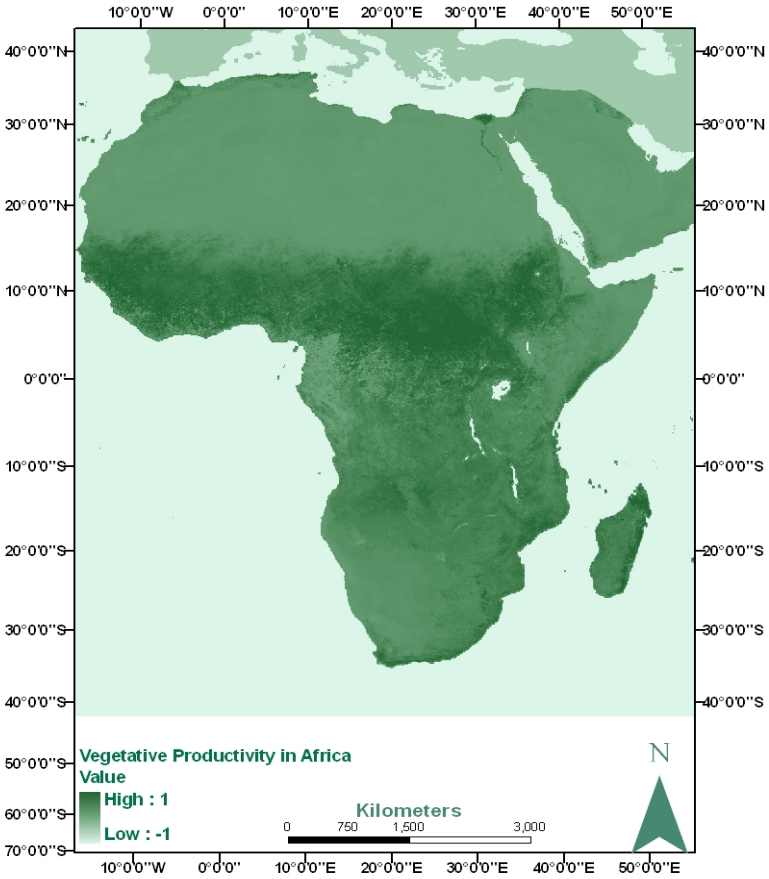
LUMA-GIS Thesis nr 10

Using remotely sensed data to explore spatial and temporal relationships between photosynthetic productivity of vegetation and malaria transmission intensities in selected parts of Africa



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Abstract

Spatial and temporal variations in malaria transmission are naturally associated with prevailing climatic and environmental factors, for example rainfall, humidity, temperature and human activities. These factors influence malaria transmission mainly in non-deterministic ways, making them less appropriate for accurate geographical mapping of malaria risk. One distinctive phenomenon, 'photosynthetic productivity of vegetation', is similarly affected by these factors, yet it can be easily estimated from remotely sensed data using standardized indices. In this study, multiple linear regression techniques are used to explore spatial and temporal associations between photosynthetic productivity of vegetation (measured as Normalized Difference Vegetation Index (NDVI)) and malaria transmission intensities (measured as Entomological Inoculation Rate (EIR)). The study shows significant relationships between NDVI and EIR both at continental level and at a number of the selected study sites. Moreover, in three of four sites where temporal analysis was conducted, a similarity of linear trends is observed between EIRs and means of current and previous month NDVIs. Both NDVI and EIR are significantly associated with altitude as well as to a rural/urban dummy variable. It is concluded that spatial and temporal variations in photosynthetic productivity of vegetation are strongly related to variations in malaria transmission at respective places and periods. Results of this basic exploration imply that vegetation production is a potential indicator of situations favourable for malaria transmission, and can therefore be used to improve mapping of geographical extents of risk of malaria, and perhaps several other vector borne diseases.

Key words: Vegetation production, vegetation index, geographical information systems and remote sensing, malaria transmission, NDVI, EIR

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1.0. Introduction

The description of malaria as one of the world's most devastating human diseases is indisputably appropriate. An estimated 3.2 billion people worldwide live in areas at risk of the disease, with at least five hundred million clinical episodes annually, mostly in Africa (WHO, 2008). To estimate the risk of malaria exposure among human populations and to enable equitable allocation of resources for its control, it is vital to accurately map the geographical distribution of the disease. Such maps could also help to evaluate impacts of existing intervention programs such as the current Global Malaria Action Plan (WHO, 2009), which aims at sustained universal coverage with malaria prevention measures but also at country by country elimination of risk from the disease.

Spatial and temporal variations in the transmission of vector-borne diseases such as malaria are largely dependent upon prevailing environmental and climatic factors. Most malaria risk maps are generated using climate based models, which essentially generalize whether any given location is suitable or not suitable for malaria transmission to occur based on regional climate estimates (Githeko and Ndegwa, 2001, Hay *et al*., 2003, Kleinschmidt *et al*., 2000a, Rogers *et al*., 2002b, Guerra *et al*., 2006, Hay *et al*., 2001). Effects of these climatic factors can however be extremely random especially at local level, making them less appropriate for accurate mapping of malaria. It would also be difficult to measure all individual environmental and climatic factors and then to compute a single estimate for any geographical area or point. The probability of erroneous outputs would obviously increase with increasing number of climatic and environmental variables used.

To counter these challenges, a separate but more distinctive natural phenomenon could be identified for use as a surrogate variable upon which improved malaria risk mapping can be based. That phenomenon should have three important characteristics namely: 1) it must be influenced by the same environmental and climatic factors as those that are proven to affect local malaria transmission, 2) changes upon it must be measurable in a standardized format and 3) it must be correlated to malaria transmission in a statistically determinable trend. One candidate phenomenon is the '*photosynthetic productivity of vegetation*', which can be estimated as a vegetation index. Vegetation indices are widely used in different fields of research to assess conditions of plants at different places and times (Myneni *et al*., 1997, Tucker, 1979, Myneni *et al*., 1998).

At any geographical location, plant production depends on climatic factors such as amount of precipitation received, temperature and altitude as well as human activities, factors which also affect malaria transmission (Gilles, 2001). Therefore, even though vegetation production and malaria transmission may be two completely independent events in nature, they are linked by similar climatic and environmental factors e.g. humidity and temperature. This confluence provides an opportunity to link the patterns of these two natural events, but also the potential to predict likelihood of malaria exposure at any geographical location on the basis of vegetation production trends.

This study is a basic exploration of spatial and temporal relationships between photosynthetic productivity of vegetation (hereafter also referred to as vegetation production) and malaria transmission intensities in selected parts of Africa.

1.1. Study objectives

1.1.1. General objective

The general objective of this study is to explore spatial and temporal associations between malaria transmission intensities and photosynthetic productivity of vegetation in selected parts of Africa. It is envisaged that if there exists a significant relationship between these two variables, then perhaps it would be possible to define geographical and temporal extents of malaria transmission simply by analysing and interpreting spatial and temporal patterns of vegetation growth; especially in situations where actual empirical data on malaria transmission is scarce or unavailable.

1.1.2. Specific objectives

1. To compare seasonal variations of vegetation growth against seasonal variations of rainfall in selected malaria endemic areas with different climatic conditions, in Africa. Since rainfall is a major determinant of plant growth, it is could possibly modify any relationships between malaria transmission and vegetation growth.

2. To explore temporal associations between vegetation indices and malaria transmission intensities in selected localities in Africa. This objective covers only those study sites with malaria transmission data available over several consecutive months; allowing for direct comparison with vegetation productivity data for the same areas and the same period.

3. To determine whether high or low vegetation indices in different parts of Africa are spatially correspondent to high or low malaria transmission intensities in the same areas and at the same times. Unlike objective 2 above, this objective

involves malaria transmission data from a number of selected study sites with spatially clustered malaria transmission data, not necessarily collected over consecutive months.

1.2. Study hypothesis

The underlying hypothesis of this work is that since both malaria transmission and vegetation production are dependent upon similar environmental and climatic factors, changes in temporal and spatial patterns of these variables would be comparable. If this is true, then perhaps it could also be possible to estimate geographical and temporal extents of malaria transmission by simply interpreting vegetation production trends in respective localities, especially where actual empirical data on malaria transmission is scarce, unavailable or difficult to obtain.

2.0. Literature review

2.1. Overview of malaria transmission

Human malaria is caused by protozoan parasites, *Plasmodium falciparum, Plasmodium ovale*, *Plasmodium vivax* and *Plasmodium malariae,* all of which are transmitted by female mosquitoes of the *Anopheles* species. In Africa, the most common and most virulent form of malaria is the one caused by *P. falciparum* (MacDonald, 1956). Malaria transmission occurs when a plasmodium infected blood-seeking female *Anopheles* bites a susceptible human. There are approximately 430 species of *Anopheles*, about 70 of which are known malaria vectors (Service, 2004). Of these species, *Anopheles gambiae* and *An. funestus* are the primary Afro-tropical vectors (MacDonald, 1956).

The mosquito vector (*Anopheles*) acquires the malaria parasite (*Plasmodium*) when it is at the gametocyte stage and is circulating in human peripheral blood. Over approximately 11-12 days, the parasite develops inside the mosquito gut and becomes a different life form called sporozoite. This is the infective stage of the malaria parasite and is usually concentrated in the mosquito salivary glands. At this stage, the parasites can possibly be transmitted into the blood steam of humans that these mosquitoes bite.

Adult mosquitoes convert their vertebrate blood meals into eggs, which they lay, usually in open sunlit pools of clear water. The eggs hatch into larvae and develop through three instars to reach the fourth instar, after which these larvae become pupae (a stage of minimal physical activity). After 1-2 days, the pupae hatch into adult male and female mosquitoes. Adults can survive on sugars, naturally from plants, but the females will require also vertebrate blood so as to develop eggs (Clements, 1992).

2.2. Relationship between malaria transmission and local environmental factors

Growth and development of both the malaria mosquitoes and malaria parasites are influenced by prevailing climatic factors, which must interact in a favourable way for transmission to occur at any geographical location. These factors may include, among other factors: 1) amount of precipitation 2) temperature changes over a given period of time, 3) elevation of the land above sea level and 4) humidity. These factors interact in different ways to dictate total risk of malaria exposure that people experience in a given area (Kiswewski *et al*., 2004, Snow *et al*., 2005). Like several other vector-borne diseases, the intensity and distribution of malaria is also modified by human activities over geographical landscapes. Notable examples of such anthropogenic factors are urbanization (Trape and Zoulani, 1987, Trape *et al*., 1992, Robert *et al*., 2003) and agricultural activities (Kitron, 1987, Ijumba and Lindsay, 2001).

For nearly all arthropod-bone infections including malaria, the period during which the parasite undergoes further development and maturation inside a female mosquito i.e. the extrinsic incubation period depends on prevailing climatic factors such as temperatures, rainfall and humidity (Watts *et al*., 1987, Turell *et al*., 1985, Saul, 1996, Noden *et al*., 1995, Gilles, 2001). It is established that the optimal temperature range is between 25^{o}C and 30^{o}C and that the parasites stop to develop when temperatures reduce to below 16^{o}C (Figure 1). Furthermore, malaria transmission intensities depend on the development and population dynamics of mosquitoes, processes which are also strongly linked to local environment and climate (Bayoh and Lindsay, 2007, Lindsay and Birley, 1996a). The average time taken from egg stage to the time when mosquito adults emerge is 6-8 days. This interval reduces with increasing temperature (Bayoh and Lindsay, 2004,

Bayoh and Lindsay, 2007), and development is nearly interrupted at very low or very high temperatures. These relationships have previously been exploited through attempts to map temperature ranges within which malaria mosquitoes can survive and thus consider these ranges as indicators of potential malaria zones (Bayoh *et al*., 2001).

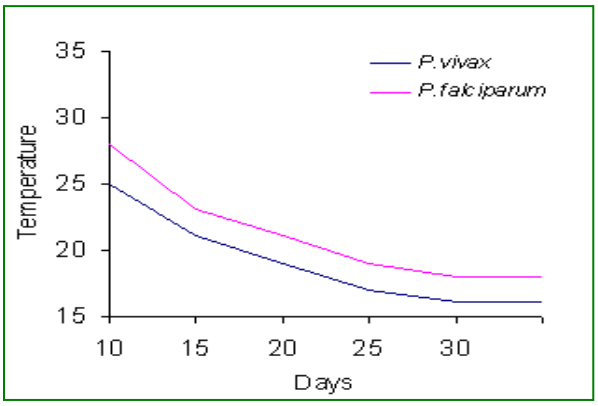

Figure 1: Time taken for two different malaria parasites (*P. vivax* and *P. falciparum*) to mature inside adult *Anopheles* mosquitoes (adapted from Gilles, 2001).

