CHANGE DETECTION OF MANGROVE FORESTS IN WEST AND CENTRAL AFRICA WITH LANDSAT IMAGERY

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KEY WORDS: Mangrove forest, Remote Sensing, Landsat data, Change detection

ABSTRACT: Mangroves are distributed along the coastal wetlands of tropical and subtropical regions throughout the world. They provide various ecological and socioeconomic services for humans, including coastal protection, water filtration, tourist attraction and the provision of building material, and they also serve as habitats for a variety of coastal wildlife species. The dramatic decline of mangroves in West and Central Africa during the last half century due to the conversion of mangrove forests to agricultural lands and urbanization has caused environmental issues including habitat loss, reduction of biodiversity, and increased coastal erosion. This study aims to investigate the changes of mangrove forests in the West and Central Africa (mainly located in three nations: Senegal, The Gambia and Guinea-Bissau) using Landsat imageries during the periods of 1988 to 2014. The data was processed through five main steps: (1) data pre-processing including geometric and atmospheric corrections and image normalization; (2) image classification using the decision tree algorithm; (3) accuracy assessment for the classification results, (4) change detection analysis. From the classification results, 2.1% of the mangroves were lost from 1988 to 2014, while the newly planted mangroves during the same period was 1.3%. Hence, freely available Landsat imagery provides adequate monitoring and change detection for mangrove forests.

1. INTRODUCTION

Mangrove forests are usually located in the tropical and sub-tropical regions around the world. They provide various ecological and economical ecosystem services. They also contribute to coastal erosion protection, water filtration, provision of favorable living environments for fish and faunas, provision of building materials and medicinal ingredients (Brown *et al.*, 2006; Giri *et al.*, 2011; Costanza *et al.*, 2001 and Nagelkerken *et al.*, 2008). In the recent three decades, mangrove forest area in the world has decreased by 3.6 million hectares (from 18.8 million ha in 1980s to 15.2 million ha in 2000s) (Valiela *et al.*, 2001; Giri *et al.*, 2008; FAO, 2007).

Mangrove forest in West and Central Africa accounts for one fifth of the total mangrove forest area in the world and 70% of them is located in 19 nations from Liberia to Anglola. The area of mangrove forest in this region has decreased very significantly, about 25% area from 1980 to 2006 (Emily *et al*, 2007). The major effects of changes in mangrove forests are; water pollution, economic growth, local policies, climate change and the change of environment in the upper streams (Emily *et al*, 2007). Therefore, monitoring the spatiotemporal distribution of mangrove forests is thus critical for natural resources management of mangrove ecosystems in West and Central Africa. Nowadays, many approaches are developed to extract mangrove forest for recent years (Kuenzer *et al*, 2011; Wang and Sousa, 2004; Heumann, 2011 and Vo *et al*, 2012). Algorithms applied in previous studies have used unsupervised and supervised or object-based classifications, with limited ground reference data for checking their mapping accuracies. Hence, the main objectives of this research are: (1) develop an algorithm to map mangrove forests using satellite imagery from 1988 to 2014; and (2) detecting the mangrove forest change from spatial mangrove distribution map on the same periods.

2 METHOD AND MATERIALS

2.1 Study area

Mangrove forests are located in 19 countries in West and Central Africa, from Liberia in the North to Angola in the South. Mangroves are usually distributed along the coastal line and river. Due to the concentration of mangroves in West and Central Africa, this study therefore focuses on this region to extract the coverage of mangrove forest in three countries: Senegal, The Gambia and Guinea-Bissau.

