REDUCTIONS IN DROUGHT CONDITIONS AS A DRIVER OF THE POLEWARD EXPANSION OF MANGROVES ON THE WEST COAST OF AFRICA

BSc Geography with Applied GIS at the University of Exeter

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I certify that this dissertation is entirely my own work and no part of it has been submitted for a degree or other qualification in this or another institution. I also certify that I have not collected data nor shared data with another candidate at Exeter University or elsewhere without Specific Authorisation.

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Abstract

Global changes to the climate as a response to natural and anthropogenic factors are the cause of global species redistribution and abundance change. The adaptation and migration of the species is dependent on the facilitation of the surrounding environment and it is therefore important to understand the implications of change for biogeographical purposes. This study investigates the northernmost extent of mangrove cover on the West African coast over a 34 year period, and the effects of changes in precipitation regimes within this time. Both established and experimental remote sensing techniques are evaluated for the effective mapping of mangrove area change throughout the study period. An evaluation of precipitation regime change including drought, defined by the Standardised Precipitation and Evapotranspiration Index (SPEI), as well as other extreme precipitation indices identify that a significant relationship exists between increasing moisture at timescales of 3 to 4 years, and increases in mangrove cover. However, results were unable to define a threshold value of precipitation through any precipitation index or indices and were unable to account for all observed change with regression values suggested to be attributed to variations in nutrient supply, hydrological influence and anthropogenic influence.

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1. Introduction and Literature Review

This chapter outlines the context and topic of this dissertation, and summarises how the study will contribute to existing knowledge. In addition, it presents the primary aims of the project and objectives which will be used to achieve this.

1.1 Mangrove Ecosystems

1.1.1 Characteristics of Mangroves

Mangrove forests consist of groups of shrubs and small trees fringing the intertidal zones of tropical and subtropical coastlines. They inhabit water of sheltered shores, islands and estuaries with an extensive range of 69 species. Mangroves have adapted to live within these saline and brackish conditions through the use of salt-excreting leaves, water-dispersed propagules and stilt roots which provide the foundation for much of the productivity of the ecosystem (Tomlinson, 2016; Kuenzer et al., 2011; Lugo et al., 1974).

1.1.2 Value of Mangrove Ecosystems

Prior to the 1980s, mangrove ecosystems were viewed with much insignificance, with reports considering the land use as a form of 'wasteland' (Lugo and Snedaker., 1974). These views showed consistency with governmental action towards mangroves with little conservation and protection leading to frequent conversion towards aquaculture, crops and pasture (Lugo and Snedaker, 1974). Since then, research has gone into establishing great value in the ecosystem from both ecological and economical perspectives. Saenger et al (1983), identifies physical products provided by the ecosystem from firewood to glue, as well as outlining services such as coastal protection and habitat for educational flora and fauna. In 1999, Rönnbäck identified amplified economic value of mangrove ecosystems by recognising the biome as a support network for fish nurseries, increasing their value for local fishing industry.

Ecosystem services	Ecosystem processes and functions	Important controlling components	Ecosystem service value examples	Human drivers of ecosystem change
Raw materials and food	generates biological productivity and diversity	vegetation type and density, habitat quality	US\$484–585·ha^{-1}·yr^{-1} capitalized value of collected products, Thailand (Barbier 2007)	mangrove disturbance, degradation, conversion; coastline disturbance; pollution; upstream soil loss; overharvesting of resources
Coastal protection	attenuates and/or dissipates waves and wind energy	tidal height, wave height and length, wind velocity, beach slope, tide height, vegetation type and density, distance from sea edge	US\$8966–10 821/ha capitalized value for storm protection, Thailand (Barbier 2007)	
Erosion control	provides sediment stabilization and soil retention in vegetation root structure	sea level rise, tidal stage, fluvial sediment deposition, subsidence, coastal geomorphology, vegetation type and density, distance from sea edge	US\$3679·ha^{-1}·yr^{-1} annualized replacement cost, Thailand (Sathirathai and Barbier 2001)	
Water purification	provides nutrient and pollution uptake, as well as particle retention and deposition	mangrove root length and density, mangrove quality and area	estimates unavailable	
Maintenance of fisheries	provides suitable reproductive habitat and nursery grounds, sheltered living space	mangrove species and density, habitat quality and area, primary productivity	US\$708-\$987/ha capitalized value of increased offshore fishery production, Thailand (Barbier 2007)	
Carbon sequestration	generates biological productivity, biogeochemical activity, sedimentation	vegetation type and density, fluvial sediment deposition, subsidence, coastal geomorphology	US\$30.50·ha^{-1}·yr^{-1}†	
Tourism, recreation, education, and research	provides unique and aesthetic landscape, suitable habitat for diverse fauna and flora	mangrove species and density, habitat quality and area, prey species availability, healthy predator populations	estimates unavailable	

† Based on Chumra et al. (2003) estimate of permanent carbon sequestration by global salt marshes of 2.1 Mg C·ha^{-1}·yr^{-1}and 23 September 2009 Carbon Emission Reduction (CER) price of the European Emission Trading System (ETS) of €12.38/Mg, which was converted to US\$2000.

Figure 1.1: *Ecosystem Services provided by mangrove ecosystems (Barbier et al., 2011)*

Current levels of understanding are identified by Barbier et al (2011) in a review of mangrove ecosystem services outlined in Figure 1.1 above. Values are placed on all previously outlined services such as coastal protection and provision of habitats and nurseries for vertebrates, as well as attributing value to local communities through tourism, water filtration and erosion control. As a result of the various services provided above, an estimation of the ecosystem services provided by Costanza et al (2014) places a value of US$200,000 $ha^{-1}yr^{-1}$ to local and global communities from mangrove land cover.

One of the most valuable benefits of mangrove ecosystems, specifically in a time of unprecedented increases in atmospheric C02, is the ability of the ecosystem to capture carbon. Vai et al (2011) emphasise how mangrove ecosystems are ‘among the most carbon rich forests in the tropics’ through an enhanced ability to sequester carbon to both aboveground and belowground carbon storage. Donato et al (2011) determined the root system to be the source of the increased ability to sequester carbon by trapping sediment from aboveground littering as well as upstream sediment to form a peat layer accumulating an average of 1,023MG C ha^{-2}, with the organic rich soils accounting for 49-98% of carbon storage within the systems. Compared to typical carbon storage values of around 200-250Mg C ha^{-1} in Brazilian Amazonian forest (Malhi et al., 2009) and 319-561 Mg C ha^{-1} for Bornean forest (Slik et al., 2010; Banin et al., 2012), this highlights the potential the ecosystem has for mitigation of harmful anthropogenic emissions, with applications for schemes such as the Reducing Emission from Deforestation and Forest Degradation in Developing Countries programme (REDD) for conservation and reforestation efforts. Despite the services outlined above, global mangrove cover is reducing at a rate of 1-2% per year, with global estimates of 35% loss from 1980-2000 (Duke at al., 2007; Valiela et al., 2001).

1.2 Climate Change and the Effects on Mangrove Cover

Despite paleoclimatology showing evidence of Earth experiencing multi-millennial variations in climate seen through many avenues of evidence, the current rate of changing environments throughout the globe is unprecedented (IPCC., 2014). As a result of both natural and anthropogenic factors, precipitation regime changes have been documented throughout the world. Examples include recorded evidence of increases in rainfall in the mid latitudes of the Northern Hemisphere since the 20th century, as well as evidence of intensification of rainfall events globally (Rayner et al., 2003; Dore 2005).

Additionally, since 1900, mostly as a result of melting ice throughout the high latitudes and high elevations, sea level has risen globally by an average of 19cm (IPCC., 2014). These changes in climate and environment subsequently impact terrestrial and marine ecosystems affecting their spatial distribution, seasonal lifecycles and biodiversity.

Hickey et al (2017) recognise coastal zones to be the most susceptible to the impacts through the exposure to both land and marine drivers. Consequently, sea level rise, changing ocean currents and precipitation regimes, temperature change and increases in extreme weather events are affecting the abundance and spatial variation of mangroves in a variety of magnitudes. Reductions in available habitable area through sea level rise and destruction of cover as a result of extreme weather events are significantly contributing to a global decline in cover (Ward et al., 2016).

Predictions of future climate indicate that the near future is expected to be turbid with global average temperature increases of 0.2°C per decade anticipated for the coming two decades, as well as continuation of changes in precipitation regimes worldwide (IPCC., 2014). Inferences from this suggest future degeneration from unfavourable environmental conditions for mangroves, and therefore with the aim of conservation, an understanding of the full effects of future environmental changes on these ecosystems is paramount. Mangrove resilience to these changes, however, is remarkable with documented poleward and landward migration as a response to changes in environmental gradients, altering the range limits of the ecosystem which provides a compelling avenue for investigation.

1.3 Geospatial Thresholds

Biological range limits, defined as 'the point in space beyond which no living individual of that species occurs' (Sexton et al., 2009), are changing as a result of climate change. Changes observed today force, or facilitate the migration of species to new areas within their biological environmental limits. Observations of tree taxa shifting latitudinal range is frequently documented throughout literature with changes averaging 16.9 kilometres per decade in locations such as Europe, North America and Chile (Chen et al., 2011; Davis et al., 2001). Yet, with the unprecedented changes in climate seen from recent records and future predictions (IPCC., 2014), challenges to vegetation are present through accelerated distancing from environments which they are adapted. This poses substantial risk for ecosystem as stability for suitable environments for global vegetation such as mangroves is compromised.

An extensive investigation by Saintilan et al (2014) analysed range shifts in mangrove populations throughout the globe and identified multiple locations where this phenomena is occurring. Different species were observed to be shifting biogeographical ranges with the *Avicennia* genus extending its range into salt marsh in southern USA. The paper also identified the same genus increasing its cover at its southern limits in Peru, the West coast of Mexico and South Africa. Other species such as *Rhizophora Stylosa* were reported to have expanded latitudinal extent in the Guangdong Province in China, as well as Eastern Australia, although no attempt to identify environmental drivers were attempted in this paper.

More specifically, a study by Cavanaugh et al (2011) established a latitudinal range shift on the East Florida coastline with a poleward expansion of the mangrove population, whilst determining the cause of the changes to be as a result of a temperature threshold for mangrove species of -4°C. The study identified a correlation between decreasing amounts of extreme cold days of -4°C to a significant increase in mangrove cover area at higher latitudes. This demonstrates potential for anticipating global expansion of mangroves around the world with the increases in average temperatures anticipated by the IPCC (2014). Within Cavanaugh et al (2014) study, the identification of a temperature threshold occurs alongside an acknowledgement that other thresholds may be stronger influencers in other areas. Particularly, the study suggests areas with very low precipitation or freshwater input may be limited by factors such as drought tolerance identifying further scope for research.

1.4 Salinity and Freshwater Thresholds

Although mangroves survive in the intertidal zones, freshwater remains a vital input for the species to reduce salinity levels in the water to within tolerable levels. Optimum saline conditions suggested by Downton (1982) range between 10% and 50% seawater vs freshwater. The input of freshwater is variable throughout time and space depending on precipitation and thus, is a range limiting factor for the mangrove species (Saintilan et al., 2014).

Depending on the area of occurrence, the input of freshwater from precipitation within the catchments of the rivers is a strong determinant of the freshwater input and therefore drought conditions have serious impacts on the spatial variability and range limits of mangroves as a species with drought tolerances and salinity thresholds inseparable from one another.

1.5 Documented drought related changes

Sakho et al (2011) undertook research to understand the natural and anthropogenic drivers of change for mangrove cover in West Africa. The paper describes drought as a main cause of degradation for Senegalese mangrove, through a lack of recirculation of water ultimately leading to hypersalinisation and acidification. Yet, this is merely descriptive and no quantification for reductions in mangrove cover were established as a result of drought.

Mafi-Gholami et al, (2017) more explicitly defined this connection through an in depth analysis of the relationship between drought events and mangrove cover changes in the Persian Gulf and Oman Sea. The paper established that a change in area and canopy cover of mangroves on the northern coast of the Persian Gulf shows a linear regression exceeding 0.89 with the Standardised Precipitation Index (SPI). Though a precipitation or drought threshold was not identified within this study, opening up more scope for research into this relationship.

1.6 Climate and Mangrove Extent on the West Coast of Africa

At the northernmost extent of mangrove cover on the West African Coast, temperatures stay well above the temperature thresholds identified by Cavanaugh et al of -4°C with average minimum temperatures of 13°C (Otero et al., 2016). Despite this, mangrove area has a latitudinal range limit of around 20°N at Iouik, Mauritania (Hickey et al., 2017; Dahdouh-Guebas, 2001). A report on the global poleward limits of mangroves by Hickey et al (2017) identified limiting factors for mangroves in this area to be topography and freshwater/salinity which directly correlates to freshwater from precipitation. Multiple reports have also recognised the northern sections of West Africa to have experienced a recovery of rainfall within the last 30 years, compared to a long term lack of rainfall experienced over the last 100 years (Sanogo et al., 2015; Lebel et al., 2009; Nicholson, 2005). This also coincides with recorded widespread recovery of vegetation greenness throughout the wider Sahel region (Herrmann et al., 2005). These conditions lead the area to be favourable to investigate the effects of precipitation regimes and drought on mangrove ecosystems with the intent on identifying threshold values for tolerance levels enabling the survival of mangroves.

As well as this site providing the conditions required to test such relationships, the African continent as a whole has progressed slowly with adequate legislation to protect and conserve mangrove forest (FAO, 2007), meaning any status reviews taken place here can also aid positive conservation efforts in the area, providing valuable information for planning and management.

1.7 Efficient and Effective Mapping

As well as the intentions of adding to mangrove biogeographical knowledge and aiding local communities and policy makers, this study also intends on increasing the information on the remote sensing of mangroves to aid future mapping efforts.

Within the last 20 years, although many studies conducting spatial extent analysis for mangroves have occurred, including global status reviews by Spalding et al (1997; 2010), and Giri et al (2011), a distinct lack of data on temporal mangrove population response to climate change has been documented (Hickey et al., 2017). This could be due to the methodologies involved in established methods of mapping, such as the Maximum Likelihood Classification method. This method involves large amounts of time investment and is subsequently labour intensive, and therefore time series analysis on land cover change is inaccessible.

As a result, an evaluation of the effectiveness of more time efficient methodologies of unsupervised classification using the Unsupervised ISODATA Classification algorithm and a novel method of forest detection developed by Ye et al (2014) is evaluated for the use of mangrove mapping with the intentions of increasing the accessibility of such studies for future research.

1.8 Project Purpose

This project is a multi-dimensional study with intentions on increasing knowledge for multiple stakeholders in various forms.

