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**ASSESSING MALARIA RISK FROM SPACE
USING RADAR REMOTE SENSING**

by

Shannon Kaya

**A thesis submitted to the Faculty of Graduate Studies and Research
in partial fulfilment of the requirements
for the degree of
Master of Arts**

**Department of Geography and Environmental Studies
Carleton University
Ottawa, Ontario
April 4, 2002**

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ASSESSING MALARIA RISK FROM SPACE USING RADAR REMOTE SENSING

submitted by Shannon Kaya, B.A.

in partial fulfilment of the requirements for the degree of Master of Arts

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ABSTRACT

Over one million new cases of malaria are reported each year, and more than 80% are in Sub-Saharan Africa. An effective surveillance tool to monitor vector-borne diseases like malaria is needed to facilitate efficient control and mitigation activities. This paper discusses the potential of remote sensing and Geographic Information System (GIS) technologies for monitoring and mapping malaria risk. Background research includes a discussion of the malaria disease vector, a basic theory of remote sensing, especially radar technology, and a review of the use of remote sensing for disease monitoring and mapping. These are followed by a case study using multi-temporal RADARSAT-1 imagery for mapping malaria risk in coastal Kenya.

This work demonstrates the potential of remote sensing for assessing disease presence and risk, and will be of particular interest to health officials and international development specialists. It shows how critical environmental factors can be detected with satellite imagery, and how GIS technology can be used to map potential disease risk to human populations.

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1.0 INTRODUCTION

This project analyses the applicability of radar remote sensing for mapping and monitoring disease risk. Included in this work is an analysis of malaria as a prime example of an environmental, vector-borne disease, and an introduction to remote sensing, with a special focus on radar technology and Canada's current operating radar remote sensing satellite, RADARSAT-1. In addition, relevant work on epidemiology and remote sensing research is reviewed and analysed, considering the gaps in current research and how radar remote sensing technology may address the challenges in this field. A study area in coastal Kenya is used to demonstrate the potential of radar remote sensing for identifying environmental indicators of malaria, although discussions will be applicable to many parts of the world where malaria and other vector-borne diseases are a major concern.

Specific interrelated objectives of this research are:

- 1) To provide a review of geomatics technology that can be used to familiarize health officials, international development specialists, and policy analysts with its potential for disease monitoring and risk mapping;**
- 2) To review recent research activities which use geomatics technology for monitoring disease vectors, and to identify gaps and challenges in this field;**
- 3) To determine the usefulness of RADARSAT-1 SAR imagery for identifying land cover variables which can be related to the potential presence of a malaria mosquito vector;**
- 4) To use RADARSAT-derived land cover information and proximity analysis to assess malaria risk to the human population in the case study area in coastal Kenya;**
- 5) To propose future research activities to be carried out in order to realise the operational potential of geomatics technology for malaria risk mapping.**

Nearly one-half of the human population lives in areas where they are at risk of contracting one or more vector-borne diseases such as malaria (WHO, 1998). These diseases were once mainly associated with rural and impoverished areas; however today, greater attention is being given to the relationship between disease and environmental change and global warming (Leaf, 1989; Haines,

1993; Randolph, 1993; Garrett, 1994; Moore, 1995; Bradley, 1996; Patz, 1996; Shell, 1997; Connor, 1998; WHO, 1998; WRI, 1998; ISU, 2000). In many parts of the world, populations are increasing at alarming rates. There is evidence that environmental degradation and global climate change are rapidly reaching crisis conditions (Garrett, 1994; WHO, 1998). With these global concerns comes an increasing threat to the health and well being of the human community.

Malaria is plaguing much of the world's population, particularly in tropical areas. Recently, the World Health Organization's Roll Back Malaria (RBM) initiative released the following facts about malaria, indicating a global crisis situation:

- There are an estimated 300-500 million clinical cases of malaria each year, killing over one million people each year, which is an average of about 3000 a day.
- Over 700,000 children under the age of five die from malaria each year.
- With acute cases of malaria, a child may die within 24 hours of infection.
- 40 per cent of the world's population lives in areas with malaria risk, but nine out of ten cases occur in Africa, south of the Sahara.
- Drug resistance, population movement, deteriorating sanitation, and climate change are contributing to the spread of malaria.
- In many parts of the world, strains of the malaria parasite have developed a resistance to the four leading anti-malarial drugs.

(WHO, 1998)

Environmental variables such as temperature, humidity and vegetation type have become key components in tracking and monitoring vector-borne diseases (Hugh-Jones, 1989; Chen, 1991; Kitron *et al.*, 1991; Washino and Wood, 1993; Beck *et al.*, 1994; Thomson *et al.*, 1997; Hassan *et al.*, 1998; WHO, 1998). Conventionally, labour-intensive survey techniques were used to study such environmental processes; however, newer geomatics technologies are becoming more widely applied in this area by a growing list of researchers (see, for example, Clarke *et al.*, 1990; Hugh-Jones, 1991; Linthicum *et al.*, 1991; Pope *et al.*, 1992, 1993; Kitron *et al.*, 1994; Wood *et al.*, 1991, 1993, 1994; Connor *et al.*, 1995; Beck *et al.*, 1995, 1997; Hay *et al.*, 1997, 1998, 2000; Thomson *et al.*, 1997, 2001). Remote sensing and Geographic Information Systems (GIS) have the capability of storing, manipulating, and retrieving large amounts of spatial data, and can be useful tools for health officials, governments and research scientists. In recent years, there has been a great deal of interest in using remote sensing and GIS to understand temporal and spatial patterns of vector-borne diseases, as well as monitor and map potential risk to human populations.

Although the idea of using satellite-based mapping techniques (mainly optical data) for surveillance of disease is not new (Woodzick and Maxwell, 1977; Barnes and Cibula, 1979; King, 1979; Wagner *et al.*, 1979; Fleetwood *et al.*, 1981; Mayer, 1983; Hayes *et al.*, 1985; Jovanovic, 1987, 1989; Welch *et al.*, 1989), the use of satellite radar remote sensing technology has not been

extensively explored by the scientific community (Hay *et al.*, 2000). This deficiency may be related to the lack of commercially available radar image data in the past. However, a new generation of commercial radar satellites including Canada's RADARSAT is changing this situation.

Since many infectious diseases such as malaria are prevalent in tropical areas where there is substantial cloud cover, it is often difficult to obtain useful cloud-free satellite data from commonly used optical sensors. Radar offers a solution to this with its capability to penetrate clouds and haze, as well as to image both day and night. This "all-weather" capability makes satellites such as RADARSAT-1 potentially useful tools for surveillance in tropical areas (Ross *et al.*, 2001).

This paper is structured to provide the reader with background theoretical knowledge before discussing the data analysis and results of the case study. Due to the multi-disciplinary nature of the research topic, it is necessary to provide some epidemiological background relating to malaria, scientific and technical information on the science of remote sensing, and a summary of how these disciplines may be integrated to provide geospatial analysis of vector-borne disease. The following chapter discusses the malaria disease vector in terms of characteristics and geographic distribution. Attention is given to the relationship between the malaria vector and its environment, to help determine which environmental components should be considered when monitoring and

mapping malaria distribution and risk. Malaria control, prevention and mitigation efforts are considered at both a global and local scale, and reference is made to on-going efforts for malaria eradication around the world.

Chapter 3 focuses on the fundamental principles of remote sensing technology. The basics of image processing and analysis relevant to this thesis are identified, including image enhancement, transformation and image classification. In order to meet the objectives of this research, an understanding of microwave remote sensing in the context of remote sensing as a whole is necessary. Section 3.3 explains the uniqueness of radar remote sensing and describes Canada's Earth observation satellite, RADARSAT-1.

Several objectives of this research are addressed in Chapter 4, which describes recent research and development in the field of geomatics for health applications. This section outlines the key geographic variables that are important in monitoring disease from a geospatial standpoint, and provides the reader with an understanding of how geomatics and health domains may be integrated. The main challenges with respect to the research requirements in this relatively new field are discussed. It is noted that the vast majority of previous research on geomatics and health integration has made use of optical remote sensing systems, with very little done using radar remote sensing. Partly for this reason, the potential use of radar for disease monitoring is discussed in Chapter 4.

The practical application of this knowledge is described in Chapter 5, which focuses on a case study of mapping malaria risk in coastal Kenya with RADARSAT. For purposes of the case study, RADARSAT-1 standard mode data were acquired over coastal Kenya in 1999 and 2001. Field epidemiological data on mosquito abundance in the area were collected by local researchers in Kenya, and generously provided as ground truth information for the RADARSAT-1 images. These images were processed, geo-corrected, and classified using a segmentation process. Resulting classifications were assessed for accuracy and correlated with mosquito abundance data to assess the potential of RADARSAT-1 standard mode data for identifying areas of high mosquito abundance. Based on the proximity of these regions to populated areas, malaria risk was analysed and mapped. The methodology and results of this case study will be described in detail.

A final chapter discusses the research findings. Conclusions following the case study will be drawn and recommendations will be proposed based on gaps and limitations found. A final discussion concentrates on the operability of SAR remote sensing for responding effectively and efficiently to the growing concerns about vector-borne diseases in many parts of the world.

2.0 MALARIA

This chapter describes the characteristics of malaria and how the environment defines the potential presence of malaria-carrying mosquitoes. First, the mosquito, as the malaria vector, will be discussed in terms of its vector life cycle, characteristics, and the current global geographic distribution of malaria. The ecological indicators of the vector are then analysed, with a focus on the main environmental factors that influence its presence and abundance, including precipitation, seasonality, vegetation, and temperature. This leads to a summary of a debate concerning the effects of global warming on the movement and abundance of malaria, at a global scale. The final section of the chapter discusses malaria prevention, eradication and control programs. This chapter is intended to provide an understanding of the current state of global human health, specifically with respect to malaria, and explore the extent to which

environmental conditions provide indicators of the potential presence and abundance of malaria in a given region.

It is important to stress at the outset that malaria is a complex disease. Although it is clear that malaria is associated with environmental and ecological factors, these only determine the potential for transmission. Actual disease risk (or vulnerability of a given population) is influenced by a number of variables including human behaviour, socio-economic conditions, and level of host immunity or drug resistance (WHO, 1998; Hamoudi and Sachs, 1999; Thomson & Connor, 2001). Understanding the influence of all these variables is essential to any effective malaria control or eradication program. For the purpose of this thesis, however, the main focus will be on the environmental conditions necessary for malaria.

2.1 The Malaria Vector

2.1.2 Vector Characteristics

Malaria is caused by parasites of the genus *Plasmodium*, carried by the female *Anopheles* mosquito. There are four species of *Plasmodium* that can produce malaria in humans, in varying forms and degrees of severity. These species are *Plasmodium falciparum*, *Plasmodium vivax*, *Plasmodium ovale*, and *Plasmodium malariae*. *Plasmodium falciparum* is by far the most widespread and dangerous of the four species, and can be fatal within a very short time after infecting the human host. The other species vary in severity, with *Plasmodium vivax* and

Plasmodium ovale possibly remaining dormant for several months and exhibiting a delayed reaction in the host. This study will focus on *Plasmodium falciparum*, since this species is most severe and widespread.

Figure 2.1 The female *Anopheles* mosquito – the malaria vector
(www.malaria.org)

Malaria parasites are transmitted to human beings through the saliva of the female *Anopheles* mosquito (Figure 2.1), the malaria vector, which is very efficient at this task and has been described as a "flying syringe" (Shell, 1997). The mosquito attacks the host, and the malaria parasite infects and kills the red blood cells, restricting the transport of oxygen from the lungs to the rest of the body. Once injected, the parasites quickly move to the liver, where they mature and multiply. When they re-enter the bloodstream, red blood cells are attacked and symptoms appear. The parasites reproduce rapidly, and in some cases death may result within hours of infection (WHO, 1995). Figure 2.2 illustrates the life cycle of the female *Anopheles* mosquito, carrying the *Plasmodium* parasite to the human host. It shows the process of parasite infection in the host after blood is extracted, and circulation to the liver where multiplication occurs and red blood cells are attacked. A new mosquito then acquires these infected cells as she

extracts a blood meal from the infected human, and the process begins again if this mosquito infects another human host.

Figure 2.2 The life cycle of Plasmodium parasite in the Anopheles mosquito
(www.whyfiles.news.wisc.edu)

Like HIV and tuberculosis, malaria does not elicit what is called a complete immune response in human beings. A human may be infected with the parasite repeatedly, or carry it for a long time, without developing a full resistance. Humans also do not develop a protective immune response to malaria, as we do for such viral infections as polio, measles, and smallpox. Whatever immune reaction humans do develop appears to occur deep in the cell, and is not always strong enough to effectively protect against the disease (Shell, 1997).

2.1.2 Geographic Distribution

Although once prevalent in many first world nations, malaria is now mainly associated with the poor and under-developed parts of the world (Leaf, 1989; Haines, 1993; Randolph, 1993; Garrett, 1994; Moore, 1995; Bradley, 1996; Shell, 1997; Connor, 1998; WHO, 1998; WRI, 1998; ISU, 2000). It has long been a serious problem and cause of death in most of Africa, although it was successfully suppressed to a certain extent in many developing countries during the 1950s and 1960s through DDT-based eradication programs. The disturbing news is that malaria has returned to many areas in recent years (Bradley, 1996; WHO, 1998; WRI, 1998; Hamoudi and Sachs, 1999). Shell (1997) comments that in North Africa, India, Southeast Asia, China, South America, and the Caribbean, the incidence of the disease has quadrupled in the past five years.

Ninety percent of fatal malaria cases occur in sub-Saharan Africa, where over 90 per cent of the population is at risk of the disease (WHO, 1998). This is largely due to the socio-economic conditions, such as poor sanitation, found in much of Africa, although environmental conditions on the continent, particularly the tropical and sub-tropical regions, are certainly conducive to the breeding habitats of the *Anopheles* mosquito. In some areas, malaria is found as a result of degraded land, drought and famine, which have encouraged increased resettlement to areas where the host-vector relationship is newly introduced. In other parts of East Africa, cyclical malaria epidemics have been related to meteorological patterns, aggravated by changes in agriculture, deforestation and population patterns (Leaf, 1989; Moore, 1995; Bradley, 1996; Connor, 1998;

WHO, 1998; WRI, 1998; Hamoudi and Sachs, 1999). Mass refugee movements in Burundi and Rwanda during the 1990s have resulted in increased malaria epidemics in central Africa (WHO, 1995). In addition, increased drug resistance throughout the continent has led to higher death rates related to malaria (Garrett, 1994; WHO, 1995; Bradley, 1996; Shell, 1997; Connor, 1998; WHO, 1998).

In Central and South America, the incidence of malaria has increased significantly in recent years (WHO, 1995; WRI, 1998). This is primarily due to the changes in the settlement patterns caused by deforestation. Changes in land use have resulted in the development of habitats that are conducive to the *Anopheles* mosquito. Increased agricultural development, often associated with irrigation, is providing suitable breeding grounds for the malaria parasite. Mosquitoes have been moving into previously uninhabited areas, and infecting those with little or no immunity to the disease. It is estimated that there are 500,000 new cases of malaria per year in Brazil (over a half of all malaria cases in the Americas), and 6,000 to 10,000 malaria-related deaths due to new settlements in forested areas of Brazil (WRI, 1998).

Malaria is the most important vector-borne disease in the eastern Mediterranean region, and is endemic in 14 of 22 countries (WHO, 1995). Again, agricultural development has been cited as a leading cause of the increased malaria cases in malaria-prone areas, as well as civil disturbances resulting in population displacement. Parasite resistance to drugs and insecticides is also a major

problem in the Middle East, where there is a great need for effective malaria control programs.

Figure 2.3 Global geographic distribution of malaria endemic countries, as of 2000
(<http://www.dpd.cdc.gov>)

Malaria is also endemic in regions of Southeast Asia, although the WHO reported that the situation has remained relatively static since the early 1980s, with the incidence of malaria being 2.3 to 3 million new cases per year (WHO, 1995). Eighty-eight percent of Southeast Asians live in areas at risk of malaria, and many of the cases are thought to be due to land use changes in forested areas and to increased agricultural development (WHO, 1995; Hamoudi and Sachs, 1999). In addition, malaria infections in parts of Vietnam and Thailand are reported to have the most severe drug resistance in the world (WRI, 1998).

