



# **Application of Satellite Imagery in the Differentiation of the Invasive Species of Nipa from Mangrove Vegetation**

**John Onwuteaka<sup>1</sup> and Mike Uwagbae<sup>2\*</sup>**

<sup>1</sup>*Department of Animal and Environmental Biology, Rivers State University of Science and  
Technology, Nigeria.*

<sup>2</sup>*Department of Animal and Environmental Biology, University of Benin, Benin City, Nigeria.*

## **Authors' contributions**

*This work was carried out in collaboration between both authors. Author JO designed the study, performed the statistical analysis, wrote the protocol and wrote the first draft of the manuscript. Author MU managed the literature searches. Both authors read and approved the final manuscript.*

## **Article Information**

DOI: 10.9734/JGEESI/2017/38454

### Editor(s):

(1) Kaveh Ostad-Ali-Askari, Department of Civil Engineering, Isfahan (Khorasgan) Branch, Islamic Azad University, Iran.

(2) Masum A. Patwary, Geography and Environmental Science, Begum Rokeya University, Bangladesh.

### Reviewers:

(1) Uzay Karahalil, Karadeniz Technical University, Turkey.

(2) Muhammad Luqman, University of Melbourne, Australia.

Complete Peer review History: <http://www.sciencedomain.org/review-history/22990>

**Original Research Article**

**Received 7<sup>th</sup> November 2017**

**Accepted 24<sup>th</sup> January 2018**

**Published 1<sup>st</sup> February 2018**

## **ABSTRACT**

Mangrove forests form one of the primary coastal ecosystems in the tropical and subtropical regions of the world with a high biodiversity value. Mangrove species are uniquely adapted to the Nigerian coasts, providing numerous biodiversity and ecosystem services and supporting coastal livelihoods within the Niger Delta. The gradual decline in the size of the Mangrove ecosystem, due to *Nipa fruticans* infestation, has spanned a period of over 40 years. So far, no quantitative estimate of loss of these Mangrove habitats has been carried out. This is as a result of the closeness in spectral characteristics between Nipa and different species of Mangrove and the difficulty of differentiating Nipa using earlier remote sensing products such as Landsat, JERS, Radarsat, SPOT and ERS. To address this gap, new satellite imagery was used to extract both textural and spectral

\*Corresponding author: E-mail: [mikeuwagbae@gmail.com](mailto:mikeuwagbae@gmail.com);  
E-mail: [Onwuteaka.john@ust.edu.ng](mailto:Onwuteaka.john@ust.edu.ng);

information. This imagery, Pleiades and GeoEye-2, contained 16 high-resolution spectral bands that capture information in the visible and near-infrared (VNIR) for the first time. The study was validated with groundtruth surveys leading to the differentiation of Mangrove and Nipa in an area of interest measuring 162 sq. km along the Andoni River Estuary. From the results, major threats of Nipa to Biodiversity of the Mangrove were compiled. A ratio of 1:24 of Mangrove to Nipa within an area of over 16,200 hectares is indicative of a very high threat that can lead to extinction of Mangrove species. This TEXVEG tool's capacity to determine loss of Mangrove species from Nipa infestation across the Niger Delta landscape will help environmental decision makers provide guidance for biodiversity conservation of Mangrove species. This technique has great potential for mitigating economic and environmental consequences for coastal communities, especially in areas with low Mangrove diversity and high Mangrove area and species loss.

*Keywords: High resolution satellite imagery; mangrove; Nipa; differentiation; TEXVEG; classification; texture; NDVI; Nigeria; estuary.*

## **1. INTRODUCTION**

The Biodiversity potential and ecosystem services that Mangroves offer are well documented in literature. Mangroves are considered to behave like a natural barrier against ocean dynamics along the shoreline. Their ability to protect shoreline and inland areas from natural hazards (hurricanes, cyclones, tsunamis) was recently discussed [1,2,3,5,6]. They can break the force of waves and help to prevent coastal-erosion processes [7,8,9,10]. Mangrove ecosystems support aquatic food chains and form habitats for marine fauna, such as juvenile crabs, prawns, offshore fish, reef fish, and larvae [11,12,13,14]. Terrestrial fauna, such as birds, insects, mammals, and reptiles, and associated flora, such as fungi, algae, and sea grass, build rich communities with Mangroves [15,16]. Mangroves maintain water quality by acting as biological filters, separating sediments from nutrients in polluted coastal areas [17,18,19]. Globally Mangrove loss is affected by the conversion of Mangrove areas into shrimp farms [20,21,22,23]. This portion accounts for a global Mangrove loss of more than 50% [19,24]. Other globally known factors include industrial lumber and wood chip operations. Increasing human populations, industrialization, and agriculture have caused dramatic forest loss as well natural forces, such as tsunamis, cyclones. These reductions in Mangrove-related services and product delivery impose serious limitations on the residents.

