# Identifying Diseased Areas using a Geospatially Developed Human African Trypanosomiasis Vector Habitat Classification Scheme

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## 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. 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. 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. To achieve effective deployment of control strategies, accurate knowledge of the spatial distribution of the disease is vital. The current study is based in Nigeria, and looks at part of Delta State, in which HAT has been identified. The study utilizes a previously geospatially developed HAT vector habitat classification scheme, to explore the dynamics of HAT propagation. The goal was to map the direction and magnitude of HAT and identify HAT vulnerable/risk areas. This helped identify 'HAT priority intervention areas'. The study highlights the significance of geospatial techniques where epidemiological data are limited, for improving understanding of HAT. The study findings suggested HAT propagation in the study area was multidirectional, and that this may have been influenced by landscape characteristics. The study also suggested that the study area could be regarded as highly hazardous and that the human population residing in the area could be said to be at moderate risk of HAT. The method employed in this study will facilitate efficient decision making, planning for resource allocation as well as support active HAT surveillance.

**Keywords:** Propagation, geospatially, multidirectional, disease,

## 1.0 Introduction

HAT is a form of vector-borne disease transmitted by the bite of an infected tsetse fly (Sterverding 2008). 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. During the late phase parasites are present in the cerebrospinal fluid, causing the classical symptoms of sleeping sickness which include confusion, lethargy and progressive emaciation. If untreated, the disease overcomes the host defences leading to coma and death (Steverding 2008; Berrang-Ford 2007; Jordan 1986). 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).

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 (Dede and Mamman 2011). 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).

Disease surveillance in Nigeria has been impeded by poor facilities and funding (Nduka and Yennan 2007). 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.

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).

The present study attempts to remedy the lack of digital locational based information, applied a geospatially developed HAT vector habitat classification scheme previously published by the authors of this study (Akiode & Oduyemi 2014), to identify: the direction and magnitude of HAT and vulnerable/risk locations in the study area. This will aid disease surveillance and effective/efficient prioritization and deployment of limited resources.

### *1.1 Geospatial Technology*

Geospatial technology is pervasive in modern life, and is used in areas such as law enforcement, disaster management, environmental protection, public health, etc (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 (Cimons 2011). Such datasets are usually gathered from various sources, such as remote sensing, reconnaissance survey, 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.

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. Geospatial data, on the other hand, identifies the geographical location and characteristics of particles 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. Zoller et al. 2008 used buffers radius ranging from 400m to 5000m around homesteads to analyzed risk of ***T. brucei rhodesiense*** sleeping sickness in villages in south-east Uganda.

Integration of geospatial approaches with disease management decisions can permit efficient and effective prioritisation and deployment of limited resources.

### *1.2 Fuzzy Membership Functions*

The fuzzy 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 and 2 (Tsoukalas and Uhri 1997).

$$\mu(x) = \frac{1}{(\quad)^{S_i}} \qquad 1$$

$$\mu(x) = \frac{1}{(\quad)^{-S_i}} \qquad 2$$

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. (details in Zadeh 1965). The steps involved in the integration of fuzzy logic with geospatial-MCDA, which, in the context of this study, can be regarded as geospatial-fuzzy MCDA is similar to MCDA procedures.

### *1.3 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 3) as unsafe locations of element at risk.

$$V = f({}^{l}er) \qquad 3$$

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:

$$DR = hazard * f\left({}^{l}er\right) \qquad 4$$

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 study 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).

### *1.4 Choice of Study Area*

Two local government areas (Ethiope-east and Ukwuani) within Delta state, Nigeria (located between latitudes 5o30'N and longitude 6o00'E; Figure 1) were chosen for this study as they have been identified as active HAT foci, and records indicated continuous HAT positive cases (Osue et al. 2008; Abenga and Lawal 2005). 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.

The region is one of the most hydrocarbon-rich regions in the world (Ophori 2007), The flourishing petrochemical industries have however, been shown to be causing severe environmental damage (Tolulope 2004), as well as potentially reducing the human population's ability to resist vector-borne diseases (Sutherst 2004). These changes could alter the human-HAT vector relationship (Sutherst 2004). More details about the study area are provided in Akiode & Oduyemi (2014).

Figure 1. The Delta State of Nigeria

## 2. Material and Methods

Both spatial and non-spatial data projected to the World Geodetic System (WGS) 84 datum Universal Transverse Mercator (UTM) Zone 32N, were integrated with statistical analyses towards the realisation of the study aim.

The existing administrative map of the Delta States, Nigeria obtained from Mapmakerdata, were imported into ArcMap to extract the study area polygon boundaries. The boundaries which served as base maps were subsequently used to subset the RS image (2002 Landsat 7 ETM+, Path/row- 189/56) used in this study.

Ground control points (GCPs) for settlements in the study area were collected. The GCPs and anonymised geo-referenced hospital records (HAT record of cases between 1994 and 2006 obtained from Eku

Baptist hospital, Delta State Nigeria) of HAT patients identified in each settlement were stored in Microsoft Excel, exported into ArcMap, converted into shape files and merged with the base map for further analysis.

Fuzzy logic approach was used to partly-quantitatively examines the vulnerability/risk of HAT in the study area. 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. The analysis made use of the geospatially developed HAT vector habitat classification scheme results from Akiode & Oduyemi (2014). Akiode & Oduyemi 2014, delineated the study area into three habitat zones , namely 'Breed', 'Feed' and 'Rest' using geospatial fuzzy multicriteria analysis. The HAT vector habitat zones (breed, feed, and rest) were taken as hazard indicators while settlements within the study area were taken as vulnerability indicators. Based on these indicators, HAT risk was determined for the 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 are incorporated into the final selection of priority areas.

