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Abstract

The validation of the Liverpool Malaria Model (LMM) was planned for this study. However, sufficient entomological and parasitological malaria data is not available from the Kumasi area. The QWeCI project was not allowed to use standard bite catches due to additional ethical review issues at the contracting stage and the performed spray catches were not sufficient for the computation of representative malaria transmission rates. Regarding parasitological malaria data, the QWeCI project was not allowed to undertake representative parasite surveys within Kumasi. Instead confirmed malaria cases from hospitals were gathered for the Kumasi region. However, the output from the applied malaria models cannot be directly compared to the hospital malaria.

Instead of the validation of the LMM, both VECTRI and LMM simulations were performed and compared for Kumasi. The malaria models were driven by observed data from the Kumasi airport and with data from the Tropical Rainfall Measuring Mission (TRMM) and other satellite daily precipitation estimate. The comparison with observed precipitation reveals similar rainfall amounts between the rainfall observations at the Kumasi airport and that of the TRMM and other satellite precipitation estimate. VECTRI was driven with an urban, peri-urban and rural population density, respectively. As expected, the VECTRI simulations lead to higher transmission values in rural than in urban locations and reveal a lower interannual variability than the LMM.

The output of the model was qualitatively compared to the hospital malaria. The malaria cases showed a small interannual variability, whereas the models reveal a strong interannual variability in the malaria transmission. However, it is argued that the models seem to reproduce realistic malaria conditions for the Kumasi region. In general, both malaria models reveal the same bimodal cycle in malaria transmission. During the dry season no or very low transmission values are simulated in the models.

Exemplary local seamless monthly-to-seasonal malaria forecasts were produced for the Kumasi region. The feasibility of such local forecasts is demonstrated for the 31 January 2013. The LMM and VECTRI were both forced by the 120-day seamless monthly-to-seasonal weather forecasts from the ECMWF. At the beginning of March, low malaria transmission rates were predicted. The set up of the main malaria season is forecasted for about April. In comparison to the hindcasts (period: 1995-2012) above average malaria transmission is forecasted to occur. Both models disagree with regard to the forecast of the malaria prevalence indicating that the malaria models neglect important aspects of the malaria disease within humans.

1 Introduction

Malaria in Africa, especially the sub-Saharan Africa, is known to be one of the major setbacks to human development. Several reports (e.g. Snow et al. 1999; Donnelly et al. 2005; Omumbo et al. 2005; Hay et al. 2005; Klinkenberg et al. 2006) indicate the veracity of the disease transmission dynamics in the area. The severity of the social and economic burden (Mills 1998; Gallup and Sachs 2000; Lindblade et al. 2000) of the disease in the area is known to be governed by the highly populated long live and competent key malaria vectors. Several control interventions such as Indoor Residual Spraying (IRS), Insecticides Treated Nets (ITNs) have been employed geared towards a complete eradication of the parasite and/or for a drastic reduction of the vector population (Lindsay et al. 1993). Despite these

control interventions, malaria still remains a leading, effective and persevering cause of morbidity and mortality among many urban and rural populations of which most are children under five (World Health Organization (WHO) 2010; Rollback Back Malaria (RBM) 2010, 2012; President's Malaria Initiative Fiscal Year (PMI FY) 2013). The inability of the continent to be totally free from the burden of malaria could be attributable to vector adaptation to humans (Della et al. 2001), weak health systems and poor governance. Other attributes include the increasing resistance of the vector to insecticides and parasite to drugs (Whitty and Allan 2004; Reimer et al. 2005; Casimiro et al. 2006), Centre de Suivi Ecologique (UCAD/CSE) vectorial adaptations to varying ecological and climatological situations namely feeding preference and outdoor resting (Killeen et al. 2002).

Malaria in Ghana is described as hyperendemic and perennial in all parts (Ghana Ministry of Health (GMOH) 2010; PMI FY 2012), with seasonal variations more pronounced in the north (PMI, FY2013). The entire population of 24.2 million (Ghana Population and Housing census, GPHC 2010) is reported to be at risk of malaria with higher risk in children under five and pregnant women (WHO 2011). The 2008 WHO world malaria report estimated total malaria-attributable child deaths at 14,000 per year in Ghana. The Demographic Health Survey (DHS) household survey in 2008 found that about half of the deaths in children under five occurred at home. The Ghana Health Service (GHS) health facility data reported in PMI FY (2013), reveals that malaria is the number one cause of morbidity and mortality in children under five years of age, leading to 33% of hospital deaths in children under five years and about 38% of all outpatient illnesses and 36% of all admissions. Moreover from this report, between 3.1 and 3.5 million cases of clinical malaria are reported in public health facilities each year, of which 900,000 cases are children under five years and 3,000-4,000 result in patient deaths. *Plasmodium falciparum* is found to account for a larger percentage (about 85-90%) of all infections with the major vectors being the *Anopheles gambiae* species complex and *An. funestus* (Klinkenberg et al. 2006; GMOH 2010; PMI FY 2012, 2013). These species known to bite late in the night, are indoor resting, and are most common in the rural and peri-urban areas.

The influence of the seasonal climate changes on the disease transmission dynamics is undoubted (Hay et al. 1998; Masendu et al. 2004). The main climate drivers include temperature, rainfall, humidity, and wind. The development dynamics of both the vector and the parasite are found to be dependent on the conditions of these climate drivers (Martens et al. 1995; Bayoh and Lindsay 2003; Thompson et al. 2005; Kirby and Lindsay 2009). Recent mathematical modelling of malaria accounting for the impact of these climate drivers has been developed (Hay et al. 2002; Hoshen and Morse 2004; Ermert et al. 2010; Tompkins and Ermert 2013). Constructed were among other dynamical weather-driven malaria models the Liverpool Malaria Model (LMM) and VECTRI (VECTor-borne disease community model of the International Centre for Theoretical physics, TRIeste). These models are able to simulate realistic transmission rates for epidemic and endemic malaria areas. The LMM and VECTRI are now used to predict the near malaria future in Africa. Pan-African prototype seamless monthly-to-seasonal malaria forecasts are produced on a weekly basis with a lead-time of 120 days (i.e. four months). These malaria predictions, however, lack a validation with malaria observations meaning that their accuracy is largely unknown.

This study was mainly designed to understand more fundamentally the influence of the climate drivers on malaria dynamics in the Ashanti region, Kumasi-Ghana using the 2010 version of the Liverpool Malaria Model (LMM₂₀₁₀) and VECTRI. This is possible by driving the models with weather data (such as

temperature and rainfall) as inputs, which simulate Entomological Inoculation Rates (EIR; i.e. the number of infectious bites per person per a given time period) as output. This has the potential of assisting with their short-term management as well as projecting their future likely impacts. The study therefore serves as a baseline work for monitoring malaria transmission dynamics and the impact of malaria control interventions within the region.

The objectives of the present study are to:-

- 1) Compare observed rainfall amounts from the synoptic weather station at the Kumasi airport with satellite-based precipitation estimates.
- 2) Drive the LMM₂₀₁₀ and VECTRI with observed temperature and rainfall data from the Kumasi airport and compare these runs with simulations that are driven by satellite-based rainfall estimates.
- 3) Compare the LMM₂₀₁₀ and VECTRI simulations with observed malaria cases from health clinics.
- 4) Generate exemplary local seamless monthly-to-seasonal malaria forecasts for the Kumasi area.

The study area, data sources, and methods are described in sections 2, 3, and 4. Results are presented and discussed in section 5 and 6 respectively. Concluding remarks are provided in section 7.

2 Study area

The Ashanti Region is located centrally in the middle belt of Ghana approximately between longitudes 0°15'W and 2°25'W, and latitudes 5° 50'N and 7° 40'N. The region has a population of about 4.8 million with a density of about of 148 per km⁻² (GPHC 2010). It is also currently the second most urbanized in the country, with the urban population exceeding that of the rural.

The vegetation is broadly classified into semi deciduous forest and Guinea Savannah woodland. More than half of the region is located in the forest zone. It experiences two main rainy seasons with an average annual rainfall of about 1500 mm. The major rainy season starts in March, with a major peak in July. August being the month of transition between the two seasons reveals a decrease in the rainfall amount. The second season starts in September and ends in November. December to February is dry, hot, and dusty due to the Harmattan winds. Temperature is generally high, averaging daily over 27°C in the forest zone and 29 degree Celsius on the northern fringes of the forest zone. The humidity is relatively high, averaging about 85% in the forest area and 65% for the Savannah belt (Kwamena and Benneh 2004).

Nine health clinics within the region as a matter of data availability were chosen for the study namely Manhyia, Atonsu, South Suntresso, Emena, Akropong, Ejisu, Agogo, Owabi and Nkawie. The first four hospitals are located within the Kumasi metropolitan assembly that is the most urbanized and heavily populated (about 1.5 million of the region's total). The health clinic in Ejisu is located in the Ejisu-Juaben district, which is the second most populated, described as a semi-urban area. The others namely the

Akropong hospital in the Amase West district, the Agogo health clinic in the Asante Akim North district and the Owabi and Nkwawie hospitals in the Atwima Nwabiagya districts are rural. The urban districts are characterised by many slums and squatter settlements with very poor sanitation systems. With the exception of Kumasi metropolis, which has many health facilities, the other districts have health facilities only at the district capitals. They are therefore scarce and located at far distances especially in the rural districts. It is common to find that traditional methods of healing are applied within these rural districts.

