Grant agreement no. 243964

QWeCI

Quantifying Weather and Climate Impacts on Health in Developing Countries

Deliverable 5.2d: DSS and Malaria Early Warning System for Kumasi

Start date of project: 1st February 2010 Duration: 42 months

Lead contractor: KNUST
Coordinator of deliverable: KNUST
Evolution of deliverable

Due date : M36
Date of first draft : 30 June 2013
Start of review : 20 August 2013
Deliverable accepted : 30 August 2013

Project co-funded by the European Commission within the Seventh Framework Programme (2007-2013)		
Dissemination Level		
PU	Public	PU
PP	Restricted to other programme participants (including the Commission Services)	
RE	Restricted to a group specified by the consortium (including the Commission Services)	
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Report on D5.2d M36 DSS and Malaria Early Warning System for Kumasi

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August, 2013

Executive Summary

The report presents a malaria early warning study carried out over the Rural, Peri-urban and Urban communities within the Kumasi metropolis, using Ghana Meteorological Agency's synoptic station data as model input and reported malaria cases in some selected hospitals within the study areas. Two independent models (Liverpool Malaria Model and VECTRI model) were employed for this study. In addition, the correlation between climate variables (rainfall, temperature and relative humidity) and reported outpatient malaria cases in Rural, Peri-urban and Urban communities in the Kumasi Metropolis for the entire study period were reported. Poor positive correlations were found with rainfall and negative correlations were seen with temperature. The model results revealed higher malaria prevalence in the rainy season (from May to October) with peaks in June and July for the first (major) rainy season and October and November for the minor rainy season. The seasonality shown is evidence of strong climatic influence on malaria transmission in the study area.

1. Introduction

Malaria continues to place a huge social and economic burden on African communities, because it is one of the most important endemic tropical diseases, which has been identified to be responsible for 60 % of the world's 300 - 500 million clinical cases in sub-Saharan Africa. At least 80 % of worldwide malaria deaths occur in this region (WHO, 2005). Malaria prevalence is affected by spatial and seasonal distributions and inter-annual variability in climate and long-term trends (Githeko and Ndegwa, 2001). Climate variables such as rainfall, temperature and relative humidity have been identified to influence the spread of malaria (Craig et al., 1999). The ecology of the breeding habitat of mosquitoes is changing and rainfall onset and cessation could affect creation and stability of the breeding habitat. Hydrologic controls on the persistence time of mosquito-breeding sites can be used to regulate mosquito emergence and significantly impact the mosquito development cycle (Gianotti et al., 2009). Also, variation in daily temperature affects the aquatic stage development of mosquitoes. In addition, human interaction with the ecosystem strongly affects the life cycle of mosquitoes.

Climate therefore has a large impact on the incidence of vector-borne diseases such as malaria; directly via the development rates and survival of both the pathogen in the vector and the vector, and indirectly through changes in vegetation and land-surface characteristics such as the availability of breeding sites (Martens et al., 1995).

Climate and its variability therefore have a major impact on the public health system in Africa in general and Ghana in particular. Malaria is the leading cause of morbidity, accounting for about 37.5% of Out Patients Department (OPD) attendance (NMCP, 2009). It is estimated that malaria cases accounted for 48.8 % of children under five and in total 32.5 % of all outpatients visits to hospitals in Ghana (NMCP, 2009). The whole population of Ghana are at risk of malaria as cases of it are reported throughout the year with the rainy season causing some seasonality (GNMSP, 2008). Malaria is therefore not only a health issue as it has a huge indirect cost on Ghana's economy due to lost of productivity; those infected by malaria are in and out of hospital and unable to work to contribute effectively to the economic growth of the country.

