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Application of Geographical Information Systems and Remote Sensing technologies for assessing and monitoring malaria risk

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Abstract. Despite over 30 years of scientific research, algorithm development and multitudes of publications relating Remote Sensing (RS) information with the spatial and temporal distribution of malaria, it is only in recent years that operational products have been adopted by malaria control decision-makers. The time is ripe for the wealth of research knowledge and products from developed countries be made available to the decision-makers in malarious regions of the globe where this information is urgently needed. This paper reviews the capability of RS to provide useful information for operational malaria early warning systems. It also reviews the requirements for monitoring the major components influencing emergence of malaria and provides examples of applications that have been made. Discussion of the issues that have impeded implementation on a global scale and how those barriers are disappearing with recent economic, technological and political developments are explored; and help pave the way for implementation of an integrated Malaria Early Warning System framework using RS technologies.

Key words: malaria, epidemic, Remote Sensing, Geographical Information Systems, Early Warning System.

Given its impact on populations and the gravity of its pathology, malaria remains one of the most significant infectious diseases. Malaria is a leading cause of morbidity and mortality in the developing world, especially sub-Saharan Africa where the transmission rates are highest and where it is considered to be a major impediment to economic development (Sachs and Malaney, 2002). Malaria is a preventable and curable disease whose causal agent, a *Plasmodium* spp. parasite, is transmitted throughout the globe by a select number of *Anopheles* vector mosquitoes. It is essentially an environmental disease since the vectors require specific habitats with surface water for reproduction, humidity for adult mosquito survival and the development rates of both the vector and parasite populations are influenced by temperature. In Sub-Saharan Africa the pattern of malaria transmission varies markedly from region to region, depending on climate and biogeography, and broad ecological categories have been widely used to describe variations in the observed epidemiological patterns (Mouchet *et al.*, 1993). Towards either end of this spectrum of variation malaria transmission is classified as stable or unstable (Gilles, 1993). A region prone to stable malaria is characterized by high transmission levels with little inter-annual variation. In these areas, collective immunity to the disease in the population is high and epidemics are unlikely. A region prone to unstable malaria is characterized by transmission levels that vary from year to year. In these areas, collective immunity is low and disease, when it does occur, affects all age groups and is often severe (Wernsdorfer and McGregor, 1988). Unstable malaria areas are essentially found in warm, semi-arid zones, tropical mountainous areas, and regions where previous levels of control are beginning to fail. It has long been known that in these areas any change in temperature, relative humidity or rainfall can have a major impact on malaria transmission, possibly leading to epidemics (Najera, 1989).

Although tremendous progress has been made globally in fighting the vector and the parasite (Najera, 1989), the situation is far from being resolved, especially in Africa.

Since 1993 there has been a pragmatic global malaria control strategy based on a Primary Health Care approach. Its aims are to: a) reduce mortality and the negative social and economic consequences of the disease; b) prevent epidemics; c) protect malaria free areas; d) eradicate malaria where possible (WHO, 1993). Such a control strategy requires recognition of the underlying variability in the epidemiology of the disease, potential for modification, availability of resources and need to adapt malaria control planning to local conditions in areas where there is a reasonable chance of success.

One of the new approaches to better understand the variability in the epidemiology of the disease depends on knowledge of biodiversity. Specifically, the distribution and ecology of the vectors and the parasites are considered within a context of a climatic and anthropogenic environment which is in perpetual evolution.

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This biodiversity is determined by many factors:
- Environmental: rainfall, temperature, vegetation;
- Biological: competence of the vectors (transmission), biology of each species of *Plasmodium*; and suscecptibility of the host to disease;
- Anthropogenic: deforestation, irrigation, urbanization, movements of populations and economic changes.

Although successful eradication of malaria has been achieved in many countries, in Europe and the USA, where it was still endemic not so long ago (last century), the situation is still problematic in many regions of the globe (Najera, 1989). Several initiatives have been launched to reduce malaria on the various continents where the disease still prevails or is re-emerging. In May 1998, the Director-General of the World Health Organization (WHO) announced a United Nations-led campaign to Roll Back Malaria (RBM), pledging to halve malaria deaths by 2010. One of the Millennium Development Goals (MDGs), initiated at the turn of the century, is to combat malaria while Global Fund to Fight AIDS, Tuberculosis and Malaria (GFATM) also provides a mechanism for increasing the global resources allocated for fighting the disease. The African situation is by far the worst where the number of deaths is actually increasing (Attaran, 2004). The reasons for the persistence and re-emergence of malaria are many and varied. Environmental changes, economic reasons, declining control programs and mosquito/parasite adaptation to pesticides/drugs, all contribute to the development of the disease.

During the last twenty years, the development of Geographical Information Systems (GIS) and satellites for earth observation have made it possible to make important progress in the monitoring of the environmental and anthropogenic factors which influence the reduction or the re-emergence of the disease. Analyses resulting from the combination of GIS and Remote Sensing (RS) have improved knowledge of the biodiversity influencing malaria. A better understanding of the stratification of malaria and the burden of the disease on the population is in–progress (Craig *et al.*, 1999; Snow *et al.*, 1999; Omumbo *et al.*, 2004). This knowledge can help decision-makers to better allocate limited resources in the fight against the disease.

This review summarizes the recent advances in GIS and RS in the prevention and fight against malaria. Examples of applications in various areas of the globe are provided to support current knowledge on the use of the new monitoring and early warning systems.

Principles that govern emergence of malaria

The severity of malaria is a function of the interaction between the **parasite**, the *Anopheles* **mosquito vector**, the **human host** and the **environment**. Vector abundance, duration of the extrinsic incubation period and survival rate of the vector, combined with the probability of the vector feeding off a susceptible human host determine the risk of malaria infection, the stability of disease transmission, and seasonal patterns. Many factors are involved in determining the evolution of the parasite, the vector, the human and the environment. Hackett wrote 'Everything about malaria is so molded by local conditions that it becomes a thousand epidemiological puzzles'. Like chess, it is played with few pieces, but is capable of an infinite variety of situations'. If we are to see order within the chaos we must consider that most of the factors are interrelated and it is necessary to take into account these inter-relationships in a holistic approach to understand the components which influence the development of malaria; we must also understand the differing scales at which each factor play out its influence on the overall game. In our review we have tried to separate them into three different components for analysis knowing that their interactions are key elements. The following sections review the importance of each component and discuss the possibility of mapping its spatial and temporal distribution.

Ecology of Malaria

Rainfall

Different malaria vectors use a variety of sites in which to lay their eggs (irrigation canals, tire ruts, mangrove swamps, pools, etc.) as long as the water is clean, not too shaded and, for most species, relatively still. In many semi-arid areas these sites are only widely available with the onset of the seasonal rains unless dry season irrigation is undertaken. The association between rainfall and malaria epidemics has been recognized for many decades (Christophers, 1911) but while increasing precipitation may increase vector populations in many circumstances by increasing available anopheles breeding sites, excessive rains may also have the opposite effect by flushing out small breeding sites, such as ditches or pools (Fox, 1957) or by decreasing the temperature, which in regions of higher altitude can stop malaria transmission.

In tropical Africa rain is largely produced from deep convective storms and the clouds with the coldest top surface temperature produce the heaviest rainfall. It is possible to derive estimates of rainfall by measuring cloud top temperatures using thermal infrared images from Meteosat. At a certain threshold temperature (-40 to -70ºC depending on latitude and season) clouds will precipitate into rainfall. By measuring the length of time a cloud is at this critical threshold temperature, knows as the Cold Cloud Duration (CCD), it is possible to estimate the amount of rainfall using a simple regression technique (Milford and Dugdale, 1990).

