The use of Environmental Information Systems (EIS) for malaria control planning in Africa

Thesis submitted in accordance with the requirements of the University of Liverpool for the degree of Doctor in Philosophy

by Stephen John Connor

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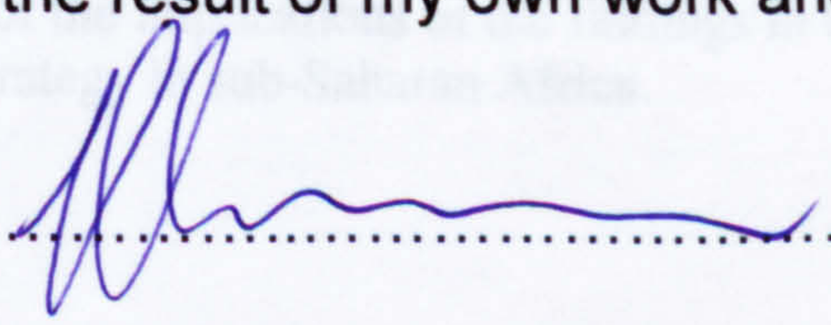
Declaration: This thesis has not been submitted for any other application for a degree and is the result of my own work and composition



Abstract

This thesis reviews the potential for the application of Geographical Information Systems and environmental remote sensing products to malaria control planning needs in sub-Saharan Africa with regard to: the stratification of malaria; routine monitoring of environmental variables which may influence changes in endemicity and epidemic risk; and the scope for their use in malaria early warning systems.

The history and body of knowledge to date, in the field of 'geographical malariology' is reviewed, including the concept and process of stratification of malaria. The following outcomes are presented which represent novel findings in our understanding of the geography of malaria and its inter-annual variability: 1) a new interactive method of mapping the spatial and temporal distribution of malaria risk (based on climatic suitability for transmission) in the 'African Savannah' is developed; 2) the 'highland and desert-fringe' malaria strata is discussed and a new method of identifying and mapping the desert-fringe areas (based on the combination of mean rainfall distribution and interannual variability) is produced; 3) a method for the integration of long-term mean monthly climate data, and routine meteorological satellite information, into a biological model of malaria transmission potential (vectorial capacity) suitable for mapping potential malaria risk is developed. This process permits a more dynamic mapping of malaria risk than hitherto available.

The paucity of reliable epidemiological data for Africa is acknowledged. However, to be effective malaria control managers have to make rational decisions on the information routinely available. Time series of malaria incidence data (clinical and laboratory confirmed) at the district level were obtained from the routine Health Information Systems operating in four countries in Southern Africa (Zimbabwe, Botswana, Namibia and Swaziland) at a range of temporal scales. The data were analysed in conjunction with a range of environmental variables including the vectorial capacity products. The seasonal structure of the epidemiological data was explored and modelled as a function of these environmental variables.

Tests of association between monthly malaria incidence anomalies, and time-lagged anomalies of environmental variables, indicate that routine monitoring of the latter would provide a useful warning of epidemic risk in certain districts or, where appropriate, strata. In Zimbabwe, for example, the models were based on seven altitude zones. In Botswana, which is almost entirely defined as desert-fringe, predictive models for three latitude zones were developed.

Multivariate regression models using combinations of environmental variables were developed to predict malaria incidence as a function of environmental variables, with at least two months warning, for both districts and strata. The results show clear evidence that there are areas where this early warning approach to mapping malaria risk would be useful within each of the countries studied.

The thesis concludes with a discussion of the implications of the findings in the current context of the malaria control strategy in sub-Saharan Africa.

Acknowledgements

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Needless to say my partner Madeleine Thomson has been a staunch ally in my getting this work to fruition. And last but by no means least, I thank my children: Sarah, Zachary and Megan; and my grandchildren, Amelia, Jacob and Callum; for being who they are, putting up with me being too busy to pay them the attention they deserve, and providing me with a sound reference point in an often turbulent sea.

Publications arising from this work to date

Aspects of the work developed here have been published in the following:

Connor, S. J., S. Flasse, A. Perryman and M. C. Thomson (1997). The contribution of satellite derived information to malaria stratification monitoring and early warning. Geneva, World Health Organisation. WHO *Mimeograph document* WHO/MAL/97.1079. Geneva.

Thomson, M. C., S. J. Connor, P. J. W. Milligan and S. Flasse (1997). Mapping malaria risk in Africa - what can satellite data contribute? Parasitology Today **13**(8): 313-318.

Connor, S. J. (1998) Malaria: Risk and Vulnerability in a Changing World, The Globe: Focus on Global Change and Human Health, April 1998, 42, pp 8-9.

Connor, S. J., S. Flasse, A. Perryman and M. C. Thomson (1998). Environmental information systems: can they help improve malaria risk mapping and forecasting of epidemics? Disasters **22**(1): 39-56.

Connor, S. J., M.C. Thomson, U.D'Alessandro, C. Green and M. Cresswell (1998). Developing environmental information systems for improved malaria control planning in Africa. Proceedings of the Ninth International Congress of Parasitology (ICOPA IX), Makuhari, Chiba, Japan. 24-28th August, 1998, 209-215.

Connor, S. J. (1999). Malaria in Africa: the view from space. Biologist **46**(1): 22-25.

Connor, S. J. and M. C. Thomson (1999). Mapping Malaria in Africa. Post-Graduate Doctor: Africa, **21**(3): 46-52.

Connor, S. J., M. C. Thomson and D. H. Molyneux (1999). Forecasting and prevention of epidemic malaria: new perspectives on an old problem. Parassitologia **41**(1-3): 439-448.

Thomson, M. C., S. J. Connor, B. Rowlingson, P. Diggle, M. Cresswell and B. M. Greenwood (1999). Predicting malaria infection in Gambian children from satellite data and knowledge of bednet usage: the importance of spatial correlation in the interpretation of the results. American Journal of Tropical Medicine and Hygiene **6**: 2-8.

Thomson, M. C. and S. J. Connor (2000). "Environmental information systems for the control of arthropod vectors of disease." Medical and Veterinary Entomology **14**: 227-244.

Thomson, M. C. and S. J. Connor (2001). "The development of malaria early warning systems for Africa." Trends in Parasitology **17**(9): 438-445.

Connor, S. J. (2002). Managing health and disease in developing countries. Arnold Companion to Development Studies. Edited by R. D. Potter & V. Desai, London, Arnold: 396-400.

Oral presentation at scientific/technical meetings

Aspects of the work in this thesis have been presented, by the author, at a number of national and international conferences and workshops. These include:

Connor, S. J. (1997) "The contribution to be gained from weather satellite data in improving malaria stratification, environmental monitoring and epidemic forecasting in Southern Africa." The 1st Southern African Malaria Conference, Maputo, Mozambique, June 1997.

Connor, S. J. (1997) "The use of satellite imagery to monitor malaria risk." Imaging in Biology, Annual Symposium of the Institute of Biology, University of Bradford, November 1997.

Connor, S. J. (1998) "Forecasting and Prevention of Malaria Epidemics: Current research activities and progress to date." 1st Meeting of the Roll Back Malaria Resource Support Network on Epidemic Malaria Prevention and Control, WHO-Geneva, November 1998. CDS\RBM\RSN\EPI\98.8.

Connor, S. J. (1998) "Mapping malaria risk in Africa using environmental remote sensing." Meeting of the Roll Back Malaria Resource Support Network on Mapping Malaria and Health Care, WHO-AFRO, December 1998, Harare, Zimbabwe.

Connor, S. J. (1998) "Developing environmental information systems for improved malaria control planning in Africa." Ninth International Congress of Parasitology (ICOPA IX), Makuhari, Chiba, Japan, August 1998.

Connor, S.J. (1998) "Using climate and remote sensing data for mapping malaria risk in Africa." WMO/IRI/NOAA-OGP Climate and Health Training Workshop, Bamako, Mali, April 1998.

Connor, S. J. (1998) "Environmental Information Systems for Malaria Control Planning in Africa." CTD-MAL Seminar, WHO Geneva, February 1998.

Connor, S. J. (2000) "Environmental information systems for malaria." WHO-AFRO Southern Africa Malaria Control Planning and Consultation Conference, August 2000, Victoria Falls, Zimbabwe.

Connor, S. J. (2000) "Identification and assessment of risk factors implicated in 'desert-fringe' or 'post-drought' epidemic malaria situations." RBM Expert meeting to finalize a methodological guideline on early warning and detection systems to control malaria epidemics, Chateau de Penthes, Geneva, June 2000.

Connor, S. J. (2001) "The need for multisectoral partnership building for the development of malaria early warning systems in Africa." 3rd Meeting of the Roll Back Malaria Technical Resource Network on Epidemic Malaria Prevention and Control, WHO-Geneva, December 2001. CDS\RBM\TSN\EPI\01.12.

List of Abbreviations

ADDS:	Africa Data Dissemination Service
AFRO:	WHO African Regional Office
ARTEMIS:	Africa Real-Time Environmental Monitoring Information System
AVHRR:	Advanced Very High Resolution Radiometer
CCD:	Cold Cloud Duration
CD-ROM:	Compact Disk – Read Only Memory
CDS:	WHO Division of Communicable Disease Surveillance
CRU:	Climatic research Unit, UEA
CTD-MAL:	WHO Division for Control of Tropical Diseases (Malaria Unit)
DDT:	Dichlorodiphenyltrichloroethane persistent organochlorine insecticide
DEM:	Digital Elevation Model
EIS:	Environmental Information System
EWS:	Early Warning System
FAO:	United Nations Food and Agriculture Organization
FEWS:	Famine Early Warning Systems
FEWS-NET:	USAID supported FEWS Network
GDP:	Gross Domestic Product
GIEWS:	Global Information and Early Warning System
GIS:	Geographical Information System
GMCS:	Global Malaria Control Strategy
HIMAL:	MARA Highland Malaria Project
HIS:	Health Information System (Surveillance)
IDRC:	Canadian International Development Research Centre
ITN:	Insecticide-Treated Nets (materials)
IRI:	International Research Institute for Climate Prediction
MARA:	Mapping Malaria Risk In Africa Project
MoH:	Ministry of Health
METEOSAT:	European Meteorological Satellite Series
MEWS:	Malaria Early Warning System
MSS:	Multi-Spectral Scanner, Landsat Satellite
NDVI:	Normalised Difference Vegetation Index
NGO:	Non-Governmental Organization
NOAA:	US National Oceanographic and Atmospheric Administration
NOAA-OGP:	NOAA Office of Global Programs
NMCP:	National Malaria Control Programme
NVDCP:	Namibian National Vector-borne Disease Control Programme
OAU:	Organization of African Unity
PHC:	Primary Health Care
RBM:	Roll Back Malaria Project
RFE:	Rainfall estimate (satellite derived)
RS:	Remote Sensing
SADC:	Southern African Development Cooperation
SADC-DMC:	SADC Drought Monitoring Centre
SADC-FSU:	SADC Food Security Unit
SADC-RRSU:	SADC Regional Remote Sensing Unit/Project
SAMC:	WHO Southern Africa Malaria Control Intercountry Team
SPOT:	Satellite Pour l'Observation de la Terre
TDR:	WHO Tropical Disease Research

TIR:	Thermal Infra-Red
TM:	Thematic Mapper, Landsat Satellite
TSN:	Roll Back Malaria Technical Support Network
UEA:	University of East Anglia
UNDP:	United Nations Development Programme
UNICEF:	United Nations Children's Fund
USAID:	United States Agency for International Development
WHO:	United Nations World Health Organization
WINDISP:	Windows Image Analysis and Display Software
WMO:	United Nations World Meteorological Organization

Abbreviations of the lagged environmental variables used in the analyses are listed and described in Tables 5.3 a-d.

Abbreviations used in mathematical notation are described in the text in the appropriate sections.

Table of Contents

1. General Literature Review

"The microbe is nothing, the terrain everything," Pasteur: cited Learmonth, (1988).

1.1. Disease, location and environment.

1.1.1. The origins of medical cartography.

The origins of medical cartography and the establishment of its role in the epidemiology and control of disease is often attributed to the work of John Snow, a medical doctor working in London during a cholera epidemic in 1854. The dominant belief of the time was that cholera, like malaria, was transmitted through the inhalation of bad vapours. Snow, who had hypothesised that cholera was instead transmitted through contaminated water, was able to test and support his theory by documenting and correlating cholera cases with their use of water from one of two of the city's water supply companies (Learmonth 1988). The Lambeth Waterworks Company drew its supplies from the upper Thames. The Southwark and Vauxhall Water Company took its water from much further downstream where it had subsequently been contaminated by sewage from the city. Snow found that users of the latter company's water died of cholera in large numbers. In one particular Soho neighbourhood, the concentration of cases was so high that more than 500 deaths occurred during a period of just ten days. From his investigations, Snow concluded that the focal cause of the epidemic was a single pump on Broad Street. He advised that the handle of the pump be removed immediately. This was carried out and the epidemic subsided. Snow later mapped the distribution of cholera cases in relation to the Broad Street pump (Snow 1854) demonstrating the potential value of maps (when combined with appropriate epidemiological understanding and enquiry) as a useful tool in public health decision making[1].

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[1] Since the 1854 publication of Snow's Broad Street Map questions of its role in guiding Snow's hypothesis, investigations and conclusions has been the subject of anecdote and prolonged debate. Recent argument suggests that Snow did not use a map as a primary deductive tool, but rather to provide illustrative support for his existing hypothesis and epidemiological investigations. It is also believed that the epidemic was already in decline when the Broad Street pump handle was removed Brody, H., M. Rip, R, P. Vinten-Johansen, N. Paneth and S. Rachman (2000). "Map-making and myth-making in Broad Street: the London cholera epidemic, 1854." The Lancet **356**: 64-68.

While Snow's 1854 map came to be seen as a keystone in the use of cartography in guiding epidemiology and disease control, it was certainly not the first documented use of maps in studies concerning disease. Snow, and others, had produced earlier maps showing the locations of cases in previous cholera outbreaks (Brody, Rip et al. 2000). Jarcho identified 36 authors who published maps of cholera between 1820 and 1836 (Jarcho 1970). Other work draws attention to an epidemic of yellow fever in East-side New York which was mapped by physician Valentine Seaman in 1798 (Stevenson 1965). Maps had also been used during the 17th and 18th century to identify the more unhealthy parishes of Essex, Kent and Sussex. Many of those parishes bordering on the marshes of the River Thames and its estuarine tributary the River Medway were perceived as being subject to high risk of 'marsh fever' or 'ague' and many professional people, including the clergy, avoided residence in them (Dobson 1994).

The perception of a linkage between malaria and a particular location or environment is an ancient one. Indeed reference is made to the association between intermittent fevers and environment in Vedic manuscripts of 1600 BC (Desowitz 1991) and the writings of Hippocrates 400 BC (Najera 1999a). Paludisme, the older French term for malaria, derives from *paludal*: meaning of, or pertaining to, the marshes (Watson 1976). However, neither the causative agent of malaria nor its mode of transmission were known until the end of the 19th Century, so the presence of mosquitoes in the marshes was not the reason associated with this. The use of the term malaria in the English language is believed to be attributed to Horace Walpole writing from Rome in 1740, where the Italians used *mal'aria* derived from 'bad' or 'evil' air to describe the local marsh fever (Desowitz 1991). This illustrates the then widely held belief that malaria was caused by *miasma* a cold, damp, misty effluvium rising from the ground in marshy lands.

Despite Laveran's discovery and identification of the malaria parasite (*Plasmodium malariae*) in a patient's blood in Constantine, Algeria, in 1880, the mode of transmission of the disease remained elusive. Did the parasite get into the body through inhalation of an air-borne microbe, or the ingestion of a water-borne or soil-borne microbe? The miasma theory still held much persuasion and any of these possibilities accommodated the perception of malaria as a 'marsh fever'.

In 1889 an 'Atlas of Tropical Diseases' was published (Felkin 1889). Felkin's world map of malaria distribution, Figure 1.1, was produced at a time when evidence was beginning to suggest that malaria was due to "an earth-borne poison, generated in soil, the energies of which are not expended in the growth and sustenance of healthy vegetation" (Felkin 1889).

What is striking about Felkin's map is that while the mosquito's role in the parasite life cycle, and as the actual mode of malaria transmission, was yet to be discovered and established by both Ross and Grassi in 1898, the map shows a remarkable similarity to those widely available more than a century later. The map itself was produced by a combination of expert opinion and the use of rainfall isohyets and temperature isotherms to 'fill in the gaps' (a process still very much in evidence today). Comparison of Felkin's map with that produced more recently by WHO, Figure 1.2, shows that in the intervening century malaria has disappeared from the more developed countries of Europe and North America, but that the disease has persisted in (or returned to) much of tropical Africa, Latin America, India and South-east Asia.

During the British colonial period detailed maps of malaria distribution in Bengal, India were produced following surveys carried out during 1901-1911. Bentley measured enlarged spleens in the Bengali population (Bentley 1916) a technique devised by Dempster in 1848 to indicate levels of malaria parasitaemia. From these same surveys Bentley then produced maps showing the varying endemicity occurring throughout the Province. Similar but more extensive surveys, undertaken largely during 1914-1918, were later collated by Christophers and Sinton in 1926 (Learmonth 1957), and related to altitude and rainfall patterns to form the basis of a malaria endemicity map for the whole of the Indian subcontinent, Figure 1.3.

The geographical context of malaria transmission continued to be studied and played an increasing role in understanding the differing endemicities of the disease and in guiding control options up until World War II (Boyd 1949). Maps showing the world distribution of human malaria parasites and the principal malaria vectors were produced by Jacques May in his "World Atlas of Diseases" (May 1950-55; May 1961). May's work is recognised as offering a major contribution to medical

FIGURE 1.1. CHART OF THE WORLD SHOWING THE AREA OF ENDEMIC MALARIA. REPRODUCED FROM FELKIN (1889).

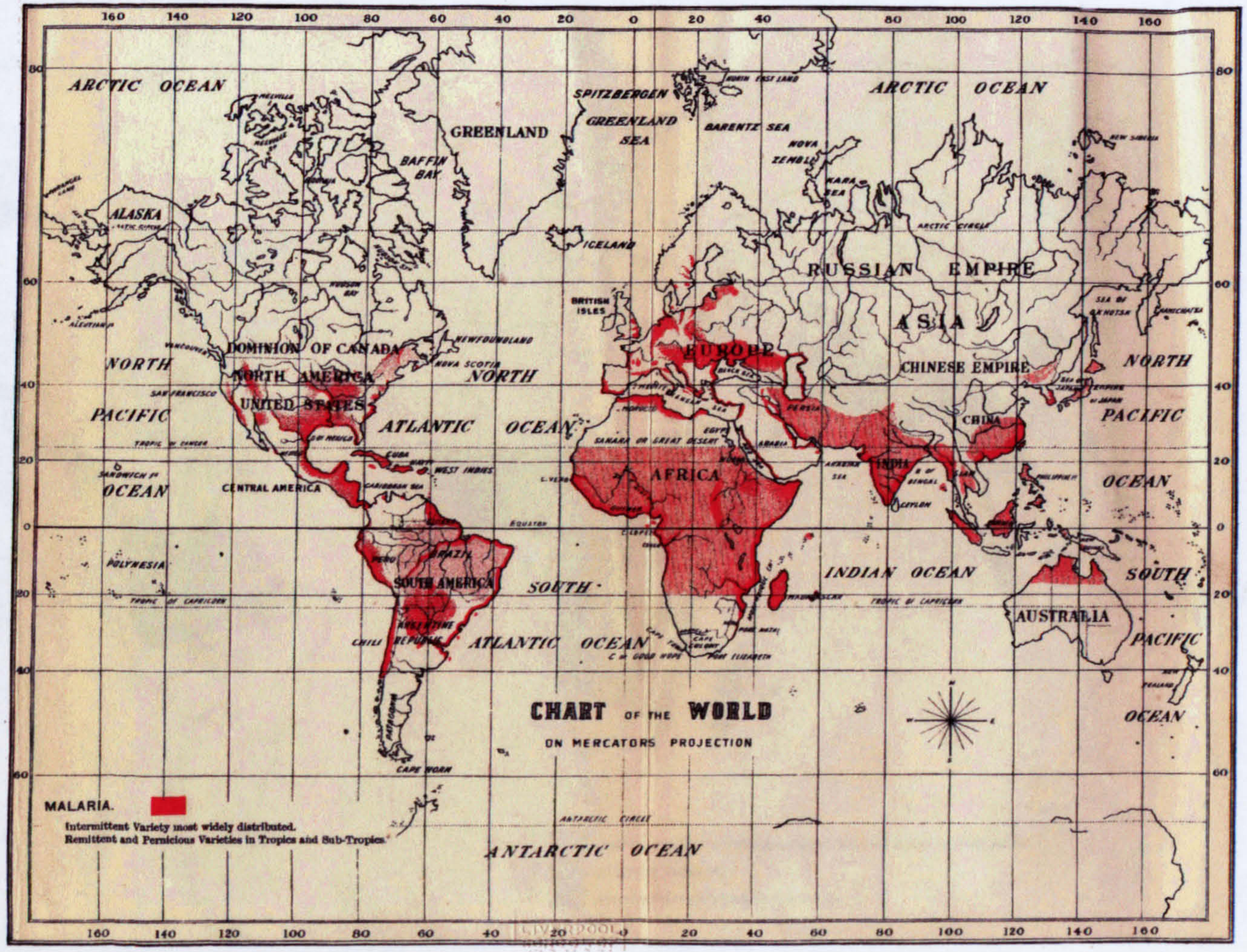


FIGURE 1.2. GLOBAL MALARIA STATUS, CIRCA 2000. SOURCE, WHO EXPERT COMMITTEE REPORT 2000 (WHO, 2000).

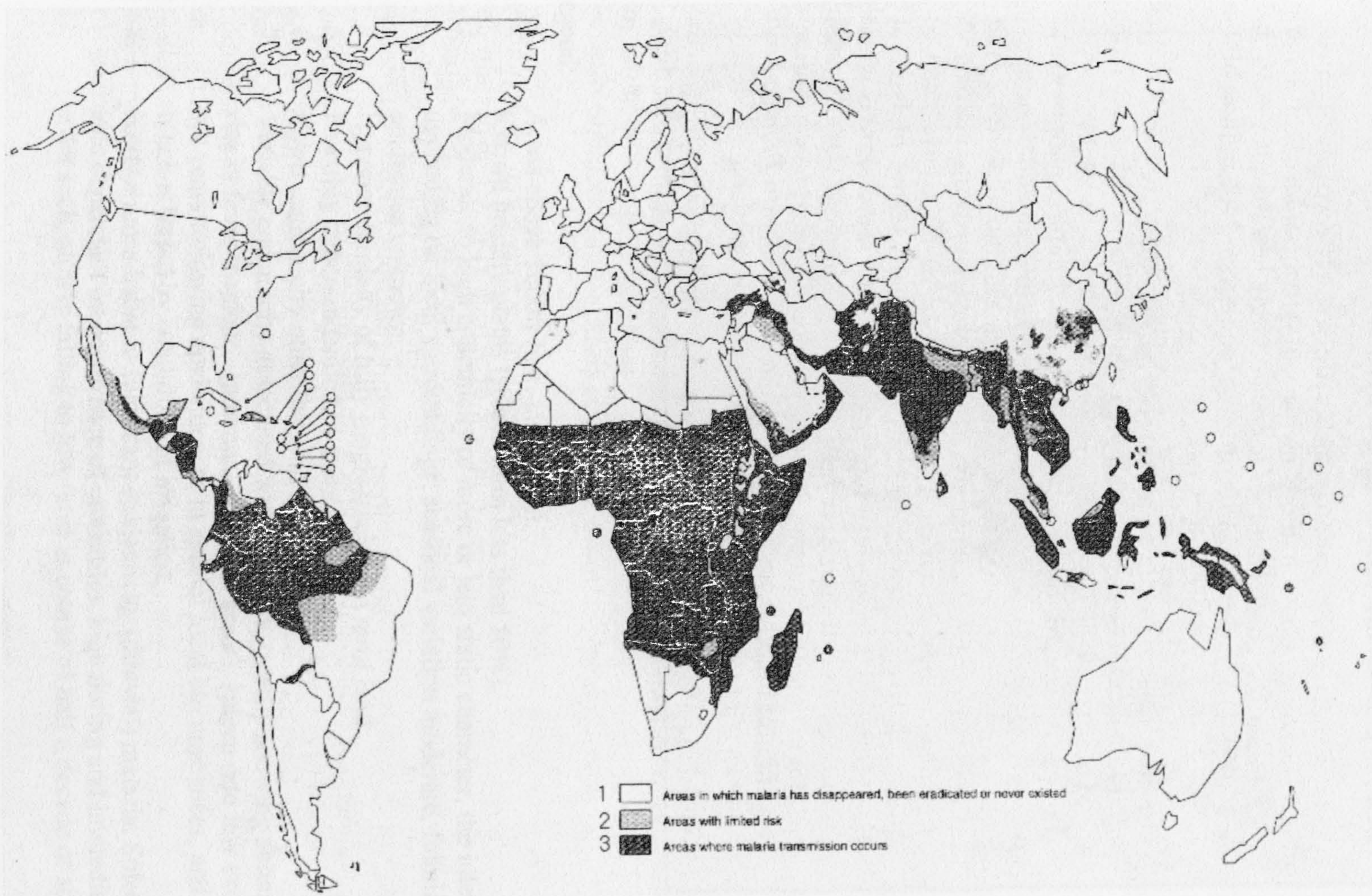
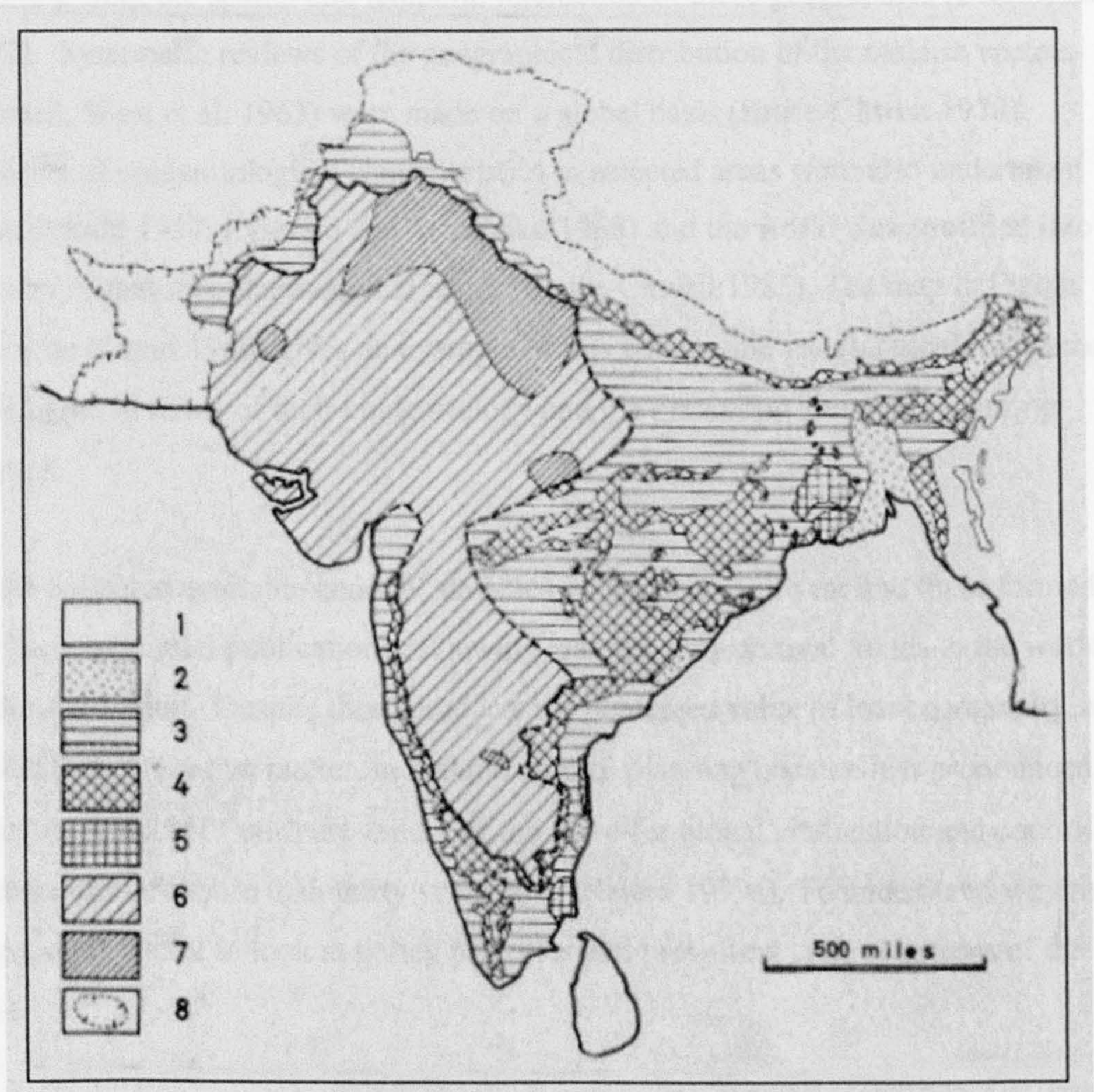


FIGURE 1.3. CHRISTOPHERS' AND SINTON'S MAP OF MALARIA ENDEMICITY FOR THE INDIAN SUB-CONTINENT – CIRCA 1926. REPRODUCED FROM LEARMONTH (1957).



Legend:

1. Areas above 5000ft (non-malarious).
2. Known healthy plains (spleen rates less than 10%).
3. Moderate to high endemicity of more or less static character, the intensity depending on local surroundings; seasonal variation moderate, fulminant epidemics unknown.
4. Hyper-endemicity of hilly jungle tracks and *terai* land.
5. Probably hyper-endemic hill areas.
6. Hyper-endemicity other than hill areas.
7. Variable endemicity associated with dry tacts, usually showing autumnal rise in fever incidence (potential epidemic areas), spleen rate low except for years following epidemics, or in special local circumstances, and much affected by conditions of irrigation.
8. Known areas liable to fulminant epidemicity (diluvial) malaria. Spleen rate dependant on occurrence of epidemics, high during and immediately after such, slowly falling to low rates in course of half a decade or so.

geography and disease ecology. May offered the perspective of multifactorial diseases, each factor having its own geography, and manifestation of disease resulting from the spatial and temporal interaction of these geographies (Learmonth 1972). Systematic reviews of the geographical distribution of the malaria vectors (Russell, West et al. 1963) were made on a global basis (Bruce-Chwatt 1970). Reviews of epidemiological characteristics in selected areas were also undertaken (MacDonald 1957; Lysenko and Semashko 1968) and the world was stratified into a number of major epidemiological zones (Bruce-Chwatt 1985). The map in Figure 1.4, after (Onori 1986) gives an example of this where nine geographical regions are considered in terms of their epidemiology and the prevailing situation regarding control.

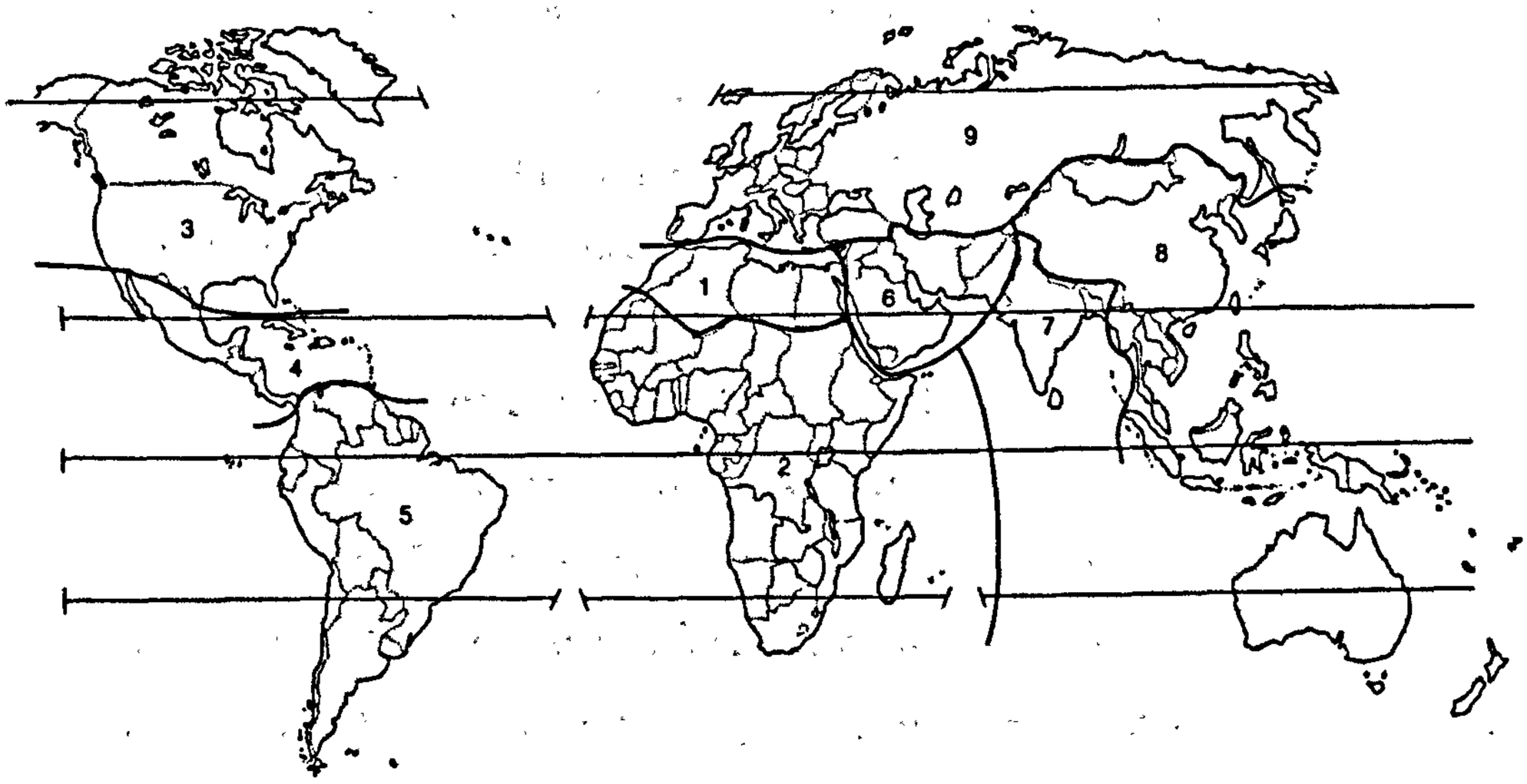
WHO collected available national statistics on malaria each year and these formed the basis of annual publications reviewing and mapping general trends in the world malaria situation. Despite these products the perceived value of local geography, and epidemiology for that matter, in malaria control planning became less pronounced from the mid 1950s until the failure of the drive for global eradication and control became explicit more than thirty years later (Najera 1999a). To understand why this was so it is useful to look at policy priorities and prevailing control options of the time.

1.2. The technical 'solution' to the malaria problem.

Prior to the eradication era malaria had been seen as a complex disease which varied markedly according to its local epidemiology and ecology. Hackett writing in 1937 suggested "Everything about malaria is so moulded by local conditions that it becomes a thousand epidemiological puzzles. Like chess it is played with few pieces, but is capable of an infinite variety of situations." (Hackett 1937) cited in (Gilles 1993).

During the 1950s interests largely shifted away from the prerequisite need to understand the local geography and epidemiology of malaria for its control (Najera 1998b). Two very cheap and effective control tools had become available in the forms of the insecticide DDT and the anti-malarial drug Chloroquine. Which many

FIG 1.4. *EPIDEMIOLOGICAL ZONES OF THE WORLD WHERE MALARIA EXISTS OR MAY OCCUR. REPRODUCED FROM ONORI (1986).*



Legend.

Onori's map is based on a stratification of malaria into the following zones:

1) Africa, North of the Sahara,
2) Africa South of the Sahara,
3) North America,
4) Middle America,
5) South America,
6) Asia West of India,
7) Middle South Asia,
8) East Asia and Oceania, and
9) Europe including Turkey and the USSR.

considered could be universally applied, irrespective of local conditions. During the inception of the World Health Organization (1946-1948) its Interim Committee established an Expert Committee on Malaria which recommended the assistance of governments of endemic countries worldwide to accomplish malaria control along 'modern scientific' lines. This policy, though subject to contentious debate, was ratified at the Kampala Conference in 1950 (WHO 1951).

The perceptions of malaria as a major public health problem has been a central concern of WHO and over the past fifty-sixty years the perceived wisdom regarding priorities and options for eradication and control have changed markedly. The value of epidemiological and geographical understanding of malaria, and the perceived need for personnel trained in these disciplines, varied accordingly. During the drive for eradication Macdonald's mathematical model was offered to provide a 'complete picture of the epidemiology of malaria' and a 'realistic representation of natural happenings' (Najera 1999a).

A number of writers provide a historical description of the changing role of WHO, and its partners, in global malaria control activities. Najera divided the various control approaches into four key periods (Najera 1989). Bradley categorises these periods and their changes in approach to control by decade: 1940s – Control, 1950s – Eradication Attack Phase, 1960s – Eradication Consolidation Phase, 1970s – Resurgence, 1980s – Chaos, 1990s – Hope (Bradley 1992). A more recent publication (Connor 2002) provides a review of these various approaches including recent changes of emphasis resulting from the WHO's New Global Malaria Control Strategy (WHO 1993a) and the Roll Back Malaria Initiative (WHO 1998b).

1.2.1. The Global Malaria Control Strategy 1946-54.

This period saw the adoption of malaria control as a major international humanitarian initiative. The world had seen the mobilisation of huge forces during World War II and it was felt that concerted efforts could now be made against one of the world's major public health problems. Intervention relied primarily on spraying the interior walls of dwellings with DDT to kill resting mosquito vectors, any subsequent malaria cases were treated with Chloroquine to reduce the parasite pool in the human population. In the USA, Europe, North Africa, and the Middle East malaria control

campaigns based on this two pronged approach were so successful that global eradication was seen as a realistic possibility.

1.2.2. The Global Malaria Eradication Campaign 1955-69.

Fears over the growing resistance to both of these cheap and effective control tools and the costs of maintaining recurrent control measures spurred the drive for eradication. While eradication in the developed nations of Europe and the USA was expected, eradication in India and Ceylon looked as if it too might succeed (Kondrachine and Trigg 1997). In India prevalence levels of 70 million per year declined by 1967 to about 100,000 cases (Learmonth 1988). Ceylon also virtually achieved eradication.

Eradication efforts did not include most sub-Saharan African countries despite the recommendations of the First Conference on Malaria in Equatorial Africa which was held in Kampala, Uganda in 1950:

> '.... to governments responsible for the administration of African territories that malaria should be controlled by modern methods as soon as feasible, whatever the original degree of endemicity and without awaiting the outcome of further experiments.' (WHO 1951).

There were two basic schools of thought on control in sub-Saharan African. The interventionists with their strong commitment to eradication were convinced of the need to vanquish malaria from every continent (Macdonald 1951). The conservationists argued that the equilibrium reached between humans and parasites under intense malaria transmission offered a high degree of adult protection and should not be interfered with lightly (Wilson, Garnham et al. 1950). Ultimately vector control campaigns were not considered feasible in sub-Saharan African, due to the technical difficulties of intense malaria transmission, requiring extensive control efforts in countries which had very limited health infrastructure (Bradley 1992). However, Ethiopia, South Africa, Swaziland and the former Rhodesias did carry out effective malaria control campaigns. Major research experiments which included vector control also occurred in Kenya and Tanzania (Bradley 1991b) and Nigeria (Molineaux and Grammicia 1980) which did produce significant reductions

in infant and child mortality. A 1977 paper by Kuznetsov gives a detailed account of experiences with vector control in Africa (Kouznetsov 1977).

During the latter part of this phase however, the considerable gains that had been made began to lose ground. Donors saw that eradication was going to be a long process. While they were prepared to invest significant funding for a limited term intervention, they were reluctant to maintain recurrent vector control operations. They began to argue that further improvement in the malaria situation could only be achieved through greater national commitment and improved public health infrastructure. This was followed by an immediate reduction in bilateral and international financial support to anti-malarial campaigns. In recognition of this, combined with the devastating epidemics in Sri Lanka during 1968, and the wide scale re-emergence of malaria in Asia, the 1969 World Health Assembly radically re-examined the malaria eradication strategy.

1.2.3. Malaria Control with the Ultimate Goal of Eradication 1969-78.

During this period the capability of many endemic countries to continue anti-malarial operations, especially those involving vector control, were further reduced and many countries including India experienced widespread and dramatic resurgence of malaria (Akhtar and Learmonth 1977).

While anti-malarial programmes were in decline the efforts to establish basic health care services in the more peripheral areas of endemic countries met with little success. In 1975 a collaborative WHO/UNDP/World Bank Special Programme of Tropical Disease Research was established to identify new and improved tools for malaria control and to strengthen research capabilities in endemic countries. While its central thrust focused on clinical and field research, a significant component of this new initiative was the drive for greater epidemiological and sociological inputs into the planning of appropriate control programmes (Kondrachine and Trigg 1997). Extensive resurgence of malaria in South Asia and Latin America led to calls to develop malaria control programmes appropriate to the infrastructure existing in endemic countries.

1.2.4. Malaria Control as part of Primary Health Care 1978-89.

This approach was formulated during the Alma-Ata Conference in Russia, September, 1978 (WHO 1978). It centred on an actively participating community working closely with health services. Its aims: to ensure that malaria control activities would be integrated into the priority setting of the general health services, reflect the prevailing infrastructure and the level of service delivery possible, and to be able to maintain the gains achieved. It was argued that the fundamental element of the new approach reflected recognition of the variability of epidemiological situations, the feasibility of their modification and the availability of resources.

A decade after Alma-Ata, progress towards Primary Health Care and 'Health for all by the year 2000' was slow and disappointing. Only China had made significant inroads against malaria. Elsewhere the malaria situation was stagnant or deteriorating, especially in sub-Saharan Africa (Kondrachine and Trigg 1997). Financial resources available to health care in developing countries continued to decline dramatically. To support primary health care provision UNICEF launched the 'Bamako Initiative' in 1987 to encourage financing through cost recovery. In many countries, where malaria control had been carried out as a public health measure, people were now expected to meet the cost of treatment themselves. By the end of the 1980s the global malaria control strategy was in crisis.

1.2.5. Redefining Malaria as a Global Health Issue – after 1989.

In view of the increasing prominence of malaria as a major public health problem, the Executive Board of WHO and the World Health Assembly adopted resolutions in 1989 asserting that control of malaria must again become a global priority. Malaria was seen as an excessive drain on limited health resources, a major constraint to child survival programmes, and maintained poverty through low productivity and impaired economic growth in developing countries. International meetings in Brazzaville, New Delhi and Brasilia during 1991 and 1992, followed by consultation with experts at national and regional levels led to the formulation of a new strategy which was adopted by the Ministerial Conference on Malaria in Amsterdam in October, 1992. The New Global Malaria Control Strategy recognises malaria has no

single formula for its control, but is a disease of differing epidemiological types determined by a diversity of social, ecological and economic settings (WHO 1993a).

Strong political support for concerted action against malaria, especially in Africa, grew throughout the 1990s. It was recognised that there was a serious shortfall of trained malaria epidemiologists available to support health services (Najera 1999a), there had been a drastic under funding of malaria research (Anderson, MacLean et al. 1996), and malaria had come to be seen as a neglected disease (Marsh 1992). In 1996 an Accelerated Strategy for Malaria Control in the Africa Region was approved by WHO and in 1997 the Meeting of Heads of State of the Organisation of African Unity made a declaration on malaria control (OAU 1997). Further international support came in 1997 with the Multilateral Initiative on Malaria and in 1998 with the 'Roll Back Malaria' Global Partnership which includes the United Nations Development Programme, the World Bank, UNICEF and support from a number of Bilateral Agencies (WHO 1998b). Roll Back Malaria aims to identify stakeholders, consolidate research, and deliver concerted support to malaria control through strengthened health systems development (Nabarro and Tayler 1998). It aims to draw more commitment from the private sector in a drive for new control tools through its Medicines for Malaria Venture, and the Malaria Vaccine Fund which is substantially supported, for example, by the Bill and Melinda Gates Foundation.

1.3. Re-establishing the need for mapping malaria risk.

In its explicit recognition of malaria as a disease that has no single formula for its control the New Global Malaria Control Strategy (WHO 1993a) promotes the view that malaria is a disease of differing epidemiological types that are determined by a diversity of social, ecological and economic settings[2]. Arguably, there is a clear role for mapping the spatial variation in these factors and using the results to guide control efforts.

[2] Hackett's viewpoint from 1937 is rediscovered Hackett, L. W. (1937). Malaria in Europe. London, Oxford University Press..

The four basic technical elements of the New Global Malaria Control Strategy are:

1. to provide early diagnosis and prompt treatment;
2. to plan and implement selective and sustainable preventative measures, including vector control;
3. to detect early, contain or prevent epidemics;
4. to strengthen local capacities in basic and applied research to permit and promote the regular assessment of a country's malaria situation, in particular the ecological, social and economic determinants of the disease.

The strategy aims to control malaria through a concerted approach using various methods of intervention based on knowledge of the local epidemiology of the disease, availability of resources and the ability to maintain a sustainable impact. The successful implementation of the New Global Malaria Control Strategy therefore depends on a radical shift from highly prescriptive, centralised control programmes to flexible, cost effective and sustainable programmes adapted to local conditions and responding to local needs. Mapping could clearly provide useful inputs into all but the first[3] of these technical elements, i.e. planning of preventative measures; identification of epidemic prone regions; and assessment of a country's ecological, social and economic determinants of the disease. This is acknowledged by a WHO Study Group on Implementation of the Global Strategy (WHO 1993b) and in the fact that the newly established Roll Back Malaria Initiative immediately set up a Technical Support Network on Mapping Malaria and Healthcare in 1998 (WHO 1998a).

The New Global Malaria Control Strategy departs somewhat from the previous approaches to malaria stratification, such as that defined purely by geographical region (Onori 1986), and instead suggests the elaboration of identifiable ecological and socio-economic situations in areas where malaria is common and has been more difficult to control. These basic malaria patterns have been referred to as 'prototypes' or 'paradigms' (Najera, Leise et al. 1993). The ecological categories

[3] Although even here mapping could inform the development of localised diagnostic algorithms in countries with regions of varying seasonal transmission. Prompt treatment may also be supported by mapping of health facilities in relation to those at risk.

identified are: 1) African savannah, 2) Plains and valleys outside Africa, 3) Forest and forest fringe, 4) highland and desert fringe, 5) Seashore and coastal malaria, 6) Urban malaria. In addition, there are a number of patterns associated with specific occupational activities or social conditions. These are: 7) Agricultural colonization of jungle areas, 8) Gold and gem mining, 9) Migrant agricultural labour, 10) Displaced populations (Najera, Leise et al. 1993).

In view of this renewed focus on the epidemiology of malaria it is not surprising that workers in malaria research and control began once again to demand maps showing the variation in malaria endemicity as a tool to guide control efforts (Najera, Leise et al. 1993; Snow, Marsh et al. 1996). A map of malaria endemicity may be considered a basic epidemiological tool that can be used to help stratify a region, a nation, a province, or a district into areas of relative risk. This may then be used to assess the numbers of people at risk; guiding choice of control options, and estimating the resources required to implement an effective control programme. Where maps can be updated regularly they may also play a role in monitoring changes in factors related to transmission patterns and potentially provide a component input into early warning of epidemic risk (Connor, Flasse et al. 1997). The wide availability of personal computers and the development of geographical information and satellite remote sensing technologies may be especially useful in this regard.

1.4. Geographical Information Systems (GIS)

The advent of computer-based cartography dates back to the 1960s when computer screens and plotters were used to plot Cartesian coordinates to make up points, lines, grids and areas. The 'SYMAP' sofware programme was the first developed, by Harvard University. This programme was used experimentally to produce maps for various natural resource applications (Burroughes and McDonnell 1998). It had at least one application in health when a map of mortality statistics was produced for Hawaii (Armstrong 1972). The concept of Geographical Information Systems stems from workers in the Canadian Government in the early 1960s (Coppock and Rhind 1991) but it was during the 1970s that the development of GIS came about as the technology was driven by rapid demand from city planners and utility companies.

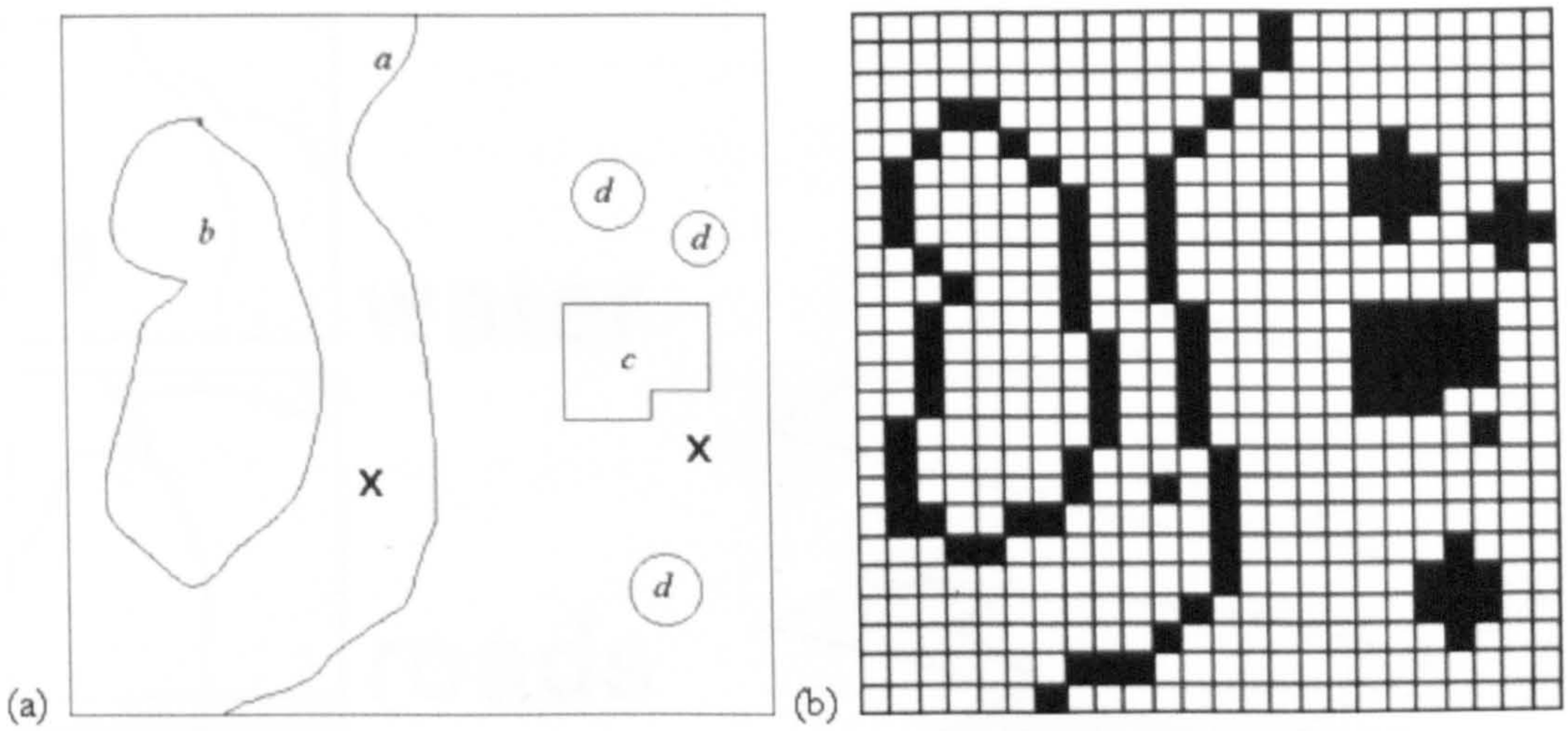
GIS is defined variously according to whether it is viewed as an industry, a product, a technology, a database, a tool, or a science (Martin 1991; Reader 1995; Wright, Goodchild et al. 1997; Burroughes and McDonnell 1998).

A simple working definition of a GIS used here, as a tool, is: 'A geo-referenced computer database used for data management, locational enquiry, spatial association, modelling and mapping.' The key factor in GIS being that each of the database records have locational information (geographic co-ordinates) associated with them, and can be examined in relation to any other variables sharing those co-ordinates.

GIS technologies have developed along two basic architectures: 1) arc-based (or vector-based) systems, where all geographical features are represented by points, lines and polygons with associated attributes linked to codes in a database; and 2) grid-based (or raster-based) systems where all features and their associated attributes are stored as digital records in grids, Figure 1.5. The former found many applications in the service sector and utilities where information on streets, city blocks, pipe and cable lines were readily stored in this format. The latter was mostly used for image processing of remote sensing data obtained from satellite and airborne survey systems for natural resource management applications. Arc-based formats can also be readily used for network analysis and distance operations, such as in transportation. Grid-based formats lend themselves readily to applications where changes occur gradually over surfaces and where boundaries between features are less distinct. Over the past ten years the interaction between these two systems has been increasing and many GIS packages can handle both arc-based and grid-based data type. For instance the overlaying of rivers and roads on to a satellite image, Figure 1.6. However, the majority of analytical procedures will usually require data to be in the common base format, either arc or grid, and software systems often try to incorporate conversion utilities between the two formats.

The rapid advance in personal computer technology revolutionised the GIS industry and during the 1980s many research applications were demonstrated. In 1991 a comprehensive three volume text on GIS and its applications was published (Maguire, Goodchild et al. 1991). Yet, as Glass and colleagues pointed out (Glass, Aron et al. 1993) health researchers had been slow to exploit this technology, and in

FIGURE 1.5. COMPARATIVE REPRESENTATION OF FEATURES IN VECTOR AND RASTER GIS.

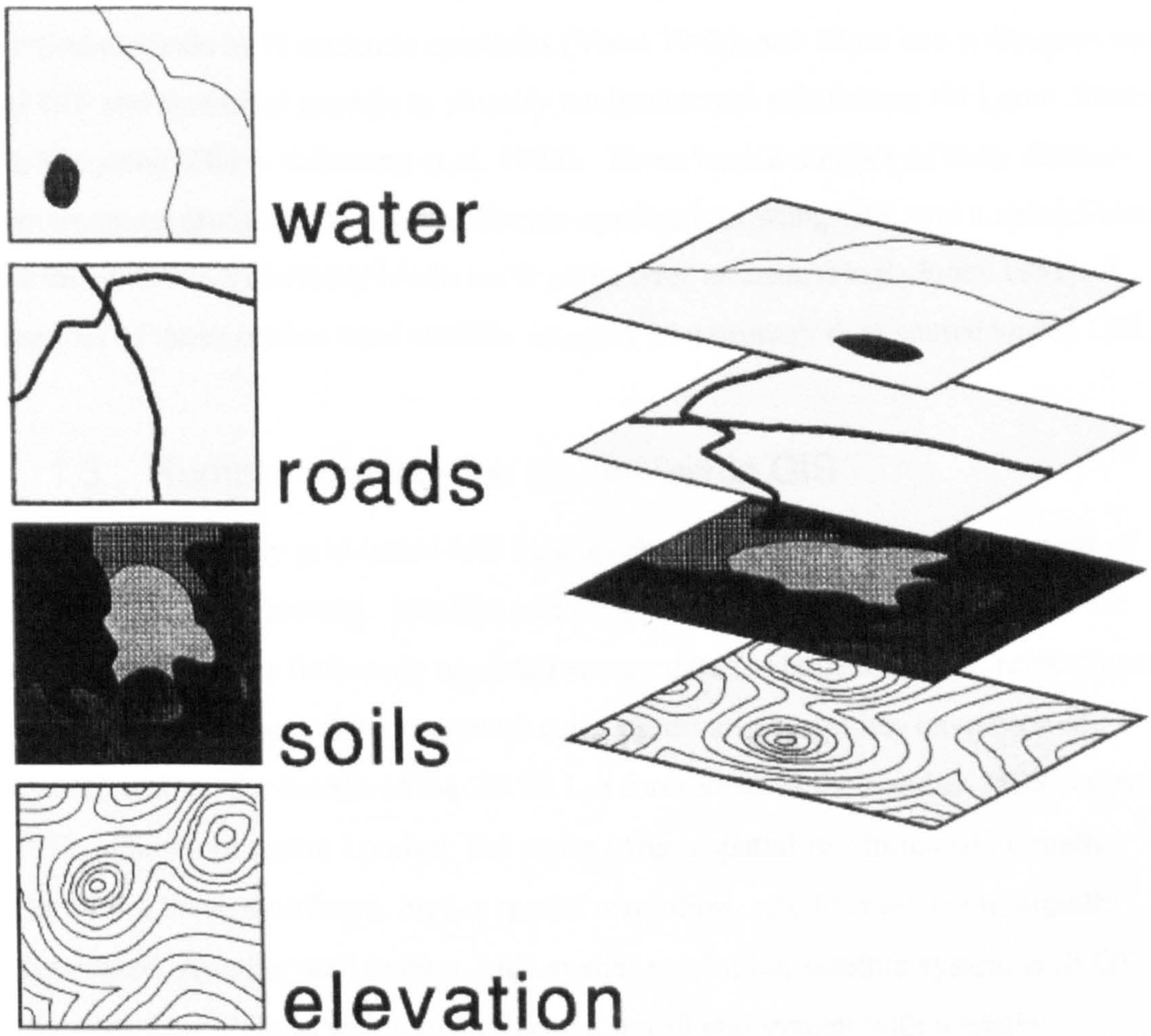


Legend:

(a) In vector-based GIS features are represented by points lines and polygons. In this illustration a road *a* is shown by a curved line, a lake *b,* a building *c* and trees *d* are shown by polygons, and drainage access points *x* are shown using points. The characteristics (attributes) of these features are stored in an associated database.

(b) In raster-based GIS these same features must be represented by different values in a matrix (image). Their attributes are classified according to the different values in those cells.

FIGURE 1.6. OVERLAYING DIFFERENT INFORMATION LAYERS IN A GIS.



Legend:

GIS allow several different information layers to be stored, displayed, queried and analysed in relation to one another. Reproduced from Eastman (1993).

the whole of this 1096 page treatise, not a single paper examined GIS and disease. There were a few studies during the early 1990s, notably those of WHO's Schistosomiasis Control Unit which had developed a GIS database on schistosomiasis in 76 endemic countries (Yoon 1993); and Glass and colleagues use of GIS and statistical models to identify environmental risk factors for Lyme disease in Maryland (Glass, Schwartz et al. 1995). There were a number of early disease-environment studies in veterinary disease applications using GIS, and a special issue of Preventative Veterinary Medicine is given over to these (Hugh-Jones 1991). A number of these studies used satellite imagery as a primary data source within GIS.

1.5. Remote sensing and its use within GIS

As stated previously grid-based GIS had developed primarily to meet the needs of satellite image processing. Satellite and aerial survey data provides a method for obtaining recent, or frequently up-dated survey data for large and often remote areas of the earth's surface. Environmental earth observation satellites have been in operation since the launch of the ERTS 1, a forerunner of the Landsat MSS series in 1972. The more recent Landsat TM series offer a spatial resolution of 30 metres. Data from these multiband, higher spatial resolution, satellites are commercially distributed. Another well known, high spatial resolution, satellite system is SPOT (Satellite Pour l'Observation de la Terre) a multiband system with a spatial resolution of 20 and 10 metres. There are numerous satellites systems, which operate in the visible, thermal and microwave bands, both experimental and operational (Lillesand and Kiefer 1994).

High spatial resolution satellite data tends to have a low repeat cycle. That is they may only observe the same place on the earth's surface twice in 16 days in the case of Landsat and 26 days in the case of SPOT. By contrast, weather monitoring satellite data, such as that from Meteosat and NOAA-AVHRR provide information at a much coarser spatial resolution ($5km^2$ - $1km^2$) but with a rapid repeat cycle of several times daily. Weather satellite data is usually freely available, or at low-cost. So in general there is a trade off between spatial and temporal resolution (and cost). Perryman provides a concise, but thorough, overview of remote sensing, including a useful description of issues of spatial, temporal, spectral and radiometric resolution

(Perryman 1996). Connor and colleagues review these in relation to their use in malaria research and control (Connor, Flasse et al. 1998).

Satellite data have long been used in many natural resource applications, including: forestry and land-use, monitoring of cropping patterns, rainfall, drought and vegetation conditions (Keech 1983; Power, Rosenburg et al. 1996). There have also been a number of studies relating to infectious disease. The potential for use of remote sensing in landscape ecology studies of vector-borne and other diseases was recognised as early as 1970 (Cline 1970). During the 1970s the implications of its use in mosquito control programmes and public health campaigns, and its technical limitations, were considered (Barnes and Cibula 1979). Among the earliest of the major studies using satellite data in examining human disease vector distributions were those of Linthicum and colleagues who used environmental satellite data in a study of the association between outbreaks of Rift Valley Fever and vegetation status in Kenya (Linthicum, Bailey et al. 1987). Rogers and colleagues examined relationships between satellite derived estimates of vegetation status, and the mortality rates and abundance of vectors of human trypanosomiasis (Rogers and Randolph 1991; Rogers and Williams 1994). Wood and colleagues used satellite data to map the landscape components surrounding Californian rice fields from which they were able to identify areas of high anopheline production (Wood, Beck et al. 1992). Washino and Wood provide a review of this and a similar study including malaria vectors and risk of malaria in villages in Chiapas, Mexico, as well as further studies on Lyme disease (Washino and Wood 1994). The UNICEF Guinea Worm Eradication Programme was also one of the earlier users of remote sensing data within GIS for a disease application (Clarke, Osleeb et al. 1991; Mott, Nuttall et al. 1995).

The 1990s saw a rapid expansion of health research interest in GIS and remote sensing. In 1994 the Canadian Government's International Development Research Centre (IDRC) drew together a number of researchers from around the world for an International Conference on GIS for Health and Environment, in Columbo, Sri Lanka. IDRC stated that this was the first major international meeting dedicated to the use of these technologies in health (de Savigny and Wijeyaratne 1995). A number of papers at this conference discussed the use of remote sensing in studies of

human disease transmission and control. These were, for instance, a study of malaria in Nadiad Takula, Kheda district, Gujurat, India using Landsat data to create detailed thematic maps showing landscape features around Nadiad Takula (Malhortra and Srivastava 1995); and one on the use of Landsat imagery and GIS in a study of malaria transmission along forest fringe settlements in Amazonia, Brazil (Bretas 1995). A paper by Connor and colleagues outlined applications of weather and environmental monitoring satellite data in GIS studies of malaria transmission in The Gambia, epidemic Kala azar in Southern Sudan, and health impact assessment and monitoring in major irrigation schemes (Connor, Thomson et al. 1995).

There have, since 1995, been a number of reviews of applications of remote sensing and GIS in studies of disease ecology. Reviews by Hay and colleagues explored the impact of environmental proxies from remote sensing in the study and control of arthropod-borne disease (Hay, Tucker et al. 1996; Hay, Packer et al. 1997). Studies of epidemic Kala azar in Sudan explored the associations between the vector *Phlebotomus orientalis* and environmental factors including vegetation and soil-type (Elnaiem, Connor et al. 1998; Thomson, Elnaiem et al. 1999). Thomson and colleagues investigated the association between satellite derived rainfall and vegetation proxies and seasonal malaria transmission patterns in The Gambia (Thomson, Connor et al. 1996) and considered how remote sensing could be used in mapping malaria risk in Africa (Thomson, Connor et al. 1997). Hay and colleagues used a similar approach looking at differing malaria settings and their seasonality in Kenya (Hay, Snow et al. 1998a). Papers by Connor and colleagues consider these techniques (use of weather satellite data within GIS) with respect to how they might contribute to improved malaria control in the sub-Saharan African countries (Connor, Flasse et al. 1997; Connor, Flasse et al. 1998; Connor 1999b) including their operational use use in epidemic forecasting (Connor, Thomson et al. 1998; Connor, Thomson et al. 1999). A 1999 paper outlines one of the first studies which specifically considers appropriate spatial statistics for interpretation of remote sensing data in studies of disease and their corresponding control decisions (Thomson, Connor et al. 1999). A more recent review by Thomson and Connor provides a broad overview of how GIS, remote sensing, and satellite positioning technologies might be used in a range of entomological research studies and arthropod disease control problems (Thomson and Connor 2000). Hay and

colleagues recently produced a compilation of papers outlining the current 'state-of-the-art' in use of these technologies in disease research (Hay, Randolph et al. 2000). Contributing papers include linkages between land cover and disease (Curren, Atkinson et al. 2000); use of spatial statistics in GIS applications in public health (Robinson 2000); remote sensing applications in studies of African trypanosomiasis (Rogers 2000), *P. falciparum* malaria in Africa (Hay, Omumbo et al. 2000), tick-borne disease (Randolph 2000), remote sensing and GIS in studies of human helminth infections (Brooker and Michael 2000), advances in satellite sensors and environmental proxies (Goetz, Prince et al. 2000), epidemic disease forecasting (Myers, Rogers et al. 2000); as well as discussion on technology transfer, training and the future of GIS and remote sensing in human health applications (Wood, Beck et al. 2000). A framework document by the Roll Back Malaria Technical Resource Network for Prevention and Control of Malaria Epidemics was published in 2001 which sets out the role of EIS, along with other monitoring and surveillance tools, within the development of malaria early warning systems in Africa (WHO 2001b). A more recent article considered the prospects for the use of satellite data in biological models of malaria transmission and their use in early warning systems and concluded that this is the next challenge for workers in this discipline (Rogers, Randolph et al. 2002).

1.6. GIS/RS/EIS: their role in control decision making?

While it is now broadly recognised that GIS and remote sensing can play a useful role in disease research their value in the control setting remains subject to debate. Questions on whether GIS and remote sensing are appropriate tools for use in developing countries have been asked for a number of years. The issues raised over their use in the health sector (Boelaert, Arbyn et al. 1998) largely reflect debate for their use in other sectors such as agriculture and natural resource management a decade previously. Consideration of the challenges of using these computer-based information technologies, appropriate training and technology transfer have been the subject of detailed review (Hastings and Clark 1991; Kabbaj and Ben Mehrez 1994). Since the time of these writings however, computers have become much more commonplace in health facilities, even at a district level, and many district health officers use computers regularly to record and analyse case data. Remote sensing

can be seen as just one of a number of information sources and the use of GIS as just one of a number of data management approaches, not mutually exclusive of any other (Connor 1995; Dunn, Atkins et al. 1997). Clearly, what works well in one situation may not work well in another, and technology transfer and appropriate training may be particularly difficult in situations where human resources are too few.

There are however, a number of examples where GIS and remote sensing are beginning to be used effectively by health services. The development of the HealthMapper software by WHO-HealthMap provides a useful example of how GIS can be designed specifically with the health services in developing countries in mind (Meert, O'Neill et al. 1995). The HealthMapper is a customised system which allows health services the opportunity to enter and manage data, tabulate that data for surveillance reporting and provide a variety of mapping options (Nuttall, O'Neill et al. 1998). Whilst simple in its basic functionality, the HealthMapper is built upon an industry standard GIS architecture (Arc-View) which allows added complexity of functions as appropriate. The HealthMapper is also able to incorporate remote sensing products and grid-based maps, and these are being used and tested by health services at a number of levels (district, provincial, national and international) in Zimbabwe (O'Neill, Connor et al. 1999), with a view to using them elsewhere throughout Southern Africa (WHO-SAMC 2000). A training programme for health workers in the use of GIS and remote sensing for disease surveillance and epidemic prediction was held jointly with WHO-HealthMap and the MALSAT[4] team in Liverpool in 1999 (Thomson, Connor et al. 2000).

Another example of use of GIS in health services supply and disease control planning is provided by workers at the Medical Research Council, Durban who describe the use of GIS and GPS, by the health services, to map homesteads in a rural area of Kwa Zulu Natal (Le Sueur, Ngxongo et al. 1997). This information was then used to identify areas that were poorly served by existing facilities and where mobile clinics should attend. Information from this study was also used to determine

[4] MALSAT is an interdisciplinary research team based at the Liverpool School of Tropical Medicine. First established in 1994 this team have been involved in the development of Environmental Information Sytems for multi-disease surveillance and epidemic prediction.

areas where existing control efforts were being used ineffectively and where anti-vectoral residual spraying practices should be concentrated, or discontinued.

A further example of the use of GIS for malaria control planning is that of the MARA/ARMA collaboration. This initiative is an ambitious continental scale attempt to map malaria risk and produce an Atlas of Malaria in Africa which is then intended to form the basis of an intervention planning platform for malaria control in Africa (MARA 1998). A brief summary of the MARA/ARMA initiative is given here and reference will be made to MARA products in subsequent chapters.

MARA/ARMA aims to mount a considerable data collection exercise (parasite ratio and annual incidence), it will then analyse and map the distribution of malaria across the African continent.

The MARA group is made up of five regional data collection centres and a main GIS laboratory based in Durban, RSA. The MARA/ARMA products will become available in phases. The first of these is complete, and is a climate-based distribution model of malaria in Africa (Craig, Snow et al. 1999). A further sub-product of this includes an assessment of the populations at risk of malaria in Africa and their distributions (Snow, Craig et al. 1999a; Snow, Craig et al. 1999b). A second phase is the development of more detailed national level risk maps. Two of these have been developed to date, one for Kenya (Omumbo, Ouma et al. 1998), and one for Mali (Kleinschmidt, Bagayoko et al. 2000).

Use of long-term climate data can be found in mapping and GIS studies aimed at defining the distribution of the principal malaria vectors in Africa. Work by White (1989) produced interpolated maps of continental distributions of malaria vectors in Africa based on point collections (White 1989). More recent work used long-term mean continental climate surfaces in combination with published point collection data to model the range and relative abundance of the two major malaria vectors across the African continent (Lindsay, Parson et al. 1998). The mapping of species of the *Anopheles gambiae s.l.* complex using climate data has also been published as part of the MARA project (Coetzee, Craig et al. 2000). Further information on the MARA/ARMA collaboration and its products can be found on their internet site: www.mara.org.za

1.7. Aims of this thesis, and review of methods

GIS and remote sensing (combined here as Environmental Information Systems: EIS) are tools which can assist research into vector-borne diseases such as malaria. This thesis is based on the premise that EIS can also contribute to malaria control planning (Connor, Flasse et al. 1997). As such it aims to test the hypotheses:

a) That EIS can provide information on the spatial and temporal patterns of malaria transmission found in Africa, at four levels of scale: continental, regional, national and district

b) and further, that EIS may be readily used alongside epidemiological data (as routinely available to national malaria control managers in Africa) to inform malaria control planning. More specifically in relation to:

- Stratification of malaria endemicity,
- Monitoring of environmental factors influencing variability in transmission, in unstable malaria situations
- Early warning of malaria epidemics based on changes in environmental factors in areas vulnerable to epidemics

The utility of EIS for these objectives will be explored at four levels of scale; continental, regional, national and district; and will include: assessing the epidemiological data readily available to national malaria control planners; assessing the value of routinely available environmental variables, and where appropriate creating new monitoring products for use in malaria stratification and epidemic early warning; testing the value of the data described at a regional and national level in four case study countries (Botswana, Zimbabwe, Namibia and Swaziland) in Southern Africa.

2. Mapping Malaria in Africa

"Maps of the distribution of malaria usually depict nearly the whole of Africa in dark red, indicating high risk, but this is a gross simplification of a complex epidemiological picture." (Greenwood 1999)

2.1. Introduction

Global malaria maps such as those in Chapter 1, Figure 1.2, may be useful for advocacy in that they show malaria has a global dimension, and compared against similar historic maps may show where malaria has increased or decreased. However, they give very little useful information on patterns of malaria transmission or intensity, even at a continental scale. Such maps may also perpetuate the idea of malaria as a purely 'tropical' disease, i.e. one which is determined by geography alone. This perception was never strictly accurate, as malaria transmission was endemic in many temperate zones. Malaria reached its northernmost recorded distribution in the area of Archangelsk, at 64°N, close to the Arctic Circle in the former Soviet Union (Wernsdorfer 1980). Other non geographical factors such as poverty, under-development and social conditions have played an important role in the distribution and persistence of the disease. Currently it is in the countries of sub-Saharan Africa that malaria poses the greatest public health problem, accounting for an estimated 80 per cent of the world's malaria cases and 90 per cent of total malaria deaths (WHO 1993a). Recent estimates of the minimum numbers of deaths from malaria range between 700,000 and 2.7 million each year, with over 75 per cent of these in African children (Breman 2001).

2.1.1. Continental level risk mapping

Malaria in parts of Africa reaches the highest transmission rates anywhere in the world (Bradley 1991a). However, the burden of illness and death attributable to the disease varies enormously between and within countries. Information on this burden by country, region or district is important as it may enable targeting of control interventions in areas where they are likely to be most effective, rather than most administratively convenient (Greenwood 1999). Yet, as Snow and colleagues

(Snow, Marsh et al. 1996) point out, in African countries where malaria is the largest single cause of mortality, maps of malaria endemicity often do not exist. Where such maps do exist they are often out of date and unavailable to control staff. There is a strong case for having accurate data and maps of malaria in Africa. But is it possible to obtain this information given that most cases of malaria are diagnosed without the aid of laboratory facilities, and any fever episode may be recorded as malaria? For example, studies of malaria case data in Niger by Julvez showed that during the dry season over diagnosis may exceed 90% (Julvez, Develoux et al. 1992). Furthermore, as many as 90% of deaths from the disease occur outside of any health facility (Greenwood 1999). For example, in Morogoro Rural District, Tanzania verbal autopsies revealed that more than 80% of deaths occurred at home and in more than half of those cases, no contact had been made with a health facility before death. This is in a district where 85% of the population live within 5km of a health facility (de Savigny, Setel et al. 1999). A further confounding factor is the role of malaria in all cause mortality (Molineaux 1997). Where patients suffer more than one life threatening health condition simultaneously, malaria may contribute to fatality but may or may not be considered, or recorded, as the primary cause of death.

2.1.1.1. Classifying malaria endemicity in Africa

A method of classifying malaria endemicity in Africa was produced at the first malaria conference in Equatorial Africa, held at Kampala in 1950 (WHO 1951). According to this classification, based on spleen rates, malaria is:

Holoendemic - if spleens enlarged in greater than 75% of 2-10 year olds

Hyperendemic – if spleens enlarged in greater than 50% of 2-10s

Mesoendemic - if spleens enlarged in between 11-50% of 2-10s

Hypoendemic - if spleens enlarged in less than 10% of 2-10s

Macdonald introduced the concept of a more simple classification of malaria endemicity into *stable* or *unstable* (MacDonald 1957). In the case of stable malaria,

the level of transmission is high without marked fluctuations over the years. In unstable malaria, the level of transmission varies from year to year. While the two terms were meant to represent extremes along a wide range of situations (Onori 1986), Metselaar and van Thiel suggest that the stable or unstable classification is too simplistic for everyday use in malariology (Metselaar and van Thiel 1959). They suggest that something similar to the classification which came out of the Kampala Conference would be more useful. However, they argue that spleen rates are not sufficient to differentiate endemicity. The usefulness of the spleen rate measure assumes that the response of the spleen to immunity is always and everywhere the same. Their analysis of data from Tanzania and Papua New Guinea, however, shows that this is not the case. They conclude that differences in spleen response are likely to be due to nutrition, parasite species, sickle cell and patho-geography. As an alternative measure Metselaar and van Thiel suggested that the classification should instead be based on parasite rates:

Holoendemic - greater than 75% of 2-10 year olds infected (constantly)

Hyperendemic – greater than 50% of 2-10s infected (may vary with season)

Mesoendemic - between 11-50% of 2-10s infected (will vary with season)

Hypoendemic - less than 10% of 2-10s (will vary with season and year)

They suggest that "Difficulties will remain but it is always difficult to encompass biological events within a watertight classification system." (Metselaar and van Thiel 1959). Unfortunately, reliable data on parasite ratios in Africa did not prove as readily available as Metselaar and van Thiel implied.

Bradley argues that there is insufficient reliable data on malaria in Africa to determine the mortality rates occurring in different endemic regions, and discusses this problem along with the different approaches that have been tried to overcome it (Bradley 1991a). These are: (a) observing the increase in mortality during malaria epidemics, (b) measuring the fall in mortality when malaria is temporarily brought under control, and (c) calculating the mortality necessary to maintain the observed

level of the sickling gene in a balanced polymorphism. However, as Bradley suggests, the problems of using these approaches in the African research context have themselves produced results that yield equally inconclusive evidence.

Table 2.1, summarizes epidemiological data which may be available and briefly discusses their uses and limitations. As Gilles states "There is no satisfactory way of expressing in an arbitrary way the dynamics of malaria transmission" and suggests instead that "methods which estimate the vectorial capacity and subsequent risk of infection may come closest to such an appraisal" (Gilles 1993).

2.2. Aims of this chapter

- To discuss the concept of stratifying malaria in Africa.
- To review ways in which new tools such as Geographical Information Systems can be used to assist in the stratification of malaria in Africa.
- To develop example products based on the use of GIS for specific strata.

2.3. Malaria Stratification in Africa

Given the paucity of reliable epidemiological data for Africa, other means of categorising malaria transmission patterns have been developed. Malaria stratification has been defined as: "the process of uniting areas, populations or situations, which exhibit a relative resemblance by a specified relevant characteristic, thereby distinguishing them from other areas, populations or situations dissimilar through the same set of characteristics" (WHO 1985). Thankfully this definition is made somewhat less unwieldy by Kouznetsov and colleagues: "stratification consists of the identification, characterisation and delimitation, within an area (or population) affected by malaria, of the different situations in which distinct control (and evaluation) strategies may be appropriate. Strata may be geographical areas and/or population groups. Stratification designates both a process and its outcome" (Kouznetsov, Molineaux et al. 1986).

TABLE 2.1. EPIDEMIOLOGICAL DATA FOR CLASSIFYING MALARIA ENDEMICITY IN AFRICA?

Epidemiological data	Uses and Limitations in Stratification
Spleen rate	Age specific cross-sectional surveys providing evidence of previous malaria infection. Different responses between ethnic groups and people of differing nutritional status limit it usefulness as a comparative measure (Metselaar & van Thiel, 1959). Can be confounded by other infections e.g. kala azar and schistosomiasis.
Parasite rate	Age specific cross-sectional survey showing presence of current malaria infection. Quality of diagnosis, immunity and migration can confound its use as a comparative measure of transmission (Gilles, 1993). Parasitaemia often does not reflect the seasonality of transmission (Greenwood, et al, 1987; Smith, et al. 1993). Main data source that will be used by MARA*.
Laboratory diagnosis	Clearly shows infection and species type, but question over who is selected for testing and consistency of diagnosis limits its use as a comparative measure (slide positivity rates). Delays in process and reporting may also mean it does not accurately reflect transmission context. Rarely available in rural Africa.
Clinical diagnosis	Most widely available information source for 'malaria' in Africa. More immediate process of reporting may give better reflection of transmission context. But may not be malaria, over diagnosis can be very high (Julvez, 1992).
Deaths	The relationship between malaria deaths and malaria is not simple and has been recently reviewed (Molineaux, 1997). Comparative malaria death rates are notoriously difficult to obtain since over 80% of deaths occur in the community and are rarely recorded. Verbal autopsies may be used to determine the cause of death but this technique is of limited validity. Death may be due to several contributing factors and the cause of death unclear (Greenwood, 1999).
Birthweight ratios for primagravidae:multigravidae	Relatively widely available information source†. May give useful indication of infection pressure (Brabin, 1999). Large sample size needed. May be confounded by HIV-AIDS.
Entomological inoculation rate	Estimate of actual transmission based on number of infective mosquitoes biting an individual over a unit of time. Difficult to make comparisons between areas because of differing host vector interactions and varying methodologies (Hay, et al. 2000). Longitudinal surveys very expensive and not widespread.

* The MARA/ARMA project is in process of compiling a database of parasite ratio data from literature and grey literature searches. Not yet available for the continent or in the public domain.
† A database of African birthweight data explored for mapping malaria distribution and found general agreement with climatic and environmental models of malaria in Africa, Savage (1999).

Mapping may be seen as a necessary, but not in itself sufficient, component of the malaria stratification process. Stratification delimits areas or populations based not just on their geographical, ecological, social and economic characteristics but uses these in consideration of options for planning control efforts. The current malaria stratification (or malaria 'paradigms') used in the New Global Malaria Control Strategy is basically that set out by Najera and colleagues (Najera, Leise et al. 1993). These are reproduced here in Table 2.2.

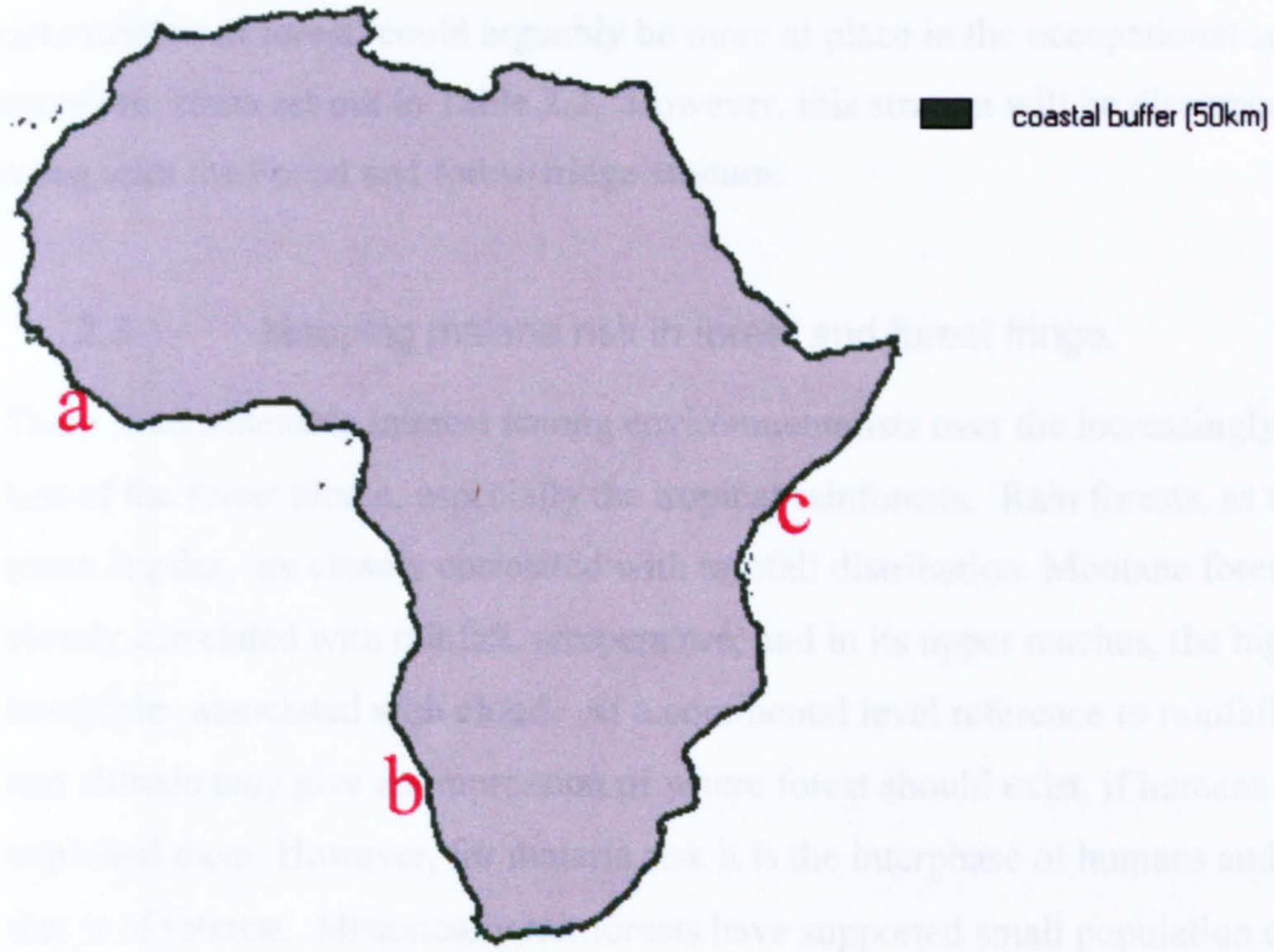
Within the listed ecological categories or strata all but one (plains and valleys outside Africa) are applicable to malaria transmission in Africa: 1) African savannah, 2) Forest and forest-fringe, 3) Highland and desert-fringe, 4) Seashore and coastal, 5) Urban, 6) Agricultural colonization of forest. However, not all of these are appropriate for mapping at the continental scale. For example, urbanization entails changes which should, in theory, reduce malaria transmission due to limiting the availability of the clean fresh water pools favoured by *Anopheles gambiae s.l.* and consequently man-vector contact. Studies in Brazzavile, Congo and Ouagadougou, Burkina Faso provide evidence where levels of transmission were generally lower in urbanized areas compared to their rural surroundings (Sabatinelli and Bosman 1986). However, examples also exist from Cotonou, Benin where transmission levels are higher in urban and peri-urban areas than in surrounding rural areas (Bosman and Coluzzi 1992). From the disease perspective urbanization is a complex situation which is occurring across a wide range of epidemiological and ecological situations, which themselves change relatively quickly, and as such generalisation is difficult over the larger scale.

While it may be relatively easy to produce a map of the African seashore and coastal margins this too would be of little value in differentiating malaria endemicity. Figure 2.1. provides a simple illustration of this. A map of the African continent was produced using the Idrisi raster-based software with an arbitrary 50km buffer around the continent's coastline. At site (a) malaria is perennial along this humid tropical forest coastal zone, whereas at site (b) the coastal zone comprises the Skeleton Coast and the Namib desert which are malaria free (NVDCP 1995). At site (c) work by Snow and colleagues has shown that malaria varies significantly between two sites on the Kenyan coast just 60 km apart (Snow, Bastos de Azevedo et al. 1994).

TABLE 2.2. PATTERNS OF MALARIA ASSOCIATED WITH ECOLOGICAL AND SOCIAL CONDITIONS – REPRODUCED FROM NAJERA, ET AL. (1993).

Control intervention	Major ecological conditions							Specific occupations/social - conditions		
	African savannah	Plains & valleys outside Africa	Forest & forest fringe	Highland & desert fringe	Seashore and coastal	Urban	Agricult-ural colo-nization of forest	Gold mining	Migrant agricult-ur labour	Displaced populat-ions
Management of clinical malaria										
diagnosis and treatment	+	+	+	+	+	+	+	+	+	+
care of treatment failures	+	+	+	+	+	+	+	+	+	+
Protection of pregnant women										
chemoprophylaxis	+	-	+	-	-	-	+	-	-	-
bednets & personal protection	+	+	+	+	+	+	+	+	+	+
Vector control										
residual spraying	-	Selective	Selective	Epidemic	Selective	Limited	Selective	-	Limited	Epidemic
fogging ULV	-	-	-	-	+	Limited	-	-	Limited	+
impregnated bednets/curtains	+	+	+	-	+	-	+	+	-	-
Environmental control										
drainage & source reduction	-	-	-	-	+	+	-	-	+	-
larviciding	-	-	-	-	+	+	-	-	+	-
biological control	-	-	-	-	Limited	+	-	-	+	-
Surveillance										
epidemiological surveillance	+	+	+	+	+	+	+	+	+	+
monitoring epidemic risk	-	+	+	+	-	-	-	+	+	+
Health education	+	+	+	+	+	+	+	-	-	-

FIGURE 2.1. AN AFRICA COASTAL BUFFER ZONE (50 KILOMETRES) PRODUCED IN IDRISI.



Legend:

At site (a) malaria is perennial along this humid tropical forest coastal zone, whereas at site (b) the coastal zone comprises the Skeleton Coast and the Namib desert which are malaria free. At site (c) it has been shown that malaria can vary considerably between two sites on the Kenyan coast only 60 km apart.

Those strata that may be relevant to mapping at the continental scale are those where macroclimatic factors play a significant role. In Africa these are: Forest and forest-fringe, African savannah, and Highland and desert-fringe. The stratum 'Agricultural colonization of forest' could arguably be more at place in the occupational/socio-economic strata set out in Table 2.2. However, this stratum will be discussed briefly along with the Forest and forest-fringe stratum.

2.3.1. Mapping malaria risk in forest and forest fringe.

There is considerable interest among environmentalists over the increasingly rapid loss of the forest biome, especially the tropical rainforests. Rain forests, as their name implies, are closely correlated with rainfall distribution. Montane forest is also closely correlated with rainfall, temperature, and in its upper reaches, the high humidities associated with cloud. At a continental level reference to rainfall regimes and altitude may give an impression of where forest should exist, if humans had not exploited them. However, for malaria risk it is the interphase of humans and forest that is of interest. Historically rainforests have supported small population densities of hunter gatherers. This has of course changed in the face of development pressures and exploitation of forest resources, and changes in land use along their margins are happening rapidly on all continents (Myers 1993).

In its 'natural' state dense forest vegetation is thought to be unsuitable for the major African malaria vectors of the *Anopheles gambiae s.l.* complex. However, as forest canopies are opened up the habitat changes considerably and may provide ideal opportunities for colonization by efficient malaria vector species, and bring them into close contact with their human hosts (Coluzzi 1992). The impact of deforestation on evolutionary changes and species adaptation among vectors can be considerable over relatively small spatial and temporal scales. Detailed studies from West Africa illustrate the biological effects of ecological change over time and the level of detail required to understand the impact of deforestation on malaria vectors (Coluzzi 1979; Coluzzi 1992). A broad discussion of the impacts of deforestation on malaria and a number of other vector-borne diseases, in Africa and elsewhere, is reviewed in (Walsh, Molyneux et al. 1993).

Deforestation will impact on the local ecology, but from an epidemiological perspective its effects will depend greatly on the existing endemicity and levels of immunity, in the local population, and any new migrants who exploit or settle in them. Generalisation at the continental level should clearly be approached with caution. However, Figure 2.2. provides a map of forest distribution in Africa by type, and Figure 2.3. example maps of where those forests are under pressure from human populations. Maps such as this provide information about where forests are currently being exploited, and combined with focussed consultation and investigation at a more localised level, could provide information on the degree of risk the exploiters face. Large scale forest maps have also been used in studies of the distribution of vectors of loaiasis (Thomson, Obsomer et al. 2000).

2.3.2. Mapping malaria risk in the African Savannah

The category African savannah encompasses a wide range of transmission patterns, from perennial to epidemic (i.e. Macdonald's two extremes: stable to unstable) and would clearly benefit from further subdivision. The ecological definition of the term savannah is: "the tropical and subtropical grassland biome (....) transitional in character between desert and rain forest," (Lincoln, Boxshall et al. 1982). Earlier attempts at malaria stratification have used meteorological information to help subdivide the broad category of 'Africa south of the Sahara' (Onori 1986). Rainfall amounts and seasonal distribution patterns vary markedly across the African continent. Figure 2.4. provides an annual rainfall distribution map, and Figure 2.5. an illustration of the mean dry and rainy seasons with respect to latitude.

Temperatures of course also vary with latitude and Figure 2.6. illustrates this. Locally, rainfall amount and temperature are also influenced by altitude. As a general rule rainfall may be expected to double with an increase of 1000m, up to a maximum which varies with local conditions (Le Houerou, Popov et al. 1993). Temperatures are subject to a mean lapse rate of 5.5°C per 1000m. However, the moisture content of the air will affect this considerably and the lapse rate may be 10°C per 1000m where the air is dry (Wilson 1983).

FIGURE 2.2. CLASSIFICATION MAP OF FOREST TYPES IN AFRICA. REPRODUCED FROM THE JOINT UNEP-WCMC INTERNET SITE: WWW.UNEP.WCMC.ORG

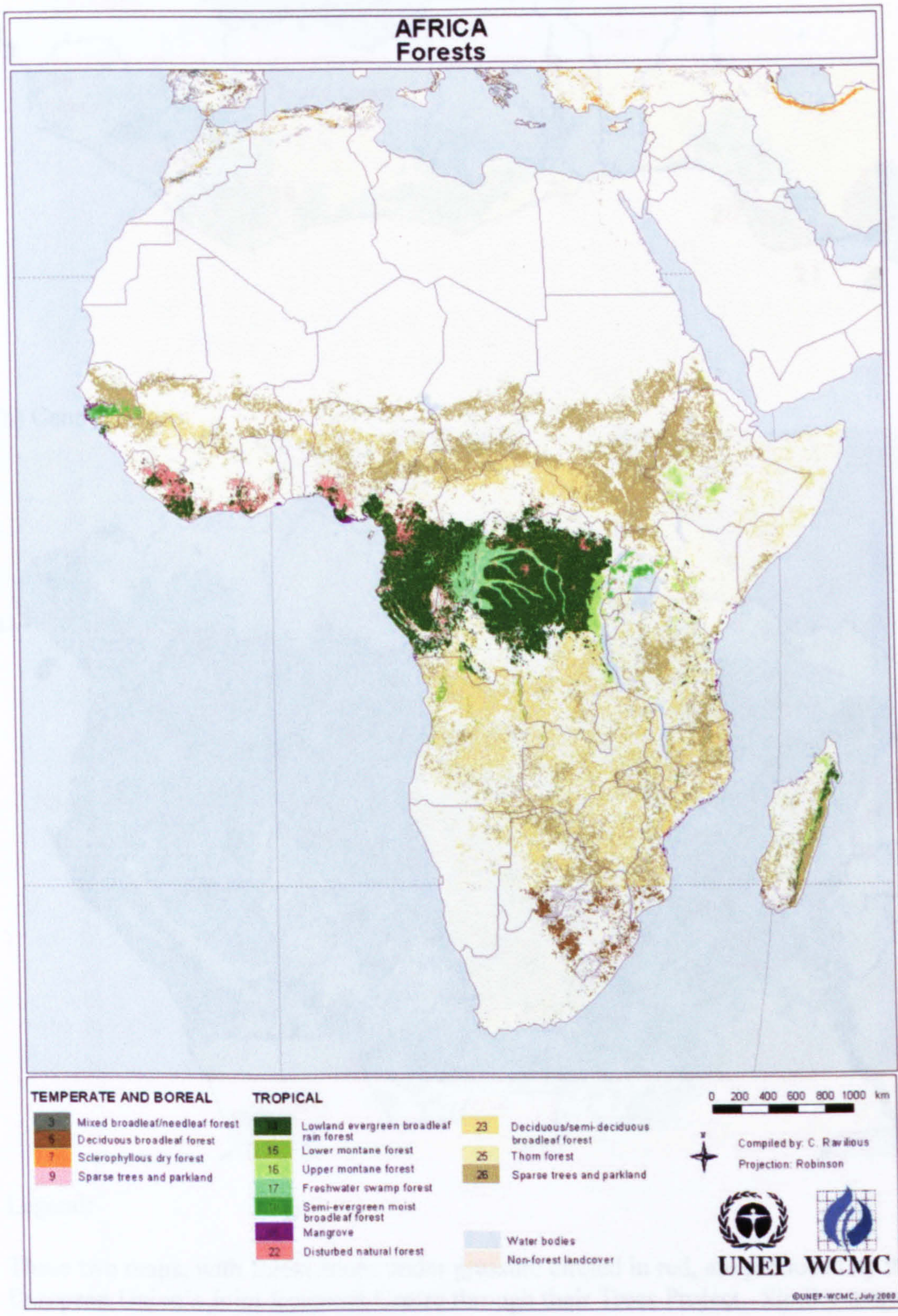
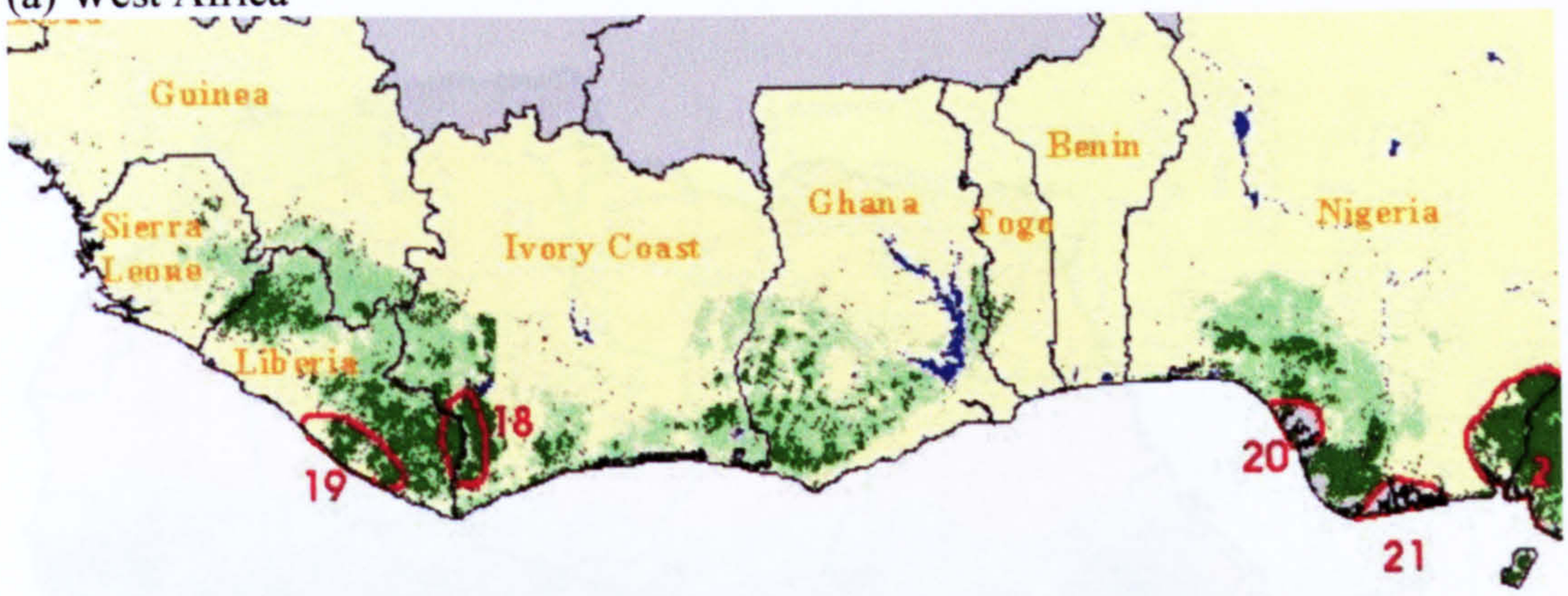
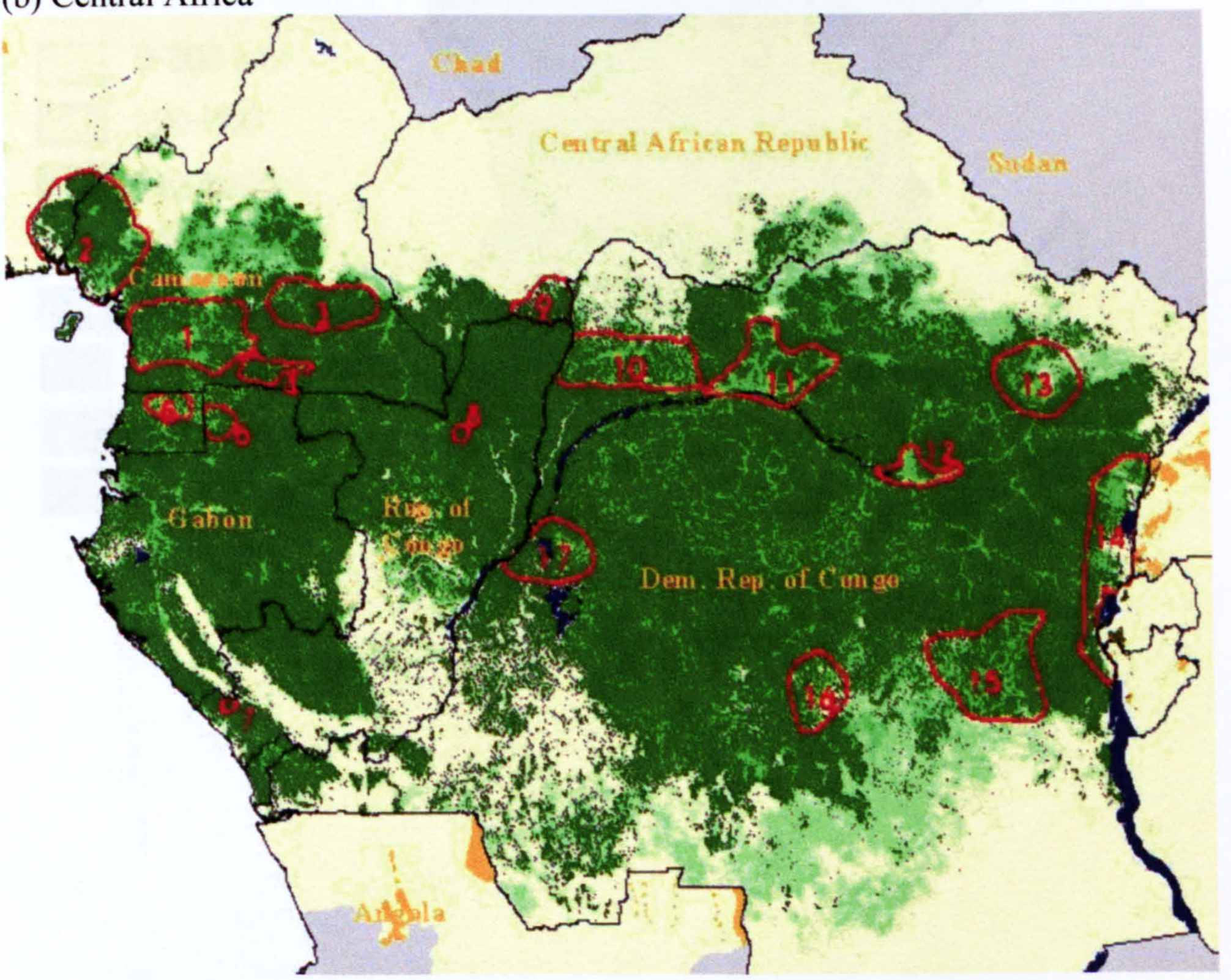


FIGURE 2.3. MAPS OF FOREST ZONES UNDER HUMAN ECONOMIC PRESSURE IN AFRICA.

(a) West Africa



(b) Central Africa



Legend:

These two maps, with forest zones under pressure circled in red, are produced by the European Union's Joint Research Centre through their Trees Project. Similar maps for other regions of the world are available on their website:
www.gvm.sai.jrc.it/Forest/Africa/hotspots.htm

FIGURE 2.4. ANNUAL MEAN RAINFALL DISTRIBUTION IN AFRICA 1951-1995 (UEA).

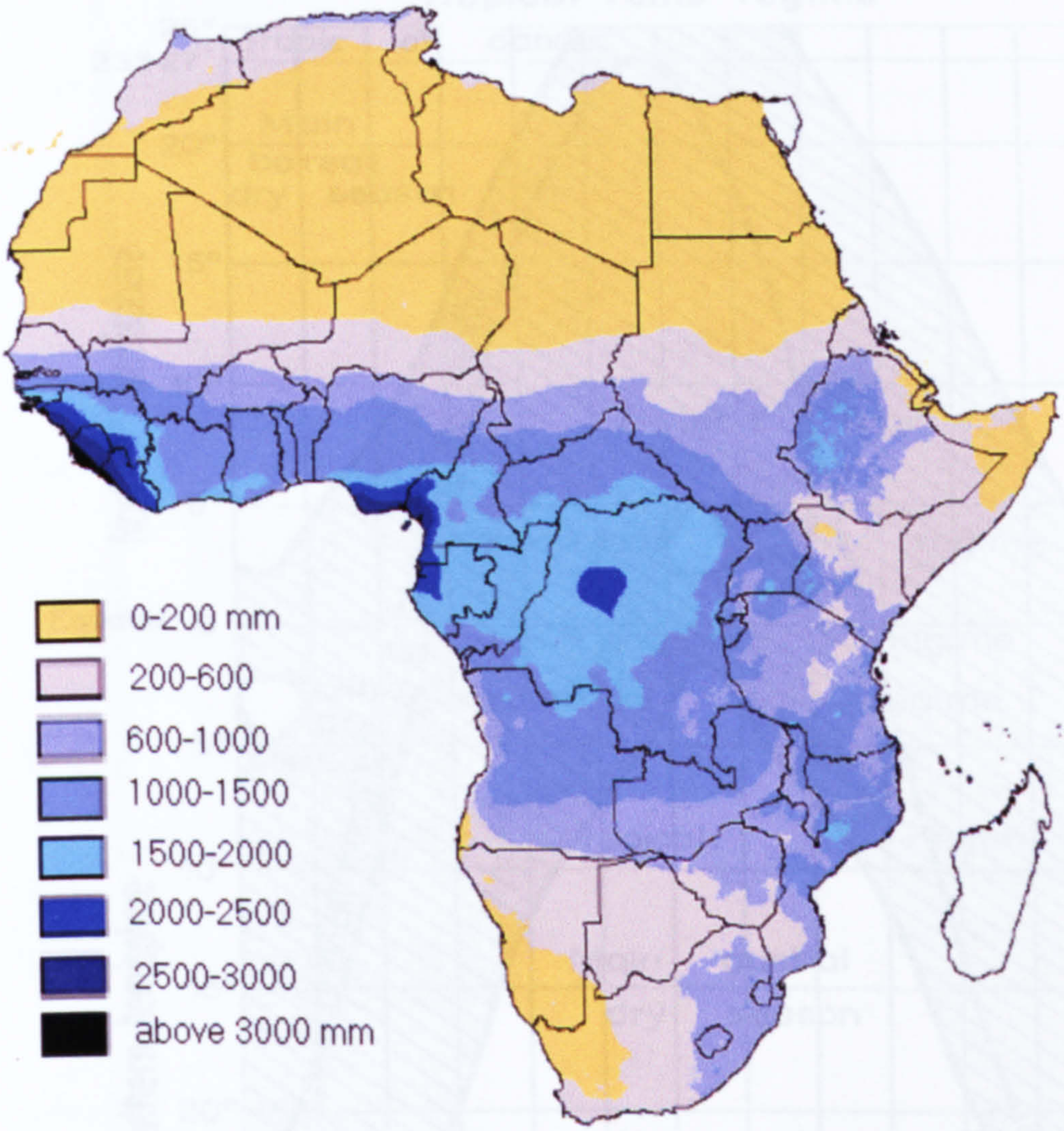
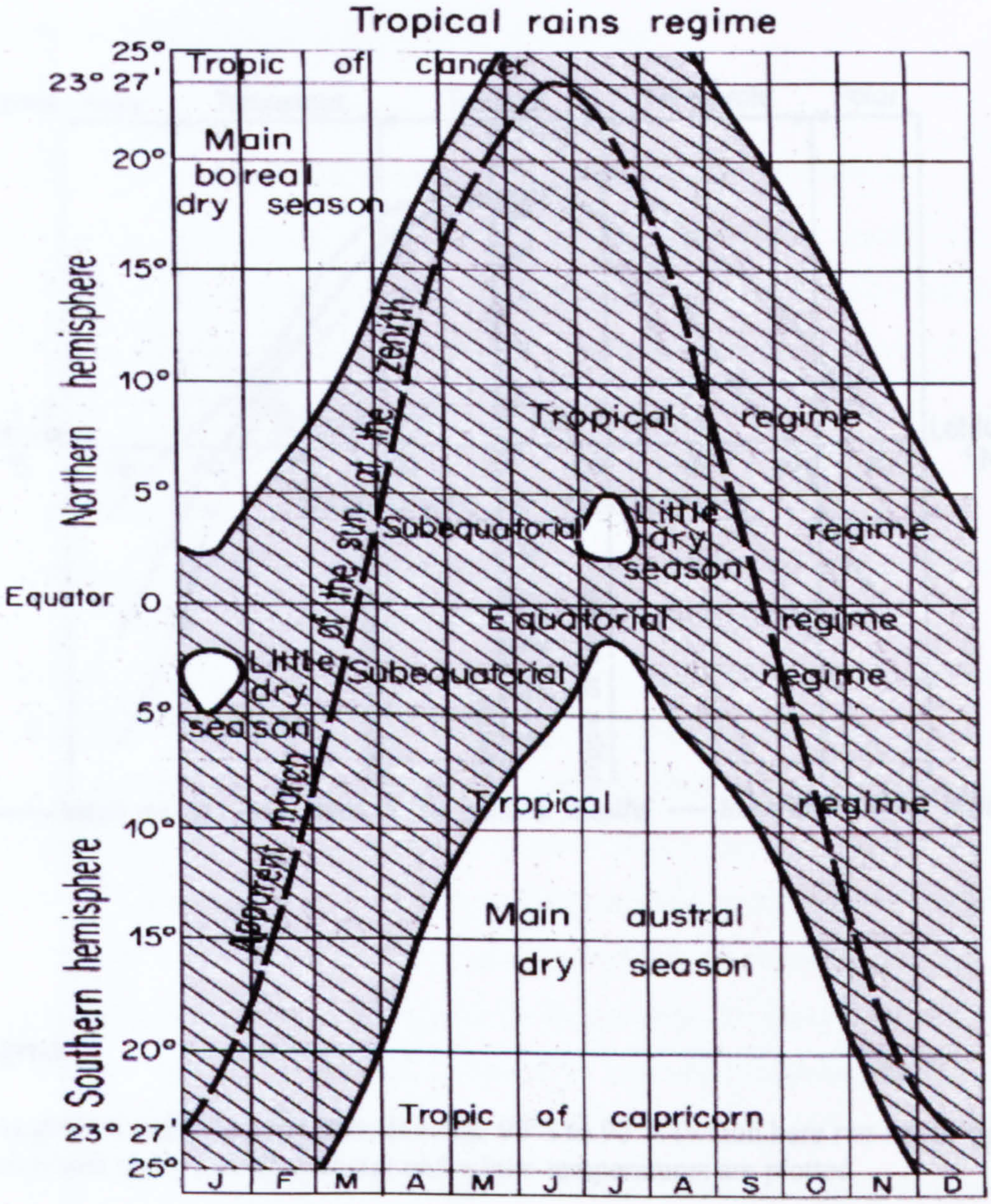


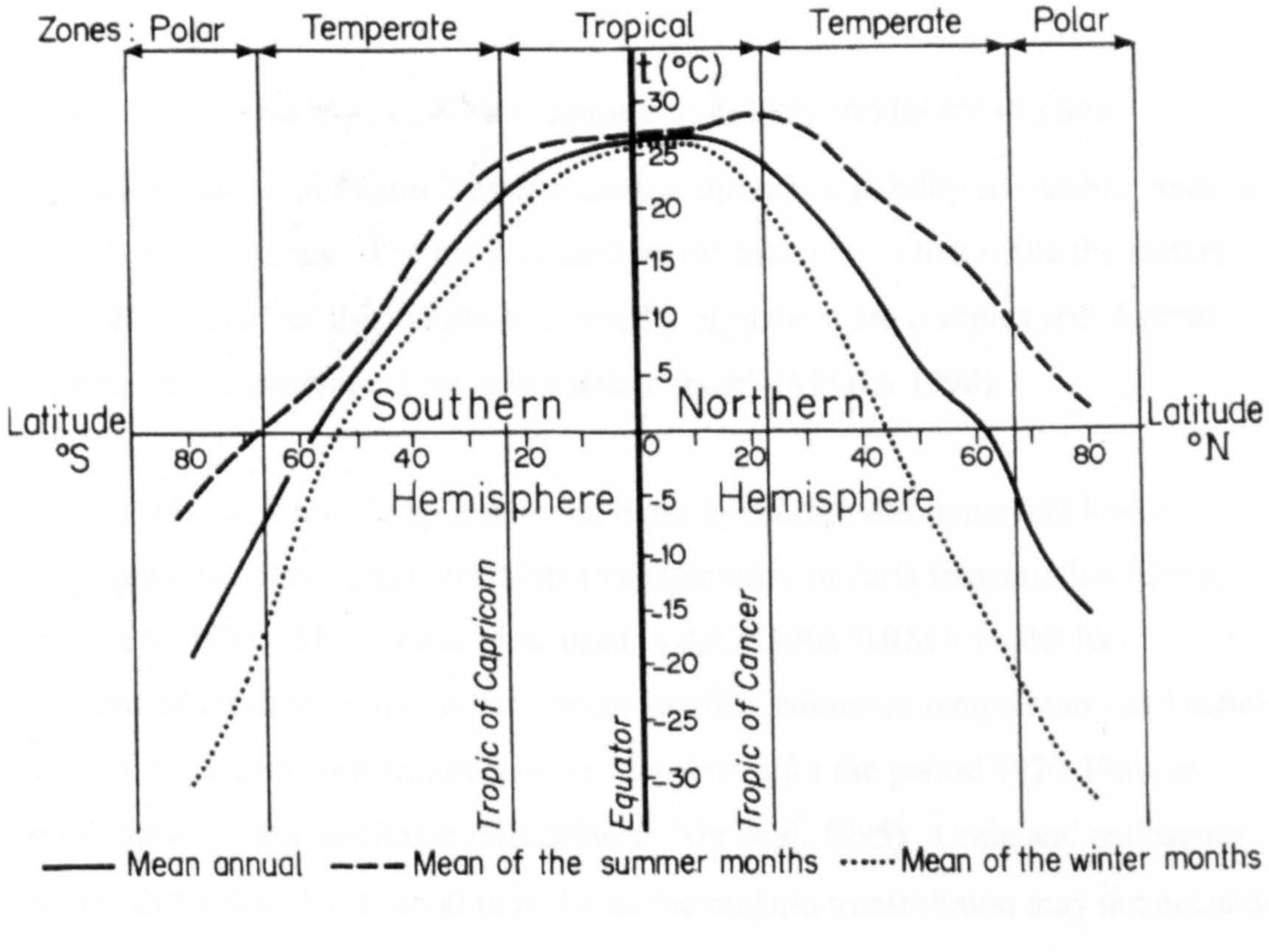
FIGURE 2.5. DISTRIBUTION OF DRY AND RAINY SEASONS IN THE INTER-TROPICAL ZONE. REPRODUCED FROM LE HOUEROU (1993).