## 2.1 Methods

### *2.1.1 Directional Distribution Analysis*

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

#### *2.1.1.1 Standard Deviational Ellipse Analysis*

The ArcMap 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 2 – Appendix 1) was computed to show two standard distances axes of the mean centre, the orientation of the ellipse, and the case field using standard deviation levels 1.

## *2.2 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 HAT vector habitat 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 Figures 3 - 5 (Appendix 1) and Tables 1- 3 (Appendix 2).

## *2.3 Vulnerability Assessment*

In this context vulnerability is equal to the location of an element at risk to hazard (Equation 3 – section 1.3). A factor analysis was carried out to identify vulnerable areas within each HAT vector habitat zones.

### *2.3.1 Factor Analysis of HAT Vector Habitat Zones*

A geo-processing model was made using the ArcMap 10.1 model builder to identify vulnerable areas within 400m (Zoller et al. 2008) of 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 4 – Appendix 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. The fuzzification of each land cover was carried out in Akiode & Oduyemi 2014.

### *2.3.2 HAT Vulnerability Assessment*

Using equation 3, the distance map of the land cover classes were combined with the hazard map generated in section 2.2 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 Figures 6 – 8 (Appendix 1).

### *2.4 HAT Risk Assessment*

To determine the magnitude of risk for the settlements in the study area, HAT risk (Equation 4 – section 1.3) 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 Figures 9 – 11 (Appendix 1) were categorised as very high, high, moderate and low. In addition, a geo-processing model was created to identify the direction 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 12 – Appendix 1). The direction of settlements at risk of HAT within the HAT vector zones (breed, feed and rest) is summarised in Table 5 (Appendix 2).

### *2.5 Prioritisation of HAT Risk Settlements*

The three HAT vector habitat zones were overlaid using the fuzzy overlay function *'AND'* (intersection) to identify areas that need urgent attention in the 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 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 13 (Appendix 1) presents the priority map for the study area while all the settlements that need urgent attention are presented in Figure 14 (Appendix 1).

## 3. Discussion and Results

Using the classification scheme developed for managing HAT, the areas prone to hazard of HAT were identified and categorised. From tables 1 – 3 (Appendix 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 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 study area is highly vulnerable. 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 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

**Table 6: 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 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 study area as settlements of the highest priority.

The SDE analysis in section 2.1.1.1 revealed one direction (north-eastern) of HAT propagation. Further assessment of the study area using the HAT vector classification scheme not only confirmed the north-eastern direction of HAT propagation in the 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 study area. The one direction (north-east) of HAT revealed by the spatial distribution analysis 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.

To overcome the burden of HAT, policy was formulated to strengthen surveillance programmes in Nigeria. 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 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.

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 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 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. Constant active surveillance in these areas can ensure the detection of the parasite in infected people early enough to allow timely treatment.

## 4. Conclusion

The aim of this study was to apply a geospatially developed HAT vector habitat classification scheme, to identify diseased locations within the study area toward efficient management of the disease.

The HAT vector habitat classification scheme 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 directional analysis carried out using the HAT vector habitat classification scheme revealed a multidirectional magnitude of HAT propagation in the study area. The method employed in this research will facilitate efficient decision making, planning for resource allocation as well as support active HAT surveillance. To further enhance disease management/control, subsequent studies will focus on the application of the HAT vector classification scheme to identify factors influencing propagation of HAT as well as assessing the suitability of these factors for the HAT vector within each HAT vector habitat zone.

Assessing vulnerability of each settlement in the 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.