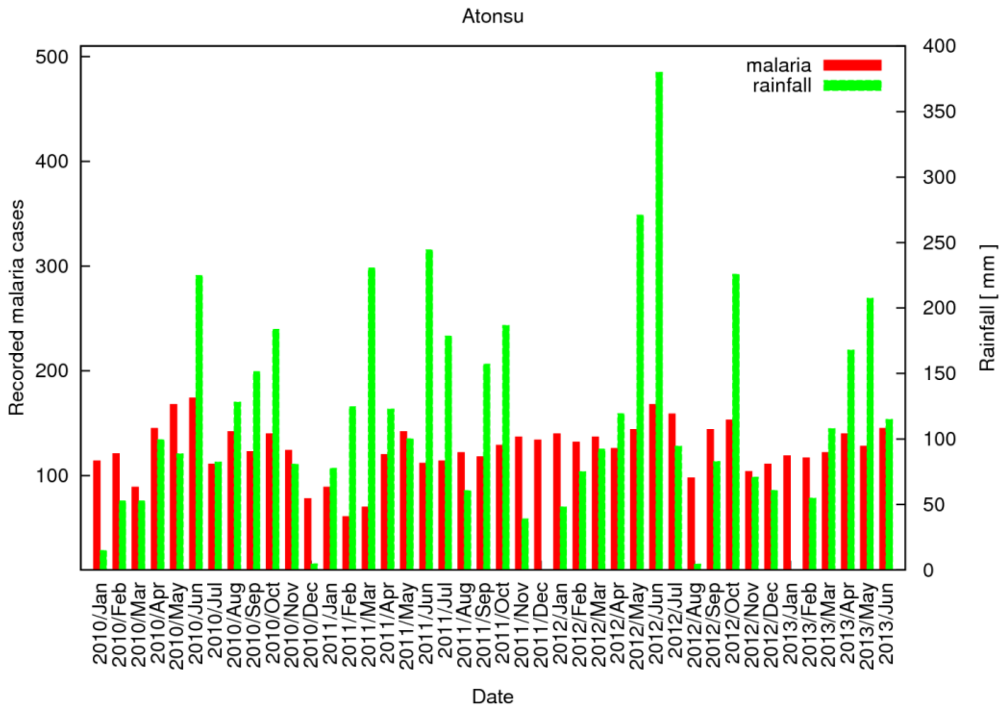
Mosquitoes may exploit any available water for oviposition, natural or man-made (Imbahale et al., 2011; Fillinger et al., 2004), permanent or temporary (Fillinger et al., 2004) and of various sizes from hoof-print of animals to the edge of large water bodies (Sattler et al., 2005; Mutuku et al., 2006; Imbahale et al., 2011), clean or polluted (Sattler et al., 2005; Awolola et al., 2007; Chinery, 1984), though individual species have preferences of habitat type. Anopheles gambiae complex mosquitoes and Anopheles funestus, the principal malaria transmission vector in Sub-Sahara Africa prefer small, clear, temporary and sunlit water for their breeding which becomes abundant during the rainy season, although their larvae have also been found in polluted waters (Awolola et al., 2007; Sattler et al., 2005). These temporary habitats contains less or no competitors and predators which decrease larvae mortality rate (Koenraadt et al., 2004; Sunahara et al., 2002). Furthermore, these habitats are usually available close to human settlements, the gambiae complex being anthropophilic (Highton et al., 1979) and as such time spent by the gravid mosquito to locate surface water for oviposition is reduced along with its associated risks and this would in effect increase the sporogonic cycle (Mutuku et al., 2006; Minakawa et al., 1999).

The goal of the study is to understand malaria transmission for Kumasi metropolis, using the Liverpool Malaria Model (hereafter LMM) (Hoshen and Morse, 2004; Ermert et al., 2011b,a) and VECTRI malaria model (Tompkins and Ermert 2013). Both model run were carried out Kumasi using the Ghana Meteorological Agency (hereafter GMet) data for the past 30 years (from 1980 to the 2012).

2.0 Climate and malaria hospital data

The climate input data for the malaria-vector model are daily rainfall and mean temperature. Therefore the first step for running the model is to prepare this climate data in the model desired format. The challenge here requires ensuring that all daily temperature and rainfall data for the study period are available.

Rainfall and malaria transmission do not peak at the same time, as there is always a time lag between them. The time variation is due to the time required for mosquitoes to complete their life cycle and the parasite to fully develop in the human host. Therefore poor positive correlation in the range of 0.25 – 0.31 were seen for these study cases. It was observed that the rainfall and malaria recorded cases do not peak simultaneously. Thus, increasing rainfall amounts are therefore not leading to an increase in malaria transmission even under the consideration of time lags. This could point to the fact that, some productive breeding habitats are permanent and semi-permanent.


