Development and evaluation of temperature and surface hydrology schemes for dynamical vector-borne disease models



ASAREERNESTOHENE

(BSc Physics, PGDip Earth system physics)

A Thesis submitted to the Department of Physics, Kwame Nkrumah University of Science and Technology in partial fulfilment of the requirements for the degree of

DOCTOR OF PHILOSOPHY

(Atmospheric Physics)

College of Science

CORSUS

H

c Department of Physics

SANE

July 2015

Declaration

I hereby declare that this submission is my own work towards the PhD and that, to the best of my knowledge, it contains no material previously published by another person nor material which has been accepted for the award of any other degree of the University, except where due acknowledgement has been made in the text.

Asare Ernest Ohene (20255667)		
Student Name & ID	Signature	Date
Certified by:	My	
Dr. Leonard K. Amekudzi		
Supervisor Name	Signature	Date
Certified by:	18P	TI
Prof. Sylvester K. Danuor		
Head of Dept. Name	Signature	Date
THE I		T
AP STR	SANE NO	BAD



Abstract

Surface hydrology and water temperature are two key factors for the life cycle of mosquito larvae, and thus their realistic representation is required for the latest generation of dynamical disease models. A new prognostic surface hydrology scheme based on diagnostic area-depth relations and nonlinear treatments of infiltration and run-off terms has been developed to simulate temporal evolution of the pond surface area and depth. The scheme is evaluated using in situ data from daily observations of potential mosquito developmental habitats in a suburb of Kumasi, Ghana. The ponds reveal a strong variability in their water persistence times, which ranged between 11 and 81 days. The pond persistence was strongly tied with rainfall, location and size of the puddles. Based on a range of evaluation metrics, the prognostic model is judged to provide a good representation of the in situ pond coverage evolution at most sites. It was further demonstrated that this developed prognostic equation can be generalized and applied to a grid-cell to derive a fractional pond coverage, and thus can be implemented in spatially distributed models for relevant vector-borne diseases such as malaria. Th new prognostic scheme is implemented in the vector-borne disease community model of the International Centre for Theoretical Physics, Trieste (VECTRI) model and in addition to the VECTRI default surface hydrology scheme are validated using a resolution Hydrology, Entomology, and Malaria Transmission Simulator (HYDREMATS) model. Based on multi-member ensemble Monte Carlo technique, the VECTRI model parameter setting that minimizes water fraction differences was identified. Despite the simplicity of the two VECTRI surface hydrology parametrization schemes, they perform relatively well (NS E > 0.85) at reproducing the seasonal and intraseasonal variability in pond water fraction, with the prognostic scheme able to produce a closer match to the explicit benchmark model, HYDREMATS. However, the default VECTRI scheme tends to overestimate water fraction in 2005 and underestimate it in 2006, and also relatively overestimates water fraction during the monsoon onset period. This systematic error was improved by treating run-off and infiltration terms in the prognostic scheme. Simulations of vector densities with the prognostic scheme implemented in the VECTRI model were also close (NS E = 0.71) to the detailed agent based model contained in HYDREMATS. The results indicate that, with knowledge of local soil parameters and terrain, VECTRI schemes parameters could be adjusted to simulate malaria transmission on a local scale. Furthermore, VECTRI driven by satellites rainfall estimates produces a reasonable simulation of the sub-seasonal evolution of the pond fraction for the study area, thus indicating the possibility of driving the malaria model with satellite rainfall estimates in the absence of ground observations. In addition to the surface hydrology scheme, a new energy balance scheme that assumes a

homogeneous mixed water column driven by empirically derived fluxes has been developed. The model shows good agreement at both diurnal and daily time scales with 10-minute temporal resolution observed water temperatures monitored between June and November 2013 within a peri-urban area of Kumasi, Ghana. In addition, there was a close match between larvae development times calculated using either the model-derived or observed water temperatures, with the modelled water temperature providing a significant improvement over simply assuming the water temperature to be equal to the 2-metre air temperature. Furthermore, the results show that diurnal variations in water temperature are important for simulation of aquatic-stage development times, however, effect of sub-diurnal variations on larval development are similar to that of the diurnal. This highlights the potential of the model to predict mosquito developmental habitat water temperature, thus can be implemented in dynamical malaria models to predict larvae development times, especially in regions without observations of the input energy fluxes. Finally, VECTRI runs over Ghana reveal malaria transmission ranging from six to twelve months, with minimum intensity occurring between February and April. The correlation between mean annual model predicted entomological inoculation rate (EIR) and recorded national malaria cases from public health facilities was more than 0.5. On a local scale, the agreement between hospital recorded monthly malaria cases and VECTRI simulated EIR values was better relative to using only rainfall. This result demonstrates the potential ability of the VECTRI model to predict malaria transmission dynamics at both local and national scales. Thus VECTRI model can provide early warning information for malaria and in addition, provide useful information about intervention targeting aquatic and adult stages. The performance of the VECTRI model is likely to improve significantly when the developed temperature scheme is implemented.



Contents

Abstract	iii
List of Tables	x
List of Figures xiv	xi
List of Symbols and Acronyms	xv
Acknowledgement	xvi
Dedication	xviii
1 Introduction	1
1.1 Background and Motivation	1
1.2 Problem statement	6
1.3 Justification	9
1.4 Objectives	10
1.5 Research questions	11
1.6 Outline of the thesis	12
2 Literature review	13
2.1 Overview of malaria	13
2.1.1 Life Cycle of Plasmodium Parasite	15
2.1.2 Symptoms of malaria	17
2.2 Mosquito life cycle	18
2.2.1 Egg stage	19
2.2.2 Larvae stage	20
2.2.3 Pupae stage	21
2.2.4 Adult stage	21
2.3 Impact of climatic and environmental variability on malaria transmission	22
2.3.1 Temperature and malaria transmission	22
2.3.2 Rainfall and malaria transmission	26
2.3.3 Relative humidity and malaria transmission	27
2.3.4 Wind speed and malaria	28

2.3.5 Land use change and malaria	29
2.3.6 Urbanization impacts on malaria	30
2.3.7 Local hydrology and malaria vector abundance	31
2.4 Geographical distribution of malaria	32
2.5 Climate change and future malaria transmission	34
2.6 Malaria control	37
2.6.1 Aquatic stage intervention	37
2.6.2 Prevention of host vector contact	39
2.7 Malaria in Ghana: An Overview	40
2.7.1 Socio-economic costs of malaria in Ghana	41
2.7.2 Distribution of malaria vectors in Ghana	42
2.7.3 Malaria Parasites in Ghana	44
2.7.4 Spatio-temporal malaria distribution in Ghana	45
2.7.5 Malaria control strategy in Ghana	47
2.8 Malaria models	48
2.8.1 Statistical models	49
2.8.2 Dynamical models	50
2.9 Representation of surface hydrology and water temperature in dynamicalmodels	51
2.10 VECTRI model overview	54
2.10.1 Surface hydrology scheme	56
2.10.2 Larvae development scheme	57
2.10.3 Vector scheme	59
2.10.4 Sporogonic cycle	60
2.10.5 Gonotrophic cycle	62
2.10.6 Host vector interaction scheme	63
2.10.7 Model output	64
3 A breeding site model for regional, dynamical malaria simulations evaluatedusing in situ temporary ponds observations in Ghana	ו 65
3.1 Introduction	66
3.2 Method and model description	70

3.2.1 Study area and data	70
3.2.2 Diagnostic pond geometry model	72
3.2.3 Prognostic pond area model	73
3.3 Results and discussion	80
3.3.1 Pond measurements	80
3.3.2 Evaluating the Hayashi diagnostic model	84
3.3.3 Evaluating the prognostic model	85
3.3.4 Application to regional distributed models	88
3.4 Summary	91
4 A regional model for malaria vector developmental habitats evaluated using explicit,p resolving surface hydrology simulations	ond- 92
4.1 Introduction	94
4.2 Method and Data	98
4.2.1 Data for study Region	98
4.2.2 VECTRI Malaria Model	<mark> 1</mark> 00
4.2.2.1 Default model hydrology	100
4.2.2.2 Modified model hydrology	101
4.2.2.3 Vector model	103
4.2.3 HYDREMATS malaria model	104
4.2.3.1 Surface hydrology	104
4.2.3.2 Vector model	105
4.2.4 Hydrology Comparison method	105
4.3 Results and discussion	107
4.3.1 High resolution integrations	107
4.3.2 VECTRI hydrology parametrization evaluation	110
4.3.3 VECTRI simulation with satellite products	117
4.4 Summary	120
5 Evaluating an energy balance pond water temperature scheme suitable for vector- bornedisease transmission models with in situ measurements in Ghana	121
5.1 Introduction	122

5.2 Method and model description	127
5.2.1 Study area and data	127
5.2.2 Energy balance model for water temperature	128
5.2.3 VECTRI simulated larval density	133
5.2.4 Model evaluation	135
5.3 Results	137
5.3.1 Observed water temperature variability	137
5.3.2 Model output	141
5.3.3 Larvae development time	143
5.3.4 VECTRI simulated larvae density	145
5.3.5 Discussion	147
5.4 Summary	151
6 Assessing climate driven malaria variability in Ghana using a regional scale dynamicalmodel	152
6.1 Introduction	<mark> 1</mark> 53
6.2 Method	159
6.2.1 Study area and data	159
6.2.2 Malaria morbidity data	160
6.2.3 VECTRI model	161
6.3 Results and Discussion	163
6.3.1 Rainfall and temperature variability	163
6.3.2 Model results	164
6.3.3 VECTRI simulated EIR and annual malaria cases	167
 6.3.3 VECTRI simulated EIR and annual malaria cases 6.3.4 Local scale malaria transmission	167 168
6.3.3 VECTRI simulated EIR and annual malaria cases6.3.4 Local scale malaria transmission6.4 Summary	167 168 170
 6.3.3 VECTRI simulated EIR and annual malaria cases 6.3.4 Local scale malaria transmission 6.4 Summary 7 Conclusions and Recommendations 	167 168 170 171
 6.3.3 VECTRI simulated EIR and annual malaria cases 6.3.4 Local scale malaria transmission 6.4 Summary 7 Conclusions and Recommendations 7.1 Conclusions 	167 168 170 171 171
 6.3.3 VECTRI simulated EIR and annual malaria cases 6.3.4 Local scale malaria transmission 6.4 Summary 7 Conclusions and Recommendations 7.1 Conclusions 7.2 Recommendations 	167 168 170 171 171 176



List of Tables

3.1 Average area (Avg area) and depth (Avg depth), maximum area (Max area) and depth (Max depth), elevation, total number of days when pond contained water (pond water) and maximum number of days of continuous water presence (Max water) of the 10 temporary breeding habitats. The italics represents sites that did not endure the entire experiment. Site 3 was destroyed and site

9 measurement started later on 26 June.	 79
9 measurement started later on 26 June.	 79

3.2 Computed p values, RMAE, R^2 and NSE between observation and model output for various sites for both area and depth simulations. For these calculations, 84 missing days were left out....

5.1 Summary of the computed statistics for model evaluation. L_D(T_{obs}/T_{sim}) represents larvae development time between observed and simulated water temperatures, L_D(T_{obs}/T_{air}) represents larvae development time between

observed

water and air temperatures..... 140 BADW

WJSANE

List of Figures

station AgroMet.

- 1.1 Trend in percentage of hospital reported cases or death attributed to malaria in Ghana. Source of data: (Adams et al., 2004; NMCP, 2008; GHS, 2011). 3
- 2.1 The cycle of the malaria parasite between human hosts and mosquitoes. . . 16
- 2.2 Schematic diagram illustrating the mosquito life cycle and the various climatic variables influencing each stage. Adapted and modified from Smith et al.

42

70

- 2.3 Temperature impacts on (a) sporogony; (b) vector survivability; (c) vectors surviving sporogony; and (d) larval duration. Adapted from Craig et al. (1999) 23
- 2.4 The global malaria distribution map. Adapted from Hay et al. (2004). ... 32
- 2.5 An. gambiae s.l mosquitoes distribution map. Adapted from De Souza et al.(2010).
- 2.6 Schematic of VECTRI model divided into compartments representing growth stages of the vector and parasite development in the host and the vector.
 - Adapted from Tompkins and Ermert (2013). 53
- 3.1 Location of the study area KNUST campus and peri-urban areas of the Ayeduase. Also indicated are the 10 temporary sites together with the meteorological
- 3.2 Two typical monitored potential mosquito breeding habitats within the study

	area. Left: site 10; right: site 9.	70
3.3	Schematic illustrating the various processes in the pond model	73
3.4	Top: Average area (left axis, red line) and average depth (right axis, blue line) of the monitored breeding habitats. Bottom: Daily precipitation amounts of	
	the automated rain gauge from the KNUST campus	78
3.5	Example of power function fit for sites 5 and 8 using the area-depth relation.	
	The estimated <i>p</i> values for all the sites are listed in Table 3.2.	82
3.6		
	Comparison of daily observed and simulated pond water surface area and	

water depth of temporary water bodies. Solid lines are simulated values of area (blue) and depth (red). Dots and crosses represent the observed values of the surface area and water depth, respectively. Sites names are shown

	under each plot.	83
3.7	Power function fit for average of 8 sites (excluding sites 3 and 9) (a) and	
	comparison of simulated and estimated water fraction (b).	88
4.1	and the second	

HYDREMATS model simulated output of daily pool water depth at each grid cell over the entire model domain of 4 consecutive days in 2005 (left panel) and 2006 (right panel). The date (Julian day) and rainfall recorded are

shown under each plot.

106

4.2

RMSE error of water fraction between VECTRI (different surface hydrology parametrization) and HYDREMATS. Left panel: VECTRI hydrology V1.2.6, middle panel V1.3.0 varying maximum infiltration with a constant *CN* of 85

and right panel V1.3.0 varying *CN* with constant I_{max} of 500 mm day⁻¹... 108 4.3 Comparison of 7-day moving average time series of water fraction simulated by

HYDREMATS and VECTRI (using one set of parameters resulting in smaller RMSE

	with HYDREMATS). a): V1.2.6 scheme; b): V1.3.0 varying infiltration at a cons	tant
	CN of 85; c): V1.3.0 varying CN at a constant I_{max} of 500 mm day ⁻¹ ; d):	The
	difference between HYDREMATS and VECTRI. 111	
4.4 (Comparison of 7-day moving average time series of vector abundance simula by HYDREMATS and VECTRI (using one set of parameters resulting in smaller RMSE with HYDREMATS)	ted 114
4.5	A 7-day moving average time series of VECTRI simulated water fraction using station rainfall observations, TRMM 3B42 and FEWS RFE2 rainfall	
	estimates	116
5.1	Picture of study site showing the temperature logger.	126
5.2 5.3	Schematic representation of the energy balance model. \dots Left panel: Observed 10-minute (Tw_{10m}), maximum (Tw_{max}), minimum (Tw_{min})	128), daily
ę	average (<i>Tw_{Avg}</i>) water temperature and daily average air (<i>Ta_{Avg}</i>) temperature	2
	Right panel: Diurnal temperature difference (water minus air).	135
5.4	Comparison of DTR and daily average temperature difference (water minus	
	air).	137
5.5	Daily number of hours with water temperature \geq 35°C	138
5.6 (Comparison of (left panel)the diurnal observed and model temperature differe	nces
	(observed minus model) and (middle panel) daily average time series of	air,
	observed and model water temperatures. Also shown is correlation betw	veen
	observed and simulated diurnal water temperatures (right panel) 139)
5.7 Comparison of BA and JA schemes estimated mosquito larvae development time		
	using observed 10-minute, hourly and daily average water and air temperatu	res.
	JA10-munite, JAhourly and JAdaily represents Jepson approximation and BA10-minute,	

BA _{hourly} and BA _{daily} the results using Bayoh approximation	141

5.8

Comparison of BA and JA schemes estimated mosquito larvae development time using observed water, simulated water and air temperatures. J_{obs} , J_{sim} and Jair represents Jepson approximation and Bobs, Bsim and Bair the results

using Bayoh approximation.	142
Comparison of 7-day moving average time series of VECTRI simulated larva density driven by air and simulated water temperatures using JA and	e
BA schemes. Map showing the 22 synoptic Gmet stations grouped into the four agro-ecolog zones. The Emena hospital and Agromet station are also shown.	143 gical 157
The monthly daily (a) temperature, (b) rainfall, (c) water fraction (d) EIR	
over the 31 year period (1980 to 2010) for various Gmet synoptic stations	161
Comparison of average VECTRI simulated EIR and annual malaria morbidity	2
from public health facilities.	165
Comparison of monthly VECTRI simulated single location EIR and Emena	
hospital morbidity data	166
ATTACK AND	
	using Bayoh approximation.

KNUST

List of Symbols and Acronyms

GDP	Gross Domestic Product
WHO	World Health Organization
GHS	Ghana Health Service
MDGs	Millennium Development Goals
NHIS	National Health Insurance Scheme
NMCP	National Malaria Control Programme
OPD	out-patient attendance
SSA	sub-Saharan Africa
OMaWa	Open Malaria Warning
VECTRI	vector-borne disease community model of the International Centre for Theoretical Physics, Trieste
LLM	Liverpool Malaria Model
HYDREMATS	HYDrology, Entomology and MAlaria Transmission Simulator

Acknowledgement

My first and foremost appreciation goes to the Almighty God for His unending mercies and grace towards me throughout the duration of this work. My deepest appreciation goes to my supervisors: Prof. Adrian Tompkins, Dr. Leonard Amekudzi and Prof. Sylvester K. Danuor. I am proud and grateful for having had the privilege to work with them, and to learn from them. They provided the expertise, guidance and encouragement which made this thesis work possible.

Thanks to Dr. Volker Ermert and Dr. Robert Redl for their effective and fruitful collaboration that helped in improving the work. I once again thank Dr. Robert Redl for providing the water temperature sensor. I acknowledge the help of Mr. Elvis Agyapong in setting up of the water temperature logger.

I warmly thank Dr. Arne Bomblies for providing HYDREMATS simulation data and for helpful scientific discussions that greatly improved this thesis.

I greatly appreciate the valuable assistance of the entire academic and non-academic staff of the physics department KNUST and ICTP Earth System section for their immense support and encouragements throughout my work.

Lastly, I would like to thank my parents and family for their unconditional support and understanding through this experience.

This study was generously funded by two International Centre of Theoretical Physics (ICTP) programmes, namely the Italian government's funds-in-trust programme and the ICTP PhD Sandwich Training and Educational Programme (STEP). Additional founding was obtained from two European Union's Seventh Framework Programmes; HEALTHY FUTURES under the grant agreement number 266327 and QWeCI (Quantifying Weather and Climate Impacts on health in developing countries) under the grant agreement number 243964.



Dedication



CHAPTER 1

Introduction

1.1 Background and Motivation

Malaria is a mosquito-borne, protozoal disease that continues to be a major public health issue of the world, although high severity occurs across sub-Saharan Africa (SSA). For instance, WHO (2014) estimated 198 million malaria cases worldwide, with around 585 thousand mortalities in 2013. Interestingly, about 82% and 90% reported cases of morbidity and mortality respectively, occurred in Africa. Although malaria affects people of all ages, significant proportions of mortality and morbidity are found in the most vulnerable groups, that is, children under five years, pregnant women and population with low immunity. These groups account for about 90% of reported malaria-related deaths in SSA (Organization, 2000; Greenwood and Mutabingwa, 2002). In addition to the enormous public health impact of malaria, the disease negatively impedes socio-economic development. For instance, WHO (2014) estimated funding for malaria control and elimination to be US\$ 2.7 billion in 2013, which is about 53% of the required amount to achieve global malaria control and elimination targets. In countries with high malaria transmission, Gallup and Sachs (2001) estimated positive economic growth of 0.3% after 10% reduction in malaria transmission over 25 year period.

On the country level, in Tanzania, Jowett and Miller (2005) found that malaria costs about 1% and 39% of the national Gross Domestic Product (GDP) and health budget, respectively. Similarly, in 2009, Sicuri et al. (2013) estimated the annual cost of treatment and prevention of malaria for children under five to be 0.14%, 0.62% and 0.36% of the GDP of Ghana, Tanzania and Kenya, respectively. Furthermore, malaria poses a substantial economic burden on individual households and as in 2009 the average household paid 55% and 70% of the total cost of malaria treatment in Tanzania and Ghana, respectively (Sicuri et al., 2013). Consequently, controlling malaria remains one of the key factors for the attainment of Millennium Development Goals (MDGs) for sub-Saharan countries (Sachs and McArthur, 2005).

In Ghana, malaria poses a significant challenge to public health. Malaria is hyperendemic in Ghana and remains the leading cause of morbidity and mortality among the entire population. For instance, between 2000 and 2011 (Fig. 1.1), malaria alone accounted for an average of about 40% of all out-patient attendance (OPD) in public health facilities (Adams et al., 2004; NMCP, 2008; GHS, 2011). Similarly, between 2000 and 2011 an average of 28% (range: 18 to 44) and 11% (range: 6 to 17) reported mortality for children under five and pregnant women respectively, at the public hospitals are as result of malaria (GHS, 2011). Most importantly, actual malaria cases are likely to be higher than the reported cases since private health facilities and the home treatment of uncomplicated malaria are not taken into account. This high incidence of the disease suggests that effective and sustainable control strategies are still required to suppress malaria in the country.





In addition to health implications, malaria also presents a substantial economic and developmental challenges in Ghana. Asante and Asenso-Okyere (2003) found a negative association between malaria cases and GDP. Furthermore, a large fraction of Ghana's health budget goes to treatment and prevention of malaria. The estimated budget for National Malaria Control Programme (NMCP) strategy plan for effective malaria prevention and treatment between 2008 and 2015 is US\$ 880 million (GHS, 2009). In addition, the disease is adversely affecting sustainability of the National Health Insurance Scheme (NHIS) due to high reported cases at various hospitals across the country (Dontwi et al., 2013). On the household level, Akazili et al. (2008) found the cost of treatment of malaria to be about 1% and 34% of the household's income for the poor and the wealthy respectively in the

Kassena-Nankana district of northern Ghana. More recently, Sicuri et al. (2013) estimated that about 55% of the total cost of malaria treatment , which ranges from US\$ 7.99 to 229.24 per episode was borne by the patient in 2009. This clearly shows that successful implementation of an effective malaria control program will have a huge socio-economic and public health impact on the country.

Climatic, hydrological, and environmental variability greatly impact malaria transmission dynamics and to some extent define the geographical distribution and seasonal variations of the disease. Among these, temperature (both water and air temperatures) and rainfall are two key climate drivers known to influence malaria vectors development and survival rates. The parasite development inside both the human host and the vector is strongly dependent on ambient temperature (Nikolaev, 1935; Patz and Olson, 2006). Rainfall directly influences mosquito density by creating additional, or modifying the existing, developmental habitats (Fillinger et al., 2004) and indirectly impacting adult mosquito longevity through its effects on relative humidity. In addition to rainfall and temperature, relative humidity and wind speed are other important climate drivers that influence the adult lifespan and activity of the adult mosquito (Wernsdorfer and MacGregor, 1988). The interplay between these climate parameters and non-climatic factors, such as local hydrological parameters (controls stability of breeding habitats), land use changes (that modify both air and water temperatures and also creates favourable breeding habitats), human immune system, irrigation and economic levels, controls transmission intensity. Understanding how these factors interact and their influence on each stage of the vector and parasite life cycles and present day disease dynamics is key to predicting future malaria distribution patterns under climate change.

Recently dynamical weather-driven malaria models have become extremely important tools used in an attempt to understand malaria transmission and potential of the available control intervention. Various models have been developed based on interaction between climate factors and vector and parasite ecology which can provide an early warning system (Hoshen and Morse, 2004; Thomson et al., 2006; Tompkins and Di Giuseppe, 2015), identify effective control intervention for a particular epidemiological setting (Okell et al., 2008; Smith et al., 2009; Chitnis et al., 2010) and understand disease patterns under future climate change (Bomblies and Eltahir, 2009; Gething et al., 2010). Although, modeling has played a significant role to aid our understanding of the complexity of malaria transmission dynamics, considerable model limitations are apparent and thus improvement in simulating key stages of the mosquito and parasite life cycles are still required.

Notable model limitations include the representation of surface hydrology and water temperature of the developmental habitat. These are the two key factors that control the aquatic stage life cycle of mosquitoes and thus adult abundance by influencing the stability of habitat and larvae growth rates, respectively. For instance, accurate model simulation of surface water stability and water temperature of aquatic stage development habitat can reveal much useful information about vector population and distribution dynamics. While accurate prediction of water temperature provides egg to adult emergence time, skillful prediction of habitat lifespan differentiates productive from unproductive habitats. Consequently, if existing models could forecast these processes realistically, the output will indicate which breeding sites to target for aquatic stage control strategies and in addition, the time interval to conduct adult residual spraying (Gu and Novak, 2005; Mutuku et al., 2006b). Despite the importance of these drivers, there exist substantial research challenges associated with their representation in available dynamical models. Adequate representation of surface hydrology and water temperature of the developmental habitat could improve the predictability of existing dynamical models, which is the focus of this present study.

KNUST

1.2 Problem statement

In order to model malaria effectively using a dynamical modeling approach, a realistic representation of the surface hydrology and developmental habitat water temperature is required. However, models incorporate surface hydrology schemes that vary in complexity. For instance, Hoshen and Morse (2004) ignores surface hydrology treatment and thus simply relate the oviposition rate to the 10 day rainfall rate in the Liverpool Malaria Model (LMM). Lunde et al. (2013b) parameterized surface hydrology as a function of river length and soil moisture based on the assumption that potential habitats are located within the vicinity of rivers and lakes. The Open Malaria Warning (OMaWa:Lunde et al. (2013b)), designed to be run on a large scale, may have limited application in areas of relatively flat topography where habitats are only rain-fed and can be located far away from permanent water bodies. Another recently introduced regional scale dynamical malaria model, the vector-borne disease community model of the International Centre for Theoretical Physics, Trieste (VECTRI; Tompkins and Ermert (2013)) uses a simple surface hydrology parameterization that models the evolution of the fractional water coverage within each grid cell. However, the scheme ignores the nonlinearities of infiltration and runoff. For local, village scale modeling, Bomblies et al. (2008) introduced the high-resolution Hydrology, Entomology, and Malaria Transmission Simulator (HYDREMATS). HYDREMATS runs with 10 meter spatial scale grid-cells to explicitly simulate pool formation and persistence time which control aquatic stage development of mosquito for each individual pond. The scheme application on regional scale would be expensive to run and in addition the required input data may not be available from most meteorological stations.

Similarly, many spatial, dynamical mathematical-biological malaria models lack a precise simulation of water temperatures. For instance, the Liverpool Malaria Model (LMM) (Hoshen and Morse, 2004; Ermert et al., 2011b;a) completely neglects the influence of water temperatures on the larval development since the aquatic stage duration is constant in the model. Tompkins and Ermert (2013) in their grid-point distributed dynamical model (VECTRI), which runs on a regional scale, simply equate 2 m mean air temperature to water temperature to drive the aquatic stage component of the model, which uses development times and mortality rates derived from Craig et al. (1999) and Bayoh and Lindsay (2003), as detailed in Tompkins and Di Giuseppe (2015). This leads to inaccurate prediction of larvae development time which negatively affects the models simulated malaria transmission.

Some attempts have been made to develop more complex representations of water temperature. Lunde et al. (2013b) in their model equated the mean breeding water temperature to top soil temperature obtained from the NOAH land surface model. Depinay et al. (2004) also introduced a simple water temperature scheme. They used relative humidity to estimate cloud cover and then predict maximum water temperatures from both the cloud cover and maximum air temperature, whereas the minimum water temperature was equated to the minimum air temperature. Neither the Lunde et al. (2013b) nor Depinay et al. (2004) schemes were evaluated using in situ data.

Various energy balance schemes to predict water temperature are available (Paaijmans et al.,

2008a;b). Despite good performance of some of these models, their application regionally over Africa and other malaria endemic areas are hindered by a lack of the appropriate in situ observations required to define some of the energy fluxes.

Achieving the goal of a realistic representation of surface hydrology and habitat water temperature is hindered by the fact that the two key African malaria vectors, *Anopheles gambiae sensu stricto* and *Anopheles arabiensis* prefer shallow water breeding sites that are usually small in spatial scale, ranging from small permanent ponds to temporary puddles. This small spatial scale confounds modeling efforts as the topography on such small scales is unknown, and also renders detection by remote sensing techniques difficult. This cause for the use of in-situ observations to evaluate parametrization assumptions.

More importantly, in Ghana, studies linking climate fluctuations and malaria transmission across the various agro-ecological zones are limited. A few available studies are based on a single or at most two ecological zones and over a short time period (Danuor et al., 2010; Tay et al., 2012; Klutse et al., 2014). Thus, it becomes clearly difficult to understand malaria transmission dynamics over the entire country.

8

1.3 Justification

Despite a recent increase in malaria treatment and control intervention strategies, the disease still remains a major public health (Fig. 1.1) and economic burden in Ghana and other parts of SSA. This is partly due to lack of comprehensive understanding of the biology of the vector and parasite and its relation to the climate drivers. On the other hand, difficulty exists in assessing the appropriate cost effective and sustainable control interventions for a particular epidemiological zone.

The above challenges could be addressed using dynamical modeling approach if existing models are able to accurately represent the various local hydroclimatic and environmental variables that control the mosquito and the parasite life cycles. Without this, models cannot be used to properly evaluate and identify effective control strategy, develop early warning systems or assess disease transmission patterns under future climate change.

This study attempts to address some of the shortcomings of mosquito aquatic stage simulations by introducing and validating simple schemes to improve representation of habitat water temperature and surface hydrology in dynamical models. The significance of the introduced surface hydrology and habitat water temperature schemes relative to the others are that evaluation was performed using in-situ field observations. In addition, the driving climatic variables are available from most meteorological stations making the schemes applicable at regional and local scales. Furthermore, these schemes can be useful in other vector-borne disease models.

9

Due to limited financial resources available for malaria control in Ghana, understanding the spatio-temporal variability of the epidemiology of the disease is required for well-planned effective control programs such as liviciding, indoor and outdoor residual spraying. The VECTRI model output variables such as vector and larvae densities provide estimated time such interventions are likely to have a greater impact. More importantly, this study reveals the potential of VECTRI model to simulate seasonal, inter- and intra-ecological transmission variations and therefore could be used to develop real-time operational malaria early warning system for Ghana.

1.4 Objectives

The primary objective of this study is to develop and validate water temperature and surface hydrology schemes for use in dynamical vector-borne disease transmission models using in situ measurements. The potential application of these schemes in regional distributed disease transmission models is assessed using the vector-borne disease community model of the International Centre for Theoretical Physics, Trieste (VECTRI; Tompkins and Ermert (2013)).

The specific objectives include, to:

• Develop and evaluate a breeding site model for regional, dynamical malaria simulations using in situ temporary ponds observations in Ghana.

- Evaluate a regional model for malaria vector developmental habitats using explicit, pond-resolving surface hydrology simulations.
- Develop and evaluate an energy balance pond water temperature scheme suitable for vector-borne disease transmission models using in situ measurements in Ghana.
- Assess climate driven malaria variability in Ghana using a regional scale dynamical model.

1.5 Research questions

This research seeks to answer the following questions in an attempt to address some dynamical modeling deficiencies in simulating the aquatic stage development of mosquito in an effort to improve model performance in predicting malaria transmission dynamics.

- 1. Does a simple prognostic geometrical model have potential in the representation of surface water evolution?
- 2. How applicable is a geometrical model in dynamical distributed models?
- 3. How relevant is the regional scale VECTRI model in simulating local scale malaria transmission?
- 4. Can a simple energy balance model, driven by derived input fluxes, produce accurate prediction of water temperatures that are typical of mosquito developmental habitats?
- 5. Does VECTRI provide reliable malaria transmission patterns in Ghana?

1.6 Outline of the thesis

The work is organized into seven chapters. Chapter one has given a brief overview of the motivation, objectives and justification of the study. Chapter two provides a detailed review of the present state of malaria distribution and transmission dynamics. The chapter further presents current gains in dynamical modeling approaches to understand malaria transmission as well as existing challenges.

The next four chapters are based on four manuscripts submitted to peer-review journals for publication as a result of this thesis work. Chapter three deals with the development and evaluation of prognostic geometrical model. The chapter provides an answer to the first research question and partly addresses the second question. Part of the second question is answered in Chapter four. In addition, chapter four deals with an evaluation of the potential of the developed prognostic scheme implemented in VECTRI model and the default VECTRI hydrology scheme to simulate local scale surface water dynamics. Furthermore, this chapter explores the impact of the differences in these two hydrology schemes on VECTRI simulated malaria transmission at a single location. The results provide a comprehensive answer to the third research question. Chapter five assesses the potential of a simple energy balance scheme to represent water temperature dynamics relevant for larvae development. Answers to the fourth research are provided in this chapter. The sixth chapter demonstrates the potential of VECTRI model to predict spatio-temporal variability in malaria transmission in Ghana which provides an answer to the last research question. Finally, the last chapter concludes the thesis by presenting the summary of the main findings drawn from the whole study and suggestions for policy action and possible future modifications of the VECTRI model.

CHAPTER 2

KNUST

Literature review

2.1 Overview of malaria

Malaria transmission is an interplay between the *Anopheles* mosquitoes, the *Plasmodium* parasites, the human host and favourable hydroclimatic and environmental variables that support the development and survival of the vector and the parasite. The disease transmission is through the bites of infective female *Anopheles* mosquitoes, and therefore disease transmission depends on their existence.

Traditionally it has been understood that human malaria is caused by four distinct parasites belonging to genus *Plasmodium: Plasmodium falciparum, Plasmodium vivax, Plasmodium ovale* and *Plasmodium malariae*, although now it is also known that *Plasmodium knowlesi* causes malaria in humans (Cox-Singh et al., 2008). The parasite exhibits a complex replication and life cycle that involves two distinct stages: asexual replication (within vertebrates/host) and sexual replication (within mosquito/vector). Plasmodium falciparum, which is transmitted by mosquito Anopheles gambiae, is the most lethal form of human malarial pathogen, affecting 200-300 million individuals per year worldwide (Bozdech et al., 2003). It is predominately confined to tropical and subtropical regions and is the primary cause of malaria in sub-Saharan Africa (SSA) (Hay et al., 2009). Plasmodium falciparum is developed over 48 hours in the red blood cells producing around 20 merozoites per mature parasite (Miller et al., 2002) and has the shortest incubation period, relative to the other parasites and usually takes about 12 days. *Plasmodium vivax* is the most widely distributed of the four species and is the second most dangerous form of human malaria with 48 hours periodicity. According to Mendis et al. (2001), Plasmodium vivax is estimated to account for approximately 70-80 million global malaria cases annually, with SSA accounting for approximately 10-20% of the cases and majority of cases coming from Middle East, South East Asia, and the Western Pacific. Plasmodium malariae has similar geographic distribution as that of *Plasmodium falciparum* but with a development cycle that lasts on average of 72 hours (Collins and Jeffery, 2007) which is the longest incubation period of all the parasites. *Plasmodium malariae* infections not only produce typical malaria symptoms but the parasite may remain inactive in the liver for very long periods, possibly decades, without ever producing symptoms but can come out of the hibernation to cause malaria. *Plasmodium ovale* (restricted within the tropical West Africa) also exhibits 48-hour asexual schizogonic developmental cycle, and like Plasmodium malariae, exhibits relapse infection. The transmission of *Plasmodium ovale* was thought to SANE NO be restricted to tropical

Africa, however, recently there has been reported cases outside tropical Africa (Lysenko and

Beljaev, 1969).

