Examination and Management of Human African Trypanosomiasis Propagation Using Geospatial Techniques

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EXAMINATION AND MANAGEMENT OF HUMAN AFRICAN TRYPANOSOMIASIS PROPAGATION USING GEOSPATIAL TECHNIQUES

By

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I certify that this is a true and accurate version of the thesis approved by the examiners, and that all relevant ordinance regulations have been fulfilled

Signed Principal Supervisor: ………………………….. Date:...........................

Declaration

I, Olukemi Adejoke Akiode, hereby declare that this thesis is my own original work and has not been submitted elsewhere in fulfilment of the requirement of any other award. Where information has been derived from other sources, I can confirm that this has been indicated in the thesis.

Signed …………………………………………… Date: ……………………………..

Abstract

Human African Trypanosomiasis (HAT) is a vector-borne disease transmitted by the bite of the tsetse fly that results in high human morbidity and mortality. The propagation of the disease has been linked to environmental factors, and understanding the vector's habitat is vital to its control. There is no HAT vaccine, but biological control of the vector has been successful in reducing HAT incidence. However, in recent years the disease has re-emerged and spread. Due to insufficient knowledge of HAT endemic foci, the disease management remains challenging. To achieve effective deployment of control strategies, accurate knowledge of the spatial distribution of the HAT vector is vital.

The current study is based in Nigeria, and looks at part of Delta State, and a part of Jigawa State, in which HAT has been identified. The work utilizes remote sensing satellite imaging and fuzzy logic to develop a HAT vector habitat classification scheme, to explore the dynamics of HAT propagation. The goal was to develop a surveillance methodology to identify factors that influence HAT epidemiology. Land cover and ancillary data were integrated to classify HAT vector habitat using geospatial-fuzzy multicriteria analysis.

The work highlights the significance of geospatial techniques where epidemiological data are limited, for improving understanding of HAT. This study helped distinguish HAT vector habitat into different zones (breed, feed and rest), which allowed the direction and magnitude of HAT, and factors influencing propagation to be determined. This helped identify 'HAT priority intervention areas'.

The study findings suggested propagation of HAT resulted from suitability of water bodies, shrub and less-dense forest for the HAT vector, and continued exposure of human populations to these land cover classes. Overlapping of HAT vector habitat zones within built-up areas was also a cause. The study also found that HAT propagation was multidirectional, and that this may have been influenced by landscape characteristics.

This novel approach can also be used in other part of Nigeria as well as adapted to investigate other diseases. In conclusion, the HAT vector habitat classification scheme is a transparent tool for policy makers for identifying vulnerable and at risk areas.

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ACRONYMS

DEM	Digital Elevation Model
DN	Digital Number
ESRI	Environmental Systems Research Institute
FMOH	Federal Ministry of Health
GCPs	Ground Control Points
GIS	Geographic Information System
GPS	Global Positioning System
HAT	Human African Trypanosomiasis
IDSR	Integrated Disease Surveillance and Response
IVM	Integrated Vector Management
Landsat ETM+	Landsat Enhanced Thematic Mapper Plus
Landsat MSS	Landsat Multispectral Scanner
Landsat TM	Landsat Thematic Mapper
LGA	Local Government Area
LP DAAC	Land Processes Distributed Active Archive Center
LST	Land Surface Temperature
MDG	Millennium Development Goals
NASRDA	National Space Research and Development Agency
NBS	National Bureau of Statistics
NDRDMP	Niger Delta Regional Development Master Plan
NDDI	Normalized Difference Drought Index
NDVI	Normalized Difference Vegetation Index
NDWI	Normalized Difference Water Index
NIMET	Nigerian Meteorological Agency
NITR	Nigerian Institute for Trypanosomiasis Research
PATTEC	Pan African Tsetse and Trypanosomiasis Eradication Campaign
PC	Principal Component Analysis
RH	Relative Humidity
RS	Remote Sensing
SRTM	Shuttle Radar Topography Mission
TOA	Top of Atmosphere
UNDP	United Nations Development Program
USGSEROS	United State Geological Survey Earth Resources Observation and Science
USGS UMESC	USGS Upper Midwest Environmental Sciences Center
UTM	Universal Transverse Mercator
WGS	World Geodetic System
WHO	World Health Organisation

Chapter 1: Introduction

1.1 Overview

Human African Trypanosomiasis (HAT) or ‘sleeping sickness’ is a fatal disease caused by infection by protozoan parasites of the species *Trypanosoma brucei*. HAT is amongst the top thirteen neglected tropical diseases (NTD) in the world (Hoskins 2009) and is most common in the countries of sub-Saharan Africa (SSA), such as Nigeria and the Democratic Republic of Congo; it currently has limited treatment options. NTDs are often called poverty diseases, as they affect almost exclusively very poor remote populations beyond the reach of health services and are responsible for more than half a million deaths annually (Hoskins 2009; Boutayeb 2007). The HAT parasite is endemic and free-living in the environment, and infection of the human population can be caused either through sexual transmission (Rocha et al. 2004), mother-to-child infection (Olowe 1975) or through insect vectors such as the tsetse fly (Steverding 2008). This study focuses on infection is caused by insect bite.

NTDs are common amongst the poor in SSA, especially in Nigeria and the Democratic Republic of Congo (Hotez and Kamath 2009). HAT affects thousands of people each year, primarily in areas of conflict, where they cause high mortality. There is dearth of information on Africa’s protozoan NTDs and the overall burden of African’s NTDs may be severely underestimated (Hotez and Kamath 2009). Although numbers of cases voluntarily presenting for treatment each year have increased, in Nigeria the exact number of HAT cases is unclear (Abenga and Lawal 2005).

Despite control efforts, HAT has become resurgent in some locations (e.g. Southern Nigeria) and resistance to available medication has been reported in sub-Sahara Africa (Hoskins 2009). Finding a lasting cure for the disease will aid its eradication, however, other approaches are also important as a cure alone will not prevent disease spread. Examination of factors that make an environment conducive for HAT are essential for sustainable disease management and to understand HAT propagation. These factors may vary significantly within indigenous clustered settlements, and it is important to characterise these variations and detect hazardous areas.

Technological innovations, such as Remote Sensing (RS) and Geographic Information Systems (GIS) have permitted epidemiologists to perform disease mapping and spatial analyses (Leonardo et al. 2005; Bavia et al. 2005; Mushinzimana et al. 2006; Symeonakis, Robinson and Drake 2007). A better understanding of the dynamics of disease propagation in a population and the spatio-temporal variations in disease incidence provides a basis for effective disease control (Clements et al. 2009; Kelly-Hope and McKenzie 2009; Noor et al. 2008). However, spatial aspects of HAT are rarely addressed, and most HAT studies, particularly in the Delta State Nigeria – the main research area of this study, are based on medical diagnostics (Wang et al. 2008; John, Kazwala and Mfinanga 2008). In Nigeria, the existing HAT surveillance system and the establishment of precise demarcation of the disease magnitude is limited by unstable security (Simarro et al. 2010).

Conscious of the constraints in managing HAT in sub-Sahara Africa, between 2000 and 2009, the World Health Organisation (WHO) granted exclusive support to some HAT endemic nations, including Nigeria, in order to improve epidemiological understanding and establish innovative disease management tools (Simarro et al. 2011). Geospatial techniques such as RS, GIS and spatial statistics were implemented and have been shown previously to be effective in developing efficient disease management (Leonardo et al. 2005; Eisen and Lozano-Fuentes 2009; Mushinzimana et al. 2006; Hotez and Kamath 2009). These techniques have also been used previously for monitoring HAT (Berrang-Ford et al. 2006; Sindato, Kimbita and Kibona 2008; DeVisser and Messina 2009; Symeonakis, Robinson and Drake 2007; Odiit et al. 2006). This approach will contribute to both the local and international understanding of how best to manage HAT propagation in study area with poor security (Symeonakis, Robinson and Drake 2007) as well as provide insights into the underlying factors affecting the disease.

Reversing the trend of HAT resurgence is a key challenge and vector control will be necessary to disrupt propagation. The present research work will carry out a detailed characterisation of the study areas environment using geospatial techniques to identify and classify potential HAT vector habitats into zones, to ease disease management. Zoning the potential habitat could permit both quick preventative and diagnostic management of HAT. The rationale for classifying the HAT vector habitat is based on studies that emphasised their significance to vector survival and HAT resurgence. (DeVisser and Messina 2009; Green and Hay 2002; Roger, Hay and Packer 1996; Goetz et al. 2000; Rogers 1979; Lennon and Tunner 1995; Leak 1999).

1.2 Human African Trypanosomiasis

HAT is a form of vector-borne disease transmitted by the bite of an infected tsetse fly (Sterverding 2008). Female tsetse fly produce larva roughly every 9-10 days depending on favourable temperature, humidity and suitable site (Jordan 1986). Although attempts to control HAT have been successful, mainly though eradication programmes for the tsetse fly vector, resurgence of the disease in some foci has been reported. The closure of most Nigerian Institute for Trypanosomiasis Research (NITR) epidemiological out-stations in 1985 led to a drastic decline in active surveillance for HAT, making it difficult to assess the true numbers of infected individuals in Nigeria. However, the number of HAT reported cases rose from 619 in 2002 to 7,104 in 2004 and although declining slightly to 5,548 in 2005, rose again to 6,419 in 2006. The numbers of reported cases of death from HAT from 2002 to 2007 are not available (National Bureau of Statistics (NBS) 2007). In July, 2010, 6 out of 2000 screens in 2 local government areas of Delta State were seropositive. Resurgence of the disease has been attributed to a number of factors ranging from political and civil insecurities, displacement of human population, changes in public health policy, pathogenic change, land use change, drug resistance and climate change (Berrang-Ford 2007).

1.2.1 Epidemiology of HAT

Trypanosomiasis or 'sleeping sickness' is an infectious disease of man and animals caused by infection with protozoan parasites of the species *Trypanosoma brucei*. Once infected, the disease has two distinct stages: an early haemolymphatic phase and a later neurological phase. The early phase is characterised by highly variable and non-specific symptoms such as fever, headaches, joint pain and itching, which are often mis-diagnosed as malaria or influenza. During the late phase parasites are present in the cerebrospinal fluid, causing the classical symptoms of sleeping sickness which include confusion, lethargy, weakness, progressive emaciation, slurred speech, disturbed sleep patterns and sensory disturbances. If untreated, the disease overcomes the host defences leading to coma and death (Steverding 2008; Berrang-Ford 2007; Jordan 1986).

Two different species of the protozoan parasite can cause disease in humans. *T. brucei gambiense*, found in Central and West-Africa, causes a chronic disease and typically follows a chronic clinical course progressing over several years (Steverding 2008; Berrang-Ford 2007). Conversely, *T. brucei rhodensiense*, which is found in Southern and Eastern-Africa, causes an acute disease which progresses from non-specific symptoms to infection of the central nervous system and death within months (Steverding 2008; Berrang-Ford 2007). Figure 1.1 shows the life cycle of the *T. brucei* parasites. Although parasites are slow to reproduce, they have a very high survival rate as they reside and multiply in the blood and tissue fluids of their mammalian hosts until third- larval stage (Steverding 2008).

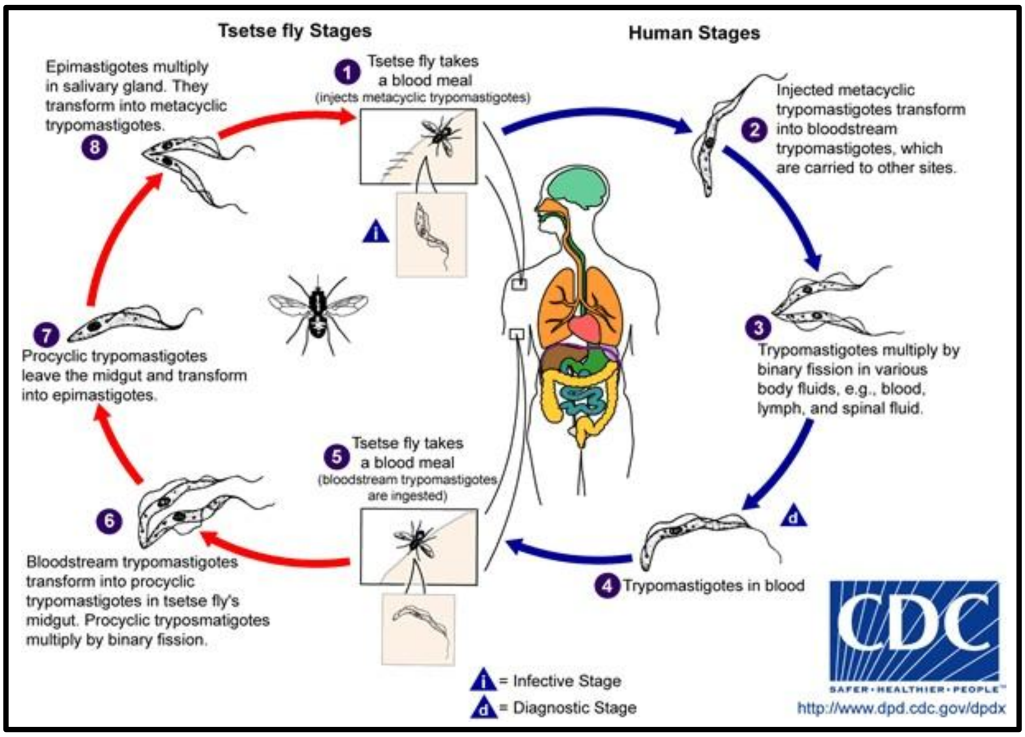


Figure 1.1: Life cycle of T. brucei parasites (source: Centres for Disease Control and Prevention 2012).

1.2.2 Geographical distribution of HAT

An adult female tsetse fly can survive up to three months, reproducing up to ten times in that period (Jordan 1986), and the HAT vector *Glosina palpalis* can fly up to 4km (Jordan 1986) within a given zone depending on suitable conditions such as relative humidity, land surface temperature, etc. The distribution of the disease in Africa corresponds to the range of tsetse flies and comprises currently an area of 8 million km^2 between 14 degrees North and 20 degrees South latitude (Steverding 2008). The disease is endemic in certain regions of Sub-Saharan Africa, covering about 36 countries (WHO 2008). Figure 1.2 shows the distribution of HAT in Africa.

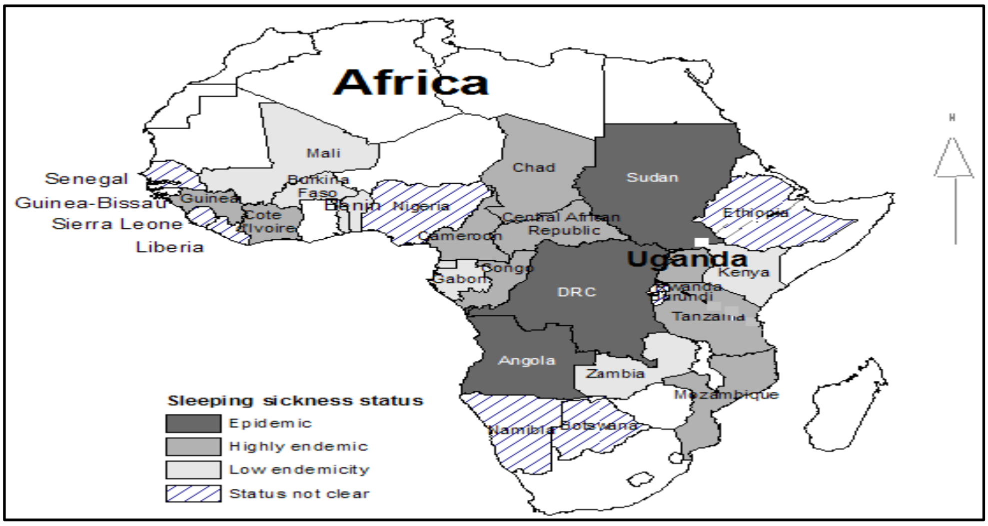


Figure 1.2: Distribution of human African trypanosomiasis in Africa

(adapted from Berrang-Ford 2007)

1.2.3 HAT treatment and control

There is no vaccine for HAT, and its development faces significant economic challenges due to the limited market and lack of financial incentives for pharmaceutical companies to produce vaccines for low-income countries (Hoskins 2009). Existing treatment of HAT is both expensive and complicated, and can be dangerous for the patient (Simarro et al. 2012). The predominant treatment for late-stage sleeping sickness with neurological involvement is melarsoprol, an organoarsenic compound with high toxicity and rate of treatment failure (Berrang-Ford 2007). Melarsoprol is reported to kill 5% of patients who receive it (Kennedy 2008).

A disease thought to have been conquered during the 1960s in Nigeria through the use of biological control of the tsetse fly (BICOT), is re-emerging with areas becoming re-infested (Dede and Mamman 2011) and a shift from the north to the southern part of the country. The recurrence of HAT in both old and new foci prompted WHO at the 50th World Health Assembly to adopt a resolution to increase the disease awareness and, Nigeria was reported as one of the highest ranked endemic countries for HAT (WHO, 1997, 2007).

Active surveillance and case treatment have been found to be very effective in reducing disease transmission, particularly for *T. b. gambiense* (Berrang-Ford 2007), which is generally confined to human-fly-human cycle. *T.b. rhodensiense* transmission to humans is influenced by prevalence of the parasite in animal reservoirs; such as cattle in East Africa and human-infective parasites have also been identified in animals in West Africa (Abenga and Lawal 2005). Control of livestock infection and tsetse populations are important for reducing transmission to humans (Batchelor 2010). The recent history of sleeping sickness has shown that the disease can be controlled but probably cannot be eradicated and new anti-sleeping sickness drugs are urgently required (Steverding 2008).

1.2.4 Economic and environmental impact of HAT

HAT has restricted the cultural and economic development of the people in Sub-Saharan regions (Steverding 2008), thus, there is the need for a concerted approach of systematic case- detection and treatment. African trypanosomiasis always prevented the introduction of stock farming in endemic areas, which resulted in much of tropical Africa not being converted into grassland for cattle (Steverding 2008). From an environmental angle, the presence of the HAT vector in the tropics has prevented vast portion of the rain-forest being depleted; thereby maintaining the natural ecosystem, and increased cattle number may result in less vegetal cover and eventually increase runoff and erosion as well as reduction in biodiversity (Symeonakis, Robinson and Drake 2007).

1.2.5 HAT surveillance

Resurgence of HAT in Nigeria has been blamed on a weak surveillance system, inappropriate government policies and poor funding as well as ignorance about the disease (Anagbogu I, personal communication 2010). Surveillance can be regarded as the continuing methodical gathering, ordering, examination, and interpretation of data; and the dissemination of information to the relevant stakeholders for effective decision making (Garcia-Abreu, Halperin and Danel 2002). Surveillance can help establish the need for public health intervention programmes, monitor their progress and help identify at-risk populations and locations for targeted intervention, whilst identifying factors that influence disease propagation.

Disease surveillance in Nigeria has been impeded by poor communication equipment, absence of case management protocols, inadequate laboratory facilities and funding as well as inadequate medicine and vaccines (Nduka and Yennan 2007). The Nigerian Federal Ministry of Health (FMOH) formally established the HAT elimination programme in 2006, building on work over the previous twenty years of disease surveillance (Nduka and Yennan 2007). This included a regional pan African Integrated Disease Surveillance and Response (IDSR) plan, started in 2000 in Nigeria and organised at local, state and federal levels of government. The haphazard implementation of such programmes has resulted in duplication of efforts and materials.

Repeated World Health Assembly calls for global elimination of HAT have led to establishment of the Pan African Tsetse and Trypanosomiasis Eradication Campaign (PATTEC). PATTEC’s goal is for Africa to become tsetse fly free through creation, and subsequent expansion, of tsetse-free zones (Cecchi et al. 2008). To achieve this goal, the knowledge of the disease vector ecology and detailed spatial distribution datasets integrated with existing disease surveillance schemes is vital. It is therefore important that the present study support surveillance activities through the use of tools that have capability to gather data in remote or conflict areas.

The Nigerian HAT elimination program is domiciled in the department of public health and was established to operate in line with the existing structures for the Nigerian Guinea worm Eradication Program

(NIGEP) and WHO guidelines. The program is expected to work in collaboration with PATTEC, WHO and other stakeholders such as the Federal Ministries of Environment, Agriculture and Water Resources, Science and Technology and the NITR, to eliminate HAT from Nigeria.

Information is vital to effective disease management, but the level of underreporting of disease, most especially HAT in Nigeria, impedes progress. The information gap, such as comprehensive digital spatial epidemiological information/data, could be reduced with geo-referenced studies, lacking in some previous work (Osue et al. 2008; Anere, Fajinmi and Lawani 2006; Sterverding 2008; Berrang-Ford et al. 2006; Priotto et al. 2008; Reid et al. 2012).

The present study attempts to remedy the lack of digital locational based information by combining spatial and non-spatial data to develop a digital HAT vector habitat classification scheme used to assess the propagation of HAT in the study area.

1.3 Geographic Information Systems and Remote Sensing in Disease Study

This section reviews the tools and technologies being used in the development of disease management and how these can be applied to HAT vector mapping.

1.3.1 Geospatial technology

Geospatial technology is pervasive in modern life, and is used in areas such as law enforcement, fire response, disaster management, land use identification, flood plain mapping and environmental protection. It is also used in public health to track the spread of disease (Cimons 2011). Due to its exceptional precision, aerial coverage and cost effectiveness, geospatial technology tools have revolutionised disease mapping (Simarro et al. 2010). Such systems allow health officials to rapidly identify areas experiencing distress; and have immediate access to the information required to address the underlying problem without leaving the office. However, for this to function effectively there must be access to useful and near-real-time datasets in order to facilitate quick response. Such datasets are usually gathered from various sources, such as remote sensing, reconnaissance survey, mapping, socio-economic datasets and other sources. To derive maximum benefits from them, spatially referenced information or geo-referencing is required, and it is the integration of these geographically referenced datasets with other information that brings about geospatial technology.

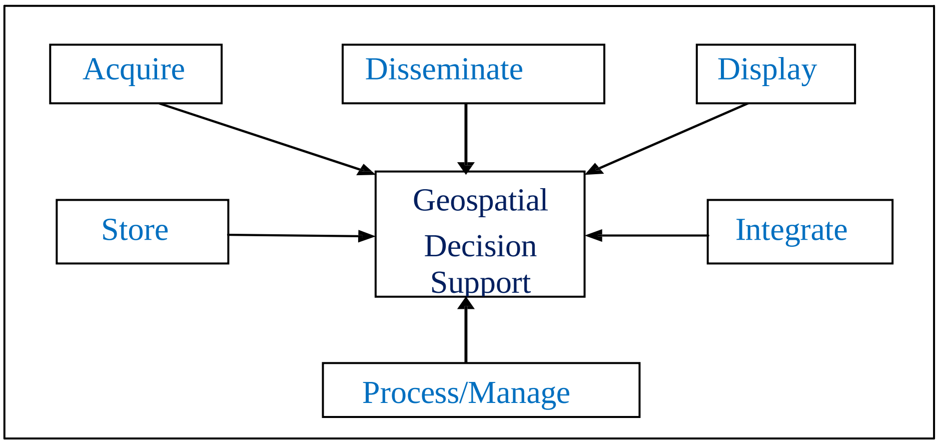


Figure 1.3: Diagram showing decision support system (adapted from Cimons 2011)

Geospatial technology is a discipline associated with technologies such as, Remote Sensing (RS), the Global Positioning System (GPS), Geographic Information Systems (GIS), Information Technologies (IT) and *in-situ* field survey data that helps in the acquisition, storage, processing, management, integration, display and dissemination of geospatial data, and supports effective decision making. Figure 1.3 summarises geospatial decision support.

Geospatial data, on the other hand, identifies the geographical location and characteristics of entities on the earth's surface. Recently, geospatial techniques have been applied at varying geographical scales to determine the risk of vector-borne diseases and classify vector habitat using remotely-sensed derived variables (Mushinzimana et al. 2006; Odiit et al. 2006). Geospatial techniques have the ability to identify factors that influence disease propagation within the endemic area. Thus, it is vital to our understanding of the link between geospatial techniques, RS and GIS and a vector-borne diseases physical environment.

1.3.2 Geographic information systems

GIS could be said to be acquisition, storing, processing/manipulation and presentation of geo-referenced data (Akiode 2008). GIS could also be defined as the use of hardware, software, people, procedures, and data (Murayama and Estoque 2010).

According to James Madison University (2004), a successful GIS is a function of its combined components, which include:

People:

- The general public who are mainly searching geographic database for references.
- People that apply GIS to businesses or professional services.
- Specialists responsible for GIS database maintenance and technical support for users.

Data: Creation of a GIS database, which must take into account data quality and source, positional accuracy, attribute accuracy, logical consistency (compatibility of a datum with other data in a project) and checks for completeness.

Hardware: The technical materials for smooth GIS running, (e.g. desktop, laptop, digitiser, GPS, printers, scanners etc).

Software: GIS packages and database software. Different GIS software has different functionalities and the type chosen for a project must match the needs and the capability of the end user.

Procedures: The methods used to input, store, manage, transform, analyse/query and present data.

A GIS map contains layers or a collection of geographic objects that are alike. These layers contain features or surfaces (a surface is a continuous expanse). While features, for example, settlements and rivers, have distinct shapes and are represented as polygons, lines or points depending on the scale, surfaces, (e.g. land surface temperature, relative humidity, elevation, etc), have no shape, but do have measurable values (Ormsby et al. 2004). In GIS, entities or features have locational values (x, y, coordinates), and these features can be displayed at different scales, depending on the size of the project under consideration. Also, features can be linked to their attributes (metadata of the feature or entity of interest). The attributes provide greater in-depth detail that helps better understand the entity. With the aid of coordinates, GIS can help in establishing spatial relationships among features, as well as help in transforming features from one form to another (Ormsby et al. 2004).

1.3.3 Remote sensing

RS could be regarded as the art and science of obtaining information about phenomena with little or no contact (Lillesand, Kiefer and Chipman 2004; Buiten and Clevers 1993). This is achieved by sensing and recording reflected or emitted energy and processing, analysing, and applying the information (Sabins 1996 and Canada Centre for Remote Sensing 2012). Satellite imageries are example of RS data. In RS, surfaces may be in form of a raster. A raster is a regularly spaced set of cells with associated values. In reality, the world is not partitioned clearly into features and surfaces and objects can be represented both as features and/or surfaces. When represented as feature, the boundary becomes discrete; but in reality most entities on earth surface, for example land cover types does not have discrete boundary. Thus, representation of such entity as surface is ideal.

1.3.3.1 Mechanism of remote sensing

RS depends on the measuring electromagnetic (EM) energy. EM energy can be detected on the earth's surface from the sun, in the form of visible and ultra violet light, and heat. All substances emit EM energy as waves, resulting from their molecular movement. An object that can absorb and re-emit all the thermal radiation (EM energy) it receives is called a blackbody and a blackbody's emissivity and absorptivity are equal to 1 (Woldai 2004). In reality no object radiates EM energy perfectly; rather, different objects reflect or absorb energy better at different wavelengths, based on their absolute temperature and emissivity. Absorptivity is the ability of an object to absorb EM energy while emissivity is the ratio of radiant energy emitted by an object and blackbody radiation, expressed by Planck's law. Land surface emissivity (LSE) plays a major role in the derivation of land surface temperature (LST).

The total electromagnetic wave produced by an object during radiation is called the electromagnetic spectrum. This spectrum ranges from gamma rays to radio waves (Woldai 2004). Several regions of the electromagnetic spectrum are useful for remote sensing. The amount of energy detected by a RS sensor depends on the energy's interaction with matter, both on the earth surface and in the atmosphere. The source of RS data for disease study is mostly recorded images of portions of the Earth's surface. There are seven elements involved in the RS process, shown in Figure 1.4.

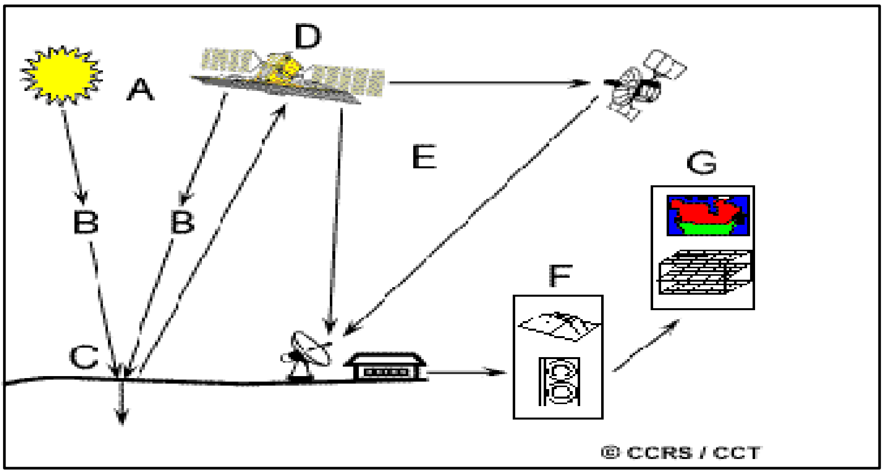


Figure 1.4: Elements of the remote sensing process A = source of energy providing EM energy to object on earth's surface; B = emitted energy and the atmosphere (energy interacts with the atmosphere as it travels from the energy source to the object or sensor); C = energy interaction with the object or entity (the level of interaction is a function of the entity's properties); D = sensor recording the emitted energy from 'C'; E = receiving station where transmitted energies from the sensor are processed; F = processed images from receiving station are interpreted and analysed ; G = application of information extracted from the object of interest towards better understanding of the object (source: Canadian Centre for Remote Sensing).

1.3.3.2 Characteristics of remote sensing images

The RS image is a measure of electromagnetic energy, which is recorded in regular square format called a pixel; the elementary unit of image data (Janssen and Bakker 2004). Each unit and reflectance is represented as a numeric value or digital number (DN; Canada Centre for Remote Sensing 2012). Pixel sizes adopted by varying RS sensor systems may range from 1, 30 or 1000 square metres for high, medium and low spatial resolution images, respectively (Janssen and Bakker 2004).

The values of image data are associated with the features of the RS sensor. The image features can be specified by coverage and resolution. The resolution is the least discernible distinction at which entities can be separated. In the RS environment, resolution refers to spatial, spectral and radiometric resolution. Spectral resolution describes the ability of a sensor to define fine wavelength intervals, while radiometric resolution describes its ability to distinguish minute differences in energy (Canada Centre for Remote Sensing 2012).

The details detectable in recorded RS images are a function of the spatial resolution of the RS sensor. Spatial resolution is the smallest possible object or entity that can be seen on an image (Janssen and Bakker 2004). The spatial resolution depends primarily on instantaneous field of view (IFOV), that is, the angle of the RS sensor that determines the swath width or resolution cell of an image from a known height per time (Janssen and Bakker 2004, Bakker 2004). The RS sensor records the average reflectance of all objects within the swath width, thus an object that has uniform characteristics can only be detected if the dimensions are the same or outsized the swath width. Objects with smaller dimensions can nevertheless be detected, if they have a higher reflectance value than other objects within the swath width (Canada Centre for Remote Sensing 2012).

1.3.4 GIS and remote sensing integration

The integration of RS and GIS will produce useful result for effective disease management. The availability of high-resolution satellite imagery has revolutionized the process of thematic mapping and spatial database creation, and technologies such as GIS have emerged as powerful tools in integrating and analysing the various thematic layers along with attribute information to create various planning scenarios for decision making (Tiwari 2006).

RS data provides reliable, timely, accurate and periodic data, while GIS provide various methods of integrating tools to create different planning scenarios for decision making. Thus the adoption of these technologies in examining and managing HAT propagation in the study area is appropriate. RS and GIS tools could be regarded as the catalyst needed to dissolve the regional-systematic and human-physical dichotomies that have long plagued disciplines connected with spatial information (Akiode 2008). When investigating a phenomenon with an aim of progressing to efficient management, (e.g. disease control and prevention), some connection is vital to understanding and managing activities and resources that are often missing. With RS and GIS, it is possible to make connections between activities based on geographical proximity. Currently, GIS and RS are crucial in many fields in assisting in the decision making process. It was opined in ILWIS 2.1 that, most decisions are influenced to some extent by geography. What is at a location? Where are the most suitable sites? Where, when and which changes took place? ILWIS 2.1 further stated that, in order to be able to make the right decisions, access to different sorts of information is required. Data should be maintained and updated and should be used in the analysis to obtain useful information. In support of this opinion, the present study will make use of relevant RS and GIS software (ArcMap 10.0 and IDRISI Selva 17.0) to carry out analysis on which useful information was deduced. IDRISI offers a set of support tools that are specifically appropriate for image processing and multi-criteria decision making, for example, weighting of criteria, while ArcMap is GIS software used mainly to display, edit, create, and analyse/manipulate geospatial data.

1.3.4.1 Integration of geospatial decisions in vector-borne disease management

Integrated RS and GIS technologies have been utilised to improve our environmental knowledge. Images of earth phenomenon taken remotely provide opportunities to capture the interrelationship of environmental elements. Integration of geospatial approaches with disease management decisions can permit efficient and effective prioritization and deployment of limited resources. Decision making processes are complex; involving the use of concepts and tools, some of which are discussed in more detail in this chapter.

1.3.5 HAT distribution mapping: previous efforts

The resurgence of Trypanosomiasis in some endemic foci continues to impact rural development in sub-Saharan Africa. Efforts to control and free these foci from disease have led to introduction of targeted programs. Achieving HAT free foci depends largely on tsetse fly ecology and suitable vector spatial distribution datasets. Thus, HAT vector habitat maps are indispensable, but, in some endemic regions, this spatial distribution and HAT vector prevalence information is still limited and inadequate for wider area planning and management. To address this issue, requires examination of how land cover datasets may influence HAT vector habitat mapping.

The significance of land cover was acknowledged in past research, in which vegetal and other environmental variables, such as climatic and elevation data, were used to assess the spatial distribution boundary of various types of HAT vector (Katondo 1984). Lately, geospatial techniques such as, RS and GIS have been used in mapping tsetse distribution at continental and regional scales (Courtin et al. 2005; Rogers and Robinson 2004; Rogers and Williams 1994; Rogers and Randolph 1993). There is also an increasing numbers of studies in the literature on the usage of RS images for HAT vector habitat mapping at a higher spatial resolution (Bouyer et al. 2006; De Deken et al. 2005; Mahama et al. 2005). In spite of this progress, the level of detail and accuracy of some of the existing HAT vector spatial distribution maps/datasets, are still not sufficient for the difficult tasks posed by the scheduling and execution of wide area surveillance programmes.

Other studies that acknowledge the importance of land cover in HAT mapping include DeVisser and Messina (2009), who used a broad method to evaluate the existing land cover products that performs best for habitat modelling. Sutherst (2004) highlighted the impact of deforestation and irrigation on HAT, while Reid et al. (2012), pointed out that epidemiology of HAT cannot be analysed in the absence of precise environmental data. In Berrang-Ford (2007), land cover change and proximity to certain land cover types were listed among the factors responsible for HAT resurgence, while Courtin et al. (2005) carried out a landscape assessment of an area of Bonon, Côte d'Ivorie. Land cover is generally considered in these studies, but (except for Courtin et al. 2005) was not actually examined as an indicator of habitats appropriate for the HAT vector. Nevertheless, there is link between land cover and other major contributing factors, (e.g. climatic variables, in HAT vector habitat). It is also obvious from the literature that the physical landscape is very important to HAT propagation; yet, few efforts have been made to pinpoint the exact locations where HAT patients are infected. Emphasis was put on domestic units or settlements as a geographic unit to which disease datasets were linked, even though this type of landscape analysis will not permit the detection of highly HAT hazardous locations. It is very important that the landscape within HAT endemic areas is well examined.

A study by Courtin et al. 2005 highlighted the worth of GIS in gaining a perception of HAT distribution and spatial dynamics, as well as identified active transmission areas. A disparity between HAT infection in the northern and southern part of the study area (Bonon, Côte d'Ivoire), was explained using spatial analysis. The authors, with the aid of GIS, spatially analysed the link between the human host, tsetse vector and trypanosomes in their landscape.

These studies, irrespective of their level of details, accuracy, and original goals have served as basis for HAT control programmes across sub-Sahara Africa. However, due to the heterogeneous nature of the sub-Sahara Africa environment and the importance - economic or otherwise - of varying biotic and abiotic components, HAT management and controlling activities will benefit from detailed landscape characterisation studies.

Underreporting is one of the factors affecting HAT (Osue et al. 2008). Underreporting of HAT cases, most especially *T. b. gambiense*, is an indication that supplementary data gathering approaches, other than the existing active and passive case surveillance, are required. The existing case surveillance methods are insufficient to fully describe the extent of HAT. While infected people may not access passive surveillance facilities for treatment until a late stage, due to the asymptomatic nature of the West African form of HAT, the active surveillance team may not detect the case because of constraints such as limited resources and the nature of the terrain, etc. This results in underreporting and eventually resurgence of the disease. To overcome the limitations of the existing system as well as promote improved HAT management; the integration of geospatial techniques is very important.

1.3.6 The link between RS/GIS and environ-climatic variables and disease management

The principle behind the association of RS and the study of disease origin and propagation is the development of a logical chain that connects emitted energy from a remote sensing sensor to disease measures and the disease transmitting organism (Kalluri et al. 2007). For instance, RS sensors at different wavelengths records energy emitted by phenomena on the earth surface or within vector-bone diseased endemic areas. The emitted energy is then pre-processed to generate different land cover classes. The land cover classes can be re-classified into vector habitat; the survival of disease vector and its propagation is associated to the vector habitat. Thus, RS data can give insights into the factors influencing disease propagation using habitat information. Emitted energy recorded of phenomena on the earth's surface could also be pre-processed to obtain data such as normalised difference vegetation index (NDVI), land surface temperature, digital terrain dataset, normalised difference water index (NDWI) etc. All of these could be analysed singly or in combination with other datasets/information to examined and manage the disease in a given environment.

The importance of land cover in the application of RS in the study of disease origin and propagation cannot be over emphasised; land cover can be used to link disease vectors to their habitat or to generate substitute environmental indicators. The landscape is central to the study of disease origin and propagation; and in-depth knowledge of the landscape and factors that affect disease propagation retrieved using RS is, therefore, a function of the spatio-temporal interaction between the land cover classes. The potential link between HAT and the RS factors or variables used in the present study for HAT habitat classification is summarised in Table 1.1.

Table 1.1: Potential links between remotely sensed factors and HAT Disease. Source: Adapted from Beck *et al*. (2000).

Factor	**Mapping prospect**
Vegetal cover (dense forest, Less dense forest)	Vector habitat
NDVI	Vector Survival
Ecotones	Human/vector contact risk.
Deforestation (cultivated area, shrub)	Unfavourable habitat/ human/vector contact Risk
Water bodies	Breeding habitat / human/vector contact risk
Mangrove	Breeding/Resting habitat
Soil moisture / relative humidity	Vector survival / influenced vegetal cover vigour
Human Settlements(built-up area)	Source of infected humans; populations at risk for propagation
Land surface temperature	Vector survival

1.3.7 Application of GIS and RS to disease management

Remote Sensing and GIS have been used to successfully identify environmental factors that correlate with the distribution of malaria and schistosomiasis (Leonardo et al. 2005). Use of these technologies permits rapid assessments of disease situations and facilitates decision making regarding interventions and treatments. GIS software are becoming more user-friendly and now are complemented by free mapping software that provide access to satellite imagery and basic feature-making tools, that have the capacity to generate static as well as dynamic time-series maps (Eisen and Lozano- Fuentes 2009). Eisen and Lozano-Fuentes (2009) in their work on Dengue fever, discussed how mapping and spatial and space-time modelling approaches have been used in disease management and how these approaches can be included as routine activities in operational vector control programmes. This, they said, will enable such programmes to, for example, generate risk maps of exposure to dengue virus, develop priority area classification for vector control, and explore socioeconomic association with dengue risk. This present study will develop a classification scheme for identifying HAT risk areas using RS images in a GIS environment.

1.3.8 RS and GIS in disease control

RS data has proved useful in disease prediction; not only because RS can be accessed for near real-time data, but also its ability to provide archival data for predictions and has been used in several studies. Williams and Peterson (2009) tested the hypothesis that spatial distributions of avian influenza (HPAI-H5N1) cases are related consistently and predictably to coarse-scale environmental features in the Middle East and north eastern Africa. They combined RS data with other datasets (e.g. topographical data), and using ecological niche models, the authors documented a variable environmental "fingerprint" for areas suitable for HPAI-H5N1 transmission.

Examining the association between aerosol air pollution as indicated by aerosol optical depth (AOD) and chronic ischemic heart disease (CIHD) in the eastern United State, Hu and Rao (2009), used satellite data to establish strong association between CIHD mortality risk and air pollution, in areas with elevated levels of outdoor aerosol air pollution, as indicated by satellite derived AOD. They concluded that RS could help fill pervasive data gaps that impede efforts to study air pollution and protect public health. The use of RS data in the present study will greatly help in alleviating the problems of dearth of HAT related data.

The integration of RS and GIS has been vital to development of disadvantaged regions towards sustainable health. According to Angeles et al. (2009), the concentration of poverty and adverse environmental circumstances within slums, particularly in developing countries, are an increasingly important concern for both public health policy initiatives and related programmes in other sectors. Angeles et al. (2009) pointed out that GIS and RS integrated with traditional fieldwork methodologies was used to obtain up-to-date information about slum life in major cities in Bangladesh including Dhaka. According to the authors, the method allowed programmers and planners to precisely target their efforts towards areas of concentrated poverty and poor environmental conditions effectively. The methodologies employed were very efficient in terms of processing speed and access to information.

RS and GIS techniques have been vital in aiding planning strategies for reducing disease risk, by eliminating the vector population. For example, in planning and implementing area-wide integrated pest management activities in northern Sudan, Ageep et al. (2009), used RS, GIS and GPS to select survey locations for malaria research. They noted that the GIS-based survey strategies developed in their study provided key data on the population dynamics of the malaria-carrying *Anopheles arabienses* mosquito. This, they said, provided a basis for planning a strategy for reducing malaria risk, through elimination of the vector population.

RS/GIS integrated with statistical methods can facilitate an understanding of disease management. According to Kelly-Hope and Mckenzie (2009), understanding the dynamics of disease transmission in a population is vital as it provides insight into the extent of the problem and helps define when and where the greatest risk occurs. This facilitates development of appropriate control strategies. In order to identify key differences and similarities and highlight corresponding risk factors, Kelly-Hope and Mckenzie (2009), pointed out that it is important to determine how the level of risk within a population may compare with other or surrounding populations.

Noor et al. (2008) stated that the use of geo-statistical methods can help focus surveillance efforts and define those areas where uncertainty exists, to better estimate disease burden. For example, to enhance the understanding of the multiplicity of malaria transmission, Kelly-Hope and Mckenzie (2009) examined the distribution of transmission intensity across sub-Saharan Africa, and reviewed the range of methods used. They explored ecological parameters in selected locations by building on an extensive geo-referenced database using GIS. Noor et al. (2008), on the other hand, in emphasising the importance of distribution maps in optimal allocation of resources in disease activities, pointed out that reliable contemporary malaria maps are lacking in endemic countries in sub-Saharan African. They used instead geo-statistical models to provide the best contemporary map on malaria prevalence in Somalia. In the present study, RS/GIS will be integrated with spatial statistics to prioritise HAT diseased areas.

Other examples of studies emphasising the importance of geo-spatial and geo-statistical techniques in disease management include Osei and Duker (2008), whose study demonstrated the use of GIS based spatial analysis and statistical analysis, in mapping hotspots, and the spatial dependency of cholera distribution within the Ashanti region of Ghana. Additionally, Ekpo et al. (2008) used GIS and RS data to develop predictive risk maps of the probability of occurrence of urinary schistosomiasis, and quantify the risk for infection in Ogun State, Nigeria to boost control programme.

GIS application is not limited to vector-borne diseases management. Presenting their findings from a workshop held in June 16-17, 2005, Pickle et al. (2006) pointed out how cancer control researchers seek to reduce the burden of cancer by studying interventions, their impact in defined populations, and the means by which they can be better used. According to the authors, identifying locations where interventions are needed is vital to cancer control. GIS and other spatial analytic methods provide such a solution, and thus can play a major role in cancer control (Pickle et al. 2006).

1.3.9 Disease management

The decision by policy makers across the globe to manage disease propagation is governed by varying spatial factors. It is these factors that drive the balance between disease prevention and treatment. Disease prevention involves education of the population as to how a disease is transmitted, and thus provides strategies that can help in reducing the disease propagation. In some countries, access to effective and efficient health care is constrained by the cost of disease treatment, which is higher compared to preventive disease management (The British Geographer no date). Disease management, especially vector-borne disease management is very important.

1.3.10 Integrated vector management

Integrated Vector Management (IVM) is a decision-making process that supports the maximum benefits that can be derived from linking the management of a disease vector, to the physical landscape (WHO 2012). The intent is to decrease or disrupt propagation of disease. An IVM method makes judicious use of existing health infrastructure and resources; it supports integration of different methods to effectively manage a disease vector towards realisation of Millennium Development Goals (wellbeing content), such as: reduction of child mortality rates, improve maternal health and combating diseases (UNDP no date).

IVM emphasises (Robert Bos no date):

- Adoption of strategies based on knowledge (evidence-based) of local vector ecology and disease propagation.
- Use of multidisciplinary methods.
- Multi-sectorial teamwork and involvement of the local communities.
- Public health policy and functioning measures.
- Sustainable chemical methods of vector control.
- Cost-effectiveness.

1.3.11 Decision support systems

Large-scale information systems have become cheaper to build and run over the last fifty years, and have begun to be used to support healthcare decision-makings. Improvements in computer technological sophistication have allowed GIS mapping programs, previously run on mainframe computers to be run on personal computers and laptops, enhancing mapping ability and flexibility. In the 1960s very little detail other than locational coordinates were stored in databases using mainframe systems, but in 1981, Environmental Systems Research Institute (ESRI) introduced the ArcInfo GIS software package, that utilised a second generation geographic data model known as the coverage data model (Figure 1.5; Zeiler 1999).

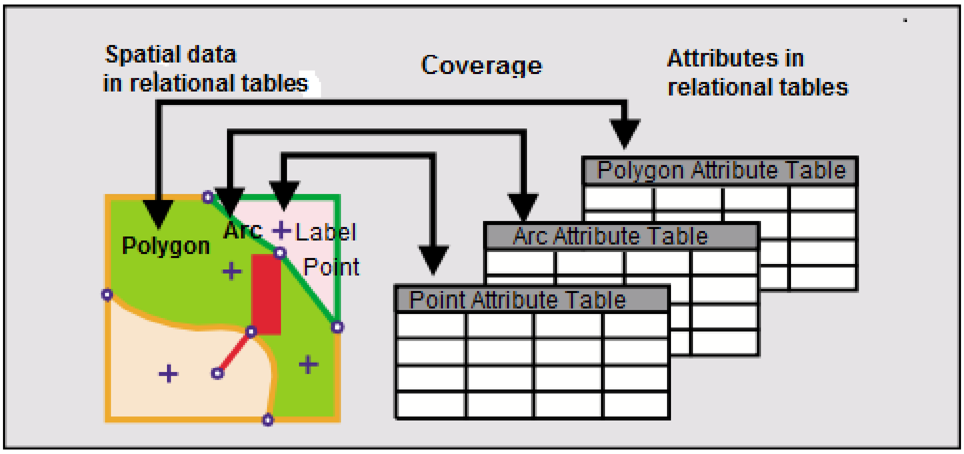


Figure 1.5: Elements of the coverage data model (Source: Zeiler 1999).

The coverage data model allows storage of spatial information with secondary attributes such as address, time and demographic characteristics in a manner available to a range of computational approaches, using algorithms built into the software, or in complementary programs like Microsoft Excel. Thus, GIS can be used as a medium for both graphic and statistical consideration of spatial problems, whose resolution can be reported immediately in charts, graphs, maps, and tables (Koch 2005).

The advent of the internet has allowed multiple disparate studies pertinent to diseases to be retrieved and joined with locational attributes files (Koch 2005). The result according to Koch (2005) has been an unprecedented availability of social and health-related data that can be downloaded to the desktop and independently manipulated using GIS systems, whose analytic and graphic capabilities are far beyond those that were available a generation ago.

A Decision Support System (DSS) can be defined in many ways. The broad definition by USGS Upper Midwest Environmental Sciences Center (2013) is georeferenced computer applications or data that assists a researcher or manager in making decisions. DSS according to Turban (1995) is an interactive computer based system that helps decision makers utilise data and models to solve unstructured problems. DSS improve the performance of decision makers, while reducing the time and human resources required for analysing complex decisions.

The development of a particular DSS depends on the type of problem that is being addressed, for example, 'what-if' analysis can be used to examine how changes to selected variables will affect other variables, or carry out optimisation analysis to find the optimum solution given certain constraints. GIS is a special type of DSS that deals with analysis of geo-spatial data. There has been a lot of focus on the use of GIS as a DSS (Eastman 1999; Geneletti 2004), but the tool is limited in supporting decision making, most especially when regarding complex problems. Thus, there is a need to integrate GIS and DSS in a flexible way towards effective decision making (Akinyemi 2004). In order to improve the capabilities of GIS as a DSS, algorithms are developed within the GIS (Eastman et al. 1995), for example, multicriteria decision tool in IDRISI Selva software. Alternatively, GIS is integrated with other statistical software packages, and/ or with dedicated analytical or socio-economic models (Jankowski 1995).

1.3.12 Geospatial multi-criteria decision analysis in vector-borne disease management

The complexity of vector-borne disease epidemiology poses considerable challenges in the design of effective and efficient management methods. Disease risk prediction studies (Reisen 2010; Eisen and Eisen 2011; Ostfeld, Glass and Keesing 2005) based on geospatial models have been developed towards management and control programs. Nevertheless, these methods usually provide technical information on geographic distribution of disease risk. Spatially explicit information will help decision makers prioritise surveillance and prevention/control measures. Spatially explicit information varies, therefore, it is vital that these are combined to aid decision making using a method that will facilitate quick and effective decision making.

A Geospatial or Spatial Decision Support System (SDSS) is a computer aided information system that can help users generate optimal solutions to spatial puzzles. SDSS users can influence decisions using spatial and non-spatial data, application models, software tools and expert knowledge, (Rayed 2012). Decision making has been considered an art, because a variety of individual styles could be used in approaching and successfully solving the same types of managerial problems, which were based on creativity, judgement, and experience rather than on systematic quantitative methods grounded in scientific approach (Turban and Aronson 2001). However, decision making is becoming increasingly complex and cannot rely solely on artistic talents acquired over long period of time through experience. Precise and rapidly accessible information is very important for making correct decisions and in order to facilitate this, decision makers use modern technologies, such as databases, model bases, computer networks and the internet (Janakiraman and Sarukesi 2004).

Using geospatial techniques, such as GIS and DSS for disease management, different data can be combined to generate useful information that will influence decision making. There are policies/regulations as well as activities that can help in preventing or alleviating disease propagation. Such activities include mapping and monitoring the time and location of the disease occurrence using spatial data. GIS can facilitate the integration of such spatial data and its attributes with statistical data to generate thematic maps to help effective decision making. One can easily model the relationship between diseases and the factors responsible for the disease using geo-statistical models. Such models, according to Mesgari and Masoomi (2008), can help decision makers to prioritise not only the affecting factors of disease, but also the actions and regulations required for fighting the disease. Mesgari and Masoomi (2008) also stressed the fact that such models can help in carrying out the generation of different scenarios and evaluation of the results of terms of potential actions.

It is very important to identify factors responsible for diseases or those that can ease infection rates, and to model disease propagation in a given environment. Environmental and socio-cultural factors may affect disease propagation, thus, there is the need to identify the spatio-temporal distribution of such factors which will boost the modelling of disease direction and propagation speed. This in turn impacts on prioritisation of disease locations and the human populations at risk.

Integration of DSS and geospatial techniques also helps information dissemination, and early warnings are vital in disease management. Geospatial techniques help stakeholders involved in health related matters to carry out spatial analysis on data derived from different sources, and publish the result in suitable formats, depending on the target audience through various media.

The present study will utilise spatial data analysis with data derived from various sources, (e.g. RS, or hospital records in a GIS environment), and to detect HAT risks areas and factors contributing to the disease propagation within the study area. This will help the policy makers, health officials and even the human populations at risk to make quick decision that will benefit all.

In the area of study for this work, spatial disease characteristics have not been clearly emphasised (e.g. hospital records lack geographic location of cases, residential address, date that patients contacted disease and year of cure or death missing from the database; data hoarding by organisations, etc). In order to address the issue of dearth of information, multiple dataset need to be derived from RS imagery in a GIS environment. GIS provides analytical capabilities; and GIS metadata can be processed and used as inputs to modelling, to aid decision making. Spatial decision problems usually involve a large set of viable options and several evaluation criteria, which are often weighed by multiple stakeholders with conflicting interests (Tsiko and Haile 2011). Thus, factors to be considered while developing efficient strategies to manage HAT or vector-borne diseases are many, and the links between or among these factors are complex. In order to facilitate scrupulous selection of optimal choices, in a situation where several criteria apply concurrently (Mendoza and Prabhu 2000) GIS can be integrated with multi-criteria decision analysis (MCDA). In MCDA, problems are divided into sub-sets, analysed logically then merged them to generate an optimal solution (Malczewski 1999).

In MCDA a number of terms are used. According to Eastman *et al.* (1995) these are:

- ***Decision***: This is a choice between alternatives, which could be varying courses of action, hypothesis about an entity characteristic or varying groups of entities, etc.
- ***Criterion:*** A rule or standard by which something may be judged or decided (Oxford dictionary). Criterion can be divided into factors and constraints.
- ***Factor:*** A criterion that influences the fitness of a particular alternative for the activity under consideration, thus, it is measured on a continuous scale.
- ***Constraint:*** A criterion used to control the alternatives under consideration within certain limit.

- ***Decision Rule:*** A method that allows decision makers to choose one or more alternatives using a given set of evaluation criteria as a guide (Malczewski 1999). The method involves the use of choice functions; sometimes called a performance index or objective function and choice heuristic processes.
- ***Choice function***: This provides a mathematical means for evaluating alternatives.
- ***Choice heuristic:*** States a process to be followed rather than evaluating a function.
- ***Objective:*** The measure by which the decision rule operates.

MCDA is now a favourite option for decision making, involving several stakeholders and key players with varying backgrounds (Tsiko and Haile 2011). Apart from being open and explicit, MCDA has characteristics that make it appropriate for providing solutions to intricate problems given a set of criteria or indicators. Though the procedure involved in evaluating multiple criteria may be risk prone and may impact the final decision reached, the involvement of a group of stakeholders and key players will greatly reduce the intrinsic risk.

MCDA can accommodate the integration of qualitative and quantitative data/information; but data does not necessarily have to be intensive; specialist opinions can augment limited data. The method of merging multiple criteria can be non-compensatory or compensatory. Non-compensatory in the sense that alternatives are required to meet one, few, or all criteria based on cut-off values; here any addition or enhancement in the value of one criterion cannot be compensated for by the reduction or devaluation of another criterion. Compensatory methods aid criteria trade-offs; here reduction or loss in a criterion can be offset by an increase in another criterion (Greene et al. 2011).

MCDA can be divided into multi-attribute decision analysis (MADA), sometimes referred to as a multi-criteria evaluation or multi-attribute evaluation and multi-objective decision analysis **(**MODA) or a multi-objective evaluation **(**Jankowski 1995). In MADA, decisions are concerned with a discrete, usually limited number of feasible alternatives, while MODA is concerned with an infinite or large number of alternatives or objectives, to be determined in a continuous or integer domain **(**Jankowski 1995). This means an optimal solution may be found in any location within the limit of feasible solution

(Malczewski 2006). According to Malczewski (2004) and Eastman et al. (1995), with MODA, it is vital to ascertain whether the interaction of the objectives, when combined, will produce an effect greater than the sum of their individual objectives or conflict (e.g. assigning land cover classes to either HAT vector breeding habitat, or to the area where there is human-vector contact, and to cluster the criteria by objectives). In MCDA, the adoption of methods depends on the problem to be solved and the anticipated solution. For example**,** according to Greene et al. (2011), if multi-objectives are complementary or can be prioritised, then MADA methods can be used repeatedly in a two-level or stepwise way. However, if the multi-objectives are not complimentary, MODA will be the appropriate methods to employ. The present research will adopt the former approach because of the complementary nature of its multi-objectives.

MCDA have been integrated with geospatial techniques, for example, GIS, to resolve spatial problems (Carver 1991). In geo-spatial multi-criteria decisions, analysis of result is a function of not only spatial distribution of attributes, but also of the judgements involved in the decision making process (Ascough et al. 2002). Thus, there are two important aspects of geospatial multi-criteria decision analysis (the GIS aspect and the MCDA aspect). The spatial component involves analyses such as aggregation of locational data and decision makers' choice into discrete decision alternatives (Jankowski 1995).

The GIS aspect can be divided into raster and vector data models. Data model is an abstraction of the real world which integrates only pertinent features in an application, distinguishes particular classes of entities, their attributes and the link between the entities. A raster data model represents features as a matrix/lattice of cells in continuous space, while a vector model represents discrete features as discrete points, lines, and polygons. Subject to the type of criteria, raster and vector-based GISMCDA methods can be further grouped into: explicit criteria, whereby the decision problem involve spatial features such as size, shape, proximity, and density as criteria; and implicit criteria, whereby the decision problem involve the use of spatial data to calculate the performance level of the criterion. Both or either explicit or implicit spatial criteria can be carried out in MCDA. MCDA has been applied in many fields

(Guipponi 2007; Jankowski, Andrienko and Andrienko 2001). GIS-MCDA is also well documented (Eastman et al. 1995; Jankowski 1995; Malczewski 1999; Chakhar and Martel 2003). In GIS-MADA and GISMODA, decision rules are applied. According to Malczewski (2006), in GIS-MCDA, integration of rules is restricted to methods such as weighted summation, ideal/reference point, and outranking. According to the author, some studies have successfully integrated weighted summation with other methods such as linear transformation method for normalizing criteria and the pairwise comparison method for deriving the criterion weights. Other method such as ordered weighted averaging (OWA) is an expansion and simplification of the Boolean operations and the weighted summation methods. The processes employed for carrying out MCDA can also be used for geospatial or GIS-based MCDA. Figure 1.6 shows the steps involved in the application of MCDA.

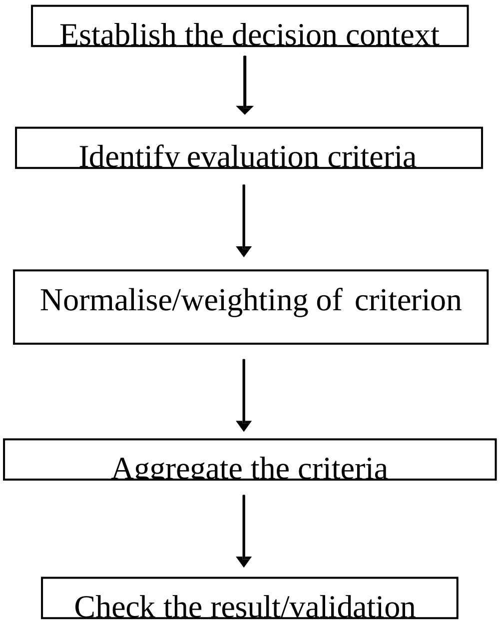


Figure 1.6: Multi criteria decision analysis procedure

(Source: Crown copyright, London 2009)

1.3.12.1 The MCDA procedure

The MCDA procedures (Figure 1.6) are described in this sub-section:

- ***Establish the decision context:*** At this step, the purpose and the expected result of the MCDA is clearly established along with the identification and selection of major participants (Crown copyright, London 2009). In the present research work, participants are responsible for criteria selection and weights assignment. The nature of the participants' inputs and type of MCDA/implementation strategy are also established at this stage.

- ***Identify evaluation criteria:*** Identifying suitable evaluation criteria is vital to the realisation of the objective in a decision analysis process. This step involves identifying a broad set of relevant alternatives that will be needed for the MCDA, and the level of details required, proxies are also identified for some criteria when and if necessary. The format in which criteria are represented is very important; due to the link between the evaluation criteria and spatial features, the criteria can be presented as attribute maps.
- ***Normalised/weighting of criterion:*** Weight is assigned to criteria by decision makers to reveal variations in the level of significance of each criterion in the decision set. One of the popular weighting methods is pairwise comparison (Malczewski 1999) whereby decision makers judge each single criterion against all other criterion in pairs (Yoe 2002). In MCDA, the main focus is how to merge information from varying criteria to generate an index of evaluation (Eastman, 2001). Due to the different units and scales of criteria, there is the need to adjust the values of the criterion to a common scale for fair comparisons among criteria before merging them, thus normalising using suitable method (Eastman (2001). The Analytic Hierarchy Process (AHP) is a pairwise comparison method. AHP is the most popular MCDA tool and has been applied in varied area of decision support, including, health care management Rakotomanana et al. (2007). In AHP, problems are structured into hierarchy (Suedel, Kim and Banks 2009).

Elements in the hierarchical structure are compared in pairwise comparison using a relational scale (Table 1.2) to determine their relative significance.

Table 1.2: AHP significance scale (Source: Saaty 1980)

Strength scale	**Description**
1	Evenly significant
2	Evenly to moderately significant
3	Moderately significant
4	Moderately to strongly significant
5	Strongly significant
6	Strongly to very strongly significant
7	Very strongly significant
8	Very strongly to extremely significant
9	Extremely significant

In AHP, it is important that the opinion of the decision makers be consistence, thus, consistency test is required to authenticate their judgment. The consistency ratio (CR) is the likelihood that the weights were randomly generated (Eastman 2001). According to Saaty (1980), any CR (Equation 1.1) up to 0.10 is considered satisfactory.

$$CR = (CI) / (RI) \leq 0.1 \qquad 1.1$$

Where: *CI* = Consistency Index derived from Equation 1.2, *RI* = Random consistency index (Table 1.3).

$$CI = (\lambda max – n) / (n – 1) \qquad 1.2$$

Where: *λmax (Lambda max)* = the maximum eigenvalue of the AHP matrix,
n = number of criteria.

Table 1.3: Random consistency index (RI) Source: Saaty (1980)

N	1	2	3	4	5	6	7	8	9	10
RI	0.0	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

Having accepted *CR*, the overall rating for the alternatives are established by aggregating the relative weights of the decision elements. Aggregation technique is needed to assess the performance of prioritization method used in AHP. An example of this technique is weighted summation method (WSM) which is highly popular due to its simplicity and time effectiveness (Von Winterfeldt and Edwards 1986), thus, it is adopted in the present research work. AHP which was developed by Saaty (1980) has been criticized as weak, due to its inability to take into consideration the uncertainty inherent in the quantification of decision makers' judgment (Yang and Chen 2004).

1.3.13 Integration of fuzzy logic with geospatial-MCDA

Fuzzy membership function has been used to improve the uncertainty associated with AHP decision (Chang 1996; Buckley 1985). Fuzzification, according to Erensal et al. 2006, can capture the uncertainty inherent in complex multi-attribute decision analysis problems. Fuzzy set theory, which was introduced by Zadeh (1965), has been applied in epidemiological studies (Wang and Wang, 2010; Hongoh et al. 2011; Rajabi, Mansourian and Bazmani 2012*)*. Fuzzy theory permits the membership functions to function over a range of real numbers [0, 1] to delineate the extent or strength of membership of element(s) in a fuzzy set (Nedeljkovic 2004).

The membership functions differ in their equation and application; among the available membership functions are: fuzzy small, fuzzy large. Fuzzy small is used when the smaller input variable values have the highest possibility of being a fuzzy set while fuzzy large is the opposite of fuzzy small. The functions algorithms are defined as Equations 1.3 and 1.4 (Tsoukalas and Uhri 1997).

$$\mu(x) = \frac{1}{1+\left(\frac{x}{s_j}\right)^{s_i}} \qquad 1.3$$

$$\mu(x) = \frac{1}{1+\left(\frac{x}{s_j}\right)^{-s_i}} \qquad 1.4$$

Where: *Si* = the spread of the change from a membership value of 1 to 0, *Sj* = the mid point where the membership value is 0.5.

In fuzzy logic analysis, if the rule upon which feature fuzzification was based is multifaceted, operators such as fuzzy union (fuzzy *OR*), intersection (fuzzy *AND*) and gamma are used to assess the compound strength of the rule. Fuzzy *OR* and fuzzy *AND* are restricted to maximum and minimum fuzzy membership values respectively (details in Zadeh 1965) while fuzzy *gamma* yields values that ensure flexibility between fuzzy *OR* and fuzzy *AND* (details in Zimmermann 1985; Bonham-Carter 1994). The steps involved in the integration of fuzzy logic with geospatial-MCDA, which, in the context of this research work, can be regarded as geospatial-fuzzy MCDA is similar to MCDA procedures.

1.3.14 Validation Analysis

Due to lack of validation and objectives, decisions made with multicriteria methods are connected with some form of uncertainty. The uncertainty, according to Voogd (1983) could be reduced by sensitivity analysis and participation of experts in choosing appropriate criteria endorsed by all stakeholders. Sensitivity analysis is a process whereby the input data are somewhat adapted so as to observe the effect on the outcomes.

Geostatistical analysis such as ordinary kriging, local polynomial interpolation, empirical Bayesian kriging etc. can be carried out to assess the spatial variations in a model. The concept of spatial variability is based on the fact that entities within the same location range are more similar than the entities that are far apart (Alexander et al. 2003).

Ordinary kriging which can be conducted using semivariogram has been used for measuring spatial variation of point data in space (Ibrahim 2011). ArcGIS Help 10.0 defined Ordinary kriging as Equation 1.5

$$Z(s) = \mu + \varepsilon(s) \qquad 1.5$$

Where: μ = unknown constant, $\varepsilon(s)$ = random fluctuations.

When a model is fit through the measured sampled locations, the semivariogram function can be explained with terms such as the sill, nugget and range. When the semivariogram levels off at a certain peak, this peak is the sill. The sill has two components (nugget effect and partial sill). Nugget is the sum of observational and microscale variation. In microscale, slight variations in location produce spatially independent residuals. The range is the distance at which the semivariogram levels out to the sill; if the distances between the sampled locations are shorter than the range, there is said to be spatial autocorrelation, otherwise no autocorrelation (ArcGIS help 10.0).

The basis of local polynomial interpolation (LPI) is to fit smaller overlapping planes, and then predict each location in the area under consideration using the centre of the plane. LPI provides spatial condition number surface which is a measure of stability and reliability of the outcome of a prediction equation for a given location. The rules of thumb for critical values for spatial condition number surface are: for 1st order polynomial, the threshold is 10, 2nd polynomial order threshold is 100 while 3rd order polynomial has 1000 critical threshold (ArcMap 10.0 help).

Empirical Bayesian kriging (EBK) is used to assess the quality of fit of models and it produces more accurate results than the other kriging methods in that it measures the underlying semivariogram. Also, cross validation can be used to diagnose the reliability of a semivariogram model whereby smaller difference indicates a good quality model (ArcMap 10.0 Help).

1.4 Vulnerability Assessment

Vulnerability assessment is necessary as it will serve as early warning and response measures to manage economic cost effectively (Diop 2003). The vulnerability of human population in a given region to a disease depends on a number of factors. Rusty Binas [no date] defined vulnerability which he interpreted mathematically (Equation 1.6) as unsafe locations of element at risk.

$$V = f\,({}^{l}er) \qquad 1.6$$

Where: V = vulnerability, ${}^{l}er$ = the location of element at risk to hazard, f = function of.

According to Rusty Binas no date, the gap between the secure conditions and the insecure conditions of the element at risk determine the degree of exposure to the impact of hazards. Thus:

$$DR = hazard\ *\ f\ ({}^{l}er) \qquad 1.7$$

Where: DR = disaster risk.

A risk can be assessed qualitatively using comparative risk groups as in Cecchi et al. 2008 tsetse fly suitability index, partly-quantitatively, based on comparative significance assignment by known criteria using numeric indices whereby relative indication rather than real expected impact are conveyed or quantitatively; using numeric terms to depict risks as chance or expected impact. Both qualitative and partly-quantitative are useful when risk is being evaluated at regional or national level and when there is limited numeric data and funding (Australian Geomechanics 2000). The present research work adopts the use of partly-quantitative method to assess risk of HAT in the study area. This approach has been applied to generating landslide risk index (CastellanosAbella and VanWesten 2007).

1.5 Computer Systems Components of Analysis

In developing a classification scheme for managing HAT propagation there is the need to incorporate certain computer systems. These include digital image processing and statistical analysis. In classifying an area for prioritization towards effective management, there is the need to have a synoptic view of the said area. Satellite RS other than conventional method is the appropriate choice for this. In selecting RS data for classification, it is very vital to understand the characteristics of the data. There are studies that have reviewed the basic characteristic of RS data (refer to section 1.3.3.2). According to Lu and Weng 2007, the users need to determine the nature of classification and the scale of the study area, thus affecting the selection of suitable spatial resolution of remotely sensed data. For example, for the present study, the stakeholders/researcher agreed to adopt 1 hectare minimum mapping unit (MMU) and scale of between 1:50,000 – 1:100,000. Thus, Landsat 7 ETM+ with 30m x 30m spatial resolution can comfortably be used to identify and map the tsetse fly habitat. The RS image (Landsat 7 ETM) was chosen to carry out this study for the reasons specify below:

The successful use of RS images at regional scale, in mapping or classifying vector habitat has long history (e.g. Cecchi et al. 2008b; Zeilhofer et al. 2007; Cross et al. 1984; Pope et al. 1992). RS data have also been used in predicting vector presence and disease propagation risks (Haley et al. 2011; Courtin et al. 2005; Barnes and Higuera 1975; Linthicum et al. 1987), nevertheless, from the perspective of developing a functioning/transferable surveillance or management program, continuing availability of RS data beyond the initial application is very essential. Thus the adoption of Landsat RS data for the present study; Landsat data (archived and recent) is readily available free of charge globally.

It is necessary that raw image be processed before being used for any application. The four major processing function categories are: pre-processing, image enhancement, image transformation and image classification and analysis.

1.5.1 Digital image processing

Digital image processing involves procedure that is required before accurate quantitative data/information can be extracted from an image. This process can be classified into geometric and radiometric corrections.

1.5.1.1 Geometric Correction

Raw image may be distorted as a result of rotation of the earth during scanning, thus the need for pre-processing before using such image (Lillesand, Kiefer and Chipman 2004). Geometric correction will enable the visualization of image as well as combining data from different sources in a GIS environment for further analysis. Image visualization and image combining in a GIS environment requires georeferencing (Janssen et al. 2004). To determine how accurately an uncorrected image registers over the georeferenced image, the root mean squared error (RMSE) must be within acceptable limit.

1.5.1.1.1 Digital elevation model void filling

Digital elevation model (DEM) datasets is an important determinant of tsetse fly distribution within a region. The DEM of Shuttle Radar Topography Mission (SRTM) is available at 3 arc-second (approximately 90-meter) medium spatial resolutions. The SRTM DEM have been applied in many image analysis (vanZyl 2001) and a validation of its accuracy revealed that the datasets are indeed very good (Berry, Garlick and Smith 2007). Nonetheless, some areas of the SRTM datasets are without values otherwise known as voids (Grohmann, Kroenung and Strebeck 2006).

Many techniques have been developed to fill the no-data areas in SRTM DEM. According to Fisher and Tate (2006), none of the interpolation technique can be said to be most accurate following their review on the source and nature of errors in digital elevation models. However, some techniques perform better in certain terrain (Chaplot et al. 2006), for example, inverse distance weighted (IDW) interpolation or kriging may perform better to fill voids in relatively flat terrain (Jarvis et al. 2008).

1.5.1.2 Radiometric Correction

Atmospheric components affect the electromagnetic signal reaching the sensor in diverse ways, thus the need to remove noise caused by the atmospheric components so as to obtain clean radiances from entity on earth surface. The removal or reduction of noise is vital to allow normalization, most especially when multispectral and different epochs images are used.

According to Parodi and Prakash (2004), radiometric correction can be grouped into:

Cosmetic rectification; this is mainly for reducing data errors such as line striping and random noise.

Atmospheric correction (AC); this correction helps in rescaling raw radiance data provided by the sensor to reflectance. The methods can be grouped into relative and absolute methods (Parodi and Prakash, 2004). Popular radiative transfer models (RTM) for absolute AC include image-based dark object subtraction (Image-based DOS). Image-based DOS method compensates for differences in solar output base on the time of year and the solar elevation angle. The requirements for DOS include the estimation of parameters such as: image date/time, wavelength of the image band centre, sun elevation, haze value, radiance conversion and solar irradiance. Solar irradiance can be obtained using Equation 1.8 (Hussein 2012).

$$I_o = I_{sc}\left[1 + 0.033\, cos\ \left(\frac{JD}{365} * \ 360^0\right)\right]1 \qquad 1.8$$

Where: I_o = spectral irradiance of electromagnetic energy at the top-of-the-earth-atmosphere (TOA), I_{sc} = solar constant 1353W/m^2, *JD* = Julian day of the year. According to Jefferys (1996), *JD* can be calculated as Equation 1.9:

$$JD = C+D+E+F-1524.5 \quad 1.9$$

Where: $C = Y/100 + (Y/100)/4$, Y= year, D = day of month,
$E = 365.25x(Y+4716)$, $F = 30.6001x (M+1)$, M = month of year.

Atmospheric correction is also very vital towards creating image mosaics as well as a very important requirement for the measurable use of RS data such as: retrieving land surface temperature (LST) using Equation 1.10 (Weng, Lu and Schubring 2004), normalized difference vegetation index (NDVI) from near-infrared and red bands of Landsat images, normalized difference water index (NDWI) from near-infrared and mid-infrared bands, relative humidity (RH) (Equation 1.11; Lawrence 2005), tasseled cap transformation, etc.

$$LST = \frac{T}{1+\left(\lambda * \frac{T}{\rho}\right) 1n\varepsilon} \quad 1.10$$

Where: LST = corrected land surface emissivity temperature (land surface temperature) in degree Kelvin, T = at-satellite brightness temperature, λ = emitted radiance wavelength = ($11.5\mu m$), ρ = h * c/σ ($1.438 * 10^{-2}$ m K); h = Planck's constant ($6.626 * 10^{-34}$ Js), σ = Boltzmann constant ($1.38 * 10^{-23}$ J/K), c = velocity of light ($2.998 * 10^{8}$ m/s), ε = land surface emissivity (LSE)

$$RH = (e/es) \ x \ 100 \quad 1.11$$

Where: RH = relative humidity, es = saturated water vapour pressure in units of milibar at the dry bulb temperature, e = actual water vapour pressure in units of milibar.

