Feature extraction of coastal surface inundation via water index algorithms using multispectral satellite on North Jakarta

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Abstract. The study aims to characterize water index algorithms using Sentinel 2A-MSI and Landsat 8-OLI sensors to generate the performance of CSI and its proper uses in science. Feature extraction of the 35 combinations of CSI specifically uses information deriving from a number of water index spectral bands. Supervised classification is used to categorize water and non-water features using Spectral Angle Mapper (SAM). Furthermore, Dynamic Surface Water Extent (DSWE) algorithm was taken to mapping inundation and non-inundation. Result of this research shows that the best water index algorithms is exhibited by the MNDWI algorithm where it can enhance the water reflectance to be positive value. Re-classification on all water index algorithms indicates a similar pattern to the feature extraction of water and non-water. It is determined by overall accuracy (99.56-99.99%), Kappa coefficient (0.97-1.00), producer accuracy (99.05-99.99%) and user accuracy (93.43-99.94%). Substituting all water index algorithms into DSWE algorithm points out that the MNDWI is still the good performance and other substituted algorithms generate low performances. Overall feature extractions of CSI in North Jakarta at this research manifests that the MNDWI algorithm using multi-spectral and satellites is the best algorithm.

1. Introduction
Global climate change causes North Jakarta included in 10 major cities in Southeast Asia, which is vulnerable to environmental pressure [1]. Its location in the coastal area makes it the most vulnerable coastal city to environmental pressure in Indonesia. This area is potentially vulnerable to coastal surface inundation (CSI), because of its lowest topography, severe impact of land subsidence, and the impact of local sea level rise due to ongoing climate change. Over the last five years, the flood-prone points have increased rapidly and spread evenly across all regions. Information about CSI is important to take into account, because the causes of inundating in this city by natural and anthropogenic factors affect the environmental and ecological aspects [2], as well as efforts to protect the regional environment, health and economic activities.

The main approach to obtain information about CSI changes in recent years can use remote sensing satellite [3-6]. U.S. Geological Survey (USGS) specifically developed Landsat 8, to assess aspects of Dynamic Surface Water Extent (DSWE), which focused on ground surface inundation [7]. Development of Landsat 8 has more bands and better bandwidth design as a form of evolutionary technical improvement [8]. Likewise with Sentinel 2A developed by European Space Agency (ESA) since it was launched in mid-2015. Sentinel 2A data has a better special resolution than Landsat 8. The study of CSI feature extraction refers to the approach of water body extraction. The water body extraction approach itself initially used a spectral band-based approach. It is then developed into a Water Index Algorithm
to map the body of water. The method of feature extraction of CSI specifically is still evolving, but in general the extracting process refers to two major Water Index Algorithm approaches; first is the Traditional Supervised and Unsupervised Classifications by using one band or multiple bands [9-11], and another approach is the Spectral Index approach related to water and threshold [12-16]. This approach has been widely used, due to the unique spectral characteristics of water bodies in Visible and Infrared bands. Generally, spectral analysis can effectively identify and detect bodies of water based on supervised classification techniques. The Water Index Algorithm remains an important option to be implemented in rapid water mapping in large-scale areas [17], although this approach has limitations [18].

Implementation of Water Index Algorithm itself to separate the object of water and non-water has experienced a fairly rapid development and has lasted for more than three decades. Recently, a Water Index Algorithm implementation was developed to map surface inundation using the DSWE algorithm [7]. History records that in the beginning, Crist and Cicone [19] and Crist [20] suggested Tasselep Cap Wetness (TCW) index derived from six-band surface reflection data and setting a threshold of 0 to separate the water and non-water objects. Furthermore, McFeeters [21] proposed Normalized Difference Water Index (NDWI) by using the green band value minus the near-infrared band (NIR) and divided by total of both bands, and the water body has a positive value while the non-water has a negative value. NDWI can suppress and eliminate non-water to a large extent, but NDWI cannot efficiently suppress ground signals. After nearly a decade, then developed various modifications of Water Index Algorithms. Successively developing Modified Normalized Difference Water Index (MNDWI) by Xu [22], Sum457 index (Al-Khudhairy et al. [23], combined by Sum457, ND5723, and ND571 indices by Beeri and Phillips [24], New Water Index (NDWI) by Haibo et al. [25], Automatic Water Extraction Index (AWEI) by Feyisa et al. [26], Land Surface Water Index (LSWI) by Dong et al. [27]. Combinations of each of the three water indices (LSWI, MNDWI, and NDWI) with EVI and NDVI by Menarguez [28]. The latter index is more sensitive to water bodies, especially mixed water pixels and vegetation pixels.

