Mapping and Monitoring Wetland Vegetation used by Wattled Cranes using Remote Sensing: Case of Kafue Flats, Zambia

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Mapping and Monitoring Wetland Vegetation used by Wattled Cranes using Remote Sensing: Case of Kafue Flats, Zambia

by

Zacchaeus Kinuthia Ndirima

Thesis submitted to the International Institute for Geo-information Science and Earth Observation in partial fulfilment of the requirements for the degree of Master of Science in Geo-information Science and Earth Observation, Specialisation: (Geo-Information Science for Environmental Modelling & Management)

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I certify that although I may have conferred with others in preparing this assignment, and drawn upon a range of sources cited in it, the content of this thesis report is solely my original work.

Zacchaeus Kinuthia Ndirima
Abstract

Kafue flats host one of the most threatened bird species, the wattled crane, where it depends on floodplain grasses and *Eleocharis*. However, little was known on the spatial distribution and growth patterns of this vegetation, nor the distribution of cranes in the environment. We explored vegetation distribution, temporal dynamics and relationship with ecoclimatic and hydrological conditions. We further investigated the crane-environment relationship by predicting its suitable habitat. ASTER (March 2005) and MODIS (September 2006) images were classified into six and four cover classes, respectively. Time series MODIS vegetation indices were derived to monitor vegetation temporal dynamics and relate observed changes with environmental variables. The derived Aster classes were regressed with crane presence/absence data to reveal habitat use and trend.

*Eleocharis* and floodplain grasslands were mapped with high accuracy using MLC (> 83%) and MDC (> 78%). Presence of both cover classes declined with elevation although *Eleocharis* was found to favour low elevation areas liable to flooding due to its requirement for wet conditions. Both classes exhibited four growth phases over April-November as revealed by vegetation indices. Moreover, ANOVA revealed July-November as the best time to monitor *Eleocharis* due to its significant differentiation from the rest using EVI. Monitoring during the other months would be limited by its inseparability with other classes. Results further showed significant correlation between hydrodynamics and wetness index (LSWI), and positive correlation with vegetation greenness (NDVI). Logistic regression further revealed that *Eleocharis* and floodplain grasses are crucial in determining the presence of wattled cranes. This is irrespective of the fact that *Eleocharis* is likely to support cranes for a relatively longer duration than floodplain grasses owing to variation in wetness conditions. In addition, vegetation greenness (NDVI) improved the predictive power of the model thereby enabling to delineate suitable foraging habitats from April to November. Nevertheless, the habitat declined from 18000 in April to 6000 hectares in November.

We therefore concluded that *Eleocharis* and floodplain grasses could be mapped with high accuracy using Aster; while MODIS derived indices would provide data for monitoring temporal dynamics. Moreover, the two classes form crucial habitat for wattled cranes despite exhibiting fluctuations over time. We recommend long-term study on the influence of vegetation temporal changes on resource use, distribution and breeding of cranes.
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ABREVIATIONS & ACRONYMS

ANOVA – Analysis of Variance
ASTER – Advanced Spaceborne Thermal Emission Radiometer
AVHRR – Advanced Very High Resolution Radiometer
AVIRIS – Airborne Visible/Infrared Imaging Spectroradiometer
DEM – Digital Elevation Model
EL – Eleocharis
EVI – Enhanced Vegetation Index
fAPAR – Fraction of Absorbed Photosynthetically Active Radiation
FLG - Floodplain Grassland
GCP – Ground Control Point
GPS – Global Positioning System
ITCZ – Inter-Tropical Convergence Zone
LAI – Leaf Area Index
LSWI – Land Surface Water Index
MD – Minimum Distance
MLC – Maximum Likelihood Classifier
MODIS – Moderate Resolution Imaging Spectroradiometer
MSAVI – Modified Soil-Adjusted Vegetation Index
NASA – North Atlantic Space Agency
NDVI – Normalised Difference Vegetation Index
NIR – Near Infra-Red
NOAA – National Oceanic & Atmospheric Administration
SAVI – Soil Adjusted Vegetation Index
Ses – Sesbania sesban
SRTM – Shuttle Radar Topographic Mission
SWIR – Short Wave Infra-Red
TIR – Thermal Infra-Red
TSAVI – Transformed Soil Adjusted Vegetation Index
UTM – Universal Transverse Mercator
Ver – Vernonia glabra
VH – Vetiveria & Hyperrhenia
WWF – World Wide Fund for nature
ZAWA – Zambian Wildlife Authority
1. INTRODUCTION

Wetlands are considered valuable ecosystems although they occupy only 4% of the earth’s ice-free land surface (Prigent, 2001) or an estimated 1.2 million square kilometres (Millennium Ecosystem Assessment, 2005). Their importance ranges from economic, social, recreational, scientific, and cultural perspectives; to providing ecological habitats for flora and fauna. They also perform crucial ecological functions, such as enabling ground water recharge, nutrient retention, flood and erosion control, and sediment filtration (Simonit et al., 2005; Junk, 2002; Rundquist et al., 2001; Junk, 2002; Millennium Ecosystem Assessment, 2005). Within the southern Africa region, there are numerous wetlands renowned as hotspots for biodiversity conservation, among them the Kafue wetlands. They not only provide habitats to species that inhabit them permanently, but also provide long-distance migrant birds that nest in temperate zones with critical habitats during winter (Thompson & Polet, 2000).

Among the bird species that utilise these wetlands are members of the Crane family, the *Gruidae* (ICF, 2006). The family *Gruidae* comprises two subfamilies, *Gruinae* (with 13 species) and *Balearicinae* (with 2 species) (Jones, 2003). Species within the sub-family *Gruinae* inhabit all continents except Antarctica and South America with some being migratory and others sedentary (Jones, 2003). However, despite the wide geographical spread, cranes are among the world’s most threatened birds. According to Meine & Archibald (1996), 10 of the 15 known species are globally threatened.

The Wattled Crane (*Bugeranus carunculatus*), the only member of the genus *Bugeranus*, is the largest and rarest of the six crane species found in Africa (Jones, 2003; McCann et al, 2001). They are endemic to the Afro-tropical region, where they occur in disjunct populations between Ethiopia and South Africa. They inhabit wetlands and river systems in 11 countries (see figure 1.1) although the largest population is found in riparian wetlands of southern Africa (Kamweneshe & Beilfuss, 2002; Jones, 2003). According to (Meine & Archibald, 1996), the species is the most wetland-dependent of African cranes. This is because they forage and breed in wetlands although they sometimes utilize grasslands in neighbourhood for nesting and foraging. This implies that grasslands form part of their critical habitat worth consideration in their conservation.

Unlike other crane species, wattled cranes are non-migratory. They exercise local movements in response to floodwater availability (Meine & Archibald, 1996). They
tend to be localized in certain regions for most of the year. Kamweneshe et al (2003) report that of the global population of 8000 individuals, an estimated 4500 are found in Zambia where they are spread in all major wetlands. However, within the Kafue flats, a survey conducted in 2001 showed they were concentrated between 15°30’-15°42’S and 27°00’-27°38’E (Kamweneshe & Beilfuss, 2002). This raises the question of what confines them to wetlands and river ecosystems and not other areas.

Meine & Archibald (1996) suggest three main reasons: 1) cranes live on tubers excavated from wet/swampy zones, and these plants grow favourably in wetland conditions, 2) shallow wetlands provide security from predators/invaders and wildfires during nesting period while still ensuring that the nesting is not swept away by running water; and 3) wetlands by virtue of being inaccessible reduces human interference and this allows for successful breeding. Although their argument seems to conclude that feed source, breeding and security are the main influencing factors
in distribution, there are no records of predictive modelling relating presence with vegetation or other factors as has been carried out for other wildlife species.

Nevertheless, literature indicates wattled cranes as omnivorous species that feed on bulbs and rhizomes of grasses and sedges, water lilies, grass seeds, insects, small reptiles (Meine & Archibald, 1996; Beilfuss, 2000; Kamweneshe & Beilfuss, 2002; O’Glady, 2003; ICF, 2006), as well as *Nymphoides* spp. (Kamweneshe, Per. Comm.). They however have preference for the *Eleocharis dulcis* (Bokach, 2002; ICF, 2006; Kamweneshe & Beilfuss, 2002), which grows in abundance along the extensive riparian floodplains of major river systems (Meine & Archibald, 1996). It has been alleged that the availability of *Eleocharis* feed source is the main factor behind the distribution pattern.

*Eleocharis* is a stoloniferous perennial herb with tufted culms from a contracted base, and attains heights of more than a metre (Haines & Lye, 1983). The sedge grows favourably under shallow flooding conditions, with slightly acidic fertile soil conditions (Bokach, 2002; Percy Fitzpatrick Institute, 2002). It performs best at temperatures between 30 - 35°C during growth, and about 5°C lower during tuber formation (Plants for a Future, 2006). However, although favouring flooding conditions, cycles of wetness and drying are necessary for its survival and abundant tuber production (Beilfuss, 2000). This is because growing under constantly flooded conditions leads to sexual reproduction which lowers tuber formation (Percy Fitzpatrick Institute, 2002), consequently limiting the feed source for cranes (Morrison, Per. Comm.). Moreover, wet/swampy conditions are required to enable tuber extraction by cranes. Bokach (2002) observed the tendency among wattled cranes to abandon dry zones because the ground was impenetrable and, hence, difficult to extract tubers.

Within the Kafue ecosystem, the growing conditions of *Eleocharis* depend on the seasonal variation in inundation. The floodplains experience distinct flooding with water levels starting to rise by November-December, peaking in March to May, before receding during the dry season (Schelle & Pittock, 2005). This cycle has for decades ensured the survival of inundation tolerant emergent species, grasses and sedges that provide feed supply to the diverse species of birds and fauna.

However, like many wetlands around the world that have experienced hydrological alterations (Brinson & Malvarez, 2002; Junk, 2002; Gibbs, 1998), the Kafue
wetlands has since 1970s faced similar conditions, with enormous effects on the flooding regime and extent.

The hydrological changes started with the construction of two dams: a 45m high hydro-electric power dam at Kafue Gorge in 1972 and a 65m high Itezhi-tezhi reservoir dam in 1978 (Munyati, 2000). The Kafue Gorge dam was constructed to generate electric power for local use and export to Zimbabwe and South Africa. However, it proved inadequate to meet the demand over time. To keep pace with rising power demand, Itezhi-tezhi Dam was constructed to store water, some 200 kilometres upstream on the western end of Kafue flats. Since then two main problems arose. First, water outflow was regulated to achieve maximum power generation throughout the year (Nyambe & Schepers, 2004). Secondly, water discharge was maximised during the dry season to allow the Kafue Gorge dam to supply electricity at the time of high power demand during winter (Schelle & Pittock, 2005). This management created a non-natural discharge such that some areas continue to be flooded even during the dry season.

What is the effect of these hydrological changes on wattled cranes? Ecologically, the two episodes have profound effects that put a pressure on the feeding habitat and conservation of wattled cranes. First, water regulation and release in minimal amounts has affected the previous extent of flooding, such that some areas are no longer inundated. Secondly, the non-natural floods have altered the ecology of the flood plain thereby impacting on the spatial distribution of floodplain vegetation. According to Mumba & Thompson (2005), the ecological implication of hydrological change is well reflected by species composition and structure. They reported rapid expansion of woody species (Mimosa pigra) in permanently flooded areas or at least those flooded for longer periods than in the past. They also reported an increase of tall inundation tolerant grasses, papyrus reeds and Typha, and a decline of less inundation tolerant species in continuously flooded zones. Inundation dependent species have also declined in areas deprived of natural flooding or where inundation was shortened (Mumba, 2004). Kamweneshe (Per. Comm.) reiterated that Eleocharis has not been spared either by these changes. In continuously flooded zones, it produces less tubers and is inaccessible to cranes, while in high elevation areas and those far from the Kafue river with short lived inundation it does not produce tubers as it dries out soon after water recession.