3 Data sources

The data required for this study are meteorological time series of temperature and precipitation, entomological data from the disease vectors and parasitological observations (Ermer et al. 2011a,b). In this regard, daily weather observations of temperature and precipitation for the Kumasi airport synoptic weather station were obtained from the Ghana Meteorological Agency (GMet). These time series spanning from 1963 to 2012, formed the input data to drive the malaria models. On the other hand, time series were not available for each of the nine health clinics. Hence, the Kumasi airport synoptic station data records were used instead. The Tropical Rainfall Measuring Mission (TRMM) and other satellite daily precipitation estimate (the 3B42 version 7 data product) area averaged over $0.25^{\circ} \times 0.25^{\circ}$ longitude–latitude grid boxes (25 km x 25 km) for the Kumasi airport was also applied. This data is a daily three hourly precipitation record and covers the period 1998 to 2012, and was downloaded from <http://www.mirador.gsfc.nasa.gov>. It was additionally used in order to compare the effects of different rainfall products on the model output. This has the ability of informing the degree of certainty in these databases.

In terms of entomological data, KNUST (Kwame Nkrumah University of Science and Technology) undertook for periods of four and three months spray catches in ten rooms, respectively. Due to ethical issues and not wanting to delay the project start further with additional ethical discussions, QWeCI project was not allowed to use standard bite catches. The amount of data gathered was far insufficient to allow for the calculation of monthly Entomological Inoculation Rates (EIR_m ; i.e. the number of infectious mosquito bites per person per month) for urban, peri-urban and rural areas within the region. Moreover, parasitological malaria data was not gathered with the reason that QWeCI project was not allowed to undertake representative parasite surveys within Kumasi. However, the project was enabled to gather confirmed malaria cases from hospitals of the Kumasi metropolis. The malaria cases are confirmed by either Giemsa staining or rapid diagnostic tests methods. For purposes of quality control both methods are used in the hospitals. These methods used by the hospital have not changed and are still used. Generally, the hospital malaria data covered the period 2000 to 2012. However, not all the hospitals owned data covering this entire period. Some hospitals had records starting later or ending earlier. Between the record length, some monthly records were found missing. Most of these missing data occurred towards the end of the year. The data is also highly inconsistent in the age and gender characteristics. Table 1 provides a summary of the nature of the data obtained from the hospitals.

Table 1: Summary of nature of data obtained from the hospitals.

Name of Hospital	Data length (yyyymm)	Missing data	Age and gender characteristics
South Suntresso	200001-201212	200907-08, 200912	Entirely nonspecific

Akropong	200001-200910	-	Only gender specific for 200801-200902
Atonsu	200001-201212	-	Entirely nonspecific
Emena	200801-201212	200907-12	Specific only for 201001-201212
Manhyia	200001-201212	200907-12	Specific only for 201001-201212
Ejisu	201101-201212	-	Entirely specific
Nkwawie	200601-201212	-	Specific only for 201001-201212
Agogo	201101-201212	-	Entirely nonspecific
Owabi	200801-200902	-	Entirely nonspecific

With regards to the exemplary monthly-to-seasonal malaria forecasts, data was obtained from the ECMWF starting from 31 January 2013. This starting date was chosen due to the fact that January is located at the end of the dry season in boreal winter. Usually, January is a fairly dry month with only occasional rainy events. Therefore, it is assumed that only a low malaria transmission would take place. Within the following months the first rainy season starts and malaria transmission is expected to increase significantly due to the availability of more mosquito breeding sites. Therefore, the malaria models should be able to forecast the start of the malaria season.

The ECMWF provided seamless monthly-to-seasonal temperature and precipitation forecasts with a temporal and spatial resolution of a day and $1^\circ \times 1^\circ$, respectively. The data consists of 51 ensemble members and includes hindcasts between 1995 and 2012 (5 members for each year). With regard to the precipitation data the calibrated values were used. Furthermore, the ECMWF also provided the seasonal malaria forecast data from VECTRI. The data was allocated on a ftp server of the ECMWF and was successfully downloaded.

4 Methods

The models accept only continuous daily temperature and precipitation measurements as input data. The first step then was to prepare the input data into this format by compensating for any gaps. This purpose was achieved by quality checking the meteorological time series and filled the missing values by a procedure described by Ermert 2010. TRMM and other satellite precipitation estimate values for the Kumasi airport synoptic weather station were extracted from nine grid boxes of size $0.25^\circ \times 0.25^\circ$ and are represented as box-and-whisker plots. The two time series (GMet record and the TRMM and other satellite precipitation estimate) were then compared (Figure 1) to see their disparities.

The LMM and the VECTRI were then driven with the daily time series of temperature and precipitation separately from the GMet observations and TRMM and other precipitation estimate to produce EIR_m values as output. In the case of TRMM, all the nine grid box time series were fed separately into the

models. The model simulations from them were then calculated and plotted as box-and-whisker plots. VECTRI runs were applied for three different population densities describing urban, peri-urban and rural areas as captured in the model parameterization. The essence of this was to simulate realistic entomological and parasitological values for different population densities in the area of Kumasi. The runs for the nine grid boxes of the TRMM and other satellite precipitation estimate were only undertaken for rural population densities. The model simulations (using both GMet and the TRMM and other satellite precipitation estimate) were then compared with the observed hospital malaria records. The evaluation of the malaria risk was based on the definition of Ermert et al. 2011b. They defined a malaria risk month as a month with EIR value above 0.01 infectious bites per person and per months. Besides, the simulated EIR_m value the monthly hospital malaria cases were computed. The choice of the models was based on the fact that they are able to simulate a realistic spread of malaria in space and time and for that matter remain useful tools for a weather- or climate-disease modelling system (Ermert et al. 2011b, Tompkins and Ermert, 2013).

With regard to the exemplary malaria forecasts, the monthly-to-seasonal weather forecast was used to drive the LMM_{2010} . Before driving the LMM_{2010} with the weather forecast data, the model was initialised since 2000 by means of ERA-Interim data (ERA: ECMWF Re-Analysis) and from 2010 with the operational analysis of the ECMWF. The VECTRI model starts from saved initial conditions and needs therefore not to be simulated before the forecast period starts. The results of both malaria models (LMM_{2010} and VECTRI) were processed to obtain weekly transmission and parasite rates. Quartile statistics were computed with regard to the 51 ensemble members of the monthly-to-seasonal forecast and in terms of the 90 (18*5) hindcasts. The data is used to provide local malaria forecasts. In contrast to the pan-African prototype malaria forecasts from the ECMWF (see <http://nwmstest.ecmwf.int/products/forecasts/d/inspect/catalog/research/qweci>), the local disease prediction focuses on the generation of time series of two key malaria variables.

5 Results

5.1 GMet rainfall observations vs. TRMM and other satellite precipitation estimate

In this section, the rainfall observations from the synoptic weather station at the Kumasi airport are compared with the TRMM and other satellite precipitation estimate of the region. The precipitation amounts of both data sets are comparable to each other (Figures 1). In terms of intra-seasonal and interannual variability, the two data sets reveal similar characteristics. The satellite-based precipitation product is well correlated with the station observations. There are few exemptions, when the TRMM and other precipitation estimate underestimates or overestimates the monthly rainfall amounts (see, e.g., the first rainy season in 2009 and 2012).

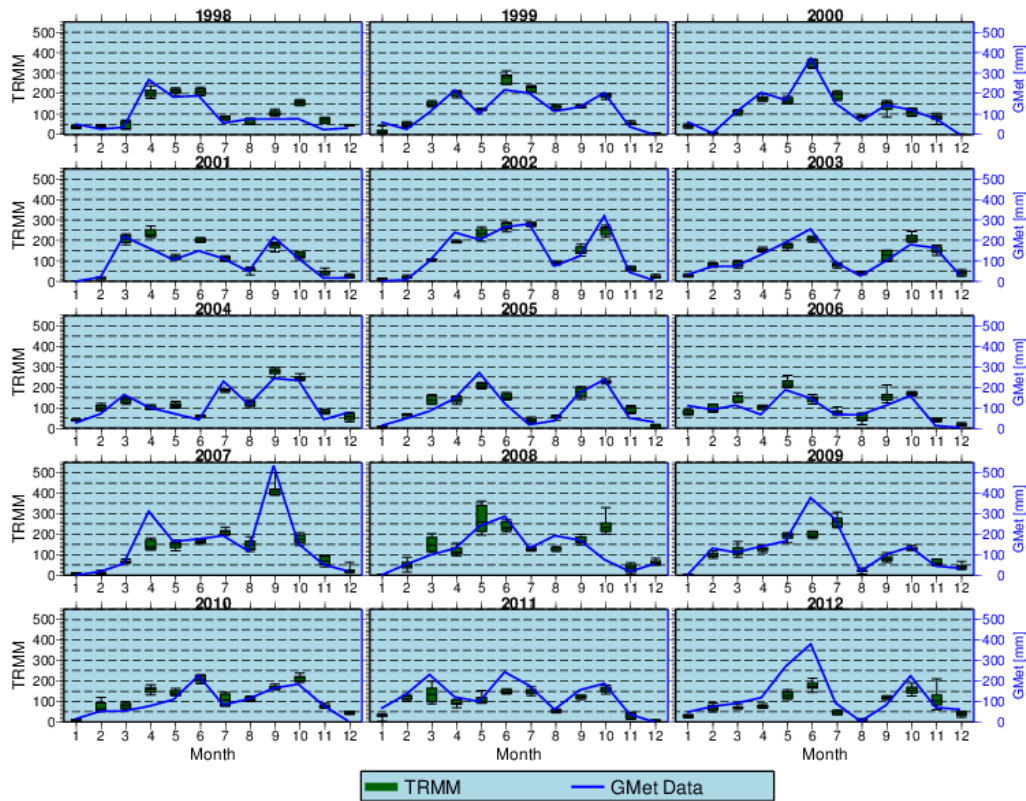


Figure 1. Comparison of TRMM and other satellite precipitation estimate and GMet rainfall records. Inter-seasonal and annual comparison of TRMM and GMet rainfall data for Kumasi metropolis from 1998 to 2012. The green box-and-whisker boxes display the TRMM and other satellite precipitation estimate extracted from nine grid boxes (0.25 x 0.25 degrees) around the Kumasi airport. The blue line displays the ground based GMet rainfall observations of the synoptic weather station.

