

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

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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
8 path/row 117/062 and 117/063. The threshold method which was used to separate the wetland features from the
9 spectral indices imagery is Otsu method. The results of this research showed that, generally MNDWIs2 was the
10 most optimal spectral indices in the wetlands extraction. Especially tropical wetlands that rich with green
11 vegetation cover. However, MNDWIs2 is very sensitive to dense vegetation, this feature has the potential to be
12 detected as wetlands. Furthermore, to improve the accuracy and prevent detection of the dryland vegetation as
13 wetlands, the threshold value should be 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
21 Landsat 8 OLI path/row 117/062 and 117/063. Metode pembatasan nilai yang digunakan untuk memisahkan fitur
22 lahan basah dari citra indeks spektral adalah metode Otsu. Hasil penelitian ini menunjukkan bahwa, secara
23 umum MNDWIs2 merupakan indeks spektral yang paling optimal dalam ekstraksi lahan basah. Khususnya lahan
24 basah tropis yang kaya dengan penutupan vegetasi hijau. Akan tetapi, MNDWIs2 sangat sensitif terhadap vegetasi
25 rapat, fitur ini berpotensi untuk terdeteksi sebagai lahan basah. Lebih jauh, untuk meningkatkan akurasi dan
26 mencegah 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
5 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
10 water bodies (rivers) in this area, the waters have high enough levels of turbidity. In South
11 Kalimantan there are also quite a lot of open pit coal mining activities. The water inside the
12 pits the rest of the coal mine will be mixed with the toxic minerals out of the mine. Hence, on
13 the ground the pits look green. The green colour was formed distinct spectral signatures in
14 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)
17 (McFeeters, 1996), Modified Normalized Difference Water Index (MNDWI) (Xu, 2006), and
18 so forth. Besides NDWI or MNDWI, there are also a number of other spectral indices that
19 can 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
27 Rivers and Lakes (AMERL) for the extraction of rivers and lakes automatically from Landsat
28 TM/ETM +. It was found that in general MNDWI is the most excellent among the three other
29 spectral indices.

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

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
14 level.

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

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

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

1 wetlands, by taking the case of the tropics area, that is, the South Kalimantan Province,
2 Indonesia.

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4 **2.The Methods**

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6 **2.1.Materials**

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

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



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Figure 1. Research location

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2 2.2. Water Indices

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

$$9 \quad \text{NDWI} = \frac{\rho_g - \rho_n}{\rho_g + \rho_n}$$

10 Where:

11 ρ_g : green band

12 ρ_n : near infrared band

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

$$16 \quad \text{MNDWI} = \frac{\rho_g - \rho_s}{\rho_g + \rho_s}$$

17 Where:

18 ρ_s : shortwave infrared band

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

$$22 \quad \text{MNDWI}_{s2} = \frac{\rho_g - \rho_{s2}}{\rho_g + \rho_{s2}}$$

23 Where:

24 ρ_{s2} : shortwave infrared 2 band

25 Xu (2006) replaces NIR with SWIR1 in NDWI (McFeeters, 1996) with the aim to
26 suppress building features, because in the SWIR1, soil and building reflectance higher than
27 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.

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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	Shen (2010)

					than 1	
7.	NDPI	Normalized Difference Pond Index	$\frac{\rho_s - \rho_g}{\rho_s + \rho_g}$		Negative	Lacaux et al. (2007)
8.	TCWT	Tasseled-Cap Wetness Transformation	$0.1877\rho_{ca} + 0.2097\rho_b + 0.2038\rho_g + 0.1017\rho_r + 0.0685\rho_n - 0.7460\rho_{s1} - 0.5548\rho_{s2}$		-	Li et al. (2015)
9.	AWEI _{nsh}	Automated Water Extraction Index with no shadow	$4(\rho_g - \rho_{s1}) - (0.25\rho_n + 2.75\rho_{s2})$		-	Feyisa et al. (2014)
10.	AWEI _{sh}	Automated Water Extraction Index with shadow	$\rho_b + 2.5\rho_g - 1.5(\rho_n + \rho_{s1}) - 0.25\rho_{s2}$		-	Feyisa et al. (2014)

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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
 17 threshold 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.
 19 One 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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2.4. 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, 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.

