Quest Journals
Journal of Research in Environmental and Earth Sciences
Volume 9 ~ Issue 1 (2023) pp: 26-31
ISSN(Online) :2348-2532
www.questjournals.org

Research Paper

Automatic Land Water transition zone detection from satellite images using Python

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A R T I C L E I N F O

Keywords:

Index
mNDWI
threshold
python
dynamic range
land
water
land-watertransition zone
coast
Landsat 8/9

A B S T T R A C T

Water detection by index computation and thresholding is a widelyused technique in remote sensing. Most of the work involves single threshold to determine water and non-water substance. A novel approach is taken in the work to apply specific range of values of mNDWI to identify land-water boundary/transition region along with land and water region separately for the satellite images of optical sensors using Python platform. This enables to identify land, water and land water transition region with the same indexing scheme for images of various geographical locations. This scheme is very useful to estimate land water transition region which aids to monitor erosion/growth of coastal region, island, water bodies etc. in a very convenient way. Also as entire processing is carried out in python, each step of processing is completely transparent and flexible enabling user for appropriate tuning if required. The scheme may be extended to use for other indices also in order to enhance detection capability of various features in target scene.

***R**eceived 01 Jan., 2022; **R**evised 09 Jan., 2023; **A**ccepted 11 Jan., 2023 © The author(s) 2023.*
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I. Introduction

Water is one of the most important ingredients for existence of mankind. Hence it is essential to monitor the resource regularly for its sustainable management considering climatic, geographical, anthropological and ecological effects. Mapping of water resource using satellite imagery has become popular tool in remote sensing for its wide coverage, ease of useconsidering cost, time and effort effectiveness compared to tedious field survey. Hence it is essential to establish reliable and robust method to observe and estimate water on earth over diverse terrain. Water is generally detected from space with two types of sensor namely optical and microwave sensor. Synthetic Aperture Rader (SAR) technique is used in microwave sensor[1]. SAR images have advantage of detecting capability in night or clouded condition also. On the other hand, optical sensors have advantage of high resolution and availability. Several approaches have been developed to delineate water bodies from satellite imagery using the phenomenon of reflectance spectra of water in comparison with other land features from visible to infrared spectral wavelengths in optical imaging payloads and are being used widely [2]. Based on such optical characteristics, various types of water classification methods have been developedand used in image processing application software like supervised support vector machine (SVM) classification [3], maximum likelihood supervised classification[4], Iso-cluster unsupervised classification[5]. Combinations of methodologies also have been used to extract water in target images like water boundary detection[6], Gabor filter etc. [7], collaborative decision making[8].Google earth engine (GEE) is also used as a platform for applying various methodologies to detect water viz. study in the Murray-Darling Basin, Australia[9], cloud computing[10],multisource data fusion[11]etc. The simple and common approach of unsupervised classification which uses an interactive self-organizing data analysis technique provides results with very low accuracy, when there is spectral overlap between water bodies with other classes. In contrast, supervised classification presents more accurate and reliable outputs than unsupervised method. Moreover, the supervised technique requires sufficiently large spectral training data sets and is not a fully automated method.

Water index and threshold technique are applied extensively for detection of water.It is an easy and effective way to extract water, where indices are calculated from two or morebands, to identify the differences between water and non-water areas[2].NDWI (normalized difference water index)is basic water index derived using green and NIR band[12].mNDWIi.e. modified NDWI is moresuitable for enhancing and extracting water information for a water region because of its advantage inreducing built-up land noise[13].Thresholding is one of the most critical issues in using water indices to extract water bodies. Based on thereflectance characteristics of water, NDWI and mNDWI values for water are usually greater than 0.Therefore, a threshold of 0 is considered nominally to extract water from index images. However, it may need some variation from image to image depending upon the proportion of water content in mixed pixels and other factors. Index based water identification has been carried out using QGIS[14], Arc GIS[15] and ENVI[16, 17]and GEE [18]as platform. Python based deep learning method also has been studied for water detection[19].In this paper a new approach has been adopted for land-watertransition zone detection including land and water region separately by applying specific range of values of mNDWI. Entire computation has been carried out on Python platform which is an open source software. The scheme is implemented without using any commercial image processing software and hence is convenient, transparent and cost effective and also has scope for extension, modification as per future requirement. Thus, a flexible and explorative method has been evolved to identify land water junction that may be used for extracting other feature also applying other indices.

