Modelling Patterns of Mosquito Density Based on Remote Sensing Images

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Vector borne diseases, like Malaria and arboviral diseases, are affecting a growing number of people causing millions of deaths every year. Recent arboviruses (arthropod-borne viruses) epidemics in the United States demonstrated that they can emerge or reemerge in temperate climates causing increasing problems in public health. In Portugal, although the presence of arboviruses has been documented, their current activity and spatial dynamics is not thoroughly understood. The assessment of environmental conditions that influence the spatial patterns of arthropod vector borne diseases using climate and remote sensing data has been performed at a continental scale with coarse temporal and spatial resolutions. The RARIMOSQ project aims to evaluate the risk of vector borne-diseases, using medium and high resolution remote sensing images for two areas in Portugal. This paper presents the methodology and preliminary results concerning modeling spatial patterns of *Anopheles atroparvus* density through remote sensing data, supported by 3 sampling sites near the Sado estuary, monitored bimonthly from 2001 to 2004. Preliminary results showed (i) temperature is a limiting factor for mosquitoes growth, being 15ºC identified as a threshold, and (ii) NDVI can be used as a proxy variable of local conditions (vegetation and water) for the development of mosquitoes. High correlations were obtained between NDVI values corresponding to agricultural and especially to rice fields and mosquito populations. The results are very promising to create mosquito density maps applying remote sensing data.

KEYWORDS

Malaria, Arbovirus, Emerging and reemerging diseases; Ecological Modeling; Remote Sensing; Geographical Information Systems and Monitoring.

INTRODUCTION

Climate is expected to change due to an overall net global warming, which has been predicted to result from the increased global concentration of a number of "greenhouse gases" such as carbon dioxide, methane, nitrous oxides and fluor gases [6]. Temperature predicting models, as from the Climate Impacts LINK Project of the East Anglia University, are unanimous presenting a global warming of 3 to 5 ºC on average with a doubling in CO_2 [6].

There are at least two ways by which climate change may impact vector-borne diseases. One mechanism of change is brought about by the direct impact of climate change on the agent, vector, or host. For instance, changes in temperature, rainfall, humidity, or storm patterns may directly affect the multiplication or differentiation rate of the vector or the agent, the biting rate of the vector, or the amount of times that the host is exposed to the vector. A second mechanism of change is brought about by the indirect impacts of climate. In this category, climate influences some parameters that are important to vector spread or survival, such as the type of agriculture or vegetation, which, in turn, changes the relationship between the parasite, the vector, and the host.

Remote sensing data is commonly used in diverse disciplines such as agriculture, forestry, geology, and environmental planning. The use of this data for monitoring environmental conditions that influence the patterns of arthropod vector borne diseases has been increasingly applied. One of the first uses of multispectral scanner data refers to the early 1970's when investigators from NASA and Mexico's National Commission of Outer Space developed a remote sensed approach for monitoring the environmental parameters required for the propagation of the screwworm fly [2]. In 1984, Cross *et al.* [3] used Landsat MSS data to describe the geographic characteristics of sites in Philippines Islands where cases of schistosomiasis were reported. These measurements were combined with temperature and precipitation data to estimate the probability of disease occurrence at specific locations. One year after, Hayes *et al.* [7] used Landsat MSS data to identify and map mosquito larval habitats in Nebraska and South Dakota based on their association with freshwater plant communities.

Linthicum *et al*. [9] used Advanced Very High Resolution Radiometer (AVHRR) data to infer ecological parameters associated with Rift Valley Fever (RVF) in Kenya. Correlations between vegetation index values and ecological parameters indicated the possibility of predicting RVF viral activity in the mosquito vector. Recently, NASA's Earth Science and Public Health Program team are using real time climate data and satellite images for mapping and monitoring the ecological and climate patterns associated with diseases outbreaks [10]. The aim is to provide disease surveillance tools to public health authorities enabling officials to take preventive measure (e.g., vaccination, vector control) and, thus reduce associated human and animal losses.

