Development of a Classification Scheme for Managing Human African Trypanosomiasis using Geospatial Techniques

Akiode Olukemi Adejoke[1]*   Oduyemi Kehinde O K[2].

1.   School of Science, Engineering and Technology, University of Abertay, Dundee Scotland UK; National Space Research and Development Agency, Abuja, Nigeria.
2.   School of Science, Engineering and Technology, University of Abertay, Dundee, Scotland UK
   *Emails of the corresponding authors: olukemiadejoke@yahoo.co.uk, aakiode@nasrda.net

Abstract

Distinctive environ-climatic variables have been associated with *Trypanosoma brucei gambiense* spatial characteristics, signifying the importance of physical landscape in H A T propagation/risk. Nevertheless, techniques projected to classify human African trypanosomiasis (HAT) vector habitats tend to be generalised, time wasting and costly. Despite control efforts, HAT has become resurgent in some locations. No model to acquire detailed and comprehensive HAT 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. This paper proposes a geospatial technique to explore vector habitat mapping. The goal was to develop a surveillance methodology t h a t will facilitate quick and efficient management of HAT. Supervised classification and fuzzy logic were integrated to classify land cover and ancillary datasets into HAT vector habitat. 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.

This study helped distinguish HAT vector habitat into d i f f e r e n t zones (breed, feed and rest), the classification scheme is expected to offer effective decision support to all stakeholders.

Keywords: Geospatial, Remote Sensing, Geographic Information Systems, Fuzzy, Vector

1. Introduction

Human African Trypanosomiasis (HAT) or 'sleeping sickness' is an 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 & 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 & Kamath 2009). Although numbers of cases v o l u n t a r i l y presenting for treatment each year have increased, in Nigeria the exact number of HAT cases is unclear (Abenga & 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). The resurgence o f 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 f l y 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 insufficient for wider area planning and management. To address this issue, requires examination of how land cover datasets may influence HAT vector habitat mapping.

1.1 HAT Distribution Mapping: Previous Efforts

The significance of land cover was acknowledged in past studies, in which environ-climatic variables 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 varying scales (Courtin et al. 2005; De Deken 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 scheduling and execution of wide area surveillance programmes.

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. Geographic unit to which disease datasets were linked were generalized, 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 characterised. 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.

1.2 Geospatial Techniques in Disease Mapping

Geospatial techniques such as Remote Sensing (RS) and Geographic Information Systems (GIS) have permitted epidemiologists to perform disease mapping and spatial analyses (Symeonakis, Robinson & 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 (Kelly-Hope & McKenzie 2009). However, spatial aspects of HAT are rarely addressed, and most HAT studies, particularly in the Delta State of Nigeria - the research area of this study, are based on medical diagnostics (Wang et al. 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, 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 (Hotez & Kamath 2009). These techniques have also been used previously for monitoring HAT (DeVisser &Messina 2009; Symeonakis, Robinson & Drake 2007). 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 & 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 study will carry out a detailed characterisation of the study area environment (at a regional scale) using geospatial-fuzzy multi-criteria decision analysis to identify and classify potential HAT vector habitats into zones, to ease disease management.

1.3 Geospatial Multi-criteria Decision Analysis

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 & 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 & 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). Analytic hierarchy process (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 & Banks 2009). Elements in the hierarchical structure are compared in pairwise comparison using

a relational scale (Saaty 1980) to determine their relative significance.

Fuzzy membership function has been used to improve the uncertainty associated with AHP decision (Buckley 1985). Fuzzification, according to Erensal et al. 2006, can capture the uncertainty inherent in complex multi-attribute decision analysis problems. 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.

The use of fuzzy logic to integrate ancillary datasets with land cover to improve classification had been attempted in the past (Gopal et al. 1999), 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; Rajabi, Mansourian & Bazmani 2012). Zoning the potential vector 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 & Messina 2009; Goetz et al. 2000).

1.4 The Study Region: The Niger Delta

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; Nigeria National Population Commission 2006). The Niger delta region is one of the five geopolitical zones in Nigeria (Figure 1) and is one of the world's largest wetlands.
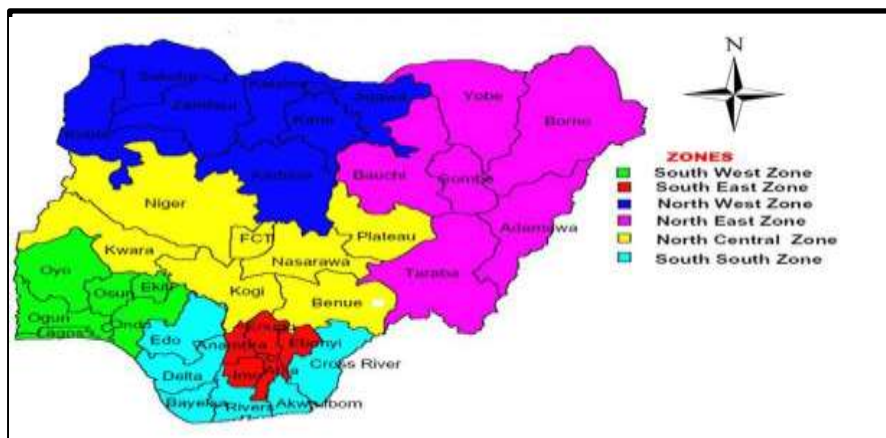

Figure 1: Nigeria geopolitical zones (from: www.naijanedu.com/the-19-new- proposed-states-to-be-created-in-nigeria/

The region is mainly vegetated by mangrove forests, the largest in Africa (Ibe 1998). The climate is characterised by high humidity (between 90% and 100%) and heavy rain falls (annual average is between 2500-3550 mm). The annual mean temperature is 26°C, but fluctuates seasonally between 21-33 ^{O}C, (Leroux 2001). These humid and hot conditions are favourable for HAT vector survival (Courtin et al. 2005). The predominant occupations include farming, fishing and hunting (Niger Delta Environmental Survey 1997). These activities exacerbate HAT propagation as the population is exposed to the disease vector on daily basis.