2.1.1 Life Cycle of Plasmodium Parasite

Transmission of malaria from one person to another is through the bite of infective female *Anopheles* mosquito. This is shown schematically in Fig. 2.1. During feeding, the infective mosquito injects salivary fluids containing the *sporozoites* into the bloodstream of the host, and thus initiates host infection. The *sporozoites* enter the circulatory system and rapidly invade the liver cell, usually within one hour after a bite (Goldsmith, 2010). Once inside the liver cell, the parasite undergoes an asexual replication to form *schizont* resulting in the production of *merozoites* (Makler, 1992). This process lasts between 5 and 16 days depending on the *Plasmodium* species (*Plasmodium falciparum*: 5-7 days; *Plasmodium vivax*: 6-8 days; *Plasmodium ovale*: 9 days; *Plasmodium malariae*: 12-16 days) (Ngasala, 2010). However, some *sporozoite* from *Plasmodium vivax* and *Plasmodium ovale* infections remain dormant in the liver for months or years to form *hypnozoites* before asexual replication. The relapse parasite development can be reactivated later to cause future infections (Krotoski, 1988).





Figure 2.1: The cycle of the malaria parasite between human hosts and mosquitoes.

Once the *schizont* matures, it bursts to release the *merozoites* and quickly enters the red blood cells. The parasite feeds on hemoglobin while asexual replication continuous with release of additional *merozoites* into the red blood cell. This cycle of invasion and maturing of new blood cell by *merozoites* is completed and repeated every 48 hours for *Plasmodium falciparum*, *Plasmodium ovale* and *Plasmodium vivax* (tertian periodicity), but 72 hours for *Plasmodium malariae* (quartan malaria) and *Plasmodium knowlesi* requires only 24 hours (Ngasala, 2010). The disease infection and complication occurs from this cycle and is continuous until it is brought under control through either treatment or immune system of the body.

In addition, some of the *merozoites* that invade the red blood cell fail to undergo asexual replication but instead form one nucleus *gametocytes* male and female sexual cells (Miller

et al., 2002). During feeding on an infected host, the female *Anopheles* mosquito ingests the *gametocytes* along with human blood to start the *Plasmodium* sexual life cycle.

Parasite development in an uninfected female *Anopheles* mosquito begins with ingestion of blood containing *gametocytes* when feeding on an infected host. Inside the mosquito gut, the female and male gametes fertilize to form *zygote*. After some hours, the *zygote* develops into elongated actively mobile cell *ookinetes*, which penetrates the mid-gut to form *oocysts*. At this stage, the multiplication of the *sporozoites* takes place inside the *oocysts* until it matures. After maturation, *oocysts* rupture and release the *sporozoites* which migrate to the mosquito salivary glands to complete the sexual stage of the life cycle. The infected mosquito injects the matured *sporozoites* into human host during feeding to initiate the asexual stage. The duration between the time of ingestion of the parasite by the mosquito and the time it becomes infectious (*sporogonic* cycle) is about 6-12 days (WHO, 2010) which depends on ambient temperature (Nikolaev, 1935). In addition, transmission is sustained only if mosquitoes live long enough to complete this cycle.

2.1.2 Symptoms of malaria

Early clinical symptoms of malaria are similar to other viral infections and typically include periodic fever and chills, usually associated with headache, elevated body temperature, fatigue, vomiting and diarrhea (Hänscheid, 1999). In addition to these general symptoms exhibited by all the *plasmodium* parasites, *plasmodium* falciparum infections can be life
threatening leading to further complications including disruption of blood circulation, cerebral malaria, acute renal failure and coma (WHO, 2010). Due to the rapid replication of the parasite, the patient may die within few hours if treatment is delayed (CDC, 2004). Despite this, *plasmodium falciparum* is not always fatal, especially within highly endemic regions where human population have developed natural immunity due to repeated infections. This is not the case for children; it is estimated that one out every five children suffering from cerebral malaria results in death (Goldsmith, 2010).

2.2 Mosquito life cycle

The study of each stage of the mosquito life cycle is very important for understanding malaria transmission. All mosquitoes go through four basic developmental stages in their life cycle consisting of two parts: the aquatic stage (i.e., egg, larvae and pupae) and the terrestrial or adult stage. The various developmental stages and the relevant climatic factors that interact to influence the development are shown in Fig. 2.2.





Figure 2.2: Schematic diagram illustrating the mosquito life cycle and the various climatic variables influencing each stage. Adapted and modified from Smith et al. (2013).

2.2.1 Egg stage

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), clean or polluted (Sattler et al., 2005; Awolola et al., 2007; Chinery, 1984) and of various sizes from hoof-prints of animals to the edges of large water bodies (Sattler et al., 2005; Mutuku et al., 2006b; Imbahale et al., 2011), although individual species have preferences of habitat type. For example, *Anopheles gambiae* complex mosquitoes, the principal malaria vector in Sub-Sahara Africa, prefer small (example, cattle hoof prints), temporary and sunlit water bodies for their breeding, which become abundant during the rainy season (Mutuku et al., 2006a; Minakawa et al., 2004), although their larvae have also been found in polluted waters (Imbahale et al., 2011; Awolola et al., 2007; Sattler et al., 2005). Adult females lay between 50 and 200 eggs per oviposition which takes between 2 and 4 days but can be longer depending on temperature after blood meal (Becker et al., 2010). The eggs are laid on the water surface, either singly (*Anopheles*) or in rafts (*Culex*), and are hatched within a week depending on water temperature of the habitat and the mosquito species. The factors that determine the choice of oviposition site of gravid mosquito remain unknown, however some proxy factors have been proposed. According to Becker et al. (2010) factors such as water quality, incidence of light, existing eggs, available food, and local vegetation may play an important role in the choice of a particular mosquito.

2.2.2 Larvae stage

The eggs are hatched within two to three days in contact with water depending on water temperature. The legless larvae undergoes four distinct transformations (instar) prior to reaching the pupal stage. Most larvae have siphon tubes for breathing and hang from the water surface but *Anopheles* larvae do not have a siphon and they lay parallel to the water surface. This stage of the mosquito life cycle experiences high mortality rate due to both biotic and abiotic factors.

Aboitic factors like temperature and rainfall influence the survival of larvae as high intensity rainfall flushes larvae from their habitats (Paaijmans et al., 2007) and larvae can be exposed to temperatures outside the viable range for mosquitoes development (Haddow, 1943; Bayoh and Lindsay, 2004; Kirby and Lindsay, 2009). In addition, biotic factors such as the presence of predators, crowding, competition with other species, availability of nutrients and substrate type affect larval survival and thus influence habitat productivity (Minakawa et al., 1999; Schneider et al., 2000; Koenraadt and Takken, 2003; Ye-Ebiyo et al., 2003; Fillinger et al., 2009). The consequence of this interaction between biotic and aboitic factors is that small fraction of the larvae are able to reach the adult stage. For instance, between 2-8% survivorship has been reported (Service, 1977; Aniedu et al., 1993; Mwangangi et al., 2006).

2.2.3 Pupae stage

After the fourth instar, larvae pupate which is resting and non-feeding stage. This stage usually lasts for about two days but the duration can be reduced or extended depending on water temperature of the breeding habitat. During this stage, metamorphosis takes place where pupal skin splits and the mosquito emerges as an adult. Any aquatic habitat that supports full completion of these three stages can be classified as productive (Gianotti et al., 2009).

2.2.4 Adult stage

The emerging adult mosquito rests temporarily on the surface of the water until it is able to fly. Mating occurs within the few days after emerging from the pupal stage. The female mosquitoes locate a potential blood meal host for feeding. After feeding, the protein in the blood meal is used for eggs development. Once the eggs are fully developed, which usually takes between 2 and 3 days depending on ambient temperature (Gillies, 1953; Detinova, 1962), the gravid mosquito locates suitable water body for oviposition. This feeding and oviposition cycle (*gonotrophic* cycle) repeats itself until the female dies. Temperature, rainfall and humidity significantly influence the life span of the adult mosquito. In addition to these climatic variables, wind speed also influences mosquito dispersal ability in searching for host and oviposition sites.

2.3 Impact of climatic and environmental variability on malaria

transmission

Temperature and rainfall are two key climatic parameters influencing malaria transmission (see Fig. 2.2), although relative humidity and wind speed are also important. In addition to climatic variables, environmental parameters are equally important, modifying the existing equilibrium between vector, host and parasite. More importantly, all these factors do not act in isolation, however, what needs to be considered is their collective influence on the biology of the disease and vector development.

2.3.1 Temperature and malaria transmission

Temperature is one important abiotic environmental factor that influences the entire life cycle of mosquitoes (see Fig. 2.2) as well as malaria parasite development rate (Detinova, 1962; Garrett-Jones and Grab, 1964; Kirby and Lindsay, 2004; Bayoh and Lindsay, 2004). Temperature regulates mosquitoes vectorial density in an area by increasing or decreasing the time required for larval development to adult emergence, shortening the life span of the adult mosquito and can even stop development at any stage of the life cycle below or above threshold temperatures (see Fig. 2.3 for temperature range that supports key transmission cycles). In addition, the *plasmodium* parasite development is linked with temperature

variation.



Figure 2.3: Temperature impacts on (a) sporogony; (b) vector survivability; (c) vectors surviving sporogony; and (d) larval duration. Adapted from Craig et al. (1999)

The aquatic stage developmental rate is highly temperature dependent provided that the biotic conditions are favourable. Extensive laboratory experiments have been conducted to understand how water temperature influences the aquatic life cycle of mosquitoes. For example, Bayoh and Lindsay (2003) showed that *Anopheles gambiae sensu stricto* emerge

as adults only when water temperatures ranged between 18 and 34°C. Most adults emerge between 22 and 26°C. In a related study by Bayoh and Lindsay (2004), when larvae were reared at constant temperatures from 10-40°C, they survived less than 7 days at temperatures of 10-12°C and 38-40°C and no adult mosquito were able to emerge. Adult mosquitoes could only be produced between water temperatures of 18 and 32°C. The optimum temperature in which development of larvae is favoured was found to be 27°C by Lyimo et al. (1992) when larvae were reared at constant temperatures (24, 27 and 30°C) in the laboratory.

Water temperature also controls larval longevity and survival. For instance, Bayoh and Lindsay (2004), observed larval survival ranged between 10 and 38 days at constant temperature of 18°C whereas at 32°C longevity varied between 5 and 13 days. Similarly, Kirby and Lindsay (2009) observed, as expected, rapid development rates but decreases in survival rates with an increase in water temperature when larvae were reared at constant temperatures of 25, 30 and 35°C. At the upper temperature threshold where development time is short, it is associated with a high larval mortality rate (Bayoh and Lindsay, 2004; Kirby and Lindsay, 2009). The variation in development times of the larvae within these range of temperatures have additional impacts on the survival probability of adult mosquitoes in natural settings. At the lower temperatures, larvae are subjected to predation over longer periods and there is also the possibility of the habitat drying out.

Furthermore, ambient temperature substantially influences adult mosquito feeding rates and life span. Although increasing temperature shortens the *gonotrophic* cycle (Afrane et

SANE

24

al., 2005), extreme temperatures generally limit survival times of mosquitoes. For instance, when adult mosquitoes were exposed to constant temperature of 40°C, Kirby and Lindsay (2004) observed survival duration of less than a day for *Anopheles gambiae s.s.*. However, *Anopheles arabiensis* survived up to a day. In addition, adult mosquitoes tend to feed frequently at warmer temperatures due to rapid digestion of blood meal. The consequence is that the the female mosquito becomes infective within fews days after biting infectious host.

In addition, development of parasite inside the mosquitoes is only possible within certain environmental temperature range. Higher temperature shortens the incubation period of the parasite and below certain temperature, sporogony failed to occur. For instance, threshold temperatures for *plasmodium falciparum* and *plasmodium vivax* development are 16°C and 15°C, respectively (Nikolaev, 1935). The upper threshold for parasite development ranges between 33 and 39°C (Patz and Olson, 2006). Within this range of temperatures, rate of development increases with temperature. For example, the *plasmodium falciparum* development completes in 10 days and 27 days at constant temperatures of 30°C and 20°C, respectively (Macdonald, 1957). Despite this trend of parasite development with temperature, higher temperatures do not necessarily lead to increase in malaria incidence as too high temperature is detrimental to adult mosquito survival.

2.3.2 Rainfall and malaria transmission

Rainfall is a key determinant of mosquito density (Fillinger et al., 2004; Minakawa et al., 2005) and in addition influences the life span of adult mosquitoes. The availability, area coverage and persistence of temporary surface water (which serves as developmental habitat for gravid mosquitoes) are tied with depth, intensity and frequency of rainfall. In addition, rainfall indirectly influences activity and life span of adult mosquitoes through its effect on surface humidity,

Attempts to link rainfall incidence to malaria vector abundance and disease incidence have yielded varied results in different geographical locations. For instance, the 1997 El Ni^{*} *no* southern oscillation (ENSO) caused an increase in rainfall in parts of eastern Africa leading to a malaria epidemic in southwest Uganda (Kilian et al., 1999), but conversely a reduction in malaria cases was observed in the Usambara Mountains of Tanzania (Lindsay et al., 2000). In Botswana, Thomson et al. (2006) developed a malaria early warning system based on multi-model ensemble prediction of precipitation and found that the relationship between November-February precipitation and the anomaly in malaria incidence is best explained by a quadratic relationship with malaria incidence decreasing once rainfall exceeded a certain threshold. In Malawi, Lowe et al. (2013) found a similar quadratic relation.

Similar nonlinear linkage between rainfall patterns and both larvae and vector density has been reported. Kelly-Hope et al. (2009) observed a weak correlation between precipitation and abundance of mosquito vectors with a correlation coefficient (r^2) of 0.246 and 0.315 for Anopheles gambiae s.s and Anopheles arabiensis respectively. Similarly, Molineaux and Gramiccia (1980) found a poor correlation between mosquito abundance and seasonal rainfall using data from Garki district in northern Nigeria. In addition weak positive correlation between annual rainfall and adult mosquito density has been reported (Kelly-Hope et al., 2009).

Furthermore, in Banizoumbou village in southwestern Niger, Bomblies (2012) showed that temporal patterns of individual rainfall events can explain a large part of the variance in mosquito abundance, partially explaining previously observed poor correlations which typically consider monthly or seasonal total precipitation. In relation with larvae, interesting findings have been reported. For instance, in western Kenya, Imbahale et al. (2011) observed that an increase in weekly rainfall intensity resulted in an increase in mosquito larval abundance with fourteen day time lag in Fort Ternan (highland village), but caused a reduction in larval density in Nyalenda (peri-urban area). The nonlinear relationship of mosquito abundance to precipitation is poorly understood and may be partially due to intense rainfall reducing larvae density by flushing first stage larvae (Paaijmans et al., 2007).

2.3.3 Relative humidity and malaria transmission

Relative humidity prolongs mosquito survival (Wernsdorfer and MacGregor, 1988) and influences dispersal range (Shaman and Day, 2007) of adult mosquitoes. For example, Molineaux et al. (1988) reported 60% as the minimum relative humidity that supports malaria transmission because adult survival is reduced below this relative humidity value. Jawara et al. (2008) observed that increase in relative humidity resulted in an increase in *Anopheles gambiae s.l.* abundance. Similarly, in the Nile basin, Wernsdorfer and Wernsdorfer (1967) found daily mortality rates of 5% and 15% for *An. gambiae* at relative humidities of 65% and 50% respectively. Bhattacharya et al. (2006) using 30-year average monthly mean data found a relative humidity ranging between 55 to 80% to be favourable for malaria transmission with temperature within the transmission range (15-35°C). In Burkina Faso, Yé et al. (2007) observed a nonlinear relationship between relative humidity and clinical malaria risk among children under five years. Although there is no direct relationship between relative humidity and parasite development inside the mosquito, the former influence on the vector longevity indirectly allows the parasite to develop completely in the mosquito.

2.3.4 Wind speed and malaria

Wind speed and direction is important in malaria transmission in terms of passive dispersal and distribution of the vectors. Due to wind action, mosquito flight range varies on the order of 1 to 5 km (Gillies, 1961; Rowley and Graham, 1968; Thomson et al., 1995). In addition, the ability of a mosquito to locate their host through the body odor and carbon dioxide plumes is controlled by wind direction and speed (Healy and Copland, 1995). However, extreme strong winds could also blow mosquitoes away from their host thereby reducing biting rates considerably.

2.3.5 Land use change and malaria

Land use and land cover changes such as deforestation, urbanization, agriculture, irrigation among others significantly influence the spatio-temporal distribution of malaria by creating or destroying suitable vector development habitat. In addition, land use modifications can change the microclimate to support or suppress local scale transmission dynamics. For example, in Uganda, Lindblade et al. (2001) found a significant high malaria patterns among villages located along swamps converted to farm land relative to natural papyrus swamps. Land cover changes also impact the larval development rate through its effects on water temperature of developmental habitats. For instance, in western Kenya highlands, Wamae et al. (2010) observed difference in maximum water temperature as much as 5.7°C between habitats located along non-shaded and shaded channels. Consequently, they observed high anopheline larvae density at the non-shaded area relative to the shaded area. In a related study, Afrane et al. (2008) observed a decrease in the length of the sporogonic cycle by 1.1 days due to deforestation. Thus, these changes in turn would be expected to have a potential impact on the local malaria transmission and should be accounted for in latest generation of dynamical disease models to simulate spatial heterogeneities in disease W J SANE patterns.

BADH

2.3.6 Urbanization impacts on malaria

Malaria burden within the urban areas are less relative to the rural settings (Robert et al., 2003), nevertheless transmission is still high. For example, Keiser et al. (2004) estimated between 24.8 and 103.3 million clinical malaria cases among urban dwellers in SSA. Due to human activities, urban transmission tends to be unevenly distributed and often more focal. It has been established that urban agriculture plays an important role in creating conducive breeding grounds. For instance, in Kumasi Ghana, Afrane et al. (2004) consistently captured more mosquitoes from urban areas surrounding irrigated farms relative to non-agricultural areas. Similar heterogeneity in the vector density and malaria incidence between irrigated and non-irrigated areas within the same locality have been reported elsewhere (Matthys et al., 2006; Dongus et al., 2009; Yadouléton et al., 2010; Sovi et al., 2013).

Another important factor accounting for heterogeneity in urban malaria transmission is the disparity in socio-economic status of the population. While wealthier households have adequate resources to protect themselves using appropriate control intervention, this is not the case for poorer households. For example, in Kumasi and Accra, Klinkenberg et al. (2006) found higher malaria parasitemia prevalence among children living in poorer households relative to their counterparts in wealthier households.

SANE

2.3.7 Local hydrology and malaria vector abundance

Due to the nonlinear relationship between habitat stability and rainfall, other studies have focused on using local hydrological parameters that are more directly connected to the surface hydrology to predict mosquito vector abundance and incidence of malaria. Patz (1998) observed an improvement in predicting An. gambiae biting rate from 8% with raw precipitation to 45% with modeled soil moisture. In a related study in South Africa, Montosi et al. (2012) found that soil moisture predicts better sub-seasonal variability in malaria cases relative to rainfall and temperature. Shaman et al. (2002) found a positive association between modeled local surface wetness with \approx 10 days time lag and abundance of Anopheles walkeri and Aedes vexans in the eastern United States. On a local scale, observed changes in surface hydrological parameters have been used to predict mosquito abundance and malaria transmission variabilities. Bomblies et al. (2009), showed intervillage difference in abundance of mosquitoes vectorial density between two villages in Niger which are only 30 km apart. This difference was due to the difference in hydrological conditions that influence the persistence time of breeding habitat after the end of the rainy season.

Furthermore, Shaman et al. (2010) demonstrated that the differences in human cases of West Nile virus between eastern plains and western mountains of Colorado are due to hydrological variability.

The key advantage of hydrological modeling lies in its ability to incorporate climatic variables, soil characteristics, topography and vegetation at smaller scales that depict the

ecology of the mosquito larvae (Bomblies et al., 2008; Patz, 1998; Gianotti et al., 2009; Cohen et al., 2010; Hardy et al., 2013; Smith et al., 2013). Despite this, in situ observations at the resolution of these mosquito development habitats are not available to evaluate these hydrology models over a wider area. In addition, due to numerous mosquito developmental habitats especially for the important vectors, explicitly modeling individual breeding sites would be expensive to run and computational time requirements make this approach impossible for regional scale simulations. However, recently Tompkins and Ermert (2013) proposed a surface hydrology scheme based on a parametrization approach that requires the representation of the net aggregated dynamics of micro habitats at each grid cell instead of modeling individual ponds. This scheme is implemented in the VECTRI model and has been successfully used to delineate periods where climate variables, particularly rainfall and temperature, significantly controls interannual variability in malaria transmission over Africa (Tompkins and Di Giuseppe, 2015). Thus, this hydrology scheme can be useful for both local and regional scale dynamical models.

2.4 Geographical distribution of malaria

Malaria is extremely sensitive to climatic variables. The intensity and spatio-temporal distribution of the disease is constrained by interaction between climatic factors, environmental conditions, vector competence, parasite, host population and control intervention. On the global scale, malaria endemicity is highly confined within the tropical and subtropical regions (see Fig. 2.4) where humid and warm climate favours the timely

development of both the parasite and the vector (Kiszewski et al., 2004; Sachs and Chambers, 2009).



Figure 2.4: The global malaria distribution map. Adapted from Hay et al. (2004).

In SSA, which experiences the majority of malaria mortality, the disease transmission dynamics can be classified as seasonal (comprising areas where temperature or rainfall limit transmission) and perennial (areas with year-round transmission). In most parts of this region, with the exception of highland areas, temperatures are almost always above the minimum threshold that favours both the vector and parasite development. However temperatures above the upper threshold are often encountered (Holstein, 1954).

Temperature limits malaria transmission over the East African highlands. The general lower temperatures in these areas negatively affect vector development and parasite replication. However, few malaria cases have been recorded for the past century over this region during periods of suitable climatic conditions. Recently, due to climate variability and other factors, the number of epidemics has substantially increased resulting in a weak level of endemicity in some parts of the region (Lindsay and Martens, 1998; Cox et al., 1999; Hay et al., 2002;

Omumbo et al., 2011).

Rainfall variability that controls surface water dynamics plays a dominant role in defining seasonal and intraseasonal vector population and disease patterns. For example, in waterlimited areas such as the Sahel, malaria transmission exhibits seasonal variation with a rapid increase in both the mosquito population and disease incidence after the onset of rain (Bomblies et al., 2008; Ye et al., 2009; Bomblies, 2012). Bomblies et al. (2008) observed that seasonal peaks in weekly malaria cases in Niger lag several weeks behind rainfall peaks. In addition, in the Sudanian region, the length of intense transmission is determined by the duration of the rainfall season. For example, in the Kassena-Nankana District of northern Ghana, Koram et al. (2003) found that seasonal increase in transmission starts from June and ends in November. Despite these, focal year-round transmission is possible in this region due to presence of permanent water bodies, such as man made dams (Dolo et al., 2004).

2.5 **Climate change and future malaria transmission**

Due to strong influence of climate drivers on interaction between the malaria vector, the parasite and the human host, changes in future climate variables are likely to create favorable conditions to alter the spatial and temporal transmission dynamics (Martens et al., 1997; McMichael et al., 2000). Consequently, the effects of global climate change on

survival and development of mosquitoes and *plasmodium* parasite and in addition, future malaria incidence variability and geographical (latitudinal and altitudinal) distribution have attracted increasing attention in recent years (Craig et al., 1999; Kovats et al., 2001; Hay et al., 2002). Within malaria endemic regions, climate change may alter seasonal temperature and rainfall patterns which can, in turn, affect disease transmission and intensity dynamics (Tanser et al., 2003). For instance, there has been a reduction in disease morbidity and mortality despite rising global mean temperatures (Hay et al., 2009; Gething et al., 2010).

Attempts have been made to attribute the recent increase in the number of malaria epidemics in most highland areas of Africa to climate change in general and rising temperatures in particular. However, considerable uncertainty with regard to the potential role of climate change still exists. While some authors associate the resurgence of malaria in the highlands to climate change, others suggest non climatic factors (Hay et al., 2000; Shanks et al., 2000; Pascual and Dobson, 2005). For instance, Hay et al. (2002) attributed rise in malaria cases to factors other than climate since there was very little change in climatic parameters over the study period between 1911 and 1995. Conversely, Pascual et al. (2006) using the same data and study sites, observed significant positive warming trend which is enough to alter mosquito population dynamics and disease transmission. A clear limitation of these two studies was that the use of mean monthly climate variables may not account for the diurnal temperature variability which is relevant for vector and parasite development rates (Paaijmans et al., 2010).

In Africa, Sahel marks the northern limit of malaria transmission due to low rainfall. However, there has been a shift between dry and wet conditions in this zone and the Sahara desert (Claussen, 1998; Wang and Eltahir, 2000). This is likely to impact the disease transmission dynamics in a number of ways. Firstly, there is potential of disease epidemic whenever climatic variables favour the survival and development of the vector and parasite inside them. For instance, Bomblies and Eltahir (2009) demonstrated that the number of rainfall events and interstorm duration is important for the disease interannual variability over the Sahel. In the Gambia, Brewster and Greenwood (1992) attributed the increase in malaria epidemic to the shorter rainy season. Secondly, there is low level of immunity among the population due to unstable patterns of the disease, thus increasing human susceptibility to influence epidemic (Kiszewski and Teklehaimanot, 2004).

Aside these fringe regions where epidemics are common, there are other uncertainties about whether climate change will lead to latitudinal shift of global malaria belt (Rogers and Randolph, 2000; Reiter, 2001; Tanser et al., 2003). Gething et al. (2010) observed reduction in both the malaria transmission intensity and geographical extent despite rise in global mean temperatures. Similarly, Tanser et al. (2003) using different climate scenarios observed insignificant latitudinal shift in malaria distribution at the end of 2100. On the contrary, (Martens et al., 1995b; 1999) predicted possibility of malaria extending to temperate regions where *Anopheles* mosquito are present but low temperature inhibits parasite development.

A possible cause of this disparity might be due to the increase in global control interventions which in effect suppress transmission (O'Meara et al., 2010). In addition, models that attempt to assess the spatial and temporal malaria distribution under future anthropogenic climate change all ignore the contribution of non-climatic factors such as

control interventions, economic development and host behaviour (Tatem et al., 2008). This tends to amplify the effect of climate variables on future projected disease transmission from models.

2.6 Malaria control

Effective control of malaria consists of minimizing host vector contact, reduction of vector population and effective case management. These control strategies include environmental management, residual spraying, insecticide treated nets, chemoprophylaxis for the vulnerable groups and laviciding. However, it is evident that a single strategy is not sufficient to be effective in controlling malaria, an integrated approach which combines multiple interventions is therefore proposed for different epidemiological settings (Killeen et al., 2004; Chanda et al., 2008).

2.6.1 Aquatic stage intervention

This is an ancient but still the most effective control method (WHO, 1982; Walker and Lynch, 2007), with the aim of preventing the completion of aquatic stage development. The aquatic stage intervention includes habitat manipulation (temporary changes to the vector habitats), habitat modification (permanent changes to vector habitats), larviciding and biological control. In spite of the successes of aquatic stage control intervention, it has been neglected in tropical Africa. A possible reason has to do with the diverse range of temporary development habitats of the prolific vectors which become abundant especially during the rainy season (Holstein, 1954). This makes larval control extremely difficult and costly targeting all available habitats. However, Gu and Novak (2005) demonstrated that not all habitats need to be covered to achieve the desired impact. For instance, they showed that targeting 30% of the productive habitats for effective larval control translated to a 70% reduction in the total habitats productivity. Gianotti et al. (2009) showed that environmental (manipulation and modification) methods have the potential to control malaria over the Sahel. More importantly, aquatic stage intervention also has a significant impact on adult life span and gonotrophic cycle duration (Killeen et al., 2004; Gu et al., 2006).

Aquatic stage productivity can also be controlled through larviciding and biological agents which act as predators (Scholte et al., 2005). Although some fish species are effective predators, its application on a large scale is difficult due to the quantity of fish required (Garcia, 1983). In addition, this approach will have limited impact on temporary habitats. Furthermore, bacterial pathogens such as *Bacillus thuringiensis israelensis* and *Bacillus sphaericus* have been reported to be effective against mosquito larvae (Das and Amalraj, 1997; Mittal, 2003; Raghavendra et al., 2011; Abdul-Ghani et al., 2012). These microbial agents are considered safe for the environment and humans. However, biological control agents tend to be species specific and their efficiency varies under different ecological conditions (Das and Amalraj, 1997).

For effective and efficient larval control method, a model that accurately simulates the stability of development habitats would therefore be useful in identifying the productive habitats. For example, if the model is able to predict habitats persistence times, then pools with stability less than 7 days are unproductive and should be neglected for aquatic stage intervention.

2.6.2 Prevention of host vector contact

The adult mosquito control strategies rely on insecticide-based interventions such as insecticide-treated nets (ITNs) and indoor residual spraying (IRS) of insecticide. These are the current preferred control strategies (Malaria, 2008), and its purpose is to prevent or reduce contact between the host and the vector.

The ITNs which were later improved to long-lasting ITNs (LLINs) that do not require retreatment is the most common and widely accepted adult control strategy. This approach prevents host vector contact in three different ways: the insecticide kills some of the mosquitoes after some exposure time, the net acts as a barrier and the insecticide also works as repellent. This intervention tool proved to be successful in reducing disease transmission and child mortality due to malaria in SSA as well as other endemic regions (Lengeler, 2004). Even though ITNs have been recommended as one key malaria control strategy, they tend to be less effective for predominantly exophilic and exophagic vectors (Hill et al., 2007). Consequently, it is clearly necessary to implement ITNs in addition with other strategies aimed at reducing vector population to achieve greater impact. In addition, due to the single use of pyrethroid insecticide to treat the bed nets, the malaria vectors are

39

increasingly developing resistance to it (Coleman and Hemingway, 2007). This calls for an alternative insecticide development.

The IRS strategy for malaria control reduces transmission by decreasing the daily survival rate of mosquitoes. It is one of the widely used methods for vector control and became very popular and mainstay during first global malaria control programme using dichlorodiphenyltrichloroethane (DDT) as the insecticide (Robert et al., 2003). Although DDT was successful in the regions of low transmission, it failed to make significant impact in Africa. This was partly due to development of resistance to DDT among *anophelines* species in Africa (Coleman et al., 2006). Similarly, resistance to alternative insecticides such as carbamates, dieldrin and pyrethroids used for IRS have been reported especially in Africa (Ryciak and Vujoen, 1999; Coleman et al., 2006). Aside these, IRS is less effective in the control of mosquitoes which rest and bite outdoors (Najera and Zaim, 2001).

2.7 Malaria in Ghana: An Overview

Malaria is hyperendemic with year-round transmission in Ghana and remains a key major threat to public health (NMCP, 2008). The disease has consistently been the leading cause of morbidity, mortality and productivity loss due to work loss days in the country. For example, GHS (2011) report indicates that suspected malaria cases account for about 40.2% outpatient morbidity, 35.2% hospital admissions and 18.1% of all recorded death at the hospitals. This high percentage of hospital visits attributed to malaria has been the same over the past years. The average of all outpatient cases due to malaria between 2000 and 2011 is about 40%. Although the whole population is at risk of malaria, high mortality and morbidity are among children under-five years and pregnant women. For instance, GHS (2009) estimated that up to 30% and 11% of all mortalities in children less than 5 years and pregnant women respectively, in Ghana are related to malaria.

2.7.1 Socio-economic costs of malaria in Ghana

Malaria has a significant impact on Ghana's economy due to cost of treatment and loss of productivity days as those severally infected are unable to work (Asenso-Okyere, 1994; Asante and Asenso-Okyere, 2003; Akazili et al., 2008; Okorosobo et al., 2011; Sicuri et al., 2013). For instance, Asante and Asenso-Okyere (2003) found a negative association between malaria cases and Gross Domestic Product (GDP). Their model estimated 0.41% decrease in GDP for 1% increase in the malaria morbidity. In a related model study, Sicuri et al. (2013) estimated annual total cost of malaria treatment and prevention for children under-five years to be US\$ 37.8 million in 2009. In addition, they estimated the expenditure for treating a single malaria episode to range between US\$ 7.99 and US\$ 29.24 depending on disease severity. A large fraction of Ghana's health budget goes to treatment and prevention of malaria and also remains a major threat to sustainability of the National Health Insurance Scheme (NHIS) (Dontwi et al., 2013).

On the household level, Asenso-Okyere and Dzator (1997) estimated average treatment cost of a single malaria episode to be US\$ 8.67 in two districts in the Ashanti region. The estimated amount, which includes both direct and indirect costs, is equivalent to 3.7 or 4.7

SANE NO

average working days loss to male or female patients respectively. In a related study, Akazili et al. (2008) found the cost of malaria treatment to be about 34% and 1% of the incomes for poor and wealthy households respectively, in the Kassena-Nankana district in the Upper East region. Malaria therefore is not only a serious health issue but also has significant economic implications for the country and individual households (the patient). As a result, more studies need to be carried out to understand the vector dynamics, assess the present control strategies and to provide an integrated approach best suited for the nation to reduce the burden, but to do those things we need better dynamical models of malaria.

2.7.2 Distribution of malaria vectors in Ghana

Similar to other SSA countries, *Anopheles gambiae sanso lato complex* and *Anopheles funestus* are the key and most abundant malaria vectors in Ghana (Appawu et al., 1994; 2004; Yawson et al., 2004; GHS, 2009; De Souza et al., 2010; Kasasa et al., 2013; Dadzie et al., 2013). *An. gambiae s.s., An. arabiensis* and *An. melas* are the three species within the *Anopheles gambiae sanso lato* complex found in Ghana (Appawu et al., 2004; Yawson et al., 2004). The *An. gambiae s.s.* are the most common within the complex and are distributed throughout the malaria epidemiological zones in Ghana (De Souza et al., 2010) as shown in Fig. 2.5. However, the other two vectors have limited distribution within the country with *An. arabiensis* being the predominant vector in the savannah and coastal regions while *An. melas* are confined within the mangrove swamps along the coast (Yawson et al., 2004; De Souza et al., 2010). Although their study did not cover the entire country, it

indicates to some extent that *Anopheles gambiae sanso lato* mosquitoes are distributed countrywide. Regarding *An. funestus*, Dadzie et al. (2013) found *An. funestus sensu stricto* is the only malaria transmission vector in the sub group found in the country. Although *An. funestus sensu stricto* are found all over the country, they are predominant in the savannah area



Figure 2.5: An. gambiae s.l mosquitoes distribution map. Adapted from De Souza et al. (2010).

The distributions of these vectors are heterogeneous and follow climate and ecological conditions (Appawu et al., 1994). For instance, GHS (2009) found that about 95% of all mosquitoes caught are made up of *An. gambiae* complex and *An. funestus*. Similarly,

Yawson et al. (2004) found that *Anopheles gambiae s.l.* and *An. funestus* are sympatric in eleven different locations within the country. In Kassena-Nankana district of northern Ghana, Kasasa et al. (2013) sampled adult mosquitoes using Center for Disease Control (CDC) light traps over a three year period and found 52% constituting *An. gambiae* and the rest *An. funestus*. In Kintampo within the transition belt of Ghana, Dery et al. (2010) using similar method found more *An. gambiae* than *An. funestus* in 2004 but *An. funestus* dominated the

2005 catch. Similarly, a study in a village within the coastal savannah belt, Tchouassi et al. (2012) collected about 99.5 % *An. gambiae s.l.* relative to 0.4 % of *An. funestus*.

Clearly these results show that malaria vectors are present within all the ecological zones of the country and thereby putting the whole population under malaria risk. In addition, these studies are limited to specific locations and therefore extensive vector survey all over the country is required to provide a detailed spatial and temporal distribution of malaria vectors.

