

# 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 (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.

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## 11 **2.The Methods**

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### 13 2.1.Materials

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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).

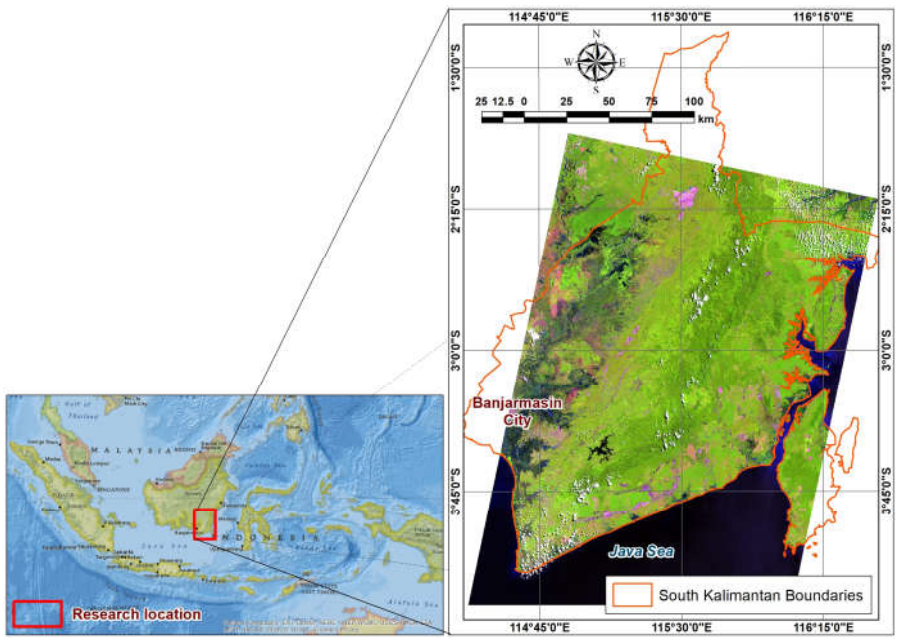


Figure 1. Research location

## 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:

- $\rho_g$ : green band
- $\rho_n$ : near infrared band

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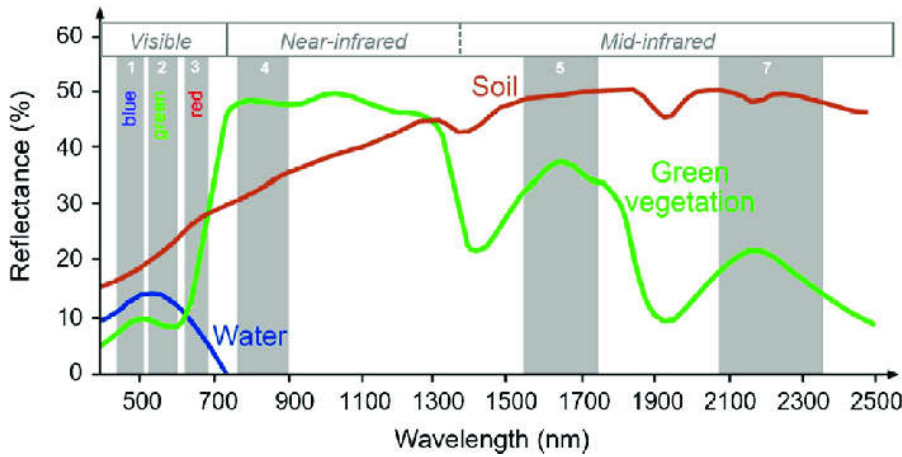


Figure 2. Spectral value curves on three base surface features (Chen et al., 2019)

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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:

- $\rho_s$ : 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:

- $\rho_{s2}$ : 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<sub>s2</sub>, 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.