Portugal has potential conditions for the development of vector bone diseases. In fact, there are 40 species of mosquitoes and among them several disease vectors [6, 12]. In Portugal, yellow fever outbreaks happened in the late XIX century, malaria was endemic up to the 1950s, and West Nile Virus has been detected in the last 3 decades [1, 4, 5]. Some local characteristics, natural and man made, such as the recent Alqueva dam and wetlands, migratory bird's sanctuaries and water reservoirs, may offer the conditions to infectious agents to put at risk animals and humans. Also, the growing number of travelers is considered to be a risk factor. If the actual environmental conditions represent already a potential risk for vector borne diseases, the climate scenarios from the Hadley Centre (http://www.met-office.gov.uk/research/hadleycentre/) show us an increasing potential risk due to higher average temperature for 2100.

The RARIMOSQ project aims to evaluate the risk of vector borne-diseases reemergence using remote sensing images, for two sampling areas in Portugal, the Sado estuary and the Alqueva dam area. Four methodological stages are considered: (1) monitoring of the mosquito life cycle, density and habitat; (2) modelling the patterns of mosquito density, taking into consideration the relationships of its spatial and temporal patterns with climate data and remote sensing data, (3) performing risk analyses, combining geographical information concerning migratory birds tracks, population density and human travelling, (4) estimating the vectorial capacity for actual and future climate This paper presents the preliminary results of stages one and two for the Sado estuary region, regarding the mosquito species Anopheles atroparvus, the former malaria vector in Portugal. Results were based on a previous four years mosquito monitoring study (Sousa, PhD under preparation) with emphasis for the remote sensing data analysis to explain seasonal patterns of mosquito density values.

1. METHODOLOGY

The monitoring of the mosquito life cycle, density and habitat and the modelling patterns of mosquito density, based on the relationships of its spatial and temporal patterns with climate data and remote sensing data, are the main tasks addressed in this paper. This section presents the methodological framework supporting theses tasks, applied to the study area.

1.1. Study Area

The study area comprises a coastal land strip with *ca.* 15-20 km long and 5-10 km wide, starting in the left bank of the Sado river and running south along the coast. It is a flatland area with altitudes between sea-level and less than 60 m, with a variegate landscape. The north and northwest part of the study region is a national protected landscape area occupied by marshlands and *ca.* 600 ha of rice fields. In the west, along the seashore and next to the sand dunes system, there is an extensive area of rice paddies. The south and east areas are mainly occupied by maritime pine forest and some semi-natural agro-forestry systems of evergreen-oaks.

1.2. Mosquito collection

Adult mosquito collections were carried-out in three localities: Comporta, Carvalhal and Pego. Sampling was performed through indoor resting (IR) collections, using mechanical aspirators, to assess relative abundance and seasonal population dynamics. IR collections were carried-out twice a month, between May 2001 and May 2004 and mosquitoes were identified according to Ribeiro and Ramos [11]. *Anopheles atroparvus* monthly average densities were estimated as the mean number of females captured per collector per minute.

1.2. Exploratory analysis of mosquito density

As described in previous section, there are three monitoring sites, located in the Sado estuary area. For each sampling site, the data set includes a time series, from 2001 to 2004, of monthly average density values. Although the three sites are close to each other, the local conditions may impose spatial differentiation, which may prevent to consider the three samples as from the same statistical population. To understand if the observations of mosquito densities in the three sampling sites can be considered as from the same statistical population, a z test was performed[†], considering the total number of observations and a confidence level of 0.95. The mean values for each two sampling sites were compared and tested with the null hypotheses being that the mean values are equal. This result allows considering if data collected is representative of the same population, and thus can be handled together, or if the different factors in each location imposes that the mosquito density pattern should be studied separately. This issue is crucial to guide the design and development of the mosquito density model in terms of its relationship with the spatial and temporal patterns of climate and remote sensing data.