The first purpose of the study is to provide a current status review of mangroves at their northernmost extent on the Atlantic coast of Africa, with the objective to provide valuable information for local communities and policy makers to increasing operational information for conservation efforts.

The second purpose of this study is to provide information on the spatial redistribution of mangrove species as a result of changing environmental parameters. Specifically, the study aims to identify a drought tolerance threshold for mangroves. This can then be used for understanding the potential spatial distribution of mangroves in line with future precipitation regimes predicted by the IPCC (2014) report on climate change. With this information, anticipatory conservation efforts may also be utilised as well as used to increase the effectiveness of forestation or reforestation efforts to ensure the survival of species.

The third purpose of this study is to identify an efficient method of processing large datasets of satellite imagery to increase the accessibility of temporal land cover analysis. Thus, this may aid in the lack of current data on changes of mangrove to climate variables identified within the literature (Hickey et al., 2014).

With the project purposes in mind, three study sites at the northernmost extent of mangroves are established at varying latitudes, the Saloum Delta, Senegal

(13°45′N 16°38′W), the Senegal River estuary, Senegal (16°02′N 16°30′W) and Cape Timiris, Mauritania (19°24'02"N, 16°30'09"W). Landsat Level-2 data for these study sites are processed with 3 different methodologies to identify the most efficient and accurate method of mapping, followed by a 34 year analysis of area change. The Standardised Precipitation and Evapotranspiration Index (SPEI) data, as well as daily climate data from the NOAA database, are processed and employed for statistical analysis investigating the relationships between precipitation values and area cover change.

1.9Aims and Objectives

1.9.1 Aims

This dissertation aims to quantify mangrove area cover and area cover change on the West African coast for the years 1984-2017, whilst understanding the freshwater drivers of the change, furthering understandings of the effects of potential future environment has on the biogeographical range limits of mangrove species. Additionally, this paper aims to provide a critical evaluation of techniques of mapping large quantities of space borne imagery to identify the most appropriate method for deriving large datasets of long term change.

1.9.2 Research Questions:

1. Which remote sensing technique is most appropriate for large scale, long term change detection for mangroves on within the study sites outlined?

2. Using this method, what are the initial conditions at the sites and what changes can be observed?

3. Which areas have changed the most and why is this the case?

4. Is there a link between the recorded recovery of rainfall in the area and the changes in mangrove cover observed?

5. Can the observed changes in the past, be used to aid policy in future?

1.9.2 Research Objectives:

1. Download Landsat Imagery and drought data consisting of SPEI values and daily precipitation data for all study sites.

2. Evaluate existing and experimental mapping techniques, identifying the most appropriate technique for long term mangrove cover change detection with the use of a confusion matrix to determine the accuracy of each method.

3. Using the most appropriate method identified, process all acquired images to assess the status of mangroves within the study sites and to identify any changes that may be observed throughout the study period.

4. Examine the changes in drought conditions for each individual study site to identify various potential drivers of change for the changes in cover observed.

5. Investigate relationships between various methods of drought detection and the observed changes in mangrove cover to identify the potential relationship between increases in freshwater availability and changes in mangrove cover.

6. Discuss the findings for the mapping techniques to identify the main outcomes from the comparison of methods, recommending pathways for future studies looking to perform long term analysis of change.

7. Discuss the implications of findings for future of mangrove cover on the West African coast as well as for mangrove populations elsewhere, suggesting avenues for further research in the area.

2. Methodology

This section provides a description of the study sites and justification for these sites followed by an exploration of remote sensing techniques used within existing research, identifying the benefits and drawbacks of each method for mangrove detection. Following this, this section provides a comprehensive outline of data acquisition, pre-processing and processing methods used within this study to calculate area cover change as well as a justification. This section also provides an account of the statistical analysis used to analyse the various drivers of the observed area cover changes.

2.1 Study Sites

The area of interest on the West African coast used within this study has low density sporadic cover of mangrove vegetation. As the topography and moisture levels allow, only small volumes of mangrove are present at the mouths of rivers and other low lying areas. Therefore, the study sites for this investigation were identified with a synergistic approach using the shapefiles derived from Spalding et al's (2010) mangrove atlas, Giri et al's global distribution of mangroves (2011), as well as literature reviews outlining northern extents of mangrove cover which have not been identified by the shapefiles. The three study sites were chosen to represent a variety of different latitudes to determine latitudinal variance which may occur throughout the study period.

Study site one, the Saloum Delta, is a river delta lying at the mouth of the rivers Sine and Saloum on the coast of Senegal. The site is part of a 190,000 acre national park located where the rivers enter the Atlantic Ocean (13°45′N 16°38′W). The site is a Ramsar Convention and UNESCO World Heritage Site comprising of a large area of intertidal mangroves approximately 7,000ha (UNESCO, 2017). The mangrove within this site provides valuable habitat for fish spawning grounds, and is also vital for providing habitat for millions of wintering European birds (Zwarts et al., 2014), meaning status reviews are vital for many stakeholders.

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The second study site is the Senegal River estuary where the river reaches the Atlantic Ocean at the border between Senegal and Mauritania at St Louis (16°02′N 16°30′W). This area seasonally floods corresponding to the wet or dry season, with mangrove area smaller than the Saloum Delta site, yet significant cover of around 100ha.

The third study site lies within the Parc National du Band d'Arguin (PNBA), Mauritania (19°24'02"N, 16°30'09"W). This study isn't included within the global shapefiles due to coarse resolution techniques used within Spalding et al (2010) and Giri et al (2011). As techniques used within this study limit identification of cover to no less than $30m^2$, the chosen site is not the very most Northerly extent of Iouik, Mauritania identified by Dahdouh-Guuebas et al (2001), yet a site 60km further south, Cape Timiris. The justification for this site is that cross referencing from recent literature from Otero et al (2016) is available for Cape Timiris and with a land cover approximately 20ha, which with methods used in this study explained ahead, ensures the accuracy of the results to be preserved. Figure 2.1 below shows an overview of the study sites highlighting mangrove cover and its current location (2018).

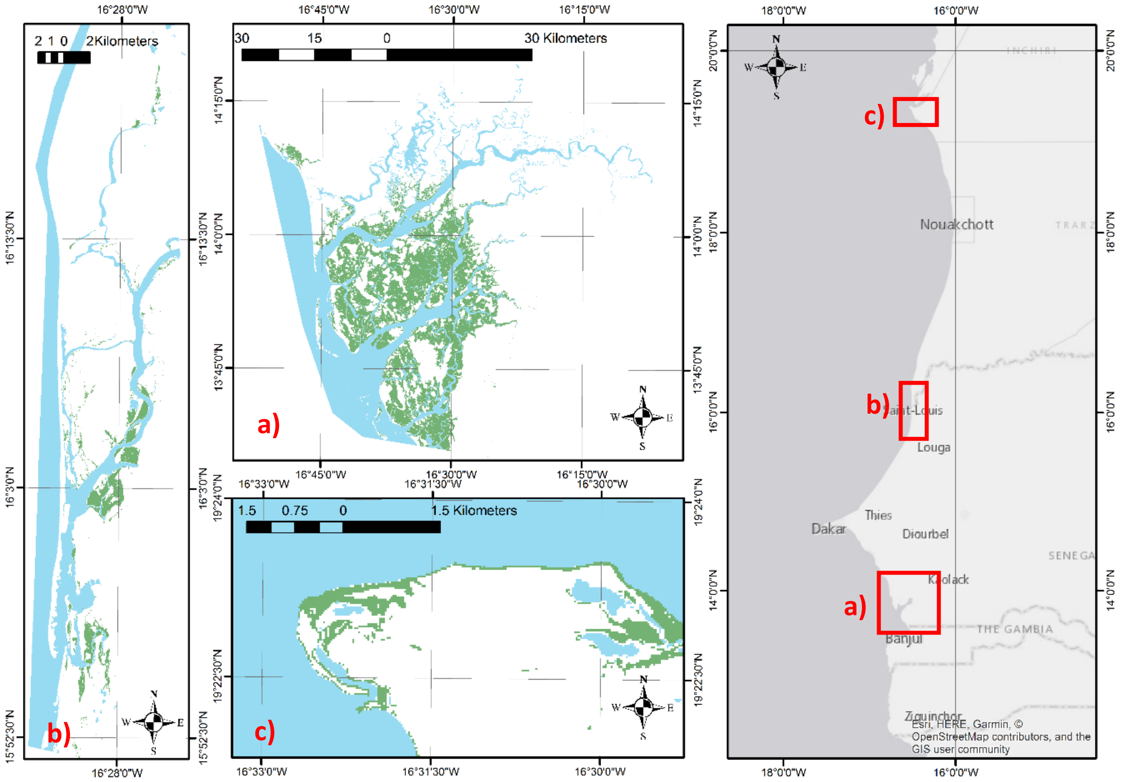

Figure 2.1: *Overview map of the three study sites; the Saloum Estuary (a) St Louis (b) and Cape Timiris (c).*
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2.2 Remote Sensing of Mangroves

2.2.1 Data Types and Collection Methods

For mangrove cover detection, traditional geographical fieldwork is generally inappropriate due to the habitat in which the ecosystems occur being intertidal and therefore highly inaccessible. Research would therefore be labour intensive and financially impractical. As well as this, the locations of mangrove areas are not just limited directly to coastal and estuarine areas as occasionally mangrove stands occur on smaller offshore islands of sediment increasing the inaccessibility of the vegetation type.

For change detection analysis, additional difficulties in terms of traditional field measurements occur through the timescales which change occurs. Inter decadal timescales for significant change isn't uncommon for mangroves and subsequently the most efficient contemporary ways of measuring change is through remote sensing techniques (Kuenzer et al., 2011). Remote sensing methods make the use of imagery obtained from altitude to obtain information. With regard to mangrove studies, remote sensing methods make use of the spectral components of the mangrove forest canopy to identify mangrove cover.

Prior to the 1970s, aerial photography was the dominant method for remote sensing of surface change. Kuenzer et al., (2011) describes that aerial photography was effective for highly detailed mapping of mangrove cover in small study areas and narrow coastal environments. However, due to the birth of space borne remote sensing techniques established in the 70s and 80s, aerial photography had been pushed into the background as new techniques become more efficient. Multiple types of space borne imagery are freely available through multiple distribution networks at a variety of spatial and spectral resolutions and therefore provide valuable data for spatial sciences.

Medium resolution imagery such as the Landsat Archive, SPOT, the Indian Remote Sensing Satellite (IRS) and ASTER datasets are commonly used with spatial resolutions ranging from 2 to 30m^2. The benefits of employing medium resolution images is that at a relatively low computational cost, effective analysis of large geographical regions can be made. In addition to this, an abundace of medium resolution satellite imagery data are freely available from the last three decades, leading medium resolution imagery to be one of the most widely used datasets for determination of change detection (Kuenzer et al, 2011). However, at these resolutions, discrimination between mangrove species is difficult (Vaiphasa et al., 2005), as well as providing insufficient information to analyse marginal areas where mangrove extent is smaller than the pixel size derived from medium resolution images. As this could be an issue in studies such as this, other finer resolution data may be beneficial.

High resolution imagery such as IKONOS-2 and Quickbird have contributed to a new era of high-resolution space borne sensors since 1999, increasing the spatial resolution to $2m^2$ or better, opening the doors to many enhanced earth surface and mangrove studies. The main benefits of high resolution data are seen through increased ability to discriminate between species. However, it is reported that due to governmental and other agencies being interested in regional or county wide scale information for planning and conservation, high resolution imagery is superfluous as medium-resolution imagery provides adequate information in a more time and cost effective manner (Kuenzer et al., 2011).

For this study therefore, the medium resolution Landsat archive is adopted. The data is most appropriate owing to the scale of change being observable with medium resolution data, and due to the consistency of the data throughout the large timescale of 1984 to present, allowing large scale time series data to be obtained. Sentinel-2 data is used for cross verification data points with higher resolution images of $10m^2$ providing heightened ability to distinguish mangrove stands, the techniques for this are explored in the Accuracy Assessment chapter later on in this paper.

2.2.2 Classification Methods

Methods of data processing vary significantly between studies concerning mangrove cover analysis. Among the most widely used processing methods, are image classification techniques such as the Maximum Likelihood Classification and vegetation indexes such as the Normalised Difference Vegetation Index.

Image classification methods extract information from images comprising of multiple bands, classifying these images into a defined number of classes. The two main variations within image classification techniques are supervised classification, and unsupervised classification.

Unsupervised classification requires no data analyst intervention, using only computational power to cluster images. Algorithms are used to cluster images, with one of the most commonly used algorithms being the ISODATA algorithm. This algorithm calculates class means, distributed evenly throughout the image, iteratively re-clustering the pixels within the image using minimum distancing techniques, until the distances between each cluster from the following iteration are below a threshold value. The benefits of unsupervised classifications are the moderately high accuracy results without the requirement of a large labour investment. The benefits within land cover change studies such as this is that large quantities of remote sensing data can be efficiently processed, improving the accessibility of high temporal resolution data at large spatial scales for effective data acquisition of land cover change. This information may then be used to derive statistically significant relationships between drivers of change and the change observed. This unsupervised classification technique is adopted within Long et al's (2011) study assessing the status of mangrove cover within the Philippines. The results suggest from this study that methods adopted underestimate mangrove cover in the Philippines in context to previous understandings. Unsupervised classification methods do typically have lower accuracies than other methods of land cover classification (Kuenzer et al., 2011; Green et al., 1998; Aschbacher et al., 1995) and thus, the results derived from this study may be dissimilar to other studies due to the techniques adopted.

Where unsupervised classification techniques require no data analyst intervention, supervised classification techniques require the user to manually allocate a spectral signature to each class with the use of training areas within each image. Following this, algorithms use these spectral signatures to classify the whole image into each signature class using various computational techniques. Some of the most common supervised classification techniques adopted are the Maximum Likelihood Classification and the Minimum-Distance Classification techniques. Throughout the literature, it is established that the most accurate of all the supervised classification methods is the Maximum Likelihood method (Kuenzer et al., 2011). This technique assumes the normal distribution of pixels within each class, followed by a calculation of the probability that a given pixel in the image belongs to a specific class, subsequently assigning each pixel to that class according to this probability. The benefits of using this technique is an increased accuracy of classification compared to unsupervised. However, the demands for manual allocation of spectral signatures within each image leads the method to have much higher costs through its labour intensive foundation. Thus, the Maximum Likelihood Classification has potential for reducing the accessibility of high temporal resolution, large scale analysis through investment costs.