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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 <sub>s2</sub> 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 <sub>nsh</sub> 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 <sub>sh</sub> 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 •  $\rho_{ca}$ : aerosol coastal bands (bands 1 Landsat 8)
- 2 •  $\rho_b$ : blue band (band 2 Landsat 8)
- 3 •  $\rho_g$ : green band (band 3 Landsat 8)
- 4 •  $\rho_r$ : red band (band 4 Landsat 8)
- 5 •  $\rho_n$ : near infrared band (band 5 Landsat 8)
- 6 •  $\rho_s$ : shortwave infrared band (band 6 or 7 Landsat 8)
- 7 •  $\rho_{s1}$ : shortwave infrared 1 band (band 6 Landsat 8)
- 8 •  $\rho_{s2}$ : shortwave infrared 2 band (band 7 Landsat 8)

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### 10 2.3. Wetlands Extraction

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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,

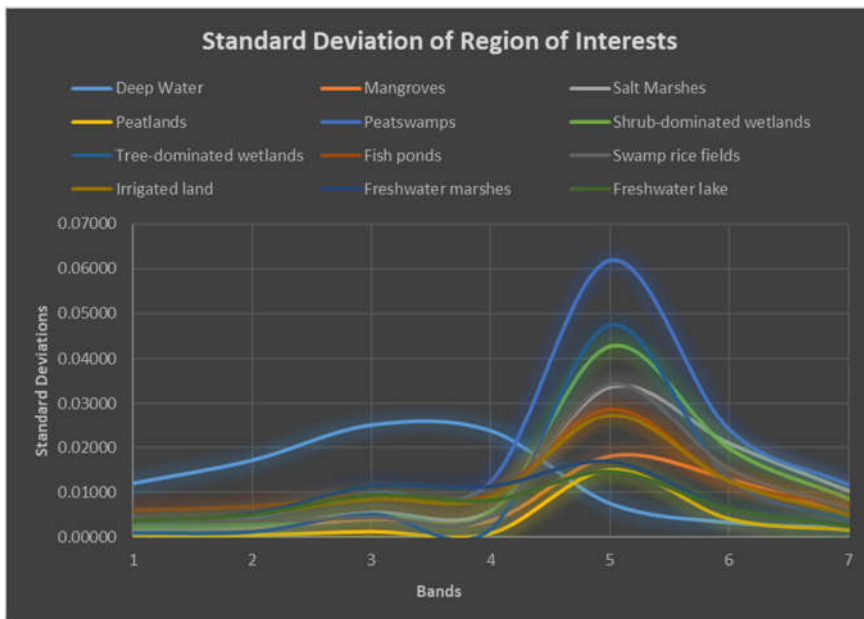
1 to obtain a quantitative description of the ability of the spectral index to avoid the detection of  
2 one type of dryland. So that a description of NDWI's ability to avoid detecting Dryland Forest  
3 as a wetland will be obtained, for example. Recapitulation of commission error values for each 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

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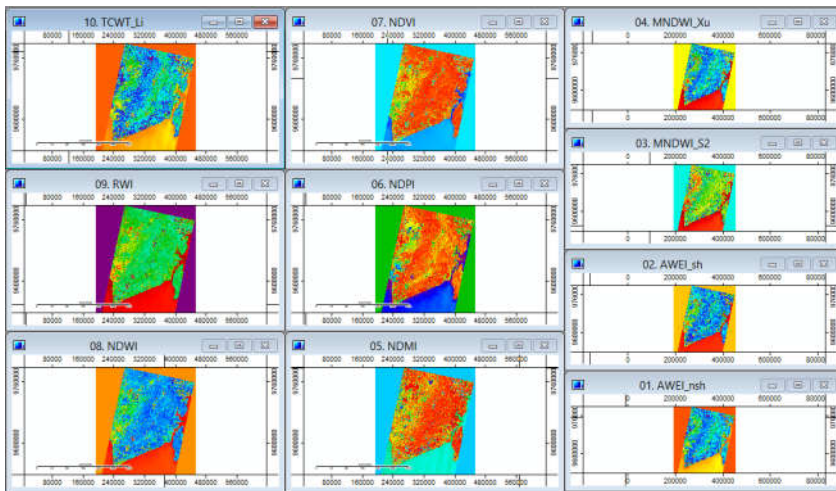
16 Figure 3. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