![Figure 1](image-url). Photo of Satellite imagery using composite GREEN, NIR and MIR bands of Sentinel 2A (Right view). In Left view show Sentinel 2A (BLUE insert) and Landsat 8 (GREEN insert), ground truth survey area inundation (RED) and non-inundation (BLUE). Photos of cloud/shadow coverage also appear on Sentinel 2A.

Apart from the various implements of Water Index Algorithm above using multispectral satellites, especially for extracting the performance of CSI in North Jakarta that has not been conducted. It is the main objectives of this research.
2. Method

2.1. Time and description of study area
This study was conducted in the area of North Jakarta City, DKI Jakarta Province, Indonesia (figure 1) on June 2016 until July 2017. This city is a coastal city located in the lowlands of DKI Jakarta (6°7-22’S and 106°40-55°E).

2.2. Data acquisition and processing
The acquisition of satellite data is listed in table 1. The data are corrected products that have surface reflection data from Level 1 Terrain (L1T) Landsat 8-OLI from USGS, and Level 2A products Sentinel 2A from the European Space Agency (ESA). All such data are in the format of the Archive Standard European Format (SAFE) [29].

Table 1. Landsat 8-OLI and Sentinel 2A-MSI used in this study.

| Sensors          | Data type take | Acquisition Date/Time at Scene | Sun Zenith Angle (°) | Sun Azimuth Angle (°) |
|------------------|----------------|--------------------------------|----------------------|-----------------------|
| Landsat 8 OLI    | Path/Row 122/64 | 13 May 2016/02:59:3           | 35.98                | 47.04                 |
|                  | Path/Row 122/64 | 30 June 2016/02:59:55         | 49.72                | 43.06                 |
|                  | Path/Row 122/64 | 17 August 2016/03:00:10       | 55.68                | 56.02                 |
| Sentinel 2A MSI  | Orbit number 32 | 19 July 2016/03:14:23         | 35.83                | 41.16                 |
|                  | Orbit number 32 | 07 October 2016/03:18:51      | 20.53                | 90.25                 |

The Landsat 8 OLI satellite is the new generation of Landsat launched since February 11, 2013, bringing two earth observation sensors, Operational Land Imager (OLI) and Thermal Infrared Sensor (TIRS). OLI collects imagery data for 9 spectral bands with 30 m spatial resolution (15 m panchromatic band) and TIRS collects image data for 2 thermal infrared spectral bands with a 100 m spatial resolution. Both sensors have an area of view coverage of 15° with a spatial resolution of 185 km across a height of 705 km [29]. Sentinel 2A was launched on June 23, 2015, equipped with 13 multispectral bands producing high resolution imagery and a wide sweeping capacity for a new perspective of science. The combination of high resolution, spectral capabilities, and 290 km of sweep width will provide a view of the earth with an unprecedented 20.6° field of view coverage. Characteristics of the Landsat 8 and Sentinel 2A sensor bands are shown in table 2 and figure 2.