In the Niger Delta, the leading cause of Mangrove loss is from Nipa palm which had become a major invasive species for over 35 years, overtaking the Mangrove at Imo River, parts of Bonny River, Opobo and Qua Iboe River and their tributaries [25,26,27,28]. A basic

prerequisite for any assessment of the rate and magnitude of Nipa invasion is the establishment of an intensive field campaign. Such an intensive field campaign for the size of the Mangrove/Nipa ecosystem in the Niger Delta is hindered by the inaccessibility of the large area and the prohibitive cost associated with such an effort. Remotely sensed information therefore remains the only cost-effective method that can be used to obtain facts and data on the condition and extent of threat to the Biodiversity of Mangrove ecosystems by Nipa. Remote sensing has been widely proven to be essential in monitoring and mapping highly threatened Mangrove ecosystems [29,30,31,32,33,34,35]. Many research studies on this subject have been carried out around the globe. Tropical and subtropical coastal Mangroves are among the most threatened and vulnerable ecosystems worldwide [24]. The habitat area loss during the last two decades is estimated to be about 36% of the total global Mangrove area [32]. Because Mangrove ecosystems have an outstanding relevance ecologically and economically, there is an urgent demand for conservation and restoration measures.

However, efforts to determine the magnitude of change has not been successful as Mangroves are difficult to differentiate from Nipa by remote-sensing based approach. First, Nipa and Mangrove both grow in monotypic stands and more frequently, completely interspersed with each other. Also, multispectral response between the two is not so different in Visible/Near Infra-Red (VNIR) imagery such that a distinct spectral signature for each could simply be derived. Trying to distinguish between the two species, based entirely on spectral characteristics, using 0.5 to 2-meter pixels, has not been successful. Secondly, texture is not enough to isolate either

of the species from other categories because of several factors, such as growth form, density, and stand height. Remote sensing applications for Mangrove mapping at the fundamental level are already well established but, surprisingly, a number of advanced remote sensing applications have remained unexplored for the purpose of discrimination of Nipa and Mangrove mapping at a finer level. Currently, imagery texture at the 0.5 meter has been found to be a good discriminator using imagery products such as Geo-eye 1 and Pleiades. Consequently, the aim of this paper is to unveil the potential of some of the unexplored remote-sensing techniques for discrimination of Nipa and Mangroves. Specifically, this paper focuses on improving class separability between Mangrove and Nipa species in order to provide an automatic method of evaluating the

magnitude of Nipa invasion within the Niger Delta without the extremely costly and inconvenient method of traditional field survey.

## 2. STUDY AREA

The study area of approximately 162 sq km was chosen at the eastern portion of the Andoni River as shown in Fig. 1. The area is populated by the Andoni communities such as Asarama, Amanku, and Ama Sunday. Most of these communities are situated adjacent to dense Nipa areas. Many intersecting creeks, which drain the area into the Andoni River through Kelele creek, are tidally inundated diurnally from the Atlantic Ocean. The River serves as a major transportation route for many communities located along its bank, many of whom are fisher folks.