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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	$\leq 0.21$	44.20	0.18	43.59	88.49	11.51	56.41
2.	NDWI	$\geq -0.17$	45.19	0.19	44.84	89.73	10.27	55.16
3.	MNDWI	$\geq -0.06$	68.59	0.50	84.22	99.74	0.26	15.78
4.	MNDWI <sub>12</sub>	$\geq 0.07$	74.82	0.59	97.54	98.13	1.87	2.46
5.	NDMI	$\geq 0.13$	32.68	-0.14	38.86	60.48	39.52	61.14
6.	WRI	$\geq 0.51$	73.02	0.50	98.61	84.61	15.39	1.39
7.	NDPI	$\leq 0.05$	65.02	0.45	77.15	99.85	0.15	22.85
8.	TCWT	$\leq 0.45$	59.32	0.37	66.37	99.95	0.05	33.63
9.	AWEI <sub>inh</sub>	$\geq -0.55$	54.15	0.31	57.11	99.99	0.01	42.89
10.	AWEI <sub>sh</sub>	$\geq -0.20$	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<sub>s2</sub>, 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<sub>s2</sub> 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 <sub>s2</sub>	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 <sub>mh</sub>	100	69.97	88.46	0	95.87	25.47	5.92	99.88	96.38	100	100	100
10.	AWEI <sub>sh</sub>	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<sub>s2</sub> 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 <sub>s2</sub>	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 <sub>nsh</sub>	0	0	0	0	0.06	0	0	0
10.	AWEI <sub>sh</sub>	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.

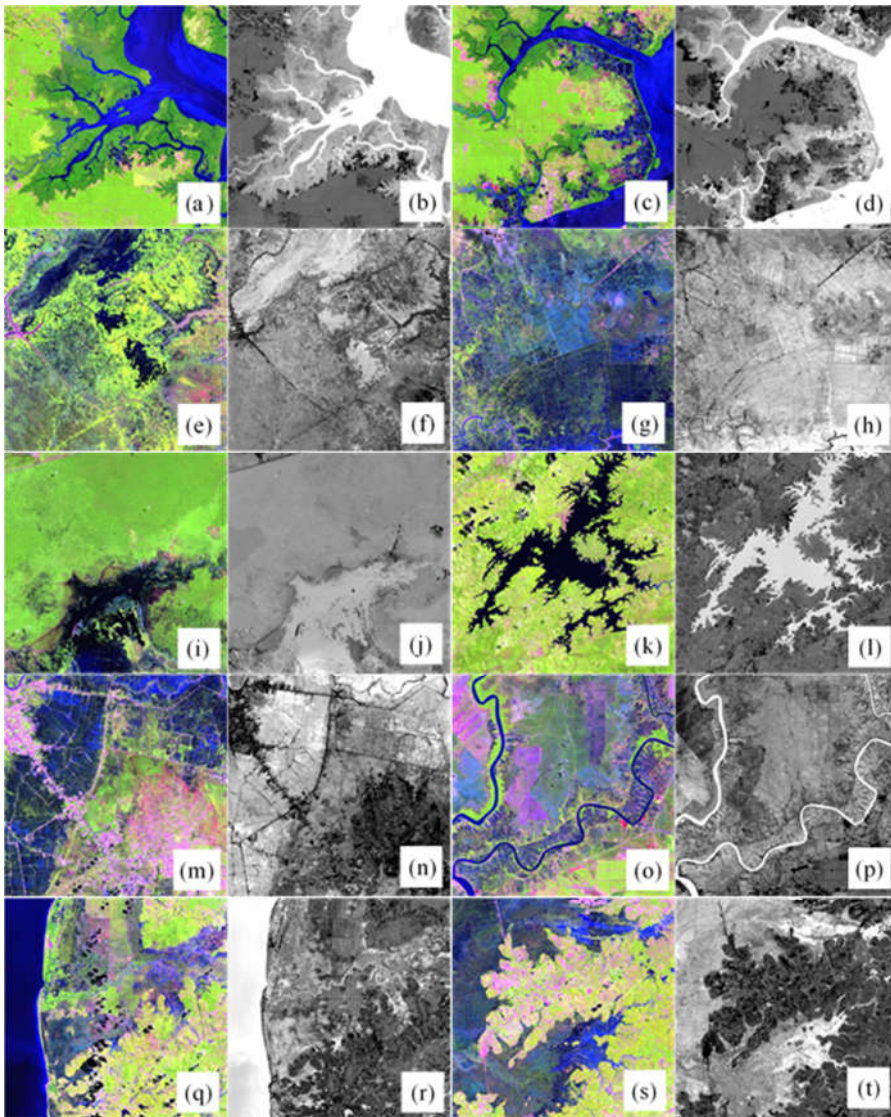
12 NDVI and NDWI that have the same character, they are also sensitive to built-up lands,  
13 roads, and barelands. NDPI better than NDVI and NDWI in distinguishing between built-up  
14 lands or barelands and wetlands. However, NDPI also slightly failed in distinguishing the paved  
15 roads to the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