Legend:

This graphic represents the latitude range 25°S to 25°N onto which mean annual rainfall regimes are plotted, with month along the horizontal axis.

FIGURE 2.6. MEAN TEMPERATURE AS A FUNCTION OF LATITUDE. REPRODUCED FROM LE HOUEROU (1993).



Legend:

This graphic represents the latitude range 90°S to 90°N (which here run left to right) onto which mean annual, summer and winter temperatures are plotted.

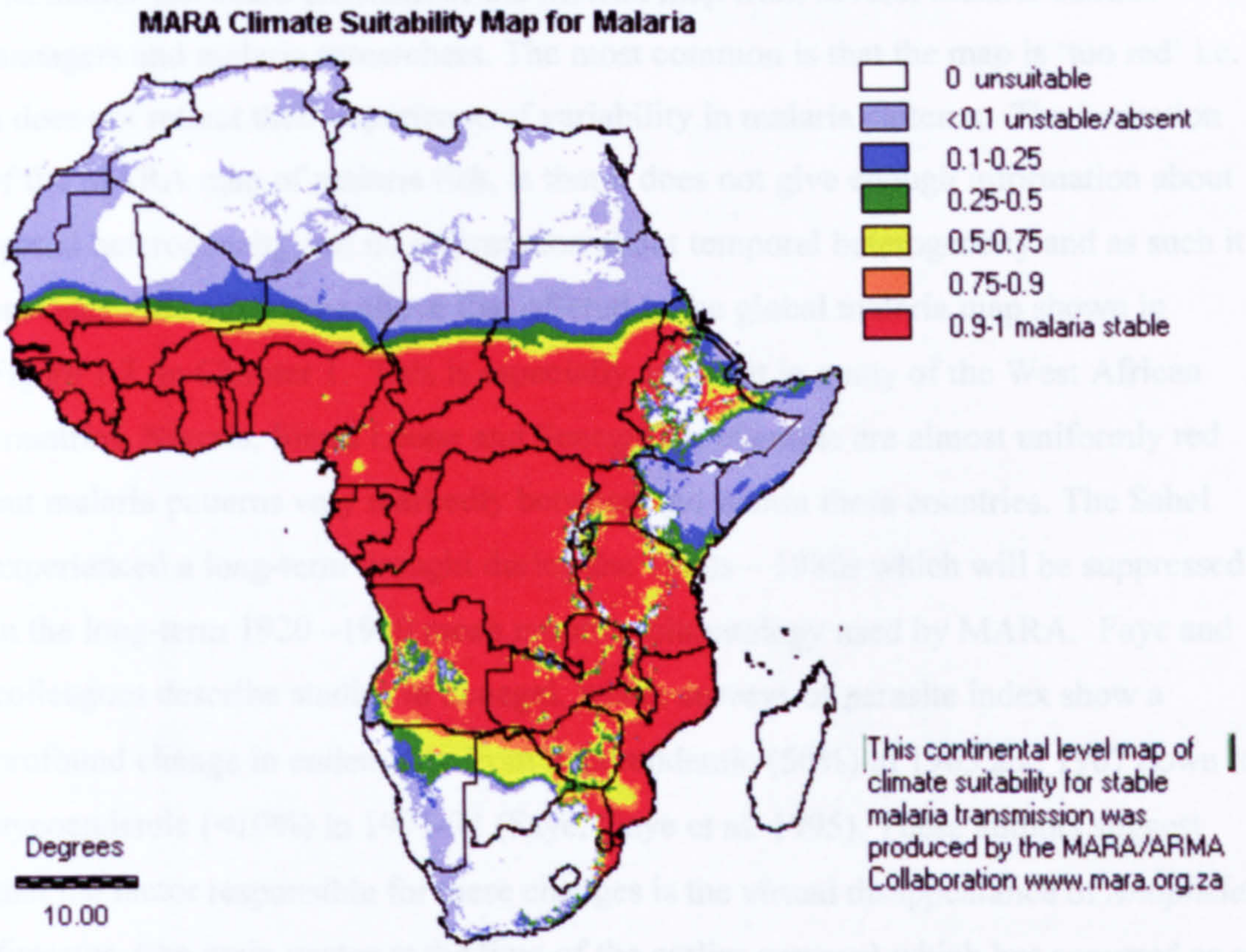
Clearly, climatic factors such as rainfall and minimum and maximum temperatures do have an impact on malaria transmission, and invariably appear in transmission models. However, empirical verification is difficult and the number of such studies in Africa are limited (Thomson, Savage et al. in press).

2.3.3. The MARA/ARMA climate suitability model for malaria

The map produced in Figure 2.7 represents a climatic suitability for 'stable' malaria transmission in Africa. The map is based on the assumption that while the factors which determine the distribution and severity of malaria are complex and diverse, "climate can be considered the major determinant" (MARA 1998).

This spatial model uses long-term mean monthly rainfall and upper and lower temperature parameters as constraints to characterize malaria transmission (Craig, Snow et al. 1999). The climatic data used in the MARA/ARMA model has interpolated mean monthly rainfall, mean monthly minimum temperature, and mean monthly maximum temperature surfaces for Africa for the period 1920-1980, at approximately 5km resolution (Hutchinson, Nix et al. 1995). Craig and colleagues assume that below 18° C conditions for stable malaria transmission may not occur as too few adult mosquitoes survive sporogeny and mosquito numbers are limited by long larval duration, and above 22°C transmission would be stable if sufficient rainfall, 80mm per month, were available for long enough. To develop the model they used the Idrisi GIS software (Eastman 1993) to produce the mean monthly average temperature surfaces. They then used Idrisi's 'Fuzzy Logic' module which is basically an extension of Boolean logic allowing a 'less clear' distinction between conditions of suitability (1) and unsuitability (0). For rainfall 0 = 00mm and 1 = 80mm per month. For average temperatures 0 = 18° C and 1 = 22° C, for the increasing curve, and 1 = 32° C and 0 = 40° C for the decreasing curve. For winter minimum temperatures 0 = 4° C and 1 = 6° C. To gain temporal coincidence of suitability conditions each of the fuzzy images were overlaid in Idrisi. The minimum time period of continuous conditionality for transmission to occur was decided on the basis of whether rainfall or temperature were the limiting factor. This time period was decided as being three months for the region greater than 8°N, and five months

FIGURE 2.7. MARA/ARMA CLIMATE SUITABILITY MAP FOR MALARIA IN AFRICA. REPRODUCED FROM CRAIG, ET AL. (1999).



for the rest of the continent. The resulting model produces the map in Figure 2.7. showing the area ranging in increments from fully unsuitable (0 - coloured white) to fully suitable (1 - coloured red).

The author has heard criticism of the MARA map from several malaria control managers and malaria researchers. The most common is that the map is 'too red' i.e. it does not reflect their experience of variability in malaria patterns. The limitation of the MARA map of malaria risk, is that it does not give enough information about spatial heterogeneity and no information about temporal heterogeneity and as such it provides little advantage above that offered in the global malaria map shown in Figure 1.2, in Chapter 1. This is especially apparent in many of the West African countries, Nigeria, Sierra Leone and Senegal for example are almost uniformly red but malaria patterns vary markedly between and within these countries. The Sahel experienced a long-term drought during the 1960s – 1980s which will be suppressed in the long-term 1920 –1980 mean monthly climatology used by MARA. Faye and colleagues describe studies in Senegal, where surveys of parasite index show a profound change in endemicity from hyperendemic (50%) in 1963 and 1967 down to hypoendemic (<10%) in 1991-92 (Faye, Gaye et al. 1995). These authors suggest that the factor responsible for these changes is the virtual disappearance of *Anopheles funestus* (the main vector at the time of the earlier surveys) which has occurred as a result of the environmental impact of the long-term changes in rainfall. The MARA map will therefore over-represent the stability of malaria in West Africa and the Sahel. Further criticism is that of the real meaning of the 'fuzzy classisfication' of stable malaria. What for example should the categories less than 0.5 stable conditionality mean for the control manager - is it to be considered epidemic prone? Not according to Craig and colleagues who suggest "because interannual variation is not reflected in long-term mean climate data, epidemic zones are not detectable" (Craig, Snow et al. 1999). Such a map might be adequate were the only control option for sub-Saharan Africa to remain that of effective case management. However, if the MARA/ARMA map is to be used as an intervention planning platform for Roll Back Malaria in Africa then further information on the spatial and temporal heterogeneity of malaria would be useful if this is truly to become the 'formidable planning and management tool now available to malaria control programmes," Dr. E. Samba cited in MARA (1998).

2.4. Continental risk mapping: an interactive GIS approach.

Interpolated climate data, satellite data and the Idrisi GIS software are used here to create a more dynamic, or interactive, map of malaria risk. That is one which uses GIS to indicate where and when conditions deemed suitable for malaria transmission exist and how long they can be expected to exist in a normal year.

Optimal temperatures for malaria transmission are suggested to lie between 20°C and 30°C (Gilles 1993) and this temperature range should be adequate to map continental climatic suitability for malaria given the inherent crudity of interpolated 5km monthly mean surfaces. While rainfall is an essential component in malaria suitability little is known about the quantitative relationships (Service 1978) and it has been argued that temporal distribution may be more important than total amount, and a wetness index (number of rainy days times total rainfall/number of days in month) has been proposed (Russell, West et al. 1963). However, this information is not available at the continental scale and so the somewhat arbitrary figure of 80mm per month used in the MARA model is retained. Gilles states that for optimal malaria conditions a Relative Humidity greater than 60% is also required (Gilles 1993). Monthly mean relative humidity surfaces were not available for the African continent (Fulvia Petrassi, FAO: pers comm). However, a number of writers have outlined the relationships between atmospheric moisture indices, satellite derived vegetation indices (NDVI) and disease vectors of trypanosomiasis (Rogers and Williams 1994) and malaria (Thomson, Connor et al. 1996; Hay, Snow et al. 1998a). An NDVI figure of 0.35 – 0.4 was suggested by Hay and colleagues (1998) for malaria suitability across a range of epidemiological settings in Kenya and the lower of these values will be used here as a proxy for greater than, or equal to, 60% relative humidity at the continental scale. NDVI is also described as a measure of biologically effective rainfall and this may help to overcome the limitations regarding information on the number of rainy days in the month, mentioned previously.

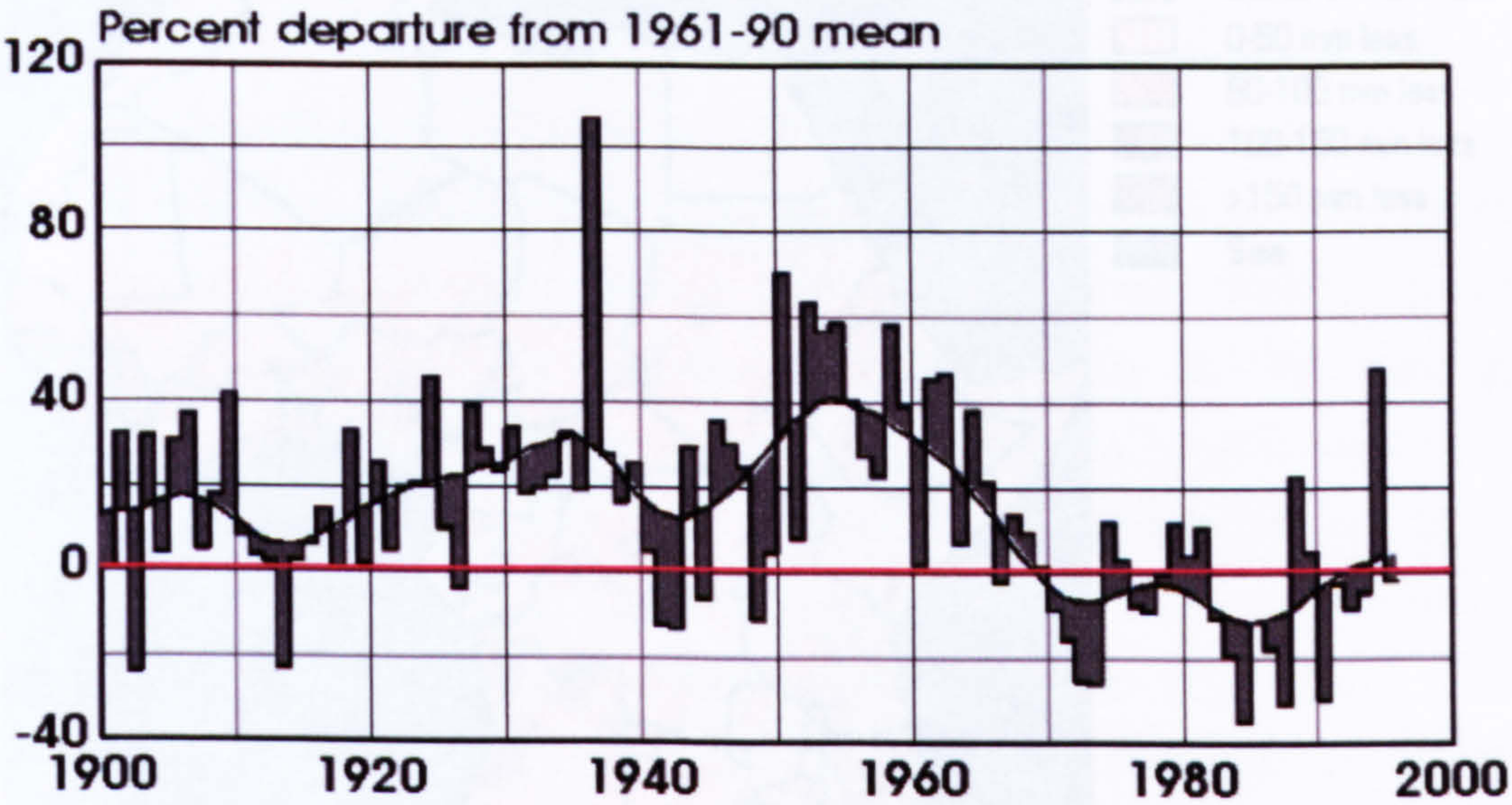
Climatic variability over time can be very significant and the choice of which period to use in long-term means is an important one. The general aim is to map malaria risk as it may relate to the current perceptions, or recent experience. An assessment

of mean temperatures for the continent shows that temperatures during the past thirty to forty years there have been increasing compared to those of the earlier decades of the 20th century (Watson, Zinyowera et al. 1998). The rainfall situation during this time period varied according to region (Gommes 1994). Figure 2.8. shows fluctuations in Sahelian rainfall during the 20th century. The last few decades of the 20th century are much more akin to our 'living institutional memory' than the period 1920-1980, so an alternative to the Hutchinson data used by MARA (Hutchinson, Nix et al. 1995) is desirable.

The Climatic Research Unit at the University of East Anglia produced an archive of monthly climate surfaces for Africa for the period 1951-1995 (New and Hulme 1997). The interpolated climate surfaces of rainfall, minimum and maximum temperature and range describe departures from the 1961-1990 mean climatology using observations at 2307 rainfall stations, 1485 temperature stations and 1431 diurnal temperature range stations throughout Africa. In total 540 monthly climate surfaces for each variable were produced and distributed on CD-ROM. New monthly and annual rainfall and temperature means were produced from this data set using Idrisi's Overlay and Scalar modules (Eastman 1993), and comparison made with those of the Hutchinson 1920-1980 climatology. Idrisi was used to produce a difference image between annual mean rainfall from 1920-1980 compared with 1956-95. The result showing those areas which experienced lower rainfall is produced in Figure 2.9.

A dynamic, interactive, climate suitability map for malaria distribution was produced using the UEA climate surfaces for temperature constraints outside of the optimal range described by Gilles, 20°C - 30°C (Gilles 1993). In addition the arbitrary figure of <80mm of rainfall per month, and the <0.35 NDVI values were used as constraints. The mean monthly NDVI surfaces were produced from the 10 daily NDVI data disseminated by the USAID Famine Early Warning System's Africa Data Dissemination Service: 1983-1999 with inter-satellite series sensor corrections carried out (minus 1991-93 which were subject to atmospheric dust contamination).

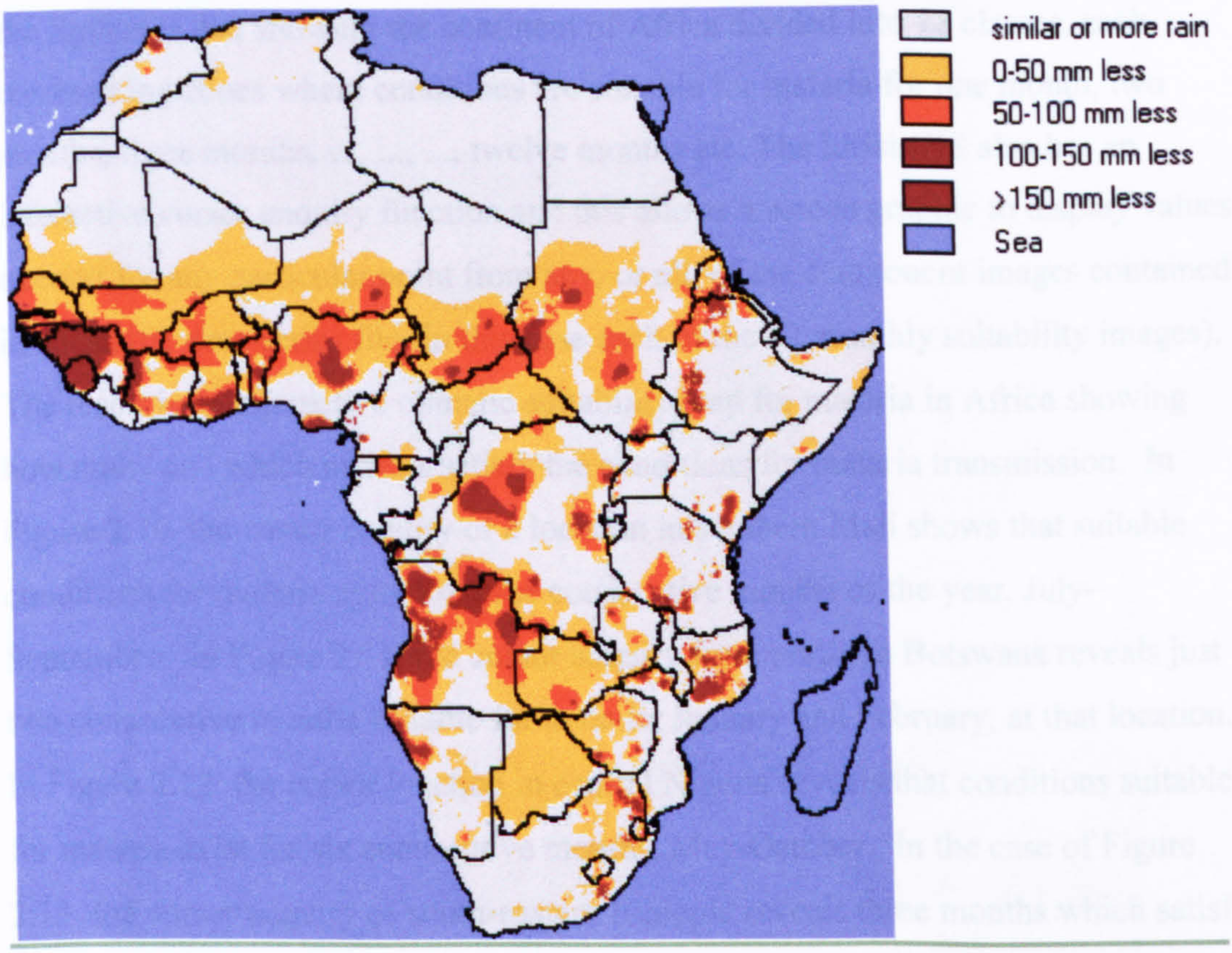
FIGURE 2.8. *ANNUAL RAINFALL DISTRIBUTION IN THE SAHEL (JUNE-SEPTEMBER) EXPRESSED AS A PERCENTAGE OF THE 1961-90 MEAN. SOURCE FAO* WWW.FAO.ORG



Legend:

The bars represent annual rainfall amounts in individual years expressed as a percentage of the 1961-1990 mean.

FIGURE 2.9. DIFFERENCE IMAGE SHOWING RAINFALL DEFICIT: MEAN ANNUAL RAINFALL 1920-1980 COMPARED WITH MEAN ANNUAL RAINFALL 1956-1995.



Legend:

This map illustrates the areas that experienced less annual rainfall on average during the period 1920-80 compared with 1956-95. The legend, top right represents a relative measure of this shortfall in annual rainfall.

One of the major values of GIS is that many of the constraints of the two dimensional paper map can be overcome. This is particularly useful where time trends need to be shown. The following four figures, Figures 2.10-2.13, represent outputs from the interactive climate suitability map for malaria. The map produced in the figures is that showing the continent of Africa divided into 12 classes, each representing zones where conditions are suitable for malaria for one month, two months, three months, ..., ..., ..., twelve months etc. The Idrisi GIS also has an interactive cursor enquiry function and this allows a screen graphic to display values queried for any particular point from any, or all, of the component images contained in a specific time series file (in this case each of the 12 monthly suitability images). The result is an interactive climatic suitability map for malaria in Africa showing how many and which months satisfy the conditions for malaria transmission. In Figure 2.10 the cursor enquiry of a location in southern Mali shows that suitable conditions for malaria exist for three consecutive months of the year, July-September. In Figure 2.11 the cursor enquiry from northern Botswana reveals just two consecutive months suitable for malaria, January and February, at that location. In Figure 2.12 the cursor location in central Nigeria reveals that conditions suitable for malaria exist for six consecutive months, May-October. In the case of Figure 2.13 the cursor enquiry of south-eastern Ethiopia reveals three months which satisfy suitable conditions for malaria, but that there is a bimodal pattern of two consecutive months, April and May, followed by a further one month in October.

Each of these represents climatic suitability in a 'normal' year. Experience of earlier, heavier or extended rainfall, or unseasonal temperatures, in any given year will of course change the prospects of malaria transmission in that particular year, and monitoring of these factors would be valuable for control purposes. Variability in these factors, especially in those zones which do not allow sufficient time for malaria transmission to occur, or where the season is very brief, may result in the risk of epidemics occurring. It would be useful for malaria control services to identify zones that are epidemic prone, and this is an essential first step towards monitoring of epidemic risk, which will be covered in a later section.

FIGURE 2.10. CLIMATE SUITABILITY FOR MALARIA MAP SHOWING INTERACTIVE CURSOR ENQUIRY FOR A LOCATION IN SOUTHERN MALI.

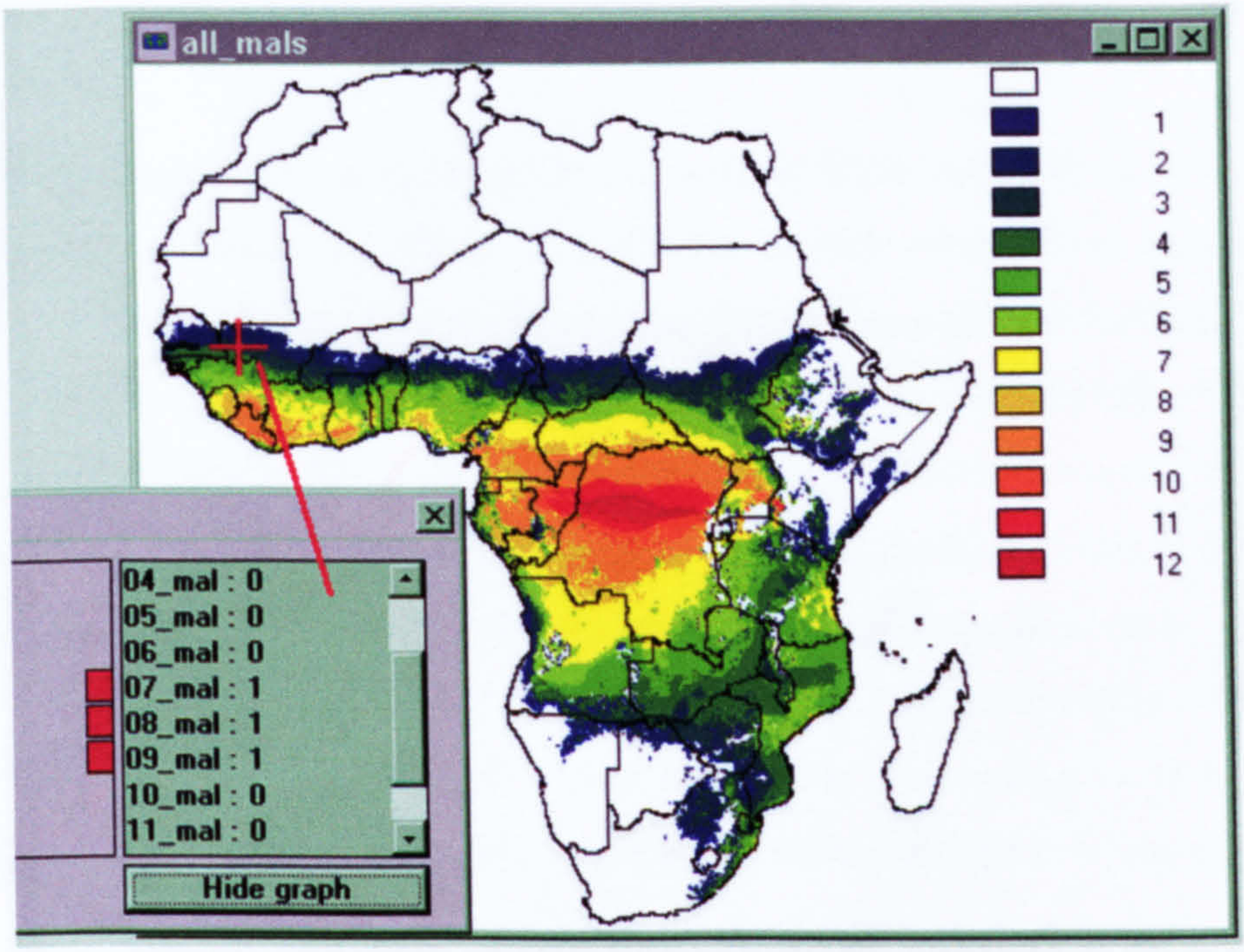
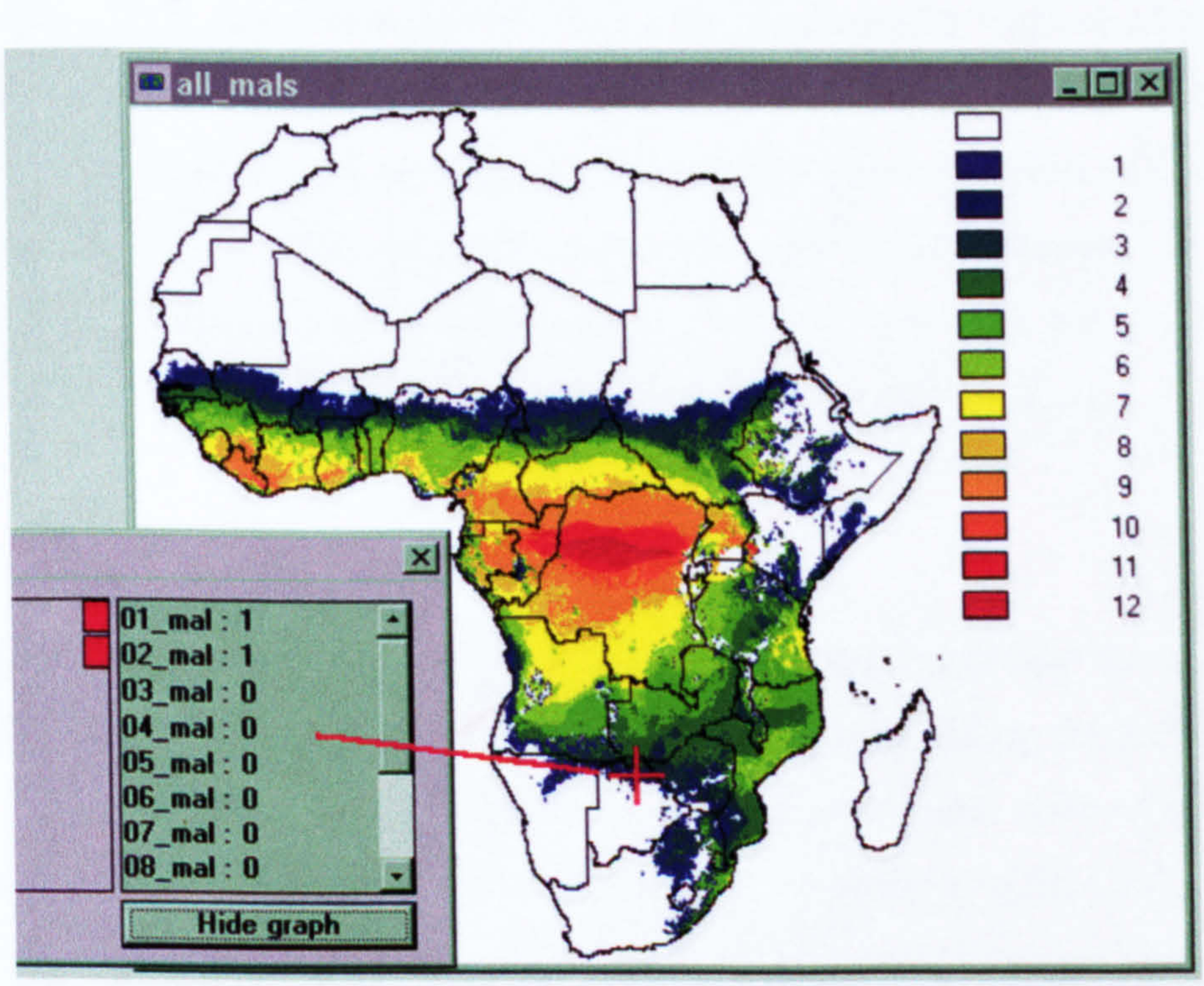


FIGURE 2.11. CLIMATE SUITABILITY FOR MALARIA MAP SHOWING INTERACTIVE CURSOR ENQUIRY FOR A LOCATION IN NORTHERN BOTSWANA.



Legends. The graphics, bottom left, shows the distribution of months (red bars in horizontal histogram) where mean climatic conditions are deemed suitable for malaria transmission at the cursor location. The map legend, upper right, shows the number of months meeting the conditions of suitability generally.

FIGURE 2.12. CLIMATE SUITABILITY FOR MALARIA MAP SHOWING INTERACTIVE CURSOR ENQUIRY FOR A LOCATIONS IN CENTRAL NIGERIA.

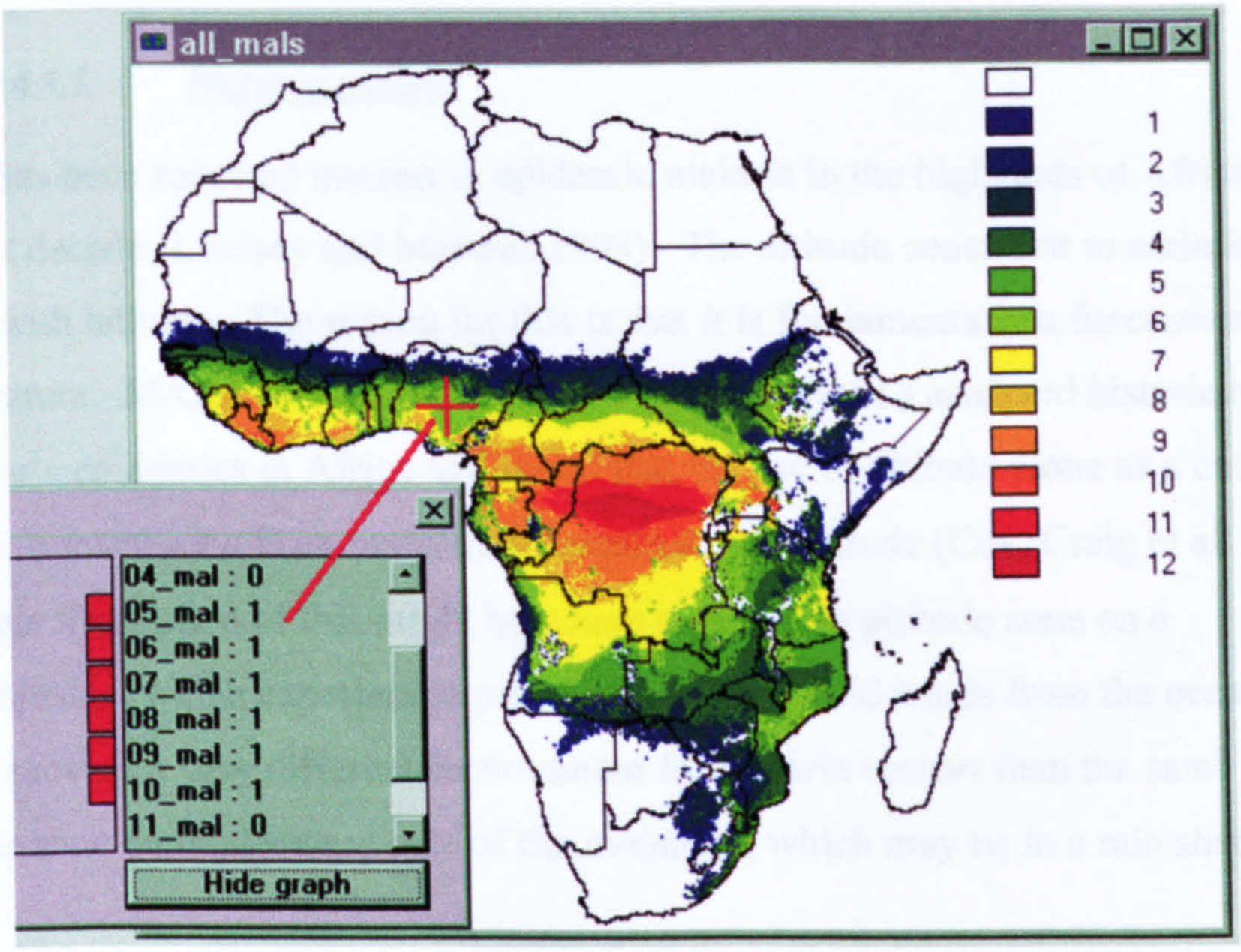


FIGURE 2.13. CLIMATE SUITABILITY FOR MALARIA MAP SHOWING INTERACTIVE CURSOR ENQUIRY FOR A LOCATION IN SOUTHERN ETHIOPIA.

Legend. The graphics, bottom left, shows the distribution of months (red bars in horizontal histogram) where mean climate conditions are deemed suitable for malaria transmission at the cursor location. The map legend, upper right, shows the number of months meeting the conditions of suitability generally.

2.4.1. Mapping malaria risk in highland and desert-fringe.

2.4.1.1. Highland malaria

There has been renewed interest in epidemic malaria in the highlands of Africa over the past decade (Lindsay and Martens 1998). The altitude constraint to malaria varies with latitude. The reason for this is that it is fundamentally a function of temperature. MARA's Highland Malaria Project (HIMAL) analysed historic records of malaria epidemics in Africa and found that the use of altitude alone as a cut-off to malaria transmission is an oversimplification at any latitude (Cox, Craig et al. 1999). A simple illustration of this might be where a particular altitude zone on a mountainside, which experiences prevailing warm humid winds from the ocean, would provide a very different environment for malaria vectors than the same altitude zone on the leeward side of the mountain, which may be in a rain shadow.

The lower level temperature constraint to malaria used by MARA was chosen at 18°C as the extrinisic parasite development rate is seriously compromised at this temperature (Craig, Snow et al. 1999). Here a series of monthly Boolean images were produced in Idrisi using the 18°C cut-off as the condition unsuitable for malaria transmission. These images, see Figures 2.14 and 2.15 show that parts of the highland areas of East Africa persist throughout the year in their apparent unsuitability to malaria. Elsewhere, in southern Africa for example, the condition is a function of changes in seasonal temperatures rather than altitude alone.

2.4.1.2. Desert-fringe malaria

Too little rainfall is the major constraint to stable malaria transmission throughout much of tropical Africa and inter-annual variability in rainfall along the 'desert-fringes' may be a contributing component in many 'post-drought' epidemics. To identify where these 'desert-fringes' are distributed, an analysis of the UEA monthly rainfall anomalies was carried out.

A Coefficient of Variation analysis of 540 monthly rainfall anomaly surfaces, covering the period 1951 – 1995, was achieved using the Idrisi GIS software.

FIGURE 2.14. LOWER TEMPERATURE CONSTRAINTS TO MALARIA JANUARY-JUNE AVERAGES (RED AREAS UNSUITABLE FOR MALARIA ASSUMING <=18 ℃ CUT-OFF).

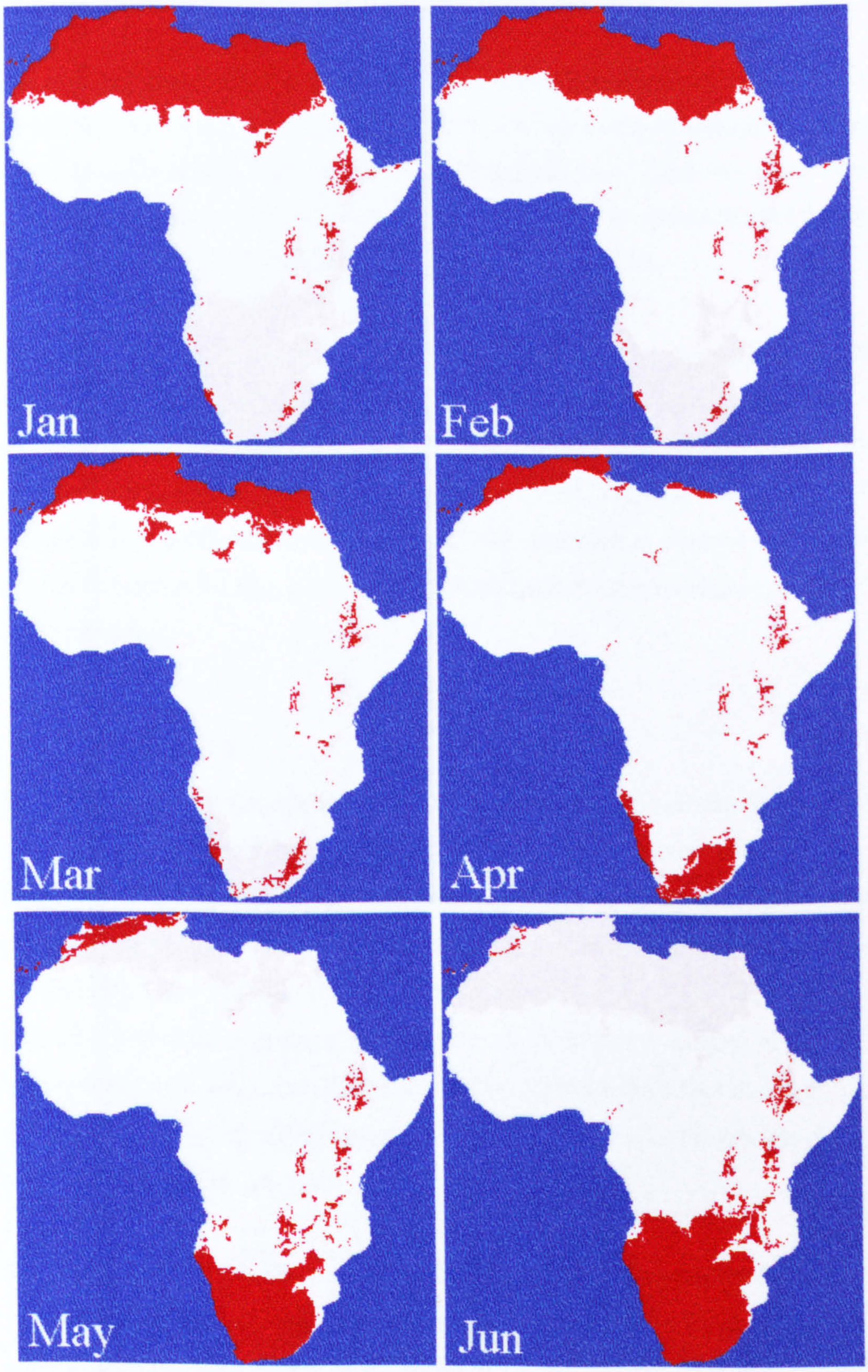
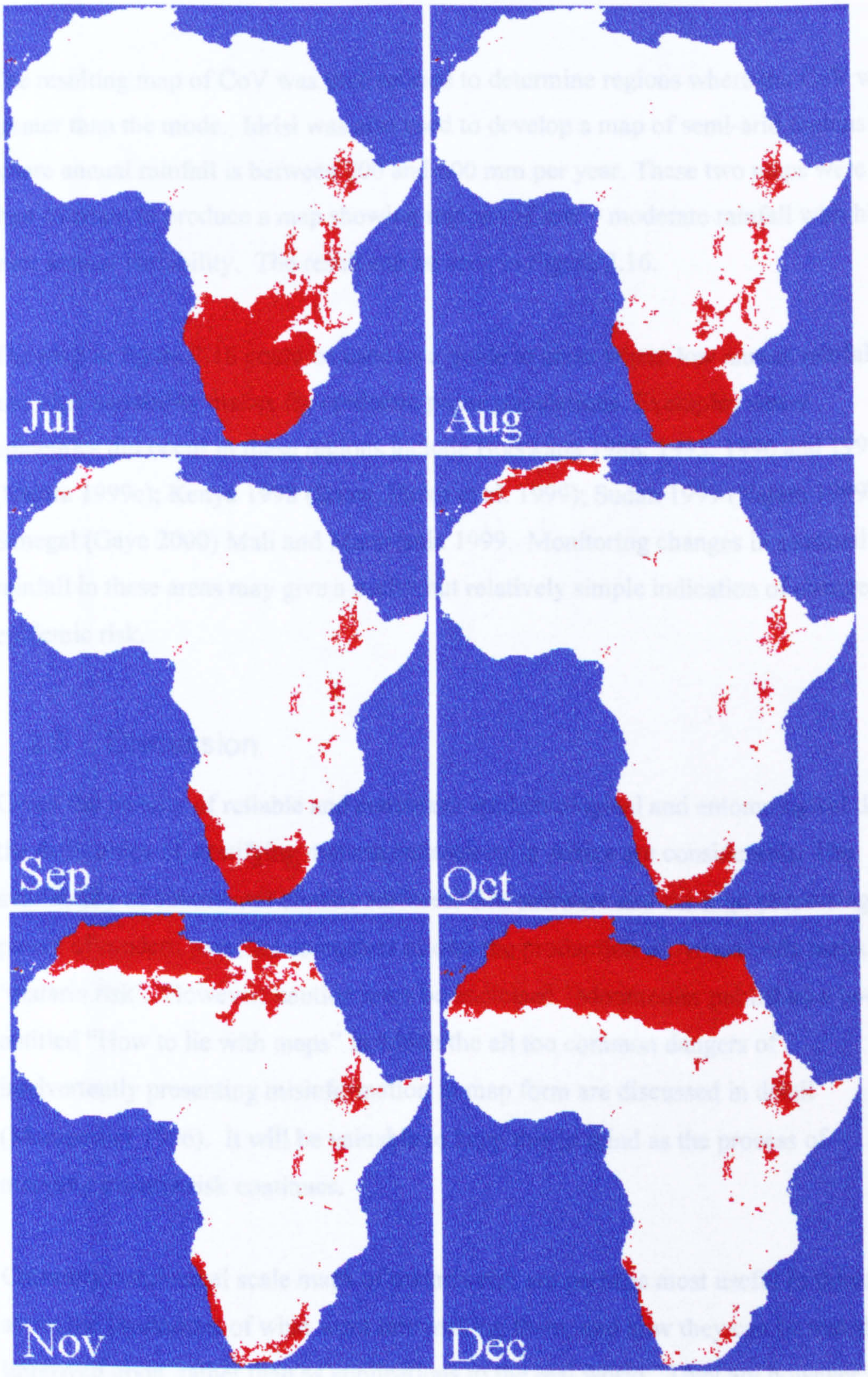


FIGURE 2.15. LOWER TEMPERATURE CONSTRAINTS TO MALARIA JULY-DECEMBER AVERAGES (RED AREAS UNSUITABLE FOR MALARIA ASSUMING <=18 ℃ CUT-OFF).



Macros were written to automate the considerable image processing involved.

$$CoV = \text{Standard deviation/mean}$$

The resulting map of CoV was then refined to determine regions where the CoV was greater than the mode. Idrisi was also used to develop a map of semi-arid regions where annual rainfall is between 200 and 600 mm per year. These two maps were then overlaid to produce a map showing regions of low – moderate rainfall with high inter annual variability. The result can be seen in Figure 2.16.

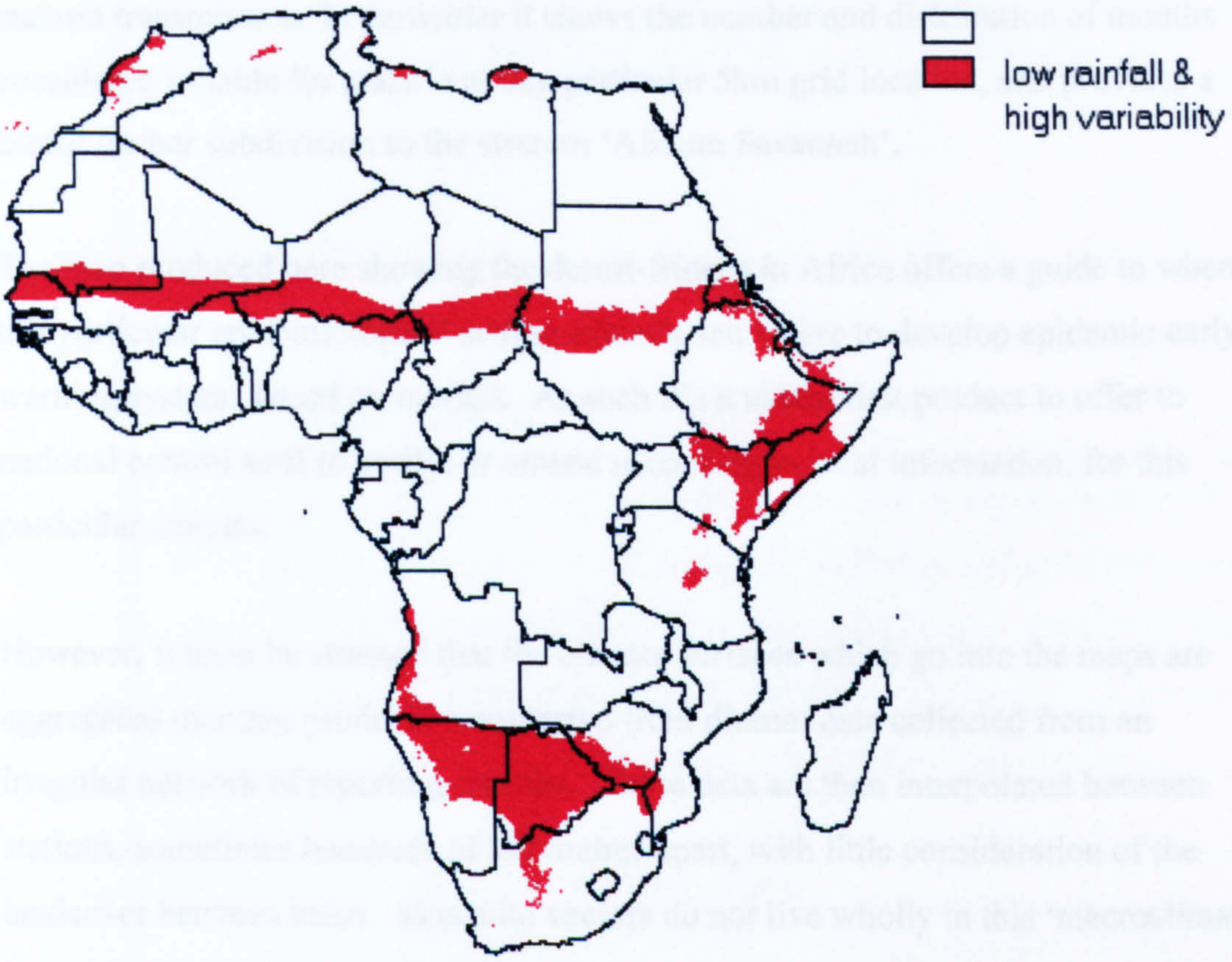
The map in figure 2.16 could be used as a guide to areas where low annual rainfall and high variability makes for epidemic prone populations. Examples where epidemics did occur in these regions include Botswana 1988, 1993, 1996 and 1997 (Najera 1999c); Kenya 1998 (Snow, Ikoku et al. 1999); Sudan 1999 (Najera 1999b); Senegal (Gaye 2000) Mali and Mauritania 1999. Monitoring changes in seasonal rainfall in these areas may give a useful but relatively simple indication of changes in epidemic risk.

2.5. Discussion

Given the paucity of reliable and consistent epidemiological and entomological data the difficulties of stratifying malaria endemicity in Africa are considerable. The availability of continental climate surfaces, GIS software and the high processing power of modern personal computers allows the production of Africa wide maps of 'malaria risk'. However, caution must be exercised. Monmonier published a book entitled "How to lie with maps" in which the all too common dangers of inadvertently presenting misinformation in map form are discussed in detail (Monmonier 1996). It will be valuable to keep this in mind as the process of mapping malaria risk continues.

Currently continental scale maps of malaria risk are perhaps most useful in thinking about the limitations of what went into making them, and how they can be tested and improved upon, rather than as applications to the real world. They are however, a necessary first step in a long journey.

FIGURE 2.16. MAP SHOWING AREAS COINCIDENTAL FOR BOTH 'LOW-MODERATE' ANNUAL MEAN RAINFALL AND 'HIGH' INTERANNUAL VARIABILITY IN RAINFALL.



Legend:

The map was produced from a coefficient of variation analysis of 540 monthly rainfall images (UEA 1951-1995) overlaid with lower and upper limits in annual mean rainfall of 200mm and 600mm respectively. These zones can be considered as a guide to the desert-fringes for epidemic malaria in Africa.

The interactive GIS approach to malaria risk mapping presented here is arguably a step forward in climate based malaria risk mapping. It makes more explicit the greater spatial and temporal information on the assumed climate constraints to malaria transmission. In particular it shows the number and distribution of months considered suitable for malaria at any particular 5km grid location, and provides a useful further subdivision to the stratum 'African Savannah'.

The map produced here showing the desert-fringes in Africa offers a guide to where this particular epidemiological setting extends and where to develop epidemic early warning systems based on rainfall. As such it's a useful first product to offer to national control staff to verify, or amend according to local information, for this particular stratum.

However, it must be stressed that the climate surfaces which go into the maps are aggregated monthly products constructed from diurnal data collected from an irregular network of reporting stations. These data are then interpolated between stations, sometimes hundreds of kilometres apart, with little consideration of the landcover between them. Mosquito vectors do not live wholly in this 'macroclimatic space' but instead occupy the microclimatic situations required by their survival. How would the maps differ if we could take this into account? How reliable, detailed and consistent would the epidemiological data available need to be to verify them?

3. Environmental monitoring for epidemic early warning

"whoever would study medicine aright must first learn of the following subjects. First he must consider the effects of the seasons of the year and the differences between them. Secondly he must study the warm and the cold winds, both those which are common (.....) and those that are peculiar" Hippocrates cited by (Committee on Climate 2001)

3.1. Introduction

3.1.1. Malaria epidemics

During the past five years the author has participated in three meetings of the Roll Back Malaria Technical Resource Network on Epidemic Prevention and Control, and two WHO-AFRO Workshops on Epidemic Prevention and Control. Invariably these meetings begin and end with the question "what is a malaria epidemic?" It seems this is a perennial question and is never answered to everyone's satisfaction.

A 'double-barreled' definition which has been used is:

"a sharp increase of the incidence of malaria among a population in which the disease was unknown. Conversely it may refer to a seasonal or other increase of clinical malaria in an area with moderately endemic malaria" (Gilles 1993)

Alternatively it may be useful to begin with a simple working definition, *"an increase in the disease beyond that normally expected"* and then to classify epidemics according to their cause and their epidemiological setting (Connor, Thomson et al. 1999).

Malaria epidemics can generally be considered as a disturbance of an existing epidemiological equilibrium. They arise in a variety of situations and while there may be several causative processes at work, it is usually possible to classify them according to a main precipitating factor. This is of course an important requirement in the process of identifying appropriate control interventions. For instance epidemics may arise following the development of dams, fisheries and/or irrigation

schemes that change the local environment and, as a result, the previous ecological equilibrium. Epidemics may also occur where mass migration of partial or non-immune populations into regions of higher endemicity follows political and economic instability. Occasionally epidemics occur through importation, or invasion, of an exotic vector species into an area, thereby changing the vectorial capacity of local transmission. The commonest causative factor in malaria epidemics is, however, that of abnormal meteorological conditions which temporarily change the equilibrium between host(s), vector(s) and parasite(s). The situations described above have been termed as 'true epidemics' (Najera 1998a). In contrast, 'resurgent outbreaks' result from control failure where declining health infrastructure, combined perhaps with increasing drug and insecticide resistance, enable malaria to re-emerge in areas where it had previously been controlled.

3.2. Aims of this chapter

- To present a conceptual model for early warning and early detection of malaria epidemics.
- To review the suitability of environmental monitoring products used in other sectors for application to the problem of early warning of malaria epidemics in Africa.
- To develop a methodology for integrating both rainfall and temperature information into a monitoring product which may be used for malaria early warning.

3.3. The influence of climate on seasonal and interannual variation in malaria transmission in Africa

Meteorological variables rainfall (R) temperature (T) and humidity (H) influence patterns of malaria transmission, through their effects on parasite/vector development and survival rates. There are three basic, climate related, models of malaria endemicity for the African continent: (i) rainfall-limited seasonal malaria, as seen in

much of West Africa and the Sahel; (ii) temperature and rainfall-limited seasonal malaria, found in parts of Southern Africa and the East African Highlands; and (iii) unconstrained perennial transmission, found in many parts of Central and Coastal Africa. Our interest here lies with situations (i) and (ii). Figure 3.1. sets out a conceptual model of one possible scenario in an area of seasonally endemic malaria, showing: (a) seasonal changes in meteorological variables; (b) their potential effects on vector bionomics; and (c) possible epidemiological surveillance methods that may be used to monitor seasonal patterns of malaria.

3.3.1. Climate induced malaria epidemics

In his treatise on malaria endemicity and epidemic prevalence, Christophers describes the development of climate induced epidemics that take the form of a 'Seasonal Epidemic Rise' [5] in cases beyond the normal pattern (Christophers 1949). The vast majority of surveillance systems in African countries would be unable to detect such an abnormal (though perhaps periodic) event until it is too late to act effectively on its outcome. Instead, the majority of surveillance systems merely confirm that an epidemic did occur. For political reasons control services may mount an emergency control campaign consisting of inter-domiciliary residual spraying and larviciding, but in view of its poor timing it may have little, or no, effect on transmission (Najera 1999a). At certain times climate induced epidemics may occur over very large areas, as experienced recently in East Africa during 1998, and before that in Southern Africa in 1996. Christophers described severe and extensive epidemics 'Regional Epidemic Malaria' as experienced in Northern India, as a feature of the sub-tropical malaria zones which were essentially an exaggeration of the seasonal epidemic rise (Christophers 1949).

The surveillance methods described in Figure 3.1. are based on the principle that the malaria season is a discreet *event*. In Figure 3.2. the same seasonal malaria pattern is shown again.

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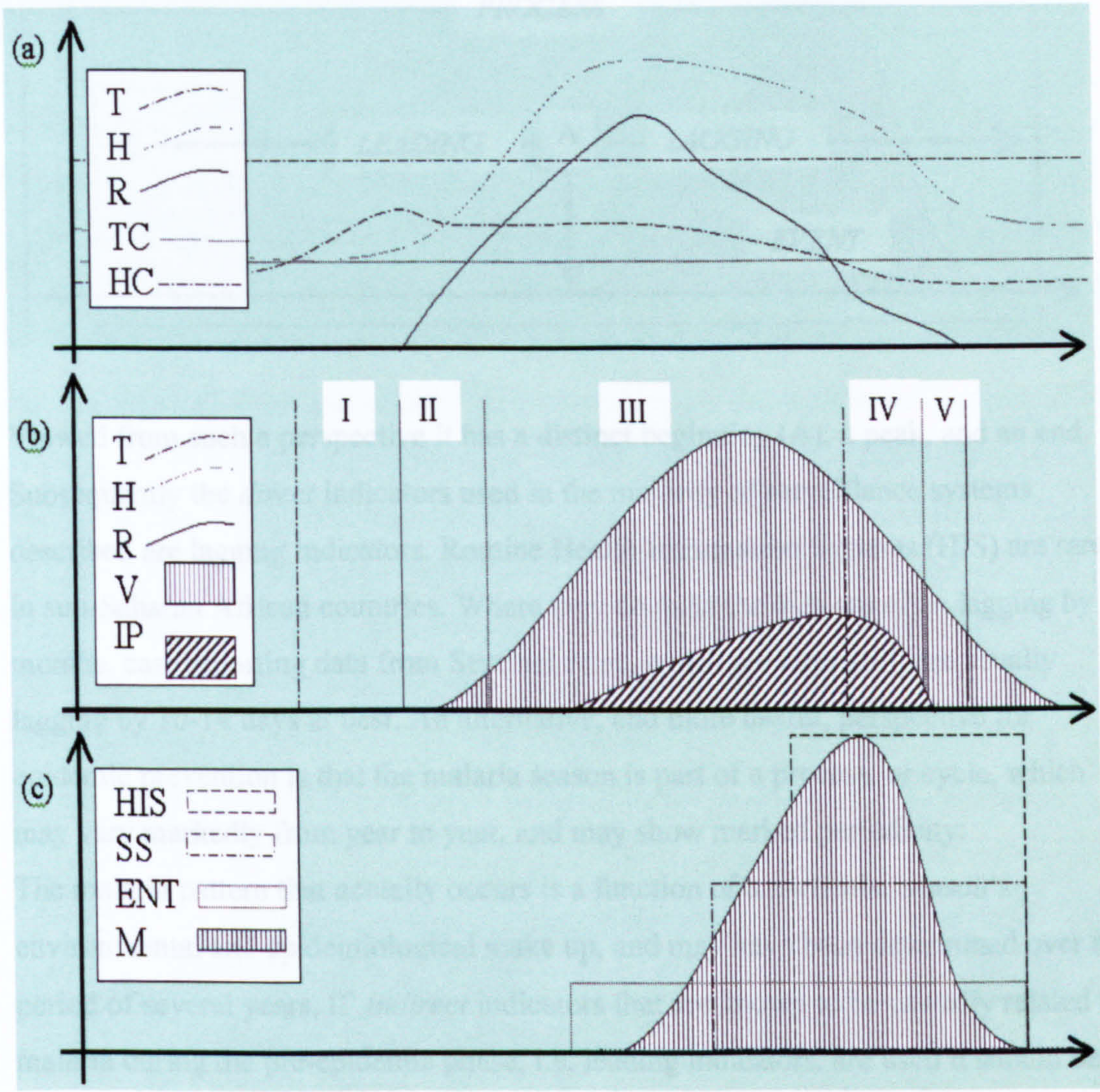
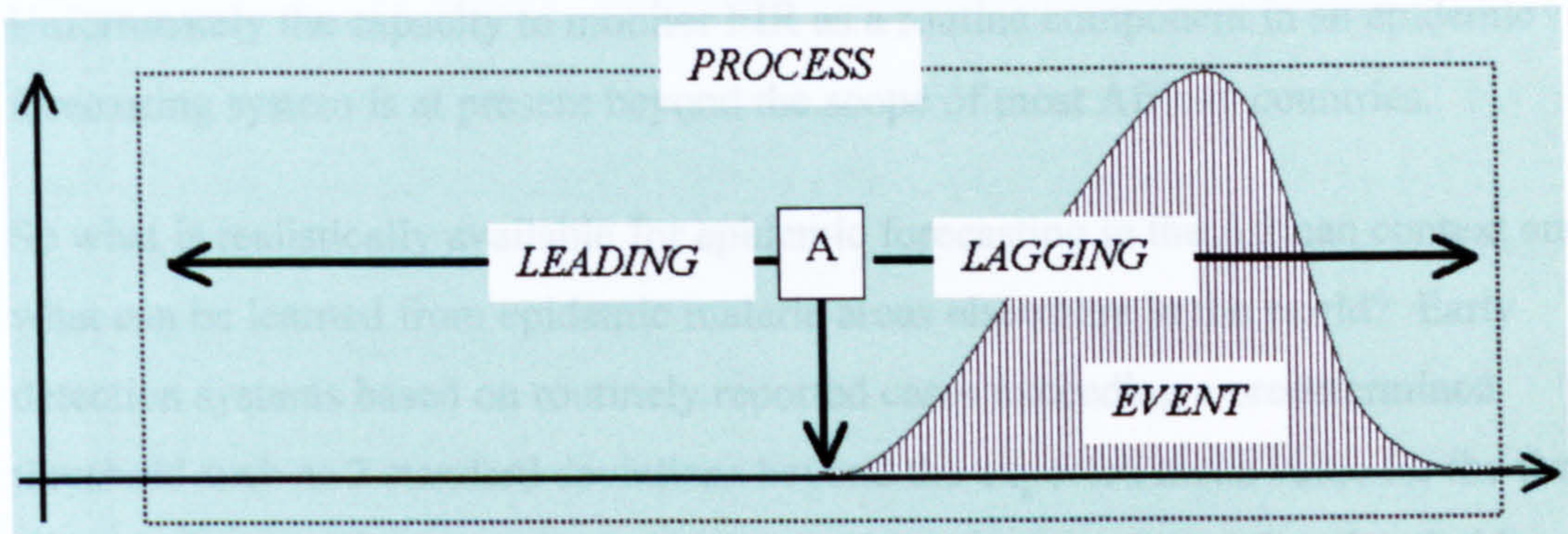
[5] See also Gill's writing on the 'Seasonal Epidemic Wave' Gill, C. A. (1938). The seasonal periodicity of malaria and the mechanism of the epidemic wave. London, J.A. Churchill Ltd..

FIGURE 3.1. CONCEPTUAL MODEL OF MALARIA SEASONALITY AND SURVEILLANCE (REPRODUCED FROM CONNOR ET AL 1999)



Legend: (a) represents an annual distribution (x = time, y = amplitude) of the variables R, T and H. The horizontal dotted lines represent the lower temperature constraint of 18°C (TC) for *P. falciparum*, and a (60%) humidity constraint for sufficiency of anopheline survival (HC). In Fig 1 (b) a 'periodicity' of these constraints are set out in phases I to V. During phase I, T rises above 18°C but no surface water is available for mosquito breeding. The arrival of the rains mark the beginning of phase II with a consequent rise in H to above 60% and the establishment of surface pools. During phase III the vector population (V) increases and peaks shortly after Rmax while the infective proportion (IP) continues to develop. During phase IV the infective vector population declines quickly once T and H are no longer sufficient to support rapid parasite development and longevity of the vector. Phase V continues to produce mosquitoes but these are unlikely to transmit malaria. Fig 1 (c) shows a seasonal distribution of malaria (M) in the human population along with various methods which may be used to provide information for the planning of malaria control activities. The Health Information System (HIS) records cases presenting at health facilities. This source of information may be valuable for planning resource allocation to particular diseases but it is usually too slow to act on in a given season. In some countries Sentinel Surveillance (SS) from a few representative sites are used to monitor what is happening in the current season, but again delay is inevitable as it relies on cases presenting. Entomological surveillance methods (ENT) can be used to provide an assessment of infective mosquito populations prior to the increase in human cases but these are very costly and not realistic in the current sub-Saharan African context.

FIGURE 3.2. A PROCESS PERSPECTIVE ON THE EPIDEMIC WAVE



Viewed from such a perspective it has a distinct beginning (A), a peak, and an end. Subsequently the *direct* indicators used in the majority of surveillance systems described are lagging indicators. Routine Health Information Systems (HIS) are rare in sub-Saharan African countries. Where they do exist the data are often lagging by 3 months, case reporting data from Sentinel Sites, which are rarer still, are usually lagging by 10-14 days at best. An alternative, and more useful, perspective for epidemic prevention is that the malaria season is part of a process, or cycle, which may vary markedly from year to year, and may show marked periodicity.

The malaria pattern that actually occurs is a function of a particular season's environmental and epidemiological make up, and may have been determined over a period of several years. If *indirect* indicators that are known to be causally related to malaria during the pre-epidemic phase, i.e. leading indicators, are used it should be possible to gain information that can aid in the advance planning of control interventions which are more appropriate to the forthcoming conditions. This is, of course, a vital consideration if information systems, which can be used to aid timely decision making for greater epidemic preparedness, are to be developed.

The process perspective on epidemic malaria is evident in Onori and Grab's review of potential indicators for epidemic forecasting (Onori and Grab 1980). They suggest that malaria epidemics have a four stage cycle: pre-epidemic, epidemic wave, post epidemic and inter-epidemic. Their work argues for the development of a two stage epidemic forecasting system based on the monitoring of meteorological variables and changes in the Entomological Inoculation Rate during the pre-epidemic period. It is explicit in Onori and Grab's writing that their system may be suited to the forecasting of resurgent outbreaks where comprehensive surveillance systems have

already been developed and operated as part of the routine malaria control services. Unfortunately the capacity to monitor EIR as a routine component in an epidemic forecasting system is at present beyond the scope of most African countries.

So what is realistically available for epidemic forecasting in the African context and what can be learned from epidemic malaria areas elsewhere in the world? Early detection systems based on routinely reported cases exceeding a predetermined threshold such as 2 standard deviations beyond the expected mean value for the time of year (Cullen, Chitprarop et al. 1984) have been suggested. Another threshold method for early detection is that where reported cases exceed the median normal value to the extent of reaching the third quartile (Najera 1998b). These two methods and variations on their themes have recently been tested in Southern Africa by the WHO-SAMC team and have been shown to perform poorly in the African context (WHO 2001a). Epidemic forecasting based on climatological and socio-economic variables, were used routinely in some parts of the world[6]. Unfortunately, much of the interest in the further development of epidemic forecasting methods was lost during the period of the Global Malaria Eradication Campaign (Najera 1998a).

3.3.2. Environmental monitoring in epidemic prone regions

Environmental variables such as: rainfall, temperature, humidity, sunshine hours, cloud cover; and seasonal vegetation/crop status and development can be monitored on a routine basis. These may be direct observations from meteorological or agricultural stations, or in some cases, proxies derived from satellite remote sensing. In sub-Saharan Africa the former only comprise of a sparse network of reporting stations. The production of continental scale maps will, therefore, require interpolation between stations causing, not only loss of accuracy but also, delay in data availability. Conversely, the use of environmental proxies, from satellites, may allow frequent observation of a uniform sampling grid of a few kilometres squared. These do however, have their own problems of observational accuracy, and some degree of ground 'truthing' is desirable. Estimates of rainfall and vegetation condition derived from meteorological satellites (METEOSAT and NOAA-AVHRR)

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[6] The historical use of epidemic early warning in the Punjab and its potential for use in some parts of Africa have been reviewed Connor, S. J., M. C. Thomson and D. H. Molyneux (1999). "Forecasting and prevention of epidemic malaria: new perspectives on an old problem." Parassitologia 41(1-3): 439-448..

have been used for more than two decades in programmes such as the FAO Africa Real Time Monitoring and Environmental Information System (ARTEMIS), mostly as an input to Famine Early Warning Systems (Hielkema and Snijders 1994) and Locust Control (Bonifacio and Ouladichir 1996). Their use in monitoring epidemic prone regions in Africa is arguably a logical extension of their routine use by other sectors (Connor, Flasse et al. 1997).

Cold Cloud Duration (CCD) is a method of rainfall estimation which uses Meteosat's thermal infrared sensors (TIR) to observe critical cloud top temperature thresholds (corresponding to a given latitude) to estimate the amount of rainfall occurring during a set period of time, at a nominal 5km spatial resolution (Milford and Dugdale 1990). CCD is commonly used to estimate rainfall for 10 daily periods (dekads: three per month) and has been used routinely by African meteorological services to estimate rainfall over large and remote areas (Tadesse, Sear et al. 1995). While CCD is known to underestimate rainfall in some localities (especially mountainous and coastal areas) it has been shown to offer a better estimation of total rainfall occurring throughout a regional catchment than that available through conventional rain-gauge networks (Milford, McDougall et al. 1994). Relationships have been shown between CCD and interannual variation in seasonal malaria in West Africa (Thomson, Connor et al. 1996), East Africa (Hay, Snow et al. 1998b) and Southern Africa (Connor 1999b). CCD was shown to be spatially associated with the length of the transmission season and the variation in malaria incidence in village studies in The Gambia (Thomson, Connor et al. 1999). CCD data archives are available on request from FAO's ARTEMIS Programme covering the period 1988-1999.

It is possible to estimate Land Surface Temperature using the thermal channels of meteorological satellites (Carlson, Taconet et al. 1995). However, the relationship between this proxy and ambient temperature is less reliable. In a comparison of satellite derived proxies of rainfall and temperature (from Meteosat and NOAA-AVHRR) with interpolated data from meteorological stations, spatial interpolation of station data gave a better prediction of temperature, while CCD gave a better prediction of rainfall (Hay and Lennon 1999). Work by Cresswell and colleagues developed a method to improve the estimation of ambient temperature through the combined use of Meteosat TIR and calculation of solar zenith angle (Cresswell,

Morse et al. 1999). This method however, requires further validation and is not, as yet, an operational product available for routine monitoring.

The desert-fringe regions outlined in Figure 2.17. (Chapter 2) were described previously as being prone to malaria epidemics due to their high variability in annual rainfall combined with low to moderate annual total rainfall distribution. Rainfall is the primary limiting factor in these regions. While temperature falls below the critical minimum threshold value for malaria transmission for part of the year in the southern African region, temperature is not limiting to transmission during September to April – the period in which the rainy season occurs (see Figures 2.15 and 2.16 in Chapter 2). Therefore simple routine monitoring of rainfall in both these regions could provide useful information to malaria control services regarding changes in epidemic risk. Monitoring for unusually high rainfall in the desert-fringe regions, or monitoring for a return to 'normal' rainfall in regions which have recently experienced a number of years of drought may be particularly appropriate as a first step in the development of a routine malaria epidemic early warning system (Connor, Thomson et al. 1999).

The USAID's FEWS supports an internet facility, the "Africa Data Dissemination Service" (ADDS) which provides satellite derived rainfall estimates (RFE) and vegetation condition (NOAA-AVHRR-NDVI). Continental RFE images are produced for FEWS NET by NOAA's Climate Prediction Center. The RFE are prepared on a 0.1-degree grid from thermal infrared images acquired from Meteosat every 30 minutes. These are used to identify areas of cold cloud top temperatures (less than 235°K). The duration of these temperatures over a dekad is used to make an initial estimate of convective rainfall. Then, dekadal rainfall totals from ground stations that report electronically through the WMO Global Telecommunication System (GTS) are used to remove bias from the cold cloud estimates. Finally, areas of "warm cloud" rainfall, associated with orography, coastal areas, and frontal activity, are estimated from analysis fields of NOAA's operational Global Data Assimilation System (GDAS). Fields of wind direction, relative humidity, and a digital elevation model are used to identify areas of non-convective lifting and condensation (Xie and Arkin 1997; Herman, Kumar et al. 2001). Dekadal RFE are produced on the 1st, 11th, and 21st of each month and posted to the website soon

after. The historical archive for these data covers the period July 1995 - present. The images currently available are at a spatial resolution of 8km squared in Alber's equal area conic projection (Bugayevskiy and Snyder 1995).

RFEs are commonly used by international food security and drought monitoring systems to produce dekadal rainfall difference images. These difference images show the comparison between the estimated dekadal or monthly rainfall and that which would be expected for that time of the year. Images based on long-term averages have commonly been used for the comparison. However, the ADDS site has recently provided a short-term mean for an alternative comparison. The long-term mean used for the ADDS RFE is derived from interpolated station data 1920-1980. The short-term mean is itself derived from the 1995-1999 RFE.

Comparison between current seasonal rainfall and distributions in recent rainy seasons may be especially pertinent for monitoring changes in malaria epidemic risk, especially in 'desert-fringe' regions where there is a history of post-drought malaria epidemics.

The RFE image shown in Figure 3.3 gives the estimated rainfall distribution for the 10 day period 11-20th November, 1997. This image was downloaded from the ADDS website. A freely available image processing, analysis and display software called WINDISP has been developed by USAID/FAO FEWS (Pfirman, Hogue et al. 1999). The WINDISP software was used to produce a rainfall difference image (current rainfall estimate minus the mean for time of year) for 11-20th of November, 1997 and the result is shown in Figure 3.4.

The red areas in Figure 3.4. show rainfall deficit, the green areas show rainfall in excess of expected. This particular period saw extensive, heavy rainfall over much of sub-Saharan Africa[7]. Reference back to Figure 2.17 (Chapter 2) shows that this rainfall event occurred over areas which usually experience low annual rainfall. A single dekad of higher rainfall may well not produce an epidemic, even in an

[7] The unusually heavy rainfall was associated with a strong El Nino event. NOAA-OGP (1999). An experiment in the application of climate forecasts: NOAA-OGP activities related to the 1997-98 El Nino event. Washington, United States National Oceanographic and Atmospheric Administration, Office of Global Programs: 134..

FIGURE 3.3. SATELLITE RAINFALL ESTIMATE IMAGE FOR PERIOD 11-20TH NOVEMBER, 1997.

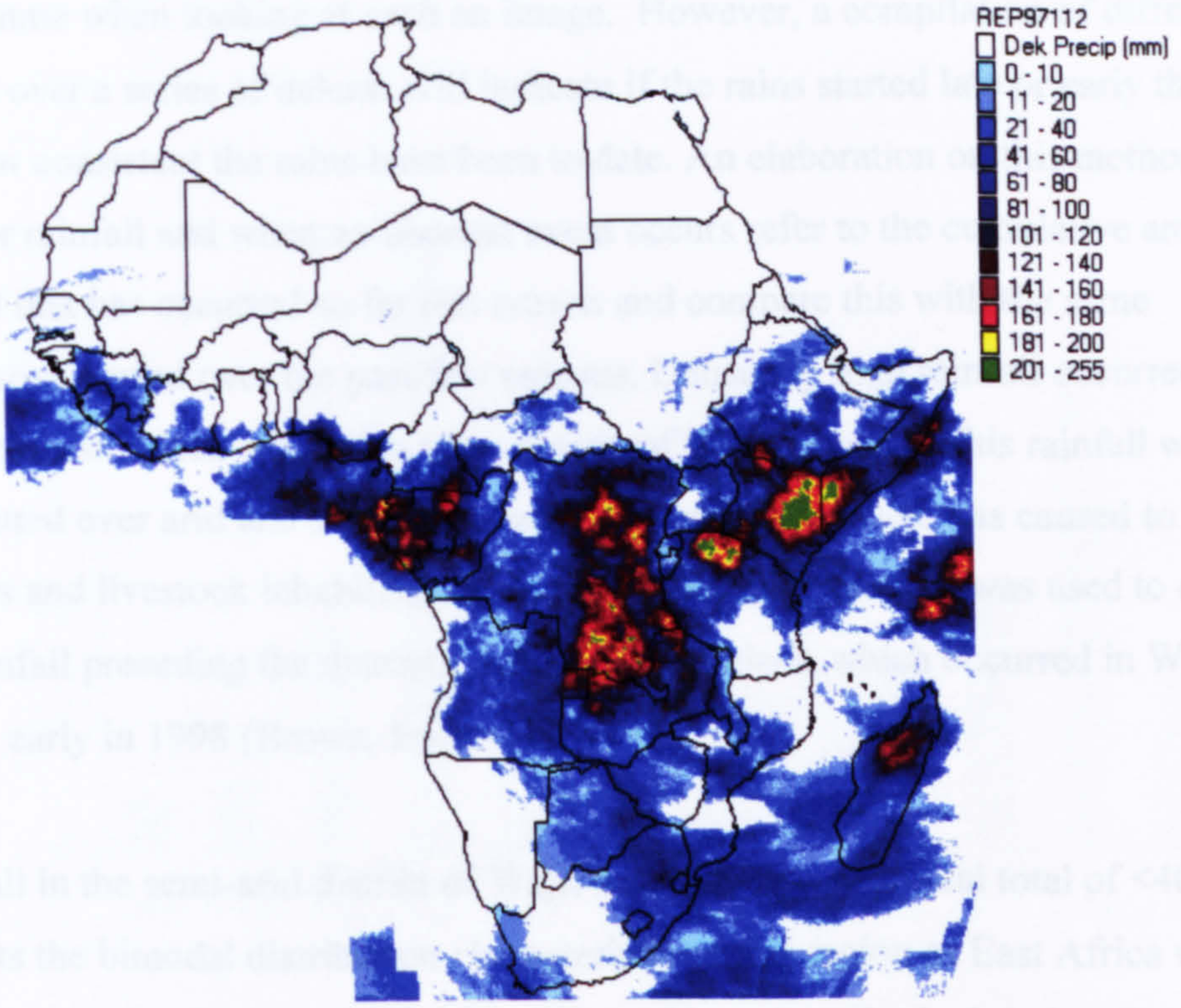
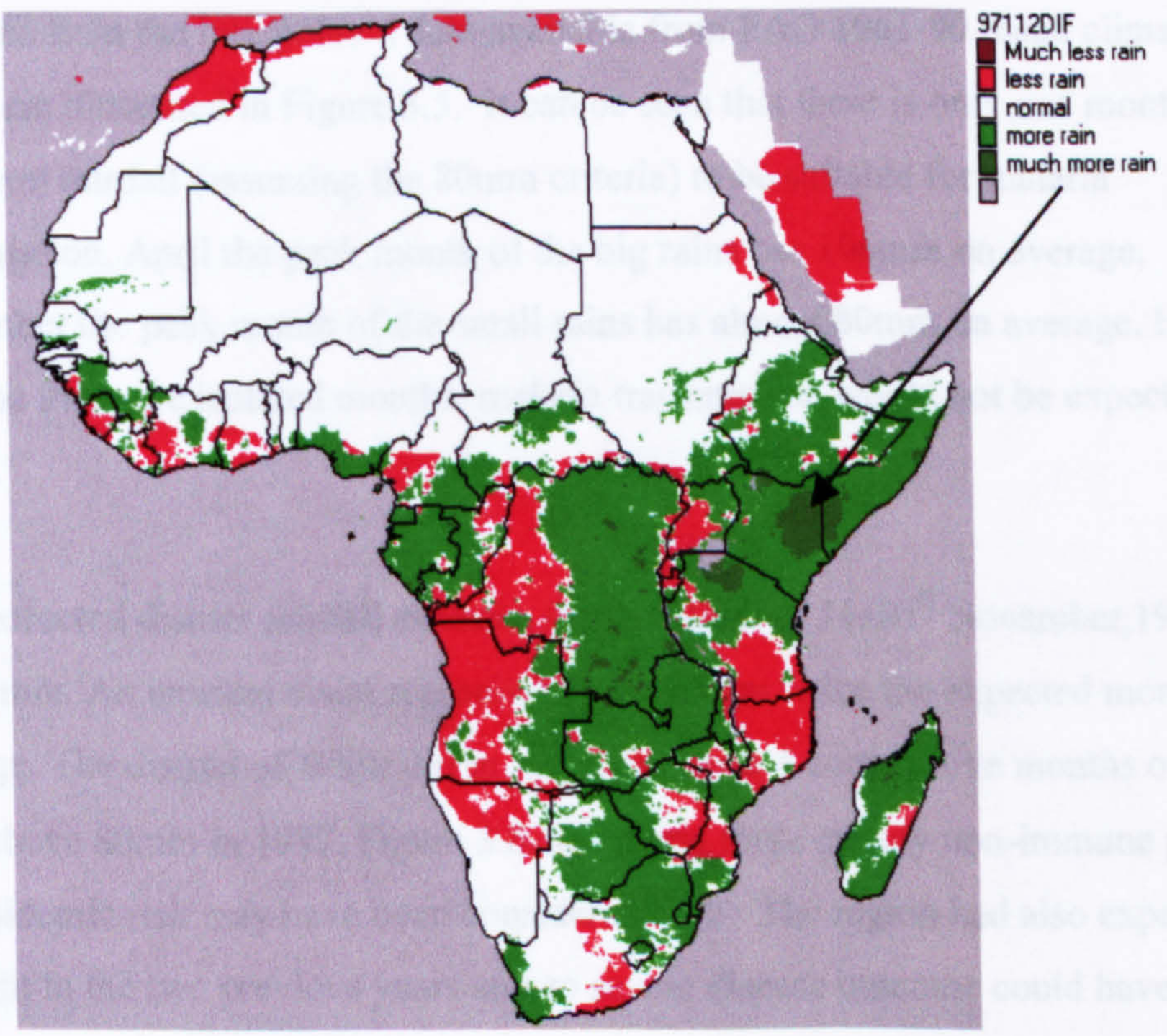


FIGURE 3.4. RAINFALL DIFFERENCE IMAGE FOR THE PERIOD 11-20TH NOVEMBER, 1997.



Note. The arrow in Figure 3.4, highlights the area around north-eastern Kenya where estimated rainfall was well in excess of what would normally be expected.

epidemic prone area, and some caution would need to be used by any malaria control programme when looking at such an image. However, a compilation of difference images over a series of dekads will indicate if the rains started late or early this year and how consistent the rains have been to date. An elaboration on this method is to monitor rainfall and when an unusual event occurs refer to the cumulative amount of rainfall that has occurred so far this season and compare this with the same cumulative period over the past few seasons. Unusually high rainfall occurred over much of East Africa during the rainy season of 97/98, much of this rainfall was distributed over arid and semi-arid areas and major disruption was caused to the peoples and livestock inhabiting these areas. This latter method was used to explore the rainfall preceding the dramatic epidemic of malaria which occurred in Wajir, NE Kenya early in 1998 (Brown, Issak et al. 1998).

Rainfall in the semi-arid district of Wajir normally has an annual total of <400mm. It exhibits the bimodal distribution characteristic of this region of East Africa with a 'big rains' during March, April, May followed by a 'small rains' during October, November, December. The WINDISP software was used to extract district rainfall averages from the interpolated data available from FAO 1961-90 mean climatology. These are illustrated in Figure 3.5. It can be seen that there is only one month with sufficient rainfall (assuming the 80mm criteria) to be suitable for malaria transmission. April the peak month of the big rains has 106mm on average, November the peak month of the small rains has almost 80mm on average. However because these are isolated months, malaria transmission would not be expected to occur.

The extracted district rainfall estimate for the dekad of 11-20th November,1997 alone is 160mm. An unusual event representing more than twice the expected monthly average. The district of Wajir did in fact experience 4 consecutive months of rainfall well above 80mm in 1997, Figure 3.6, so among these largely non-immune people the epidemic risk may have been considered high. The region had also experienced drought in the two previous years and so severe disease outcome could have been expected.

FIGURE 3.5. AVERAGE MONTHLY RAINFALL IN WAJIR, NORTHEASTERN KENYA 1961-1990.

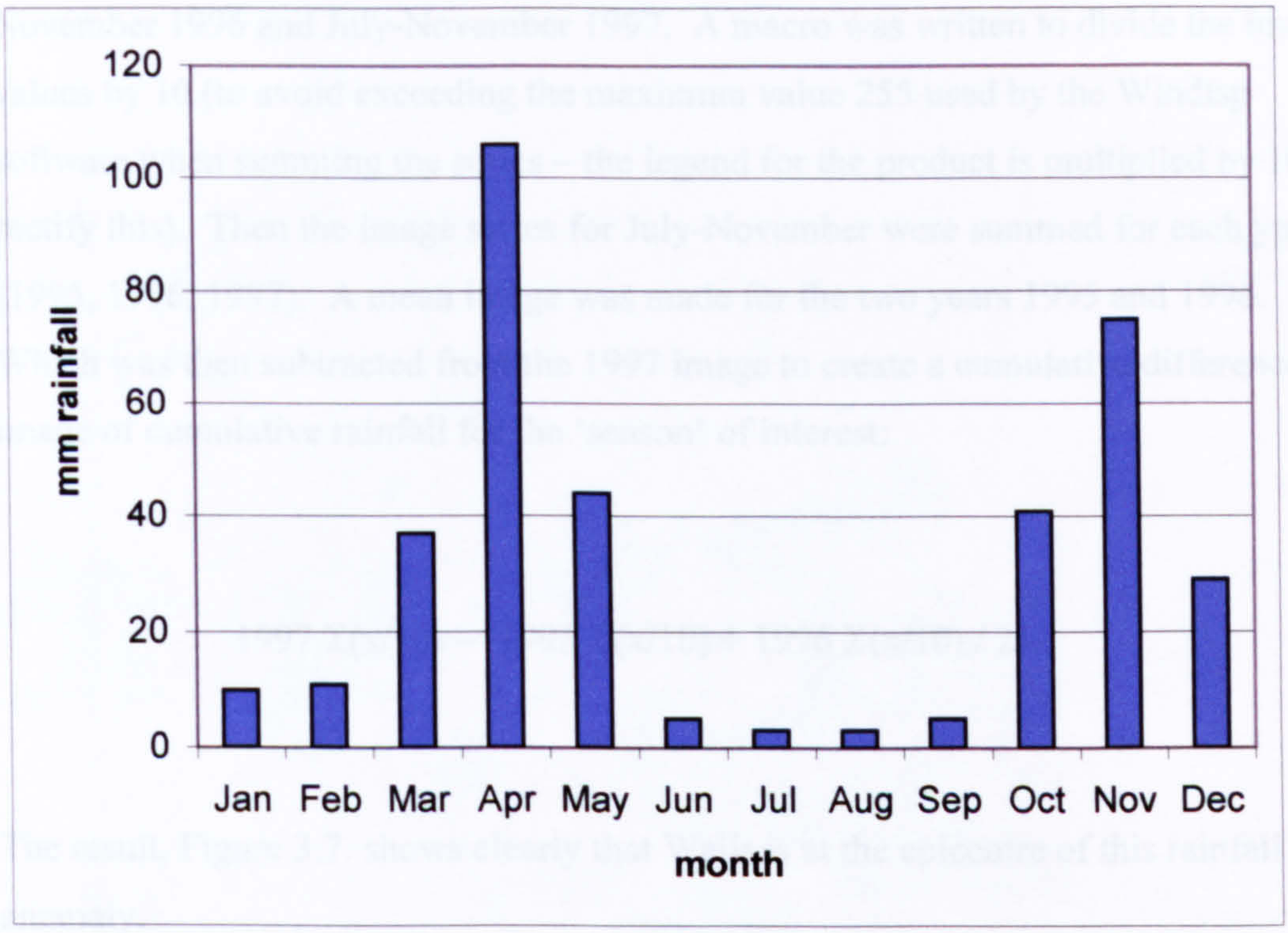
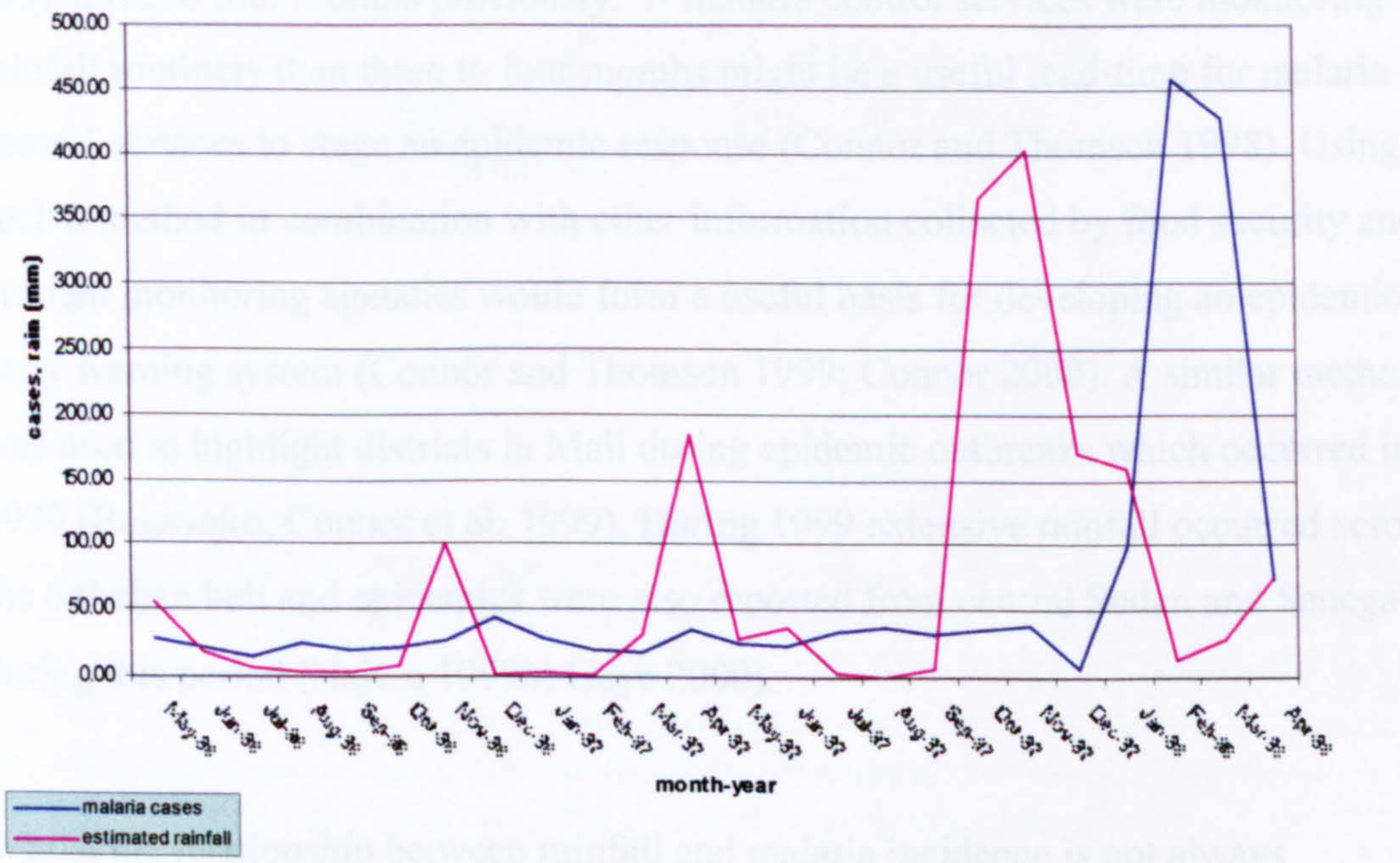


FIGURE 3.6. RELATIONSHIP BETWEEN RAINFALL AND EPIDEMIC MALARIA IN WAJIR, KENYA.



The WINDISP software was used to create summed images of estimated rainfall for the Africa continent covering each of the periods July-November 1995, July-November 1996 and July-November 1997. A macro was written to divide the image values by 10 (to avoid exceeding the maximum value 255 used by the Windisp software when summing the series – the legend for the product is multiplied by 10 to rectify this). Then the image series for July-November were summed for each year (1995, 1996, 1997). A mean image was made for the two years 1995 and 1996. Which was then subtracted from the 1997 image to create a cumulative difference image of cumulative rainfall for the 'season' of interest:

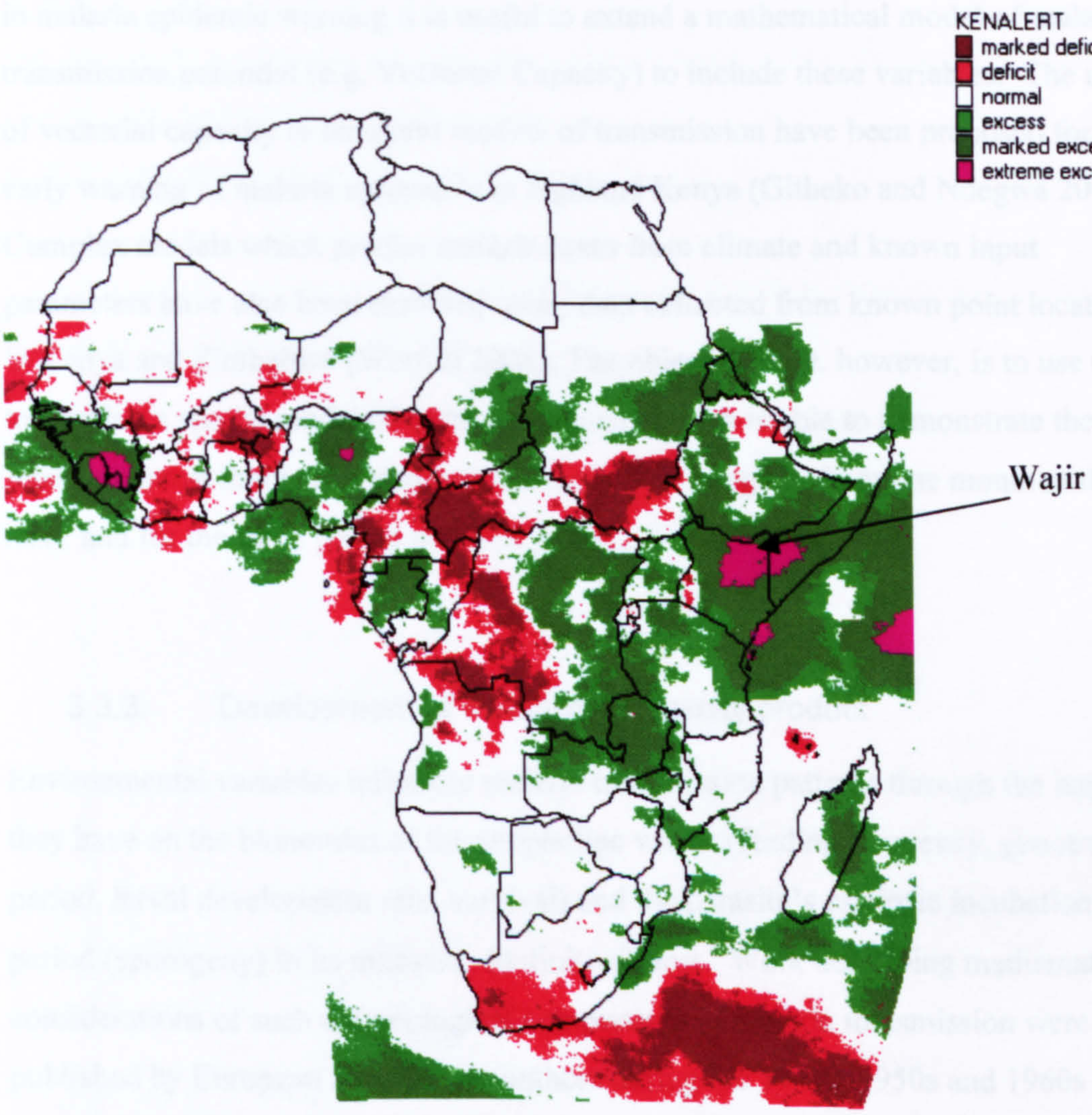
$$1997\ \Sigma(x/10) - (1995\ \Sigma(x/10) + 1996\ \Sigma(x/10) / 2)$$

The result, Figure 3.7. shows clearly that Wajir is at the epicentre of this rainfall anomaly.

The epidemic in Wajir (Brown, Issak et al. 1998) which occurred in February 1998 was preceded by an unusual extended peak in rainfall during October and November 1997 three to four months previously. If malaria control services were monitoring rainfall routinely then three to four months might be a useful lead-time for malaria control services to stage an epidemic response (Connor and Thomson 1998). Using such a method in combination with other information collected by food security and drought monitoring agencies would form a useful basis for developing an epidemic early warning system (Connor and Thomson 1999; Connor 2000). A similar method was used to highlight districts in Mali during epidemic outbreaks which occurred in 1999 (Bagayoko, Connor et al. 1999). During 1999 extensive rainfall occurred across the Sahelian belt and epidemics were also reported from central Sudan and Senegal during this period (Najera 1999b; Gaye 2000).

Whilst the relationship between rainfall and malaria incidence is not always straightforward, and temperature may act as a limiting factor in some regions, epidemics which are primarily rainfall-related are common in sub-Saharan Africa.

FIGURE 3.7. CUMULATIVE RAINFALL DIFFERENCE IMAGE FOR THE PERIOD JULY-NOVEMBER 1997 COMPARED TO JULY-NOVEMBER MEAN FOR THE PREVIOUS TWO YEARS.



Legend:

Note the palette here is slightly modified from the FAO palette used in Figure 3.4, in order to highlight the area of high excess in estimated rainfall. It is also noteworthy that the use of colour palette may mean different things to different people. The FAO palette was produced as part of their Famine Early Warning Systems (FEWS). For FEWS people, green means more rainfall therefore more vegetation. Red means dry. When the author has used this palette with malaria control staff they have invariably linked red to high malaria risk and green to 'all is well'.

The routine development of rainfall difference images could form a useful element in monitoring for malaria epidemic early warning in many situations. However, to explore more fully the interplay between rainfall and temperature and their potential in malaria epidemic warning it is useful to extend a mathematical model of malaria transmission potential (e.g. Vectorial Capacity) to include these variables. The use of vectorial capacity in temporal models of transmission have been proposed for early warning of malaria epidemics in highland Kenya (Githeko and Ndegwa 2001). Complex models which predict malaria cases from climate and known input parameters have also been explored using data collected from known point locations in Kenya and Zimbabwe (Worrall 2001). The objective here, however, is to use GIS to develop a spatial model of vectorial capacity which is able to demonstrate the relative change in this transmission indicator over a region, from one month to the next, and for the same period between years.

3.3.3. Development of a vectorial capacity product

Environmental variables influence malaria transmission patterns through the impact they have on the bionomics of the anopheline vector (feeding frequency, gonotrophic period, larval development rate, survival) and the parasite's extrinsic incubation period (sporogeny) in its mosquito (definitive) host. Work describing mathematical considerations of such entomological components of malaria transmission were published by European and Russian authors during the 1940s, 1950s and 1960s with much of this work culminating in the development of a mathematical model of vectorial capacity (Garrett-Jones 1964). Vectorial capacity V has been defined as the daily rate at which future inoculations could arise from a currently infected case (Dye 1992). It has also been described as a convenient way of expressing malaria transmission risk, or the receptivity of an area to malaria (Gilles, 1993). While vectorial capacity does not take into account parasite availability in the human (intermediate host) population, it is considered to be analogous to the environmental-biological driving force under-pinning the transmission potential in an area.

Vectorial capacity may be expressed:

$$V = ma^2P^n/-lnP$$

Where:

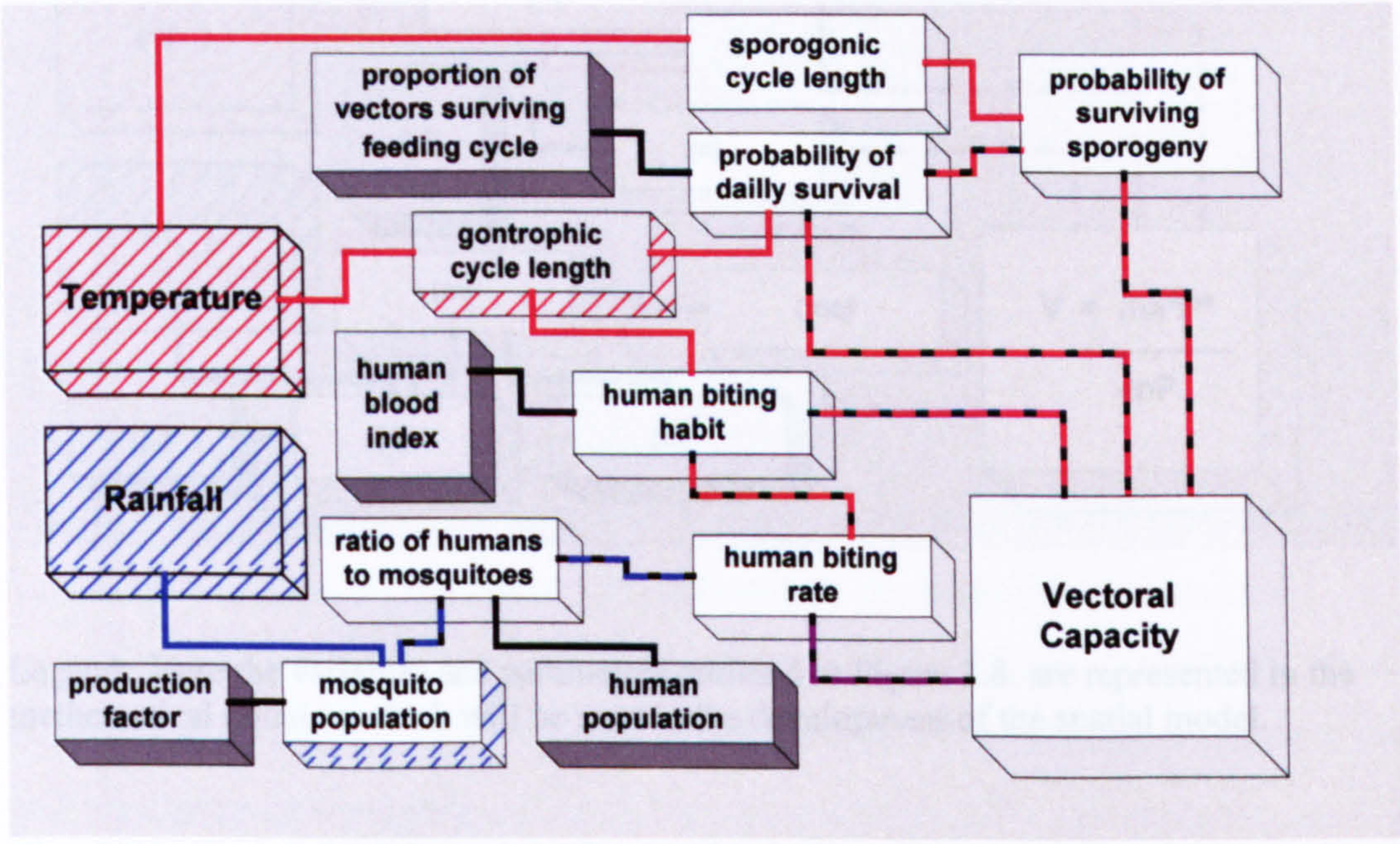
ma represents the number of bites received per person over a fixed period of time,

P represents daily survival of the vector,

n represents the length of the sporogonic cycle.

Clearly rainfall and temperature have an impact on vectorial capacity as illustrated in the model illustrated in Figure 3.8.

FIGURE 3.8. DIAGRAMMATIC REPRESENTATION OF A VECTORIAL CAPACITY MODEL EXTENDED TO INCLUDE ITS RELATIONSHIP WITH TEMPERATURE AND RAINFALL.

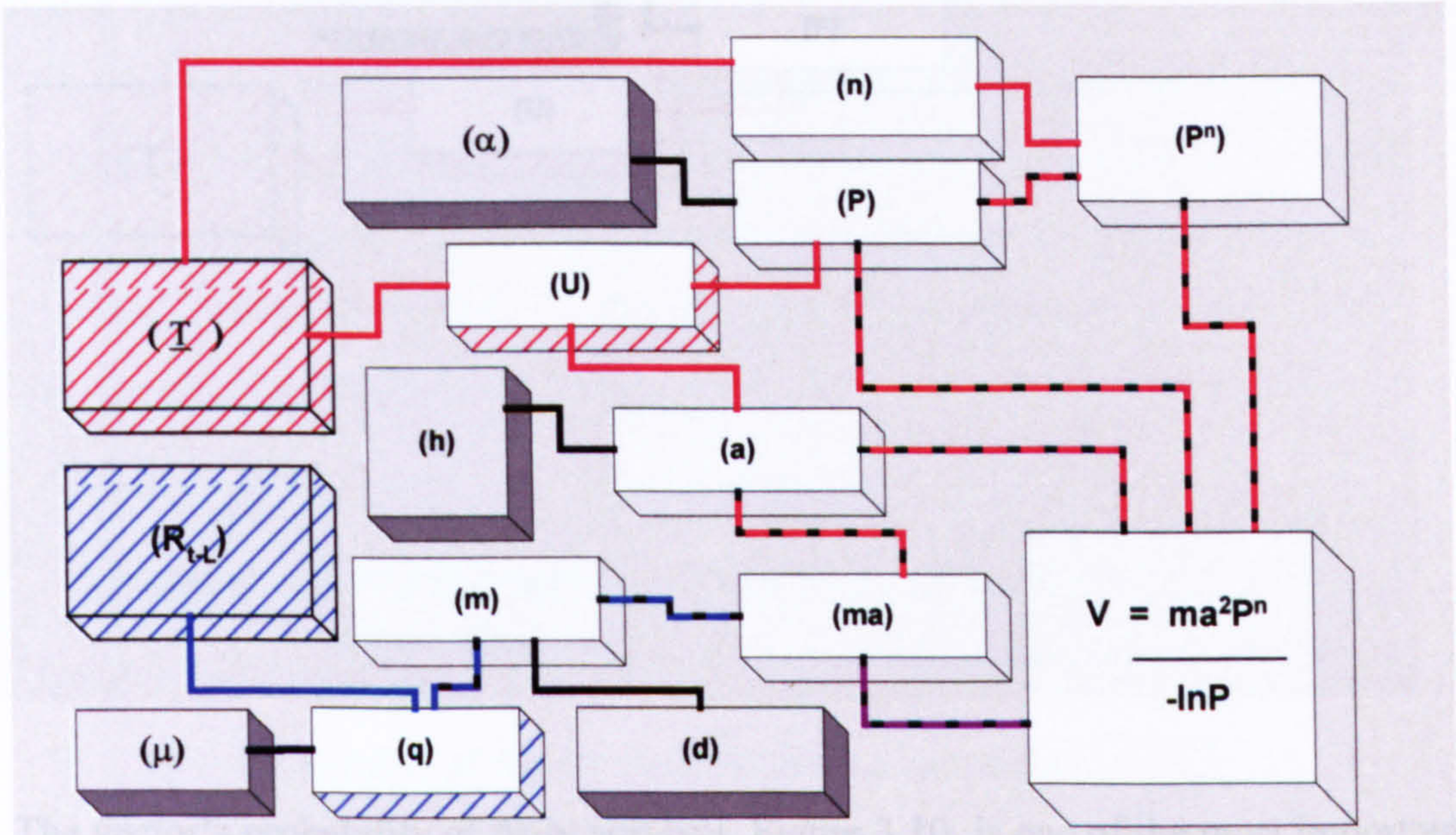


Legend: The coloured lines illustrate the direct and indirect nature of the relationship between the variables. Red represents the temperature driven relationships, blue represent those affected by rainfall, purple the joint influence. The bicoloured lines represent the dual affects of one of the environmental variables plus one of the parameters where the input value is set at an assumed level (Human blood index, human population, proportion of vector surviving the feeding cycle, production factor relating mosquito numbers to rainfall).

Temperature is known to impact directly on sporogonic cycle length and gonotrophic cycle length (Detinova 1962). Indirectly, temperature has an impact on the probability of daily survival, probability of surviving sporogeny, human biting habit, human biting rate and vectorial capacity. Rainfall has a direct impact on the vector

population through availability of surface water for breeding sites and is indirectly linked with the human/vector ratio, human biting habit and vectorial capacity. If the temperature and rainfall variables used in the model are in the form of continental images, then maps can be produced of vectorial capacity and its components, modelled at a continental Africa scale.

FIGURE 3.9. A MATHEMATICAL REPRESENTATION OF THE 'EXTENDED' VECTORIAL CAPACITY MODEL.



Legend: Here the variables and parameters outlined in Figure 3.8. are represented in the mathematical notation which will be used in the development of the spatial model.

The following methodology describes in detail how the components laid out above, Figure 3.9 are translated into continental maps of relative vectorial capacity through a seven stage process using the Idrisi raster-based GIS software.

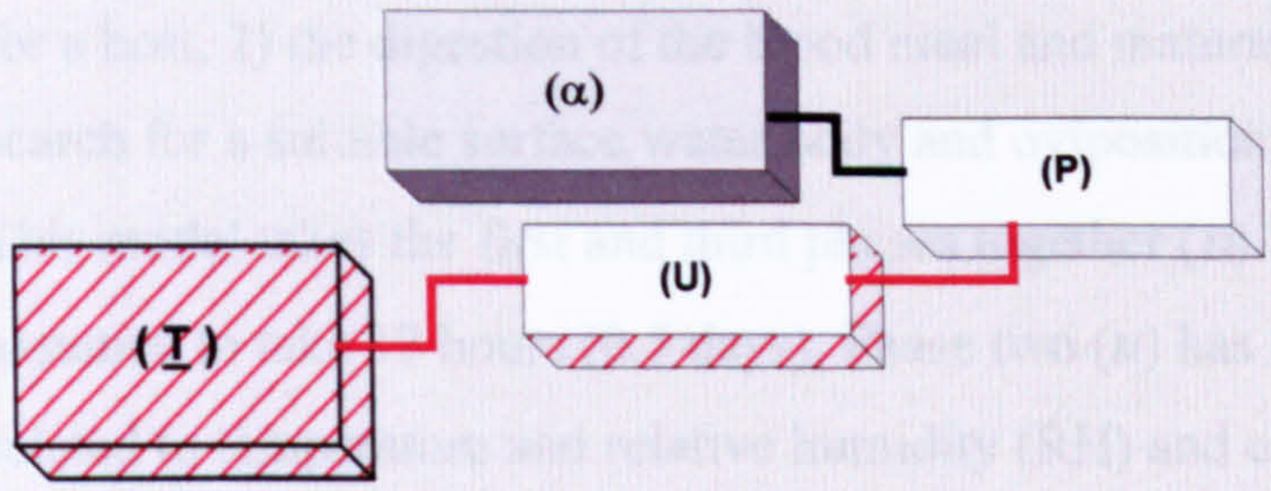
3.4. Materials and methods

The materials used here are the mean climatology derived from the UEA climate surfaces (New and Hulme 1997). It was decided to create and use the mean interpolated rainfall and temperature surfaces for the period 1965-1995.

3.4.1. Stage 1 – probability of daily survival

The first stage is to derive the probability of daily survival $\boldsymbol{P}$.

FIGURE 3.10. RELATIONSHIP BETWEEN TEMPERATURE AND PROBABILITY OF DAILY VECTOR SURVIVAL



The vector's probability of daily survival, Figure 3.10, is one of the most important variables in malaria transmission, as it determines the longevity of individual mosquitoes. Since the vector must live longer than the parasite's extrinsic incubation period (sporogeny) it is only the older mosquitoes in the population which have the potential to transmit malaria.

The probability of daily survival has been modelled by Lindsay and Birley (Lindsay and Birley 1996) and Martens (Martens 1997). The former is used here.

$$\boldsymbol{P} = \alpha^{1/U}$$

where:

α is the proportion of vectors surviving each feeding/gonotrophic cycle

$\boldsymbol{U}$ is the gonotrophic cycle length.

The model assumes that the mosquito's probability of survival decreases as temperature increases and the feeding cycle length decreases. The survival rate per cycle α is assumed to be constant and independent of cycle length. The α value of 0.5 used here represents the middle of its usual range 0.4-0.6 (Hii, Birley et al 1990).

The gonotrophic cycle length is influenced by both temperature and humidity. Beklemishev (1940) described three phases of the gonotrophic cycle: 1) the search for a host, 2) the digestion of the blood meal and maturation of the ovaries, and 3) the search for a suitable surface water body and oviposition; cited by (Detinova 1962). This model takes the first and third phases together (υ). Phases one and three are assumed to take 12 hours (0.5 days). Phase two (u) has been shown to be directly related to temperature and relative humidity (RH) and can be derived from the formulas given by Detinova[8]. For the purposes of this model the middle range formula associated with RH of between 70%-80% are used (Detinova 1962).

$$\text{Gonotrophic cycle length } U = \upsilon + (u = f_U / T - g_U)$$

where:

f_U = the number of degree days needed for maturation = 36.5,

T = ambient temperature °C,

g_U = threshold beneath which development ceases = minus 9.9

$\underline{T}$ is modified to reflect the difference between internal and external phases of the cycle. In this model the mean diurnal temperature image [$\underline{T}$] for a given month (1955-95) is raised by 2°C for the internal phase (u) to give [T].