Precipitation also has direct effects on malaria transmission. It leads to the presence of water in potential breeding grounds thus the population of mosquitoes naturally increases a few weeks after the start of rains. In addition, increased precipitation also leads to increased humidity thereby enhancing the survival of malaria mosquitoes (Gilles, 2001). These are the main reasons that malaria epidemics are so often associated with the arrival of rainy seasons (Gilles, 2001). Similarly, limited precipitation in arid areas is associated with limited presence of malaria vectors in such areas.

Finally, human activities such as rice farming, dam construction, drainage system constructions and urbanization may modify environments in ways that make them more or less suitable for malaria transmission (Omumbo *et al*., 2005a, Mutero *et al*., 2000, Ijumba and Lindsay, 2001, Ijumba *et al*., 2002, Keiser *et al*., 2005). Urbanization may

lead to thousands of new man-made mosquito breeding sites but can also leads to the clearing of vegetation thus modifying local climate. Other examples are rice irrigation and dam construction which may lead to increased water flowing, onto otherwise dry lands. Such artificial precipitation also increases local suitability for malaria transmission (Ijumba and Lindsay, 2001).

2.3. Vegetation production as a local environmental variable and how to measure it

Plants very readily respond to changes in environmental conditions, thus their condition of photosynthetic productivity can be an indication of several processes in the environment. In the past, photosynthetic productivity of vegetation was measured merely by observation. Even today many communities still rely on the physical appearance of leaves to know when it is time to plant crops or time to harvest the crops. Variations of vegetation production can generally be detected by studying leaf phenology; whereas highly productive plants are green, leafy and have increased biomass, reduced photosynthetic activity is evidenced by reduced or loss of green coloration, the wilting leaves and a general decrease in overall plant biomass.

Measurements of vegetation production have improved tremendously with the transformation of camera technologies and space-borne satellites (Janssen and Huurneman, 2001). The first large scale attempt to measure either vegetation production or vegetation biomass using remotely sensed satellite data was by Compton Tucker and his colleagues working in the Sahelian desert, Senegal between 1980 and 1984 (Tucker *et al*., 1983, Tucker *et al*., 1985). Thirty years later, satellite imageries have become the main source of data for vegetation monitoring. These techniques rely on electromagnetic

reflectance from plant leaves, which is captured and recorded as readable images by sensors aboard the satellites.

To interpret satellite vegetation data, the spectral reflectances recorded by the satellite sensors are fitted onto a predefined scale to enable distinction between two or more states of vegetation production, for example green-leafy rice fields versus bare rock or surfaces covered only with patchy shrubs. These restricted scales define the different vegetation indices useful for vegetation monitoring. Of the many different vegetation indices, with different specific purposes (Baret and Guyot, 1991), the most common and perhaps most suitable for general vegetation monitoring is Normalized Difference Vegetation Index (NDVI), originally described by Tucker in 1979.

2.3.1. The theory of Normalized Difference Vegetation Index (NDVI)

All matter with temperature above zero radiate energy in the form of electromagnetic waves (Janssen and Huurneman, 2001). Known electromagnetic waves vary from gamma rays, which have the smallest wavelengths, to radio waves, which have the longest wavelengths. The entire range of energies is referred to as Electromagnetic Spectrum (EMS). Though a few bodies can emit their own electromagnetic energies, for most they only reflect energy that is originally from the sun.

In the visible part of the electromagnetic spectrum, plants using their chlorophyll content, absorb most of the red and blue radiation, which they use for photosynthetic activity within the leaves (Figure 2). Reflection of visible radiation occurs only in the green segment of the EMS. This is fundamentally why human eyes perceive healthy plants as green. However, in the near-infrared part of the EMS, the spongy mesophyll content reflects most of the energy. Healthy leaves have high chlorophyll content

therefore they reflect proportionally more energy in the visible part of the electromagnetic spectrum. When these plants dry up, their chlorophyll content and consequently the photosynthetic activity decreases. The reflectance of energy on the green part of the EMS and absorption on the red part of the EMS are proportionately reduced. Mesophyll however continues to reflect in the near-infrared wavelengths.

In the mid-infrared segment, the water content in the leaves absorb most of the energy and so there is very little reflection. The EMS sections at which electromagnetic energy is absorbed by the plant water are the 'water absorption bands'. When plants dry up, reflectance in the mid-infrared region increases. Thus dry plants (e.g. during harvesting seasons) tend to loose their green coloration and instead turn brown. The relationship between photosynthetic productivity of plants and climatic factors can therefore be indirectly understood simply by observing changes on plant leaves.

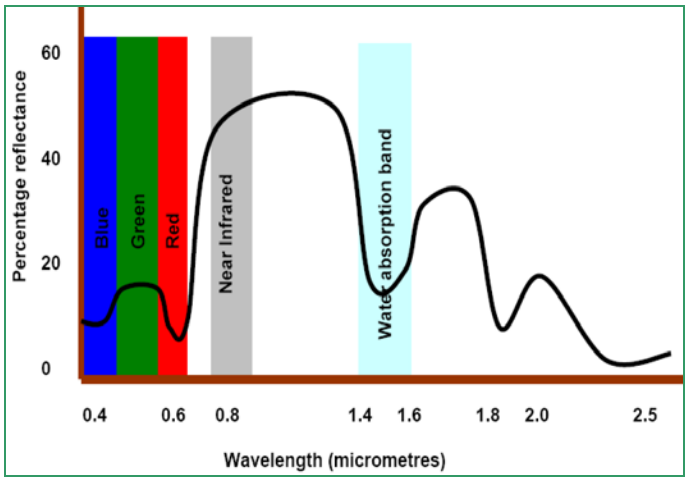

Figure 2: Electromagnetic energies reflected or absorbed by healthy leafy plants (Not to scale).Figure adapted with slight modification from Janssen and Huurneman, 2001.

Normalized Difference Vegetation Index (NDVI) is a standardized measure of changes upon vegetation production and is based on reflectances from plants within the

optical range of the electromagnetic spectrum. It is calculated as a ratio between the difference of reflectances in visible red (R) and near-infrared (NIR) wavelengths and the sum of these two reflectances:

$$NDVI = \frac{NIR - R}{NIR + R} \text{.....Eq...1}$$

The index has a range of -1 to +1, with no units. Increasing positive values represent blooming plant growth, while lower positive values can represent poor and less productive plants, land degradation or bare soils. On the other hand negative NDVI values represent the presence of water, ice or clouds. Highly photosynthetic plant life such as in dense forest canopies usually have NDVI values of 0.6 or more, while bare soil or places with scanty vegetation or dried up plants have NDVI values of between 0.1 and 0.2 (Jackson and Huete, 1991, Tucker, 1979).

Acquisition of NDVI-relevant satellite data has been promoted over the past three decades, principally by the United States National Oceanic and Atmospheric Administration (NOAA) earth observation programs, and NDVI has today become the most widely used vegetation index. Lately, the largest NDVI compilation relies on data from the Advanced Very High Resolution Radiometer (AVHRR), a sensor mounted on US-NOAA satellites (Tucker *et al*., 2005). This data (NOAA-NDVI data) is readily available, easy to use, covers nearly the entire globe and spans over 25 years.

2.3.2. Relationship between NDVI and rainfall

One of the most important determinants of vegetation phenology is temporal pattern and intensity of local rainfall (Richard and Poccard 1998, Davenport and Nicholson 1993, Nicholson 1990, Zhou et al 2001). Indeed rainfall is also the main reason that NDVI can

be expected to be associated with transmission of mosquito-borne diseases such as malaria. Studies have shown that in various ecosystems, vegetative productivity often increases following an increase in amount of precipitation, and that within certain precipitation ranges, local vegetation indices are linearly correlated to intensity of rainfall. For example, in a study conducted to investigate relationships between NDVI and rainfall in East Africa, temporal and spatial patterns of both variables and their inter-relationships were assessed across different vegetation formations in East Africa (Davenport and Nicholson 1993). Using data from 65 different weather stations across ten different climate formations, this study demonstrated a strong similarity between patterns of these two variables as long as annual rainfall remained below 1000mm and monthly rainfall below 200mm. The best correlation was found to occur between monthly composite NDVIs and three-monthly averages of rainfall in the current and two previous months (Davenport and Nicholson 1993).

In another study, using data from southern Africa countries, NDVI and annual rainfall were found to be comparable as well, even though at such temporal scales (annual means), there was minimal sensitivity of NDVI to rainfall (Richard and Poccard, 1998). Like in the first study, this analysis also found the strongest correlation to occur between monthly composite NDVI and lagged rainfall data, in this case the average rainfall received in previous two months. It is therefore clear that phenology of vegetation as depicted by NDVI closely resembles seasonal cycles of rainfall, even though vegetation productivity tends to peak, one to two months after peak rainfall.

2.4. Malaria transmission as a local environmental variable and how to measure it

Quantitative estimates of malaria can be expressed in two ways: 1) based on malaria parasite data obtained from tests conducted on humans, or 2) based on parasite data from tests conducted on mosquitoes. The two ways may be denoted simply as parasitological or entomological estimates respectively. Parasitological estimates are the more common method and involve examination of blood using microscopes or rapid diagnostic kits, to detect malaria parasites. Malaria prevalence rates or incidence rates can then be expressed as proportions of the tested samples that are positive for malaria (Gilles, 2001). Parasitological estimates are often interpreted as the relevant indicators of the malaria disease burden.

On the other hand, to estimate the actual force of malaria transmission or the actual exposure that humans experience, entomological estimates remain the most suitable. To determine malaria transmission based on entomological survey data, the following steps are necessary:

1) Estimation of mosquito densities in the study area. Malaria transmitting mosquitoes that enter human houses to bite people, or those that bite people outdoors, are sampled using appropriate trapping techniques (Silver, 2008) after which, their numerical counts and characteristics are analyzed. This data itself can already provide coarse estimates of biting risk and malaria transmission potential.
2) Estimation of parasite infection rates among the mosquitoes. Percentage of *Anopheles* mosquitoes that carry sporozoites (infective stage of malaria parasite) is determined. This is called the sporozoite rate and is a measure of the natural infection rates circulating among populations of mosquitoes, and which would

possibly translate into real human infection if the infected mosquitoes bite humans. The sporozoite analysis is done using special techniques like Enzyme Linked Immunosobent Assays (ELISA) techniques (Beier *et al*., 1990b).

3) Estimation of human biting rates. Proportion of bites that occur on humans as opposed to any other blood hosts is determined. This proportion represents biting preferences of mosquitoes and therefore the likelihood that any blood fed mosquito would have bitten a human rather than any other animal. This involves molecular analysis of blood extracted from mosquito guts (Beier *et al*., 1990a).
4) Estimating the number of infectious bites that people receive in a given period of time at a given place. This is the most accurate and most common estimate of transmission intensities. It is referred to as entomological inoculation rate (EIR) and is calculated based on human biting rates and mosquito sporozoite rates.

2.4.1. The theory of Entomological Inoculation Rate (EIR)

Entomological Inoculation Rate (EIR) is the most commonly used estimate of malaria transmission intensities and is considered a fairly standard method for estimating risk of malaria exposure that humans experience (Beier *et al*., 1999, Smith *et al*., 2005). Specifically, EIR at any place is the number of infectious mosquito bites that an average individual receives over a given period of time at that particular place. It is usually measured as annual EIR but can also be represented as daily EIR or monthly EIR. Computationally, it is the product of number of bites from malaria vectors that an individual gets in a defined period, i.e. the biting rate (BR) and proportion of those mosquitoes that are actually infected with sporozoites, i.e. sporozoite rate (SR):

$$EIR = BR \times SR \quad \text{.....Eq...2}$$

In Africa, where malaria transmission is very highly heterogeneous, there are places with EIR values that are too low to detect using standard techniques, yet there are also places where malaria transmission is so intense that annual EIR exceeds 1000 (Okello *et al*., 2006, Beier *et al*., 1999, Smith *et al*., 2005). Nevertheless, these rates have been found to strongly correlate with malaria parasite prevalence (Beier *et al*., 1999, Smith *et al*., 2005) as well as malaria related child mortality and morbidity (Smith *et al*., 2001, Smith *et al*., 1998), reaffirming the relevance of EIR estimates (Figure 3).

