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Predictive risk mapping of schistosomiasis in Brazil using Bayesian geostatistical models

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ABSTRACT

Schistosomiasis is one of the most common parasitic diseases in tropical and subtropical areas, including Brazil. A national control programme was initiated in Brazil in the mid-1970s and proved successful in terms of morbidity control, as the number of cases with hepato-splenic involvement was reduced significantly. To consolidate control and move towards elimination, there is a need for reliable maps on the spatial distribution of schistosomiasis, so that interventions can target communities at highest risk. The purpose of this study was to map the distribution of *Schistosoma mansoni* in Brazil. We utilized readily available prevalence data from the national schistosomiasis control programme for the years 2005–2009, derived remotely sensed climatic and environmental data and obtained socioeconomic data from various sources. Data were collated into a geographical information system and Bayesian geostatistical models were developed. Model-based maps identified important risk factors related to the transmission of *S. mansoni* and confirmed that environmental variables are closely associated with indices of poverty. Our smoothed predictive risk map, including uncertainty, highlights priority areas for intervention, namely the northern parts of North and Southeast regions and the eastern part of Northeast region. Our predictive risk map provides a useful tool for to strengthen existing surveillance-response mechanisms.

1. Introduction

Schistosomiasis remains one of the most common parasitic diseases in tropical and subtropical areas. Indeed, more than 200 million people are infected among the almost 800 million people at risk of schistosomiasis (Steinmann et al., 2006). The disease is intimately connected with conditions of poverty, poor sanitation and lack of clean water, and schistosomiasis is emerging in areas undergoing major water resources development and management (Southgate, 1997; Steinmann et al., 2006; King, 2010; Utzinger et al., 2011).

In Brazil, schistosomiasis is a largely neglected disease, although it is of considerable public health relevance, especially in the poorest regions of the country (Katz and Peixoto, 2000). During the last decades, the distribution of schistosomiasis has changed as a result of demographic and ecological transformations, such as the expansion of rural areas to the outskirts of large urban centres. Due to the lack of adequate sanitation, sewage released into freshwater bodies and re-use of wastewater in agriculture, schistosomiasis persists as a public health problem (Graeff-Teixeira et al., 1999; Leal Neto et al., 2012). In the mid-1970s, Brazil established a national control programme (NCP) against schistosomiasis, led by the Ministry of Health (MoH). At the onset of this programme, the key strategy was morbidity control using the antischistosomal drug oxamniquine (Katz, 2008). By 2003, more than 12 million treatments were administered. At the beginning, the programme was centralized at the MoH in Brasilia. Over time, the municipalities took leadership in surveys and control efforts. The NCP was successful in reducing the prevalence of *Schistosoma mansoni* infection and the number of cases with hepato-splenic involvement (Amaral et al., 2006). However, it did not prevent the occurrence of new outbreaks (Carvalho et al., 1997; Graeff-Teixeira et al., 1999; Katz and Almeida, 2003).

The control of schistosomiasis and other poverty-related diseases requires reliable risk maps, so that interventions can focus on high-risk communities, which in turn enhance cost-effectiveness

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(Brooker et al., 2009; Carvalho et al., 2010; Guimarães et al., 2010a; Hürlimann et al., 2011; Leal Neto et al., 2012). Recent studies determined the spatial distribution of *S. mansoni* in several states of Brazil. For example, the risk of schistosomiasis has been associated with environmental variables and/or social determinants in the states of Bahia, Pernambuco and Minas Gerais, and regions designated for ecotourism, *e.g.* "Estrada Real" (Bavia et al., 2001; Guimarães et al., 2006, 2008, 2010a, 2010b; Carvalho et al., 2010; Galvão et al., 2010; Paredes et al., 2010; Leal Neto et al., 2012). However, a country-wide risk map of schistosomiasis does not exist. Studies carried out thus far used data from the NCP and employed ecological niche modelling or biology-driven and standard statistical models for risk profiling, assuming spatial independence of the data. Survey data, however, are spatially correlated because neighbouring geographical areas share similar environmental exposures, thus influencing disease risk in a similar way. Ignoring spatial correlation could lead to incorrect estimates of the significance of the risk factors and model-based predictions. Bayesian geostatistical models have been successfully applied to *Schistosoma* spp. prevalence data in different parts of Africa and Asia to generate predictive risk maps and to identify underlying risk factors that govern the spatial distribution of schistosomiasis (Raso et al., 2005; Clements et al., 2006, 2008; Beck-Wörner et al., 2007; Koroma et al., 2010; Peng et al., 2010; Schur et al., 2011, 2013).

In the current study, we analyzed *S. mansoni* prevalence data from the NCP in Brazil that were obtained between 2005 and 2009. We obtained climatic, environmental and socioeconomic data from various sources, established a geographical information system and used Bayesian statistical models to generate a smoothed predictive risk map of schistosomiasis in Brazil.