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## Appendix

## Figures and tables refer to in the study

*Appendix 1: Figures*

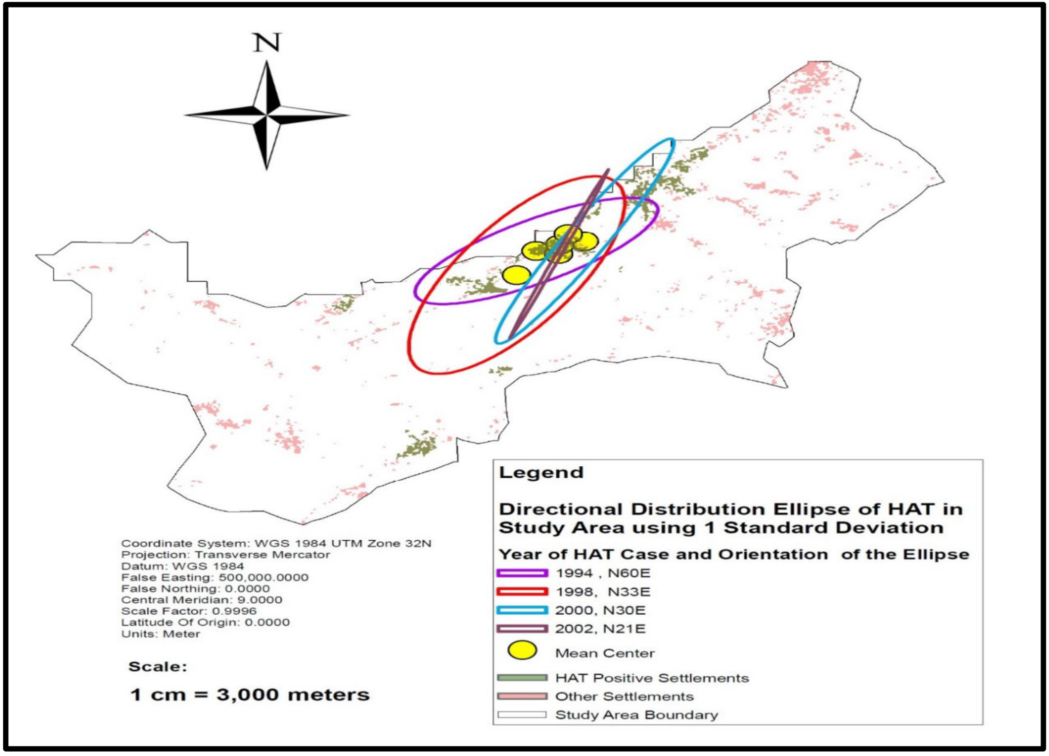

**Figure 2: Standard deviational ellipse of HAT distribution in the study area**

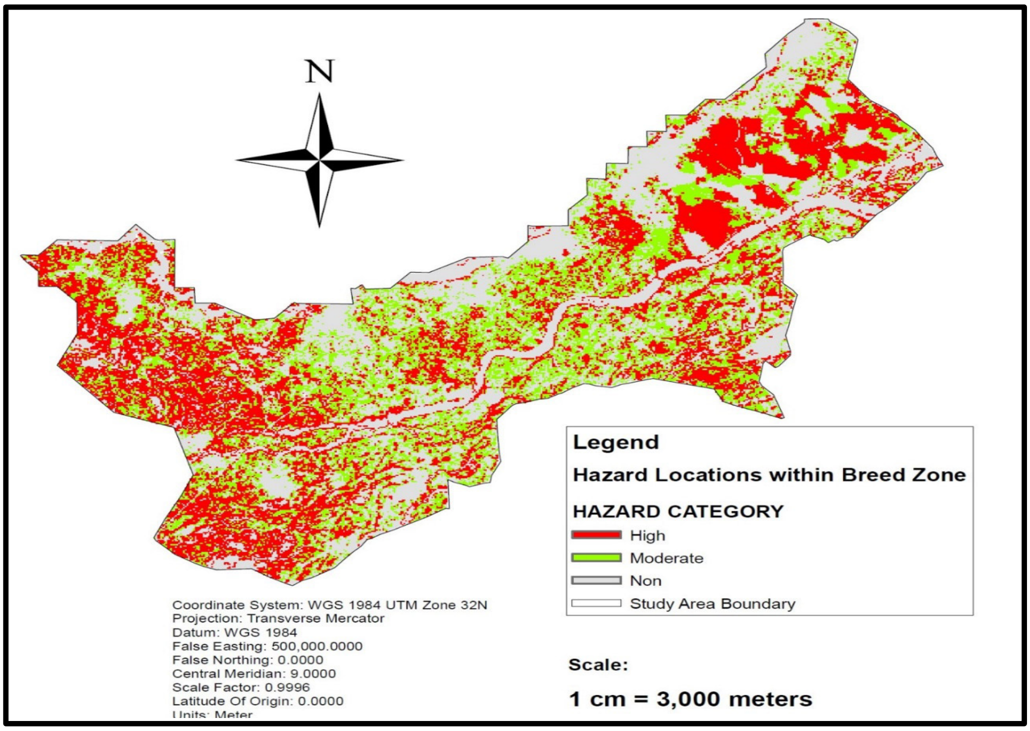

**Figure 3: Map showing hazard locations within the HAT vector breed zone in the study area**

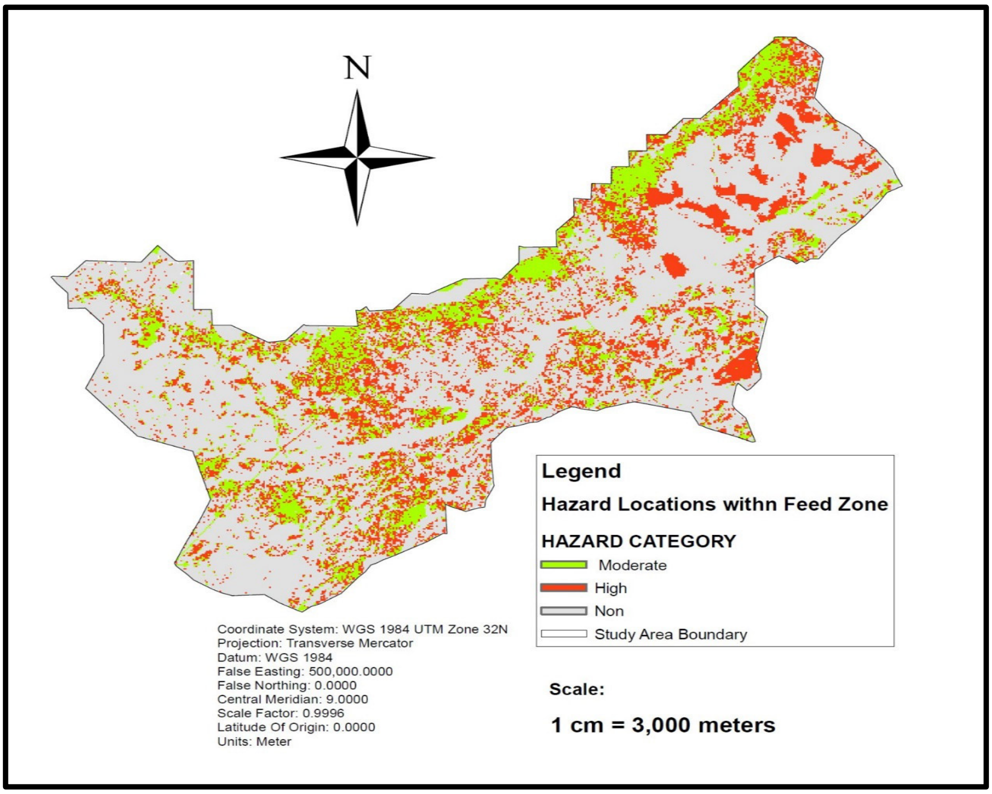

