The spatial distribution of Schistosoma mansoni infection in four regions of western Côte d’Ivoire

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Abstract

Schistosomiasis poses a considerable public health burden in sub-Saharan Africa and a sound understanding of the spatial distribution facilitates to better target control interventions. The objectives of this study were i) to assess the prevalence of Schistosoma mansoni among school-aged children in four regions of western Côte d’Ivoire; ii) to determine demographic, climatic and environmental factors that influence the distribution of S. mansoni; and iii) to map and predict the distribution of S. mansoni in non-sampled locations. Parasitological surveys were carried out in 264 schools from June to December 2011. In each school, we aimed to examine 50 children for S. mansoni infection using duplicate Kato-Katz thick smears. Schools were georeferenced using a handheld global positioning system receiver. Demographic data were obtained from readily available school lists, while climatic and environmental data were extracted from open-access remote sensing databases. Multivariable, binary non-spatial models and a Bayesian geostatistical logistic regression model were used to identify demographic, climatic and environmental risk factors for S. mansoni infection. Risk maps were developed based on observed S. mansoni prevalences and using Bayesian geostatistical models to predict prevalences at non-sampled locations. Overall, 12,462 children provided a sufficiently large stool sample to perform at least one Kato-Katz thick smear. The observed overall prevalence of S. mansoni infection was 39.9%, ranging from 0 to 100% at the unit of the school. Bayesian geostatistical analysis revealed that age, sex, altitude and difference in land surface temperature at day and night were significantly associated with S. mansoni infection. The S. mansoni risk map presented here is being used by the national schistosomiasis control programme for spatial targeting of praziquantel and other interventions.

Introduction

Despite increasing efforts to control schistosomiasis, this chronic, parasitic disease still affects more than 250 million people and causes a global burden of 3.3 million disability-adjusted life years (DALYs) (Murray et al., 2012; Hotez et al., 2014). There are six Schistosoma species infecting humans and the most important ones are: S. haematobium, S. japonicum and S. mansoni (Gryseels et al., 2006; Colley et al., 2014). In sub-Saharan Africa, urogenital schistosomiasis (caused
by *S. haematobium* and intestinal schistosomiasis (caused by *S. mansoni*) inflict a considerable public health problem, particularly in poor rural communities (King, 2010; Utzinger et al., 2011).

The main measures for controlling schistosomiasis are i) preventive chemotherapy (*i.e.* large-scale distribution of the antischistosomal drug praziquantel to populations at risk of infection to prevent morbidity); ii) improvement of clean water supply and sanitation; iii) intermediate host snail control; and iv) information, education and communication (IEC) targeting high-risk populations to limit their infection exposure by behaviour change (Engels et al., 2002; WHO, 2002; Utzinger et al., 2011; Knopp et al., 2013; Rollinson et al., 2013; Grimes et al., 2014). To adequately target preventive chemotherapy and other control measures against schistosomiasis, the endemicity levels need to be known. High-risk communities can be identified, for example, by screening urine or stool specimens of school-aged children for *Schistosoma* eggs, or by assessing self-reported blood in urine or stool, or self-reported exposure to natural open freshwater bodies using questionnaires (WHO, 2002; Lengele et al., 2002a).

Numerous studies have demonstrated that geographical information system (GIS), remote sensing and geostatistical analysis are powerful approaches for disease risk profiling and risk mapping at large-scale (Brooker et al., 2003; Raso et al., 2006; Clements et al., 2009; Karagiannis-Voules et al., 2015). Particularly in developing countries, where resources for disease control are scarce, these means can assist health authorities in identifying high-risk areas, including very remote settings, which are difficult to access, and in adequately targeting intervention measures for disease control (Stensgaard et al., 2005). In Côte d’Ivoire, these epidemiological and geostatistical tools were previously applied to study the impact of environmental change on the prevalence of Buruli ulcer (Brou et al., 2008) and to map and predict the spatial distribution of schistosomiasis in the mountainous region of Man (Raso et al., 2005) and across the country (Chammartin et al., 2014).