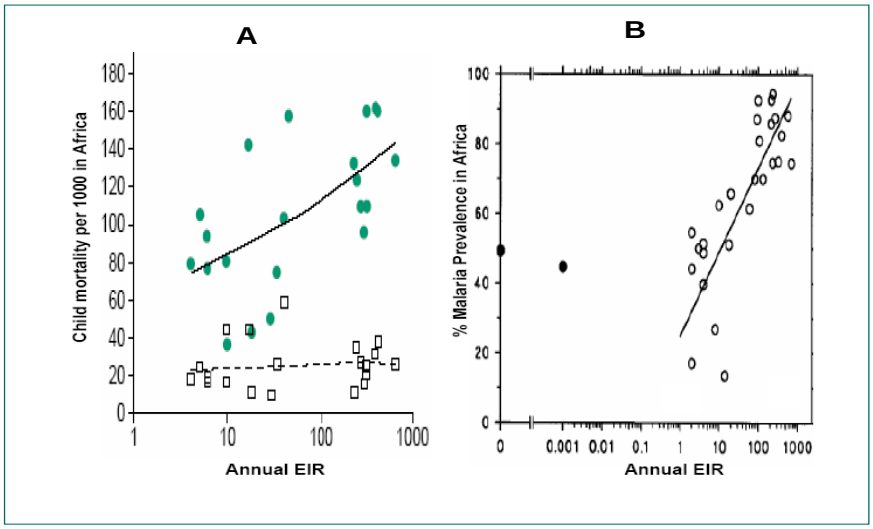

Figure 3: Relationship between mean annual EIR and: **A)** child mortality in Africa or **B)** malaria prevalence in Africa. In Panel **A**, the green circles represent mortality rates among infants (0-11 months of age), while the open squares represent mortality rates among children less than five years (12-59 months) of age. In Panel B, the solid circles represent two outlier villages where EIR was undetectable or barely detectably but where malaria prevalence was above 40%. The two figure panels have been adapted from Smith *et al*., 2001 and Beier *et al.*, 1999 respectively.

2.5. Significance of the study

This work is a basic exploration of spatial and temporal relationships between malaria transmission measured as Entomological Inoculation Rate (EIR) and photosynthetic productivity of vegetation, measured as Normalized Difference Vegetation Index (NDVI). No attempt is made to actually develop any algorithms for purposes of predicting malaria transmission on the basis of vegetation production.

The primary motivation of the work was the need to determine whether or not patterns of vegetation productivity are geographically related to patterns of malaria transmission intensities and therefore whether there is any potential of using NDVI in future as a reliable indicator of places where environmental conditions are suitable for malaria transmission to occur. It was envisaged that if reasonably strong relationships between vegetation production and malaria transmission were observed, then such relationships could potentially be incorporated in models that use vegetation production, instead of or together with the usually numerous and often random effects of climatic factors (such as precipitation, humidity, temperatures, altitude, topography, etc) to more accurately define geographical and temporal extents of malaria exposure; or simply to determine likelihood and level of malaria exposure at any given location and at any given time. This would be especially useful where there is no empirical field data available for malaria transmission.

3.0. Study areas

3.1. General description

This study is generally focused on the entire continent of Africa. However, spatial and temporal associations are explored at local level for selected areas depending on availability of EIR data in published literature (Figure 4), and whether the data was sufficiently clustered or temporally repeated enough to allow for the analyses:

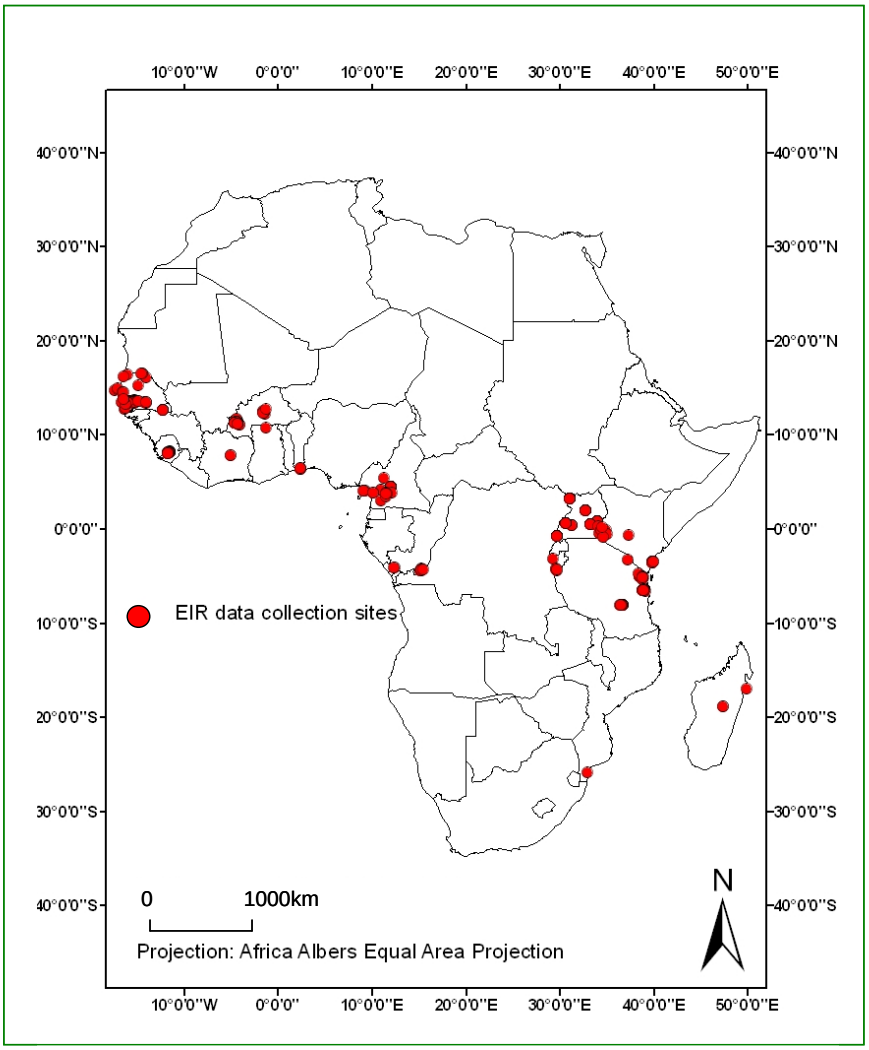

Figure 4: General study area showing locations from where EIR data was available (n=302).

3.2. The Gambia

Data obtained from the Gambia (Figure 5) were dated between 1989 and 1995, at a time when average EIR was below 20 and the primary malaria vector was *An. gambiae.* Only one of the 25 study sites was urban (Lindsay *et al*., 1992, Lindsay *et al*., 1990, Lindsay and Janneh, 1989) and the study sites were generally below 50m above sea level.

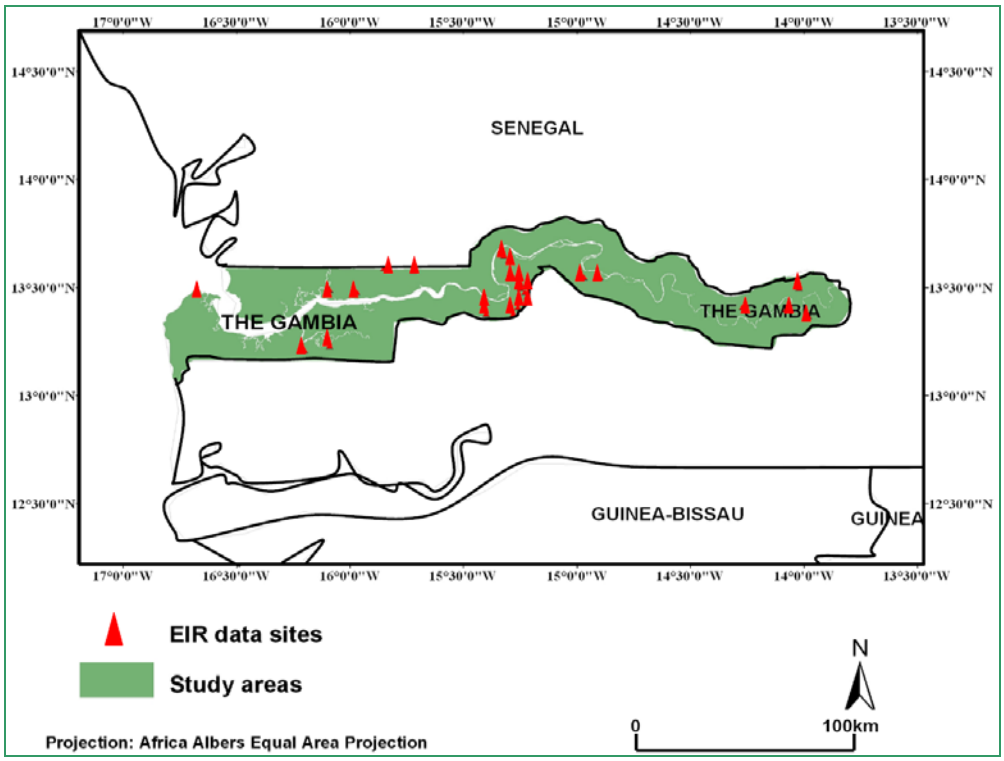

Figure 5: Locations in the Gambia for which EIR data was available (n = 25).

3.3. The United Republic of Tanzania

Selected sites in Tanzania included: an area in Kilombero district, in south eastern part of the country and two clusters in north eastern part, one in Bagamoyo district and another cluster covering parts of Muheza, Korogwe and Pangani districts (Figure 6).

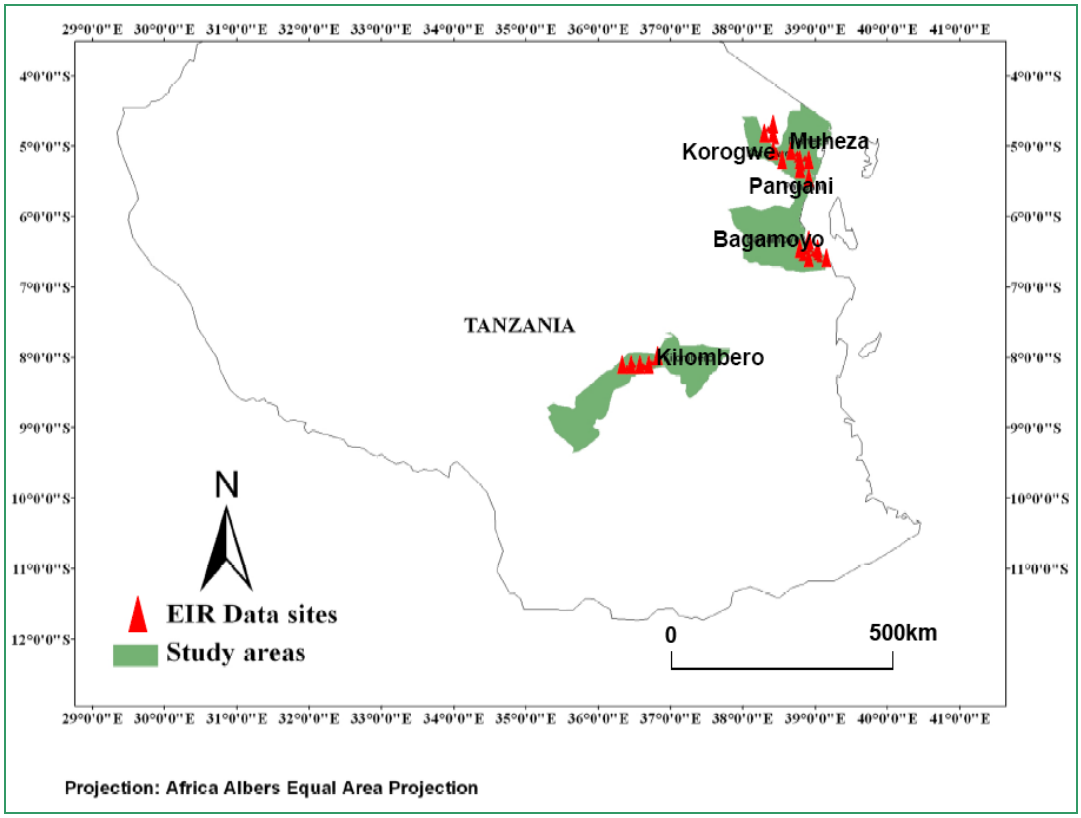

Figure 6: Locations in Tanzania for which spatially clustered EIR data was available (n = 35)

