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Application of remotely sensed environmental variables for predicting malaria cases in Nkomazi municipality, South Africa

By

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Submitted in partial fulfilment of the requirements for the degree of

Doctor of Philosophy

(Geoinformatics)

In the Faculty of Natural & Agricultural Sciences

University of Pretoria

Pretoria

July 2016

Application of remotely sensed environmental variables for predicting malaria cases in Nkomazi municipality, South Africa

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Declaration

I, **Adeola Abiodun Morakinyo** declare that the thesis, which I hereby submit for the degree of ***PhD Geoinformatics*** at the University of Pretoria, is my own work and has not previously been submitted by me for a degree at this or any other tertiary institution.

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Disclaimer

This thesis mainly adapts the publication style of writing. This six chaptered study basically has four objectives and it was intended that all objectives would be published. Consequently, three articles have been published in peer reviewed journals; the three articles cover objectives 1, 2 and 3. The fourth objective is accomplished in the fourth paper. The paper is currently under review for publication.

To this end, the content and style of presentation may vary or overlap between chapters in this thesis in order to meet with the publication specific journal requirements. Figures in some chapters appear within the text, and in other chapters they have been added at the end of the chapters.

Some of the publications have more than three authors, but this does not mean that work was done proportionately. Work in these publications is solely my effort and originally initiated by me as the principal investigator.

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Dedication

This research is dedicated to my late mother; Mrs Olabamigbe Mercy Adeola nee Fagoroye, a woman of inestimable value. Keep resting in the bosom of the Lord till we meet and part no more.

Acknowledgements

Firstly, my gratitude goes to the Almighty God; the keeper, the provider, the healer and the helper who gave me life and strength during this unfamiliar terrain in South Africa. I say Lord you are wonderful!

This study would not have been successful without significant support and assistance from a number of angels in human flesh. I would like to thank my supervisor Dr. Joel Botai who linked me up with my co-supervisor; Dr. Jane Olwoch. I sincerely want to appreciate you both for your academic intellectual prowess that knows no-bound. Thank you for the 2-year bursary from QWeCI project (European Commission's Seventh Framework Research Programme). The opportunities I had and utilised were far reaching.

I would like to express my appreciation to my father; Joel Akinkunmi Adeola, for giving me a solid foundation to build on. To my brother and sisters, my uncles and aunties for their prayers and words of encouragement during this study. Particularly, I am indebted to Mrs. Ojuolape Matilda Ojuri for your motherly role in my life. You are such a God-sent.

I am eternally grateful to Dr. Olalekan Taiwo of the department of Geography, University of Ibadan, for instilling the academic training I had under him during my Masters programme. It extremely paid off giving me an edge for endurance, perseverance and thoroughness in academic/research pursuit in South Africa. Thank you for being the channel to which this study was possible in South Africa through one of the numerous opportunities I had under you by linking me up with Dr. Olumuyiwa Ojo who invited me to South Africa.

I want to appreciate all friends and colleagues of the department of Geography, Geoinformatics and Meteorology, University of Pretoria for providing such a unique environment for this study. Your inputs during the writing of the articles are indeed appreciated.

Many thanks to the Pastorate and the entire members of the Redeemed Christian Church of God (RCCG) Mount Zion Parish, Pretoria for providing the spiritual support that saw me through this study.

In all, I deeply appreciate my jewel and wife of inestimable value; Omolola Mayowa '*Ayotemi*' my daughter; Toluwalase Olabamigbe and son; Toluwalope Josiah for their immeasurable love, encouragement, understanding, tolerance and patience throughout this bumping journey. My queen thank you for your smiles that always keep me going.

Abstract

The national department of health is targeting the year 2018 for the elimination of malaria which is mainly endemic in the low altitude (below 1200 m) regions of Mpumalanga, Limpopo and KwaZulu-Natal located in the North-eastern part of South Africa. To develop effective malaria control strategies, it requires the analysis of vector's habitat, detail understanding of the environmental and climatic associates, good knowledge of the socio-demographic factors among others. The aim of this study is to create a model that can integrate remotely derived environmental factors with malaria cases and social (population) factors for effective monitoring and forecasting of incidences of malaria. The aim is to be achieved through set objectives which include; 1) to appraise the use of remote sensing and GIS technologies for malaria study in South Africa, 2) to determine the spatial distribution of mosquito habitats and areas that are prone to epidemics in Nkomazi municipality, 3) to evaluate the link between environmental factors and incidences of malaria and the population at risk using GIS and RS, 4) to predict the seasonal and spatio-temporal variability of incidences of malaria. Results from this study indicated that space and time are key factors in the epidemiology of malaria, to determine spatial and temporal windows of opportunities for elimination strategies. However, there is a limited understanding of the spatio-temporal dynamic of this transmission and of the spatial factors that includes environment, meteorology and social. Until now, satellite earth observation data which provides uniformity, rapid measurements and data continuity that allows for the collection of data over large areas, which cannot be accessed by other means has not been used extensively in the understanding of the spatial-temporal dynamics of malaria in South Africa. In addition, using data from earth and meteorological observing satellites, in particular, Landsat, MODIS and TRMM and notified malaria cases acquired from the malaria control programme in Mpumalanga. This study found that satellite-derived climatic/environmental factors such as Rainfall from TRMM, NDVI, EVI, NDWI and LST from both Landsat and MODIS are associated with malaria incidence. Furthermore, it was found that irrigation activities (agriculture) in the study is largely associated with malaria incidence. In addition, the study found that the economically active population (age 15–64) are the most at risk of malaria infection. The population in Komatipoort village are mostly 4exendangered with lot of imported malaria cases from Mozambique and Swaziland. Seasonal autoregressive integrated moving average models (SARIMA) was developed. The level of prediction, either under-prediction where predicted is less than observed or over-prediction where predicted is greater than observed, are within 10% of the notified malaria cases for all

predictions across the 5 villages. Hence, the study, if implemented will strengthen the existing control measures for proper targeting and effective distribution of the scare resources towards malaria elimination and subsequent eradication.

Abbreviations

AL:	Artemether/Lumefantrine
ARIMA:	Autoregressive Integrated Moving Average Models
CFR:	Case Fatality Rate
CHC:	Community Health Centre
CI:	Confidence Interval
DDT:	Dichlorodiphenyltrichloroethane
EVI:	Enhanced Vegetation Index
GIS:	Geographic Information Systems
GPS:	Global Positioning System
IRS:	Indoor Residual Spraying
LSDI:	Lubombo Spatial Development Initiative
LST:	Land Surface Temperature
LULC:	Land use/Land cover
MARA:	Mapping Malaria Risk in Africa
MEWS:	Malaria Early Warning System
MIS:	Malaria Information System
MODIS:	Moderate Resolution Imaging Spectroradiometer
MRC:	Medical Research Council
MRP:	Malaria Research Programme
NCBI:	National Centre for Biotechnology Information

NDoH: National Department of Health. South Africa

NDVI: Normalised Difference Vegetation Index

NDWI: Normalised Difference Water Index

NGI: National Geospatial Information

PCA: Principal Component Analysis

RBM: Roll Back Malaria

RDT: Rapid Diagnostic Tests

RS: Remote Sensing

SA: South Africa

SAMJ: South African Medical Journal

SARIMA: Seasonal Autoregressive Integrated Moving Average Models

TRMM: Tropical Rainfall Measuring Mission

USGS: United States Geological Survey

WHO: World Health Organisation

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CHAPTER 1

Introduction

This chapter focuses on a brief introduction to the study. It start by giving background to the subject matter 'malaria' in term of its biology and epidemiology. This session went further to give a snap shot of malaria, globally, nationally and locally to the specifics of the study area, Nkomazi local municipality of South Africa. The session, gave an insight to the general malaria situations, past and present control strategies, major stakeholders in malaria control, cross-border initiatives, surveillance and elimination. In addition, this chapter gave a preview to the major themes of the study. The major themes of this study aside malaria are; environment, climate, remote sensing and prediction. These themes are discussed in detail within each of the corresponding chapters. This chapter, went further giving the research motivation, a wrap of rationale for developing a forecasting system using remotely sensed environmental/climatic variables, research question and the chapter concluded with the aim and objectives of the study and a conceptual framework to the study.

1.1. Malaria, the parasite and vector

Malaria is classified as one of the major health problems globally, constituting a menace to the public health. Malaria is a life threatening disease dominant in most tropical countries particularly sub-Saharan Africa. The transmission is influenced by several inter-linking factors such as climate, environment, socio-economy and demography. This chapter gives a brief background of malaria disease, the parasite and vector. It gives a brief account of malaria globally, in Africa and in South Africa with particularly focus on the study area, Nkomazi municipality in Mpumalanga province. Some key epidemiological concepts and the conceptual framework for the study is also discussed. This session also shows the research motivation, the objectives and hypotheses.

1.1.1. The malaria parasite

Malaria is transmitted through a bite of infested female *Anopheles* mosquito on human, caused by parasitic protozoa of the genus *Plasmodium*. Generally, reptiles, birds and mammals are also infected by various plasmodia species (e.g. *P. falciparum* and *P. vivax, P. malariae* and *P.*

ovale in man) or veterinary (e.g. *P. gallinaceum* in chickens, *P. reichenowi* in chimpanzees, *P. knowlesi* in monkey, *P. berghie* in rodents and *P. relictum* in birds) (Paul *et al*., 2003).

According to World malaria report (WHO, 2014) there are about 400 different species of *Anopheles* mosquitoes, but only 30 of these are vectors of major importance, of which four of them occur in humans: *P. falciparum*, *P. vivax*, *P. ovale*, and *P. malariae*. Although all the species belong to the same genus, there is variation in their biology within the human and mosquito host. These species also differ with respect to their spatial distribution. The *P. falciparum* is the most prevalent on the sub-Saharan Africa and it accounts for majority of deaths from malaria. *P. falciparum* is also associated with widespread of resistance to anti-malaria drugs (Deponte and Becker, 2004; Mayxay *et al*., 2004). *P. vivax* has a wider geographic distribution than *P. falciparum* because it can develop in the Anopheles mosquito vector at lower temperatures, and can survive at higher altitudes and in cooler climates. *P. falciparum* is found in most tropical regions throughout the world while *P. vivax* is prevalent in many sub-tropical zones, but more prevalent in Asia, Oceania and Latin America than Africa. Although there is possible occurrence of *P. vivax* throughout sub-Saharan Africa, there is low risk of infection with this species, this is largely due to the absence of Duffy gene which produces the protein necessary for *P. vivax* to invade red blood cells in many African populations. *P. ovale* is dominant in West Africa and has a similar biology to *P. vivax*. *P. malariae* has an extensive distribution area (Breman *et al*., 2006).

In South Africa, *P. falciparum* is responsible for more than 90% of malaria infections, with *Anopheles arabiensis* being the major vector. *P. malariae*, *P. ovale* and *P. vivax* occasionally occur alone or in mixed infections with *P. falciparum (*Department of Health, South Africa, 2013).

The development of the parasite and breeding of the vectors is dependent on warm and moist climatic conditions (Sutherst, 2004). Temperature is one of the main environmental factors affecting the transmission of malaria. Increase in temperature shorten the sporogony cycle of the parasite and hence transmission is accelerated. The duration of sporogony can be calculated by the formula n=T/(t-tmin) where n=duration of sporogony in days, t=average temperature in °C and for *P. falciparum* T =105 and tmin =16 °C. For the parasite to develop optimally in the vector, it requires temperature of about 20-30 °C, higher temperatures reduce the life span of adult mosquitoes and at temperature below 16 °C the parasites stop to develop in the mosquito. When humidity is high the life span of the vector is prolong, consequently transmission is extended. In the case of *P. falciparum* the incubation period of the parasite in the mosquito takes 13 days to complete at 24 °C. Thus, there are upper and lower thresholds outside which malaria transmission cannot occur.

As shown in (Fig.1), the four major species have a similar life cycle which include the mosquito insect (vector) and the human (host). When his bitten by an infested *Anopheles* mosquito, sporozoites are injected through the mosquito's saliva into the human's body. At its entrance into the human body, it goes into the bloodstream and the blood carries it to the liver. The sporozoites invades the liver cells (hepatocytes) once it had entered the circulatory system. There, it infiltrates hepatocytes leading to its growth and multiplication. For *P. vivax* and *P. ovale*, some sporozoites are converted to hypnozoite, which could stay viable for up to 50 years. The hypnozoites can be activated months later to relapses (Krotoski *et al*., 1982).

The *Plasmodium* cell undergoes asexual replication inside the host's hepatocytes. After 9-16 days they return to the bloodstream and re-invade the red cells as merozoites. Further growth and multiplication occurs and gradually breaking down the red cells. This induces bouts of fever and anaemia in the infected individual. In cerebral malaria, the infected red cells obstruct the blood vessels in the brain. The invasion of the red cells can lead to the damage of other vital organs often resulting to the death of the patient (Lambert, 2005).

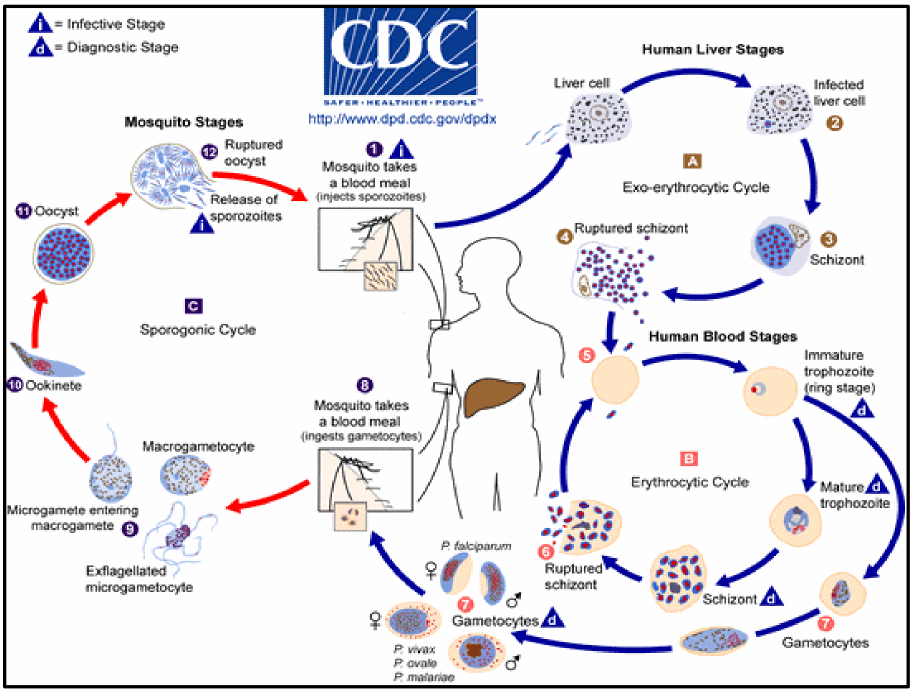

Figure 1: Figure 1: Life cycle of Plasmodium species.

Source: CDC http:// www.dpd.cdc.gov/dpdx/HTML/Malaria.htm.

1.1.2. The malaria vector

There are about 400 different species of *Anopheles* mosquitoes, but only 30 of these are vectors of major importance for human malaria transmission (WHO, 2014). Genus of the *Anopheles gambiae* and *Anopheles funestus* are dominant and responsible for malaria transmission in the sub-Saharan Africa. *Anopheles gambiae* is the most anthropophagic species in the complex and the most important, probably the world's most efficient malaria vector with characteristic indoor and outdoor resting. *Anopheles arabiensis* a species of the *Anopheles gambiae* complex is dominant vector in malaria endemic region of South Africa. Other species of vectors regarded as secondary malaria vectors found in South Africa include *Anopheles pharoensis* and *Anopheles maculipalpis* (Bedford 1928).

In general, malaria as a disease is govern by conditions which favour the survival of the vector (suitable breeding habitats) and which supports the life cycle of the parasite. Besides, human interference such as untidy environment, farmland etc., these conditions are largely determined by climatic and environmental factors (Sutherst, 2004).

1.2. Global malaria situation

Children under age of 5 years and pregnant women are most prone to malaria infection (Greenwood *et al*., 2005). Other groups at risk include non-immune travellers, refugees, displaced persons and labourers entering endemic areas (WHO, 2000d). Under 5 years children are particularly at risk because of their relatively less developed immunity to malaria and the decrease in passively acquired immunity.

Globally, it is estimated that about 3.3 billion people in 97 countries and territories are at risk of being infected with malaria, out of which 1.2 billion are at high risk of being infested with malaria in a year. It is estimated that globally between 2000 and 2013, malaria cases fell from 227 million to 198 million respectively. Malaria cases is estimated to have fell by 25% globally and by 43% in the sub-Saharan Africa. On the other hand, deaths associated to malaria also decreased by 47% globally and by 54% in the sub-Saharan African. This indicated an estimated global decreased by 53% in children aged under 5 years, and by 58% in the sub-Saharan African (WHO, 2014). The disease because of its high human morbidity and mortality rate, there is an enormous stress on the world's medical and economic sector (WHO, 2005a).

1.3. Malaria in Africa

Malaria burden is heaviest in the sub-Saharan African region, where an estimated 90% of all malaria deaths occur, and in children aged under 5 years, who account for 78% of all deaths (WHO, 2014). Malaria kills an African child every 30 seconds (RBM, 2006) This is largely as a result of deteriorating health systems, growing drug and insecticide resistance, climate change, natural disasters and population movement (WHO, 2000d).

In total, 18 countries account for 90% of infections in sub-Saharan Africa; about 37 million infections representing 29% is accounted for in Nigeria and 14 million representing 11% is accounted for in the Democratic Republic of the Congo. These two countries together accounts for 40% of malaria infections in the region (Fig. 3a). Infection prevalence varied greatly across sub-Saharan Africa in 2013. Estimated rates of infection, standardized to children aged 2–10 years, is reported to be highest in West Africa. Overall, 15 malaria endemic sub-Saharan African countries had an infection prevalence in children of above 20%, a further 16 countries of 5–20%, and 16 countries and areas of below 5% (Fig. 3a), (WHO, 2014).

1.4. Malaria in South Africa

1.4.1. Overall situation

The Republic of South Africa has population of approximately 52 million (Statistics South Africa, 2011 census) and is divided into 9 provinces and 52 districts. About 5 million of the population representing 10% of the total population live in malaria endemic area in South Africa. The low altitude areas (below 1000 m above sea level) of the northern and eastern parts of the country along the border with Mozambique and Zimbabwe are the malaria endemic regions of the country. Hence, malaria is endemic in three provinces; Limpopo, Mpumalanga and KwaZulu-Natal. However, few major occurrences are occasionally sighted in Northern Cape and North West provinces along Orange and Molopo rivers as a result of provision of suitable breeding habitats for mosquitoes to survive (National Department of Health, South Africa, 2013). In Gauteng province, the economic hub of the country, 'imported' malaria cases are reported among returning travelers and migrants. Imported malaria cases from neighboring countries (Mozambique and Zimbabwe) increases the disease burden in the country particularly in Mpumalanga and Limpopo provinces (Fig. 4). *Plasmodium falciparum* accounts for about 95% of the total malaria infections in South Africa through *Anopheles arabiensis* as the major local vector. As a result of its local climate, malaria transmission follows a markedly seasonal pattern, and experiences distinct inter-annual fluctuations leading to periodic epidemics. Generally, notifications increases September to May with peaks in the rainy months of December and January. The peak rates within health facilities malaria outpatients usually occur in April and decline by June (National Department of Health, South Africa, 2013).

1.4.2. Past and present malaria control actions in South Africa

Although, malaria cases were first reported in Durban in 1902, the South African government notice number 2081; formally acknowledged its prevalence in 1956 making malaria a notifiable disease (Hill et al., 1905). Malaria control measures in South Africa has been in accordance with the WHO's strategy for malaria control. In a broader view major malaria control measures in South Africa include surveillance, focal larviciding, indoor residual spraying (IRS), case management, health promotion and cross-border malaria initiatives.

Quinine treatment and prophylaxis were the first malaria control measures in South Africa. This was followed by Anti-larval control measures through the use of Paris green and oil in 1920 and it became the major control measure until 1946 (Ingram et al., 1927). In 1932, Park Ross, (The Assistant Secretary for Health of the Union of South Africa) with his team in Natal carried out the first trial of indoor spray of adult malaria mosquitoes using Pyagra (Kerosene and liquid pyrethrum) (Sharp et al., 1996). The Pyagra was discontinued because of its labour intensive, it was then replaced with Dichlorodiphenyltrichloroethane (DDT) in 1946. The use of DDT for indoor spraying of house in all malaria endemic areas of South Africa attained a full coverage in 1958.

The use of DDT for IRS was phased out of the malaria control programme in Mpumalanga and KwaZulu-Natal provinces in 1996 due to negative community perceptions over the use of the chemical, and was replaced with synthetic pyrethroids. Deltamethrin was proven at the time to be an equally effective chemical for malaria vector control. However, the re-discovery of pyrethroid-resistant Anopheles funestus which had been previously eradicated in northern KwaZulu-Natal, consequently the national Department of Health ordered DDT which showed 100% mortality for collected mosquitoes should be used as the major chemical for IRS (NDoH, 2007).

As a result, the burden of malaria in the endemic provinces has greatly decreased by 88% (NDoH, 2007). For example, the adopted control strategies saw the number of reported malaria cases reduced from 64 622 cases in 2000 to 7 626 in 2010. Additionally, the number of deaths reduced by 81% i.e. from 458 deaths in 2000 to 87 deaths in 2010. Malaria cases were high during the 1997-2001 periods (Figure 2) and concur with years of substantial rainfall and year when DDT was stopped as the major chemical for IRS (Coetzee et al., 2013). During this period, two main consecutive years i.e. 1999 and 2000 had the highest frequency of reported cases amounting to 51 444 and 64 622 respectively.

1.4.3. Major stakeholders in malaria control

Malaria control programme is majorly driven by the National Department of Health under the directorate of malaria and other vector-borne diseases and supported by several stakeholders. Stakeholders involve in the malaria control programmes in SA, include the national malaria advisory group (MAG); the Sub-committee on vector control (SVC) and the Sub-committee on Chemoprophylaxis and treatment (SCAT). The control programme is also supported by other government departments such as the departments of environmental affairs (DEA), industrial development corporation (IDC), the medical research council (MRC), the national institute for communicable diseases (NICD) and non-governmental organisations (NGOs). Other partners include universities and research institutions like the University of Pretoria (centre for sustainable malaria control) and the University of Witwatersrand. The programme facilitates the development of policies and guidelines which serves as input for public health decision makers.

1.4.4. Cross-border initiatives

The Lubombo spatial development initiative (LSDI) and the Trans-Limpopo malaria initiative (TLMI) are the two existing trans-border initiatives initiated by South Africa. This is based on the need to address trans-border issues of population movement leading to the movement/spread of vector and parasite into SA from her bordering countries of Mozambique, Swaziland and Zimbabwe (see figure 2). The LSDI commenced in 1999 as a tri-lateral agreement between Mozambique, Swaziland and South Africa.

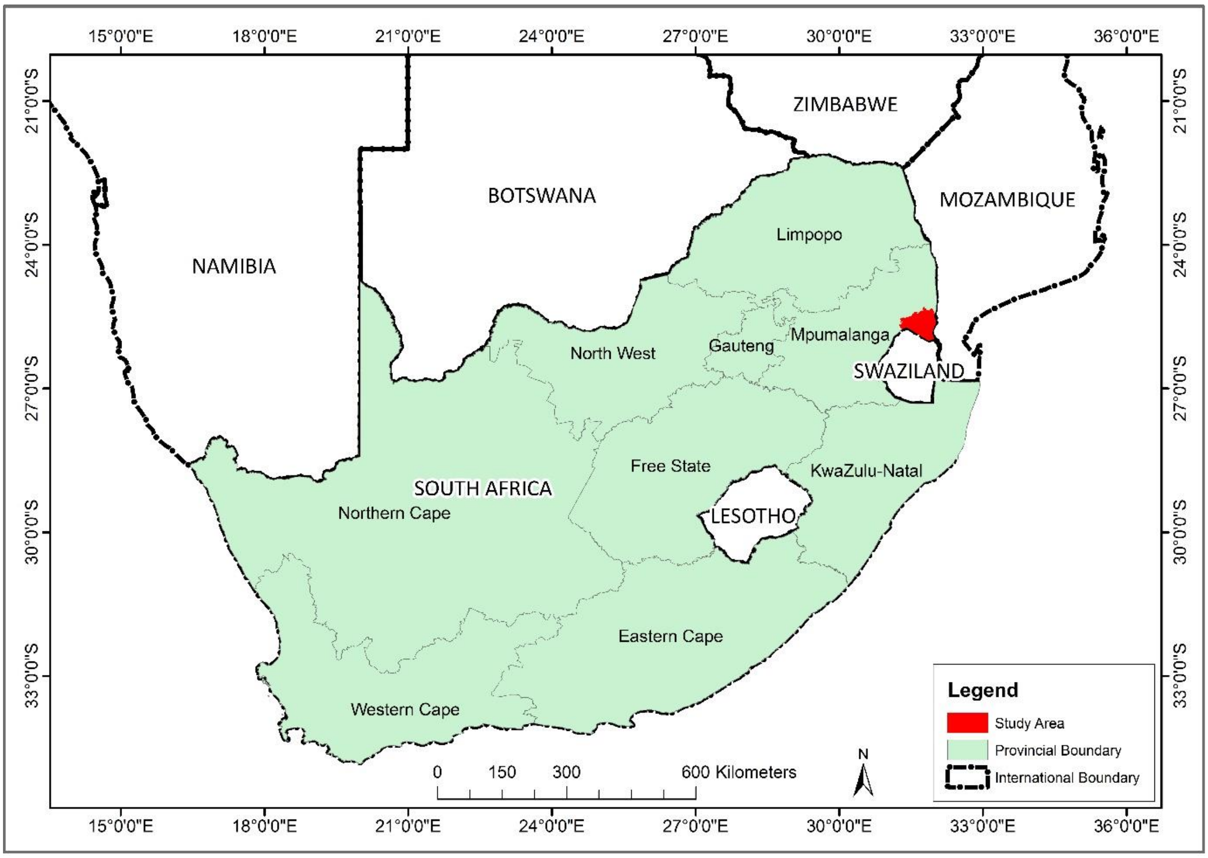

Figure 2: Illustration of cross border relationship of Nkomazi municipality with neighbouring countries.

The project was aimed at unlocking the agricultural and tourism potentials of the Lubombo mountains regions that cut across the three nations. However, malaria was seen as major set-back to achieving the aim. Hence, the need for a regional and intra-country collaboration to fight malaria in the Lubombo mountainous region characterized by high level of poverty and lack of general well-being among the dwellers. On the other hand, the TLMI commenced in 2001 as project aligned to the Trans-Limpopo spatial development initiative (TLSDI). The TLMI project was focused on four districts (Beitbridge, Mangwe, Bulilima and Gwanda) of Matabeleland South Province in Zimbabwe and Vhembe District of Limpopo in South Africa. The collaboration was initiated for the purpose of sharing information in order to reduce malaria transmission on the borders along the Limpopo River.

1.4.5. Surveillance

Malaria control is majorly challenged by tracking progress of transmission. Currently, malaria surveillance systems that are available only detect about 10% of the world's estimated number of malaria cases (WHO, 2010). Consequently, more robust malaria surveillance systems are needed to facilitate an apt and effective malaria response in endemic regions, to inhibit outbreaks and resurgences, to track progress, and to hold governments and the global malaria community accountable. As part of the determination to speed up diagnostic testing, treatment and surveillance for malaria, the Director-General of the WHO in April 2012 launched new global surveillance manuals for malaria control and elimination, and urged endemic countries to strengthen their surveillance systems for malaria.

1.4.6. Elimination

Malaria elimination is defined as interruption of local transmission of malaria in a defined geographical area. Meaning recording zero incidence of locally contracted cases. On the other hand, malaria eradication is defined as the stable reduction to zero of the global occurrence of malaria infection. South Africa is scheduled to achieve malaria elimination by 2018. Recently, the Director-General of the WHO has certified 4 countries as having eliminated malaria: United Arab Emirates (2007), Morocco (2010), Turkmenistan (2010), and Armenia (2011).

1.5. Malaria in Mpumalanga, Nkomazi

Mpumalanga is one of the three malaria endemic provinces of South Africa. Although the use of IRS and focal larviciding for malaria vector control have proved to be successful in reducing malaria transmission in South Africa, mortality and morbidity related to malaria in Mpumalanga remain worrisome (Sharp et al., 1996 and Ngomane et al., 2012). In addition, malaria related studies have been more focused on other endemic provinces particularly KwaZulu-Natal leading to drastic decrease of malaria mortality and morbidity (Kleinschmidt et al., 2002, Craig et al., 2004, Rajendra et al., 2012). A major challenge to malaria control in the province is the high proportion of imported cases from neighbouring Mozambique country with particular influence on Nkomazi local municipality.

1.6. Malaria, environment and climate

Malaria is disease that exhibit a complex ecology, with many biophysical (environmental and climatic) and socio-economic factors influencing the disease (Ceccato et al., 2005; Machault et al., 2011). Malaria and many other infectious diseases are environmental and climatic dependent. The successful development of the disease agent (*Plasmodium*) and the Anopheles mosquitoes are strongly controlled by both environmental and climatic elements such as temperature, rainfall, humidity, altitude and other derivatives like land use/land cover (vegetation, water body, irrigation). Temperature influences the development of the parasite and the vector. High temperatures accelerate the rate of development of the parasite in the mosquito. It takes about 10 days for the parasite to complete its development in the mosquito's gut. The number of days can either be reduced or increased depending on the temperature. The required time for the parasite to complete its development in the vector, decreases to less than 10 days with increase in temperature from 21°C to 27°C, with 27°C being the optimum. The maximum temperature for parasite development is 40°C and temperature below 16°C negatively impact the Sporogonic cycle. Larva development of the mosquito is also temperature dependent. Larva develops more swiftly at higher temperatures. The number of eggs laid by the mosquitoes and the number of blood meals taken also increases with higher temperatures, thereby increasing the number of mosquitoes in a given area and an increase the biting rate which ultimately leads to more malaria transmission (Craig et al., 1999). On the other hand, rainfall directly and indirectly impact on malaria transmission by providing mosquito breeding habitats. Directly, it makes available water (ponds, streams etc.) and indirectly provides vegetation which are potential breeding and resting places for the vector. However, heavy or excessive rainfall could negatively affect malaria transmission because it can wash away potential breeding habitats (Craig et al., 2004).

