SPATIAL HABITAT DETECTION OF MOSQUITOES IN A FRAGMENTED LANDSCAPE ON THE SOUTHERN COASTAL PLAIN OF VIRGINIA USING REMOTE-SENSING TECHNIQUES AND A GIS

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Abstract—My primary objective is to create a predictive, spatially explicit classification model capable of identifying, categorizing, and ranking suitable mosquito habitat in heterogeneous landscapes with an emphasis on those mosquito species known to be vectors of West Nile Virus. Life-history processes dictate organismal distributions, and these distributions are often a function of spatial land cover patterns (*i.e.*, land cover composition and configuration). Thus, I hypothesized that local mosquito abundance could be predicted from a parsimonious set of measurable landscape factors. Thematic layers digitally representing landscape factors in the model's first iteration include: land-cover, wetland characteristics, and soil and vegetation characteristics. Spatial composition and configuration of vegetation are closely linked with species diversity and abundance. The vegetation indices (VI) used here (*i.e.*, normalized difference vegetation index, tasseled-cap transformation) are useful tools for inferring photosynthetic activity and vegetative structure. Results of these VIs were derived via direct interpretation of Landsat ETM+ imagery by incorporating mathematical operations between and among spectral bands. Collectively, these layers will be used to statistically elucidate relationships between mosquito abundance landscape factors. These relationships will in turn, be used to rank habitat suitability. The integration of digital satellite remote sensing and GIS technologies with applied ecology and epidemiology will produce an effective and cost efficient model for remotely locating, and subsequently controlling, mosquitoes across large areas.

Introduction

In the last 30 years, geographic information system (GIS) technology has grown from relative obscurity to a worldwide industry that is expanding at a rate of more than 20%/yr (Bernhardsen 1999). Prior to the relatively widespread availability of GIS, global positioning systems (GPS), and remotely sensed techniques and data, modeling spatial and temporal heterogeneity was often difficult, if not impossible. This difficulty was primarily associated with a general inability to manage, store, and analyze the huge banks of data needed to model complex real-world patterns and processes (Johnson, 1993). Applications for GIS are now as diverse as the broad range of data types relevant to this technology; this is reflected in recent literature. A burgeoning source of such information, GIS, GPS, and digital satellite remote sensing provide promising data and analytical tools for applied and multi-disciplined study.

GIS is becoming a valuable approach in the field of spatial epidemiology for the study of vector-ecology in disease transmission (Clarke *et al.*, 1996). Surveillance and monitoring, and subsequent health policies, associated with the study of vector-borne emerging infectious diseases (EIDs), such as hantavirus (Glass *et al.*, 2000), Lyme disease (Dister *et al.*, 1997), Sin Nombre virus (Boone *et al.*, 2000), and West Nile virus (Beasley *et al.*, 2003), are becoming more useful and dynamic through the integration of spatial, ecological, and epidemiologic data (Clarke *et al.*, 1996).

This study is being conducted with the cooperation of the Chesapeake Mosquito Control Commission (CMCC), Chesapeake, Virginia. It will complement an earlier study by Allen (NASA research grant NAG-13-01009 "Virginia Access") using field-based data collection (mosquito captures), satellite remote sensing (Landsat Enhanced Thematic Mapper+ [ETM+]), and geostatistical analysis (*i.e.*, spatial interpolation) to map transmission risk of West Nile Virus (WNV).

WNV is a form of Japanese encephalitis (Flaviviridae: *Flavivirus*). Flaviviruses are transmitted via a sanguivorous arthropod vector (a.k.a., arboviruses), usually a tick or mosquito (Twiddy *et al.*, 2003). Primary vectors of WNV are bird-feeding mosquitoes of the genus *Culex*; however, this virus has been recovered from 43 mosquito species from 11 genera (Dauphin *et al.*, 2004) and eight genera of ticks (Higgs *et al.*, 2004). WNV was first isolated in 1937, from a woman in the West Nile province of Uganda. Until recently, human and equine outbreaks were restricted to the Eastern Hemisphere. The first North American case involving humans was reported in 1999, in New York City (Devine, 2003). This outbreak marked the onset of the largest documented arboviral epidemic recorded for the western hemisphere, and the largest worldwide for WNV (Makar and Stowell, 2004). WNV has now been detected in dead birds of ~138 bird species and seems to be particularly virulent to the family Corvidae (crows and jays; Dauphin *et al.*, 2004). As of December 2003, there have been 8,912 human cases of WNV reported in 46 states, including 211 deaths. Like other mosquito-borne viruses, there is no vaccine available for WNV and the best preventative is effective mosquito control (Li, 2004).

