

Schistosomes, snails and satellites

S. Brooker *

Department of Infectious Disease Epidemiology, Imperial College School of Medicine, Norfolk Place, London W2 1PG, UK

Abstract

This paper gives an overview of the recent progress made in the use and application of geographical information systems (GIS) and remotely sensed (RS) satellite sensor data for the epidemiology and control of schistosomiasis in sub-Saharan Africa. Details are given of the use of GIS to collate, map and analyse available parasitological data. The use of RS data to understand better the broad scale environmental factors influencing schistosome distribution is defined and examples detailed for the prediction of schistosomiasis in unsampled areas. Finally, the current practical application of GIS and remote sensing are reviewed in the context of national control programmes. © 2002 Elsevier Science B.V. All rights reserved.

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1. Introduction

The small-scale focality of schistosomiasis (both intestinal *Schistosoma mansoni* and urinary *S. haematobium*) is well recognised. The causes of such heterogeneity are varied and reflect numerous human and ecological factors (Kloos et al., 1997, 1998; Woolhouse and Chandiwana, 1989), making small-scale distributions difficult to predict. Yet, because the effects of local heterogeneity are averaged out at broader scales, ecological patterns often appear more regular (Wiens, 1989; Levin, 1992). Identifying the broad scale patterns

of schistosomiasis is crucial because schistosomiasis control is often diluted at a national level but remains a public health problem in geographically restricted areas (WHO, 1999), and as such, there is a need to identify these areas.

The increasing use of geographical information systems (GIS) and remote sensing provides an opportunity to investigate the distribution of schistosomiasis at broad scales in Africa for the purposes of control. Although progress in this area has been made in China and Brazil (see Zhou et al., 2001; Bavia et al., 1999; Kloos et al., 1998) few studies have been undertaken in Africa, where the disease burden is greatest. The aim of the present paper is to review studies investigating the use of GIS and remote sensing for the mapping and prediction of schistosomiasis in Africa.

* Tel.: + 44-207-594-3291; fax: + 44-207-262-7912.

E-mail address: s.brooker@ic.ac.uk (S. Brooker).

2. Mapping schistosomiasis using GIS

GIS allows the ready collation, mapping and analysis of empirical survey infection data. The current use of GIS in mapping available data on schistosomiasis distribution builds upon the seminal *Atlas of the Global Distribution of Schistosomiasis* (Doumenge et al., 1987), which maps the occurrence of schistosomiasis in 76 countries worldwide, along with tables of observed prevalence for each study location. This work remains a valuable resource, but has the major disadvantage that the derived maps cannot easily be updated, and comparison between different maps is difficult. Yet, national control programmes require the latest data, which can be manipulated according to country needs. In an effort to provide a data resource for control, WHO with Imperial College London launched an international initiative that is collating the available survey data in a single database (Brooker et al., 2000a). This initiative has the twofold aim of describing, where possible, the prevalence of schistosome and intestinal nematode species across the continent and highlighting areas for which further information is required.

To date, the database incorporates 667 references, which includes 4355 independent cross-sectional surveys conducted since 1970, providing information on schistosomiasis for 33.0% of administrative areas with population density greater than five persons per square km (Fig. 1). The construction of such detailed distribution maps of infection is central to operational questions of defining endemic areas, quantifying populations at risk, and estimating programme costs (Brooker et al., 2000b). In many African countries, however, the paucity of epidemiological data hinders the quantification of disease burden for even this basic planning. In an effort to overcome this problem, environmental data often derived from satellite sensors, are increasingly used to map the spatial risk of disease (Hay et al., 2000; Rogers, 2000; Lindsay and Thomas, 2000).

3. Schistosomiasis risk models

It is well documented that climate and environmental variables influence the distribution of schistosomiasis (Brown, 1994; Appleton, 1978). So it is unsurprising that remotely sensed (RS)-derived environmental variables and meteorological variables are of potential in predicting broad-scale patterns of schistosome transmission (Brooker and Michael, 2000).

For example, in the investigation of *S. mansoni* distribution in Egypt, Malone et al. (1994) used 1 km resolution RS data recorded by the Advanced Very High Resolution Radiometer (AVHRR) onboard the National Oceanic and Atmospheric Administration's (NOAA) polar-orbiting meteorological satellites. They use these data to derive maps of diurnal temperature differences (dT), which indicate surface and sub-surface moisture contained in soil and plant canopy and hence may act as a surrogate for the abundance of the snail vector, *Biomphalaria alexandrina*, whereby wetter and more suitable habitats for *B. alexandrina* corresponded to lower dT values. They found that low values of dT are associated with increased snail abundance in wet areas with a slow current flow, and is closely mirrored in the patterns of *S. mansoni* prevalence.

