Delineation of water body from Sentinel 2 MSI imagery – A comparative study

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Abstract. Remote sensing gives a synoptic view of the extent of water area and also assists in understanding the spatial and temporal variations in the water surface coverage. Several methods have been adopted for extracting water pixels from an imagery. Delineation of water bodies has been attempted based on threshold values at a single band, band ratios or normalized difference indices. The accuracy of a method depends on the geophysical and spectral characteristics of the area of study. The present study attempts to compare the performance of widely used water extraction indices NDWI, MNDWI, SNN with the water pixels extracted by atmospheric correction processors C2RCC and Acolite. The Sentinel 2 imageries of the northern region of Vembanad Lake has been used for the study. The comparison on these methods indicated that C2RCC could extract even the finer streams that were not identified by most of the other methods. The presence of turbidity may be a reason for these pixels to be unidentified by the other methods. The temporal variations in the water surface coverage was also attempted here, by comparing the water area in March 2019, October 2019, December 2019.

1. Introduction

Inland and coastal water bodies is a primary resource for life on land. Anthropogenic activities and climate changes have brought considerable changes in the extent of water bodies [1,2]. Monitoring changes in water bodies has become easier with the advent of satellite remote sensing. Water body delineation can be carried out by using spectral indices [3-7] or by supervised and unsupervised classification of images. The supervised classification uses statistical pattern and ground truthing for separating water pixels, while the unsupervised classification uses spectral similarity of pixels for grouping them into different categories. Thorough information on how the water body affect the response in various spectral classes is essential for the accuracy of these methods. The spectral behaviour of inland water bodies is found to vary widely based on the constituents in the water body [8,9]. The classification of water bodies based on the spectral characteristics may lead to the erroneous inclusion of mixed pixels and some land features too [9].

Density slicing is a simple method of identifying water by using a simple threshold in single or multiple bands, but this method identifies several non-water pixels as water spread area [10]. Multiband approach utilizes the difference in reflectance for land and water in various spectral bands. Spectral indices are based on the theory that water absorbs all incident radiant flux while land reflects NIR and SWIR energy. Water has high reflectance in the green band compared to land pixels [4,5].
The single band and band ratios methods could suppress the non-water pixels, but could not completely remove them. Tasseled Cap Water index (TCW) used six bands with empirical coefficients determined from simulated and actual data of clear and turbid waters [3]. NDWI proposed by Mcefeeters [4] normalized the difference between green and NIR bands. As reflectance of water in the green band was high and that in NIR was negligible, a value greater than a threshold of zero indicated water. This worked well with soil and vegetation, but the built-up land could not be separated as they gave positive values for NDWI. Xu [5] modified the index to MNDWI by replacing the NIR with SWIR and found that there was an enhancement in the accuracy of water body delineation due to the greater absorbance of water in SWIR than in NIR. Combination of various indices (NIR, SWIR and red bands) were used by Khudhairy [11] and Beeri [6]. Feyisa [7] proposed Automated Water Extraction Index (AWEI) which used NIR and SWIR bands for removing shadow pixels and for urban backgrounds.

Though the objective of atmospheric correction processors is the removal of path irradiation, these processors could extract water pixels, masking out all other pixels. The basic theory behind atmospheric correction over water surfaces is that pure water has very high absorption in the NIR and SWIR regions and any reflectance observed in this spectrum is assumed to be contributed by atmospheric interference, and hence it is subtracted from all the bands [12,13]. Recently developed Dark Spectrum Fitting (DSF) [14,15] use multiple dark targets in a band on a particular scene to detect the darkest target, and this, in turn, is used for the estimation of path radiance. There are algorithms based on neural networks developed from large data sets which relate water leaving radiance or reflectance to absorption and scattering properties of water. The evaluation of the atmospheric correction capability of these processors have been carried out in various studies, but studies on the accuracy of their water delineation capability is limited. Hence, the present study compares the water pixels extracted by widely used indices, NDWI, MNDWI and SNN, derived from L1C images, atmospherically corrected by Sen2Cor processor, with that extracted by the atmospheric correction processors C2RCC and Acolite. Level 1C imagery of the northern portion of Vembanad Lake (i.e. Kochi Kayal) from Sentinel 2 satellite is used for the study.

