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Assessment of Mangrove Spatial -Temporal Dynamics and Biomass by Remotely Sensed Data, Case Study Kilifi County: Kenya

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Abstract This research uses multi-temporal medium resolution satellite images and ground truthing to analyze the patterns and dynamics of Kenyan coastal mangrove forest cover changes spanning over 30 years from 1990-2015. The major aims of this study were to first analyze and assess mangrove forest cover and change over the period 1990 to 2015 together with the specific drivers. Replacement of cloudy pixels with the best available non-cloud pixels from a secondary image was followed by maximum likelihood classification from which change detection analysis was carried out. Literature reviews and interviews were then used to correlate these land use changes with their potential drivers. Metrics were extracted from the image and correlated with the ground observed biomass values to model the linear relationship between the selected variable and biomass. Independent component transformation 3 was found to show the strongest correlation with biomass with a coefficient of determination value of about 0.7. Based on the post classification change detection, during the epoch 1990-2000, mangrove area decreased by about 7.03%, forestland decreased by about 21.11%, cropland also decreased by about 0.39%. Grassland, however, increased by about 3.54% while settlement increased by a significant 74 percentage points.

Keywords: *mangroves, biomass, correlation, clouds, Landsat*

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1. Introduction

Mangrove refers to brackish-water-tolerant trees that together constitute mangrove forest. Along the Kenyan coast to be specific, there exist about 8 species namely Rhizophora mucronata, Ceriops tagal, Bruguiera gymnorrhiza, Sonneratia Alba, Xylocarpus granatum, Avicennia marina, Lumnitzera racemosa and Heritiera littoralis.

Mangroves are distinctive ecological units [1] and grow along coastlines in the inter-tidal zone between land and sea [2]. Mangroves support coastal ecosystems by providing environmental services and critical ecological functions, affecting both inland and oceanic resources [3].

Mangrove ecosystems exchange matter and energy with the adjacent marine and terrestrial ecosystems [4].

These forests are nutrient-rich environments which support a variety of food chains and function as nursery and feeding ground for fish and invertebrates [5].

Mangrove forests along the Kenya coast cover approximately 60,323 ha (National Mangrove Plan 2015). These forests offer a range of benefits and opportunities to both local and national economic development, improved livelihoods and provision of environmental goods and services such as habitat for fish and other wildlife, shoreline protection, and carbon sequestration.

Mangroves play a protective role against detrimental climatic impacts .They also support numerous species and serve to protect coastlines from storms [6] by breaking the storm-waves and dampening the tidal currents, and the sediments they trap help to build the coastline against forces of erosion [7].

Mida Creeks holds substantial mangrove stands [8] it is also an important sea bird haven. Traditionally, mangrove forests provide the coastal human population with a variety of goods and services on which the poorer strata of society depend strongly [9]. However mangrove degradation at the Kenyan coast has occurred at an alarming rate as the result of growing subsistence needs [5].

This is observed along the Watamu-Mida creek area [19]. Mangroves grow on muddy and anaerobic soils which suffer from tidal inundation; as a result they show a distinctive pattern of biomass allocation [11].

There exist several mangrove sites in Kenya such as Kiunga, Lamu, Tana Delta, Mida Creek, Kilifi Creek, Mtwapa Creek, Tudor Creek, Funzi Bay, Vanga, and others. Cumulatively, they occupy a total area of approximately 60,323 hectares. Out of this, the region with the greatest acreage of mangroves is Lamu, whose mangrove cover is more than half the total area covered by Kenyan mangrove (30,475 ha).

In Kenya, mangroves supply quite a number of products directly – both timber and non- timber. Timber products include firewood, building poles and charcoal for use in both urban and rural areas. Poles for use in construction are usually graded into different utilization classes based on their intended uses. Also mangrove poles find use in activities that include boat masts and fish traps/stakes preparation.

In addition to protecting the coastline from natural hazards, mangrove forests provide goods and services that are of economic, ecological and environmental value to man [5].

In many developing countries, the survival of coastal communities is largely dependent upon the sustainable harvest of seafood, and the cultivation of fish and crabs in mangroves. Several studies have shown that, despite the numerous uses of mangrove forests they have been overexploited and converted to other land use. For instance, State of the Coast Report Kenya the [12] stated that, in Kenya, mangrove forest cover has been lost either due to conversion pressure, over-exploitation or pollution during the last twenty years.

Sadly, similar to most parts of the world mangroves in Kenya are an endangered species due to a number of factors. Overexploitation for wood products for instance is the main agent of degradation.

Major causes of mangrove cover loss include, but not limited to, excessive exploitation of the mangrove wood and non-wood products, haphazard conversion of mangrove vegetation for the purposes of urban and infrastructural development, pesticide and fertilizer pollution-induced degradation (eutrophication), exploitation of hydrocarbons and gas and mangrove vegetation clearance for agriculture and human settlement purposes[20].

The absence of cutting plans contribute largely to problems of mangrove management in Kenya. In most cases, the selective removal of quality poles of suitable species has left out very inferior species unsuitable for the market. Quality poles have been wiped out in most mangrove areas of Mombasa, Kwale and Kilifi districts where population density is highest along the coast.

The major problem facing the management of mangrove forests in Kenya is the absence of baseline data and information to be used in the development of a comprehensive management plan. Unlike inland terrestrial forestry, very little attention is given to mangrove forestry. Mangrove harvesting is controlled by Kenya Forest Service (KFS) through licensing procedures and recommendation of mangrove poles to be harvested. However, these recommendations are based on wood demand rather than the actual resource base.

Mangrove forests degradation are as a direct result of human driven factors such as over exploitation by the local communities, conversion of land use from forest to other land uses, industrial pollution among others. Deforestation of mangrove forests will also compromise their ability to sequester carbon. Approximately one-third of mangrove forests vegetation has been lost globally in the last 50 years alone. In China, specifically in the Guangdong Province, two-thirds of the mangrove forest cover has been lost in the previous two decades due to drivers such as coastal land reclamation, tidal waves destruction and the ever growing rates of urbanization [14].

One of the main sources of information that can highlight all areas degraded / deforested or those areas still healthy is satellite remote sensing. Using satellite imagery such as Landsat Thematic Mapper, the degree of mangrove cover degradation can be defined to acceptable accuracy level. Inclusion of these datasets in a GIS can enable comprehensive change detection analysis and biophysical modeling [15].

This research thus aims at assessing the spatio-temporal dynamics of the mangrove forest cover to quantify the extent of degradation, to quantify the biomass and carbon stocks in mangrove forests and assess their carbon sequestration ability as a function of their biomass. The main objective of the study is to assess both the temporal and spatial dynamics of mangrove forests at the Kilifi County, as well as determine their biomass.

This study is very significant in a number of respects. First, it can be used as a decision support tool to inform policies on environmental conservation. In addition, the research can be useful in quantification of carbon sequestration efforts, contributing to climate change and global warming prevention efforts.

Also, this research could be useful in directing targeted campaigns to the community surrounding mangrove vegetation, since the hotspot maps can identify areas of the community that should be prioritized for environmental conservation.