The western Pacific region, particularly Papua New Guinea and the Philippines, report nearly 300,000 cases of malaria yearly and relate much of the malaria problem to colonisation of new areas with increased deforestation and agricultural development (WHO, 1995; Hamoudi and Sachs, 1999).

At present, over 300 million people are affected by malaria globally, with well over one million malaria deaths per year (WHO, 1998). In general, malaria is endemic in most tropical regions, with extensions into the sub-tropics. Increased air-travel to tropical destinations is an important consideration with respect to exposing new populations to risk, and malaria is now a serious cause of death in previously non-malarious areas (Bradley, 1996). Distribution varies considerably from country to country, and within countries, as very specific habitats are required for both malaria vector breeding and human infection. Considering that the flight range of the malaria vector is limited to a maximum of 2 kilometres from the breeding habitat, and most mosquitoes fly less than this in their lifetimes, the geographic distribution of risk is widely varied at local scales (e.g., within villages) (Connor *et al.*, 1995; Bradley, 1996; Hay, 1997; Connor, 1998)

2.2 Malaria and the Environment

2.2.1 Precipitation

The relationship between rainfall and malaria is well known, and in general, high amounts of precipitation result in increased incidence of malaria where a conducive temperature range exists (Thomson *et al.*, 1996, 1997; Connor, 1998).

Anopheles mosquitoes breed in areas of high moisture, although specific types of water habitats are necessary for the parasite to develop and breed. Large bodies of water are not conducive to mosquito breeding, but small puddles of standing water provide suitable conditions for the malaria parasite. With respect to types of water bodies available, the distribution of rainfall is more important than the quantity. Breeding sites must not be too small or temporary, as the water must remain long enough for the vector to lay eggs and for the adult mosquitoes to emerge (Hugh-Jones, 1989; Chen, 1991; Kitron *et al.*, 1991; Washino *et al.*, 1993; Beck *et al.*, 1994; Thomson *et al.*, 1997; Hassan *et al.*, 1998). The amount of suitable surface water is also dependent on the topography of the environment, soil type and porosity. Soils with large particle size (high porosity) will have less surface water resulting from rainfall, whereas soils such as clays, with a small particle size (low porosity), will not allow water to penetrate as much, resulting in puddling on the surface.

There is no consistent correlation between rainfall and malaria. In some cases, too much rainfall may have the opposite effect. High amounts and intensity of precipitation may flush out the breeding sites such as small puddles, and in effect eliminate some breeding grounds (Thomson *et al.*, 1996). In addition, too little rainfall, as during drought conditions, can result in increased malaria incidence: as an environment dries up, larger water bodies that were once not suitable for mosquito breeding, become small puddles and perfect breeding habitats for mosquitoes. The way in which precipitation affects the incidence of malaria in a

given environment is primarily a function of the characteristics of the surface water. High amounts of rainfall may induce or reduce the risk of malaria vector breeding, depending on the general conditions related to the size of water bodies and the local topography (Thomson *et al.*, 1996, 1997; Connor, 1998).

In addition to rainfall, irrigation practices can affect the potential of a site for breeding the malaria parasite. Although not always directly related to precipitation, most irrigation routines result in increased surface water, often in the form of puddles, and have been strongly associated with the presence of malaria (Beck *et al.*, 1994; Washino *et al.*, 1993; WHO, 1995; Thomson *et al.*, 1997; Connor, 1998; Hassan *et al.*, 1998). Irrigation puddles provide suitable grounds for vector breeding and should be considered in assessing the risk of malaria in a given environment. Malaria outbreaks are often associated with the development of agricultural lands in areas previously not necessarily conducive to mosquito breeding (WHO, 1995). The problem is particularly severe in these conditions, as the human hosts around the newly cultivated and irrigated areas often have little or no immunity to malaria.

2.2.2 Vegetation and Land Cover

Land cover type can be an important indicator of malaria. Different vegetation types and growth stages provide varying levels of suitability for vector breeding sites. In particular, wetland vegetation, or areas with high moisture content encourage the breeding of malaria parasites. Rice paddies or mangrove forests,

for instance, have flooded ground cover. As stated in the previous section, still water is an ideal habitat for breeding of the malaria vector. In addition to the type of vegetation, plant growth stage may influence the presence of malaria. With rice, flooding of the paddies occurs at the beginning of the growing season, which is every three to four months (Ross *et al.*, 1998). This allows many opportunities for the mosquito to lay eggs and grow to adulthood. As a plant grows, moisture increases in the plant, and decreases in the soil, thus reducing malaria habitats. Harvesting often destroys habitats temporarily (Wood *et al.*, 1991).

Malaria vectors require human hosts in order to be considered a risk. Cultivated vegetation usually implies a close proximity to humans. For this reason, malaria outbreaks often occur as lands become developed and inhabited by humans, and urban or populated land cover variables are important when considering risk of malaria in a given region (Hugh-Jones, 1989; Kitron *et al.*, 1991; Wood *et al.*, 1991; Washino *et al.*, 1993; Beck *et al.*, 1994; Thomson *et al.*, 1997; Hassan *et al.*, 1998).

2.2.3 Seasonality

Malaria is endemic to most tropical areas where there is at least one rainy season per year (WHO, 1995; Hamoudi and Sachs, 1999). In general, rates of malaria increase during the rainy season and decrease as local water patches dry up and eliminate mosquito breeding grounds. In terms of high malaria risk,

the rainy season is considered the “transmission season” for malaria (Flasse *et al.*, 1994; Thomson *et al.*, 1996; Hamoudi and Sachs, 1999). It has been suggested that variations in the length of the transmission season alone can affect the rate of malaria in a region (Wood *et al.*, 1991; Thomson *et al.*, 1996). In some areas, malaria is only present during the transmission season, often with very high infection rates over short periods of time.

Malaria epidemics can also be associated with climatic variations, such as the El Niño phenomenon. It is now well established that El Niño events are associated with increased precipitation in south-eastern Africa, and with drought in south-western Africa (Ropelewski *et al.*, 1987; Leaf, 1989; Haines *et al.*, 1993; Thomson *et al.*, 1996; ISU, 2000). The reverse tends to occur during the opposite event (La Niña). Essentially, rapid fluctuations in precipitation and temperature patterns associated with El Niño or La Niña can cause environmental conditions leading to increased incidence of malaria over a short period of time and often confined to small geographic areas (ISU, 2000).

2.2.4 Temperature

The relationship between the development of the malaria vector and temperature may be the most definitive and important factor when considering the risk of a given population to malaria infection. In describing this relationship, Lactin (1995) states that the developmental rates of malaria-carrying mosquitoes increase from zero at a low temperature threshold, reach a maximum at an

optimal temperature and decrease rapidly to zero at an optimal upper, lethal temperature.

The temperature factor in determining mosquito development refers to both air temperature and water temperature – both of which must be suitable within a given range. For *Plasmodium falciparum*, it is suggested that an outside air temperature of 20-32 degrees Celsius is required for breeding and development (Thomson *et al.*, 1995; WHO 1995). Outside of this temperature range, the parasite will die. This temperature-related factor partially accounts for the current limits of malaria transmission to tropical, warmer climates (refer to Figure 2.3). Current annual mean temperatures in northern and far southern regions of the world are not suitable for parasite breeding. Air temperature is also important in determining the time period between egg breeding cycles (i.e., the period between successive egg laying). On average, breeding cycles are two days apart at 25 degrees Celsius, but may be three to five days apart at cooler temperatures (Thomson *et al.*, 1996). At high elevations (i.e., above 4000 feet above sea level (ASL)), malaria outbreaks may be closely associated with periods of higher than average minimum temperatures, and last only a short time until the temperatures drop to a normal range (Lactin *et al.*, 1995; WHO, 1995; Thomson *et al.*, 1996).

The past 150 years have seen a general trend of increasing global surface temperatures. Although the reason for this is not completely validated, there has been a strong connection made to the increase in emissions from fossil fuel burning associated with modernisation and industrial development (Garrett, 1994; Moore, 1995; Flavin, 1998; WRI, 1998). Figure 2.4 displays the annual increase of global surface air temperatures, and shows that the average global temperatures have risen by roughly one degree Celsius over the past century.

Figure 2.4 Global surface air temperatures, 1860-2000
(Flavin, 1998)

Because of the close association between malaria and temperature, many scientists have postulated on the effect global warming will have on the state of the world's health (Leaf, 1989; Haines and Roberts, 1994; Lactin *et al.*, 1995;

Patz *et al.*, 1996; NCPA, 1997; Shell, 1997; Connor, 1998). It has been argued that increases in temperatures of air and water around the world will result in a migration of many vector borne diseases, including malaria, pole-ward into previously malaria-free areas (Leaf, 1989; Haines *et al.*, 1993; Garrett, 1994; Patz *et al.*, 1996; Epstein *et al.*, 1998). This argument, as well as counter arguments, will be discussed in the next section.

2.3 Global Warming and Malaria

How does global warming really affect the overall health of the human population and more specifically, the risk of malaria to the human population? Obvious effects on general health and well being include increased occurrence of droughts resulting in malnutrition in some parts of the world, and flooding and hurricanes endangering lives in other parts of the world. Other equally serious problems relate to global temperature changes. As seen in Figure 2.4, the Earth's surface temperature is increasing steadily. Researchers warn that an increase of half a degree per century can pose a substantial risk to the natural environment and to human health (Leaf, 1989; Haines *et al.*, 1993; Garrett, 1994; Patz *et al.*, 1996; Epstein *et al.*, 1998). Hazards related to global warming are also associated with increased risk of malaria infection, with increased mosquito breeding habitats as a result of higher temperatures and increased surface water from flooding.

Regarding the impact of global warming on disease-carrying insects, Garrett (1994) discusses the link between mosquito population and migration, and global temperature. It was determined that the relationship between geographical location of mosquito habitats and climate was such that the global warming effect could result in a huge shift in mosquito populations. As the Earth's temperature increases, several types of mosquito could comfortably move northward, invading many large urban areas like New York and Tokyo (Garrett, 1994). This hypothesis was confirmed by historical evidence showing a geographical shift in malaria-carrying mosquitoes related to the climate change over the millennia (Garrett, 1994). In studies of climate change and its impact on mosquito-borne diseases such as malaria, Epstein *et al.* (1993, 1998) agree with the popular argument correlating climate change and the spread of infectious diseases and suggest this to be one of the most significant threats to global human health. As much of the globe experiences increased annual temperatures related to greenhouse gas emissions, studies have indicated that areas at risk of malaria could increase from 45% of the globe to 60%, if current emission levels are sustained (NCPA, 1997; Epstein, 1998).

It is also argued that, rather than movement northward into developed countries, perhaps a greater risk is the movement of the vector into higher elevation areas (Leaf, 1989; Haines *et al.*, 1993; Epstein *et al.*, 1998). Cities like Nairobi, Kenya, which has previously been at little risk of malaria due to its elevation close to 1600 metres ASL sustaining relatively cooler temperatures, may soon be at risk

of malaria with increasing global warming. These marginal zones, surrounded by malaria endemic areas at lower elevations, are inhabited by those with limited immunity to malaria, and will likely result in an increase in the number of populations at risk of malaria (Connor, 1998).

Contrary to popular opinions, however, there are those who argue that the “warnings” associated with the spread of diseases related to global warming effects are “alarmist” and highly exaggerated (Moore, 1995; NCPA, 1997). In this respect, it is argued that although all vector-borne diseases are influenced by climate, it is simplistic and misleading to say that climate change will necessarily bring an increase in all these diseases.

Malaria, as well as many other insect-borne diseases, was once common in many regions of the world including North America, but has disappeared during the past century, likely because of factors such as improved housing and sanitation (WHO, 1995; Bradley, 1996; WRI, 1998). An article published by the National Centre for Policy Analysis (NCPA, 1997) indicates that even if warmer climates are indeed a reality for the near future, there is no reason for alarm, since the prime factor controlling communicable diseases is not global temperature, but relative wealth and the ecological and medical interventions people use to control diseases and their hosts. Although the disease is nearly non-existent inside the United States’ borders (with the exception of some imported cases), malaria is certainly a serious concern just outside its borders,

where economic and social conditions are often not of the standard seen in the United States. The NCPA briefing (1997) also notes the variations in reported malaria deaths between Singapore and its neighbour, Malaysia. While Singapore reported no malaria deaths in 1994, Malaysia reported 36,853. It is argued that this wide variation cannot be attributed to temperature and climate fluctuations, but is more clearly linked to relative socio-economic conditions.

Regardless of the arguments against the effects of global warming on human health, malaria is a serious disease and an important cause of death in much of the world. The time scale associated with global warming and climate change makes it less of an issue requiring immediate action. However, the number of people dying today from malaria calls for urgent and prompt attention to control and eradication programs.

2.4 Malaria Control and Mitigation

Malaria is considered a curable disease, although the infrastructure and logistical co-ordination required to treat all those infected is not feasible; therefore, an approach to malaria prevention is required instead. Prevention of malaria includes a variety of measures to protect against infection or against the further development of the disease in infected individuals. Considering the mosquito vector as the target, prevention measures include the use of protective clothing, insecticide treated bed-nets or suitable mosquito repellent. On a community

level, insecticide spraying and environmental management practices are assisting in the control of malaria.

Several drugs have been developed to control the malaria parasite in an infected individual. However, potential for effective use of these drugs is limited, given their restricted availability to the infected population, the type of malaria parasite infection, and the ever-increasing resistance of malaria parasites to the drugs. Side effects of many of the anti-malarial drugs available have been widely documented and serious warnings are now associated with some. Since malaria is found primarily in poorer countries, in areas of limited infrastructure and resources, drugs are often either unavailable, or not used correctly.

As a result, drug resistance has become a serious problem for malaria control in much of the world. Over-use and misuse of anti-malarial drugs has caused the parasites to build a strong tolerance, which has led to the banning of many drugs in some countries. The WHO notes drug-resistant malaria as a top priority in malaria control initiatives, with the increased risk of multi-drug resistant malaria in the near future (WHO, 1995).

Malaria is clearly a disease in need of control, and prevention is the answer. It is also clear that many malaria prevention initiatives are not proving fully suitable. The wide variety of malaria strains, as well as the wide geographic distribution of the disease makes it very difficult to control on all levels, and in all areas. The

long-term goal in controlling malaria focuses on the development of a malaria vaccine. Although this is likely years away, there are several programs aimed at developing a safe and effective vaccine against malaria (Richie and Saul, 2001).

There are many factors to consider when developing any type of malaria control or prevention program, and strategic planning and implementation is crucial. The WHO (1995) has recognised that a key consideration in malaria control and prevention lies in the link to effective surveillance of environmental conditions related to malaria. With knowledge of the environmental indicators discussed earlier in this chapter, and with the integration of remote sensing technology that will be fully described in the following chapter, an effective surveillance tool can be developed and widely applied to malaria control and prevention initiatives.

The following chapter will discuss the basic principles of remote sensing – a technology which can be an important tool for mapping and monitoring the global malaria situation. This introduction to the discipline of remote sensing will serve to educate non-geomatics professionals, and will allow for further discussion on its specific application to geospatial analysis of disease to be discussed in Chapter 4.

3.0 Principles of Remote Sensing

3.1 Basic Remote Sensing Theory

Remote sensing is defined as “the science and art of obtaining information about an object, area, or phenomenon through the analysis of data acquired by a device that is not in contact with the object, area, or phenomenon under investigation” (Lillesand and Kiefer, 1994, pg. 1). This procedure is achieved by recording energy that is reflected or emitted from the surface of the target under investigation. Furthermore, this detected and recorded energy is processed, analysed and applied to a given problem. Radiation interaction between a target of interest and the measuring sensor is summarised in Figure 3.1.