1.3. Climate Analysis

One of the key elements for mosquito development is temperature. Studies developed by Patz J. *et al* [10], of *An. atroparvus*, indicated that they do not usually survive where the mean winter temperature drops below 16°-18°C. Since the larval and adult development is conditioned by temperature. Pearson correlation coefficients[†] were calculated between mosquito density records and mean temperatures of the 2, 5, 10, 15, 20, 25 and 30 days prior to the mosquito collection date, in order to identify the time lag that better explains temporal mosquito density patterns. Daily mean temperature values were selected from the Water Portuguese Institute (INAG), for the time series 2001 to 2004. The function obtained from plotting mosquito density against temperature allowed the identification of seasonal periods with suitable conditions for mosquito development and provided guidelines for the remote sensing studies.

1.4. Remote Sensing Analysis

The RARIMOSQ project states the hypothesis that the remote sensing data can be used as a proxy for mosquito favorable conditions, due to its preference for vegetated and humid areas. In fact, the distribution of mosquitoes is, in part, related to land use factors such as the presence or absence of wetlands, the type of surrounding vegetation, elevation, among others [9]. Many of these environmental factors can be mapped using remotely sensed data. In this paper, NDVI (normalized difference vegetation index) was considered to explore the relation between mosquito density and vegetation/water seasonal patterns.

For each sampling site, NDVI values for each land cover class, within increasing circular windows centered at the site location, were selected in order to evaluate the relationship between each NDVI data set and the mosquito density. The goal is to identify the NDVI range values that better explain the mosquito density seasonal patterns. Two steps have been performed: (1) land cover classification of the study region, and (2) NDVI analysis related with mosquito density values.

Land cover classification

The land cover map for the study area was derived from a supervised classification of the LANDSAT image from December 2002, in particular the bands TM-1, TM-3, TM-5 e TM-7, and the ratios TM-4/TM-3 e TM-3/TM-7[††]. A neural network was used with the back propagation method[†††], the learning rate of 0.2, the momentum factor 0.5. The neural network was trained with 20 000 interactions, being estimated accuracy 88%. Test areas confirmed an accuracy value of 79%. The classes obtained included fresh water, wet lands, rice fields, agriculture and forestry.

The rice fields were separated from other type of agriculture due to the irrigation method used. In this case, the irrigation period starts between April and June with open channels of fresh water causing the surrounding vegetation, mainly shrubs, to grow with suitable conditions of water and temperature.

NDVI analysis

The NDVI values of each land use are from the NDVI MOD13Q1 16 day's product, which has a spatial resolution of 250 meters, and a temporal resolution suitable to the time frame of mosquito density data set. The NDVI data set refers to the time series between 2001 and 2004. Some NDVI images were excluded, due to cloud cover. For each sampling site, NDVI values within increasing circular buffers, from 250 to 3000 meters centered at the site location, were selected. For each buffer, NDVI values were averaged per land use class. Each land use type was compared with the mosquito densities through a Pearson correlation coefficient during the seasonal period selected, and a function between the NDVI values and the mosquito density was plotted. This period was selected as a function of mosquito growth as its development is greatly conditioned under 15ºC.

† - Microsoft Excel XP Data Analysis Toolpak

†† - Clark Labs Idrisi Kilimanjaro

††† - Idrisi Kilimanjaro NeuralNet Back Propagation Classifier

2. RESULTS

2.1. Mosquito density analysis

The analysis of *Anopheles atroparvus* densities estimated as mean of the monthly values for the years 2001 to 2004, for the three sampling sites, showed an exponential growth starting in May for Carvalhal and in June for the other locations. The results show that the maximum density occurs in July, decreasing from here until December. (Figure 1)