2. Materials and Methods

2.1. Study Area
The area chosen for study is the northern region of Vembanad lake, i.e., Kochi Kayal. The lake is the longest in India, the largest in Kerala and one of the three protected Ramsar sites in Kerala. Various studies conducted on the environmental status of the lake have revealed its deteriorating condition as a result of anthropogenic activities [16-18]. Several fishery industries are located near the Kochi Kayal. It is surrounded by a populated urban area with several tourist resorts and high-rise buildings, discharging inadequately treated domestic wastes into the nearby water sources, all of which empties into the lake.

2.2. Satellite Data
Sentinel 2 is a multispectral satellite mission commissioned by European Space Agency (ESA) in July 2015. The sun-synchronous, polar orbiting dual satellite mission (S2A and S2B) phased at 180° to each other provides support for land and water monitoring. The revisit time of a satellite is 10 days and hence the temporal resolution is 5 days with the data from two satellites. The temporal resolution for for mid latitudes is 2-3 days. The imageries provide radiometrically and geometrically corrected top of atmosphere (TOA) reflectance in 13 bands (4 in Visible region, 6 in NIR region and 3 in SWIR) with a spatial resolution of 10, 20 and 60 m. The better spatial resolutions for the widely used visible bands. The bands 8A and 9 are water vapour retrieval bands. The band 10 is used for the Cirrus cloud correction and does not contain surface information. The high temporal resolution combined with better spatial resolution, and the free availability has made it advantageous for research purpose.
Sentinel data is freely downloadable at Copernicus Open Access Hub [https://scihub.copernicus.eu]. The data products available are Level 1C (L1C) - top of atmosphere (TOA) reflectance) and Level 2 B (L2B) - Bottom of Atmosphere (BOA) reflectance, both in cartographic geometry. They are ortho-rectified images in UTM projection with WGS84 datum.

The L1C images from S2A for the days 30th December 2019, 14th October 2019 and 25th March 2019 were considered for the study. The image of 30th December 2019 is corrected from path interference using three Atmospheric correction processors, C2RCC, Acolite and Sen2Cor. The water pixels extracted by C2RCC and Acolite processors were compared with those obtained from water extraction indices.

### 2.3. Water extraction indices.

The study compared three indices used for water delineation, viz., NDWI, MNDWI and SNN (Table 1). They were chosen from a wide range of indices based on their performance in various studies and their region of study [19,20]. NDWI, MNDWI, SNN algorithms were applied to BOA reflectance bands obtained from Sen2Cor processor.

| Index | Algorithm | Threshold rules for water pixels | Author | Area of study |
|-------|-----------|---------------------------------|--------|---------------|
| NDWI  | (Green – NIR)/(Green + NIR) | positive values | Mcfeet [4] | Clear water; water soil & vegetation |
| MNDWI | (Green – SWIR)/(Green +SWIR) | positive values | Xu [5] | Clear water, water & urban background |
| SNN   | $\text{SUM457} = \text{NIR} + \text{SWIR}_1 + \text{SWIR}_2$ | $(\text{SUM457} < 0.188)$ or $(\text{ND5723} < -0.457)$ or $(\text{ND571} < 0.04)$ | Beeri [6] | Clear water; water soil & vegetation |
|      | $\text{ND5723} = \frac{((\text{SWIR}_1 + \text{SWIR}_2) - \text{(green+red)})}{((\text{SWIR}_1 + \text{SWIR}_2) + \text{(green+red)})}$ | | | |
|      | $\text{ND571} = \frac{\text{[(SWIR}_1 + \text{SWIR}_2)\text{-blue]}}{\text{[(SWIR}_1 + \text{SWIR}_2)\text{+blue]}}$ | $(\text{SUM457} < 0.269$ and $\text{ND5723} < -0.234$ and $\text{ND571} < 0.40)$ | | |

### 2.4. Atmospheric Correction Processors

The pre-processing and analysis of imageries were carried out using SeNtinel Application Platform (SNAP) software developed by European Space Agency (ESA). It consists of several open source toolboxes and bundled packages for the processing of MERIS, Sentinel and Landsat imageries. The pre-processing steps include resampling, reprojecting to WGS and masking out the study area from the downloaded images. Three atmospheric Correction Processors were used in this study, Case 2 Regional Coast Colour (C2RCC), Acolite and Sen2COR. Sen2cor and C2RCC are available as plugins in SNAP.

Case 2 Regional Coast Colour processor (C2RCC), developed by Doerffer and Schiller [21] uses artificial neural networks (ANN) based on a large database generated by radiative transfer simulations. It derives the water leaving radiance reflectance (rhow) by using ANN. It consists of a large database
of around 5 million cases, generated from in-situ measurements obtained from NOMAD database, Coastcolour database and also simulated results from radiative transfer model (HYDROLIGHT).

