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Multi-Scale Modeling of Anopheles Mosquito Distribution in Southern Mali

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MULTI-SCALE MODELING OF *ANOPHELES* MOSQUITO DISTRIBUTION IN SOUTHERN MALI

By

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The advent of developing outdoor malaria vector control methods creates a demand for distribution models of *Anopheles* mosquitoes at regional (~30 meters) and fine spatial scales (~2 meters). The distributions Anopheline mosquitoes in West Africa have been modeled in the past, yet always at relatively coarse resolutions. In this study, I worked to develop methods to ascertain the distribution of Anopheline mosquitoes at these little studied spatial scales. The species distribution modeler Maxent was used to create a species distribution model at a regional scale for *Anopheles gambiae* and *Anopheles arabiensis* which relied on Landsat derived environmental indices. Models for both species preformed reasonably well with a training area under the curve value (AUC) of 0.767 & a test AUC of 0.783 for *Anopheles gambiae*, and a training AUC of 0.822 & a test AUC of 0.680 for *Anopheles arabiensis*. The result of the created models agrees with the known bionomics of these species and demonstrated the reliance on the area around and in urbanized areas as being important to both species. The second aim of this research was to observe the distribution of mosquitoes at a fine spatial scale by mapping possible areas of resting habitats that these malaria mosquitoes use to rest during daylight hours. This was performed by using two different models, Maxent and Dempster-Shafer

modeling, along with the high resolution satellite images from the WorldView 2 satellite. The results of the two modeling methods appear to agree with the results of the other fairly well with a linear regression R-squared value of 0.428 ($p < 0.001$) and both appear to be capable of mapping out the presence of areas likely used as resting sites by mosquitoes. Yet to accurately determine which resting sites are more important than others may require additional data that is difficult to determine by using remote sensing alone.

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ABBREVIATIONS & ACRONYMS

ATSB	Attractive Toxic Sugar Baits
AUC	Area Under the Curve
BRT	Boosted Regression Tree
CDC	Center for Disease Control
DEM	Digital Elevation Model
D-S	Dempster-Shafer
EBBI	Enhanced Built-Up and Bareness Index
GARP	Genetic Algorithm for Rule-set Prediction
IBI	Index-based Built-Up Index
IRS	Indoor Residual Spraying
Km	Kilometers
ITNs	Insecticide-Treated Nets
Maxent	Maximum Entropy Modeling
m	Meters
MNDWI	Normalized Difference Water Index
NDBaI	Normalized Difference Bareness Index
NDBI	Normalized Difference Built-up Index
NDISI	Normalized Difference Impervious Surface Index
NDMI	Normalized Difference Moisture Index
NDVI	Normalized Difference Vegetation Index
RBM	Roll Back Malaria program
SAVI	Soil Adjusted Vegetation Index
TSS	True Skill Statistic
TWI	Topographic Wetness Index
UI	Urban Index
WHO	World Health Organization

CHAPTER I

INTRODUCTION

Problem Definition

Malaria is one of the most serious public health problems in the developing world today, and as a result it is considered a high priority for control efforts and its elimination within the global health community. (Tanner and de Savigny 2008; Mendis et al. 2009; Bousema,Teun 2011; Cotter,Chris 2013). Recent incentives by researchers and health communities have aimed to make this goal possible with establishments such as The Roll Back Malaria (RBM) program. Programs such as these have already had a positive impact with reports showing that malaria mortality rates decreased by an impressive 47% between 2000 and 2013 globally and by 54% in the WHO African Region (World Health Organization 2014). These successes can be attributed to the continuing development of new drugs, and international funding that supports various malaria vector control strategies. RBM has set new goals for global malaria reduction by 2015. These include reduction of global malaria deaths to near zero, reducing global malaria cases by 75% relative to the 2000 levels and eliminating the disease in at least 8 to 10 new countries (Roll Back Malaria Partnership 2011).Yet, it is clear from recent data that this ambitious target remains elusive (World Health Organization 2014).

Focusing on Africa, malaria control efforts have resulted in a 23% decrease in cases and a 33% decrease in deaths associated with malaria when compared to data from 2000 (World Health Organization 2011). Yet this average figure does not represent the entirety of the continent. In 15 out of the 18 countries that fall within the region of West Africa, malaria transmission rates are among the highest in the Sub-Saharan part of the continent with infections almost exclusively due to *Plasmodium falciparum* (World Health Organization 2011).

The problem of malaria in Africa can be partially attributed to the ecology and behavior of a highly competent vector system of *Anopheles* mosquitoes, primarily *Anopheles gambiae* and *Anopheles arabiensis* of the *Anopheles gambiae* complex, and *Anopheles funestus* (Coetzee, Craig, and le Sueur 2000). Although each of these species is potentially dangerous to humans, each one has different habitat preferences. *An. gambiae* and *An. funestus* feed frequently and predominantly on humans, rest mainly inside houses (endophilic), and can survive for long periods. Peak densities of *An. gambiae* and *An. arabiensis* follow seasonal patterns of rainfall and both use a range of freshwater larval habitats (White 1974). *An. funestus* proliferate typically in permanent swamps and reach peak densities after seasonal rains into the dry season (White 1974). *An. arabiensis* is adapted to arid environments and has the most extensive geographic range in Africa. It is more difficult to control because of its outdoor (exophilic) resting and partial zoophilic feeding behaviors (Coluzzi 1984; WHO Study Group 2006).

Spatial Considerations

To further malaria control efforts in West Africa it is important to consider the spatial constraints that limit the disease. The risk of transmission is not uniform across the landscape; this is because risk is spatially heterogeneous due to the fact that pathogens, vectors and susceptible human populations are unevenly distributed in space and time (Brooker et al. 2004). Furthermore, the certain environmental variables required for the different vector mosquito species result in nonrandom distributions that can be analyzed and predicted with spatial models. Spatial models are advanced spatial analysis techniques that help identify the spatio-temporal patterns of both disease and vectors and provide a better understanding of environmental influence on the patterns observed; information which may then be used to direct surveillance and monitoring, decision-making and disease risk management (Stevens and Pfeiffer 2011; Eisen and Eisen 2011).

Previous Distribution Studies

As the RBM program focuses on reducing malaria transmission as one of its goals it is important to understand the distribution of the vector species throughout the landscape. An accurate and predictive understanding of the different geographic distributions of the malaria vectors in West Africa would permit efficient planning strategies for targeted control to reduce vector populations and identification of areas in which particular species are potentially involved in transmission. Modelling mosquito distribution is not a new concept. Researchers have used a variety of methods to map and predict mosquito ranges from regional to global scales. The most basic method for this distribution was to map out the frequency of different mosquito species and different chromosomal forms at different sampling locations (Toure et al. 1998). This technique has been traditionally used at the country-level (Toure et al. 1998; Onyabe and Conn 2001) and continental level (Coetzee,et al, 2000) spatial scales with plot locations distributed throughout the study area. Some studies also implemented rainfall data to understand how this climatic variable correlates with what was seen (Toure et al. 1998; Coetzee et al,2000; Drake,and Beier 2014). This technique provides valuable snapshots of information pertaining to mosquito frequency, density, and composition at the sampled locations. Yet it does not provide a continuous surface of information that might respond to the unique ground conditions that vary across the landscape. Other research has mapped mosquito distribution and abundance using GIS functions with environmental data such as climate, topography, human population density and soil water holding capacity (Lindsay et al. 1998). One study published maps that were displayed at a one-degree square grid (4 km^2 at equator) and created maps of multiple Anopheline species for the entirety of Africa. These maps were then validated using public mosquito location data. This research as shown that the relative abundance of *An. gambiae s.s.* and *An. arbiensis* are correlated with temperature and precipitation at a regional scale (Moffett et al. 2007). Another study created predictive maps for *An. arabiensis* for the entirety of Mali using Bayesian geostatistical logistic regression (Sogoba et al. 2007). This study found that *An. arabiensis* was positively correlated with NDVI, soil water storage index, the maximum temperature and the distance to water bodies. It was also found that elements such as rainfall and minimum temperature were negatively correlated with *An. arabiensis* distribution (Sogoba et al. 2007).

More recent research (Levine, et al, 2004; Drake and Beier 2014) has used ecological niche modeling to predict mosquito distribution in Africa. Drake and Beier (2014) specifically worked to develop models which would forecast the future distribution of *An. arabiensis* may be impacted by climate change. These ecological models were created using a program called GARP (Genetic Algorithm for Rule-set Prediction). This method maps ecological niches of species based on the relationship between point-occurrence data to maps of relevant ecological conditions, producing a heterogeneous set of rules that describe the potential distribution of species in ecological dimensions. Other research has used different modeling algorithms, such as Boosted Regression Tree (BRT) (Sinka et al. 2010; Conley et al. 2014). Sinka et al. (2010) created a total of 41 vector distribution models for different areas of the world. They used public mosquito data (presence and absence points) and various environmental and climatic variables to create distribution maps using BRT methods. These species maps provide some of the most extensive mosquito distribution maps at the resolution of 5km by 5km.

Outdoor Vector Control

Even though these models provide useful information concerning mosquito distribution in Africa the spatial resolution is usually much too coarse for possible outdoor vector control. Vector control is the application of various strategies with the intent of preventing malaria transmission by limiting contact with the vector species. This also includes any methods intended to eliminate the vector species in some way. The use of vector control in areas where malaria is prevalent, such as sub Saharan Africa, is considered of high importance (WHO 2012). The current options for vector control in African countries are limited (Muller et al. 2010) and the vector control strategies available are meant for indoor control. The main control is insecticide-treated nets (ITNs) and long-lasting insecticide-treated nets (LLINs) which have increased in usage in sub-Saharan Africa from 3% of the population in 2000 to now around 53% in 2011 (WHO 2012). Another popular vector control strategy is indoor residual spraying (IRS), which involves spraying the inside of dwellings with an insecticide. The proportion of the population protected by indoor residual spraying increased substantially in Africa during 2006–2008, and the increased coverage was then maintained above 10% during 2009–2011; in 2011, 77 million people in the Region, or 11% of the population at risk, were protected (WHO 2012). Even though these methods have been proven to reduce parasite transmission they do not consistently reduce malaria prevalence rates because even barely detectable numbers of infective bites per person per year can be associated with malaria prevalence rates over 20% (Beier, Killeen, and Githure 1999; Mueller et al. 2010). In terms of outdoor vector control the options are still in development yet there is growing interest in pursuing these ventures. Much of the focus on the development of outdoor strategies has been on larval control. Killeen, Fillinger, and Knols 2002 and Gu and Novak 2005 demonstrated that larval control may be highly effective, complementary to adult control interventions, and should be considered as an integral part of Rolling Back Malaria. Fillinger et al. 2009 also demonstrated that vector control with microbial larvicides enhanced the malaria control achieved with ITNs alone. With reference to adult targeted vector control strategies research has shown that spraying vegetation with insecticides such as Bifenthrin reduces mosquito populations in outdoor environments (Cilek 2008). Also, the use of phytochemicals, which are intended to attract mosquitoes, could be used to trap and eliminate mosquitoes in outdoor environments. (Foster 2008). Another possible outdoor vector control method are attractive toxic sugar baits (ATSB), which aim to control mosquito populations by creating baits that consist of plant-based attractants combined with sugar and a low-risk toxin such as boric acid (Muller and Schlein 2006; Muller and Schlein 2008; Schlein and Mueller 2008; Muller et al. 2010; Muller et al. 2010). The use of ATSB has been shown to decrease male and female *An. gambiae* populations by 90% when compared to pre-treatment levels. ATSB methods may prove to be a highly effective, technologically simple, inexpensive, and environmentally safe mosquito control method (Muller et al. 2010).

Local Scale Distribution

To effectively use any of these vector control strategies requires knowledge of where the mosquitoes are within the environment surrounding the areas at risk. While distribution maps for the country of Mali were produced in the past (Sogoba et al. 2007), the literature lacks maps for species distribution at a finer spatial resolution, specifically at local-to-regional scales, which are consistent with many forms of freely available satellite imagery such as Landsat TM/ETM+, ASTER, or Quickbird imagery, for example.

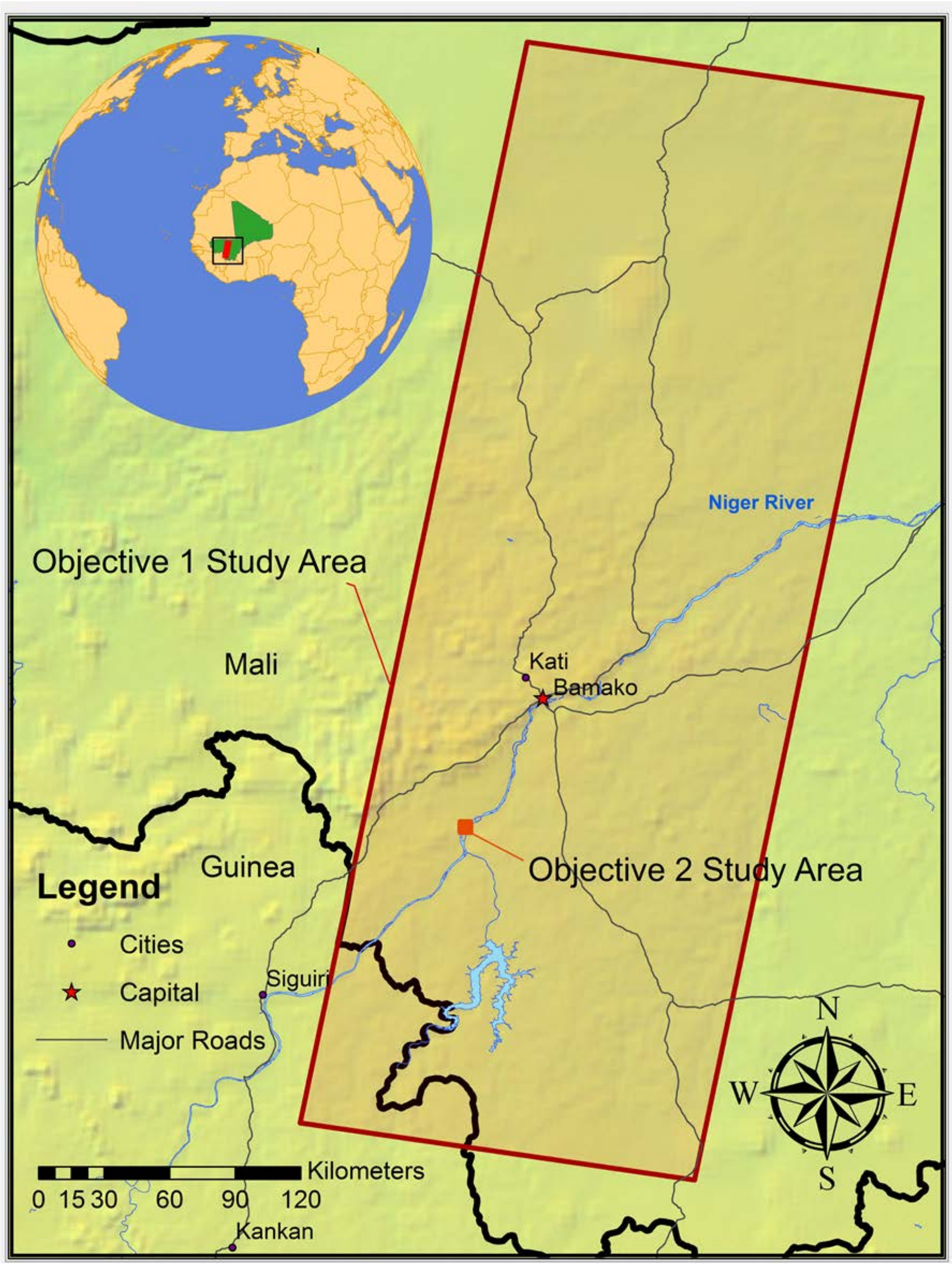
At the village level, understanding resting habitats for the different malaria vectors becomes important to help create management plans that aim to reduce transmission. The resting sites of adult mosquitoes in general are a poorly documented subject in the literature, despite its importance in the ecology of these organisms (Burkett-Cadena, Graham, and Giovanetto 2013). Resting habitat for mosquitoes are areas where mosquitoes rest after taking in blood meals before oviposition or during periods of inactivity during the day light hours. Understanding and identifying hotspot resting habitats can serve to help in vector control in rural areas (Afrane et al. 2006). To eliminate malaria in this region of the world understanding both large scale and small-scale mosquito resting habitat preferences is necessary to efficiently allocate vital vector control to areas that need it most. Once these hotspots are located then the usage of ATSB, or insecticide can be deployed to produce the maximum effect in reducing mosquito populations as well as malaria transmission.