1.5.2 Remote Sensing data Classification

Classification of remote sensing imagery is one of the methods used to identify the spatial distribution of land-cover classes. The general objective of RS data classification processes is to group all pixels in an image to particular classes according to their similarities (Aitkenhead, Flaherty and Cutler 2008). Essentially, classification involves three steps (Foody 1999), namely, training, classification and accuracy assessment. There are generally two traditional classification techniques: unsupervised classification and supervised classification.

Unsupervised classification often requires comparison with other reference data in order to deduce relevant information from it. In unsupervised classification, grouping parameters, according to Yang and Lo (2002), is determined by the number of classes. Supervised classification is an empirical modelling tool in that the process derives statistical relationships between the input variables and the ground-truth habitats. This algorithm uses a set of user-defined spectral signatures to classify an image. An adequate number of training samples and their representativeness are vital for supervised image classifications (Chen and Stow 2002; Mather 2004). Depending on the algorithm used, the statistical description of the classes such as; number of samples, the means and covariance matrices derived from the samples are computed. Groundtruth data, previous knowledge of the study area and the result of the unsupervised classification can aid the training set samples.

In order to improve the quality of classifications (Harris and Ventura 1995), post-classification is necessary. Also, the quality of information contained in a classified map is very vital towards a beneficial application, thus the need to assess the maps accuracy prior to its use. To evaluate the result of the classification, the spectral characteristics of the classes represented by the training samples are compared with referenced data usually from various sources, for example, ground control points (GCPs), higher resolution image, etc. Though it has been criticized due to the problem of mixed pixels (Foody 2002), the error matrix is the most popular accuracy assessment technique. Kappa (Equation 1.12) is also used to estimate the coefficient of agreement (Khat) between classified outcome and reference data

$$K = \frac{Observed\ accuracy - chance\ agreement}{1 - chance\ agreement} \qquad 1.12$$

Kappa value that is over 80% shows that there is strong agreement between the classified pixels and the reference data, values between 40% and 80% stands for moderate agreement while less than 40% kappa value means poor agreement (Landis and Koch 1977). Confidence level can be used to assess unsupervised classification with the least values indicating the highest reliability. Some context taking from this section has resulted in a publication (Akiode and Badaru 2014).

1.5.3 Change Detection Algorithm

Change detection using RS techniques involves the analysis of spatio-temporal as well as spectral characteristics of RS dataset so as to derive information about changes or no changes of a given landscape. Observing difference in the landscape characteristics could be based on different time (Singh 1989) or seasonal scale using two or more images epochs.

The theory of change detection is that the spectral value of cells from datasets covering the same landscape but of different epochs will differ if the physical characteristics have changed overtime (Jensen 1986). Change detection techniques are many, for example, image algebraic technique which includes tasseled cap transformation. There is also the multi-date composite technique (Morisette 1997) change detection technique. Some techniques are mainly used to detect the presence or absence of change (Currit 2005). The algebraic technique can be combined with the multidate technique because of its simplicity, especially with the use of Landsat images; several studies (Skakun, Wulder and Franklin 2003; Collins and Woodcock 1996; Cohen and Spies 1992) have employed and attested to its value. This research applies the algebraic technique and the multidate technique to simply detect the presence or absence of change.

1.5.4 Spatial Data Analysis

Spatial analysis helps in getting answers to questions towards efficient decisions by predicting unknown values from known samples values (Mitchell 2005). In GIS, varying spatial data operations can be carried out. These operations rely on statistics (spatial statistics and geostatistics) to answer questions such as: how features are distributed in space, what are the patterns formed by the features and where are the locations of the clusters, for example, the mean centre. Also, questions such as, what are the types of association between or among features are answered by spatial statistics. To find answers to questions such as the centre of a disease, the underlying factors affecting the disease and to identify areas at risk of the disease, spatial analysis, for example overlay analysis, could be carried out. Overlay analysis which is a method for applying a common scale of values to multiple input data to create an integrated analysis (ArcGIS Help 10.0) sometimes entails the analysis of varying factors. These factors may not be of the same relevance in answering the question under consideration, thus the need to prioritize.

Other relevant statistical analyses are factor analysis (FA) and principal component analysis (PCA). FA is a statistical approach used to examine the interrelationships among variables. There are two types of factor analysis: exploratory and confirmatory (DeCoster 1998). Principal component analysis (PCA) on the other hand is a linear transformation statistical method similar to factor analysis; it allows superfluous data to be compressed into fewer more interpretable or uncorrelated bands (Jensen 1996) without significant loss of information (Gibson and Power 2000). Only few components (two or three) of multispectral RS image band set are able to describe almost all of the unique variability in reflectance image values. The remaining components (bands) thus tend to be influenced by noise effects (Eastman 2003). Exploratory FA was used in the present study to assess and explain the underlying factors that affect the variables in a data structure while PCA was used to ascertain the degree of correlation between multispectral images.

1.6 The Study Region: The Niger Delta

1.6.1 Nigeria

Nigeria is a large country in West Africa, of over 900 000 square kilometres and is the most densely populated country in Africa (140,431,790; National Population Commission 2006). The Niger delta region is one of the five geopolitical zones in Nigeria (Ojo 2011; Figure 1.7). Geographically, Nigeria is characterised by uplands, such as the Jos and Udi plateaus and coastal areas which include Niger Delta (Udo 1970).

The Nigerian climate is influenced by two trade winds known as the south-west monsoon and north-east trades (Udo 1970) and is characterised by two distinct seasons; rainy and dry. The south of the country enjoys longer rainy season than the north and mean temperature and rainfall increase from the coast to the hinterland. Mean monthly humidity values vary from 90% in the coastal area to between 20 and 25% in the north.

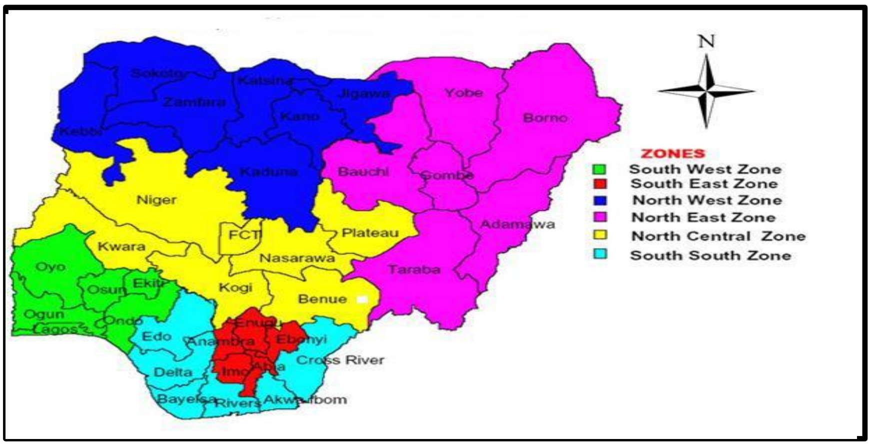


Figure 1.7: Nigeria geopolitical zones (from: www.naijanedu.com/the-19-new-proposed-states-to-be-created-in-nigeria/**)**

1.6.2 Description of the Niger Delta Region

The Niger Delta is one of the world's largest wetlands and is in the south-central and south- eastern part of the country, between latitudes $4^{o}15'$ and $9^{o}21'$N and longitude $4^{o}21'$ and $9^{o}29'$E. It comprises the flood plain of the Niger and Benue rivers, which discharge into the Atlantic Ocean (Ophori 2007), and is mainly vegetated by mangrove forests, the largest in Africa, which extend for several kilometres inland (Rim-Rukeh, Ikhifa and Okokoyo 2007; Salami and Balogun 2006; Ibe 1998). The area is composed of various ecological zones: mountain region, derived savannah, lowland rainforest, freshwater swamp forest and mangrove and coastal vegetation (Niger Delta Regional Development Master-plan (NDRDMP) 2006). These ecological characteristics favour the vector responsible for spreading HAT in West Africa (Jordan 1986). The Delta State is one of the states that makes up the Niger Delta Region, and is the main area of study for this research work (Figure 1.8). It is bounded in the north by Edo State, in the east by Anambra State, and in the south-east by the Bayelsa and River states. In the south lies the Bight of Benin.

The region experiences the prevalence of tropical maritime air mass almost all year round, with little seasonal change in wind directions (Olaniran 1986). The climate is characterised by high humidity and heavy rain falls. Humidity rarely dips below 60% and fluctuates between 90% and 100% for most of the year, while average annual rainfall is between 2500-3550 mm. The annual mean temperature is 26^{O}C, but fluctuates seasonally between 21-33 ^{O}C, with maximum temperatures recorded between January and March and minimum temperatures in July and December (Leroux 2001). These humid and hot conditions are favourable for HAT vector survival (Courtin et al. 2005; Rogers and Randolph 1986). During the rainy season (March-October), cloud cover is nearly continuous (World Wildlife Fund 2008) making it difficult to acquire clear optical satellite data for the region for regular monitoring.

1.6.3 Hydrocarbon resources

The Niger Delta is one of the most hydrocarbon-rich regions in the world (Doust and Omatsola 1990; Chukwu 1991; Ophori 2007), with an estimated 25 billion barrels and 130 trillion cubic feet of crude oil and gas reserves, respectively (Chokor 2004). Exploration of these resources is central to the Nigerian economy. The flourishing petrochemical industries have however, been shown to be causing severe environmental damage, as well as potentially reducing the human population's ability to resist vector-borne diseases (Sutherst 2004). Degradation of the region's biodiversity by gas and oil exploration is also a highly sensitive issue globally (Tolulope 2004) and these changes could alter the human-HAT vector relationship (Sutherst 2004).

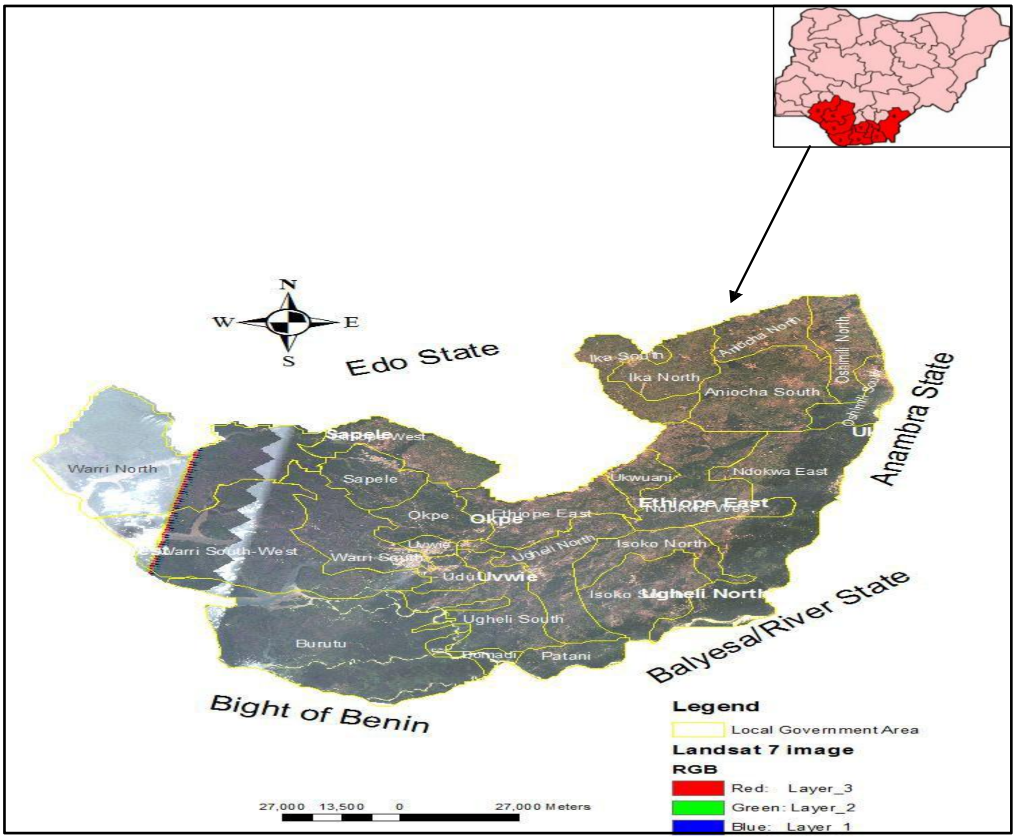


Figure 1.8: A Landsat 7 ETM+ true colour image of Delta State with local government areas (inset Niger Delta region in red**)**

1.6.4 The social environment

Though the Niger Delta region of Nigeria is rich in natural resources, basic amenities are lacking in some areas and a large portion of the region is inaccessible to the health service workers due to geography and frequent civil unrest (NDRDMP 2006). The predominant occupations include farming, fishing and hunting (NDRDMP 2006; Niger Delta Environmental Survey 1997). These activities exacerbate HAT propagation as the population is exposed to the disease vector on daily basis. Water-related diseases are a critical health problem for these people, representing around 80% of all reported illnesses in the region (NDRDMP 2006). Communities also suffer from weak infrastructure including water supply and sewerage. Only 5.4% households in Delta State have access to treated pipe-borne water, with the majority dependent on sources such as rivers and wells (National Bureau of Statistics (NBS) 2008a). Only 11.2% of households have toilets with septic tanks (NDRDMP 2006), with most utilising bush latrines (NBS 2008b). These socio-economic characteristics show the importance of the physical environment to the livelihood of the human population, as well as its contribution to exposure to vector-borne HAT.

1.6.5 Choice of main study area

The main study area selected for this research work comprises two local government areas (Ethiope-east and Ukwuani) within Delta state, which were chosen as they have been identified as active HAT foci, and records indicated continuous HAT positive cases (Osue et al. 2008; Abenga and Lawal 2005). The region is remote and rural, and HAT has been linked to populations living in areas beyond the reach of health services (Boutayeb 2007), a situation compounded by the terrain and continuous conflicts within the region, which pose difficulties to health care delivery (NDRDMP 2006). The area is, however, economically important to the state, both in term of resources and human capital.

The 2008 WHO initiative to map all reported HAT cases at village level (Simarro et al. 2011), is difficult due to restricted disease surveillance and access to diagnoses. No model to acquire detailed and comprehensive spatial or epidemiological data exists for the study area, meaning many of those most in need, especially those residing in remotest parts of the region, may not be benefitting from good health care due to lack of information about them. It is thus imperative to develop a HAT habitat classification scheme to identify high-priority areas where surveillance and health care delivery should be directed.

The present study intends to examine HAT propagation in all the settlements and land cover types within the study area. That is, the research is intended for community level intervention that can be applied to monitor magnitude and trends of HAT, or other vector borne diseases or adapted for other diseases at national level.

Mapping of habitat suitability for the trypanosomiasis vector has a long history, and the advent of geospatial techniques provides unique platform to forecast the vector distribution at continental and regional levels using low resolution images (Cecchi et al. 2008). HAT vector habitats have previously been mapped both at local level and in larger areas using high spatial resolution images (Cecchi et al. 2008). However, the use of high- resolution spatial images for wide-spread trypanosomiasis control programmes in most endemic countries is often not feasible due to the high cost. Previous studies on wide area community level HAT mapping have used low and medium spatial resolution images to map and identify disease-influencing factors (Courtin et al. 2005; Cecchi, et al. 2008).

Considering the scope of this research, the availability of medium spatial resolution satellite images, the present study will uniquely develop HAT vector habitat classification schemes at a regional scale for the study area. The scheme was developed by classifying land cover classes and other environ-climatic variables into different zones. The detailed HAT vector habitat classification scheme will assist in HAT vector habitat mapping nationwide, and will enhance efficiency of the existing surveillance and HAT case detection exercises in the country.

1.7 Summary

This chapter has reviewed HAT, previous studies related to HAT, as well as highlighted some of the tools applied in the development and application of decision/management systems. HAT disease management in the Niger Delta region is hampered by difficult terrain, poor infrastructure, inadequate surveillance, ineffective health policies and an underfunded human and laboratory research capacity. Those resources that are available are also often poorly focussed. Fresh, innovative thinking (e.g. geospatial techniques) relevant to local circumstances is required to examine HAT propagation, enhance surveillance and coordinate an effective disease response.

Due to the gaps observed in the previous studies, illustrate a need to develop a geospatial methodology towards effective decision making regarding HAT management.

1.8 Research Aim and Objectives

The aims of this research are to examine the potential habitats of the HAT vector in the Delta State Nigeria, to identify the processes that give rise to spatial distribution of HAT and to map the direction and magnitude of HAT in the study area. This will involve using available datasets as well as deriving other spatial datasets from remotely sensed data in a GIS environment. This will be used to define areas that are at risk of HAT, and provide more insights into HAT propagation to support existing surveillance strategies, towards robust surveillance and management of HAT.

Objectives:

To achieve the aims of this research, the objectives are:

- To review past studies and identify gaps in knowledge inhibiting effective management of HAT.
- Examine geospatial decision support concepts and tools, with a goal of developing a classification scheme for HAT management in the study area.
- Investigate the spatial distribution of HAT, and examine the significance of HAT in the study area.
- Identify and weigh criteria for development of HAT management classification scheme.
- Derive remotely sensed datasets for the development of the classification scheme.
- Develop a classification scheme for identifying HAT and its various types from remotely-sensed images.
- Apply the developed classification scheme to the study area, to identify HAT vulnerable regions and establish a 'HAT risk' to prioritise aid for settlements
- Investigate the factors that encourage the distribution of HAT in the study area using the developed classification scheme.
- Assess land cover suitability for the HAT vector in the study area, using the developed classification scheme.

Chapter 2: Data Collection and Methodology

This chapter describes the data and methods used in the development and evaluation of the HAT management classification scheme. Both spatial and non-spatial data were integrated with statistical analyses towards the realisation of the study aim. All of the data used were projected to the World Geodetic System (WGS) 84 datum Universal Transverse Mercator (UTM) Zone 32N.

2.1 The Main and Minor Study Areas

The main study area is the Ethiope-east and Ukwuani local government areas (LGAs) of Delta State in Nigeria. The two LGAs were chosen as the main study area because past studies confirmed evidence of HAT cases in the area. Within the State (Delta), two other LGAs (Oshimili North/South and Patani) were also randomly chosen to establish if there is HAT risk in other areas. This was necessary because, the literature only revealed HAT incidence in the main study area (Ethiope-east and Ukwuani LGAs). To examine HAT propagation in a different region of Nigeria, two LGAs (Dutse and Birnin-Kudu, Jigawa State; Figure 2.1) were chosen as minor study area.

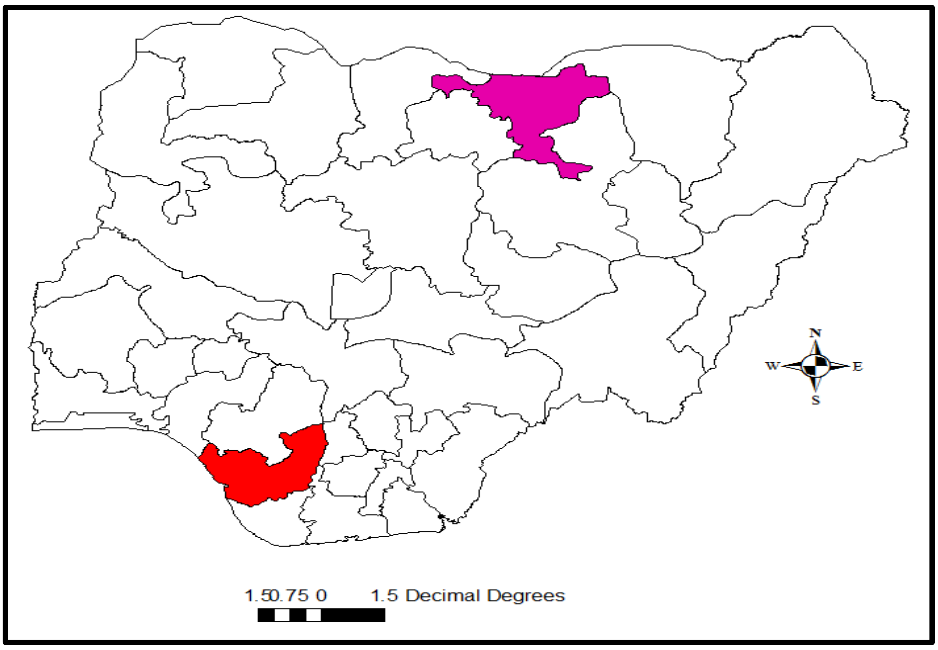


Figure 2.1: Administrative map of Nigeria showing Jigawa state in pink and Delta state in red.

Jigawa State is in the north-western part of Nigeria (latitude: 11.00^{O}N - 13.00^{O}N; longitude: 8.00^{O}E-10.15^{O}E), and is in a different ecological zone to the main study area (Figure 2.2). The topography of the state consists mostly of plains covered by wooded savannah in the south and shrub vegetation in the north. The main occupations of the people are farming and rearing cattle, goat and sheep. The population of the state as at 2006 was 4,348,649 (NBS 2008c). Dutse and Birnin-Kudu population as at 2006 are 246,143 and 313,373 respectively (NBS 2008d). The climate of Jigawa state is semi-arid, characterised by a long dry season and a short wet season, with a mean annual temperature of about 25°C, and relative humidity ranging from 80% in August to 23% between January and March. The total annual rainfall ranges from 600mm in the north to 1000mm in the southern parts of the state.

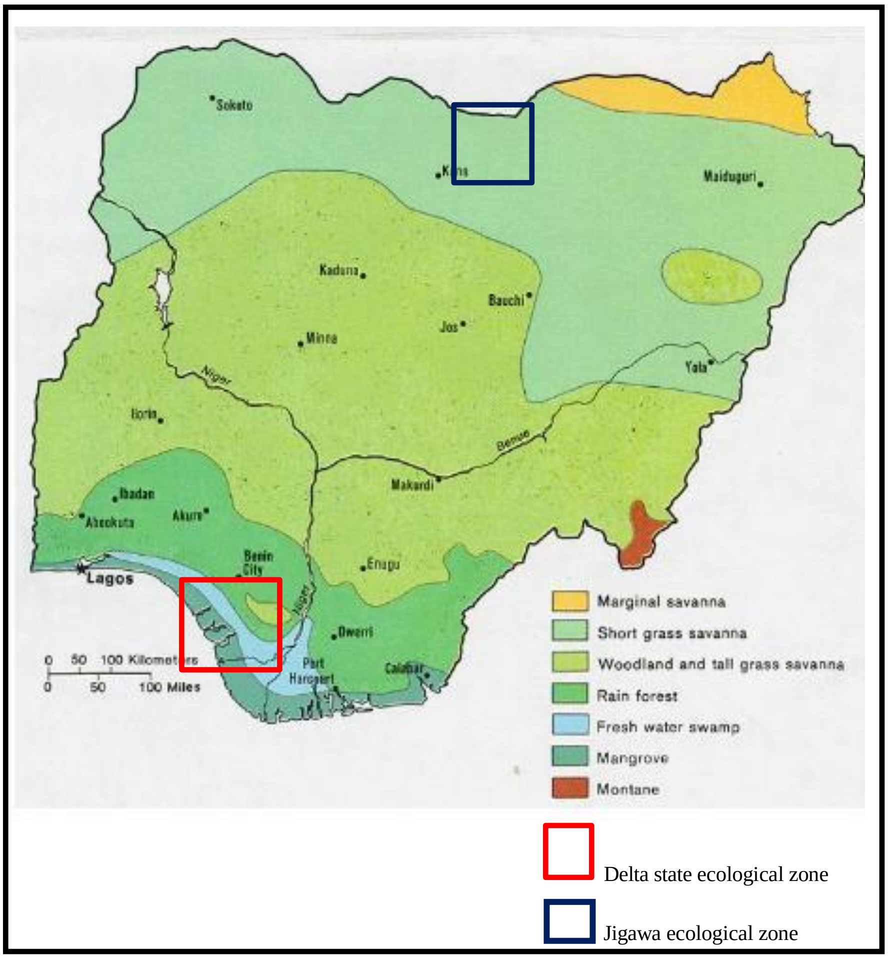


Figure 2.2: Ecological map of Nigeria, highlighting the main and minor study areas.

There has been evidence of trypanosomiasis in the control area as far back as the 1970 (Figure 2.3), and evidence of cattle herding/trading (Figure 2.4) between the state and other parts of Nigeria. Domestic animals are important host to HAT vector most especially *T.b. rhodesience.*

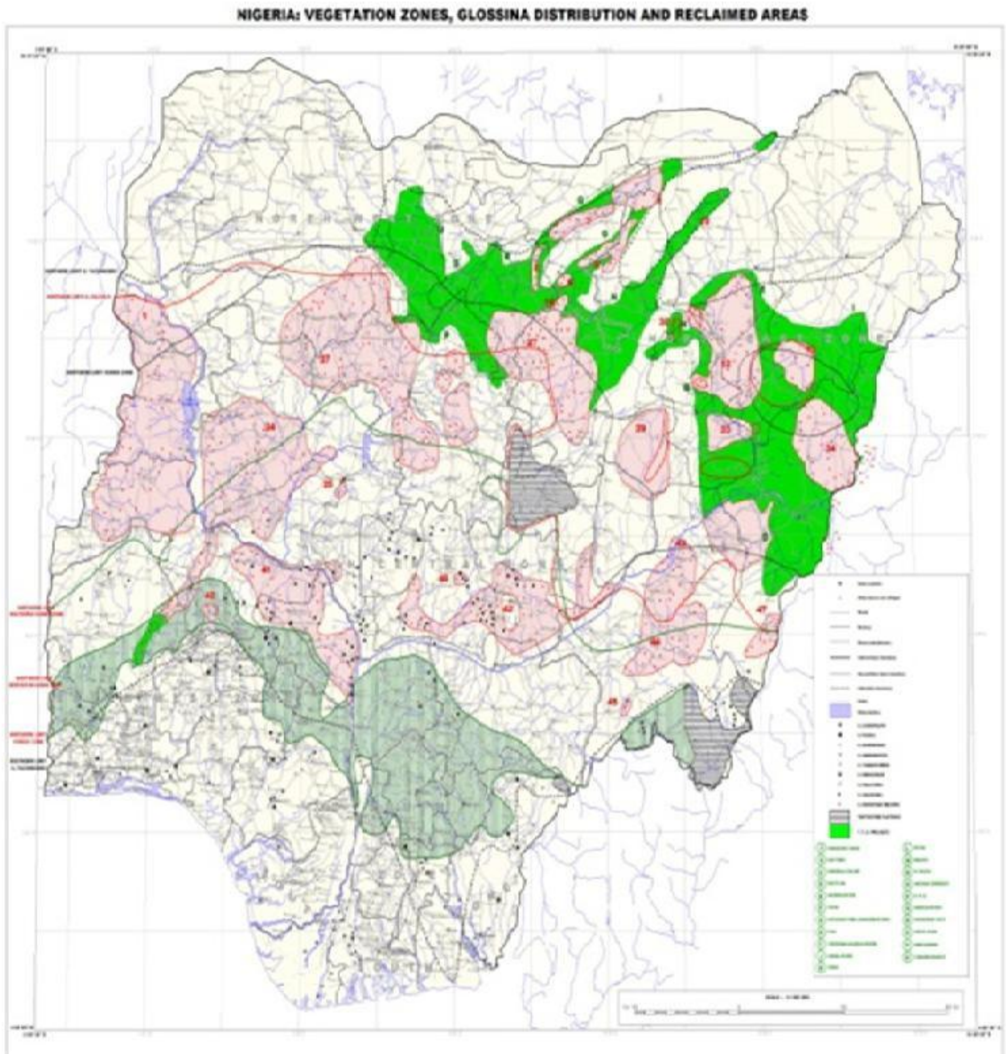


Figure 2.3: 1971 Glossina distributions in Nigeria (source: NITR).

The existing administrative map of the Delta and Jigawa States, Nigeria were obtained from Mapmakerdata as shapefiles. The shape files were imported into ArcMap to extract the main study area (Ethiope East and Ukwuani LGAs) and the other LGAs (Oshimili South/North and Patani) as well as the minor study area polygon boundaries. The boundaries which served as base maps were subsequently used to subset the RS images used in this research. The Oshimili South/North and Patani LGAs as well as the result obtained from the analysis of the Jigawa State foci were used to validate the result of the application of the classification scheme in identifying HAT risk areas.

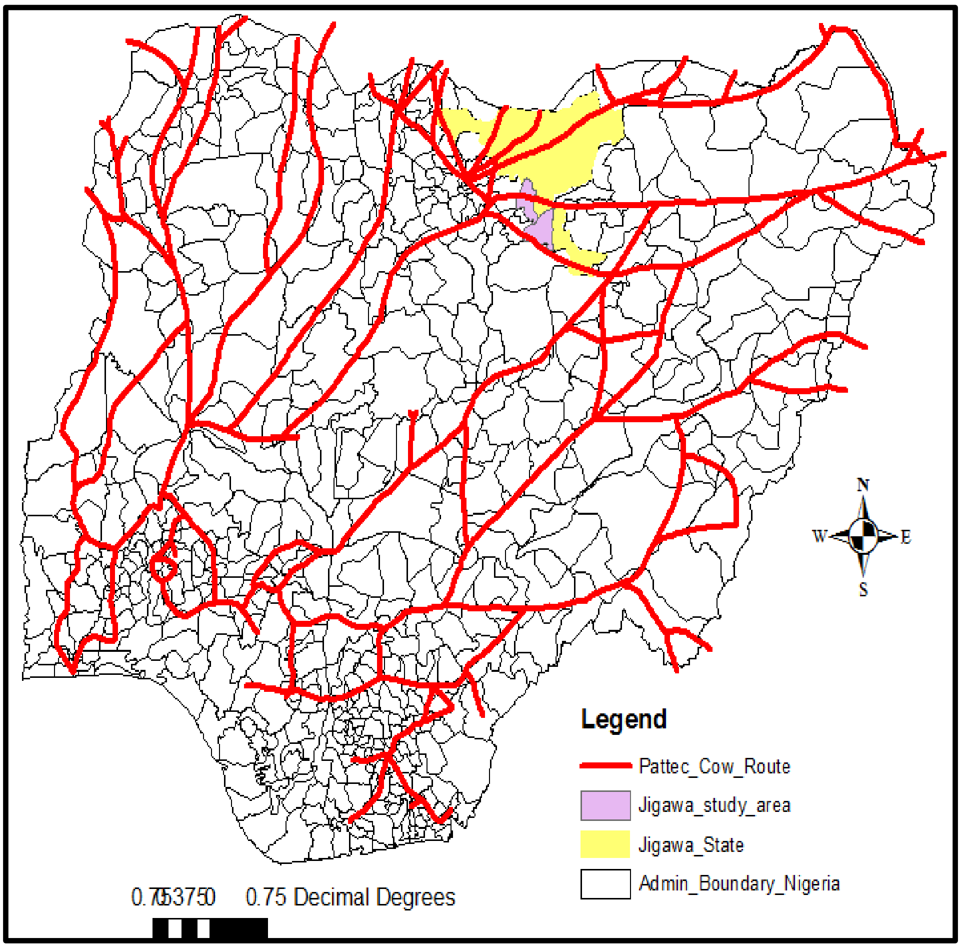


Figure 2.4: 1971 Cattle trade routes in Nigeria with Jigawa State insert (source: NITR).

Using Global Positioning Systems (GPS), ground control points (GCPs) for settlements in the main study area and the other local government areas were collected. The GCPs and HAT case records were stored in Microsoft Excel and later exported into ArcMap and converted into shape files using the same coordinate systems as the other spatial data. The GCP shape files were merged with the base map for further analysis. Hospital records of HAT patients identified in each settlement were geo-referenced using their GCPs, and linked with the base map of the main study area. Geo-spatial-fuzzy MCDA was applied at every stage of the research work particularly in delineating

HAT vector habitat (Chapter 5) and in querying the GIS database created for this research work (Chapter 6), to obtain factors influencing HAT in the study areas among other analyses carried out. The computer systems analysis component was vital to the derivation of the required datasets for this research work (Chapter 3). Since success depended on correct understanding and use of tools, it was necessary to review some of the tools algorithms.

2.2 Data Collection Process

The main steps in collecting the data highlighted in Table 2.1, existing HAT case records and other relevant data to address the study's working objectives are grouped into two: preliminary and field surveys.

2.2.1 Preliminary data collection

The researcher travelled to Nigeria to collect existing data relevant to the study, which included both spatial and non-spatial data as summarised below:

- Administrative map of Delta State Nigeria (Appendix A-1a) acquired from the directorate of lands and surveys, showing all local government areas at the scale of 1: 300,000. This data was used to map points where ground control points were obtained during field survey.
- Administrative map of Jigawa State and Delta State, Nigeria acquired from the Mapmakerdata (Appendix A-1b, c).
- Socio-economic data such as occupational, demographic and infrastructural characteristics, as well as conflict level were obtained from various sources in Nigeria, including: National Population Commission, National Bureau of Statistics, Federal Ministry of Health Nigeria (FMOH), Nigerian Institute for Trypanosomiasis Research (NITR) and relevant literature.
- HAT data; including: GCPs of HAT case settlements obtained from the field during ground thruthing; anonymised HAT hospital case records (1994, 1998, 2000, 2002, 2005 and 2006; Appendix A-4c). The hospital record was obtained from the Eku Baptist Hospital in Ethiope East, Local Government Area of Delta State. The hospital is the main sentinel centre for HAT in the region. Also, a tsetse trap site record was used. The record showed the GCPs where traps were set to harvest tsetse flies in Jigawa State.

Other data acquired are listed in Table 2.1. The RS images used in this research are shown in Appendix A-2 while examples of their metadata file is shown in Appendix A-3a.

Table 2.1: Remotely sensed data used in this research

Data Type	Acquisition Date	Path/Row	Bands used	Spatial Resolution (m)	Source
Landsat1 MSS	29/12/1972	202/52	4, 5, 6	82	LP DAAC (USGSEROS)
Landsat4 TM	21/12/1987	189/056	1, 2, 3, 4, 5 & 7	30	LP DAAC (USGSEROS)
Landsat5 TM	17/11/1986	188/52	1, 2, 3, 4, 5 & 7	30	LP DAAC (USGSEROS)
Landsat7 ETM+	30/12/2002	189/56	1, 2, 3, 4, 5 ,6 & 7	30	LP DAAC (USGSEROS)
Landsat7 ETM+	9/02/2003	188/52	1, 2, 3, 4, 5, 6 & 7	30	LP DAAC (USGSEROS)
Landsat7 ETM	21/01/2011	189/52	2, 3, 4, 5, & 7	30	LP DAAC (USGSEROS)
Landsat7 ETM	17/01/2012	188/52	2,3,4,5,6, & 7	30	LP DAAC (USGSEROS)
SRTM (DEM)	February 2002	SRTM3N05E006V1		3-ARC	LP DAAC (USGSEROS)
SRTM (DTM)	February 2002	SRTM3N11E009V1		3-ARC	LP DAAC (USGSEROS)

2.2.1.1 Environ-climatic data

The environ-climatic datasets (Table 2.2) were mainly derived from Landsat images; these include: NDVI, NDWI, NDDI DEM, land surface temperature (LST) and land cover data. Also relative humidity (RH) data acquired from the Nigerian Meteorological Agency (NIMET) (Appendix A-4d) was combined with other Landsat image-derived data to calculate relative humidity for the entire study area. Land cover types (Appendix A-5) identified by the researcher and stakeholders as appropriate for this research were also extracted from RS images.

Table 2.2: Environ-climatic data and sources

Data	Unit	Source
Land surface temperature	Kelvin/Celsius	RS image
Relative humidity	%	NIMET/RS image
Digital terrain model	Meters	USGS
NDVI		RS image
NDWI		RS image
NDDI		RS image
Land cover types		RS image

2.2.2 Field survey

For the field survey phase of this research, three trips were made to Nigeria. The first trip was made in 2009 to meet with relevant stakeholders to discuss and agree on appropriate datasets and other related details. During the field survey, GCP data that served as test samples for the land cover classification and accuracy assessment were obtained from different land cover types. The GCPs were obtained using Trimble Global Positioning System (GPS).

The GCP collection exercise involved in-situ data collection from different land cover classes at different locations. Some of the land cover classes were easy to identify and sample, (e.g. water bodies and built-up areas), while due to the nature of the terrain, accessibility to other land cover types such as mangroves and dense forest were very difficult. Thus, to obtain samples of the classes that could not easily be sampled, samples were taken from roads very close to them. The sampling exercise was jointly carried out by the researcher, a registered surveyor and a representative from local government councils.

The second trip was to meet experts/stakeholders to administer a questionnaire (Appendix B) on the significance of the environ-climatic variables to HAT habitat. Experts/ stakeholders from the ministry of health, epidemiologists, other academics/scientists, and some member of the local government councils participated in the questionnaire survey.

2.2.2.1 Collection of data using GPS

The satellite images used for this research work were obtained as geometrically corrected, but, in order to be able to use the images for change detection, it was necessary to geo-reference images to each other. Geo-referencing aligns two or more images of the same scene taken at different times. GCPs used for geo-referencing were obtained at road intersections within the study and control areas. A total of 51 and 47 control points were obtained from the main and minor study areas, respectively.

2.2.2.2 Questionnaire survey

In order to delineate the study areas into different HAT vector habitat zones, it is very important that information regarding the HAT vector habitat characteristics is obtained. To obtain these information, pairwise questionnaires (Appendix B), designed with contributions from experts (Appendix, C-1) were administered. Instructions were given regarding how participants are expected to answer the survey questions (Appendix B- Sections A & B). The questionnaire survey included optional participants' profile from which the characteristics and the factual information each expert has relating to AHP questionnaire and their ability to deduce information from landscape attributes to manage HAT was obtained.

Contact was initially made in the form of cover letter through email/direct approach to build rapport and to motivate the experts. The researcher credential, the goal of the research and why the expert was selected was explained to the experts in the cover letter. The cover letter also included a consent form, how long it will take to complete the questionnaire survey and what the result will be used for. The experts' privacy, right to decline to participate and answer certain question(s) is stated in the consent form (see Appendix B- Section A).

2.2.2.2.1 Sampling frame

Designing a sampling frame for the questionnaire was difficult because of lack of population characteristic data to determine a representative survey sample and problem of obtaining consents of potential participants in order to elicit weights. To obtain weights for the selected criteria, the stakeholders/experts were purposively selected from the potential users of the classification scheme. The selection of the experts are based on known common characteristics (all have basic knowledge of AHP and have background in landscape/vector borne diseases research). These included the main regulatory and coordinating government organisations, epidemiologists, academics from higher institutions and other organisations were also included. Table 2.3 shows a brief description of the participants selected for expert judgement while an expanded list of participants and their details: address, nature of expertise, and type of questionnaire survey response (interview or by email) are presented in Appendix C-1. Due to research ethics and the privacy clause in the information for participant's letter (Appendix B- Section A) sent to all participants, the name and full contact details of participants are excluded from the expanded list (Appendix C-1)

Table 2.3: Participants for assignment of weights to criteria

Participants	Organisation	No.
Regulator/ Research	Nigerian Institute for Trypanosomiasis	**4**
Regulator	Epidemiology Control Unit	**2**
Regulator	National Cereal and Disease Institute	**1**
Coordinator	Federal Ministry of Health	**3**
Coordinator	State Ministry of Health	**1**
Coordinator	Health Services Unit, State House	**1**
Coordinator	Niger Delta Development Council	**4**
Evaluator	Monitoring and Evaluation of Diseases Control	**1**
Lecturer /Epidemiologist	University/Others	**9**
Lecturer (Geographer)	University	**8**
Medical Geography	Private	**1**
Total		**35**

Thirty-five participants (thirty-one by interview and four by email) were involved in the pairwise comparison method. The questionnaires were designed to be of average, manageable length, as long questionnaires discourage interviewees. The questionnaires were divided into two and disseminated using pairwise comparison, to discern relative importance of land cover criteria and environ-climatic variables for classification of HAT vector habitat.

2.3 Spatial and Non-spatial Database

To store and manage spatial and non-spatial data/information in this research, two types of database were used (GIS and worksheet). ArcMap was used to develop the spatial database. The software was used with permission from the Environmental Systems Research Institute (ESRI). Other software used included, IDRISI Selva 17.0 and Erdas Imagine 9.1, to carry out image processing before further analysis in ArcMap. Ortho-rectified images (Table 2.1) were obtained from USGSEROS. The spatial information required for creation of land cover classes and other environ-climatic datasets were derived from the Landsat images. The land cover classes were created by means of unsupervised and supervised classification, while the ancillary datasets (environ-climatic) were derived from the Landsat images through image processing. Other spatial data used were the administrative maps of the study areas for the sub-setting of the main and minor study areas boundaries. The administrative boundaries were obtained as an ESRI shape file, and were subjected to logical query to subset the required area from the main maps. The subsets were later used to extract the study areas from the Landsat images.

Microsoft Excel was used for the non-spatial database. The hospital record and GCPs were stored in Microsoft Excel and exported into ArcMap as shape files to link the datasets with the other datasets obtained from the Landsat images. The information obtained from the questionnaire survey was managed using IDRISI software.

2.4 Methodology

The classification scheme developed in this research has been developed such that it will be applicable in areas other than the study areas and for other vector- borne diseases.

2.4.1 Stakeholders/experts involvement

After the identification of participants/stakeholders, participants (Appendix C-1) were drawn mainly from prospective classification scheme users and made up of government and intellectuals in the field of epidemiology, to provide expert judgement for assigning weights to the criteria. The experts have basic knowledge of MCDA and most especially AHP method; nevertheless, further explanation was provided during the survey exercise. To test the robustness of the pairwise comparison output, it was very important to carry out sensitivity analysis as discussed in sections 5.3.1.1 and 5.4.1.

2.4.2 Questionnaire survey method

Survey can be carried out through varying means such as e-mail, telephone, mail and interview. The researcher opted for both e-mail and interview questionnaire survey. For the direct interview and questionnaire sent by mail, the participants (Appendix C-1) were asked to rank the relative significance of each criterion against the others in terms of its impact on realising the overall goal. They were instructed to carry out the ranking based on Saaty's (1980) significance scale (Table 1.2), i.e. to compare the row representing each criterion to each column in terms of significance (Appendix B).

The option for e-mail was to get across to the experts that were not available at the time of the interview. The interview method helped to clarify some interpretation problems. The e-mail method took some time because some experts required clarifications on certain issues related to the questionnaire; this involved/required several correspondences (e.g. Appendix C-2)

.

2.4.3 The structure of the HAT habitat classification scheme

The need to develop a classification scheme that will be widely accepted informed the use of widely applied structure. One of such structure is the MCDA procedure. The following subsections provided the details of how the MCDA was restructured to make it applicable to the present research work:

Intelligence phase: This phase starts with problem identification. The overall goal was to examine the landscape towards the management of HAT propagation, which required classification of HAT vector habitat into different zones and application of the classification scheme, to examined and prioritise vulnerable and at risk areas within the study area for efficient HAT management. Other issue considered at this stage are the scale/spatial resolution of the classification scheme, which informed the type of datasets needed (see section 1.5). Once the problem had been identified, the adapted database structure was used to structure the research work. In order to achieve the research goal, criteria were selected (by researcher/stakeholders) using AHP hierarchical structuring process (Figure 2.5; details in section 1.3.12.1).

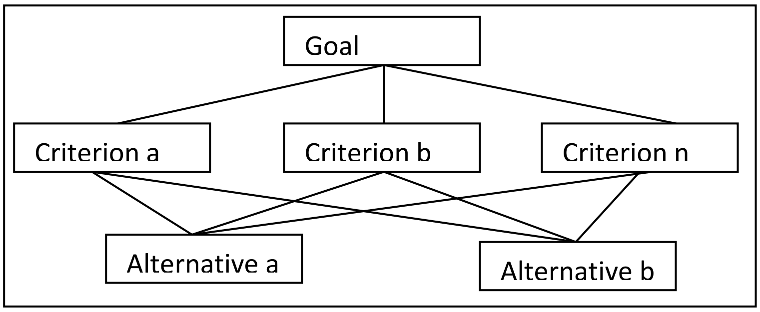


Figure 2.5: AHP hierarchy structure (Suedel et al. 2009)

The Design/Decision Phase: The design phase dealt with the identification and selection of appropriate relevant evaluation criteria and how the criteria will be represented in a database to realise the research goal, while the decision phase involved sensitivity analysis and decision making.

2.4.4 Habitat classification scheme modules

The main modules of the classification scheme developed in this research work are summarised in Figure 2.6. It comprises three units: personal geodatabase, geospatial-fuzzy multicriteria analysis and computer systems usage.

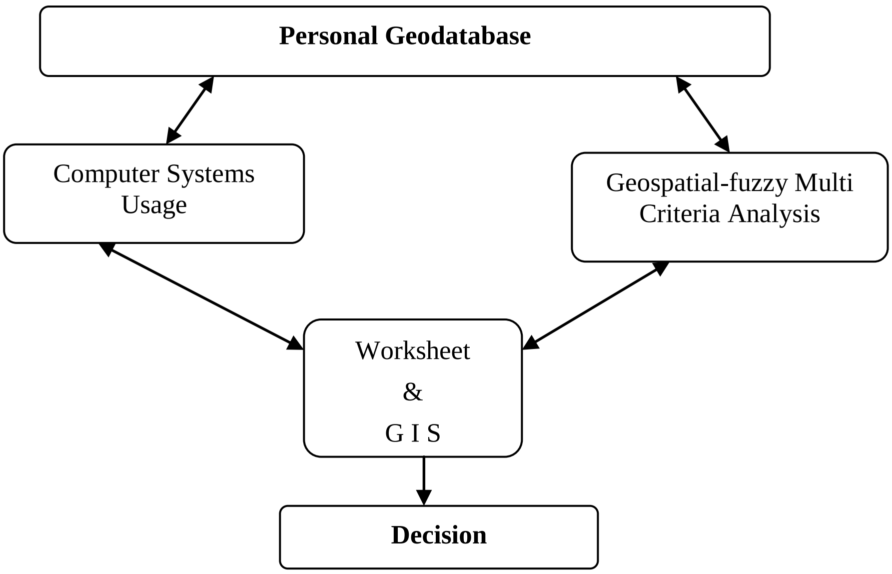


Figure 2.6: Main modules of the habitat classification scheme

2.4.4.1 Personal geodatabase

Creation of a database that contains all the data/information for the research work is vital. Among the requirements are quick access to data and easy querying for further analysis. In this study, GIS was the major database used, because of its ability to link both non-spatial and spatial datasets.

2.4.4.2 Geospatial-fuzzy multi criteria analysis

The main tools used for geospatial-fuzzy MCA in the present study are Microsoft Excel, IDRISI Selva 17.0 and ArcMap software. Questionnaire survey arranged as AHP pairwise matrices were presented to experts for individual judgment using AHP significance scale (Table 1.2). The AHP incorporated as a decision support tool in the IDRISI software was used to manage the questionnaire responses. In IDRISI, the AHP module (Weight) is in form of n by n grid, each row and column of the grid was filled up from the experts' responses (the reciprocal value of the AHP significance scale assigned to the row by experts were entered into the column for each criterion). The AHP matrices were evaluated for consistency in order to ascertain the reliability of judgment from individual expert, as recommended by Saaty (1980). The consistency ratio must be up to 0.10 (10%) for the matrix to be considered consistent. Inconsistent matrices were re-evaluated (the IDRISI module was used to analyze the inconsistent matrices to establish where the inconsistencies arose), after which each pairwise matrix was analyzed to obtain the local priorities (weights) for each criterion using Saatys' eigenvalue method implement in the IDRISI software (example in Appendix D2-d). To obtain group weight for each variable, geometric mean was estimated from the local weights.

The zonal classifications of the HAT vector habitat were based on weights assigned by the experts, who used the AHP technique to assign weights to the criteria. The assigned weights were aggregated and normalized into 0 – 1 scale, using ArcMap software fuzzy membership function tool, before the classification (detail in chapter 5), but before the optimal selection of the potential HAT vector habitats, the assigned weights were altered for sensitivity analysis. This was to investigate the appropriate value that will not change considerably the original weights obtained from the experts.

2.4.4.3 Usage of computer systems

Computer system usage has already been discussed in chapter 1. The processes employed in this research work included digital image processing. Due to the lack of existing digital spatial data, it was necessary to extract land cover classes and other ancillary datasets from remotely sensed images. The methodology used for this is discussed in detail in Chapter 3.

2.4.4.4 Worksheets and GIS

The personal geo-database is housed in a GIS. Microsoft Excel, IDRISI and ArcGIS software were used to calculate, normalize and aggregate the criteria weights obtained from experts. Spatial statistics were carried out to assess hazards and vulnerabilities to HAT in the study area. Statistical analysis was also applied to obtain the suitability of land cover for HAT vector in the study area. This is discussed in detail in Chapters 5 and 6.

2.5 Sensitivity Analysis

In the present research, the use of analytic hierarchy processes and a weighted sum for evaluation, helped to address uncertainty related to the analysis technique. In order to reduce uncertainty related to the criterion, experts participated in choosing appropriate criteria endorsed by all stakeholders for the HAT habitat classification scheme. Sensitivity analyses (Chapter 5) were also performed to assess the fit and to validate the classification model.

2.6 Summary

The major datasets required for developing classification scheme towards HAT management have been enumerated. Data obtained from groundthruth and other sources were used to supplement primary data. The datasets were housed in the personal geodatabase. Survey method was based on the information needed and the type of sample population.

The classification scheme developed by the researcher requires contribution from experts in the field of epidemiology and other related fields. The integration of geospatial-fuzzy MCA methods into HAT vector habitat classification in a GIS environment enabled the decision makers to input significance opinions into the decision making processes.

Delineation of HAT habitat into zones can be realized using geospatial-fuzzy MCA based on stakeholders choices, while further spatial and geostatistical analysis can be applied to prioritize the study area for intervention and resource allocations.

Chapter 3: Satellite Image Processing and Land Cover Classification

3.1 Introduction

This chapter deals with satellite image classification methods and image processing for land cover maps, and the derivation of other landscape data from RS images in a GIS environment. All the procedures used are rapid, efficient and cost effective. This chapter is vital to augment the dearth of spatial data in the study areas, as well as obtaining up-to-date data suitable for the HAT management classification scheme. To achieve this, supervised classification was used. Non-supervised classification was also carried out, to aid selection of training samples for the supervised classification; this was necessary because of limited access to certain parts of the study areas. Part of the work in this chapter has resulted in a publication (Akiode and Oduyemi 2014a).

3.2 Land Cover Classification Systems

Due to the dearth of spatial data for the study areas, varying environmental variables were derived from satellite imagery; these derived datasets were then combined with land cover classes, using supervised classification. The classification exercise was carried out at a regional scale using Landsat images (detail in section 1.5) by applying mathematical or logical expressions. Seven and five land cover classes were chosen, representing the main distinct (though fuzzy) classes in the main and minor study areas respectively. These included; water bodies, shrub, mangrove, less dense forest, dense forest, cultivated area and built-up areas for the main study area and water bodies, wetland/flood plain, light vegetation/shrub, savannah grass and cultivated area for the minor study area. Apart from past studies (section 1.3.5, Table 1.1) that confirmed the importance of these land covers to HAT, the present study researcher and the major stakeholders involved (section 2.1.1.1) also identified the land cover types as appropriate for this research. The methodology used for the land cover classification included, image pre-processing, image classification, and classification accuracy assessment.

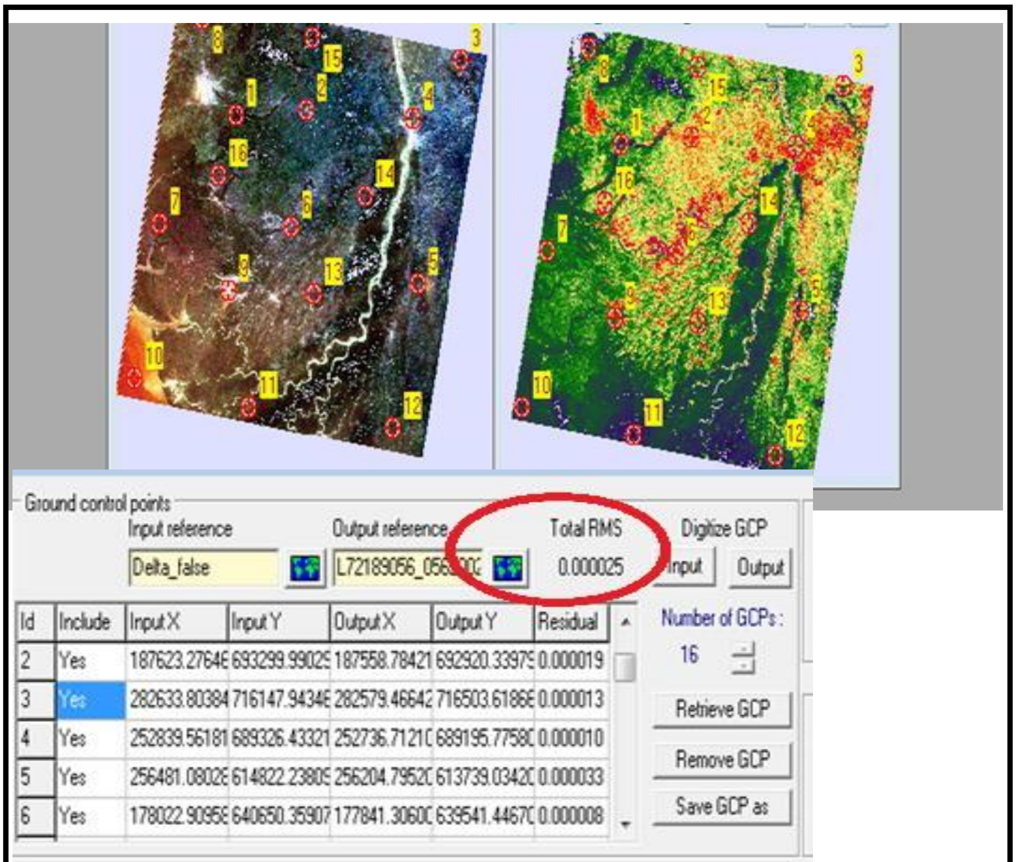
3.2.1 Image pre-processing

To derive maximum benefits from satellite imagery, there is the need to reduce or eliminate errors embedded in the data due to sensor effects, atmospheric and illumination effects as well as mis-registration. The satellite images used were pre-processed in IDRISI Selva software before further analysis in ArcMap. IDRISI was adopted for the pre-processing because of its capability for image processing while ArcMap is mainly for GIS analysis (refer to section 1.3.4). The procedures used in this research are described in the following subsections:

3.2.1.1 Geometric transformation

All the images (Table 2.1) used for the main study area were registered to the 2002 Landsat 7 ETM+ image, while the images used for the minor study area were registered to the 2003 Landsat 7 ETM+ image. Images were projected using Universal Transverse Mercator (UTM) Zone 32N, World Geodetic System (WGS) 1984 datum. Because the study areas were somewhat plain and in order not to alter the images pixel values; thereby maintaining their spectral and radiometric contents, first order or affine transformation and nearest neighbour resampling methods were used. The registration outcome root mean square error (RMSE) for both the main and minor study area were between 0.00003 and 0.05 pixels; (i.e. less than 1), and thus represents good quality registration (refer to section 1.5.1.1).

The DEM data used for this research was obtained as 3-arc seconds; this is approximately 90 metres. In order to be able to use it in combination with the other data derived from the Landsat 7 ETM+ image of 30 meters spatial resolution, the DEM data was re-sampled to 30 metres using the 2002 and 2003 Landsat ETM+ for the main and minor areas, respectively. The RMSE outputs for the DEM for both areas were about 0.42 and 0.4 pixels respectively. The geometric restorations were carried out in IDRISI Selva 17.0 software. An example of the image registration carried out in this research is presented in Figure 3.1.



Note: the RMSE within the red circle

Figure 3.1: Diagram showing satellite image registration

The main study area DEM data used for this research consists of three scenes. The scenes were mosaicked to form a one band image. The SRTM data available for the main study area contained data voids. To fill the voids after resampling to 30 metres, the following process was carried out: A point map containing x, y coordinates and z value covering the entire study area and particularly the data void areas was created, using GCPs from groundthruth as well as coordinates obtained from the satellite image. The point data was then used to interpolate a raster surface using inverse distance weighted (IDW) interpolation (see section 1.5.1.1.1). The data void areas were then filled using the ArcMap spatial analyst zonal fill toolset, to assign minimum cell values from the interpolated output to the data void areas of the DEM data. Figure

3.2 shows the void filled data. The minor study area DEM was acquired without voids.

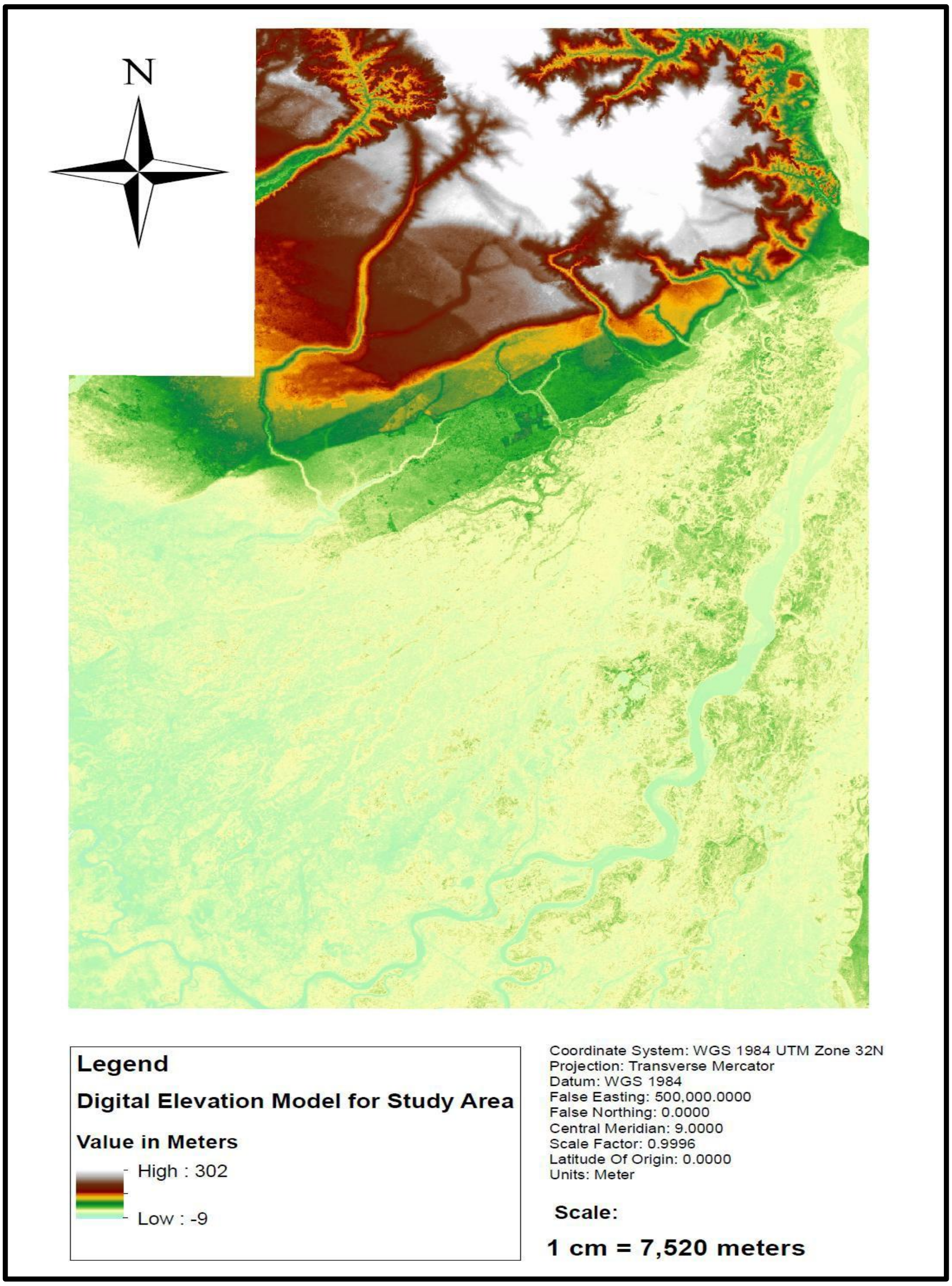


Figure 3.2: Void-filled DEM derived for the main study area

(source: derived from SRTM image acquired from USGS using IDW

3.2.1.2 Radiometric restoration

All the images used in this research were radiometrically corrected in IDRISI Selva 17.0 software. The radiometric restoration was carried out using image-based dark object subtraction (DOS). The parameters required for the DOS (section 1.5.1.2) were obtained from each image metadata file (e.g. Appendix A-3a); these include: Lmax, Lmin, the year, month, date, GMT, wavelength of the band center, haze value, radiance, satellite viewing angle, sun elevation, etc.

The time was rounded to the nearest minute and divided by 60 to convert the minutes to a single decimal place because the Idrisi module (ATMOSC) used accepts time in decimals. Wavelength of the band center was calculated by finding the average of the minimum and the maximum spectral resolution (Appendix A-3d) of each image band while the haze value was the lowest reflectance value identified on each image band. To calibrate radiance, gain and bias (offset) values (Equation 3.1) were used. The sun elevation for each image was also obtained from the image header file and the satellite viewing angle was set to zero.

For measurable use of the RS images, the bands digital number - DN (which has no unit and any physical connotation) were converted to at-satellite spectral radiance and converted from at-satellite spectral radiance to top-of-atmosphere (TOA) reflectance (for consistency in images' scene-scene). The at-satellite spectral radiance data (all image bands) was derived using Equation 3.1 (Landsat 7 science data users handbook), while the TOA reflectance data was derived for all the images bands (excluding thermal bands) using Equation 3.2 (Irish 2008; Chander et al. 2009). All the parameters used are contained in the image metadata file (an example is included in Appendix A-3a).

$$L\lambda = Grescale * QCAL + Brescale \qquad 3.1$$

Where:

$L\lambda$ = spectral radiance at the sensor's aperture in watts/ (metersquared *ster*µm), *Grescale* = rescaled gain in watts/(metersquared * ster * µm)/DN, *Brescale* = rescaled bias (offset) in watts/(metersquared * ster*µm), *QCAL* = the quantized calibrated pixel value in DN.

$$P_\lambda = \frac{\pi * L_\lambda * d^2}{ESUN_\lambda * COS\vartheta_S} \qquad 3.2$$

Where:

P_λ = TOA reflectance (no unit), π = Pi approximately equal to 3.14159 (no unit), L_λ = Equation 3.34, d = Earth-Sun distance (astronomical units] (Appendix A-4a), $ESUN_\lambda$ = mean exoatmospheric solar irradiance (watts/(meter squared *ster*µm) (Appendix A-4b i, ii, iii), $COS\vartheta_S$ = solar zenith angle (degree). Solar zenith angle = 90^0 – solar elevation angle (solar elevation angle is in the accompany image metadata file). Figures 3.3 and 3.4 show examples of at-satellite spectral radiance and TOA reflectance data generated respectively.

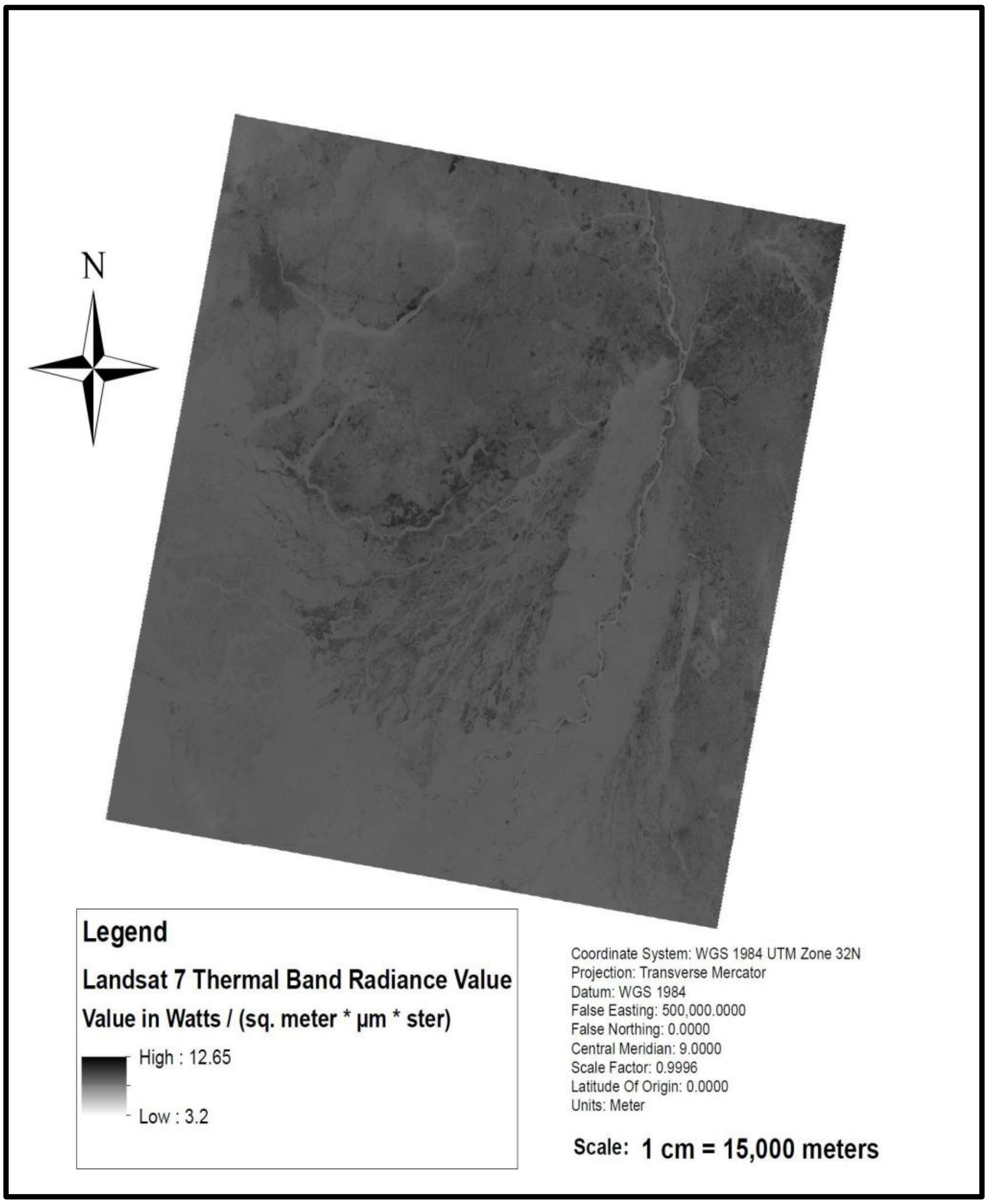


Figure 3.3: Diagram showing Landsat 7 ETM+ band 6 at-satellite spectral radiance value (source: The main study area 2002 Landsat 7 ETM+ band 6 raw DN).

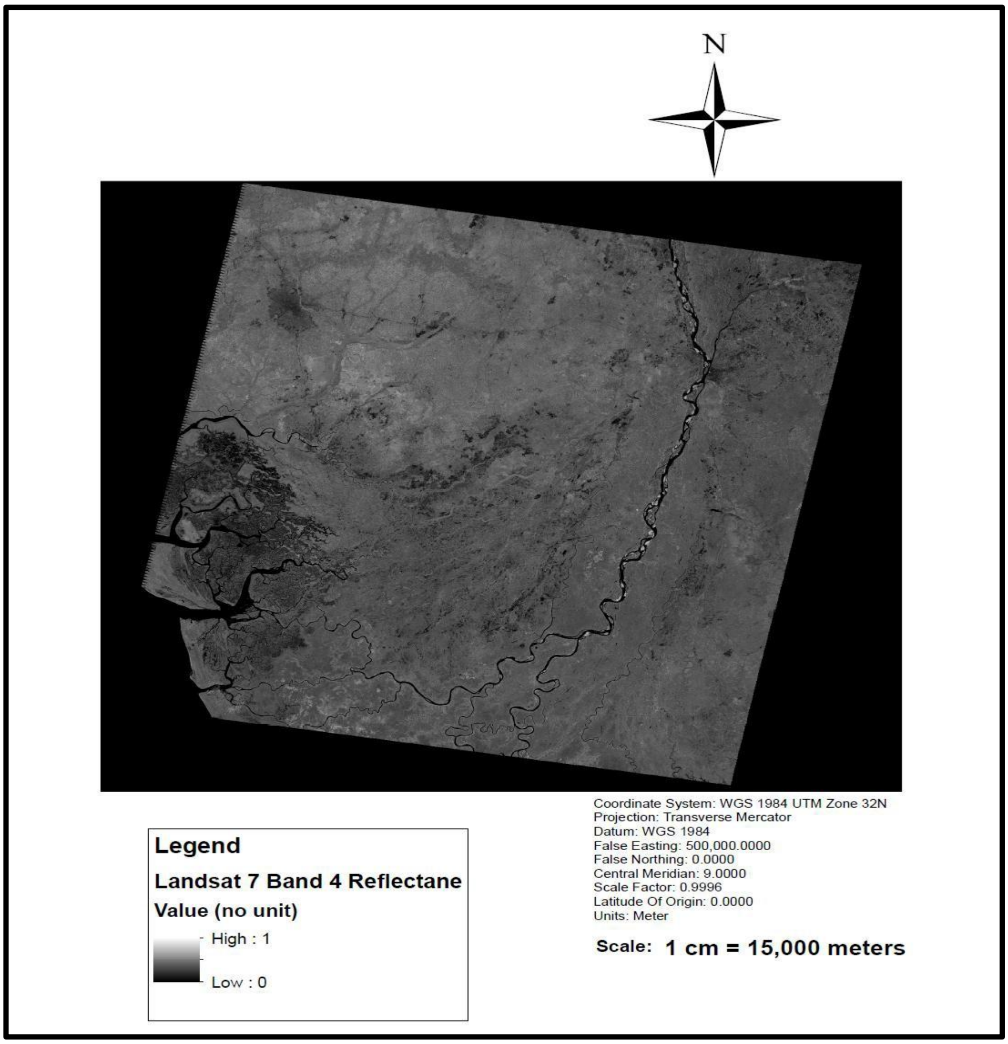


Figure 3.4: Diagram showing Landsat 7 ETM+ band 4 TOA spectral value (source: The main study area 2002 Landsat 7 ETM+ band 4 at satellite spectral radiance value).

3.2.1.3 Satellite image transformation

To derive the ancillary datasets required for this research work, the at-satellite spectral radiance and TOA spectral reflectance data derived above were transformed using appropriate algorithms.

The image transformations included:

<u>Conversion of satellite image thermal band to land surface temperature</u>

Land surface temperature (LST) is one of the ancillary variables used in classifying HAT vector habitat in this research work. To derive LST, the spectral radiance value of thermal band of the 2002 and 2003 Landsat 7

ETM+ images used for the main study area and minor study area respectively were converted to at-satellite brightness temperature using Equation 3.3 (Chander et al. 2009).

$$T = K2 / \ln(K1/ L\lambda)+1 \qquad 3.3$$

Where: T = effective at-satellite temperature in Kelvin, K1 & $K2$ = Landsat calibration constants 1 & 2(Appendix A-3b), $L\lambda$ = at-satellite spectral radiance, ln = natural log.

At-satellite brightness temperature only represents blackbody temperature, thus, it was corrected for spectral emissivity (land surface emissivity (LSE)). The LSE was estimated by combining the proportion of vegetation (soil and vegetation emissivity values) in the study areas with other parameters using Equation 3.4 (Sobrino et al. 2004).

$$\varepsilon_{Thermal\ band} = 0.004 \quad PV + 0.986 \qquad 3.4$$

Where: $\varepsilon_{Thermal\ band}$ = satellite image thermal band soil and vegetation emissivity, PV = proportion of vegetation derived from Equation 3.5.

$$PV = \left[\frac{NDVI - NDVI_{lowest}}{NDVI_{highest} - NDVI_{lowest}}\right]^2 \qquad 3.5$$

Where: $NDVI_{lowest}$ and $NDVI_{highest}$ = 0.2 and 0.5 respectively.

After estimation of LSE, the LST for the two areas were estimated in degrees Kelvin using Equation 1.10 and converted to degree Celsius (Equation 3.6). The results (LST values) are presented in Figures 3.5 and 3.6.

$$LST\ ^{o}C = LST\ (^{o}K) - 273.15 \qquad 3.6$$

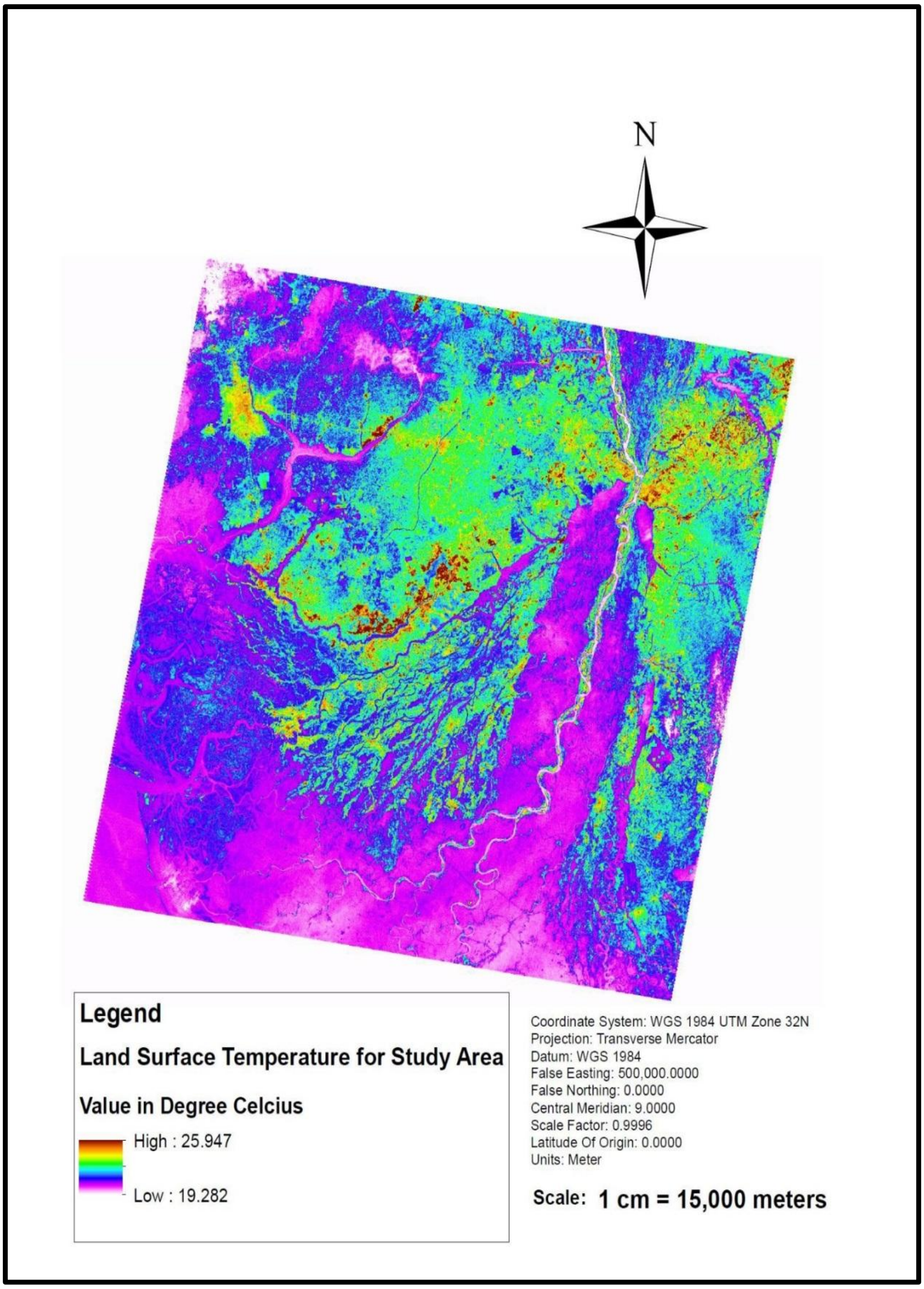


Figure 3.5: The main study area land surface temperature (source: 2002 Landsat **7** ETM+ radiometrically corrected band 6).