The Kilombero district cluster lies within a low-lying flood plain (averaging 270m altitude) with 1200-1800mm annual rainfall. Data obtained here dated between 1993 and 2004, during which time EIR varied from 4 to 420 and the primary vector was *An. gambiae* (Drakeley *et al*., 2003). Four of the nine study sites were at the edge of a small town, Ifakara town, while the others were rural villages. The second cluster, the Bagamoyo district cluster lies at the Indian Ocean coast at approximately 30m altitude. Here also, EIR was highly variable (26.7 to 547.5) during the data collection period which was 1992 to 1996 (Shiff *et al*., 1995, Temu, 1997). The primary vectors were *An. gambiae* and *An. funestus* and all data for this cluster were from rural areas. Lastly, the cluster that covers areas around Muheza, Korogwe and Pangani Districts, north eastern Tanzania is on the side of a mountain range, the Usambara mountain range, which rises

from 300 metres to 1650 metres above sea level and is characterized by steep undulating slopes (Balls *et al*., 2004). In this entirely rural cluster, EIR was also highly heterogeneous (2 to 702) during the data collection period (1988 to 1996) and the primary vector at that time was *An. gambiae.*

3.4. Burkina Faso

In Burkina Faso, there are two areas, where locally clustered EIR data was available (Figure 7) and both of which are approximately 300m above sea level,

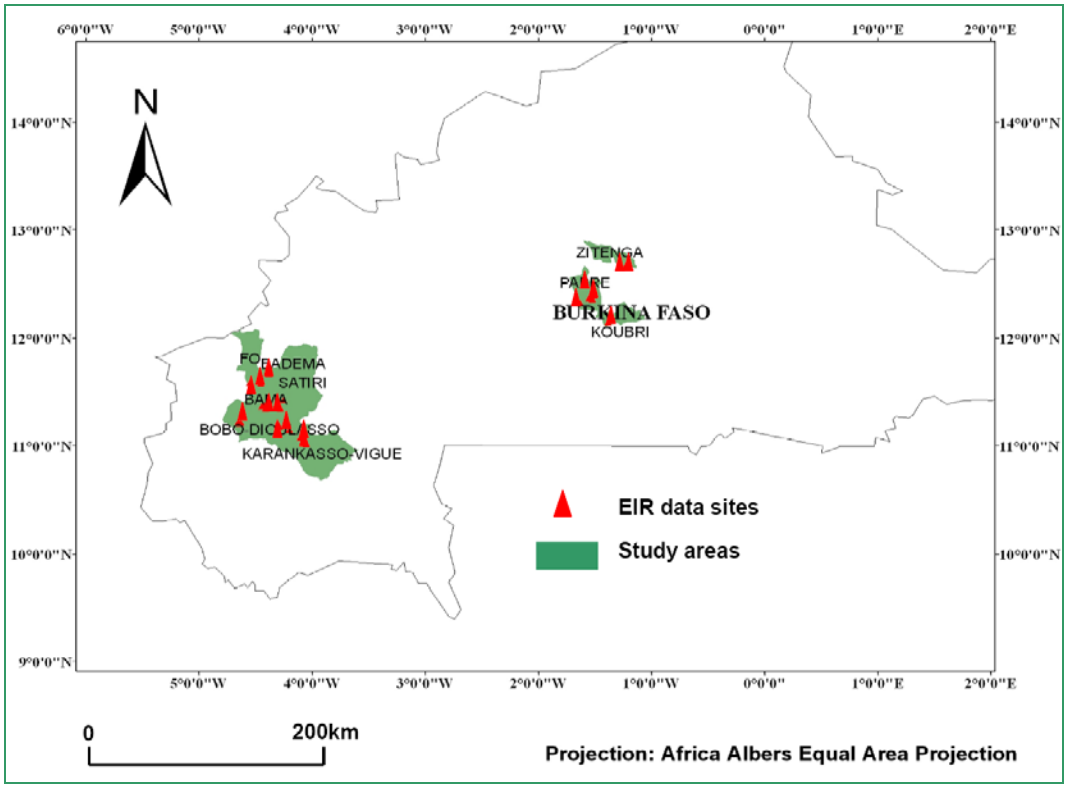

Figure 7: Locations in Burkina Faso for which spatially clustered EIR data was available (n = 37)

As shown in figure 7, the first study area covered six districts in the south western region of the country and the second area covered four districts in the central part of the country. In both regions, the main malaria vector was *An. gambiae* even though there

were also considerably high proportions of *An. funestus* (Robert and Carnevale, 1991, Robert *et al*., 1988, Carnevale *et al*., 1992, Carnevale *et al*., 1988). Whereas in the western region only 5 out of 23 EIR data sites were urban, half of the data points in the central region were urban.

3.5. Uganda

In Uganda, there are three districts where repeated monthly EIR data had been collected from single point locations between 2001 and 2002 period, as part of a malaria drug efficacy trial (Okello *et al*., 2006). This allowed not only for spatial analysis but also for temporal exploration of local level EIR-NDVI relationships. The three sites are in: 1) the north western frontier district of Arua, 2) Apac district in the central part of the country and 3) district in south eastern part (Figure 8).

In Arua district, the data was collected from Cillio village, an area of 930m altitude and 289mm annual rainfall. In Apac, data came from Olami-A village, 1000m altitude with annual rainfall of 1474 mm. This district experiences arguably the world's most intense malaria transmission; unprotected residents here receiving up to 3500 infectious bites annually (Okello *et al*., 2006). Finally in Tororo district, data had been collected from Namwaya Central village (1125m altitude and 1459mm annual rainfall). All these three study sites were rural villages. While the main malaria vector in Arua district during the time when the EIR data was collected was *An. funestus*, it was *An. gambiae* which was the predominant species in Apac and Tororo.

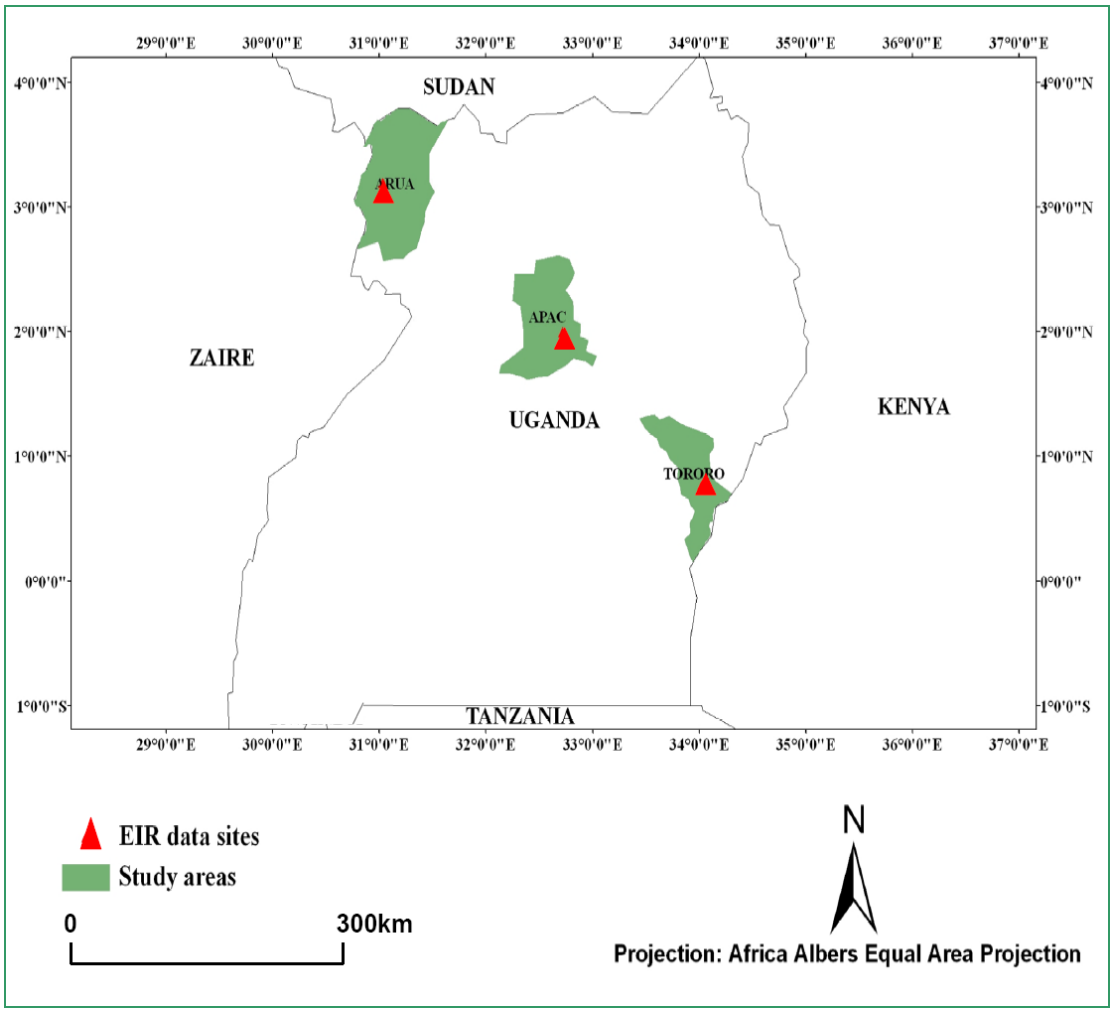

Figure 8: Locations in Uganda for which temporally repeated EIR data was available (n = 39)

3.6. Cameroon

Another area for which repeated monthly EIR data was available, and where temporal variations of EIR and NDVI could therefore be analyzed, was a rural village in the district of Haute Sanaga in central Cameroon (Figure 9). This village lies at approximately 583m altitude and has mean annual rainfall of 1719mm. Between February and December 1999 when data was collected, EIR varied from 48 to 188 and the main vector was *An. funestus* (Cohuet *et al*., 2003).

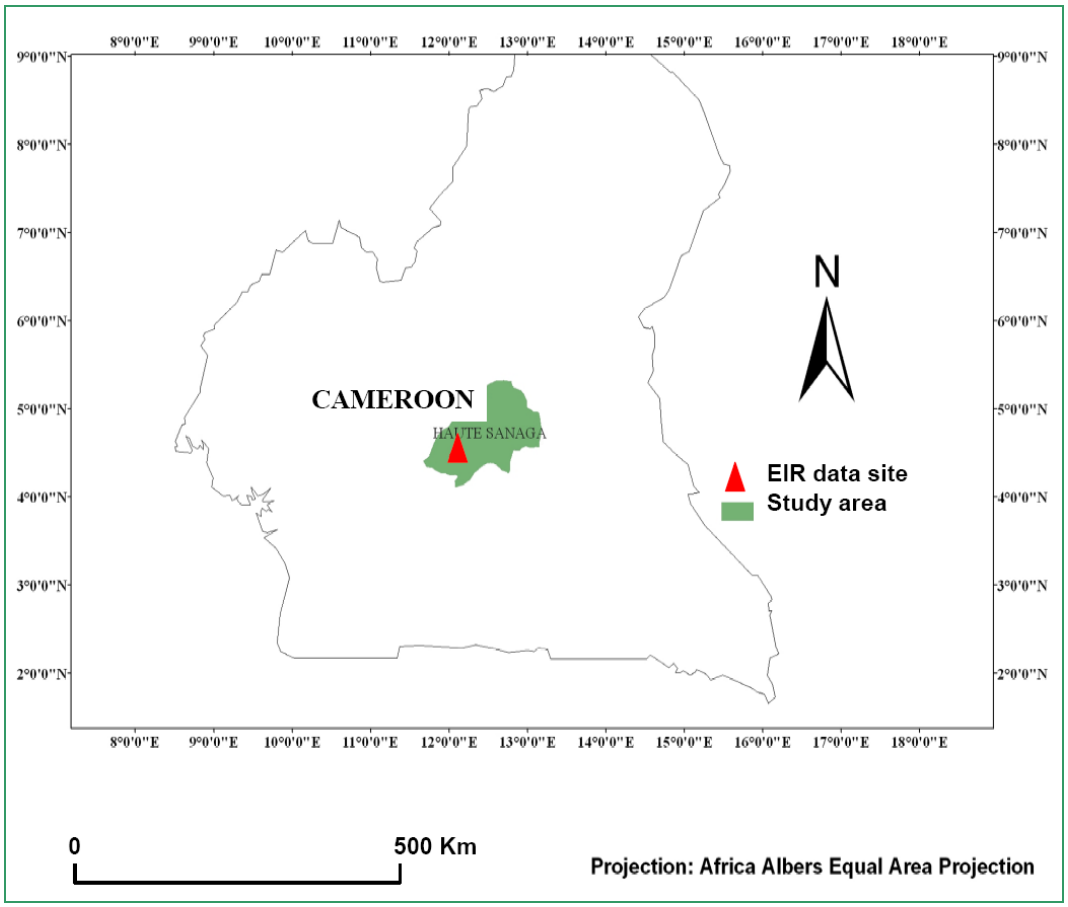

Figure 9: Locations in Cameroon for which temporally repeated EIR data was available (n = 8)

4.0. Datasets

4.1. Malaria transmission intensities

4.1.2. Published EIR data

The EIR data used here comes from published research papers dating from as early as 1981.The following inclusion criteria was used to select EIR data for this purpose: 1) the data must have been collected from Africa, 2) it must have been collected between 1981 and 2006, so as to match availability of the NDVI data (see section 4.2), 3) the author(s) must have explicitly specified the geographical coordinates of the study area, 4) the author(s) must have explicitly specified the start and end dates of their study and 5) the EIR must have been explicitly defined as daily, monthly or as annual EIR. A list of all the EIR data used here, including referenced sources is included in Appendix 1.