Another method used within research for mangrove detection is vegetation indices and other types of indices as a pre-processing step to classifications (Kuenzer et al., 2011). Rasolofoharinoro et al (1998) uses a combination of a vegetation index (VI) and brightness index (BI) to create images to subsequently be classified using supervised classification methods in a mangrove status review in Madagascar. Yet, this study found larger variation in results from various classification algorithms than without the use of these pre-processing steps subsequently increasing uncertainty. However, as indices make the use of information within specific bands and place this information within formulae, the potential to use these methods within coding software as a moderate accuracy, low time investment alternative to supervised classifications are high.

One untried method of mangrove detection is through the use of an index developed by Ye at al (2014), the Forest Index (FI). This index was developed to distinguish forest from non-forest vegetation (NFV) with the intention to make forest cover mapping simple and rapid. This method includes using the reflectance values of the green, red and near-infrared bands adjusted by constants to increase the differentiation between spectral values of forest and water as seen from formula X below. A threshold can then be applied to the output of the index to determine forest versus non-forest vegetation and other land use types with reported accuracies of 96.8% (Ye et al., 2014).

$$FI = \left(\frac{\rho_{NIR} - \rho_{red} - L}{\rho_{NIR} - \rho_{red}}\right) - \left(\frac{c_1 - \rho_{NIR}}{c_2 + \rho_{green}}\right)$$

Where L = 0.01

$C_1 = 1$

And $C_2 = 0.1$

Although this method is an absolute calculation for the estimation of all forest within an image, this method has the potential to be used after image pre-processing steps eliminating any areas which are non-tidal, or within areas such as presented within this study; whereby drought conditions allow only strongly drought tolerant species of flora such as mangroves to survive.

Within this study therefore, three separate types of mangrove mapping techniques are adopted to identify the most time effective and accurate methods of mangrove detection which allow for a high temporal resolution and large spatial scale analysis of land cover change. The Unsupervised Classification using the ISODATA algorithm is evaluated against the established Maximum Likelihood Supervised Classification method and the experimental Forest Index method to identify the most appropriate method of mapping with high accuracy and high efficiency as the objective.

2.2.3 Accuracy Assessments

A key step in any interpretation of land cover analysis is an accuracy assessment (Otero et al., 2016). Accuracy is frequently defined as the degree to which a classification output of an image agrees with reality (Foody, 2002). Thus, an error within the classification relates to inconsistencies between the classification results and reality.

Accuracy assessments from mapping techniques have developed significantly from the 1980s to present with early accuracy assessments often performed post analysis, with visual analysis dominating the techniques towards acceptable accuracy assessments (Foody, 2002; Congalton, 2008). However, the subjective nature of this method principally makes it redundant for scientific analysis as a more robust method to objectively quantify errors is required for research (Congalton et al., 2008). Other methods since have included comparing measured extent within the derived classification (for example, with km^2 or % cover) in relation to a 'true' dataset from a reference dataset or ground truth data. Although this method is prone to errors in the sense that spatial extent may be accurate only as a result of miscalculation of area in the wrong place as to include true-negatives and false-positives (explained in greater detail below).

Today, the most commonly used accuracy assessment throughout land cover research is the confusion matrix (Congalton et al., 2008; Foody, 2002). This method uses a cross-tabulation of the mapped class against observed or reference data for a sample of sites at specified locations. One strength of the confusion matrix lies within the ability of the user to identify the nature of the errors by highlighting interclass confusion, as well as the quantities of these errors. With the information of the source of the errors, these errors then may be reduced by increasing the discriminatory information within the classification method, compounding the use of the accuracy assessment.

Another benefit from the confusion matrix lies within the multiple results which can be gained from this assessment such as overall accuracy, specific accuracy which relates to the specific class accuracies, and the ability to derive statistically sound information which calculates the accuracy taking into consideration the chance that the pixels can be randomly assigned to the correct classes. The Kappa coefficient can be derived from the confusion matrix and makes compensation for chance agreement.

To be used within planning and management, land cover classifications tend to have a requirement for overall accuracy of 85% or more (Anderson et al., 1976). Therefore within this study, the confusion matrix accuracy assessment method is adopted. It is used to identify the highest accuracy potential for each classification method individually, as well as identify the greatest accuracy method from all those proposed, to understand which is most appropriate for planning and management purposes. The results for an example confusion matrix are shown below in Table 2.1:

Table 2.1*: An example output from a confusion matrix. The Validation data placed into a pivot table with true-negatives and false-positives in red, and true-positives in green*

	Forest	Urban	Water	Total
Forest	45	4	5	54
Urban	8	56	6	70
Water	2	9	37	48
Total	55	69	48	172

2.3 Landsat Data Acquisition

70 images from the Landsat archives were acquired from the USGS data explorer application. The recent release of Level-2 data from the archives were selected which are more appropriate for land surface change analysis. The Level-2 data is atmospherically adjusted prior to download which accounts for local water vapour levels, ozone levels, geopotential height, aerosol optical thickness and digital elevation to generate surface reflectance values. Without these corrections, inconsistencies within the data increase the uncertainties within the resulting classification data increasing the error of calculated outputs.

Landsat 5 TM data was used for its period of operation of 1984-2013, with Landsat 8 OLI/TIRS data being used for the years 2013-2018. Landsat 7 ETM+ images were omitted due to the SLC off error occurring post May 2003 (Figure 2.2), and to retain continuity between images throughout the time series. Landsat 8 OLI/TIRS images were also left without panchromatic adjustment to further maintain continuity between images and avoid errors within calculations as a result of differences in the quality of data. Images for every year were not available for all three study sites due to excessive cloud cover and a lack of available data. Within the data acquisition, an attempt to download images from within the dry season of each year between January and April was implemented to reduce the influence seasonality had on the results. Yet, priority was given to gaining data from as many years available so therefore inconsistencies within the dates of data collection exist within the dataset. Figure 2.2 below shows the timeline of Landsat Missions as well as a typical SLC off error within the Landsat 7 mission which occurred from May 31st2003, highlighting the issues which would be present had this data been used. Table

2.2 below also highlights all data acquired from the Landsat archives as well as the date of capture and which satellite the images originate.

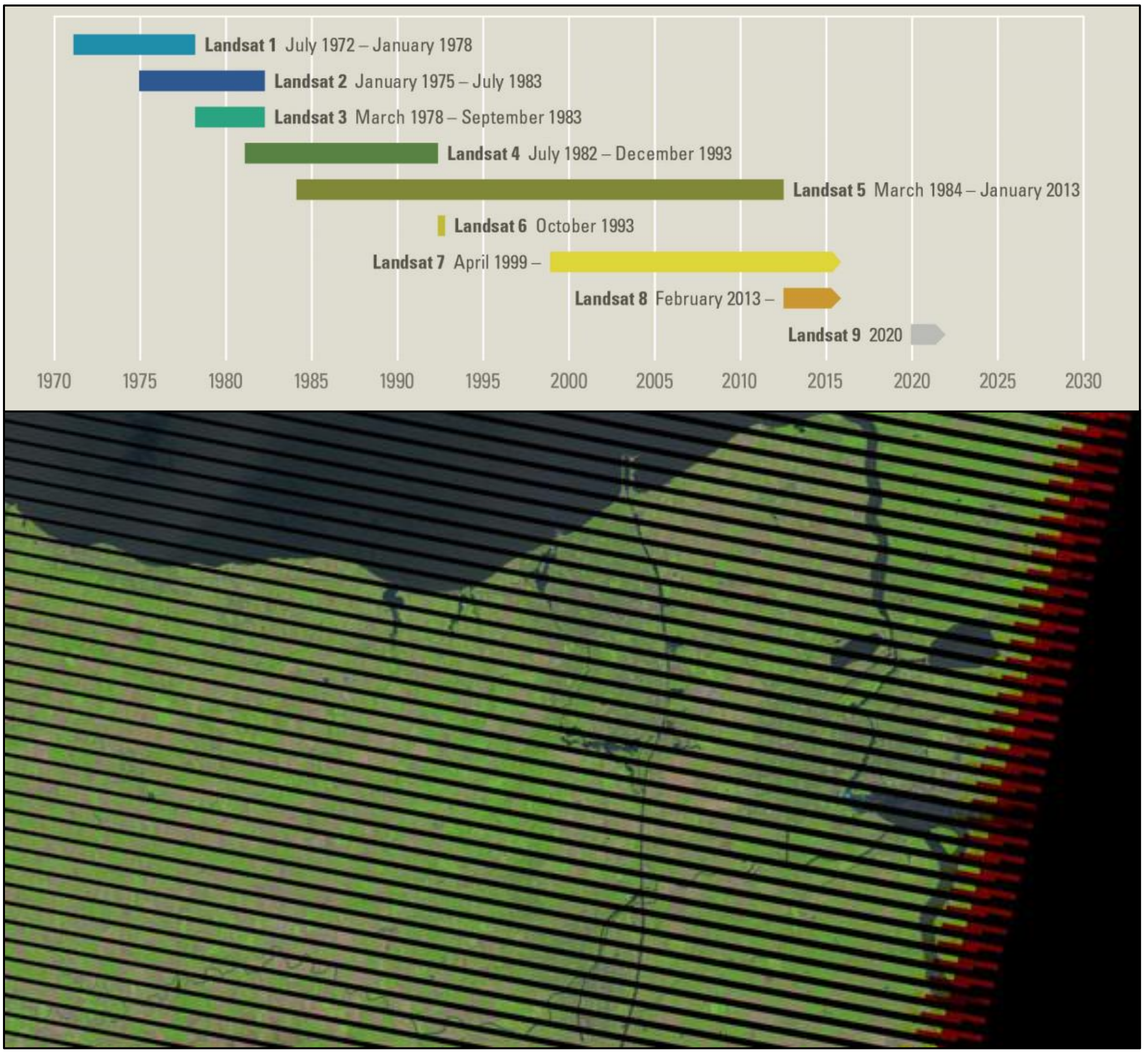


Figure 2.2: *A time series of available Landsat Imagery provided by the US Geological Survey, as well as an example of a Landsat-7 SLC off image highlighting the impacts the use of such imagery would have on the results gained in this investigation.*

Table 2.2: *The years and dates of the Landsat Imagery downloaded for land use change classifications.*

	Cape Timiris		*St Louis*		*Saloum Delta*		
Year	Month	Day	Month	Day	Month	Day	Satellite
1984	6	2	5	10	4	8	L5
1985	1	12	1	21	2	6	
1986	10	14	2	9	2	25	
1987	1	2	1	27	1	11	
1988	2	14	3	10	3	10	
1989	11	23	9	13	9	13	
1990			8	15	1	13	
1991							
1992					10	31	
1993							
1994	3	26	4	4			
1995	5	16	5	9	5	9	
1996							
1997							
1998	3	5	2	26			
1999	9	24			11	4	
2000	4	3	4	12	5	30	
2001	2	1	12	27	1	9	
2002	3	24	2	13			
2003	1	26	1	31	1	31	
2004							
2005							
2006	10	21	10	30			
2007	1	9	3	7	1	2	
2008							
2009	9	7	7	18	6	16	
2010	1	17	4	16	2	27	
2011	2	5	2	14	2	14	
2012							L5
2013	5	17	6	11	6	11	L8
2014	1	12	1	21	2	6	
2015	1	31	3	13	2	25	
2016	1	2	1	11	1	11	
2017	1	20	3	2	1	29	
2018	1	23	1	16	1	16	L8

2.4 Data Pre-Processing

For both the unsupervised and supervised classification methods, the raw Landsat data must be stacked into composite bands to provide the best differentiation of spectral bodies within an image. Particularly within mangrove forest ecosystems, three main types of land cover can be distinguished; mud or bare land, water, and forest. Table 2.3 identifies the bands within each satellite mission used as well as the spatial resolutions and wavelengths each band comprises. Within the Landsat 5 and Landsat 8 bands, Band 1 provides increased penetration for water bodies which helps distinguish mud from water within the intertidal zone. Band 2 increases the distinction between soil and vegetation; further increasing distinctions between land cover types. Band 3 emphasises peak vegetation, strengthening distinction between non vegetation and vegetation. Band 5 emphasises biomass content and aids in distinguishing shoreline. Band 6 discriminates moisture content of soil and vegetation which all aid in the variance in the spectral reflection of classes. Within this study, the most effective band combinations identified through visual analysis are bands 5, 2 and 1 for Landsat-5 and 5, 6 and 2 for Landsat-8. Using these band combinations (Table 2.4), the composite bands tool was used to create the stacked images required, an example of the resultant composite image is shown in Figure 2.3.

Prior to classification attempts, data management techniques were adopted to reduce the extent of the stacked images with the use of the clipping tool within ArcMap to the three study sites, with the intentions of reducing computational requirements when classifying. Although no image stacking was required for the Forest Index method, the clipping tool was adopted alone for the green red and NIR bands prior to calculations for this method.