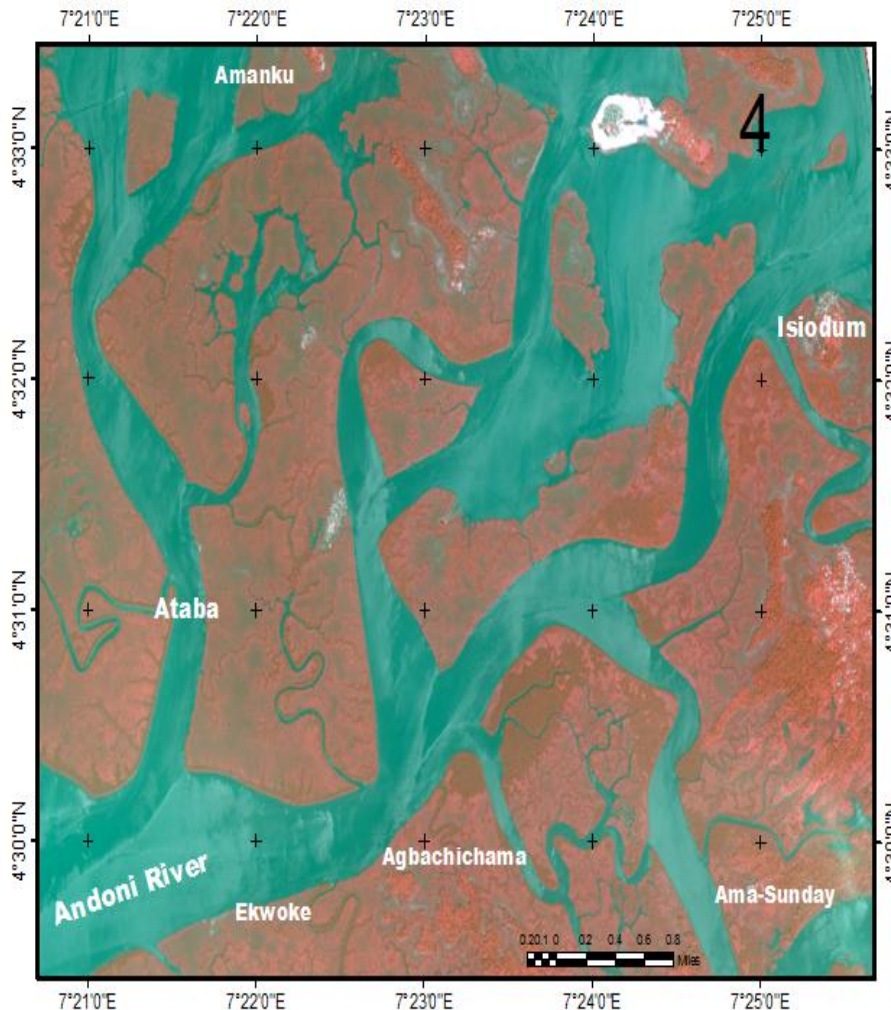


Fig. 1. Study area






### 3. METHODOLOGY

#### 3.1 Remote Sensing Data

Pleiades imagery which provides a spatial resolution of 0.5m in the Panchromatic band was acquired in January 2014. Imagery products were delivered at a certified 50-cm panchromatic and 2-m multispectral with wavelengths of Panchromatic – 470 to 830; Blue (B0) – 430 to 550 ; Green (B1) – 500 to 620; Red (B2) – 590 to 710 and NIR (B3) – 740 to 940. Orthorectification, using MDA Information Systems proprietary digital terrain model, was performed to control for topographic distortion, calibration of the pixel values against sun angle differences and other astronomical phenomena such as differences in distance between the Earth and Sun. The final process used the empirical radiometric calibration coefficients to transform the data into reflectance values.

A set of control points was acquired as training sites in February 2014 for classification and validation to cover the study area. The imagery was pansharpened using the Wavelet Transformation algorithm at 0.5 meter resolution in order for the imagery to maintain as much of the original spectral radiometry as possible for algorithms to produce the most meaningful results. The imagery was classified in a hybrid object-oriented CART-based classification which involved combining image segmentation with the use of a maximum likelihood classifier at the pixel level with four classes recorded as shown in Table 1. After a filter was run to remove pixel speckles.

**Table 1. Land cover classification scheme**

	<b>Class Names</b>	<b>Color</b>
0	<b>Background</b>	
1	<b>Nipa</b>	
2	<b>Mangrove</b>	
3	<b>Water</b>	
4	<b>Other</b>	

Training points were selected and used to identify land cover classes including Urban, Herbaceous, Trees, Shrubs, and Grass. These additional categories were identified to help isolate the Nipa and Mangrove features.

A texture and vegetation algorithm TEXVEG layer which is pixel-based was created and applied to the pansharpened imagery. This allowed the imagery to be reordered so that both chlorophyll and texture factors contribute to a layer which was threshold processed to distinguish the target features from themselves as well as other non-target features. TEXVEG is an algorithm which uses both texture and chlorophyll production variables to distinguish the two species and was run on pan-merged hi-res (~0.5m) data.

TEXVEG is represented as:

$$(T * V) / i \tag{1}$$

$$(T_{sd} * NDVI) / C \tag{2}$$

Where:

T is a texture transformed image using standard deviation filter

V is a vegetative health transformed image

i is a coefficient

NDVI is a vegetative health transformed image (Normalised Difference Vegetation Index)

C is a coefficient used to scale the output.

The classified imagery was taken to the field from 21st -23rd September 2015 and groundtruthed to capture coordinates of areas classified as Mangrove and Nipa. Geotagged photos were taken at each location. The GPS coordinates and the photographs were used in an expert classification to validate image content interpretation according to the landcover types identified from training points during image processing. Kappa Coefficients were calculated to measure consistency on each of the land cover results between the raw and final classifications.

### 4. RESULTS

Tables 2 to 2.2 show the overall accuracy and consistency measure of the landcover type separation between Mangrove and Nipa. Table 2 shows an overall accuracy of 93% for the seven classes of landcover and Table 2.1 shows an overall accuracy of 95% for the edited classes of Mangrove and Nipa. A summary of the overall accuracy in Table 2.2 shows an overall accuracy of 90%-93% and a Kappa Statistic of 87%-91%. This indicates a good agreement between thematic maps generated from image and reference data.

**Table 2. Classification accuracy assessment for seven classes (7) of land cover**

Classification/Validation	Nipa	Mangrove	Water	Urban	Forest	Wetland	Grass	Totals	Users Accuracy	
Nipa	143	3	0	0	0	4	0	150	0.95333	
Mangrove	4	4	0	0	0	0	0	8	0.5	
Water	1	0	212	6	0	5	0	224	0.94643	
Urban	0	0	0	38	1	0	0	39	0.97436	
Forest	1	3	0	0	52	0	0	56	0.93857	
Wetland	7	0	1	1	1	176	4	190	0.92632	
Grass	0	0	0	2	0	2	2	6	0.33333	
Total	156	10	213	47	54	187	6	627	correct	
Producer's Accuracy	0.91667	0.4	0.99530516	0.80851064	0.96296296	0.94118	0.33333		673 (total)	
				Overall Accuracy = 0.931649331						
				Kappa Coeff = 90.9%						