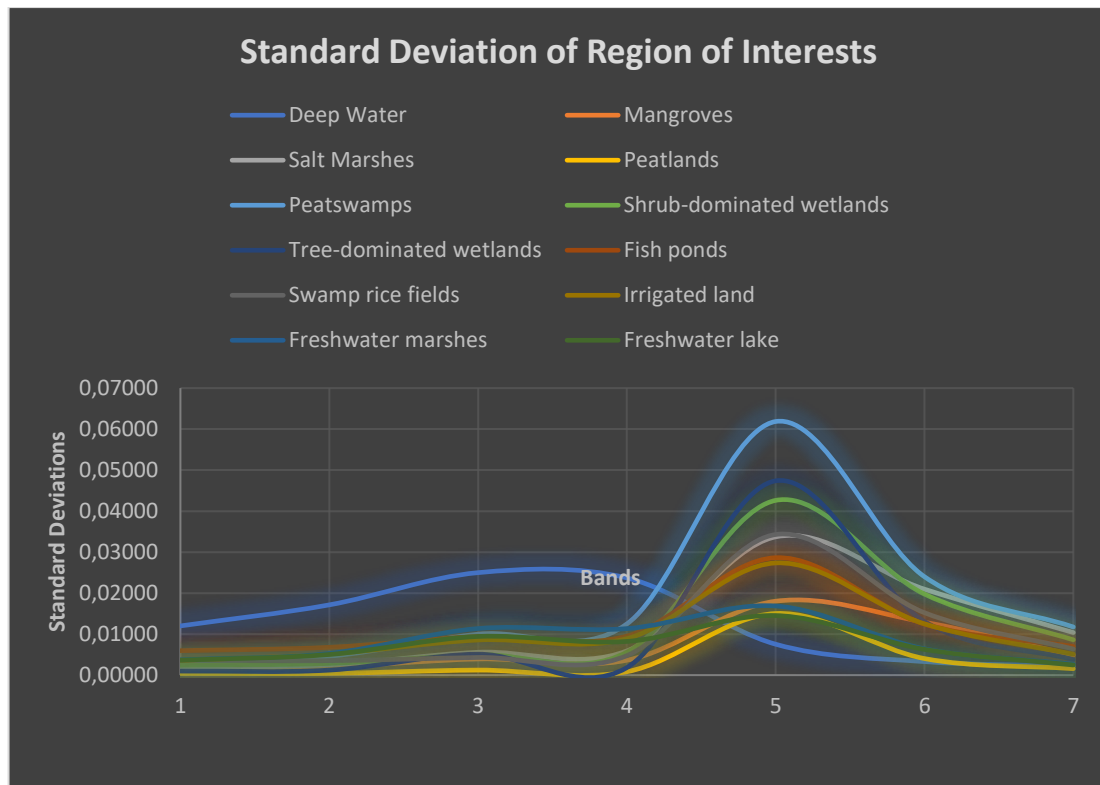


Figure 2. Standard Deviation of all wetlands types ROI in each band of Landsat 8 OLI

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.