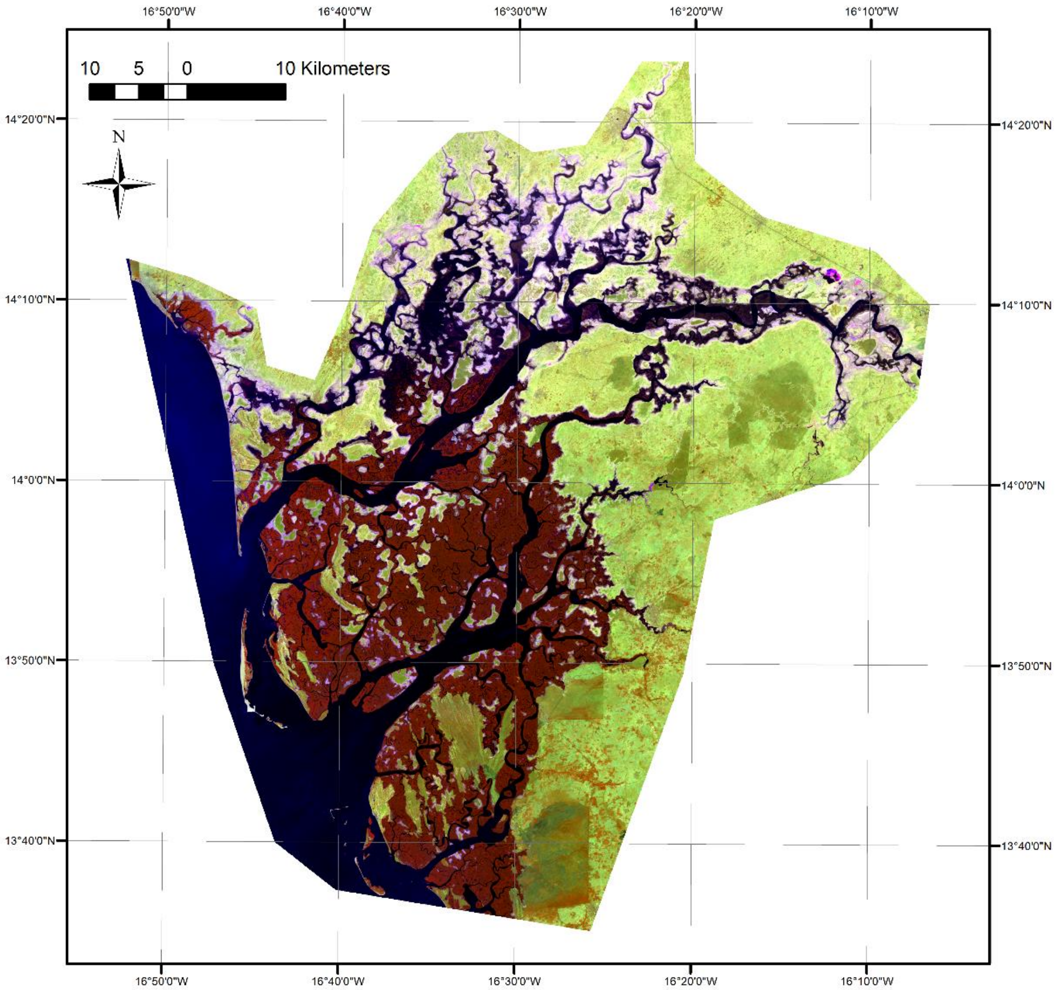


Figure 2.3: *An example of a clipped stacked image from the Landsat-8 data using band combinations 5, 6 and 3.*

Table 2.3: *The list of bands and their respective wavelengths and spatial resolutions.*

Landsat Satellite	*Band*	*Wavelength*	*Spatial Resolution*
Landsat 5 TM	1 - Green		30
	2 - Red		30
	3 - Red		30
	4 – Near Infrared (NIR)		30
	5 – Shortwave Infrared (SWIR)		30
	1		30
	6 – Thermal		30
	7 – Shortwave Infrared (SWIR)		
	2		
Landsat 8 (OLI/TIRS	1 – Ultra Blue (coastal/aerosol)		30
	2 - Blue		30
	3 - Green		30
	4 - Red		30
	5 – Near Infrared (NIR)		30
	6 – Shortwave Infrared (SWIR)		30
	1		30
	7 – Shortwave Infrared (SWIR)		15
	2		30
	8 - Panchromatic		100 * (30)
	9 - Cirrus		100 * (30)
	10 – Thermal Infrared (TIRS) 1		
	11 – Thermal Infrared (TIRS) 2		
Sentinel 2	1 – Coastal Aerosol		60
	2 - Blue		10
	3 - Green		10
	4 - Red		10
	5 – Vegetation Red Edge		20
	6 – Vegetation Red Edge		20
	7 – Vegetation Red Edge		20
	8 – NIR		10
	8A - NIR		20
	9 – Water Vapour		60
	10 – SWIR - Cirrus		60
	11 - SWIR		20
	12 - SWIR		20

Table 2.4: *The bands used from each Landsat image to create the largest spectral differentiation between images.*

Landsat Mission	*Landsat 5 TM*	*Landsat 8 ETM*
Band Combination	5,2,1	5,6,2

2.5 Identification of Appropriate Mapping Methodology

Within this study, the accuracy assessment outlined above is adopted to find the most accurate method of satellite data processing. Validation points for the confusion matrix were visually derived using a stratified sampling method from Sentinel-2 data obtained for the Saloum Delta study site. Sentinel-2 data was utilised for its increased spatial resolution of $10m^2$, increasing the accuracy for visual interpretation to identify 120 reference points spread evenly across three classes; mangrove forest, land/mud, and water. Images for years 2015, 2016, 2017 and 2018 were used at dates similar to those collected for the Landsat data, one image for each year since the launch of Sentinel-2. These validation points were classed as the 'true' data points which were then used to quantify the correctly identified areas within each subsequent classification attempt.

Table 2.5: *Land cover types included in the three clusters throughout classifications*

Land Use Class	*Land-uses and land-covers included in class*
Mangrove	Mangrove Forest
Land/Mud	Desert, intertidal land, urban areas
Water	Water

All classification attempts required user input prior to accuracy assessment modifications to reach the highest potential accuracy for each classification type. The Unsupervised Classification required a user defined number of clusters, whereby visual analysis was utilised. Accuracy assessments led to alterations to the number of clusters chosen until the highest accuracy could be found for each image from 2015 to 2018. The

Supervised Classification required a definition of spectral reflectance values for each cluster through training areas prior to classification. Spalding et al's (2010) and Giri et al's (2011) shapefiles provided distinct areas for mangrove training areas which were used to run initial classification attempts. This, followed by accuracy assessments and modifications to the training areas, led to the highest achievable accuracy attempts for the Maximum Likelihood Classifications for the years 2015-2018. The Forest Index required a threshold value to be set for mangrove extent which was initially selected based Ye et al's (2014) paper as 3.5, then altered to find the highest accuracy based upon the results from the confusion matrix. The workflow from this is shown in Figure 2.4 below.

Following from the identification of the highest accuracy method, this method was subsequently used on all 70 Landsat images to derive long term area data for the three study sites.

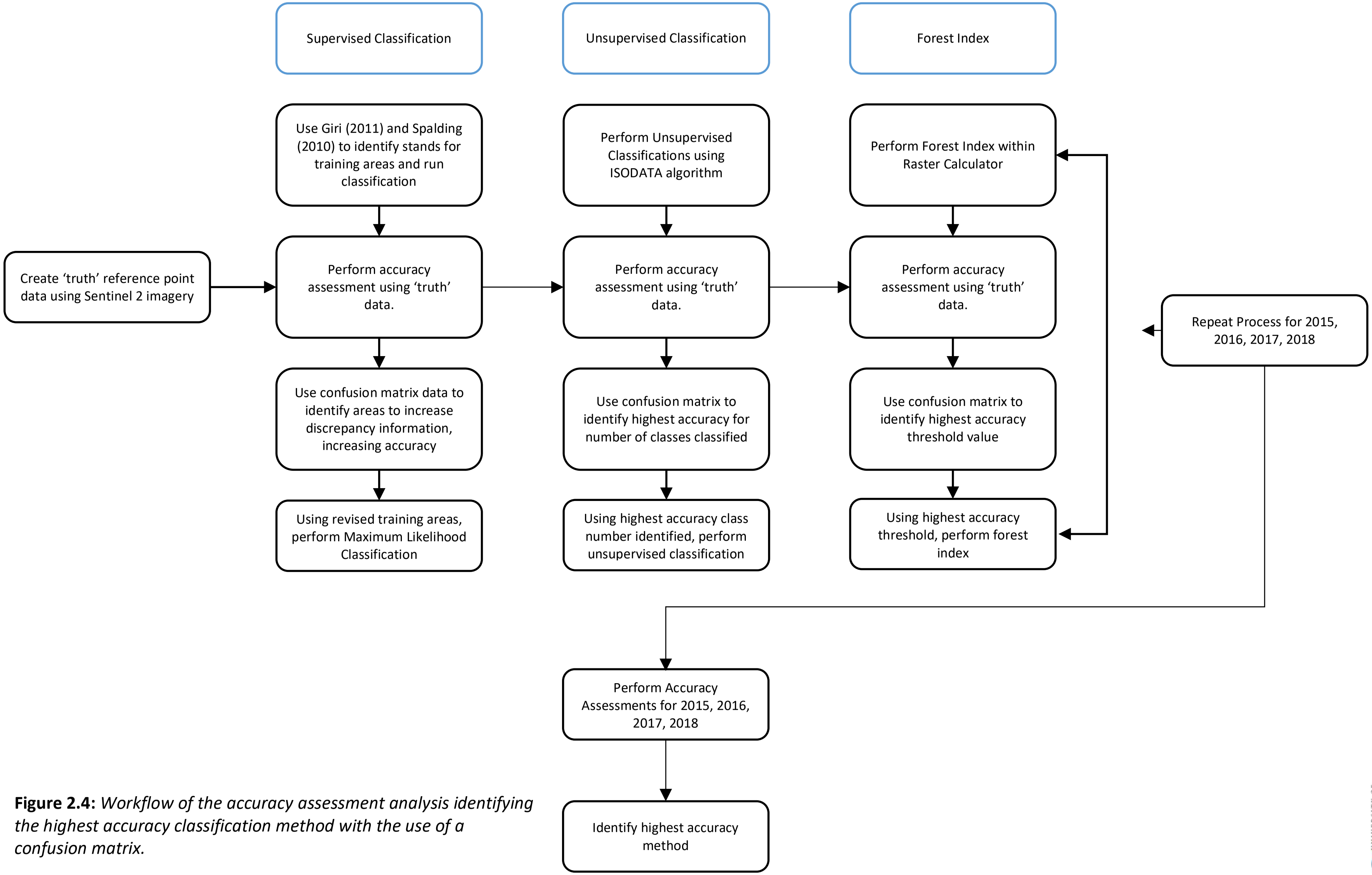


Figure 2.4: *Workflow of the accuracy assessment analysis identifying the highest accuracy classification method with the use of a confusion matrix.*

2.6 Climate Data Acquisition

To represent values for drought throughout the study period, SPEI values were downloaded through the global SPEI database (http://spei.csic.es/database.html). The index is based on monthly precipitation and evapotranspiration potential and offers robust drought estimates. The database offers long term information about drought conditions at 0.5 degree spatial resolution with a monthly time resolution. The multi-scale characteristics provided by the SPEI data ranges between 1 and 48 months providing wider analytical capabilities for timescales of effects. Three separate datasets were collected for the three study sites; the Saloum Delta, St Louis and Cape Timiris using the single location identifier tool within the website. The data returns drought values from 1901-2015, and data for the years within this study from 1984 to 2015 were then extracted.

Precipitation data were downloaded from the National Climatic Data Centre (NCDC), U.S. Department of Commerce. The website allows users to download 'Summary of the Day' data selected from any meteorological station globally. The weather stations with closest proximity to each study site were selected to represent the climatic conditions for each study site. The weather stations chosen are outlined in Table 2.6 and Figure 2.5.

Table 2.6: The meteorological stations used for climate data at each study site

Study Site	*Weather Station*
Saloum Delta	Kaolack
St Louis	St Louis
Cape Timiris	Nouadihiou

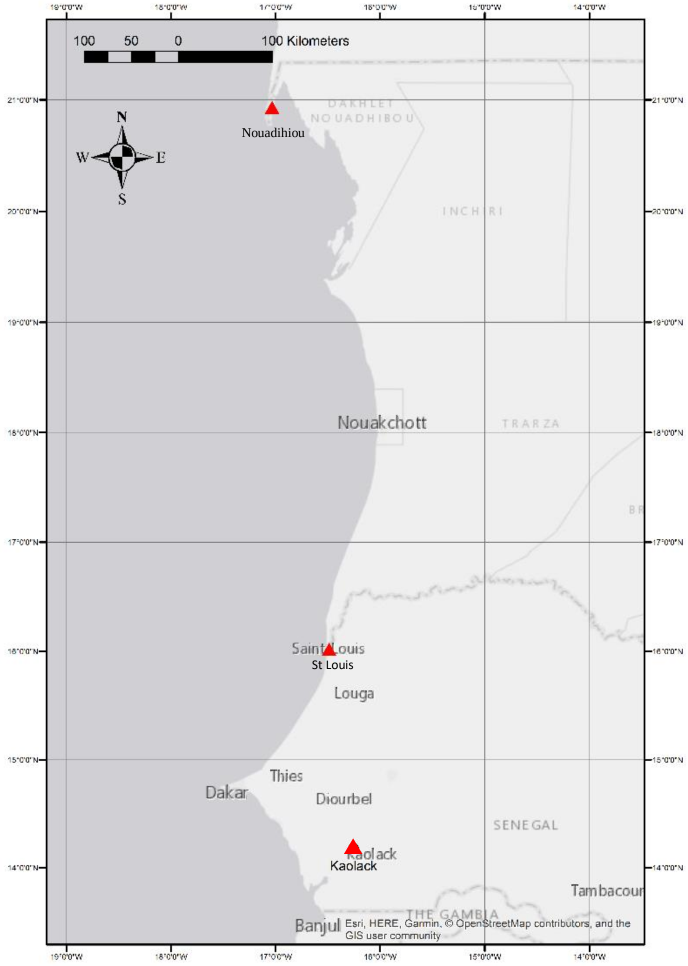


Figure 2.5: *Location of meteorological stations used to derive precipitation extreme metrics using daily averaged data as well as location of study sites.*

2.7 Climate Data Processing

Standardisation of the climate data from a csv to useable formats took place and conversions of all necessary data points to correct units (all precipitation data saved as 0.1inch) was undertaken as well as eliminating all null values.

As an alternative to SPEI values, extreme precipitation indices and their corresponding values were derived with the use of indices developed by the joint team of Climate and Ocean Variability, Predictability and Change (CLIVAR) the WMO Commission for Climatology (CCI) and the World Climate Research Programme (WCRP). Of the 40 indices outlined, 5 drought related indices were chosen to identify long term changes in drought in the study area. These indices were also used to identify any potential threshold values which may correspond to changes in area of mangrove communities. The indices used are outlined in Table 2.7 below.

These metrics were standardised to observe long term changes within the study period. The standardisation involved calculated the average of each metric for each study site throughout the study period, then subtracting the average value from the raw value (Formula 2).

$$M = x - \bar{x}$$

Table 2.7: Precipitation extremes used as alternative measures of drought

Abbreviation	*Name*	*Definition*	*Unit*
RTOT	Total annual Precipitation	Total amount of rainfall to fall within a year	Mm
R10mm	Heavy Precipitation Days	Annual count of days with daily precipitation totals above 10mm	Days
CDD	Consecutive Dry Days	Maximum number of consecutive days with rainfall less than 1mm	Days
CWD	Consecutive Wet Days	Maximum number of consecutive days with rainfall of at least 1mm	Days
R1mm	Number of Rainy Days	Number of wet days (i.e.) when daily rainfall is at least 1mm)	Days

2.8 Trend Detection in Climate Variables

Trend detection for climate data requires non-parametric statistical tests to identify statistically significant change. The Mann-Kendall (MK) test and Sen's slope estimator (Kendall, 1955; Mann, 1945) is identified by the World Meteorological Organisation as a suitable statistical test for the means. The aim of the MK test is to statistically evaluate whether a monotonic upward or downward trend can be identified from a variable of interest. The MK test and Sens slope estimate is used throughout literature including evaluation of trends in drought (Zhang et al., 2011). Within the test, Sen's slope is used to estimate the size of the trend deriving a value for the rate of change, whilst the significance of this value is evaluated by the MK test. A null hypothesis for no statistically significant change identifiable is accepted with a significance (α) value higher than 0.05, whereby α values lower than 0.05 represent statistically significant results and the slope estimate can be accepted. The MAKESENS 1.0 environment developed by the Finnish Meteorological Institute was developed for detecting and estimating trends in time series data for annual values for atmospheric and precipitation concentrations. It is therefore appropriate to use this within this study to identify trends in drought conditions with the use of the extreme metrics outlined above and has been used to identify and describe trends in the data.