Schistosomiasis is characterised by a focal distribution, which is the result of a complex interplay of behavioural, climatic and environmental factors that influence the dynamics and density of intermediate host snails and the infection prevalence and intensity in humans. For example, distance from people’s residency to open freshwater bodies is usually negatively associated with the prevalence of *S. haematobium* (Rudge et al., 2008) and *S. mansoni* (Handzel et al., 2003; Odiere et al., 2012). Altitude is also an important factor associated with the occurrence of schistosomiasis (Kabateriene et al., 2004; Raso et al., 2005). *Biomphalaria pfeifferi*, the intermediate host snail of *S. mansoni*, requires temperature values ranging between 15 and 31°C and pH values ranging from 6.8 to 8.6, to thrive successfully (Utzinger et al., 1997; McCrereh and Booth, 2014; Walz et al., 2015). *Bulinus globosus*, one of the intermediate host snails of *S. haematobium*, shows preferences for freshwater bodies with temperatures ranging from 14 to 32°C and pH values from 6.0 to 7.8 (Woolhouse and Chandiwana, 1990; Yapi et al., 2014c; Walz et al., 2015). Hence, for schistosomiasis risk prediction, it is important that multiple environmental factors are considered.

The goal of the current study was to generate a risk map for *S. mansoni* in four regions of western Côte d’Ivoire that can help the national schistosomiasis control programme in decision making for adequately targeting preventive chemotherapy and other control interventions. The data were obtained from a large-scale eligibility survey conducted as part of a sustaining schistosomiasis control project requested by the Schistosomiasis Consortium for Operational Research and Evaluation (SCORE) (Assaré et al., 2014). The risk maps already proved useful for the national schistosomiasis control programme in Côte d’Ivoire.

### Materials and Methods

#### Ethical considerations

The institutional research commissions of the Swiss Tropical and Public Health Institute (Basel, Switzerland) and the Centre Suisse de Recherches Scientifiques en Côte d’Ivoire (Abidjan, Côte d’Ivoire) approved the study protocol. Ethical clearance was provided by the ethics committees in Basel (reference no. EKBB 279/10) and the Ministry of Public Health in Côte d’Ivoire (reference no. 1994 MSHP/CNER).

Before launching any field activities, the region education directors, education inspectors and officers were informed about the objectives and procedures of the study. These authorities informed village leaders and teachers who then informed village committees and schoolchildren, respectively. At the day of the survey, teachers and schoolchildren were provided with additional information about the study purpose and field and laboratory procedures. Written informed consent was obtained from parents and legal guardians of children. Children found infected with *S. mansoni* were treated with praziquantel, administered at a single oral dose of 40 mg/kg of body weight (WHO, 2002).

#### Study area and population

The study was carried out in four regions of western Côte d’Ivoire: Cavally, Guémon, Tonkpi and Haut-Sassandra, extending from 6°28′47.5″ to 7°52′10.0″ N latitude and from 6°44′09.8″ to 8°21′30.0″ W longitude (Figure 1). The Cavally, Guémon and Tonkpi regions are mountainous areas with an average elevation ranging from 300 m above mean sea level (amsl) to slightly above 1000 m amsl (Raso et al., 2005; Kouassi et al., 2012; Gone Bi et al., 2013). The rainy season occurs from March to October. The Haut-Sassandra region is located east of the Sassandra River and its average altitude ranges between 200 and 300 m amsl (Yapi et al., 2014a). The climate is sub-equatorial, characterised by two rainy seasons. The long rainy season lasts from March to July and the short rainy season occurs in September and October.

People living in the western part of Côte d’Ivoire belong to two main ethnicities: Mandé and Krou. People are mainly engaged in subsistence agriculture (cassava, maize, plantain and rice). Rice growing is the most important agricultural activity, leading to a high frequency of contact with water. There is also production of cash crops (coffee, cocoa and rubber cultivation) and a small forestry industry in the town of Man (Utzinger et al., 2000).

Schistosomiasis, soil-transmitted helminthiasis, malaria, giardiasis and amoebiasis are highly endemic in the study area (Raso et al., 2005; Matthys et al., 2006; Ouattara et al., 2008; Silué et al., 2008).