Temperature is a major environmental factor that influences malaria mosquitoes (Paaijmans and Thomas 2011) and their resting behaviors. Mosquitoes are small poikilothermic organisms that are dependent on the surrounding environment for temperature regulation (Paaijmans and Thomas 2011). As such these malaria vector mosquitoes need to remain in shaded areas for the majority of the time to avoid desiccation and death, which would result from extended periods in the African sun (May 1979). This means that the daytime resting habitat for these organisms can be closely tied to dense vegetation, which would likely provide shade and a cooler microclimate when compared to open areas. Furthermore proximity to a water body and to blood meals is potentially important to consider as well, as they are crucial to the mosquitoes' life history. Blood meals are important to female mosquitoes as they require blood for egg maturation which is part of the gonotrophic cycle (Paaijmans and Thomas 2011). Besides water being important for hydration of the adult mosquitoes, they also require open water to deposit their eggs at the end of their gonotrophic cycle (Sumba et al. 2004). The vicinity to water can be considered of utmost importance when identifying resting habitats. Previous studies have shown that proximity to swamps, as well as distance to streams or other water bodies are strong predictors of malaria incidence (Trape et al. 1992; Staedke et al. 2003; Gouagna et al. 2011; Zhou et al. 2012).

Research Objectives

The overall purpose of this research was to test the possibility and the feasibility to map the distribution of the anopheline mosquito species at regional scales found in public satellite imagery described earlier, using the popular species niche modeler, Maxent (**Chapter 2**) to describe *Anopheles* mosquito distribution across a landscape. The second objective of the research is to test if microhabitat preferences, such as resting habitats, can also be mapped using satellite images and remote sensing methods (**Chapter 3**). These aims address the gaps in the literature in respects to malaria vector modeling. Furthermore, this research will be focused on Southern Mali which can be seen in **Map 1.1**, an area in West Africa where malaria is highly prevalent (WHO 2014).

Map 1.1 The Study area in Mali, West Africa; this map shows the location and extent of the two different remotely sensed images in this study.



Ecological Considerations

Mali is a West African landlocked country that covers a total area of 1,242,248 square kilometers. The country is relatively flat, altitude variations are minimal, ranging from 200 to 350 m above sea level (Sogoba et al. 2007). The majority of the country lies within the Sahara desert, which covers the northern part of the country that includes the regions of Tombouctou, Kidal, and Gao. Yet these regions, due their aridity, have limited vegetation or moisture which are associated with mosquito habitats. Therefore, the study area of this thesis falls in the southern region of Mali, which is defined by the second aim of this study. This area covers the Koulikoro, Bamako, and parts of the Sikasso and Ségou regions of the country. A small part of the study area also falls in the country of Guinea. This area overlaps the Sahel ecosystems in the north and Sudanian savanna ecosystems in the south.

Sahel Region

The Sahel is a transitional region that separates the Sahara from the southern savannah regions of Central and Western Africa. This unique zone of Africa occupies an area of 2.5 million km^2 in a 400- to 500-km wide belt which has a strong north south precipitation gradient that follows a general 1mm/km (White 1983; Le Houerou 1980). This region is characterized by short single rainy seasons which normally last 2-4 months then are followed by a long dry season which last the remainder of the year. Being near the Sahara the average maximum temperatures for the Sahel region can range from $40^{o}C$ to $45^{o}C$ from

April to possible as late as September. The lowest average temperatures for the Sahel occur around December to January which is around 15 ^{o}C (Tucker et al. 1985). Due to the short rainy seasons the growing season is also very brief, ranging from 2-2.5 months. As a result, this region is mainly dominated by annual grasses such as *Chloris prieurri, Aristida mutabilis, Cenchrus biflorus, Schoenefeldia gracilis, Dactylocteuium aeyptium*, and *Tragus berteroniauus* just to name a few (Tucker et al. 1985). The coverage of woody vegetation in this area is very low. On soils where the rainwater is well absorbed, the average coverage of these trees is less than 5 percent (Breman and Dewit 1983). Yet in areas where the soil does not absorb the rainfall, the water runs-off and accumulates in temporary puddles. It is around these areas where conditions are suitable enough for canopy cover to exceed coverages of 20 percent (Breman and Dewit 1983). The typical woody species in the Sahel include *Acacia tortilis*, *A. laeta*, *Commiphora africana*, *Balanites aegyptiaca* and *Boscia senegalensis* (Shorrocks 2007). The trees in this region have various adaptations to cope with the harsh, arid conditions. Many species have an extensive root system which is meant to utilize the largest amount of water and minerals from a large volume of soil (Shorrocks 2007). Many species also have a downward directed tap root which is meant to access deep sources of water as well as an anchor for smaller lateral roots to expand laterally into the different soil layers (Hopkins and Jenkin 1962; Sarmiento and Monasterio 1983). Yet in areas such as the Sahel, root systems have been known to flatten out near the surface to capture the most amount of water after relatively light rain (Walter 1973). These extensive strategies all result in many trees to remain green long after the grasses have senesced. This leads to available shaded areas that may provide resting habitats to anopheline mosquitoes within the dry season (Paaijmans and Thomas 2011).

The people who live in the Sahel region are mainly pastoralists and farmers although livestock production provides greater wealth potential than farming because of high rainfall variability in space and time and an abundance of nutritious forage for livestock. The people of the Sahel usually follow one of two traditional systems of livestock farming which include nomadism and seminomadism animal husbandry (Breman and Dewit 1983). These different ways of life are determined by the environment of the inhabitants and are associated with the different climatological zones. Within the northern edge of the Sahel where is there is little water and little arable land, people follow the purely nomadic lifestyle as the need to find sufficient biomass for their herds constantly drive them to new areas (Breman and Dewit 1983). In the heart of the Sahel region itself the people tend to follow the seminomadic lifestyle as there is more water and arable land so they can afford to spend time growing crops such as Millet. Yet even if there is more water and biomass in this region the quality of that biomass is less than in the north, so people still need to move around to accumulate sufficient nutrients for their cattle.

Yet, how might these different lifestyles might affect malaria transmission? Previous research has shown that populated areas, which were found to be in close proximity to irrigated fields in the Sahel, had consistently high rates of malaria transmission throughout the year (Dolo et al. 2004). Conversely, in areas which were not nearby an irrigated field, the transmission rates were found to be below detectable levels during the dry season. Furthermore in the non-irrigated areas the mosquito densities were found to be generally lower (Dolo et al. 2004). In the past researchers were unsure whether these populations survived the dry season through aestivation or were reestablished by migrants from distant locations. Yet recent research has shown that, in fact, aestivation goes occur in at least one Anopheline mosquito species (*An*. *gambiae*) (Lehmann et al. 2010).

With reference to the presence of cattle in these areas, other research has shown that cattle are a major influence on host choice of mosquitoes (Garret-Jones et al. 1980). In areas with cattle present, mosquitoes were diverted to livestock reducing malaria transmission rates on humans, especially in irrigated areas (Dolo et al. 2004, Robert et al. 1985). This suggests that even in dry areas of the Sahel where long-distance transhumance is practiced, malaria may be problematic.

Savannah Region

The southern area of the study area is the savannah region in Mali, which is where the study site of the second aim of this thesis will be located. Within this area the rainfall is around 1000 to 1200mm per year (Breman and Dewit 1983; Nasi, R., and Sabatier, M. 1988). In the natural landscape there is a near continuous layer of perennial grasses over 1 m in height (*Andropogon gayanus, Hyparrhenia dissolute, Cymbopogon giganteus*, and *Schizachyrium pulchellum*) (Laris 2002; Shorrocks 2007). Due to the increase of rainfall in this area there is a slightly different assemble of tree species such as *Isoberlina doka, Pterocarpus erinaceus*, *Lannea microcarpa, Parkia biglobosa* and *Vitellaria paradoxa* (Nasi, R., and Sabatier, M. 1988). Yet the vegetation in the settled regions is quite different than from what is found in the natural areas. For instance, perennial grasses have been found to be less common and they are replaced by annual grasses such as *Andropogon pseudapricus* and *Pennisetum pedicellatum* (Laris 2002). In terms of trees, those that have a use for valuable seed crops are usually favored. Trees such as *Parkia biglobosa* and *Vitellaria paradoxa* and are usually found in agricultural fields (Laris 2002). In this region, people resort to more agricultural means of employment although pastoral livestock is still in occurrence. The principal crops, which are farmed in a rotational agricultural system, are sorghum, millet, corn, peanuts, and cotton (Laris 2002). Most crops are exclusively rain-fed and even during years of high rainfall crops may fail on average once every three years. Due to increasing population pressure there has been increasing conversion of rangeland to agricultural fields which tend to be marginal due to the drastic annual variation of precipitation (Le Houerou 1980). Past research has shown that open-space irrigated vegetable fields near cities can provide suitable breeding sites for mosquito species such as *Anopheles gambiae* and these areas resulted in higher numbers of adult *An. gambiae* when compared to the control areas without irrigated urban agriculture (Afrane et al, 2004). Moreover, people living in the vicinity of urban agricultural areas reported more malaria episodes than the control group in the rainy as well as dry seasons (Afrane et al, 2004).

CHAPTER II

LANDSCAPE LEVEL DISTRIBUTION

Introductory Remarks

Previous maps, discussed earlier, (Sinka et al. 2010; Sogoba et al. 2007) have been helpful in the understanding of the macro-ecology of the different Anopheline mosquito species, and the risk for malaria transmission at these scales. Yet what are the distributions for these mosquito species at finer scales? How are environmental variables such as the moisture, vegetation, bareness, urban development, and elevation affecting mosquito presence? In this Chapter, I used Landsat images along with public online mosquito databases for presence points to create new species distribution models within southern Mali. To approach this, I have used the publically available species distribution algorithm software, Maxent. Maxent (maximum entropy) is similar to the models described above in that it can be described as a general purpose, machine-learning method with a simple and precise mathematical formulation, and it has a number of aspects that make it well suited for species distribution modeling including the ability to be able to make predictions from incomplete data (Phillips et al, 2006b; Baldwin 2009). This algorithm estimates the most uniform distribution (maximum entropy) of provided sampling points compared to background locations given the constraints derived of the data (Phillips, Anderson, and Schapire 2006b). The maximum entropy algorithm is deterministic and will converge to the maximum entropy probability distribution (Phillips et al. 2006b). Therefore, the resultant output represents how much better the model fits the location data than would a uniform distribution (Phillips, Anderson, and Schapire 2006b). The area under the curve (AUC) statistic is the main method of evaluating the Maxent model performance. AUC is used to estimate the ability of the model to differentiate species occurrence from a random selection of background pixels. This method is commonly used for statistically measuring Maxent model performance (Baldwin 2009, Elith et al. 2011). Maxent offers many advantages over other species modelling approaches. For instance, it can be used at any scale and it has the added advantage of allowing the use of both continuous and categorical variables (Baldwin 2009). Other traditional distribution models require both presence and absence data (e.g., logistic regression discriminant function analysis) (Baldwin 2009) Maxent requires presence-only data, along with environmental information for the area of interest (Phillips, Anderson, and Schapire 2006b).

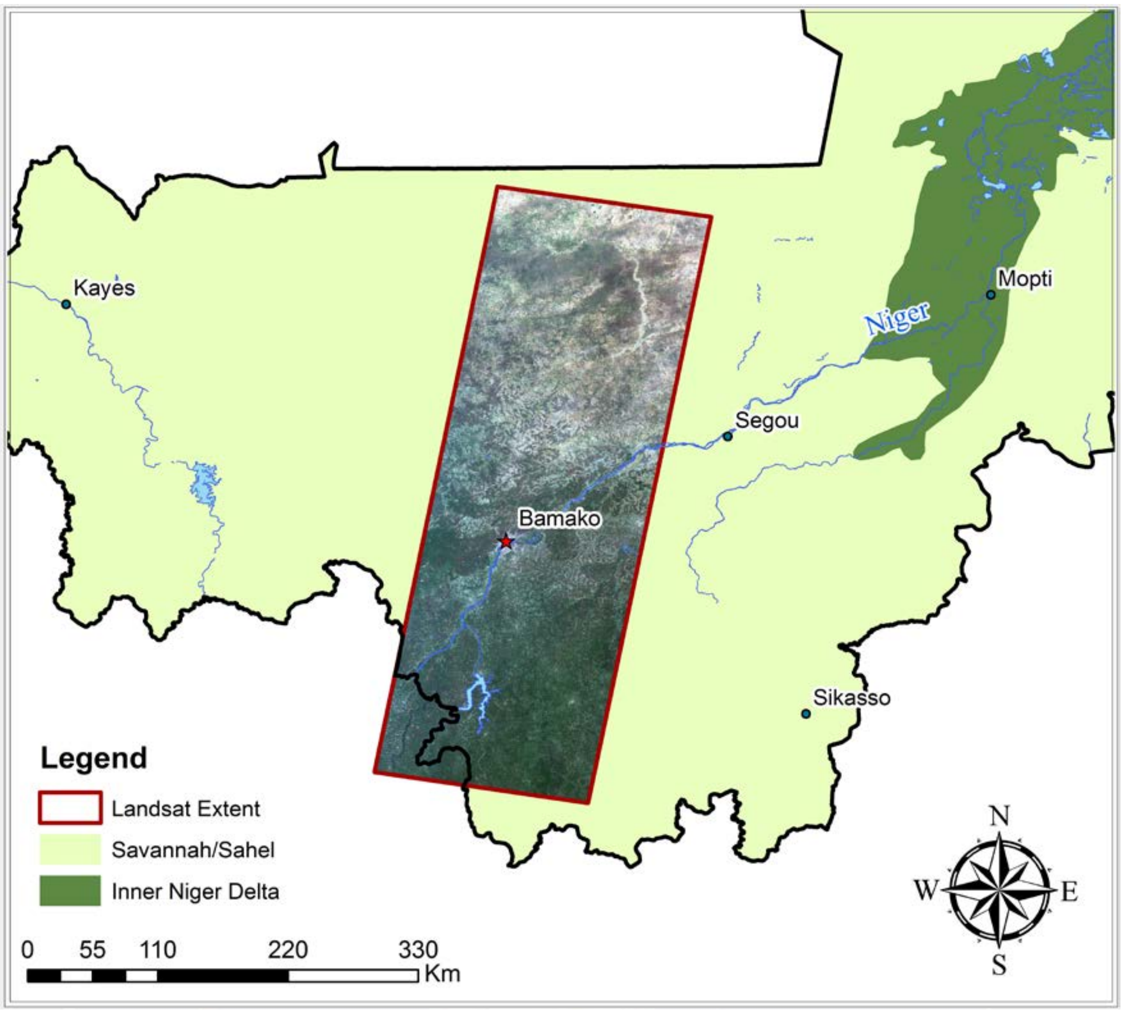
The aim of the present work is to investigate the possible relationship between the distribution of anopheline mosquitoes and the environment in southern Mali and subsequently derive vector distribution surfaces at landscape level scales (30m).

