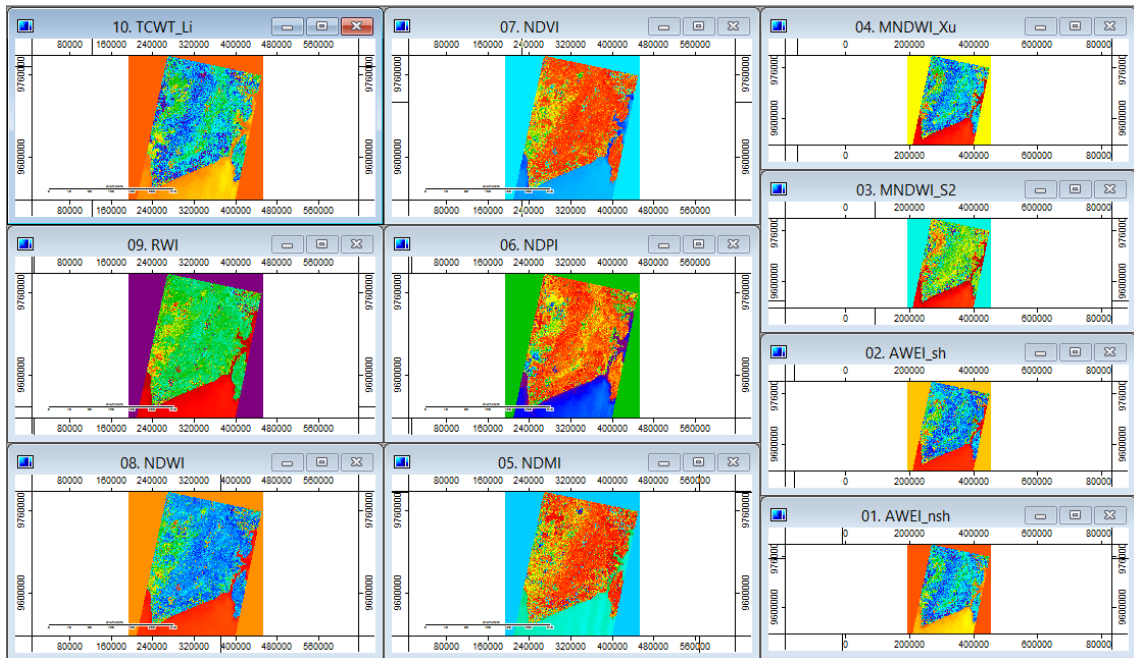
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12 Of course, spectral indices such as NDWI cannot distinguish between mangroves and
 13 peatswamps, for example. Because spectral indices such as NDWI are only designed to
 14 recognize and separate water/wetlands from dryland features. While mangroves 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.

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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 _{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

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.

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

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 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).

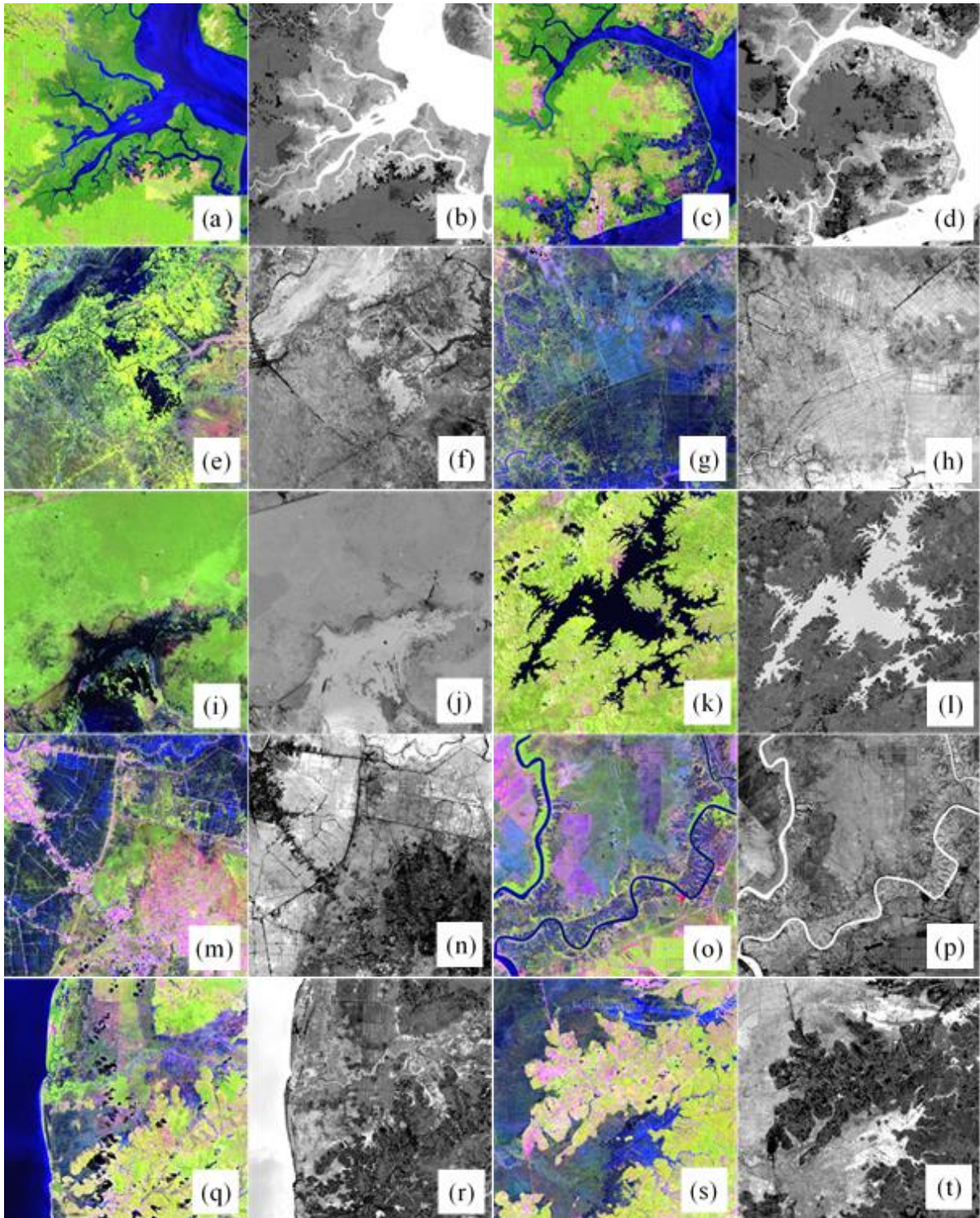


Figure 4. Comparison between Landsat 8 OLI composite 654 and MNDW_{s2}

(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.

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.

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14
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