**Table 2.1. Classification accuracy assessment for Nipa and mangrove land cover**

Classification/Validation	Nipa	Mangrove	Water	Other	Totals	Users accuracy
Nipa	144	3	0	4	151	0.953642
Mangrove	4	3	0	0	7	0.428571
Water	1	0	212	13	226	0.938053
Other	7	4	1	277	289	0.958478
Total	156	10	213	294	636	correct
Producer's accuracy	0.923077	0.3	0.995305	0.942177		673 (total)
			Overall accuracy = 0.9450222288			
			Kappa Coeff= 91.6%			

**Table 2.2. Summary of the land cover classification accuracy assessment**

Classification version	Overall accuracy	Kappa	Nipa	Mangrove
Asarama, 7 classes, edited	0.931649331	0.909298	0.953333	0.5
Asarama, 7 classes, raw	0.907875186	0.877593	0.860606	0.583333333
Asarama, 4 classes, edited	0.945022288	0.915932	0.953642	0.428571429
Asarama, 4 classes, raw	0.922734027	0.883109	0.860606	0.583333333

Fig. 2 shows the TEXVEG results of Mangrove and Nipa within the training sites of the study area. The multicolor and gray scale images show selected zones of analysis. The highest values (green pixels) are the Nipa and the Mangrove. Both the Nipa and Mangrove features are growing interspersed. Nevertheless, it is evident in the mid-gray pixels speckled with slightly lighter gray pixels. The darker mid-gray pixels are Nipa trees and the lighter speckle represent Mangrove trees. Mangrove is more textured while Nipa is smoother. Also, Mangrove appears to have higher chlorophyll content per pixel. As a result, Nipa is light-gray and Mangrove is mid-gray in the TEXVEG, Nipa.

## 5. DISCUSSION

The resulting maps show the TEXVEG classification used in this study accurately assigned pixels to the Mangrove and Nipa classes. This result demonstrates that the discrimination mapping approach of spectral and textural techniques using Pleiades, for Mangrove and Nipa, has promising results. It validates the importance of high resolution images which contribute higher spatial resolution to classification accuracy. Overall, the dataset and algorithms and field validation mapped the target classes with high accuracy. The study has therefore shown that the combination of the texture and vegetation indices (TEXVEG)

algorithm has the capacity to leverage chlorophyll differences in the plants in combination with texture to distinguish between Nipa and Mangrove using high resolution imagery.

The use of spectral information and Normalized Difference Vegetation Index (NDVI) has been valuable in many studies in the discrimination of Mangrove and other vegetation species [36,37,38,39,40,41,42,43].

In order to improve the use of spectral information for better performance of vegetation

classification, contextual techniques beyond per-pixel spectral information have led to many other vegetation classification methods [44,45,46]. However, due to the unique spectral signature conferred on each vegetation by its chemistry, structure and moisture content, discrimination of species has continued to seek for improved methods. Some early and recent studies have started focusing on texture in addition to spectral indices and reflectance characteristics [47,48,49,50]. Many of these have shown promise in increasing the classification accuracy for both vegetation heights and tree species. In an early study by Bunting, et al. [51] classification