II. Objective

Intent of the work is to automatically identify land-water transition region through applying selected range of water index (mNDWI) of satellite imagery using python software. Land water cross border detection is a useful study for delineating the changing scenario around island border or coastal region. It may be used to estimate decay/erosion or growth of the target border zone. Various water indices are there to identify water region from other region.Here satellite imagery of various bands are read as an array and mNDWI algorithm is applied on each pixel to get the output. Afterwards applying different range of values of mNDWI obtained, different characteristics namely land, water and land-water junction are extracted. The range selected are providing similar results for various scenes. Landsat 8 imagerieshave been used with necessary bands.

III. Materials and Methods

Landsat 8 and Landsat 9 provides bands data including green (band 3) and swir(band 6) available in USGS data archive. Fifteen images over various geographical regions over various parts of the world have been selected to apply the developed code. The regions are chosen over different terrains viz. coastal region, estuary etc. from various continents with open sea and other water bodies. Then mNDWI computation is done on each of the pixel of thescen

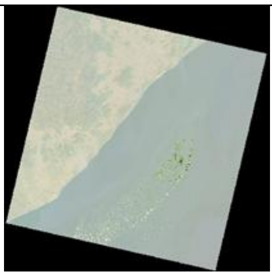
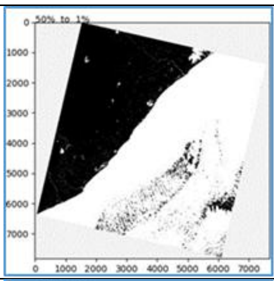
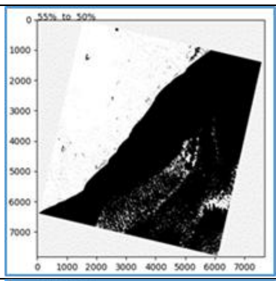
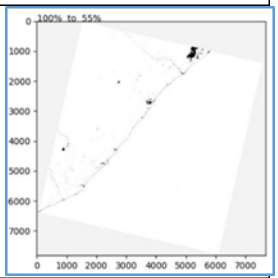
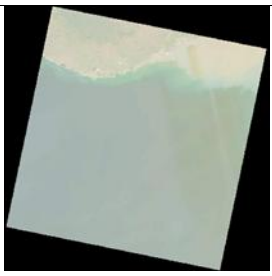
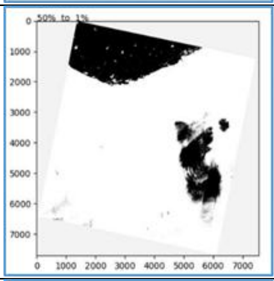
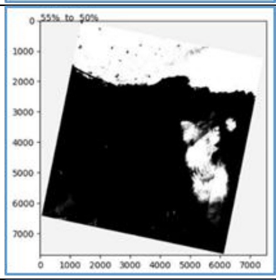
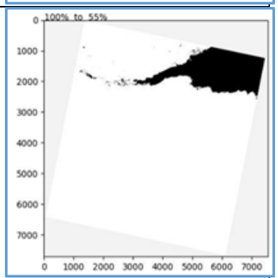
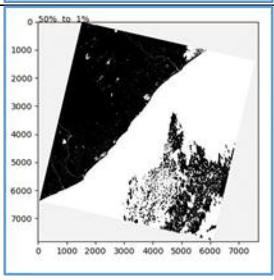
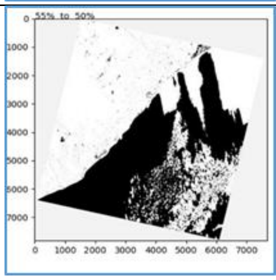
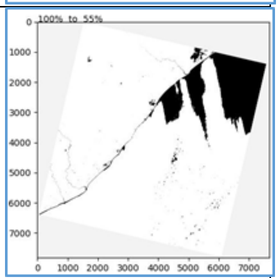
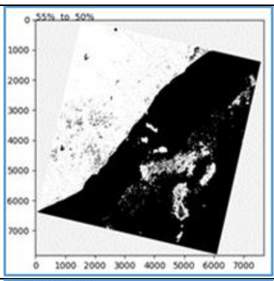
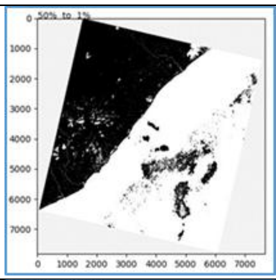
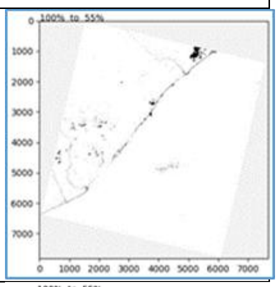
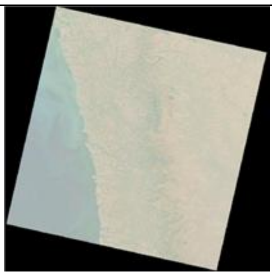
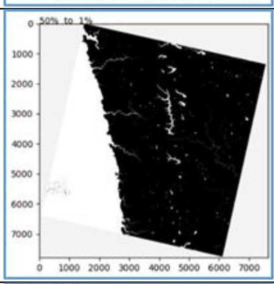
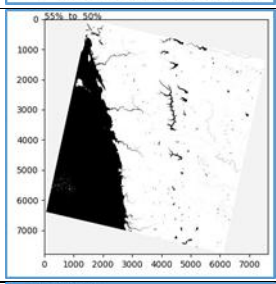
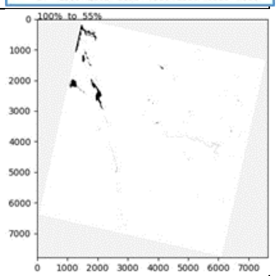
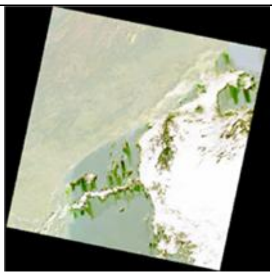
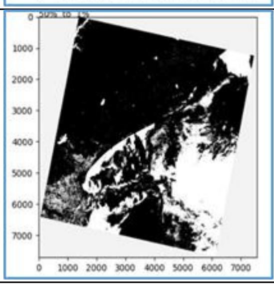
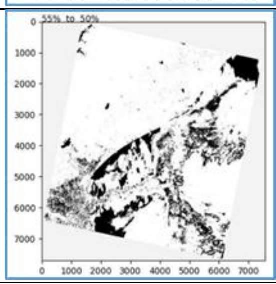
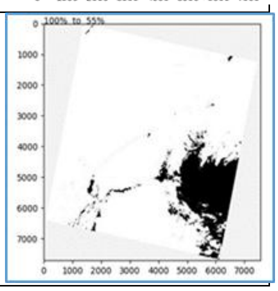
$$m\text{NDWI} = \frac{green - swir}{green + swir}$$