2.9 Correlation Analysis

Once significant change within drought conditions were identified, correlation analysis between drought indices and calculated area change were taken place to identify statistically significant relationships between drought conditions and mangrove cover. Non-parametric statistical tests of Spearman’s Rho within SPSS software were adopted for this correlation analysis. A null hypotheses of no statistically significant correlation was accepted with an α value of above 0.05.

Initially, correlation analysis between SPEI values at all available timescales were tested to identify appropriate timescales for the effects of drought conditions on mangrove cover from 1 to 48 months. The information from this was then used as an indicator for appropriate time scales for further analysis.

Relative percentage change in mangrove cover between measurements were then calculated and compared to averages of SPEI values between mangrove measurements of 1, 12 and 42 months to investigate the positive or negative effects of SPEI values on mangrove cover. Spearman's Rho within SPSS was used for this correlation analysis to identify whether any statistically significant relationships could be identified.

After this, the identification of trends within the extreme indices above were followed by correlation analysis identifying trends between area of mangrove and the extremes indices using Spearman's Rho in SPSS.

3. Results

This section describes the key experimental results, identifying the results of the statistical analysis and the significance of these results.

3.1 Mapping Accuracy

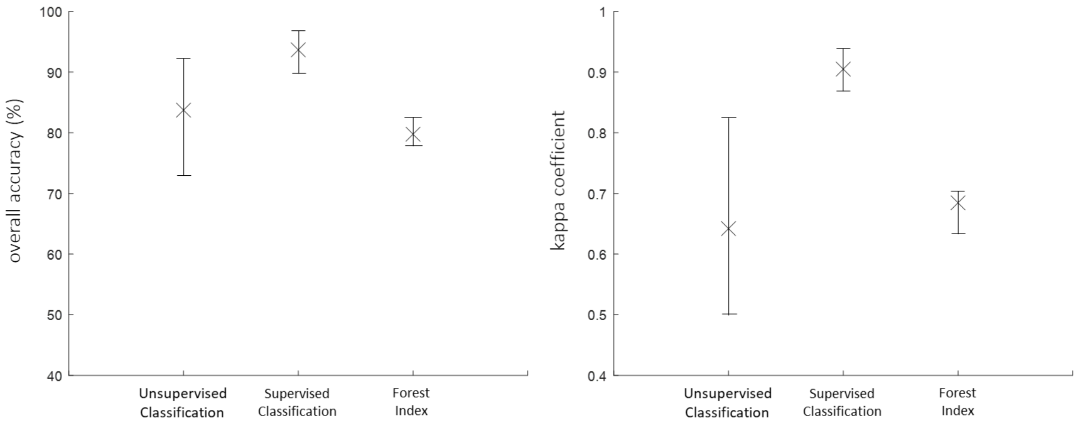


Figure 3.1: *Results from the accuracy assessments. Left is the results from the overall accuracy and right is the results from the Kappa Coefficient.*

Firstly, an evaluation for which of the common classification techniques identified within this study and the new classification brought back the highest results was undertaken. Out of the three classification methods, the Maximum Likelihood Classification method returned the highest average overall accuracy results of 93.7% compared to an average of 83.74% and 79.76% for unsupervised and the Forest Index respectively. The results showed similar levels of variance between accuracies for Maximum Likelihood Classifications and the Forest Index method, whilst the Unsupervised Classification method returned highly variable accuracy results, an indication of the risks of using this method as increased levels of variability in accuracy is present.

The Kappa Coefficient identifies similar results whilst taking into consideration randomly correctly assigned pixels. The statistically strongest classification method was again the Maximum likelihood classification, with an average Kappa Coefficient of 0.905, compared to a 0.642 and 0.685 for Unsupervised Classification and the Forest Index. All levels, however, fall below the statistical confidence intervals of 0.05, possibly as a result of inadequate number of verification pixels.

Table 3.1 below highlights the results for the confusion matrices of the classifications show that Unsupervised Classification has high omission and commission of mangrove classification between 21.25% and 25.72%, highlighting the miscalculation of all classes. The Supervised Classification has a much lower overall level of commission and omission of 6.25% and 6.24%, highlighting a far lower level of incorrectly classified pixels with far fewer confusion between classes. For the Forest Index though, the results show moderate levels of mangrove omission of 13.75%, yet has far greater commission of 27.97%, meaning mangrove classification pixels are far more likely to be allocated from other classes into the mangrove class within the Forest Index than for mangrove to be misclassified into another class. It is likely that this is a result of the confusion between similar spectral reflectance values for water and forest whereby darker water pixels are included into the values of mangrove cover.

Table 3.1: Results from the Commission and Omission errors

Classification	*Type of Error*	*Error*
Unsupervised Classification	Omission	21.25±9%
	Commission	25.72±13%
Supervised Classification	Omission	6.25±4%
	Commission	6.24±3%
Forest Index	Omission	13.75±8%
	Commission	27.97±9%

3.2 Mangrove Area Cover Change

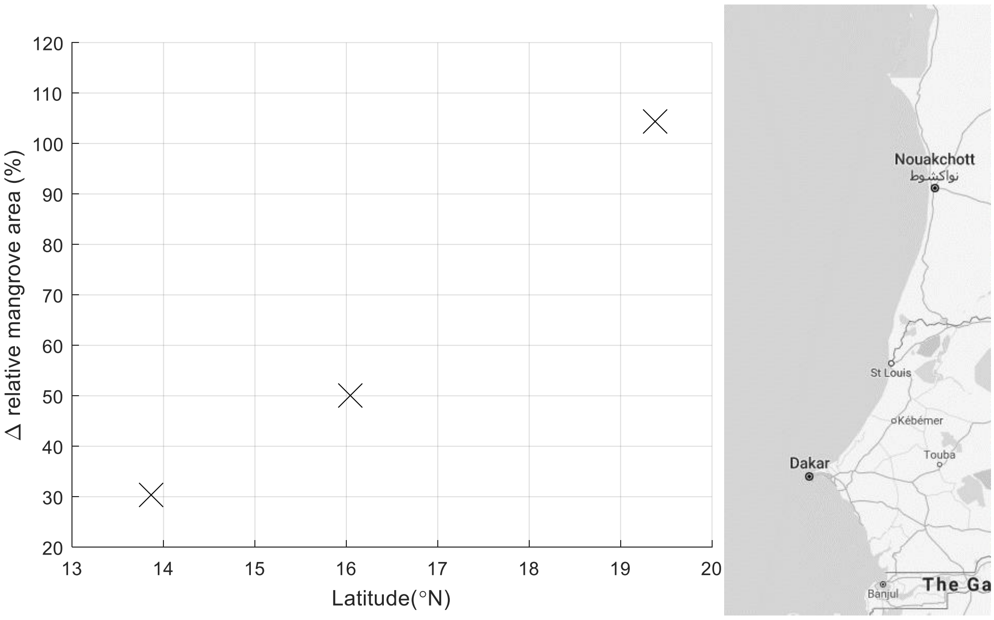


Figure 3.1: *Results from the mangrove area change results. The results are derived from the average of the last five years of the study (2014-2018) minus the average of the first five years of the study (1988-1984) to eliminate the effects of short term seasonality on the long term trend results. These results are then plotted against latitude*

Table 3.2: *Long term results for raw area change and the relative long term percentage changes.*

	Δkm² Mangrove Cover	*Δ % Mangrove Cover*
Cape Timiris	0.0368	104.37
St Louis	0.1955	50.06
Saloum Delta	6.3577	30.354

Using the MLC methodology, mangrove area cover was identified to increase significantly throughout the study period with significant increases of cover at all three sites. Long term area change is defined as the change between the averages of the first five (1984-1988) and last five (2014-2018) years of the study to eliminate short term variability in the results. In absolute terms, Cape Timiris showed an increase in 0.0368km^2, which translates to a 104.37% increase in mangrove area throughout the study period (Table 3.2). Study site two, the Senegal Estuary, showed an increase in area of 0.1955km^2, a 50.06% increase throughout the study period. Study site three, the Saloum delta, showed an increase in area of 6.3577km^2 or 30.364% increase in cover, these results shown in Figure 3.1 above. The long term area cover results show a correlation between the latitude of the study site, and the long term relative increases seen. Though all study sites show a strong increase in area cover, the further north the study site, a stronger increase in relative increase is identifiable.

3.3 Spatial and Temporal Patterns of SPEI

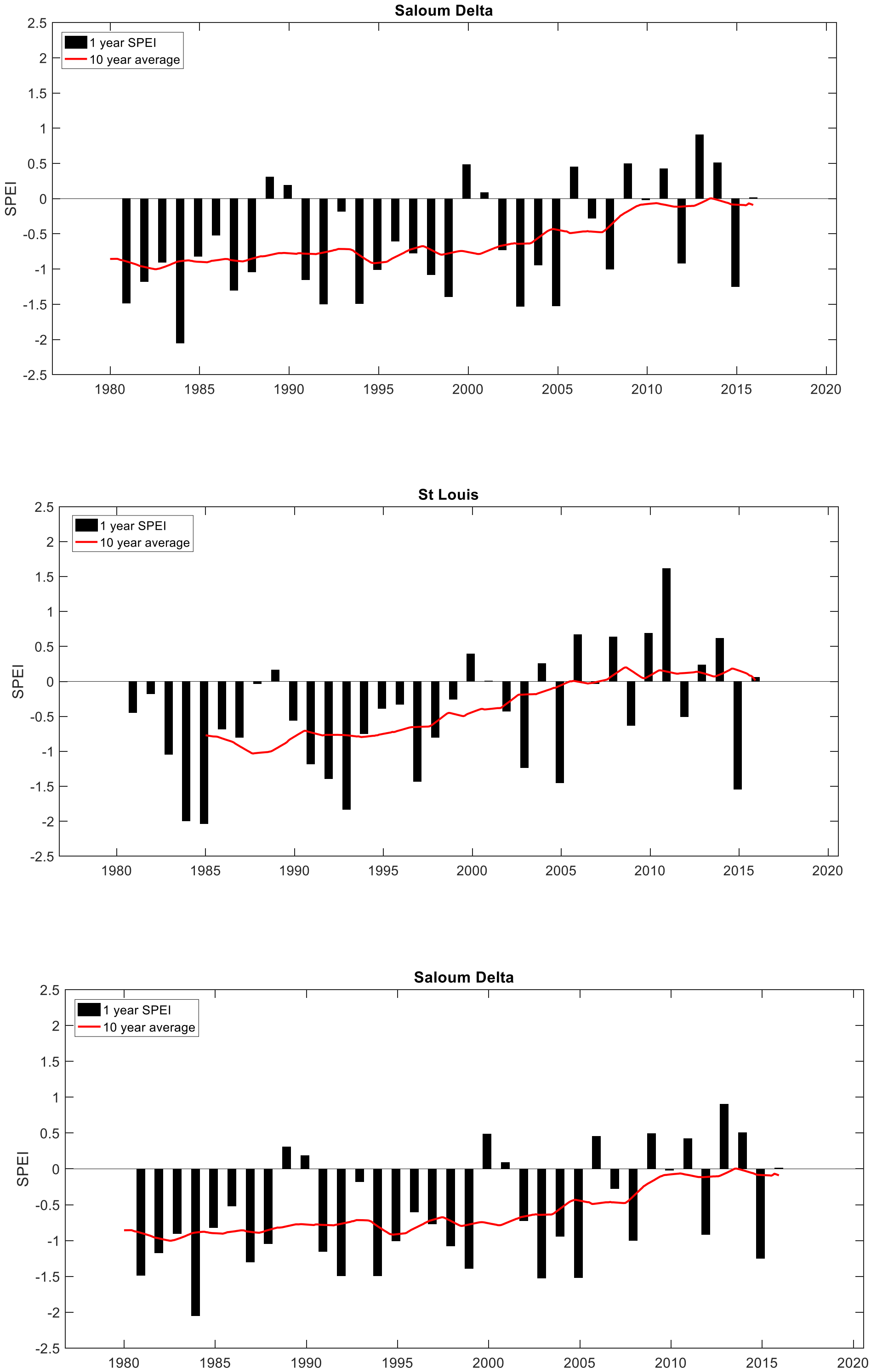


Figure 3.2: *Long Term trends in SPEI data from 1984-2018. The black bars within this figure represent the one year averages showing the variation between years and the red line represents a 10 year moving average to identify smooth long term trends in the data.*

The data for SPEI values are shown in Figure 3.2 above with 1 year SPEI averages represented by the black bars, and a 10 year running mean highlighted in red. The figure gives an illustration of the significant changes in drought conditions seen throughout the study period. All three study sites showed reduced droughty conditions throughout the 34 year timescale all at different temporal scales and magnitudes. The driest years for all three study sites occurred prior to 1985 with respective SPEI values around -1.5 to -2. This dry period is identifiable throughout the 1980s in all study sites.

Following this dry period, all three study sites showed a steady increase in long term SPEI values with both the Saloum Delta and St Louis sites showing a steady increase in moisture throughout the span of the data range to around 2010 where both sites show a plateau of moisture levels just below normal. Cape Timiris however showed a sharp increase from the 1980 strong drought conditions in the 1990s which then equalised around average moisture levels, with slight increases in the latter stages of the study period between 2010 and 2015. For all three study sites, the wettest yearly recorded SPEI value were post 2010, indicating a steady increase for all three study sites from the dry conditions experienced in the 1980s, to current experienced conditions.