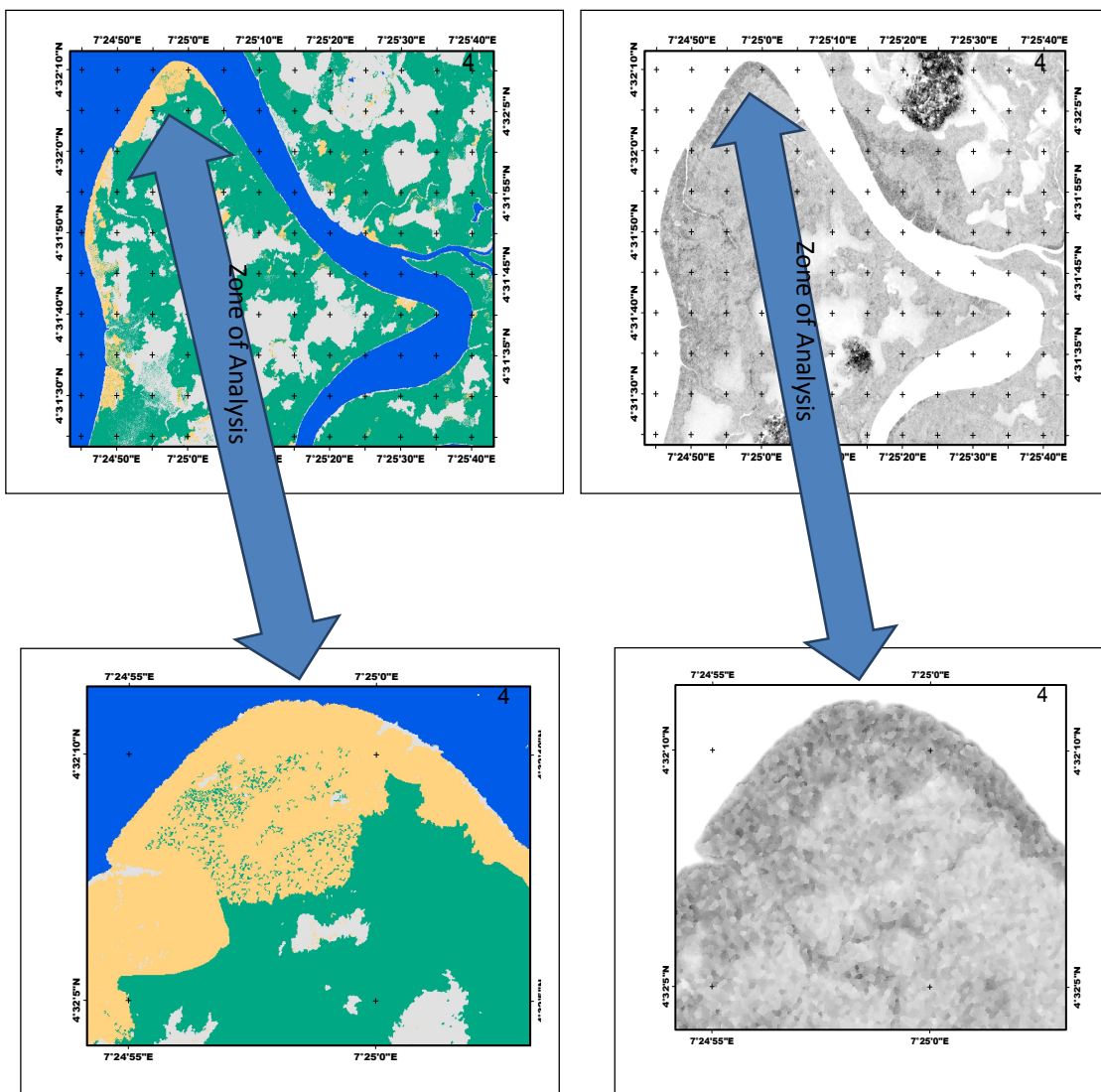


Fig. 2. TEXVEG image interpretation of Mangrove and Nipa

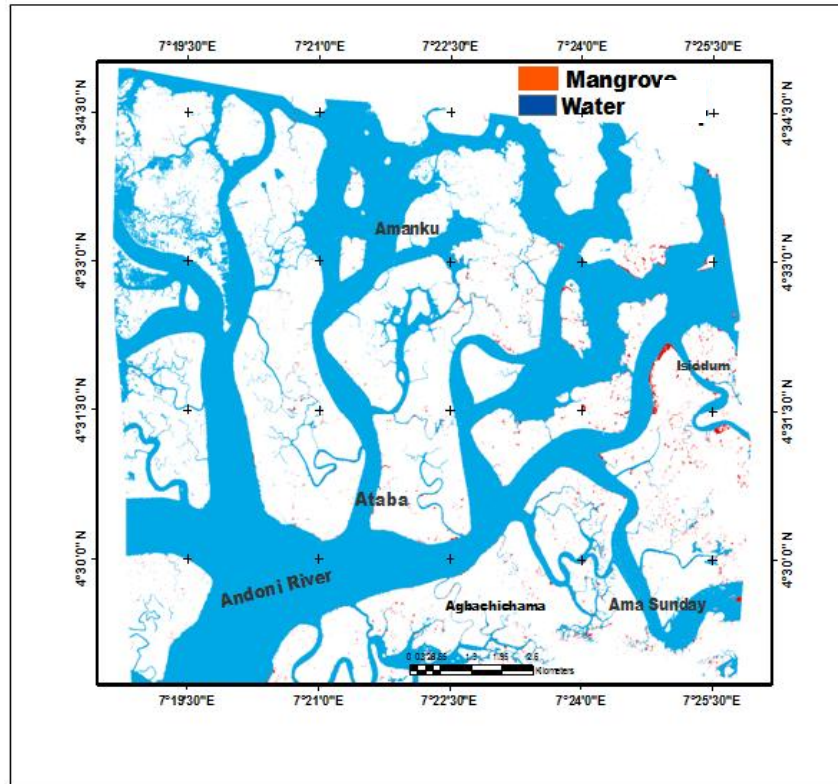


Fig. 3. Mangrove distribution within the study area

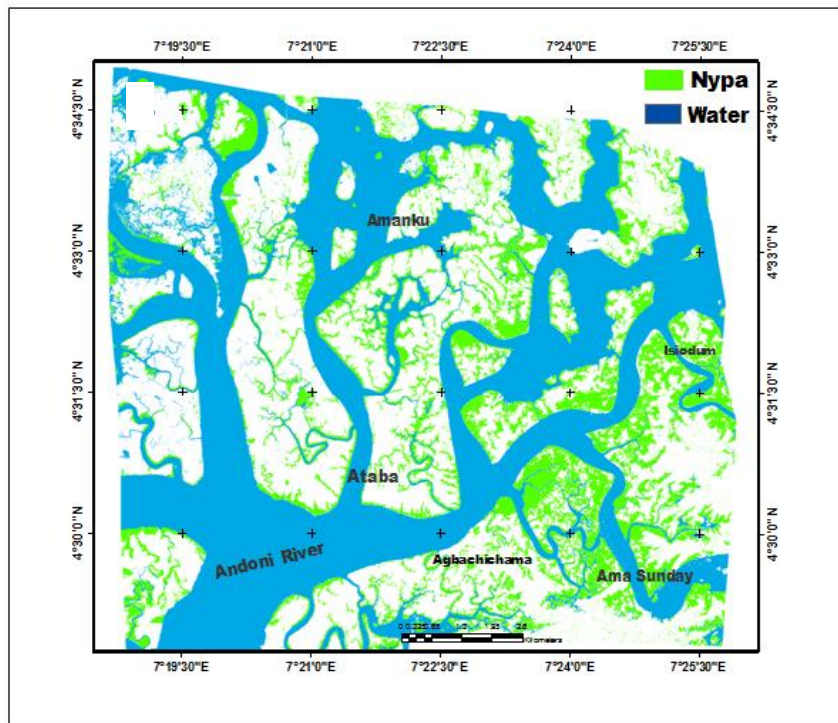


Fig. 4. Nipa distribution within the study area

accuracies of tree species in forest vegetation were improved between 5-17% when textural information was combined with spectral information. The application of the principle of integrating textural information into the mapping process is opening new paths for extracting higher accuracies as in the present study between Mangrove and Nipa where the vegetation types have similar spectral responses. In the study, the kappa coefficient of 0.50 based on tonal averages was improved to 0.90 with the inclusion of the texture measure. This discrimination of Nipa from Mangrove is a significant study objective as it translates the findings into a Biodiversity conservation assessment tool. Thus, Nipa which is fast displacing mangroves [25,26,27,28], can be effectively monitored over large areas in the three river systems of Imo River, Qua Iboe River and Cross River systems. In these wetland ecosystems, the valuation of ecosystem services with The Economics of Ecosystem and Biodiversity (TEEB) tool underscored Nipa as low in value compared to the productive services conferred by the wetlands and tidal mudflats from mangroves being displaced. Nipa is deemed a "nuisance" species in the Niger Delta [52] because of the low range of social and economic values to the rural population. The study which was part of a Sustainable Livelihood project of Wetlands International in the Niger Delta has provided the potential to map the biodiversity conservation status of mangroves in areas under Nipa invasion. It provides a pioneering effort in the capacity to accurately assess the ecosystem services valuation of both mangrove and Nipa with its attendant socioeconomic implications.