My primary objective is to construct a predictive, spatially explicit, and scale-dependent habitat suitability index (HSI) capable of identifying, categorizing, and ranking suitable areas, or "patches," within a landscape where mosquito species are most likely to occur. I am currently developing such a model based on "within-patch" factors of ecological importance to mosquitoes, especially those species suspected to be vectors of WNV.

Many life-history aspects that dictate organismal distributions (*e.g.*, competition, physiological and behavioral niche tolerances) are driven by spatial variation in landscape factors (*e.g.*, moisture, vegetative structure) (Bellows *et al*., 2001). Because direct measurement of patch factors is not practicable at the landscape-level, appropriate surrogates used in this study were carefully selected, and digital representation of these factors was largely based on the measurability and accuracy that selected surrogates corresponded to macro- and microhabitat niche requirements of mosquitoes.

Levin (1992) suggested that difficulties associated with the unification of population biology and ecosystems science or of basic and applied science could largely be attributed to problems of pattern and scale. Considering these hierarchical relationships, it can be assumed that the effects of factors influencing landscape- or ecosystem-level patterns, processes, and functions are scale-dependent (Turner, 1989). Integration these relationships and organismal habitat parameters, will introduce variation in scale dependency among patch factors from an organismal point of view. Therefore, the conception of a parsimonious set of measurable factors designed to collectively assess habitat suitability must also incorporate issues of scale, *i.e.*, the spatial scale that a species, or group of species, most strongly respond to. These issues of scale are statistically integrated into this habitat suitability model from both within- (*i.e.*, niche) and among-patch (*i.e.*, landscape) perspectives.

Many of the patch factors included in this HSI (described below) are relatively static (*e.g.*, land cover/use, soil properties, topography). Without attributes representing temporal change the model is limited to repeatedly detecting the same "potential" areas of mosquito habitat. Because spatial and temporal fluctuations in mosquito abundance can be dramatic within a single season (Rogers, 1967), a dynamic aspect will be incorporated to enhance the HSI's ability to map, in real time, hot spots of mosquito activity. Considering the ephemeral nature of many habitats of mosquito larvae (Laird, 1988), I suggest that fluctuations in mosquito abundance are largely a function of the temporal heterogeneity associated with spatial attributes. Larval development and adult emergence are totally dependent on the presence of water. Gravid females select larval habitat, with oviposition occurring over or in permanent or ephemeral water sources; the latter includes existing pools or dry areas likely to become flooded (Laird, 1988). I will use recent and spatially explicit precipitation data to create an "accumulated water" grid. This grid will be overlaid on other thematic patch layers (*e.g.*, hydrology, soils) to extract areas of potential and current adult emergence.

The significance of this model is that it not only serves as a baseline classification model, but that it will be based largely on habitat suitability; as such, will be an effective and useful tool for locating mosquito activity across large areas by the use of remote-sensing techniques. Because this model is applied in nature, it must not be cost-prohibitive and provide effective mosquito control strategies that consider spatial and temporal distributions of mosquitoes.

In summation, this model will be useful to the CMCC and other mosquito control agencies because it will consist of a series of streamlined, user-friendly components that are based on empirical data. The incorporation of rainfall accumulations will allow the CMCC to pinpoint, in nearly real time, areas most likely to experience mosquito outbreaks.