The main study area selected for this research work comprises two local government areas (Ethiope-east and Ukwuani) within Delta state (Delta State is one of the states that comprises Niger delta region), 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 that is located between latitudes $5^{O}30$'N and longitude $6^{O}00$'E (Figure 2), 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 for health care delivery. 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 vector habitat classification

scheme that can be applied to identify high-priority areas where surveillance and health care delivery should be directed.
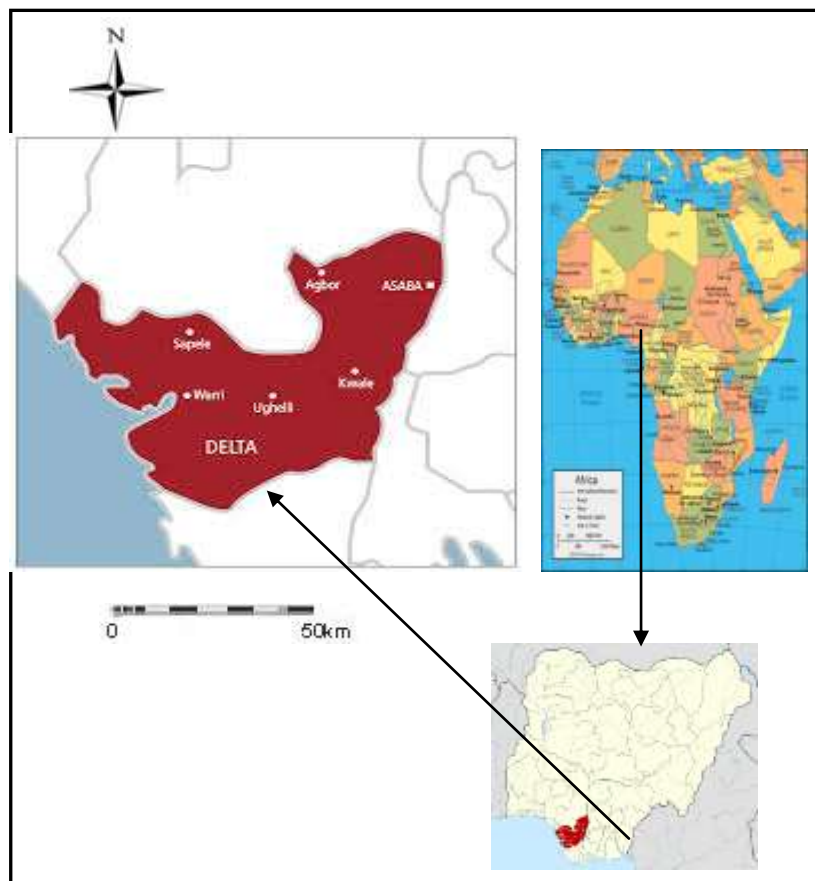

Figure 2. The Delta State of Nigeria

2. Materials and Methods

All the data used were projected to the World Geodetic System (WGS) 84 datum Universal Transverse Mercator (UTM) Zone 32N. Using Global Positioning Systems (GPS), ground control points (GCPs) for settlements in the study area were collected, exported into ArcMap and converted into shape files using the same coordinate systems as the other spatial data. Geospatial-fuzzy MCDA was applied at every stage of the research work particularly in delineating HAT vector habitat. The remote sensing images used in this study are presented in Table 1 and the criteria (Table 2) used in this study were derived manly from the RS images.

Table 1: Remotely sensed data used in this study

Data Type	Acquisition Date	Path/Row	Bands used	Spatial Resolution (m)	Source
Landsat7 ETM+	30/12/2002	189/56	2, 3, 4, 5 ,6 & 7	30	LP DAAC (USGSEROS)
SRTM (DEM)	February 2002	SRTM3N05E006V1		3-ARC	LP DAAC (USGSEROS)

2.1 Methods

2.1.1 Image Processing

The Landsat 7 ETM+ image was preprocessed to reduce or eliminate errors embedded in the data due to sensor effects, atmospheric and illumination effects as well as mis-registration. Both geometric and atmospheric corrections were carried out to derive the environ-climatic (Table 2) criteria required for this study from the RS image. The algorithms (equations) used are presented in the appendix .

 Geometric Correction: using IDRISI Selva 17.0 software, the DEM data used for this study was re-sampled to 30 metres from 3-arc seconds (approximately 90 metres) using the 2002 Landsat ETM+. The root mean square error (RMSE) output for the DEM was about 0.42 indicating a good re-sampling.

Atmospheric correction: using image-based dark object subtraction method, the digital number (DN) of the image bands were converted to at-satellite spectral radiance and from at-satellite spectral radiance to top-of-atmosphere (TOA) reflectance. The at-satellite spectral radiance data (all image bands) was derived using Equation1 while the TOA reflectance data was derived for all the image bands (excluding thermal band) using Equation 2. All the parameters used are contained in the image metadata file.

The at-satellite spectral radiance and TOA spectral reflectance data derived were transformed to retrieve land surface temperature (LST), normalized difference vegetation index (NDVI), normalized difference water index (NDWI), and relative humidity (RH), using appropriate algorithms (see appendix). To derive land surface temperature (LST), the spectral radiance value of thermal band of the 2002 image was converted to at-satellite brightness temperature using Equation 3. Because at-satellite brightness temperature only represents blackbody temperature, it was corrected for spectral emissivity (land surface emissivity) before estimating LST using equation 4. NDVI (Equation 5), was retrieved using the near-infrared (band 4) and red (band 3) components of the Landsat 7 ETM+ while NDWI (Equation 6) was extracted from the images because it is required to estimate normalized difference drought index (NDDI). The NDDI was estimated using Equation 7. Meteorological data obtained from Nigerian Meteorological Agency (NIMET), was combined with the LST to derive relative humidity (RH) using Equation 8.

All the criteria derived from the RS image were stored in a personal geodatabase. An analytic hierarchy process (AHP) questionnaire survey was carried out to compare the relative importance of the criteria in relation to each HAT vector habitat zone. In order to ascertain the likelihood that the weights obtained from the experts (35 in total; comprises of epidemiologists, geographers, HAT regulatory/coordinating and evaluator bodies) was randomly generated, the weights consistency ratios were calculated. The consistency ratios (CR) were less than 1 thus, consistent. According to Saaty (1980), any CR up to 0.10 is considered satisfactory. The individual priority weights obtained from experts were then aggregated using geometric mean to obtain the overall priority weight for each criterion.