The two precipitation time series both reveal the two distinct wet seasons of the region. The first wet season builds up gradually from small rains in March and peaks in about June. It then declines from this month and reveals a minimum in August. Building up after August, the second wet season peaked in September/October. November through to February reveals very low or no rainfall amounts. In each case, the first wet season was observed to be longer than the second season described as the main and minor rainy seasons, respectively.

5.2 LMM₂₀₁₀ simulations for Kumasi

The LMM simulated driven by the GMet observations revealed a strong year-to-year variability of the malaria transmission for Kumasi (Figure 2). The annual EIR (EIR_a) values range between about 10 and 620 infectious bites per person per year. The corresponding annual Human Biting Rates (HBR_a) and CircumSporozoite Protein Rate (CSPR_a; fraction of infectious mosquito bites) reveal values between about 2,000 and 11,000 bites per person per year and about 2 and 6%, respectively. The simulated EIR_a values are somewhat lower between 1975 to 1997 but with intermittent high peaks in years such as 1980, 1986, and 1991. After 1997 the malaria transmission is more stable and reveals always more than 100 infectious bites per human and year.

Despite the high interannual transmission variability, the LMM simulates nearly constant maximum annual parasite ratios ($PR_{max,a}$). This is related to the fact that the transmission was always high enough meaning that during parts of the year all humans in the model were either infected by the parasite or recovered from malaria. On the contrary, the mean and minimum annual parasite ratios (PR_a and $PR_{min,a}$ respectively) reveal a stronger interannual variability as a result of the strong year-to-year transmission variability. Both simulated variables reveal about the same annual variations, which means that they are largely correlated.

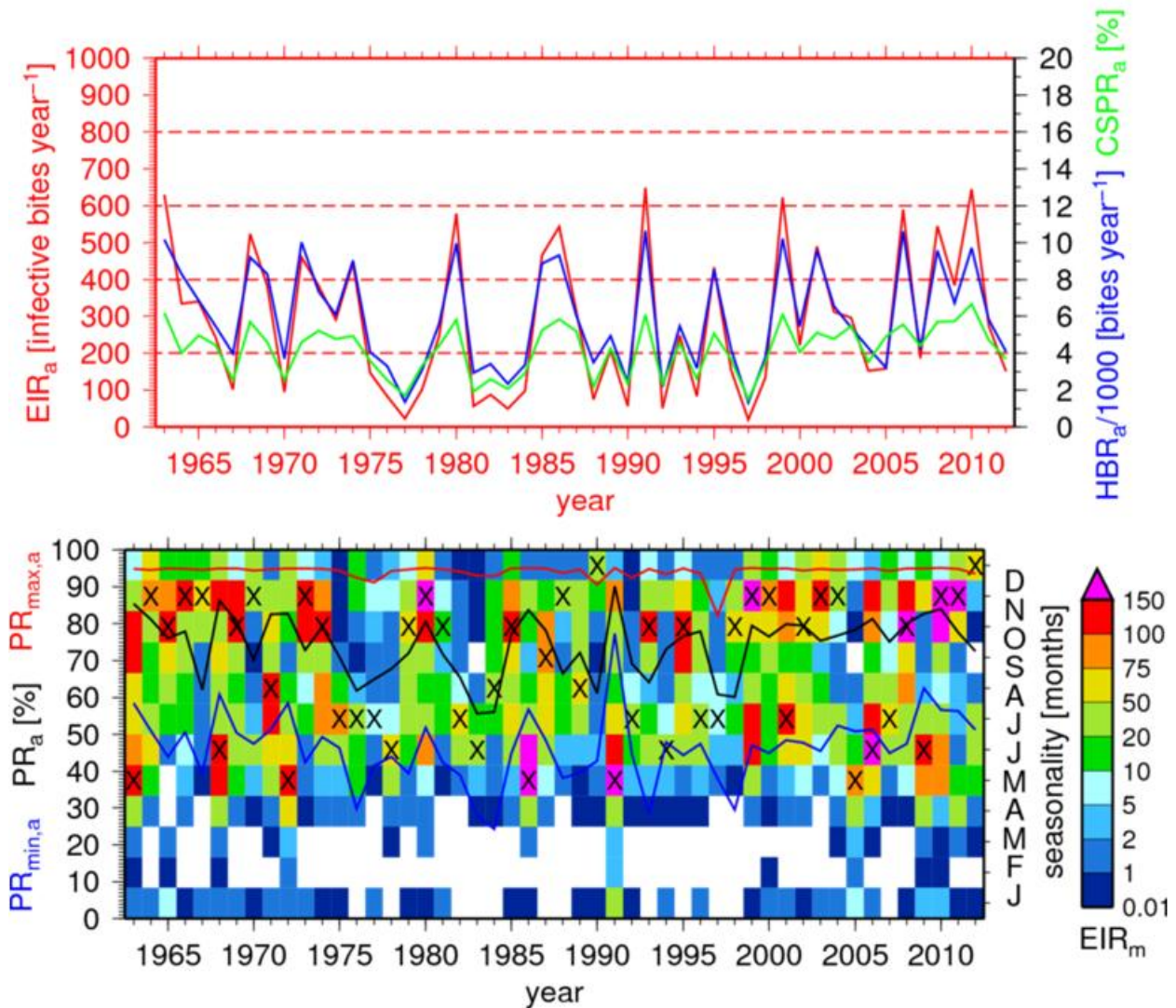


Figure 2. LMM₂₀₁₀ simulated malaria conditions using the GMet data from 1963 to 2012. The upper panel displays the annual Entomological Inoculation Rate (EIR_a ; number of infectious mosquito bites per human per year; red line; left scale), annual Human Biting Rate (HBR_a ; number of mosquito bites per human per year; blue line; right scale; divided by 1000), and annual CircumSporozoite Protein Rate ($CSPR_a$; fraction of infectious mosquito bites; in %; green line; right scale). The bottom panel displays the annual mean (PR_a ; in %; black line; left scale), annual minimum ($PR_{min,a}$; in %; blue line; left scale) and annual maximum ($PR_{max,a}$; in %; red line; left scale) parasite ratio. In addition is the the malaria seasonality (right scale; in month) described by months with Entomological Inoculation Rate (coloured

squares) of at least 0.01 infectious mosquito bites per human per month. The month with the maximum transmission is marked via an „X“.

Within the LMM simulation the malaria transmission starts in most years between March and April (Figure 2). The main transmission month is predicted to occur in general between May and December, which is related to the fact that two main transmission seasons are simulated. The seasonal peaking nature intermittently varied mostly between June or July and October or November for the first and second seasons respectively. The intraseasonal variability within the entire period was observed high. The transmission season are related to the two rainy seasons (see Figures 1). The first season spans between May/April to June/July. The months August and September indicate the months of transition from the first to second malaria season. The second season finally picks up in September apexing in October/November and declining to lower values in December. The end of the malaria season is simulated for about December and January. However, some years reveal even a year-around transmission.