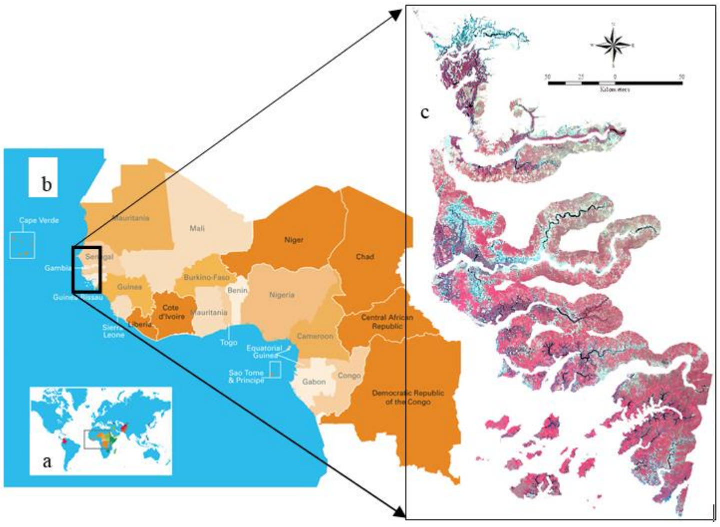

Figure 1. Overview of study area: (a) Global map; (b) West and Central Africa; and (c) study area after subset (Landsat 8 imagery acquired in 2014; R, G, B =NIR, Red, Green)

2.2 Data collection

Landsat imagery for three periods: 1988, 2001 and 2014, were used in this research. The data were download from the USGS website (http://earthexplorer.usgs.gov/), and processed in the level L1 (geometrically corrected with UTM, WGS zone 28N datum system). Landsat TM and ETM+ were stored in HDF format and Landsat 8 OLI was in GeoTIFF file format. Digital Elevation Model (DEM) with a 30 m spatial resolution collected from National Aeronautics and Space Administration (NASA) was used to remove regions of elevation higher than 30m and the ocean (elevation of zero).
The mangrove forest map of USGS 2011 was downloaded from the Ocean Data Viewer website (http://data.unep-wcmc.org/datasets/21) for validating interpreted mangrove map of 2014.

2.2 Data pre-processing

Since the Landsat TM (1988) and ETM+ (2001) datasets used in this research are CDR products, they was no need for atmospheric correction. Therefore, atmospheric correction was perform only for the Landsat 8 imagery. It was conducted using ATCOR2 software. ATCOR contains a large number of pre-calculated atmospheric conditions based on the MODTRAN radiative transfer code. Standard parameters for tropical maritime land surfaces were used, and sun and sensor geometries were modified according to the image recording conditions as extracted from the image's metadata.
Based on the characteristics of mangrove forests, the DEM data and NDVI (Normalize Different Vegetation Index) were used to mask out the ocean and water bodies. Moreover, the river systems are used to remove the area where mangrove forest disappear by creation 150m buffer from the river line to the mainland.

2.3.3 Mangrove spectral characteristics and band selection

Many studies such as Hirose, or Masayuki, (2004) have demonstrated that mangrove forest have a lower reflectance in the shortwave infrared (SWIR) band than other vegetation types. Mixing between mud, sediment and water with the mangrove forest are the main reason that it causes mangrove forests to have a low reflectance in the SWIR. From these spectral lines in Figure 2, mangrove forest have lower reflected radiance in SWIR bands 5 and 6. Reflectance of leaves in the SWIR bands are determined by water absorption and scattering caused by refractive index discontinuation between leaf cell walls and the intercellular air Spaces (Woolley, 1971 and Gausman 1973). Another reason is that satellite imagery observe mangrove forest as a mixture of mangrove and mud or water at the forest floor.

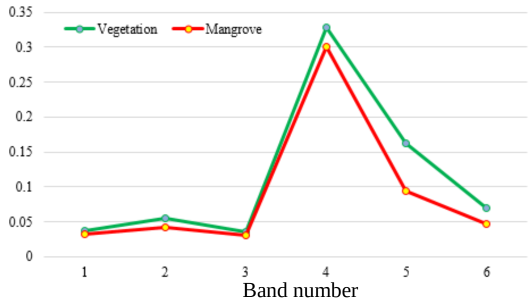

Figure 2: Spectral profiles of sample areas with the red line is mangrove and the green line is vegetation.