Figure 3.1 Summary of the process of remote sensing
 (<http://www.ccrs.nrcan.gc.ca/ccrs/eduref/tutorial/tutore.html>)

Remote sensing systems require the transmission, reflectance and return of energy in the form of electromagnetic radiation. Basic wave theory explains the behaviour of electromagnetic radiation, focusing on two primary characteristics: wavelength and frequency. The wavelength is the length of one wave cycle,

measured as the distance between two successive wave crests. Frequency is the number of wave cycles that pass a fixed point during a fixed unit of time. (Lillesand and Kiefer, 1994). The following formula relates to wavelength and frequency of electromagnetic radiation, which travels at the speed of light.

$$c = \lambda \nu$$

where:

λ = wavelength in metres

ν = frequency in cycles per second (Hz)

c = speed of light (3×10^8 metres per second)

The electromagnetic spectrum summarises electromagnetic radiation by wavelength from short wavelength radiation (e.g. x-rays) to longer wavelength radiation (e.g. microwaves). Figure 3.2 shows the electromagnetic spectrum with corresponding wavelength and frequency information for different types of radiation. For remote sensing purposes, the shortest usable wavelengths start at the ultraviolet portion of the spectrum, and range in length to long wavelengths found in the microwave portion of the spectrum. The light that we see with our eyes is the visible part of the spectrum, which is only a very small part of the full electromagnetic spectrum. Some remote sensors optimise the visible wavelengths to produce "real colour" images that are representative of what we see with our eyes (e.g. SPOT). Other sensors make use of the ultraviolet wavelengths (smaller than visible wavelengths) or infrared (IR) radiation (larger than visible wavelengths). Radar remote sensing technology (e.g. RADARSAT,

ERS) utilises the microwave portion of the electromagnetic spectrum, with considerably longer wavelengths than visible or IR radiation

Figure 3.2 The electromagnetic spectrum
(<http://www.ccrs.nrcan.gc.ca/ccrs/eduref/tutorial/tutore.html>)

Electromagnetic radiation detected by remote sensors must travel through the atmosphere before it reaches its target on the Earth and returns to the sensor. These journeys through the atmosphere can have a significant effect on the energy, altering the intensity and spectral composition of the radiation before the sensor detects it. The main mechanisms for atmospheric effects are scattering and absorption. Scattering relates to the unpredictable redirecting of radiation through interaction with gas molecules in the atmosphere. In general, there are three main types of atmospheric scattering: Rayleigh, Mie and non-selective scattering. Rayleigh scattering occurs when the gas particles are very small compared to the wavelength of the travelling radiation, resulting in significant

scattering of shorter visible wavelengths (i.e. blue). Mie scattering occurs when the gas particles are of a comparable size to the wavelength of the radiation, and it therefore tends to affect longer visible wavelengths. Mie scattering occurs in lower parts of the atmosphere where greater numbers of particles such as dust, smoke and water vapour are present. When particles in the atmosphere are larger than the wavelength of the radiation being affected, non-selective scattering can occur. With this, all wavelengths are scattered about equally, which often results in a white appearance on images (e.g. clouds or fog) (Lillesand and Kiefer, 1994; CCRS, 1998).

Electromagnetic radiation may also be absorbed when passing through the atmosphere. The process of absorption results in a loss of energy to the atmosphere, which can occur at various wavelengths. Ozone, carbon dioxide and water vapour are the three most efficient absorbers of radiation and can play a critical role in determining the most suitable wavelength to use for various remote sensing applications (Lillesand and Kiefer, 1994; CCRS, 1998). For example, atmospheric absorption and scattering affect microwave wavelengths much less than other smaller wavelengths.

Electromagnetic radiation that is not absorbed or scattered in the atmosphere will interact with the Earth's surface in one or more ways. The three primary forms of interaction between incident energy (I) and a surface are absorption (A), transmission (T) and reflection (R). Figure 3.3 illustrates these interactive

mechanisms. Absorption occurs when the energy is absorbed into the target, while transmission occurs when the energy passes through the target. Reflection occurs when the energy bounces off the target and is redirected.

Figure 3.3 Interaction of incident energy (I) with target: Absorption (A), Transmission (T) and Reflection (R)
 (<http://www.ccrs.nrcan.gc.ca/ccrs/eduref/tutorial/tutore.html>)

Energy can be reflected from a target in a number of different ways. The two main reflection processes referred to in remote sensing are specular and diffuse reflection. When a surface is smooth (relative to the wavelength), incident energy interacts with the target and nearly all the energy is directed back into the atmosphere in a single direction. Diffuse scattering, on the other hand, occurs on rougher targets where the energy is reflected in all directions. These scattering mechanisms represent two extreme cases and in fact most targets on the Earth reflect energy somewhere between the two, depending on the surface roughness and wavelength particularly. For example, a sandy target would appear smooth (specular reflectance dominates) with a longer incident wavelength, whereas it might appear rough to a smaller (more diffuse reflectance) to a smaller incident wavelength (CCRS, 1998).

Figure 3.4 Primary reflecting mechanisms: A) Specular reflectance and B) Diffuse reflectance

(<http://www.ccrs.nrcan.gc.ca/ccrs/eduref/tutorial/tutore.html>)

Remote sensing platforms can be situated on the ground, in the air, or in space. Ground-based sensors often collect information to be compared with space-borne or air-borne data, permitting better interpretations of space or airborne information. However, aircraft are often used to collect detailed information over a large area. Helicopters, balloons or aircraft are often equipped with a sensor and auxiliary equipment to compensate for motion on board the aircraft. Today, space-borne sensors are becoming a popular source for remotely sensed information. The Space Shuttle has been used for remote sensing of the Earth, and more commonly now, Earth observation satellites are being launched and used for regular data collection. There are many trade-offs to be considered between these different platforms, mainly related to cost versus coverage and/or resolution. Some of these issues will be addressed later in this thesis.

Regardless of the platform on which a sensor is mounted, it is important to consider the source of energy affecting the sensor. A remote sensor may be either passive or active, depending on the energy source. Systems that measure energy that is naturally available (e.g. sunlight) are called passive sensors. Conversely, sensors that generate their own source of illuminating energy are called active sensors. Advantages to active sensing include the ability to image at night when there is no source of natural energy available from the sun. In addition, some active sensors may be used to examine wavelengths that are not sufficiently provided by the sun, such as microwaves. An example of an active space-borne sensor is RADARSAT-1, which will be discussed in detail in section 3.3.2.

Figure 3.5 Passive (A) versus active (B) remote sensing systems.
(<http://www.ccrs.nrcan.gc.ca/ccrs/eduref/tutorial/tutore.html>)

The basic theory behind how remote sensing as a science and art operates has been outlined. The following section will look at the next step of processing and analysing data provided by remote sensing systems, with attention to different sensors commonly used by today's Earth observation community.

3.2 Image Processing and Analysis

3.2.1 Sensors

With rapid developments in the space-technology industry, Earth observation satellites are being launched regularly. The International Committee on Earth Observation Satellites (CEOS, 1999) publishes an annual yearbook that outlines the numerous satellite missions and instruments available for all applications of remote sensing. Application categories of available sensors include atmospheric measurements, land applications, ocean applications, and snow and ice applications. Both space-borne and airborne platforms can use all portions of the electromagnetic spectrum (Optical, Infrared, Near-IR, Thermal, Microwave, etc.). This section will focus on popular space-borne sensors that have been used for health related applications in the past. Results of research done with the sensors to be discussed will be reviewed in Chapter 4.

In terms of health applications, data from the American Landsat Thematic Mapper (TM) satellite has been used most commonly. Nearly all of the projects with published results used Landsat data, although often in combination with other sensors. The U.S. National Oceanographic and Atmospheric Administration (NOAA) satellites are also frequently used to assess atmospheric characteristics of an area. For example, the NOAA Advanced Very High Resolution Radiometer (AVHRR) instrument is used extensively to calculate vegetation indices including NDVI (Normalised Difference Vegetation Index)

measurements related to vegetation conditions. Details on how NDVI contributes to mapping environmental variables relating to disease will be discussed in the following chapter. For the purpose of this discussion, it is important to understand that Landsat TM and NOAA AVHRR are currently the most widely used sensors for health applications. Hugh-Jones (1991) outlined these two common sensors and their characteristics. Tables 3.1 and 3.2 summarise his discussion.

Table 3.1 Landsat Thematic Mapper characteristics
(Hugh-Jones, 1991)

LANDSAT Thematic Mapper (TM) spectral bands

Band	Wavelength (nm)	Characteristics
1	450-520	Blue - Green; maximum penetration of water; useful for bathymetric mapping of shallow water; distinguishing soil from vegetation, and deciduous from coniferous.
2	520-600	Green; matches green reflectance peak of vegetation; useful for assessing plant vigour
3	630-690	Red; matches chlorophyll absorption band; important in discriminating plant types
4	760-900	Reflected Infrared; useful for determining biomass and mapping shorelines, separating vegetation from dark soils
5	1550-1750	Reflected infrared (IR); indicates moisture content of soil and vegetation; penetrates thin clouds and provides contrast between vegetation types
6	10400-12500	Thermal IR; night time images for thermal mapping and estimating soil moisture
7	2080-2350	Reflected Infrared (IR); coincides with absorption band caused by hydroxyl ions in minerals; useful for mapping hydro-thermally altered rocks and mineral deposits

Table 3.2 Advanced Very High Resolution Radiometer (AVHRR) characteristics
(Hugh-Jones, 1991)

Advanced Very high Resolution Radiometer (AVHRR)

Channel	Wavelength (nm)	Comments
1	580-680	Red-albedo; for snow and ice, daytime clouds, and vegetation
2	725-1100	Reflected Infrared (IR); for shorelines and vegetation
3	3550-3930	Thermal IR; for fires and volcanoes, contaminated by solar radiation so nocturnal images are preferred
4	10300-11300	Thermal IR; for day and night land and water temperatures, volcanic plumes, sea surface temperatures and clouds
5	11500-12500	Thermal IR, similar to channel 4

Each of the seven bands of Landsat TM have a specific use, as seen in Table 3.1. For example, band 4 would clearly show differences between vegetation and water, as well as differences between types of vegetation. This band is particularly useful in epidemiological studies since vegetation type (e.g. grassland, swamp, forest) is often a distinct environmental indicator for many vector-borne diseases. But there are also other satellites available to collect data in the optical region of the electromagnetic spectrum, including SPOT, the French Earth observation satellite, which has three multi-spectral bands, corresponding to bands 2,3 and 4 of Landsat. SPOT provides higher resolution and more frequent viewing of a given region than Landsat (Hugh-Jones, 1991).

Remote sensing researchers must make 'trade-offs' when choosing the sensor that they will use for their studies. Bandwidth, resolution, coverage, and

available repeat cycle characteristics need to be taken into account. Often researchers will opt for a greater coverage, and sacrifice in having lower resolution. Other times, resolution is considered the most important factor, and the area covered will be smaller. Of course, these decisions are application dependent.

Both Canada and Europe have commercially operational space-borne microwave sensors – RADARSAT and ERS respectively. Given radar's unique capability to penetrate clouds and darkness, these sensors can be particularly useful in tropical areas of high cloud cover. Since most infectious diseases are prevalent in tropical areas, radar appears to be a logical tool for imaging these environments. However, radar also has its limitations related to resolution and inherent noise (speckle) characteristics that are often difficult to overcome.

The complexity of radar physics and engineering requires a steep learning curve associated with utilising radar technology, especially when one is conditioned to the variables associated with optical remote sensing. Clearly, there are many sensors, each with specific capabilities and functions available to the user. The differences between radar and optical data are great, as are the differences between space-borne and air-borne sensors. The optimal sensor for monitoring human health issues remains to be determined, although recommendations will be made and will be discussed later in this research. An in-depth discussion of radar remote sensing technology is contained in section 3.3.

3.2.2 Image Processing

Image processing includes all the operations that can be applied to an image after it is acquired, but before it is analysed or interpreted. The purpose of these procedures is to increase the interpretability and usability of the data. Operations may include image enhancement, resampling, rectification, filtering and other image pattern recognition techniques. Image pre-processing techniques of error correction, motion compensation and image calibration are often carried out either during image acquisition or as the data are received by the data reception facility. Depending on the sensor and application area, different levels of processing are required by the user. There are numerous image processing operations to be considered, but the most common include image enhancement and image transformation, which are performed to obtain imagery that has the important features highlighted and is spatially correct.

Image enhancement is carried out for the purpose of improving the appearance of an image to make it more easily interpretable. In the case of single channel SAR data, for instance, enhancing the grey tones to improve the appearance of certain features is a routine task prior to image interpretation. Enhancement functions involve the manipulation of the data histogram to increase tonal contrast between different features in an image. Spatial filtering is used to selectively differentiate spatial patterns in an image and to either reduce or enhance image speckle ("salt and pepper effect"), depending again on the application. There are several filtering algorithms that are specifically designed

to deal with the noise characteristics of SAR data. Examples of these include Lee, Kuan and Frost filters (Lillesand and Kiefer, 1994), although other filters are commonly used with optical data, such as median or mean filters. Most image processing and analysis software includes a wide range of filters and filter characteristics which can be adapted to a given image type and application of interest.

Texture analysis is a common image enhancement technique used to identify unique spatial distribution of tones within a given image (Hay and Niemann, 1994; Jensen, 1996). Particularly for highly speckled images, texture analysis can allow for texture information to be used in advanced image analysis operations such as image classification. In fact, some researchers have concluded that higher classification accuracy is found with the inclusion of texture information, as opposed to solely spectral information (Peddle and Franklin, 1991). Texture analysis will be discussed in more detail later, with respect to the methodology carried out for the case study (Chapter 5).

Image transformation operations are carried out on remotely sensed data in order to combine multiple images, for example, multiple bands, multiple time sequence, or multiple polarizations in the case of SAR data. Images are combined using logical arithmetic operations (e.g. addition, subtraction, multiplication and division) to most effectively and efficiently display multiple images in one database.

Once an image has been suitably processed, the user may analyse the data.

3.2.3 Image Classification

Image classification routines are part of a standard practice in remote sensing to produce thematic maps of land use or land cover. There is a range of techniques that can be applied to classify an image; the most conventional ones include algorithms such as the Maximum Likelihood classifier (Peddle *et al.*, 1994). A classification can be based on either intrinsic variation in brightness (unsupervised classification), or based on a subset of samples of known cover types whose brightness characteristics are matched with those of the rest of the area (supervised classification). Segmentation analysis allows images to be parcelled into objects prior to classification, allowing for an object-oriented classification rather than a pixel-oriented classification. Most classifiers, such as the Maximum Likelihood, rely on a normally distributed dataset whereas some classifiers, such as a neural network, can incorporate data that are not normally distributed, as is often the case with SAR data (Augusteijn and Warrender, 1998; Hao and Yun, 1996). Intelligence-based classifiers have become more popular in recent times, as they allow for a more integrated approach to classification (Maselli, 2001).

3.3 Microwave Remote Sensing

The purpose of this section is to address the unique characteristics of remotely sensed data that are collected in the microwave portion of the electromagnetic spectrum. Microwave remote sensing is complex and has consequently had limited operational use in the past. However, with recent space-borne SAR sensors such as RADARSAT-1, users are researching the applicability of radar for monitoring a wide variety of targets. This section will discuss the generalised theory behind microwave remote sensing, and then focus on RADARSAT-1, Canada's only commercial Earth observation satellite. This will provide an intuitive understanding of microwave remote sensing, rather than the technical details of SAR physics.

3.3.1 Fundamentals of Microwave Remote Sensing

Radar waves fall into the microwave portion of the electromagnetic spectrum (Figure 3.6). Compared to the more commonly exploited wavelengths used in optical remote sensing, microwaves are quite long (approximately 1cm to 1m), which allows for penetration through cloud cover and haze. This is a major advantage of SAR remote sensing over optical sensing, since it allows for the use of SAR in nearly all environmental conditions. Figure 3.6 shows a more detailed view of the microwave portion of the electromagnetic spectrum, where the energy is sub-divided and identified by various band labels. Bands range from K-bands with short wavelengths, to P-band with the longest radar

wavelength. C- and L- bands are most commonly used on airborne and space-borne radar remote sensing systems, including RADARSAT-1 (C-band) (Lewis *et al.*, 1998).

Figure 3.6 The microwave portion of the electromagnetic spectrum
(<http://www.ccrs.nrcan.gc.ca/ccrs/eduref/tutorial/tutore.html>)

Microwave sensors can either be passive or active, as discussed earlier in this chapter. Passive microwave sensors can record several sources of energy, including surface reflection, surface emission, or energy transmitted from the subsurface. Depending on the wavelength, microwaves can either image the atmosphere (small wavelengths) or penetrate through the atmosphere to image the surface below (longer wavelengths). Common passive microwave applications include hydrology and oceanography for looking "through" the

atmosphere, or meteorology for looking “at” the atmosphere (e.g. Doppler radar) (Raney, 1998).