5.3 VECTRI simulations for rural, peri-urban, and urban areas of the Kumasi region

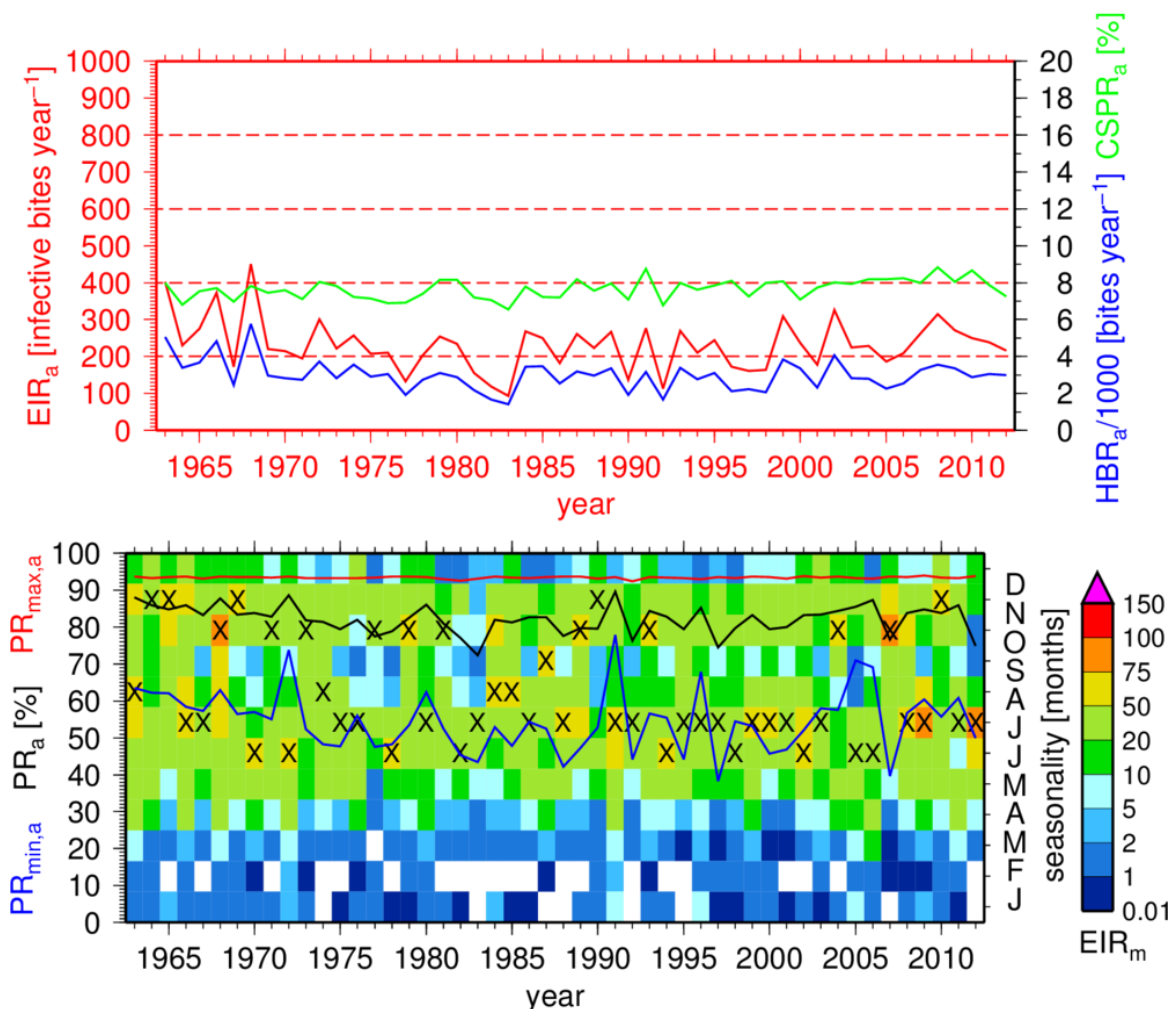


Figure 3. Same as Figure 2 but for VECTRI simulated malaria conditions for a rural area (100 inhabitants per km²) within the Kumasi region.

Driving VECTRI for a rural population (100 inhabitants per km²) with daily weather observations from the Kumasi airport results in a much lower interannual variability in comparison to the LMM₂₀₁₀ simulation. The EIR_a values from VECTRI vary only between about 100 and 450 infectious mosquito bites per human per year. The CSPR_a values hardly vary between 7 and 9% and reveal therefore a higher value than that of the LMM₂₀₁₀. The HBR_a is strongly correlated with the EIR_a value due to the nearly constant CSPR_a value. The HBR_a values range between about 2000 and 4000 mosquito bites per person per year. VECTRI reveals not only a fairly low year-to-year variability but also much weaker malaria seasonality than the LMM₂₀₁₀. The maximum transmission month shows only values between about 20 and 100 infectious mosquito bites per months. Like for the LMM run, also in the VECTRI simulation the month of maximum transmission strongly varies from year-to-year. However, the maximum transmission is simulated to occur only in six different months and not in eight different months like in the LMM₂₀₁₀. VECTRI reveals nearly a year-around transmission. Only some years like 1983 show a malaria transmission gap of two years. Mostly only one or no month without malaria transmission is simulated. Therefore, VECTRI simulates longer transmission seasons than the LMM₂₀₁₀. Like for the LMM₂₀₁₀ the annual maximum of the PR is nearly unchanged from year-to-year. Stronger interannual changes are found for the mean and minimum value of the PR. However, VECTRI reveals also here a smaller variability in comparison to the LMM₂₀₁₀.

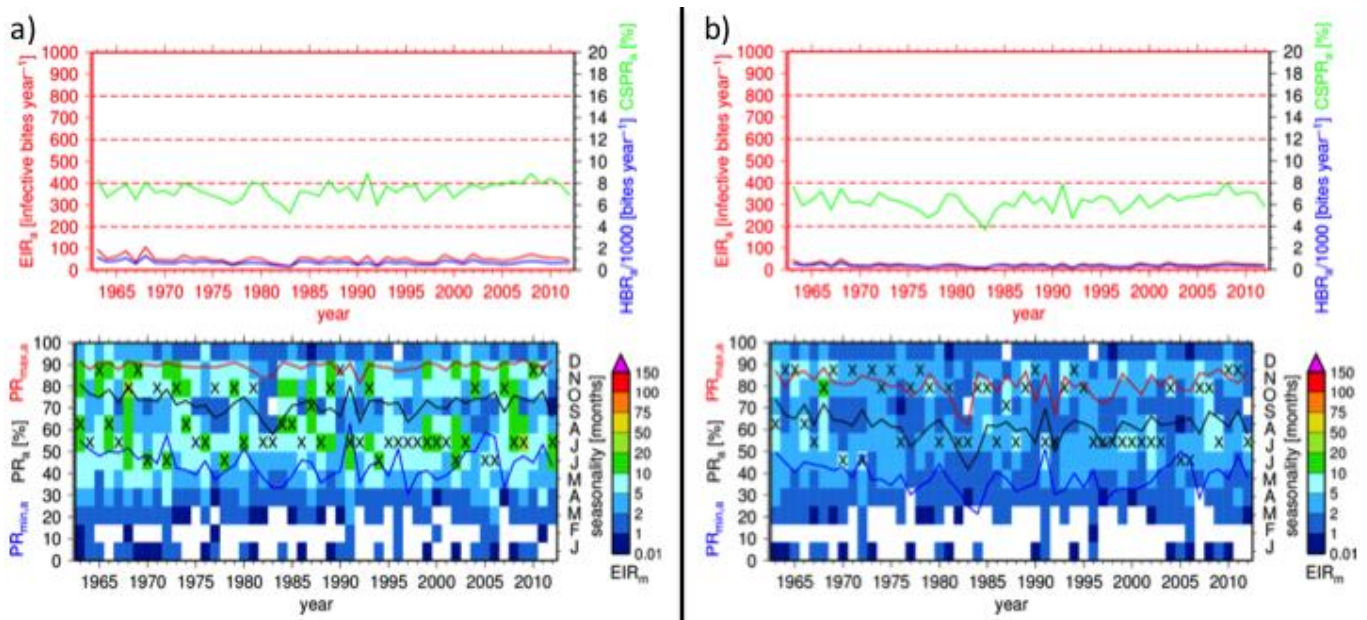


Figure 4. Same as Figure 3 but here for (a) a peri-urban (250 inhabitants per km²) and (b) urban area (1000 inhabitants per km²) within the Kumasi region.

Running VECTRI for a peri-urban (250 inhabitants per km²) and urban area (1000 inhabitants per km²) results in lower malaria transmission and infectiousness of the human population (Figure 4a & b). The EIR_a values for the peri-urban and urban population range only between 10 and 100 and 5 and 50 infectious bites per human per year, respectively. It is interesting to note that the CSPR_a value decreases significantly in the VECTRI simulations when the population density is increased. CSPR_a ranges only between 4 and 8% for the urban population. The increased population density also affects the occurrence of the malaria season. The higher population density leads in VECTRI to a shorter malaria season due to the increases gap in the malaria transmission at the start of the year. Of course,

also the single values of the monthly EIR values are smaller under the peri-urban and urban environment. The lower transmission also impacts the infectiousness of the human population. In the VECTRI simulation, fewer humans are infected by the malaria parasite and the maximum PR value stronger varies under higher population densities.