This EIR data is of two different types namely: 1) those obtained from MARA (Mapping Malaria Risk in Africa), an online database (http://www.mara.org.za/) and 2) those obtained directly from scientific publications. The MARA database has EIR records dating between 1979 and 1996, and was the source of most of the malaria transmission data used here (Appendix 1). In addition, direct internet searches were conducted, which yielded extra EIR data covering the period between 1995 and 2004 including a few studies conducted in mid 1990s, which were not in the MARA database. A total of 302 EIR entries matching the set inclusion criteria were obtained. These were distributed in 16 African countries, occasionally occurring in localized clusters or repetitively for several months (Figures 4-9). Generally, the EIR data was highly heterogeneous, across time and space with values ranging from as low as 0 (undetectable transmission) to as high as 3545 infectious bites per year in a rural village in Uganda (Okello *et al*., 2006).

This is illustrated in figure 10, which shows a frequency distribution of the data when grouped in classes with an arbitrary class-size of 50 values each.

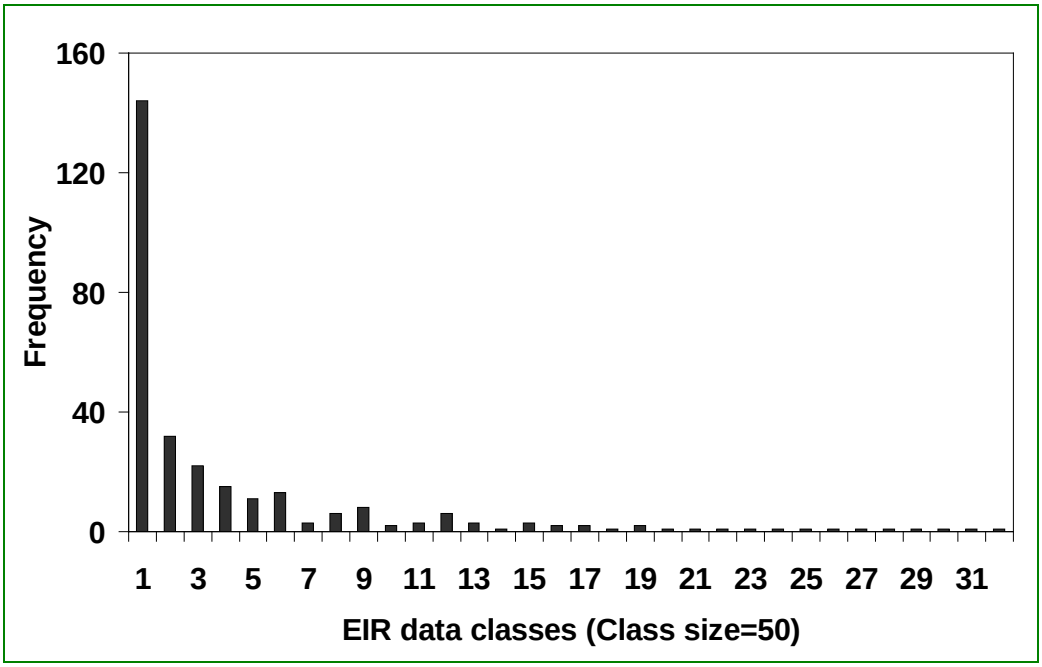

Figure 10: Frequency distribution of EIR data when grouped in consecutive classes of 50 values each from 0 to 3545. Classes with zero frequency are not included.

4.2. Vegetation production

4.2.1. The GIMMS NOAA-AVHRR NDVI data

The vegetation production data used for this study has previously been described in detail by Tucker *et al* 2005. It is archived at the Global Land Cover Facility http://glcf.umiacs.umd.edu/data/gimms/ in GeoTIFF format (Geographic Tagged Image Files), and is publicly available for download via a file transfer protocol (FTP) server. This data is most accurately identified as *Global Inventory Modeling and Mapping Studies (GIMMS) Satellite Drift Corrected and NOAA-16 incorporated Normalized Difference Vegetation Index (NDVI), monthly 1981-2006*, or simply as the GIMMS NOAA-AVHRR NDVI data (Tucker *et al*., 2005).

The data was derived from reflectances captured by Advanced Very High Resolution Radiometers (AVHRR), mounted on National Oceanic and Atmospheric Administration (NOAA) earth observation satellites. These satellites had originally been designed for meteorological purposes, but have increasingly been used for vegetation monitoring since early 1980s. Their sensors acquire data on five different spectral bands (or channels) including the red (0.5-0.7 micrometres) and infrared (0.7-1.1 micrometres) wavelength bands useful for vegetation monitoring, as well as three thermal infrared bands, mainly applicable for sea surface temperature monitoring. The GIMMS-NDVIs are computed based on reflectance data, measured as digital counts on bands 1 and 2 (red and infrared bands respectively), as described in equation 1.

The data is originally captured as 1.1km pixels but are resampled to 4km pixels using onboard data transformation algorithms (Tucker *et al*., 2005). Further resampling is done to achieve a spatial resolution of 8km, as a trade-off to suite storage requirements and maximize area of coverage. The data is available for the entire globe except Greenland and Antarctica and is composited such that for each month since July 1981 to 2006, there are two NDVI data files for all locations; first composite covering days 1 to 15 and a second composite for the same months covering days 16 to 30th or 31st.

Prior to archiving, this data underwent comprehensive processing to correct for several inherent effects, namely: 1) atmospheric interference such as persistent cloud cover, water vapor and volcanic aerosols, 2) intercalibration differences in characteristics between the different sensors used in different NOAA missions, 3) overtime change in sensitivities of the sensors due to sensor degradation and 4) satellite drift in the orbits. Also already performed was the conversion of data units from digital values measured by

the sensors to the actual reflectances necessary to calculate NDVIs. Lastly, the archived data is provided on Albers Equal Area Conic Projection, set on Clarke 1866 ellipsoid and it has been scaled so that the NDVI values range from -10000 to 10000. All water pixels are assigned the value of -10000 and masked pixels assigned the value of -5000.

4.3. Rainfall data

Rainfall data was obtained free of charge from the research data archives of the National Centre for Atmospheric Research, Colorado, USA (http://dss.ucar.edu/datasets/ds571.0. This dataset had originally been compiled by Dr. Sharon Nicholson at the Florida State University, USA. It consists of monthly rainfall totals for more than sixty weather stations across Africa, and covers the period between 1901 and 1984. For the purposes of this analysis, data was extracted for two weather stations located in two different climatic zones in Kenya, namely: i) Kitale, a forested agricultural area with high annual rainfall (averaging 1231mm) and ii) Mandera, a semi-arid grassland receiving low amounts of rainfall (130.5mm annual average).

This data set has been extensively reported upon, and rainfall-NDVI analyses have previously been conducted for several locations in Africa, including the two Kenyan sites considered here (Davenport and Nicholson 1993, Nicholson 1990, Richard and Poccard 1998). The data is therefore used here specifically to emphasize the fact that rainfall is the major factor affecting vegetation growth, and to highlight the potential of rainfall-NDVI relationships as a confounder of any relationships between NDVI and EIR.

4.4. Supplementary data

For each EIR data point, the following additional information was extracted from the research publications: 1) geographical coordinates, i.e. latitude and longitudes of the data collection site, 2) settlement status, i.e. whether the study site was urban or rural, 3) start and end dates of the study, 4) primary malaria vector specie(s) in the area during the period of the study, and 5) the elevation of the study site (in metres) above sea level.

In many cases, elevation data was available in the respective EIR publications but in some of the publications, it had not been expressly reported. Therefore to obtain a complete and uniform dataset, all the heights were determined anew using earth viewing software, Google Earth, version 5 (Google™, USA). These heights were generalized to represent each entire study area. Google Earth uses digital elevation model (DEM) data collected by NASA's Shuttle Radar Topography Mission and most land areas are covered in the satellite imagery with resolution of about 15m per pixel, which is considerably finer than the NDVI dataset used in this analysis. Similarly where the publications did not have explicit records of whether a study area was urbanized or rural, that information was obtained by direct viewing of the area in Google Earth (Google™, USA), to determine if it was urban or rural. Obviously, there may be other elevation datasets with greater accuracy and resolution than the Google Earth data, for example the 1 arc-minute resolution ETOPO-1 global relief model published by National Geophysical Data Centre (http://www.ngdc.noaa.gov/mgg/global/global.html). Nevertheless, the Google Earth data, apart from being readily and freely available in a fully processed format, was also considerably sufficient for this particular application, as the NDVI and EIR datasets with which it is compared, were compiled for higher resolutions of at least 8km per pixel.

5.0. Methods

5.1. Processing data in GIS

The collected data was first checked and corrected for inconsistencies such as inaccuracies of coordinate records and improper labelling. All the EIR data was then converted to a single standard unit of representation, i.e. annual EIR. Second, study dates obtained from the EIR published records were arranged in a chronological order so that NDVI images corresponding to these dates and locations could be identified and collated. This way, for each study and study site, all NDVI images for the entire study period were obtained and matched to respective dates and areas. The NDVI images were imported into ArcGIS® Desktop 9.2 (ESRI, USA) and projected to Africa Albers Equal Area Conic projection. To minimize file size and avoid mismatches, the NDVI data was grouped by dates and different data files created for each set of consecutive dates. For example if in one given area there had been three different studies dated Jan 1981 to Dec 1981, July 1981 to June 1982 and Jan 1982 to Dec 1982 respectively, would conveniently be analyzed from the same map file bearing all the NDVI map data for the period between January 1981 and December 1982.

Third, a shape file containing EIR data points for each study area was imported to the same map file as the respective NDVIs. Using the study area coordinates, the month and the year when the research had been conducted, NDVI values were sampled for each study site and the respective study durations. For example in the case of a study lasting January 1991 to December 1991, the entire range of NDVI values for that particular geographical location, were extracted for the whole of 1991. This means 24 NDVI parameter values for that particular study (since there were 2 NDVI composites per

month). The NDVI extraction was repeated for all the EIR data points. This procedure is analogous to '*drilling*' through layers of NDVI data files for different dates and extracting for each particular location, the respective NDVI values from every layer.

Since the original NDVI data had been scaled to the range of -10000 to +10000, (water pixels being represented as -10000) to facilitate storage, the extracted NDVI values needed were rescaled so as to fit the actual NDVI data range (-1 to +1) using the following formula as elucidated in the original data documentation (Tucker *et al*., 2005):

$$NDVI = Float \times \left(\frac{Raw}{10000} \right) \text{.....Eq...3}$$

5.2. Statistical analysis

The following estimates were computed for each EIR data point: mean NDVI, maximum NDVI, minimum NDVI and median NDVI. The importance of using these multiple estimates of NDVI was to extend the statistical spectrum of this exploration. Since EIR was highly heterogeneous, with initial scatter plots revealing considerable skewness, the data was first logarithmically transformed to minimize these excessive variations and to make it readily amenable to statistical analysis using parametric methods:

$$y = Log_{10}(X + 1) \text{.....Eq...4}$$

where **'**X**'** is the actual EIR value for any data point and the value 1 is added to give statistical meaning to any zero values in the dataset, during the transformation.

The elevation data was grouped into classes of 250 metres each and the classes were ranked from lowest to highest (rank values: 1-7). On the other hand, urbanization was coded as 1 or 0 to represent rural and urban areas respectively. Statistical tests were conducted using SPSS® software version 15 (SPSS inc. Chicago USA).