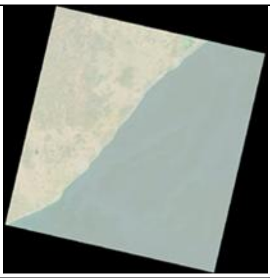
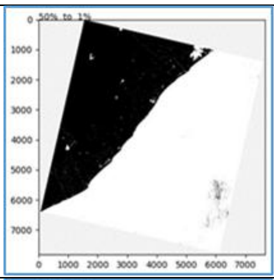
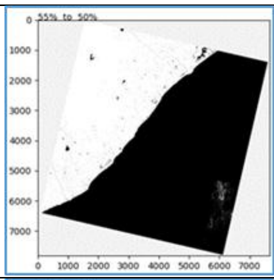
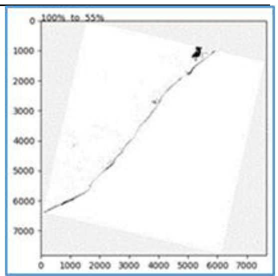
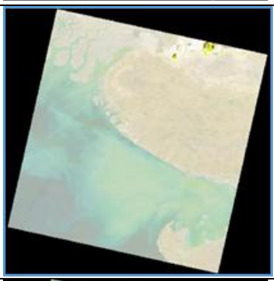
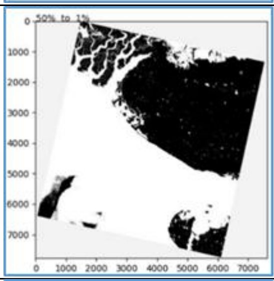
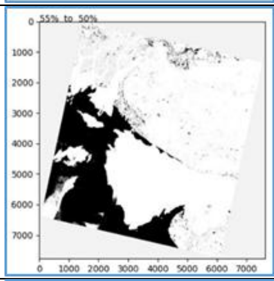
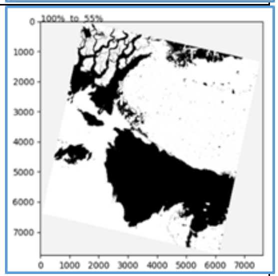
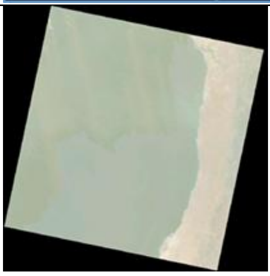
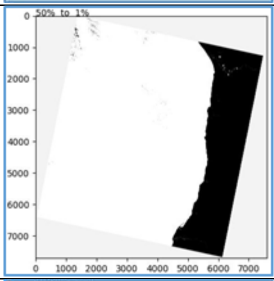
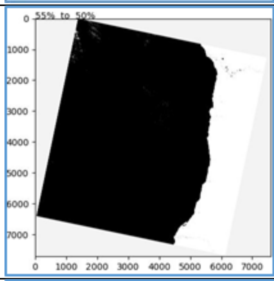
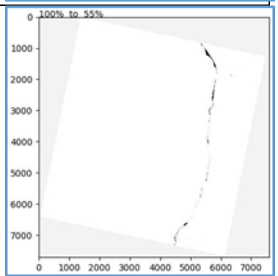
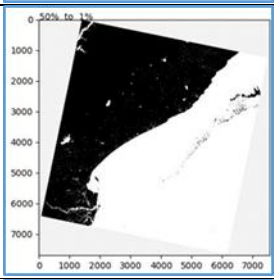
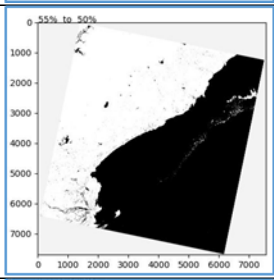
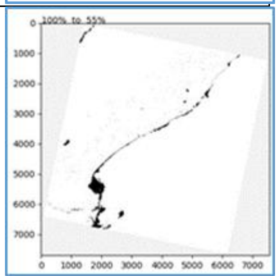
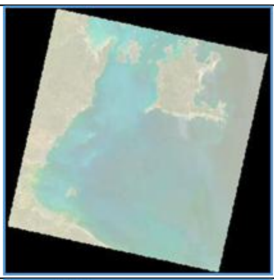
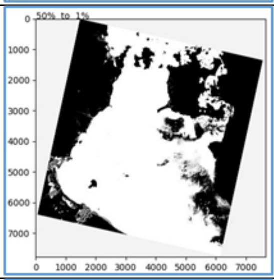
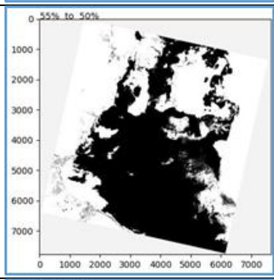
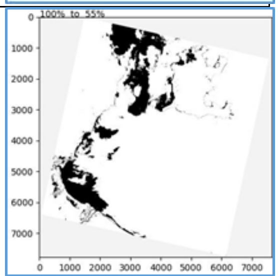
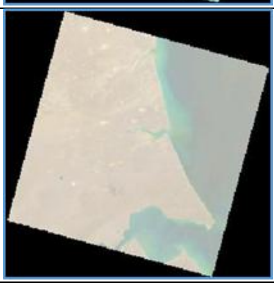
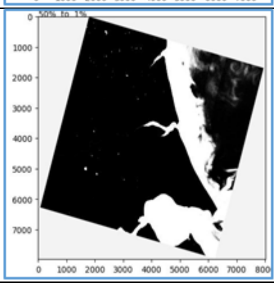
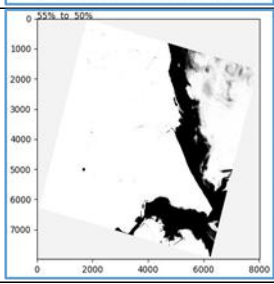
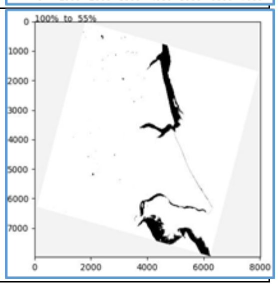
Thus mNDWI image obtained is translated to a dynamic range of 0-100. Applying specificpercentage range of values in mNDWI image, land , water and land-water junction region have been detected and visualized with plotted images. Range values are tuned based on observation of image scenarios through trial and error method, so that with the same range definition relevant features are detectable in all scenes.