The above information suggests that the flooding gradient influences vegetation composition, distribution and growth patterns, as well as extent of suitable foraging
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habitat for cranes. However, hardly any information exists about it. We therefore anticipated that: 1) based on vegetation types resulting from varying inundation, it would be possible to map the distribution of *Eleocharis* and associated grasslands; 2) the varying growth patterns of *Eleocharis* would help understand the time spans of food availability to wattled cranes; and 3) the distribution of wattled cranes would be closely related to that of their main foraging habitat - *Eleocharis* and grasslands. To fill this knowledge gap, mapping and monitoring of vegetation seasonal changes became pertinent.

Wetland mapping has been used to determine the spatial extents of vegetation types for situational assessment and monitoring (Moser *et al*., 1999). Traditionally, it has involved carrying out ground surveys/on-site analysis (Barthlott *et al*., 1999) that provided detailed data sets. However, due to inaccessibility, it has always meant that collected data be extrapolated to describe the conditions in unmapped areas (Thorsell *et al*., 1997). Moreover, the variation in sizes, location, inaccessibility and costs related to additional personnel, equipment and time has rendered such efforts less valuable (Rundquist *et al*., 2001; Harvey & Hill, 2001).

Increasingly, remote sensed data are being used for wetland mapping and monitoring (Harvey & Hill, 2001; Johnson *et al*., 1999; Hessa *et al*., 2003). This is because remote sensing provides a synoptic view, multi-spectral and multi-temporal coverage while still being cost effective (Rundquist *et al*., 2001). Such remotely sensed data are interpreted visually or through automated image classification (Zalazar, 2006) to help understand wetland dynamics. We therefore anticipated that using time series data, we would not only map the spatial distribution of *Eleocharis* and grasslands, but also understand their dynamics.

Studies based on optical remote sensing have demonstrated this capability owing to their long period of data acquisition. Such studies have also shown that it’s possible to map the resource in question at high accuracy. For example, Sader *et al* (1995) used Landsat TM in forested wetlands of Maine and achieved accuracy of 82%. Similarly, Harvey and Hill (2001) using SPOT, and Landsat data in Australia achieved accuracies of over 70% for each. In the recent years, the Advanced Spaceborne Thermal Emission Radiometer (ASTER) is increasingly being recognised as a source of remotely sensed data because of its high spatial resolution (Mendoza *et al*., 2004). Similarly, high temporal resolution sensors, NOAA-AVHRR and Moderate Resolution Imaging Spectroradiometer (MODIS), have been applied with preference for MODIS due to high spatial resolution (Huete *et al*., 2002) and data quality.
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(Pettorelli et al., 2005). Use of Radar in wetland vegetation mapping has been minimal though well demonstrated by Baghdadi et al. (2001); Dwivedi & Rao (1999); Augusteijn & Warrender (1998) and Horrit et al. (2003). Recently, hyperspectral remote sensing has been applied (Schmidt and Skidmore, 2003) and is proving adequate for wetland mapping.

While most of the above data sources are sufficient for single time mapping, monitoring of seasonal phenology requires regular availability of data. Studies (Delbart et al., 2005; Zhang et al., 2003; Beck et al., 2006; Boles et al., 2004; Xiao et al., 2006; Ahl et al., 2006; Elmore & Asner, 2005; Pettorelli et al., 2005; Zhang et al., 2003; Davidson & Csillag, 2003) have demonstrated the fundamental importance of multi-temporal remotely sensed data in revealing vegetation dynamics. Nevertheless, the need for multi-temporal data brings into perspective the question of availability and affordability. This drives the consideration of freely available sources like MODIS and NOAA-AVHRR. In the recent past, MODIS due to its narrower nIR band that avoids water absorption regions of the spectrum, and increased chlorophyll sensitivity in the red band (Huete et al., 2002) has been preferred. The derived data are used to calculate vegetation indices (VIs) for monitoring.

Vegetation indices are mathematical quantities based on spectral reflectance in the visible and infrared bands that inform about presence or absence of vegetation (Lillesand & Kiefer, 2002). Huete et al., (2002) argue that they help isolate green photosynthetically active signal from the spatially and temporally mixed pixels for meaningful intercomparisons of vegetation activity. They include the Normalized Difference Vegetation Index (NDVI), Land Surface Water Index (LSWI), Enhanced Vegetation Index (EVI) (Sakamoto et al., 2005; Lunetta et al., 2006; and Reed, 2006); normalized water vegetation index (NWVI) (Delbart et al., 2005); soil-adjusted, modified soil-adjusted and transformed soil-adjusted vegetation indices (SAVI, MSAVI and TSAVI) (Purevdorj et al., 1998; Reed, 2006). Among these, NDVI is the most commonly used and relies on the absorption of red radiation by chlorophyll and other leaf pigments in the red spectrum, and strong scattering in infrared spectrum (Beck et al., 2006). Its application is broad and includes the assessment of leaf area index (LAI), green cover, biomass, and fraction of absorbed photosynthetically active radiation (fAPAR) (Pettorelli et al. 2005, Huete et al., 2002).
Time series of vegetation indices have also been used to generate spectral profiles for revealing vegetation phenological changes (see Huete et al, 2002, Chen et al, 2006). This involves the use of algorithms/logistic functions (Beck et al., 2006) to identify transition dates: green up, maturity, senescence and dormancy (Zhang et al., 2003) both in cultivated crops and natural environments (Zhang et al., 2003; Sakamoto, 2005; Dennison & Roberts, 2003; Elmore & Asner, 2005). More so, when correlated with environmental variables they help understand the spatial-temporal variations of vegetation that are related to environmental changes - ecoclimatic and hydrological (Wang et al., 2001; Xiao et al. 2005; Paruello et al., 2005).

With this backdrop, we anticipated that remotely sensed data would enable us map the distribution and understand the seasonal dynamics of *Eleocharis* and grasslands, in addition to revealing the relationship with environmental changes.

1.1. **Study Objectives**

This study explored the possibility of mapping the spatial distribution of *Eleocharis* and floodplain grasslands using ASTER and MODIS imagery; investigated temporal dynamics using MODIS derived vegetation indices; and explored the relationship between observed dynamism and environmental variables. The study also assessed the relationship between wattled cranes and vegetation classes using predictive modelling.

1.2. **Specific Objectives**

The specific objectives were to:

- Explore the possibility of mapping the spatial distribution of *Eleocharis* and grasslands with high accuracy using ASTER imagery;
- Explore whether MODIS data and derived vegetation indices enabled mapping the distribution and monitoring temporal dynamics of *Eleocharis* and grasslands;
- Explore whether the temporal dynamics of *Eleocharis* and grasslands is related hydrodynamics and ecoclimatic conditions;
- Assess the distribution of *Eleocharis*-Leersia and floodplain grasslands along elevation gradient; and
- Assess the relationship between crane presence and vegetation classes using predictive modelling.
1.3. **Research Questions**

- Can distribution of *Eleocharis* and associated floodplain grasslands in Kafue flats be mapped with high accuracy using ASTER imagery?
- Can MODIS data and derived vegetation indices enable mapping the distribution and monitoring of the temporal dynamics of *Eleocharis* and associated grasslands?
- Is the temporal dynamics of *Eleocharis* and floodplain grasslands in Kafue flats related to hydrodynamics and ecoclimatic conditions?
- How are *Eleocharis*-Leersia and floodplain grasslands distributed along the elevation gradient?
- How does crane presence relate to vegetation classes? and can it be identified using predictive modelling?

1.4. **Structure of the Thesis**

This thesis comprises five chapters and they are as follows:

- Chapter 1 introduces the study in the context of existing literature about the wattled cranes and their habitats, and how remote sensing has been used in wetland mapping. This is in laying ground work and exploring ways that remotely sensed data can help us understand the wattled cranes habitat and its temporal changes. This enables the identification of missing information, upon which the study objectives and research questions are based on;
- Chapter 2 provides a detailed outline of the biophysical characteristics of the study area, methods employed in data collection, preparation of satellite images and eventual data analysis;
- Chapter 3 provides the derived study results;
- Chapter 4 provides the discussion of the obtained results in relation to existing literature in a bid to meet study objectives by answering the research questions; and
- Chapter 5 provides the study conclusions and recommendations for the way forward.
2. MATERIALS AND METHODS

2.1. Study Area

2.1.1. Location

The study was conducted in Blue Lagoon National Park in Kafue flats. Kafue Flats are located in southern Zambia along the Kafue River. The flats are flood plain extending over 255km along the river and covering an area of 6,500 km² (Chabwela & Siwela, 1986; Munyati, 2000). They are situated towards the lower end of the Kafue river basin at approximately 26°-28°E and 15°20’-15°55’S (Figure 2.1) (Mumba & Thomson, 2005). The Kafue flat wetlands are internationally renowned for their great contribution to endangered species conservation. In addition, they provide Zambia with water, tourism potential, hydro-electric power generation from Kafue Gorge dam, livestock keeping and agriculture. They are also home to more than 1.3 million people, living as agriculturalists, fishermen or pastoralists (Davis, 1993).

The Blue Lagoon National Park lies on the northern bank of Kafue river between 27° 15’ 00” and 27° 30’ 56” East and 15° 15’ 83” and 15° 30’ 82” South. It is one of the smallest national parks in Zambia with an area of 450 km² (ZAWA, 2004). The Park is accessible by both road, and located approximately 119 km south-west
of Lusaka (ZAWA, 2004). We considered the floodplains leaving out the woodlands because they are not utilised by wattled cranes.

2.1.2. Climate

The climate is influenced by the Inter-Tropical Convergence Zone (ITCZ). The rainy season extend from November through March followed by a cool dry season from April to July and a hot dry season from August to October (Munyati, 2000). Minimum and maximum temperatures range between 19°C and 36°C while mean annual rainfall is 535 mm at Itezhi-tezhi and 795 mm at Kafue Gorge (Mumba, 2004). Data obtained from the Meteorological Department of Zambia for the Mumbwa station over the period 1991-2005 showed mean monthly temperature to range between 18°C and 25°C while mean monthly precipitation varied significantly from zero to 170mm (Figure 2.2).

![Mean Monthly Temperature & Precipitation](image)

**Figure 2.2:** 1991-2005 mean monthly temperature and rainfall

2.1.3. Hydrology

The Kafue River extends for 1,577 kilometres from eastern Zaire to its confluence with the Zambezi River (Mumba & Thompson, 2005). The water feeding the Kafue flats comes from the upper catchment of the river where rainfall is high. Nevertheless, flooding in Kafue flats is caused by both direct rainfall, inflow from tributaries and discharge of the Kafue River. Floods begin to rise by mid-November, and peak by April-June. The timing of peak flooding does not coincide with the peak rainfall. There is a time lag of several weeks between rainfall in upper catchments and discharge in the Kafue flats (Kapungwe, 1993). Water levels start receding from late June, reaching their lowest point in November when only lagoons and
depressions continue to be inundated (Kapungwe, 1993). Nevertheless, the pattern varies from year to year depending on prevailing climatic conditions.

2.1.4. Geology and Soils

Mumba (2004), Ellenbroek (1987); and Chabwela & Siwela (1986) have reported that the soils are predominantly alluvial clays. However, there are variations due to differences in hydrological conditions. The variations range from 1) very fine black clays that remain moist almost to the surface through the dry season; 2) black clays that are very hard and dry to depths of more than 30cm by end of dry season on the margins of floodplain; and 3) black clays that are very hard by end of dry season and exhibiting ferrolysis, mostly in the termitaria and wooded zones (Kapungwe, 1993). The elevation of Kafue flats averages at about 1000m a.s.l. The flats have a longitudinal slope of less than 1% in the flow direction (Alsterhag & Petterson, 2004). However, there are variations depending on micro-topography. For example, the elevation of Blue Lagoon area varies between 975m and 1050m.

