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Predicting *Schistosoma Haematobium* Risk Distribution in Zambia Using Geographic Information System (GIS) and Remote Sensing (RS) Technologies

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ABSTRACT

Introduction: This study explores the spatial distribution and climatic influences on schistosomiasis in Zambia using remote-sensed data, specifically focusing on the Normalized Difference Vegetation Index (NDVI) and maximum temperature (Tmax).

Material and Methods: By analysing prevalence data over a decade (2002-2012) and employing Geographic Information System (GIS) and Remote Sensing (RS) technologies, we identified regions conducive to the transmission of the disease.

Results: The findings revealed significant variability in schistosomiasis prevalence across Zambia. Climatic cut-offs for schistosomiasis transmission were established, highlighting NDVI values between 134 - 153 and Tmax ranges of 19.4 – 27.6°C as optimal for sustaining transmission.

Conclusion: The study underscores the pressing need for comprehensive control strategies that extend beyond school-based treatments, addressing the broader community and targeting at-risk populations. Furthermore, the established climatic cut-offs provide a framework for future research and public health initiatives aimed at reducing the burden of schistosomiasis in Zambia. This work emphasizes the intricate relationship between climate, health interventions, and disease dynamics, calling for adaptive strategies in the face of climate change.

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INTRODUCTION

In Zambia, schistosomiasis has long been a major public health concern. As of recent estimates, the prevalence of schistosomiasis in the country stands at approximately 26.6%, with an estimated 2.39 million individuals infected and an additional 3 million at risk of contracting the disease. However, the WHO suggests that the number of infected individuals may be as high as 4 million [1]. Transmission of schistosomiasis occurs in localized areas where humans come into contact with water infested with cercariae. Factors such as environmental and climatic changes, sanitation projects, control interventions, and the distribution of snail hosts are critical for effective schistosomiasis control [2]. A thorough understanding of the environmental and climatic factors that favour the survival of these snail intermediate hosts is essential for developing effective control interventions [2–8].

A complex interplay of environmental and climatic factors in the emergence and spread of infectious diseases, necessitates robust methodologies and tools for risk assessment, early warning systems, and informed policy-making [9]. Geographic Information Systems (GIS) and Remote Sensing (RS) are valuable tools in this context. However, despite the promise of spatial epidemiology using GIS and RS to enhance understanding of the ecology and epidemiology of schistosomiasis worldwide and guide control interventions [10–14], their application in Zambia remains limited. This is particularly concerning given that controlling schistosomiasis in the country continues

to pose challenges, even where interventions have been implemented, amid indications that climate change may influence disease transmission [11,15].

Currently, the climatic and environmental factors contributing to the distribution of schistosomiasis across various regions in Zambia remain poorly understood. This study was aimed at generating a disease risk distribution model for Schistosomiasis in Zambia. This was achieved through determining suitable temperatures and NDVI for the risk distribution of schistosomiasis and to generate temperature and NDVI-based disease risk distribution models for Schistosomiasis in Zambia.

MATERIAL AND METHODS

Climate Data Sources

This study utilized a desk review approach, leveraging existing prevalence and image data to create disease risk distribution models using Geographic Information Systems (GIS) and Remote Sensing (RS). The climatic and environmental data used in model developed has been indicated in the **Table 1**. Satellite images, including LANDSAT and NDVI data from 2002 to 2012, were purposively selected to correspond with the years of collected data. All seasonal images were processed, and a composite image spanning the decade was generated using ArcMap Version 9.2 (ESRI) (**Fig.1**).

Climatic data regarding NDVI and Land Surface Temperatures (LST) at a spatial resolution of 250 m were obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS) via the US Geological Survey (USGS) Earth Resources Observation and Science (EROS) data centre, which are recognized as reliable sources for remote sensing and GIS research. Prevalence data were gathered by reviewing literature on schistosomiasis in Zambia, primarily from the Zambia Bilharzia Control Program (ZBCP). Data from other researchers on schistosomiasis were also reviewed, with all points geo-referenced in a GIS system (**Fig.2**).

Prevalence Data Sources

There were three data sources for prevalence data namely; community, occupational and school-based. **Table 2** shows that literature search resulted into 136 data points for the country. These were from community surveys, occupational surveys, and school surveys. Majority 105 (77%) were from school surveys, followed by community surveys 28 (21%), and then occupational surveys 3 (2%).