#### Parasitological survey

A cross-sectional parasitological survey was carried out in 264 schools from June to December 2011. The schools were selected based on accessibility by 4 wheel drive cars and number of registered children (≥200 pupils). Lists of schools and sketch maps of the four regions were used for planning the surveys. After receiving consent from the headmaster, teachers prepared class lists, including name, age and sex of all children. In each school, we aimed at selecting 50 children attending grades 4–6, as described elsewhere (Assaré et al., 2014). In brief, children aged 13 years and above were selected from grades 4–6 until the number of children reached 50. In settings where less than 50 children in this age range were present, the sample was completed with younger children. Children with written informed consent from their
Parents or legal guardians were given a 125 mL plastic container and asked to return it with a small portion of their own stool. The containers were collected and labelled with unique identification numbers.

Stool specimens were transferred to central laboratories in Douékoué and Man and processed with the Kato-Katz technique (Katz et al., 1972). Duplicate Kato-Katz thick smears were prepared from each stool specimen using 41.7 mg templates. After a clearing time of 60 min, the thick smears were examined under a microscope by one of five experienced laboratory technicians. *S. mansoni* eggs were counted and recorded. For quality control, 10% of the slides were selected (one slide chosen out of each 10 slides read) and re-examined the same day by a senior microscopist. In case of conflicting results, the slides were read a third time and the results discussed until agreement was reached (Speich et al., 2015).

Climatic and environmental data

Geographical coordinates of each school were collected using a hand-held global positioning system (GPS) receiver (Garmin Etrex 30; Garmin, Olathe, KS, USA). Climatic data were obtained from readily available remote sensing sources (Table 1). Land surface temperature at day (LSTDay), land surface temperature at night (LSTNight) and rainfall estimate (RFE) were obtained for the period of 2011-2012. Rainfall estimate data with an 8×8 km spatial resolution from Meteosat 7 satellite were obtained from the Africa Data Dissemination Service (http://earlywarning.usgs.gov/adds/index.php). Land surface temperature at day and night data were downloaded from the Moderate Resolution Imaging Spectroradiometer (MODIS) from the United States Geographical Survey - Earth Resources Observation and Science Data Center (http://modis.gsfc.nasa.gov).

Figure 1. Map of Côte d’Ivoire with the four study regions in the western part of the country.
Statistical analysis

Children were classified into three age groups (i.e. 8-12, 13-14 and 15-19 years). Land cover was included into the model as categorical covariate. Continuous variables were standardised to mean zero, including standard deviation (SD). Pearson’s correlation was calculated between continuous variables and was further used to check for variables with a high correlation coefficient (>0.9) to avoid collinearity.

We implemented Bayesian variable selection to identify the best set of predictors. Briefly, normal mixture of inverse Gaussians with parameter expansion (peNMIG) spike-and-slab priors was applied on the model (Scheipl et al., 2012). We used mixed inverse Gamma distributions for the priors of the coefficients. One component (exclusion component) is a narrow spike around zero, while the other component (inclusion component) is a wide slab away from zero. For categorical variables, we applied a peNMIG prior that allows to simultaneously including or excluding all coefficients related with the categories of the same variable, by improving shrinkage properties (Scheipl et al., 2012).

We included the variables with the inclusion component predominant (i.e. a posterior probability higher than 50%) into our final geostatistical model. The details of the method have been described elsewhere (Lai et al., 2013).