Table 2. Characteristics of Landsat 8 and Sentinel 2A used in this study.

| Landsat 8-OLI | Wavelength (µm) | Resolution (m) | Bands          | Wavelength (µm) | Resolution (m) |
|---------------|-----------------|----------------|----------------|-----------------|----------------|
| 1 Coastal/Aerosol | 0.43-0.44       | 30             | 1 Coastal/Aerosol | 0.43-0.46       | 60             |
| 2 Blue (B)    | 0.45-0.51       | 30             | 2 Blue (B)      | 0.44-0.54       | 10             |
| 3 Green (G)   | 0.53-0.59       | 30             | 3 Green (G)     | 0.55-0.58       | 10             |
| 4 Red (R)     | 0.63-0.67       | 30             | 4 Red (R)       | 0.65-0.68       | 10             |
| 5 Near infrared (NIR) | 0.85-0.88   | 30             | 5 Red edge 1 (RE1) | 0.70-0.72       | 20             |
| 6 Shortwave infrared 1 (SWIR-1) | 1.36-1.39   | 30             | 6 Red edge 2 (RE2) | 0.73-0.75       | 20             |
| 7 Shortwave infrared 1 (SWIR-1) | 2.10-2.29   | 30             | 7 Red edge 3 (RE3) | 0.77-0.79       | 20             |
| 8 Panchromatic | 0.50-0.68       | 15             | 8 NIR           | 0.76-0.90       | 10             |
| 9 SWIR/cirrus | 1.36-1.39       | 30             | 8a NIR narrow (NIRn) | 0.86-0.88     | 20             |
| 10 Shortwave infrared 1 (SWIR-1) | 1.57-1.65   | 30             | 9 Water vapour  | 0.94-0.96       | 60             |
| 11 SWIR-1     | 1.54-1.68       | 20             | 10 Shortwave infrared 1 (SWIR-1) | 1.36-1.39 | 60             |
| 12 SWIR-2     | 2.08-2.32       | 20             | 11 SWIR-1       | 1.54-1.68       | 20             |
| 13 SWIR-2     | 2.08-2.32       | 20             | 12 SWIR-2       | 2.08-2.32       | 20             |
Figure 2. Sentinel-2 and Landsat Spectral Bands (Source: https://earth.esa.int/).

Data processing of Landsat 8 and Sentinel 2A to map water bodies and inundation can divide into 2 stages, pre-processing and post-processing (figure 3). Data pre-processing used the Semi-Automatic Classification Plugin (SCP) developed by Congedo [30] to perform atmospheric correction [31,32] to convert the images into product 2A, which is the Bottom Of Atmosphere (BOA) reflectance data. QGIS has an interface with Free Open Source Plugin (FOSS). One of them was used in this research process that is Semi-Automatic Classification Plugin (SCP). It included assisting in the downloading of satellite data, determining ROI signatures, classification, error matrix test, masking, and etc. Multispectral data processing refers to the equation in table 3.

Table 3. A summary of open surface water body mapping algorithms based on different Water Indices Algorithms using Landsat 8 and Sentinel 2A.

| Water Index Algorithms | Formulas | References |
|------------------------|----------|------------|
| NDVI                   | (NIR – Red)/(NIR+Red) | [33]       |
| NDWI                   | (Green – NIR)/(Green+NIR) | [21]       |
| NDMI                   | (NIR – MIR)/(NIR+MIR) | [35]       |
| MNDWI                  | (Green – MIR)/(Green+MIR) | [22]       |
| WRI                    | (Green + Red)/(NIR+MIR) | [34]       |
| NWI                    | Blue – (NIR+MIR+SWIR) / Blue + (NIR+MIR+SWIR) | [25]       |
| AWEI                   | 4 x (Green – MIR) – (0.25 x NIR + 2.75 x MIR) | [26]       |
| DSWE                   | (MNDWI > 0.123) or MNDWI>0.5 and NIR<0.2 and SWIR<0.1 | [7]        |

Figure 3. Data processing of Landsat 8 and Sentinel 2A to map water bodies and inundation.
2.3. Data validation
The result of CSI mapping based on the visible extraction of the Landsat 8-OLI and Sentinel 2A-MSI satellites needs to be validated. Data validation, such as by direct measurement using a tide gauge MOTIWALI (Mobile Tide Water Level Instrument). MOTIWALI has a good precise. This instrument was first developed by the Laboratory of Marine Instrumentation of Department Marine Science and Technology, Bogor Agricultural University since 2007. It is designed to measure real tidal data in real time to predict the Sea Level Rise during May-June 2016, even water levels during peak flooding (3-6 June 2016). In addition, tracing information from various online mass media sources and direct surveys (figure 1), including checking of some reservoir dikes and coastal dikes were destroyed (table 4).