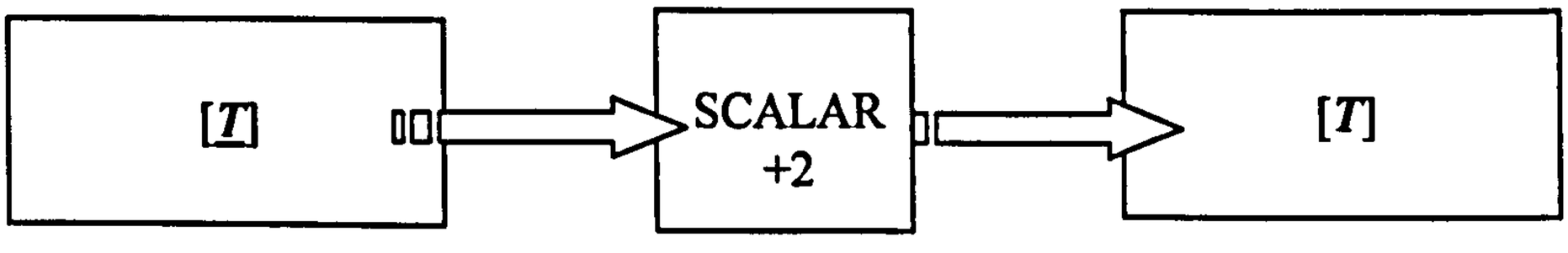
The following products were produced using map algebra techniques (Eastman 1993). While Idrisi has a MAP CALCULATOR function that can handle complex mathematical procedures, this was not used here, as it does not facilitate the batch processing required. Instead, individual modules were used in combination using

---

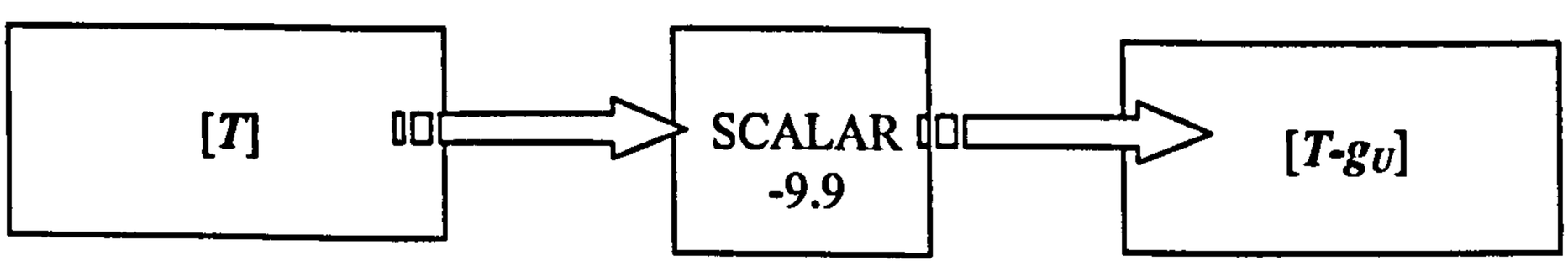
[8] Detinova's formulas relate to studies of *A. maculipennis*. Comparable values for *A. gambiae* are not available. While the relationship between temperature and gonotrophy are unlikely to be the same between a temperate and a tropical mosquito it is assumed that the shape of the relationship will be similar.

branched macros. Some of the Idrisi modules cause floating point errors. In order to overcome this, intermediary images require multiplying up by a factor of a hundred or a thousand, and then dividing by the same amount after the operation has been carried out. Re-scaling of products so that background values (the seamask) do not over-stretch the 0-255 value colour palettes used by Idrisi is also required in some instances. For clarity, these steps are not included here.

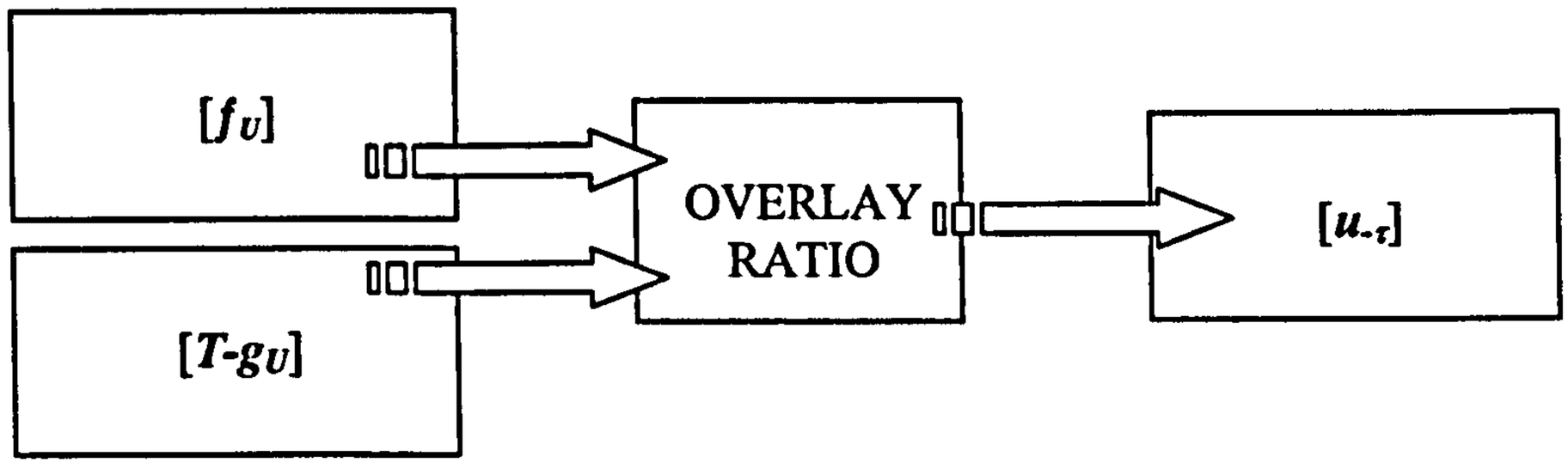
Using Idrisi's SCALAR module, 2°C is added to a mean diurnal temperature image [$\underline{T}$] for a given month. The product is [T]. This is represented using the following cartographic modelling method (Eastman 1993).



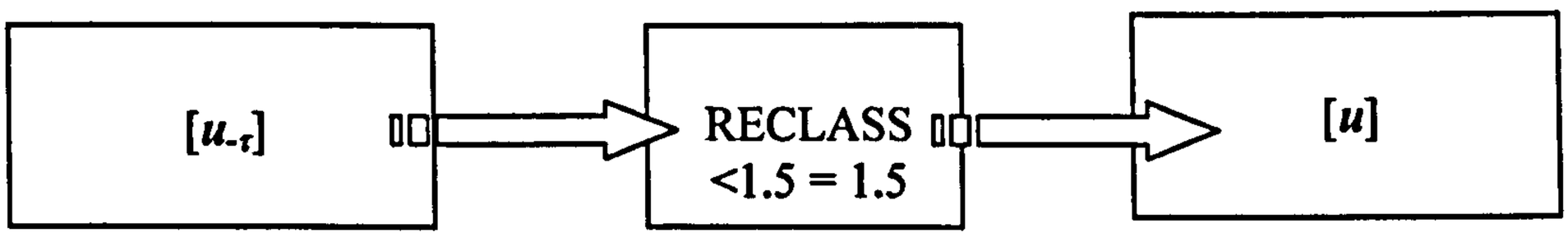
SCALAR is then used to subtract 9.9 from [T]. The result being [T-gv].



Idrisi's INITIAL module is used to create an image with a uniform value of f_V [36.5]. The OVERLAY module is then used to divide [f_V] by [g_V] to produce [u_{-T}].

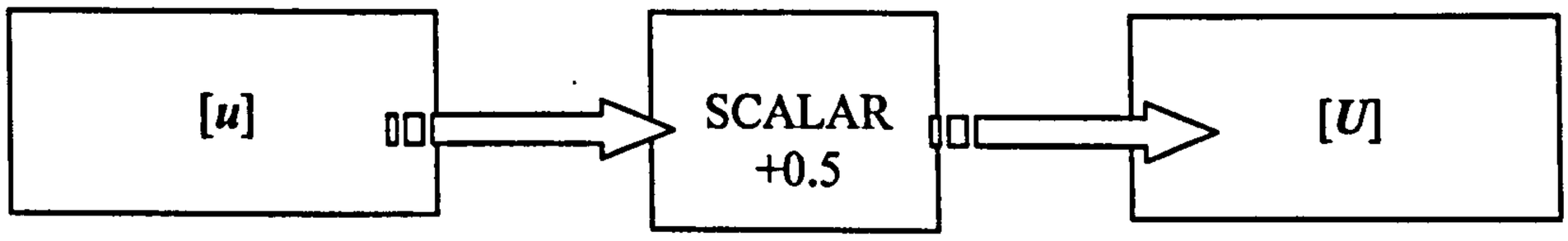


A review of published data on gonotrophic cycle length for *A. gambiae s.l.* quoted figures of between 2 and 3.8 days (Thomson, Savage et al. in press). The gonotrophic cycle length is unlikely, anywhere, to be less than two days as the high average temperatures required to achieve this would occur in an environment unsuitable for malaria transmission. In order to prevent this occurring here Idrisi's RECLASS module is used to remove the impact of high temperatures giving a [*u*] value less than 1.5 (which would, when added to [υ] the half day for phases 1 and 3, produce less than the minimum [*U*] of two days).



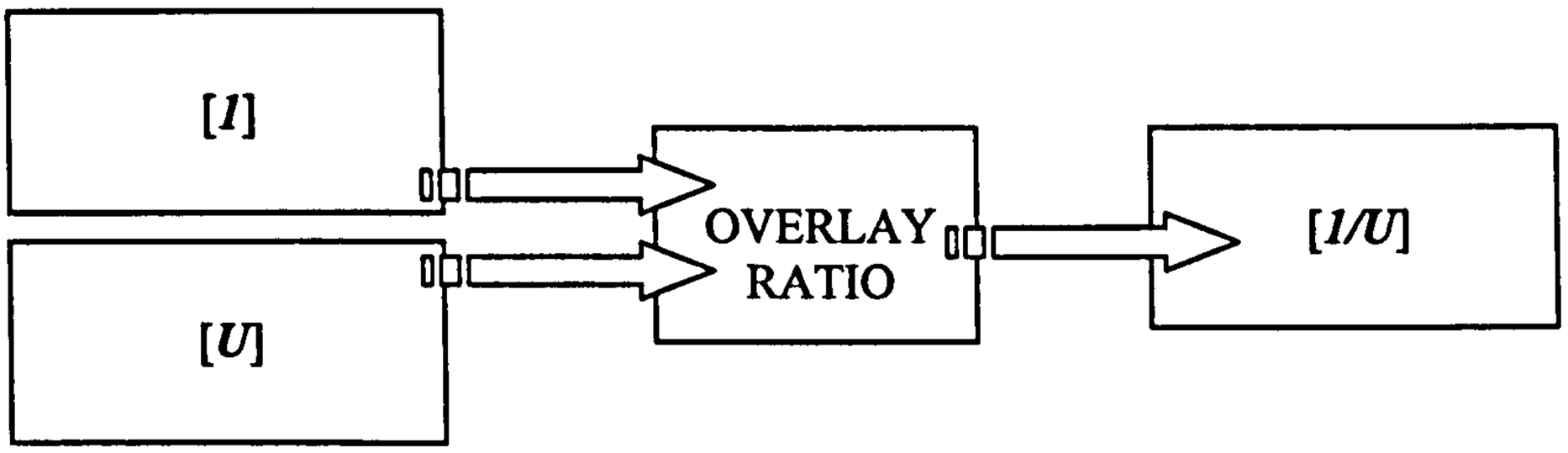
INITIAL is used to produce an image of υ with a value of [0.5].

SCALAR is then used to add υ [0.5] to [*u*]. The product is [*U*] the gonotrophic cycle length.

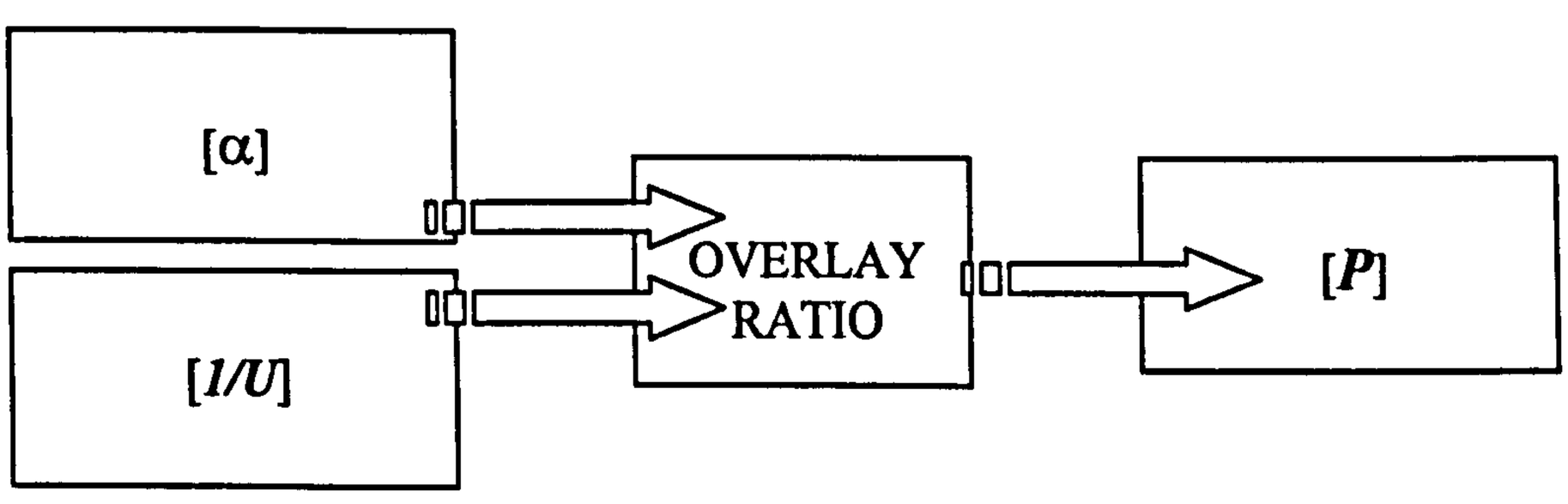


INITIAL is used to create an image with a value of one [*I*].

The OVERLAY module is then used to produce the reciprocal of [*U*].



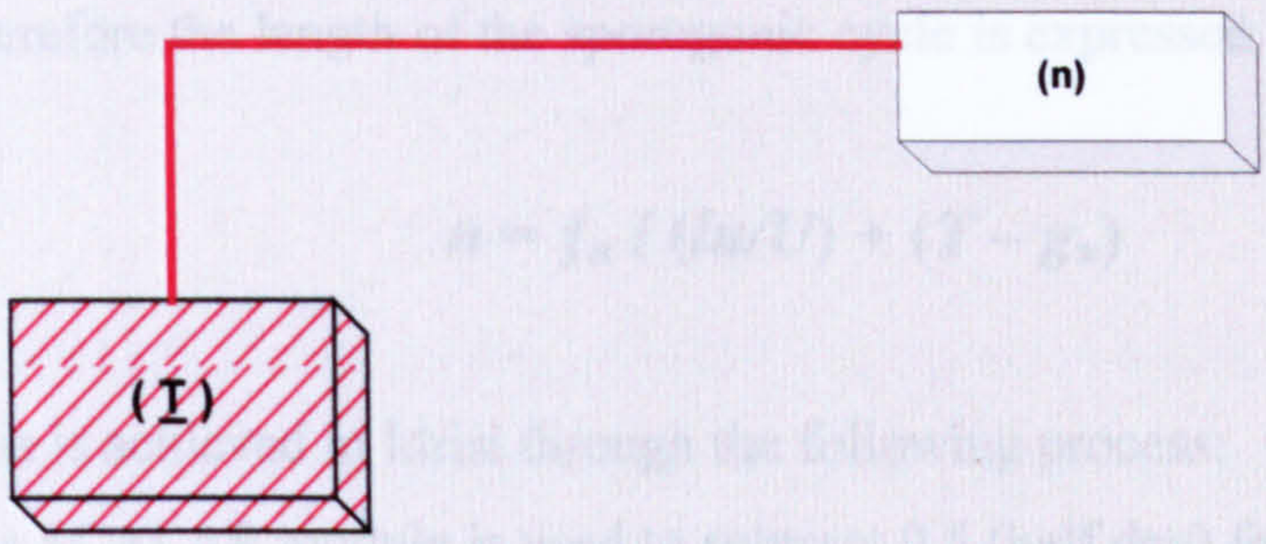
OVERLAY is used again to raise α (the proportion of vectors surviving the feeding cycle - given here as 0.5) to the reciprocal of *U* to give *P* the probability of daily survival.



3.4.2. Stage 2 –the sporogonic cycle length

The second stage is to derive the sporogonic cycle length (Figure 3.11.).

FIGURE 3.11. RELATIONSHIP BETWEEN TEMPERATURE AND SPOROGONIC CYCLE LENGTH.



The period of time between an infected blood meal being ingested by the mosquito and the time when sporozoites appear in its salivary glands is known as the extrinsic incubation period, or sporogonic cycle length. This process is also highly temperature dependent with an inverse relationship. It is expressed by Detinova as:

$$n = f_n / (T - g_n)$$

where:

f_n is the number of degree days required for parasite development

g_n is the threshold below which parasite development ceases.

Here 111°C (degree days: *P. falciparum*) is used for f_n and 18°C taken as the adjusted minimum temperature threshold for *P. falciparum*, as stated by Detinova (Detinova 1962). Temperature is adjusted through a weighting method based on the time the mosquito is estimated to be inside a house (phase 2, u of the gonotrophic

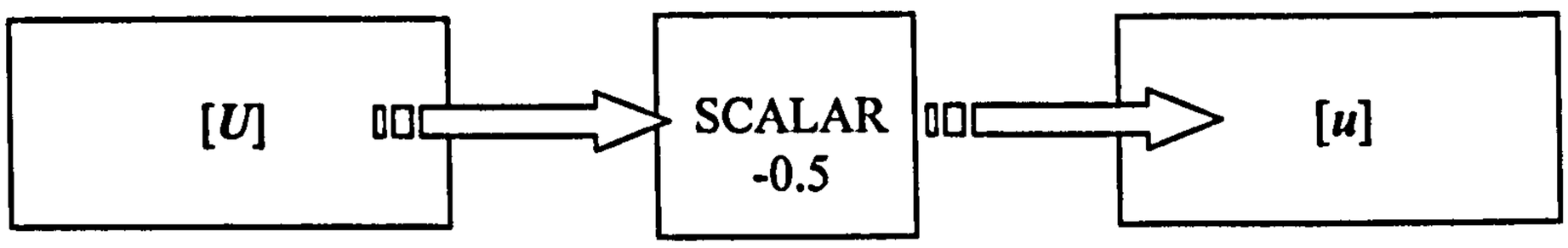
cycle) as a proportion of the total gonotrophic cycle length (*U*). The temperature correction factor is calculated (*u/U*) and multiplied by a user defined correction factor *l* (which represents the difference between the indoor and outdoor temperature) to produce a weighted correction factor. This is added to *T* to give the temperature governing the sporogonic cycle.

Therefore the length of the sporogonic cycle is expressed as:

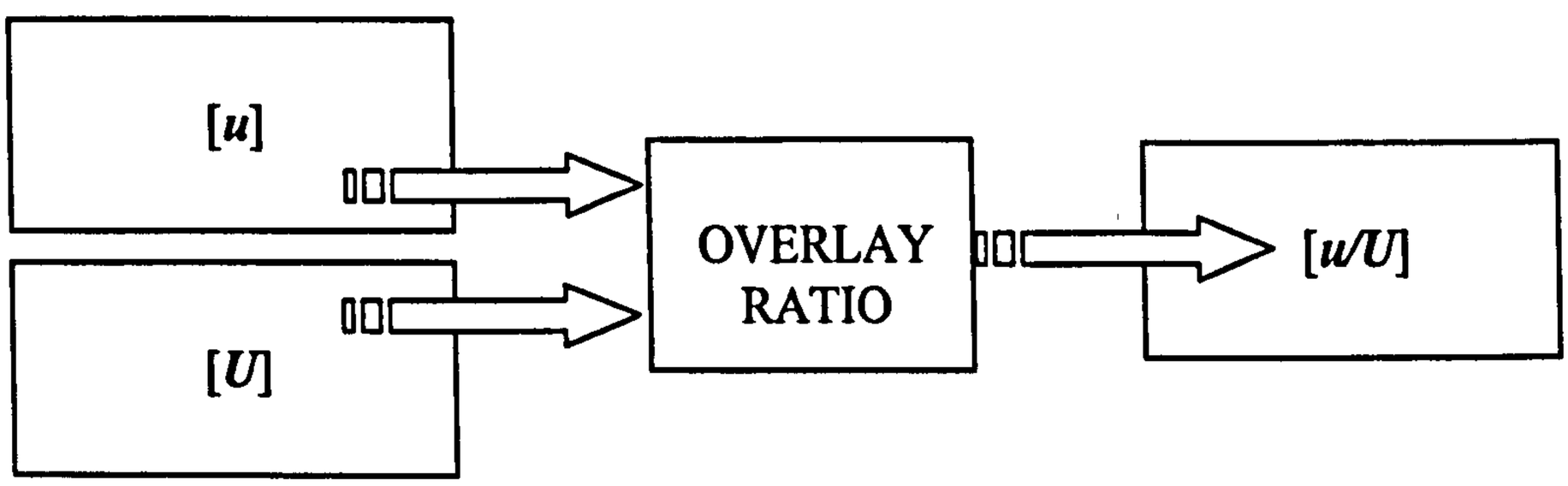
$$n = f_n / (lu/U) + (T - g_n)$$

This is achieved in Idrisi through the following process:

The SCALAR module is used to subtract 0.5 (half day) from *U* to recreate *u* [9]

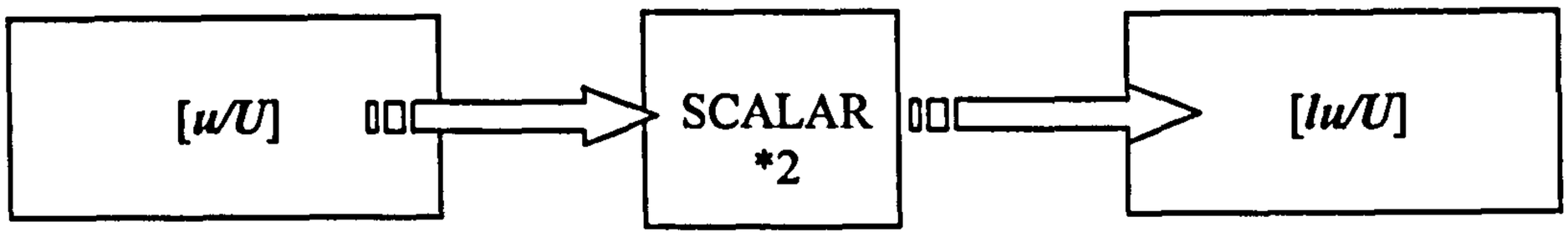


OVERLAY is then used to obtain the ratio of [*u*] / [*U*] the proportion of time spent indoors.

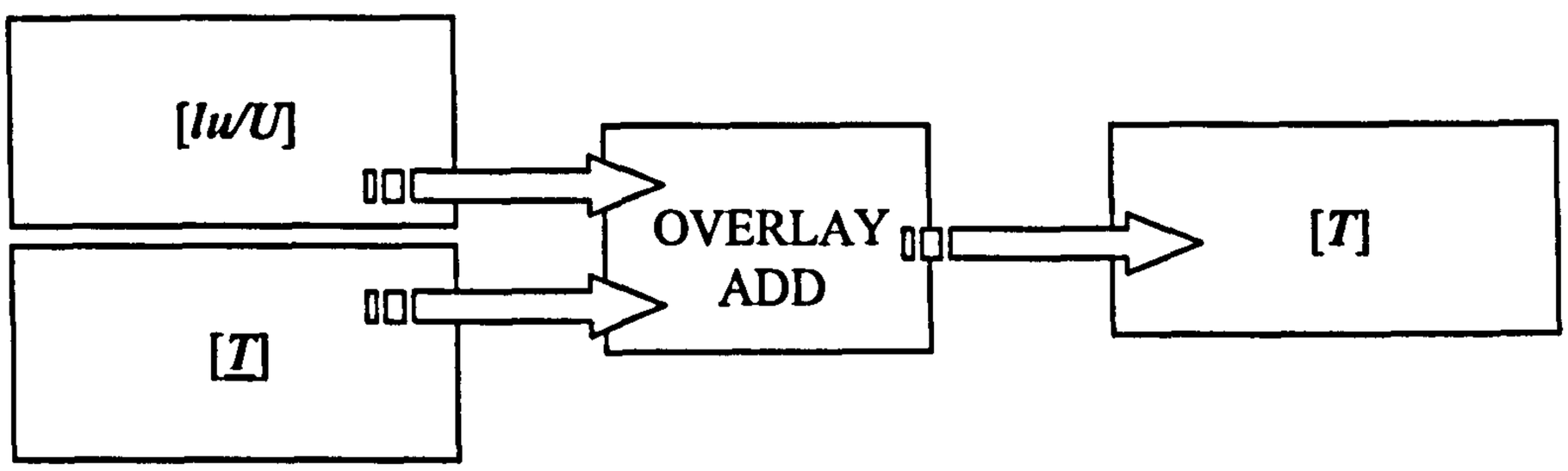


[9] The macros used in Idrisi produce a large number of temporary input and output files which were automatically deleted during the previous branch of the process. Therefore, it is necessary to recreate the monthly value images for Phase 2 (*u*) here.

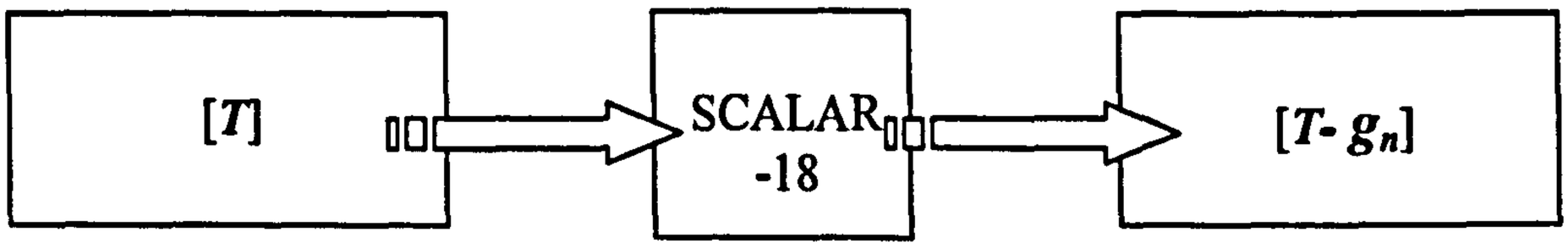
SCALAR is used to multiply the product above by 2°C to take into account the higher temperatures acting on the proportion of time spent indoors.



OVERLAY is then used to add [*Iu/U*] to the mean diurnal temperature image [$\underline{T}$] to produce [*T*] the temperature governing the sporogonic cycle.

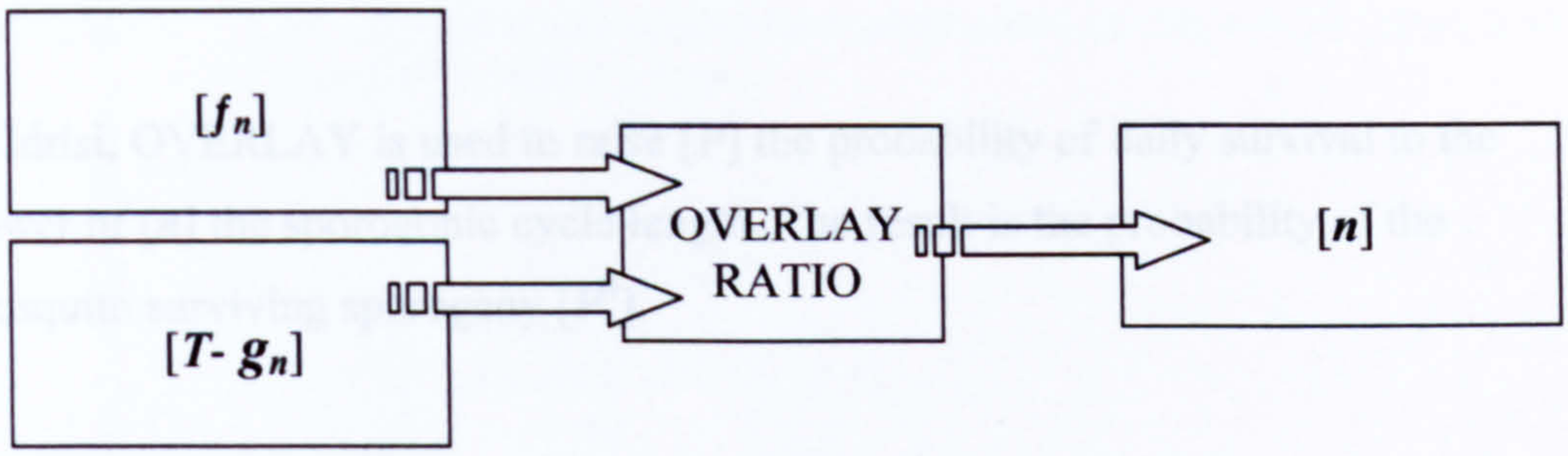


SCALAR is then used to subtract g_n (18°C) from [*T*] the product being [$T - g_n$]



INITIAL is used to create an uniform image with a value of 111 (degree days) the product of this is [f_n]

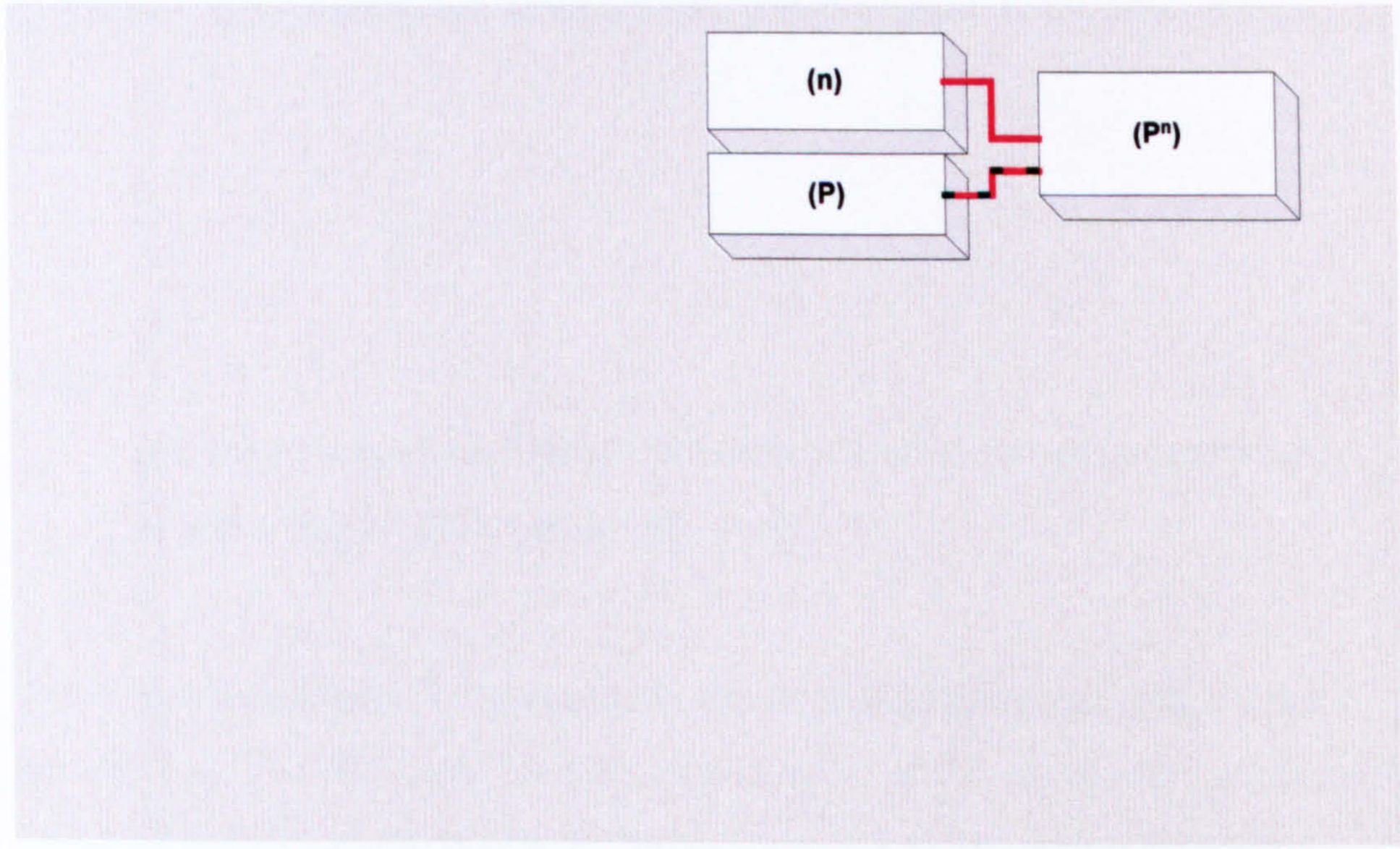
OVERLAY is then used to divide [f_n] by [T- g_n] the product of this is [n] the sporogonic cycle length.



3.4.3. Stage 3 – probability of surviving sporogeny

The third stage is to derive the probability of the vector surviving sporogeny (Figure 3.12).

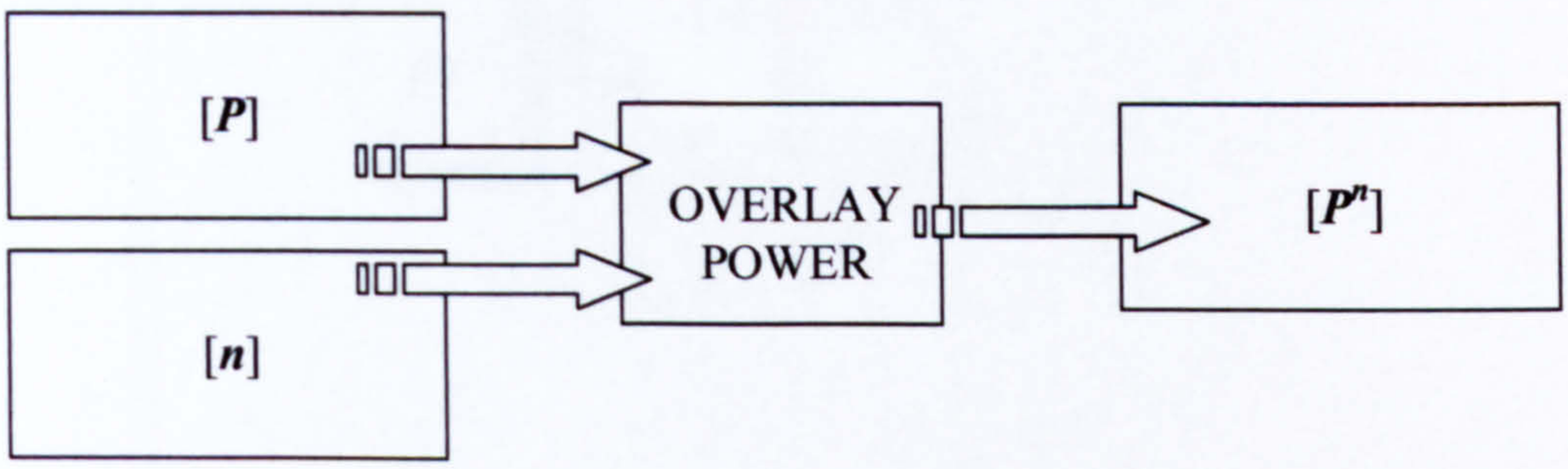
FIGURE 3.12. THE INDIRECT RELATIONSHIP BETWEEN TEMPERATURE AND PROBABILITY OF SURVIVING SPOROGENY.



To determine the probability of the mosquito surviving long enough to complete sporogeny, the probability of daily survival ***P*** is raised to the power of the sporogonic cycle length ***n*** :

$$P^n$$

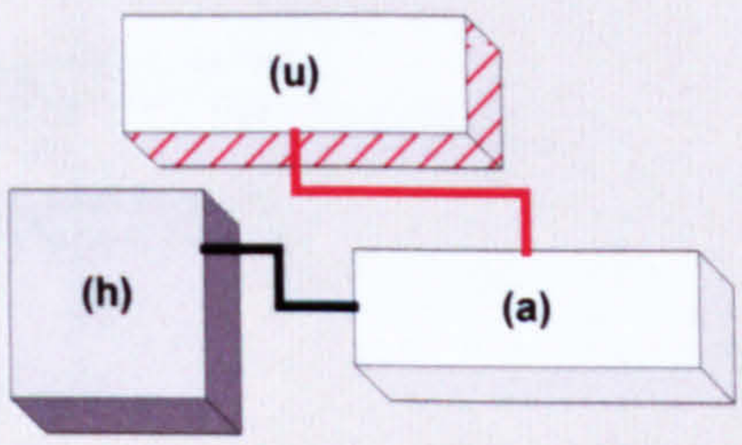
In Idrisi, OVERLAY is used to raise [***P***] the probability of daily survival to the power of [***n***] the sporogonic cycle length. The result is the probability of the mosquito surviving sporogeny [P^n].



3.4.4. Stage 4 – human biting habit

The fourth stage is to derive the human biting habit (Figure 3.13).

FIGURE 3.13. THE INDIRECT RELATIONSHIP OF TEMPERATURE TO THE HUMAN BITING HABIT COMPONENT OF THE MODEL.



The human biting habit (***a***) represents the frequency of mosquito blood meals taken on humans as opposed to any other animal. It is expressed by the relationship:

$$a = h/U$$

where:

h is the human blood index (proportion of human blood fed mosquitoes)

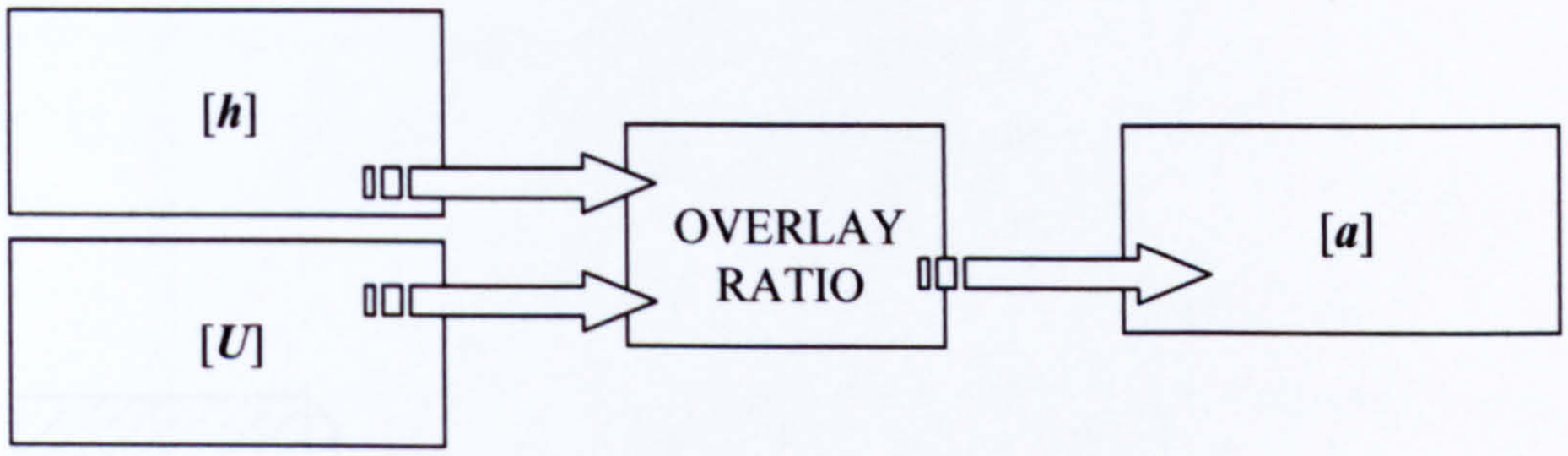
U is the length of the gonotrophic cycle.

The human blood index is a measurable entomological parameter with a value between 0-1. The HBI value here is assumed as 0.7 as this represents a mean value found for indoor resting *Anopheles gambiae s.s.* in a recent review (Thomson, Savage et al. in press).

The human biting habit is achieved here in Idrisi using the following method:

INITIAL is used to create a uniform image with a value of 0.7 [***h***]

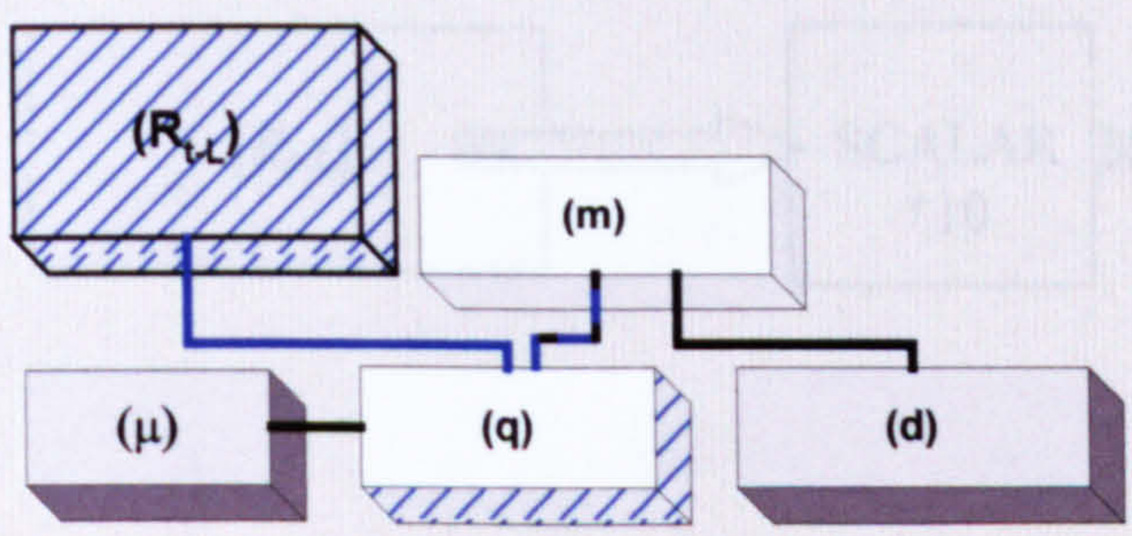
OVERLAY is then used to divide [***h***] by [***U***] the result is the human biting habit [***a***].



3.4.5. Stage 5 – the ratio of mosquitoes to humans

The fifth stage is to establish the ratio of mosquitoes to humans (Figure 3.14).

FIGURE 3.14. RELATIONSHIP BETWEEN RAINFALL AND THE RATIO OF MOSQUITOES TO HUMANS.



The ratio of mosquitoes to humans m is expressed:

$$m = q/d$$

where:

q is the mosquito population

d is the human population.

The mosquito population is assumed here to be a linear function of rainfall R_{t-L} recorded at time $t-L$ where t is the present day and L is the lag between rainfall and its impact on the mosquito population. The average rainfall is multiplied by a constant μ to give the number of mosquitoes resulting from that rainfall.

$$q = \mu R_{t-L}$$

The value of μ was chosen as 10 (i.e. 10 mosquitoes, per person, per mm rainfall, per day) to allow a reasonable biting rate to occur[10]. The human population ***d*** is assumed to remain constant and is set here to an arbitrary figure of 100,000.

m is produced here simply by the following process:

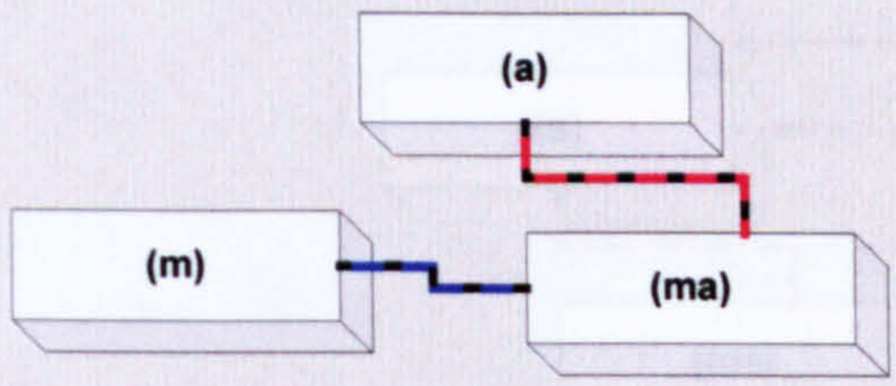
SCALAR is used to multiply average rainfall [R_{t-L}] by μ to produce ***m*** .

[10] While the relationship between rainfall and mosquito numbers can be shown to approximate a linear relationship in some studies: Fontenille, D., L. Lochouarn, N. Diagne, C. Sokhna, J. J. Lemasson, M. Diatta, L. Konate, F. Faye, C. Rogier and J. F. Trape (1997). "High annual and seasonal variations in malaria transmission by anophelines and vector species composition in Dielmo, a holoendemic area in Senegal." American Journal Of Tropical Medicine And Hygiene **56**(3): 247-53. Krafsur, E. S. and J. C. Armstrong (1978). "An integrated view of entomological and parasitological observations on falciparum malaria in Gambela, Western Ethiopian Lowlands." Transactions of the Royal Society of Tropical Medicine & Hygiene **72**(4): 348-356.; this will not always be the case as local soils, slope, land use and hydrology will undoubtedly play a significant role. Extreme rainfall events may also wash away breeding sites.

3.4.6. Stage 6 – human biting rate

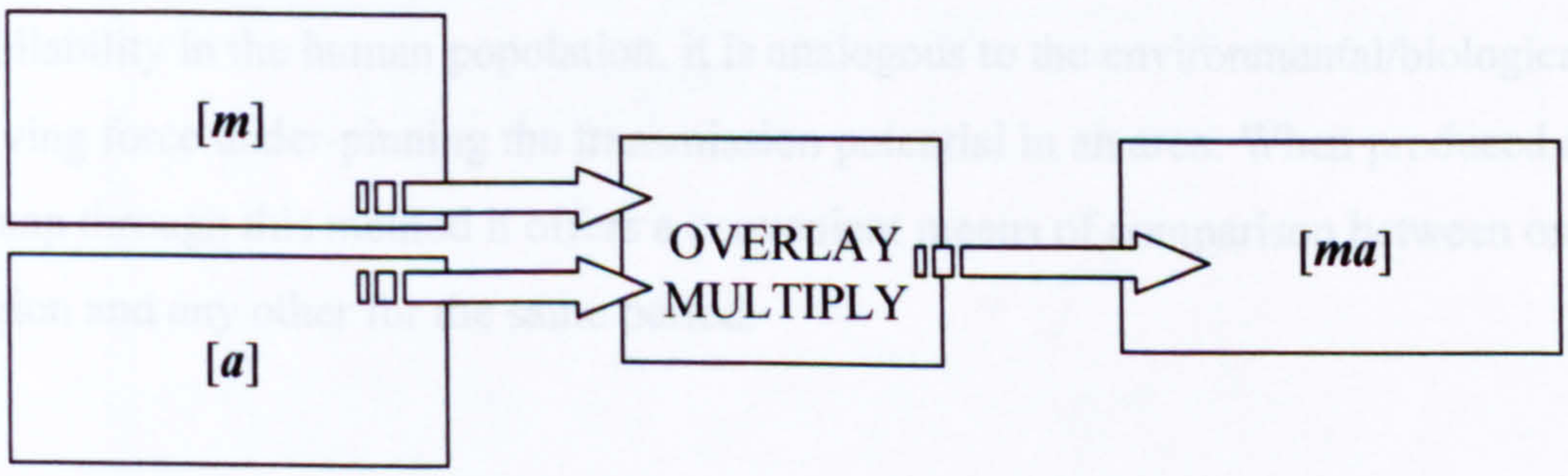
The sixth stage is to determine the human biting rate (Figure 3.15).

FIGURE 3.15. THE INDIRECT RELATIONSHIP BETWEEN RAINFALL AND TEMPERATURE ON THE HUMAN BITING RATE COMPONENT OF THE MODEL.



The human biting rate ***ma*** is the composite entomological measure of the number of bites received per person per night, and is produced here using the following method:

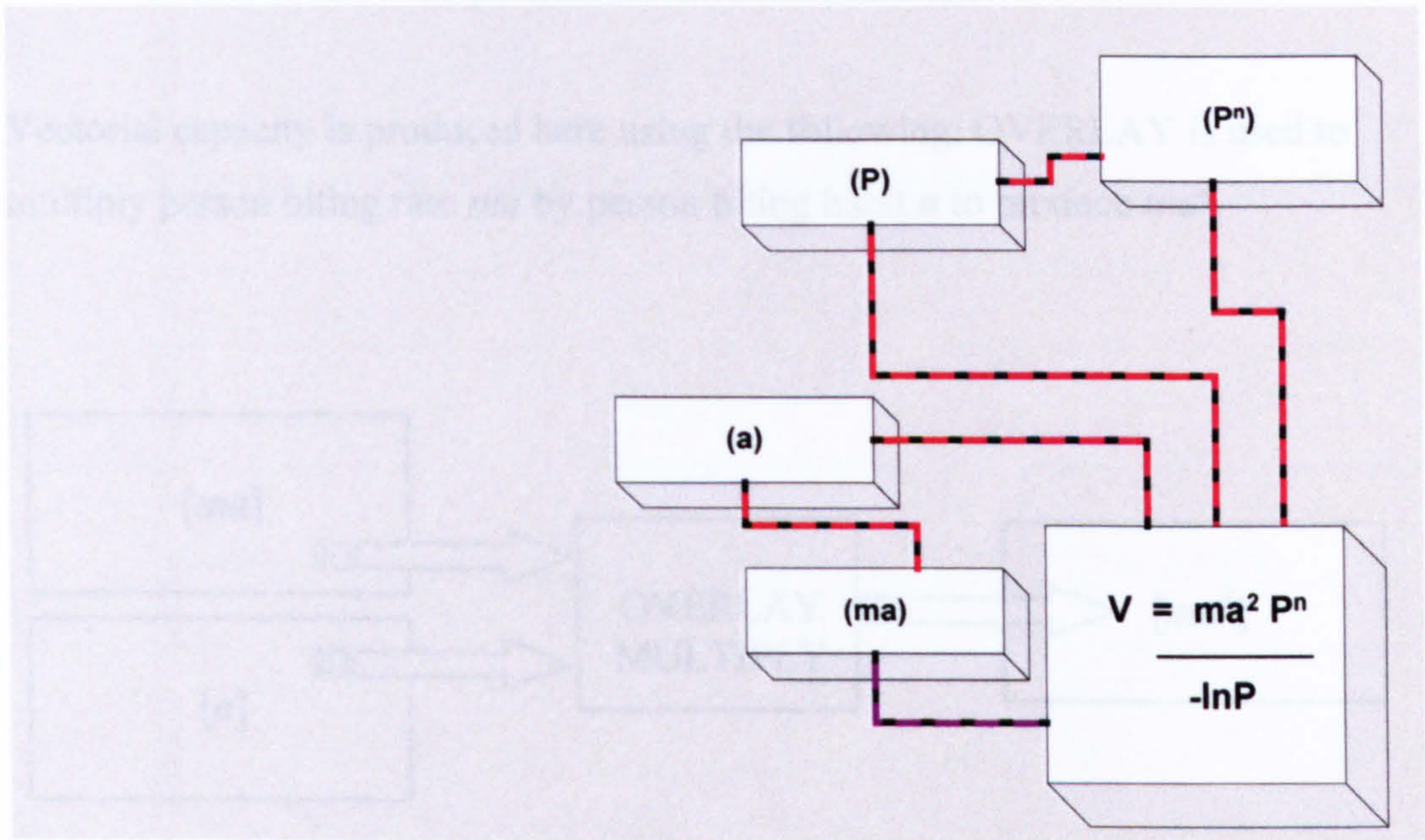
OVERLAY is used to multiply ***m*** (the mosquito/human ratio) by ***a*** (the human biting habit) the product is the human biting rate ***ma***.



3.4.7. Stage 7 – vectorial capacity

The seventh stage produces the vectorial capacity images (Figure 3.16).

FIGURE 3.16 INDIRECT RELATIONSHIPS BETWEEN RAINFALL, TEMPERATURE AND VECTORIAL CAPACITY



This final stage produces the mean diurnal Vectorial Capacity images for the African continent, per month.

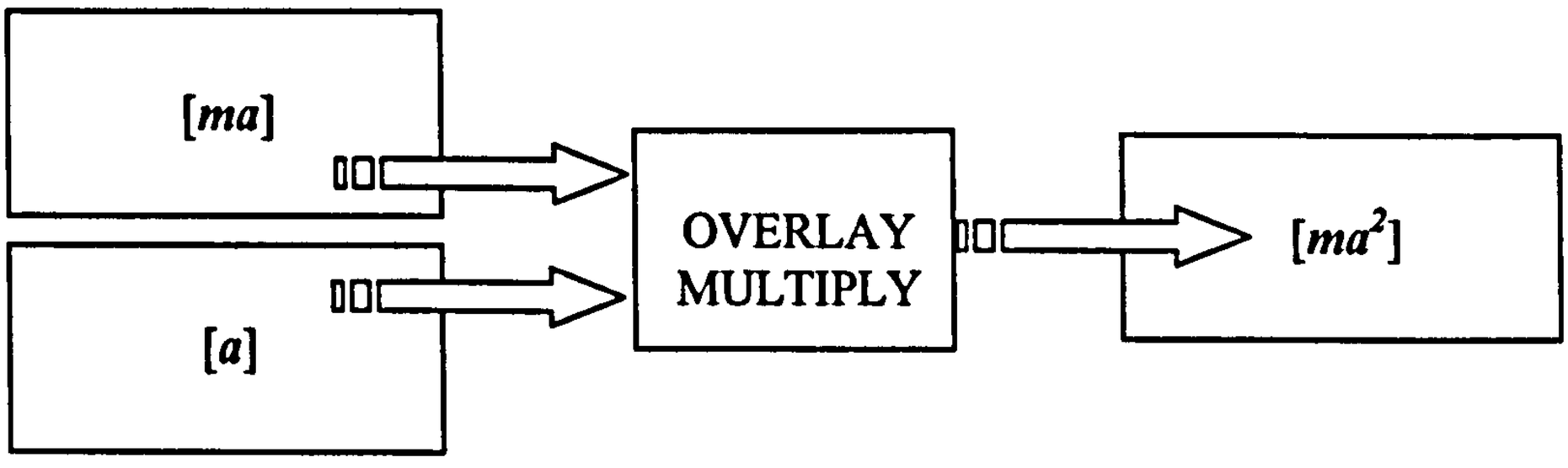
To reiterate: Vectorial capacity V is the daily rate at which future inoculations could arise from a currently infected case (Dye 1992) and is described as a convenient way of expressing malaria transmission risk, or the receptivity of an area to malaria [Gillies, 1993 #178]. While vectorial capacity takes no account of parasite availability in the human population, it is analogous to the environmental/biological driving force under-pinning the transmission potential in an area. When produced as a map through this method it offers a convenient means of comparison between one region and any other for the same period.

Vectorial capacity may be expressed:

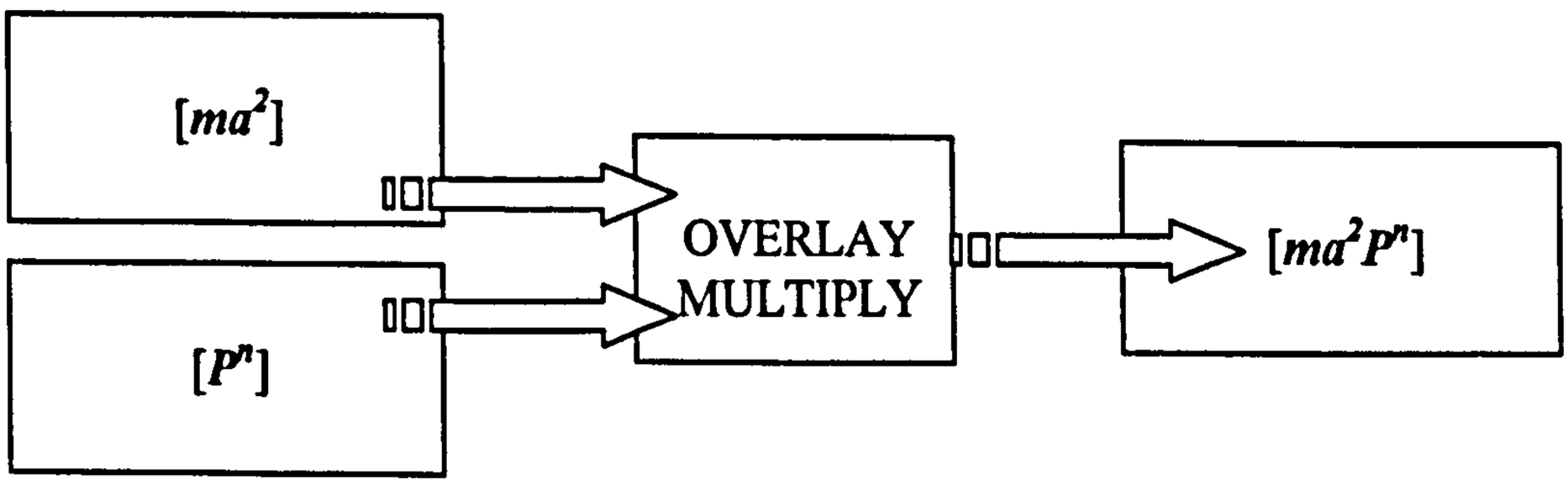
$$V = ma^2P^n/-lnP$$

a is squared as it appears both in human biting habit and again in human biting rate (also reflecting the fact that the mosquito must bite humans twice in order to have the potential to transmit malaria).

Vectorial capacity is produced here using the following: OVERLAY is used to multiply person biting rate *ma* by person biting habit *a* to produce ma^2.

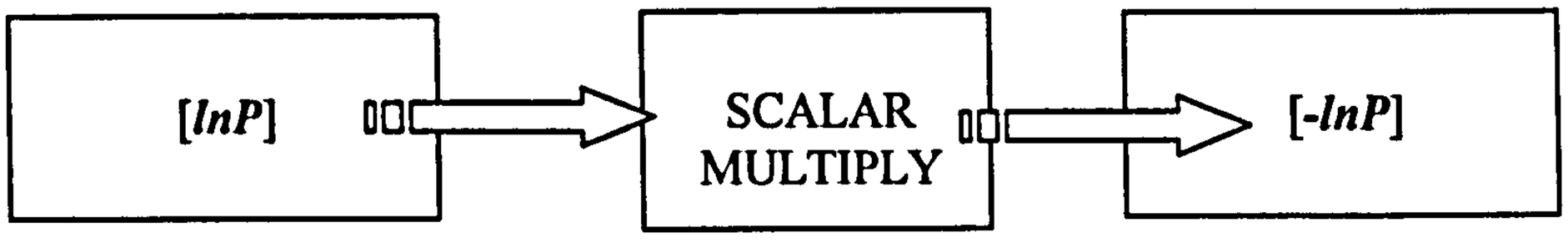


and again to multiply ma^2 by the probability of surviving sporogeny P^n

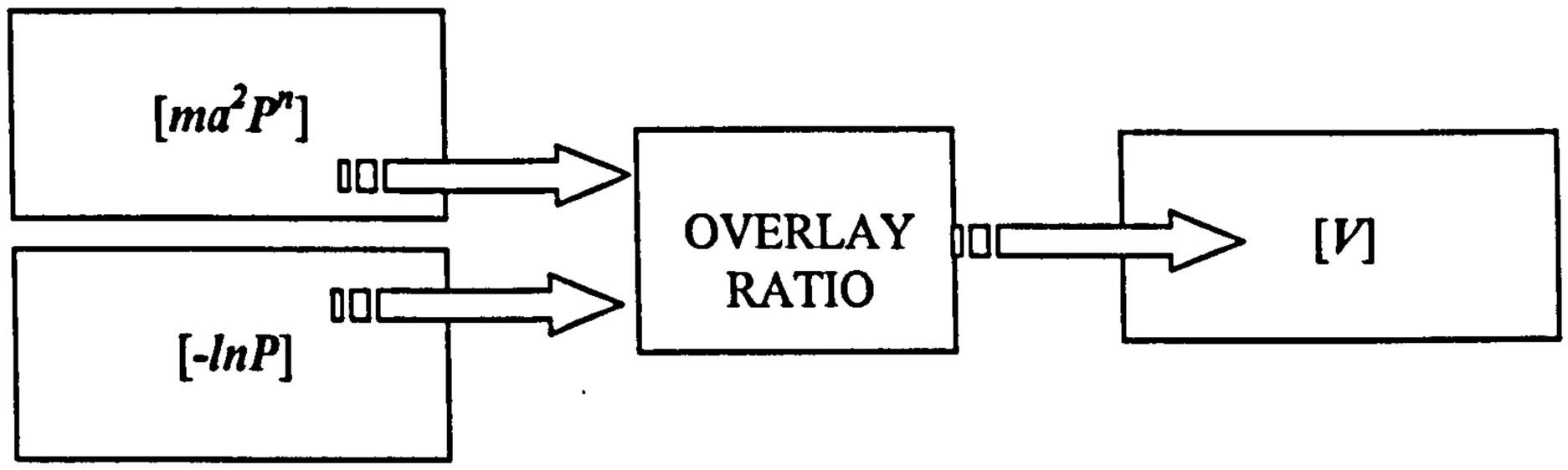


TRANSFOR is then used to obtain the log of *P*

SCALAR is then used to multiply *lnP* by –1 to derive the negative log. And finally



OVERLAY is used to divide ma^2P^n by $-lnP$ to produce V.



The continental images (maps) of vectorial capacity can then be displayed in Idrisi using the DISPLAY module.

3.5. Results

3.5.1. Rainfall estimates

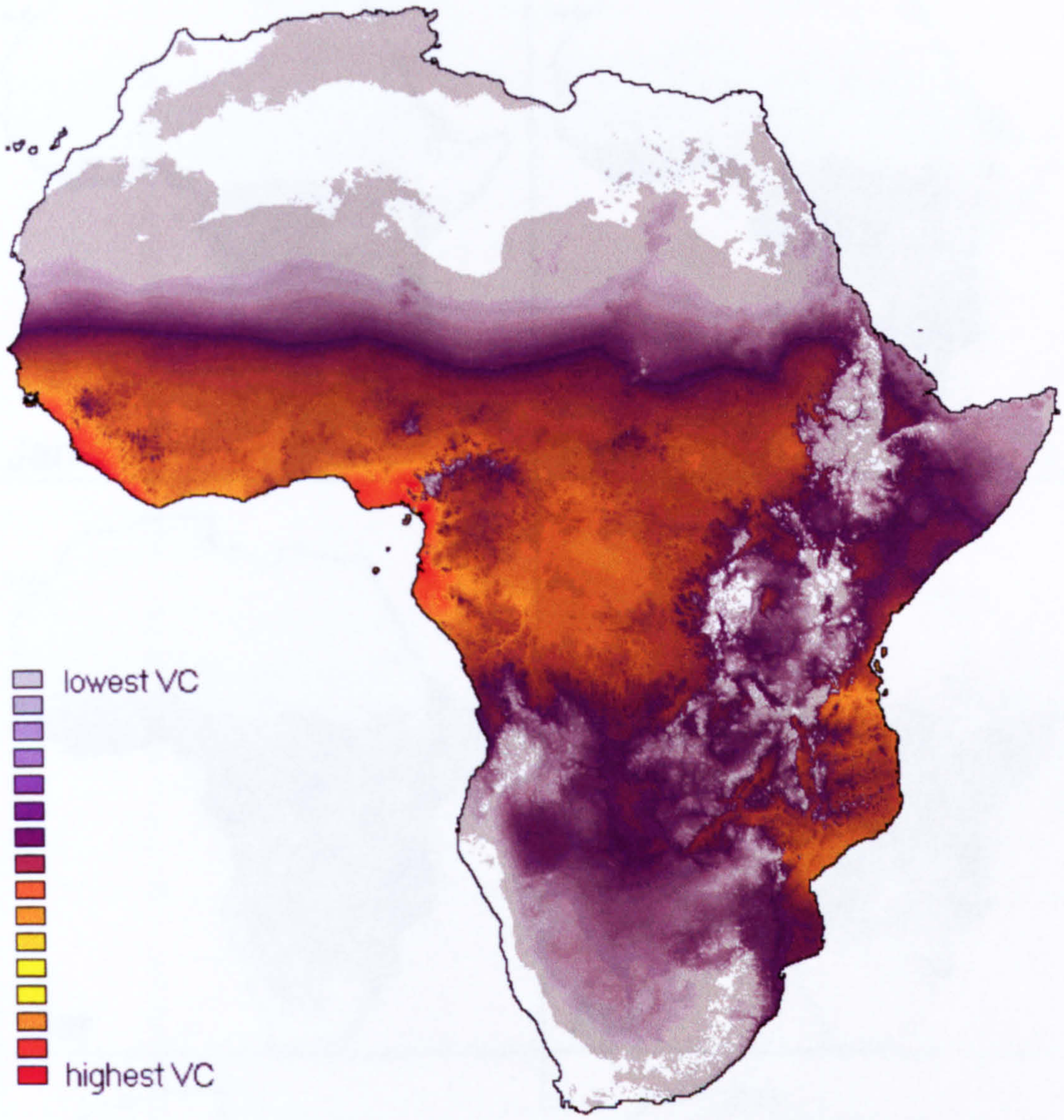
In certain regions satellite derived rainfall estimate images may provide a useful, easy to monitor indicator of changes in epidemic potential. In desert-fringe locations where temperature is not a limiting factor in transmission potential, these may be processed to assess the changes occurring in the current malaria season compared with recent experience. However, rainfall alone is not the only environmental factor influencing changes in transmission potential. Temperature too is very important in some regions. It is therefore important to explore the interplay between these two components in a malaria transmission model, such as vectorial capacity, and map these dynamics accordingly.

3.5.2. Vectorial capacity

The resulting annual average vectorial capacity map for continental Africa is shown in Figure 3.17. The annual map of Vectorial Capacity represents a further method of using climate to map differences in malaria endemicity. The monthly images show the seasonal dynamics that occur in this indicator across the continent in an average year. The monthly average vectorial capacity maps for the African continent are illustrated in figures 3.18. and 3.19.

The Vectorial Capacity maps produced above are based on long-term monthly rainfall and temperature averages. However, by replacing the long-term average rainfall input into the model with the routinely available satellite derived rainfall estimates it is possible to monitor changes in vectorial capacity in epidemic prone areas in near real-time. At present there are no routinely available images which could replace the temperature input in the same way. While there is evidence of increasing temperatures across the African continent associated with global warming (Watson, Zinyowera et al. 1998) the inter annual variability in temperature is much less pronounced than that of rainfall. There is therefore an argument for using the estimated monthly rainfall inputs along with the average temperatures as an indicator of deviations from the normal in epidemic prone regions. Hopefully, satellite

FIGURE 3.17. AN AVERAGE ANNUAL VECTORIAL CAPACITY MAP FOR AFRICA (1951-1995).



Legend:

Vectorial capacity is mapped here as a relative indicator of environmentally induced transmission pressure across the Africa continent in an average year. The colour palette used in the legend represents a relative scale of vectorial capacity from lowest to highest.

FIGURE 3.18. MEAN MONTHLY VECTORIAL CAPACITY PRODUCTS JANUARY-JUNE.

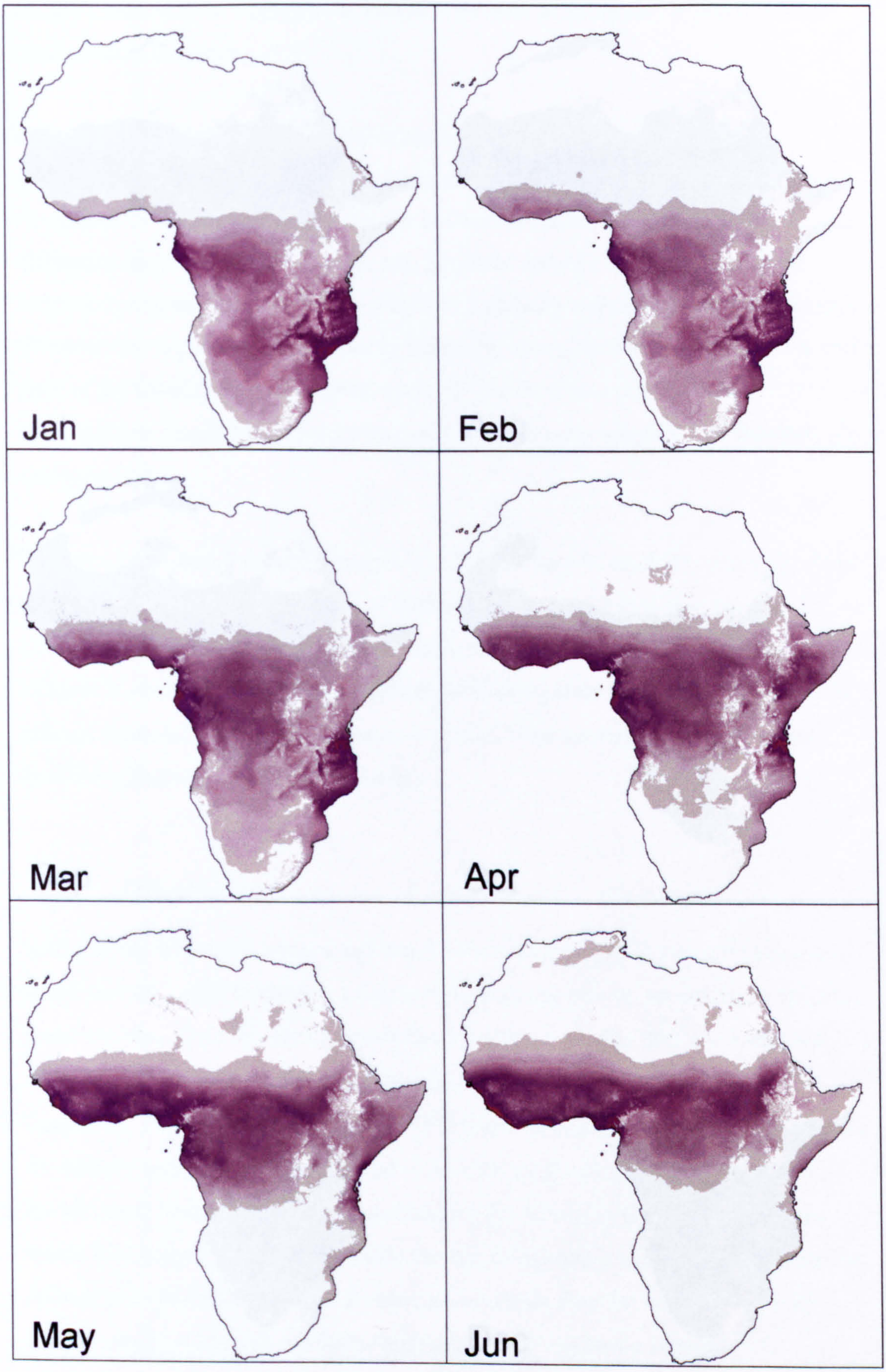
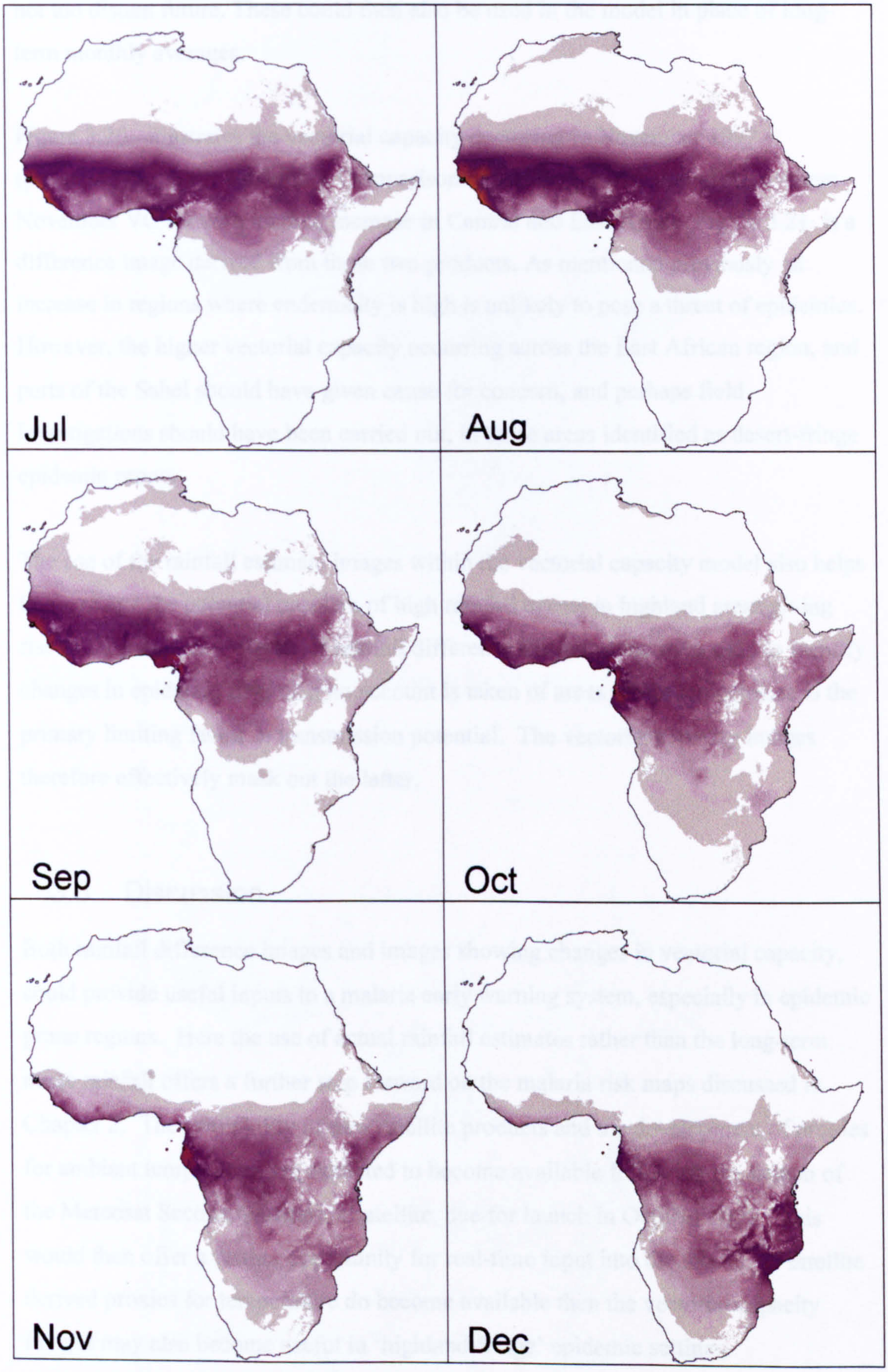


FIGURE 3.19. MEAN MONTHLY VECTORIAL CAPACITY PRODUCTS JULY-DECEMBER.



derived estimates of ambient temperatures may become operationally available in the not too distant future. These could then also be used in the model in place of long-term monthly averages.

Figure 3.20. illustrates the vectorial capacity occurring in November 1997 (preceding the Wajir epidemic). Comparison of this image with that of the average November VC shows a marked increase in Central and East Africa. Figure 3.21. is a difference image derived from these two products. As mentioned previously an increase in regions where endemicity is high is unlikely to pose a threat of epidemics. However, the higher vectorial capacity occurring across the East African region, and parts of the Sahel should have given cause for concern, and perhaps field investigations should have been carried out, in those areas identified as desert-fringe epidemic prone.

The use of the rainfall estimate images within the vectorial capacity model also helps to overcome the potential problem of high rainfall events in highland areas giving rise to false epidemic alerts. If rainfall difference images alone were used to identify changes in epidemic risk, then no account is taken of areas where temperature is the primary limiting factor in transmission potential. The vectorial capacity images therefore effectively mask out the latter.

3.6. Discussion

Both rainfall difference images and images showing changes in vectorial capacity, could provide useful inputs to a malaria early warning system, especially in epidemic prone regions. Here the use of actual rainfall estimates rather than the long-term mean rainfall offers a further step forward on the malaria risk maps discussed in Chapter 2. The availability of new satellite products and the development of proxies for ambient temperature are expected to become available following the launch of the Meteosat Second Generation satellite, due for launch in October 2002. This would then offer a further opportunity for real-time input into the model. If satellite derived proxies for temperature do become available then the vectorial capacity images may also become useful in 'highland-fringe' epidemic settings.

FIGURE 3.20. VECTORIAL CAPACITY MAP FOR AFRICA NOVEMBER, 1997.

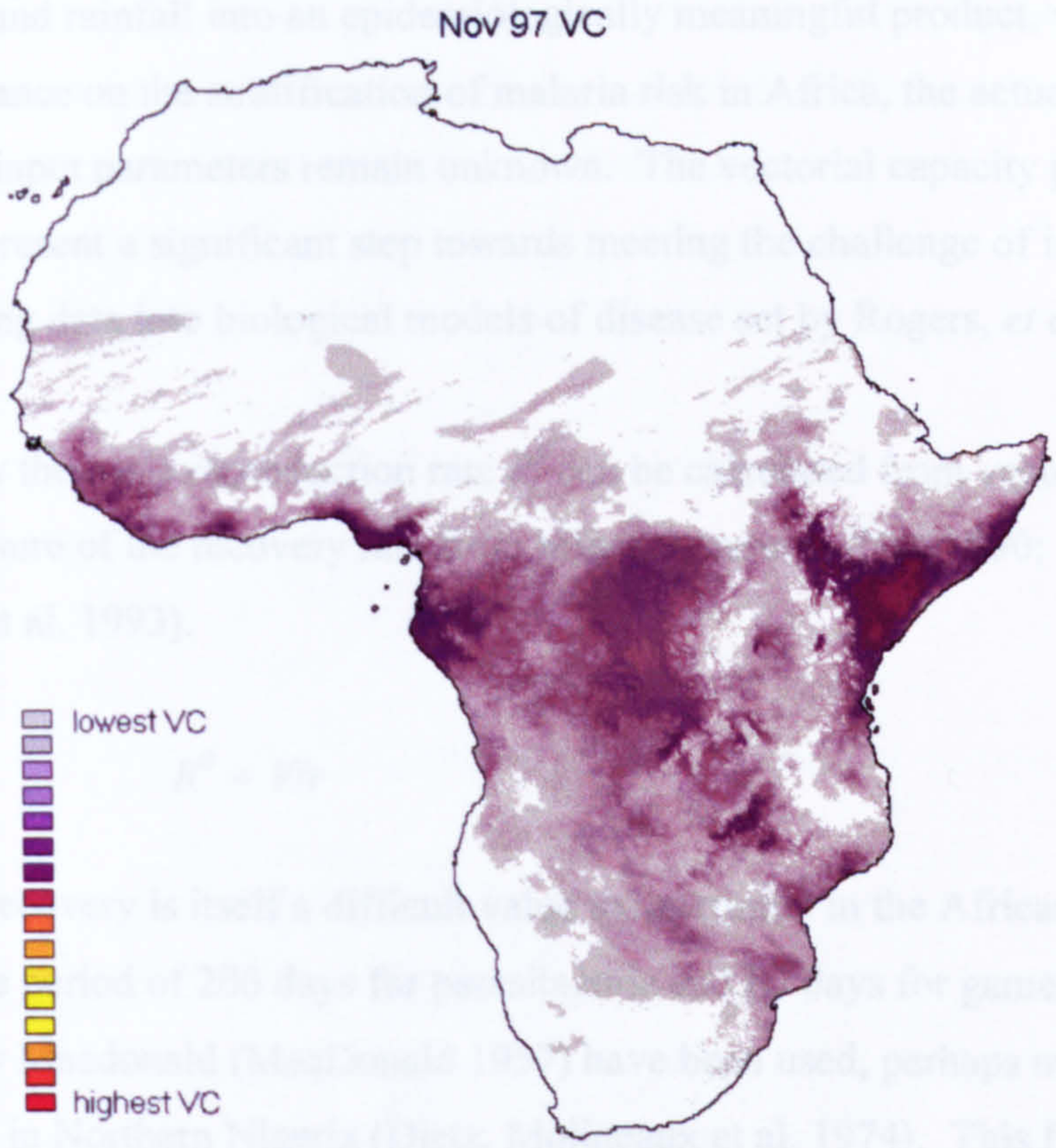


FIGURE 3.21. VECTORIAL CAPACITY DIFFERENCE MAP FOR AFRICA, NOVEMBER, 1997.

While the vectorial capacity images present a methodology for integrating temperature and rainfall into an epidemiologically meaningful product, which can provide guidance on the stratification of malaria risk in Africa, the actual value of many of the input parameters remain unknown. The vectorial capacity products do however, represent a significant step towards meeting the challenge of integrating remote sensing data into biological models of disease set by Rogers, *et al.* (2002).

Theoretically the basic reproduction rate R^0 can be calculated from vectorial capacity V and a measure of the recovery rate from infectiousness r (Dye 1990; Smith, Charlwood et al. 1993).

$$R^0 = V/r$$

The rate of recovery is itself a difficult value to determine in the African field context. The period of 200 days for parasitaemia and 80 days for gametocytaemia suggested by Macdonald (MacDonald 1957) have been used, perhaps most notably in field tests in Northern Nigeria (Dietz, Molineaux et al. 1974). This figure was highly contentious however, and Dutertre drew attention to a number of studies providing evidence of much longer duration (Dutertre 1976). Nedelman provides a detailed review and discussion of the inferences of recovery and other parameters used in the major mathematical models of malaria (Nedelman 1985). Technically it would be easy to produce a map of 'R^0' using the continental image products for vectorial capacity. This is not done here however as the product (R^0) relies on factors within the homoiothermic human host and represents too much of a departure from the environmental variables temperature and rainfall used to drive the model.

While it is possible to use continental scale inputs and produce continental scale products, and while these products may be pertinent to epidemic malaria control planning, it may be questionable to consider the development of malaria early warning at this scale. The biggest limiting factor is the absence of institutions with the required technical capacity, in combination with the political legitimacy, to ensure an appropriate response. Malaria endemicity changes markedly between the various regions of Africa, both spatially and temporally, and the sub-continental level may offer a better option for the development of malaria early warning systems.

These issues will be explored further at a regional level, in Southern Africa. In subsequent chapters the mapping products outlined above will be tested against available epidemiological data in four country case studies. The country case studies used are Botswana, Zimbabwe, Namibia and Swaziland.

4. Malaria and Environment in Southern Africa

4.1. Geographical background

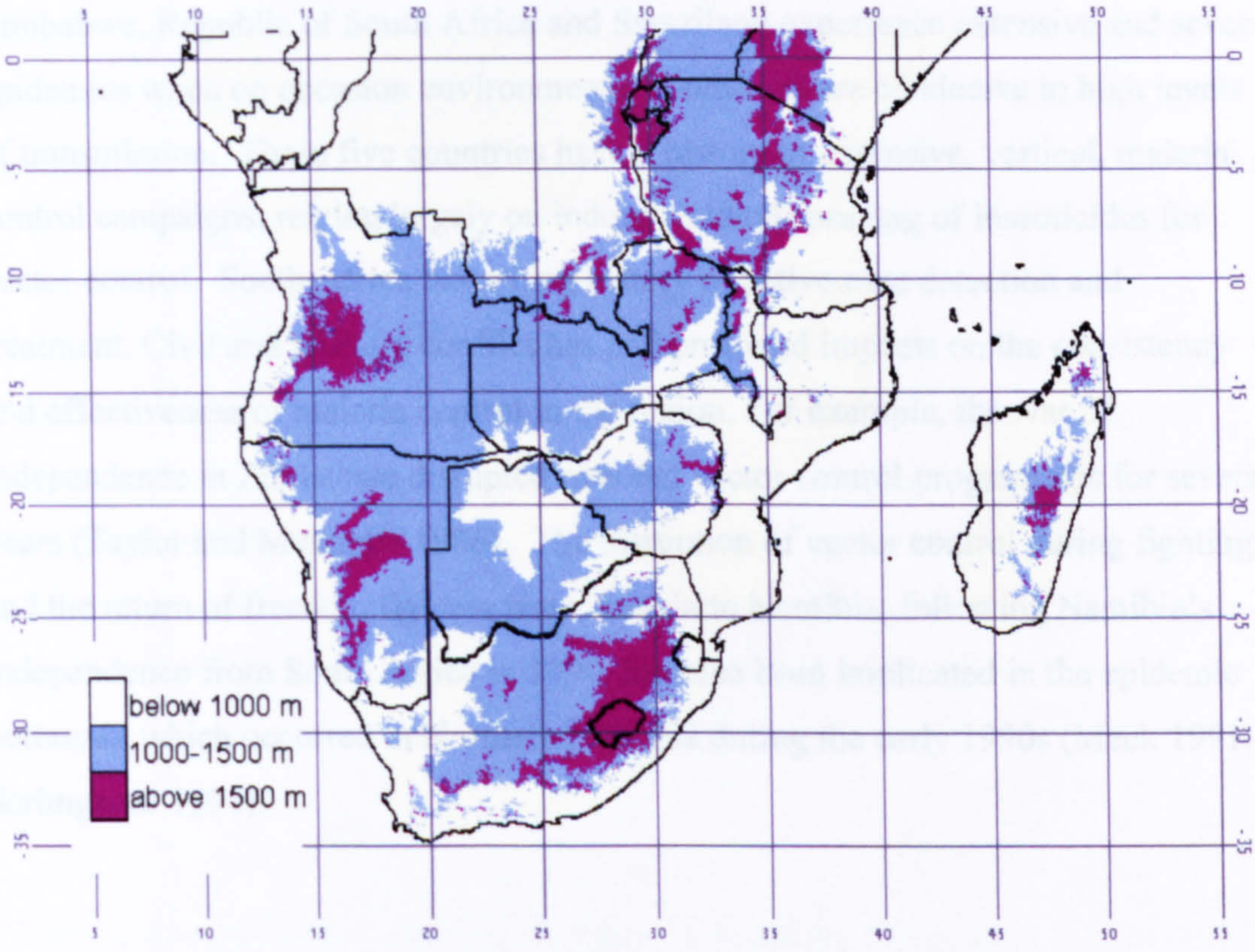
Here the term Southern Africa collectively includes the member States of the Southern Africa Development Cooperation: Angola, Botswana, Lesotho, Malawi, Mozambique, Namibia, Republic of South Africa, Swaziland, Zambia and Zimbabwe. Madagascar is also included in a survey of NMCP managers. The high mountain kingdom of Lesotho does not have malaria transmission.

4.1.1. The influence of topography and climate on malaria

Much of Southern Africa is comprised of upland plateau with land averaging above 1000 metres, Figure 4.1. The main drainage basins are those of the Great Lakes, the Zaire and the Zambezi river systems, along with the Orange River to the south. In addition, many other rivers impact on the environment at a more localised scale.

Altitude and latitude play an important role in temperature regulation and, along with rainfall, help determine the endemicity of malaria. Many highland areas, most notably the Highland Kingdom of Lesotho, are non-malarious, while in the lower river valleys and flood plains perennial transmission occurs. Between these two extremes, malaria transmission is of varying seasonal length. The southernmost limits of malaria transmission in Southern Africa are markedly skewed due to the different influences of the Atlantic and Indian Oceans on regional climate and localised weather systems. Along the South Atlantic Coast, the Benguela Current moves northward from the Antarctic bringing low winter temperatures, which along with the aridity this causes in the region, act as major constraints to malaria transmission. Historic surveys describe the area along the Kunene River, forming Namibia's North-west border, as having a very low endemicity (De Meillon 1951) and transmission appears to cease at latitudes greater than 17.5°S. Conversely the influence of the warmer Aghulas Current flowing southward from the Indian Ocean has, historically, enabled perennial malaria to occur south of Durban (Sharp and Le

FIGURE 4.1. SOUTHERN AFRICA PLATEAU. DERIVED FROM 1KM DIGITAL ELEVATION MODEL.



Legend:

The map uses a digital elevation model to indicate the extent of highland areas in Southern Africa. Produced from Corbett, J. & O'Brien, S (1997) Spatial characterization Tool, Texas A&M University.

Sueur 1996) at approximately 31°S (Bagster Wilson 1949) approximately 1500km further to the south.

Periodically the countries along this southern margin: Namibia, Botswana, Zimbabwe, Republic of South Africa and Swaziland experience extensive and severe epidemics when on occasion environmental conditions are conducive to high levels of transmission. These five countries have a history of extensive, vertical, malaria control campaigns, relying largely on indoor residual spraying of insecticides for vector control. South Africa has a long history of active case detection and treatment. Civil and military conflict has had profound impacts on the consistency and effectiveness of malaria control in the region. For example, the war of independence in Zimbabwe disrupted national vector control programmes for several years (Taylor and Mutambu 1986). The disruption of vector control during fighting and the return of freedom fighters from Angola to Namibia, following Namibia's independence from South Africa in 1990, has also been implicated in the epidemic outbreaks which occurred in Northern Namibia during the early 1990s (Meek 1991; Scrimgeour 1991).

4.1.2. Vector populations

A significant body of work on the distribution of the *Anopheles gambiae s.l.* complex, within Southern Africa, has been carried out by workers at the South African Institute for Medical Research (Coetzee, Hunt et al. 1993). The major vectors implicated in malaria transmission in Southern Africa have been *Anopheles arabiensis* and *Anopheles funestus*, with a lesser role played by *Anopheles merus*. In South Africa *Anopheles funestus* populations were dramatically reduced as a result of concerted indoor residual spraying programmes over many years (Sharp and Le Sueur 1996). However, the external resting habit of *Anopheles arabiensis* makes this mosquito less susceptible to indoor residual insecticides such as DDT and as a consequence these populations have remained viable, and this species is now considered to be the principal vector in South Africa. The same is thought to be true by a number of NMCP managers in other Southern Africa countries where vector control by residual spraying has been practised. There is however, little direct empirical evidence to support this.

4.1.3. Parasite populations

While infections of *Plasmodium malariae* (Laveran, 1881) and *Plasmodium vivax* (Grassi and Feletti, 1890) are found throughout Southern Africa (Bagster Wilson 1949) according to workers at the South African Medical Research Council in Durban, it is *Plasmodium falciparum* (Welch, 1897) which accounts for more than 95% of all malaria infections in South Africa and Southern Africa (Sharp and Le Sueur 1996).

4.1.4. Human population

The human population in Southern Africa is more urbanised than elsewhere in Africa, and many of the major population centres are in highland regions. Rural populations tend to be concentrated in highland areas, coastal regions and river valleys. Elsewhere populations are sparsely distributed, Figure 4.2. Migration is an important factor in malaria distribution (Prothero 1965) and in Southern Africa migration between and within nations is among the highest on the continent (Prothero. Pers. comm.).

Clearly it is unrealistic to discuss population in Southern Africa without considering the impact of HIV/AIDS on the region. Botswana and Zimbabwe are suffering the highest prevalence of HIV/AIDS, among adults, anywhere in the world at 30% and 25% respectively. Swaziland, Namibia and Zambia follow with prevalence rates above 20%. HIV-AIDS has had a profound influence on population growth in Southern Africa and since 1995 growth rates have been substantially reduced (Root: pers comm[11]). For example recent population growth rate estimates for Botswana, Zimbabwe, Namibia and Swaziland are: 0.76%, 0.3%, 1.6%, and 1.8% respectively. Life expectancy figures have reduced as a consequence to: 39, 38, 42 and 40 years respectively[12]. The burden that HIV/AIDS is putting on health services in Southern Africa is severely compromising their capacity to maintain their former levels in human development indicies. The populations of these countries are becoming more vulnerable to an infectious 'disease complex' (Kalipeni 2000). In the face of the

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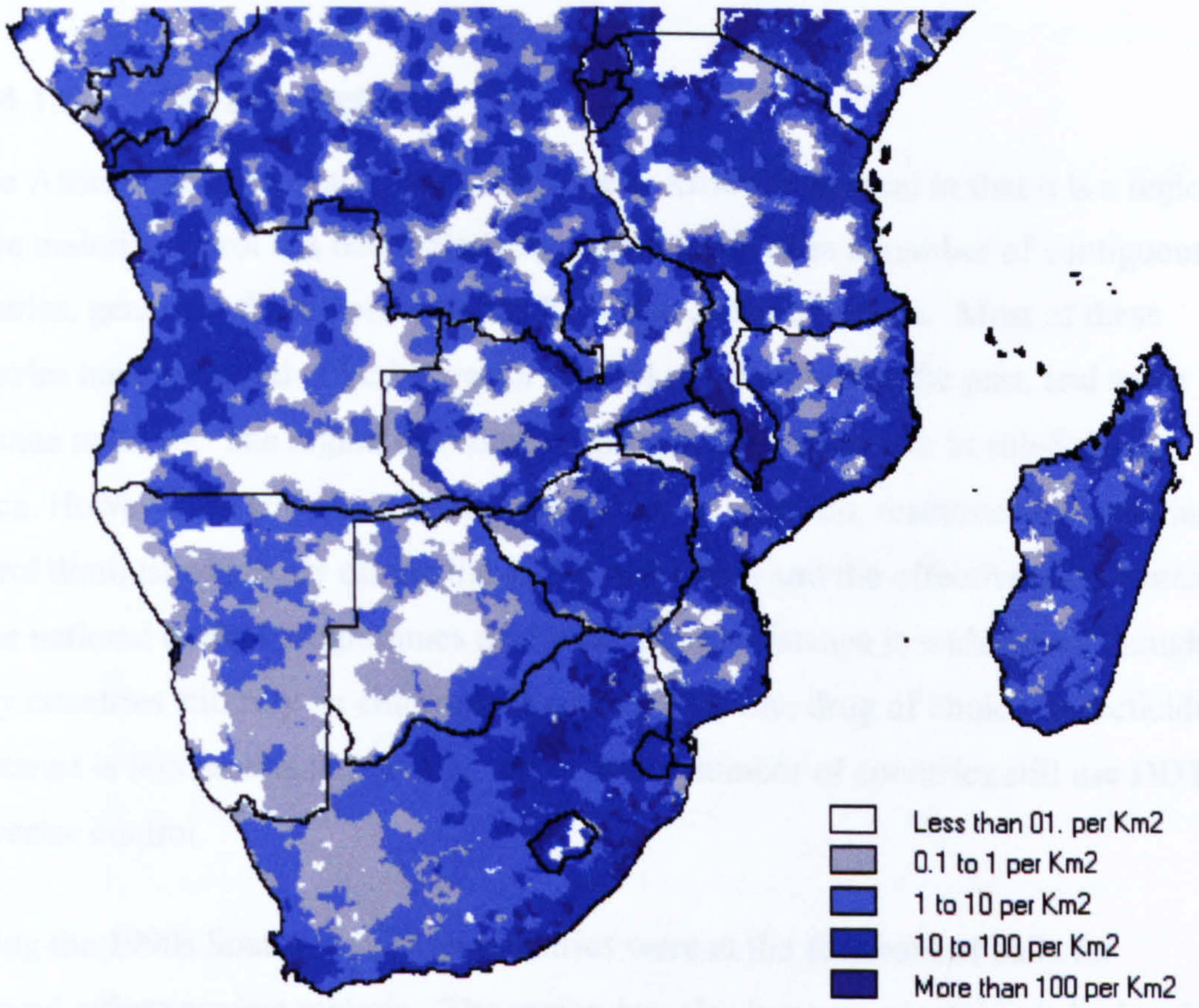
[11] Dr. Root is a demographer who was working with the WHO Southern African Inter-Country Team.
[12] Source: International Programs Centre, Population Division, U.S. Census Bureau, HIV/AIDS Surveillance Data Base, June 2000.

FIGURE 4.2. HUMAN POPULATION DENSITY DISTRIBUTION IN SOUTHERN AFRICA, 1990, DERIVED FROM DEICHMANN (1994).



Legend:

The population density shown here is derived from interpolated 1990 estimates for the African continent, using a log scale.

severe HIV/AIDS situation in Southern Africa, and the need to protect sufferers, effective prevention and control of infectious diseases such as malaria and tuberculosis is perceived to be essential.

4.1.5. Malaria control

In the African malaria control context Southern Africa is unusual in that it is a region where malaria control has been relatively well developed in a number of contiguous countries, generally those bordering the Republic of South Africa. Most of these countries have mounted effective vector control programmes in the past, and some continue to do so. The region has some of the wealthier countries in sub-Saharan Africa. However, as with the global malaria control situation, resources for malaria control diminished greatly during the 1970s and 1980s and the effectiveness of many of the national control programmes declined. Drug resistance is widespread though many countries still rely on chloroquine as their first line drug of choice. Insecticide resistance is less problematic in this region and a number of countries still use DDT for vector control.

During the 1990s Southern African countries were at the forefront of calls for renewed efforts against malaria. The region has also been successful in bringing the neighbouring countries together for meetings and workshops to share experiences and discuss national and regional control issues. The WHO-Southern Africa Intercountry Team (SAMC) in particular have been hosting annual intercountry planning and consultation meetings for malaria control managers during the past five years. The technical support provided by SAMC to the member countries is now recognised to be an example of 'best practice' in sub-Saharan Africa (WHO 2001a).

4.2. Aims of the chapter

The general aims of this chapter are to explore perceptions of climate, environment and malaria distribution in Southern Africa and to provide background information for subsequent chapters, which will look in more detail at four case study countries.

The specific aims are:

- To review the perceptions of national malaria control programme managers in Southern Africa with respect to malaria transmission patterns, and their linkage with climate and environment.
- To present the environmental and epidemiological data available here for analysis.
- To create a simple climate suitability map for 'more stable' and 'less stable' malaria for use by malaria control managers in Southern Africa.

4.3. Materials and methods

4.3.1. Perceptions of Climate and Malaria among Control Programme Managers in Southern Africa

In June 1997, the author attended the 1st Southern Africa Conference for Malaria, which was held in Maputo, Mozambique. The conference was host to all the countries of the Southern Africa Development Cooperation (SADC) and in addition, Madagascar, Figure 4.3. Whilst at the conference the author was involved in a survey of the National Malaria Control Programme managers to explore their perceptions of linkages between inter-annual climate variability, seasonal malaria transmission patterns and vulnerability to epidemic malaria[13]. The survey included: NMCP managers from Angola, Botswana, Madagascar, Mozambique, Namibia, South Africa, Swaziland, Tanzania and Zimbabwe (Zambia and Malawi did not return the questionnaire).

4.3.2. Survey questionnaire

4.3.2.1. *Part A: General introduction*

1. Does your country have a malaria control programme?

   Does it cover the whole country?

---

[13] The survey questionnaire was drawn up in collaboration with Dr. David Le Sueur, MRC Durban and Macol Stewart, NOAA Office of Global Programs. The analysis of the survey results were conducted by the author in part fulfilment of a contract with NOAA-OGP Connor, S. J. (1999a). Improving epidemic preparedness for malaria control in Africa. the utility of seasonal forecasting and monitoring of climate variability. Final Report to NOAA-OGP. Washington DC, NOAA Office of Global Programs: 8 pages + 7 Appendices..

FIGURE 4.3 MEMBER COUNTRIES COMPRISING THE SOUTHERN AFRICA DEVELOPMENT COOPERATION (SADC).

Legend:

The map shows national boundaries of the SADC member states. The map is derived from administrative boundary files supplied by SADC-RRSP (1997).

Just rural areas?
Just urban areas?
Other?

2. What are the main forms of intervention?

a) case detection
b) case management
c) vector control (residual spraying/larviciding)
d) health education (early recognition and personal protection)
e) mobilisation of additional manpower/transport/supplies
f) chemoprophylaxis
g) other

3. Do you have a malaria notification system?

If so what?

4. Do you currently receive climatological/meteorological data?

If so what data do you receive?
When and how often?
From whom?
How do you use it?

5. How reliable do you perceive this data to be?

very reliable
somewhat reliable
not very reliable

Explain:

6. Does your control programme have access to qualified malaria scientists?

National scientists:
Vector Yes_____ No_____
Parasite Yes_____ No_____
Clinical Yes_____ No_____
Foreign scientists:
Vector Yes_____ No_____
Parasite Yes_____ No_____
Clinical Yes_____ No_____

7. How long is your country's data set for malaria incidence?

Is diagnosis clinical?
Is diagnosis lab confirmed and clinical?
Is diagnosis lab confirmed?

8. What other data sets do you have that might act as a longer term indicator of year to year trends which might be useful for modelling? (for example, hospital admissions for complicated malaria for one major hospital)
9. What do you see as the main challenges to malaria control in your country over the next 10 years?

4.3.2.2. *Part B: Perceptions of malaria incidence (last 5-10 years)*

10. Has there been an increase in malaria incidence in your country in the last five to ten years?

If so what do you believe the reasons to be. Rank in order of importance.
a) Financial
b) Drug resistance
c) Climate
d) War/civil unrest
e) Refugees
f) Lack of skilled manpower
g) Agriculture and irrigation
h) Other

11. In the last ten years, list the years in which your country experienced severe epidemics.

12. Which was the most severe year in the last ten years?

13. How would you define a severe epidemic in your country?

14. Are severe years becoming more or less frequent?

If so, what do you believe to be the reasons. Rank in order of importance.
a) Financial
b) Drug resistance
c) Climate
d) War/civil unrest
e) Refugees
f) Lack of skilled manpower
g) Agriculture and irrigation
h) Other

15. Were your recent epidemics:

a) Widespread over large geographic regions of your country
b) Localised to small areas
c) A combination of both in different years

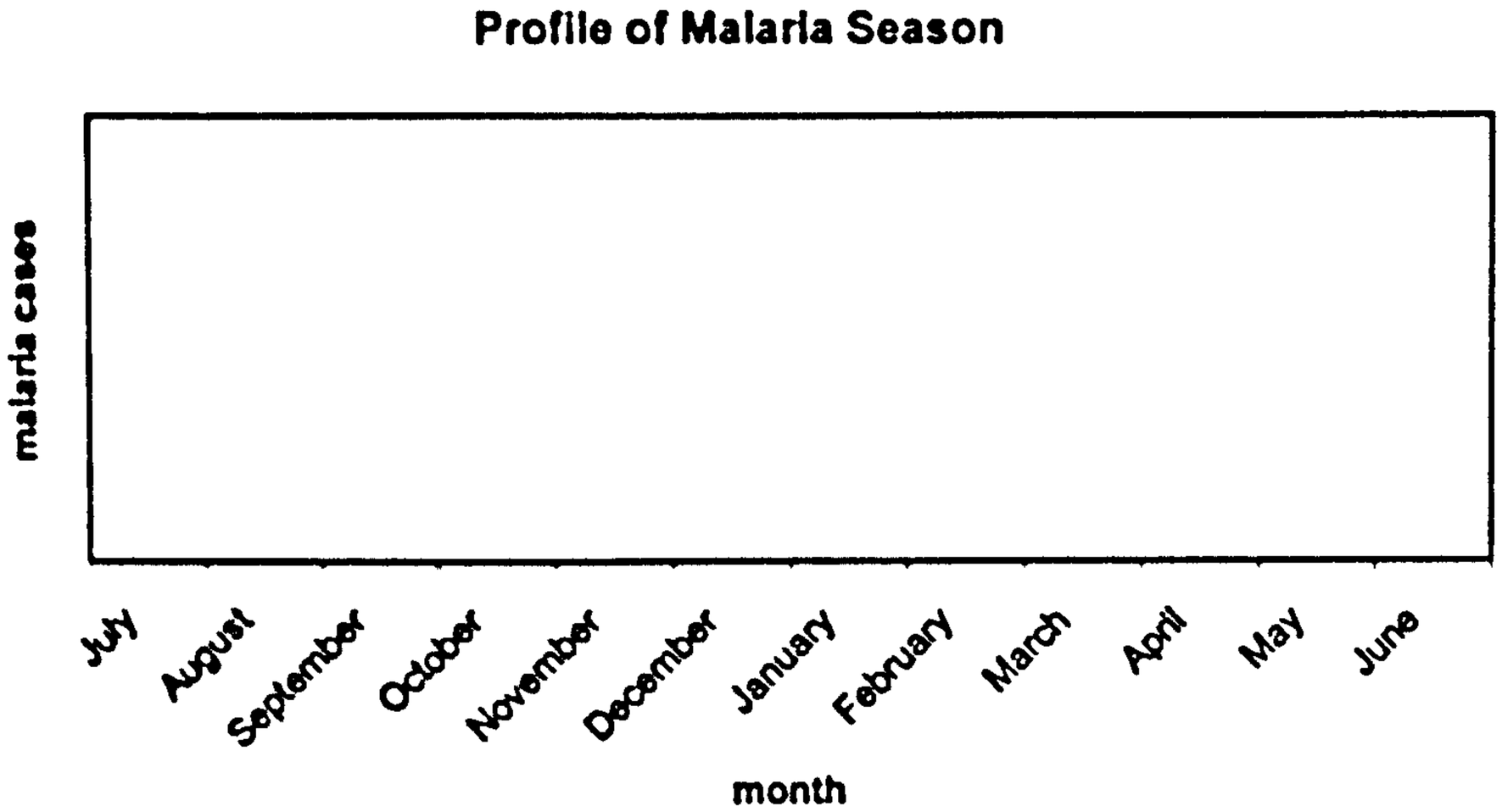
Explain if necessary.

16. Over the next 20 years, how many years would you expect to experience severe epidemics?

4.3.2.3. *Part C: Responses to severe epidemics*

17. When was the last severe epidemic in your country?

18. On the axes below, please draw the seasonal transmission profile for your country:



When (and how) were you first notified that an epidemic was underway during that year? Please draw an arrow in the diagram above indicating in which month you were notified/became aware of the epidemic.

19. How did you respond and what were the main challenges of response?

20. How did malaria control practices change in the following year in response to this experience?

21. If you received early warning of an epidemic, how would you respond?

22. How far in advance of the malaria transmission season would you need to receive early warning information? (in what month)

4.3.2.4. *Part D: Responses to past climate*

23. Over the past five years what have been the impacts of wet periods/years for your malaria control operations?

24. What, if anything, have you done in response to these wet periods/years?

25. What, if any, features of your country's malaria control operations are different now (from five years ago) because of wet periods/years?

26. Are there characteristics of your country which make control in your country more or less vulnerable to wet years than neighbouring countries?

27. What, if any, climatic conditions or events are problematic for your country's malaria control operations? (specify the climatic conditions and the potentially vulnerable aspects of malaria control)

4.3.2.5. *Part E: Adaptation to climate variability*

28. In what ways can malaria control programme managers reduce their vulnerability to malaria epidemics in wet years?

29. What are the main obstacles to reducing vulnerability to wet years?

30. Would you like to be involved in collaborative research on prediction in your country?

4.3.3. Perceptions of malaria endemicity in Southern Africa – Mapping Expert Opinion

During November 1998 a WHO-AFRO Planning and Consultation Meeting for Accelerated Malaria Control in Southern Africa was held in Harare, Zimbabwe. During the meeting the author asked a number of National Malaria Control Programme managers to create maps of malaria distribution in their countries. The maps were to be classified according to whether malaria in a district or province was: absent (A), seasonal with transmission for less than 6 months of the year (B1), seasonal with transmission longer than 6 months of the year (B2), or periodic and did not occur every year (C). The NMCP managers that responded were from: Botswana, Namibia, South Africa, Swaziland and Zimbabwe. The baseline maps provided were produced from the SADC CD-ROM and were the latest available at the time (SADC-RRSP 1997). The administrative districts shown on the maps were not in every case the same as those used by the Ministry of Health and so the NMCP managers were invited to draw in additional lines and make changes where appropriate[14].

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[14] This exercise was carried out in collaboration with workers from the South African Medical Research Council, Durban who used expert opinion maps as a baseline for the MARA maps Craig, M.

4.3.4. Data collection for the Southern Africa region

4.3.4.1. Epidemiological data

A number of field visits were made in collaboration with SAMC and WHO-HealthMap[15] to develop local capacity in the use of GIS/EIS for malaria control. During these visits epidemiological data available from the central levels in Botswana, Namibia, Swaziland and Zimbabwe were obtained.

4.3.4.2. Environmental data

Grid surfaces for a range of environmental variables were collected from a number of different sources, these were acquired over the internet, on CD-ROM or through visits to climate monitoring institutes.

4.3.5. A model of stable and unstable malaria in Southern Africa

A simple climate based map of malaria endemicity in Southern Africa was produced in Idrisi using climate constraints to malaria discussed in Chapter 2. The climate constraints chosen were mean annual temperatures <18°C and annual rainfall <250mm for the non malarious class; mean monthly temperatures between 18-22°C for five consecutive months and annual rainfall >250mm for the less stable malaria class; mean monthly temperature >22°C for five consecutive months and annual rainfall >400mm for the more stable malaria class.

H., R. W. Snow and D. Le Sueur (1999). "A climate-based distribution model of malaria transmission in Sub-Saharan Africa." Parasitology Today **15**(3): 105-111..

[15] The WHO-CDS team responsible for developing GIS for health services.

4.4. Results

4.4.1. Perceptions of Climate and Malaria among Malaria Control Programme Managers in Southern Africa

4.4.1.1. Section A. Background Information

1. All countries reported having a National Malaria Control Programme (NMCP). All countries, except Mozambique and South Africa, reported that their NMCP covered the whole country.

2. The respondents answers are summarised in Table 4.1.

Table 4.1. Malaria control intervention in Southern Africa.

Form of intervention	Number of countries	Comment
Case detection	3	
Case management	9	
Vector control (residual spraying/larviciding)	8	
Health education (early symptom recognition/personal protection)	9	
Mobilize additional manpower/transport/supplies	7	
Chemoprophylaxis	8	Travellers/pregnant women
Other	1	Treated bednets

3. All countries reported having a malaria notification system. Five respondents indicated some form of routine Health Information System based on monthly reporting from districts. South Africa includes malaria as a notifiable disease and operates an Active Case Detection System.

4. Five respondents reported receiving regular meteorological information, the exceptions were: Angola, Madagascar, Mozambique and Tanzania. The data available are generally monthly rainfall and temperature statistics from the Meteorological Department.

5. The available meteorological data are reported as being either very reliable or somewhat reliable in availability. Madagascar commented that the malaria cases in the arid southern region were related to rainfall.

6. Eight countries reported having access to national malaria scientists. The exception was Swaziland who reported only having access to foreign scientists. Madagascar reported a lack of parasitologists. Angola reported a lack of entomologists.

7. Only three countries reported having long-term data on malaria incidence. These were: Angola with data from 1970 (covering a few major cities); South Africa with data from 1970; and Botswana with data from 1981/82. Others report data being available for the last 4 to 5 years. The data (with the exception of South Africa and Botswana) were records of clinical diagnosis. Eight of the respondents stated that parasitological confirmation of a proportion of cases is carried out at selected facilities. Madagascar stated that parasitological confirmation was rarely carried out.

8. There was little apparent awareness of other long-term data sets which could be used as indicators in modelling year to year variation in malaria. Three respondents suggested hospital admission data (Madagascar, Swaziland and Zimbabwe) while one (Namibia) suggested rainfall station data might be useful.

9. There was little clear consensus on challenges to malaria control over the next 10 years, although a number of countries (3) expressed concern over increasing drug resistance. Three countries mentioned the need for improved forecasting and management of epidemics (Namibia, Botswana and Swaziland). Madagascar mentioned implementation of a large scale, bednet programme. South Africa mentioned the need for geographical stratification for improved coverage by the NMCP.

4.4.1.2. Section B. Perceptions of malaria incidence (last 5-10 years)

10. All countries reported increased levels of malaria in their countries over the past 10 years – see table 4.2. for reasons stated.

Table 4.2. Perceptions of increasing malaria trends.

Perceived reason for increase in malaria over last 10 years	Respondents ranking within top 3 categories
Financial	4
Drug resistance	4
Climate	7
War/Civil unrest	1
Refugees	2
Lack of skilled personnel	4
Agriculture and irrigation	2
Other	
Migrations	2
Post drought epidemics	1

11. The respondents answers are summarized in Table 4.3.

12. The respondents answers are summarized in Table 4.3.

Table 4.3. Epidemics experienced in the last 10 years 1985-1996.

Year	Countries reporting epidemics in year	Year of most severe epidemic
1985/86	1	
1986/87	3	
1987/88	3	1
1988/89		
1989/90	1	
1990/91		
1991/92		
1992/93	5	
1993/94	2	1
1994/95	1	
1995/96	6	6

13. The majority of respondents defined an epidemic simply as an increase in the number of cases and deaths above that expected. One respondent defined an epidemic as an increase in incidence beyond the 10 year mean (South Africa). Another as an increase in cases above the previous 5 years for the same period (Botswana).

14. Six of the nine respondents perceived that years of severe transmission were becoming more frequent. Three respondents attributed this to climate variability, three to increasing drug resistance, two to financial considerations.

15. Five of the respondents reported the epidemics as being wide spread, three as localised in small areas, and one as a combination of both, depending on the year.

16. There was a low response to this question. However, three respondents expected to have 4 to 5 epidemics over the next 20 years.

4.4.1.3. Section C. Responses to severe epidemics

17. Most respondents cited 1996 as their last epidemic year, the exceptions were Mozambique which was 1993, and Madagascar which was 1988.

18. The respondents were asked to draw a seasonal profile of malaria for their country and indicate where on the graph they noticed an epidemic was occurring in the year of the last epidemic. Most respondents (7) claimed to have become aware of the epidemic one month prior to its peak.

19. Only one country reported being unprepared for the last epidemic (Zimbabwe). Response was generally based on vector control and mass drug administration. Only one country reported a lack of available personnel (Botswana).

20. Five respondents report improved preparedness the following year, development of national epidemic response plans, and improved surveillance in epidemic prone areas.

21. If an Epidemic Early Warning were available eight respondents claimed that they would send field teams out to confirm the epidemic, then mobilise resources. Response generally based on mass drug administration, vector control and increasing community awareness.

22. The perceived lead-time required for an Epidemic Early Warning System

ranged between one month and six months prior to the beginning of the transmission season.