Effects of elevation and urbanization on vegetation production were first analyzed separately using generalized linear regression models. Next, a multivariate regression analysis was conducted in which EIR was modelled as a function of NDVI, making sure that effects of both urbanization and elevation were corrected for:

$$y = a + bx + b_1x_1 + b_2x_2 + e \text{.....} Eq...5$$

where y is the log transformed value of EIR, a is the y-intercept and b, b_1 *and* b_2 refer to the slopes of the regression line representing change in EIR for each respective change in NDVI (x), elevation (x_1) or urbanization (x_2) and e is the residual error estimate. In order to include urbanization, as a categorical variable in the multiple regression analysis, rural areas were coded as 0 while urban areas were coded as 1. To estimate the strength of the modelled relationships, a goodness of fit statistic, i.e. R-squared (R^2), representing the proportion of variations in EIR, which can be explained by the best fit linear regression equations, and the probability that the regression model is not the correct fit so that the slope is zero (significance value) were also calculated.

Using this method, the relationships were explored for different categories as follows: 1) continent-wide relationship, explored on the basis of all the data obtained, 2) local level spatial relationships, explored for areas where spatially clustered EIR data were available (The Gambia, three clusters in Tanzania and two clusters in Burkina Faso) and 3) temporal relationships explored for areas where consecutively repeated EIR measurements collected on monthly basis were available (one village in Cameroon and three villages in Uganda).

For the temporal analyses, the NDVI data was lagged by combining means of previous month and current month NDVIs. This lag considers the fact that vegetation

production and malaria transmission respond at different rates to the different climatic factors, such as rainfall, and therefore enabled representation of changes manifesting as late as one month after being initiated. None of the data obtained from the MARA database was suitable for this temporal analysis; thus only the data extracted directly from research publications was used for this purpose. A similar regression analysis was performed to assess relationships between NDVI and rainfall. In this case however, three-month composite moving averages of rainfall were used, such that each NDVI value was matched with the average of the concurrent and two previous monthly rainfall data, as originally described by Davenport and Nicholson (1993).

6.0. Results

6.1. Relationship between vegetation growth and rainfall

When NDVI data is analysed against three-monthly moving averages of rainfall, the patterns and intensity of rainfall are directly comparable to patterns and intensity of vegetative productivity for the 1983-84 period in both Kitale ($t = 6.25$, $R^2 = 0.71$, $P < 0.001$) and Mandera ($t = 9.44$, $R^2 = 0.77$, $P < 0.001$)) (Figure 11).

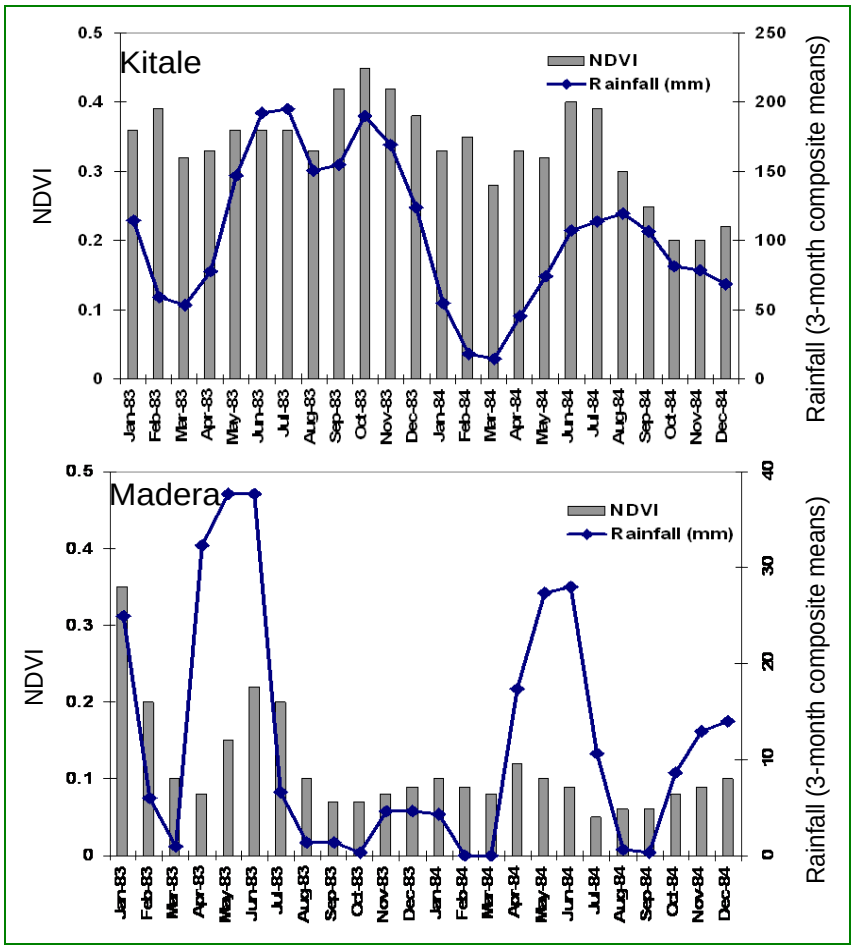

Figure 11: Relationship between vegetation productivity (grey bars) and 3-monthly moving rainfall averages (line graphs) for Kitale (a forested agricultural zone in western Kenya) and Mandera (a semi-arid grassland area in northern Kenya).

Since the Nicholson rainfall data extended only up to the end of 1984, even though the NDVI data spanned from as early as mid 1981, this NDVI-rainfall trend analysis was restricted to cover only the period during which the two datasets overlapped.

6.2. Effects of elevation and urbanization on vegetation production and malaria transmission intensities

Initial analysis indicates that elevation is strongly associated with NDVI in the different study sites (table 1). Analysis of trends shows that NDVI is significantly higher in high altitude areas, when compared to low altitude areas ($t = 8.75$, $P < 0.001$, $R^2 = 0.23$). Malaria transmission intensities also increase with altitude but only up to about 1000m, after which transmission evidently reduces despite continued increase in altitude (Figure 12). In fact, when both NDVI and EIR are plotted against altitude in the same graph, it appears that any association between vegetation production and malaria transmission is limited to areas not exceeding approximately 1000m altitude, and that beyond this height, there is no linear relationship between the two variables (Figure 12).

Similarly it is observed that NDVI is significantly higher in rural areas that in urban areas ($F = 16.09$, $P < 0.001$). Rural areas have a mean NDVI value of 0.478 (95%CI 0.458 - 0.497), n=250, while urban areas have mean NDVI value of 0.387 (95%CI 0.337 – 0.437), n=42. Analysis using a Generalized Linear Model also shows significantly higher malaria transmission intensities in rural areas than in urban areas. In fact, analysis of odds of being infected with malaria reveals that people living in rural areas (which in general are areas with higher NDVIs) are 2.14 (1.58 - 2.89) times more likely to contract malaria than people living in urban areas, which generally have lower NDVIs ($P < 0.001$).

Table 1: Correlation between elevation and NDVI in the different parts of Africa from where EIR data was collected.

Elevation (Meters)	Mean NDVI	95% CL	N
0-250	0.391	0.359 - 0.423	104
250-500	0.426	0.401 - 0.451	69
500-750	0.452	0.398 - 0.506	23
750-1000	0.582	0.529 - 0.635	18
1000-1250	0.545	0.506 - 0.584	51
1250-1500	0.628	0.588 - 0.669	24
Above 1500	0.620	0.554 - 0.686	3

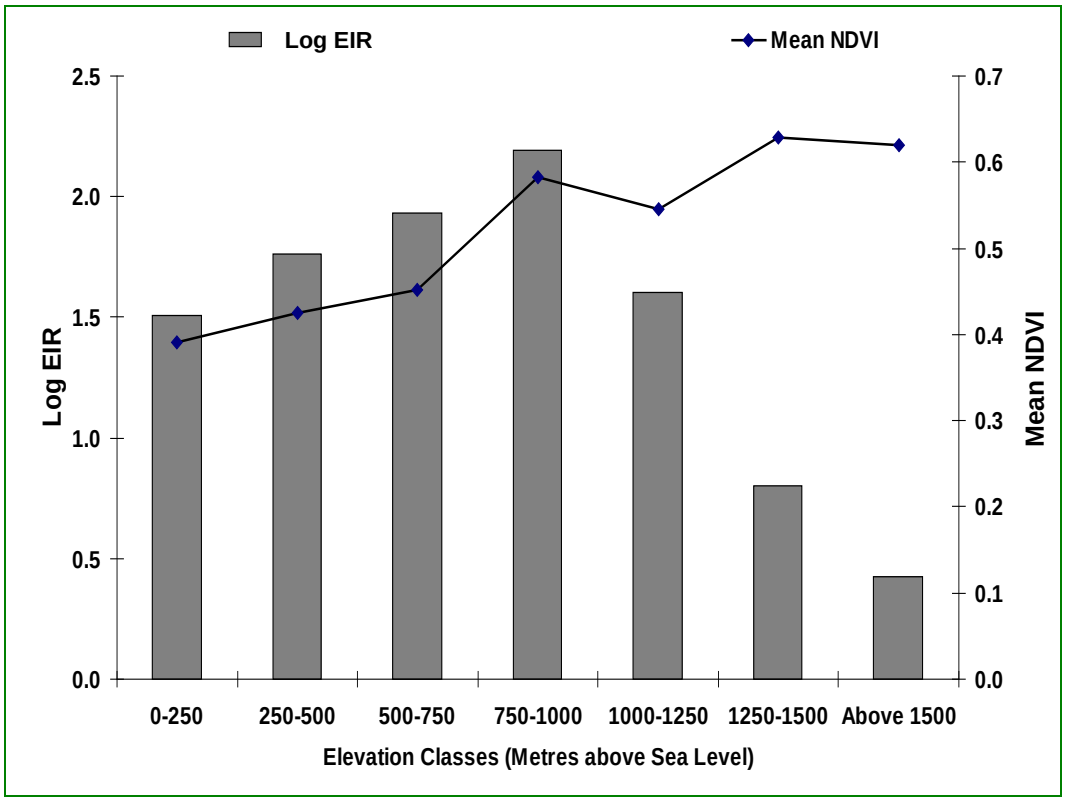

Figure 12. Trends of variations in malaria transmission intensities (grey bars) and vegetation production (line graph), when plotted alongside increasing elevation (metres above sea level). While NDVI increases with elevation even beyond 1000m, malaria transmission intensities increase only up to about 1000m, after which it evidently reduces despite any further increase in altitude.

6.3. Overall continent-wide association between vegetation production and malaria transmission intensities

A scatter plot showing the overall relationship between LogEIR and Mean NDVIs is shown in figure 13. If all the data from the continent is considered, and after correcting for effects of urbanization and elevation, malaria transmission intensities (EIR) remains significantly associated with vegetation production ($t=3.329$, $P<0.001$). Table 2 shows effects of the different variables on malaria transmission in Africa.

Table 2: Results of the multiple regression analysis showing effects of vegetation production on malaria transmission intensities, after correcting for effects of urbanization and elevation[$].

Factors	Regression Coefficients	Std. Error	t	P	95%CL
Urbanization	0.762	.154	4.942	.000	.459 to 1.066
Elevation	-0.114	.034	-3.321	.001	-.181 to -0.046
NDVI	**1.347**	**.405**	**3.329**	**.001**	**.551 to 2.144**
Intercept	0.627	.193	3.252	.001	.247 to 1.007

[$] Since urbanization was treated as a binary variable and coded as either 1 or 0 for rural and urban areas respectively, the given urbanization coefficient is applicable only where a place is rural, otherwise the coefficient is zero. Similarly, the elevation coefficients are based on height class values (1 to 7) as opposed to the actual elevation values. The regression coefficient for NDVI represents the effects of vegetative productivity on malaria transmission intensities, having allowed for effects of urbanisation and elevation.