2. Materials and Methods

2.1. Study Area

Administratively, the forest area in Kilifi falls under the jurisdiction of Sokoke Forest Station which together with Gede and Jilore Forest Stations form the Complex Arabuko Sokoke Forest ecosystem. The forest is under Kilifi Ecosystem management. The Forest area is divided into four (4) smaller management units called beats where two or more forest guards are supposed to be assigned for ease of surveillance and management; however, only one beat is currently manned by two (2) Forest guards.

2.2. Data Requirements

Table 1 shows the datasets that were sourced from the respective indicated sources and used for the purpose of this research.

2.3. Image Acquisition and Preprocessing

Multi-temporal Landsat satellite imagery was acquired from Regional Centre for Mapping of Resources for Development (RCMRD) and was subjected to pre-processing before information extraction. Pre-processing operations, sometimes referred to as image restoration and rectification, are intended to correct for sensor- and platform-specific radiometric and geometric distortions of data.

Table 1. Datasets and their sources

Data	Source
Landsat Imagery	USGS
Administrative Boundaries	Survey of Kenya
Gazetted forest boundaries	Kenya Forest Service
Mangrove boundaries	Kenya Forest Service
Spot Imagery	RCMRD

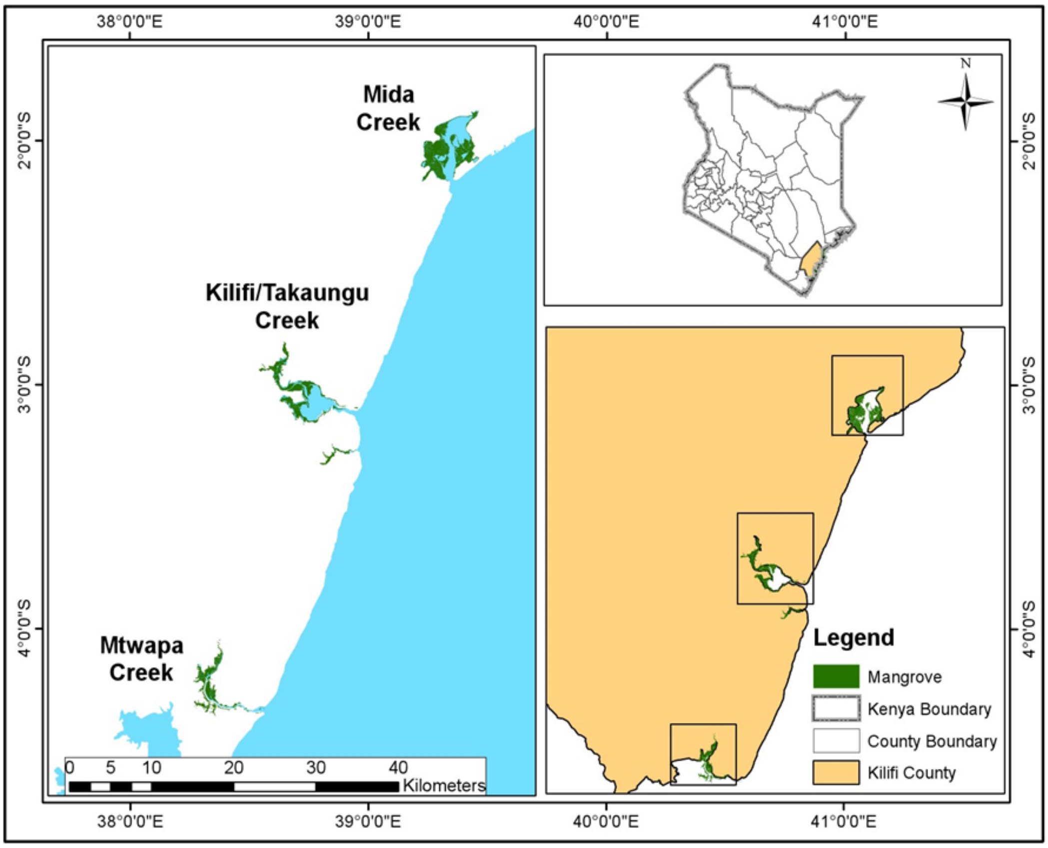

Figure 1. Distribution of mangroves in Kilifi County with the different patches highlighted

Radiometric corrections were necessary to account for variations in scene illumination and viewing geometry, atmospheric conditions, and sensor noise and response. Each of these will vary depending on the specific sensor and platform used to acquire the data and the conditions during data acquisition. Also, it may be desirable to convert and/or calibrate the data to known (absolute) radiation or reflectance units to facilitate comparison between data.

The geometric correction process involves identifying the image coordinates of several clearly discernible points, called ground control points (or GCPs), in the distorted image and matching them to their true positions in ground coordinates (e.g. latitude, longitude). Once several well-distributed GCP pairs have been identified, the coordinate information is processed to determine the proper transformation equations to apply to the original image coordinates to map them into their new ground coordinates.

Contrast enhancement, on the other hand, involves changing the original values so that more of the available range is used, thereby increasing the contrast between targets and their backgrounds.

2.4. Generation of False Color Composites

The display color assignment for any band of a multispectral image can be done in an entirely arbitrary manner. In this case, the color of a target in the displayed image does not have any resemblance to its actual color. The resulting product is known as a false color composite image.

For this research, the false color composite scheme for displaying the Landsat multispectral imagery was Red = (NIR band), Green = (Red band) and Blue = (Green band). This false color composite scheme allows vegetation to be detected readily in the image. In this type of false color composite images, vegetation appears in different shades of red depending on the types and conditions of the vegetation, since it has a high reflectance in the NIR band.

2.5. Information Extraction

The intent of the classification process is to categorize all pixels in a digital image into one of several land cover classes, or "themes". This categorized data may then be used to produce thematic maps of the land cover present in an image.

Normally, multispectral data are used to perform the classification and, indeed, the spectral pattern present within the data for each pixel is used as the numerical basis for categorization The objective of image classification is to identify and portray, as a unique gray level (or color), the features occurring in an image in terms of the object or type of land cover these features actually represent on the ground.

In this research, we used the supervised classification technique where 7 information classes were adopted namely mangrove, forestland, cropland, settlement, wetland, bareland and grassland. In supervised classification, we identify examples of the Information classes (i.e., land cover type) of interest in the image. These are called "training sites".

[16] Employed a more advanced approach to distinguish mangrove and non-mangrove regions in Gulf of California in Mexico. Maximum likelihood classification was first employed to generate spectral distance map then a receiver operating characteristic curve analysis applied to improve on the classification.

The image processing software system is then used to develop a statistical characterization of the reflectance for each information class. This stage is often called "signature analysis". Once a statistical characterization has been achieved for each information class, the image is then classified by examining the reflectance for each pixel and making a decision about which of the signatures it resembles most.

2.6. Post Classification Change Detection

Change detection refers to the process of identifying differences in the state of land features by observing them at different times. In post-classification change detection, the images from each time period are classified using the same classification scheme into a number of discrete categories (i.e., land cover types). The two (or more) classifications are compared and the area that is classified the same or different is tallied and reported as change detection statistics.

2.7. Removal of Cloud Pixels

The images used in this research were severely affected by cloud cover, primarily because it is located in the coastal region of Kenya. This posed a challenge particularly during image classification because the clouds were interpreted as noise. To try and compensate for this, we prepared a custom model application that attempted to replace cloud pixels with best available alternative pixels from a secondary image, of the same area but captured on a different date.