4.4.1.4. Section D. Responses to past climate

23. Six respondents replied to the question of impacts of wet periods on malaria control operations. These stated that wet periods were related to increased malaria and higher risk of epidemics.

24. Low response to question on response to wet years (5). However, increased surveillance (South Africa), resource mobilisation (Namibia) and additional vector control (Mozambique) is carried out in some countries.

25. The response to the question of changes in control in response to wet periods over the past 5 years was low (4). Both Zimbabwe and South Africa said there was no change. Namibia and Swaziland reported emphasis on developing national preparedness plans.

26. Regarding characteristics of the country which make malaria control more or less vulnerable in wet years than in neighbouring countries. The response was again low (5). One mentioned post drought epidemic risk as being an important factor (Namibia). Both South Africa and Zimbabwe stated no difference between normal and wet years. Angola reported concerns over adequacy of sanitation in wet years.

27. Regarding whether climatic conditions or events are problematic for the country's malaria control operations, again a low response to question (4). Rainfall variability (Angola) and a 2-3 year drought prior to wet period were suggested by Namibia. Mention of El Nino was made by South Africa. Zimbabwe stated "none."

4.4.1.5. Section E. Adaptation to climate variability

28. Regarding ways malaria control programme managers can reduce their vulnerability to malaria epidemics in wet periods, six responded to the question. There was little consensus apparent but better preparedness and improved

management were mentioned twice. Access to epidemic early warning (South Africa, Namibia and Botswana) and identification of epidemic prone areas (Mozambique and Namibia) were also mentioned. Improved health education, greater access to resources and training were also mentioned as issues Angola and Zimbabwe).

29. With respect to the main obstacles to reducing vulnerability to wet years, again a low response to question. However, unpredictability of rains (Zimbabwe), poor sanitation (Angola), and access to skilled personnel (Namibia) were cited by respondents. The need for epidemic early warning was mentioned by Mozambique.

30. All respondents answered that they would like to be involved in collaborative research on malaria epidemic prediction. Tanzania's NMCP said it was interesting, but because Tanzania is an endemic country epidemic prediction is not an important issue in Tanzania.

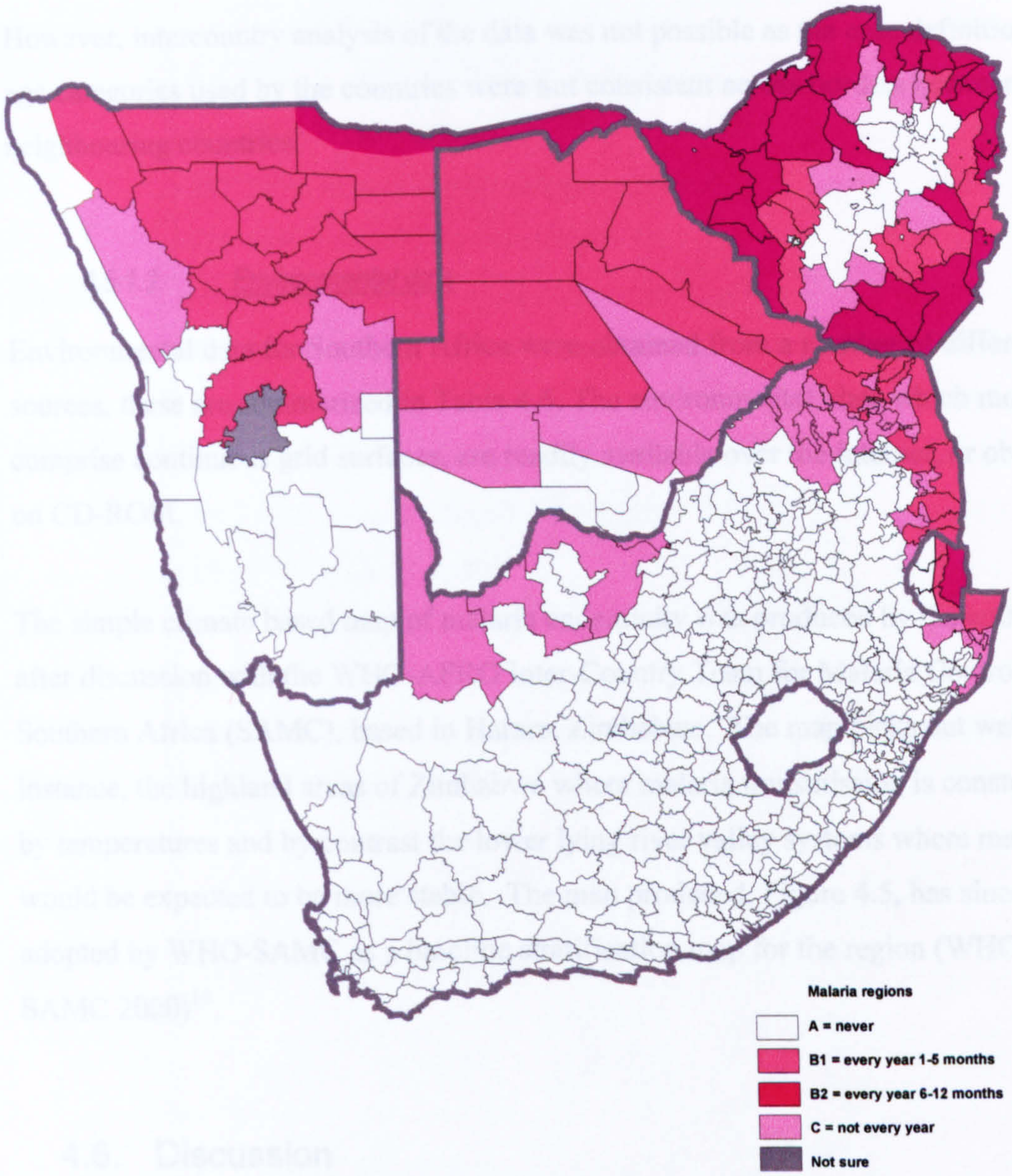
4.4.2. Perceptions of malaria endemicity in Southern Africa – Mapping Expert Opinion

Here the expert opinion of national malaria control programme managers was sought with regard to spatial and temporal distribution of malaria in their countries. The map showing the results for the five countries involved is shown in Figure 4.4. Much of the Republic of South Africa is seen to be malaria free, with transmission occurring along the northern borders with its neighbours Botswana, Zimbabwe, Mozambique and Swaziland.

4.5. Data available for the Southern Africa region

4.5.1.1. Epidemiological data

The epidemiological data gathered from field visits to Botswana, Namibia, Swaziland and Zimbabwe consists mostly of that which is available through each of the countries' routine national Health Information Systems. This data is gathered for decision making by the NMCP at the national level, its intention is not primarily for rapid disease surveillance. Other, supplementary data was also collected (blood slide



Legend:

The map represents expert opinion of malaria distribution in selected Southern African countries. The map was produced using administrative boundary files supplied by SADC-RRSP (1997).

surveys, age specific data, district populations, parasite surveys) where possible and these will be discussed along with case definitions at the individual country level as appropriate. The data available from the four countries are summarised in Table 4.5. The author had intended to use this data to assess 'malaria' across the region. However, intercountry analysis of the data was not possible as the case definition and age categories used by the countries were not consistent across borders between neighbouring countries.

4.5.1.2. Environmental data

Environmental data for Southern Africa were obtained from a number of different sources, these are summarized in Table 4.6. The environmental, data which mostly comprise continuous grid surfaces, are readily available over the internet, or obtained on CD-ROM.

The simple climate based map of malaria endemicity was produced by the author after discussion with the WHO-AFRO Inter-Country Team for Malaria Control in Southern Africa (SAMC), based in Harare, Zimbabwe. The map picks out well, for instance, the highland areas of Zimbabwe where malaria transmission is constrained by temperatures and by contrast the lower lying river valley systems where malaria would be expected to be more stable. The map produced, Figure 4.5, has since been adopted by WHO-SAMC as a baseline stratification map for the region (WHO-SAMC 2000)[16].

4.6. Discussion

Malaria in Southern Africa is perceived, by national malaria control programme managers, to vary markedly within and between countries. Challenges to malaria control in Southern African countries are not perceived by these experts to be uniform problems. According to the survey, malaria is considered to be a highly endemic disease in Tanzania and as a consequence epidemic early warning and surveillance do not rank as priorities for the national malaria control programme in

[16] The map is also currently distributed by WHO-HealthMap-Geneva with the malaria module of the HealthMapper software.

TABLE 4.5. SUMMARY OF AVAILABLE EPIDEMIOLOGICAL DATA ON MALARIA COLLECTED FROM FOUR SOUTHERN AFRICA COUNTRIES.

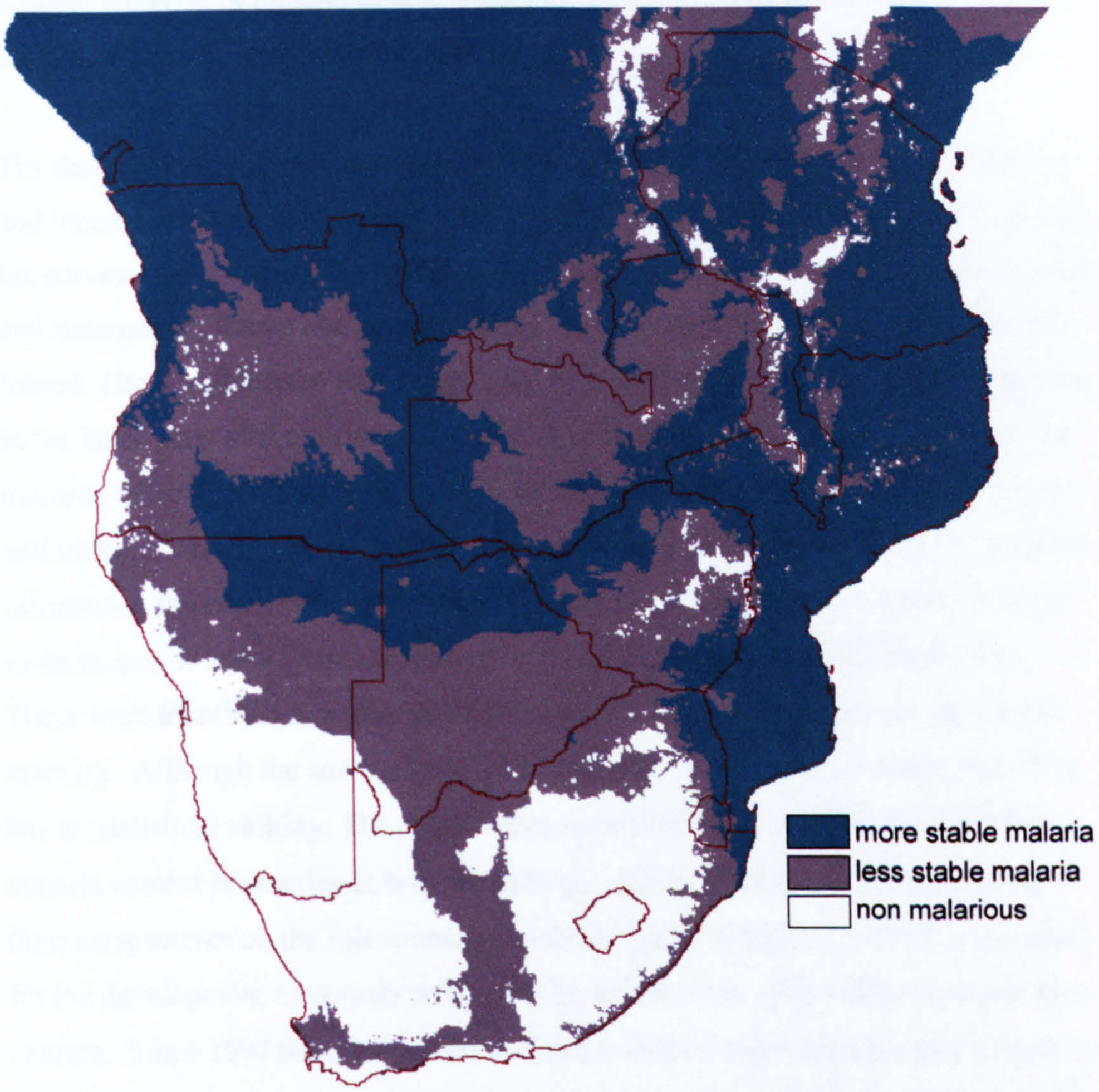
Country	Time period/frequency/case definition	Spatial Scale
Botswana	1996-1999 Weekly confirmed/unconfirmed	District
	1996-1999 Weekly deaths	District
	1982-1999 Annual confirmed/unconfirmed	District
	1974-1998 Annual outpatient/inpatient	District
Namibia	1996-2000 Monthly clinical outpatient/inpatient	Directorate
	1993-2000 Monthly clinical inpatient	National
	1996-2000 Monthly deaths	National
Swaziland	1985-1999 Annual clinical inpatient	District
	1992-1999 Annual clinical outpatient	District
	1994-1999 Annual deaths	District
Zimbabwe	1994-1999 Monthly clinical unconfirmed, 0-4 years	District
	1994-1999 Monthly clinical unconfirmed, 5-14 years	District
	1994-1999 Monthly clinical unconfirmed, > 15 years	District

TABLE 4.6. ENVIRONMENTAL VARIABLES USED IN THE ANALYSES.

VARIABLE	Spatial resolution	Temporal resolution	Time period	Original projection*	Source
NDVI	8km	Monthly (derived from decadal)	July 1982-Dec 2000	Alber's Equal Area	ADDS
RFE	8km	Monthly (derived from decadal)	July 1995-December 2000	Alber's Equal Area	ADDS
CCD	7.6	dekadal	1988-1999	Hammer-Aitoff	FAO
Climate anomalies (min, max temperature and diurnal range, rainfall	5km	monthly	1951-1995	Geographic (Lat/Long)	UEA-CRU
Mean, min, max altitude	5km			Geographic (Lat/Long)	ANU-CRES
Vectorial capacity	5km	monthly	July 1995-December 2000	Geographic (Lat/Long)	Derived from UEA-CRU and ADDS
Lat/ Long of district centroids				Geographic (Lat/Long)	Derived and adapted from SADC-RRSU
Rainfall climatology	7.6km	monthly	Mean 19-61-1990	Geographic (Lat/Long)	SADC-RRSU
Humidity limatology	7.6km	monthly	Mean 19-61-1990	Geographic (Lat/Long)	SADC-RRSU
Temperature climatology	7.6km	monthly	Mean 19-61-1990	Geographic (Lat/Long)	SADC-RRSU

* All image products were converted into a common 'Geographic Projection' (Lat/Long) at 5km spatial resolution using Windisp4.

FIGURE 4.5. ENVIRONMENTAL BASED MAP OF MALARIA ENDEMICITY IN SOUTHERN AFRICA



Legend:

This simple map of more stable – less stable malaria distribution in Southern Africa was produced in discussion with WHO-SAMC and WHO-HealthMap using climate surface data. The climate constraints chosen were mean annual temperatures <18°C and annual rainfall <250mm for the non malarious class; mean monthly temperatures between 18-22°C for five consecutive months and annual rainfall >250mm for the less stable malaria class; mean monthly temperature >22°C for five consecutive months and annual rainfall >400mm for the more stable malaria class.

that country. Other countries express a need for stratifying their country to improve the focus of control activities. Elsewhere better access to information on seasonal weather patterns, or climate trends, were seen to offer potential for improvements in control of periodic malaria epidemics.

The design of the survey questionnaire unfortunately allowed a degree of ambiguity and inconsistency of response, making it difficult to quantify the findings. However, the survey was carried out in 1997 before the heightened interest in malaria mapping and linkages in climate and health became so widespread that some results became biased. The questionnaire was perhaps too long and respondent fatigue was apparent in the latter parts of the survey. However, it is clear from the survey results that the majority of NMCP managers are aware of linkages between variability in seasonal and inter-annual malaria patterns and climate. The importance of climate as a factor influencing the occurrence of malaria epidemics was apparent, as was the need for some means of Early Warning System for notifying of increased epidemic risk. These were identified at a general malaria conference, rather than a climate health meeting. Although the survey included a maximum of 9 respondents and therefore has no statistical validity. The respondents consisted of key personnel who effect malaria control in practice at both the national and regional level. Understanding their perspectives on the role climate variability plays in malaria control is essential for the development of outputs which can be tested in the field reality in which they operate. Since 1997 there have been a number of epidemic outbreaks in Tanzania in which climate has been one of the reasons implicated, along with malnutrition (Juan Garay: pers. comm.), and increased drug resistance (Bodker, Kisinza et al. 2000).

In general malaria endemicity in Southern Africa is thought to increase from South to North, but within this overall trend there are anomalous areas where perceived endemicity changes markedly at international borders, e.g. Botswana/Zimbabwe, Figure 4.4, and where non-malarious areas in Southern Botswana meet areas where malaria occurs periodically across the border in the Republic of South Africa. Is this due to differentials in control achievements on either side of the border[17], differences

[17] Surveys in South Africa during the 1930s by Park Ross showed that malaria was endemic all along its northern borders with Botswana, Zimbabwe, Swaziland and Mozambique. Reviewed in Le Sueur et al (1993).

in the importance of malaria as a public health problem and therefore differences in surveillance of malaria in remote regions? The climate based endemicity map of Southern Africa, Figure 4.5, does not support these border differences, and neither does it support so clear a north-south trend. Extensive highland areas of Zambia and Angola fall clearly into the category of less stable malaria. A basic problem with this expert opinion map is that it does not indicate whether the NMCP manager who produced it was basing his or her perceptions on transmission or case reporting. Both the expert opinion maps and the climate based maps of malaria endemicity should be tested against good quality epidemiological data to verify their worth as endemicity maps.

The epidemiological data available varies greatly in its quality and availability over time. Unfortunately the lack of comparability of the epidemiological data across all the different countries makes it difficult to test for regional patterns. Therefore each of four countries (Botswana, Zimbabwe, Namibia and Swaziland) will be dealt with as individual case studies in subsequent chapters.

By contrast there is a growing availability of environmental information for the region. Much of it has been archived by the SADC Regional Remote Sensing Unit (RRSU), in Harare, Zimbabwe and is available on a CD-ROM. The problems of cross border comparability with the environmental variables is less of an issue, as these are available as continuous grid surfaces covering the entire region. The regular dissemination of frequently updated environmental information, throughout the region by the SADC-RRSU, is also encouraging for intersectoral collaboration on development of epidemic early warning initiatives.

5. Malaria and Environment in Botswana

5.1. Introduction

5.1.1. Geographical background

Botswana is a landlocked country with a total land area of 581,730 square kilometres. It shares borders with Namibia, Zambia, Zimbabwe and South Africa. The country is mostly comprised of land above 1000 meters, with substantial tracts of desert, including the Kalahari in the Southwest. The major river system in Botswana is the Okavango, which flows from the Bie Plateau in Angola, into the north-western part of the country forming the extensive Okavango Delta. Occasionally floodwaters from the Okavango will enter the Boteti River and flow south-easterly into Lake Xau and the Makgadikgadi Pan. The average annual rainfall is 635mm in the north decreasing to 230mm in the south. Although rainfall is concentrated into the summer months, November to April, it is subject to high inter-annual variability and periodic drought (van Regenmortel 1995). Botswana's Gross Domestic Product, is relatively high for sub-Saharan Africa at US$3070 per capita (UNDP 2000). The population comprises approximately 30% urban and 70% rural. Literacy rates are 60% for women and 81% for men. Prevalence of HIV/AIDS is high (30%) and current population growth rates and life expectancy levels (0.76% and 39 years respectively) are much reduced as a consequence.

5.1.2. Overview of malaria and its control in Botswana

Malaria is ranked as one of the major public health problems in Botswana and as such is included among the notifiable diseases reported routinely through the Ministry of Health's National Health Information System (NHIS). There is a well established National Malaria Control Programme in Botswana with permanent staff members. The NMCP is based within the Epidemiology and Disease Control Unit, of the Ministry of Health, in Gabarone. A multi-sectoral advisory body, the Malaria Reference Group (MRG), was established in 1993 to provide professional and technical expertise to the NMCP. Additional resources at the national level include

an Entomology Unit with two permanent staff, based in Francistown. The primary responsibility for malaria control, however, lies with the District Health Teams who may access support from the national level as and when necessary.

The main malaria control activities carried out in Botswana according to the Ministry of Health are:

1. Vector control through annual indoor residual house spraying in endemic areas (Gumare, Ngami, Chobe, Tutume, Boteti and more recently Ghanzi and Northeast districts). Between 1997 and 1999, Botswana changed from the use of DDT to Deltamethrin (due to poor availability of DDT rather than insecticide resistance).

2. Chemoprophylaxis for target groups during the malaria season:
   - Pregnant women in endemic areas throughout pregnancy and until six weeks after delivery.
   - Residents of non-endemic areas travelling to endemic areas – including tourists, defence forces and special labour groups.
   - School children may be subject to mass administration where and when the need arises during epidemic outbreaks.

3. Prompt and effective case management including drug therapy to affected individuals. Sulfadoxine-Pyrimethamine is the recommended first line choice for uncomplicated malaria cases, and Quinine is recommended for severe and complicated cases. Chloroquine was abandoned as the first line treatment in 1997 due to surveys which showed increasing resistance and high rates of treatment failure.

4. Community health education, raising awareness of malaria symptoms and appropriate action, encouraging the use of personal protection measures such as mosquito repellents and bednets.

5. Environmental hygiene and sanitation.

6. Programme Monitoring and Evaluation.

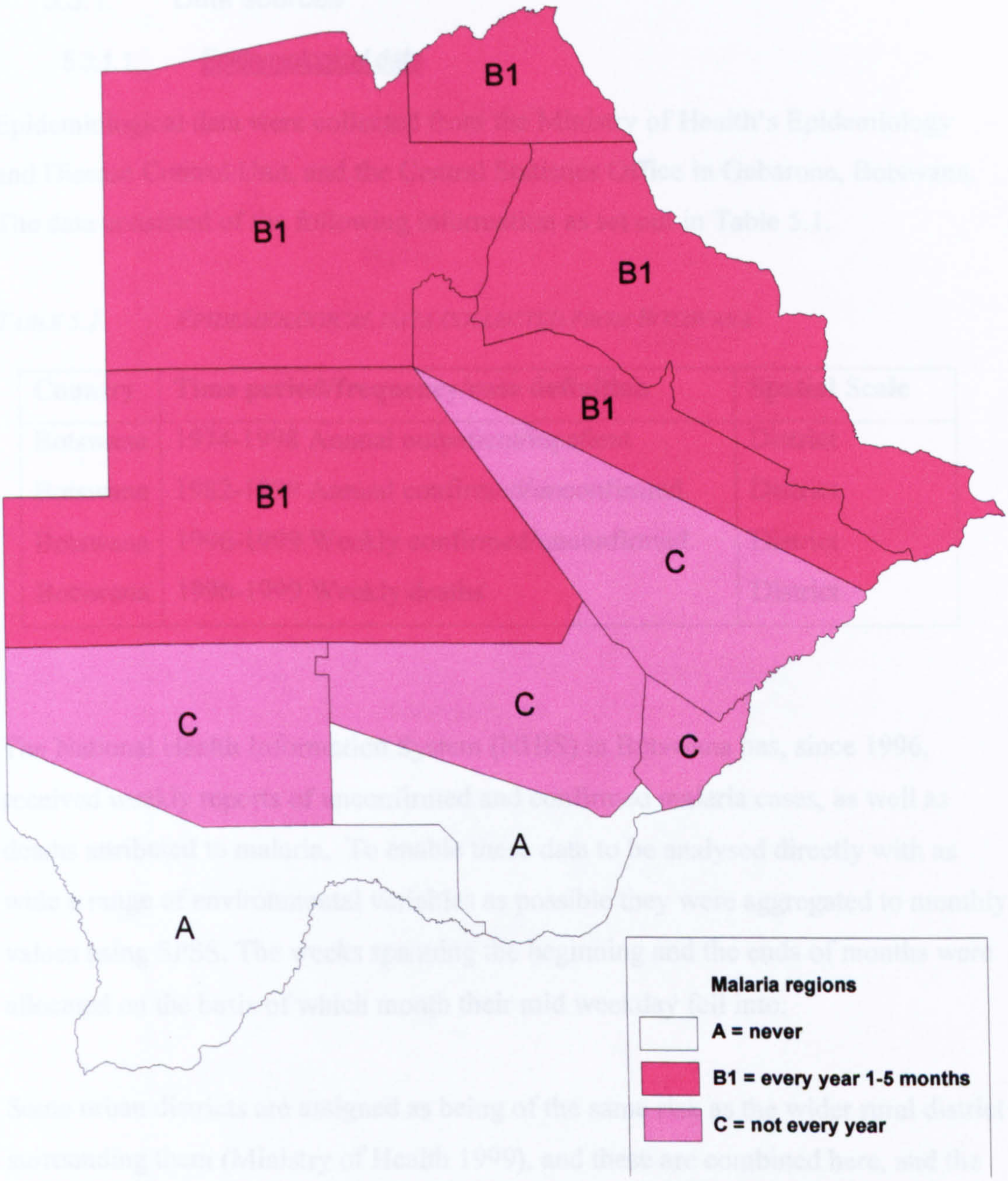
The achievement of malaria control through the above is a major policy goal of the NMCP and is integrated wherever possible through the country's Primary Health Care strategy and referral system (Ministry of Health 1999).

According to the NMCP malaria distribution is highest in the North of the country with seasonal transmission patterns of less than six months each year. The central section of the country is considered to be one of low endemicity where malaria does not occur every year, but where epidemics may occur. The South is perceived to be largely non-malarious, apart from sporadic cases (Ministry of Health 1999). Figure 5.1 presents the 'Expert Opinion' map of malaria distribution in Botswana gathered during the survey described in Chapter 4.

5.2. Aims of this chapter

- To describe the spatial and temporal distribution of malaria incidence in Botswana from district level data collected through the health information system.
    - If successful, to use this data to create a model of the seasonality of malaria transmission in Botswana at the district level.
- To relate the spatial and seasonal variation in malaria incidence to environmental variables
    - If successful, to a create a map of the seasonality of transmission in Botswana at the sub-district level.
- To relate spatial and inter-annual variation in malaria incidence to spatial and inter-annual variation in environmental variables
    - If successful, to explore the use of these relationships in the development of early warning indicators for malaria epidemics at the sub-district level.

FIGURE 5.1. EXPERT OPINION MAP OF MALARIA IN BOTSWANA – CIRCA 1998.



Legend:

The expert opinion map of malaria distribution in Botswana was produced using administrative boundary files provided by SADC-RRSP (1997).

5.3. Materials and methods

5.3.1. Data sources

5.3.1.1. Epidemiological data

Epidemiological data were collected from the Ministry of Health's Epidemiology and Disease Control Unit, and the Central Statistics Office in Gabarone, Botswana. The data consisted of the following information as set out in Table 5.1.

TABLE 5.1 EPIDEMIOLOGICAL DATA COLLECTED FROM BOTSWANA

Country	Time period/frequency/case definition	Spatial Scale
Botswana	1974-1998 Annual outpatient/inpatient	District
Botswana	1982-1999 Annual confirmed/unconfirmed	District
Botswana	1996-1999 Weekly confirmed/unconfirmed	District
Botswana	1996-1999 Weekly deaths	District

The National Health Information System (NHIS) in Botswana has, since 1996, received weekly reports of unconfirmed and confirmed malaria cases, as well as deaths attributed to malaria. To enable these data to be analysed directly with as wide a range of environmental variables as possible they were aggregated to monthly values using SPSS. The weeks spanning the beginning and the ends of months were allocated on the basis of which month their mid weekday fell into.

Some urban districts are assigned as being of the same risk as the wider rural district surrounding them (Ministry of Health 1999), and these are combined here, and the latter are used for extracting statistics on the environmental variables.

5.3.1.2. District boundaries

Some district names and district boundaries have changed during recent years and this has also been taken into account here for data aggregation, Table 5.2. Figure 5.2.

FIGURE 5.2. HEALTH DISTRICTS REPORTING TO THE HEALTH INFORMATION SYSTEM (INCORPORATING URBAN AREAS AND RECENT BOUNDARY CHANGES).

Legend:

The map was produced from health district boundaries supplied by the Ministry of Health, Botswana.

Table 5.2. Administrative districts in Botswana

Administrative District	Formerly or Incorporating
Bobirwe	SPTC (Selibe-Phikwe Town Council)
Boteti	
Chobe	
Ghanzi	
Gumare	Okavango
Kgalagadi	Kgalagadi North and Kgalagadi South
Kgatleng	
Kweneng_E	
Kweneng_W	
Mahalapye	
Ngami	Ngamiland
Northeast	Francistown
Serowe-Palapye	
Southeast	Gabarone and Lobatse
Southern(S)[18]	Good Hope
Southern(N)	
Tutume	

District population totals were produced for each year using available information on growth rates. Following reference to population statistics held by the US Census Bureau and discussion with a demographer based in the WHO Intercountry Team Offices, in Harare, annual population growth rates were revised to reflect a rate of 1% per annum, since 1995. Incidence data were produced for each of the districts by year. The district boundaries used in the extraction were adapted from those provided by SADC in line with changes in the Health Districts.

5.3.1.3. *Environmental data*

The Windisp4 software was used to extract district, regional and national statistics from the digital surfaces of the environmental variables (described in Chapter 4). Administrative boundaries used for the data extraction were amended to correspond with the administrative units used by the various national Health Information Systems. Extracted data included: the latitude and longitude co-ordinates of the district centroids, altitude; decadal CCD, RFE, NDVI aggregated to monthly values;

[18] In the Botswana HIS, the administrative district 'Southern' is divided into two areas: the southerly area was formerly called Good Hope. Here it is simply called Southern(S). Other sectors do not appear to use this division.

monthly Vectorial Capacity, and long-term monthly averages for rainfall, temperature and relative humidity. The monthly Vectorial Capacity images (described in Chapter 3) were produced with monthly average temperature and actual rainfall estimates input into the model at lags of 0, 1 2, and 3 months. With the exception of altitude, latitude and longitude, all environmental variables including Vectorial Capacity (with rainfall to temperature lags) were then lagged at 1-5 months, Tables 5.3 a-d.

The extracted statistics, were then entered into SPSS V.10.0 along with the respective epidemiological data. Image products required for spatial modelling were re-projected into a common spatial and temporal resolution using the Windisp4 software. Windisp4 was then used to export the products into Idrisi format for subsequent modelling using Idrisi's 'Image Calculator' function.

5.3.2. Data analysis

SPSS and Microsoft Excel were used to explore and assess the relationships between the data sets. The preliminary analyses included comparing time series of unconfirmed (outpatient and inpatient) and laboratory confirmed malaria cases using exploratory scatterplots and Pearson's correlation coefficient. Comparisons were made of relationships between contemporaneous environmental variables such as NDVI and RFE and the respective long-term mean monthly climatology variables. The relationships between the epidemiological data and the environmental variables were also explored using curve estimation techniques in SPSS. The best overall relationships between environmental variables and the epidemiological data occurred when the natural log of the confirmed malaria incidence was used. As a result of this, and the fact that laboratory confirmed data was available for all districts in Botswana, the prime malaria case data chosen for further analysis was the natural log of the monthly incidence of confirmed cases, 1996-1999.

Difference anomalies for both contemporaneous environmental variables, and the log confirmed incidence data, were created by aggregating annual mean monthly statistics and then subtracting mean from actual. These were then classified: zero <=0, one >0. Chi square (using 'exact' where N<=5) statistics on differences

TABLE 5.3A. SUMMARY OF ENVIRONMENTAL VARIABLES FROM REMOTE SENSING.

Environmental proxies derived from remote sensing		
Variable	**Description**	**Notation used in models**
NDVI smoothed average	Monthly NDVI made from dekadal data using a simple smoothing technique (Robinson, 1996).	NDVI_SAV
NDVI smoothed average lag 1	Monthly NDVI smoothed and lagged by one month	LAGS(NDVI_SAV,1)
NDVI smoothed average lag 2	Monthly NDVI smoothed and lagged by two months	LAGS(NDVI_SAV,2)
NDVI smoothed average lag 3	Monthly NDVI smoothed and lagged by three months	LAGS(NDVI_SAV,3)
NDVI smoothed average lag 4	Monthly NDVI smoothed and lagged by four months	LAGS(NDVI_SAV,4)
NDVI smoothed average lag 5	Monthly NDVI smoothed and lagged by five months	LAGS(NDVI_SAV,5)
NDVI maximum	maximum NDVI value in month	NDVI_MAX
NDVI maximum lag 1	maximum NDVI in month lagged by one month	LAGS(NDVI_MAX,1)
NDVI maximum lag 2	maximum NDVI in month lagged by two months	LAGS(NDVI_MAX,2)
NDVI maximum lag 3	maximum NDVI in month lagged by three months	LAGS(NDVI_MAX,3)
NDVI maximum lag 4	maximum NDVI in month lagged by four months	LAGS(NDVI_MAX,4)
NDVI maximum lag 5	maximum NDVI in month lagged by five months	LAGS(NDVI_MAX,5)
Rainfall estimate	Monthly rainfall estimate (sum of dekadal estimates)	RFE
Rainfall estimate lag 1	Monthly rainfall estimate lagged by one month	LAGS(RFE,1)
Rainfall estimate lag 2	Monthly rainfall estimate lagged by two months	LAGS(RFE,2)
Rainfall estimate lag 3	Monthly rainfall estimate lagged by three months	LAGS(RFE,3)
Rainfall estimate lag 4	Monthly rainfall estimate lagged by four months	LAGS(RFE,4)
Rainfall estimate lag 5	Monthly rainfall estimate lagged by five months	LAGS(RFE,5)
Cold Cloud Duration	Monthly CCD (sum of dekadal CCD)	CCD
Cold Cloud Duration lag1	Monthly CCD lagged one month	LAGS(CCD,1)
Cold Cloud Duration lag2	Monthly CCD lagged two months	LAGS(CCD,1)
Cold Cloud Duration lag3	Monthly CCD lagged three months	LAGS(CCD,1)
Cold Cloud Duration lag4	Monthly CCD lagged four months	LAGS(CCD,1)
Cold Cloud Duration lag5	Monthly CCD lagged five months	LAGS(CCD,1)

FIGURE 5.3B SUMMARY OF ENVIRONMENTAL VARIABLES FROM MEAN CLIMATOLOGY

Mean monthly climatology (1951-1995)		
Variable	**Description**	**Notation used in models**
Mean rainfall	Monthly mean rainfall (1951-95)	RAIN
Mean rainfall lag 1	Monthly mean rainfall (1951-95) lagged by one month	LAGS(X_RAIN_1)
Mean rainfall lag 2	Monthly mean rainfall (1951-95) lagged by two months	LAGS(X_RAIN_2)
Mean rainfall lag 3	Monthly mean rainfall (1951-95) lagged by three months	LAGS(X_RAIN_3)
Mean rainfall lag 4	Monthly mean rainfall (1951-95) lagged by four months	LAGS(X_RAIN_4)
Mean rainfall lag 5	Monthly mean rainfall (1951-95) lagged by five months	LAGS(X_RAIN_5)
Mean temperature	Monthly mean temperature (1951-95)	TEMP
Mean temperature lag 1	Monthly mean temperature (1951-95) lagged by one month	LAGS(X_TEMP_1)
Mean temperature lag 2	Monthly mean temperature (1951-95) lagged by two months	LAGS(X_TEMP_2)
Mean temperature lag 3	Monthly mean temperature (1951-95) lagged by three months	LAGS(X_TEMP_3)
Mean temperature lag 4	Monthly mean temperature (1951-95) lagged by four months	LAGS(X_TEMP_4)
Mean temperature lag 5	Monthly mean temperature (1951-95) lagged by five months	LAGS(X_TEMP_5)
Mean relative humidity	Monthly mean relative humidity (1961-1990)	RH
Mean relative humidity lag 1	Monthly mean relative humidity (1961-1990) lagged by one month	LAGS(X_RH_1)
Mean relative humidity lag 2	Monthly mean relative humidity (1961-1990) lagged by two months	LAGS(X_RH_1)
Mean relative humidity lag 3	Monthly mean relative humidity (1961-1990) lagged by three months	LAGS(X_RH_1)
Mean relative humidity lag 4	Monthly mean relative humidity (1961-1990) lagged by four months	LAGS(X_RH_1)
Mean relative humidity lag 5	Monthly mean relative humidity (1961-1990) lagged by five months	LAGS(X_RH_1)

FIGURE 5.3C. NON-TEMPORAL ENVIRONMENTAL VARIABLES USED

Variable	**Description**	**Notation used in models**
Latitude	Latitude of district centroid	LATS
Longitude	Longitude of district centroid	LONGS
Minimum altitude	Minimum altitude in distict	MIN_ALT
Maximum altitude	Maximum altitude in district	MAX_ALT
Average altitude	Average altitude in district	AVG_ALT
Altitude class	Altitude range considered to be pertinent to malaria endemicity, e.g. (Taylor and Matumbo, 1986)	ALT_CLASS

TABLE 5.3D. SUMMARY OF ENVIRONMENTAL VARIABLES CREATED.

Vectorial Capacity product using both mean climatology (T) and remote sensing (RFE)		
Variable	**Description**	**Notation used**
Vectorial Capacity lag 0	Monthly vectorial capacity with both T and RFE simultaneous	VCLAG_0
Vectorial Capacity lag 1	Monthly vectorial capacity with RFE lagged by 1 month	VCLAG_1
Vectorial Capacity lag 2	Monthly vectorial capacity with RFE lagged by 2 months	VCLAG_2
Vectorial Capacity lag 3	Monthly vectorial capacity with RFE lagged by 3 months	VCLAG_3
Vectorial Capacity lag 0_1	Monthly vectorial capacity (T and RFE simultaneous) lagged 1 month	LAGS(VCLAG_0,1)
Vectorial Capacity lag 0_2	Monthly vectorial capacity (T and RFE simultaneous) lagged 2 months	LAGS(VCLAG_0,2)
Vectorial Capacity lag 0_3	Monthly vectorial capacity (T and RFE simultaneous) lagged 3 months	LAGS(VCLAG_0,3)
Vectorial Capacity lag 0_4	Monthly vectorial capacity (T and RFE simultaneous) lagged 4months	LAGS(VCLAG_0,4)
Vectorial Capacity lag 0_5	Monthly vectorial capacity (T and RFE simultaneous) lagged 5 months	LAGS(VCLAG_0,5)
Vectorial Capacity lag 1_1	Monthly vectorial capacity (input RFE lagged by 1 month) lagged 1 month	LAGS(VCLAG_1,1)
Vectorial Capacity lag 1_2	Monthly vectorial capacity (input RFE lagged by 1 month) lagged 2months	LAGS(VCLAG_1,2)
Vectorial Capacity lag 1_3	Monthly vectorial capacity (input RFE lagged by 1 month) lagged 3 months	LAGS(VCLAG_1,3)
Vectorial Capacity lag 1_4	Monthly vectorial capacity (input RFE lagged by 1 month) lagged 4 months	LAGS(VCLAG_1,4)
Vectorial Capacity lag 1_5	Monthly vectorial capacity (input RFE lagged by 1 month) lagged 5 months	LAGS(VCLAG_1,5)
Vectorial Capacity lag 2_1	Monthly vectorial capacity (input RFE lagged by 2 months) lagged 1 month	LAGS(VCLAG_2,1)
Vectorial Capacity lag 2_2	Monthly vectorial capacity (input RFE lagged by 2 months) lagged 2 months	LAGS(VCLAG_2,2)
Vectorial Capacity lag 2_3	Monthly vectorial capacity (input RFE lagged by 2 months) lagged 3 months	LAGS(VCLAG_2,3)
Vectorial Capacity lag 2_4	Monthly vectorial capacity (input RFE lagged by 2 months) lagged 4 months	LAGS(VCLAG_2,4)
Vectorial Capacity lag 2_5	Monthly vectorial capacity (input RFE lagged by 2 months) lagged 5 months	LAGS(VCLAG_2,5)
Vectorial Capacity lag 3_1	Monthly vectorial capacity (input RFE lagged by 3 months) lagged 1 month	LAGS(VCLAG_3,1)
Vectorial Capacity lag 3_2	Monthly vectorial capacity (input RFE lagged by 3 months) lagged 2 months	LAGS(VCLAG_3,2)
Vectorial Capacity lag 3_3	Monthly vectorial capacity (input RFE lagged by 3 months) lagged 3 months	LAGS(VCLAG_3,3)
Vectorial Capacity lag 3_4	Monthly vectorial capacity (input RFE lagged by 3 months) lagged 4 months	LAGS(VCLAG_3,4)
Vectorial Capacity lag 3_5	Monthly vectorial capacity (input RFE lagged by 3 months) lagged 5 months	LAGS(VCLAG_3,5)

between classified epidemiological and environmental anomalies. These were graphed for visual analysis prior to modelling.

5.3.3. Mapping malaria

Methods of presenting summary data in map format were explored. These included:

- Identifying the malaria positive months in each district using: presence or absence of any confirmed malaria cases reported in any given month, per district.
- Identifying the malaria transmission season in each district. This was achieved through:

    - identifying months in which confirmed malaria incidence exceeded a specified percentage threshold of the annual total
    - Following explorations using the monthly unconfirmed and confirmed cases for 1996-1999 the figure of 5% of annual total was chosen as being the most useful indicator of whether a particular month belongs to the malaria transmission season. This technique was also used by Hay and colleagues to determine seasonality of malaria in Kenya (Hay, Snow et al. 1998b) who coincidently found 5% to be the best indicator of the beginning and end of the transmission season.
    - Identifying months in which malaria incidence equal to or in excess of the percentage threshold value and neighbouring at least one other similar month. Months fulfilling this criteria were deemed to be part of the malaria transmission season.
    - Mapping the number of months fulfilling the malaria transmission season criteria including the first month, the last month and the duration of the season.

- Development of a map describing a seasonal model of malaria incidence, based on environmental variables, using logistic regression techniques. Logistic regression computes the percentage of class membership, 1 or 0, of malaria season using differences between a number of independent variables.

The 'Forward Stepwise' method in SPSS was used to run a number of exploratory logistic models using the environmental variables described in Tables 5.3a-d.

5.3.4. Monitoring changes in epidemic risk

Linear regression modelling was used to identify combinations of selected environmental variables most closely associated with the monthly variability in the confirmed malaria incidence data. Tests of association between environmental variable anomalies and malaria incidence anomalies were explored. The environmental variables which were lagged (0,1,2,3,4 and 5 months) were analysed against variability in the monthly incidence data. The products were then used in the development of predictive maps of confirmed monthly malaria incidence, at national and sub-national scales, using linear regression methods.

5.4. Results

5.4.1. Patterns of malaria in Botswana

Annual totals (1982-1999) of confirmed malaria cases plotted against time show that malaria in Botswana has a high inter-annual variability (Figure 5.3a). There is also a clear trend of increased malaria cases over time apparent in Figure 5.3a. The MoH have suggested that this is due to increased parasite resistance to drug treatment (Chloroquine was changed to S.P. as the first line drug in 1997) and a shift southward of the margins of transmission (Ministry of Health 1999). Ghanzi was first declared a malarious district in 1997. While the confirmed cases are a sub-set of unconfirmed (total) malaria cases that may have varied in proportion over the years, the correlation between unconfirmed and confirmed cases in Botswana is relatively strong (R^2=0 .7982), Figure 5.3b. The relationship between confirmed and unconfirmed malaria cases varied over the months of the year, and between districts, Table 5.4a-b.

FIGURE 5.3A. ANNUAL TOTALS OF CONFIRMED CASES OF MALARIA IN BOTSWANA 1982-1999.

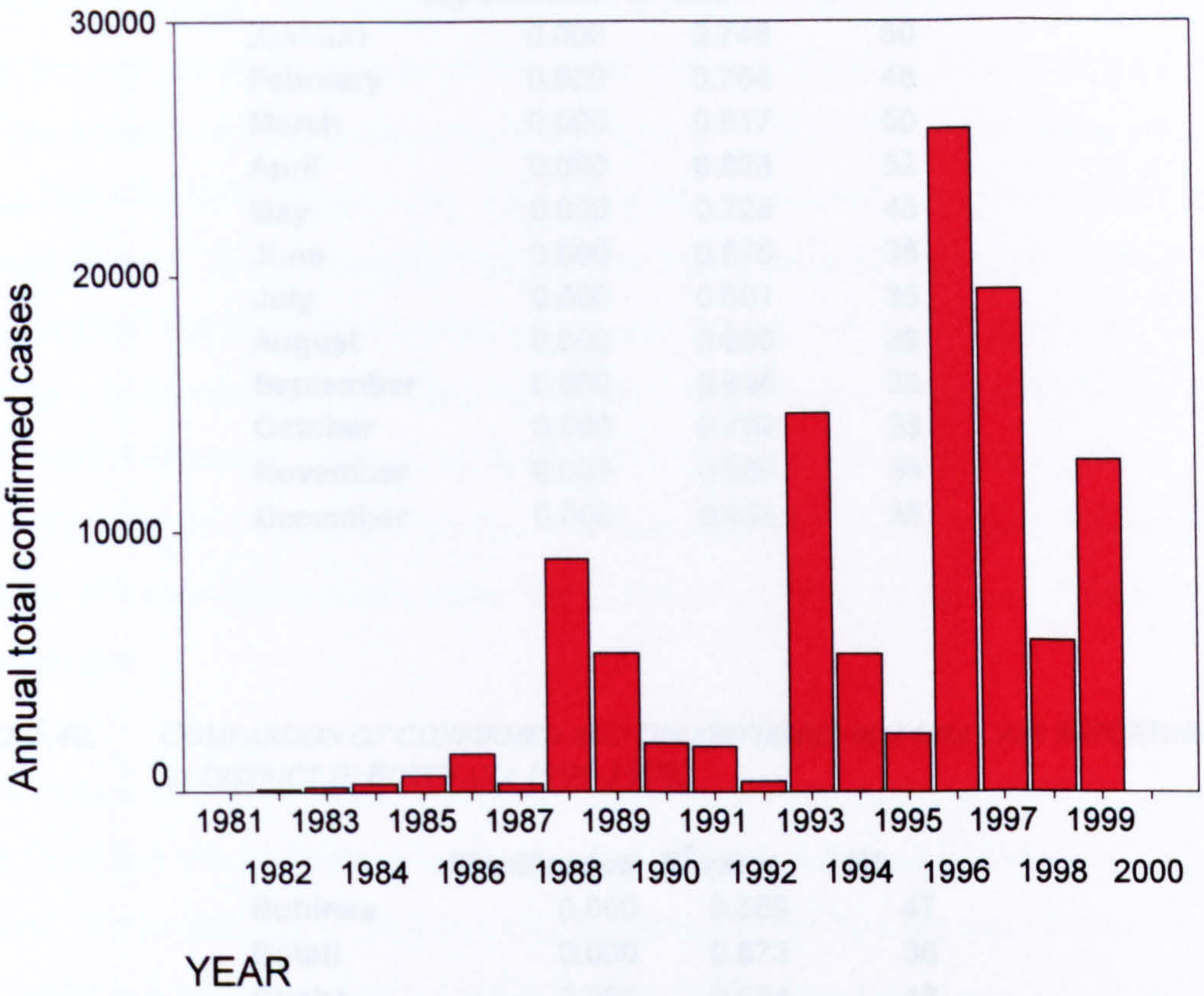


FIGURE 5.3B. RELATIONSHIP BETWEEN CONFIRMED AND UNCONFIRMED MALARIA CASES IN BOTSWANA 1982-1999.

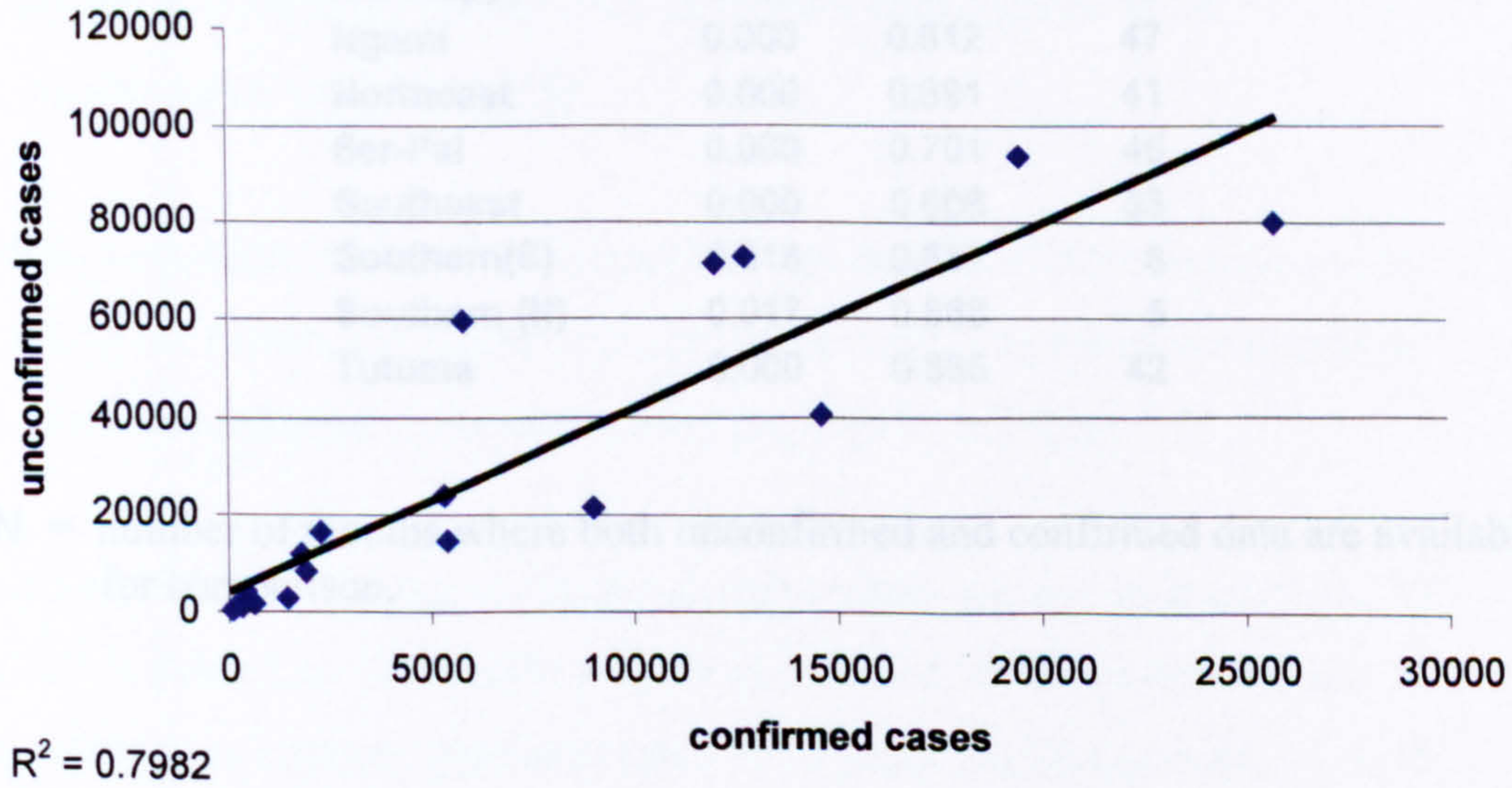


TABLE 5.4A. COMPARISON OF AVERAGE MONTHLY CONFIRMED AND UNCONFIRMED MALARIA CASE REPORTING IN BOTSWANA 1996-1999.

	Significance	R^2 value	N*
JANUARY	0.000	0.746	50
February	0.000	0.764	48
March	0.000	0.817	50
April	0.000	0.823	52
May	0.000	0.728	48
June	0.000	0.576	38
July	0.000	0.601	35
August	0.000	0.660	29
September	0.000	0.646	33
October	0.000	0.702	33
November	0.001	0.286	36
December	0.000	0.615	35

TABLE 5.4B. COMPARISON OF CONFIRMED AND UNCONFIRMED MALARIA CASE REPORTING BY DISTRICT IN BOTSWANA 1996-1999.

	Significance	R^2 value	N*
Bobirwe	0.000	0.559	47
Boteti	0.000	0.673	36
Chobe	0.000	0.624	48
Ghanzi	0.000	0.626	35
Gumare	0.000	0.767	48
Kgalagadi	0.038	0.436	10
Kgatleng	0.282	0.096	14
Kweneng_E	-	-	0
Kweneng_W	-	-	0
Mahalapye	0.002	0.340	26
Ngami	0.000	0.812	47
Northeast	0.000	0.691	41
Ser-Pal	0.000	0.701	45
Southeast	0.000	0.606	35
Southern(S)	0.018	0.637	8
Southern (N)	0.017	0.888	5
Tutume	0.000	0.885	42

* N = number of months where both unconfirmed and confirmed data are available for comparison.

The most consistent agreement between the two data sets corresponds generally with the main months of the malaria season, March and April, and the more endemic districts, e.g. Ngami. However, there are anomalies. These are caused mostly by sporadic cases occurring in some of the more southern districts. The correlation between malaria inpatients and confirmed cases for 1992-1998 was found to be very strong (R2 = 0.9559), Figure 5.3c. This suggests a high level of accurate diagnosis in hospital care. The relationship between the longer-term unconfirmed (1974-1998) outpatient and inpatient malaria data was found to be $R^2 = 0.611$, Figure 5.3d, showing a wider spread in the data, especially when case numbers are high. The relationship between confirmed cases and malaria deaths (1992-1999) was $R^2 = 0.861$, Figure 5.3e. This indicates that inter-annual variation in malaria deaths was a function of transmission levels rather that variation in cases and access to effective drug therapy.

The average confirmed monthly incidence figures for the years 1996-1999 (Figure 5.4.) show that Chobe District has the highest malaria, followed by Gumare, Ngami, Tutume, Boteti and Ghanzi respectively. However, it can be seen from Figure 5.5. that confirmed malaria incidence varies markedly between years, and among the different districts.

SPSS was used to analyse the correlation between reported malaria cases and latitude (the district centroid). The scatter plot produced in Figure 5.6. shows that monthly confirmed malaria cases during 1996-1999 were concentrated in the northern part of the country (areas less than 23°S).

A cross tabulation of simple presence (YES) or absence (NO) of confirmed malaria reporting per month, per district was also carried out. The result is outlined in Table 5.5. and the confirmed cases represented graphically in Figure 5.7.

Presence (YES) or absence (NO) of reported malaria per month is tabulated by district in Table 5.6. The results suggest that no district in Botswana is free of unconfirmed or confirmed malaria cases being reported. Furthermore, 11 of the 17 districts report confirmed malaria cases for 6 months or more and that 4 of those

FIGURE 5.3C. RELATIONSHIP BETWEEN MALARIA INPATIENT AND CONFIRMED CASE DATA 1992-1998.

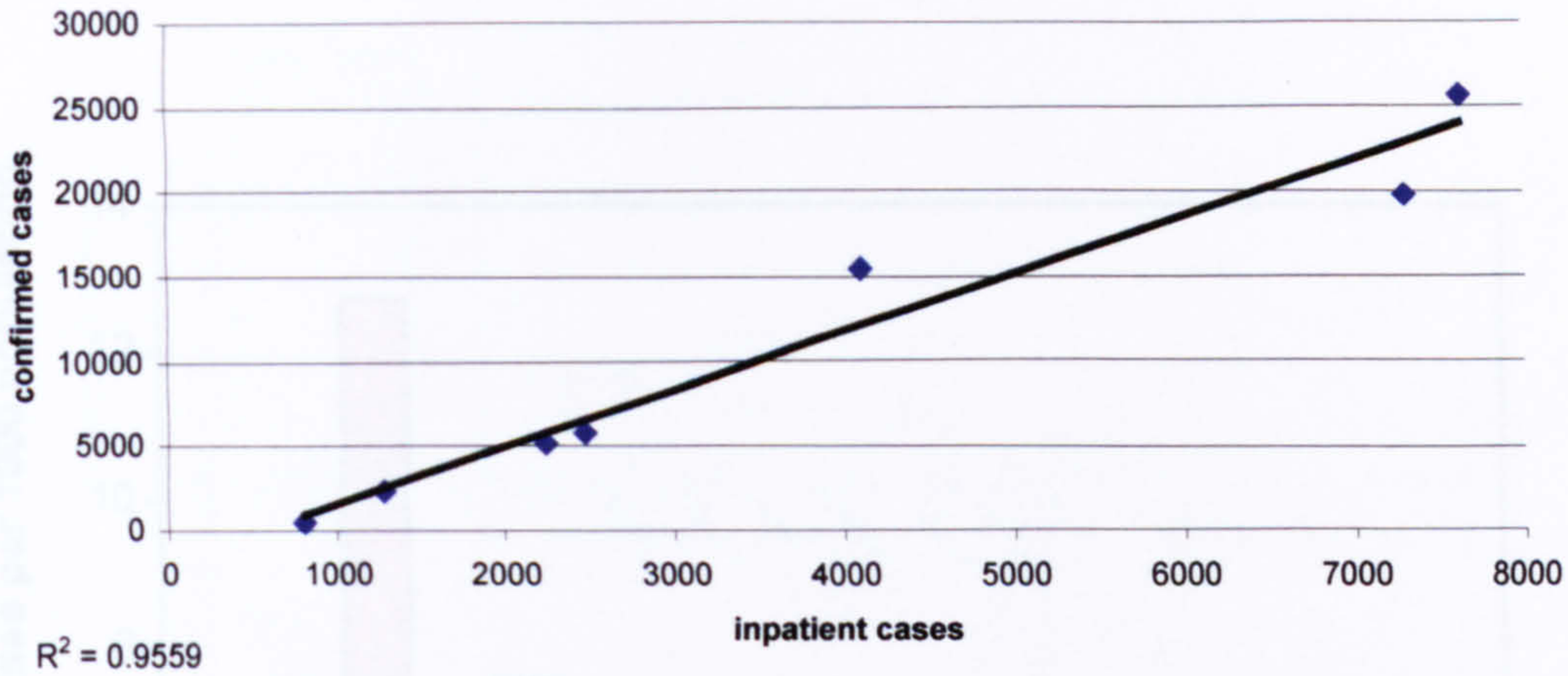


FIGURE 5.3D. RELATIONSHIP BETWEEN OUTPATIENT AND INPATIENT MALARIA CASES, BOTSWANA 1974-1998.*

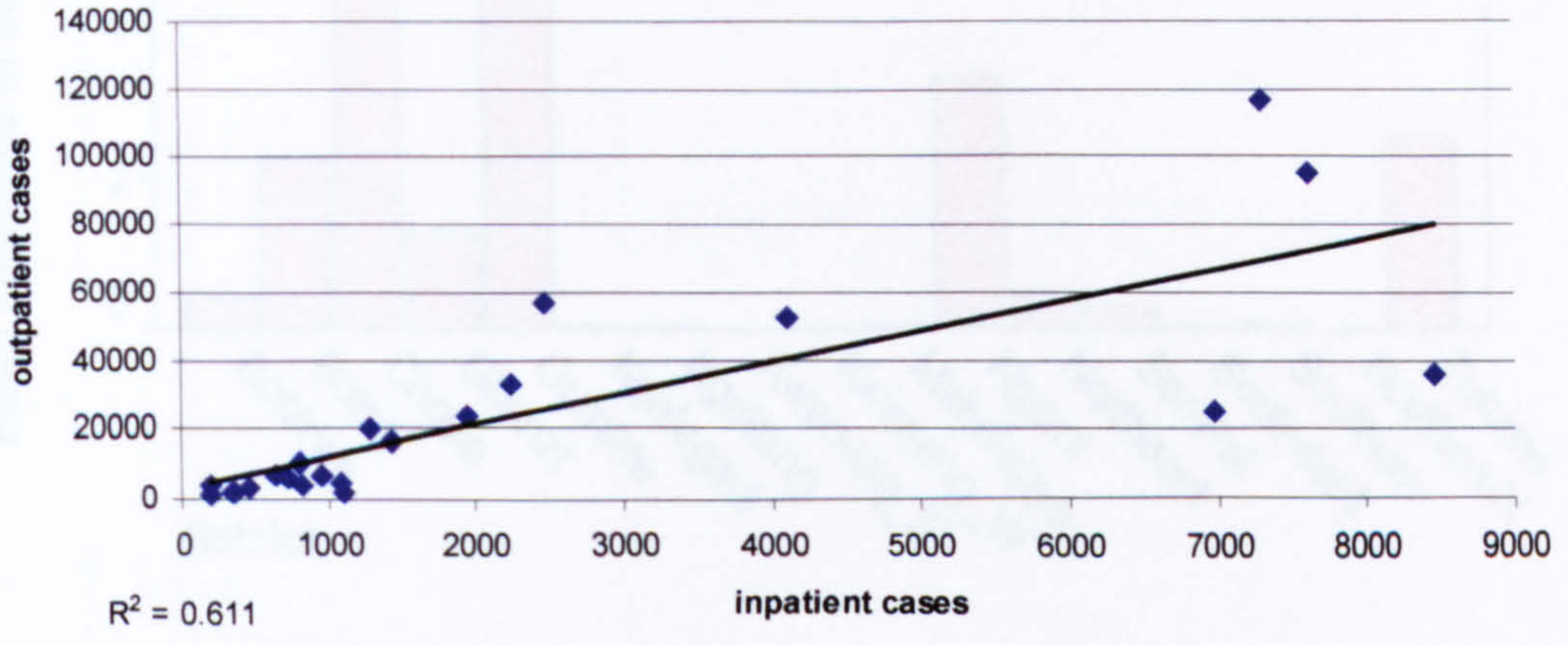
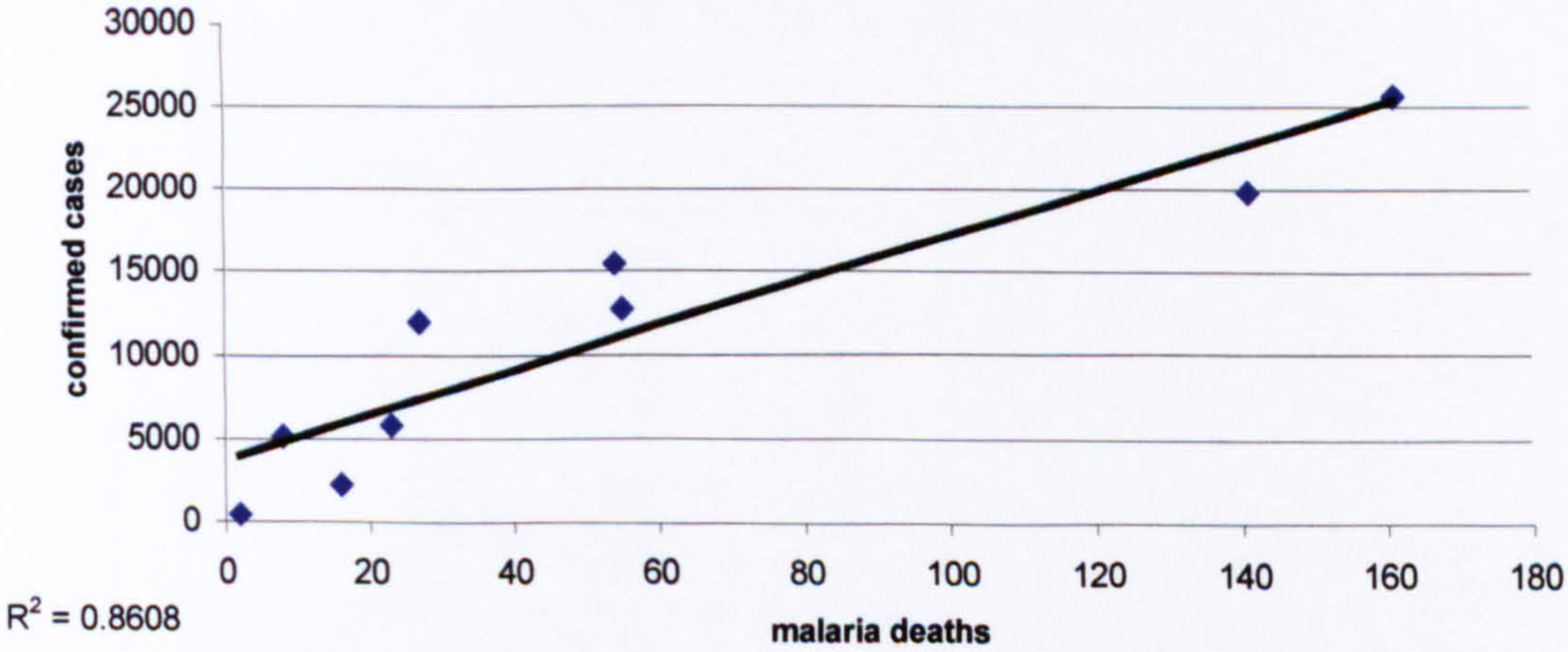


FIGURE 5.3E. CORRELATION BETWEEN CONFIRMED MALARIA CASES AND MALARIA DEATHS IN BOTSWANA, 1992-1998.



* inpatient cases are admissions with presumptive malaria which may or may not be confirmed at the time of reporting

FIGURE 5.4. INCIDENCE OF CONFIRMED CASES BY DISTRICT (MONTHLY AVERAGE FOR 1996-1999 PER 1000 POPULATION).

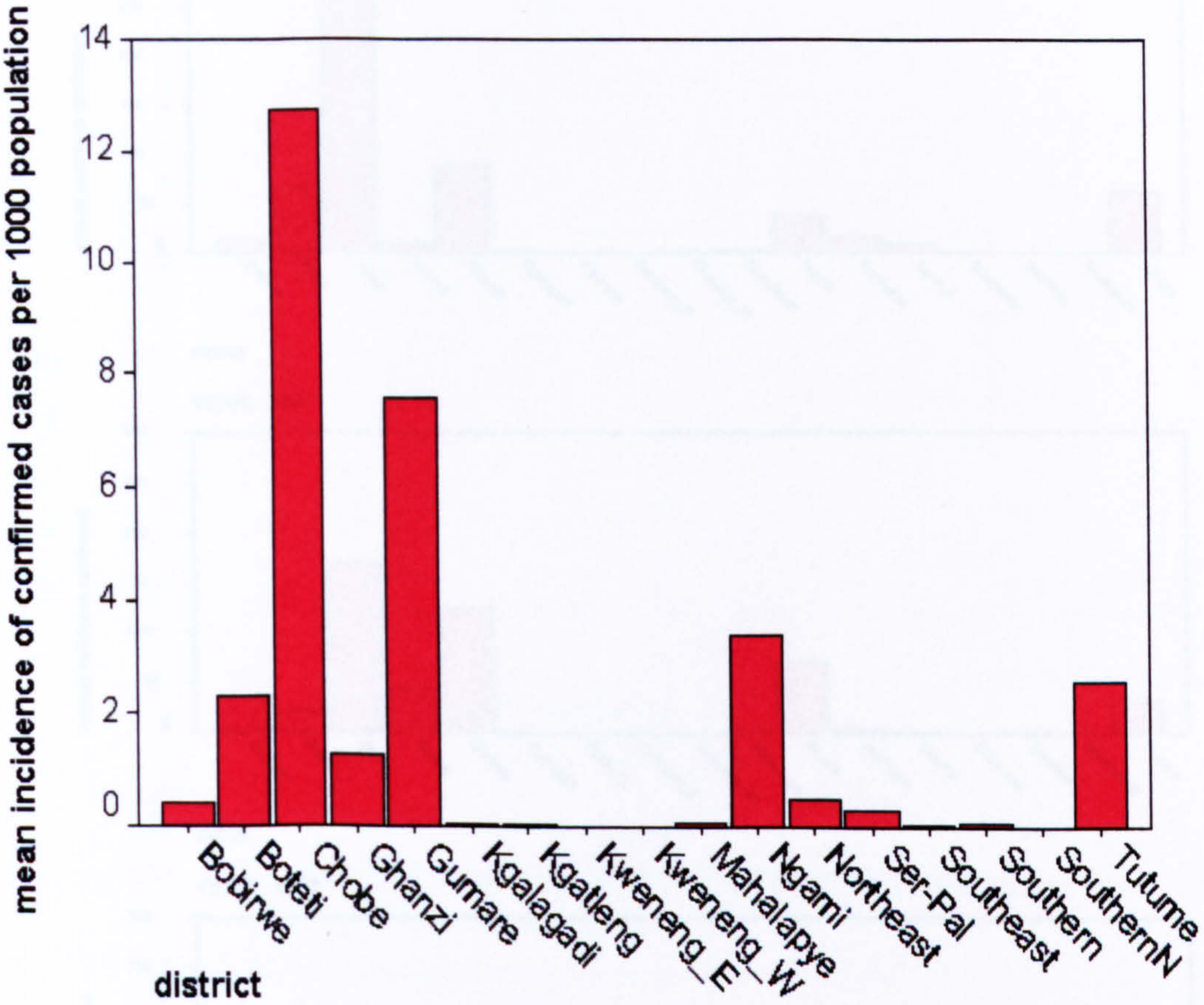


FIGURE 5.5. COMPARISON OF ANNUAL CONFIRMED MALARIA INCIDENCE (PER 1000, PER YEAR) BY DISTRICT 1996-1999.

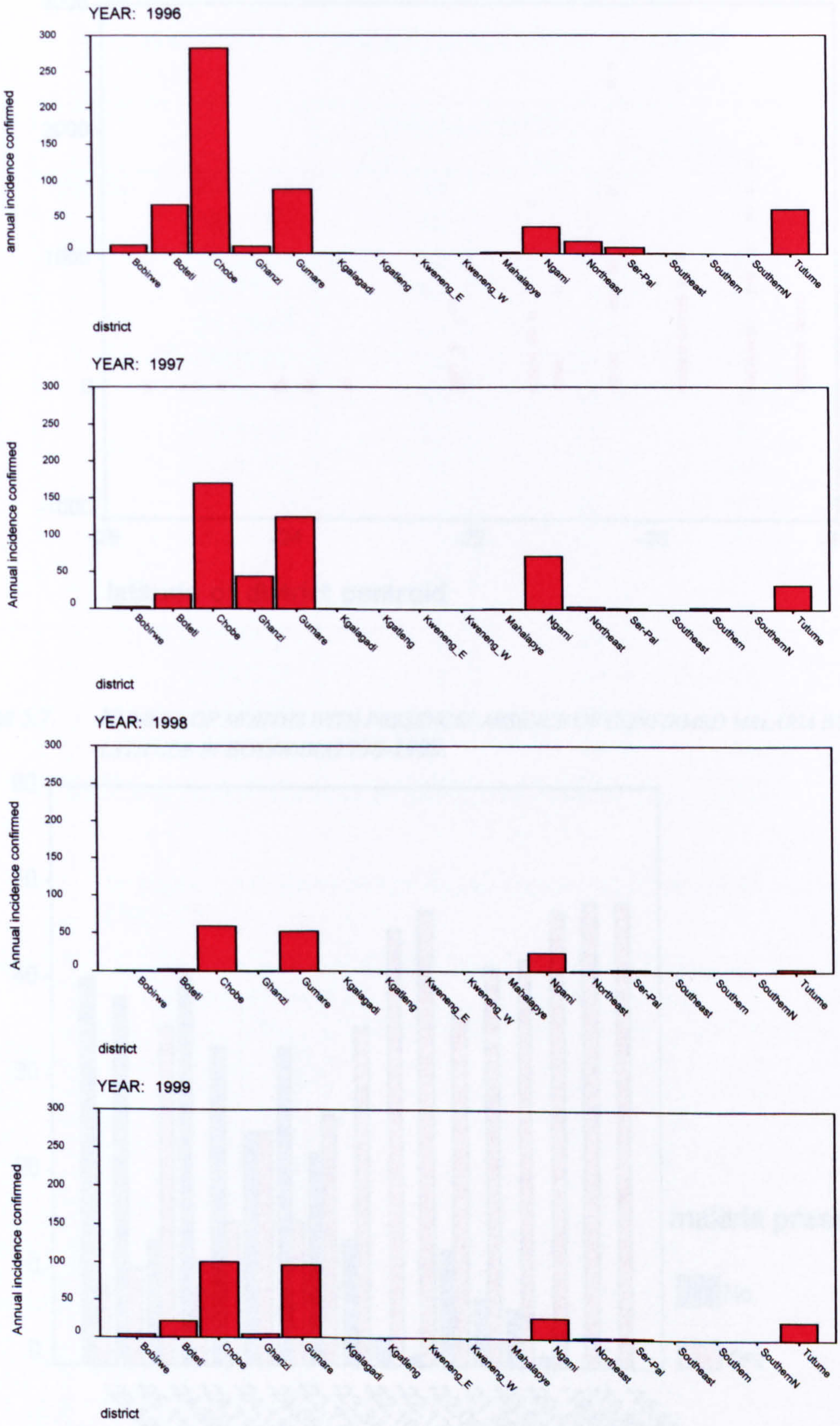


FIGURE 5.6. NORTH-SOUTH DISTRIBUTION OF MALARIA IN BOTSWANA 1996-1999.

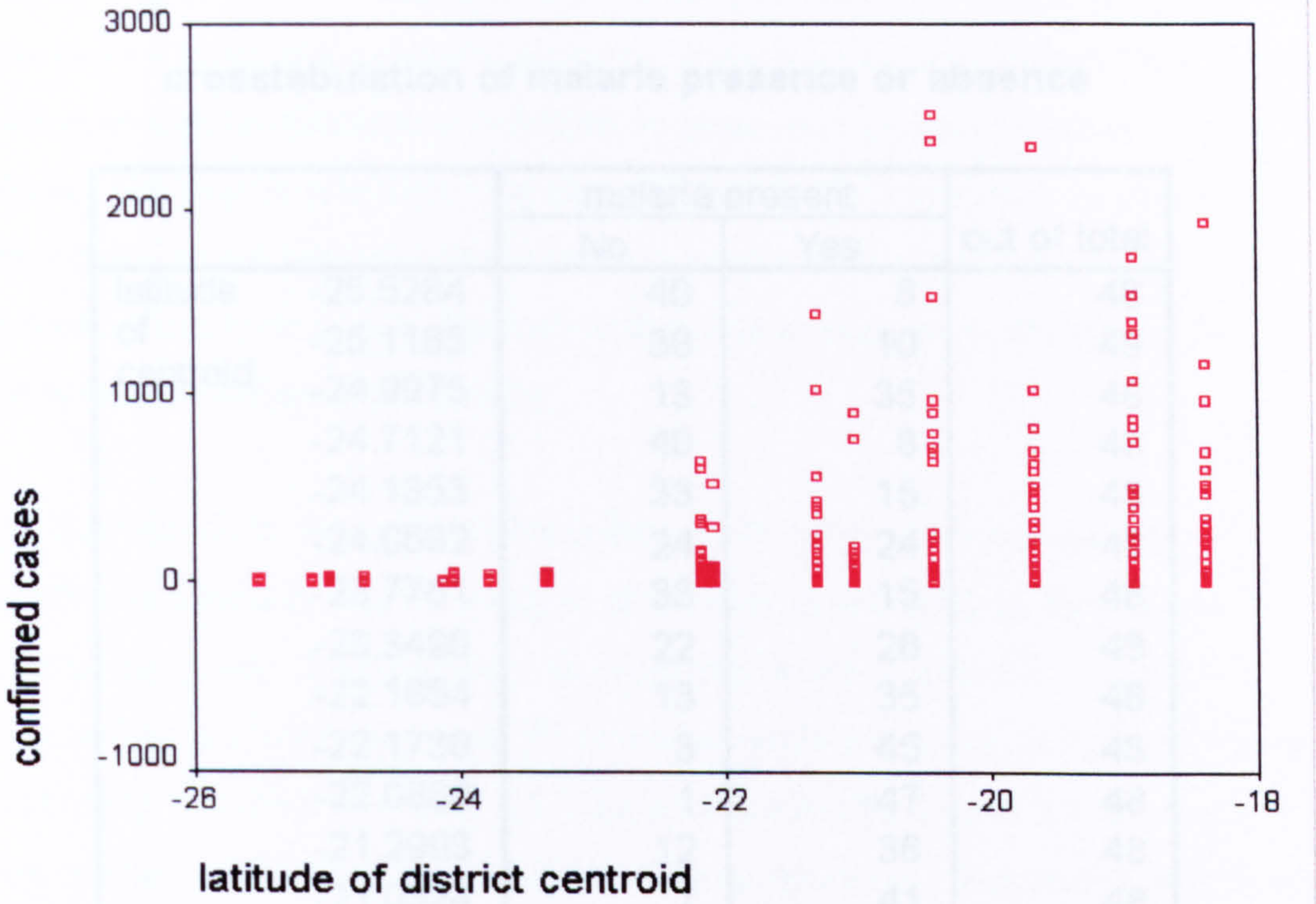


FIGURE 5.7. NUMBER OF MONTHS WITH PRESENCE/ ABSENCE OF CONFIRMED MALARIA BY LATITUDE IN BOTSWANA1996-1999.

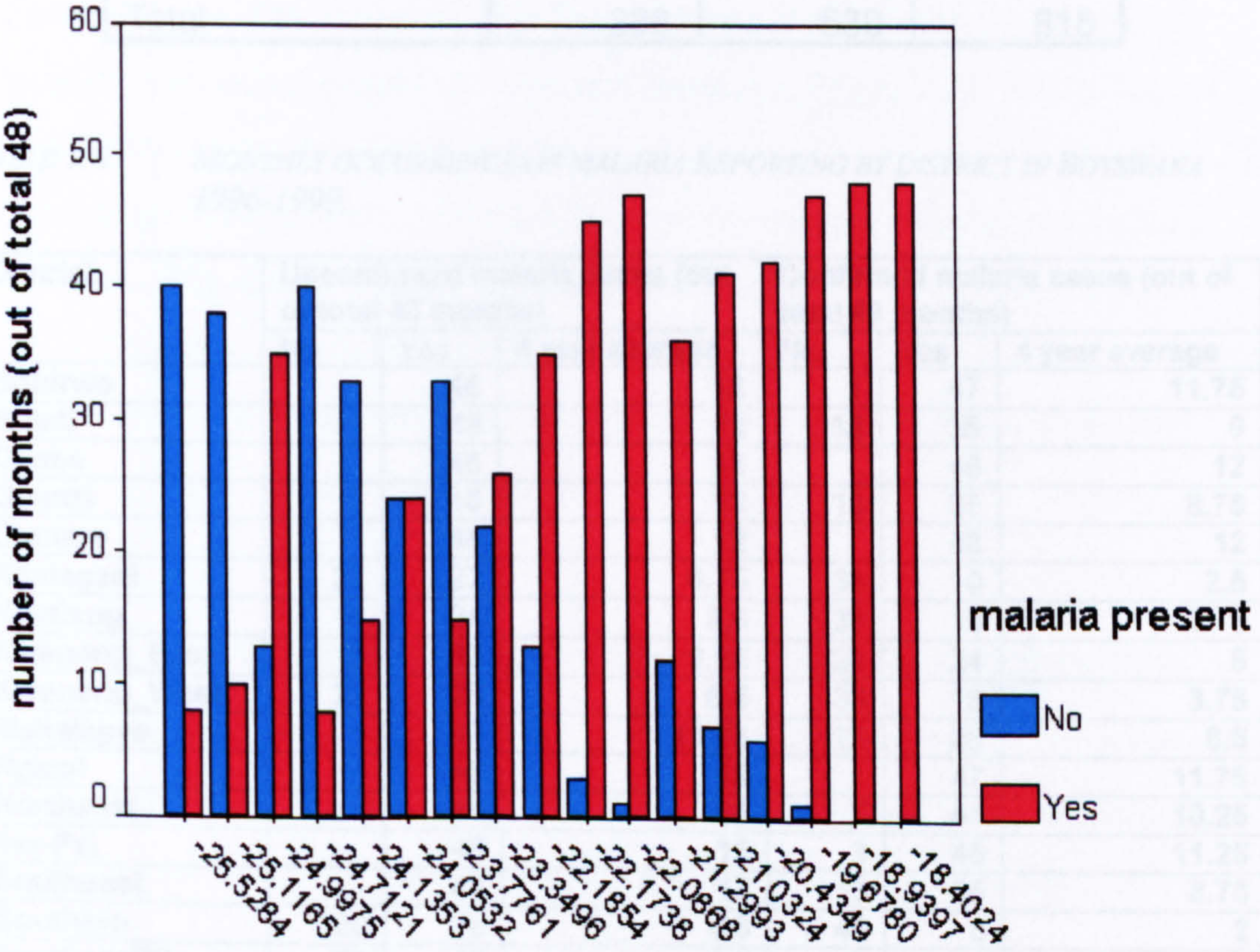


TABLE 5.5. NUMBER OF MONTHS WITH PRESENCE OR ABSENCE OF CONFIRMED MALARIA BY LATITUDE IN BOTSWANA1996-1999.

crosstabulation of malaria presence or absence

		malaria present		out of total
		No	Yes	
latitude of centroid	-25.5284	40	8	48
	-25.1165	38	10	48
	-24.9975	13	35	48
	-24.7121	40	8	48
	-24.1353	33	15	48
	-24.0532	24	24	48
	-23.7761	33	15	48
	-23.3496	22	26	48
	-22.1854	13	35	48
	-22.1738	3	45	48
	-22.0868	1	47	48
	-21.2993	12	36	48
	-21.0324	7	41	48
	-20.4349	6	42	48
	-19.6780	1	47	48
	-18.9397		48	48
	-18.4024		48	48
Total		286	530	816

TABLE 5.6. MONTHLY OCCURRENCE OF MALARIA REPORTING BY DISTRICT IN BOTSWANA 1996-1999

District	Unconfirmed malaria cases (out of total 48 months)			Confirmed malaria cases (out of total 48 months)		
	No	Yes	4 year average	No	Yes	4 year average
Bobirwe		48	12	1	47	11.75
Boteti		48	12	12	36	9
Chobe		48	12		48	12
Ghanzi		48	12	13	35	8.75
Gumare		48	12		48	12
Kgalagadi	21	27	6.75	38	10	2.5
Kgatleng	14	34	8.5	33	15	3.75
Kweneng_East	15	33	8.25	24	24	6
Kweneng_West	22	26	6.5	33	15	3.75
Mahalapye	1	47	11.75	22	26	6.5
Ngami		48	12	1	47	11.75
Northeast		48	12	7	41	10.25
Ser-Pal		48	12	3	45	11.25
Southeast		48	12	13	35	8.75
Southern	30	18	4.5	40	8	2
Southern(N)	38	10	2.5	40	8	2
Tutume		48	12	6	42	10.5

districts report confirmed malaria cases year round. To illustrate this the results were mapped, Figure 5.8. The map still supports the perception of malaria being greatest in the northern half of the country. However, it does depart substantially from Expert Opinion on malaria distribution in Botswana in terms of average seasonal duration of malaria. The map merely shows the occurrence of malaria reporting by district and does not distinguish between districts with one isolated case and others with hundreds of cases per month. The map is therefore inadequate in illustrating the 'endemicity' of malaria in Botswana.

The cross tabulation was repeated using the results of the months of malaria transmission obtained from the analysis of monthly membership of the malaria transmission season. Membership was considered to be '1' if totals of monthly confirmed cases were greater than 5% of annual totals and not sporadic[19], otherwise membership would be '0', Table 5.7. The seasonal results, Figure 5.9. are much closer to expert opinion on malaria distribution in Botswana. The results were then mapped, Figure 5.10.

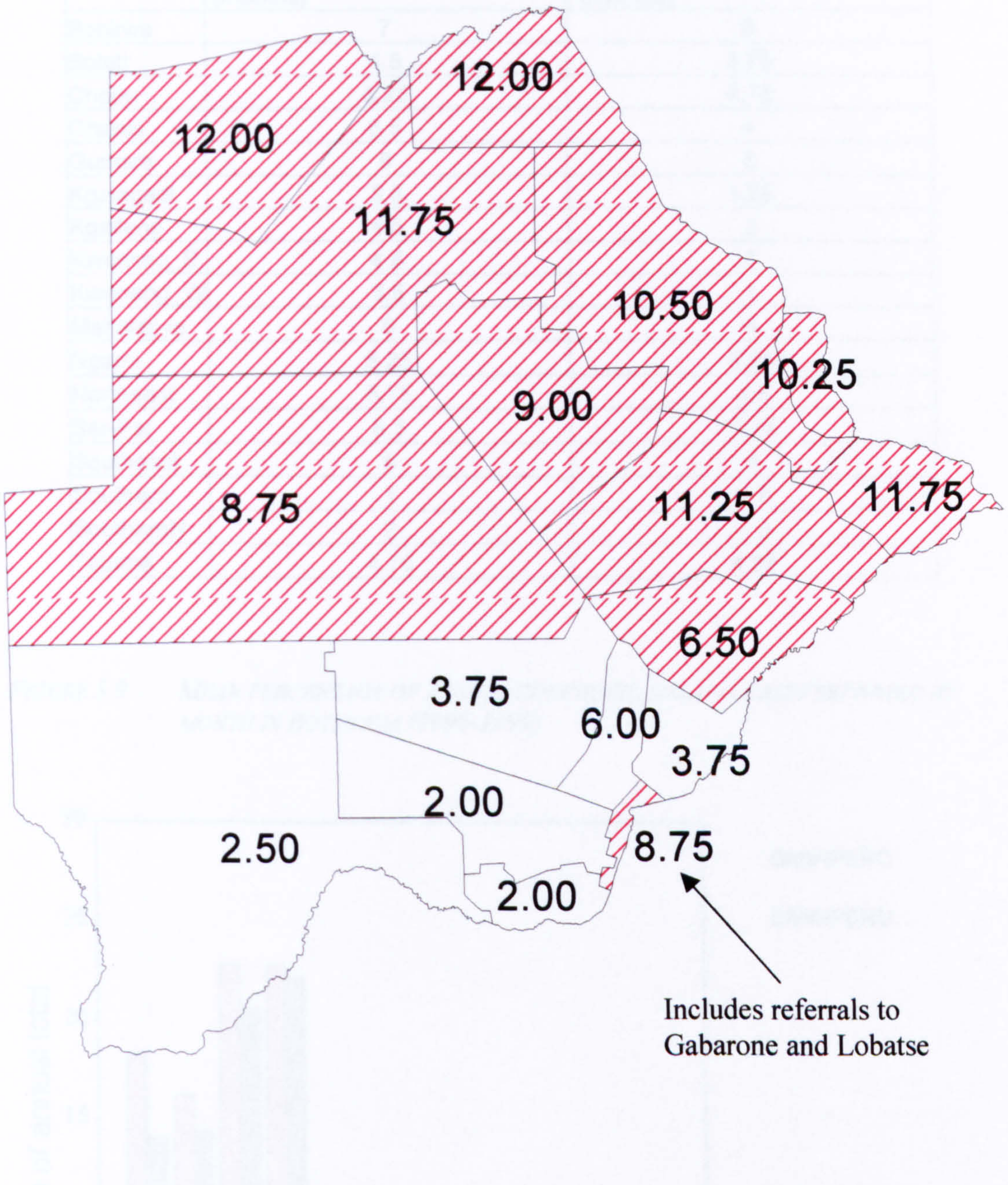
It can be seen from the map that the average malaria 'season' is longer in districts in the northern part of the country. This finding does not agree with the climate suitability map, cursor enquiry for northern Botswana, Figure 2.12. While it should be noted that the cursor enquiry in Figure 2.12, represents only that specific pixel the colour categories over northern Botswana generally suggest a shorter season than found here. The district Southeast is somewhat anomalous with a value of five months. However, this district contains both Gabarone and Lobatse, two major urban districts, and it was considered that many of the cases appearing here would be referrals, a result of transmission outside of the district.

5.4.2. A logistic regression model of malaria season in Botswana

The monthly presence (1 = monthly totals =>5% of annual totals, N=247) or absence (0 = monthly totals <5% of annual totals and sporadic, N=569) of confirmed malaria cases was used to create a logistic regression model of the malaria season in

[19] Sporadic is used here to describe low numbers of reported cases in an isolated month where neighbouring months do not have reported cases.

FIGURE 5.8. MAP OF BOTSWANA SHOWING AVERAGE DURATION IN MONTHS OF CONFIRMED MALARIA CASE REPORTING BY DISTRICT.



Legend:

Hatched areas indicate districts with malaria reporting for longer than 6 months per year on average.

TABLE 5.7. AVERAGE DURATION OF MALARIA SEASON IN MONTHS , BY DISTRICT, IN BOTSWANA 1996-1999.

District	Unconfirmed malaria season (months)	Confirmed malaria season (months)
Bobirwe	7	6
Boteti	4.5	3.75
Chobe	8.25	4.75
Ghanzi	6.5	4
Gumare	6	5
Kgalagadi	3.5	1.25
Kgatleng	4.5	3
Kweneng_E	4.5	3
Kweneng_W	3.5	1
Mahalapye	6	4
Ngami	5.25	4.25
Northeast	5.75	4.5
Ser-Pal	6.5	5.25
Southeast	6	5
Southern	1	1.5
SouthernN	2	1.5
Tutume	4.75	4.25

FIGURE 5.9 MEAN PERCENTAGE OF ANNUAL CONFIRMED MALARIA CASES REPORTED BY MONTH IN BOTSWANA (1996-1999).

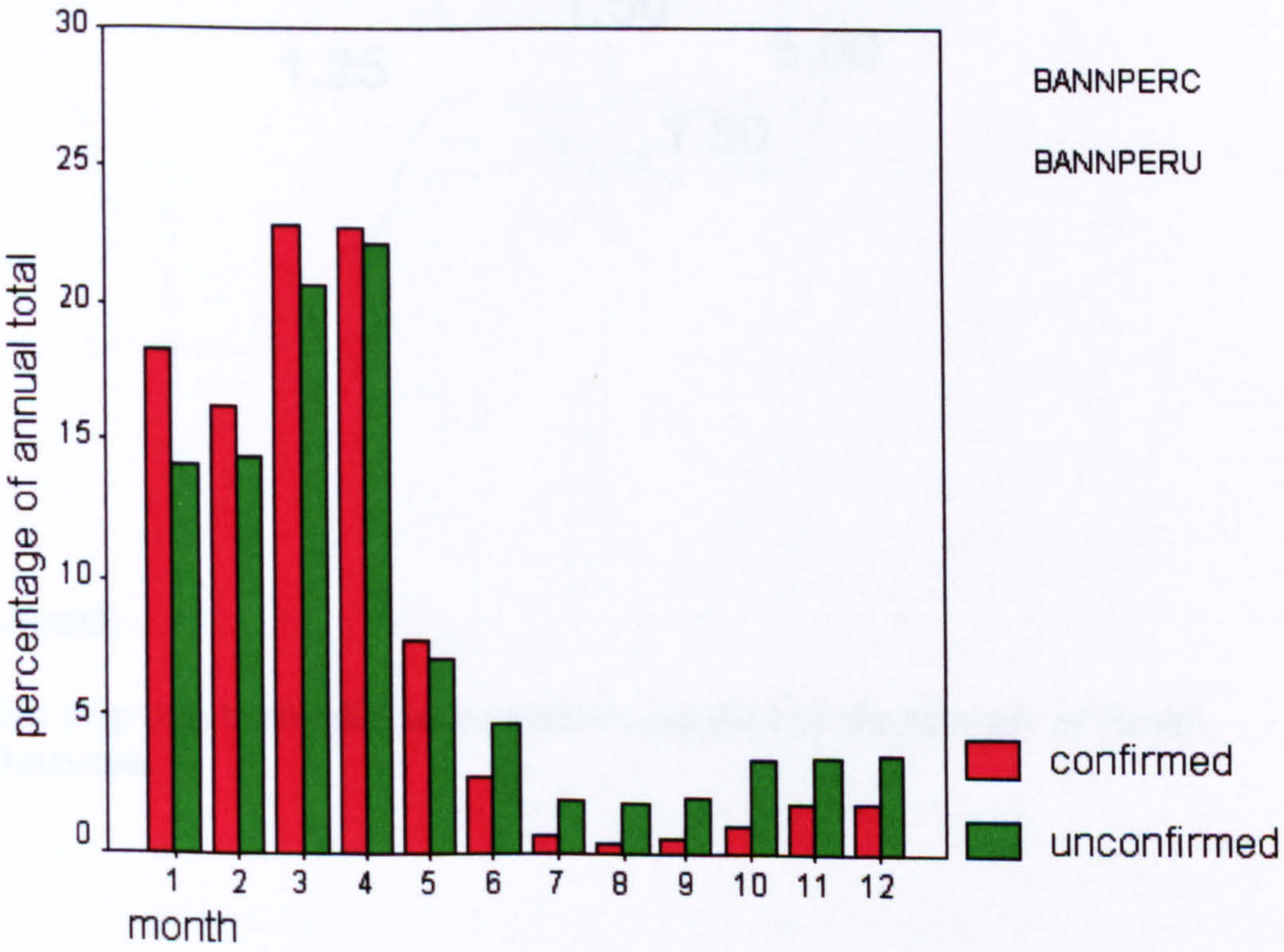
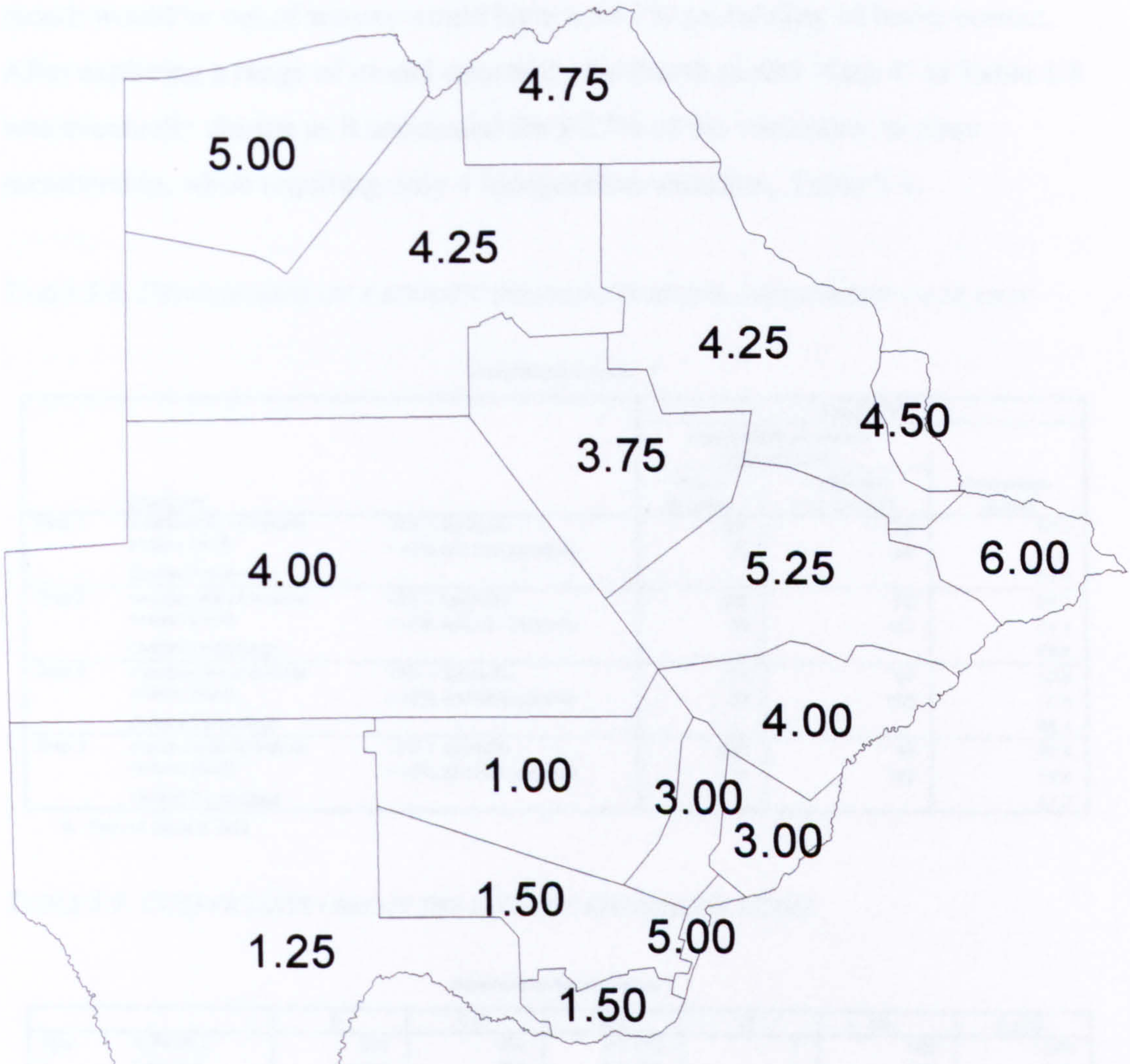


FIGURE 5.10 MAP OF DURATION OF MALARIA SEASON, BY DISTRICT, IN BOTSWANA



Legend:

The map uses health district boundaries supplied by the Ministry of Health, Botswana.

Botswana based on environmental variables. The number of district/months which fulfil the membership criteria for malaria season are 247 compared to 569 months which do not. This means that without the model guessing whether any district/ month would be out of season would have a 69.7% probability of being correct. After exploring a range of model structures the fourth model 'Step 4' in Table 5.8 was eventually chosen as it accounted for 87.7% of the variability in class membership, while requiring only 4 independent variables, Table 5.9.

TABLE 5.8. DEVELOPMENT OF A LOGISTIC REGRESSION MODEL MEMBERSHIP OF SEASON

Classification Table [a]

			Predicted		
			membership of malaria season (conf)		
	Observed		<5% + sporadic	> =5% and non sporadic	Percentage Correct
Step 1	membership of malaria season (conf)	<5% + sporadic	497	72	87.3
		> =5% and non sporadic	79	168	68.0
	Overall Percentage				81.5
Step 2	membership of malaria season (conf)	<5% + sporadic	506	63	88.9
		> =5% and non sporadic	64	183	74.1
	Overall Percentage				84.4
Step 3	membership of malaria season (conf)	<5% + sporadic	515	54	90.5
		> =5% and non sporadic	57	190	76.9
	Overall Percentage				86.4
Step 4	membership of malaria season (conf)	<5% + sporadic	520	49	91.4
		> =5% and non sporadic	51	196	79.4
	Overall Percentage				87.7

a. The cut value is .500

TABLE 5.9. COEFFICIENTS USED IN THE LOGISTIC REGRESSION MODEL

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	X_RAIN_2	.061	.004	217.588	1	.000	1.063
	Constant	-3.607	.240	225.176	1	.000	.027
Step 2[b]	X_RAIN_2	.042	.005	77.852	1	.000	1.043
	NDVI_SAV	14.664	1.974	55.176	1	.000	2335912
	Constant	-7.072	.574	152.042	1	.000	.001
Step 3[c]	X_RAIN_2	.049	.005	83.472	1	.000	1.050
	NDVI_SAV	14.707	2.086	49.713	1	.000	2437960
	AVG_H	-.007	.001	35.173	1	.000	.993
	Constant	-.024	1.250	.000	1	.985	.976
Step 4[d]	X_RAIN_2	.034	.007	21.960	1	.000	1.035
	NDVI_SAV	13.428	2.127	39.870	1	.000	678567.9
	AVG_H	-.004	.002	7.445	1	.006	.996
	X_RH_1	.080	.029	7.676	1	.006	1.084
	Constant	-6.704	2.741	5.984	1	.014	.001

a. Variable(s) entered on step 1: X_RAIN_2.
b. Variable(s) entered on step 2: NDVI_SAV.
c. Variable(s) entered on step 3: AVG_H.
d. Variable(s) entered on step 4: X_RH_1.

The four independent variables: mean monthly Rainfall (lagged by 2 months); the average monthly smoothed NDVI; the average altitude of the district; and the mean

monthly Relative Humidity (lagged by 1 month) were each examined further to determine their function in the model.

Membership of the malaria season for district/months are characterised by a median monthly rainfall of 72 mm, lagged by two months (the rainfall two months previous to malaria cases), Figure 5.11; a median monthly NDVI of 0.34 without any lags, Figure 5.12; a median district altitude of 1000m, Figure 5.13; and a median relative humidity of 66%, Figure 5.14. The summary 'box and whisker' plots are based on the median, quartiles, and extreme values. The boxes represent the interquartile range which contains the 50% of values. The 'whiskers' extend from the box to the highest and lowest values, excluding outliers. The line across the box indicates the median.

FIGURE 5.11 RAINFALL CHARACTERISTICS FOR MEMBERSHIP OF SEASON

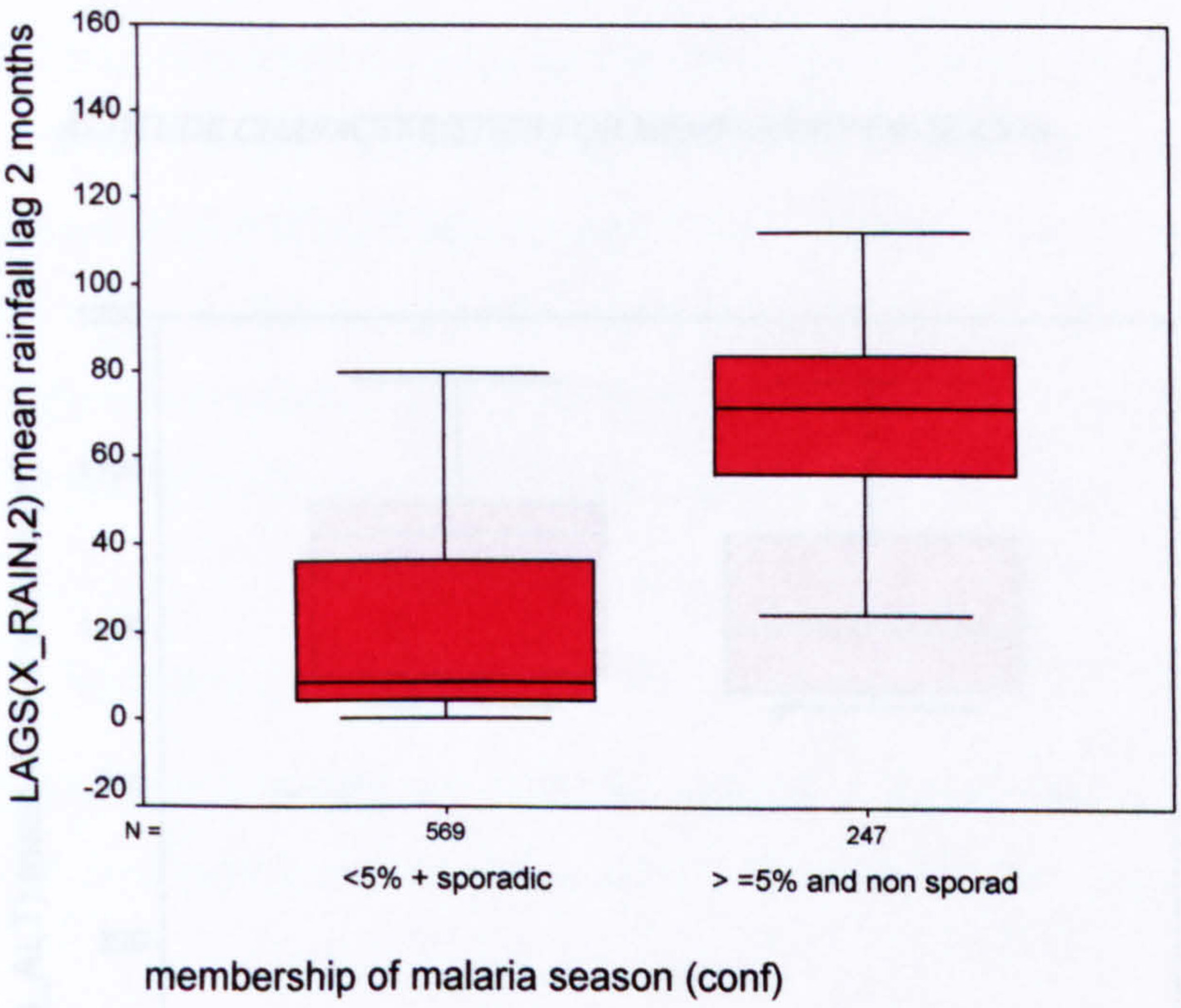


FIGURE 5.12. NDVI CHARACTERISTICS FOR MEMBERSHIP OF SEASON

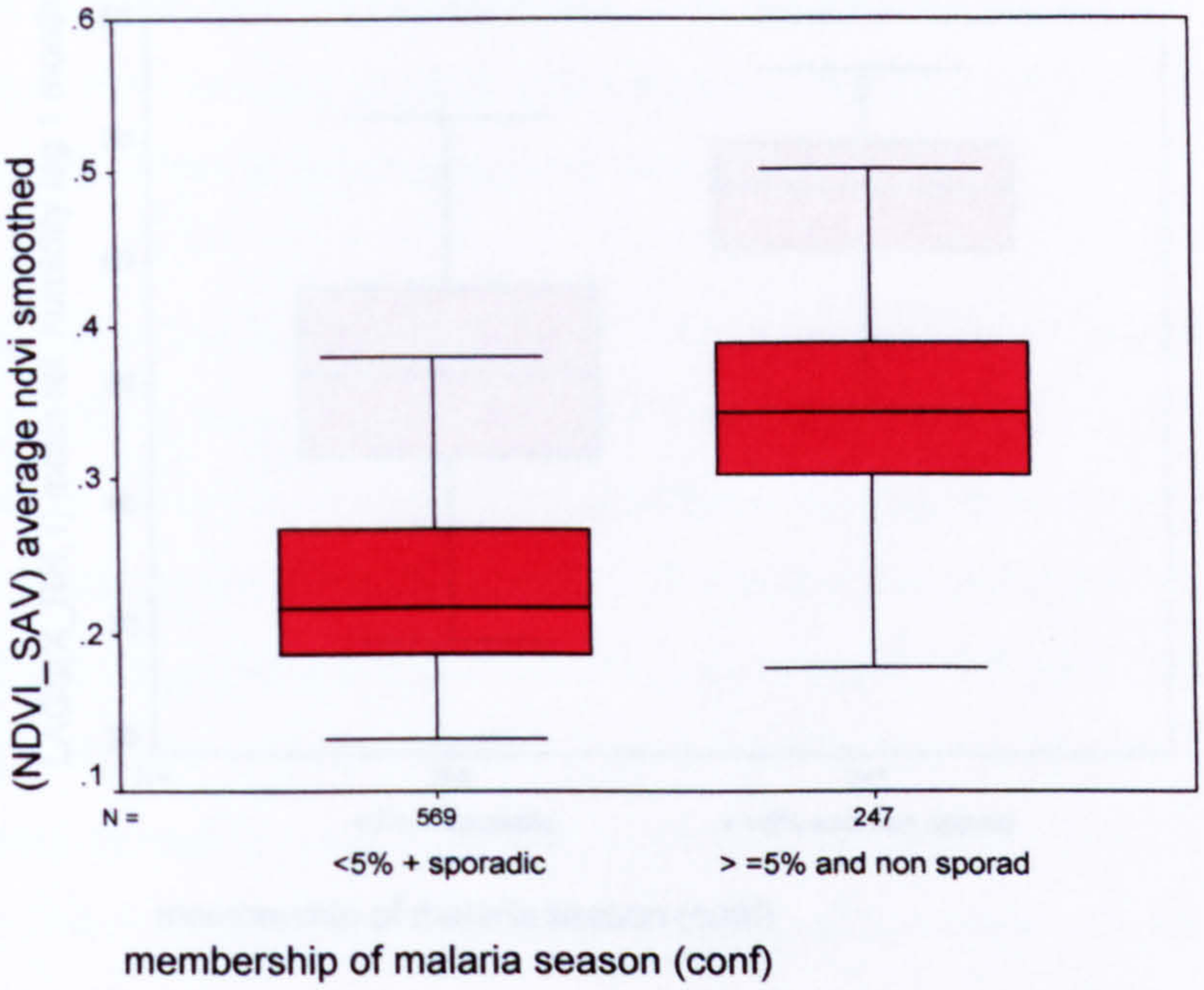


FIGURE 5.13. ALTITUDE CHARACTERISTICS FOR MEMBERSHIP OF SEASON

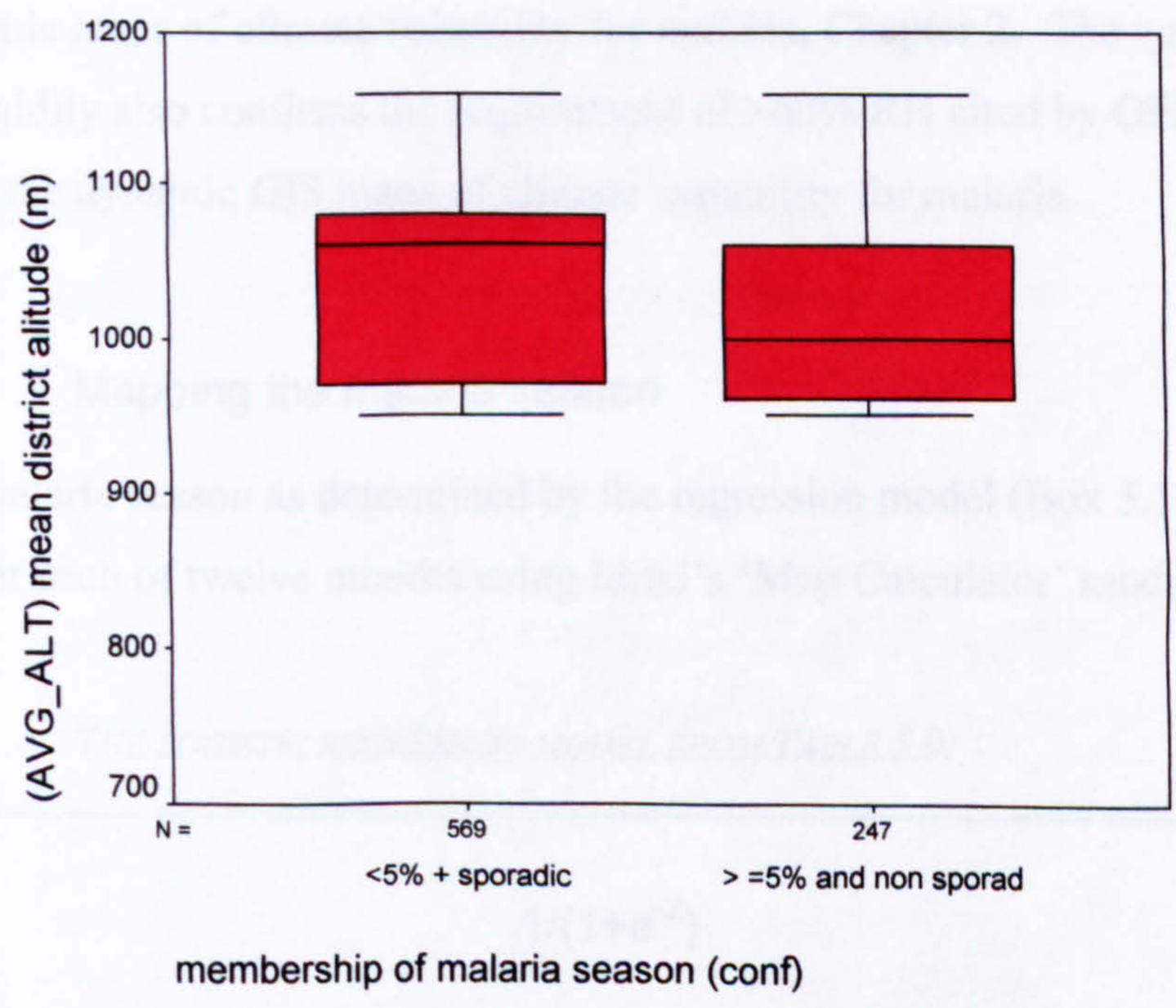
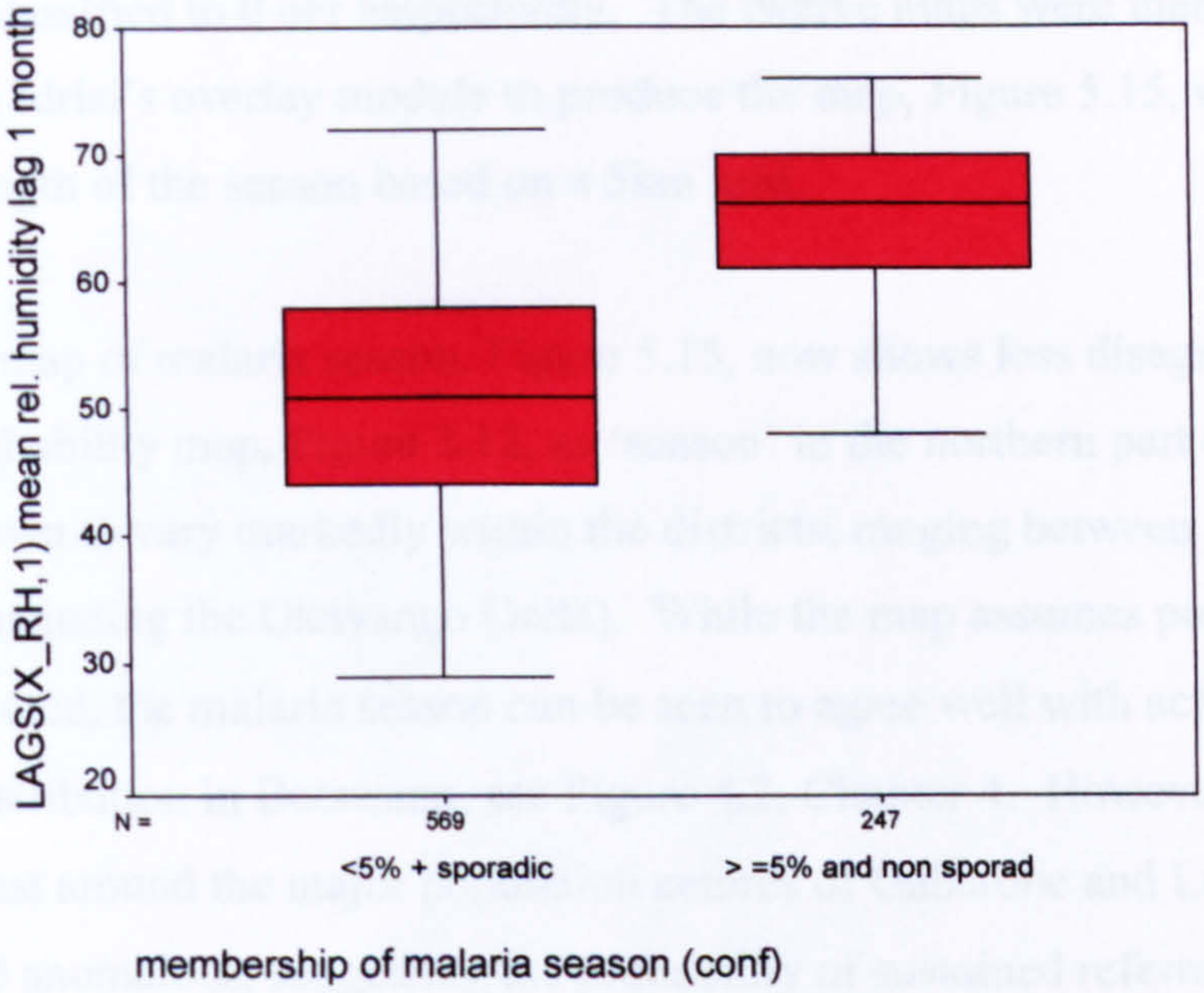


FIGURE 5.14. RELATIVE HUMIDITY CHARACTERISTICS FOR MEMBERSHIP OF SEASON



The value of 72mm of rainfall required for membership of malaria season relates relatively well to the choice of 80mm chosen by MARA for their climate suitability map. The value of 0.34 NDVI relates strongly to the choice used in the development of the dynamic maps of climate suitability for malaria, Chapter 2. The value of 66% relative humidity also confirms the requirement of >60% RH cited by Gilles (1993) and used in the dynamic GIS maps of climate suitability for malaria.