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Figure 5. Comparison between Landsat 8 OLI composite 654 and MNDW<sub>s2</sub>

(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 MNDWI<sub>2</sub> 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 MNDWI<sub>2</sub>. This makes MNDWI<sub>2</sub> 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 MNDWI<sub>2</sub> 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

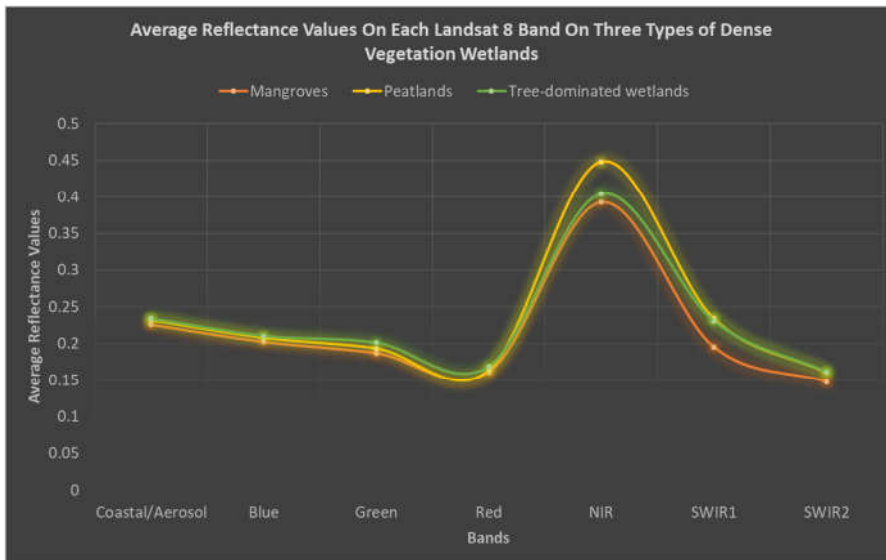


Figure 6. Average reflectance values on each Landsat 8 band on three types of dense vegetation wetlands

MNDWI<sub>s2</sub> 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<sub>s2</sub> still able to capture the reflection of background water or soil moisture beneath the canopy. In the MNDWI<sub>s2</sub> 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<sub>s2</sub>.

#### 4. Conclusion

Based on this research, the spectral indices recorded the most accurate and optimal in extracting wetlands is MNDWI<sub>s2</sub>. But MNDWI<sub>s2</sub> should be used wisely, given MNDWI<sub>s2</sub> very sensitive to dense vegetations. MNDWI<sub>s2</sub> also has potential error in wetlands with dominant soil background features. MNDWI<sub>s2</sub> 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<sub>s2</sub> 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<sub>s2</sub>. The advantage of MNDWI<sub>s2</sub> 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<sub>s2</sub> 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<sub>s2</sub> 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

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23 Mangkurat, Banjarbaru.

24

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26

27 **References**

28

**Commented [A11]:** Please make sure that all your cited references are listed here and vice versa

**Commented [A12R11]:** I've made sure that all the references I cite are listed here, and vice versa

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