2.1.5. Vegetation

The vegetation of the Kafue flats is complex and varies considerably in space and time depending on hydrology, soil types, topography, and human influences (Ellenbroek, 1987). Mumba (2004), Kamweneshe & Beilfuss (2002) and Ellenbroek (1987) have documented the existence of three distinct vegetation zones: the floodplain vegetation, termitaria and woodlands. The floodplains are areas flooded in normal years despite that low elevation areas may experience flooding over long periods. The termitaria zone comprises the transition between floodplain and woodlands and supports scattered trees/shrubs intermixed with tough perennial grasses (*Hyperrhenia* spp. & *Setaria* sp.) amongst numerous termite moulds. Woodlands, on the other hand, occupy areas of slightly higher elevation that are not liable to seasonal flooding, unless in exceptional high flood years.

Floodplains are the most biologically the most diverse ecosystems comprising complex patterns of lagoons, ox-bow lakes, marshes, levees and grasslands. Each of these environments carries distinct vegetation types. Chabwela and Siwela (1986) have classified the floodplain vegetation into three main categories: 1) *Voscia-Oryza* grasslands that remain flooded most of the time comprising the *Eleocharis* species and associated grasses (*Leersia* sp. and *Panicum repens*); 2) *Acroceras macrum* grassland that desiccate and collapse upon water recession to form thick mats of vegetative material; and 3) *Setaria* grasslands near the margins of floodplains.
Detailed description of the various vegetation types are provided by Ellenbroek (1987).

2.2. Study Materials

(a) ASTER image
ASTER is a high spatial resolution sensor that captures images of 60 by 60 kilometres in size. It provides multispectral images with 14 bands: 3 within the visible and near infrared (VNIR, 0.52-0.86um) (plus 1 back looking), 6 bands in short wave infrared (SWIR, 1.60-2.43um) and 5 bands in thermal infrared (TIR, 8.12-11.65um) wavelengths (NASA, 2006). These spectral bands vary in spatial resolution from 15m in Visible and near infrared, 30m in Short wave infrared and 90m in Thermal infrared. The image was pre-processed, as explained in section 2.3.2 for classification purposes.

(b) MODIS composite images
Kafue flats experience heavy clouds over long period of time, which renders optical images less valuable due to clouds problem. To overcome the challenge, MODIS surface reflectance 8-day L3 Global 500m (MOD09A1 V4) composites were used with consideration of 16 days intervals when calculating vegetation indices.

(C) Environmental data
The environmental data included the recorded precipitation, temperature and evapotranspiration for Kafue area from Mumbwa and Magoye meteorological stations. The data were purchased from the Meteorological Department of Zambia and used to explain the seasonal variations of vegetation.

(d) Topographic maps
Topographic maps of the study area produced in 1980 at the scale of 1: 50,000 were used since there was no recent map. Their application was based on the fact no major changes have occurred in that park since then. The maps were purchased from the Survey Department of Zambia.

(e) SRTM digital elevation model
The SRTM digital elevation model of Kafue flats was obtained at 90 x 90m resolution. The DEM was georeferenced and although meant purposely to show the general trend rather than relative height, it was first tested using five spot heights in the georeferenced topographic maps. The study area was subset, reclassified to 1
metre vertical interval in ArcGIS, and resampled to 15m x 15m using nearest neighbour method.

(f) GPS and compass were used for field navigation, recording geographic coordinates and direction bearing during field campaign.

(g) Pair of Binoculars for sighting cranes in the field

(h) Measuring tape for sampling plots size estimation

(i) Computer and software (ArcGIS, ENVI 4.2, ERDAS, Minitab 14, JMP 6, SYSTAT, SPSS, Ms-Excel, Ms-Word) for data analysis and write up.
2.3. **Research Methods**

Figure 2.3 shows the schematic diagram of the steps followed in this study.
2.3.1. Image selection and acquisition

MODIS and Aster images were selected for this study. Kafue region is characterised by heavy clouds and hence most remotely sensed images for wet seasons are unsuitable for classification purposes. During the dry season, on the other hand, the flats are subjected to annual burning resulting in a lot of dust and smoke that make it difficult to obtain clear images for mapping. With this background, ASTER image of 9th March 2005 was acquired through ITC despite the fact that it coincided with the wet season. It was the only suitable image over the recent past. MODIS 8-day surface reflectance product (MOD09A1) was downloaded from the EOS data gateway (http://edcdaac.usgs.gov/modis/dataproducts.asp) and used to calculate the vegetation indices and classification.

2.3.2. Image Pre-processing

The ASTER image was imported and geocoded using ERDAS Imagine based on the provided image ground control points (GCPs). A RMSE of 0.0001 was achieved. The image was reprojected from WGS 84 system to Zambian coordinate system and resampled using the nearest neighbour method to 15 metres pixel resolution. The reprojected image was tested using the acquired and georeferenced topographic sheets for fit. Finally, it was atmospherically corrected using ATCOR 2 in ERDAS.

MODIS composite images are atmospherically corrected and cloud screened (see Huete et al., 2002 & Vermote et al., 2002). The composite of 2006273 was prepared by projecting it from sinusoidal to UTM system by georeferencing it using the already corrected ASTER image. It was then resampled (band 3-7) to 250m using nearest neighbour method to coincide with bands 1 & 2. Other composite images were registered to it and resampled as well. The 7 bands for terrestrial sensing were layer stacked for further analysis.

2.3.3. Sampling Design and Size

The ASTER image was used in identifying possible vegetation classes and allocation of sampling units. The imagery was first interpreted visually based on false colour composite. Kafue flats are heterogeneous and to capture this variation for classification purposes, sampling points were selected based on stratified random sampling design (Cochran, 1963). Stratification was done using unsupervised classification of the image into 8 land cover types. Clustered random
sampling was used at each selected sampling point to increase the sampling size while reducing travelling time. This sampling strategy has been used by Van Gils et al. (2006) in mapping invasive species in South Africa.

Sample size for vegetation survey depends on the required accuracy and have been estimated based on expected standard error. A minimum of 30 or 50 sampling units is recommended (Thompson, 1992; Hay, 1979). Observations for a total of 132 sample sites were collected during the October field campaign for ASTER classification and testing. Sites that coincided with uniform vegetation classes and large enough for MODIS pixel were noted for later classification. In total, 48 sites were randomly recorded for MODIS classification.

2.3.4. Field Data Collection and Analysis

A set of hand held GPS was used to navigate to the selected sites for data collection. Circular plots of radius 11.3m were established using a 50m tape measure for vegetation attributes assessment. Data on key plant species, height, % grass, % *Eleocharis*, ground condition (dry/moist/flooded), and total vegetation cover in the plot were visually estimated. Species dominant was helpful in assigning the sites to cover classes. This was set at 60% cover and above. During the same period, presence of wattled cranes was noted. Observations were made using a pair of binoculars. For every sighting, the birds’ activity, point of location, and numbers were noted. I would then walk to the point where sighted to record the geographical coordinates, vegetation type, presence of *Eleocharis* and percentage cover and composition within a radius of 11.3m similar to vegetation sampled plots. Only two points were inaccessible due to swampy conditions and their coordinates were estimated based on distance and compass direction. A total of 14 crane sightings were made during the field survey.

The field vegetation data were then used for cover classes’ separation, distribution analysis along elevation gradient and in regression analysis for wattled cranes distribution. Distribution analysis along the elevation gradient was based on presence-absence. HOF models (Huisman et al, 1993) were explored to select the best fitting one.

Records on wattled sightings were entered in Ms-Excel and projected in ArcMap to show their distribution. There are a variety of possible techniques to develop models relating species to their environment. A first consideration in such a situation is
whether to model recorded species number or merely their presence. We deemed the second option more appropriate since there was considerable variation in group size, which would lead to extremely high residuals and low predictive power of the models. We thus selected logistic regression to analyse crane – environment relationship. Logistic regression analyses were performed based on the algorithm provided by Keating & Cherry (2004) as:

\[
P(y=1/x) = \frac{\exp (\beta'x)}{1+\exp (\beta'x)}
\]

\[
= \beta_0 + \beta_1x_{1i} + \beta_2x_{2i} + \ldots\ldots + \beta_kx_{ki}
\]

where \( p_i \) is probability that the species will be present at site, \( \beta_0 \) is intercept, \( x_k \) are habitat variables and \( \beta_k \) are habitat variable coefficients.

The derived model using vegetation classes, presence/absence data and vegetation indices was further applied to monitor the dynamics of wattled crane habitat. Figure 2.5 summarises the steps performed in relating cranes to environment.

![Figure 2.5: Crane-environment relationship analysis](image-url)
2.3.5. **Image Classification**

There are several methods used in classification of remotely sensed data. Such include the maximum likelihood classification (MLC) (Munyati, 2000), spectral angular mapper (SAM), neural networks (NN) (Augusteijn & Warrender, 1998), decision tree approaches (DTA), K-Means clustering (Giri & Jenkins, 2005), parallelepiped and minimum distance classification (MDC) (Campbell, 2002). However, most of these classifiers are sophisticated and require good knowledge of remote sensing and classification, and sometimes advanced equipment. This may be a challenge to many resource managers in developing countries despite the need for mapping skills in resource monitoring. As an applied remote sensing study, I investigated MLC and MDC suitability in vegetation mapping in order to provide an insight on how reliable the two methods would be to such resource managers.

MLC has been reported to provide reliable results (Richards, 1993) since it bases the classification on probability (South et al., 2004; Campbell, 2002). Hence, good results were anticipated. Minimum distance, on the other hand, though based on Euclidean distance (Wang & Tenhunen, 2004) provided better results than MLC in a study by South et al. (2004) in mapping agricultural tillage. It was therefore applied to test its performance in mapping wetland vegetation. Part of the field collected data was used to train the classifiers and the remaining to validate the classification.

2.3.6. **Monitoring Vegetation Dynamics**

Wallace et al. (2006) acknowledge that single date mapping provides a static view of vegetation resource. However, it does not put into consideration the dynamic nature that would provide significant information for management. They argue that understanding the dynamic component, observable in responses to seasons and disturbance, may provide indicators of condition that are not evident at a single time observation. Beck et al. (2006); Sakamoto et al. (2005); Zhang et al. (2003) and Pettorelli et al. (2005) have demonstrated this based on MODIS derived data.

Eight-day image composites were used for this task. Vegetation indices were calculated from the images surface reflectance in blue, red, NIR and SWIR using ENVI 4.2 and ERDAS Imagine over the 2006097 (7th April) to 2006321 (17th November) period. The algorithms used to derive the indices are as provided by Huete et al. (2002); Ahl et al. (2006); Xiao et al. (2006), where:
Spectral indices were extracted from the resultant coverages using coordinates of sites. The median and mean values for the four cover classes over time were generated. Huete et al (2002) evaluated time series MODIS data products of 500m and 1 km and found that multi-temporal (time series) spectral profiles represented the phenology of the biomes they considered quite well. Chen et al (2006) further established phenological stages of corn based on NDVI and EVI spectral profiles. Hence, the spectral profiles obtained were used to study seasonal changes of the four cover classes.

Correlation analyses were performed using the maximum monthly vegetation indices and environmental variables to investigate for relationship. Dennison & Roberts (2003); Elmore & Asner (2005); and Weber (2001) have reported that phenological changes are related to environmental conditions and, hence, can be explained using environmental variables. The average monthly precipitation, temperature, evapotranspiration and water levels in Kafue River were used for this purpose. Recorded water levels at Nyimba station served as proxy for flooding during April-September while October and November values were averaged from the last three years’ figures. Similarly, the 2001-2005 monthly temperature, evapotranspiration and precipitation were used to derive monthly average values. Evapotranspiration rates for the year 2005 were used due to missing data for the other years. The data were applied on assumption that the study period (April-November) did not significantly vary from the previous years’ climatic conditions.