Malone et al. (2001) also used 1 km AVHRR data to produce maps of Land Surface Temperature (LST) and Normalised Difference Vegetation Index (NDVI) to study the distribution of *S. mansoni* in Ethiopia. They found that annual composite maximum LST values of 20–33 °C and wet season values of 18–29 °C defined the distribution of *S. mansoni* prevalence greater than > 5% in Ethiopia, and used these limits to predict infection risk within the country.

Brooker et al. (2001a, 2002a) have used 8 km resolution AVHRR data to develop predictive models of *S. haematobium* in Cameroon and Tanzania. To examine the relationship between environmental factors and the prevalence of infection, they used uniquely detailed data from school-based studies country-specific. In Cameroon, infection prevalence was assessed parasitologically by examining urine samples for the presence of schistosome ova (Ratard et al., 1990). In Tanza-

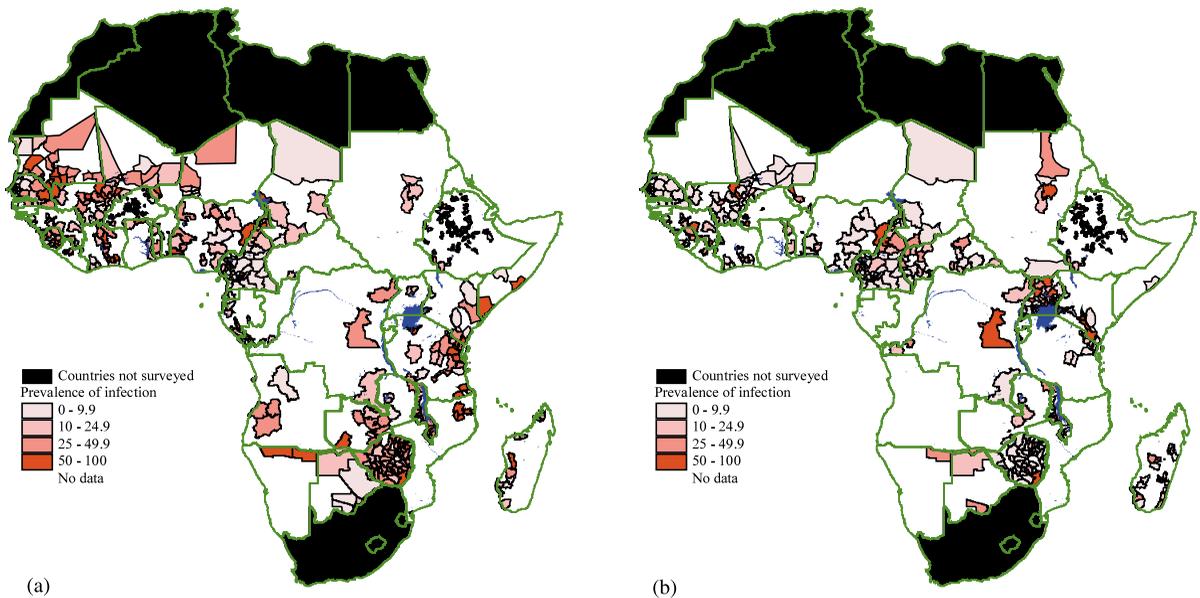


Fig. 1

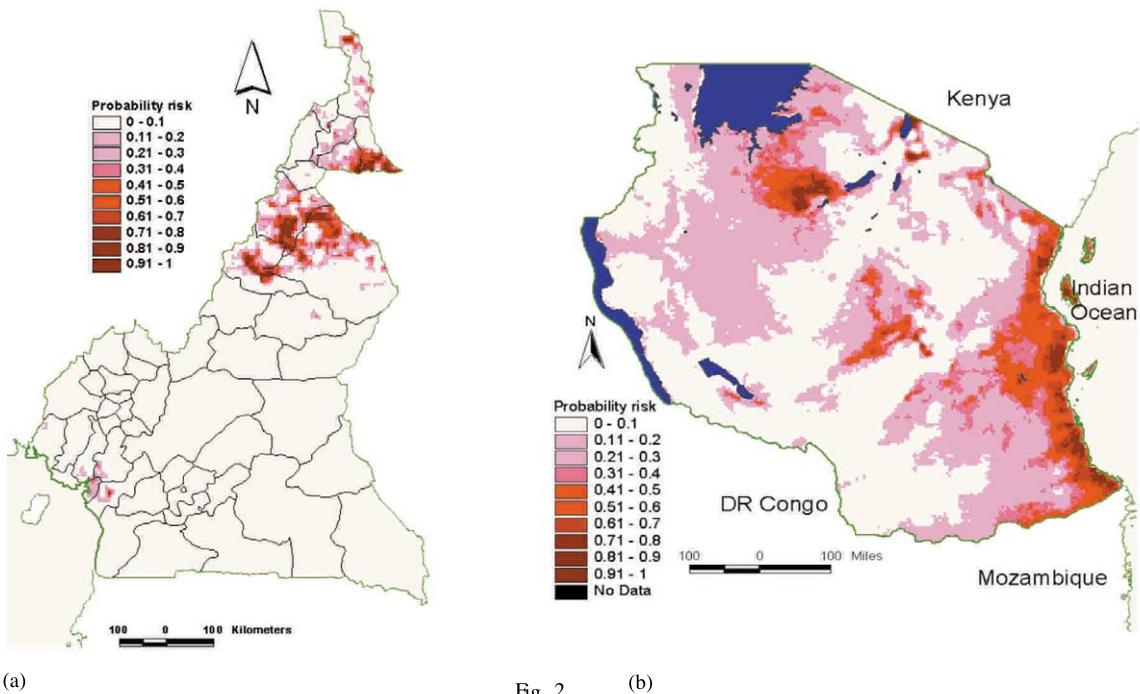


Fig. 2

Fig. 1. District-level distribution of: (a) *S. haematobium*; and (b) *S. mansoni* in sub-Saharan Africa based on available empirical prevalence data (Brooker et al., 2000a).

Fig. 2. Infection risk models for *S. haematobium* transmission in: (a) Cameroon; and (b) Tanzania. The map shows the probability of an area having an infection prevalence > 50% (Brooker et al., 2001a, 2002a).

nia, infection prevalence was estimated from carefully validated morbidity questionnaire surveys in which schoolchildren were asked whether they have urinary schistosomiasis or blood in urine (termed locally *kichocho*) (Partnership for Child Development, 1999; Lengeler et al., 1991; Guyatt et al., 1999). Several studies show that the prevalence in schools of self-reported *kichocho* underestimates the parasitological prevalence of infection, but by a consistent amount. This means that for each school the prevalence of *kichocho* can be reliably calibrated and used to exclude areas of low transmission from control efforts. Consequently, these data from Tanzania are used to define the extrapolated risk of having infection prevalence > 50%, and thus comparable to the parasitological data from Cameroon. They used these datasets to develop and validate models which predict whether the prevalence is > 50%. This threshold was chosen because it represents the WHO's recommended threshold for mass treatment.