2.7.3 Malaria Parasites in Ghana

In Ghana, three out of the four main species of human malaria parasites are present. *Plasmodium falciparum*, the most severe and life threatening, is predominant in the country accounting for about 80 to 90% of all malaria infections. This is followed by *Plasmodium malariae* responsible for between 20 and 36% of malaria cases while *Plasmodium ovale* is less prevalent accounting for less than a percent (about 0.15%) of all malaria parasitemia (Klinkenberg et al., 2005; Koram et al., 2003). Moreover, mixed infections of *Plasmodium falciparum* and *Plasmodium malariae* are also common. For instance, in Accra, Klinkenberg et al. (2005) detected a single case of mixed infection of *Plasmodium falciparum* and *Plasmodium malariae* for a three month study period among children between 6 and 60 months of age. However, 258 out of the 261 infections detected were due to *Plasmodium falciparum* with 2 cases of *Plasmodium malariae*. Similarly, in the Kassena-Nankana District located within the savannah zone, Koram et al. (2003) identified 963, 63 and 36 cases of *Plasmodium falciparum*, *Plasmodium malariae* and mixed infections of the two, respectively. In addition, Dinko et al. (2013) found all the three species in the Ahafo Ano

South District of the Ashanti region which is within the forest ecological zone.

2.7.4 Spatio-temporal malaria distribution in Ghana

Malaria transmission occurs throughout the year in Ghana, however, significant variability exists between the three main malaria epidemiological zones. These differences in malaria incidence are due to a combination of factors such as vector and parasite distribution (Afari et al., 1992; De Souza et al., 2010), climate drivers (Dery et al., 2010; Donovan et al., 2012) and land use change (Klinkenberg et al., 2008; Okoye et al., 2005). On the impact of climate variables, rainfall tends to control the temporal distribution of malaria vectors as temperature most of the time is within the range favorable for mosquito survival and parasite development. For instance, in the northern savannah epidemiological zone covering the three northern regions, transmission is intense but seasonal due to a prolonged dry season (Baird et al., 2002; Appawu et al., 2004). Within this zone, Appawu et al. (2004) found an average decrease in human biting rate (bites/person/night) from

45

about 24.3 in the wet season to about 8.3 in the dry season. In addition, they observed increase in *An. gambiae s.s* abundance from the onset of rain in June and peaked in September but decrease occurred in the dry season. Similarly, in the Kassena-Nankana District in the Upper East Region, Baird et al. (2002) found incidence density approximately between 5 and 7 infections/person/year for the dry and wet seasons respectively among children with age range between 6 and 24 months. In the same district in 2011, Koram et al. (2003) found a significant increase in prevalence of malaria parasitaemia from 22% in May representing the lowest in the dry season to 61% in November the highest in the wet season.

This variation of malaria transmission levels due to seasonal rainfall patterns does not only pertain in the north but also other epidemiological zones. In Accra, Donovan et al. (2012) observed that seasonal peaks in malaria follow peaks in rainfall with one or two months lag time for children under five years. In this zone also, transmission in the dry season is quite high. For instance, Tchouassi et al. (2012) found mean biting rate for three anopheline species to be 11.43 bites/human/night between November 2005 and April 2006 using both human landing catches and indoor pyrethrum spray catches. Despite this, studies comparing seasonal and intraseasonal variations in malaria incidence across the various ecological zones are limited and the few available are over a short period (Danuor et al., 2010; Tay et al., 2012; Klutse et al., 2014). As a result, studies that attempt to understand these variations maybe useful to identify the appropriate time for effective control programs within various ecological zones.

2.7.5 Malaria control strategy in Ghana

The National Malaria Control Programme has prioritized the use of insecticide-treated mosquito nets (ITNs), indoor residual spraying (IRS) and effective treatment and case management as a key strategy for malaria control (GHS, 2009). Significant successes have been reported due to increased households use of ITNs. For example, in the Kassena-Nankana District, Binka et al. (1996) observed 22% reduction malaria mortality in children below four years due to provision of Permethrin impregnated bednets.

In spite of these successes, the increase *Anopheles* resistance to most widely used insecticides is a major problem. For instance, in Obuasi located in Ashanti region, Coetzee et al. (2006) found both *An. funestus* and *An. gambiae* S form to be resistant to DDT and carbamates, and in addition *An. gambiae* was resistant to pyrethroids. Similarly, Yawson et al. (2004) reported a high pyrethroid resistance gene (kdr) mutation in S molecular form relative to M molecular form of *An. gambiae* across various ecological zones. Furthermore, in four mining towns within the forest zone, Hunt et al. (2011) observed high resistance of *An. gambiae* S form to pyrethroids, DDT and carbamates, but organophosphates showed good efficacy at these study locations. Interestingly, *An. gambiae* S form is widely distributed in the country and its insecticide resistance is confounding the effectiveness of several available insecticides in vector control programmes.

2.8 Malaria models

Mathematical models have long been applied to assess potential factors that control malaria transmission dynamics and effective control interventions to reduce disease burden (Ross, 1911; Koella, 1991; Chitnis et al., 2010; Mandal et al., 2011). Ross (1911) developed the first mathematical model based on few sets of differential equations that describe how malaria parasite is transmitted between mosquito vectors to human hosts and vice versa. This model was further improved by Macdonald (1957) by introducing additional factors such as latent period of infection to account for Anophelines population that are infective and are able to transmit the disease. The key conclusion from the Ross-Macdonald malaria model was that malaria transmission strongly depends on both sporogonic rate and mosquito life span and hence effective eradication of malaria in any region requires reduction of Anopheles mosquitoes density below certain threshold (Ross, 1928; Macdonald, 1956). The findings from this model became the basis for early malaria control programmes involving reduction of mosquito population through DDT application, larviciding and breeding habitat elimination. Despite the success of this simplified model, it was criticized for ignoring incubation periods of the parasite in mosquitoes and immunity in the human host. A significant number of malaria models have been developed by extending the Ross-Macdonald malaria model using different approaches or methodologies. Some of the available models are differential equation-based (Dietz et al., 1974; Koella and Antia, 2003; Hoshen and Morse, 2004), agent-based or individual-based (Bomblies et al., 2008; Gu and

Novak, 2009; Zhou et al., 2010; Griffin et al., 2010; Arifin et al., 2011; Tompkins and Ermert,

48

2013), habitat-based (Gu and Novak, 2005; Gu et al., 2008) and integrated (McKenzie and Bossert, 2005; Smith et al., 2008). Some of the models have been applied to assess the potential impacts intervention (Gu and Novak, 2005; Gianotti et al., 2009; Griffin et al., 2010), climate change or variability (Tanser et al., 2003; Tonnang et al., 2010; Parham and Michael, 2010) and immunity (Aron, 1988).

2.8.1 Statistical models

Considerable research has been focused on using statistical models to assess the relationship between malaria incidence variability and variation in environmental variables influencing disease vector dynamics (Rogers and Randolph, 2000). Most of these statistical models are mostly based on regression approaches and other statistical techniques to establish a link between past malaria cases to observed climate anomalies, particularly rainfall and temperature to make prediction of present and future disease incidence and distribution (Githeko and Ndegwa, 2001; Tanser et al., 2003; Thomson et al., 2006; Tonnang et al., 2010). The disadvantages of statistical models include difficulties in applying the models across different geographical locations. In addition, the predictability of statistical based models largely depends on the quality and span of the data to which they are trained. This approach has been used to assess the impact of climate change on malaria distribution (Tanser et al., 2003), parasite prevalence at different agro-ecological zones (Kleinschmidt et al., 2001).

2.8.2 Dynamical models

The dynamical models instead explicitly model the key fundamental equations driving the malaria transmission dynamics. This class of models has the advantage of being able to incorporate day-to-day and even diurnal variations in climate variables' impact on various stages of vector and parasite life cycles. The main difficulty here has to do with better understanding of relative influence of biological and ecological factors on all aspects of the disease to aid in the formulation of equations to represent them in the model. This has been one difficult aspect of dynamical models approach as knowledge about certain aspects of disease biology are not clearly understood and therefore difficult to represent dynamically (Rogers and Randolph, 2000). Nevertheless, the main advantage of this approach is that it can be applied in other areas aside where the model was calibrated.

These models have been employed to predict mosquito distribution (Shaman et al., 2002), local scale transmission dynamics (Bomblies et al., 2009), transmission under future climate scenarios (Caminade et al., 2014; Pointek et al., 2014), effects of malaria control strategies (Killeen et al., 2004; Gianotti et al., 2009) and in addition used as forecasting and early warning tool (Jones and Morse, 2010; 2012; Tompkins and Di Giuseppe, 2015). Despite the successful application of these models, considerable improvements in the representation of some key factors are still required. Among these is the surface hydrology and habitat water temperature which improvement is the focus this study.

2.9 Representation of surface hydrology and water temperature in dynamical models

Despite the importance of surface hydrology and water temperature for larvae development and survival, their representation in dynamical models is still inadequate especially for regional scale models. For instance, Hoshen and Morse (2004) relate the oviposition rate to a 10 day rainfall rate in the Liverpool Malaria Model (LMM). In addition, the LLM completely neglects the influence of water temperatures on the larval development since the aquatic stage duration is constant in the model (Hoshen and Morse, 2004; Ermert et al., 2011a;b). Consequently, this model is more likely to produce inaccurate prediction of transmission dynamics in rainfall limited areas dominated by semi-permanent and permanent habitats. In another regional scale model, Open Malaria Warning (OMaWa), Lunde et al. (2013b) parametrized surface hydrology as a function of river length and soil moisture based on the assumption that potential habitats are located within the vicinity of rivers and lakes. In their model, habitat water temperature was equated to mean top soil temperature obtained from the NOAH land surface model. This model may have limited application in areas of relatively flat topography where habitats are only rain-fed and can be located far away from permanent water bodies. Further uncertainties could arise from the difference between actual water temperature and the proxy temperature leading to inaccurate larvae development rate. In another recently introduced regional scale dynamical malaria model VECTRI, Tompkins and Ermert (2013) used a simple surface hydrology parametrization scheme that predicts the evolution of the fractional water coverage within each grid cell. The scheme is highly simplified and neglects many factors,

including topographical slope, soil texture, pond geometry and heterogeneity in water infiltration rates. For example, the rate of infiltration decreases towards the middle of these temporary ponds due to the effect of clogging by sediment over time (Desconnets et al., 1997; Martin-Rosales and Leduc, 2003). This nonlinearity in infiltration relation will therefore lead to constant infiltration assumptions over- or underestimating loss of water from the ponds. As another shortcoming, the VECTRI model does not incorporate scheme for water temperature, but simply use mean air temperature to drive the aquatic stage component of the model, which leads to inaccurate estimation of aquatic stage development times.

Some attempts have been made to develop more complex surface hydrology representation at local scale. For example, Depinay et al. (2004) introduced a local scale dynamical vector life cycle scheme designed to explicitly model individual breeding sites using the shapes of the water bodies in question to simulate mosquito population dynamics. Application of this model over a large region might prove elusive as it requires the knowledge of the shape of all individual ponds making its application difficult. For a complete local scale malaria model, Bomblies et al. (2008) introduced the high-resolution Hydrology, Entomology, and Malaria Transmission Simulator (HYDREMATS). HYDREMATS runs with 10 meter spatial scale grid-cells to explicitly simulate pool formation and persistence time which control aquatic stage development of mosquito for each individual pond. In order to set up this model, Banizoumbou village in southwest Niger was manually mapped at this 10 m scale using survey-grade differential GPS instrumentation. The model simulated daily water depth and showed good agreement with observations, predicting seasonal and sub-seasonal mosquito abundance (Bomblies et al., 2008). Bomblies et al.

(2009) using HYDREMATS found good agreement with observed interannual variability in mosquito abundance between two villages located 30 km apart, but with contrasting local hydrological and environmental conditions. Furthermore, HYDREMATS has been used to assess the impact of environmental management in malaria control (Gianotti et al., 2009) and the sensitivity of the model to various climate change scenarios has been evaluated (Bomblies and Eltahir, 2009). Despite HYDREMATS good performance, its application over larger scales is hindered by the intensive input data and in addition, the model require recalibration when applied at different region. However, these local scale models (e.g. Bomblies et al., 2008) can serve as proxy for in situ observations to validate regional scale surface hydrology assumptions.

In addition, there are available energy balance schemes to predict water temperature of temporary water bodies. Depinay et al. (2004) developed a simple water temperature scheme, using relative humidity to estimate cloud cover and then applied both the cloud cover and maximum air temperature to predict maximum water temperatures, whereas the minimum water temperature was equated to the minimum air temperature. However, this scheme was not evaluated with in situ data. Paaijmans et al. (2008a) developed a more detailed model that predicts the diurnal water temperature based on radiation and energy fluxes at the air-water and soil-water interfaces of small artificially created ponds of varying dimensions. Predicted temperatures agreed with in situ observations to within 2.5°C between the simulated and observed water temperature using three consecutive days of different weather conditions. Despite good model performance, the application of these models regionally over Africa is hindered by a lack of the appropriate in situ observations required to define some of the energy fluxes. This model was further simplified by
Paaijmans et al. (2008b) to use only easily obtained weather data as input, but even this modified scheme still required cloud cover observations to compute incoming shortwave radiation, a parameter not readily available from most meteorological stations.

It is clearly evident that there is still need for realistic surface hydrology and water temperature parametrization schemes that could be useful at both local and regional scales. In addition, the key driving climate variables or derived parameters should be available from meteorological stations especially across malarious regions. This thesis addresses these limitations by introducing surface hydrology and water temperature schemes that can be implemented in available dynamical models, evaluated using in situ observations.

2.10 VECTRI model overview

The VECTRI model is a grid-point distributed dynamical model designed to run at daily time step and with flexible spatial resolution that ranges from a single location to a regional scale (10-100 km) depending on the resolution of the driving climate data (for detailed review, see Tompkins and Ermert, 2013). The model uses multiple compartment structure to represent key stages in the transmission for each grid cell. The VECTRI model explicitly resolves important temperature-dependent stages such as egg-larvae-pupa development time in addition to the gonotrophic and sporogonic cycles. In addition, the model accounts for the impact of human population density in estimating daily biting rates. The progression rates of these cycles are presented in arrays of bins and the process continues to advance once temperatures are within the range for growth. This allows the model to represent the inverse relation between malaria intensity and population density (e.g. Robert et al., 2003). The model incorporates a simple but physically-based surface hydrology scheme which controls larvae development. A brief description of various schemes implemented in the VECTRI are provided below.



Figure 2.6: Schematic of VECTRI model divided into compartments representing growth stages of the vector and parasite development in the host and the vector. Adapted from Tompkins and Ermert (2013).

WJSANE

NO

2.10.1 Surface hydrology scheme

The VECTRI model incorporates a simple surface hydrological parametrization scheme that estimates at each time step the fractional water coverage area in each grid cell. Total fractional water coverage area is a sum of both permanent and temporary habitats ($w = w_{perm} + w_{pond}$), although presently no parametrization of permanent water bodies is included, allowing the user to set value for the permanent water fraction with knowledge of the study area hydrology. In this study the permanent water fraction is set to zero as detailed permanent water body data are not available. The net aggregated fractional water coverage of temporary pools in each grid cell was expressed as in Eq. 2.1:

$$\frac{dW_{pond}}{dt} = K_W P(W_{max} - W_{pond}) - W_{pond}(E+I)$$
(2.1)

where w_{pond} is net aggregated fractional water coverage in a grid cell, w_{max} is maximum temporary pond coverage area, *P* is precipitation rate, *E* and *I* which were set to a fixed constant are evaporation rate and infiltration rate respectively and K_w is a constant that links rainfall to the growth of the temporary ponds. For details see Tompkins and Ermert (2013).

The scheme is highly simplified and neglects some factors, including topographical slope, soil texture, pond geometry and heterogeneity in water infiltration rates. For example, the rate of infiltration decreases towards the middle of these temporary ponds due to the effect of clogging by sediment over time (Desconnets et al., 1997; Martin-Rosales and Leduc, 2003). This nonlinearity in infiltration relation will therefore lead to constant infiltration assumptions over- or underestimating loss of water from the ponds. The stability of ponds has also been linked with their shape. For instance, Garmendia and Pedrola-Monfort (2010) observed rapid drying of cylindrical shaped ponds relative to conic shape ponds.

2.10.2 Larvae development scheme

The VECTRI incorporates larvae growth rate scheme based on degree day approach expressed as:

 $T_w - T_{L,min}$ $R_L =$ K

(2.2)

where R_L is the fractional growth rate, $T_{L,min}(K)$ is the threshold temperature below which larval development ceases and K_L is the degree days required for adult emergence. The value of K_L has been estimated from laboratory studies to be 90.9 degree days (Jepson et al.,

1947) while 200 degree days was estimated from linear approximation of the relationship (Bayoh and Lindsay, 2003). In the model, the egg hatching and pupa development duration are fixed and last for a day. In between these stages, rate of the progression of larvae through the successive growth stages are divided into series of bins representing fractional growth state *f* ranging between 0 and 1 (where 0 and 1 is the egg and pupa stage respectively). The fractional growth rate through the bins at each time step is predicted using a simple one-dimensional advection equation:

$$\frac{dL}{dL} = R_L = \frac{dL}{dL} = (2.3) dt df$$

Furthermore, the model accounts for important factors such as water temperature, competition for food and flushing effects that control larvae mortality and daily survival rate. To represent combined effects of these factors on habitat productivity, VECTRI uses a base daily larvae survival rate ($P_{L,surv0}$) value of 0.825 following (Ermert et al., 2011b).

In addition, maximum water temperature threshold ($T_{L,max}$) above which all larvae die is provided as a model parameter. However, the aquatic stage development rate is driven by daily mean temperature calculated from daily minimum and maximum temperatures ($T_{min}+_2T_{max}$). This model limitation, which is common in most available regional scale models is addressed in this present study.

In addition, density-dependent processes such as competition for food and overpopulation have been observed to cause high larvae mortality rate, thus affecting habitat productivity

(Armstrong and Bransby-Williams, 1961; Gimnig et al., 2002; Koenraadt and Takken, 2003; Paaijmans et al., 2009). The VECTRI model treats these effects by introducing parametrization for the biomass holding capacity such that larvae survival rate probability ($P_{L,surv}$) is high when larvae carrying capacity is low relative to the maximum defined larval biomass density:

ML

where M_L is the total larvae biomass per unit surface area of a water body, $M_{L,max}$ is maximum carrying capacity set to 300 mg m⁻² but linearly increases with the fourth instar capacity (Depinay et al., 2004; Bomblies et al., 2008) and K_{flush} flushing rate.

The K_{flush} parameter accounts for reduction of larva density especially first instar due to effect of intense rainfall events (Paaijmans et al., 2007). The flushing rate is expressed as a combination of exponential and linear function of rain rate and larvae fractional growth state L_f:

 $K_{flush} = L_f + (1 - L_f) (1 - K_{flush,\infty}) e_{\tau flush} + K_{flush,\infty}$ (2.5)

where R_d is the rain rate in mm day⁻¹, $K_{flush,\infty}$ is the maximum value of K_{flush} for newly hatched first instar larvae at high-intensity rain rates and τ_{flush} is a set parameter (50 mm day⁻¹) that describes the rate of flushing effect as a function of R_d . The flushing effect at pupa stage is zero irrespective of the rain rate.

2.10.3 Vector scheme

The VECTRI model simulates the total vector density per square metre by dividing larvae into a number of development bins and vectors into a number of bins that represent the state of the gonotrophic and sporogonic cycles (see middle block of Fig. 2.6). Temperature impacts rate of the progression of these key processes and in addition to the temperature-dependent adult mortality rates are well resolved by the model. As a result, VECTRI is able to describe nonlinear response of malaria transmission to temperature variability (Craig et al., 1999; Beck-Johnson et al., 2013; Lunde et al., 2013a).

$$P_{V,surv1} = 0.45 + 0.054T_{2m} - 0.0016T_{22m}$$
(2.6a)The daily mosquito!survival probability in-1.0 $P_{V,surv2} = exp$ 2the VECTRI model is $-4.4 + 1.31T_{2m} - 0.03T_{2m}$ (2.6b)parametrized following (Martens et al., 1995b;a) for scheme I (Eq. 2.6a) and (Martens et al., 1997; Craig et al.,1999) for scheme II (Eq. 2.6b).where $P_{V,surv1}$ and $P_{V,surv2}$ are the daily mosquito survival probability for scheme I and schemeII respectively and $T_{2m}(K)$ is the 2-metre air temperature. The main difference between thetwo schemes is for scheme I, adult survival probability starts decreasing at earlytemperature of 20°C (see Ermert et al., 2011b). In addition, scheme II agrees well with theBayoh (2001) approximation based on laboratory experiment. Consequently, scheme II isimplemented in VECTRI as the default scheme.

2.10.4 Sporogonic cycle

During feeding, there is probability of transfer of parasite either from the host to vector or vice versa depending on the status of the host or vector. The maximum probability of

BAD

transmission from infective host to the vector P_{hv} is set to 0.2 following (Ermert et al., 2011b).

The probability of transmission $(P_{h \rightarrow v})$ is given by:

$$\begin{array}{c}
H_{inf} \\
P_{h \rightarrow v} = & \underline{\qquad} P_{hv} \\
H
\end{array}$$
(2.7)

where H_{inf} and H are the infected and total host population densities respectively. This equation simply implies random biting rate and in addition ignores heterogeneous biting rate that greatly influences transmission dynamics (Smith et al., 2005; 2007). The expression for $P_{h\rightarrow\nu}$ parameter may require future modification to include effects such as bed net usage distribution and location of host relative to breeding habitat among others that control heterogeneous biting.

At each time step, a fraction of biting vectors $(P_{h \rightarrow v})$ gets infected and the progression in steps of the parasite development inside the mosquito is solely controlled by temperature and follows degree day concept (Eq. 2.8). The sporogonic cycle completes once the vector reaches the last bin, and becomes infective and remains so until death which is determined by the survival probability.

W J

T2m - Tsporo,min R_{sporo} = _____ Ksporo

(2.8)

where $K_{sporo} = 111$ K day value for *Plasmodium falciparum* at temperatures above 18°C (Detinova, 1962), $T_{sporo,min}$ is minimum threshold temperature below which sporogony ceases is set to 16°C following (Ermert et al., 2011b).

2.10.5 Gonotrophic cycle

The VECTRI model assumes by default that all female vectors find blood meal the first night of searching, although this value can be tunned in the model. After the blood meal, the egg development starts controlled by ambient temperature using the degree day concept (Eq. 2.9). Advection equation is used to predict successive growth stages until the final bin is reached. At this stage oviposition takes place after which the vector moves back into the blood meal searching bin. This process continues as long as the vector survives.

T2m — Tgono,min

Kgono

(2.9)

where $K_{gono} = 37.1$ K day is the gonotrophic cycle degree days following (Detinova, 1962), $T_{gono,min} = 16$ K is the minimum temperature that supports sporogonic cycle (Ermert et al., 2011b).

 $R_{qono} =$

2.10.6 Host vector interaction scheme

One novel aspect of the VECTRI model is that it incorporates human population which influences vector-host interaction dynamics in estimating biting rates. At each grid cell, the VECTRI model parametrized the human biting rate (hbr) as:

$$\frac{-H}{PNj=sporo1} V(1, j)$$

$$hbr = 1 - e^{tzoo} - (2.10)$$

PNsporo

<u>-H</u> i=1 v(1,j) where $(1 - e^{\tau z z z 0})$ is a factor that accounts for vector zoophilic preferences, (_____H) represents the fraction of biting vectors to the host population. The $\tau_{z z 0} = 50$ km⁻² is significant for rural settings with population lower than $\tau_{z 0 0}$ value.

The transmission from the vector to the host depends on the infectious status of vectors and the host population (H(N_{host})). In the VECTRI model, the probability (P_{vh}) of host getting infected through a single bite from an infective vector is constant, then at each time step, daily probability of *n* infectious bites per individual is expressed as $1 - (1 - P_{vh})n$. Thus the daily transmission probability per person each time step is:

$$\sum_{n=1}^{\infty} X = \overline{G_{EIR_d}(n)(1 - (1 - P_{vh})n)}$$
(2.11)

where $G_{__EIRd}$ is the Poisson distribution for mean EIR_d (the daily number of infectious bites

by infectious vectors). The EIR_d is estimated for each time step as the product of hbr and the circumsporozoite protein rate (CSPR: proportion of infective vector). Although Eq. 2.11 could be modified to incorporate factors that influence biting rate such as bed nets usage, these are not accounted for in the present scheme. Once infected, the host acquires infective status after 20 days (Shute and Maryon, 1951; Day et al., 1998).

2.10.7 Model output

The key model-predicted variables are the EIR (which measures transmission intensity), parasite ratio (PR: proportion of hosts infected). In addition to these malaria variables, the VECTRI model also predicts variables such as hbr, CSPR, detectable parasite ratio (PRd: Proportion of people that have detectable cases after day 10), vector to host ratio, vector density (density m⁻²), larvae density (density m⁻²) and larvae biomass (mg m⁻²). Furthermore, the model predicts fractional water coverage in each grid cell which can be extremely useful in other applications.

Although preliminary VECTRI performance is promising (Caminade et al., 2014; Pointek et al., 2014; Tompkins and Di Giuseppe, 2015), the model still needs further development. This study tends to improve two key important variables, surface hydrology and developmental habitat water temperature.

CHAPTER 3

A breeding site model for regional, dynamical malaria

simulations evaluated using in situ temporary ponds

observations in Ghana



Abstract

Daily observations of potential mosquito developmental habitats in a suburb of Kumasi, Ghana reveal a strong variability in their water persistence times, which ranged between 11 and 81 days. The pond persistence were strongly tied with rainfall, location and size of the puddles. A simple area-depth geometrical model that requires only two measurements of the pond water depth and surface area is evaluated and found to fit the relationship between the pond depth and area well. Using the geometrical model as a basis, a prognostic model is derived for the temporal evolution of the pond area, which increases in response to rainfall, while evaporation and infiltration act as sink terms. Based on a range of evaluation metrics, the prognostic model is judged to provide a good representation of the pond coverage evolution at most sites. Finally, it was demonstrated that the prognostic equation can be generalized and equally applied to a grid-cell to derive a fractional pond coverage, and thus can be implemented in spatially distributed models for relevant vectorborne diseases such as malaria.

3.1 Introduction

Surface hydrology and water body temperature are two key factors that control the aquatic stage life cycle of mosquitoes and thus adult abundance by influencing the stability of habitat and larvae growth rates, respectively. 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), clean or polluted (Sattler et al., 2005; Awolola et al., 2007; Chinery, 1984) and of various sizes from hoof-prints of animals to the edges of large water bodies (Sattler et al., 2005; Mutuku et al., 2006b; Imbahale et al., 2011), although individual species have preferences of habitat type. For example, *Anopheles gambiae* complex mosquitoes, the principal malaria vector in Sub-Sahara Africa prefer small (example, cattle hoof prints), temporary and sunlit water bodies for their breeding, which become abundant during the rainy season (Mutuku et al., 2006a; Minakawa et al., 2004), although their larvae have also been found in polluted waters (Imbahale et al., 2011; Awolola et al., 2007; Sattler et al., 2005).

These small-sized breeding habitats have many advantages over larger permanent breeding sites that increase the developmental rate or survival probability of the aquatic stage. Firstly, these habitats contain small amounts of water and therefore their temperatures are high relative to deeper water bodies which shortens the larval-pupal development time (Munga et al., 2005; Bayoh and Lindsay, 2004; Ndenga et al., 2011), although extremely high temperature increases larval mortality (Bayoh and Lindsay, 2003). Several studies have found these micro habitats to be productive and therefore their contribution to mosquito vector abundance, especially during the rainy season, should not be ignored in dynamical models (Bomblies, 2012; Imbahale et al., 2011; Sattler et al., 2005). For example, in western Kenya, Minakawa et al. (2004) found more than 80% of Anopheles gambiae s.s. in isolated pools with water surface areas lower than 0.1 m². Secondly, such pools are temporary and therefore contain fewer or no competitors and predators decreasing the larvae mortality rate (Koenraadt et al., 2004; Sunahara et al., 2002). Thirdly, human activities contribute to the creation of these habitats which are found near human settlements and thus time spent by the gravid mosquito to locate surface water for oviposition is reduced (Mutuku et al., 2006b; Minakawa et al., 1999). Another critical

parameter determining mosquito breeding habitat productivity is its stability because only habitats that persist long enough can produce adult mosquitoes (Gianotti et al., 2009).

These mechanisms emphasize the importance of small-sized breeding habitats during the rainy season and how they can account for the seasonal variation in malaria vector abundance. Therefore, critical factors influencing the stability and productivity of these transient habitats need to be examined. The intensity and frequency of precipitation is very important since low frequency and intensity of rainfall can lead to desiccation of habitat before adult emergence (Himeidan et al., 2009; Srivastava et al., 2001). Other important factors that can control the stability of these small-sized habitats are hydrological parameters of the area which include soil type, soil moisture content and water table depth (Bomblies et al., 2009; Montosi et al., 2012).

In order to model malaria effectively using a dynamical modeling approach, a realistic representation of the surface hydrology is required. However, present dynamical malaria models have simple or no representation of surface hydrology since the small spatial scale of these developmental habitats limits the use of remote sensing techniques to make parametrization assumptions, a situation not aided by the lack of in situ observations. A complete understanding of all factors that control productivity and stability of breeding habitats and accurate prediction of mosquito aquatic stage life cycle duration are important factors for malaria control activities that intend to reduce vector density. For instance, information about stability and productivity of habitats indicates which breeding sites to target for aquatic stage control strategies and also the time interval to conduct adult residual spraying (Gu and Novak, 2005; Mutuku et al., 2006b).

Hayashi and Van der Kamp (2000) introduced a power function area-depth (A-h) relationship which requires two independent measurements of pond area and depth to determine scaling and shape constants. This model (hereafter referred to as Hayashi model) is a diagnostic model of water bodies, that relates the volume, area and depth. This Hayashi model has been used extensively to study permanent and semi-permanent pond dynamics in Senegal relevant for vectors of rift valley fever that have spatial scales of tens of metres (Soti et al., 2010). In addition, the model has also been evaluated for regional terrain (Brooks and Hayashi, 2002; Minke et al., 2010). However, no study has examined whether such a model can also be successfully applied to small temporary sub-metre scale water bodies. The current study here uses in situ measurements of a range of such developmental habitats in a peri-urban area of Kumasi in Ghana, and then evaluate whether the Hayashi model can describe the relationship between area and depth of these small breeding sites.

Since there is considerable variability in the availability and size of small-scale breeding sites over the course of a rainy season, a prognostic treatment is required that models the sources and sinks of ponds, namely rainfall, evaporation and infiltration. The geometrical model of Hayashi is thus used as a basis for developing a prognostic treatment for the evolution of a pool areal coverage, which is evaluated using the in situ pond data. Finally, to apply the surface hydrology model to regional distributed disease transmission models, the equation is generalized to predict the fractional water coverage of grid-cells of order of kilometer scales. Using an average, best-fit pond geometrical factor for all monitored sites in the study area, the evaluation shows that the scheme can be used in spatially explicit malaria transmission models with confidence.

3.2 Method and model description

3.2.1 Study area and data

The study was conducted in the Kumasi (Ghana) metropolis comprising parts of the Kwame Nkrumah University of Science and Technology (KNUST) campus and peri-urban areas of Ayeduase, a town sharing a boundary with the university (see Fig. 3.1). For 81 days between 6 June (day 157 in 2011) and 25 August (day 237 in 2011) daily observations of small-scale potential mosquito breeding habitats were undertaken. Ten sites with continuous water presence for at least 10 days were considered for this study. The monitored ponds were generated during the course of the monsoonal rains of 2011.

The potential mosquito developmental habitats consisted of a tyre truck, small surface depressions, puddles and ditches which collect water during the wet season (see Fig. 3.2). At each site, parameters measured include water temperature, water depth and the major and minor dimensions of water. However, irregular puddles were divided into segments before measuring major and minor dimensions. The daily depth of water in each pond was calculated as average of three readings taken at three marked points within the water coverage area of the pond using a tape measure of 1 mm measurement accuracy.

Although study of mosquito larvae was not undertaken, mosquito larvae were observed (by visual inspection without larvae identification) in all habitats at some point during the study period. Pond measurements were not performed every day during the study period

SANE

resulting in some data gaps existing in the time series. The number of potential water bodies decreased over the period since various ponds dried out and those that persisted decreased in size and depth in August 2011 due to the reduction of rainfall during that month (Owusu and Waylen, 2009; Manzanas et al., 2014). While some of the habitats dried out within a few days of rainfall events, others persisted throughout the study period of 81 days. The geographical-coordinates of the sites were recorded using a simple hand held global position system receiver (GARMIN eTrex series). Daily rainfall and evaporation data were obtained from a minute temporal resolution automated rain gauge installed at the KNUST AgroMet station (see Fig. 3.1).

The rainfall (*P*) and evaporation (*E*) data used to drive the models developed in this work were obtained from Agromet weather station which was located very close to the pond sites (see location *AgroMet* in Fig. 3.1). In this study, evaporation from the water surface was simply equated to the ambient air evaporation measured from the weather station.



Figure 3.1: Location of the study area KNUST campus and peri-urban areas of the Ayeduase. Also indicated are the 10 temporary sites together with the meteorological station AgroMet.



(a) Average area = 5.0 m^2 Average depth = 13.3 cm

(b) Average area = 1.4 m^2 Average depth = 8.3 cm

Figure 3.2: Two typical monitored potential mosquito breeding habitats within the study area. Left: site 10; right: site 9.

3.2.2 Diagnostic pond geometry model

9,0

Hayashi and Van der Kamp (2000) developed an area-depth (A-h) relation for water bodies

expressed as A α h^{2/p}, with the pond water area estimated from Eq. 3.1:

! ₂₀h ___ (3.1) href

where A is the pond water surface area, h is the pond water depth, and h_{ref} and A_{ref} are

reference pond water depth and surface area measurements, respectively.

 $A = A_{ref}$

The key assumption of the model is that, averaged radially, variations in the water body geometry average out, so that the relationship between the water body depth and its areal coverage can be given by a simple power law. The relationship is specified by the exponent factor p, which is a constant representing the geometry of the habitat, describing how the depth relates to the area. Since p is assumed a constant, only two, coincident representative values of pond depth and area are required in order to close the equation, h_{ref} and A_{ref} . Several options exist to set these two parameters. For example, they could be set using the maximum values of the pond, an ad-hoc pair of measurements taken on a random day, or the average values over an entire measurement campaign. The latter approach is employed here to reduce sensitivity to measurement error.

Once *h_{ref}* and *A_{ref}* are known, the key *p* parameter is estimated using a least-squared fit of the power function of the form of Eq. 3.1 to all the data points. Again, by using all measurements, the sensitivity to measurement error should be reduced relative to the method of Minke et al. (2010), who computed *p* based on two separate measurements of water surface area and depth. The *p* parameter is therefore equal to 2 divided by the index of

the best fit regression line.

3.2.3 Prognostic pond area model

As pond size and breeding site availability fluctuate significantly in response to rainfall during a rainy season, a prognostic model for the ponds dynamics is required. The source

of small-sized transient breeding habitats is determined by rainfall and runoff while infiltration, evaporation and overflow events control their lifespan. These processes are schematically represented in Fig. 3.3. The daily volumetric water balance of a puddle is approximated by Eq. 3.2:

$$dV = [PA + (A_{max} - A)R] 1 - \frac{A!}{A_{max}} - (E + I)A$$
(3.2)

BADW

where $\frac{dV}{dt}$ represents the rate of change in puddle water volume, A_{max} is pond catchment area approximated as maximum measured water surface area of the pond, A is daily pond water surface area, P, R, E and I are the daily amount of rainfall, runoff, evaporation and infiltration, respectively. The first term on the right-hand side of Eq. 3.2 represents the direct contribution of rainfall, the second term represents the input surface runoff, while the last term represents loss of water from the puddle through evaporation and infiltration. The coefficient of the second term ($A_{max} - A$) is zero when the area of the puddle reaches its maximum (i.e A_{max}). In this case, the contribution of runoff is zero and additional rainfall will lead to outflow from the puddle.

ENSAD J W J SANE



Figure 3.3: Schematic illustrating the various processes in the pond model.