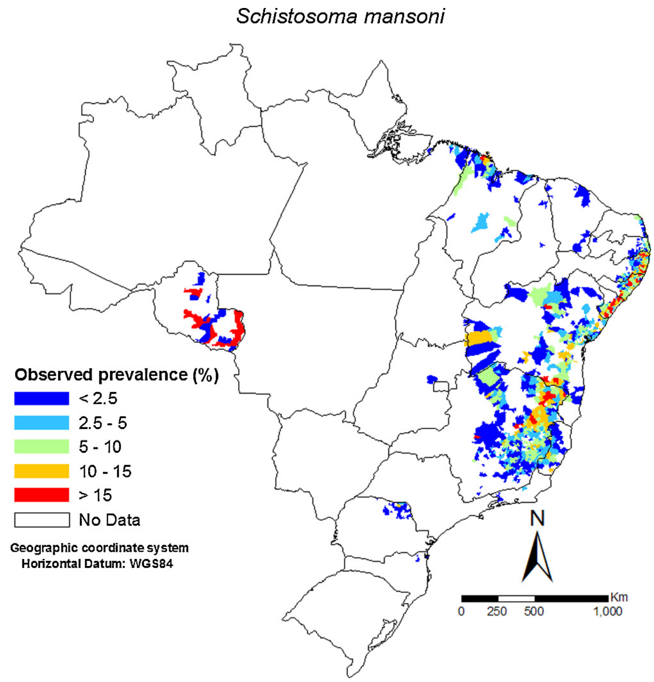

Fig. 1. Observed prevalence of schistosomiasis in Brazil from 2005 to 2009 (NCP).

2. Materials and methods

2.1. *Schistosoma mansoni prevalence data*

Our prevalence data of *S. mansoni* were obtained from 1004 municipalities in Brazil surveyed in the years 2005–2009 within the frame of the NCP (http://tabnet.datasus.gov.br/cgi/tabcgi.exe?sinan/pce/cnv/pce.def, accessed 8 March 2010). Surveyed municipalities, together with observed prevalence data have been plotted using ArcGIS version 9.3 (ESRI, Redlands, CA, USA) and are presented in Fig. 1. Of note, the NCP was primarily implemented in known schistosome-endemic areas with entire communities being surveyed. The Kato–Katz technique with single stool samples subjected to duplicate Kato–Katz thick smears was utilized for the diagnosis of *S. mansoni* infection (Katz et al., 1972), as recommended by the World Health Organization (WHO) (1994).

2.2. *Climatic and environmental data*

Climatic and environmental proxies were considered in our analyses since these are the main predictors for the distribution of intermediate host snails that play a central role in the life cycle of schistosomiasis (Appleton, 1978; Stensgaard et al., 2013). Climatic data were extracted from Worldclim Global Climate Data (Hijmans et al., 2005). These data consist of 19 bioclimatic variables (Table 1), which are generated through interpolation of average monthly climate data from weather stations for a 50-year period (1950–2000) at a spatial resolution of 1 km.

Environmental data were obtained from different freely accessible remote sensing sources, as summarized in Table 1. Land surface temperature (LST) data were utilized as proxy for day and night temperature, the normalized difference vegetation index (NDVI) and enhanced vegetation index (EVI) as proxies for moisture and vegetation, respectively, whilst a digital elevation model (DEM) was employed for extracting altitude estimates.

2.3. *Socioeconomic data*

Socioeconomic indicators were included to enable evaluation of the influence of poverty on the risk of schistosomiasis (Table 2). Data were gathered, as recent as possible, from different open sources, such as: (i) population data from 2010, human development index (HDI) from 2000 and rural population from 2000 (census data) provided by the Instituto Brasileiro de Geografia e Estatística (IBGE); (ii) unsatisfied basic needs (UBN) from 2000 provided by the Pan American Health Organization (PAHO); and (iii) infant mortality rate (IMR) from 2000 and human influence index (HII) from 2005 provided by the Center for International Earth Science Information Network (CIESIN).

2.4. *Snail data*

Scholte et al. (2012) recently presented maps of the distribution of schistosomiasis intermediate host snails in Brazil. Based on these maps, the probability of the presence of intermediate host snails at specific locations was determined and considered as an additional covariate in the present study. The raw data were obtained from peer-reviewed publications and from a database held at the Laboratory of Medical Malacology and Helmintology in Fiocruz, Minas Gerais, Brazil. The probability of the presence of the intermediate host snails was determined using a maximum entropy (MaxEnt) approach.

2.5. *Statistical analysis*

We established a geographical information system with *S. mansoni* infection prevalence utilized as outcome variable. The covariates considered for the spatially explicit analysis were socioeconomic (household assets ownership, HDI, HII, IMR and UBN indicators), climatic and environmental proxies from Worldclim