A Semi-automatic approach was used to identify cloud pixels in the main/primary image from which a cloud mask was generated. This approach was semi-automatic in the sense that the analyst manually identified cloud pixels through visual interpretation. This entails inspection of the image to identify the recorded pixel value of clouds.

The assumption is that cloud pixels will tend towards the maximum pixel value in the image and as such the user simply supplies the minimum cloud pixel values. For example, if the analyst identifies that the cloud pixels in the image begin with a pixel value of 80, then all pixels whose values are greater or equal to 80 shall be masked as clouds. It is thus important that the minimum cloud pixel value be carefully chosen.

The model then converts all the identified cloud pixels to zero and uses a conditional statement that for any pixel whose value is zero should be replaced by the pixel value of a supplied secondary image. Essentially what this does is to substitute the cloud pixels (now with value 0) with non-cloud pixels from the secondary image forming a clearer image.

It must be stated that care must be taken in the identification of the minimum pixel value otherwise the image may appear patchy because some cloud pixels below the identified value will still appear whitish in the composite.

Further, it must be noted that to achieve the desired results, the selection of the secondary image should be such that the image (secondary) be cloudless in areas where the main image has clouds. This, for instance, ensures that cloud pixels on the east in the main image are replaced by non-cloud pixels of the secondary image also in the east of secondary image.

The result is an image composite that is way clearer and contains fewer cloud pixels than the original primary image and as such can be used in image analysis. The model builder application was converted to a tool in ArcGIS toolbox to take advantage of the friendly user interface.

Conceptual framework for the cloud removal algorithm is as below.

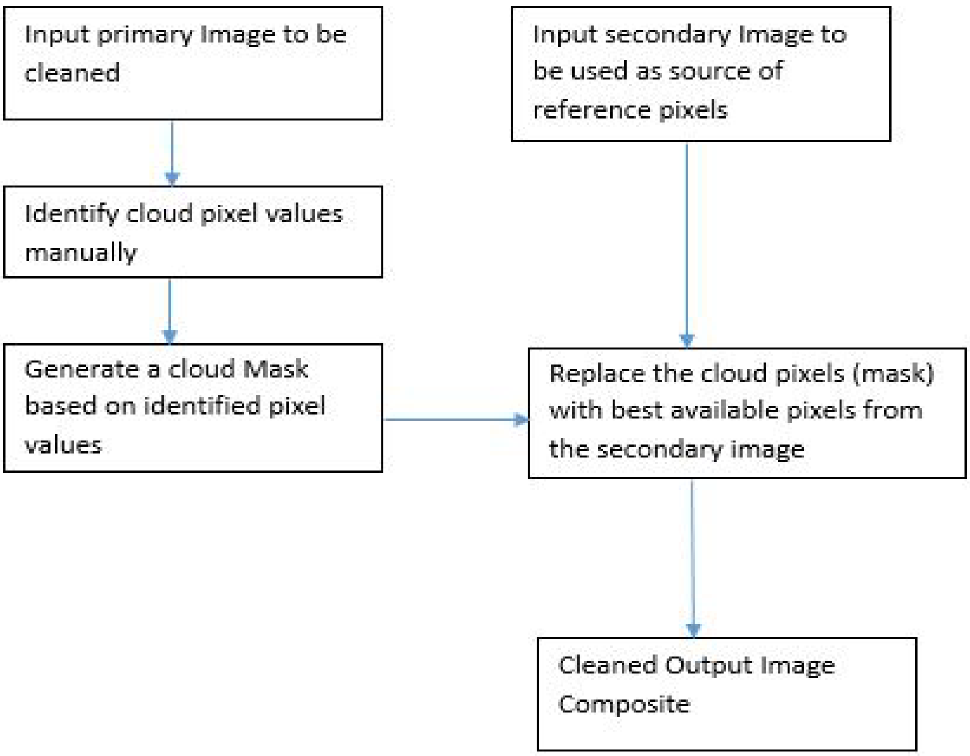

Figure 2. Flow diagram for adopted cloud removal methodology

2.8. Sample and Sampling Technique

For this study, Sample plot design for biomass estimation was random-systematic where the first plot was selected randomly with the other plots following a constant difference ranging between 100 and 200 meters.

- The cluster design comprised of four sample plots to capture the variability effectively. Each sample plot was 15 meter radius divided into concentric circles to reduce the field work to at most 1 day per sample plot.
- The difference between clusters was 500 M.
- For each sample plot, tree measurements that was taken included DBH, tree height and crown cover.

Land cover classes derived from multispectral satellite image analysis formed the basis of stratification and the allocation of the sampling sites to land cover classes also known as strata. A stratified random sampling design with the probability of sampling sites allocated to a class proportional to size of the area covered by each land cover class (stratum) was considered suitable for the sampling framework and location of sampling sites in the field survey. Minimum dataset for above ground biomass estimation include:

- Tree height (metres)
- Diameter at breast height (centimeters)
- Length of the crown (metres)
- Width of the crown (metres)
- Height to base of the crown (meters)
- Proportion of branches and foliage in canopy volume (%)
- Wood density.

2.9. Estimation of Biomass from Allometric Equations

Above ground biomass was then computed based on field observations where sampling was conducted on a total of 23 plots. A consistent assessment and research on biomass accumulation in mangroves is necessary in order to use the resources such as; yield of commercial products from forests, and for the development of silvicultural practices [18]. Estimation of biomass is significant in describing the status of mangroves, and as an essential component of carbon sequestration estimation [13].

Measurements of stem diameter and sometimes height are used to estimate tree biomass and carbon stock using allometric equations [3] defined allometry as a powerful tool for estimating tree weight from independent variables such as trunk diameter and height that are quantifiable in the field as it is stated by several [11, in order to use the mangrove forest sustainably and improve the management, it is important to estimate the amount of biomass accumulation. Kenya is mandated to develop a greenhouse gas inventory for the land based emissions for UNFCCC reporting. Since the mangrove forests are treated as a unique forest category.

Published allometric equations developed for mangrove species by [11] (Above Ground Biomass = 0.251*ρ*(D) 2.46 were used.

At local level in Kenya, the allometric equation published was the one developed by [13] applied only to *R. mucronata* which grows naturally. This is currently the only allometric equation developed for a mangrove species which grows in a natural environment in Kenya.

In each sampling quadrat, the following allometric measurements were obtained from field sampling of each tree within the boundary: Tree Height, Diameter at breast height, diameter of canopy or crown in perpendicular directions, height to the base of the crown and percentage of foliage cover in the crown canopy.

In quantification of above ground and below ground mangrove biomass and subsequent determination of carbon volumes stored in the forest ecosystem, it is easy to derive, to acceptable accuracy, estimates of carbon sequestration, emission and storage. Furthermore, mangrove structure and biomass estimation is key in addressing global climate change adaptation and mitigation efforts [17].

Despite the fact that mangrove forests only constitute about three percent of global forest cover, their potential carbon storage capacity, both in terms of forested biomass and soil carbon, exceeds that of tropical forests [17] Moreover, the cumulative amount of mangrove carbon that finds its way into offshore areas, in the form of litter and leaves, is so significant that it accounts for over 10% of the sea water's dissolved organic carbon generated from the mangroves [17].