The runoff *R* term was estimated using the Soil Conservation Service curve number (SCS-CN) method developed by the United States Department of Agriculture (USDA) USDA (1972):

$$(P - 0.2S)^{2}$$

$$R =$$

$$CN$$

$$P + 0.8S$$

$$25400$$

$$S = -254$$
(3.3a)
(3.3b)

where *P* is rainfall (mm), *S* is potential maximum retention (mm) and *CN* (range between 0 and 100) is the curve number, a dimensionless parameter indicating the land surface and soil type characteristics. At the lower *CN* threshold, all rainfall infiltrates without generating runoff while all rainfall becomes runoff at the upper *CN* threshold. USDA (1972) provides *CN* values for various land cover and soil types.

The loss of pond water due to infiltration increases with increase in water surface area with maximum infiltration occurring after rainfall events, while minimum infiltration occurs when water level reduces to reach the clogged region of the pond (Porphyre et al., 2005; Martin-Rosales and Leduc, 2003). This is represented using a linear relation with the daily pond water surface area and depth as given by Eqs. 3.4a and 3.4b for area and depth simulations, respectively:

l =____max A Amax

(3.4a)

 $I = \underline{max} h(3.4b) hmax$

where I_{max} is the estimated daily maximum infiltration, h_{max} is the measured maximum water depth and h is the daily water depth.

In order to translate the volumetric pond equation (Eq. 3.2) to prognostic equations for pond area and depth, the volume, height, area relationship of the diagnostic Hayashi model is introduced. For generic depression shape, Hayashi and Van der Kamp (2000) further provided a relation that links the water depth and surface area to its volume (V =

 $A_{ref h}(1+2/p)$ (1+2/p) h2ref/p), and substituting this into the Hayashi model (Eq. 3.1) gives the relationship between the tendencies of pond fraction and pond volume:

$$\frac{dA}{=} \frac{2}{2} \frac{A_{ref}!_2}{dV} \frac{dV}{A_{ref}}$$

$$= (3.5a) dt ph_{ref}A dt$$



It is then straightforward to solve by substituting Eq. 3.2 into Eqs. 3.5a and 3.5b to derive the prognostic pond area and depth model:

$$\frac{1}{p} dA = 2 A_{ref} \frac{1}{2} A + \frac{1}{$$

 $\frac{dh}{dt} = \frac{1}{PA} + \frac{A}{Amax} - AR = 1 - \frac{A}{Amax} - \frac{A}{Amax} + \frac{A}{Amax} - \frac{A}{Amax} + \frac{A}{Amax}$

A simple semi-implicit numerical technique is used to integrate the equation forward in time stably using a daily timestep, treating linear terms at time level t + 1 for stability. However,

treating the power terms $A^{-p/2}$ and $h^{-2/p}$ on the right hand side of Eq. 3.6 at future time levels makes the solution not generally tractable, while treating these terms at time level twould imply that the puddle would not be refilled once it dries out (i.e. $A(t) = 0 \Rightarrow dA_{dt} = 0$).

А

simple two-step solver approach is thus introduced to address this issue. The $A^{-p/2}$ and $h^{-2/p}$

terms are approximated with reference values, $A^{-}_{ref}p^{/2}$ and $h^{-}_{ref}2^{/p}$, respectively to reduce Eq. 3.6 to a simple linear equation. This is then solved implicitly to provide *first guess* puddle area and depth values at first time step:

$$A_{fg,t} = \frac{A_{t+ph\underline{2}}R(A_{max} - A_{ref})\Delta t}{h_{ref} \underline{A_{ref}} i}$$
(3.7a)
$$1 + ph\underline{2_{ref}}E + R - P + A_{max}(I_{max} + P - R)\Delta t$$

$$h_{fg,t} = (3.7b) \qquad \frac{h_t + \frac{max}{A_{ref}} (1 - \frac{h}{h_{max}})\Delta t}{1 + \frac{2}{2}} \qquad A \qquad R \qquad ref$$

$$h_{fg,t} = (3.7b) \qquad \frac{h^{2/p-1}}{1 + \frac{2}{p}} \qquad E + R \qquad \vdots$$

$$h_{tref} \qquad -P^+ \qquad h_{tref} + P - R) \Delta t$$

For the second step solution, Eq. 3.6 is solved again implicitly but replacing the power terms

 $A^{-p/2}$ and $h^{-2/p}$ terms with $A^{-}_{fg}{}^{p/2}$ and $h^{-}_{fg}{}^{2/p}$ respectively to provide the final model equation:



To assess the model performance, Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe



(1970)), the coefficient of determination (R^2) and the Relative Mean Absolute Error (RMAE) defined by Eq. 5.10 are used.

where S i refers to the *ith* simulated value, Oi is the *ith* observation, O* is the mean of observed data and N is the total number of observations. The NSE performance ratings (Nash and Sutcliffe, 1970) could be considered very good if (NSE > 0.75), good if (0.75 \ge NSE > 0.65), satisfactory if (0.65 \ge NSE > 0.5) and unsatisfactory if (NSE \le 0.5).

3.3 Results and discussion

3.3.1 Pond measurements

As expected, the depth and dimension of the ponds were strongly influenced by rainfall amounts and its frequency as well as the local hydrology of the pond location. The average pond depths of the ten monitored temporary small-sized potential mosquito breeding habitats varied between 5.9 and 14.5 cm with the average areas ranging between 1.4 and 9.1 m² and decreasing significantly towards the end of the study period (Fig. 3.4). Note that at the end of the observational period, only about half of the potential breeding habitats were available. Sites 2, 5, 6, 7 and 8 dried out, site 3 was destroyed, while sites 1, 4, 9 and 10 remained with water at the end of observational period. This observation also reveals the link between pond stability and local hydrology of the pond location.





Figure 3.4: Top: Average area (left axis, red line) and average depth (right axis, blue line) of the monitored breeding habitats. Bottom: Daily precipitation amounts of the automated rain gauge from the KNUST campus.

The average pond water depth and surface area, maximum pond water depth and surface area as well as elevation of these breeding habitats are shown in Table 3.1. The total rainfall recorded throughout the study period was 541.1 mm with July recording the highest rainfall amount (Fig. 3.4). During the months of June and parts of July (up to 21 July, day 202), the maximum dry period (number of days between rainy days) was 5 days with 49.9 mm being the maximum daily rainfall recorded during this period. However, after 21 July 2011, the maximum dry period increased to 9 days with a maximum of 15.3 mm daily rainfall recorded during this period. Most of the ponds remained stable containing water from the start of the experiment until day 207 (26 July 2011) with the exception of sites 6 and 7, which are located far from the stream and also at a higher elevation (see Fig. 3.1 and Table 3.1). After this date, about 5 of the ponds dessicated and also significant reduction in both average area and depth occurred at the end of the study period (see Fig. 3.4).

Table 3.1: Average area (Avg area) and depth (Avg depth), maximum area (Max area) and depth (Max depth), elevation, total number of days when pond contained water (pond water) and maximum number of days of continuous water presence (Max water) of the 10 temporary breeding habitats. The italics represents sites that did not endure the entire experiment. Site 3 was destroyed and site 9 measurement started later on 26 June.

Name	Elevation	pond water	Avg area	Max area	Avg depth	Max depth	Max water
	[m]	[Days]	[m²]	[m²]	[cm]	[cm]	[Days]
Site 1	259	81/81	1.9	3.8	5.5	8.8	81
Site 2	258	65/81	2.4	4.6	5.8	9.0	46
Site 3	257	31/31	5.0	8.0	7.7	10.3	31
Site 4	256	81/81	4.7	8.8	10.7	16.7	81
Site 5	258	79/81	2.5	4.9	6.8	11.0	79
Site 6	283	45/79	3.6	5.0	6.7	9.7	11
Site 7	282	51/79	7.5	12.5	7.7	10.2	13
Site 8	263	56/80	5.9	<mark>8.</mark> 8	7.5	9.8	56
Site 9	262	60/60	1.3	1.8	<u>8.0</u>	11.3	60
Site 10	260	81/81	5.0	7.4	12.9	16.8	81

3

For the ten sites studied, variability in the stability of temporary mosquito developmental habitats ranged from 11 to 81 days and was strongly linked with rainfall, local hydrology of habitat location and size of the habitat (Table 3.1). For instance, due to the short dry spell occurring at the Guinea Coast in August between the major and minor rainfall seasons (Owusu and Waylen, 2009; Manzanas et al., 2014), only about half of the monitored ponds had water towards the end of August. However, those ponds with persisted water at the end of observational period were located close to permanent streams (sites 1 to 5) and waterlogged areas (sites 9 and 10) (see Fig. 3.1 and Table 3.1). This is in agreement with the study of Himeidan et al. (2009), who also found that longer lived developmental habitats were located near streams and water sources in the eastern African highlands. In

the same district, Mushinzimana et al. (2006) made similar observations with more than 60% of positive habitats found within 50 metres from streams in both dry and rainy seasons. Similar observations were made by Bomblies et al. (2009), a different water table was detected for two Nigerien villages, which led to a strong difference in the persistence of pools. In addition, these puddles are potential mosquito breeding habitats since their stability far exceeds the time required between the eggs laying and adult emergence mosquitoes (Depinay et al., 2004). However, the productivity of the longer-lived ponds might be affected by predators due to their long water persistence times (Chase and Knight, 2003).

Minakawa et al. (2005), observed that pond stability positively correlated with habitat size and location with the former having a higher correlation coefficient. Their results are consistent with our findings where both size and location influence pond stability. However, our results point to habitat location having a more pronounced impact. For instance, site 6 (average area: 3.6 m²; average depth: 7.0 cm) and site 7 (average area: 8.5 m²; average depth: 7.7 cm) are located within the same area. In this case, site 6 with a smaller water volume had a shorter water persistence time (see Table 3.1). Conversely, site 1 (average area: 1.9 m²; depth: 5.5 cm) reveals a greater stability than sites 6 and 7, due to its close location to a permanent stream. This site contained water throughout the study period despite its smaller dimension. This confirms that both habitat size and local hydrological conditions influence pond stability and within the same area, size might be the dominant factor (Minakawa et al., 2005), however, over wider area, habitats location might be the key factor controlling its variability in stability. For instance, Himeidan et al. (2009) found that the percentage of stable habitats was 48.76% and 80.79% for habitats located on top of the hills and near streams, respectively.

3.3.2 Evaluating the Hayashi diagnostic model

Using the site data, the best fit p parameter for the Hayashi model was derived for each site. Fig. 3.5 shows example for some of the sites and the p values for all the sites are given in Table 3.2. The p values range between 1.1 and 2.0 with an average of 1.6. This range of values lies within the expected range reported for temporary pools and ponds (Brooks and Hayashi, 2002; Hayashi and van der Kamp, 2007). For instance, Brooks and Hayashi (2002) reported p values ranging between 0.6 and 2.24 for 34 vernal pools. The R^2 of the power function fit range between 0.54 and 0.94. This results indicate that the Hayashi diagnostic model can also describe reasonably well the geometry of small ponds and forms a good basis on which to build the prognostic model for pond coverage.





(b) Site 8

Figure 3.5: Example of power function fit for sites 5 and 8 using the area-depth relation. The estimated p values for all the sites are listed in Table 3.2.

3.3.3 Evaluating the prognostic model

The performance of the area-depth (A-h) relation for the 10 micro-habitats was validated against field observations. The results (see Fig. 3.6) demonstrate the model potential to simulate the daily variability of the pond water surface area and depth. To assess the performance of the model, RMAE, *R*² and NSE between observation and model output were computed and the results are summarized in Table 3.2. The model results are subdivided in relation to ponds location.





Figure 3.6: Comparison of daily observed and simulated pond water surface area and water depth of temporary water bodies. Solid lines are simulated values of area (blue) and depth (red). Dots and crosses represent the observed values of the surface area and water depth, respectively. Sites names are shown under each plot.

Sites 1 to 5 are located close to permanent stream (see Fig. 3.1), the model captured the observed variability of ponding due to rainfall events (see Fig. 3.6 a - d). During the later period of the study, the infiltration rate reduces when the pond area is small due to the clogging effect of clay, the nonlinear representation of infiltration in the model was able to account for this effect to some extent. The R^2 and NSE range between 0.78 and 0.93 and 0.66 and 0.85, respectively, indicating good to very good acceptable model performance based on NSE ratings (see Table 3.2). In addition, the RMAE range from 0.10 to 0.23 (see Table 3.2 for range) values were obtained for these sites for both the area and depth.

Table 3.2: Computed p values, RMAE, R^2 and NSE between observation and model output for various sites for both area and depth simulations. For these calculations, missing days were left out.

Site	Site 1	Site 2	Site 3	Site 4	Site 5	Site 6	Site 7	Site 8	Site 9	Site 10
p value	1.5	1.7	2.0	1.6	1.4	1.7	1.5	1.1	1.9	2.0
				Area						
RMAE	0.15	0.23	0.12	0.15	0.21	0.52	0.40	0.23	0.15	0.08
R2	0.93	0.90	0.90	0.89	0.78	0.77	0.83	0.95	0.90	0.95
NS E	0.85	0.78	0.71	0.78	0.79	0.51	0.68	0.86	0.57	0.79

				Depth						
RMAE	0.13	0.23	0.12	0.10	0.16	0.44	0.34	0.31	0.13	0.13
R 2	0.91	0.89	0.86	0.93	0.89	0.80	0.87	0.93	0.92	0.87
NS E	0.81	0.79	0.66	0.80	0.78	0.64	0.70	0.74	0.63	0.59
The model for habitats located in areas characterized by high infiltration and far from										

permanent sources of water underestimates the generation of ponds (Fig. 3.6 e - g). The model fails to simulate the intermittent drying of ponds as observed and also overestimates the area during the latter and fairly dry part of the study period for these sites. Regarding the dry period, the simulation developed ponding on day 216 due to 15.3 mm rainfall event. However, no ponding was observed. A high infiltration rate seems to characterize these sites. This indicates that the model could be improved by incorporating a treatment of soil moisture, which would increase infiltration in the drier periods as the soil dries out.

Regarding sites 6 to 8, the *R*² and NSE values range between 0.77 and 0.93 and 0.51 and 0.86, respectively. This indicates a satisfactory to a very good performance of the prognostic model based on NSE rating (see Table 3.2). The RMAE range between 0.23 and 0.52 for both depth and area simulations.

The water table of the waterlogged areas penetrated the surface at the peak of the rainy season, an effect which is not simulated by the model. In this case, the infiltration becomes zero and water loss is governed only by evaporation. For these reasons, the model underestimates the surface area and depth of the water bodies at sites 9 and 10 (see Fig. 3.6 h & i). Despite this underestimation towards the end of the observational period, the model performance range between satisfactory and very good for the waterlogged area. The R^2 and NSE values range between 0.87 and 0.95 and 0.57 and 0.79, respectively, (Table

3.2). The RMAE range between 0.08 and 0.15 (see Table 3.2) for both area and depth simulations.

Overall, the results from the presented prognostic geometrical model demonstrate the potential of the model to simulate daily and intraseasonal variability in surface water area and depth of individual ponds under different local hydrological conditions. However, further significant improvement could be achieved by including a representation of soil moisture in the model, but at the expense of a considerable more complex model system.

3.3.4 Application to regional distributed models

It has been demonstrated that the prognostic water balance model for pond area presented in this work gives a good representation when validated with individual ponds. However, in order to apply this model to a large-scale, distributed model for vectors or vector-borne disease transmission (e.g. Hoshen and Morse, 2004; Tompkins and Ermert, 2013), the model needs to be generalized to represent the total coverage of ponds over grid-cells that may range from several kilometres up to over 100 km in scale.

If we denote the distributed model grid-cell size as A_{grid} , and the area of pond *i* to be A_i , then the fractional coverage F_i of that single pond is simply $F_i = A_i/A_{grid}$. Thus the rate of change of the fractional coverage of this single pond that has a shape factor p_i is straightforward to derive:

$$= \overline{[F_iP + (F_{max} - F_i)R]} - (E + I)F_i (3.10) dt pihref FiF_{max}$$

The aggregate total fractional coverage is the summation of the *n* individual ponds in a grid

This summation would be straightforward, except for the fact that each individual pond has its own value for the shape factor p_i . If we assume, however, that an appropriate value of p can be adopted that adequately describes the mean shape of the aggregate pond (this is not

simply $n^{1}P_{n_{i}}p_{i}$ due to the nonlinearity), which will be referred to as e^{p} , then the aggregate fractional pond coverage is

$$\frac{1}{P}dF = K \begin{bmatrix} FP + (F_{max} - F)R \end{bmatrix} 1 - \frac{1}{F_{max}} - (E+I)F \quad (3.12)$$

$$dt = F = F = F_{max}$$
where $\kappa = e_{ph}^{2}_{ref}$. The value of e_{p} is set using the best fit between daily average area and

depth (Fig. 3.7*a*), which gives $e^{p=1.4}$, which is close to the average *p* value of 1.6 for the 8 sites used to estimate the fractional water coverage.

Fig. 3.7*b* shows the time series of simulated and estimated daily water fraction. The observed value is calculated by simply summing the pond fractions and assuming a value of A_{grid} equal to 100 A_{max} . The Eq. 3.12 is then integrated forward in time implicitly, assuming ep to be 1.4. The fact that the fit is close to that achieved for the individual ponds

indicates that the approximation of assuming a generalized shape parameter $_{e}p$ across all individual ponds is a reasonable one. The model agrees well (NSE = 0.84) with the estimated fractional coverage of the ponds. Consequently, the presented model by Eq. 3.12 has been implemented into the vector-borne disease community model of the International Centre for Theoretical Physics,



Trieste (VECTRI) malaria model and is available from v1.3.1 onwards.

Figure 3.7: Power function fit for average of 8 sites (excluding sites 3 and 9) (a) and comparison of simulated and estimated water fraction (b).

In summary this demonstrates the useful application of the presented geometrical model for gridded malaria vector borne disease models to improve their representation of surface hydrology using a simple model.

KNUST

3.4 Summary

Surface hydrology is one key factor that controls the life-cycle of mosquito larvae, and is therefore a required parameter for dynamical disease models. A simple prognostic model was developed based on the diagnostic geometrical model of Hayashi, with sources and sinks due to precipitation, run off, evaporation and infiltration, with a nonlinear infiltration term to represent the clogged inner regions of puddles. Based on general performance rating of NSE, the model results for all the individual sites were within acceptable level of model performance ranging between satisfactory and very good for depth and area simulations. However, during the later dry phase of the study period, the model tends to overestimate and underestimate the pond area and depth for the sites located far away from permanent streams (sites 6 to 8) and within waterlogged areas (sites 9 and 10), respectively. This indicates that the model could be improved by incorporating a treatment of soil moisture, which would increase infiltration in the drier periods as the soil dries out.

The developed single element prognostic model was further generalized to simulate the total fractional coverage of ponds within a grid-cell to assess the model application in gridded dynamical models. The model shows good agreement (NSE = 0.84) with the estimated fractional coverage of the ponds. This result highlights the useful application of

this prognostic geometrical model in spatially distributed dynamical disease models and thus could improve representation of surface hydrology in vector borne disease models.

CHAPTER 4

A regional model for malaria vector developmental habitats evaluated using explicit, pond-resolving surface hydrology

simulations



Abstract

The regional-scale dynamical malaria model VECTRI represents the coverage of small-scale breeding sites for malaria vectors in an idealized surface hydrology model. In addition to the VECTRI default surface hydrology scheme, we present a modified scheme that incorporates pond geometry and the nonlinearities of the surface runoff and the infiltration processes. These two hydrology schemes are evaluated using HYDREMATS, a 10 metre resolution village-scale model that explicitly simulates individual ponds, using a multimember ensemble Monte Carlo technique to identify the parameter setting that minimizes water fraction differences. Despite the simplicity of the two VECTRI surface hydrology parametrization schemes, they perform relatively well at reproducing the fractional water coverage evolution as simulated by the HYDREMATS model. The VECTRI model tends to overestimate water fraction in 2005 and underestimate it in 2006, and also to relatively overestimate water fraction during the monsoon onset period. This systematic error was improved by treating runoff in the revised scheme, although further improvements could be made by representing soil moisture. Simulations of vector densities with the modified VECTRI model were also close to the detailed agent based model contained in HYDREMATS. The results indicate that, with knowledge of local soil parameters and terrain, VECTRI schemes parameters could be adjusted to simulate malaria transmission on a local scale. Furthermore, VECTRI driven by satellites rainfall estimates produces a reasonable simulation of the sub-seasonal evolution of the pond fraction for the study area, thus indicating the possibility of driving the malaria model with satellite rainfall estimates in the absence of ground observations.

4.1 Introduction

The availability of water for larvae development is a key determinant of mosquito density (Fillinger et al., 2004; Minakawa et al., 2005). The availability, area coverage and persistence of temporary surface water (which serves as developmental habitat for gravid mosquitoes) are tied with depth, intensity and frequency of rainfall as well as local hydrological

conditions.

Attempts to link rainfall incidence to malaria vector abundance and disease incidence have yielded varied results in different geographical locations. For instance, the 1997 El Ni^{*} *no* southern oscillation (ENSO) caused an increase in rainfall in parts of eastern Africa leading to a malaria epidemic in southwest Uganda (Kilian et al., 1999), but conversely a reduction in malaria cases was observed in the Usambara Mountains of Tanzania (Lindsay et al., 2000). In Botswana, Thomson et al. (2006) developed a malaria early warning system based on multi-model ensemble prediction of precipitation and found that the relationship between November-February precipitation and the anomaly in malaria incidence is best explained by a quadratic relationship with malaria incidence decreasing once rainfall exceeded a certain threshold. In Malawi, Lowe et al. (2013) found a similar quadratic relation. Kelly-Hope et al. (2009) observed a weak correlation between precipitation and abundance of mosquito vectors with a correlation coefficient (r²) of 0.246 and 0.315 for *An. gambiae s.s* and *An. arabiensis* respectively. Similarly, Molineaux and Gramiccia (1980) found a poor correlation between mosquito abundance and seasonal rainfall using data

from Garki district in northern Nigeria. In addition, in Banizoumbou village in southwestern Niger, Bomblies (2012) showed that temporal patterns of individual rainfall events can explain a large part of the variance in mosquito abundance, partially explaining previously observed poor correlations which typically consider monthly or seasonal total precipitation. The nonlinear relationship of mosquito abundance to precipitation is poorly understood and may be partially due to intense rainfall reducing larvae density by flushing first stage larvae (Paaijmans et al., 2007).

Due to the nonlinear relationship between habitat stability and rainfall, other studies have focused on using local hydrological parameters that are more directly connected to the surface hydrology to predict mosquito vector abundance and incidence of malaria. Depinay et al. (2004) introduced a local scale dynamical model designed to explicitly model individual breeding sites to simulate mosquito population dynamics. Patz (1998) observed an improvement in predicting *An. gambiae* biting rate from 8% with raw precipitation to 45% with modeled soil moisture. In a related study in South Africa, Montosi et al. (2012) found that soil moisture predicts better sub-seasonal variability in malaria cases relative to rainfall and temperature. Shaman et al. (2002) found a positive association between modeled local surface wetness with \approx 10 days time lag and abundance of *Anopheles walkeri* and *Aedes vexans* in the eastern United States.

Mosquitoes exploit diverse habitats for their oviposition though species have habitat-type preferences (Fillinger et al., 2004; Sattler et al., 2005; Mutuku et al., 2006b; Awolola et al., 2007; Majambere et al., 2008; Imbahale et al., 2011; Minakawa et al., 2012). For instance,

the two key African malaria vectors, *Anopheles gambiae sensu stricto* and *Anopheles arabiensis* prefer small temporary sun-lit pools for oviposition (Minakawa et al., 1999; Gimnig et al., 2001; Koenraadt et al., 2004) although they also thrive in other water bodies (Sattler et al., 2005; Awolola et al., 2007; Minakawa et al., 2012). These temporary sun-lit pools typically have higher water temperatures, which shortens the length of the aquatic stage development of mosquitoes, but due to their size they are also prone to desiccation before larvae emerge as adults. This means that presence of water is not sufficient and that the temporal dynamics of small ponds are also important. For instance, Himeidan et al. (2009) found hilltop habitats to be unproductive, containing few *Anopheline* larvae but with zero pupation rate as result of habitat instability.

Dynamical mathematical models for mosquitoes or malaria transmission have incorporated representations of the surface hydrology that vary in complexity. For instance, Hoshen and Morse (2004) relate the oviposition rate to the 10 day rainfall rate in the Liverpool Malaria Model (LMM). Lunde et al. (2013b) parametrized surface hydrology as a function of river length and soil moisture based on the assumption that potential habitats are located within the vicinity of rivers and lakes. Their Open Malaria Warning (OMaWa), designed to be run on a large scale, may have limited application in areas of relatively flat topography where habitats are only rain-fed and can be located far away from permanent water bodies. Another recently introduced regional scale dynamical malaria model, the vector-borne disease community model of the International Centre for Theoretical Physics, Trieste (VECTRI; Tompkins and Ermert (2013)) uses a simple surface hydrology parametrization that models the evolution of the fractional water coverage within each grid cell. For local, village scale modeling, Bomblies et al. (2008) introduced the high-resolution Hydrology, Entomology, and Malaria Transmission Simulator (HYDREMATS). HYDREMATS runs with 10 meter spatial scale grid-cells to explicitly simulate pool formation and persistence time that control aquatic stage development of mosquito for each individual pond. In order to set up this model, Banizoumbou village in southwest Niger was manually mapped at this 10 m scale using survey-grade differential GPS instrumentation. The model simulated daily water depth showed good agreement with observations, predicting seasonal and sub-seasonal mosquito abundance (Bomblies et al., 2008). Bomblies et al. (2009) using HYDREMATS found good agreement with observed interannual variability in mosquito abundance between two villages located 30 km apart, but with contrasting local hydrological and environmental conditions. Furthermore, HYDREMATS has been used to assess the impact of environmental management in malaria control (Gianotti et al., 2009) and the sensitivity of the model to various climate change scenarios has been evaluated (Bomblies and Eltahir, 2009).

The small spatial scale of breeding habitats confound modeling efforts as a result of the lack of data from both field observations and remote sensing techniques to assess model parametrization assumptions. The high resolution, explicit surface hydrology simulations of the HYDREMATS model therefore offer a valuable alternative to evaluate simple representations of surface hydrology in regional malaria models. The objectives of this study are therefore, firstly to evaluate the pond parametrization used in VECTRI (Tompkins and Ermert, 2013) using output from the high-resolution, explicit surface hydrological model (HYDREMATS) introduced by (Bomblies et al., 2008) as a benchmark. A modified version of the scheme that attempts to address some shortcomings of the default VECTRI model is also presented and evaluated. Finally, we examine how the simulation of mosquito

density by the simple bulk model of VECTRI compares to the detailed agent-based treatment of the HYDREMATS model.

Rain gauge networks in most malaria endemic regions are sparse and therefore available satellites estimates of rainfall can be useful to drive these surface hydrology schemes. Recently, Yamana and Eltahir (2011), found similarities in mosquito population and malaria transmission simulated by HYDREMATS when driven by surface observations or the Climate Prediction Center morphing technique (CMORPH) rainfall estimates for Banizoumbou village in Niger. Their results revealed that in the absence of ground observations, satellite rainfall estimates may be used to drive malaria models. The second objective of this study is therefore to ascertain if replacing ground-based in situ rainfall measurements by remotely sensed rainfall data is significantly detrimental to the hydrology simulations. The results will indicate whether satellite products could be used to drive VECTRI so as to get real time prediction of malaria transmission on a regional scale.

4.2 Method and Data

4.2.1 Data for study Region

The study region, Banizoumbou village in southwestern Niger (13° 31⁰, 2° 39⁰), was mapped out at 10 m resolution and in situ pond measurements were taken throughout two rainy seasons of 2005 and 2006. In addition, vector density was estimated using Centers for

SANE

Disease Control (CDC) miniature light traps deployed in six locations (four indoor, two outdoor) in Banizoumbou. The HYDREMATS high-resolution, coupled hydrology and entomology model of Bomblies et al. (2008) was then used to successfully simulate the pool formation and daily pond water depth at the 10 m scale as well as the vector density differences between the two seasons. For a comprehensive description of the study area, the HYDREMATS simulations, and their evaluation with in situ measurements, the reader is referred to Bomblies et al. (2008).

Station rainfall data for the experiments were provided by the Banizoumbou meteorological station located just outside the village. To explore the potential of using satellite precipitation products to drive VECTRI on a regional scale, two satellite products, namely the Tropical Rainfall Measuring Mission (TRMM 3B42; Huffman et al. (2007)) and the second version of the Famine Early Warning System (FEWS RFE2; Herman et al. (1997)) were assessed as these are the two key daily rainfall products available in near real-time. The TRMM 3B42 rainfall estimates are available on a 3-hour temporal resolution and a spatial resolution of 0.25° × 0.25° between latitudes 50° north and south. Rainfall estimates from TRMM 3B42 are derived using a combination of passive microwave sensors (TMI, AMSU-B, SSM/I, and AMSR-E) and the TRMM 2A12 precipitation radar (PR) calibrated using available rain gauge data on a monthly timescale (Iguchi et al., 2000). The FEWS RFE2 rainfall retrieval combines geostationary infrared information with polar orbiting microwave sensor (SSM/I and AMSU-B) data, replaced with rain gauge data where available on the global telecommunications system (GTS). This product has a spatial resolution of $0.1^{\circ} \times 0.1^{\circ}$ (Love et al., 2004). For each product the satellite pixel was selected that contains the study area.

4.2.2 VECTRI Malaria Model

4.2.2.1 Default model hydrology

dwpond

dt

VECTRI is an open source grid-cell distributed dynamical malaria model that operates using a resolution of the driving climate data (10 - 100 km). A detailed overview of the VECTRI model is described in Tompkins and Ermert (2013). The model incorporates a simple surface hydrological parametrization scheme (V1.2.6) that estimates at each time step the fractional water coverage area in each grid cell. Fractional water coverage area is a sum of both permanent and temporary habitats, although presently no parametrization of permanent water bodies are included, allowing the user to set value for the permanent fraction with knowledge of the study area hydrology. In this study the permanent water fraction is set to zero. The net aggregated fractional water coverage of temporary pools in each grid cell was expressed as in Eq. 4.1:

 $\underline{\qquad} = K_w P(w_{max} - w_{pond}) - w_{pond}(E + I)$

(4.1)

where w_{pond} is the net aggregated fractional water coverage in a grid cell, w_{max} is the maximum fractional coverage of temporary ponds, *P* is the precipitation rate, *E* and *I* which were set to a fixed constant are evaporation rate and infiltration rate respectively and K_w is a linear constant. For details see Tompkins and Ermert (2013). The scheme is highly simplified and neglects many factors, including topographical slope, soil texture, pond geometry and heterogeneity in water infiltration rates. For example, the rate of infiltration

decreases towards the middle of these temporary ponds due to the effect of clogging by sediment over time (Desconnets et al., 1997; Martin-Rosales and Leduc, 2003). This nonlinearity in infiltration relation will therefore lead to constant infiltration assumptions over- or underestimating loss of water from the ponds. The stability of ponds has also been linked with their shape. For instance, Garmendia and Pedrola-Monfort (2010) observed rapid drying of cylindrical shaped ponds relative to conic shape ponds.

4.2.2.2 Modified model hydrology

SAPJ

To address these latter two limitations, a new surface hydrology parametrization scheme (V1.3.0) is introduced. The scheme is still based on the concept of a certain fraction w_{max} of a grid cell that collects water locally into temporary surface pools, while precipitation falling on the remaining area evaporates or drains to rivers either as surface runoff or subsurface flow. Here the relationships are modified to relax the assumption that all precipitation within the local drainage contributes to pools, and to better account for pool geometry using the simple power function relation of Hayashi and Van der Kamp (2000). Unlike V1.2.6, the relationship between volume and pond fractional coverage area is also linked to the pond's geometry in V1.3.0 as expressed in Eq. 4.2 following Asare et al. (2015a):

 $\frac{dW_{pond}}{dW_{pond}} = \frac{2 W_{ref p/2}}{PW_{pond} + Q(W_{max} - W_{pond})} 1 - \frac{W_{pond}(E + fI_{max})}{W_{pond}(E + fI_{max})} (4.2) dt phref W_{pond} W_{max}$

where *p* represents the shape factor of ponds, h_{ref} is the aggregated reference pond water depth, w_{ref} is the reference fractional coverage equated to K_w for this study, *Q* is the runoff (see Eq. 4.3), I_{max} maximum infiltration which depends on the local hydrology and soil type

and f =_____wmax} a linear scaling function that moderates daily infiltration rate (Asare et al., 2015a). Infiltration is expected to be maximum when the ponds reach their maximum surface area. For instance, in southwestern Niger, Martin-Rosales and Leduc (2003) found maximum infiltration of the order of 600 mm day⁻¹ after a rainfall event which reduced significantly as the water depth reached the clogging region of the pond. In the same region, Desconnets et al. (1997) found a similar sharp decrease in infiltration rate from the sandy to clay-clogged area of the pond.

The *Q* term in the V1.3.0 is calculated based on the United States Department of Agriculture (USDA) USDA (1972) Soil Conservation Service curve number (SCS-CN) method:



where *P* is rainfall (mm), *S* is potential maximum retention (mm) and *CN* (range between 0 and 100) is the curve number, a dimensionless parameter representing the land surface characteristics. When *CN* is 100, all rainfall will become runoff while all rainfall infiltrates without generating runoff when *CN* is 0 (Eq. 4.3b). The *CN* values for various hydrological

soil groups and land cover types are available from SCS-CN tables provided by the USDA (1972). Runoff occurs when rainfall exceeds the initial abstraction capacity of the surface layer which is assumed to be 0.2*S*.

Hayashi and Van der Kamp (2000) introduced a simple geometrical model for ponds. Studies have shown that the geometrical shape parameter in the model is approximately 2 for temporary ponds (Hayashi and Van der Kamp, 2000; Minke et al., 2010; Soti et al., 2010). This simple geometrical model showed good agreement with daily observed surface area of individual micro habitats in suburb of Kumasi Ghana as shown in previous paper.

4.2.2.3 Vector model

The VECTRI model simulates the total vector density per square metre by dividing larvae into a number of development bins and vectors into a number of bins that represent the state of the gonotrophic cycle Tompkins and Ermert (2013). Temperature impacts rate of the progression of larvae through the successive growth stages, the female adult gonotrophic rates, and the mortality of both larvae and adults. The pond fraction limits larvae density through a maximum biomass carrying capacity, the value of which was adopted from the HYDREMATS model.

BAD

APJWJSANE

4.2.3 HYDREMATS malaria model

4.2.3.1 Surface hydrology

HYDREMATS is a mechanistic model that simulates the pool water level and flow velocity at each time step and grid-cell based on distributed flow routing (Bomblies et al., 2008). The overland flow component of the model solves the two-dimensional Saint-Venant equations (continuity and horizontal momentum equations). A finite difference solution of diffusive-wave approximations of the Saint-Venant equations is used to predict pool water depth and surface-water routing. The overland flow direction is strongly linked with variations in the slope of cell topography and surface water pools are predominantly found at topographic low points in the study region. The mean velocity of the routing is parametrized by Manning's equation with roughness parameter depending on soil and vegetation characteristics of each cell.

The HYDREMATS land surface parametrization consists of two vegetation layers and six soil layers based on the land surface transfer scheme (LSX) of Pollard and Thompson (1995). This coupled atmosphere-vegetation-soil scheme simulates momentum, energy and water fluxes exchanges at each grid cell, and includes the partitioning of rainfall into infiltration and overland runoff.