3.4 Relationship between area cover and SPEI

3.4.1 Raw Values

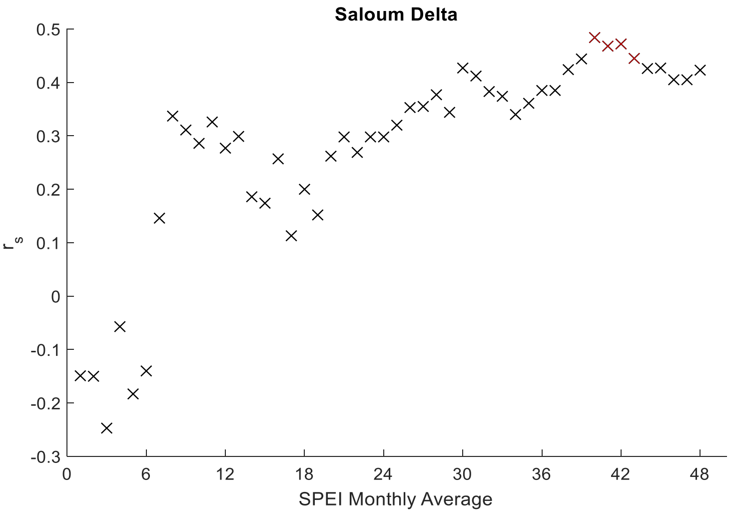
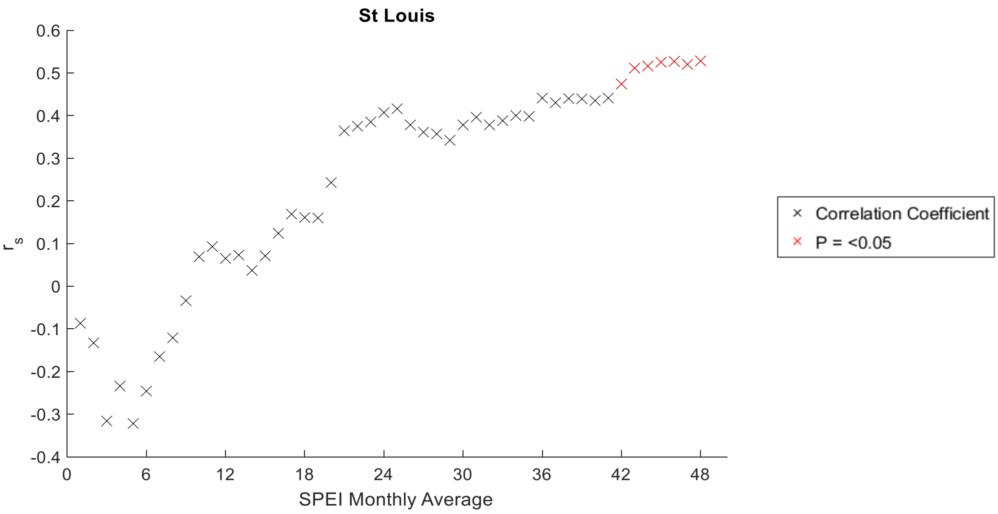


Figure 3.3: *Correlation coefficients derived from Spearman's Rho tests within SPSS. The coefficient from comparing each time average from 1 month to 48 month averages to changes in mangrove cover are plotted to identify which timescales reflect changes in cover most effectively.*



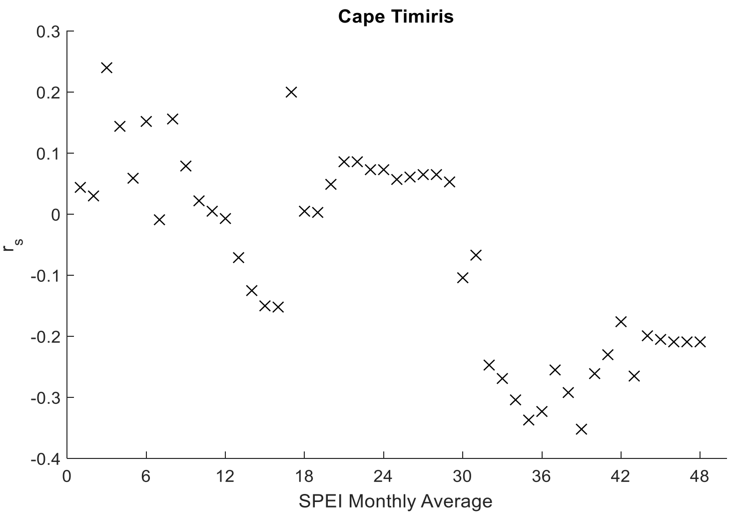


Table 3.4: Strongest *Results from the correlation analysis from SPEI values and mangrove area change.*

Study Site	*SPEI month average*	*Rs*	*P*
Saloum Delta	42	0.472	0.036
St Louis	48	0.528	0.024
Cape Timiris (Positive)	3	0.240	0.336
Cape Timiris (Negative)	39	-0.352	0.152

All 1-48 month SPEI averages were tested for correlation with changes in area cover for each study site. Two of the three sites returned statistically significant positive correlations between increases in mangrove cover and increases in SPEI values. The strongest relationships for all study sites were at 42 months for the Saloum Delta (Rs = 0.472 P = 0.036), 48 months for St Louis (Rs = 0.528 P = 0.024), and 3 months for the positive correlations for Cape Timiris (Rs = 0.240 P = 0.336) and 39 months for negative correlations for Cape Timiris (Rs = -0.352 P =0.152) shown in Table 3.4 above.

As seen above in Figure 3.3, the direction of the correlation and the significance depended strongly on the length of SPEI average in question. The Saloum Delta and St Louis sites show weak negative correlations between shorter timescale averages of SPEI values, with an increasingly strong positive correlation between the two values with the longer timescale average SPEI values. The Saloum Delta study site showed some potential seasonality within the results with continually increasing Rs values with peaks and troughs occurring 12 months apart from around 24 months to 48 months identifiable in Figure 3.3. Cape Timiris showed weak correlations throughout relationships with weak positive correlations with the shortest timescales, and weak negative correlations between the longer timescales of averaged SPEI values.

3.4.2 Relative Percentage Change in Cover

Figure 3.4: *This figure shows results derived from plotting SPEI averages between mangrove area measurements, against percentage change of mangrove cover between measurements to identify any potential threshold values for SPEI for positive or negative net growth.*

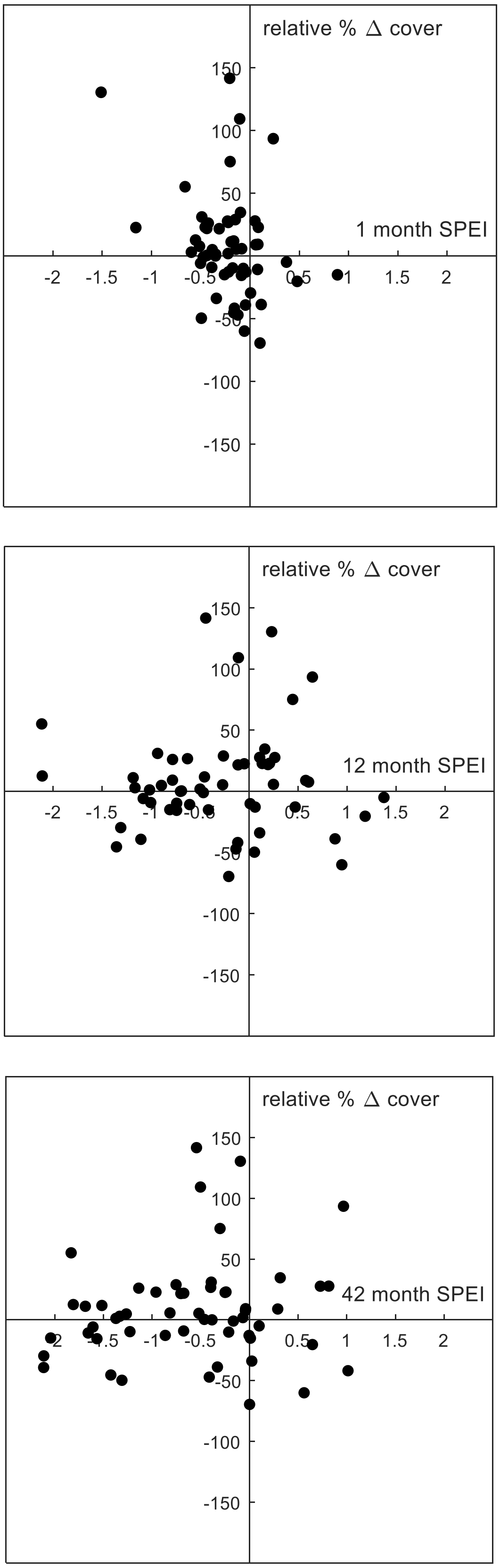


Table 3.5: Strongest SPEI averages

SPEI Average	*Rs*	*P*
1 month	-0.248	0.065
12 month	0.084	0.540
42 month	0.092	0.498

Relative percentage change in area cover between measurements were calculated and SPEI values for various timescales were averaged between these values to identify any relationships between SPEI values and direct changes in mangrove cover (Figure 3.4). 1 month averages were used to directly identify SPEI values between mangrove measurements, and then 12 month averages and 42 month averages were used to identify whether a significant increase in relationships could be identified with increasing SPEI timescale values and whether the results from previous correlation analysis would be effective in guiding direct mangrove percentage change analysis. The results show no significant relationships between 1 month averages, 12 month averages or 42 month averages. 1 month averages show a negative relationship of -0.248 ($P = 0.065$) with 12 and 42 month averages showing respective correlations of 0.084 ($P = 0.540$) and 0.092 ($P = 0.498$).

3.5 Changes in Extreme Indices

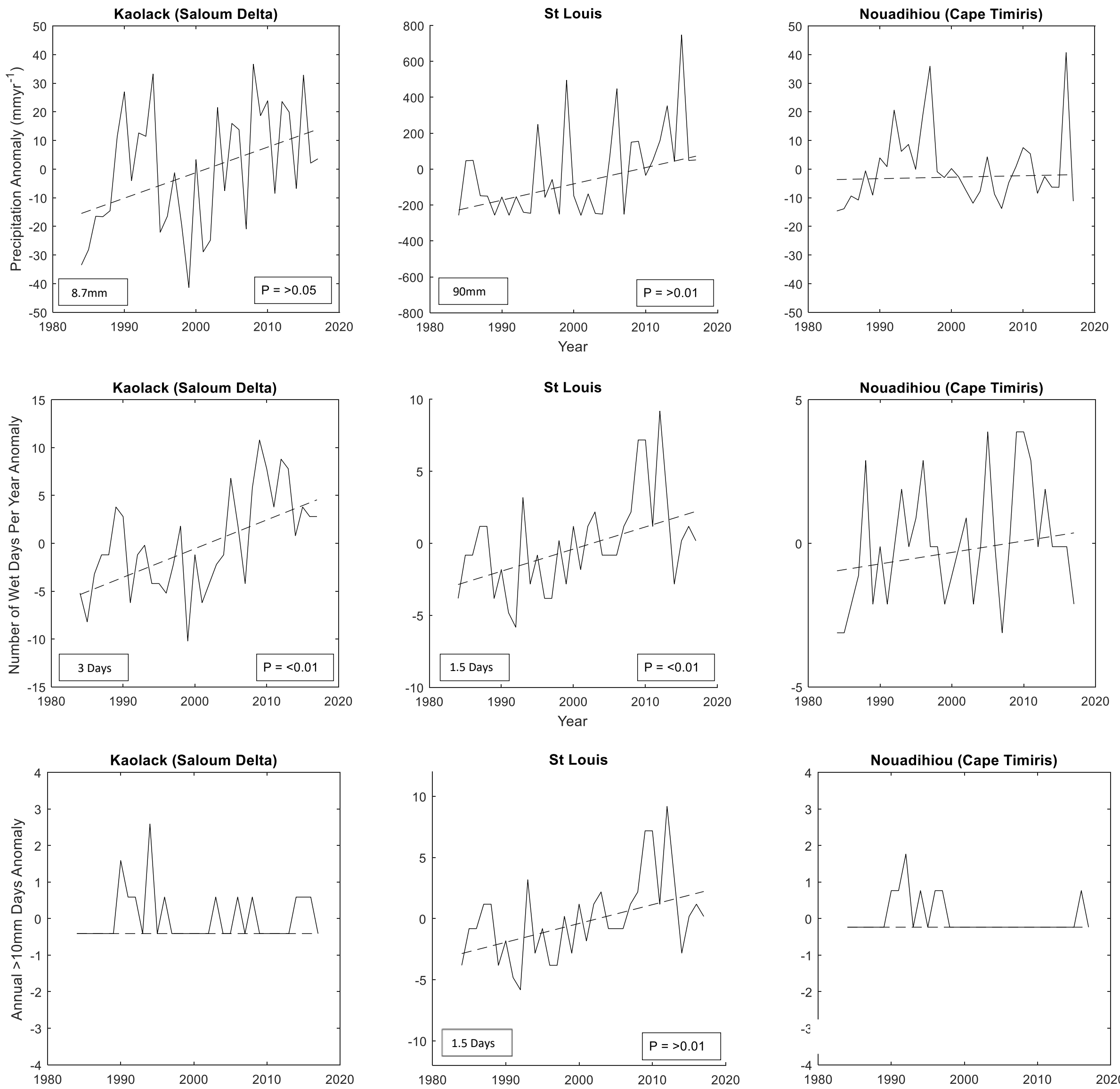


Figure 3.5: *This figure shows trends in extreme precipitation metrics derived from daily data collected from meteorological stations nearby the study sites. The direction and magnitude of the trends were identified by the Mann-Kendall and Sen's Slope estimates calculated within the MAKESENS1.0 environment developed by the Finnish Meteorological Institute. The numbers on the bottom left of each subfigure identify long term trends at units per decade of change. All statistically significant relationships are included.*

Long term changes in extreme precipitation metrics were tested to identify whether there would be any changes in precipitation variables as an alternative to SPEI values with the intention of identifying a direct driver of change for mangrove cover. The results from the MK and Sen's Slope tests for all the metrics calculated show strong variability. There is a statistically significant increase in the annual precipitation anomaly for Kaolack (P=<0.05) and St Louis (P=<0.01) weather stations although Cape Timiris showed no significant increase in accumulative annual rainfall throughout the study period. The increases in annual precipitation established are as a result of an increase in the amount of wet days per year, which also showed significant long term increases in the Kaolack and St Louis study sites (P = <0.01) (P = <0.01). Although no statistically significant change was observed, a small decrease in the maximum number of consecutive dry days is presented, however no change in the maximum number of consecutive wet days is observed. This shows that although there are increases in annual precipitation as a result of increased number of wet days, these days are variable in their presence occurring sporadically. No change in the number of heavy wet days above 10mm were observed for the Kaolack and Nouadihiou weather stations, however a significant increase in heavy wet days were observed for the St Louis study site indicating of the days that rainfall is occurring, the intensity of the rainfall is increasing also.

3.6 Relationships between Extremes and Mangrove Cover

Table 3.6: *Correlation Analysis between Precipitation Extremes and Mangrove Area Cover, the statistically significant relationships highlighted in green*

	Saloum Delta		*St Louis*		*Cape Timiris*	
	Relationship	Significance	Relationship	Significance	Relationship	Significance
RTOT	0.246	0.271	0.081	0.729	-0.098	0.665
R1mm	0.123	0.587	0.035	0.879	-0.101	0.655
CDD	-0.050	0.824	0.205	0.372	0.271	0.223
CWD	0.090	0.690	0.474	0.030	-0.144	0.612
R10mm	0.357	0.103	0.035	0.879	-0.094	0.678

Correlation analysis between the extreme weather indices and mangrove change was undertaken for all indices at all study sites. The results show no significant relationships other than a medium strength correlation between Consecutive Wet Days and mangrove cover at the St Louis site.