Methods

Study Area—The City of Chesapeake, Virginia, was selected for study because 1) the landscape's structure represents a diverse mosaic of land use, 2) the desire of the CMCC is to stay on the cusp of mosquito control technology, and 3) of the known occurrence and relative distributions, within the city, of ~30 mosquito species listed on the Center for Disease Control's (CDC) potential vectors of WNV (Table 1). Suitable habitat for a broad range of mosquito species including tidal and freshwater creeks and the Great Dismal Swamp with its canals and forested wetlands lie embedded in the landscape mosaic. In addition, an extensive ditch network to allow for agriculture, and more recently, suburban development, drains much of southern Chesapeake. Thus, the close proximity of good mosquito habitat threaded within and among high densities of humans creates a landscape conducive to the transmission of WNV and other mosquito-borne diseases.

Dependent Variable—Mosquito abundance data (Table 1) were provided by the CMCC. These data represent captures of mosquitoes, by species, from permanent trap sites (N = 38) throughout the city, using CDC light traps. Capture data represent adult females only; males and mutilated individuals were not considered. Trap sites were sampled for mosquitoes at one- to two-week intervals from spring through fall, 2003 and 2004. The number of nights sampled varied among trap sites from one to 14 trap nights (TN). Capture data were normalized, to account for variation in trapping effort, by dividing total captures of each species at each site by the number of TNs for each site.

Table—1. Raw Captures of CDC potential WNV mosquito vector species for 2003 and 2004.

Species	2003	2004
Aedes aegypti	0	11
Aedes albopictus	947	2,824
Aedes vexans	13,139	1,741
Anopheles barberi	0	7
Anopheles crucians/bradleyi	18,053	15,624
Anopheles punctipennis	348	746
Anopheles quadrimaculatus	1,984	1,828
Coquillettidia perturbans	879	6,025
Culex erraticus	311	858
Culex pipiens	98	68
Culex restuans	3,620	1,479
Culex salinarius	29,393	21,991
Culex territans	359	147
Culiseta inornata	2	0
Culiseta melanura	127,327	171,071
Ochlerotatus atlanticus/tormentor	4,335	5,821
Ochlerotatus canadensis	72,762	32,288
Ochlerotatus cantator	93	4
Ochlerotatus grossbecki	5	2
Ochlerotatus infirmatus	1,667	515
Ochlerotatus sollicitans	55	6
Ochlerotatus sticticus	115	2
Ochlerotatus stimulans	1	0
Ochlerotatus taeniorhynchus	49	9
Ochlerotatus triseriatus	364	339
Orthopodomyia signifera	36	32
Psorophora ciliata	93	94
Psorophora columbiae	2,579	4,506
Psorophora ferox	5,768	1,893
Psorophora howardii	68	19
Uranotaenia sapphirina	1,392	3,754
Totals	285,842	273,704

Independent Variables—Patch factors are represented by "thematic" layers (Table 2) in ESRI Grid format. More specifically, each layer will constitute a spatially continuous description of landscape pattern, such as image enhancement (*e.g.*, vegetation indices), land-use, hydrology, and soil properties. Predictive patch suitability for all areas within the landscape will be determined by empirical data representing patch condition (independent variables) and mosquito abundance (dependent variable) at individual trap sites. Therefore, the following described variables were selected to represent maximum landscape heterogeneity in subsequent analysis. The discussion that follows includes all current layers; further investigation will likely reveal other relevant patch factors.

Vegetation Indices—Spectral vegetation indices (VI) are algorithms used to analyze, pixel-by-pixel, vegetation biomass and vigor using the digital reflectance values of a combination of spectral bands (Campbell, 2002) using mathematical operations between and among different spectral bands. Two VIs, normalized difference vegetation index (NDVI) and tasseled-cap transformation (TC), were used to generate thematic factor layers representing aspects of vegetative cover and moisture.

Table—2. Characteristics of thematic layers. Original Source and Source (Date) = original data creator and the date it was released, respectively. Software = software used to analyze or incorporate data.