To prove the previous research and select band for image classification, a separate calculation of mangrove forest and non-mangrove forest was effectuated by using 10.000 random points that were generated from the ground reference data for each of them. After that, Normalize Mean Distance formula was applied:

$$d = \frac{|\mu_1 - \mu_2|}{\sigma_1 + \sigma_2}$$

Where $\mu_{1,2}$ are the mean value and $\sigma_{1,2}$ are the standard diviation of the mangrove and non-mangrove areas, respectively. The value of d ranged from 0 to 2. If the value is near to 2, then the distinguishment between mangrove and non-mangroves is very good, otherwise it will result to misclassification when the image is classified.

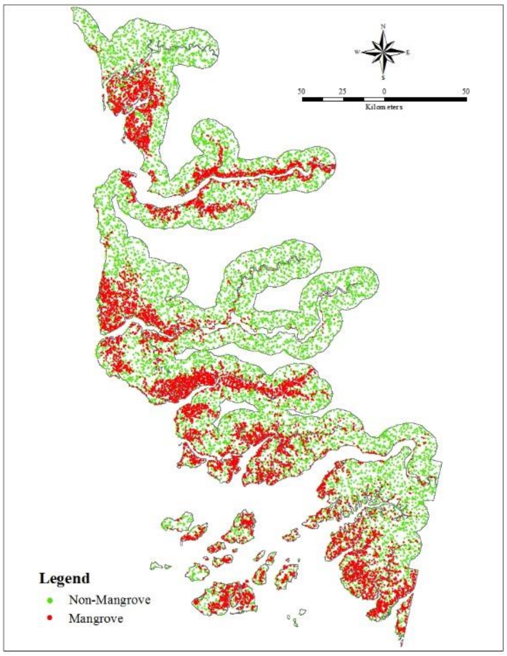

Figure 3: Random point distribution of mangrove and non-mangrove forests generated from ground reference data in 2011.

Table 2: The normal mean distance of the mangrove forest and non-mangrove forest caculated for all bands of the Landsat 8 imagery (2014).

Name of band	Landsat 8 OLI
	Mangrove vs. Non-Mangrove
Blue	0.02
Green	0.12
Red	0.35
NIR	0.63
SWIR 1	**1.96**
SWIR 2	1.36

2.3.4 Image classification

Nodes for decision tree approach to extract mangrove forest from NDVI, DEM and band SWIR1 (band 5) data according to the characteristics, singularities and distribution of mangrove forests, were developed in this study.

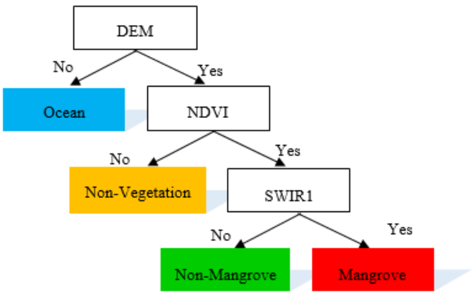

Figure 4: Flowchart showing decision tree to extract mangrove forest

DEM: if DEM > 0; the answer is yes: Land; otherwise it will be ocean.

NDVI: if NDVI > T_1; the answer is yes: Vegetation; otherwise it will be Non-Vegetation.

SWIR1: if SWIR1 $\geq T_2$ and SWIR1 $< T_3$; the answer is yes: Mangrove forest; otherwise it will be Non-Mangrove.

Where T1 is the threshold of NDVI with the value is 0.2 in this study area while T2 and T3 are the thresholds of band SWIR1 and it was determined by the histogram using the local minimum.

2.3.5 Mangrove change detection from three past decades

The classification results are effected by “salt and pepper” noise. That is why Majority filter applied to remove this kind of noise with 3x3 window size. With regards to this method, accuracy assessment was performed for 2010 using the 2011ground reference data. Spatial-temporal change of mangrove forest is detected using Change Detection tool in ENVI and overlay analysis of ArcGIS.

3. RESULT AND DISCUSSION

3.1 Spatial distribution of mangrove forest in three periods from 1988 to 2014

The classification results shows that, the spatial distribution of mangrove forest were generally sheltered along the coastlines, fringes of the estuaries, along the river banks where brackish water margin is found between land and sea.