5.4 LMM₂₀₁₀ and VECTRI simulations vs. hospital malaria cases

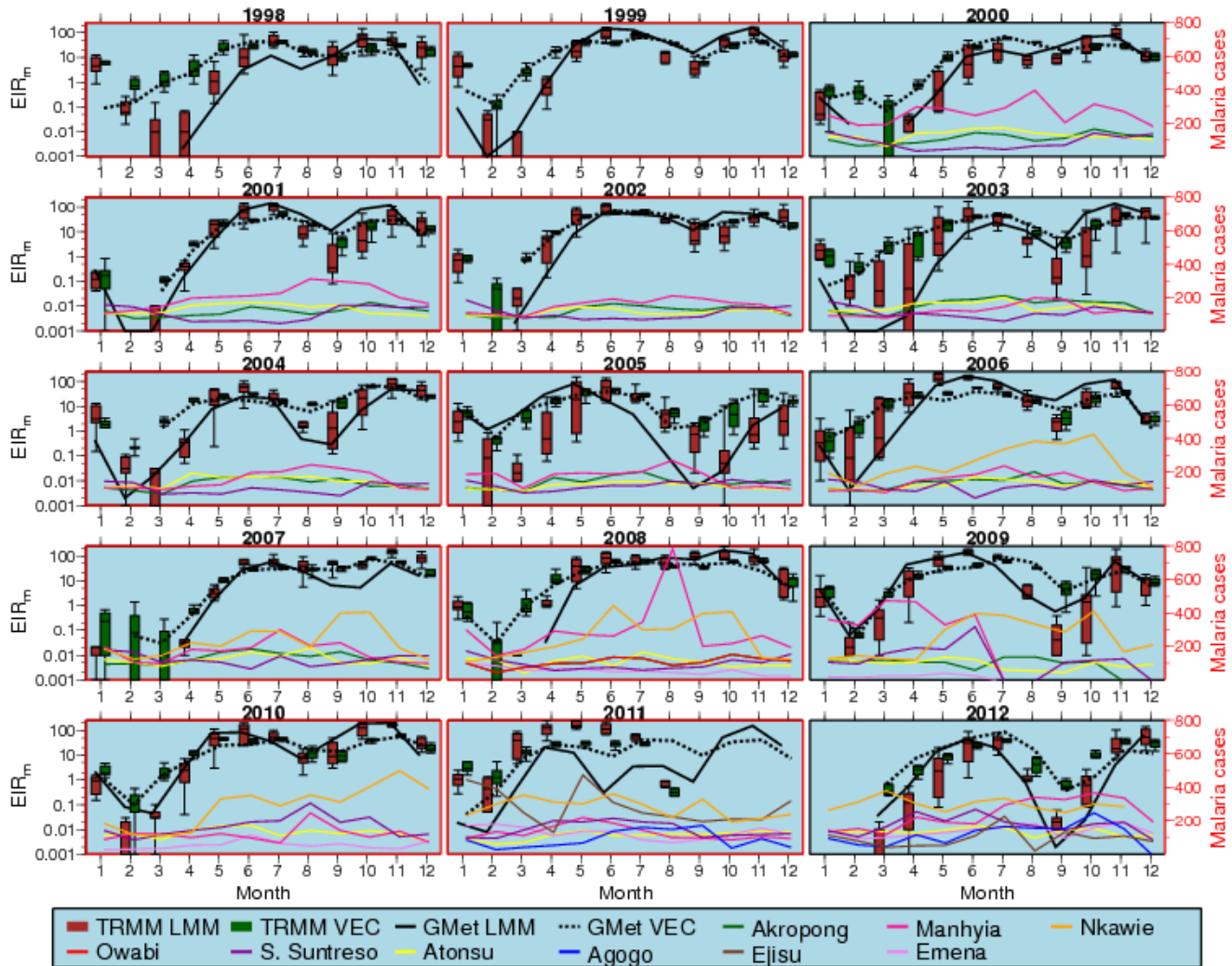


Figure 5. LMM₂₀₁₀ and VECTRI simulated monthly EIR values between 1998 and 2012 using the GMet observations and the TRMM and other precipitation estimate, and observed hospital malaria cases. Illustrated is the interannual and intraseasonal variability of the simulated monthly EIR values (EIR_m left scale) by LMM₂₀₁₀ and VECTRI using the GMet observations (solid black and dashed black line, respectively) and the TRMM and other precipitation estimate (green and red box-and-whisker plots, respectively). Also inserted are the observed confirmed hospital malaria records (coloured lines; right scale) within the Ashanti region of Ghana between 2000 and 2012.

The confirmed malaria cases from hospitals reveal only a small intraseasonal variability. Hospital malaria cases were both observed in the dry and in the wet seasons. The number of malaria hospital cases is, however, somewhat higher in the middle of the year after the first main rainy season indicating

some influence of rainfall on the occurrence of hospital malaria cases. No significant peaks were observed even though some minor instances were observed especially in the Manhyia and Nkawie hospitals. No strong intraseasonal variability is especially found for the hospitals of the Kumasi metropolis. The Manhyia and Nkawie hospitals revealed higher numbers of malaria cases than the other hospitals. In general, the number of malaria cases differs from hospitals within and outside the Kumasi metropolis. Stronger intraseasonal variations are found for the hospital malaria cases outside Kumasi than in the metropolis. A strong difference in the number of cases is identified between the Agogo and Nkawie hospitals, which are both located in rural areas. Either Nkawie represents a malaria hot spot due to special conditions or the catchment area of the hospital is larger.

In contrast to these results, the LMM₂₀₁₀ and VECTRI reveal a strong intraseasonal variability with regard to monthly EIR values. It should be noted, that small EIR values are sufficient to infect the human population. Above about 10-20 infectious bites per year no strong increase in the infectiousness of children was found (see Smith et al. 2005, their Figure One). As previously shown, both models reveal only a small gap in the malaria transmission at the end of the dry season. For some years, the LMM₂₀₁₀ and VECTRI simulate year-around malaria transmission. For these reasons, the model results might not be far off from the real malaria conditions. It must be noted, that it is not possible to directly compare the simulated malaria transmission with the observed hospital cases. The models do not distinguish asymptomatic and symptomatic malaria cases and those that are admitted to hospital.

5.5 Exemplary local monthly-to-seasonal malaria forecast for Kumasi

In order to show the feasibility of local malaria forecasts demonstrative malaria seamless monthly-to-seasonal malaria forecasts for the Kumasi region were generated. Illustrated were the seamless malaria forecasts from January 2013. In contrast to the forecasts from the ECMWF, the local forecasts mainly focus on the generation of time series of key malaria variables. In January 2013, the lead-time of 120 days includes the start of the main malaria transmission season, for which the forecast is provided by VECTRI and the LMM₂₀₁₀.

5.5.1 Forecasts and hindcasts from the LMM₂₀₁₀

The malaria forecast for Kumasi/Ghana starts at the beginning of February (week 5) and is finished at the end of May 2013 (week 21). The forecast includes entomological and parasitological malaria variables such as the simulated weekly EIR (EIR_w) values. According to the LMM₂₀₁₀ monthly-to-seasonal prediction malaria transmission is on-going throughout the forecasting period. The model runs indicate that the transmission of the malaria disease is predicted to be significant but partly low during the four forecasted months. The lowest malaria risk is simulated to occur between the end of February and beginning of March (week 7 and 9). The weekly EIR median value of the 51 ensemble members of the malaria forecasts is always higher than 0.25 infectious bites per 100 people (see the blue line in Figure 6) meaning that malaria transmission is on-going also during the driest period of the year (see the definition above). However, the risk of a malaria infection is fairly low during this time. Some ensemble members even forecast a much lower but also a higher transmission level, respectively. During week 7 and 9 the EIR_w values range between 0.0002 and 0.02 infectious bites per human per week. After the beginning of March, the simulated EIR_w value increases significantly due to the start of the main rainy season in the Kumasi area. At the end of April (week 16), every human receives already about one

infectious mosquito bite per week. The malaria risk further increases toward the end of the forecast period at the end of May (week 21), when the EIR_w value reaches about 10-20 infectious bites per human per week.