2.3.7. Accuracy Assessment

The quality of classified maps depends on their classification accuracy (Foody, 2002). This is because the accuracy of a thematic map influences the output of its application (Powell et al, 2004). Edwards et al (1998) therefore argue that this realisation has made accuracy assessment a crucial step in classification in order to check for errors propagated by the way data is acquired, analyzed, and converted.
from one form to the other. The most commonly used method to assess classification accuracy is the error or confusion matrix (Congalton, 1991). However, it may have shortcomings that result from the ambiguity of implementation, lack of acceptance on the appropriate accuracy to report or virtually the way the results are interpreted (Powell et al., 2004; Foody, 2002).

Nevertheless, the error matrix was generated and used to assess the quality of the image classification. The process involved checking the classified image against ground validation points where the results were expressed in terms of overall, producer and user accuracies, and Kappa statistic. Jensen (1996) note that producer accuracy is based on the reference data thereby providing error of omission while user accuracy is based on the total number of pixels classified in specific classes and provides error of commission. Kappa statistic, on the other hand, summarises the results of accuracy assessment (Edward et al., 1998).

2.3.8. Statistical Analyses

Several statistical analyses were performed. They included regressions for testing relationship between variables, Chi-square and analysis of variance (ANOVA) for testing significant differences, correlation analyses to test for strengths between variables, confidence interval estimation, and Tukey’s test for means separation. Test for significance of correlation coefficient was based on n-2 degrees of freedom at P<0.05 (Geese, 1990). Chi-square and Wilson estimate of confidence interval were based on procedures provided by Moore and McCabe (2003) as follows:

\[
\chi^2 = \frac{(Observed - expected)^2}{expected}
\]

Wilson estimate for one proportion at 95% confidence level:

\[
95\% \text{ CI} = p \pm z \times SE_p, \text{ where}
\]

\[
[p] = \frac{x + 2}{n + 4}
\]

\[
[SE_p] = \sqrt{\frac{p(1-p)}{n + 4}}
\]
3. STUDY RESULTS

3.1. Vegetation mapping using ASTER image

The vegetation in the study area was classified into 6 cover classes based on Maximum Likelihood and minimum distance classifiers: Eleocharis-Leersia association (EL) or simply referred as *Eleocharis*; floodplain grasslands (FLG), Hyperrhena & Vetiveria grasslands (VH) or referred as Hyperrhena-Vetiveria, *Vernonia glabra* (Ver) community, *Sesbania sesban* (Ses) community and water. Sites were assigned to these classes based on dominant species within the sampled plot. Figure 3.1 shows the spatial distribution of the cover classes based on maximum likelihood classifier.

![ASTER MLC Cover Classes](image)

Figure 3.1: Vegetation classes based on MLC

The same training dataset was used to classify the image based on MDC for comparison. Figure 3.2 shows the derived classes. The two classifiers revealed spatial distribution of *Eleocharis* quite clearly on the eastern side of study area. They both attained overall accuracy of 72.3%. They also mapped *Eleocharis* with high producer and user accuracies and Kappa statistic of above 70%. However, that of
Hyperrhena–Vetiveria and *Vernonia glabra* classes varied. Confusion between water pixels and *Eleocharis* was also recorded.

![ASTER MD Cover Classes](image)

Figure 3.2: Vegetation classes based on MD classifier

### 3.1.1. Accuracy Assessment

Tables 1 and 2 show the error matrices for the MLC and the MDC. The main confusion in MLC (table 3.1) was between *Sesbania sesban* being mapped as floodplain grasslands and water as *Eleocharis*. For MDC (table 3.2) the confusion was between floodplain grasslands and Hyperrhena–Vetiveria; *Vernonia glabra* and Hyperrhena–Vetiveria, and between water and *Eleocharis*. Hyperrhena–Vetiveria class had the poorest accuracy in both classifications. Nevertheless, there was less confusion in MLC than in MDC. Tables 3.3 and 3.4 show the classification accuracies.
Results show *Eleocharis* was mapped with high accuracy of above 78% though MLC provided high results. MLC also classified floodplain grasslands with accuracy.
above 80%. However, the Hyperrhenia-Vetiveria class was marginally mapped by MLC and poorly classified by MDC. Based on class accuracies, the results of MLC were preferred for further analysis.

3.1.2. Test of misclassified proportions

With overall accuracy of 72.3 %, test of equal classification among classes using Chi-square was conducted based on correctly and wrongly classified sampled points (table 3.5). The hypotheses were that:

- Ho: There is no significant difference between misclassified proportions among classes
- H1: the misclassified proportions differ between classes

Table 3.5: Observed versus expected values for MLC

<table>
<thead>
<tr>
<th>class</th>
<th>correct</th>
<th>expected</th>
<th>wrong</th>
<th>expected</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>EL</td>
<td>10</td>
<td>8.13</td>
<td>1</td>
<td>2.87</td>
<td>11</td>
</tr>
<tr>
<td>FLG</td>
<td>13</td>
<td>11.83</td>
<td>3</td>
<td>4.17</td>
<td>16</td>
</tr>
<tr>
<td>VH</td>
<td>2</td>
<td>2.96</td>
<td>2</td>
<td>1.04</td>
<td>4</td>
</tr>
<tr>
<td>Ses</td>
<td>2</td>
<td>2.22</td>
<td>1</td>
<td>0.78</td>
<td>3</td>
</tr>
<tr>
<td>Ver</td>
<td>4</td>
<td>5.17</td>
<td>3</td>
<td>1.83</td>
<td>7</td>
</tr>
<tr>
<td>Water</td>
<td>3</td>
<td>3.7</td>
<td>2</td>
<td>1.3</td>
<td>5</td>
</tr>
<tr>
<td>Total</td>
<td>34</td>
<td>12</td>
<td>6</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

A chi-square value of 4.90 was obtained compared with the tabulated one of 11.07 at 5 degrees of freedom and p < 0.05. Since the calculated chi-value was less than tabulated value, there was no evidence to reject the null hypothesis. It was therefore concluded that the misclassified proportions among the classes did not differ and, hence, we concluded that the cover classes share the same overall accuracy.

3.1.3. Confidence interval for Eleocharis and floodplain grassland classes

Confidence intervals were generated for the accuracies based on correctly classified sites and the respective reference and classified sample sizes (table 3.6). The overall accuracy with 34+2 correct points out of 47+4 (0.70588), had standard error of 0.0638, and confidence interval of 0.70588± 0.125. This translates to confidence interval of between 0.58088 and 0.83088 suggesting that with repeated sampling, 95% of the sampling would provide overall accuracies of between 58.1% and 83.1%. User and producer accuracies are presented in table 3.6 and range between 53% and 100%.
Table 3.6: MLC producer & user accuracies confidence interval

<table>
<thead>
<tr>
<th>Accuracy class</th>
<th>p</th>
<th>se</th>
<th>95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td>Producer EL</td>
<td>0.75</td>
<td>0.108</td>
<td>0.538 – 0.962 = 53.8 – 96.2%</td>
</tr>
<tr>
<td>FLG</td>
<td>0.75</td>
<td>0.0968</td>
<td>0.560 – 0.94 = 56.0 – 94.0%</td>
</tr>
<tr>
<td>User EL</td>
<td>0.8</td>
<td>0.103</td>
<td>0.598 – 1.002 = 59.8 – 100%</td>
</tr>
<tr>
<td>FLG</td>
<td>0.75</td>
<td>0.0968</td>
<td>0.560 – 0.94 = 56.0 – 94.0%</td>
</tr>
</tbody>
</table>

3.1.4. Spatial distribution of vegetation cover classes

Figure 3.3 shows the spatial extent of the six vegetation classes in the study area. *Eleocharis-Leersia* association has the third largest extent after floodplain grasslands and Hyperrhenia-Vetiveria classes. Floodplain grasslands occupied 33.8% and 31.8% of the area based on MLC and MDC, respectively. *Eleocharis* occupied 15.5% according to MLC and 21.1% for MDC (figure 3.3). This indicates that the area coverage under floodplain grasslands doesn’t vary much between classifiers. In terms of hectares *Eleocharis* occupied between 4219 (MLC) and 5721 (MDC) hectares out the total 27170 hectares. Extent covered by water was the least. This is probably because the study was conducted in the dry season when water was only limited to areas permanent flooded, such as the stream and few swampy vegetated areas.

![Cover dominance in the study area](image)

Figure 3.3: Histogram showing % coverage of each class
3.1.5. Distribution along elevation gradient

Kafue flats are generally low lying though variation in micro-topography influences vegetation from riverline to woody zones on higher grounds. Vegetation that requires wetness occurs at moderate to low elevation liable to floods. The SRTM DEM showed the elevation of the study area to range between 977 and 984m and the considered vegetation classes were distributed along this elevation gradient. Most *Eleocharis* observations were in the range of 977 and 979m a.s.l suggesting high dependence on wetness. Significant relationship existed between land surface water index (MODIS LSWI) of sampling sites and elevation (figure 3.4b; $R^2 = 0.137$, $df = 131$, $f = 10.33$, sig = 0.0001) showing wetness declined with elevation. *Sesbania sesban* had a narrow distribution range, mainly along river banks. *Vernonia glabra* and *Hyperrhenia-Vetiveria* grasses occurred on the higher areas both at and beyond edge of high season flood line. Figure 3.4a shows the vertical arrangement of cover classes with *Eleocharis* occupying lower elevation. Nevertheless, there were no distinct demarcations between classes due to overlaps in ecological habitats.

![Variation along elevation gradient](image)

(a)     (b)

Figure 3.4: a) Cover classes along the gradient, b) MODIS LSWI versus elevation

Regression analysis of field data indicated significant relationship between elevation and percentage cover for *Eleocharis* ($R^2 = 0.160$, $df = 2$, $F=12.27$, sig. =. .000), *Vernonia glabra* ($R^2 =0.116$, $df=2$, $F=5.59$, sig. = .001) and *Hyperrhenia-Vetiveria* ($R^2 =0.082$, $df = 2$, $F=5.74$, sig. = .004) as shown in the following figures.
Figure 3.5a, b, c: EL, VH & Ver % cover in relation to elevation

Presence-absence data at one metre interval were used to show trend along the elevation gradient. Results of HOF models based on 132 sites except for floodplain grasslands (130) since two of the outlier plots (figure 3.4a) were excluded showed that *Eleocharis*, *Vernonia glabra*, *Sesbania sesban* and *Hyperrenia-Vetiveria* were best predicted using model II while floodplain grasslands were best fitted by model
IV (see R derived graphs in Appendix 1). The predicted values were fitted using polynomial functions as follows: Hyperrhenia-Vetiveria \((Y=0.013x^2-20.18x + 9841.4, R^2=0.9886)\), *Sesbania sesban* \((Y=-0.0015x^2-2.8921x+1397.3, R^2=0.1972)\), floodplain grasslands \((Y=0.0119x^3-35.042x^2+34366x-1E+07, R^2=0.9942)\), *Eleocharis* \((Y=0.0031x^3-9.136x^2+8932.3x-3E+06, R^2=0.9983)\) and *Vernonia glabra* \((Y=0.0025x^3-7.4317x^2-7284.4x+2E+06, R^2=0.9953)\). The graphical presentations are in figure 3.6a and b. The results from the models show that *Eleocharis* and *Sesbania sesban* declined with elevation while *Vernonia glabra* and Hyperrhenia-Vetiveria classes increased. Floodplain grasslands had a near bell shaped distribution but skewed to lower elevation.