Methods

Study Site

In this study three Landsat 8 images dating from October 2014 were used. The three Landsat 8 images were mosaicked together to provide a broad study area in southern Mali which covers approximately 92,017 km^2 with the capital of

Map 2.1 Landsat 8 Imagery Extent



Mali, Bamako, near the center, see (**Figure 3.1**). The advantage to having a large study area is that it provides a range of different conditions that may affect mosquito presence which may not be present with a single Landsat 8 image. Furthermore having a large study area (92,018.7 km^2) also ensures I was able to utilize

the maximum amount of mosquito points that the data set contains which will improve model results. The decision to use imagery from the month of October was to ensure that the season in which the data points derive from is consistent

Table 2.1 Landsat 8 Band Designations

Landsat 8	Wavelength (micrometers)	Resolution (m)
Band 1 (Coastal aerosol)	0.43-0.45	30
Band 2 (Blue)	0.45-0.51	30
Band 3 (Green)	0.53-0.59	30
Band 4 (Red)	0.64-0.67	30
Band 5 (NIR)	0.85-0.88	30
Band 6 (SWIR 1)	1.57-1.38	30
Band 7 (SWIR 2)	2.11-2.29	30
Band 8 (Panchromatic)	0.50-0.68	15
Band 9 (Cirrus)	1.36-1.38	30
Band 10 (TIRS) 1	10.60-11.19	30*
Band 11 (TIRS) 2	11.50-12.51	30*

***** TIRS bands are acquired at 100 meter resolution, but are resampled to 30 meter

with the season of the imagery. Although there were data points presented from all months of the year the average month of collection was late August with a standard deviation of 2-3 months. This means that the general trend of the data points shows that most researchers collected samples during the wet season. Although this image lies roughly 5 years outside the range of

Table 2.2 Landsat-Based Indices Used in This Study

Abbreviation	Equation	Index Name
1. NDVI	$= (NIR - Red)/(NIR + Red)$	Normalized Difference Vegetation Index (Rouse et al., 1974)
2. SAVI	$= \left(\frac{NIR - RED}{NIR + RED + 0.5}\right) * (1 + 0.5)$	Soil Adjusted Vegetation Index (Huete, 1988)
3. MNDWI	$= \frac{Green - SWIR\ 1}{Green + SWIR\ 1}$	Normalized Difference Water Index (Xu, 2006)
4. NDISI	$= \frac{Green - SWIR\ 2}{Green + SWIR\ 2}$	Normalized Difference Impervious Surface Index (Xu, 2010)
5. NDMI	$= \frac{NIR - SWIR\ 1}{NIR + SWIR\ 1}$	Normalized Difference Moisture Index (Hunt et al. 1987)
6. NDBI	$= \frac{SWIR\ 1 - NIR}{SWIR\ 1 + NIR}$	Normalized Difference Built-up Index (Zha et al., 2003)
7. NDBaI	$= \frac{SWIR\ 1 - TIR}{SWIR\ 1 + TIR}$	Normalized Difference Bareness Index (Zhao and Chen, 2005)
8. UI	$= \frac{SWIR\ 2 - NIR}{SWIR\ 2 + NIR}$	Urban Index (As-Syakur et al., 2012)
9. IBI	$= \frac{2 * \frac{SWIR\ 2}{SWIR2 + NIR} - \left[\frac{NIR}{NIR + Red} + \frac{Green}{Green + SWIR\ 2}\right]}{2 * \frac{SWIR\ 2}{SWIR\ 2 + NIR} + \left[\frac{NIR}{NIR + Red} + \frac{Green}{Green + SWIR\ 2}\right]}$	Index-based Built-Up Index (As-Syakur et al., 2012)
10. EBBI	$= \frac{SWIR\ 1 - NIR}{10 * \sqrt{SWIR\ 1 + TIR}}$	Enhanced Built-Up and Bareness Index (As-Syakur et al., 2012)

years from collection (1968-2009) it at least attempts to mitigate the issue of seasonality as it was acquired during the wet season.

Satellite Imagery

The Landsat 8 satellite has been available since February 11, 2013 and has two earth observing sensors, which include the Operational Land Imager and the Thermal InfraRed Sensor. The Operational Land Imager has nine bands of data including near and shortwave infrared with a moderate spatial resolution of 30 meters (m) (**Table 2.1**). The Thermal Infrared Sensor provides bands 10 and 11, which are the thermal bands (**Table 2.1**). The data from Landsat was then used to create various environmental indices that provide useful information of surface conditions such as vegetation, urban development, bareness, and moisture. In total 10 different indices were created from the Landsat data to provide a diversity of possible indicators to species presence, which can be observed in **Table 2.2**. Furthermore, a Digital Elevation Model (DEM) was also included in the list of possible environmental factors for the model. The DEM has a spatial resolution of 90 meters and was resampled to 30 meters to match the spatial resolution of the Landsat data. Lastly a Topographic wetness index (TWI) derived from the DEM was also included as a possible environmental layer. TWI describes the tendency for water to collect in areas of topographic minima, and is defined as $\ln\left(\frac{a}{tan\beta}\right)$ where ‘a’ is the local upslope area draining through a certain point per unit con- tour length and tan ‘β’ is the local slope (Beven and Kirkby, 1979, Sorensen et al. 2006). The influence of substrate moisture has a strong correlation with the degree of Anopheles egg-laying, with standing water being the saturation point (Huang et al. 2005). Therefore a soil wetness index such as TWI would be essential to include as a possible environmental variable.

From these twelve base environmental layers only a handful was selected for the final models. Only the most important indices were retained for each species and the rest were removed as the inclusion of excess indices may lower overall model performance. This elimination procedure was based on the statistical metrics that are returned with the output of the various Maxent models that were performed. These statistics included jackknife tests which provided information that was be used to see which environmental variables have the most useful information by itself and conversely the variables that have the least useful information. The Maxent model outputs also produced variable contribution tables, which provided estimates of relative contributions of the environmental variables to the Maxent model. This table provided two estimates and the first is a percent contribution estimate, which provides information as to how much information did each variable include in the overall model. The second estimate, permutation importance, is used to see what variables have the most information that isn't present in the other variables. The contribution for each variable is determined by randomly permuting the values of that variable among the training points (both presence and background) and measuring the resulting decrease in training AUC. A large decrease indicates that the model depends heavily on that variable. The figures given with this output table were helpful in deciding which indices provided the most useful information. Numerous models were performed with different amounts and combinations of indices with the jackknife analysis and the variable contribution table as the means to determine the most important variables with the intent to return a model with the highest AUC values. This procedure was done for both species which resulted in different indices for each species, which represents the inherent ecological preferential differences that are found between *An. gambiae* and *An. arabiensis*.

Data Points

The mosquito presence points which were used for this study come from a variety of sources. The two major contributors of species presence points come from publicly available databases, the Malaria Atlas Project and Walter Reed Biosystematics Unit MosquitoMap. These databases are a unique global resource for researchers who are focused on mosquito-borne diseases and mosquito distribution and ecology (Foley et al, 2009). These are online databases of broad species distribution models and georeferenced species collections for individual mosquito species. Collection records and distribution maps come from a multitude of sources; museum specimens, the literature, and from submissions by various entomologists. These data points were supplemented by data points that were found in the literature (Toure et al. 1998; Fane et al. 2012) that were not present in the online databases to provide the maximum possible training points, which would be used (7 points for *An. arabiensis* and 11 for *An. gambiae)*. These data points had place names and coordinates at the precision of degrees and minutes. Data points were placed at the center of the towns and cities associated with the points as the coordinates were not precise. Once all the data were pooled, special attention was paid to ensure that any redundant data points were eliminated as the data points from the online databases occasionally overlapped from separate studies or multiple points from the same study.

In this study two *Anopheles* species were examined, *An. gambiae* and *An. arabiensis*. The third species, *An. funestus*, was not considered in this study due to a lack of data points found in the literature and in the online databases. In total, there were 60 presence points recorded for *An. gambiae* and 42 points for *An. arabiensis*. Roughly twenty percent of the data points for each species were randomly selected and then omitted from the algorithm to be used as test points for measuring statistical accuracy. The remaining points were used as the training points for the modeling.

To evaluate how each environmental variable contributed to the overall model, a jackknife procedure was used. A jackknife procedure can either withhold all but one variable and refit the model to see how the inclusion or exclusion of that variable would change the AUC score, or withhold all variables but one and refit the model which would tell which variable would have the most useful information by itself. The difference in AUC scores is estimated and then the predictor variables that have to most impact on the AUC are assumed to be the most important (Phillips et al, 2006a; Elith et al. 2011; Stevens and Pfeiffer 2011).

Bias Files

Due to use of pooled data points that come from a variety of public sources, the sampling efforts are not expected to be uniform and it is expected a certain level of spatial sampling bias to be present. Many of the studies that the data were drawn from were working with genetics-focused studies and the sampling effort usually is more opportunistic. This means that the sampling efforts employed in these studies may be greater in conveniently accessed locations, such as populated areas, near roads or rivers, or in habitat already known to be successful in finding the species of interest. It is quite likely that these locations may not reflect the true range of the species environmental niche, and without correction the models trained on these samples will model the distribution of sampling effort, rather than the range of the species of interest (Conley et al. 2014). To correct for this, a bias-raster file was created which would assign greater weight to presence points with fewer neighbors in geographic space (Elith et al. 2010). The bias-raster was created according to the methods outlined in Clements et al. 2012 in which all species points *(An. arabiensis, An. gambiae*, and *An. funstus*) were combined and used to represent the sampling effort across the study area. The weighted surface for both *An. gambiae* and *An. arabiensis* bias files were based on an African North Equidistant Conic Projection and calculation of the number of records in a chosen neighborhood for each cell was weighted by a Gaussian kernel. To calculate the weight of a given cell I used the Gaussian Function: $\exp\left(-\frac{d^2}{2s^2}\right)$, where *d* is the distance in meters between a target species presence point and a second background point without missing data and *s* is the standard deviation. The bias at a presence point was then taken as the sum of these weights of occurrences. A continuous raster was made using the Kernel Density function available in ArcMap using the newly created bias value as the population field, and the standard deviation of the Gaussian Function as the search radius. The resulting raster file was rescaled from 1 to 20 to ensure all values were positive to fulfill the requirement of only using positive values for the bias option in Maxent (Elith et al. 2010).

Results

Species distribution models were produced for *An. gambiae* and *An. arabiensis* to predict their geographic distribution within a portion of southern Mali. The results represent the probability (0-1) of a particular geographical location to be habitable by the particular species. **Map 2.2** shows the species distribution models for each species. The higher values correspond to higher probability of suitable environmental conditions. The resulting species distribution models produced from Maxent was found have mixed results. The model predicting the presence of *An. gambiae* was found to be significantly better than random distribution based on the AUC values (**Table 2.3**).

Map 2.2 Landsat Maxent Maps; Predicted probability of presence of *An. gambiae* and *An. arabiensis* the Southern Mali study area using Maxent.

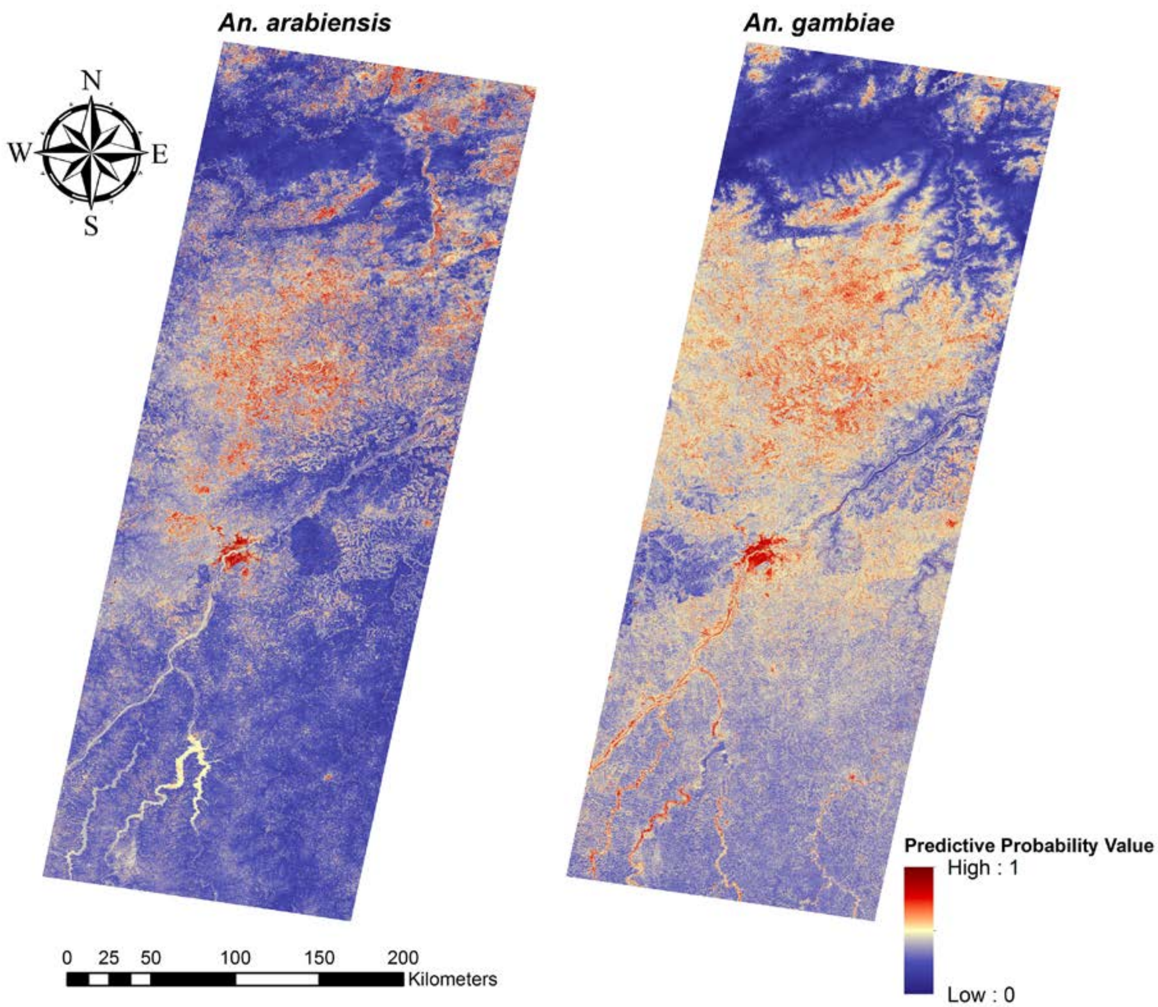


Table 2.3 Maxent Species Distribution Results

Species	# Training samples	# Test samples	Training AUC	Test AUC	AUC Standard Deviation
An. gambiae	48	12	0.767	0.783	0.071
An. arabiensis	34	8	0.822	0.680	0.072