Atonsu
malaria
rainfall
Recorded malaria cases
Rainfall [mm]
Date
500
400
300
200
100
400
350
300
250
200
150
100
50
0
2010/Jan
2010/Feb
2010/Mar
2010/Apr
2010/May
2010/Jun
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2012/Jul
2012/Aug
2012/Sep
2012/Oct
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2013/Apr
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2013/Jun

Figure 2.1: Confirmed monthly malaria cases reported at Atonsu Hospital (Urban) over the study period (red) and corresponding monthly rainfall (green)

Figure 2.2. Confirmed monthly malaria cases reported at Emena Hospital (peri-urban) over the study period (red) and corresponding monthly rainfall (green)

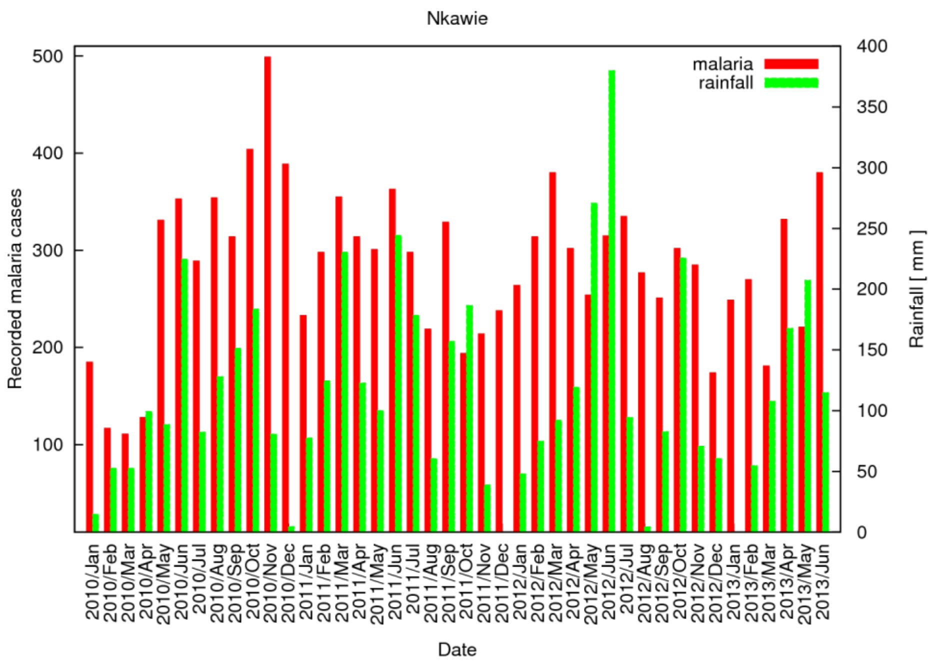
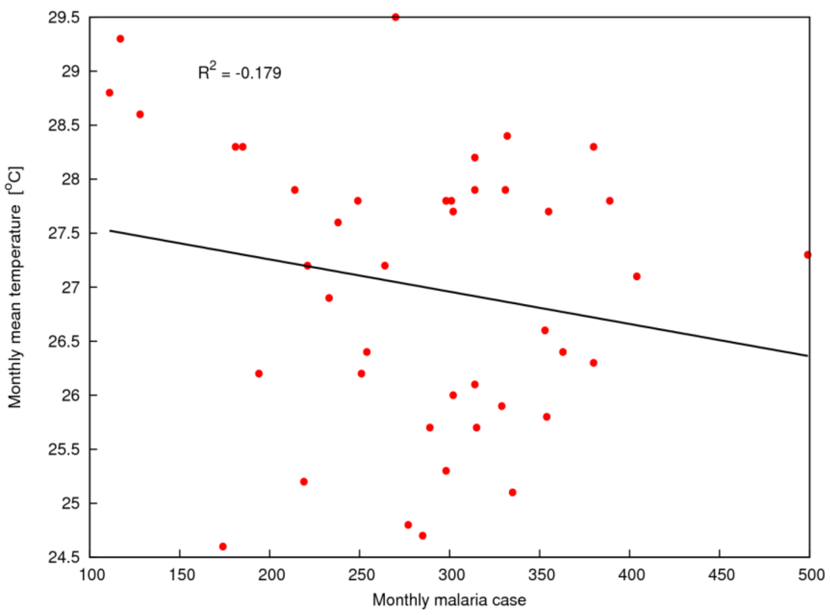