2.1.2 Image classification

Supervised maximum likelihood classification algorithm was used for land cover classification in ArcMap 10.0 software. To select appropriate image bands for colour composites, principal component analysis (PCA) was carried out. This was to ensure that the satellite image bands used for colour composite have low correlation so as to reduce problem due to linearity. Bands 7, 5 and 2 were selected from the Landsat 7 ETM+ image for the land cover classification.

Adequate number of representative training samples are vital for supervised image classifications (Chen and Stow 2002). Several training samples were collected from areas that appeared relatively similar on the 2002 Landsat 7 ETM+ image. Groundtruth data, previous knowledge of the study area aid the training set samples. The next step was the generation of signature file. This is the statistical description of the classes; 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 (bands 7, 5, 2) was used as input raster bands, and the signature file created for the training samples served as input signature file. A total of 7 land cover classes, as shown in Figures 3 were identified.

2.1.3 Post-classification processing

The seven classes in the supervised classified image were separated into separate layers, after which the built-up area layer was generalised. This was done using the ArcMap 10.0 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 study area to be identified as a separate entity, rather than a class in the domain type land cover.
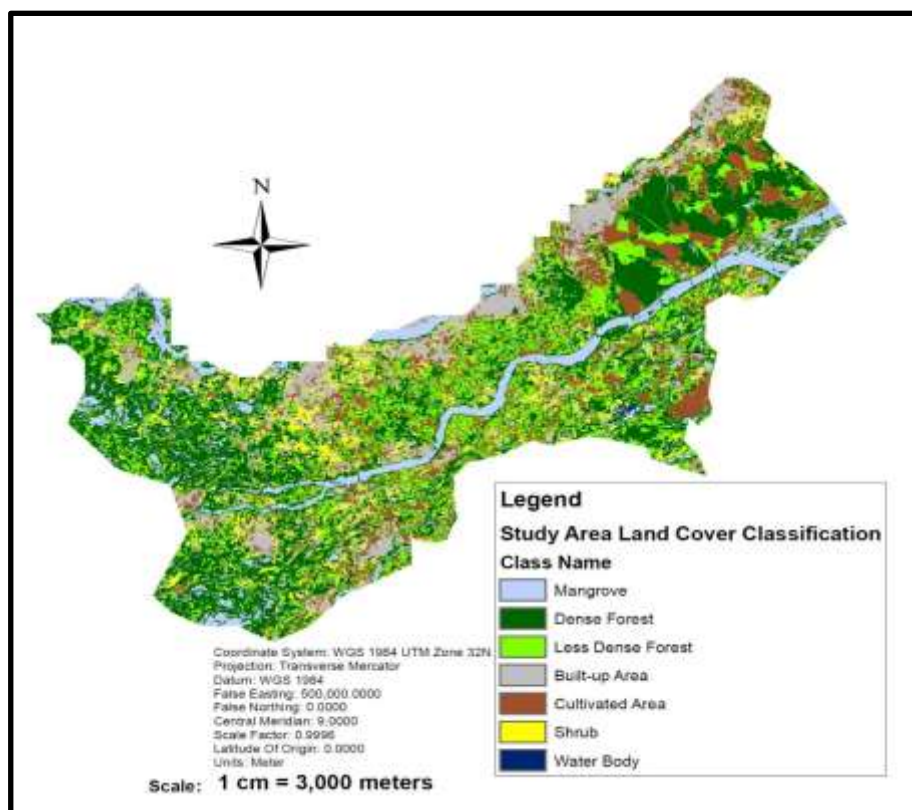
Figure 3: Supervised land cover classes in the study area (source:
2002 Landsat 7 ETM+ and groundtruth**)**

2.1.4 Image classification accuracy assessment

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 obtained from Google Earth. The Spot image shows more detail than the Landsat image used as the base data for the classification. To check the extent to which there is agreement other than that which is expected by chance, kappa statistics was also calculated for the supervised classification.

2.1.5 Development of a classification scheme for managing HAT

This section focuses on combining the land cover classes and other derived environmental/climatic variables (section 2.1.1) to develop a classification scheme. 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. The overall goal is to identify and classify HAT vector habitat in the study area into different zones, namely: breed, feed and rest zones to aid efficient management of HAT. Thus, a hierarchical structure was created with the goal, criteria/sub-criteria and alternatives (Figure 4).
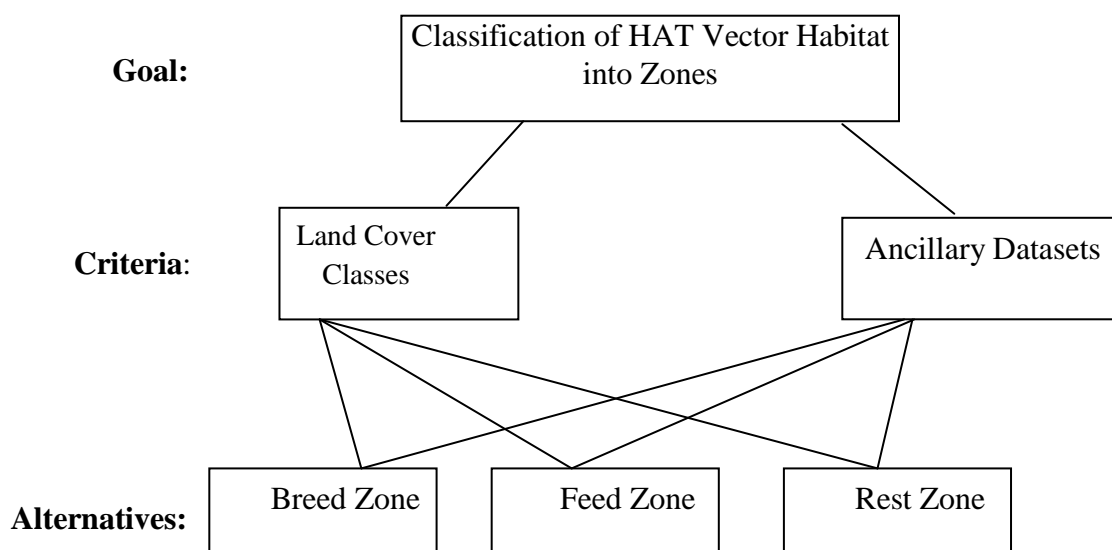
Goal:

Classification of HAT Vector Habitat into Zones

Criteria:

Land Cover Classes

Ancillary Datasets

Alternatives:

Breed Zone

Feed Zone

Rest Zone

Figure 4: 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 2. 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.