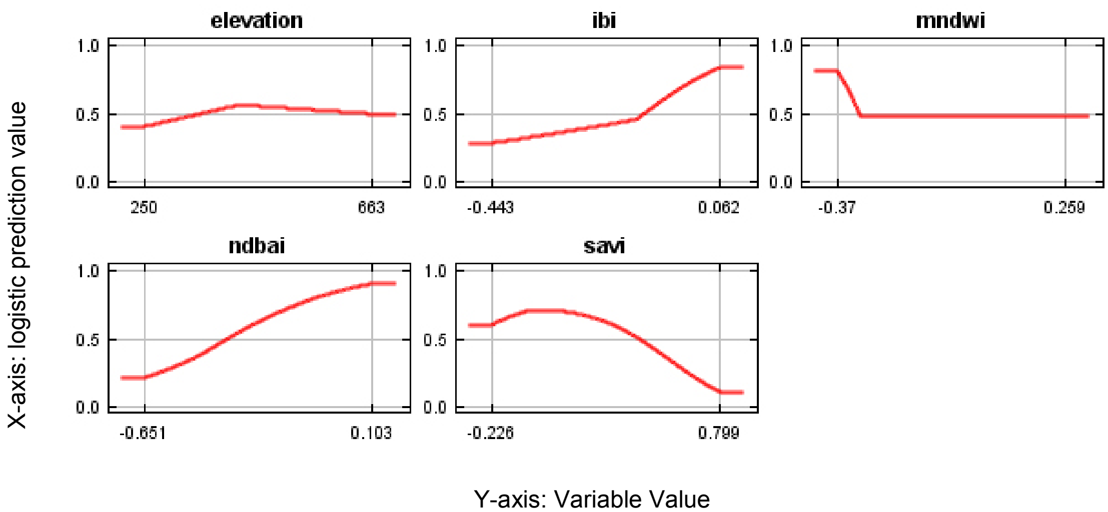
Table 2.4 Analysis of Variable Contributions

An. arabiensis		
Variable	**Percent contribution**	**Permutation importance**
Elevation	18.6	23.4
NDBaI	24.6	41.7
MNDWI	15	34.9
IBI	37.9	0
SAVI	3.9	0

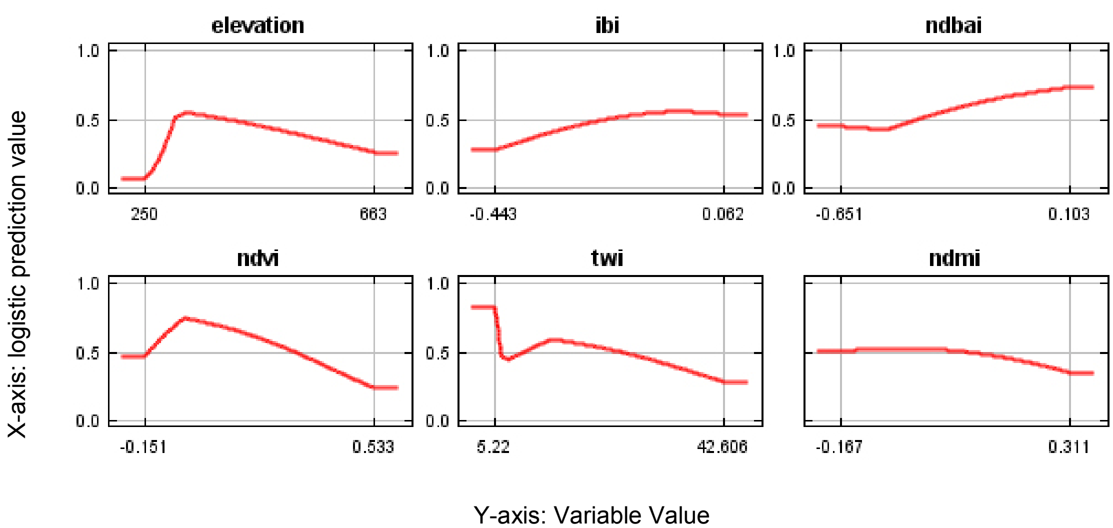
An. gambiae		
Variable	**Percent contribution**	**Permutation importance**
Elevation	29.5	19.4
NDBaI	19.2	25.4
TWI	7.9	3.3
IBI	0.3	1.5
NDVI	24.6	30.1
NDMI	8.2	20.4

Figure 2.1 Response Curves

***An. arabiensis* response curves**



***An. gambiae* response curves**



Maxent predicted distribution results show a training AUC probability of 0.767 and a test AUC of 0.783 for *An. gambiae*. The indices that provided the highest statistical values and subsequently chosen for the model were NDVI, Elevation, NDBaI, NDMI, TWI, and IBI. Meanwhile the statistical scores for *An. arabiensis* indicated that the model produced a higher training AUC (0.822) and lower for the test AUC (0.680) (**Table 2.3**) relative to the model for *An. gambiae*. The environmental indices that were included for this model were IBI, NDBaI, Elevation, MNDWI, and SAVI.

The percent contribution and permutation of importance of the different environmental indices were determined from the jackknife analysis that was produced from the Maxent model. For *An. arabiensis*, the test of variable importance showed that NDBAI was the most important when used in isolation (41.7% permutation importance) which means that this index has the most useful information by itself (**Table 2.4**). Now, the variable which had the most information on its own that is not found in the other variables was IBI, with a percent contribution of 37.9%. Meanwhile for *An. gambiae* it was found that NDVI had the most information on its own with a permutation importance percentage of 30.1%. Yet, elevation had the most unique information among the different indices that were included in the model with a percent contribution value of 29.5%. It was followed by NDVI and NDBaI with 24.6% and 19.2% contribution respectively (**Table 2.4**).

Lastly, the curves presented in **Figure 2.1** shows how each environmental variable affects the Maxent prediction. The curves show how the logistic prediction changes across the range of values found in each environmental variable used in the model, keeping all other environmental variables at their average sample value. These response curves will also help in deciding what indices are the most essential for the model. The curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together. These graphs used to determine the range of the environmental variable values that are determined to be the most important for predicting species presence by the model. This information then may be used to determine the ground conditions that are optimal habitat for the target species.

CHAPTER III

MODELING RESTING HABITATS OF ANOPHELINE MOSQUITOES IN A RURAL MALIAN VILLAGE

Introductory Remarks

The goal of this chapter is to evaluate the possibility of using remote sensing techniques to predict the distribution of *Anopheles* mosquito outdoor resting sites at a village in Mali during the dry season. Recently, the outdoor malaria transmission has become a growing concern due to a major change in malaria transmission dynamics in Africa. Extensive indoor vector control (IRS and ITN) has shifted parasite transmission from the dominant and highly endophilic *An. gambiae* to the more exophilic, outdoor-adapted *An. arabiensis* (Baber et al. 2010; Fornadel et al. 2010; Russell et al. 2011). Also, new findings demonstrate the existence of an exophilic *An. gambiae* subgroup population with high susceptibility to the malaria parasite *P. falciparum* through the use of a genetic survey that used large samples from both indoor and outdoor larval collections (Riehle et al. 2011). Anticipated increases in outdoor transmission will certainly confound attempts to successfully control malaria in Africa but currently, options are limited. Therefore, understanding the resting habitats of these exophilic species is imperative to further malaria control efforts in Africa.

Based on these points we can hypothesize the factors that will be important to consider when constructing a spatial model of resting habitat probability. As vegetation can provide substantial amounts of shade, it can be assumed that resting habitats are closely tied to areas in which vegetation as the dominant land cover. Also, resting areas close to water will likely contain higher densities of resting mosquitoes than areas secluded from water sources.

Previous Remote Sensing and Resting Habitat Research

Recently, a study has attempted to evaluate how certain small scale environmental variables affect vector ecology, but have used relatively simplistic and unacceptable methods to tackle this problem. Ricotta et al. 2014 attempted to look at this issue using the image processing software Image J along with Google Earth satellite imagery to see how vegetation is associated with malaria transmission. They claim that their method avoids the problem of using "complex satellite data and intricate calculations" for assessing vegetation cover. The first problem with their approach is the usage of imagery directly from the Google Earth software. Google Earth is not meant to be a satellite image provider and therefore does not provide band information for downloading, so is therefore limited in the amount of data available for analysis. Although this imagery can be used for a multitude of purposes the lack of spectral band data, especially bands outside of human vision, makes it problematic when trying to delineate certain land cover variables, such as vegetation by using automated based methods. Also, the usage of ImageJ for the analysis of satellite imagery is relatively unsatisfactory when compared to the software programs, such as IDRISI and ERDAS Imagine, which have been developed specifically for dealing with satellite images and creating land cover maps. For example Ricotta et al. 2014 describes that in order to perform their analysis they had to convert their images into 8 bit black and white data and that they were unable to ensure that unwanted features such as bodies of water, livestock, or houses were not included in the analysis. Problems such as these have already been considered within ERDAS Imagine or IDRISI, which each have a variety of algorithms and programs available which specifically deal with separating spectrally different features such as these, and they do not require the data to be in the limited 8 bit black and white format. Lastly the study by Ricotta et al. 2014 uses unsatisfactory levels of error assessment with their maps and models. They described that they attempted to check for accuracy by hand counting the number of plants around each area of focus but abandoned this method. Instead they rationalize their accuracy by running their analysis multiple times to determine the reproducibility. The problem with this is that the reproducibility of the model does not mean it is accurate.

Meanwhile, the methods described here uses individual bands and band combinations to identify the possible small-scale ecological factors that affect vector presence in the environment. Within this study, I have used satellite imagery, which has more data than an image file from Google Earth. The program that I have used here is the remote sensing software IDRISI, which contains image classification algorithms specifically created for dealing with satellite imagery and the production of land cover maps. These image classification techniques in conjunction with the high quality satellite images can be used to delineate features such as water, vegetation, and houses, whereas the ImageJ approach does not have any capability for preforming this function. Furthermore the use of Dempster-Shafer modeling (described below) is an acceptable way of roughly assessing spatial relationships that certain variables may have over spatial based phenomena (Malpica et al, 2007).

Proposed Methods of Resting Habitat Modeling

In this portion of the study, I used remote sensing techniques to develop and evaluate a new approach along with field-based criteria, to possibly predict concentrations of adult anopheline mosquitoes in the outdoor environment. A highly novel and flexible modeling approach was employed to assess probability of habitat occurrence based on a variant of Bayesian Theory, known as Dempster-Shafer (D-S) weight-of evidence modeling. D-S evaluates existing evidence using expert knowledge to transform evidence into probability surfaces. Unlike the Bayesian Theory, the D-S approach does not assume that one has full information, but it can handle a state of knowledge that is incomplete and changes over time (Malpica, Alonso, and Sanz 2007). As the literature on mosquito resting habitats within Mali and around the world is limited, this predictive modeling method is ideal for this study. The reason for focusing on the dry season is because adult vector densities are very low during this time of year, as larval habitats become limited, yet these habitats increase sharply at the onset of the rainy season (Charlwood et al, 2000). Focusing on mosquito control efforts during the dry season, when these vector populations are stressed, will likely yield the best results when trying to control local mosquito populations (Baber et al. 2010).

In addition to the D-S model a Maxent model was also implemented using the WorldView 2 data and sampling data. This model predicts the presence of resting habitat by using the field data which have been also used with the creation of the D-S model. The final models were then compared to each other to see if there is any overlap to what may be considered optimal resting habitat. The novelty of this approach is that Maxent has been used in the past to see species distribution over general areas. The comparison which is shown in this study looks at the congruence of the D-S model versus the Maxent model and demonstrates if Maxent can be used to measure small-scale specific habitat preferences. *Anopheles* mosquito presence, in an immediate area, depends on microclimatic and small environmental differences, as discussed before, and so will be an excellent candidate to test the flexibility of Maxent to predict these specific habitat conditions.

Methods

Study Site

The study site was in and around the village of Kenieroba (**Map 3.1**) which is located 71 km southwest of Bamako, the capital of Mali. The study area is approximately a twenty five square kilometer area with the village of Kenieroba in the center. A floodplain of about 2 km wide separates Keineroba from the Niger River. During the rainy season this area is flooded for rice agriculture and then it is used for vegetable cropping during the dry season. This site has been chosen due to its mixture of various land covers, which include a close proximity to a water body, dense agricultural plots and sparse natural vegetation, and areas of human occupation and habitation.

Field Data

The field data, which was used to create and verify the D-S model was collected by a field team consisting of researchers from the University of Miami, Department of Public Health Sciences (Dr. John Beier), and the Hebrew University, Hadassah Medical School, Kuvin Center for the Study of Tropical and Infectious Diseases (Dr. Gunter C. Muller). The field data set, which was used to create and verify the D-S model was collected by a field team consisting of researchers from the University of Miami, Department of Public Health Sciences (Dr. John Beier), and the Hebrew University, Hadassah Medical School, Kuvin Center for the Study of Tropical and Infectious Diseases (Dr. Gunter C. Muller). The data was collected by the usage of drop nets at the end of November to the beginning of December for the year of 2013 which corresponds to the early dry season. The sampling strategy of using drop nets was used as this technique aimed to capture mosquitoes which were resting amongst the grasses and herbaceous vegetation beneath the drop net. The drop-nets enclosed a 2x2 meter area and were deployed at predetermined microhabitat sites. Within the drop-net was a suspended CDC (Center for Disease Control) mosquito trap to capture the resting mosquitoes in the enclosed area. After 12 hours the traps were removed and the mosquitoes were counted and identified. At each site the drop nets were deployed for both the morning and again for the afternoon for 18 days. This equated to 36 sampling events for each microhabitat site. The mosquito counts were then averaged to represent to average amount of mosquitoes captured per day, per microhabitat site (**Table 3.1**).

Table 3.1 Field Data; this table provides information pertaining to the average amount of mosquitoes captured per day at each microhabitat sampling site. The mosquitoes belonged to the species *An. gambiae* s.l.