Using such technique, Rain Fall Estimates are produced on a decadal basis and provided to the user community by the Africa Data Dissemination Service (ADDS) website supported by USAID FEWS NET. The methodology uses an interpolation method to combine Meteosat and Global Telecommunication System (GTS) data, and includes warm cloud information for the decadal estimates. Meteosat 7 geostationary satellite infrared data are acquired in 30-minute intervals, and areas depicting cloud top temperatures of less than 235K are used to estimate convective rainfall. WMO GTS data from ~1000 stations provide station rain gauge totals and are taken to be the true rainfall within 15-km radii of each station, model analyses of wind, relative humidity and orography are also included. Two new satellite rainfall estimation instruments have recently been incorporated into the rainfall estimation, namely, the Special Sensor Microwave/Imager (SSM/I) on board Defense Meteorological Satellite Program satellites, and the Advanced Microwave Sounding Unit (AMSU) on board NOAA satellites. SSM/I estimates are acquired at 6-hour intervals while AMSU rainfall estimates are available every 12 hours (FEWS Web page: http://igskmncn-wb015.cr.usgs.gov/adds/readme.php? symbol=rf).

Rainfall data are also available from the 2.5ºx2.5º Climate Prediction Center Merged Analysis of Precipitation (CMAP) version 0309 (Xie and Arkin, 1998) dataset constructed from gauge observations, from five kinds of satellite estimates of precipitation, and from National Centers for Environmental Prediction Reanalysis precipitation.

The data area available from 1979 to date (http://www.cpc.ncep.noaa.gov/products/global_precip/html/wpage.cmap.html) are expressed as daily averages (mm per day) for each month. These data are of a much coarser spatial resolution than satellite rainfall estimates distributed by the Africa Data Dissemination Service (ADDS), but have the advantage of a consistent time series longer than the one provided by ADDS. The CMAP data were used to study the relationship of variability in rainfall to malaria incidence in Botswana (Thomson *et al.*, 2005).

Additional information for Malaria Epidemic Risk analyses is also provided via the ADDS FEWS web page. The maps provide a simple indicator of changes in malaria risk in marginal transmission areas based solely on rainfall, showing differences above and below expected levels. The maps use a mask to exclude areas where malaria is considered to be endemic (as opposed to epidemic), or absent. This mask is based solely on climatic constraints to malaria transmission (including climatic variability), and as yet does not account for areas where historic control has eliminated epidemic risk in the northern and southern margins of the continent. The maps have been tested against laboratory-confirmed malaria incidence figures in districts in Botswana where they showed a strong correlation. The maps have also been tested and correspond well with expert knowledge of epidemic risk in a number of epidemic prone countries. Their use and validation elsewhere is encouraged.

Temperature

Temperature has an effect on both the vector and the parasite. For the vector, it affects the juvenile development rates, the length of the gonotrophic cycle and survivorship of both juvenile and adult stages with an optimal temperature and upper and lower lethal boundaries. For the parasite it effects the extrinsic incubation period (Lactin *et al.*, 1995). *Plasmodium falciparum* (the dominant malaria parasite in Africa) requires warmer minimum temperatures than *Plasmodium vivax*. This helps account for the geographic limits of falciparum malaria transmission in Africa (Bruce-Chwatt, 1991). At 26ºC the extrinsic incubation period of this malaria species is about 9-10 days whereas at 20-22ºC it may take as long as 15-20 days. In highland areas, where cold temperatures preclude vector and/or parasite development during part/or all of the year, increased prevalence rates may be closely associated with higher than average minimum temperatures (Bouma *et al.*, 1994).

It is possible to estimate surface temperatures from the thermal channels of NOAA-AVHRR sensors, Meteosat and TERRA-MODIS. The Land Surface Temperature (LST), a proxy environmental variable, is commonly calculated using a split-window method which takes into account some atmospheric effects (Adding and Kauth, 1970; Price, 1984; Coll *et al.*, 1994; França and Cracknell, 1994). The relationship between air temperature and LST is not straightforward. The LST represents a spatial integration of information over the entire area observed, and therefore differs from *in situ* measurements. It also differs from the ambient temperature since it measures the temperature of the earth's "skin".

New research is underway to use temperature fields produced by the MM5 mesoscale numerical weather prediction model for this purpose, available from the Air Force Weather Agency. Estimated air temperature downscaled with a regional digital elevation model is planned to be associated with rainfall to produce an extended vectorial capacity model (Fig. 1).

Vectorial capacity V has been defined as the daily rate at which future inoculations could arise from a currently infected case (Dye, 1992). It has also been described as a convenient way of expressing malaria transmission risk, or the receptivity of an area to malaria (Gilles, 1993). While vectorial capacity does

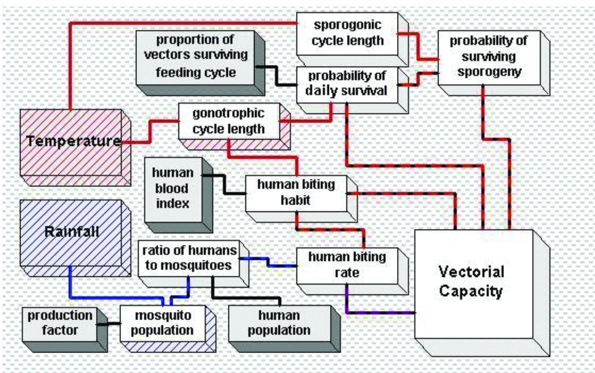

Fig.1. A diagrammatic representation of the "extended" vectorial capacity model.

not take into account parasite availability in the human host population, it is considered to be analogous to the environmental-biological driving force under-pinning the transmission potential in an area. The vectorial capacity model has more recently been extended to enable temperature and rainfall to drive the model (Connor, 2002).
The extended vectorial capacity model includes the influence of rainfall and temperature variables on malaria transmission patterns through the impact they have on the bionomics of the anopheline vector (feeding frequency, gonotrophic period, larval development rate, survival) and the parasite's extrinsic incubation period (sporogeny) in its mosquito host.

Humidity

The survival rate of adult insects is often thought to increase or decrease in relation to a factor called saturation deficit. Saturation deficit is derived by subtracting the actual water vapor pressure from the maximum possible vapor pressure at a given temperature. Evidence for other vectors (tsetse, ticks, culicoides) suggests that saturation deficit is an important environmental variable in larval and adult survivorship. Despite little direct evidence of the effect of saturation deficit on mosquito longevity, the relationship can be inferred from historical studies in Africa, India and Latin America (Macdonald, 1953).
There are no techniques currently available to extract precise quantitative estimations of saturation deficit from satellite data although Normalized Difference Vegetation Index (NDVI) has been suggested as a possible proxy (Rogers, 1991). Nevertheless, related variables can be used to infer its status such as the water deficit index obtained from AVHRR data (Moran *et al.*, 1994) or the Global Vegetation Moisture Index which provides an estimation of the vegetation water content (Ceccato *et al.*, 2002). Further research to quantify the relationship between those indices and saturation deficit must be made to determine whether they could be used as substitutes.