The spatial and temporal distribution as well as the abundance of mosquitoes can be substantively determined by considering the above environmental/climatic parameters. These variables can be quantified physically (ground weather observations) or remotely (earth/meteorological observation satellites). Long-time estimates of rainfall, temperature and humidity can be acquired from ground based meteorological stations. Environmental variables like rainfall, normalized difference vegetation index (NDVI), enhanced vegetation index (EVI), normalized difference water index (NDWI), land surface temperature (LST), Soil moisture index (SMI) and actual evapotranspiration (ETa) can be derived from earth/meteorological observation satellites. These variables can be used as surrogates for the climatic variables measured from the conventional weather stations. Other environmental variables which have relationship with malaria and can be derived from satellite include altitude, land use/land cover (Vegetation, water body, forest, plantation, irrigation). This study rely heavily on using these data from the satellite through remote sensing technology. Remote sensing provides continuous data and offer the possibility to acquire data over large areas in contrast to conventional ground surveys (Hay et al. 1998; Bogh et al., 2007).

1.7. Malaria studies

Malaria is a disease that have accrued so much attention and have been studied across several fields of disciplines ranging from medicine (biology, microbiology, genetics, biochemistry) to natural sciences (geography and environmental sciences), to engineering (chemical engineering) and to public health practitioners. Hence, several approaches and methodologies have been suggested and developed towards the effort of combating the disease. In this vain, several policies for malaria controls have been developed, several models to understanding the biology of the parasite and vector and its association with the host, environment has been developed. This multi-disciplinary research even at times multi-national collaboration is seen as an integrated approach imperative for the control and the elimination of malaria. Some of these studies are elaborated in the chapter two of this thesis particularly the mathematical, statistical and geospatial approaches as related to this study.

1.8. Research motivation

The success recorded over malaria control in South Africa has informed the international and governmental organizations to call for the adoption and implementation of elimination agenda by South Africa formally slated for 2015 but now 2018 (Rajendra et al., 2012). As against the current trend of malaria control programme in South Africa, the understanding of spatial pattern of disease will make control measures more effective and efficient (Machault et al. 2011). This was first demonstrated by Snow (1855) when he was able to identify the source of Cholera outbreak in Broad Street, London using GIS. The use of GIS has also be been implemented in South Africa through the development of malaria information system (MIS) which has recorded a remarkable success towards malaria control Booman et al., 2000, Martin et al., 2002, Booman et al., 2003).

The advancement, availability and high level of accuracy of satellite data provide a unique opportunity to conduct environmental and epidemiological studies using remotely sensed measurements (Hay et al., 2000, Curran et al., 2000). With remote sensing, different biophysical variables such as temperature, rainfall and humidity, land cover, etc. can be estimated (Julie et al, 2010, Midekisa et al., 2012). Satellite images are efficient tools for the detection of environmental factors associated with malaria risk. The integration of remotely and field acquired malaria related data such as cases, control measures and causing factors

(Ngomane et al., 2012) through spatial technology can provide timely and reliable information for public health workers and decision makers alike for prompt intervention and management.

The relationship between climate (environmental indicators), malaria cases, social factor (migration) can be combined in an empirical model to assist in providing early warning in malaria incidences or potential outbreaks as well as in improving the control programme towards strengthening the elimination strategy.

The use of remote sensing and GIS has been advocated for in (Sharp et al., 1996) only GIS has been implemented, hence this research is leveraging on bridging the gap by using remote sensing technology to develop an empirical malaria warning system in Nkomazi municipality as a pilot study area. In addition, extensive works have been done in other malaria endemic province like KwaZulu-Natal, hence resulting in the drastic decline of transmission.

The effectiveness of the development of malaria early warning systems in the fight against malaria have been demonstrated in Kenya (Githeko et al, 2001), Eritrea (Ceccato et al., 2005), Ethiopia and Sudan (WHO, 2002). This is in line with the Roll Back Malaria (RBM) Abuja declaration in 2000 to detect the occurrence of malaria within two weeks of onset, for prompt and adequate mitigation by decision makers. Therefore, this study seek to expand the frontier of knowledge in the study area to enhance effective malaria control and help to strengthens the set goal of achieving malaria elimination in SA by 2018.

1.9. Rationale for developing a forecasting system using spatial technologies

The early detection, containment and prevention of malaria epidemics are one of the four technical elements of the Global Malaria Control Strategy (WHO, 1993) on which the RBM initiative was built (WHO, 2000). There is a growing recognition of the need to implement programmes to predict and prevent malaria epidemics. A few countries have already started to develop epidemic risk monitoring using simple transmission risk indicators such as rainfall and vegetation (Grover-Kopec et al., 2005, Ceccato et al., 2005).

Usually, an early detection system is based on malaria data recorded on a monthly or weekly basis within the health care facilities which are supposed to diagnose malaria and deliver effective treatment. If the surveillance system, laboratory procedures, data analysis, reporting and notification, are well established, control measures can be taken as soon as possible although inevitably there will be some delay after the onset of the epidemic.

Through experiences gained from previous malaria epidemics it is obvious that meteorological/weather data, when routinely collected in specific locations and analysed, can provide a warning signal in predicting malaria epidemics. Unusual climatic events such as heavy rainfall after an unusually dry period or unexpected higher temperature and/or humidity for a given altitude appear to be a prominent cause of many epidemics (Bagayoko, M. M *et al* 1999). Such warning systems, which depend on good collaboration between the meteorological services and vector borne diseases control programmes, can predict an epidemic several weeks in advance allowing health district staff to be better prepared to prevent the epidemic or control the epidemic at its earliest stage. However, the availability of such weather data are lacking and in some cases not easily accessible. In addition, short and unevenly distribution of weather stations also constitute a major constraint in the development and maintenance of an early detection system.

The use of GIS and remote sensing provide the missing link to the challenges arising from the use of conventional method of data collection and analysis. With the use of these spatial technology, continuous data can be readily accessed over an extensive or remote area of study.

1.10. Research question

Through experiences gained from previous malaria epidemics, will satellite-derived climatic/environmental data like Rainfall, NDVI, EVI, NDWI, LST, Elevation and other auxiliary spatial data; population, migration etc. be sufficient to develop a system that can provide a warning signal in predicting malaria epidemics over malaria endemic region of South Africa?

1.11. Research aim and objectives

1.11.1. *Aim*

The aim of this study is to create a model that can integrate remotely derived environmental variables with malaria cases and social (population) factors for effective monitoring and predicting of incidences of malaria.

1.11.2. *Objectives*

1. To appraise the use of remote sensing and GIS technologies for malaria study in South Africa

2. To determine the spatial distribution of mosquito habitats and areas that are prone to epidemics in Nkomazi municipality
3. To evaluate the link between environmental factors and incidences of malaria and the population at risk using GIS and RS.
4. To predict the seasonal and spatio-temporal variability of incidences of malaria based on remotely sensed environmental/climatic variables.

Objective 1 is achieved with the literature reviewed paper (available online: http://dx.doi.org/10.1080/23120053.2015.1106765). Objective 2 is achieved with the second publication (available online: http://dx.doi.org/10.1080/03736245.2015.1117012). Objective 3 is achieved with the third publication with journal of Tropical Medicine and International Health (available online: http://onlinelibrary.wiley.com/doi/10.1111/tmi.12680/abstract). While objective 4 is achieved with the fourth paper under review with EcoHealth journal.

1.12. Key concepts and conceptual framework

The conceptual framework used for this study form the bases for the phases of the research and the overall outcome; the empirical malaria early warning system. The framework, as shown in figure 3 consist of six major components or systems: (1) The environmental/climatic variables, (2) malaria cases, (3) demographic and socioeconomic characteristics, (4) life cycle of the Anopheles mosquito (vector), (5) life cycle of the parasite (Plasmodium Sp.) and (6) malaria control measure.

1) Environmental/climatic variables: Studies have shown that there is direct link between environmental and climatic parameters to malaria incidences (Ceccato *et al.,* 2005, Machault *et al.,* 2011). This implies that the spatial and temporal distribution as well as the abundance of mosquitoes can be substantively determined by considering environmental parameters. These variables are further grouped under three categories: climatic (temperature, rainfall and humidity), ecology (vegetation, hydrology and wetland) and topographic (altitude and slope). All these variables will be derived from satellite images. Satellite derived Land Surface Temperature (LST) and indices like Normalized Difference Vegetation Index (NDVI), Normalized Difference Water Index (NDWI) and Soil Moisture Index (SMI) can be used as surrogate data for malaria studies (Hopp and Foley 2001). Such data provides continuous data and offer possibility of identifying mosquitoes breeding habitats over large areas in contrast to conventional

ground surveys (Hay *et al.*, 1998, Bogh *et al.*, 2007). Terrestrial measurements will be used to validate the results.

2) Vector life cycle: Mosquito life cycle is characterized by the breeding and the mortality which determine its density. Climatic/environmental conditions as well as control measures impact both the breeding and mortality rate which might either result in the vector's increase or low density.
3) The parasite cycle: The parasite cycle starts in human when infected female anopheles feeds on exposed human and injects the parasite in the form of sporozoites into the human bloodstream. The sporozoites travel to the liver, invade liver cells and multiply within 5-16 days resulting into illness and complications/death if not detected and treated early or drug failure or resistance.
4) Demographic characteristics: The level of vulnerability is associated with the demographic variables such as household size, age, gender, building material and migration. All these variables has both direct and indirect impact on control measures.
5) Malaria cases: Historic clinically reported cases can help to quantify the impact of malaria among human population within a specific geographic region. Hence, when combined in model with other factors can be used to enhance prediction.

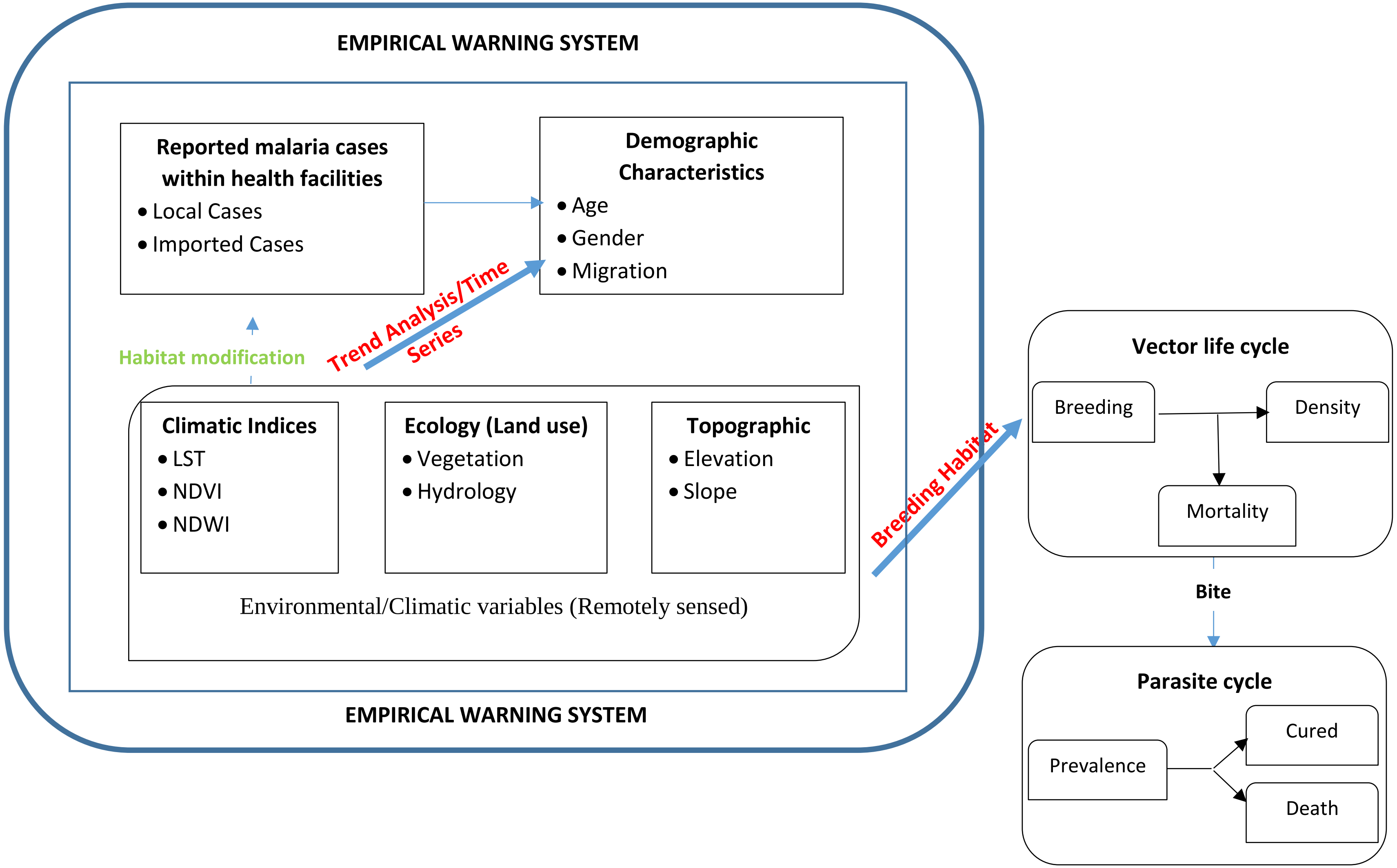

Figure 3: Conceptual framework diagram for the study

CHAPTER 2

Literature review

2.1. Introduction

The literature review in this study consist majorly of two sessions. Firstly a review of the application of mathematical and statistical models that have been used by scholars for malaria studies and secondly, the review of the application of remote sensing and GIS in malaria studies. The second session has been published in a peer-reviewed journal.

2.2. Application of mathematical and statistical models in malaria studies

Malaria as a disease has been studied over a long period of time by various researchers cutting across several fields of studies, hence, there exist vast literatures describing various approaches ranging from the understanding of the biology of the vector, the parasites, the transmission, its control and prevention. The use of several approaches can facilitate the understanding of different stages of the disease by integrating available information and extrapolating it (Mandal et al., 2011). According to the malERA Consultative Group on Modeling, it is pinioned that a combination of several approaches, instead of a solitary type of modelling, may be a bold step towards malaria eradication and its general control.

The complex nature of the parasite's life cycle, the complexities of environmental and social interactions, evolutionary pressure of drugs and control measures contributing to drug resistance of parasite, unforeseen effects of climate change, and migration of population between endemic and non-endemic areas continued to contribute to the huge burden of morbidity and mortality accompanying the disease (WHO, 2010). These have also thrown up new challenges to researchers and public health professionals in the recent years, in order to find a lasting solution to the global eradication and control (RBM, 2008; Alonso et al., 2011). Consequently, in this present day we are faced with the need to develop models that can with higher accuracy predict the dynamics and transmission of the diseases not only in a short time but also over longer periods of time, and more often with limited empirical data. These developments have led to a sudden rise in the number of malaria studies and publications (Adeola et al., 2015).

Researchers of infectious disease have a long-standing using mathematical and statistical models in providing a clear-cut framework for explaining the dynamics of disease transmission within and between hosts and parasites (Mandal et al., 2011). A mathematical expression or a model allow for the integration of several known biological and clinical information in a simplistic way to providing answers to sort of difficult or cumbersome queries surrounding the disease. Hence, a model is a representation or approximation of a complex reality in which its structure is dependent upon the questions under investigation. In accordance with questions under investigation, experimental observations can be fit into models to arrive at theoretical predictions of unknown or lesser known situations. For instance, epidemiologists have used mathematical models to predict the incidence of outbreak of infectious diseases, and for providing a research framework for the eradication of malaria (malERA Consultative Group on Modeling; Anderson & May, 1998). Several models have been developed and expounded.

These models which were designed to focus on various aspect of the disease are predominantly deterministic or differential equation based models. The models developed on the 1900's are usually simple in designs and are aimed at providing knowledge about the basic principles of the parasites' population biology and evolution. However, with increasing knowledge, data and tools such as computer over the past decades, mathematical models have become more detailed and complex.

Historically, Sir Ronald Ross, was the first to provide the descriptions of the parasite and its life cycle. He developed the classical Ross model in 1911. The model describes the relationship between incidence of malaria in humans and the number of mosquitoes. With his model, he demonstrated that the reduction of the numbers of mosquito to a certain threshold figure was ideal to combat malaria. Resulting from 20 years of fieldwork, George Macdonald in the 1950s reaffirmed the importance of mathematical models for malaria study. He improved Ross's model by adding biological information of latency in the vector as a result of the development of malaria parasite, and found that the survivorship of adult female mosquito as the weakest element in the malaria cycle. His model triggered a massive coordinated campaign led by WHO, for the use of insecticide dichlorodiphenyltrichloroethane (DDT) for vector control. Anderson and May in 1991 introduced the latency of infection in humans into Macdonald's model hence creating an additional "Exposed" class in humans. Aside the three basic models, many other researchers have improved the basic Ross model through the addition of several other elements such as effect of age structure of prevalence (Anderson and May, 1991), (Aron

& May, 1982; Aron, 1988; Hoshen, et al., 2001; Dietz, et al., 2006; Mideo, et al., 2008; McQueen & McKenzie, 2008) introduced acquired immunity. These models examine the relationship of the parasite with the immune cells in an individual host in order to determine the infection dynamics inside the individual host. Other parameters introduced are heterogeneous landscape of varying host immunity, host death, drugs, and mosquito availability (Mackinnon & Marsh, 2010; Antao, et al., 2011), human migration and visiting people (Torres-Sorando & Rodriguez, 1997) and co-infection (Dietz et al., 1974; Dutertre, 1976 & Lindsay et al., 1998). Other models are habitat based models (Gu & Novak, 2005). These models not only brought a better understanding of the transmission, but also improved the first vectorial control strategies (Anderson & May, 1998; Bailey, 1982 & McKenzie & Samba, 2004).

Majority of these models, holds in constant total population (Hethcote et al., 1982), however, Ngwa et al., 2000 introduced variable human and mosquito populations. Ngwa et al., was of the opinion that the assumption of constant population size in epidemiological models are only relatively valid when studying diseases that has short duration and limited effects on mortality which is not the case with malaria. As such, changes in population size is non-negligible for disease like malaria and in particular in endemic region of tropical Africa where the growth rate of human population is above two percent. The major aim of these early models was to use the transmission threshold criterion to provide a suitable vector control strategy, hinged on the parasite's reproductive capacity, and termed as basic reproductive number, R_0.

A summary of the historical models that have been developed as adapted from Mandal et al., 2011 is shown in figure 1. In general, many of the models have adopted the epidemiological categories or compartments models of infectious diseases proposed through the pioneering work of Kermack and Mckendrik 1922. These epidemiological compartment models are denoted by standard notation of S_h-E_h-I_h-R_h for the human population and S_v-E_v-I_v for the vector population. S_h is the first compartment consisting the fraction susceptible humans, E_h is the second compartment consisting of exposed class, they are the fraction of human population who are infected by the pathogen, but do not have the capability of transmitting the infection to others during latent period, I_h is the third compartment consisting of infectious humans, who spread the infections to other susceptible humans through the bite of the vector and the fourth compartment is R_h consisting of human populations who recovered from the infection. On the

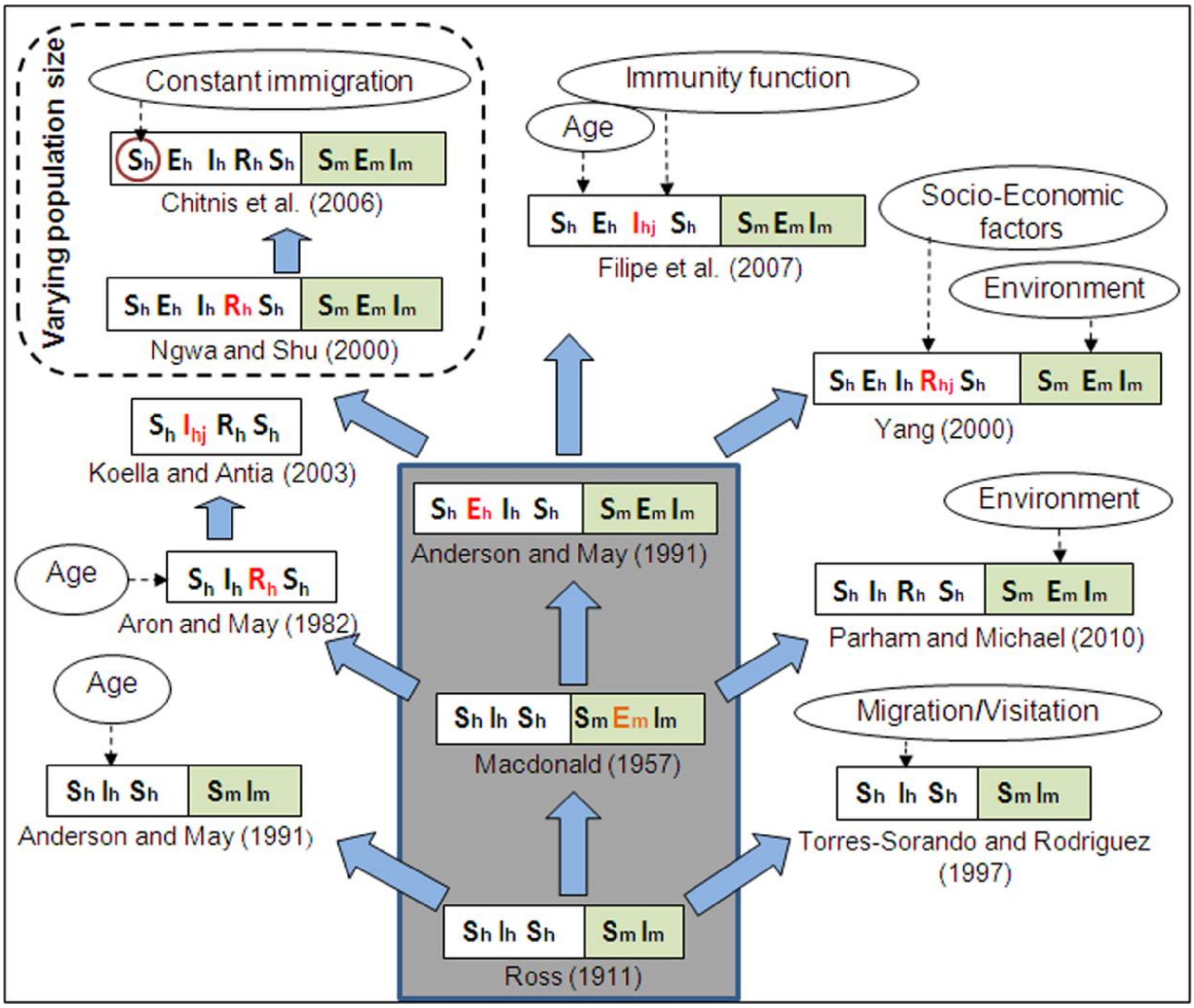

Figure 1: Evolution and grouping of different types of malaria models. Double folded boxes are for both human & mosquito population, and single fold boxes are only for human. First time addition of a new compartment is shown in red. The subscript 'j' (= 1, 2, 3) indicates further subdivision of the corresponding compartment. Three models inside the big grey box are considered as the Basic malaria models in this paper. Dotted arrows show the incorporation of complex factors in different models or specific compartment (red circle). Total population size is constant for all models, except the ones inside the dashed box.

Source: Mandal et al 2011

other hand for the vector population compartment, S_m is the first compartment with susceptible mosquitos, E_m is the second compartment consisting of incubating mosquitos and I_m is the last compartment consisting of infectious mosquitos. The mosquito population does not have the R class, since their infective period ends with their death.

As shown in figure 1, the hierarchy of the models start with Ronald Ross model which other researchers or modellers have expounded. This followed by George Macdonald's model of the theory of superinfection. The remaining of the models are then grouped based on the order of increasing complexity of the epidemiological categories in both the human and vector populations. Models in the grey colour box are the three basic models from which other models have been developed.

In conclusion, in these historical models, parameters of transmission were constant, even if vectorial behaviour presents temporal evolution (Githeko & Ndegwa, 2001 & Dutertre, 1976). Despite the strong relationship between malaria risk and environmental factors (Depinay et al., 2004; Githeko & Ndegwa, 2001 & Hoshen & Morse, 2004), environmental effects have rarely been included in malaria transmission models, probably because of technical difficulties in obtaining environmental data from field. In general, methodology used for modelling is largely deterministic and differential equation based.

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2.3. Application of geographic information systems and remote sensing in malaria research and control in South Africa: a review

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This article has been published in *Southern African Journal of Infectious Diseases* 2015; 1(1):1–8, http://dx.doi.org/10.1080/23120053.2015.1106765

Abstract

This paper presents a review of numerous published literatures on the use of spatial technology for malaria epidemiology in South Africa between 1930 and 2013. In particular, the present review focuses on the use of statistical and mathematical models as well as Geographic Information Science (GIS) and remote sensing (RS) technology for malaria research. Firstly, the review takes cognizance of the use of predictive models to determine the association between climatic factors and malaria epidemics only in KwaZulu-Natal province. Similar studies in other endemic regions such as Limpopo and Mpumalanga provinces have not been reported in the literature. While the integration of GIS with remote sensing has the potential of identifying, characterizing and monitoring breeding habitats and mapping malaria risk areas in South Africa, studies on the application of spatial technology in malaria research and control in South Africa are in-exhaustive and have not been reported in the literature. As a result, the critical robust malaria warning system which uses GIS and RS in South Africa is yet to be realized. It is recommended that the wide range of data set available from different sources including RS and Global Positioning System (GPS) ought to be integrated into a GIS system which is a core spatial technology vital for understanding the epidemiological processes of malaria and hence support in decision making in malaria control.

Keywords: malaria, modelling, GIS, Remote sensing, environment, early warning system

Introduction

Malaria is classified as one of the major health problems globally causing about one million deaths annually of which approximately 90% of these cases occur in sub-Saharan Africa (WHO, 2010). The causal agent of malaria is a parasite belonging to the *Plasmodium species* which is often transmitted between humans through the bites of female *Anopheles* mosquitoes. Largely in sub-Saharan Africa, the environmental conditions which include the physical (temperature, rainfall and humidity), social (migration patterns), economic (quality of housing stock and poverty) and political (regional collaboration) account for the prevalence of the parasites (Harrison, 1880)

Although, malaria cases were first reported in Durban in 1902, the South African government notice number 2081; formally acknowledged its prevalence in 1956 (Hill & Haydon, 1905). About 4.9 million of South Africa (SA) population representing 10% of the total population live in malaria endemic areas (STATSA, 2009). *Anopheles arabiensis* is the major local vector causing malaria in SA (DoH, 2007). In SA malaria is prevalent in three provinces, namely; Limpopo, Mpumalanga and Kwa-Zulu-Natal (Figure 1). However, some occurrences are reported in Northern Cape and North West provinces along the Orange and Molopo rivers as a result of provision of suitable breeding habitats for mosquitoes to survive (DoH, 2007).