Active microwave sensors generate their own source of illumination and can therefore be operated day or night, regardless of weather conditions. With active microwave imaging systems, the sensor transmits a microwave signal towards the target and then detects the distance and time delay of the backscattered portion of the signal.

Due to the differences in operational characteristics of radar imaging, as opposed to optical imaging described earlier, radar images can provide very different information about a target. Combining both image types with a suitable image transformation routine can often substantially improve the information content from both input images (Borgeau-Chavez *et al.*, 2001). However, when no optical data are available due to cloud cover for instance, radar can be an effective imaging tool on its own for some applications.

Two primary characteristics of a radar image are tone and texture. Image tone refers to the various grey levels in an image, from black to white. Image texture refers to the spatial distribution of image tones within an image (Lewis *et al.*, 1998; CCRS, 1998). Variability of image tones and textures may be related to several characteristics of either the radar system (frequency, polarization, incident angle) or of the surface target (land cover, topography, elevation).

Because many of these characteristics are interrelated, it is extremely challenging to separate out each of their individual contributions to the appearance of features in a radar image. Changes in the various parameters may have an impact on the response of other parameters, which together will affect the amount of radar backscatter.

Polarization is a particularly important radar sensor characteristic, and refers to the orientation of the electric vector, as it is transmitted and received (Boerner *et al.*, 1998). Most radar sensors are linearly polarized in that they transmit microwave energy either horizontally (H) or vertically (V), and then receive either horizontally or vertically polarized energy. There are thus four combinations of linearly polarized microwave radiation – HH, VV, HV and VH, according to the transmit and receive orientation. Although most current space-borne radar sensors are linearly polarized, advanced systems can provide multiple or fully polarimetric data, which would allow the user to analyse images of the same area, at the same time, but using different polarizations. Similar to image transformations which combine multi-temporal or multi-spectral data, multi-polarized data are often combined and analysed for a given area, providing increased information content for a single data collection (Boerner *et al.*, 1998; CCRS, 1997).

With radar imaging, target characteristics affecting image tone and texture are primarily related to surface roughness, target geometry and surface moisture

conditions. Surface roughness refers to the average height variations in a surface cover and is usually measured in centimetres. Whether a surface appears “rough” (bright) or “smooth” (dark) depends mostly on the wavelength of the imaging radar, as well as the incident angle of the radar beam. In other words, a surface is considered smooth if the height variations are smaller than the radar wavelength. This will result in specular reflectance, which causes most of the incident energy to be reflected away from the sensor, resulting in little backscatter and a dark tone on the image. However, when the surface height variations approximate the radar wavelength, the surface will appear to be rough, causing more radar-target interaction and producing a brighter tone on the image (Lewis *et al.*, 1998; CCRS, 1997).

Further, target moisture conditions will affect the image tone, with high surface moisture causing increased scattering and a brighter tone, and low moisture conditions giving a dark response on a radar image. This is due to the dielectric constant of a target, or electric property of the surface, which influences the radar return (Raney, 1998; Brisco *et al.*, 1993, 1996).

The geometry of a target also has a strong influence on the radar backscatter and thus the tone and textures seen on radar images (Lewis *et al.*, 1998). As mentioned earlier in this chapter, the main scattering mechanisms that occur when imaging a given target include specular reflection (A) and diffuse reflection (B). Diffuse scattering occurs when the incoming radar signal interacts with the

target in such a way that the signal is reflected in different directions. With this mechanism, a portion of the signal is returned to the sensor giving an intermediate tone. Image tones increase in brightness as more of the radar signal is reflected back to the sensor. Very bright tones occur due to corner reflection (C), whereby a large portion of the signal is returned to the sensor, due to a double or triple bounce effect that occurs when the incoming radiation interacts with one surface that is perpendicular to another (Lewis *et al.*, 1998; CCRS, 1997).

Figure 3.7 Specular reflection (A), Diffuse reflection (B) and Corner reflection (C)

(<http://www.ccrs.nrcan.gc.ca/ccrs/eduref/tutorial/tutore.html>)

With the knowledge of radar sensor characteristics, including imaging wavelength and polarization, and target characteristics, including surface roughness, target geometry and moisture conditions, one can begin to qualitatively interpret a radar image based on different tones and textures. Quantitative image interpretation may be carried out through extraction of radar backscattering values over different targets. The following section will describe

Canada's Earth observation satellite, RADARSAT-1, in order to assist the reader in understanding the radar image analysis and interpretation carried out for the case study to be discussed in Chapter 5.

3.3.2 RADARSAT-1

Launched in November 1995, RADARSAT-1 is a Canadian initiative involving the Canadian government, the United States government, and private industry. The RADARSAT-1 spacecraft carries a C-band Synthetic Aperture Radar (SAR) sensor that transmits and receives horizontally polarised (HH) microwave signals to image the Earth both day and night. In addition, the chosen frequency of RADARSAT-1 can penetrate clouds and haze, increasing the useful geographic and temporal coverage significantly over optical sensors (CSA, 2001). The main application of RADARSAT-1 is sea ice monitoring in arctic regions, although the technology has been proven useful for monitoring many of the Earth's resources and environmental changes. In particular, land applications related to hydrology, agriculture, and land use mapping have benefited from the capabilities of RADARSAT-1 to provide reliable SAR imagery (Brown *et al.*, 1996).

RADARSAT-1 has the unique ability to steer its variable mode radar beam over a wide area. The flexible swath width (50-500km), spatial resolution (8-100 metres), and incidence angle (10-60 degrees) provides users with many data options which can be suited to a variety of applications. RADARSAT's wide area swaths provide excellent regional coverage (up to 500 km.) with a coarse spatial resolution, while detailed studies may be carried out using fine resolution data

with swath coverage of 50 km (RSI, 1995; CSA, 2001; Ross *et al.*, 2001). The specifications of the RADARSAT-1 SAR are provided in Table 3.3.

RADARSAT-1 operates in a sun-synchronous polar orbit, providing complete global coverage on a regular and timely basis. The ground track of the satellite is repeated every 24 days, although the steerable beam capability and wide swath coverage allow for most regions on the Earth to be imaged more frequently. High latitudes (north of 70°) may be imaged on a daily basis, as is done for the Canadian Arctic regions, while areas closer to the equator can achieve repeat coverage every three to six days. Orbit specifications for RADARSAT-1 are presented in Table 3.4. Operating beam mode specifications are provided in Table 3.5.

Table 3.3 SAR sensor characteristics for RADARSAT-1
(CSA, 2001)

Centre frequency	5.3 GHz (C-band)
Bandwidth	11.6, 17.3 or 30 Mhz
Polarisation	HH
Spatial resolution	9-100 m
Swath width	50-500 km
Incidence angle	10°- 58°

Table 3.4 Orbit characteristics for RADARSAT-1
(CSA, 2001)

Altitude (average)	798 km
Inclination	98.6 degrees
Period	100.7 minutes
Sun-synchronous	14 orbits per day
Repeat cycle	24 days

Table 3.5 Characteristics of RADARSAT-1 operating beam modes (CSA, 2001)

Mode	Approximate Incidence Angle [degrees]	Approximate Swath Width [km]	Approximate Resolution: ¹ Rg x Az [m]	Approximate Looks ² [Rg x Az]
Standard	20-49	100	25 x 28	1 x 4
Wide	20-39	150	25 x 28	1 x 4
Extended Low	10-23	170	40 x 28	1 x 4
Extended High	50-60	75	20 x 28	1 x 4
Fine	37-48	50	10 x 9	1 x 1
ScanSAR Wide	20-49	500	100 x 100	4 x 2
ScanSAR Narrow	20-40	300	50 x 50	2 x 2

¹ Ground resolution varies in range, ² Range and processor dependent

There are several receiving stations for RADARSAT-1 around the world. In addition, the satellite can acquire up to 32 minutes of data per orbit, which are either downlinked in real time using two simultaneous x-band channels, or stored on one of two onboard recorders until the spacecraft is within range of a ground receiving station. RADARSAT-1's processing facilities cater to many customers' needs for timely data, by providing imagery to users within four hours of acquisition when necessary. This service has been particularly useful in operational disaster management and real-time ice reconnaissance operations, which require timely data at times that are often coincident with persistent cloud cover and/or darkness (Brown *et al.*, 1996; RSI, 1995; CSA, 2001).

As previously mentioned, there has been comparatively little use of RADARSAT for applications relating to socio-economic applications such as disease monitoring. The purpose of the case study, which will be described in Chapter 5,

is to evaluate the capability of RADARSAT-1 for monitoring malaria risk. The conclusions of this case study will reveal the suitability of C-band HH space-borne radar for this application. Further discussion will address the successes and limitations of RADARSAT for disease monitoring, based on the findings of the case study.

The basic principles associated with the spatial analysis of potential disease risk, with attention to the key environmental variables that may be detected using remote sensing techniques, will be the focus of the next discussion. Past research in this field will be summarised, with specific attention to the major challenges and gaps in the field. Finally, we will look at how radar remote sensing may address these challenges.

4.0 GEOSPATIAL ANALYSIS OF DISEASE

4.1 Background

There is little doubt that remote sensing (RS) and Geographic Information Systems (GIS) have the potential to be useful, efficient and effective tools in the fight against the world's infectious diseases and microbes. Most researchers in the field recognise this potential, but many also recognise the limitations associated with the technology (Beck *et al.*, 1997; Thomson *et al.*, 1998; Hay *et al.*, 1998). This chapter will provide an overview of recent research published on geomatics technologies as tools for monitoring human health, and also provide the reader with a critical analysis of the literature and a discussion of the gaps and limitations discovered.

Geomatics technology can be used to develop predictive models of vector-borne population dynamics and risks to human beings. GIS and RS offer more efficient

means of spatial analysis than traditional survey techniques, and can provide effective means of investigating spatial phenomena. GIS technology uses the idea of data layer integration to compare, analyse and manipulate spatial information. For example, a GIS database may include data layers for vegetation type, water bodies, urban areas, transportation routes, and elevation contours. Using various algorithms, one can carry out analysis on all the layers with a single query. Vector-borne diseases, because they so often exist as a function of their environment, are ideal spatial targets of geomatics tools.

Of course, in order to assess adequately the potential presence of a given disease, the ecology of the disease must be known. In light of this, a multi-disciplinary approach to the use of geomatics for disease monitoring is required (Wood *et al.*, 1993). Nearly twenty years ago, Mayer (1983) discussed the role of spatial analysis and geographic data in the detection of disease causation, and stressed the importance of merging the fields of geography with epidemiology. He noted:

There is a clear overlap between geography and epidemiology, which is “the study of the distribution of a disease or physiological condition in human populations and of the factors that influence this distribution”. While geography is concerned with spatial patterns and processes generally and includes the spatial analysis of disease as a sub-field (medical geography), epidemiology is concerned with the distribution of disease, and includes the study of

geographical variation as one particular component. Whereas the complementarities between epidemiology and geography are both striking and obvious, the dialogue between researchers in these two disciplines had been minimal. (p.1213)

It appears that the collaboration between geographers and epidemiologists has improved in recent years, perhaps due to the popularity and use of geomatics technology. Many authors have referred to maps as efficient and effective means of relaying spatial information (Barnes *et al.*, 1979; Arambulo *et al.*, 1991; Cline, 1970; Croner *et al.*, 1996; Epstein *et al.*, 1993; Hacker *et al.*, 1994; Hay *et al.*, 1997, 2000; Hoffman, 1990; Hugh-Jones, 1991; Mayer, 1983; Scholten *et al.*, 1991; Travis, 1997; Twigg, 1990; Washino *et al.*, 1993). Guthe (1993), in his discussion of the use of GIS for mosquito control, points out that maps have long been a useful tool in displaying a lot of information quickly and clearly. Maps, and often remotely sensed imagery, allow the reader to see patterns that may be otherwise unnoticeable. GIS, Guthe points out, takes mapping to another level by integrating database information and allowing output maps to be analysed based on the input layered information. Beck (1994) also refers to GIS as an objective, innovative, and potentially cost-effective tool for health applications.

By combining layers of mapped information, and relating these to environmental conditions extracted from remotely sensed imagery, one can “query” any given area in order to extract information that may then be correlated to auxiliary data

relevant to the disease being monitored. Environmental attributes are given a ranking based on their known relationship to the disease vector. For instance, a developed urban area is less likely to be a habitat for the malaria carrying *Anopheles* mosquito, and would thus be given a low ranking. Conversely, a transitional swamp is known to be a prime environment for *Anopheles* breeding and would thus be ranked much higher. These areas are then assessed with respect to their proximity to human populations in order to relate the interactions of humans to the landscape. Remote sensing imagery can be used to characterise patterns of vegetation and human settlement at a variety of scales and over large areas. GIS functions can then be used to map and model the probability of disease presence based on spatial patterns (Pope *et al.*, 1992; Guthe, 1993; Beck *et al.*, 1995).

4.2 Key Geographic Variables

Remote sensing and GIS are widely used in natural resource applications such as agriculture, forestry, geology, hydrology and ice/oceans. However, little research has been done using satellite remote sensing in the social sciences, and particularly human health sector. Jovanovic (1987) questioned why this was the case, and hypothesised the reason to be that human population simply cannot be seen from space. He pointed to the simple fact that microbes cannot be directly detected remotely – neither from space, nor by a medical doctor in a room with a patient. A physician clearly looks for symptoms caused by the microbes' detection, rather than looking for the microbe itself. However, these

symptoms cannot be detected from space-borne remotely sensed imagery. Physicians, and other researchers, must rely on indirect findings by relating conditions to, for instance, the patient's environment (Jovanovic, 1987). Essentially, medical professionals look for symptoms to detect the presence of disease, whereas remote sensing can be used to study the spatial and temporal contexts of the environment of a given disease. In this way, space technology such as remote sensing can be used to detect disease and microbial symptoms.

Many diseases are highly correlated with environmental conditions. As mentioned, the malaria parasite is carried by the *Anopheles* mosquito, which is commonly found in a very specific wetland environment. Similarly, the *tsetse* fly is found in a particular vegetative environment, and is the vector responsible for transmitting Trypanosomiasis (Rogers *et al.*, 1993). Schistosomiasis is carried by an aquatic snail and is also directly related to specific characteristics in an aquatic habitat (Malone *et al.*, 1997). Jovanovic (1987) classified health-relevant environmental components that are detectable from space into three main categories: air, water and land. He also divided the detectable parameters into physical, chemical and biological categories. Table 4.1 below summarises his classification scheme.

Based on the findings summarised in Table 4.1, primary environmental components associated with health indicators can be associated with air, water or land elements. Relating to elements found in the air, temperature, humidity

and precipitation are perhaps the most significant parameters, with chemical parameters such as pollution and biological parameters such as airborne gases also playing important roles in detecting health issues from space. Diseases associated with water may be detectable by analysing satellite data relating to sea temperature and turbidity, water salinity and pH, or surface vegetation. Land temperature, moisture content, surface conditions, and vegetation cover may also be important when considering a disease vector that breeds on a land-based target, such as malaria-carrying mosquitoes.

The extent to which all these parameters' characteristics may be detected from space is a subject of active research, and varies from one sensor to another. There are many different sensors that are designed for specific applications using various regions of the electromagnetic spectrum, as previously discussed in Chapter 3. The most common optical sensors used in recent research on remote sensing applicability to disease monitoring are Landsat TM and NOAA AVHRR.

Many projects have been carried out to detect and map regional land cover, land use and atmospheric characteristics. These variables are easily and commonly detected using remotely sensed data. In terms of land cover characteristics, the following classifications are often made and associated with specific disease habitat requirements: wetlands (Wood *et al.*, 1991, Pope *et al.*, 1992; Thomson *et al.*, 1996), forests, cultivated fields/crop type (Wood *et al.*, 1991), pasture,

swamp/marsh (Hayes *et al.*, 1985; Wood *et al.*, 1991; Beck *et al.*, 1997), and urban areas (Thomson and Connor, 2001).