Using the collected prevalence data, disease distribution models for schistosomiasis were developed. Basic schools from which data were gathered were geo-referenced by comparing them with the geo-referenced schools in the Ministry of Education (MoE) database. GPS coordinates (latitude and longitude) for all surveyed schools were collected. If only village names were available, the nearest school was geo-referenced, provided it was within a 5 km buffer radius (**Fig.3** and **Fig.4**).

In ArcGIS 9.2, the geo-referenced schools layer was integrated with the Zambia district shapefiles, along with the NDVI and Tmax images. The school points were joined with the NDVI and Tmax images, and buffer distances of 5 km were established around the data points to capture average environmental conditions. Scatter plots were created to compare prevalence against NDVI and LST, yielding defined ranges of NDVI and LST values strongly correlating with schistosomiasis prevalence. The Spatial Analyst extension in ArcGIS 9.2 was employed to set criteria for areas suitable for disease transmission, identifying points below or above the established thresholds as low-risk or no-risk areas. Risk models were generated based on these criteria, leading to three outcomes: high risk; medium risk, and little or no risk.

For model validation, basic schools or community data points not included in the model fitting (25% of all available points) were utilized. Of these, 50% represented schistosomiasis prevalence, while the other half indicated areas with zero prevalence. Using the same ArcGIS processes from the model fitting phase, these points were added to the risk model. Sensitivity

Table 1. Data [b]Source and Properties of the Climatic Covariates used to Model Schistosomiasis in Zambia

Source	Data Type	Data Period	Temporal Resolution	Spatial Resolution
Moderate Resolution Imaging Spectroradiometer (MODIS)/Terra	Maximum Temperature Tmax	2002 – 2012	8 days	250 meters
	Normalized Difference Vegetation Index (NDVI)	2002 - 2012	16 days	250 meters

[b]Source: US geological survey (USGS) Earth resource observation system (EROS) data centre Source of Tmax and NDVI data for the 10 years' period (2002 – 2012) at 250 meters spatial resolution