5.4.3. Mapping the malaria season

A map of malaria season as determined by the regression model (Box 5.1) was produced for each of twelve months using Idrisi's 'Map Calculator' module.

BOX 5.1. THE LOGISTIC REGRESSION MODEL FROM TABLE 5.9.

$$1/(1+e^{-Z})$$

where -Z = (-6.704 + (NDVI_SAV * 13.428) + (X_RAIN_2 * 0.034) + (X_RH_1 * 0.080) + (AVG_ALT * -0.004))*-1

The resulting maps describe the predicted percentage membership of malaria season in Botswana. Where the predicted percentage was less than or greater than 50% these were reclassified to 0 or1 respectively. The twelve maps were then added together using Idrisi's overlay module to produce the map, Figure 5.15, which offers a predicted length of the season based on a 5km grid.

The resulting map of malaria season, Figure 5.15, now shows less disagreement with the climate suitability map, Figure 2.12, as 'season' in the northern part of the country is shown to vary markedly within the districts, ranging between 2 and 6 months (not including the Okavango Delta). While the map assumes population is evenly distributed, the malaria season can be seen to agree well with actual population distribution in Botswana, see Figure 4.2, Chapter 4. However, the region in the southeast around the major population centres of Gabarone and Lobatse may be considered anomalous, suggesting the probability of sustained referrals in this region skewing the map.

5.4.4. A linear regression model of malaria incidence in Botswana

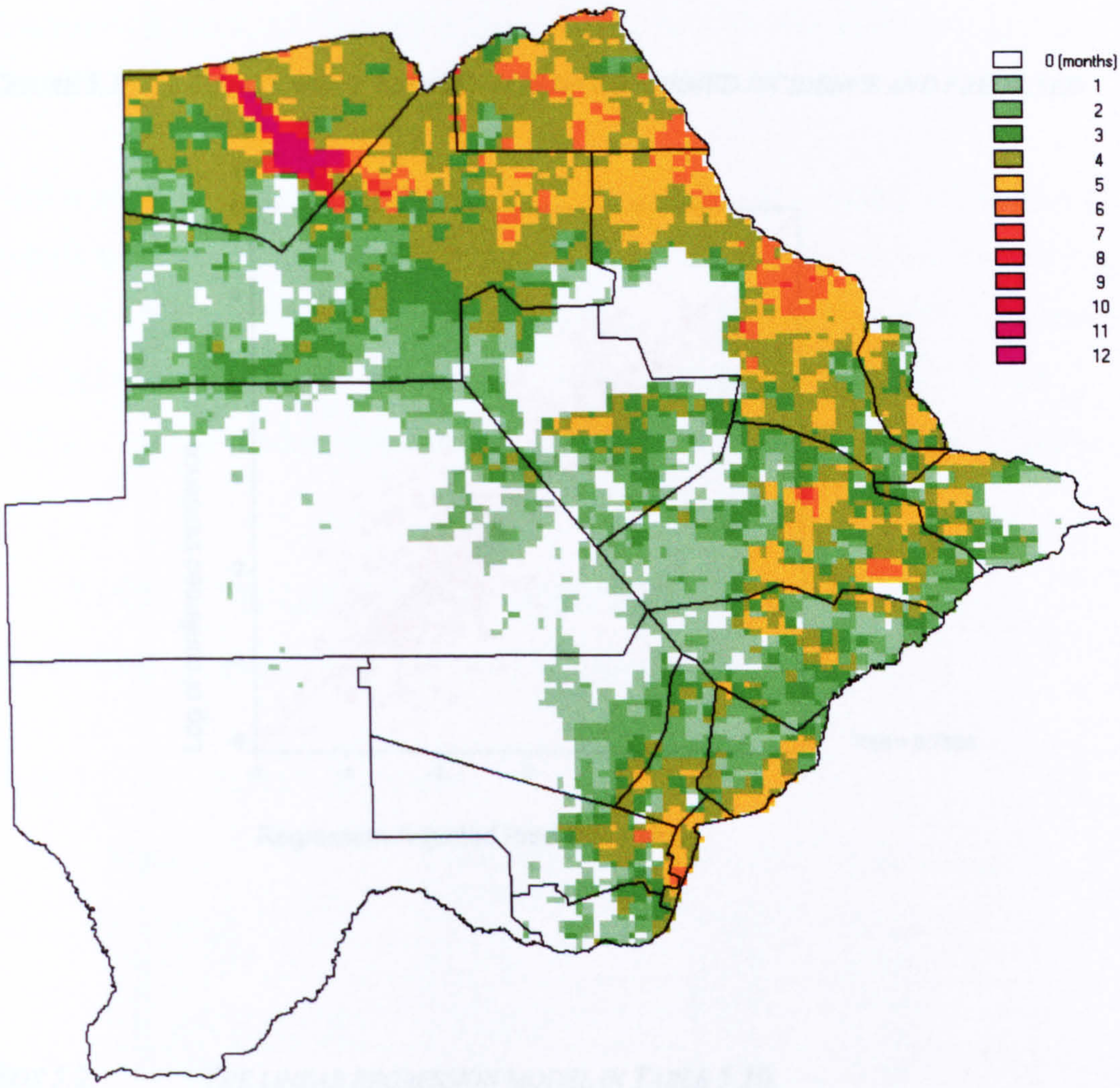
The linear 'Stepwise' regression module in SPSS was used to model the monthly confirmed incidence of malaria cases in Botswana. The model results are applicable to a specific month. The month used in this example being January 1996. Following an exploratory analysis it was decided to use 'Model 5' as the slope in the incremental improvements in subsequent models began to decrease markedly after this stage, Table 5.10.

TABLE 5.10. MODEL COEFFICIENTS

Model 5	Unstandardized Coefficients	Std. Error	Significance
(Constant)	17.531	1.095	0.000
LAGS(X_RAIN_2)	2.359E-02	0.002	0.000
LATS	0.509	0.032	0.000
NDVI_MAX	7.710	1.012	0.000
LONGS	-0.293	0.034	0.000
AVG_ALT	-3.886E-03	0.001	0.000

Dependent Variable: Log of confirmed incidence

FIGURE 5.15. MAP OF MODELLED MALARIA SEASON IN BOTSWANA (MEAN 1996-1999).

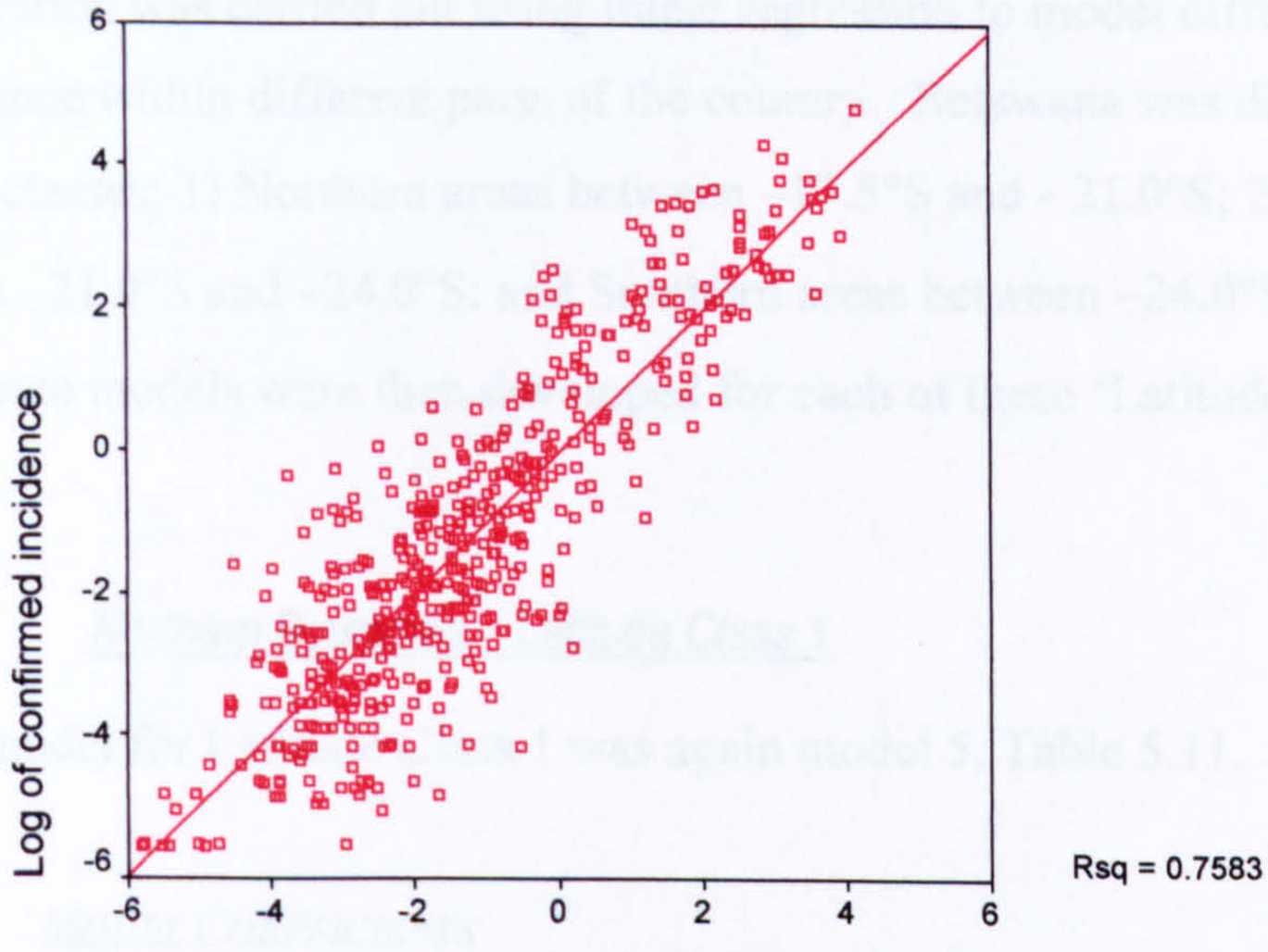


Legend:

The map models the number of months making up the malaria season in Botswana.
The legend, top right, represents the number of months of malaria season duration.

The correlation between the dependent variable (log of monthly incidence in confirmed malaria cases) and the model's predictive value ($R^2 = 0.758$) is described in Figure 5.16.

FIGURE 5.16. RELATIONSHIP BETWEEN LOG OF CONFIRMED INCIDENCE AND PREDICTED VALUE



BOX 5.2. THE LINEAR REGRESSION MODEL IN TABLE 5.10.

```
y = 17.531 + (LAGS(X_RAIN_2) * 0.0236) + (LATS * 0.509)
    + (NDVI_MAX * 7.710) + (LONGS * -0.293) + (AVG_ALT
    * -0.0039)
```

5.4.5. Mapping the results of the linear regression model of malaria incidence in Botswana

The regression equation was (Box 5.2.) entered into the Idrisi Map Calculator and the national level result is illustrated in Figure 5.17. As expected the higher incidence of cases are to be found in the northern part of the country.

Further exploration was carried out using linear regression to model differences in malaria incidence within different parts of the country. Botswana was divided into three latitude classes: 1) Northern areas between –17.5°S and - 21.0°S; 2) Central areas between –21.0°S and –24.0°S; and Southern areas between –24.0°S and 27.5°S. Separate models were then developed for each of these 'Latitude Classes'.

5.4.5.1. Northern Botswana – Latitude Class 1

The optimal model for Latitude Class 1 was again model 5, Table 5.11.

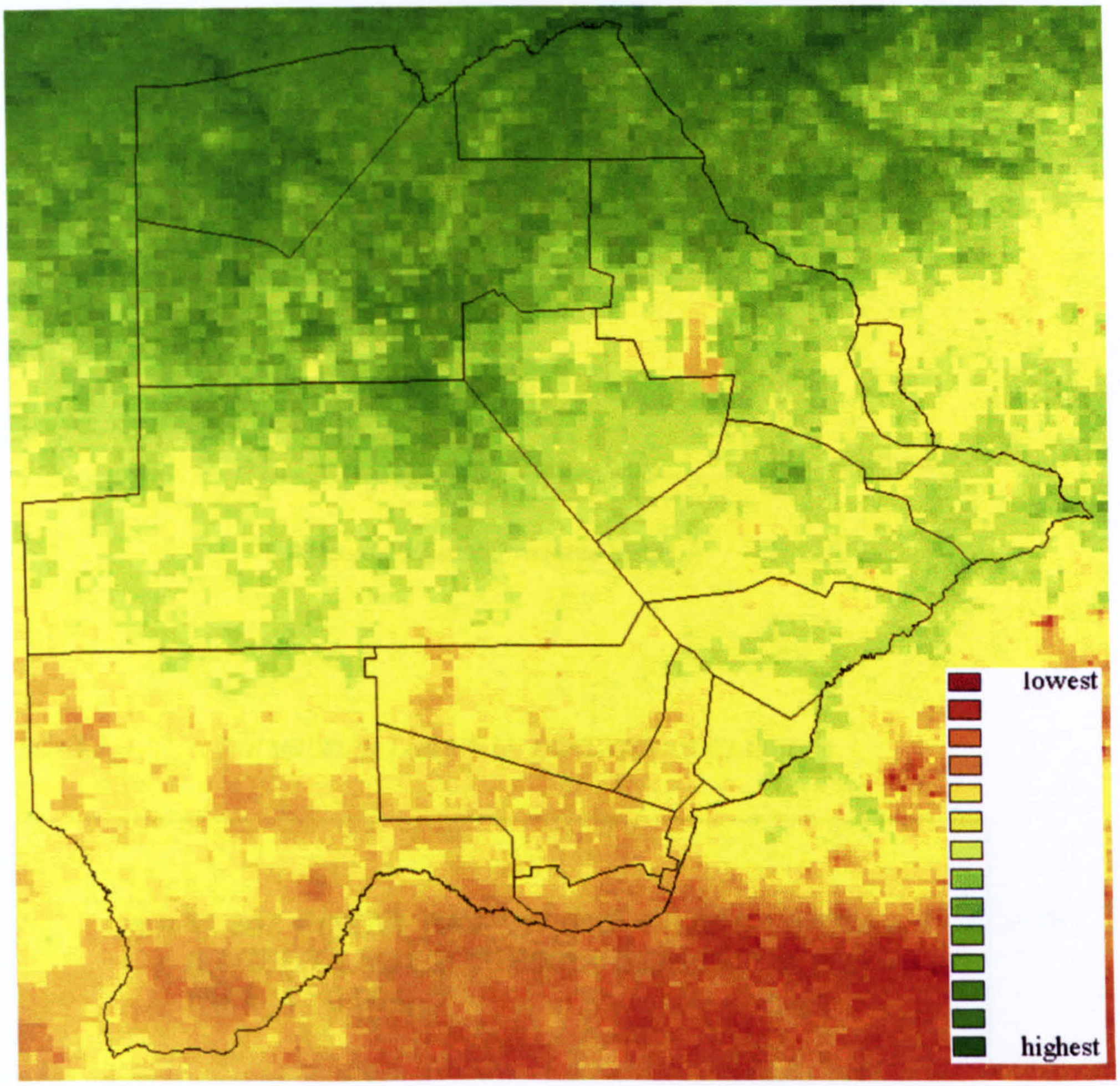
TABLE 5.11. MODEL COEFFICIENTS

Model 5	Unstandardized Coefficients	Std. Error	Significance
(Constant)	11.347	1.765	0.000
NDVI_SAV	17.510	1.023	0.000
LATS	0.670	0.096	0.000
LAGS(VCLAG1,2)	9.919E-02	0.018	0.000
LONGS	-0.163	0.045	0.000
LAGS(RFE,4)	4.045E-03	0.001	0.000

Dependent Variable: Log of confirmed incidence

For Latitude Class 1, the correlation between the dependent variable (log of monthly incidence in confirmed malaria cases) and the model's predictive value ($R^2 = 0.835$) is described in Figure 5.18.

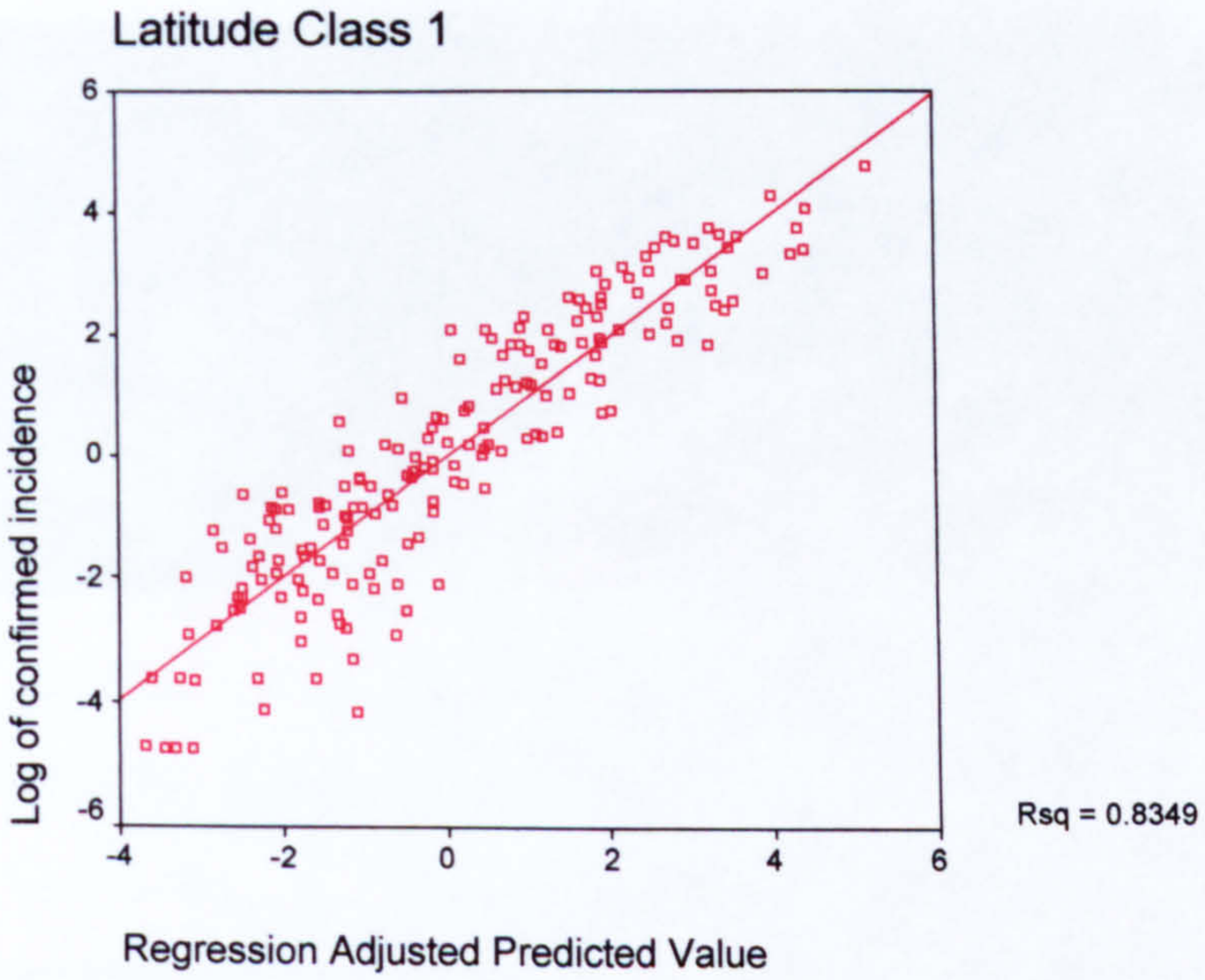
FIGURE 5.17. LINEAR REGRESSION MODEL FOR LOG OF MALARIA INCIDENCE, JANUARY 1996.



Legend:

The model (from Table 5.10) is used to produce the map (which assumes a constant population across the district). The map indicates the relative distribution of malaria incidence during the month of January 1996. The legend , bottom right, represents the relative scale.

FIGURE 5.18. RELATION BETWEEN LOG CONFIRMED INCIDENCE AND PREDICTED VALUE (LATITUDE CLASS 1)

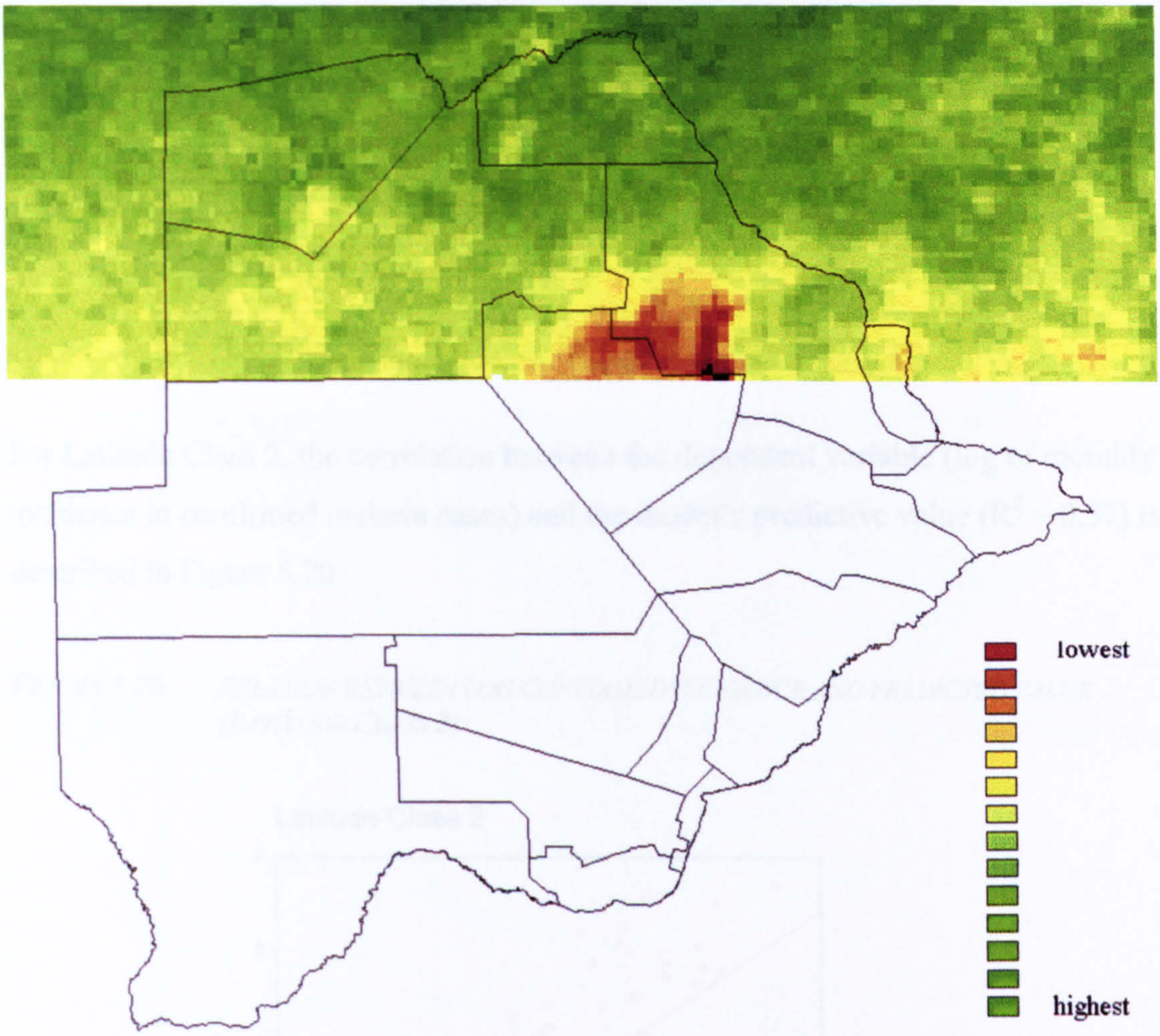


BOX 5.3. THE MODEL IN TABLE 5.11, FOR LATITUDE CLASS 1

```
y = 11.347 + (NDVI_SAV * 17.510) + (LATS * 0.670) +
    (LAGS(VCLAG1,2) * 0.099) + (LONGS * -0.163) +
    (RFE_4 * 0.004)
```

The regression equation (Box 5.3.) was entered into the Idrisi Map Calculator and the result for northern Botswana, Latitude Class 1, is illustrated in Figure 5.19.

FIGURE 5.19. LINEAR REGRESSION MODEL OF MALARIA INCIDENCE IN THE NORTH OF BOTSWANA, JANUARY 1996.



Legend:

The model (from Table 5.11) is used to produce the map (which assumes a constant population across the district). The map indicates the relative distribution of malaria incidence during the month of January 1996 in northern Botswana. The legend, bottom right, represents the relative scale applicable in this map. The palette used by Idrisi is driven by the range of values in the particular model. Consequently one map cannot be used for cross comparison with the other maps.

5.4.5.2. Central Botswana – Latitude Class

The choice for Latitude Class 2 extended to Model 7, Table 5.12.

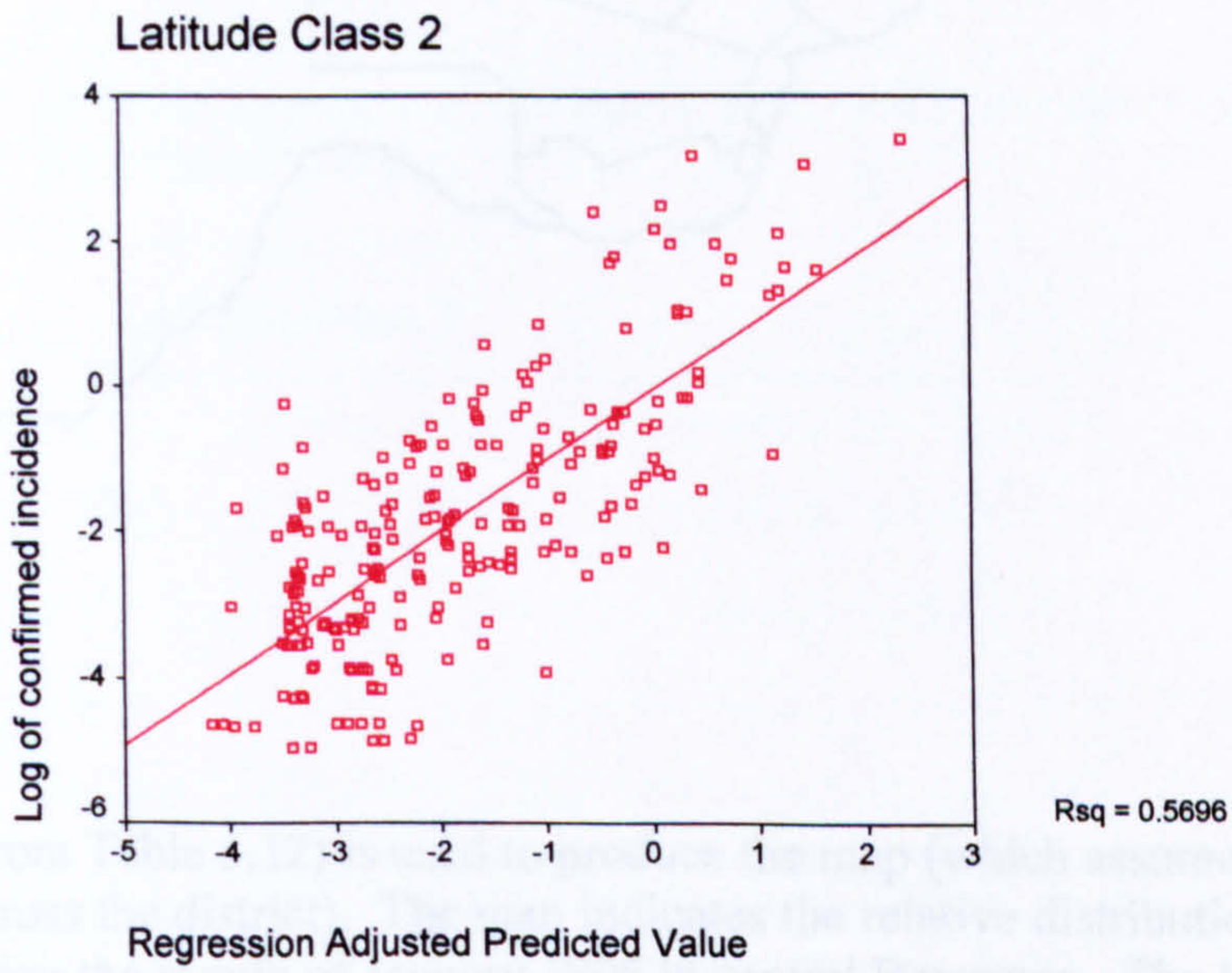
TABLE 5.12. MODEL COEFFICIENTS

Model 7	Unstandardized Coefficients	Std. Error	Significance.
(Constant)	10.637	2.474	0.000
LAGS(VCLAG0,2)	0.104	0.020	0.000
LATS	0.638	0.113	0.000
LAGS(VCLAG0,3)	9.837E-02	0.020	0.000
LAGS(VCLAG0,1)	0.102	0.021	0.000
LAGS(VCLAG0,4)	7.935E-02	0.019	0.000

Dependent Variable: Log of confirmed incidence

For Latitude Class 2, the correlation between the dependent variable (log of monthly incidence in confirmed malaria cases) and the model's predictive value ($R^2 = 0.57$) is described in Figure 5.20.

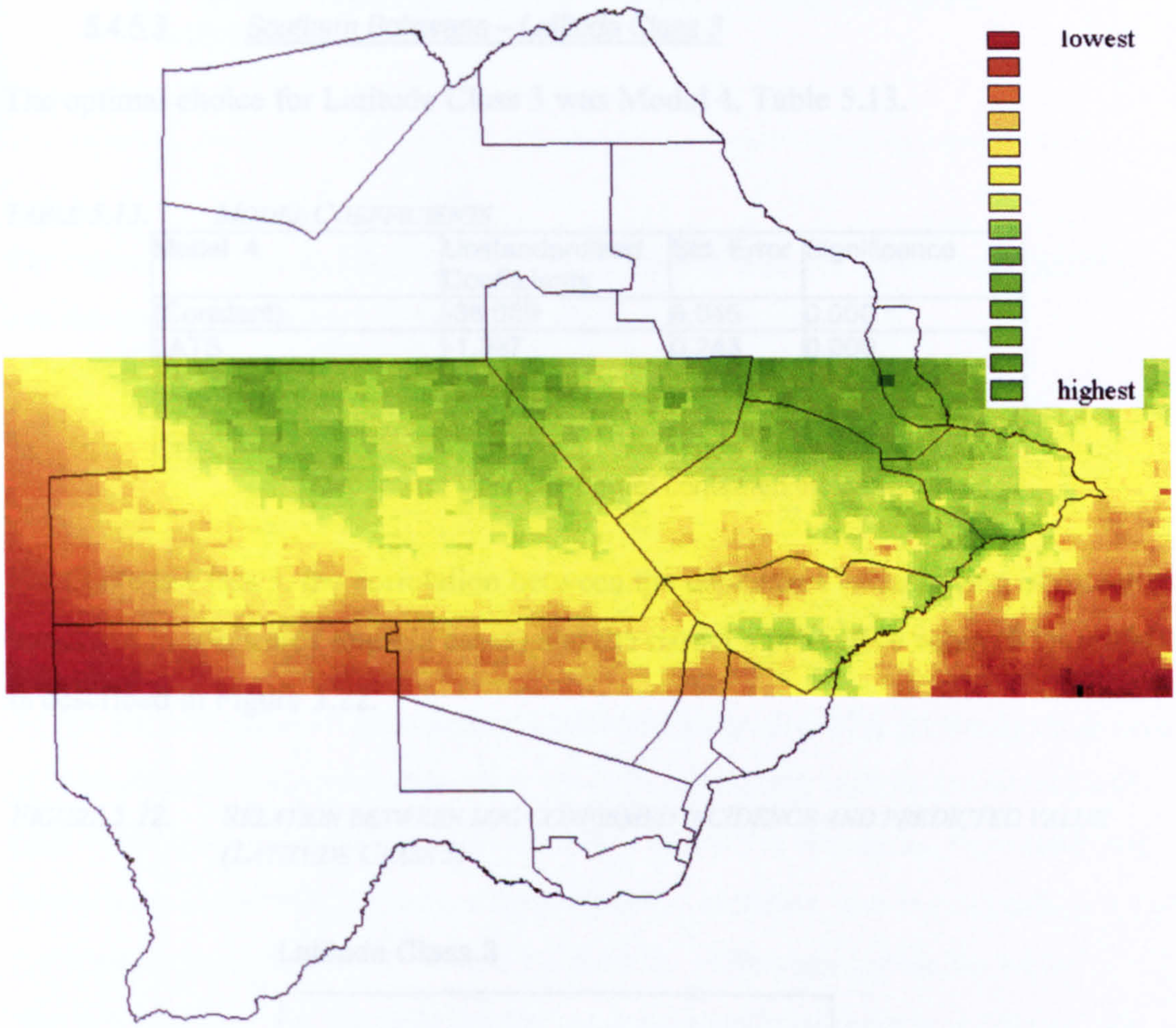
FIGURE 5.20. RELATION BETWEEN LOG CONFIRMED INCIDENCE AND PREDICTED VALUE (LATITUDE CLASS 2)



BOX 5.4. THE MODEL IN TABLE 5.12, FOR LATITUDE CLASS 2

$$y = 10.637 + (VCLAG\_0,2 * 0.104) + (LATS * 0.638) + (VCLAG\_0,3 * 0.098) + (VCLAG\_0,1 * 0.102) + (VCLAG\_0,4 * 0.079)$$

FIGURE 5.21. LINEAR REGRESSION MODEL OF MALARIA INCIDENCE IN THE CENTRAL REGION OF BOTSWANA, JANUARY 1996.



Legend:

The model (from Table 5.12) is used to produce the map (which assumes a constant population across the district). The map indicates the relative distribution of malaria incidence during the month of January 1996 in central Botswana. The legend, bottom right, represents the relative scale applicable in this map. The palette used by Idrisi is driven by the range of values in the particular model. Consequently one map cannot be used for cross comparison with the other maps.

The regression equation (Box 5.4.) was again entered into the Idrisi Map Calculator and the result for central Botswana is illustrated in Figure 5.21.

5.4.5.3. Southern Botswana – Latitude Class 3

The optimal choice for Latitude Class 3 was Model 4, Table 5.13.

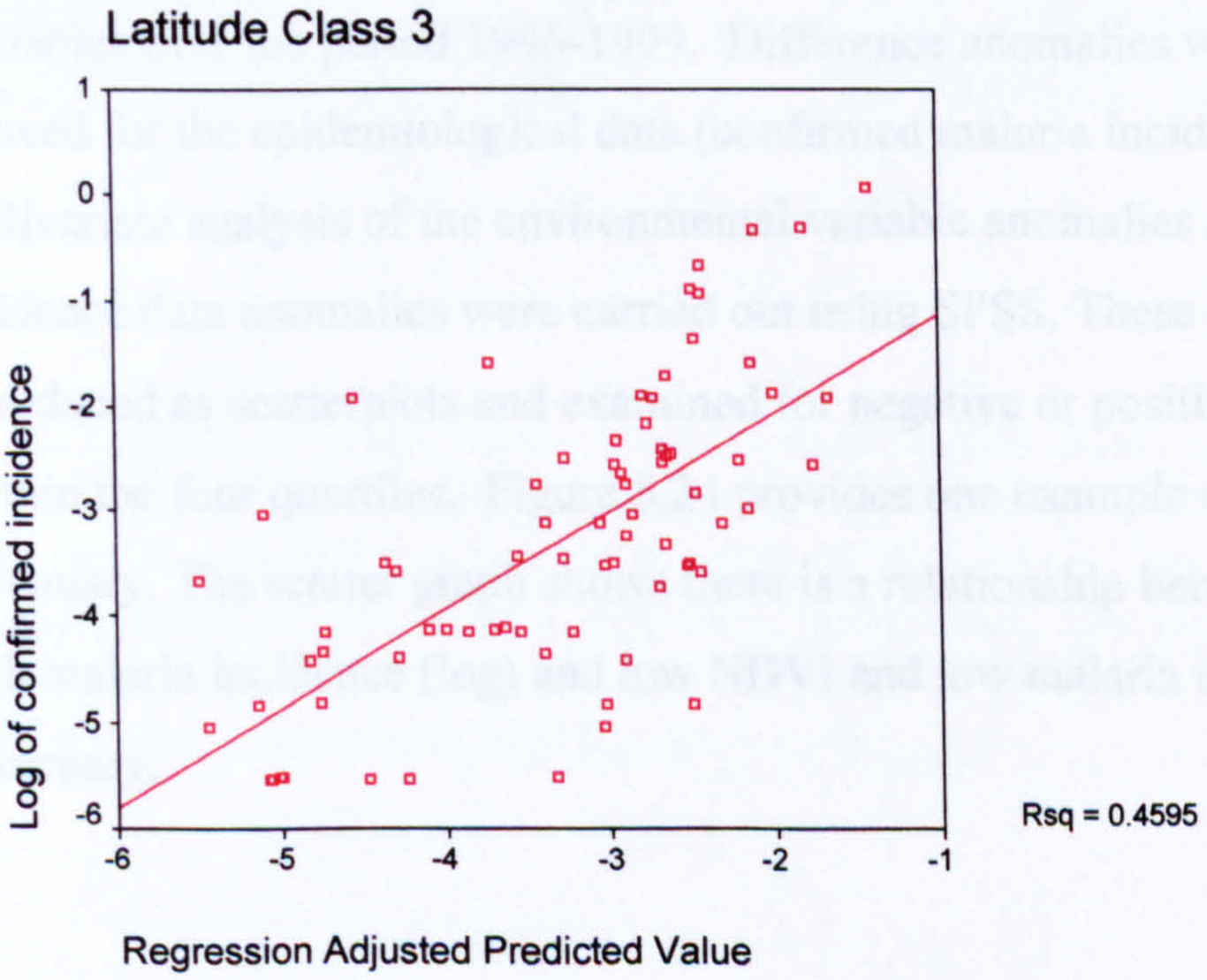
TABLE 5.13. MODEL COEFFICIENTS

Model 4	Unstandardized Coefficients	Std. Error	Significance
(Constant)	-38.089	6.045	0.000
LATS	-1.387	0.243	0.000
LAGS(RFE,3)	1.110E-02	0.003	0.001
RFE	1.189E-02	0.004	0.003
CCD	-7.564E-03	0.003	0.023

Dependent Variable: Log of confirmed incidence

For Latitude Class 3, the correlation between the dependent variable (log of monthly incidence in confirmed malaria cases) and the model's predictive value ($R^2 = 0.494$) is described in Figure 5.22.

FIGURE 5.22. RELATION BETWEEN LOG CONFIRMED INCIDENCE AND PREDICTED VALUE (LATITUDE CLASS 3)



BOX 5.5. THE MODEL IN TABLE 5.13, FOR LATITUDE CLASS 3

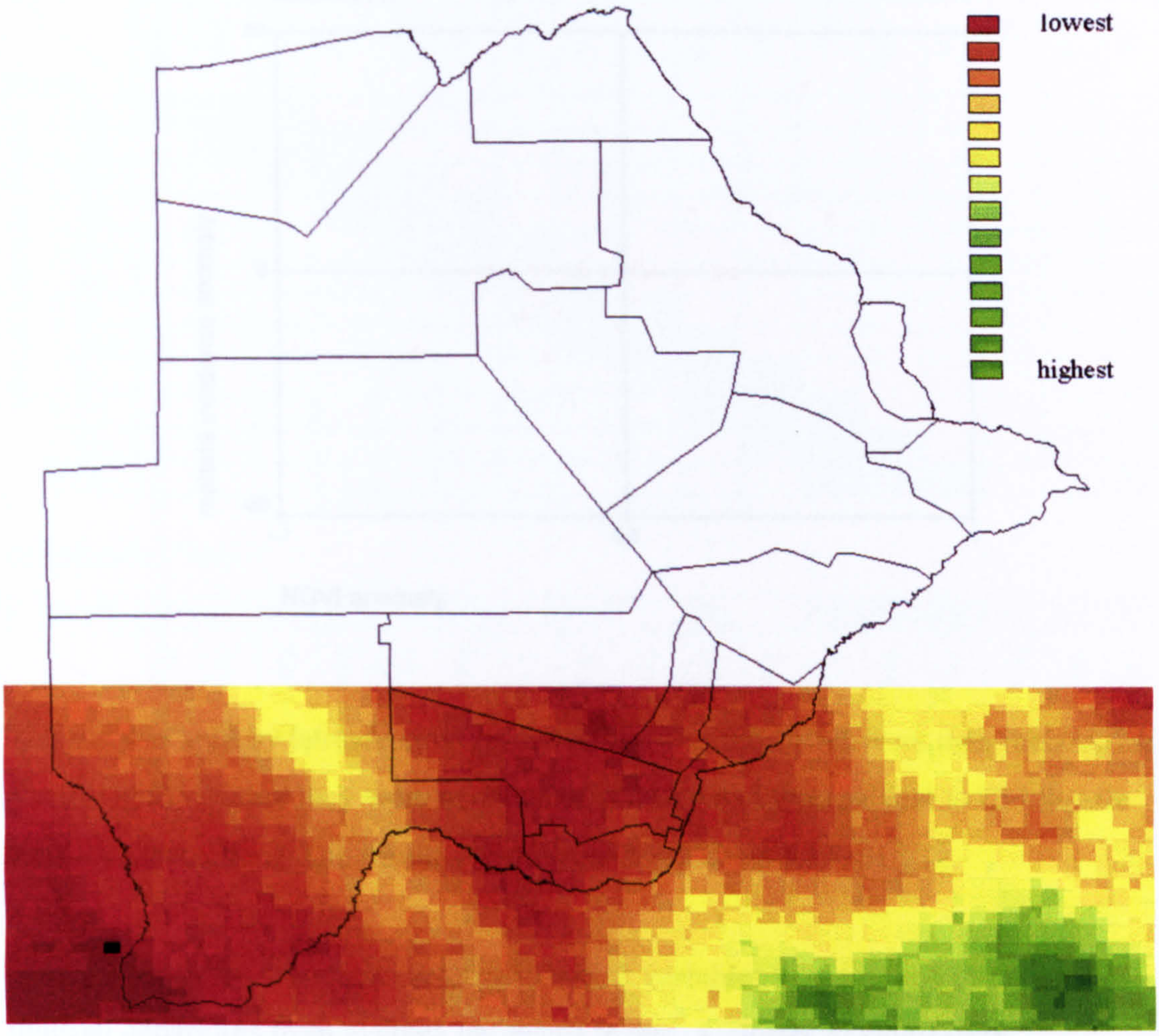
```
y = -38.089 + (LATS * -1.387) +  (RFE_3 * 0.011) + (RFE *
    00.012) + (CCD * -00.0076)
```

The regression equation (Box 5.5) was again entered into the Idrisi Map Calculator and the result for Southern Botswana is illustrated in Figure 5.23.

5.4.6. Analysis of difference anomalies

The environmental variables used in the models for latitude classes 1 to 3 include: RFE, CCD, NDVI, VC as well as the non-temporal variables latitude and longitude. To test the association of inter-annual variability alone (i.e. after removing the effects of seasonality) between the dependent variable (confirmed malaria incidence) and each of the temporal environmental variables, difference anomalies were produced between the actual monthly values for each of the variables, and the monthly mean of those same variables over the period 1996-1999. Difference anomalies were similarly produced for the epidemiological data (confirmed malaria incidence) for comparison. Bivariate analysis of the environmental variable anomalies and the confirmed incidence data anomalies were carried out using SPSS. These exploratory results were produced as scatterplots and examined for negative or positive association within the four quartiles. Figure 5.24 provides one example of this for the month of January. The scatter graph shows there is a relationship between high NDVI and high malaria incidence (log) and low NDVI and low malaria incidence for the month of January.

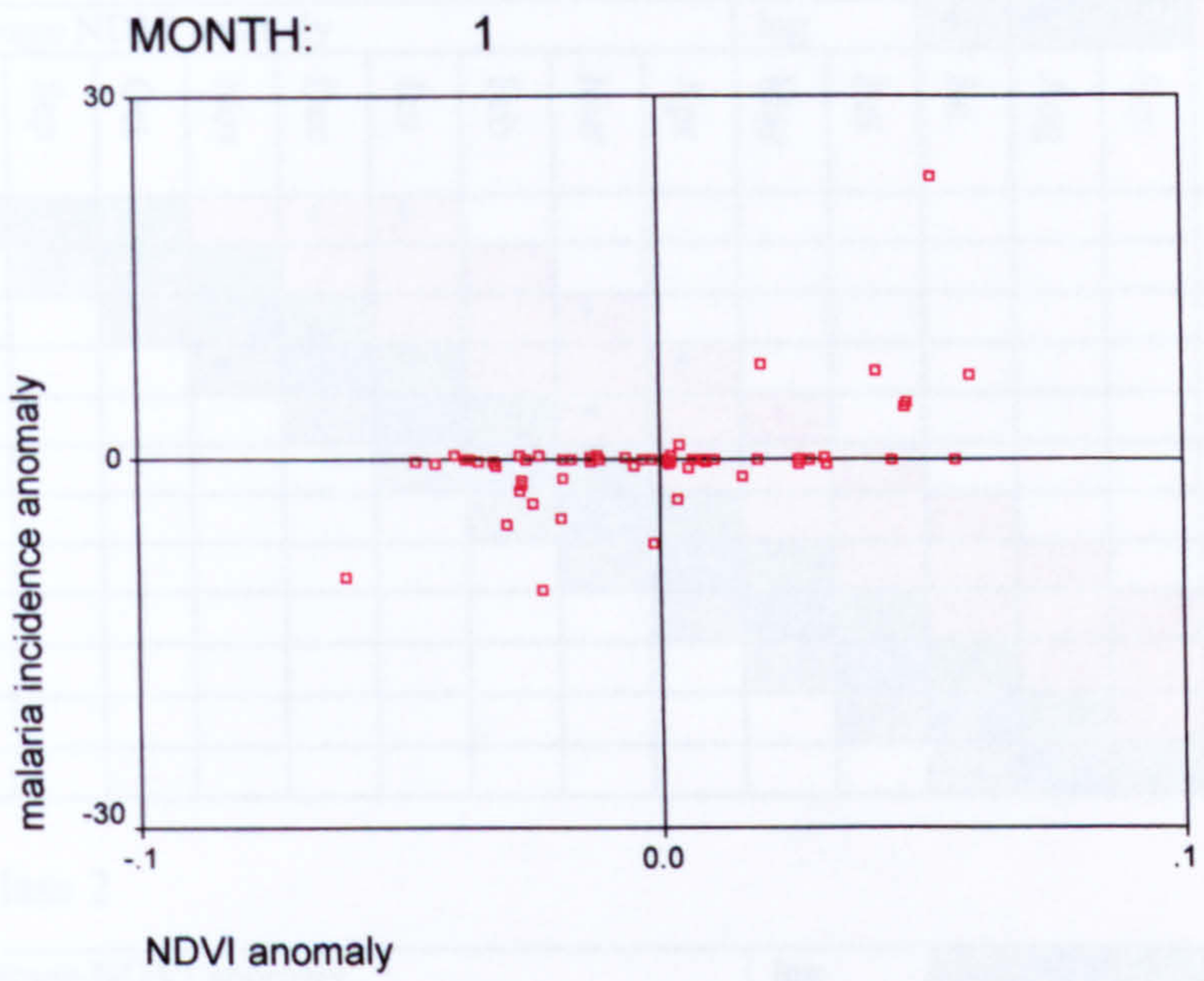
FIGURE 5.23. LINEAR REGRESSION MODEL OF MALARIA INCIDENCE IN THE SOUTHERN REGION OF BOTSWANA, JANUARY 1996.



Legend:

The model (from Table 5.13) is used to produce the map (which assumes a constant population across the district). The map indicates the relative distribution of malaria incidence during the month of January 1996 in southern Botswana. The legend, bottom right, represents the relative scale applicable in this map. The palette used by Idrisi is driven by the range of values in the particular model. Consequently one map cannot be used for cross comparison with the other maps.

FIGURE 5.24. BIVARIATE PLOT OF NDVI AND CONFIRMED MALARIA INCIDENCE ANOMALIES.



The file was split by latitude class (1, 2 and 3). The anomalies were then reclassified according to whether they were negative or positive and then subject to Chi Square tests for association. The results are presented in Tables 5.14. to 5.18.

This methodology sets out to determine which variables may be used to indicate unusual departures from average incidence levels. A cluster of significant associations in which the environmental variable precedes malaria incidence by one or more months provides evidence of the value of that environmental variable for use in an early warning system.

The associations between NDVI, RFE, CCD, VCLAG_0, and VCLAG_1 anomalies and the malaria incidence anomalies in the northern part of the country, are shown in Tables 5.14-5.18. These indicate that malaria is significantly associated in the following way:

Latitude Class 1

While significant ($P<0.05$) associations between environmental anomalies and malaria incidence anomalies can be found in latitude class 1, only 1 of these associations is highly significant (May RFE anomaly and May malaria incidence

TABLE 5.14. ASSOCIATION BETWEEN MONTHLY MALARIA INCIDENCE AND NDVI 1996-99

a) Latitude Class 1 (* = 95%, **= 99% significance, Chi Square Exact Test).

Month / Month	average NDVI anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan					*	*											
Feb																	
Mar				*				*									
Apr				*					*								
May								*									
Jun								*									
Jul								*									
Aug																	
Sep																	
Oct																	
Nov																	
Dec															*		*

b) Latitude Class 2

Month / Month	average NDVI anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan		*			*												
Feb			*														
Mar							*	*									
Apr							*	*	*								
May							*	**									
Jun																	
Jul									*								
Aug																	
Sep																	
Oct																	
Nov																*	
Dec																	

c) Latitude Class 3

Month / Month	average NDVI anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb			*														
Mar							*										
Apr				*			*										
May					*												
Jun																	
Jul																	
Aug																	
Sep																	
Oct																	
Nov																	
Dec																	

TABLE 5.15. ASSOCIATION BETWEEN MONTHLY MALARIA INCIDENCE AND RFE 1996-99

a) Latitude Class 1 (* = 95%, **= 99% significance, Chi Square Exact Test)

Month / Month	average RFE anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb																	
Mar																	
Apr																	
May										**							
Jun							*										
Jul							*										
Aug										*	*						
Sep																	
Oct																	
Nov																	
Dec																	

b) Latitude Class 2

Month / Month	average RFE anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan	*	*															
Feb				*													
Mar				*	*	**	**										
Apr						**	*										
May					*	*	*			*							
Jun																	
Jul																	
Aug									*	*							
Sep										*							
Oct																	
Nov																	
Dec																	

c) Latitude Class 3

Month / Month	average RFE anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb																	
Mar																	
Apr				*		*	*		**								
May										*							
Jun																	
Jul										*							
Aug																	
Sep																	
Oct																	
Nov																	
Dec																	

TABLE 5.16. ASSOCIATION BETWEEN MONTHLY MALARIA INCIDENCE AND CCD 1996-99

a) Latitude Class 1 (* = 95%, **= 99% significance, Chi Square Exact Test)

Month / Month	average CCD anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan						*											
Feb					*												
Mar			*														
Apr									*								
May																	
Jun										*							
Jul									*	*							
Aug									*								
Sep																	
Oct																	
Nov																	
Dec																	

b) Latitude Class 2

Month / Month	average CCD anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan			**	*	*												
Feb																	
Mar							*										
Apr									*								
May							*										
Jun																	
Jul									*	*							
Aug										*							
Sep																	
Oct																	
Nov																	
Dec																	

c) Latitude Class 3

Month / Month	average CCD anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb																	
Mar																	
Apr																	
May																	
Jun																	
Jul																	
Aug																	
Sep																	
Oct																	
Nov																	
Dec																	

TABLE 5.17. ASSOCIATION BETWEEN MONTHLY MALARIA INCIDENCE AND VCLAG0 1996-99

a) Latitude Class 1 (* = 95%, **= 99% significance, Chi Square Exact Test)

Month / Month	average Vclag0 anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb																	
Mar							*										
Apr						*											
May							*			*							
Jun										*							
Jul																	
Aug																	
Sep																	
Oct																	
Nov																	
Dec																	

b) Latitude Class 2

Month / Month	average Vclag0 anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan				*													
Feb																	
Mar					*	**	**										
Apr						**	*										
May					*	*	**			*							
Jun																	
Jul																	
Aug									*								
Sep																	
Oct																	
Nov														*			
Dec																	

c) Latitude Class 3

Month / Month	average Vclag0 anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb																	
Mar							*										
Apr				*		*											
May						*	*										
Jun																	
Jul																	
Aug																	
Sep																	
Oct																	
Nov																	
Dec																	

Table 5.18. Association between monthly malaria incidence and VCLAG1 1996-99

a) Latitude Class 1 (* = 95%, **= 99% significance, Chi Square Exact Test)

Month / Month	average Vclag1 anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb				*													
Mar								*									
Apr							*										
May								*									
Jun																	
Jul																	
Aug																	
Sep																	
Oct																	
Nov																	
Dec																	

b) Latitude Class 2

Month / Month	average Vclag1 anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb					**												
Mar						*	**	**									
Apr							**	**									
May						*	*	**									
Jun																	
Jul							*										
Aug										*							
Sep																	
Oct																	
Nov																	
Dec																	

c) Latitude Class 3

Month / Month	average Vclag1 anomaly									lag		5	4	3	2	1	0
malaria incidence anomaly	Aug	Sep	Oct	Nov	Dec	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Jan																	
Feb																	
Mar																	
Apr					*		*										
May					*												
Jun																	
Jul																	
Aug																	
Sep																	
Oct																	
Nov																	
Dec																	

anomaly). The significant associations where they do occur are not highly clustered, indicating that interannual variation in these environmental variables are not likely to provide a clear indication of interannual variability in malaria incidence when analysed in this way.

Latitude class 2

Four of the five environmental variable tested indicated substantial association between the environmental anomalies and the malaria incidence anomalies with lags of 0-4 months. The exception was CCD. VCLAG_1 produced the highest level of association, Table 5.18, with February values of VCLAG_1 anomalies highly correlated with malaria incidence anomalies in March and April ($P<0.01$) and May ($P<0.05$). March VCLAG_1 anomalies were significantly associated with malaria incidence anomalies in March, April and May ($P<0.01$).

Latitude class 3

None of the 5 environmental variables tested indicated substantial or consistent association with malaria incidence anomalies in this latitude class.

From the above it can be said that malaria incidence in Botswana is highly correlated with the individual environmental variables, but that most of this correlation is the result of the seasonal pattern of climate and disease. Only in latitude class 2 is there substantial evidence that the interannual variation in climate is associated with unusual patterns of malaria transmission. The MoH in Botswana consider the central section of the country as being epidemic prone. They also consider the more endemic region in the north to be prone to periodic epidemics. The evidence here supports the former but provides scant evidence for the latter. It should be noted however, that only 4 years of monthly epidemiological data were available in this study of Botswana, a short time period when looking for evidence of interannual variability.

5.4.7. Predictive mapping of malaria in epidemic prone districts

Epidemic prone districts in Botswana would benefit from some advance warning of levels of malaria to be expected in the forthcoming season, whether they be true epidemics or unusual sharp seasonal increases. Some of the independent

environmental variables used in the above maps are simultaneous with the dependent variable (log of malaria incidence) and some do not vary between years (altitude, latitude, longitude). Other variables, the lagged variables, offer some predictive value for malaria incidence in months to come. If for example, a District Health Team decided it required indicators which offered a warning time of 2-3 months, to mount a preventative response, then maps could be produced using only variables which offered that lead-time. The following tests this requirement in two districts considered by the MoH to be epidemic prone: Boteti and Tutume.

5.4.7.1. Boteti

Model 3 was chosen for Boteti, Table 5.19.

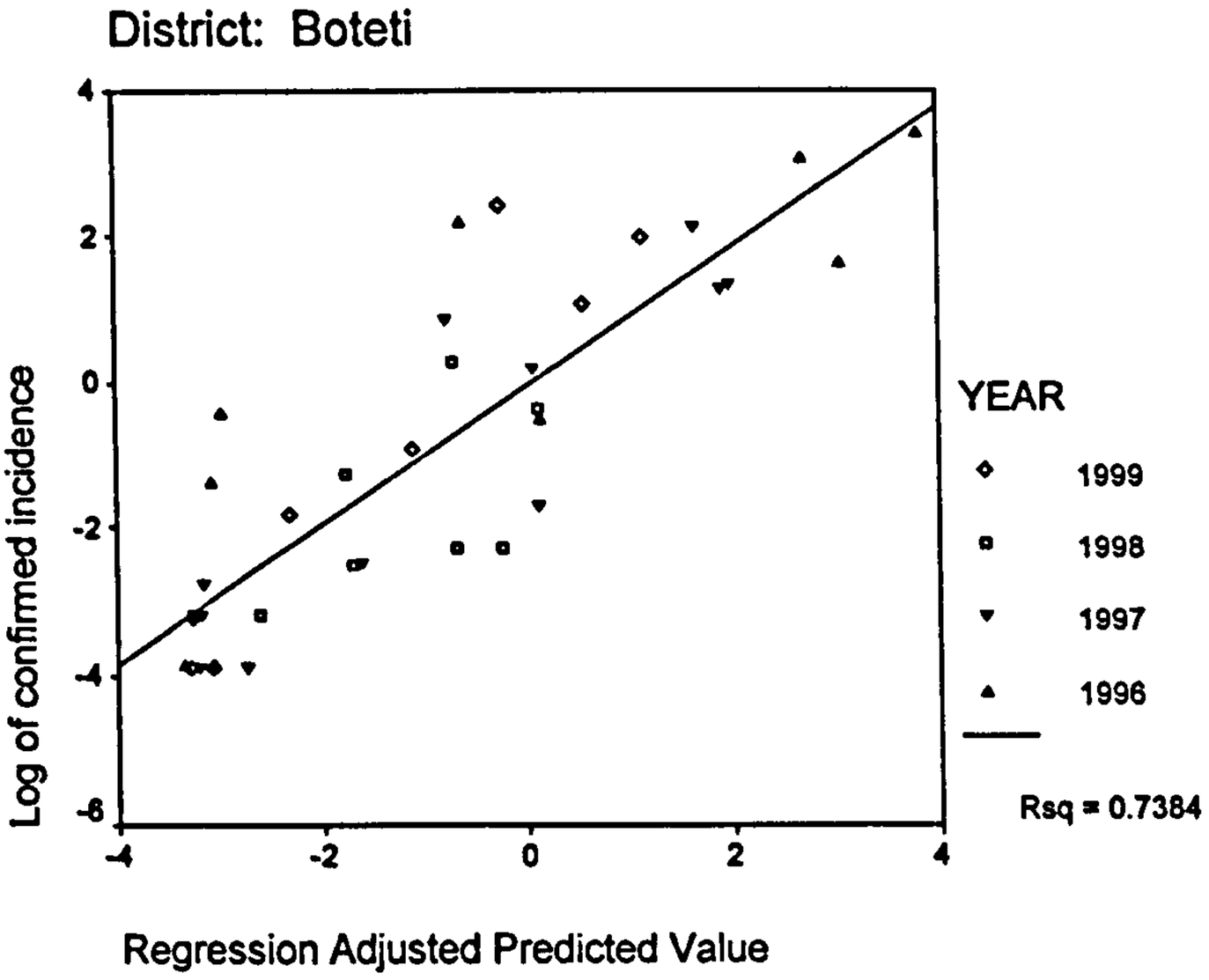
TABLE 5.19. MODEL COEFFICIENTS

Model 3	Unstandardized Coefficients	Std. Error	Significance
(Constant)	-3.389	0.294	0.000
LAGS(RFE,2)	1.815E-02	0.004	0.000
LAGS(RFE,3)	2.059E-02	0.004	0.000
VCLAG_1	0.130	0.041	0.004

Dependent Variable: Log of confirmed incidence

For Boteti, the correlation between the dependent variable (log of monthly incidence in confirmed malaria cases) and the model's predictive value ($R^2 = 0.74$) is described in Figure 5.25. The model is relatively simple in that it requires just three variables all of which are positively associated with the dependent variable.

FIGURE 5.25. RELATION BETWEEN LOG CONFIRMED INCIDENCE AND PREDICTED VALUE, BOTETI



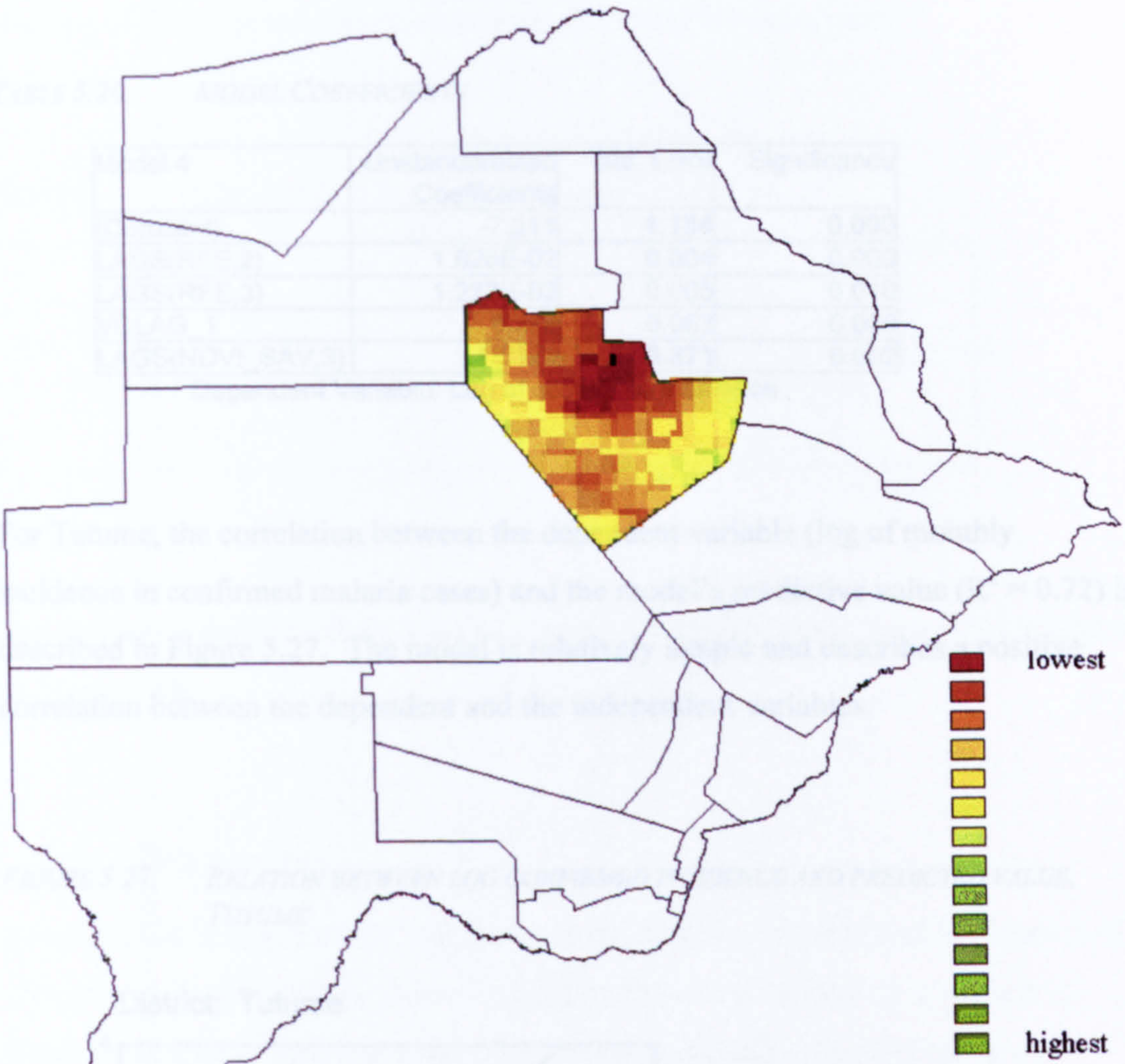
The cluster of high values for 1996 and 1997, both considered epidemic years, suggests the combination of environmental variables used in the model has some value in early warning of differences in incidence levels between years.

BOX 5.6. THE MODEL FROM TABLE 5.19, FOR BOTETI:

```
y = -3.389 + (LAGS(RFE_2) * 0.018) + (LAGS(RFE_3) * 0.02)
    + (VCLAG_1 * 0.130)
```

The regression equation (Box 5.6) was mapped using Idrisi and the result is illustrated in Figure 5.26.

FIGURE 5.26. PREDICTIVE MAP OF LOG MALARIA INCIDENCE FOR BOTETI, JANUARY 1996.



Legend:

The model (from Table 5.19) is used to produce the map (which assumes a constant population across the district). The map predicts the relative distribution of malaria incidence during the month of January 1996 in the district of Boteti. The legend, bottom right, represents the relative scale applicable in this map. The palette used by Idrisi is driven by the range of values in the particular model. Consequently one map cannot be used for cross comparison with the other maps.

5.4.7.2. *Tutume*

Model 4 was chosen for Tutume, Table 5.20.

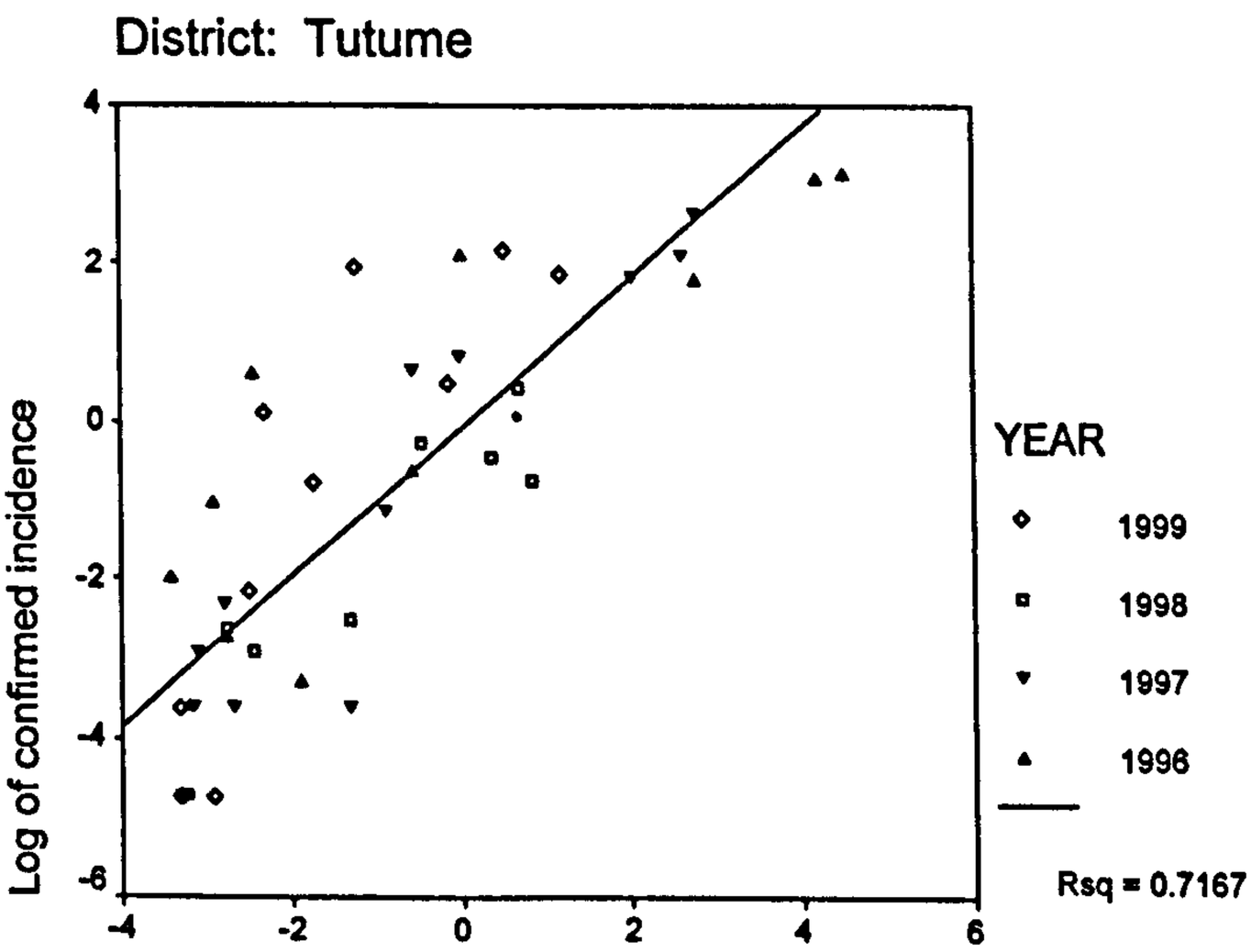
TABLE 5.20. MODEL COEFFICIENTS

Model 4	Unstandardized Coefficients	Std. Error	Significance
(Constant)	-7.211	1.154	0.000
LAGS(RFE,2)	1.626E-02	0.004	0.000
LAGS(RFE,3)	1.223E-02	0.005	0.010
VCLAG_1	0.268	0.063	0.000
LAGS(NDVI_SAV,3)	13.174	3.871	0.002

Dependent Variable: Log of confirmed incidence

For Tutume, the correlation between the dependent variable (log of monthly incidence in confirmed malaria cases) and the model's predictive value ($R^2 = 0.72$) is described in Figure 5.27. The model is relatively simple and describes a positive correlation between the dependent and the independent variables.

FIGURE 5.27. RELATION BETWEEN LOG CONFIRMED INCIDENCE AND PREDICTED VALUE, TUTUME



The clustering of high values for years 1996 and 1997 again suggest that the combination of environmental variables used in this model has value for early warning of differences in levels of malaria incidence between years.

BOX 5.7. *THE MODEL FROM TABLE 5.20, FOR TUTUME*

```
y = -7.211 + (LAGS(RFE_2) * 0.016) + (LAGS(RFE_3) * 0.012)
    + (VCLAG_1 * 0.268) + (LAGS(NDVISAV_3) * 13.174)
```

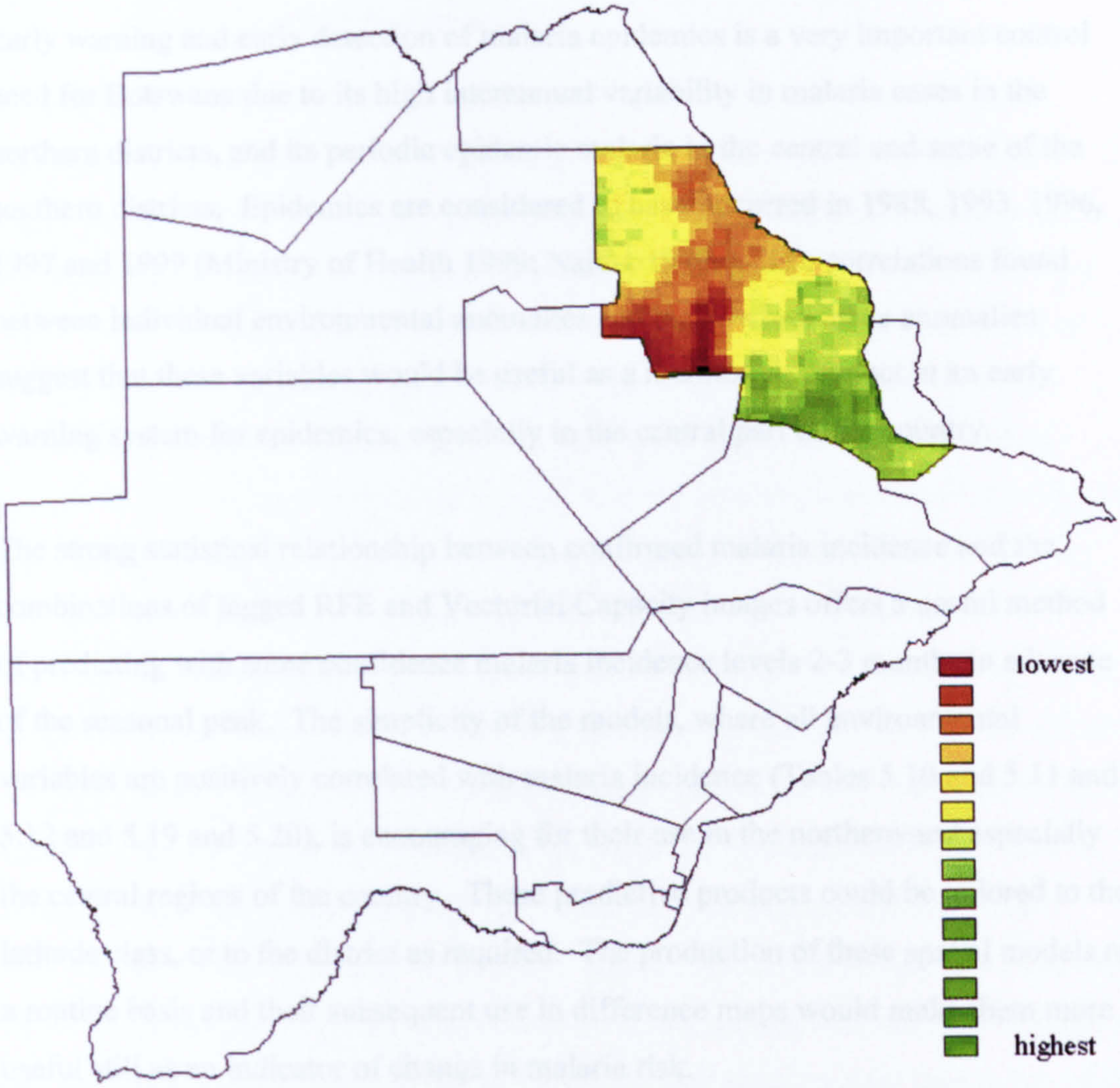
The regression equation (Box 5.7.) was mapped using Idrisi and the result illustrated in Figure 5.28.

5.5. Discussion

Botswana lies almost entirely within the desert-fringe zone identified in Figure 2.16 (Chapter 2). It is therefore, a country where interannual variability in malaria is likely to associated with interannual variability in rainfall. The availability of confirmed malaria case data for Botswana makes this case study the most critical. Unfortunately many countries in sub-Saharan African do not have confirmed data. However, the statistical relationships between unconfirmed, and confirmed malaria cases, and the environmental variables, shown here, provides tentative support for the use of regression modelling of malaria and environmental variables in close neighbouring countries where confirmed case data is unavailable.

The development of the seasonality map is based on the actual data in conjunction with temporaneous environmental variables shown to be strongly related to malaria distribution, rather than theoretical climate suitability alone, and as such represents a useful basis for a seasonal malaria transmission map of Botswana. It differs markedly from the climate based suitability map, Figure 2.11 (Chapter 2). The longer transmission season modelled here reflects case data and may therefore be

FIGURE 5.28. PREDICTIVE MAP OF LOG MALARIA INCIDENCE FOR TUTUME, JANUARY 1996.



The model (from Table 5.20) is used to produce the map (which assumes a constant population across the district). The map predicts the relative distribution of malaria incidence during the month of January 1996 in the district of Tutume. The legend, bottom right, represents the relative scale applicable in this map. The palette used by Idrisi is driven by the range of values in the particular model. Consequently one map cannot be used for cross comparison with the other maps.

strongly influenced by migration and referrals. The reality probably lies somewhere between the two.

Early warning and early detection of malaria epidemics is a very important control need for Botswana due to its high interannual variability in malaria cases in the northern districts, and its periodic epidemic malaria in the central and some of the southern districts. Epidemics are considered to have occurred in 1988, 1993, 1996, 1997 and 1999 (Ministry of Health 1999; Najera 1999c). The correlations found between individual environmental anomalies and malaria incidence anomalies suggest that these variables would be useful as a monitoring product in an early warning system for epidemics, especially in the central part of the country.

The strong statistical relationship between confirmed malaria incidence and the combinations of lagged RFE and Vectorial Capacity images offers a useful method of predicting with some confidence malaria incidence levels 2-3 months in advance of the seasonal peak. The simplicity of the models, where all environmental variables are positively correlated with malaria incidence (Tables 5.10 and 5.11 and 5.12 and 5.19 and 5.20), is encouraging for their use in the northern and especially the central regions of the country. These predictive products could be tailored to the latitude class, or to the district as required. The production of these spatial models on a routine basis and their subsequent use in difference maps would make them more useful still as an indicator of change in malaria risk.

The presence of latitude and longitude in models does however suggest something else is at work which is not captured by the environmental variables alone. Identifying what this factor is would be useful in further developing predictive models of malaria transmission in Botswana.

6. Malaria and Environment in Zimbabwe

6.1. Geographical background

Zimbabwe is a landlocked country of 390,760 square kilometres located approximately between 15°S to 22°S and 25°E to 33°E in central, southern Africa. It shares borders with Botswana, Zambia, Republic of South Africa and Mozambique. The population in 1995 was estimated at 11.4 million. Gross Domestic Product per capita in 1998 was estimated at US$620 (UNDP 2000). The country has a central upland region, the Highveld, which runs from the south-west beyond Bulawayo across to the north-east beyond Harare. This central ridge, which has an average altitude of 1525 metres, divides the country into the northern watershed forming part of Lake Kariba and the Zambezi valley; and the southern watershed draining away into the Limpopo-Sabi river systems. In the easternmost part of the country, a mountain range extending to 2596 metres forms a physical border with its low lying neighbour Mozambique. While Zimbabwe lies entirely within the tropics, its climate is moderated by its elevation. Average July temperatures are 16°C rising to 21°C in January. The average annual rainfall in the Highveld is 900mm with most rainfall occurring between October and March. However, both rainfall and temperature regimes vary markedly across the country. Annual rainfall totals vary from 400mm in the south-west, to 1200mm in the north-east; and average temperatures increase as one descends down into the valleys of the major river systems, north and south of the central highlands.

6.2. Overview of malaria and its control in Zimbabwe

Since Zimbabwe's independence in 1980 malaria has remained one of the major public health problems facing the country. In Zimbabwe malaria is classified as a legally notifiable disease. It ranks 4th nationally in terms of outpatient consultation, 2nd for inpatient admission and 4th as the stated cause of inpatient death (Ministry of Health and Child Welfare 1997).

6.2.1. Patterns of malaria in Zimbabwe.

The distribution of clinical malaria cases in Zimbabwe varies greatly between years and this is considered to be strongly related to rainfall, Figure 6.1. (Ministry of Health and Child Welfare 1997). It is also recognised that malaria in Zimbabwe varies markedly between districts and a 'Top 20' of malaria districts have been ranked by the MoH. These districts are highlighted on the map in Figure 6.2. The expert opinion map for malaria in Zimbabwe (described in Chapter 4) also illustrates how malaria is perceived to vary across the country, Figure 6.3.

6.2.2. The National Malaria Control Programme in Zimbabwe

Zimbabwe's National Malaria Control Programme has been decentralised to the Provincial level with additional support from the Department of Epidemiology and Disease Control in Harare. However, most malaria sufferers report first to a health facility based in one of the 63 districts. The NMCP is built on four main components:

6.2.2.1. Effective case management

In Zimbabwe, malaria is diagnosed, in most cases, on the basis of clinical observations. The clinical definition of a malaria case used in Zimbabwe is:

"a patient who lives in malaria areas, or visited those areas within the last six weeks, and presents a sudden onset of the following signs and symptoms: intermittent fever with shivering, sweating, headache, muscle and/or joints pain, body weakness" (Ministry of Health and Child Welfare 1997).

Chloroquine remains the first line anti-malarial treatment choice, despite reports of resistance in many areas of the country. Patients showing signs of treatment failure will usually be given sulphadoxine primethamine, the second line choice of anti-malarial, and a blood slide taken for analysis. Patients with severe treatment failure, or severe and complicated malaria, are referred to an appropriate health facility after a first dose of quinine, if available, the third line choice of anti-malarial.

Figure 6.1. Malaria incidence (clinical cases per 1000 population) in Zimbabwe 1987-1996 in relation to rainfall. Derived from (MoH, 1997)

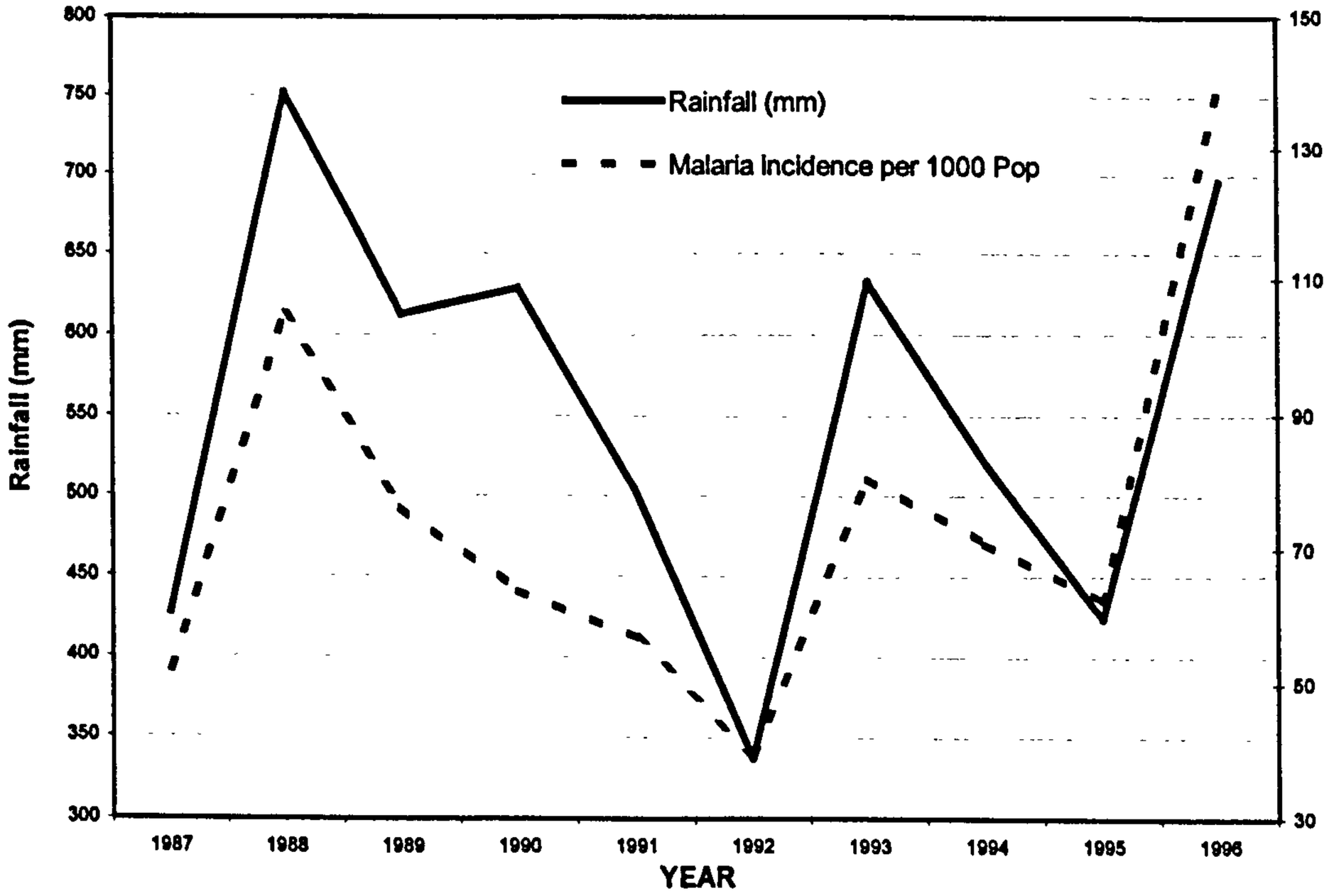
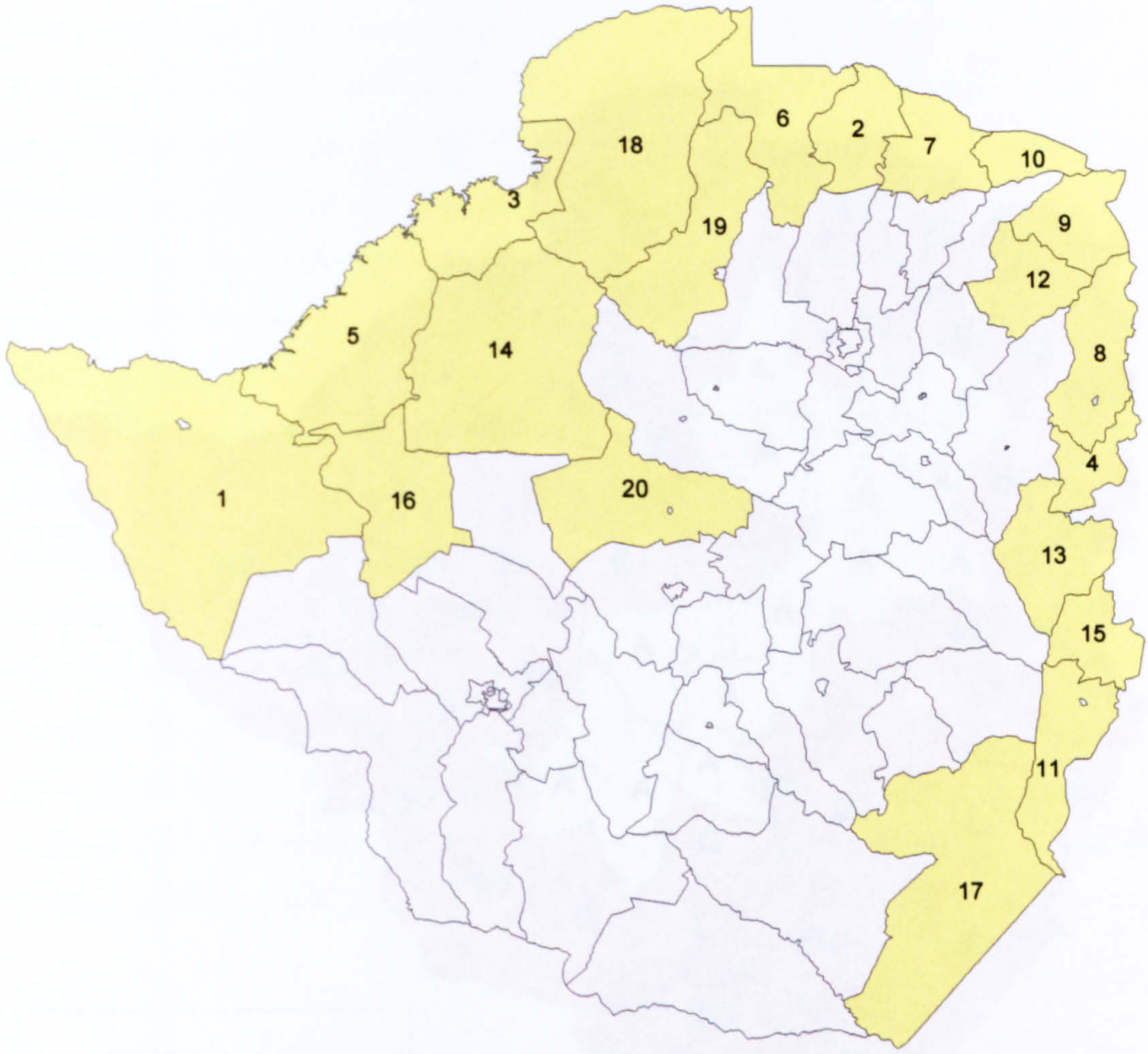
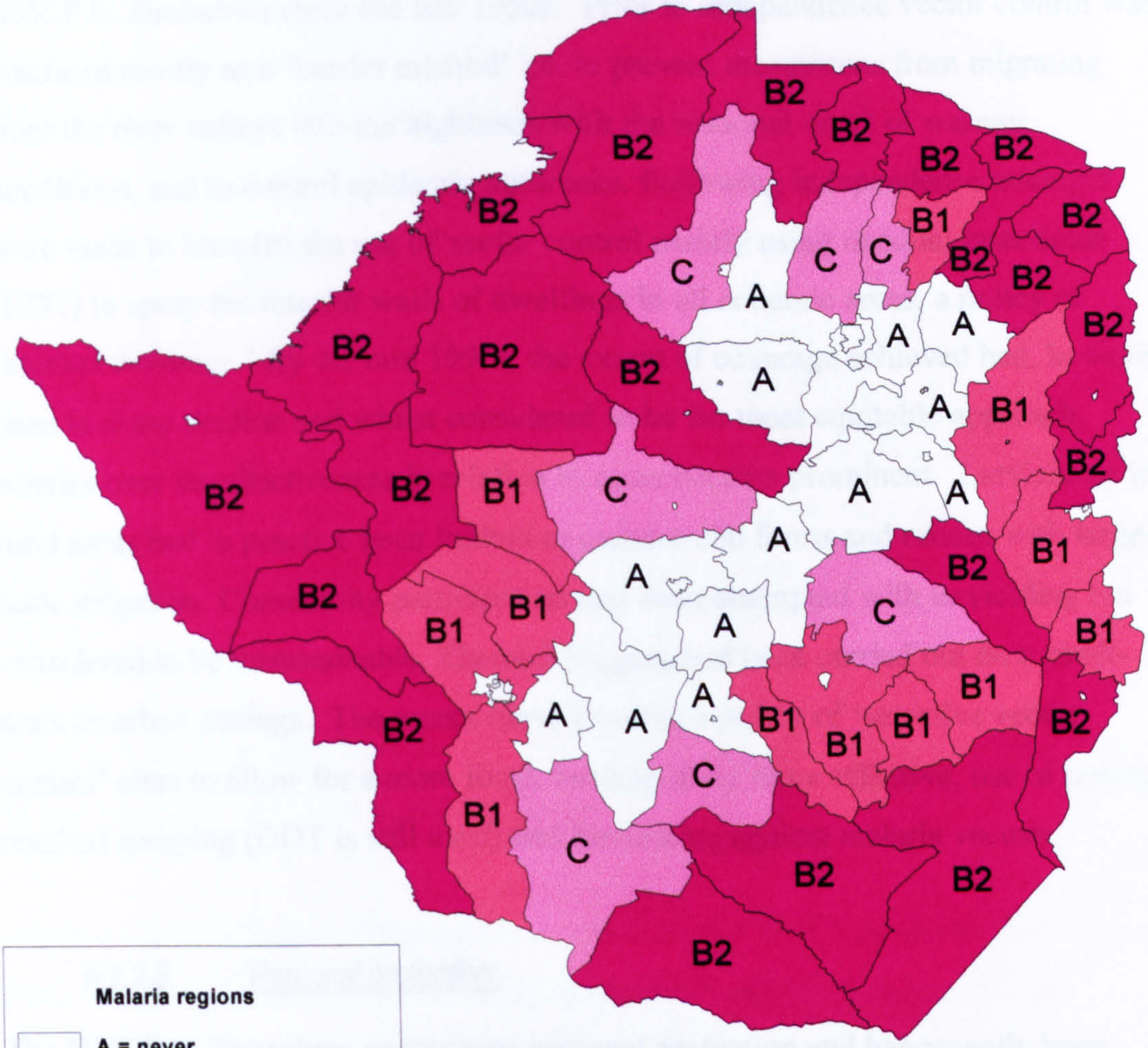


FIGURE 6.2 MAP OF THE 'TOP 20' MALARIA DISTRICTS IN ZIMBABWE.



Ranking	District	Incidence rate per 1000
1	Hwange	211.25
2	Centenary	211.04
3	Kariba	200.58
4	Mutasa	191.73
5	Binga	191.53
6	Guruve	189.5
7	Mount Darwin	181.14
8	Nyanga	164.76
9	Mudzi	164.48
10	Rushinga	148.35
11	Chipinge	138.61
12	Mutoko	116.89
13	Mutare	110.38
14	Gokwe	105.87
15	Chimanimani	105.0
16	Lupane	104.47
17	Chiredzi	95.89
18	Hurungwe	89.02
19	Makonde	87.41
20	Kwekwe	83.01

FIGURE 6.3. EXPERT OPINION MAP OF MALARIA IN ZIMBABWE, CIRCA 1998.



Legend:

The map used administrative boundary files supplied by SADC-RRSP (1997).

6.2.2.2. *Vector control.*

Vector control activities have formed a significant, though not consistent, part of the NMCP in Zimbabwe since the late 1950s. Prior to independence vector control was practiced mostly as a 'barrier method' i.e. to prevent mosquitoes from migrating from the river valleys into the highlands with the seasonal onset of warmer conditions, and to control epidemic outbreaks. Following independence attempts were made to broaden the use of vector control mainly using residual insecticide (DDT) to spray the interior walls of dwellings in all endemic areas, a policy of 'blanket coverage.' By the mid 1990s, the extent of coverage achieved had, however, been in sharp decline and whilst considered to be the most equitable approach, worries over its effectiveness in relation to costs became prominent. Larviciding in rural areas had in practice been limited to commercial farms and estates with large-scale irrigation. Community participation had been attempted with larviciding but considered to be unsustainable. Thermal fogging had been carried out on a small-scale in urban settings. The recent move towards a policy of 'selective vector control' aims to allow for a more focal, but hopefully more effective, use of indoor residual spraying (DDT is still used) and larviciding against malaria vectors.

6.2.2.3. *Personal protection.*

The NMCP in Zimbabwe encourages personal protection and has recently been focussing on increasing the use of Insecticide-Treated BedNets (ITNs). Demand for ITNs in Zimbabwe has increased, from a very low base, in recent years. A number of small-scale pilot projects have been carried out in collaboration with NGOs, and a major initiative is now being funded by the Japanese International Cooperation Agency. This new initiative aims to stimulate broad use of ITNs through provision at affordable cost, as well as setting up revolving funds and loan schemes for net re-treatment and subsequent purchases for the longer term.

6.2.2.4. *Health Education.*

Raising community awareness of seasonal malaria risk, personal protection, recognising the symptoms, the need to seek prompt treatment, compliance with drug treatment regimes and cooperation with vector control and environmental health

activities are important aspects of malaria control. This message is promoted at the community level by the NMCP in Zimbabwe through its health education activities, which are carried out in collaboration with community leaders, schools, employers, shopkeepers, commercial suppliers and the media. WHO has been a major contributor to Health Education in Zimbabwe over recent years.

6.2.2.5. *Supplementary activities*

The National Health Surveillance Unit is part of the Department of Epidemiology and Disease Control of the Ministry of Health and Child Welfare, in Harare. The National Health Information System (HIS) collects health statistics through it routine monthly reporting system from all districts. It also collects weekly reports on certain diseases, including malaria, from selected districts as part of its Rapid Notification System.

Chemoprophylaxis is recommended for vulnerable groups: pregnant women, under 5s and travellers from non-malarious areas.

Applied research is also stated as a component of the NMCP in Zimbabwe. The Blair Research Institute (BRI) allied to the Ministry of Health is based in the University of Zimbabwe. The BRI has integral links with the Department of Epidemiology and Disease Control and provides advice on control policy and implementation.

6.3. Aims of this chapter

- To describe the spatial and temporal distribution of malaria in Zimbabwe
- To compare and relate the spatial and temporal distribution of malaria to environmental variables in order to inform malaria risk mapping.
- To explore whether or not temporal environmental variables could be used in an early warning system for malaria epidemics in Zimbabwe.

6.4. Materials and methods

6.4.1. Epidemiological data

Epidemiological data for malaria were collected from the Ministry of Health's Department of Epidemiology and Disease Control in Harare. The data covering the period 1994 – 1999 consisted of the following information as set out in Table 6.2. Unfortunately there is very limited data on laboratory confirmed cases available at the central level.

TABLE 6.2. EPIDEMIOLOGICAL DATA OBTAINED

Time period/frequency/case definition	Age cohort	Spatial Scale
1994-1999 Monthly clinical unconfirmed	<5	District
1994-1999 Monthly clinical unconfirmed	5-14	District
1994-1999 Monthly clinical unconfirmed	>15	District

6.4.2. Population data

District population figures were obtained from the Central Statistics Unit and their projected growth rates between years were carried out in consultation with local expertise. Zimbabwe is suffering a high prevalence of HIV-AIDS and population growth rates are much reduced as a consequence[20]. As with Botswana annual population growth rates were revised to reflect a mean rate of 1% per annum, since 1995.

The population data were used to create incidence rates. Incidence rates were produced for each of the districts by year. The district boundaries used in the extraction were adapted from those provided by SADC.

[20] In an interview in New Scientist, Zimbabwe's Minister of Health, Timothy Stamps, stated "that Zimbabwe would reach zero population growth by 2002" New Scientist, 20 Oct 2001 p50.

6.4.3. Environmental data

The environmental data used here and the method of extraction for summary statistics per district, per month is the same as that described for Botswana, in Chapter 5, section 5.5.2.1.3.

6.4.4. Data analysis

SPSS and Microsoft Excel were used to explore and assess the relationships between the epidemiological and environmental data. The preliminary analyses included comparing time series of unconfirmed malaria cases and environmental variables using exploratory scatterplots and Pearson's correlation coefficient. Comparisons were also made of relationships between contemporaneous environmental variables such as NDVI and RFE and the respective long-term mean monthly climatology variables. The relationships between the epidemiological data and the environmental variables were explored using curve estimation techniques in SPSS to elicit the best overall relationships between environmental variables and the epidemiological data. As a result of these tests, the malaria case data was transformed (log or quadratic) where appropriate. Further analysis was carried out in SPSS using a combination of bivariate and multivariate techniques against the chosen environmental variables. The creation of difference anomaly statistics and their analysis is as described in Chapter 5, section 5.2.2.

6.5. Results

In the expert opinion map of malaria distribution in Zimbabwe, Figure 6.3, the greater proportion of the country is considered to have a malaria season of 6 months or more. The exceptions are generally those districts comprising the central highlands. The map gives the impression that there is little effect of latitude, or longitude, on malaria distribution. There is little apparent agreement between malaria distribution in the Zimbabwean districts bordering Botswana and the Republic of South Africa and those districts immediately over the border in those countries (compare with Figure 4.4, Chapter 4).

6.5.1. Malaria distribution

6.5.1.1. *Interannual variability*

Unfortunately the lack of confirmed malaria data means there is no 'gold standard' to work with in Zimbabwe. This analysis uses data routinely available to the NMCP at the national level and therefore represents the data used for decision making for malaria control in Zimbabwe. The assumption here is that, as was the case in Botswana, unconfirmed malaria cases are correlated with confirmed malaria cases. However, as discussed in Chapter 2, misdiagnosis must remain a serious consideration. The annual total unconfirmed malaria cases for the years 1994-1999 are illustrated in Figure 6.4. The dramatic rise in cases during 1996 was associated with a regional epidemic in Southern Africa (Najera 1998b) and high annual total numbers of cases have remained in subsequent years. This was not considered to be due to more complete reporting and surveillance, or changes in drug policy, but a result of increased epidemic outbreaks (Murugasampillay: pers. comm.[21]). The extent to which declining control infrastructure would have been able to regain control after the 1996 epidemic is not clear. It should be noted however, that annual rainfall for the years 1997, 1998 and 1999 were generally above average in most parts of the country.

6.5.1.2. *Seasonal variability*

The mean seasonal trend in the national data is clear, Figure 6.5. However the average monthly cases reported, do not fall below 1000 cases in any month and it is, without confirmed data, difficult at the national level to identify clearly where the malaria season in Zimbabwe season begins and ends. The method of using 5% of annual totals and 'sporadics' (as used for Botswana and described in chapter 5) was not adequate to overcome this.

Observation of the range of monthly percentages of the annual totals in Zimbabwe, Figure 6.6, suggest that 7.5% might be a more useful measure of the average

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[21] Dr. Murugasampillay (WHO-AFRO) was formerly Director of the Epidemiology and Disease Surveillance Department, Ministry of Health, Zimbabwe, and was responsible for the development of the NHIS in Zimbabwe during this time period.

FIGURE 6.4. ANNUAL TOTAL MALARIA CASES IN ZIMBABWE, 1994-1999.

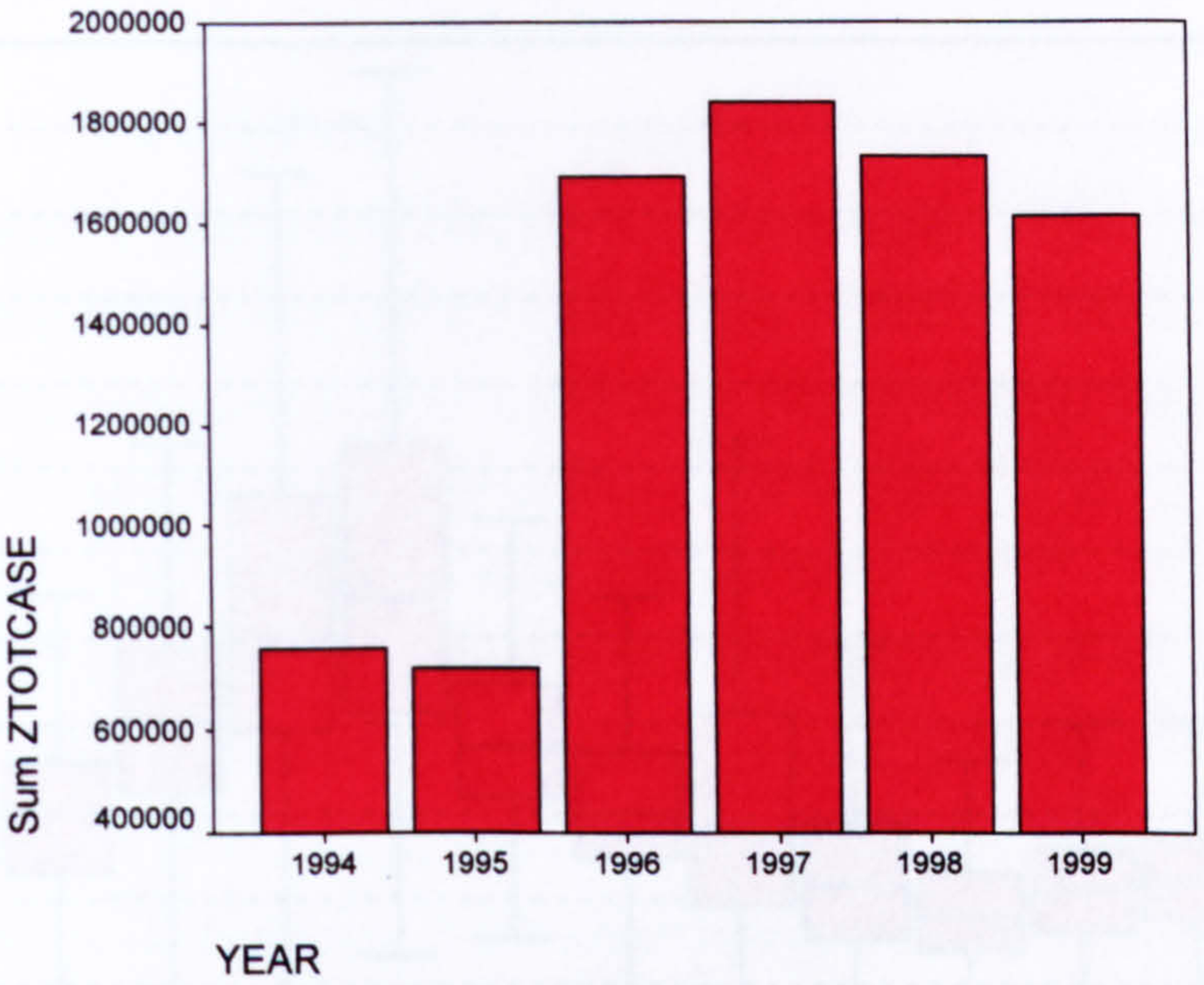


FIGURE 6.5 SEASONALITY OF REPORTED MALARIA IN ZIMBABWE (MEAN 1994-1999).

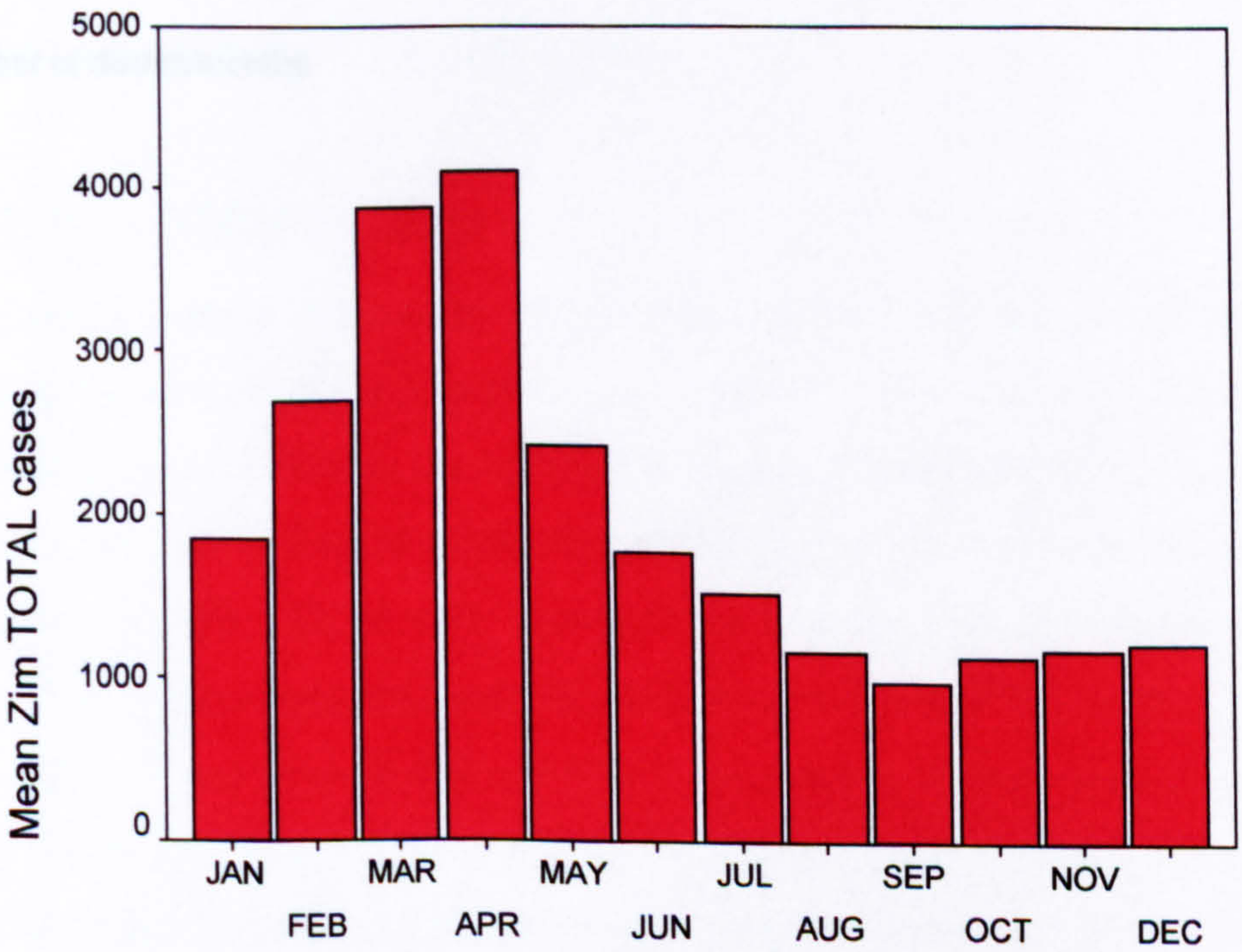
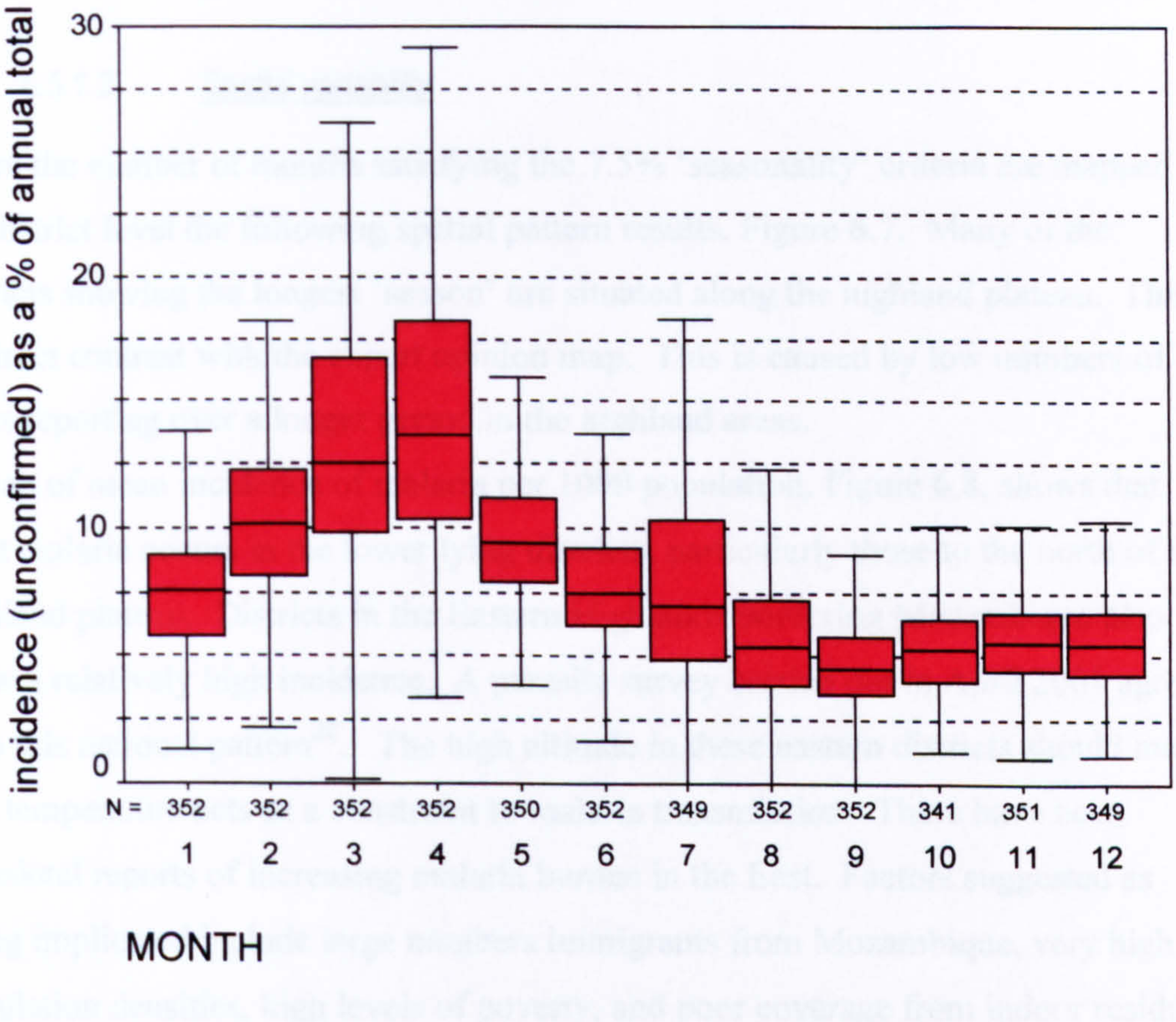


FIGURE 6.6. PERCENTAGE OF AVERAGE ANNUAL TOTAL BY MONTH 1994-1999.