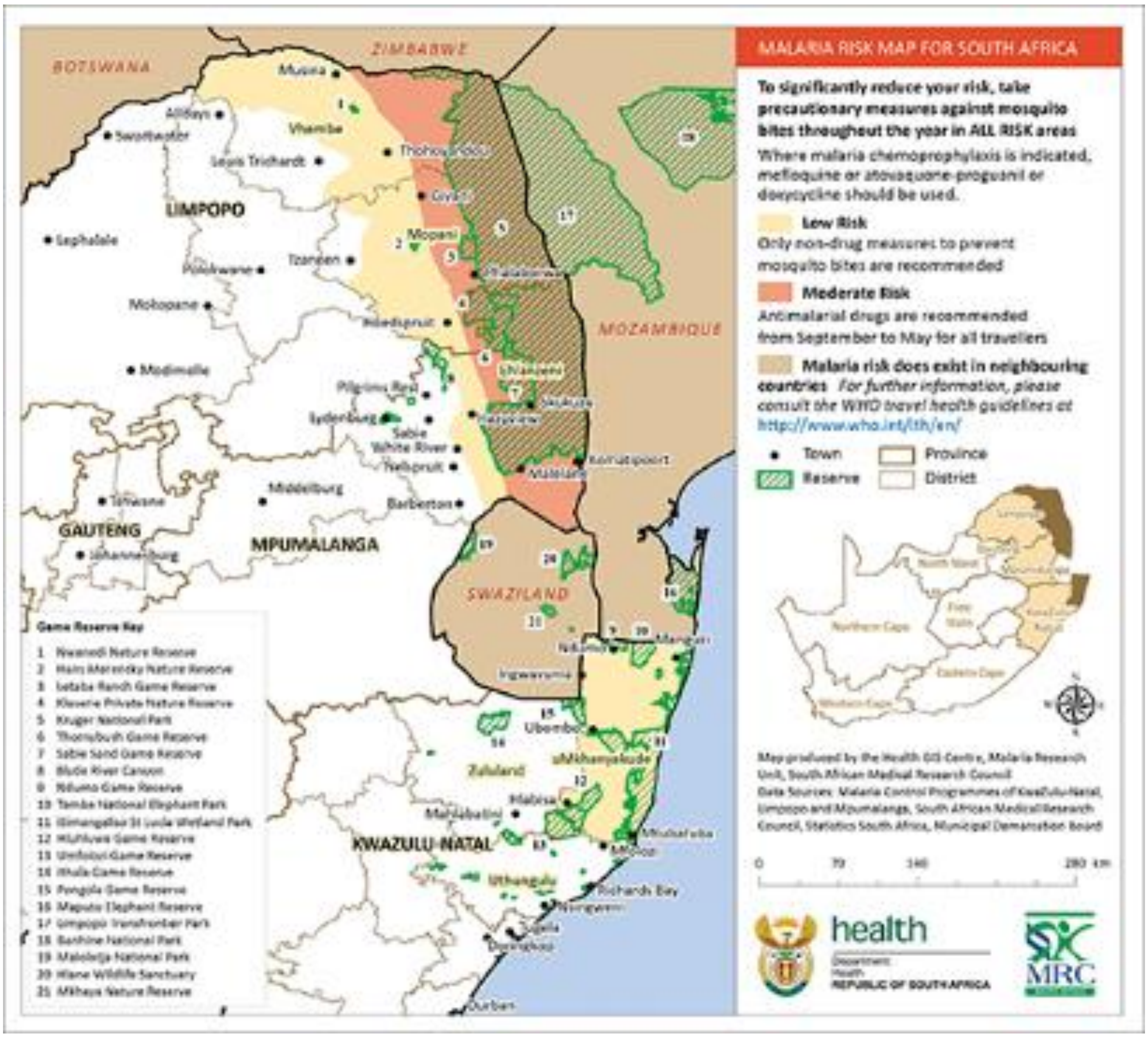

Figure 2: Official malaria risk map for South Africa, 2013

Source: (MRC)

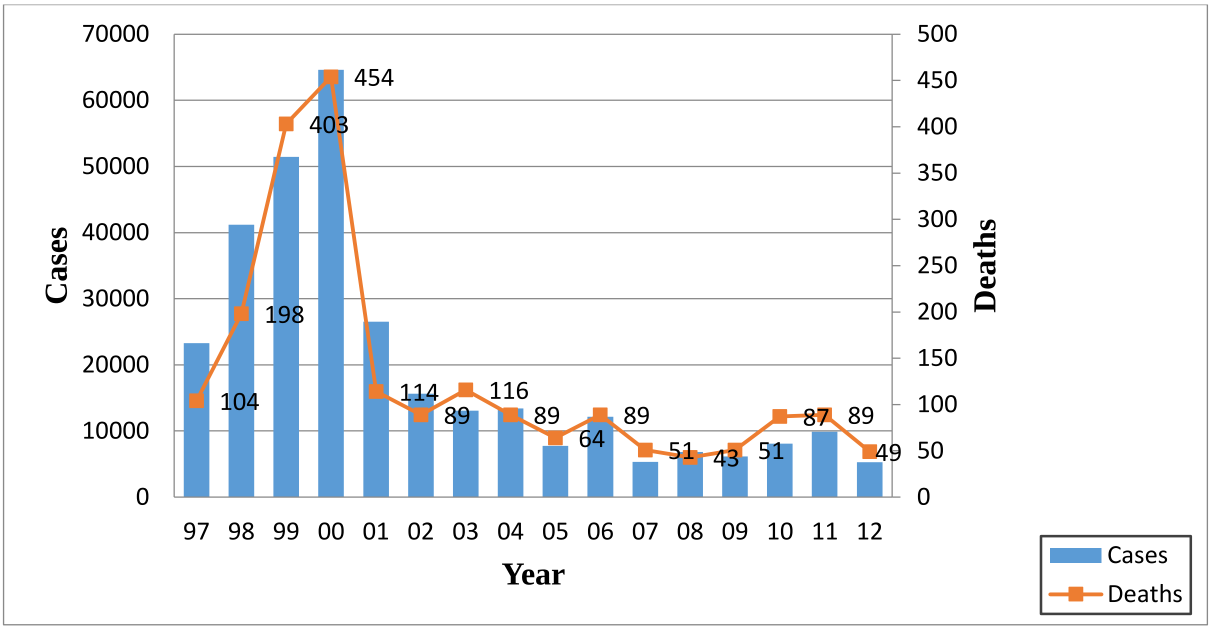

Figure 3: Multi-annual reported malaria cases and deaths spanning the period of 1997-2012 in SA. Source: SA National Department of Health

The prevention of local transmission, prompt and effective management of malaria cases have been the major control strategies adopted by the National Department of Health in malaria endemic provinces. As a result, the burden of malaria in the endemic provinces has greatly decreased by 88% (DoH, 2007). For example, the adopted control strategies saw the number of reported malaria cases reduced from 64 622 cases in 2000 to 7 626 in 2010 (Figure 2). Additionally, the number of deaths reduced by 81% i.e. from 458 deaths in 2000 to 87 deaths in 2010. Malaria cases were high during the 1997-2001 periods (Figure 2) and concur with years of substantial rainfall (Coetzee et al., 2013). During this period, two main consecutive years i.e. 1999 and 2000 had the highest frequency of reported cases amounting to 51 444 and 64 622 respectively.

Malaria is one of the oldest diseases that have been widely studied across various disciplines based on varying analysis methods. These methods accompanied by the collection, integration and analysis of relevant data sets are vital in providing insight to the different phases of the disease and widespread patterns. Consequently, it is conceived that the collective use of modelling procedures, Geographic Information Systems (GIS) and remote sensing (RS) technology as well as the associated data sets present a more effective strategy for analyzing the widespread outbreak and spatio-temporal patterns of malaria disease. According to the malERA consultative group on modeling such strategy could potentially aid efforts to control and eradicate the disease.

The aim of this paper is to review methods that have been used for malaria study in SA. However, major focus has been placed on three major (spatial and quantitative) methods which encompass statistical or mechanistic models, GIS and RS technology. The use of GIS technology has been proposed Sharp & Le Sueur, 1996, however, this paper further assesses the importance of integrating GIS, RS and proxies for malaria epidemics in SA and recommends for an integrated malaria monitoring system as a "*now and future*" paradigm for malaria research in southern Africa and the African continent. Overall, the recommended system would support the development of malaria early warning system for the country.

Materials and methods

The archives of National Centre for Biotechnology Information (NCBI) through PubMed (http://www.ncbi.nlm.nih.gov/pubmed), a U.S. government-funded national library for medicine and South African Medical Journal (SAMJ) (http://www.samj.org.za/index.php/samj/issue/archive) were used to search for literature related to malaria research. The NCBI was selected because it has access to many public databases and other references. Additionally, the SAMJ was chosen for being a local journal and it was therefore assumed to have a South African scope and content. The terms used for searching include "Malaria in South Africa", "Articles from South Africa on Malaria", and Malaria + South Africa. This was further streamlined by using definite words like 'Models' 'Geographic Information Systems' and 'remote sensing' combined with "malaria and South Africa". Short communications, letters and updates on general malaria control measures (describing the use of indoor residual spraying, use of drugs and bed nets) were excluded from the search. The search was limited to peer-reviewed paper published from 1930 to October, 2013. Also the reference lists of the selected papers were reviewed in order to get additional articles. The information extracted included year of publication, models, GIS and RS. A total of 246 articles were found in PubMed and 41 articles in SAMJ whose content related to various studies from SA and southern Africa. Results of the search revealed that SAMJ articles were also included in the PubMed database and this made the search more comprehensive. In all, 5 articles were found relating directly to the use of models, 5 articles relating to GIS and almost none was found on the use RS for malaria study in SA except for the Malareo project.

Models and malaria study in South Africa

Results from models can offer valuable information that can enhance decisions making on subjects such as determining the potential effectiveness of combining control strategies; selecting areas for prompt interventions (hot spots); forestalling the effects of introducing new interventions; predicting malaria resurgence; and informing how malaria can be monitored to enhance its control (Mandal et al., 2011). The use of models has long been applied to malaria control. For example, Sir Ronald Ross is particularly the pioneer of malaria modelling. He developed the classical 'Ross model' to study the transmission of malaria between mosquitoes and humans (Ross, 1916). In the past years, several efforts have been undertaken by various researchers to modify the Ross model in order to cater for the different compartments of malaria ranging from its transmission, to its environmental and socio-economic factors. In particular (McKenzie & Bossert, 2005; Gu & Novak, 2005; Kleinschmidt et al., 2000a) modelled the transmission of malaria, while[15] incorporated the socio-economic factors such as humans and mosquitoes population dynamics and Yang, 2000 modelled the environmental factors.

Table 1 summarizes publications on the use of models for malaria study in SA. The generalized linear mixed model was used to spatially analyze malaria incidence rates in the population of the northernmost districts of Kwa-Zulu Natal during the period 1994 and 1995 (Kleinschmidt et al., 2001). The results of the model indicated that there was a significant positive linear relationship between malaria incidences and higher winter rainfall; and a negative relationship between high average maximum temperature and increasing distance from water bodies. In 2002, the Bayesian statistical model was used to examine the spatial and temporal variations in malaria incidence rates for two districts in northern Kwa-Zulu Natal between 1986 to 1999 (Kleinschmidt et al., 2002). The results suggested an uneven increase in the spatial distribution of malaria incidence. Additionally, (Wilkins et al., 2002) developed a model to determine the cost implication of exchanging chloroquine with sulfadoxine-pyrimethamine as first-line treatment in Mpumalanga in 2002. The model suggested that sulfadoxine-pyrimethamine was found to be 4.8 times more cost-effective than chloroquine in the study area. In 2009, SaTScan method was employed to detect local malaria clusters for guiding malaria control programmes in Mpumalanga (Coleman et al., 2009). The results of the model indicated that there is a strong relationship between the identified local clustering of cases and reported malaria outbreaks in certain areas of Mpumalanga. Furthermore, the simple linear regression model was developed to analyze seasonal malaria case totals and seasonal changes against climatic factors acquired from three weather stations in Kwa-Zulu Natal (Craig et al., 2004). While the study discovered inter-annual variability in malaria incidences across the study area, the link between malaria cases and climatic data was not evident.

Table 1: Summary of publications on the use of models for malaria study in South Africa

Authors	**Malaria data**	**Other data**	**Methods**	**Main Findings**
Kleinschmidt et al., 2001	Monthly confirmed cases	Month rainfall and daily maximum temperature, distance to water bodies	Non-parametric D statistics, Generalized linear mixed models	High winter rainfall and low daily maximum temperatures are closely associated with malaria incidence in the coastal area of the study.
Kleinschmidt et al., 2002	Monthly confirmed cases	Human population	Bayesian statistical models	1.) Malaria incidence is unevenly distributed 2.) There is expansion of high malaria risk area geographically, 3.) Malaria incidence in area with highest rates was sometime stable before a sudden increase.
Wilkins et al., 2002		In-vivo drug resistance levels	Monte Carlo simulation	sulfadoxine-pyrimethamine was found to be 4.8 times more cost-effective than chloroquine in the study area
Coleman et al., 2009	Definitively confirmed individual cases	Households	Retrospective space-time permutation and Bernoulli purely spatial model	Five space-cluster and two space-time clusters were detected during the study period. There was a strong association between recognized local clustering of cases and outbreak declaration in certain areas of the study.
Craig et al., 2004	30 years Confirmed cases	Monthly mean daily temperature, monthly rainfall	Linear regression analysis	Mean maximum daily temperatures from January to October ($n = 30$, $r^2 = 0.364$, $P = 0.0004$) and total rainfall during the current summer months of November to March ($n = 30$, $r^2 = 0{,}282$, $P = 0{,}003$) were significantly associated with seasonal changes in malaria cases number.

In summary, the use of models whether statistical, mathematical or its combination has been minimal in SA. This is in comparison to the proportion of the number of publications related to malaria research t in other sub-Sahara African countries where malaria is endemic. For instance, works using model for malaria research has been published in (Kazembe et al., 2006; Kazembe et al., 2007a; Kazembe et al., 2007b; Bennett et al., 2013 & Kazembe et al., 2007c) for Malawi, (Kazembe et al., 2006b; Craig et al., 2007 & Thomson et al., 2005) for Botswana, and (Kleinschmidt et al., 2000b & Gemperli et al., 2006) for Mali. Also the existing models do not integrate other important malaria transmission factors such as the environment, social and economic factors as they are principally based on modelling the rate of malaria transmission. As reported in (Mandal et al., 2011), a single model might not be capable of integrating all the factors, but a combination of more than one factor will be more functional. Even though the models have short-comings, their results can be useful in providing information for policy makers and academic researchers towards effective framework for malaria control and its eradication. Therefore, there is need for the development of more robust (perhaps coupled) models that could be used for effective control and elimination of malaria in SA.

Geographic information system and malaria study in South Africa

The spatio-temporal dynamics of malaria and other environmental related diseases can be quantitatively analyzed using GIS. A GIS is a tool that allows for the superimposition, analysis, manipulation, storage, retrieval and display of data sets from various sources. The spatial modelling tool embedded in GIS can be used in understanding the spatial variability of the disease, the interaction of the disease causal organisms and the environment as well as other contributing factors (Loslier, 1994). Timely information on the epidemiology of the disease and other causal factors are essential to the public health practitioners. This could potentially enhance prompt and effective disease control measures which can be provided for through the use of GIS and other geospatial tools (Loslier, 1994).

The use of GIS for malaria studies in Africa has been acknowledged in the literature. For example, GIS was used for malaria study in Africa in a collaborative project called Mapping Malaria Risk in Africa/Atlas du Risque de la Malaria en Afrique (MARA/ARMA, 1998). The MARA/ARMA project involved the collection of malariometric data in the form of distribution (where), transmission intensity (how much), seasonality (when), environmental determinants (why) and population at risk (who is affected) in order to create a continental database of the spatial distribution of malaria. Furthermore, the project focused on developing environmentally determined models that define the distribution of malaria and the duration and timing of the transmission seasons. As proven through a model, the transmission of malaria in Africa is assumed to be primarily driven by climatic factors (Craig et al., 1999). The model used a fuzzy logic concept as against rigid Boolean limits to analyse mean monthly temperature and rainfall data for a period of 60 years (i.e. 1920–1980) derived from interpolated weather station data at a spatial resolution of about 5 × 5 km. The results show degrees of climate suitability for the distribution of endemic malaria, in which a fuzzy value of one predicts endemic malaria and a fuzzy value of zero predicts highly unstable or no transmission. Other studies in Africa include; the use of GIS to develop models of malaria transmission and intensity, (Omumbo et al., 1998) the mapping of the spatial distribution of mosquitoes species, habitat and density, (Coetzee et al., 2000 & Minakawa et al., 1999) and the use of GIS as a decision support system in the control of malaria (Chanda et al., 2012)

The use of GIS technology for malaria control studies in SA dates back to 1990 when a GIS was created in two Northern magisterial districts of the Kwa-Zulu-Natal province (Ingwavuma and Ubombo) by Malaria Research Programme (MRP). The project primarily created a relational database which incorporated population data, malaria cases, tribal affiliation, clinics, schools, shops, nature camps, churches, etc. through the use of Global Positioning System (GPS). Distribution maps of malaria incidences at sub-district and village level were generated from the database (Sharp & Le Sueur, 1996). The MARA/ARMA project in 1998, was substantially implemented by malaria researchers from SA. This formed an era of the foremost used of GIS for malaria studies in SA and served as a model for other African countries. The use of GIS in South Africa took a step further in 1999 when MRP established a Health GIS Centre in the South African Medical Research Council (MRC). The overall aim of introducing GIS application was to formalize the facility and to extend its support to other research areas of the MRC and to encourage the use of GIS within the health sector in southern African region (Sharp & Le Sueur, 1996 & Sharp et al., 2000).

Table 2: Summary of publications on the use of GIS for malaria study in South Africa

Authors	**Malaria data**	**Other data**	**Methods**	**Main Findings**
Le Sueur et al., 1994	On site cases	Clinic, water body, school	GPS, Spatial analysis	The spatial distribution of malaria cases coincided with water body. Also there is association between agricultural development such as irrigation and malaria cases at microlevel of the study. GIS can be used to produce risk maps at different spatial scales for effective malaria control.
Le Sueur et al., 1997	Cases from archive	Human Population, road, water body, school	GPS, Spatial analysis	Risk maps of malaria prevalence were generated. MIS is reliable to inform proper planning for effective control of malaria.
Sharp BL et al., 1999	Cases from archive	Human Population	Spatial analysis	The uses of computer with relevant tools like GIS are reliable for effective malaria incidence reporting for malaria control.
Booman M et al., 2000	Cases from archive	Notification form	GPS and spatial analysis	Displayed data on malaria cases at village and town level help in stratifying malaria risk. GIS helps to provide opportunity for more efficient malaria control in the study area.
Martin C et al., 2002	Cases from archive and notification forms	Road, school, clinics, homestead	GPS, Spatial analysis	The generated maps assist in formulating malaria insecticide and drug policies, providing appropriate information for tourists, evaluating changes in malaria transmission over time. It also helps health officials in allocating resources and informs prompt response for effective malaria control.

Results of the literature search conducted in this study showed that, the first cited paper on the usage of GIS for malaria studies in SA is traced to the work by (Le Sueur, 1994). The study, presented a malaria information system (MIS) that integrates the use of GPS and GIS technology for the KwaZulu-Natal province based on the infrastructure provided by the MRP. With the use of the MIS, breeding habitats were mapped against human population distribution data. This informed prompt intervention programme (distribution of bed nets and Indoor Residual Spraying, IRS). In addition, the MIS was used to assess the proximity of population at risk to health facilities such as clinics and hospitals. In 1997, a GIS based information system was developed to evaluate the spatial heterogeneity of malaria transmission and its implication on control strategies and research (Le Sueur, 1997). The study which was an extension of (Le Sueur, 1994) is a system that houses spatial rural database derived from existing health service activities, demographic and health information. In a follow up to previous work, Sharp et al., 1999 at a conference on multilateral initiative on malaria in Durban, presented a paper titled “Computer assisted health information system for malaria control”. The paper recapitulated the advantages of using GIS for malaria control in South Africa. As published in the bulletin of the WHO, 2000 (Booman et al., 2000) demonstrated the extended MIS from ((Le Sueur, 1994) in Mpumalanga province of South Africa. Malaria cases and other related information were gathered by the authors using a simplified notification form. The authors implemented GIS for Mpumalanga by using Microsoft Access to create a relational database in which malaria cases, demographic data and other spatial data sets with their attributes were captured. MapInfo software (MapInfo Corporation, New York, USA) was used as the GIS platform. The system was able to display malaria cases at town or village level thereby allowing the stratification of malaria risk within the districts of Barberton and Nkomazi. The overall result indicates that GIS is a reliable tool for more efficient malaria control within the study area. (Martin et al., 2002) discussed the use of a GIS based malaria information system for research and control of malaria in SA. The system which is a collaborative effort between malaria research programme and malaria control programme was developed to capture, store, analyze, retrieve and display malaria data for proper quantification, monitoring and control. Furthermore, (Booman et al., 2003) developed a GIS-based computerized management system for Maputo province of Mozambique. This is an extension of (Martin et al., 2002) as a result of the successful implementation of the GIS-based computerized system in Mpumalanga and Kwa-Zulu Natal provinces of SA. The system was designed to help in effective insecticide spraying coverage over the study area. Table 2 gives a summary of some of the characteristics of the papers in peer-reviewed publications that discuss the application of GIS in malaria research.

In summary, since the recommendation of the use of GIS as the future direction towards malaria control in SA in 1996 (Sharp & Le Sueur, 1996), limited work has been done employing the use of GIS for malaria studies when compared to other sub-Saharan African countries where malaria is endemic (Omumbo et el., 1998; Coetzee et al., 2000; Minakawa et al., 1999 & Chanda et al., 2012). Although, this could be due to some shortcomings in GIS applications to disease studies for instance, scarcity of skilled or trained GIS personnel, high costs involved in implementing a GIS project, acquiring proprietary software as well as hardware among others. However, GIS provides a handful of advantages despite its criticism (Loslier, 1994). The capability of GIS to integrate data sets from various sources and ability to analyze large volume of data makes it a useful tool. In addition, the manipulative and modelling techniques embedded in the application and other add-ins/toolboxes are of advantage particularly in Africa where there is lack of reliable statistics for diseases. GIS can be used to fill gaps for missing data and as a result, GIS technology provides a good platform to enhance the control and elimination of malaria. And more importantly, it can be used to implement early warning system.

Remote sensing and malaria study in South Africa

RS is defined as the acquisition of information about an object or phenomenon without direct or physical contact with it (Jensen, 2007). For instance; electromagnetic radiation reflected or emitted by the Earth's surface can be recorded by sensors on board satellites. Since the launch of Landsat-1 41 years ago and other satellite sensors like, Terra (ASTER and MODIS) in 1999, NOAA-M (AVHRR) in 2002, Radarsat-1 (SAR) in 1995 and Meteosat-7 (VISSR) in 1997, the use of remotely sensed data to map and monitor earth surface features has been on the increase (Ceccato et al., 2005).

In the past 30 years, a number of studies using RS data for diseases surveillance, monitoring and mapping have increased in general and in particular malaria studies (Thomson et al., 1996; Thomson et al., 1997 & Hay et al., 2000). These studies have contributed towards better understanding of malaria vector ecology. The rapid increase in the use of RS data can partly be attributed to the declaration of free usage of Landsat data in 2008. In particular, RS can be used for epidemiological studies due to the link many diseases have with certain environmental features (Curran et al., 2000 & Julie et al., 2010). Environmental factors such as land use and land cover; land surface temperature (LST), rainfall, vegetation and elevation can affect the spread of diseases associated to the environmental conditions (Curran et al., 2000). Some of the factors like the transmission parameters can be extracted indirectly from RS data (Julie et al., 2010). For example, RS derived environmental variables, such as the normalized difference vegetation index (NDVI), the enhanced vegetation index (EVI), and LST, have been used to monitor and develop a risk map for vector-borne disease (Hay et al., 1998). Additionally, precipitation, LST and vegetation indices derived from RS have been shown to be beneficial for malaria early detection and prediction and are thus vital for malaria control (Midekisa et al., 2012 & Ceccato et al., 2007). The RS data offers advantages such as large area coverage at a time, it also allow for spatially complete and almost continuous characterization of the Earth's surface (Jensen, 2007)

However, in spite of the 30 years of research and the advantages offered by the use of RS to malaria control as demonstrated in various studies in countries where malaria is endemic in sub-Saharan Africa, the use of RS technology is greatly lacking in SA. According to the search results from both the PudMed and SAMJ databases based on a string of keywords such as "Remote Sensing and Malaria in South Africa", "Malaria and Remote Sensing in South Africa" and "Remote Sensing in South Africa'; no record of studies was found directly linking the use of RS for malaria study in South Africa. Although, RS has been applied to other fields of study like land degradation, (Wessels et al., 2004) vegetation analysis (Wessels et al., 2011) and early warnings of fire (Frost et al., 2007 & Tsela et al., 2010) the use of RS in general appeared to be low in SA compared to other countries.

The closest malaria research done using RS in South Africa is the Malareo: Earth Observation (EO) in Malaria Vector Control and Management project. The project was a collaboration efforts of EUROSENSE Belfotop nv (Belgium), South African Medical Research Council (South Africa), Ministry of Health (Swaziland), Remote Sensing Solutions GmbH (Germany), University of Kwa-Zulu-Natal (South-Africa) and Swiss Tropic and Public Health Institute (Switzerland). The over-all objective of the project was to through the use of RS data from Geo-Eye (2010), Rapideye (2011), MODIS and NOAA-CPC to Build GIS, RS and spatial statistics capacities and implement the use of EO products within the malaria vector control and management programmes in southern

Africa. The project is set out to map and identify mosquito breeding habitat from the selected satellite images and perform spatial analysis towards the control of malaria within the focus area.

In summary, this finding coincided with the review of research literature carried out (Mabaso & Ndlovu, 2012). Although not directly focused on the use of models, GIS or RS but climate driven malaria epidemics in sub-Saharan Africa. As shown in (Figure 4), the authors found out that Kenya had the highest publications, closely followed by Ethiopia and Uganda while SA has relatively low publications and Sahel had none.

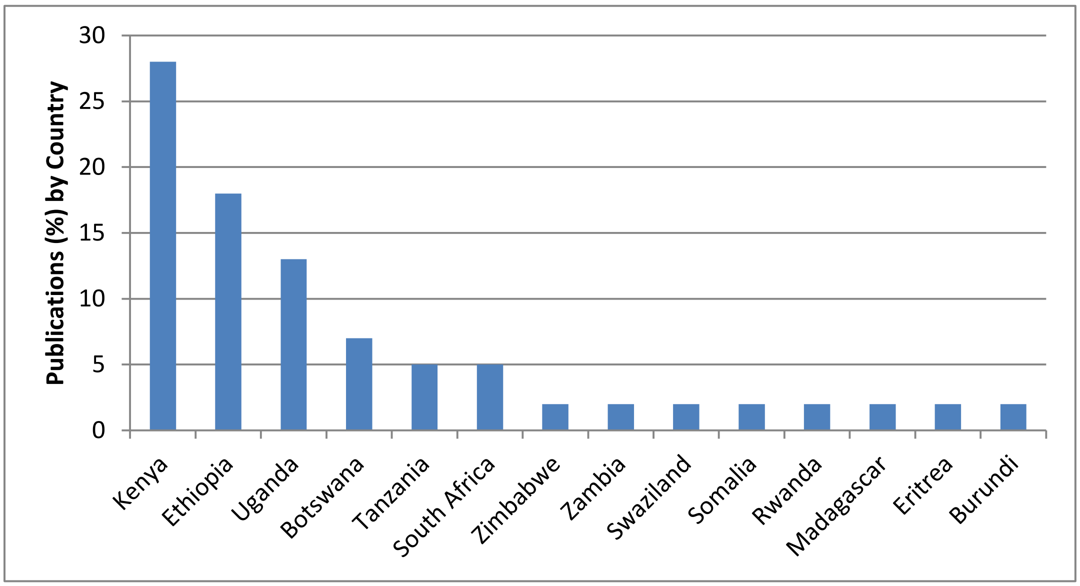

Figure 4: Distribution of research publications on climate driven malaria epidemics by country in sub-Saharan Africa from 1994 to 2009 as studied by Mabaso & Ndlovu, 2012.

The paper concluded that, the high number of publications from East Africa can be credited to the reappearance of highlands malaria epidemics which drew the attention of the political sector and stirred research interest. And on the other hand, the lower number of publications in SA and other Southern regions can be attributed to challenges related to technical and practical ability. These may include gaps in policies, institutional practices, research interest and capacity, among others.

The Future research direction on malaria: Malaria Early Warning System (MEWS)

This is a system that allows the integration of data sets like historical case data, environmental and meteorological data in a modelling form for early detection, prediction and forecasting of malaria.

The World Health Organization (WHO); Roll Back Malaria campaign had proposed the development of operational MEWS for prompt detection, prevention and control of malaria epidemics (WHO, 2004). This is sequel to the outcome from Abuja declaration which requires that 60% of epidemics should be detected within two weeks of inception and contained within two weeks of detection (WHO, 2000). To attain these goals, health professionals and program managers need reliable information on where (location), when (time) and how (magnitude) of the epidemics that are likely to occur. An effective MEWS can help provide public health decision makers with warnings of epidemic several months in advance there by helping to prioritize limited resources to most vulnerable areas and inform prompt response (Thomson & Connor, 2001; Cox & Abeku, 2007; Hay et al., 2001). As stated and proven in literature, the distribution of mosquitoes and subsequent transmission of malaria in sub-Saharan Africa is climate driven (Craig et al., 1999; Minakawa et al., 1999; Hay et al., 2000. A major approach to develop a MEWS is to use mathematical or statistical models with historical malaria cases and environmental risk indicators. This will help to establish the links between meteorological, environmental variables, malaria cases and possibly the behavior of mosquitoes. The advantage of wide spatial range and temporal consistent data from earth observing sensors provides source of environmental data that can be used as surrogate data for the development of epidemiological forecasting models. Many attempts have been made to develop and implement functional climate-driven MEWS across Africa, for instance; in Kenya (Hay et al., 2001; Thomson et al., 2003; Githeko & Ndegwa, 2001 & Hay et al., 2003), and Ethiopia (Abeku et al., 2002 & Senay & Verdin, 2005), among other malaria endemic countries, the attempt has been minimal in SA where there is no functional MEWS. Although, in 2011, an operational malaria outbreak identification and response system was developed in Mpumalanga Province of SA (Coleman et al., 2008), the system is aimed at early detection of malaria outbreak for prompt response, the system was devoid of environmental indicators. However, this can provide a framework to developing a more robust MEWS in SA.

Discussion

The review shows that there has been a moderate increase in studies related to malaria since 1902 (Hill & Haydon, 1905). Published literatures on malaria epidemics in SA includes letters, research update, commentaries, communiqué, and reviews with little primary research. From the output of the literature search, a total of 287 articles relevant to the current study were gathered of which

246 were found in the PubMed and the remaining 41 in the SAMJ. More than 96% (categorized as "others") were review papers, letters, communiqué and papers on control measures such as indoor spraying, mosquito repellents, bed nets and use of drugs and study of drugs resistance (e.g. DDT, sulfadoxine pyrimethamine, arthemeter-lumefantrine, and chlroquine among others). Although in the current review, these control measures were not considered except for (Wilkins et al., 2002) who used model to estimate recurrent direct costs between chloroquine and sulfadoxine-pyrimethamine. The remaining percentages as shown in (Figure 4) are distributed as follows, 0.3% RS, 1.7% on models and 1.7% on GIS.