Acolite is a stand-alone processor for Sentinel 2 and Landsat 5/7/8. Sentinel 2 L1C data can be input in .SAFE format. The processor does the Rayleigh correction from a Lookup table generated by 6SV and the aerosol correction using Dark Spectrum Fitting (DSF) or Exponential (EXP) method [15]. The water pixels are extracted from a threshold reflectance at 1600nm in the corrected imagery. The default value is 0.0215. The output from Acolite in .nc format can be viewed and analysed in SNAP [22]. Sentinel 2 Correction (Sen2Cor) processor is based on Dense Dark Vegetation (DDV) as it is developed for land products. The algorithm detects the dark vegetation pixels and uses these to estimate the aerosol thickness [23, 24]. It does not extract water pixels.

3. Results and Discussions
The northern region of Vembanad lake i.e., Kochi Kayal (Figure 1) was considered for the study. Three atmospheric correction algorithms, Sen2Cor, Acolite and C2RCC were applied to the imagery for obtaining the Bottom of Atmosphere (BOA) reflectance.

![Study Area - Kochi Kayal, Kerala](image)

3.1. Water Mapping Indices and atmospheric correction processors
Sen2cor processor gave corrected BOA reflectance in 11 bands (Band 8 and 10 omitted). Water vapour retrieval was carried out by using Atmospheric Pre-corrected Differential Absorption (APDA) algorithm applied on band 8A(865nm), and Band 9(945nm), the former being a reference channel in the atmospheric window and the latter the measurement channel. The aerosol type and depth was calculated using Dense Dark Vegetation Algorithm (DDV). Atmospheric corrections were carried out based on lookup tables generated by libRadtran. The processor was developed for land monitoring and hence did not separate the water pixels. Bottom of Atmosphere (BOA) reflectance obtained from Sen2Cor is used for calculating the indices. Previous studies have used BOA reflectance from L2A images which are Level 2 products from Sentinel 2. To eliminate any variation in the results due to a change in the source product, L1C imageries are used as the sole input.

The water extraction indices NDWI, MNDWI, SNN algorithms were applied to BOA reflectance bands obtained from Sen2Cor processor. The results of water mapping indices show that NDWI (Figure 2), failed to match the true colour image. NDWI image has excluded several narrow streams from water area. NDWI is a normalized difference between green and NIR bands. Only a positive value for the index is considered as water. The higher reflectance in NIR reduces the index value. The presence of turbidity and/or lesser depth in these streams can cause a higher reflectance in NIR. NDWI is mainly intended for detecting pure water and distinguishing water from soil and vegetation [4,20].
This shows that the presence of turbidity or reflectance from water bed may be a reason for these pixels to be considered as non-water pixels. The spectral characteristics of an inland waterbody is found to vary widely depending on their constituents present in them [8] and thus NIR reflectance cannot be relied upon for distinguishing water pixels in complex water bodies. This indicates that NDWI cannot be used as a tool for delineating inland water bodies.

The improved version of NDWI, i.e., MNDWI [5] considered SWIR instead of NIR. SNN is a combination of three indices SUM457, ND5723 and ND571. It includes two SWIR bands, red and blue bands, in addition to green and NIR. Sum of NIR and SWIR bands (SUM457) for extracting water pixels [11] ND5723 and ND571 for minimizing the atmospheric interference [6]. The absorbance of water is high in the SWIR region and so the impact of sediments on the reflectance is reduced in these bands. The results show that MNDWI (Figure 3) and SNN (Figure 4) could extract most of the water pixels when compared with the true colour image (Figure 1). Their better performance may be due to inclusion of SWIR bands. The influence of sediments is lesser in the SWIR bands when compared to NIR, and hence these proved to be better for separating water pixels.

C2RCC processor was based on neural network generated from a large database of around 5 million cases, consisting of in-situ measurements and simulated results from radiative transfer model. The processor extracted the water pixels, and the non-water pixels were masked out from all the corrected bands and the derived products. The extracted water pixels (Figure 5) showed a very good match when compared with the true colour image (Figure 1), even for finer streams and paddy fields. The water pixel extraction capability of C2RCC processor was found to be better than the indices. The presence of turbidity did not affect the delineation capability, as it was based on neural networks.