N = number of district/months

beginning and end of the season in Zimbabwe. The national level statistics may of course include a number of districts where malaria is perennial.

6.5.1.3. *Spatial variability*

When the number of months satisfying the 7.5% 'seasonality' criteria are mapped at the district level the following spatial pattern results, Figure 6.7. Many of the districts showing the longest 'season' are situated along the highland plateau. This is in direct contrast with the expert opinion map. This is caused by low numbers of cases reporting over a longer period in the highland areas.

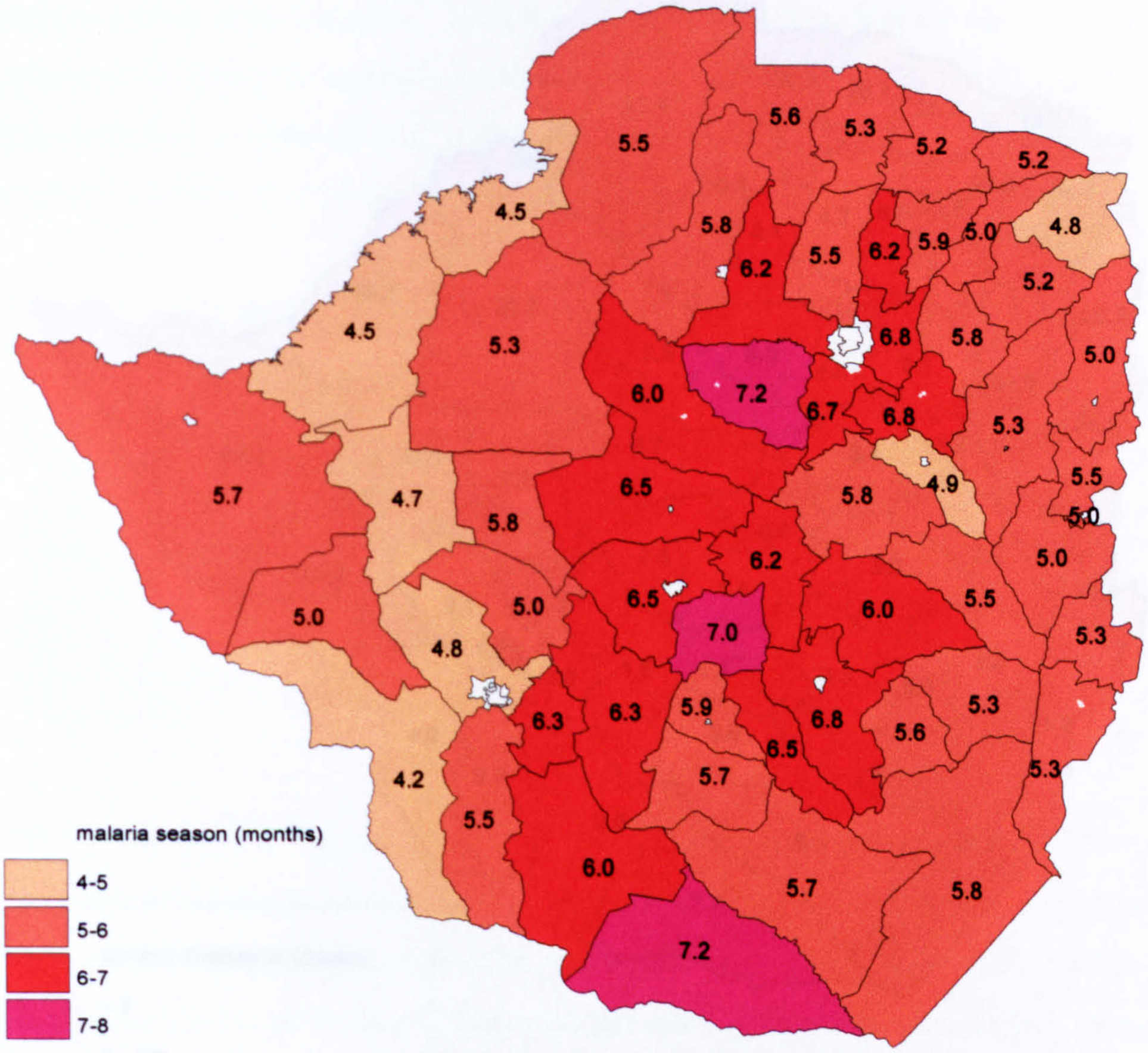
A map of mean incidence of malaria per 1000 population, Figure 6.8, shows that most malaria occurs in the lower lying districts, particularly those to the north of the highland plateau. Districts in the Eastern Highlands bordering Mozambique also show a relatively high incidence. A parasite survey carried out in April 2001 agreed with this national pattern[22]. The high altitude in these eastern districts should mean that temperature acts as a constraint to malaria transmission. There have been anecdotal reports of increasing malaria burden in the East. Factors suggested as being implicated include large numbers immigrants from Mozambique, very high population densities, high levels of poverty, and poor coverage from indoor residual spraying in some districts (Root. Pers. Comm).

6.5.1.4. *Malaria and altitude*

Altitude and its inverse relationship with temperature have long been associated with vector distributions and malaria endemicity in Zimbabwe (Leeson 1931; Ross 1932). In a published work reviewing the malaria situation in Zimbabwe (Taylor and Mutambu 1986), seven distinct altitude zones were identified to explore differences in malaria endemicity. These were: a) comprising land less than 600 metres on the northern side of the central watershed; b) land between 600 and 900 metres on the northern side; c) land between 900 and 1200 metres on the northern side; d) all land over 1200 metres; e) land between 900 and 1220 metres on the southern side of the watershed; f) land between 600 and 900 metres on the southern side; g) land less than 600 metres to the south. Analysis of blood slides surveys carried out between 1969-

[22] The national parasite survey was carried out by the Ministry of Health with the support of the WHO Southern Africa Inter-Country Team. However, the results are not available for reproduction here.

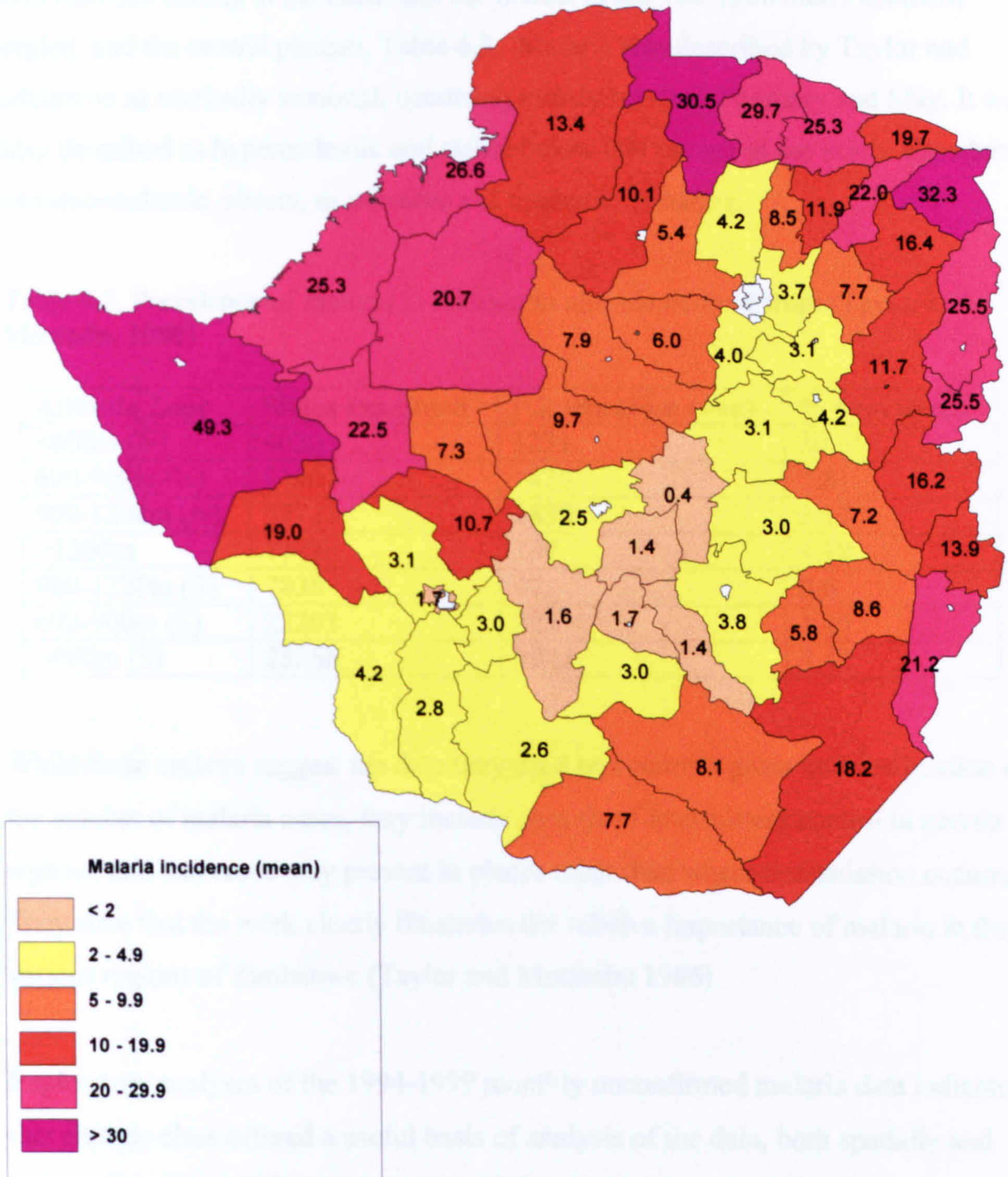
FIGURE 6.7. MALARIA 'SEASON' IN ZIMBABWE – MONTHS OF MEMBERSHIP >7.5% OF ANNUAL TOTAL.



Legend:

The map used administrative boundary files supplied by SADC-RRSP (1997).

FIGURE 6.8. INCIDENCE MAP (PER 1000) MEAN 1994-1999.



Legend:

The map used administrative boundary files supplied by SADC-RRSP (1997).

1981 showed the prevalence of malaria (*P.falciparum*) to be closely related to altitude (and latitude) with the highest prevalence in the areas of the Zambezi valley less than 600 metres in the north and the lowest in the 900-1200 metre southern region, and the central plateau, Table 6.3. Malaria was described by Taylor and Mutambu as markedly seasonal, occurring mostly between February and May. It was also described as hyperendemic and stable below 600 metres in the north, elsewhere as meso-endemic, absent, or unstable and epidemic in nature.

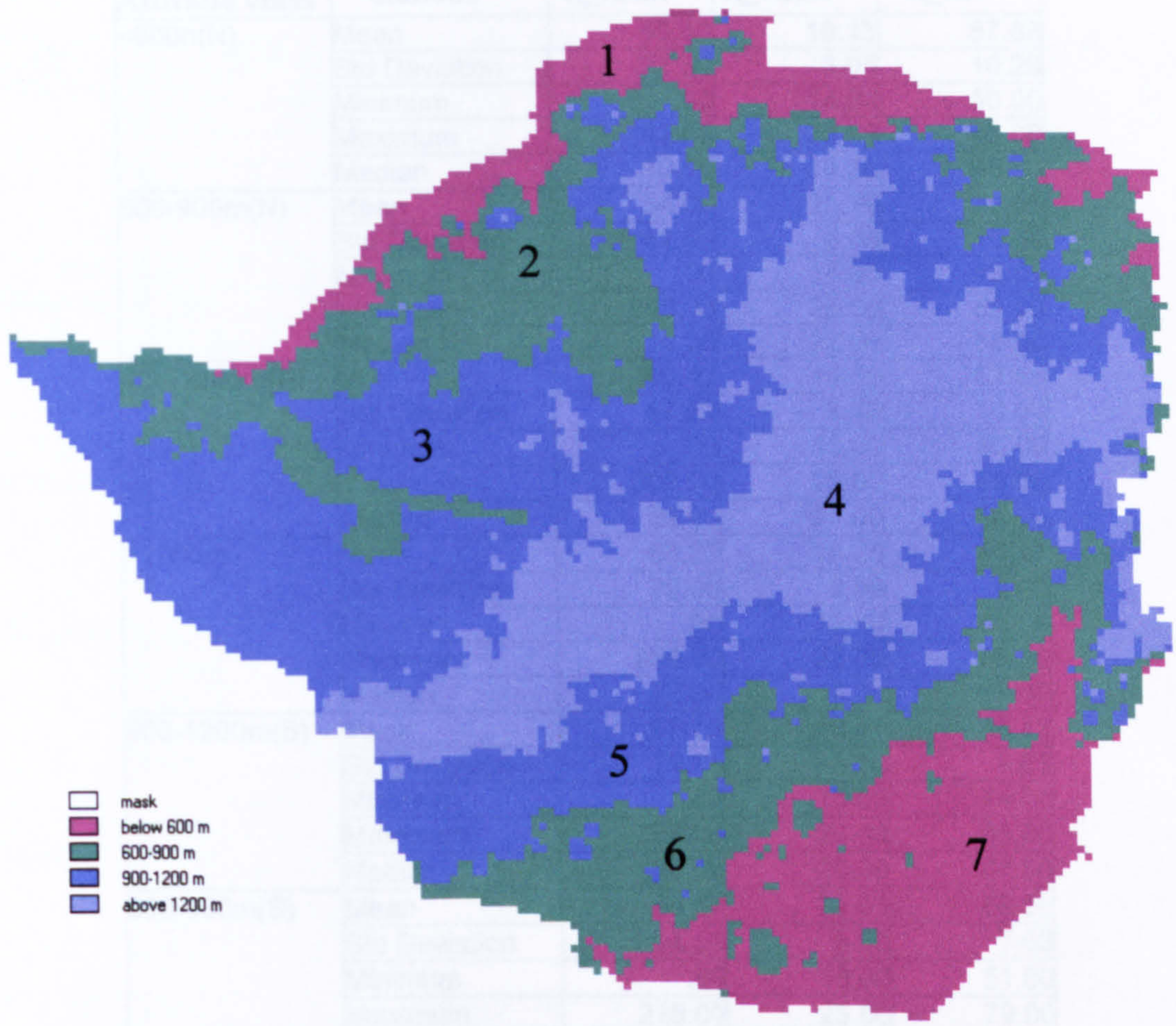
Table 6.3. Prevalence of malaria in relation to altitude derived from (Taylor and Mutambu 1986).

Altitude Zone	Slides examined	P.falciparum (+ve)	% prevalence
<600m (N)	4030	1231	30.55
600-900m (N)	24567	1428	5.81
900-1200m (N)	57723	1830	3.17
>1200m	11770	139	1.18
900-1220m (S)	7835	47	0.6
600-900m (S)	22203	321	1.45
<600m (S)	28066	2082	7.42

While these authors suggest the data they used represents a gross underestimation of the number of malaria cases, they include periods of intermittent control in certain regions, and that cases may present in places other than where transmission occurred. They state that the work clearly illustrates the relative importance of malaria in the various regions of Zimbabwe (Taylor and Mutambu 1986).

Exploratory analyses of the 1994-1999 monthly unconfirmed malaria data indicated that altitude class offered a useful basis of analysis of the data, both spatially and temporally. The 0-600, 600-900, 900-1200 and >1200m altitude classes derived from the SADC DEM (Digital Elevation Model) are illustrated in Figure 6.9. The 19°S parallel was used to ascribe whether districts fell into the northern or southern group of altitude classes. Two remaining districts with centroids to the south of 19°S but clearly north of the central highland divide were classified manually. The relationship between altitude class and the temporal environmental variables are summarised in Table 6.4.

FIGURE 6.9 ALTITUDE CLASSES IN ZIMBABWE AFTER TAYLOR AND MATUMBU (1986).



Legend:

Altitude class 1 = <600m (N); Altitude class 2 = 600-900m (N); Altitude class 3 = 900-1200m (N); Altitude class 4 = >1200m; Altitude class 5 = 900-1200m (S); Altitude class 6 = 600-900m (S); Altitude class 7 = <600m (S). The map is derived from the didgital elevation model supplied by SADC-RRSP (1997).

TABLE 6.4A. SUMMARY RELATIONSHIP BETWEEN ALTITUDE CLASS AND MEAN CLIMATOLOGY.

Altitude class	statistic	X_RAIN	X_TEMP	X_RH
<600n(N)	Mean	59.83	19.13	67.83
	Std Deviation	71.50	3.08	10.29
	Minimum	.00	14.00	50.00
	Maximum	192.00	23.00	82.00
	Median	16.00	20.50	68.50
600-900m(N)	Mean	54.00	20.79	66.55
	Std Deviation	62.90	3.05	10.80
	Minimum	.00	15.00	42.00
	Maximum	200.00	26.00	83.00
	Median	20.00	22.00	68.00
900-1200m(N)	Mean	60.42	19.39	63.86
	Std Deviation	67.62	3.20	10.93
	Minimum	.00	13.00	40.00
	Maximum	308.00	26.00	85.00
	Median	26.00	21.00	64.00
>1200m	Mean	66.27	18.25	66.37
	Std Deviation	70.06	2.99	9.46
	Minimum	.00	13.00	45.00
	Maximum	308.00	23.00	86.00
	Median	32.00	19.00	67.00
900-1200m(S)	Mean	67.78	19.41	66.12
	Std Deviation	79.31	3.30	8.63
	Minimum	.00	13.00	44.00
	Maximum	388.00	24.00	83.00
	Median	34.00	20.00	67.00
600-900m(S)	Mean	54.67	21.01	66.86
	Std Deviation	54.59	3.08	7.03
	Minimum	.00	15.00	51.00
	Maximum	216.00	25.00	79.00
	Median	26.00	22.00	67.50
<600m(S)	Mean	40.22	22.67	65.50
	Std Deviation	37.30	3.28	6.21
	Minimum	.00	17.00	53.00
	Maximum	116.00	26.00	76.00
	Median	24.00	23.50	65.50

TABLE 6.4B. SUMMARY RELATIONSHIP BETWEEN ALTITUDE CLASS AND TEMPORAL ENVIRONMENTAL VARIABLES.*

AV_H_CLS		NDVI_SAV	NDVI_SMX	RFE	CCD	VCLAG0	VCLAG1	VCLAG2	VCLAG3
<600n(N)	Mean	0.348	0.366	60.843	90.639	5.902	5.069	4.098	2.873
	Std. Dev	0.099	0.10	91.19	183.80	8.315	7.819	6.676	4.639
	Min	0.18	0.20	0.00	0.00	0.00	0.00	0.00	0.00
	Max	0.54	0.55	353.00	1012.00	33.00	30.00	27.00	20.00
	Median	0.343	0.363	5.000	8.00	1.50	1.00	1.00	1.00
600-900m(N)	Mean	0.333	0.352	61.77	88.99	6.47	5.67	4.546	3.168
	Std. Dev	0.109	0.111	90.179	179.224	8.866	8.328	7.257	5.167
	Min	0.16	0.17	0.00	0.00	0.00	0.00	0.00	0.00
	Max	0.56	0.58	383.00	1012.00	42.00	41.00	39.00	29.00
	Median	0.32	0.34	10.00	8.00	1.00	1.00	1.00	1.00
900-1200m(N)	Mean	0.349	0.367	59.977	83.319	3.937	3.299	2.546	1.732
	Std. Dev	0.098	0.099	82.705	161.214	5.17	4.725	3.955	2.645
	Min	0.17	0.17	0.00	0.00	0.00	0.00	0.00	0.00
	Max	0.57	0.59	408.00	1012.00	30.00	29.00	27.00	18.00
	Median	0.34	0.36	15.00	12.00	1.00	1.00	1.00	1.00
>1200m	Mean	0.339	.357	60.754	83.136	1.871	1.593	1.264	0.9343
	Std. Dev	0.087	0.09	79.577	161.729	2.222	2.031	1.551	1.042
	Min	0.17	0.18	0.00	0.00	0.00	0.00	0.00	0.00
	Max	0.57	0.57	416.00	1012.00	13.00	12.00	10.00	7.00
	Median	0.33	0.35	22.50	12.00	1.00	1.00	1.00	1.00
900-1200m(S)	Mean	0.329	0.347	51.1605	69.9568	2.782	2.444	1.9	1.386
	Std. Dev	0.09	0.09	63.452	134.884	3.482	3.146	2.389	1.546
	Min	0.16	0.16	0.00	0.00	0.00	0.00	0.00	0.00
	Max	0.57	0.59	345.00	968.00	20.00	18.00	13.00	8.00
	Median	0.326	0.34	22.50	12.00	1.00	1.00	1.00	1.00
600-900m(S)	Mean	0.338	.358	48.719	65.407	3.761	3.346	2.592	1.856
	Std. Dev	0.10	0.103	59.688	131.698	4.882	4.437	3.30	2.034
	Min	0.16	0.16	0.00	0.00	0.00	0.00	0.00	0.00
	Max	0.57	0.58	301.00	804.00	26.00	23.00	18.00	11.00
	Median	0.331	0.35	23.50	8.00	1.00	1.00	1.00	1.00
<600m(S)	Mean	0.303	0.322	41.58	56.926	4.536	4.111	3.118	2.222
	Std. Dev	0.103	0.107	52.212	121.387	6.18	5.592	4.171	2.606
	Min	0.15	0.15	0.00	0.00	0.00	0.00	0.00	0.00
	Max	0.54	0.57	276.00	776.00	33.00	29.00	22.00	13.00
	Median	0.284	0.305	20.00	10.00	1.00	1.00	1.00	1.00

* In ANOVA all groupings were found to be significant at better than 0.05.

FIGURE 6.10. MALARIA INCIDENCE RATIO CHILDREN UNDER 5:ADULT (OVER 15) ACCORDING TO ALTITUDE CLASS.

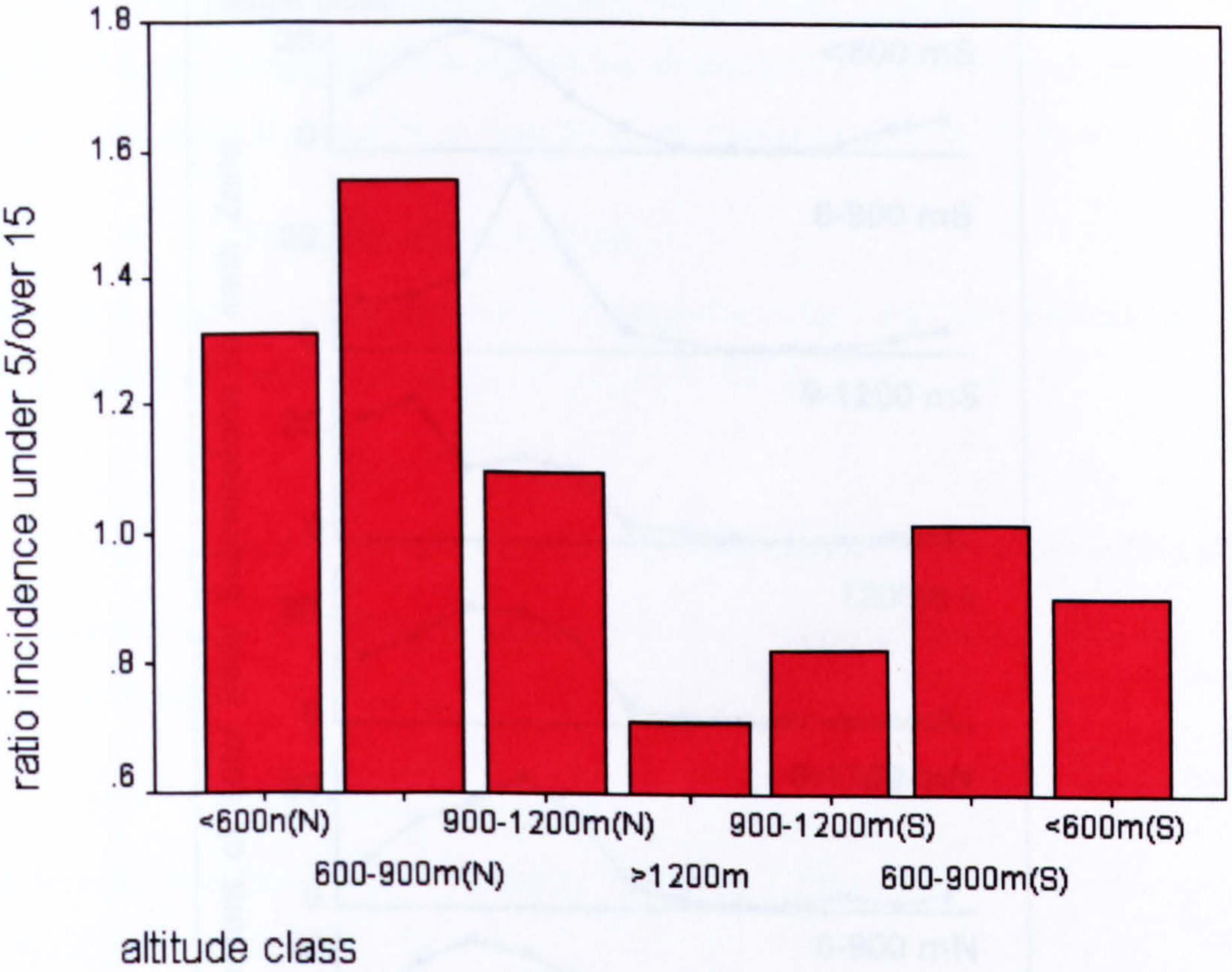
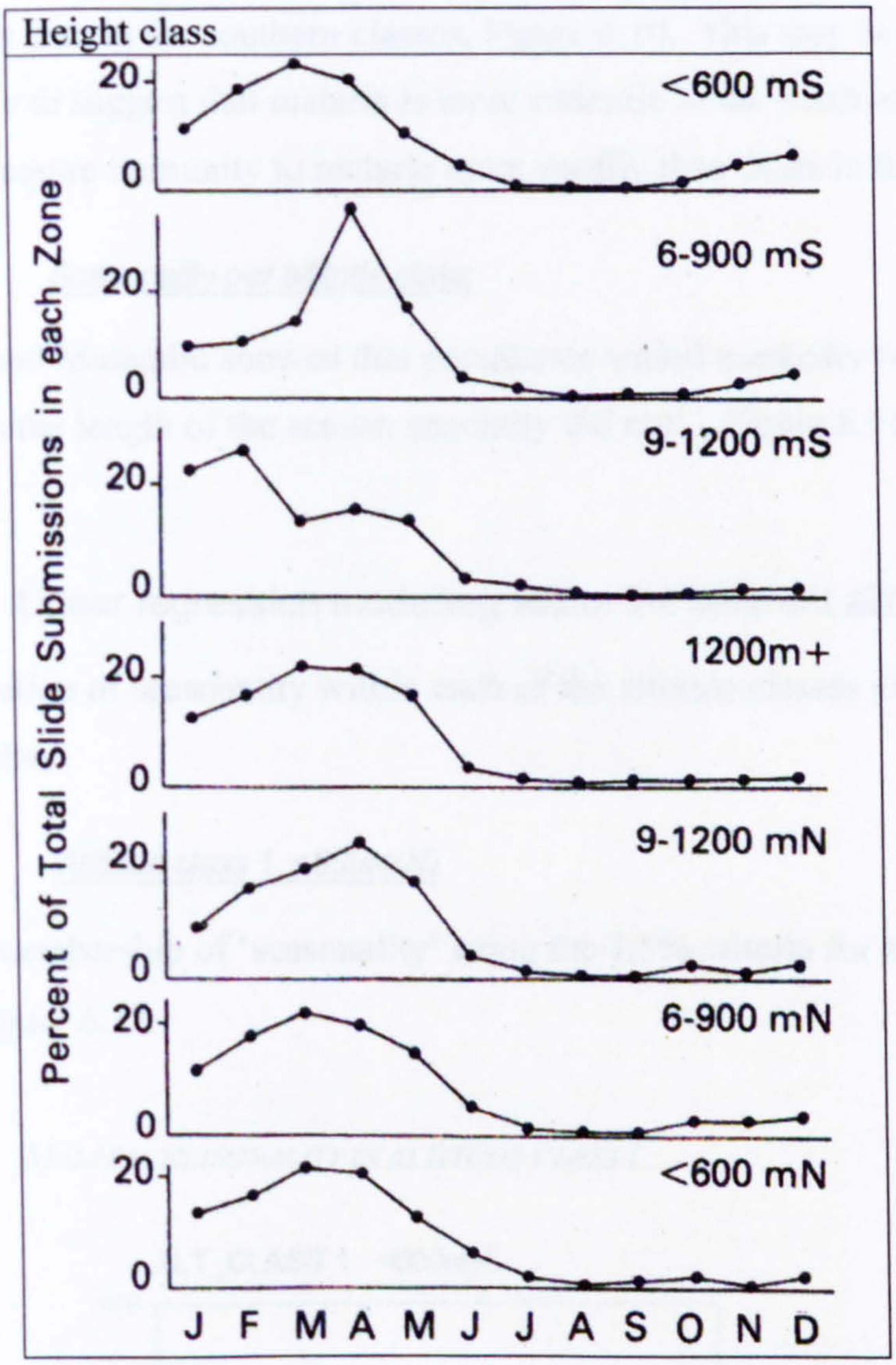


FIGURE 6.11. MALARIA SEASONALITY IN ZIMBABWE BY ALTITUDE CLASS. DERIVED FROM TAYLOR AND MUTAMBU (1987).



6.5.1.5. *Endemicity per altitude class*

Using Taylor and Mutambu's altitude classes to explore the data, the ratio of malaria in children (under 5) compared to adults (over 15) was found to be higher in the northern classes than in the southern classes, Figure 6.10. This may be used as further evidence to suggest that malaria is more endemic in the north and that adults in this region acquire immunity to malaria more readily than those in the south.

6.5.1.6. *Seasonality per altitude class*

While Taylor and Mutambu showed that prevalence varied markedly between the altitude classes the length of the season generally did not[23], Figure 6.11.

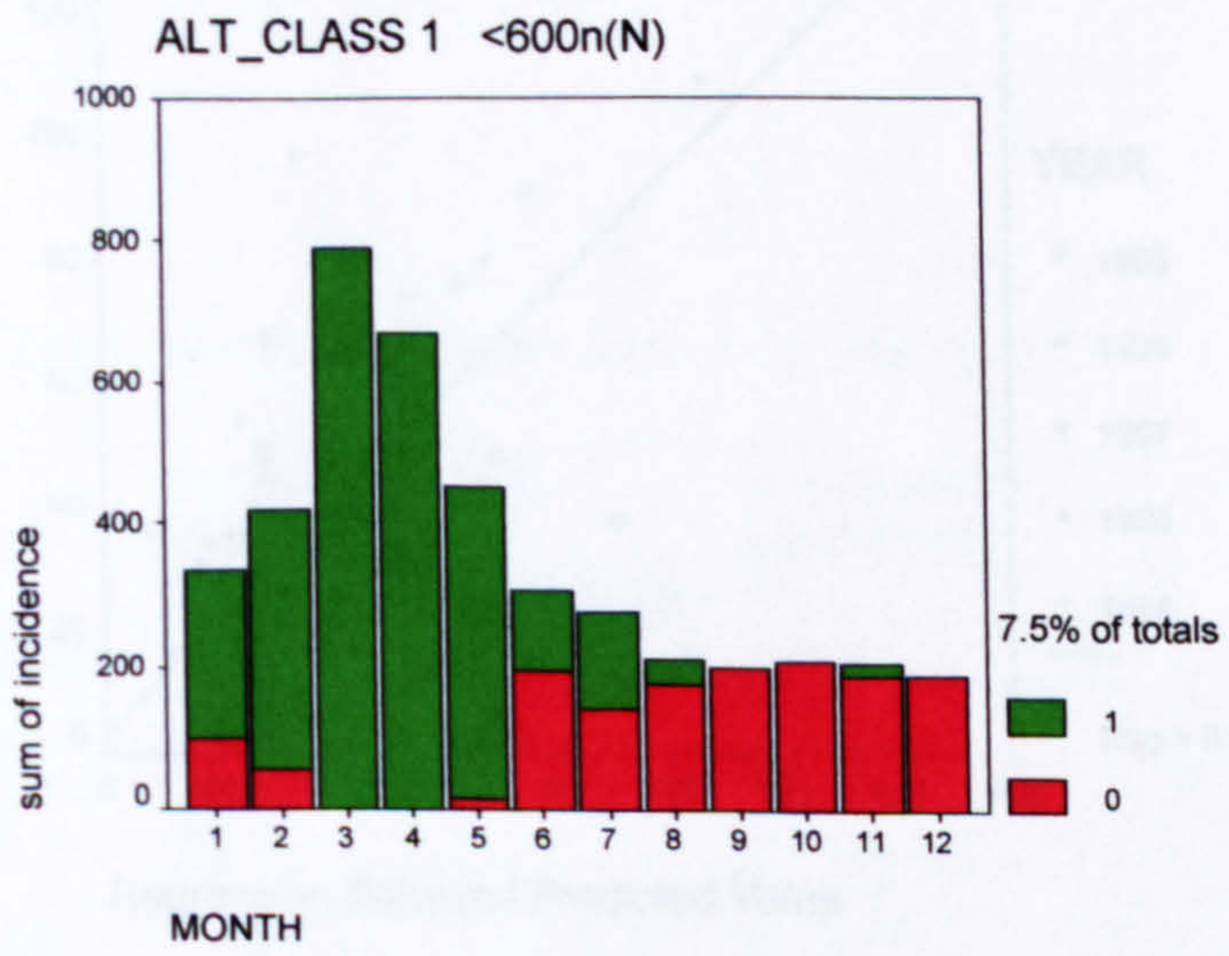
6.5.2. Linear regression modelling within the different altitude classes

Further exploration of seasonality within each of the altitude classes yielded the following results.

6.5.2.1. *Altitude class 1. <600m(N)*

The monthly membership of 'seasonality' using the 7.5% criteria for altitude class 1 is shown in Figure 6.12.

FIGURE 6.12 MALARIA SEASONALITY IN ALTITUDE CLASS 1.



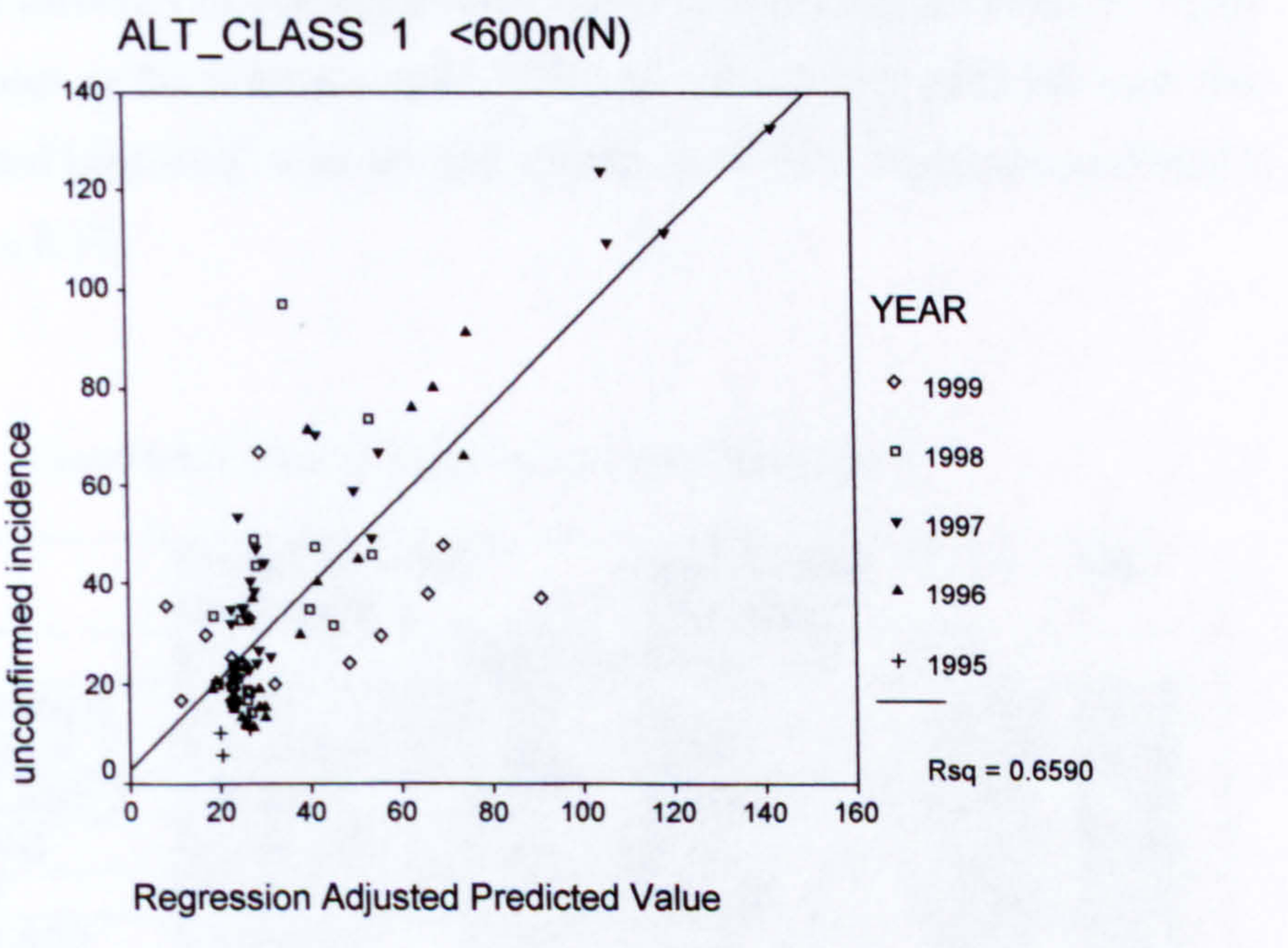
[23] The early peak in the 900-1200m(S) zone was due entirely to a high number of positive slides being submitted in January and February 1974 Taylor, P. and S. L. Mutambu (1986). "A review of the malaria situation in Zimbabwe with special reference to the period 1972-1981." Transactions of the Royal Society of Tropical Medicine and Hygiene **80**: 12-19.

Forward stepwise linear regression modelling of the 7.5% category for membership of malaria season and the relationship with environmental variables produced the following model. Step 5 was chosen as the optimal model as the incremental advantage decreased markedly after this point, Table 6.5. The relationship between the model's predicted value and the malaria incidence data is given in Figure 6.13.

TABLE 6.5. COEFFICIENTS OF THE MODEL FOR ALTITUDE CLASS 1.

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
5	(Constant)	550.124	189.686		2.900	0.005
	VCLAG3	536.657	92.613	0.794	5.795	0.000
	CCD_LAG3	-5.411	1.261	-0.358	-4.292	0.000
	CCD_LAG2	-10.103	1.633	-0.668	-6.185	0.000
	VCLAG1_1	369.485	57.004	0.924	6.482	0.000
	CCD_LAG1	-4.460	1.061	-0.296	-4.202	0.000

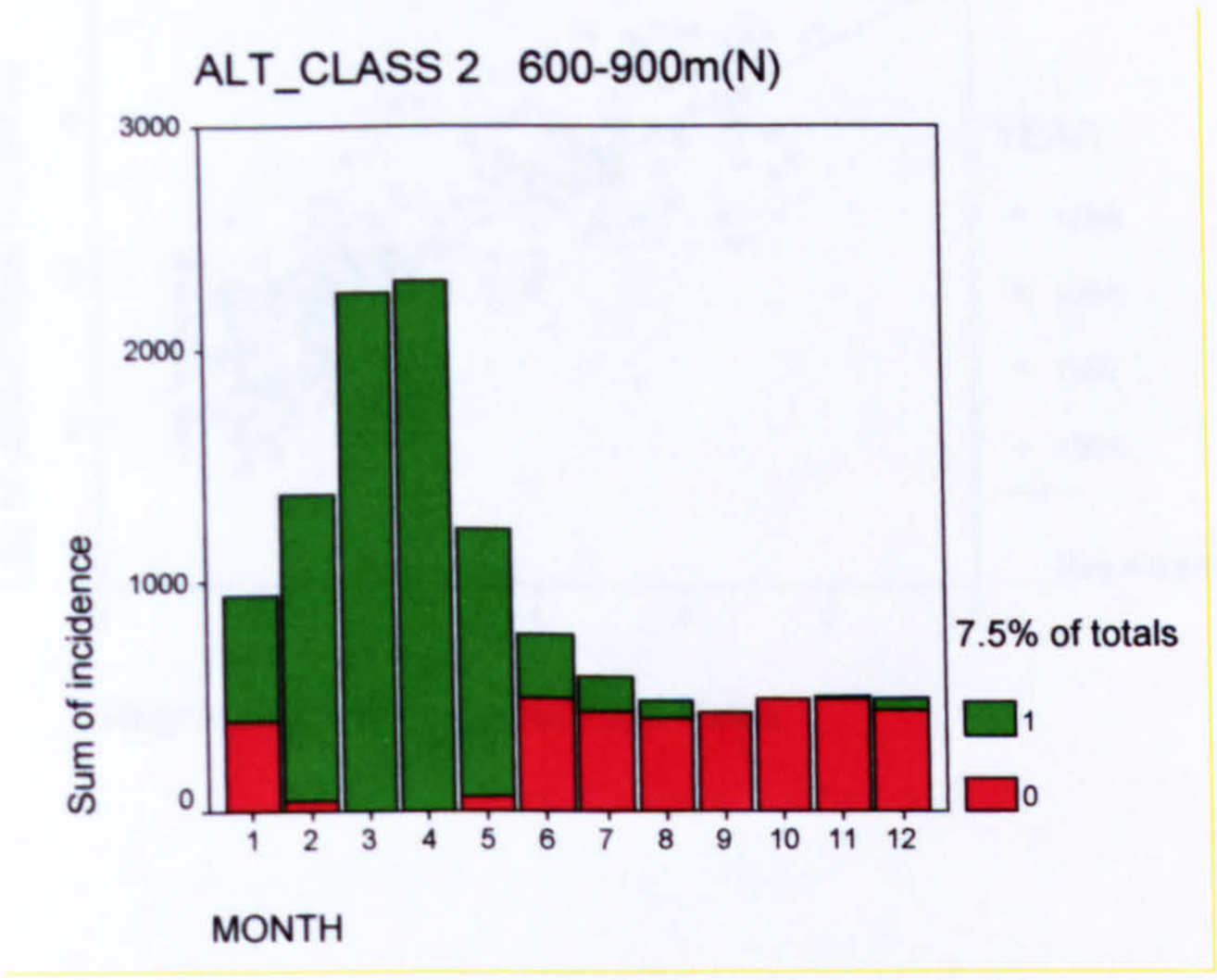
FIGURE 6.13. RELATION BETWEEN MALARIA INCIDENCE AND PREDICTED VALUE, ALTITUDE CLASS 1.



6.5.2.2. Altitude class 2. 600-900m(N)

For altitude class 2, monthly membership of seasonality is shown in Figure 6.14.

FIGURE 6.14. MALARIA SEASONALITY IN ALTITUDE CLASS 2.

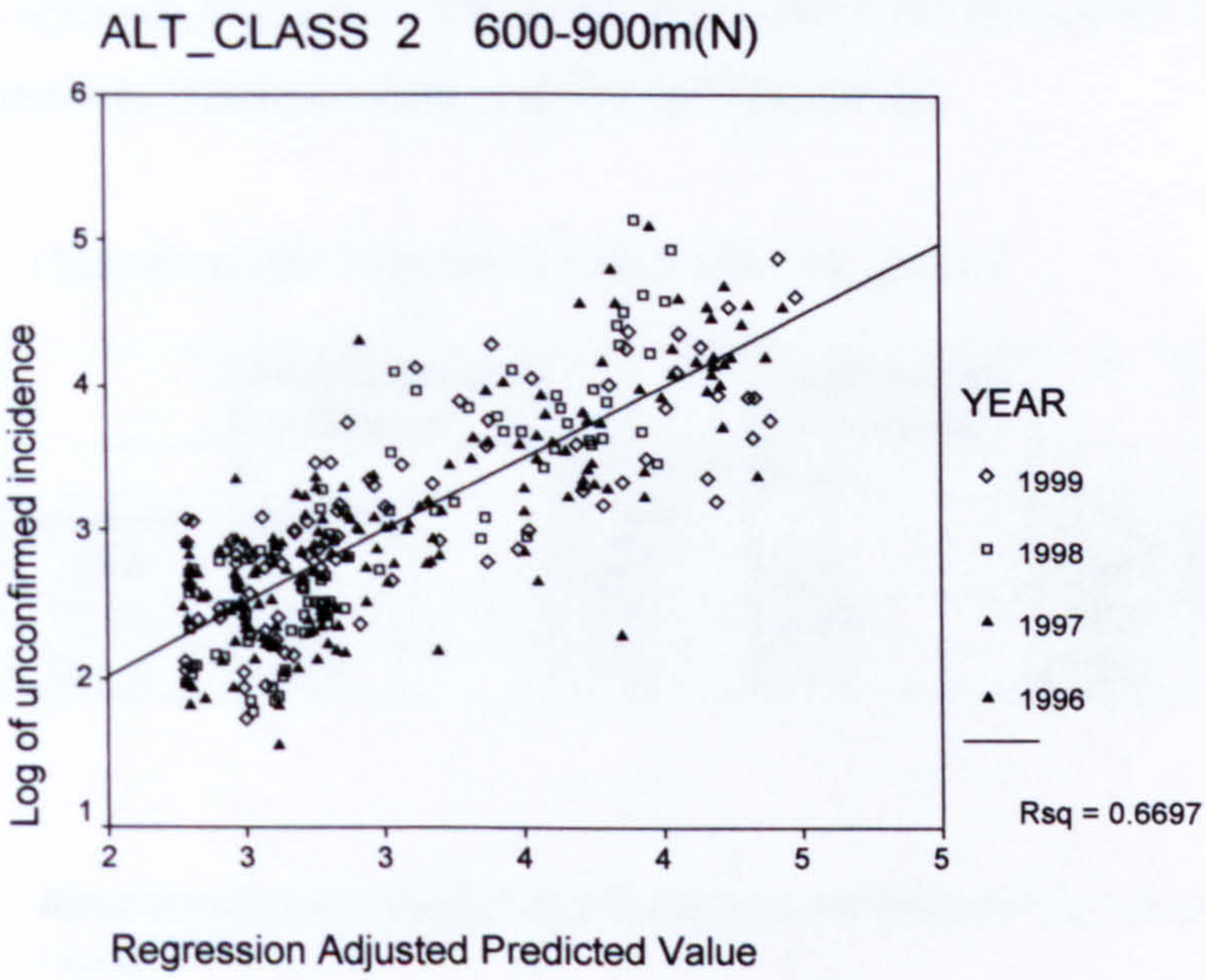


Forward stepwise linear regression modelling of 7.5% membership and environmental variables produced the following model for altitude class 2. Again step 5 was chosen as the optimal model, Table 6.6. The relationship between the model's adjusted predicted value and the malaria incidence data (log transform) is given in Figure 6.15.

TABLE 6.6. COEFFICIENTS OF THE MODEL FOR ALTITUDE CLASS 2.

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
5	(Constant)	-5.695	1.352		-4.211	0.000
	X_RAIN_2	6.948E-03	0.001	0.585	12.632	0.000
	VCLAG1_3	1.810E-02	0.003	0.206	6.309	0.000
	LONG	9.324E-02	0.014	0.232	6.572	0.000
	LAT	-0.316	0.065	-0.173	-4.890	0.000
	VCLAG3	2.546E-02	0.007	0.180	3.778	0.000

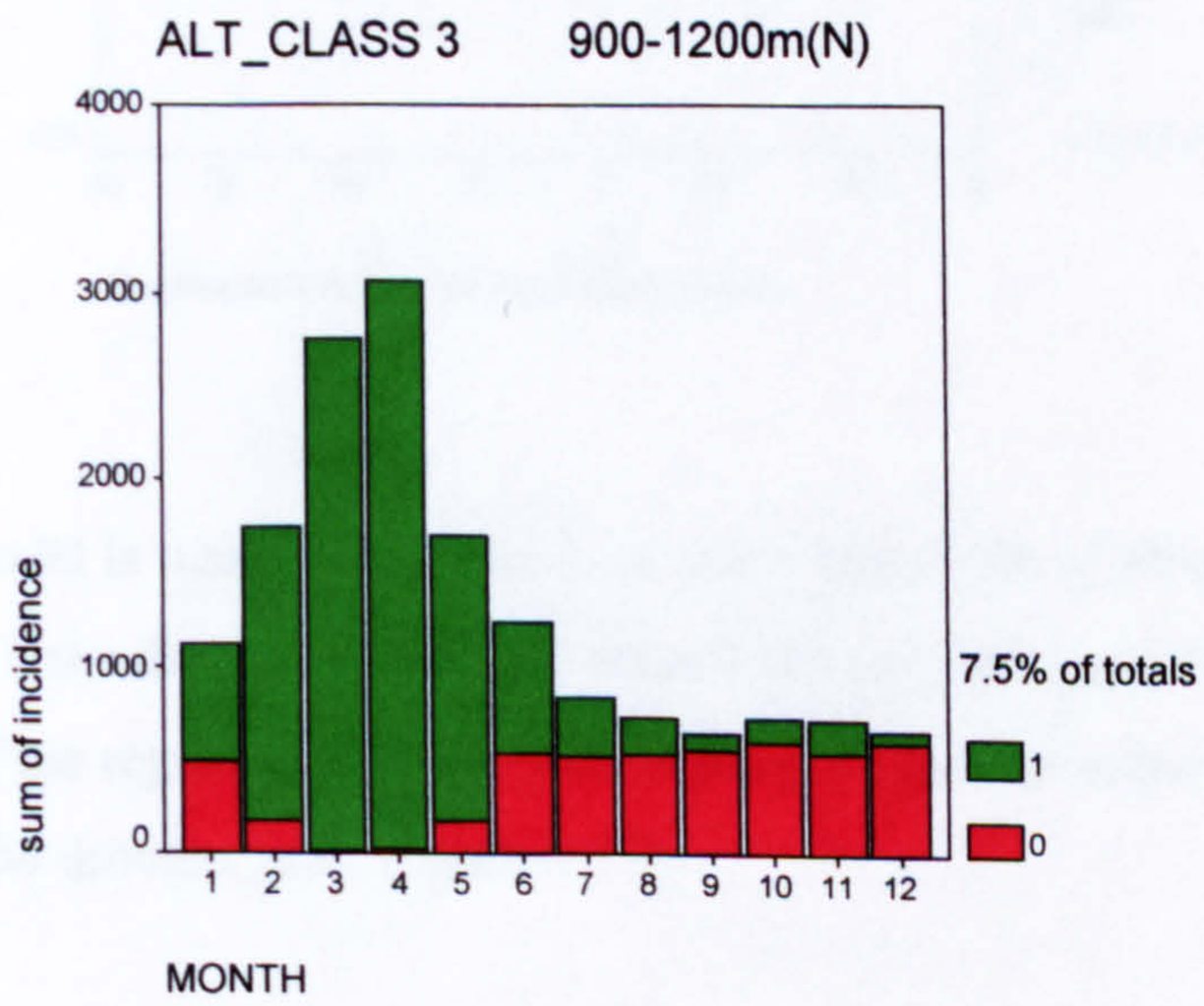
FIGURE 6.15. RELATION BETWEEN MALARIA INCIDENCE AND ADJUSTED PREDICTED VALUE, ALTITUDE CLASS 2.



6.5.2.3. *Altitude Class 3. 900-1200m(N).*

Monthly membership of seasonality in altitude class 3 is shown in Figure 6.16.

FIGURE 6.16. MALARIA SEASONALITY IN ALTITUDE CLASS 3.

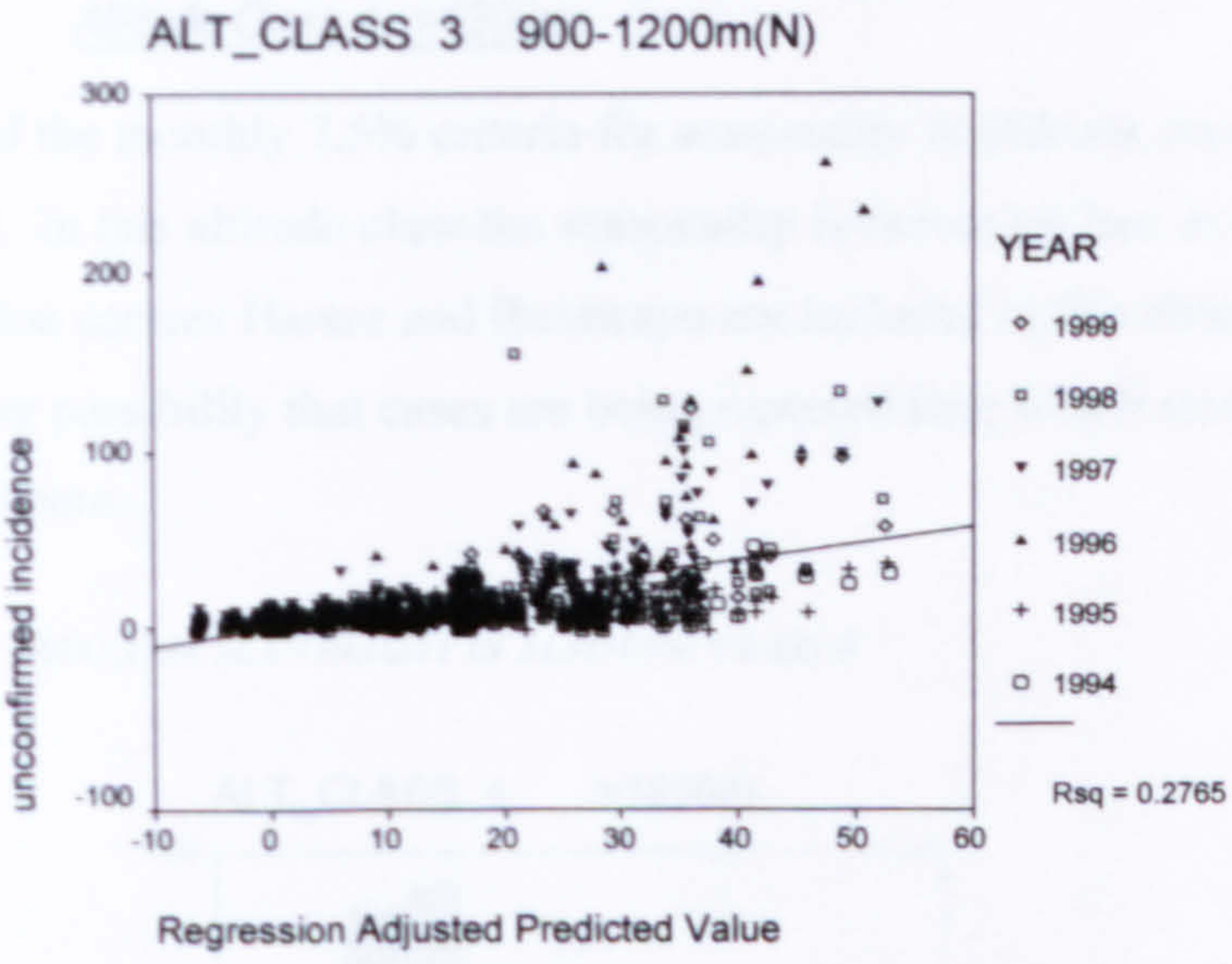


Forward stepwise linear regression modelling of 7.5% membership and environmental variables produced the following model for altitude class 3. Step 3 was chosen as optimal, Table 6.7. The relationship between the model's predicted value and the malaria incidence data is given in Figure 6.17.

TABLE 6.7. COEFFICIENTS OF THE MODEL FOR ALTITUDE CLASS 3.

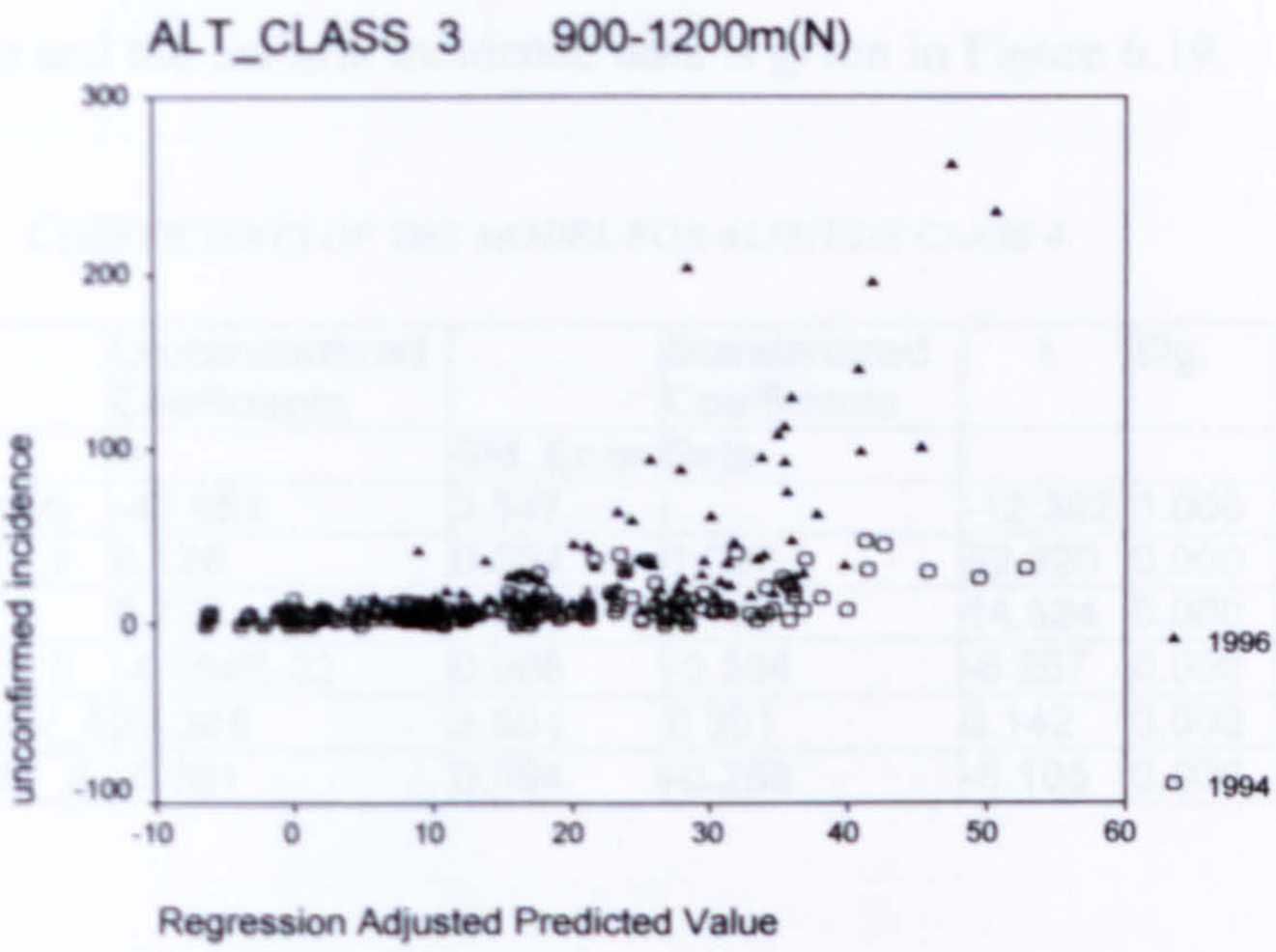
		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
3	(Constant)	-223.466	13.827		-16.162	0.000
	X_TEMP_4	4.049	0.219	0.557	18.481	0.000
	X_TEMP	4.920	0.335	0.675	14.699	0.000
	X_RH_4	1.024	0.091	0.478	11.202	0.000

FIGURE 6.17A. RELATION BETWEEN MALARIA INCIDENCE AND PREDICTED VALUE, ALTITUDE CLASS 3.



In general the model is weaker in this altitude class than those of altitude classes 1&2. However, if the data are plotted for years 1994 (drought) and 1996 (epidemic) only the slope of the regression can be seen to be much greater in the epidemic year compared with the drought year, Figure 6.17b.

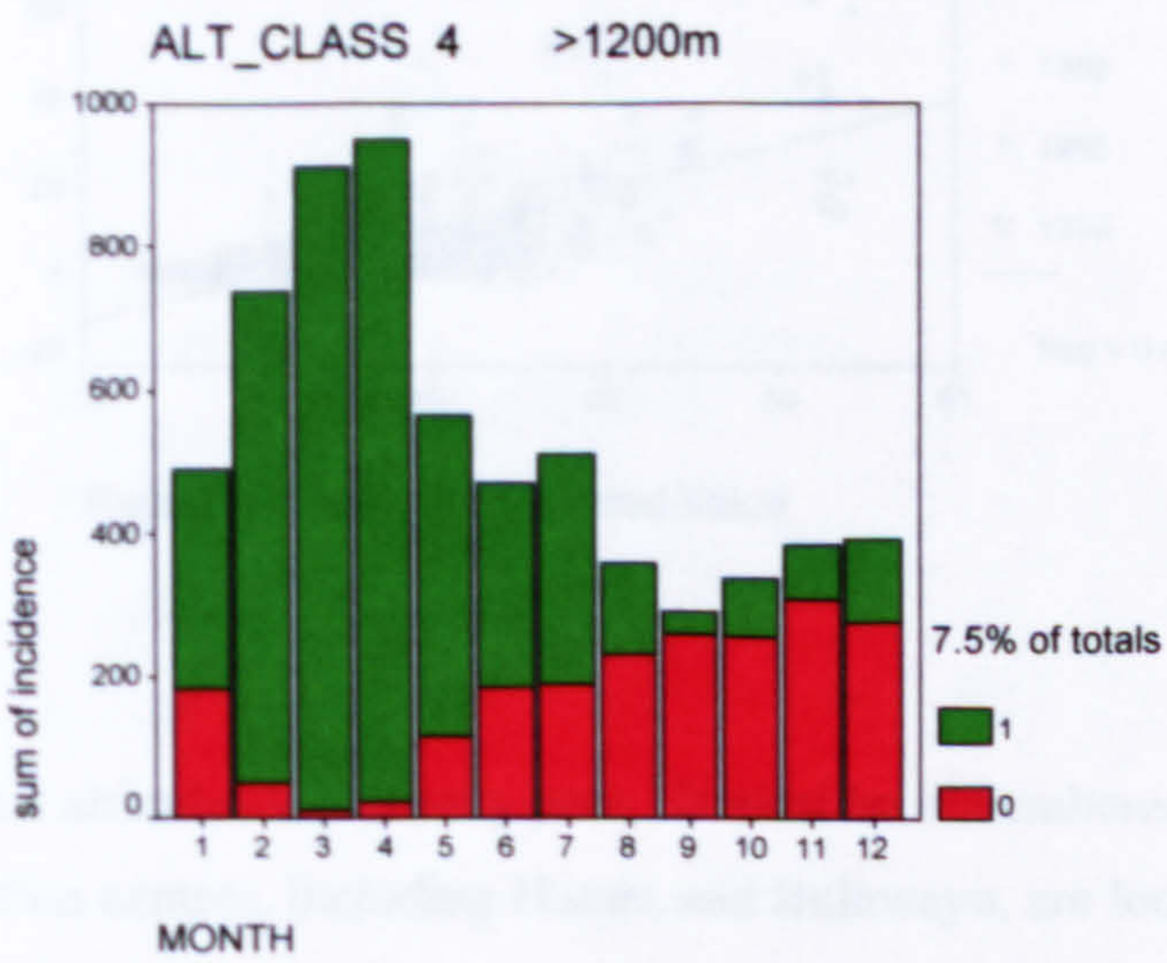
FIGURE 6.17B. RELATION BETWEEN MALARIA INCIDENCE AND PREDICTED VALUE ALTITUDE CLASS 3 1994 COMPARED WITH 1996.



6.5.2.4. *Altitude Class 4. >1200m.*

Membership of the monthly 7.5% criteria for seasonality in altitude class 4 is shown in Figure 6.18. In this altitude class the seasonality is becoming less distinct. The major population centres Harare and Bulawayo are included in this altitude class and there is a strong possibility that cases are being reported here which result from infection elsewhere.

FIGURE 6.18. MALARIA SEASONALITY IN ALTITUDE CLASS 4.

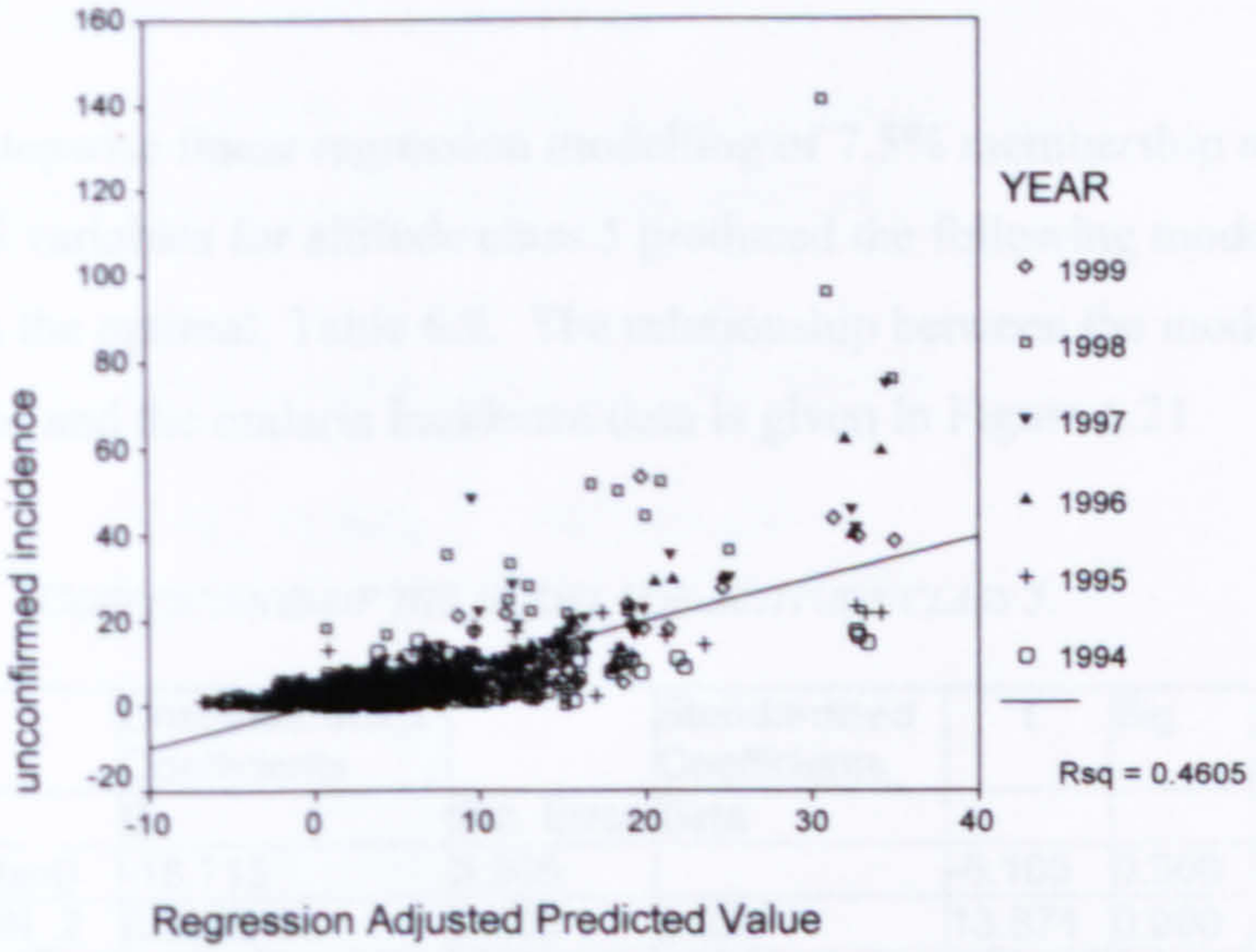


Forward stepwise linear regression modelling of the 7.5% membership and environmental variables produced the following model for altitude class 4. Step 5 was chosen as the optimal, Table 6.8. The relationship between the model's adjusted predicted value and the malaria incidence data is given in Figure 6.19.

TABLE 6.8 COEFFICIENTS OF THE MODEL FOR ALTITUDE CLASS 4.

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
5	(Constant)	-43.951	3.547		-12.392	0.000
	X_RAIN_2	0.128	0.004	1.027	32.320	0.000
	X_RH_5	0.720	0.050	0.762	14.524	0.000
	X_RAIN_5	-4.784E-02	0.006	-0.384	-8.267	0.000
	NDVISAV_5	29.345	3.604	0.301	8.142	0.000
	X_TEMP_5	-0.761	0.094	-0.258	-8.105	0.000

FIGURE 6.19. RELATION BETWEEN MALARIA INCIDENCE AND PREDICTED VALUE, ALTITUDE CLASS 4.



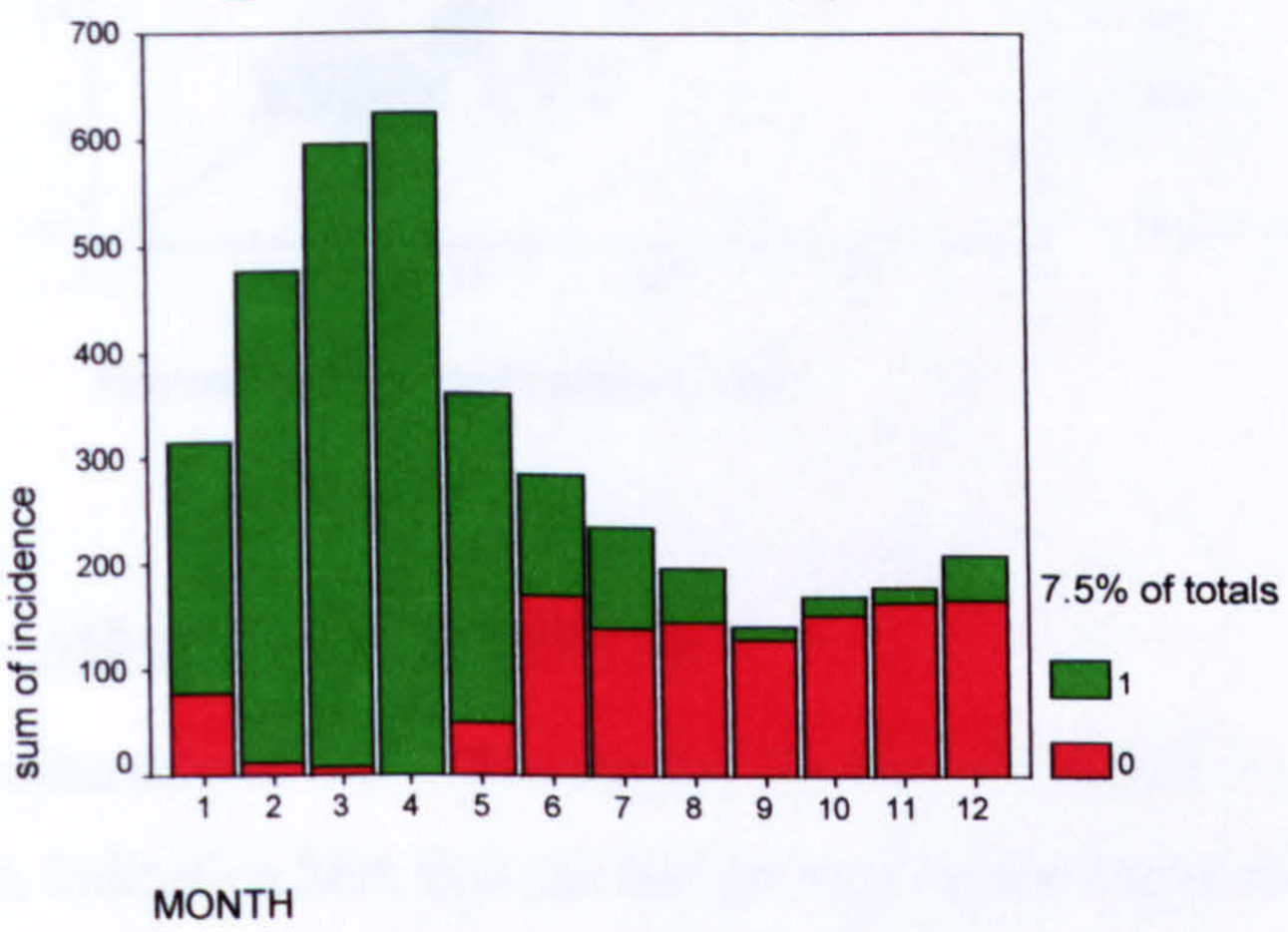
This model for this altitude class is very poor. It must be remembered however, that the major population centres, including Harare and Bulawayo, are located in this

altitude class and many cases reporting here may be a result of transmission elsewhere.

6.5.2.5. *Altitude Class 5. 900-1200m(S).*

Monthly membership of the 7.5% seasonality criteria for altitude class5 is shown in Figure 6.20.

FIGURE 6.20. SEASONALITY OF MALARIA IN ALTITUDE CLASS 5.

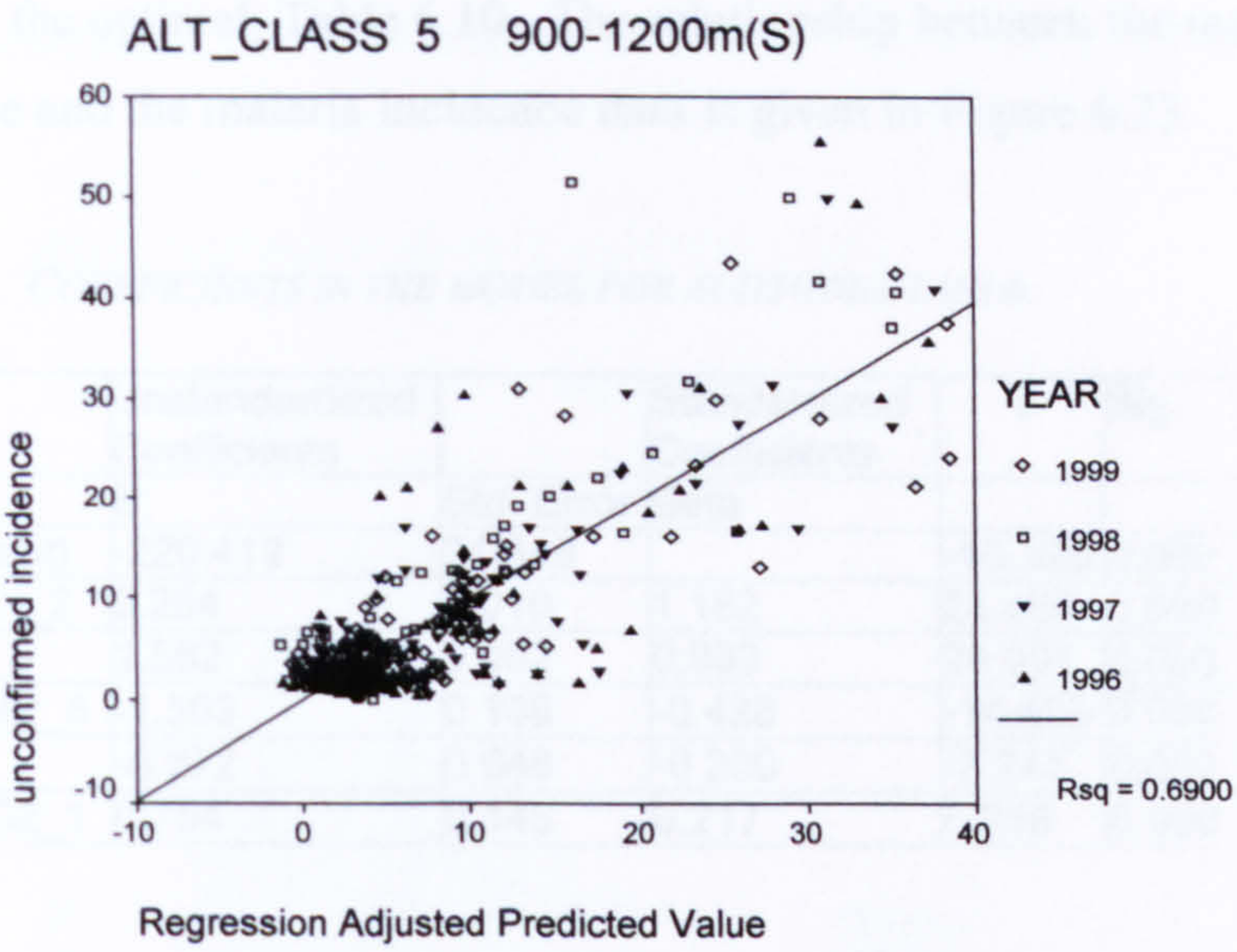


The forward stepwise linear regression modelling of 7.5% membership and environmental variables for altitude class 5 produced the following model. Step 5 was chosen as the optimal, Table 6.9. The relationship between the model's adjusted predicted value and the malaria incidence data is given in Figure 6.21.

TABLE 6.9. COEFFICIENTS OF THE MODEL FOR ALTITUDE CLASS 5.

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
5	(Constant)	-18.715	3.066		-6.105	0.000
	X_RAIN_2	6.528E-02	0.005	0.558	13.871	0.000
	X_RH_5	0.470	0.035	0.437	13.306	0.000
	VCLAG1_1	1.058	0.123	0.360	8.589	0.000
	X_TEMP_4	-0.709	0.088	-0.252	-8.034	0.000
	VCLAG0_3	0.638	0.098	0.241	6.528	0.000

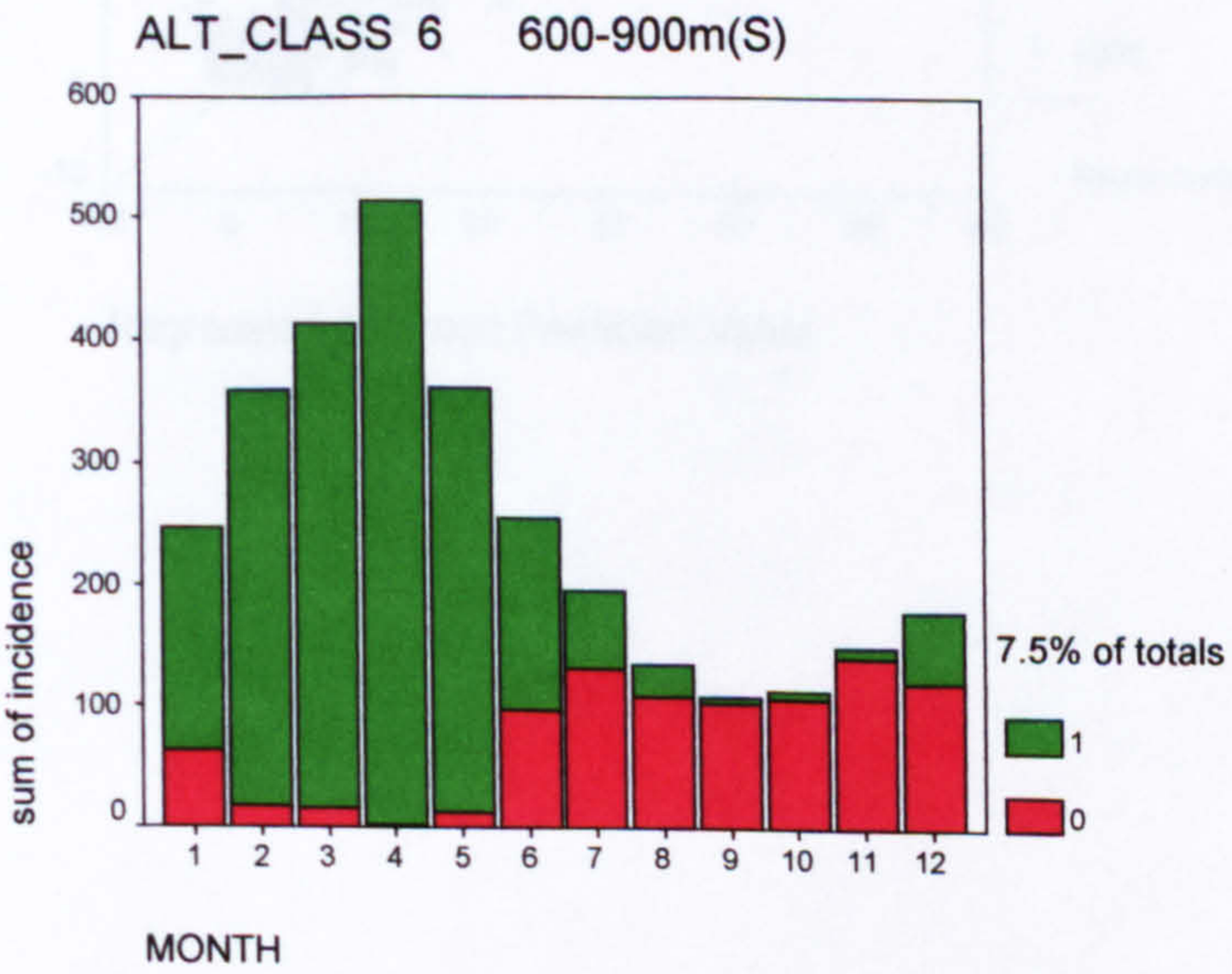
FIGURE 6.21. RELATION BETWEEN MALARIA INCIDENCE AND PREDICTED VALUE, ALTITUDE CLASS 5.



6.5.2.6. *Altitude Class 6. 600-900m(S).*

The monthly membership of the 7.5% category for altitude class 6 is shown in Figure 6.22. There is an indication here that the season may be starting earlier (November/December), a trend beginning in altitude class 5 and apparent in altitude class 7 also. This would indicate that the season generally begins earlier in the southern altitude classes compared with those of the north.

FIGURE 6.22. SEASONALITY OF MALARIA IN ALTITUDE CLASS 6.

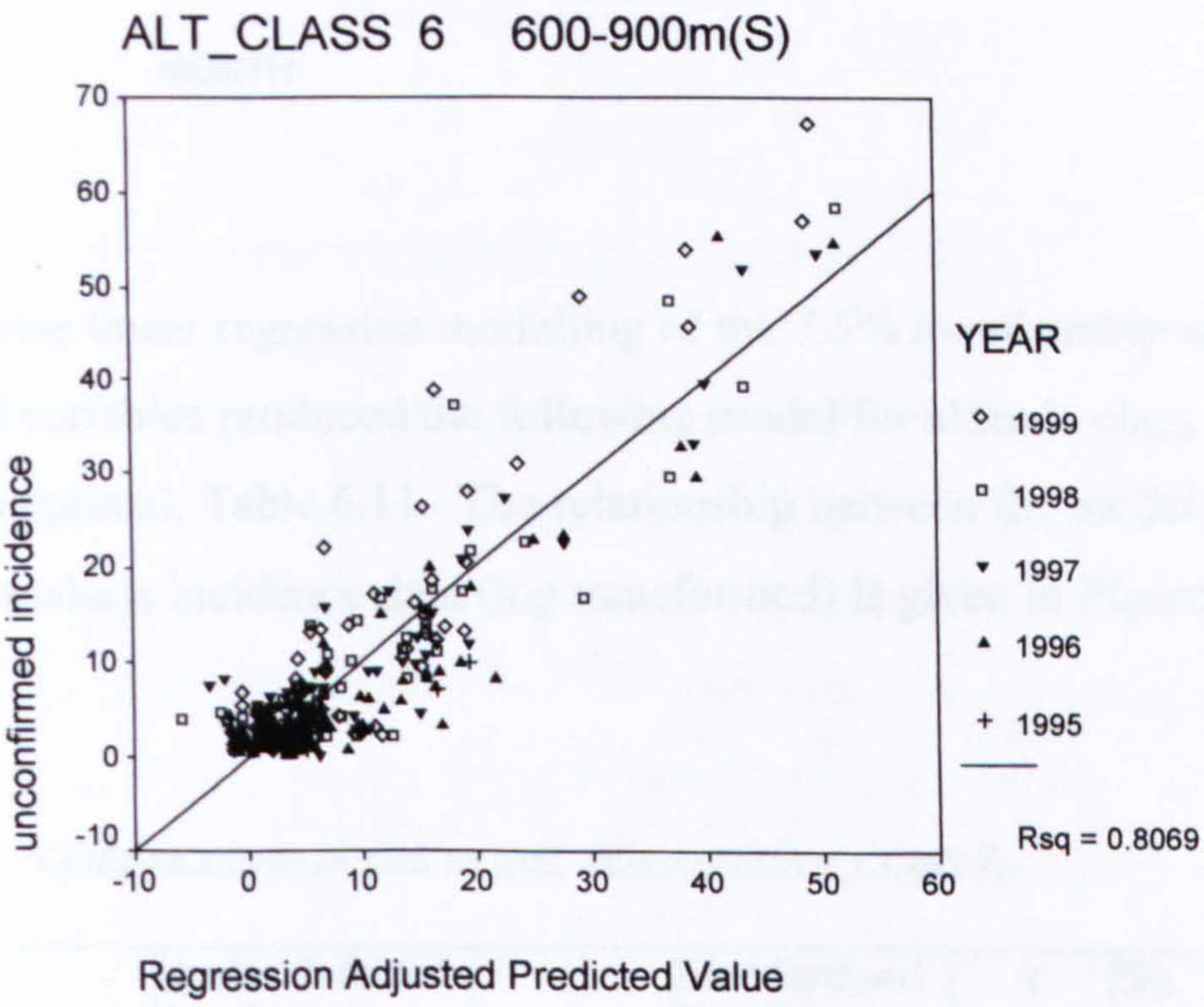


Forward stepwise linear regression modelling of 7.5% membership with the environmental variables produced the following model for altitude class 6. Step 5 was chosen as the optimal, Table 6.10. The relationship between the model's predicted value and the malaria incidence data is given in Figure 6.23.

TABLE 6.10. COEFFICIENTS IN THE MODEL FOR ALTITUDE CLASS 6.

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
5	(Constant)	-220.419	21.349		-10.325	0.000
	X_RAIN_2	0.254	0.010	1.182	24.409	0.000
	X_RH_5	1.562	0.062	0.933	25.001	0.000
	X_TEMP_5	-1.563	0.109	-0.428	-14.400	0.000
	LATS	-6.872	0.948	-0.200	-7.245	0.000
	VCLAG2_1	0.754	0.145	0.217	5.216	0.000

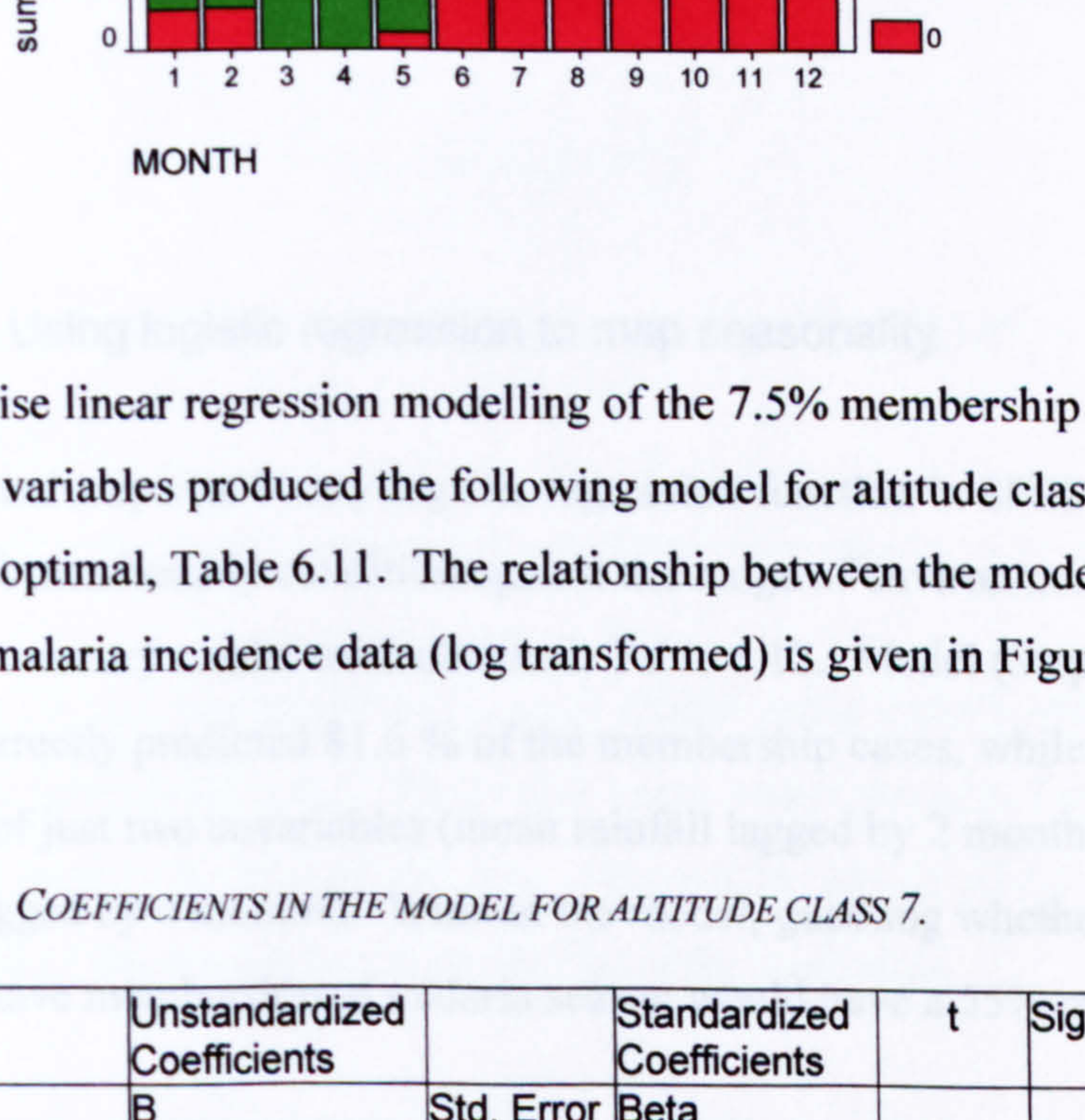
FIGURE 6.23. RELATION BETWEEN MALARIA INCIDENCE AND PREDICTED VALUE, ALTITUDE CLASS 6.



6.5.2.7. Altitude Class 7. <600m(S).

Monthly membership of the 7.5% criteria for altitude class 7 is shown in Figure 6.24.

FIGURE 6.24. SEASONALITY OF MALARIA IN ALTITUDE CLASS 7.

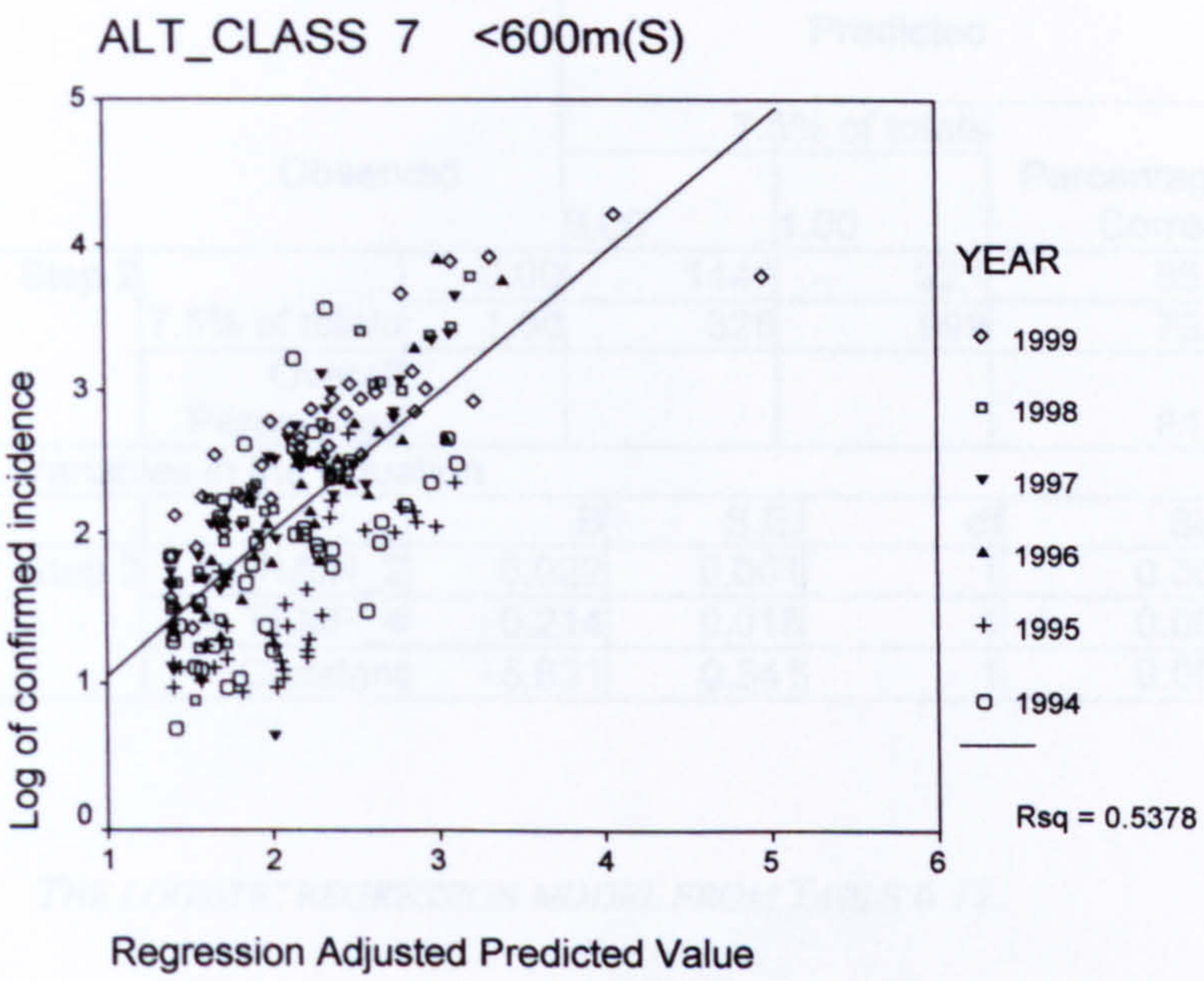


Forward stepwise linear regression modelling of the 7.5% membership and environmental variables produced the following model for altitude class 4. Step 4 was chosen as optimal, Table 6.11. The relationship between the model's predicted value and the malaria incidence data (log transformed) is given in Figure 6.25.

TABLE 6.11. COEFFICIENTS IN THE MODEL FOR ALTITUDE CLASS 7.

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
4	(Constant)	-53.254	8.133		-6.548	0.000
	X_RH	4.056E-02	0.006	0.346	6.351	0.000
	LONGS	0.698	0.081	0.638	8.631	0.000
	LAGS_CCD,3	2.450E-03	0.000	0.311	6.177	0.000
	LATS	-1.445	0.283	-0.373	-5.107	0.000

FIGURE 6.25. RELATION BETWEEN MALARIA INCIDENCE AND PREDICTED VALUE, ALTITUDE CLASS 7.



6.5.3. Using logistic regression to map seasonality

When the forward-stepwise binary logistic regression function in SPSS was used to model the 7.5% membership condition against the range of environmental variables, the following summary results were obtained, Table 6.12. Model (Step) 2 was chosen as it correctly predicted 81.6 % of the membership cases, while maintaining the simplicity of just two covariables (mean rainfall lagged by 2 months and mean temperature lagged by 4 months). Without the model, guessing whether a particular month would have membership of malaria season would have a 55% probability of being correct.

TABLE 6. 12. PREDICTIVE MODEL SUMMARY

a. Classification Table

Observed			Predicted		
			7.5% of totals		Percentage Correct
			0.00	1.00	
Step 2	7.5% of totals	0.00	1441	221	86.7
		1.00	328	999	75.3
	Overall Percentage				81.6

b. Variables in the Equation

		B	S.E.	df	Sig.
Step 2	X_RAIN_2	0.022	0.001	1	0.000
	X_TEMP_4	0.214	0.018	1	0.000
	Constant	-5.631	0.341	1	0.000

Box 6.1. *THE LOGISTIC REGRESSION MODEL FROM TABLE 6.12.*

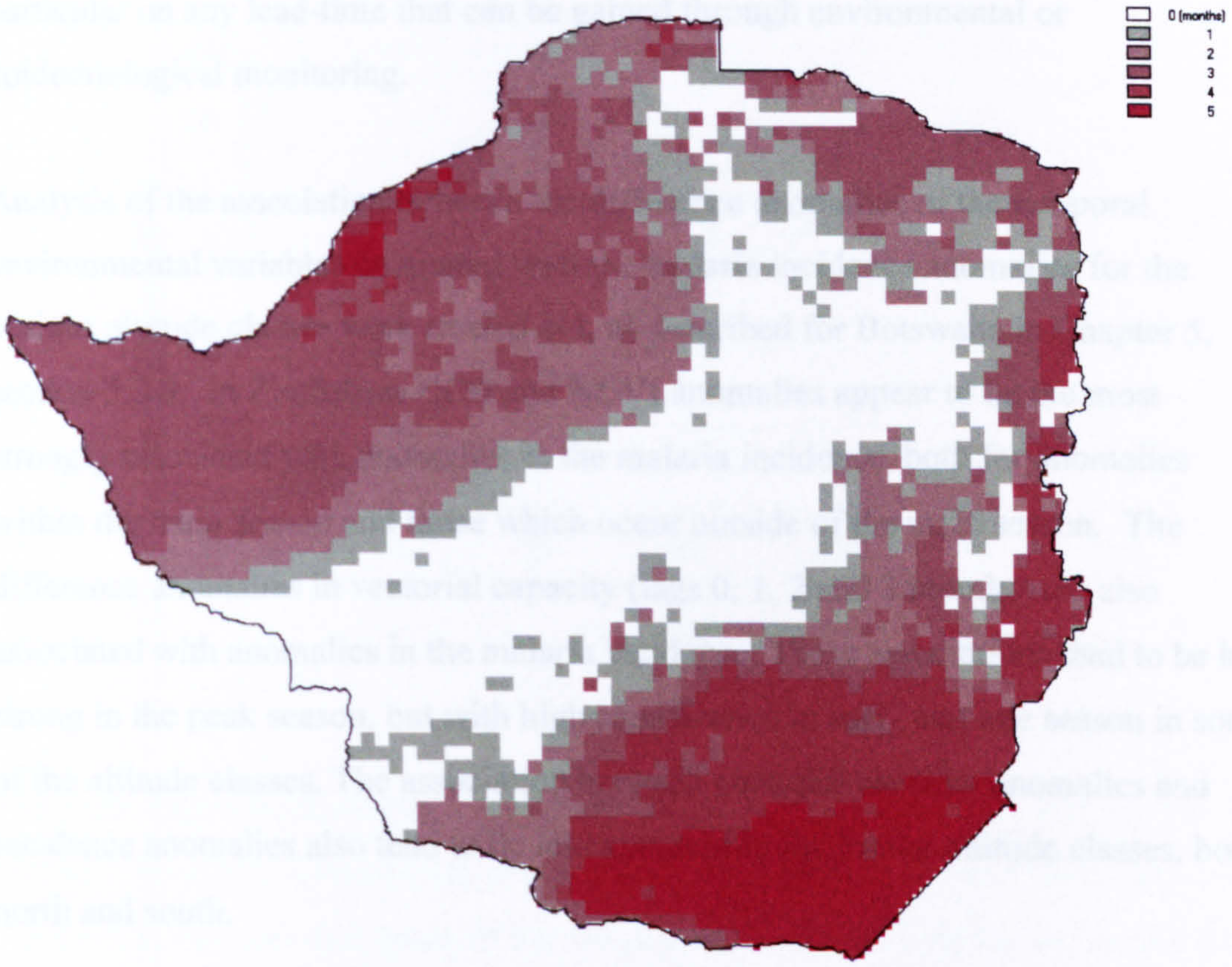
$$1/(1+e^{-Z})$$

where -Z = (-5.631 + (X_RAIN_2 * 0.022) + (X_TEMP_4 * 0.214))*-1

As in Chapter 5, a map was produced for each month using Idrisi's Image Calculator using the above formula, Box 6.1. The twelve maps were then added together using Idrisi's overlay module to produce the map, Figure 6.26, which offers a map of predicted length of the season based on the 5km grid resolution.

There is a general agreement between Figure 6.26, Figure 6.9, the altitude map showing the altitude classes, and Figure 6.8, the malaria incidence by district map. The map, Figure 6.26, also shows a greater area in the south as having the longest seasonality.

FIGURE 6.26. PREDICTIVE MAP OF MALARIA SEASON IN ZIMBABWE (1994-99).



Legend:

The map is produced from the model in Table 6.12 and predicts the mean seasonality of malaria in Zimbabwe.

6.5.4. Mapping epidemic risk

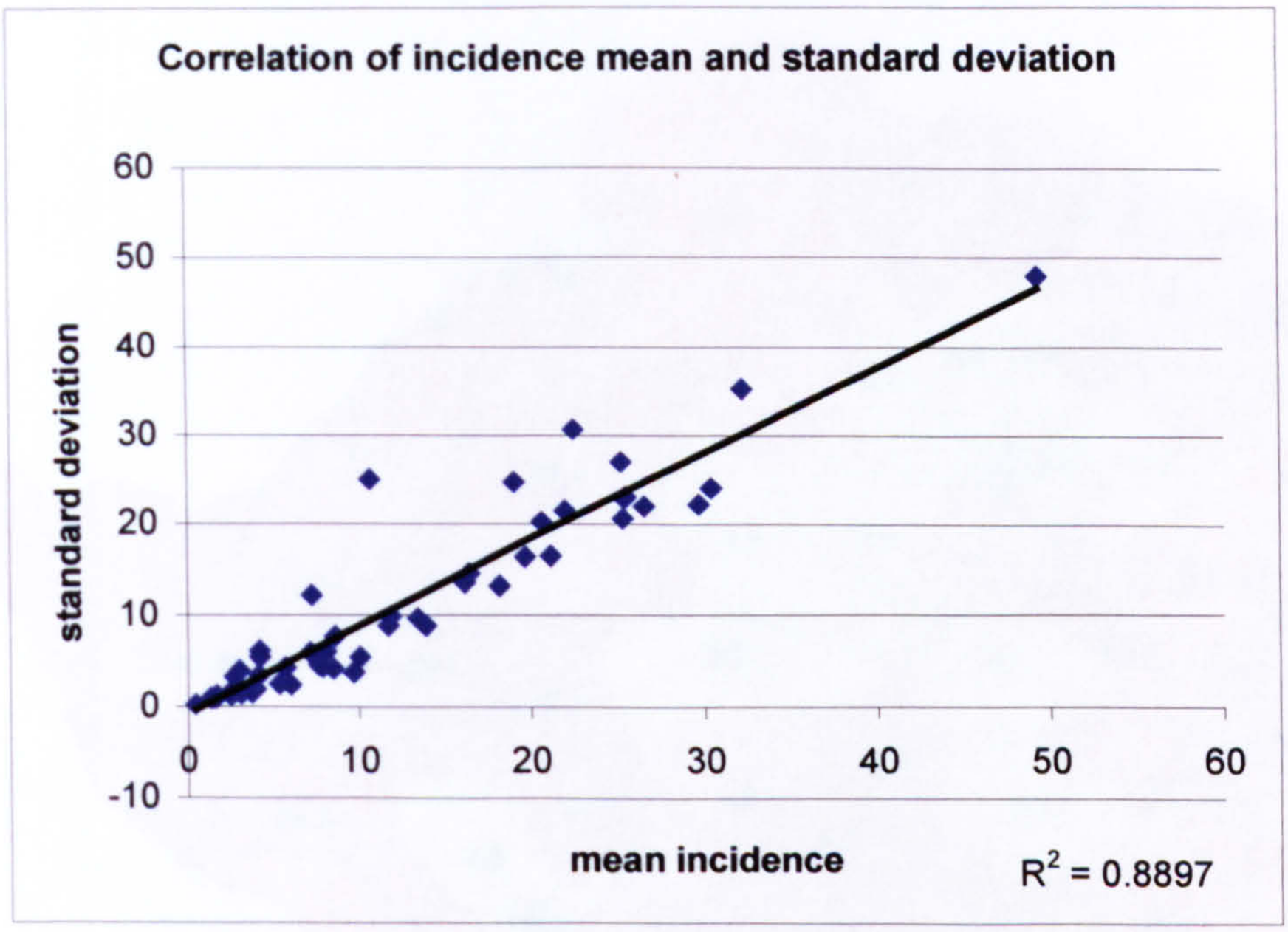
The ability to map areas of epidemic risk in Zimbabwe, especially changes in epidemic risk, could be a valuable tool in malaria control. The value depends in particular on any lead-time that can be gained through environmental or epidemiological monitoring.

Analysis of the association between the difference anomalies of the temporal environmental variables compared with the malaria incidence anomalies for the various altitude classes were carried out, as described for Botswana in Chapter 5, section 5.3.6. In Zimbabwe CCD and NDVI anomalies appear to be the most strongly associated with anomalies in the malaria incidence, both for anomalies within the main season and those which occur outside of the main season. The difference anomalies in vectorial capacity (lags 0, 1, 2 and 3 months) are also associated with anomalies in the malaria incidence. These associations tend to be less strong in the peak season, but with high significance in early and late season in some of the altitude classes. The association between vectorial capacity anomalies and incidence anomalies also tend to be less apparent in the lowest altitude classes, both north and south.

Some of the combined environmental variables used in the above analyses are simultaneous with the dependent variable (malaria incidence), some do not vary between years but reflect mean seasonal changes (mean climatology) others do not vary with time at all (altitude, latitude, longitude). Other variables, the lagged variables, may offer some predictive value for malaria incidence in months to come. If for example, a District Health Team decided it required indicators which offered a warning time of 2-3 months, to mount a preventative response, then maps could be produced using only variables which offered that lead-time. The following will test this requirement in two epidemic prone districts.

The monthly malaria incidence data for Zimbabwe 1994-1999 suggests that there is a strong correlation between mean incidence levels and the standard deviation of the same, Figure 6.27.

FIGURE 6.27. RELATIONSHIP BETWEEN MEAN INCIDENCE AND STANDARD DEVIATION OF INCIDENCE 1994-1999.

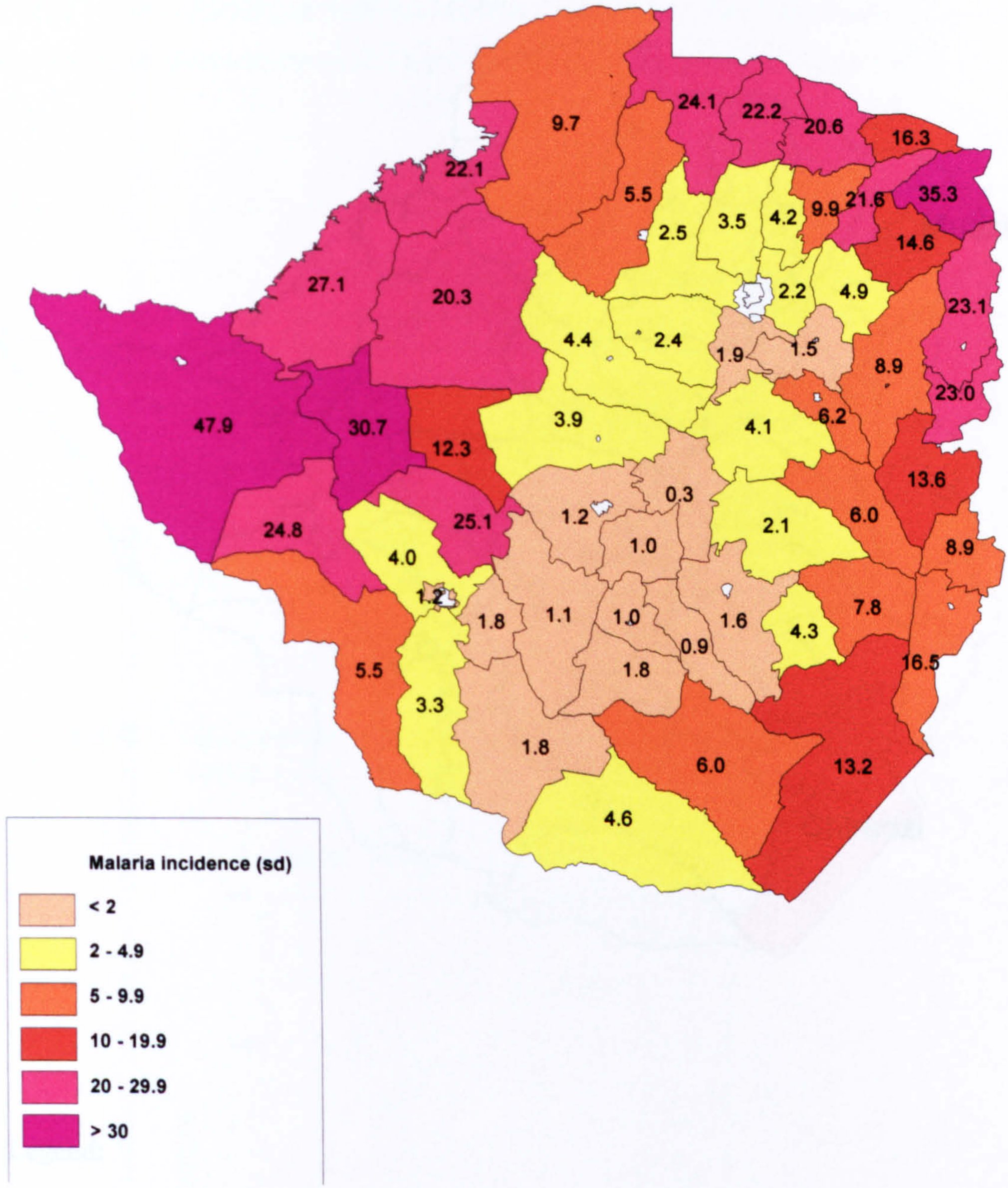


The map, Figure 6.28, shows the standard deviation in incidence, by district, over the period 1994-1999. Comparison of this map and the map of mean district incidence, Figure 6.8, indicates that many of the districts with high malaria incidence also have high variability in incidence. This would suggest that many of the malaria epidemics in Zimbabwe occur in endemic areas as increases in cases over and above the normal seasonal trend rather than as 'true epidemics', as defined in (Najera 1998b).

Two districts are chosen here, one within the high mean and standard deviation range (Mudzi), and one within the medium mean and standard deviation range (Chiredzi). Mudzi in the northeast of the country has an incidence mean of 32.3 and a standard deviation of 35.3. It is in altitude class 2. Chiredzi in the southeast of the country has an incidence mean of 18.2 and a standard deviation (13.2). It is in altitude class 7, Figure 6.29.

The stepwise linear regression method testing the relationships between mean monthly incidence totals (all age groups) against all environmental variables produced the following results.

FIGURE 6.28. STANDARD DEVIATION IN MALARIA INCIDENCE BY DISTRICT, 1994-1999.



Legend:

The map used administrative boundary files supplied by SADC-RRSP (1997).

FIGURE 6.29. LOCATION OF MUDZI AND CHIREDZI DISTRICTS IN ZIMBABWE.

Legend:

The map used administrative boundary files supplied by SADC-RRSP (1997).

6.5.4.1. Epidemic risk in Mudzi, District

For Mudzi district, step 3 of the model was optimal giving an R^2 value of 0.717 (72%) while requiring just three covariables, Table 6.13. The relationship between the incidence data and the model's predicted values are given in Figure 6.30.

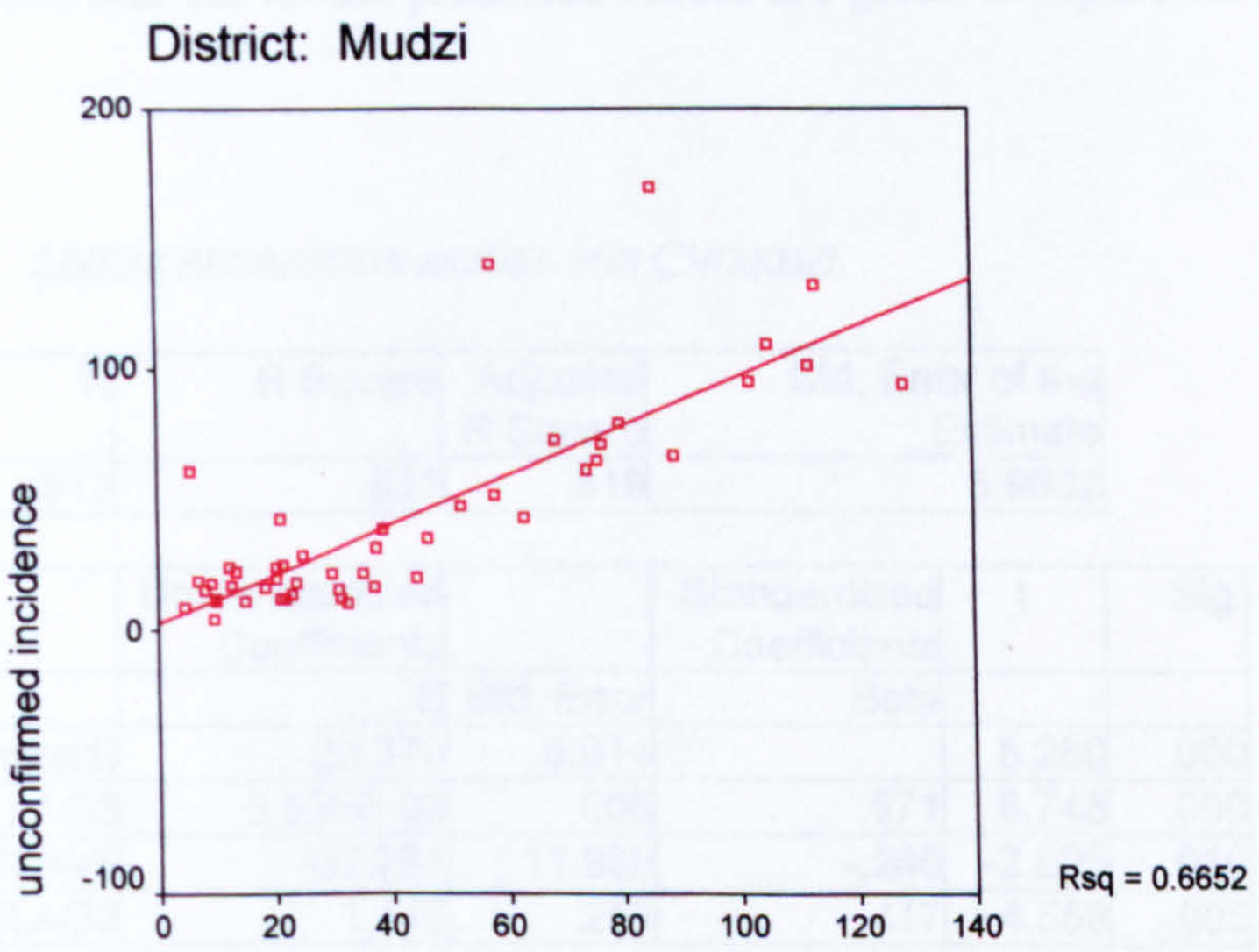
TABLE 6.13. LINEAR REGRESSION MODEL FOR MUDZI

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
3	.847	.717	.697	21.4981

Coefficients

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
3	(Constant)	-30.180	12.795		-2.359	.023
	VCLAG3	2.520	.886	.358	2.843	.007
	NDVISAV2	215.697	49.421	.615	4.365	.000
	RFE_LAG5	-.120	.047	-.289	-2.537	.015

FIGURE 6.30. RELATIONSHIP BETWEEN INCIDENCE, ACTUAL AND PREDICTED, MUDZI DISTRICT.