Thematic Layer	Data Type	Original Source	Source (Date)	Software
Mosquito Capture Data	Vector: shapefile	CMCC	June-August (2003 & 2004)	ArcView§, ArcGIS§
NDVI	Raster: image (Landsat-7, ETM+)	USGS (EDC)	29 July 2002	Erdas Imagine§§
Tasseled Cap	Raster: image (Landsat-7, ETM+)	USGS (EDC)	29 July 2002	Erdas Imagine§§
Land Cover	Raster Digital Data	USGS (EDC)	2001	ArcView§, ArcGIS§

§ ESRI, Inc., Redlands, California.
§§ Erdas, Inc. Atlanta, Georgia.

First described by Rouse *et al.* (1974), NDVI is one of the most widely used VIs for mapping primary production and leaf area index (LAI). NDVI has also been used to detect soil moisture gradients (Todd and Hoffer, 1998). Output brightness values are a function of differences in spectral reflectances in Landsat Enhanced Thematic Mapper (ETM+) band 4 (near infrared [NIR]) and band 3 (red), normalized by the sum of the two bands.

$$NDVI = (B4-B3) / (B4 + B3)$$

Tasseled-cap transformation reprojects brightness values for ETM+ bands 2 (green), 3 (red), and 4 (NIR) onto a single transformation plane containing both vegetation (greenness) and soil (brightness) information (Crist and Cicone, 1984). Output values for the first TC axis (TC1, vegetation characteristics) are the sum of weighted raw reflectances for red, NIR, middle-IR and far-IR bands. TC2 (soil characteristics) values are a weighted red band minus the sum of weighted reflectances for NIR, MIR, and FIR. A pixel's position on this plane is a function of stage of transition between bare soil (TC2, Y-axis) and vegetation (TC1, X-axis).

ETM+ digital satellite data were selected for generating spectral derivatives because its sensors detect electromagnetic radiation in spectral bandwidths useful to ecological investigation (Campbell, 2002). In addition, ETM+ is readily available, recognized by most applicable software packages (*e.g.*, ESRI products, Erdas IMAGINE), and relatively inexpensive. The ETM+ image, July 29, 2002 (acquired from the United states Geologic Survey's [USGS] EROS Data Center [EDC]), was cloud-free and in 30m x 30m-pixel size. This resolution should be an appropriate minimum unit for mapping mosquito habitat. Allen (NASA research grant NAG-13-01009) has done much of the image preprocessing and enhancement (*e.g.*, NDVI and TC) using Erdas IMAGINE v8.5 software. Much of the research associated with the current study was funded by a Graduate Research Fellowship from the Virginia Space Grant Consortium (academic Year 2004-2005).

Land-cover/land Use Data (LCLU)—LCLU data (National Land Cover Data [NLCD]: 2002) were acquired from the USGS and subset to the City of Chesapeake with a 1.5km buffer. The original USGS Level II classification scheme (Table 3) is (after Anderson *et al*., 1976) were derived by the USGS from Landsat TM digital satellite data (30 x 30m pixels) and ground-truthed on a national scale using aerial photos. I used a stratified random sampling design to select sample points (N = 1,016) throughout Chesapeake to assess "local accuracy" of NLCD (Congalton and Green, 1999). Land cover/use of these sites was referenced using USGS digital orthophotos (DOQQs: 1m resolution). Accuracy assessment results ($K^{\Lambda} = 0.232$, overall accuracy = 28.84%) well below industry standards ($K^{\Lambda} = 0.8$) were largely due to confounding land use and land cover classes inherent to the USGS's classification scheme. For example, many sites classified as upland forest were actually forested residential. Additional confusion occurred between forested upland and forested wetlands. The data were reclassified in a more cogent Level I classification scheme (Table 3) to alleviate confusion among classes ($K^{\Lambda} = 0.664$, overall accuracy = 76.28%).