IV. Results

For each of the input scene three images are generatedwith three different mNDWI range, namely land, water and land-water junction/sedimented water. Scene is represented by thumbnail image available from data bundle of Landsat imagery. Thumbnail represents the scene visibly. Three mNDWIimage plots of the scene are generated as described in methodology section. mNDWI values range from -1 to +1. The mNDWIvalues computed on each pixel is translated suitably to a dynamic range of 0 to 100. For each target scene,one thumbnail image and 3generated images are shown. First one is the thumbnail of the scene available in data bundle. Second one is with range 1-50 % of the dynamic range of

mNDWI values representing land part detected. Third picture shows the image with pixels of values 50-55% of mNDWI values depicting detected water bodies. Fourth plot shows the image with pixels in range of 55-100% of dynamic range representing land-water junction. In each plot the region of interest is shown in black. Pixels which are not falling in the specific category is represented in white. Result is shown in following Figure-1 diagram.

SR .N O	Scene	Land	Water	Land-Water Junction
1.				
2.				
3.				
4.				
5.				
6.				

7.		50% to 1%	55% to 50%	100% to 55%
8.		50% to 1%	55% to 50%	100% to 55%
9.		50% to 1%	55% to 50%	100% to 55%
10.		50% to 1%	55% to 50%	100% to 55%
11.		50% to 1%	55% to 50%	100% to 55%
12.		50% to 1%	55% to 50%	100% to 55%

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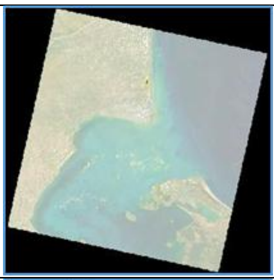

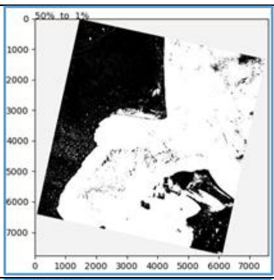

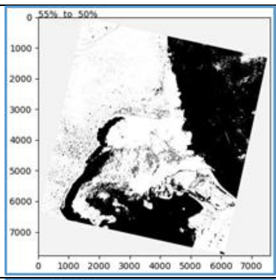

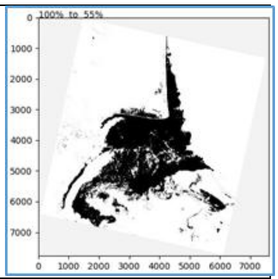

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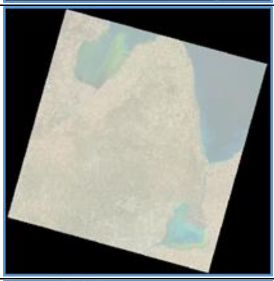