**Figure 4: Map showing hazard locations within the HAT vector feed zone in the study area**

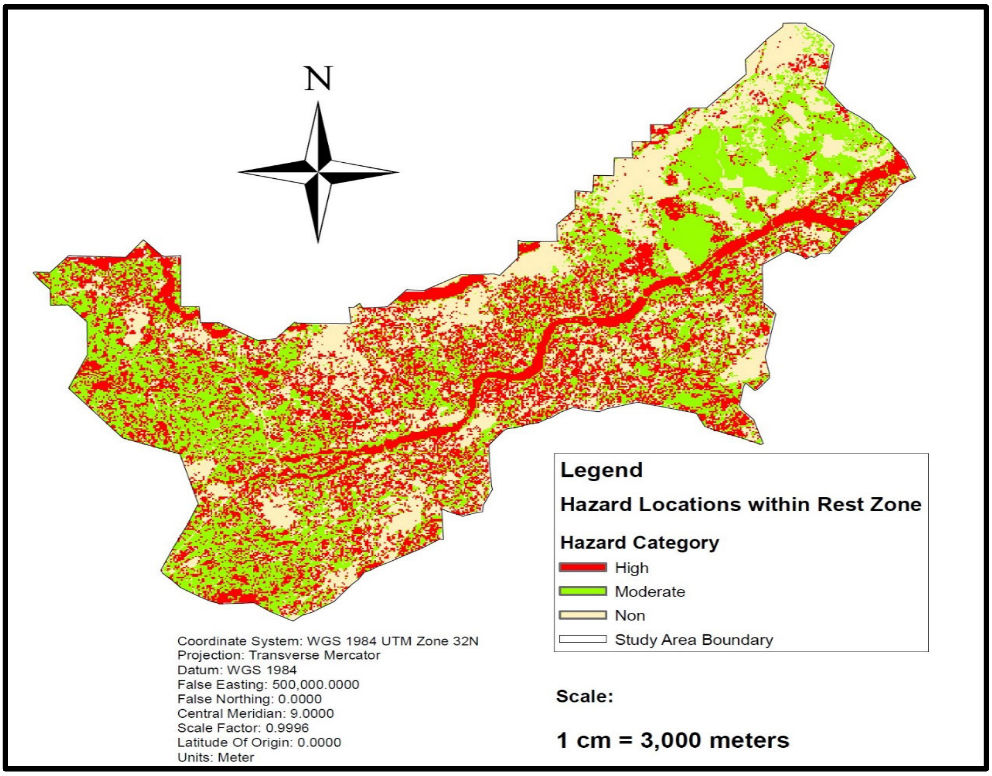

**Figure 5: Map showing hazard locations within the HAT vector rest zone in the study area**

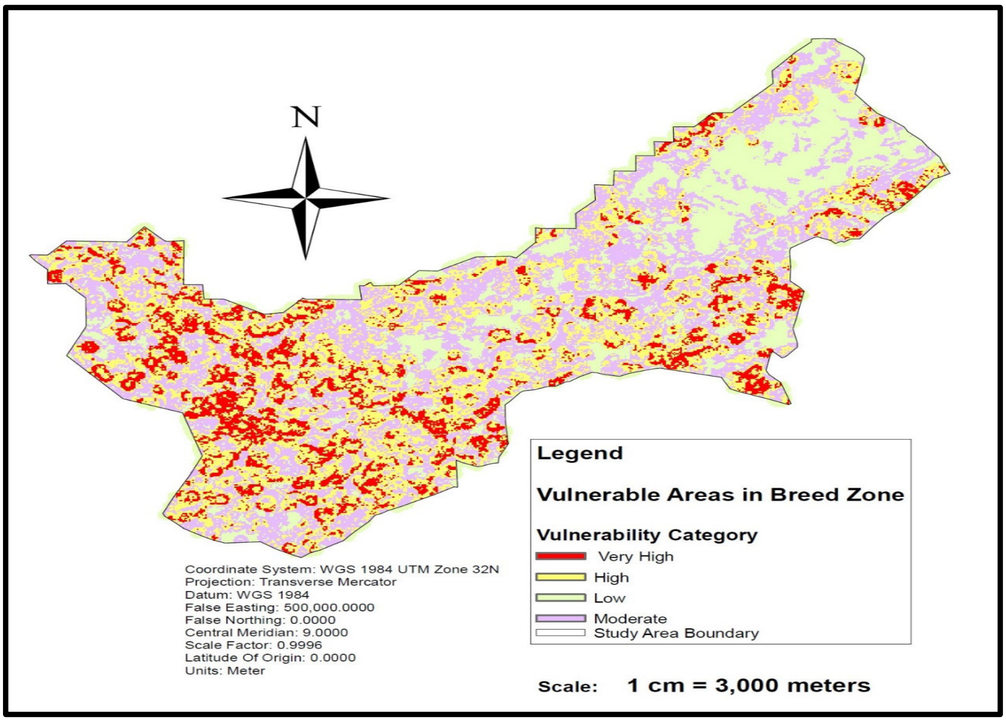

Figure 6: Vulnerable locations within HAT vector breed zone in the study area

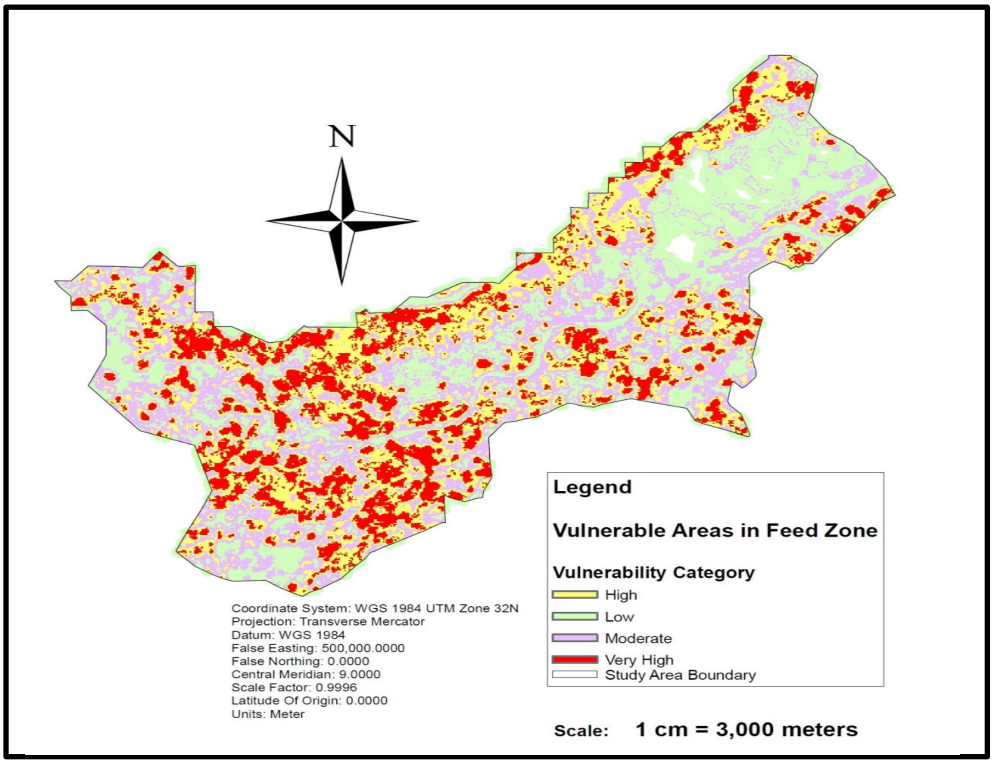