Upon determination of trunk volume, the total trunk biomass in kilograms was then be computed through multiplication by the wood density corresponding to each tree species measured. Cumulative biomass was then computed for each tree in the sample quadrat then a summation was made for the results for all trees in the sample quadrat. The value was then be converted to tones per hectare.

[17] mentions two distinct methodologies for estimation of mangrove biomass based on geospatial techniques. The first approach uses passive satellite data together with average biomass values. The second methodology uses height and/or volume measurements based on active LiDAR and radar instruments.

2.10. Conceptual Framework

The conceptual framework shown below summarizes the methodology discussed in the foregoing discussion in a flow diagram.

3. Results and Discussion

3.1. Image Classification

Figure 4 below show maps for the land use/cover status for the years in consideration as generated using maximum likelihood classification. IPCC classification scheme was adopted during the Landsat imagery classification. However, since our main focus was mangrove cover change, auxiliary dataset was used to extract mangrove class from the forestland class and so the maps below show seven classes instead of six for IPCC using medium resolution imagery.

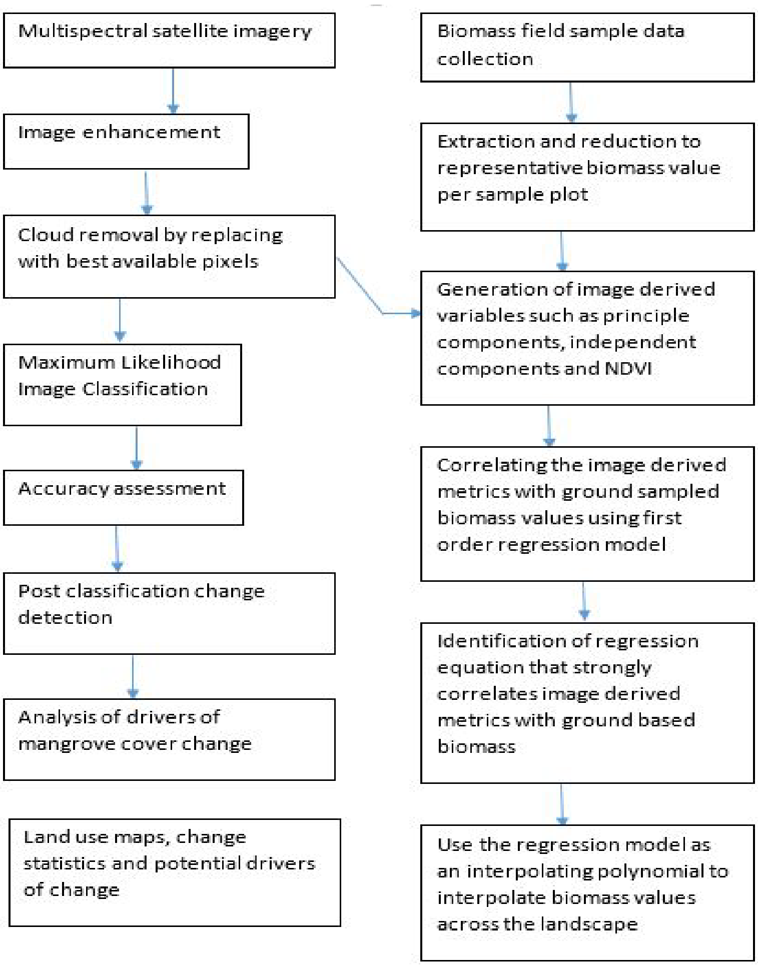

Figure 3. Flow diagram representing methodology adopted for this research

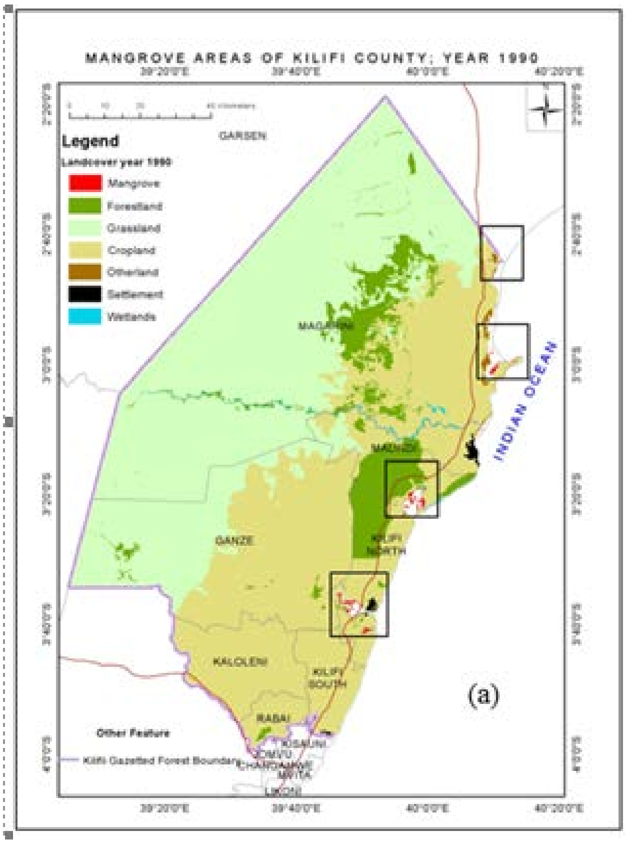

Figure 4 (a). Land use land cover map for the year 1990. Mangrove patches highlighted in black boxes

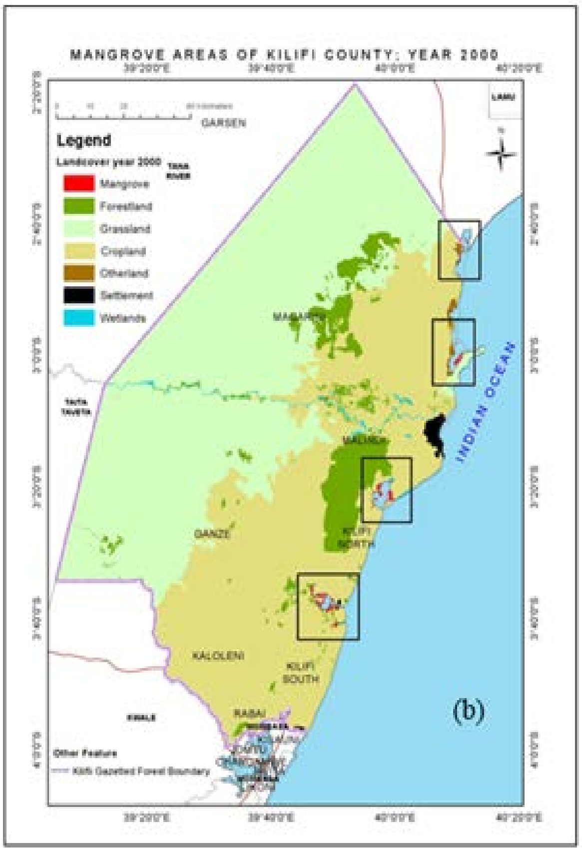

Figure 4 (b). Land use land cover map for the year 2000. Mangrove patches highlighted in black boxes