Bayesian geostatistical logistic regression models with spatially structured random effects were applied to obtain spatially explicit S. mansoni estimates. Specifically, we assumed that the number of positive individuals $Y_i$ arises from a binomial distribution $Y_i \sim \text{Bin}(p_i, n_i)$, where $\text{logit}(p_i) = b_k \cdot \sum_{k=1}^{K} X_{i,k} \cdot \sigma^2_k + \epsilon_i$, $n_i$ and $p_i$ indicate the number of those examined and the probability of infection at location $i$, $b_k$, $\epsilon_i$, and $\phi_k$ represent the regression coefficient of the $k^{\text{th}}$ covariate $X_{i,k}$, location-specific random effect and exchangeable non-spatial random effect, respectively. We assumed $\epsilon_i \sim \text{MVN}(0, \Sigma)$ with a covariance function $\Sigma_{ij} = \text{exp}(-r_{d_{ij}})$, where $d_{ij}$ is the Euclidean distance between location $i$ and $j$, and $\rho$ corresponds to the rate of correlation decay. We assumed an inverse gamma hyper-prior distribution for $\sigma^2_k$ and a gamma hyper-prior distribution for $\rho$. The spatial range, which is considered as the minimum distance of the spatial correlation, was assumed to follow a zero-mean normal distribution $\phi_k \sim N(0, \sigma^2_{\text{sp}} \cdot \rho^2_{\text{sp}})$. We assigned the prior distributions as follows: $b_k, b_0 \sim \text{N}(0, 100), \phi_k \sim \text{IG}(1, 0.01), \sigma^2_{\text{sp}} \sim \text{IG}(0.01, 0.01)$ and $\rho \sim \text{G}(0.01, 0.01)$. Markov chain Monte Carlo simulation was employed to estimate the model parameters in Openbugs version 3.0.2 (Imperial College London and Medical Research Council, London, UK) (Lunn et al., 2009). Gelman and Rubin diagnostics was used to assess the convergence by the coda library in R (Gelman and Rubin, 1992; Plummer et al., 2006). A 1×1 km grid was overlaid to the study region, resulting in 53,820 pixels. Bayesian kriging was done to predict the S. mansoni infection risk at the centroids of the grid’s pixels.

Model validation

We randomly selected a subset of the data (training set), including approximately 80% of survey locations for model fitting and subsequently assessed the model performance on the remaining 20% (test set). Mean error (ME), that is the expectation of differences between the observed and predicted prevalence, and the percentage of observations included in Bayesian credible intervals (BCI) of various probability coverages of predictions on test set locations were calculated.

Results

Study cohorts

Sufficiently large stool samples were collected from 12,462 schoolchildren. There were 8151 (65.4%) males and 4311 (34.6%) females. The age ranged between 8 and 19 years; 1914 children (15.4%) were 8-12 years old, 9043 (72.6%) were 13-14 years old and the remaining 1505 (12.0%) were 15-19 years old. Around half of the schools (n=131, 49.6%) were located in the Tonkpi region. There were 113 schools (42.8%) in the Guemon region, while only 13 (4.9%) and 7 (2.7%) schools were included in the Haut-Sassandra and Cavally region, respectively.

Table 1. Remote sensing data sources used for risk profiling of Schistosoma mansoni in western Côte d’Ivoire.

<table>
<thead>
<tr>
<th>Source</th>
<th>Data type</th>
<th>Data period</th>
<th>Temporal resolution</th>
<th>Spatial resolution</th>
</tr>
</thead>
<tbody>
<tr>
<td>MODIS LST</td>
<td>3/2011-2/2012</td>
<td>8 days</td>
<td>1 km</td>
<td></td>
</tr>
<tr>
<td>MODIS NDVI</td>
<td>3/2011-2/2012</td>
<td>16 days</td>
<td>1 km</td>
<td></td>
</tr>
<tr>
<td>MODIS Land cover</td>
<td>2001-2004</td>
<td>Year</td>
<td>1 km</td>
<td></td>
</tr>
<tr>
<td>WorldClime</td>
<td>2000</td>
<td>-</td>
<td>1 km</td>
<td></td>
</tr>
<tr>
<td>FEWS NET Rainfall</td>
<td>3/2011-2/2012</td>
<td>10 days</td>
<td>8 km</td>
<td></td>
</tr>
<tr>
<td>STRM-WBD Water bodies</td>
<td>2000</td>
<td>-</td>
<td>30 m</td>
<td></td>
</tr>
<tr>
<td>ISRIC Soil types</td>
<td>-</td>
<td>-</td>
<td>8 km</td>
<td></td>
</tr>
<tr>
<td>Bayesian kriging*</td>
<td>1991-2012</td>
<td>-</td>
<td>5 km</td>
<td></td>
</tr>
<tr>
<td>Bayesian kriging Improved sanitation</td>
<td>1991-2012</td>
<td>-</td>
<td>5 km</td>
<td></td>
</tr>
<tr>
<td>LST_Day SD</td>
<td>3/2011-2/2012</td>
<td>1 km</td>
<td></td>
<td></td>
</tr>
<tr>
<td>LST_Night SD</td>
<td>3/2011-2/2012</td>
<td>1 km</td>
<td></td>
<td></td>
</tr>
<tr>
<td>diffLST SD</td>
<td>3/2011-2/2012</td>
<td>1 km</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Rainfall SD</td>
<td>3/2011-2/2012</td>
<td>1 km</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Parasitological data