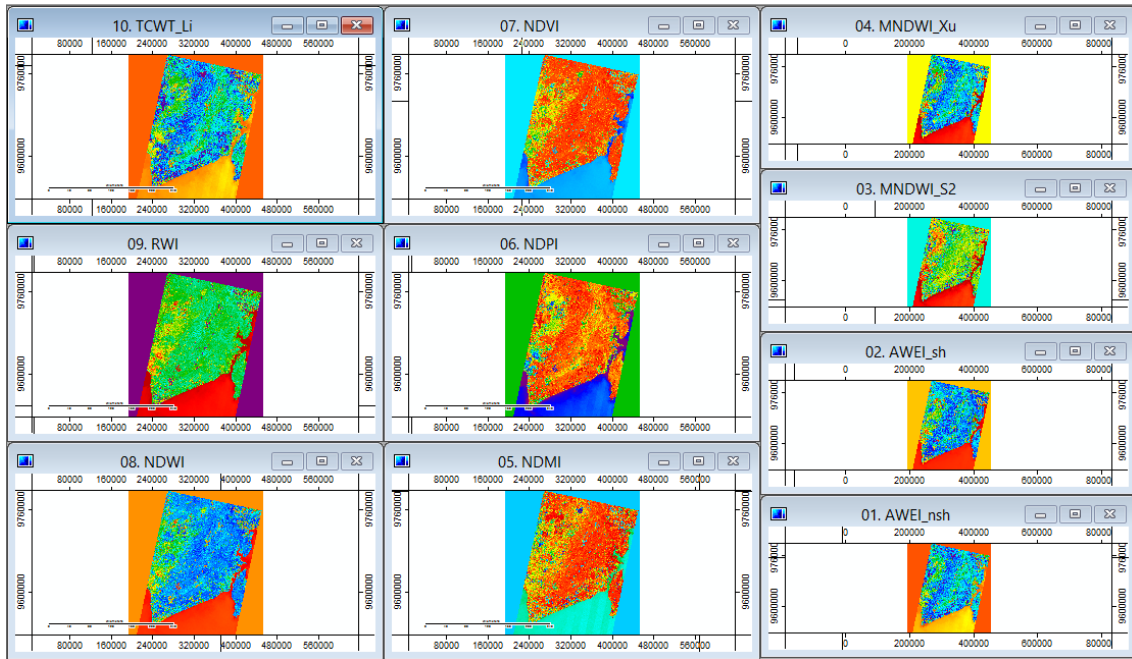


Figure 3. The result of the transformation of spectral indices on the SAGA application

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 _{s2}	≥ 0.07	74.82	0.59	97.54	98.13	1.87	2.46
5.	NDMI	≥ 0.13	32.68	-0.14	38.86	60.48	39.52	61.14
6.	WRI	≥ 0.51	73.02	0.50	98.61	84.61	15.39	1.39
7.	NDPI	≤ 0.05	65.02	0.45	77.15	99.85	0.15	22.85
8.	TCWT	≤ 0.45	59.32	0.37	66.37	99.95	0.05	33.63
9.	AWEI _{nsh}	≥ -0.55	54.15	0.31	57.11	99.99	0.01	42.89
10.	AWEI _{sh}	≥ -0.20	62.46	0.41	72.53	98.87	1.13	27.47

Information:

OA: Overall Accuracy

PA: Producer's Accuracy

UA: User's Accuracy

CE: Commission Error

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
10 more to conditionally. However, this study is sufficient to provide an overview comparison of
11 the 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
22 thresholding results imagery of spectral indices. This is because, each thresholding results
23 imagery of spectral indices does not distinguish among types of wetlands. Table 3 shows the
24 PA for each spectral 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 _{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

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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
 18 open 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
4 NDWI. Only NDPI more successful in recognizing wetlands with dense canopy. Compared
5 to NDPI, TCWT worse at recognizing wetlands topped with vegetations with a bright hue,
6 which are commonly found in shrub-dominated wetlands and freshwater marshes. $AWEI_{nsh}$
7 ability in recognizing wetlands also similar to NDPI and TCWT. However, failures in
8 identifying wetlands with dense canopy worse than TCWT. $AWEI_{sh}$ even worse at
9 recognizing wetlands 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
13 tree-dominated wetlands with almost 100% accuracy. Based on this fact, our assumption
14 when shifting SWIR1 into SWIR2 on MNDWI has been proven. $MNDWI_{s2}$ able to recognize
15 the characteristic spectral features that have water and vegetation spectral characteristics as
16 well 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.