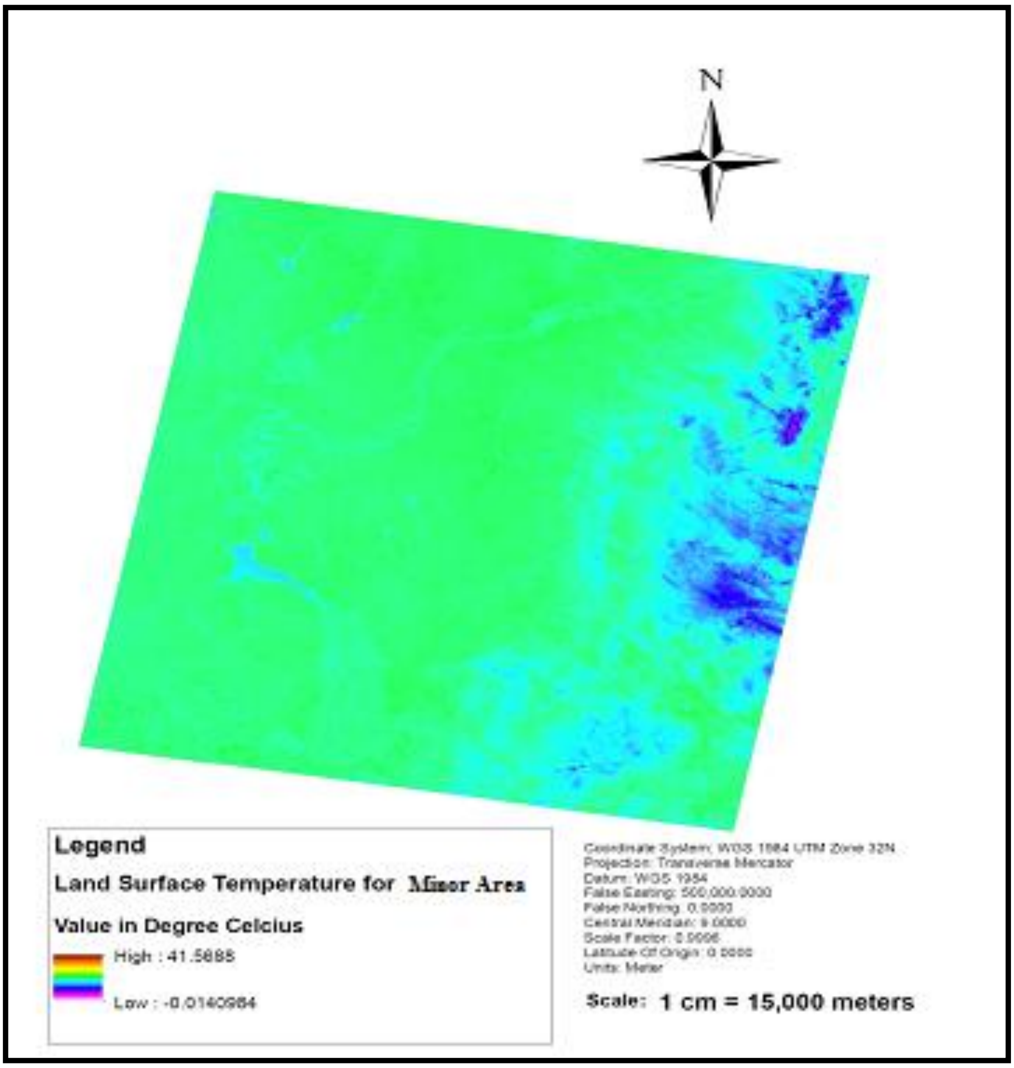


Figure 3.6: The minor study area land surface temperature (source: 2003 Landsat 7 ETM+ radiometrically corrected band 6).

Normalized difference vegetation index (NDVI)

NDVI was obtained for both study areas using the near-infrared (band 4) and red (band 3) components of the 1987 Landsat TM 4, 2002/2011 Landsat ETM+ and 1986 Landsat TM5, 2003/2012 Landsat ETM+ images, for main and minor study areas respectively. NDVI was also retrieved from bands 5 and 6 of the 1972 Landsat MSS1 for the minor study area. The NDVI was retrieved from the images using Equation 3.7 (Tucker 1979).

$$NDVI = (near\text{-}infrared - red) \,/\, (near\text{-}infrared + red) \qquad 3.7$$

The reason for deriving NDVI was to estimate the proportion of vegetation for the study areas, and because it's one of the ancillary datasets required for classification of the HAT vector habitat zones, as well as for change detection analysis. The results for the years 2002 and 2003 are presented in Figures 3.7 and 3.8 for the main and minor study areas, respectively.

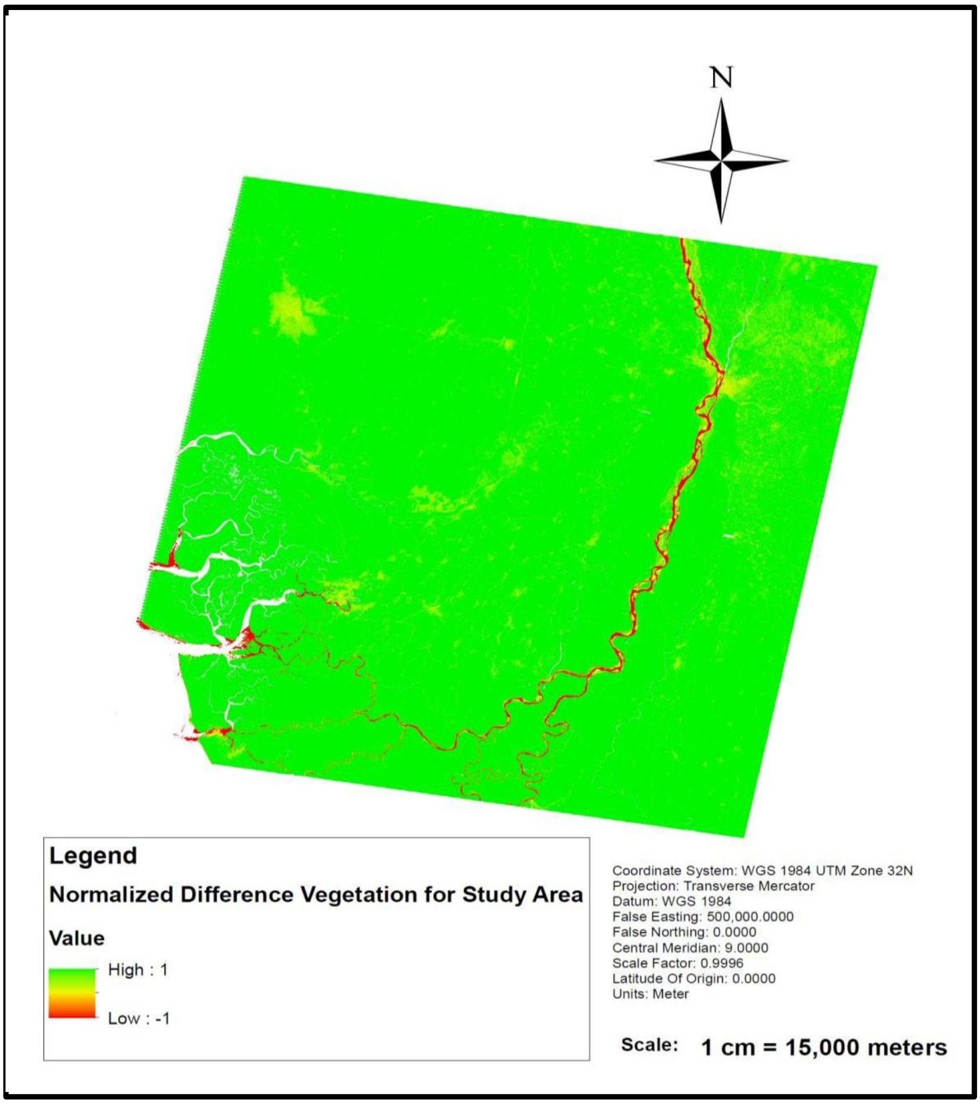


Figure 3.7: NDVI for the main study area (source: spectral reflectance values of 2002 Landsat 7 ETM+ band 4 and band 3).

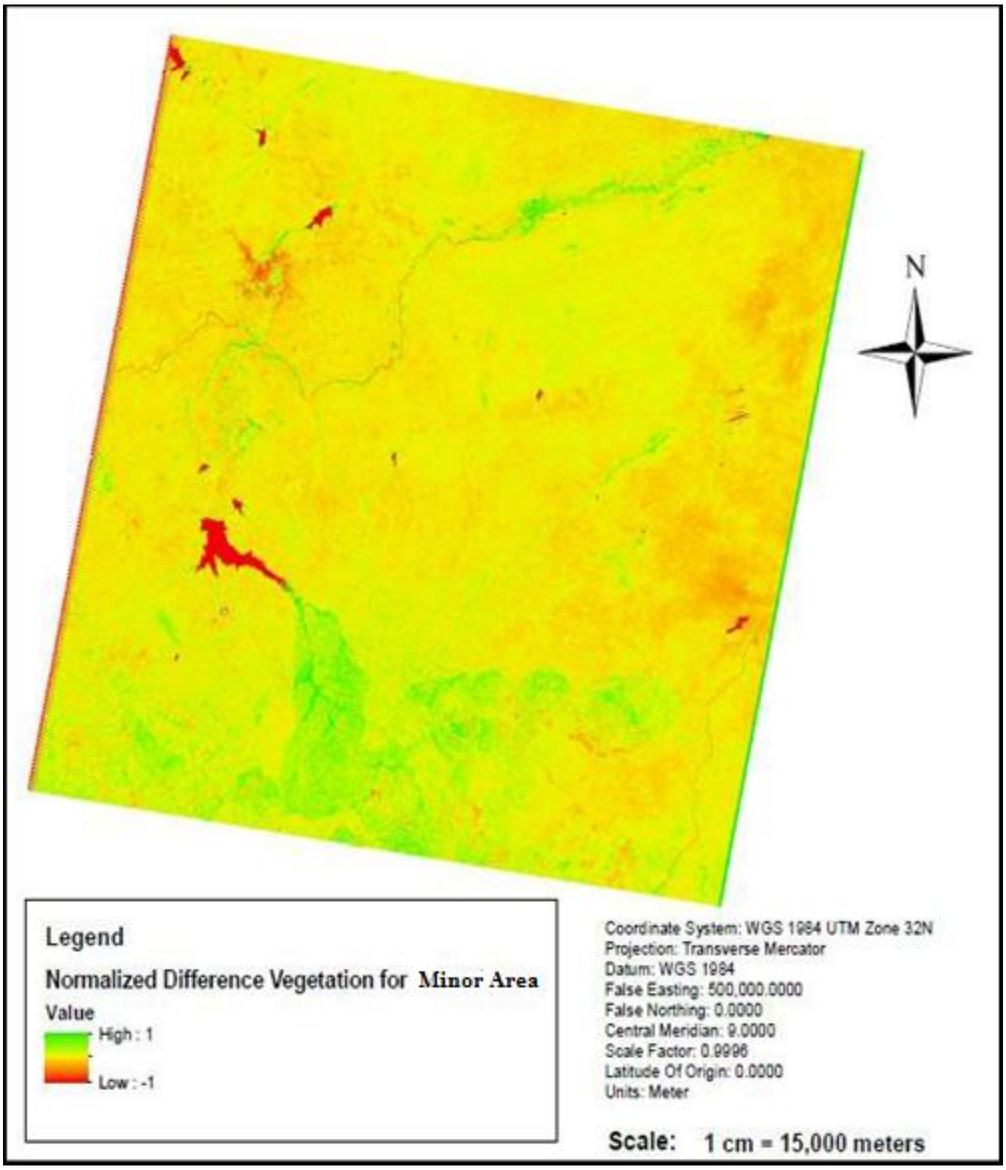


Figure 3.8: NDVI for the minor study area (source: spectral reflectance values of 2003 Landsat 7 ETM+ band 4 and band 3).

<u>Normalized Difference Water Index (NDWI) & Normalized Difference Drought Index (NDDI)</u>

NDWI for the study areas were derived from the spectral reflectance values of all the images used for NDVI, except the 1972 MSS1 image. The NDWI (Equation 3.8; Ji, Zhang and Wylie 2009) was extracted from the images because it is required to estimate NDDI and change detection analysis.

NIR –MIR / NIR + MIR (*i.e. band4 – band5 / band4 + band5)* 3.8

NDDI was also estimated for its inclusion in the classification of HAT vector habitat in both areas using Equation 3.9 (Renza et al. 2010).

$$NDVI - NDWI / NDVI + NDWI \qquad 3.9$$

The NDDI was estimated using the derived 2003/2003 NDVI and NDWI values, and rescaled into 0 – 1 ranges. The rescaling was necessary to conform to other datasets. The NDDI results are presented in Figures 3.9 and 3.10.

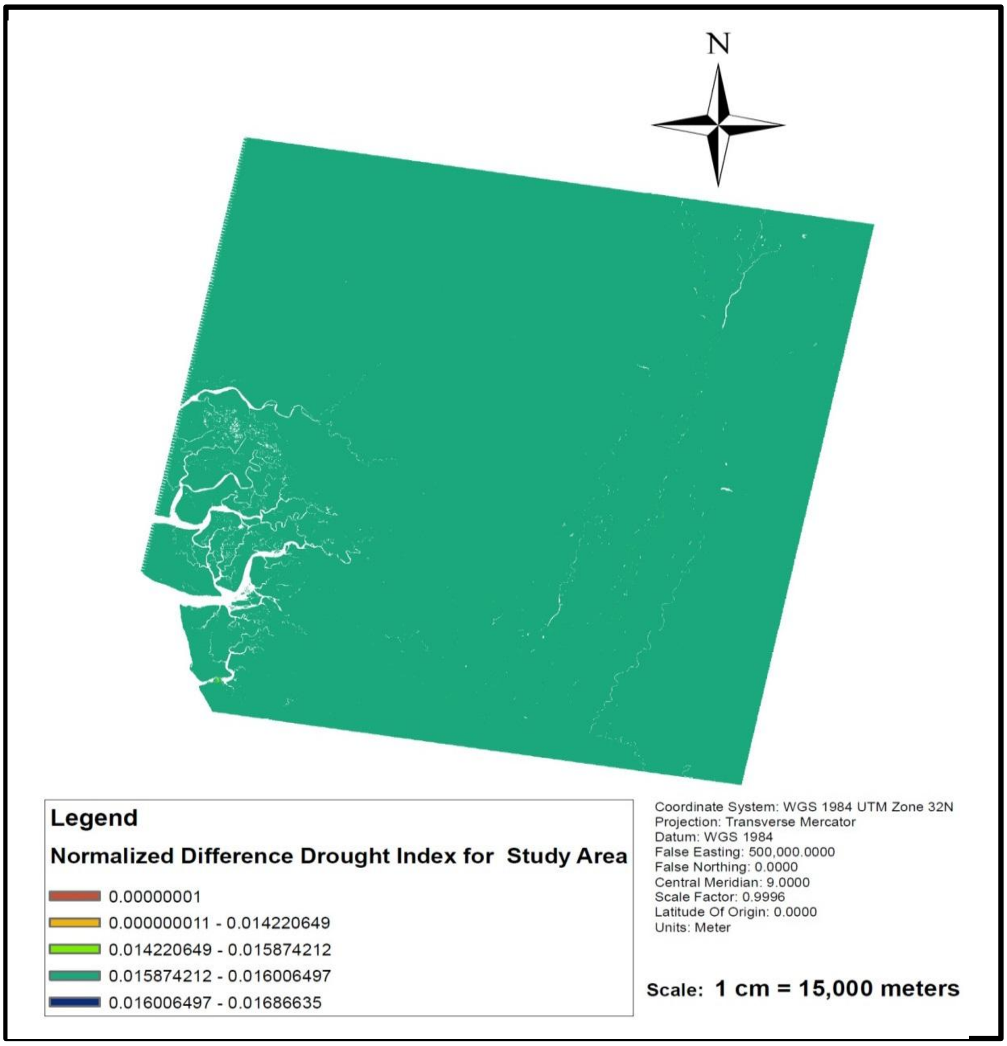


Figure 3.9: Normalized difference drought index for the main study area
(Source: NDVI and NDWI derived from 2002 Landsat 7 ETM+ of the main study area)

Figure 3.10: Normalized difference drought index for the minor study area (Source: NDVI and NDWI derived from 2003 Landsat 7 ETM+ of the minor study area).

<u>Relative humidity</u>

Relative humidity (RH) is one of the factors influencing HAT propagation. To derive RH as a map layer for its inclusion in the classification scheme, meteorological data (Appendix A-4d) obtained from NIMET was combined with the LST (Figures 3.5 and 3.6). Estimation of the relative humidity (*RH = (e/es) x 100*; Equation 1.11) entailed the estimation of saturated water vapour pressure (e_S) and actual water vapour pressure (e) using Equations 3.10 and 3.11(Lawrence 2005). The RH results obtained are presented in Figures 3.11 and 3.12.

$$es = 6.11 \, x \, 10.0 \, x \, (7.5 \, x \, Temp^0C/(243.04^0C + Temp^0C)) \qquad 3.10$$

$$e = (RH\% \, x \, es)/100 \qquad 3.11$$

Where: $Temp^0C$ = LST derived, RH = relative humidity

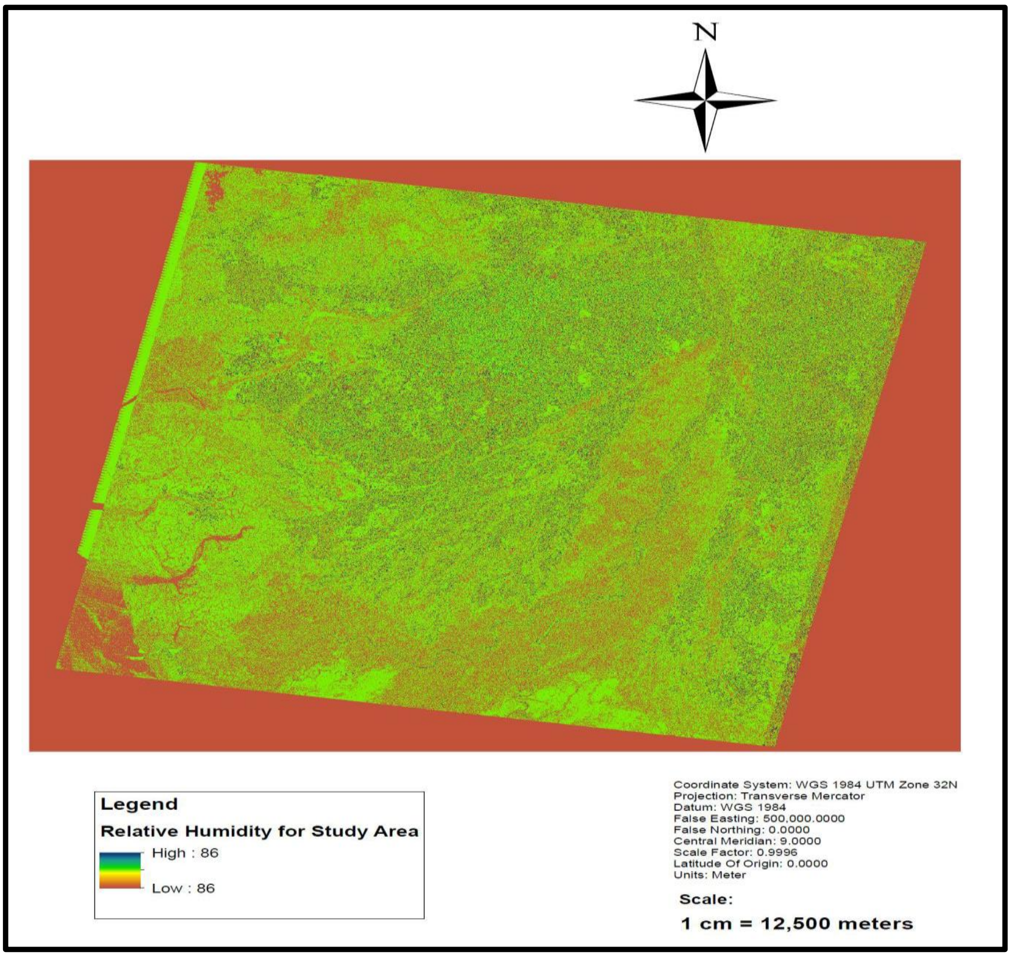


Figure 3.11: Relative humidity for the main study area (source: Derived using e_s and e).

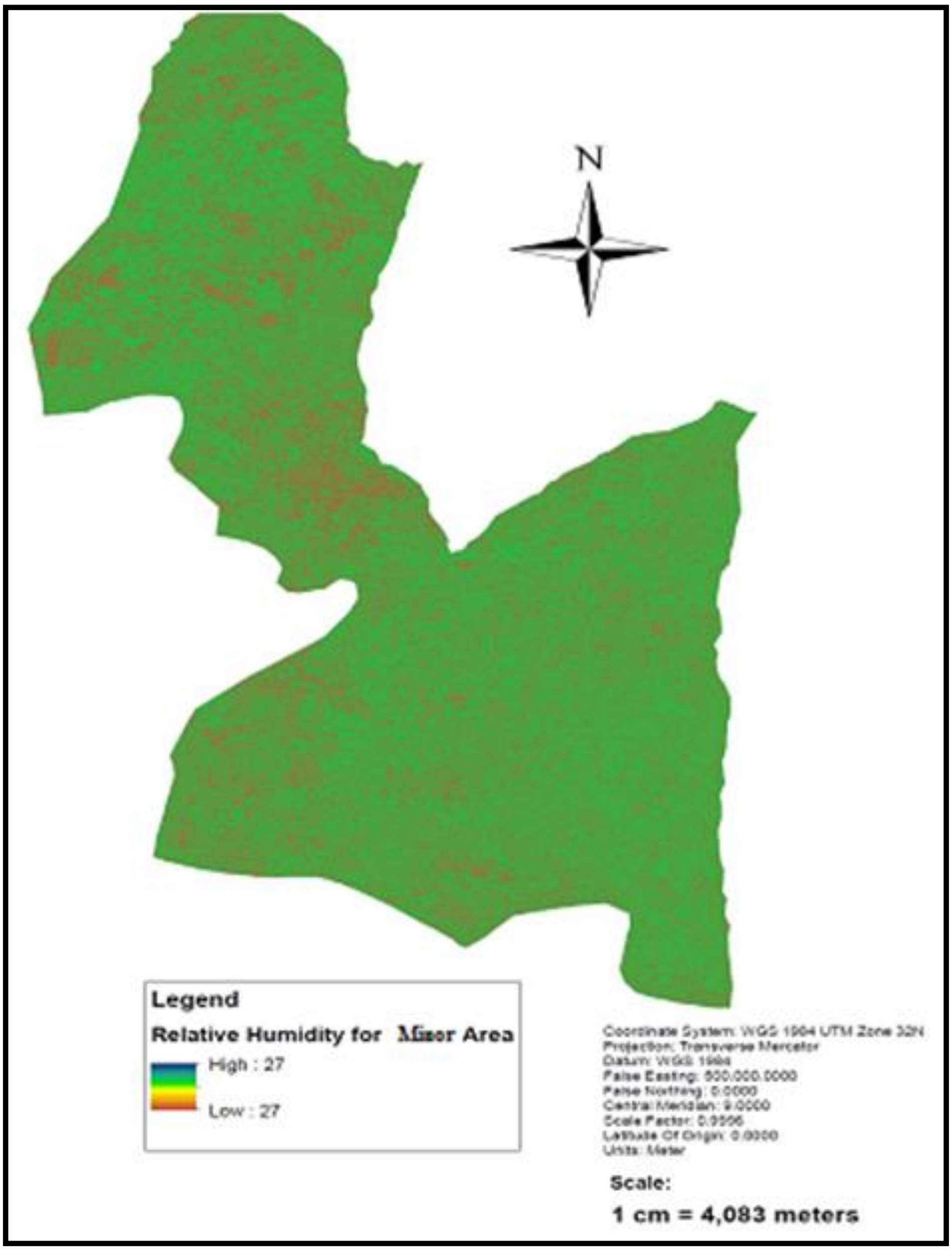


Figure 3.12: Relative humidity for the minor study area (source: derived using e_s and e).

Tasselled cap transformation

A tasselled cap transformation based on image spectral reflectance for the Landsat 7 ETM+ and Landsat 4 and 5 TM images, which covers the period between 1987 and 2011, and 1986 to 2012 for both the main and minor study areas, respectively was performed using brightness coefficients (Appendix A-3c). The transformation was carried out using the radiometrically corrected (spectral reflectance) bands 1, 2, 3, 4, 5, and 7 of the images, to extract brightness components. The tasselled transformation is an algebraic change detection technique (section 1.5.3), that consist three components namely: brightness, greenness and wetness components. The brightness component is a measure of overall reflectance of all image bands and it is associated with bare or partially covered soil, man-made and natural features. The greenness component is associated with the biomass present, while the wetness component that is orthogonal to the brightness and greenness components is associated with soil moisture, water, and other moist features. The brightness cap components were extracted to assess changes overtime in the study areas (details in section 6.9) in order to crosscheck the outcome of the HAT vulnerability assessment carried out in this research. Figure 3.13 is an example of the tasselled cap transformation map layer obtained.

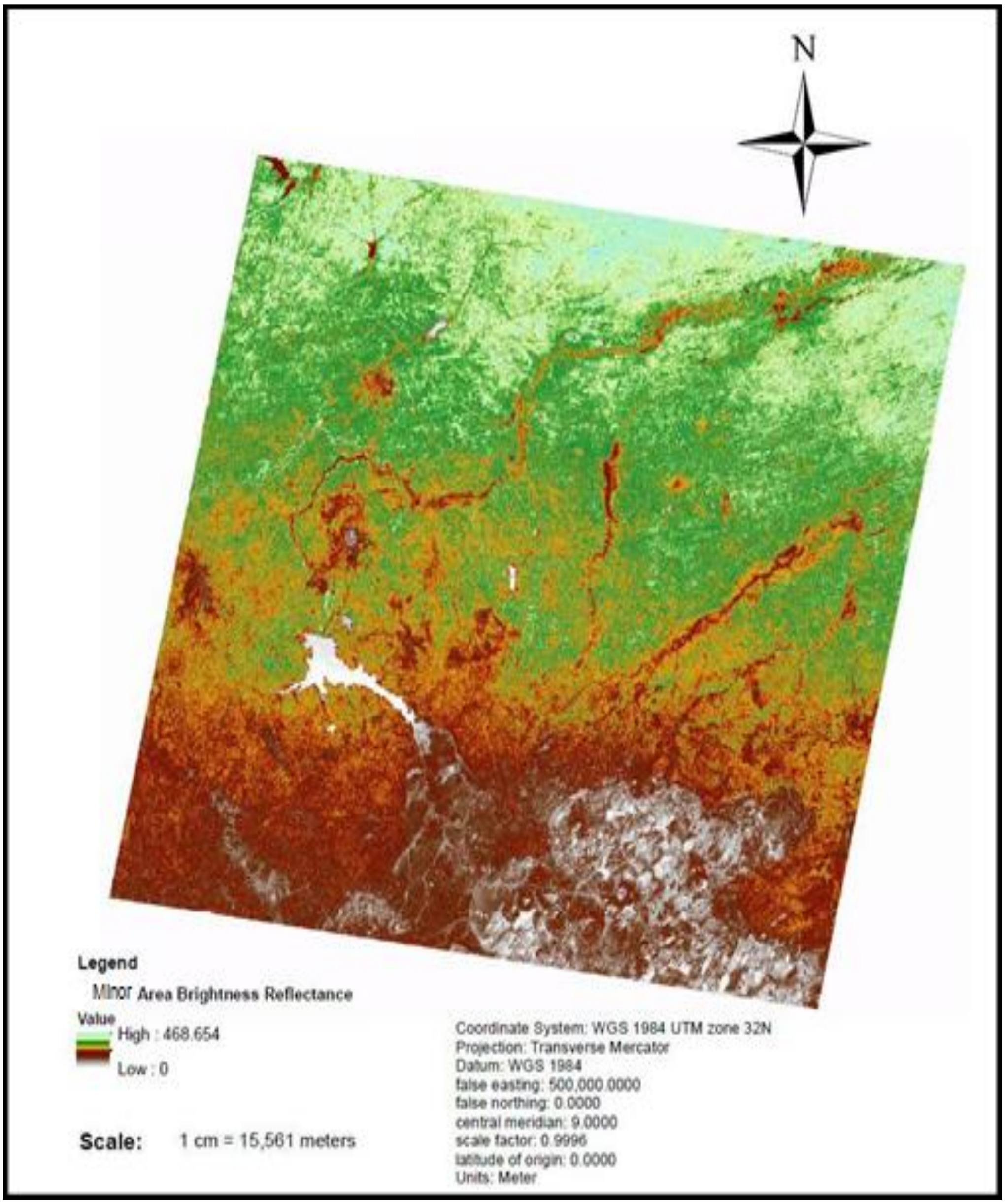


Figure 3.13: Tasselled cap transformation brightness component (source: radiometrically corrected 1986 Landsat TM 5 of minor study area).

3.2.2 Image classification

This section outlines the steps involved in the image classification. To select appropriate image bands for colour composites, principal component analysis (PCA) was carried out in ArcMap (Appendix D-1a, b). This was to ensure that the satellite image bands used for colour composite have low correlation so as to reduce any issue related to linearity (details in section 1.5.4). Principal components (PC) 7, 5 and 2 were selected for the land cover classification.

Some context taking from this section of the thesis has resulted in a publication (Akiode and Badaru 2014).

3.2.2.1 Unsupervised classification

Interactive supervised classification otherwise, known as Iso cluster unsupervised classification, was performed using the ArcMap multivariate toolset. This was done to identify the spectral clusters or natural statistical groupings present in the year 2002 and 2003 Landsat7 ETM+ images used for the main and minor study areas, respectively. The toolset was used to group the images into 14 and 10 clusters, which were later merged into desired classes as shown in Figures 3.14 and 3.15. The merging of classes was based on prior knowledge of the study areas. Parameters such as minimum class size and sample interval were specified. In order to provide appropriate statistics to create a signature file for confidence level assessment, each cluster should contain enough cells to accurately represent the cluster**.** Therefore, the minimum class size must be approximately 10 times larger than the input raster bands, and the sample interval should be small enough to accommodate the smallest desirable categories existing in the input data (ArcMap 10.0 Help). The Landsat7 ETM+ images used for the unsupervised classification consist of 3 bands (principal components); hence, 30 and 10 were specified as the minimum number of cells in a valid class and sample interval respectively.

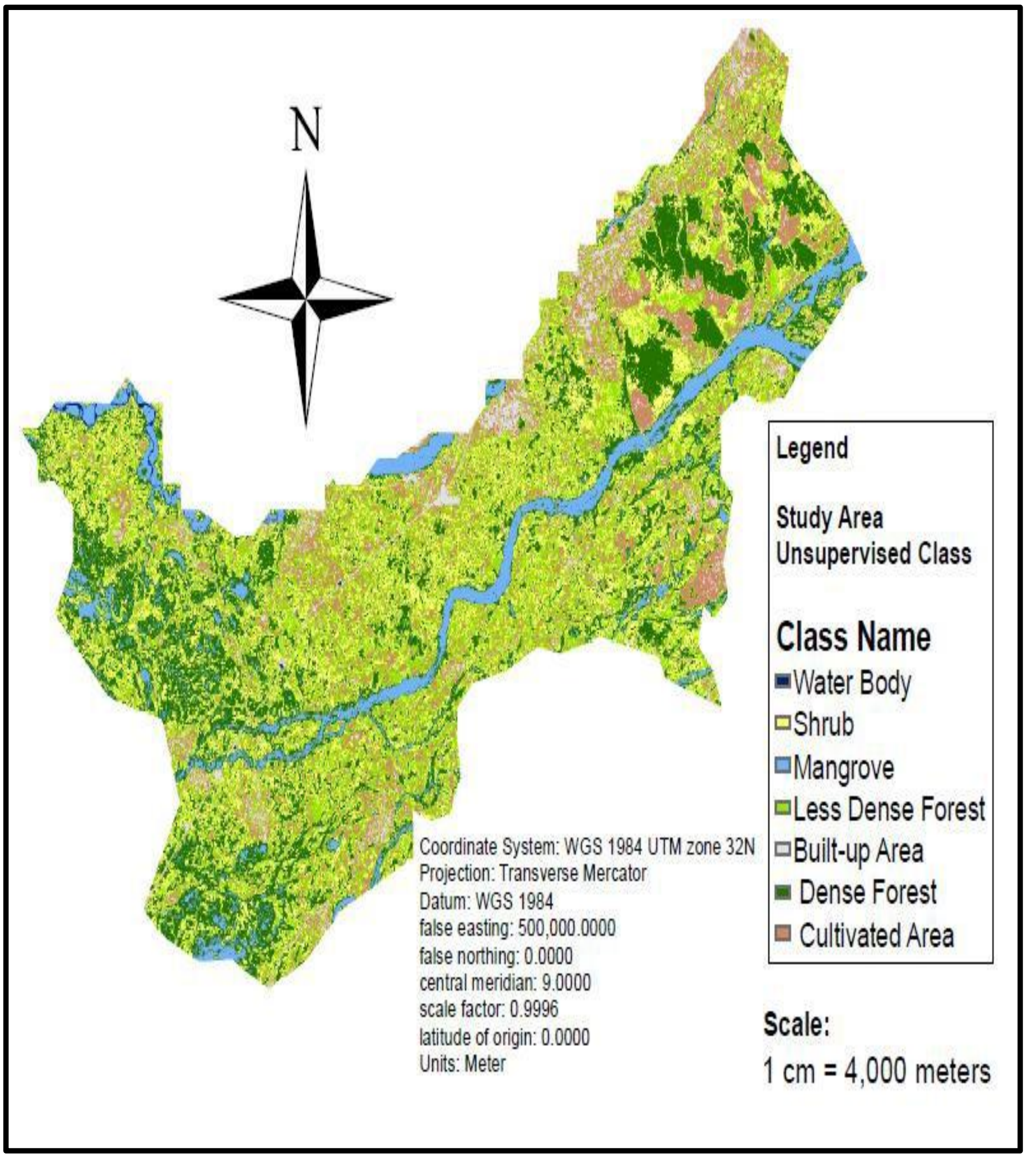


Figure 3.14: Unsupervised classification of land cover classes in the main study area (source: 2002 Landsat 7 ETM+ image).

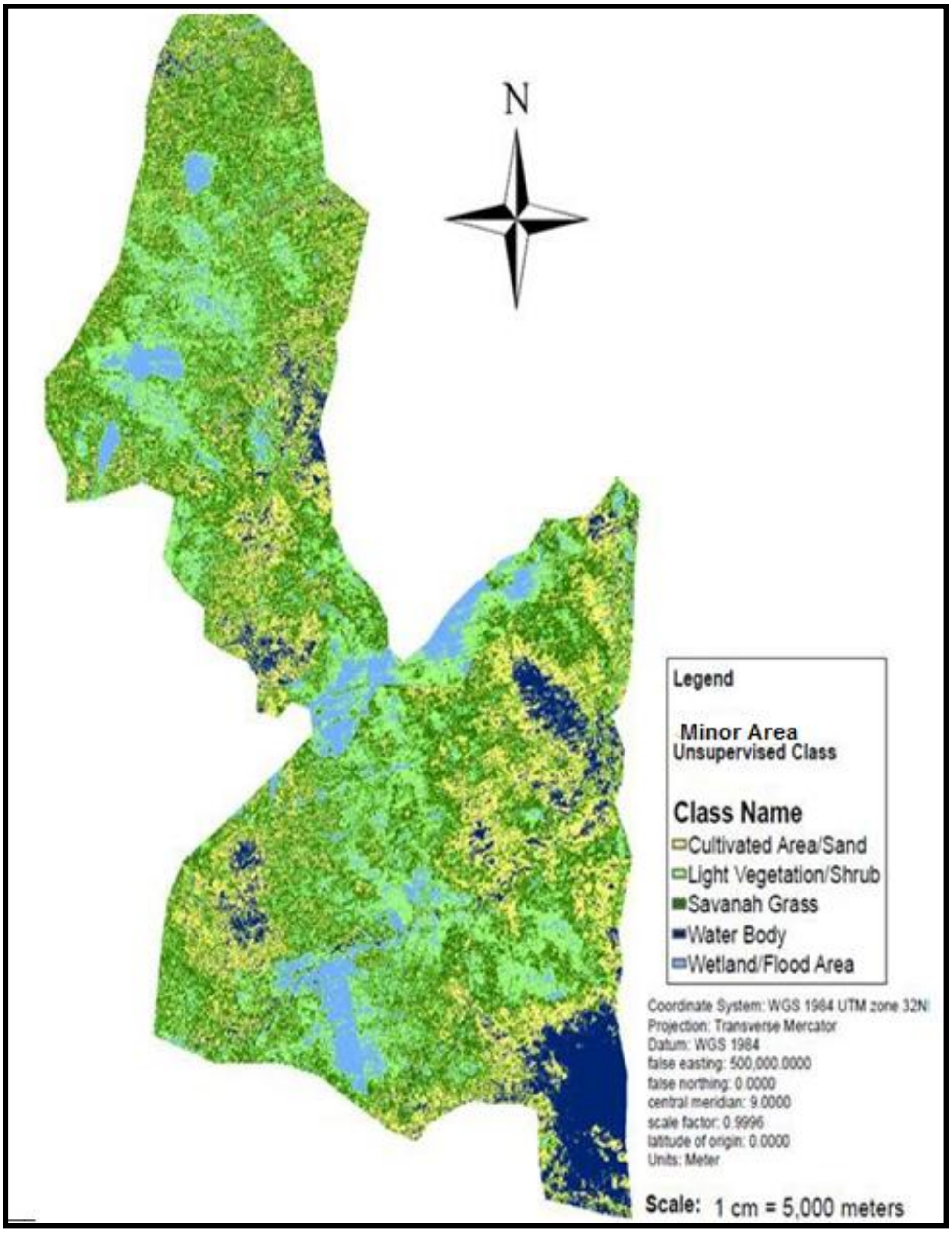


Figure 3.15: Unsupervised classification of land cover classes in minor study area (source: 2003 Landsat 7 ETM+ image).

3.2.2.2 Supervised classification

An adequate number of representative training samples is vital for image classifications. Several training samples (Appendix D-2a, b) were collected from areas that appeared relatively similar on the 2002 and 2003 Landsat 7 ETM+ images used in the main and minor study areas, respectively. Groundtruth data, previous knowledge of the study area and the result of the unsupervised classification aid the training set samples. The next step was the generation of signature file. This is the statistical description of the classes (e.g. number of samples, the means and covariance matrices derived from the samples identified on the images). These statistics are required for the supervised classification.

After the creation of signature file, the maximum likelihood classification (supervised classification) was carried out. For the supervised classification, the colour composite image (PC 7, 5, 2) was used as input raster bands, and the signature file created for the training samples served as input signature file. For every cell of the dataset to be classified, and for all classes sampled to have the same a priori probability, reject fraction 0.0 and equal a priori probability weighting was specified respectively.

A total of 7 and 5 land cover classes, as shown in Figures 3.16 a, b, c, and 3.17, were identified for both the main and minor study areas, respectively. Figures 3.16 b and c are for the other two local government areas selected for investigation in Delta State (see Chapter 1). It is very difficult to identify built-up areas on the image used for the minor study area as sand has a similar reflectance value to some of the building materials. Also, the settlements are very small.

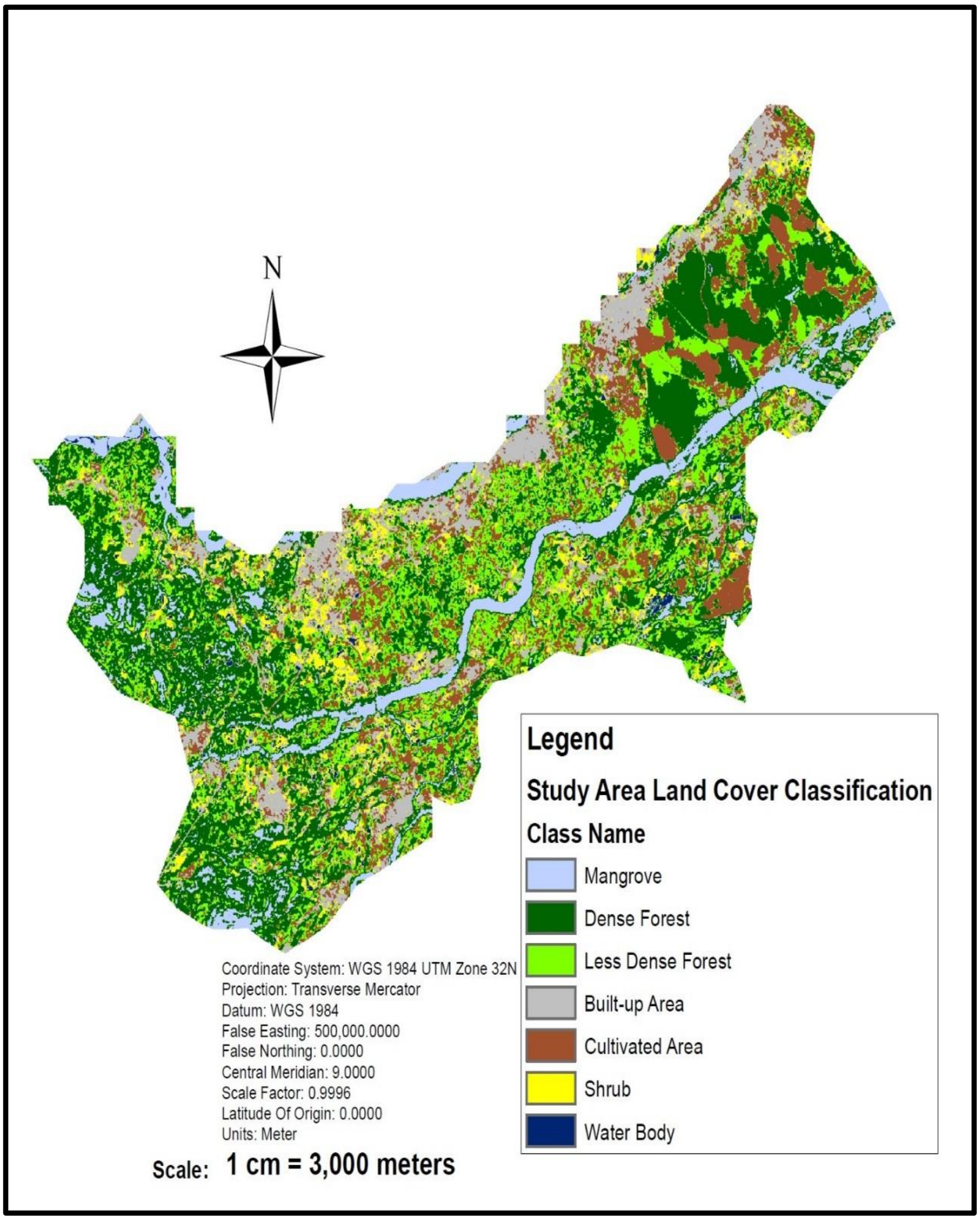


Figure 3.16a: Supervised land cover classes in the main study area

(source: 2002 Landsat 7 ETM+ and groundtruth).

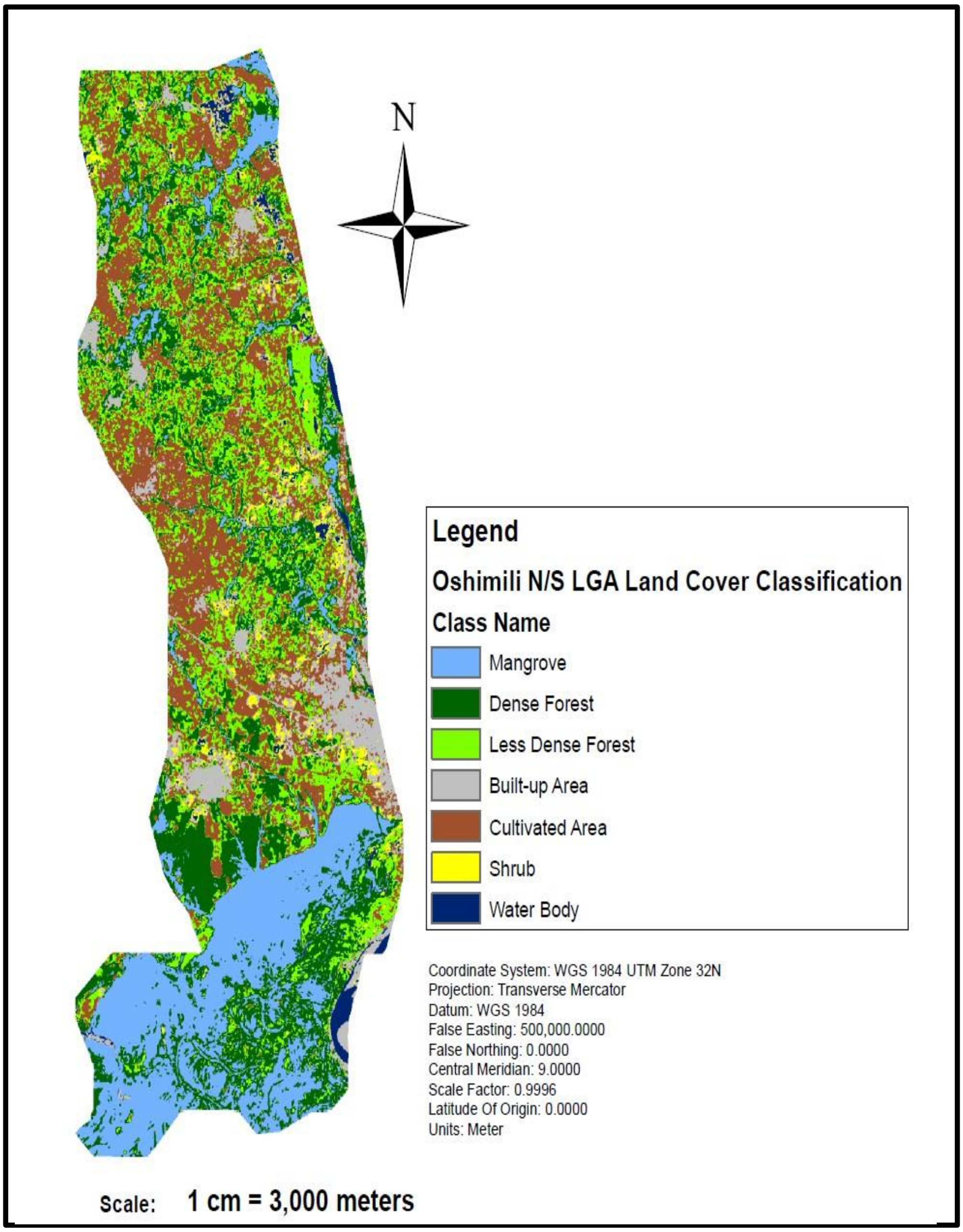


Figure 3.16b: Supervised land cover classes in Oshimili North and South LGA (source: 2002 Landsat 7 ETM+ and groundthruth).

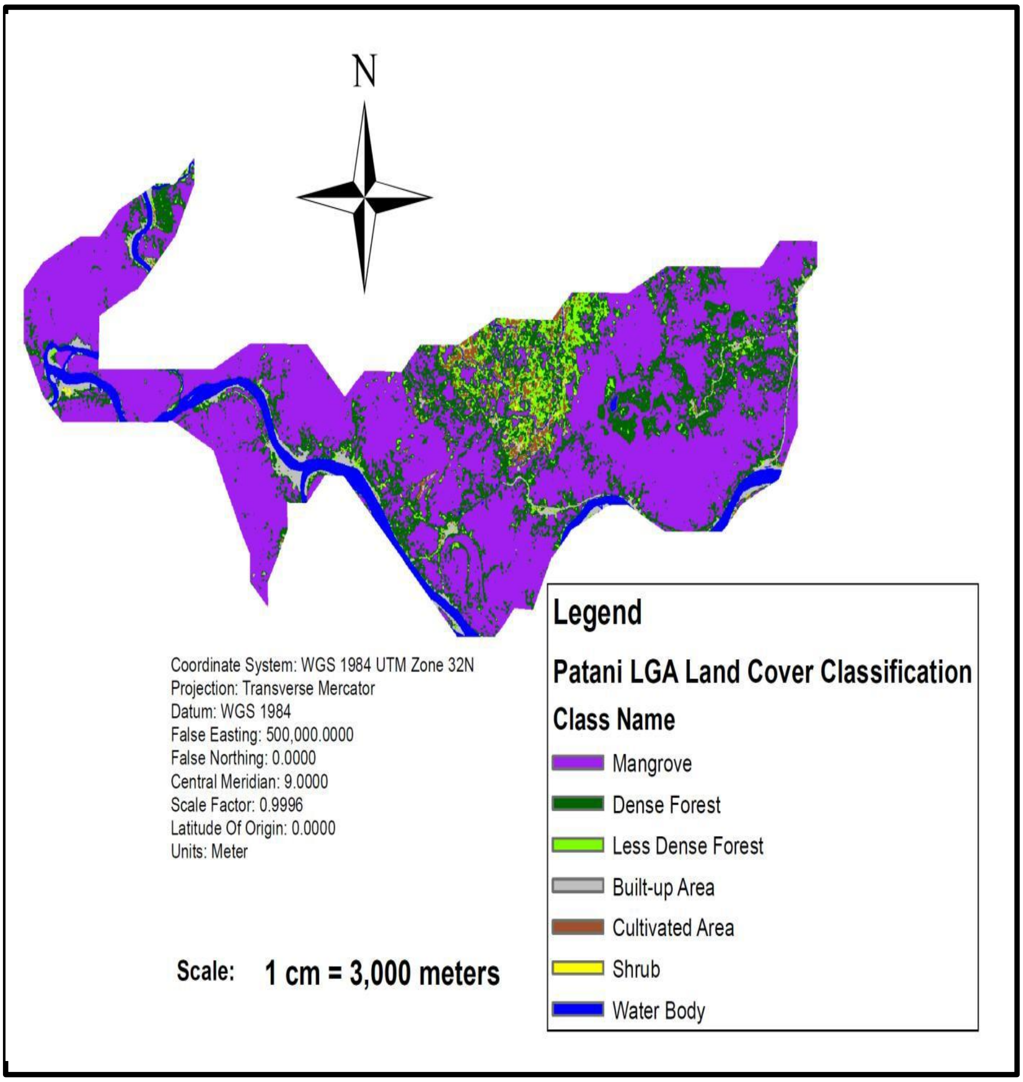


Figure 3.16c: Supervised land cover classes in Patani LGA (source: 2002 Landsat 7 ETM+ and groundthruth).

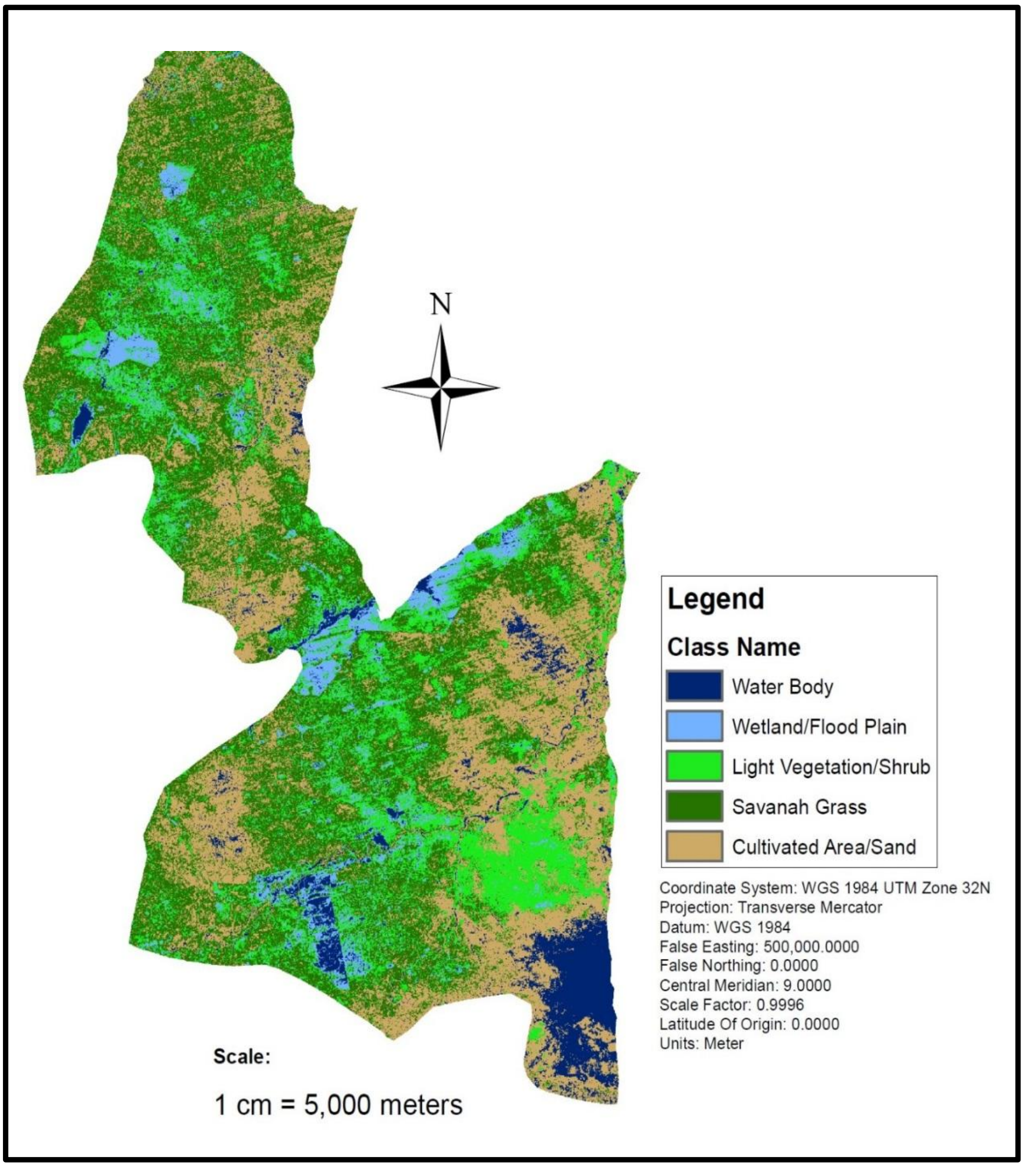


Figure 3.17: Supervised land cover classes in minor study area (source: 2003 Landsat 7 ETM+ and ground truth).

3.2.3 Post-classification processing

The seven classes in the main study area supervised classified image were separated into separate layers, after which the built-up area layer was generalised. This was done using the ArcMap region group tool set to reclassify the small isolated regions of the built-up area pixels to the nearest class. This enables each settlement in the main study area to be identified as a separate entity, rather than a class in the domain type land cover. Figure 3.18 presents the region grouped settlements.

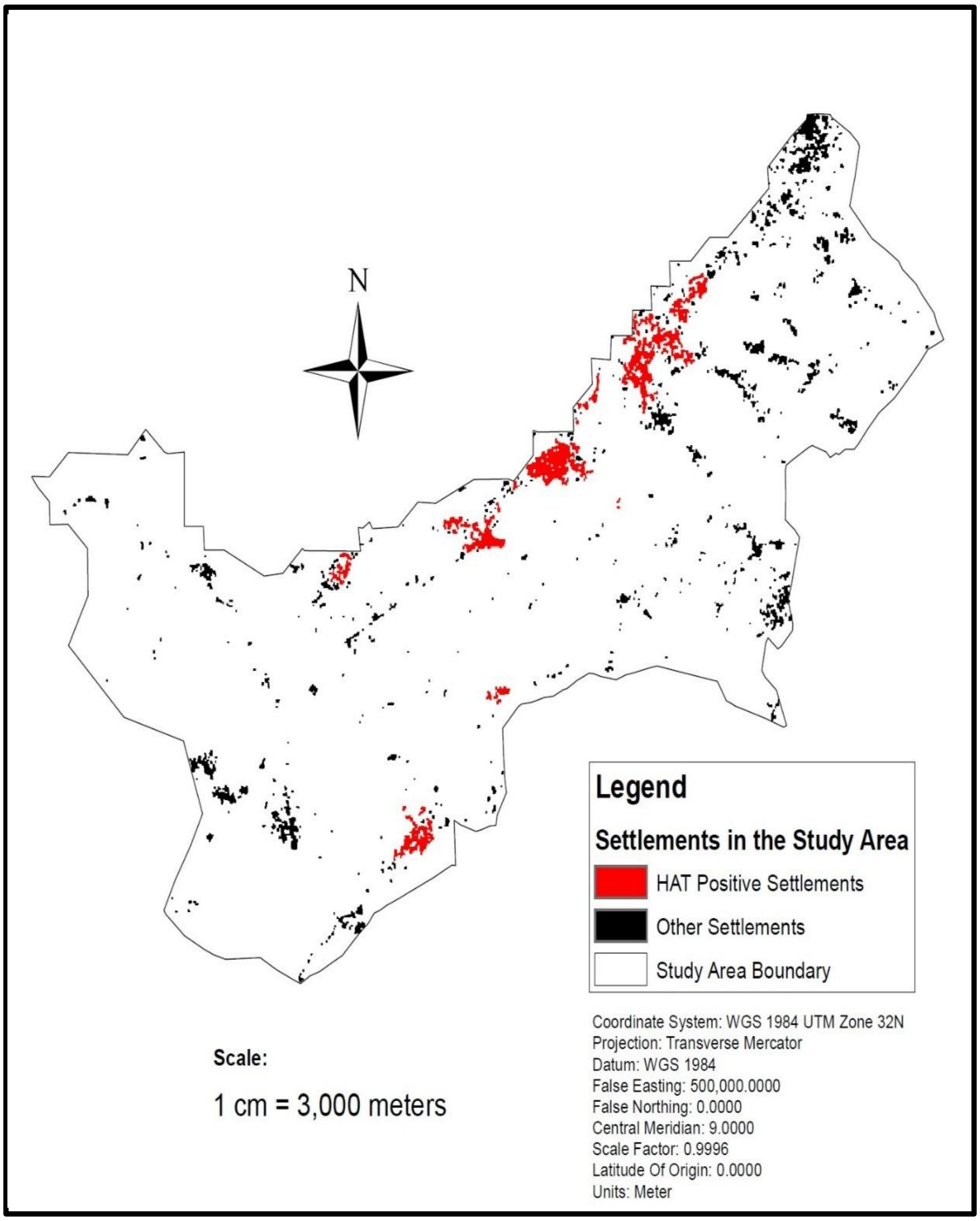


Figure 3.18: Region grouped settlements in the main study area (source: main study area supervised land cover built-up area class).

3.2.4 Image classification accuracy assessment

The classification output must resemble reality; therefore, to evaluate the result of the classification, the spectral characteristics of the classes represented by the training samples were assessed. Also, to ascertain the accuracy of the classification, the error matrix was computed using GCPs obtained during ground thruthing. The classified output was also compared with a high resolution spot image (Appendix A-2(h)) obtained from Google Earth. The Spot image shows more detail than the Landsat image used as the base data for the classification. Though unsupervised classification was carried out mainly to aid the supervised classification training samples selection, its confidence level was assessed to show the reliability of the unsupervised classes.

3.3 Results

The result of the confidence level statistics conducted for the unsupervised classification showed 14 levels of confidence. The first level of confidence with a value of 1 in the confidence level output indicates the cells that have highest certainty of being correctly classified, while the lowest level of confidence with value of 14 shows the image cells that would most likely be mis-classified.

The confidence level results shown in Figures 3.19 and 3.20, when overlaid on the unsupervised classes revealed some cells of light vegetation/shrub and savannah grass as the classes that would most likely be mis-classified in the minor study area. Also, in the main study area, shrub, less dense forest and water bodies were the classes that have cells with lowest level of confidence. It was not clear why water body had low level of confidence; while mangrove had the highest level of confidence in the main study area unsupervised classification. The researcher suspected it was dependent on the area of coverage of the water body; as the water body has the smallest coverage area. Despite the confidence levels, the unsupervised classification helped towards selection of training samples for the supervised classification.

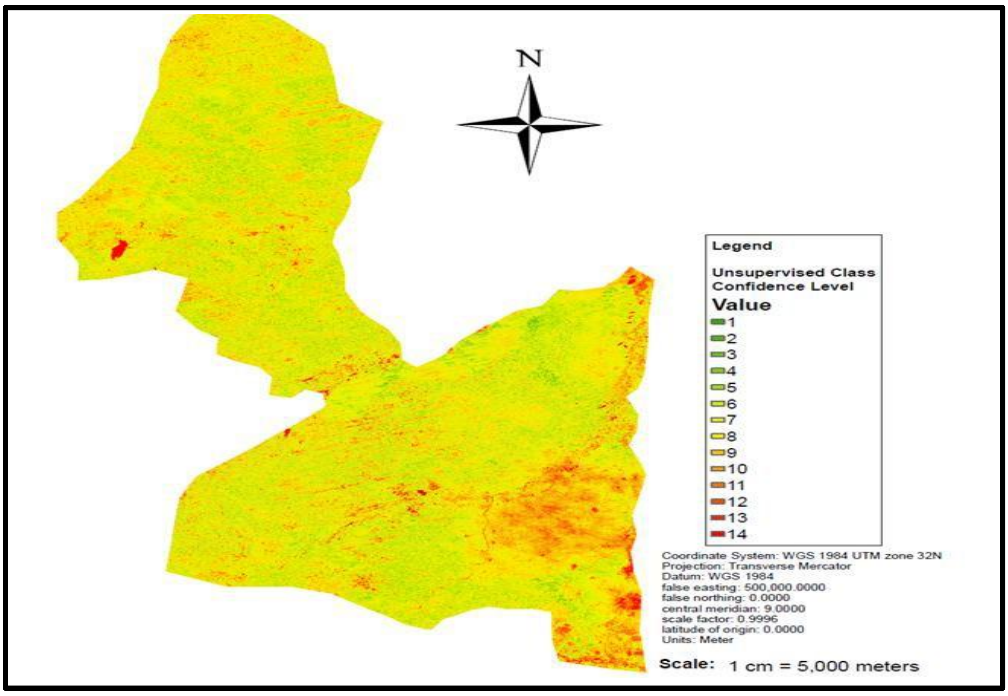


Figure 3.19: Confidence level for minor study area unsupervised classification.

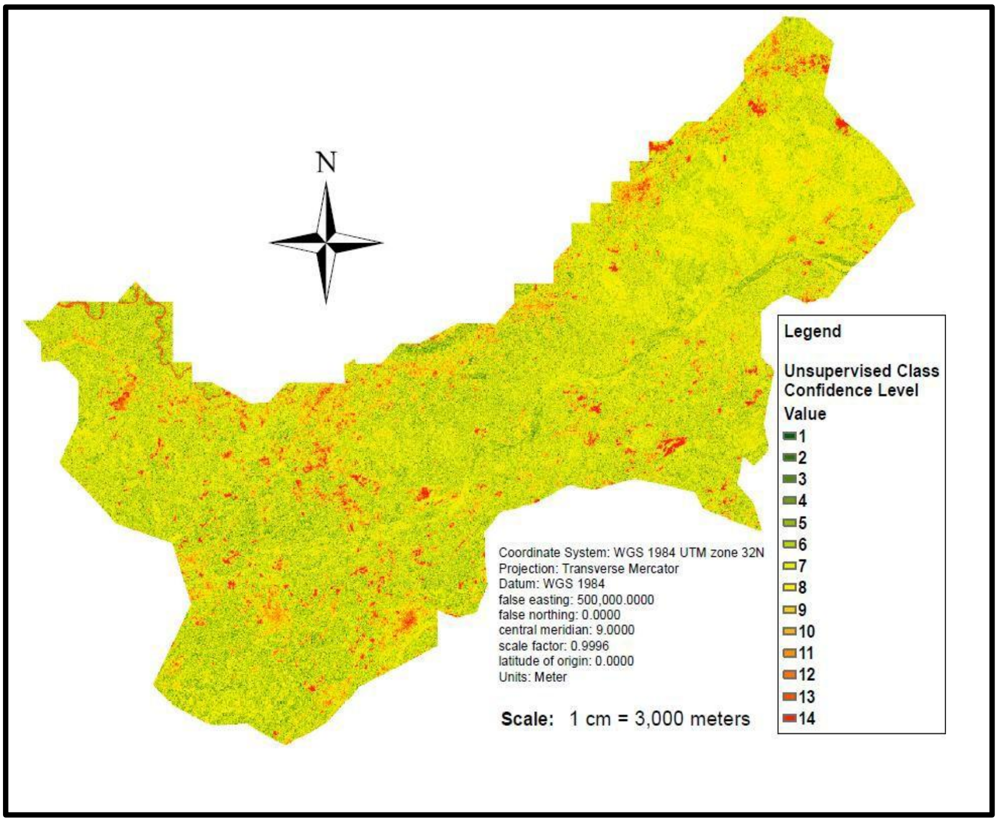


Figure 3.20: Confidence level for main study area unsupervised classification.

The evaluation of the training samples shows that they were representative for both the main and minor study areas and are statistically separate. The histograms (Appendix D-2 b, c) of the land cover classes did not overlap. The overall accuracy of the 2003 supervised image classification (for minor study area) and 2002 supervised image classification (for main study area) are 98.0% and 99.2%, respectively (Tables 3.1 and 3.2). For the minor study area supervised classification, the light vegetation/shrub and savannah grass have 90.32% and 91.66% producer's and user's accuracy respectively, while others have 100% in each category. Also, all the identified land cover class have 100% producer and user's accuracy, except for cultivated areas and shrub that have 94.59% and 94.29% producer's and user's accuracy, respectively, for the main study area classification. This may be due to the spectral reflectance of shrub similar to less dense forest reflectance and some matured/tall plants within the cultivated class in some areas.

To check the extent to which there is agreement other than that which is expected by chance, kappa statistics (Table 3.3) was also calculated for the main study area supervised classification. The overall kappa statistics was 0.9907; this is an indication of strong agreement between the classified pixels and the reference data.

Table 3.1: Error matrix for minor study area supervised land cover classification

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
Unclassified		0	0	0 ---	---
Savannah Grass	33	36	33	100.00%	91.66%
Culti Area/Sand	30	30	30	100.00%	100.00%
Wetland/Flood	29	29	29	100.00%	100.00%
Light Vege/Shru	31	28	28	90.32%	100.00%
Water Body	27	27	27	100.00%	100.00%
Totals	150	150	147		

Overall Classification Accuracy = 98.00%

Table 3.2: Error matrix for main study area supervised land cover classification

Class Name	Reference Totals	Classified Totals	Number Correct	Producers Accuracy	Users Accuracy
----------	----------	----------	-------	---------	-----
Unclassified	0	0	0	---	---
Dense Forest	37	37	37	100.00%	100.00%
Mangrove	35	35	35	100.00%	100.00%
Less Dense Fore	37	37	37	100.00%	100.00%
Shrub	33	35	33	100.00%	94.29%
Built-up Area	36	36	36	100.00%	100.00%
Cultivated Area	37	35	35	94.59%	100.00%
Water Body	35	35	35	100.00%	100.00%
Totals	250	250	248		

Overall Classification Accuracy = 99.20%

Table 3.3: Kappa statistics for main study area supervised classification

----

Overall Kappa Statistics = 0.9907

Conditional Kappa for each Category.

Class Name	Kappa
----------	-----
Unclassified	0.0000
Dense Forest	1.0000
Mangrove	1.0000
Less Dense Forest	1.0000
Shrub	0.9342
Built-up Area	1.0000
Cultivated Area	1.0000
Water Body	1.0000

3.4 Summary

The main aim of this chapter was to derive datasets that will augment the dearth of spatial data in the study area as well as obtaining up-to-date information suitable for the classification scheme for managing HAT propagation. The data extraction process reduced expensive and time consuming field measurements. The approach of using RS and GIS techniques to derive the datasets is novel most especially for the study area as all the existing data are dated.

Using RS and GIS techniques to produce supervised land cover map has proved to be cost effective, quick and efficient. The overall accuracy of 99.2% and 98.0% (in the main and minor study areas, respectively) and the distinct identification of some of the land cover class attested to the fact that, with little data, much could be achieved. Overall, this chapter has demonstrated the efficiency of geo-spatial techniques in generating useful datasets and in delineating features in a given environment.

Chapter 4: Spatial Distribution Analysis of HAT in the Main Study Area

Before developing the classification scheme, whether HAT is significantly present in the study areas must be established. In order to do this, directional distribution and spatial cluster analyses were carried out. Part of the work in this chapter has resulted in publications (Akiode and Oduyemi 2014 b, c).

4.1 Directional Distribution Analysis

In order to investigate the magnitude of some of the processes that impact HAT in the main study area in different directions, standard deviational ellipse (SDE) and weighted standard deviational ellipse (WSDE) were used to show the direction of HAT cases (Appendix A-4c), based on the settlement of each case around the mean centre (MC) for each year that the HAT case was detected.

4.1.1 The mean centre

To track changes in the distribution of HAT for the years 1994-2006, and to identify the possible origin for HAT disease in the main study area, the ArcMap spatial statistics tool was used to create a point map that illustrates the mean centre for each year of HAT case occurrence. The tool calculates the average geographical coordinates for HAT cases for specified years. Figure 4.1 shows the average mean centre calculated over this period.

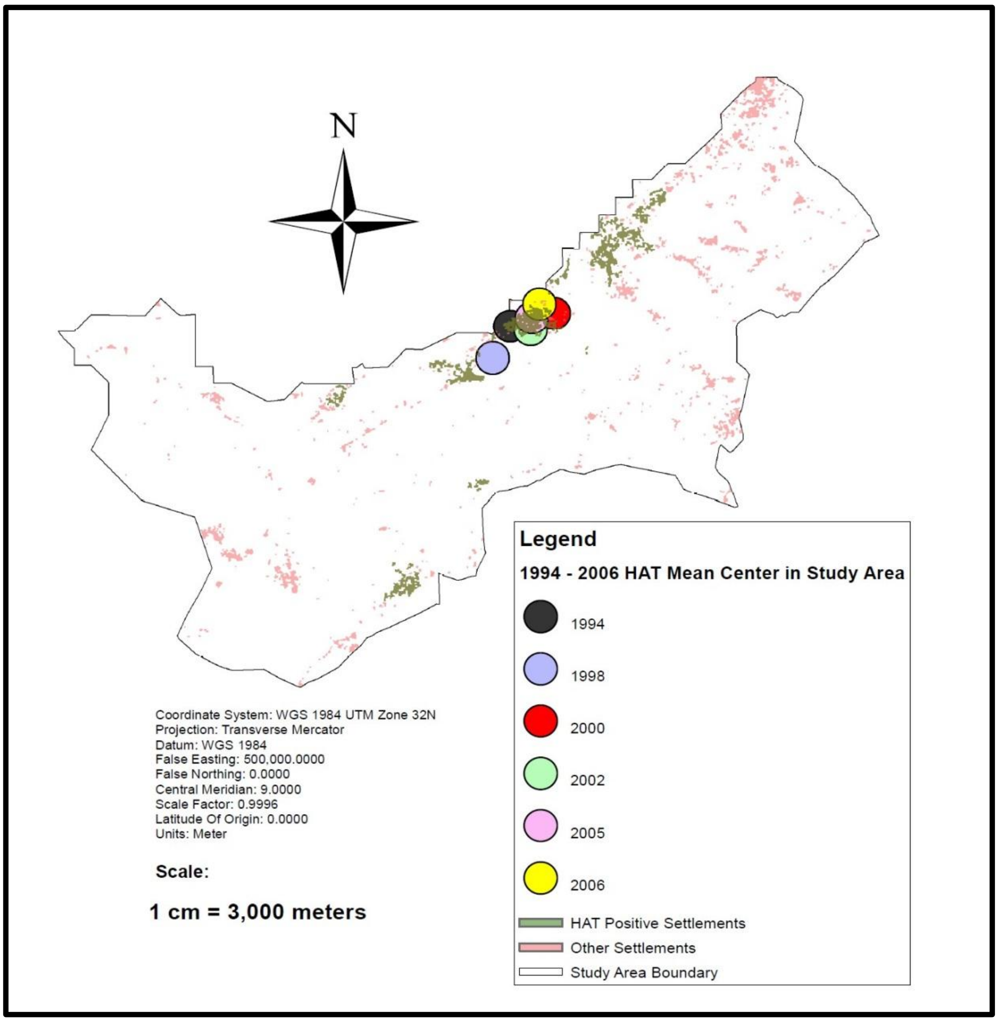


Figure 4.1: Average mean centre of HAT distribution within the case positive settlements in the main study area (source: HAT record of cases acquired from HAT sentinel centre, Eku Baptist Hospital, Nigeria).

4.1.2 Standard deviational ellipse and weighted standard deviational ellipse

The ArcMap standard deviational ellipse (SDE) tool was used to create ellipse polygon map that centred on the mean centre for all the year of HAT cases. The SDE (Figures 4.2-4.4) was computed to show two standard distances axes of the mean centre, the orientation of the ellipse, and the case field (Table 4.1) using standard deviation levels 1, 2, and 3. When features have a spatially normal distribution, one standard deviation will encompass approximately 68% of all input feature centroids. Two standard deviations will encompass approximately 95% of all features, and three standard deviations will cover approximately 99% of all feature centroids (ArcGIS 10.0 desktop help).

