INTEGRATED ANALYSIS OF MANGROVE CHANGES USING THE MANGROVE VEGETATION INDEX AND RANDOM FOREST CLASSIFICATION IN THE GAMBIA

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ABSTRACT:

The extraction of mangrove forests from satellite imagery is usually accomplished using image classification algorithms. Recently, the mangrove vegetation index (MVI) was developed for rapid and accurate mapping of mangrove extent from remotely sensed imageries. In this study, we combine two techniques (random forest classification and the MVI) to improve the detection of mangrove changes within the Bintang Bolong Estuary in The Gambia. The two techniques were implemented on Sentinel-2 multi-spectral imageries covering the study area at two periods - 2017 and 2020. The random forest classifier was used to extract the full land cover information from which the mangroves were separated, while the MVI was implemented using the green, near-infrared and shortwave infrared bands. Subsequently, the results were extracted for interpretation and analysis. The image classification results showed an increase in mangroves from 38.6 km^2 in 2017 to 41.5 km^2 in 2020. The areal extent of mangroves from image classification was positively correlated with the MVI-generated extent. The findings prove the importance of combining image classification and spectral indices for gaining more comprehensive perspectives of mangrove changes.

1. INTRODUCTION

Mangroves are vital ecosystems especially in the mitigation of climate change due to their high sequestration of carbon (Rastogi, Phulwaria and Gupta, 2021). They mainly occur on the shorelines of coastal regions within the tropics between the 30°N to 37°S latitudinal bands (Arceo-Carranza *et al.*, 2021). Mangroves have diverse benefits and are vulnerable to natural disasters and anthropogenic interference. In the mapping of mangroves, in situ measurements are not only costly but time-consuming due to the vast coverage areas of mangrove forests. Remote sensing is an efficient method of mapping and monitoring mangroves (Maurya, Mahajan and Chaube, 2021), and is widely adopted by researchers in the field (Mondal, Liu and Fatoyinbo, 2019). Common remote sensing techniques for mapping mangroves include image classification and spectral indices.

The predominant technique for mapping and monitoring of mangroves is image classification. Methods for image classification include random forest (RF), support vector machine (SVM), and artificial neural networks (ANN). The random forest algorithm (Breiman, 2001) has shown satisfactory accuracies for the classification of mangrove forests (Jhonnerie *et al.*, 2015). It is a set of decision trees from randomly selected training sets aggregating their votes to decide the final class of the test object. Additionally, several indices have been developed for mangroves, e.g., mangrove index (Winarso, Purwanto and Yuwono, 2014), mangrove recognition index - MRI (Zhang and Tian, 2013), combined mangrove recognition index – CMRI (Gupta *et al.*, 2018), mangrove probability vegetation index - MPVI (Kumar *et al.*, 2019), normalized difference wetland vegetation index – NDWVI (Kumar et al., 2017), and the mangrove forest index – MFI (Jia *et al.*, 2019).

Recently, the mangrove vegetation index, or MVI was developed as an accurate method to discriminate mangroves from other land cover types (Baloloy *et al.*, 2020). The MVI measures the greenness and moisture information to determine the probability of a pixel being mangrove, and is reported to have an index accuracy of 92%. Given its recent development, new studies are required to evaluate its reliability across regional and continental mangrove ecosystems. The equation for the MVI follows from Baloloy et al. (2020) as shown in equation 1 below.

$$MVI = (NIR - Green) / (SWIR1 - Green) \qquad (1)$$

Where NIR, Green, and SWIR1 are reflectance values in Sentinel-2′s band 8, band 3, and band 11, respectively. The numerator (NIR-Green) improves the differences of vegetation greenness between mangrove forests and terrestrial vegetation; while the denominator (SWIR1-Green) expresses the distinct moisture of mangroves due to their environment.