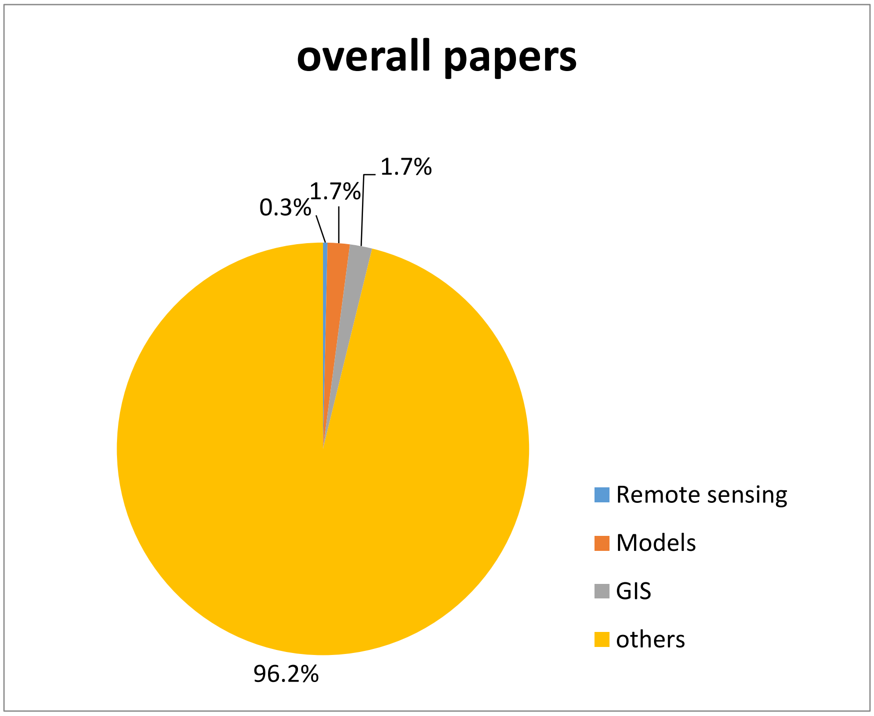

Figure 5: Literature search distribution of articles in SA (1930-2013)

The literature revealed that most studies on modelling were conducted about a decade ago, the first being (Kleinschmidt et al., 2001) developed in 2001 ((Kleinschmidt et al., 2002 & Wilkins et al., 2002) in 2002, (Craig et al., 2004) in 2004 and only (Coleman et al., 2009) was done in 2009 see (Figure 5). This implies that efforts towards implementing effective models and their validation have been minimal. Similarly, the use of GIS for malaria study in SA was initiated only in 1990 through the effort of MRC. The use of both GIS and RS tools as the future direction for malaria research in SA was echoed in 1996 (Sharp & Le Sueur, 1996). However, minimal outputs have resulted thereafter considering result from literature search, see table 2 (Le Sueur et al., 1997; Sharp et al., 1999; Booman et al., 2000 & Martin et al., 2002). Also worthy of note is that most of the reviewed articles have been authored by researchers within the medical research institutes and only a few from the purely academic institutes indicating a gap between the medical researchers and their academic counterparts. Malaria information ranging from historical clinically reported malaria cases to results from laboratory analysis on mosquitoes done by medical researchers can be an added advantage to the academic researchers to further improve the fight against malaria in SA.

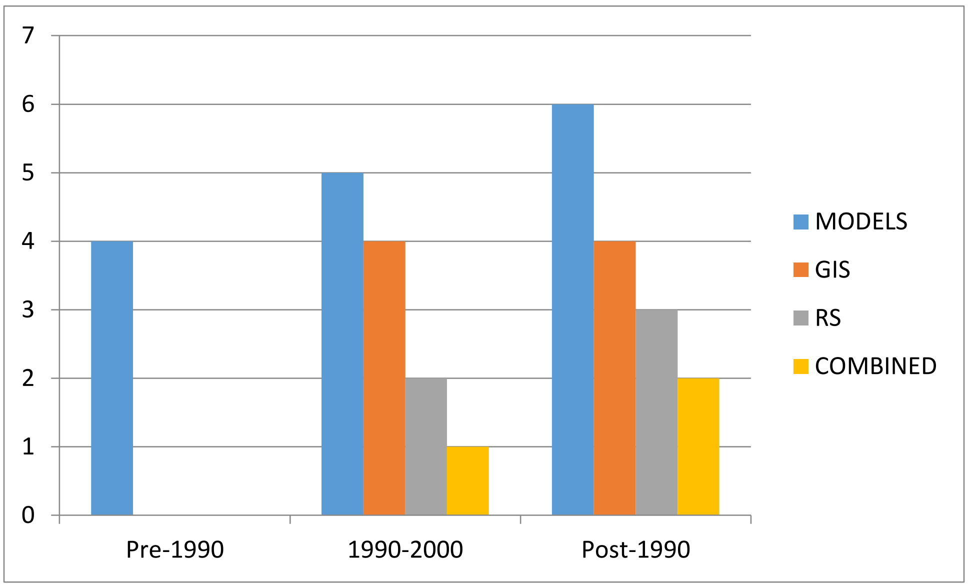

Figure 6: Epochal distribution of malaria research methods in SA

Lastly, limitations of this review is that by restricting the search to the literature published between 1930 to 2013, articles published prior to this date or after this date might have been omitted. Also the use of only PubMed and SAMJ database might not totally give a full picture of available articles because it is possible that one or more relevant journals database are not synchronized with PubMed. In addition, there is possibility that initiatives, projects and researches that have utilized both technologies may exist but are not in publication and as a result not captured in this review. However, the reliability of PubMed database has been demonstrated by (Mabaso & Ndlovu, 2012) in addition with a local journal. Therefore, it is held that this work has given a good picture of what exist in SA in terms of methods used for malaria research and control.

Conclusion

The outcome from the literature review revealed that the development of a functional MEWS remains a challenge in SA. This could be partly due to the low research output on the collective use of modern technologies (i.e. GIS and RS) in malaria studies as well as, minimal collaborative effort among academic and medical research institutes. On the other hand, predictive models have been implemented to determine the association between climatic factors and malaria epidemics in Kwa-Zulu Natal however; more research is encouraged in other endemic provinces such as Limpopo and Mpumalanga. In addition, multi-sensor satellite data that is typical of high spatial, spectral and temporal resolutions could offer valuable information for use in a GIS or RS tool. Various vegetation indices for instance, NDVI and other environmental data like LST and elevation can be extracted from satellite images and used as surrogate data to locally forecast epidemic. The extracted data can be integrated with socio-economic factor such as migration pattern either locally or internationally. Finally, existing MEWS can potentially be considered as a framework to guide the implementation of a functional MEWS in SA.

Competing interests

The authors declare that they have no competing interests.

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CHAPTER 3

Landsat satellite derived environmental metric for mapping mosquitoes breeding habitats in Nkomazi municipality, Mpumalanga province, South Africa

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This article has been published in *Southern African Geographical Journal* 2015; 1–15, http://dx.doi.org/10.1080/03736245.2015.1117012

Abstract

The advancement, availability and high level of accuracy of satellite data provide a unique opportunity to conduct environmental and epidemiological studies using remotely sensed measurements. In this study, information derived from remote sensing data is used to determine breeding habitats for *Anopheles arabiensis* which is the prevalent mosquito species over Nkomazi municipality. In particular, we have utilized the Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) coupled with Land Surface Temperature (LST) derived from Landsat 5 TM satellite data. NDVI, NDWI and LST are considered as key environmental factors that influence the mosquito habitation. The breeding habitat was derived using multi criteria evaluation (MCE) within ArcGIS using the derived environmental metric with appropriate weight assigned to them. Additionally, notified malaria cases were analysed and spatial data layers of water bodies, including rivers and dams were buffered to further illustrate areas at risk of malaria. The output map from the MCE was then classified into 3 classes which is low, medium and high. The resulting malaria risk map depicts that areas of Komatieport, Malelane, Madadeni and Tonga of the district are subjected to high malaria incidence. The time series analysis of environmental metrics and malaria cases can help to provide adequate mechanism for monitoring, control and early warning for malaria incidence.

Keywords: Remote Sensing, Geographic Information System, Multi criteria evaluation, Environmental, NDVI, NDWI, LST, Malaria.

Introduction

Malaria is classified as one of the major health problems globally; it is estimated that there are about 300-500 million cases and about one million deaths associated to malaria annually, with a larger percentage of malaria cases and deaths occurring in sub-Saharan Africa (WHO, 2013). However, there is significant reduction in malaria cases and its associated death as a result of the use Insecticide-treated mosquito nets (ITNs) and Indoor residual spraying (IRS) (WHO, 2013, WHO, 2013). (According to (STATS SA, 2009) about 4.9 million of the population representing 10% of the total population live in malaria endemic area in South Africa. Malaria is majorly endemic in three provinces; Limpopo, Mpumalanga and Kwazulu-Natal. But occasionally few major occurrences are sighted in Northern Cape and North West provinces along Orange and

Molopo rivers as a result of provision of suitable breeding habitats for mosquitoes to survive (Department of Health, South Africa, 2007). *Plasmodium falciparum* accounts for about 95% of the total malaria infections in South Africa through *Anopheles arabiensis* as the major local vector.

Studies have shown that there is direct link between environmental and climatic parameters to malaria incidences (Ceccato et al., 2005; Machault et al., 2011). This implies that the spatial and temporal distribution as well as the abundance of mosquitoes can be substantively determined by considering environmental parameters (for example vegetation, elevation and water body) and climatic parameters (for example temperature, rainfall and humidity) which could, in addition to terrestrial measurements, be derived from satellite data (Hay et al., 1997).

The use of remotely sensed data to investigate, describe and predict the spatial and temporal patterns of the transmission and prevalence of vector-borne diseases has been widely studied in the past years (Beck et al., 2000; Rogers et al., 2002; Machault et al., 2011). The goal of using such data could be to map vector densities or to detect breeding habitats of organisms responsible for vector-borne diseases, for example, to define and identify environmental parameters that are associated with mosquito distribution and malaria occurrences (see e.g., Zou et al., 2006). Satellite derived Land Surface Temperature (LST) and indices like Normalized Difference Vegetation Index (NDVI) and Normalized Difference Water Index (NDWI) can be used as surrogate data for malaria studies (Hopp & Foley, 2001). Such data provides continuous data and offer possibility of identifying mosquitoes breeding habitats over large areas in contrast to conventional ground surveys (Hay et al. 1998; Bogh et al., 2007). The mapping of the spatio-temporal distribution of mosquito breeding habitats is regarded as crucial for reducing incidences of malaria (Gu and Novak, 2005).

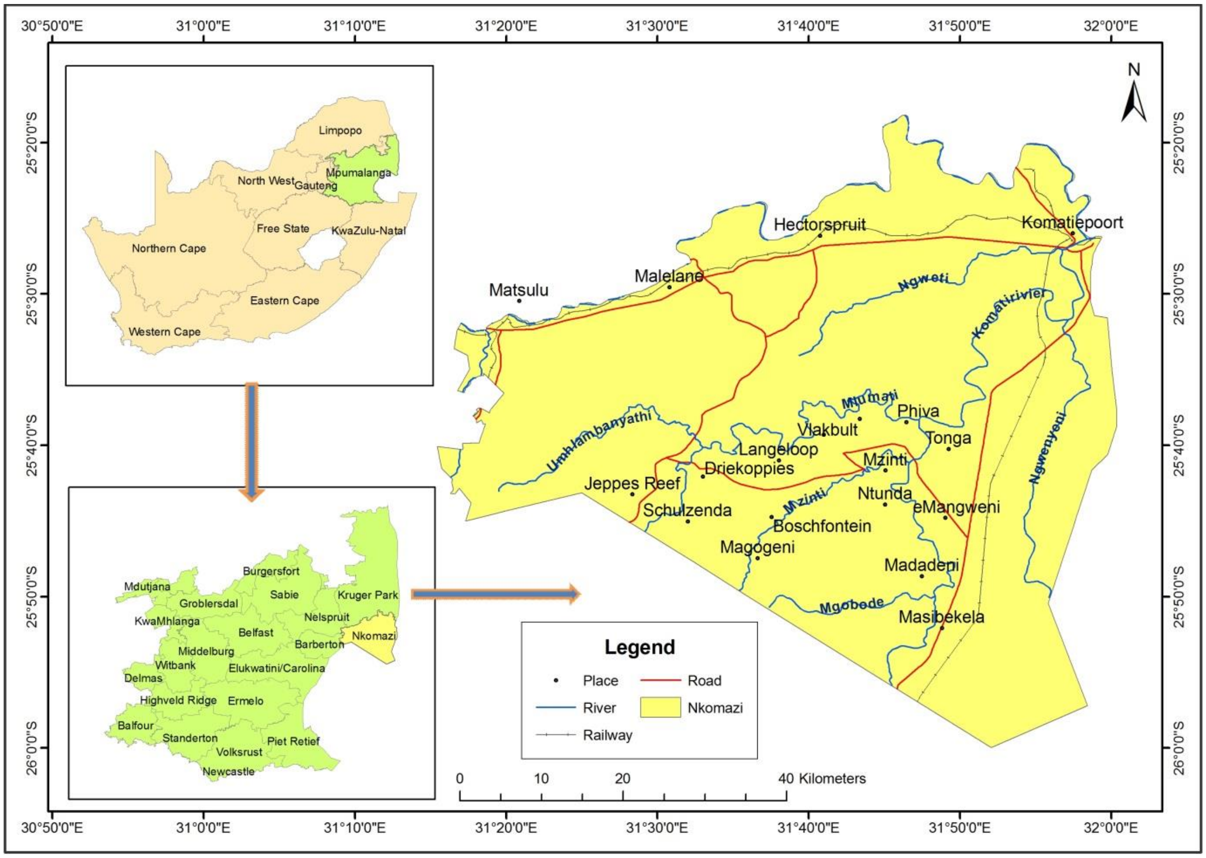
Eisele, et al., (2003) demonstrated that NDVI values derived from multispectral thermal imager overlaid on georeferenced entomological and human ecological data can be used to determine malaria prevalence in urban area. Gaudart, et al., (2009) used 15-day composite NDVI coupled with field study to derive a malaria transmission model. They found that, the seasonal pattern of *P.falciparum* incidence was significantly explained by NDVI. Similar studies have also been conducted in South and Central America (Britch et al., 2008) and Asia (Masuoka et al., 2003; Charoenpanyanet et al., 2008; Adimi et al., 2010).

This paper extends the analyses applied in the studies above, but with a focus on South Africa. Malaria study in South Africa has witnessed great input from researchers like Le Sueur et al., 1994, 1997; Sharp et al., 1999 2000; Kleinschmidt et al., 2001; Booman et al., 2000, 2003; Coleman et al., 2008 and Martin et al., 2001 to mention but a few. However, majority of these studies are based on statistical analysis and the use of Geographic Information System (GIS). For instance, (Kleinschmidt et al., 2001) use generalised linear mixed models to spatially analyse malaria incidence rate in KwaZulu Natal. Sharp et al. (1999) developed a computer assisted health information system for malaria control. Also, Martin et al. (2001), developed a GIS based malaria information system. However, the advantages offered by the use of remote sensing has not been utilised in any of this studies. In addition, most of the works have been focused on KwaZulu Natal Province which is one of the three malaria endemic Provinces. The aim of this study is to identify the potential favourable breeding habitats of the mosquito using environmental metric parameters derived from Landsat satellite imagery over the Nkomazi municipality in the Mpumalanga Province of South Africa. The environmental parameters have applications in the development of a malaria risk prediction model for the region.

Study area

The Nkomazi municipality is situated in the eastern part of the Mpumalanga Province of South Africa and occupies an area of approximately 3254.041 km^2 (Figure 1). The Mpumalanga Province is one of the malaria endemic provinces in South Africa (National Department of Health, 2007). The Province covers a surface area of 77918.298 km^2 which constitutes about 6.5% of the country's land area. According to the mid-year population estimates for 2013, the province had 4,128,000 which constitutes 7.8% of South Africa’s total population (Statistics South Africa, 2013). The climatology of the Mpumalanga Province consists of a relatively cooler Westerly half, which is often associated to its higher elevation of 1700 m to 2300 m above mean sea level. The eastern half is situated in subtropical low altitude topography, known as the Lowveld/Bushveld. This area is dominated by Savannah habitats as a result of its closeness to the warm Indian Ocean. The Kruger National Park is located in the Lowveld/Bushveld.

Figure 1: Maps of the study area depicting the Nkomazi municipality (right) located in the eastern parts of the Mpumalanga Province (left bottom) of South Africa (left top).



Material and methods

Data

Landsat data

A summer cloud free Landsat Thematic Mapper (TM) image of 1998/02/07 of path/row 168/078 was downloaded from the archive of Global Land Cover Facility hosted by the University of Maryland. Only the TM Spectral Band 2 (0.52 µm - 0.60 µm), Spectral Band 3 (0.63 µm - 0.69 µm), Spectral Band 4 (0.76 µm - 0.90 µm), Spectral Band 5 (1.55 µm - 1.75 µm) and Spectral Band 6 (10.4 µm - 12.5 µm) of the image were considered in this study. All these have a spatial resolution of 30 m x 30 m, except for the thermal Spectral Band 6, which has a resolution of 60 m x 60 m.

Malaria data

Malaria data from September 1997 to August 1998 was used. The data was obtained from the provincial integrated malaria information system (IMIS) of malaria control programme in the Mpumalanga provincial department of health. This data mainly consist of locally recorded incidences with minimal imported cases that were extracted from IMIS at clinics and hospitals at district level. The health facilities as shown of figure 6 are approximately 10 km apart.

Ancillary spatial data

Spatial data of various sources of water which included streams, rivers and dams (wetlands) were acquired for the study area.

Methods

Pre-processing

All the selected Landsat TM satellite image bands were defined in Universal Transverse Mercator (UTM Zone 36S) projections. Erdas Imagine 9.1 raster based software was used for image processing and analyses (Qinqin et al., 2010). The images were received at level 1T, so were already geo-rectified. Bands 6; the thermal band was resampled to pixel size of 30 m by 30 m using the nearest neighbour algorithm with root mean square error (RMSE) of less than 0.5 pixel. An area of interest of 3254.041 km^2 representing the total area of Nkomazi municipality was extracted for each required spectral band of the image (Figure 1). The Spatial Modeler of Erdas Imagine 9.1 was used to convert the Digital Numbers (DN) of the selected spectral bands (2, 3, 4 and 5) to radiance using equation 1 (Landsat Project Science Office, 2002). Subsequently, the exoatmospheric reflectance values were derived using equation 2 (Gyanesh et al., 2009). The DN of thermal spectral Band 6 was also converted to radiance using equation 1. Equation 3 was used to derive the at-sensor Brightness Temperature (BT) and equation 6 was used to derive the emissivity corrected LST with a unity value of 0.95 for spectral emissivity.

In other to achieve a physically meaningful radiometric scale, the image data of all the selected bands were converted to at-sensor spectral radiance (Gyanesh et al., 2009). Equation 1 was used to radiometrically calibrate the TM image.

$$L_\lambda = \left(\frac{LMAX_\lambda - LMIN_\lambda}{Q_{calmax} - Q_{calmin}} \right) (Q_{cal} - Q_{calmin}) + LMIN_\lambda \qquad (1)$$

Where, L_λ= Spectral radiance at the sensor's aperture [W/(m^{2}sr μm)], Q_{cal}= Quantized calibrated pixel value (DN), Q_{calmin}= Minimum quantized calibrated pixel value corresponding to $LMIN_\lambda$ (DN), Q_{calmax}= Maximum quantized calibrated pixel value corresponding to $LMAX_\lambda$ (DN), $LMIN_\lambda$= Spectral at-sensor radiance that is scaled to Q_{calmin} [W/(m^2 sr μm)], $LMAX_\lambda$= Spectral at-sensor radiance that is scaled to Q_{calmax} [W/(m^2 sr μm)]. $LMAX_\lambda$ and $LMIN_\lambda$ are obtained from the Meta data file available with the image, which are given in the Table 1.

Equation 2 was used to convert the spectral radiances of the selected bands (2,3,4 and 5) to planetary reflectance or albedo which is a physical measurement to achieve reduction in between-scene variability (Gyanesh et al., 2009). The mean solar exoatmospheric irradiances (ESUN) measured in [W/(m2 μm)] is shown in table 1 given in (Gyanesh *et al.*, 2009).

$$\rho = \frac{\pi * L_\lambda * d^2}{ESUN_\lambda * \cos\theta_s} \qquad (2)$$

Where: ρ= Planetary TOA reflectance (unitless), π= Mathematical constant equal to 3.14159 (unitless), L_λ= Spectral radiance at the sensor's aperture [W/(m^2 sr μm)], d= Earth–Sun distance (astronomical units), $ESUN_\lambda$= Mean exoatmospheric solar irradiance [W/(m^2 μm)], θ_s= Solar zenith angle (degrees)

Note: The cosine of the solar zenith angle is equal to the sine of the solar elevation angle.

Table 1: $LMAX_\lambda$, $LMIN_\lambda$ and ESUN values of Landsat TM satellite data

Band No	$LMAX_\lambda$	$LMIN_\lambda$	$ESUN_\lambda$
2	365	-2.84	1796
3	264	-1.17	1536
4	221	-1.51	1031
5	30.2	-0.37	220
6	15.3032	1.2378	-
7			83.44

Source: Meta data file of the image and (Gyanesh *et al.*, 2009)

Deriving NDVI, NDWI and LST from the Landsat TM satellite

After the radiometric calibration of the image data, the NDVI, NDWI and LST methods were all applied image. These methods are defined using equations (3), (4) and (5) respectively. The NDVI calculation is given in equation 3 where ρRED and ρNIR correspond to the reflectance measured in band 3 (0.63 µm – 0.69 µm) and band 4 (0.77 µm – 0.90 µm), respectively (Rouse *et al.,* 1974). Generally NDVI, ranges from -1 to +1, where water typically has an NDVI less than 0, bare soil between 0 and 0.1 and vegetation greater than 0.1.

$$\mathrm{NDVI} = \frac{\rho\mathrm{NIR} - \rho\mathrm{RED}}{\rho\mathrm{NIR} + \rho\mathrm{RED}} \tag{3}$$

The NDWI calculation is given in equation 4 where ρGreen and ρSWIR correspond to the reflectance measured in band 2 (0.52 µm - 0.60 µm) and band 5 (1.55 µm - 1.75 µm) respectively (Xu, 2006). In summary, NDWI is positive for all water features and negative for all other land features.

$$\mathrm{NDWI} = \frac{\rho\mathrm{Green} - \rho\mathrm{SWIR}}{\rho\mathrm{Green} + \rho\mathrm{SWIR}} \tag{4}$$

LST

The LST was derived from the thermal infrared (IR) band of the Landsat image (Colombi et al., 2007 and Vancutsem et al., 2010). Equation 5 was used to convert the spectral radiance to at satellite brightness temperature (T_B) under the assumption of uniform emissivity (Landsat Project Science Office, 2002). Equation 6 was used to derive the emissivity corrected LST using a unity value of 0.95 as the spectral emissivity (Artis and Carnahan, 1982).

$$T_B = \frac{K_2}{In\left(\frac{K_1}{L_\lambda} + 1\right)} \tag{5}$$

Where: T_B is effective at-sensor brightness temperature in Kelvin, L_λ is spectral radiance in W/ (m^2 ster µm); and K_1 and K_2 are pre-launch calibration constants given as K_1 = 607.76 (W/(m^2 ster µm) and K_2 = 1260.56 (Kelvin), *In*= natural logarithm.

$$LST = \frac{T_B}{1 + \left(\lambda * T_B / \rho\right) In\varepsilon} \quad (6)$$

where: λ is the wavelength of the emitted radiance (11.5μm). ρ = h.c/σ, σ = Stefan Boltzmann's constant (5.67 x 10^{-8} Wm^{-2} K^{-4}), h = Plank's constant (6.626 x 10^{-34} J Sec), c = velocity of light (2.998 x 10^{8} m/sec) and ε is the spectral emissivity.

Proximity analysis

Rivers and dams were buffered in ranges of 2.4 km and 3.2 km to define areas of high and low risk respectively based on the determined flight range of the *Anopheles* mosquitoes. The flight direction, speed and consequently the range of individual mosquitoes is influenced by wind (Cummins et al., 2012) and other anthropological factors like topography (Stephen, 2006). Habitually, adult *Anopheles* mosquitos do not fly beyond 2.4 km from their larval habitat with only a small proportion flying farther than 3.2 km. Population within 2.4 km radius of the rivers and dams are termed to be more susceptible to be bitten by mosquitos.

Clinical data analysis

The malaria data from September 1997 to August 1998 which tallies with the year of image used for this paper was statistically analysed. Descriptive analysis showing the temporal variation of malaria cases across the health facility centres were cases were reported was performed. Figure 7 illustrates the temporal and spatial variation of malaria cases across the study area.

Multi-criteria evaluation (MCE)

MCE analysis was performed in order to create spatial distribution of mosquito breeding habitats and risk map. MCE is a procedure that require the combination of several criteria to be weighed to meet a particular objective. In order to determine the weight to be assigned to the derived environmental metric (NDVI, NDWI and LST), Eigen vector was used. This is done to determine the importance of each metric compared to each other in the contribution of generating a malaria risk map. Hence, the Eigen vector of the weight of the metric was calculated in ArcGIS. The result of the Eigen vector, gives a pair wise comparison matrix of NDVI 0.1520, NDWI 0.3436 and LST 0.1317 as best fit set of weight. The environmental metric was reclassified using threshold as derived from the analysis and supported by previous findings. Table 2 gives a summary of the various thresholds and classes that was combined to develop the risk map. The standardised metric were then combined by means of weighted linear combination (Eastman, *et al.*, 1995). The resulted map (breeding habitat) was then reclassified into 3 classes (1) high, (2) medium and (3) low areas, to produce the risk map.

Table 2: Classification of remotely sensed derived environmental metric for input to create malaria risk map

LST (^{o}C)	Risk Score	Risk Level	Source
< 16.0°	1	Very Low	Bi *et al.*, (2003)
16.1° - 20.0°	2	Low	
20.1° - 25.0°	3	Moderate	
25.1° - 30.0°	4	High	
> 30.1°	2	Low	

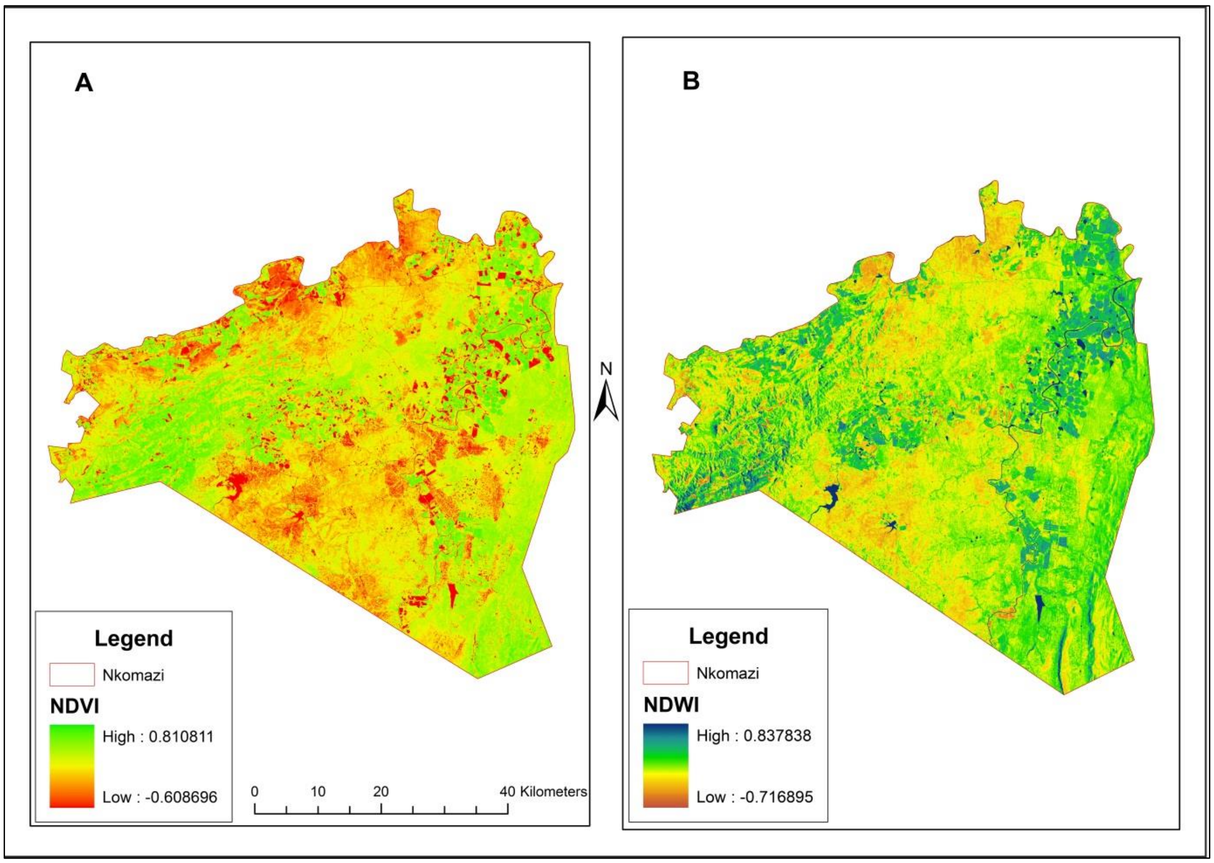
NDVI (Unit less)	Risk Score	Risk Level	Source
< 0.2	1	Very Low	Nihei *et al.*, (2002)
0.21 - 0.30	2	Low	Hay *et al.*, (1998)
0.31 - 0.40	3	Moderate	
0.41 - 0.50	4	High	
> 0.51	2	Low	

NDWI (Unit less)	Risk Score	Risk Level	Source
<=0.00	1	Very Low	McFeeters (2013)
0.01 – 0.20	2	Low	
0.21 – 0.30	3	Moderate	
0.31 – 0.80	4	High	

Results and discussion

Generally, water typically has an NDVI of less than 0, bare soil between 0 and 0.1 and vegetation >0.1 (Rouse et al., 1974). As shown in Figure 2a, the NDVI has a minimum value of -0.61, maximum value of 0.81, mean value of 0.49 and standard deviation of 0.13. The 0.81 value depicts healthy or dense vegetation. The densely vegetated areas are seen in Tonga, Komartiepoort and Masibekela of the study area. A threshold of NDVI 0.35 was set to distinguish vegetation from other feature (Hay et al., 1998). Therefore, where NDVI ≥ 0.35 it implies that the area could potentially be mosquito's breeding habitat. Similarly, NDWI has positive value for water features and zero or negative value for other land features. It has a minimum value of -0.72 and maximum value of 0.84; see Figure 2b. The study area is majorly drain by river Komati and in order to accommodate other water features like wetland and ponds a threshold of 0.3 was used. Therefore, NDWI ≥ 0.3 equals water sources, which could be potential breeding habitat for mosquito (McFeeters, 2013).