Among the 264 schools, 157 (59.5%) had a *S. mansoni* prevalence above 24%, 78 (29.5%) schools had a prevalence ranging between 10 and 24%, whilst the remaining 29 schools (11.0%) had a prevalence below 10%. The overall prevalence of *S. mansoni* was 39.9%. Boys showed a statistically significantly higher prevalence of *S. mansoni* than girls (42.9% vs 34.2%; χ²= 88.76, P<0.001). The prevalence of infection was 33.5, 41.0 and 40.9% among children aged 8-12, 13-14 and 15-19 years, respectively.

Figure 2 displays the *S. mansoni* infection prevalence in each of the 264 schools. At the unit of the school, the prevalence of *S. mansoni* ranged from 0 to 100%. High prevalence rates were predominantly found in the Tonkpi region. Moderate infection prevalences (10-24%) were mostly found in Gomon and Cavally regions. In the schools of Haut-Sassandra, the prevalence of *S. mansoni* was consistently below 24%.

Spatial statistical modelling and model validation result

The Bayesian variable selection identified the following predictors: sex, age group, difference of LST between day and night (diffLST) and altitude. The Bayesian geostatistical logistic regression model was able to correctly estimate (within a 95% BCI) 81.2% for *S. mansoni* at the test locations. The ME was 4.6%, which means the model may underestimate the risk of *S. mansoni* infection.

Relationship between *Schistosoma mansoni* and demographic and environmental factors

Table 2 summarises the key findings with respect to the relationship between *S. mansoni* and demographic, environmental and climatic factors. Children from the oldest age group (15-19 years) had higher odds of *S. mansoni* infection compared to those aged 8-12 years (odds ratio (OR)=1.35, 95% BCI: 1.12; 1.65). We did not find significant difference of *S. mansoni* prevalence rates between children aged 13-14 years and 8-12 years. Boys had higher odds of *S. mansoni* infection than girls (OR=1.58, 95% BCI: 1.43; 1.73).

Altitude was negatively associated with the prevalence of *S. mansoni* (OR=0.49, 95% BCI: 0.28; 0.70). We found a positive correlation between diffLST and *S. mansoni* infection (OR=1.36, 95% BCI: 1.12; 1.60).
Spatial analysis of Schistosoma mansoni infection

The main results derived from the multivariable and the binary non-spatial logistic regression models are summarised in Table 2. The non-spatial multivariable logistic regression model revealed a significant association between the prevalence of S. mansoni and sex (OR=1.43, 95% BCI: 1.32; 1.55), and age (age group 13-14 years, OR=1.36, 95% BCI: 1.22; 1.51; and age group 15-19 years, OR=1.34, 95% BCI: 1.16; 1.54 compared to age group 8-12 years). There was no association between S. mansoni infection and altitude and diffLST.

The binary non-spatial model showed that disease transmission was significantly associated with sex (OR=1.45, 95% BCI: 1.34; 1.55) and age (age group 13-14 years OR=1.38, 95% BCI: 1.25; 1.54; age group 15-19 years, OR=1.38, 95% BCI: 1.20; 1.58 compared to age group 8-12 years). However, there was no association between S. mansoni infection and climatic and environmental factors.

Table 2 also shows the principal findings of the Bayesian geostatistical logistic regression model. Age, sex and diffLST were positively correlated with S. mansoni, whilst altitude showed a significant negative association with S. mansoni infection prevalence.