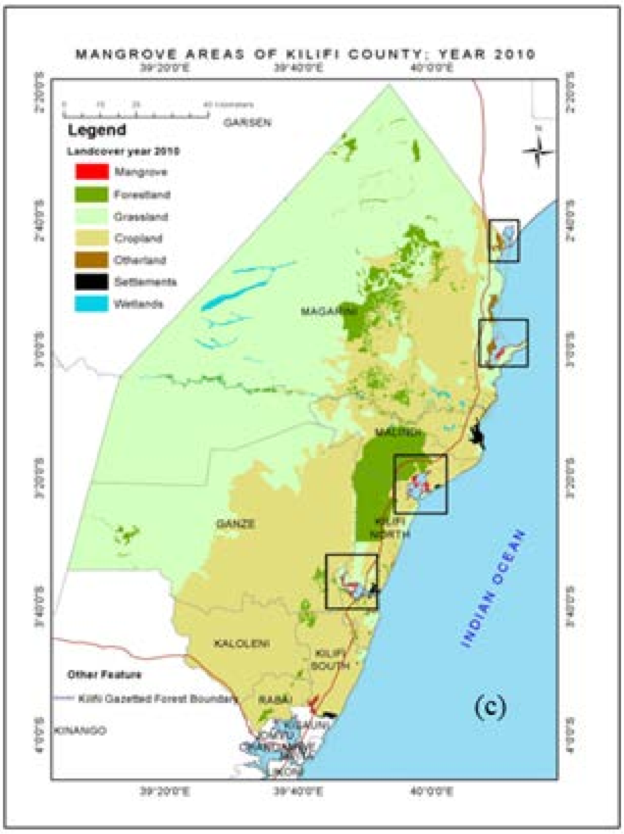

Figure 4 (c). Land use land cover map for the year 2010. Mangrove patches highlighted in black boxes

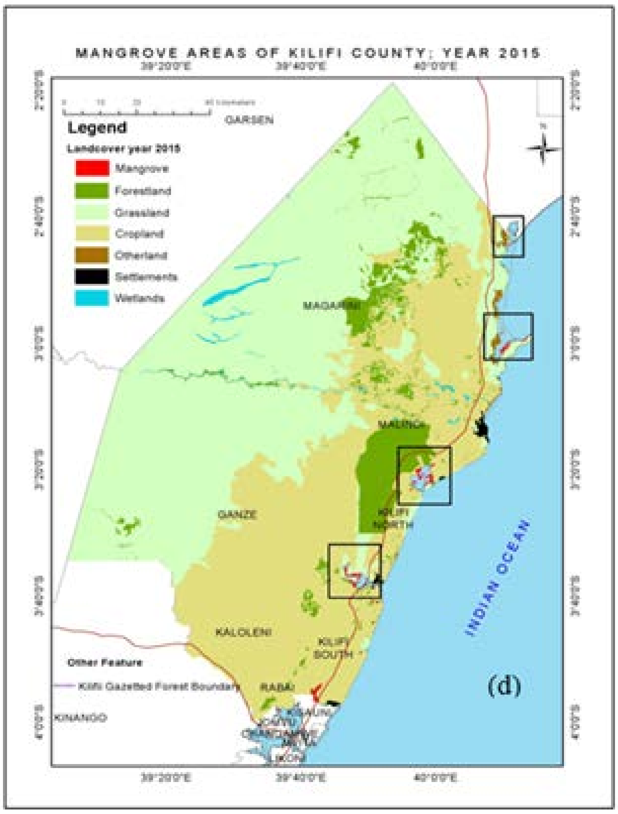

Figure 4 (d). Land use land cover map for the year 2015. Mangrove patches highlighted in black boxes

Also to be noted when interpreting the land use maps, is the fact that a buffer of 15 km was applied inland from the shore of the Indian Ocean to restrict the study area to this strip instead of the entire Kilifi County. This was informed by the fact that mangroves mostly grow within this extent and since our focus was on mangrove cover change, it would make no sense to analyze the entire county when in fact mangroves do not grow inland beyond this buffer distance. On the map, the buffer is represented by a brown line.