4.2.3.2 Vector model

The agent-based entomological component of HYDREMATS simulates individual mosquitoes interacting with their environment as they progress through their life cycle. Flight is simulated in two dimensions using a radial random walk formulation, and entomologically important attributes are tracked for all mosquitoes (e.g. age, number of blood meals, degree-days experienced since blood meal, etc). After eclosion from one of the persistent pools, a simulated female adult mosquito begins her quest for a blood meal. She flies until she encounters a house, which is assumed to be occupied. After taking a blood meal, the mosquito rests for 24 hours, and then begins seeking suitable oviposition sites. Upon encountering a pool, the mosquito deposits a clutch of eggs in the pool and continues to repeat the cycle until she dies. In this way, characteristics of the entire mosquito population arise from the collective actions of many independent individuals. Bomblies et al. (2008) gives further detail concerning the functionality of the entomology model within

HYDREMATS.

4.2.4 Hydrology Comparison method

Assuming a 5 cm water depth threshold for each cell size (10 m \times 10 m) to be considered to contain a breeding site, HYDREMATS daily average pond coverage fraction is derived for the 2.5 \times 2.5 km simulation area and used to evaluate the two VECTRI parametrization schemes which simulate a single water fraction over the study domain. Cells with water depth less than this threshold are likely to dry out within a day without rainfall and tests show little sensitivity of the results to this value (Fig. 4.1). In order to identify the set of parameters that minimizes the error between VECTRI and HYDREMATS hydrology schemes, a deterministic optimization based on the root mean square error (RMSE) is used. Various parameters including w_{max} , K_w , E + I, I_{max} and CN in the VECTRI surface hydrology schemes are perturbed from their default values. These parameters have the most influence on the pond stability on both seasonal and intraseasonal time scales. The VECTRI model is then integrated in a Monte Carlo set of ensembles using combinations of parameters. The RMSE is calculated for each experiment for the entire simulation period of 2005 to 2006.

To assess VECTRI performance in simulating the water fraction and vector density, the Nash-Sutcliffe efficiency (*NS E*) (Nash and Sutcliffe, 1970) given by Eq. 4.4 is used.

 $P(S - O_i)_2$ NSE = 1 -(4.4) $P(O - O_*)_2$ i=1

where S_i is the simulated value, O_i is the observed value, O^* is the mean of observations and N is the total number of observations. The NS E metric ranges between $-\infty$ and 1 with NS E value of 1 indicates that observed versus simulated plot perfectly fits a 1:1 line.

WJSANE

4.3 Results and discussion

4.3.1 High resolution integrations

Pond stability is determined by precipitation frequency, intensity as well as local hydrological parameters such as soil type, water table depth and micro topography. In a Sahelian environment, infiltration accounts for about 90% of the loss of water (Desconnets et al., 1997; Gianotti et al., 2009). Total rainfall recorded was 409.3 and 478.3 mm in 2005 and 2006, respectively falling in 44 and 39 wet days in the two years.

An example of HYDREMATS simulated water depth using station rainfall observations for the entire study region for a sequence of 4 days in 2005 and 2006 is shown in Fig. 4.1. This figure illustrates pond water coverage and shows how grid cells with water depth less than 5 cm tend to be short-lived in this simulation and unlikely to survive until the next day without rainfall. Although Bomblies et al. (2008) observed mosquito larvae in hoof-print of animals in this region, such habitats located far from larger scale depressions resolved by the 10 m model resolution tended to be short-lived, as persistence times were only several hours and therefore far less than the approximately seven days required under optimum conditions for completion of the mosquito aquatic stage development (Depinay et al., 2004). In contrast, animal hoof-prints located within the catchment of large depressions were stable enough to produce adult mosquitoes. Thus productive developmental habitats cluster around topographical low areas (Bomblies et al., 2008). The locations of the HYDREMATS simulated habitats are similar for the two years but with differences in habitat

extent and

stability (Fig. 4.1).





Figure 4.1: HYDREMATS model simulated output of daily pool water depth at each grid cell over the entire model domain of 4 consecutive days in 2005 (left panel) and 2006 (right panel). The date (Julian day) and rainfall recorded are shown under each plot.

Fig. 4.2 shows the pond fraction root mean square error (RMSE) for VECTRI (V1.2.6 and V1.3.0) using a combination of various tunable parameters as described in the methods section. Regarding V1.2.6 (Figs. 4.2 a - c), decreasing K_w resulted in an increase in RMSE with HYDREMATS with the exception of when E + I = 50 mm day⁻¹. Although decreasing K_w caused a decrease in pond growth for a given rain rate, at the same time it increases pond stability by reducing daily loss of water from the pond due to the linear relation between K_w and rainfall and E + I terms. Increasing the constant loss term E + I reduces lifespan of the ponds as expected. Taking an E+I value of 100 or 150 mm day⁻¹ reduces the RMSE between V1.2.6 and HYDREMATS with w_{max} of 0.5. In this case, during intense rainfall events when the pond water extends to the sandy porous fringes associated with high infiltration, the constant infiltration rate will lead to an underestimation of the total infiltrated water.





Figure 4.2: RMSE error of water fraction between VECTRI (different surface hydrology parametrization) and HYDREMATS. Left panel: VECTRI hydrology V1.2.6, middle panel V1.3.0 varying maximum infiltration with a constant *CN* of 85 and right panel V1.3.0 varying *CN* with constant I_{max} of 500 mm day⁻¹.

Smaller RMSE values were observed between HYDREMATS and VECTRI V1.3.0 with constant CN = 85 (Figs. 4.2 d - f) at smaller w_{max} compared to V1.2.6. Although varying I_{max} affects the values of w_{max} that resulted in good agreement with HYDREMATS, the range of values for w_{max} that produce lower RMSE are smaller relative to the V1.2.6. The primary reason is the scaling factor f that moderates infiltration by accounting for increases or decreases in daily infiltration rates with pond water extent (Desconnets et al., 1997; Martin-Rosales and Leduc, 2003). In addition, both the runoff and K_w coefficient in V1.3.0

are also nonlinear. The V1.3.0 scheme with fixed maximum infiltration (I_{max} = 500 mm day⁻¹) also shows a similar pattern to the previous V1.3.0 experiment but requires large values of w_{max} to minimize the RMSE (Figs. 4.2 g – i). The good agreement between V1.3.0 (I_{max} = 500 mm day⁻¹) and HYDREMATS at high values of w_{max} demonstrates that the set infiltration threshold is likely to be too high for the study region.

It is clear from these experiments that there is no unique set of parameters which leads to good VECTRI schemes performance, but many parameter sets that enable the VECTRI surface hydrology schemes to reproduce water fraction similar to that of the HYDREMATS model. This is mainly due to the fact that the VECTRI model parameters are interdependent and the error associated with perturbing a particular parameter can be reduced if at least one other parameter also changes. The VECTRI new parametrization V1.3.0, especially with fixed *CN*, showed good agreement with HYDREMATS at lower w_{max} values relative to V1.2.6. In addition, although the VECTRI surface hydrology schemes are considerably less complex relative to HYDREMATS, the model parameters closely mimic processes they are meant to represent as seen in Fig 4.2.

Fig. 4.3 shows an example of a 7-day moving average time series of simulated water fraction by the HYDREMATS and the two VECTRI schemes using combinations of parameters that resulted in the lowest RMSE with respect to HYDREMATS. The 7-day window was selected because it is the optimum time for successful completion of aquatic stage mosquito development Depinay et al. (2004). The simulation results clearly demonstrate that the variability in the daily water fraction follows trends in rainfall relating to its inter-storm period, intensity, and frequency. There was a slight increase in recorded

rainfall of about 69 mm (16%) from 2005 to 2006 with 2006 having shorter storm return period compared to 2005. The impact of rainfall variability on the model's simulated daily pond fraction over the two year period highlights that rainfall sub-seasonal variability can be as important for transmission intensity as seasonal totals within the Banizoumbou village. Whereas greater inter-storm periods may have little influence on the stability of permanent and semi-permanent ponds, they will cause desiccation of temporary ponds Gianotti et al.

(2009).





Figure 4.3: Comparison of 7-day moving average time series of water fraction simulated by HYDREMATS and VECTRI (using one set of parameters resulting in smaller RMSE with HYDREMATS). a): V1.2.6 scheme; b): V1.3.0 varying infiltration at a constant *CN* of 85; c): V1.3.0 varying *CN* at a constant I_{max} of 500 mm day⁻¹; d): The difference between HYDREMATS and VECTRI.

7.0

Fig. 4.3 further reveals that despite the simplicity of the VECTRI surface hydrology parametrization schemes, it is able to reproduce the fractional water coverage evolution as simulated by the HYDREMATS model, although the V1.3.0 scheme shows a further improvement (*NS E* = 0.96) relative to the V1.2.6 scheme (*NS E* = 0.85). A possible cause of

this disparity, for instance, the initial ponding occurring in the V1.2.6 scheme in 2005 as a result of two isolated rainfall events of order of 6 mm is absent in both the V1.3.0 and the HYDREMATS. Clearly in the area like Banizoumbou, these events are unlikely to cause ponding especially occurring at the onset of the monsoon season. However, the VECTRI model tends to overestimate and underestimate the HYDREMATS water fraction in 2005 and 2006, respectively. A possible reason for this disparity may be the different response of the two VECTRI schemes to different rainfall pattern. The relative magnitude of the water fraction predicted by the two models changes as the season progresses. This is particularly apparent with VECTRI V1.2.6 in the 2006 season, where VECTRI predicts larger water fraction during the season onset, and lower fractions later in the season. Part of the disparity is due to the simple approach of the earlier surface hydrology scheme that does not account for run off. The rainfall events during the earlier season of 2006 are small in magnitude, and by introducing the curve-number based runoff scheme V1.3.0 prevents these events from producing breeding sites, in agreement with HYDREMATS. Nevertheless, further improvements could be made by including soil moisture, which would increase infiltration in the earlier season when soil moisture is dry and reduce it in the later season, albeit at the cost of increasing the complexity of the scheme.

Furthermore, the difference in observed rainfall between the two years (see rainfall in Fig. 4.3) caused the simulated pond water fraction by both models to have a higher mean water fractional coverage in 2006 relative to 2005, more than expected by 117, 15, 82 and 82% for HYDREMATS, V1.2.6, V1.3.0 (fixed *CN*) and V1.3.0 (fixed *I_{max}*) respectively.

This variability in daily simulated water fraction due to the influence of rainfall also impacts vector abundance. For example, in this same study area, Bomblies et al. (2008) captured 140% more mosquitoes at the same locations in the village in 2006 than in 2005. The results from the simulated mosquito vector abundance by both models are consistent with the observed increase in 2006 relative to 2005 (Fig. 4.4) but with a wide range of increases. For instance, HYDREMATS simulates a 84% increase in mosquito vector density between 2005 and 2006, while the three versions of VECTRI, V1.2.6, V1.3.0 (fixed CN) and V1.3.0 (fixed I_{max}), produced increases of 4, 58 and 37%, respectively. The differences in the VECTRI simulated vectors densities are due only to the changes in the surface hydrology scheme as all other model components are identical in the simulations, highlighting the critical importance of the hydrological component of the model, that is possibly the least constrained by observations and thus likely to be one of the key contributors to malaria model uncertainty. In particular, it is seen that the V1.2.6 suffers from a too early onset, particularly in 2005, due to its neglect of the runoff process, which resulted in light rains causing pooling in the pre-onset phase of the monsoon (Fig. 4.4). From the three model versions V1.3.0 (fixed CN) appears to produce the most similar vector density compared to HYDREMATS. In fact, considering the simplicity of the bulk larvae/vector schemes in VECTRI relative to the highly detailed agent based approach employed in HYDREMATS, and the fact that no parameter tuning of these components was performed (although it is recalled that the biomass carrying capacity parameter in VECTRI is adopted from HYDREMATS), the similarity between the conversion of water fraction to vector density by the two models is quite remarkable. Based on NS E evaluation metric, VECTRI schemes performance in simulating HYDREMATS vector density ranges between good (*NS E* = 0.71) and satisfactory

(*NS E* = 0.54) for V1.3.0 and V1.2.6, respectively. This result supports the conjecture that with knowledge of the factors that affect surface hydrology, a simple model such as VECTRI can potentially be employed to simulate vector density and subsequently malaria transmission on a local scale.



Figure 4.4: Comparison of 7-day moving average time series of vector abundance simulated by HYDREMATS and VECTRI (using one set of parameters resulting in smaller RMSE with HYDREMATS).

4.3.3 VECTRI simulation with satellite products

Over the two year study period, TRMM 3B42 and FEWS RFE2 recorded 1305.5 and 1181.4 mm of rainfall, about 47 and 33% respectively more than the station measurement records.

Fig. 4.5 shows the 7-day moving average time series of VECTRI (both V1.2.6 and V1.3.0 schemes) driven by both rainfall estimates and station observation simulated water fraction. The differences in the rainfall also impact the simulated water fraction. For example, the mean simulated water fraction over the study period increased about 45 and 49% for V1.2.6 and V1.3.0 driven by TRMM 3B42 rainfall respectively, when compared to station runs. Interestingly, the FEWS RFE2 mean simulated water fraction was about 34% more than station runs for V1.2.6 but about 26% less than that of station runs for V1.3.0. One reason for this disparity is that in V1.2.6 rainfall is used directly as input to drive the model while rainfall is converted to runoff in V1.3.0. To a certain extent, the initial abstraction term in runoff computation USDA (1972) sets the threshold below which rainfall amount generates no runoff. For instance, when setting CN = 85 in V1.3.0, rainfall less than ≈ 5 mm will produce no runoff and leads to no increase in the water fraction but some increase in the water fraction occurs in V1.2.6. In addition to this, the runoff term in V1.3.0 is highly nonlinear and so greater recharge occurs with intense rainfall events. Lastly, there is also the fact that infiltration in V1.3.0 adds another nonlinearity and therefore contributes to the different simulated water fraction results from the two schemes.

The relatively good agreement between simulated water fractions using station data versus the two satellite retrievals, especially FEWS RFE2, reveals that there were few heavy rainfall events recorded by the station that were missed by FEWS RFE2 or TRMM 3B42. It is the intense rainfall events that contribute most to ponding and thus greatly influences the simulated water fraction as shown in Fig. 4.5. Light rainfall events that the satellites may miss are less important for ponding. The results clearly show that the largest disparities between VECTRI simulated water fractions occur on days when either TRMM 3B42 or FEWS

RFE2 record high rainfall amount but little or no rainfall is recorded by the ground station or vice versa.

Another important finding of the VECTRI model driven by TRMM 3B42 is the ability of the surface hydrology scheme to simulate sub-seasonal rainfall variability impacts on both water fraction dynamics and vector abundance. TRMM 3B42 recorded almost the same amount of rainfall in 2005 (653.1 mm) and 2006 (652.4 mm) but with a variable sub-seasonal pattern (see TRMM 3B42 rainfall in Fig. 4.5). The VECTRI simulated water fraction and mosquito vector abundance driven by TRMM 3B42 dataset showed a difference of about 21 and 69% respectively, for V1.3.0 and 1 and 5% respectively, for V1.2.6.



Figure 4.5: A 7-day moving average time series of VECTRI simulated water fraction using station rainfall observations, TRMM 3B42 and FEWS RFE2 rainfall estimates.

4.4 Summary

The challenge of validating surface hydrology parametrizations of dynamical malaria models arises from the lack of data from both field observations or remote sensing techniques due to the small spatial scales of the key malaria vector habitats. To partially address this, the HYDREMATS high resolution village-scale model that explicitly simulates individual ponds was used to provide a proxy for high resolution observations of breeding sites and used to evaluate the performance of the bulk parametrization scheme for water fraction used in the regional-scale malaria model, VECTRI. In addition to the default scheme, a modified scheme is proposed that accounts for pond geometry more realistically and also incorporates the nonlinearities of the surface runoff and the infiltration processes.

The results reveal that both VECTRI surface hydrology schemes were able to reproduce seasonal and intraseasonal variability in pond water fraction (*NS E* > 0.85), with the modified scheme able to produce a closer match to the explicit benchmark model, HYDREMATS. However, the default VECTRI model tended to overestimate and underestimate the HYDREMATS water fraction in 2005 and 2006, respectively, and overestimate water fraction early in the rainy season. Accounting for run-off processes in a revised scheme improved this bias, and lead to more accurate predictions of the ponding onset at the start of the rainy season, although it is likely further improvement could be made by representing soil moisture in the model. The results indicate that, with knowledge of local soil parameters and terrain, VECTRI parameters can be adjusted to simulate malaria transmission on a local scale. Numerous malaria endemic regions are characterized by inadequate ground observations of rainfall and thus the impact of replacing the local ground-based station measurements with remotely sensed retrievals of rainfall from FEWS RFE2 and TRMM 3B42 was assessed. Despite the contrasting scales of the measurements and the uncertainties related to the retrieval algorithms, the study showed that satellite data could nevertheless produce a reasonable simulation of the sub-seasonal evolution of the pond fraction for this area.

In areas like Banizoumbou village, without permanent water bodies, rainfall controls seasonal and sub-seasonal variability in surface water and to some extent malaria vector abundance. Such places stand to gain more in malaria control from early warning information which dynamical models like the VECTRI model can provide if they can incorporate reliable representations of the surface hydrology driven by accurate climate observations or forecasts Tompkins and Di Giuseppe (2015). While the modified VECTRI hydrology parametrization presented here showed an improved agreement relative to the default scheme, further work is underway to incorporate topography and soil characteristics to the scheme.

CHAPTER 5

Evaluating an energy balance pond water temperature scheme suitable for vector-borne disease transmission models with in situ measurements in Ghana

Abstract

An energy budget model is developed to predict water temperature of typical mosquito developmental habitats. It assumes a homogeneous mixed water column driven by empirically derived fluxes. The model shows good agreement at both diurnal and daily time scales with 10-minute temporal resolution observed water temperatures monitored between June and November 2013 within a peri-urban area of Kumasi, Ghana. In addition, there was a close match between larvae development times calculated using either the model-derived or observed water temperatures, with the modelled water temperature providing a significant improvement over simply assuming the water temperature to be equal to the 2-metre air temperature. Furthermore, our results show that diurnal variations in water temperature are important for simulation of aquatic-stage development times, however, effect of sub-diurnal variations on larval development are similar to that of the diurnal. Modeling results suggest that in addition to water temperature, the degree days parameter is extremely important to accurately predict the larvae development time. Our results highlight the potential of the model to predict water temperature of temporary surface water, which can thus be implemented in dynamical malaria models to predict larvae development times, especially in regions without observations of the input energy fluxes. BAD

5.1 Introduction

Temperature is one important abiotic factor that influences the life-cycle of the malaria parasite and its *Anopheles* mosquito vectors (Detinova, 1962; Garrett-Jones and Grab,

SANE

1964; Kirby and Lindsay, 2004). Aquatic stage developmental rate is highly temperature dependent. At low water temperatures adults fail to emerge while high water temperatures are associated with high larvae mortality rates. Many experiments have been conducted in laboratories to understand how water temperature influences the aquatic life cycle of mosquitoes. For example, Bayoh and Lindsay (2003) showed that *Anopheles gambiae sensu stricto* emerge as adults only when water temperatures ranged between 18 and 34°C. Most adults emerge between 22 and 26°C. The optimum temperature in which development of larvae is favoured was found to be 27°C by Lyimo et al. (1992) when larvae were reared at constant temperatures (24, 27 and 30°C) in the laboratory. In a related study by Bayoh and Lindsay (2004), when larvae were reared at constant temperatures from 10-40°C, they survived less than 7 days at temperatures of 10-12°C and 38-40°C and no adult mosquito was able to emerge. Adult mosquitoes could only be produced between water temperature of 18 and 32°C.

Water temperature also controls larval longevity and survival. For instance, Bayoh and Lindsay (2004), observed larval survival ranged between 10 and 38 days at constant temperature of 18°C whereas at 32°C longevity varied between 5 and 13 days. Similarly, Kirby and Lindsay (2009) observed rapid development rates but decreases in survival rates with an increase in water temperature when larvae were reared at constant temperatures of

25, 30 and 35°C. At the upper temperature threshold where development time is short, it is associated with a high larval mortality rate (Bayoh and Lindsay, 2004; Kirby and Lindsay, 2009). The variation in development time of the larvae within these range of temperatures have additional impacts on the survival probability of adult mosquitoes in natural settings.

At the lower temperatures, larvae are subjected to predation over longer periods and there is also the possibility of the habitat drying out.

It is therefore clear that including a realistic representation of the vector immature stage and its water temperature sensitivity could potentially improve the accuracy of malaria transmission models. Lunde et al. (2013a) argue that including water temperature effects in transmission models significantly reduces the temperature range at which peak transmission takes place, which is often estimated for adult vector mortality rates combined with the temperature-dependency of the sporogonic cycle (Craig et al., 1999; e.g.).

Presently, many spatial, dynamical mathematical-biological malaria models lack a precise simulation of water temperatures. For instance, the Liverpool Malaria Model (LMM) (Hoshen and Morse, 2004; Ermert et al., 2011b;a) completely neglects the influence of water temperatures on the larval development since the aquatic stage duration is constant in the model. Tompkins and Ermert (2013) in their grid-point distributed dynamical model (VECTRI), which runs on a regional scale, simply equate mean air temperature to water temperature to drive the aquatic stage component of the model, which uses development times and mortality rates derived from Craig et al. (1999) and Bayoh and Lindsay (2003), as detailed in Tompkins and Di Giuseppe (2015).

Simply equating water temperature with 2 metre air temperature is likely to lead to significant inaccuracies, however, Paaijmans et al. (2008a) demonstrated that mean water temperature was higher than that of ambient air temperature and therefore models using

SANE NO

air temperature may underestimate the aquatic stage life cycle duration. Paaijmans and Thomas (2013) found for Kenya that mean water temperatures of potential breeding habitats were 4-6°C higher than corresponding mean air temperatures. In western Kenya, Paaijmans and Thomas (2013) detected daily mean temperature differences of 4.6 and 5.6°C between air and water for Kisian (lowland) and Fort Ternan (highland), respectively. The implication of this result is that using air temperature to predict aquatic life span of mosquito is inaccurate and therefore a water temperature parametrization scheme would improve dynamical malaria models.

Some attempts have been made to develop more complex representations of water temperature. Lunde et al. (2013b) in their model equated the mean breeding water temperature to top soil temperature obtained from the NOAH land surface model. Depinay et al. (2004) also introduced a simple water temperature scheme, using relative humidity to estimate cloud cover and then applied both the cloud cover and maximum air temperature to predict maximum water temperatures, whereas the minimum water temperature was equated to the minimum air temperature. Neither the Lunde et al. (2013b) nor Depinay et al. (2004) schemes were evaluated using in situ data.

Energy balance models have also been used to predict water temperature. Losordo and Piedrahita (1991) developed an energy balance model to predict temperature of stratified aquaculture ponds. The model accurately predicted the occurrence time of stratification, maximum stratification and completely mixed conditions in the ponds. Paaijmans et al. (2008a) developed a model that predicts the diurnal water temperature based on radiation and energy fluxes at the air-water and soil-water interfaces of small artificially created
ponds of varying dimensions. Predicted temperatures agreed with in situ observations to within

2.5°C between the simulated and observed water temperature using three consecutive days of different weather conditions. Despite good model performance, the application of these models regionally over Africa is hindered by a lack of the appropriate in situ observations required to define some of the energy fluxes. This model was further simplified by Paaijmans et al. (2008b) to use only easily obtained weather data as input, but even this modified scheme still required cloud cover observations to compute incoming shortwave radiation, a parameter not readily available from most meteorological stations.

The aim here is to develop an energy balance parametrization scheme using approximations for some of the flux terms such that the model can be driven using readily available meteorological variables. In addition, rather than evaluating the model with measurements at artificial sites, the goal is to predict the actual mosquito habitat water temperatures which are monitored using high temporal resolution field observations. After assessing the performance of the model to predict water temperature, the resulting predicted larvae development times are assessed using a dynamical malaria model and are compared to those obtained using observed temperatures in order to assess how water temperature errors might potentially translate into malaria transmission intensity differences.

5.2 Method and model description

5.2.1 Study area and data

The study was conducted at the Kwame Nkrumah University of Science and Technology (KNUST) campus, within the Kumasi Metropolis of Ghana (0.85342°W, 5.95248°N). Between 01 June (day of the year (DOY) 152) and 26 November 2013 (DOY 330), a

10-minute water temperature of three mosquito developmental habitats were observed using CR1000 data logger (Campbell Scientific Inc., UK) with PT-100 temperature sensors. The probes of the temperature sensor were placed within 1 cm of each water column. These three observed ponds are made up of trenches between raised beds for vegetable cultivation, specifically lettuce (see Fig. 5.1). In addition, these observed ponds are completely exposed to sunlight. It is recalled that *An. Gambiae* the key vector in Kumasi (De Souza et al.,

2010) and *An. Arabiensis* prefer sunlit pools (Minakawa et al., 1999; Gimnig et al., 2001; Koenraadt et al., 2004) and thus modeling such habitats is considered key.

During the same period, various climatic input parameters (temperature, wind speed, relative humidity and pressure) were obtained from the KNUST Energy Centre Automatic Weather Station (AWS), which is located about 300 metres away from the pond sites (0.85230°W, 5.9524°N). These variables are also recorded by the AWS logger at 10-minute temporal resolution. The 10-minutely water temperature and climatic input datasets were

averaged into hourly and daily time scales for this study. In addition, the water depth was set to the average of four measurements taken at fixed locations within each pond.



Figure 5.1: Picture of study site showing the temperature logger.

5.2.2 Energy balance model for water temperature

Solar radiation, longwave radiation, latent, sensible and ground heat fluxes are the main components that control the amount of heat that is stored in or released from a water column (Fig. 5.2). The water column in this model is assumed to be well mixed at all times, such that temperature is independent of depth and diffusive and convective transports are ignored. The rate of change in the heat storage (Q) is given by Eq. 5.1.

$$dQ = R_{net} - LH - SH - G_o$$
(5.1)
$$dt$$

where R_{net} is the net radiative flux (that is sum of net solar and longwave radiation), *LH* represents the latent heat flux, *S H* the sensible heat flux and G₀ is the soil heat flux. For simplicity, it is assumed that the pond water is sufficiently turbid such that all solar radiative flux is absorbed in the water column and no transmission occurs. Thus the only transfer of energy to the sediment layer is G₀. In addition, the sensible heat flux associated with the temperature of raindrops being lower than the water temperature is also neglected. Gosnell et al. (1995) estimated this to be of the order of 2.5 Wm⁻² over tropical oceans and thus small compared to other terms. Nevertheless, in periods of intense rainfall, this flux can exceed 200 Wm⁻² and thus its neglect may lead to overestimation of water temperatures at these times. Fluxes are positive when directed towards the water surface.





Figure 5.2: Schematic representation of the energy balance model.

Due to poor spatial coverage of both solar and longwave radiation observations across most malaria endemic regions, estimates are therefore required. Hargreaves and Samani (1982) estimated daily solar radiation (R_s) based on daily maximum and minimum temperature difference given by Eq. 5.2:

 $R_s = R_a K \quad (T_{max} - T_{min})$

(5.2)

where R_a is extraterrestrial radiation (Wm⁻²), T_{max} and T_{min} are daily maximum and minimum

temperatures (°C), respectively and K empirical coefficient (°C $^{-0.5}$). Hargreaves

SAP

(1994) suggested K values of 0.16 and 0.19 $^\circ C$ $^{-0.5}$ for interior and coastal regions, respectively. In this study the location is assumed to be interior.

The extraterrestrial radiation R_a was computed following lqbal (1983):

$$R_o = I_{sc}E_o(sin\delta sin\phi + cos\delta cos\phi cos\omega_i)$$
(5.3)

where I_{sc} is the solar constant (1353 W m⁻²), E_o is the eccentricity correction, δ is the solar

declination, ϕ is the latitude and ω_i is the hour angle at the middle of an hour.

The incoming and outgoing longwave radiations are estimated following Losordo and Piedrahita (1991) and Hodges (1998) which are expressed as the second and third terms on the right-hand side of Eq. 5.4a, respectively. The first term on the right-hand side of Eq. 5.4a represents net solar radiation.

$$R_{net} = (1 - \alpha)(1 - SF)R_s + (1 - r)\varepsilon_a \sigma T_a^4 - \varepsilon_w \sigma T_w^4$$
(5.4a)

$$\varepsilon_a = 0.398 \times 10^{-5}T_{a2.148}$$
 (5.4b)
where α stands for the shortwave reflectivity, *S F* is the shade factor; *R*_s represents the
shortwave solar radiation; *r* is the albedo of water surface to longwave radiation; ε_a
emissivity of the atmosphere (Eq. 5.4b) computed following after (Swinbank, 1963); σ (W
m⁻²) is the Stefan-Boltzmann constant; ε_w is the water surface emissivity; *T_w* and *T_a*
represent the water and air temperatures (in K), respectively.

The shade factor *S F* ranges from 0 (completely shaded) to 1 (fully sun-lit) to account for influence of tall vegetation on water temperature (Sinokrot and Stefan, 1993; Younus et al., 2000). Although the model allows for vegetation effects to be included through this simple shade factor, in practise it would be difficult to set a reasonable value for such a

factor in regional simulations. The *S F* is set to zero in the simulations conducted here for sunlit ponds.

For non-radiative components, we used bulk parametrizations for the turbulent fluxes according to Fischer et al. (1979):

$$S H = \rho_a C_p C_{DH} U_a (T_w - T_a)$$
(5.5a)

 $LH = \rho_a L_v C_{DE} U_a(q_w - q_a)$ (5.5b) where ρ_a (kg m⁻³) stands for the air density, C_p (J kg⁻¹ K⁻¹) is the specific heat of air, U_a (m s⁻¹) is the wind speed at 10 m height, T_w and T_a are the water surface and 2 m air temperature respectively, q_w and q_a are the water surface specific humidity and 2 m specific humidity respectively, L_v represents the latent heat of vaporisation. C_{DH} and C_{DE} are bulk aerodynamic coefficients (Pond et al., 1971; Hicks, 1972). In this study, a constant value of 1.3×10^{-3} is assigned to these constants (Paulson et al., 1972).

The soil heat flux G_o (see Eq. 5.1), which is relatively small compared to the other fluxes, is parametrized as a fraction of R_{net} following Liebethal and Foken (2007):

 $G_o = pR_{net}$

(5.6)

where p is a fractional constant. As there are no observations of G_o in the field experiment, this term represents one of the key sources of error in the energy balance model. In this study, p was set to 0.15 after (Paaijmans et al., 2008b); which is also close to 0.14 used by Liebethal and Foken (2007). The latter found good agreement of the p value with observations.

As diffusive and convective transport is neglected and temperature is considered uniform in each water body, the prognostic temperature is integrated forward in time using a simple explicit solution (Caissie et al., 2005; Larnier et al., 2010). Paaijmans et al. (2008a) used a similar equation to predict water temperature of artificially created ponds:

$$\frac{1 \, dQ!}{T_w(t + \Delta t) = T_w(t) + \underline{\qquad} \Delta t \qquad (5.7) \, \rho C_w d \qquad dt}$$

where T_w (°C) is water temperature, ρ (kg m⁻³) is density of water, C_w ($W kg^{-1} \circ C^{-1}$) is specific heat of the water at constant pressure, d (m) is the water depth and t the time and Δt the time step used to integrate the equation which is set to one hour. The water depth (d) was assigned a constant mean value (Torgersen et al., 2001; Dupont and Mestayer, 2006). Furthermore, larvae of the prolific malaria vector *Anopheles gambiae* remain close to the water surface and diving increases its mortality (Tuno et al., 2004). Eq. 5.7 was integrated using the observed pond temperature measurement as the initial temperature.

5.2.3 VECTRI simulated larval density

Tompkins and Ermert (2013) introduced the vector-borne disease community model of the International Centre for Theoretical Physics, Trieste (VECTRI). VECTRI is an open source model for malaria that can simulate transmission at a single location, or for a grid of points over a region or even continental scale (Caminade et al., 2014; Pointek et al., 2014; Tompkins and Di Giuseppe, 2015).

VECTRI incorporates larvae growth rate schemes based on degree day approach expressed as: $T_w - T_{L,min}$

ΚL

 R_{l}

(5.8)

where $R_L(day^{-1})$ is the growth rate, $T_{L,min}$ is the threshold temperature below which larval development ceases and K_L is the degree days required for adult emergence. The value of K_L has been estimated from laboratory studies to be 90.9 degree days (Jepson approximation

(JA); Jepson et al. (1947)) and 200 degree days (Bayoh approximation (BA); Bayoh and Lindsay (2003)). These two schemes are used to evaluate the difference in VECTRI simulated larvae abundance using simulated water and observed water and air temperatures. For details on VECTRI model see Tompkins and Ermert (2013).

Generally, aquatic stage development rate simulations are based on daily average temperature calculated from daily minimum and maximum temperatures ($T_{min}+_2T_{max}$). However, recent studies showed that diurnal temperature fluctuations significantly influence the duration of larvae development (Carrington et al., 2013; Paaijmans et al., 2013). Furthermore, the difference between daily, diurnal and sub-diurnal timescales water and air temperatures driven larvae development times were assessed. For sub-daily timescales, the developmental rate was estimated following Gu and Novak (2006):

$$R_{L} = \frac{N}{N \times K_{L}}$$
(5.9)

where N is 24 for hourly observations and 144 for 10-minute measurements.





where *S*_i refers to the *ith* simulated value, *O*_i is the *ith* observation, *O*^{*} is the mean The performance of the model was evaluated using the coefficient of determination (*R*²), the Nash-Sutcliffe efficiency (NSE; Nash and Sutcliffe (1970)) and mean bias error (MBE) defined by Eq. 5.10:

of observed data and *N* is the total number of observations. The NSE performance ratings (Nash and Sutcliffe, 1970; Moriasi et al., 2007) could be considered very good if (NSE > 0.75), good if (0.75 \ge NSE > 0.65), satisfactory if (0.65 \ge NSE > 0.5), unsatisfactory if (0 > NSE \le 0.5) and unacceptable performance if (NSE \le 0).

SANE

BADY

W CORS

136

5.3 Results

5.3.1 Observed water temperature variability

Figs. 5.3*a* – *c* shows water temperature variability of the three monitored mosquito developmental habitats. The mean 10-minute maximum and minimum water temperatures were 34.17° C (range: 26.20 to 39.26) and 23.98°C (range: 21.59 to 25.50) respectively. On a daily timescale, the mean, maximum and minimum water temperatures were 27.21, 29.22 and 23.96°C, respectively.





Figure 5.3: Left panel: Observed 10-minute (Tw_{10m}) , maximum (Tw_{max}) , minimum (Tw_{min}) , daily average (Tw_{Avg}) water temperature and daily average air (Ta_{Avg}) temperature. Right panel: Diurnal temperature difference (water minus air).

During the same period, the average mean, maximum and minimum air temperatures

measured from the AWS were 29.72°C (range: 23.53 to 33.01) and 21.91°C (range: 19.47 to

23.52) respectively. The daily average mean, maximum and minimum air temperatures were 24.89, 27.54 and 22.38°C, respectively. The differences between the diurnal water and air temperatures are shown in Figs. 5.3d - f for the three observed sites. Generally, as expected, water temperatures were higher relative to air temperatures, although there were some observations where air temperatures exceeded water temperatures. The average mean, maximum and minimum differences between water and air temperatures were 2.40, 11.80 and 0.01°C, respectively. However, for the period where air temperatures were higher than water temperatures, the average mean, maximum and minimum temperatures, the average mean, maximum and minimum temperatures.

Furthermore, Figs. 5.3a - c reveal that rainfall variability controls temporary surface water stability. The gaps in the time series are dry periods. The average water depths are 14.36, 10.46 and 5.32 cm for sites 1, 2 and 3, respectively.

Fig. 5.4 shows time series of diurnal water temperature range (DTR: daily maximum minus daily minimum) and the daily average water and air temperature difference. Contrary to the diurnal difference in water and air temperatures (Figs. 5.3d - f), the daily average water temperatures were consistently higher than the air temperatures. The daily average, maximum and minimum differences are 2.32, 4.30 and 0.90°C, respectively. In addition, the ponds exhibit high DTR, implying that mosquito larvae are exposed to highly variable temperatures. The mean, maximum and minimum DTR are 10.09, 14.91 and 4.16°C, respectively. Paaijmans et al. (2008a) observed similar DTR values of 14.4 and 7.1°C for smaller and larger sized artificially created ponds in Kenya.