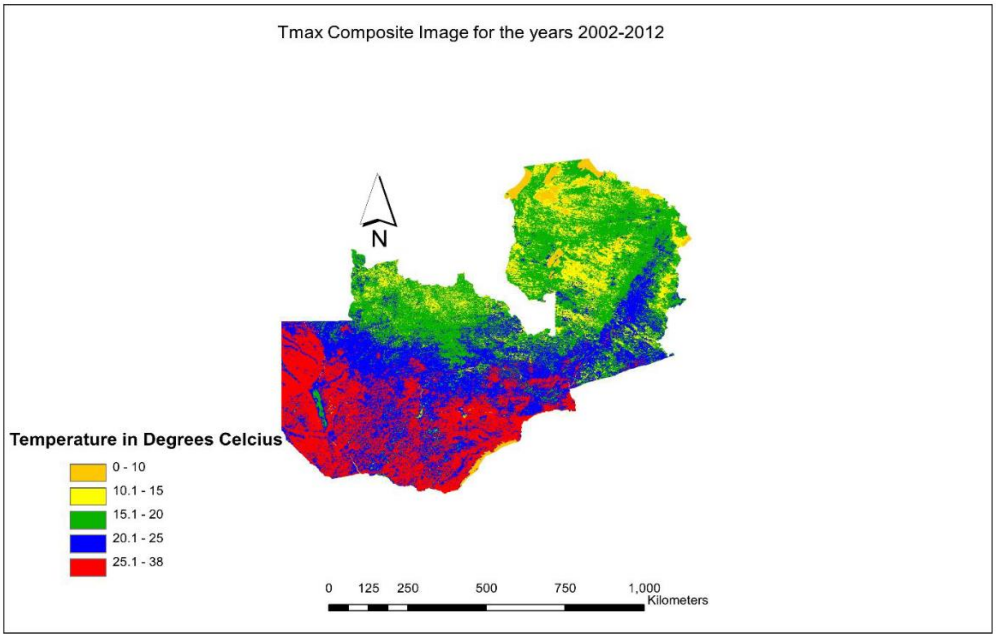


Fig. 1. Tmax Composite Image for 10 years. The highest temperature was 38°C

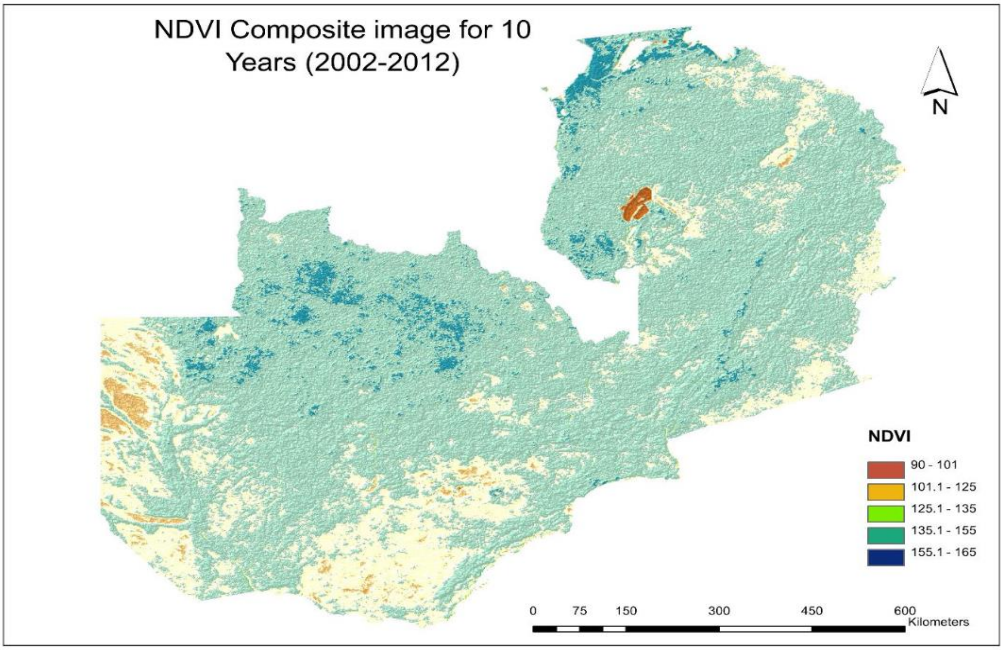


Fig. 2. NDVI 10 years (2002 - 2012) Composite Image

and specificity were calculated, using the retained points as the gold standard for validation.

Data points were divided between those used for model development and those reserved for validation. ArcGIS facilitated the identification of NDVI and LST values strongly correlated with prevalence data. The methodology employed in this study was based on Malone's model [16], where suitable NDVI and LST values for schistosomiasis transmission were obtained by plotting NDVI and Tmax against schistosomiasis data points within a GIS framework.

The analysis focused on schistosomiasis prevalence, categorized as low, medium, or high based on WHO standards within the GIS framework. Climatic images (NDVI and LST) were classified into appropriate ranges, and scatter plots were created in Stata 11.2 to

Table 2. Data Sources for Schistosomiasis Prevalence

Survey Type	Survey Years	Discovered Data Points
Community	2002, 2003, 2004	28 data points
Occupational	2002, 2004	3 data points
School	2005–2012	105 data points

identify values that correlated with prevalence. These value ranges were then applied in ArcMap Version 9.2 for query analysis, which classified areas as either low-risk or high-risk based on specific thresholds.

RESULTS

This study utilized remote-sensed data, specifically NDVI and LST, alongside prevalence data for schistosomiasis and malaria, incorporating GIS and RS technologies. These methods aimed to identify regions in Zambia that are conducive to the transmission of schistosomiasis.

Suitable NDVI and LST values for schistosomiasis transmission were established for different seasons: hot-wet, cool-dry, and hot-dry. A composite map was