Figure 2: Two output maps from Landsat TM satellite data in the Nkomazi municipality area, (A) the NDVI and (B) MNDWI.



The LST distribution over the study area is shown in Figure 3. Temperature has been proven to be one of the major indicators for the development and survival of Plasmodium parasite as well as developmental cycle and the survival of the malaria carrying mosquito (Bi et al., 2003, Machault et al., 2011). For Anopheles mosquito species, at 25 °C; the P. vivax, has survival duration of about 10 days. The associated survival duration is 8 to 14 days for P. falciparum and 18 to 20 days for P. ovale and P. Malariae (Mouchet et al., 2004). In P. falciparum the larvae can withstand even low temperatures, but do not complete their development at temperatures below 10 °C to 13 °C and no appreciable development takes place until the temperature reaches 18 °C to 23 °C. Therefore, slight increases or decreases in temperature (from a benchmark of 16 °C) negatively impact the development of the parasite (Sutherst, (2004). The LST indicate a minimum value of 21.48 °C, a maximum value of 40.75 °C, a mean value of 27.95 °C, and 2.40 °C as the standard deviation. Table 3 gives the summary of temperature ranges that determine the lifecycle and transmission of the malaria carrying mosquito. These temperature ranges are integrated as class break values for the LST variable that govern the MCE analysis to use to derive the risk map in ArcGIS.

Figure 3: **Two output maps from Landsat TM satellite data in the Nkomazi municipality area showing, (A) LST in degree Celsius and (B) reclassified LST based suitability map.**

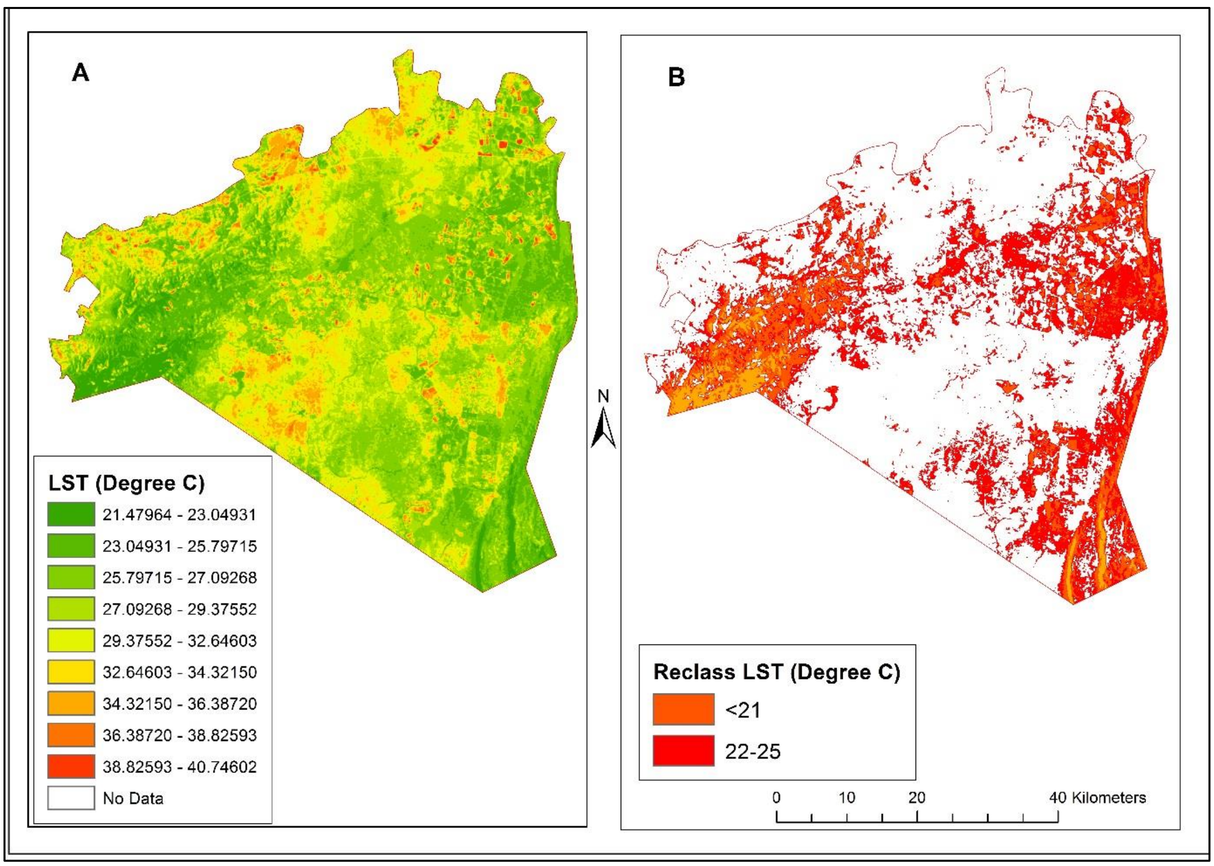
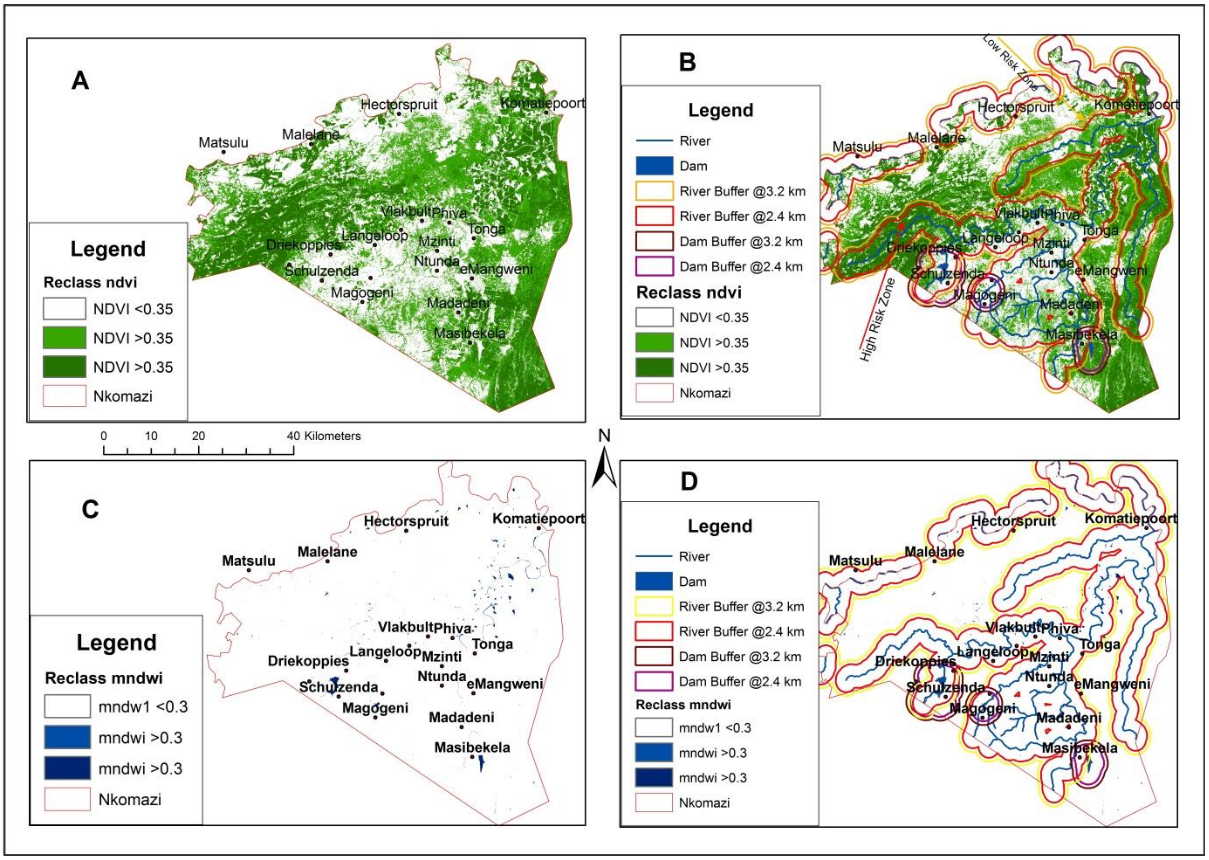


Table 3: Temperature ranges that determine the survival of mosquito, Bi *et al.*, (2003)

Temperature Range (C°)	Description
> 25°	Needed to complete the mosquito lifecycle and must be maintained for at least nine days.
20° – 30°	Optimal temperature range to acquire and transmit the parasite.
20° – 27°	Extrinsic incubation period of the parasite shortens dramatically.
≤ 16° or ≥ 30°	Negative impact on the growth rate of the mosquito and the propagation rate of the parasite is reduced.

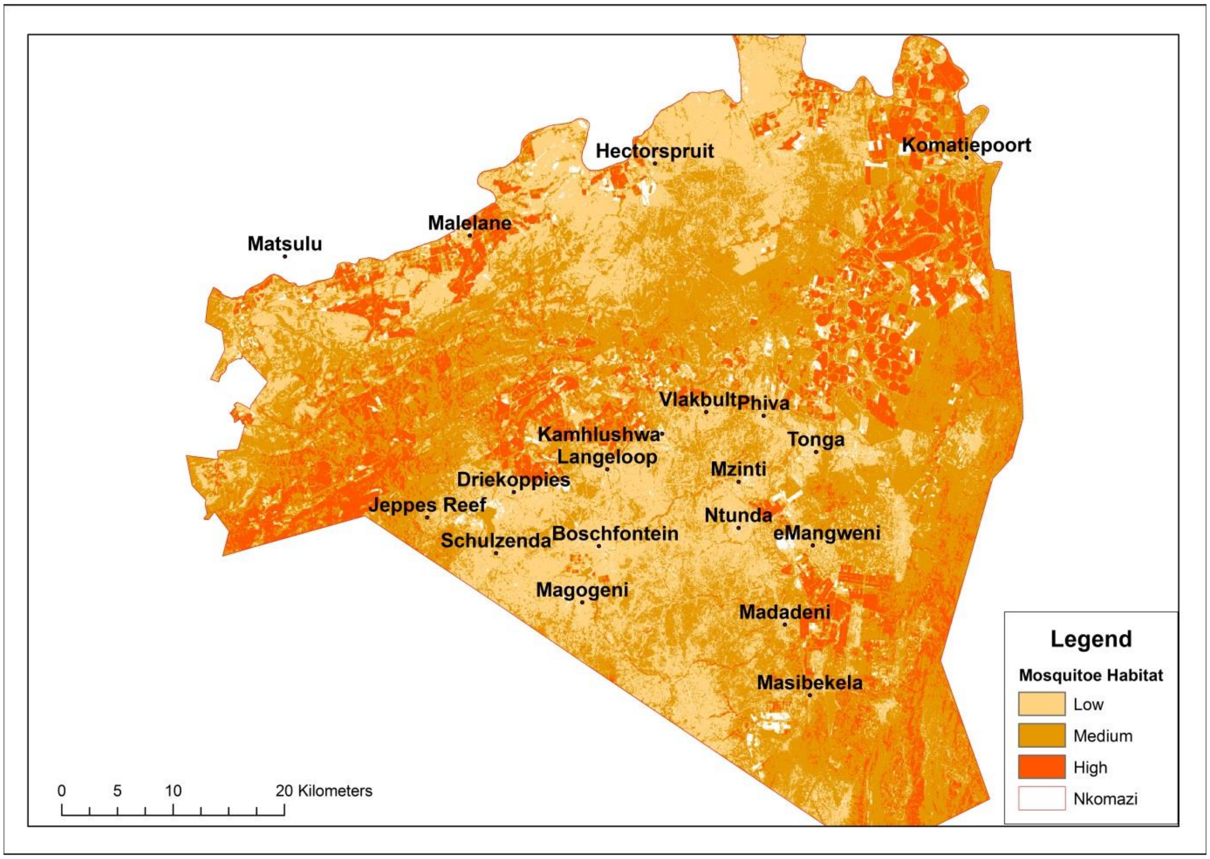
From the image, the densely vegetated areas have the lowest average temperature value of 22.3 °C, while water surface have an average of 22.6 °C, the built-up areas have an average of 29 °C and bare land with the highest LST. In consideration of the maximum and minimum temperature needed for the breeding and survival of the vector, a threshold of 22-25 °C was set for the LST (Mouchet et al., 2004 and Sutherst, (2004). In addition, the buffering analysis as shown in Figure 4: b and d, indicate that human population within 2.4 km buffer zone where NDVI ≥0.35 with the presence of water body are more susceptible to be bitten by infected vector and therefore become infected. On the other hand, human population farther away from the suitable breeding sites are at lesser risk to mosquito bite and less prone to malaria except when there is migration factor by the human population.

Figure 4: Four output maps from Landsat TM satellite data in the Nkomazi municipality area showing, (A) Reclassified NDVI (B) Malaria risk map in relation to NDVI and proximity to natural water sources (C) Reclassified MNDWI and (D) Malaria risk map in risk map in relation to MNDWI and proximity to natural water sources.



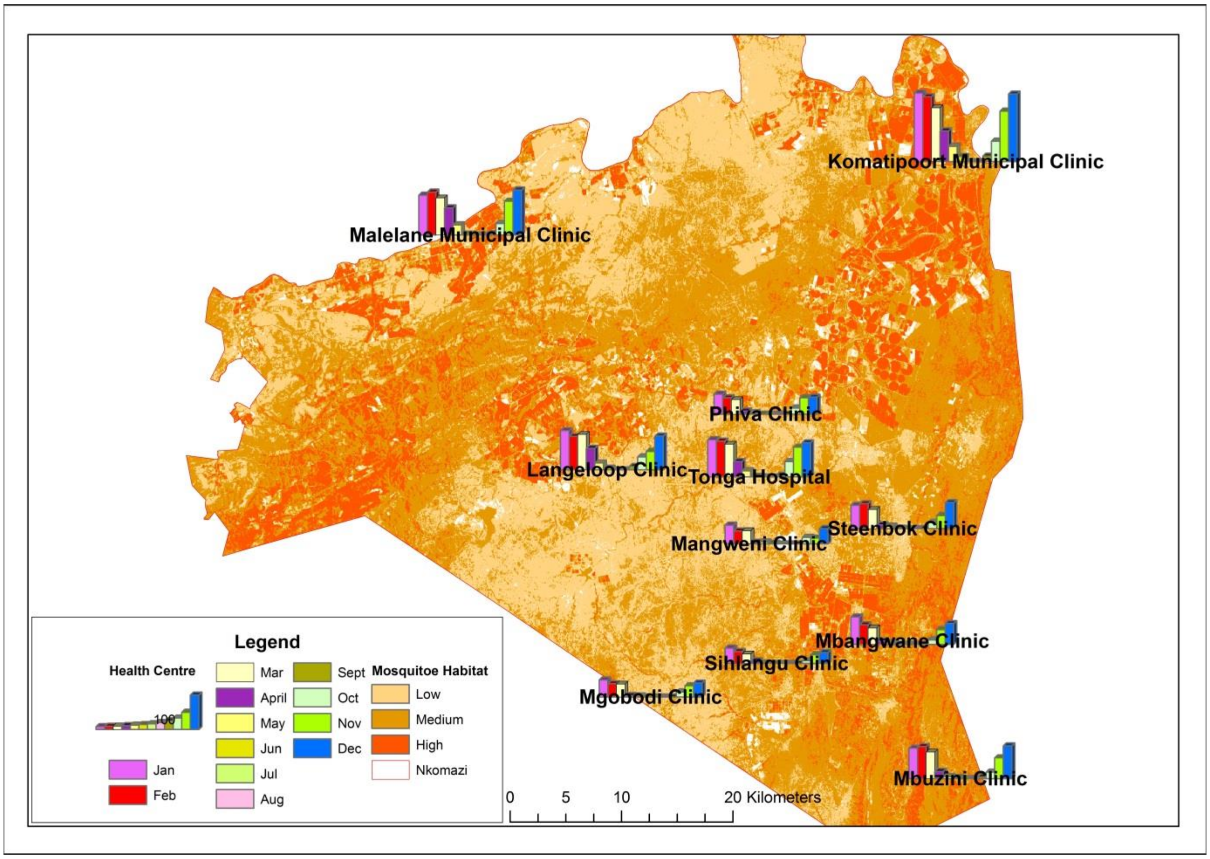
From the MCE, suitable breeding habitats were derived and reclassified into 3 classes shown in Figures 5 and 6 respectively. The high areas include Komatiepoort, Malelane, Madadeni and Tonga; medium include, Jeppes Reef, Masibekela and the Low areas include Langeloop, Ntunda and Driekoppies.

Figure 5: Malaria risk map as derived from environmental metric using Landsat satellite in the Nkomazi municipality.



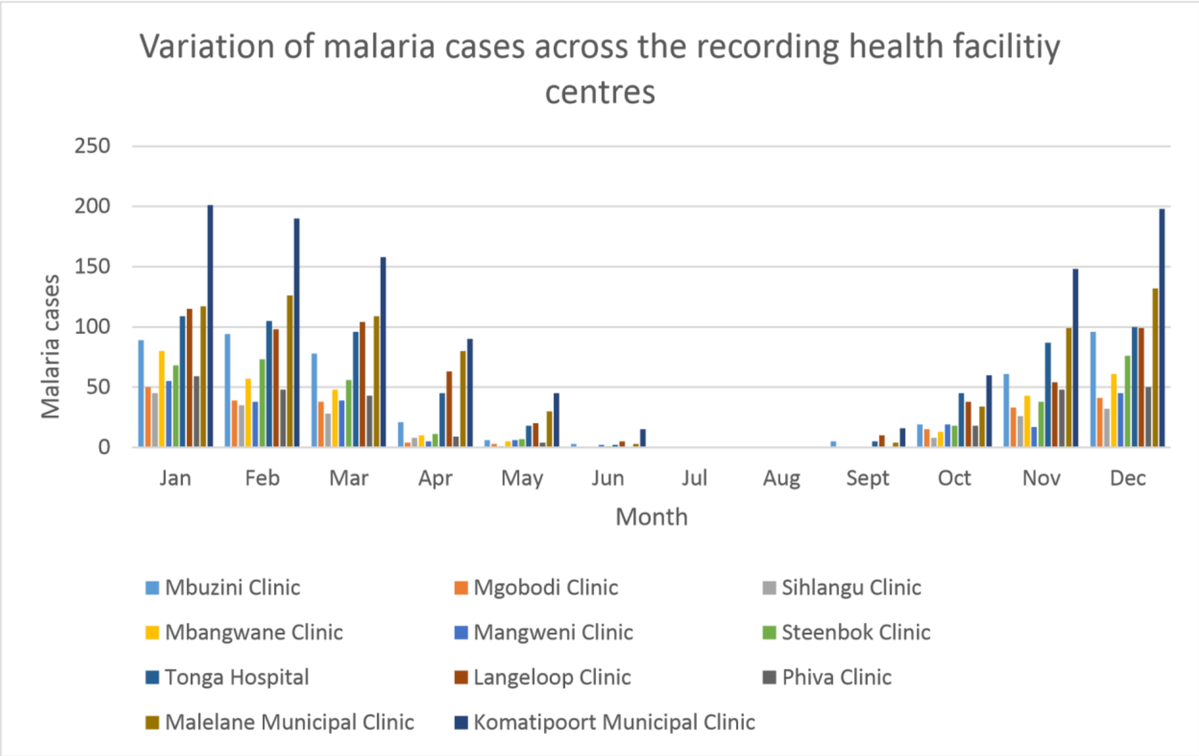
In addition, the output (the risk map) show an association with malaria cases recorded in health centres within Nkomazi municipality; from September 1997 to August 1998, which corresponds to the year of Landsat 5 TM image used for this study. Within the malaria season, September to May (Department of health, report 2007), a total of 5119 cases and 28 deaths were recorded.

Figure 6: Malaria risk map in relation to malaria cases from September 1997 to August 1998 in the Nkomazi municipality.



The month of January has the highest number of malaria cases while March has the highest number of death. Komatipoort clinic followed by Malelane clinic recorded the highest cases of malaria. From the record and as shown in Figure 7, there was a sudden rise in malaria cases between November and March which correspond with months when thresholds for mosquito's breeding are met see table 2.

Figure 7: Variation of malaria cases across the recording health facility centres in the study area.



Conclusions

Remotely sensed data can serve as a surrogate data when physically measured climatic data are not easily available (Ceccato, et al. 2005). Mosquito breeding habitat (hence a risk map) is mapped by depending on some of the environmental factors which contribute for the development and survival of *Anopheles* mosquitoes. For the purpose of identifying areas of malaria risk, this study overlay remotely sensed environmental variables in appropriate weight and determine spatial distance to conducive temperature area, distance to potential vegetated area and wet area as the factors of malaria incidence in the study area. The malaria incidence and transmission requires the environment with moderate temperature, moderate to high vegetation cover, availability of wetlands, availability of still waters and areas of lower drainage density. The overlay analysis was done after each environmental metric was given appropriate weight in relation to the degree of significance that they have for the incidence of malaria in this research. Therefore, this study has demonstrated the identification of potential breeding habitats of mosquitoes within the Nkomazi municipality using Landsat-derived NDVI, NDWI and LST images as key environmental indicators during the summer season of 1998. From the analysis, the study area is largely within a permissible threshold of environmental metric favourable for the breeding of mosquito. The result of the Eigen vector indicate that LST is the most influential metric and seconded by NDVI. This is consistent with other studies where it has been suggested that there is a linear relationship between NDVI and malaria cases with the number of breeding sites and NDVI values increases with the soil moisture where soil moisture (NDWI) is multi-factorial (Rogers et al., 2002, Eisele et al., 2003, Gemperli et al., 2006). The identification of mosquito breeding habitat is a vital step towards malaria control and its subsequent elimination. Therefore, remote sensing data integrated with GIS can be used to develop a Malaria Early Warning System (MEWS) by combining factors influencing malaria transmission (the environmental, climatic and social; population and immigration) in a model form. Hence, help in facilitating prediction, forecasting and real time monitoring of incidences with specific reference to geographic areas for prioritization of intervention.

Acknowledgements

This study was funded by the EU project QWeCI (Quantifying Weather and Climate Impacts on health in developing countries; funded by the European Commission's Seventh Framework Research Programme under the grant agreement 243964). Thanks to University of Pretoria, Centre for Sustainable Malaria Control for their support. We also appreciate department of health, Mpumalanga Province for the release of malaria data.

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CHAPTER 4

Environmental factors and population at risk of malaria in Nkomazi municipality, South Africa.

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This article has been published in *Journal of Tropical Medicine & International Health, 2016.* http://onlinelibrary.wiley.com/doi/10.1111/tmi.12680/abstract

Abstract

Background: Nkomazi local municipality of South Africa is a high risk malaria region having an incidence rate of about 500 cases per 100,000. The aim of this study was to examine the influence of environmental factors on population (age group) at risk of malaria in the study area to enhance quality targeting for prevention of malaria incidence. Hence, the study contributes to the country's aim of eliminating malaria by the year 2018. **Methods:** R software was used to statistically analyse the data. Using remote sensing technology; a Landsat 8 image of 4th October 2015 was classified using object-based classification technique and a 5 m resolution spot height data was used to generate digital elevation model of the area. **Results:** A total of 60,718 malaria cases were notified across 48 health facilities in Nkomazi municipality within the 18 year period of investigation (January 1997 to August 2015). The study found that malaria incidence is highly associated with irrigated land ($p = 0.001$), water body ($p = 0.011$) and altitude ≤ 400 m ($p = 0.001$). The multivariate model showed that with 10% increase in the amount of irrigated areas, malaria risk increased by almost 39% in the entire study area and by almost 44% within the 2 km buffer of the selected villages. Malaria incidence in the study area is more pronounced within the economically active population of age group 15-64 and the male gender are at higher risk of malaria. The result also indicated that though malaria incidence in the study area is high, the incidence and its case fatality rate have drastically declined over the study period. **Conclusion:** Hence, a predictive model, based on environmental factors would be useful in the effort towards the elimination of the disease by fostering proper malaria control targeting and resource allocation.

Keywords: Malaria, environment, Landsat, remote sensing, object-based classification, LULC, elevation

Background

Although it is curable, malaria remains a life-threatening disease mainly endemic in tropical and subtropical countries of sub-Saharan Africa. South and Central America. Asia and Oceania [1]. Exacting a huge burden on health, economy and social sectors of the endemic regions [1]. Malaria in South Africa has been studied extensively by various foremost researchers [2-5]. A major example of such studies is Mapping Malaria Risk in Africa/Atlas du Risque de la Malaria en Afrique (MARA/ARMA).The project aimed at the collection of malariometric data in the form of distribution (where), transmission intensity (how much), seasonality (when), environmental determinants (why) and population at risk (who is affected) in order to create a continental database of the spatial distribution of malaria. In addition, the project focused on developing environmentally determined models that define the distribution of malaria, the duration and timing of the transmission seasons [6].

Malaria is mainly endemic in the low altitude (below 1200 m) regions of Mpumalanga. Limpopo and KwaZulu-Natal located in the north-eastern part of the country [7]. Since the introduction of dichlorodiphenyltrichloroethane (DDT) for indoor residual spraying (IRS) in 1948, South Africa have seen a drastic decline in the transmission of malaria [4]. However, there was a surge in malaria transmission from 1999 with a major outbreak in 2000 [5]. This was traced to the discontinuation of DDT which was replaced with synthetic pyrethroid insecticides in 1996 and among other speculated factors like climatic and environmental determinants, agricultural development, biology and behaviour of vector, drug resistance and trans-border population movement (imported vector and parasite) into South Africa from bordering countries of Swaziland and Mozambique [8,9]. Consequently, there was a return to DDT in 2000 as the main insecticide for IRS and a change from Sulphadoxine-pyrimethamine (SP – Fansidar) to Artemether/Lumefantrine (AL – Coartem) in 2001 as the first-line treatment for malaria [10]. Other malaria control strategies in South Africa include; focal larviciding of identified breeding sites, rapid detection, diagnostic testing through rapid diagnostic tests (RDT) and treatment of confirmed malaria cases at health care facilities [10,11].

These control strategies saw the number of reported malaria cases reduced from 64,622 cases in 2000 to 7,626 in 2010. On the other hand, the number of deaths also reduced by 81% i.e. from 458 deaths in 2000 to 87 deaths in 2010 [7]. Malaria cases were high during the 1997-2001 periods [7]. During this period, two main consecutive years 1999 and 2000 had the highest number of reported cases amounting to 51,444 and 64,622 respectively. Despite this effort, about 4.9 million of her population, translating to about 10% of the population are still prone to malaria living in the endemic region [7,12]. In particular malaria transmission remains high in Nkomazi municipality in relation to other regions [13].

Malaria in the region is markedly seasonal with varying intensity of transmission due to altitudinal and climatic factors. The transmission increases from the wet summer months (September to May) and decreases afterward. The peak transmission occurs in January/February [14]. *Plasmodium falciparum* is the principal parasite accounting for about 95% of the total malaria infections in South Africa through *Anopheles arabiensis* as the major local vector [15].

Climatic and environmental parameter as major determinants for the spatial and temporal distribution of malaria is well documented [3,16-18]. Major climatic factors for malaria risk are temperature, rainfall and humidity. However, the lack of adequate spatial and temporal variability of these major meteorological and environmental parameters is a major limiting factor. Data from earth-observing sensors provides continuous meteorological and environmental information over large areas in contrast to conventional ground surveys [19]. Hence, the use of remotely sensed data offers the possibility of identifying mosquitoes breeding habitats [21-25] and the development of epidemiological forecasting models and early warning systems [19,25]. The understanding of the spatial and temporal distribution of the risk factors and the prevalence of malaria in endemic areas can help in predicting the abundance, determine the location and quantify the at-risk population [26]. Hence, can significantly enhance strategies for local malaria control. An in-depth understanding of the role of landscape/environmental factors in the spatial distribution of malaria is vital so that suitable localised efforts towards elimination can be established. Environmental factors such as altitude, vegetation, agricultural practices, and the presence of water bodies affect the vector and hence the quantity of malaria risk [27-29]. However, studies relating the influence of these factors to malaria incidence have not been done over the study area.

The ultimate goal of the WHO is to eradicate malaria [30]. South Africa is scheduled to achieve malaria elimination by 2018 having met the requirement of the pre-elimination phase of (<5 cases per 100.000 population at risk) set out by the WHO. Hence, as the country intensify effort towards the elimination of malaria, the identification of the spatial distribution of age group at risk of malaria transmission and its relationship with environmental factors would enhance strategic intervention by public health decision makers in the study area for proper distribution of scarce resources. Therefore, the aim of this study is to examine the influence of environmental factors on population (age group) at risk of malaria in the study area to enhance quality targeting for prevention of malaria incidence and subsequent elimination.

Methods

Ethics statement

This study uses secondary data acquired from the malaria information system (MIS) from the department of health; developed and maintained by the malaria control programme (MCP). Ethical approval for this study was obtained from the Faculty of Natural and Agricultural Sciences Ethical Committee at the University of Pretoria (EC140721-065) and the Department of Health in Mpumalanga Provincial Government (MP_2014RP39_978).

Study area

Mpumalanga Province consists of three administrative districts: Gert Sibande, Ehlanzeni and Nkangala. The three districts are subdivided into 24 local municipalities. Within Ehlanzeni district is located Nkomazi municipality with other four municipalities (Thaba Chweu. Mbombela. Umjindi, and Bushbuckridge). Nkomazi is bordered in the east by Mozambique, in the south by Swaziland and the Kruger national park is situated to the north. Nkomazi has a total area of 3255. 67 km^2 with 54 main places mostly concentrated in the southern part of the municipality. The municipality has a total population of 277,864 in 1996; 334,668 in 2001 and in 2011 the municipality has grown to 393,030 in population [2]. It enjoys a sub-tropical weather condition with an average temperature of 28 °C and annual rainfall between 550 and 1000 mm. Nkomazi varies in elevation from about 110 to about 1320 m above sea level. The western areas are densely vegetated with undulating hills and deeply incised valleys. The area is drained by two major Rivers, the Komati to the east and its main tributary, the Lomati to the west. The municipality is known for its richness in sugarcane, fruits and vegetable production under intensive irrigation.