Figure 2.3 Confirmed monthly malaria cases reported at Nkawie Hospital (rural) over the study period (red) and corresponding monthly rainfall (green)

Temporary shallow waters are the preferred breeding habitats for *Anopheles gambiae.* These breeding habitats are most productive when there are many rainy days in the month. The critical factors for malaria forecast therefore are the onset and frequency of rainfall since these determine the stability of habitat to complete aquatic stage life cycle. In general, malaria prevalence rate is high after the onset of rain. This is because at the start of the rainy season, rainfall provides additional breeding habitats. This leads to an increase in the *Anopheles gambiae* mosquito population and hence increases the malaria prevalence.

The average monthly temperature for Kumasi is in the range of 25–28°C, which is a favourable temperature for both breeding and survival of mosquitoes. Relative humidity affects malaria transmission by influencing the life span and flight range of Anopheline mosquitoes. The vector has a shorter life span when the relative humidity is below 60%, which may not allow complete development of the parasite within the vector. Results from the monthly data show that throughout the year, relative humidity is greater than 70% in Kumasi and therefore there can be a complete development of the malaria parasite within the vector to increase the probability of infectious bites. This further explains the reason for higher malaria transmission during the rainy season in Kumasi. The limiting factors however are the availability of breeding habitats, which are provided by rainfall, drainage and sewage systems and other environmental factors.

A correlation plot of the temperature with outpatient malaria cases recorded at Nkawie a rural hospital and Emena Peri-urban hospital are shown in Figure 2.4. In general, a negative correlation was observed with temperature with correlation coefficient -0.26 to -0.18.



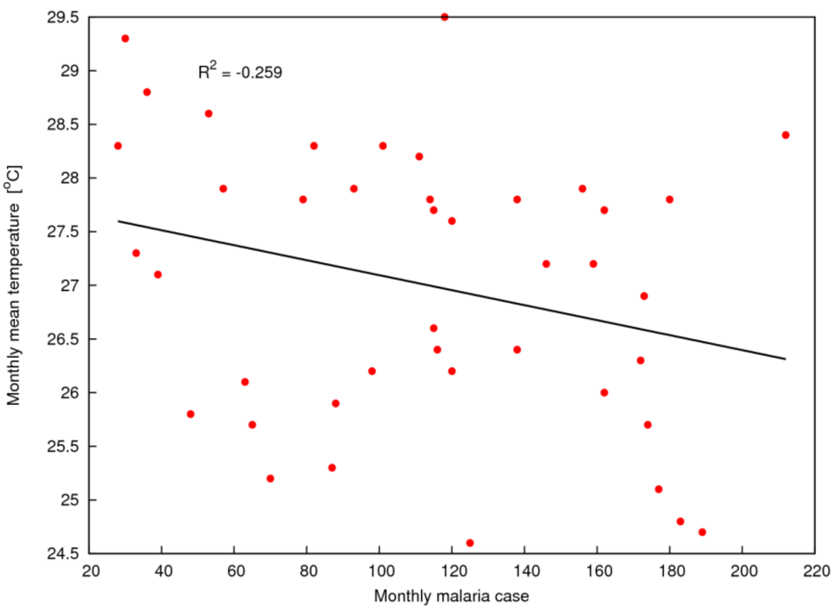


Figure 2.4: *Scatter plot for temperature as a function of outpatient malaria cases for Nkawie.*

3.0 Malaria-vector Model

The Liverpool Malaria Model (LMM) and the Vectri malaria model, are mathematical-biological models of malaria parasite dynamics driven by daily temperature and precipitation data (Hoshen and Morse, 2004). Extensive details on parameter setting and definitions are described in the 2011 LMM version (called LMM new version) which was used for this study (Ermert et al., 2011a,b). The details on Vectri malaria model are described in Tompkins and Ermert (2013).