**Figure 7: Vulnerable locations within HAT vector feed zone in the study area**

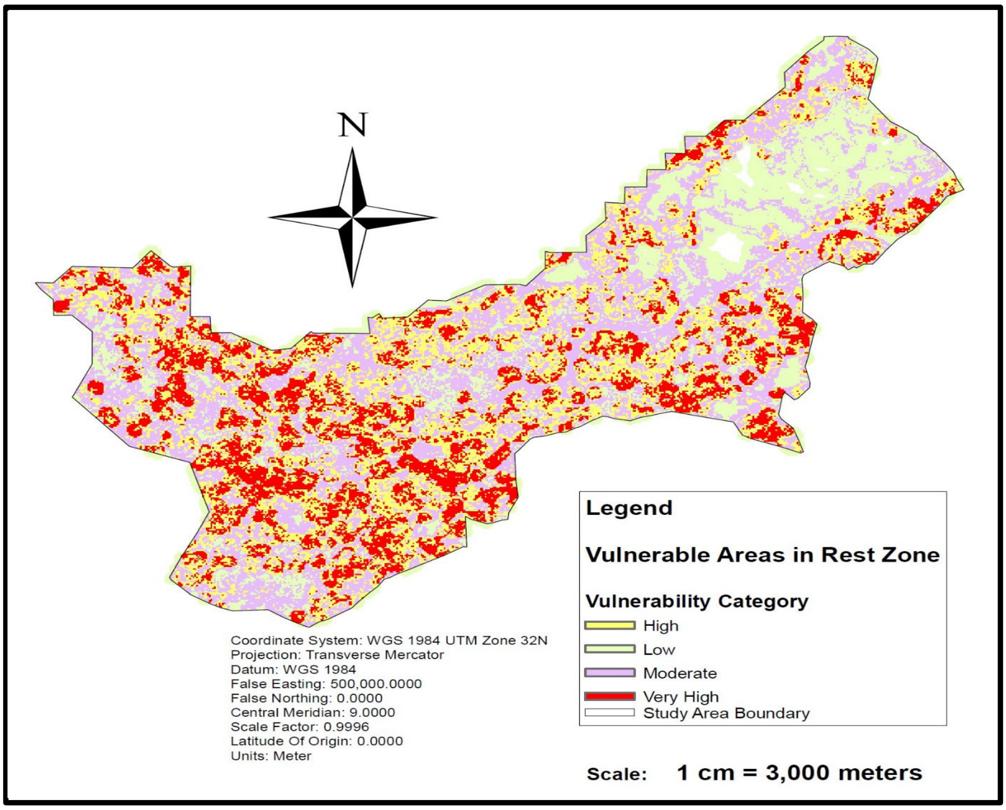

**Figure 8: Vulnerable locations within HAT vector rest zone in the study area**

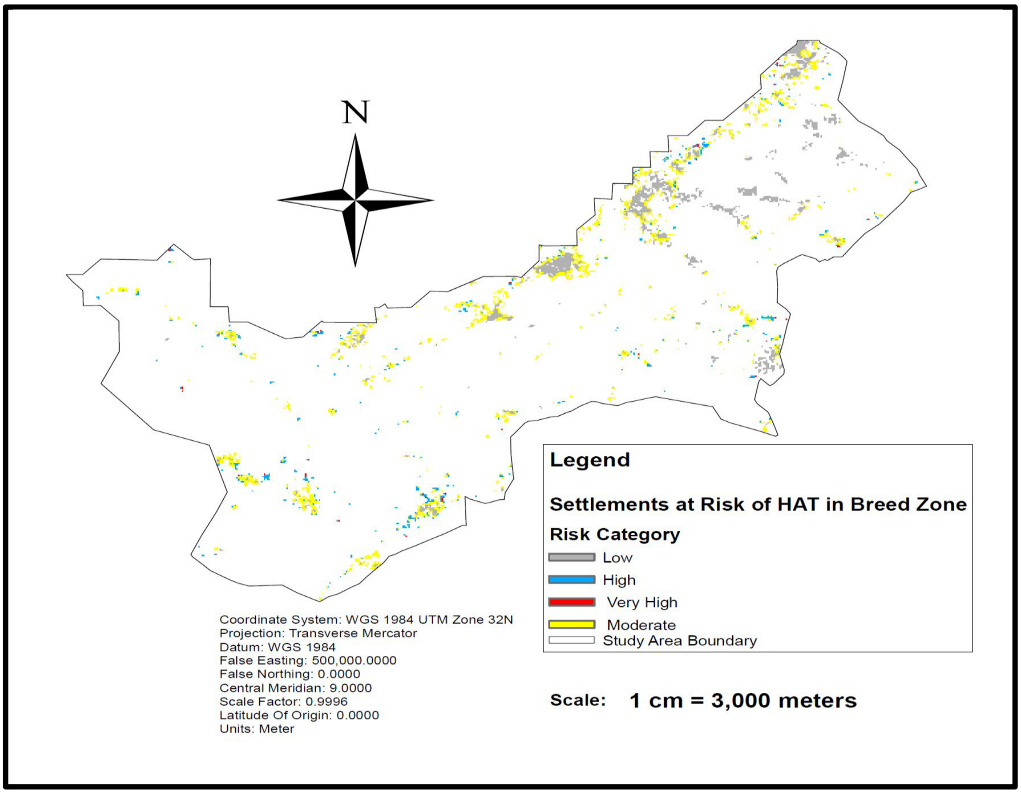

**Figure 9: Settlements at risk of HAT within HAT vector breed zone in the study area**

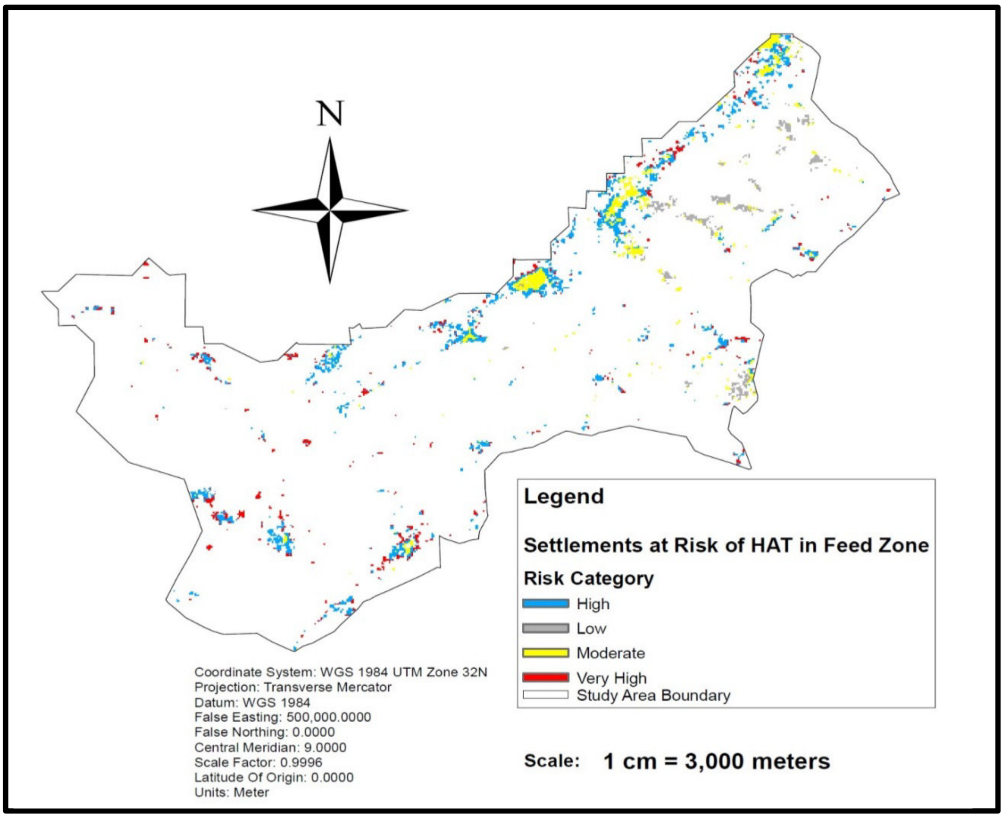

**Figure 10: Settlements at risk of HAT within HAT vector feed zone in the study area**

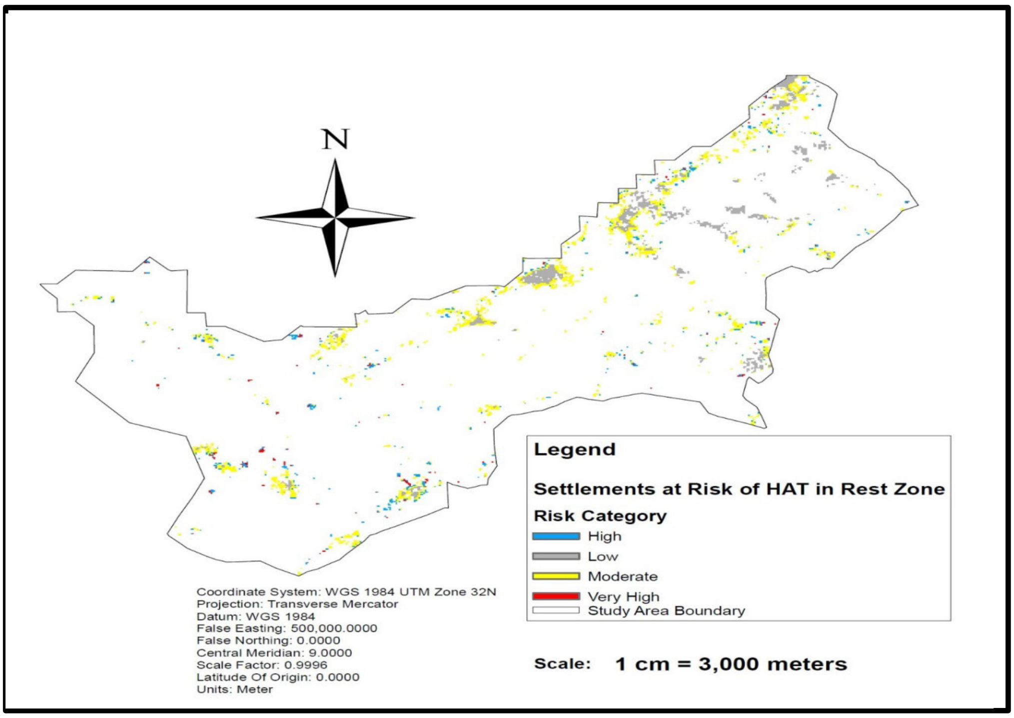