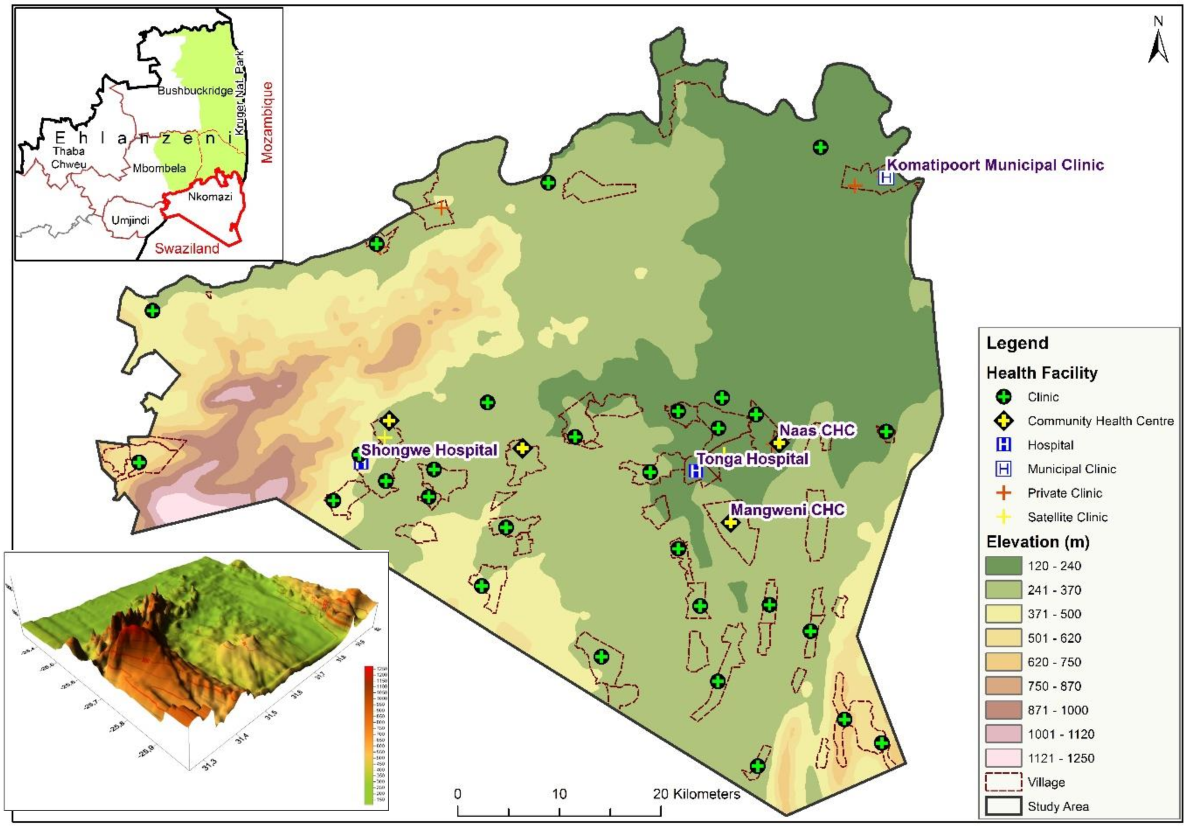

Figure 1: Location of study area: Showing the villages and health facilities

Data collection

Data on malaria incidence were acquired from the integrated MIS. The data were obtained from patients who presented themselves at health facility and were tested positive to *Plasmodium* across (passive case detection) and those collected through screening measures in which health workers go into the community to ask for individuals to be tested (active case detection). These include people with non-specific symptoms such as fever, or those residing near or in the same homesteads with recently confirmed cases. The office of the malaria control programme is located in Tonga (31.783 E. -25.706 S). The records from the facilities contain information such as facility name, date of diagnosis, the number of cases, deaths, age, gender and source of infection and place of residence.

The record spans from January 1997 to August 2015 for many of the facilities. For the purpose of this study, 5 facilities (Tonga hospital, Shongwe hospital, Mangweni CHC, Naas CHC and Komatipoort municipal clinic) accounting for 56.3% of the total cases within the period under investigation was used. The demographic data at main place/village (administrative boundary) was acquired from statistics SA for 2001 and 2011 census. There are 54 villages mostly concentrated in the southern part of the municipality, see figure 1. The data contained age group and gender population at each village. Accordingly, 5 villages in the location of selected health facilities were considered.

Geometrically corrected, summer cloud-free Landsat 8 acquired on 4th October 2015 (Path 168. Row 078) was downloaded from the United States Geological Survey (USGS). Spot height data of approximately 5 m resolution was acquired from the national geospatial information (NGI) of South Africa. Handheld GPS was used to take coordinates of easy to identify ground-truth site during an educational/mini field trip to the study area on April 23-24. 2015 (UP CSMC visit on world malaria day celebration). 15 points were randomly taken within Tonga village and additional 70 points were taken across the study area using Google Earth images for adequate representation for accuracy assessment.

Data analysis

Malaria case notification

Although as reported in [13-15] that malaria season starts at the start of July to the end of June the subsequent year, this study used calendar year in order to match the age category of Statistics SA for the population census of 2001 and 2011 national census. The daily diagnosis of malaria cases data was aggregated to monthly and yearly format. The age was categorised into groups of ages 0-14. 15-64 and 65 and above. The 0-14 and 65 above indicating the dependent population and 15-64 indicating the economically active population. The data was there after geo-coded using the coordinates of the recording health facilities. This then overlay on the main place to determine the location and proximity of the health facilities within the villages (main place). Generally, there is at least 1 health facility within each village or within 5 km radius in proximity to villages where not a specific health facility is located [31]. See figure 1. Microsoft Excel was used for the pre-processing before it was imported into R software.

Environmental parameters characterisation

Landsat 8 data was used to derive the land use/land cover (LULC) types using object-based classification technique in ENVI 5.0. A false colour composite image using bands 5.4 and 3 (R.G.B) and normalised difference vegetation index (NDVI): ([NIR-RED] / [NIR+RED]) was derived to enhance the identification of available LULC types before the actual classification. Five major broad classes were identified and classified as such (water body, forest, cultivated/irrigated land, bare land and built up). ‘Water body’ is characterised by river, stream, ponds and lakes; ‘forest’ is characterised by areas of dense tree cover with thick-closed canopy; ‘cultivated/irrigation’ refers to as area under cultivation and intensive irrigation of crops (sugar cane, orange, banana); ‘bare land’ are non-vegetated, uncultivated farmland and open space while ‘built up’ is characterised by asphaltic/concreted road, pavement, building/houses.

The rule-based feature extraction method was used. Firstly, image segmentation was performed. Edge algorithm was used for the segment setting with a scale level of 30 and full Lambda Schedule algorithm was used for the merge setting with merge level of 98. Texture kernel size of 3 was used. The classes were identified using set rules for the classification using thresholds of mean and or standard deviation of the spectral bands and NDVI. The classification was outputted to shape file and was imported into ArcGIS 10.2.1. Using the premise that adult mosquitoes generally remain up to 2 km of their breeding habitats [27] a buffer of 2 km was created around the selected five villages and their respective percentages of LULC classes within the buffer was calculated. An error matrix or confusion matrix was computed to assess the classification accuracy. The matrix relates the sample points collected via field survey and google earth (reference data) to that selected from the classified image (classified data). Hence, overall accuracy (86.51%), producer’s (86.74%) and user’s accuracies (86.28%), and Kappa statistic (0.842) were computed see table 1.

Table 1: Accuracy assessment of LULC

	Reference data						
Classified data	**Water body**	**Forest**	**Irrigated land**	**Bare land**	**Built up**	**Total**	**UA (%)**
Water body	14	0	2	0	0	16	87.50
Forest	0	12	1	0	0	13	92.31
Irrigated Land	2	1	16	0	0	19	84.21
Bare land	0	0	0	10	3	13	76.92
Built up	0	0	0	2	19	21	90.48
Total	16	13	19	12	22	80	
PA (%)	87.50	92.31	84.21	83.33	86.36		
Overall accuracy = 86.51%; Kappa statistic = 0.842.							

The 5 m resolution spot height was interpolated using the ordinary Kriging method to derive the Digital Elevation Model (DEM) in ArcGIS 10.2.1. The elevation was classified into 9 classes using the Jenks Natural Breaks classification method. The percentages of the each present class within the 2 km buffer were computed. For visual appreciation. Surfer 13 was used to perform a 3D DEM, see insert of figure 1.

All statistical analyses were performed using the R statistical software. Firstly, malaria data was tested for homogeneity of variance using Levene's test. Secondly, malaria data with variables (age group, sex, death and source of infection) and environmental parameters (water body, forest, cultivated/irrigation land, bare land and built up; and altitude) were subjected to univariate logistic regression to determine their statistical association with malaria incidence through a likelihood ratio test using a liberal *p*-value ($p = 0.20$). Variables with the significant statistical association (significant level $p > 0.05$) with malaria infection were further analysed. Hence, age group, sex, water body, forest, irrigated land, bare land and altitude were subjected to a multivariate regression analysis. The spatial autocorrelation was also determined using semivariogram to estimate malaria risk and its geographical clustering.

Results

Malaria case notification

The result of the Levene's test indicates that the spatial distribution of malaria incidence in Nkomazi local municipality is heterogeneous, $p = 0.0016$. A total of 60,718 malaria cases were notified across 48 health facilities in Nkomazi municipality between January 1997 and August 2015. Results from the 5 health facilities; Tonga hospital, Shongwe hospital, Mangweni CHC, Naas CHC and Komatipoort municipal clinic, indicate the highest cases were notified in Komatipoort municipal clinic 10,984; the lowest in Buffelspruit satellite clinic 3; mean 3195.68; 95% confidence interval (CI): 2,022.53 – 4,368.84. For the period under investigation, malaria cases, as well as malaria-related death in the study area, has been significantly declining ($p < 0.001$) although with few peaks across the period. As shown in figure 2, there was a major malaria incidence in the year 2000 (9,699) accounting for 15.97% of the total cases within the 18-year period. This is closely followed by the year 2001 (7,894) and year 1999 (6,126) both accounting for 13% and 10.09% of the 18-year period respectively. Although there is a drastic decline in the number of cases after the year 2002, there are few peaks in years 2006. 2011 and 2014.

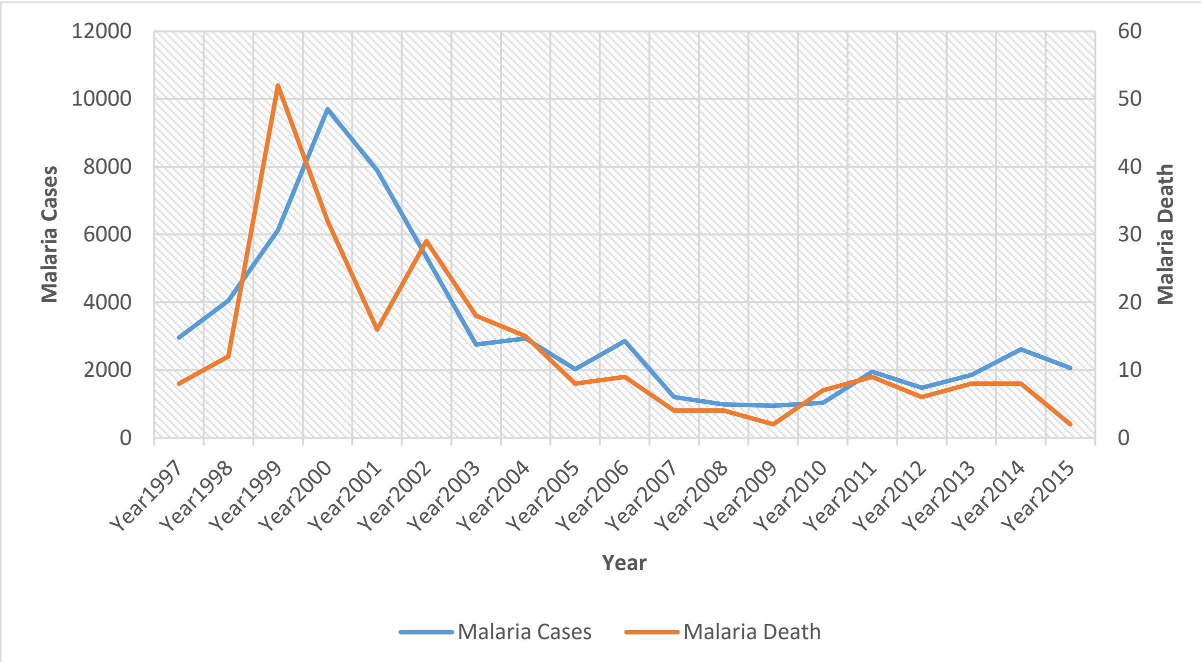

Figure 2: Notified malaria cases and related death in Nkomazi municipality Jan. 1997 - Aug. 2015

The notified malaria cases indicates that malaria affects all ages from infancy (0) to old aged (106) as the maximum, mean age (24), mode (25), Standard deviation (16). As indicated in table 1, age group 15-64; the economically active group is mostly at risk of malaria. The age group accounts for 68.91% (41,842) of the total notified cases over the study period and particularly high in the year 2005 with 79.67% (1,611) of the cases in that year. Age 0-14 ranks second accounting for 29.36% (17,824) of the total notified cases although account for 41.36% (1,675) in the year 1998. Age 65 and above is less affected by malaria accounting for only 1.73% (1,052) of the total notified cases and it highest contribution in the year 2011 with 2.11% (41). Malaria incidence rate for age 0-14 was 1,894 per 100,000 in 2001 and significantly fell to 259 per 100,000 in 2011; for group 15-64 incidence rate was 2,798 per 100,000 in 2001 and 649 in 2011; for age group 65 and above incidence rate was 1,045 and 255 per 100,000 in 2001 and 2011 respectively, see table 2.

Table 2: Notified malaria cases and related death in Nkomazi municipality Jan. 1997 - Aug. 2015

Year	**Total** Malaria Cases	Age 0-14		Age 15-64		Age 65 Above		Male		Female		Death	CFR
		Case	**%**	**Case**	**%**	**Case**	**%**	**Case**	**%**	**Case**	**%**		
1997	2955	1127	38.14	1775	60.07	53	1.79	1524	51.57	1431	48.43	8	0.27
1998	4050	1675	41.36	2291	56.57	84	2.07	2147	53.01	1903	46.99	12	0.30
1999	6126	2198	35.88	3813	62.24	115	1.88	3260	53.22	2866	46.78	52	0.85
2000	9699	3526	36.35	5996	61.82	177	1.82	5175	53.36	4524	46.64	32	0.33
2001	7894	2583	32.72	5169	65.48	142	1.80	4259	53.95	3635	46.05	16	0.20
2002	5330	1407	26.40	3831	71.88	92	1.73	2807	52.66	2523	47.34	29	0.54
2003	2749	640	23.28	2064	75.08	45	1.64	1583	57.58	1166	42.42	18	0.65
2004	2934	576	19.63	2313	78.83	45	1.53	1733	59.07	1201	40.93	15	0.51
2005	2022	383	18.94	1611	79.67	28	1.38	1245	61.57	777	38.43	8	0.40
2006	2859	553	19.34	2256	78.91	50	1.75	1741	60.90	1118	39.10	9	0.31
2007	1204	247	20.51	942	78.24	15	1.25	730	60.63	474	39.37	4	0.33
2008	983	218	22.18	756	76.91	9	0.92	575	58.49	408	41.51	4	0.41
2009	950	262	27.58	676	71.16	12	1.26	599	63.05	351	36.95	2	0.21
2010	1029	232	22.55	780	75.80	17	1.65	626	60.84	403	39.16	7	0.68
2011	1944	360	18.52	1543	79.37	41	2.11	1190	61.21	754	38.79	9	0.46
2012	1474	282	19.13	1164	78.97	28	1.90	893	60.58	581	39.42	6	0.41
2013	1850	459	24.81	1370	74.05	21	1.14	1085	58.65	765	41.35	8	0.43
2014	2609	672	25.76	1891	72.48	46	1.76	1504	57.65	1105	42.35	8	0.31
2015	2057	424	20.61	1601	77.83	32	1.56	1193	58.00	864	42.00	2	0.10

Over the year under study, the male gender is more affected by malaria than the female counterpart. The male accounts for 55.78% (33,869) as against the 44.22% (26,849) of the female. This trend is consistent throughout the study period with statistically significant ($p < 0.001$).

Table 3: **Comparison of year 2001 and 2011 notified malaria cases and population in Nkomazi municipality**

Variables	Year 2001				Year 2011			
	Malaria case	**Population**	**Case /100,000**	**Malaria Death**	**Malaria case**	**Population**	**Case /100,000**	**Malaria Death**
Age 0-14	2583	136355	1894	0	360	139234	259	0
Age 15-64	5169	184725	2798	13	1543	237731	649	9
Age 65 Above	142	13588	1045	3	41	16065	255	0
Male	4259	157855	2698	9	1190	186017	640	5
Female	3635	176813	2056	7	754	207013	364	4
TOTAL	7894	334668		16	1944	393030		9
Case per 100,000	2359				495			

However, as indicated in table 3, the picture looks different within the recording health facility in Tonga hospital were female accounts for 51.70% (1,977) of the total notified cases as against male's 48.30% (1,847). Malaria incidence rate was 2,698 and 640 cases per 100,000 for males in 2001 and 2011 respectively while incidence rate in females is 2,056 cases per 100,000 in 2001 and 754 cases per 100,000 in 2011.

On the other hand, there is a significant decline in the annual total number of malaria-related deaths in Nkomazi (x^2 = 27.9; $p < 0.001$) within the study period. A total of 249 malaria-related deaths were notified. There is no year without malaria-related death. The highest death was recorded in the year 1999 (52) while the year 2000 had (32) and subsequently a steady decline but for a sudden increase in 2002 (29). As shown in figure 3 and table 1, case fatality rate (CFR) above the national target of 0.5% for malaria in South Africa occurred in years 1999 (0.85%); 2010 (0.68%); 2003 (0.65%); and 2002 (0.54%). On the average, there is CFR of 0.41 in the Nkomazi over the period of the year under investigation.

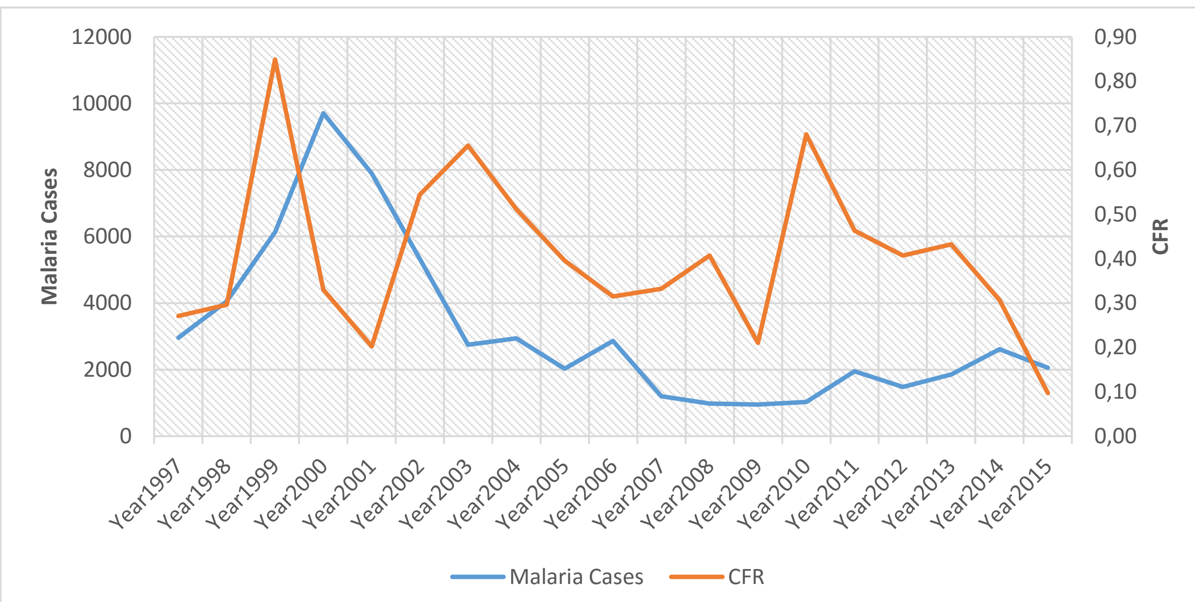

Figure 3: Notified malaria cases and Case fatality rate in Nkomazi municipality, Jan. 1997 - Aug. 2015

In general, malaria infection source per country indicates that 56.38% (34,230) of malaria infection are localised (South Africa) while the difference is imported malaria cases. Infection from Mozambique accounts for 42.12% (25,573) of the total infection and other countries like

Swaziland 1% (610); Somalia 0.2% (119); Zimbabwe 0.07% (40); Ethiopia 0.06% (35); Malawi 0.04% (26) among others make up for the difference. Across the 5 selected facilities, imported malaria cases from Mozambique is particularly high accounting for 66.1% of the total cases in Komatipoort municipal clinic and 44.8% in Naas CHC, see table 4.

Table 4: Notified malaria cases, death and Source in 5 major health facilities in Nkomazi municipality Jan. 1997 - Aug. 2015

Health Facility	Total Malaria case	Age 0-14		Age 15-64		Age 65 Above		Male		Female		Death	CFR	Source Country
		Case	**%**	**Case**	**%**	**Case**	**%**	**Case**	**%**	**Case**	**%**			
Tonga Hospital	3824 (6.30%)	814	21.29	2923	76.44	87	2.28	1847	48.30	1977	51.70	78	2.04	SA 69.2% Moz. 29.2%. Others 1.6%
Shongwe Hospital	5463 (9.00%)	1884	34.49	3452	63.19	127	2.32	2834	51.88	2629	48.12	133	2.43	SA 86.9% Moz. 11.6% Others 1.5%
Mangweni CHC	6012 (9.90%)	1779	29.59	4053	67.42	180	2.99	3401	56.57	2611	43.43	4	0.07	SA 61.1% Moz. 37.9% Others 1.0%
Naas CHC	7878 (12.97%)	2325	29.51	5442	69.08	111	1.41	4397	55.81	3481	44.19	6	0.08	SA 53.9% Moz. 44.8% Others 1.3%
Komatipoort Municipal Clinic	10984 (18.09%)	1896	17.26	9040	82.30	48	0.44	6786	61.78	4198	38.22	5	0.05	Moz. 66.1% SA 33.1% Others 0.8%

Land use/Land cover and landscape characterisation

The LULC was derived from Cloud-free Landsat 8 using object-based classification technique in ENVI 5.0. Five broad classes were classified, water body (%), forest. cultivated/irrigation land. bare land and built up. The result indicates that the study area is dominantly covered by bare land (non-vegetated, uncultivated farmland and open space) covering a total area of 1,964.59 km^2

(61%), the irrigated land ranked second with a total area of 592.38 km^2 (18%), this is closely followed by built up with total area of 447.45 km^2 (14%) and water body contributing the remaining 1%.

The altitude ranges from a minimum of 120 m to maximum of 1250 m with a mean of 395 m above sea level. The result from the natural Jenks classification of the altitude into 9 classes indicates that about 70% of the total area is between 120-400 m above sea level and its significantly associated with malaria incidence (p = 0,001).

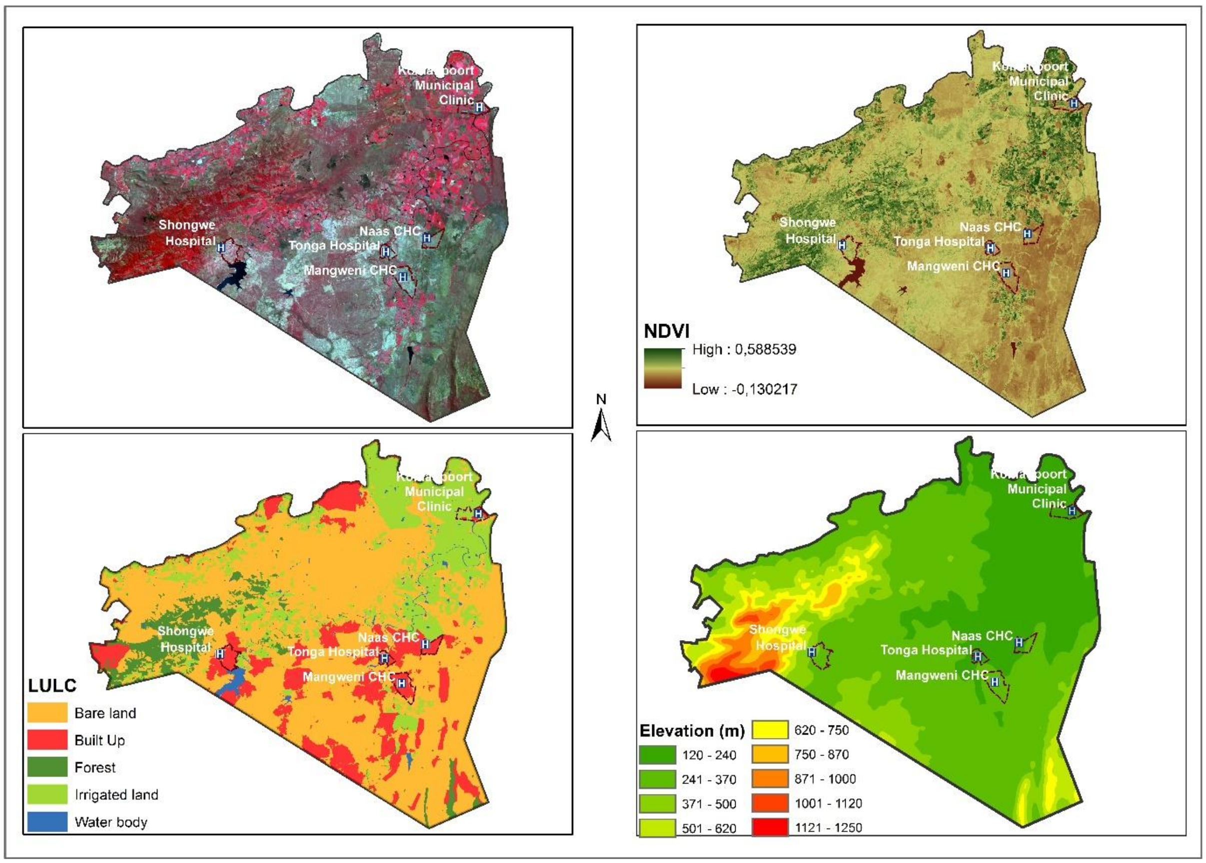

Figure 4: Outputs of Environmental factor analysis of Nkomazi municipality

Discussion

The aim of this paper was to examine the influence of environmental factors on population (age group) at risk of malaria in the study area to enhance quality targeting for prevention of malaria incidence. This is particularly because of the population movement dynamics which are high in the study area both locally and internationally, therefore, contribution to malaria elimination efforts through surveillance-response approaches focused on identifying and/or predicting pockets of transmission using remote sensing underpinned this research.

A major limitation of our study is the use of object-based classification technique on medium ranged resolution image Landsat for the LULC classification rather than a high-resolution image which might have given the opportunity of a better-simplified classes and hence a better accuracy. Although, the use of object-based classification technique on Landsat image has been shown to yield a better result than the pixel-based classifications techniques, a high-resolution image like Quick Bird would have given a better result and help to remove mixed classification of LULC for such localised/small scale study as this.

Actively and passively detected malaria cases as well as environmental parameters derived from remotely sensed data were used to establish the population risk factors. The results showed that malaria incidence and mortality in Nkomazi municipality has been on the decline in the last 18 years. However, malaria incidence remains high in the study area when compared to other endemic region [15]. This declining trend is at pal with earlier published studies by scholars from in other malaria endemic region of South Africa; Limpopo [32] and KwaZulu-Natal [33]. The drastic decline of about 71% of notified malaria incidences after the peak years of 2000, 2001 and 2002 (from 9,699 in year 2000 to 2,749 in 2003) is not unconnected to the re-introduction of DDT in year 2000 after it was discontinued in 1996 because of both environmental concerns and social conflict [8-10]. The decline could also be traced to the change in the drug policy from Sulphadoxine-pyrimethamine to Artemether/Lumefantrine as the first-line treatment as a result of the resistance developed by the parasite to Sulphadoxine-pyrimethamine [8-10]; and the trans-border initiatives among South Africa and neighbouring countries.

Although malaria risk is generally high within the 15-64 age group (economically active) in the study area, it's particularly high in Komatipoort and Kamaqhekeza (Naas CHC) where there is high irrigation practice. Across all the recording health facilities there is a statistical significant difference of ($p < 0.001$) in malaria incidence between the male and the female gender except in Tonga hospital. This is not unconnected with the high farming activities (irrigation) within the area. Agriculture ranks second to government and community services in term of the labour-absorbing sector and source of income for the people [34]. In addition, Komatipoort as a border town with Mozambique explains the 66.1% of imported cases from the youthful population of Mozambique who are mostly farm workers.

In term of the malaria case fatality rates, the pattern is similar to the pattern exhibited by malaria incidence. Over the period of study, there were high peaks of CFR (above the national target of 0.50%) in years 1999, 2010, 2003 and 2004 in order of their magnitude. However, CFR has reduced significantly within the study period with a total average of 0.41% which is less than the 0.5% of the national target. In a complete deviation from the findings in other African countries, where infant, child and pregnant women are reported to account for higher degree of malaria-related death, the age group 15-64 representing the economically active population are seen to account for more malaria-related death in the study area. This could be associated with self-management of illness leading to a late report of illness to the nearest health facilities as found by [35]. The general reduction in the death rate could be related to the change in first-line treatment and continuous awareness through various health promotion and educational projects organised by the malaria control programme and with other collaborative efforts from academic institutions like the Centre for sustainable malaria control; University of Pretoria.