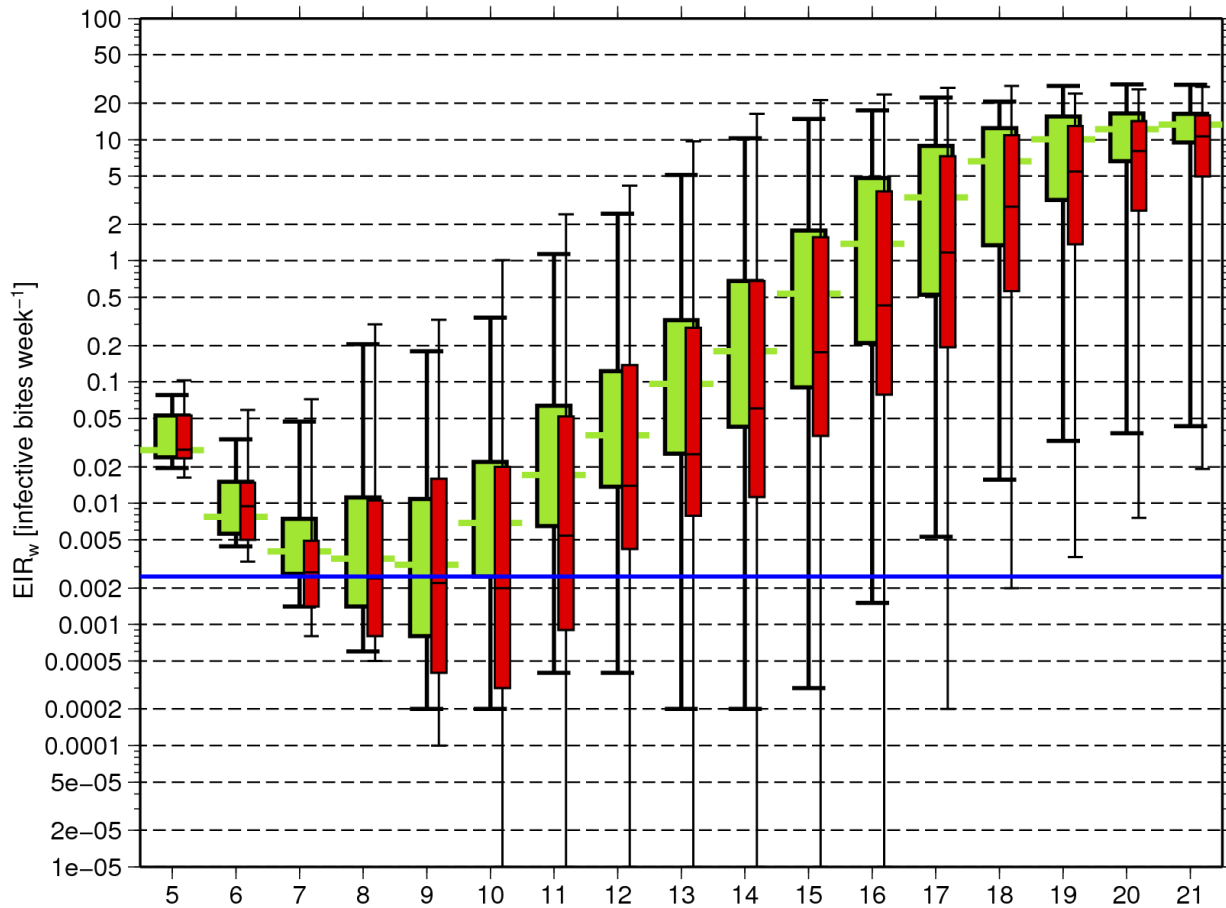


Figure 6. Demonstrative monthly-to-seamless malaria forecast (starting from 31 January 2013) of the Liverpool Malaria Model (LMM) for the Kumasi region in Ghana. Illustrated is the weekly Entomological Inoculation Rate (EIR_w ; i.e. the number of infectious mosquito bites per person per week) on a log scale between the beginning of February (week 5) and the end of May 2013 (week 21) from 51 forecast ensemble members (green box-and-whisker plots) for 2013 and from 90 hindcast ensemble members between 1995 and 2012 (red box-and-whisker plots). The blue horizontal line indicates the status when the LMM simulates 0.0025 infectious bites per human per week (i.e. about 0.01 infectious bites per human per month, which is the defined level of on-going malaria transmission).

Malaria transmission is predicted to be in general above the average as compared with the seasonal hindcasts (period: 1995-2012). The EIR_w median value of the 51 ensemble forecasts for 2013 is mostly higher than that for the hindcasts. It also seems that the malaria transmission increase starts in March 2013 about one week earlier than usual. Some hindcasts reveal a very low malaria transmission between week 10 and week 16 meaning that some years reveal a break in malaria transmission during this time interval. However, this is predicted to be not the case for 2013.

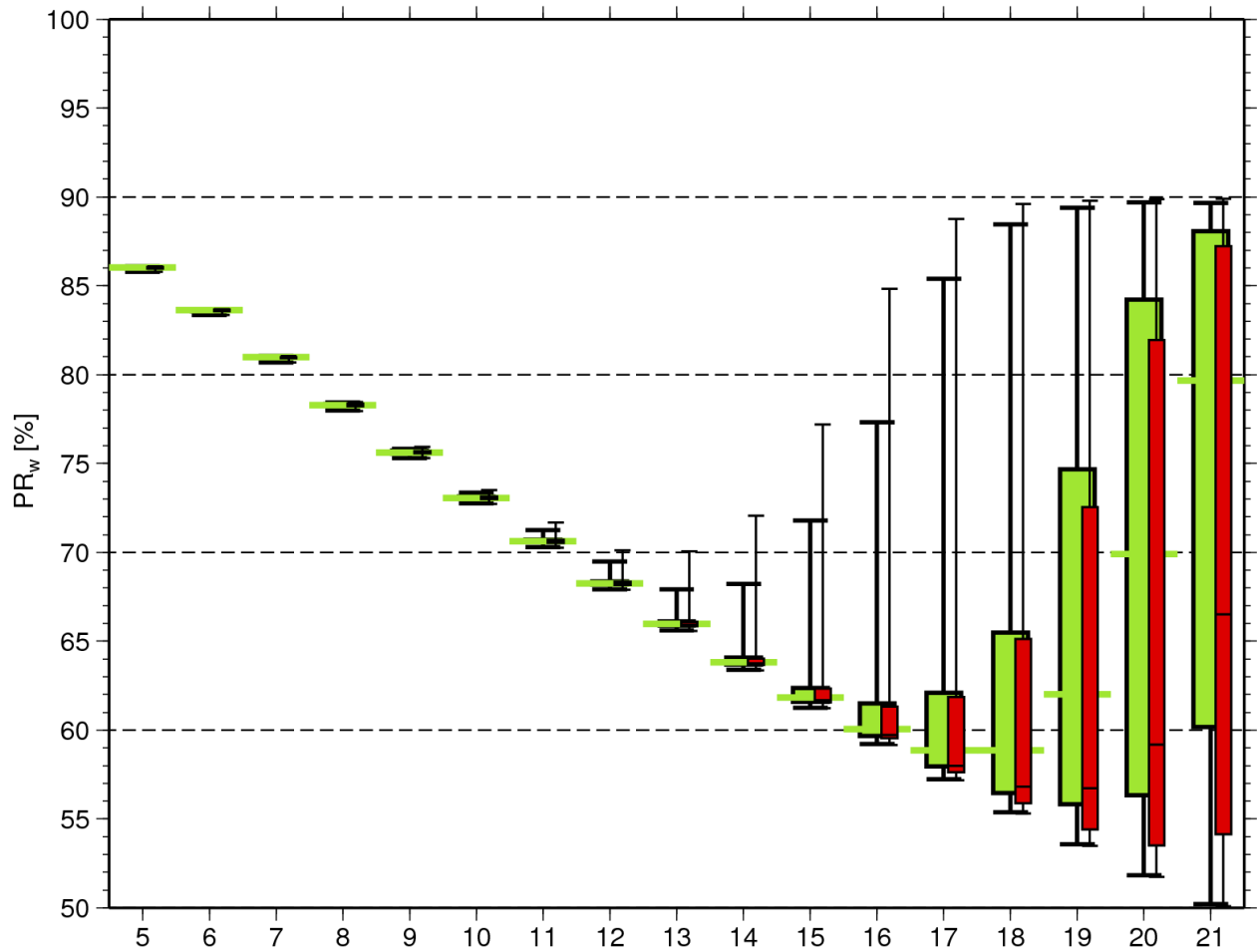


Figure 7. Same as Figure 6 but here for the weekly averaged asexual Parasite Ratio (PR_w ; in %).

In general, the malaria infectiousness is predicted to decrease during the first part of the forecasting period (Figure 7). That is due to the fact that most humans in the model got infected during the minor rainy season between September and December. At the start of the forecast period, the weekly asexual Parasite Ratio (PR_w) is about 86% both in the forecasts for 2013 and the hindcasts. In the follow-up of the second rainy season the humans recover in the model during the dry season, when the malaria transmission is very low (see Figure 6). The recovery rate is about 1.7% per week and leads to a steady decrease of the infectiousness of the population until about the beginning of May (week 18). At that time, the asexual parasite ratio reveals a minimum value below 60%. However, due to the spread of the ensemble members there is a strong uncertainty with regard to the timing and the magnitude of this minimum value.

The confined values of the ensemble members during the first half of the forecast period show that there is a low uncertainty within the simulation of the LMM_{2010} (Figure 7). However, this does not indicate an accuracy of the model in terms of the simulation of the asexual parasite ratio. Ermert et al. (2011b) found a low skill of the LMM_{2010} with regard of the simulation of parasitological values. That is mainly because of neglecting aspects like immunity or a missing age distribution of the disease in the model framework. As previously mentioned, there is also no differentiation between asymptomatic and

symptomatic malaria infections. This means that the forecast of the infectiousness needs to be treated with caution and should not be over-interpreted.

After April a strong increase in the malaria infectiousness is simulated (Figure 7). Forecasted is a significant increase of the PR_w values within May 2013. However, there is a large uncertainty in terms of the strength of this increase due to the large spread of the ensemble members. The same spread is also found for the hindcasts that reveal a somewhat lower infection rate than the actual forecast. The last is due to the stronger predicted malaria transmission of 2013 (see Figure 6).

5.5.2 Forecasts and hindcasts from VECTRI

Similar to the LMM_{2010} , VECTRI generates a malaria transmission forecast for the same period for Kumasi/Ghana. Throughout the four months of the forecasts, VECTRI predicts a relative high malaria transmission risk between about 0.5 and 15 infectious bites per person per week (Figure 8). The lowest predicted risk of a malaria infection occurs at the beginning of the forecast period in February (week 5 of Figure 8). The model however indicates an increase of malaria transmission during the following weeks. In contrast to the LMM_{2010} forecasts, the ensemble spread is quite low (quartile range). The EIR_w values of the 51 ensemble members of the malaria forecasts are all higher than 0.25 infectious bites per 100 people (see the blue line of Figure 8), which is considered as the malaria transmission limit. This means that VECTRI is not simulating a transmission break within the dry season of the Kumasi area.