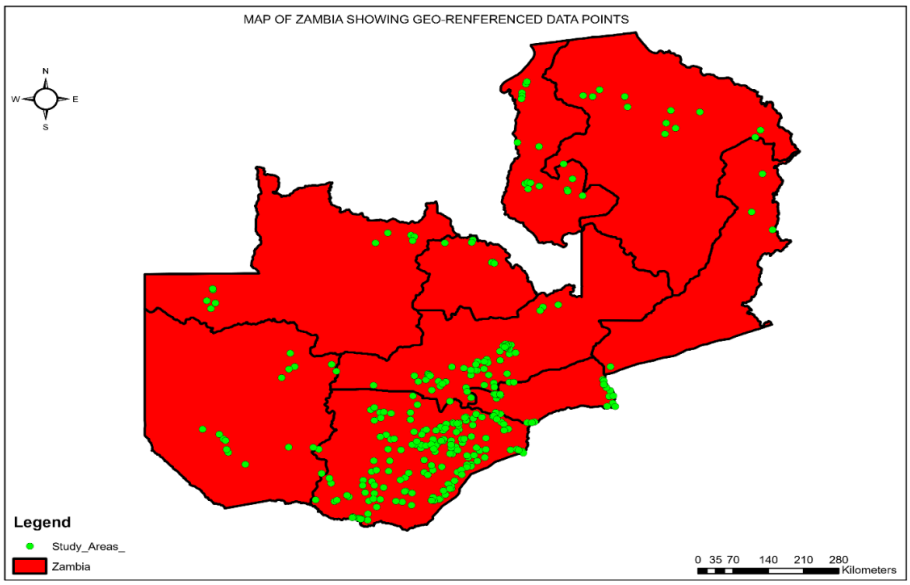


Fig. 3. Data Points used in Model Development

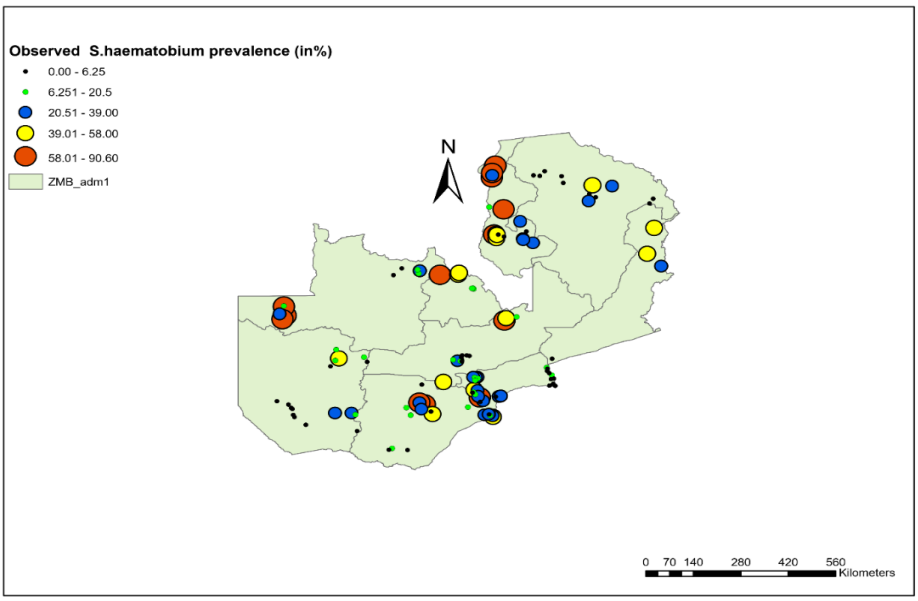


Fig. 4. Distribution of the Prevalence of *Schistosoma haematobium*. The distribution and prevalence of *Schistosoma haematobium* in Zambia. Prevalence as high as 90% was been recorded in some schools and communities in the country.

created from the data over the ten years studied, and climate suitability map for the disease was developed using query analysis within a GIS framework. The models created were subsequently validated against data from existing studies (Fig.5).

Climatic and environmental cut-offs for schistosomiasis distribution in Zambia

Climatic and environmental factors that were predicted to have the highest prevalence were used to develop the model. The climatic factors and their ranges are shown in the Table 3.

Schistosoma haematobium 10-year risk prediction based on TMAX

Scatter plots for Tmax that correlated strongly with high prevalence were plotted and prediction made (Fig.6).

Table 3.Climatic and Environmental Cut Offs used for Model Fitting

Disease	LST Cut off	NDVI Cut off
Composite		
Schistosoma haematobium	19.4 – 27.6°C	134 - 153
Cold season		
Schistosoma haematobium	10.7 – 23.1°c	108 – 157
Hot season		
Schistosoma haematobium	18.1 - 39°c	121 – 142
Rain Season		
Schistosoma haematobium	10.2 - 24°c	143 - 168

For both NDVI and LST, haematobium has a wide range of climatic and environmental conditions over which it can be transmitted.