Drop-Net catches

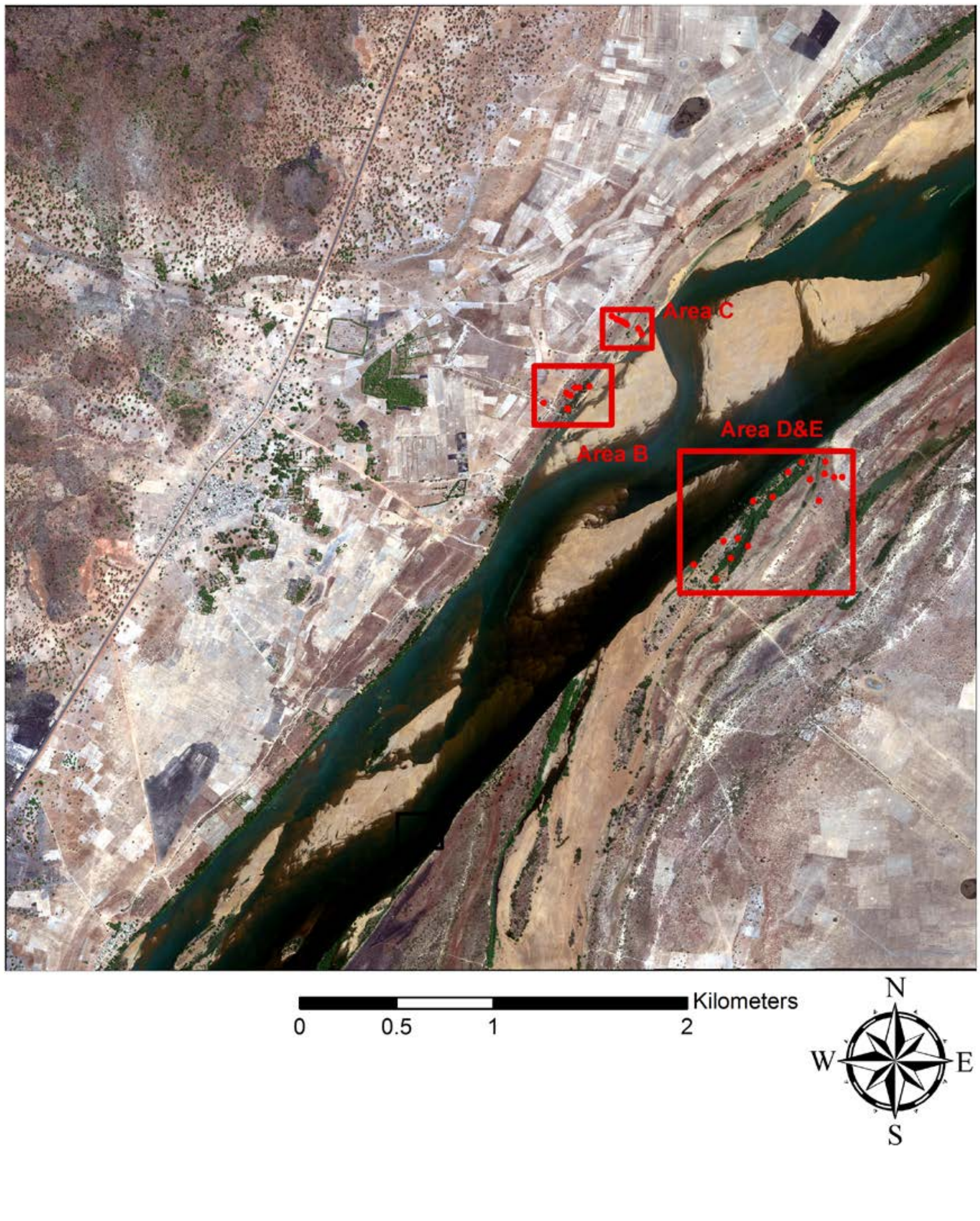
Microhabitat Site	Average Number of Mosquitoes Per Day
C-1*	6.39
C-2*	3.22
C-3*	10.4
C-4*	2.11
C-5	0.05
C-6	0
C-7	0.17
C-8	0
B-1a	0.22
B-1b*	1.83
B-2a*	11.94
B-2b*	6.28
B-3*	1.06
B-4*	2.44
B-5a	0.22
B-5b	0.05
B-6*	11.61

Microhabitat Site	Average Number of Mosquitoes Per Day
D-1*	7.11
D-2*	10.1
D-3*	1.17
D-4	0.39
D-5	0
D-6	0.11
D-7	0.06
D-8	0.06
E-1	0.17
E-2*	0.78
E-3	0.11
E-4*	11.17
E-5a*	6.44
E-5b*	7.66
E-6	0.33
E-7*	17.94

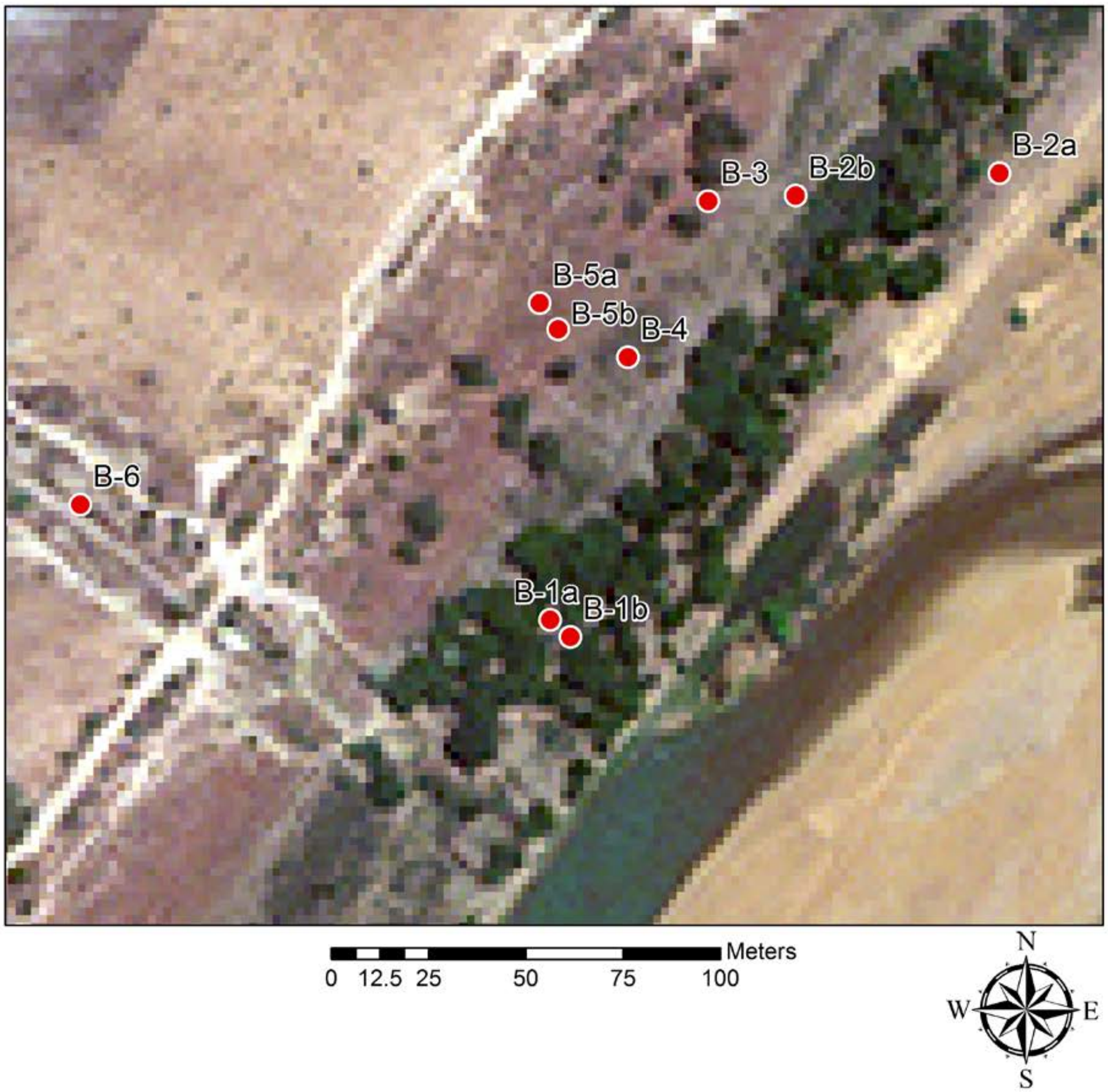
* Sampling locations found to be a statistically significant resting site

Pearson Correlation Coefficient of male to female resting site preference*: 0.894
* This statistic used the average amount of male and female mosquitoes captured per site.

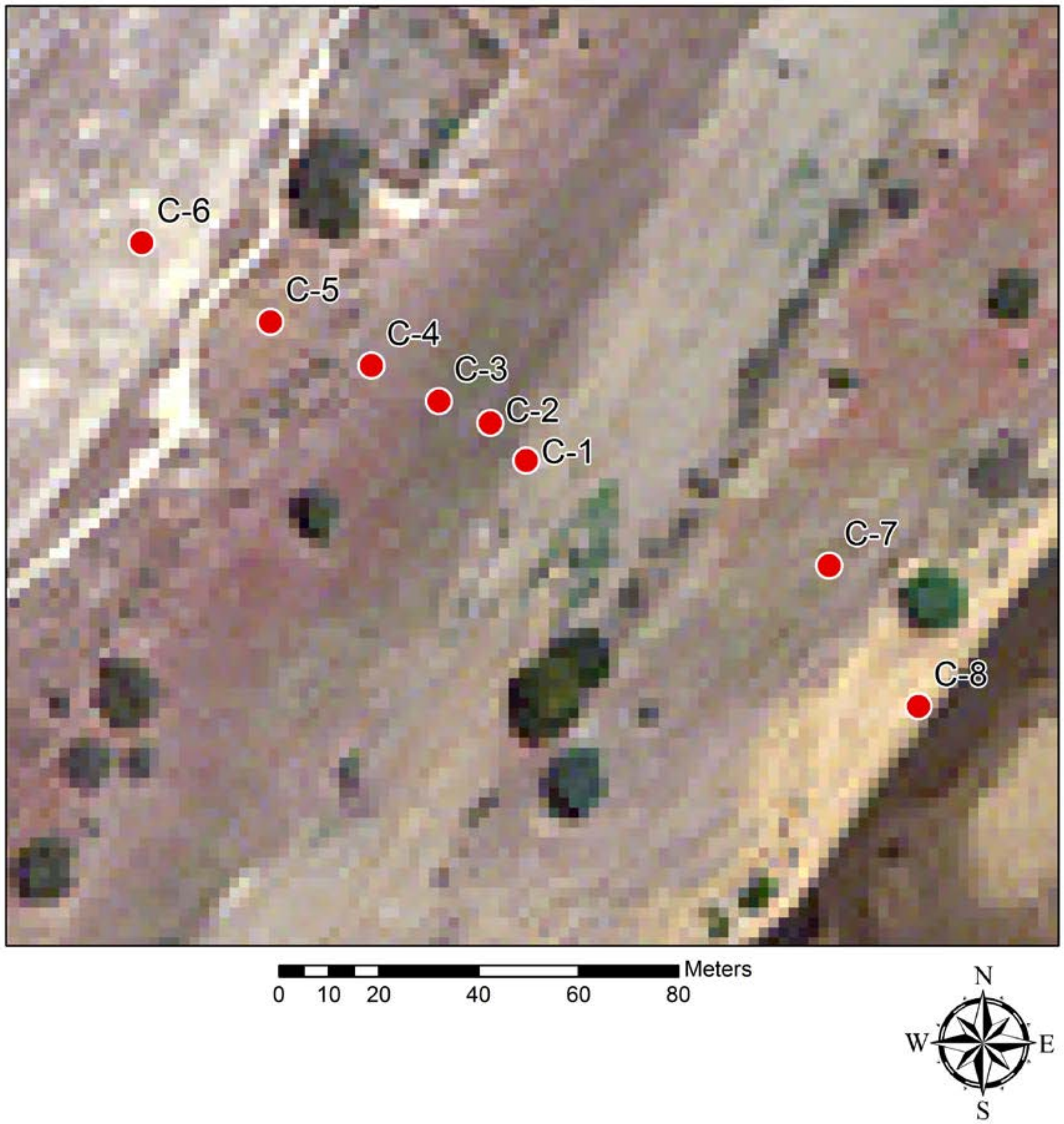
Map 3.1 WorldView 2 Imagery area. Red dots indicate sample locations.



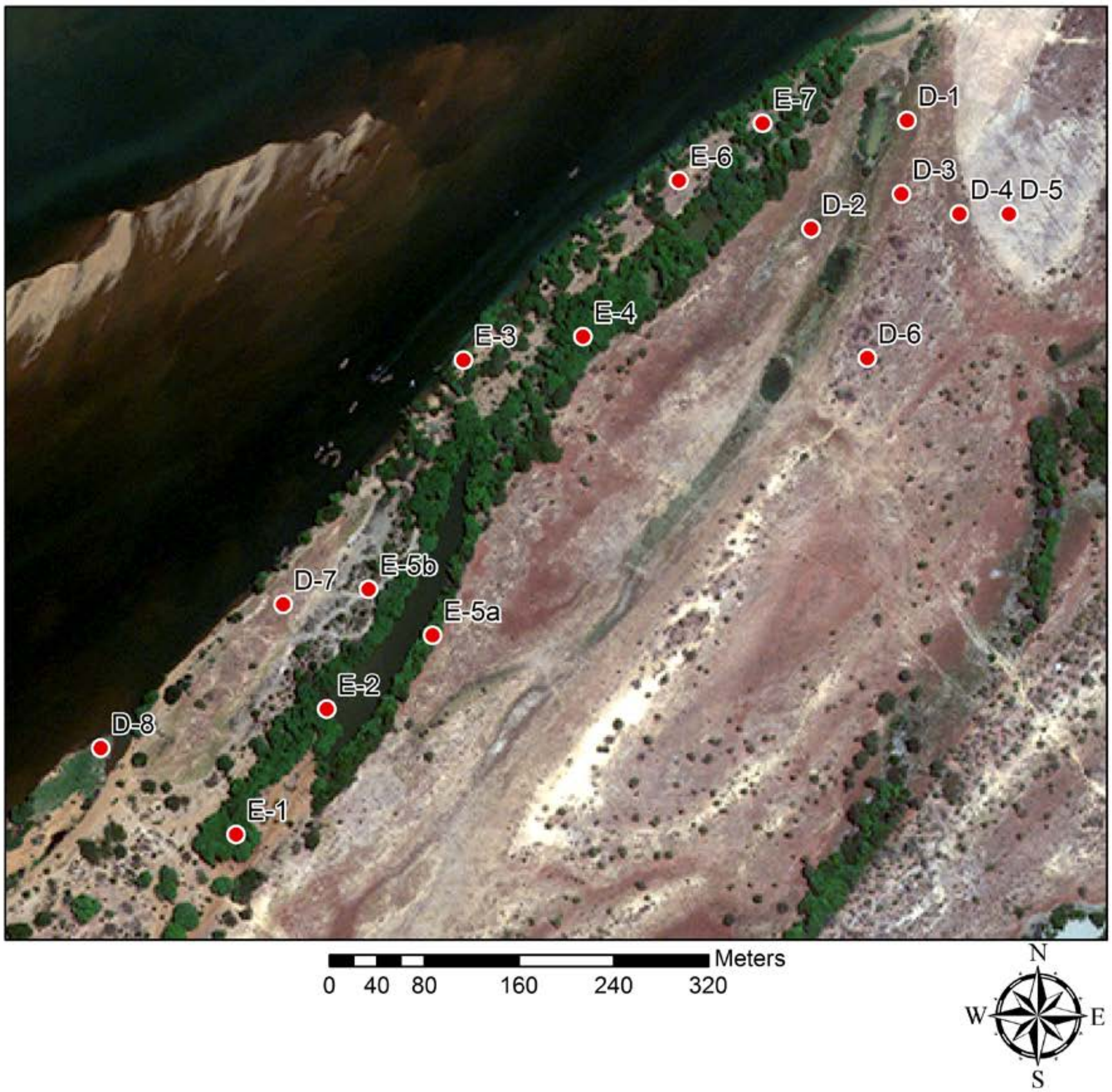
Map 3.2 Area B Field Data Points



Map 3.3 Area C Field Data Points



Map 3.4 Area D&E Field Data Points



Morning and afternoon sampling were done due to the fact that shade is dependent on the time of day, and preforming morning and afternoon sampling provides an understanding of a site's resting potential throughout the day. The locations for these microhabitat sampling sites can be seen in **Maps 3.1**-**3.4**. Additionally each site was evaluated if it could be considered a significant resting site. Although all but two sites had mosquitoes found at some point during the 18 day sampling. Yet this may not be representative of the value that a particular site may hold as a resting site. Therefore, each site was independently tested to distinguish if it can be statistically verified of its resting site potential. A one tailed t-test with an alpha level of 0.01 was preformed to see if the average number of mosquitoes collected per day per site was statistically different from zero. Sites which were statistically different from zero were considered to be statistically significant resting sites. Whereas those sites which were proven not to be different from zero were labeled as insignificant resting sites. The results of this analysis can also be seen in **Table 3.1**.Lastly information was collected in regards to the sex of the mosquitoes which were captured in an effort to understand if there were and differences in resting site selection between male and female species. A Pearson Correlation was preformed between the average amount of female mosquitoes captured per site and the amount of male mosquitoes captured per site. The results of this analysis can be seen in **Table 3.1** as well. The high correlation coefficient of 0.894 means that there was no significant difference in resting site preference between the male and female species. As a result no modeling was attempted to show the differences between the two sexes as the resulting models would have been redundant.