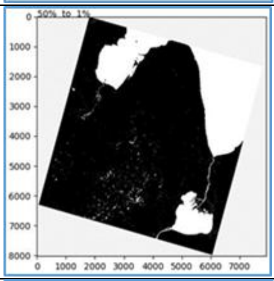

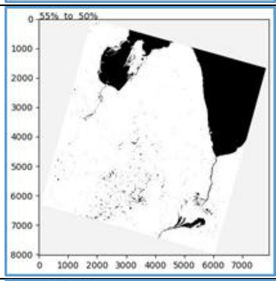

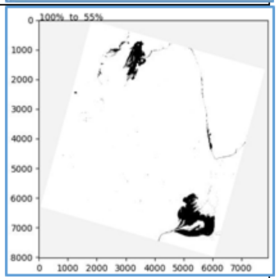

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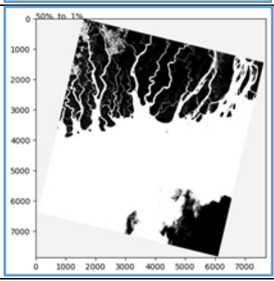

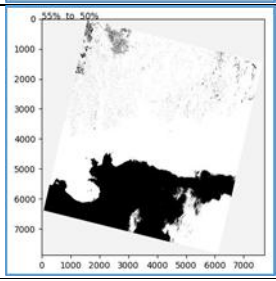

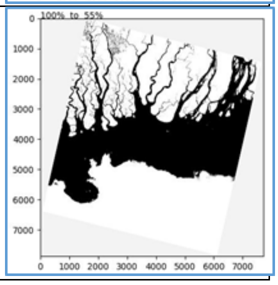

Figure 1 : Thumbnail image and extracted out Land, Water and Land-Water transition zone images for 15 scenes.

II. Discussions

The result shows that the scheme is successfully implemented on 15 target scenes and generates consistent result. It is observed that land-water transition region gives highest values of mNDWI values. Reason is the region is characterized with moderate green reflectance but is moderate between land and water, whereas swir reflectance is almost same as water. Thus difference between green and SWIR becomes higher for the transition region than for land or water region. This method is fast, easy and rugged to identify water bodies, land and land-water transition region. The same scheme for zonation of scene may be carried out based on other indices also. Various features may be detected very conveniently and reliably using various range of indices applied. It inspires to explore unknown features of a region that is not so obvious from mere image.

III. Performance comparison

There are some relevant works on coastline detection noticed by author as follows.Automatic coastline extraction from Satellite Images has been done using various platforms like ENVI[20],Arcinfo_GIS [21], Google Earth Engine(GEE) [22], Copernicus Services available to SENTINEL data[23] , GEE based Coastsat application and in MATLAB[25]. Most of the works mentioned here have been carried out using the support of some application tool, MATLAB based work has observed only one geographical location. The work presented here has been done using various geographical locations over the world using same threshold range for water-land junction region, entirely in Python platform.It provides clarity of basic level about computation techniques and flexibility to modify, simplicity to use and freely availability of open source software.

IV. Conclusion

The python program developed is capable to automatically detect water, land and land-water junction using different specific threshold ranges of mNDWI. Same threshold is used to detect the specified regions out of each target scene over a varied terrain on earth.The program identifies land-water transition region with specific range of mNDWI value consistently for each of the 15 target images.

Validation is visually done with respect to corresponding thumbnail images available.This is particularly useful for monitoring and estimation of islands, coastal area or estuary region for growth/erosion change over time. As the whole algorithm is implemented in python, unlike black box transformation function in standard image processing software, further scope of extension in the algorithm can be done very conveniently and cost effectively.

Acknowledgement :

I would express my gratitude to Shri Nilesh M Desai , Director, SAC for giving me opportunity for initiating this work at RRSC-East. I am thankful to DrDibyenduDutta , GM, RRSC-East for assigning and encouraging to pursue the work. I would like to express my gratitude to DrDebashish Chakraborty, Head-Application, RRSC-East, for his valuable comments and feedback for the work performed. I thank MsSharmishta Pandey and MsNivedita Sinha at RRSC-East, for their cooperation to establish the set-up of python platform and some data download activities. I am thankful to MrSandip Paul, Head, SCPD/SEG/SEDA for allowing me to continue and complete the work at SAC.

Declaration of Competing Interest The author declares that no known competing financial or personal interests that could have appeared to influence the work reported in this paper.

Fund:This research did not receive any specific grant from funding agencies in the public, commercial, ornot-for-profit sectors

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