Spatial prediction of Schistosoma mansoni infection

Figure 3 shows the predicted S. mansoni infection prevalence in the study area for boys and girls with different age groups, and Figure 4 displays the corresponding prediction uncertainty. A very high prevalence of S. mansoni (>50%) was predicted predominantly in the Tonkpi region. Some focal high-prevalence schools were also predicted in central Gomon and northern Haut-Sassandra regions. Moderate prevalences of S. mansoni infection according to SCORE definition (10-24%) were predicted for large parts of Cavally, Haut-Sassandra and Gomon regions. Low prevalences (<10%) were predicted for East Cavally, south-western Haut-Sassandra and a small area in the northern part of Gomon region. The predicted prevalence of S. mansoni for boys was higher than the predicted prevalence for girls.

Discussion

Schistosomiasis remains of considerable public health importance in sub-Saharan Africa and a precise knowledge of high-risk areas is required for spatial targeting of control interventions. Within the frame of a large eligibility survey to identify schools where the prevalence of S. mansoni among school-aged children is 10-24%, more than 12,000 children were screened by duplicate Kato-Katz thick smears in four regions of western Côte d’Ivoire. We adhered to the SCORE harmonisation protocol and aimed for children aged 13-14 years, but in order to have sufficient children per school, children’s age finally ranged between 8 and 19 years. We found an overall prevalence of S. mansoni of 39.9%. Our results therefore confirm that S. mansoni is highly endemic in the western part of Côte d’Ivoire (Utzinger et al., 2000; Raso et al., 2005; Beck-Wörner et al., 2007), and that the geographical extent of the problem is larger than previously thought. Our study also confirms that schistosomiasis is highly focal (Ratard et al., 1990; Lengeler et al., 2002b; Raso et al., 2005; Hodges et al., 2012). Indeed, while in some schools no child was infected with S. mansoni, more than half of the children were infected in other schools. High prevalences of S. mansoni were mostly found in the northern Tonkpi region, which is in line with results from previous studies (Roux et al., 1980; Utzinger et al., 2000; Keiser et al., 2002; Matthys et al., 2007). In the schools located in the Cavally and Gomon regions, S. mansoni infection prevalences mainly ranged between 10 and 45%. The prevalences of S. mansoni in the schools in the southern Haut-Sassandra region were consistently below 25%. Bayesian spatial statistical analysis showed that demographic, environmental and climatic covariates were useful predictors explaining the spatial distribution of S. mansoni infection prevalence. Altitude was negatively associated with the distribution of S. mansoni. These observations confirm results from previous digital elevation models and Bayesian geostatistical analysis (Raso et al., 2005; Beck-Wörner et al., 2007). Indeed, it has been shown that children living in western Côte d’Ivoire at locations below 400 m amsl were at a 5-fold higher risk of S. mansoni infection when compared with those living at higher locations (Raso et al., 2005). However, the altitude threshold limit for S. mansoni transmission varies from one study setting to another (Ghebreyesus et al., 2002; Kabaterine et al., 2004; Rubaihayo et al., 2008). Our study also revealed that a diffLST was correlated with the prevalence of S. mansoni infection. Several epidemiological studies using Bayesian geospatial, Gaussian and Poisson modelling documented that LST was negatively associated with S. mansoni, while LST was positively associated with the prevalence of S. mansoni (Hu et al., 2013a, 2013b; Scar et al., 2013; Scholle et al., 2014). In contrast, previous geostatistical analysis from the Tonkpi region found no relationship between S. mansoni infection and diffLST (Raso et al., 2005). However, a limitation of the latter study was that all surveyed schools were located in the same region with similar environmental and climatic features such as diffLST.

Environmental factors such as elevation influence flow velocity of rivers and LST shapes temperature of freshwater bodies. In turn, these

Table 2. Posterior summaries (median and 95% Bayesian credible interval) of odds ratios of the geostatistical model parameters for Schistosoma mansoni infection.