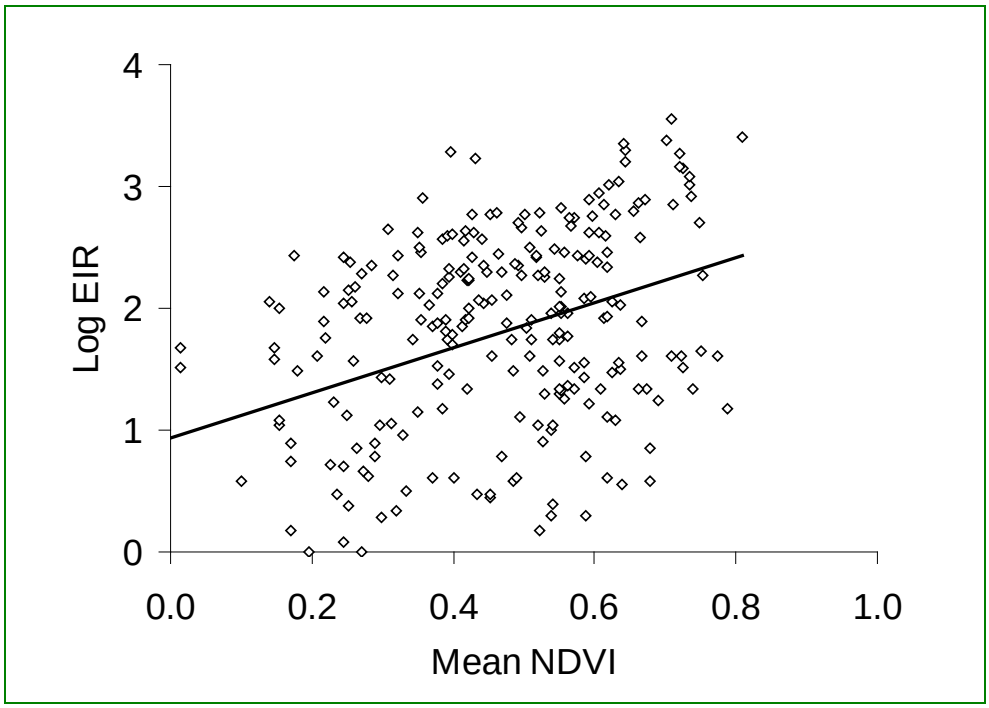

Figure 13: Continent-wide correlation between malaria transmission intensities and vegetation production in Africa (R^2 = 0.15). Based on the regression coefficients shown in table 2, the best fitting linear regression model is: *Log (EIR+1) = 0.63 + 1.35**NDVI** +0.762**R** – 0.114**E***, where ***R*** is the dummy variable referring to whether the place was rural (R=1) or urban (R=0) and ***E*** refers to elevation class value (1≤***E***-≤7).

6.4. Temporal relationships between vegetation production and malaria transmission intensities in selected study sites having monthly repeated EIR data.

6.4.1. Uganda

This analysis covers for the period between June 2001 and May 2002, when the temporally repeated data was collected. In Apac district, the peak vegetative productivity appears to have been between April and July 2001. Nevertheless, productivity remained generally high, with just a minor sink between August and October 2001. Then around January 2002, productivity was greatly decreased and NDVI remained below 0.5 for two

months. Malaria transmission clearly follows the same trend with the lowest EIR values having been at the same time as when vegetation production was also lowest (Figure 14). Linear regression analysis shows a significant relationship between malaria transmission and vegetation productivity in this area (t=3.10, P = 0.01, R^2 = 0.49), the best fit linear regression model being, Log EIR = 2.07*NDVI* + 1.80.

Generally, similar trends of NDVI and EIR for this period are observable also for Arua district, even though in this area malaria transmission remained low during the peak productivity season in June and July 2001. Data from this site shows a barely significant relationship between the two variables (t = 1.48, P = 0.69, R^2 = 0.19). Lastly in Tororo, where changes in vegetation productivity trends appear to have been mainly gentle with peaks in December and May 2001, EIR follows the same trend peaking and falling either at the same month as NDVI or a month earlier for example as observed in April 2002 (Figure 14). However, similar to Arua, statistical analysis of these trends shows no significant relationships between NDVI and EIR (t = 0.473, P = 0.646, R^2 = 0.02).

6.4.2. Cameroon

Unlike in Apaca, Uganda, data from the village in Haute Samaga district, southern Cameroon depicts no significant relationship between mean NDVI and logEIR (t = 0.758, P = 0.49, R^2 = 0.13). The monthly vegetation production trends are also not comparable to malaria transmission trends in the selected area.

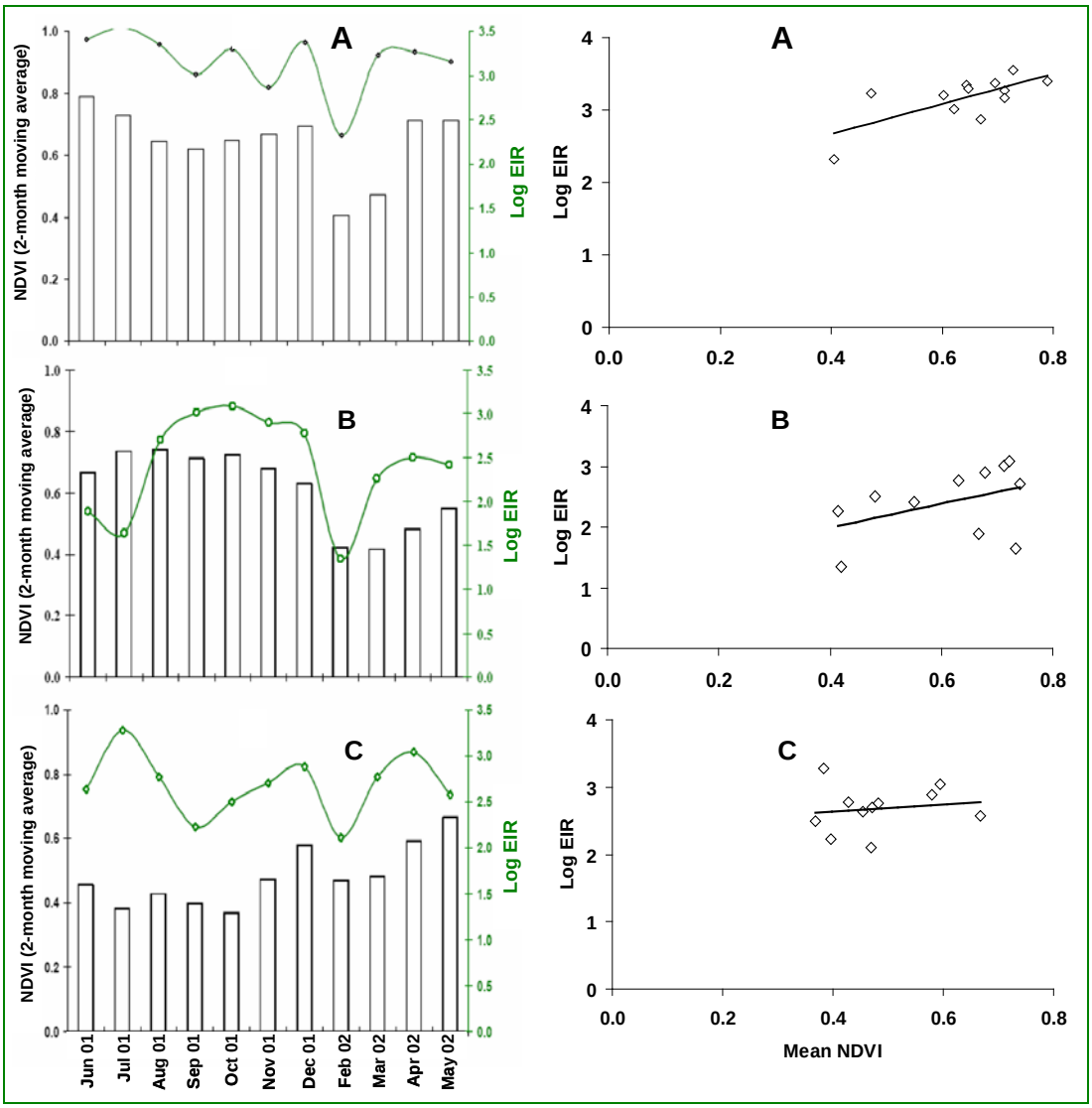

Figure 14: Comparison of monthly phenology of vegetation production (open bars), and malaria transmission (green lines) between June 2001 and May 2002 in three sites in Uganda. The regression trends of log EIR on mean NDVI shown on the right side of each graph for the three sites: **A)** Apac district (R^2 = 0.49), **B)** Arua district (R^2 = 0.19) and **C)** Tororo district (R^2 = 0.02) in Uganda.

6.5. Spatial relationship between vegetation production and malaria transmission intensities in selected study sites with locally clustered EIR data.

6.5.1. The Gambia

Based on this analysis, there is a strong and statistically significant association between vegetation production and malaria transmission in The Gambia ($t = 5.81$, $P < 0.001$, $R^2 = 0.74$). EIR clearly increased with increasing NDVI during the time when the EIR data was collected. As shown in figure 15, the best fit regression model expressing EIR as a function of median NDVI is Log (EIR+1) = 9.1 NDVI – 1.9, which explains up to 74% of variations in malaria transmission in this study area ($R^2 = 0.74$).

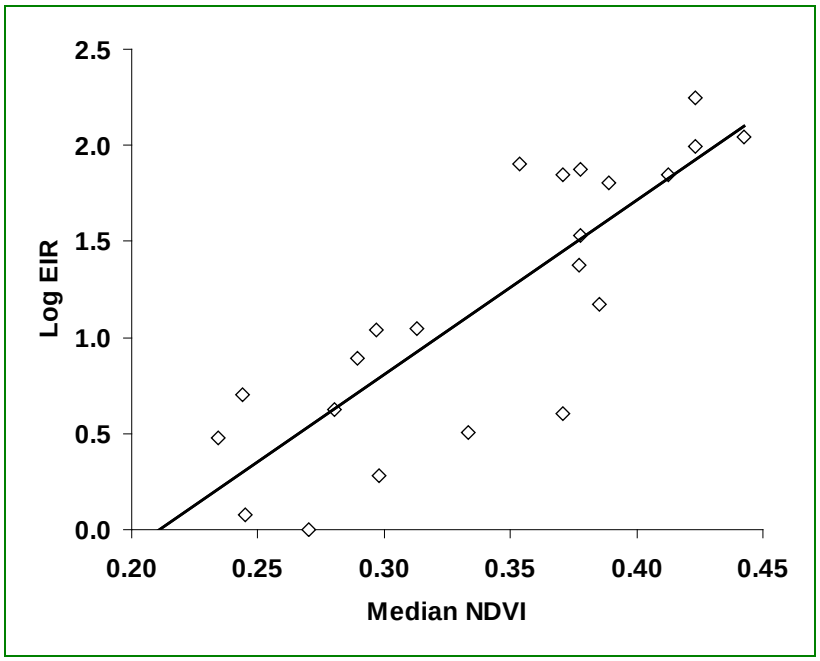

Figure 15: Relationship between vegetation production and malaria transmission intensities in The Gambia. Regression equation: LogEIR = 9.1NDVI – 1.9 and R^2 =0.74. Since all data from this area fall within the same elevation class and since all except one are in rural areas, the regression equation does not include terms for urbanization or elevation.

6.5.2. Burkina Faso

In spatial cluster 1 (i.e. the area covering six districts in south west of Burkina Faso) there appears to be a strong and significant relationship between NDVI and EIR (t = 2.95, P = 0.008). Here, EIR increases with increasing NDVI and the best-fit model was logEIR = 7.5 NDVI - 1.1, which explains nearly 30% of variations in malaria transmission in the area (R^2 = 0.29). Moreover, in cluster 2 (i.e. the area covering four districts in central part of Burkina Faso), where there were relatively fewer data points, linear regression analysis depicts the strongest relationship in this entire exploration (t = 4.81, P = 0.009, R^2 = 0.85). EIR here is evidently higher when or where NDVI is high and *vise versa*. The best-fit equation is logEIR = 15.12 NDVI– 2.0. In both clusters however, no effects are observed of urbanization (t=0.232, P=0.832) or elevation (t=1.450, P=0.243) on EIR or on the correlation between EIR and NDVI.

6.5.3. United Republic of Tanzania

Figure 16 illustrates a summary of analysis results for the Tanzanian data. In the first spatial cluster (i.e. Kilombero District, south eastern Tanzania), it is clear that after adjusting for the effects of both urbanization and elevation, EIR remains strongly associated with vegetation production (t = 2.670, P = 0.049, R^2 = 0.82). In contrast data from the second cluster (i.e. Bagamoyo district, north eastern Tanzania) shows that malaria transmission intensities in this study site are only marginally statistically associated with vegetation production (t = -2.35, P = 0.057, R^2 = 0.48). Finally, in the third spatial cluster (i.e. areas around Muheza, Korogwe and Pangani Districts, north eastern Tanzania), there is also a marginally significant relationship between EIR and NDVI (t = 2.214, P = 0.061, R^2 = 0.51,).