Table 2: Criteria for classification of HAT vector habitat

Major Criteria	Sub-Criteria	Unit	Source
ANCILLARY DATASETS	Land surface temperature Relative humidity Digital terrain model NDVI NDDI	Degree Celsius % Meters Index Index	Landsat 7 ETM+ Landsat 7ETM+/NIMET SRTM Landsat 7 ETM+ Landsat 7 ETM+
LAND COVER CLASSES	**Water body** **Mangrove** **Less dense forest** **Dense forest** **Cultivated area** **Shrub** **Built-up area**	**%** **%** **%** **%** **%** **%** **%**	**Landsat 7 ETM+** **Landsat 7 ETM+** **Landsat 7 ETM+** **Landsat 7 ETM+** **Landsat 7 ETM+** **Landsat 7 ETM+** **Landsat 7 ETM+**

2.1.5.1 Geospatial-fuzzy Multi Criteria Decision Analysis

All the criteria (land cover and anxillary) 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.   In order to ascertain the likelihood that the weights obtained from the experts was randomly generated, the weights consistency ratios (CR) were calculated. Each expert's AHP matrix was entered into IDRISI software to obtain priority vector and consistency ratio. The consistency ratios were less than 1 thus, consistent. The individual priority weights obtained from experts were then aggregated using the geometric mean to obtain the overall priority weight for each criterion.

2.1.5.2 Grouping of study area into HAT vector habitat zones

Geospatial-fuzzy multi criteria decision analysis was carried out to group the study area into HAT vector habitat zones.

The supervised land cover classes obtained were reclassified into three (breed, feed and rest) temporary HAT vector habitat zones. Also, the derived 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 (further detail in ArcMap 10.0 help).   The fuzzification was necessary partly to normalise the criteria into common scale and also to obtain their fuzzy membership sets. The process used is presented in Figure 5. Before choosing the final HAT vector habitat 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'.* 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, while the fuzzy overlay operator *'AND'* returns map layers showing minimum membership values for all location within each HAT vector habitat zone. For the final identification and classification of the HAT vector habitat zones, different fuzzy overlay operator gamma values were used. This was to investigate the appropriate value that will not change considerably the original ancillary weights obtained from the experts.
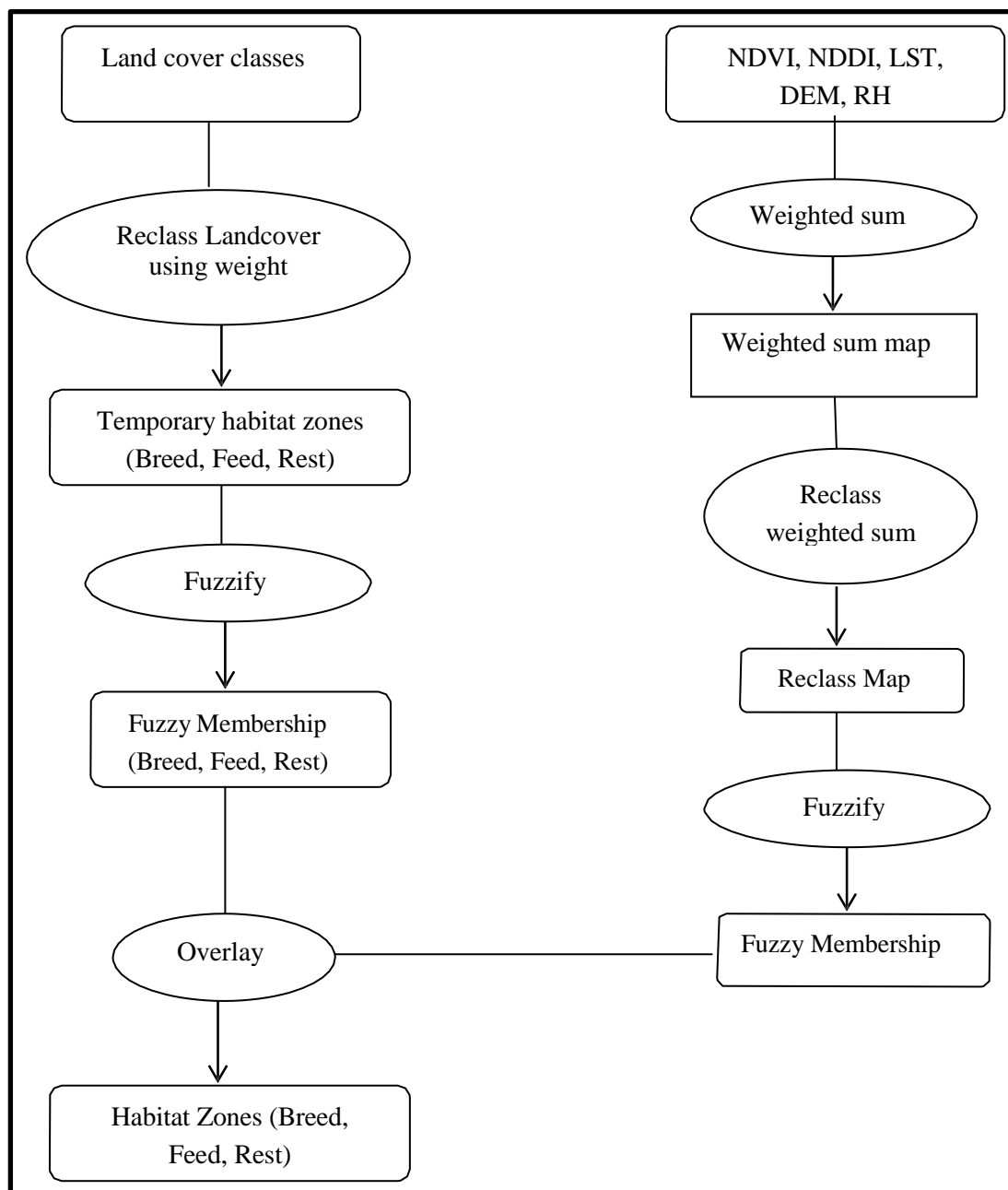
Figure 5: Habitat grouping procedure

2.1.6 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.