A major concern with this data is the issue of spatial autocorrelation. The distribution of the samples are very clustered and limited to small portions of the overall study area. Using a simple nearest neighbor statistic in ArcMap, shows that the field data is clustered based on spatial location. Yet this method may be inadequate in understanding the spatial autocorrelation of the data as this method is a location only analysis of autocorrelation and does not take into account the feature values along with the feature locations, which was highly useful for the creation the D-S model. For this reason I used Moran's I approach to measuring autocorrelation as it does take into account the feature values (drop-net mosquito sums) along with the feature locations. This analysis was also done in ArcMap, using the Moran's I tool, and it was found that the data sampling was spatially random and therefore no significant spatial autocorrelation was present within the data. The Moran's I assessment used the Euclidean distance method and an inverse distance conceptualization. The results provided a Moran's Index of 0.027, a variance of 0.025, a z-score of 0.37, and a p-value of 0.71. Given the z-score of 0.37, the pattern does not appear to be significantly different from random

Classification of remotely sensed imagery

A classified map was produced for the study site using a high-resolution WorldView 2 satellite image. This image has a spatial resolution of two meters and included the red, green, blue, and near infrared bands. The image was acquired March 5, 2013, which is during the dry season. The classified map was made using a combination of supervised classification and an image segmentation algorithm to identify discrete objects in the image such as patches of vegetation, metal-roofed buildings, water bodies, open fields, and bare earth. The application of segmentation during classification done to provide better classification results than traditional per-pixel classification approaches, especially for fine resolution images as the one used in this study (Lu and Weng 2007; Benz et al. 2004). Segmentation merges pixels into nonoverlapping homogeneous objects, and a classification method is then implemented based on objects (Thomas, Hendrix, and Congalton 2003). An additional class called 'Wetlands' was also included in the final classified image and this class was created in an attempt to make up for the differences observed in WorldView 2 image and the conditions which were present during the field collections. It was noted that certain areas nearby the Niger River were inundated whereas in the imagery they were being classified as bare earth. As the WorldView 2 images were taken in the late dry season and these areas have dried out. These bare areas and other bare areas like it were delineated from the classified image and were transformed into the class 'Wetlands'.

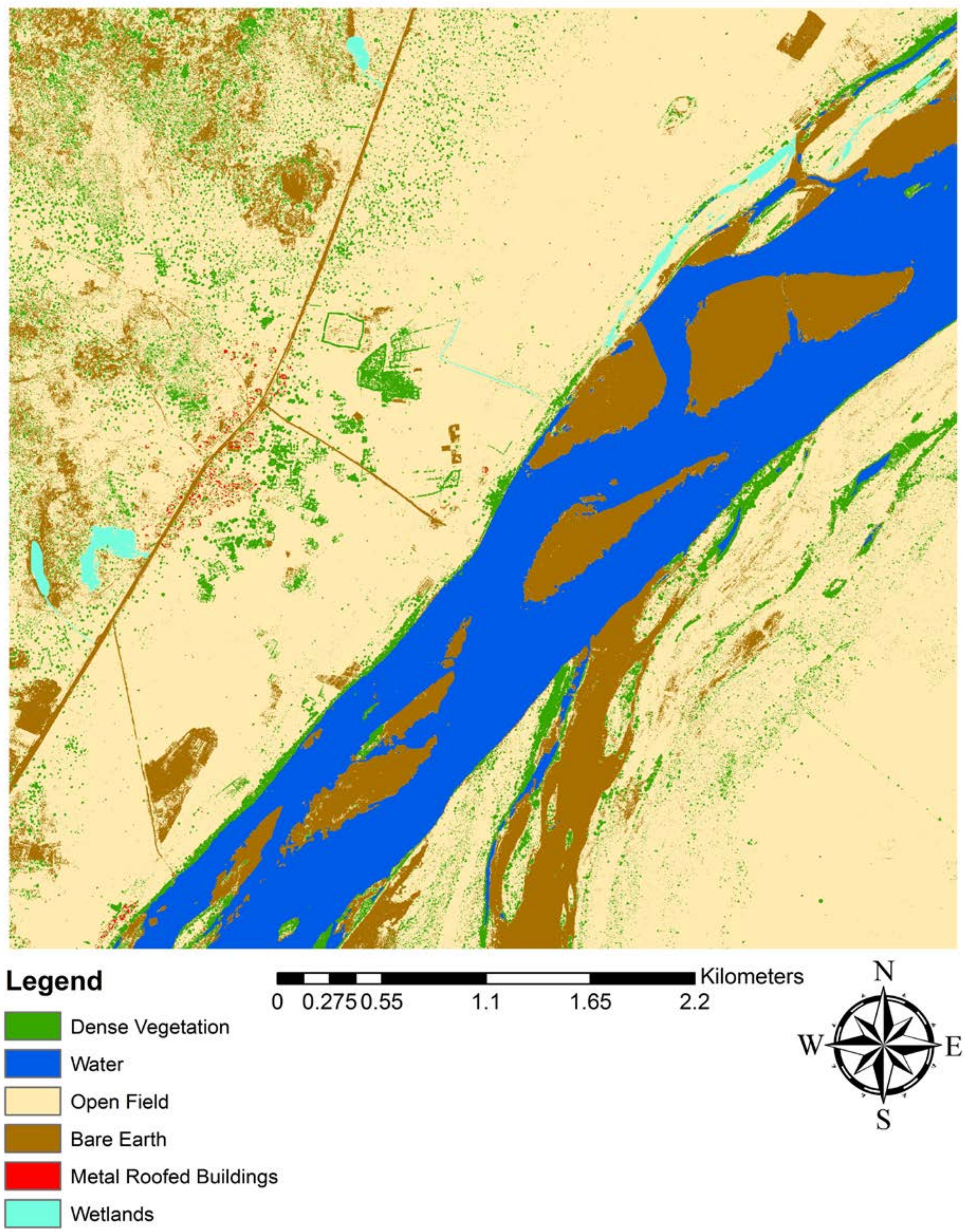
To test the accuracy of the classified image I created 700 points with the aid of the ArcMap random point generator and used a composite image of the raw imagery to ground truth these points. The points were randomly stratified across the different classes, making sure that no points were placed in the training sites used to create the classified image. Accuracy (“ground-truth”) data was then fed back into the classifications to improve map products to reduce omission and commission errors, and thus reduce error propagation in the subsequent analysis. To further increase the accuracy of key classes such as water and metal-roofed buildings a modal filter with a 3x3 window was used to eliminate various misidentified pixels. Furthermore certain shallow water bodies were classified as metal-roofed buildings by the segmentation algorithm due to the spectral similarity across the four bands. Since the water class is important to this study, the misidentified areas were reclassified manually using ArcMap with the help of Google Earth imagery to verify that these areas were indeed water bodies. It is also important to note that only buildings with metal roofs were identified in the classified map. The buildings that had roofs made of dried vegetation could not be extracted from the imagery using the methods described above as the spectral reflectance of these roofs was indistinguishable from the dead vegetation that was found in the surrounding fields. Furthermore the size of these buildings is very small, the majority of the buildings are only 3-5 meters in diameter. Since the spatial resolution of the WorldView 2 imagery is only 2 meters these small huts at best can occupy 2 to 3 pixels, or else their spectral signature and shape are dispersed in the partially.overlapping pixels making it difficult for the segmentation process to delineate these shapes from the surrounding environment.

Table 3.2 Classification Accuracy

Class	Accuracy
Dense Vegetation	96.30%
Water	98.15%
Metal Roofed Buildings	98.75%
Open Field	93%
Bare Earth	85.50%
Overall Accuracy	**92%**

The overall accuracy of the classified map is 92%, which was calculated using the ground truth points described earlier, see **Map 3.5.** More importantly are the accuracies, which are associated with the classes that will be used for the D-S model (**Table3.2**). Dense vegetation has an accuracy of 96.3%, water has an accuracy of 98.15%, and metal roofed buildings have an accuracy of 98.75%. The Open Field class had an accuracy of 93% and Bare Earth had an accuracy of 85.5%. The wetlands class was not included in the classification accuracy assessment as it was manually created and did not depend on classification algorithms.

Map 3.5 Classified Map of WorldView 2 Study Area



Dempster-Shafer Model

The classes of Dense Vegetation, Water, and Wetlands were extracted from the classified image. Each of these classes was transformed into distance maps using the IDRISI (Jiang and Eastman 2000) module Distance. These distance maps were then converted into fuzzy membership classes that are scaled from 0-1 similar to real probabilities (Jiang and Eastman 2000). A key element is where to set the breakpoints and functions for fuzzy set membership. The breakpoints which were eventually decided upon were chosen as they provided the best correlation values.

There are four hypothesis which were used for the D-S model; resting microhabitats are highly dependent on wetland areas, resting microhabitats also are highly dependent on Dense Vegetation which is found near water bodies, resting microhabitats are dependent on areas of dense foliage, and resting microhabitats do not exist directly over open water and areas directly adjacent to open water are also considered sup-optimal as these areas may be places of overhanging vegetation. These hypotheses were created as they provided the best model performance values and they are based off the fact that previous studies have shown that mosquitoes are highly dependent on moisture and shade during the day time (May 1979; Trape et al. 1992; Staedke et al. 2003; Sumba et al. 2004; Gouagna et al. 2011; Zhou et al. 2012).

It must be stated that the vast majority of the areas classified as dense vegetation was associated with tree crowns. The implication that these areas are important as resting habitats does not mean that the trees serve as resting habitats but rather the areas covered by this land cover support crucial areas that are used by *Anopheles* mosquitoes for day time resting habitat.

WorldView 2 Maxent Model

The Maxent model produced for this study follows a similar procedure to the methods outlined in **Chapter 2**. The model depends on environmental indices and presence data to create the final model. The environmental indices include NDVI and NDWI (Normalized Difference Water Index) (Gao BS, 1996), which were created from the WorldView 2 data. The equation used for NDVI follows the same equation seen in **Table 2.1** yet NDWI is specified by a different equation, which can is seen below.

$$NDWI = \frac{Green - NIR}{Green + NIR}$$

The last environmental index used was the classified image used for the development of the D-S model as the Maxent program can also utilize categorical data. The data used for training comes from **Table 3.1**. The sampling sites marked as statistically significant resting sites were used as the presence points. As with the Maxent model produced in **Chapter 2,** 20% of the training points were reserved to act as testing points, which equated to there being 15 presence records used for training, and 3 for testing.

To compare the outputs of the two different models discussed thus far, a Pearson correlation was performed. This correlation was done to see if the areas that the D-S model predicts as resting habitats are similar to the areas of resting habitat that the Maxent model predicts.

Results

The following information was used for the breakpoints for the fuzzy membership in the final D-S model. Fuzzy membership transforms the input distance data to a 0 to 1 scale based on the possibility of being a member of a hypothesis. 0 is assigned to those locations that are definitely not supporting the hypothesis, 1 is assigned to those values that definitely support the hypothesis, and the entire range of possibilities between 0 and 1 are assigned to some level of possible support (the larger the number, the greater the possibility).The distance that this range covers is defined by the break points, which are determined by the user. The first point (breaking point C) marks the location where the prediction value begins to fall from a prediction value of 1. The second point (breaking point D) indicates where the prediction value reaches 0. It also must be stated that providing a negative value for the starting break point ensures that the maximum value within a feature is less than 1. As some variables may be more important than others, providing a maximum value less than 1 can reflect this importance. Below is a bulleted list of the final model assumptions.

- The wetlands hypothesis used a linear membership function with a monotonically decreasing variant.
    - The C-break point was set at 0 and the D-breaking point at 45 meters.
- For the healthy foliage hypothesis I used a sigmodal membership function with also a monotonically decreasing variant.
    - The C-break point for this hypothesis was set at -10 meters with a D-break point of 15 meters.
- The ‘vegetated areas near water bodies’ hypothesis depended on two different fuzzy membership layers, which were eventually multiplied together using the overlay function in IDRISI to create the actual hypothesis used in the D-S model module. Both layers were made with a sigmodal membership function and used a monotonically decreasing variant
    - The first fuzzy membership layer was a simple distance from water layer. The C-break point was set at 0 and the D-breaking point at 150 meters.
    - The second layer used for this hypothesis was a distance from vegetation layer in which the C-Breaking point was -10 and the D-breaking point was set at 15 meters.

- The last hypothesis, resting habitats do not exist directly above or adjacent to open water, also used a sigmodal membership function with also a monotonically decreasing variant.
    - The C-break point for this hypothesis was set at 4 meters with a D-break point of 7 meters.

These breakpoints were varied experimentally to maximize the goodness of fit (R^2) between the predicted probability of presence and average counts. The resulting D-S model that was produced using the hypotheses was put through a 3X3 filter using the Filter function found in the ArcMap program. This filtering function averages the pixel values based on the surrounding window of N pixels. This was done in an effort to smooth the data by reducing local variation and

Table 3.3 Linear Regression Model

Linear Model Summary					**Parameter Estimates**	
R Square	F	df1	df2	Sig.	Constant	b1
0.387	19.57	1	31	0	0.235	0.042

Independent Variable: average number of mosquitoes caught per day.

Dependent Variable: D-S Model values

removing noise. Model values were extracted from the predicted surface that was provided by the field data, which were then used for regression analysis seen in **Table 3.3**. The model produced an R-Squared value of 0.387 using a linear regression. (**Table 3.3**).