The hindcasts (period: 1995-2012) follow a similar fashion to the forecasted malaria transmission as elaborated above. Comparing the hindcasts with the forecasts, the actual predicted malaria transmission is in general above that of the hindcasts. Therefore, the forecasts indicate a higher transmission risk than the hindcasts. The hindcasts reveal a much high variability with regard to the malaria transmission rates than the forecasted values.

Comparing the EIR_w simulations of the two models (Figures 6 & 8), they both reveal a similar pattern of low to high transmission rates in the dry to wet period, respectively. In comparison to the hindcasts both models reveal above average EIR_w values. Malaria transmission is ongoing in the dry season both in the LMM_{2010} and VECTRI. However, there are some disparities in the simulations of the models. VECTRI simulates much higher transmission values in the dry season than the LMM_{2010} . While both models simulate an increasing malaria risk during the forecast period, the LMM_{2010} produces a transmission minimum at the end of February. Unlike VECTRI the LMM_{2010} reveals a much stronger variability of the EIR_w values in both the forecasts and hindcasts runs.

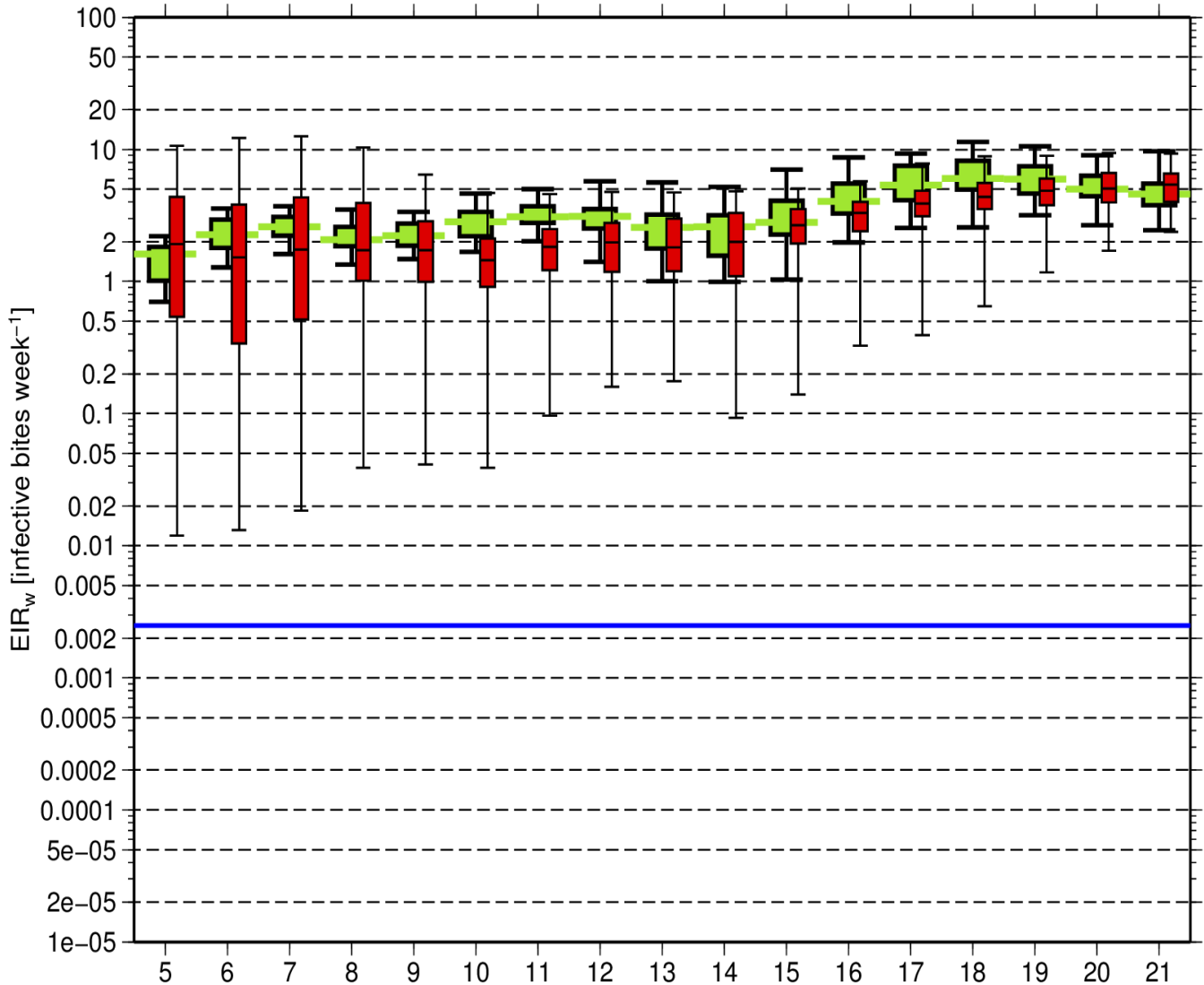


Figure 8. Same as Figure 6 but here for VECTRI forecasts and hindcasts.

In contrast to the LMM₂₀₁₀ simulations, the VECTRI forecasted malaria infectiousness is high throughout the period (Figure 9) ranging only between a minimum and maximum values of about 85 and 93%, respectively. The variability of the infectiousness is generally weak throughout the forecast period. A strong PR_w variability is only found for the hindcasts indicating that the forecasted abnormal high transmission rates lead to the high infectiousness of the population. However, also for most hindcast runs the malaria prevalence remains at a very high level above about 80%. Therefore, VECTRI reveals mostly even during the dry period no significant recovery of the population from the malaria parasite. Dissimilar to VECTRI (see Figures 7 & 9), the LMM₂₀₁₀ indicates a steady decrease in malaria infectiousness of the population both in the forecasts for 2013 and hindcasts from the first half of the period.

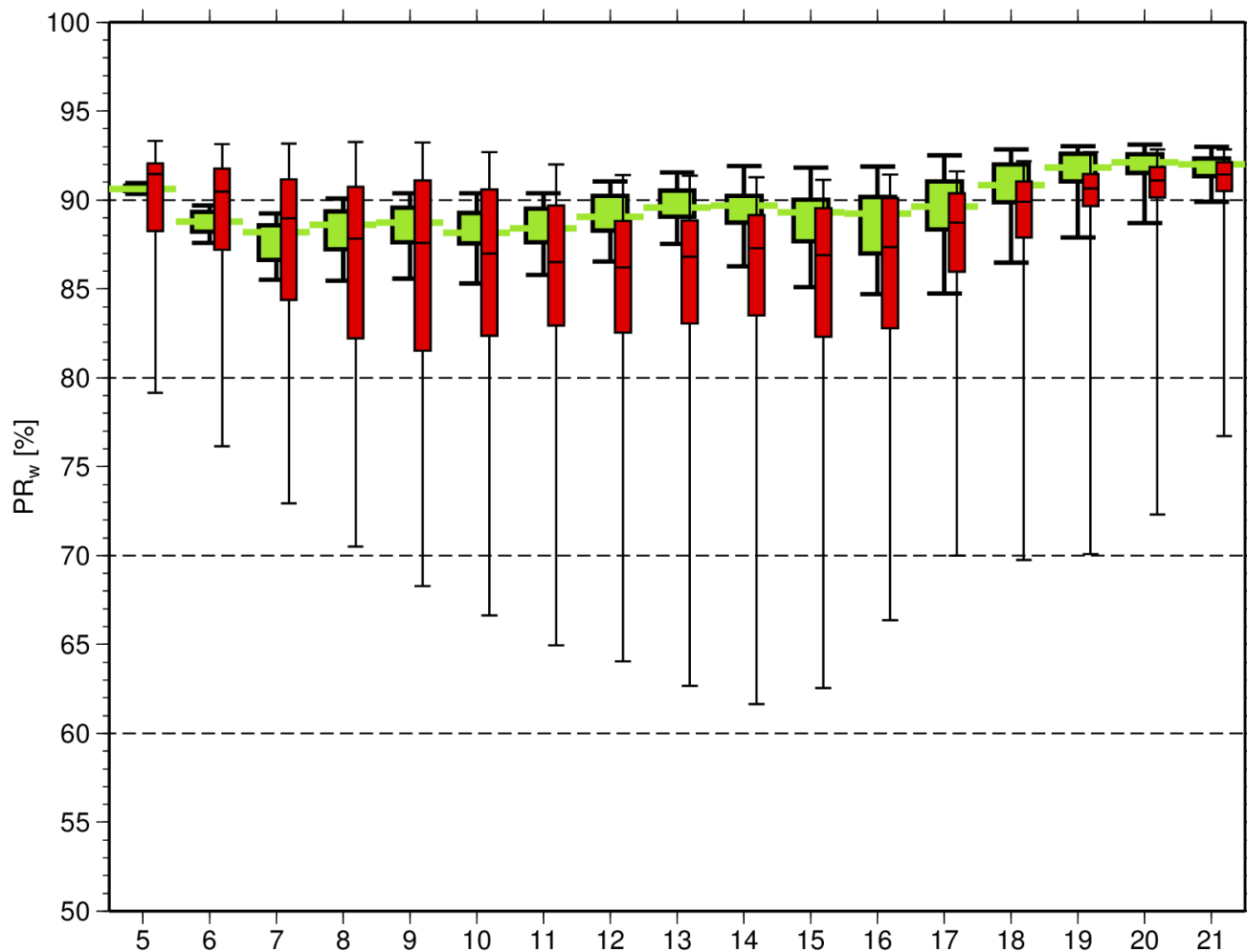


Figure 9. Same as Figure 8 but here for the weekly averaged asexual Parasite Ratio (PR_w ; in %)

6 Discussion

The most favourable measure of malaria transmission is the entomological inoculation rate (Burkot and Graves 1995; Drakeley et al. 2003) since there is a strong correlation between EIR and the prevalence of malaria in a population (Dery et al. 2010). The simulation of the EIR_m values by the two malaria models is therefore a favourable tool for evaluation of the prevalence and the degree of endemicity of malaria the region.