Surface Water

Surface water provides the habitat for the juvenile stages (egg, larvae, pupae) of malaria vectors. Monitoring the state of small water bodies and wetlands using satellite data is therefore very useful to identify the source of malaria vectors. The Short Wave Infrared (SWIR) is a wavelength (1.55-1.75 µm) absorbed by water and therefore can be used to retrieve information on the presence of water bodies and vegetation water content (Ceccato *et al.*, 2001). The SWIR is available on sensors such as LANDSAT-TM, SPOT-VEGETATION and TERRA-MODIS. Recently, research has been developed to use the SWIR to retrieve vegetation water content (Ceccato *et al.*, 2002) and water bodies (Gond *et al.*, 2004) using SPOT-VEGETATION. New indices such as the Global Vegetation Moisture Index (GVMI, Ceccato *et al.*, 2002); Normalized Difference Water Index (NDWI, Gao, 1996) have been developed to retrieve vegetation water content and a contextual algorithm developed by Gond *et al.* (2004) to retrieve water bodies using the sensor SPOT-VEGETATION. However, SPOT-VEGETATION spatial resolution of 1km does not allow the detection of small ponds important for mosquito breeding. TERRA-MODIS (with a spatial resolution of 250 m) and LANDSAT-TM (30 m) provide improved quality of images and can be used as shown later in section 3 for monitoring water bodies.
In addition to the potential of the SWIR, further research was also carried out using RADARSAT Synthetic Aperture Radar (SAR) images to monitor wetland ecosystem and flooded areas (Kandus *et al.*, 2001). The use of radar systems provides the possibilities to monitor earth features during night or when covered heavily by clouds. The signal amplitude wavelength emitted and received by the sensors are not influenced by atmospheric conditions and allow the detection of area flooded even during cloudy days. Radar RS programs, like ENVISAT, RADARSAT 2, have been developed and a panel of products made available, increasing the possibility for using operationally radar images to monitor water bodies. RADARSAT was successfully used in different ecosystems and combined with SPOT-VEGETATION data to enhance the accuracy of mapping the surface area of flooded wetland areas (Toyra *et al.*, 2002).

Vegetation

Vegetation type and growth stage may play an important role in determining vector abundance irrespective of their association with rainfall. It has been noted that whilst rice irrigation schemes may provide excellent breeding sites for *An. gambiae* s.l. early in the growth cycle of the plants – this changes as the rice plants mature and form a dense canopy over the water (Lindsay *et al.*, 1991). Methods of rice field classifications were successfully developed using Synthetic Aperture Radar (SAR) sensors onboard ERS1 (Chakraborty *et al.*, 1997) and RADARSAT (Panigrahy *et al.*, 1999, Shao *et al.*, 2001).
The type of vegetation which surrounds the breeding sites, and thereby provides potential resting, sugar feeding supplies for adult mosquitoes, and protection from climatic conditions, may also be important in determining the abundance of mosquitoes associated with the breeding site (Beck *et al.*, 1994). Furthermore, vegetation type may influence mosquito abundance by affecting the presence or absence of animal or human hosts and thereby affecting the availability of blood meals. Large-scale changes in vegetation class and phenology have been extensively researched using AVHRR (Townshend and Justice, 1986; Tucker *et al.*, 1985) and SPOT-VEGETATION (Mayaux *et al.*, 2004) data. Satellite images at higher spatial resolution such as Landsat, SPOT-HRVIR and TERRA-MODIS have been used to map changes in vegetation in particular defor-

estation, a process widely thought to be associated with changing levels of malaria transmission (Walsh *et al.*, 1993). MODIS images at 250m spatial resolution are accessible free of charge. Therefore, they are used on a regular basis to detect vegetation in Africa (where the spatial resolution of SPOT-VEGETATION cannot detect it) by the Desert Locust community for operational field campaigns to fight against the Desert Locust (Ceccato, in press).

Seasonality in Climate

The combined influence of rainfall, temperature and humidity, re-grouped underneath weather (short-term) and climate (long-term) on malaria is very complex, especially for extreme weather conditions. Direct effects of climate on vector and parasite development are easy to see but indirect effects may also be important such as the effects of previous exposure (related to direct effects), nutritional status, and co-infection may help determine the disease outcome.

Just as climate is one of the determinants of malaria endemicity, climate variability is one of the main factors behind inter-annual fluctuations of malaria. Literature abounds with examples of how unusual, anomalous or extreme weather conditions have led directly and indirectly (through destructive crop pests and diseases) to human malnutrition and in turn to health problems or to both at the same time (Gommes *et al.*, 2004).

In recent years there have been significant scientific advances in our ability to predict climate on the seasonal timescale (Goddard *et al.*, 2001). The skill associated with these predictions varies from region to region, but is generally higher within the tropics. Information on climate forecast and weather anomalies can be accessed on line through the IRI web site (IRI Climate Information Digest: http://iri.columbia.edu/climate/cid/index.html). The World Health Organizations Technical Support Network for Malaria Epidemic Prevention and Control has suggested that such forecasts may be relevant to malaria early warning (WHO, 2001). Recently, the information provided by regional forecasters in Southern Africa has been presented and used by decision-makers to forecast an increase in malaria risk in epidemic prone areas during seasonal Outlook Forums (DaSilva *et al.*, 2004).

The importance of the factors influencing malaria is not only limited to climatic factors. Anthropic changes in the environment, in land use, deforestation, in hydraulic network, also induce continuous changes in the intensity of malaria transmission.

Ecology of Anthropogenic Components of Malaria Transmission

Consequences of demographic and technological developments during the last century have considerably modified the environment. Forest and swamp regions were shifted to agriculture to feed an ever-increasing population. Water requirements for many crops have led to modifications of surface waters. Development of urban areas has also modified the spatial distribution of populations and lead to high concentrations of population in restricted areas. Already more than 50% of the total global population lives in cities. These demographic changes in cities can impact malaria, either by increasing the potential for malaria transmission where the development of irrigated cultures surrounding the city increases the vector population or by decreasing it, if adequate measures are taken to reduce the vector and parasite population in the cities.

In some countries, and in particular in Africa, movements of population for political or economical reasons create another risk factor to the spread of malaria. Migrants and refugees may bring new parasites (including drug resistant parasites) to an area and increase transmission in the settled population, or because they come from a low, no transmission area migrants and refugees may be highly vulnerable to severe disease when the enter a malaria endemic area (Giada *et al.*, 2003). Development of urban cities (Small, 2003) can be monitored with high spatial resolution images such as Ikonos and QuickBird (respectively, 1m and 0.61m for the panchromatic channel).

Control Components

Malaria is a preventable and curable disease. The most important factors that determine the survival of patients with *P. falciparum* malaria are (i) the patients personal vulnerability (in terms of immunity, malnutrition, other diseases) and (ii) early diagnosis and prompt treatment with effective anti-malaria drugs. Drug therapy may not only save the patient but also decrease the reservoir of gametocyte available for further transmission (Mouchet *et al.*, 2004). Vector control is essentially based on (i) in-house spraying with insecticides (ii) personal protection through the use of mosquito nets/repellants and (iii) larviciding of breeding sites. A good control strategy is to use the best combination of control methods available where and when they can be most effective.

In endemic malaria areas where the intensity of transmission varies little from year to year it is possible to organize control programs according to the calendar of the transmission season and RS may be used to help stratify different levels of endemicity, and the local seasonality of transmission (Thomson *et al.*, 1999). However, in areas where there is considerable inter-year variation in transmission and the potential for epidemics, a control program can benefit from more cost effective early warning systems supported by the use of satellite data for environmental monitoring which can be used to predict unusually high malaria 1-2 months in advance as well as satellite data for the location of breeding sites; and where necessary, satellite data for monitoring dispersed populations or population on the move. In recent years the use of GIS within the health services in many malaria affected countries has increased and although this process remains problem-

Table 1. List of satellite currently available or available in the near future for monitoring malaria components. PAN = Panchromatic, VNIR = Visible/Near-Infrared, SWIR = Shortwave Infrared, TIR = Thermal Infrared, SAR = Synthetic Aperture Radar (Spatial resolution - m), LST = Land Surface Temperature. Satellite which have been used for malaria studies are highlighted.