Figure 5.4: Comparison of DTR and daily average temperature difference (water minus air).

The maximum number of hours per day with water temperature higher than or equal to 35°C was 5 hours, with average of about 1.68 hours (Fig. 5.5). Interestingly, larvae were observed (visual inspection) in the habitats throughout the observational period despite maximum temperature of excess of 35°C encountered.

W COR



Figure 5.5: Daily number of hours with water temperature \ge 35°C.

5.3.2 Model output

Figs. 5.6*a* – *c* show the diurnal observed and simulated temperature differences (observed minus simulated), and the scatter plots of the diurnal simulated versus observed temperatures are shown in Figs. 5.6*g* – *i*. The resulting daily average time series of simulated, observed and air temperatures are shown in Figs. 5.6*d* – *f*. The diurnal pattern of bias (Figs. 5.6*a* – *c*) demonstrates a relatively good agreement between model and observations. The average NSE, R^2 and MBE are 0.768, 0.888 and -0.191°C (Table 5.1), respectively. However, in most cases, the model overestimates the observed water temperature in the late evening and early morning before sunrise (see Figs. 5.6*a* – *c*) but slightly underestimates it outside this time range. Due to this under-/overestimation on

diurnal scale, the daily average model and observed water temperature show good agreement (Figs. 5.6*d* – *f*). The average NSE, R^2 and MBE are 0.587, 0.814 and -0.187°C (see Table. 5.1), respectively.



Figure 5.6: Comparison of (left panel)the diurnal observed and model temperature differences (observed minus model) and (middle panel) daily average time series of air, observed and model water temperatures. Also shown is correlation between observed and simulated diurnal water temperatures (right panel).

Table 5.1: Summary of the computed statistics for model evaluation. $L_D(T_{obs}/T_{sim})$ represents larvae development time between observed and simulated water temperatures, $L_D(T_{obs}/T_{air})$ represents larvae development time between observed water and air temperatures.

Diurnal Temp	Daily Temp	LD(Tobs/Tsim)	LD(Tobs/Tair)
--------------	------------	---------------	---------------

	MBE	-0.003	-0.102	-0.468	-0.026	-0.119	-0.417	-0.142	-0.313	-2.445	-5.379
	NSE	0.802	0.771	0.733	0.706	0.545	0.508	0.766	0.766	-5.094	-5.095
	R 2	0.902	0.889	0.872	0.852	0.790	0.801	0.905	0.905	0.900	0.900
		site 1	site 2	site 3	site 1	site 2	site 3	JA	BA	JA	BA

5.3.3 Larvae development time

The JA and BA schemes predicted mosquito larvae development time using observed water (site 1), simulated water and observed air temperatures between the period 152 and 217 DOY are compared. Site 1 was selected because it contained water throughout this period.

To assess the importance of sub-daily temperature variability in larvae development, 10minute, hourly and daily average observed water and air temperatures driven aquatic development duration are compared (see Fig. 5.7). There was a remarkably close match between predicted larvae development time at 10-minute and hourly timescales for both water and air temperatures. However, using daily average temperatures (both water and air) consistently predicted a faster aquatic stage lifespan relative to both the 10-minute and hourly observations. The average difference of simulated larvae lifespan between daily and 10-minute timescales are about 8.8% (air temperature) and 13.6% (water temperature) for both schemes. These differences resulted in MBE of about (JA: 1 day; BA: 2 days) for both water and air temperatures. Similar developmental times were observed at daily and hourly timescales.

WJ SANE NO



Figure 5.7: Comparison of BA and JA schemes estimated mosquito larvae development time using observed 10-minute, hourly and daily average water and air temperatures. JA_{10-munite}, JA_{hourly} and JA_{daily} represents Jepson approximation and BA_{10-minute}, BA_{hourly} and BA_{daily} the results using Bayoh approximation.

Due to similar developmental times predicted from both 10-minute and hourly timescales, the model is run with hourly timestep. The potential of the model to accurately reproduce mosquito aquatic lifespan were assessed. Generally, there were good agreement between larvae developmental time predictions from observed and simulated water temperatures from both schemes (Fig. 5.8). The NSE (JA: 0.766; BA: 0.766), *R*² (JA; 0.905; BA: 0.905) and MBE (JA: -0.142 days; BA: -0.313 days) values were observed between observed and simulated water driven larvae developmental time simulations. However, as expected, the schemes driven by air temperature constantly predicted longer development time relative to both the observed and simulated water temperatures (Fig. 5.8). This resulted in NSE (JA: -5.094 ; BA: -5.094) and large MBE (JA: -2.445 days; BA: -5.379 days) values between observed water and air temperatures simulated larvae development time. On the other hand, a high *R*² value 0.900 was observed between predicted larvae development time using air and observed water temperatures indicating that these two variables have a similar trend.



Figure 5.8: Comparison of BA and JA schemes estimated mosquito larvae development time using observed water, simulated water and air temperatures. Jobs, Jsim and Jair represents Jepson approximation and Bobs, Bsim and Bair the results using Bayoh approximation.

5.3.4 VECTRI simulated larvae density

The 7-day moving average time series of the VECTRI simulated larvae density from the two schemes and water fraction are shown in Fig. 5.9. The mean modeled water temperature is 27.22°C about 9% more than mean observed air temperature of 24.88°C. This difference in temperature also impacts VECTRI simulated larvae density. As expected mean larvae density from modelled water temperature driven simulations were higher relative to the air temperature driven simulations. In addition, a significant difference in the simulated

larvae density between water and air temperatures were observed for the two schemes. For example, while JA scheme (Fig. 5.9) predicted mean larvae density difference of about 18% between modelled water and observed air temperatures as input for VECTRI, BA scheme predicted difference of about 71% (see Fig. 5.9).

In addition, VECTRI simulated water fraction limits larval density. For instance, between 218 and 252 DOY the ponds dried out, however minimum simulated water fraction occurred between 230 and 250 DOY. Interestingly, this coincides with the period with a close match between the simulated larval densities. This explains the link between water fraction and larvae density, as water fraction reduces, the larvae density also reduces as larvae are instantaneously killed once the pond dries out (Tompkins and Ermert, 2013).



Figure 5.9: Comparison of 7-day moving average time series of VECTRI simulated larvae density driven by air and simulated water temperatures using JA and BA schemes.

5.3.5 Discussion

AP

This study has revealed that water temperatures of temporary surface water are highly variable and if colonized by larvae, they would be exposed to temperatures ranging from about 21.59 up to 39.26°C with daily average of 27.21°C. Interestingly, this observed mean temperature is within the optimal temperature range for aquatic stage development based on laboratory studies (Bayoh and Lindsay, 2003; Bayoh, 2001; Lyimo et al., 1992). A similar range of puddle temperatures have been reported elsewhere. For instance, in western Kenya, Koenraadt et al. (2004) observed maximum and minimum temperatures of about 37.4 and

14.6°C respectively with mean temperature of about 28°C from field measurements. In Gambia, Bayoh (2001) observed temperature range between 20.7 and 36.9°C with mean of 27.1°C from artificially created puddle measurements. Similarly, with three artificially created puddles of different dimensions and depths in western Kenya, Paaijmans et al. (2008a) observed mean water temperature between 27.4 and 28.1°C. Furthermore, these observed temperatures are likely to support larvae development as a similar range found elsewhere supported full larvae development (Gouagna et al., 2012; Mwangangi et al., 2007).

The observed minimum water temperature from these three potential mosquito developmental habitats were higher than the minimum threshold temperature of 16°C that supports larvae development under constant temperature in laboratory experiment (Bayoh and Lindsay, 2003). On the other hand, despite the water temperature exceeding

147

the upper temperature limit of 35°C that has been reported from laboratory studies (Bayoh and Lindsay, 2003), the water temperature threshold of 41°C that kills larvae at a short period exposure (Haddow, 1943) was never encountered. In addition, larvae are likely to survive the maximum number of 5 hours per day with water above or equal to 35°C. For instance Kirby and Lindsay (2009) observed larvae to adult development at 35°C when larvae were reared at fixed temperatures.

The results from the evaluation of the energy balance scheme reveal that despite the simplified assumptions made to derive estimates of energy fluxes, the model reproduces the observed diurnal water temperature quite well. However, it mostly overestimates the observed water temperature during early morning before sunrise and late evening during the period of lower observed water temperatures (Figs. 5.6g - i). This could be due to the presences of nocturnal clouds observed during monsoon period over West Africa including Kumasi (Knippertz et al., 2011; Schrage et al., 2007). These low clouds increase the surface temperature at night and since surface temperature was used instead of top of the atmosphere temperature to estimate the downward longwave radiation, this could lead to a slight overestimation of the downward longwave radiation.

Furthermore, the low performance of the model for site 3 could be due to its shallow water depth, which results in a high water temperature variability. For instance, the diurnal water temperature model of Paaijmans et al. (2008a) underperformed in predicting water temperature of the shallow pond of depth 4 cm relative to ponds with depths of 16 and 32 cm. Despite this, on the average the model underestimates the observed water temperatures slightly as given by the MBE values are shown in Table 5.1. In addition, based on NSE and R^2 evaluation metrics, the model performed well in representing observed temperature.

In addition, aquatic stage lifespan simulations at various timescales reveals the importance of sub-daily variability which is in agreement with other studies (Carrington et al., 2013; Paaijmans et al., 2013). Our results, however, indicate that temperature fluctuations below diurnal timescale has little or no effect on larvae development rate (see Fig. 5.7). As a result, hourly timestep model could accurately predict aquatic stage development time.

Interestingly, there was good agreement between observed and simulated water temperature predicted larvae developmental time (see Fig. 5.8) with mean difference of about 1.72%. Furthermore, the mean estimated larvae development time (8.22 days: observed water; 8.37 days: simulated water) from the JA scheme are approximately close to the mean value of 8.4 days observed by Gimnig et al. (2002) when 20 larvae were reared in artificial habitats without nutrient in western Kenya. In addition to this, the range of JA scheme estimated development times (6.73-10.84 days: observed water; 6.80-12.33 days: simulated water) are within their observed range of days when different number of larvae were reared. This agreement may be due to the almost similar range of temperatures they observed (24.6°C: average minimum; 36.0°C: average maximum). In the laboratory, when larvae were reared at constant temperatures of 24, 27 and 30°C, Lyimo et al. (1992) observed age to pupation range between 6 to 17 days with an average of 9.79 days. Although longer development times have been reported elsewhere (Minakawa et al., 2006; Munga et al., 2006), their observed temperature ranges were lower relative to what we

149

observed. This clearly demonstrates the potential of this simplified easy to implement scheme to accurately predict aquatic stage development time of mosquito.

As expected, air temperature predicted longer larvae duration time with mean difference of about 29.67% relative to the observed water temperature. In western Kenya town of Kisian, Paaijmans and Thomas (2013) observed similar high difference in larvae development time of 25-28% using air and water temperatures. Their observed mean air temperature of

23.4°C is close to the 24.89°C we observed. However, in the same study, they observed higher difference ranging between 39-45% for two highland towns of Lyanaginga and Fort Ternan in western Kenya. As expected, they observed a lower mean air temperature of about 19°C for these two towns. These results reveal that models using air temperature to simulate larvae development are overestimating larvae development time. In addition, though the high R^2 indicates similar trends between observed water and air temperatures, the negative NSE values indicate unacceptable performance using air temperature to predict larvae development.

Comparing the larvae duration time predicted from these two schemes reveals the importance of the K_L parameter. Interestingly, JA scheme driven by air temperature predicted faster larvae development relative to the BA scheme driven by both observed and simulated water temperatures (see Fig. 5.8). This results suggest that water temperature and K_L are two key important variables for the accurate simulation of the larvae development time.

150

The VECTRI simulation results highlight the nonlinearity of the relationship between temperature and larvae development rate. The percentage difference between modelled water and observed air temperatures did not produce the same percentage change in the VECTRI simulated larvae density. Pascual et al. (2006) and Bayoh and Lindsay (2003) also found nonlinear relation between change in climate variables and mosquito population dynamics. In addition, the large disparity between the schemes simulated larval density clearly shows the importance of the K_L term. This highlights the fact that the challenge of modeling the aquatic stage life cycle of mosquito arises not only from the water temperature but also the

*K*_L term introduces another uncertainty.

5.4 Summary

Water temperature is key for the life-cycle of mosquito larvae, and is therefore a required parameter for the latest generation of dynamical disease models. The presented energy balance model performed well (NSE > 0.7) in predicting the diurnal observed temperature variability and larvae development times (NSE = 0.76), despite driving the model by estimated fluxes instead of real observations. In addition, the results show that diurnal variations in water temperature are important for simulation of aquatic-stage development times, however, effect of sub-diurnal variations on larval development are similar to that of the diurnal.

Furthermore, the model predicted water temperature was used to drive the VECTRI model aquatic stage development time. The VECTRI simulated results suggest that in addition to the water temperature, the degree days parameter K_L is extremely important to accurately

predict the larvae development time. Our results highlight the potential of the model to predict water temperature of temporary surface water, which can thus be implemented in dynamical malaria models to predict larvae development times, especially in regions without observations of the input energy fluxes.

(NUST

CHAPTER 6

Assessing climate driven malaria variability in Ghana using a

regional scale dynamical model



Abstract

The regional-scale dynamical malaria model VECTRI is used to assess the influence of climate forcing on the spatio-temporal variability in malaria transmission over the four agro-ecological zones in Ghana. The model is run simply under the same conditions with the exception of the driving temperature and rainfall datasets obtained from Ghana Meteorological Agency (Gmet) synoptic stations between 1980 and 2010. In addition, the potential of the VECTRI model to simulate seasonal pattern of local scale malaria incidence is assessed. The model results reveal that the simulated malaria transmission follows rainfall peaks with a one month time lag. Furthermore, malaria transmission ranges from six to twelve months, with minimum transmission occurring between February and April. The correlation between mean annual model predicted entomological inoculation rate (EIR) and the national recorded malaria cases from public health facilities was more than 0.5. On a local scale evaluation, the correlation between monthly predicted and hospital recorded malaria cases was greater than 0.4. Interestingly, this correlation ($R^2 = 0.4$) was higher than the best obtained using rainfall. This result demonstrate the potential of the VECTRI model to predict malaria transmission dynamics at both local and national scales.

6.1 Introduction

Malaria is hyperendemic and poses a significant public health challenge in Ghana. Despite recent scale up malaria treatment and control intervention strategies, malaria still remains the leading cause of morbidity and mortality among the entire population. For example, between 2000 and 2011, malaria alone accounted for an average of about 40% of all outpatient attendance (OPD) in public health facilities (Adams et al., 2004; NMCP, 2008; GHS, 2011). Similarly, in 2011, GHS (2011) report indicates that suspected malaria cases account for about 40.2% outpatient morbidity, 35.2% hospital admissions and 18.1% of all recorded death at public hospitals. Most importantly, actual malaria cases are likely to be higher than the reported cases since private health facilities are not taken into account, in addition to home treatment (self medication) of the disease using both orthodox and traditional medicine.

In addition to health implications, malaria also presents a substantial economic and developmental challenges in Ghana. Asante and Asenso-Okyere (2003) found a negative association between malaria cases and GDP. In a related model study, Sicuri et al. (2013) estimated annual total cost of malaria treatment and prevention for children under-five years to be US\$ 37.8 million in 2009. In addition, they estimated the expenditure for treating a single malaria episode to range between US\$ 2.89 and US\$ 123 depending on disease severity. Furthermore, large fraction of Ghana's health budget goes to treatment and prevention of malaria. For instance, the estimated budget for National Malaria Control Programme (NMCP) strategy plan for effective malaria prevention and treatment between 2008 and 2015 is US\$ 880 million (GHS, 2009). In addition, the disease is adversely affecting sustainability of the National Health Insurance Scheme (NHIS) due to high reported cases at the various hospitals across the country (Dontwi et al., 2013).

On the household level, Akazili et al. (2008) found the cost of treatment of malaria to be about 34% and 1% of the household's income for the poor and the wealthy respectively in the Kassena-Nankana district of northern Ghana. More recently, Sicuri et al. (2013)

SANE N

estimated that about 55% of the total cost of malaria treatment in 2009 which ranges between US\$ 7.99 and US\$ 229.24 per malaria episode are borne by the patient. These clearly show that successful implementation of effective malaria control program will have a huge socio-economic and public health impact on the country.

Similar to sub-Saharan African countries, *Anopheles gambiae sanso lato complex* and *Anopheles funestus* are the main malaria vectors in Ghana (Appawu et al., 1994; 2004; Yawson et al., 2004; De Souza et al., 2010; Kasasa et al., 2013; Dadzie et al., 2013). The distribution of these vectors is heterogeneous and somehow follows climate and ecological conditions (Appawu et al., 1994). *An. gambiae s.s., An. arabiensis* and *An. melas* are the three species within the *Anopheles gambiae sanso lato complex* found in Ghana (Appawu et al., 2004; Yawson et al., 2004). The *An. gambiae s.s., An. arabiensis* and *An. melas* are the three species within the *Anopheles gambiae sanso lato complex* found in Ghana (Appawu et al., 2004; Yawson et al., 2004). The *An. gambiae s.s.* vector predominates the complex and distributed throughout the country (De Souza et al., 2010). However, the other two vectors have limited distribution within the country, *An. arabiensis* predominates in savanna region while *An. melas* are confined along the coast (Yawson et al., 2004; De Souza et al., 2010). Regarding *An. funestus*, Dadzie et al. (2013) found *An. funestus sensu stricto* as the only malaria transmission vector in the sub group found in the country. Although *An. funestus sensu stricto* are found all over the country, they are the predominant and important vectors in the savanna ecological zone (Dadzie et al., 2013).

Three out of four main species of human malaria parasites are present in Ghana. *Plasmodium falciparum* the most severe and life threatening is predominant in the country accounting for about 80 to 90% of all malaria infections. This is followed by *Plasmodium malariae* responsible for between 20 and 36% of malaria cases while *Plasmodium ovale* is

155

less prevalent accounting for less than a percent (about 0.15%) of all malaria parasitemia (Afari et al., 1995; Asante and Asenso-Okyere, 2003). Moreover, mixed infections of *Plasmodium falciparum* and *Plasmodium malariae* are also common. For instance, in Accra, Klinkenberg et al. (2005) detected a single case of mixed infection of *Plasmodium falciparum* and *Plasmodium malariae* for a three month study period among children between 6 and 60 months of age. However, 258 out of the 261 infections detected were due to *Plasmodium falciparum* with 2 cases of *Plasmodium malariae*. Similarly, in the Kassena-Nankana District located within the savanna zone, Koram et al. (2003) identified 963, 63 and 36 cases of *Plasmodium falciparum*, *Plasmodium malariae* and mixed infections of the two, respectively. In addition, Dinko et al. (2013) found all the three species in the Ahafo Ano South District of the Ashanti region which is within the forest ecological zone.

Heterogeneities in malaria transmission dynamics across the four agro-ecological zones have been reported. These variations are to a large extent due to a complex interplay between climatic variability, parasite and vector distribution, behavior of human host as well as other non-climatic factors. For instance, within the coastal, forest and transition zones with bimodal rainfall regime, malaria transmission tends to be perennial and intense but with slightly higher cases during the wet season (Owusu-Agyei et al., 2009; Dery et al., 2010; Donovan et al., 2012). In the savanna zone with unimodal rainfall regime with long dry season, malaria transmission although intense shows more pronounced seasonality relative to the other zones. For example, Appawu et al. (2004) observed transmission peaks between June and October in the Kassena-Nankana District in northern Ghana. Similarly, in the same district, Baird et al. (2002) found malaria incidence density of five which increased to seven infections/person/year in the dry and wet seasons, respectively among children under two years. Despite this, non-climatic factors such as urban agriculture and irrigation among others introduce local hot spots transmission within the various ecological zones which modify local disease dynamics.

Rainfall, temperature, wind speed and relative humidity are the key climate drivers that influence the spatio-temporal malaria transmission. Areas like Ghana where mean temperatures are within the range that supports malaria transmission, variations in rainfall play a key role in understanding disease dynamics. Consequently most studies attempt to associate malaria incidence with rainfall. However, contrasting results have been observed. For instance, across Atonsu (urban), Emena (peri-urban) and Akropong (rural) towns within Ashanti region of Ghana, Tay et al. (2012) observed weak but variable R² between rainfall and hospital morbidity data at various time lags. Klutse et al. (2014) found a poor correlation between rainfall and malaria at Winneba (coastal) and Ejura (transition) zones. Interestingly, a strong but negative correlation was observed for these two locations with two month lag time between malaria and rainfall. In the forest zone, Danuor et al. (2010) observed a strong negative correlation between rainfall and malaria incidence. Similarly, in the forest zone, Krefis et al. (2011) using a regression model found about two month time lag between rainfall and malaria incidence. This nonlinearity between rainfall and malaria intensity has been observed elsewhere (Kelly-Hope et al., 2009; Lowe et al., 2013).

Due to this strong nonlinear relationship between malaria incidence and rainfall, a model that incorporates surface hydrology (e.g. the International Centre for Theoretical Physics, Trieste (VECTRI); Tompkins and Ermert, 2013) is likely to perform better in predicting

SANE

malaria incidence relative to those that use rainfall as proxy for aquatic habitats. For instance, rainfall in addition to local scale hydrological conditions control mosquito developmental habitat dynamics and to some extent its productivity (Smith et al., 2013; Asare et al., 2015a). More importantly, in Ghana, studies linking climate fluctuations and malaria transmission across the various agro-ecological zones are limited, the few available studies are based on a single or at most two ecological zones and over a short time period (Danuor et al., 2010; Tay et al., 2012; Klutse et al., 2014). Thus, it becomes clearly difficult to understand malaria transmission dynamics over the entire country.

The aim of the study is to address some of the challenges above by modeling malaria transmission dynamics over the various agro-ecological zones from 1980 to 2010 using VECTRI model (Tompkins and Ermert, 2013) driven by data from the 22 synoptic stations operated by the Ghana Meteorological Agency (hereafter GMet). Furthermore, the average model simulated entomological inoculation rate (EIR) is compared with national malaria recorded malaria cases. In addition, the potential of the model to predict seasonal variability of local scale malaria transmission is assessed using a monthly hospital data from Emena. Results evaluation demonstrates the ability of VECTRI model to provide malaria early warning information over Ghana and in addition the model possesses the potential to predict malaria seasonality at a local scale.

BADY

WJSANE

6.2 Method

6.2.1 Study area and data

In this study, daily rainfall and maximum and minimum temperatures from 22 Gmet synoptic stations data over the country between 1980 and 2010 were considered. The names and locations of the station over the four agro-ecological zones are shown in Fig. 6.1. In addition to these, daily observations of the same variables were obtained from Gmet agro-meteorological station (Agromet) located at Kwame Nkrumah University of Science and Technology (KNUST) campus at Kumasi (see Fig. 6.1). These data were used as inputs to drive the VECTRI model to simulate malaria transmission dynamics.





Figure 6.1: Map showing the 22 synoptic Gmet stations grouped into the four agroecological zones. The Emena hospital and Agromet station are also shown.

Rainfall is highly variable in Ghana in terms of its onset and cessation times across different zones but exhibits less variability within the zones. These spatio-temporal variability in rainfall is mainly controlled by the north- and south-ward movement of the Inter-Tropical Discontinuity (ITD) (Owusu and Waylen, 2013; Manzanas et al., 2014; Amekudzi et al.,

2015).

6.2.2 Malaria morbidity data

Annual malaria morbidity data were compiled from annual Facts and Figures bulletin obtained from Ghana Ministry of Health GHS (2013) between 2000 and 2008. These morbidity data come from only public health facilities. In addition, monthly records of confirmed malaria data were obtained from Emena hospital (see Fig. 6.1) from January 2010 to July 2013. These two datasets are used to evaluate the VECTRI model on national and

local scales respectively.

6.2.3 VECTRI model

Tompkins and Ermert (2013) introduced VECTRI, a grid-point distributed open source dynamical model that simulates malaria transmission dynamics running with a daily integration timestep and flexible spatial resolution that ranges from a single location to a regional scale (10-100 km) depending on the resolution of the driving climate data. The VECTRI model explicitly resolves important temperature-dependent stages such as egg-larvae-pupa, gonotrophic and sporogonic cycles. The growth stages within these cycles are presented in arrays of bins and the process continues to advance once temperatures are within the range for growth. For complete description of the model we refer reader to Tompkins and Ermert (2013).

One novel aspect of the VECTRI model is that it incorporates human population which influences vector-host interaction dynamics in estimating biting rates. Consequently, the model explicitly reproduces the reduction of EIR with increasing population density (Robert et al., 2003). As a result, the model is able to differentiate heterogeneities in transmission intensity between rural, peri-urban and urban areas.

161
VECTRI includes a simple surface hydrology scheme that estimates at each time step the fractional water coverage area in each grid cell. Fractional water coverage area is a sum of both temporary and permanent developmental habitats, however, at present, spatial parametrization of permanent water bodies is not available, but incorporated as user defined parameter which can be tuned with knowledge of the area hydrology. Importantly, this scheme also indirectly controls habitat productivity and adult density as larvae are killed once the habitat dries out. Furthermore, although simple, the surface hydrology scheme is able to account for negative effect of high intensity rainfall on larvae habitat productivity through flushing effect (Paaijmans et al., 2007).

Recently, modifications to the default hydrology scheme Eq. 6.1a to incorporate pond geometry and nonlinearities of infiltration and runoff (Eq. 6.1b) have been introduced by Asare et al. (2015b) which is available from VECTRI Version V1.3.1. In the present work, VECTRI is run with constant population over the entire period using these two schemes.



where w_{pond} is the net aggregated fractional water coverage in a grid cell, w_{max} is the maximum fractional coverage of temporary ponds, p is the pond geometry power factor, h_{ref} is the aggregated reference pond water depth, w_{ref} is the reference fractional coverage,

P is the precipitation rate, *E* and *I* which were set to a fixed constant are evaporation rate and infiltration rate respectively and K_w is a linear constant, I_{max} is the maximum infiltration rate from ponds, *Q* is the runoff calculated from SCS formula (USDA, 1972) and *f* is the proportion of maximum pond area factor.

6.3 Results and Discussion

6.3.1 Rainfall and temperature variability

The temperature observations from various synoptic stations range from 22 to 34°C which are within the range that supports malaria transmission (Fig. 6.2a). The high temperatures occur regularly between February and May, while low temperatures generally occur between June and October across all the various zones. The mean daily rain rates at the stations vary between 0 to 16 mm day⁻¹ (see Fig. 6.2b). In the coastal agro-ecological zone, the major and minor rainfall peaks occurred in June and October, respectively. Similar peaks in major and minor seasons were observed over the forest agro-ecological zone with the exception of Abetifi where the minor season peaked in September. In the transitional zone, the peaks occurred in June and September for Suyani and Kete-Krachi. However, early peak in the major season occurred in April for Wenchi but minor season peaked was in September. Over the savanna zone, rainfall peaked in September for Bole, Tamale and Yendi. However, rainfall onset is one month earlier at Navrongo and Wa.



Figure 6.2: The monthly daily (a) temperature, (b) rainfall, (c) water fraction (d) EIR over the 31 year period (1980 to 2010) for various Gmet synoptic stations.

Fig. 6.2 shows daily monthly average rainfall, temperature, VECTRI (V1.3.0 hydrology scheme) simulated water fraction and EIR. The results clearly show that malaria transmission generally follows rainfall pattern. The timing of peaks in the simulated EIR follows peaks in rainfall but with a lag time of approximately a month (see Figs. 6.2 *b,d*). For instance, in the savanna zone with unimodal rainfall, model simulated a single peak in

malaria transmission. On the contrary, in the remaining zones with bimodal rainfall regimes, simulated malaria dynamics exhibit two peaks. For example in Asutifi, a town located about 56 km from Sunyani, Asante et al. (2011) observed the highest EIR values between June and July. This agrees with the highest simulated EIR value at Sunyani, which occurs in July followed by June. Interestingly, the major rainfall peak is in June at Sunyani. However, in the Kassena Nankana district, of which Navrongo is the capital, Appawu et al. (2004) and Kasasa et al.

(2013) observed EIR peak in September, but our results showed a peak in October for Navrongo, despite peak in rainfall in August for this station. Although a possible explanation is not apparent, it maybe due to the prolonged dry season in the area. Consequently, the model simulates no incidence of malaria (EIR <= 0.01, Tompkins and Ermert, 2013) from January to June which could result in the two month lag time between rainfall and malaria peaks.

Furthermore, Fig. 6.2 *d* shows that transmission length corresponds to the variability in rainfall onset and cessation times. For example, Amekudzi et al. (2015) found rainfall onset is from second to third dekad of March for coastal and forest zones, between second dekad of March and third dekad of April for transition zone and middle of April to first week in May for savanna zone. Based on VECTRI model EIR threshold for malaria transmission (EIR > 0.01, Tompkins and Ermert, 2013), the length of malaria season varies across the various agro-ecological zones. In the coastal zone, transmission is eleven to twelve months, all year transmission in the forest and transition zones and between six and ten months in the savanna zone. In addition transmission is remarkably seasonal in the savanna zone although all year round transmission has been reported for some areas within this zone.

For example, Koram et al. (2000) reported all year round malaria transmission but with lower cases in the dry relative to the wet seasons in the Kassena-Nankana district in northern Ghana for children under two years. To some extent, this results fall within the range reported from field observations (GSS, 2011).

Temperature was also found to play a significant role in malaria transmission variability in Ghana. For instance, despite Abetifi and Oda having almost similar rainfall pattern (see Fig. 6.2 b) and simulated water fraction (Fig. 6.2 c), the VECTRI simulated EIR shows a consistent lower values at Abetifi relative to Oda (see Fig. 6.2 d). This observation is significantly due to the lower temperatures recorded at Abetifi relative to Oda (see Fig. 6.2 a).

The most interesting aspect of Fig. 6.2 d is that the model tends to agree with some field observed studies at some locations. For instance in Accra in the coastal zone, Klinkenberg et al. (2008) found EIR values of 19.2 and 6.6 infective bites/person/year (ib/p/y) (0.052 and 0.018 infective bites/person/night (ib/p/n)) respectively for areas located near to and far from agricultural sites. These were consistent with model values for Accra ranging between

0.011 and 0.133 with average of 0.051 ib/p/n. Similarly, the model predicted EIR values (see Fig. 6.2 a) are in good agreement with the range (0.1 and 0.7 ib/p/n) estimated by Dadzie et al. (2013) from mosquitoes captured by human landing method at some locations within the country. In addition, the mean annual EIR value of 0.02 ib/p/n reported by Robert et al. (2003) for urban city centers across sub-Saharan Africa is within the range of simulated EIR values. However, in Navrongo, monthly VECTRI predicted EIR values (0 to

0.18 ib/p/n) were lower comparable to the range observed by Kasasa et al. (2013) (0 to 1.06 ib/p/n).

Averaging simulated EIR values within the various agro-ecological zones reveals malaria prevalence ranging from forest, transition, savanna and to the coast. Despite these observations, it is likely that real transmission intensity may deviate from the model predicted values due to other local effects such as contribution from permanent water bodies, uneven distribution Gmet stations and different population densities at the various cities where the synoptic stations are located. Although VECTRI takes into account the population and vector interaction in estimating EIR, in the present study, the same population density was used to run the model. This is in line with our objective, which is to assess the effects of climate alone on malaria transmission dynamics.

6.3.3 VECTRI simulated EIR and annual malaria cases

The average annual malaria cases from various public health facilities and average VECTRI simulated EIR over the 22 synoptic stations between 2000 and 2008 are compared (Fig. 6.3). The results reveal that despite using only 22 stations to represent the entire country, there is relatively good agreement between VECTRI EIR and hospital morbidity data with R² (V1.3.0: 0.52; V1.2.6: 0.51). Furthermore, although there has been an increase in intervention programs, malaria transmission is still intense and high. In addition, the VECTRI simulated EIR also showed less interannual variability in transmission. The annual simulated EIR values range from 16 to 28 and 32 to 52 ib/p/y for V1.2.6 and V1.3.0,

respectively. These are within the range from 2.6 to 44.7 estimated by Klinkenberg et al. (2008) using human landing catches in Accra, Ghana. However, these values are higher than annual EIR value of 7.1 reported for urban centers in sub-Saharan Africa (Robert et al., 2003).



Figure 6.3: Comparison of average VECTRI simulated EIR and annual malaria morbidity from public health facilities.

6.3.4 Local scale malaria transmission

The output from a single location VECTRI runs is compared to the Emena monthly recorded malaria cases (Fig. 6.4). Reported cases from the hospital indicate that transmission is slightly stable and exhibits a small intraannual variability.

SANE



Figure 6.4: Comparison of monthly VECTRI simulated single location EIR and Emena hospital morbidity data.

The two VECTRI hydrology schemes reproduce a realistic trend in the reported cases, however VECTRI V1.3.0 performed relatively well ($R^2 = 0.48$) relative to VECTRI V1.2.6 ($R^2 = 0.44$). Interestingly, these correlations are higher than the best correlation ($R^2 = 0.23$) obtained using rainfall directly. This value was obtained at one month time lag. A similar small correlation ($R^2 = 0.297$ at two month lag time) between rainfall and monthly malaria cases was observed by Tay et al. (2012) at this same study location. This further confirms the potential of VECTRI model to simulate local scale malaria transmission dynamics (Asare et al., 2015b).

6.4 Summary

In this study, we explored the potential of regional scale dynamical model VECTRI to simulate spatio-temporal malaria transmission dynamics over the four agro-ecological zones in Ghana. The simulated results reveal intra- and inter-agro-ecological variability in terms of intensity and duration of malaria transmission which are predominantly controlled by rainfall. However, temperature was found to suppress transmission only at Abetifi, a town located on the Kwahu plateau. The correlation between annual model predicted malaria incidence (EIR) and national recorded malaria cases from public health facilities was more than 0.5. On a local scale evaluation, the correlation between monthly predicted and hospital recorded malaria cases was greater than 0.4. Interestingly, this correlation ($R^2 = 0.4$) was higher than the best obtained between rainfall and malaria cases. This indicates the VECTRI model superior predictive ability relative to using rainfall directly.

These results demonstrate useful application of the VECTRI model to simulate malaria transmission dynamics at both national and local scales. Nevertheless, improved VECTRI model performance could likely be achieved by including parametrization for permanent water bodies, topography, soil characteristics, habitat water temperature and immunity.

CHAPTER 7

7.1 Conclusions

Surface hydrology and water temperature of mosquito developmental habitats are two key climatic factors that control the aquatic stage life cycle and thus adult abundance by influencing the stability of habitat and larvae growth rates, respectively. However, the small spatial scale of breeding habitats of important malaria vectors confound modeling efforts due to the lack of data from both field observations and remote sensing techniques to evaluate model parametrization assumptions. Consequently, available spatial, dynamical mathematical-biological malaria models lack a precise simulation of mosquito developmental habitat water temperature with majority of them simply equating water temperature with 2 metre mean air temperature. Similarly, some of these malaria transmission models have no representation of or incorporate schemes that vary in their complexity for surface hydrology. To address this challenge, new energy balance and surface hydrology parametrization schemes are developed and validated using in situ observations. Furthermore, the new developed surface hydrology scheme is implemented in the VECTRI model and in addition to model default scheme, their potential to simulate spatio-temporal malaria transmission variability at both local and regional scales are SANE assessed.

The results between June 6 and August 25 in 2011 field observations show that small-sized breeding habitats, which are difficult to model should not be ignored in malaria models because they have sufficient life time during the rainy season to allow larvae to fully

develop into adult mosquitoes. The observed variability in the puddles stability ranged between 11 and 81 days was strongly tied with rainfall, location and size of the puddles. In addition, results from a 10-minute temporal resolution observed water temperatures monitored between June and November 2013 revealed that water temperatures of temporary surface water are highly variable. Consequently, if colonized by larvae, they would be exposed to temperatures ranging from about 21.59 up to 39.26°C with daily average of 27.21°C. These in situ observations are used to evaluate the performance of the developed surface hydrology and habitat water temperature schemes.