With the increased proliferation of multi-sensor and multi-temporal satellite images available to end-users, it is advantageous to combine several techniques for mapping which can yield complementary perspectives of target landscapes. Consequently, we integrate random forest classification and the mangrove vegetation index for mapping and monitoring mangroves in the Bintang Bolong estuary of The Gambia. Despite the ecological importance of mangroves in The Gambia, there is limited information on their spatial distribution and ongoing changes. To our knowledge, this is the first study to integrate both methods for mapping and monitoring mangroves.
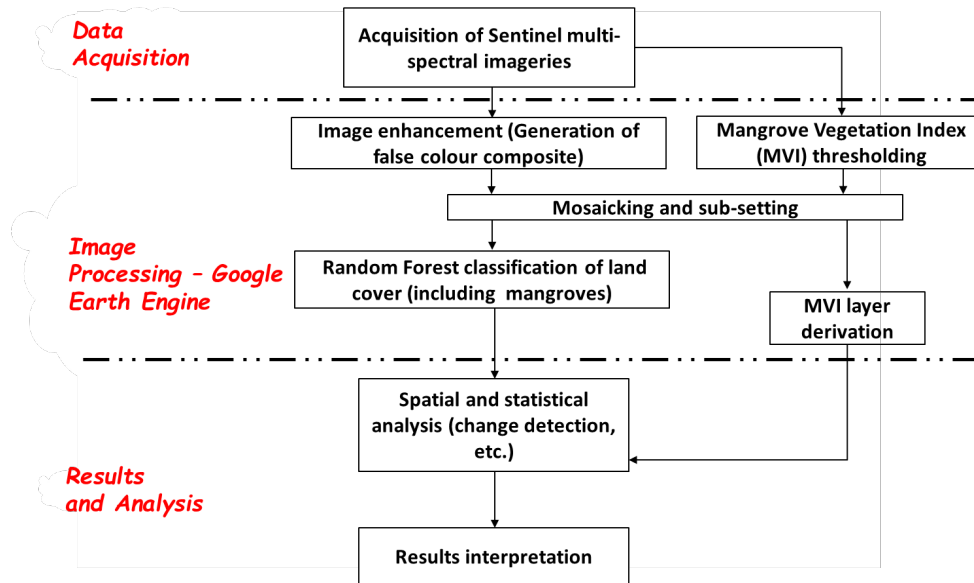
Figure 1. Methodology workflow

2. METHODOLOGY

Figure 1 presents the workflow diagram of the methodology, and the stages are discussed in the sections that follow.

2.1 Study Area

The Gambia is a small country in mainland Africa occupying an area of approximately 10,000km^2 (Fent *et al.*, 2019). The country lies between longitudes 13 - 17°W and latitudes 13 - 14°N. It has a coastline with the Atlantic Ocean to the west that extends for about 80km. Other parts of the country are surrounded by Senegal. According to Fent *et al*. (2019), the country had 867.88km^2 of mangrove forests as at 2018. The Gambia is host to some of West Africa's tallest mangroves (+20m). The most dominant species are the *Rhizophora mangles* and *Avicennia germinans*. The Bintang Bolong estuary study site shown in Figure 2 once had an extensive belt of mangrove forests, especially along the shorelines of the Bintang Bolong estuary. However, natural and human interferences have affected the sustainable existence of these forests. Recently, numerous dead stumps showing the remnants of mangrove trees could be seen along the estuary (Dia Ibrahima, 2012; Moudingo *et al.*, 2019).

2.2 Data Acquisition

The main datasets used for this study are Sentinel-2 multi-spectral imageries acquired during the following dry season periods - January 11, 2017 and May 14, 2020. Sentinel-2 is a Copernicus mission launched in 2015 comprising twin (Sentinel 2A/B) polar-orbiting satellites with a high revisit time dependent on the latitude. Several researchers have adopted Sentinel-2 imageries for mapping and monitoring changes in mangroves (Tieng *et al.*, 2019; Jamali, 2020; Wu *et al.*, 2020; Cissell *et al.*, 2021; Ghorbanian *et al.*, 2021). The Sentinel-2 Multi-spectral Instrument (MSI) has 13 spectral bands with different spatial resolutions.
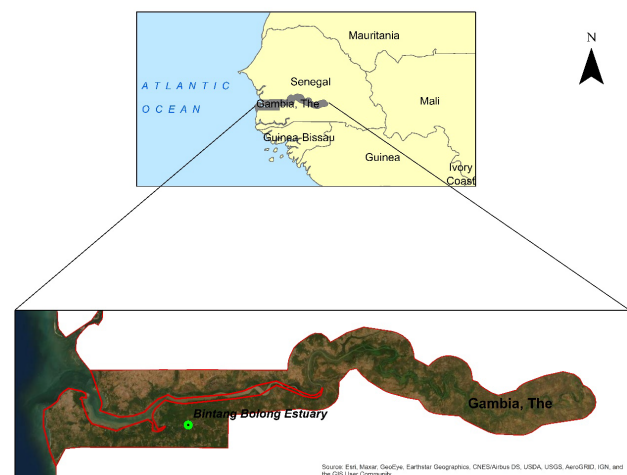