Mission	Sensor	PAN	VNIR	SWIR	TIR	SAR/Band	Swath (km)	Launch	Applications
Orbview-3	Orbview-3	1	4				8	2003	Urban and sub-urban areas, refugee camps, land planning & infrastructures
Ikonos	Ikonos	1	4				11	1999	Urban and sub-urban areas, refugee camps, land planning & infrastructures
Quickbird-2	Quickbird	0.61	2.44				22	2001	Urban and sub-urban areas, refugee camps, land planning & infrastructures
ALOS	AVNIR-2	3	10-15				35-70	2004	Land coverage and land-use classification maps
SPOT-5a	HRG	5	10	20			60	2002	Land coverage and land-use classification maps, vegetation and water bodies
SPOT-5b	HRG	5	10	20			60	2004	Land coverage and land-use classification maps, vegetation and water bodies
Landsat-7	ETM+	15	30	30	30		185	1999	Land coverage and land-use classification, vegetation and water bodies
Landsat-5	TM		30	30	120		185	1984	Land coverage and land-use classification, vegetation and water bodies
CBERS	CCD/IR-MSS	20/80	20	20/80	80		120	1999	Land Surface Temperature (LST)
Terra	ASTER		15	20	90		60	1999	Vegetation, water bodies, LST
ADEOS-2	GLI		250	250	1000		1600	2002	Vegetation, water bodies, LST
Terra	MODIS		250-1000	500-1000	1000		2300	1999	Vegetation monitoring, water bodies, LST
SPOT-5a	Vegetation		1000	1000			2200	2002	Vegetation and water bodies
ENVISAT-1	AATSR		1000	1000	1000		512	2002	Forest and natural vegetation
NOAA-M	AVHRR		1100	1100	1100		3000	2002	Vegetation monitoring, water bodies, LST
Orbview-2	SeaWiFS		1100-4500				1500-2800	1997	Vegetation, water bodies, dust
Meteosat 7	VISSR		2500		5000		Hemisphere	1997	Rainfall estimation, LST
Meteosat-Second Generation	SEVIRI		1400		4800		Hemisphere	2002	Rainfall estimation, LST
Radarsat-1	SAR					10-100/C	45-500	1995	Forest, water bodies
Radarsat-2	SAR					3-100/C	10-500		Forest, water bodies
ENVISAT	ASAR					30/C	100	2002	Weather, water bodies
ERS-2	AMI-SAR					30/C	100	1995	Vegetation, water bodies, weather
ALOS	PALSAR					10/L	70		Vegetation, water bodies

atic in some areas (Snipe and Dale, 2003) the routine mapping of health surveillance data, distribution of clinics, breeding sites, etc. means that spatial information, derived from satellite data, can now be directly compared with health data.

Progress is being made, but much could be learnt from the development of GIS and RS tools for routine surveillance for desert locust control monitoring which is currently operational in 15 countries affected by desert locust from Mauritania to India (Ceccato, in press).

The different sensors available for monitoring the components influencing malaria are summarized in Table 1.

Use of Remote Sensing in malaria control

Satellite sensors developed in US, Europe, Canada and India, have contributed to a better understanding of malaria vector ecology. The history of RS and its application to malaria and other vector-borne diseases has been recorded over time in a series of review papers (Washino and Wood, 1994; Wood *et al.*, 2000; Thomson *et al.*, 1997; Hay *et al.*, 2000; Manguin and Boussinesq, 1999; Beck *et al.*, 2000; Thomson and Connor, 2001). Yet, despite 30 years of research on the potential applicability of remote sensing technologies to malaria control, these tools are only now beginning to have an impact on policy and practice in operational control of malaria in affected countries.

Research initially focused on the spatial rather than temporal dynamics of malaria transmission indices. In particular, efforts were made to gain a detailed understanding of the population dynamics of the *vectors*, rather than the distribution of disease in the *human* population. The use of high-resolution imagery and expensive software also limited these studies to well-resourced research groups. Thus, demonstration studies have been difficult for national malaria control to incorporate into their routine planning activities. It has taken the intervening 30 years for many of the worst affected countries to begin to collect and routinely map frequently updated information on malaria incidence.

The following sections review applications developed with high-resolution and low-resolution data and also discuss future development of an operational system of satellite images which could be used directly by the decision-maker community in countries. Operational use of these images is now feasible due to the free access of the necessary images.

Use of High Spatial Resolution Images for Mapping Landscape Ecology

Since the launch of Landsat-1 30 years ago, remotely sensed data have been used to map and monitor features on the earth's surface and the atmosphere above. Over the following three decades an increasing number of studies used remotely sensed data for monitoring, surveillance and risk mapping of vector borne disease indicators, in particular malaria (Barnes and Cibula, 1979; Rogers and Randolph, 1991; Connor *et al.*, 1995; Hay *et al.*, 1996; Thomson *et al.*, 1996; Beck *et al.*, 1997; Beck *et al.*, 2000). More recently there have also been studies on the use of RS for non-vector borne infectious disease transmission (Molesworth *et al.*, 2003).

In the early years, investigations were led by NASA scientists in the Earth Observations Division (EOD) at the Johnson Space Center in Houston, Texas. Some of the studies, which demonstrated the potential utility of data acquired from both cameras and sensors onboard aircraft platforms, used them to identify mosquito-breeding habitats associated with *Aedes sollicitans*; relate disease with housing quality; and identify *Calladium* sp., the plant associated with the intermediate snail host for the schistosoma parasite. The EOD group also integrated weather data from the National Oceanic and Atmospheric Administration's (NOAA) Tiros Operational Satellite into an insect model to describe habitats in Mexico that supported the screwworm fly. After a decade of demonstration projects, NASA ended the program, assuming that the health community would take up the use of airborne and satellite data for research, surveillance, and control activities. This was a reasonable assumption, given that the forestry, geological, and agricultural communities had begun actively incorporating these data into their own activities. However, the health community did not adopt the use of remotely sensed data, and NASA's involvement lapsed until 1985, when scientists from the original EOD program initiated a new human health applications program Global Monitoring and Human Health (GMHH) at Ames Research Center. This program ran from 1985 until its transition in 1995 to the Center for Health Applications of Aerospace Related Technologies (CHAART) (http://geo.arc.nasa.gov/sge/health/chaart.html). The GMHH program's purpose was to demonstrate the application of RS and GIS technologies in the areas of landscape epidemiology focusing on the interaction of land use and vector bionomics. The first GMHH program used Landsat Multispectral (MSS) data to map areas with high abundances of *Anopheles freeborni* larvae within rice fields in California (Wood *et al.*, 1991) which could then be targeted by the states vector control program. By using a time-series of Landsat MSS data, GMHH scientists discovered that those fields that produced higher numbers of larvae 'greened-up' sooner than neighboring rice fields; this gave an early season advantage to the anophelines, which needed vegetated water to attach egg rafts. A spatial analysis also indicated that high larval-producing fields were found in areas where there was a mix of land uses, including orchards, cattle pastures, and native vegetation; the areas in which rice was the only land use had significantly fewer mosquitoes. This was explained by an understanding of the vector's limited flight range (3 km) and habitat preferences. Within her flight range, the female required a blood meal (preferably from cattle or small mammals associated with native vegetation), followed by a resting site (such as a cool orchard environment), and finally a rice field in which to lay her eggs. GMHH scientists used the Landsat MSS data to map the vegetation canopy green-up in the rice fields; the location of the orchards, cattle pastures, and rice fields; and then used this map to describe the temporal and spatial relationships between them. In this way, high larval-producing rice fields could be identified up to two months prior to peak larval production.