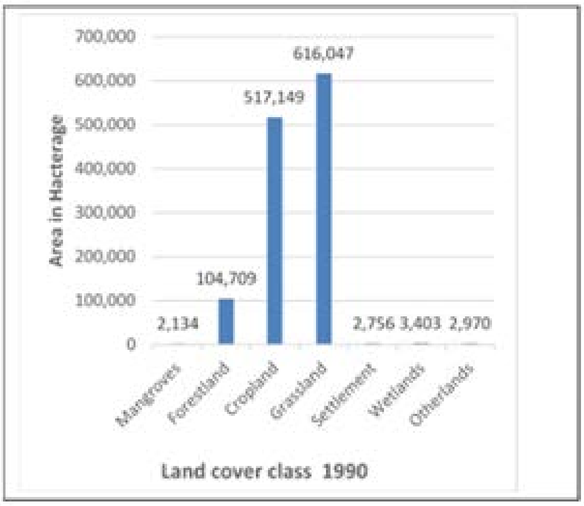

Figure 5 (a). land use land cover classes for 1990

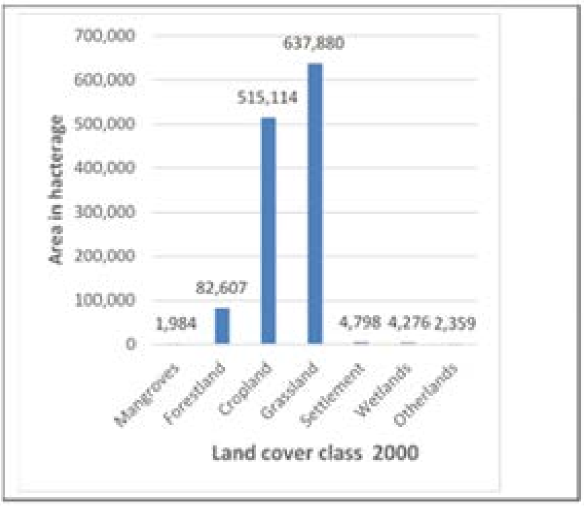

Figure 5 (b). land use land cover classes for 2000

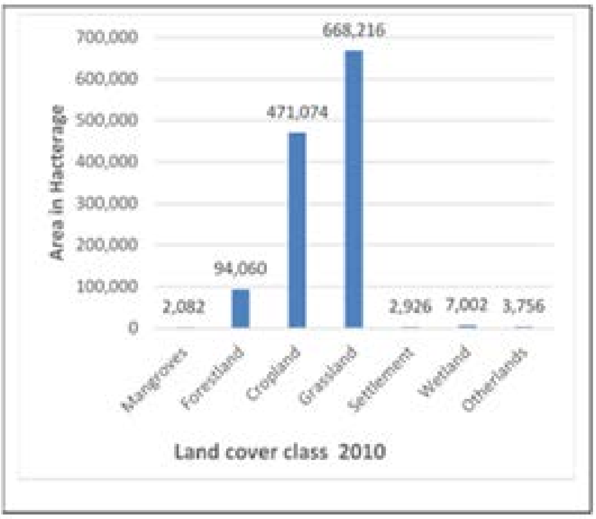

Figure 5 (c). land use land cover classes for 2010

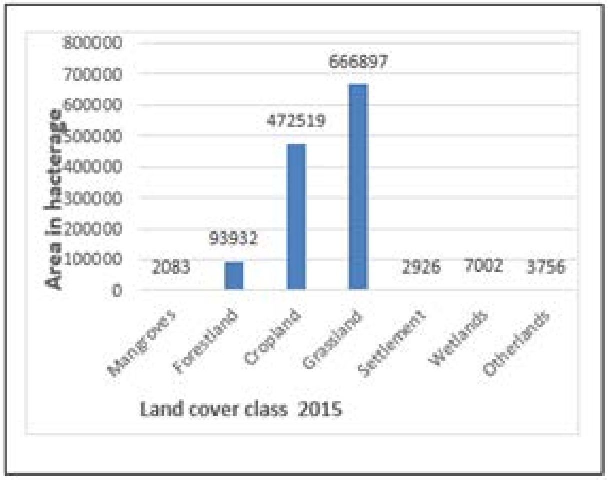

Figure 5 (d). land useland cover classes for 2015

Black squares on the map serve to draw the map readers' attention to the mangrove growing areas since they are the focus of this research but are small in extent relative to the entire county. Labeling for the figures is as under.

Bar graphs in Figure 5(a-d) below are also presented to visually represent the acreages for each land cover class and a brief description of each is given.

3.2. Change Detection

Results in this section are presented with some significant caveats that should be considered when interpreting the results. The spatial resolution of the imagery used in this research was 30 m which is relatively low and this effectively limits identification of the localized small scale land cover changes that are less than 30 meters. For instance, a particular forest could be degraded to some degree but not completely deforested but this may not be directly evident from the satellite imagery analyzed.

In addition, Kilifi County has severely high levels of cloud cover and as such, acquisition of cloud free Landsat imagery was near impossible. To attempt to get rid of the clouds from the images so as to achieve a clearer image for use in classification in our area of interest, imageries for the year of consideration, separated by months, were acquired and merged together forming a clearer composite in a process that selected the best quality pixels from all the input imagery, further decreasing the accuracy of our analysis since the pixel values used were not the original values.

Despite these caveats, the results presented in the following section have been prepared with a high degree of confidence in terms of their representation of the reality. Data obtained through change detection analysis of multi-temporal satellite imagery of our area of interest are registered in Table 2 below.

Table 2 reveals that in 1990 about 0.17% area of Kilifi was under mangrove, 8.38% was under forestland, 41.40% was under cropland, 49% was under grassland 0.22% was under settlement, 0.27% was under wetland while 0.24% was under otherland. Similarly, in 2000 about 0.15% area was under mangrove, 6.61% was under forestland, 41.24% was under cropland, 51.07% was under grassland 0.38% was under settlement, 0.34% was under wetland while 0.19% was under other land.

Table 2. Land use land cover changes for the years 1990 to 2015

Land Use/Land Cover	Chang 1990-2000		Chang 2000-2010		Chang 2010-2015	
	Km^2	Percentage	Km^2	Percentage	Km^2	Percentage
Mangrove	-150.00	-7.03%	98.00	4.94%	1.58	0.08%
Forestland	-22102.00	-21.11%	11453.00	13.86%	-128.00	0.14%
Cropland	-2035.00	-0.39%	-44040.00	8.55%	1445.00	0.31%
Grassland	21833.00	3.54%	30336.00	4.76%	-1319.00	0.20%
Settlement	2042.00	74.09%	-1872.00	39.02%	0.11	0.00%
Wetland	873.00	25.65%	2726.00	63.75%	0.54	0.01%
Other land	-611.00	20.53%	1397.00	59.22%	0.31	0.01%

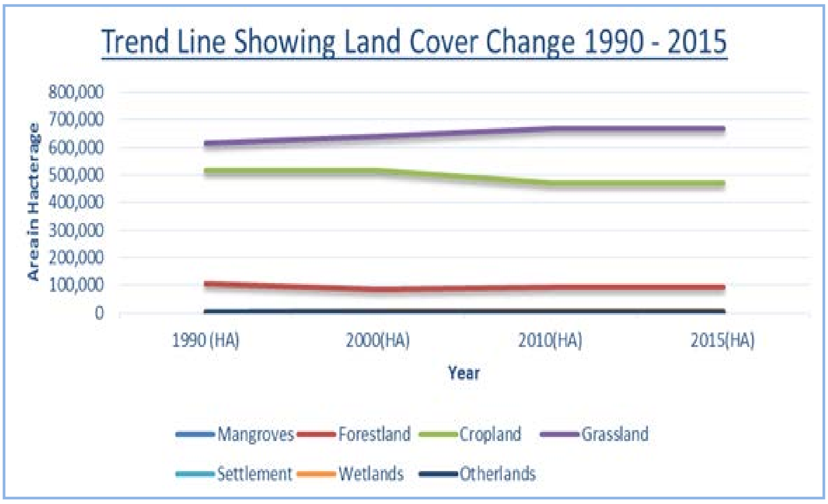

Figure 6. Trend line showing the mangrove trend from the year 1990 to 2015

The trend line graph in Figure 6 above shows a graphical representation of the changes in acreage across the years of consideration and as can be seen, the trend lines are relatively flat showing that no significantly noticed positive or negative trend was noted over the years. Cropland however showed a slightly significant negative trend between in the epoch 2000-2010 but evened out onwards. Mangroves, on the other hand, witnessed a slight positive trend in the two epochs 1990-2000 and 2000-2010 but evened out onwards. A slight negative trend was witnessed in forestland during the epoch 1990-2000 but then the trend line evened onwards. Generally, it can be reported that there was no significant trend, positive or negative, that was observed in land cover change in the epoch 1990-2015.

3.3. Mangrove Cover Change

The classified maps were then delineated along the three creeks to show Mangrove loss over time (1990_2015), degradation and land use cover change over the Project area over the specified time. Figure 7(a-c) shows the maps that indicate mangrove loss along Mtwapa creek.