Although this is true, the relationship is no stronger than the relationships derived from the correlation analysis from the SPEI values and therefore indicate SPEI values are a better determinant of drought conditions and subsequently salinity and drought related thresholds than the extreme metrics derived by the joint team CLIVAR, CCI and WCRP.

4. Discussion

This section reviews the results observed within the study, placing the results into context of wider literature and existing knowledge, assessing their contribution to the main research questions (Section 1.7).

4.1 Classification Accuracies

The differences in classification accuracy shown within this study are typical of results gained from land cover accuracy assessment analysis. Kuenzer et al (2011) concludes that in general, applications of the Maximum Likelihood Classifier is the most effective and robust methodology for the production of land classification maps for mangrove mapping using traditional space borne data. The improvement of 9.96% and 13.94% of the Maximum Likelihood Classification compared to the Unsupervised ISODATA Classification and the Forest Index is subsequently reliable is it reflects considerable quantities of the literature.

The explanations for performance differences between the classifications used within this study are identifiable within the mechanisms of each classification. The ISODATA algorithm is known to have difficulties correctly identifying clusters when cluster means are not normally distributed. The iterative splitting and regrouping of clusters and recalculations of class means used within the algorithm works well for classes with distinct spectral reflectance values such as desert pixels, yet underperforms when analysing variable land types such as forest. Thus, the ISODATA algorithm effectively arbitrarily classes these pixels leading to high discrepancy within results (Bezdek, 1980). This is reflected in the high variance between accuracy results shown in this study, with lower overall accuracies than MLC.

The design of the Forest Index from Ye et al (2014) is based upon the understanding that the spectral features of forest tends to be darker compared to other vegetated surface types (Colwell, 1974). Yet issues with the difficulty differentiating between dark forest and dark water bodies are reported within this method are and addressed in Ye et al's (2014) paper. Although reports suggest accuracy rates up to 97.8% within Ye et al's (2014) work, highest accuracies achievable within this study are 79.76% as a result of confusion between water and mangrove forest (Figure 3.1). Thus, it can be suggested that the accuracy of the results from this method can be strongly affected by the quantity of water bodies within the images being processed. Of the three land cover types within this study and other mangrove related research, water represents a large percentage of the area and consequently the confusion between water bodies and mangroves deems the Forest Index to be mostly inappropriate for such purposes. However, it can also be suggested that the Forest Index is still a viable methodology of fast paced forest detection, with the prerequisite that water bodies be mostly absent within the images, or water mask production as a pre-processing being a prerequisite.

As well as this, Ye et al (2014) identifies that the difficulties distinguishing the spectral reflectance values only occur on images with atmospheric corrections, the poor performance of the classifications within this study might be representative of the atmospheric processing methods used on images by the USGS, compared to those methods used within Ye et al's (2014) paper. Thus, to identify the effects of the type of atmospheric correction applied, further research must be undertaken.

As a function of its working, the MLC extracts information from a user defined, multiple raster band composite image. The increased accuracy of these classifications over the Forest Index, therefore, is that the user can select bands which provide the best spectral differentiation between classes, reducing the confusion between these classes. Over the Unsupervised Classification, the MLC produces higher results through the user defined spectral reflectance values in which the algorithm classes pixels on a Maximum Likelihood basis. Yet, (Rozenstein et al., 2011) reports Unclassified ISODATA Classification results to show 70.57% over 60.83% for MLC. The low MLC accuracies however are determined to be as a result of low prior knowledge of study site and subsequently poor use of training areas. Within this study, the aid of mangrove shapefiles to determine mangrove area from Spalding et al (2010) and Giri et al (2011) research, provides accurate spectral reflectance values attributed to mangrove classes and subsequently accuracies exceeded those of the Unsupervised Classification.

Although the ranking of classification results show similar trends to the literature, the overall accuracies however appear to be influenced by the methodology behind the accuracy assessment. Otero et al (2016) identifies an overall accuracy of between 87 and 90% for a MLC for mangrove identification with the use of a comprehensive cross validation method of 2100 randomly sampled validation points. Other studies typically show similar results of 78.3-88.5% (Xian et al., 2009; Homer et al., 2004). With the knowledge that biases can emerge from various methods of accuracy assessment in accordance with the verification data collected (Congalton et al., 2008), it can therefore be determined that a potential cause of the unusually high accuracy results in this study are as a result of the methods and sampling strategy for collection of validation points. Yet, although this bias may lead toward higher than realistic overall accuracies, the overall ranking of classification methods identified remains reliable. The use of identical accuracy methodologies for all classifications as well as the MLC the only method which shows indication of exceeding the 85% accuracy threshold identified by Anderson et al (1976) for management and planning purposes shows this.

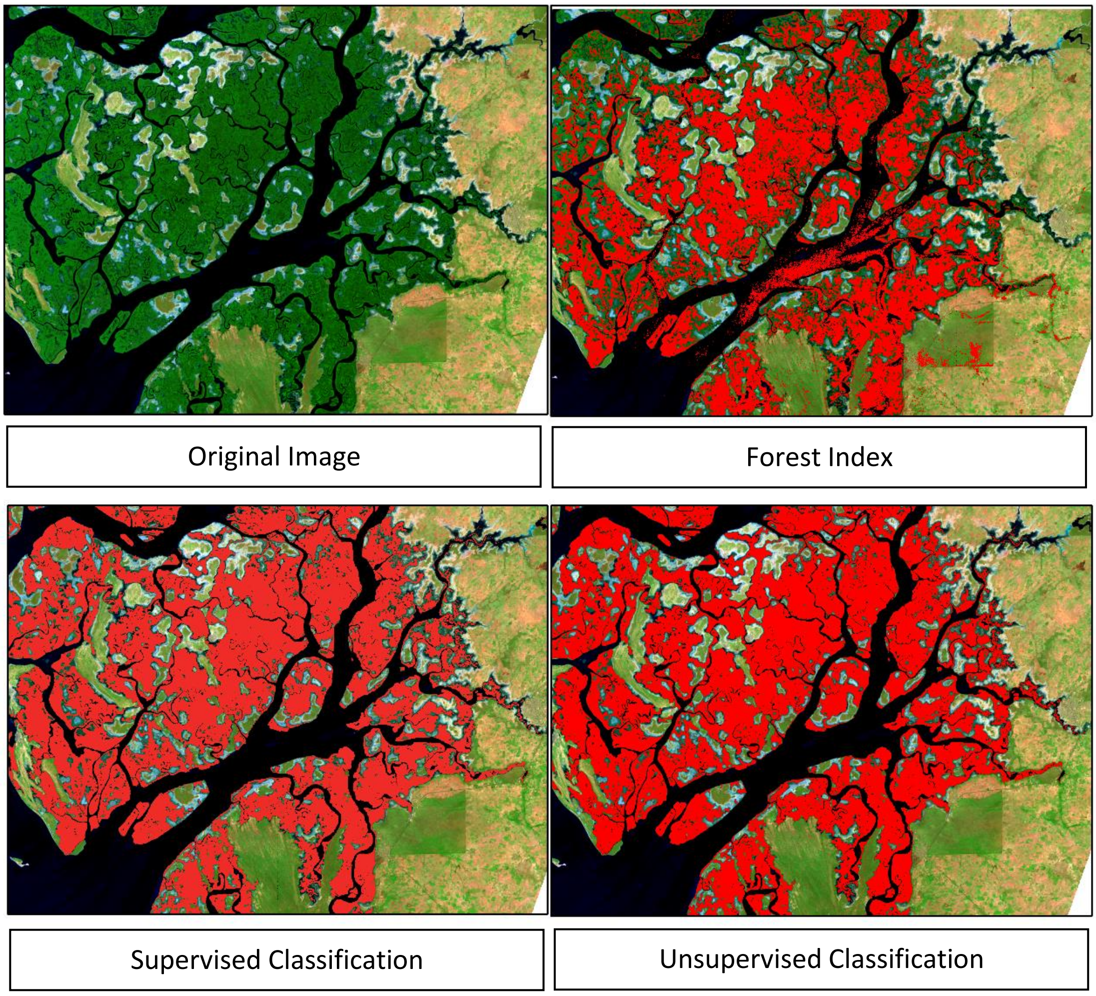


Figure 4.1: *An example of the typical classifications derived from each classification type. The original image is shown in the top left followed by each classification from the Forest Index, the Supervised Classification and the Unsupervised Classification Method*

4.2 Spatial Variation in Mangrove Area Cover

The lack of research on long term change analysis identified by Hickey et al (2017) is reflected by the inability to identify large quantities of sources of cross referencing for the spatial variation in mangrove cover within the study sites identified. Sakho et al's (2011) investigation to identify the drivers of change for a small estuary in Senegal identifies a long term decline in mangrove cover from 1946-1978, followed by a stabilisation of area between 1978 and1992 and a strong increase in area of 550% between 1990 and 2007. The trend in the data follows that identified within this study, yet the magnitude vastly exceeds those calculated here. Conchedda et al (2008) identifies changes in mangrove from south Senegal with an increase in mangrove area of around 0.75% yr^{-1} from 2002-2006. The results here reflect similar values to the long term increase of the Saloum Delta study site of approximately 0.89% yr^{-1}, further validating results that overall increases in mangrove area within the area are occurring, strengthening the idea of the rate of increase to be linked to latitude with the study site located south of those presented here at 12.5°N. These results are, however, not wholly comparable due to generation of results from information with different spectral and spatial resolutions and processing methods.

4.3 Trends in Precipitation and Drought Conditions

Trends in the results for precipitation regimes follow the findings of many lines of research identifying long term recovery of rainfall since the 1980s (Sanogo et al., 2015; Munemoto et al., 2012, Lebel et al., 2007, Herrmann et al., 2005; Nicholson et al., 2005). Most studies outline similar patterns of drought conditions to those identified in this study, with strong drought levels present from 1980-1990, followed by positive linear trends from 1990 to present conditions. Although research such as Sanogo et al's (2015) use SPI values as an indication of drought as opposed to SPEI values used here, the trends identified in both studies are comparable with results for all study sites observed here.

As well as overall droughty conditions, changes in extreme precipitation metrics within this study show similar results to other literature. Increases in annual rainfall of 8.7mm and 90mm per decade for Kaolack and St Louis show like results for the whole of the Sahel calculated by Sanogo et al (2015) of results between 5 and 200mm per decade reinforcing the results shown here. However, divergences appear when looking at the exact mechanisms resulting in increasing moisture conditions spatially and temporally. The statistically significant increase in very wet days (>10mm) shown at the St Louis site of 1.5 days per decade is representative of more localised conditions which do not occur throughout the wider Sahel region (Sanogo et al., 2015). As well as this, an increase in the number of consecutive wet days for the wider Sahel of 0.4 days per decade observed by Sanogo et al (2015) is not reproduced within the study sites here. This suggests that where increases in rainfall in the wider Sahel are as a consequence of increases in smaller, more frequent precipitation events, the results for the coastal study sites shown here are an outcome of sporadic, yet more intense rainfall events.

The recovery of moisture conditions within the area are suggested to be related to changes in the tropical rain belt over West Africa (Nicholson, 2005). Within the literature, this change is arguably credited to a recent increase in Atlantic Multidecadal Oscillation (AMO) values. These values have attributed to large sea surface temperature anomalies in the Northern Hemisphere Atlantic Ocean within the last two decades (Sanogo et al., 2015). Other studies identifying an increasing correlation between Atlantic Sea Surface

Temperatures and recovery of rainfall within the Sahel by Diatta and Fink (2014) strengthen these claims and provide explanation for the trends seen in the data.

4.4 Relationships between Mangrove Area and Drought Conditions

Trends found within this study establish a statistically significant relationship between drought values averaged over a minimum of three and a half years. This result shows strong comparability to suggestions by Davenport and Nicholson (1993) of a delay of three years for responses of mangroves to changes in precipitation regimes and freshwater input. Yet, results found in this study identify that this may only hold true for populations of mangrove with freshwater supply from riverine systems. Although the Saloum Delta and St Louis study sites showed statistically significant relationships between long term drought averages of no less than 40 months, the Cape Timiris site, although showing now statistical significance, shows opposing interactions with more positive relationships between area cover and drought levels over shorter timescales, and more negative relationships over larger timescales. As the only site within this study to receive no supply of freshwater from an upstream hydrological system, and the strongest positive correlation between SPEI and mangrove cover for this site being 3 months, it can be inferred that this site responds to changes in soil moisture, which strongly reflect short timescale SPEI values between 1-3 months (Mafi-Gholami et al., 2017). It can also therefore be suggested that the behaviour of mangrove populations without freshwater influx from upstream systems are more reflective of relationships between rainfall and wider vegetation types in the greater Sahel region of short timescale rainfall events (Herrmann et al., 2016), than mangrove systems with such provision of upstream resources. The results from the correlation analysis here also highlight indications of seasonality for the longer timescale averages of SPEI values (Figure 3.3). The results from the Saloum Delta study site show stronger relationships between half seasons than whole seasons. This is again reflective of the delay of the response of mangroves to precipitation values as the results show stronger relationships to multiple years of wet seasons over the intersecting wet and dry season alternatives.

Results of linear regression between patterns of rainfall and mangrove expansion by Elsami-Andargoli et al (2009) mirror correlation analysis results shown within this study of 0.472 and 0.528 for SPEI and area cover with R-square values of 0.4875 (P = 0.0006) for relationships of mean annual rainfall and changes in mangrove cover. Although not directly comparable, SPEI values are a derivative of total precipitation, and therefore results are related. Both results indicate that although precipitation determines some of the variation seen within mangrove area cover change, the full variance is not explained solely by precipitation. Other factors which are likely to influence the unexplained variance are fluctuations in the quantity of fluvial sediment and nutrient delivery, as well as reduced contact with sulphates and the direct salinity levels within sites (Elsami-Anargoli et al., 2009).

Although attempts to identify threshold values for drought and precipitation levels were attempted within this study (Figure 3.4), no identifiable threshold could be established due to an array of reasons. The moderate explanation values of the correlation analysis identifies that drought and precipitation doesn't explain all of the variation in area cover, thus other variables influencing the results make the identification of a threshold difficult. As well as this, the lack of large quantities of latitudinal variable study sites meant that only a small amount of data could be derived and subsequently not enough information was gathered to make any reasonable threshold results.