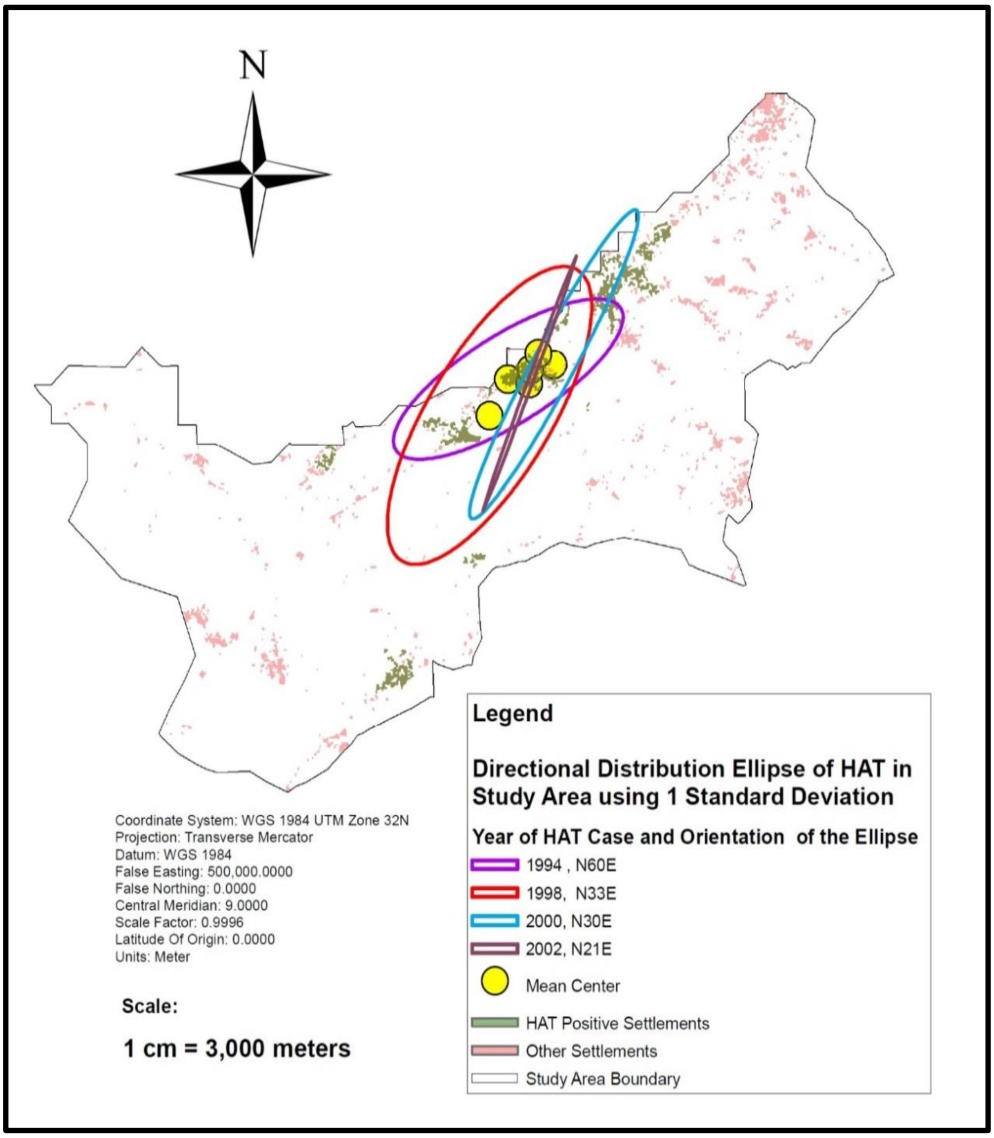


Figure 4.2: Standard deviational ellipse of HAT distribution in the main study area shown as standard deviation-1

Table 4.1: Attributes of standard deviational ellipse of HAT distribution in the main study area in standard deviation-1

FID	Shape	CentreX	CentreY	XStdDist	YStdDist	Rotation	YEAR
0	Polygon	177693.5	640207.8	2560.6	7943.6	59.5	1994
1	Polygon	176563.6	638126.9	3665.9	9896.8	32.9	1998
2	Polygon	180465.5	641048.6	1239.6	10176.6	29.5	2000
3	Polygon	178992.2	639961.9	153.5	7820.4	21.2	2002

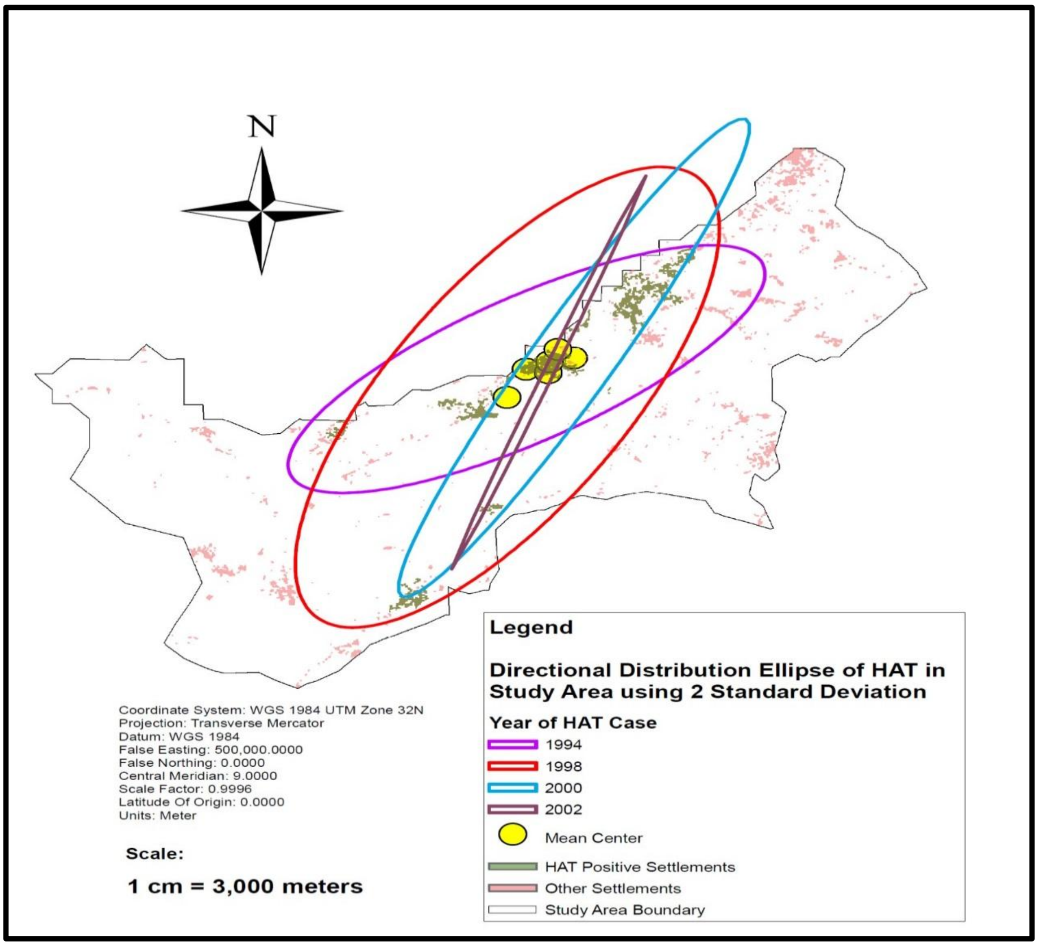


Figure 4.3: Standard deviational ellipse of HAT distribution in the main study area shown as standard deviation-2

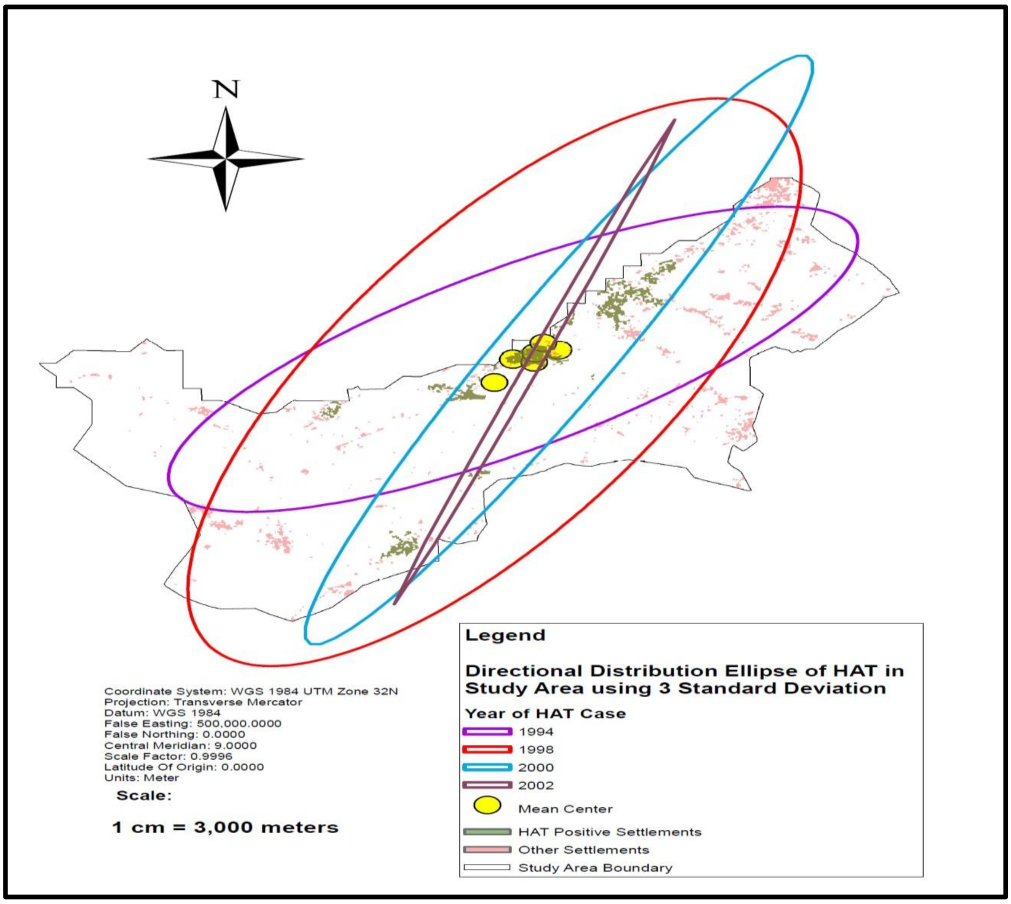


Figure: 4.4: Standard deviational ellipse of HAT distribution in the main study area shown as standard deviation-3.

To enhance the result of the SDE analysis, WSDE (Figure 4.5, 4.6) was computed for the sex and occupation of individuals affected by HAT, using case year as weight for sex and occupation, and age of patients as weight for year of individual cases. The attributes of WSDE for gender are presented in Tables 4.2.

Table 4.2: Gender spatial characteristic attributes affected by HAT

FID	Shape	CentreX	CentreY	XStdDist	YStdDist	Rotation	SEX
0	Polygon	178909.9	641101.6	8091.6	19419.0	50.4	F
1	Polygon	179424.4	640864.9	4770.0	25180.0	32.9	M

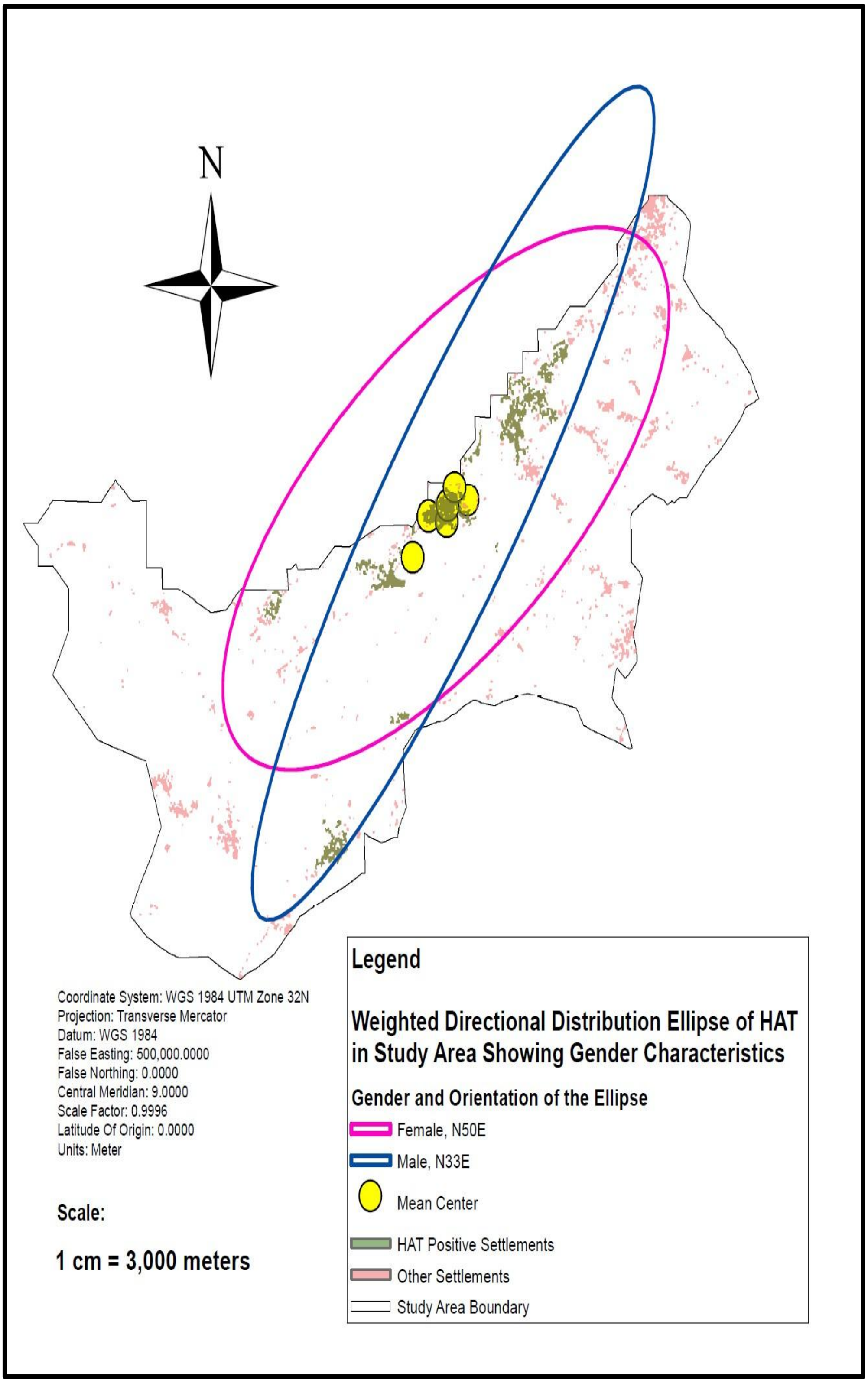


Figure 4.5: Weighted standard deviational ellipse summarizing the distribution of gender affected by HAT from 1994 – 2006 in the main study

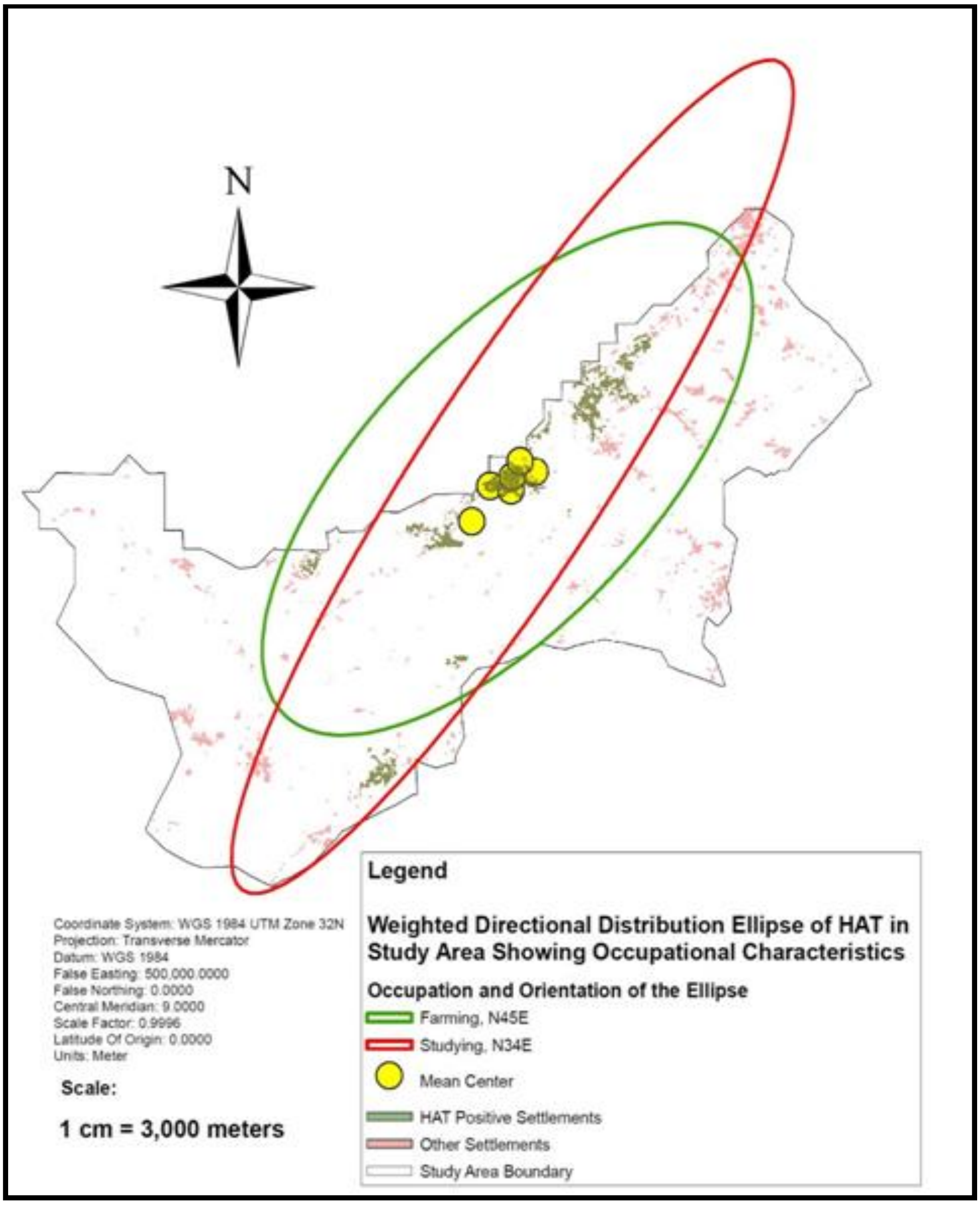


Figure 4.6: Weighted standard deviational ellipse summarising the spatial characteristic of occupation affected by HAT from 1994 – 2006 in the main study area

4.2 Spatial Cluster Analysis of HAT Distribution in the Main Study Area

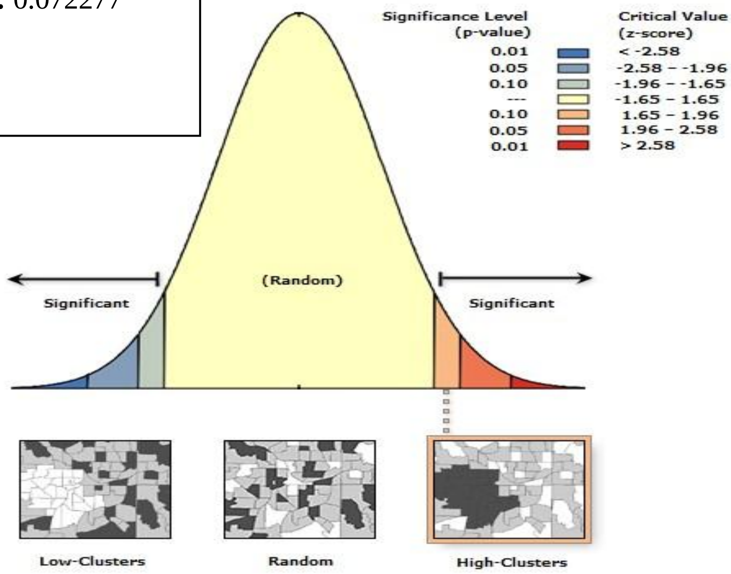
The degree of clustering of HAT cases between 1994 and 2006 within the main study area was measured using the Getis-Ord General G statistic. The ArcGIS high/low clustering (Getis-Ord General G) tool is an inferential statistic, that is, it interprets analysis results within the context of the null hypothesis. The null hypothesis for this section of the research states that, there is no spatial clustering of HAT in the study area.

The Getis-Ord General G statistic was calculated using each HAT case settlement in the main study area, and based on the year of occurrence of the disease (Appendix A-4c). The HAT case settlements were extracted from the region grouped built-up area (section 3.2.3). The attributes of each settlement, for example, local government area and x, y coordinates were added to the settlement database (Appendix A-4c). The extraction of the settlements was based on the x, y coordinate of each settlement obtained during ground thruthing. The parameters used in the calculation of the Getis-Ord General G statistic are shown in Figure 4.7. Presently, there is no available record of HAT cases for the minor study area; thus, the directional analysis for this area could not be carried out.

4.3 Results

From tables 4.1 and 4.2, and Figures 4.2, and 4.6, the SDE and WSDE show the direction (north-eastern) of HAT cases in the main study area, based on the settlements of cases around the mean centre for each of the year, sex and occupational characteristics. The HAT mean centre from 1994-2006 was identified to be in Abraka. Abraka is the headquarters of the Ethiope East local government council. The WSDE reveals that HAT has a relationship with socio-demographic characteristics of the main study area, for example, the broader shape of the female gender ellipse in Figure 4.5 suggested that females are more susceptible to HAT in the study area than males. Also, Figure 4.6 revealed that farmers and students are more exposed to HAT.

Observed General G: 0.221862
Z-Score: 1.797371
P-Value: 0.072277



Given the z-score of 1.80, there is less than 10% likelihood that this high-clustered pattern could be the result of random chance.

General G Summary

Observed General G:	0.221862
Expected General G:	0.221637
Variance:	0.000000
z-score:	1.797371
p-value:	0.072277

Dataset Information

Input Feature Class:	Region group_HAT _+ve settlements
Input Field:	Year
Conceptualisation:	Inverse_distance
Distance Method:	Euclidean
Row Standardisation:	False
Distance Threshold:	42233.899713
Weights Matrix File:	None

Figure 4.7: Summary of the degree of cluster of HAT distribution in the main study area using Gestis-Ord General G statistics.

The Getis-Ord General G statistic result shown in Figure 4.7 reveals that HAT distribution in the main study area is highly clustered, with less than 10% likelihood that the pattern could be the result of random chance. Figure 4.7 shows that the p-value (0.072) was small and statistically significant; therefore the null hypothesis is rejected. There was an indication that settlements with higher frequencies of HAT were clustered. This is because the Z-score has positive value (1.80) and the Observed General G index has higher value (0.2219) than the Expected General G index (0.2216). Thus, the spatial distribution of high frequency of HAT cases in the main study area was more clustered than would be expected if underlying spatial processes were truly random.

4.4 Summary

The analysis carried out in this chapter gives an idea of the direction of HAT propagation in the main study area; this may be used to facilitate mitigating measures. Since HAT has been significantly established, there is the need to investigate factors responsible for HAT propagation for efficient management and control. Also, the control area needs to be investigated to ascertain the situation on the ground. The development of a classification scheme will help manage HAT, as well as other vector borne diseases.

Chapter 5: Development of a classification scheme for managing HAT

5.1 Introduction

This chapter focuses on combining the land cover classes and other derived environmental/climatic variables (see Chapter 3) to develop a classification scheme that will facilitate quick and efficient management of HAT.

The importance of criteria and how they were prioritised were determined by the judgments of experts', the impact of the criteria on HAT propagation and previous studies. Spatial distribution/habitat characteristics play an important role in HAT propagation. Therefore, locations which have all or most of these criteria present are vital for HAT propagation. To achieve the goal of this section, geospatial-fuzzy MCDA was used (section 1.3.13). Boolean logic, when used for land cover classification, partitions the gradual variability of the Earth's surface into distinct non-intersecting groups. This type of method is often unsuitable due to the continuous nature of some landscape attributes. Besides, this type of approach often brings about loss of information as the continuous measurable spectral value of the landscape is reduced into a set of distinct groups, thus, uncertainty in the end product. In order to quantify the associated uncertainties (section 1.3.13) and to account for the indistinctness of the study areas' landscape, fuzzy logic was used to merge the identified landcover classes with the derived environ-climatic variables (see Chapter 3) towards HAT vector habitat classification. MCDA and the procedures involved were discussed in Chapter 1. The real procedures used to uniquely group the study areas into three HAT vector habitat zones; namely: breed, feed and rest using land cover, environmental and climatic data in this research are elaborated in this chapter. The classification scheme outcome is expected to offer effective decision support to all stakeholders. Part of the work in this chapter has resulted in a publication (Akiode and Oduyemi 2014a).

5.2 Defining the Problem

The overall goal is to identify and classify HAT vector habitat in the study areas into different zones, namely: breed, feed and rest zones to aid efficient management of HAT. As mentioned previously, there is need to create a hierarchical structure with the goal, criteria/sub-criteria and alternatives (Figure 5.1). The alternatives are the delineated habitat zones.

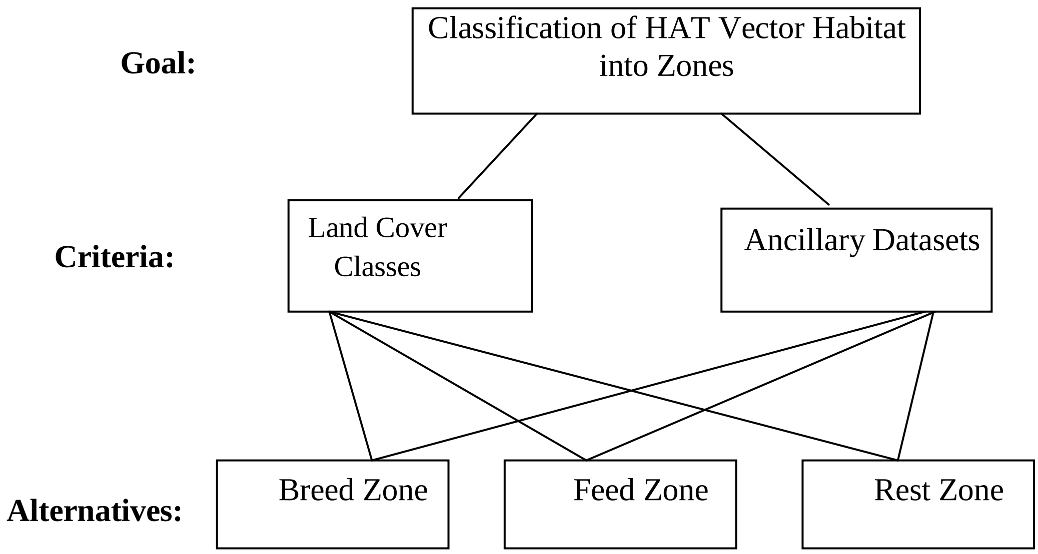


Figure 5.1: Hierarchical structure of goal, criteria and alternatives

The selection of criteria is a vital procedure in geospatial-fuzzy MCDA. Criteria used in the HAT vector habitat classification scheme were categorised into two: Land cover classes and ancillary datasets. These two criteria were separated into sub-criteria for clarification purposes, as highlighted in Table 5.1. The criteria were jointly chosen by the researcher and experts to ensure suitability for the classification scheme. Some decision rules were applied to manipulate the criteria to obtain the alternatives. The criteria were derived mainly from RS image as processed in Chapter 3.

Table 5.1: Criteria for classification of HAT vector habitat

Major Criteria	Sub-Criteria	Unit	Source	
ANCILLARY DATASETS	Land surface temperature	Degree Celsius	Landsat 7 ETM+	MAIN/MINOR STUDY AREAS
	Relative humidity	%	Landsat 7ETM+/ NIMET	
	Digital terrain model	Meters	USGS/ground thruth	
	NDVI	Index	Landsat 7 ETM+	
	NDDI	Index	Landsat 7 ETM+	
LAND COVER CLASSES	Water body	%	Landsat 7 ETM+	MAIN STUDY AREA
	Mangrove	%	Landsat 7 ETM+	
	Less dense forest	%	Landsat 7 ETM+	
	Dense forest	%	Landsat 7 ETM+	
	Cultivated area	%	Landsat 7 ETM+	
	Shrub	%	Landsat 7 ETM+	
	Built-up area	%	Landsat 7 ETM+	
LAND COVER CLASSES	Water body	%	Landsat 7 ETM+	MINOR STUDY AREA
	Wetland/flood plain	%	Landsat 7 ETM+	
	Light vegetation/shrub	%	Landsat 7 ETM+	
	Savannah grass	%	Landsat 7 ETM+	
	Cultivated area/sand	%	Landsat 7 ETM+	

5.3 Geospatial-fuzzy Multi Criteria Decision Analysis

All the criteria obtained in Chapter 3 were stored in a personal geodatabase. An AHP questionnaire survey was carried out to compare the relative importance of the criteria in relation to each HAT vector habitat zone. The selected participants are thirty-five in number. Thirty-one of the participants responded by direct interview while four participants responded by email and a response rate of 100% was achieved.

In order to ascertain the likelihood that the weights obtained from the experts was randomly generated, the weights consistency ratios (CR) were calculated (detail in section 1.3.12.1). To view the differences in each respondent judgment, each expert's AHP matrix was entered into IDRISI software to obtain a range of priority vector (eigenvector of weights) and consistency ratio for each criterion (an example is shown in Appendix D2-d). The consistency of the responses from each respondent was estimated so as to test for the transitivity of opinions. The consistency test returns consistent for all the respondents' matrices except one which returns not consistent. To re-assess the inconsistent matrices, the respondent concerned was contacted via phone and agreed to settle the inconsistencies in his responses (this was eventually done). After the correction of the inconsistent matrices by the respondent, the matrices local priorities were re-evaluated to obtain consistent results. After ascertaining the consistency of each respondent matrix (consistency ratios were less than 1 thus, consistent), the local priorities obtained from each respondent matrix were then aggregated using the geometric mean to obtain the overall priority weight for each criterion (detail in section 2.4.4.2).

5.3.1 Grouping of main and minor study areas into HAT vector habitat zones

Geospatial-fuzzy multi criteria decision analysis was carried out to group the main study area (Ethiope-East and Ukwuani Local Government Areas) as well as other two local government areas namely Oshimili North/South and Patani into HAT vector habitat zones. The extra two local governments were chosen to investigate the presence of HAT in other parts of Delta State. This was because all the existing literature on HAT only identified the main study area. The minor study area was also grouped into HAT vector habitat zones for comparison.

The supervised land cover classes obtained in Chapter 3 were reclassified into three (breed, feed and rest) temporary HAT vector habitat zones. Also, the ancillary datasets were grouped into each habitat zone using a weighted sum. The reclassification of the land cover and grouping of the ancillary datasets were done using the weights obtained from the experts. The temporary HAT habitat zones were fuzzified and combined with fuzzified weighted ancillary datasets to obtain the final HAT vector breed, feed and rest zones. The fuzzification was carried out using fuzzy membership type 'large' whereby large values of the input map criteria layer have high membership in the fuzzy set. The fuzzification was necessary partly to normalise the criteria into common scale and to obtain their fuzzy membership sets. The process used is presented in Figure 5.2. The fuzzified temporary HAT vector habitat zones for the main study area and their weight graphs are shown in

Figures 5.3 and 5.4, while Figure 5.5 shows the fuzzified minor study area temporary HAT vector habitat zones. Temporary habitat zones were also generated for Oshimili N/S and Patani local government areas.

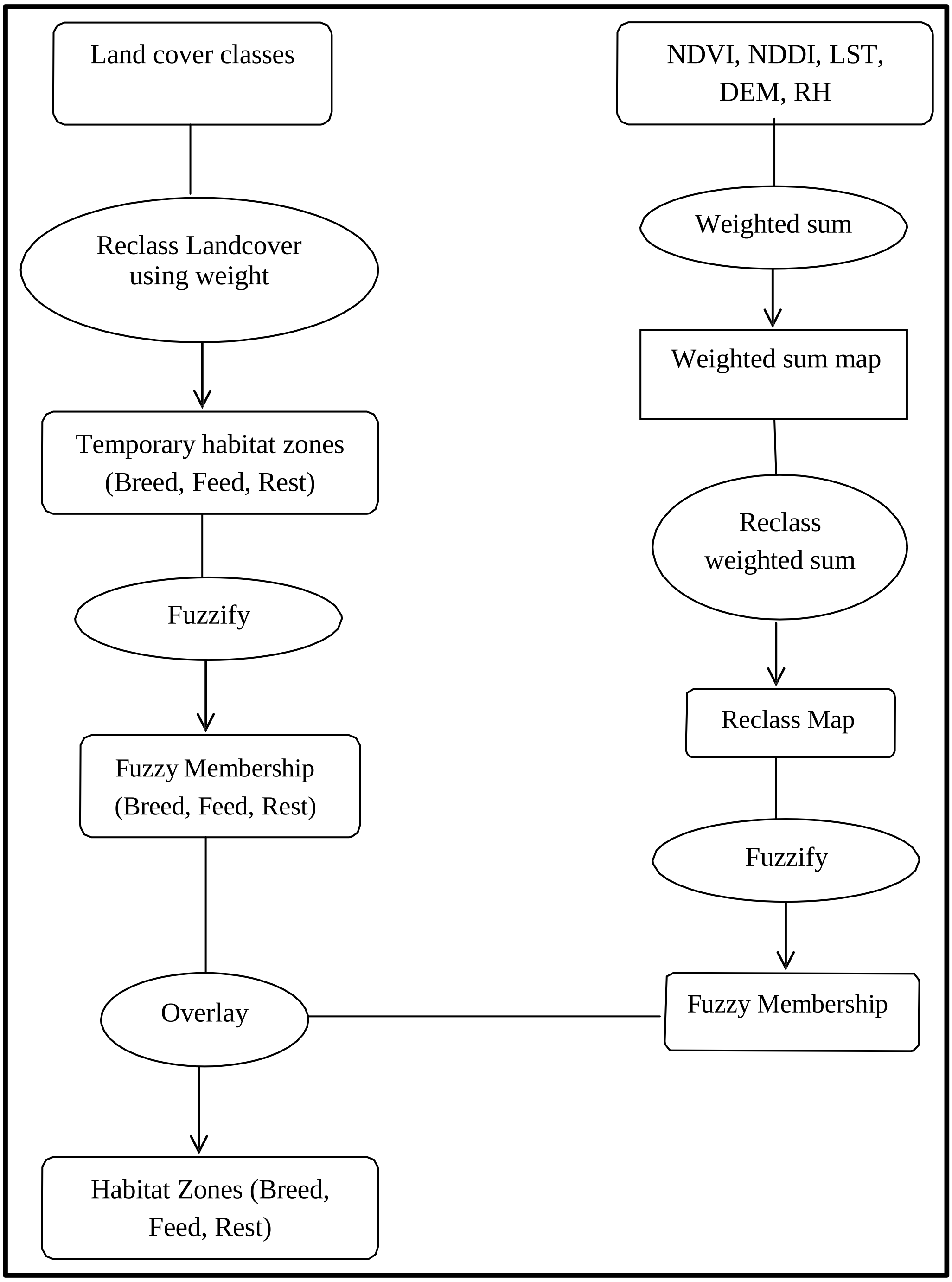


Figure 5.2: Habitat grouping procedure

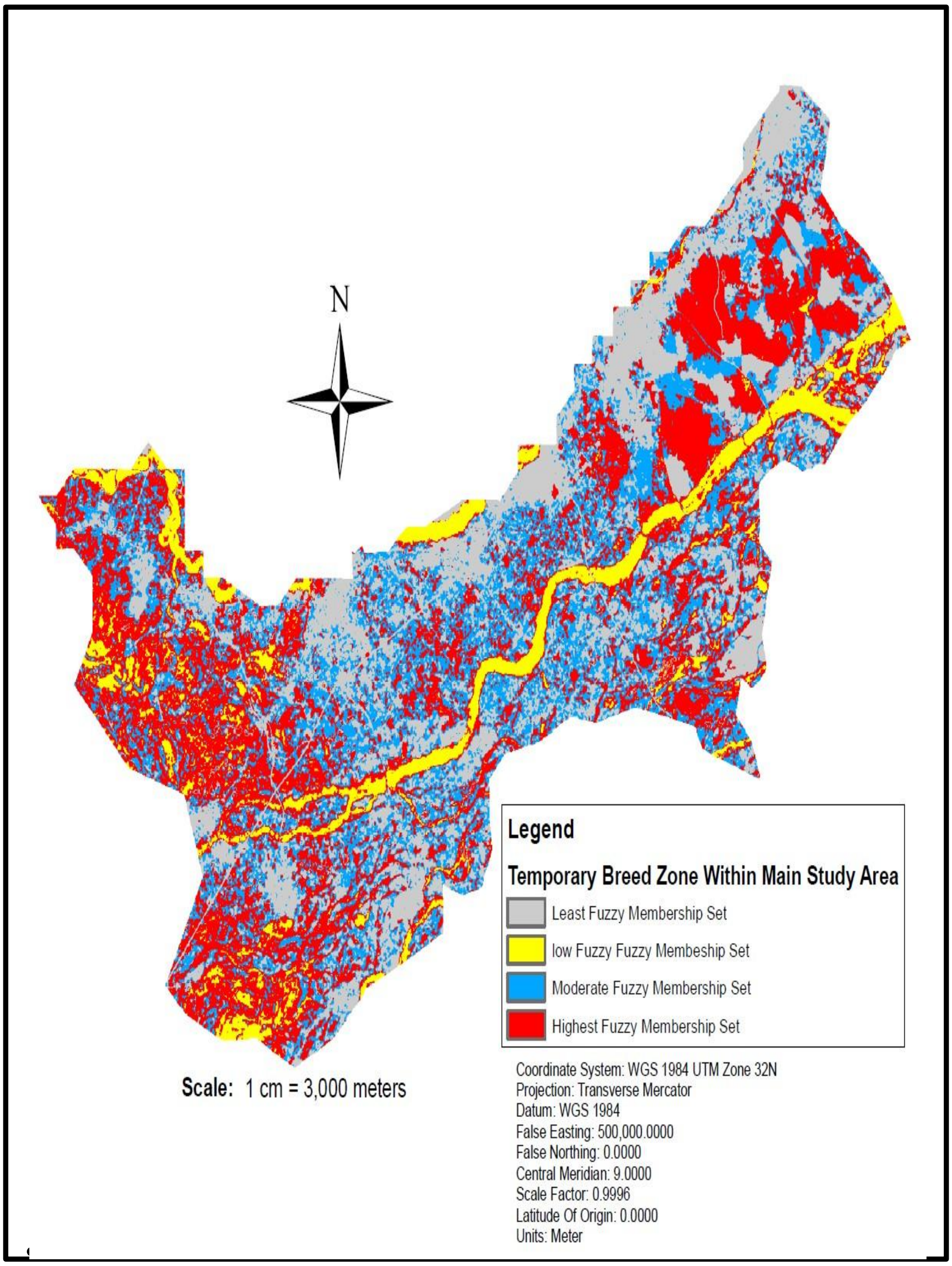


Figure 5.3a: Fuzzified temporary HAT vector breed zone in the main study area

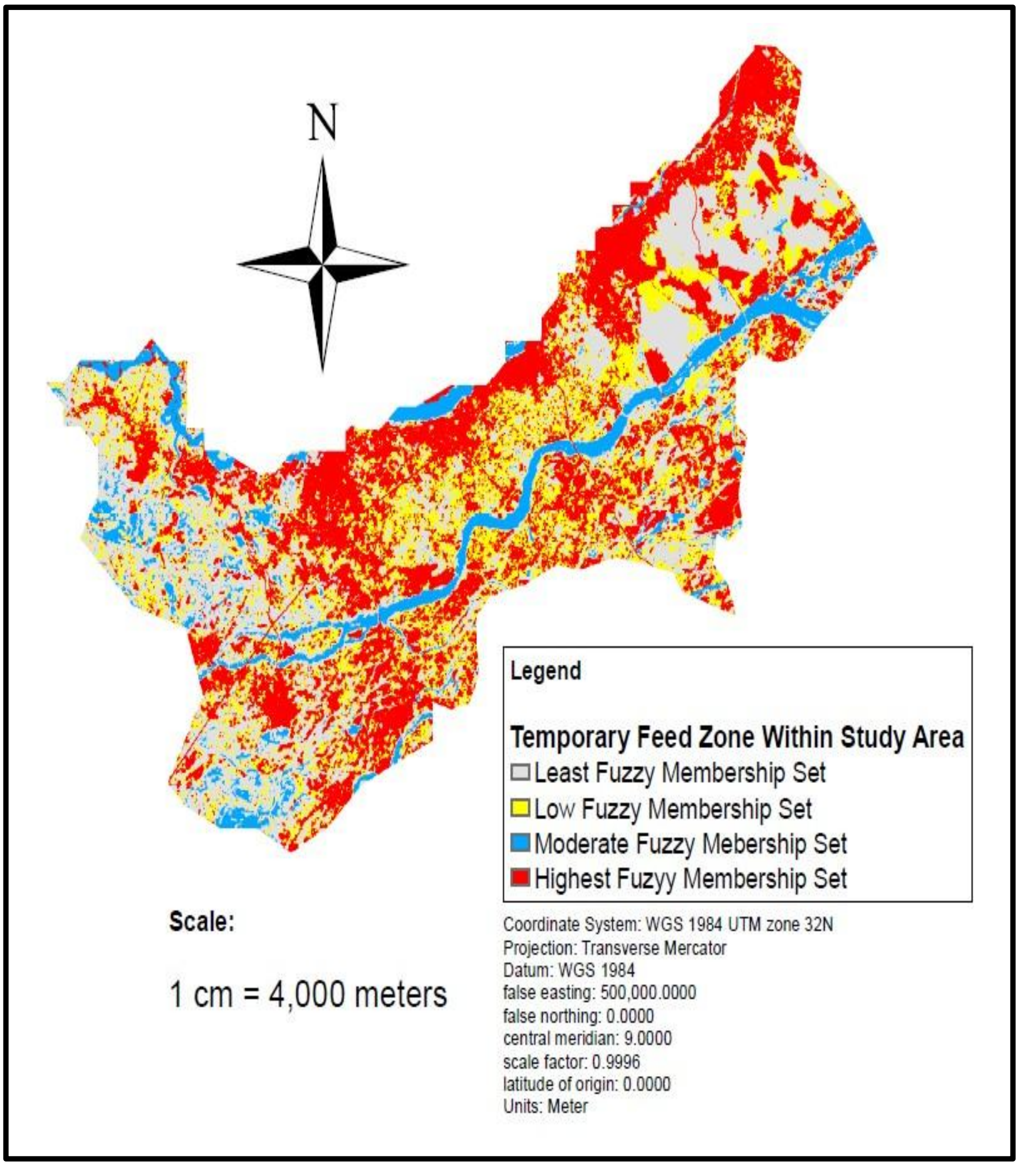


Figure 5.3b: Fuzzified temporary HAT vector feed zone in the main study area

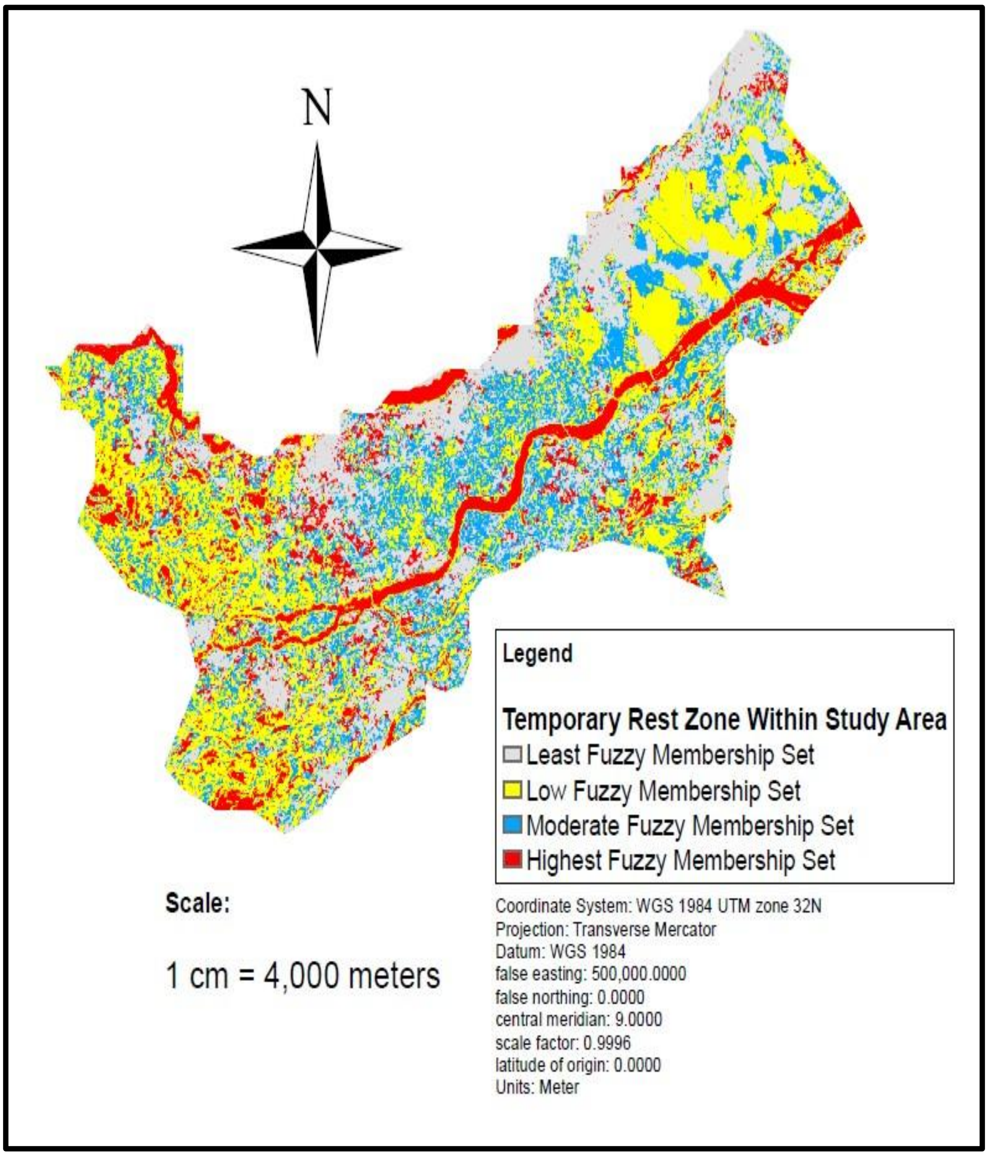


Figure 5.3c: Fuzzified temporary HAT vector rest zone in the main study area

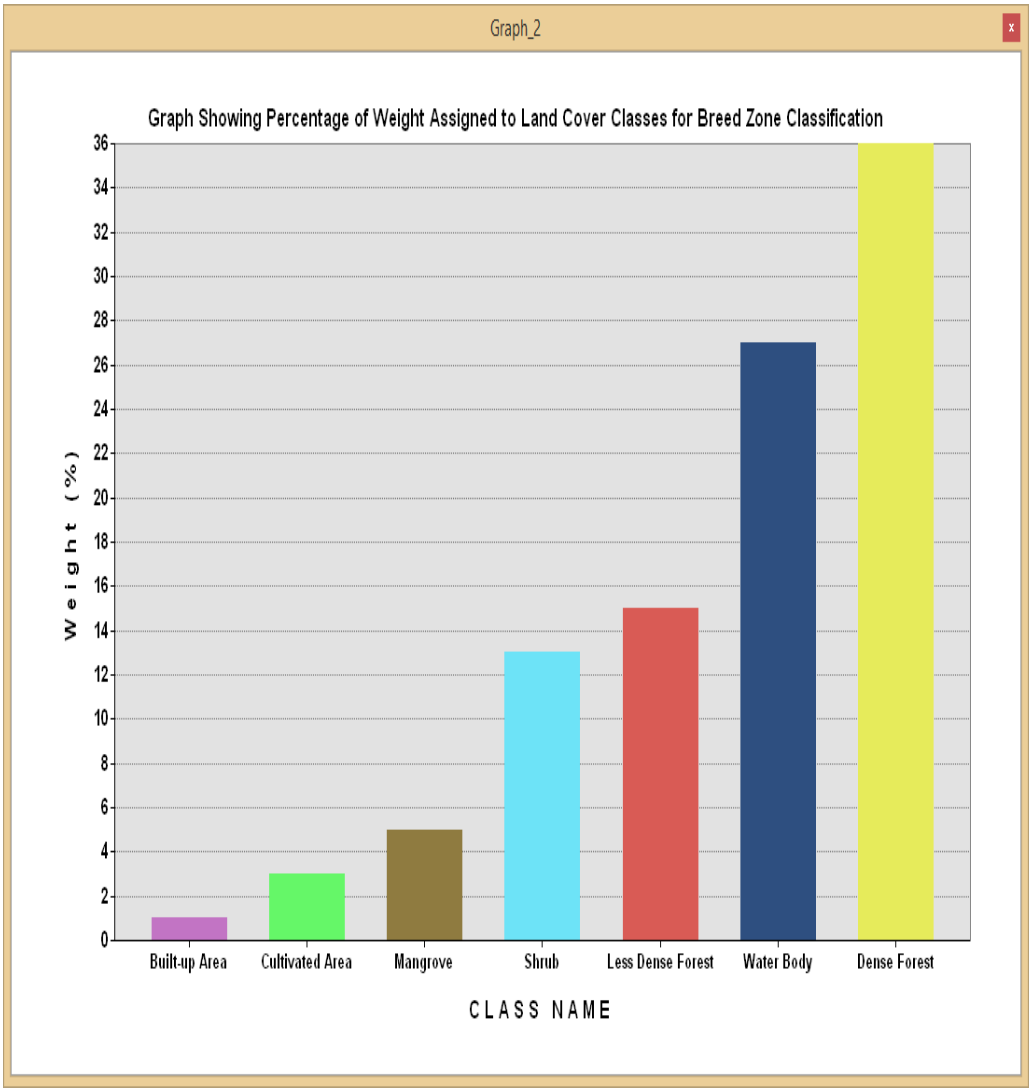


Figure 5.4a: Percentage of weight assigned to main study area land cover classes for breed zone classification

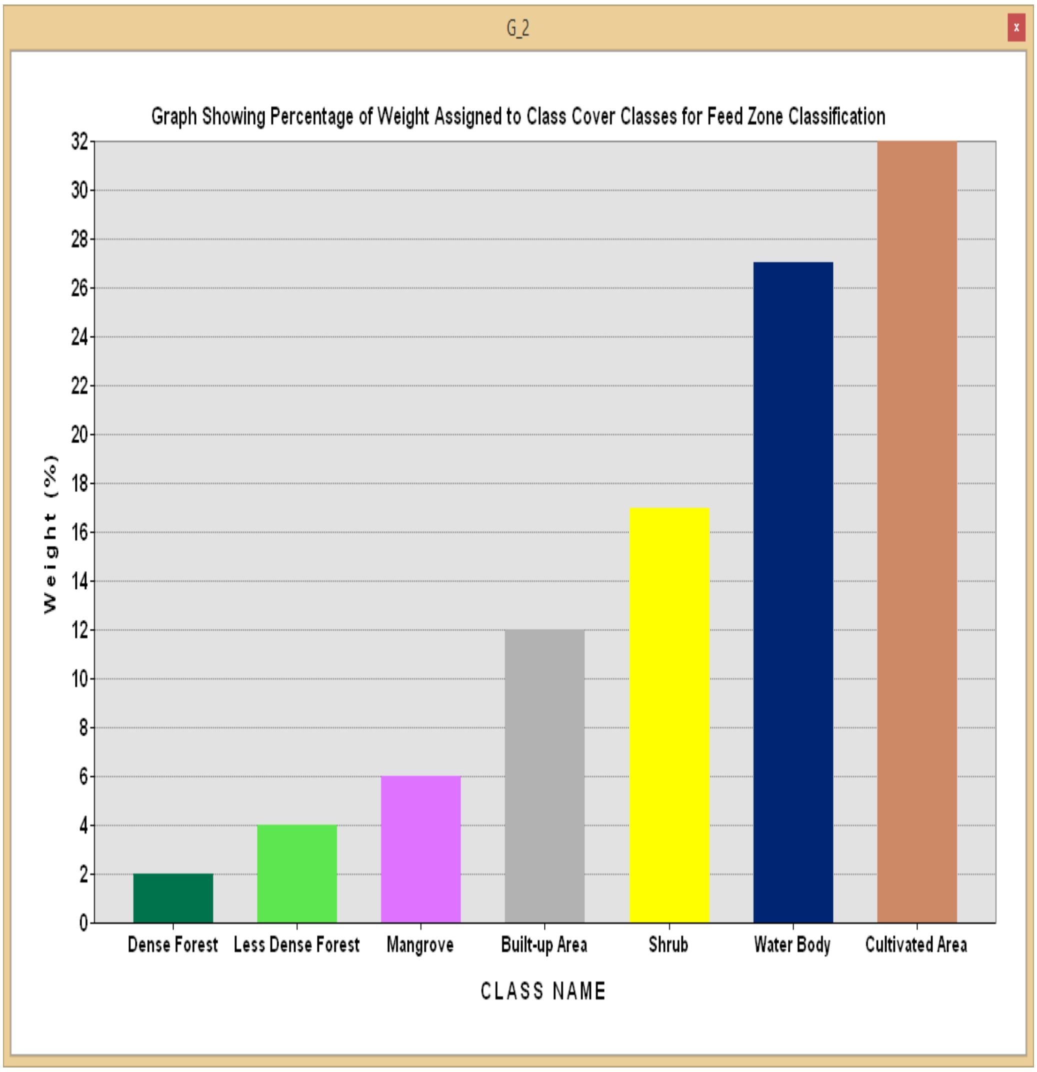


Figure 5.4b: Percentage of weight assigned to main study area land cover classes for feed zone classification

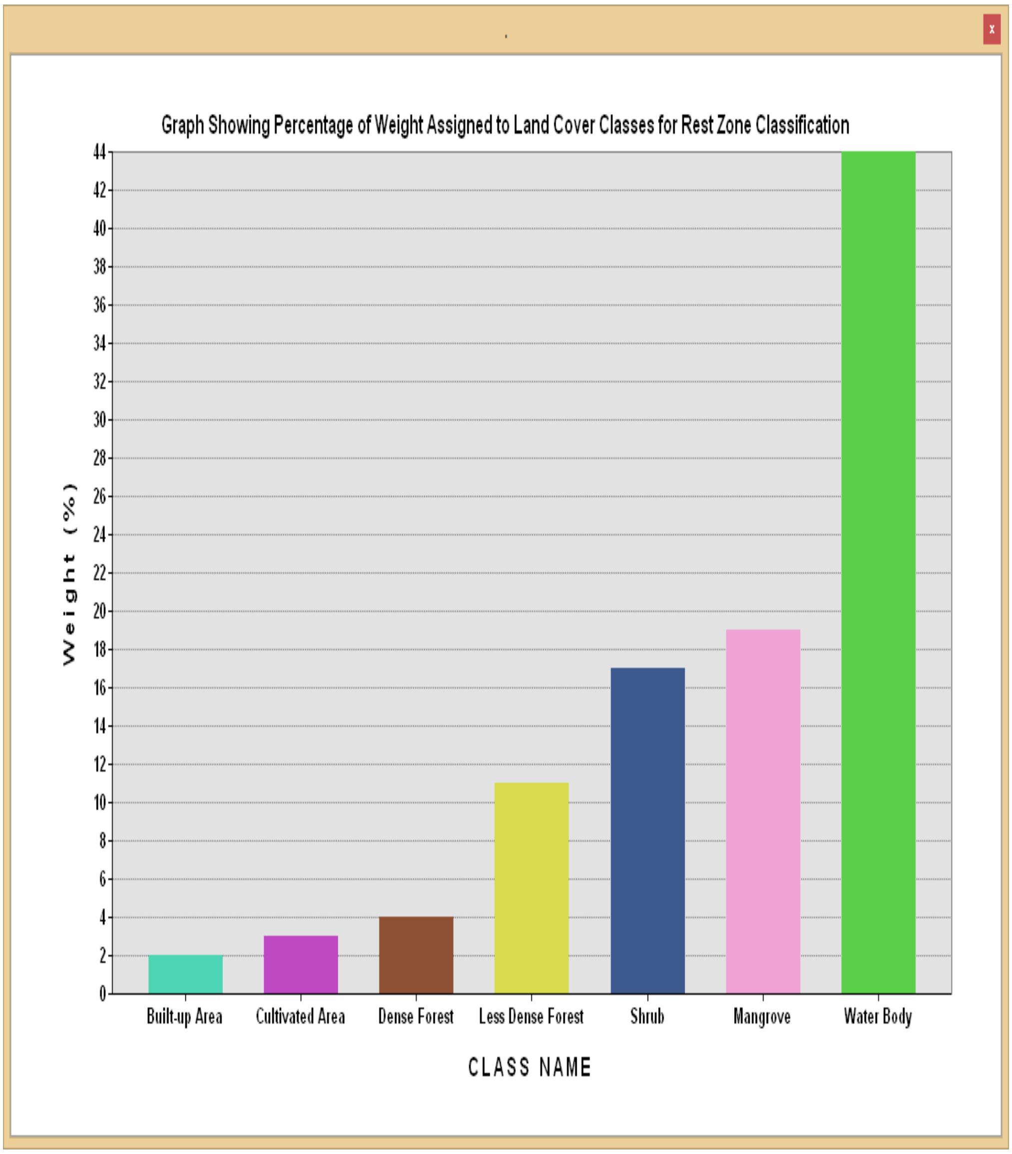


Figure 5.4c: Percentage of weight assigned to main study area land cover classes for rest zone classification

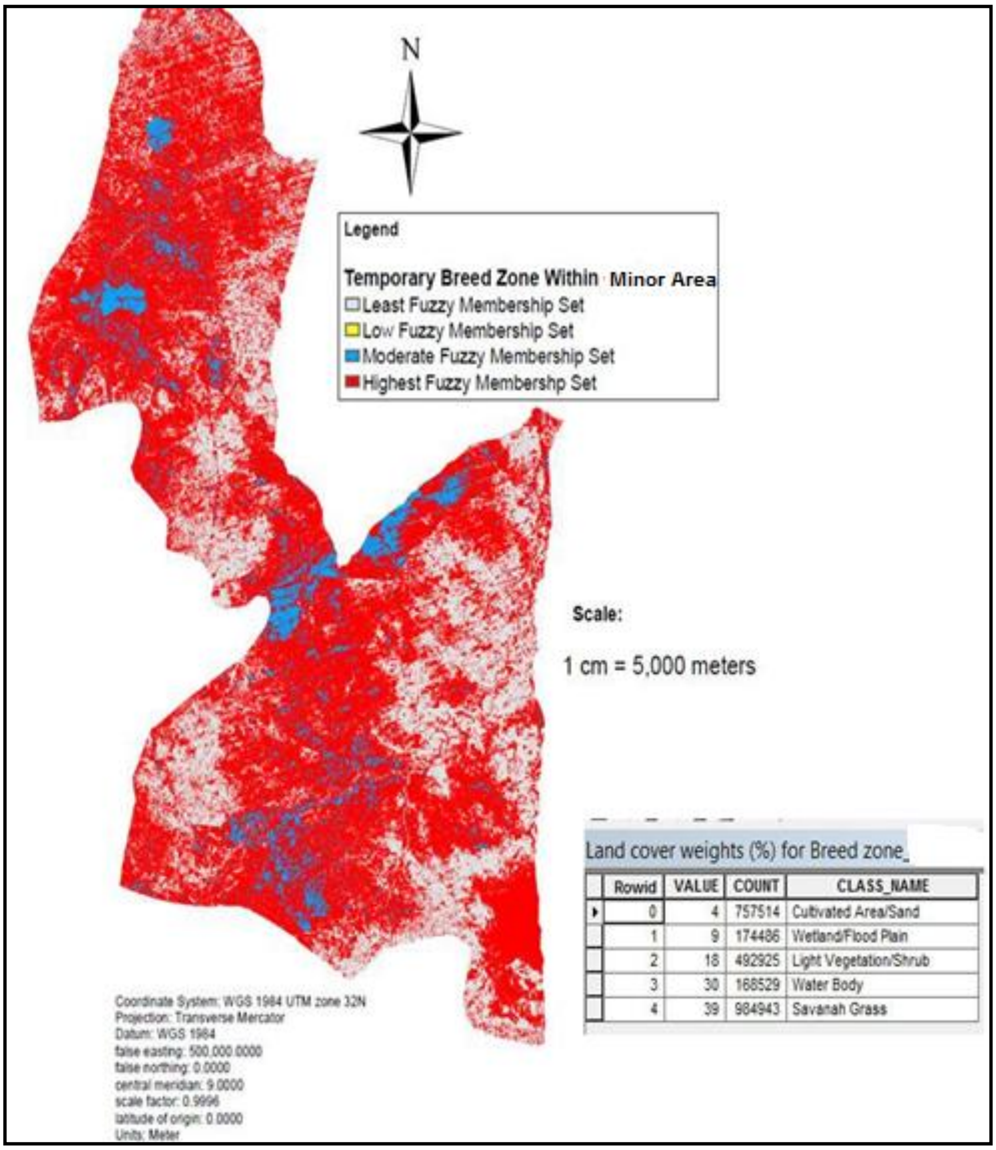


Figure 5.5a: Fuzzified temporary HAT vector breed zone in the minor study area

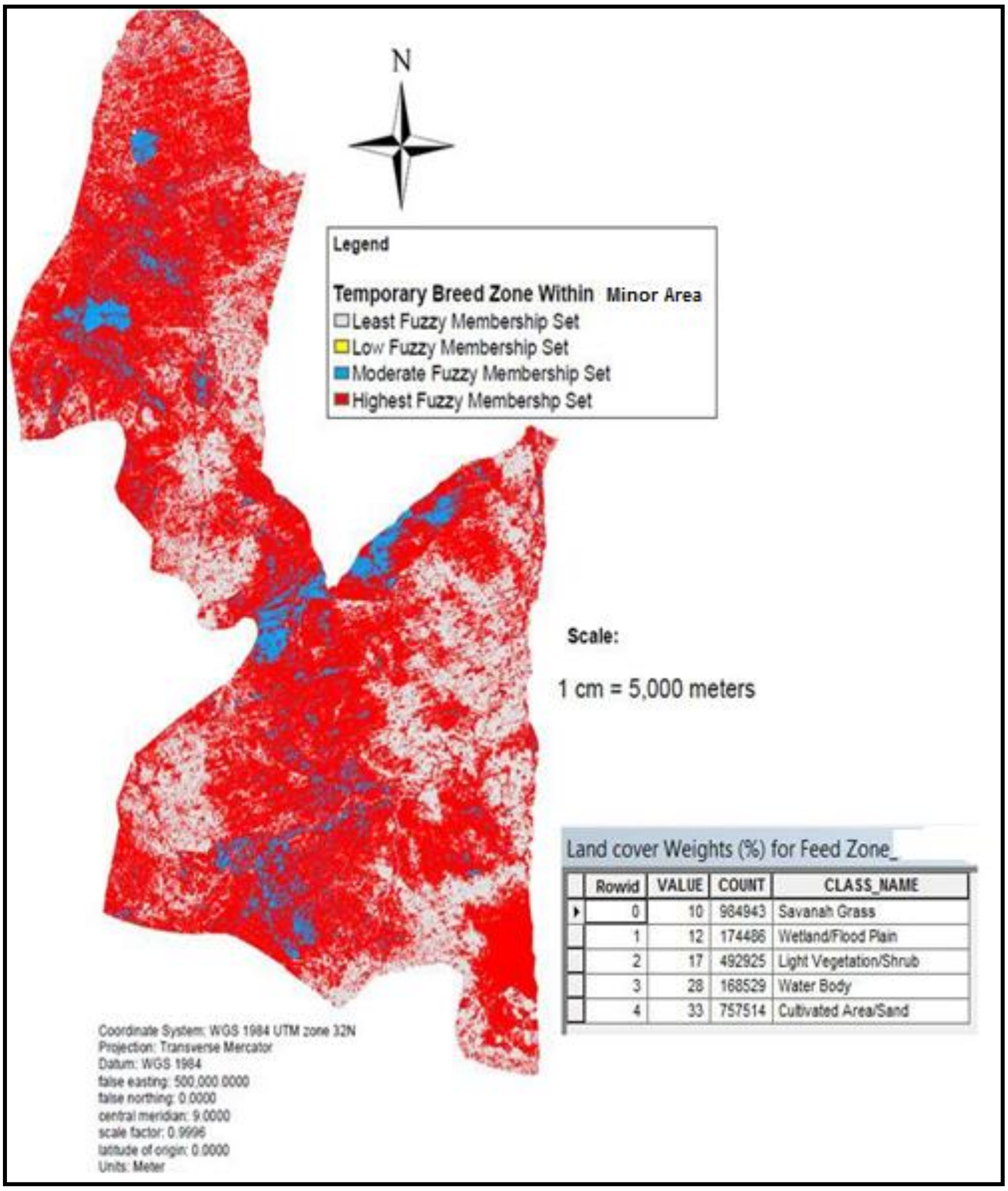


Figure 5.5b: Fuzzified temporary HAT vector feed zone in the minor study area

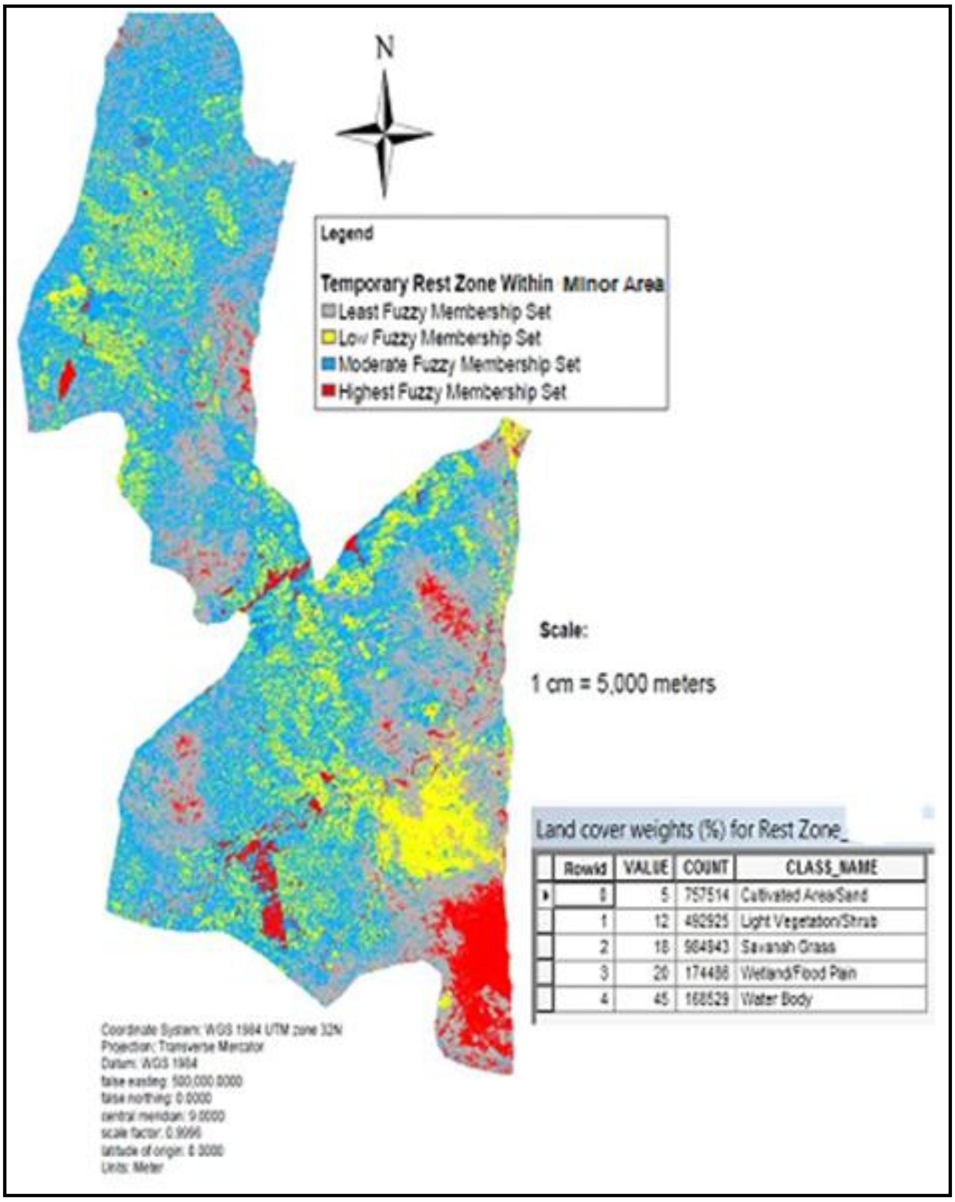


Figure 5.5c: Fuzzified temporary HAT vector rest zone in the minor study area

5.3.1.1 Delineation of HAT vector habitat into zones using fuzzy overlay

Fuzzy overlay analysis was performed to achieve the final HAT vector habitat zones. Before choosing the final zones, sensitivity analysis was carried out. The weights of the ancillary datasets obtained for each zone from experts, were changed as follows:

- **Equal weight:** Each criterion was assigned 0.2 values before calculating their weighted sum.

- **Five percent weight increase:** Each criterion's weight was increased by 5% before calculating their weighted sum.
- **Ten percent weight increase:** Each criterion's weight was increased by 10% before calculating their weighted sum.

After the weight change and the calculation of weighted sum, each outcome map layer (for each zone) was overlaid on the corresponding HAT vector habitat temporary zones. The overlay analysis was done using fuzzy overlay operator 'OR' 'AND' and 'GAMMA' (details in section 1.3.13).

5.3.1.1.1 Fuzzy overlay operator 'OR'

The overlay type 'OR 'was carried out using fuzzy maximum operator to generate map layer that contained maximum fuzzy membership value for locations within each HAT vector habitat zone. Figure 5.6 shows the outcome of the overlay analysis with fuzzy overlay operator 'OR' in the main study area.