## 6. CONCLUSION

The paper has shown that, using textural features that reveal differences in leaf morphology and spectral information and groundtruth, Nipa was distinguished for the first time from Mangrove. The second objective which is also significant was the indicative capacity to map the Biodiversity conservation status of the Mangrove species which is being aggressively displaced by the Nipa species.

## ACKNOWLEDGEMENTS

The work presented was supported by Wetlands International within the scope of the Project on the Ecosystem Service Mapping and

Socioeconomic Valuation of Niger Delta Wetland Ecosystem Services. Technical collaboration was with MDA Inc USA.

## COMPETING INTERESTS

Authors have declared that no competing interests exist.

## REFERENCES

1. Fromard F, Vega C, Proisy C. Half a century of dynamic coastal change affecting mangrove shorelines of French Guiana. A case study based on remote sensing data analyses and field surveys. *Marine Geology*. 2004;208:265-280.
2. Kathiresan K, Rajendran N. Coastal mangrove forests mitigated tsunami. *Estuarine, Coastal and Shelf Science*. 2005;65:601-606.
3. Danielsen F, Sørensen MK, Olwig MF, Selvam V, Parish F, Burgess ND, Hiraishi T, Karunagaran V, Rasmussen MS, Hansen LB, Quarto A, Suryadiputra N. The Asian tsunami: A protective role for coastal vegetation. *Science*. 2005;310:643.
4. Barbier EB. Natural barriers to natural disasters: Replanting mangroves after tsunami. *Frontiers in Ecology and the Environment*. 2006;4:124-131.
5. Kerr AM, Baird AH, Campbell SJ. Comments on —Coastal mangrove forests mitigated tsunamill by Kathiresan K. and Rajendran N. *Estuarine, Coastal and Shelf Science*. 2005;65:601-606. *Estuarine, Coastal and Shelf Science*. 2006;67:539-541.
6. Alongi DM. Mangrove forests: Resilience; protection from tsunamis; and responses to global climate change. *Estuarine, Coastal and Shelf Science*. 2008;76:1-13.
7. Blasco F, Bellan MF, Chaudhury MU. Estimating the extent of floods in Bangladesh—using SPOT data. *Remote Sensing of Environment*. 1992;39:167-178.
8. Mazda Y, Magi M, Kogo M, Hong PN. Mangroves as coastal protection from waves in the Tong King delta, Vietnam. *Mangroves Salt Marshes*. 1997;1:127-135.
9. Mazda Y, Magi M, Nanao H, Kogo M, Toyohiko M, Kanazawa N, Kobashi D. Coastal erosion due to long-term human impact on Mangrove forests. *Wetlands*