DISCUSSION

Currently, Zambia lacks specific climatic cut-offs regarding LST and NDVI for schistosomiasis transmission. This study sought to establish the first such cut-offs for the country. In scenarios where the biological requirements of the vector are not well characterized but survey data (e.g., disease prevalence or vector abundance) are available, statistical software can identify key environmental and climatic variables to aid in prediction and model development [17,18]. This approach was mirrored in the current study.

The derived climatic suitability maps show that S. haematobium is widely distributed in Zambia with the exception of some few pockets in Eastern, Northern and North-Western province. The climatic cut-offs generated for the composite data from 2002 to 2012 align closely with findings from other researchers in the field. Mukaratiwa et al. [19] conducted a study in Zimbabwe, reporting NDVI ranges of 128 to 160 and Tmax ranges of 20 to 21°C as suitable for sustaining Bulinus globosus, the intermediate host for *S. haematobium*. The primary difference in findings lies in the narrower temperature range reported in their study compared to this study's findings (19.4°C to 27.6°C).

Simoonga et al. [4–6], utilizing a spatial epidemiology approach akin to that of this study, explored the influence of environmental factors on the abundance of intermediate snail hosts. However, their studies included altitude as an environmental variable,

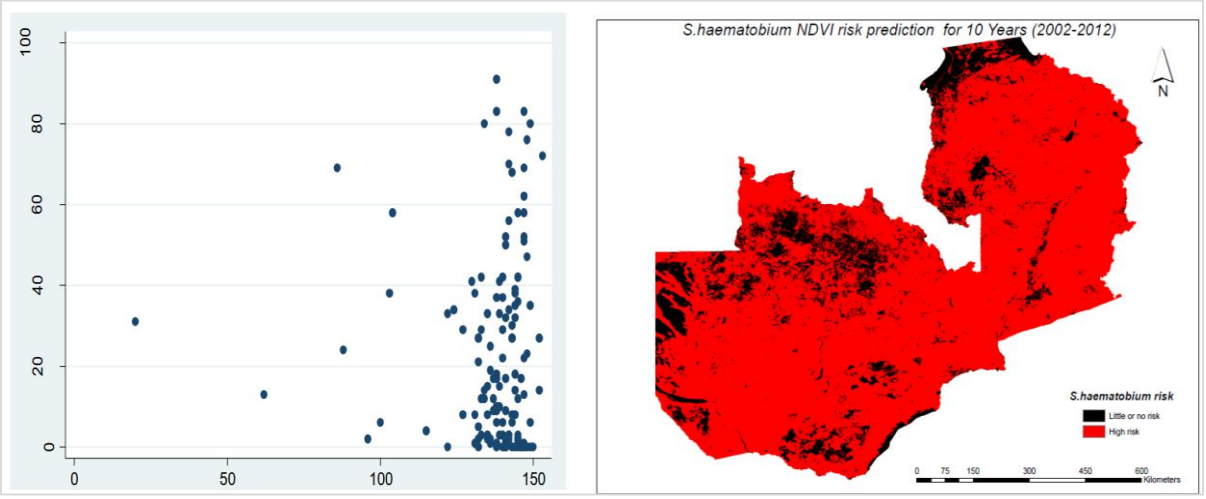


Fig. 5. Scatter plot for suitable NDVI Transmission bands for *S. haematobium* in Zambia for the yearly composites (2002–2012). Scatter plots for NDVI that correlated strongly with high prevalence were plotted and prediction made. NDVI range of 134–153 was obtained at *S. haematobium* prevalence ≥ 50. Therefore, areas below NDVI value 140 and above 153 where classified unsuitable for transmission and hence low risk.