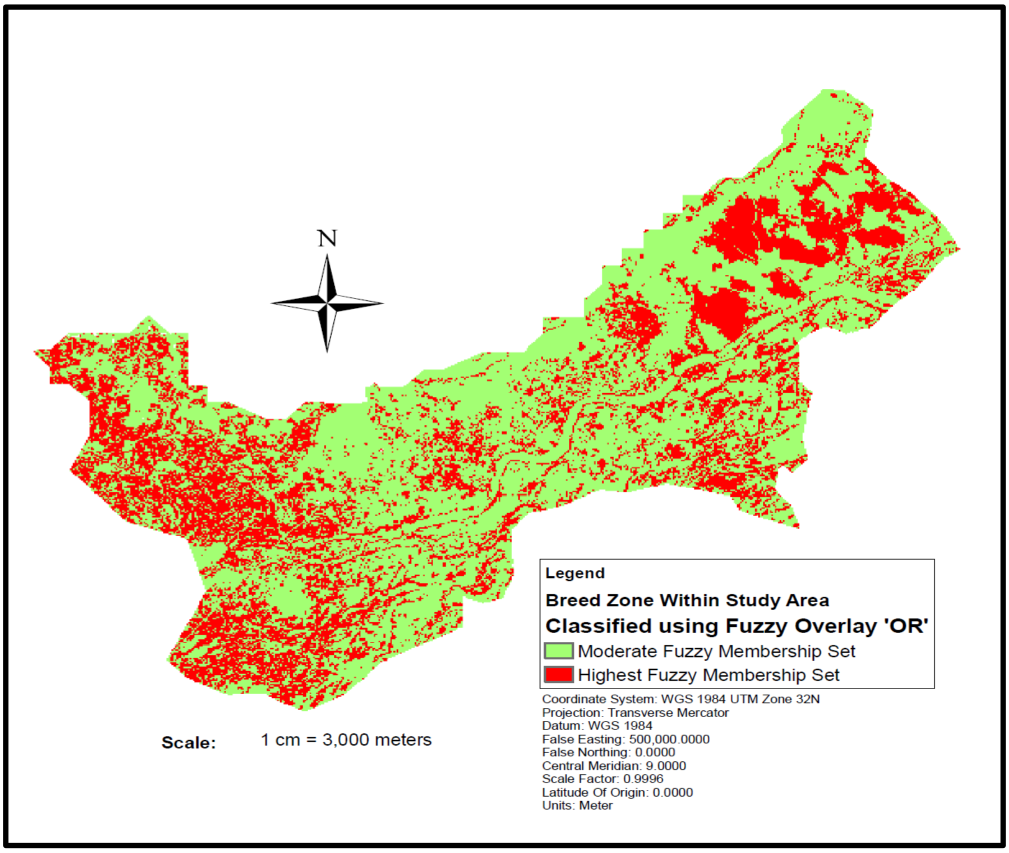


Figure 5.6a: HAT vector breed zone within main study area classified using fuzzy overlay operator 'OR'

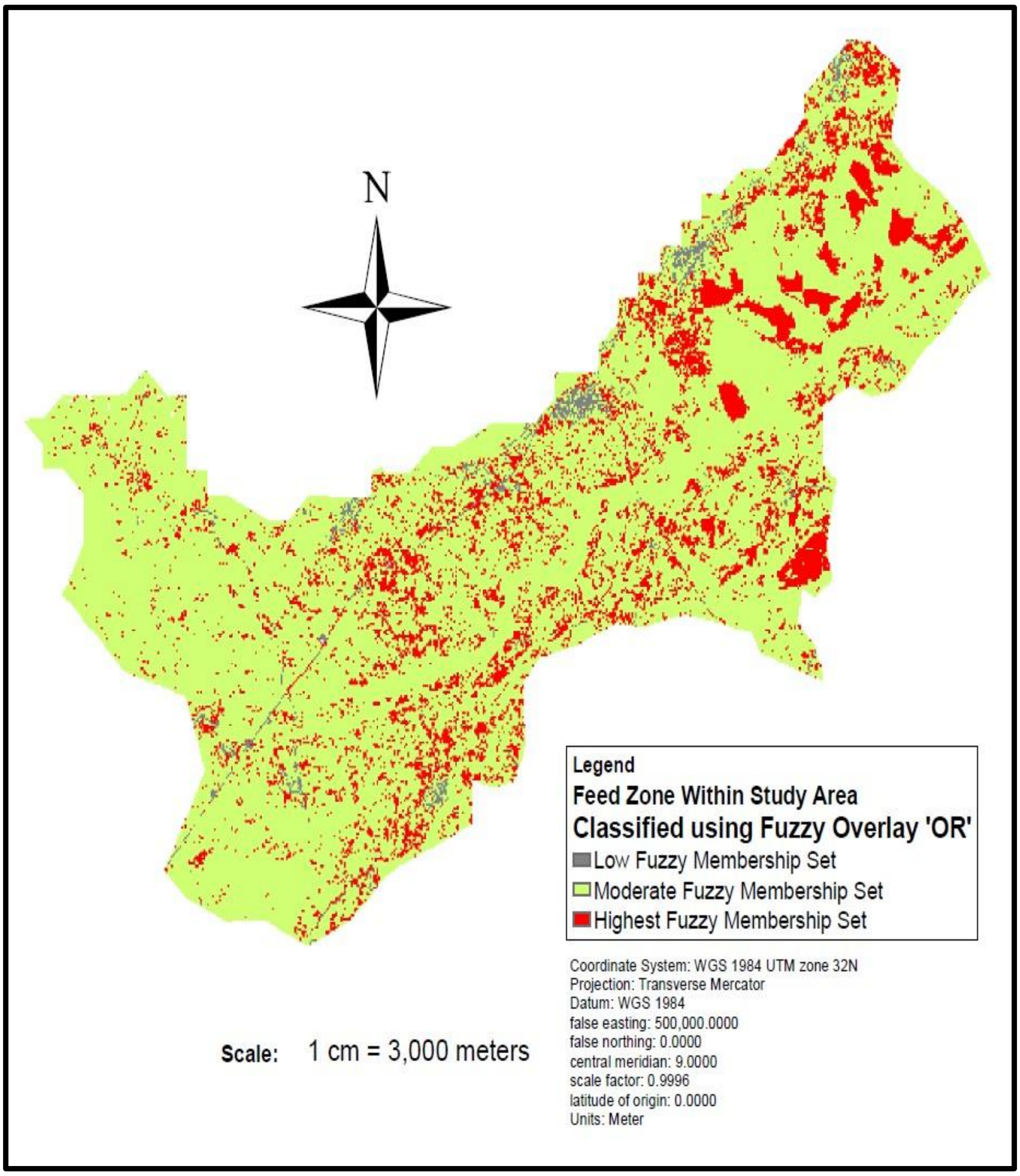


Figure 5.6b: HAT vector feed zone within main study area classified using fuzzy overlay operator 'OR'

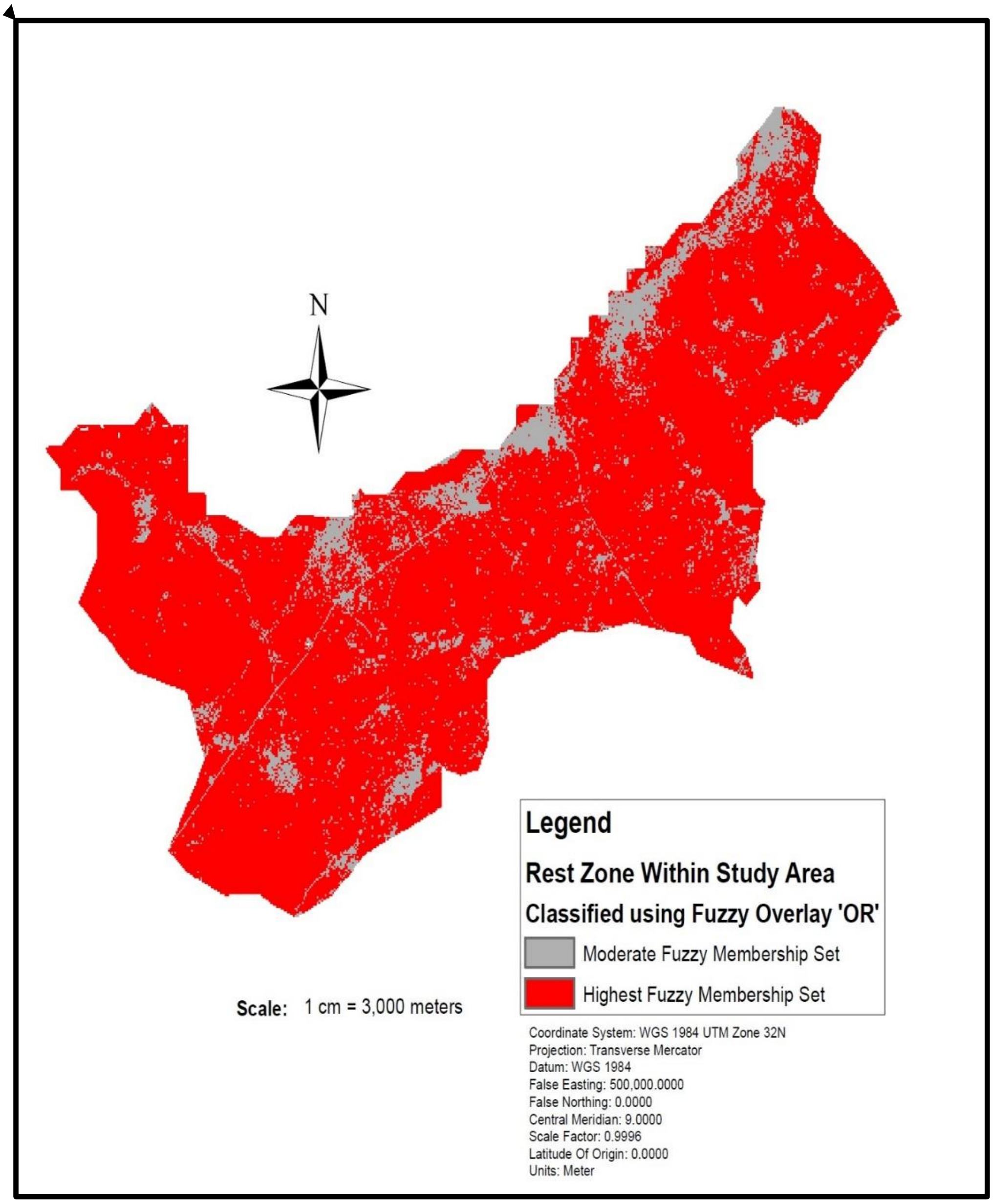


Figure 5.6c: HAT vector rest zone within main study area classified using fuzzy overlay operator 'OR'

5.3.1.1.2 Fuzzy overlay operator 'AND'

The fuzzy overlay operator 'AND' returns map layers showing minimum membership values for all location within each HAT vector habitat zone, thus the output map layer was a conservative approximation of the fuzzy membership sets that would likely generate small values. The results of this overlay analysis for the each HAT vector habitat zone in main study area are shown in Figure 5.7.

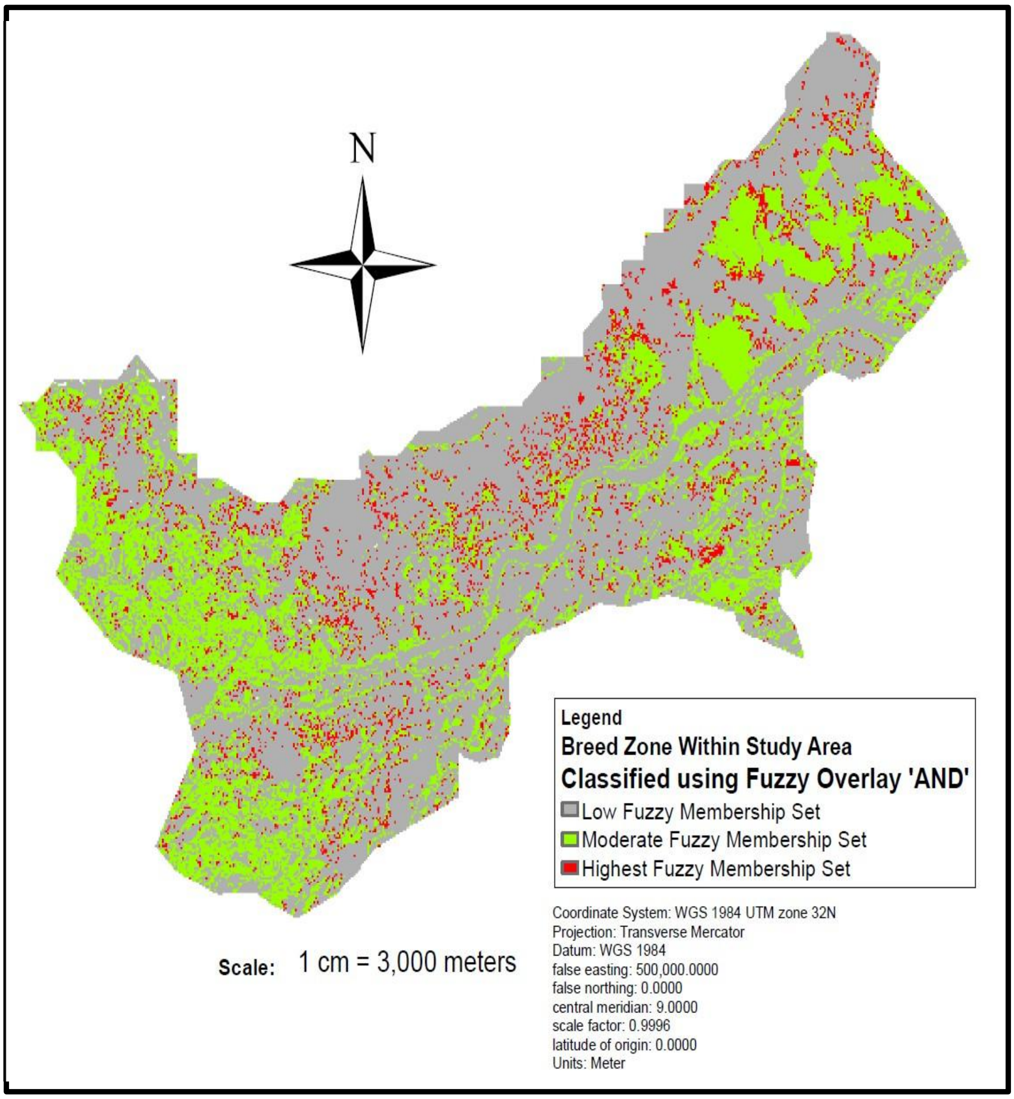


Figure 5.7a: HAT vector breed zone within main study area classified Using fuzzy overlay operator 'AND'

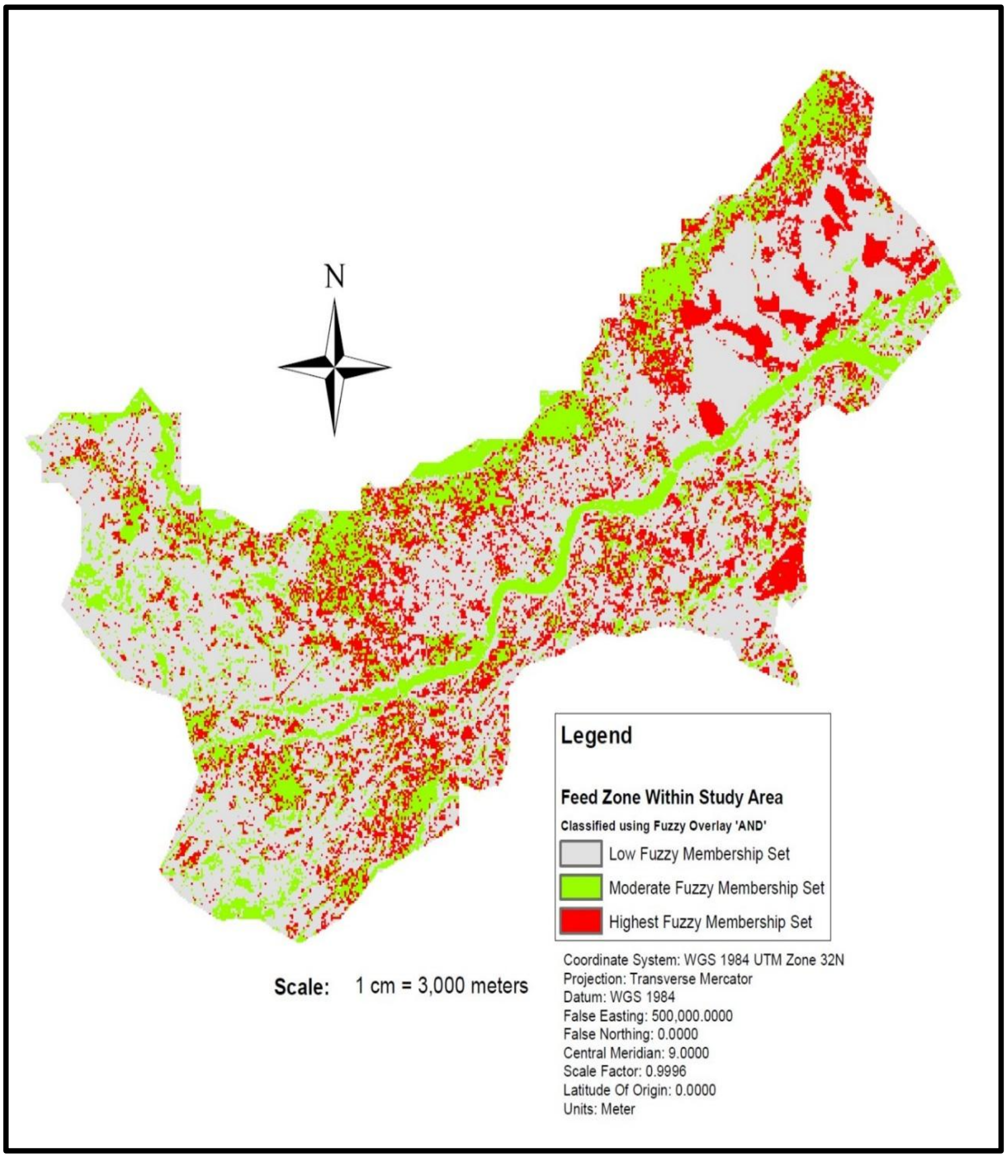


Figure 5.7b: HAT vector feed Zone main within study area classified using fuzzy overlay operator 'AND'

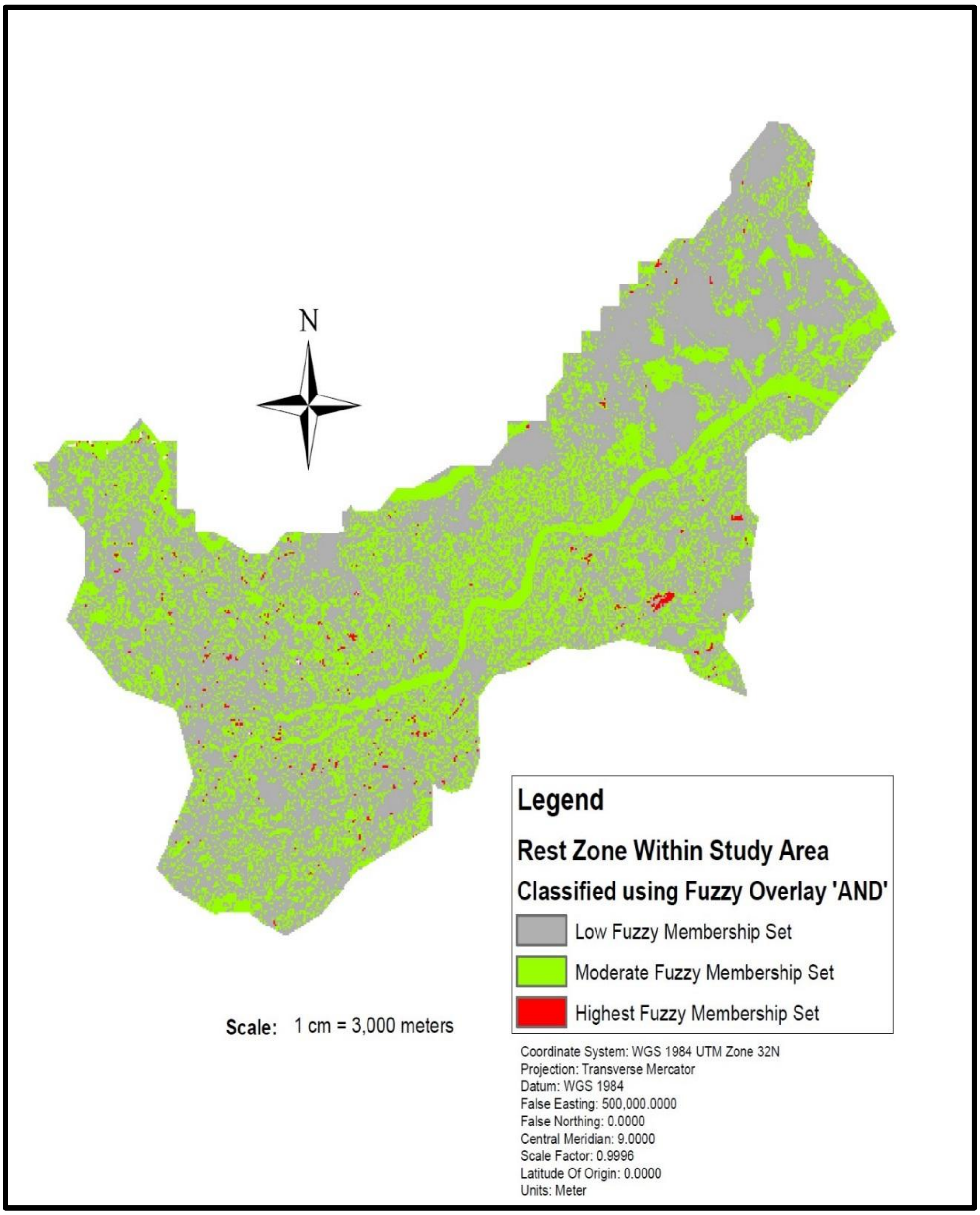


Figure 5.7c: HAT vector rest zone within main study area classified using fuzzy overlay operator 'AND'

5.3.1.1.3 Fuzzy overlay operator 'GAMMA'

For the final identification and classification of the HAT vector habitat zones, different fuzzy overlay operator gamma values were used. Though the AHP matrices by all the experts were consistent (section), the sensitivity analysis was necessary to investigate the appropriate value that will not change considerably the original ancillary weights obtained from the experts. The area of fuzzy membership categories (low, moderate and high) did not change considerably from the area estimated with the weights obtained from experts, when using fuzzy gamma operator values ranging from 0.1 to 0.8. However, gamma value above 0.8 decreased the area estimates considerably. Thus fuzzy values in the 0.1 to 0.8 range, appear to be suitable gamma values for combining the fuzzy membership sets of the HAT vector temporary habitat zones and the ancillary datasets towards the final HAT vector habitat zones. The final HAT vector habitat zones were generated using a value of 0.8, as it was the most consistent value in that range. Table 5.2 shows the result obtained using a gamma value 0.8 and fuzzy overlays '*OR*' and '*AND*', while Figures 5.8 and 5.9 shows the final HAT vector habitat zones.

The final selection of locations for each zone was based on the gamma overlay operator outcome, because the fuzzy overlay operators *OR* and *AND* only utilised the maximum and minimum fuzzy membership values of the criteria. Since, the essence of this research work is to identify all possible HAT vector habitats in the study areas; fuzzy overlay operator gamma was adopted. The use of gamma overlay type produced output values that ensure a flexible compromise between the two extremes (minimum and maximum).

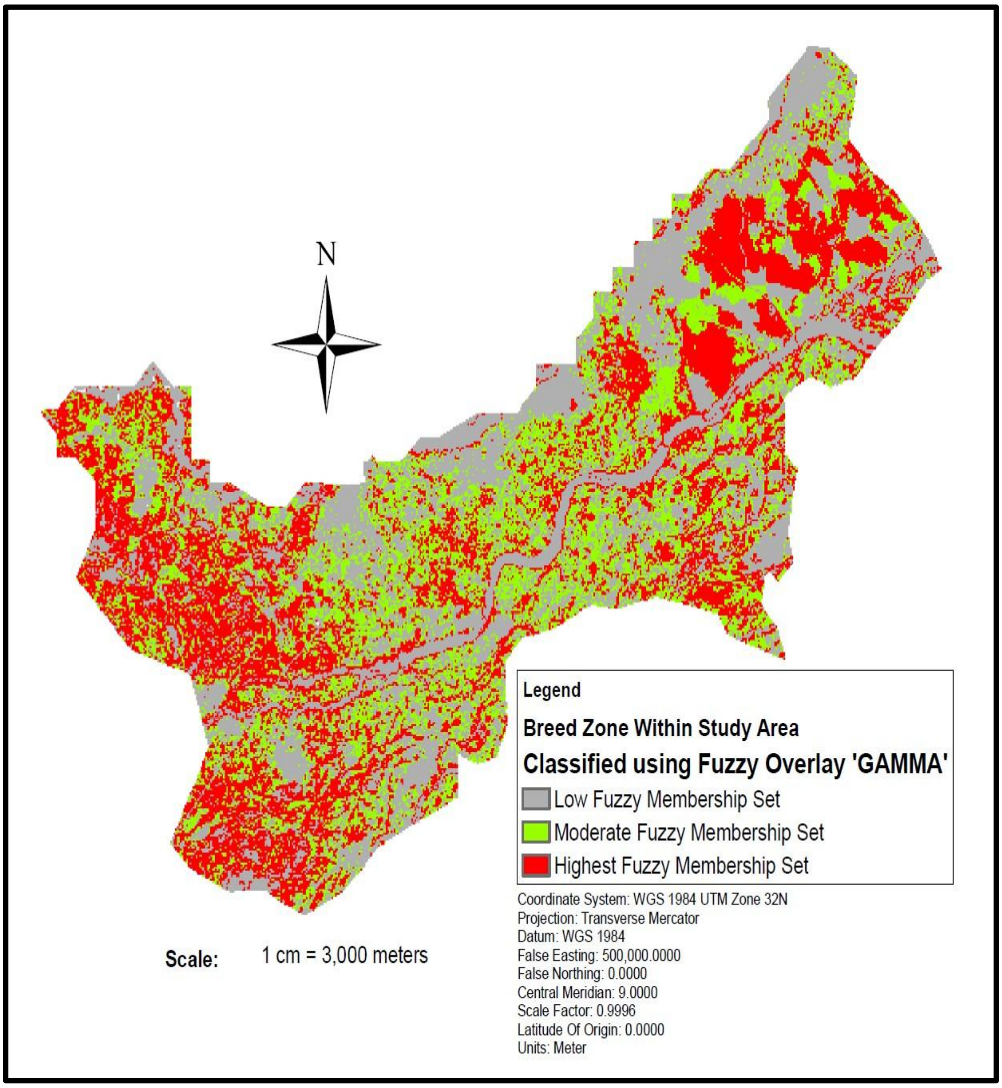


Figure 5.8a: HAT vector breed zone within the main study area classified using fuzzy overlay operator 'GAMMA'

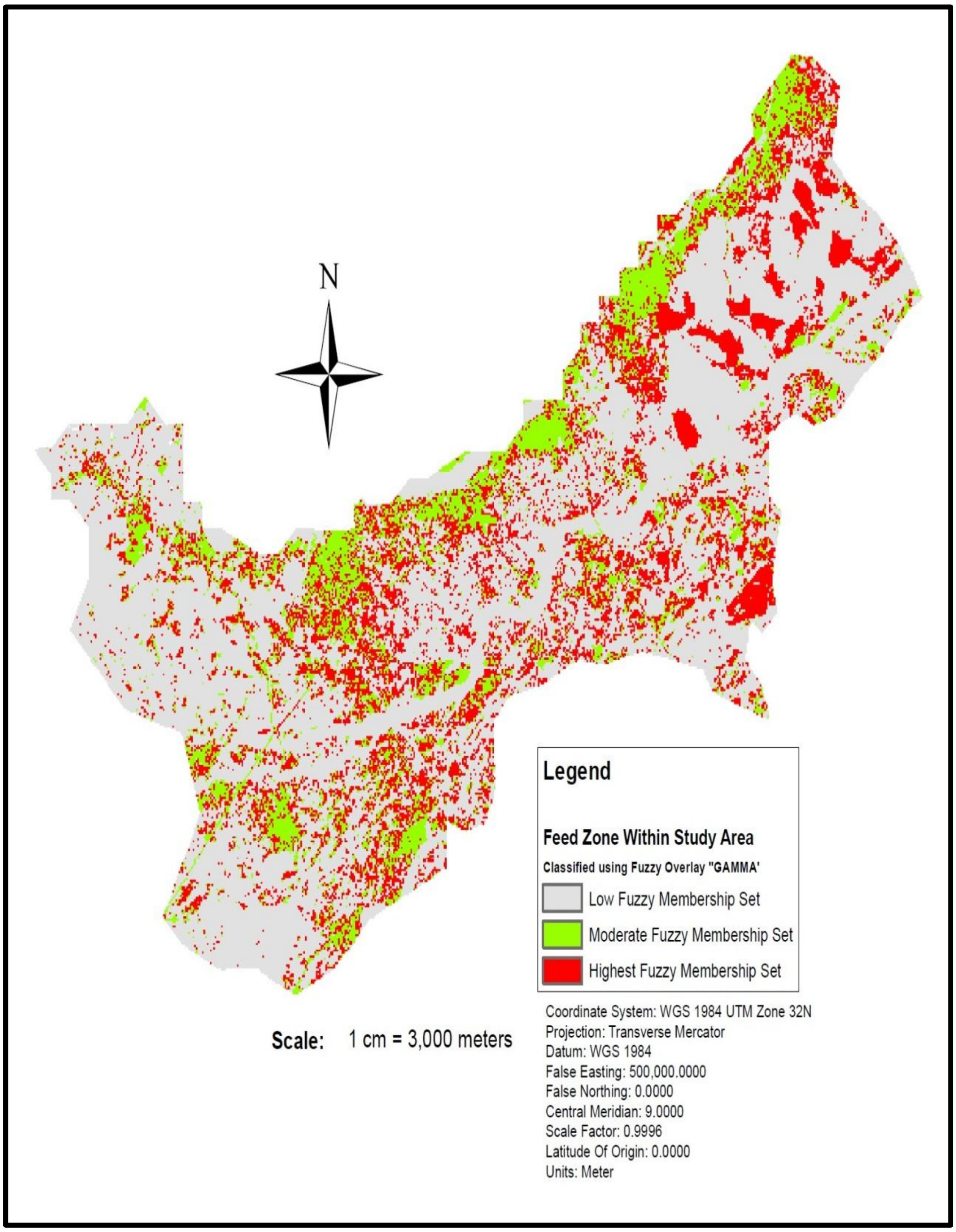


Figure 5.8b: HAT vector feed zone within the main study area classified using fuzzy overlay operator 'GAMMA'

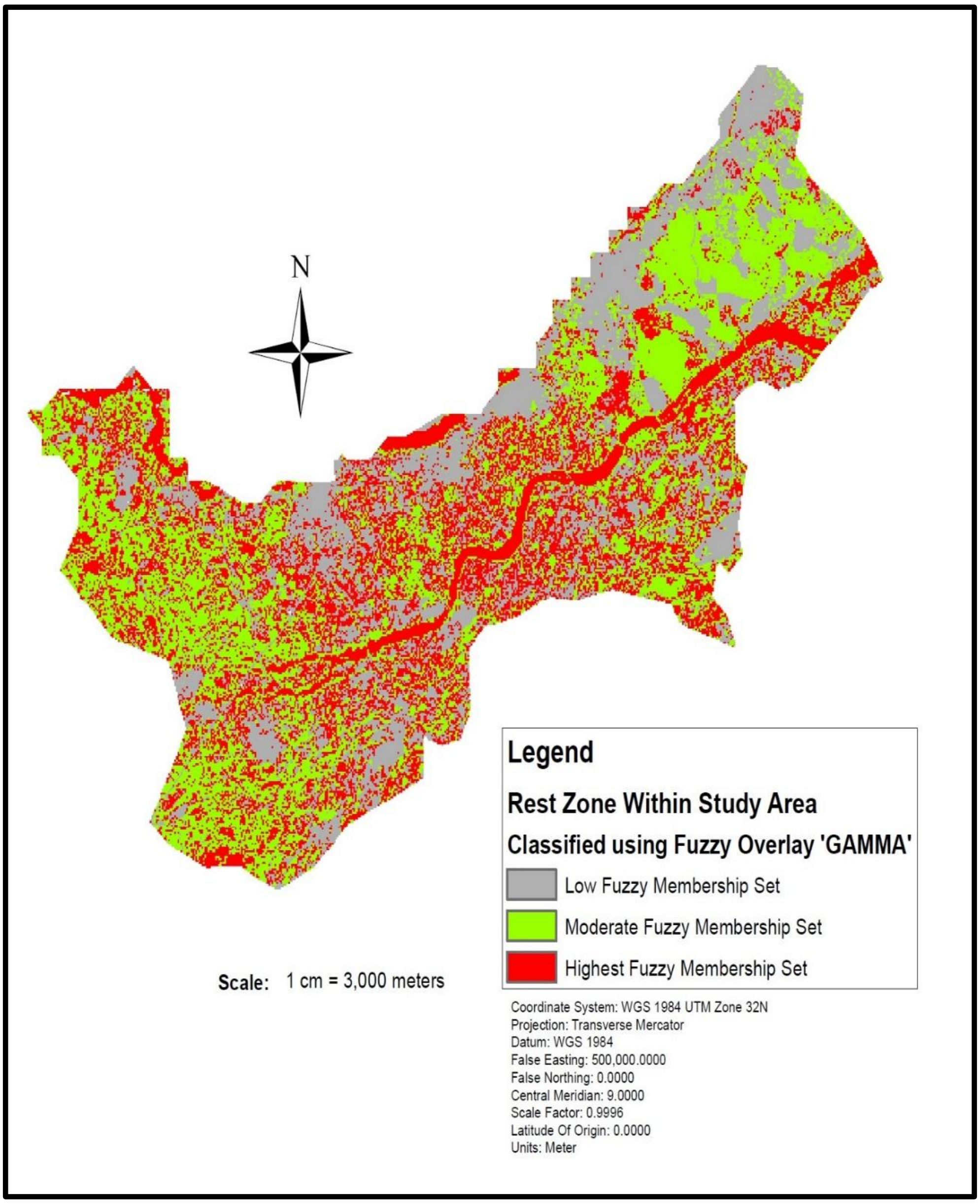


Figure 5.8c: HAT vector rest zone within the main study area classified using fuzzy overlay operator 'GAMMA'

Table 5.2: Summary of sensitivity analysis used to verify the weights of criteria assigned by experts

Fuzzy Operator	Weight of Criteria	Zone Category (Area %)		
		LFM	MFM	HFM
	BREED ZONE			
Overlay OR	Experts	-	65	35
Overlay AND	Experts	65	28	7
γ = (0.8)	Experts	38	27	35
	Equal weights	31	32	37
	5% increase weights	35	30	35
	10% increase weights	38	27	35
	FEED ZONE			
Overlay AND	Experts	69	11	22
Overlay OR	Experts	7	75	18
γ = (0.8)	Experts	64	14	22
	Equal weights	56	22	22
	5% increase weights	62	16	22
	10% increase weights	63	15	22
	REST ZONE			
Overlay AND	Experts	71	28	1
Overlay OR	Experts	-	19	81
γ = (0.8)	Experts	30	36	34
	Equal weights	30	55	15
	5% increase weights	33	31	36
	10% increase weights	30	34	36

γ = fuzzy overlay operator Gamma, 0.8 = fuzzy gamma value

LFM = low fuzzy membership set, MFM = moderate fuzzy membership set

HFM = highest fuzzy membership set

The minor study area

Four categories of fuzzy membership sets were generated for the minor study area; namely: least, low, moderate and highest. The least category was added because cell values for some locations were very small, and since the analysis was based on fuzzy logic, it was deemed appropriate to classify the locations as a fuzzy set rather than referring to them as non-habitat locations. Based on fuzzy overlay operator gamma with value 0.8 the following outcomes (Figure 5.9) were the final HAT vector habitat zones identified in the minor study area.

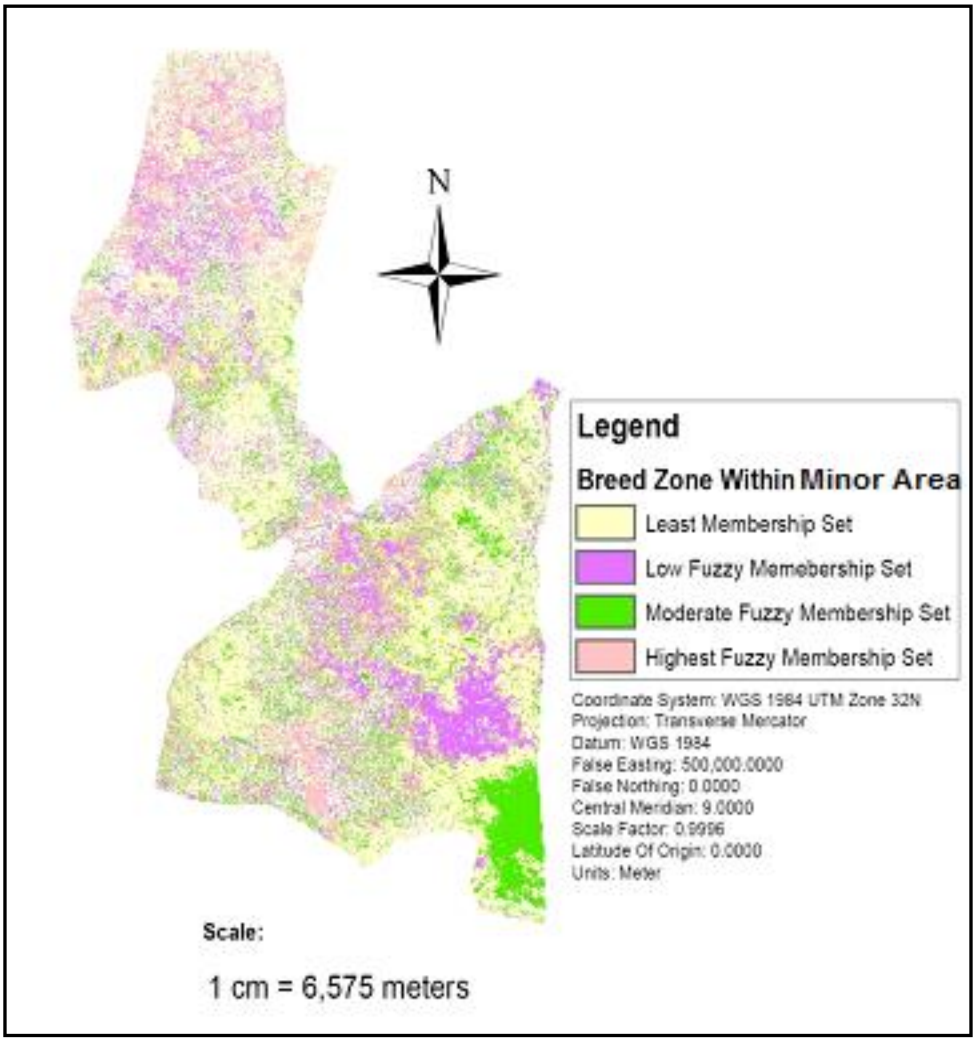


Figure 5.9a: HAT vector breed zone within minor study area classified using fuzzy overlay operator 'GAMMA'

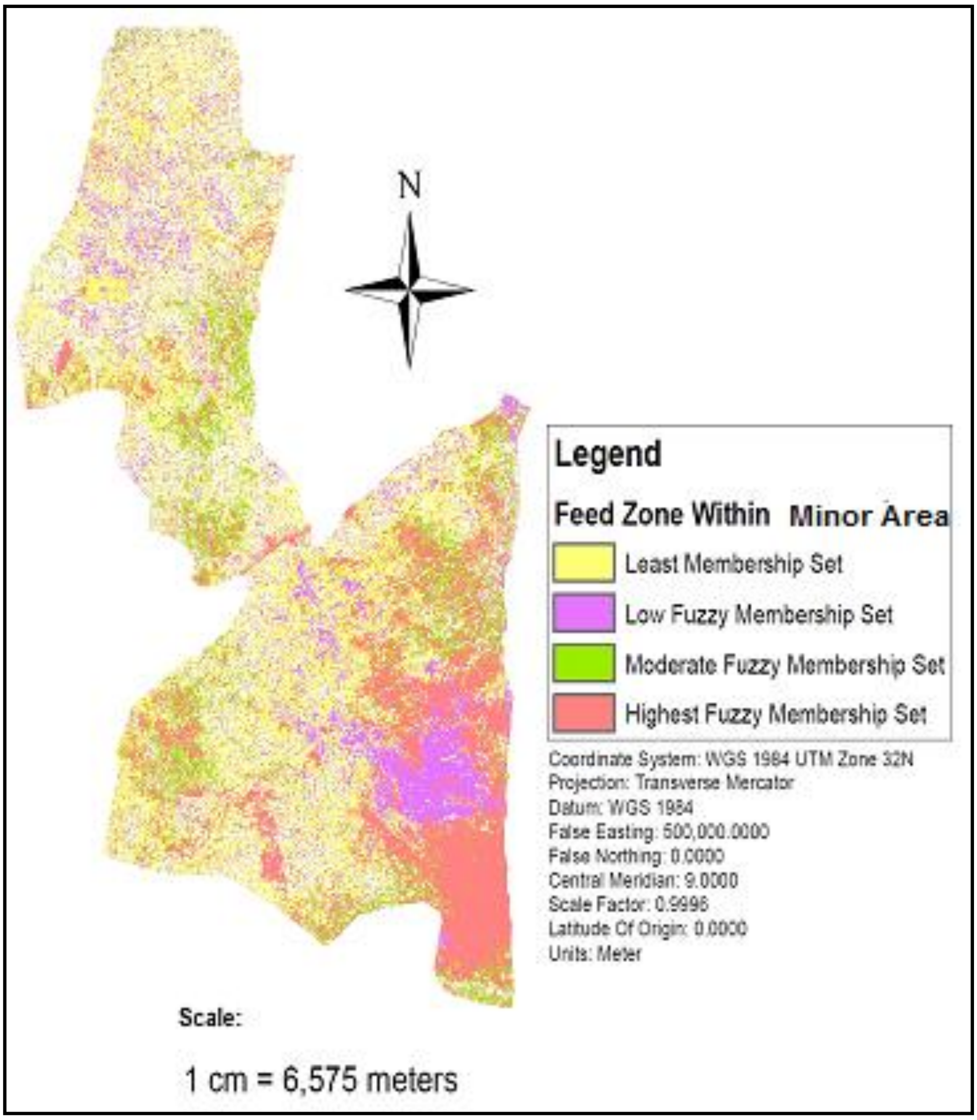


Figure 5.9b: HAT vector feed zone within minor study area classified using fuzzy overlay operator 'GAMMA'

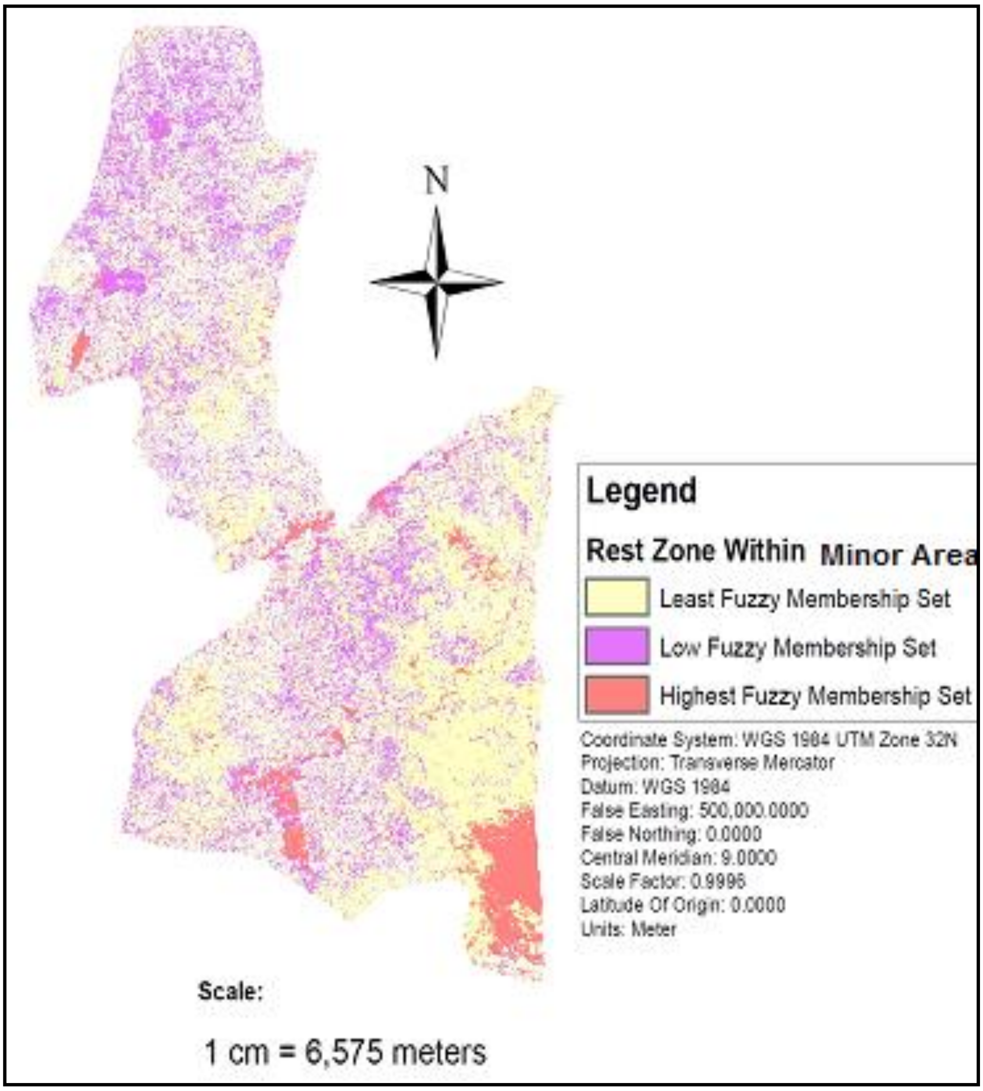


Figure 5.9c: HAT vector rest zone within minor study area classified using fuzzy overlay operator 'GAMMA'

5.3.2 Distance operation

Apart from the main model (Figure 5.2), a sub-model utilising Euclidean distance, and Euclidean direction were generated. The aim of this sub-model was to help in establishing spatial interactions between the criteria used for the main model. To do this, a surface of distance based on straight-line distance was created from each land cover class. The values obtain were fuzzified and later used in Chapter 6 as criteria for analysis of HAT vector habitat. The operation carried out area described in the following sub-sections:

5.3.2.1 Euclidean distance

Using the ArcMap spatial analyst tool, a spatial statistical analysis (refer to sections 1.3.12 and 1.5.4 for details) called Euclidean distance operation was performed on the land cover classes. This gives the distance from each cell in the land cover classes to the closet HAT vector habitat. The Euclidean distance operation was necessary to identify areas where human population might be at risk if exposed to certain land cover class within a specified HAT vector habitat zone. Based on past literature (Gueriini et al. 2008; Zoller et al. 2008), a distance of 400m was specified for the land cover classes. Figure 5.10 and Table 5.3 show an example of the Euclidean distance map layer and its attributes, respectively.

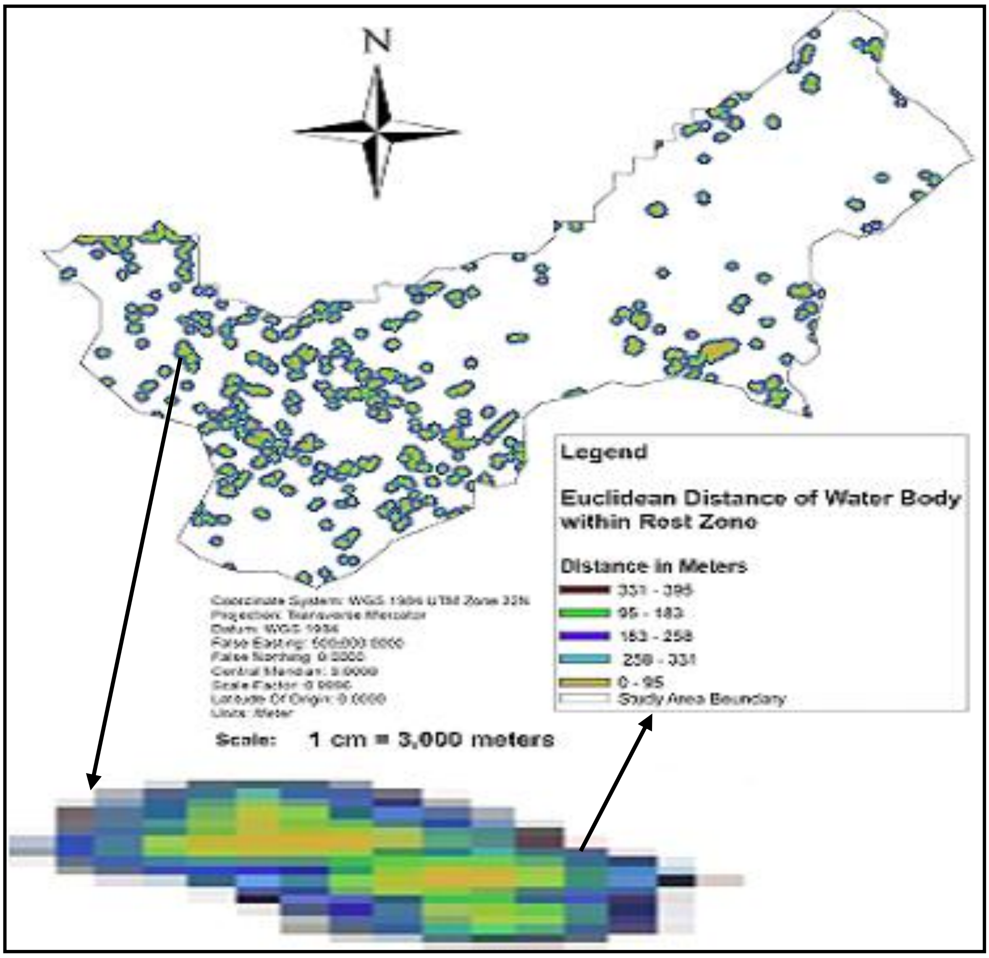


Figure 5.10: Euclidean distance buffer around water bodies within HAT vector rest zone in the main study area (Places within buffer with minimal distance values (0-95m) around a landcover class within a specified HAT vector habitat, are potential highest HAT risk areas)

Table 5.3: Attributes of Euclidean distance buffer around water bodies within the HAT vector rest zone in the main study area

ROW ID	VALUE	COUNT	DISTANCE (m)	AREA	AREA %
0	1	4407	331-395	3753116	21
1	2	4269	95-183	3635592	20
2	3	4606	183-258	3922590	21
3	4	4538	258-331	3864679	21
4	5	3674	0-95	3128874	17

5.3.2.2 Euclidean direction

This gives the direction from each cell of the settlements in the main study area to the closest HAT habitat. The Euclidean direction output contains directions calculated, with values ranging from 0 to 360 degrees. The value increases clockwise with value 0 mainly for the HAT habitat zones.

5.4 Validation of HAT Vector Habitat Classification Scheme

Geo-statistical analysis was carried out to make decision as to whether the classification scheme values could be practical (detail in section 1.3.14).

5.4.1 Semivariogram sensitivity analysis

After obtaining the final HAT vector habitat zones, the output map layers were defuzzified. This was necessary so as to be able to perform sensitivity analysis on the data. Using the predicted values and standard errors of the defuzzified map layers obtained from kriging geo-statistical analysis, semivariogram sensitivity analysis was performed by changing the kriging model's parameters; such as, partial sill and nugget (detail in section 1.3.14) within the percentage of the initial values.

The initial nugget and partial sill for each HAT vector habitat zone were changed using 5%, 10%, 15% and 20% nuggets and partial sills. The semivariogram analysis revealed very minute variation in the original data (habitat zones). It was observed that with increased distance from a given location, the nugget for that location reduces while the partial sill for the same location increases (example in Appendix D-1c). Though variations were observed with the semivariogram sensitivity analysis, the variations were between 0.0 – 0.1%, thus, the researcher has high confidence in further application of the newly developed HAT vector habitat classification scheme.

5.4.2 Local polynomial interpolation quality of fit analysis

Local polynomial interpolation (LPI), which provides spatial condition number surface, was performed to measure the reliability of the model. The LPI used for accuracy assessment of the HAT vector habitat model (classification scheme) was carried out using a 1st order polynomial transformation. The spatial condition number (detail in section 1.3.14) obtained for each habitat zone was below the critical threshold value of 10, thus the model can be regarded as reliable and stable. Apart from the spatial condition number, the LPI was also used to assess the uncertainty associated with the cell values of each habitat zone; this was done by measuring their predicted standard errors.

The LPI surface was derived for each HAT habitat zone to form a geo-statistical layer for cross-validation. The outcome of the cross validation for each habitat zone produced mean and standardised mean prediction errors (Figure 5.11) that was near zero, this was an indication of unbiased prediction that was centred on true values.

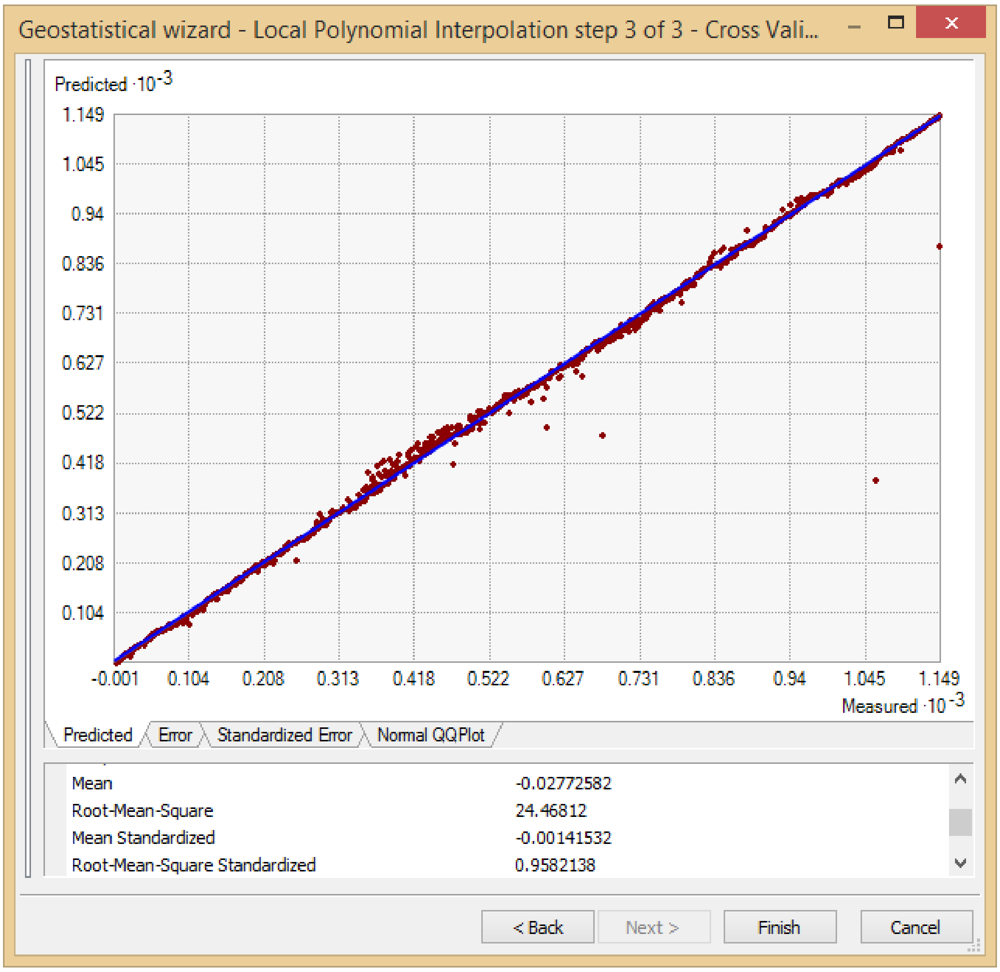


Figure 5.11a: Quality of fit assessment of HAT vector breed zone model in the main study area using local polynomial interpolation (source: Cross validation analysis)

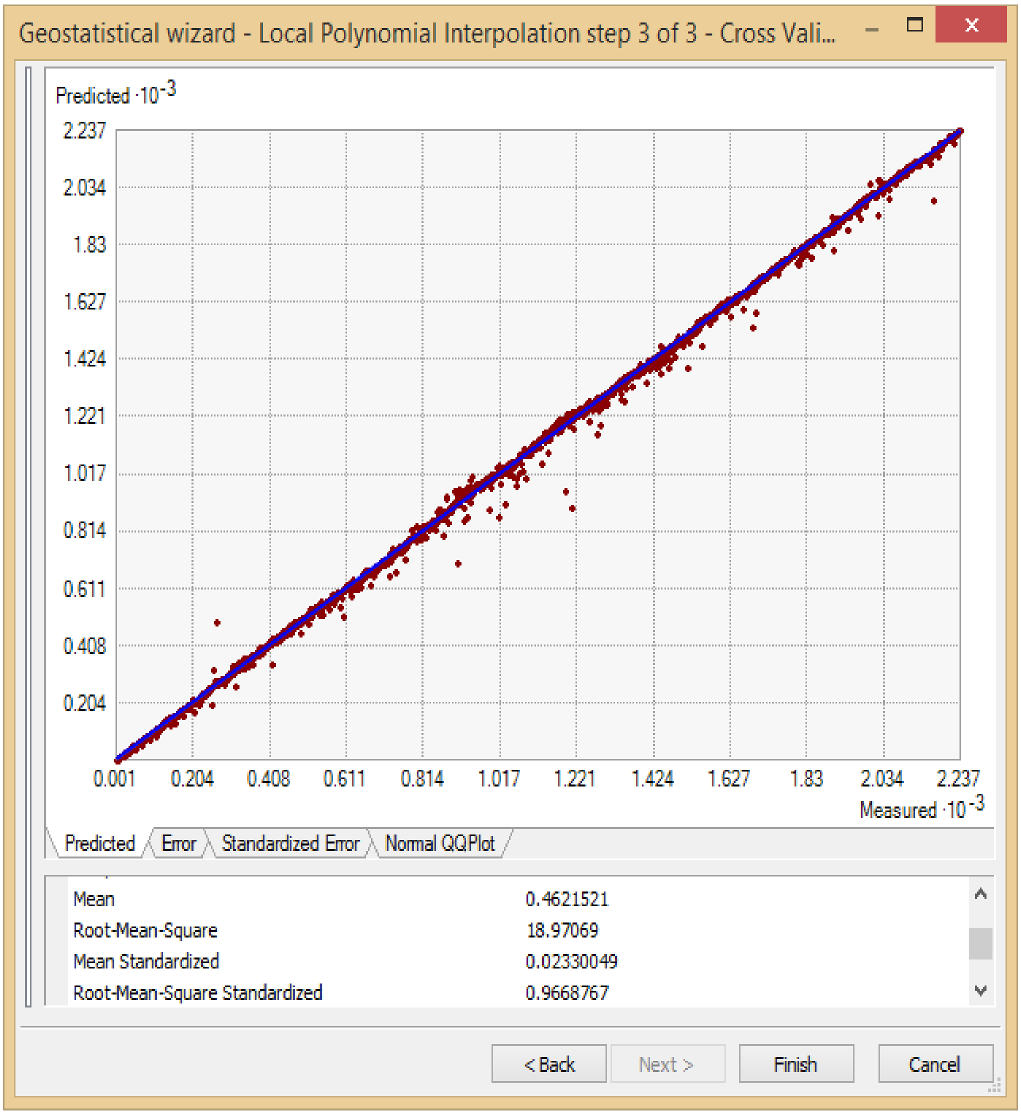


Figure 5.11b: Quality of fit assessment of HAT vector feed zone model in the main study area using local polynomial interpolation (source: Cross validation analysis)

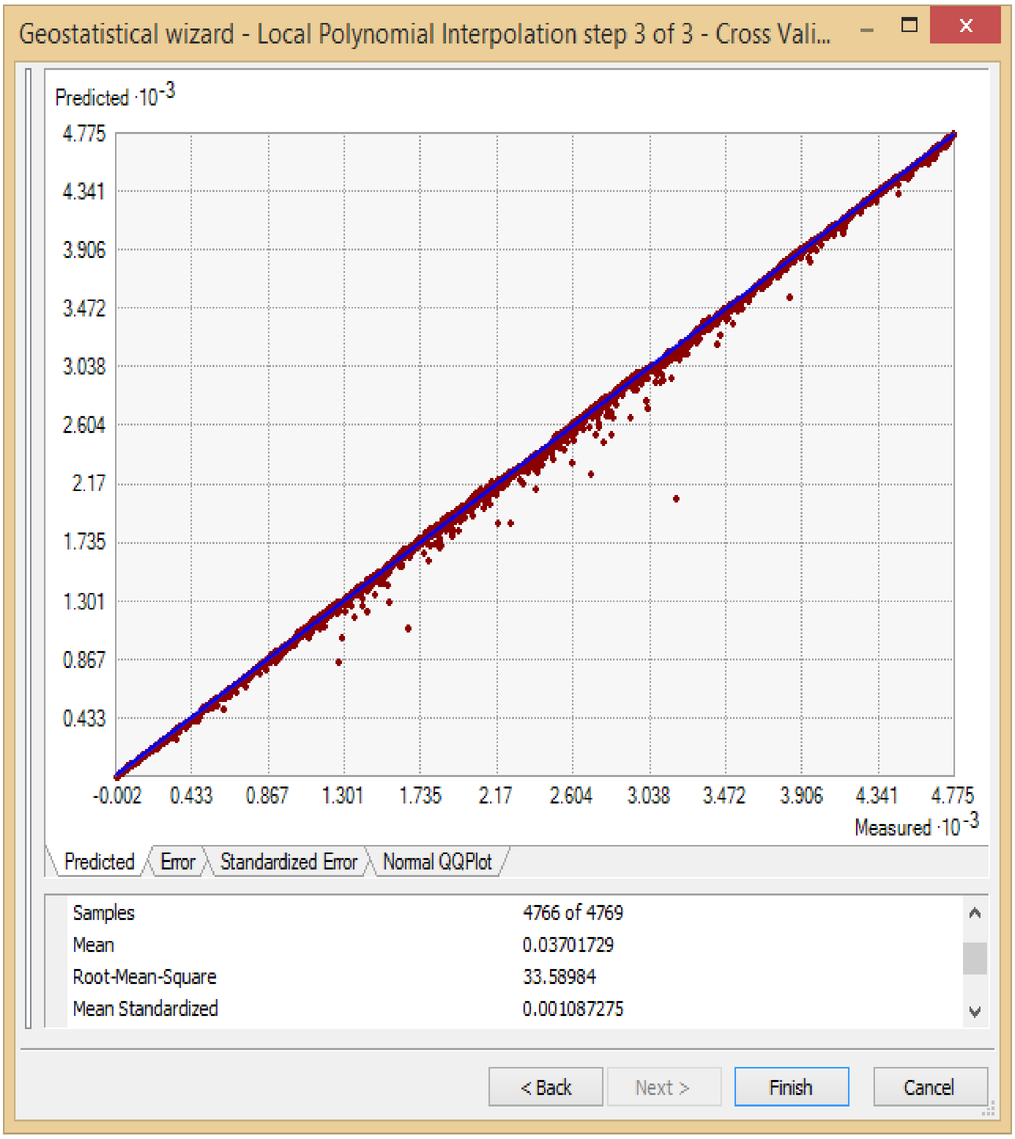


Figure 5.11c: Quality of fit assessment of HAT vector rest zone model in the main study area using local polynomial interpolation (Source: Cross validation analysis)

5.4.3 Empirical Bayesian kriging quality of fit analysis

Empirical Bayesian kriging (EBK) was also carried out to assess the quality of fit of the classification models. The main reason for this was to use a more accurate method (detail in section 1.3.14). EBK standard errors of prediction are more accurate than LPI measurement. The EBK produced mean and standardised mean prediction errors that were near zero as shown in Figures 5.12.

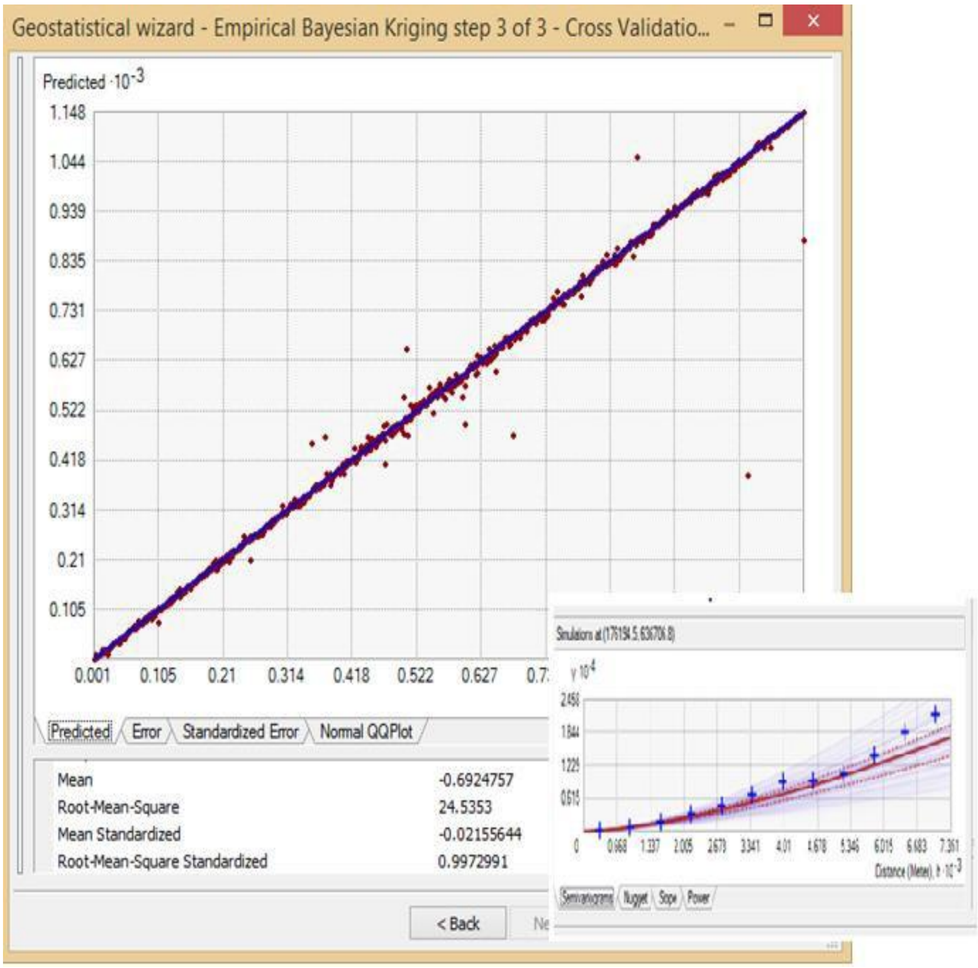


Figure 5.12a: Quality of fit assessment of HAT vector breed zone in the main study area using empirical Bayesian kriging (source: Cross validation analysis (*Note: simulated semivariogram insert*))

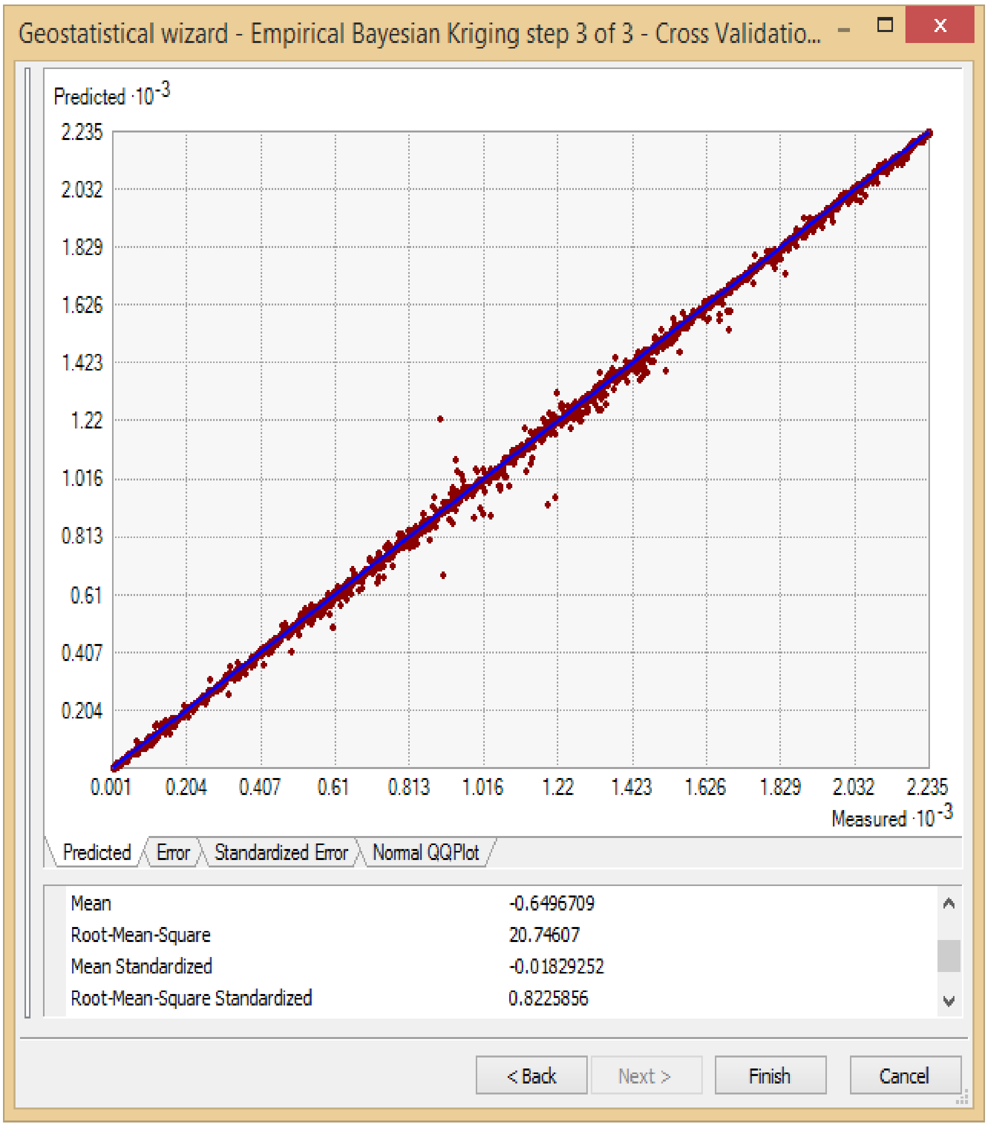


Figure 5.12b: Quality of fit assessment of HAT vector feed zone model in the main study area using empirical Bayesian kriging (source: Cross validation analysis)

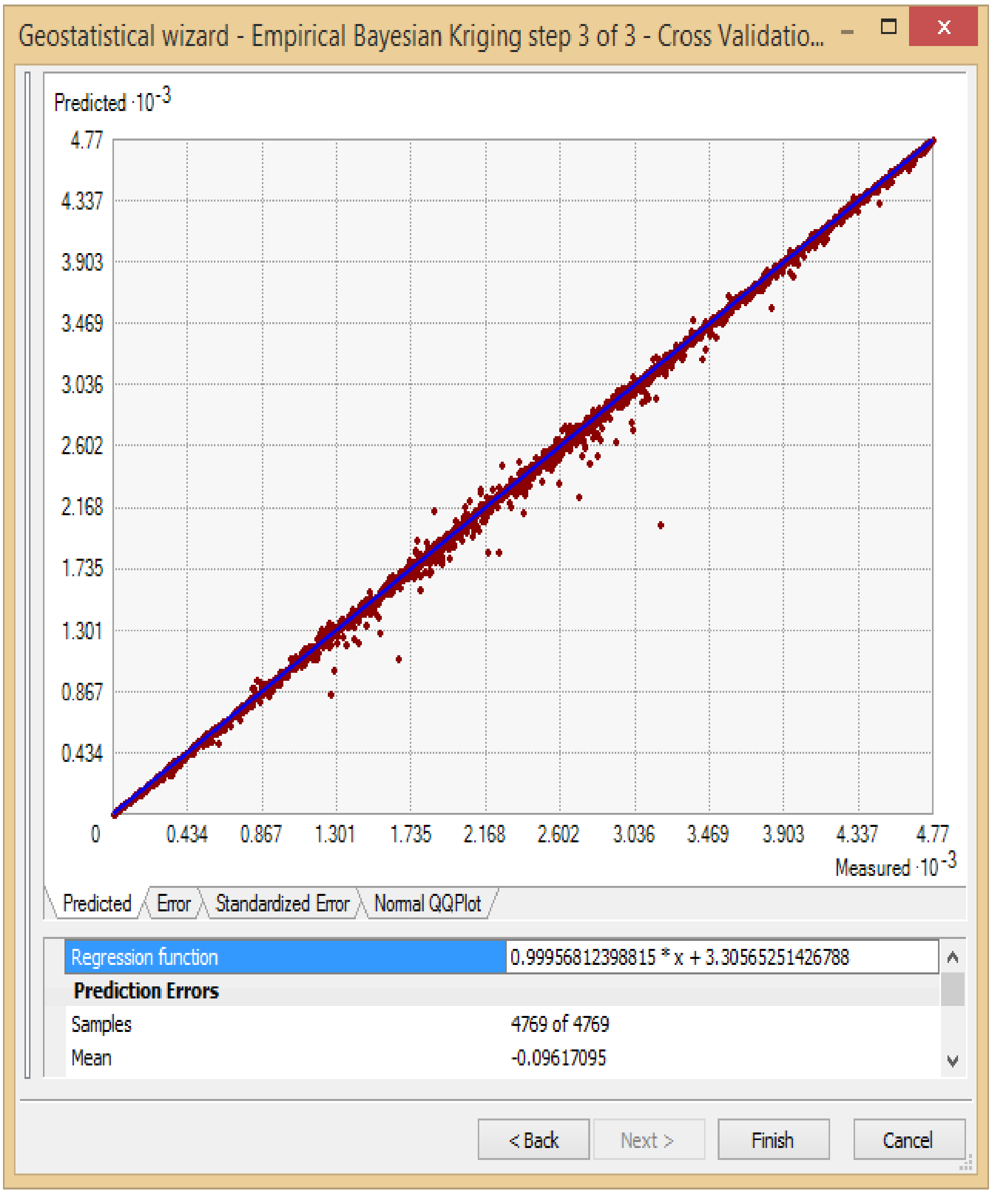


Figure 5.12c: Quality of fit assessment of HAT vector rest zone model in the main study area using empirical Bayesian kriging (source: Cross validation analysis)

The scatter plot of the cross-validation analysis for both LPI and EBK revealed three and one data locations that were set aside from all the other locations in the Breed and Rest zone, respectively. Ideally, this should have called for the autocorrelation models to be refit with misfit data removed. However, the data was retained to truthfully represent real world relationships and not an existing theory.

5.5 Summary

The use of geospatial techniques in developing the classification scheme for managing HAT was successful. The semivariogram analysis and the best fit analysis showed that the classification model was reliable and practical. The integration of supervised classification and fuzzy logic have not been previously used with land cover classes and remotely derived continuous ancillary data to map out vector habitat zones, at the level of thematic detail shown here. Therefore, the present research work is unique.

Chapter 6: Application of HAT Classification Scheme to Identify Diseased Areas

6.1 Introduction

This chapter partly-quantitatively examines how effective the risk with respect to HAT can be assessed using the fuzzy logic approach. The dearth of quantitative data, for example, inadequate hospital records for HAT cases, lack of demographic data for individual settlement, etc. influenced the decision to opt for a partly-quantitative examination (refer to section 1.4). The analysis made use of the results from Chapters 4 and 5. The HAT vector habitat zones (breed, feed, and rest) were taken as hazard indicators while settlements within the main study area were taken as vulnerability indicators. Based on these indicators, HAT risk was determined for the main study area.

Factors such as, closeness of human population to water bodies, shrub, cultivated area, less-dense forest, mangrove and, socio-economic activities are important, hence distance maps (section 5.3.2) are incorporated into the final selection of priority areas. To investigate factors that influence HAT propagation in the study area, statistical analysis was carried out. Part of the work in this chapter has resulted in publications (Akiode and Oduyemi 2014 b, c).

6.2 HAT Hazard Assessment

HAT hazard assessment is the estimation of overall adverse effects of HAT on the study area. Spatial analysis; local and zonal statistics were performed to determine the hazard factor for the HAT membership set (fuzzy membership) of each habitat zone. These analyses indicate the extent and percentage area exposed to hazard in each zone. The parameters considered were the fuzzy membership of the breed, feed and rest zones and the percentage area that satisfy the criteria for being in each zone.

The fuzzy membership was used to categorise the degree of hazard in the zones. Since the human population are likely to be exposed to harm in an environment that is most suitable for the HAT vector, the level of risk was therefore categorised based on locations that have fuzzy membership values approximately or close to 1, as locations where the hazard is highest and where fuzzy membership values are less than 0.5 as no hazard locations. Other locations with fuzzy membership values between 1 and 0.5 were regarded as moderate hazard locations. Thus, three hazard categories were used and each category was represented by a hazard value. To devise a value scale, the zones were divided into three categories based on three degrees of fuzzy membership. Based on these three values of fuzzy membership, hazards were classified as presented in Figure 6.1 and Table 6.1.