Soil Data—Soil survey data for the City of Chesapeake, Virginia (Soil Survey # va550, publication date: 10/05/2004) were exported in SSURGO format (Soil Survey Geographic Data) from the United States Department of Agriculture (USDA), Natural Resources Conservation Service's (NRCS) Soil Data Mart. SSURGO data describes the characteristics and distribution of soil types within the landscape. These data are delivered in tabular (ASCII delimited) and spatial (ArcView shapefile [polygons]: UTM Zone 18, Northern Hemisphere [NAD 83]) formats. There are challenges associated with incorporating SSURGO data into a GIS. Themes in thematic maps are based on map units; however, SSURGO map units are made up of one or more named soil types (components), each with a distinguishing suite of properties. As such, thematic representations of map unit properties (*i.e.*, runoff potential, hydric class, and water table depth) had to be created by pooling the properties (*e.g.*, weighted averages) of each component as a function of the percent of map unit composition. A series of thematic layers representing ecologically important soil properties will be overlaid to generate a cumulative, pixel-by-pixel, index of soil quality in terms of suitable mosquito habitat. In addition, the integration of this soil index with a hydrologic model (described below in *Additional Objectives*) will be used map areas susceptible to runoff and sustained flooding.

Table—3. USGS NLCD classification (Level I and Level II) including USGS class codes (Code) and the reclassification codes (RC) and descriptions (RD) used in the current study.

Code	Level I	Level II	RC	RD
11	Water	Open Water	1	Open Water
21	Developed	Open Areas	2	Developed
22	Developed	Low Intensity	2	Developed
23	Developed	High Intensity	2	Developed
32	Barren	Quarries / Strip Mines / Gravel Pits	2	Developed
33	Barren	Transitional	2	Developed
41	Upland Forest	Deciduous Forest	4	Forest
42	Upland Forest	Evergreen Forest	4	Forest
43	Upland Forest	Mixed (41 and 42) Forest	4	Forest
81	Herbaceous (Planted / Cultivated)	Pasture / Hay	8	Upland Herbaceous/ Shrub
82	Herbaceous (Planted / Cultivated)	Row Crops	8	Upland Herbaceous/ Shrub
85	Herbaceous (Planted / Cultivated)	Urban / Recreational Grasses	8	Upland Herbaceous/ Shrub
91	Wetland	Woody Wetland	4	Forest
92	Wetland	Emergent Herbaceous Wetland	9	Herbaceous Wetland

Topography—Vertical resolution used in USGS's digital elevation model (DEM) that includes Chesapeake, Virginia (5 ft), is insufficient to accurately describe the ecological influence of elevation in this coastal landscape. Instead, I created a 2-ft interval DEM (ESRI Grid format) of the city (ArcGIS-9, Spatial Analyst) from a 2ft-interval contour map provided by the CMCC. Elevation data for all nodes of all contour lines was extracted to create a new point shapefile. Interpolation of the data from this point shapefile produced a 2-ft interval continuous surface of elevation to be used as both a patch factor in this HSI and in a hydrologic model capable of mapping active mosquito breeding habitat (described below in *Additional Objectives*).

Scale Dependency—There are issues of scale associated with thematic representation that must be resolved before the final HSI can be validated. One inherent problem of increasing scale is the loss of spatial variation (Levin, 1992). I have accounted for a portion of this lost variation by creating a series of grids for each thematic raster layer by operationally combining pixel data in an increasingly larger area (1 x 1 through 21 x 21 30m/side pixels; Table 4) using a moving window function (ArcGIS-9, Spatial Analyst extension). Data for most layers (*e.g.*, capture data, spectral reflectance, topographic) were aggregated using a neighborhood mean. Some data were ordinal (*e.g.*, hydric soil properties) or categorical (*e.g.*, land-use, soil type); I used neighborhood majority to aggregate these data.

I am currently comparing mosquito capture data with patch layers at each spatial scale to isolate the most explanatory scale for each habitat variable. Thus, representing each theme in a layer at an appropriate scale(s) should minimize unnecessary loss of spatial variation.

Analyses—I am comparing the capacity of linear multiple regression model and an artificial neural network (ANN) to predict mosquito abundance based on patch characteristics represented in digital thematic layers. Linear regression models are commonly used in studies seeking to describe relationships between organismal abundance and environmental factors; however, they are only practical when applied correctly. They are parametric statistical modeling techniques that describe these relationships in the form of a single equation for a best-fit line. The power of these relationships is depicted by a single value (P) representing the probability that the relationship is true. As with all parametric statistical analyses, credibility is based on adherence to a strict set of assumptions describing data distributions. However, ecological phenomena are often nonlinear, and data sets are inherently riddled with anomalies and background variation that often result in violations of assumptions.