**Figure 11: Settlements at risk of HAT within HAT vector rest zone in the study area**

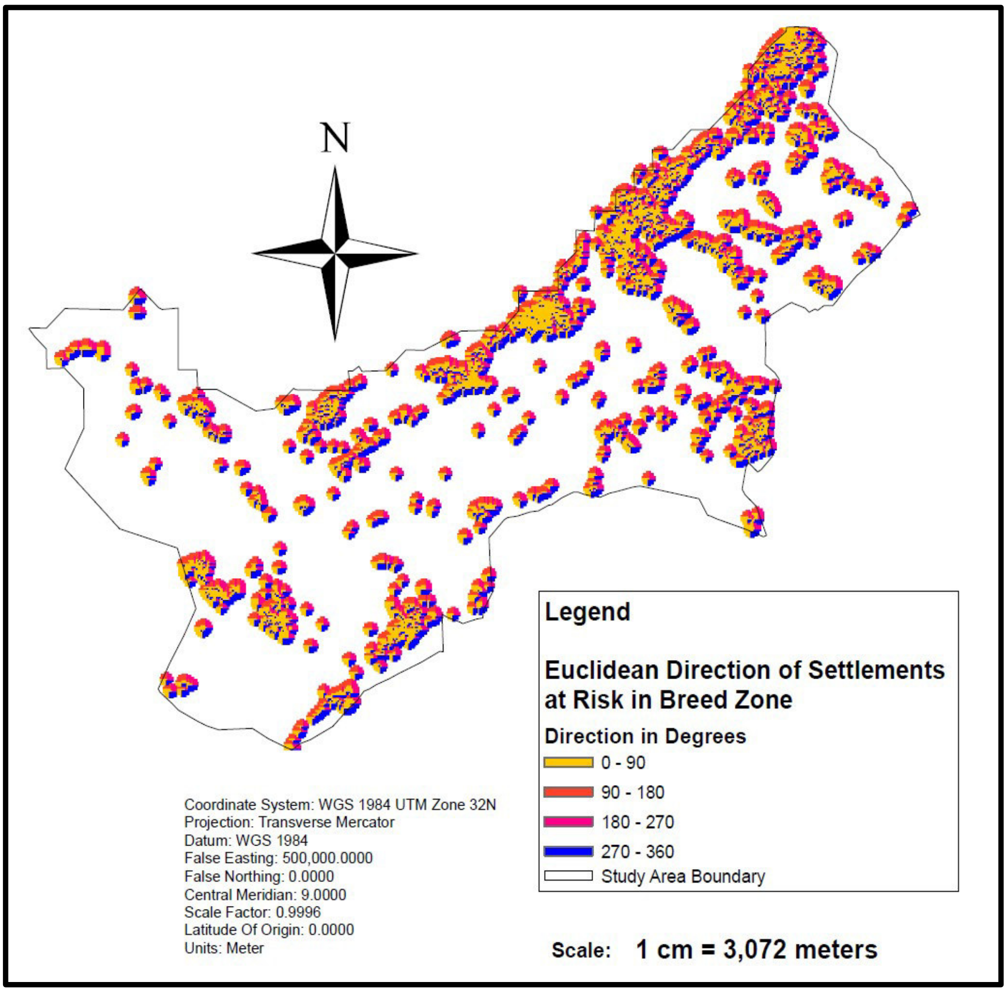

**Figure 12: Directional map of settlements at risk of HAT within HAT vector breed zone in the study area**

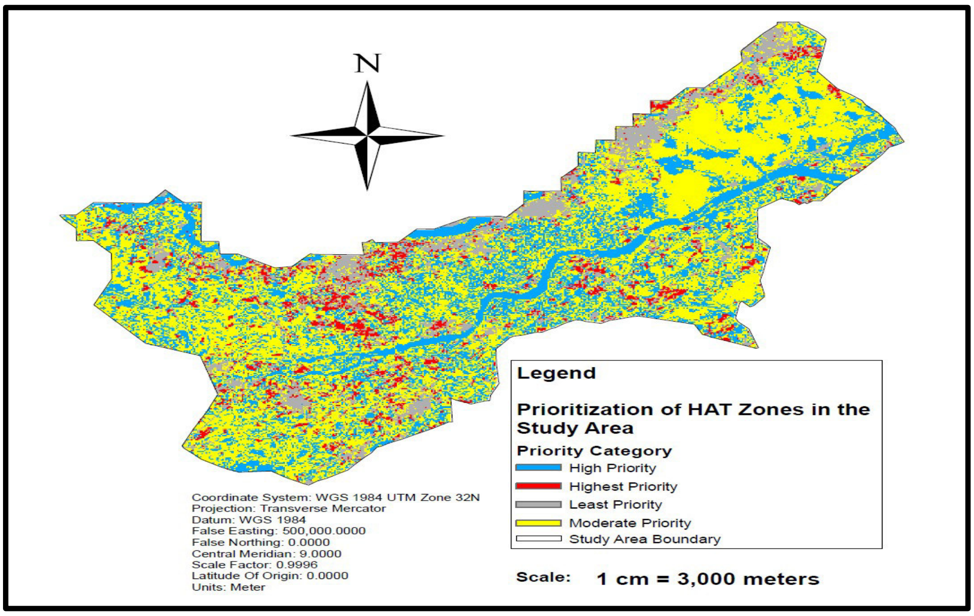

**Figure 13: HAT priority areas within the study area**

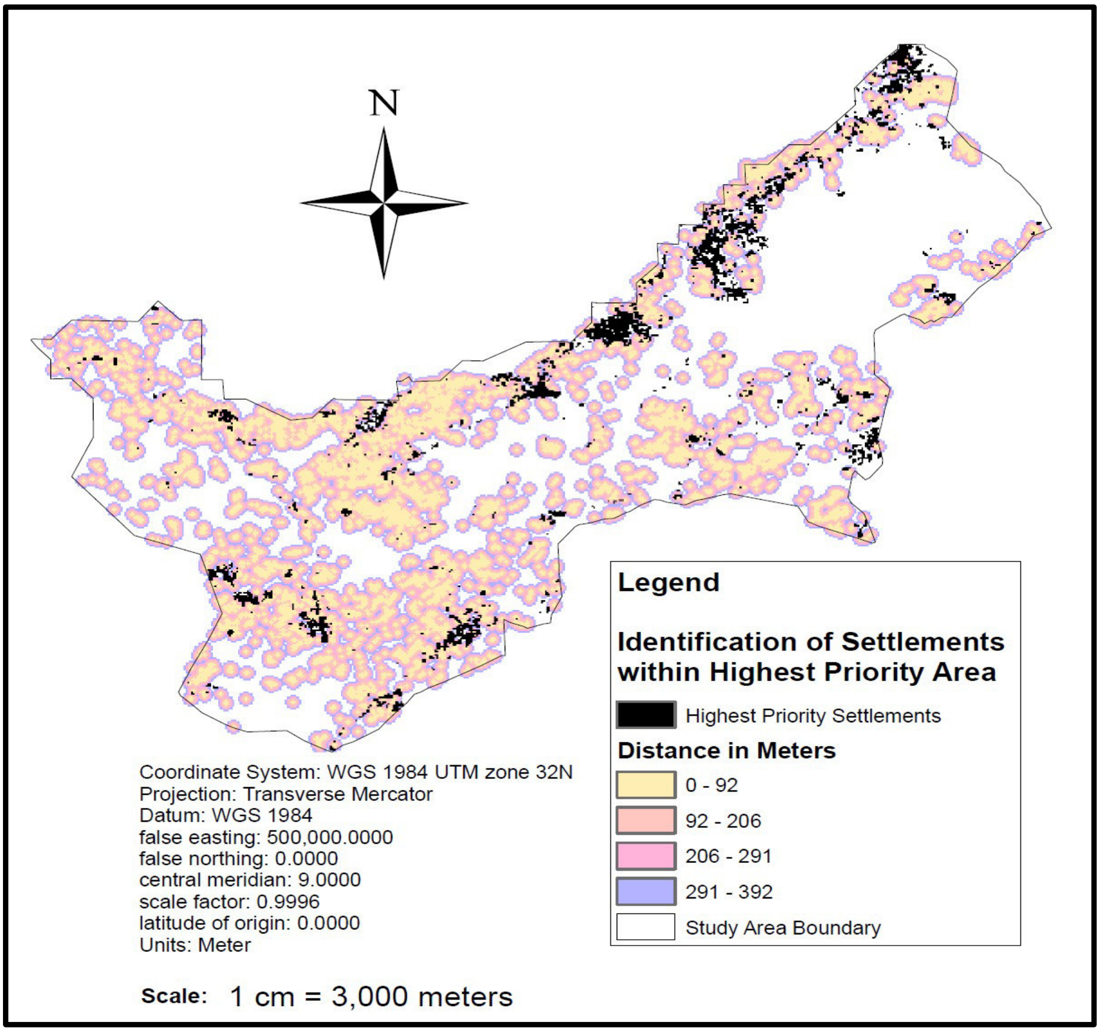

**Figure: 14: Highest HAT priority settlements within 400m of highest priority areas**

## Appendix 2: Tables

**Table 1: Attributes of the hazard locations within the HAT vector breed zone**

| ROW ID | COUNT | AREA | 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)

**Table 2: 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)

**Table 3: 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)

**Table 4: 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 |

**Table 5: Attributes of directional map of settlements at risk of HAT within HAT vector zones in the 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 |

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We thank USGSEROS for the Landsat image obtained through their website. We also, thank the ESRI for providing free ArcMap software and granting us permission to use it for the research analysis.