<table>
<thead>
<tr>
<th>Variable</th>
<th>Multivariable non-spatial</th>
<th>Binary non-spatial</th>
<th>Geostatistical model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex</td>
<td>1.43 (1.32; 1.55)*</td>
<td>1.45 (1.34; 1.55)*</td>
<td>1.58 (1.43; 1.73)*</td>
</tr>
<tr>
<td>Age group 1 (13-14 years)</td>
<td>1.36 (1.22; 1.51)*</td>
<td>1.38 (1.25; 1.54)*</td>
<td>1.15 (0.99; 1.35)</td>
</tr>
<tr>
<td>Age group 2 (15-19 years)</td>
<td>1.34 (1.16; 1.54)*</td>
<td>1.38 (1.20; 1.58)*</td>
<td>1.35 (1.12; 1.65)*</td>
</tr>
<tr>
<td>Altitude</td>
<td>1.01 (0.98; 1.05)</td>
<td>1.03 (0.99; 1.06)</td>
<td>0.49 (0.28; 0.70)*</td>
</tr>
<tr>
<td>diffLST</td>
<td>1.00 (0.96; 1.04)</td>
<td>1.01 (0.98; 1.05)</td>
<td>1.36 (1.12; 1.60)*</td>
</tr>
<tr>
<td>Range</td>
<td>181.31 (72.98; 460.24)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi^2$-spatial</td>
<td>3.03 (1.36; 8.26)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\chi^2$-nonspatial</td>
<td>0.88 (0.63; 1.14)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

diffLST, difference between land surface temperature at day and at night. *Significant correlation based on 95% confidence interval or 95% Bayesian credible interval.
Figure 3. Predicted Schistosoma mansoni infection prevalence in the four study regions of western Côte d’Ivoire. Predicted prevalence among girls aged 8-12 years (A), boys aged 8-12 years (B), girls aged 13-14 years (C), boys aged 13-14 years (D), girls aged 15-19 years (E) and boys aged 15-19 years (F).
Figure 4. Prediction uncertainty of the posterior predictive distribution of *Schistosoma mansoni* infection prevalence in western Côte d’Ivoire. Standard deviation (SD) of the posterior predictive distribution among girls aged 8-12 years (A), boys aged 8-12 years (B), girls aged 13-14 years (C), boys aged 13-14 years (D), girls aged 15-19 years (E) and boys aged 15-19 years (F).
factors impact on the presence of intermediate host snails, the parasite development within the snails and the infectivity of *Schistosoma* cer- cariae (Foster, 1964; Appleton, 1978; Kloos et al., 2001; Malone, 2005; McCrereh and Booth, 2014). A possible explanation for the observed higher prevalences of *S. mansoni* infection in the lower parts of the mountainous Tonkpi region may be the favourable temperature and velocity of rivers for *B. pfeifferi* (Shiff and Hustung, 1966). Indeed, recent malacological studies carried out in Tonkpi region confirmed a high population density of *B. pfeifferi* (Tian-Bi et al., 2013; Yapi et al., 2014b). The lower *S. mansoni* prevalences in the Haut-Sassandra region might be due to less favourable environmental conditions for the development of *B. pfeifferi*. Instead, the conditions in this area seem to rather suit the development of *B. globosus*, an important intermediate host snail of *S. haematobium* (Cadot et al., 1998; Fournet et al., 2004).

A limitation of our study is that no intermediate host snails were collected. Moreover, only one stool sample per individual was subjected to duplicate Kato-Katz thick smears. This diagnostic approach has a low sensitivity for *S. mansoni*, particularly for detection of light-intensity infections (Engels et al., 1996; Utzinger et al., 2001; Booth et al., 2003; Enk et al., 2008). Few schools were surveyed in Cavally and Haut-Sassandra regions. The relatively small number of survey locations in this area may have negatively affected the prediction accuracy. Lastly, our final model did not include rainfall and socioeconomic status, as these factors were not picked up by our variable selection procedures. However, both variables play a role for snail breeding and human infection as shown before (Raso et al., 2005; Muhumuza et al., 2009; Xue et al., 2011).

**Conclusions**

In conclusion, pursuing a Bayesian geostatistical analysis using a large set of georeferenced *S. mansoni* prevalence data from a SCORE-eligibility survey (Assaré et al., 2014) allowed risk profiling of *S. mansoni* in four regions of western Côte d’Ivoire. The generated risk maps have already been utilised by the national schistosomiasis control programme. As control efforts in the western part of Côte d’Ivoire and elsewhere in the country move ahead, it will be very interesting to monitor changes over time.

**References**


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