![Graph a](image1.png)

![Graph b](image2.png)

Figure 3.6a, b: Probability presence of cover classes along elevation gradient
3.2. Vegetation Mapping using MODIS image

The MODIS composite of 30th September was used for classification. Attempts to classify the image into six cover classes similar to those of ASTER resulted in misclassification of water and *Sesbania sesban* since they existed in patches not big enough for MODIS image. The image was classified into 15 classes using unsupervised classification and then recoded to 4 main cover classes (figure 3.7). Unsupervised classification performed poorly with overall accuracy of 54.6% and kappa statistic of 36% (tables 3.7 & 3.8). However, *Eleocharis* was mapped with producer accuracy of 100%, user accuracy of 62.5% and kappa statistic of 51%. Hyperrhenia–Vetiveria accuracy was lowest as it was confused with both *Eleocharis* and floodplain grasslands. Only in the south-western zone was it well classified. Similarly, there was confusion between floodplain grasslands and *Vernonia glabra*.

Supervised classification (figure 3.8) provided overall accuracy of 81.8% and kappa statistic of 75.6% (tables 3.9 & 3.10). *Eleocharis* was mapped with user and producer accuracies above 70% and kappa statistic of 63%. Hyperrhenia-Vetiveria class was mapped with accuracy above 80%. However, some floodplain grassland portions were confused for *Eleocharis* in the wetter zones and with *Vernonia glabra*. Moreover, due to low spatial resolution there was tendency to generalise features such that it could not provide detailed mapping as ASTER. *Eleocharis* proportion thereby increased to 31% compared to maximum of 21% obtained using ASTER image. Floodplain grasslands occupied 21.4%, Hyperrhenia-Vetiveria (32.9%) and *Vernonia glabra* (14.2%).

![Unsupervised Classification](image)

**Figure 3.7: Cover classes based on unsupervised classification**
Table 3.7: Error matrix for unsupervised classification of MODIS image

<table>
<thead>
<tr>
<th></th>
<th>EL</th>
<th>Ver</th>
<th>FLG</th>
<th>VH</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>EL</td>
<td>5</td>
<td>0</td>
<td>2</td>
<td>1</td>
<td>8</td>
</tr>
<tr>
<td>Ver</td>
<td>0</td>
<td>2</td>
<td>2</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>FLG</td>
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<td>3</td>
<td>4</td>
<td>2</td>
<td>9</td>
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</tr>
<tr>
<td>Total</td>
<td>5</td>
<td>5</td>
<td>8</td>
<td>4</td>
<td>22</td>
</tr>
</tbody>
</table>

Table 3.8: Accuracy assessment of data in error matrix

<table>
<thead>
<tr>
<th>Class</th>
<th>Ref</th>
<th>Classified</th>
<th>Number Correct</th>
<th>Producer Accuracy</th>
<th>User Accuracy</th>
<th>Kappa statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Totals</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>EL</td>
<td>5</td>
<td>8</td>
<td>5</td>
<td>100</td>
<td>62.5</td>
<td>0.5147</td>
</tr>
<tr>
<td>Ver</td>
<td>5</td>
<td>4</td>
<td>2</td>
<td>40</td>
<td>50</td>
<td>0.3529</td>
</tr>
<tr>
<td>FLG</td>
<td>8</td>
<td>9</td>
<td>4</td>
<td>50</td>
<td>44.44</td>
<td>0.127</td>
</tr>
<tr>
<td>VH</td>
<td>4</td>
<td>1</td>
<td>1</td>
<td>25</td>
<td>100</td>
<td>1</td>
</tr>
<tr>
<td>Total</td>
<td>22</td>
<td>22</td>
<td>12</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall Accuracy = 54.55%  
Kappa Statistic = 0.3678

Figure 3.8: Cover classes based on supervised classification
Mapping and Monitoring Wetland Vegetation used by Wattled Cranes using Remote Sensing: Case of Kafue Flats, Zambia

Table 3.9: Error matrix for supervised classification

<table>
<thead>
<tr>
<th>Reference data</th>
<th>VH</th>
<th>FLG</th>
<th>Ver</th>
<th>EL</th>
<th>Total</th>
</tr>
</thead>
<tbody>
<tr>
<td>VH</td>
<td>4</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>4</td>
</tr>
<tr>
<td>FLG</td>
<td>0</td>
<td>5</td>
<td>1</td>
<td>0</td>
<td>6</td>
</tr>
<tr>
<td>Ver</td>
<td>0</td>
<td>1</td>
<td>4</td>
<td>0</td>
<td>5</td>
</tr>
<tr>
<td>EL</td>
<td>0</td>
<td>2</td>
<td>0</td>
<td>5</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>4</td>
<td>8</td>
<td>5</td>
<td>5</td>
<td>22</td>
</tr>
</tbody>
</table>

Table 3.10: Accuracy assessment of data in the error matrix

<table>
<thead>
<tr>
<th>Class</th>
<th>Ref Correct</th>
<th>Classified Totals</th>
<th>Number correct</th>
<th>Producer Accuracy</th>
<th>User Accuracy</th>
<th>Kappa statistic</th>
</tr>
</thead>
<tbody>
<tr>
<td>VH</td>
<td>4</td>
<td>4</td>
<td>4</td>
<td>100</td>
<td>100</td>
<td>1</td>
</tr>
<tr>
<td>FLG</td>
<td>8</td>
<td>6</td>
<td>5</td>
<td>62.5</td>
<td>83.33</td>
<td>0.7381</td>
</tr>
<tr>
<td>Ver</td>
<td>5</td>
<td>5</td>
<td>4</td>
<td>80</td>
<td>80</td>
<td>0.7412</td>
</tr>
<tr>
<td>EL</td>
<td>5</td>
<td>7</td>
<td>5</td>
<td>100</td>
<td>71.43</td>
<td>0.6303</td>
</tr>
<tr>
<td>Totals</td>
<td>22</td>
<td>22</td>
<td>18</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Overall Accuracy = 81.82%  Overall Kappa Statistic = 0.7556

Chi-square analysis was performed to test for significance difference between misclassified proportions based on the null hypothesis that there is no significance difference (table 3.11). A calculated chi-value of 1.46 compared to tabulated 7.81 at 3 df and P<0.05 was obtained. Hence, the null hypothesis was not rejected. This implied that misclassified proportions did not vary between cover classes but rather shared same accuracy of 81%.

Table 3.11: Observed and expected values for $\chi^2$ estimation

<table>
<thead>
<tr>
<th>Class</th>
<th>Correct</th>
<th>Expected</th>
<th>Wrong</th>
<th>Expected</th>
<th>total</th>
</tr>
</thead>
<tbody>
<tr>
<td>FLG</td>
<td>5</td>
<td>4.64</td>
<td>1</td>
<td>1.36</td>
<td>6</td>
</tr>
<tr>
<td>Ver</td>
<td>4</td>
<td>3.86</td>
<td>1</td>
<td>1.14</td>
<td>5</td>
</tr>
<tr>
<td>VH</td>
<td>4</td>
<td>3.09</td>
<td>0</td>
<td>0.91</td>
<td>4</td>
</tr>
<tr>
<td>EL</td>
<td>5</td>
<td>5.41</td>
<td>2</td>
<td>1.59</td>
<td>7</td>
</tr>
<tr>
<td>Total</td>
<td>17</td>
<td>5</td>
<td></td>
<td></td>
<td>22</td>
</tr>
</tbody>
</table>

Summary

- The distribution of Eleocharis and grasslands was mapped with high accuracy above 78% for both producer and user accuracies.
- Classification using MLC and MDC based on same training set provided equal overall accuracy though class accuracies varied among the two classifiers.
- Chi-square analysis showed lack of significance difference in misclassified proportions for MLC classified image.
Confidence intervals for user and producer accuracies ranged between 53% and 100% suggesting possible classification outcomes for repeated sampling.

*Eleocharis* occupies about 15%, an equivalent of 4219 hectares compared to the total 27170.9 hectares, of the study area. Floodplain grasslands were dominant with 33% (MLC).

*Eleocharis* and floodplain grasslands presence declined with elevation. Their presence was higher in low elevation areas.

Both supervised classification and unsupervised classification of MODIS image mapped the distribution of *Eleocharis* with fairly good accuracy. However, flood plain grasslands were mapped with marginal accuracy.

### 3.3. Monitoring vegetation temporal dynamics using spectral profiles

#### 3.3.1. NDVI and EVI

To understand changes of the cover classes, spectral profiles reflecting median values were generated for the period between April and November. The spectral profiles show variation between cover classes especially in the first four months (figure 3.9). However, the range narrows during the last three months that characterise the dry season. Comparing *Eleocharis* and grasslands the differences were not large except in April.

![NDVI spectral profiles of the four cover classes](image-url)

Figure 3.9: NDVI spectral profiles of the four cover classes
The figure also shows that the NDVI values were high before 23rd April, with *Eleocharis* having the highest. The probable reason could be that the period corresponded with the wet season such that vegetation was rapidly growing. This was followed by a period of declining NDVI with peak minimum by 10th June. This is the period that *Eleocharis* recorded the lowest NDVI unlike Hyperrhenia-Vetiveria that did not indicate much change. This could probably be due to its location on the elevation gradient.

Between June and August, the NDVI increased to the optimum. This suggests vegetation recovery from floods and being in lush green state. However, the rapid NDVI increase for floodplain grasslands was short lived. This is unlike *Eleocharis* NDVI that gradually increased, peaking in July and declined by August. The short lived nature of the greening of the grasses relative to *Eleocharis* is associated with the prevailing warm season when moisture content declines fast causing water stress in non-flooded zones.

By end of August through October, a phase of near constant NDVI values was observed. Most floodplain grasses and *Eleocharis* are weak stemmed and when water recedes, they collapse forming mats which remain partially green. The vegetation mats keep the ground cool enabling the grasses to remain relatively green during the dry season. Nevertheless, since some sections of *Eleocharis* are by then still under wet conditions, it maintains slightly higher NDVI values than other classes.

Hyperrhenia-Vetiveria class depict gradual NDVI decline from May until November when the next wet season begins. *Vernonia glabra* herb had the lowest values by May but increased up to September when it declined during the dry season. This could be attributed to the fact that it’s a perennial herb capable of drawing water below ground to maintain greenness. Almost similar patterns were observed for EVI spectral profiles of the four cover classes despite that EVI had lower values than NDVI (figure 3.10).
3.3.2. LSWI

The dryness index (LSWI), which signifies soil and leaf moisture content (Xiao et al., 2005), indicated relative periods of wetness between 23rd April and 12th July for floodplain grasslands, *Eleocharis* and partly for *Vernonia glabra* (figure 3.11). *Eleocharis* showed gradual decline in wetness that lasted relatively longer compared to other cover types. Floodplain grasslands achieved an upsurge in wetness between 7th April and 12th July but quickly declined such that by 29th August, most grassland zones had LSWI below zero, signifying dry ground condition.

*Vernonia glabra* are located on slightly higher grounds than *Eleocharis* and floodplain grasslands, and the moisture content is low under normal conditions. However, during wet season the area gets flooded causing an upsurge in LSWI observed during April-May period. Because of elevation gradient the water drains fast and the zone gets back to its normal dry condition. This is however alleviated by the re-establishment of vegetation after the floods when LSWI increases due to leaf moisture content.
3.3.3. **Eleocharis versus floodplain grassland spectral indices**

Spectral indices (figures 3.12 & 3.13) indicate NDVI and EVI to follow almost similar patterns for each cover class with NDVI being higher than EVI. The phases are as explained in section 3.3.2

![Eleocharis spectral profiles](image-url)

Figure 3.12: *Eleocharis* spectral profiles

![Timeseries Median LSWI](image-url)

Figure 3.11: LSWI profiles of the cover classes
During the May-June period, LSWI exceeded EVI for both classes and equalled the NDVI for floodplain grasslands. This suggests a period of high rising floods when vegetation gets submerged. Then the LSWI profile declines relative to other indices and reaches zero by August for floodplain grasslands and late October for *Eleocharis*. This suggests that the floodplain grasslands lose their wetness/moisture much earlier than in *Eleocharis* zones.