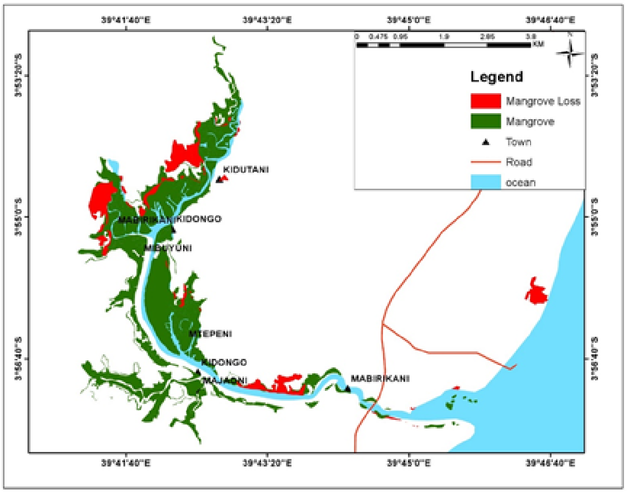

Figure 7 (a). Areas of Mangrove loss for the years 1990_2000, along Mtwapa creek

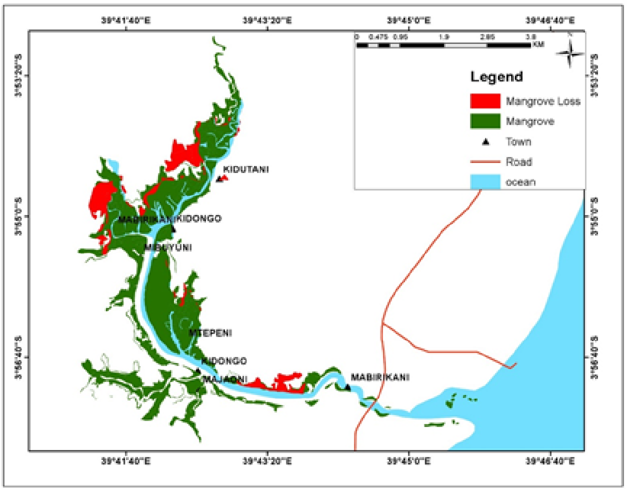

Figure 7(b). Areas of Mangrove loss for the years 2000_2010 along Mtwapa creek

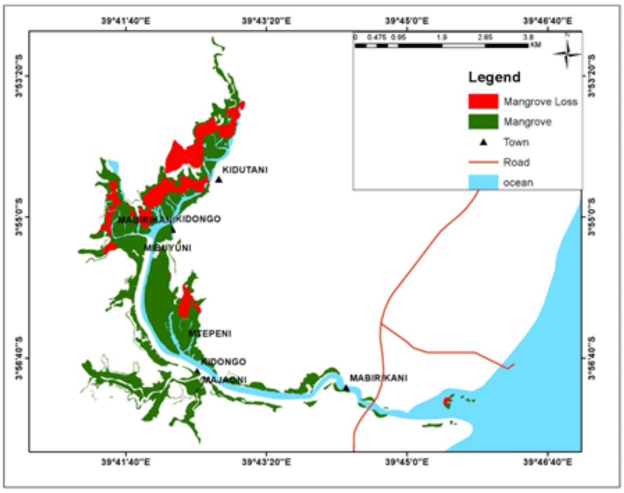

Figure 7(c). Areas of Mangrove loss for the years 1990_2000, 2000_2010 and 2010_2015 respectively along Mtwapa creek

3.4. Accuracy Assessment

The accuracy assessment results are summarized as in Table 3 below:

Table 3. Accuracy assessment results for years 1990_2015

Year	Overall Accuracy	Kappa Coefficient
1990	85.80%	0.8254
2000	85.73%	0.8302
2010	84.98%	0.8187
2015	87.04%	0.8459

3.5. Above Ground Biomass Determination

A non-destructive method of biomass estimation was done to record all the trees within a 10 m × 10 m quadrat sample. 23 sample plots were randomly distributed on 10 m × 10 m plots. According to USDA protocols for the measurement, monitoring and reporting of structure, biomass and carbon stocks in mangrove forests, in order to estimate the carbon pool of above ground components, we must derive the biomass of each forest component like small trees, large trees etcetera. The determination of carbon pools of above ground biomass is achieved through multiplication of the individual component biomass by their percentage carbon concentration-published carbon concentrations could be employed [22].

In each plot tree Diameter at Breast Height (DBH) which is 1.3 m above the ground (where the highest prop-roots reach) was measured using a diameter tape. Tree height was measured using a Laser Ace for each mangrove tree. For saplings and seedlings qualitative methods were used to enumerate per species within 3 m × 3 m and 1 m × 1 m subplots at the center of the main plot for determination of species regeneration. The minimum distance between the plots was 50 m.

3.5.1. Allometric Equations

Published allometric equations developed for mangrove species by [11] (Above Ground Biomass = $0.251*\rho*(D)$ 2.46 were used. Where ρ = wood density, D = Diameter at breast height (DBH), 0.251 is constant. A total of six different species for mangroves were identified during the project.

Figure 8. Field points distributions for biomass estimation

At local level in Kenya, the allometric equation published was the one developed by [13] applied only to R.mucronata which grows naturally. This is currently the only allometric equation developed for a mangrove species which grows in a natural environment in Kenya.

The wood density for each species of mangrove was taken from which has been developed for this region [21].

3.5.2. Linear Regression

In statistics, linear regression is an approach for modeling the relationship between a scalar dependent variable y and one or more explanatory variables (or independent variables) denoted X. The case of one explanatory variable is called simple linear regression.

In this research, the dependent variable to be modeled was biomass whereas the explanatory variables were the satellite imagery data (and deliverables). Simply put, we attempt to model the linear relationship between satellite imagery data and biomass values collected through ground survey such that the generated linear equation can be adopted as the interpolating polynomial which accepts the imagery pixel value and transforms it to a biomass value for the pixel in question.

To this end, 23 image pixels were extracted that geographically corresponded to the field surveyed plots and were correlated to determine the relationship between the two setoff variables. Imagery pixels extracted for correlation were those of the original image transformation. This means that the original image was transformed to generate the Principal Components Transformation, Independent Component Transformation, Normalized Difference Vegetation Index.

This resulted in a set of 21 images (10 principal components, 10 independent components and 1 NDVI image). In all these images, the 23 pixels geographically corresponding to the field surveyed plots were extracted and a linear regression was performed to generate the linear relationship between the image and the biomass. Coefficient of Determination statistic was used to indicate the degree of linear correlation and the linear model with the strongest correlation was adopted to serve as the interpolating polynomial.

3.5.3. Image Derived Metrics

In order to generate an interpolating polynomial that would be used to interpolate biomass across the landscape based on satellite imagery, it was necessary that we generate a few metrics from the image from which we would correlate with the ground sampled biomass values thus coming up with the interpolating polynomial.

To this end, therefore, we generated three image derived metrics which included Principle components Transformation images, Independent component transformation images and NDVI images. The principle components and independent components transformations each resulted in 8 images based on each Landsat band. Each of these images were then correlated with the ground based biomass sample values.

This was accomplished by extracting the pixel values, from the image metrics, that geographically corresponded to the ground biomass values and these were used to generate first order linear regression models. The Coefficient Of Determination statistic was then determined for each of these linear models and the model with the highest Coefficient Of Determination statistic, in this case the equation relating independent component 3 metrics with biomass, was adopted as the interpolating polynomial to estimate biomass across the landscape since it statistically provided a stronger correlation.

Using this approach, we were able to derive biomass maps for the entire landscape under study by simply generating the image metrics and then applying the interpolating polynomial equation on the metrics to estimate biomass per pixel in other words transforming image metrics image to biomass image, using the first order interpolating polynomial. Graphs for each of these polynomials together with their Coefficient of Determination statistics are shown below.

Graphs showing the linear regression models for each image and the Coefficient of Determination value for each are shown below in Figure 9. The adopted interpolating polynomial was that between independent component analysis 3 and biomass that showed a Coefficient of Determination value of 0.6. For demonstration, only graphs for principle component 1 and 2 have been shown. Also, independent component 3 and 4 have been shown.