A simple prognostic model was developed based on the diagnostic geometrical model of Hayashi, with sources and sinks due to precipitation, run off, evaporation and infiltration. The model accounts for pond geometry more realistically and also incorporates the nonlinearities of the surface runoff term and the infiltration term to represent the clogged inner regions of puddles. This model was able to reproduce the daily observed variability in pond water surface area and depth under different hydrological conditions. Based on general performance rating of NSE, the model results for all the individual sites were within acceptable level of model performance ranging between satisfactory and very good for depth and area simulations. However, during the later dry phase of the study period, the model tends to overestimate and underestimate the pond area and depth for the sites located far away from permanent streams (sites 6 to 8) and within waterlogged areas (sites 9 and 10), respectively. This indicates that the model could be improved by incorporating a treatment of soil moisture, which would increase infiltration in the drier periods as the soil dries out. More importantly, the key advantage of the scheme is that it can be implemented in dynamical models that run at different scales; a single location, or for a grid of points over a region or even a global scale.

This single element prognostic model developed was further generalized to simulate the total fractional coverage of ponds within a grid-cell to assess the model application in gridded dynamical models. The model results show good agreement (NSE = 0.84) with the estimated fractional coverage of the ponds. This result highlights the useful application of this prognostic geometrical model in spatially distributed dynamical disease models and thus could improve representation of surface hydrology in vector borne disease models.

Furthermore, the developed prognostic model is implemented in the regional-scale dynamical malaria model VECTRI, and in addition to the VECTRI default surface hydrology scheme, are evaluated using output from HYDREMATS, a 10 metre resolution village-scale model that explicitly simulates individual ponds. Based on multi-member ensemble Monte Carlo technique, the VECTRI model parameter setting that minimizes water fraction differences was identified. Despite the simplicity of the two VECTRI surface hydrology parametrization schemes, they perform relatively well (*NS E* > 0.85) at reproducing the seasonal and intraseasonal variability in pond water fraction, with the prognostic scheme able to produce a closer match to the explicit benchmark model, HYDREMATS. However, the default VECTRI scheme tends to overestimate water fraction in 2005 and underestimate it in 2006, and also relatively overestimates water fraction during the monsoon onset period. This systematic error was reduced by nonlinear treatment of runoff and infiltration terms in the prognostic scheme, and lead to more accurate predictions of the ponding onset at the start of the rainy season. However, it is likely that further

improvement could be made by representing soil moisture in the prognostic scheme. Simulations of vector densities with the prognostic VECTRI model were also close, both in terms of season length and magnitude to the detailed agent based model contained in HYDREMATS. The results indicate that, with knowledge of local soil parameters and terrain, VECTRI parameters can be adjusted to simulate malaria transmission on a local scale.

In addition, VECTRI driven by satellites rainfall estimates (FEWS RFE2 and TRMM 3B42) over the Banizoumbou village produces a reasonable simulation of the sub-seasonal evolution of the pond fraction for the study area, thus indicating the possibility of driving the malaria model with satellite rainfall estimates in the absence of ground observations. Such areas without permanent water bodies stand to gain more in malaria control from early warning information which dynamical models like the VECTRI model can provide if they can incorporate reliable representations of the surface hydrology driven by accurate climate observations or forecasts (Tompkins and Di Giuseppe, 2015). In addition, these results also demonstrate that VECTRI model can be driven with satellite-based rainfall data, and thus the model is applicable in areas where ground observation is not available.

To improve representation of water temperature of mosquito developmental habitats in dynamical models, an energy budget scheme that assumes a homogeneous mixed water column driven by empirically derived fluxes is developed. The model shows good agreement at both diurnal and daily time scales with the observed water temperatures. In addition, there was a close match between larvae development times calculated using either the model-derived or observed water temperatures, with the modelled water

temperature providing a significant improvement over simply assuming the water temperature to be equal to the 2-metre air temperature.

The results from the temperature scheme suggest that diurnal variations in water temperature are important for simulation of aquatic-stage development times, however, effects of sub-diurnal variations on larval development are similar to those of the diurnal. Modeling results further show that in addition to water temperature, the degree days parameter K_L is extremely important to accurately predict the larvae development time. The findings highlight the potential of the model to predict water temperature of temporary surface water, which can thus be implemented in dynamical malaria models to predict larvae development

times.

An important aspect of the presented scheme is that it uses approximations for some of the flux terms derived from readily available meteorological variables. In addition, the model can be run at different temporal scales depending on the resolution of the input data. Thus, this simple scheme could be useful for dynamical vector-borne disease models to improve aquatic life-cycle simulation especially in regions without observations of the input energy

fluxes.

Finally, VECTRI runs over Ghana reveal malaria transmission ranging from six to twelve months, with minimum intensity occurring between February and April. The simulated results reveal intra- and inter-agro-ecological variability in terms of intensity and duration of malaria transmission which are predominantly controlled by rainfall. However,

temperature was found to suppress transmission only at Abetifi, a town located on the Kwahu plateau. The correlation between mean annual model predicted malaria incidence (EIR) and recorded national malaria cases from public health facilities was more than 0.5. On a local scale, the agreement between hospital recorded monthly malaria cases and VECTRI simulated EIR values was better relative to using only rainfall. This result demonstrates the potential ability of the VECTRI model to predict malaria transmission dynamics at both local and national

scales.

The results from this study provide useful information for policy and decision makers responsible for planning malaria control strategies. Firstly, the VECTRI model possesses the potential to be adopted as malaria early warning tool for Ghana. This is due to the fact that the model simulated EIR tends to agree with the recorded morbidity data at both national and local scales to some extent. Consequently, other VECTRI output variables such as larvae and adult spatial and temporal densities would provide reliable information about the appropriate timing to carry out effective interventions targeting these stages.

7.2 Recommendations

Although the developed prognostic scheme already addresses many shortcomings of existing schemes and improved surface hydrology representation, some potential refinements are still necessary. For instance, incorporating soil moisture treatment in the prognostic scheme would moderate infiltration effects during wet and dry periods. Furthermore, the current VECTRI hydrological scheme does not account for topographical effect that plays an important role in controlling spatial distribution of potential habitats especially over a regional scale. As a result future development should consider defining the VECTRI w_{max} parameter as a function of topography. As is evident that permanent water bodies sustain all year round transmission, including a detailed parametrization for their contribution would likely improve the performance of the VECTRI model.

Another important factor neglected in the VECTRI model is the treatment of human immunity. The level of host immunity plays a significant role in controlling transmission intensity especially in the endemic relative to epidemic regions. Consequently, a regionalscale model such as the VECTRI model, effects of human immunity must be considered.

As it stands now, the application of the temperature scheme, although extremely useful for aquatic stage simulations, is limited to areas with ground observations of meteorological variables used to derive the estimated fluxes. The future research direction regarding this scheme is to assess the potential of using satellite-based meteorological variables to drive this scheme. Thus could make the scheme when implemented in dynamical models applicable even over regions without ground meteorological observations. Nevertheless, this temperature scheme is going to be implemented fully in the next release of the VECTRI model.

Notwithstanding the limitations of the VECTRI model, it can still be adopted by policy makers especially the NMCP to improve malaria control programs. Further studies are

required to assess the potential of VECTRI to provide early warning information about malaria incidence especially in the savanna region where transmission is seasonal. In addition, future VECTRI runs should specifically examine the sensitivity of timing of initiating control intervention targeting aquatic and adult mosquito stages in reducing transmission intensity. Lastly, the NMCP should make compiled morbidity data from individual hospitals accessible to aid model evaluation at local scale.

Bibliography

- Abdul-Ghani, R., Al-Mekhlafi, A. M., and Alabsi, M. S. (2012). Microbial control of malaria: biological warfare against the parasite and its vector. *Acta tropica*, 121(2):71–84.
- Adams, I., Darko, D., and Accorsi, S. (2004). Malaria: A burden explored. *Bull Health Info*, 1:28–34.
- Afari, E., Akanmori, B., Nakano, T., and Ofori-Adjei, D. (1992). Plasmodium falciparum: sensitivity to chloroquine in vivo in three ecological zones in Ghana. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, 86(3):231–232.
- Afari, E., Appawu, M., Dunyo, S., Baffoe-Wilmot, A., and Nkrumah, F. (1995). Malaria infection, morbidity and transmission in two ecological zones Southern Ghana. *African journal of health sciences*, 2(2):312–315.
- Afrane, Y., Klinkenberg, E., Drechsel, P., Owusu-Daaku, K., Garms, R., and Kruppa, T. (2004). Does irrigated urban agriculture influence the transmission of malaria in the city of Kumasi, Ghana? *Acta Tropica*, 89(2):125–134.
- Afrane, Y. A., Lawson, B. W., Githeko, A. K., and Yan, G. (2005). Effects of microclimatic changes caused by land use and land cover on duration of gonotrophic cycles of Anopheles gambiae (Diptera: Culicidae) in western Kenya highlands. *Journal of medical entomology*, 42(6):974–980.
- Afrane, Y. A., Little, T. J., Lawson, B. W., Githeko, A. K., and Yan, G. (2008). Deforestation and vectorial capacity of Anopheles gambiae Giles mosquitoes in malaria transmission, Kenya. *Emerging infectious diseases*, 14(10):1533.
- Akazili, J., Aikins, M., and Binka, F. N. (2008). Malaria treatment in Northern Ghana: What is the treatment cost per case to households? *African Journal of Health Sciences*, 14(1):70–79.

- Amekudzi, L. K., Yamba, E. I., Preko, K., Asare, E. O., Aryee, J., Baidu, M., and Codjoe, S. N. (2015). Variabilities in Rainfall Onset, Cessation and Length of Rainy Season for the Various Agro-Ecological Zones of Ghana. *Climate*, 3(2):416–434.
- Aniedu, I., Mutinga, M. J., and Mutero, C. M. (1993). Vertical estimates of survivorship of larvae and pupae of Anopheles gambbiae Giles complex in Baringo District, Kenya. *International Journal of Tropical Insect Science*, 14(01):39–48.
- Appawu, M., Baffoe-Wilmot, A., Afari, E., Nkrumah, F., and Petrarca, V. (1994). Species composition and inversion polymorphism of the Anopheles gambiae complex in some sites of Ghana, west Africa. *Acta tropica*, 56(1):15–23.
- Appawu, M., Owusu-Agyei, S., Dadzie, S., Asoala, V., Anto, F., Koram, K., Rogers, W., Nkrumah, F., Hoffman, S. L., and Fryauff, D. J. (2004). Malaria transmission dynamics at a site in northern Ghana proposed for testing malaria vaccines. *Tropical Medicine & International Health*, 9(1):164–170.
- Arifin, S., Davis, G. J., and Zhou, Y. (2011). A spatial agent-based model of malaria: model verification and effects of spatial heterogeneity. *International Journal of Agent Technologies and Systems (IJATS)*, 3(3):17–34.
- Armstrong, J. and Bransby-Williams, W. (1961). The maintenance of a colony of Anopheles gambiae, with observations on the effects of changes in temperature. *Bulletin of the World Health Organization*, 24(4-5):427.
- Aron, J. L. (1988). Mathematical modelling of immunity to malaria. *Mathematical Biosciences*, 90(1):385–396.
- Asante, F. A. and Asenso-Okyere, K. (2003). Economic burden of malaria in Ghana. *World Health Organ (WHO)*, pages 1–83.
- Asante, K. P., Zandoh, C., Dery, D. B., Brown, C., Adjei, G., Antwi-Dadzie, Y., Adjuik, M., Tchum, K., Dosoo, D., Amenga-Etego, S., Mensah, C., Owusu-Sekyere, K. B., Anderson, C., Krieger, G., and Owusu-Agyei, S. (2011). Malaria epidemiology in the Ahafo area of Ghana. *Malar J*, 10(1):211.
- Asare, E. O., Tompkins, A. M., Amekudzi, L. K., and Ermert, V. (2015a). A breeding site model for regional, dynamical malaria simulations evaluated using in situ temporary ponds observations in Ghana. *Geospatial health*, :(Submitted).
- Asare, E. O., Tompkins, A. M., and Bomblies, A. (2015b). A regional model for malaria vector developmental habitats evaluated using explicit, pond-resolving surface hydrology simulations. *PLoS ONE (submitted)*.
- Asenso-Okyere, W. (1994). People and Health Socioeconomic factors in malaria control. In *World health forum*, volume 15, page 265.
- Asenso-Okyere, W. and Dzator, J. A. (1997). Household cost of seeking malaria care. A retrospective study of two districts in Ghana. *Social science & medicine*, 45(5):659–667.

- Awolola, T., Oduola, A., Obansa, J., Chukwurar, N., and Unyimadu, J. (2007). Anopheles gambiae ss breeding in polluted water bodies in urban Lagos, southwestern Nigeria. *Journal of Vector Borne Diseases*, 44(4):241.
- Baird, J. K., Agyei, S. O., Utz, G. C., Koram, K., Barcus, M. J., Jones, T. R., Fryauff, D. J., Binka, F. N., Hoffman, S. L., and Nkrumah, F. N. (2002). Seasonal malaria attack rates in infants and young children in northern Ghana. *The American journal of tropical medicine and hygiene*, 66(3):280–286.
- Bayoh, M. and Lindsay, S. (2003). Effect of temperature on the development of the aquatic stages of Anopheles gambiae sensu stricto (Diptera: Culicidae). *Bulletin of entomological research*, 93(5):375–382.
- Bayoh, M. and Lindsay, S. (2004). Temperature-related duration of aquatic stages of the Afrotropical malaria vector mosquito Anopheles gambiae in the laboratory. *Medical and Veterinary Entomology*, 18(2):174–179.

Bayoh, M. N. (2001). Studies on the development and survival of Anopheles gambiae sensu stricto at various temperatures and relative humidities. PhD thesis, Durham University.

- Beck-Johnson, L. M., Nelson, W. A., Paaijmans, K. P., Read, A. F., Thomas, M. B., and Bjørnstad, O. N. (2013). The effect of temperature on Anopheles mosquito population dynamics and the potential for malaria transmission. *PLoS One*, 8(11).
- Becker, N., Petric, D., Boase, C., Lane, J., Zgomba, M., Dahl, C., and Kaiser, A. (2010).' *Mosquitoes and their control*, volume 2. Springer.
- Bhattacharya, S., Sharma, C., Dhiman, R., and Mitra, A. (2006). Climate change and malaria in India. *CURRENT SCIENCE-BANGALORE-*, 90(3):369.
- Binka, F. N., Kubaje, A., Adjuik, M., Williams, L. A., Lengeler, C., Maude, G., Armah, G., Kajihara, B., Adiamah, J., and Smith, P. G. (1996). Impact of permethrin impregnated bednets on child mortality in Kassena-Nankana District, Ghana: a randomized controlled trial. *Tropical Medicine & International Health*, 1(2):147–154.
- Bomblies, A. (2012). Modeling the role of rainfall patterns in seasonal malaria transmission. *Climatic change*, 112(3-4):673–685.
- Bomblies, A., Duchemin, J., and Eltahir, E. (2008). Hydrology of malaria: Model development and application to a Sahelian village. *Water Resour Res*, 44:W12445.
- Bomblies, A., Duchemin, J.-B., and Eltahir, E. (2009). A mechanistic approach for accurate simulation of village scale malaria transmission. *Malaria Journal*, 8(1):223.
- Bomblies, A. and Eltahir, E. (2009). Assessment of the impact of climate shifts on malaria transmission in the Sahel. *EcoHealth*, 6(3):426–437.

- Bozdech, Z., Llinás, M., Pulliam, B., Wong, E., Zhu, J., and DeRisi, J. (2003). The transcriptome of the intraerythrocytic developmental cycle of Plasmodium falciparum. *PLoS biology*, 1(1):e5.
- Brewster, D. and Greenwood, B. (1992). Seasonal variation of paediatric diseases in The Gambia, west Africa. *Annals of tropical paediatrics*, 13(2):133–146.
- Brooks, R. and Hayashi, M. (2002). Depth-area-volume and hydroperiod relationships of ephemeral (vernal) forest pools in southern New England. *Wetlands*, 22(2):247–255.
- Caissie, D., Satish, M. G., and El-Jabi, N. (2005). Predicting river water temperatures using the equilibrium temperature concept with application on Miramichi River catchments (New Brunswick, Canada). *Hydrological Processes*, 19(11):2137–2159.
- Caminade, C., Kovats, S., Rocklov, J., Tompkins, A. M., Morse, A. P., Colón-González, F. J., Stenlund, H., Martens, P., and Lloyd, S. J. (2014). Impact of climate change on global malaria distribution. *Proceedings of the National Academy of Sciences*, 111(9):3286– 3291.
- Carrington, L. B., Armijos, M. V., Lambrechts, L., Barker, C. M., and Scott, T. W. (2013). Effects of fluctuating daily temperatures at critical thermal extremes on Aedes aegypti life-history traits. *PloS one*, 8(3):e58824.

CDC (2004). The impact of malaria, a leading cause of death worldwide.

- Chanda, E., Masaninga, F., Coleman, M., Sikaala, C., Katebe, C., MacDonald, M., Baboo, K., Govere, J., and Manga, L. (2008). Integrated vector management: the Zambian experience. *Malaria journal*, 7(1):164.
- Chase, J. M. and Knight, T. M. (2003). Drought-induced mosquito outbreaks in wetlands. *Ecology Letters*, 6(11):1017–1024.
- Chinery, W. (1984). Effects of ecological changes on the malaria vectors Anopheles funestus and the Anopheles gambiae complex of mosquitoes in Accra, Ghana. *Tropical Medicine* & International Health, 87(2):75–81.
- Chitnis, N., Schapira, A., Smith, T., and Steketee, R. (2010). Comparing the effectiveness of malaria vector-control interventions through a mathematical model. *The American journal of tropical medicine and hygiene*, 83(2):230–240.
- Claussen, M. (1998). On multiple solutions of the atmosphere–vegetation system in present-day climate. *Global Change Biology*, 4(5):549–559.
- Coetzee, M., van Wyk, P., Booman, M., Koekemoer, L., and Hunt, R. (2006). Insecticide resistance in malaria vector mosquitoes in a gold mining town in Ghana and implications for malaria control. *Bulletin de la Société de pathologie exotique*, 99(5):400–403.
- Cohen, J. M., Ernst, K. C., Lindblade, K. A., Vulule, J. M., John, C. C., and Wilson, M. L. (2010). Local topographic wetness indices predict household malaria risk better than land-use and land-cover in the western kenya highlands. *Malar J*, 9(328):1–10.

Coleman, M. and Hemingway, J. (2007). Insecticide resistance monitoring and evaluation in disease transmitting mosquitoes. *Journal of Pesticide Science*, 32(2):69–76.

- Coleman, M., Sharp, B., Seocharan, I., and Hemingway, J. (2006). Developing an evidencebased decision support system for rational insecticide choice in the control of African malaria vectors. *Journal of medical entomology*, 43(4):663–668.
- Collins, W. and Jeffery, G. (2007). Plasmodium malariae: parasite and disease. *Clinical microbiology reviews*, 20(4):579–592.
- Cox, J., Craig, M., Le Sueur, D., and Sharp, B. (1999). Mapping malaria risk in the highlands of Africa. *MARA/HIMAL Technical Report*, page 114.
- Cox-Singh, J., Davis, T., Lee, K., Shamsul, S., Matusop, A., Ratnam, S., Rahman, H., Conway, D., and Singh, B. (2008). Plasmodium knowlesi malaria in humans is widely distributed and potentially life threatening. *Clinical infectious diseases*, 46(2):165–171.
- Craig, M., Snow, R., and Le Sueur, D. (1999). A climate-based distribution model of malaria transmission in sub-Saharan Africa. *Parasitology Today*, 15(3):105–111.
- Dadzie, S. K., Brenyah, R., and Appawu, M. A. (2013). Role of species composition in malaria transmission by the Anopheles funestus group (Diptera: Culicidae) in Ghana. *Journal of Vector Ecology*, 38(1):105–110.
- Danuor, S., Tay, S., Annor, T., Forkuo, E., Bosompem, K., and Antwi, V. (2010). The impact of climate variability on malaria incidence and prevalence in the forest zone of Ghana–A case study at two (2) hospitals located within the Kumasi Metropolitan area of the Ashanti Region of Ghana. In 2nd International Conference: Climate, Sustainability and Development in Semi-arid Regions, pages 16–20.
- Das, P. and Amalraj, D. D. (1997). Biological control of malaria vectors. *The Indian journal* of medical research, 106:174–197.
- Day, K., Hayward, R., and Dyer, M. (1998). The biology of Plasmodium falciparum transmission stages. *Parasitology*, 116(S1):S95–S109.
- De Souza, D., Kelly-Hope, L., Lawson, B., Wilson, M., and Boakye, D. (2010). Environmental factors associated with the distribution of Anopheles gambiae ss in Ghana; an important vector of lymphatic filariasis and malaria. *PloS one*, 5(3):e9927.
- Depinay, J., Mbogo, C., Killeen, G., Knols, B., Beier, J., Carlson, J., Dushoff, J., Billingsley, P., Mwambi, H., Githure, J., Toure, A. M., and McKenzie, F. E. (2004). A simulation model of African Anopheles ecology and population dynamics for the analysis of malaria transmission. *Malaria Journal*, 3(1):29.
- Dery, D. B., Brown, C., Asante, K. P., Adams, M., Dosoo, D., Amenga-Etego, S., Wilson, M., Chandramohan, D., Greenwood, B., and Owusu-Agyei, S. (2010). Patterns and seasonality of malaria transmission in the forest-savannah transitional zones of Ghana. *Malaria Journal*, 9(1):1–8.

- Desconnets, J.-C., Taupin, J.-D., Lebel, T., and Leduc, C. (1997). Hydrology of the HAPEX-Sahel Central Super-Site: surface water drainage and aquifer recharge through the pool systems. *Journal of Hydrology*, 188:155–178.
- Detinova, T. (1962). Age-grouping methods in Diptera of medical importance with special reference to some vectors of malaria. *Monograph series. World Health Organization*, 47:13.
- Dietz, K., Molineaux, L., and Thomas, A. (1974). A malaria model tested in the African savannah. *Bulletin of the World Health Organization*, 50(3-4):347.
- Dinko, B., Oguike, M. C., Larbi, J. A., Bousema, T., and Sutherland, C. J. (2013). Persistent detection of Plasmodium falciparum, P. malariae, P. ovale curtisi and P. ovale wallikeri after ACT treatment of asymptomatic Ghanaian school-children. *International Journal for Parasitology: Drugs and Drug Resistance*, 3:45–50.
- Dolo, G., Briët, O. J., Dao, A., Traoré, S. F., Bouaré, M., Sogoba, N., Niaré, O., Bagayogo, M., Sangaré, D., and Teuscher, T. (2004). Malaria transmission in relation to rice cultivation in the irrigated Sahel of Mali. *Acta tropica*, 89(2):147–159.
- Dongus, S., Nyika, D., Kannady, K., Mtasiwa, D., Mshinda, H., Gosoniu, L., Drescher, A. W., Fillinger, U., Tanner, M., Killeen, G. F., and Castro, M. C. (2009). Urban agriculture and Anopheles habitats in Dar es Salaam, Tanzania. *Geospatial Health*, 3(2):189–210.
- Donovan, C., Siadat, B., and Frimpong, J. (2012). Seasonal and socio-economic variations in clinical and self-reported malaria in Accra, Ghana: Evidence from facility data and a community survey. *Ghana medical journal*, 46(2):85–94.
- Dontwi, I., Dedu, V., and Aboagye, N. (2013). Ascertaining the Financial Cost of Malaria and Mitigating against It Using Actuarial Models for Financial Cost. *International Journal of Financial Research*, 4(3):p94.
- Dupont, S. and Mestayer, P. G. (2006). Parameterization of the urban energy budget with the submesoscale soil model. *Journal of applied meteorology and climatology*, 45(12):1744–1765.
- Ermert, V., Fink, A., Jones, A., and Morse, A. (2011a). Development of a new version of the Liverpool Malaria Model. II. Calibration and validation for West Africa. *Malaria Journal*, 10(1):62.
- Ermert, V., Fink, A. H., Jones, A. E., and Morse, A. P. (2011b). Development of a new version of the Liverpool Malaria Model. I. Refining the parameter settings and mathematical formulation of basic processes based on a literature review. *Malar J*, 10(1):35.
- Fillinger, U., Sombroek, H., Majambere, S., Van Loon, E., Takken, W., and Lindsay, S. (2009). Identifying the most productive breeding sites for malaria mosquitoes in The Gambia. *Malaria Journal*, 8(1):62.
- Fillinger, U., Sonye, G., Killeen, G., Knols, B., and Becker, N. (2004). The practical importance of permanent and semipermanent habitats for controlling aquatic stages of Anopheles

gambiae sensu lato mosquitoes: operational observations from a rural town in western Kenya. *Tropical Medicine* & *International Health*, 9(12):1274–1289.

- Fischer, H., List, E., Koh, R., Imberger, J., and Brooks, N. (1979). *Mixing in inland and coastal waters*. Academic press, New York.
- Gallup, J. and Sachs, J. (2001). The economic burden of malaria. *The American journal of tropical medicine and hygiene*, 64(1 suppl):85.
- Garcia, R. (1983). Mosquito management: ecological approaches. *Environmental Management*, 7(1):73–78.
- Garmendia, A. and Pedrola-Monfort, J. (2010). Simulation model comparing the hydroperiod of temporary ponds with different shapes. *Limnetica*, 1(29):145–152.
- Garrett-Jones, C. and Grab, B. (1964). The assessment of insecticidal impact on the malaria mosquito's vectorial capacity, from data on the proportion of parous females. *Bulletin of the World Health Organization*, 31(1):71.
- Gething, P. W., Smith, D. L., Patil, A. P., Tatem, A. J., Snow, R. W., and Hay, S. I. (2010). Climate change and the global malaria recession. *Nature*, 465(7296):342–345.
- GHS (2009). Strategic plan for malaria control in Ghana 2008-2015. Ministry of Health, Ghana.
- GHS (2011). Annual Report. Ministry of Health, Ghana.
- GHS (2013). Facts and figures. Available online at http://www.moh-ghana.org/pub_ content.aspx?id=4.
- Gianotti, R., Bomblies, A., and Eltahir, E. (2009). Hydrologic modeling to screen potential environmental management methods for malaria vector control in Niger.
- Gillies, M. (1953). The duration of the gonotrophic cycle in Anopheles gambiae and Anopheles funestus, with a note on the efficiency of hand catching. *East African medical journal*, 30(4):129.
- Gillies, M. (1961). Studies on the dispersion and survival of Anopheles gambiae Giles in East Africa, by means of marking and release experiments. *Bulletin of Entomological Research*, 52(01):99–127.
- Gimnig, J., Ombok, M., Kamau, L., and Hawley, W. (2001). Characteristics of larval anopheline (Diptera: Culicidae) habitats in Western Kenya. *Journal of Medical Entomology*, 38(2):282–288.
- Gimnig, J. E., Ombok, M., Otieno, S., Kaufman, M. G., Vulule, J. M., and Walker, E. D. (2002). Density-dependent development of Anopheles gambiae (Diptera: Culicidae) larvae in artificial habitats. *Journal of Medical Entomology*, 39(1):162–172.
- Githeko, A. and Ndegwa, W. (2001). Predicting malaria epidemics in the Kenyan highlands using climate data: a tool for decision makers. *Global change* & *human health*,

2(1):54-63.

- Goldsmith, C. (2010). *Battling Malaria: On the Front Lines Against a Global Killer*. Twenty-First Century Books.
- Gosnell, R., Fairall, C., and Webster, P. (1995). The sensible heat of rainfall in the tropical ocean. JOURNAL OF GEOPHYSICAL RESEARCH-ALL SERIES-, 100:18–437.
- Gouagna, L. C., Rakotondranary, M., Boyer, S., Lempérière, G., Dehecq, J.-S., and Fontenille, D. (2012). Abiotic and biotic factors associated with the presence of Anopheles arabiensis immatures and their abundance in naturally occurring and man-made aquatic habitats. *Parasit Vectors*, 5(1):96.
- Greenwood, B. and Mutabingwa, T. (2002). Malaria in 2002. Nature, 415(6872):670-672.
- Griffin, J. T., Hollingsworth, T. D., Okell, L. C., Churcher, T. S., White, M., Hinsley, W., Bousema, T., Drakeley, C. J., Ferguson, N. M., Basáñez, M.-G., and Ghani, A. C. (2010).
 Reducing Plasmodium falciparum malaria transmission in Africa: a model-based evaluation of intervention strategies. *PLoS medicine*, 7(8):e1000324.
- GSS (2011). Ghana Multiple Indicator Cluster Survey with an Enhanced Malaria Module and Biomarker . Ghana Statistical Service. Final Report.
- Gu, W. and Novak, R. (2009). Agent-based modelling of mosquito foraging behaviour for malaria control. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, 103(11):1105–1112.
- Gu, W. and Novak, R. J. (2005). Habitat-based modeling of impacts of mosquito larval interventions on entomological inoculation rates, incidence, and prevalence of malaria. *The American journal of tropical medicine and hygiene*, 73(3):546–552.
- Gu, W. and Novak, R. J. (2006). Statistical estimation of degree days of mosquito development under fluctuating temperatures in the field. *Journal of Vector Ecology*, 31(1):107–112.
- Gu, W., Regens, J., Beier, J., and Novak, R. (2006). Source reduction of mosquito larval habitats has unexpected consequences on malaria transmission. *Proceedings of the National Academy of Sciences*, 103(46):17560.
- Gu, W., Utzinger, J., and Novak, R. (2008). Habitat-based larval interventions: a new perspective for malaria control. *The American journal of tropical medicine and hygiene*, 78(1):2–6.
- Haddow, A. (1943). Measurements of temperature and light in artificial pools with reference to the larval habitat of Anopheles (Myzomyia) gambiae, Giles, and A.(M.) funestus, Giles. *Bulletin of Entomological Research*, 34(02):89–93.
- Hänscheid, T. (1999). Diagnosis of malaria: a review of alternatives to conventional microscopy. *Clinical & Laboratory Haematology*, 21(4):235–245.

- Hardy, A. J., Gamarra, J. G., Cross, D. E., Macklin, M. G., Smith, M. W., Kihonda, J., Killeen, G. F., LingâA[×] Zala, G. N., and Thomas, C. J. (2013).[′] Habitat hydrology and geomorphology control the distribution of malaria vector larvae in rural Africa. *PloS one*, 8(12):e81931.
- Hargreaves, G. (1994). Simplified coefficients for estimating monthly solar radiation in North America and Europe. *Dept. Paper*.
- Hargreaves, G. H. and Samani, Z. A. (1982). Estimating potential evapotranspiration. *Journal* of the Irrigation and Drainage Division, 108(3):225–230.
- Hay, S., Cox, J., Rogers, D., Randolph, S., Stern, D., Shanks, G., Myers, M., and Snow, R. (2002). Climate change and the resurgence of malaria in the East African highlands. *Nature*, 415(6874):905–909.
- Hay, S., Guerra, C., Gething, P., Patil, A., Tatem, A., Noor, A., Kabaria, C., Manh, B., Elyazar,
 I., Brooker, S., Smith, D., Moyeed, R., Snow, and W., R. (2009). A world malaria map:
 Plasmodium falciparum endemicity in 2007. *PLoS Medicine*, 6(3):e1000048.
- Hay, S., Guerra, C., Tatem, A., Noor, A., and Snow, R. (2004). The global distribution and population at risk of malaria: past, present, and future. *The Lancet infectious diseases*, 4(6):327–336.
- Hay, S. I., Myers, M. F., Burke, D. S., Vaughn, D. W., Endy, T., Ananda, N., Shanks, G. D., Snow, R. W., and Rogers, D. J. (2000). Etiology of interepidemic periods of mosquitoborne disease. *Proceedings of the National Academy of Sciences*, 97(16):9335–9339.
- Hayashi, M. and Van der Kamp, G. (2000). Simple equations to represent the volume-areadepth relations of shallow wetlands in small topographic depressions. *Journal of Hydrology*, 237(1-2):74–85.
- Hayashi, M. and van der Kamp, G. (2007). Water level changes in ponds and lakes: the hydrological processes. *Plant Disturbance Ecology: The Process and the Response*, pages 311–339.
- Healy, T. and Copland, M. (1995). Activation of Anopheles gambiae mosquitoes by carbon dioxide and human breath. *Medical and veterinary entomology*, 9(3):331–336.
- Herman, A., Kumar, V. B., Arkin, P. A., and Kousky, J. V. (1997). Objectively determined 10day African rainfall estimates created for famine early warning systems. *International Journal of Remote Sensing*, 18(10):2147–2159.
- Hicks, B. (1972). Some evaluations of drag and bulk transfer coefficients over water bodies of different sizes. *Boundary-layer meteorology*, 3(2):201–213.
- Hill, N., Lenglet, A., Arnez, A., and Carneiro, I. (2007). Plant based insect repellent and insecticide treated bed nets to protect against malaria in areas of early evening biting vectors: double blind randomised placebo controlled clinical trial in the Bolivian Amazon. *BMJ*, 335(7628):1023.

- Himeidan, Y. E., Zhou, G., Yakob, L., Afrane, Y., Munga, S., Atieli, H., El-Rayah, E.-A., Githeko,
 A. K., and Yan, G. (2009). Habitat stability and occurrences of malaria vector larvae in western Kenya highlands. *Malaria Journal*, 8:234.
- Hodges, B. (1998). Heat budget and thermodynamics at a free surface: Some theory and numerical implementation. *Centre for Water Research, University of Western Australia*.
- Holstein, M. H. (1954). *Biology of Anopheles gambiae: research in French West Africa*. Number 9. World Health Organization.
- Hoshen, M. and Morse, A. (2004). A weather-driven model of malaria transmission. *Malaria Journal*, 3(1):32.
- Huffman, G. J., Bolvin, D. T., Nelkin, E. J., Wolff, D. B., Adler, R. F., Gu, G., Hong, Y., Bowman, K. P., and Stocker, E. F. (2007). The TRMM multisatellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of Hydrometeorology*, 8(1):38–55.
- Hunt, R. H., Fuseini, G., Knowles, S., Stiles-Ocran, J., Verster, R., Kaiser, M. L., Choi, K. S., Koekemoer, L. L., and Coetzee, M. (2011). Insecticide resistance in malaria vector mosquitoes at four localities in Ghana, West Africa. *Parasit Vectors*, 4:107.
- Iguchi, T., Kozu, T., Meneghini, R., Awaka, J., and OKAMOTO, K. (2000). Rain-profiling algorithm for the TRMM precipitation radar. *Journal of Applied Meteorology*, 39(12):2038–2052.
- Imbahale, S., Paaijmans, K., Mukabana, W., van Lammeren, R., Githeko, A., and Takken, W. (2011). A longitudinal study on Anopheles mosquito larval abundance in distinct geographical and environmental settings in western Kenya. *Malaria Journal*, 10(1):81.
- Iqbal, M. (1983). An introduction to solar radiation.
- Jawara, M., Pinder, M., Drakeley, C. J., Nwakanma, D. C., Jallow, E., Bogh, C., Lindsay, S. W., and Conway, D. J. (2008). Dry season ecology of Anopheles gambiae complex mosquitoes in the Gambia. *Malar J*, 7(1):156.
- Jepson, W., Moutia, A., and Courtois, C. (1947). The malaria problem in Mauritius: the bionomics of Mauritian anophelines. *Bulletin of entomological research*, 38(01):177–208.
- Jones, A. and Morse, A. (2010). Application and validation of a seasonal ensemble prediction system using a dynamic malaria model. *Journal of Climate*, 23(15):4202–4215.
- Jones, A. and Morse, A. (2012). Skill of ENSEMBLES seasonal re-forecasts for malaria prediction in West Africa. *Geophysical Research Letters*, 39(23).
- Jowett, M. and Miller, N. J. (2005). The financial burden of malaria in Tanzania: implications for future government policy. *The International journal of health planning and management*, 20(1):67–84.