Logistic regression models were developed to identify significant environmental variables affecting the transmission of infection. Separately, prevalence data from a 50% training set in Cameroon and that in Tanga Region, Tanzania were used to develop ecological models of the probability of having an infection prevalence > 50% (Fig. 2). The predictive accuracy of the models was then assessed using data from a validation set, which showed that the models for both Cameroon and Tanga Region allow reasonable discrimination between high and low prevalence schools, at least within those geographical areas in which they were originally developed.

The real test of accuracy and usefulness of any risk model lies in applying it to different locations (Brooker et al., 2002b). Validation of the model for Tanga Region using data from elsewhere in Tanzania indicated that the model performed reasonably well in neighbouring Kilosa District and further south in the similar coastal area of Mtwara Region, but performed less well in comparison in the Great Lakes area of Magu District. By contrast, the ecological model for Cameroon cannot reliably be applied to any region of Tanzania. These results are explained by reference to an

RS-derived ecological zone map, which suggests that the developed models have predictive accuracy only within the same ecological zone in which the model was developed (Brooker et al., 2001b). To understand these results further, it was also shown useful to consider the distribution of the snail species involved in local transmission since the models performed well in areas with similar snail species. Unsurprisingly, Malone et al. (2001) also found that the *S. mansoni* model for Ethiopia had limited application elsewhere in East Africa where different ecological conditions and snail species prevail.

Overall, these studies indicate that although schistosomiasis risk models can be developed, different habitat types and environmental requirements of each snail hosts will necessitate separate models for each snail–schistosome system. The challenge now is to build upon the current studies and to construct a composite risk map of schistosomiasis across the continent.