Map 3.6 Final D-S Model with a 3x3 Filter

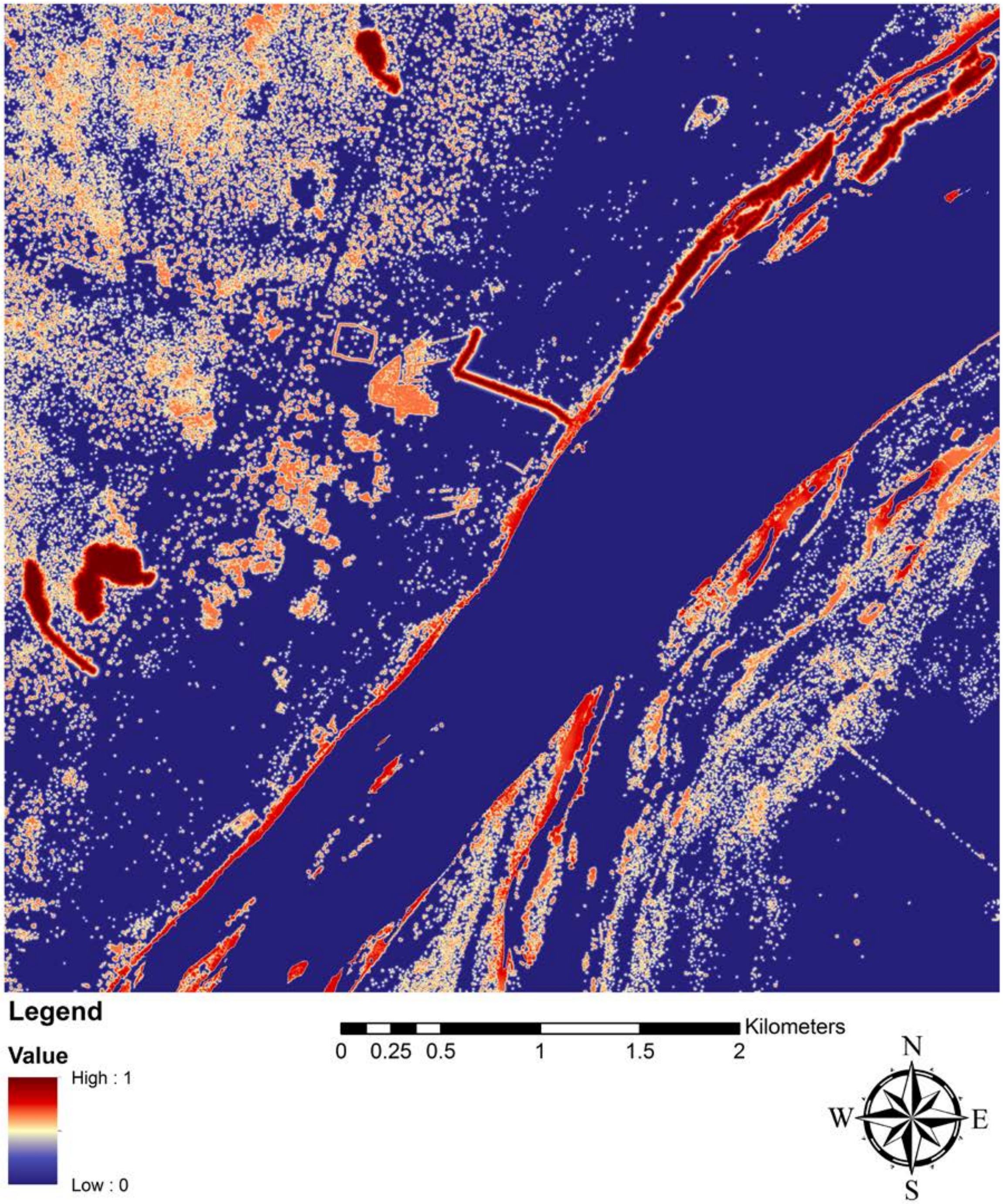


Figure 3.1 Linear Regression for D-S Model & Field Data Comparison

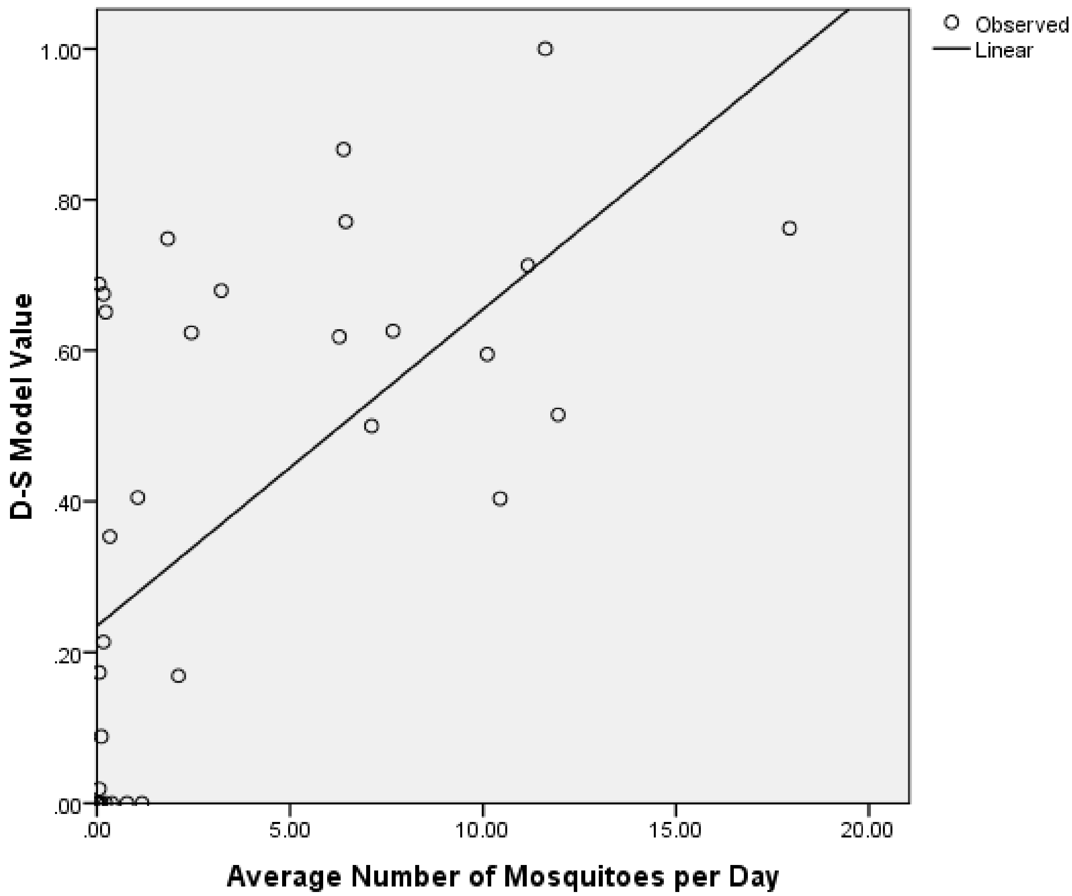


Figure 3.2 Average D-S Model values and error bars for resting sites and non-resting sites

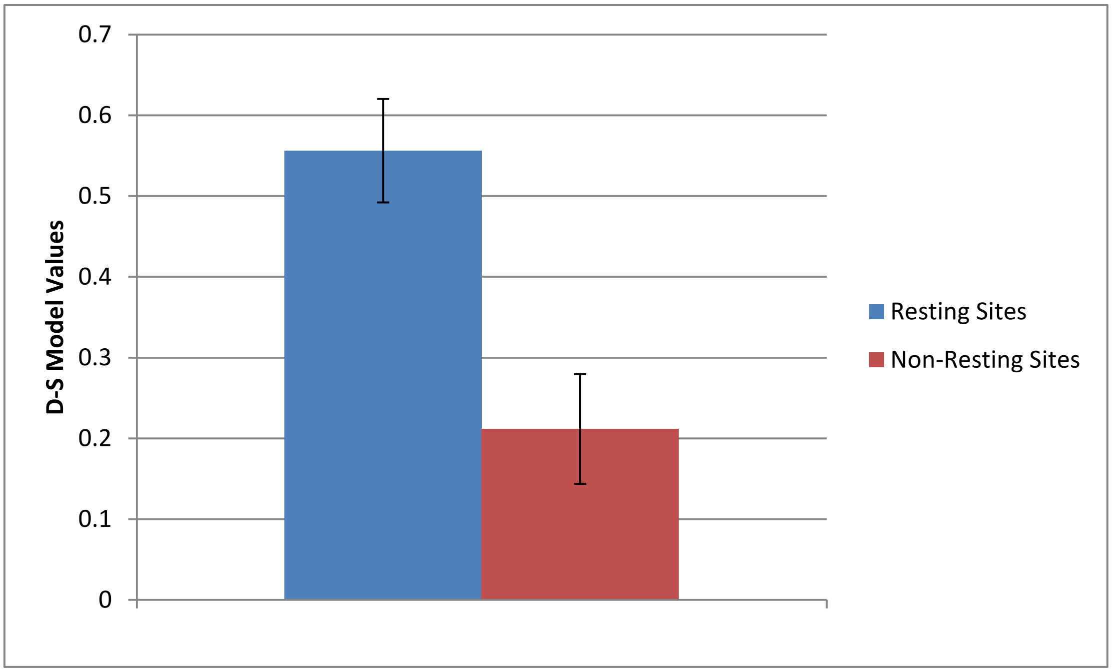


Table 3.4 t-Test Two-Sample Assuming Unequal Variances

	Resting Sites	*Non-Resting Sites*
Mean	0.56	0.21
Standard Error	0.06	0.07
Variance	0.07	0.07
Observations	18	15
Hypothesized Mean Difference	0	
Degrees of Freedom	30	
t-Statistic	3.69	
P(T<=t) one-tail	0.00	
t-Critical one-tail	1.70	
P(T<=t) two-tail	0.00	
t-Critical two-tail	2.04	

Figure 3.2 displays in bar graph form the average D-S model values for collection sites deemed statistically significant and statistically insignificant in **Table 3.1**, using error bars which display the standard error. **Table 3.4** displays the results of the two sample t-test which aims to determine if the D-S model values for the statistically significant resting sites are different from the D-S model values found for the insignificant resting sites. With a one-tailed p value of 0.0004~ it can be assumed with greater than 99% certainty that sites that have been identified as statistically significant resting sites have larger D-S values than the statistically insignificant resting sites.

Maxent Model Results

The resulting Maxent model for the probability for resting habitat can be seen in **Map 3.7**. The training AUC that produced by the model was 0.801 with a test AUC of 0.789 seen in **Table 3.5**. Furthermore according to the test of variable importance (**Table 3.6**) revealed that NDVI is the most important variable when used in isolation (77.4% permutation importance), which means that this index has the most useful information by itself. Conversely, the variable that had the most information on its own, with a Percent contribution of 73.7% (**Table 3.6**) was the Classified Image which was produced for the D-S model. NDWI showed no importance for the model and did not contribute any useful information in the modeling of possible resting habitat.

Map 3.7 Maxent Model of Possible Habitats in Kenieroba

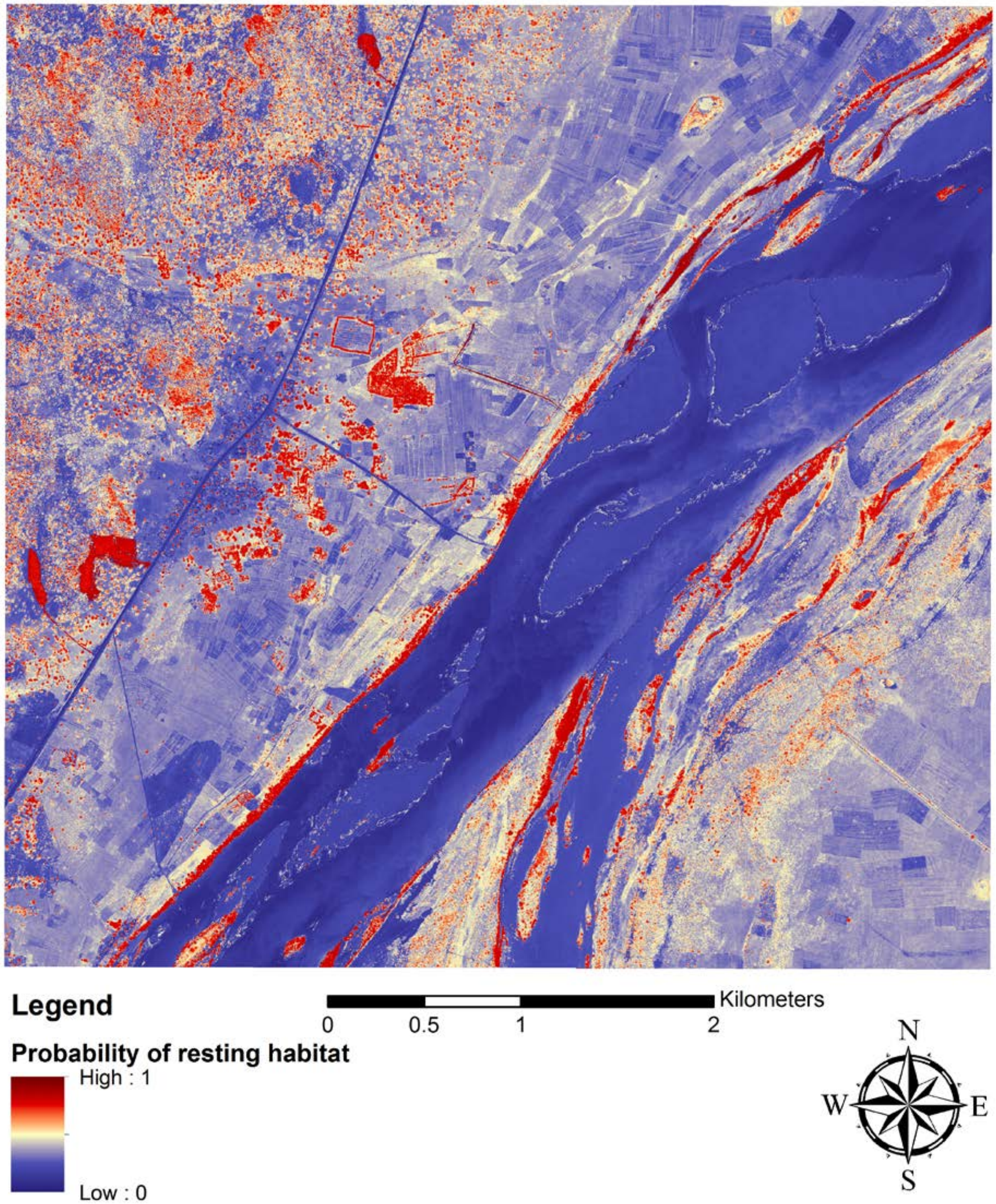


Table 3.5 Analysis of Maxent Model Performance

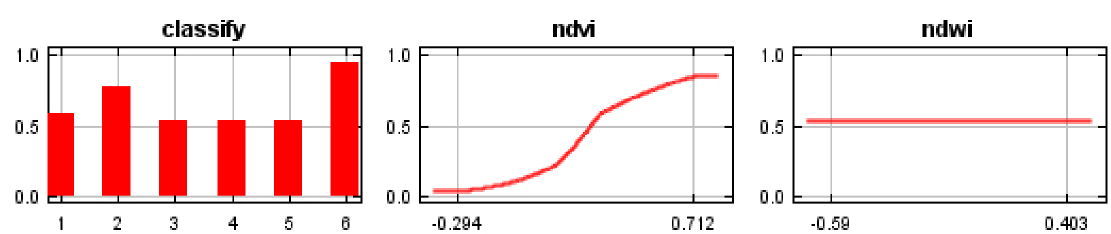
Training AUC	Test AUC	Standard Deviation
0.801	0.789	0.028

Table 3.6 Analysis of Maxent Variable Contribution

Variable	Percent Contribution	Permutation importance
Classified Image	73.7	22.6
NDVI	26.3	77.4
NDWI	0	0

Figure 3.3 Resting Habitat Maxent Model Variable Response Curves

X-axis: logistic prediction value



Y-axis: Catagorical Value*

Y-axis: Variable Value

* 1. Dense Vegetation, 2.Water, 3. Open Field, 4. Bare Earth, 5. Metal Roofed Buildings, 6. Wetlands

These curves shown in **Figure 3.3** display the response curves for the variables which were inserted to the Maxent model. As was explained in **Chapter 2** the curves show how the logistic prediction changes as each environmental variable is varied, keeping all other environmental variables at their average sample value. The curves show the marginal effect of changing exactly one variable, whereas the model may take advantage of sets of variables changing together. The response curve for the classified image is displayed as a bar graph with each category displaying its own logistic prediction value as a column in a bar graph (**Figure 3.3**).This shows that areas considered as wetlands and water by the classified image were of the most important to the model, whereas the other classes were of only moderate importance. The response curve for NDVI displays areas with a high NDVI value were very important, which translates to areas that are covered by dense vegetation. Lastly NDWI showed no importance in the model as already confirmed by **Table 3.6**.

Model Comparison

The direct model to model comparison was done using band collection statistic tool found in Arcmap. This tool uses Pearson correlation coefficient to measure the correlation between the different raster inputs. The results for the correlation method can be seen in **Table 3.7**. The Pearson correlation coefficient ranges between -1 and 1, where 1 is total positive correlation, 0 is no correlation, and −1 is total negative correlation. The correlation coefficient found in **Table 3.7** shows a moderately positive correlation with a coefficient of 0.663.