In this study, temperature and precipitation measurements were taken from GMet synoptic station at Kumasi airport. Entomological malaria field studies frequently sample biting mosquitoes on humans (Le Go et al., 1997). Standard measurements include the Human Biting Rate (HBR), which is the number of mosquito bites per human per time. However, it is known that only female mosquitoes with sporozoites in their salivary glands are able to infect humans [(Ermert et al., 2011b) and references therein]. This fraction of the biting females is called Circumsporozoite Protein Rate (CSPR) (Awolola et al., 2002). By multiplying HBR with CSPR results in the Entomological Inoculation Rate (EIR), which is deemed as the number of infectious mosquito bites per human per time. Only months revealing infectious mosquito bites (EIR values above zero) are usually used to define the malaria season at a certain location. By contrast, parasitological malaria studies usually measure the asexual parasite ratio (PR) representing the proportion of the survey population, which is positive for the malaria parasite. Extensive literature has been reviewed on all these parameters in Ermert (2010). Other parameters such as entomological and parasitological variables are taken into account in the model; these are: the annual Human Biting Rate (HBRa), the annual Entomological Inoculation Rate (EIRa), the annual mean Circumsporozoite Protein Rate (CSPRa), the length, onset, and end of the malaria season, the length of the main malaria season (MSeas); i.e. the number of months in which 75 % of EIRa is recorded (Hay et al., 2002), the month of maximum transmission (XSeas; i.e. the month with the largest entomological inoculation rate, the annual mean, maximum, and minimum of the asexual parasite ratio (PRa, PRmax; a, and PRmin, a, respectively). The output results of all these parameters from LMM are reported in this study. This new version of the LMM described in Ermert et al. (2011b,a) provides 12 to 15 days life cycle of mosquitoes comprising the egg, larval, pupal, and adult stages. The egg, larval, and pupal stages are entirely aquatic and, therefore, mostly depend on weather conditions. Besides climatic conditions, competition due to over-crowding, water quality, food supply, cannibalism, predators, parasites, as well as pathogens are limiting factors for aquatic stages of mosquitoes (Ermert et al., 2011a,b). In addition to all these in the LMM, the VECTRI model takes into account the surface hydrology (relative small breeding pond size) climate and population density(Tompkins and Ermert 2013).

The model results shown in Figures 3.1 and 3.2 revealed higher malaria prevalence in the rainy season (from May to October) with peak in June, July for the first season and October - November for the minor rainy season. The seasonality shown are evidence of strong climatic influence on malaria transmission in the study areas. The box-and-whisker plot shown in Figure 3.3 indicate relatively high monthly EIR values (greater than 50) for the peak malaria transmission seasons and relatively low EIR values for the dry season (December to March).