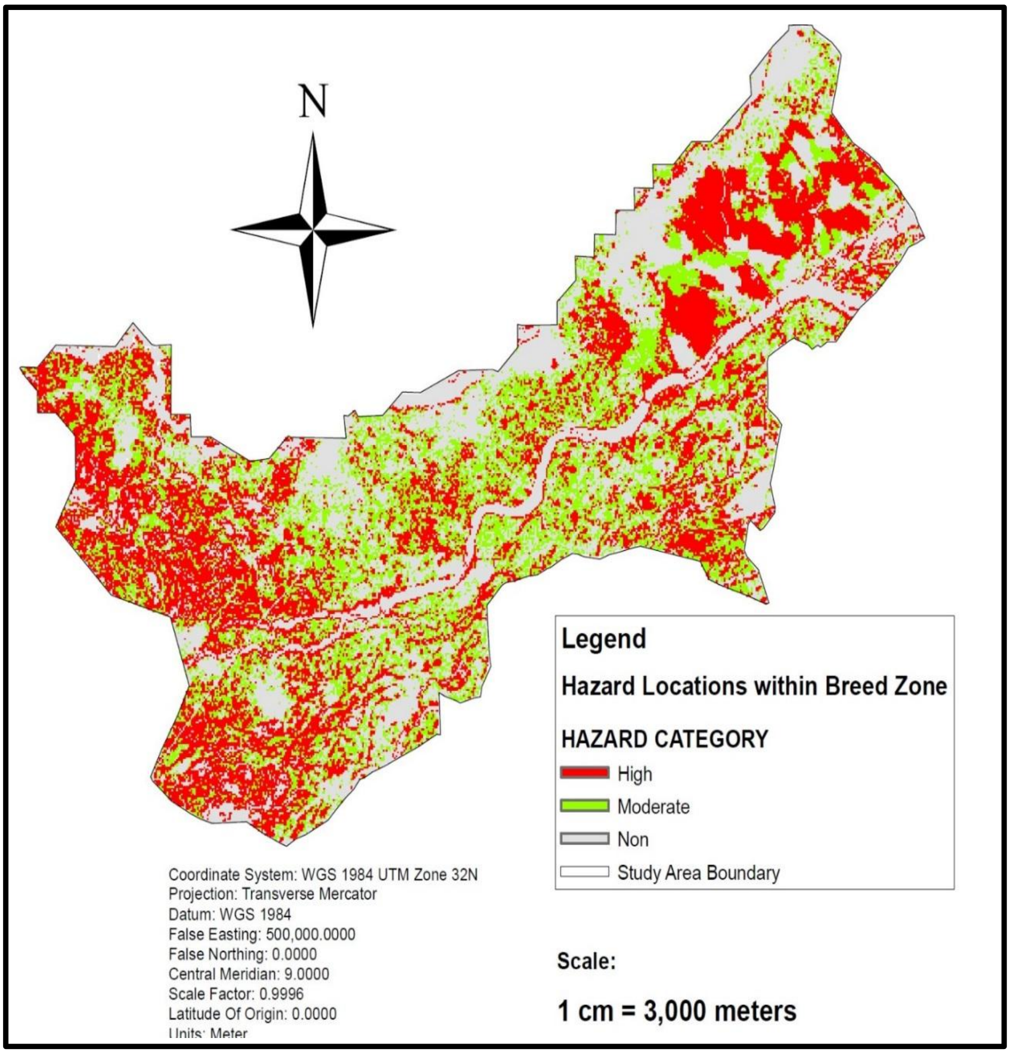


Figure 6.1a: Map showing hazard locations within the HAT vector breed zone in the main study area

Table 6.1a: Attributes of the hazard locations within the HAT vector breed zone

ROW ID	COUNT	AREA		CATEGORY	HAZARD CAT.
0	34251	291690564	38	no fuzzy	Non
1	24307	207004768	27	mod fuzzy	Moderate
2	31102	264872752	35	high fuzzy	High

(no fuzzy = no fuzzy membership, mod fuzzy = moderate fuzzy membership, high fuzzy = high fuzzy membership)

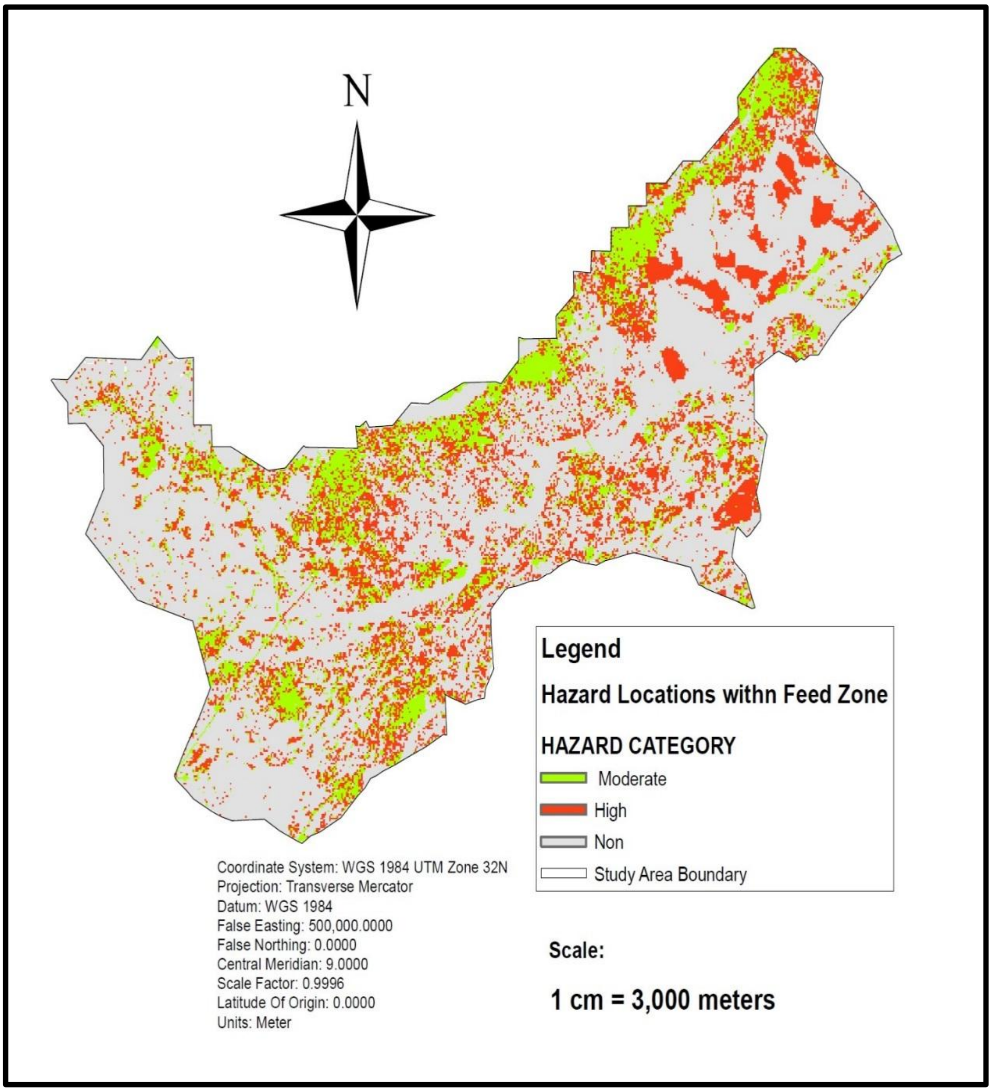


Figure 6.1b: Map showing hazard locations within the HAT vector feed zone in the main study area

Table 6.1b: Attributes of the hazard locations within the HAT vector feed zone

ROW ID	COUNT	AREA	AREA %	CATEGORY	HAZARD CAT.
0	57613	490647360	64	no fuzzy	Non
1	12402	105618672	14	mod fuzzy	Moderate
2	19645	167301952	22	high fuzzy	High

(no fuzzy = no fuzzy membership, mod fuzzy = moderate fuzzy membership, high fuzzy = high fuzzy membership)

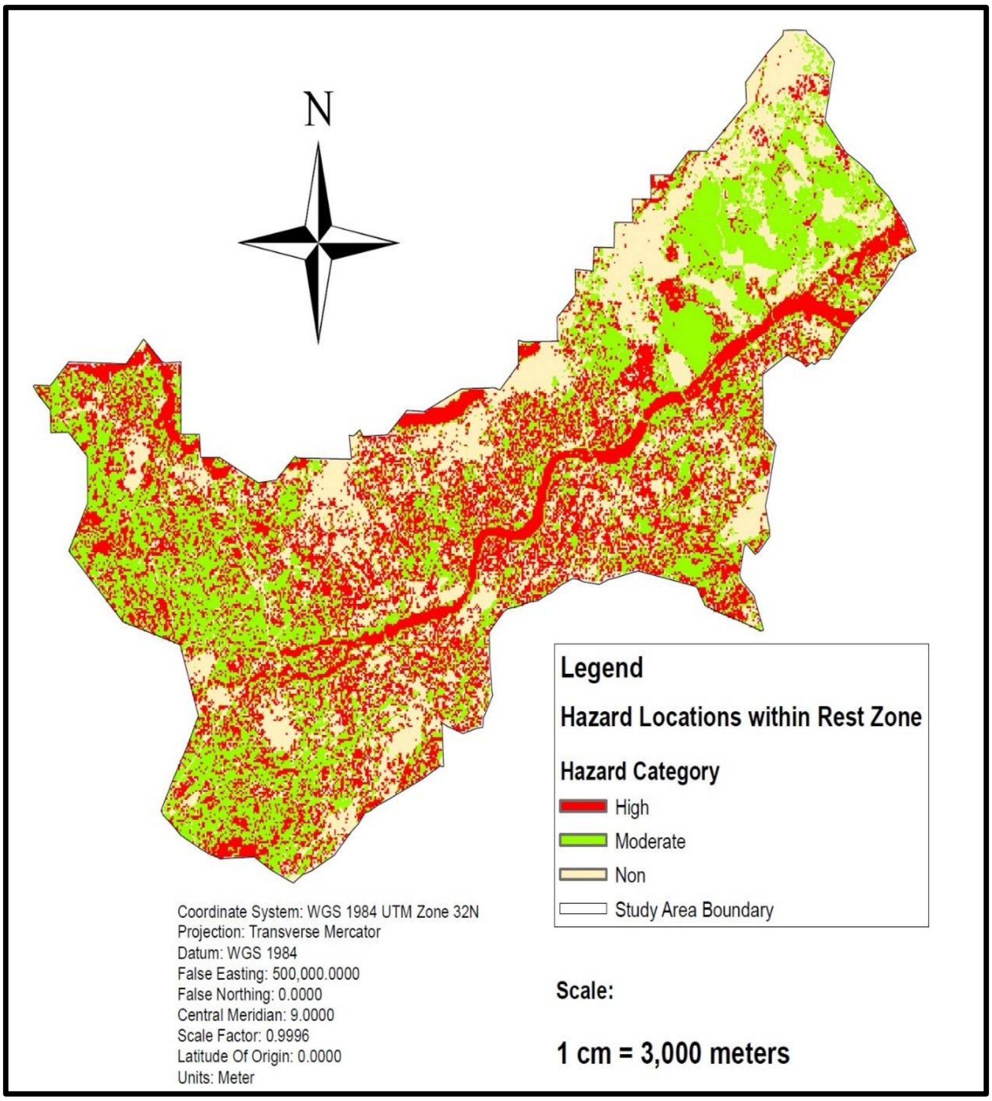


Figure 6.1c: Map showing hazard locations within the HAT vector rest zone in the main study area.

Table 6.1c: Attributes of the hazard locations within the HAT vector rest zone

ROW ID	COUNT	AREA	AREA %	CATEGORY	HAZARD CAT.
0	27104	230824752	30	no fuzzy	non
1	32529	277025472	36	mod fuzzy	moderate
2	30027	255717776	34	high fuzzy	high

(no fuzzy = no fuzzy membership, mod fuzzy = moderate fuzzy membership, high fuzzy = high fuzzy membership)

6.3 Vulnerability Assessment

As in this context vulnerability is equal to the location of an element at risk to hazard (Equation 1.6 – section 1.4), a factor analysis was carried out to identify vulnerable areas within each HAT vector habitat zones.

6.3.1 Factor analysis of HAT vector habitat zones

A geo-processing model was made using the ArcMap model builder to identify vulnerable areas within each HAT vector habitat zone (i.e. areas where human population might be at risk if exposed to certain land cover class within a specified HAT vector habitat zone). The datasets used were the fuzzified Euclidean distance built-up area, shrub, cultivated area, water bodies, mangrove and less-dense forest (e.g. Table 6.2). These land cover classes were selected for the factor analysis based on their importance to HAT propagation and the fact that the human population activities in the study area are centred on the land cover classes on daily basis.

Table 6.2: Attributes of Euclidean distance of less dense forest within 400m of feed zone

ROW ID	VALUE	COUNT	DIST_METER	AREA	AREA %
0	1	11074	192 - 395	94309080	13
1	2	25598	57 - 192	217999248	29
2	3	50396	0 - 67	429185504	58

6.3.2 HAT vulnerability assessment

The distance map of shrub, water-body, mangrove, built-up area, less-dense forest and cultivated area were combined with the hazard map generated in section 6.2 to jointly calculate the sum of the values of each distance map locations and HAT vector habitat zones, on a cell-by-cell basis. The output was reclassified based on the 400m distance to the land cover classes into four vulnerability categories as summarised in Figure 6.2.

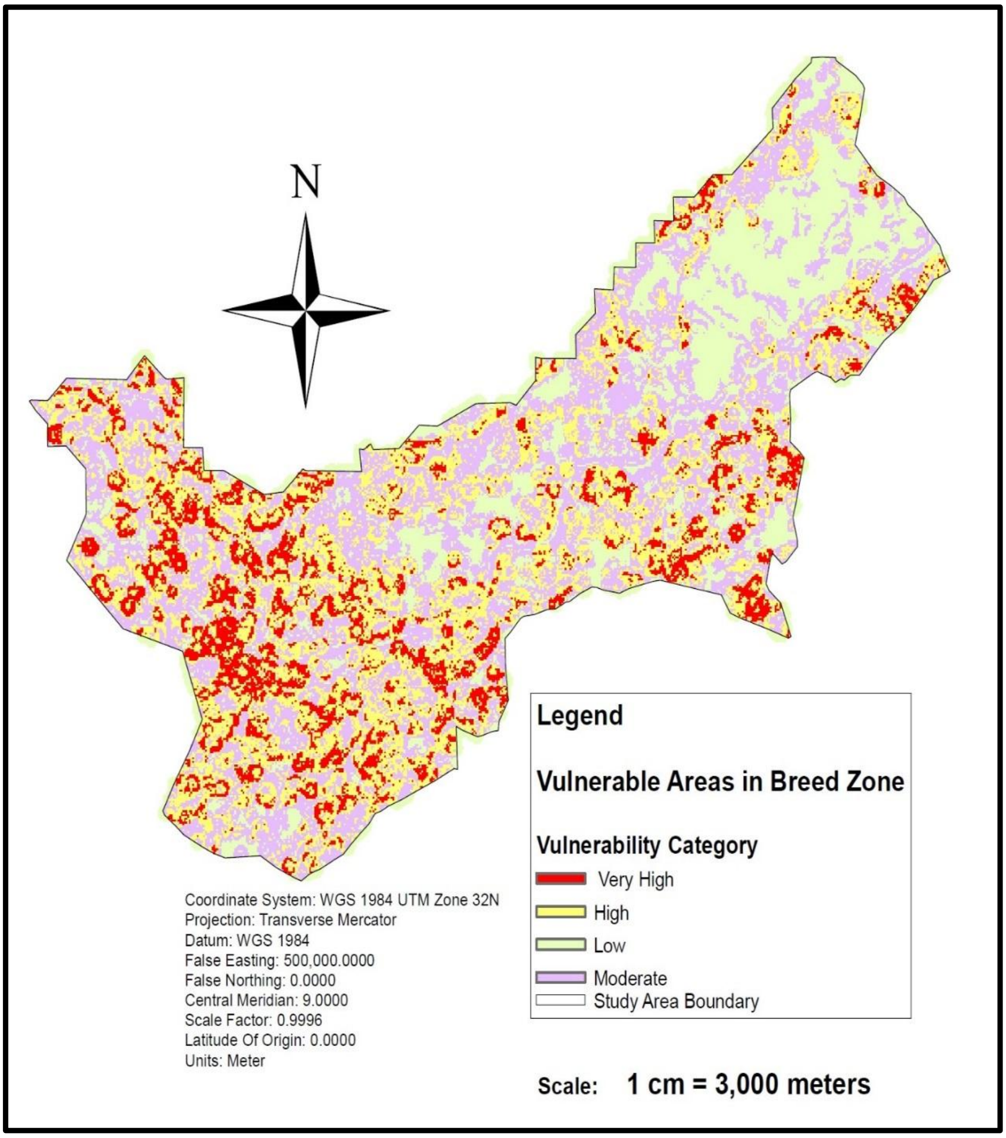


Figure 6.2a: Vulnerable locations within HAT vector breed zone in the main study area

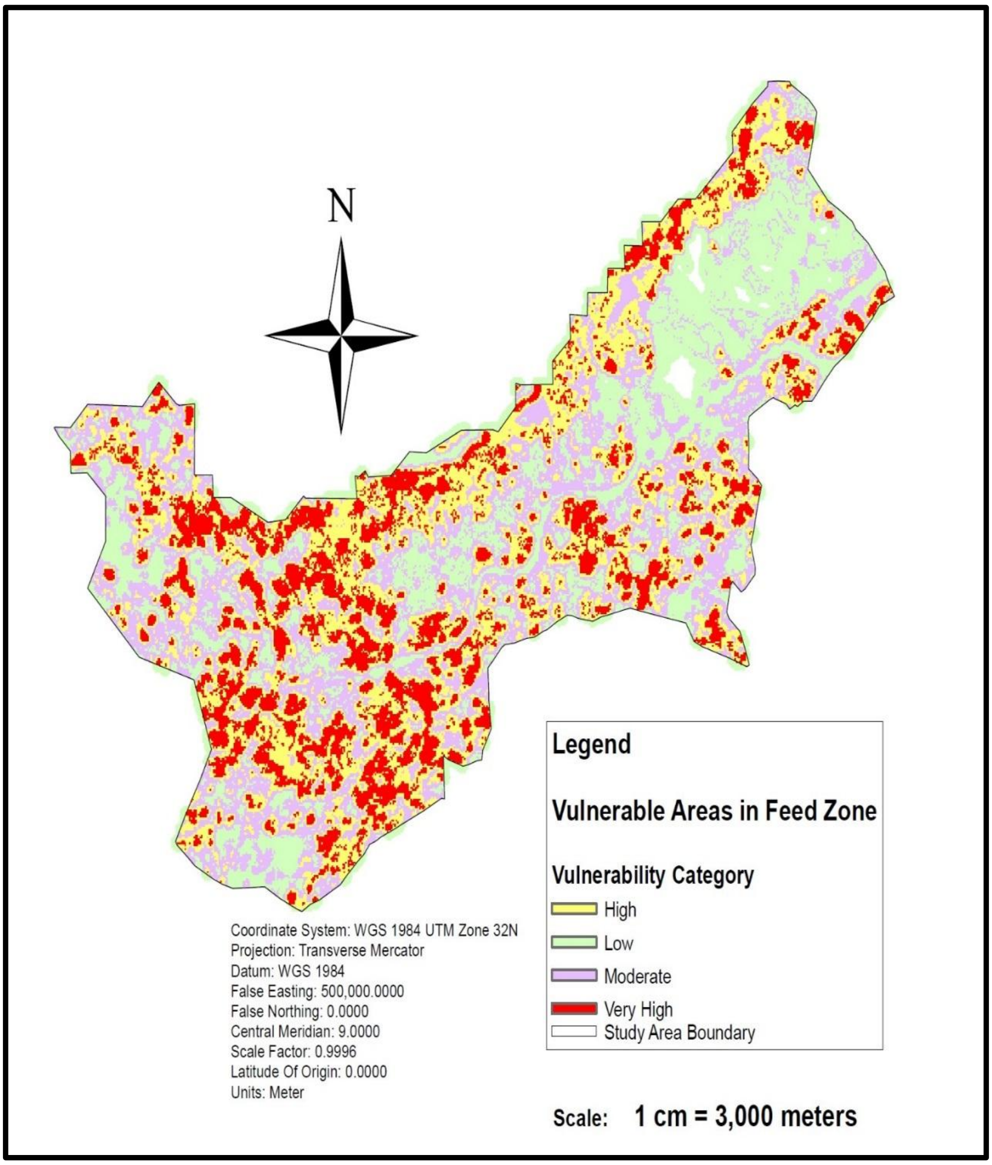


Figure 6.2b: Vulnerable locations within HAT vector feed zone in the main study area

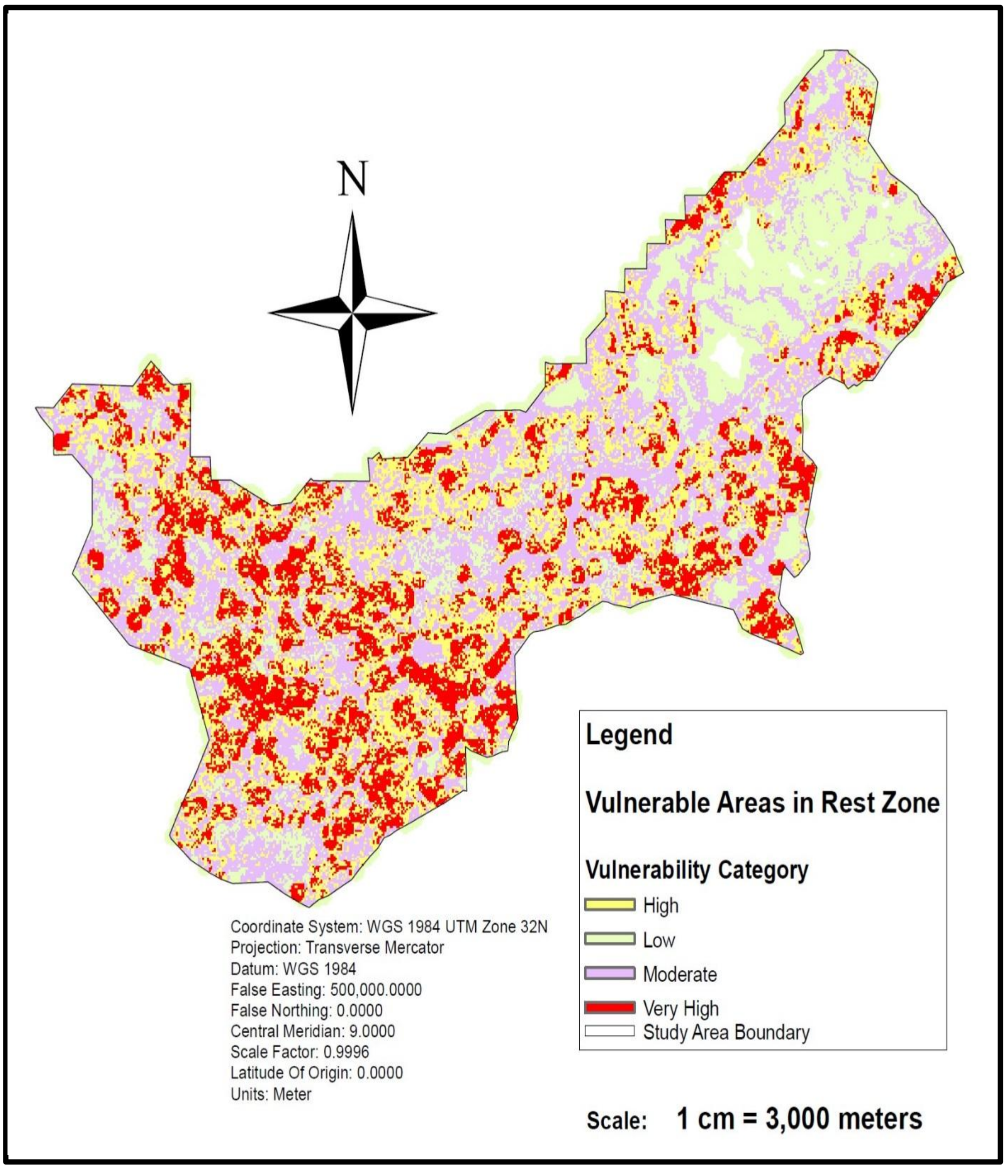


Figure 6.2c: Vulnerable locations within HAT vector rest zone in the main study area

6.3.2.1 Assessing vulnerability of HAT positive settlements

The vulnerability of settlements that recorded one or more cases of HAT between 1994 and 2006 in the main study area was assessed by adapting Cecchi et al. 2008 tsetse fly (HAT vector) suitability threshold. After calculating the average of the percentage of HAT vulnerability categories (Section 6.3.2) within each settlement, the outcome was categorised as Table 6.3. The settlement vulnerability assessment results are shown in Table 6.4.

Table: 6.3: Proposed threshold for determining vulnerability of settlements within HAT vector habitat zones (source: proposed by researcher, adapted from Cecchi et al. 2008)

Predicted area of presence within settlement (%)	Vulnerability category for HAT vector zone	Vulnerability index	Description
> 50	High	3	**Potential highest vulnerable locations**
> 25 and ≤ 50	Moderate	2	**Potential fairly high vulnerable locations**
> 5 and ≤ 25	Low	1	**Potential low vulnerable locations**
≤ 5	**Non**	**0**	**Vulnerability free locations**

Table 6.4a: Vulnerability of HAT positive settlements within HAT vector breed zone in the main study area

Settlement Name	Vulnerability Category	Vulnerability Index
Kokori	Moderate	2
Ugono	Moderate	2
Abraka	Moderate	2
Ekpan	High	3
Eku	Moderate	2
Obiaruku	Moderate	2
Oria	Moderate	2
Ugonao	High	3
Urhuoka/Umeghe	Moderate	2

Table 6.4b: Vulnerability of HAT positive settlements within HAT vector feed zone in the main study area

Settlement Name	Vulnerability Category	Vulnerability Index
Kokori	Moderate	2
Ugono	Moderate	2
Abraka	Low	1
Ekpan	Moderate	2
Eku	Moderate	2
Obiaruku	Moderate	2
Oria	Moderate	2
Ugonao	High	3
Urhuoka/Umeghe	Moderate	2

Table 6.4c: Vulnerability of HAT positive settlements within HAT vector rest zone in the main study area

Settlement Name	Vulnerability Category	Vulnerability Index
Kokori	Low	1
Ugono	Moderate	2
Abraka	Low	1
Ekpan	Moderate	2
Eku	Moderate	2
Obiaruku	Moderate	2
Oria	Moderate	2
Ugonao	High	3
Urhuoka/Umeghe	Moderate	2

6.4 HAT Risk Assessment

To determine the magnitude of risk for the settlements in the main study area, HAT risk (Equation 1.7 – section 1.4) was calculated for all the settlements using a raster calculator.

Settlements at risk of HAT were identified within each HAT vector habitat zone. The risk maps presented in Figure 6.3 were categorised as very high, high, moderate and low. In addition, a geo-processing model was created to identify the direction (section 5.3.2.2) of each settlement at risk within each HAT vector habitat zone using the ArcMap model builder. The direction map was reclassified into four equal interval directions (example in Figure 6.4). The direction of settlements at risk of HAT within the HAT vector zones (breed, feed and rest) is summarised in Table 6.5.

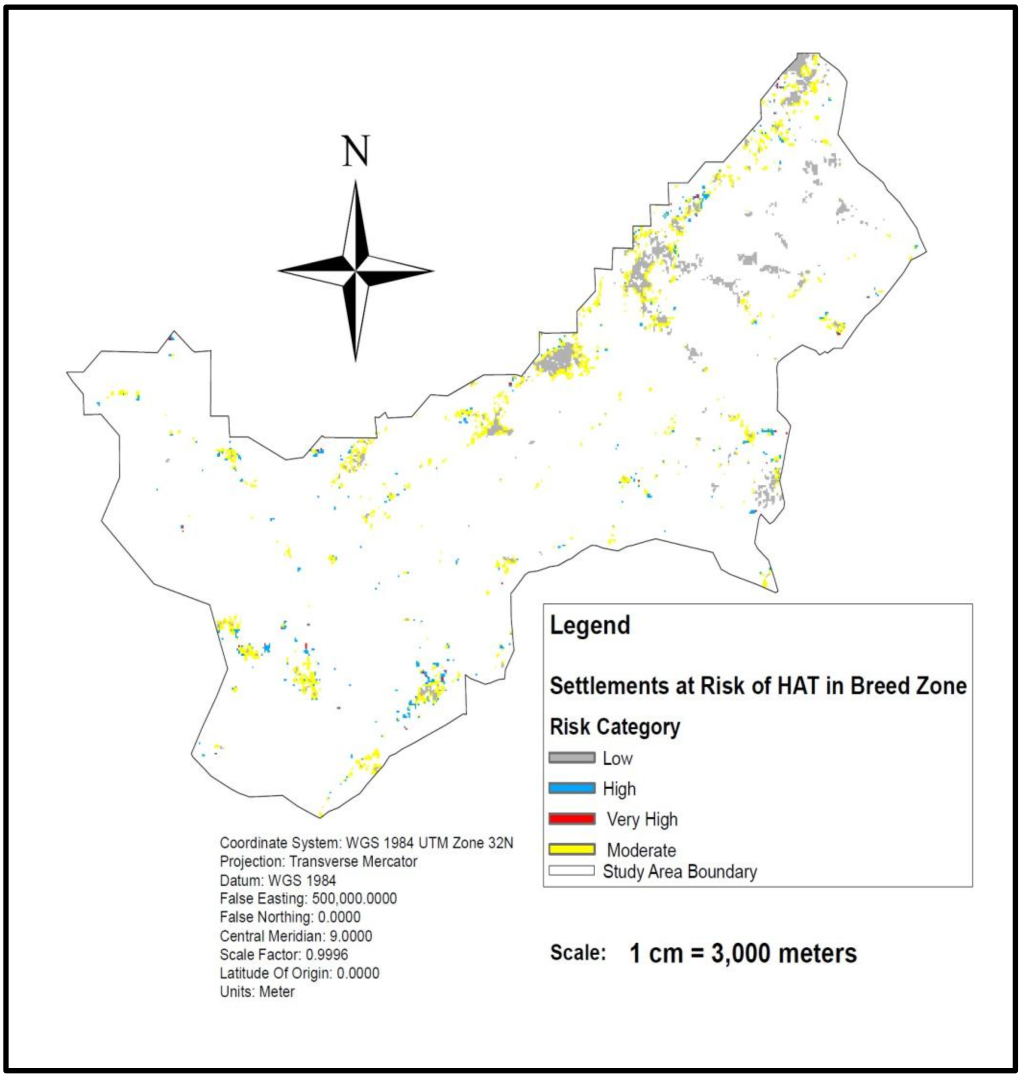


Figure 6.3a: Settlements at risk of HAT within HAT vector breed zone in the main study area

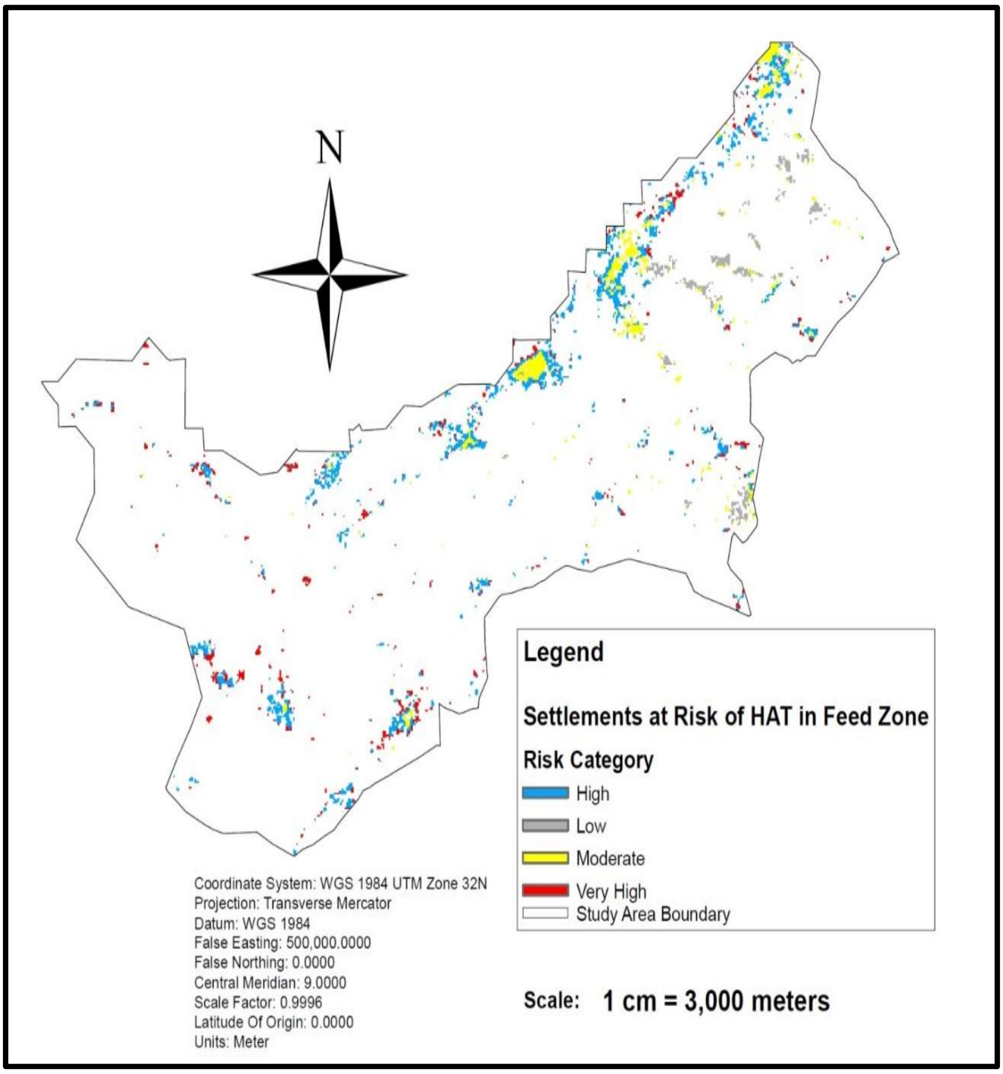


Figure 6.3b: Settlements at risk of HAT within HAT vector feed zone in the main study area

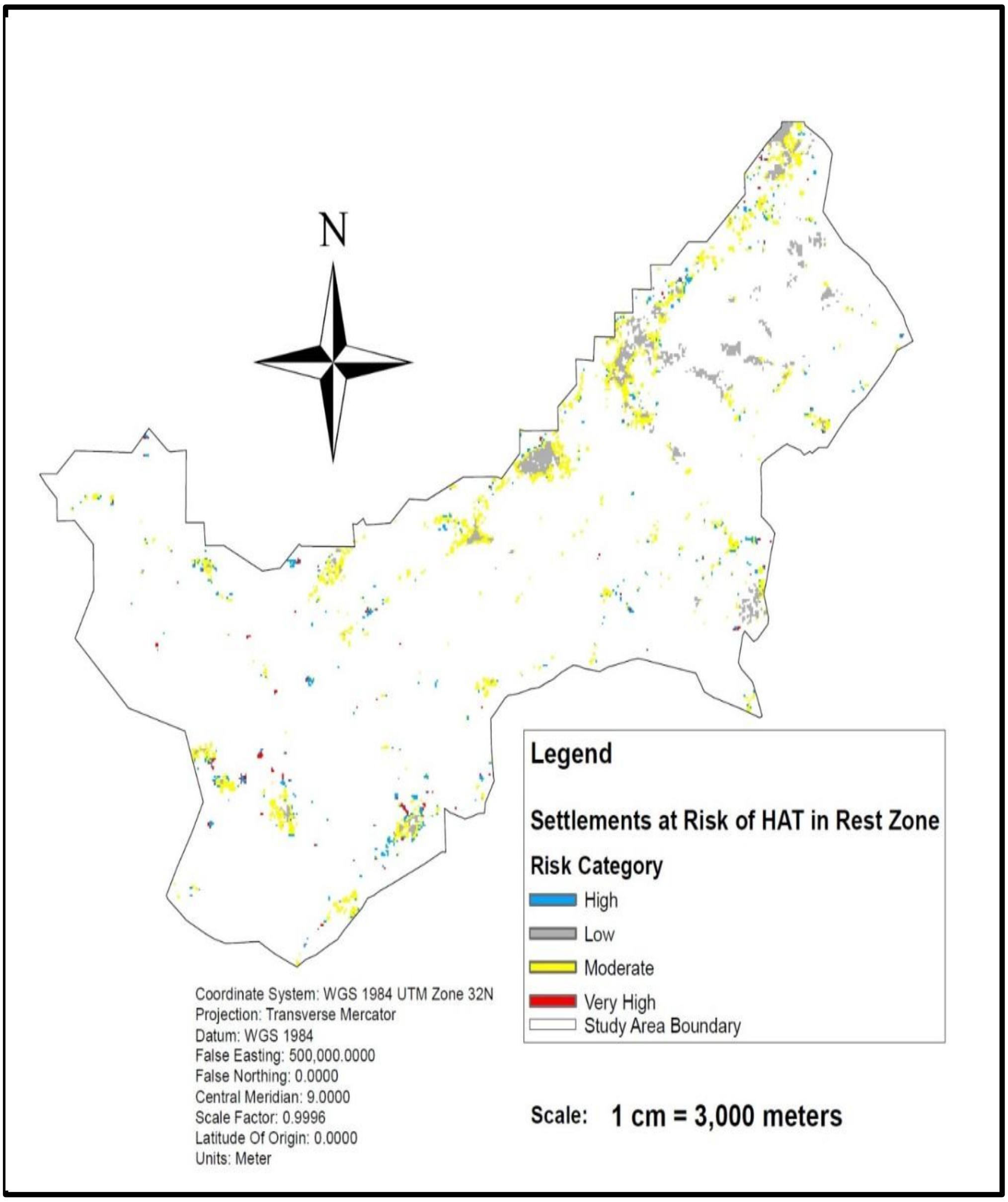


Figure 6.3c: Settlements at risk of HAT within HAT vector rest zone in the main study area

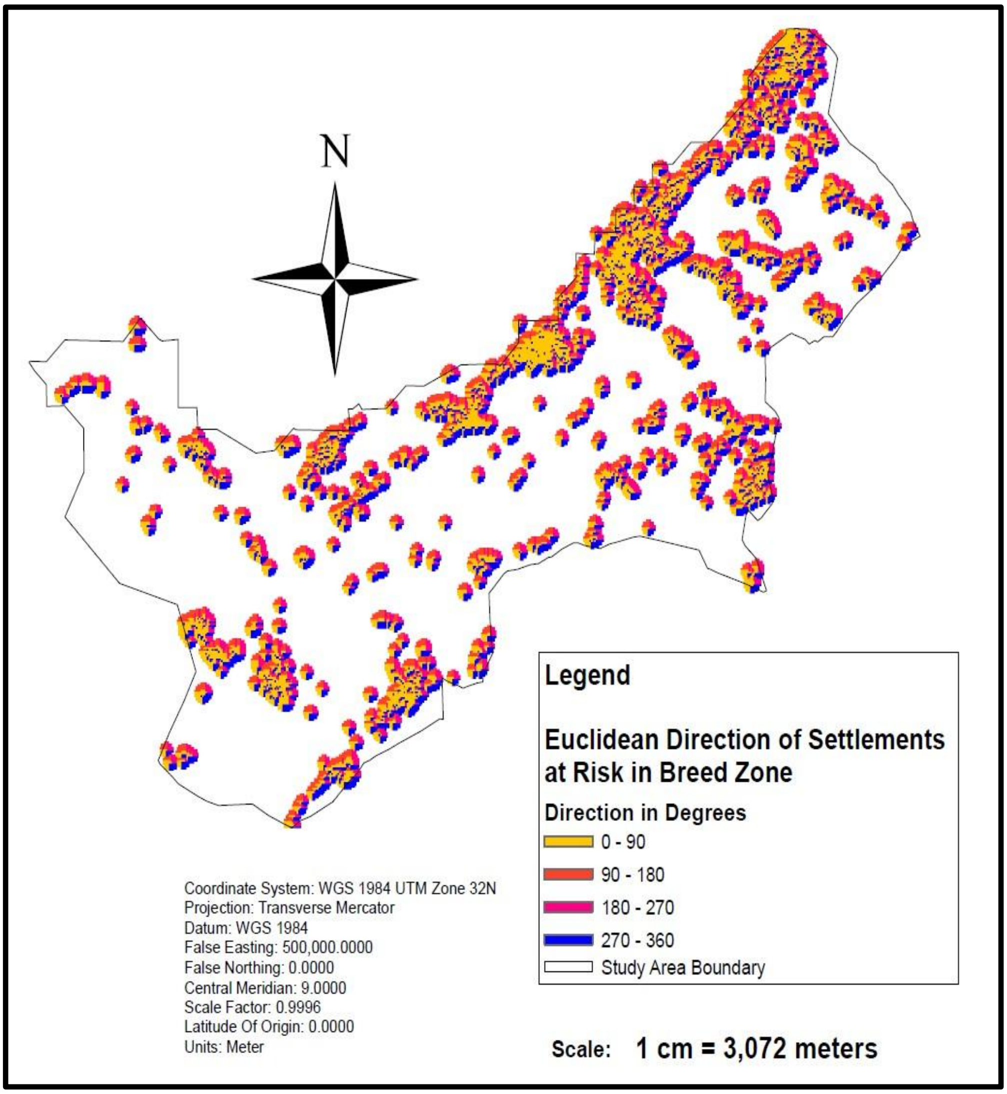


Figure 6.4: Directional map of settlements at risk of HAT within HAT vector breed zone in the main study area

Table 6.5: Attributes of directional map of settlements at risk of HAT within HAT vector zones in the main study area

OBJECT ID	Direction_Degree	Direction	Direction_Category
1	0 – 90	North-East	Very High
2	90 – 180	East-South	Moderate
3	180 -270	South-West	Low
4	270 – 360	West-North	High

6.5 Prioritisation of HAT Risk Settlements

The three HAT vector habitat zones were overlaid using the fuzzy overlay function ‘AND’ (intersection; see section 1.3.13) to identify areas that need urgent attention in the main study area. This result into priority map categorised as highest priority, high priority, moderate priority and lowest priority.

The highest priority category area was extracted and subjected to a distance operation with a threshold of 400m. The settlement map of the main study area was then overlaid on the priority distance map to identify the settlements that are within 400m of the highest priority area. The identified settlements constitute the settlements that need urgent attention. Figure 6.5 presents the priority map for the main study area while all the settlements that need urgent attention are presented in Figure 6.6.

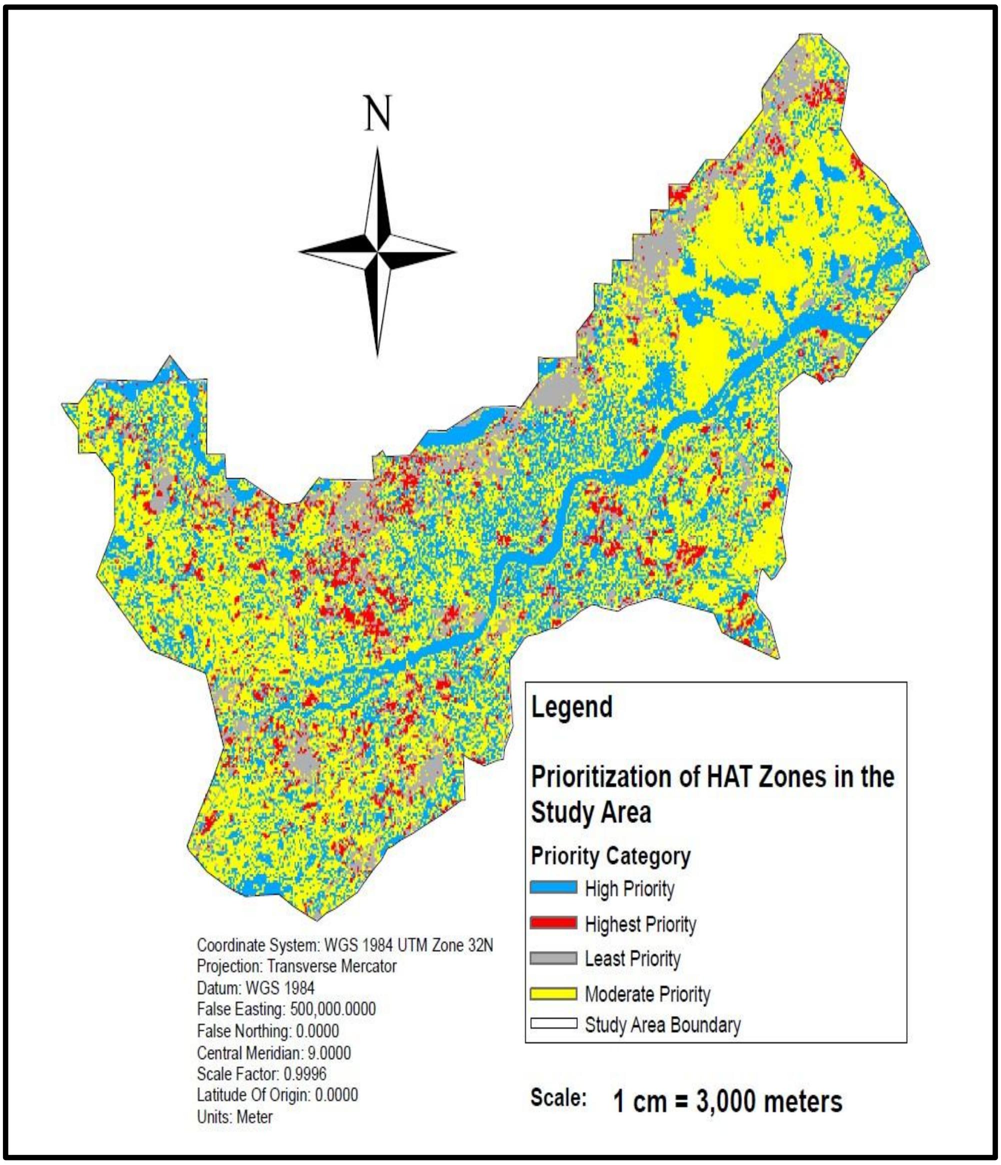


Figure 6.5: HAT priority areas within the main study area

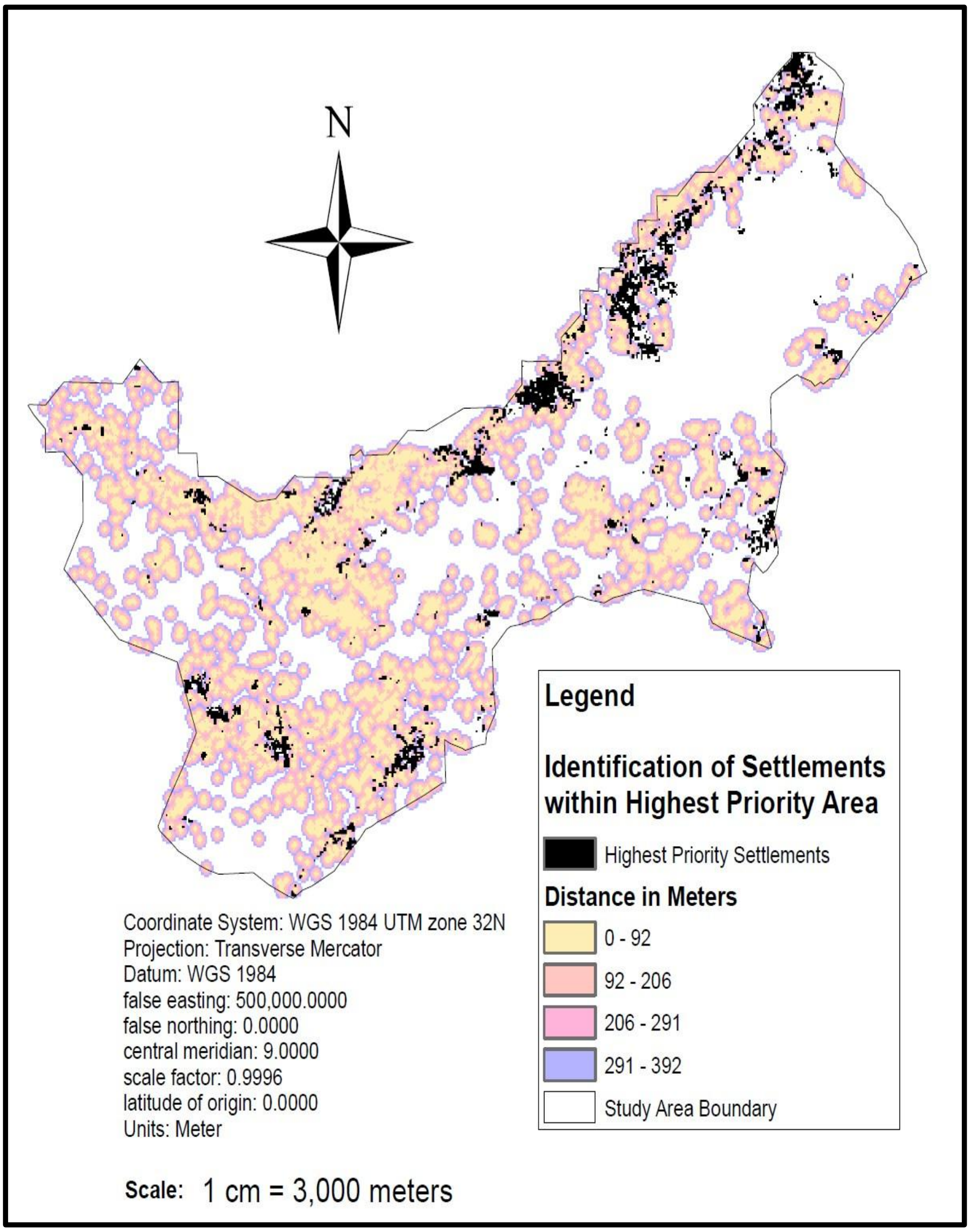


Figure: 6.6: Highest HAT priority settlements within 400m of highest priority areas

6.6 Investigating Factors Responsible for HAT Propagation in the Study Areas

Having established the significance and risk of HAT in sections 4.2 and 6.4, there is the need to investigate factors responsible for HAT propagation in the study areas. A spatial analysis called zonal histogram was used to investigate the frequency distribution of values of land cover classes (Chapter 3) present within the vulnerable areas of each HAT vector habitat zone in both the main and minor study areas. The vulnerable areas within the other selected two local government area in Delta State were also investigated. The zones were earlier categorised (section 6.3.2) as “Very High”, “High”, “Moderate” and “Low”. Figure 6.7, presents the histogram of land cover classes within each HAT vector habitat zone in the main study area. For the other two local government areas (Oshimili north/south and Patani), the histogram of their land cover are presented in Figures 6.8 and 6.9, respectively, while the minor study area results are shown in Figure 6.10.

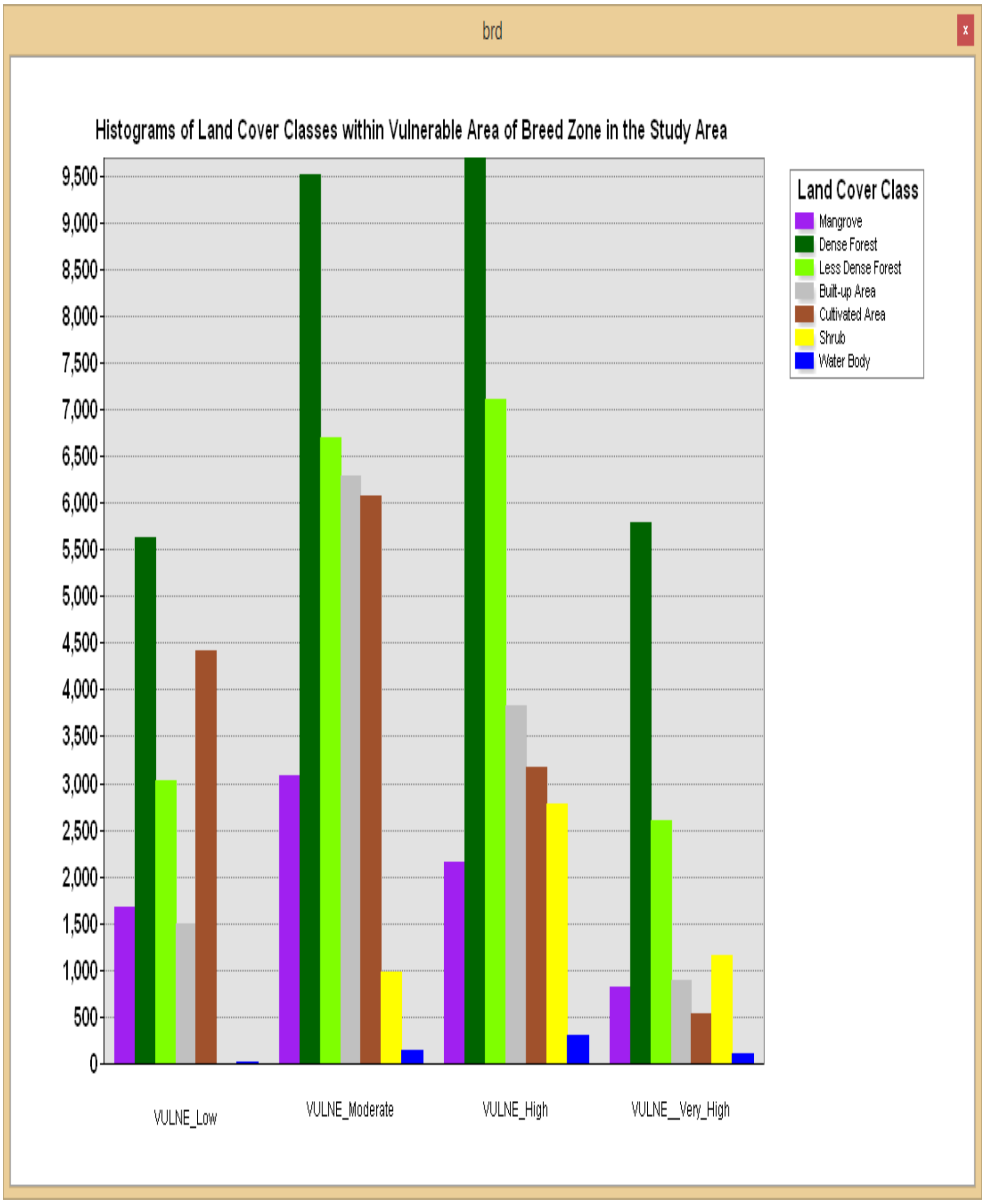


Figure 6.7a: Frequency distributions of land cover classes within HAT vector breed zone in main study area (VULNE_Low = low vulnerability category; VULNE_ Moderate = moderate vulnerability category; VULNE_ High = high vulnerability category and VULNE_Very_High = very high vulnerability category).

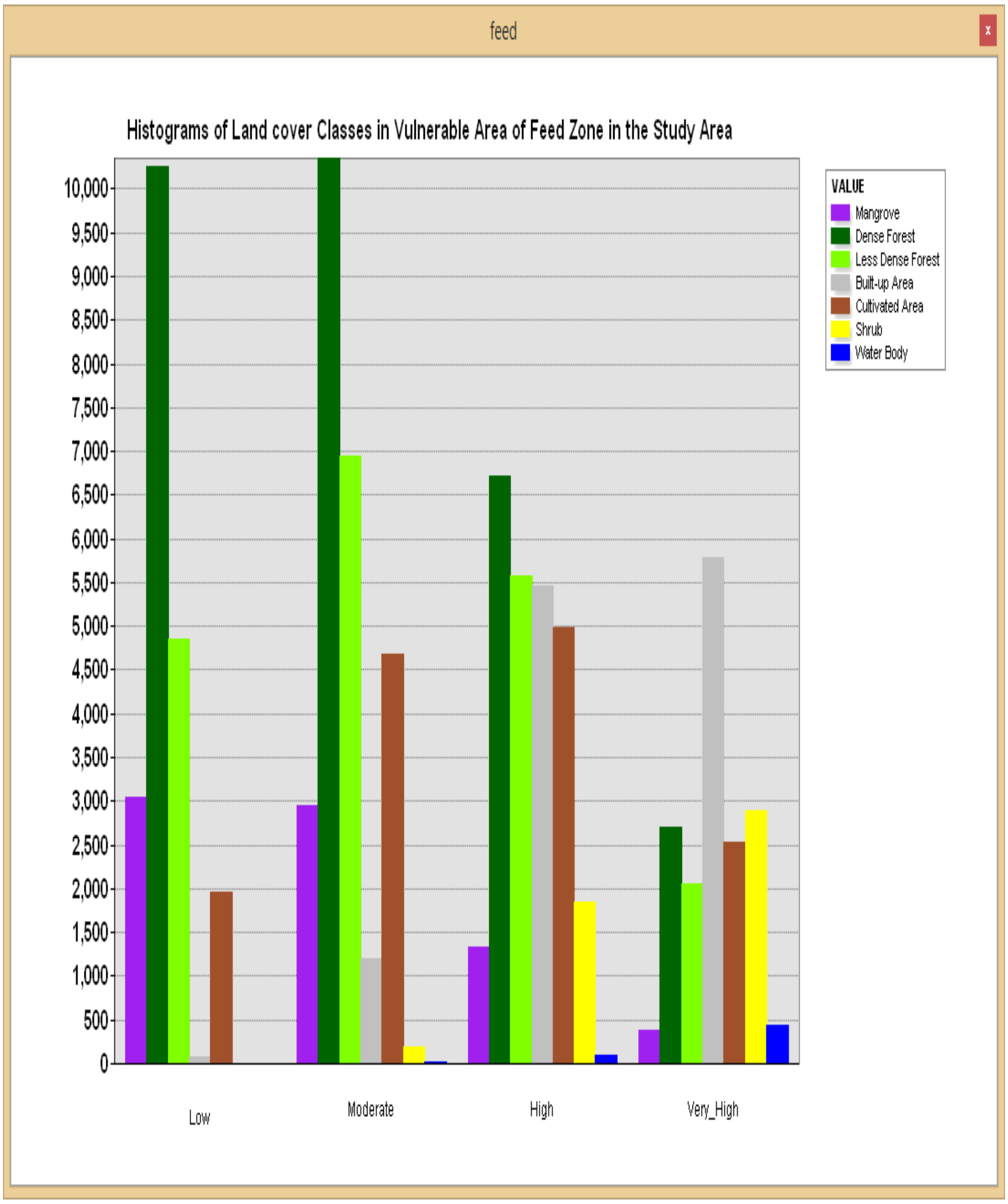


Figure 6.7b: Frequency distributions of land cover classes within HAT vector feed zone in the main study area

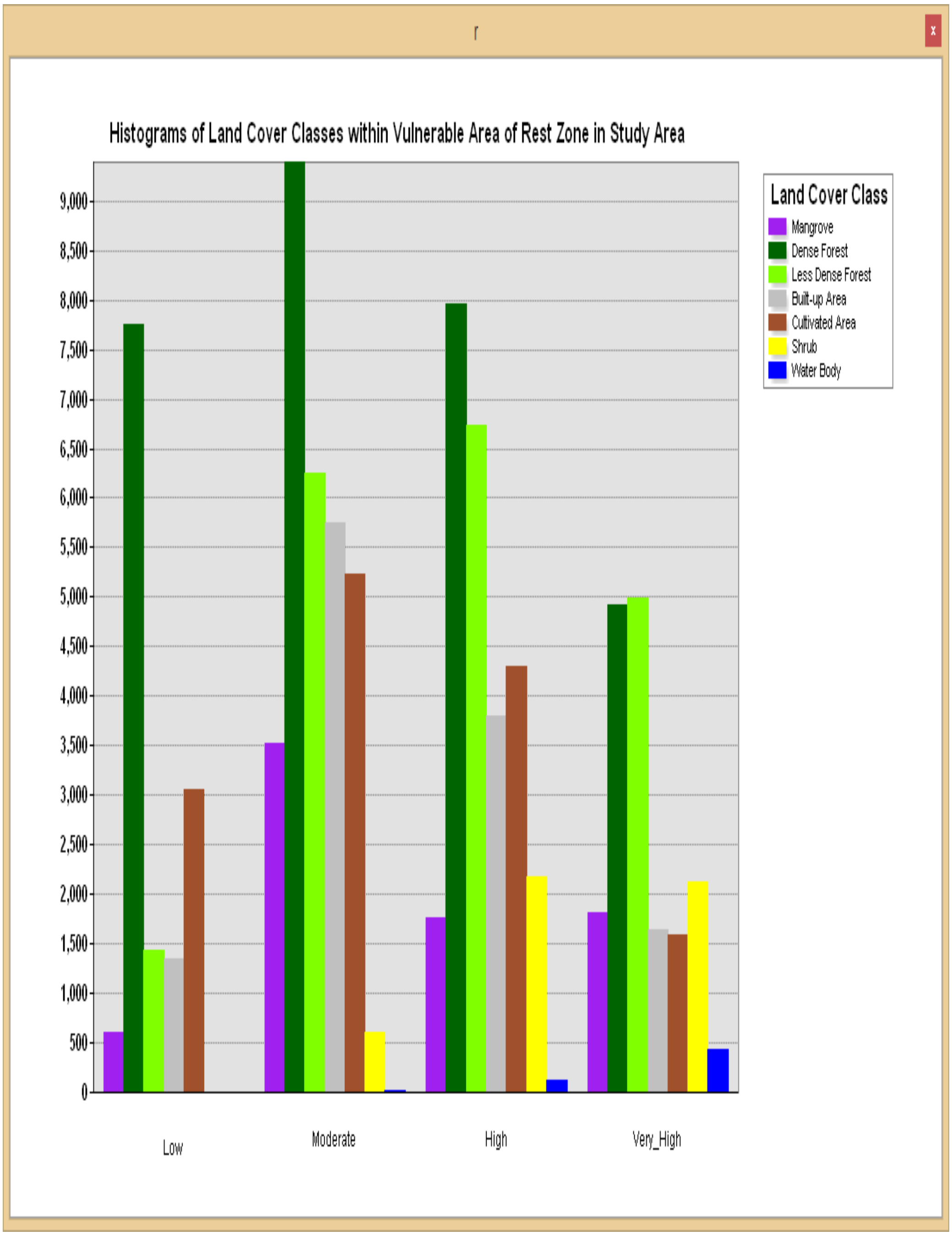


Figure 6.7c: Frequency distributions of land cover classes within HAT vector rest zone in the main study area

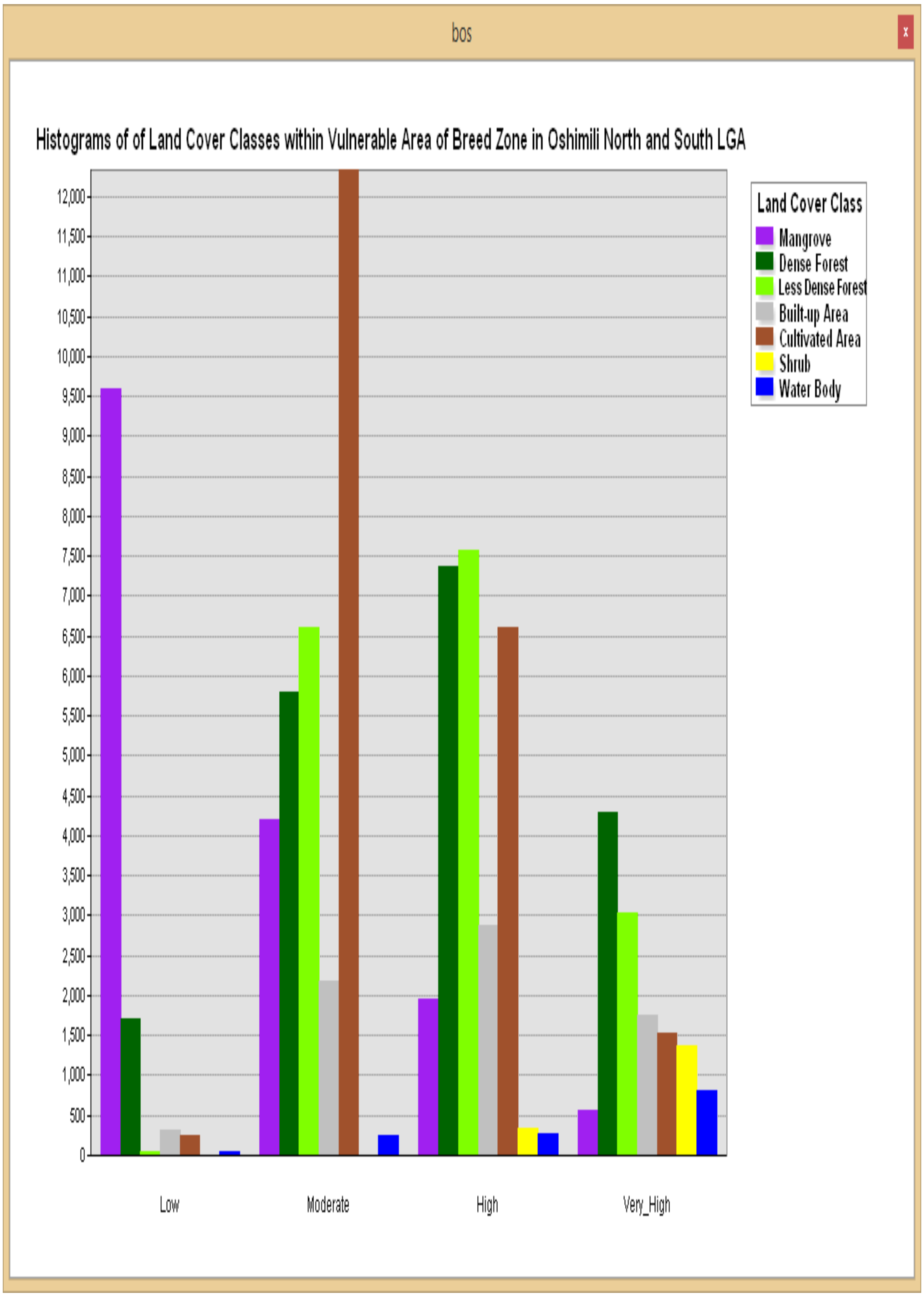


Figure 6.8a: Frequency distributions of land cover classes within HAT vector breed zone in Oshimili North/South LGA

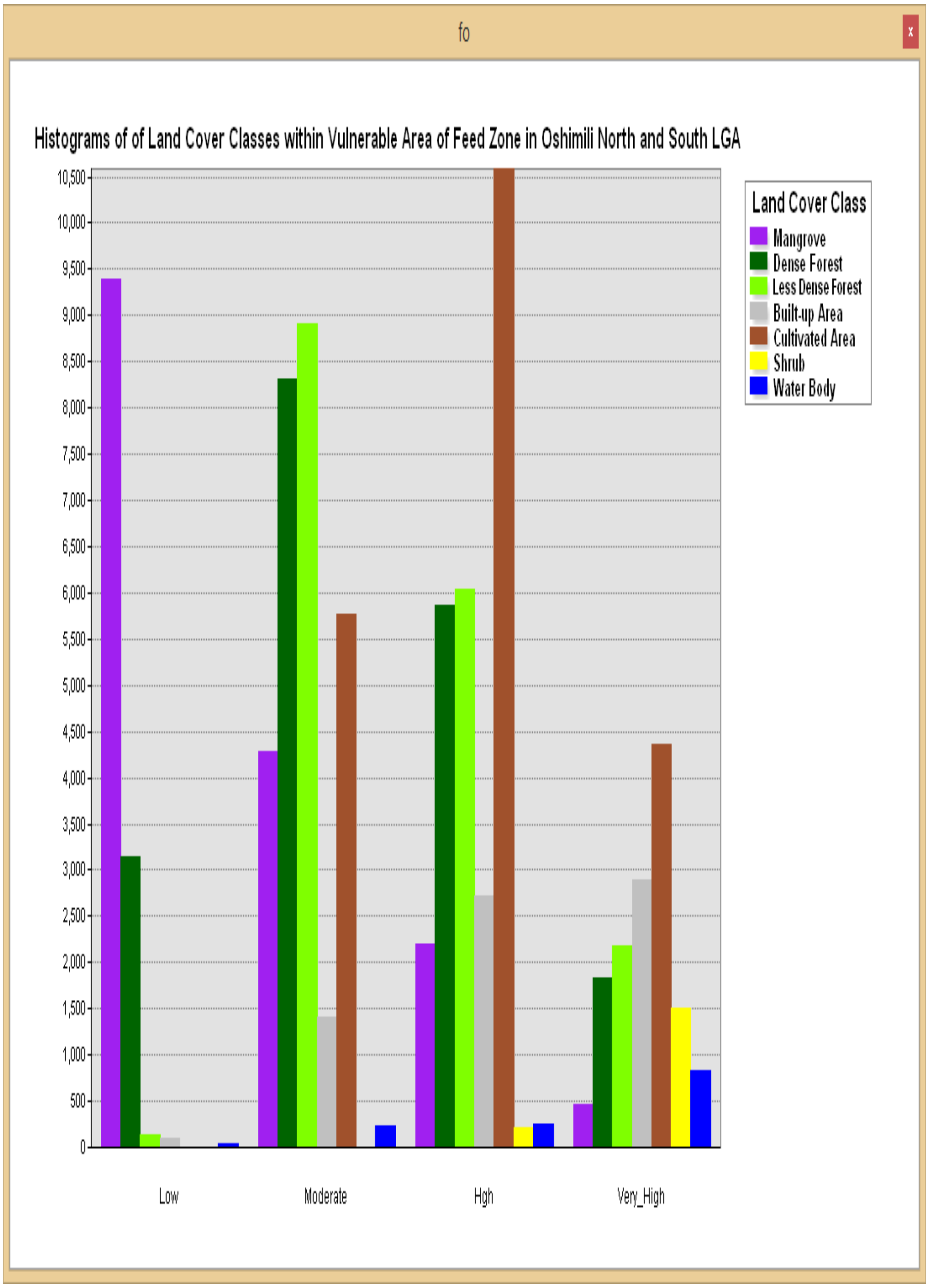


Figure 6.8b: Frequency distributions of land cover classes within HAT vector feed zone in Oshimili North/South LGA

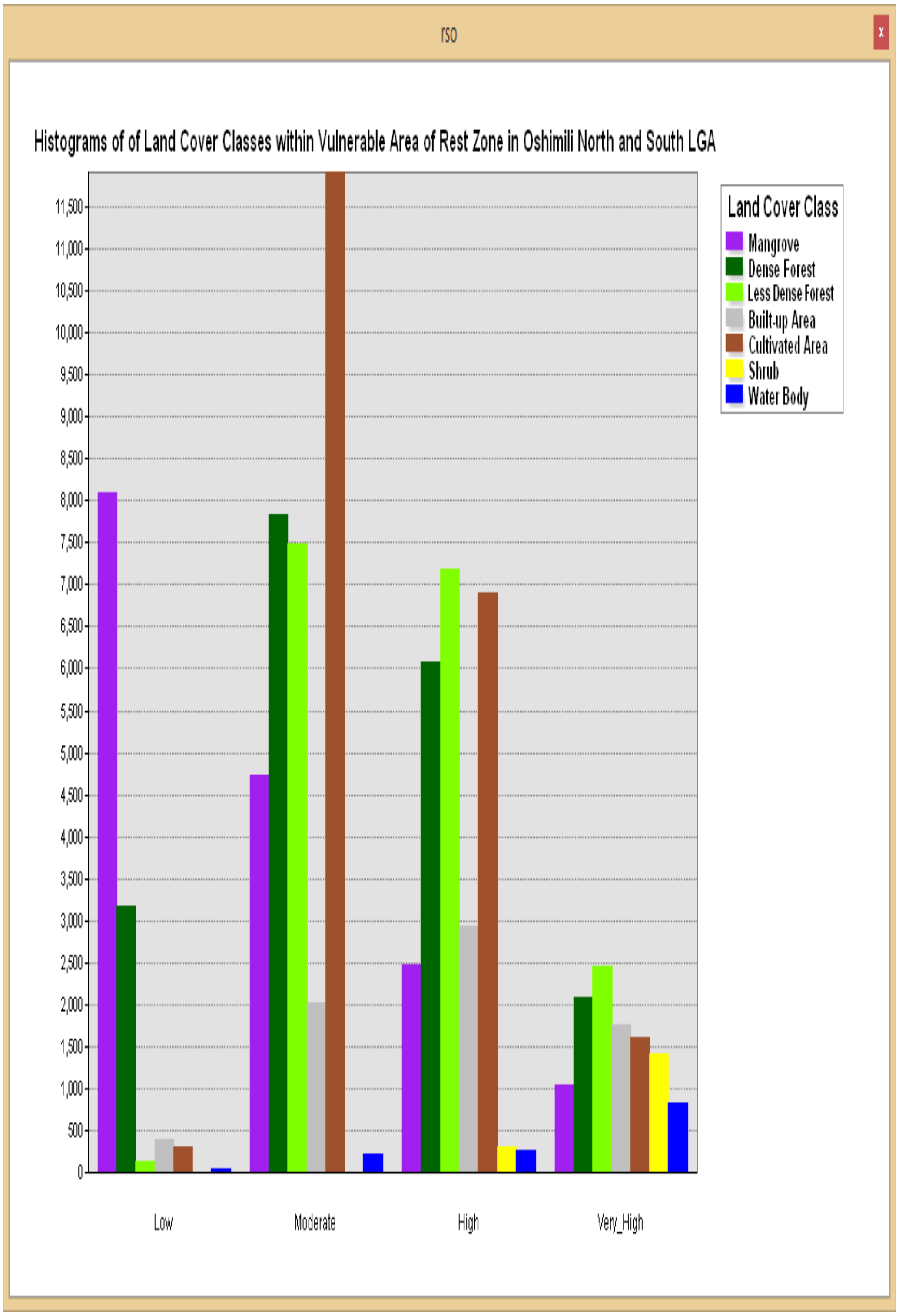


Figure 6.8c: Frequency distributions of land cover classes within HAT vector rest zone in Oshimili North/South LGA