The univariate logistic regression model indicated that only the covariates age group, sex, water body, forest, irrigated land and altitude were significantly associated with malaria infection. In the further step of analysis using the multivariate model, the model shows that all age groups, particularly age 15-64 living in lower altitude (< 400 m above sea level) are at more risk of malaria infection than others in higher altitude (p = 0.001). Hence, malaria infection increases with decreasing altitude. The population living in close proximity to the irrigated sites were significantly at higher risk of getting infected compared to the area without irrigation or cultivated land. Additionally, malaria risk also increased with the presence of water body. However, these covariates varied when conducting the analysis within the buffered 2 km of the selected villages. For instance, in Kamataso village/Shongwe hospital, there is the presence of forest which accounts for 1% of the total LULC within the 2 km buffer.

Studies have shown that malaria risk increases with decreasing distance to irrigated area which are suitable mosquito breeding habitats and hence, can be used as an internal tool to validate the analyses [36,37]. Our model showed that with 10% increase in the amount of irrigated areas, malaria risk increased by almost 39% in the entire study area and by almost 44% within the 2 km buffer of the selected villages. This, therefore, tends to underpin the high rate of malaria incidence in Komatipoort (Komatipoort hospital) and Kamaqhekeza (Naas CHC) where irrigated land within their 2 km buffer accounts for 82% and 19% of the total LULC. Furthermore, a proportion of bare land within the 2 km buffer were associated with a slightly increased risk of malaria. This could be largely traced to the fact that large proportion of the classified bare land contained uncultivated farmland with some within the irrigated areas which are suitable habitat for mosquitoes to breed. In our model, the forested area; also on a high altitude ranging from 900 to 1,250 m above sea level seems not to be significantly associated with increased malaria incidence ($p = 0.166$). Hence, the proximity of forest may not account for increased malaria incidence. Although, we proposed a more detail study for adequate reporting on this. In addition, our model showed a likelihood of an association between malaria incidence and an increase in the proportion of built-up areas. Although, this scenario changed after adjustment of the mostly correlated variables (irrigated land and water body). Hence, the scenario could partly be explained by the presence of few pockets of seemly irrigated land which are mixed classes between the irrigated land and green/open areas classified as part of the bare land.

Conclusion

Nkomazi local municipality of South Africa is a high risk malaria region having an incidence rate of about 500 cases per 100,000. Studies have shown that the understanding of the spatial and temporal distribution of the risk factors and the prevalence of malaria in endemic areas can help in predicting the abundance, determine the location and quantify the at-risk population. Hence, can significantly enhance existing control strategies and influence the establishment of localised system towards elimination of malaria. Studies using remotely sensed images in the study of vector-borne diseases have been done in other malaria endemic countries in sub-Saharan Africa areas [20,23,38-41]. However, studies of the relationship between malaria and environmental factors, particularly using object-based classification technique on remotely sensed image to quantify LULC has not been done in the malaria endemic regions of South Africa [42]. The study found that malaria incidence is highly associated with irrigated land, water body and altitude. There is high rate of population movement locally and internationally Malaria incidence in the study area is more pronounced within the economically active population of age group 15-64 and the male gender are at higher risk of malaria. The result also indicated that though malaria incidence in the study area is high, the incidence and its CFR have drastically declined over the period of study. Hence, a predictive model, based on environmental factors would be useful in the effort towards the elimination of the disease by fostering proper malaria control targeting and resource allocation. In general, these findings offer current information about the target group and the hot spots for malaria infections which is fundamental in fostering the development of a local based warning/specific surveillance response system and the strengthening of trans-border control measure.

This study recommends that further studies, such as a detailed identification of the crop types within the irrigated/cultivated area should be conducted as well as the determination of peak growing season to establish the relationship of certain crop type with malaria.

Acknowledgements

This study was funded by the EU project QWeCI (Quantifying Weather and Climate Impacts on health in developing countries, funded by the European Commission’s Seventh Framework Research Programme under the grant agreement 243964). We also acknowledge the support of the University of Pretoria, Centre for Sustainable Malaria Control (UP CSMC) and Earth and Atmospheric Remote Sensing research group, University of Pretoria.

Competing interests

The authors declare that they have no competing interests.

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CHAPTER 5

Predicting malaria incidence using remotely sensed climatic factors in Nkomazi local municipality, South Africa.

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This article is under review for publication with *EcoHealth Journal*. http://www.springer.com/public+health/journal/10393

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Abstract

This study aim at quantifying the association of satellite-derived environmental/climatic variables with malaria cases towards the development of a predicting model even as South Africa progresses towards achieving elimination by 2018. In particular, environmental variables including the vegetation indices; NDVI and EVI, water index; NDWI and land surface temperature; LST derived from MODIS and Rainfall estimate from TRMM all spanning the period of 2000 to 2015 were used in this study. The malaria cases were collected from the malaria control programme of the Department of health, Mpumalanga. Seasonal autoregressive integrated moving average model; (SARIMA), was able to explain 86% variability in the time series data, hence, was found to be the best fit model among other models. Rainfall (p = 0.001), NDVI (p = 0.004), EVI (p = 0.003) and NDWI (p = 0.002) all with lag of one to three months were found to be significant predictors of malaria occurrence in Nkomazi. The seasonally adjusted factor (SAF) for malaria cases indicates that peak transmission occurs during the months of December to February.

KEYWORDS: Malaria, environment, MODIS, TRMM, remote sensing, forecasting

Introduction

Malaria affects about 5 million of the population in South Africa, this implies that about 10% of her population are prone to malaria infections (STATS SA, 2015). Malaria is majorly endemic in the north-eastern part of the country of low altitude (below 1200 m). The endemic regions are in the provinces of Mpumalanga, Limpopo and KwaZulu-Natal (Department of Health, South Africa, 2007). The disease is markedly seasonal with varying intensity of transmission due to altitudinal and climatic factors. The transmission increases from the wet summer months (September to May) and decreases afterward. The peak transmission occurs in January/February (Ngomane, et al., 2012).

Malaria control in South Africa is mainly through the use of dichlorodiphenyltrichloroethane (DDT) for indoor residual spraying (IRS). Since its introduction in 1948 the country has recorded success in the decline of malaria transmission of malaria (Kleinschmidt, et al., 2002). However, the DDT was discontinued and replaced with synthetic pyrethroid in 1996 this among other factors led to a sudden rise in malaria transmission from 1999 with a major outbreak in 2000 (Sharp, et al., 2007). Other factors that were attributed to the surge include factors like climatic and environmental determinants, agricultural development, biology and behaviour of vector, drug resistance and trans-border population movement (imported vector and parasite) into South Africa from bordering countries of Swaziland and Mozambique (Sharp, et al., 1996; Craig, et al., 2004). Consequently, there was a return to DDT in 2000 as the main insecticide for IRS and a change from Sulphadoxine-pyrimethamine (SP - Fansidar) to Artemether/Lumefantrine (AL - Coartem) in 2001 as the first-line treatment for malaria (Blumberg, et al., 2007). Other malaria control strategies in South Africa include; focal larviciding of identified breeding sites, rapid detection, diagnostic testing through rapid diagnostic tests (RDT) and treatment of confirmed malaria cases at health care facilities (Blumberg, et al., 2007; Coetzee, et al., 2013). *Plasmodium falciparum* accounts for about 95% of the total malaria infections in South Africa through *Anopheles arabiensis* as the major local vector (Govere, et al., 2000).

The relationship between environmental/climatic variables and malaria incidences has been well studied (Ceccato, *et al.*, 2005, Machault, et al., 2011). Temperature, rainfall, humidity and other environmental factors like vegetation and elevation are major determining factors for malaria occurrence (Gething, et al., 2011). Rainfall has an indirect relationship with malaria incidence by creating suitable breeding habitats for the vector to lay eggs and to complete it life cycle, however, heavy or excessive rainfall can have negative effect on the mosquitos by washing away mosquitos' larvae (Adimi, et al., 2010). Temperature is associated with the transmission cycle of *Plasmodium falciparum*, survival of adult mosquito and the extrinsic incubation period of the parasite within the vector (Weiss, et al., 2014). Vegetation provides a resting habitat for adult Anopheles and also serves as an indicator for the availability of moisture. Elevation/altitude is associated with the flight range of the vector (Thomas, et al., 2013).

Consequently, attempts have been made integrating the environmental/climatic variables to develop a malaria early-warning system for control and prevention of malaria outbreaks (Thomson, et al., 2003; WHO, 2001). However, the lack of adequate environmental/climatic data covering the ideal spatial and temporal extent for a reliable warning system is a major constraint. Remote sensing (RS) data offers advantages such as large area coverage and continuous representation of the earth's surface both in time and space in contrast to the conventional data gathering method (Jensen, 2007).

Environmental as well as climatic variables derived from Earth observing satellite, for instance; land surface temperature (LST), enhanced vegetation index (EVI), normalized difference vegetation index (NDVI), normalized difference water index (NDWI), elevation and Tropical Rainfall Measuring Mission (TRMM) have been used to identify mosquito breeding habitats (Mushinzimana, 2006; Julie et al., 2010; Adeola et al., 2015), quantify malaria cases (Craig, et al., 1999), prediction (Hay, et al., 1998; Adimi, et al., 2010) and development of a malaria early warning system (Midekisa, et al., 2012). Thus, RS offers a reliable means to reduce cost and time towards the establishment of a suitable localised system for the elimination of malaria.

The use of RS in malaria studies is quite limited in South Africa (Adeola et al., 2015) despite its great potential. A large percentage of malaria studies in South Africa are based on the use of spatial statistics and mathematical models (Kleinschmidt, et al., 2000; Kleinschmidt, et al., 2001; Kleinschmidt, et al., 2002; Craig et al., 2004). Hence, as the country is aiming 2018 for malaria elimination, the characterization of malaria incidence with remotely derived environmental/climatic variables will provide adequate spatial orientation for targeted local malaria control effort. Therefore, this paper aimed at relating malaria incidences with environmental/climatic variables derived from Earth observing sensors and secondly, to develop a forecasting model capable of predicting future malaria incidences in Nkomazi local municipality of South Africa.

Methods

Ethics statement

The malaria data used in this study was collected from the Malaria Control Programme of the Department of Health; Mpumalanga Province. Ethical approval for this study was obtained from the ethical committee of Faculty of Natural and Agricultural Sciences, University of Pretoria (EC140721-065) and the Department of Health in Mpumalanga Provincial Government (MP_2014RP39_978).

Study area

Nkomazi municipality is located on latitude 25.6667° S and longitude 31.6667° E. Nkomazi is bordered in the east by Mozambique, in the south by Swaziland and the Kruger National Park to the north. Nkomazi has a total area of 3255, 67 km^2 representing 4.1% and 23% of the total land mass of Mpumalanga province and Ehlanzeni district municipality respectively. It has 54 towns/villages mostly concentrated in the southern part of the municipality. The municipality has a total population of 277 864 in 1996; 334 668 in 2001 and in 2011 the municipality has grown to 393 030 in population (STATS SA, 2011). It enjoys a sub-tropical weather condition with an average temperature of 28 °C and annual rainfall between 550 and 1000 mm. Nkomazi varies in elevation from about 120 to about 1250 m above sea level. The western areas are densely vegetated with undulating hills and deep incised valleys. The area is drained by two major Rivers, the Komati to the east and its main tributary, the Lomati to the west. The municipality is known for its richness in sugarcane, fruits and vegetable production under intensive irrigation.

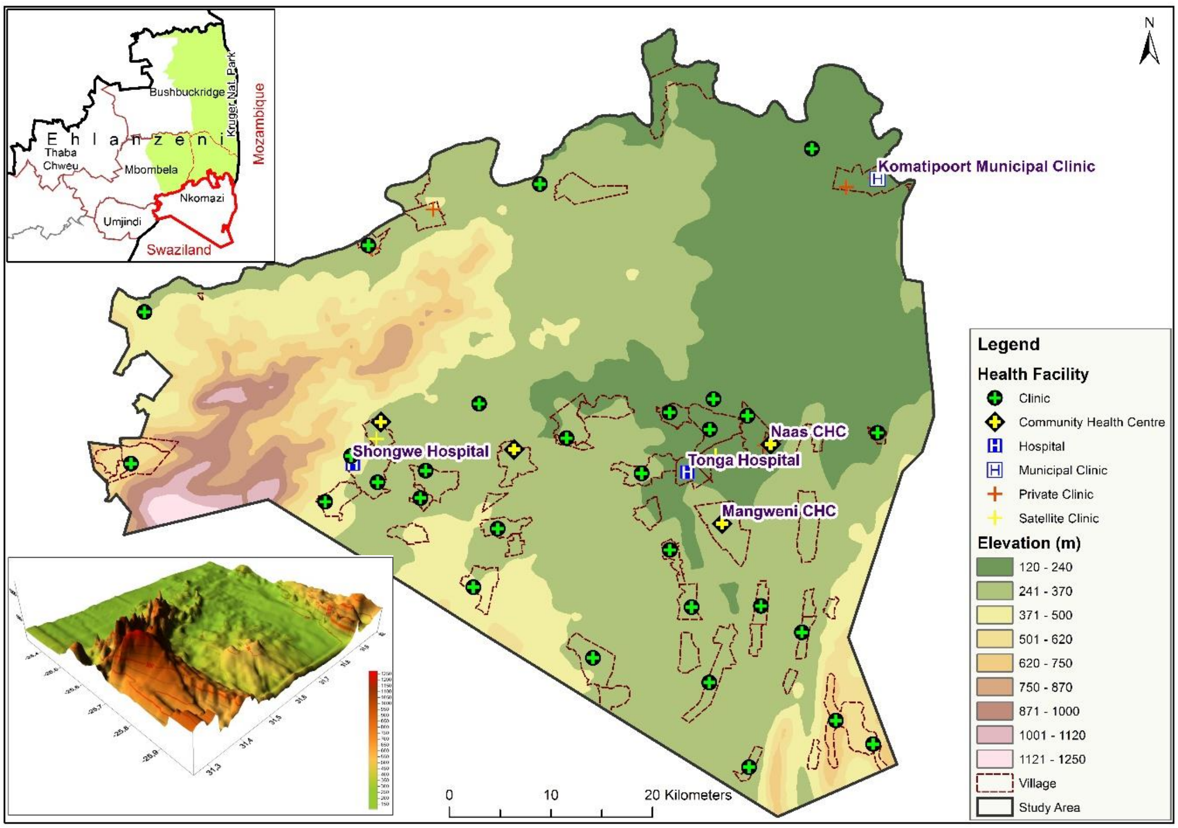


Figure 1: Location of study area: Showing the villages and health facilities (inset: 3D DEM of the study area)

Data collection

Notified malaria cases were acquired from the malaria control programme of the Department of Health, Mpumalanga. The data include both passive and active data. The passive data are data obtained from patients who presented themselves at health facility and were tested positive to *Plasmodium* while the active data are those collected through screening measures in which health workers go into the community to ask for individuals to be tested. These include people with non-specific symptoms such as fever, or those residing near or in the same homesteads with recently confirmed cases. There are 48 healthcare facilities (Hospitals, community health centres CHC, private clinics, satellite clinics and mobile clinics) across the municipality. The records from the facilities contain information such as facility name, date of diagnosis, number of cases, deaths, age, gender, infection source and the coordinates of the facilities. The record spans from January 1997 to August 2015 for many of the facilities. However, malaria cases from only 5 health facilities; accounting for about 56.3% (both locally and imported) of the total malaria cases were used in this study. Only locally sourced cases were utilised in the model for better relation and interpretation with the local environmental variables.

All environmental parameters used in this study were derived from satellites imageries. Vegetation indices consisting of NDVI, EVI and water index; NDWI were extracted from a 16-day composite of the Moderate-resolution Imaging Spectroradiometer (MODIS) MCD43 on board Terra satellite for a period of 2000 - 2015. The vegetation and water indices are corrected for atmospheric effects, soil, polarization, and directional effects at 250 m and 500 m resolution. The LST, from year 2000 - 2015 was derived from MODIS MOD11A2 thermal sensor on board the NASA-Terra satellite system with spatial resolution of 1 km, temporal resolution of 8-day, with absolute accuracy of 0.3°C – 0.5°C over oceans and 1°C over land (NASA, 2013; Tatem, et al., 2004; Wan et al., 2002). Mean monthly rainfall (mm) estimates (3B43) were derived from the Tropical Rainfall Measuring Mission (TRMM) using the Mirador platform of NASA. The rainfall estimates is a gridded product with a spatial resolution of 0.25° x 0.25°.

Data Analysis

Daily locally notified malaria cases from January 2000 – August 2015 across the 5 selected health facilities were aggregated monthly using Microsoft Excel. The malaria cases were used as the dependent variables while the environmental variables were used as the independents variables. Spatial analysis and statistical modelling were performed using ArcGIS 10.2 and R software respectively.

Using the premise that adult mosquitoes generally remain up to 2 km of their breeding habitats (Thomas, et al., 2013) a buffer of 2 km was created around the 5 villages within which the selected facilities are located. The 2 km encompasses farm lands (irrigation) which is the major source of job for the population (Adeola et al., 2016). The villages, their corresponding health facilities and percentage contribution to overall malaria cases include; Tonga A village (Tonga hospital, 6.3%), Kamataso village (Shongwe hospital, 9.0%), Mangweni village (Mangweni CHC, 9.9%), Kamaqhekeza village (Naas CHC, 12.9%) and Komatipoort (Komatipoort hospital, 18.09%). Consequently, monthly means of Rainfall, NDVI, EVI, NDWI and LST within the 2 km radius were computed.

The malaria data across the selected 5 facilities were characterised by testing for homogeneity of variances, normality and randomness. Bartlett's test for homogeneity of variance indicates that the variances in the notified cases across the facilities differ (chi-square = 112.86; deg. freedom = 4; *p-value* <0.05). In order to determine the best model to be used for the prediction, malaria cases were fitted into a number of statistical models. Autoregressive Integrated Moving Average (ARIMA), Linear Regression Models with and without seasonal features (LRM), Harmonic Seasonal Models (HSM), Seasonal Autoregressive Integrated Moving Average Models (SARIMA) and log-transformed SARIMA models were fitted into the data for comparison. The SARIMA was found to have the best fitting. Hence, SARIMA models were developed.

The SARIMA model provides a robust set of tools for performing time series analysis, parameter estimation and forecasting. SARIMA model is structured as SARIMA $(p, d, q)(P,D,Q)^s$ where p and P are order of autoregresion and seasonal autoregression, respectively, d and D are the degree of non-seasonal differencing and degree seasonal differencing, respectively, q and Q are the order of non-seasonal moving average and seasonal moving average, respectively, and s is the seasonal period. Different combinations of the SARIMA models were tested to fit the malaria cases data only. Consequently, the model with the lowest akaike information criterion was selected as the best model. Furthermore, to determine the statistical associations of the environmental parameters with malaria incidence, a multivariate SARIMA models were developed with the environmental covariates (Rainfall, NDVI, EVI, NDWI and LST) inputted as the independent variables. Hence, environmental variables with significant statistical association $p < 0.05$ with malaria incidence were retained for the final models. Hence, Rainfall, NDVI, EVI and NDWI all with time lag of one to three months were used in the final models. Although, NDVI and EVI are significantly associated with malaria incidence as derived from the SARIMA model, EVI was preferred above NDVI because EVI exhibits more sensitivity in vegetation (Matsushita, et al., 2007; Huete, et al., 2002).

To achieve constant mean and variance for the time series as required for good fitting for ARIMA models the data were transformed into stationary series by using first order and seasonal differencing. A stationary *R*-squared value of 0.768 was achieved which implies that the model could explain 76.8% of the observed variation in the series. The peak of seasonal variation (seasonality) was determined using seasonal adjustment factor (SAF). Accordingly, seasons were defined as follows: summer = December to February (DJF); autumn = March to May (MAM); winter = June to August (JJA) and spring = September to November (SON).

Notified malaria cases and environmental variables (Rainfall, EVI and NDWI) showed significant seasonality and inter-annual variation during the period under investigation (Figure 2). Time series analysis was performed individually for the 5 villages. The data sets were divided into 2 parts. The first part was used for the estimation of model parameters and the second part for prediction. Hence, data sets from January 2000 to December 2013 were used for estimating model parameters. Root mean square error (RMSE) was used to assess the fits of the models for each village/facility. On the other hand, data sets from January 2014 to December 2014 (12 months) were used to make a one-step-ahead prediction. Predictions were made using the observed values of notified malaria case data at lags of one month and one year and environmental parameters at lags of one to three months. Again, RMSE was used to determine the differences between observed and predicted cases. August to December year 2015 were not considered in the model because August data is incomplete and there was no data for the remaining months of the year as at when this analysis was done.

Results

In general over the study area from January 1997 to August 2015, the total number of notified malaria cases and deaths associated to malaria indicated a declining trend since a major outbreak in the year 2000 (9699 malaria cases) to (2609 malaria cases) in 2014 figure 2. However, there are few peaks of malaria cases recorded in the years 2006, 2011 and 2014. A very similar trend is seen over the selected 5 facilities. Although imported malaria cases within the study area is a major challenge towards the elimination of the disease, a larger percentage of the infection is locally sourced. Data analysis revealed that 56.38% (34,230) of malaria infection are localised (South Africa) while the difference are imported malaria cases. Infection from Mozambique accounts for 42.12% (25,573) of the total infection and other countries like Swaziland 1% (610); Somalia 0.2% (119); Zimbabwe 0.07% (40); Ethiopia 0.06% (35); Malawi 0.04% (26) among others make up for the difference. Across the 5 selected facilities, imported malaria cases from Mozambique is particularly high accounting for 66.1% of the total cases in Komatipoort municipal clinic and 44.8% in Naas CHC, see table 1.

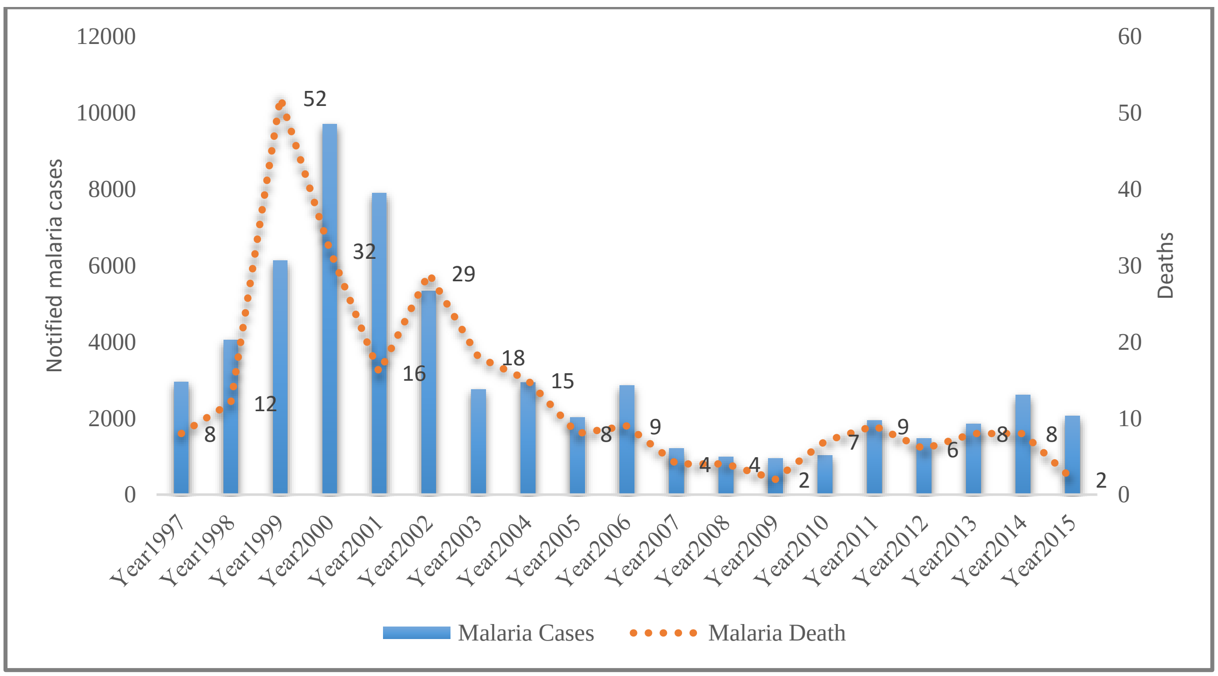


Figure 2: Notified malaria cases and associated deaths in Nkomazi municipality from 1997 to 2015

Table 1: Locally notified malaria cases, death and comparison with imported cases in the 5 major health facilities in Nkomazi municipality January 1997 - August 2015

Health Facility	Total malaria case	Local malaria cases	Total death	Local death	CFR	Source Country
Tonga Hospital	3824 (6.30%)	2646	78	50	2.04	SA 69.2%
						Moz. 29.2%.
						Others 1.6%
Shongwe Hospital	5463 (9.00%)	4750	133	106	2.43	SA 86.9%
						Moz. 11.6%
						Others 1.5%
Mangweni CHC	6012 (9.90%)	3674	4	3	0.07	SA 61.1%
						Moz. 37.9%
						Others 1.0%
Naas CHC	7878 (12.97%)	4248	6	3	0.08	SA 53.9%
						Moz. 44.8%
						Others 1.3%
Komatipoort Municipal Clinic	10984 (18.09%)	3638	5	4	0.05	Moz. 66.1%
						SA 33.1%
						Others 0.8%

The comparison of statistical models to determine the best forecasting model by fitting malaria cases indicated that SARIMA model was the best based on its lower RMSE. Multivariate SARIMA model indicated that Rainfall, NDVI, EVI and NDWI are the significant environmental predictors of malaria incidence in the study area. LST (temperature) is only marginally significant ($p = 0.051$) with malaria infection. Monthly malaria infections in all the 5 facilities exhibited a significant positive relationship with all the predictors. Time series of malaria cases and environmental predictors is shown in figure 3. However, NDWI with a lag time of 1 month was more significantly related to local malaria cases (Figure 3). A seasonal component in the time series data was confirmed by partial autocorrelation function which indicated significant peaks at a lag of 3 months. Malaria incidence is generally recorded throughout the months of the year across the study area. However, as shown in table 2 the SAF of malaria in the months of January to May is more than 1. Hence, this indicates that malaria infections during these months were above the typical months. This period tallies with the summer and autumn months (DJF/MAM) in South Africa when the summer rainfall is experienced.

Figure 3: Time series of average monthly local malaria cases, NDVI, NDWI and EVI and time series of monthly local malaria cases and total monthly rainfall 2000 to 2013.

Table 2: Seasonally adjustment factor (SAF) for locally notified (Observed) malaria cases across the 5 selected facilities from 2000 to 2013 (*Note: OB = Observed*)

Month/Village	Komatipoort		Naas		Mangweni		Shongwe		Tonga	
	OB	SAF	OB	SAF	OB	SAF	OB	SAF	OB	SAF
January	254	1,19	366	1,25	280	1,23	523	1,96	375	1,51
February	253	1,08	422	1,57	210	1,11	383	1,44	246	1,29
March	411	1,51	625	2,56	307	1,35	538	1,88	342	1,37
April	361	1,69	486	2,21	324	1,56	341	1,39	344	1,63
May	415	2,37	488	1,82	361	1,91	321	1,21	331	1,57
June	117	0,75	63	0,37	114	0,86	87	0,47	114	0,66
July	35	0,26	28	0,23	64	0,48	40	0,33	60	0,31
August	29	0,17	15	0,12	12	0,08	27	0,19	61	0,29
September	71	0,36	41	0,17	66	0,39	85	0,35	118	0,51
October	134	0,63	67	0,23	142	0,75	159	0,60	158	0,69
November	153	0,79	92	0,34	134	0,79	149	0,56	212	1,01
December	141	0,72	88	0,33	160	0,85	154	0,63	204	0,97

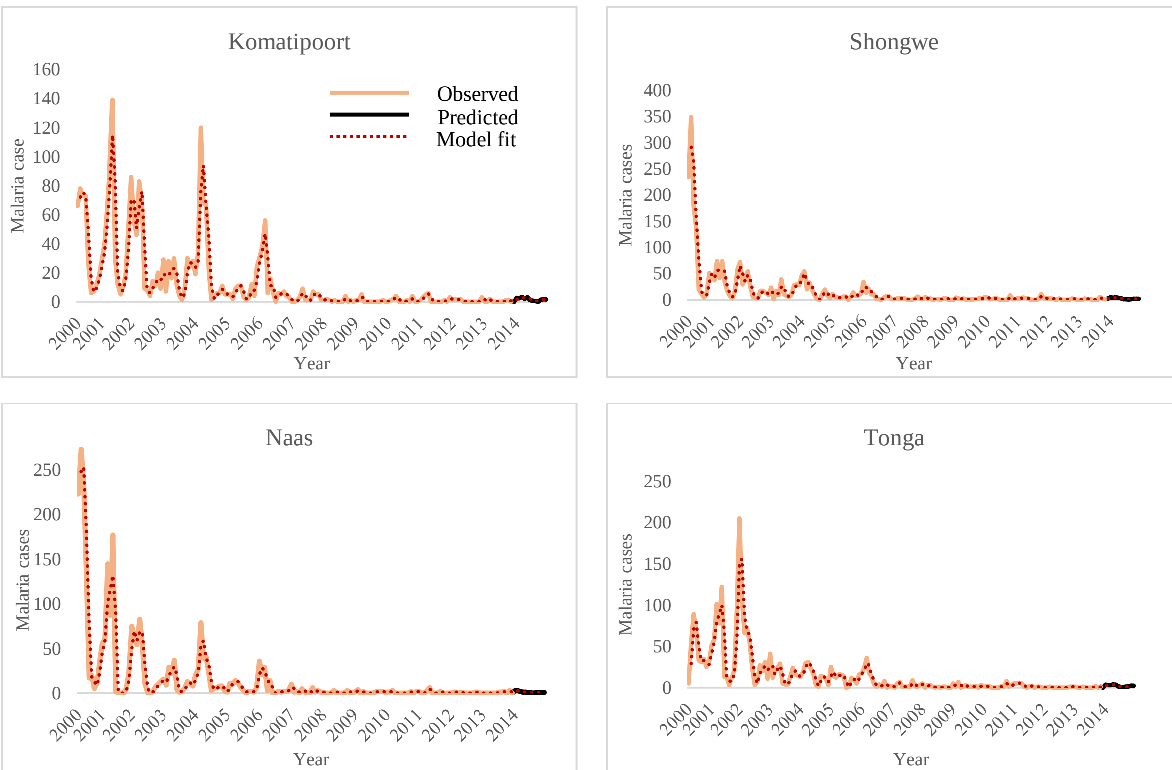
Monthly malaria cases including environmental variables were fitted in SARIMA models and prediction were made for 12 months (January 2014 to December 2014) shown in figure 4. A total of 20 malaria cases is predicted as against 15 observed cases in Komatipoort, 13 malaria cases is predicted as against 6 observed cases in Naas and 20 predicted cases as against 23 observed cases in Mangweni health facility. Overall, across the 5 facilities, there are 90 observed cases and the model predicted a total of 106 cases. See table 3. Generally, the model predicted an increase in malaria cases with distinct seasonal pattern and significant peaks during the summer months (DJF) and start of autumn in March/April which are the rainy season.