- Ecology and Management. 2002;10:1-9.
10. Dahdouh-Guebas F, Jayatissa LP, Di Nitto D, Bosire JO, Lo Seen D, Koedam N. How effective were mangroves as a defence against the recent tsunami? *Current Biology*. 2005;15:R443-R447.
  11. Naylor RL, Goldburg RJ, Primavera JH, Kautsky N, Beveridge MC, Clay J, Folke C, Lubchenco J, Mooney H, Troell M. Effect of aquaculture on world fish supplies. *Nature*. 2000;405:1017-1024.
  12. Mumby PJ, Edwards AJ, Arias-González E, Lindeman KC, Blackwell PG, Gall A, Gorczyńska MI, Harborne AR, Pescod CL, Renken H, Wabnitz CC, Llewellyn G. Mangrove enhance the biomass of coral reef fish communities in the Caribbean. *Nature*. 2004;427:533-536.
  13. Manson FJ, Loneragan NR, Skilleter GA, Phinn SR. An evaluation of the evidence for linkages between mangroves and fisheries: A synthesis of the literature and identification of research directions. In *Oceanography and Marine Biology: An Annual Review*; Gibson RN, Atkinson RJA, Gordon JDM, Eds. Taylor and Francis: London, UK. 2005;43:485-515.
  14. Nagelkerken I, Blaber SJ, Bouillon S, Green P, Haywood M, Kirton LG, Meynecke JO, Pawlik J, Penrose HM, Sasekumar A, Somerfield PJ. The habit function of mangroves for terrestrial and marine fauna: A review. *Aquatic Botany*. 2008;89:155-185.
  15. Primavera JH. Socioeconomic impacts of shrimp culture. *Aquaculture Research*. 1997;28:815-827.
  16. Kathiresan K, Bingham BL. Biology of mangroves and mangrove ecosystems. *Advances in Marine Biology*. 2001;40:81-251.
  17. Lugo AE, Snedaker SC. The ecology of mangroves. *Annual Review of Ecology, Evolution, and Systematics*. 1974;5:39-64.
  18. Marshall N. Mangrove conservation in relation to overall environmental considerations. *Hydrobiologia*. 1994;285:303-309.
  19. Walters BB, Rönnbäck P, Kovacs JM, Crona B, Hussain SA, Badola R, Primavera JH, Barbier E, Dahdouh-Guebas F. Ethnobiology, socio-economics and management of mangrove forests: A review. *Aquatic Botany*. 2008;89:220-236.
  20. Everitt JH, Judd FW. Using remote sensing techniques to distinguish and monitor black Mangrove (*Avicennia germinans*). *Journal of Coastal Research*. 1989;5:737-745.
  21. Everitt JH, Judd FW, Escobar DE, Davis MR. Integration of remote sensing and spatial information technologies for mapping black Mangrove on the Texas Gulf Coast. *Journal of Coastal Research*. 1996;12:64-69.
  22. Dahdouh-Guebas F. The use of remote sensing and GIS in the sustainable management of tropical coastal ecosystems. *Environment, Development and Sustainability*. 2002;4:93-112.
  23. Everitt JH, Yang C, Summy KR, Judd FW, Davis MR. Evaluation of color-infrared photography and digital imagery of map black Mangrove on Texas Gulf Coast. *Journal of Coastal Research*. 2007;23:230-235.
  24. Valiela I, Bowen JL, York JK. Mangrove forests: One of the world's threatened major tropical environments. *Bioscience*. 2001;51:807-815.
  25. Isebor CE, Ajayi TO, Anyanwu A. The incidence of *Nipa fruticans* (Wurmb) and its impact on fisheries production in the Niger Delta mangrove ecosystem. Paper Presented at: 16th Annual Conference of the Fisheries Society of Nigeria (FISON); Nov 4–9; Maiduguri, Nigeria; 2001.
  26. Okugbo OT, Usunobun U, Esan A, Adegbeji JA, Oyediji JO, Okiemien CO. A review of Nipa palm as a renewable energy source in Nigeria. *Research Journal of Applied Sciences, Engineering and Technology*. 2012;4(15):2367-2371.
  27. Chima UD, Larinde SL. Deforestation and degradation of mangroves in the Niger Delta region of Nigeria: Implications in a changing climate. 38th Annual Conference of Forestry Association of Nigeria (FAN). 2016;521-537.
  28. Olowokudejo JD, Oyebanji OO. Floral diversity of the littoral vegetation of Southeastern Nigeria. *International Journal of Biodiversity and Conservation*. 2016;8(12):320-333.
  29. Green EP, Mumby PJ, Edwards AJ, Clark CD, Ellis AC. The assessment of mangrove areas using high resolution multispectral airborne imagery. *Journal of Coastal Research*. 1998;14:433-443.