Beginning in 1987, the GMHH program began intensive vector ecology studies of *Anopheles albimanus*, a primary vector of malaria in the Americas. The study took place in southern Chiapas, Mexico, an area of unstable malaria. As was found in the California rice-field study, not all villages (fields) had the same abundance of mosquitoes, and the hypothesis was that the landcover/land use (*i.e.* landscape) functioned as the limiting factor to mosquito distribution. To test this, Ames scientists used multi-temporal Landsat Thematic Mapper (TM) data to map landscape elements in the study area, while Ames' colleagues sampled adult mosquito abundances surrounding 40 randomly selected villages. GIS functions were used to determine the proportion of different remotely sensed landscape elements surrounding the village within the flight range of *An. albimanus*. The results showed that the proportions of two landscape elements (unmanaged pasture and transitional swamp) could predict villages with high abundances of adult mosquitoes throughout the annual calendar, with an overall accuracy of 90% (Beck *et al.*, 1994). These landscape elements provided opportunities for blood meals and breeding sites, and could be easily mapped using Landsat TM data. The statistical models generated in the study were then applied in another location in Chiapas using a blind test. Meanwhile, Ames' Mexican colleagues sampled mosquito abundances throughout the year. At the end of the season, the modeled predictions were compared with the observed abundances, and the scientists found that the regression model was able to predict seven of the ten highest abundance villages (Beck *et al.*, 1997). This result indicated that RS/GIS could indeed be used to help malaria control agencies target villages at high vector-human contact risk, thus avoiding a waste of valuable resources being used to treat villages with little to no risk.

NASA scientists at Goddard Space Flight Center's Healthy Planet program are conducting a landscape-based malaria study in the Mekong River area. The team, which includes scientists from Thailand, is using data from Landsat TM, Ikonos, and NASA's Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER) and Moderate Resolution Spectroradiometer (MODIS) to identify potential breeding sites of the major vector species in order to better focus larvicide and adulticide applications. The project is also developing a malaria transmission model that includes parasites, hosts, vectors, human factors, and the environment, as well as a risk model to predict transmission intensity that incorporates meteorological data. These models use sophisticated techniques such as discrete wavelet transformation to generate landscape patterns from the various satellite data types.

In Africa the landscape ecology approach has also been successfully used in studies of malaria transmission associated with rice irrigation, landuse change and urban – rural interactions (Eisele *et al.*, 2003). Irrigated rice cultivation has been associated with an extended breeding season and higher densities of the main vectors of malaria compared with neighboring, non-irrigated areas in many parts of Africa (Ijumba and Lindsay, 2001). Landsat imagery has been frequently used in these studies to provide a detailed map of the spatial ecological characteristics of the irrigated areas and their surroundings. Resurgence of malaria in Madagascar after 20 years of effective control has resulted in the disease becoming a major public health issue once again – responsible for between 5-20% of all outpatient visits and a major cause of morbidity and mortality (Ariey *et al.*, 2002). While the disease is endemic in the coastal areas it is seasonal and unstable in the highlands – where epidemics marked the comeback of the disease in the late 1980s. It has been ascertained that rice fields are the principle breeding sites of *Anopheles funestus*, the malaria main vector in the highlands (Marrama *et al.*, 1995), and that altitude plays a major role both in the anopheles ecology and the length of the sporogonic cycle via temperature (Mouchet and Blanchy, 1995).

Knowledge of topography and rice field distribution is therefore key to the malaria stratification of the highlands necessary for control purposes. An epidemiological early warning and control system developed by the Ministry of Health (MoH) in conjunction with the Italian Cooperation (Albonico *et al.*, 1999) was already in place in Madagascar. However, the system, based on clinical and parasite data, was producing numerous false positive cases of alert and the forecast was not made sufficiently early in the season to allow the implementation of actions to decrease malaria risk. It was therefore necessary to improve the predictability of malaria by forecasting it with a longer lead time before the outbreak. By adding climatic and environmental factors to the model, the predictive accuracy of the system could have been improved. This was achieved by developing a new epidemic early warning and control system which integrated parasite, clinical, and environmental data. The system, called SIGREP (*Système d'Information Géographique pour la prévention du Risque d'Epidémie de Paludisme dans la région des Hautes Terres centrales de Madagascar* – Geographic information system for malaria risk prevention in the Malagasy Highlands), was developed by the Malaria Research Group (GRP – *Groupe de Recherche sur le Paludisme*) of the Institut Pasteur of Madagascar, the Italian Cooperation and the Malaria Control Service of the Malagasy Ministry of Health (Jeanne, 2000). Implementation of SIGREP was planned in four phases:

- Phase 1: Setting a RS method to monitor rice-fields using SPOT Xi+P images collected after the rainy season (Fig. 2).

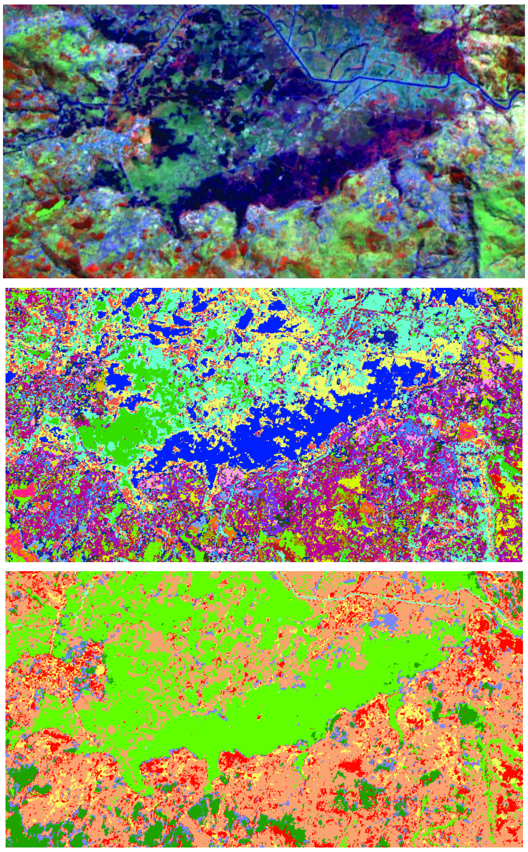

Fig. 2. SPOT Xi + P for prevention of malaria risk in the highlands of Madagascar.
Legend:
SIGREP, Spot 4 Xi- 168-369 27/04/2000
1. Color composite RGB 342
2. Classification of 22 classes (maximum likelihood)
3. 7 class groups with all types of rice field in bright green

- Phase 2: Analyzing the links between rice-fields characteristics (type, area, distance from houses) and malaria transmission (vector studies).
- Phase 3: Creating a model to assess malaria risk.
- Phase 4: Integrating the new model within the malaria control unit of the MoH planning system.

To date, Phases 1 and 2 have been implemented and the information collected for SIGREP has been incorporated into an Atlas of Malaria in Madagascar (http://www.pasteur.mg/AtlasPalu/index.htm) designed to inform the Ministry of Health of the current status of the biogeography, vector and parasite species and malaria incidence across the country. The plan is to update this atlas on a regular basis and implement Phases 3 and 4 in the near future.

In French Guyana, l'Institut Pasteur and Geoscience Francilian Institute of Marne la Vallée University used radar JERS-1 RS data to detect potential vector larval breeding sites for use in control malaria program. Tropical amazonian forests cover 90% of French Guyana. Malaria remains a public health priority along the two rivers that demarcate its border. Vector abundance and malaria risk varied considerably in both space and time. Local climate and hydrological variations were examined to identify whether they could explain this heterogeneity. The river margins (Fig. 3) were studied in both wet and dry seasons to understand whether rainfall and river flow were linked to the potential vector larval breeding sites. This was achieved using radar remote sensing using the L band of the JERS-1 satellite system (Rudant *et al.*, 1996). Thanks to L-Band wavelength, flooded areas along river margins in Amazonian forest were identified. These shady flooded areas are potential larval habitats of malaria vectors, such as *Anopheles darlingi*.