Using this model, Box 6.2, in Idrisi's Map Calculator module produced the following spatial model of predicted malaria incidence for Mudzi district, for January 1996,

Figure 6.31. In terms of lead-time available such a map could have been produced in November 1995, offering two months warning of where, relative to this district, malaria incidence would be lower or higher. However, the relationship between the models predicted values and malaria incidence shown in Figure 6.30, suggests the model would not perform particularly well for predicting epidemics in Mudzi.

BOX 6.2 THE REGRESSION MODEL FROM TABLE 6.13.

$$Y = -30.180 + (VCLAG\_3 * 2.52) + (NDVISAV\_2 * 215.697) + (RFE\_LAG5 * -0.120)$$

6.5.4.2. Epidemic risk in Chiredzi, District

For Chiredzi district, step 5 of the model was optimal giving an R^2 value of 0.831 (83%) again requiring just three covariables, Table 6.14. The relationship between the incidence data and the model predicted values are given in Figure 6.32.

TABLE 6.14. LINEAR REGRESSION MODEL FOR CHIREDZI.

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
5	.912	.831	.819	5.9602

Coefficients

		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
Model		B	Std. Error	Beta		
5	(Constant)	26.370	5.014		5.260	.000
	CCD_LAG3	5.596E-02	.006	.571	8.748	.000
	NDVISAV5	-32.291	11.980	-.246	-2.695	.010
	VCLAG2	1.146	.251	.417	4.558	.000

FIGURE 6.31. SPATIAL MODEL OF PREDICTED MALARIA INCIDENCE, MUDZI, JANUARY 1996.

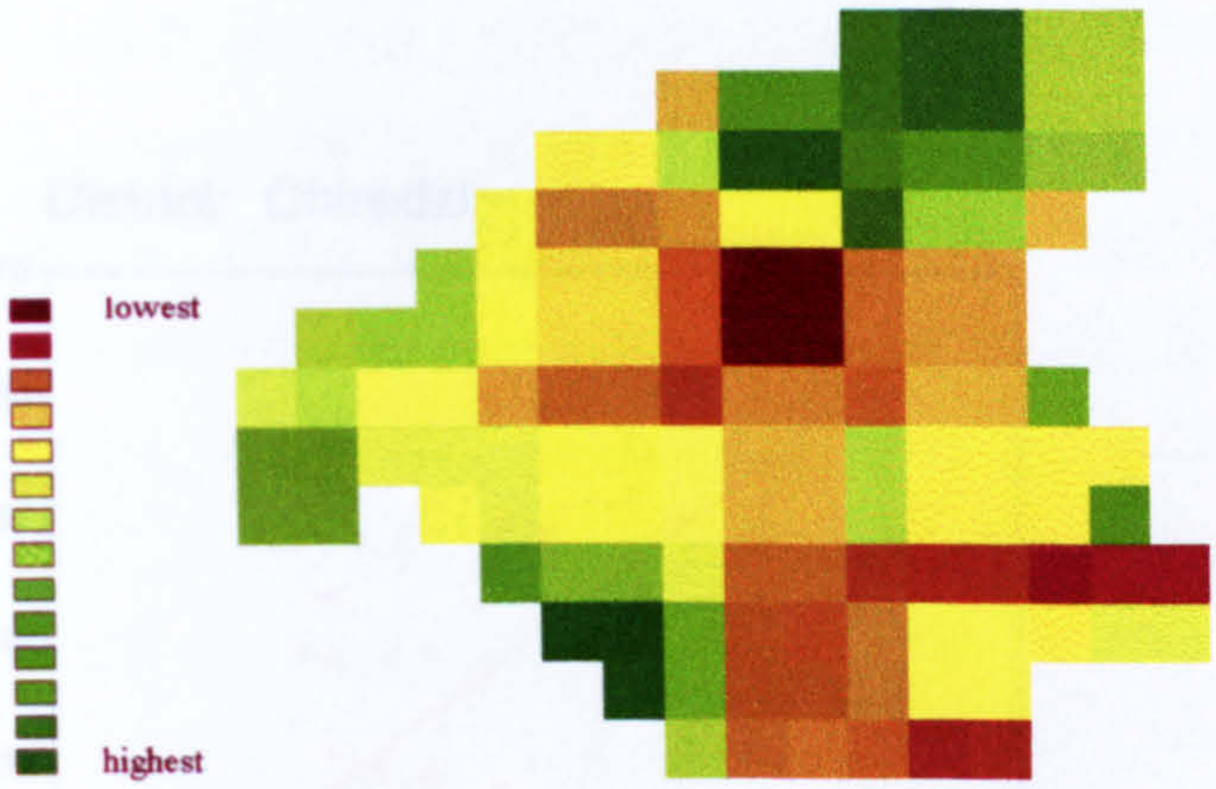
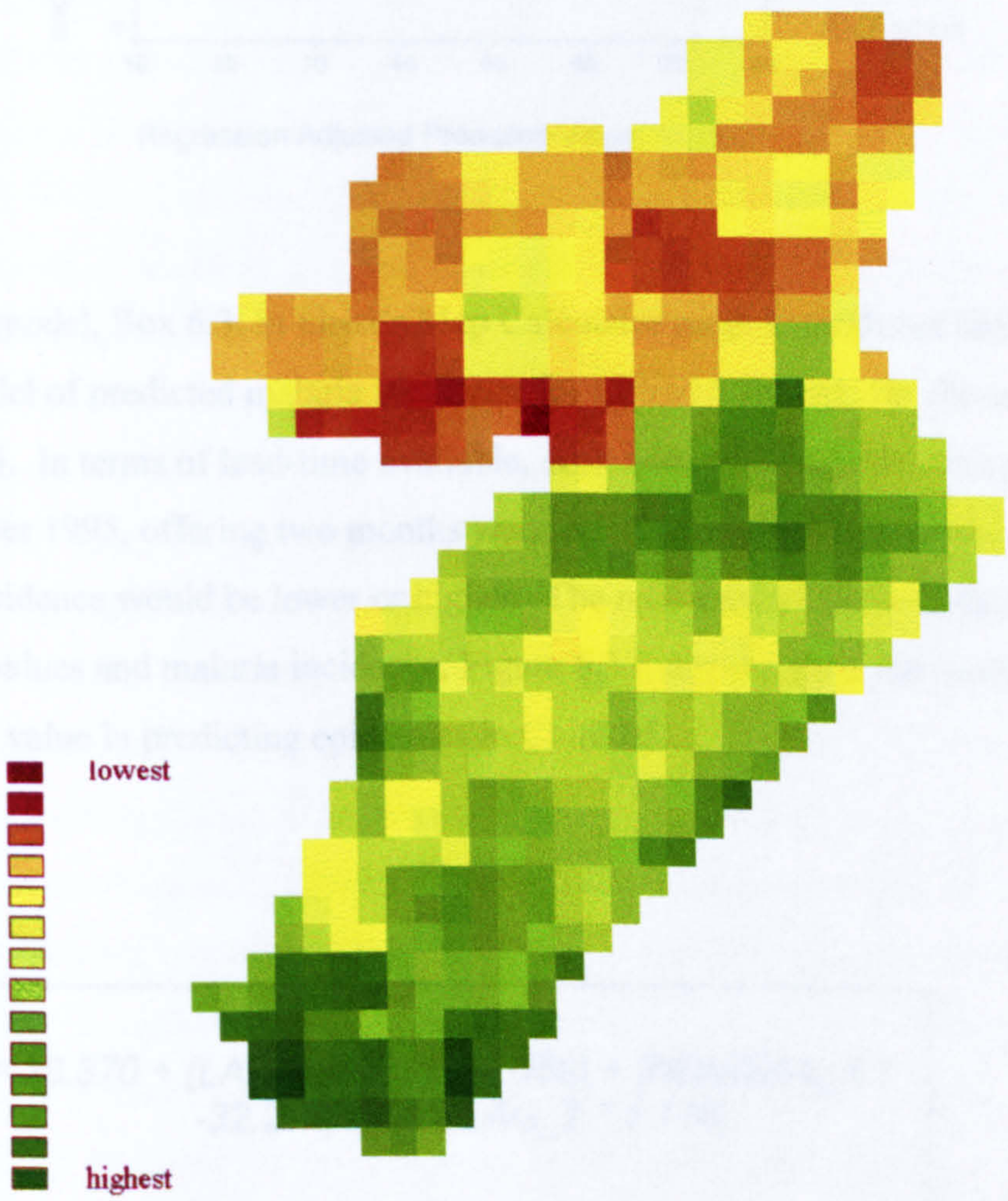
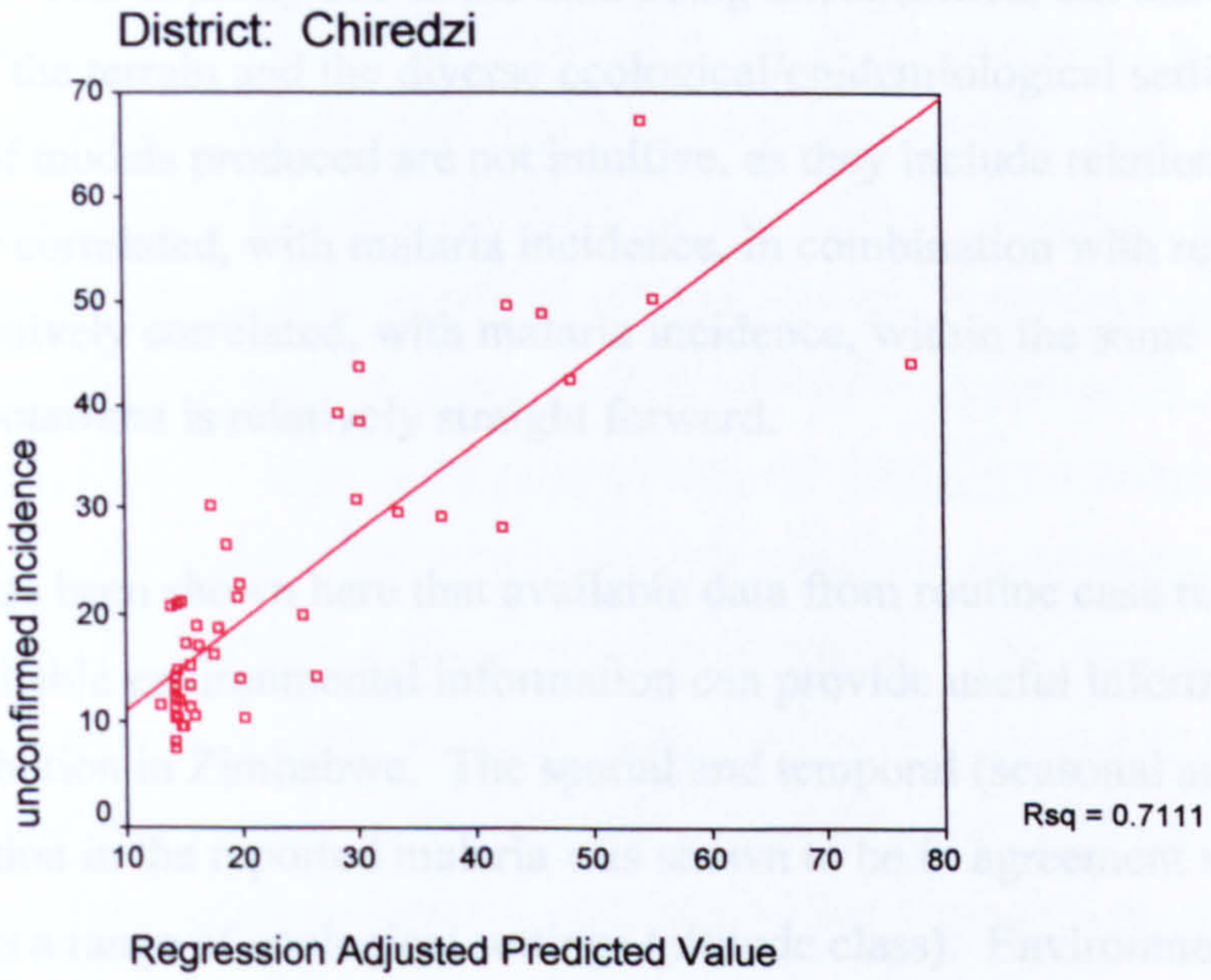


FIGURE 6.33. SPATIAL MODEL OF PREDICTED MALARIA INCIDENCE IN CHIREDZI DISTRICT, ZIMBABWE, JANUARY 1996.



Legend: The maps for Mudzi and Chiredzi are developed from the models in Tables 6.13 and 6.14 respectively. They predict where in the district malaria incidence would be higher or lower on a relative scale. They assume uniform population distribution within the district. They use separate models and are not comparable to each other.

FIGURE 6.32. RELATIONSHIP BETWEEN INCIDENCE, ACTUAL AND PREDICTED, CHIREDZI DISTRICT.



Using this model, Box 6.3, in Idrisi's Map Calculator module produced the following spatial model of predicted malaria incidence for Chiredzi district, for January 1996, Figure 6.33. In terms of lead-time available, such a map could have been produced in November 1995, offering two months warning of where, relative to this district, malaria incidence would be lower or higher. The relationship between the models predicted values and malaria incidence, Figure 6.32, does suggest the model would have some value in predicting epidemics in Chiredzi.

Box 6.3.

*Y = 26.370 + (LAGS(CCD_3 * 0.056) + (NDVISAV_5 * -32.291) + (VCLAG_2 * 1.146)*

6.6. Discussion

The malaria situation in Zimbabwe is relatively difficult to assess from the data available here. This is partly due to the data being unconfirmed, but also due to the complexity of the terrain and the diverse ecological/epidemiological settings which exist. Some of models produced are not intuitive, as they include relationships which are negatively correlated, with malaria incidence, in combination with relationships which are positively correlated, with malaria incidence, within the same model. By comparison Botswana is relatively straight forward.

However, it has been shown here that available data from routine case reporting used alongside available environmental information can provide useful information on malaria distribution in Zimbabwe. The spatial and temporal (seasonal and inter annual) variation in the reported malaria was shown to be in agreement with historic surveys across a range of ecological settings (altitude class). Environmental information modelled against the case data was also shown to be useful in identifying spatial variation in season length, and an indication of when the season begins and ends in each altitude class.

It would appear that malaria epidemics in Zimbabwe are less likely to be 'true epidemics' (R^0 becomes greater than 1) but result from sharp seasonal increases, possibly including resurgent outbreaks, during years when environmental conditions are favourable for transmission. If this is the case, then routine malaria control based on a calendar of events would be the best option for most districts, with monitoring and surveillance carried out to ensure the efficiency of the control programme. There is evidence that some advance warning of increased seasonal malaria may be achieved by routine reference to environmental monitoring products such as NDVI, CCD and RFE in certain altitude classes. These are all available from the SADC Food Security System and Drought Monitoring Centres in Harare. Spatial models including these variables are also important in this respect, and examples were shown from two districts for a month early in the season in a given year. If such models were routinely available to malaria control services then their acquisition over time would allow monthly difference products to be made of these, providing further

development of localised 'epidemic' risk indicators which could be used at the district level.

The linear models were generally more robust in the altitude classes 1 and 7, the lower altitude classes. Altitude class 3 included a positive relationship between mean temperature lagged by 4 months and malaria incidence. Work by Freeman and Bradley suggested that malaria severity was correlated to temperatures in the September preceding the malaria season in Zimbabwe (Freeman and Bradley 1996). They concluded, from analysis of 80 years of malaria data and meteorological data from Harare, that high September temperatures would predict increased severity in malaria throughout the middle altitude zones in Zimbabwe. However, the models here for altitude classes 4, 5 and 6 suggest mean temperature lagged by 4 and 5 months are negatively correlated with malaria incidence. The presence of latitude and longitude in the models suggests there is some other factor(s) not captured by the environmental variables. Identifying what this factor is would be valuable in further developing predictive models for these regions.

7. Malaria and Environment in Namibia

7.1. Geographical background

Namibia is a large country of 824,290 square kilometres in Southwest Africa. It is located between 11° 45′ E and 25° 15′ E; and between 17° 00′ S and 29° 00′ S. Namibia has an Atlantic coastline of approximately 1500 km as its western border. To the north and northeast it shares land borders with Angola and Zambia, to the east with Botswana, and to the south and southeast with the Republic of South Africa. Topographically Namibia is divided into three distinct regions: the arid, low lying coastal belt which ranges from 100-160 km in width and includes the Namib Desert in the south and the Skeleton Coast in the north; the central plateau which has a mean elevation of 1100m with several mountainous areas rising to elevations greater than 1800m; and the Kalahari Desert which is a continuation of the plateau.

Namibia is the driest country in Southern Africa. With 92% of its surface classed as arid. The climate is generally described as hot and dry, but rainfall and temperatures vary markedly across the country. Annual rainfall totals along the coast average around 50mm. Inland, average annual total rainfall is 559mm in the north, decreasing to 152mm in the south. Most of the rainfall occurs during the summer (October – March). The average annual temperature along the coast is 17°C, inland it is 21°C but again this varies markedly across the country. Average monthly summer temperatures range from 19-34°C. The 'summer' months are October to April. Winter temperatures range between 6-19°C although temperatures may fall below zero in the highland and Southern regions. Relative humidity varies between 61-71% in the north and between 24-40% in the south.

The only permanent rivers are the Kunene, Okavango, Zambezi, in the north, and the Orange river in the south, all of which form international borders. There is very little surface water apart from seasonal flooding of the Oshanas in the north of the country. The Oshanas are large shallow lakes flowing slowly southwards across the border from Angola down towards the Etosha Pan. Occasionally, heavy rainfall in Angola

will cause the Etosha Pan to flood and normally dry water courses will discharge into the Atlantic.

The population in Namibia, estimated at approximately 1.8 million people (Obeid, Mendelsohn et al. 2001) is sparsely distributed, having a population density of only 2 persons per km^2. The north is essentially rural and the economy is based on traditional agriculture and livestock farming. However, Tsumeb is an important economic base for mining, industry and commercial agriculture. The population in 1995 was split into 37% urban and 63 % rural. Urbanisation is rapid and the urban population was expected to grow to 40% by 2000. Internal migration in Namibia is high. GDP per capita is also relatively high for sub-Saharan Africa estimated in 1998 at US$1940 (UNDP 2000).

7.2. Malaria and its control in Namibia

While Namibia is the driest country in Southern Africa, malaria is seen to be one of the leading public health problems in the country. It is ranked as the first cause of outpatient attendance in children over 5, in under 5s it is second only to Acute Respiratory Infections. It has first ranking as the reason for inpatient admission in all age groups. In 1995 malaria was ranked as the first cause of death in Namibia (NVDCP 1995). By 2001 it was ranked as the sixth cause of death overall but remained as the first cause of death in the 5-15 age group (Obeid, Mendelsohn et al. 2001). This change is largely a result of the impact of HIV/AIDS in the region.

In 1965 extensive malaria control operations were begun using DDT for indoor residual spraying. This resulted in a marked reduction in malaria among the general population. The conflict in the region during Namibia's war of independence disrupted the control programme during the 1980s. This coupled with several years of drought (and declining immunity) was considered to have led to the devastating malaria epidemic of 1990 (NVDCP 1995). As a result of this epidemic the Ministry of Health and Social Services (MOHSS) launched an extensive National Vector-

borne Disease Control Programme (NVDCP) to control malaria and other vector-borne diseases[24].

7.2.1. Malaria control activities in Namibia

The main malaria control activities in Namibia are implemented in conjunction with the Primary Health Care Programme and include:

7.2.1.1. Disease management

Effective disease management requires early diagnosis, followed by prompt and correct treatment in line with national guidelines on treatment of uncomplicated malaria, and severe and complicated malaria. Chloroquine is the first line drug of choice in Namibia, S.P. is the second line choice for drug resistant malaria, except in pregnant women or infants under 6 months where the drug of choice is oral quinine. For in patients with severe and complicated malaria I.V. quinine is recommended.

7.2.1.2. Disease prevention

Continual assessment of the malaria situation is recognised as an essential prerequisite to effective disease prevention. Information required includes data on morbidity and mortality, drug and insecticide resistance, population movement and environment. Mosquito nets, especially insecticide treated nets are recommended. However, their use in Namibia is limited. Protective clothing, use of repellents and screening of doors and windows are recommended also. Use of anti-malarial drugs is recommended for special risk groups. These are: pregnant women, young children and non-immune travellers to malarious areas.

7.2.1.3. Vector control

The control of vectors is considered to be the best method of protecting a community against malaria infection. Selective vector control, using DDT for indoor residual spraying, is carried out in the endemic regions of the Northwest and Northeast Health Directorates. Additional spraying may be carried out in other areas considered to be at risk. The recommendations are that spraying should begin 4 months prior to the start of the transmission season. Monitoring for insecticide resistance should be

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[24] The programme was initially called the National Malaria Control Programme but was renamed in its first year to include diseases such as schistosomiasis and plague.

carried out regularly. Additional use of insecticides may be directed at larval stages of the vector in selected areas as part of environmental management.

7.2.1.4. *Community participation*

This includes raising awareness of malaria risk through education and training of local communities in the importance of removing mosquito breeding sites and personal protection against biting.

7.2.1.5. *Prevention and control of epidemics*

The ability to detect early, prevent and control epidemics is recognised as an essential component of effective malaria control in Namibia. The importance of mapping areas at risk and the monitoring of climatic indicators are seen as essential steps in the forecasting of epidemics. A national malaria epidemic response plan for Namibia was drawn up following a WHO-AFRO Workshop on Prevention and Control of Malaria Epidemics in 1996.

7.3. Patterns of malaria in Namibia

Malaria is most prevalent in the northern regions of the country where more than 60% of the population live (NVDCP 1995). The most extensive survey of malaria prevalence was carried out between 1947 and 1951. This survey showed that 64% of the population in Okavango, and 49% of the population of Ovamboland were infected with malaria parasites. The potential for malaria transmission was found to be high in the north and northeast and low in central and southern regions (De Meillon 1951).

Malaria in Namibia is seasonal and unstable with a potential for epidemic outbreaks when environmental conditions are favourable for transmission. Acquired immunity in the population appears to be low with morbidity and mortality extending into all age groups, although the annual incidence of malaria is approximately twice as high in children compared with adults (Kamwi and Connor in press). A number of epidemics have occurred in recent years: the first in 1990, the second in 1993, a third along the Caprivi Strip in 1996. In 1997 malaria cases and deaths increased yet further, with a fifth epidemic in 2001. This most recent epidemic occurred in the

Northwest of the country where the first six months of the year produced 22,258 confirmed malaria cases and 690 deaths. The epidemic was thought to have been caused by prolonged warm conditions with late and heavy rainfall (Hamata 2001).

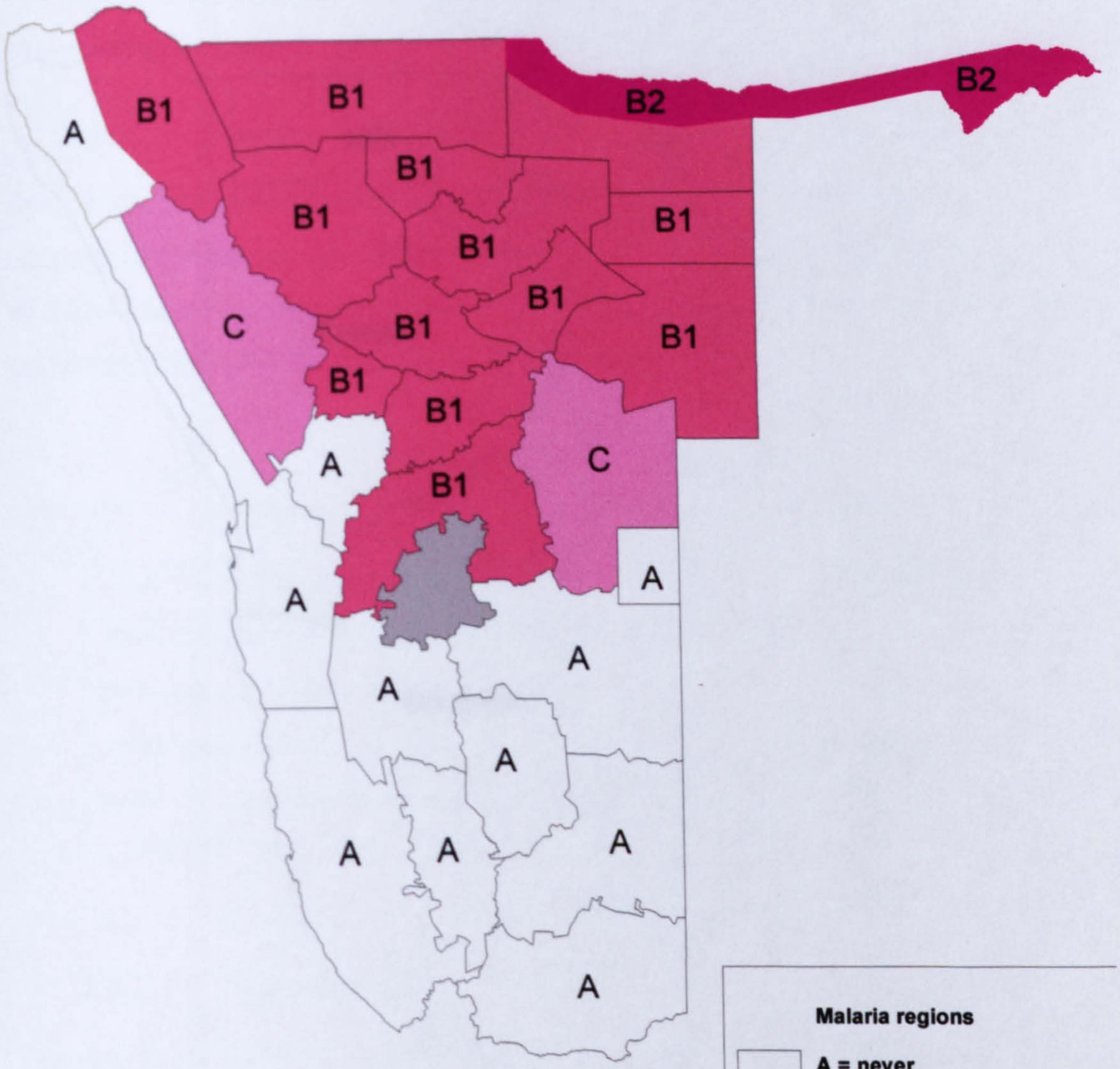
The expert opinion map for malaria in Namibia, Figure 7.1, suggests malaria to be confined to the northern half of the country, with a trend for increasing malaria towards the northeast.

The administrative boundaries in Namibia have been subject to significant changes during the past decade. The expert opinion, Figure 7.1, map used the 2nd level administrative boundaries (Regions) available from the SADC CD-ROM. These 28 regions were redrawn in 1992 to 13 new regions. However, the Health Information System in Namibia was based on different administrative units. It had four regional Health Directorates (Northwest, Northeast, Central and Southern) in turn divided into 34 Health Districts. This management structure is however currently under review and the 4 Directorates will be reorganised according to the 13 new political regions, each with a regional management team reporting to the MoHSS in Windhoek (Obeid, Mendelsohn et al. 2001). The monthly malaria statistics available from the HIS were organised at the Health Directorate level, Figure 7. 2. Therefore the environmental and population data used here were also organised at this level for comparative analysis.

7.4. Aims of this chapter

- To describe the spatial and temporal distribution of malaria in Namibia.
- To compare and relate the spatial and temporal distribution of malaria to environmental variables in order to inform malaria risk mapping.
- To explore whether or not temporal environmental variables could be used in an early warning system for malaria epidemics in Namibia.

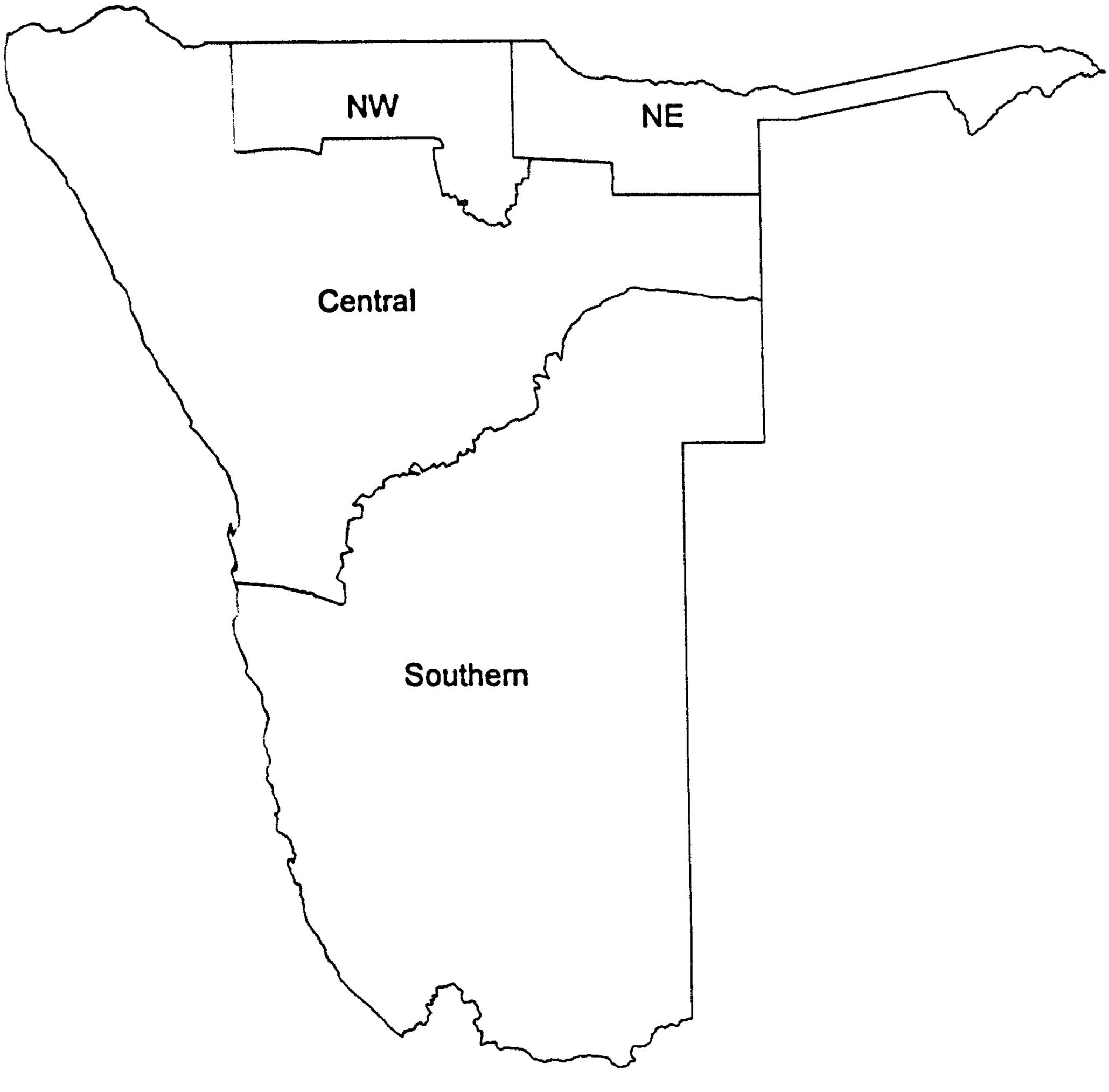
FIGURE 7.1. EXPERT OPINION MAP OF MALARIA IN NAMIBIA, CIRCA 1998.



Legend:

The map is produced using the administrative boundaries supplied by SADC-RRSP (1997).

FIGURE 7.2. THE FOUR REGIONAL HEALTH DIRECTORATES IN NAMIBIA[•].



Legend:

The map is based on the 4 Health Directorates, boundary files supplied by the Ministry of Health and Social Services, Namibia.

[•] The Directorates NW and NE correspond generally with the former Ovamboland and Okavango regions described in DeMeillon's survey (de Meillon, 1951).

7.5. Materials and Methods

The materials and methods used here are generally similar to those described previously in Chapters 5 and 6.

7.5.1. Epidemiological data

Epidemiological data covering the period 1993-2000 were collected from the Ministry of Health and Social Services routine Health Information System. Details of these data are summarised in Table 7.1. Unfortunately there was limited data on laboratory confirmed cases available at the national level.

TABLE 7.1. SUMMARY OF AVAILABLE EPIDEMIOLOGICAL DATA ON MALARIA

Time period/frequency/case definition	Spatial Scale
1996-2000 Monthly clinical outpatient/inpatient	Directorate
1993-2000 Monthly clinical inpatient	National
1996-2000 Monthly deaths	National
1997 Laboratory confirmed slide positivity data	Facility

7.5.2. Population data

Namibia has a high prevalence of HIV-AIDS. Population growth rates were estimated at approximately 3.0% p.a. for the period 1990-1995. However, growth rates declined to 1.6% p.a. by 2000. To accommodate this figures for the Health Directorate level were revised downward to reflect an estimated population growth of 2% per annum since 1995. Incidence figures were produced for each of the four Health Directorates by year.

7.5.3. Environmental data

The environmental data used and the method of extraction of summary statistics per Directorate, per month is the same as that described in Chapter 5, section 5.5.2.1.3. The administrative boundary files used for the extraction were made according to information obtained from the NVDCP.

7.5.4. Data analysis

SPSS and Microsoft Excel were used to explore and assess the relationships between the epidemiological and environmental data. The preliminary analyses included comparing time series of unconfirmed malaria cases using exploratory scatterplots and Pearson's correlation coefficient. Comparisons were made of relationships between contemporaneous environmental variables such as NDVI, RFE and CCD and the respective long-term mean monthly climatology variables. The relationships between the epidemiological data and the environmental variables were explored using curve estimation techniques in SPSS. As a result of this, the malaria inpatient data were log transformed, where appropriate, prior to further analysis in SPSS using a combination of bivariate and multivariate techniques against the chosen environmental variables.

7.6. Results

The relationship between inpatient and outpatient data for Namibia is shown in Figure 7.3. The correlation is strong with an R^2 of 0.843. Annual totals for malaria inpatient admissions in Namibia vary markedly between years, Figure 7.4. The inpatient malaria data, while not necessarily slide confirmed, are assumed to be generally more reliable than the outpatient data.

7.6.1. Seasonality of malaria

The mean seasonality of malaria in Namibia 1996-2000 is presented in Figure 7.5. The graph suggests that the season begins in January peaks in April and ends in June.

Unfortunately there is little laboratory confirmed data available at the central level in Namibia. However, blood slide results were obtained for laboratory facilities for each month of 1997. The blood slide positivity results for 1997 vary drastically between the different facilities (22 in total). Nankudu in the NE showed the best results with an overall positivity rate of 41.61% over the year and a clear seasonality in the data, Figure 7.6. Not surprisingly correct clinical diagnosis of malaria is higher during the main malaria season (60.18%) falling off to (31.52%) during the latter half of the year.

FIGURE 7.3. RELATIONSHIP BETWEEN OUTPATIENT AND INPATIENT CASES IN NAMIBIA 1996-2000.

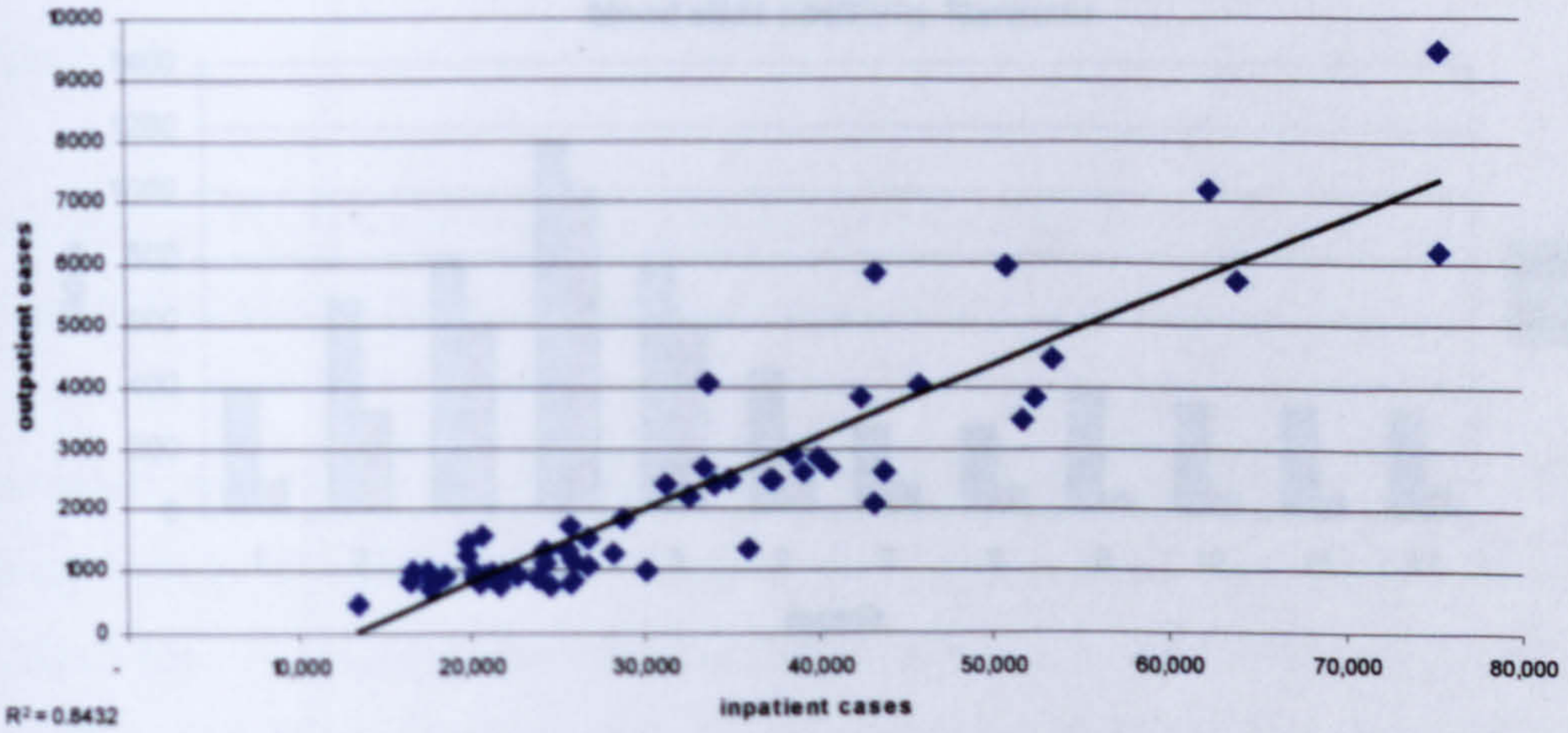


FIGURE 7.4. ANNUAL TOTAL INPATIENT MALARIA CASES NAMIBIA 1993-2000.

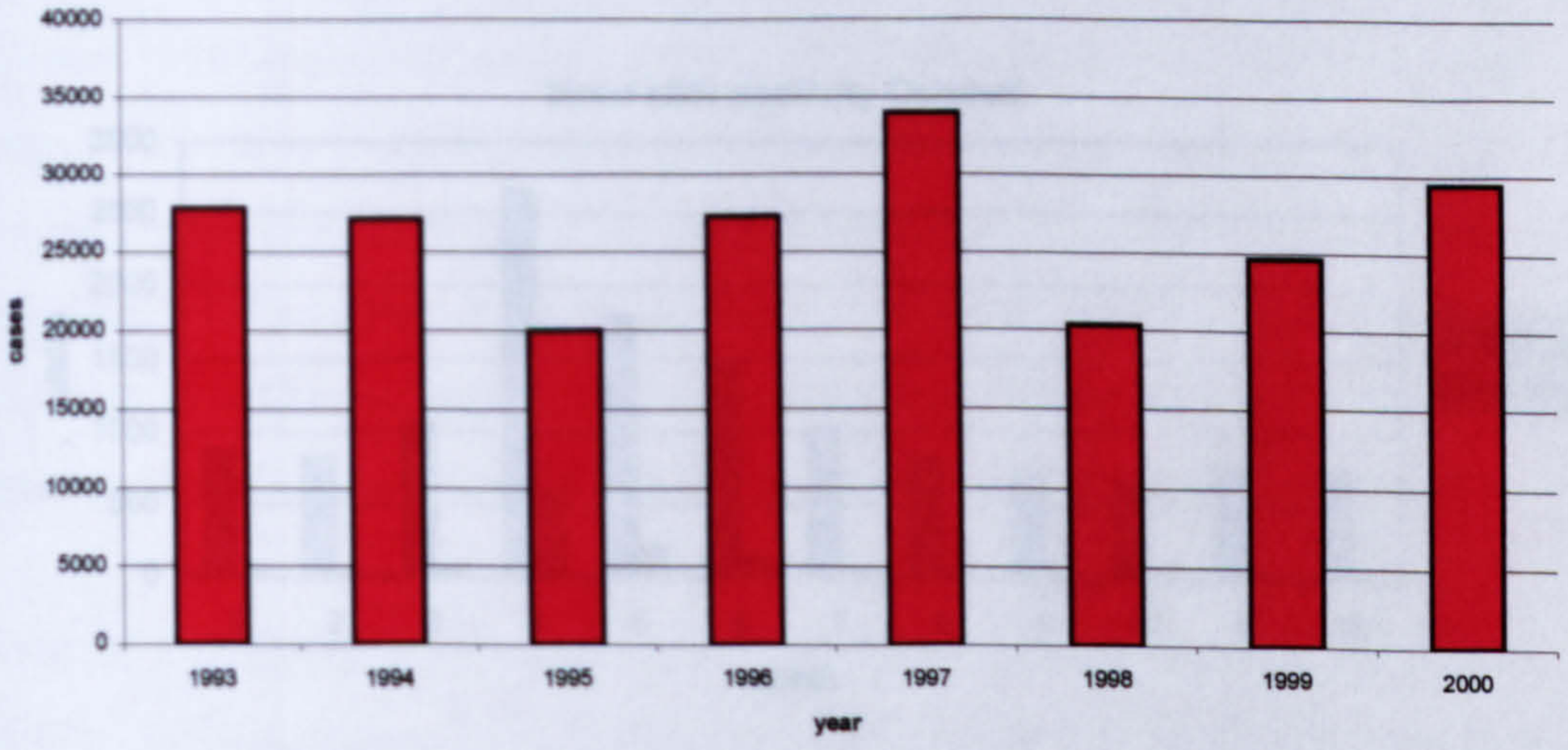


FIGURE 7.5. THE MEAN SEASONALITY OF MALARIA IN NAMIBIA 1996-2000.

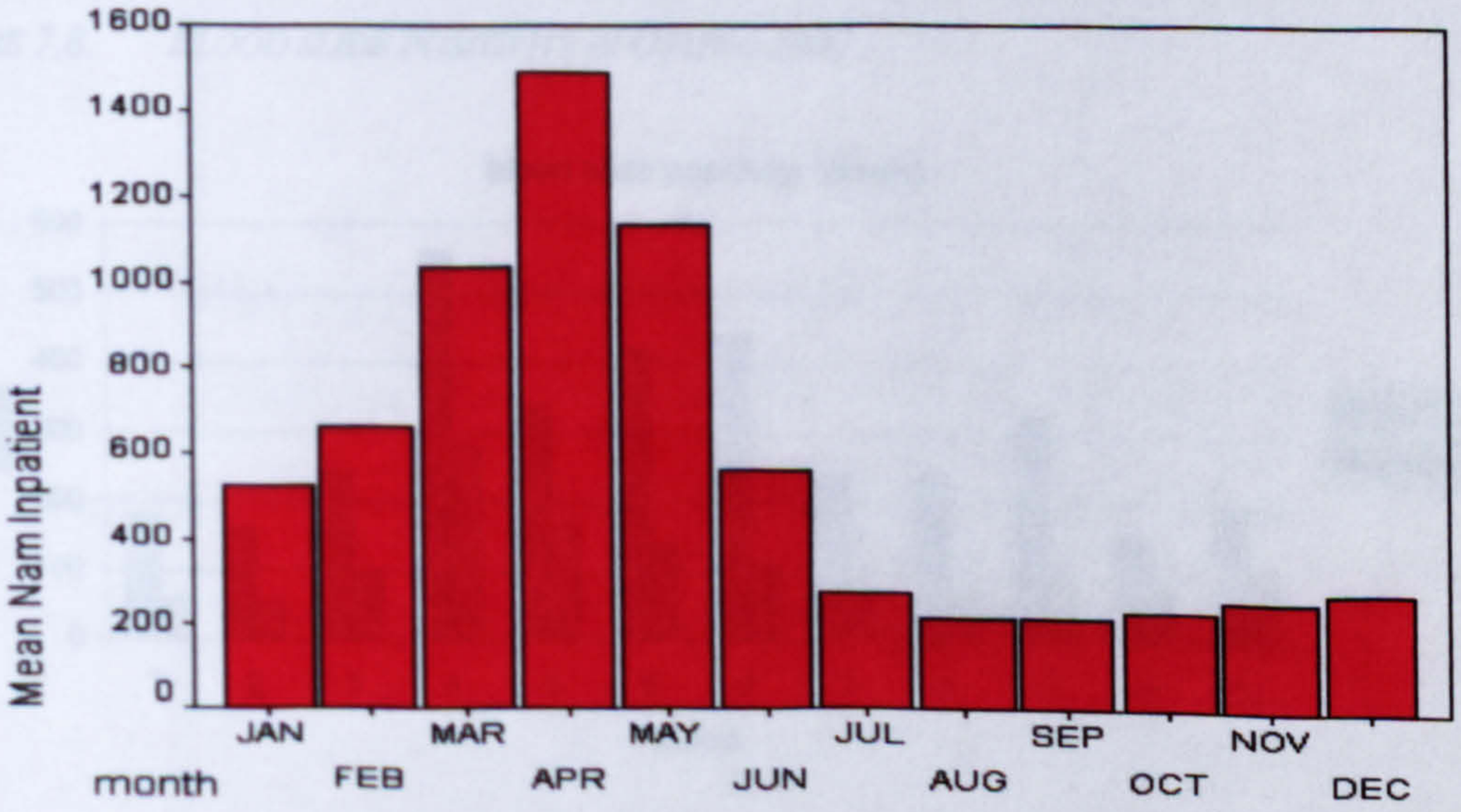


FIGURE 7.6. BLOOD SLIDE POSITIVITY RATES IN NANKUDU 1997.

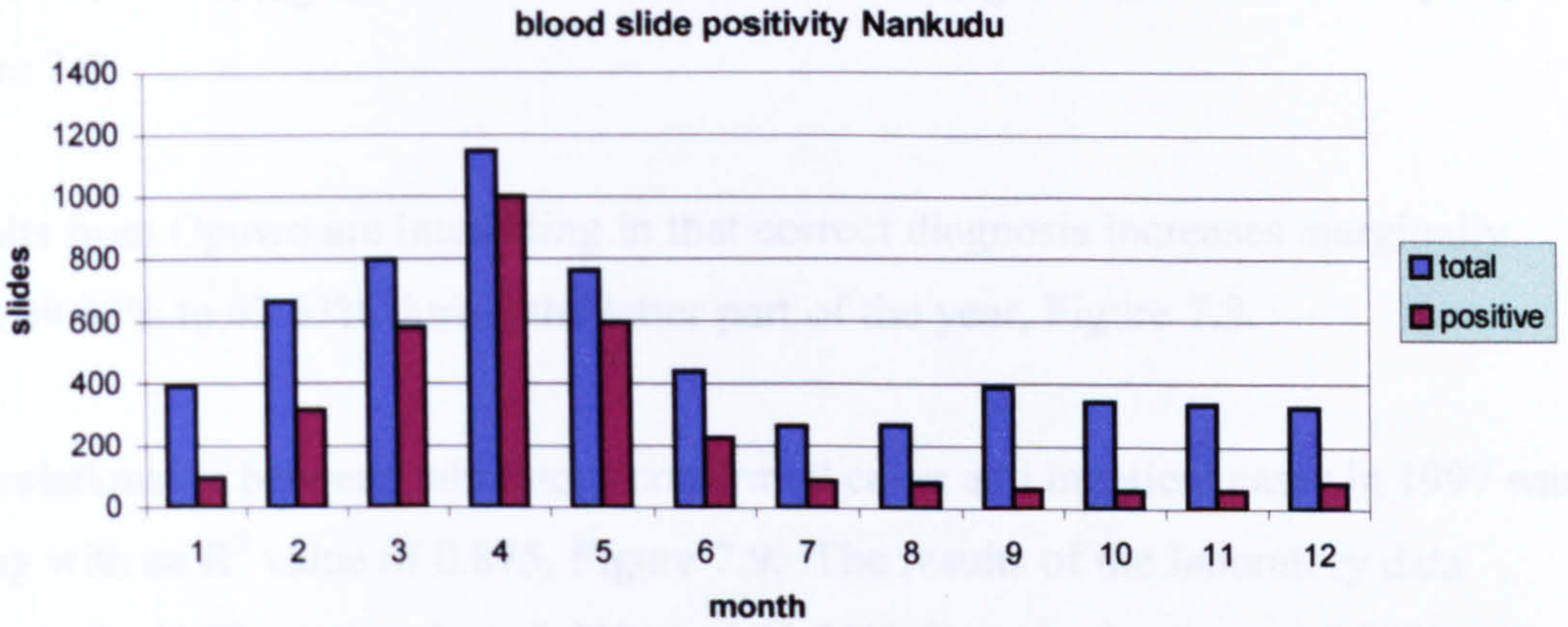


FIGURE 7.7. BLOOD SLIDE POSITIVITY OSHAKATI 1997.

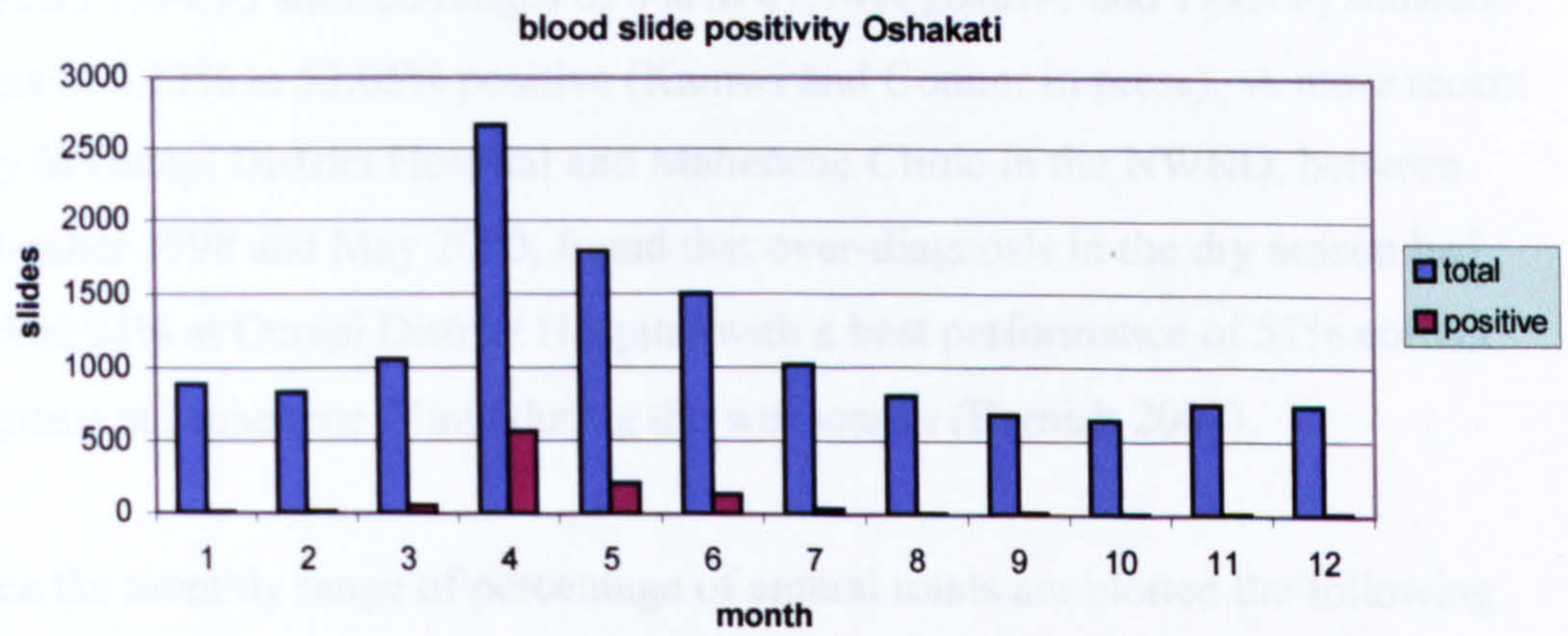
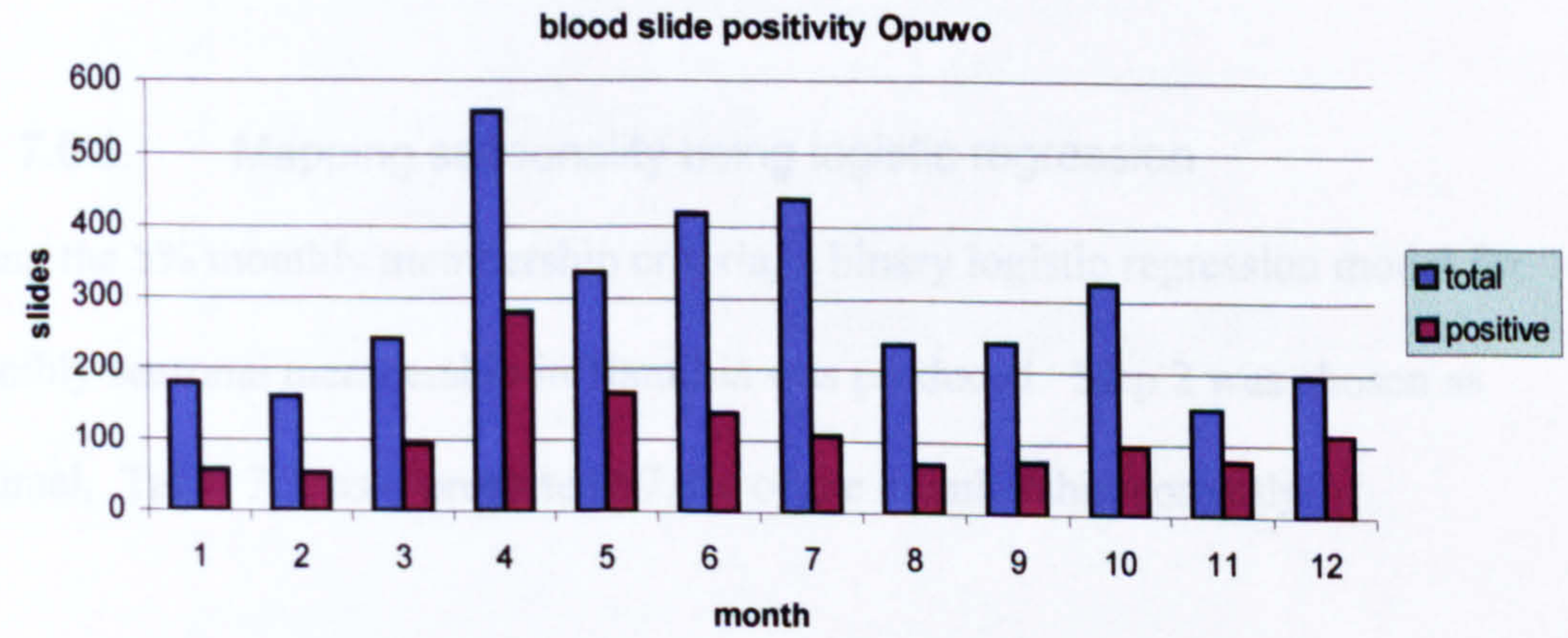


FIGURE 7.8. BLOOD SLIDE POSITIVITY IN OPUWO 1997.



The poorest diagnostic results come from Oshikati with an overall correct diagnosis of 5% (8.26% during the main season and 3.29% during the latter half of the year, Figure 7.7.

Results from Opuwo are interesting in that correct diagnosis increases marginally from 39.53% to 42.63% during the latter part of the year, Figure 7.8.

The relationship between laboratory confirmed cases and inpatient cases in 1997 was strong with an R^2 value of 0.875, Figure 7.9. The results of the laboratory data analysis for 1997 ranging from 5.01% and 41.61% for annual rates and 7.72% and 60.18% seasonal rate (January-June) are summarised in Table 7.2. Results on blood slide positivity rates from the various laboratory facilities are likely to change from year to year, or as staff change. Blood slide results from 26 laboratory facilities for the years 1994/95 showed ranges of 5% to 47.74% positive and 1995/96 showed ranges of 5.13% to 53.05% positive (Kamwi and Connor in press). A more recent study in Outapi District Hospital and Mahenene Clinic in the NWHD, between September 1998 and May 2000, found that over-diagnosis in the dry season had reached 94% at Outapi District Hospital with a best performance of 57% correct diagnosis at Mahenene Clinic during the wet season (Barnish 2000).

When the monthly range of percentage of annual totals are plotted the following result is obtained, Figure 7.10. If the results are produced for each Directorate the variability in seasonal and interannual patterns can be compared, Figure 7.11. A figure of 5% of annual totals would appear to identify the beginning and end of the season.

7.6.2. Mapping seasonality using logistic regression

Using the 5% monthly membership criteria, a binary logistic regression model for monthly seasonal membership in Namibia was produced. Step 2 was chosen as optimal, Table 7.3, as it predicted 87.8% of the membership correctly.

FIGURE 7.9. RELATIONSHIP BETWEEN LABORATORY CONFIRMED CASES AND INPATIENT CASES, NAMIBIA 1997.

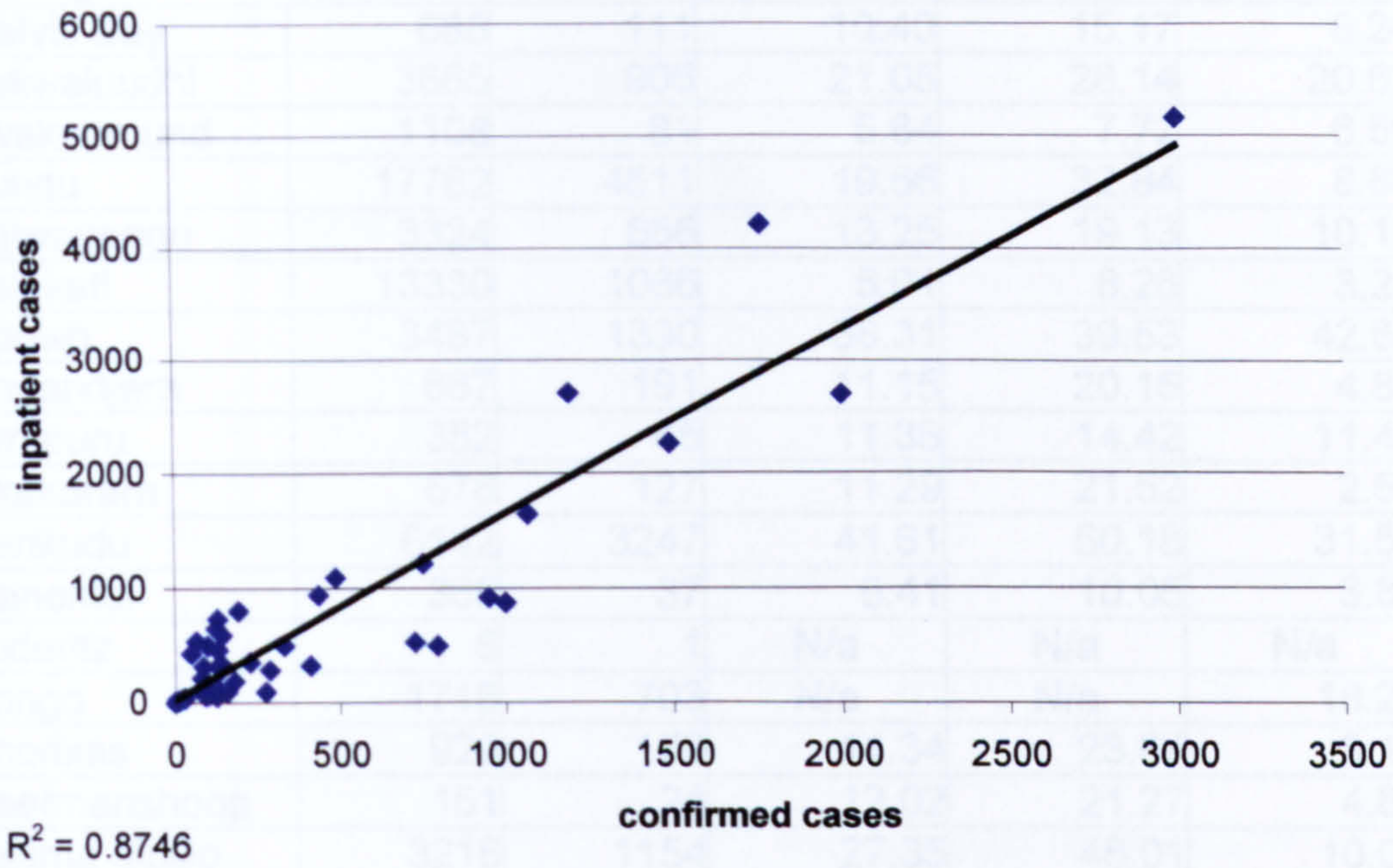


FIGURE 7.10. MONTHLY INPATIENT INCIDENCE AS A PERCENTAGE OF ANNUAL INPATIENT TOTALS.

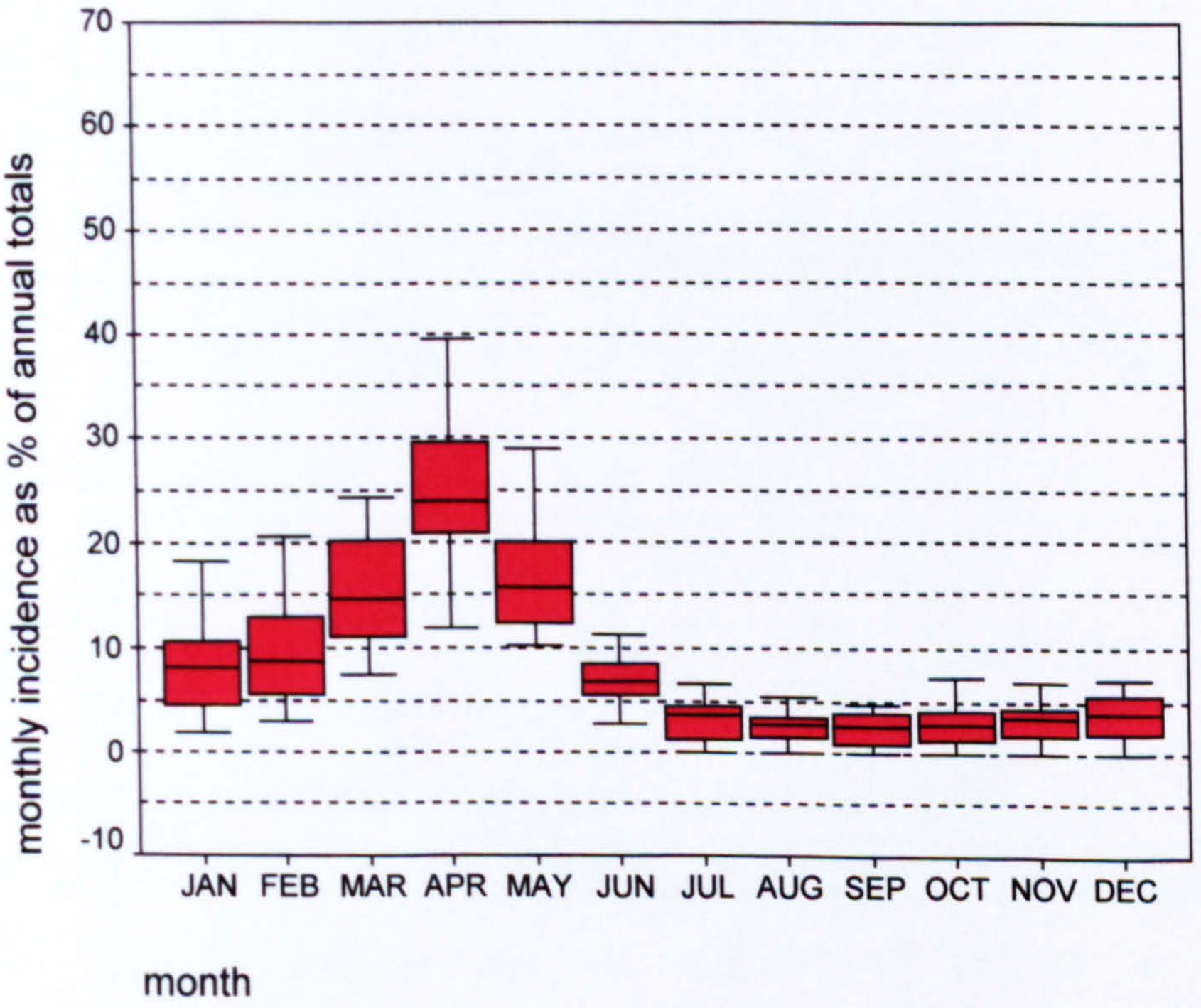


TABLE 7.2. LABORATORY CONFIRMED MALARIA POSITIVITY RATES FOR 22 FACILITIES IN NAMIBIA 1997.

Laboratory Facility	Total slides	Positive slides	Annual (+)ve rate	Jan-Jun (+)ve rate	Jul-Dec (+)ve rate
Walvis Bay	685	111	10.40	15.17	6.24
Uukwaluudhi	3665	906	21.05	28.14	20.62
Swakopmund	1108	81	5.84	7.72	6.59
Rundu	17762	4511	19.66	32.84	8.89
Otjiwagongo	3324	656	13.25	19.13	10.18
Oshikati	13330	1066	5.01	8.26	3.29
Opuwo	3487	1330	38.31	39.53	42.63
Ongandjera	887	191	11.15	20.15	4.81
Omaruru	352	65	11.38	14.42	11.40
Okakarara	678	127	11.29	21.52	2.53
Nankudu	6142	3247	41.61	60.18	31.52
Mariental	365	37	6.41	10.05	3.85
Luderitz	8	1	N/a	N/a	N/a
Kongo	1718	703	N/a	N/a	18.26
Khorixas	929	179	14.34	23.67	8.12
Keetmanshoop	151	24	12.02	21.27	4.86
Katima Mulilo	3216	1154	27.35	48.01	10.00
Kambaku	4978	1580	25.14	37.02	20.52
Grootfontein	1935	754	25.29	37.33	18.95
Gobabis	3432	1252	13.95	26.97	4.89
Ennhana	3787	950	15.80	26.30	10.10
Engela	5375	805	10.39	18.54	6.21

FIGURE 7.11. MONTHLY INPATIENT INCIDENCE AS A PERCENTAGE OF ANNUAL INPATIENT TOTALS BY DIRECTORATE.

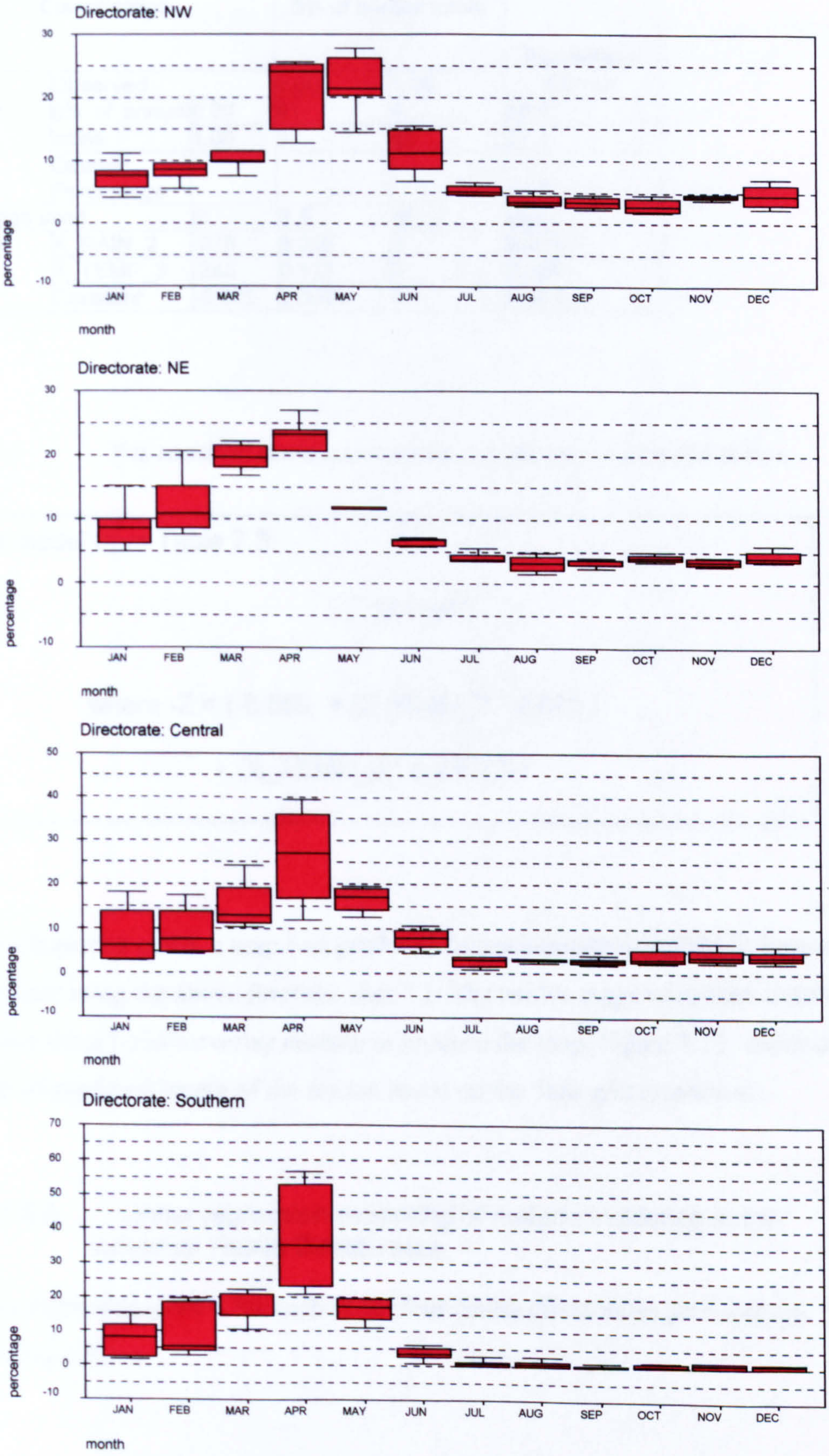


TABLE 7.3. MEMBERSHIP CLASSIFICATION AND VARIABLES USED IN THE MODEL.

Classification			Predicted		
			5% of annual totals		Percentage Correct
	Observed		0.00	1.00	
Step 2	5% of annual totals	0.00	61	8	88.4
		1.00	9	61	87.1
	Overall Percentage				87.8
Variables used		B	S.E.	df	Sig.
Step 2	X_RAIN_2	.075	0.026	1	0.004
	X_TEMP_3	.245	0.127	1	0.054
	Constant	-6.569	2.393	1	0.006

BOX 7.1 THE LOGISITIC REGRESSION MODEL FOR MALARIA SEASON IN NAMIBIA.

The model from Table 7.3:

$$1/(1+e^{-Z})$$

where -Z = (-6.569 + (X_RAIN_2 * 0.075)

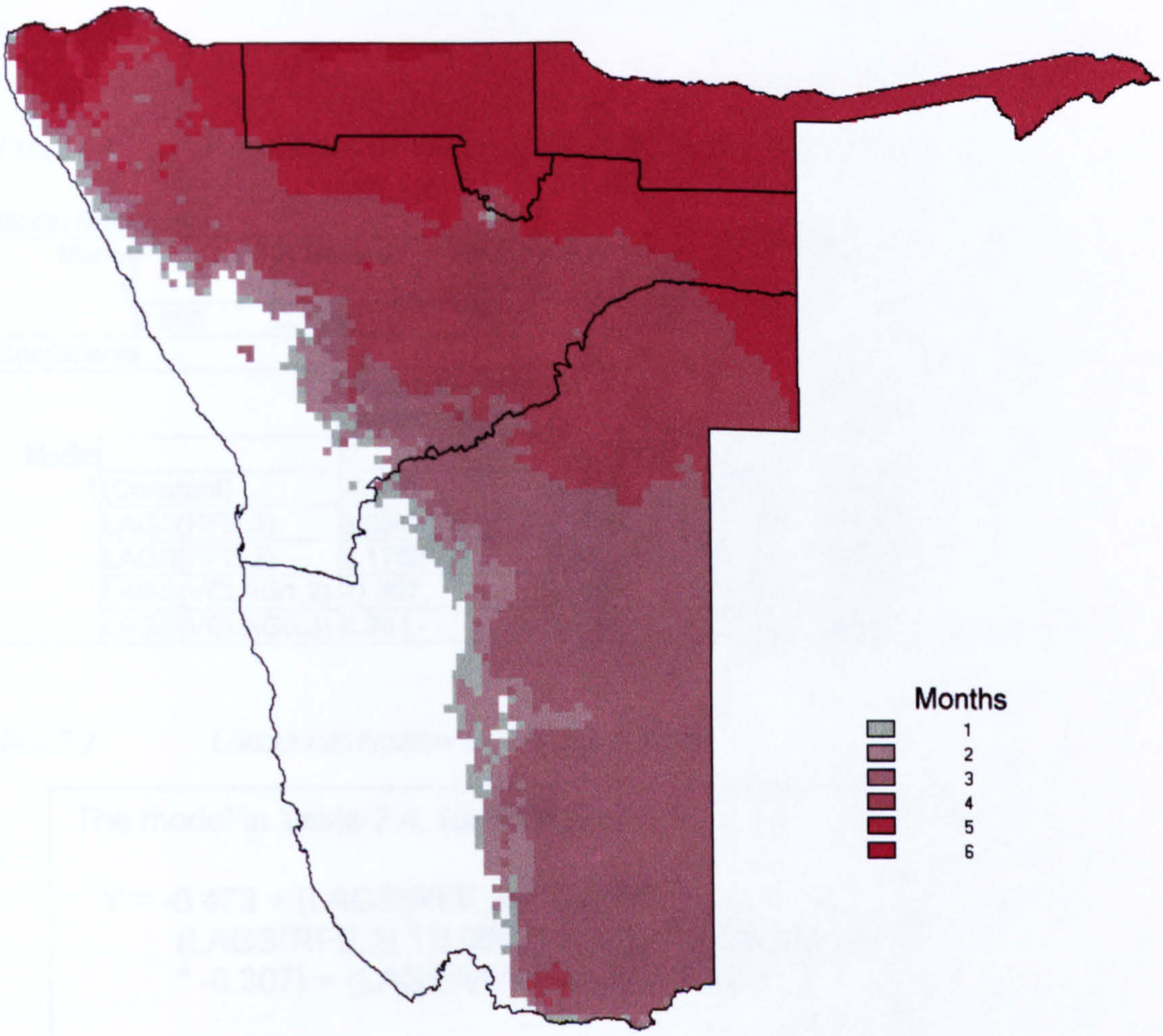
+ (X_TEMP_3 * 0.245))*-1

As in Chapters 5 and 6, a map was produced for each month using Idrisi' Image Calculator using the above formula, Box 7.1. The twelve maps were then added together using Idrisi's overlay module to produce the map, Figure 7.12, which offers a map of predicted length of the season based on the 5km grid resolution.

7.6.3. Linear regression modelling of malaria incidence in the individual Health Directorates

Linear regression models for each of the four health directorates produced the following results:

FIGURE 7.12. MODELLED MAP OF MALARIA SEASONALITY IN NAMIBIA.



Legend:

The model in Table 7.3 is produced as a map showing the number of months comprising the malaria season in Namibia.

7.6.3.1. Northwest

The fourth step in the model was chosen as optimal, with an R^2 value of 0.796, see Table 7.4.

TABLE 7.4. PARAMETERS OF THE LINEAR REGRESSION MODEL, NWHD.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
4	0.892	0.796	0.774	0.3190

Coefficients

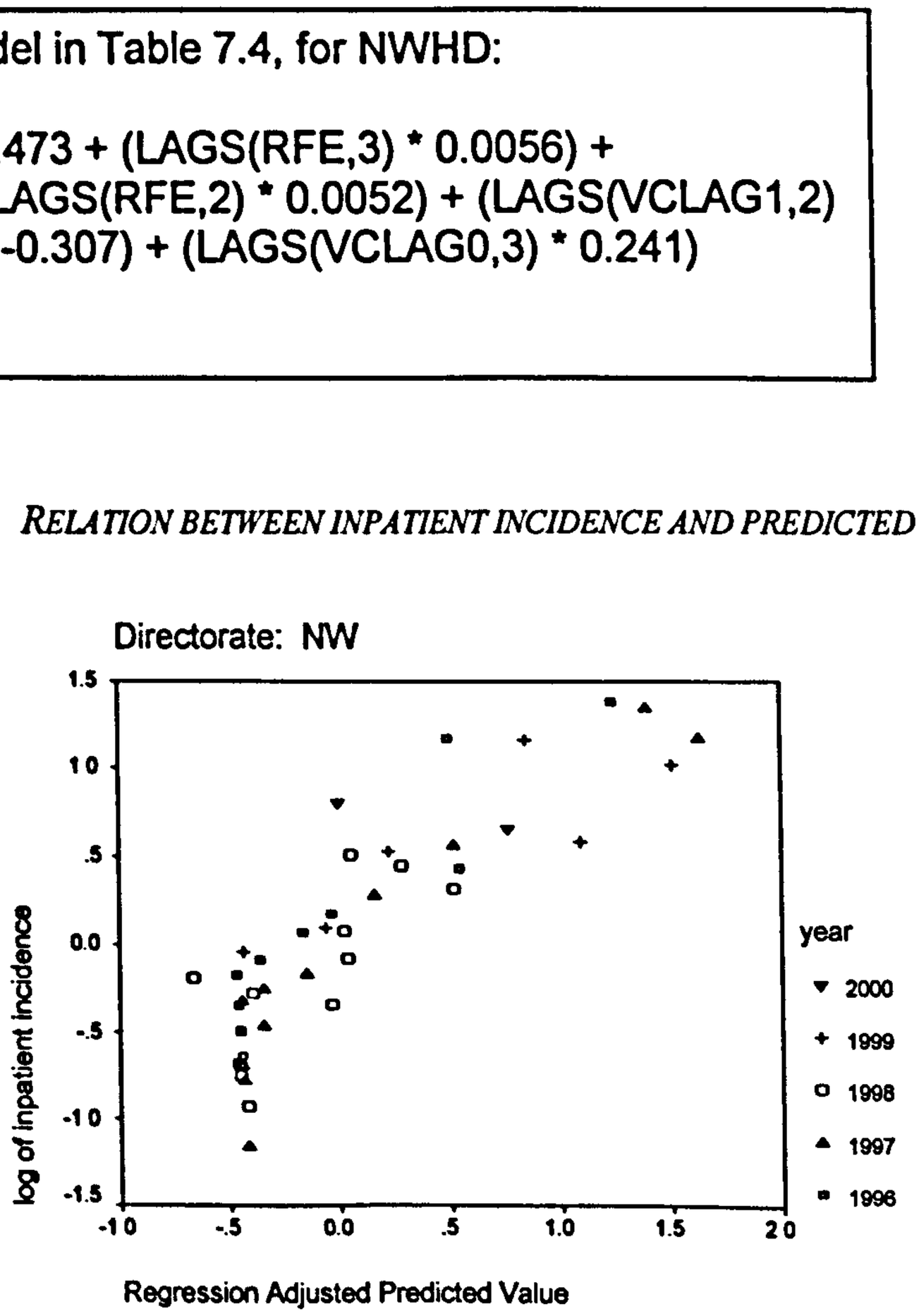
Model		Unstandardized Coefficients		t	Sig.
		B	Std. Error		
4	(Constant)	-0.473	0.068	-6.991	0.000
	LAGS(RFE,3)	5.631E-03	0.004	1.266	0.213
	LAGS(RFE,2)	5.175E-03	0.001	4.431	0.000
	LAGS(VCLAG1,2)	-0.307	0.100	-3.070	0.004
	LAGS(VCLAG0,3)	0.241	0.114	2.116	0.041

BOX 7.2 LINEAR REGRESSION MODEL FOR NWHD

The model in Table 7.4, for NWHD:

$$Y = -0.473 + (LAGS(RFE,3) * 0.0056) + (LAGS(RFE,2) * 0.0052) + (LAGS(VCLAG1,2) * -0.307) + (LAGS(VCLAG0,3) * 0.241)$$

FIGURE 7.13. RELATION BETWEEN INPATIENT INCIDENCE AND PREDICTED VALUES NWHD.



7.6.3.2. Northeast

TABLE 7.5. PARAMETERS OF THE LINEAR REGRESSION MODEL FOR NEHD.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
4	0.960	0.922	0.914	1.2655

Coefficients

		Unstandardized Coefficients		t	Sig.
Model		B	Std. Error		
4	(Constant)	1.691	0.258	6.550	0.000
	LAGS(VCLAG1,2)	0.724	0.084	8.645	0.000
	LAGS(CCD,3)	-7.442E-03	0.002	-3.710	0.001
	LAGS(RFE,2)	4.258E-02	0.006	6.658	0.000
	LAGS(CCD,2)	-9.331E-03	0.002	-5.321	0.000

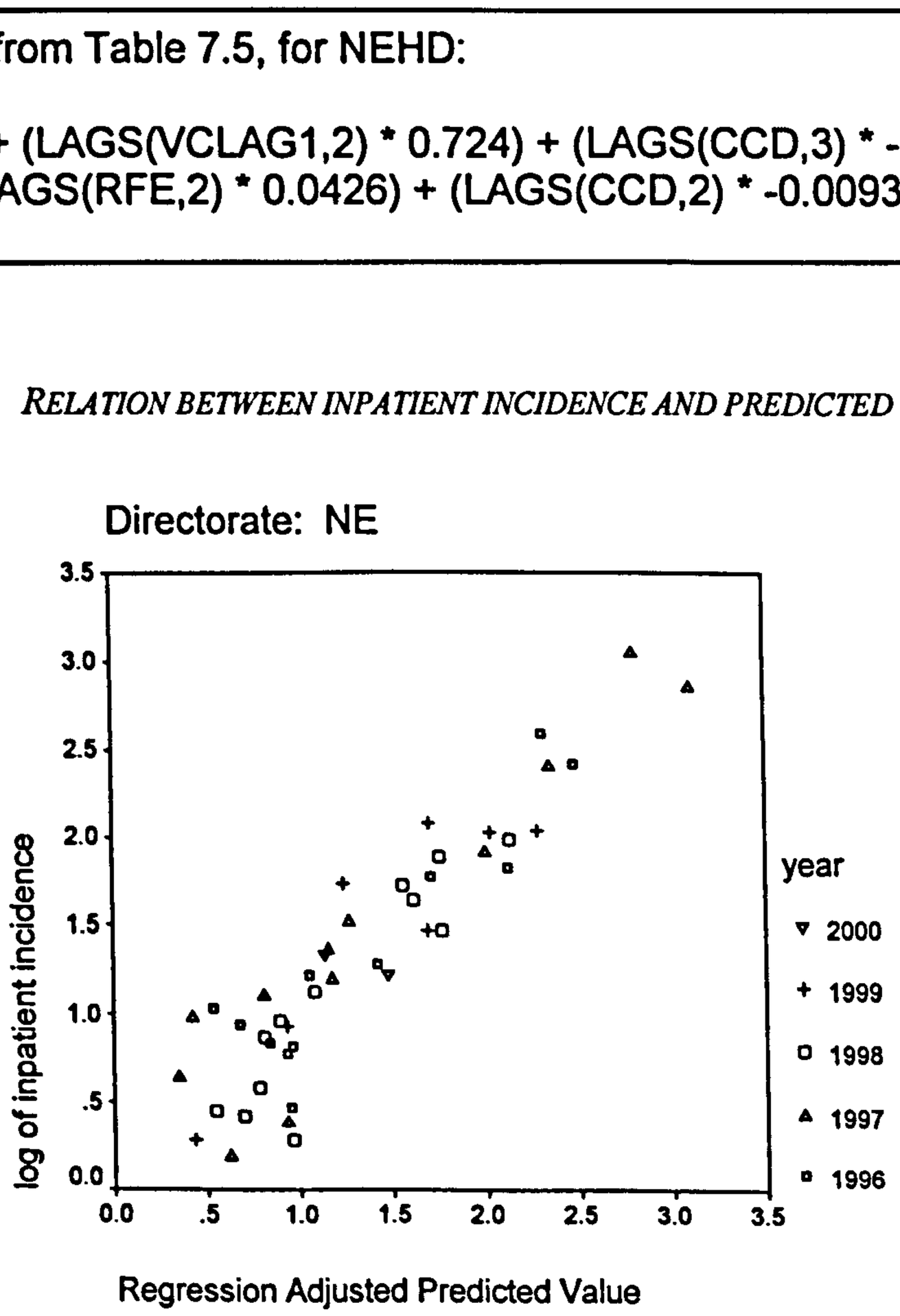
Dependent Variable: inpatient incidence

BOX 7.3. LINEAR REGRESSION MODEL FOR NEHD.

The model from Table 7.5, for NEHD:

Y = 1.691 + (LAGS(VCLAG1,2) * 0.724) + (LAGS(CCD,3) * -0.0074) + (LAGS(RFE,2) * 0.0426) + (LAGS(CCD,2) * -0.0093)

FIGURE 7.14. RELATION BETWEEN INPATIENT INCIDENCE AND PREDICTED VALUES NEHD.



7.6.3.3. Central

TABLE 7.6. PARAMETERS OF THE LINEAR REGRESSION MODEL FOR CENTRAL HD.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.867	0.752	0.746	0.3038

Coefficients

		Unstandardized Coefficients		t	Sig.
Model 1		B	Std. Error		
	(Constant)	0.133	0.061	2.167	0.036
	LAGS(VCLAG0,3)	0.257	0.024	10.875	0.000

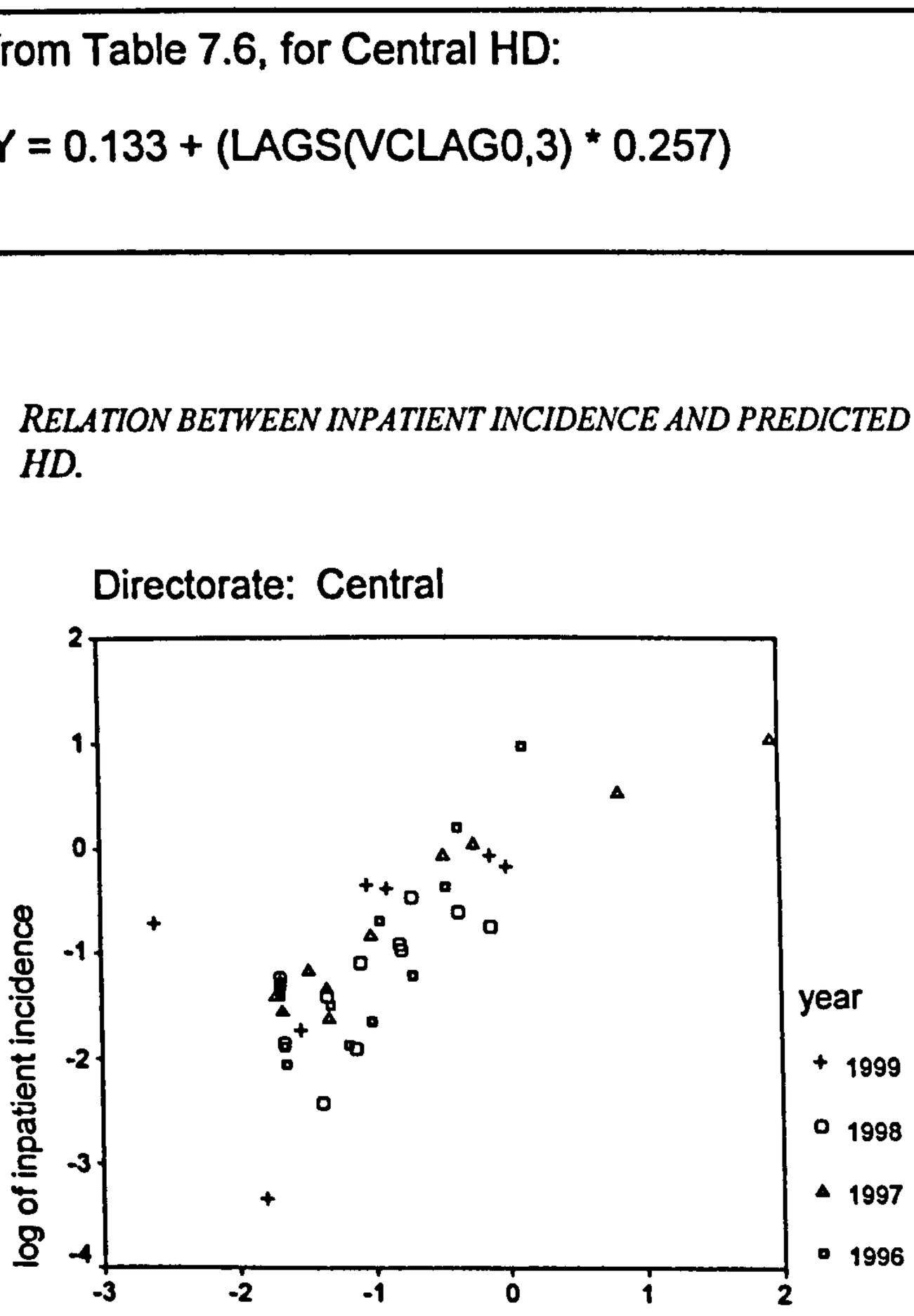
Dependent Variable: inpatient incidence

BOX 7.5. LINEAR REGRESSION MODEL FOR CENTRAL HD.

The model from Table 7.6, for Central HD:

$$Y = 0.133 + (LAGS(VCLAG0,3) * 0.257)$$

FIGURE 7.15. RELATION BETWEEN INPATIENT INCIDENCE AND PREDICTED VALUES CENTRAL HD.



7.6.3.4. Southern

TABLE 7.7 PARAMETERS OF THE LINEAR REGRESSION MODEL FOR SOUTHERN HD.

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
3	0.907	0.823	0.811	9.415E-02

Coefficients

		Unstandardized Coefficients		t	Sig.
Model		B	Std. Error		
3	(Constant)	-4.974E-02	0.021	-2.390	0.021
	LAGS(VCLAG0,3)	0.125	0.009	13.981	0.000
	LAGS(VCLAG3,4)	-0.116	0.024	-4.770	0.000
	LAGS(VCLAG3,5)	7.490E-02	0.022	3.402	0.001

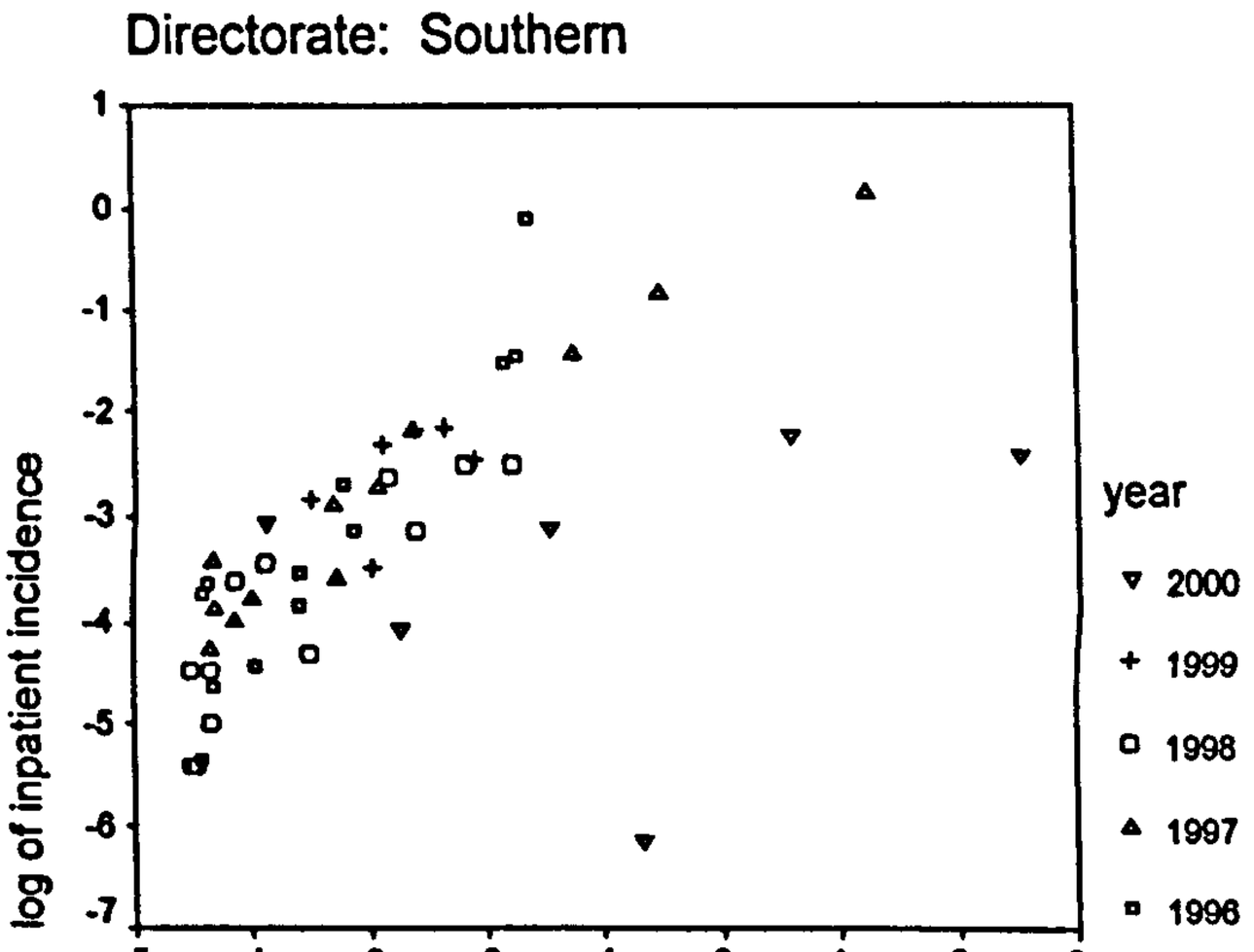
Dependent Variable: inpatient incidence

BOX 7.6. LINEAR REGRESSION MODEL FOR SOUTHERN HD.

The model from Table 7.7, for Southern HD:

Y = -0.0497 + (LAGS(VCLAG0,3) * 0.125) + (LAGS(VCLAG3,4) * -0.116) + (LAGS(VCLAG3,5) * 0.0749)

FIGURE 7.16. RELATION BETWEEN INPATIENT INCIDENCE AND PREDICTED VALUES SOUTHERN HD.



7.6.4. Predictive mapping using linear regression

The Map Calculator function of Idrisi was used to map the results of the linear regression models for each Health Directorate.

7.6.4.1. Northwest

Using the model, Box 7.2, produced the following spatial model of predicted malaria incidence for NWHD, for January 1996, Figure 7.17. In terms of lead-time available such a map could have been produced in November 1995, offering two months warning of where in the district malaria incidence would be highest.

7.6.4.2. Northeast

Using the model, Box 7.3, produced the following spatial model of predicted malaria incidence for NEHD, for January 1996, Figure 7.18. Again in terms of lead-time available such a map could have been produced in November 1995, offering two months warning of where in the district malaria incidence would be highest.

7.6.4.3. Central

The linear regression model in Box 7.4, produced the following spatial model of predicted malaria incidence for Central HD, for January 1996, Figure 7.19. In this case lead-time available was three months and such a map could have been produced in October 1995, offering three months warning of where in the district malaria incidence would be highest.

7.6.4.4. Southern

The linear regression model in Box 7.5, requires inputs from vectorial capacity images with RFEs lagged by three months, which are then in composite lagged by a further four and five months respectively. While values for these could be produced in SPSS for the modelling, the images are unavailable for mapping January 1996 as used in the previous examples (as the required RFEs were not available for input). So in this example the spatial model of predicted malaria incidence for Southern HD, is for January 1997, Figure 7.20. Again the lead-time available was three months and such a map could have been produced in October 1996, offering three months warning of where in the district malaria incidence would be highest.

FIGURE 7.17. PREDICTIVE MODEL OF MALARIA INCIDENCE NWHD JANUARY 1996.

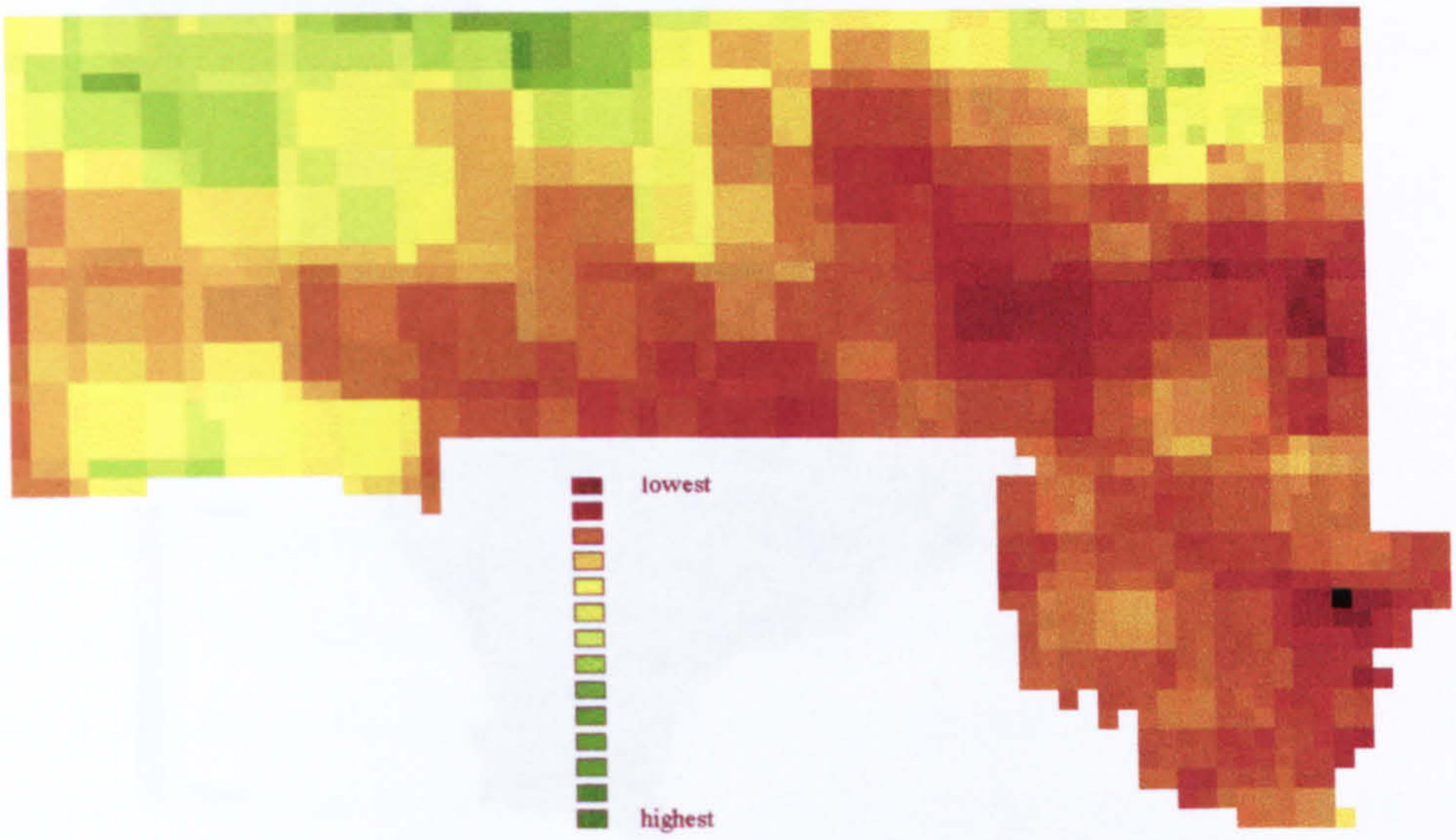
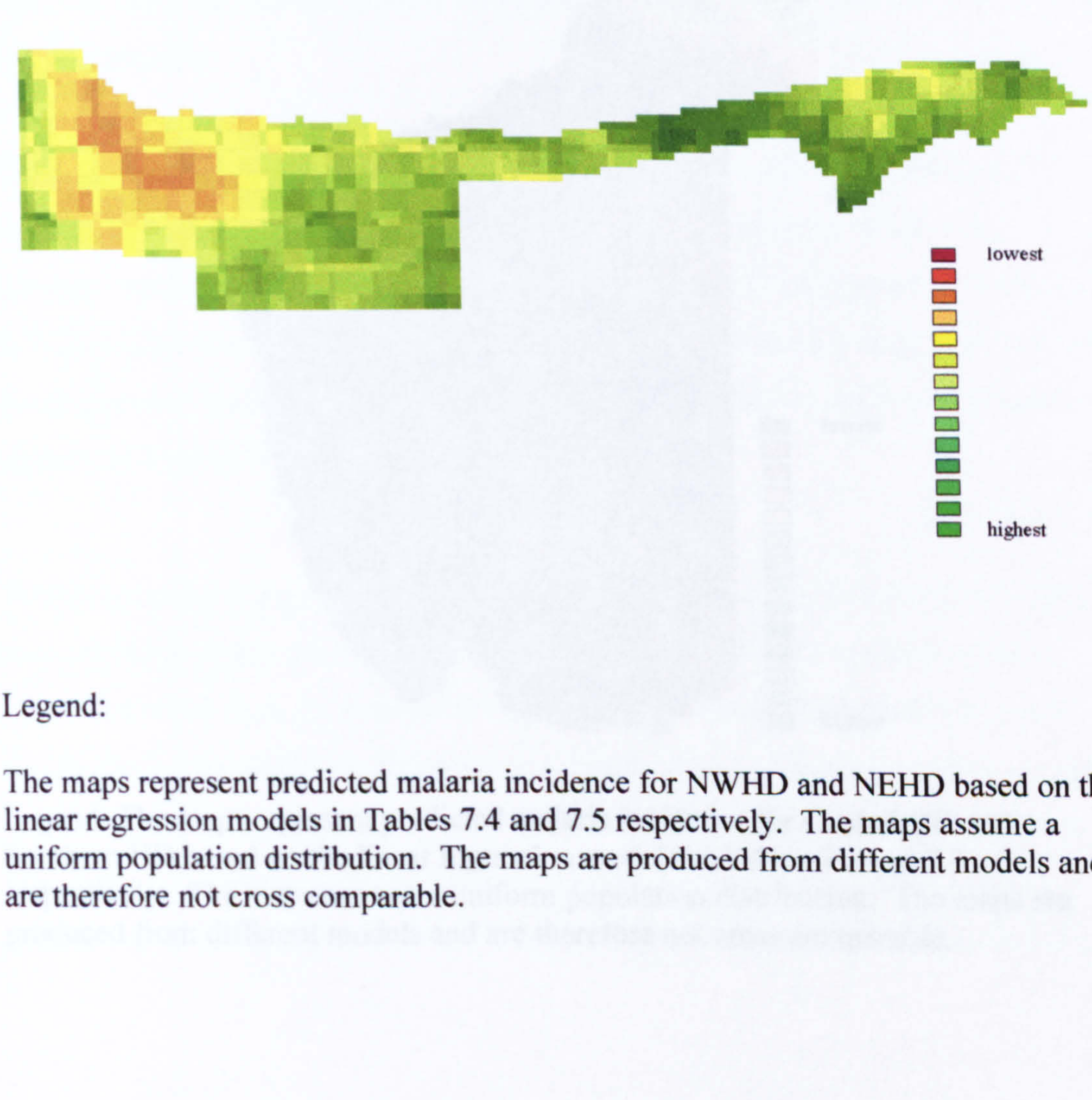


FIGURE 7.18. PREDICTIVE MODEL OF MALARIA INCIDENCE NEHD JANUARY 1996.



Legend:

The maps represent predicted malaria incidence for NWHD and NEHD based on the linear regression models in Tables 7.4 and 7.5 respectively. The maps assume a uniform population distribution. The maps are produced from different models and are therefore not cross comparable.

FIGURE 7.19. PREDICTIVE MODEL OF MALARIA INCIDENCE CENTRAL HD JANUARY 1996.

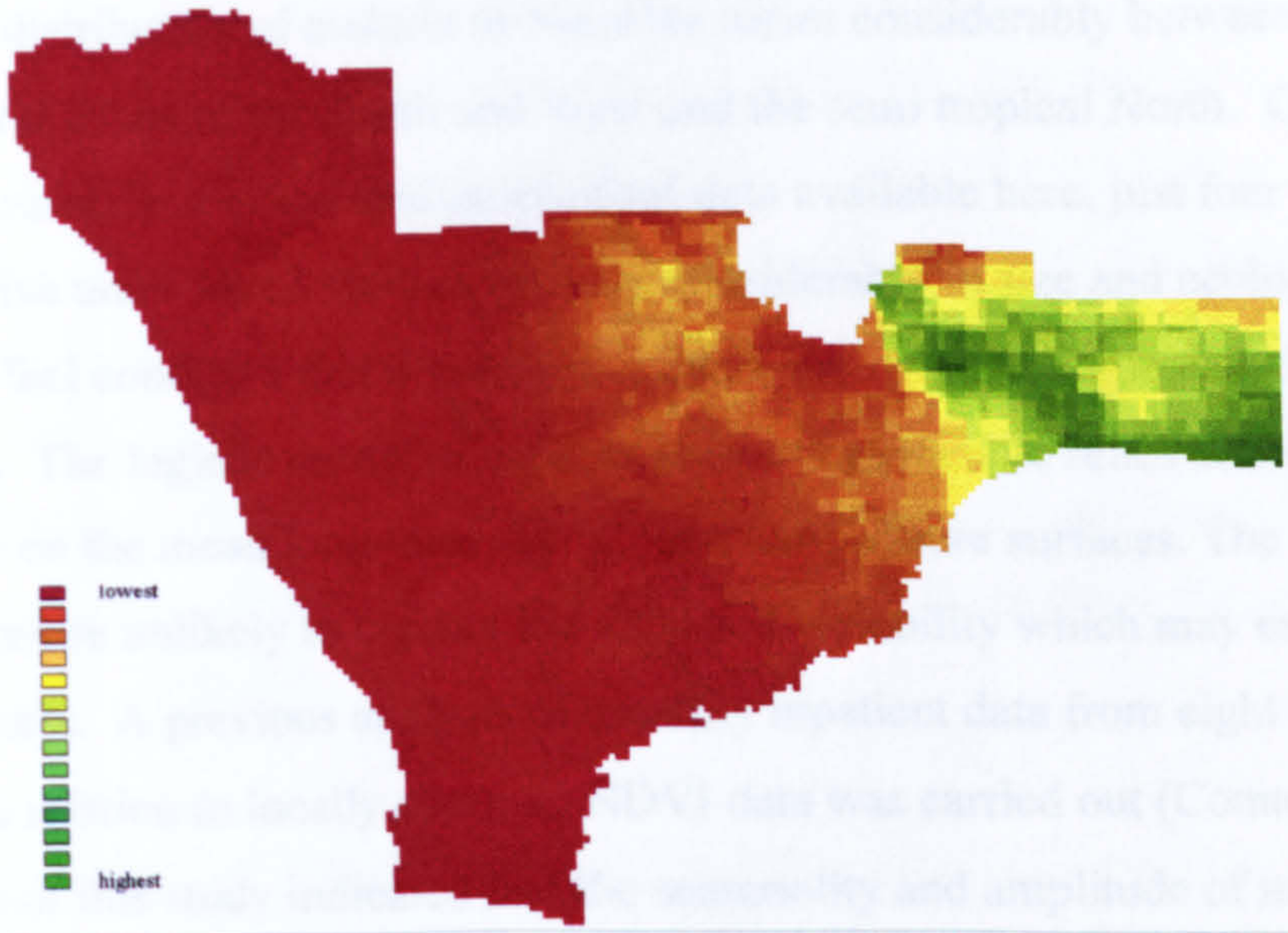
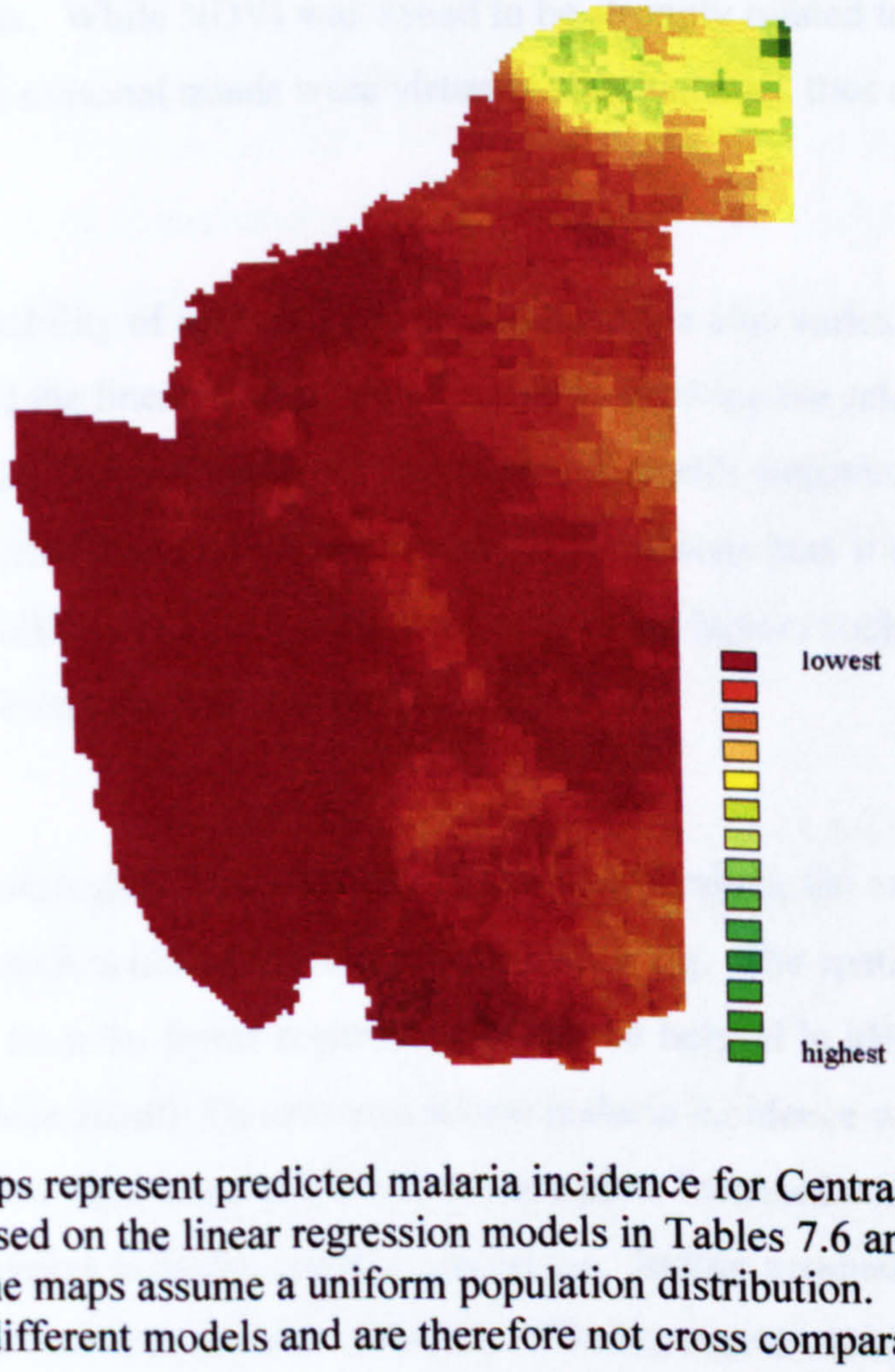


FIGURE 7.20. SPATIAL MODEL OF MALARIA INCIDENCE SOUTHERN HD, JANUARY 1997.