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28 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

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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

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

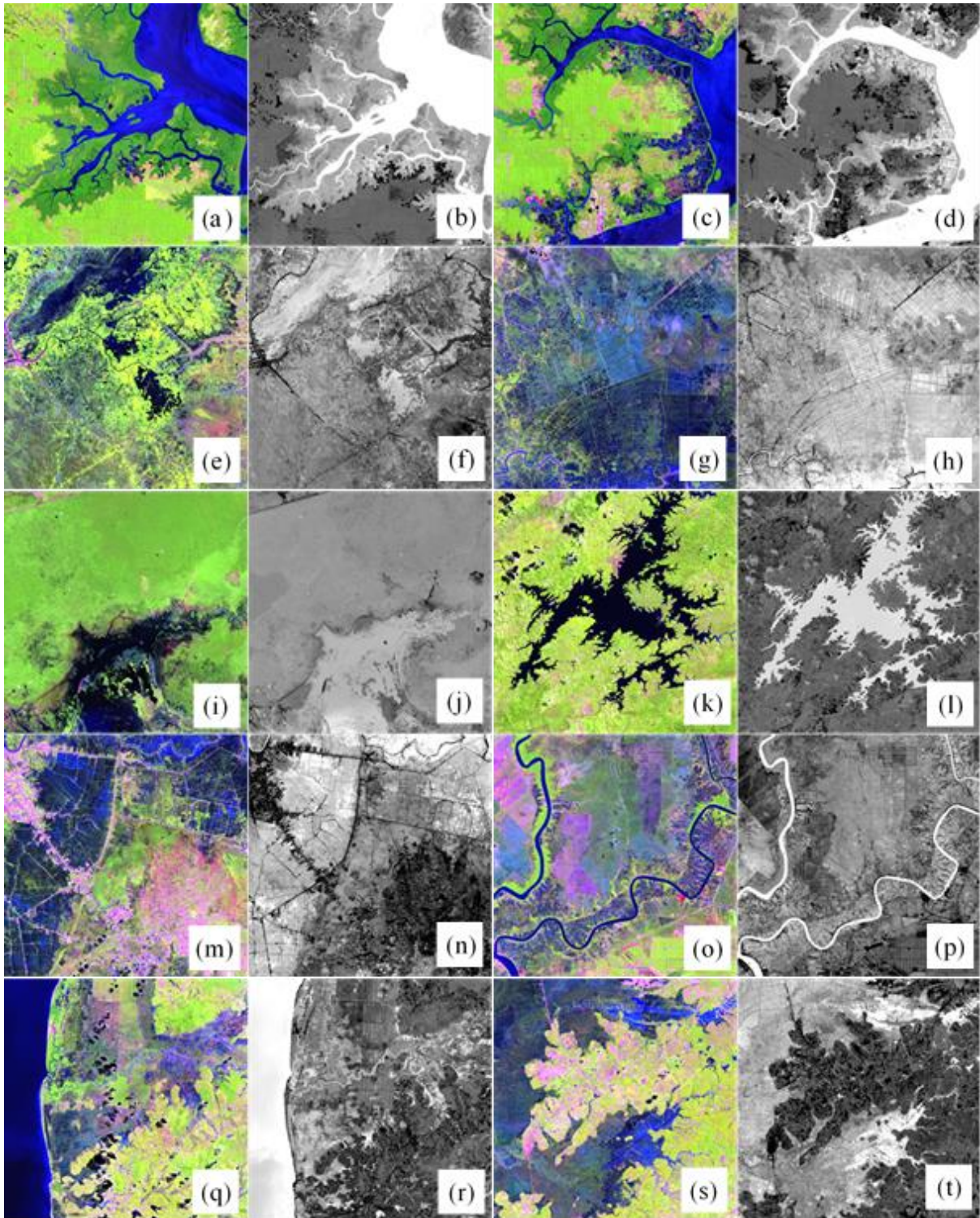
18 NDVI and NDWI that have the same character, they are also sensitive to built-up
19 lands, roads, and barelands. NDPI better than NDVI and NDWI in distinguishing between