2.1.6.1 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 (in ArcMap 10.0) by changing the kriging model's parameters; such as, partial sill and nugget 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.

2.1.6.2 Local polynomial interpolation quality of fit analysis

Local polynomial interpolation (LPI), which provides spatial condition number surface, was performed. Spatial condition number surface 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). The LPI surface was derived for each HAT habitat zone to form a geo-statistical layer for cross-validation using a 1st order polynomial transformation. Empirical Bayesian kriging (EBK) was also carried out to assess the quality of fit of the classification models. The main reason for EBK was to use a more accurate method; E B K standard errors of prediction are more accurate than LPI measurement.

3. Results

The evaluation of the image classification training samples shows that they were representative for the study areas and are statistically separate. The histograms of the land cover classes did not overlap. The overall accuracy of the image classification was 9 9 . 2 % (Tables 3). 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. 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. The overall kappa statistics (Table 4) was 0.9907; this is an indication of strong agreement between the classified pixels and the reference data.

Table 3: Error matrix for 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 4: Kappa statistics for study area supervised classification

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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

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. Figures 6, 7 a n d 8 shows the final HAT vector habitat zones, while Table 5 shows the result obtained using a gamma value 0.8 and fuzzy overlays *'OR'* and '*AND',*

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 study is to identify all possible HAT vector habitats in the study area; 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).
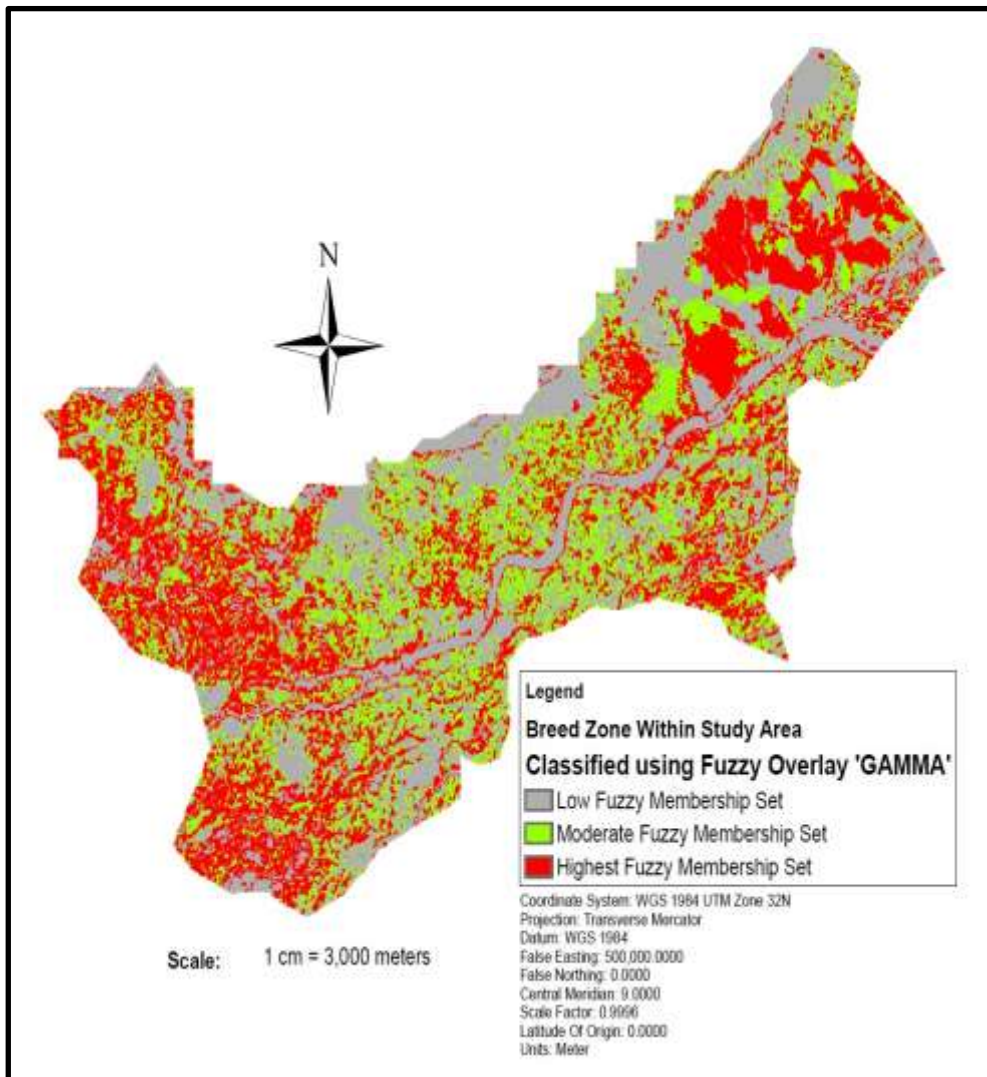
Figure 6: HAT vector breed zone within the study area classified using fuzzy overlay operator 'GAMMA'
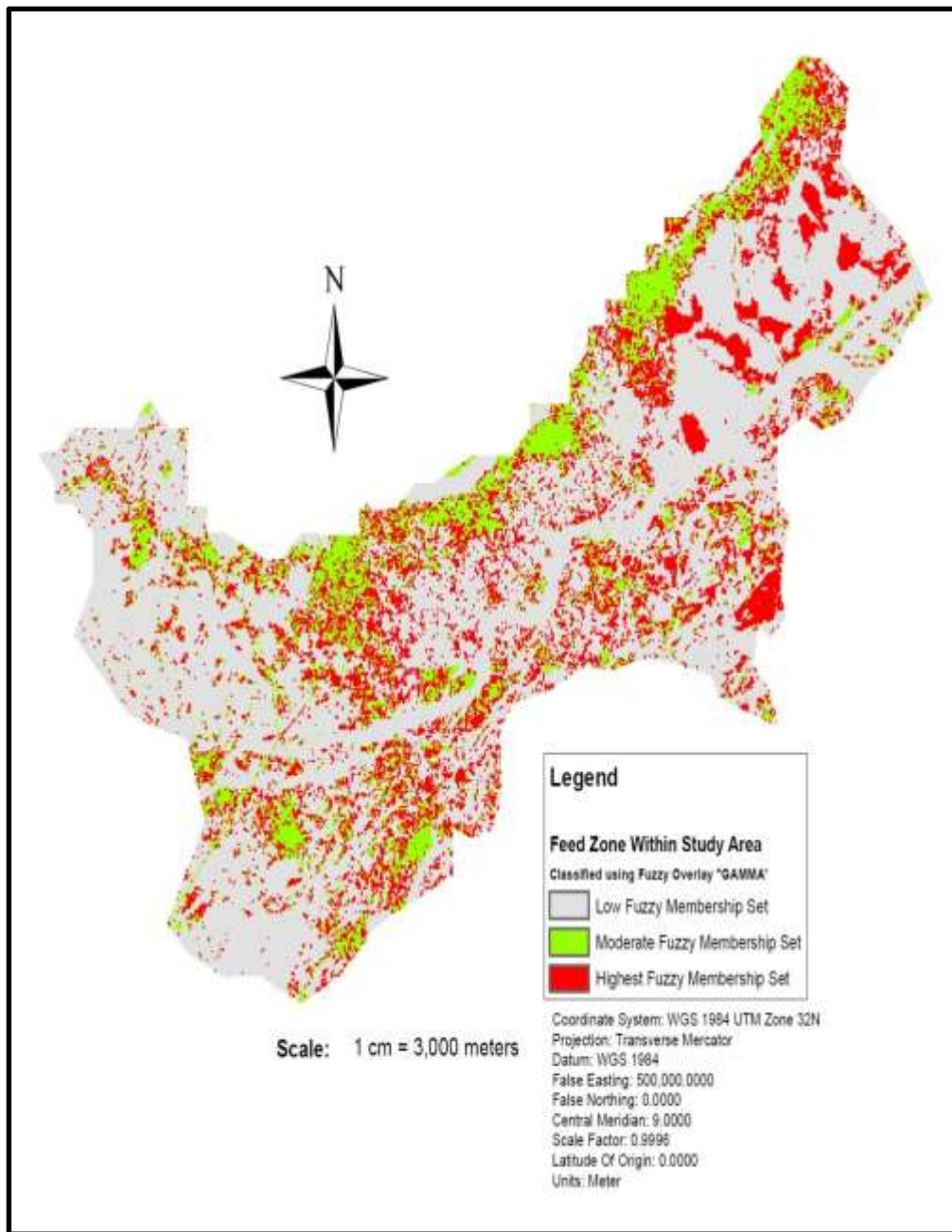
**Figure 7: HAT vector feed zone within the study area classified using fuzzy
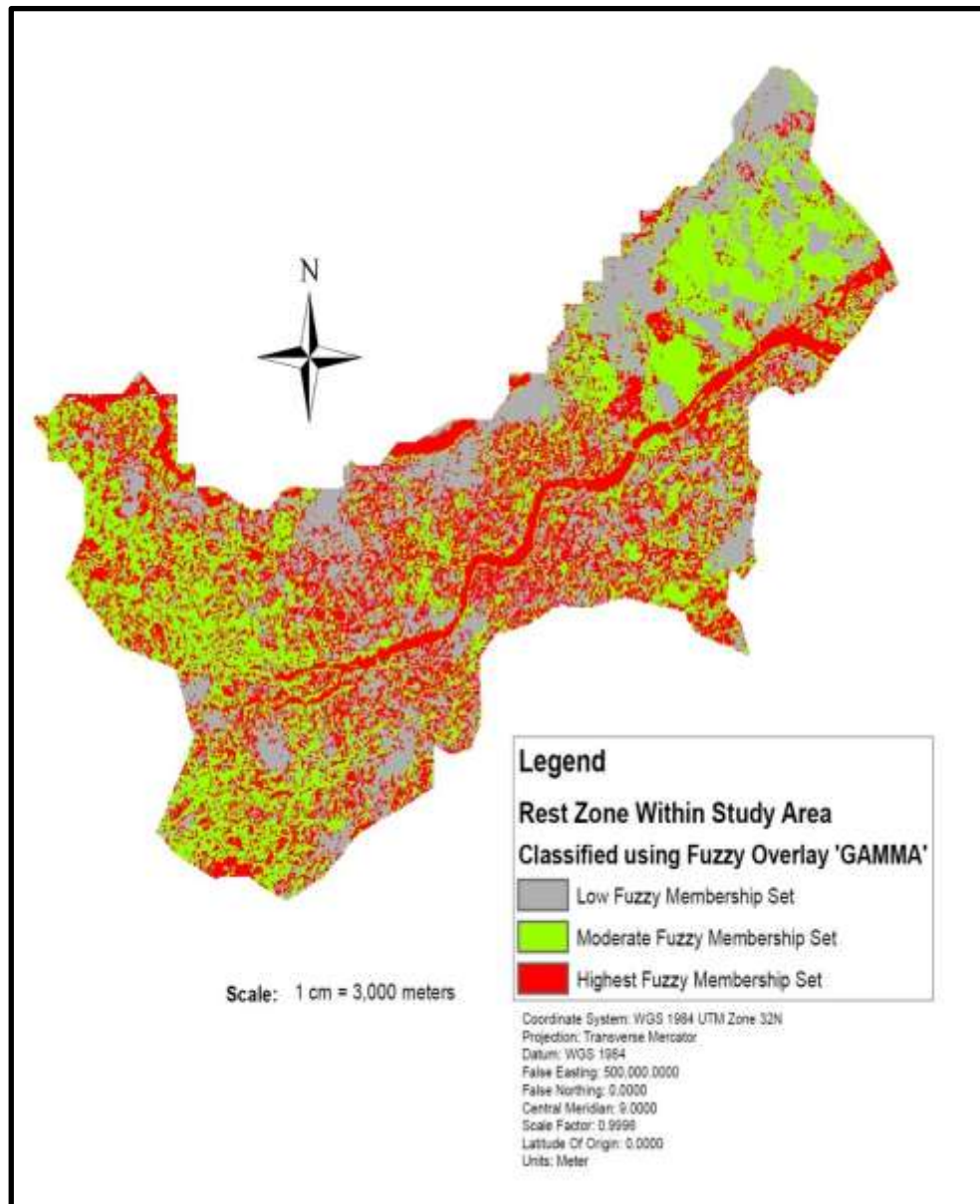 overlay operator 'GAMMA'**

Figure 8: HAT vector rest zone within the study area classified using fuzzy overlay operator 'GAMMA'

Table 5: 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
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

=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 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. 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.