Table 4.1 Classified health relevant environmental parameters detectable from space
(Jovanovic, 1987)

Environmental Component	Physical Parameter	Chemical Parameter	Biological Parameter
AIR	Temperature Humidity Dew point Radiation budget Wind velocity Snow delineation Precipitation Atmospheric pressure Evapo-transpiration	Trace gases Aerosols Toxic gases Air pollution Ozone	Organic gases Nitrogen compounds Airborne pathogens Vector-hosts
WATER	Temperature Turbidity Size of body Depth Surface roughness Wind speed Wave amplitude Current velocity Ice type Sedimentation rates	Acidity Alkalinity Salinity PH Pollution (e.g.. oil spills)	Phytoplankton Surface vegetation Submerged vegetation Chlorophyll content
LAND/SOIL	Temperature Moisture content Surface water Ground water Soil depth Bedrock interface Topography / slope Geologic structure	Salinity Alkalinity Acidity PH Mineralization	Vegetative cover Vegetation stress Insect infestation Biomass content Vegetation canopy Wildlife census

Similarly, atmospheric characteristics can be mapped and related to a particular area. Historical meteorological data are often input into a GIS layer and used to identify weather patterns that may be conducive to various disease pathogens. The following atmospheric classifications are most commonly used to identify areas at risk of a specific disease: precipitation, humidity, temperature, dew point, and wind speed (Bryceson, 1989; Linthicum *et al.*, 1991; Wood *et al.*, 1991; Hugh-Jones *et al.*, 1992; Pope *et al.*, 1992; Randolph, 1993; Beck *et al.*, 1994, 1995, 1997; Ahearn *et al.*, 1996; Rogers *et al.*, 1996; Serpi *et al.*, 1996; Thompson *et al.*, 1996, 1997; Dister *et al.*, 1997; Hay *et al.*, 1998).

Using remotely sensed data, Dister *et al.* (1997) determined relative measures of vegetation structure and moisture (wetness), as well as vegetation abundance (greenness), conducive to Lyme disease. It was found, for example, that wetter and greener areas posed a much higher risk of Lyme disease than the drier non-vegetated areas, which were classified as low-risk (Kitron *et al.*, 1991; Dister *et al.*, 1997).

Similarly, researchers have investigated land cover variables that relate to the abundance of malaria carrying mosquitoes. Beck *et al.* (1994, 1995, 1997) associated transitional (seasonally variable) swamp and flooded grassland with areas of high risk of malaria in Mexico. Temperature, precipitation, humidity and

landscape elevation were also considered as major variables related to malaria environments.

Several researchers including Ambrosia *et al.* (1989) Linthicum *et al.* (1991) and Pope *et al.* (1992) investigated another mosquito-borne virus, Rift Valley Fever (RVF). Pope *et al.* used Landsat Thematic Mapper (TM) to map flooded areas of depressed topography and associated these regions with high risk of Rift Valley Fever. They also considered vegetation characteristics, and used the Advanced Very High Resolution Radiometer (AVHRR) on board the National Oceanographic and Atmospheric Administration (NOAA) satellite to determine the NDVI (Normalised Difference Vegetation Index). NDVI is a standard measure of vegetative health, which looks at the normalised difference between red and infrared reflectance. NDVI analysis quantifies the levels of photosynthetic activity of the vegetation from which vegetative condition can be inferred, as well as the amount of rainfall in an area. Areas of high rainfall relate to flooding and thus increased mosquito populations. NDVI is a measurement used commonly by researchers interested in vegetation type and condition (Bryceson, 1989; Pope *et al.*, 1992; Randolph, 1993; Ahearn *et al.*, 1996; Rogers *et al.*, 1996; Thomson, 1997; Hay *et al.*, 1998).

Although certainly more difficult a task, human characteristics such as migration patterns and urbanisation characteristics may also be interpreted from imagery from suitable sensors. These factors may be related to disease in terms of the

movement of refugee communities, for example. Earth observation satellite sensors rarely provide the resolution required for monitoring and mapping small-scale human movements and activities, but several new high-resolution sensors, such as IKONOS, may address this limitation (Hay, 2000). The idea of monitoring human activities with remotely sensed information is certainly more challenging than monitoring natural environmental phenomena, and is indeed a challenge to the field of remote sensing for epidemiological studies.

4.3 Recent Research

Proposals to use remote sensing for monitoring disease-related environments were put forth as early as 1977, when Woodzick *et al.* presented a paper entitled “Multi-date Mapping of Mosquito Habitat” at the Eleventh International Symposium on Remote Sensing of Environment. In this project, Landsat data from three separate dates were used to create a land cover map of a region in the United States. Quite simply, the land cover classification was used as an indicator of potential mosquito larval habitats by distinguishing different land cover classes. Although this idea was proposed before efficient GIS software was readily available, the concept of mapping and monitoring disease with remotely sensed data has remained the same for the past two decades.

Today, geomatics technologies are beginning to be used in many parts of the world to monitor vector-borne diseases, map high-risk areas, quantify hazardous zones, and assist in disease policy and planning. In 1985, the National

Aeronautics and Space Administration (NASA) established the Global Monitoring and Disease Prediction Program in response to the World Health Organisation's (WHO) plea for an effective tool to cope with the growing concern over malaria infection (Clarke *et al.*, 1996). It was hoped that geomatics technology could be used to build a model to predict and control malaria outbreaks by detecting and monitoring the environmental factors that affect patterns of disease risk and transmission. In collaboration with a number of universities and agencies, a project was started which aimed at developing a predictive model to analyse the villages in the Chiapas region of Mexico that were "at risk" for malaria transmission. In this study, "risk" was defined by the proximity of a village to the breeding, feeding and resting habitats required by the malaria vector, *Anopheles* mosquito (Washino, 1998). Essentially, areas of greater risk of human-mosquito contact were considered to be at the highest risk of malaria transmission.

Supplementary to traditional ground-based approaches, the above project combined remote sensing and GIS technologies to develop landscape predictors of mosquito abundance. Atmospheric factors that were taken into consideration included precipitation, humidity, and temperature. Land-use classes were also considered, including wetlands, woodlands, agriculture, pasture, plantations, burned areas, riparian forests and urban areas (Beck *et al.*, 1997). Each of these factors and landscapes has different associated levels of mosquito populations and can be analysed to predict the location of high-risk malaria areas using a weighted variable scheme.

Beck (1995, 1997) discusses this project as it was carried out in 1992. The data used in her development of a remote-sensing based model for predicting malaria transmission risk in Chiapas, Mexico, included Landsat TM data, GIS overlays and extensive field information. Although the spatial resolution of most satellite data is not capable of identifying individual trees or residences, the Landsat TM data were able to identify general landscapes that contained these specific characteristics. The hypothesis was simple: that the villages close to landscapes with higher mosquito habitat elements such as high humidity, low elevation, wetlands and grasslands, would have a higher risk of malaria transmission.

Forty randomly selected villages in the area were used as sample sites, and landscape elements around these villages were compared during the wet season when the mosquito populations were highest. Multi-temporal Landsat TM images provided the landscape data, and allowed the researchers to consider the change in landscape features on a seasonal basis. GIS data layers were integrated with the remotely sensed data to develop a final landscape map. Buffer zones were created around the villages and GIS procedures allowed the computation of the proportion of each landscape element within a village buffer. The results of the analysis indicated that the most important landscape elements related to mosquito populations were transitional swamps and unmanaged

pasture (Beck *et al.*, 1995, 1997). This project demonstrated the predictive capability of GIS and remote sensing for malaria transmission.

Several other studies have used geomatics technology as a tool for monitoring human health. Thomson *et al.* (1997) developed a project that involved mapping malaria risk in Africa. For this research, detailed weather data were collected from the advanced very high-resolution radiometer (AVHRR) on board a NOAA satellite. This imagery provided meteorological information for large areas of the Earth's surface several times per day. Based on the ecological flexibility of particular mosquito species, the researchers mapped areas where mosquito populations may be highest. Land surface temperatures, soil and vegetation moisture content, and vegetation state were also taken into account. This project concluded that low-cost remote sensing in local environmental monitoring is of great value and provided the capability to predict and map areas at high-risk of malaria transmission in Africa (Thomson *et al.*, 1997).

Many of the studies using geomatics for disease monitoring have focused on malaria, perhaps because it is a disease that is in the forefront of research and funding opportunities. But there have also been some developments in the use of geomatics technology for other health-related issues. For instance, Rogers and Randolph (1991) investigated African Trypanosomiasis, transmitted by the bite of the tsetse fly, as it occurred in Sub-Saharan Africa. Again, NOAA AVHRR satellite imagery was used to relate measurements of vegetation type to field

measurements of tsetse fly populations. Further to the earlier mention of Dister's (1997) study of Lyme disease, this phenomenon was studied in 1990 using Landsat MSS data to identify landscape elements in the Czech Republic (Washino, 1998).

Besides malaria, other diseases, both human and non-human, are being researched to determine the potential for monitoring using GIS and remote sensing. Table 4.2 summarises these diseases and the researchers who have investigated them.

Table 4.2 Summary of research using RS and GIS for monitoring disease

Australian Plague	Bryceson, 1989
Drancunculiasis	Ahearn <i>et al.</i> , 1996, Clarke <i>et al.</i> , 1990
Ixodidae	Hugh-Jones, 1992
Leishmaniasis	Cross <i>et al.</i> , 1996; Hay <i>et al.</i> , 1997
Lymphatic Filariasis	Hay <i>et al.</i> , 1997; Hassan <i>et al.</i> , 1998
Lyme disease	Dister <i>et al.</i> , 1997, Kitron <i>et al.</i> , 1991
Malaria	Armstrong <i>et al.</i> , 1998; Beck <i>et al.</i> , 1994, 1997; Bretas, 1995; Conner <i>et al.</i> , 1997, 1998, 1999; Hay <i>et al.</i> , 1998, 2001; Kitron <i>et al.</i> , 1994; Pope <i>et al.</i> , 1993; Rejmankova <i>et al.</i> , 1995; Roberts <i>et al.</i> , 1991, 1996; Rodriguez <i>et al.</i> , 1996; Ross <i>et al.</i> , 2001; Thomson <i>et al.</i> , 1996, 1997, 2001
Onchocerciasis	Baker <i>et al.</i> , 1986; Hay <i>et al.</i> , 1997
Rift Valley Fever	Ambrosia <i>et al.</i> , 1989; Linthicum <i>et al.</i> , 1991; Pope, 1992
Schistosomiasis	Chen <i>et al.</i> , 1991; Hay <i>et al.</i> , 1997; Malone <i>et al.</i> , 1997
Trypanosomiasis	Hay <i>et al.</i> , 1997; Kitron <i>et al.</i> , 1996; Rogers <i>et al.</i> , 1993
West Nile Virus	Rogers <i>et al.</i> , 2002

4.4 Challenges

Several of the limitations faced by the community of users researching the applicability of geomatics technology in disease monitoring have already been

mentioned, including the most common obstacle: high cloud cover in optical data. The obvious solution to this problem is the substitution of radar data, although there are many challenges to be overcome with radar too. Extensive training is required to understand how a radar operates, and in particular how to manipulate and interpret radar data. Thus, knowing which sensor is best for a given application is an on-going challenge faced by the geomatics community. One must deal with the consequences of various swath coverage, resolutions, bandwidths, and other sensor characteristics. Hugh-Jones (1989) stresses the importance of identifying the habitat and area of the occurrence of a vector, before choosing the platform for monitoring it.

Many authors mention the potential usefulness of radar, but few seem to have actually explored these possibilities. However, Pope (1992) did attempt to use an air-borne imaging radar, ERIM/NADC P-3 SAR, to complement Landsat data in identifying Rift Valley Fever vector habitats in central Kenya. He found it to be effective for his investigation, but noted the limitations related to data timeliness, and the high cost and logistical difficulties associated with carrying out an air-borne data collection campaign. Space-borne SAR imagery overcomes these obstacles by providing timely data at a relatively low cost. However, satellite images rarely provide the spatial resolution attainable with air-borne sensors.

Another concern in using geomatics technology for health applications is presented by Thomson (1997) and Mayer (1983) and relates to the inability to

monitor behavioural traits and genetic variations using remote sensing. These authors point to the potential importance of these factors in determining the exposure of individuals to disease, and reflect on the idea that these factors may account for variation in disease patterns among communities. An example of a behavioural trait may be the use of mosquito nets, which would greatly reduce the risk of disease in a given area. Genetic factors relating to the host vector are also not detectable remotely. However, it may be possible to integrate these ideas into a subjective GIS layer, given appropriate field information (Corbley, 1996). Although the objective is most often to map the environmental factors that relate to a given disease, the actual usefulness of a map product is likely altered by behavioural or genetic traits.

Further consideration relates to the importance of field verification. As with previous techniques of traditional ground survey, geomatics technology also requires fieldwork to be carried out. In fact, no remotely sensed image or GIS output map should be taken at 'face value'. The scientific community stresses the importance of ground truth in order to verify results time and time again. There are several challenges in terms of monitoring diseases and conducting fieldwork. One is the accessibility of the area, since most of the diseases to be monitored are prevalent in less developed parts of the world. Remote areas will often be difficult to access, and may lack the infrastructure necessary to carry out effective field investigation. The second challenge relates to the risk and danger factors when working with infectious diseases – an aspect of fieldwork that those

in the geomatics industry do not often contend with. A third challenge relates to field data collection. Many researchers quantitatively evaluate the presence of the vector host through field data collection, using light traps to catch mosquitoes, and egg bed collection to predict the reproductive capabilities of various species (Ambrosia *et al.*, 1989; Bryceson, 1989; Wood *et al.*, 1991; Pope *et al.*, 1992; Rogers *et al.*, 1993; Beck *et al.*, 1994). These techniques are not commonly used in standard field data collection techniques applied to monitoring natural resources, and again point to the importance of a multi-disciplinary team in using geomatics for epidemiological studies.

A further concern relates to the timeliness of data delivery. When monitoring vector-borne diseases, it is very important for the user to analyse the data as quickly as possible after acquisition. Often there are long delays related to data storage on-board the aircraft or spacecraft, and down linking times can be very lengthy. Hay (1997) stresses the importance of near-real time data delivery, especially in the application of disease risk mapping, since risk of disease is related to a wide range of dynamic variables. Many satellite remote sensing platforms, such as Canada's RADARSAT, offer near-real time service which can provide the user with digital data in as little as four hours. This type of service usually comes at an additional cost, but is a valuable tool in the health industry, particularly in monitoring epidemic and outbreak situations.

The relative cost of adopting geomatics technology is often a topic of discussion when considering the applicability of the technology to the medical field. The high cost of air-borne data was noted earlier as a limitation by some researchers. However, satellite data offer a more cost effective solution to remotely sensed data, with larger regional coverage and lower logistical costs relating to data collection (Pope, 1992; Beck, 1994). Beck (1994) refers to space-borne remote sensing as a potentially cost effective way to improve assessments of the location of malaria vector populations with respect to human settlements. And Jovanovic (1989) points out that although resources and manpower may be limited with the initial introduction of geomatics in health related fields, the technology is not expensive relative to traditional data collection techniques.

Clearly, geomatics technology has many limitations related to its use for monitoring and mapping disease related phenomena, but none of the above-mentioned challenges are insurmountable.

4.5 Research Requirements

It follows, based on the noted limitations of remote sensing and GIS to disease surveillance, that there are several research requirements that are necessary for the future success of this technology in the health field. The obvious obstacles to overcome relate to cloud cover, appropriate resolution, effective training, useful field campaigns, and near real-time data delivery.

Appropriate training for those outside the geomatics industry, and those inexperienced with geomatics tools, is imperative for the appropriate use of geomatics technology. Although the steep learning curve faced by a medical professional entering into geomatics is mentioned several times in the literature, there was no discussion of appropriate training. It would be advantageous to determine a specified training curriculum for those attempting to utilise geomatics technology in the health industry. Knowledge of sensor capabilities and limitations, as well as sensor-target relationships must be known before effectively studying disease characteristics with remote sensing. Also within the realm of training, it is important for the researcher to conduct appropriate field campaigns in order to make their data and output maps meaningful. Field data allow for an accuracy assessment of output products, thus validating any research that is conducted.