One important objective of this study was to validate the Liverpool Malaria Model (LMM). However, lack of sufficient entomological and parasitological malaria data for the region became a hindrance due to ethical controls imposed during the contracting stage of the project. This was due to the fact that the quantity of spray catches collected by KNUST during the period of survey was insufficient to allow for the calculation of monthly entomological inoculation rates. Moreover, the number of rooms per study site was also insufficient, hence EIR values for urban, peri-urban, and rural areas within the Kumasi region could not be calculated. In addition, the gathered confirmed malaria cases from the hospitals of the region could not be compared to the model output. The reason being that the model simulate the

parasite ratio, which comprises both asymptomatic and symptomatic malaria cases and does not distinguish symptomatic malaria cases and those that are admitted to hospital.

The simulated EIR_m of the two malaria models are high in the wet seasons and very low in the dry season. The peaks in the rainy seasons demonstrate that transmission is high in these seasons and that individuals in the region are exposed to a high amount of infectious bites from the vectors in these seasons. This can explicitly be explained by the fact that the transmission of the disease is dependent on the vectors, whose vectorial activity and population become often high in the rainy season due to the availability of ideal breeding sites and humidity. Anopheline mosquitoes breed in water. Water collections that support vector breeding appear mainly after the rains, and therefore malaria transmission is highest following the rainy season.

Malaria prevalence is usually low during the dry season as demonstrated by the models due to the low density and spatial confinement of the vectors as against the peak transmission season (the rainy season). This can be attributed to the fact that the models are sensitive to rainfall which produces breeding sites. Since the inputs rainfall values are low in this season, low EIR values are simulated. On the contrary, malaria is found to be high in this season as indicated by the observed hospital malaria cases. This suggests that the model downplays the potential factors that could cause the disease within this time. Hence does not involve the parameters that could produce malaria in the season. The high seasonal variations of the models output suggest that the models are highly sensitive to input parameters such precipitation, which show a high seasonal variation within the year. The LMM is found to reveal a much stronger year-to-year variability than VECTRI, which was also discovered by Tompkins and Ermert (2013).

However, the high incidence of the hospital malaria cases in the dry season can be attributed to the fact that the vector profile changes during the dry season and hence influence the pattern of transmission (Moiroux et al. 2012). Moreover, reports (Awolola et al. 2002; Kelly-Hope and McKenzie 2009; Adja et al. 2011) indicate that during the dry season in Africa, there is switch from *An. gambiae* to other anopheline species such as *An. moucheti* and *An. melas* that are active in this season. Their persistence in the dry season can be attributed to their dependence on occasional rain showers and the existence of permanent, domestic breeding sites (Kelly-Hope and McKenzie 2009). The presence of *An. funestus* in the dry season accounts for a significant component of malaria transmission and prevalence in this season (Fontenille et al. 1997, Djenontin et al. 2010, Damien et al. 2010). The high incidence is also an indication that the vector control in the dry season is not sustained, which rejuvenate their activity. For instance, mosquito nets are either not or less used during the season (Korenromp et al. 2003, Frey et al. 2006) because of the low biting nuisance of the mosquito in the season (Ahorlu et al. 1997, Toe et al. 2009) and probably the discomfort of sleeping under the net in the hot nights of the hot season. Note that the two malaria models does not include the different behaviours of different malaria vectors. This might be one reason for the low simulated transmission values in the dry season.

In addition, the stable nature and low seasonal variations in the observed hospital malaria cases throughout the year demonstrates that the region is endemic with regard to the malaria disease. This further suggests that the mosquito vectors are in constant contact with the inhabitants throughout the year.

Malaria incidence varied between the different areas of the region covered in the study. The variation is further eminent in the simulations for the rural, peri-urban and urban areas by VECTRI. These variations are an indication of marked spatial heterogeneity in the distribution and density of malaria vectors in the study area. The pronounced cases in the rural areas and low in urban areas corroborates with research reports that incidence of malaria is generally lower in urban areas than in rural areas. The reason is that there are numerous vector-breeding sites in rural villages, most water collections in urban settlements are polluted and unfavourable for mosquito breeding and that people in urban areas may have more access to health care and malaria prevention strategies than people in rural villages. Also the ratio between humans and mosquitoes is more favourable in urban areas due to the higher population density, which is accounted for by VECTRI.

Manhyia located almost in the heart of the Metropolis showed very high record of malaria cases, which is expected to be otherwise. This area is still undergoing rapid urbanisation and for that matter could be characterised by crowded conditions, poor quality housing, and temporary construction. Research indicates that such places are characterised by several pits due house construction, creating numerous breeding grounds for mosquitoes. Hence such circumstances can lead to explosive growth of mosquito vectors, increasing the exposure of the population to vectors due to poor housing. This is moreover known that such characteristics could amplify the disease to epidemic proportions through lack of effective treatment.

The monthly-to-seasonal malaria forecast for Kumasi demonstrates the possibility of local disease forecasts. Ermert et al. (2011b) worked out that the simulation of entomological variables like the EIR is much more reliable than the reproduction of parasitological data. For this reason, it is noted that the EIR_w forecasts should provide more skill than the prediction of the PR_w values. The comparison between the LMM2010 and VECTRI forecasts strongly disagree in the prediction of the infectiousness of the population. Nevertheless, the forecast with regard to PR_w can be used by decision makers to compute the likely time period when the majority of people will get infected with the malaria parasite.

That notwithstanding, both models show some level of similarities in their forecasting patterns. The LMM₂₀₁₀ and VECTRI reveal low but above average transmission rates. However, malaria transmission is in general higher in VECTRI during the dry season resulting in the high infection rates of the human population. As the forecast progresses into the rainy season, as expected both models forecast a higher malaria transmission.

Malaria transmission is known to be ongoing but low in dry and high in the wet period, respectively. This suggests that the modelled forecasts might depict a good representative picture of the malaria transmission in the region. However, the models need to be improved with regard to the presence and characteristics of different vector species. In terms of the forecast of the infectiousness of the population, immunity and age aspects need to be considered. It is unclear if transmission is really above average in the Kumasi region during the dry season of 2013. No entomological observations are available from the past and for 2013 to verify this modelling result. Neither the models nor the monthly-to-seasonal forecasts or hindcasts can be fully validated.

7 Conclusions

The validation of the Liverpool Malaria Model (LMM) was planned but was not possible due to insufficient entomological and parasitological malaria data for the region, due to additional ethical conditions imposed at the contracting stage and length. However, this work has led to an important cross validation of the two malaria models in the QWeCI project LMM and Vectri and has given many additional insights to their performance and some key differences. Nevertheless the results are quite promising and that the models are probably useful running in such an area with a complex transmission regime. Confirmed malaria cases from hospitals of the Kumasi metropolis were gathered by KNUST. Instead of the validation of the LMM, both VECTRI and LMM simulations were performed and compared for Kumasi. The malaria models were driven by observed data from the Kumasi airport and with data from the Tropical Rainfall Measuring Mission (TRMM, 3B42 version 7). The comparison between the precipitation values revealed a good correlation between the observed precipitation (GMet) and TRMM and other precipitation estimate. VECTRI was driven with an urban, peri-urban and rural population density, respectively. The VECTRI simulations led as expected to much higher transmission values in rural than in urban locations.

The output of the two malaria models was qualitatively compared to the malaria cases from hospitals. The malaria cases showed a small interannual variability, whereas the models reveal a strong interannual variability in the malaria transmission. In general, both malaria models reveal the same annual cycle in malaria transmission. During the dry season the models simulate very low transmission values or in case of the LMM₂₀₁₀ a break in the malaria season. The simulated malaria transmission is bimodal. The first transmission peak follows the stronger first rainy season of the year and is simulated for June/July. The second peak is predicted for October/November after the shorter second rainy season of the Guinea Coast. In comparison to the LMM, VECTRI reveals a much lower interannual and spatial variability with regard to the EIR values.

This study demonstrates the feasibility of local monthly-to-seasonal malaria forecasts. The LMM₂₀₁₀ and VECTRI were used to assess the near future malaria conditions within the Kumasi region. The LMM₂₀₁₀ and VECTRI runs reveal ongoing malaria transmission during the dry season and at the beginning of the main rainfall season. A strong increase in the transmission and infection rates is predicted to occur in May 2013. The comparison with the hindcasts reveals that the malaria risk is above average. Decision makers like health planners can use the entomological information of the forecast to set up tailored disease control measures. However, the forecasts and hindcasts lack a validation procedure due to missing entomological and parasitological malaria observations.

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