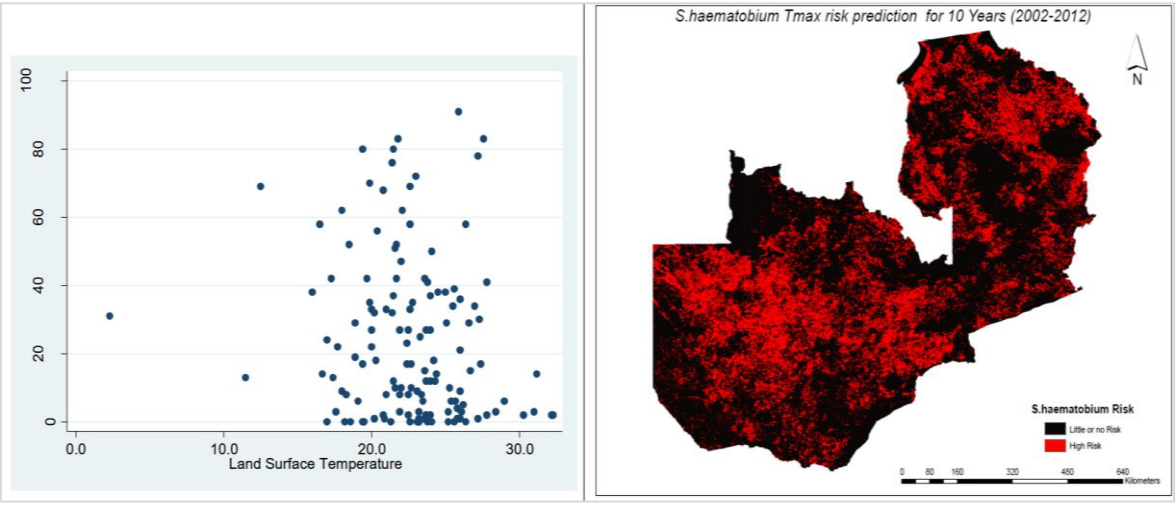


Fig. 6. Scatter plot for suitable LST Transmission ranges for *S. haematobium* in Zambia for the yearly composites (2002–2012). Scatter plots for Tmax that correlated strongly with high prevalence were plotted and prediction made. NDVI range of 19.6–27.6°C was obtained at *S. haematobiu*m prevalence ≥ 50. Therefore, areas below LST value 19.4° and above 27.6°C where classified unsuitable for transmission and hence low risk.

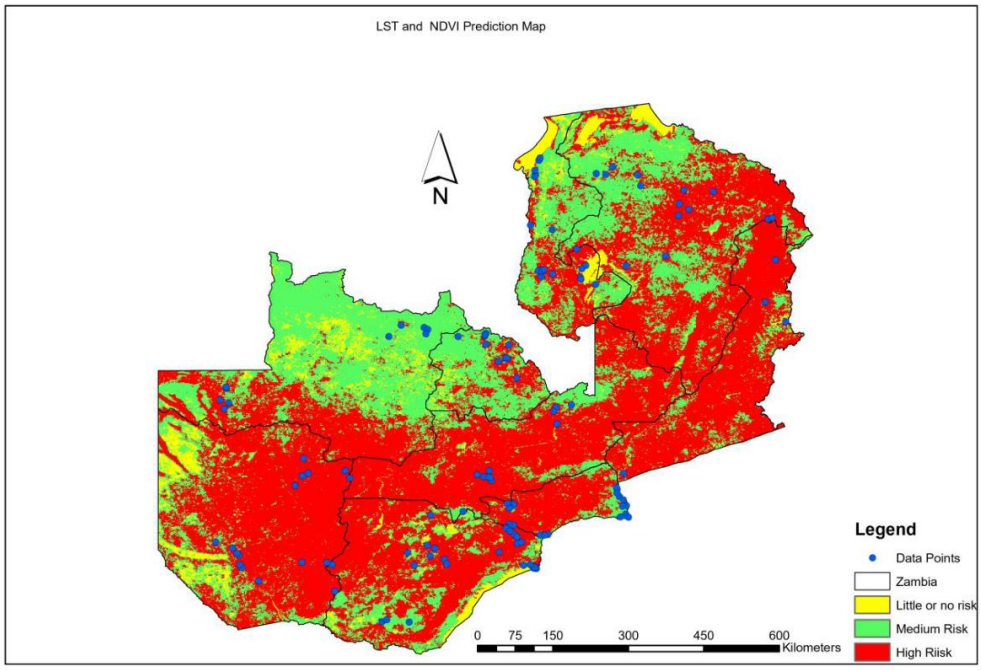


Fig. 7. **The Final Model developed NDVI Model and LST Model.** Three Outcomes for *Schistosoma haematobium* Transmission were generated: High Risk, Medium Risk and Low Risk.

which was not considered in the current research. Additionally, the species of snail intermediate hosts were not identified in this study, in contrast to the Simoonga studies. In another Kenyan study (20), NDVI and Tmax values of 125 to 145 and 22°C to 33°C, respectively, were deemed suitable for the maintenance of *S. mansoni*, which corresponds closely with the extracted ranges in this study.