Table 4. The Location of coastal walls were destroyed, estimated the height of inundation, and predict of tide in North Jakarta during early period June, 3 until 6, 2016.

| Date/Day/Time          | Locations                                  | Height of Inundation (m) | Height of Tide (m)*                  |
|------------------------|--------------------------------------------|--------------------------|--------------------------------------|
| 6/3/2016 (Friday) 20.55 PM | Mutiara Beach                             | 0.30-0.50                | 0.84 (2:12 AM)                      |
| 6/4/2016 (Saturday)   | Muara Angke Penjaringan                    | 0.40                     | 0.79 (1:12 AM)                      |
| 6/5/2016 (Sunday)     | East side of coastal wall of Muara Baru Penjaringan (near of the TPI) | 0.50                     | 0.30 (15:24 AM)                     |
| 6/6/2016 (Monday) 22.00 PM | Reservoir wall of Muara Angke Penjaringan | 0.80                     | 0.35 (15:36 AM)                     |

Source: Primer data processed from trace study (2016)
*Data analysis of real time of tide gauge station was designed by AIK Laboratory IPB

3. Results and discussion
3.1. Inundation extraction of coastal surfaces based on water index algorithm
This result study shows that there are similarities of feature extraction results of similar spectral characteristics and different spatial resolution between Sentinel 2A and Landsat 8 sensors (figure 4). A contrasting difference exists in the extraction of water and non-water feature of each Water Index Algorithm classification. Sentinel 2A can be partially attributed to higher spatial resolution. All classifications of Water Index Algorithms indicate any abilities to increase water reflectance, and the MNDWI is more capable than other water index.

Figure 4. Feature extractions of different combination of the seven Water Index Algorithms.

All results of the CSI feature of 35 combinations generating from seven algorithms (except DSWE algorithm) of both satellite sensors in figure 4 above, show similar patterns, whereas Sentinel 2A-based results show resolution against higher water areas than Landsat 8. Nevertheless, the feature extraction
of CSI’s is showing that Landsat 8 sensor on condition some days after inundating and dikes were destroyed (30th of June 2016) shows a better performance than Sentinel 2A (July 17, 2016). Unlike the case of CSI's feature on both sensors prior to inundation of Landsat 8 (May 31, 2016) data and after inundation of Landsat 8 (August 17, 2016) and Sentinel 2A (October 7, 2016) sensors. Clouds/shadows cause the water's feature to be reduced on both sensors. It was clearly the worse by the Sentinel 2A sensor (July 17, 2016). In addition, the degree of clouds/shadows of varying optimum thresholds at different locations and times of all indices cannot effectively eliminate shadow and cloud noise in some places.

Of the seven Water Index Algorithms above, the extraction of MNDWI results over other algorithms, the quality is different in yielding three things: (1) water has a positive value greater than any other index, since water absorbs more MIR than NIR; (2) the wake land has a negative value; and (3) the soil and vegetation have a negative value, because the soil is more reflective of MIR than the NIR and its vegetation reflects MIR still more than GREEN. Consequently, compared to other Water Index Algorithms, the contrast between water and artificial landmass MNDWI is greatly enhanced due to an increase in the value of water reflectance and a decrease in the value of land built-up from positive to negative. A reflectance water increase in the MNDWI image will result in a more accurate extraction of open water, such as water bodies on land. While the mixture of soil and vegetation built up throughout the negative value and therefore can be suppressed, even thrown away, this condition is also described equally by Xu [22]. Unlike the case with the NWI, although the ability to extraction the appearance of water bodies includes small bodies of water both, but it is not good to separate the residents and water bodies. This is reflected from the water and non-water reflectance values, which are all negative. While the water and non-water reflectance values of WRI are all positive and larger than all other water indexes, making it difficult to separate water with other objects.