Figure 2. Map of the study area.

2.3 Image Processing

The Random Forest (RF) classifier was used in the extraction of mangroves and other land cover classes within the Google Earth Engine (GEE) platform. The Sentinel-2 imageries were imported into GEE and sub-setted to the area of interest (AOI). True image composites were generated with spectral bands in the following order - band 4 (red), band 3 (green) and band 2 (blue). Interpretation of the composite revealed 4 main land cover classes - mangroves, water bodies, bare lands and mixed forests. Training data were created at selected points on the imageries to represent the land cover classes. The classification was executed with the RF classifier and the results were converted to GeoTiff format for further analysis in ArcGIS.

For the MVI, a script was written within GEE to implement equation 1 on the Sentinel imageries using the NIR, green and SWIR1 bands. Following the guideline of Baloloy et al. (2020), the optimal minimum threshold was set to 4.5 for Sentinel-2.
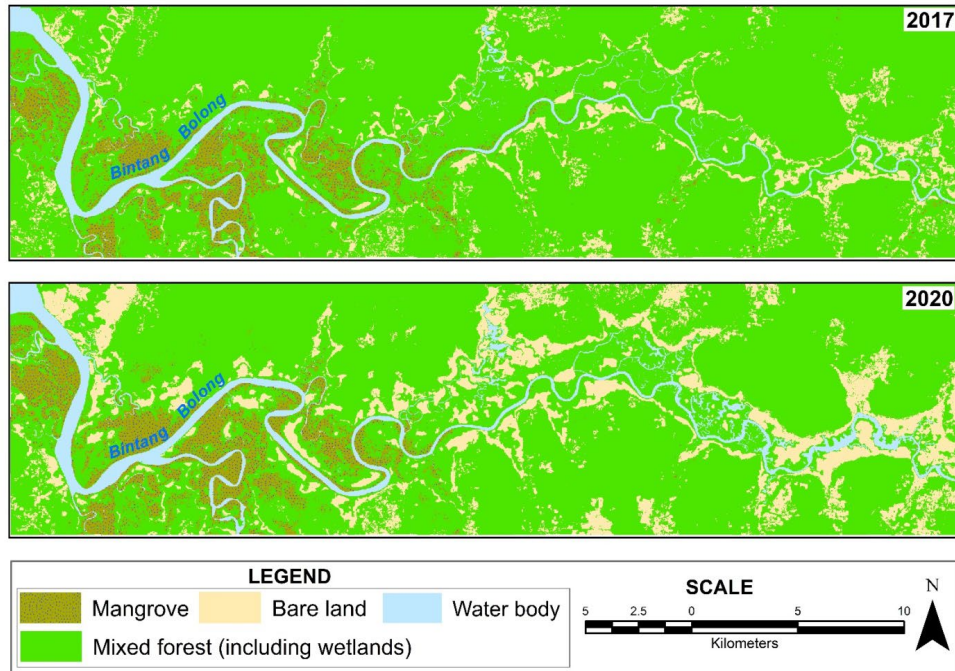
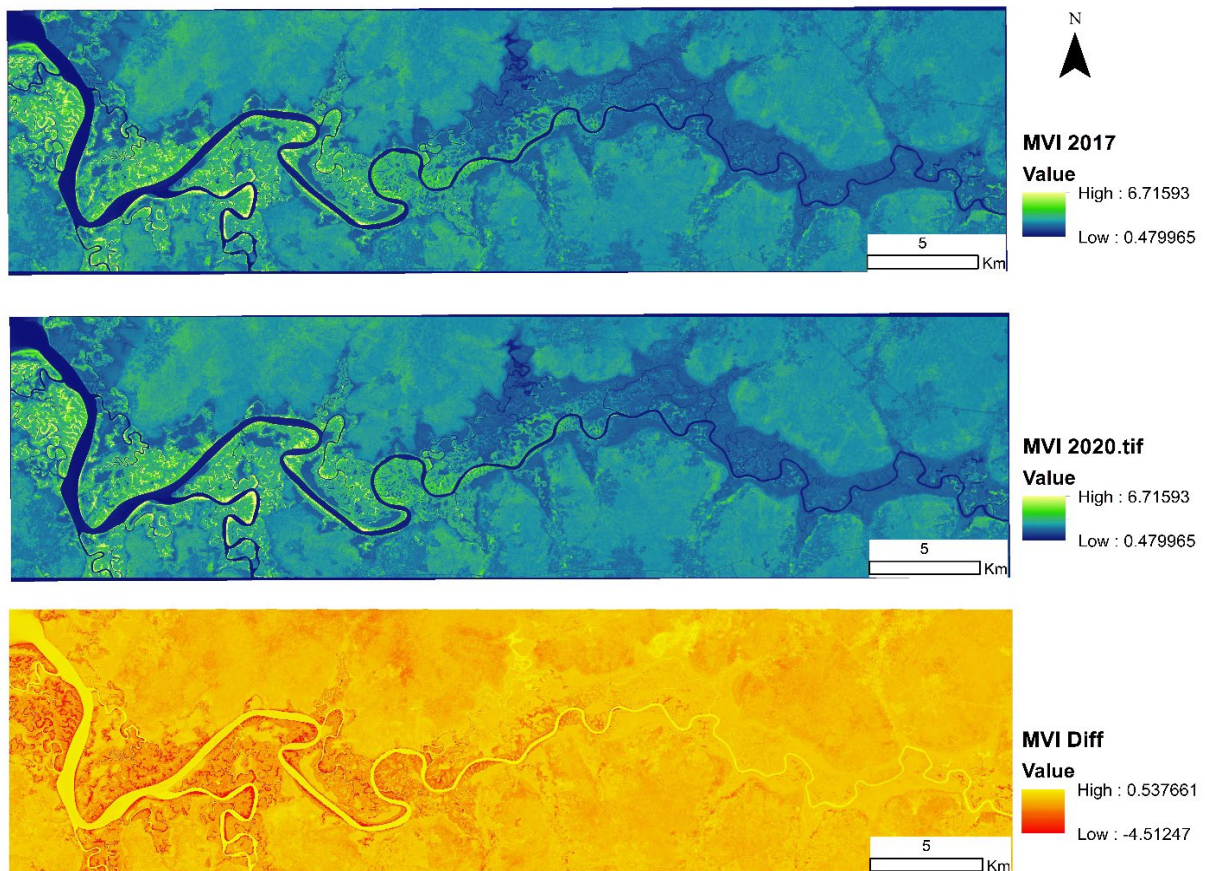**Figure 3**. Random forest classification – 2017 (top) and 2020 (bottom)