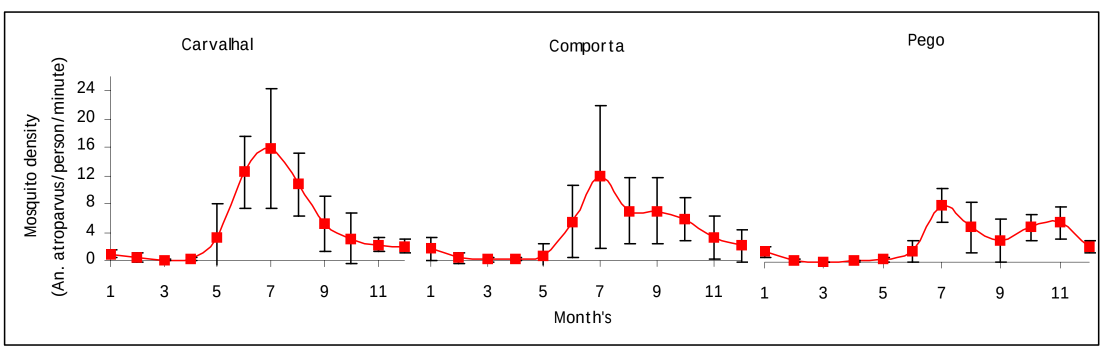

Figure 1 – Mosquito densities (number of Anopheles *atroparvus* per person and per minute, *An. atroparvus*/person/minute) monthly average and standard deviations for the three sampling sites, between 2001-2004.

Since the annual behavior for the different sampling sites appears very similar, a z test analysis was performed in order to find out if the mosquito populations from the three sites can be considered as from the same statistical population. Regarding the comparison of the mosquito mean monthly densities between the three sampling sites, only Carvalhal and Comporta were found to be similar (z test, $P > 0.05$) (Table 1). However, an F-test on the variances revealed that even for the Carvalhal and Comporta sites, these can not be considered as belonging to the same statistical population. Therefore, the three sites should not be considered together for further analysis, namely for modeling purposes. This means that probably the three sites have local different conditions that impose different seasonal patterns, thus the mosquito density modeling should follow a spatially explicit approach. Remote sensing is a very appropriate approach to accommodate such local differentiation.

Table 1 – z-test results for Carvalhal, Comporta and Pego mosquito densities.

	Carvalhal	Comporta	Carvalhal	Pego	Comporta	Pego
Average	5,3	3,8	5,3	2,53	3,8	2,53
Variance	43,18	26,02	43,18	8,13	26,02	8,13
Observations	82		82		82	
$z_{0.05}$	-1,682		3,565		1,976	
z critical two tail	1,959		1,959		1,959	
P(Z<=z) two tail	0,0920		0,0003		0,0480	
F	1,659		5,311		3,200	
$F_{0.05;\,80}$	1,482		1,482		1,482	

2.4. Comparing mosquito density with climate data

The average of the mean daily temperature for the 15 days prior to mosquito collection (T-15) showed the best correlation with *Anopheles atroparvus* densities. For this time lag, Carvalhal has a significant response to temperature showing a 0.67 direct Pearson correlation, while Pego and Comporta show 0.51 and 0.50, respectively.

Mosquito density plotted as a function of temperature (Figure 2), shows, for Carvalhal, an exponential density increase when T-15 is above 15 ºC. No such response was found for Comporta and Pego, although it can also be observed a trend of mosquito density growth for T-15 above 15 ºC. Therefore, it is assumed that temperatures below 15 ºC could be a limiting factor for mosquito development. Consequently, only the remote sensing data for periods with such suitable temperature conditions, usually between May and September, was processed.

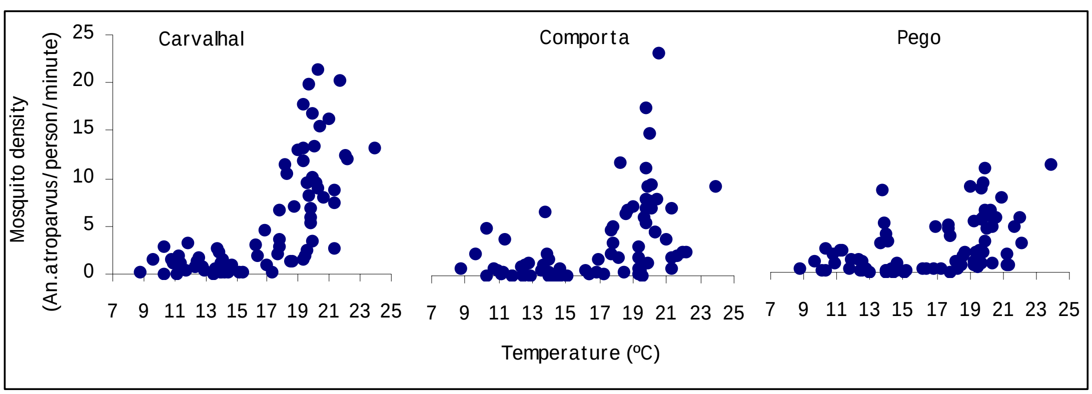

Figure 2 –*Anopheles atroparvus* densities as a function of 15 days average temperature for each sampling site.