Fig. 3. River margin in French Guyana.

Use of Low Spatial Resolution Images for Mapping Environmental Components

Low spatial resolution images such as NOAA-AVHRR and Meteosat have been used to update and improve the spatial resolution of malaria transmission intensity maps in several countries, especially in Africa. NDVI computed from NOAA-AVHRR and cold cloud duration (CCD) inferred from Meteosat have been used as secondary predictors of transmission intensity (Omumbo *et al.*, 2002).

NDVI is an empirical formula designed to produce quantitative measures related to vegetation properties such as vegetation biomass and conditions. NDVI values vary between -1.00 and 1.00 and are computed as shown in Eq. 1:

$$\mathrm{NDVI} = \frac{(NIR\text{-}Red)}{(NIR+Red)} \qquad (1)$$

Where: *NIR* is the reflectance measured in the near infrared channel (expressed in %); *Red* is the reflectance measured in the red channel (expressed in %).

The higher the NDVI value is the denser or healthier the green vegetation is. Visible and near-infrared channels are available on most optical satellite sensors including NOAA-AVHRR, TERRA-MODIS and SPOT-

VEGETATION. However, only the NOAA-AVHRR sensors have an historical data series long enough (July 1981 to current) to be used for comparison with long-time series data. Since NDVI values can vary depending on the sensor and atmospheric conditions, it is impossible to compare NDVI values computed from different sensors used between July 1981 and the current date. It is therefore required to:

1) Calibrate the NDVI values for inter-sensor differences (several sensors have been used between 1981 and current date) and intra-sensor degradation.

2) Correct the NDVI values for atmospheric perturbations such as El Chichon and Mt. Pinatubo volcanic events.

These calibrations and corrections were implemented by NASA and ten-day composite period products were made available at 8km pixel resolution on an Albert Equal Area projection (Pinzón *et al.*, in press). The resulting NDVI time-series products were used to analyze trends in malaria incidence in Eritrea from 1996 to 2003 showing high correlation between NDVI values and malaria incidence (Thomson *et al.*, 2004).
Meteosat satellite has also been operationally used for monitoring areas where excess rainfall is the major epidemic indicator (*e.g.* the Sahel, semi-arid lowlands in the Horn of Africa, and the desert-fringes of Southern Africa). During the third meeting of the Roll Back Malaria Technical Support Network on Epidemic prevention and Control (WHO, 2002), it was noted that MEWS have immediate operational value in areas where excess rainfall is the major epidemic indicator (*e.g.* the Sahel, semi-arid lowlands in the Horn of Africa, and the desert-fringes of southern Africa). Further, those simple products such as rainfall difference maps for these epidemic-prone regions should be developed and made available through the existing Famine Early Warning System's Africa Data Dissemination Service (WHO, 2002). These products were subsequently developed and have, since mid-2002, been routinely available (WHO, 2002) (Fig. 4). A review of their utility in desert fringe settings in Southern Africa has shown a high correlation between rainfall difference anomalies and both confirmed (Botswana) and unconfirmed (Namibia, Swaziland and Zimbabwe) malaria incidence anomalies, with a lead-time of at least 2 months (Connor, 2002; Connor, 2003). Further review of their utility in East and West Africa is currently planned (Connor, 2003; WHO, 2003).
While these routine products were primarily aimed at lowland 'desert-fringe' epidemic settings, it has been shown that they offered a potential 4 week lead time for true epidemics, during 2002, in highland settings in Kenya (Hay *et al.*, 2003; WHO, 2003). These same rainfall difference products were also used for operational monitoring of changes in epidemic risk, during 2002, in highland Uganda (Connor, 2003).

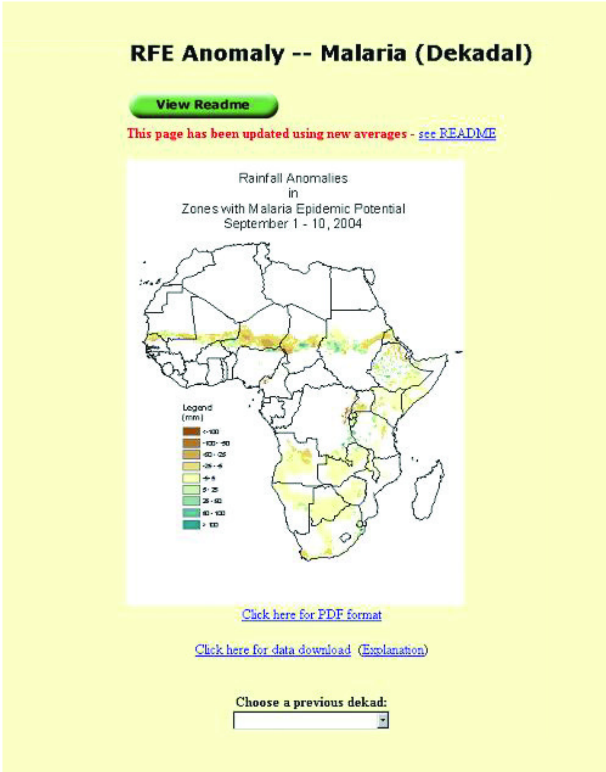

Fig. 4. Rain Fall Anomaly (for Malaria) produced every decade with a spatial resolution of 10 km. Data are available on the website of the USGS, Africa Data Dissemination Service: http://igskmncnwb015.cr.usgs.gov/adds/.

Future Operational Use of Satellite Data in Affected Countries

Operational use of remotely sensed images has taken a long time to be implemented in technologically developing regions because image and processing software costs were prohibitive. This problem is now diminishing since: (i) computer processing and data storage facilities are now accessible at lower cost, (ii) satellite images at high spatial resolution have become accessible free of charge (MODIS data) via the Internet and (iii) processing tools such as Healthmapper (GIS tool), Windisp (image display tool), and ADDAPIX (image analysis tool) are being made available to the user community at no cost by organizations such as the World Health Organization and the UN Food and Agriculture Organization (FAO).
The recent availability of free images and processing tools has enabled the rapid development of applications using RS and GIS for operational purposes. In the case of Desert Locust monitoring using RS, GIS and data collection tools including GPS and palmtop computers shows that technology can be made operational in Africa under harsh conditions and at low cost. This successful operational early warning system for Desert Locust monitoring developed by FAO could also be

applied for Malaria Early Warning System. The major challenge would be to harmonize data collection and tools in the Malaria community in order to enable data dissemination and analyses. This harmonization for the African continent should be made by an organization such as the UN which has the ability to develop standards and negotiate processes to reach consensus on methodologies and best practices between countries.