Table 3: Predicted malaria cases across the 5 selected facilities (January 2014 – December 2014)

Month/Village	Komatipoort		Naas		Mangweni		Shongwe		Tonga	
	OB	FC	OB	FC	OB	FC	OB	FC	OB	FC
January	3	3	2	2	1	2	3	5	3	4
February	1	2	0	3	2	2	1	3	1	3
March	5	3	1	2	6	4	3	4	5	3
April	1	2	0	1	2	2	0	3	1	4
May	2	3	0	1	2	3	2	3	4	4
June	0	1	0	1	1	1	2	1	1	2

July	0	1	0	0	0	1	0	1	0	1
August	0	0	0	0	0	0	3	0	0	1
September	1	0	0	0	5	1	4	1	1	1
October	0	1	0	0	3	1	2	1	2	2
November	0	2	1	1	1	1	1	1	2	2
December	2	2	2	1	0	1	0	1	5	2
TOTAL	15	20	6	13	23	20	21	26	25	28

The level of prediction, either under-prediction where predicted is less than observed or over-prediction where predicted is greater than observed, all predictions across the 5 villages are within 10% of the notified malaria cases, see table 3.



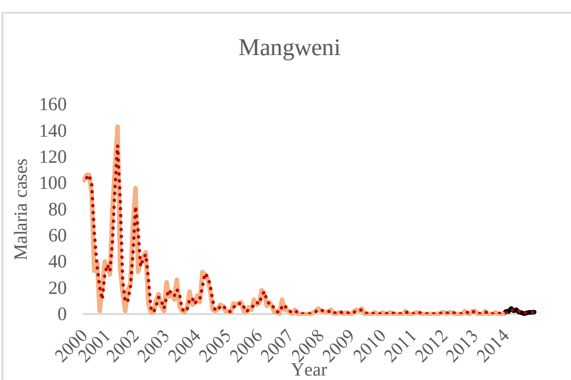


Figure 4: Output of SARIMA model with observed and predicted malaria cases including environmental covariates. *Models were fitted using data from February 2000 to December 2013. Predictions were made for the last 12 months of the time series.*

Discussions

The spatial and temporal distribution of malaria transmission is largely determined by climatic and environmental variables (Kleinschmidt, et al., 2001; Craig, et al., 2004). These determinants range from the provision of suitable thresholds for the survival of both the parasites and vectors; to the provision suitable breeding habitats; to the availability of host (human or animals). For this study, SARIMA models which are predominantly useful for epidemiological studies that exhibit seasonal pattern were developed (Helfenstein, et al., 1991). In all the 5 facilities/villages; rainfall, EVI and NDWI were found to be significantly associated with malaria cases. The statistically significant relationship of rainfall with malaria cases is in pact with other studies who had used satellite-derived rainfall estimates to study its relationship with malaria transmission. For instance, Midekisa, et al., 2012 in their study found a lag of one to three months between satellite-derived rainfall and malaria cases in five study site in Ethiopia. Similarly, Ceccato, et al., 2007 in Eritrea indicated that satellite derived rainfall is statistically associated with malaria cases with two to three months of lead time. In addition, this present study is consistent with studies conducted within the study area in which climatic data including rainfall temperature data from ground weather station were used to examine their (climatic data) associations with malaria cases. These studies found that rainfall is significantly associated with malaria cases and not temperature (Ngomane, et al., 2012; Silal, et al., 2013). Various studies have demonstrated the positive relationship of temperature (either satellite derived or observed data) to malaria cases (Teklehaimanot, et al., 2004; Craig, et al., 2004). However, the situation is particularly different in Nkomazi municipality where rainfall is seen to be the major predictor of malaria infection Ngomane, et al., 2012; Silal, et al., 2013). This situation seems not to be generalised over South Africa. Craig, et al., 2004 found that temperatures during the preceding summer and current spring were significantly associated with delta log malaria cases in KwaZulu-Natal; one of the three malaria provinces of South Africa. Hence, the marginal significance of LST (temperature) in this current study over the study area is corroborated by these previous studies.

While NDVI exhibits a positive statistical significance with malaria infection in this study as also shown in other studies (Ceccato, et al., 2005; Adimi et al., 2010), EVI was preferred because of its sensitivity over denser vegetation. The comparison of the time series of NDVI and EVI indicated that EVI is more sensitive over the Nkomazi municipality which its dominant land cover type is cropland under intensive irrigation covering 65% of its total area (Adeola, et al., 2016).

Although, the use of NDWI to detect mosquitoes breeding habitats has been reported (Adeola, et al., 2015; McFeeters, 2010) the water index has not been used in any model to determine its relationship with malaria infection. This tends to be a major novel result emanating from this study. The NDWI showed a high association with malaria cases in all the villages. The significant relationship of NDWI with malaria cases may be explained by the presence of open water body (river and ponds) for irrigation (Adeola, et al., 2016). The NDWI is a well-established method of detecting surface water which could serve as potential breeding and resting sites for mosquitoes. Thus, NDWI may offer additional index for quantifying environmental factors in relation to malaria infection and, conceivably, other vector-borne diseases.

In general, this study found that the spatial and temporal patterns of malaria cases in Nkomazi municipality were associated with satellite-derived environmental factors. Nevertheless, the relationship of the environmental predictors for malaria varies across the 5 villages. For example, NDWI was found to be more associated to malaria cases in Komatipoort rather than rainfall has exhibited in other villages. The variation in the environmental factors could be explained by other factors such as topography, local hydrology and land use/land cover type which were not considered in this study. Aside from the environmental/climatic factors, several other factors such as population movement and migration, urbanization, drug resistance in parasites and insecticide resistance in mosquitoes and proximity to health facilities determine the prevalence and severity of malaria. Although some of these factors like topography and land use/land cover could be held constant over a period of time. A scrutiny of the topography indicates that the study area is a low lying area with altitude ranging from a minimum of 120 m to maximum of 1250 m with a mean of 395 m above sea level. It further reveals that altitude in the 5 villages is averaged at 400 m above sea level which are generally found to be associated with malaria incidence (Thomas, et al., 2013).

The none consideration of socio-demographic factors such as such as population movement and migration, urbanization, drug resistance in parasites and insecticide resistance in mosquitoes and proximity to health facilities can be seen as a limitation for this study. Hence, a further research will be required in order to determine the impact of these factors and their possible inclusion into prospect models for the development of a robust malaria early warning system. Furthermore due to the fact that 65% of the total area of Nkomazi is under intensive irrigation, a study investigating the length of growing period by incorporating the start of season and end of season will be recommended in the area. This will believe will further strengthen existing control strategies for targeted action.

Conclusion

The aim of this is to use multivariate analysis techniques to link malaria incidences with remotely derived environmental/climatic variables towards the development of a forecasting model capable of predicting future malaria incidences. As South Africa, progresses in her effort to eliminate malaria in her three endemic provinces by 2018, an effective early warning system incorporating environmental/climatic predictors is an imperative. This study has, therefore, quantified the lagged association of satellite-derived environmental/climatic variables with notified malaria cases and forecasted malaria cases in 5 major villages/health facilities in Nkomazi municipality of Mpumalanga province using SARIMA model. This study found that vegetation indices (EVI and NDVI); water index (NDWI) and rainfall are statistically associated with malaria cases. Rainfall estimates derived from TRMM was the major predictor of malaria in 4 villages while NDWI was the major predictor of malaria in Komatipoort. Hence, these variables are essential in developing a malaria early warning system.

Although, imported malaria cases is a major strain on the effort towards eliminating the disease within the study area, particularly because of its increasing trend from 2001 particularly in Komatipoort, imported cases were not included in the model because environmental variables within the study area might not be representative of the environmental variables from the imported sources.

Competing interests

The authors declare that they have no competing interests.

Acknowledgements

This study was funded by the EU project QWeCI (Quantifying Weather and Climate Impacts on health in developing countries, funded by the European Commission's Seventh Framework Research Programme under the grant agreement 243964). We also acknowledge the support of the University of Pretoria, Centre for Sustainable Malaria Control (UP CSMC) and Earth and Atmospheric Remote Sensing research group, University of Pretoria.

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CHAPTER 6

Summary and conclusions

1. Summary of findings

Malaria is mainly endemic in the low altitude (below 1200 m) regions of Mpumalanga. Limpopo and KwaZulu-Natal located in the north-eastern part of the country. South Africa have seen a drastic decline in the transmission of malaria since the major outbreak in 2000. Despite this effort, about 4.9 million of her population, translating to about 10% of the population are still prone to malaria living in the endemic region. Malaria in the region is markedly seasonal with varying intensity of transmission due to altitudinal and climatic factors. The transmission increases from the wet summer months (September to May) and decreases afterward. The peak transmission occurs in January/February. Malaria incidence in the study area is more pronounced within the economically active population of age group 15-64 and the male gender are at higher risk of malaria. Komatipoort is the major malaria endemic town with about 66% of imported malaria cases from Mozambique as found from the results in Chapter 4 (published).

The aim of this study is to create a model that can integrate remotely derived environmental factors with malaria cases and social (population) factors for effective monitoring and forecasting of incidences of malaria incidences.

It has been established that malaria incidence and prevalence is climatically and environmentally dependent. Climatic/meteorological variables like rainfall, temperature and humidity and environmental variables like vegetation, altitude and surface water all are directly related to the malaria transmission. In addition, human activities such as agriculture, irrigation, deforestation, urbanisation, population movements and constructions such as dam and roads are also connected to malaria transmission and epidemiology (Thomson et al., 1996; Ceccato et al., 2005).

Malaria is one of the oldest diseases to have been widely studied across various disciplines based on varying analysis methods. These methods, accompanied by the collection, integration and analysis of relevant datasets, are vital in providing insight into the different phases of the disease and the widespread patterns. Consequently, it is conceived that the collective use of modelling procedures, geographic information systems and remote sensing, as well as the associated datasets, presents a more effective strategy for analysing the widespread outbreak and spatio-temporal patterns of malaria disease. Such a strategy could potentially aid efforts to control and eradicate the disease. However, malaria studies in South Africa is largely based on the use of statistical models and the use of climatic data from conventional weather stations. Many malaria endemic countries have adopted the use of remote sensing techniques for disease control and have since then achieved great strides in malaria control (Chapter 2: Published literature review).

Remote sensing is defined as the acquisition of information on an object or phenomenon without direct or physical contact with it. It offers a means to collection of useful indirect information, e.g. geo-climatic, ecological and anthropogenic factors related to malaria and other environmentally dependent infectious diseases. With almost continuous data over a large area can be collected against the conventional data collection technique from ground weather stations. Hence, due to its

At a local scale, the mapping of mosquito breeding sites has been described as vital to malaria control. It is argued to be more effective in ensuring targeted interventions like insecticide spraying of mosquito larva (larviciding) rather than random control measures. By focusing on active breeding sites significant reduction in the number of adult mosquito can be achieved and consequently leading to reduction in the incidence and prevalence of malaria (Gu and Novak, 2005). In addition risk maps at appropriate scales can provide valuable information for selective malaria control as found in the results of Chapter 3 and already published.

In line with the Roll Back Malaria Abuja declaration in 2000; to detect the occurrence of malaria within two weeks of onset, for prompt and adequate mitigation by decision makers, anticipating future risk and incidence is critical to success in the fight against malaria. The history of malaria early warning systems goes back to 1921. Consequently, development of operational malaria early warning systems has been proposed by the WHO to fight malaria epidemics particularly in climate sensitive regions. In particular, an integrated malaria early-warning system can be developed using environmental monitoring and epidemic surveillance. One of the major steps to develop effective malaria early warning is to quantify the relationship between malaria cases and meteorological and environmental determinants.

Having reduced its malaria burden significantly since 2002, South Africa has embraced a malaria elimination target of 2018. Hence, a predictive model, based on environmental factors becomes imperative in the effort towards the elimination of the disease by fostering proper malaria control targeting and resource allocation. A time series regression SARIMA modelling approach was developed to quantify the lagged association of environmental variables with malaria cases and predict malaria cases among 5 villages in Nkomazi local municipality. The major finding in this study is that there are positive lagged association between malaria cases and satellite-derived meteorological and environmental variables across the 5 selected villages. Rainfall estimates from TRMM was found to be the major predictor of malaria cases and followed by NDWI with lead time of one to three month. The lead time of one to three months can be used to develop a robust malaria early-warning system for the municipality. The time series model used in this study can also be adapted to other diseases like environmental infectious diseases like Dengue, Cholera, Diarrhoea and rift valley fever (Chapter 5).

Malaria transmission in Nkomazi is high compared to other endemic municipalities in Mpumalanga and a change in climate and the source of infection may lead to a spike in infection and generally a modification of the incidence pattern. The findings in this study may be useful as they enhance the understanding of the current incidence pattern and can be incorporated into models that enable one to predict the impact changes in these drivers will have on malaria transmission. Furthermore, early warning systems can be used in understanding the seasonal trends of malaria which is key to designing a targeted temporal and spatial approach that can be applied in resource-scarce settings.

In conclusion, based on the findings of this study, the following need to be considered by the Mpumalanga Malaria Control Programme in order to achieve the goal to eliminating malaria;

- Firstly, focus more attention of larva spraying to detected active breeding sites in this study;
- Secondly, strengthen awareness of malaria infection among farm workers, residence and visitors in Komatipoort particularly during the festive periods (Christmas and Easter holidays);
- Thirdly, detail study of the growing season in area under intensive irrigation, characterisation of the crop to determine their association with malaria.
- Fourthly, address importation of malaria cases through intensification of the regional cross-border collaboration efforts.

2. Scientific contribution of this study

All objectives of this study is intended to be published in peer-reviewed journal hence the choice of the publication style of thesis writing. According to the first objective, the use of spatial technology (remote sensing and GIS) is very limited in South Africa despite the advantage it offers for malaria control as proven in other malaria endemic countries.

The second objective was clearly shown in the chapter 3 of this study, it found remote sensing and GIS are reliable tools for detecting vector breeding habitats which is crucial towards targeted vector control. It indicated that environmental metrics (LST, NDVI and NDWI) derived from satellite when combined at certain thresholds can be used to detect suitable breeding and resting sites for mosquito.

Results from chapter 4 of this study indicated that environmental factors (altitude) and the land use/cover (irrigation, water, forest) of Nkomazi play significant role in malaria transmission. A univariate logistic regression model indicated that only the covariates age group, sex, water body, forest, irrigated land and altitude were significantly associated with malaria infection. In the further step of analysis using the multivariate model, the model shows that all age groups, particularly age 15-64 and male living in lower altitude (< 400 m above sea level) are at more risk of malaria infection than others in higher altitude ($p = 0.001$). Hence, malaria infection increases with decreasing altitude. The model also indicated that 10% increase in irrigation land will increase malaria In our model, the forested area; also on a high altitude ranging from 900 to 1,250 m above sea level seems not to be significantly associated with increased malaria incidence ($p = 0.166$). The finding, that malaria incidence is more prominent within the economically active population and more among the male gender is against previous reports in Africa where infants and pregnant woman have been reported to be more prone to malaria infection.

The fourth objective is demonstrated in chapter 5 which is currently under review with *Ecohealth Journal*. Spatial and temporal relationship of malaria incidences with environmental variables were established. The result indicated that environmental variables including the vegetation indices; NDVI and EVI, water index; NDWI and land surface temperature; LST derived from MODIS and Rainfall estimate from TRMM all spanning the period of 2000 to 2015 are good predictors of malaria incidence in the study area. The result showed that rainfall estimates from

TRMM was the best predictor followed by NDWI and EVI. Furthermore, the result indicated a seasonal trend in malaria transmission in the study area using the seasonally adjusted factor (SAF) with peak transmission occurring in the months of December to February. Consequently, SARIMA models was develop to forecast malaria incidence, the comparison between the predicted and the actual observed malaria cases showed that the predictions either over-prediction or under-prediction are within 10% of the observed malaria cases.

Overall, this study has demonstrated and strengthen the fact that remote sensing and GIS are strong tools that can be used towards the elimination of malaria.

3. The potential contribution of this work to malaria control

The results also indicate that the malaria cases will continue to occur in the near future if appropriate actions are not initiated on time. The potential implication of this study is that by developing forecasting models for predicting the expected number of malaria cases, timely prevention and control measures can be effectively planned like eliminating vector breeding sites through targeted insecticides spraying, allocation of appropriate resources and creating public awareness months before the peak season. The empirical model used in this study can also be adapted to other environmental dependent diseases like rift valley fever, Cholera, Dengue etc. The result can also be used to inform travellers about malaria risk and screening and to take necessary precautionary measures.

4. Limitations of the study

This study amidst of its good outputs are not free from limitations. There may be concerns about a possible effect of non-climatic/environmental factors such as, economic status, population growth, development of drug resistance, change in diagnostic criteria, changes in local health infrastructure, access to care and public health interventions which have not been considered in this study. In addition, the use of higher resolution image rather than Landsat which is a medium resolution image particularly for the breeding habitat detection is opinioned that it might yield an improved result.

5. Future research direction

The developed model will be improved upon by considering some of the above highlighted factors towards the development of a robust operational malaria early-warning system that can provide predictions of the temporal and spatial pattern of epidemics in both short and long time range to enhance the decision making process of public health practitioner in prioritizing scarce resources to areas and periods most at risk.

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4. WHO: The Abuja declaration on roll back malaria in Africa, Nigeria 25 April, 2000

Curriculum Vitae

Mr. AM ADEOLA CURRICULUM VITAE

(GISc. Professional Practitioner, PLATO Reg. No: PGP1352)

1. BIOGRAPHICAL SKETCH

1.1 GENERAL INFORMATION					
Surname	Adeola				
First names	Abiodun Morakinyo	**Passport number**	A04447069		
Citizenship	Nigerian	**Title**	Mr.	**Sex**	Male
Place of birth	Oye-Ekiti	**Date of birth**	Dec 19th 1983		
Population group	African	**Marital Status**	Married		
Department	Geography, Geoinformatics and Meteorology	**Cell phone**	+27 83 3717253		
E-mail	amadeola@yahoo.com OR u12355004@tuks.co.za				

1.2 ACADEMIC QUALIFICATIONS OBTAINED				
Degree/ **Diploma**	*Field of study*	Higher education institution	**Year**	**Distinctions**
PhD	Geo-informatics	University of Pretoria; South Africa	2012 - 2016	Application of remotely sensed environmental variables for predicting malaria cases in Nkomazi municipality, South Africa
MSc GIS	GIS and Remote Sensing	University of Ibadan; Nigeria	2010	PhD Grade (Master Thesis entitled: “Analysis of the Spatial and Temporal Dynamics of Lake Chad using GIS and Remote Sensing”

BSc (Hons) Geography	Geography Science	University of Ibadan; Nigeria	2007	Second Class (Project) entitled: "Floods in Ibadan; Its Characteristics, Causes, Impacts and Possible Solutions"
Certificate	Remote Sensing and Digital Image Processing	University of Twente, ITC, The Netherlands	2014	Excellent

1.3 WORK EXPERIENCE TO DATE		
Name of employer	**Capacity and/or type of work**	**Period From** (mm//yy to *mm//yy)*
University of Pretoria, GGM	Lecturer	02/2016 till date
J&G Consultants	Professional GIS and Remote Sensing Expert	08/2014 to 09/2015
University of Pretoria, GGM	Part time Lecturer	03/2014 to 06/2014
University of Pretoria, GGM	Student Assistant	07/2012 to 11/2014
Ogun State Water Corporation, Abeokuta Nigeria	Spatial Analyst, Head GIS Unit (permanent)	03/2011 to 04/2012
University of Ibadan, Nigeria	Student Assistant	06/2010 to 10/2010
Urban Heritage Consultant Limited, Lagos Nigeria	Data Officer, (Contract)	05/2010 to 01/2011
Mapmatics Nigeria Limited, Ibadan, Nigeria	Internship	11/2008 to 04/2010
Urban and Regional Planning, Agege LG, Lagos, Nigeria	Community Service	10/2007 to 09/2008
Nigerian Meteorological Agency (NIMET), Ibadan	Industrial Training (IT)	07/2005 to 02/2006

2. TEACHING ACTIVITIES

2.1 Courses presented		
Course	**Level** *(e.g. second year, Masters)*	**Period from** (mm//yy to *mm//yy)*
GGY 283 – Introduction to GIS	Second year	02/2016 to 06/2016
GMA 220 – Remote Sensing	Second year	03/2014 to 06/2016
GMA 705 – Advance Remote Sensing	Honors	07/2012 to 11/2014
GMA 320 – Remote Sensing	Third year	07/2012 to 11/2016
GEO 301 – Introduction to GIS	Third year	06/2010 to 10/2010

3. RESEARCH OUTPUTS

3.1 Publications in peer-reviewed or refereed journals

3.1.1 ***AM Adeola***, OJ Botai, JM Olwoch, C.J.deW Rautenbach, OM Adisa, AM Kalumba, OJ Taiwo. Environmental factors and population at risk of malaria in Nkomazi municipality, South Africa. *Tropical Medicine and International Health 2016.* doi:10.1111/tmi.12680

3.1.2 ***Adeola A Morakinyo***, Botai O Joel, Olwoch J Mukarugwiza, Rautenbach C.J.deW *et al.*, Application of geographical information system and remote sensing in malaria research and control in South Africa: a review.*Southern African Journal of Infectious Diseases* 2015; 1(1):1–9. http://dx.doi.org/10.1080/23120053.2015.1106765

3.1.3 ***Adeola AM***, Olwoch JM, Botai OJ, Rautenbach CJ de W, Kalumba AM, et al: Landsat satellite derived environmental metric for mapping mosquitoes breeding habitats in the Nkomazi municipality, Mpumalanga Province, *South Africa. South Africa Geographical Journal*, 2015. http://dx.doi.org/10.1080/03736245.2015.1117012

3.1.4 Nsubuga F. W. N, Olwoch JM, Botai OJ, Rautenbach CJ deW, Kalumba AM, ***Adeola AM***, Tsela LP, Mearns K. Detecting changes in surface-water area of Lake Kyoga sub-basin using remotely sensed imagery in a changing climate. *Theor Appl Climatol* 2015.

3.1.5 Muchuru S, Botai JO, Botai MC, Landman WA, ***Adeola AM***. Variability of rainfall over Lake Kariba catchment area in the Zambezi river basin. *Theor Appl Climatol, 2015*

3.1.6 Muchuru S, Botai MC, Botai JO, ***Adeola AM***. The hydro-meteorology of the Kariba catchment area based on the probability distributions. *Earth Interactions*, 2015

3.1.7 O.A. Bamisaiyea, P.G. Eriksson, J.L. Van Rooya, H.M.Brynard, S. Foyab, V. Nxumalo, ***A.M. Adeola***. A. Billay. Three dimensional geometry of the Rustenburg layered suite. *Canadian Journal of Tropical Geography*, 2015

3.1.8 Kalumba A. M, Olwoch J. M, I. van Aardt, Botai O. J, Tsela P, Nsubuga F. W. N & ***Adeola A. M*.** Trend Analysis of Climate Variability over the West Bank - East London Area, South Africa (1975 – 2011), 2013.

3.2 Publications for Submission/in manuscript.

3.2.1 ***Adeola AM,*** Olwoch JM, Botai OJ, Rautenbach CJ deW, Kalumba AM, Adisa OM and Tsela P. Remote sensing based model for predicting malaria incidence in Nkomazi local municipality of South Africa.

3.2.2 ***AM Adeola***, OJ Botai, JM Olwoch, OM Adisa, AM Kalumba, A Mabuza. Forecasting malaria incidence using remotely sensed climatic factors in Nkomazi local municipality, South Africa. *Plos One* 2016.

3.2.3 Kalumba A. M, Olwoch J. M, I. van Aardt, ***Adeola A. M***, Nsubuga F. W. N. Assessing Industrial Development influence on Land-Use/Land-Cover Drivers and Change Detection for West Bank East London, South Africa, *Physical Geography* 2015.

3.2.4 Kalumba A. M, Olwoch J. M, I. van Aardt, Botai O. J, Tsela P, Nsubuga F. W. N & ***Adeola A. M***. Detecting vegetation cover change of West Bank, Buffalo City Metropolitan, South Africa. South. *South Africa Geographical Journal* 2014

3.2.5 O.A. Bamisaiye, P.G. Eriksson, J.L. Van Rooy, H.M.Brynard, A.Y. Billay, S. Foya, V. ***A..M. Adeola***, V. Nxumalo. Subsurface mapping of Rustenburg Layered Suite (RLS) Structural feature using borehole data and spatial analysis. (Under review with Journal of Spatial Science, Taylor and Francis)

3.2.6 O.A. Bamisaiye, P.G. Eriksson, J.L. Van Rooy, H.M.Brynard, A.Y. Billay, S. Foya, V. ***A..M. Adeola***. Geospatial analysis of northwestern bushveld complex, South Africa. (Under review with Geocarto International journal, Taylor and Francis)

3.3 Published full-length conference papers

3.3.1. ***Adeola AM,*** Olwoch JM, Botai OJ. Spatial analysis of the linkage between climatic and environmental factors and malaria vector habitat in Mpumalanga Province, South Africa, GISSA Ukubuzana 2012 conference proceedings, *eepublishers*, ISBN: 978-0-620-52913-6, South Africa October 25 - 30, 2012.

3.4 Published conference presentation

3.4.1**. *Adeola AM,*** Olwoch JM, Botai OJ, Rautenbach CJ deW, Kalumba AM, Tsela LP, Adeola OM, and Nsubuga FW (2013). Landsat satellite derived environmental metric for mapping mosquitoes breeding habitats in the Nkomazi district, South Africa, QWECI, Science talk presentation, Barcelona, May 16-18, 2013. Available online: http://www.liv.ac.uk/media/livacuk/qweci/QWeCI_Barcelona_Landsat,derived,environmental,metric,for,mapping,mosquitoes,habitat.pdf

3.5 Published conference abstract

3.5.1. ***Adeola AM,*** Botai OJ, Olwoch JM. Satellite derived metrics for monitoring malaria incidences in Nkomazi region, South Africa, American Association of Geographers, Annual Conference Book of Abstracts. AAG 2016, March 29 – April 2, 2016, San Francisco, Califonia.

4. CONFERENCE INVITATION

4.1 Invitations to conferences

4.1.1. Gave an oral presentation at the annual conference of American Association of Geographers, AAG 2016, March 29 – April 2, 2016, San Francisco, California.

4.1.2. Gave an oral presentation at the annual QWECI conference in Nairobi Kenya. Linkage Between Climatic and Environmental Factors and Malaria Vector Habitat in Mpumalanga Province, South Africa, October 2012

4.1.3. Gave an oral presentation at the final QWECI conference in Barcelona, Spain. Landsat satellite derived environmental metric for mapping mosquitoes breeding habitats in the Nkomazi district, May 2013

5. COMPETENCIES & OTHER PROFESSIONAL SKILLS

5.1 Competencies

5.1.1 GIS & Remote sensing applications

5.1.2 Software proficiency: ERDAS Imagine, ENVI, IDRISI, Arc GIS/Arc View.

5.1.3 Hardware proficiency: Real time kinematic GPS, handheld GPS, Total Station

5.1.4 Statistical and Modeling proficiency (R, MATLAB, SPSS, Microsoft excel)

5.1.5 Computer programming (Visual Basic)

5.1.6 Operating systems: Windows

5.2 Special skills & other training

5.2.1 Certificate in Remote Sensing and Digital Image Processing: University of Twente, Faculty of Geo-information Science and Earth Observation (ITC), April – July, 2014

5.2.2 Training on *Remote Sensing Data in Water Management*, by Prof Wim Bastiaanssen (UP, South Africa), 25-28 March, 2013

6. RESEARCH INTERESTS

6.1. Application of GIS and Remote Sensing to:

- Health (Malaria studies)
- Environmental monitoring (e.g. flood modeling, Land use/land cover)
- Water management (Surface and Ground water)
- Geo-database management
- Agriculture
- Digital image processing

7. ACADEMIC AND PROFESSIONAL MEMBERSHIP

7.1 South African Council for Professional and Technical Surveyors (PLATO) PGP1352

7.2 The *Geo-Information Society of South Africa* (*GISSA)*

7.3 *Society of South African Geographers (SSAG)*

7.4 African Association of Remote Sensing of the Environment (AARSE)

7.5 American Association of Geographers (AAG)

8. REFEREES

8.1. **Dr. Joel Botai.** "Department of Geography, Geoinformatics & Meteorology, University of Pretoria, Private Bag X20 Hatfield 0028, South Africa. *Email: joel.botai@up.ac.za* Tel: +27 12 420 2170, Fax: +27 12 420 3808.

8.2. **Dr. Jane Olwoch**. Managing Director, Earth Observation Directorate, South African National Space Agency (SANSA), Innovation Hub, Pretoria, South Africa, *E-mail: jolwoch@sansa.org.za*, Tel: +27 12 844 0385, Fax: +27 12 844 0397

8.3. **Dr. Olalekan Taiwo.** "GIS programme coordinator" Department of Geography, University of Ibadan, Oyo State, Nigeria. *Email: olalekantaiwo@gmail.com* Tel: +2348029188696