2.5. Land covers analysis and comparison with mosquito density

The land cover analysis started with a supervised classification of the study area using LANDSAT 7 ETM+, following the methodology described above. Figure 3 shows the color composition of Landsat 7 for the study area, and the land cover map resulted from the neural network classification.

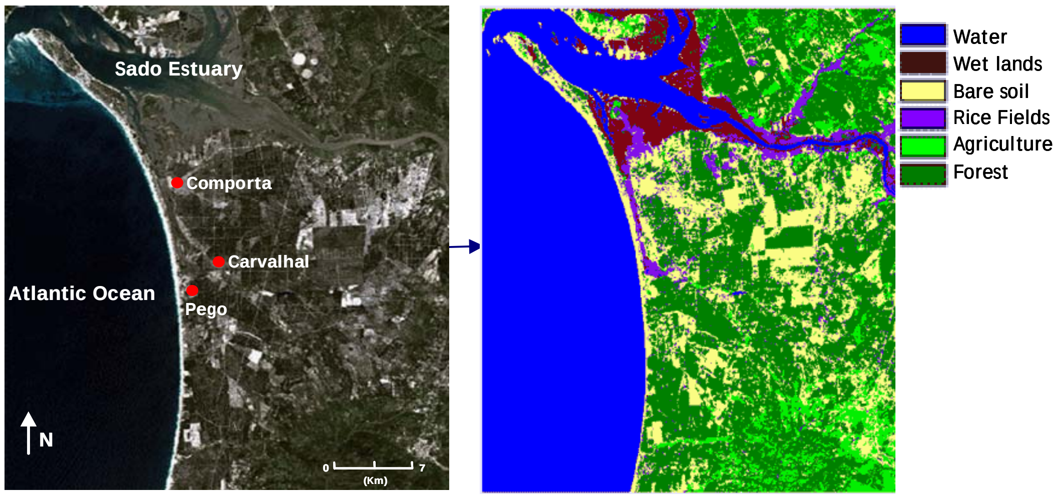

Figure 3 – December 2002 LANDSAT ETM+ RGB321 composition (left image) and land use supervised classification (right image).

For each mosquito sampling site the analysis with different buffers per land use produced results with interest for modelling purposes. At Carvalhal, the *An. atroparvus* population has a high direct correlation with the NDVI values from rice fields, agriculture and forest, as illustrated in Figure 4. For buffers higher than 1000 meters this relation becomes less significant and drops when increasing the distance from the sampling site. For Comporta and Pego, the results showed lower correlations with land use change but in both cases rice farming seems to be associated with *An. atroparvus* density levels.

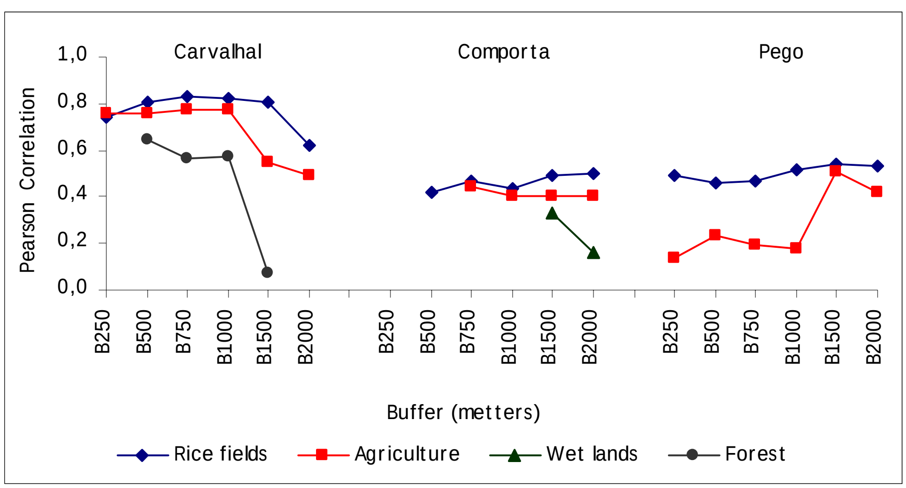

Figure 4 – Correlation values between NDVI values and mosquito density for different buffers, centered at the sampling site (e.g. B250= buffer 250 meters)