4.5 Future Predictions

As for predictions of future changes of mangrove cover on the West African coast for management and planning purposes, difficulties arise in predicting long term rainfall values. Although attempts to increase the predictability of the Atlantic Multidecadal Oscillation, which have resulted in the increased levels of rainfall since the 1980s, have been attempted (Tebaldi et al., 2007), there is no demonstrated method to determine when the AMO will switch, reducing the availability of long term future predictions. Yet, as identified within this study, a three and a half year delay is identifiable between increased rainfall patterns and increase mangrove extent and subsequently anticipation of short term variability may be achievable using precipitation and drought values for current and previous two years, which could aid in management and planning for various mangrove protective and economical uses.

5. Conclusion

5.1 Major Findings of the Study

The results from this study identify that remote sensing techniques can be used to accurately identify mangrove cover in arid environments. Accuracy assessments reinforce the current knowledge that the supervised classification method of Maximum Likelihood Classification produces the most accurate results for this ecosystem over Unsupervised ISODATA Classification algorithms and the experimental Forest Index method. Although these methods produce moderately accurate classification attempts whilst requiring lower levels of investment compared to the Maximum Likelihood Classification, neither the Unsupervised Classification method nor experimental Forest Index method produces results which indicate recommended accuracy for planning and management suggested by Anderson et al (1976) of 85%.

Thus as a result of the adoption of the MLC technique, although not certain due to a lack of quantity of study sites, this study establishes an apparent positive linear relationship between latitude and mangrove area cover change indicating a poleward expansion of mangrove in West Africa. Positive changes observed are statistically proven to be as a result of reductions in long term drought like conditions through site specific increases in moisture levels. Yet, this study suggests hydrological conditions of each study site may affect the timescales at which precipitation regimes affect cover change. The results suggest for sites without freshwater influx from an upstream hydrological system, mangrove populations are more reflective of soil moisture levels represented by 1-3 months of past rainfall in line with relationships between rainfall and wider vegetation types found in the wider Sahel region. Those systems which receive influx of freshwater from upstream catchment systems, however, show that relationships between rainfall and area change are only show statistical significance with no less than 40 months of drought data averages.

Although significant attempts to infer a threshold value for drought conditions and precipitation extremes are conducted here, multiple factors led to a result not being found. One factor influencing this is a lack of high temporal resolution data availability throughout the Landsat archives. As year on year change was not available throughout this study, no significant relationships could be derived. However, although the possibility of increased data availability may have increased the likelihood of a relationship to be found, SPEI values only showed moderate correlations to change. Subsequently, the influence of other factors such as delivery of sediment and nutrient from upstream sources, as well as direct salinity levels may make determining thresholds more difficult, and no conclusive threshold could therefore be found.

5.2 Limitations

One of the limitations involved within this research is a distinct lack of accessible method of calculating large quantities of land use change data. Although the results shown within this study provide an indication of the relationships expected, strong statistical relationships between mangrove percentage change cover and precipitation were limited by the lack of long term mangrove area change over a large spatial area. As well as this, although an apparent linear relationship between latitude and long term percentage change can be identified, no statistically significant relationship could be found through a lack of quantity of study sites across a range of latitudes. A low investment, accessible method of classification could therefore be pivotal for studies such as these by increasing the accessibility of the processing methods of large quantities of space borne imagery. Larger spatial areas including larger latitudinal ranges could be used as well as a temporal resolution below 1 year shown within this study, further increasing the chances of finding statistically significant relationships.

Another limitation regarding data accessibility is a lack of freely available high resolution datasets. Although for study sites shown within this study, which are large enough for medium resolution data to accurately reflect land cover, access to higher resolution (<$2m^2$) images could further increase the scope of studies such as this by increasing the range to less densely populated areas at higher latitudes, more susceptible to variation in climate variables (Dadough-Guebas et al., 2014). This study was restricted to areas where large continuous stands of no less than $30m^2$ occurred, limiting the latitudinal range to no further north than 19°N on the West Coast of Africa. Another benefit from increased availability of high-resolution satellite imagery is increased accuracy of validation data for the accuracy assessment. Although Sentinel-2 data provides higher spatial resolution data than the Landsat archives of $10m^2$, allowing for stronger distinction between land cover types, high resolution imagery such as IKONOS (<$1m^2$) adopted in Dabough-Guebas et al (2014) for similar uses of validation are more appropriate as 'mangrove trees are easily distinguishable at this level'. Thus the use of higher resolution data would increase the reliability of validation data reducing uncertainty.

More potential areas for uncertainty involve the dates of availability of the Sentinel-2 data used for the validation datasets. Although all years of data matched up, there were slight differences between the dates of the Landsat images and Sentinel-2 images being compared, increasing uncertainties within the accuracy assessments. As well as this, the Sentinel-2 data only stretched back to 2015, which restricted results to only four iterations of the accuracy assessment for each classification type, thus more accessible high resolution data would greatly benefit studies such as this.

The largest issue for validation data however arises from the lack of ground truth data present here. Throughout the literature, it is identified that to create a fully justifiable accuracy assessment for land cover analysis, ground truth data is a prerequisite (Congalton et al., 2008; Foody, 2002). Within this study, no ground truth data was accessible and thus, based on the sole interpretation of satellite imagery alone, the accuracy assessment is floored. However, although ground truth data isn't available, a cross validation method is still a respected accuracy assessment method (Dabough-Guebas et al., 2014; Otero et al., 2016) and thus, with the resources available, the highest achievable results were made within this study.

A source of uncertainty in regards to the climate data used within this study to derive extreme metrics could be the location of meteorological stations. Although efforts were made to find stations with the least distance possible from study sites, assumptions were made that the climate data collected from the met. Stations were representative of the climate at the study sites.

5.3 Improvements

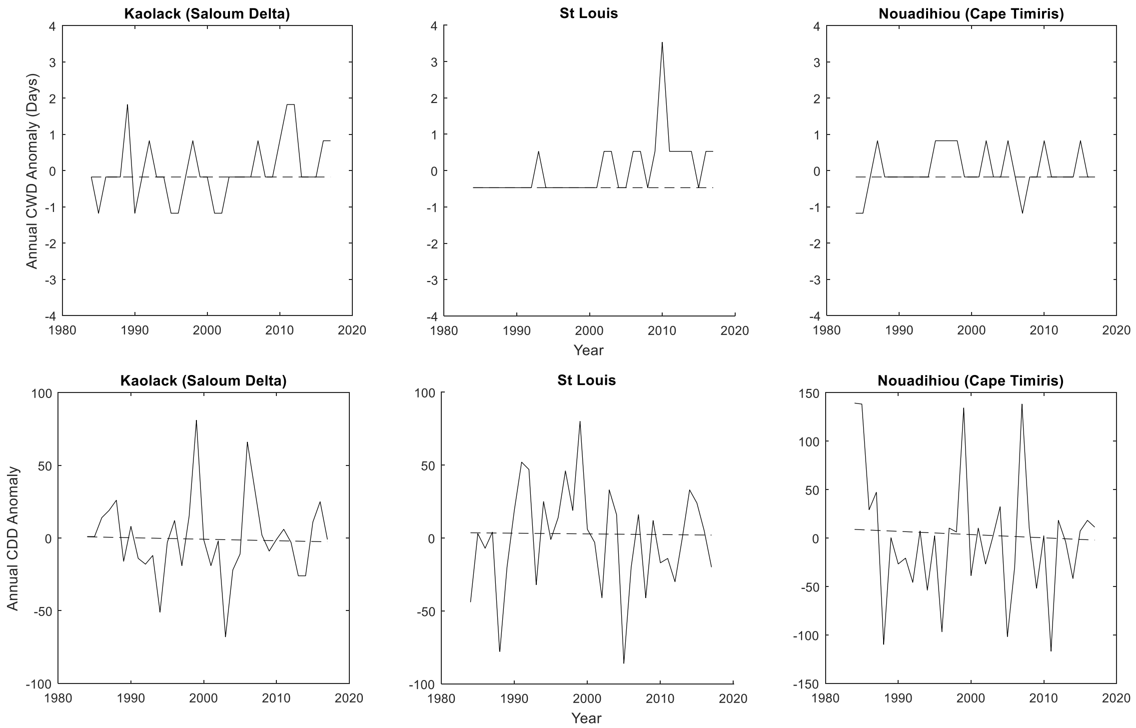
Many improvements within this study could be made with the use of high resolution satellite imagery. The possibilities of increasing the range of the study to areas of vegetation with lower population densities, as well as reducing the uncertainties involved with the creation of a validation dataset are two of the possible ways high resolution data are some of the benefits of high resolution data.

Potential improvements to the overall accuracy of classifications for the Forest Index method could be to include a water mask over images as a pre-classification step. This method would then have the potential to act as a fast paced method of image classification through the use of computational scripts. Yet, the feasibility of this would have to be determined with further research.

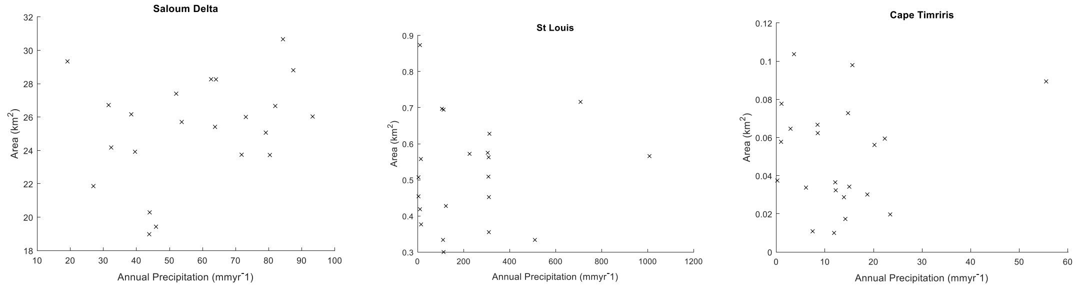
5.4 Suggestions for Future Research

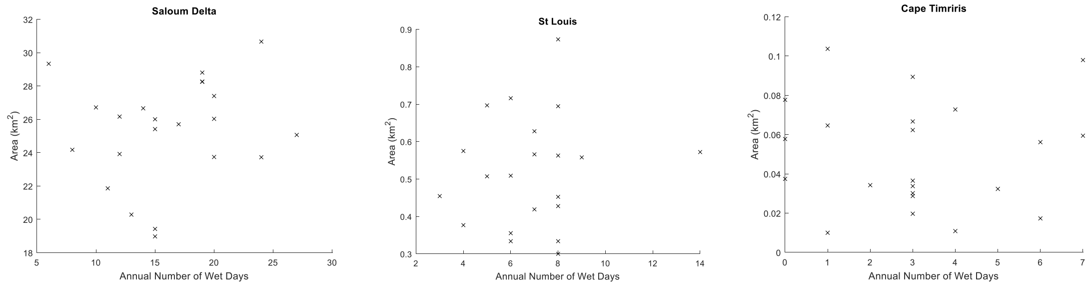
While results within this study determine increases in rainfall result in increases in mangrove cover, it cannot explain which of the many benefits for mangroves this brings. As explained above, increases in freshwater affect multiple elements of the environment from salinity levels to increases in nutrient input. Thus, further research collecting data on such variables could then couple this information with precipitation and area cover change to not only correlate changes in overall hydrological conditions, but the effects these conditions have on the composition of the water and how this affects growth. Examples of new methods to collect such data are through new technologies such as the GRACE satellite mission, which provides gravitational data, enabling the calculation of salinity based on the density of the water within the intertidal area (Yirdaw, 2008).

6. Appendices

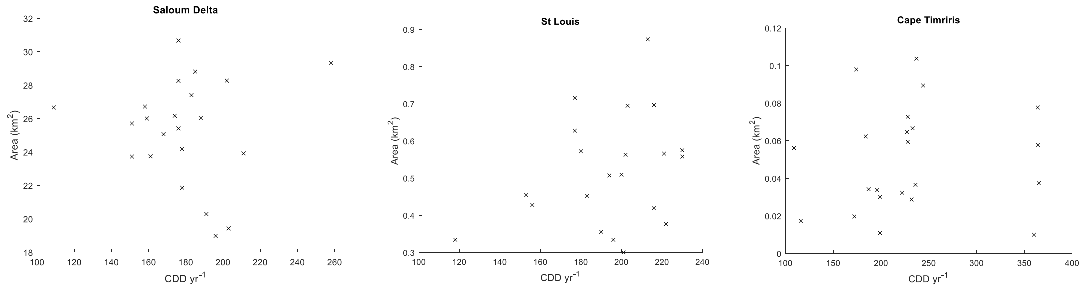


Appendix 1: *This figure shows the statistically insignificant relationships which were derived from the long term analysis of precipitation extreme metrics*

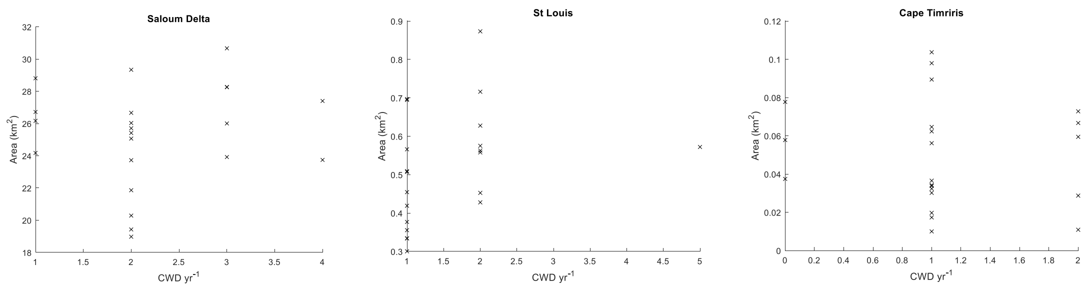


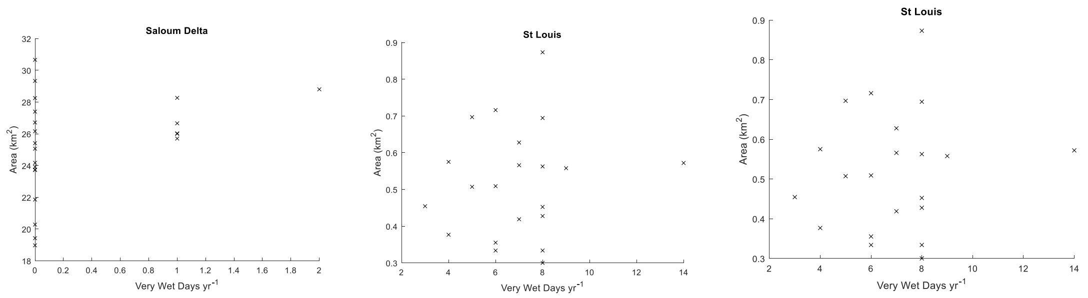


CDD



CWD





Appendix 2: *This figure shows the relationships between extreme precipitation metrics and raw mangrove area cover for each year with available data.*

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