![Figure 5. Feature extractions of different combination of the seven algorithms using SAM.](image)

The result study show also similar performance and pattern on both sensors and all Water Index Algorithms for water and non-water classes using supervised classification Spectral Angle Mapper (SAM) (figure 5). The feature is more clearly seen. SAM is a physical-based spectral classification that uses n-D angles to match pixels with the reference spectrum. The spectrum membership is used by SAM coming from the ROI file extracted directly from the image of the water index algorithm classification results. The overall performance of CSI based on the classification of Water Index Algorithms and SAM (figures 2 and 3) of Landsat 8 and Sentinel 2A sensors using MNDWI was more accurate to identify CSI compared to other algorithms, since it is supported by four things: (1) water has a larger positive absorbing value more MIR than NIR; (2) the land built-up has a negative value more reflecting the MIR than the NIR; (3) land and vegetation have negative values, reflecting more MIR than GREEN; and (4) the contrast between water and the land build-up use MNDWI is clear and more accurate than other algorithms based on an increase in the value of water reflectance and a decrease in the value of land
built-up from positive to negative.

![Figure 6](image)

**Figure 6.** Contrast of the surface inundation from 35 combinations of the seven algorithms refers to Jones [7] using DSWE₁ in table 4 and the two sensors.

The positive or zero water reflectance value allows to extract the inundation and non-inundation, not only water bodies or shallow waters use the DSWE₁ algorithm [7] that not only applies MNDWI to the Landsat sensor, but also Sentinel 2A and the other Water Index Algorithms. Based on figure 6 and 7 shows that the contrast of inundation and non-inundation appears clearly, for example using the DSWE₁ and DSWE₂ algorithms [7]. DSWE₁ = MNDWI > 0.123 applied to Landsat sensor [7,36] and developed for Sentinel 2A sensor. The inundation feature is still clearly from the DSWE₁ algorithm using NDWI > 0.123 substitution, although not optimal than MNDWI. While DSWE₁ is substituted with other Water Index Algorithms (NDMI, NDVI, WRI, AWEI, NWI) shows the ability to extract the feature to be reduced even not seen at all.

![Figure 7](image)

**Figure 7.** Contrast of the surface inundation from DSWE algorithms refers to Jones [7] in table 4 and the two sensors.

The changes of CSI are also apparent (figure 7) from Landsat 8 and Sentinel 2A data using DSWE₂ [7], where DSWE₂ = MNDWI > -0.5 AND NIR < 0.2 AND SWIR < 0.1. DSWE₂ uses a combination of GREEN, MIR, NIR and SWIR bands. The feature of CSI processed by DSWE₂ is more contrast than DSWE₁. Both of the DSWEs are not able to effectively eliminate shadow and cloud noise in different locations. Nevertheless, the feature of CSI is still clearly from Landsat 8 sensors prior to inundation (May 31, 2016), after subsequent inundating in the next few months (August 17, 2016), and even the results of sedimentation in shallow waters in the days after the dykes destroyed (June 30, 2016). The application of DSWE using Sentinel 2A sensor shows the performance of CSI's appearance was not clearly visible compared to Landsat 8. Unlike the case with the Sentinel 2A sensor (October 7, 2016)
after subsequent inundating in the next few months, the appearance of CSI is clearly indicated with better spatial resolution. Overall it was formulated that the application of DSWE using the threshold of MNDWI compared to other water indices greatly affects the inundation mapping, since the MNDWI water threshold value is not the same on other water indices.

3.2. Assessment of sensor accuracy and water index algorithms for water and non-water mapping

The results of the study found that the overall accuracy averaged of 95.56-99.99% and Kappa coefficient 0.97-1.00 (table 5). Both Landsat 8 and Sentinel 2A sensors perform a better performance in mapping the CSI. The study area is an urban area dominated by land built-up, that it has own advantages for satellites to extract CSI visibility by separating water and non-water objects.