Thanks to the availability of free image data at high spatial resolution (MODIS images), a new generation of applications can be now implemented to help decision-makers in the field. The image (Fig. 5) shows the area

Fig. 5. Location of the MODIS image within the NOMADE project.

between Niger-Mali and Burkina Faso where a project is currently underway (NOMADE project). The following image (Fig. 6) shows the presence of vegetation and water bodies with sufficient spatial resolution to allow

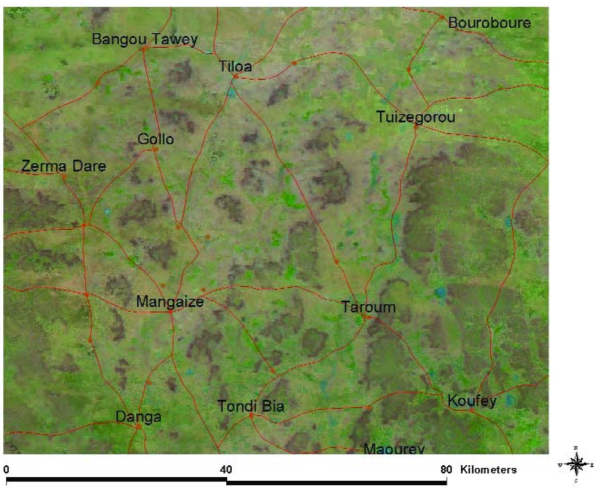

Fig. 6. MODIS image September 2004 color composite RGB where the SWIR channel is in red, the NIR channel in green and the RED channel in blue. This composition allows the vegetation to appear in green, the water in blue and the bare soil in brown-pink color.

analyses of where and when (i) vector can develop and (ii) where nomad herds can congregate for food and water and therefore be at risk of malaria. The NOMADE project will allow direct access of information to the user community by using MODIS images which are free of charge via the Internet.

The use of MODIS images is also operational in the desert locust monitoring systems implemented in 20 countries where the Department of Plant Protection (DPP) of the Ministry of Agriculture has access via a FTP site at FAO to the MODIS images processed locally in Rome. Each DPP downloads the images and integrates them into a customized GIS developed specifically to monitor desert locust. The desert locust Officer is then able to analyze where and when to send survey teams in the desert to scout for desert locust. Once found, information can be provided to the control team on the area to be treated (Ceccato, in press). This approach can also be adapted for the malaria control community.

The launch of initiatives to reduce malaria such as the Roll Back Malaria (RBM), the Millennium Development Goals (MDGs) and the Global Fund to Fight AIDS, Tuberculosis and Malaria (GFATM) can also provide a platform to help the transfer of these new technologies toward the most affected countries. Data and good intentions alone, however, are not sufficient. Developing countries will also need assistance in the process of technology transfer, and in structuring their national information systems and decision-making processes, if they are to derive full benefit from this exceedingly powerful technology.

Integration GIS-RS-Models to produce Malaria Early Warning System

The ready availability of frequently updated data on environmental variables pertinent to malaria transmission over large and remote regions makes RS a useful source of information for epidemic early warning systems. The concept of an early warning system for the prediction of malaria epidemics predates satellite technology by many decades. In fact an early warning system in response to the massive epidemics that occurred periodically in pre-independence India was operated routinely in the Pubjab from the early 1920s until the early 1950s (Najera, 1999). Christophers (1911) observed that between 1868-1908 severe and explosive ‘fever’ epidemics of two-three month duration (August-October) were common in the region. In particular he noted that the worst of the epidemics, which had a periodicity of 7-8 years, coincided with high grain prices and famine. Christophers saw this ‘human factor’ as an ‘essential requirement’ which undermined the population and resulted in high death rates as a result of the epidemics (Christophers, 1911). Christophers’ suggestions for an early warning system were taken up by Gill (1923) who developed a system based on a set of risk indicators: epidemiological assessment of previous infection, economic assessment of grain prices; the July-August rainfall levels; and occurrence of an epidemic within the last 5 years (Gill, 1923). Gill tested the system in 1921 and it went into routine operation in 1923. Retrospective reviews of the system outlined the statistical significance and its operational value in epidemic early warning (Yacob and Swaroop, 1944; Swaroop, 1949) but also identified the potential significance of May rainfall, offering a lead warning time of three months (Connor *et al.*, 1999).

Despite this example, much of the interest in early warning systems for malaria epidemics was lost during the Global Malaria Control/Eradication Era (Najera, 1998). It was not until the 1990s when a number of epidemics were reported from the East African highlands and a regional epidemic in Southern Africa stimulated renewed interest. At its launch in 1998 the Roll Back Malaria partnership identified Early Detection and Control of Epidemics as one of its four key elements (RBM, 1998). RBM established a Technical Resource Network on Epidemic Prevention and Control which held its first meeting in Geneva in 1998. Among the recommendations of the meeting was the development of a research framework to establish Malaria Early Warning Systems (MEWS) in sub-Saharan Africa and the identification of indicators and thresholds which could be used for early detection of epidemics by epidemiological surveillance systems. The MEWS framework was developed and published in 2001 (WHO, 2001). It set out a series of activities which together form the basis of an integrated monitoring process to identify changes in epidemic potential and increased risk of transmission in areas prone to epidemics (Fig. 7). A pre-requisite to MEWS is the mapping of areas prone to epidemics, either through historical analysis, or in combination with climatic suitability and environmental suitability for malaria transmission. Epidemic risk mapping should be dynamic and updated frequently to reflect changes in vulnerability factors. Clearly an epidemic response plan and the capacity to respond in the vulnerable areas are also essential.

The first of the MEWS monitoring processes involves consideration of the dynamic factors which may make populations more vulnerable to severe epidemic outcome. As with the Punjab model, drought, inadequate food security and nutritional/economic status may be important. Increasing levels of drug or insecticide resistance, reduction in health service provision or a high burden of other diseases, such a HIV/AIDS, may also compromise any immunity and increase vulnerability to epidemics. While these factors are unlikely to give an indication of when an epidemic might occur, they do provide some warning of the severity that can be expected if one does occur and is not prevented.

The second MEWS monitoring process considers the forthcoming season's climate. Will it be a drier, normal, or wetter season? What does this mean for epidemic risk considering the recent history? A number of years of drought may disrupt populations, may lower immunity and make populations more susceptible when higher, or even normal, rainfall levels occur. In recent years there have been a number of regular regional meetings (Regional Climate Outlook Fora) where available climate forecasts for the forthcoming seasons are discussed, and considered by the various sectors, such as agriculture, water resources and, increasingly, health. In September 2004, the first Southern African Regional Epidemic Outlook Forum was held in Harare, Zimbabwe. The forthcoming seasons' climate was presented and discussed to develop action plans for epidemic preparedness and response in the countries that are part of the Southern Africa Development Community (SADC) (http://www.malariajournal.com/content/3/1/37).

The third MEWS process is monitoring the weather as it occurs. Are temperatures unusual for this time of year? Is the rainfall higher than would normally be expected? The latter is now freely monitored through meteorological satellites and these are often more readily and frequently available than rain station data through the local meteorological services, who often have to charge for their data. Considering where high rainfall, following two or three years of drought occurs on a vulnerable population in a desert-fringe area which has had epidemics in the past may be one of the most realistic early warning systems available in many African countries.

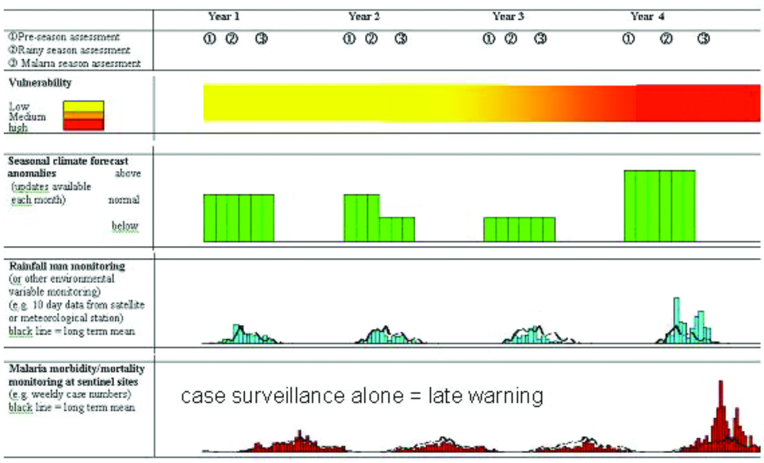

Fig. 7. MEWS integrated framework: gathering cumulative evidence for early and focused response (WHO, 2004).