- Kasasa, S., Asoala, V., Gosoniu, L., Anto, F., Adjuik, M., Tindana, C., Smith, T., Owusu-Agyei,
 S., and Vounatsou, P. (2013). Spatio-temporal malaria transmission patterns in Navrongo demographic surveillance site, northern Ghana. *Malaria journal*, 12(1):63.
- Keiser, J., Utzinger, J., De Castro, M., Smith, T., Tanner, M., and Singer, B. (2004). Urbanization in sub-saharan Africa and implication for malaria control. *The American journal of tropical medicine and hygiene*, 71(2 suppl):118–127.
- Kelly-Hope, L., Hemingway, J., and McKenzie, F. (2009). Environmental factors associated with the malaria vectors Anopheles gambiae and Anopheles funestus in Kenya. *Malaria journal*, 8(1):268.
- Kilian, A., Langi, P., Talisuna, A., and Kabagambe, G. (1999). Rainfall pattern, El Nino and malaria in Uganda. *Trans R Soc Trop Med Hyg*, 93(1):22–3.
- Killeen, G., Seyoum, A., and Knols, B. (2004). Rationalizing historical successes of malaria control in Africa in terms of mosquito resource availability management. *The American journal of tropical medicine and hygiene*, 71(2 suppl):87–93.
- Kirby, M. and Lindsay, S. (2004). Responses of adult mosquitoes of two sibling species, Anopheles arabiensis and A. gambiae ss (Diptera: Culicidae), to high temperatures. *Bulletin of entomological research*, 94(05):441–448.
- Kirby, M. and Lindsay, S. (2009). Effect of temperature and inter-specific competition on the development and survival of Anopheles gambiae sensu stricto and An. arabiensis larvae. *Acta Tropica*, 109(2):118–123.
- Kiszewski, A., Mellinger, A., Spielman, A., Malaney, P., Sachs, S. E., and Sachs, J. (2004). A global index representing the stability of malaria transmission. *The American journal of tropical medicine and hygiene*, 70(5):486–498.
- Kiszewski, A. E. and Teklehaimanot, A. (2004). A review of the clinical and epidemiologic burdens of epidemic malaria. *The American journal of tropical medicine and hygiene*, 71(2 suppl):128–135.
- Kleinschmidt, I., Omumbo, J., Briet, O., Van De Giesen, N., Sogoba, N., Mensah, N. K., Windmeijer, P., Moussa, M., and Teuscher, T. (2001). An empirical malaria distribution map for West Africa. *Tropical Medicine & International Health*, 6(10):779–786.
- Klinkenberg, E., McCall, P., Hastings, I., Wilson, M., Amerasinghe, F., and Donnelly, M. (2005). Malaria and irrigated crops, Accra, Ghana. *Emerging infectious diseases*, 11(8):1290.
- Klinkenberg, E., McCall, P., Wilson, M., Amerasinghe, F., and Donnelly, M. (2008). Impact of urban agriculture on malaria vectors in Accra, Ghana. *Malaria journal*, 7(1):151.

ANE

Klinkenberg, E., McCall, P., Wilson, M. D., Akoto, A. O., Amerasinghe, F. P., Bates, I., Verhoeff, F. H., Barnish, G., and Donnelly, M. J. (2006). Urban malaria and anaemia in children: a cross-sectional survey in two cities of Ghana. *Tropical medicine* & *international health*, 11(5):578–588.

- Klutse, N. A. B., Aboagye-Antwi, F., Owusu, K., and Ntiamoa-Baidu, Y. (2014). Assessment of Patterns of Climate Variables and Malaria Cases in Two Ecological Zones of Ghana. *Open Journal of Ecology*, 4(12):764.
- Knippertz, P., Fink, A. H., Schuster, R., Trentmann, J., Schrage, J. M., and Yorke, C. (2011). Ultra-low clouds over the southern West African monsoon region. *Geophysical Research Letters*, 38(21).
- Koella, J. and Antia, R. (2003). Epidemiological models for the spread of anti-malarial resistance. *Malaria Journal*, 2(1):3.
- Koella, J. C. (1991). On the use of mathematical models of malaria transmission. *Acta tropica*, 49(1):1–25.
- Koenraadt, C., Githeko, A., and Takken, W. (2004). The effects of rainfall and evapotranspiration on the temporal dynamics of Anopheles gambiae ss and Anopheles arabiensis in a Kenyan village. *Acta tropica*, 90(2):141–153.
- Koenraadt, C. and Takken, W. (2003). Cannibalism and predation among larvae of the Anopheles gambiae complex. *Medical and veterinary entomology*, 17(1):61–66.
- Koram, K., Owusu-Agyei, S., Fryauff, D., Anto, F., Atuguba, F., Hodgson, A., Hoffman, S., and Nkrumah, F. (2003). Seasonal profiles of malaria infection, anaemia, and bednet use among age groups and communities in northern Ghana. *Tropical Medicine* & *International Health*, 8(9):793–802.
- Koram, K. A., Owusu-Agyei, S., Utz, G., Binka, F. N., Baird, J. K., Hoffman, S. L., and Nkrumah,
 F. K. (2000). Severe anemia in young children after high and low malaria transmission seasons in the Kassena-Nankana district of northern Ghana. *The American journal of tropical medicine and hygiene*, 62(6):670–674.
- Kovats, R., Campbell-Lendrum, D., McMichel, A., Woodward, A., and Cox, J. (2001). Early effects of climate change: do they include changes in vector-borne disease? *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, 356(1411):1057–1068.
- Krefis, A., Schwarz, N., Krüger, A., Fobil, J., Nkrumah, B., Acquah, S., Loag, W., Sarpong, N., Adu-Sarkodie, Y., Ranft, U., and May, J. (2011). Modeling the Relationship between Precipitation and Malaria Incidence in Children from a Holoendemic Area in Ghana. *The American journal of tropical medicine and hygiene*, 84(2):285–291.
- Krotoski, W. (1988). The hypnozoite and malarial relapse. *Progress in clinical parasitology*, 1:1–19.
- Larnier, K., Roux, H., Dartus, D., and Croze, O. (2010). Water temperature modeling in the Garonne River (France). *Knowledge and Management of Aquatic Ecosystems*, (398):04.
- Lengeler, C. (2004). Insecticide-treated bed nets and curtains for preventing malaria. *Cochrane Database Syst Rev*, 2(2).

Liebethal, C. and Foken, T. (2007). Evaluation of six parameterization approaches for the ground heat flux. *Theoretical and Applied Climatology*, 88(1-2):43–56.

- Lindblade, K., Walker, E., Onapa, A., Katungu, J., and Wilson, M. (2001). Land use change alters malaria transmission parameters by modifying temperature in a highland area of Uganda. *Tropical Medicine & International Health*, 5(4):263–274.
- Lindsay, S., Bødker, R., Malima, R., Msangeni, H., and Kisinza, W. (2000). Effect of 1997–98 El Niño on highland malaria in Tanzania. *The Lancet*, 355(9208):989–990.
- Lindsay, S. and Martens, W. (1998). Malaria in the African highlands: past, present and future. *Bulletin of the World Health Organization*, 76(1):33.
- Losordo, T. and Piedrahita, R. (1991). Modelling temperature variation and thermal stratification in shallow aquaculture ponds. *Ecological modelling*, 54(3-4):189–226.
- Love, T. B., Kumar, V., Xie, P., and Thiaw, W. (2004). A 20-year daily Africa precipitation climatology using satellite and gauge data. In *American Meteorological Society Conference on Applied Climatology, Seattle, WA*.
- Lowe, R., Chirombo, J., and Tompkins, A. M. (2013). Relative importance of climatic, geographic and socio-economic determinants of malaria in Malawi. *Malaria journal*, 12(1):416.
- Lunde, T. M., Bayoh, M. N., and Lindtjørn, B. (2013a). How malaria models relate temperature to malaria transmission. *Parasites & Vectors*, 6:20.
- Lunde, T. M., Korecha, D., Loha, E., Sorteberg, A., and Lindtjørn, B. (2013b). A dynamic model of some malaria-transmitting anopheline mosquitoes of the Afrotropical region.
 I. Model description and sensitivity analysis. *Malar J*, 12(1):28.
- Lyimo, E., Takken, W., and Koella, J. (1992). Effect of rearing temperature and larval density on larval survival, age at pupation and adult size of Anopheles gambiae. *Entomologia experimentalis et applicata*, 63(3):265–271.
- Lysenko, A. and Beljaev, A. (1969). An analysis of the geographical distribution of Plasmodium ovale. *Bulletin of the World Health Organization*, 40(3):383.
- Macdonald, G. (1956). Epidemiological basis of malaria control. *Bulletin of the World Health Organization*, 15(3-5):613.

Macdonald, G. (1957). The epidemiology and control of malaria. London, Oxford Univ. Pr.

Majambere, S., Fillinger, U., Sayer, D., Green, C., and Lindsay, S. (2008). Spatial distribution of mosquito larvae and the potential for targeted larval control in The Gambia. *The American journal of tropical medicine and hygiene*, 79(1):19.

Makler, M. T. (1992). Method for diagnosing malaria. US Patent 5,124,141.

Malaria, R. B. (2008). The global malaria action plan. Roll Back Malaria partnership.

- Mandal, S., Sarkar, R. R., and Sinha, S. (2011). Mathematical models of malaria-a review. *Malar J*, 10(1):202.
- Manzanas, R., Amekudzi, L., Preko, K., Herrera, S., and Gutiérrez, J. M. (2014). Precipitation variability and trends in Ghana: An intercomparison of observational and reanalysis products. *Climatic change*, 124(4):805–819.
- Martens, P., Kovats, R., Nijhof, S., De Vries, P., Livermore, M., Bradley, D., Cox, J., and McMichael, A. (1999). Climate change and future populations at risk of malaria. *Global Environmental Change*, 9:S89–S107.
- Martens, W., Jetten, T., Rotmans, J., and Niessen, L. (1995a). Climate change and vectorborne diseases: a global modelling perspective. *Global environmental change*, 5(3):195– 209.
- Martens, W., Niessen, L., Rotmans, J., Jetten, T., and McMichael, A. (1995b). Potential impact of global climate change on malaria risk. *Environmental health perspectives*, 103(5):458.
- Martens, W. J., Jetten, T. H., and Focks, D. A. (1997). Sensitivity of malaria, schistosomiasis and dengue to global warming. *Climatic change*, 35(2):145–156.
- Martin-Rosales, W. and Leduc, C. (2003). Dynamiques de vidange d'une mare temporaire au Sahel: l'exemple de Banizoumbou (Sud-Ouest du Niger). *Comptes Rendus Geoscience*, 335(5):461–468.
- Matthys, B., N'Goran, E. K., Koné, M., Koudou, B. G., Vounatsou, P., Cissé, G., Tschannen, A. B., Tanner, M., and Utzinger, J. (2006). Urban agricultural land use and characterization of mosquito larval habitats in a medium-sized town of Cote d'Ivoire. *Journal of Vector Ecology*, 31(2):319–333.
- McKenzie, F. E. and Bossert, W. H. (2005). An integrated model of Plasmodium falciparum dynamics. *Journal of theoretical biology*, 232(3):411–426.
- McMichael, A., Confalonieri, U., Githeko, A., Haines, A., Kovats, R., Martens, P., Patz, J., Sasaki, A., and Woodward, A. (2000). Human health. *Special Report on Methodological and Technological Issues in Technology Transfer: A Special Report of IPCC Working Group III*, pages 329–347.
- Mendis, K., Sina, B., Marchesini, P., and Carter, R. (2001). The neglected burden of Plasmodium vivax malaria. *The American journal of tropical medicine and hygiene*, 64(1 suppl):97–106.
- Miller, L., Baruch, D., Marsh, K., and Doumbo, O. (2002). The pathogenic basis of malaria. *Nature*, 415(6872):673.
- Minakawa, N., Dida, G. O., Sonye, G. O., Futami, K., and Njenga, S. M. (2012). Malaria vectors in Lake Victoria and adjacent habitats in western Kenya. *PLoS One*, 7(3):e32725.

- Minakawa, N., Mutero, C., Githure, J., Beier, J., and Yan, G. (1999). Spatial distribution and habitat characterization of anopheline mosquito larvae in Western Kenya. *The American journal of tropical medicine and hygiene*, 61(6):1010–1016.
- Minakawa, N., Omukunda, E., Zhou, G., Githeko, A., and Yan, G. (2006). Malaria vector productivity in relation to the highland environment in Kenya. *The American journal of tropical medicine and hygiene*, 75(3):448–453.
- Minakawa, N., Sonye, G., Mogi, M., and Yan, G. (2004). Habitat characteristics of Anopheles gambiae ss larvae in a Kenyan highland. *Medical and veterinary entomology*, 18(3):301–305.
- Minakawa, N., Sonye, G., and Yan, G. (2005). Relationships between occurrence of Anopheles gambiae sl (Diptera: Culicidae) and size and stability of larval habitats. *Journal of medical entomology*, 42(3):295–300.
- Minke, A., Westbrook, C., and van der Kamp, G. (2010). Simplified volume-area-depth method for estimating water storage of prairie potholes. *Wetlands*, 30(3):541–551.
- Mittal, P. (2003). Biolarvicides in vector control: challenges and prospects. *Journal of vector borne diseases*, 40(1-2):20–32.
- Molineaux, L. and Gramiccia, G. (1980). The Garki Project. Research on the epidemiology and control of malaria in the Sudan Savanna of West Africa. *World Health Organization*.
- Molineaux, L., Wernsdorfer, W., and McGregor, I. (1988). The epidemiology of human malaria as an explanation of its distribution, including some implications for its control. *Malaria: principles and practice of malariology. Volume 2.*, pages 913–998.
- Montosi, E., Manzoni, S., Porporato, A., and Montanari, A. (2012). An ecohydrological model of malaria outbreaks. *Hydrology and Earth System Sciences*, 16(8):2759–2769.
- Moriasi, D., Arnold, J., Van Liew, M., Bingner, R., Harmel, R., and Veith, T. (2007). Model evaluation guidelines for systematic quantification of accuracy in watershed simulations. *Trans. ASABE*, 50(3):885–900.
- Munga, S., Minakawa, N., Zhou, G., Barrack, O., Githeko, A., and Yan, G. (2005). Oviposition site preference and egg hatchability of Anopheles gambiae: effects of land cover types. *Journal of medical entomology*, 42(6):993–997.
- Munga, S., Minakawa, N., Zhou, G., Mushinzimana, E., Barrack, O., Githeko, A., and Yan, G. (2006). Association between land cover and habitat productivity of malaria vectors in western Kenyan highlands. *The American journal of tropical medicine and hygiene*, 74(1):69.
- Mushinzimana, E., Munga, S., Minakawa, N., Li, L., Feng, C., Bian, L., Kitron, U., Schmidt, C., Beck, L., Zhou, G., Githeko, A., and G., Y. (2006). Landscape determinants and remote sensing of anopheline mosquito larval habitats in the western Kenya highlands. *Malaria Journal*, 5(1):13.

- Mutuku, F., Alaii, J., Bayoh, M., Gimnig, J., Vulule, J., Walker, E., Kabiru, E., and Hawley, W. (2006a). Distribution, description, and local knowledge of larval habitats of Anopheles gambiae sl in a village in western Kenya. *The American journal of tropical medicine and hygiene*, 74(1):44–53.
- Mutuku, F., Bayoh, M., Gimnig, J., Vulule, J., Kamau, L., Walker, E., Kabiru, E., and Hawley, W. (2006b). Pupal habitat productivity of Anopheles gambiae complex mosquitoes in a rural village in western Kenya. *The American journal of tropical medicine and hygiene*, 74(1):54–61.
- Mwangangi, J., Muturi, E., Shililu, J., Muriu, S., Jacob, B., Kabiru, E., Mbogo, C., Githure, J., and Novak, R. (2006). Survival of immature Anopheles arabiensis (Diptera: Culicidae) in aquatic habitats in Mwea rice irrigation scheme, central Kenya. *Malaria journal*, 5(1):114.
- Mwangangi, J. M., Muturi, E. J., Shililu, J. I., Muriu, S., Jacob, B., Kabiru, E. W., Mbogo, C. M., Githure, J. I., and Novak, R. J. (2007). Environmental covariates of Anopheles arabiensis in a rice agroecosystem in Mwea, Central Kenya. *Journal of the American Mosquito Control Association*, 23(4):371–377.
- Najera, J. and Zaim, M. (2001). Malaria vector control. insecticides for indoor residual spraying. *WHO Dengue Bulletin*, 25:126–127.
- Nash, J. and Sutcliffe, J. (1970). River flow forecasting through conceptual models part I-A discussion of principles. *Journal of hydrology*, 10(3):282–290.
- Ndenga, B. A., Simbauni, J. A., Mbugi, J. P., Githeko, A. K., and Fillinger, U. (2011). Productivity of malaria vectors from different habitat types in the western Kenya highlands. *PloS one*, 6(4):e19473.
- Ngasala, B. E. (2010). Improved malaria case management in under-fives in the era of Artemisini-based combination therapy in Tanzania.
- Nikolaev, B. (1935). On the influence of temperature on the development of malaria plasmodia in the mosquito. *Leningrad Pasteur Institute of Epidemiology and Bacteriology*, 2:108–109.
- NMCP (2008). Annual Report. National Malaria Control Programme (NMCP), Ministry of Health, Ghana.
- Okell, L. C., Drakeley, C. J., Bousema, T., Whitty, C., and Ghani, A. C. (2008). Modelling the impact of artemisinin combination therapy and long-acting treatments on malaria transmission intensity. *PLoS Med*, 5(11):e226.
- Okorosobo, T., Okorosobo, F., Mwabu, G., Orem, J. N., and Kirigia, J. M. (2011). Economic burden of malaria in six countries of Africa. *European Journal of Business and Management*, 3(6):42–62.
- Okoye, P., Wilson, M., Boakye, D., and Brown, C. (2005). Impact of the Okyereko irrigation project in Ghana on the risk of human malaria infection by Anopheles species (Diptera: Culicidae). *African entomology*, 13(2):p–249.

- O'Meara, W. P., Mangeni, J. N., Steketee, R., and Greenwood, B. (2010). Changes in the burden of malaria in sub-Saharan Africa. *The Lancet infectious diseases*, 10(8):545–555.
- Omumbo, J. A., Lyon, B., Waweru, S. M., Connor, S. J., and Thomson, M. C. (2011). Raised temperatures over the Kericho tea estates: revisiting the climate in the East African highlands malaria debate. *Malaria Journal*, 10(1):12.
- Organization, W. W. H. (2000). WHO expert committee on malaria. 20th Report. WHO Tech. Rep. Ser., 892:71.
- Owusu, K. and Waylen, P. (2009). Trends in spatio-temporal variability in annual rainfall in Ghana (1951-2000). *Weather*, 64(5):115–120.
- Owusu, K. and Waylen, P. R. (2013). The changing rainy season climatology of mid-Ghana. *Theoretical and applied climatology*, 112(3-4):419–430.
- Owusu-Agyei, S., Asante, K., Adjuik, M., Adjei, G., Awini, E., Adams, M., Newton, S., Dosoo, D., Dery, D., Agyeman-Budu, A., Gyapong, J., Greenwood, B., and Chandramohan, D. (2009). Epidemiology of malaria in the forest-savanna transitional zone of Ghana. *Malar J*, 8(1):220.
- Paaijmans, K., Blanford, S., Bell, A., Blanford, J., Read, A., and Thomas, M. (2010). Influence of climate on malaria transmission depends on daily temperature variation. *Proceedings of the National Academy of Sciences*, 107(34):15135–15139.
- Paaijmans, K., Huijben, S., Githeko, A., and Takken, W. (2009). Competitive interactions between larvae of the malaria mosquitoes Anopheles arabiensis and Anopheles gambiae under semi-field conditions in western Kenya. *Acta Tropica*, 109(2):124–130.
- Paaijmans, K., Jacobs, A., Takken, W., Heusinkveld, B., Githeko, A., Dicke, M., and Holtslag,
 A. (2008a). Observations and model estimates of diurnal water temperature dynamics in mosquito breeding sites in western Kenya. *Hydrological Processes*, 22(24):4789–4801.
- Paaijmans, K., Wandago, M., Githeko, A., and Takken, W. (2007). Unexpected high losses of Anopheles gambiae larvae due to rainfall. *PLoS One*, 2(11):e1146.
- Paaijmans, K. P., Heinig, R. L., Seliga, R. A., Blanford, J. I., Blanford, S., Murdock, C. C., and Thomas, M. B. (2013). Temperature variation makes ectotherms more sensitive to climate change. *Global change biology*, 19(8):2373–2380.
- Paaijmans, K. P., Heusinkveld, B. G., and Jacobs, A. F. (2008b). A simplified model to predict diurnal water temperature dynamics in a shallow tropical water pool. *International journal of biometeorology*, 52(8):797–803.
- Paaijmans, K. P. and Thomas, M. B. (2013). Relevant temperatures in mosquito and malaria biology. In *Ecology of parasite-vector interactions*, pages 103–121. Springer.
- Parham, P. E. and Michael, E. (2010). Modelling climate change and malaria transmission. In *Modelling Parasite Transmission and Control*, pages 184–199. Springer.

- Pascual, M., Ahumada, J., Chaves, L., Rodo, X., and Bouma, M. (2006). Malaria resurgence in the East African highlands: temperature trends revisited. National Acad Sciences.
- Pascual, M. and Dobson, A. (2005). Seasonal patterns of infectious diseases. *PLoS Med*, 2(1):e5.
- Patz, J. (1998). Predicting key malaria transmission factors, biting and entomological inoculation rates, using modelled soil moisture in Kenya. *Tropical Medicine* & *International Health*, 3(10):818–827.
- Patz, J. A. and Olson, S. H. (2006). Climate change and health: global to local influences on disease risk. *Annals of Tropical Medicine and Parasitology*, 100(5-6):535–549.
- Paulson, C. A., Leavitt, E., and Fleagle, R. (1972). Air-sea transfer of momentum, heat and water determined from profile measurements during BOMEX. *Journal of Physical Oceanography*, 2(4):487–497.
- Pointek, F., Müller, C., Pugh, T., Clark, D., Deryng, D., Elliott, J., Colón-González, F., Flörke, M., Folberth, C., and Neumann, K. (2014). Multisectoral climate impact hotspots in a warming world. *Proceedings of the National Academy of Sciences of the United States of America*, 111(9):3233–3238.
- Pollard, D. and Thompson, S. L. (1995). Use of a land-surface-transfer scheme (LSX) in a global climate model: the response to doubling stomatal resistance. *Global and Planetary Change*, 10(1):129–161.
- Pond, S., Phelps, G., Paquin, J., McBean, G., and Stewart, R. (1971). Measurements of the turbulent fluxes of momentum, moisture and sensible heat over the ocean. *Journal of the Atmospheric Sciences*, 28(6):901–917.
- Porphyre, T., Bicout, D., and Sabatier, P. (2005). Modelling the abundance of mosquito vectors versus flooding dynamics. *Ecological modelling*, 183(2-3):173–181.
- Raghavendra, K., Barik, T. K., Reddy, B. N., Sharma, P., and Dash, A. P. (2011). Malaria vector control: from past to future. *Parasitology research*, 108(4):757–779.
- Reiter, P. (2001). Climate change and mosquito-borne disease. *Environmental Health Perspectives*, 109(Suppl 1):141.
- Robert, V., Macintyre, K., Keating, J., Trape, J., Duchemin, J., Warren, M., and Beier, J. (2003). Malaria transmission in urban sub-Saharan Africa. *The American journal of tropical medicine and hygiene*, 68(2):169–176.
- Rogers, D. J. and Randolph, S. E. (2000). The global spread of malaria in a future, warmer world. *Science*, 289(5485):1763–1766.
- Ross, R. (1911). The prevention of malaria. John Murray, London, UK.
- Ross, R. (1928). Studies on malaria. John Murray, London, UK.

- Rowley, W. A. and Graham, C. L. (1968). The effect of age on the flight performance of female Aedes aegypti mosquitoes. *Journal of insect physiology*, 14(5):719–728.
- Ryciak, R. and Vujoen, J. (1999). DDT, dieldrin and pyrethrold Insecticide resistance In African malaria vector mosquitoes: an historical review and implications for future malaria control in southern Africa. *South African Journal of Science*, 95:215.
- Sachs, J. and McArthur, J. (2005). The millennium project: a plan for meeting the millennium development goals. *Lancet*, 365(9456):347–353.
- Sachs, J. D. and Chambers, R. G. (2009). The new global war on malaria. *Realizing the right to health*, 3:305–320.
- Sattler, M., Mtasiwa, D., Kiama, M., Premji, Z., Tanner, M., Killeen, G., and Lengeler, C. (2005). Habitat characterization and spatial distribution of Anopheles sp. mosquito larvae in Dar es Salaam (Tanzania) during an extended dry period. *Malaria Journal*, 4(1):4.
- Schneider, P., Takken, W., and McCall, P. (2000). Interspecific competition between sibling species larvae of Anopheles arabiensis and An. gambiae. *Medical and veterinary entomology*, 14(2):165–170.
- Scholte, E., Ng'habi, K., Kihonda, J., Takken, W., Paaijmans, K., Abdulla, S., Killeen, G., and Knols, B. (2005). An entomopathogenic fungus for control of adult African malaria mosquitoes. *Science*, 308(5728):1641.
- Schrage, J. M., Augustyn, S., and Fink, A. (2007). Nocturnal stratiform cloudiness during the West African monsoon. *Meteorology and Atmospheric Physics*, 95(1-2):73–86.
- Service, M. (1977). Mortalities of the immature stages of species B of the Anopheles gambiae complex in Kenya: comparison between rice fields and temporary pools, identification of predators, and effects of insecticidal spraying. *J Med Entomol*, 13(4-5):535–545.
- Shaman, J., Day, J., and Komar, N. (2010). Hydrologic conditions describe West Nile virus risk in Colorado. *International journal of environmental research and public health*, 7(2):494–508.
- Shaman, J. and Day, J. F. (2007). Reproductive phase locking of mosquito populations in response to rainfall frequency. *PLoS One*, 2(3):e331.
- Shaman, J., Stieglitz, M., Stark, C., Le Blancq, S., and Cane, M. (2002). Using a dynamic hydrology model to predict mosquito abundances in flood and swamp water. *Emerging Infectious Diseases*, 8(1):8.
- Shanks, G., Biomndo, K., Hay, S., and Snow, R. (2000). Changing patterns of clinical malaria since 1965 among a tea estate population located in the Kenyan highlands. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, 94(3):253–255.

- Shute, P. and Maryon, M. (1951). A study of gametocytes in a West African strain of Plasmodium falciparum. *Transactions of the Royal Society of Tropical Medicine and Hygiene*, 44(4):421–438.
- Sicuri, E., Vieta, A., Lindner, L., Constenla, D., and Sauboin, C. (2013). The economic costs of malaria in children in three sub-Saharan countries: Ghana, Tanzania and Kenya. *Malar J*, 12(1):307.
- Sinokrot, B. A. and Stefan, H. G. (1993). Stream temperature dynamics: measurements and modeling. *Water Resources Research*, 29(7):2299–2312.
- Smith, D., Dushoff, J., Snow, R., and Hay, S. (2005). The entomological inoculation rate and Plasmodium falciparum infection in African children. *Nature*, 438(7067):492–495.
- Smith, D. L., Hay, S. I., Noor, A. M., and Snow, R. W. (2009). Predicting changing malaria risk after expanded insecticide-treated net coverage in Africa. *Trends in parasitology*, 25(11):511–516.
- Smith, D. L., McKenzie, F. E., Snow, R. W., and Hay, S. I. (2007). Revisiting the basic reproductive number for malaria and its implications for malaria control. *PLoS Biol*, 5(3):e42.
- Smith, M., Macklin, M. G., and Thomas, C. J. (2013). Hydrological and geomorphological controls of malaria transmission. *Earth-Science Reviews*, 116:109–127.
- Smith, T., Maire, N., Ross, A., Penny, M., Chitnis, N., Schapira, A., Studer, A., Genton, B., Lengeler, C., Tediosi, F., and Tanner, M. (2008). Towards a comprehensive simulation model of malaria epidemiology and control. *Parasitology*, 135(13):1507–1516.
- Soti, V., Puech, C., Seen, D., Bertran, A., Vignolles, C., Mondet, B., Dessay, N., and Tran, A. (2010). The potential for remote sensing and hydrologic modelling to assess the spatio-temporal dynamics of ponds in the Ferlo Region(Senegal). *Hydrology and Earth System Sciences*, 14(8):1449–1464.
- Sovi, A., Govoétchan, R., Tokponnon, F., Hounkonnou, H., Aïkpon, R., Agossa, F., Gnanguenon, V., Salako, A. S., Agossou, C., Ossè, R., Okè, M., Gbènou, D., Massougbodji, A., and Martin, A. (2013). Impact of land-use on malaria transmission in the Plateau region, southeastern Benin. *Parasites & vectors*, 6(1):352.
- Srivastava, A., Nagpal, B., Saxena, R., and Subbarao, S. (2001). Predictive habitat modelling for forest malaria vector species An. dirus in India-A GIS-based approach. *CURRENT SCIENCE-BANGALORE*-, 80(9):1129–1134.
- Sunahara, T., Ishizaka, K., and Mogi, M. (2002). Habitat size: a factor determining the opportunity for encounters between mosquito larvae and aquatic predators. *Journal of vector ecology*, 27:8–20.
- Swinbank, W. C. (1963). Long-wave radiation from clear skies. *Quarterly Journal of the Royal Meteorological Society*, 89(381):339–348.
- Tanser, F., Sharp, B., and le Sueur, D. (2003). Potential effect of climate change on malaria transmission in Africa. *The Lancet*, 362(9398):1792–1798.
- Tatem, A., Guerra, C., Kabaria, C., Noor, A., and Hay, S. (2008). Human population, urban settlement patterns and their impact on Plasmodium falciparum malaria endemicity. *Malaria journal*, 7(1):218.
- Tay, S., Danuor, S., Mensah, D., Acheampong, G., Abruquah, H., Morse, A., Caminade, C., Badu, K., Tompkins, A., and Hassan, H. (2012). Climate Variability and Malaria Incidence in Peri-urban, Urban and Rural Communities Around Kumasi, Ghana: A Case Study at Three Health Facilities; Emena, Atonsu and Akropong. *International Journal of Parasitology Research*, 4(2):83.
- Tchouassi, D. P., Quakyi, I. A., Addison, E. A., Bosompem, K. M., Wilson, M. D., Appawu, M. A., Brown, C. A., and Boakye, D. A. (2012). Characterization of malaria transmission by vector populations for improved interventions during the dry season in the Kpone-on-Sea area of coastal Ghana. *Parasit Vectors*, 5:212.
- Thomson, M., Doblas-Reyes, F., Mason, S., Hagedorn, R., Connor, S., Phindela, T., Morse, A., and Palmer, T. (2006). Malaria early warnings based on seasonal climate forecasts from multi-model ensembles. *Nature*, 439(7076):576–579.
- Thomson, M. C., Connor, S. J., Quinones, M. L., Jawara, M., Todd, J., and Greenwood, B. M. (1995). Movement of Anopheles gambiae sl malaria vectors between villages in The Gambia. *Medical and veterinary entomology*, 9(4):413–419.
- Tompkins, A. M. and Di Giuseppe, F. (2015). Potential predictability of malaria in Africa using ECMWF monthly and seasonal climate forecasts. *Journal of Applied Meteorology and Climatology*, 54(3):521–540.
- Tompkins, A. M. and Ermert, V. (2013). A regional-scale, high resolution dynamical malaria model that accounts for population density, climate and surface hydrology. *Malar J*, 12:65.
- Tonnang, H., Kangalawe, R., and Yanda, P. (2010). Predicting and mapping malaria under climate change scenarios: the potential redistribution of malaria vectors in Africa. *Malaria journal*, 9(1):111.
- Torgersen, C. E., Faux, R. N., McIntosh, B. A., Poage, N. J., and Norton, D. J. (2001). Airborne thermal remote sensing for water temperature assessment in rivers and streams. *Remote Sensing of Environment*, 76(3):386–398.
- Tuno, N., Miki, K., Minakawa, N., Githeko, A., Yan, G., and Takagi, M. (2004). Diving ability of Anopheles gambiae (Diptera: Culicidae) larvae. *Journal of medical entomology*, 41(4):810–812.
- USDA, S. (1972). National Engineering Handbook, Section 4: Hydrology. Washington, DC.

- Walker, K. and Lynch, M. (2007). Contributions of Anopheles larval control to malaria suppression in tropical Africa: review of achievements and potential. *Medical and Veterinary Entomology*, 21(1):2–21.
- Wamae, P. M., Githeko, A. K., Menya, D. M., and Takken, W. (2010). Shading by Napier grass reduces Malaria vector larvae in Natural habitats in Western Kenya highlands. *Ecohealth*, 7(4):485–497.
- Wang, G. and Eltahir, E. A. (2000). Ecosystem dynamics and the Sahel drought. *Geophysical Research Letters*, 27(6):795–798.
- Wernsdorfer, G. and Wernsdorfer, W. (1967). Malaria in the middle Nile basin and its bordering regions. *Zeitschrift fur Tropenmedizin und Parasitologie*, 18(1):17–44.
- Wernsdorfer, W. and MacGregor, I. (1988). Malaria: principles and practice of malariology.
- WHO (1982). *Manual on environmental management for mosquito control: with special emphasis on malaria vectors*. World Health Organization.
- WHO (2010). Guidelines for the treatment of malaria. secondth edition.
- WHO (2014). World malaria report 2014. World Health Organization.
- Yadouléton, A., N'Guessan, R., Allagbé, H., Asidi, A., Boko, M., Osse, R., Padonou, G., Kindé,
 G., and Akogbéto, M. (2010). The impact of the expansion of urban vegetable farming on malaria transmission in major cities of Benin. *Parasit Vectors*, 3:118.
- Yamana, T. and Eltahir, E. (2011). On the use of satellite-based estimates of rainfall temporal distribution to simulate the potential for malaria transmission in rural Africa. *Water Resources Research*, 47(2):W02540.
- Yawson, A., McCall, P., Wilson, M., and Donnelly, M. (2004). Species abundance and insecticide resistance of Anopheles gambiae in selected areas of Ghana and Burkina Faso. *Medical and Veterinary Entomology*, 18(4):372–377.
- Ye, Y., Hoshen, M., Kyobutungi, C., Louis, V., and Sauerborn, R. (2009). Local scale prediction of Plasmodium falciparum malaria transmission in an endemic region using temperature and rainfall. *Global Health Action*, 2.
- Yé, Y., Louis, V., Simboro, S., and Sauerborn, R. (2007). Effect of meteorological factors on clinical malaria risk among children: an assessment using village-based meteorological stations and community-based parasitological survey. *BMC Public Health*, 7(1):101.
- Ye-Ebiyo, Y., Pollack, R. J., Kiszewski, A., and Spielman, A. (2003). Enhancement of development of larval Anopheles arabiensis by proximity to flowering maize (Zea mays) in turbid water and when crowded. *The American journal of tropical medicine and hygiene*, 68(6):748–752.
- Younus, M., Hondzo, M., and Engel, B. (2000). Stream temperature dynamics in upland agricultural watersheds. *Journal of Environmental Engineering*, 126(6):518–526.

Zhou, Y., Arifin, S., Gentile, J., Kurtz, S. J., Davis, G. J., and Wendelberger, B. A. (2010). An agent-based model of the anopheles gambiae mosquito life cycle. In *Proceedings of the 2010 Summer Computer Simulation Conference*, pages 201–208. Society for Computer Simulation International.