Table 5. (a) Overall accuracies and (b) Kappa coefficients of different combination of the seven algorithms and the two sensors.

| Sensors | Data acquisitions | Overall accuracy (%) | Kappa Coefficients |
|---------|-------------------|----------------------|--------------------|
|         | MNDWI | NDWI | NDMI | NDVI | WRI | AWEI | NWI | MNDWI | NDWI | NDMI | NDVI | WRI | AWEI | NWI |
| Landsat 8 | 13-May-16 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 0.99 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
|         | 30-Jun-16 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
|         | 17-Aug-16 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 99.98 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 0.99 |
| Sentinel 2A | 17-Jul-16 | 99.90 | 99.40 | 94.34 | 99.96 | 99.82 | 99.91 | 97.80 | 0.99 | 0.97 | 0.84 | 0.99 | 0.99 | 0.99 | 0.96 |
|         | 7-Oct-16  | 99.97 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 | 1.00 |
| Average  | 99.97 | 99.88 | 98.87 | 99.99 | 99.96 | 99.98 | 99.56 |

The results of Landsat 8 and Sentinel 2A image accuracy based on producer accuracy reaching 99.05-99.99% and user accuracy is about 93.43-99.94% (table 6). The achievement of such accuracy test results, as the result of spectral classification of water bodies/inundation and non-water/non-inundation on land built-up is easily detected in the study area. Even the detection of inundations along the highway at the bottom along the highway, the appearance of water is still clearly through the classification. This result is very clearly performing water in residential areas, mangrove ecosystems, reservoirs and others.

Table 6. Producer accuracies (a) and User accuracies (b) of different combination of the seven algorithms and the two sensors.

| Sensors | Data acquisitions | Producer accuracy (%) | User accuracy (%) |
|---------|-------------------|----------------------|-------------------|
|         | MNDWI | NDWI | NDMI | NDVI | WRI | AWEI | NWI | MNDWI | NDWI | NDMI | NDVI | WRI | AWEI | NWI |
| Landsat 8 | 13-May-16 | 99.99 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
|         | 30-Jun-16 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
|         | 17-Aug-16 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 99.98 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Sentinel 2A | 17-Jul-16 | 99.96 | 96.07 | 96.90 | 99.96 | 99.82 | 95.89 | 95.26 | 99.25 | 64.75 | 74.30 | 99.50 | 99.72 | 90.23 | 92.96 |
|         | 7-Oct-16  | 99.98 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 99.96 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 | 100.00 |
| Average  | 99.99 | 99.21 | 99.38 | 99.99 | 99.96 | 99.18 | 99.05 | 99.84 | 94.83 | 94.88 | 99.90 | 99.94 | 93.85 | 98.59 | 98.39 |

4. Conclusion

Feature extraction of 35 combined CSI can be generated from water index algorithms (MNDWI, NDWI, NDMI, NDVI, WRI, AWEI, NWI, and DSWE and also two sensors form Landsat 8 OLI and Sentinel 2A MSI in North Jakarta area. To enhance the characteristics of those both sensors, atmospheric correction is conducted in best performance. Supervised classification using SAM shows a good performance in water and non-water where indicating by overall accuracy (99.56-99.99%), coefficient Kappa (0.97-1.00), producer accuracy (99.05-99.99%) and user accuracy (93.43-99.94%). Both sensors and all various Water Index Algorithms have good performance in open surface water mapping. MNDWI has different quality for water body, inundation and non-inundation mapping accurately in study area. Performance of all Water Index Algorithms using both sensors will be optimal if the capture...
has low cloud coverage. The results of DSWE Algorithm are not good enough to be applied in conjunction with other water indices, except MNDWI. DSWE algorithm applied with MNDWI can map the inundation and non-inundation, but cannot effectively eliminate the shadow and cloud noise in different areas and locations for Landsat 8 and Sentinel 2A sensors. It is needed a caution and wisely decision in implementing those algorithms above to mapping CSI.

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