Geomatics technology has come a long way in the past 30 years, since the beginning of space-borne information technology. Every year brings newer, and more sophisticated technology to capture massive amounts of information about our environment. Higher resolutions, greater coverage, faster delivery, cheaper data are but a few of the on-going improvements that are rapidly integrating into the geomatics industry. With the availability of data from many different sensors, relative cost to the user is decreasing. It is evident that there has been a great deal of interest in the use of remote sensing and GIS in mapping and monitoring

disease related issues. The approach to this concept is clear and well published, but how operational is the application in reality?

The vast majority of published literature refers to the “potential usefulness” of geomatics to assist in the battle against increasing global disease. Many have even completed pilot studies that demonstrate this proposed usefulness (Linthicum *et al.*, 1991; Hugh-Jones *et al.*, 1992; Pope *et al.*, 1993; Wood *et al.*, 1993, 1994; Kitron *et al.*, 1994; Beck *et al.*, 1994, 1997; Dister *et al.*, 1997; Malone *et al.*, 1997; Thomson *et al.*, 1997, 1996). Many of these authors also suggest the use of this technology by major global institutions such as the World Health Organisation, or the Centre for Disease Control (CDC), but there is little literature outlining any specific operational uses of geomatics to monitor global disease issues.

One indication of a step towards operational use of remote sensing in the medical field was in a publication by Wood (1993) and his colleagues at the Ames Research Centre (NASA). This group proposed a research satellite specifically designed for the surveillance of tropical vector-borne diseases. Recognising the obstacles in the application of current remote sensing systems to the monitoring of tropical diseases, they described the need for, and preliminary design of, a research satellite (Medsat) devoted to the surveillance of environmental and epidemiological factors that influence patterns of vector-borne diseases. The Medsat program planned to take on an interdisciplinary approach;

joining engineering, natural resources, biology and public health departments to design optimal specifications of the satellite. The proposed characteristics of Medsat included visible/near-infrared and radar sensors, with a dual polarization L-band SAR, a spatial resolution of 50 metres, and a scene coverage of 50km by 50km. The near real-time turnaround of the data was stressed and the design included advanced storage and downlinking systems. Essentially, this proposal sought to design the perfect satellite surveillance system for monitoring diseases. Unfortunately, this was proposed in 1986, and there is no trace of advancement of the research or any sign of the Medsat program since its introduction.

As recently as December 14, 1998, the CDC released a global news bulletin warning of an imminent plague of "super bugs" that resist current antibiotics. Infectious disease experts have publicly declared a serious need for better detection and surveillance of infections, as the only way to fight this battle (www.pdp.cdc.gov). The geomatics community is in a position to embrace this opportunity, establish optimum conditions for data collection, and move forward into operational use. The published literature available clearly describes a whole field that has been practically untouched by the capabilities of operational geomatics technology. The theoretical groundwork is firmly in place and now it is time to demonstrate the benefits of remote sensing and GIS for monitoring global human health on an operational level.

4.6 SAR for Disease Monitoring

To date, there have been few published results on the applicability of SAR imagery specifically for disease monitoring, particularly using the recent space borne SAR sensors. Pope (1992) considered the use of a high-resolution airborne three-band polarimetric radar system (ERIM / NADC P-3 SAR) for the identification of central Kenyan Rift Valley Fever virus vector habitats. This work concluded that airborne SAR imagery is useful for detecting flooded areas that can be related to active vector breeding sites of the Kenyan Rift Valley Fever virus. In particular, Pope noted the advantage SAR's 'all-weather capability' and sensitivity to moisture as major advantages.

Several concerns relating to the use of SAR remote sensing appear to be limiting its broader use in the field of disease monitoring. Hay (2000) cites these limitations as 1) difficulty of image interpretation and information extraction due to the complexity of SAR imagery, 2) lack of well calibrated SAR data, 3) lack of adequate software to handle SAR data, and 4) topography problems unique to SAR images and inherent image speckle. These are valid concerns based on historical use of SAR data, which have for the most part been airborne. Because radar remote sensing operates in the microwave portion of the electromagnetic spectrum, it is not intuitive for the human eye to interpret, as is the case with optical imagery. For this reason, interpretation of SAR data is more complex and requires a skilled user for effective information extraction. In recent years, however, especially with space-borne SAR sensors like ERS and RADARSAT,

data are being provided as well-calibrated products that are increasingly straightforward to process, interpret and analyse. Commercial image processing software packages are being developed to deal with unique SAR characteristics, such as speckle interference and topographic effects; however, many of these packages require significantly more effort to facilitate accurate analysis, ease of use and automation of routines. Although it is recognised that radar data have limitations relating to their inherent complexity, the availability of data from recent sensors such as RADARSAT-1 should facilitate increased use of SAR data for appropriate applications such as disease monitoring.

Some of the hypothesised advantages of space borne SAR imaging to disease monitoring are the capability for long-term monitoring, regional coverage, and near real-time capabilities. The high-cost and logistical difficulties associated with airborne remote sensing could be reduced with space borne monitoring. Although the use of high-resolution imagery (often available with airborne SAR systems) is important for detecting small area vector breeding grounds, lower resolution (20-30m) space borne SAR sensors can be useful for large area monitoring. Over the past decade, there has been a clear need for cost-effective, timely, high-resolution space borne SAR systems. RADARSAT-1, as well as other space borne SAR platforms (ERS, ENVISAT, RADARSAT-2) are meeting these challenges.

The methodology of using SAR data for disease monitoring is similar to that which has been used with optical remote sensing in recent years. With well-calibrated, multi-temporal RADARSAT-1 imagery, a geo-referenced, co-registered dataset may be used for image classification. Advanced intelligence-based classification routines are most suitable for SAR data, since an assumption of normal data distribution can pose a problem with common routines such as parameterized supervised classifications. The availability and usability of advanced classification algorithms is increasing with the development of several object-oriented software packages that are designed to contend with some of the inherent challenges of SAR data (Definiens, 2000).

Based on SAR's sensitivity to surface moisture conditions, ecological variables relating to vector breeding grounds may be readily identified with a classified SAR image. The land cover parcels associated with the disease vector under investigation may then be correlated with ground data of vector abundance. This condition allows areas of high vector abundance to be tagged as high to low risk, depending on proximity to areas populated by the vectors' host (e.g. human hosts for malaria carrying mosquito vectors).

This chapter has provided a review of recent research on the use of geomatics technology for disease monitoring activities. We have discussed the limitations that have been noted in past research and discussed requirements for future research. The potential of SAR remote sensing to address some of the

limitations found with optical remote sensing techniques has been introduced. The following chapter will outline a case study that was carried out to assess this potential of SAR for monitoring and mapping malaria risk in coastal Kenya.

5.0 CASE STUDY: MALARIA IN COASTAL KENYA

5.1 Objectives

The primary purpose of this case study is to investigate the theories and assumptions identified in Chapter 4, in the applicability of SAR remote sensing for identifying land cover classes that are representative of malaria mosquito breeding grounds. Specific objectives include:

- 1) Determine and carry out suitable image analysis and processing routines in order to obtain useful input RADARSAT-1 images for image classification;
- 2) Assess the applicability and suitability of segmentation and object-oriented classification on SAR data (as compared with per-pixel classification), for the purpose of identifying land cover variables conducive to malaria-carrying mosquito breeding;

- 3) Visually correlate object-based classified image data with mosquito abundance data;
- 4) Complete GIS-based proximity analysis between classified wetland objects and populated objects, in order to determine areas of high risk of malaria transmission.

This chapter will describe the study site in Kenya, the ground and remotely sensed data that were analysed, the methodology used, and the results obtained.

5.2 Data

5.2.1 Study Site

The study site is located along the eastern coastal plain for Kenya, near the town of Mombasa (Figure 5.1). The full study area covers three main districts (south to north): Kwale, Kilifi and Malindi, although the primary site of interest for this study is around Kilifi district. The study area is home to two-thirds of the rural population of coastal Kenya, where malaria is a severe health concern. The environment mainly consists of a mix of indigenous forest, grassland savanna, mangrove swamps, and wetland vegetation – with each land cover type occupying large blocks of land along the coast and inland. Plantation agriculture (mainly coconut, sisal and cashews) are also found along the coast. The ground elevation ranges from sea level to approximately 400 metres above sea-level

(ASL) and there are several small rivers that flow from the highlands to the Indian Ocean.

Mosquito larval habitats in this area are diverse and change with the season. Coastal Kenya has two rainy seasons: from April to June and from October to November. Mean annual precipitation differs greatly in different parts of the coast, from over 1,200 mm in the Kwale area of the coastal strip to less than 750 mm on the western border of the inhabited area. Several rivers flowing from the hills to estuaries on the Indian Ocean transect the area. During the dry season, some rivers and streams become completely dry, while others have reduced flow and numerous isolated, residual pools of water in the main riverbed. Portions of mangrove swamps stay permanently flooded. In Kwale, two rivers, the Uмба and Ramisi, and smaller permanent and seasonal streams drain the area. The Jaribuni and Sabaki rivers drain the Kilifi and Malindi areas, respectively. Seasonal swamps are also present and some are used for rice cultivation during the rainy season. These land cover types are particularly conducive to mosquito breeding.

The natural vegetation varies widely from patches of rain forest in the Shimba Hills and Sokoke forests to areas of dry thorn bush on the western border. Most of the population lives in the 10 kilometre wide coastal strip and in the hills farther inland. Sisal, coconut and cashew nut plantations characterise the agriculture of the coastal area, while inland agriculture is mainly subsistence farming. Further

inland, it becomes too dry for farming and only nomadic tribes inhabit the land, which is predominantly grassland. Many households keep goats and chickens, with cattle in some villages.

Figure 5.1 Kenya, East Africa (left) with enlarged view of study site along coast of Kenya (right)

5.2.2 Remotely Sensed Data

The focus of this research is on the usefulness of SAR data for monitoring and mapping malaria in coastal Kenya. One of the main reasons for the use of SAR for this application is the lack of available cloud-free optical data. Between 1995-2001, there was virtually no cloud-free optical space-borne imagery acquired (Landsat and SPOT). Although it is recognised that data integration of optical and SAR data would likely provide the most useful results, the lack of available optical data limits this possibility in the case of this research.

A total of four RADARSAT-1 standard mode scenes were acquired from the RADARSAT-1 satellite and archive of RADARSAT-1 data. All the images were collected using the same orbit configurations, on ascending passes. The specifications of these images are provided in Table 5.1.

Table 5.1 Summary of RADARSAT-1 data used in this research

Date of Acq.	Time of Acq.	Beam Mode	Orbit	Nominal Resolution (m)	Swath Width (km)
20/3/1999	15:49 UTC	S7	Ascending	25	100
9/3/2001	15:49 UTC	S7	Ascending	25	100
11/10/2001	15:49 UTC	S7	Ascending	25	100
4/11/2001	15:49 UTC	S7	Ascending	25	100

The use of standard mode imagery was based on a compromise between image resolution and swath coverage compared to other operational RADARSAT-1 beam modes. With a nominal resolution of 25 metres and a swath coverage of 100 kilometres by 100 kilometres, standard mode imagery was assessed as the most useful RADARSAT-1 beam mode for this application. The use of an ascending pass resulted in the images being acquired in the evening (approximately 7:00 p.m. local time). This was seen as optimal timing, since morning dew and common early afternoon rain events may alter the radar backscatter image in the descending pass mode. Figure 5.2 shows the first RADARSAT-1 acquisition for this project, collected on 20/03/1999 and obtained through the RADARSAT-1 archive of images. The area imaged covers mainly the central district of Kilifi.

5.2.3 Ground Data

One of the main species of malaria-carrying mosquitoes in this area is the *Anopheles gambiae* mosquito. Researchers with the International Centre for Insect and Parasite Ecology (ICIPE) in Kenya collected mosquito abundance data for several species in the area including *Anopheles gambiae*. A more in-depth look at malaria risk in a given area would require considering all of the mosquito species independently, since the biology of these species in terms of larval habitats can be quite different. However, for the purposes of this study, only the *Anopheles gambiae* data are considered and analysed in relation to the classified wetland land cover areas.

Figure 5.1 shows the ground truth sites identified for Kilifi District. In each of the three districts (Kwale, Kilifi, and Malindi), ten sites were geographically charted using a hand-held navigational system (GPS, Garmin Inc.). *Anopheles gambiae* mosquitoes were sampled in ten randomly selected houses that were within a two-kilometre radius surrounding schools in each district. Each of these houses was sampled once every two months for one year (1997). Figure 5.3 shows the location and average abundance of the mosquito data collected for all three districts, overlaid on an NDVI image that shows the vegetation index ("greenness") of the area (provided by Tulane University, 2001). The RADARSAT-1 data cover only Kilifi district where nine of the 30 sample sites are located. The usable data samples are given in Table 5.2.

Figure 5.3 Mosquito abundance data for *Anopheles gambiae* species, overlaid on NDVI image covering Kwale, Kilifi and Malindi districts (Tulane University, 1999)

Table 5.2 Mosquito abundance data collection for 9 sites that correspond to geographic coverage of RADARSAT-1 imagery of Kilifi district.

ID	SITE	LONGITUDE	LATITUDE	Anopheles Gambiae
1	Dabaso	39.9978	-3.3436	163
11	Barani	39.7920	-3.9304	105
12	Chasimba	39.7100	-3.7260	2
13	Dindiri	39.7939	-3.7414	235
14	Jaribuni	39.7430	-3.6219	233
15	Kitsoeni	39.7263	-3.7030	59
17	Majajani	39.7869	-3.6588	184
18	Mtepeni	39.7259	-3.9078	113
19	Shariani	39.8200	-3.7961	58
20	Takaungu	39.8558	-3.6950	13

Land cover ground data were provided via personal communication with researchers working in the study site, who identified areas of known land cover on the RADARSAT images. Six main land cover classes were identified for this study: water, forest type 1, forest type 2, agriculture, grassland, wetland and urban areas. The water areas are primarily the Indian Ocean, and rivers and streams flowing to the ocean. Forest type 1 consists mainly of mangrove forest, and forest type 2 consists mainly of indigenous trees and rain forest. The agricultural areas are primarily coconut, sisal and cashew plantations. The grassland is found in the higher elevations inland from the ocean. The wetland targets are found surrounding inlets and streams, and in swampy areas near mangrove forests, for example. Mombasa is the main urban area and is an island town in the southern portion of the study site. Other populated areas are scattered along the coast, including the town of Kilifi and smaller villages of Takaungu, Kikambala, and Mtwapa. For each class, 7-12 areas were identified and used as training sites in the image classification routine. Figure 5.4 shows the location of these known land cover sites, and Figure 5.5 displays a multi-temporal RADARSAT-1 composite in which the land cover classes are displayed with ground photos.

Figure 5.4 Land cover data areas used as training sites in supervised classification

Figure 5.5 Multi-temporal RADARSAT-1 composite image, showing ground photos of known land cover areas

The RADARSAT-1 images were acquired for both the dry season (20/03/1999 and 09/03/2001) and for the wet season (11/10/2001 and 4/11/2001). Both 1999 and 2001 showed generally typical weather conditions, with 1999 being a slightly drier year than 2001. In this region of the Kenya coast, March marks the end of the dry season (January/February), which has an average monthly rainfall of 60 mm (www.worldclimate.com). The October 2001 and November 2001 images were both acquired during the short annual rainy season, with average monthly rainfalls of 90.2 mm (October) and 96.4 mm (November) (www.worldclimate.com). The longer rainy season in this region occurs in May with an average rainfall of 320 mm for that month. Unfortunately, the timing of data acquisition for this project did not allow for data collection in May. However, the data that were collected sufficiently represents two different seasons in the study site. The following meteorological data summarise the conditions on the dates of acquisition:

Table 5.3 Meteorological data corresponding to dates of RADARSAT-1 acquisitions
(www.wunderground.com)

DATE	Mean Temp (°C)	Dew Point (°C)	Precipitation
20/03/1999	29.2	22.8	Light Rain
9/3/2001	27.9	22.7	Nil
11/10/2001	22.0	21.0	Nil
4/11/2001	26.5	23.3	Rain

5.3 Methodology

The methodology followed to process, enhance, manipulate, analyse and interpret the RADARSAT-1 imagery is summarised in Figure 5.6, and may be broken down into three major activities: image processing, image classification

and map production. Each activity was performed independently, although the results of each were used as input to the next activity. This section will discuss the procedures carried out for each of these activities.