1 built-up lands or barelands and wetlands. However, NDPI also slightly failed in
2 distinguishing the paved roads to the wetlands. TCWT and AWEInsh are two spectral indices
3 of the nicest in minimizing error detection wetlands. Since both spectral indices have the
4 lowest CE. Different from AWEInsh, AWEIsh disadvantaged in distinguishing between the
5 paved roads to the wetlands.

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

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

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

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

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

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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
6 imagery. It is an implication of the subtraction with SWIR₂. This can cause the dominant soil
7 in wetlands background features will bring potential OE to MNDWI_{s2}. Figure 4 shows the
8 comparison 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
15 soil background features. MNDWI_{s2} not only able to recognize the deep waters as well as
16 MNDWI, 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
18 very impressive. Given the peatlands actually not always saturated with water on the surface,
19 most of them just has a very high water content in the ground with very high moisture
20 surfaces. Will MNDWI_{s2} be considered as Normalized Difference Wetlands Index (NDWLI)?
21 Well, of course, more research needs to be done to investigate.

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24
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6 **References**

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8 Ashraf, M. and Nawaz, R..(2015). A Comparison of Change Detection Analyses Using
9 Different Band Algebras for Baraila Wetland with Nasa's Multi-Temporal Landsat
10 Dataset. *Journal of Geographic Information System*, 7, 1-19.

11 Boschetti, M., Nutini, F., Manfron, G., Brivio, P.A., Nelson, A..(2014). Comparative Analysis
12 of Normalised Difference Spectral Indices Derived from MODIS for Detecting Surface
13 Water in Flooded Rice Cropping Systems. *PLoS ONE* 9 (2), e88741.
14 doi:10.1371/journal.pone.0088741

15 Chavez, P.S..(1988). An Improved Dark-Object Subtraction Technique for Atmospheric
16 Scattering Correction of Multispectral Data. *Remote Sensing of Environment*, 24,
17 459–479.

18 Chavez, P.S..(1996). Image-based Atmospheric Corrections—Revisited and Improved.
19 *Photogrammetric Engineering and Remote Sensing*, 62, 1025–1036.

20 Chen, D., Huang, J., and Jackson, T.J..(2005). Vegetation Water Content Estimation for Corn
21 and Soybeans Using Spectral Indices Derived from MODIS Near- and Short-wave
22 Infrared Bands. *Remote Sensing of Environment*, 98, 225-236.

23 Conrad, O., Bechtel, B., Bock, M., Dietrich, H., Fischer, E., Gerlitz, L., Wehberg, J.,
24 Wichmann, V., and Boehner, J..(2015). System for Automated Geoscientific Analyses
25 (SAGA) v. 2.1.4.. *Geoscientific Model Development*, 8, 1991-2007, doi:10.5194/gmd-
26 8-1991-2015.