Acolite does the Rayleigh correction using 6SV generated Look Up Tables and aerosol corrections based on multiple dark targets in a scene, i.e., Dark Spectrum Fitting algorithm (DSF) [14]. There is also an option for computing aerosol reflectance from two SWIR bands 1.6µm and 2.2µm and then for extrapolating it into the visible and NIR (i.e., EXP method) spectrum. DSF Option was chosen as it was recommended for inland and coastal water bodies. Water pixels were extracted by masking out the pixels which had a reflectance greater than 0.0215 (default threshold value) at 1600nm. The non-water pixels were identified by considering the threshold reflectance at 1.6 µm as 0.0215 (Figure 6). But the obtained image left out several water pixels in the narrow streams due to the higher reflectance in the considered band. The threshold was raised to then 0.05 and then to 0.06. Figure 7 shows the improved water pixel extraction of Acolite at threshold set at 0.06. Hence, it is seen that Acolite can also extract the water pixels better than the indices NDWI, MNDVI and SNN provided the threshold value is appropriately modified. However, the extraction of paddy field filled with water and minor stream is better in C2RCC method.

Among the five methods, performance of C2RCC was found to be best in extracting the water pixels. Hence the C2RCC method was used for comparing the seasonal variation.
3.2 Seasonal Variation
The imageries of the study area on 14\textsuperscript{th} October 2019 (left), 25\textsuperscript{th} March 2019 (middle) and 30\textsuperscript{th} December 2019 (Figure 8) were compared to understand the seasonal variation in the water body. The FCC image of October 2019 displayed significant variations from the other two imageries. Many of the streams have narrowed down and become very feeble. Several patches (highlighted in red) along the banks of the lake were excluded from water pixels. The reason for this nonintuitive behaviour of the lake after a heavy monsoon in August needs to be investigated. The FCC image obtained from C2RCC shows a higher reflectance in October 2019 which may be an indication that the lake has become shallow, and reflectance from the bed has influenced the reflectance from the water column. March 2019 and December 2019 imageries displayed similarity in the delineated map.

Observing the temporal variations in the delineated maps across years give a quick indication on the fluctuations in the extent of water body and its seasonal impacts. The delineated maps of Kochi Kayal obtained from Sentinel imagery corrected by C2RCC for the months of March, October and
December 2019 may be an indication that October was a drier month, contrary to the belief that summer months are drier. However, the authenticity of the statement needs to be verified by collateral information from other sources.

**Figure 8.** FCC image from C2RCC processor for 14th October, 25th March and 30th December

### 4. Conclusions

In this study, water pixels extracted by indices NDWI, MNDWI and SNN derived from L1C images corrected by Sen2cor processor were compared with that extracted by atmospheric correction processors, viz., C2RCC and Acolite. The area chosen for the study is the Kochi Kayal which is a typical urban area, greatly impacted by anthropogenic activities. The results of water mapping indices show that NDWI failed to match the true colour image, with several streams excluded from the identified water pixels. The water pixel extraction capability of C2RCC processor was found to be better than the indices, and the extracted pixels matched very well with the true colour image. Water pixels extracted by Acolite also showed a good match with the true colour image once the threshold value for delineation was revised to 0.06.

The following conclusions are derived from the study.

1. NDWI performed the worst with all the narrow streams excluded from water pixels. Considering NIR band for delineating water pixels is not advisable for inland water bodies.
2. SWIR bands are better suitable for delineating turbid inland water bodies.
3. The performance of indices MNDWI and SNN in delineating the water body is found to be less than that of the atmospheric correction processors C2RCC and Acolite.
4. The presence of turbidity reduces the efficiency of indices used for delineating the water body.
5. The performance of the atmospheric correction processors C2RCC and Acolite in delineating the water body are similar, provided the threshold value used for delineation in Acolite is appropriately modified.
6. The C2RCC method can be considered as the robust method, as it derived the delineated map using neural network from a large data set. The result was not impacted by the presence of sediments or turbidity. It has given the best performance without any prior knowledge of the area.
7. The results show that choosing the algorithm for water body delineation needs prior understanding of the physical and optical status of the area of study.
8. The temporal variation in the delineated maps of Kochi Kayal in the year 2019 showed that there was significant reduction in the water area in October. However, the reason behind this nonintuitive behaviour needs to be investigated further.
9. Observing the seasonal variation in a water body from satellite imageries is a quick way to understand the impact of seasonal changes and anthropogenic activities on the water body.
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