Malone et al. [16], using known prevalence points for *S. mansoni* developed a suitable NDVI and Tmax range suitable for *S. mansoni* transmission in Ethiopia. Further, [21] used geographical patterns and predictors of malaria risk in Zambia where a range of values for rainfall, temperature, altitude, and NDVI were captured. Models based on an integrated RS and GIS approach have also been applied successfully for mapping the distribution of *S. haematobium* in Chad and

Tanzania [12,22], and hence to guide control interventions.

The optimal temperatures observed for schistosomiasis transmission in the current study are notably higher than those reported in a study conducted in South Africa, which identified suitable temperature ranges of 17°C to 23°C for schistosomiasis transmission [23]. The findings of this study underscore the increasing risks associated with schistosomiasis transmission as temperatures rise, particularly in light of climate change.

The relationships among NDVI, LST, and schistosomiasis transmission dynamics revealed in this study underscore the need to prioritize prevention strategies for vulnerable populations. The observed trends also highlight the relationship between climate and public health, particularly as Zambia has experienced increased rainfall and temperatures in recent years [24]. This necessitates proactive measures to adapt to changing climate conditions and their potential impact on schistosomiasis transmission dynamics.

Sensitivity and Specificity of the Schistosomiasis Risk Model

Some researchers have suggested that the predictive performance of infection risk models can be evaluated by examining the agreement between predictions and observations by using data that was collected from study sites other than those that were used in model development [12]. This was the approach adopted in this study. Results of model validation predicted accurately positive locations of 94.4% and negative locations of 88.8% for *Schistosoma haematobium*. When we combined NDVI and LST, specificity of 75% was achieved. The model is therefore able to correctly classify risk areas for schistosomiasis.

The findings of the study agree with other studies which have been conducted before using methods similar to this study. Kristensen et al., [16] using already collected snail data predicted model accuracy of 97%, 83%, and 98% for the dry season, wet season, and annual season composite images for Ethiopia. The only difference of the Ethiopia study from the current study is that they used snail data to predict schistosomiasis prevalence while in this study prevalence data was used to predict prevalence data from the satellite images for Zambia. In another study in China, a model developed by Jia-Gang et al., [25] had specificity and sensitivity of 94.9% and 93.1% respectively for the prediction of *Oncomelania humpensis*, the intermediate host for *Schistosoma japonicum*. Similarly using Bayesian statistics, prevalence as well as climatic and environmental data, an approximated 122 million people were estimated to be infected with either *Schistosoma haematobium* or *Schistosoma mansoni* in Eastern Africa [3].

The high accuracy of the predictions is an indication that the generated risk maps can be relied upon to guide interventions in the predicated high-risk areas. Although the maps do not show the actual schistosomiasis risk alone but rather possibility of risk, the probability of 50% prevalence used for model fitting coupled with the high model accuracy are good indications of the usefulness of the model. WHO recommends that in basic schools where the prevalence of schistosomiasis is above 50%, then mass drug administration has to be conducted for the whole community [26].

In summary, this study emphasizes the complex interactions between climate, disease prevalence, and health interventions in Zambia. The establishment of climatic cut-offs lays a foundation for future research and public health initiatives aimed at controlling schistosomiasis.

Implications of the Findings

One of the greatest challenges with Neglected Tropical Diseases (NTDs) control in Africa is lack of data. MDA is feasible only in regions where baseline prevalence data is available to inform when and where treatment should occur [27–30]. Surveys conducted from 2005 to 2008 aimed to establish baseline levels of schistosomiasis and soil-transmitted helminths in Zambia to facilitate effective treatment of these neglected tropical diseases [31]. It is crucial to note that extensive data on schistosomiasis control in Zambia began to be gathered in 2005 under the Schistosomiasis Control Initiative. This aligns with the London Declaration on Neglected Tropical Diseases, established in 2012, which engaged endemic countries, pharmaceutical companies, and various stakeholders to combat NTDs through enhanced research and funding [32]. Since that time, Zambia has employed the cost-effective drug praziquantel for the treatment of schistosomiasis.