Table—4. Spatial scales used in thematic layers of the HSI. Length, side, and area are post-aggregation pixel attributes.

Number of pixels / side	Length / side (m)	Perimeter (m)	Area (ha)
1	30	120	0.09
3	90	360	0.81
5	150	600	2.25
7	210	840	4.41
9	270	1,080	7.29
11	330	1,320	10.89
13	390	1,560	15.21
15	450	1,800	20.25
17	510	2,040	26.01
19	570	2,280	32.49
21	630	2,520	39.69

In contrast, ANNs are nonparametric and nonlinear and, thus, not bound by strict assumptions. They are designed to process information and learn from experience in much the same manner as the human brain. ANNs are capable of assaying, extracting, and predicting complex patterns and relationships from nonlinear, noisy, and imprecise data (Lek and Guégan, 1999). Learning, or "training," is achieved by the use of a back propagation algorithm that iteratively adjusts internal parameters, or weights (similar to regression coefficient) of input layers (similar to independent variables) until an error threshold of the output is reached (Manel *et al.*, 1999).

Thematic layers (Table 2) will serve as both independent variables in regression models and as input nodes of an ANN. Relationships between mosquito abundance and the habitat characteristics of sampling sites will be used to model the suitability of habitat types and ultimately to predict mosquito abundance anywhere within the landscape. A subset of the mosquito capture data, ~ 80% of TNs, will be used to train the regression model and ANN and the remaining capture data, ~ 20% of TNs, will be reserved for model validation.

Additional Objectives—The semi-static HSI described above will be augmented by the addition of a more dynamic model designed to assess current conditions of potentially suitable mosquito habitat. These results will produce a subset of the suitable patches (from the HSI) with elevated probabilities of adult mosquito emergence based on recent precipitation data. NEXRAD (NEXt-generation RADar) meteorological data (NOAA, National Weather Service), is georeferenced radar data (Weather Service Doppler Radar [WSR:88D]) that includes spatial data for various forms of precipitation and convective activity (Beringer and Ball, 2004). These data will be used to create dynamic layers representing amounts and distribution of recent precipitation. Precipitation runoff has the potential to quickly create conditions needed by mosquito larvae. Such areas will be identified by overlaying a hydrologic model created from topographic data (*i.e*., DEM), with a layers representing soil moisture potential. Soil layers will be used here as they were before; to determine where surface runoff is impeded and surface water will likely accumulate. NEXRAD layers will be integrated with the 2-ft interval DEM and soil layers to produce dynamic hydrologic models of the City of Chesapeake. Knowing current rainfall patterns and the developmental periods of mosquitoes, I should be able to predict what patches of suitable habitat (from the previously described HSI) currently have the hydrologic conditions conducive to potential outbreaks of emerging adult mosquitoes. Such knowledge would enable the CMCC to apply insecticides in a more effective, timely, and economical manner, while reducing the health risks of WNV and similar diseases.

Conclusions

The results of this study will be a series of user-friendly components that allow the CMCC and other such agencies to control mosquitoes more effectively by providing cost-reducing, spatial and temporal strategies using real-world data. More effective mosquito control will result in a lower risk of transmission of mosquito-borne diseases such as WNV.

Continuation of this research is needed to refine the model and to increase its robustness. The significance of my research will be that it serves not as just a baseline classification scheme, but the scheme will be based largely on habitat suitability; as such, it may be an effective and cost efficient tool for remotely locating mosquito “hot spots” across large areas. In addition, this model will serve as a stepping-stone for a more in-depth landscape analysis investigating the influence of spatial variation within a landscape (*e.g*., landscape fragmentation and patch size, shape, and connectivity) on processes that regulate populations, metapopulations, or in this case metacommunitites.

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