Since there is a higher mosquito density and a better environmental response in Carvalhal site, the NDVI monthly average values, from rice fields and agriculture, were plotted as a function of the *An. atroparvus* monthly mean values. Figure 5 shows a linear direct relation between these two variables. This result indicates that NDVI values, typical for those two land uses, can be used as a proxy variable of local conditions (vegetation and water) for the development of mosquitoes. These results are very promising to create mosquito density maps applying remote sensing data.

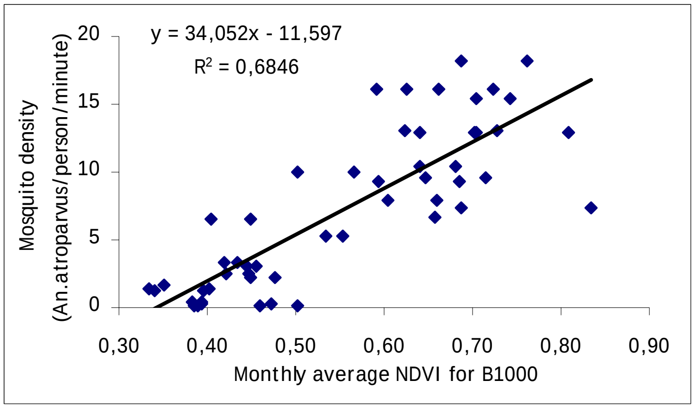

Figure 5 – *Anopheles atroparvus* density as a function of monthly average NDVI values, for Carvalhal sampling site.

3. DISCUSSION AND CONCLUSIONS

This paper addresses mosquito density spatial and temporal patterns through the use of remote sensing data. In particular, emphasis has been put on the tasks of monitoring of the mosquito life cycle, density and habitat, and modelling the patterns of mosquito density, taking into consideration the relationships of its spatial and temporal patterns with climate data and remote sensing data. The three sampling sites showed *An. atroparvus* different seasonal patterns, probably due to different local conditions. Thus mosquito density modeling should follow a spatially explicit approach, being remote sensing an appropriate methodology to accommodate such local differentiation.

Preliminary results showed that temperature is a limiting factor for the *An. atroparvus* population growth. A very low activity is observed when the 15 days average temperature is below 15 ºC. For example, at Carvalhal sampling site the mosquito density reacts exponentially when temperature rises from that threshold.

Annual land use change was found to be another factor responsible for the *An. atroparvus* population seasonal dynamics. In this case rice farming is in part responsible for creating breeding sites, as the farming method used creates a perfect environment of water availability that, when combined with high temperature, allows for high mosquito densities. In fact, the farming method, with flooding, creates an appropriate environment of water availability that, when combined with high temperature, allows vegetation to grow at a higher rate in the surrounding areas. The difference found in densities values among the three sample sites can be explained by the different percentages of rice fields in the 1000 m buffer. Carvalhal has the largest extension of rice areas (about 30%) while Pego the smallest one (about 15%), corresponding to the higher and smaller mosquito density values, respectively.

Therefore, NDVI was used as a proxy variable of local conditions (vegetation and water) for the development of mosquitoes. The results are very promising to create mosquito density maps applying remote sensing data. Independently of the land use and for the Mediterranean type ecosystem, abnormally high NDVI values during the summer (>T-15) usually occur close to water bodies or irrigated agriculture fields. For this reason the *An. atroparvus* population density is directly correlated with NDVI values and temperature providing suitable conditions for mosquito development, both at the larval and adult stages. However, the spatial generalization of the linear relationship encountered between NDVI values and mosquito density should be deeply analyzed and other local conditions/factors/variables explored.

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