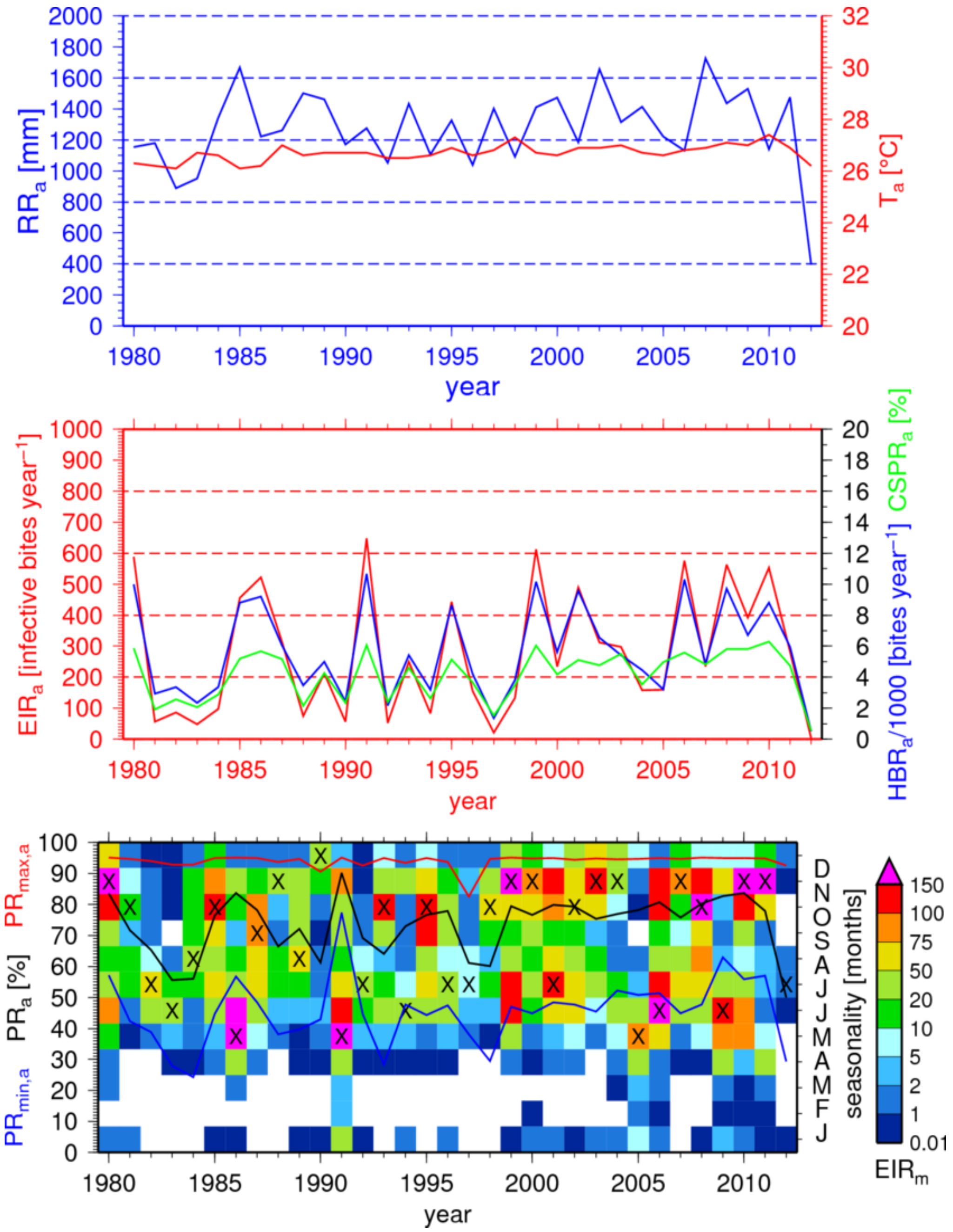


Figure 3.2: The inter-annual variability of rainfall and temperature as well as the simulated inter-annual malaria transmission and asexual parasite ratio between 1980 and 2012 for Kumasi using LMM. The top panel annual rainfall (RRa; in mm; blue line) and annual mean temperature (Ta; in ^{o}C; red line). Middle: Annual Entomological Inoculation Rate (EIRa; red line), annual Human Biting Rate (HBRa; blue line; right scale divided by 1000), and annual CircumSporozoite Protein Rate (CSPRa; in %; green line). Bottom panel: Annual mean parasite ratio (PRa; in %; black line), the annual minimum (PRmin,a; in %; blue line) and annual maximum (PRmax,a; in %; red line) of the parasite. The malaria seasonality (right scale; in month). The monthly Entomological Inoculation Rate (coloured squares) of month when the monthly Entomological Inoculation Rate reaches at least 0.01 infectious mosquito bites per human per month. The month with the maximum transmission is marked via an "X".