The spatial condition number obtained (from LPI) for each habitat zone was below the critical threshold value of 10, thus the model can be regarded as reliable and stable. The outcome of the LPI and EBK (Figures 9-11)cross validation for each habitat zone produced mean and standardised mean prediction errors that was near zero, this was an indication of unbiased prediction that was centred on true values. The scatter plot of the cross-validation analysis 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
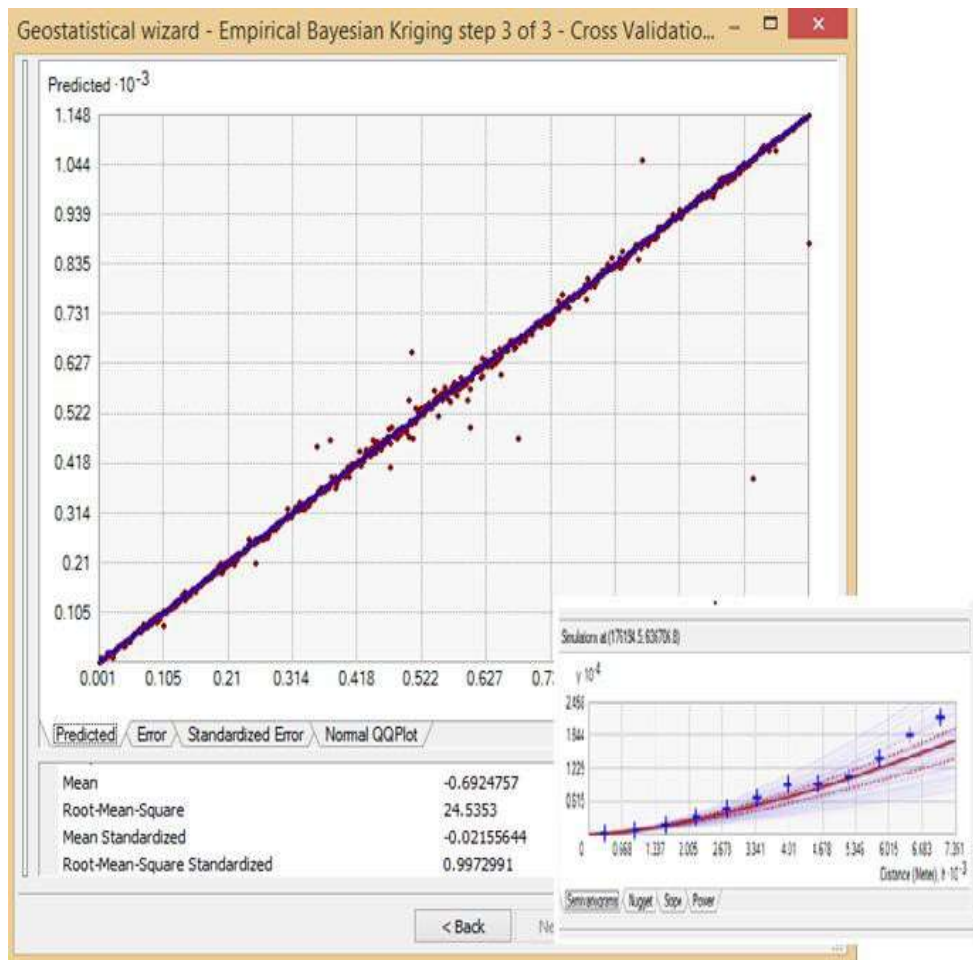
Figure 9: Quality of fit assessment of HAT vector breed zone in the study area using empirical Bayesian kriging (source: Cross validation analysis (*Note: simulated semivariogram insert*))
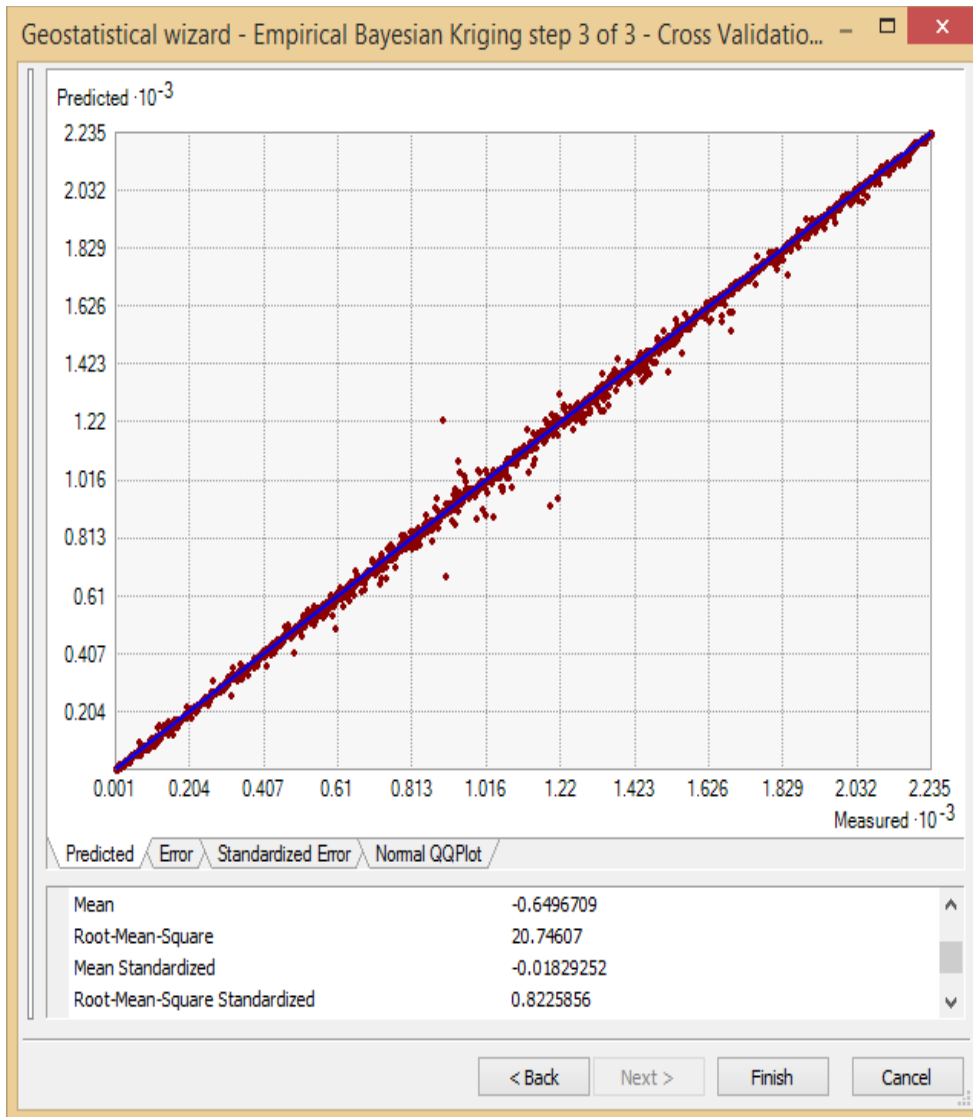
Figure 10: Quality of fit assessment of HAT vector feed zone model in the study area using empirical Bayesian kriging (source: Cross validation analysis)