![FLG Timeseries Median Indices](image)

**Figure 3.13: Floodplain grasslands spectral profiles**

### 3.3.4. Spectral separability for vegetation monitoring

Monitoring requires an understanding on the best time when one vegetation type could be discriminated from the other. Using analysis of variance (ANOVA) to test for significance difference between means of cover classes NDVI and EVI at each date, and Tukey’s test for means separation, results showed significant difference especially for *Vernonia glabra*. However, mean separation between *Eleocharis* and Hyperrhena-Vetiveria and floodplain grasslands was impossible between April and June due to overlaps. However, during the July-November period, separation of *Eleocharis* from the other classes was possible using EVI than NDVI (see Appendix 2 and 3). During then the *Eleocharis* NDVI was only significantly different from the rest on 13\textsuperscript{th} August and 1\textsuperscript{st} November. EVI values were significant in seven dates except on 1\textsuperscript{st} November. Figure 3.14 highlights the R\textsuperscript{2} for the relationship between cover classes and indices derived using ANOVA.
3.4. **Relationship between temporal dynamics and environment**

3.4.1. **Water level and vegetation indices**

Figure 3.15 shows the variation of water levels recorded at Nyimba station for the 2005/06. The highest water level was attained between March and May, and declined thereafter. Figure 3.16 shows the monthly maximum NDVI of *Eleocharis* and of floodplain grasses relative to water level variation. An almost similar pattern was observed for EVI though not presented. Correlation analysis based on 0.707 as level of significance (6 df, p<0.05) showed that water level had positive correlation with NDVI of both *Eleocharis* \( r = 0.6373 \) and grasslands \( r = 0.3203 \) but was not significant (table 3.12). It was however negative significantly correlated to EVI of grasslands \( r = -0.7517 \) but not with that of *Eleocharis* \( r = -0.1685 \). However, we observe the variation in NDVI as water level varies. When water level was highest, NDVI declined, only to increase again as water level dropped. However, the NDVI increase was short lived and declined again as water level drop before stabilising. This suggests that extremely high and low water levels negatively impact on NDVI.
Mapping and Monitoring Wetland Vegetation used by Wattled Cranes using Remote Sensing: Case of Kafue Flats, Zambia

Figure 3.15: 2005/6 water level variation at Nyimba station

Figure 3.16: Water level variation against NDVI

Table 3.12: correlation between environmental variables and vegetation indices

<table>
<thead>
<tr>
<th>Class</th>
<th>Index</th>
<th>Water level</th>
<th>Temperature</th>
<th>Evapotranspiration</th>
<th>Precipitation</th>
</tr>
</thead>
<tbody>
<tr>
<td>EL</td>
<td>NDVI</td>
<td>0.6373</td>
<td>-0.2474</td>
<td>-0.5666</td>
<td>-0.1439</td>
</tr>
<tr>
<td></td>
<td>EVI</td>
<td>-0.1685</td>
<td>0.4261</td>
<td>0.1411</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>LSWI</td>
<td>0.8645</td>
<td>-0.7869</td>
<td>-0.7831</td>
<td>-0.7614</td>
</tr>
<tr>
<td>FLG</td>
<td>NDVI</td>
<td>0.3203</td>
<td>-0.2563</td>
<td>-0.4393</td>
<td>-0.1108</td>
</tr>
<tr>
<td></td>
<td>EVI</td>
<td>-0.7517</td>
<td>0.6592</td>
<td>0.5936</td>
<td>0.4836</td>
</tr>
<tr>
<td></td>
<td>LSWI</td>
<td>0.91</td>
<td>-0.8607</td>
<td>-0.9036</td>
<td>-0.6075</td>
</tr>
</tbody>
</table>

Considering LSWI (figure 3.17), which denotes soil wetness that enables plant growth and extraction of tubers by cranes, floodplain grassland had high wetness between April and June. However, it drastically declined with water recession from
0.3 to almost -0.2. *Eleocharis*, on the other hand, exhibited a gradual declining pattern. Significant relationship existed between water level and LSWI for both *Eleocharis* ($r = 0.8645$) and floodplain grasslands ($r = 0.9100$), which is reflected by the graphs below. The results suggest that the water level fluctuation in Kafue River has great impact on the wetness conditions in the study area.

![Figure 3.17: Water level variation compared with LSWI](image)

**3.4.2. Temperature, evapotranspiration and precipitation versus indices**

The three variables had varied relationship with the vegetation indices. Temperature and evapotranspiration were negatively correlated with both the NDVI and LSWI while positive with EVI. They had significant correlation with LSWI of more than -0.78 while that of NDVI was less (table 3.12). They were however positively correlated with EVI for both cover classes though weak.

Precipitation, on the other hand, was negative significantly correlated with LSWI for *Eleocharis* ($r=-0.7614$) but not for floodplain grasslands ($r=-0.6075$). Like temperature and evapotranspiration, it showed weak positive correlation with EVI of both classes. This indicates that like the water level, the three environmental variables are significantly correlated with wetness (LSWI) but not with NDVI and EVI.

**Summary**
• The LSWI was significantly correlated to the environmental variables while NDVI and EVI were not. Hence, environmental variables can only explain wetness variation in the study area;
• Temperature and evapotranspiration showed negative relationship with NDVI and LSWI but positive with EVI.

3.5. Crane – Environment Relationships

*Eleocharis* and grasslands are purported to be the main feed sources for wattled cranes, and this has raised concern for their conservation. We evaluated the distribution of cranes among the six cover types to reveal habitat use. Consideration was based on 400sqm plots where vegetation was sampled, and pixel level of the classified map.

Figure 3.18 shows the recorded presence and absence locations. The figure clearly indicates the presence on the eastern and southern side of the study area. The eastern side carried the *Eleocharis* while the southern part had grasses as the main cover though sometimes mixed with *Eleocharis*. Some of these zones carried the remaining wet patches with lush green vegetation. A total of 170 birds were recorded in all the observation points. Based on field sampling sites, 101 (59%) were in *Eleocharis* and the remaining 69 (41%) were in floodplain grasslands.
3.5.1. Analysis of field records

(i) Logistic regression based on single variable

Logistic regression of the presence/absence of crane versus the percentage cover of the various plant communities in the 400m² sites, resulted in the model presented in table 3.13. The table shows that both *Eleocharis* and floodplain grasses were significantly related to presence of cranes. However, the McFadden Rho-square for each variable was low probably due to low observations. The combination of *Eleocharis* and floodplain grasses cover provided improved deviance (-2LL) of 18.067 compared to single factors. This suggests that where floodplain grasses and *Eleocharis* are plenty, there is higher probability for crane presence.

EVI and NDVI also showed significant relationship (table 3.13). The results indicate that the indices would predict the presence of wattled cranes with slightly better McFadden Rho-square than cover classes. However, since both indices were highly correlated ($r = 0.906$), only NDVI was considered for further analysis.
Table 3.13: Logistic regression of each variable with presence/absence data

<table>
<thead>
<tr>
<th>Variable</th>
<th>Intercept estimate</th>
<th>SE</th>
<th>t-ratio</th>
<th>P value</th>
<th>-2LL</th>
<th>df</th>
<th>(\chi^2)</th>
<th>P value</th>
<th>McFadden Rho-square</th>
</tr>
</thead>
<tbody>
<tr>
<td>EL</td>
<td>-2.758</td>
<td>0.015</td>
<td>0.007</td>
<td>2.208</td>
<td>0.027</td>
<td>4.666</td>
<td>1</td>
<td>0.031</td>
<td>0.051</td>
</tr>
<tr>
<td>FLG</td>
<td>-2.888</td>
<td>0.018</td>
<td>0.009</td>
<td>2.073</td>
<td>0.038</td>
<td>4.374</td>
<td>1</td>
<td>0.036</td>
<td>0.047</td>
</tr>
<tr>
<td>EL+FLG</td>
<td>-5.933</td>
<td>0.048</td>
<td>0.018</td>
<td>2.749</td>
<td>0.006</td>
<td>18.067</td>
<td>1</td>
<td>2.13E-05</td>
<td>0.196</td>
</tr>
<tr>
<td>NDVI</td>
<td>-11.049</td>
<td>23.15</td>
<td>9.243</td>
<td>2.505</td>
<td>0.012</td>
<td>8.875</td>
<td>1</td>
<td>0.003</td>
<td>0.092</td>
</tr>
<tr>
<td>EVI</td>
<td>-8.302</td>
<td>27.25</td>
<td>10.348</td>
<td>2.634</td>
<td>0.008</td>
<td>8.508</td>
<td>1</td>
<td>0.004</td>
<td>0.096</td>
</tr>
</tbody>
</table>

(ii) Logistic regression based on multiple variables

Like in single variable case, only *Eleocharis* and floodplain grasslands were significantly related to cranes presence based on stepwise regression method (table 3.14). The model had deviance of 18.519 with 2 df chi-square value of 9.52E-05, and McFaddens Rho-squared of 0.201. This suggests that considered together, the two classes would predict 20% of the cranes presence. The prediction function for wattled cranes in the 400sqm sampling plots is derived as \[ Y = -6.195 + 0.048 \text{ (EL cover)} + 0.054 \text{ (FLG cover)}. \]

Table 3.14: Logistic regression of vegetation classes with presence/absence data

<table>
<thead>
<tr>
<th>Variable</th>
<th>estimate</th>
<th>SE</th>
<th>t-ratio</th>
<th>p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-6.195</td>
<td>1.718</td>
<td>-3.606</td>
<td>3.22E-04</td>
</tr>
<tr>
<td>EL</td>
<td>0.048</td>
<td>0.018</td>
<td>2.651</td>
<td>0.008</td>
</tr>
<tr>
<td>FLG</td>
<td>0.054</td>
<td>0.02</td>
<td>2.668</td>
<td>0.008</td>
</tr>
</tbody>
</table>

Figure 3.19 shows the prediction of the model as contours in a two dimensional biplot of percentage cover of floodplain grasses versus percentage cover of *Eleocharis*-Leersia. Similarly, floodplain grasses show a higher predictive probability as in single factor case.
Although NDVI was significant as a single variable, its inclusion in the model however was not significant. The model results therefore did not vary from those in table 3.14.

3.5.2. Analysis of crane – environment relationship using classified Aster image

A stepwise logistic regression to establish the relation between crane presence and the class membership of the site according to the classified Aster image showed Eleocharis and floodplain grasses were significant (table 3.15). The model had deviance of 9.046 with 2 df chi-square p-value of 0.011 and McFadden’s Rho-square of 0.098. This indicates that the model deviance from the null model was not large enough.

Table 3.15: Logistic regression of Aster vegetation classes with presence/absence data

<table>
<thead>
<tr>
<th>variable</th>
<th>estimate</th>
<th>SE</th>
<th>t-ratio</th>
<th>p-value</th>
<th>Odd ratio</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-4.078</td>
<td>1.008</td>
<td>-4.043</td>
<td>5.26E-05</td>
<td></td>
</tr>
<tr>
<td>FLG</td>
<td>2.328</td>
<td>1.079</td>
<td>2.158</td>
<td>0.031</td>
<td>10.261</td>
</tr>
<tr>
<td>EL</td>
<td>2.391</td>
<td>1.12</td>
<td>2.135</td>
<td>0.033</td>
<td>10.926</td>
</tr>
</tbody>
</table>
The inclusion of Modis derived vegetation indices to the model however improved both the deviance to 15.641 with 3df chi-square p-value at 0.001, and McFadden’s Rho-squared of 0.170. The results suggest that the model would provide better predictive power than when considering vegetation communities of the classified image alone based on $Y = -13.869 + 2.265*FLG \text{ cover} + 1.997*EL \text{ cover} + 25.885*NDVI$.