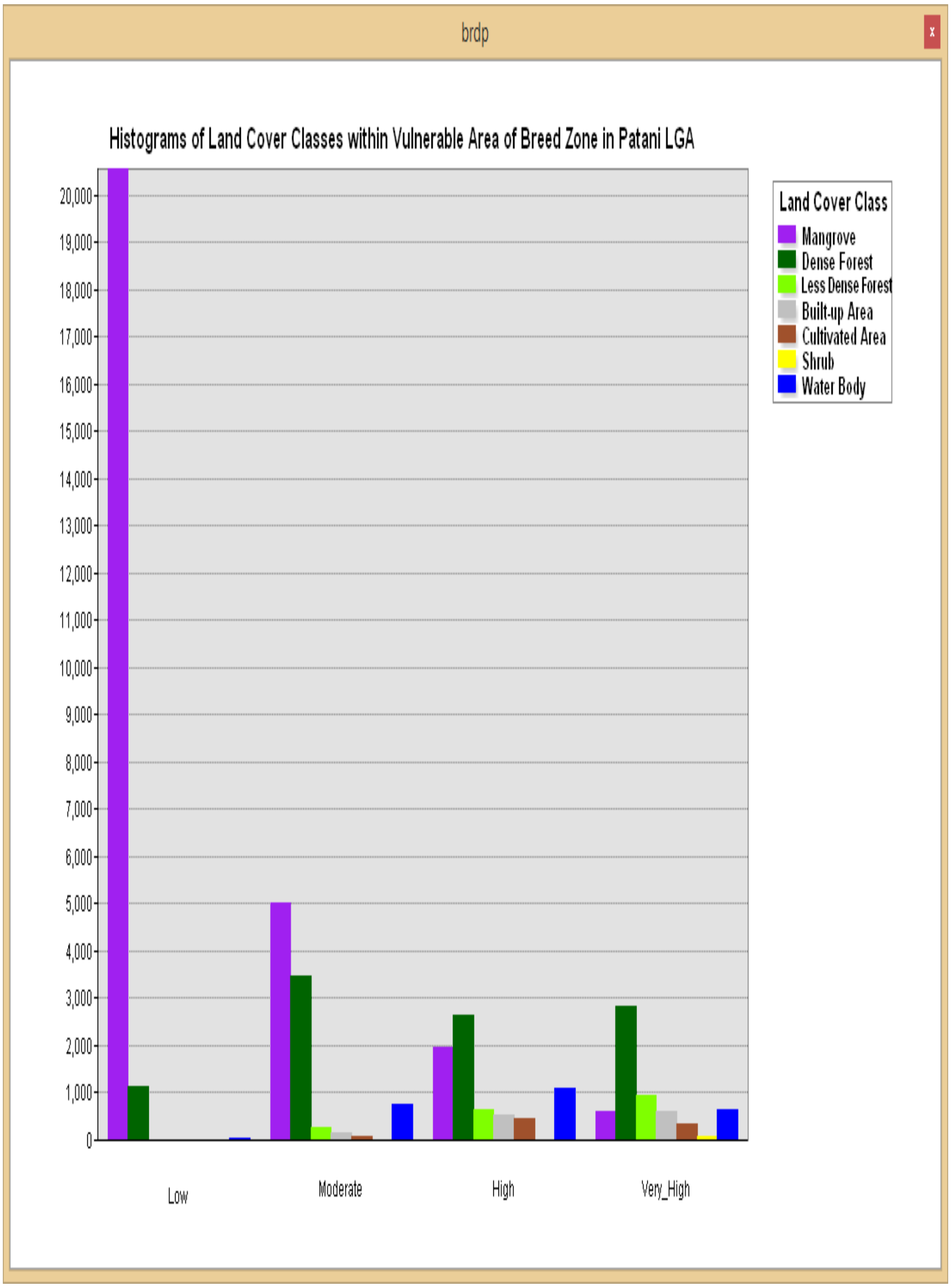


Figure 6.9a: Frequency distributions of land cover classes within HAT vector breed zone in Patani LGA

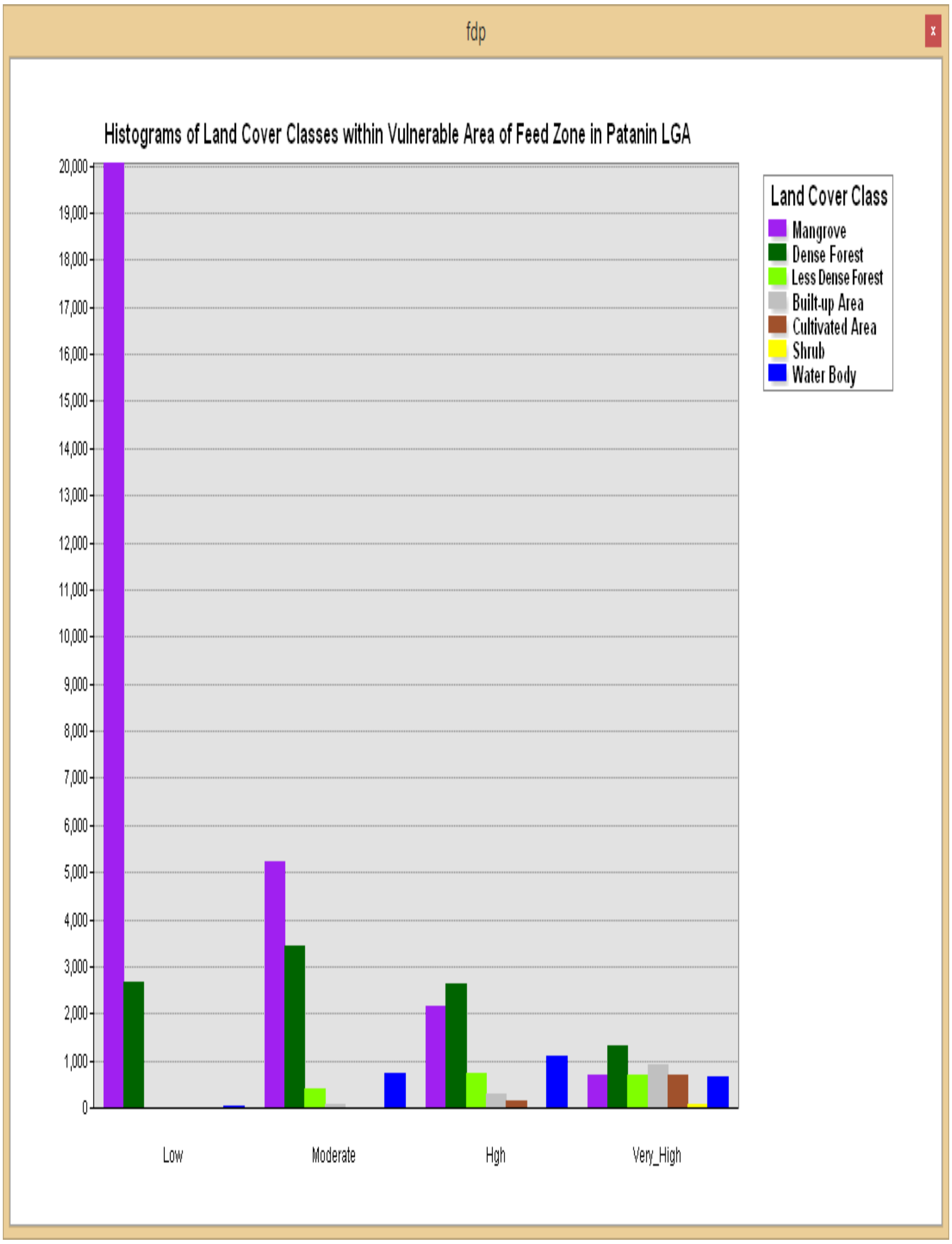


Figure 6.9b: Frequency distributions of land cover classes within HAT vector feed zone in Patani LGA

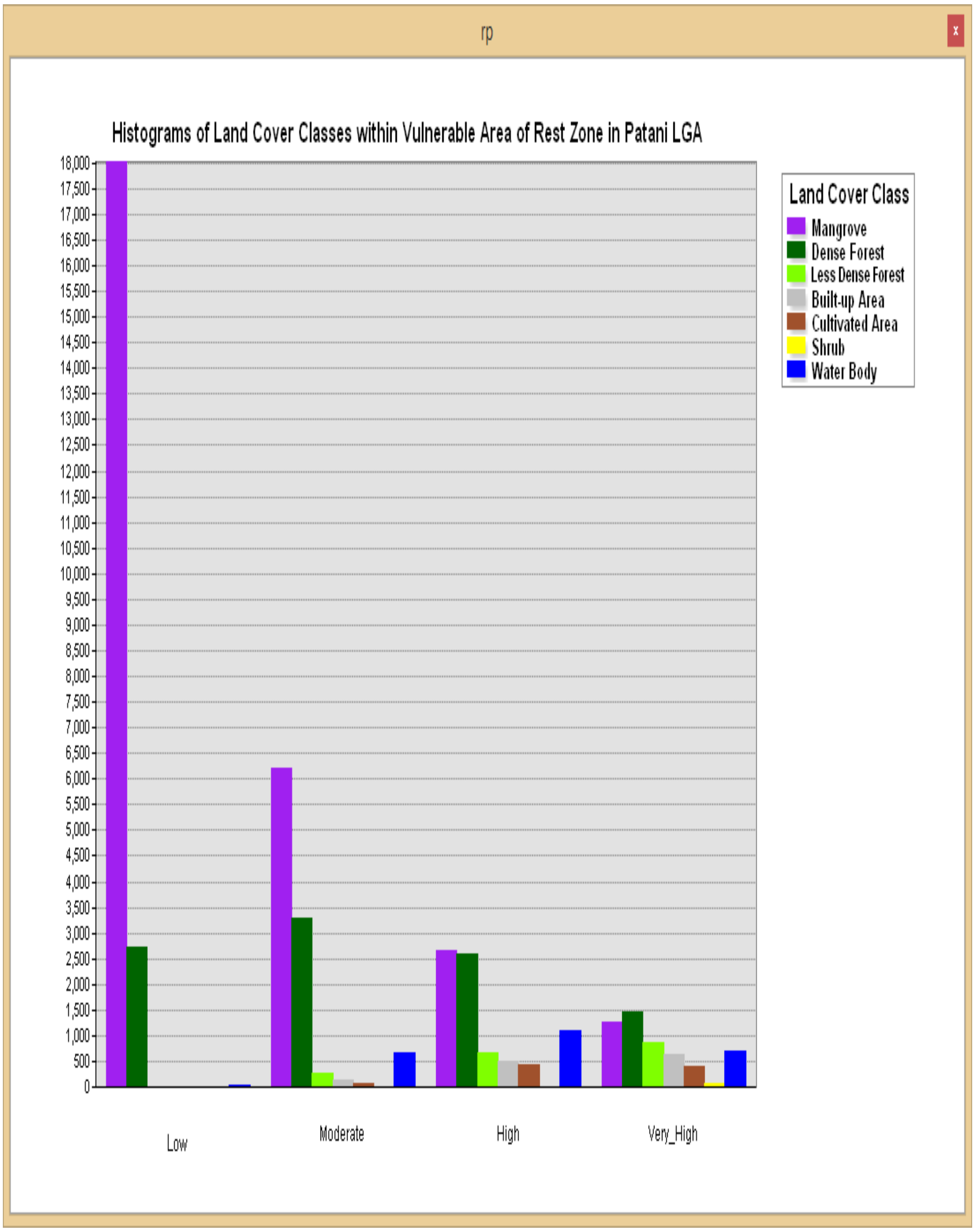


Figure 6.9c: Frequency distributions of land cover classes within HAT vector rest zone in Patani LGA

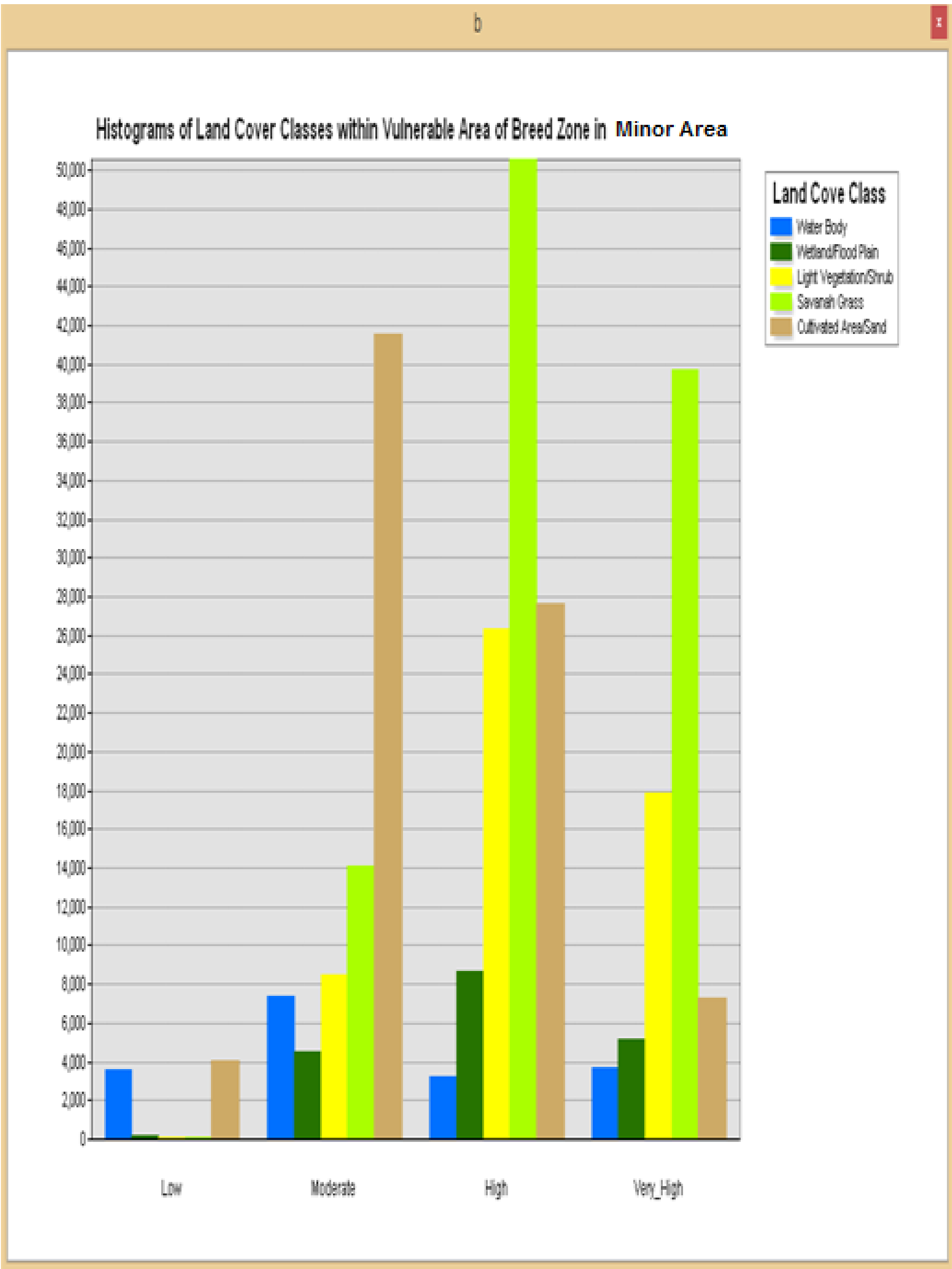


Figure 6.10a: Frequency distributions of land cover classes within HAT vector breed zone in minor study area

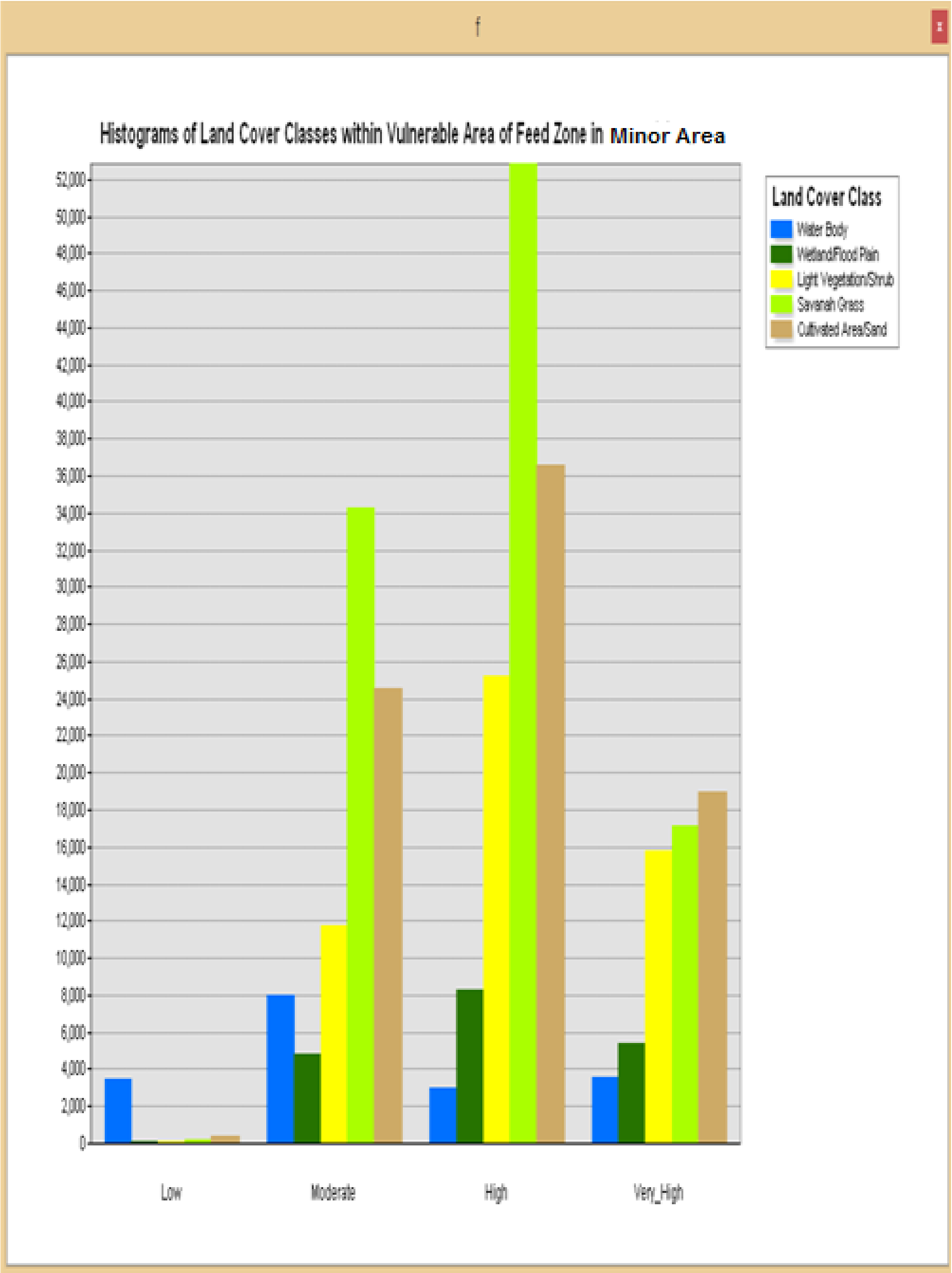


Figure 6.10b: Frequency distributions of land cover classes within HAT vector feed zone in minor study area

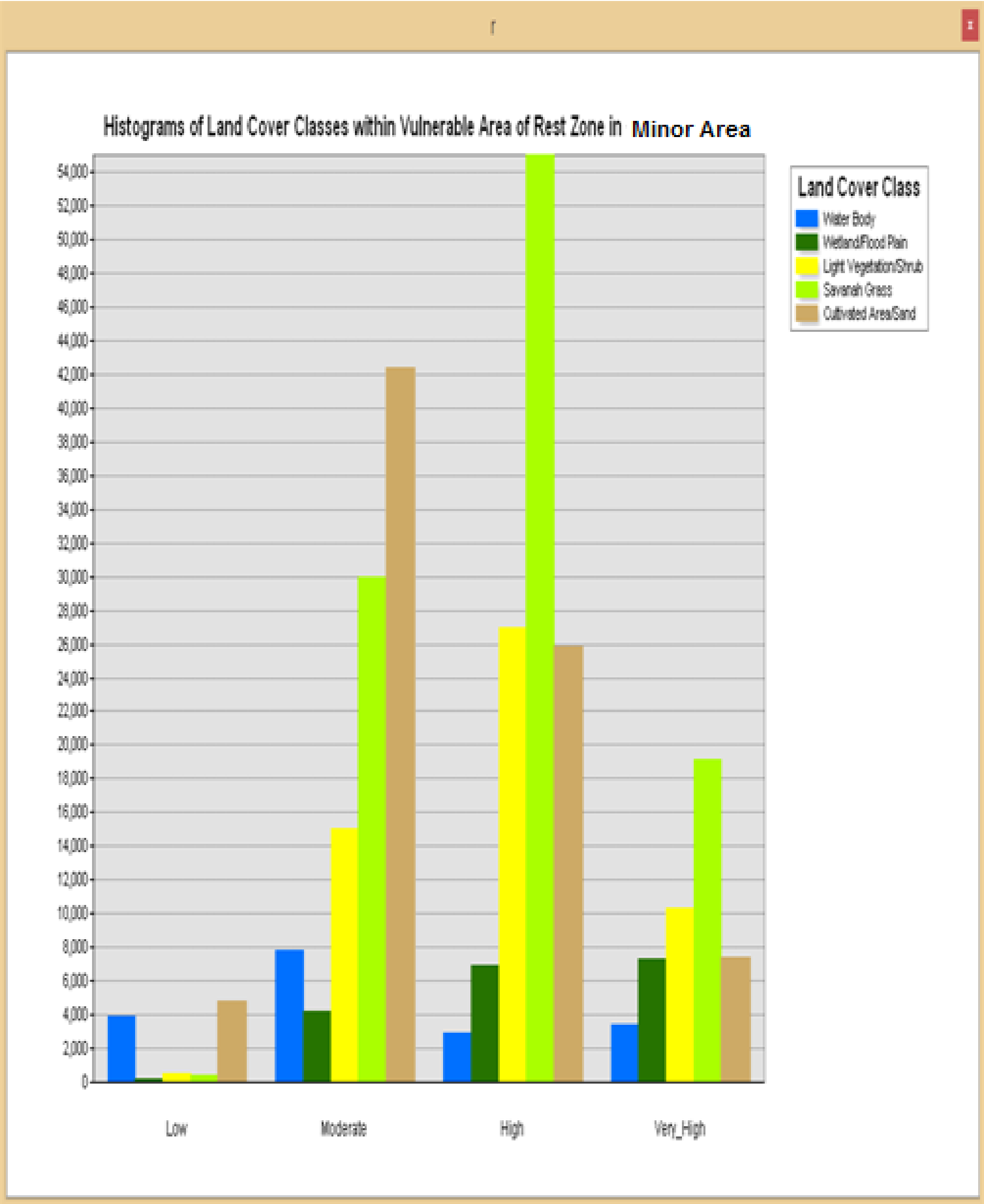


Figure 6.10c: Frequency distributions of land cover classes within HAT vector rest zone in minor study area

6.7 Land Cover Suitability Assessment for HAT Vector within Habitat Zones

In order to establish the suitability of the land cover classes for the HAT vector, the classes grouped within the very high and high vulnerability categories in each vector habitat zone (section 6.6 histograms), were investigated. The researcher adapted the Cecchi et al. (2008) tsetse fly suitability index for the suitability analysis. Cecchi et al. (2008), determined land cover suitability for tsetse flies based on the percentage of the entire surface affected by the fly within a land cover class. In the context of this research, the land cover suitability for the HAT vector was determined based on the percentage of each HAT vector habitat zones (breed, feed and rest), within a specified land cover class. The land cover suitability analysis was carried out for both the main and minor study areas and the results are presented in Tables 6.6 for the main study area and Tables 6.7 for the minor study area.

Table 6.6a: Suitability of land cover classes for HAT vector within HAT vector breed zone in the main study area

Land cover class	Area of land cover within Study area (m^2)	Area of breed zone within land cover class (m^2)	% of breed zone within land cover	Suitability category for tsetse	Suitability Index	Description
Mangrove	65528100	6634167.5	10.1	Low	1	**Potential low hazard locations**
Dense Forest	260262900	248478954.5	95	High	3	**Potential highest hazard locations**
Less-dense Forest	165814200	147229124.5	89	High	3	**Potential highest hazard locations**
Built-up Area	105891300	15269656.4	14	Low	1	**Potential low hazard locations**
Cultivated Area	121106700	15763599.6	13	Low	1	**Potential low hazard locations**
Shrub	42045300	34414211.7	82	High	3	**Potential highest hazard locations**
Water Body	4968900	3687541.1	74	High	3	**Potential highest hazard locations**

Table 6.6b: Suitability of land cover classes for HAT vector within HAT vector feed zone in the main study area

Land cover class	Area of land cover within Study area (m^2)	Area of feed zone within land cover (m^2)	% of feed zone within land cover	Suitability category for tsetse	Suitability Index	Description
Mangrove	65528100	289552.9	0.4	Non	0	**Potential Hazard free locations**
Dense Forest	260262900	7017399.3	3	Non	0	**Potential Hazard free locations**
Less-dense Forest	165814200	20140957.9	12	Low	1	**Potential low hazard locations**
Built-up Area	105891300	98303203.6	92.8	High	3	**Potential highest hazard locations**
Cultivated Area	121106700	105048082.5	86.7	High	3	**Potential highest hazard locations**
Shrub	42045300	37488582.0	89	High	3	**Potential highest hazard locations**
Water Body	4968900	4309228.2	86.7	High	3	**Potential highest hazard locations**

Table 6.6c: Suitability of land cover classes for HAT vector within HAT vector rest zone in the main study area

Land cover class	Area of land cover within Study area (m^2)	Area of rest zone within land cover (m^2)	% of rest zone within land cover	Suitability category for tsetse	Suitability Index	Description
Mangrove	65528100	58549296.1	89.3	High	3	**Potential highest hazard locations**
Dense Forest	260262900	28333601.2	11	Low	1	**Potential low hazard locations**
Less-Dense Forest	165814200	128135666.8	49	Moderate	2	**Potential fairly high hazard locations**
Built-up Area	105891300	10756038	10.2	Low	1	**Potential low hazard locations**
Cultivated Area	121106700	14383965.3	12	Low	1	**Potential low hazard locations**
Shrub	42045300	32710959.5	78	High	3	**Potential highest hazard locations**
Water Body	4968900	3755671.2	76	High	3	**Potential highest hazard locations**

Table 6.7a: Suitability of land cover classes for HAT vector within HAT vector breed zone in the minor study area

Land cover class	Area of land cover within control area (m^2)	Area of breed zone within land cover (m^2)	% of breed zone within land cover	Suitability category for tsetse	Suitability index	Description
Water Body	151676100	147489662.8	9	High	3	**Potential highest hazard locations**
Wetland/ Flood Plain	157037400	7613180.	5	Low	1	**Potential low hazard locations**
Light Vegetation/ Shrub	443632500	304552334.4	67	High	3	**Potential highest hazard locations**
Savannah Grass	886448700	600578577	68	High	3	**Potential highest hazard locations**
Cultivated Area/Sand	681762600	0	0	Non	0	**Potential Hazard free locations**

Table 6.7b: Suitability of land cover classes for HAT vector within HAT vector feed zone in the minor study area

Land cover class	Area of land cover within control area (m^2)	Area of Feed zone within land cover (m^2)	% of feed zone within land cover	Suitability category for tsetse	Suitability index	Description
Water Body	151676100	147338906.8	97	High	3	**Potential highest hazard locations**
Wetland/ Flood Plain	157037400	8760601.2	6	Low	1	**Potential low hazard locations**
Light Vegetation/ Shrub	443632500	69900552.3	16	Low	1	**Potential low hazard locations**
Savannah Grass	886448700	301512.1	0.03	Non	0	**Hazard free location**
Cultivated Area/Sand	681762600	558919656.9	82	High	3	**Potential highest hazard locations**

Table 6.7c: Suitability of land cover classes for HAT vector within HAT vector rest zone in the minor study area

Land cover class	Area of land cover within control area (m^2)	Area of rest zone within land cover (m^2)	% of rest zone within land	Suitability category for tsetse	Suitability index	Description
Water Body	151676100	139005447.7	92	High	3	**Potential highest hazard locations**
Wetland/ Flood Plain	157037400	15184483.7	10	Low	1	**Potential low hazard locations**
Light Vegetation/	443632500	13124151.1	3	Non	0	**Hazard free location**
Savannah Grass	886448700	301512.1	0.03	Non	0	**Hazard free location**
Cultivated Area/Sand	**681762600**	**0**	**0**	**Non**	**0**	**Hazard free location**

6.8 Validation of the Classification Scheme Application

Apart from the validation analysis carried out in section 5.4, the classification scheme was further validated by investigating its practicability. To achieve this aim, two other local government areas in Delta State namely, Oshimili North/South and Patani were investigated to identify potential hazard areas and potential HAT propagation factors.

A HAT surveillance exercise sponsored by the WHO in collaboration with FMOH, Nigeria and NITR took place in the last quarter of 2010 in some parts of Delta state. Oshimili North/South and Patani local government areas were included to validate the practicability of the HAT classification scheme developed in this research. The minor study area (Jigawa State) was also investigated using the developed classification scheme. HAT surveillance sponsored by the WHO in collaboration with FMOH, Nigeria and NITR took place in the minor study area. This was done by dividing the Jigawa State study area into 10km by 10km grids; within each grid, traps (Appendix A-5k) baited with cattle urine and acetone were deployed at 200 meters interval (Figure 6.11). Traps were set on the 22/11/2011 between the hour of 11am to 5pm at potential tsetse habitats; that is, vegetal and water body areas as well as open areas. On the 23/11/2011, the sites were visited for harvest between the hours of 5-6.30pm. Traps were then left until 24/11/2011, when they were removed between 3pm to 6pm.

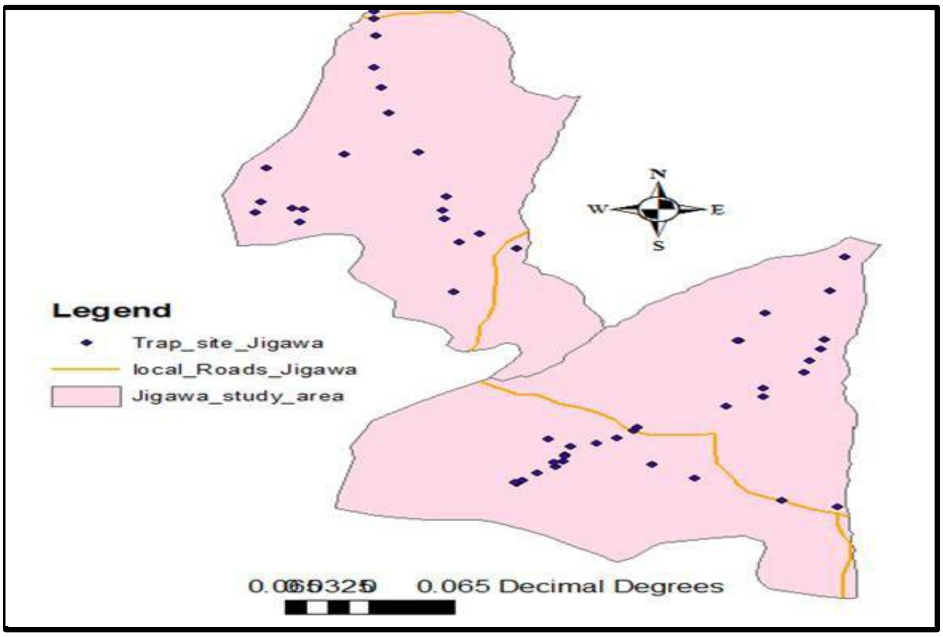


Figure 6.11: Tsetse flies trap Sites within the minor study area

6.9 Assessment of Landscape using Change Detection

Due to none harvesting of tsetse fly in the minor study area (Jigawa State) during the field survey, it became necessary to investigate why the main study area is considered an active foci and the minor study area is no longer active. This was necessary, as there was previous evidence of HAT in the minor study area (section 2.1; Figure 2.3). The land cover suitability analysis carried out also indicated the suitability of some land cover classes for HAT vector in the minor study area.

To investigate the landscape characteristics of both the main and minor study areas, change detection assessment was used. The algebraic technique (details in section 1.5.3) was used to classify each image used separately, while the multi-date composite technique was used to assess and detect the presence or absence of change. The difference epoch images used to access change in the study areas are: 1987 Landsat TM 4, 2002/2011 Landsat ETM+ for the main study area and 1972 Landsat MSS1, 1986 Landsat TM5, 2003/2012 Landsat ETM+ images for the minor study area. The algebraic technique includes tasseled cap transformation (TCT). The TCT involved the brightness component only; this was because of the constraints associated with the RS images epochs available for the present research. For example, Landsat 7 ETM+ acquired for years 2011 and 2012 has stripes and cloud cover. In order to obtain enough evidence of the level of change in the study areas, NDVI and NDWI were calculated. These indexes were very vital to HAT propagation. Part of the work in this chapter has resulted in publications (Akiode, Oduyemi and Badaru 2014a, b).

6.9.1 Change detection using brightness tasseled transformation

The study areas were masked from the transformed image generated in section 3.2.1.3, after which statistical threshold was assigned to the pixel values of the transformed images. This was done by calculating the z-score (Equation 6.1) of the transformed image pixel values. Based on the z-score, the brightness map for each year was grouped into four categories namely:

- Least: for areas with least brightness value
- Low: for areas with low brightness value
- Moderate: for areas that are moderately bright
- High: for areas that recorded the highest brightness value

Example of the brightness tasseled cap transformation is presented in Figure 6.12.

$$\text{Z-score} = [\text{Pixel Value}] - \mu / \sigma \qquad 6.1$$

Where: μ = mean of the image pixel, σ = standard deviation of the image pixel

The brightness categorical map was overlaid on the land cover maps of both the main study area and the minor study area in a GIS environment using 70% transparency. This was to view the land cover class that match each brightness category.

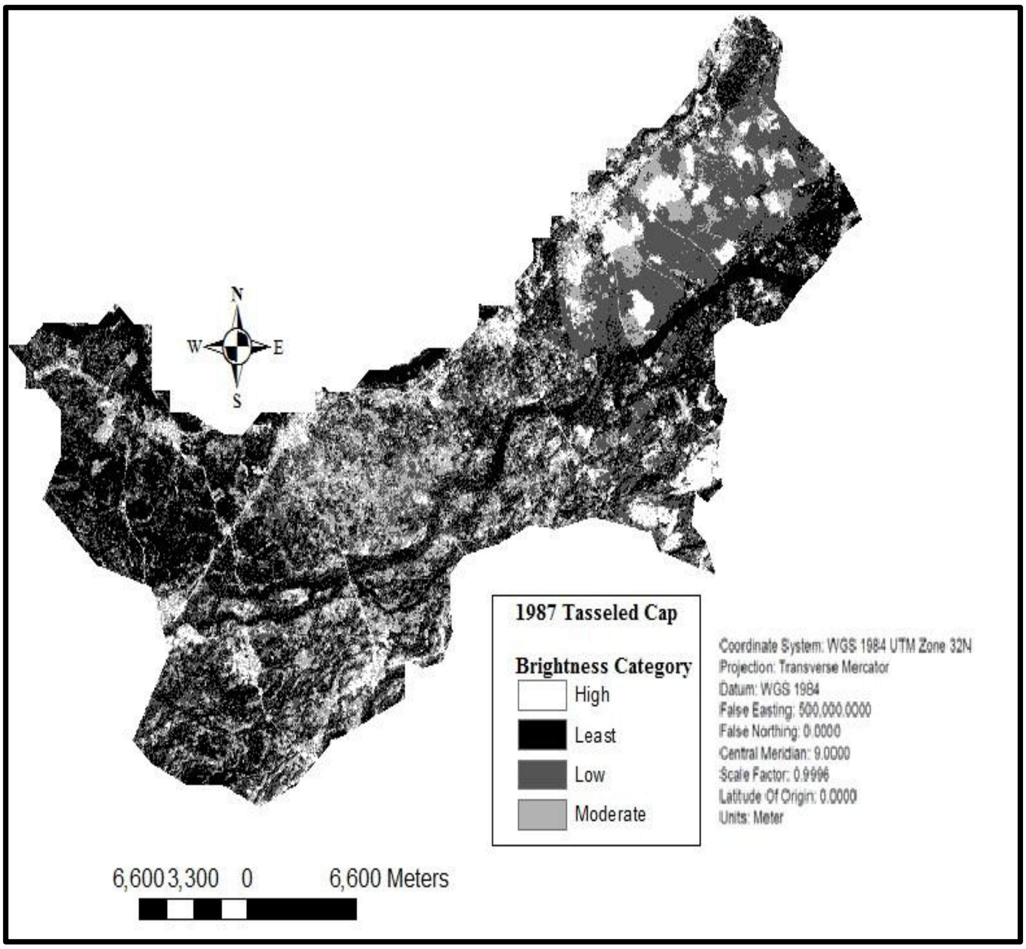


Figure 6.12: 1987 Tasseled cap transformation brightness components for the main study area

6.9.2 Change detection using NDVI and NDWI

The main and minor study areas were masked from the NDVI and NDWI derived in section 3.2.1.3. The NDVI and the NDWI were reclassified into two classes based on their pixel values. The pixels with negative values were classified as "NDVI/NDWI Negative" and pixels with positive value were classified as "NDVI/NDWI Positive". To establish change, the differences between the resulting calculations were found.

6.10 Courtin et al. (2005) Vis-a-Vis Present Research

The study by Courtin et al. (2005) entitled "Towards understanding the presence/absence of human African trypanosomiasis in a focus of Cote d'Ivoire:

a spatial analysis of the pathogenic system", was carried out on a regional scale covering two different parts of Cote d'Ivoire. The present research was also carried out at regional scale within two distinct regions of Nigeria (the main study area is in the south while the minor study area is in the northern part).

Courtin et al. (2005) applied transect methodology to assess landscape, this was able to produce areas at risk of HAT within their study area. However, their result was not detailed enough as their landscape analysis only provided a "summarised" or broad-risk assessment. According to Tildesley and Ryan (2012), there was considerable model divergence from actual data when broadly grouped land cover data were applied to map locations within a landscape, but when more detailed land cover data were applied, moderate to highly precise spatiotemporal prediction of disease epidemic were achieved.

The approach used in the present research provides detailed HAT vector habitat classification, with this approach, precise HAT vulnerable and hazardous locations were identified. Also, the approach was able to identify the spatial direction of HAT propagation in the main study area.

Courtin et al. (2005), pointed out that one of the reason for HAT propagation in the southern part of their study area is the suitability of patches of both relict forest and fallow lowland; however, the method used by the authors did not enable them to assess the real suitability of said land covers for the HAT vector. The presence of a patch of forest may not necessarily pose a HAT threat, for example, in the present research, the vegetal covers within and around the settlement that was considered to be the mean centre of HAT (section 4.1.1) was found to have low suitability for the HAT vector when used the classification scheme developed in this research to assess land cover suitability.

The level of detail in the present research will offer more information toward precise and efficient HAT surveillance planning/execution and resource allocation, thus, promoting the general wellbeing of the human population in the study area. Also, targeted control programmes can be planned and executed efficiently with the aid of the classification scheme developed in this research work due to the delineation of the HAT vector habitat into zones.

6.11 Discussion and Results

Using the classification scheme developed for managing HAT, the areas prone to hazard were identified and categorised. From tables 6.1, only 38% of the breed zone was not prone to hazard while only 64% and 30% of the feed and rest zones are free from hazard, respectively. With 46% of the feed zone prone to hazard, the human population could be said to be at moderate risk of HAT. Also, the entire main study area could be classified as highly hazardous, since a greater part of the entire HAT habitat zones (except for the feed zone) fall within the “very high” and ‘high’ hazard categories.

The combination of the factorised distance maps with hazard maps revealed that all the land cover classes were highly concentrated within 0 – 200 metres of each HAT habitat zone. Thus, the main study area is highly vulnerable. Also, all the HAT positive settlements were contained within each zone. The overlapping of the three HAT zones within each settlement revealed the vulnerability of these settlements. This suggests that, human population in each settlement could be at risk of HAT at any time of the day, if any of the HAT vector habitats is disturbed. Overlapping of the HAT habitat zones within the built-up areas negates the assertion by Zoller et al. 2008 that localised transmission around a family home is less likely due to the ecology of the vector, which typically prefers bushes and thickets around wetlands or rivers, away from homesteads.

The result of vulnerability assessment conducted for all the settlements with one or more cases of HAT between 1994 and 2006, revealed, as shown in Table 6.4a, that two out of the nine settlements were highly vulnerable to the breed zone, while the others are moderately vulnerable. Table 6.4b showed that only one settlement is highly vulnerable to the feed zone and one settlement has low vulnerability, while others are moderately vulnerable. For the rest zone (Table 6.4c), two of the settlements have low vulnerability. High vulnerability was recorded for one settlement while others are moderately vulnerable to rest zone.

One important observation was the settlement Abraka, which has low vulnerability to both the feed and rest zones and is moderately vulnerable to the breed zone. The analysis carried out in Chapter 4 revealed Abraka as the mean centre (Figure 4.1) for all the HAT case years except for 1998. The researcher concluded that there may be other factors apart from landscape characteristics contributing to propagation of HAT in the specified settlement. Another settlement that caught the attention of the researcher is Ugonao, which has the highest vulnerability to all the zones. When the three habitat zones were overlaid on the settlement map, the three habitat zones overlapped and completely covered the settlement; this could be responsible for its high vulnerability status.

Risk due to HAT was computed at settlement level. The result of the hazard assessment and vulnerability assessment helps in generating a risk map for the 865 settlements (extracted from Landsat 7 ETM+ image) in the main study area. The risk settlements were categorised into four levels of risk (very high, high, moderate and low) based on the fuzzy membership of each group using natural break, with the highest fuzzy membership grouped as very high risk. Using a logical query, each category of risk was extracted from the main risk map. The output is presented in Table 6.8.

Table 6.8: Number of Settlement at Risk of HAT within HAT Vector Habitat Zones in the study area

	Number of Settlement at Risk of HAT		
Risk Category	**Breed Zone**	**Feed Zone**	**Rest Zone**
Very High	38	357	**94**
High	266	427	**341**
Moderate	553	212	**515**
Low	**270**	**89**	**191**

The total number of settlements at risk of HAT in each category exceeds the total number of settlements in the main study area because the categories overlapped. Two or more categories may be present within a settlement. The prioritisation analysis identified all the settlements in the main study area as settlements of the highest priority.

The directional analysis highlighted the areas that should be looked at closely. It showed that the human population residing at the north-eastern and north-western parts of the main study area are most at risk. The directional analysis indicated that the disease is spreading north-east and north-west as well as south-east. Thus, one can conclude that the magnitude of HAT in the main study area is multidirectional. Therefore, there is need to allocate more resources to the identified areas to support the existing surveillance system. Though, the prioritisation analysis classified all settlements as very high priority, the settlements in the north-eastern and north-western parts need urgent attention.

The vulnerability assessment revealed that, among the factors responsible for HAT propagation in the main study area was overlapping of the "breed", "feed" and "rest" zones within built-up areas. The histogram analysis for the main and minor study areas as well as the other two local government areas in Delta State revealed the land cover types that contributed or are contributing most to HAT propagation in the areas.

The researcher observed that the histogram analysis did not reveal true information, it was noticed that the area coverage of the vulnerability category within specified locations influenced the result. Therefore, high frequency distribution of a land cover in a location may not necessarily mean high suitability. As a result of this observation, a land cover suitability assessment was performed for both the main and minor study areas. The results, shown in Table 6.6, revealed water bodies and shrub as potentially the highest contributing factors to HAT propagation in the main study area. Another factor highlighted was less-dense forest, which can be categorised as a moderate potential contributing factor based on the analysis. In the minor study area (this area is in different ecological zone to the main study area, thus different land cover combinations; section 2.1 and Figure 2.1), major potential contributing factors (Table 6.7) deduced from the suitability analysis were water bodies and to a lesser extent wetland/flood plain. The researchers' deduction was based on the fact that these land covers were prominent in all the three HAT vector habitat zones. The continuous exposure of human population to these land cover classes (water bodies, shrub and less-dense forest) in the main study area could increase HAT propagation.

The main study area is a portion of Delta State, Nigeria. From the information obtained from the National Bureau of Statistics, Nigeria (2008 a, b, e), 76.6% of the total population of the state depends on fire wood for cooking, and only 7.3 % have access to pipe borne water, while 53.6% do not have access to high grade toilet facilities. It should be noted that these figures are for the entire state, that is, both urban and rural areas. There is no doubt that if these statistics are estimated for the rural areas alone, the lack of basic infrastructure would be higher.

Majority of the human population in the main study area depends on the identified land cover classes (water bodies, shrub and less-dense forest) for survival. For example, because of lack of good toilet facilities, people depend on the shrub in and around the settlement. In addition, agriculture and fishing are the major occupations in the state; people are exposed to water bodies on a daily basis. For fire wood collection, the less-dense forested and shrubs are the major sources. As a result of the above, the risk of exposure of the human population to HAT in the main study area may continue to soar if other conditions such as climate are favourable.

For the other two LGAs (Oshimili North/South and Patani), the result identified all the factors identified in the main study area as potential HAT propagation factors. Also the three HAT habitat zones overlapped in and around their built-up areas.

The surveillance exercise that took place in 2010 in Delta State, Nigeria yielded Card Agglutination Trypanosomiasis Test (CATT) positive results in selected settlements within the feed zone identified with the aid of the new HAT classification scheme. CATT is a field and laboratory test for diagnosis of *T.b.gambiense* sleeping sickness; the test is conducted using the blood serum or other bodily fluid. In the main study area, blood sample was taken from people in three existing foci settlements and two new settlements. All of the selected five settlements in the main study area recorded CATT-positive cases, with a total number of 25 CATT-positive cases recorded out of 672 sampled. The other two LGA (Oshimili North/South and Patani) also recorded CATT-positive cases. Out of 473 human populations sampled at Oshimili North/South LGA, 5 CATT-positive cases were recorded and in Patani LGA, 1 CATT-positive case was recorded out of 115 sampled. Figure

6.13 and Table 6.9 show the settlements that confirm the practicability of the developed HAT classification scheme and their attributes respectively.

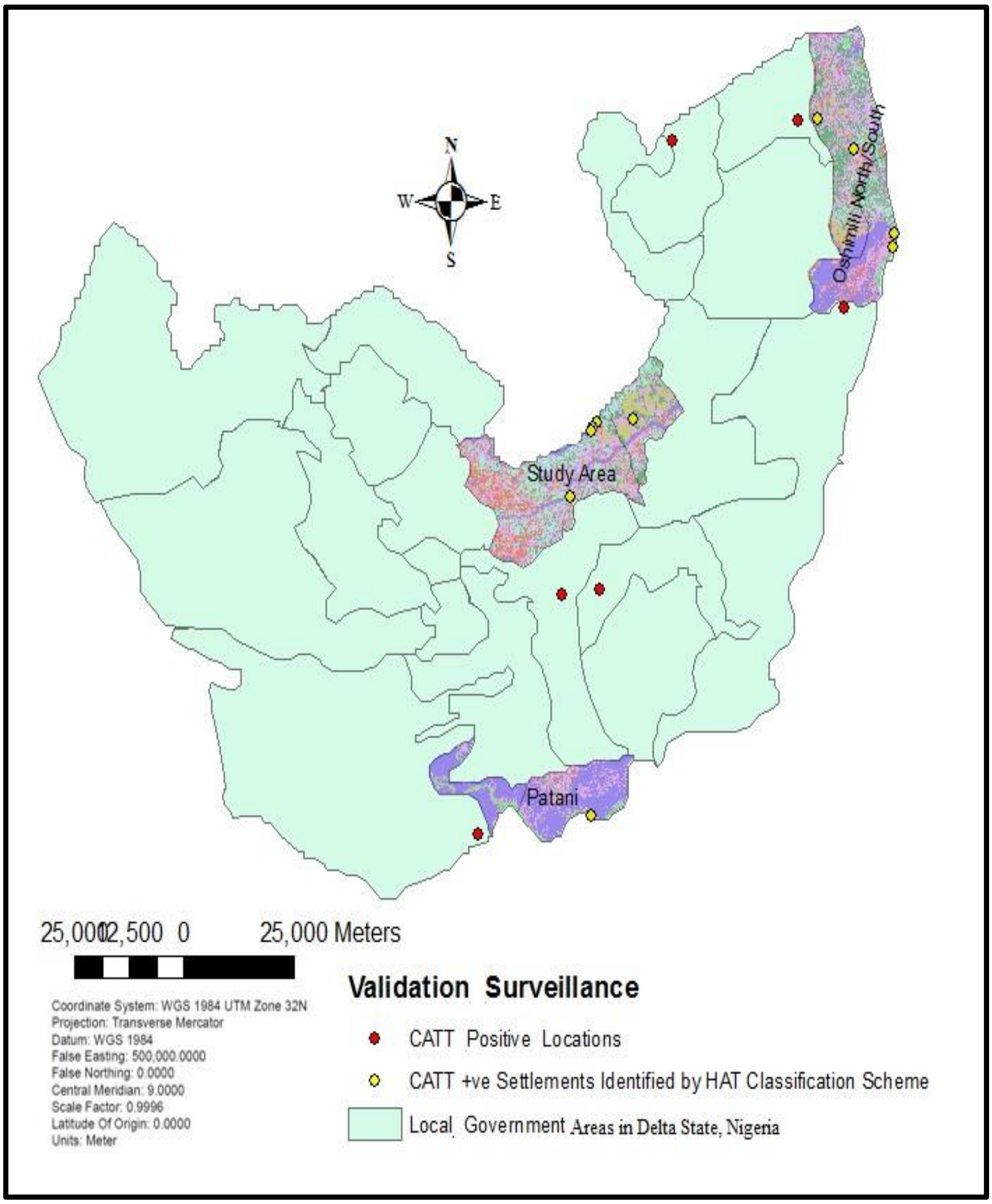


Figure 6.13: Map showing CATT-positive case settlements identified using the newly developed HAT classification scheme

Table 6.9: Attributes of CATT-positive case settlements

Table

CATT_positive_delta

OBJECTID *	Shape *	LGA	VILLAGE	X_COORD	Y_COORD	ESTM_POPUL	NO_SAMPLED	NO_CATT_PO	Z	YEAR_2010
1	Point ZM	Ndokwa East	Aballa Uno	238013.26	665618.03	2088	167	3	23	2010
2	Point ZM	Burutu	Tuomo	154327.983	574456.968	9607	50	1	15	2010
3	Point ZM	Ethiope East	Ugono	175101.325	629933.837	1500	60	5	17	2010
4	Point ZM	Ethiope East	Umeghe	181274.59	643864.01	2150	119	4	32	2010
5	Point ZM	Ethiope East	Urhuoka	180259.46	643056.21	17500	153	13	31	2010
6	Point ZM	Ethiope East	Urhuovie	180155.17	642289.62	1211	74	1	30	2010
7	Point ZM	Isoko North	Owhelogbo	181879.97	612131.62	2000	97	3	18	2010
8	Point ZM	Ika North East	Mbiri	198754.16	697541.14	4894	100	2	220	2010
9	Point ZM	Aniocha North	Iselle Mkpitime	227457.31	701312.522	3508	100	1	222	2010
10	Point ZM	Oshimili South	Oko Amakom	249512.57	677189.14	1100	178	1	26	2010
11	Point ZM	Oshimili North	Atuma	231794.18	701651.58	1432	100	2	197	2010
12	Point ZM	Patani	Ogeinware	179919.914	569340.892	2000	115	1	10	2010
13	Point ZM	Ukwuani	Akokuno/Umuosele	190402.85	644592.43	5947	266	2	37	2010
14	Point ZM	Ughelli North	Imadje Orogun	173317.729	611415.056	1500	112	2	15	2010
15	Point ZM	Oshimili South	Ugbolu (Mile 5)	248910.73	679619.57	1000	127	1	23	2010
16	Point ZM	Oshimili North	Agwe	239907.72	696169.86	500	68	1	70	2010

1 (10 out of 16 Selected)

CATT_positive_delta

6.11.1 Change detection analysis results

<u>Tasseled Cap Transformation:</u>

The comparison of the brightness categorical map with the land cover maps revealed the land cover classes in each category as presented in Table 6.10, while the brightness index changes between 1987 to 2002 and 1986 to 2003 for the main and minor study areas are presented in Tables 6.11 and 6.12, respectively.

Table 6.10: Land cover classes within the tasseled cap brightness compartment

	Main Study Area	Minor Study Area
Brightness Category	**Land Cover Class**	**Land Cover Class**
Least	Water body, Mangrove	Water body, Wetland/flood plain
Low	Dense forest, Less-dense forest	Light vegetation/shrub
Moderate	Mixture of Shrub, Cultivated area, Less-dense forest	Mixture of Savannah grass, Cultivated area, Light vegetation/shrub
High	Built-up area, Cultivated area	Cultivated area/sand

Table 6.11: 1987 – 2002 brightness tasseled cap transformation for the main study area

	1987		2002		Change Detected	
Brightness Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
Least	252.9	33	221.6	29	-31.3	-4
Low	285.4	37	319.2	42	33.8	5
Moderate	157	21	170.5	22	13.5	1
High	72	9	56	7	-16	-2
Total	**767.3**	**100**	**767.3**	**100**		

Table 6.12: 1986 – 2003 brightness tasseled cap transformation for the minor study area

	1986		2003		Change Detected	
Brightness Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
Least	240.6	10.37	120.0	5	-120.6	-5.37
Low	693.6	29.9	443.04	19	-250.56	-10.9
Moderate	867.2	37.36	1016.10	44	148.9	6.64
High	519.2	22.37	741.41	32	222.21	9.63
Total	2320.6	100	2320.6	100		

From Table 6.11, the least category result indicated that water bodies and mangrove area reduced by 4% between 1987 and 2002 in the main study area. This may be as a result of human activities; parts of the mangrove have been opened up for farming or cultivation and other activities. Farming is an activity associated with the HAT vector feed zone (Table 6.6b). It may also be that the water depth has dropped. The low category indicated a 5% increase in the forested area. The reason for this could be the transformation of parts of the dense forest. The vegetation in the transformed area has been opened up, thus, increasing the reflectance of the soil. Also, some farm produce such as cassava, which is one of the staple foods in the main study area, when fully grown could be classified as shrub. The spectral reflectance of this crop could be mistaken for less-dense forest spectral reflectance.

The moderate category showed a 1% increase over the 15 years. The reason for the low change in the category may be because of a mixture of different land cover classes, which may affect the soil reflectance. The high category revealed a 2% reduction in the area open to high soil reflectance within the built-up and cultivated areas. This may be due to the fact that open spaces within the built-up area are being converted to farm land, thereby reducing the reflectance value of the soil, thus, favouring active propagation of HAT within the feed zone.

From Table 6.12, the least category indicated a 5.37% reduction in brightness of water bodies and flood plains in the minor study area. Reasons for this may include: increased land surface temperature, fadama or wetland farming and deforestation, which tends to open up the terrain leading to high evaporation. The low category showed a brightness reduction of 10.9% in the area covered by light vegetation (savannah forest) between 1986 and 2003. This could be because of grazing activities and deforestation as well as farming activities.

The moderate and high categories revealed increases of 6.64% and 9.63% in brightness, respectively. This increase may be attributed to socio climatic impact such as intense grazing, cultivation activities, desert encroachment as well as very high temperatures; apart from cultivation; these conditions, are not favourable for HAT propagation.

NDVI

The results on change detected in the main and minor study areas using NDVI are presented in Tables 6.13 and Table 6.14, respectively.

Table 6.13a: Percentage of NDVI change in the main study area between 1987 and 2002

	NDVI_1987		NDVI_2002		Change Detected	
NDVI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDVI Positive	613.5	80	515.5	67	-98	-13
NDVI Negative	153.8	20	251.8	33	98	13
Total	**767.3**	**100**	**767.3**	**100**		

Table 6.13b: Percentage of NDVI change in the main study area between 2002 and 2011

	NDVI_2002		NDVI_2011		Change Detected	
NDVI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDVI Positive	515.5	67	386.2	52.6	-129.3	-14.4
NDVI Negative	251.8	33	386.2	47.4	96.2	14.4
Total	**767.3**	**100**	**734.2**	**100**		

Table 6.13c: Percentage of NDVI change in the main study area between 1987 and 2011

	NDVI_1987		NDVI_2011		Change Detected	
NDVI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDVI Positive	613.5	80	386.2	52.6	-227.3	-27.4
NDVI Negative	153.8	20	386.2	47.4	232.4	27.4
Total	**767.3**	**100**	**734.2**	**100**		

Table 6.14a: Percentage of NDVI change in the minor study area between 1972 and 1986

	NDVI_1972		NDVI_1986		Change Detected	
NDVI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDVI Positive	1350.3	58	993.1	43	-357.2	-15
NDVI Negative	970.3	42	1327.5	57	357.2	15
Total	**2320.6**	**100**	**2320.6**	**100**		

Table 6.14b: Percentage of NDVI change in the minor study area between 1986 and 2003

	NDVI_1972		NDVI_1986		Change Detected	
NDVI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDVI Positive	993.1	43	62.3	3	-930.8	-40
NDVI Negative	1327.5	57	2258.3	97	930.8	40
Total	**2320.6**	**100**	**2320.6**	**100**		

Table 6.14c: Percentage of NDVI change in the minor study area between 2003 and 2012

	NDVI_2003		NDVI_2012		Change Detected	
NDVI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDVI Positive	62.3	3	262.7	14.6	200.4	11.6
NDVI Negative	2258.3	97	1539.7	85.4	-718.6	-11.6
Total	**2320.6**	**100**	**1802.4**	**100**		

Table 6.14d: Percentage of NDVI change in the minor study area between 1972 and 2012

	NDVI_1972		NDVI_2012		Change Detected	
NDVI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDVI Positive	1350.3	58	262.7	14.6	-1087.6	-43.4
NDVI Negative	970.3	42	1539.7	85.4	569.4	43.4
Total	**2320.6**	**100**	**1802.4**	**100**		

From Tables 6.13 and 6.14, there was decrease in NDVI in both the main and minor study areas, within the study period, except for the period between 2003 and 2012 in the minor study area, which showed an increase. This may be as a result of afforestation programme on-going in the area. The overall result showed that between 1987 and 2011, the rate of NDVI change in the main study area was 27.4% while between 1972 and 2012 the rate of NDVI change in the minor study area was 43.4%. The NDVI decrease indicated an increase in bare surface in both areas, which may affect the propagation of HAT as vegetation is vital to the survival of HAT vector.

The NDVI analysis revealed that a total 33.1Km^2 and 518.2Km^2 area were not included in the NDVI calculation for 2011 and 2012 for the main and minor study areas, respectively. This was because of the presence of stripes in the Landsat7 ETM+ data used. The stripes return no data value, thus, the no data voids were not accommodated in the NDVI calculation. This might have affected the overall result. The higher rate of NDVI decreased in the minor study area despite the 11.6% increase between 2003 and 2012, is an indication of unfavourable environment for HAT vector survival.

<u>NDWI</u>

The results on change detected in the main and minor study areas using NDWI are presented in Tables 6.15 and Table 6.16.

Table 6.15a: Percentage of NDWI change in the main study area between 1987 and 2002

	NDWI_1987		NDWI_2002		Change Detected	
NDWI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDWI Positive	101.5	13	90	12	-11.5	-1
NDWI Negative	665.8	87	677.3	88	11.5	1
Total	**767.3**	**100**	**767.3**	**100**		

Table 6.15b: Percentage of NDWI change in the main study area between 2002 and 2011

	NDWI_2002		NDWI_2011		Change Detected	
NDWI Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDWI Positive	90	12	102.4	14	12.4	2
NDWI Negative	677.3	88	632.6	86	-44.7	-2
Total	**767.3**	**100**	**735**	**100**		

Table 6.15c: Percentage of NDWI change in the main study area between 1987 and 2011

	NDWI_1987		NDWI_2011		Change Detected	
NDWI_ Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDWI Positive	101.5	13	102.4	14	0.9	1
NDWI Negative	665.8	87	632.6	86	-33.2	-1
Total	**767.3**	**100**	**735**	**100**		

Table 6.16a: Percentage of NDWI change in the minor study area between 1986 and 2003

	NDWI_1986		NDWI_2003		Change Detected	
NDWI_ Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDWI Positive	2.9	0.13	1.84	0.1	-1.06	-0.03
NDWI Negative	2317.7	99.87	2318.72	99.9	1.02	0.03
Total	**2320.6**	**100**	**2320.6**	**100**		

Table 6.16b: Percentage of NDWI change in the minor study area between 2003 and 2012

	NDWI_2003		NDWI_2012		Change Detected	
NDWI_ Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDWI Positive	1.84	0.1	30.3	1.6	28.46	1.5
NDWI Negative	2318.72	99.9	1812.7	98.4	-2220.32	-1.5
Total	**2320.6**	**100**	**1843**	**100**		

Table 6.16c: Percentage of NDWI change in the minor study area between 1986 and 2012

	NDWI_1986		NDWI_2012		Change Detected	
NDWI_ Category	**Area (Km^2)**	**Area (%)**	**Area (Km^2)**	**Area (%)**	**Change (Km^2)**	**Change (%)**
NDWI Positive	2.9	0.13	30.3	1.6	27.1	1.47
NDWI Negative	2317.7	99.87	1812.7	98.4	-505	-1.47
Total	**2320.6**	**100**	**1843**	**100**		

From Tables 6.15 and 6.16, the margin of NDWI change in both the main and minor study areas appeared almost the same. Between 1987 and 2011 the rate of change in the main study area was 1% while that of the minor study area between 1986 and 2012 was 1.5%. The main study area assessment covers 24 years, while the minor study area covers 26 years. This rate of change might be as a result of a similar factor for both areas.

6.12 Summary

The classification scheme developed in this research has been applied for the prioritisation of vulnerable and at risk of HAT settlements. It emphasised the ability of the scheme to enhance decision making. Also, it has been demonstrated that geospatial techniques most especially fuzzy logic, which takes uncertainty into account yield accurate results.

Given the asymptomatic nature of HAT at its early stage, and the possibility of underreporting of HAT, the risk assessment method employed in this research based on the developed HAT vector habitat classification scheme would help stakeholders in identifying all potential risk areas/population and thus, early diagnosis of HAT. The SDE and WSDE analysis (section 4.1.2) based on the available record of HAT cases only revealed north-eastern direction of HAT propagation, while the directional analysis (section 6.4) carried out using the newly developed HAT vector habitat classification scheme revealed a multidirectional magnitude of HAT propagation in the main study area. The method employed in this research will facilitate efficient decision making, planning for resource allocation as well as support active HAT surveillance.

Assessing vulnerability of each settlement in the main study area using the newly developed classification scheme is novel as there are no such studies for the study area or other known areas in sub-Saharan Africa.

Chapter 7: Discussion and Conclusions

7.1 General Discussion

The aims of this research were to examine the potential habitats of the HAT vector, to identify the processes that give rise to spatial distribution of HAT and to map the direction and magnitude of HAT in the main study area.

Chapter 1 gave insights into why this research is necessary and justifications for using geospatial techniques. The main study area terrain characteristics, the inability of the existing health policies to achieve their goal towards efficient health/HAT management, under-reporting of disease and lack of digital spatial data/information were some of the problems revealed in the literature review. Also, the link between RS and landscape features highlighted justifies its use to derive the criteria for the development of HAT vector habitat classification.

Using land cover and ancillary datasets derived from remotely sensed data (as discussed in Chapter 3), geospatial-fuzzy multi-criteria decision analysis was applied for the identification and classification of potential HAT vector habitats into three zones namely ‘Breed’, ‘Feed’ and ‘Rest’ (Chapter 5). The developed classification scheme was applied (Chapter 6) to examine and assess the degree of vulnerability and risk of the human population (using settlements as a proxy) in the main study area to HAT, consequently, highest priority areas were identified. Furthermore, the direction and magnitude of HAT was mapped using the developed HAT vector habitat classification scheme. Also, the newly developed classification scheme was applied to identify the landscape factors influencing propagation of HAT as well as assessing the suitability of these factors for the HAT vector within each HAT vector habitat zone. The landscape suitability assessment carried out using an adapted tsetse fly suitability-threshold, revealed the landscape features that contribute most to the propagation of HAT in the main study area. Using non-spatial data, spatial distribution analysis (Chapter 4) was also applied to identify the direction of HAT propagation and to examine the spatial significance of HAT in the main study area.

7.2 HAT Propagation

The spatial distribution analysis in chapter 4 suggested that HAT is highly clustered in the main study area, most especially in the north-eastern part. It also revealed that females are more susceptible to the disease than the males. The mean centre of HAT in the main study area was highlighted based on the available record of HAT cases; the analysis also highlighted farming and studying as the most vulnerable occupations for HAT.

Further assessment of the main study area in chapter 6 using the HAT vector classification scheme developed in this research not only confirmed the north-eastern direction of HAT propagation in the main study area, but also revealed additional directions. This emphasised the significance of geospatial techniques in precise exploratory analysis. The direction of the disease in the study area may have resulted from the land cover characteristics of the main study area. The north-eastern part tends to have more shrub and pools of water and the less-dense forest is concentrated in this area. The susceptibility of women compared to men to HAT can also be linked to land cover. The land cover suitability analysis carried out in chapter 6 revealed water body, shrub and less dense forest as the landscape features that are influencing HAT propagation in the main study area the most. The risk of HAT propagation is not, however, completely linked to land cover, but depends also on other factors not considered in this research. Women seemed to be more exposed to these land cover classes than men due to, for example, washing of cloths or fetching of water from the stream, this being mainly the responsibility of women and young people (probably students). Also, some of the local markets are surrounded by shrubs and less dense forest (Appendix A-5g). Women are more prominent in these markets than men, and additionally, most women in the main study area are farmers, thus are more exposed to the disease vector. The propagation of HAT in the main study area is, therefore, likely to be due to the favourable landscape and probably the continuous exposure of the human population to water bodies, shrubs and less dense forest.

Another important contributing factor to HAT propagation in the main study area is the overlapping of the HAT vector habitat zones (Breed, Feed and Rest) within the built-up areas. This negates the assertion by Zoller et al. (2008) that localised transmission around a family home is less likely due to the ecology of the vector, which typically prefers wetland bushes and thickets near rivers, away from homesteads. The implication of this for the main study area or other places with similar characteristics is continuous human-vector contact at all times, day or night. This may have serious consequences. Apart from shrub, the identification of water bodies and less dense forest as the largest contributing factors to HAT propagation in the main study area supports previous studies in other parts of sub-Sahara Africa, which have associated the HAT vector with these land cover classes (Courtin et al. 2005; Batchelor 2010; DeVisser and Messina 2009 ; Zoller et al. 2008). Previous, studies generally highlight water bodies, and vegetation as contributing factors. However, the method applied in this research and the level of detail has revealed shrub as one of the most important contributing factors. The implication of this for the main study area is that the majority of human populations may be vulnerable to HAT, because most places of residence are surrounded by shrub, and irrespective of the people's occupation, age or gender, could be infected provided the shrub that is closest is suitable for the HAT vector.

The one direction (north-east) of HAT revealed by the analysis carried out in Chapter 4 may be as a result of insufficient data, as data used was obtained from only one source; the main HAT sentinel centre. People living very far from the sentinel centre may not have been visiting the centre for treatment. Thus, the result may have been underestimated.

Water bodies and wetland/floodplain were identified as the most prominent potential land cover that may influence HAT propagation in the minor study area. However, the disease seemed to have been phased out in the area, due to the absence of the HAT vector, as the survey exercise carried out to harvest HAT vector in the minor study area did not yield any results. This prompted the change detection analysis carried out in Chapter 6, in order to investigate the reason for this. From the change detection analysis, it was deduced that the landscape has changed considerably over the years. Therefore, the absence of the HAT vector in the minor study area may be because the landscape is not for now favourable. Presently, there is no evidence of the disease in the minor study area, but, there is an on-going afforestation and forestation program in the area (this may have influenced the land cover classification obtained for the minor study area). Also, irrigation farming and water reservoir projects are on-going in the area. If these programs continue, the implication for the minor study area may be re-introduction of favourable landscape, thus, re-invasion of the area by the HAT vector.

To overcome the burden of HAT, policy was formulated to strengthen surveillance programmes in Nigeria as discussed in Chapter 1. However, due to the asymptomatic nature of HAT and some constraints, active surveillance may not be sufficient or efficient to manage the disease in Nigeria. There is no doubt that surveillance is important in providing a quantitative assessment of disease burden, and thus help in prioritising resources towards disease management and control, but are insufficient to wholly capture the effect a disease has on the human populations and the environment. For HAT in the main study area, the hospital record of HAT cases failed to give comprehensive details of the disease. Past research only revealed cases in few settlements. This may be due to the fact that the symptoms of HAT are not easily detected in the early stages, or the inadequacy of diagnostic centre. Also, surveillance exercises always take place in selected settlements and thus, may be underreporting the situation.

Based on past surveillance exercises, previous studies, for example, Osue et al. (2008), have suggested a particular settlement as the most vulnerable to HAT in the main study area. In the present research, the said settlement was found to have low vulnerability to the HAT vector when vulnerability assessment was performed for all the settlements that had previous cases of HAT. This suggests there may be other underlying factors responsible for high frequency of HAT in the settlement.

7.3 Method for the Classification and Application of HAT Vector Habitat Scheme

The application of geospatial-fuzzy MCDA to delineate HAT vector habitat has offered precise identification of the direction and magnitude of HAT, the areas at risk of HAT and the factors influencing HAT propagation in the main study area (the other two local government areas inclusive).

The geospatial-fuzzy MCDA used in this research considered the vagueness of the landscape and offered detailed knowledge and improved understanding of the HAT ecology when compared with Courtin et al. 2005. Although not detailed enough, Courtin et al. (2005) achieved their goal and was able to produce results for management of HAT. However, unlike the transect method used by Courtin et al. 2005 that might be difficult to replicate; the present research method is flexible and could be replicated easily (i.e. transferable). The transferability quality and the approach of integrating RS/GIS and fuzzy-multicriteria analysis with experts' inputs make the present research method a transparent tool for policy makers for identifying vulnerable and at risk areas. The integration of ancillary data with land cover classes using geospatial-fuzzy MCDA in Chapter 5 offered a unique technique for the classification of HAT vector habitat into different zones. The use of fuzzy logic to integrate ancillary datasets with land cover to improve classification had been attempted in the past (Gopal, Woodcock and Strahler 1999; Stathakis and Kanellopoulos 2008), however, it had not been used to delineate HAT vector habitat into different zones. The application of geospatial-fuzzy MCDA to disease epidemiology is also becoming popular, with past studies demonstrating its effectiveness (Wang and Wang 2010; Hongoh et al. 2011; Rajabi, Mansourian and Bazmani 2012). Obviously, future studies should focus on continuing usage of geospatial-fuzzy MCDA to ensure precise and reliable values.

The cross validation (Chapter 5) of the vector habitat classification scheme using both local polynomial interpolation and Bayesian kriging, emphasised the ability of the classification scheme and geospatial techniques to enhance decision making. Also, the use of both error matrix and kappa statistics to assess the accuracy of the supervised land cover classification carried out in this research produced highly accurate data. However, the confidence level analysis used to assess the accuracy of the non-supervised classification seems less certain. The confidence level revealed water bodies as the least confident, that is, the land cover class most likely to be misclassified. Water bodies being a very prominent feature should not have been judged as such; but it was observed that the area attributed to water bodies compared to other land covers is small. This may have influenced the outcome, therefore in order to avoid biased result(s); it is not advisable to use confidence level analysis to assess the accuracy of non-supervised classification.

7.4 Research Limitations

There are many factors influencing the propagation of HAT other than land cover. The classification scheme developed in this research only used environ-climatic data, and other data such as socio-economic information, may influence considerably the delineation of the HAT vector habitat into zones. However, these data are not always readily available, socio-economic data regarding HAT are lacking, and the existing data are either insufficient or outdated. The protocols used in obtaining even the dated data are too long, while access to Nigerian literature online is very limited. The integration of socio-economic data in delineating the HAT vector habitat in future could enhance the classification scheme developed in this research. Furthermore, seasonal variations could be investigated using radar image to classify the landscape. The option for radar image is due to the peculiar nature of the study area discussed in Chapter 1, which has limited the availability of cloud free optical data for seasonal studies.

The identification of one of the settlement (Abraka) as the mean centre (Chapter 4) of HAT in the main study area, which from the result of further analysis (Chapter 6) turned out to have low vulnerability to HAT, illustrated underlying factors contributing to the high frequency of HAT in the settlement, yet, this research has not considered all other potential factors. The incorporation of socio-economic/cultural characteristic data (as in Courtin et al. 2005) of the settlement and/ or other settlements in the main study area may provide further knowledge of some of the underlying factors influencing HAT propagation in the settlement, and the main study area.

The land cover suitability analysis carried out in this research (Chapter 6) has not been validated; the suitability analysis was based on the area coverage of land cover class within the HAT vector habitat zones. Sensitivity analysis using different thresholds or integration of other criteria such as HAT vector abundance with this analysis may have influenced the outcome considerably; the abundance of the HAT vector could be combined with environ-climatic datasets for delineating the vector habitat into zones in future, and also incorporated into the suitability analysis.

7.5 Research Implications for HAT Management/Control

Finding a lasting cure to HAT is one of the mechanisms for eradicating the disease. However, there are other ways of approaching the problem that should be considered, as a cure will not prevent the disease from spreading. Preventing the propagation of HAT in the main study area will involve limited or no contact between the HAT vector and humans.

The results of the application of the HAT vector habitat classification scheme (Chapter 6) revealed water bodies, shrub and less dense forest as the largest contributing factors influencing HAT propagation in the main study area. This suggests that strategies that will limit the exposure of human populations to these land cover should be a high priority for the Federal Government of Nigeria. Limiting the exposure of the human population to these land covers is a challenge, more so that another potential factor influencing the propagation of HAT in the main study area is overlapping of the three HAT vector habitat zones within the built-up areas. The Federal Government, State Government and most especially the Local Government, should embark on a public awareness programme, educating the people in the main study area about the dangers of exposure to the HAT vector and suggest some precautionary measures. The government could ensure provision of basic amenities, such as constant pipe-borne water at an individual household level and provide affordable gas or electricity for cooking to reduce constant exposure to water bodies and less dense forest. Also, provision of public toilets and encouraging/enforcing construction of toilet facilities in households to limit exposure to shrub/water body should be government priority.

The overlapping of the HAT vector habitat zones within built-up areas is a threat to human population in the main study area. Thus, control programmes targeting individual vector habitat zones should also be a priority for the Governments. The use of insecticide to control the vector is one option, but this may not be healthy to the environment, thus, environmental friendly control measures such as biological control could be used. However, this may be difficult to achieve due to constraints such as, the heterogeneous nature of the landscape, inadequate funding, low capacity buildings for health workers and little or no technical know-how. The continuous exposure of the human population to the HAT vector, most especially within the feed zone, may ensure continuous propagation of the HAT in the main study area.

The settlements at the north-eastern and north-western part of the main study area (these were identified as the direction of HAT propagation in Chapter 6), should be targeted for timely intervention. Also, provision of adequate health care facility with HAT diagnostic capabilities/capacity in the north-eastern and north-western part of the main study area is essential.

This research has been able to identify areas at risk of HAT and areas that require urgent attention. Constant active surveillance in these areas can ensure the detection of the parasite in infected people early enough to allow timely treatment.

There is no HAT vector in the minor study area at present. However, the on-going afforestation/forestation and irrigation/water reservoir programmes in the area may lead to re-invasion of the area by the HAT vector. Strategies that will maintain the present HAT- free status of the minor study area, without adverse effect on the environment should be a government priority.