4. Ecology of schistosomiasis

In addition to predicting infection risk, studies using RS data also provide the opportunity to understand more completely the processes underlying broad scale patterns of distribution and so potentially improve our knowledge of the ecology of infection. Such studies can complement intensive studies of parasites and hosts that have investigated the micro-environmental determinants of transmission (reviewed in Brown, 1994; Appleton, 1978). Integration of these types of studies however, will depend on an appreciation of the central importance of spatial scale (Rogers, 2000; Brooker and Michael, 2000; Kitron, 2000). By appreciating the issue of scale, we can begin to link biological and RS data studies in epidemiology that will enhance our understanding of disease ecology.

Several types of remote sensing studies in East Africa highlight the importance of temperature in influencing the broad-scale distribution of schistosomiasis. First, Malone et al. (2001) showed that annual composite maximum LST values of 20–33 °C and wet season values of 18–29 °C defined

the distribution of *S. mansoni* prevalence > 5% in Ethiopia. These results are supported by experimental data: according to Pflüger (1980), Joubert et al. (1984, 1986) *B. pfeifferi* when infected with *S. mansoni* dies at temperatures below 16 and above 30 °C. Second, throughout the highlands of East Africa, populations of intermediate host species and schistosomiasis rarely occur in areas 1800–2000 m above sea level (reviewed in Brooker and Michael, 2000), where maximum LST temperature typically falls below 20 °C. Third, analysis of the distribution of schistosomiasis in Tanzania (Brooker and Michael, 2000) showed that a maximum mean LST threshold of 23 °C is necessary to yield an equivalent parasitological prevalence of 30%. However, above LST of 23 °C prevalence ranged from 0 to 97%, highlighting the role of small scale factors, that are suggested to differ from those influencing the broad scale distribution of infection (Wiens, 1989).

An important conclusion of these studies in East Africa is that schistosomiasis is not a public health problem in areas with temperature < 20 °C. In Cameroon, by contrast, a threshold maximum value of > 45 °C and a rainfall value of < 1500 mm is required for prevalence > 10% (Brooker et al., 2001a). The explanation for this difference with patterns in East Africa is that the predominant snail species in areas of high prevalence in Cameroon is *Bulinus senegalensis*, which inhabits semi-permanent water bodies and can survive the dry season by aestivation (Greer et al., 1990). In addition, the rarity of water points in the north leads to a concentration of human water contacts with fewer water points available, thus increasing the risk of transmission. The observed ecological distribution of transmission support Wright's (1959) original contention that *B. senegalensis* occurs throughout the semi-arid areas of West African Sudan Savanna.

The apparent differences in the ecology of infection between East and West Africa further emphasise the need for multi-scale investigations into the environmental requirements of the major snail host–parasite systems.

5. Application to control programmes

The recent developments in the mapping of schistosomiasis have the ultimate objective of providing information on the distribution of infection for purposes of control. Although unable to capture the well-known focality of schistosomiasis, large-area RS/GIS models can usefully stratify areas for planning national control activities. In particular, they can help exclude areas where schistosomiasis is unlikely to be a public health problem, and so help focus on priority areas where local targeting of treatment using specific procedures should be undertaken.

For *S. haematobium*, a simple questionnaire, administered by teachers to their pupils, can be used to identify individual schools/communities in which prevalence is 50% or greater and is high enough to warrant mass treatment. This approach has been validated by WHO and PCD (Red Urine Study Group, 1995; Partnership for Child Development, 1999) and used in over 10 countries in Africa.

For *S. mansoni*, by contrast, the use of questionnaires cannot be recommended at this time. The technique has been attempted but has not been uniformly successful (Booth et al., 1998; Utzinger et al., 2000; Lengeler et al., 2000; Brooker et al., 2001b). However, GIS studies in Kenya (Brooker et al., 2001b) and Tanzania (Lwambo et al., 1999) show that a single rapid assessment indicator of the need for mass treatment for *S. mansoni* is distance from the shore of large water bodies (Fig. 3). In Kenya a threshold of 5 km from the lakeshore correctly identified 90% of both low and high prevalence schools (Brooker et al., 2001b). Thus distance to the lakeshore assessed using GIS analysis may be used to include or exclude schools for mass treatment for *S. mansoni* in areas where transmission occurs near large water bodies. However, the actual distance to be used may need to be validated for each region, and further procedures are required in other areas such as irrigation schemes.