Table 3.16: Logistic regression of multiple variables with presence/absence data

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Therefore, from the analysis on wattled cranes- environment relationship, the results show that *Eleocharis*, floodplain grasses and NDVI were significantly related to presence probability in the study area. Nevertheless, although these variables could explain the phenomenon to some extent, the obtained McFadden Rho-square were relatively lower (less than 0.25) probably to low presence data.

3.5.3. Mapping suitable crane foraging habitat over time

Assuming that cranes preference for greenness (NDVI) does not change during the year, we next mapped the spatial distribution of suitable crane foraging habitat based on the derived model. As inputs we combined the Aster derived information on the distribution of floodplain grasses and Eleocharis-Leersia, with NDVI derived from MODIS imagery. The resulting probability maps were reclassified into two: areas with probability below and above 0.2. It was assumed that the probability of sighting a rare species at 0.2 and above (as recorded with field data, figure 3.19) would indicate its habitat. Figures 3.20a-h show the variation in suitable crane habitat. 1 and 2 denotes the suitable and unsuitable areas, respectively.
Mapping and Monitoring Wetland Vegetation used by Wattled Cranes using Remote Sensing: Case of Kafue Flats, Zambia
Mapping and Monitoring Wetland Vegetation used by Wattled Cranes using Remote Sensing: Case of Kafue Flats, Zambia
Figures 3.20a-h show the variation of the suitable habitat for crane as predicted using the model. The area reduced from around 18000 hectares in April to about 6000 hectares in October-November (figure 3.21). This was however with fluctuations observed in May-June when the NDVI of central part with short grasses drastically declined due to flooding. This was followed by recovery in June-July before eventual decline from August. From August the habitat was confined to wetter areas on the south and south-eastern part along the riverline and near the water lagoon. The trend in area coverage seems to follow the earlier observed pattern in vegetation indices.
Mapping and Monitoring Wetland Vegetation used by Wattled Cranes using Remote Sensing: Case of Kafue Flats, Zambia

Figure 3.21: Summary of area coverage in hectares for suitable habitat
4. Discussion of the Results

4.1. Mapping of *Eleocharis* and grasslands using ASTER imagery

Rundquist *et al* (2001) noted that mapping wetlands could be a challenging task owing to variation in sizes, inaccessibility, and sometimes lack of resources for field surveys. However, remotely sensed data has provided a new source that has been proved valuable by Baghdadi *et al.* (2001); Dwivedi & Rao, (1999); Augusteijn & Warrender (1998) and Horrit *et al.* (2003) among others. In this study, we used ASTER imagery to map the distribution of *Eleocharis* and floodplain grasslands utilised by wattled cranes. We demonstrated that the two cover classes could be mapped with high accuracy.

We argue for high accuracy because *Eleocharis* was mapped with user accuracy of 90% and producer accuracy of 83% using MLC. Producer and user accuracies of over 78% were attained using MDC, which are also high. The grasslands were also mapped with user accuracy of above 80% (MLC) and 100% (MDC). This indicates that the pixels representing the two cover classes were well allocated and therefore the mapping exercise provides a clear representation of the field situation. Moreover, both classes achieved kappa statistic above 70%, which indicates substantial to almost perfect strength of agreement (Landis and Koch, 1977). The results compare favourably with other published work. Bernthal & Willis (2004) achieved user accuracy of 86% in mapping *Phalaris arundinacea* grass in a wetland ecosystem in Wisconsin, USA; Lopez (2003) attained user accuracy of 91% and Pengra *et al.* (2006) attained producer accuracy of 68%, both in mapping *Phragmites australis* using Hyperspectral data. Nevertheless, low producer accuracies for Hyperrhenia-Vetiveria and *Sesbania sesban* classes (40% and 50%, respectively) suggest that these classes were not well represented in the classification. This resulted due to misclassification with floodplain grasslands, which is attributed to the time of image capture – March. March is a wet month (Mumba, 2004; Ellenbroek, 1987) and by then most vegetation is in lush green state, such that chances of spectral confusion are high.

In addition, the study obtained overall accuracy of 72.3% and kappa statistic of 64.7% (MLC) and 65.4% (MDC). Both classifiers provided similar results based on same training set. Chances of classifiers obtaining similar results due to use of same training set have been documented by Campbell (2002) citing Scholz *et al* (1979). Nevertheless, the results tally well with other published work. For example, Kokaly
et al (2003) obtained 74.1% in mapping forest cover in Yellowstone National Park using hyperspectral AVIRIS data; Bernthal & Willis (2004) obtained 71% in mapping *Phalaris arundinacea* grass in Wisconsin wetland; Marcal et al (2005) obtained 70.5% and 72.2% using SVM and LD classifiers on ASTER images; while Helmer et al. (2002) achieved 71% in mapping forests in Puerto Rico.

The study also showed that MLC provided better class accuracies than MDC. Misclassification was higher in MDC than in MLC. This is probably due to mode of pixel allocation used by each classifier. MLC uses probability and takes into account the variance brought by the nature of object (South et al, 2004) while MDC only relies on Euclidean distance to classify the image (Campbell, 2002). Moreover, wetlands are heterogeneous and, therefore, distance classifiers might not reflect the variation adequately as probability based ones. This is unlike agricultural landscapes where conditions may be uniform such that MD provided better results than MLC (South et al., 2004). This implies the need for appropriate selection of classifier in mapping heterogeneous wetlands.

The 95% confidence interval of both producer and user accuracies for *Eleocharis* and floodplain grasslands provided a range of between 53% and 96%. Rossiter (2004) note that the confidence intervals estimate the likely outcome if sampling was conducted many times. Hence, we deduce fairly good results would be obtained in mapping *Eleocharis* distribution in Kafue flats using MLC. In addition, Chi-square analysis for misclassified proportions showed lack of significant difference between classes. This implies that the classes shared the same overall accuracy. We therefore deduce that the proportions occupied by each cover class, and especially *Eleocharis*, in the classified map do not significantly vary from the actual coverage in the field.

Based on the classified image statistics, *Eleocharis* and floodplain grasslands occupy between 15-21%, and 31-33%, respectively. This indicates *Eleocharis* occupies a small proportion of the study area. This calls for its effective management if at all to conserve cranes in this park. Such measures would include prioritising the 15% most viable portion to ensure favourable conditions for *Eleocharis* growth. This calls for the re-evaluation of water regulation in the ecosystem in a bid to enhance adequate wetness across seasons for *Eleocharis* growth and production.
4.2. **Elevation and distribution of *Eleocharis* and floodplain grasslands**

Elevation gradient plays a major role in the distribution of vegetation classes, composition and cover in riparian ecosystems (Castelli *et al.*, 2000; Denslow *et al.*, 2002 & Dwire *et al.*, 2006). Statistical analysis showed that the percentage cover of *Eleocharis* was significantly related to elevation despite low $R^2$. Moreover, HOF models illustrated that presence was high in lower than slightly higher areas. For *Eleocharis*, this could be due to its requirement for wetter conditions for growth. Although not much has been done on *Eleocharis*-environment relationship, Finlayson (2005) reported *Eleocharis* has preference for water prone areas, especially the regularly flooded ones. The writer further notes having observed it perform poorly above the water line. This underscores the observed skewed distribution towards lower zones.

The study further revealed vegetation stratification along the elevation gradient though with overlaps. This supports Sheppe and Osborne (1971) argument that although Kafue flat is generally low lying, slight variation in elevation has significant impacts on vegetation type and composition. Comparatively, *Eleocharis* occupied the lower zones while Hyperrzenia-Vetiveria class occupied the upper ones. Since flood extent is associated with elevation, low elevated areas that are liable to annual flooding are likely to support inundation dependent species. The possible implications on the management of Kafue flats is that adequate understanding of the ecological requirements of sensitive species or those with high value for nature ought to be understood in order to inform the decisions on water resource management.

4.3. **Mapping *Eleocharis* using MODIS**

One major challenge facing resource managers in many developing countries is resource unavailability to afford expensive high spatial resolution satellite images for mapping and monitoring. However, NASA avails free and daily MODIS images or composites suitable for mapping purposes as demonstrated by Sedano (2005). In this study, both unsupervised and supervised classifications were tested in revealing the distribution of *Eleocharis* and floodplain grasslands. The unsupervised classification proved incapable of accurately mapping floodplain grassland despite mapping *Eleocharis* with good producer accuracy (100%) and marginal user accuracy (62.5%). The overall accuracy was marginal (54%) and kappa statistic of 36.8%. This demonstrated that although *Eleocharis* was fairly classified, other classes were poorly represented due to misclassification. Hence, unsupervised classification cannot be relied on to reveal the spatial distribution of vegetation in
this wetland owing to similarity in growth conditions at certain times in the growth cycle.

Supervised classification improved overall accuracy to 81.8% and kappa statistic of 75.6%. Like unsupervised classification, *Eleocharis* was mapped with producer accuracy of 100% and improved user accuracy of 71%. The low user accuracy was attributed to misclassified pixels for floodplain grasslands that were included in this class. However, there was general improvement in accuracies of Hyperrhena-Vetiveria and *Vernonia glabra* classes. Only the floodplain grasslands were fairly mapped with producer accuracy of 62.5%, implying they were not well represented in the classification. Although the results could reflect the validation data used, the results tally well with those of Wessels et al (2004) who classified the coniferous forest with producer accuracy of 77% in Yellowstone National Park. This demonstrates that MODIS data under supervised classification would be valuable in mapping the spatial distribution of *Eleocharis*. Nevertheless, there is need for consideration when applying such low spatial resolution images in mapping heterogeneous areas at local scale. It’s likely to overestimate some classes while still not revealing the heterogeneity due to generalisation. Therefore, application of MODIS data at local scale would be feasible for understanding phenological development than in mapping spatial extents.

### 4.4. Vegetation temporal dynamics and implications on cranes feed source

Time series NDVI and EVI showed that the cover classes have well-defined spectral profiles though with some overlaps at certain times of growth. They further indicated that *Eleocharis* and floodplain grasslands experience four major phases over the considered period whose time span slightly varies. The four phases could be described as green stage (up to April), flood time (May-June), second green up (June-August) and senescence or slow growth (Late August-early November). The first three could be associated with the difference in timing of rainfall and flooding. Kapungwe (1993) noted that rainfall and flooding don’t occur simultaneously in this ecosystem. Floods occur slightly after rains are over because it takes time for water inflow from the upper catchments to reach Kafue flats. This means that floods occur in the midst of green stage thereby causing the observed decline in May-June when LSWI was high relative to NDVI/EVI. Xiao et al (2002) reported the occurrence of floods to be associated with water index being equal or higher than NDVI as observed over the May-June period. However, both *Eleocharis* and floodplain
grasslands manage to maintain NDVI of about 0.4 by fast growing to keep pace with rising water.

After the floods, the second green up characterised by increased NDVI and EVI is attributed to emergence of new leaf materials. Young leaves have increased photosynthetic activity and moisture content that increases vegetation indices (Xiao et al, 2005). However, this doesn’t last for long (for floodplain grasslands) due to prevailing warm weather conditions. The green vegetation quickly attains maturity before wetness is lost. With the fast growth, the leaves age and accumulate more non-photosynthetic material, which leads to indices decline by August. The results demonstrate that using spectral profiles and knowledge about vegetation response to environmental conditions we could identify the growth phases of our target classes as other published studies (Huete et al, 2002; Chen et al, 2006).