5.3.1 Image Processing

In order to meet the primary objective of obtaining useful input images for image classification, the case study methodology begins with image processing, geo-correction, registration, filtering and enhancement. These processes were carried out using the PCI Geomatics suite of image processing software. Images were imported to PCI using the CDSAR task that was developed specifically for reading SAR data in the standard CEOS (Committee on Earth Observation Satellites) format from a CD-ROM, which represents the format by which RADARSAT-1 data are delivered.

CDSAR reads the imagery into a 16-bit single channel database, with georeferencing data stored in an image segment that is created using the ephemeris data created during image acquisition. For each of the four RADARSAT-1 images, CDSAR was used to import the images into a readable format. The next step in the image processing routine was geo-correction of the images so that they correspond to the geographic grid of latitude and longitude co-ordinates. Due to a lack of user-specified ground control points, the ground

Figure 5.6 Methodology flow chart for malaria risk mapping

control information provided in the georeferencing segment was used to create a master corrected image from the first RADARSAT-1 image (20/03/1999). Although this method does not produce the highest possible accuracy for geo-correction, it has been found that the 255 Ground Control Points (GCPs) provided in the georeferencing segment allow for a geo-correction to an accuracy of approximately 100 kilometres. (RSI, 2002).

Once one of the images was geo-corrected, the remaining three images were geo-referenced to the corrected database using the REGPRO set of tasks within PCI, which transformed one set of image data (uncorrected images) to a second set of data (corrected image) (PCI, 2001). Common GCPs were selected between the corrected and uncorrected imagery in order to warp the uncorrected image to the same geographic plane of the corrected image. For the purpose of this project, a simple image rotation was carried out using a first order nearest neighbour transformation. For each uncorrected image, 25 GCPs were collected, with a relatively even distribution over the image.

Once the images were co-registered into a single, geo-corrected database, image filtering and texture analysis were carried out. The purpose of the filtering procedure was to smooth the data and remove unnecessary noise. The images were filtered using a Frost filter (PCI task: FFROST), with a 5 by 5 pixel window. The Frost filter is an adaptive filter primarily used on radar data to remove high frequency noise (speckle) to smooth the data while preserving sharp features

such as edges (PCI, 2001). After experimentation with several other filters such as Mean, Lee and Kuan, a visual analysis identified the Frost filter as providing most suitable results for speckle reduction on the imagery used in this thesis.

Figure 5.7 illustrates the results of the Frost filter on one of the RADARSAT images of the study site, showing the smoothed data after filtering, with edges preserved. This smoothed data allows for easier extraction of homogeneous areas during the image classification procedures.

Figure 5.7 Results of Frost filtering on RADARSAT-1 imagery of coastal Kenya

Texture analysis was also carried out on the images to extract information about the variations in image tone, to use as input to the classification. As discussed previously in Chapter 3, texture analysis has been found to contribute to higher classification accuracies, as compared to classifications using only spectral information (Peddle and Franklin, 1991).

Texture analysis was performed using the PCI task developed for this purpose, called TEX. The TEX routine calculates a set of texture measures for all pixels in the input images (PCI, 2001). There are several different input parameters that must be selected for the texture analysis. The two primary inputs are the texture measure to be computed, and the window size to use for the development of the output texture image. For this research, a mean texture measure is used, with a window size of 7 by 7. Again, some experimentation was performed using other texture measures such as homogeneity and contrast; however, the mean texture measure produced suitable results for land cover classification, enhancing the wetland areas in particular.

Figure 5.8 summarizes the image filtering and texture analysis resulting images. These images were used as input into the classification routine, which will be the subject of the next section of this chapter.

Figure 5.8 Resulting images from Frost filtering and mean texture analysis

5.3.2 Image Analysis and Interpretation

Image analysis for this case study was performed with *eCognition*, version 2.0, and PCI Geomatica, version 7.0. *eCognition* is a classification analysis package that was developed by a German software company called Definiens Imaging (www.definiens.com), and the software was provided with an evaluation license for use on this thesis. *eCognition* is used to perform the object-oriented

classification for input to the malaria risk map. PCI Geomatica is used to perform a per pixel classification for comparison with the object-based classification.

eCognition was developed with a new approach to standard image analysis and classification, looking at image data from an object-based point of view, rather than the traditional pixel-based approach. With object-oriented classification, image data are classified based on parcels of pixels known as 'objects'. These objects are created using a pre-classification segmentation routine (Definiens, 2001, Benz *et al.*, 2001)). This section will discuss the details of the image analysis and classification tasks that were performed.

Following the image processing procedures outlined in section 5.3.1, the co-registered, geo-corrected image layers were exported from PCI as 8-bit files and imported to *eCognition*. The 12 images displayed in Figure 5.8 were imported and used in the segmentation and classification routines.

Object-oriented classification is based on the technique of segmenting the image into parcels or objects. *eCognition's* multi-resolution segmentation separates adjacent regions in an image that are significantly contrasted based on image brightness values, and extracts the homogeneous regions as individual objects. The user defines the composition of what is considered to be a homogeneous area, based on three criteria: smoothness, colour and compactness. These three criteria can be applied using different weighting schemes, based on the

most important criterion for the identification of homogeneous regions in a given dataset. With most data, the colour criterion is most important as it represents the spectral information (optical data) or radar brightness (for SAR data). However, smoothness and compactness criteria can be important in order to obtain less fractured object boundaries (Benz *et al.*, 2001). For this case study, a factor of 0.8 was given to colour, with 0.2 to shape. Within the shape criterion, a factor of 0.9 was given to smoothness and 0.1 to compactness in order to maximise the smoothness of the filtered data.

The segmentation routine also allows the user to define a scale parameter, which allows control of the size of image objects. Depending on the size of landscape variables to be classified, a scale parameter is specified between 1 and 100. Based on the land cover variables in the Kilifi area, a scale parameter of 35 was chosen to provide the most suitably sized image objects. Figure 5.9 shows the software window for the multi-resolution segmentation in *eCognition*, with the input parameters used for this case study.

Once an image is segmented into image objects, the classification routine can be performed. With *eCognition*, the user can specify which image layers to include in the classification. In this research, eight images were considered as input to the classification: the Frost filtered results for each of the four dates of acquisition, and the texture analysis results for each of the four dates of acquisition. The original data were not included in the classification as there was

deemed to be little useful information in these image layers, and the inherent speckle noise may confuse the classification (Benz *et al.*, 2001).

Figure 5.9 Multi-resolution segmentation input window in eCognition

As with standard supervised image classification procedures, the user specifies classes and indicates training sites to be used during the classification process. This applies to object-oriented classification as well, although training areas are selected as objects of known land covers, rather than on a pixel basis. For this case study, image objects were selected as samples based on the land cover information provided by researchers in the study area, as discussed in section 5.2.3.

A nearest neighbour object-oriented classification was performed, using the sample objects as training sites, and the output image layer provided the resulting classification. Figure 5.10 displays the results of the segmentation and classification procedure.

Figure 5.10 Segmentation and classification procedure and results

The resulting classification was validated using the *eCognition* accuracy assessment tool. With this, test areas were selected in a similar manner to the collection of training areas. Due to the limited amount of accurate field validation information, only eight test sites were collected for each class. These were carefully selected based on the land cover information provided by researchers in

the study site. These test sites were input to the accuracy assessment routine in order to evaluate how well the image segments were classified. The resulting classification for this case study was assessed at 85.5% accuracy, and a Kappa coefficient of 0.818. There was some confusion between classes, which will be analysed further in the results section of this chapter. Figure 5.11 shows the co-occurrence matrix for the accuracy assessment, as well as illustrates the test areas that were used for this procedure.

Figure 5.11 Classification accuracy assessment routine and results

Figure 5.12 Per-pixel classification versus object-based classification results

For comparison sake, a nearest neighbor per-pixel classification was done using the same input images (four filtered images, and four texture analysis image) and a standard nearest neighbor routine. Similar to the object-based classification described, training areas were identified for the supervised classification, and test sites were identified for the accuracy assessment. Figure 5.12 shows the results of the per-pixel classification, as compared to the results of the object-based classification. The results of the accuracy assessment for the per-pixel classification are given in Table 5.4, where it can be seen that the overall accuracy is 78.8%. Perhaps more important than the values given in Table 5.4 is the visual usability of the per-pixel classification for identifying parcels of land cover classes. The inherent speckle seen in the RADARSAT images is apparent in the per-pixel classification and reduces the operational value of the classified image. For the purpose of identifying landscape indicators of disease for input to a risk map, it is important to establish generalized homogeneous areas of land cover, which is difficult with the speckled results of the per-pixel classification.

Table 5.4 Confusion matrix for per-pixel classification

Name	Code	Pixels	1	2	3	4	5	6	7
WATER	1	12769	99.98	0.00	0.02	0.00	0.00	0.00	0.00
WETLAND	2	1229	0.00	70.79	1.38	8.46	10.09	9.28	0.00
AGRI	3	4481	0.00	2.48	55.88	10.73	0.65	14.19	16.07
GRASSLAND	4	10674	0.00	7.05	1.93	72.01	2.30	10.60	6.12
POPULATED	5	805	0.00	10.93	0.50	2.61	82.86	2.98	0.12
FOREST 1	6	2236	0.00	22.23	7.33	23.79	4.92	39.13	2.59
FOREST 2	7	7744	0.00	0.17	9.56	7.94	0.14	2.92	79.27

Overall accuracy = 78.89

The object-oriented classification established these homogeneous areas, and provided polygons for each class that were exported as GIS layer files for use in the malaria risk map generation procedure.

5.3.3 Malaria Risk Map Generation

The premise for assessing areas at risk of malaria infection is based on the maximum distance a malaria-carrying mosquito can travel from its breeding ground to infect human hosts. For this case study, a two-kilometre buffer zone around the suspected larval breeding grounds is used (Connor *et al.*, 1995; Bradley, 1996; Hay, 1997; Connor, 1998). Based on previous research, the wetland class was considered to be most conducive to larval breeding, and populated areas are considered as areas of human host presence (Hugh-Jones, 1989; Chen, 1991; Kitron *et al.*, 1991; Washino *et al.*, 1993; Beck *et al.*, 1994; Thomson *et al.*, 1997; Hassan *et al.*, 1998). Quite simply, a risk map was generated to show the populated areas that lie within the two-kilometre buffer zone around the wetland areas.

From *eCognition*, each group of classified objects were exported as vector layers, and then imported to the RADARSAT-1 image database in PCI. The vectors were then rasterized in order to create filled polygons for the wetland and populated classes. The buffer zone around the wetland polygons was created using the 'proximity analysis' (PRX) tool in PCI, which used a proximity of 40 pixels – the equivalent of two kilometres. A model function was then created for

the generation of risk areas relating to the populated areas that lie within the wetland buffer zone. A new layer of polygons represents these risk areas.

In order to investigate the correlation of mosquito abundance with land cover, the geographic location and corresponding abundance data provided by ICIPE was overlaid on the RADARSAT-1 image with classified wetland areas. This was done using the PCI module called GCP Works, which allowed for user input coordinates of the point data.

The results of the procedures outlined in this chapter will be shown in the following section, and are used to provide insight into the gaps and limitations of using radar remote sensing technology for monitoring and mapping malaria, as well as highlight some of the successful capabilities of SAR in this respect. The results of this case study are analysed, with special attention to the assessment of accuracy, and the suitability of input parameters and methodology.

5.4 Results

The methodology followed for this case study was developed as a relatively simple procedure for demonstrating the potential of SAR for disease risk mapping. Although this type of analysis is not new, two main components of this case study present new ideas for the use of remote sensing for health applications. First, the case study investigated the use of SAR image data at the

resolution and coverage provided by RADARSAT-1. With little research reported on the use of the microwave portion of the electromagnetic spectrum for health applications, this research contributes to the known potential of new and advanced space-borne sensors. Second, this research endeavoured to test the usefulness of object-oriented classification, as opposed to the more traditional pixel-based method of classifying remotely sensed data. A direct comparison with a per-pixel based classification of the study area is used to demonstrate this component of the research. The results show varying degrees of success in both new areas, but do pave the way for the development of future research using SAR and object-oriented classification for the identification of environmental indicators of malaria risk.

Figure 5.13 shows the classification results for the populated areas, overlaid on a RADARSAT-1 image. The town of Mombasa (island in southern part of image) is clearly identified as populated. The smaller town of Kilifi is in the northern part of the image, with smaller villages (Takaungu, Kikambala and Mtwapa) found in the area between Mombasa and Kilifi. The bright radar backscatter response and textural information allowed for accurate classification of the populated areas, at 93.2%. Some of the inaccuracies are hypothesised to be in the higher inland terrain, and are likely due to image artefacts relating to topography effects (e.g. image shadow or layover with increased terrain slope).

Figure 5.13 Map of populated areas in the coastal Kenya study site

For the purpose of this case study as a demonstration tool, wetlands are considered to be the primary land cover associated with larval breeding of the *Anopheles gambiae* mosquito. The reality of malarious regions is far more complex in terms of variables influencing mosquito presence and malaria risk, and this will be addressed in Chapter 6. Figure 5.13 shows the areas of the study site that were classified as wetlands. The accuracy for this class was found to be 65.3%, with significant confusion found between the wetland and forest type 1 classes. Forest type 1 is mainly mangrove forest, which is characterised by flooded areas with emergent vegetation. For this reason, backscattering characteristics, as well as textural information, are similar. However, due to the similarities in environmental conditions of wetlands and mangrove forests, both landscape variables may be considered as high risk in terms of malaria breeding sites.

The ground data of mosquito abundance for nine sites in the study area were overlaid on the wetland classification in order to assess whether or not there is in fact a correlation between the high abundance sites and areas classified as wetlands. A moderate correlation can be seen in Figure 5.14, where all sites of mosquito abundance are within one kilometre of wetland areas, with the exception of sites 12 and 15, which are only 1.5 kilometres from wetland areas.

As previously mentioned, a radius of two kilometres around the classified wetland areas served to determine the areas where malaria-carrying mosquitoes may be

present. A buffering algorithm was used to produce the results seen in Figure 5.15.

Establishing an area with potentially high mosquito abundance does not necessarily relate to areas of high risk, since the presence of human hosts for the malaria parasite is required for transmission of the disease. For this reason, a final step identified populated areas that fall within the two-kilometre radius of the wetland areas. Figure 5.16 shows the results of this routine – a map of populated areas at risk of malaria. More than 95% of the classified populated areas are identified as risk areas based on their proximity to wetland targets. This information emphasises the severity of malaria risk in this region of Kenya.

Figure 5.14 Map of wetland areas in coastal Kenya study site

Figure 5.15 Mosquito abundance data integration with wetland classification

Figure 5.16 Map of 2 km. buffer zones around wetland areas in coastal Kenya

Figure 5.17 Map of populated areas at risk of malaria in coastal Kenya

The results from this case study successfully demonstrate the methodology developed to use radar remote sensing for mapping malaria risk. They provide an example of how SAR data can be classified using the unconventional object-oriented classification method to obtain an overall classification accuracy of 85%. Confusions between individual classes can be explained by known scattering interactions of microwaves and surface characteristics, as described in Chapter 3. Due to the relatively simple scattering mechanism with water targets, a high accuracy of 98.6% was achieved. The large areas of grassland savannah in the highlands of the study site are relatively homogeneous and were classified with 97.3% accuracy. More complex targets such as wetlands and forests were classified between 60-75% accuracy. Perhaps the most complex class was agriculture, which produced an accuracy of only 53.8%, due to the different tones and textures from various crop types and growth stages. More accurate agricultural classification could be important to disease vector breeding, particularly with irrigated crops.

There were several limitations with this research, including the limited amount of field validation data and inability to conduct field data collection personally, limited entomology (mosquito abundance) data points within the study area, lack of RADARSAT-1 data during the primary rainy season (May-June), and inconsistent timing of ground data collection (1997) and remotely sensed data collection (1999, 2001). The conclusions of the case study, including these identified limitations of this work, will be discussed in the following section.