Before undertaking the local targeting of control, there is a need to estimate the initial target population for targeted interventions to support political decision-makers with data on which in-

ternational priorities for schistosomiasis control can be set. Overlaying available risk model predictions with available population data allows the school-aged population at risk of significant schistosomiasis transmission, and the target of local targeting approaches, to be quantified. Using such an approach, Brooker et al. (2002b) estimated that 1.9 million children (in 11 of the 49 districts) in Cameroon and 4.9 million children (in 37 of 97 districts) in Tanzania would be the target for a school-based national schistosomiasis control programme. Recent cost analysis of school-based programmes showed that the overall financial costs per child treated using praziquantel, which involved a dose related to body mass and a questionnaire screening at the school level, were US\$ 0.67 in Ghana and US\$ 0.21 in Tanzania. Using the Tanzania and Ghana costs as lower and upper estimates, it is envisaged that the cost of control in Tanzania would be US\$ 1–3.2 million and in Cameroon would be US\$ 0.4–1.3 million.

6. Conclusions and future work

Studies using GIS and remote sensing of schistosomiasis in Africa are beginning to show some

clear patterns. The most important is the role of temperature and vegetation in determining the distribution of schistosomiasis at broad scales, which can be used to predict the distribution of disease risk. Although progress has been made in developing risk models, several important issues remain to be investigated, and require detailed and integrated studies of the distribution of infection and disease across Africa.

First, developing separate models for each snail–schistosome system in the context of a given ecological zone is an essential task for the development of accurate and useful infection risk models. Through developing separate models for each snail–schistosome system, it should be possible to construct a composite risk map of schistosomiasis across Africa. This remains a major challenge. Second, an unresolved issue concerns the relation between small- and broad-scale patterns of infection. Field studies are needed that relate the distribution of schistosomiasis across different spatial scales. Analysis of the inherent spatial heterogeneity of infection at different scales may prove a useful starting point. Third, our understanding of the temporal variation in infection risk has received far too little attention, despite the relevance to understanding to the spatial distribution of infection.

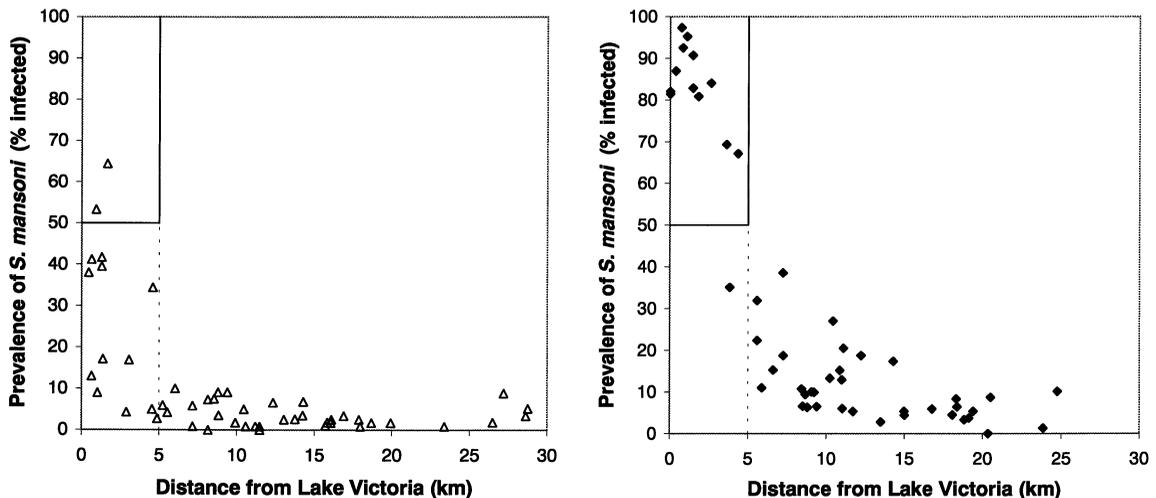


Fig. 3. Observed prevalence relationship between *S. mansoni* infection and distance from Lake Victoria in: (a) Tanzania (Lwambo et al., 1999); and (b) Kenya (Brooker et al., 2001b). The square box in the upper left corner represents those schools < 5 km from the lake shore and have a prevalence of *S. mansoni* infection > 50%.

Understanding the broad-scale distribution of schistosomiasis has benefited from the integrated use of GIS and remote sensing. Such approaches will continue to prove useful tools to the planning and targeting of control activities. At present, however, very few studies have adequately evaluated the predictions of risk models; future studies not only should do this, but also should pay particular attention to applying GIS and remote sensing technologies to actual control scenarios. In a continent where schistosomiasis is often diluted at the national level, demonstrable usefulness of GIS and remote sensing is important, and should be a research priority.

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