Legend: The maps represent predicted malaria incidence for Central HD and Southern HD based on the linear regression models in Tables 7.6 and 7.7 respectively. The maps assume a uniform population distribution. The maps are produced from different models and are therefore not cross comparable.

7.7. Discussion

The spatial distribution of malaria in Namibia varies considerably between the extensive arid zones of the South and West and the semi tropical North. Given the low spatial resolution of the epidemiological data available here, just four administrative units which themselves vary considerably in size and ecology, it is difficult to feel confident that the models capture the epidemiological setting adequately. The logistic model of malaria season for example relies almost exclusively on the mean long-term rainfall and temperature surfaces. The resulting map is therefore unlikely to capture the localised variability which may exist at sub-national levels. A previous analysis of monthly inpatient data from eight health facilities in relation to locally obtained NDVI data was carried out (Connor 1999b). The results of this study indicated that the seasonality and amplitude of malaria inpatient cases was strongly related to the seasonality and amplitude of NDVI. A malaria distribution map was produced which was modelled at the 1km grid resolution available from the NDVI satellite imagery captured locally at the Etosha Ecological Institute. While NDVI was found to be strongly related to malaria inpatient cases the seasonal trends were virtually simultaneous, thus offering no lead-time information.

The temporal variability of malaria incidence in Namibia also varies markedly between years and the linear models are effective in showing the relationship between 'epidemic' and non epidemic years in some health directorates. Epidemics in Namibia are periodic and while environmental conditions may trigger these events the progressive build up of case numbers suggests other factors such as inadequate control, or drug resistance, may be implicated.

While the epidemiological inputs available here were limited, the examples highlight some methods which could be useful in control planning. The spatial predictive models (derived from the linear regression) should be helpful in identifying areas within the extensive Health Directorates where malaria incidence would be greatest, and this could have significant implications for active, focussed control operations responsive to changes in environmental conditions. Indoor residual spraying is carried out in the Northern areas of Namibia. The two months lead-time available

through the predictive modelling could be useful in highlighting areas of increased risk in any given month, especially if produced as difference maps. If these were compared to the geographical reconnaissance information produced by the spray teams then any areas that were not covered, or considered to have been poorly covered, could be revisited, and local availability of drugs could also be ensured. Results from the predictive model in the Central Health Directorate give slightly longer lead-times (three months using vectorial capacity alone) and while routine control operations may not be carried out in these areas such lead-times should be adequate to plan and initiate an appropriate response in years when indicators suggest an increase in risk.

Regular production and archiving of such indicators would allow monthly difference maps to be developed which would further add to the local applicability of the modelling process for focal epidemic prediction. The predictive relationships appear to stem mostly from the lagged vectorial capacity products, alone or in combination with lagged RFEs. The exception to this is in the NEHD where lagged CCD exhibits a negative relation with inpatient incidence and other environmental variables. Previous analysis of inpatient data from health facilities in former Ovamboland (roughly corresponding to the current NWHD) showed a strong relationship between monthly inpatient cases and the quadratic of CCD lagged by three months (Connor, Thomson et al. 1998).

That malaria ranks as the leading cause of outpatient consultation in a country as arid as Namibia is suspicious. It is recognised that malaria over-diagnosis is a problem in Namibia and clearly case definitions, or confirmations, need to be improved. The availability of better epidemiological data collected routinely from smaller spatial units would allow the models to be improved much further. This is in theory due to happen once the four Health Directorates are broken down into the thirteen regional management units.

8. Malaria and Environment in Swaziland

8.1. Geographical background

Swaziland is a small independent monarchy in the east of Southern Africa comprising a land area of 17,363 square kilometres. It is a landlocked country surrounded mostly by the Republic of South Africa. Part of its eastern border however is shared with Mozambique.

Topographically Swaziland can be divided into four regions which run north-south and slope generally downwards from west to east: the mountainous Highveld to the west, which has an average altitude of 1300m and comprises 32% of the national land surface area, extends from the Drakensburg Mountains of South Africa; the hilly Middleveld covering 25% of the land area has an average altitude of 700m; the Lowveld to the east has a rolling landscape between 300m and 120m and accounts for a further 35% of surface area; the fourth area to the extreme east, the Lumombo Plateau, bordering Mozambique and comprising 8% of land area has an average altitude of 400m.

The climate in Swaziland changes from near temperate in the west to subtropical in the eastern Lowveld. The temperature in Mbabane the capital city (Highveld) ranges from 25°C in January to 5°C in July. Rainfall is concentrated in the warmer months of the year October-April. Average annual rainfall totals, in the west, range from 1000mm-2280mm. In the east these range from 500mm-1000mm.

The main rivers are the Komati, Umbuluzi, Lusutfu and the Ngwavuma which flow eastwards from the Highveld and provide abundant water for hydroelectric power and extensive irrigation projects in the Lowveld region.

The population of Swaziland was determined at 965,000 in the 1997 census. Population density in Swaziland overall is 64 per Km^2. The population is divided into approximately 35% urban 65% rural. The annual population growth rate is currently estimated at 1.8%, with life expectancy at birth figures of 39.4 years for

women and 37.9 years for men, both of these have declined markedly due to the impact of HIV/AIDS over recent years. Literacy rates are 91% and GDP was estimated in 1998 at $US1,400 per capita (UNDP 2000).

8.2. Overview of malaria and its control in Swaziland.

Malaria is recognised as a serious public health problem in Swaziland. It is estimated that 30% of the population live in malarious areas, 38% live in malaria receptive areas, and 32% in non-malarious areas (Kunene 1999). While malaria accounted for only 4.8% of inpatient admissions nationally in 1999, this figure varies proportionately between the four administrative districts, and between years, Figure 8.1. Lubumbo District in the Lowveld region typically has 70-80% of the national total malaria inpatient admissions. Due to its high altitude the Highveld region is considered to be non-malarious, Figure 8.2. Malaria in Swaziland is considered to be highly seasonal with transmission occurring between November and May (Kunene 1999) and unstable with periodic epidemics, especially in years of high rainfall (Kunene 2000).

Figure 8.1. Annual total laboratory confirmed malaria cases, 1981/82 - 1998/99.

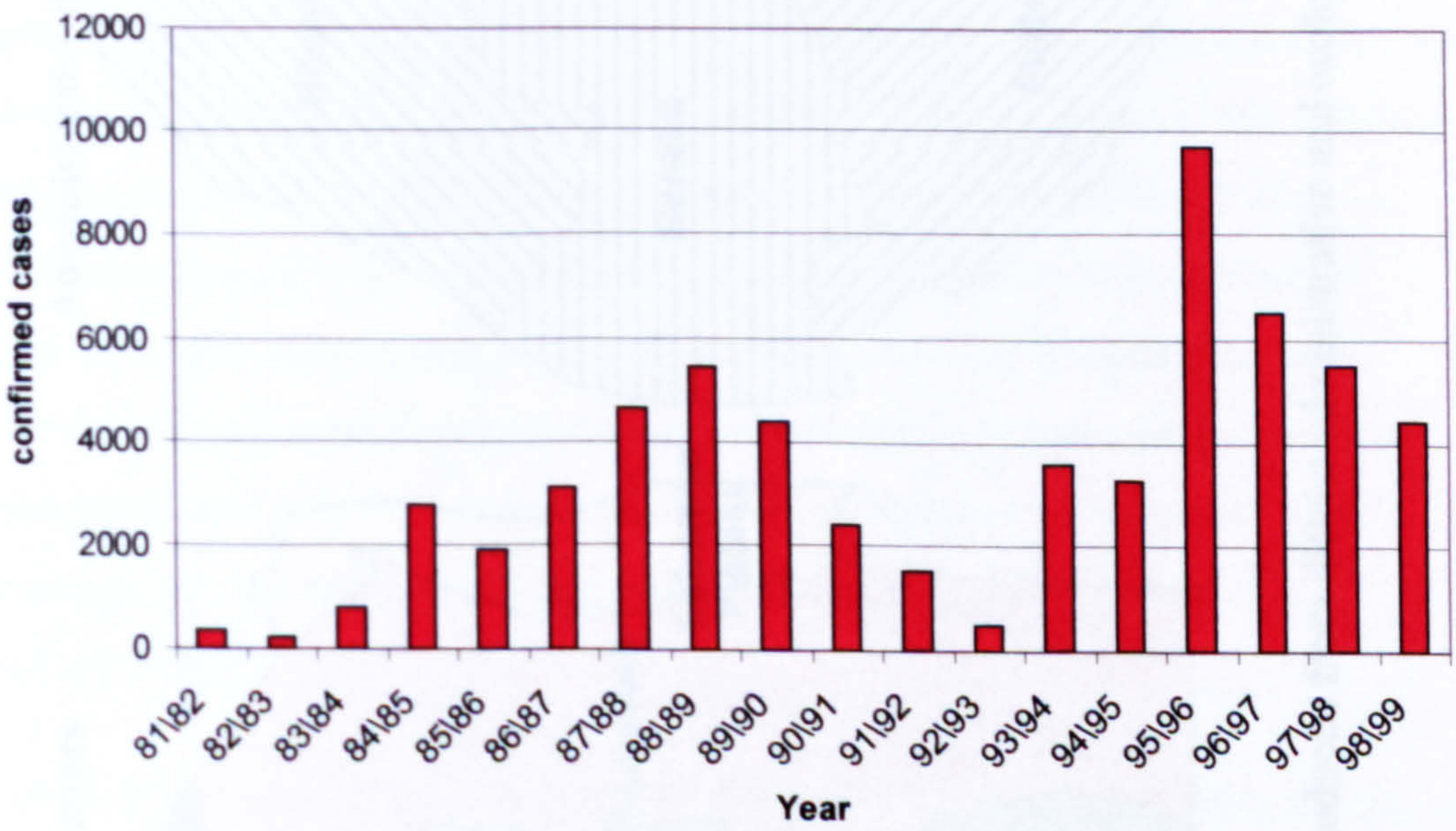
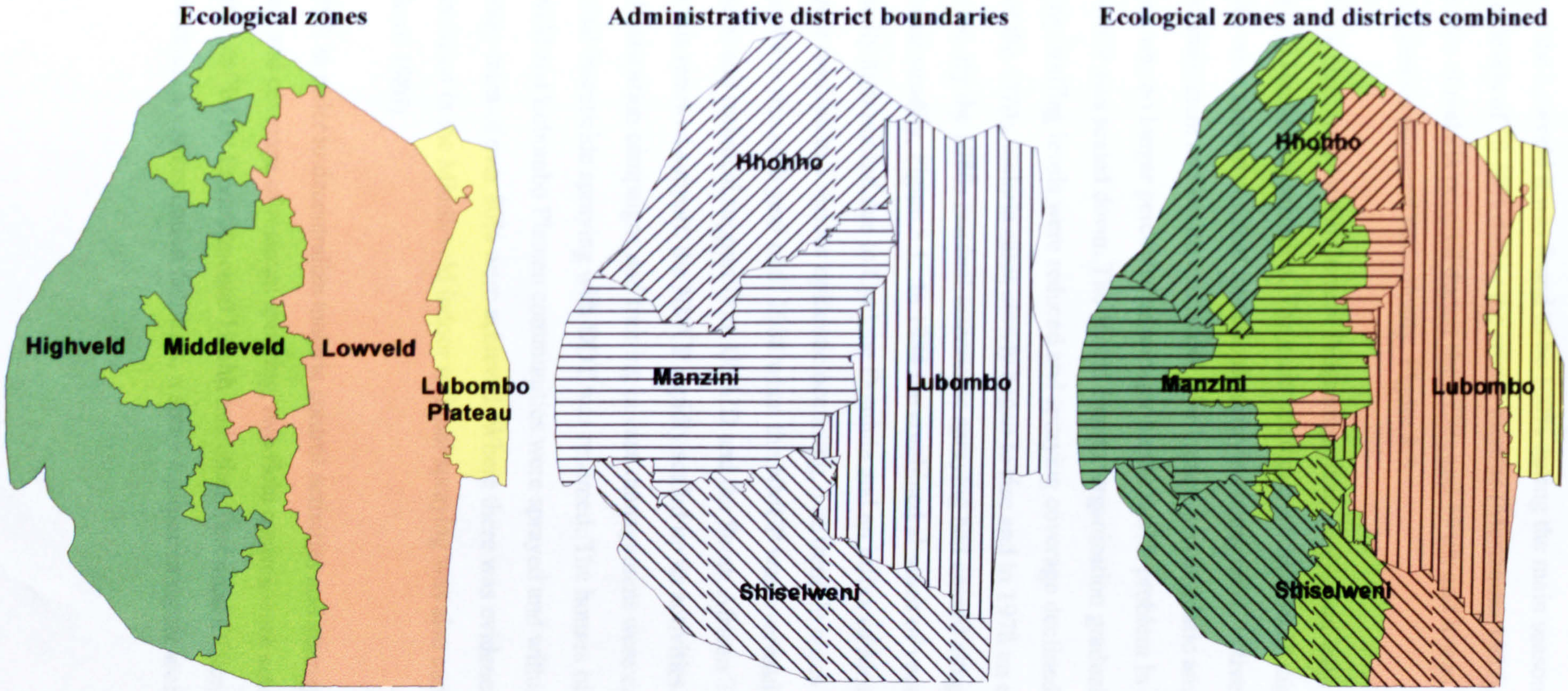


FIGURE 8.2. ECOLOGICAL ZONES AND ADMINISTRATIVE DISTRICTS IN SWAZILAND.



Legend: The maps were produced from district administrative and ecological zone boundary files supplied by SADC-RSSP (1997).

8.2.1. The National Malaria Control Programme in Swaziland

Prior to the 1940s malaria prevalence levels in Swaziland were high, with parasite prevalence rates generally over 40% (Mastbaum 1954). In young children living in areas of the Lowveld it was found to be 100% during the main season where it would drop to levels of 50-60% during the winter months (Mastbaum 1957). Major epidemics of malaria occured during the 1930s and 1940s and it was recognised that such epidemics occurred periodically, Figure 8.3.

In 1948 a National Malaria Control Programme was established with funding from the World Health Organization. The main strategies of the NMCP during the 1950s and 60s were blanket residual insecticide spraying using DDT, active case detection, case management and health education. The impact was dramatic and by 1970 malaria was no longer perceived as a major public health problem in the country and the NMCP was scaled down. The World Health Organization gradually cut back its funding, staffing levels were reduced and spraying coverage declined. By the latter half of the 1970s, malaria cases slowly began to rise and in 1978 an epidemic occurred. By the 1980s residual insecticide spraying had ceased altogether and cases increased steadily, Figure 8.1. In 1984 the combined absence of vector control, unusually high rainfall due to Cyclone Dominia and an influx of Mozambican refugees resulted in a serious epidemic occurring. The trend in cases generally continued to rise each year until 1988 when the NMCP was overhauled and received financial and technical support from USAID and the South African Trade Mission. With this renewed support, the NMCP rapidly scaled up its activities. Extensive health education campaigns and training in case management were carried out. Residual insecticide spraying with DDT was resumed. The houses of the entire Lowveld and Lubombo Plateau communities were sprayed and within a few years coverage rates of over 80% were achieved. Where there was evidence of local transmission in the Middleveld indoor residual spraying was also carried out (Packard 1986).

In 1990, in order to decentralize malaria control activities and strengthen the timing, quality and coverage of residual spraying, two field centres were established. The centres, staffed by Environmental Health and other Technical Officers, include laboratories, accommodation facilities, a spray equipment repair workshop and

FIGURE 8.3. EPIDEMICS IN SWAZILAND 1917-1946: SOURCE PACKARD (1984).

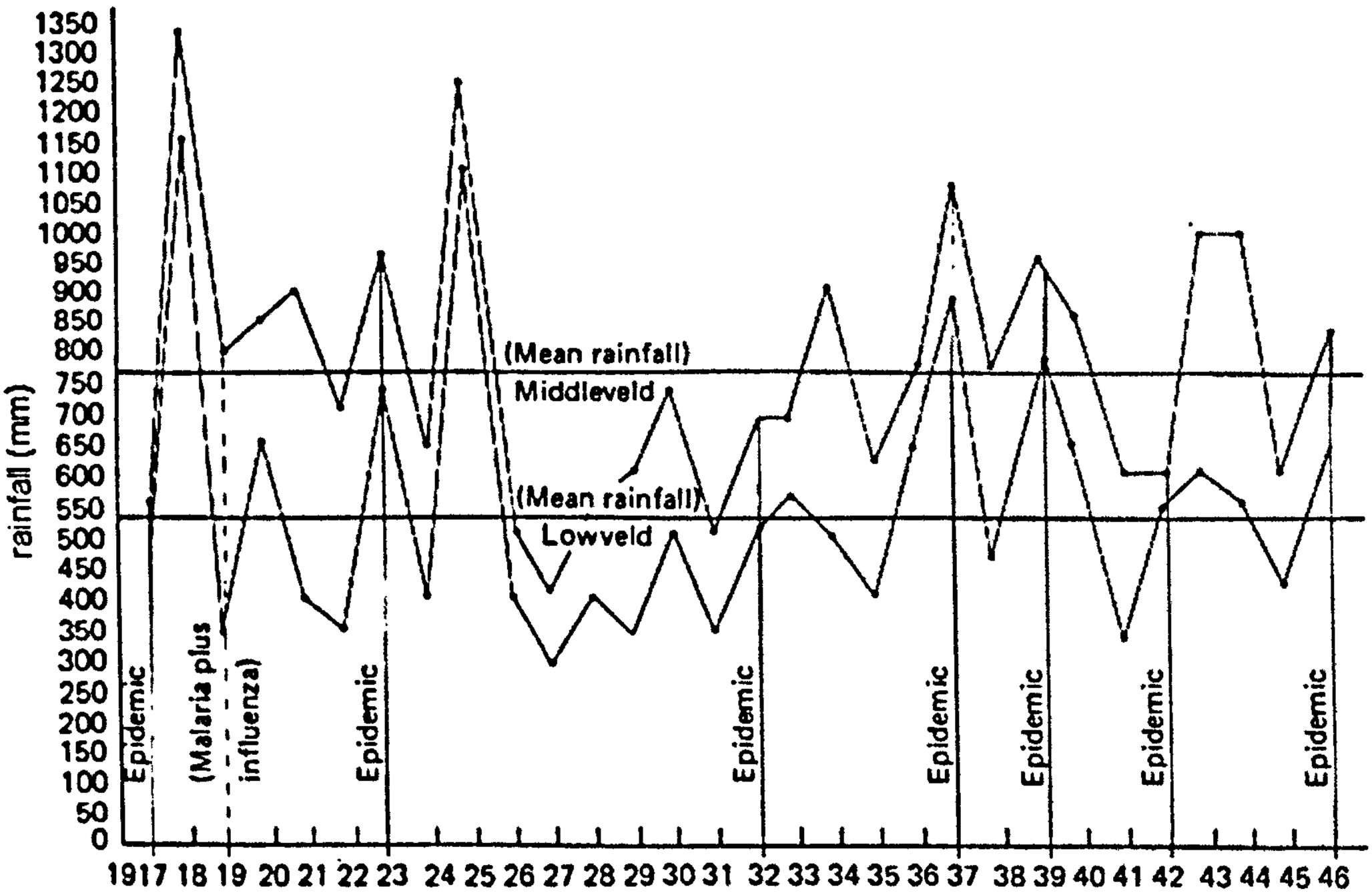


Figure 2. Annual summer rains (November–April) in lowveld (Homestead Station) and Middleveld (Manzini) and regional malaria epidemics.

insecticide storage facilities. The combination of these activities led to significant reductions in malaria morbidity and mortality. In 1992, only 480 laboratory-confirmed cases, 6258 clinical cases and no deaths were reported. During this period, the Government of Swaziland increased funding for malaria control and, as donor-support declined, absorbed the running costs of the programme. Currently, 95% of the NMCP's budget comes from the Government with the remaining 5% from the World Health Organisation. The NMCP receives about E2 million[25] per annum (1998/99 budget) as its recurrent expenditure budget from the Government of Swaziland, representing about 2% of the Ministry of Health and Social Welfare budget. Approximately E6.00 per person living in malarious areas per year is spent on malaria control (Kunene 1999).

In 1996 there was a serious malaria epidemic associated with high rainfall following several years of drought. Since then outpatient and inpatient cases have not fallen back to levels achieved in the early 1990s. There are likely to be a number of reasons for this. Between 1996 and 1999 Swaziland experienced higher than average rainfall totals, however since the cessation of the Mozambican civil war in 1996, the movement of people between Mozambique and Swaziland has increased. Relatively poor access to health facilities on the Mozambican side of the Lubombo Plateau, means that people frequently seek treatment in Swaziland. In addition to increasing the number of cases health facilities have to attend to, which is likely to have increased drug pressure and parasite prevalence rates, the efficacy of chloroquine, which has been the first-line drug since the mid1940s, appears to be declining. Both Mozambique and South Africa have reported high levels of chloroquine resistance and a chloroquine efficacy study conducted at one sentinel site in Swaziland in 2000 found a 16% treatment failure rate (Kunene: pers comm).

Currently the NMCP relies on the following control interventions:

8.2.1.1. Disease management

Prompt diagnosis and treatment with appropriate antimalarial drugs is recommended. At the community level Rural Health Motivators are trained to recognise malaria

[25] The Lilangeni (E) is the unit of currency in Swaziland it is tied to the value of the Rand at 1:1.

symptoms and refer suspected cases to a clinic. Diagnosis at the clinic is based on clinical observations. All patients suspected of malaria are treated with chloroquine and a blood slide should be taken and forwarded to a laboratory facility. The second line drug S.P. should always be available at clinics and all cases which do not appear to respond to chloroquine by the third day of treatment should be given this drug. It is estimated that blood slides are taken from 70% of suspected cases. The limited laboratory facilities often cannot cope during the peak malaria season and many cases are not parasite confirmed during this period. In an analysis of laboratory cases by age it was found that 6.7% of cases were in children under five, 9.8% in children aged between 5-9, 13.4% in children aged 10-14, and 70.2% in people aged over 15. Confirmed cases by district were: Lubombo 86.3%, Manzini 8.4%, Hhohho 2.6% and Shiselweni 2.6%. Cases by gender were 55% males and 45% females (Kunene 2000).

For severe and complicated malaria all patients are referred to an appropriate health facility. Diagnosis at this level is based on microscopy. Quinine remains the preferred drug of choice for severe and complicated malaria. The recent case fatality rate (average 4% between 1994-1998) is a current cause of concern.

8.2.1.2. Disease prevention

The success of the malaria control programme in Swaziland is largely attributed to vector control measures. Residual spraying of dwelling houses in malarious areas is carried out prior to each rainy season. On average 120,000 structures are sprayed. The programme aims to maintain a spray coverage of >90%. Larviciding is carried out by private companies in irrigated commercial agricultural estates to protect their workforce.

Chemoprophylaxis is recommended for pregnant women residing in the Lowveld, the Lubombo Plateau and some parts of the Middleveld. Visitors to these regions from nonmalarious areas are also recommended to use chemoprophylaxis, though it is recognised that compliance is very poor.

Community education in the use of personal protection (repellents and knock-down sprays) is carried out. However, there has been little success to date in the promotion

of insecticide-treated bednets in Swaziland. Public health education is carried out in schools and work places to raise awareness of the symptoms and appropriate treatment of malaria.

While it is recognised that there is a need for early detection and control of epidemics there is as yet no adequate routine surveillance system capable of achieving this. A number of sentinel sites have been established for a weekly reporting system (manual paper tally sheets) and collaborations have been developed with the National Meteorological Services. The NMCP has also been attending the Southern Africa Regional Climate Outlook Forum during the past few years and have used the information provided in control planning (Kunene 1998).

8.2.1.3. *Operational research*

The programme regularly monitors for insecticide resistance in collaboration with the SAIMR, Johannesburg, RSA. Studies on drug resistance are carried out in collaboration with the Medical Research Council in Durban, RSA.

8.3. Aims of this chapter

- To describe the spatial and temporal distribution of malaria in Swaziland.
- To compare and relate the spatial and temporal distribution of malaria to environmental variables in order to inform malaria risk mapping.
- To explore whether or not temporal environmental variables could be used in an early warning system for malaria epidemics in Swaziland.

8.4. Materials and Methods

The epidemiological data available for Swaziland was limited mostly to annual totals of inpatient cases by district for the period 1985-1999. Annual data on confirmed cases nationally were also obtained for the period 1982-1999. These data were entered into SPSS and analysed along with the environmental variables (as detailed

in previous chapters) which were also aggregated to annual figures. Incidence figures (per 1000 population) for each district were calculated using 3% annual growth rates prior to 1995 and 2% growth rates post 1995. The bivariate and multivariate analyses which could be carried out were limited in comparison to previous chapters. For example there was insufficient data to determine seasonality of malaria in Swaziland. Perceptions of malaria distribution and its control in Swaziland are linked strongly with the topographical zones. Unfortunately this is not reflected in the epidemiological data which is collected and aggregated by administrative district. Environmental data was therefore extracted using the administrative district (method as described in Chapter 5, section 5.5.2.1.3. to allow direct comparison with the epidemiological data.

8.5. Results

8.5.1. Distribution of malaria in Swaziland

The 'expert opinion' map of malaria distribution in Swaziland reflects the topographical settings quite well, Figure 8.4.

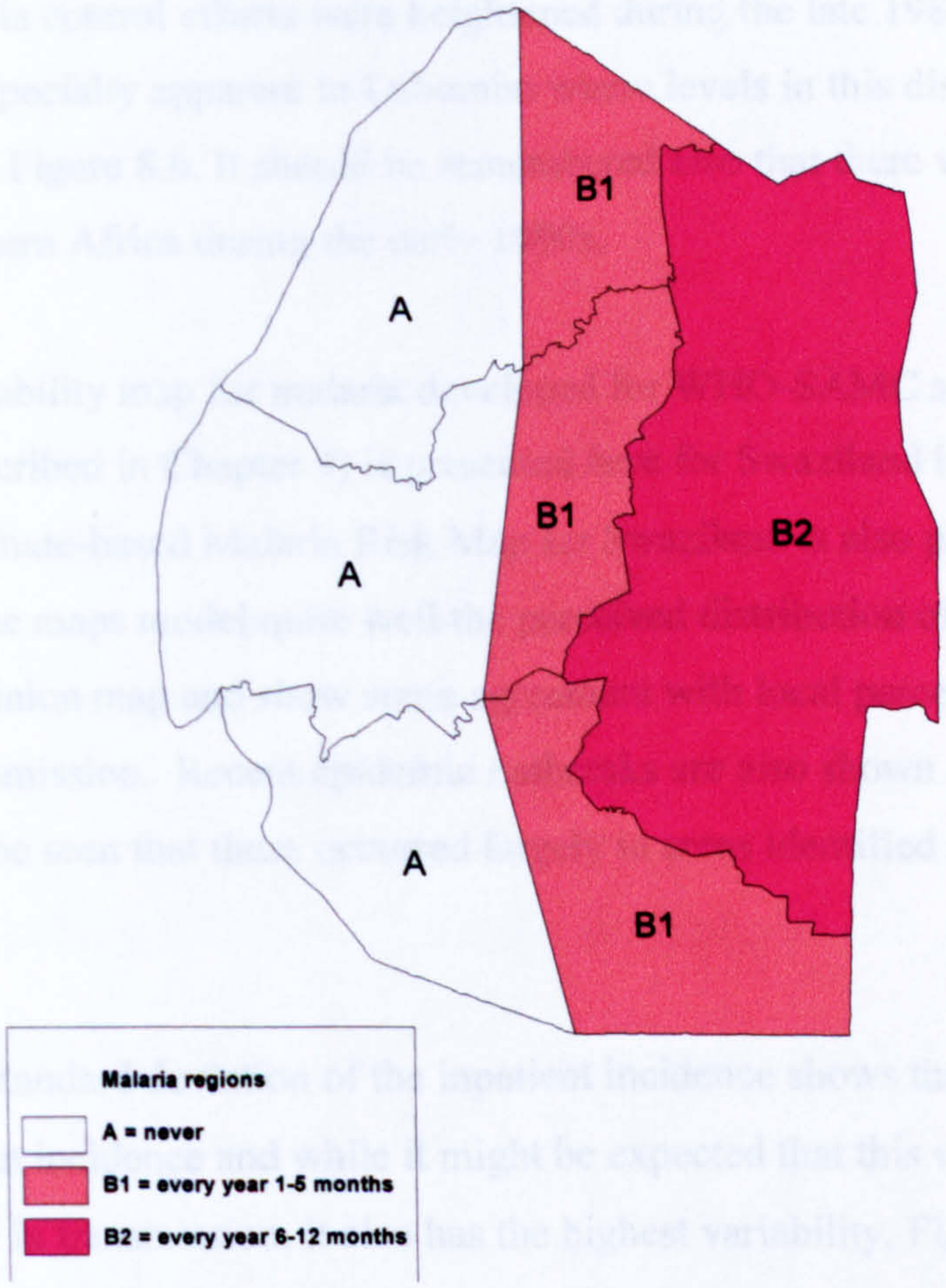
Due to its altitude, the Highveld is the only region that is considered completely non-malarious. The transmission season is expected to occur between November and May with March being the peak transmission month (Health Statistics Unit 1998). Approximately, 260,000 people live in malarious areas, and in Lubombo District all inhabitants are considered to be at risk of malaria, Table 8.2.

TABLE 8.2. ESTIMATED POPULATION AT RISK OF MALARIA, SWAZILAND 2001[26]

District	Total population		Number in malarious areas	
	<5	Total	<5	Total
Hhohho	40356	276502	4036	27650
Lubombo	31369	210341	31369	210341
Manzini	42350	304133	2118	15207
Shiselweni	33565	215380	1678	10769
Total	147640	1006357	39200	263967

[26] Source: 1997 Swaziland Population and Housing Census Vol 1 Statistical Tables, Central Statistics Office.

FIGURE 8.4. EXPERT OPINION MAP OF MALARIA DISTRIBUTION SWAZILAND, CIRCA 1998.



Legend:

The map was produced using district administrative boundary files supplied by SADC-RRSP (1997).

The incidence of malaria among the districts is shown in Figure 8.5. Lubombo has the highest, followed by Hhohho and Manzini with Shiselweni having the lowest incidence. Shiselweni did however have an epidemic in 1999, Figure 8.5. As stated previously malaria control efforts were heightened during the late 1980s and early 1990s. This is especially apparent in Lubombo where levels in this district fell below those elsewhere, Figure 8.6. It should be remembered also that there was a regional drought in Southern Africa during the early 1990s.

The climate suitability map for malaria developed for WHO-SAMC and WHO-HealthMap (described in Chapter 4) is presented here for Swaziland in Figure 8.7. The MARA Climate-based Malaria Risk Map for Swaziland is also produced for comparison. The maps model quite well the perceived distribution of malaria shown in the expert opinion map and show some agreement with local perceptions of stability of transmission. Recent epidemic outbreaks are also shown on the SAMC map and it can be seen that these occurred largely in areas identified in the map as less stable[27].

The mean and standard deviation of the inpatient incidence shows that Lubombo has the highest mean incidence and while it might be expected that this would suggest greater stability in transmission, it also has the highest variability, Figure 8.8.

8.5.2. Bivariate analysis of epidemiological and environmental data

The exploratory bivariate analysis of individual environmental variables against incidence showed that there is a good relationship between lagged RFE and malaria inpatient incidence in Hhohho, Manzini and Lubombo. The strongest relationship was RFE lagged by 4 months in Hhohho ($R^2 = 0.994$). The second strongest relationship was RFE lagged by 3 months in Lubombo ($R^2 = 0.764$). Manzini had the third strongest relationship with RFE lagged by 4 months ($R^2 = 0.584$). Shiselweni did not exhibit strong relationships with any of the environmental variables, the best relationship was with vectorial capacity (RFE lagged 3 months) lagged by 1 month ($R^2 = 0.292$).

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[27] The epidemic outbreaks were identified in collaboration with members of the Swaziland NMCP.

FIGURE 8.5. INPATIENT MALARIA INCIDENCE BY DISTRICT 1985-1999.

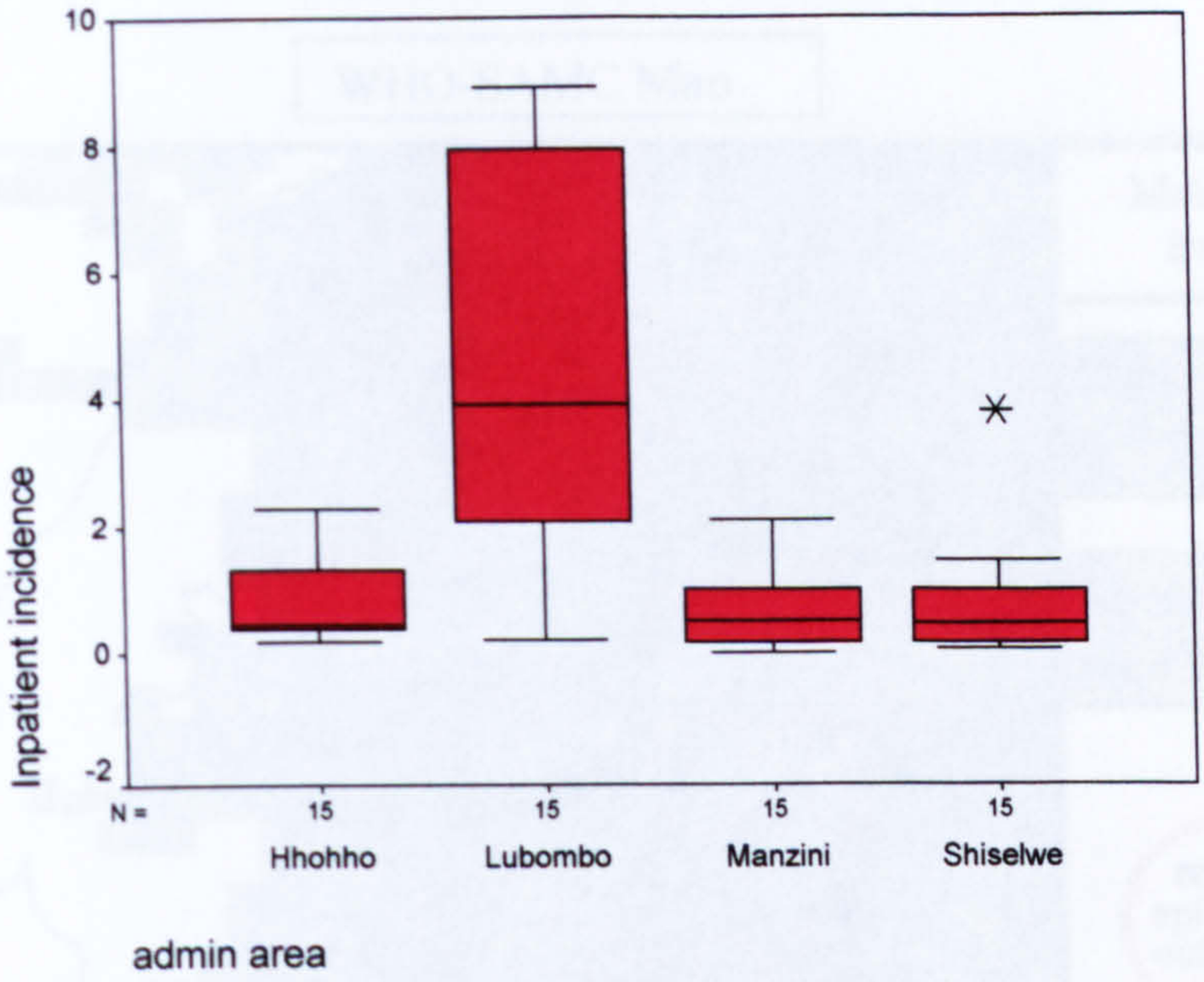


FIGURE 8.6. INPATIENT MALARIA INCIDENCE BY YEAR, BY DISTRICT, 1985-1999.

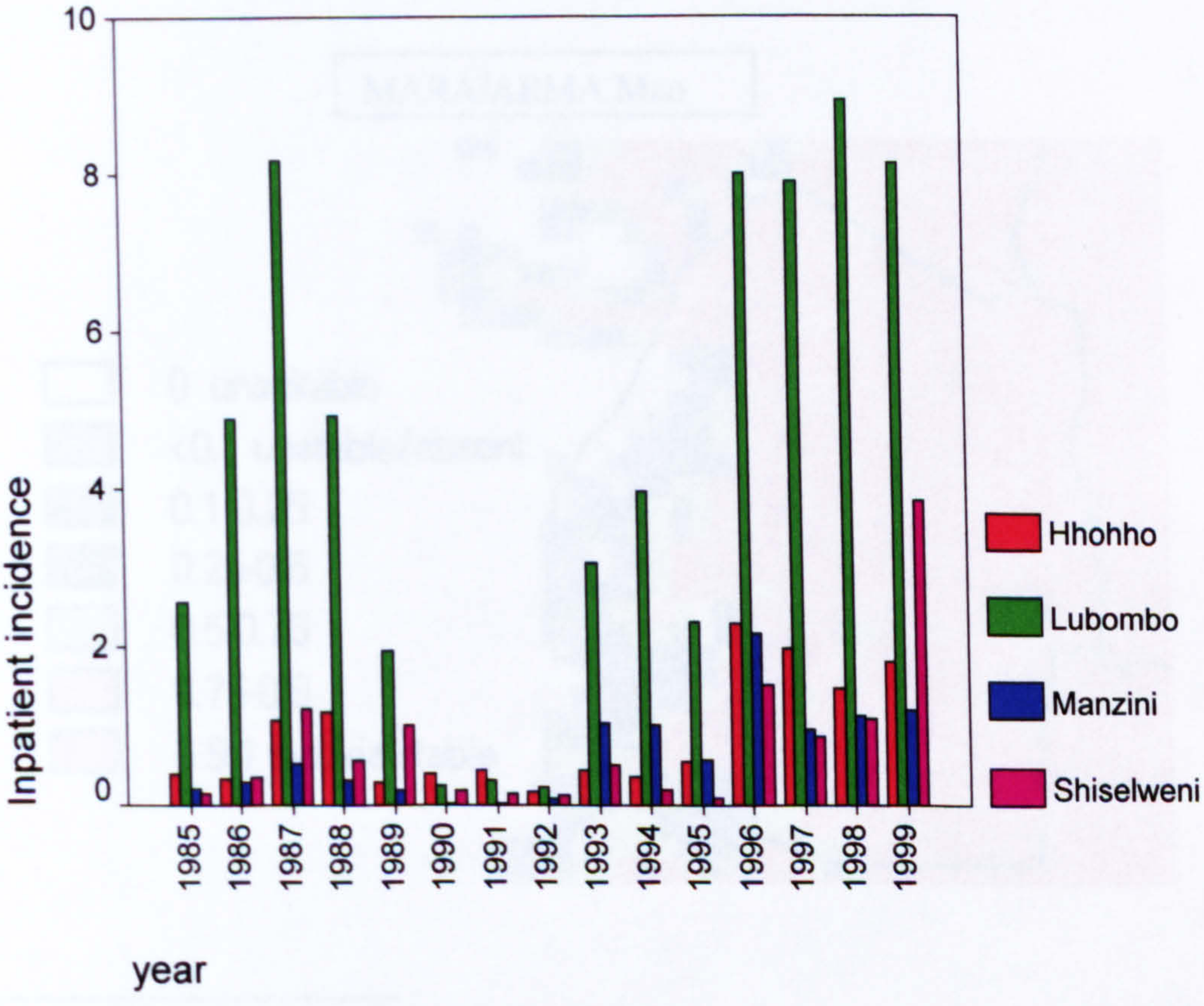
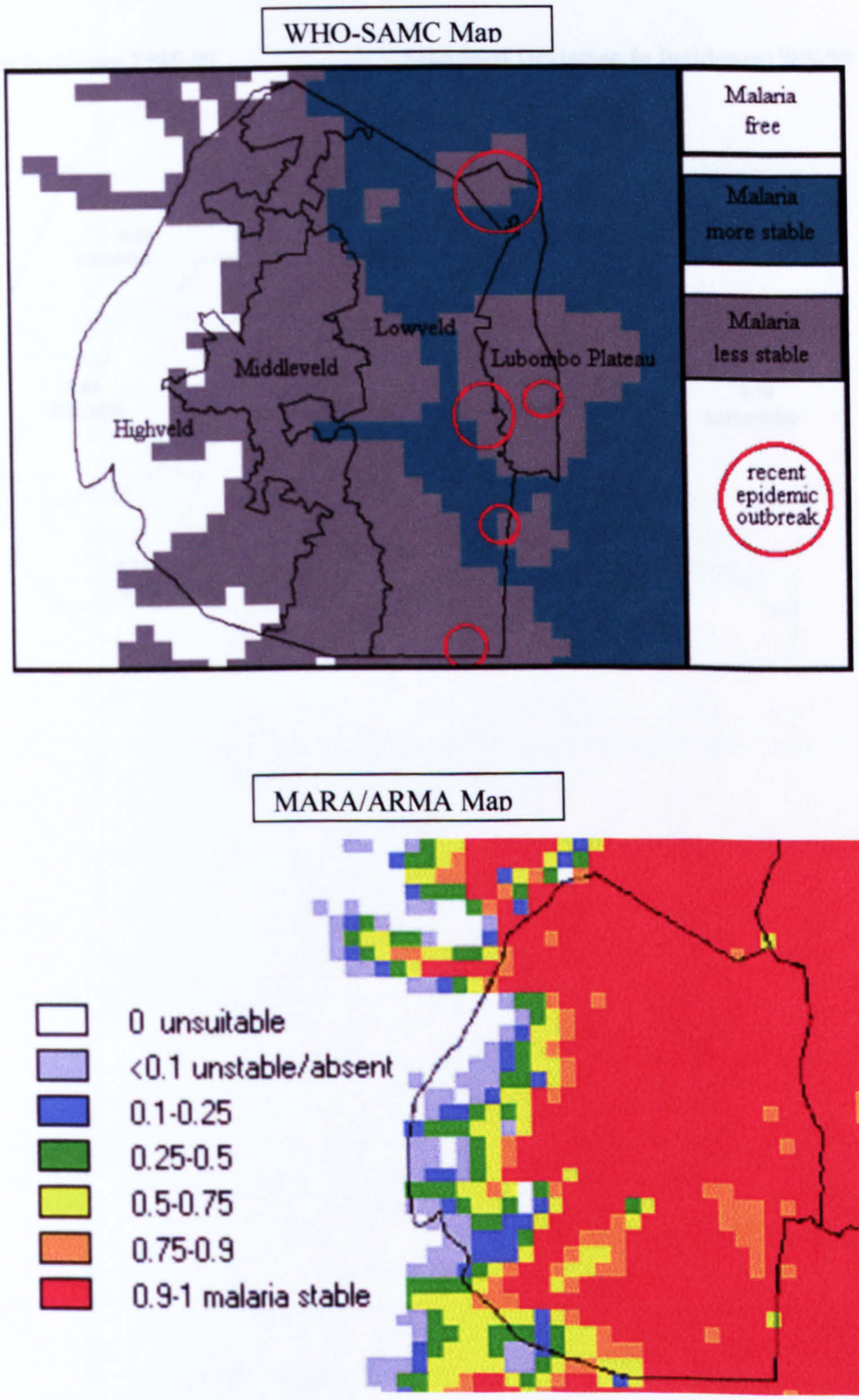
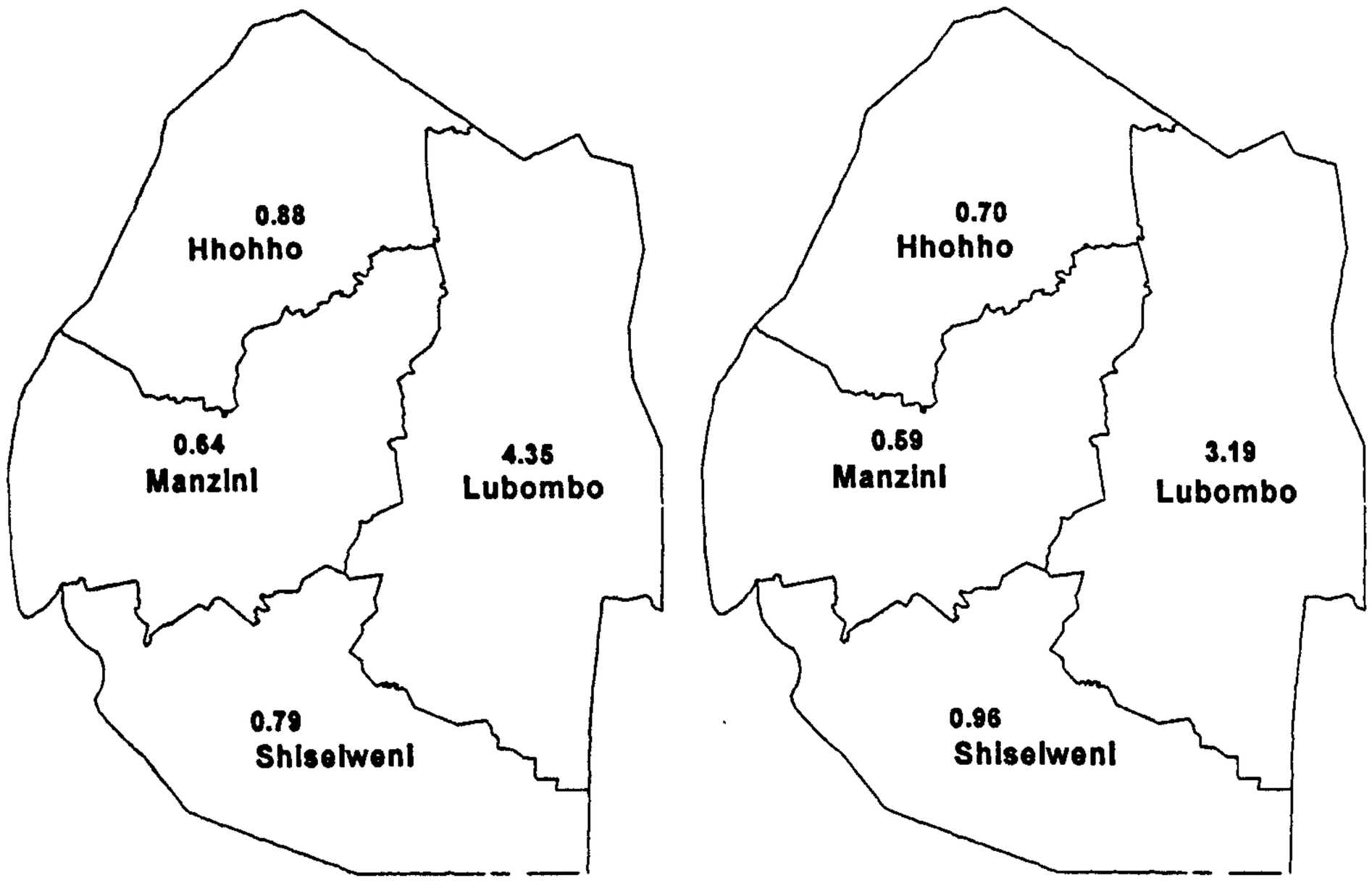


FIGURE 8.7. CLIMATE SUITABILITY MAPS FOR MALARIA IN SWAZILAND[*].



[*] The WHO-SAMC map is that described in Chapter 4. The MARA/ARMA Map produced here is derived from the country products available from the MARA website: www.mara.org.za

FIGURE 8.8. INPATIENT INCIDENCE, MEAN AND STANDARD DEVIATION, BY DISTRICT.



8.5.3. Linear regression modelling

The multiple linear regression modelling produced the following results:

8.5.3.1. Hhohho

In Hhohho District the single variable RFE lagged by 4 months out performed all combinations of variables, Table 8.3. Producing an R^2 value of 0.994.

TABLE 8.3 MODEL SUMMARY

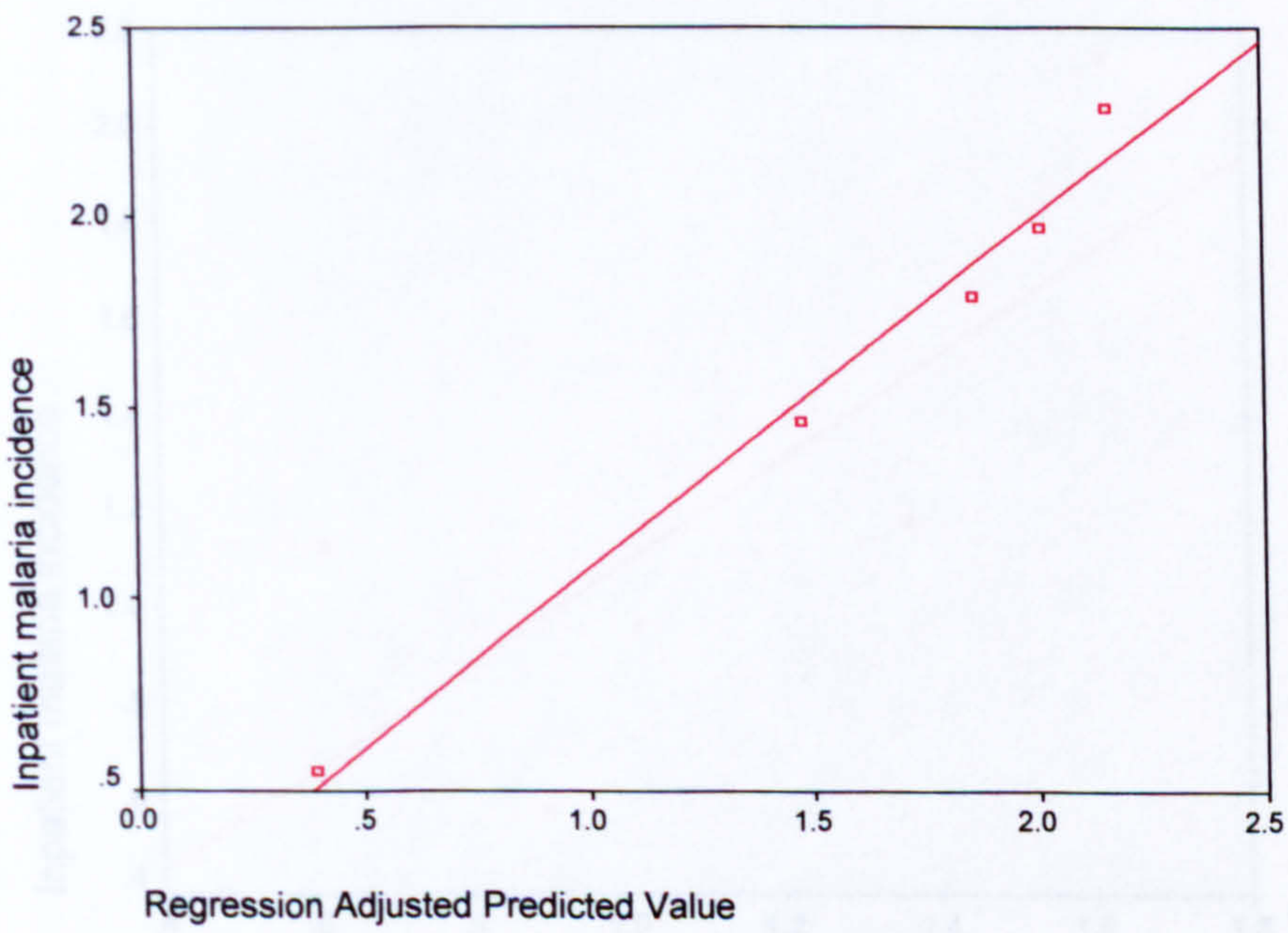
Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.997	0.994	0.992	5.941E-02

Coefficients of the model

		Unstandardized Coefficients		t.	Sig.
Model		B	Std. Error		
1	(Constant)	0.274	0.066	4.165	0.025
	RFE_LA_4	2.461E-02	0.001	22.256	0.000

Dependent Variable: inpatient incidence

FIGURE 8.9. RELATIONSHIP BETWEEN INPATIENT MALARIA INCIDENCE AND PREDICTED VALUES HHOHHO.



8.5.3.2. Manzini

TABLE 8.4. MODEL SUMMARY

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	0.928	0.861	0.814	0.2501

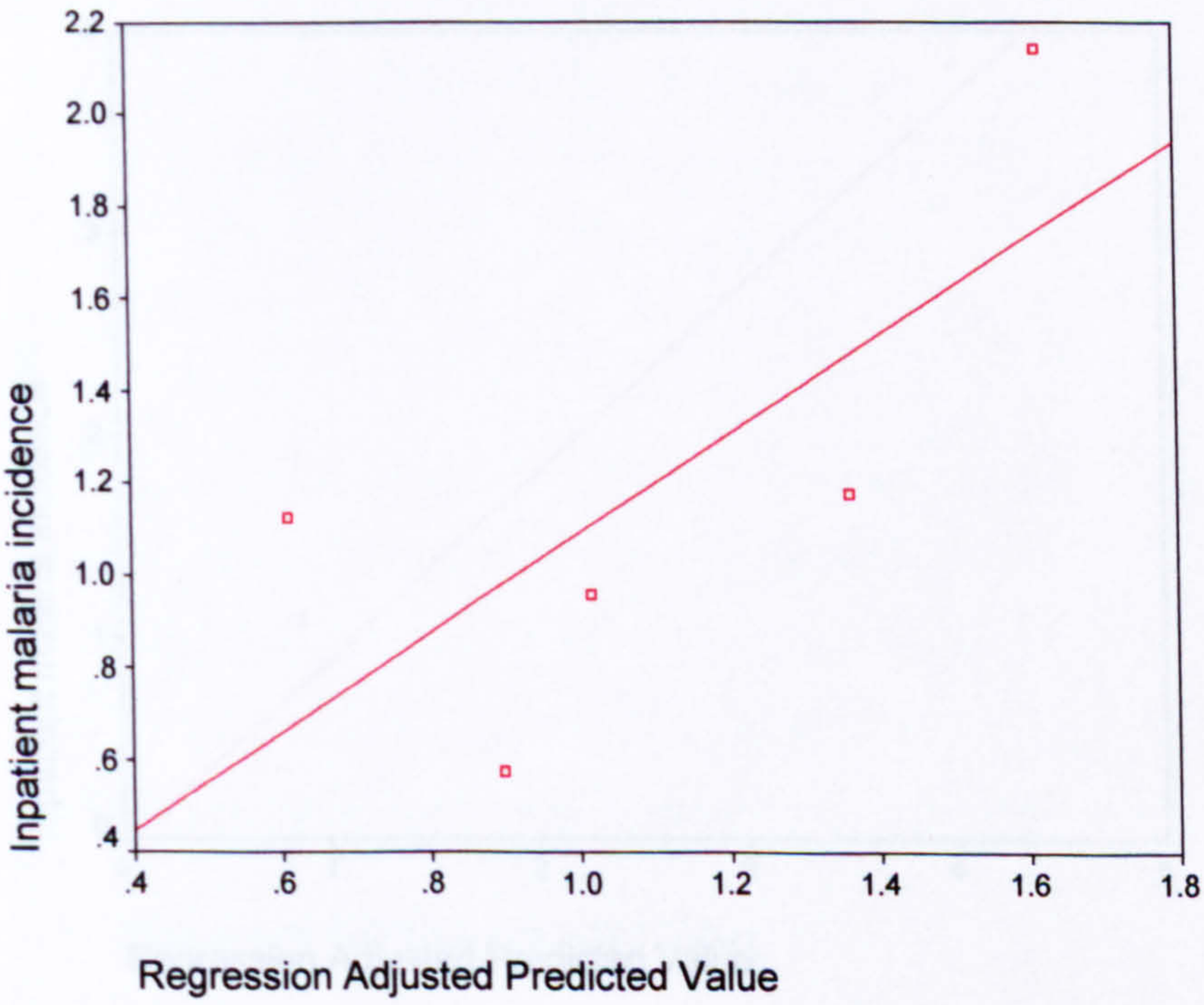
Coefficients

		Unstandardized Coefficients		t	Sig.
Model 1		B	Std. Error		
	(Constant)	-1.358	0.603	-2.251	0.110
	VCLAG2_1	1.287	0.299	4.304	0.023

Dependent Variable: inpatient incidence

In Manzini the single variable lagged vectorial capacity product showed a good correlation, R^2=0.86, against inpatient incidence.

FIGURE 8.10. RELATIONSHIP BETWEEN MALARIA INPATIENT INCIDENCE AND PREDICTED VALUES, MANZINI.



8.5.3.3. Shiselweni

TABLE 8.5. MODEL SUMMARY

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	0.998	0.996	0.992	0.1308

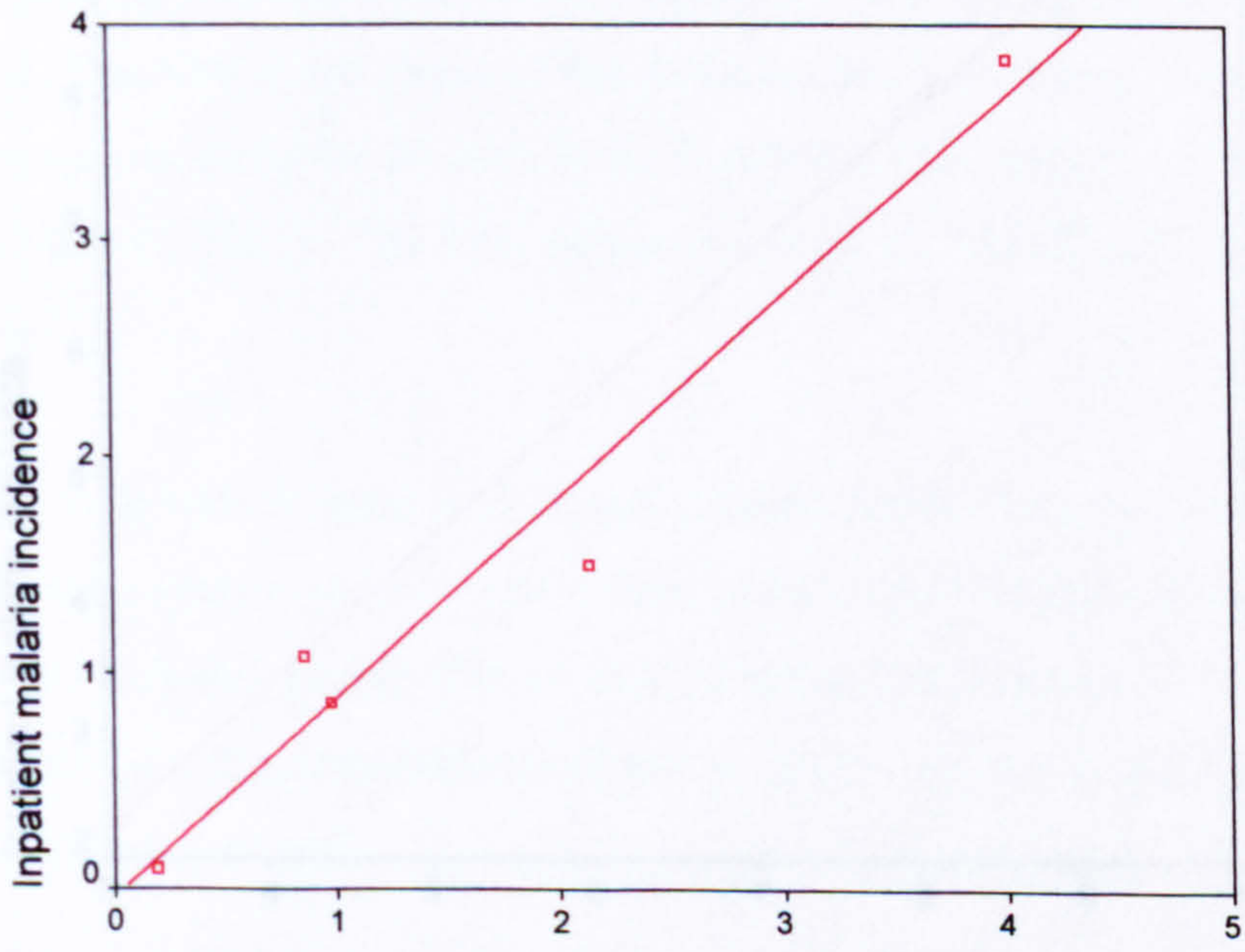
Coefficients

		Unstandardized Coefficients		t	Sig.
Model 2		B	Std. Error		
	(Constant)	-2.504	0.273	-9.164	0.012
	CCD_LAG_5	3.028E-02	0.002	19.065	0.003
	VCLAG2_1	0.717	0.131	5.491	0.032

Dependent Variable: inpatient incidence

The model for Shiselweni required 2 environmental variables to produce an R^2=0.996. The model suggests that the lagged vectorial capacity product and CCD are strongly and positively related to inpatient malaria incidence.

FIGURE 8.11. RELATIONSHIP BETWEEN INPATIENT MALARIA INCIDENCE AND PREDICTED VALUES, SHISELWENI.



8.5.3.4. Lubombo

TABLE 8.6. MODEL SUMMARY

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
2	0.999	0.998	0.995	0.1872

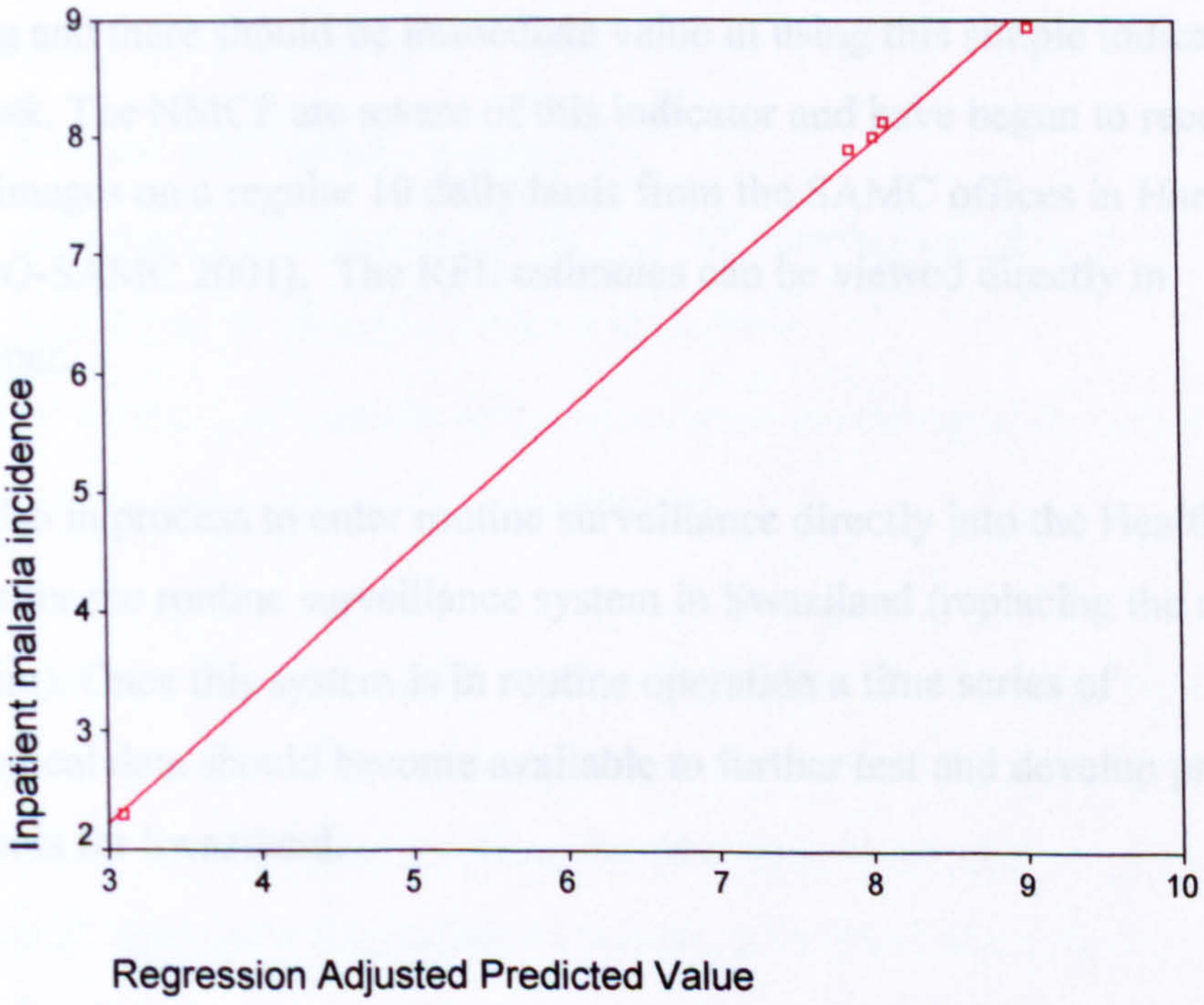
Coefficients

		Unstandardized Coefficients		t	Sig.
Model		B	Std. Error		
2	(Constant)	-8.850	1.010	-8.760	0.013
	VCLAG3_1	11.537	0.987	11.692	0.007
	RFE_LA_5	-0.389	0.041	-9.512	0.011

Dependent Variable: inpatient incidence

The model for Lubombo is also very strong with an R^2=0.998. It shows that the lagged vectorial capacity product is positively correlated with inpatient malaria incidence, while estimated rainfall five months previous is negatively correlated.

FIGURE 8.12. RELATIONSHIP BETWEEN INPATIENT MALARIA INCIDENCE AND PREDICTED VALUES, LUBOMBO.



8.6. Discussion

Despite the lack of monthly time series data on malaria in Swaziland there are interesting relationships apparent between specific environmental variables (especially RFE and vectorial capacity products) and inpatient malaria incidence in Swaziland. The combination of environmental variables in models to predict malaria incidence in all districts in Swaziland is encouraging. Significant correlations were observed between environmental variables and annual malaria incidence in all four districts.

The climate suitability models for malaria also appear to fit the situation in Swaziland quite well and the SAMC version of the map has been adopted by the NMCP as a provisional part of its malaria stratification. Use of the map along with other geographical information within the HealthMapper[28] will form a basis for its malaria surveillance system (WHO-SAMC 2001).

To develop predictive spatial models that can be used as part of an early warning system for the early months of the season, as shown in previous chapters, then monthly epidemiological data needs to be available to drive the development of the maps. However, the strong relationship of lagged RFE in Hhohho is very encouraging and there should be immediate value in using this simple indicator of epidemic risk. The NMCP are aware of this indicator and have begun to receive RFE difference images on a regular 10 daily basis from the SAMC offices in Harare via email (WHO-SAMC 2001). The RFE estimates can be viewed directly in HealthMapper.

Plans are also in process to enter routine surveillance directly into the HealthMapper as the basis for the routine surveillance system in Swaziland (replacing the current paper system). Once this system is in routine operation a time series of epidemiological data should become available to further test and develop predictive mapping tools for Swaziland.

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[28] The HealthMapper is a freely available software distributed by WHO for routine data entry, surveillance data management and reporting.

9. Discussion of findings

9.1. Summary

The work in this thesis is based on the premise that Environmental Information Systems (EIS) are tools that can assist research into vector-borne diseases such as malaria. Furthermore, that these same tools can also contribute to malaria control planning.

The stated hypotheses of this thesis are:

a) That EIS can provide information on the spatial and temporal patterns of malaria transmission found in Africa, at four levels of scale: continental, regional, national and district

b) and further, that EIS may be readily used alongside epidemiological data (as routinely available to national malaria control managers in Africa) to inform malaria control planning. More specifically in relation to:

- Stratification of malaria endemicity,
- Monitoring of environmental factors influencing variability in transmission, in unstable malaria situations
- Early warning of malaria epidemics based on changes in environmental factors in areas vulnerable to epidemics

The approach here has focussed on the use of information that is routinely available to malaria control planners at the national level, or in some cases sub-national level. The epidemiological data used is therefore the data malaria control programme managers routinely rely upon for decision making, whether that be confirmed or unconfirmed. The environmental information used is mostly derived from that used by regional food security and drought monitoring systems or international environmental monitoring organizations.

The review carried out in Chapter 1 provides background discussion of the role of geography in health. It clearly demonstrates the use of GIS and remote sensing as research tools and discusses their application to the ecology and epidemiology of a number of infectious diseases, including malaria. In Chapter 2 the concept of malaria stratification and attempts at its application to Africa are discussed and EIS products are demonstrated for use in a number of different Strata. The strata most appropriate for consideration here at the continental/regional level are:

1) The Forest and forest fringe stratum: where satellite derived information and map products are available from groups responsible for monitoring development pressure on forest resources. Changes in forest use or settlement can have a profound effect on malaria transmission. This EIS information can be readily accessed by, or provided to, national malaria control programmes to further develop or update their national malaria stratification, and help focus any entomological or epidemiological surveys as considered necessary.

2) African Savannah: this category includes vast regions of the continent within which malaria endemicity varies enormously. However, climate-based models of suitability for malaria distribution are available, or can be easily produced, which attempt to outline areas where malaria is stable or unstable, and of varying seasonality. While these products have become 'popular' they remain contentious and further validation is required before they can be considered valuable as control planning tools.

3) Malaria in highland or desert-fringe settings: Continental altitude surfaces are available and a number of studies have applied EIS information to historical and recent highland malaria epidemics in Africa. Highland areas are by their nature complex terrain and generally have an equally complex interaction with regional climate and seasonal weather systems. The relationship between altitude and temperature is also markedly affected by latitude and rainfall patterns. Their use in the highland setting is perhaps more appropriate to smaller area studies in combination with localised climate data. The use of EIS in desert-fringe settings are

considered to be more promising, as in Africa the vast majority of the deserts are warm deserts and temperature is a less critical factor in constraining malaria transmission. It is possible, therefore, to produce maps of potential epidemic risk based on low to moderate annual rainfall combined with high inter-annual variability of rainfall.

The use of EIS in the other strata identified: seashore and coastal, urban; and those linked to specific occupations and social conditions, gold mining, migrating agricultural labour and displaced populations (Najera, Leise et al. 1993) clearly require a much more localised and focussed approach.

In Chapter 3 the influence of weather variables on malaria transmission are discussed and consideration is given to the potential lead times available which may be gained by including and monitoring these variables in routine surveillance systems. The use of satellite derived rainfall estimates and their application to early warning in desert-fringe epidemic malaria settings is discussed. The development of a routine monitoring product that integrates both rainfall and temperature in a biological model of malaria transmission potential (an extended vectorial capacity product) is outlined.

The perceptions of malaria distribution, its endemicity, and its linkages with climate, surveyed from national malaria control programme managers in Southern Africa, are described in Chapter 4. Additionally the development of a climate-based map of 'more stable – less stable' malaria as a basis for further stratification of endemic-epidemic malaria zones in Southern Africa is outlined.

Chapters 5-8 test the relationships between routine epidemiological data on malaria and a range of environmental variables (including the vectorial capacity products) in four Southern African countries, Botswana, Zimbabwe, Namibia and Swaziland. A regional analysis was not possible due to lack of comparibility (case definitions and age cohorts) of the epidemiological data between the four countries.

There is evidence that EIS information in combination with routine epidemiological data can be used to map the seasonality and distribution of malaria within a country. While the quality and reliability of the results rely on the quality and reliability of the data used, the models and maps produced for Botswana (based on confirmed cases) and Zimbabwe (based on unconfirmed cases) provide information of value to control services. Namibia by contrast relied on data aggregated to a few very large administrative units and as a consequence the spatial patterns in the modelled map of seasonality are questionable, especially in regard to the central and southern health directorates. The lack of a useful time series of monthly epidemiological data for Swaziland prevented mapping the seasonality of malaria. However, strong relationships between annual malaria incidence and environmental variables were shown for some districts.

The strength of the relationships between interannual and seasonal changes in both epidemiological and environmental data shows promise for the use of EIS in the development of malaria early warning systems in these countries. It was shown that combination products derived from environmental variables could be used in many situations, to provide a prediction of malaria incidence with at least two months advance warning. In some situations the use of rainfall estimates alone performed equally well. The best example is Hhohho district in Swaziland which, while data was limited, showed a relationship between unconfirmed malaria incidence and rainfall estimates with an R^2 of 0.99 which provides a lead-time of 4 months. In a situation such as this, there appears to be an immediate benefit in monitoring these products as a first component in epidemic malaria early warning systems.

The remainder of this chapter will consider the application of these findings in the current context of malaria control in Africa and its prospects for the near future.

9.2. Malaria control in Africa in the New Millennium

Within the context of potentially high mortality rates coupled with a limited capacity for control intervention, case management has been the mainstay of malaria control in Africa during the past 50 years. Recent targets to halve malaria related deaths by 2010 and halve them again by 2015, promoted by RBM (WHO 1998b), and adopted

by African ministers (WHO 2000) with support from their international partners, means that malaria control in Africa must become more proactive, more focussed and more effective. What are the prospects for this? The global burden of malaria is reported to be increasing, especially in sub-Saharan Africa, due to drug and insecticide resistance coupled with social and environmental change (Greenwood and Mutabingwa 2002). A study of 15 years of data from Kwazulu Natal, South Africa, shows a sharp rise in the incidence of malaria, especially in areas in close proximity to the Mozambique border (Kleinschmidt, Sharp et al. 2002). This is in a country which has practiced malaria control very successfully in the past (Sharp and Le Sueur 1996). The use of insecticide treated mosquito nets and other materials have been promoted heavily as an appropriate technology for prevention of malaria in Africa. However, their acceptance by communities in Africa has been mixed. In Tanzania for example, the production and uptake of nets has increased rapidly over the past few years. While in Southern Africa their uptake has been very limited. A number of countries in Southern Africa maintain preventative malaria control activities based primarily on the use of indoor spraying with residual insecticides. These activities have been shown to be very effective in the past at limiting the number of malaria cases. Especially so in areas where malaria is less stable. However, during recent years the spraying programmes have been in decline once more and the number of epidemics being reported in the region has grown as a consequence. Some of the epidemics have occurred in areas where transmission only happens periodically. However, most of these epidemics are sharp increases on the normal seasonal pattern beyond levels normally expected, and many of these are resurgent outbreaks due to inadequate control coverage. Both types of event can be triggered by unusual rainfall distribution.

In recognition of the role played by climate and seasonal weather patterns in malaria epidemics, there have been calls for increased collaboration between health services and other sectors. For example, the recommendations for the development of Health Information Systems in Africa ratified at the MIM Conference in Durban, 1999 stated:

"Forecasting tools producing simple summary indicators for use at the district level (.....) should be developed outside the health sector by climate/meteorological

forecasters, food security and drought monitoring systems and made available to public health services" (MIM 1999).

There are clear benefits in this approach as the cost to the health services appear minimal (in that the information is provided as a service by others). Also human resources in the health sector are often over-stretched, especially in the more peripheral areas where many epidemics occur. However, in order to minimise inappropriate response to epidemic warnings, health service personnel need to have some training in the interpretation of early warning indicators and be aware of the reliability of such information. While the use of rainfall difference images in some districts may show promise as a simple epidemic risk indicator, the occurrence of high rainfall alone does not necessarily mean an epidemic will occur. Other factors, such as recent drought, inadequate food security, or an influx of migrant workers, may be equally important. These need to be taken into account in deciding on levels of epidemic risk and in planning and focussing an adequate response. Historical analysis of malaria epidemics in Swaziland illustrate this well.

In the process of colonization in Swaziland, restrictive land practices were put in place that favoured the white settlers. This included agricultural policies which undermined local production and in turn led to impoverishment and social disruption among indigenous peoples. By the 1920s Swaziland was only able to produce 20% of its food requirement. It is suggested that the most profound impact of these changes can be seen in patterns of ill health and infectious disease (Packard 1984).

The four ecological zones in Swaziland stem from work by the Ministry of Agriculture in the 1960s (Murdoch 1969) when it was recognised that the economic development of these zones had, and would continue to have, a major impact on the epidemiology of malaria in the country.

In the pre-colonial period the vast majority of Swazis had inhabited the middleveld. They subsequently relocated to the lowveld encouraged by work in large-scale irrigated agricultural schemes in the area. Malaria transmission levels in the lowveld were endemic with periodic epidemics (see Figure 8.3, Chapter 8). In the epidemic of 1946, the first year in which extensive surveys were carried out, 50,000 cases of suspected malaria were recorded, and parasite rates among children of up to 100%

were found in the eastern lowveld (Packard 1984). The colonialists attributed malaria epidemics to high rainfall events which increased the availability of vector breeding sites. A study by a WHO consultant looked at rainfall and malaria incidence levels during 1966-1973 and found a significant relationship of R=0.9. The consultant immediately recommended using rainfall to forecast malaria epidemics in Swaziland (Ramakrishna 1974).

However, later analyses of the epidemic malaria situation in Swaziland suggests that while rainfall does indeed play a significant role in determining the incidence of malaria in a given year, it is not the only factor involved (Packard 1984). Packard argues that other equally important factors are parasite carriers migrating into areas where there are non-immunes, and the population's vulnerability to severe morbidity and increased mortality. It is suggested that the first of these is a function of labour pricing. The latter is considered to be a function of reduced immunity and poor nutrition. These may be brought about by drought, reduced access to grain, loss of cattle, and loss of milk in the diet. Packard supports these views with evidence from the particularly severe epidemics of 1932 and 1946 which were both clear examples of post-drought epidemics. Indeed with the exception of the epidemics in 1919 and 1937 (the first confounded by an influenza epidemic and the second a poorly reported extension of the previous year's epidemic) it appears that all epidemics in Swaziland had been post drought phenomena (Packard 1984). This analysis adds further weight to the need to include information on food security and drought assessment, as well as rainfall monitoring, in epidemic malaria forecasting systems. This is broadly in agreement with historical studies of epidemics in Ethiopia (Fontaine 1961) and early warning systems operated in pre-independence India (Christophers 1911; Connor, Thomson et al. 1999).

Despite its history of severe epidemics, Swaziland has also shown remarkable success in the control of malaria. Following the establishment of the NMCP in 1949 and the extensive use of indoor residual spraying, malaria parasite rates in children in the lowveld had, by 1952, declined to 2%. By 1959 surveys found rates had declined further to 0.11% (Packard 1986). By 1970 the perception was that malaria was firmly under control in Swaziland.

According to Packard (1986) the malaria control efforts in Swaziland mirrored the situation elsewhere in the developing world. The initial success and optimism of the 1950s and 1960s were followed by a dramatic resurgence in the 1970s. Packard argues that much of the blame for this resurgence was attributed to the 'Green Revolution' with increased vector resistance following widespread use of insecticides in extensive commercial agriculture. A WHO technical report of the time suggested "resistance is probably the biggest obstacle against vector-borne disease" and that this resistance is "a side effect of agricultural pesticide use"(WHO 1976). However, as Packard points out the resurgence occurred in Swaziland and other Southern African countries in the absence of widespread pesticide resistant strains of the vector (Packard 1986).

The activities and resources of the NMCP had been reduced dramatically following the decrease in the number of annual malaria cases. Simultaneously there was an increased resettlement of many Swazis into the lowveld. Many of the Swazis at this time preferred not to work in the commercial sugar estates and in response to this there was a rapid increase in the number of Mozambicans employed in Swaziland. Packard suggests that it was this combination of an influx of high numbers of parasite carriers living in close proximity to large numbers of non-immunes and low levels of malaria control which fuelled the resurgence of malaria in Swaziland during the 1970s. Here Packard argues that any programme designed to cope with Swaziland's malaria problem must go beyond the purely biomedical approach to malaria control. Further to this, a combination of effective surveillance (including food security, drought and rainfall monitoring) needs to be put in place alongside flexible vector control capacity and the screening of migrant workers (Packard 1986).

9.3. Malaria Early Warning Systems for Africa

9.3.1. What is an epidemic?

It is important to revisit this question. To some an epidemic is simply defined as 'a situation where malaria occurs due to a temporary imbalance in the existing

equilibrium such that R^0 rises above 1.0. This according to Najera (1998) is a 'true epidemic'. They can occur for a number of reasons (as discussed in Chapter 3) but are most commonly due to abnormal meteorological conditions (Najera 1998b). To others the definition of an epidemic has to include unusual sharp increases in the normal seasonal malaria pattern (Gilles 1993). These may, or may not, be due to declining levels of control coverage or the effectiveness of control tools used. If they are they can be termed 'resurgent outbreaks.' Either way, they too are often associated with abnormal meteorological conditions (Najera 1998b). A third type of 'epidemic' can be identified which is a slower, insidious increase in malaria which results from a number of factors. These factors include, political unrest, wide spread population movement, declining health infrastructures, poor levels of food security. These epidemics, as in the recent case of Rwanda, may manifest themselves as a build up in the number of cases over a period of years, sometimes as a series of 'steps', until the level of malaria cases reaches a point where the situation becomes an 'epidemic emergency'. Is this latter situation an epidemic? If so when did it start? Was it a series of epidemics which were not dealt with and so escalated into one component of a complex emergency? Although this latter situation does not fit comfortably even within the broader definitions of an epidemic (Gilles 1993). It is still an example of a situation of control need that effective malaria early warning and surveillance systems need to be able to inform upon.

These three epidemic situations were recently recognised as discreet contexts requiring different types of early warning approach (WHO 2001a). The first should be based primarily on environmental monitoring with other supplementary information (such as community vulnerability reports from food security and drought monitoring services) collected to inform control response as appropriate. The second should primarily rely on calendar-based control with environmental monitoring and surveillance to guide intervention and inform of risk of unusual circumstances and help focus additional control response in situations of increased risk. The third requires a broad approach to community vulnerability and risk monitoring. While environmental monitoring information will be important in warning of risk of 'trigger events', information on population movement, nutritional and economic status, health service delivery (and access) and the political context are critical.

It would appear to be the case that in the majority of epidemic situations there is a progression of vulnerability among affected communities, which is then 'triggered' by an event such as unusual rainfall (Connor and Thomson 1998). This premise forms the basis of the recent RBM framework on developing malaria early warning systems (MEWS) in Africa (WHO 2001b). The recommendations are that MEWS are developed on four 'pillars': vulnerability assessment, seasonal climate forecasting, environmental monitoring and epidemiological surveillance.

9.3.2. Vulnerability assessment

It is often the case that the 'desert-fringe' epidemic prone countries in Africa are those same countries which suffer chronic food insecurity, and in the worse cases periodic famine. The benefits of linking epidemic malaria early warning (MEWS) within existing food security and drought monitoring (FEWS) are clear. In many cases the FEWS have an operational surveillance and vulnerability assessment process gathering information directly relevant to MEWS, Table 9.1. FEWS consider malaria to be a food security issue and are willing to collaborate more closely with health services. The issues concerning FEWS offer significant lead-times in respect to changes in epidemic risk in affected communities. FEWS also run training workshops in selected countries to enable local services to interpret information gathered, gauge the reliability of indicators, and assess the severity of drought and food shortfalls that are likely to occur. The opportunity to include epidemic risk is there, as is the opportunity to include health service personnel among the workshop participants. Clearly it would also be valuable for any workshop on the development of MEWS to include participants from these other sectors.

9.3.3. Seasonal climate forecasting

A further element in forecasting epidemics is the use of seasonal climate forecasts. These forecasts are often regionally focussed and involve a consensus of results from various climate prediction models, produced by groups in Europe and the USA. In 1996 the regional forecasts for Southern Africa began to be disseminated through regional workshops, held prior to the rainy season, and involving participants from

TABLE 9.1. SUMMARY OF DROUGHT MONITORING, FOOD SECURITY SYSTEMS AND MALARIA EARLY WARNING AND PREPAREDNESS[•]

Drought Cycle: (after Chelagatt, 1997)	Entering drought	1	Epidemic Cycle: (after Onori and Grab, 1980)	Pre-epidemic phase	1
	Suffering drought	2		Epidemic phase	2
	Recovering from drought	3		Post epidemic phase	3
	Between droughts	4		Inter-epidemic phase	4
Mapping/ Vulnerability Assessment	Drought history/climate variability		Mapping/ Vulnerability Assessment	Epidemic history/climate variability	
	Land-use/ecological zones			Land-use/ecological zones	
	Farming system			High risk occupations/activities	
	Medium-range seasonal forecasts			Medium-range seasonal forecasts	
Monitoring and Surveillance	Rainfall distribution		Monitoring and Surveillance	Rainfall distribution/Temperature anomalies	
	Vegetation condition			Vegetation condition	
	Recent production history			Recent epidemiological history	
	Status of agricultural extension			Status of routine control activities	
	Market prices cereals/livestock			comparable economic indicator? ^charges?	
	Livestock/People ratio			Livestock/People ratio	
	Malnutrition			Malnutrition	
	FAD/FED			Health care availability/entitlement	
	Displacement			Displacement/Migrations	
Intervention options	Maintain cereal availability		Intervention options	Check feasibility of timely residual spraying	
	Veterinary campaigns			Awareness campaign	
	Subsidised livestock purchase			Distribution of bednets/personal protection	
	Emergency health and nutrition			Larviciding	
	Relief feeding			Mass drug administration	

[•] It should be apparent that many of the indicators collected by existing Drought Monitoring and Food Security Systems are likely to be of benefit to malaria control staff. There is a good possibility of co-operation between DM&FSS as many see malaria and other epidemic diseases as a food security issue. It is recommended that liaison takes place between malaria control services and DM&FSS at the appropriate level. Regional DM&FSS may run training regular training courses that may benefit malaria control staff.

various sectors to consider the usefulness of the climate forecasts for planning purposes (NOAA 1996). The regional workshops: Southern Africa Regional Climate Outlook Forum (SARCOF); the Greater Horn of Africa Regional Climate Outlook Forum (GHARCOF): and les Previsions Saisonnieres de l'Afrique Ouest (PRESAO) have all included health personnel in their workshops to date. Where climate predictions forecast unusual rainfall (either above normal or returning to normal following drought) with levels of accuracy better than chance, then useful lead-times may be gained by malaria control services in respect of any increased epidemic risk. The current levels of accuracy achieved by these forecasts (believed to be 60-70%, but validation is limited) mean that they should be used as a 'first alert' only, a signal to make preliminary investigations of drug and insecticide stocks for example. Discussions are in process regarding the possibility of disseminating regional forecasts in a format that could be viewed directly in HealthMapper, a basic GIS tool being promoted by WHO for use in health systems surveillance.

9.3.4. Environmental Monitoring

The routine monitoring of rainfall distribution is a logical forward step on from forecasting. Observing if, when, and where forecasts for higher than normal rainfall did actually prove correct. If and where it did, then there can still be useful lead-times in terms of identifying and considering increases in epidemic risk and planning and implementing an appropriate control response. This 'second alert' is the time to act on preventative measures, as well as focussing the distribution of therapeutic drugs and services. National meteorological services in most African countries have access to 10 daily (dekadal) rainfall estimates. Most are able to produce difference images showing current estimates compared with expected for the time of year, as outlined in Chapter 3. A number of countries in Southern Africa (Botswana, Swaziland and Zimbabwe) now receive 10 daily rainfall difference images from WHO-SAMC via email. These images are viewable directly in HealthMapper and can be used by surveillance teams to identify, and consider, any rainfall anomalies which may increase epidemic risk.

9.3.5. Epidemiological Surveillance

Routine epidemiological surveillance systems capable of sufficiently early detection of malaria epidemics are yet to be developed in sub-Saharan Africa. However, there is a strong international commitment to improving and developing routine health surveillance systems which include malaria. There is also a growing acceptance of simple, purpose designed GIS systems, such as the HealthMapper, which can form the basis of health systems surveillance (WHO-HealthMap 1999). The availability of maps outlining areas of epidemic risk and updated information on changes in risk offer the possibility of at least informing surveillance teams where to look for epidemics, and when to be extra vigilant. A number of countries in Southern Africa are beginning to use HealthMapper as a basis for their health surveillance systems. However, if the sudden rise in the number of cases is the alert used to prompt activity, then unfortunately much of the opportunity for prevention is already lost.

9.4. Cost effectiveness of early intervention in malaria epidemics

Not surprisingly, the effectiveness of epidemic malaria control would be greater if the epidemic could be detected early and control activities put in place in sufficient time to avoid the high increase in case numbers. Recent work has investigated the financial benefits that could be realised from early warning systems which allowed adequate lead-times to ensure early response. The work shows that the cost:benefit ratio changes markedly in terms of timeliness and uncertainty and that much could be gained through the development of reliable early warning systems (Worrall 2001).

9.5. Drug policy

Effective malaria treatment requires effective drugs. The availability, affordability and use of effective drugs in Africa is in a state of flux. Many countries have high rates of resistance to their first line drugs and rapidly increasing rates of resistance in second line treatment. The alternatives are few, some are prohibitively expensive, and there are concerns over releasing these new drugs, or drug combinations, into a situation where inconsistencies and poor compliance are likely to produce rapid resistance pressure. It has been suggested that epidemic prone areas should have

regionally agreed policies on drug use, specifically for epidemics. Once an epidemic is past, those drugs should be withdrawn (Delacollette: pers. comm.). Mapping of epidemic prone areas is a clear requirement for this and should help stimulate cross border agreements on drug policy.

9.6. Vector control

Interest in vector control is currently being rekindled by its supporters, and its acceptability is beginning to grow amongst its opponents. If vector control activities can be seen to be flexible and effective control tools, selected rationally and based on evidence, from a number of control options then it is likely that further support will grow. Vector control has worked well in many areas in the past, and a number of writers continued to draw attention to this over the years (Kouznetsov 1977; Davidson 1982; Coluzzi 1992; Schofield 1993; White 1999).

A WHO-AFRO Workshop on a framework for the development and implementation of vector control interventions in the Africa region was held in Harare in 2001 (WHO-AFRO 2001). The workshop was opened by the WHO Regional Director for Africa, Dr Ebrahim M. Samba. In his opening remarks, Dr Samba emphasized that vector control was important in Africa because the majority of diseases of public health importance in the region were vector-borne. He regretted that most countries in the region tended to give priority only to curative measures while very little attention was given to prevention in general and vector control in particular.

The workshop focused on the concept of 'Integrated Vector Management.' It was stated that: "Vector-borne diseases constitute the major public health problem in the African Region. This transmission is influenced by vectoral, environmental and socio-economical factors. Due to this fact, control of vector-borne diseases requires an integrated approach that has a strong vector control component. Integrated vector management, therefore, seems to be the most appropriate approach to Vector Control" (WHO-AFRO 2001). The type of activities that would be carried out under integrated vector management are summarized in Table 9.2.

There are obvious applications in IVM where mapping and routine environmental monitoring would be useful. For instance:

TABLE 9.2. COMPONENTS OF INTEGRATED VECTOR MANAGEMENT. SOURCE WHO-AFRO (2001).

Type	Intervention	Targets	Products
Chemical control	Larviciding	Urban mosquitoes, blackflies	Microbial larvicides, organophosphates, neem extracts and other herbal insecticides
	Space spraying	Urban mosquitoes	Pyrethroids
	Indoor residual spraying	Vectors of malaria, lymphatic filariasis, leishmaniasis	Pyrethroids, organophosphates, carbamates, DDT
	Insecticide-treated materials	Vectors of malaria, leishmaniasis, lymphatic filariasis, trypanosomiasis	Pyrethroids
	Households products	Mosquitoes, flies, fleas	Coils, mats, repellents, natural products, etc…
Biological control	Larvivorous fishes	Mosquitoes	
	Predators and competitors	Snails	
Environmental management	Environmental changes	Mosquitoes, blackflies, snails, etc..	

- EIS have been used to identify areas where insecticide-treated bednets would have greatest impact
- EIS have been used to predict areas with high anopheline densities
- EIS have been used to identify areas where malaria is less stable and are therefore epidemic prone
- EIS can be used to monitor climatic, meteorological, environmental and hydrological changes which increase epidemic risk

An Integrated Vector Management for Malaria in Africa Symposium is to be held in Kampala, April 2002 to discuss these issues among many others.

9.7. Information Delivery

Who should produce EIS products for malaria control planning? The most simple products, the rainfall difference images, can be accessed directly from the USAID funded Africa Data Dissemination Service (ADDS) internet site. In Southern Africa these products are downloaded every 10 days by WHO-SAMC, processed for viewing in HealthMapper, and emailed out to countries able to use them. To date those countries (Botswana, Swaziland and Zimbabwe) are using HealthMapper, have been sensitised to the use of rainfall images, and have been trained, by the author, to interpret them for epidemic malaria control planning.

The rainfall difference images are currently being adapted specifically for use in desert-fringe epidemic risk areas. The areas where rainfall is sufficiently high and reliable to support endemic malaria, and cooler highland areas, will be masked out, leaving only the desert-fringe epidemic areas showing the rainfall difference. This work is being carried out by workers at the USGS who maintain the ADDS internet site, these products will become routinely available on the ADDS internet site.

In respect of the vectorial capacity images, these could also be distributed by WHO-SAMC in Southern Africa. Local information on the entomological inputs used in the vectorial capacity model should also be incorporated where available. For example, if the principal vector in a country is known to be *Anopheles arabiensis* and this vector is known to have a lower man-biting rate than the one used in the

continental model. An individual in the SAMC inter-country team has been trained, by the author, in the production of the vectorial capacity images and macros have been written to automate the process.

There are a number of options for delivery of EIS products for epidemic malaria control planning.

- Through a regional technical support office for malaria control, as stated above.
- Via regional or international FEWS services.
- Via regional or national meteorological services.

The actual route of delivery should be chosen according to what is possible and most reliable. It is important however, that MEWS products are developed in conjunction with broader health information systems development. It is also very important, that if such products are to be meaningful and useful, the end users are trained in their use and interpretation. Local use will help show what does work and where, and what does not work and where, and perhaps what else is needed. This will help in the validation of the products and enable their further refinement for local situations.

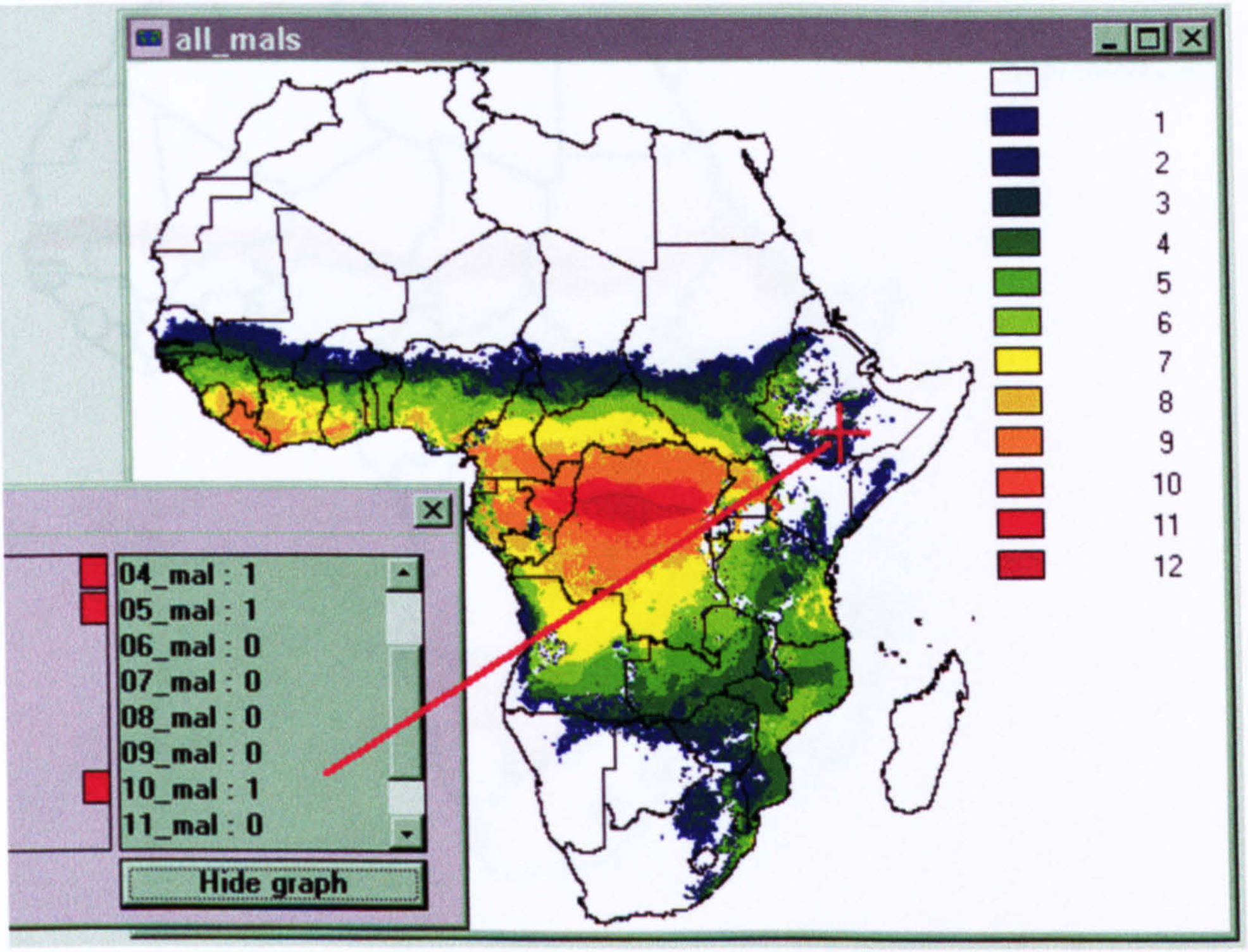
10. Conclusions

For the current malaria control strategy to succeed in reaching the agreed targets, to halve malaria related deaths by 2010 and half them again by 2015, the strategy must become more proactive, more focussed and more effective in sub-Saharan Africa where most malaria related deaths occur. To do this malaria control needs a variety of tools including rational and effective use of drug treatment, vector control, personal protection, community education, combined with the development of routine health surveillance systems and human resource development. Stratifying and monitoring areas at risk of perennial, seasonal and epidemic malaria is needed to help focus the use of the above control tools to most effect.

EIS have been shown to be useful research tools and have a clear role in helping to understand the ecology, and guide the control of a number of infectious diseases. The availability, to the health services, of purpose designed GIS (such as the HealthMapper produced by WHO-CDS) provides a useful platform for the development of routine health surveillance systems and focussed control planning. The ability to use EIS information within this same platform offers malaria control services supporting information on the seasonality of disease, and access to frequently updated information on changes in the local climate or environment, which can give warning of changes in epidemic risk occurring within their jurisdiction.

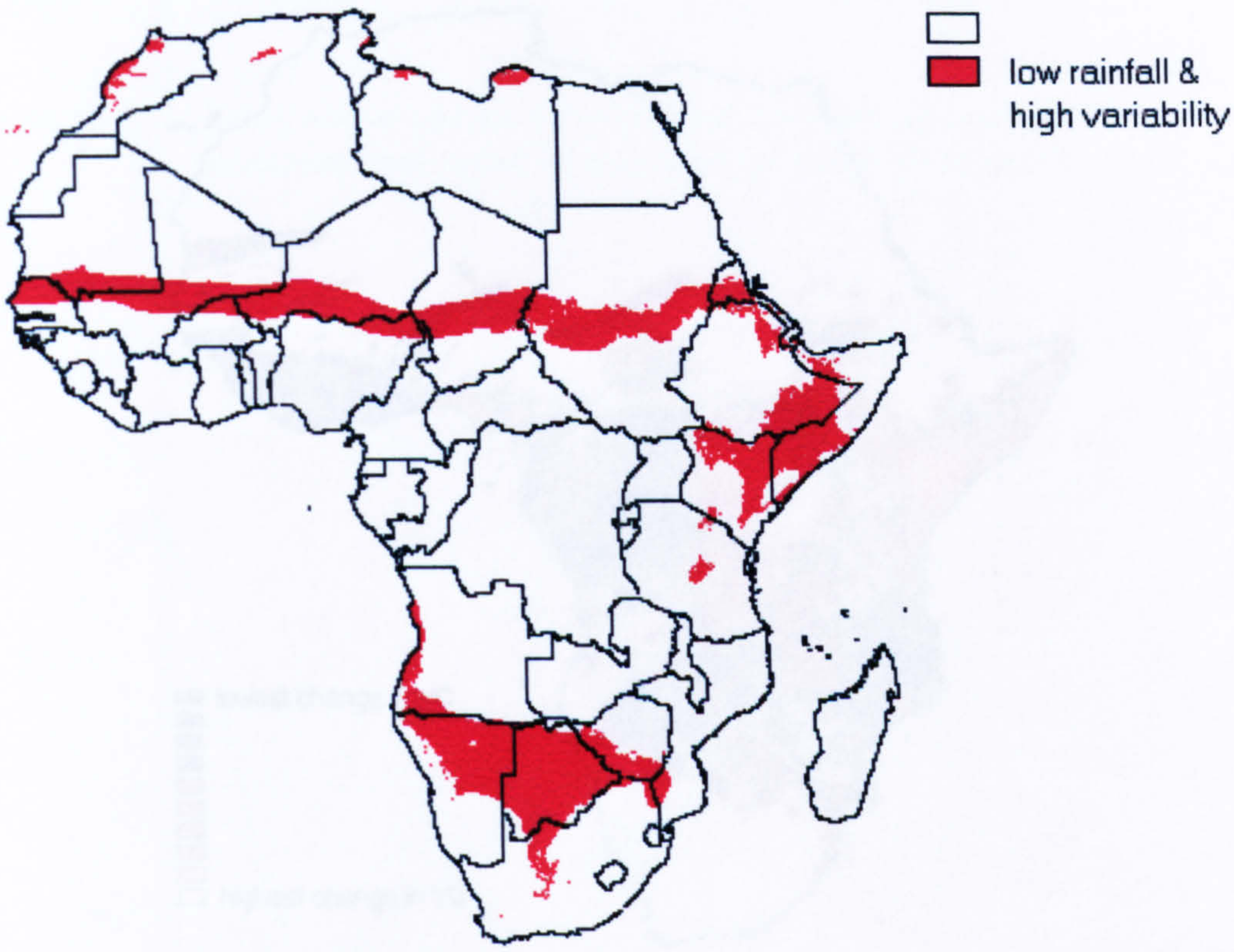
An 'interactive' climate based model of suitability for malaria transmission (developed here and described in Chapter 2) can provide guidance on where, and in which months, the climate may be considered suitable for malaria transmission to occur, Figure 10.1. This is a new development which goes further than previous attempts at developing climate-based maps of malaria risk. The active use of such a model within a GIS framework is useful in sub-dividing the extensive African Savannah malaria stratum, and makes a step towards answering Greenwood's criticism of existing malaria maps for the African continent (Greenwood 1999), cited Chapter 2.

Figure 10.1. Interactive GIS model of 'malaria risk' in Africa (developed and described in Chapter 2). Showing a specific enquiry for an area in southern Ethiopia.



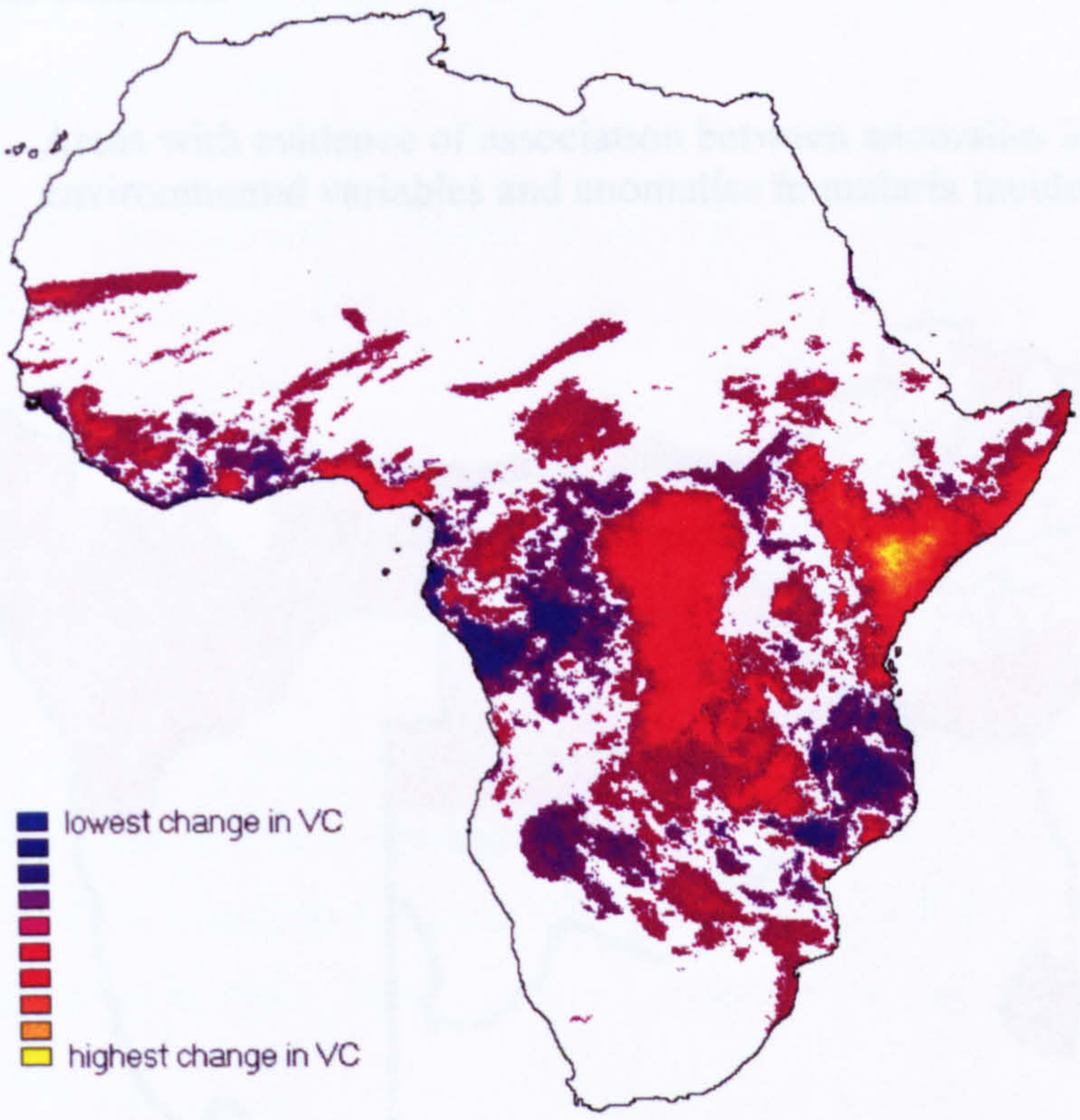
EIS have also been used here (as described in Chapter 2) to identify 'desert-fringe' zones, and map areas where the combination of low-moderate annual rainfall and high interannual variability in rainfall occurs, *Figure 10.2. These* are the areas of marginal endemicity, in which malaria epidemics are likely to occur when rainfall is abnormally high in a particular year, or as a result of a return to more 'normal' rainfall following drought years. These are the areas where routine rainfall monitoring should form the basis of a simple malaria epidemic early warning system, using rainfall difference products as described in Chapter 3. Other strata, Table 2.2 Chapter 2, need more detailed information which EIS may contribute to.

Figure 10.2. Desert-fringe strata for epidemic prone areas in Africa. Based on mean annual rainfall amount and interannual variability.



A method has been demonstrated here which uses EIS to provide frequently updated inputs (satellite derived rainfall estimates) into a vectorial capacity model (developed and described in Chapter 3). Currently the use of the vectorial capacity images effectively masks out areas where temperature (on average) acts as a constraint to malaria transmission (highland-fringes) and are a more focused malaria risk monitoring product for desert-fringe epidemics, than rainfall estimates alone. When improved, satellite derived, proxies for temperature become available these too will be able to be used as inputs into the models (substituting long-term mean temperatures) and may then become useful in monitoring highland-fringe epidemic settings, Figure 10.3.

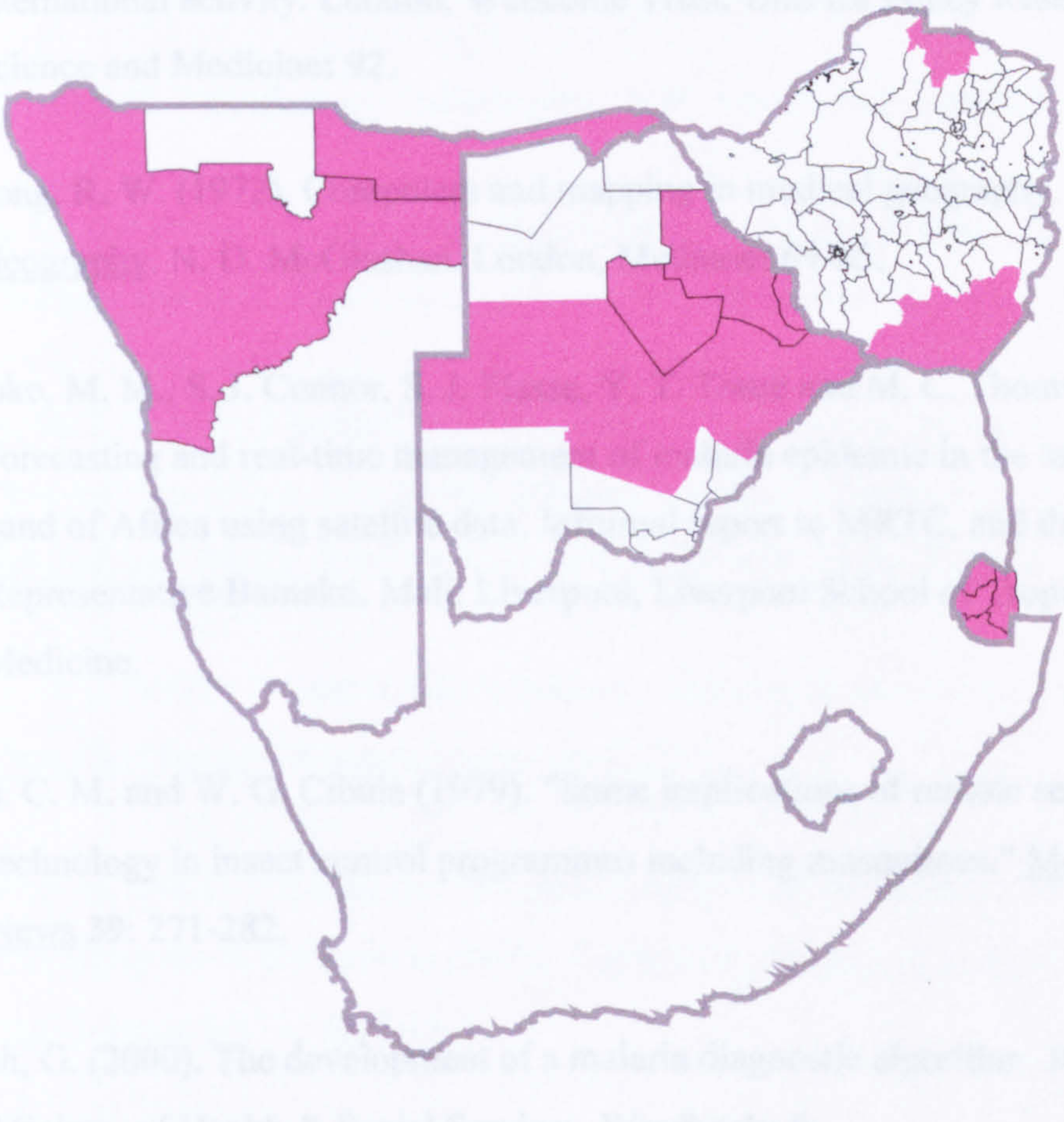
Figure 10.3 Vectorial capacity difference product for November, 1997.



Where countries have routinely available malaria incidence data (as defined and used by the NMCP for decision making) EIS can be used to model the seasonality of malaria transmission in its regions or districts based on the relationships between the malaria incidence data and environmental data available. This information will help in choosing control options, and in the preparation and timing of routine calendar based control planning in these regions or districts. The modelling of routine malaria incidence data and environmental information has shown that anomalies in environmental variables are correlated with anomalies in malaria incidence in certain regions or districts of the case study countries in Southern Africa. The map, Figure 10.4 shows the regions and districts of Namibia, Botswana, Zimbabwe and Swaziland that were tested here, and where evidence suggests, that routine monitoring of environmental variables (with at least 2 months lead-time) would be a useful component in malaria epidemic early warning systems in those countries. The map does not represent the results of exhaustive testing in all individual districts in Botswana (which was tested primarily according to latitude class) and Zimbabwe

(which was tested primarily according to altitude class) and it is possible that models for individual districts might also yield promising results, as shown from example districts in both countries.

Figure 10.4. Areas with evidence of association between anomalies in environmental variables and anomalies in malaria incidence levels.



Where possible, the development of Malaria Early Warning Systems should be fully integrated within the development of routine health systems surveillance, and in close collaboration with other sectors, who may collect supplementary information that provides greater precision in deciding where and when epidemics may occur. The information available from Food Security and Drought Monitoring Systems (information on migration and nutritional status) may also help determine the risk of severe disease outcome should an epidemic occur, Chapter 9, Connor et al (1999) and WHO (2001).

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