The mangrove forest were more concentrated in the west of this area because those regions were managed and consecrated by governments and local policies. The density of the mangrove forests along rivers and streams in the East is sparser than that of the West because they were fragmented and the main reasons for this are; pollution from industrial zones, economic, and the change of environmental in the upper streams. The spatial distribution of mangroves in three past decades are shown for three particular epochs i.e. 1988, 2001, and 2014 in Figure 5.

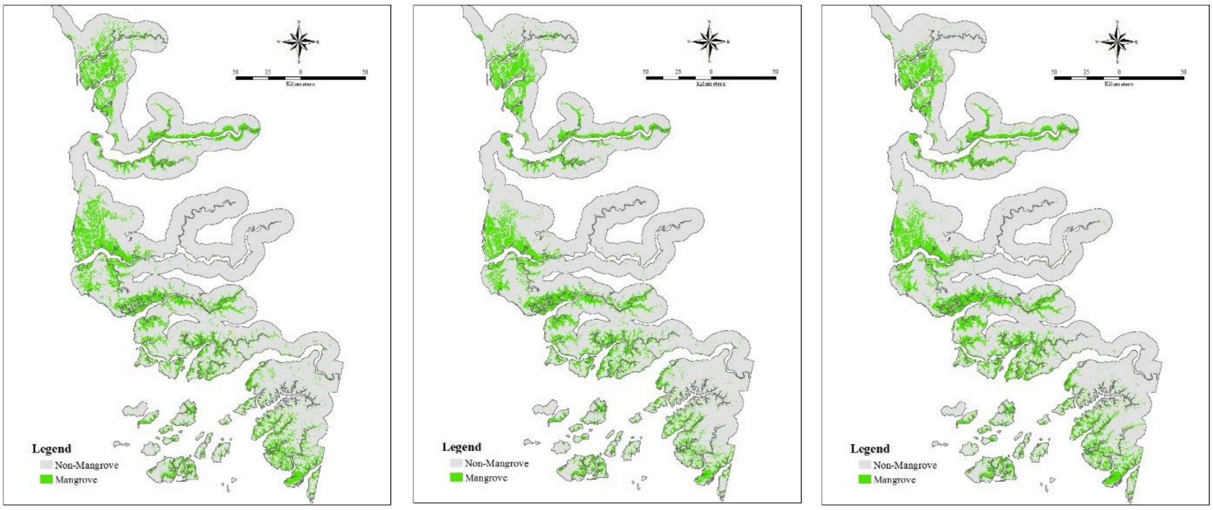

Figure 5: Spatial distribution of mangrove forest in three periods. a: 1988; b: 2001; and c: 2014

3.2 Accuracy assessment

Since the ground reference is that of 2011, this research therefore applied the same method to extract mangroves in 2010 as mentioned above. After the classification of the image in 2010, random points from the ground truth data were used to conduct the accuracy assessment by using confusion matrix. The results show that the overall accuracy and kappa coefficient are 85.14% and 0.74 respectively. The confusion matrix is shown in the Table 3. Since there is a one year difference between ground truth and classified image, there were some changes that occurred during this time, and that is why the accuracy is not very high.

Table 3: Accuracy assessment from the classification in 2010.

Reference data	**Classification result**		
	Mangrove	Non-Mangrove	Total
Mangrove	7,354	326	1,136
Non-Mangrove	2,646	9,674	864
Total	10,000	10,000	20,000
Producer Accuracy	73.54%	96.74%	
User accuracy	94.45%	78.52%	
Overall Accuracy	85.14%		
Kappa Coefficient	0.74		

3.3 Mangrove forest change detection

Mangrove change detection between was performed at three intervals i.e. 1988-2001; 2001-2014 and 1988-2014. Change in land use is the main cause that effected change of mangrove forest in this area. The overall change in this study area resulted to the loss of 2.1% of mangroves, while 1.3% of mangrove forest in the region were newly planted or restored.