Of the three independent variables the independent component transformation (ICA) was found to correlate more with Biomass (Field data), therefore the equation for the ICA was adopted for interpolation of Biomass across the study area.

Equation:

$y = -0.8982x - 868.15$

$R^2 = 0.5718$

Y= dependent variable (Biomass)

X= independent variable (satellite observations)

R^2= A number that indicates how well data fit a statistical model. A Coefficient of Determination of 1 indicates that the regression line perfectly fits the data, while a Coefficient of Determination of 0 indicates that the line does not fit the data at all.

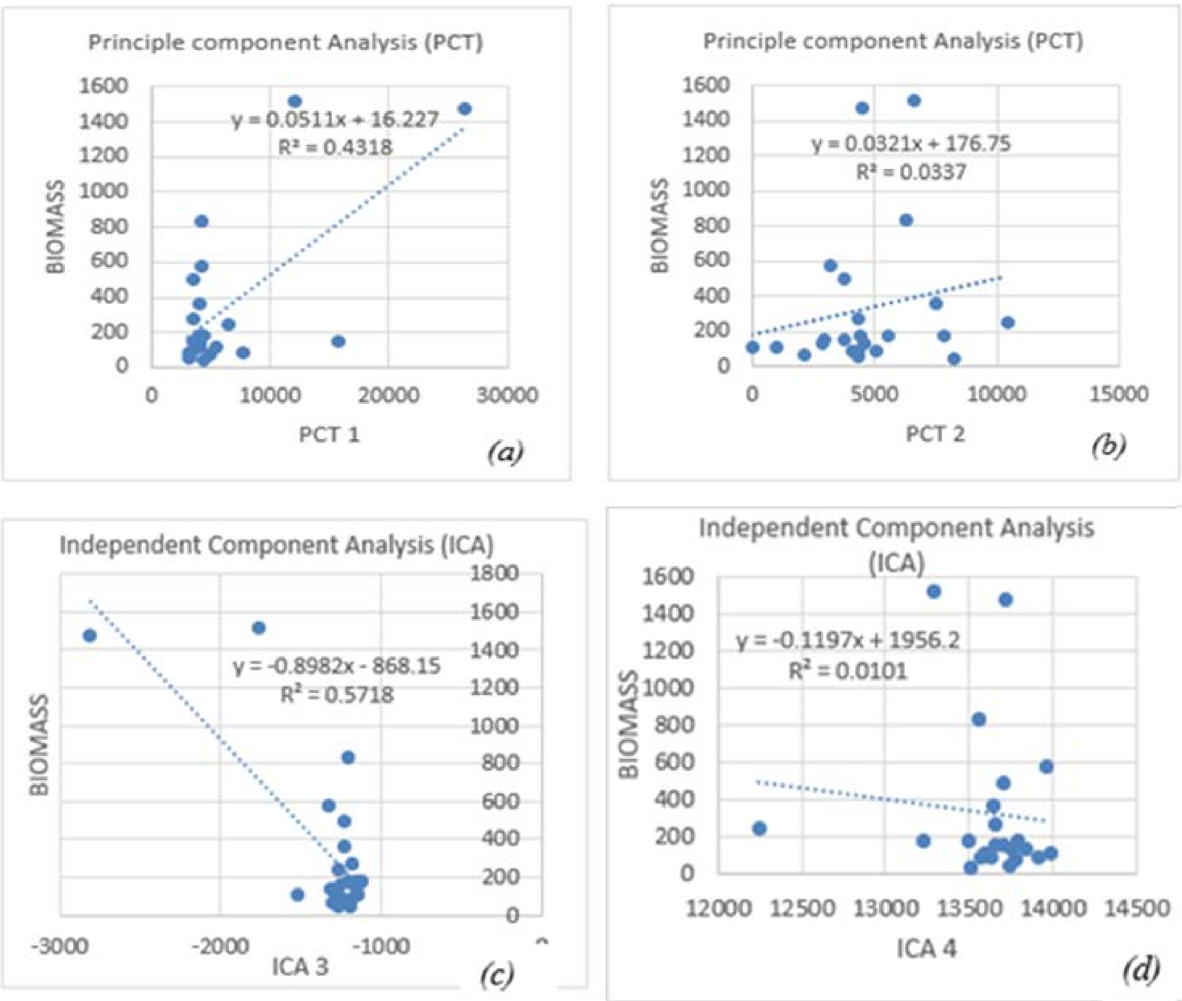

Figure 9 (a – d). Examples of Transformation Graphs that were generated

4. Conclusion

The research that was carried out in Kilifi County located in the Kenyan coast clearly illustrated the usefulness of multispectral satellite imagery in detecting changes in land use, and particularly mangrove cover change, in a quick yet accurate fashion. Also, the research has clearly demonstrated the usefulness of satellite imagery in estimation of biomass across the landscape through correlation of image derived variables with field sampled biomass data.

The study reveals that between 1990 and 2015, the mangrove cover change did not show any noticeable trend i.e. in the epoch 1990-2000, the percent cover change was -8%. In the epoch 2000-2010, the percent cover change was 5% while in the epoch 2010-2015, the percent cover change was 0.04%. These figures show that there was no trend in the mangrove cover change over the study area in the epoch 1990-2015.

It was also demonstrated, through this research, that an interpolating polynomial – used to interpolate biomass values across the landscape – can easily be generated based on imagery derived variables. Specifically, this research used imagery generated variables such as NDVI, Principle Components Transformation and Independent Component Transformation as the independent variables in generation of the interpolating polynomial whereas field sampled biomass values were used as dependent variables.

Based on the Coefficient of Determination statistic comparison, independent component transformation (ICT) and particularly ICT 3 showed a strong correlation with the field sampled biomass values. Specifically, the Coefficient of Determination value for ICT 3 was about 0.6 which was the highest of all. Consequently, the interpolating polynomial that was a result of the correlation between biomass and ICT 3 was adopted to interpolate biomass across the landscape.

Also, it was noted that the area near the ocean, particularly in Kilifi near Indian Ocean is severely affected by cloud cover. This causes a challenge, especially during image classification because these cloud pixels ‘confuse’ the classifier and in effect act as noise. This therefore means that the results of the classification, change detection and all other secondary processes that depend on their results shall give misleading values, rendering the entire analysis useless.

For the purpose of this research, an attempt was made to replace cloud pixels with best available pixels from secondary image as discussed in methodology section. This partially solved the problem but the cloud shadows still persisted. In further research, we propose that an automated (or semi-automated) approach be formulated that shall not only replace cloud pixels but shall also take care of shadows that usually form at an angle from cloud pixels.

Also, in the generation of interpolating polynomial, we focused on first order polynomial. Even in the first order polynomial, we only focused on single variable polynomial. For purpose of further research, we recommend a test to be done using multi-variate approach i.e. linear regression where the predicted outcome is a vector of correlated random variables rather than a single scalar random variable. We also recommend that the outcome of the two procedures be compared with the outcome in this research for purposes of accuracy reporting.

Furthermore, in the post-classification change detection, this research only focused on the change statistics over the epoch 1990 – 2015 which primarily was the time interval of interest for this study. We recommend for further research that an attempt be made to model and predict future changes in mangrove cover change, say in the next 50 years or so for purposes of guiding policy making and planning.

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