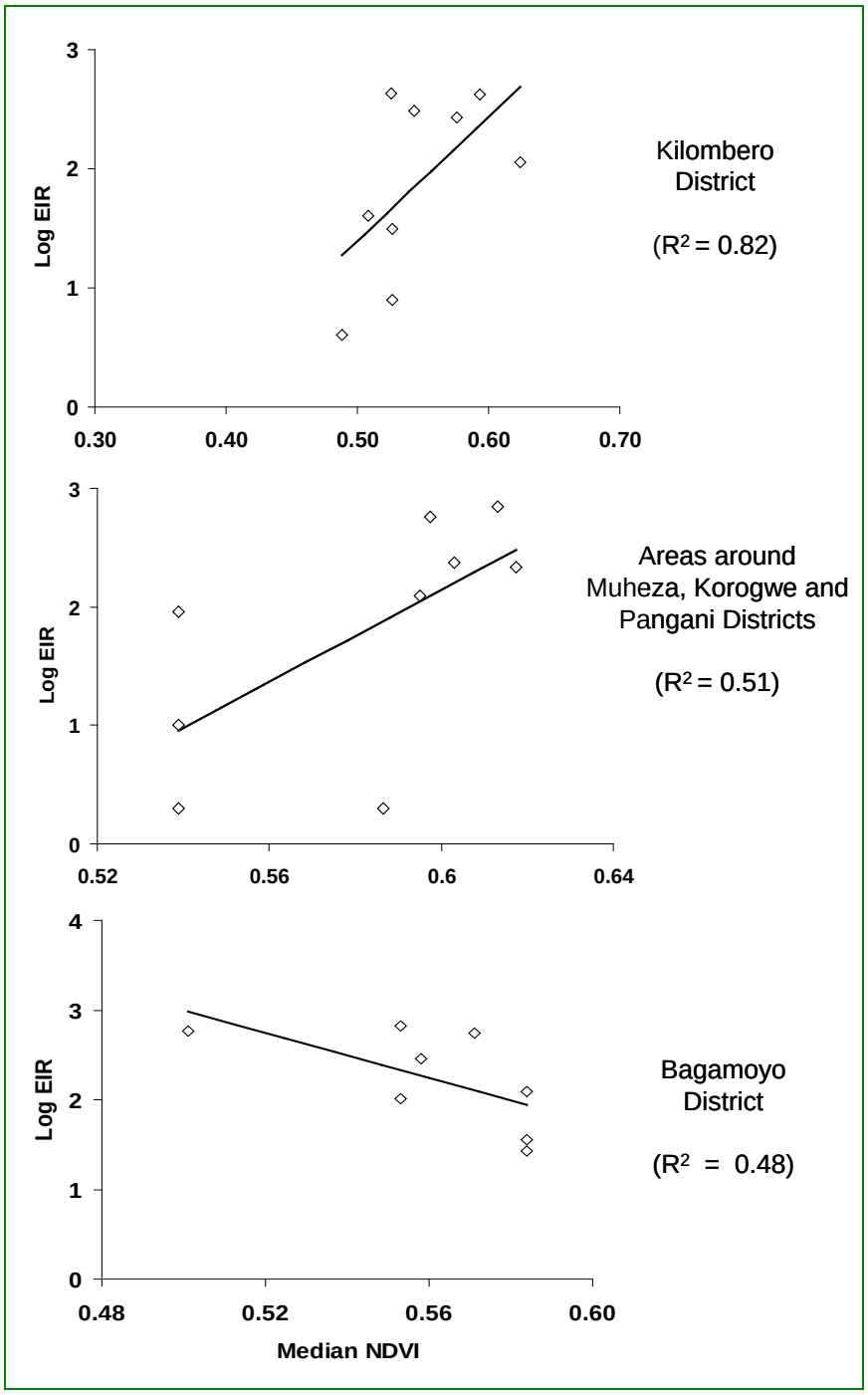

Fig. 16: Relationship between vegetation production and malaria transmission intensities in three selected areas in Tanzania, for which clustered EIR data was available.

7.0. Discussion

Vegetation production is a unique environmental variable which is essentially dependent on the same climatic factors as malaria transmission, but which can be more accurately represented using indices calculated from remotely sensed data such as Normalized Difference Vegetation Index (NDVI). This kind of data can be obtained at varying spatial resolutions, allowing vegetation production to be measured as a local environmental variable, depicting differences even for small villages.

Using GIS-based techniques, together with multiple linear regression analysis, this study has confirmed the hypothesis that variations in malaria transmission intensities in Africa are very closely associated, both spatially and temporally, to photosynthetic productivity of vegetation. This study was restricted to basic exploration and therefore no attempt has been made to predict malaria transmission on the basis of vegetation production. However, the results demonstrate that indeed vegetation production is a potential indicator of conditions for malaria transmission and that NDVI may therefore be incorporated in existing or new techniques to improve mapping of geographical and temporal extents of malaria risk.

Though the NDVI-EIR relationship exists on a continent-wide scale, it is evidently stronger when localized data are considered. One especially interesting finding of this study is that people living in rural areas in Africa are at least two times more likely to contract malaria than people living in urban areas in Africa. Also, urban areas have poorer or fewer quantities of vegetation than rural areas, which may be due to the fact that urban areas consist of more built up areas with hard surfaces. Indeed, this study also shows that differences in vegetation production between urban areas and rural areas

correspond to differences in malaria transmission intensities in these areas. A similar confounding effect was observed for altitude, which also likely affects vegetation production in a manner equivalent to its effects on malaria transmission. These findings thus reinforce vegetation production as a potential indicator of areas suitable for malaria transmission, and thus a potential candidate to consider when fine-tuning transmission extents in malaria risk maps (Hay *et al*., 2005, Hay and Tatem, 2005).

NDVI data sets, particularly those derived from NOAA-AVHRR are already widely popular in several fields e.g. agriculture, industrialization and environmental monitoring. For example, it has previously been used for assessing land degradation and evaluating environmental conservation programs (Chen *et al*., 2005, Runnström, 2000) and also to monitor progression of deserts (Tucker *et al*., 1983, Tucker *et al*., 1985). Moreover, public health applications of this data are also gradually increasing (Hay *et al*., 1998, Rogers *et al*., 2002a). Other than the many characteristics of the GIMMS-NDVI dataset (Section 4.2.1), another advantage of using vegetation production (rather than natural climatic factors) to describe geographical patterns of disease, is the greater susceptibility of vegetation to human activities. There are situations where vegetation production responds to human activities in ways that are not in any way correlated to changes in natural factors such as temperature and rainfall. An example is when artificial precipitation, such as crop irrigation, causes an increase in vegetative productivity. This situation of 'productive vegetation without rainfall' would likely render rainfall-based mapping-algorithms erroneous. Situations like these, which in Africa commonly occur around rice irrigation schemes, large water projects or river valleys, may be readily corrected by incorporating vegetation production data in the analyses. This is because

both malaria transmission and vegetation production readily respond to increased precipitation, whether natural or man made.

As revealed by this exploratory study, these associations between vegetation production and malaria transmission are however not universal throughout the continent; there are places with strong significant correlations between these two variables, and also areas where no such associations exist. Moreover the observed NDVI-EIR relationships appear to be actually stronger in some places than in others. While it was not possible to precisely determine causes of these differences, they are likely to be because of the fact that other than the underlying primary climatic factors such as rainfall and temperatures, there may be several other modifiers affecting vegetation growth and malaria transmission independently. For example, vegetation production may be affected by factors such as soil type acting independently of rainfall (Baret and Guyot 1991). Similarly, vegetation-rainfall relationships are known to remain valid only when rainfall is at least 1000mm annually (Nicholson, Davenport 1993), meaning that even if there were a perfect relationship between NDVI and EIR, it would potentially be confounded by amount of rainfall, soil type, human activities or other local environmental factors.

The broad spatial and temporal coverage of the GIMMS-NDVI and the EIR data used in this analysis makes it particularly appropriate. This study covers not only the entire region of malaria endemic Africa, but also 23 years of NDVI data (1981-2004). While the 8km pixel size of the GIMMS-NDVI data may be considered extra-coarse for some applications, it has been a practically reasonable dataset for this work, given the fact that EIR data with which it is compared has been generalised for entire villages or towns.

One limitation of this work is its restriction to only the available data, i.e. the archived NDVI data and published EIR results. This biased sampling means that other malaria endemic places with no recorded previous entomological surveys could not have been included in the analysis. It can be argued therefore that this analysis would have greatly been improved if there had been evenly distributed sentinel data collection stations across the study area. Good examples where such an approach have been of immense benefit include the use climate stations data for land degradation monitoring in semi-arid China (Runnström, 2000) and vegetation growth and rainfall trends in Africa (Richard and Poccard 1998).

Another limitation of this study was that it did not consider whether of not there had been any major malaria intervention projects at the time when the EIR data was collected. It is possible that such interventions would have lowered malaria transmission in ways that would weaken the correlations with vegetation production. Indeed malaria control methods such as the use of Insecticide Treated Nets (ITNs) or Indoor Residual Spraying (IRS) of insecticides are proven to greatly disrupt transmission (Kusnetsov, 1977, Curtis and Mnzava, 2000, Mabaso *et al*., 2004). Nevertheless, such effects may not have been widespread in the 1980s and 1990s when most studies considered here were conducted. At that time, ITNs were not yet part of public health policy in Africa, IRS had been stopped in most countries after the failure of the global malaria eradication program in late 1960s and malaria transmission control activities had generally been nearly relegated (Lengeler, 2004). These results may therefore be confidently considered as being closely representative of natural relationships between malaria transmission and vegetation production.

8.0. Conclusion and recommendations

It is concluded that changes which occur in the photosynthetic productivity of vegetation from time to time and from place to place are related to the changes in malaria transmission at the respective places and times. This relationship is stronger when localised data is considered as opposed to when data from the whole continent is considered. Moreover, factors such as urbanization and elevation which affect vegetation growth are also correlated to malaria transmission intensities. The implication of these results is that vegetation production is a potential indicator of geographical locations where existing factors are favourable for malaria transmission to occur. For purposes of delineating geographical extents of malaria risk areas, vegetation production may for the basis of mapping techniques that are free numerous errors that abound when climatic factors such as precipitation, humidity, temperatures, altitude, topography, among others are used for mapping the risk and extents of malaria and perhaps other vector borne diseases. More accurate results would be obtained if such vegetation based algorithms are used for small local areas such as neighbouring villages and districts than if they are used for large scales such as an entire continent.

9.0. References

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Appendix 1: Data sources

1. Vegetation production data_
    - Obtained from the Global Land Cover Facility archives: http://glcf.umiacs.umd.edu/data/gimms/
2. Rainfall data
    - Obtained from the research archives of the National Centre for Atmospheric Research, Colorado, USA: http://dss.ucar.edu/datasets/ds571.0.
3. Altitude and urbanization data
    - Obtained from Google Earth
4. Malaria transmission data
    - Obtained from MARA (Mapping Malaria Risk in Africa): http://www.mara.org.za/.
    - For a complete list of references to the data including those from the MARA database as well as all the other data, see Appendix table 1 below.

5. Number and references of EIR data points obtained from different publications (Includes both the MARA publications and those obtained from elsewhere)

Author(s)	*Number of EIR data points obtained
Akogbeto & Nahum, 1996 , Akogbeto *et al*., 1992, Akogbeto, 1995	1, 3, 1
Babiker *et al*., 1997	1
Beier *et al*., 1990, Beier *et al*., 1994	2, 1
Biro, 1987	1
Bockarie *et al*., 1993, Bockarie *et al*., 1994, Bockarie *et al*., 1995	1, 4, 1
Boudin *et al*., 1991	1
Carnevale & Robert, 1987, Carnevale *et al*., 1988, Carnevale *et al*., 1992	12, 3, 1
Charlwood *et al*., 1998	1
Coene, 1993	2
Coosemans, 1985	1
Curtis, 1998	1
Dossou-yovo *et al*., 1995	2
Faye, 1992, Faye *et al*., 1993, Faye *et al*., 1994, Faye *et al*., 1995a, Faye *et al*., 1995b	1, 3, 2, 1, 2
Fondjo *et al*., 1992	1
Fontenille *et al*., 1990, Fontenille *et al*., 1992, Fontenille *et al*., 1997a , Fontenille *et al*., 1997b	1, 1, 5, 3
Gazin *et al*., 1988, Gazin *et al*., 1996	2, 1
Githeko *et al*., 1993	2
Ijumba *et al*., 1990	1
Karch *et al*., 1992, Karch *et al*., 1993	3, 1
Konaté *et al*., 1994	1
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