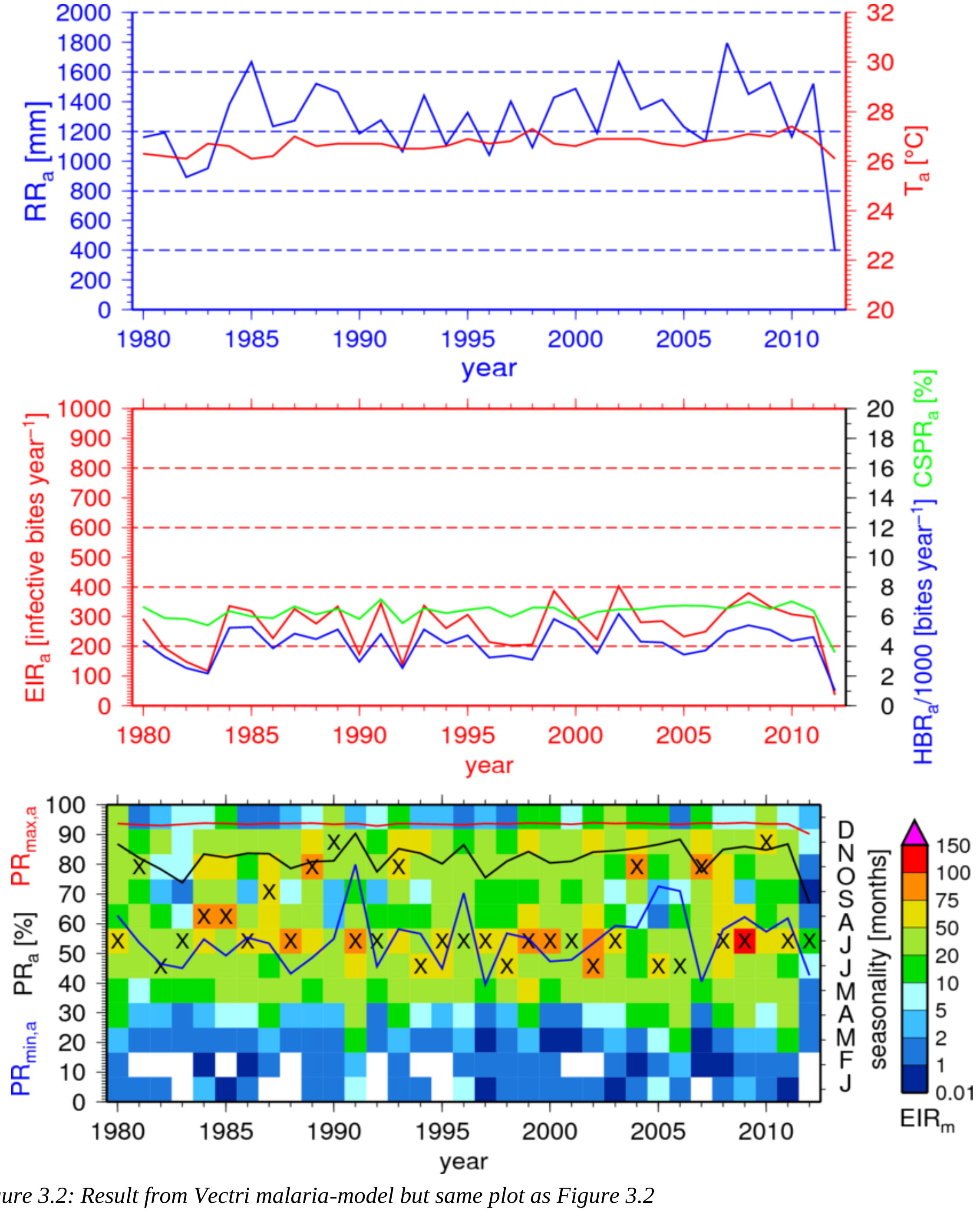


Figure 3.2: Result from Vectri malaria-model but same plot as Figure 3.2

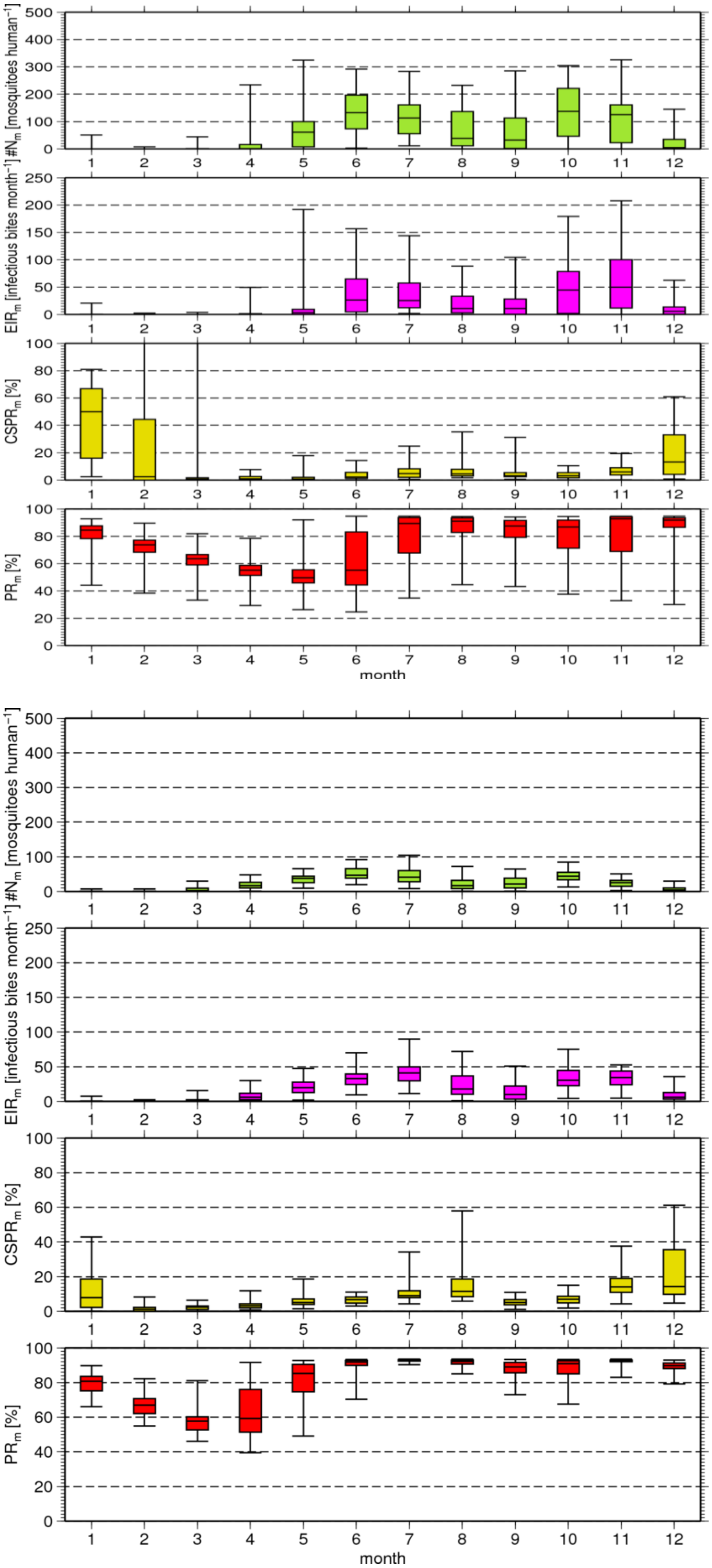


Figure 3.3: Box-and-whisker plot with regard to simulated monthly entomological and parasitological values for 1980 – 2012 from LLM (top) bottom (Vectri). Illustrated are the box-and-whisker plots of the simulated number of mosquitoes per humans (Nm; green box-and-whisker plots), the monthly Entomological Inoculation Rate (EIRm; i.e. the number of infectious mosquito bites per human per month; ma-genta box-and-whisker plots), the monthly CircumSporozoite Protein Rate (CSPRa; fraction of infectious mosquito bites; in %; yellow box-and-whisker plots), and the monthly averaged asexual parasite ratio (PRm; in %; red box-and-whisker plots).

4.0 Summary

Malaria early warning study has been carried out over the Rural, Peri-urban and Urban communities within the Kumasi metropolis. Liverpool Malaria Model and VECTRI model were employed for the study. The model results revealed higher malaria prevalence in from May to November with peaks in June, July for the major rainy season and October - November for the minor rainy season. The seasonality shown is evidence of strong climatic influence on malaria transmission in the study areas. The study reveals relatively high monthly EIR values for the peak malaria transmission seasons and relatively low EIR values for the month of December to March.

In addition, the correlation between climate variables (rainfall, temperature and relative humidity) and the out patient malaria cases in rural, peri-urban and urban communities in the Kumasi Metropolis for the entire study period were reported. Poor positive correlations were found with rainfall and negative correlations were seen with temperature.

This study will serve as a first step of developing Malaria Early Warning System (MEWS) for the study area. Currently a downscaling of a regional climate model (ERA-Interim) to be used to prepare temperature and rainfall data for the past, present and future malaria seasonal forecast. This climate data generation is been done using the downscaling scheme described in Gutierrez et al. (2004); Brands et al. (2011). The climate data generated would be us as input data to run the LMM and VECTRI models and the results will be prepare for publication.

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