Figure 4. Mangrove vegetation index – MVI 2017 (top), MVI 2020 (middle) and MVI Difference (bottom)
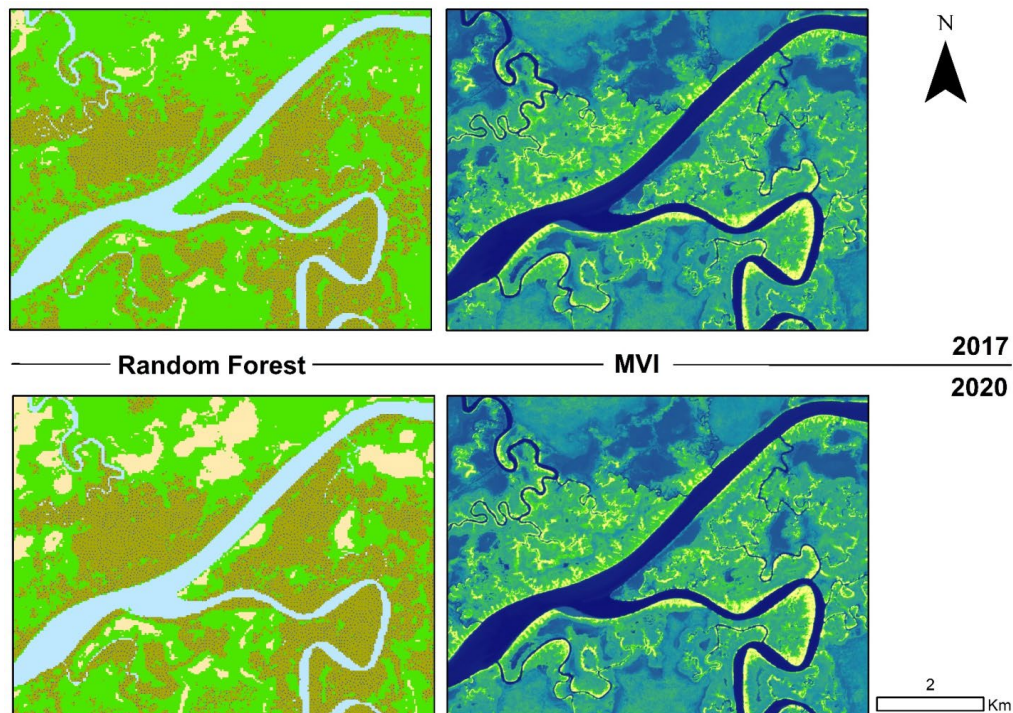
Figure 5. Comparison of RF (left) and MVI (right)

The script was executed and the MVI layers were generated and exported to ArcMap for further analysis.

3. RESULTS AND DISCUSSION

3.1 Random Forest Classification

Figure 3 shows the output of the random forest classification. There is an increase in mangroves from 38.6 km^2 in 2017 to 41.5 km^2 in 2020. A total of 0.3618 km^2 and 9.9783 km^2 of water bodies and bare lands in 2017 were converted into mangroves in 2020. The detection of mangroves was however problematic along the shoreline where some mangroves were submerged below water, with the incidence of mixed pixels.

3.2 Mangrove Vegetation Index

Figure 4 shows that a more comprehensive delineation of the mangrove extent was realized by the MVI, including the adjoining wetland areas. An MVI difference map was generated through subtraction of the 2017 MVI layer from the 2020 MVI layer. The resultant image was an MVI change map between the two years. Positive MVI values in Figure 4 are pointers to increased mangrove presence and negative values point to a decrease in mangroves between the periods. The distribution of values on the MVI change map indicates a general increase in the extent of mangroves, and this is corroborated by the RF classification results which showed an increase in mangroves from 38.6 km^2 in 2017 to 41.5 km^2 in 2020.

3.3 Comparison of the RF and MVI algorithms

The RF and MVI outputs are compared in Figure 5. The regions that exhibited higher MVI values coincided with the regions classified by Random Forest as mangroves for both years. In both maps, a greater concentration of mangroves is depicted along the estuary shorelines exhibiting higher MVI values, whereas regions with water and bare land depicted lower MVI values. This is explained by the fact that water and bare land both have high reflectance values within the NIR and SWIR1 regions.

4. CONCLUSION

The integration of RF and MVI algorithms in this study is promising for the mapping of mangroves. The areal extent of mangroves from image classification was positively correlated with the MVI-generated extent. Despite the computational differences, mangrove forests were distinguished from other land cover types in the satellite imagery. The MVI however, was able to distinguish the mangroves from other closely related wetlands. The wetland extent was clearly demarcated using the MVI. This illustrates the sensitivity the MVI has in the identification of mangrove pixels.

This study exemplifies the ability to better map mangrove forest extent by combining classification algorithms and spectral indices. The combined perspective can enable a more comprehensive inventory and sustainable management of mangrove forests by the relevant stakeholders.

Remote Sensing for enabling the presentation of these research findings during the 2022 conference.

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