30. Blasco F, Aizpuru M, Gers C. Depletion of the mangroves of continental Asia. *Wetlands Ecology and Management*. 2001;9:245-256.
31. Vaiphasa C, Skidmore AK, de Boer WF. A post-classifier for mangrove mapping using ecological data. *ISPRS Journal of Photogrammetry and Remote Sensing*. 2006;61:1-10.
32. Giri C, Pengra B, Zhu Z, Singh A, Tieszen LL. Monitoring mangrove forest dynamics of the Sundarbans in Bangladesh and India using multi-temporal satellite data from 1973 to 2000. *Estuarine, Coastal and Shelf Science*. 2007;73:91-100.
33. Seto KC, Fragkias M. Mangrove conversion and aquaculture development in Vietnam: A remote sensing-based approach for evaluating the Ramsar convention on wetlands. *Global Environmental Change*. 2007;17:486-500.
34. Everitt JH, Yang C, Sriharan S, Judd FW. Using high resolution satellite imagery to map black mangrove on the Texas Gulf Coast. *Journal of Coastal Research*. 2008;24:1582-1586.
35. Food and Agricultural Organization (FAO). The world's mangroves 1980–2005: A thematic study prepared in the framework of the Global Forest Resource Assessment. *FAO Forestry Paper*. 2007;153.
36. Van Aardt JAN, Wynne RH. Spectral separability among six southern tree species. *Photogrammetric Engineering and Remote Sensing*. 2001;67(12):1367–1375.
37. Vaiphasa C, Vaiphasa T, Vaiphasa A, Skidmore K, Ongsomwang S. Tropical Mangrove species discrimination using hyperspectral data: A laboratory study. *Estuarine Coastal and Shelf Science*. 2005;65(1).
38. Clark ML, Roberts DA, Clark DB. Hyperspectral discrimination of tropical rain forest tree species at leaf to crown scales. *Remote Sensing of Environment*. 2005;96(3):375–398.
39. Kamaruzaman J, Kasawani I. Imaging spectrometry on Mangrove species identification and mapping in Malaysia. *WSEAS. Transactions on Biology and Biomedicine*. 2007;4(8):118-126.
40. Ajithkumar TT, Thangaradjou T, Kannan L. Spectral reflectance properties of mangrove species of the Muthupettai mangrove environment, Tamil Nadu. *Journal of Environmental Biology*. 2008; 29(5):785–788.
41. Wang L, Sousa WP. Distinguishing mangrove species with laboratory measurement of hyperspectral leaf reflectance. *International Journal of Remote Sensing*. 2009;30(5):1267–1281.
42. Koedsin W, Vaiphasa C. Discrimination of tropical mangroves at the species level with EO-1 hyperion data. *Remote Sensing*. 2013;5:3562-3582.
43. Heenkenda K, Joyce KE, Maier SW, Bartolo R. Mangrove species identification: Comparing worldview-2 with aerial photographs. *Remote Sensing*. 2014;6: 6064-6088.
44. Lo CP, Choi J. A hybrid approach to urban land use/cover mapping using Landsat 7 Enhanced Thematic Mapper Plus (ETM) images. *International Journal of Remote Sensing*. 2004;25:2687-2700.
45. Jungho I, Jensen JR. A change detection model based on neighborhood correlation image analysis and decision tree classification. *Remote Sensing of Environment*. 2005;99:326-340.
46. Sluiter R. Mediterranean land cover change: Modelling and monitoring natural vegetation using GIS and remote sensing. *Nederlandse Geografische Studies*. 2005; 333.
47. Carr JR. Spectral and textural classification of single and multiple band digital images. *Computers and Geosciences*. 1996;22(8): 849-865.
48. Petrou ZI, Tarantino C, Adamo M, Blonda P, Petrou M. Estimation of vegetation height through satellite image texture analysis. *Archives of the Photogrammetry, Remote Sensing and Spatial Information Sciences*. 2012;XXXIX-B8:321–6.
49. Petrou ZI, Manakos I, Stathaki T, Tarantino C, Adamo M, Blonda P. A vegetation height classification approach based on texture analysis of a single VHR image. *Earth and Environmental Science*. 2014; 17.
50. Petrou ZI, Manakos I, Stathaki T, Múcher CA, Adamo M. Discrimination of vegetation height categories with passive satellite sensor imagery using texture analysis. *IEEE Journal of Selected Topics in Applied Earth Observations and Remote Sensing*. 2015;8(4):1442-1455.

51. Bunting P, Wenda H, Zwigelaar R, Lucas R. Combining texture and hyperspectral information for the classification of tree species in Australian savanna woodlands. In: S. Jones, K. Reinke (eds.), *Innovations in Remote Sensing and Photogrammetry*. 2009;XXXII: 19-26.
52. WIA. Economic valuation of wetland biological resources for three states in the Niger Delta. Technical Report of Wetland International Africa. 2015;376.

---

© 2017 *Onwuteaka and Uwagbae*; This is an Open Access article distributed under the terms of the Creative Commons Attribution License (<http://creativecommons.org/licenses/by/4.0>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

*Peer-review history:*  
*The peer review history for this paper can be accessed here:*  
<http://www.sciencedomain.org/review-history/22990>