- 1 Das, R.J. and Pal, S..(2016). Identification of Water Bodies from Multispectral Landsat
2 Imageries of Barind Tract of West Bengal. *International Journal of Innovative*
3 *Research and Review*, 4 (1), 26-37.
- 4 Du, Y., Zhang, Y., Ling, F., Wang, Q., Li, W., and Li, X..(2016). Water Bodies' Mapping from
5 Sentinel-2 Imagery with Modified Normalized Difference Water Index at 10-m Spatial
6 Resolution Produced by Sharpening the SWIR Band. *Remote Sensing*, 8, 354-372,
7 doi:10.3390/rs8040354.
- 8 Feyisa, L.G., Meilby, H., Fensholt, R., and Proud, S.R..(2014). Automated Water Extraction
9 Index: A New Technique for Surface Water Mapping Using Landsat Imagery. *Remote*
10 *Sensing of Environment*, 140 (2014), 23–35.
- 11 Gao, B.C..(1996). NDWI A – Normalized Difference Water Index for Remote Sensing of
12 Vegetation Liquid Water from Space. *Remote Sensing of Environment*, 58, 257-266.
- 13 Hong, G., Xing-fa, G., Young, X., Tau, Y., Hai-liang, G., Xiang-qin, W., and Qi-yue, L..(2014).
14 Evaluation of Four Dark Object Atmospheric Correction Methods Based on XY-3
15 CCD Data [Abstract]. *Spectroscopy and Spectral Analysis*, 34 (8), 2203-2207.
- 16 Islam, Md.A., Thenkabail, P.S., Kulawardhana, R.W., Alankara, R., Gunasinghe, S., Edussriya,
17 C., and Gunawardana, A..(2008). Semi - automated Methods for Mapping Wetlands
18 using Landsat ETM+ and SRTM Data. *International Journal of Remote Sensing*, 29
19 (24), 7077-7106, doi: 10.1080/01431160802235878.
- 20 Jackson, T.J., Chen, D., Cosh, M., Li, F., Anderson, M., Walthall, C., Doriaswamy, P., and
21 Hunt, E.R..(2004). Vegetation Water Content Mapping Using Landsat Data Derived
22 Normalized Difference Water Index for Corn and Soybeans. *Remote Sensing of*
23 *Environment*, 92, 475-482.
- 24 Ji, L., Zhang, L., and Wylie, B..(2009). Analysis of Dynamic Thresholds for the Normalized
25 Difference Water Index, *Photogrammetric Engineering and Remote Sensing*, 75, (11),
26 1307-1317.
- 27 Jiang, H., Feng, M., Zhu, Y., Lu, N., Huang, J., and Xiao, T.. (2014). An Automated Method
28 for Extracting Rivers and Lakes from Landsat Imagery. *Remote Sensing*, 6, 5067-5089.

- 1 Kwak, Y. and Iwami, Y..(2014). Nationwide Flood Inundation Mapping in Bangladesh by
2 Using Modified Land Surface Water Index. ASPRS 2014 Annual Conference,
3 Louisville, Kentucky, March 23-28, 2014.
- 4 Lacaux, J.P., Tourre, Y.M., Vignolles, C., Ndione, J.A., Lafaye, M..(2007). Classification of
5 Ponds from High-spatial Resolution Remote Sensing: Application to Rift Valley Fever
6 epidemics in Senegal. *Remote Sensing of Environment*, 106, 66–74.
- 7 Li, B., Ti, C., Zhao, Y., and Yan, X..(2015). Estimating Soil Moisture with Landsat Data and Its
8 Application in Extracting the Spatial Distribution of Winter Flooded Paddies. *Remote
9 Sensing*, 8, 38-55, doi:10.3390/rs8010038.
- 10 Li, W., Du, Z., Ling, F., Zhou, D., Wang, H., Gui, Y., Sun, B., and Zhang, X..(2013). A
11 Comparison of Land Surface Water Mapping Using the Normalized Difference Water
12 Index from TM, ETM+ and ALI. *Remote Sensing*, 5, 5530-5549.
- 13 Matthews, G.V.T..(2013). The Ramsar Convention on Wetlands: its History and
14 Development. Ramsar Convention Bureau, Gland, Switzerland, p. 41.
- 15 McFeeters, S.K..(1996). The Use of the Normalized Difference Water Index (NDWI) in the
16 Delineation of Open Water Features. *International Journal of Remote Sensing*, 17 (7),
17 1425-1432.
- 18 Otsu, N..(1979). A Threshold Selection Method from Gray-level Histograms. *IEEE
19 Transactions on Systems, Man, and Cybernetics*, 9, 62–69.
- 20 Rouse, J.W., Haas, R.H., Schell, J.A., Deering, D. W..(1973). Monitoring vegetation systems in
21 the Great Plains with ERTS. Third ERTS Symposium, NASA SP-351 I, 309-317.
- 22 Schneider, C.A., Rasband, W.S., and Eliceiri, K.W..(2012). NIH Image to ImageJ: 25 Years of
23 Image Analysis. *Nature Methods*, 9(7), 671-675, PMID 22930834.
- 24 Schindelin, J., Rueden, C.T., and Hiner, M.C. et al..(2015). The ImageJ Ecosystem: An open
25 Platform for Biomedical Image Analysis. *Molecular Reproduction and Development*,
26 PMID 26153368.
- 27 Shen, L. and Li, C..(2010). Water Body Extraction from Landsat ETM+ Imagery Using
28 Adaboost Algorithm. In *Proceedings of 18th International Conference on
29 Geoinformatics*, 18–20 June, Beijing, China, 1–4.