Based on gaps in existing research and results of this case study, a discussion of overall conclusions and recommendations for future research in this area will be considered in the final chapter of this thesis.

5.5 Conclusions of the Case Study

The case study on malaria risk mapping in coastal Kenya served to demonstrate the methodology of using SAR images for identification of land cover variables that may be associated with malaria-carrying mosquito breeding. Many of the discrepancies in the classification results have been explained, and further image manipulation is required in order to achieve higher accuracies on a per class, and overall basis. The similarities in spectral and textural information between wetland and mangrove forest classes lead to the conclusion that a merging of these classes may provide higher overall classification accuracy, with the resulting class being indicative of mosquito breeding grounds. Using the merged class as input to the final risk map generation may provide the best results. Further analysis of the mosquito abundance data and a merged wetland-mangrove forest class may also be indicative of the importance of including mangrove forest areas as high risk, if located within the 2-kilometre buffer zone of populated areas.

Use of *eCognition* in the case study demonstrated the importance of object-oriented classification for SAR data, particularly when compared to the per-pixel classification of the same area. The object-based approach produced higher overall classification accuracy, and provides a usable output map for

identification of landscape parcels. Without this identification of homogeneous areas, suitable land cover classification would be far less acceptable for correlation with disease vector habitats. The segmentation approach to image processing is new in the field of remote sensing, and will likely take some time before it is fully adopted by the user community. However, such an approach does allow for quantification of surface patterns, which is not adequately done with per-pixel approaches (Bauer and Steinnocher, 2001; Blaschke and Strobl, 2001).

Further, the multi-resolution segmentation method of object-oriented classification demonstrated in the case study only scratches the surface of *eCognition's* capabilities with respect to image classification. There exists the potential to include a range of inputs beyond spectral and textural characteristics used in the case study. Advanced classification techniques can incorporate elements relating to shape, directionality, distance, location, neighbourhood and spatial distribution, and are performed after the basic object segmentation and first level of classification is complete. For instance, a user may perform a more detailed classification to separate water objects into river/streams and main water bodies by specifying the size and shape of an object (e.g. less than 5 pixels wide and more than 100 pixels long for identification of small rivers and streams). Agriculture objects can be further classified into crop types or farm types based on shape, size, and/or location of objects, or their relative distance to other classified objects. Populated areas may be identified as cities, towns or villages,

based on size of classified objects. The depth of analysis possible with intelligence-based classification routines such as *eCognition*, opens up a wide range of possibilities for obtaining useful and logical classification results.

The use of RADARSAT-1 imagery in this research filled a gap where no cloud-free optical satellite data were available. This is concluded as the main advantage of SAR data for disease monitoring, as well as SAR's sensitivity to surface geometry and moisture for identification of wetland environments. The use of multi-temporal images is seen as critical in order to account for seasonal variations in the area, including effects of ENSO-related climatic conditions.

Many tropical areas, such as coastal Kenya, face a serious and growing problem relating to environmental health. There is a strong need for an operational disease surveillance tool in these areas. The case study described in this thesis serves as preliminary research into how SAR remote sensing may play a critical role in addressing this need. More in-depth research is required in order to make the most effective use of SAR images for mapping malaria risk in areas such as coastal Kenya, and the remaining sections of this thesis will address how this may be accomplished.

6.0 CONCLUSIONS AND RECOMMENDATIONS

6.1 Conclusions

The main objective of this thesis was to analyse the applicability of radar remote sensing for mapping and monitoring malaria risk. Through a discussion of the disease of malaria and the science of remote sensing, as well as an in depth literature review on the topic, this primary objective has been met. More specifically, this work strived to review recent research and identify gaps and challenges in the field. This was achieved based on the past research, present activities and the case study that was described in Chapter 5.

This thesis has outlined the characteristics of malaria, as a prime example of an environmental vector-borne disease. Further, the basics of remote sensing theory and application have been summarized as an introduction to the

capabilities of geomatics technology, and specifically radar remote sensing. A discussion on the past research conducted on the application of remote sensing to environmental disease monitoring indicated a general acceptance of the concept, although there were few operational applications, and almost no indications on the use of SAR technology for health applications. The case study sought to demonstrate the applicability of RADARSAT for malaria risk assessment in coastal Kenya. Results indicated that RADARSAT data allowed for identification of landscape variables that are indicative of malaria breeding grounds, namely wetland environments, and further demonstrated the enhanced capability of object-oriented image classification for identifying these areas of interest. GIS analysis was used to create a map of areas at risk of malaria, based on a proximity analysis between wetlands and populated areas. Although the detailed reliability of this case study requires further investigation, the principles of the methodology were realised.

Previous works in the field of geomatics for health-related applications have used optical satellite data, and several limitations were noted. The published challenges on the use of space-borne data for health applications include the need for timely and cost-effectiveness data. Sensors with spatial resolution exceeding 20 metres have limited large-scale mapping and detection capability for local vector breeding sites. Other challenges, which were of direct relevance to the case study, include available amount and density of ground validation data. Ideally, a greater number of sites should be identified and sampled for

mosquito abundance, in order to conduct a detailed correlation with the image classification. Further, an increased number of training and test sites (~20 training sites per class, and ~10 test sites per class) for the land cover classification routine would likely improve the image classification accuracy greatly.

Another challenge in using remote sensing techniques for health applications relates to the role of human behavior, and the impact this can have on the final “risk map”. Understanding the meaning of “risk” is very complex, particularly with regard to diseases that are influenced by a number of factors. In the case study outlined in Chapter 5, the areas identified as high risk are based solely on environmental variables such as land cover type, and do not take into consideration how human behavior, economic conditions and institutional intervention may alter the risk of a given population to a disease. One example of how human behavior can greatly reduce the risk of malaria is in the use of mosquito bed nets. More than 20 studies of insecticide-treated nets (ITNs) have been conducted in different areas of the world where malaria is endemic. Most studies have shown a reduction in malaria disease rates of 20-63% following the introduction of ITNs (IDRC, 2001). Economic conditions also play a direct role in terms of malaria risk in a given community, whereby the level of poverty in an area is often an indicator of disease risk. Reduced standards of sanitation, higher levels of toxins and overall lower standards of living are likely to increase the risk of disease transmission and infection in a given community (Gallup and

Sachs, 2000; Fellers, 2000; WHO, 2001). The idea of institutional interference refers to activities such as education and awareness programs, distribution of medication, the practice of pesticide spraying – all of which will impact the risk of an area to malaria and other environmental diseases. Other factors that will influence an area's risk level with respect to malaria are immunity status, nutritional status and genetics (Thomson and Connor, 2001).

Figure 6.1 illustrates the complexity of understanding factors influencing the risk of malaria. The flow diagram shows the role of individual indicators in assessing malaria risk. The first three factors - local environment, weather/seasonal conditions, and parasite/vector environment, may be monitored using geomatics technology. Further indicators including socio-economic conditions, protection practices, education, nutrition and immunity cannot be monitored using remote sensing, but may be collected externally as spatial data input to a GIS for a more comprehensive analysis of risk (Thomson and Connor, 2001). Extensive field data collection including interviewing and community observation would be required for this level of data input. Observations may be given a spatial context for input to a GIS (e.g. locations of health institutions or locations of houses using ITNs).

Figure 6.1 Flow of malaria risk indicators and opportunities for geomatics technology.

Another specific objective of this research set out to identify the usefulness of RADARSAT-1 SAR imagery for identifying land cover variables that can be related to the potential presence of a malaria mosquito.

The most recent generation of space-borne SAR systems, including RADARSAT-1, address some of these challenges by providing all weather, day and night imaging at a resolution as high as 9 metres. RADARSAT-1's selectable beam modes allow for user-specified configurations to meet the needs of a given region or application. Orbit characteristics allow for near-real time data processing, which meets the requirement for rapid environmental assessment to facilitate early action and mitigation of disease impacts (Ambrosia *et al.*, 1989; Hay, 1997).

Many sensors have proven useful for disease monitoring in cloud-free conditions. Unfortunately, vector-borne diseases are prevalent in tropical areas where cloud-free conditions are not the norm. SAR has great potential for imaging at high spatial and temporal resolutions during periods of persistent cloud cover. The most useful tool for monitoring and mapping vector borne disease will naturally be discovered with the integration of both optical and SAR datasets. Land cover classification accuracy calculated with combined radar and visible-NIR bands has been found to be significantly higher than with either radar or visible-NIR bands alone, particularly using advanced classification routines (Augusteijn *et al.*, 1998). Further to this, accurate field reference data will complement remotely

sensed data and allow for validation exercises to be conducted. For example, Ritchie (1993) investigated the value of tide gauge data coupled with remotely sensed rainfall estimations for the surveillance of the black salt marsh mosquito found in coastal environments. It was found that this type of information, analysed in an integrated manner, provided accurate detection of the mosquito habitats. Advanced *in situ* data collection techniques, including the use of advanced Global Positioning Systems (GPS) and on-line geospatial databases are allowing for improved ground truth routines.

Since the application of geomatics technology to disease monitoring requires expertise in many fields, including geography, remote sensing, ecology, and epidemiology, a multi-disciplinary approach is critical. In order for this application to become operational, a team of experts would be required to ensure suitable integration of technology and knowledge. Image interpretation requires expert knowledge of ground conditions, field ecology and vector behaviour – further demonstrating the value and importance of an interdisciplinary approach to analysis.

Based on the conclusions of the case study, and an inventory of the challenges and limitations mentioned, future use of geomatics technology for disease monitoring is considered. The following discussion will address the last specific objective of this thesis – to propose future research activities to be carried out in

order to realise the operational potential of geomatics technology for malaria risk mapping.

6.2 A Look to the Future

The operational application of remote sensing to health related applications is relatively new, although researchers have considered the idea for decades. In recent years, environmental health issues are being given urgent attention by national governments and the United Nations. Geomatics technology can clearly fill a gap in monitoring and surveillance of human health, with an integrated multi-disciplinary approach.

The WHO Roll Back Malaria (RBM) initiative aims to strengthen and sustain human resources, institutional capacity and community capability to achieve RBM's objectives at the global, regional and country levels. The specific goals of RBM identified by the WHO are:

- To advocate and support the development of effective policies and systems to optimise capacity development efforts.
- To strengthen the capacity to plan and manage malaria prevention and control programmes.
- To improve and maintain the competence of service providers involved in the prevention and control of malaria.

- To build on community capability to recognize, prevent and control malaria.
- To build, strengthen and coordinate collaboration among all partners in capacity development for RBM.

(WHO, 2001)

Geomatics technology can address each of these goals. First, the development of an operational malaria risk assessment information system can be a critical tool for decision-making and policy analysis at all levels, from local to regional and national. Effective analysis of a malaria area, in terms of potential areas at risk, can facilitate efficient planning and implementation of malaria prevention and control programs. This will in turn improve the service provided to malaria endemic areas, so that those in greatest need of assistance are attended to in priority sequence. Additionally, this will facilitate more conservative and targeted use of pesticides and medication distribution, so as to reduce the health risks associated with over use of pesticides, and reduce the rate of immunity toward anti-malaria medication.

The potential exists for such a malaria information system to be web-based, with wide access to a large community of interested users. This will help build a strong community capability, so that all users recognize, prevent and control malaria using a common tool. With increasingly wide access to the Internet, and ease of use of an interactive web site, such a tool will likely be accessible to a critical community of researchers, policy makers, and health practitioners. With

consistent updating and development by a core group of individuals (likely based with the WHO), such a web site will serve as a dynamic, accessible, and valuable tool to develop a coordinated effort to prevent and control malaria.

Thomson and Connor (2001) produced a framework analysis for a "Malaria Early Warning System" (MEWS) for Africa, as part of the RBM technical support network on malaria epidemic prevention and control. The report addresses the concepts, indicators and partners needed for such a system to be implemented and operational, and outlines the complexity of malaria risk assessment, the importance of recognition of all malaria indicators, and the requirements for setting up a MEWS. The importance of geomatics technology for both mapping and monitoring areas of epidemic risk is seen, with specific attention to the need for surveillance of seasonal climatic patterns and hydrology of an area. Although Thomson and Connor do not focus on specific sensors, the results of this thesis indicate that radar remote sensing can play a key role in collecting important data for a MEWS.

With this in mind, the future of radar remote sensing of vector-borne disease risk looks bright. The capabilities of RADARSAT-1 will be further developed with RADARSAT-2, which is scheduled for launch in late-2003. RADARSAT-2 will provide all the imaging modes of RADARSAT-1, as well as some new modes that incorporate significant innovations and improvements. Hence, the satellite will offer data continuity to RADARSAT-1 users and new data that will support

development of improved and new applications. The new capabilities associated with RADARSAT-2 will allow for high-resolution imaging (up to 3 metres), right and left-looking geometry and fully polarimetric remote sensing. The selective look direction option will increase imaging revisit time and allow for increased temporal resolution to better provide near real-time imagery for disease outbreak monitoring. High spatial resolution data will allow for more localised analysis of vector breeding sites. Polarimetric data will provide increased information content useful for improved land cover classifications with single-date imagery. Table 6.1 outlines the characteristics of each RADARSAT-2 imaging mode.

Table 6.1 RADARSAT-2 imaging mode specifications

RADARSAT-2 Imaging Modes	Mode	Approximate Incidence Angle [degrees]	Approximate Swath Width [km]	Approximate Resolution: ³ Rg x Az [m]	Approx. Looks [Rg x Az]
Selective Polarization Transmit H or V Receive H and/or V	Standard	20-49	100	25 x 28	1 x 4
	Wide	20-45	150	25 x 28	1 x 4
	Low Incidence	10-23	170	40 x 28	1 x 4
	High Incidence	50-60	70	20 x 28	1 x 4
	Fine	37-49	50	10 x 9	1 x 1
	ScanSAR Wide	20-49	500	100 x 100	4 x 2
	ScanSAR Narrow	20-46	300	50 x 50	2 x 2
Selective Single Polarization Transmit H or V, Receive H or V	Triple Fine	30-50	50	11 x 9	3 x 1
	Ultra-Fine Wide	30-40	20	3 x 3	1 x 1
	Ultra-Fine Narrow	30-40	10	3 x 3	1 x 1
Polarimetric Transmit H and V on alternate pulses Receive H and V on each pulse	Standard Polarimetric ¹	20-41	25	10.5 ² or 15.7 ² x 8.9	1 x 1
	Fine Polarimetric ¹	30-41	25	6 x 8.9	1 x 1

¹ Single-look
Complex

² Slant Range

³ Ground
resolution varies
in range

One of the main advancements with RADARSAT-2 will be its capability for multiple and fully polarimetric imaging. Although the scientific community has not had much opportunity to explore the possibilities of space-borne polarimetry, several studies using airborne polarimetric SAR have concluded that classification accuracy is higher as compared to linearly polarized data (Foody *et al.*, 1994; Lee *et al.*, 1994; Schmullius *et al.*, 1997; Boerner *et al.*, 1998). Although C-band, HH polarization is optimal for monitoring environments where vector breeding is likely to occur (e.g. wetlands), increased information content with polarimetric data will facilitate accurate land cover mapping (Ambrosia *et al.*, 1989; Linthicum *et al.*, 1991; Crevier *et al.*, 1996).

In addition to the RADARSAT family of SAR sensors, the European Space Agency has recently launched ENVISAT, an advanced multi-sensor satellite, equipped with a multiple polarization C-band SAR sensor providing imagery at resolutions from 30 to 150 metres (ESA, 2001). ENVISAT's SAR sensor provides researchers an opportunity to become familiar with polarimetric SAR data, in anticipation of RADARSAT-2. With these opportunities, the next decade should see a consistent increase in the operational use of SAR remote sensing for many applications.

As scientists begin to exploit the new generation of satellite based data sources available, including new SAR sensors, the use of geomatics technology for

disease monitoring will become a viable solution to some of the challenges faced by the field of remote sensing and disease monitoring over the past several decades. An integrated, multi-disciplinary effort to merge geomatics technologies with disease control and mitigation activities will be critical to the development of an operational tool. With greater understanding of remote sensing and GIS, health officials and international development specialists will be able to exploit the vast potential available through geomatics technology for disease monitoring and risk mapping.

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