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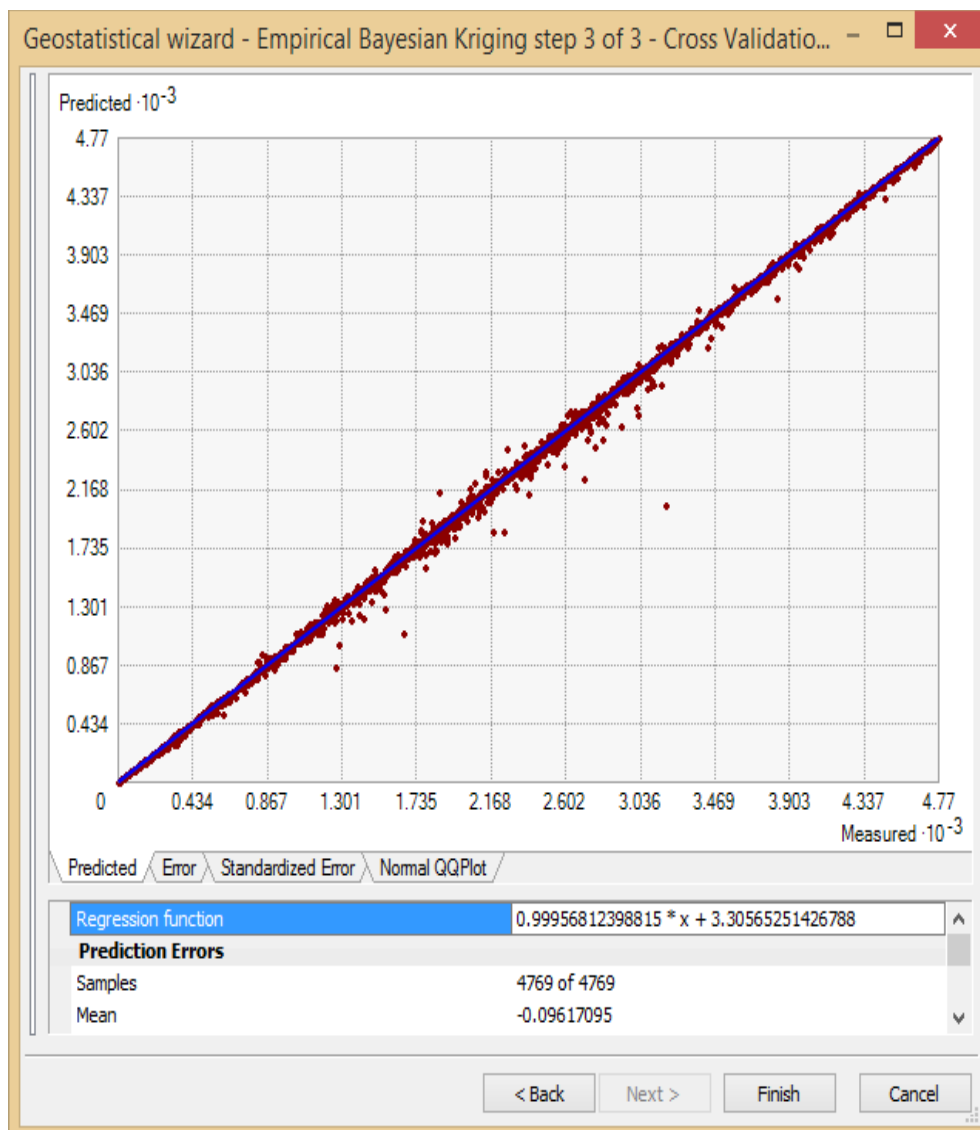ISSN 2224-3216 (Paper) ISSN 2225-0948 (Online)
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Figure 11: Quality of fit assessment of HAT vector rest zone model in the study area using empirical Bayesian kriging (source: Cross validation analysis)

4. Discussion and Conclusion

The aim of this study was to carry out a detailed characterisation of the study area environment (at a regional scale) using geospatial techniques to identify and classify potential HAT vector habitats into zones, to ease disease management. The use of geospatial techniques in developing the classification scheme was successful. The criteria used for this study were derived from RS images because of dearth of digital data/information in the study area. 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.

The classification scheme developed in this study 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. Thus, 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, Nigeria.

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 study 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 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 can help to precisely identify the direction and magnitude of HAT, the factors influencing HAT propagation, and the priority areas in the 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 study can be adapted to map other vector borne diseases habitat.

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Appendix

Equation s used in the study

Equation1 (Landsat 7 science data users handbook):

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

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.

Equation 2 (Irish 2008; Chander et al. 2009):

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

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).

Equation 3 (Chander et al. 2009):

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

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.

Equation 4 (Weng, Lu and Schubring 2004):

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

Equation 5 (Tucker 1979):
$$NDVI = (near\text{-}infrared - red) / (near\text{-}infrared + red)$$

Equation 6 (Ji, Zhang and Wylie 2009):

$$NIR - MIR / NIR + MIR \ (i.e.\ band4 - band5 / band4 + band5)$$

Equation 7 (Renza et al. 2010):

$$NDVI - NDWI / NDVI + NDWI$$

Equation 8 (Lawrence 2005):

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

Where: RH = relative humidity, *es* = saturated water vapour pressure, *e* = actual water vapour pressure.

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