- 1 Stehman, S.V. and Czaplewski, R.L..(1997). Design and Analysis for Thematic Map Accuracy
2 Assessment: Fundamental Principles. *Remote Sensing of Environment*, 1998 (64),
3 331-344.
- 4 United States Environmental Protection Agency (EPA).(2004). Wetlands Overview, EPA 843-
5 F-04-011a. Office of Water, December 2004.
- 6 Wilson, E.H. and Sader, S.A..(2002). Detection of Forest Harvest Type using Multiple Dates
7 of Landsat TM Imagery. *Remote Sensing Environment*, 80, 385–396.
- 8 World Wildlife Fund (WWF).(2004). Global Lakes and Wetlands Database: Lakes and
9 Wetlands Grid (Level 3). Washington, D.C., [http://www.worldwildlife.org/
10 publications/global-lakes-and-wetlands-database-lakes-and-wetlands-grid-level-3](http://www.worldwildlife.org/publications/global-lakes-and-wetlands-database-lakes-and-wetlands-grid-level-3).
- 11 Yang, L., Tian, S., Yu, L., Ye, F., Qian, J., and Qian, Y..(2015). Deep Learning for Extracting
12 Water Body from Landsat Imagery. *International Journal of Innovative Computing,
13 Information and Control*, 11 (6), 1913–1929.
- 14 Xiao, X., Boles, S., Froking, S., Salas, W., Moore, B., et al..(2002). Observation of Flooding
15 and Rice Transplanting of Paddy Rice Fields at the Site to Landscape Scales in China
16 using VEGETATION Sensor Data. *International Journal of Remote Sensing*, 23,
17 3009–3022, doi:10.1080/01431160110107734.
- 18 Xie, H., Luo, X., Xu, X., Pan, H., and Tong, X..(2016). Automated Subpixel Surface Water
19 Mapping from Heterogeneous Urban Environments Using Landsat 8 OLI Imagery.
20 *Remote Sensing*, 8 (7), 584-599.
- 21 Xu, H..(2006). Modification of Normalized Difference Water Index (NDWI) to Enhance
22 Open Water Features in Remotely Sensed Imagery. *International Journal of Remote
23 Sensing*, 27 (14), 3025–3033, doi: 10.1080/01431160600589179.
- 24 Zhai, K., Wu, X., Qin, Y., and Du, P..(2015). Comparison of Surface Water Extraction
25 Performances of Different Classic Water Indices using OLI and TM Imageries in
26 Different Situations. *Geo-spatial Information Science*, 18 (1), 32-42, doi: 10.1080/
27 10095020.2015.1017911.
- 28 Zhang, Z., He, G., and Wang, X..(2010). A Practical DOS Model-Based Atmospheric
29 Correction Algorithm. *International Journal of Remote Sensing*, 31 (11), 2837-2852.