Results further revealed that during the four growth phases, Eleocharis exhibited slightly higher NDVI and EVI values than the rest of the classes, except during floods when Hyperrhenia-Vetiveria had the highest. The high values for Hyperrhenia-Vetiveria were attributed to elevation that minimises the effects of floods such that the photosynthetic process is not affected. Moreover, the spectral profiles of each class (Eleocharis and floodplain grasslands) depicted similar patterns although NDVI was higher than EVI (figures 3.12 & 3.13). This concurs with Huete et al (2002) who upon evaluating four biomes observed similar multitemporal NDVI and EVI profiles, with NDVI being higher than EVI. LSWI on the other hand declined implying that the wetness condition declined over time.

Visual interpretation of spectral profiles (figures 3.9 and 3.10) would suggest easier separability of Eleocharis from the rest of the classes based on the observed dynamism. However, mean separation of NDVI values showed lack of significance difference except on 13th August and 1st November. Eleocharis EVI values were significantly different during the August-November dates suggesting this would be the suitable time for mapping. This corresponds to the dry season. The observation supports Munyati (2000) who suggested for mapping of Kafue flats vegetation during the dry season when vegetation classes exhibit spectral variability. It should however be borne in mind that the spectral profiles employed in deriving the observation depict median values and there exists intra-class variability due to differences in environmental conditions, which is likely to bring in spectral overlap among classes. Careful selection of mapping date based on knowledge of the target class and area concerned need to be taken into consideration.
The observed dynamism has potential implications on wattled cranes feed source and habitat, especially based on wetness abundance and scarcity. Three conditions could help identify critical periods. First, Meine & Archibald (1996) report wattled cranes to prefer areas with shallow water for feeding as it allows vegetation growth and easier extraction of tubers. Assuming shallow water to imply water levels not greater than in the lagoon (permanent water), we derive the first condition as \( \text{LSWI} < 0.25 \). Secondly, taking NDVI or EVI as indicators of actively growing vegetation (Oindo & Skidmore, 2002) or a measure of biomass productivity (Wang et al, 2003), we would expect the vegetation to be of value to cranes when EVI is higher than LSWI (EVI > LSWI). Thirdly, the soils in the study area are clays that compact and become impenetrable when dry (Kapungwe, 1993) such that excavation of tubers by wattled cranes would be impossible. In fact, Bokach (2002) noted the tendency for wattled cranes to abandon their foraging sites when the ground became dry and impenetrable. We therefore derive the third condition that extraction of tubers by cranes is only feasible when LSWI > 0.

Based on the three conditions, and the consideration of temporal profiles, it is conclusive that both \textit{Eleocharis} and grasslands would be unavailable between 23\textsuperscript{rd} April and end of June due to high water level. Moreover, floodplain grasslands would be of less value from mid August due to low moisture. Hence, we deduce that floodplain grasslands would only support wattled cranes through rhizomes for a shorter period than \textit{Eleocharis}.

4.5. Relationship between water level and ecoclimatic variables with spectral indices

We demonstrated significant relationship between water level in Kafue River and LSWI for \textit{Eleocharis} and floodplain grasslands (\( r = 0.8645 \) and 0.9100, respectively). This implies that the variation in water levels in the Kafue River influences the wetness condition and water content in vegetation. This is probably because of its influence on the extent of floods in the floodplains. Of particular interest is the observation that the \textit{Eleocharis} and floodplain grasses LSWI patterns closely followed that of water level. This signals the fact that LSWI would be a good indicator of water level and wetness conditions in the study area. This supports Xiao \textit{et al} (2002) observation of close association between flooding and NDWI in rice paddies.
Water level was also closely associated with the greening condition (NDVI) of the vegetation classes. NDVI was positively correlated though not significant. However, under extremely high wetness conditions, NDVI declined (May-June). Thereafter it increased as water level declined but for a while before declining again. This shows the likely effects of water level variation on the growth of both *Eleocharis* and floodplain grasses. The above two observations have implications on water management in the ecosystem. Although water is released during the dry season, the extent of inundation is limited and does not extend far from the Kafue river as during normal floods. Most areas are not inundated but remain dry. During May-June, floods inundate most vegetation thereby hampering its growth. Seeking ways of enhancing water balance by managing floods in the wet season and availing it during the dry season would help maintain the ecological integrity of the ecosystem. This would not only aid in crane conservation, but also for other wildlife species.

While water level was positive significantly correlated with LSWI, temperature and evapotranspiration were negatively and significantly correlated with it. This is because both tend to increase water loss from the soil and vegetation surfaces. LSWI was also negatively correlated with precipitation owing to that it increased during period of low rainfall. Lack of association between water index and precipitation has been reported by Xiao *et al.* (2005) in modelling primary production in a tropical forest.

Our study also highlights lack of significant relationship between the three other variables (temperature, precipitation and evapotranspiration) with NDVI and EVI. The results agree with Wang *et al.* (2001) on lack of significant relationship between NDVI and temperature, but differ on positive correlation between NDVI and precipitation. The situation in Kafue flats could be explained in several ways. First, the rainy season lasts between November and March (Mumba, 2004; Kapungwe, 1993; Ellenbroek, 1987) and rarely extends beyond April. In fact, no precipitation was recorded for the months of May to September in all years considered in deriving averages (see also figure 2.3). Precipitation in April, October and November was extremely low to make any significant difference. Secondly, NDVI and EVI fluctuated while both temperature and evapotranspiration increased over time lowering the correlation. There could also be bias with average data values used in that they might not have adequately reflected the weather conditions for the considered months. Moreover, the influence of these environmental variables on NDVI and EVI might not be immediate but could be characterised by time lags.
4.6. **Crane – environment relationship**

Logistic regression revealed significant relationship between *Eleocharis* and floodplain grasses cover with presence of cranes. More so, slightly higher deviance was obtained with combined *Eleocharis* and floodplain grasses cover. This supports Meine & Archibald (1996) who related wattled cranes habitat to sedge/grasslands that occur along riparian floodplains. There are possible reasons for the above observations. First, wattled cranes are specific feeders with preference for rhizomes and tubers of submerged species (Meine & Archibald, 1996; Bokach, 2002; Kamweneshe & Beilfuss, 2002). *Eleocharis* is the main tuber producing species in the area while some grasses produce rhizomes. Hence, in search of tubers and rhizomes, wattled cranes are bound to concentrate in areas where such plants grow. Floodplain grasslands are also likely to provide supplemental seeds and insects as noted by Meine & Archibald (1996). The results indicate the importance of both *Eleocharis* and floodplain grasslands as feed sources and habitats for wattled cranes. Nevertheless, the probability values were low, a factor attributed to the low field observations. It’s likely that probability values might vary if more observations were included.

While vegetation classes were important for presence of cranes, NDVI and EVI were also significantly associated with crane presence (table 3.15). The consideration of vegetation indices strengthened the predictive power of the logistic model. NDVI informs about vegetation condition in terms of biomass productivity (Wang *et al.* 2003) and status of growth (Oindo & Skidmore, 2002). Hence, the improved predictive power of the model could be related to the fact that wattled cranes are likely to select high NDVI zones since actively growing vegetation during the dry season is likely to provide adequate feed through tubers and fresh sprouts. Moreover, following our earlier observation of positive correlation between water level and NDVI, it is logical to associate such areas with adequate soil moisture content. This would influence presence due to the ease of extracting tubers and rhizomes from the ground. The results tally with Wallin *et al.* (1992) and Seto *et al.* (2004) who reported association between birds’ presence and NDVI.

Nevertheless, the McFadden Rho-square of the logistic models was relatively low. This resulted due to low number of observations made during the dry season. Information revealed that cranes migrate to wetter zones near the Kafue River in search of greener vegetation. However, based on the significant model results, we
deduce that the presence of cranes is closely associated with their main feed sources, *Eleocharis* and floodplain grasses.

Based on the above information, we predicted the suitable foraging habitat using the model results. Suitable habitat was considered as that above probability of 0.2. This was based on the assumption that sighting a rare species at 0.2 and above (as recorded with field data, figure 3.19) would indicate its habitat. This is unlike other wildlife species where probability of sighting might be high. The model predicted declining habitat from the largest in April (18395 hectares) to the least in November (5502 hectares) but with fluctuations in May and June as a result of floods. During May-June flooding, the central part was unsuitable because the short grasses were flooded, thereby, lowering NDVI. This signalled low productivity. Between September and November, on the other hand, these zones loose moisture too fast due to dry weather and NDVI is consequently lowered. This implies that only the lower zone with floodplain grasses and *Eleocharis* that grow fast during floods, as well as those that maintain wetness for relatively longer period are suitable across the seasons. The varying habitat reflects the influence of hydrodynamics through its influence on vegetation greenness (NDVI). It underscores the need for effective water management in the ecosystem in order to maintain crane habitats.

4.7. Study limitations

While this study has provided insight on the distribution of *Eleocharis* and floodplain grasslands, their temporal dynamics, and relation to cranes, there were limitations worth mentioning in order to shape future research. First limitation related to unavailability of suitable high spatial resolution of the study area. This led to the use of wet season ASTER image, a fact attributed to the noted misclassification due to spectral confusion. Secondly, due to time limitation and field conditions, it was not possible to collect sufficient data for validation. Probably better results would have been obtained. Moreover, data collection on cranes was limited by the season of study, which led to low predictive ability of the model. A long-term study cutting across seasons would probably provide better understanding of the relationship between cranes and the environment.

5. Conclusions and Recommendations

5.1. Conclusions

The following conclusions are derived from this study:
The spatial distribution of *Eleocharis* was mapped with high producer (83%) and user (90%) accuracies using ASTER imagery. Similarly, were the floodplain grasslands with above 78% for both accuracies;

MODIS imagery provided a good source for tracking temporal dynamics of vegetation classes. However, care is needed for its application in mapping and monitoring spatial changes especially in heterogeneous areas or when undertaking detailed mapping at local scale. This is due to inseparability between classes and generalisation resulting from low spatial resolution of the sensor;

Both *Eleocharis* and floodplain grasslands presence declined with elevation. *Eleocharis* showed preference for lower zones prone to regular flooding due to requirement for wetness to growth;

*Eleocharis* and floodplain grasses exhibit four growth phases over the April-November period reflected by vegetation indices. The changes are more related to hydrodynamics than ecoclimatic factors;

The temporal dynamics of *Eleocharis* and floodplain grasses has possible implications on wattled cranes feed source. April-June was the most likely feed insecure period due to effects of floods. Nevertheless, *Eleocharis* is likely to remain useful relatively longer than floodplain grasses due to differences in wetness conditions;

The presence of wattled cranes is related to *Eleocharis* and floodplain grasses, hence, the need for their conservation. Moreover, their growth or greenness condition (NDVI) is crucial in determining crane presence as reflected by the improved predictive power of the model;

The predicted crane foraging habitat declined from April to November, a fact attributed to hydrodynamics in the area.

### 5.2. Recommendations

This study explored the spatial distribution and dynamics of wattled cranes feed resource. It further evaluated the relationship between wattled crane and environment and how its habitat changes over time. However, there is need to investigate how the observed vegetation dynamism relate to breeding and resource use across seasons. Moreover, adequate understanding of the appropriate timing of water release for flooding and the right amount to ensure extensive and sustainable growth of *Eleocharis* and grasslands is called for.
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Appendix 1

R modelling of vegetation classes distribution along elevation gradient

R derived model output for predicting probability presence for EL, Ses, Ver, VH & grasslands (g)
### Appendix 2: Relationship between cover classes and NDVI over time

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### Appendix 3: Relationship between cover classes and EVI over time

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