However, the interplay of temperature with rainfall are crucially important in highland-fringe epidemic settings, where the impact of high rainfall may increase epidemic risk or cool the environment to levels which lower transmission potential. Current work is investigating the development and implementation of near-real-time temperature information along with rainfall as a routinely available environmental monitoring product for use in the highland-fringe epidemic settings (Fig. 8).

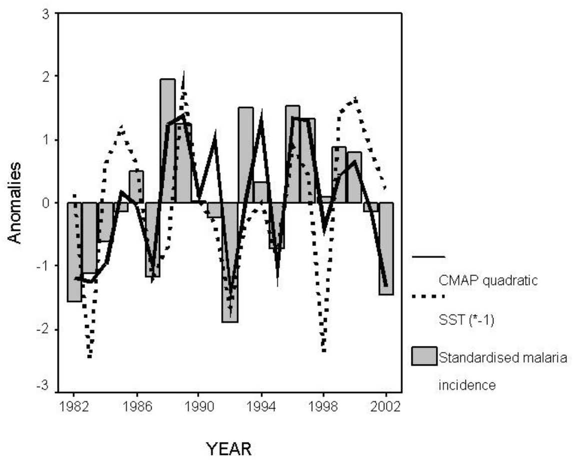

Fig. 8. Malaria incidence anomalies in Botswana related to climate anomalies (reprinted with permission of the American Society of Tropical Medicine and Hygiene, from Thomson MC, Mason SJ, Phindela T, Connor SJ, 2005. Use of rainfall and sea surface temperature monitoring for Malaria early warning in Botswana. Am J Trop Med Hyg 72: in press). Anomalies in Sea Surface Temperatures (SST) (Nino 3.4), December - February (DJF) a quadratic rainfall model (measured using satellite derived CMAP: Climate Prediction Center Merged Analysis of Precipitation) for the same months are overlaid on standardized malaria cases per 1000/population (incidence) anomalies (1982-2003; main transmission period January-May). The malaria data has been standardized to remove non-climate related trends in the data and the impact of a major policy intervention in 1997. There are many factors which can cause changes in malaria incidence data including changes in reporting, drug resistance and control initiatives. However, in the semi-arid areas of Africa rainfall is a major driving force of inter-annual variability in malaria.

The fourth monitoring process is epidemiological surveillance. Entomological surveillance may offer valuable insights into the vector- parasite-host dynamics and provide warning of changes in epidemic risk. This is generally beyond the scope of most African health services. However, the example of Desert Locust monitoring at Ministry of Agriculture level in 15 countries in Africa, Middle East and South-West Asia showed that surveillance is possible using simple GIS tools (Ceccato, in press). It may be possible to establish sentinel sites in particular locations, known to be epidemic prone and where rapid detection and reporting is possible, and a number of studies are attempting this. While the detection of an epidemic through a rapid increase in the number of cases would be the most reliable, it is unfortunate that routine case reporting systems in sub-Saharan African countries are, at present, unable to detect epidemics in sufficient time to enable an effective response. Due to the complexity of the variables to be considered and the remoteness of the areas affected, RS is an ideal source on which to base an early warning system for malaria epidemics. The research framework established by the RBM partnership provides a useful structure on which to base the required system. Specifically, a comprehensive system must take into account 1) population vulnerability, 2) the forthcoming season's climate, 3) current weather conditions and 4) vector/parasite/host dynamics. Ideally a country will monitor all of these processes in an integrated framework, which when taken together act as a series of compounding indicators which give control services sufficient confidence to prepare and act early (in accordance with their pre-formulated epidemic response plan) to prevent the rapid rise in cases before they occur.

Conclusions

Malaria is a deadly but preventable and curable disease. Although the environmental drivers that determine the life cycles of both the vector, host and the *Plasmodium* parasite are complex, they can be monitored and analyzed using newly available technologies such as RS and GIS. Research has shown that the technological building blocks are available to create an operational early warning system which could prevent epidemics and limit the scale of outbreaks until such time as the disease can be eradicated, as it has in Europe and the USA. A holistic early warning system must consider all of the factors that influence the development of malaria as well as their interactions. Rainfall, temperature, humidity, vegetation and seasonality in weather and climate can all have an effect on the vector, the parasite and susceptibility of the human to the disease. Over the years, many tools have been developed to monitor these factors which are currently available. Rainfall Estimates and Malaria Risk Analyses are available on the ADDS FEWS web page. The vectorial capacity model was developed to express malaria transmission risk and has since been extended to enable temperature and rainfall to drive the model. Information on climate forecast and climate anomalies is becoming more reliable with recent scientific advances and is made available through the IRI Data Library.
Also to be considered in a comprehensive Early Warning System are the anthropogenic factors which influence disease transmission. Changes in agricultural practices, development of urban areas and movement of populations for political and economic reasons can all help determine whether an outbreak will occur and if so, how severe it will be. The robustness of control processes in countries can also, evidently, be a deter-

mining factor. Effective control systems should: 1) have access to forecast information on diseases outbreaks and 2) have the means and the organization required to implement control measures. A good early warning system should take into account the effect of any strengths or weaknesses in these areas.

Research over the last three decades has shown RS to be an efficient way to monitor many of these factors both on a global and regional scale. Global Monitoring and Human Health (GMHH) used a time-series of Landsat MSS data to determine that high larval producing rice fields greened up faster and were located in areas where there was a mix of land uses. Temporal and spatial analyses in light of these two phenomena meant that high larval-producing rice fields could be identified up to two months prior to peak larval production and control measures, if the correct mechanisms were in place, could be taken in time to avoid an outbreak. GMHH also showed that the proportions of two landscape elements (unmanaged pasture and transitional swamp) could predict village with high quantities of adult mosquitoes, another factor which could be used to target efficient control measures. Ongoing studies at Goddard Space Flight Center's Health Planet Program and the Pasteur Institute of Madagascar are yielding similar scientific advances. But while the successful evidence and the building blocks were accumulating, two factors remained which impeded the operational use of the tools being developed: 1) the complexity of the information that needed to be considered, and 2) cost of using the tools that were becoming available.

Until recently, image and processing costs prevented local decision-makers from implementing RS decision-support systems on a large scale. More recently, computer processing and data storage facilities have become available at low cost and high spatial resolution images have become accessible free of charge. Processing tools are also being made available to the user community at no cost by WHO and FAO. These developments are paving the way toward making countries more receptive to the implementation of remote sensing system. For example, a successful operational early warning system for Desert Locust which was implemented by FAO has proven the viability of implementing a similar system for malaria.

The launch of the Roll Back Malaria partnership in 1998 has also provided new impetus to the global fight against the disease. In 2001, an integrated framework was developed which recognized the complexity of the factors determining transmission and also serves as a convenient framework on which to base a future Early Warning System. This MEWS framework established four processes which must be monitored: 1) population vulnerability, 2) the forthcoming season's climate, 3) current weather conditions and 4) vector/parasite/host dynamics. This integrated framework shows great promises to structure decision-support systems and aid in communications during implementation of response to such a system.

After 30 years of research and development to create the capabilities to control malaria using RS technologies, the pieces are finally falling into place to support global implementation of such technologies. A comprehensive and integrated Early Warning System is required to minimize the impact of the deadly disease and the barriers to implementation, namely cost and data management capabilities are disappearing. At this fateful moment, the Roll Back Malaria program is also providing the impetus which should enable us to harvest the fruits of many years of scientific research. Data and good intentions alone, however, are not sufficient. Developing countries will also need assistance in the process of technology transfer, and in structuring their national information systems and decision-making processes, if they are to derive full benefit from this exceedingly powerful technology.

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