To effectively reduce or control HAT propagation, integrated prevention schemes should be developed and executed. Adequate funding and stakeholder's capacity building are required to develop and execute sustainable prevention programmes. Health policy must also be amended to support multidisciplinary approaches to disease prevention.

7.6 Conclusions

The aims of this research were to examine the potential habitats of the HAT vector, to identify the processes that give rise to spatial distribution of HAT and to map the direction and magnitude of HAT in the study area using geospatial techniques. To achieve the aims, specific objectives (all of which were met in this study) were set (section 1.8). Gaps inhibiting effective management of HAT were identified in previous studies to inform the direction of the study, geospatial decision support concepts and tools were examined toward the development of the HAT vector classification scheme. The significance of HAT in the study area was investigated, while the developed classification scheme which involved inputs (chosen of criteria and weight assignment) from experts was used to prioritise vulnerable and at risk of HAT areas. Furthermore, the factors influencing HAT propagation and land cover suitability for HAT in the study areas were investigated.

Accurate mapping of the spatial distribution of HAT vector habitat is a vital step towards effective and efficient deployment of management/control strategies. As with other studies, this research highlights the significance of geospatial techniques in attaining a better perceptive of the spatial characteristics of HAT, and the basic settings for effective management of the disease, particularly in the main study area and in sub-Sahara Africa. Unlike previous studies, however, the approach used in this study has helped to distinguish (though containing fuzzy boundaries) the HAT vector habitat into three zones. Delineating the vector habitat into zones helps to precisely identify the direction and magnitude of HAT, the factors influencing HAT propagation, and the priority areas in the main study area, as well as identifying the areas with least chance of HAT propagation. This suggests that geospatial techniques may be valuable where epidemiological data/information are limited, to allow precise analyses to be carried out regarding the spatial propagation of a disease. The technique used in this research can be used for contingency planning in partnership with policy makers, to decide ideal management/control schemes in the case of unforeseen disease plagues. The approach can also be used in other parts of Nigeria with similar landscape characteristics, to identify potential active and non-active HAT foci.

The major findings in this research are summarised as follows:

- HAT is highly clustered in the main study area.
- The propagation of HAT in the main study area (Ethiope East/Ukwuani LGAs), and the other two local government areas (Oshimili North/South and Patani), probably resulted from the suitability of water bodies, shrub and less dense forest for the HAT vector and probably because of the continued exposure of human population to these land cover classes.
- Overlapping of the HAT vector habitat zones (‘breed’, ‘feed’ and ‘rest’) within the built-up areas, may probably have contributed to HAT propagation in the main study area.
- The direction and magnitude of HAT in the main study area were multidirectional (north - east and west - north), and this may have been

influenced by landscape characteristics.

- There may be other reasons aside from environ-climatic factors, influencing HAT propagation in the HAT mean centre of the main study area.
- The main study area can still be considered active HAT foci.
- The minor study area is free of the HAT vector for now, thus can be regarded as non-active foci.

7.7 Future Research Recommendations

The integration of socio-economic/cultural datasets in the HAT vector habitat classification scheme would improve future research by providing a more all-inclusive HAT vector habitat delineation, which can be used to strengthen the surveillance and control strategies by the Federal Ministry of Health/NITR.

Due to the overlapping of the HAT vector habitat zones within human settlements, future studies focusing on the development of effective environmental friendly measures that will reduce the vulnerability of human population to HAT, as well as ensure sustainable environment, is essential.

The existing surveillance system, rural health care institutions and facilities cannot adequately inform the extent of the disease. The present research method due to its flexibility (see section 7.3) could be use to easily transform value added RS data (for example, already classified land cover data/information of any or a given landscape) into vector habitat (HAT or any other disease); thus, speed-up decision making most especially in the case of emergencies. This researcher, therefore, finally recommends the application of the newly developed classification scheme on a nationwide scale, to ascertain the magnitude of not only HAT, but other vector borne diseases.

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Appendices

Appendix	A:	Spatial and non-spatial data used in this research
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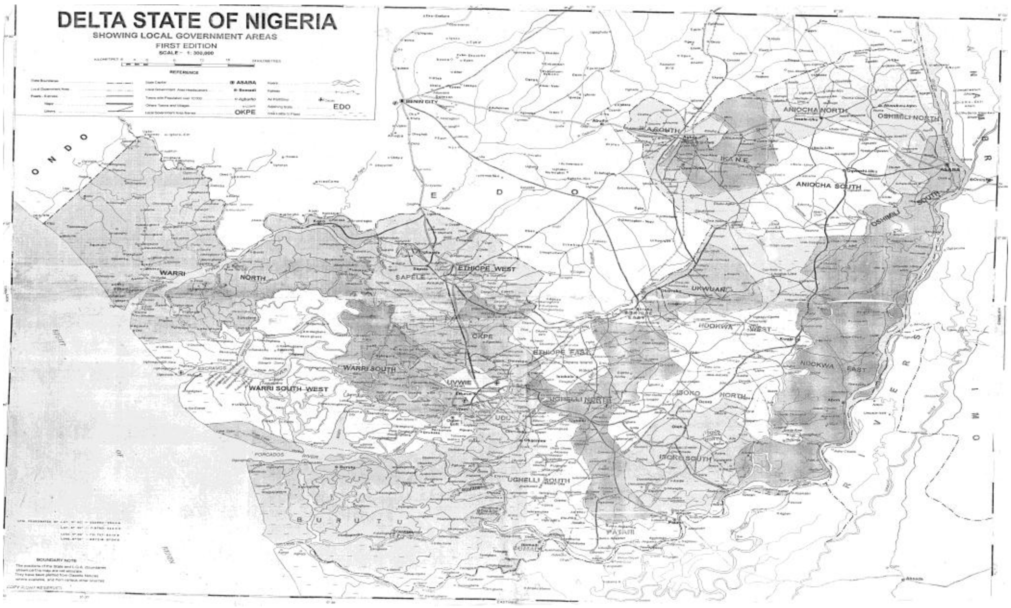
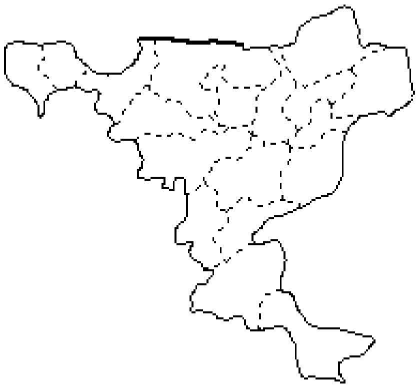
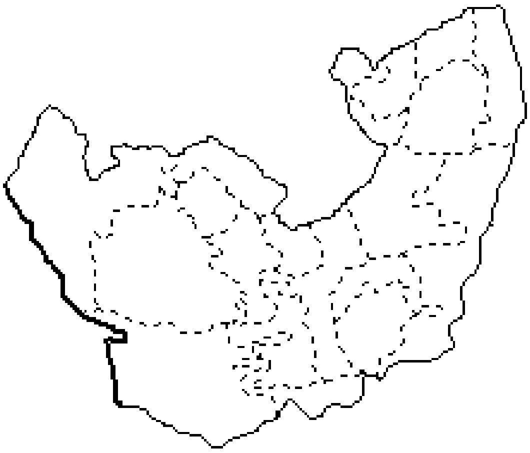
Appendix A: Spatial and Non-spatial Data used in this research

A-1: Thematic data



A-1 (**a**): Administrative map of Delta State Nigeria (scanned copy)
Source: Delta State Survey Department

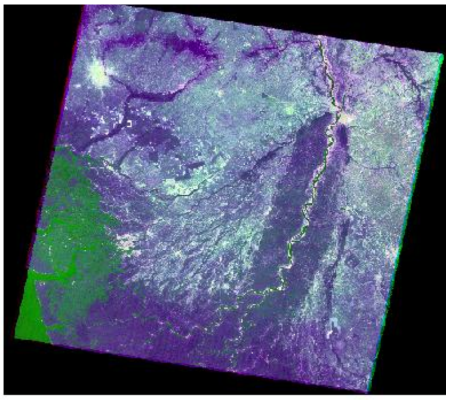




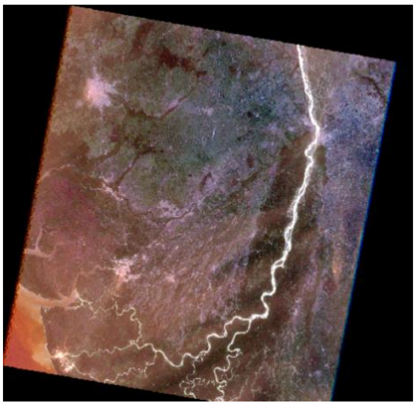
A- 1(b): Jigawa State, administrative boundaries boundaries. Source: Maplibrary.org

A-1(c): Delta State, administrative. Source: Maplibrary.org

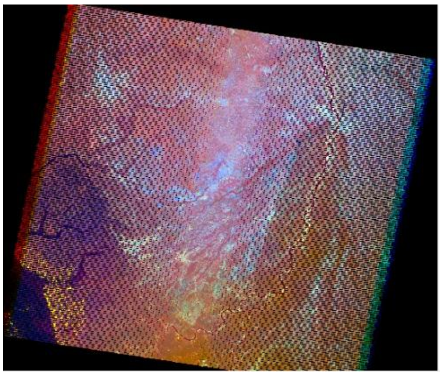
A-2: Remote sensing images composite bands (Source: LP DAAC USGSEROS)



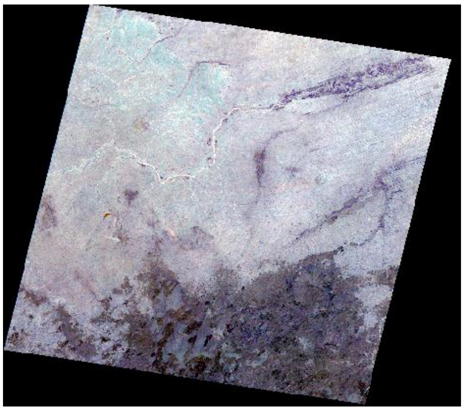
A-2(a): Study area 1987 image



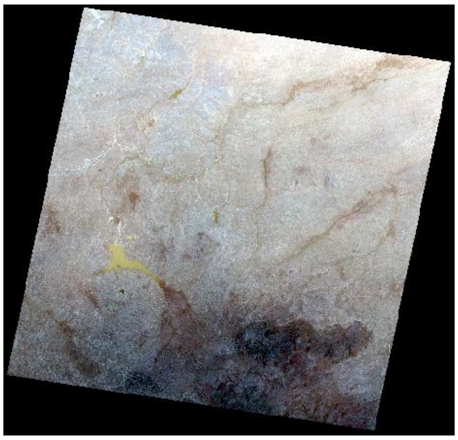
A-2**(**b): Study area 2002 image



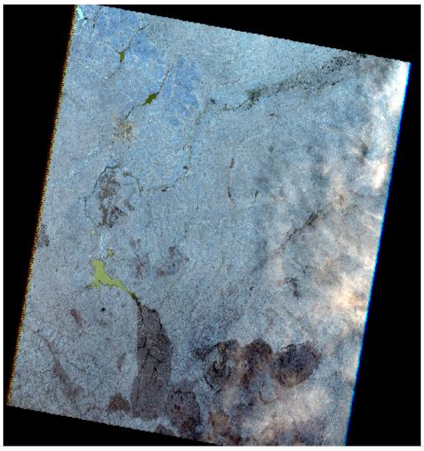
A-2(c): Study area 2011 image



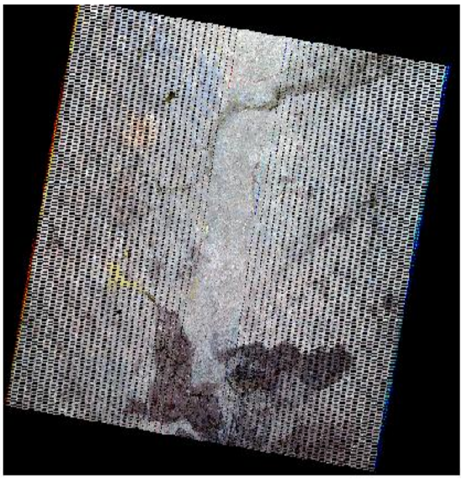
A-2(d): Control area 1972 image



A-2(e): Control area 1986 image

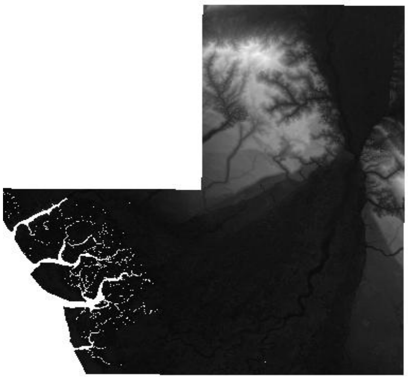


A-2(f): Control area 2003 image

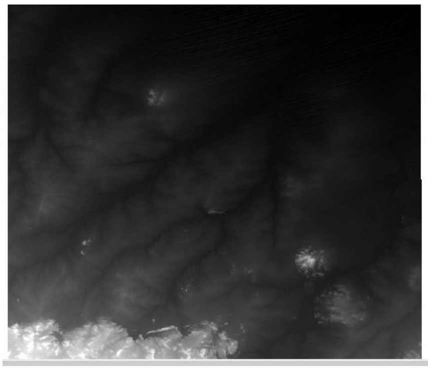


A-2(g): Control area 2012 image

A-2(h): Spot 5 image used for classification accuracy.
Source: Google maps



A-2(i): Study area DEM image



A-2(j):Control area DEM image

A-3: Remote image metadata, calibration constants data and Tasseled cap coefficients

A- 3**(**a): <u>2002 Landsat 7 ETM+ metadata</u>

```
 GROUP = L1_METADATA_FILE
  GROUP = METADATA_FILE_INFO
  ORIGIN = "Image courtesy of the U.S. Geological Survey"
  REQUEST_ID = "0101011013707_00001"
  PRODUCT_CREATION_TIME = 2010-11-04T03:53:22Z
  STATION_ID = "EDC"
  LANDSAT7_XBAND = "2"
  GROUND_STATION = "EDC"
  LPS_PROCESSOR_NUMBER = 1
  DATEHOUR_CONTACT_PERIOD = "0236415"
  SUBINTERVAL_NUMBER = "01"
END_GROUP = METADATA_FILE_INFO
GROUP = PRODUCT_METADATA
  PRODUCT_TYPE = "L1T"
  ELEVATION_SOURCE = "GLS2000"
```

```
  PROCESSING_SOFTWARE = "LPGS_11.2.1"
  EPHEMERIS_TYPE = "DEFINITIVE"
  SPACECRAFT_ID = "Landsat7"
  SENSOR_ID = "ETM+"
  SENSOR_MODE = "SAM"
  ACQUISITION_DATE = 2002-12-30
  SCENE_CENTER_SCAN_TIME = 09:39:19.3392220Z
  WRS_PATH = 189
  STARTING_ROW = 56
  ENDING_ROW = 56
  BAND_COMBINATION = "123456678"
  PRODUCT_UL_CORNER_LAT = 6.7315488
  PRODUCT_UL_CORNER_LON = 5.0948242
  PRODUCT_UR_CORNER_LAT = 6.7441995
  PRODUCT_UR_CORNER_LON = 7.2963289
  PRODUCT_LL_CORNER_LAT = 4.8172790
  PRODUCT_LL_CORNER_LON = 5.1079307
  PRODUCT_LR_CORNER_LAT = 4.8263126
  PRODUCT_LR_CORNER_LON = 7.3020610
  PRODUCT_UL_CORNER_MAPX = 68100.000
  PRODUCT_UL_CORNER_MAPY = 745800.000
  PRODUCT_UR_CORNER_MAPX = 311700.000
  PRODUCT_UR_CORNER_MAPY = 745800.000
  PRODUCT_LL_CORNER_MAPX = 68100.000
  PRODUCT_LL_CORNER_MAPY = 533700.000
  PRODUCT_LR_CORNER_MAPX = 311700.000
  PRODUCT_LR_CORNER_MAPY = 533700.000
  PRODUCT_SAMPLES_PAN = 16241
  PRODUCT_LINES_PAN = 14141
  PRODUCT_SAMPLES_REF = 8121
  PRODUCT_LINES_REF = 7071
  PRODUCT_SAMPLES_THM = 8121
  PRODUCT_LINES_THM = 7071
  BAND1_FILE_NAME = "L71189056_05620021230_B10.TIF"
  BAND2_FILE_NAME = "L71189056_05620021230_B20.TIF"
  BAND3_FILE_NAME = "L71189056_05620021230_B30.TIF"
  BAND4_FILE_NAME = "L71189056_05620021230_B40.TIF"
  BAND5_FILE_NAME = "L71189056_05620021230_B50.TIF"
  BAND61_FILE_NAME = "L71189056_05620021230_B61.TIF"
  BAND62_FILE_NAME = "L72189056_05620021230_B62.TIF"
  BAND7_FILE_NAME = "L72189056_05620021230_B70.TIF"
  BAND8_FILE_NAME = "L72189056_05620021230_B80.TIF"
  GCP_FILE_NAME = "L71189056_05620021230_GCP.txt"
  METADATA_L1_FILE_NAME = "L71189056_05620021230_MTL.txt"
  CPF_FILE_NAME = "L7CPF20021001_20021231_07"
END_GROUP = PRODUCT_METADATA
GROUP = MIN_MAX_RADIANCE
  LMAX_BAND1 = 191.600
  LMIN_BAND1 = -6.200
  LMAX_BAND2 = 196.500
  LMIN_BAND2 = -6.400
  LMAX_BAND3 = 152.900
  LMIN_BAND3 = -5.000
  LMAX_BAND4 = 241.100
  LMIN_BAND4 = -5.100
  LMAX_BAND5 = 31.060
  LMIN_BAND5 = -1.000
  LMAX_BAND61 = 17.040
  LMIN_BAND61 = 0.000
  LMAX_BAND62 = 12.650
  LMIN_BAND62 = 3.200
  LMAX_BAND7 = 10.800
```

```
    LMIN_BAND7 = -0.350
    LMAX_BAND8 = 243.100
    LMIN_BAND8 = -4.700
  END_GROUP = MIN_MAX_RADIANCE
  GROUP = MIN_MAX_PIXEL_VALUE
    QCALMAX_BAND1 = 255.0
    QCALMIN_BAND1 = 1.0
    QCALMAX_BAND2 = 255.0
    QCALMIN_BAND2 = 1.0
    QCALMAX_BAND3 = 255.0
    QCALMIN_BAND3 = 1.0
    QCALMAX_BAND4 = 255.0
    QCALMIN_BAND4 = 1.0
    QCALMAX_BAND5 = 255.0
    QCALMIN_BAND5 = 1.0
    QCALMAX_BAND61 = 255.0
    QCALMIN_BAND61 = 1.0
    QCALMAX_BAND62 = 255.0
    QCALMIN_BAND62 = 1.0
    QCALMAX_BAND7 = 255.0
    QCALMIN_BAND7 = 1.0
    QCALMAX_BAND8 = 255.0
    QCALMIN_BAND8 = 1.0
  END_GROUP = MIN_MAX_PIXEL_VALUE
  GROUP = PRODUCT_PARAMETERS
    CORRECTION_METHOD_GAIN_BAND1 = "CPF"
    CORRECTION_METHOD_GAIN_BAND2 = "CPF"
    CORRECTION_METHOD_GAIN_BAND3 = "CPF"
    CORRECTION_METHOD_GAIN_BAND4 = "CPF"
    CORRECTION_METHOD_GAIN_BAND5 = "CPF"
    CORRECTION_METHOD_GAIN_BAND61 = "CPF"
    CORRECTION_METHOD_GAIN_BAND62 = "CPF"
    CORRECTION_METHOD_GAIN_BAND7 = "CPF"
    CORRECTION_METHOD_GAIN_BAND8 = "CPF"
    CORRECTION_METHOD_BIAS = "IC"
    BAND1_GAIN = "H"
    BAND2_GAIN = "H"
    BAND3_GAIN = "H"
    BAND4_GAIN = "L"
    BAND5_GAIN = "H"
    BAND6_GAIN1 = "L"
    BAND6_GAIN2 = "H"
    BAND7_GAIN = "H"
    BAND8_GAIN = "L"
    BAND1_GAIN_CHANGE = "0"
    BAND2_GAIN_CHANGE = "0"
    BAND3_GAIN_CHANGE = "0"
    BAND4_GAIN_CHANGE = "0"
    BAND5_GAIN_CHANGE = "0"
    BAND6_GAIN_CHANGE1 = "0"
    BAND6_GAIN_CHANGE2 = "0"
    BAND7_GAIN_CHANGE = "0"
    BAND8_GAIN_CHANGE = "0"
    BAND1_SL_GAIN_CHANGE = 0
    BAND2_SL_GAIN_CHANGE = 0
    BAND3_SL_GAIN_CHANGE = 0
    BAND4_SL_GAIN_CHANGE = 0
    BAND5_SL_GAIN_CHANGE = 0
    BAND6_SL_GAIN_CHANGE1 = 0
    BAND6_SL_GAIN_CHANGE2 = 0
    BAND7_SL_GAIN_CHANGE = 0
    BAND8_SL_GAIN_CHANGE = 0
```

```
    SUN_AZIMUTH = 136.0611476
    SUN_ELEVATION = 49.0530921
    OUTPUT_FORMAT = "GEOTIFF"
  END_GROUP = PRODUCT_PARAMETERS
  GROUP = CORRECTIONS_APPLIED
    STRIPING_BAND1 = "NONE"
    STRIPING_BAND2 = "NONE"
    STRIPING_BAND3 = "NONE"
    STRIPING_BAND4 = "NONE"
    STRIPING_BAND5 = "NONE"
    STRIPING_BAND61 = "NONE"
    STRIPING_BAND62 = "NONE"
    STRIPING_BAND7 = "NONE"
    STRIPING_BAND8 = "NONE"
    BANDING = "N"
    COHERENT_NOISE = "Y"
    MEMORY_EFFECT = "N"
    SCAN_CORRELATED_SHIFT = "N"
    INOPERABLE_DETECTORS = "N"
    DROPPED_LINES = "N"
  END_GROUP = CORRECTIONS_APPLIED
  GROUP = PROJECTION_PARAMETERS
    REFERENCE_DATUM = "WGS84"
    REFERENCE_ELLIPSOID = "WGS84"
    GRID_CELL_SIZE_PAN = 15.000
    GRID_CELL_SIZE_THM = 30.000
    GRID_CELL_SIZE_REF = 30.000
    ORIENTATION = "NUP"
    RESAMPLING_OPTION = "CC"
    MAP_PROJECTION = "UTM"
  END_GROUP = PROJECTION_PARAMETERS
  GROUP = UTM_PARAMETERS
    ZONE_NUMBER = 32
  END_GROUP = UTM_PARAMETERS
END_GROUP = L1_METADATA_FILE END
```

A-3 (b): Landsat ETM+ and TM thermal band calibration constants

	Constant1-K **watts/(metersquared *ster*μm)**	**Constant 2 -K2** **Kelvin**
Landsat7	666.09	1282.71
Landsat5	607.76	1260.56

Source: Landsat 7 science data users hand book

A-3 (c): Brightness Tasseled cap coefficients

Tasseled cap coefficients for Landsat 4 and 5 thematic mapper (TM) (User's Guide TASSELCP):

Brightness coefficients for:
Landsat 5 TM: (0.2909, 0.2493, 0.4806, 0.5568, 0.4438, 0.1706)

Landsat 4 TM: (0.3037, 0.2793, 0.4743, 0.5585, 0.5082, 0.1863)

Tasseled cap coefficients for Landsat 7ETM+ (Huang et al., 2002**):**

Brightness coefficients: (0.3561, 0.3972, 0.3904, 0.6966, 0.2286, 0.1596)

A-3 (d) Landsat imagery radiometric characteristics

Satellite	Spectral Resolution (µm)	Band	Spatial Resolution
Landsat 1-3	**MSS**		(meters)
	Band 4: 0.50 - 0.60	Green	79
	Band 5: 0.60 – 0.70	Red	79
	Band 6: 0.70 – 0.80	Near IR	79
	Band 7: 0.80 – 1.10	Near IR	79
Landsat 4-5	**MSS**		
	Band 4: 0.50 - 0.60	Green	82
	Band 5: 0.60 – 0.70	Red	82
	Band 6: 0.70 – 0.80	Near IR	82
	Band 7: 0.80 – 1.10	Near IR	82
	TM		
	Band 1: 0.45 – 0.52	Blue	30
	Band 2: 0.52 – 0.60	Green	30
	Band 3: 0.63 – 0.69	Red	30
	Band 4: 0.76 – 0.90	Near IR	30
	Band 5: 1.55 – 1.75	Mid IR	30
	Band 6: 10.4 – 12.5	Thermal	120
	Band 7: 2.08 – 2.35	Mid IR	30
Landsat 7	**ETM+**		
	Band1:0.450–0.515	Blue	30
	Band2:0.525–0.605	Green	30
	Band 3: 0.630 – 0.69	Red	30
	Band4:0.760–0.900	Near IR	30
	Band 5: 1.550 -1.750	Mid IR	30
	Band6*:10.40–12.5	Thermal	60
	Band 7: 2.080 – 2.35	Mid IR	30
	Band 8: 0.52 – 0.92	Pancromatic	15

Source: University of Maryland, 2004
* Band 6 on Landsat 7 is divided into two bands, high and low gain.

A-4: Astronomical data, HAT record of cases and meteorological data

A-4(a): Earth-sun distance (d) in astronomical units for day of the year (DOY) used in this research

Image Date	*DOY*	*D*
17/01/2012	017	0.98378
21/01/2011	021	0.98410
9/02/2003	040	0.98662
21/12/1987	355	0.98376
17/11/198	321	1.01205
30/12/2002 & 29/12/1972	364	0.98335

Source: '*DOY*' from Equation 1.9 and 'd' from Landsat 7 science data users hand book.

A-4(b i): Landsat ETM+ exoatmospheric solar spectral irradiances

Band	watts/(meter squared * µm)
1	1969.000
2	1840.000
3	1551.000
4	1044.000
5	225.700
7	82.07
8	1368.000

Source: Landsat 7 science data users hand book

A-4(b ii): Landsat MSS 1 exoatmospheric solar spectral irradiances

Band	watts/(meter squared * µm)
1	1823
2	1559
3	1276
4	880.1

Source: Chander et al., 2009.

A-4(b iii) Landsat TM 4 and Landsat TM 5 exoatmospheric solar spectral irradiances

	watts/(meter squared * µm)	watts/(meter squared * µm)
Band	Landsat 4 TM	Landsat 5 TM
1	1957	1957
2	1825	1826
3	1557	1554
4	1033	1036
5	214.9	215.0
7	80.72	80.67

Source: Chander and Markham, 2003.

A-4 (c): HAT record of cases (Source: Eku Baptist hospital, Delta State, Nigeria)

Table

HAT_RECORD_CASE

OBJECTID *	Shape *	SEX	AGE_YEAR	YEAR_CASE	ADDRESS	X_COORD	Y_COORD	Z	LGA_CASE	OCCUPATION
1	Point ZM	M	18	1994	ORIA ABRAKA	173783.72	637364.98	24	Ethiope East	Farming
2	Point ZM	M	55	1994	OBIARUKU	184497.51	646975.3	34	Ukwuani	None
3	Point ZM	M	45	1994	URHUOKA ABRAKA	180259.46	643056.21	31	Ethiope East	Farming
4	Point ZM	M	23	1994	ABRAKA	179030.99	640736.07	26	Ethiope East	Tailoring
5	Point ZM	F	15	1994	ORIA ABRAKA	173783.72	637364.98	24	Ethiope East	Student
6	Point ZM	F	50	1994	UGONAO VILLAGE ABRAKA	182742.53	638522.25	31	Ethiope East	Farming
7	Point ZM	F	34	1994	EKU	168504.6	637047.06	19	Ethiope East	Farming
8	Point ZM	F	51	1994	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming
9	Point ZM	M	49	1998	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming
10	Point ZM	F	70	1998	EKU	168504.6	637047.06	19	Ethiope East	Farming
11	Point ZM	F	65	1998	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming
12	Point ZM	F	10	1998	URHUOKA ABRAKA	180259.46	643056.21	31	Ethiope East	Student
13	Point ZM	M	30	1998	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming
14	Point ZM	F	58	1998	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming
15	Point ZM	M	10	1998	ONOHWAKPOR VILLAGE KOKORI	170920.05	623925.8	12	Ethiope East	Student
16	Point ZM	M	16	2000	OBIARUKU	184497.51	646975.3	34	Ukwuani	Student
17	Point ZM	M	56	2000	ABRAKA	179030.99	640736.07	26	Ethiope East	Driving
18	Point ZM	M	28	2000	EKPAN ABRAKA	179030.99	640736.07	26	Ethiope East	Student
19	Point ZM	M	33	2000	UGONO VILLAGE ABRAKA	175101.325	629933.837	17	Ethiope East	Farming
20	Point ZM	F	37	2000	UMUOSELE VILLAGE OBIARUKU	190402.85	644592.43	37	Ukwuani	Farming
21	Point ZM	F	38	2002	URHUOKA ABRAKA	180248.46	643056.21	31	Ethiope East	Farming
22	Point ZM	F	18	2002	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming
23	Point ZM	F	29	2002	UGONO VILLAGE ABRAKA	175101.325	629933.837	17	Ethiope East	Farming
24	Point ZM	F	20	2002	URHUOKA ABRAKA	180259.46	643056.21	31	Ethiope East	None
25	Point ZM	F	70	2002	URHUOKA ABRAKA	180259.46	643056.21	31	Ethiope East	Farming
26	Point ZM	M	19	2005	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming
27	Point ZM	F	25	2006	URHUOKA ABRAKA	180259.46	643056.21	31	Ethiope East	Farming
28	Point ZM	F	46	2006	URHUOKA ABRAKA	180259.46	643056.21	31	Ethiope East	Farming
29	Point ZM	M	18	2006	ABRAKA	179030.99	640736.07	26	Ethiope East	Student
30	Point ZM	F	25	2006	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming
31	Point ZM	F	31	2006	ABRAKA	179030.99	640736.07	26	Ethiope East	Farming

0 (0 out of 31 Selected)

HAT_RECORD_CASE

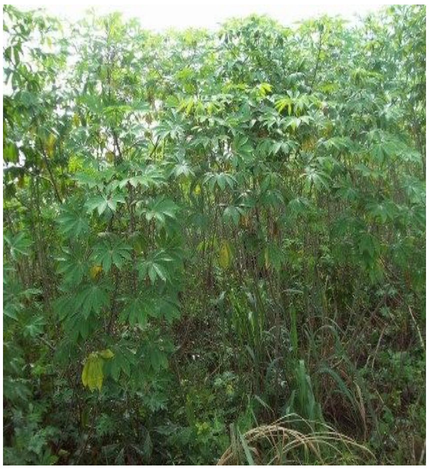
A-4 (d): Monthly Mean Relative Humidity,% (Warri Station) (source: NIMET, Nigeria)

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1991	90	81	81	80	81	85	91	90	89	84	83	83
1992	81	84	83	83	81	84	87	90	87	85	84	83
1993	68	83	83	79	87	84	91	90	85	85	75	83
1994	75	84	79	82	87	84	91	88	85	82	83	79
1995	75	83	79	81	84	89	-	89	88	87	79	65
1996	79	83	83	81	84	85	89	90	88	85	83	84
1997	87	85	82	83	83	85	88	88	87	85	83	85
1998	82	76	82	81	82	86	87	-	86	83	84	80
1999	71	81	79	77	79	85	89	84	87	83	82	81
2000	81	84	81	81	80	84	88	85	89	87	84	80
2001	83	72	79	81	83	85	88	92	89	87	85	80
2002	86	78	80	82	83	86	86	89	86	84	81	86
2003	75	77	83	84	82	85	90	89	88	87	81	77
2004	86	83	82	79	81	86	89	88	88	83	83	81
2005	83	80	81	82	85	84	88	86	84	54	82	76
2006	74	84	83	82	84	86	90	85	85	84	83	83
2007	87	85	83	79	83	81	89	89	89	86	-	81

A-5: Land cover classes and material used for tsetse fly harvest

A-5(a): Cultivated are-a

A-5(b): Water body/mangrove



A-5(c): Cultivated area/shrub

A-5(d): Shrub

A-5(e): Built-up area/shrub

A-5(f):Built-up area/less dense forest/shrub and Eku hospital (HAT sentinel center)

A-5(g): Market proximity to less dense forest/shrub and dense forest at the background

A-5(h): Savannah grass (control area)

A-5(i): Cultivated area/sand (control area)

A-5(j): Water body/wetland/flood plain (control area)

A-5(k): Traps used for tsetse fly harvest in control area

A-6: Letter acknowledging this research by the Federal Ministry of Health, Nigeria

FEDERAL MINISTRY OF HEALTH
DEPARTMENT OF PUBLIC HEALTH

21st July, 2008

The Secretary,
Research Degree Committee,
Secretariat, Central Services,
The University of Abertay,
Bell Street, Dundee DDIIHG,
SCOTLAND.

Dear Sir,

DEVELOPMENT OF A METHODOLOGY FOR MANAGING HAT IN REMOTE AREAS OF NIGERIA: FEDERAL MINISTRY OF HEALTH (FMOH) IN COLLABORATION WITH NATIONAL SPACE RESEARCH AND DEVELOPMENT AGENCY (NASRDA), NIGERIA

This is to acknowledge that the National Space Research and Development Agency (NASRDA), Nigeria has informed us that their organization is embarking on a research "Development of a Methodology for Managing HAT in Remote Areas of Nigeria".

The Federal Ministry of Health (FMOH), Nigeria, through the Department of Public Health will be collaborating with NASRDA in realizing the goal of the research.

FMOH will make available all relevant data/information in its possession towards the success of the research and the Principal Investigator is AKIODE OLUKEMI ADEJOKE who works as an Assistant Chief Scientific Officer in NASRDA.

Do not hesitate to contact us if you require further clarification on this issue.

Thank you.

Yours sincerely,

Mrs. I.N. Anagbogu
Deputy Director/National Coordinator, NIGEP/HAT

Appendix B: Questionnaire survey for the derivation of relative importance (weights) using analytical hierarchy process (AHP) of criteria used for the classification of human African trypanosomiasis vector habitat

Abertay University

11th February 2014

To Whom It May Concern

Dear Sir/Madam

Olukemi Akiode

I am writing to you in my capacity as the first supervisor for Olukemi Akiode's PhD research work and am writing in support of her request for assistance with her research work.

Olukemi is in the final stage of her PhD work and she is conducting a questionnaire survey on her work on Human African Trypanosomiasis. Her PhD research work has been scrutinised at Abertay and has been approved by the relevant School Research Ethics Committee in the University.

I will be pleased to see you give her any assistance possible with this questionnaire survey.

Yours faithfully

Dr Kehinde Oduyemi
Director of Academic Programmes

School of Science, Engineering and Technology

Bell Street | Dundee | Scotland | DD1 1HG

T: 01382 308180 (Direct) | 01382 308000 (Switchboard)
E: set@abertay.ac.uk | **W:** abertay.ac.uk

Questionnaire survey for the derivation of relative importance (weights) using analytical hierarchy process (AHP) of criteria used for the classification of human African trypanosomiasis vector habitat

Dear Sir/Madam,

We are presently undertaking a research project into examination and management of human African trypanosomiasis (HAT) propagation using geospatial techniques in a part of Nigeria.

As part of this research, we are carrying out a multicriteria analysis in order to elicit stakeholders' judgment in providing relative significance of identified criteria with respect to HAT vector (*glossina palpalis gambiense*) habitat.

The physical landscape is very important to HAT propagation, thus, it is very important that the landscape within HAT endemic areas is well examined. To achieve this goal, we intend to use landscape datasets to develop a methodology towards effective/efficient management of the disease.

In the following pages we would like to obtain your judgment as an expert through an AHP survey questionnaire, in which you are requested to compare and provide relative significance of the identified criteria with respect to HAT vector breeding, feeding and resting habitats. The information you give will be of immense value for this research,

Thank you for participating in this questionnaire survey.

Akiode, Olukemi Adejoke

PhD Candidate
Built & Natural Environment
School of Contemporary Sciences
University of Abertay Dundee
Room ACE, Level 5
Kydd Building
Bell Street
Dundee DD1 1HG
Email 0805401@live.abertay.ac.uk
Phone +44 (0) 755 2597 639

Questionnaire survey for the derivation of relative importance (weights) using analytical hierarchy process (AHP) of criteria used for the classification of human African trypanosomiasis vector habitat

Investigator: Akiode, Olukemi Adejoke - PhD candidate
Chief Supervisor: Dr. Oduyemi, K.O.K.

INFORMED CONSENT FORM:

Dear participant,

Please read the information provided in sections A and B carefully. For further clarification of any sections unclear to you, please ask the investigator (Akiode, Olukemi Adejoke), using the number and/or address given at the end of this form.

If you agree to take part in this research, please complete the survey and return it directly to the investigator via email, post or direct handling over to the investigator or her representative. Please keep a copy of this consent form for your records as it contains vital contact information you may wish to have in the future.

By carrying out and returning the attached survey, you are consenting to take part in this research.

Section A: Information for Participants

Participants
Experts are identified as main participants of this study. Experts include those identified as having broad knowledge of, or ability in vector borne disease management/research, landscape classification, natural resource planning, and basic knowledge and or AHP questionnaire survey competency. Experts are expected to include epidemiologist, university academics, public health professional, vector borne disease researchers, etc.

Right of participants to refuse
Your participation is voluntary and you are free to withdraw from the survey after agreed to take part. You are not compelled to answer any question you do not want to provide information about.

Survey completion time
The survey will take approximately 20 - 25 minutes to complete.

Survey method
The survey will be carried out by:

- Delivering the questionnaires in person to the experts, give details about the study, and then collect the answered questionnaires at a set date.
- Email questionnaires directly to experts and asking the respondents to email the answered survey back.

For either method, each concerned expert will be sent a survey pack, including a cover letter, an informed consent form, a project description and an AHP questionnaire

Privacy
Participant personal data, if provided, will be removed from the questionnaire and not known to others. Exact answer provided by individual expert will not be disclosed. The answers provided by experts will only be used for research purposes and for writing a report. However, information will be reported with caution to reduce the research users/readers' ability to deduce each experts judgment.

Application of information: The information and outcomes obtain will be used for completing the requirements for the degree of PhD thesis. Also, they may be used in research publications, seminars and conference presentations.

Risk
The known possible risk to the participants could be time loss while completing the questionnaire. The questionnaire is likely to take approximately 20-25 minutes to complete.

Accessibility to research results
A summary of the results is likely to be available by September 2014. Experts wanting a copy should forward their request directly to Akiode, Olukemi Adejoke at University of Abertay, through email to: 0805401@live.abertay.ac.uk or olukemiadejoke@yahoo.co.uk, through mobile phone: + 44 (0)7552597639

Ethical statement
This research was scrutinised and approved by the University of Abertay research degree ethical committee. Any concerns/complaints concerning the ethical conduct of this research by the participants (experts) should please, be directed to the:
The Secretary,
Research Degree Committee,
University of Abertay, DD1 1HG, Bell Street,
Dundee Scotland, United Kingdom.

Contact numbers
A. For answers to questions concerning the research or for concern/complaint about the research:

Akiode, Olukemi Adejoke
PhD Candidate
School of Contemporary Sciences
University of Abertay Dundee
Dundee DD1 1HG
Email 0805401@live.abertay.ac.uk, olukemiadejoke@yahoo.co.uk
Mobile Phone +44 (0) 755 2597 639

B. For questions, problems, concerns/complaints about the research, or for information about your rights as a research participant:

The Secretary,
Research Degree Committee,
University of Abertay, DD1 1HG, Bell Street,
Dundee Scotland, United Kingdom.
.

Survey participant statement

I have read this consent form. I have been able to ask questions and my questions were answered satisfactorily.

I understand that I may decline to participate in this research and that if I decline to participate; my access to the research outcome will not be denied. I consent to participate in this study. I am also aware that if, for any reason, I wish to discontinue participating, I will be free to do so, and this will not affect my future services. A copy of this consent form has been given to me for my records.

Date:

Questionnaire survey for the derivation of relative importance (weights) using analytical hierarchy process (AHP) of criteria used for the classification of human African trypanosomiasis vector habitat

Section B: AHP Multicriteria Analysis to compare and provide relative significance of the identified criteria with respect to HAT vector breeding, feeding and resting habitats.

Experts Profile (optional):				
Name (Mr., Mrs., Ms, Dr, Prof)				
Name of organization				
Are you familiar with AHP questionnaire survey or have you carried out AHP multicriteria analysis before?				
Do you think spatial distribution of HAT in endemic foci could be deduced from landcover information? Please, indicate your answer on the scale below by marking one of the followings:				
1- no	2- a bit	3- fairly	4- very	5- extremely

Table A: Scale for comparison

Strength scale	**Description**
1	Evenly significant
2	Evenly to moderately significant
3	Moderately significant
4	Moderately to strongly significant
5	Strongly significant
6	Strongly to very strongly significant
7	Very strongly significant
8	Very strongly to extremely significant
9	Extremely significant

Using the scale in **Table A,** make a pair-wise comparison of the criteria in **Tables B – G** according to their level of importance with respect to *glossina palpalis* gambiense habitat (i.e. breeding, feeding and resting sites).

Table B:

	Relative importance with respect to **g**lossina *palpalis* gambiense **breeding sites**						
Criteria	Water Body	Mangrove	Dense Forest	Less Dense Forest	Culti-vated Area	Shrub	Built-up Area
Water Body							
Mangrove							
Dense Forest							
Less Dense Forest							
Cultivated Area							
Shrub							
Built-up Area							

Table C:

	Relative importance with respect to **g**lossina *palpalis* gambiense **feeding sites**						
Criteria	Water Body	Mangrove	Dense Forest	Less Dense Forest	Culti-vated Area	Shrub	Built-up Area
Water Body							
Mangrove							
Dense Forest							
Less Dense Forest							
Cultivated Area							
Shrub							
Built-up Area							

Table D:

	Relative importance with respect to Glossina *palpalis* gambiense **resting sites**						
Criteria	Water Body	Mangrove	Dense Forest	Less Dense Forest	Culti-vated Area	Shrub	Built-up Area
Water Body							
Mangrove							
Dense Forest							
Less Dense Forest							
Cultivated Area							
Shrub							
Built-up Area							

Table E:

Criteria	Relative importance with respect to Glossina *palpalis* gambiens**e** **breeding sites**				
	NDVI	NDDI	Relative Humidity	Land Surface Temperature	Elevation
NDVI					
NDDI					
Relative Humidity					
Land Surface Temperature					
Elevation					

Table F:

Criteria	Relative importance with respect to Glossina *palpalis* gambiens**e** **feeding sites**				
	NDVI	NDDI	Relative Humidity	Land Surface Temperature	Elevation
NDVI					
NDDI					
Relative Humidity					
Land Surface Temperature					
Elevation					

Table G:

Criteria	Relative importance with respect to Glossina *palpalis* gambiens**e** **resting sites**				
	NDVI	NDDI	Relative Humidity	Land Surface Temperature	Elevation
NDVI					
NDDI					
Relative Humidity					
Land Surface Temperature					
Elevation					

Please note:

NDVI = Normalized Difference Vegetation Index

NDDI = Normalized Difference Drought Index

Thank you for taking time to complete this questionnaire survey.
Your contribution is highly appreciated.

Appendix C: List of experts involved in questionnaire survey and examples of questionnaire e-mails from experts

C-1: List of experts involved in questionnaire survey

Participants	S/NO	Organisation	Expertise	Type of Respon
Vector Borne Disease Regulator/ Researcher	1	Nigerian Institute for Trypanosomiasis Research	Epidemiology, MCDA	By interview
	2	Nigerian Institute for Trypanosomiasis Research	Entomology/ Parasitology, Zoology, MCDA	By interview
	3	Nigerian Institute for Trypanosomiasis Research	Biochemistry, MCDA	By interview
	4	Nigerian Institute for Trypanosomiasis Research	Epidemiology, MCDA	By interview
	5	Epidemiology Control Unit, Nigeria	Epidemiology, MCDA	By interview
	6	Epidemiology Control Unit, Nigeria	Epidemiology, MCDA,	By interview
	7	National Cereal and Disease Institute, Nigeria	Entomology, MCDA	By interview

Vector Borne Disease Coordinator	8	Federal Ministry of Health, Nigeria	Vector Borne Disease Surveillance/ Management, MCDA	By interview
	9	Federal Ministry of Health, Nigeria	Epidemiology, MCDA	By interview
	10	Federal Ministry of Health, Nigeria	Zoology, Epidemiology, MCDA	By interview
	11	Department of Primary Health care and Disease Control, Delta State Ministry of Health, Nigeria	Disease Surveillance, MCDA	By interview
	12	Health Services Unit, State House, Nigeria	Disease Management, MCDA	By interview
	13	Niger Delta Development Council (NDDC), Health unit, Nigeria	Public Health, MCDA	By interview
	14	NDDC, Health unit, Nigeria	Public Health, Parasitology MCDA	By interview
	15	Primary Health Programme Unit, NNDC, Nigeria	Public Health, MCDA	By interview
	16	NNDC, Health unit, Nigeria	Disease Surveillance, MCDA	By interview
Disease Evaluator	17	Monitoring and Evaluation of Diseases Control, Nigeria	Public Health, Vector Control, MCDA	By interview

Epidemiologist	18	Tsetse Ecology & Control, CIRDES, Burkina Faso	Epidemiology, Entomology/ vector control, MCDA	By email
	19	Equipe Inter Pays OMS pour l'Afrique Centrale, Gabon	Epidemiology, Spatial Data Analysis, MCDA	By email
	20	World Health Organization	Epidemiology, Geo-spatial Data Analysis, MCDA	By email
	21	College of Health Sciences, Nnamdi Azikiwe University, Nigeria	Epidemiology, Medical Research, Immunology, MCDA	By email
Lecturer (Geographer)	22	Department of Geography, University of Ilorin, Nigeria	Population Geography, MCDA, Natural Resource Analysis	By interview
	23	Faculty of Natural and Applied Sciences, Umaru Musa Yaradua University, Katsina, Nigeria	RS/GIS Analysis, Geography/ Planning, MCDA	By interview
	24	School of Physical Sciences, Federal University of Technology, Mina, Nigeria	Climatology, Natural Resource Analysis, MCDA	By interview
	25	School of Physical Sciences, Federal University of Technology, Mina, Nigeria	Geomorphology, Natural Resource Allocation/ Planning, MCDA	By interview

Lecturer (Geographer)	26	Department of Geography, University of Abuja, Nigeria	Geography (Natural Resource Mapping/Planning), GIS, MCDA	By interview
	27	Department of Geography, University of Abuja, Nigeria	Geography (Land use/cover Mapping), MCDA	By interview
	28	Department of Geography, University of Abuja, Nigeria	Geography (Climate Change), MCDA	By interview
	29	Department of Geography, University of Abuja, Nigeria	Geography, Ecology, MCDA	By interview
	30	Department of Geography, University of Abuja, Nigeria	Geography (Natural Resource Planning), GIS Analysis, MCDA	By interview
	31	Department of Geography, University of Abuja, Nigeria	RS/GIS Analysis, Geography (Natural Resource Planning), MCDA	By interview
	32	Federal University of Petroleum Resources , Delta State, Nigeria	RS/GIS Analysis, Spatial Multicriteria Analysis/ Decision, Vulnerability Analysis	By interview
	33	Department of Geography, Kogi State University, Nigeria	Geography (Landcover/use Mapping/Analysis), MCDA	By interview
	34	Department of Geography, Benue State University, Nigeria	Land cover/use Mapping/ Analysis, MCDA	By interview

Remote Sensing/Medical Geographer	35	Private Organisation	GIS/RS Analysis, Epidemiology, Land cover/use Mapping, MCDA	By interview

* MCDA = Multi-criteria Decision Analysis

C-2: Examples of questionnaire e-mails to and from experts

- **From:** [redacted]
- **Sent:** 15 November 2013 12:45
  To: AKIODE, OLUKEMI
  Subject: RE: Human African Trypanosomiasis_question_help

Dear Sir,
Thanks for your mail. You can just send me your questions by email. I'm quite busy by these times but I think we could manage...if you are not in rush.
Best regards

From: 0805401@live.abertay.ac.uk
To: [redacted]
Subject: RE: Human African Trypanosomiasis_question_help
Date: Mon, 18 Nov 2013 13:25:52 +0000

Dear sir,

Thank you for your response.

Please, see the attached for the questionnaire survey.

Regards,

Olukemi A. Akiode

Olukemi Adejoke Akiode
BSc PGD MSc (PhD-ongoing)

Built & Natural Environment
School of Contemporary Sciences
University of Abertay Dundee
Room ACE, Level 5
Kydd Building
Bell Street
Dundee DD1 1HG
Email 0805401@live.abertay.ac.uk
Phone +44 (0) 755 2597 639

Regards,

Olukemi Akiode.
Olukemi Adejoke Akiode
BSc PGD MSc (PhD-ongoing)

From: .[redacted]

Sent: 18 November 2013 13:44
To: AKIODE, OLUKEMI
Subject: RE: Human African Trypanosomiasis_question_help

OK. Thanks.
Please tell me the "realistic" deadline you would like to receive your survey. Do you think that one weak is feasible? I'm abroad on duty mission.

Best regards
[redacted]

From: 0805401@live.abertay.ac.uk
To: [redacted]
Subject: RE: Human African Trypanosomiasis_question_help
Date: Tue, 19 Nov 2013 09:50:11 +0000

Dear Dr [redacted]

Yes, one week is okay.

Thanks for your help.

Regards,

Olukemi Akiode

Olukemi Adejoke Akiode
BSc PGD MSc (PhD-ongoing)

Built & Natural Environment
School of Contemporary Sciences
University of Abertay Dundee
Room ACE, Level 5
Kydd Building
Bell Street
Dundee DD1 1HG
Email 0805401@live.abertay.ac.uk
Phone +44 (0) 755 2597 639

- **From:** [redacted]

Sent: 30 November 2013 08:44
To: AKIODE, OLUKEMI
Subject: RE: Human African Trypanosomiasis_question_help

Dear Olukemi,
I'm trying to fill your questionnare but it seems I need some explanations:
- Should the comparison always be done vs the "Water body" as in the table below? In this case, what about those factors whose importance is less than the Water Body's? For example, I suppose that Dense forest importance is lower than Water body for Gpg breeding. How to note it, since it is not equal? Please explain to me more how to proceed.
- I would also suggest you to also send your questions to [redacted] if it not already done.
Best regards

[redacted]

- **From:** [redacted]

Sent: 02 December 2013 10:37
To: AKIODE, OLUKEMI
Subject: Re: Human African Trypanosomiasis_question_help

Dear Akiode

Sorry for the delay. Please see the attached for response. Please feel free to reach me if I can still be of any help

Best Wishes
[redacted]

- **From:** [redacted]

Sent: 18 November 2013 11:32
To: AKIODE, OLUKEMI
Subject: RE: Human African Trypanosomiasis_question_help

Dear
Thank you for your message and courage for your doctoral studies. No problem you can send the questionnaire via email as an attachment.
Best wishes.

[redacted]

- **From:** AKIODE, OLUKEMI
  Sent: 18 November 2013 13:15
  To: [redacted]
  Subject: RE: Human African Trypanosomiasis_question_help

Dear sir,

Thank you for your response.

Please, see the attached for the questionnaire survey.

Regards,

Olukemi A. Akiode

- **From:** [redacted]
  Sent: 16 December 2013 12:29
  To: AKIODE, OLUKEMI; MERCADO, Raquel
  Subject: RE: Human African Trypanosomiasis_question_help

Dear Ms Olukemi,

You can send the questionnaire via email, but we would like to know the reference of your work. Please could you send the protocol of your study.

Best regards

[redacted]

- On Dec 3, 2013, at 9:05 AM, "AKIODE, OLUKEMI" <0805401@live.abertay.ac.uk> wrote:

Dear sir,

I will like you to please help me forward the attached questionnaire to the DG, [redacted]

He requested that the questionnaire survey be sent officially to .[redacted] through [redacted]

Also, you can help me send the questionnaire to [redacted] and any relevant stakeholder you know. It is very difficult to get people from Nigeria; some of the stakeholder I sent it to in Nigeria said they were only familiar with the medical aspect of trypanosomiasis.

Thank you for your immediate action.

Regards,

Joke

Olukemi Adejoke Akiode
BSc PGD MSc (PhD-ongoing)

From: [redacted]
Sent: 03 December 2013 10:48
To: AKIODE, OLUKEMI; [redacted]
Subject: Re: Qeustionnaire_HAT survey Help

Your above referred,
Pls ask [redacted] or any of your colleagues to draft such letter for my onward communication.
With best regards.

[redacted]
National Space Research and Development Agency,
Umar Musa Yar'Adua Road
Pyakasa Abuja.
2348037874003

- **From:** AKIODE, OLUKEMI
  Sent: 05/12/2013 16:47
  To: [redacted]
  Subject: FW: Qeustionnaire_HAT survey Help

Dear [redacted]

Dr. [redacted] said I should forward this mail to you.

Please, read his response to my mail and act accordingly.

Regards,

Joke
Olukemi Adejoke Akiode

- **From:** [redacted]
  Sent: 05 December 2013 16:25

To: AKIODE, OLUKEMI
Subject: RE: Qeustionnaire_HAT survey Help

Dear Mrs Akiode,

Could you please make a draft of the letter and send it to me? Since I am not privy to previous correspondence between you and the DG, [redacted], it would be helpful to get the first draft from you.

Best regards, ma.

[redacted]

Appendix D: Tables and Figures from some analysis carried out in this research work

D-1: Tables

D-1a: Principal component analysis of Delta State study area 2002 Landsat7 ETM+ image

pca_d

# Data file produced by Principal Components							
#The number of components = 7							
#Output raster(s):							
#C:\Users\Olukemi\Documents\ArcGIS\Default.gdb\Princip_2							
# COVARIANCE MATRIX							
# Layer	1	2	3	4	5	6	7
# --							
1	4283.27377	3215.45875	2823.79836	3224.12699	3833.31626	8835.36533	2202.92704
2	3215.45875	2438.51291	2151.35785	2439.75906	2924.34236	6691.75408	1689.68979
3	2823.79836	2151.35785	1934.29682	2146.05848	2633.28767	5939.39545	1547.74193
4	3224.12699	2439.75906	2146.05848	2613.29969	3089.65094	6883.70377	1745.57666
5	3833.31626	2924.34236	2633.28767	3089.65094	3991.50908	8460.98180	2324.42261
6	8835.36533	6691.75408	5939.39545	6883.70377	8460.98180	19457.67221	4844.45599
7	2202.92704	1689.68979	1547.74193	1745.57666	2324.42261	4844.45599	1406.90674
# ==							
# CORRELATION MATRIX							
# Layer	1	2	3	4	5	6	7
# --							
1	1.00000	0.99493	0.98103	0.96367	0.92708	0.96781	0.89739
2	0.99493	1.00000	0.99058	0.96647	0.93734	0.97148	0.91225
3	0.98103	0.99058	1.00000	0.95452	0.94769	0.96813	0.93822
4	0.96367	0.96647	0.95452	1.00000	0.95663	0.96534	0.91036
5	0.92708	0.93734	0.94769	0.95663	1.00000	0.96008	0.98088
6	0.96781	0.97148	0.96813	0.96534	0.96008	1.00000	0.92591
7	0.89739	0.91225	0.93822	0.91036	0.98088	0.92591	1.00000
# ==							

D-1b: Principal component analysis of Jigawa State study area 2003 Landsat7 ETM+ image

Table

pca_jig

Data file produced by Principal Components

COVARIANCE MATRIX

Layer	1	2	3	4	5	6	7
1	3219.66709	3076.18228	3972.76408	3893.12524	5134.87371	6657.01717	4070.14448
2	3076.18228	2976.51876	3856.76307	3770.95299	4979.78198	6399.61946	3959.88640
3	3972.76408	3856.76307	5057.32627	4939.93821	6534.81845	8332.89285	5207.53654
4	3893.12524	3770.95299	4939.93821	4892.86455	6463.40747	8284.92832	5132.50053
5	5134.87371	4979.78198	6534.81845	6463.40747	8781.81735	11196.92135	6932.33664
6	6657.01717	6399.61946	8332.89285	8284.92832	11196.92135	14888.38261	8771.79538
7	4070.14448	3959.88640	5207.53654	5132.50053	6932.33664	8771.79538	5547.80177

CORRELATION MATRIX

Layer	1	2	3	4	5	6	7
1	1.00000	0.99369	0.98453	0.98087	0.96568	0.96150	0.96304
2	0.99369	1.00000	0.99405	0.98813	0.97401	0.96134	0.97447
3	0.98453	0.99405	1.00000	0.99307	0.98058	0.96031	0.98313
4	0.98087	0.98813	0.99307	1.00000	0.98602	0.97070	0.98512
5	0.96568	0.97401	0.98058	0.98602	1.00000	0.97923	0.99318
6	0.96150	0.96134	0.96031	0.97070	0.97923	1.00000	0.96517
7	0.96304	0.97447	0.98313	0.98512	0.99318	0.96517	1.00000

D-1c: Table showing example of semivariogram sensitivity analysis for HAT vector habitat (rest zone) classification in the main study area using 15% increased nugget and partial sill

Table

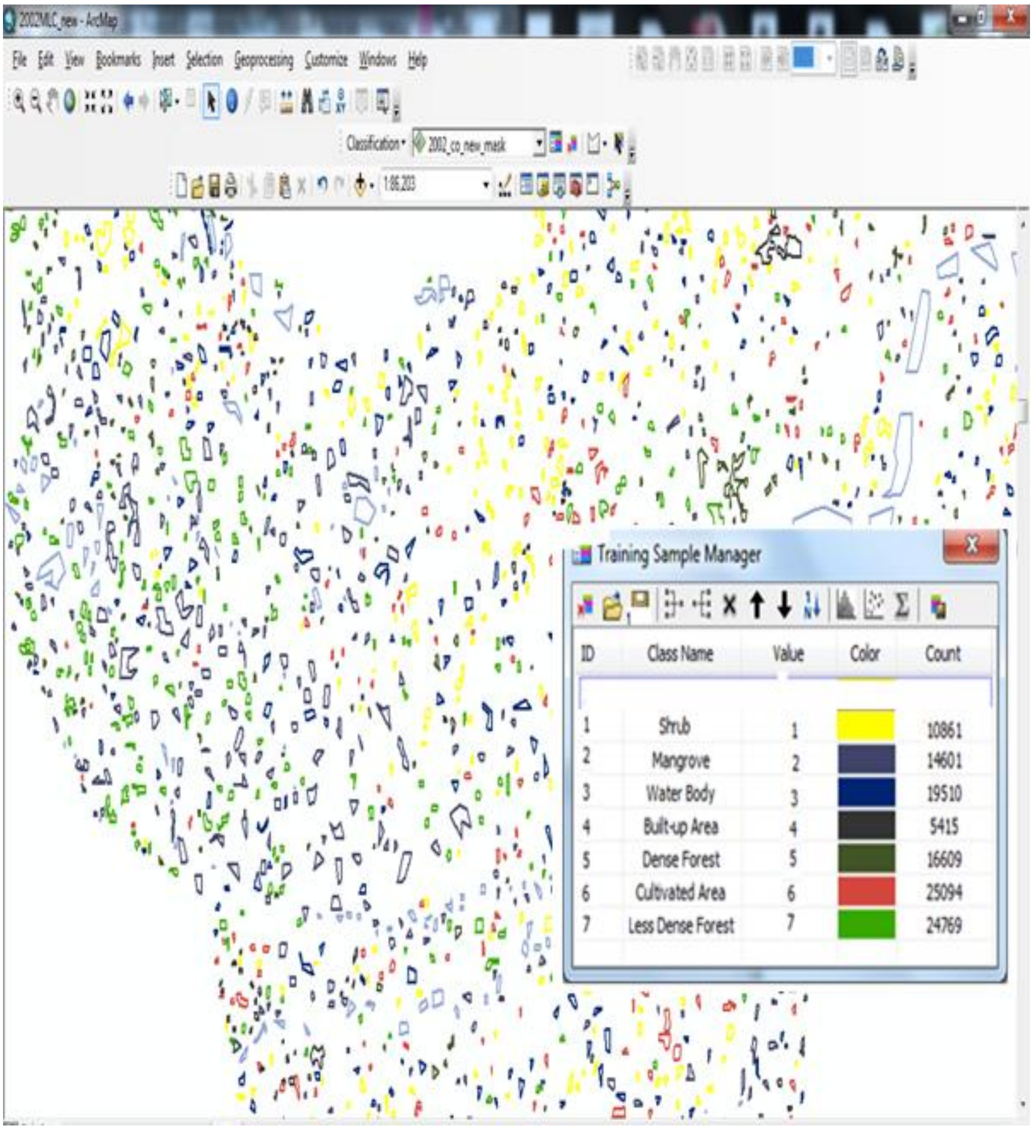
semivario_Rest_15

OID *	PtID	RndParam	X	Y	Prediction	StdErr	Nugget	PartSill	Range
1	0	Ngt	179055.54	640767.57	948.884309	9.385579	0.009743	1.052247	13091.257417
2	1	Ngt	173759.53	637352.77	1430.06053	5.085756	0.009743	1.052247	13091.257417
3	2	Ngt	180248.46	643055.13	756.258218	13.860474	0.009743	1.052247	13091.257417
4	3	Ngt	182507.6	638483.19	1233.177018	5.42749	0.009743	1.052247	13091.257417
5	4	Ngt	184544.58	646979.36	466.174029	7.689875	0.009743	1.052247	13091.257417
6	5	Ngt	173246.61	638257.26	1308.960717	9.195389	0.009743	1.052247	13091.257417
7	6	Ngt	170921.53	623928.85	4084.90921	6.231607	0.009743	1.052247	13091.257417
8	7	Ngt	155336.693	638935.429	1188.797049	5.768397	0.009743	1.052247	13091.257417
9	8	Ngt	175054.89	630153.86	3196.359319	6.14924	0.009743	1.052247	13091.257417
10	9	Ngt	184544.58	646979.36	466.174029	7.689875	0.009743	1.052247	13091.257417
11	0	Ngt	179055.54	640767.57	949.055247	9.101309	0.008535	1.054976	13091.257417
12	1	Ngt	173759.53	637352.77	1429.985557	4.838501	0.008535	1.054976	13091.257417
13	2	Ngt	180248.46	643055.13	756.658298	13.156201	0.008535	1.054976	13091.257417
14	3	Ngt	182507.6	638483.19	1232.87741	5.190537	0.008535	1.054976	13091.257417
15	4	Ngt	184544.58	646979.36	466.001535	7.4208	0.008535	1.054976	13091.257417
16	5	Ngt	173246.61	638257.26	1310.258474	8.776721	0.008535	1.054976	13091.257417
17	6	Ngt	170921.53	623928.85	4084.978369	5.957842	0.008535	1.054976	13091.257417
18	7	Ngt	155336.693	638935.429	1188.110881	5.511106	0.008535	1.054976	13091.257417
19	8	Ngt	175054.89	630153.86	3196.673103	5.89267	0.008535	1.054976	13091.257417
20	9	Ngt	184544.58	646979.36	466.001535	7.4208	0.008535	1.054976	13091.257417
21	0	Ngt	179055.54	640767.57	949.113255	8.999115	0.008127	1.055913	13091.257417
22	1	Ngt	173759.53	637352.77	1429.955498	4.751399	0.008127	1.055913	13091.257417
23	2	Ngt	180248.46	643055.13	756.792621	12.902428	0.008127	1.055913	13091.257417
24	3	Ngt	182507.6	638483.19	1232.761855	5.106614	0.008127	1.055913	13091.257417
25	4	Ngt	184544.58	646979.36	465.932337	7.324861	0.008127	1.055913	13091.257417
26	5	Ngt	173246.61	638257.26	1310.733604	8.62579	0.008127	1.055913	13091.257417
27	6	Ngt	170921.53	623928.85	4085.003812	5.860893	0.008127	1.055913	13091.257417
28	7	Ngt	155336.693	638935.429	1187.843263	5.420554	0.008127	1.055913	13091.257417
29	8	Ngt	175054.89	630153.86	3196.794586	5.802336	0.008127	1.055913	13091.257417
30	9	Ngt	184544.58	646979.36	465.932337	7.324861	0.008127	1.055913	13091.257417
31	0	Sll	179055.54	640767.57	947.671302	10.634699	0.014086	0.947327	12061.874979
32	1	Sll	173759.53	637352.77	1429.89631	5.944771	0.014086	0.947327	12061.874979
33	2	Sll	180248.46	643055.13	755.359212	16.237586	0.014086	0.947327	12061.874979
34	3	Sll	182507.6	638483.19	1233.219517	6.29179	0.014086	0.947327	12061.874979
35	4	Sll	184544.58	646979.36	466.535452	8.792694	0.014086	0.947327	12061.874979

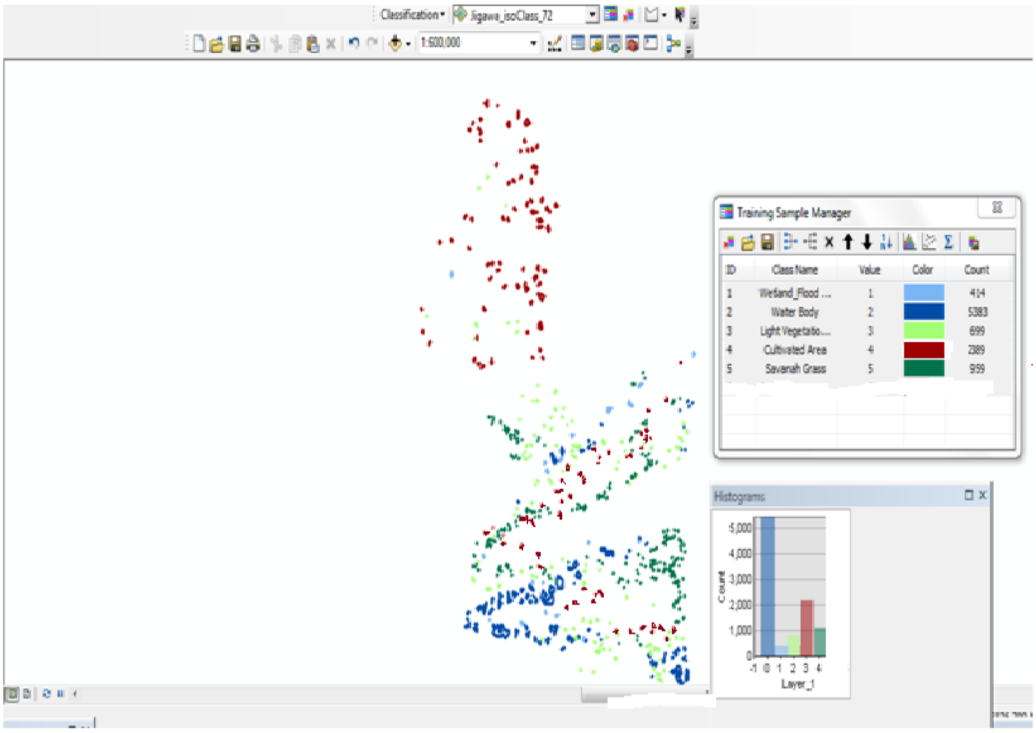
51 (0 out of 60 Selected)

semivario_Rest_15

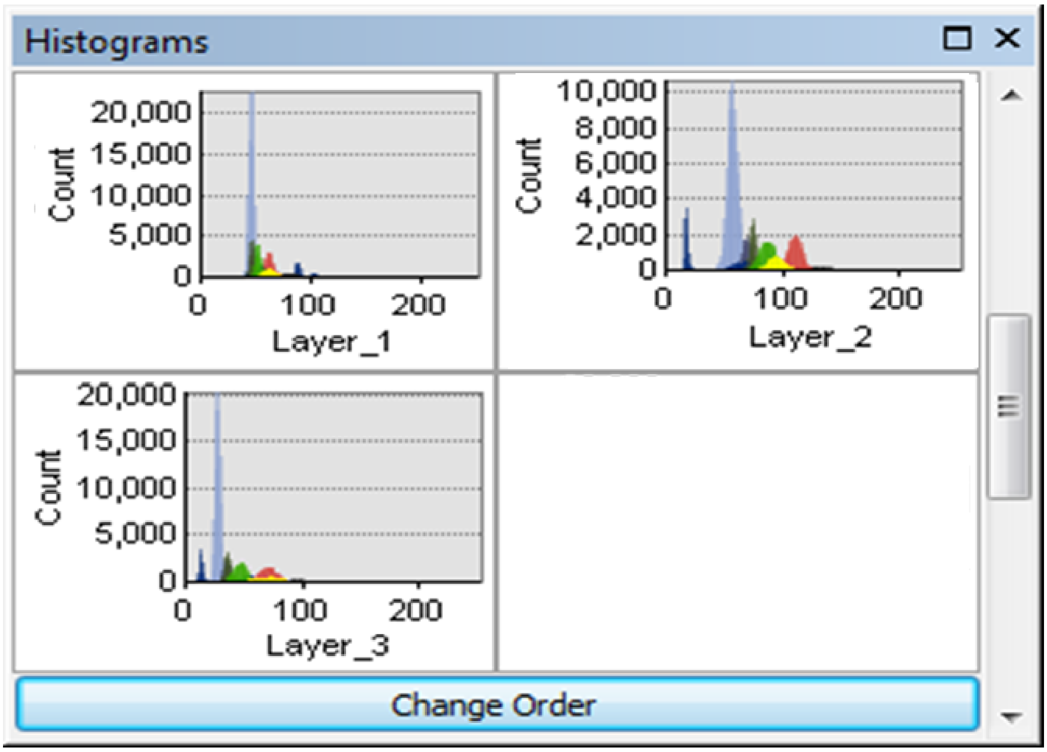
D-2: Figures



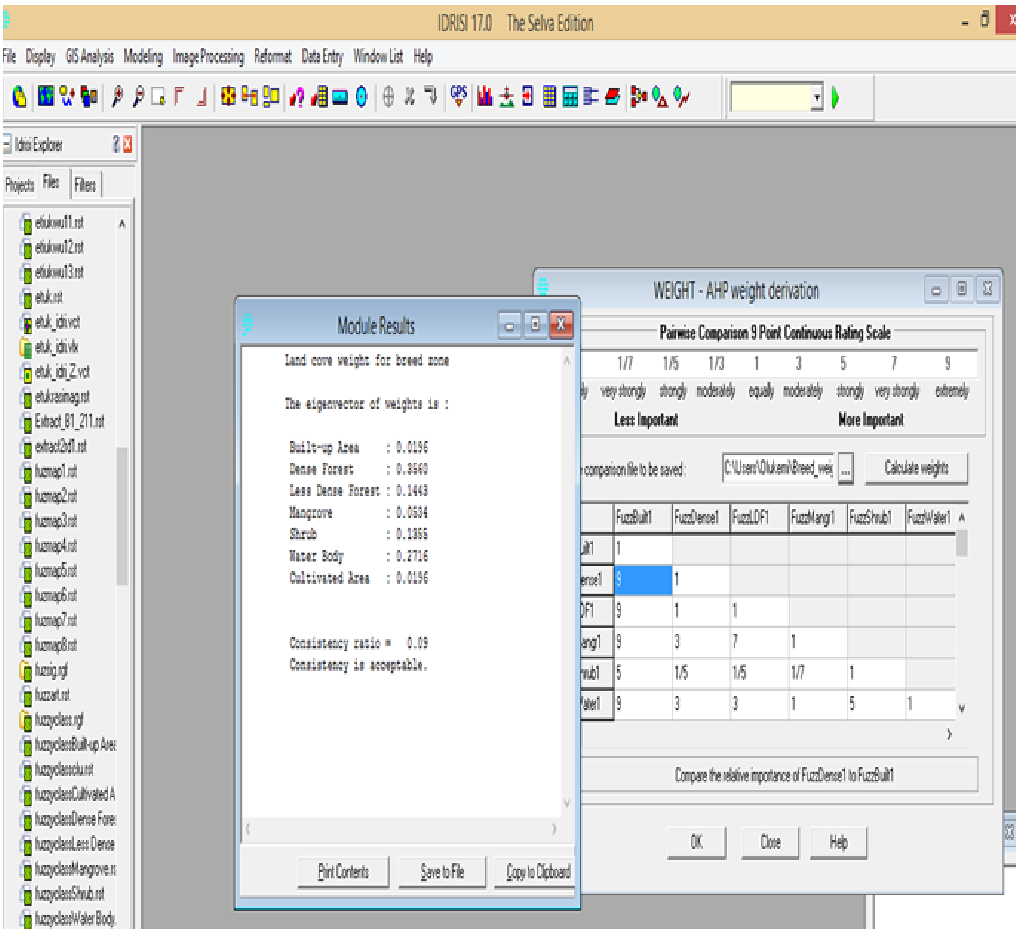
D-2a: A cross section of training samples collected for the Delta State study area supervised classification with number of training samples cells collected insert.



D-2b: Samples collected for the supervised classification of the Jigawa Study area with number of training samples cells and histogram of training samples insert



D-2c: Histogram of Delta State study area supervised land cover classes training samples



D2-d: Example of AHP consistency ratio test for questionnaire survey carried out in IDRISI software

Appendix E: Publications taken from this thesis

I. Akiode, O. A. and Oduyemi, K. O. K. 2014a. Development of a classification scheme for managing human African trypanosomiasis using geospatial techniques. *Journal of Environment and Earth Science,* (4)21: pp. 216 – 236.

II. Akiode, O. A. and Oduyemi, K. O. K. 2014b. Identifying diseased areas using a geospatially developed human African trypanosomiasis vector habitat classification scheme. *Journal of Environment and Earth Science*, (4)22: pp. 31 – 45.

III. Akiode, O. A. and Oduyemi, K. O. K. 2014c. Assessment and management of human African trypanosomiasis propagation using geospatial techniques. *Journal of Environment and Earth Science,* (4)23: pp. 1 – 12.

IV. Akiode, O. A., Oduyemi Kehinde O. K. and Badaru , Y. U. 2014a. Analysis of change detection of Birnin-kudu land cover using image classification and vegetation indices. *Journal of Environment and Earth Science*, (4)21: pp. 1 – 10.

V. Akiode, O. A., Oduyemi Kehinde O. K. and Badaru , Y. U. 2014b. Assessment of human African trypanosomiasis foci using change detection algorithms. *Journal of Environment and Earth Science*, (4)22: pp.166 -183.

VI. Akiode, O. A. and Badaru , Y. U. 2014. Accuracy assessment of pixel-based image classification of Kwali council area, Abuja, Nigeria. Journal of Natural Sciences Research, 4(22): pp. 133 – 140.

VII.