Agricultural, aqua-cultural and industrial developments effected changes on the mangrove forests. Changes in mangrove forest calculation have shown that the largest conversion of mangrove to non-mangrove was detected on 1988-2001 period. The decline registered for mangrove forests during this period was 3.23% area while 1.79% was rehabilitated or renew planted.

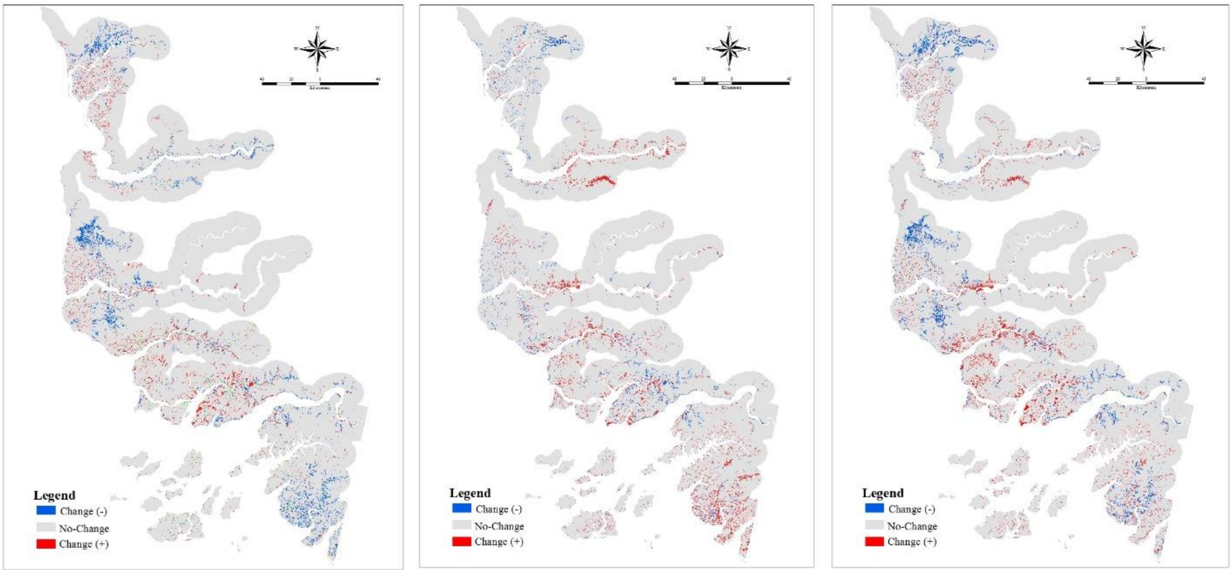

Figure 6: Mangrove change detection in the three past decades. a: changes in 1988-2001; b: changes in 2001-2014; and c: changes in 1988-2014.

Table 4: Changes in mangrove forest in three past decades from 1988 to 2014

1988	2001	2014	Area	
			ha	%
Mangrove	Mangrove	Mangrove	428,715.0	14.6
Non-Mangrove	Non-Mangrove	Non-Mangrove	2,278,820.0	77.4
Mangrove	Mangrove	Non-Mangrove	28,585.4	1.0
Mangrove	Non-Mangrove	Non-Mangrove	62,088.3	2.1
Non-Mangrove	Mangrove	Non-Mangrove	24,140.9	0.8
Mangrove	Non-Mangrove	Mangrove	33,106.7	1.1
Non-Mangrove	Non-Mangrove	Mangrove	51,066.3	1.7
Non-Mangrove	Mangrove	Mangrove	37,610.5	1.3

4. CONCLUSION

From these classification results, it can be seen that the method used in this research was successfully applied to extract mangrove forest based on characteristics, singularities, and distribution as well as reflectance value and spectral properties of mangrove forest in the images from 1988 to 2014. Result of comparison between ground reference data with classification in 2010has shown that the overall accuracy is 85.14% while the Kappa is 0.74.

From three past decades, mangrove forests have decreased by a proportion of 2.1%, while the newly planted mangroves during the same period (1988 to 2014) was 1.3%. The reason for land use change in this region is due to pollution, economy, local policies, climate change and the change of environment in the upper streams.

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