Table 3.7 D-S model and Maxent Pearson Correlation

Covariance	Correlation Coefficient
0.024	0.663

CHAPTER IV

CONCLUSION

Landsat Maxent Models

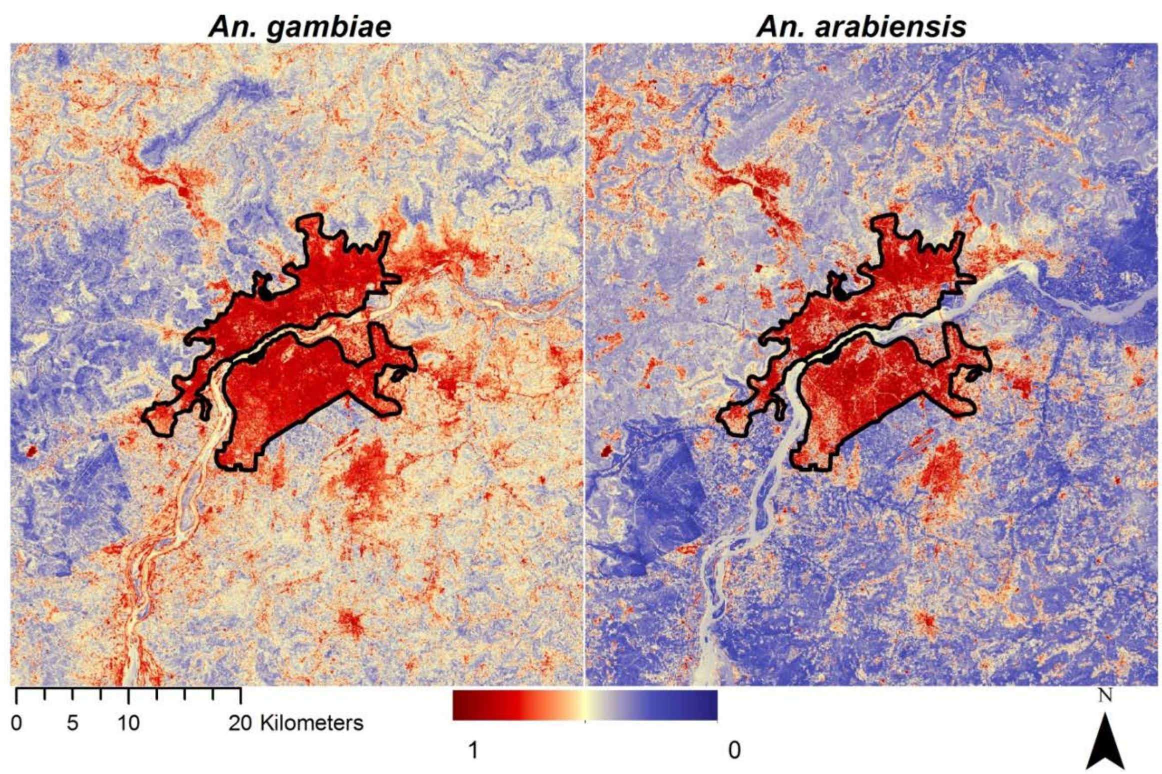
Anopheles gambiae

The Maxent model of *An. gambiae* performed well in this study based on the AUC scores that were generated by the model (**Table 2.3**). Furthermore, the predicted map can be considered consistent with the existing bionomics of that species. Important predictors of *An. gambiae* presence, found on the prediction map, are the areas comprised of vegetation near water bodies and irrigated agricultural fields. *An. gambiae* is a very prolific species, with a wide range of preferences yet they typically use sunlit, shallow, temporary bodies of fresh water such as ground depressions, puddles, pools and hoof prints for oviposition and subsequent larval development (Betson, Jawara, and Awolola 2009; Blackwell and Johnson 2000; Bockarie et al. 1993; Edillo et al. 2002; Koenraadt, Githeko, and Takken 2004; Minakawa et al. 2004; Mutuku et al. 2006; Mwangangi et al. 2007). Additionally there are studies showing that this species also uses sites which contain floating and submerged algae, emergent grass, and rice fields for oviposition (Blackwell and Johnson 2000; Edillo et al. 2002; Koenraadt, Githeko, and Takken 2004; Minakawa et al. 2004; Mutuku et al. 2006; Mwangangi et al. 2007; Bogh et al. 2003). Other major landcovers that proved to be highly important for predicting the presence of *An. gambiae* are areas of human development such as the capital city of Bamako (**Figure 4.1**). Besides the fact that *An. gambiae* uses anthropogenic disturbed areas for larval development as discussed earlier, this species has shown to be highly reliant on human hosts for blood meals. However, it is important to mention that many studies that report host preference using blood-meal analysis are conducted on resting, blood-fed specimens collected inside houses. This introduces a potential study design sampling bias, which favors the likelihood that the blood meal will be from a human host (Diatta et al. 1998). This bias may be reflected in the data points and the subsequent Maxent model generated predictions in this study. Nonetheless, urbanized areas provide a combination of adequate habitat and feeding opportunities that could serve to provide optimal habitats for this largely endophilic species (Knudsen and Slooff, 1992). Furthermore breeding conditions in this area for mosquitoes are also favorable due to the presence of impoverished areas. In areas such as these where we find high human population densities in combination with poor infrastructure and inadequate services, conditions perfect to promote an optimal habitat for malaria vectors (Knudsen and Slooff, 1992).

An. arabiensis

Although the map for *An. arabiensis* had a low test AUC (0.680) it is encouraging to see that the Maxent map agrees with many major points of this species' bionomics as well. As described in previous research, *An. arabiensis* is a largely generalist species that can utilize a variety of habitats (Giles and Coetzee 1987; Sharp and Lesueur 1991; Sinka et al. 2010). A very common habitat preference of *An. arabiensis* is dry savannah and sparse woodland habitat types (Coetzee et al. 2000; Coluzzi et al. 1979; Giles and Coetzee 1987; Service 1985). Specifically this species seems to prefer sunlit areas of water and limited emergent vegetation (Abdullah et al. 1995; Himeidan et al. 2008; Mutero et al. 2000).

Figure 4.1 Maxent prediction values near in Bamako; This figure displays a close view of the Maxent models for both species focusing on the city of Bamako.



Conversely, it has been shown that there is a tendency for *An. arabiensis* to have decreased densities in areas of dense vegetation which provide ample shade (Sinka et al. 2010). Observing the Maxent map of *An. arabiensis* it is evident that the areas of high predictive value coincide with places of sparse vegetation nearby streams (and other areas of moisture) in the northern region of the study area. According to the Maxent map, this species does not seem to utilize areas of rice fields in the southern region of the study area. This is supported by the findings of previous research showing that although *An. arabiensis* makes ready use of rice fields for oviposition, mosquito densities for this species drop off substantially as the rice plants mature (Mutero CM et al. 2000; Mwangangi JM et al. 2006, Mwangangi J et al. 2006; Mwangangi JM et al. 2007). As with *An. gambiae*, another factor that has shown to be a high predictor of presence within the model output, are areas of urban development, highlighted in the city of Bamako (**Figure 4.1**), which in its entirety is nearly optimal for the presence of *An. arabiensis*. Traditionally *An. arabiensis* is considered an exophagic species. However, there has been research done showing that this species is becoming more of an urban-dwelling mosquito (Tirados et al. 2006). It must be pointed out that these models seem to over predict the presence of *An. arabiensis* and *An. gambiae* in areas of urban development .Features such as runways and streets show up as high predictors of their presence, which is inconsistent with our present knowledge of mosquito distribution and habitat preferences. This over-prediction is an effect of using index-based environment variables which do not distinguish between roads and buildings.

The Maxent model's predictions of the presence *An. arabiensis* are consistent with the results of previous mapping attempts. In Sogoba et al (2007), the predicted proportion of *An. arabiensis* was higher in the areas north of Bamako. A lower frequency of *An. arabiensis* was observed in the southern and northern savannah while higher frequencies were observed in areas which could be considered the Sahelian zone. This feature can also be seen in the Maxent map where in the areas north of Bamako there is a more concentrated area of high predictive values, and there are much lower predictive values in the south. It also stated that *An. arabiensis* density was lower along the rivers irrespective of the eco-climatic zone. In the Maxent map produced here, the predictive value of *an. Arabiensis* was also quite low around rivers such as the Niger River.

Resting Habitat Modeling

The results from the D-S modelling yielded important insights to mosquito-resting behavior. It also revealed that remote sensing based techniques have the potential to make significant advances in our understanding of resting habitat preferences of malaria mosquitoes. The R-squared value of 0.387, which resulted from a linear regression, suggests that there is a moderate yet significant relationship between D-S model values and the average number of mosquitoes found per day at the sampling sites. Yet when looking at the T-test results shown in **Figure 3.1** and **Table 3.5** the D-S model performed quite well in distinguishing between suitable and unsuitable resting areas. This means that the D-S model can be very useful in determining which areas will be used as resting habitat. However, when trying to determine the relative importance of various resting habitats, the D-S model provides no information.

A possible reason that the R-squared value of the D-S model remains at a moderate level of ~0.4 could be due to the factors that may help determine which resting habitats are more valuable compared to others from a mosquito's perspective, and are not entirely limited to factors of distance to-and-from major land cover variables. The difference between a moderate resting habitat site and an ideal resting habitat may lie in conditions such as micro-elevation differences, soil moisture, or undergrowth density. Also information pertaining to the different species of plants that might constitute the areas within the dense vegetation class could yield information that would be useful in determining resting site potential. One factor that would be important in establishing resting habitats is the amount of shade provided by the trees within the densely vegetated areas. The D-S model works on the assumption that all areas covered by the dense vegetation class are equal. In reality some tree species may provide more shade than others due to different leaf areas, and this could have an effect on the quality of a resting habitat. Furthermore, flowering phenology can also be a factor to consider. Understanding the time of year that different plant species may flower would likely impact mosquito concentrations. Both male and female mosquitoes rely on the reproductive cycles of different plant species for their sugar production. Resting habitats nearby trees producing fruit or flowers could be favored when compared to resting sites nearby trees which are not producing any sugar.

The comparison between the Maxent model of possible resting habitats and the D-S model shows a moderate amount of agreement with a correlation coefficient of 0.663. The result of this correlation analysis shows that there is a significant amount of agreement between the two models. This means that the assumptions used by the hypothesis in the D-S model is verified to some degree by an automated computer algorithm, which has been widely accepted as a powerful modeling method for the distribution of species presence (Phillips, et al. 2006). The Maxent and the D-S models differ in the areas marked as unimportant to resting habitat which are portrayed as zero in the D-S model. This is partly due to the Maxent algorithm being a presence-only modeling method. Areas that have been shown to be poor resting habitats by the field data could not be used as training points to inform the Maxent algorithm, which areas are unsuitable for resting habitats. As a result, many areas that were considered as unsuitable by the D-S model had a range of low to medium prediction values in the Maxent model. Since the D-S model is able to take the absence values into account during the model creation to avoid over-prediction, it may be more reliable as a tool to use by public health workers who may wish to deploy the various outdoor control methods mentioned in **Chapter 1**. Lastly, the hypothesis that wetlands are important to resting habitats was very important to both the D-S and the Maxent models. As stated before, previous research has also found that vicinity to streams, wetlands, and other shallow water bodies to be reliable predictors of mosquito presence (Trape et al. 1992; Staedke et al. 2003; Gouagna et al. 2011; Zhou et al. 2012). The confirmation of this theory by the two different models supports the idea that these areas should be considered high priority targets when implementing outdoor control methods.

Limitations and Future Studies

Landsat Maxent Models

There are certainly limitations in the current study. For instance, with regards to the Landsat-Maxent models, the reliance on public malaria databases for mosquito presence points, carries with it a sampling bias. As stated in **Chapter 2**, the pooling of mosquito presence points from a variety of previous research and other sources means that there is no overall sampling strategy. Although bias files were created for the Maxent model trying to mitigate this limitation, there may still be some bias present. Previous research has made claims describing an urgent need for baseline surveys to be carried out in many West African countries since little to no reliable data exists for large areas (Coetzee et al, 2000). Also the use of a set of Landsat 8 images dating from 2014 means that the imagery lies outside the time range of collected data points by 5 years, as the collection of these field data range from 1968 to 2009. As stated before the set of images used for this modeling was chosen to be congruent with the seasonality of the data points. Unfortunately the Landsat database is scarce of cloud free imagery during the wet season for the study area within the presence point’s time span.

Future studies may wish to attempt to test the accuracy of the Landsat-Maxent maps produced within this study by sampling for mosquitoes at certain areas within the study site. Sampling for mosquito presence would help in verifying or refuting the results of the Maxent models. In addition to testing the models, the new presence points can be used to help further validate the models as well. Recent research published by Drake and Beier (2014) suggests that the future potential distribution of *An. arabiensis* in Africa is likely to be reduced as a result of climate change. Future distribution models of *An. arabiensis* and *An. gambiae* could be produced with more contemporary field data to investigate this possible change in mosquito distribution. Furthermore, future research into the mapping of mosquito distribution at a regional scale in other parts of West Africa, using a similar methodology, should be conducted to see if results of this study can be replicated.

Resting Habitat Modeling

The largest limitation with the resting habitat modeling was the clustering of the data points that were used to train the models. This clustering made it such that only features located nearby the areas of collection could be used to make assumptions regarding parameters impacting resting habitat selection. The other limitation in the resting habitat modeling portion of this thesis is the time difference between the date of collection (November-December) and the date of the World View 2 imagery (March). It must be acknowledged that steps were taken to account for these differences such as the creation of the wetlands class in the classified image as discussed in **Chapter 3**. It also must be stated that further land-cover discrepancies may still exist. Yet as there were no cloud free images available for the field sampling time period, the imagery used in this study was consistent with the same season of collection (i.e., the dry season).

Further research into predicting resting habitat using D-S or Maxent modeling of resting habitat should focus on optimizing the data sampling strategy. As stated above, one of the major drawbacks with the modeling preformed in the current study is the restricted sampling area. There are two major recommendations to be considered at this time. The first is to ensure that a random sampling effort be made taking into account the entire study area. Even though there may be many areas that could be considered unsuitable for resting habitats, the inclusion of sampling points from such areas will only improve the training of the model and its overall performance. Secondly, transects leading away from areas of interest can also help in understanding how resting habitat selection is influenced by vicinity to certain land cover features. For instance the inclusion of transects which would lead away from populated areas could help in understanding how distance from human dwellings may effect outdoor resting habitat selection by mosquitos.

And finally, this study tends to only take into account resting behavior that involves mosquito use of the field layer, which is largely herbaceous. There may be resting habitats being used by mosquitoes in the tree canopies, and a future study may wish to investigate whether mosquitoes utilize these areas for resting as well. Lastly D-S modeling of resting habitats could be performed at different locations in West Africa to test if the assumptions made by this study pertaining to the importance of certain land cover features, such as wetlands or densely vegetated areas, remain important.

Summary of Major Contributions

Below is a bulleted list of the major conclusions that are supported by the results of the research.

- Maxent models can be derived from Landsat based indices to model mosquito presence across large regions.
- Populated areas are highly important for both *Anopheles* species
- *An. gambiae* is predicted to use agricultural sites more regularly than its congener *An*. *arabiensis*.
- Modeling microhabitat preferences of mosquitoes using remote sensing is feasible
- Wetlands are highly important to resting habitats
- Areas covered by dense vegetation support resting habitats

The findings of this study do provide new insights regarding what areas within Southern Mali that are at major malaria risk due to high probabilities of mosquito presence. This research also provides the fundamental science-based information necessary to support more effective outdoor control efforts based on the location of existing resting habitats. With the inclusion of richer field datasets it is anticipated that even more reliable models can be generated providing a better understanding of mosquito distribution across regional areas. This in turn can help identify places that are at greater risk of outdoor malaria contraction.

These areas can then be assessed to identify areas of resting habitat using the knowledge gained from the D-S models. The implementation of more effective outdoor control methods at these identified resting sites can then be used to help significantly reduce the spread of malaria.

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