However, treatment statistics indicate that significant gaps remain in alignment with the objectives set forth in the London Declaration. For instance, as of 2016, only 32% of targeted school-aged children in Zambia had received treatment, with similar challenges observed across many African nations, except for Burkina Faso, Sierra Leone, Togo, and Malawi, which reached approximately 75% of their targets, placing them on a trajectory toward schistosomiasis elimination (Mass Treatment Coverage for NTDs, 2016). Thus, the strategies were reevaluated to meet the goal of treating at least 75% of high-risk groups by 2020 [33] and targeted schistosomiasis for elimination as a public health problem by 2030 [1].

The high prevalence observed in various regions of Zambia, despite an active national control program, is concerning and signals the need for a shift in the treatment paradigm. It is plausible that lapses exist within the treatment and control frameworks, which could apply not only to Zambia but also to other nations, attributable to multiple factors.

One key issue may stem from the current school-based treatment strategy. While this approach prioritizes children—given that they experience greater health benefits compared to adults and schools are more accessible—this method fails to address morbidity adequately. Excluded populations, such as out-of-school children, children under five, fishermen, and women, continue to harbor infections [34]. Consequently, school-aged children may return to infested environments and re-acquire infections. In rural schools, absenteeism rates can reach up to 5.1%, a statistic substantial enough to sustain the parasite within communities where water and sanitation facilities are inadequate.

Therefore, a shift towards both school and community-based treatments is recommended, ensuring comprehensive coverage across all community members throughout the year [35,36]. Simoonga et al. [4–6] have similarly recognized this challenge, suggesting that future research should focus on households within high-risk areas to control the disease at the local level. The findings of this study advocate for utilizing schools as reference points; when children are diagnosed with the disease, follow-up actions should ensure community-wide screening and treatment. Nonetheless, a challenge persists regarding the lack of praziquantel formulations for preschool-aged children, although clinical trials are ongoing [37] The inclusion of preschool-aged children would enhance the control efforts.

Another critical challenge concerning school-aged treatment involves the frequency and timing of administration. WHO guidelines recommend annual or semi-annual treatment based on disease epidemiology [33,37–39]. However, current research data indicate that such frequency is insufficient, as prevalence levels of schistosomiasis return to baseline within six months post-treatment [40]. While this could be attributed to factors such as lack of awareness about schistosomiasis, it also raises concerns regarding the parasite's response to the drug, necessitating consideration of the schistosome's life cycle dynamics. Praziquantel primarily affects adult schistosomes, exhibiting minimal impact on juvenile forms [41,42].

Additionally, current control programs may have overly concentrated on chemotherapy while neglecting other effective strategies, such as intensified case management, vector control, provision of safe water, sanitation and hygiene, and veterinary public health measures [39]. It is crucial to recognize that no single control method is sufficient for most diseases. For significant progress against schistosomiasis, comprehensive strategies must be employed synergistically [43,44].

The successful implementation of these strategies has led to notable reductions in schistosomiasis prevalence in China, where a combination of chemotherapy, snail control, sanitation efforts, and public health education has decreased infection rates from 12 million to fewer than 100,000 within 60 years [45]. While the WHO roadmap for NTD control emphasizes chemotherapy, water and sanitation hygiene (WASH) initiatives, attention is now shifting toward the need for complementary drugs, snail control, disease surveillance, and the development of sensitive diagnostic tools.

CONCLUSION

The study has generated a disease risk distribution model for schistosomiasis in Zambia. The study also established high sensitivity and specificity using independent data. Findings of this study confirm that GIS and RS can be used as a basis for planning national disease control programmes as well as for early warning systems. Climate suitability maps developed can help programme managers to target limited resources for control to high-risk areas. Findings of this study can help Zambia priotise the ongoing treatment of school-going children by starting with children in the high-risk areas.

Although the study has shown that GIS may have many benefits, it must be emphasized that it must be used with caution. The major challenges most African researchers have in as far as where application of various technologies is concerned, include access to tools and the capacity to deliver vital evidence-based knowledge on environment–health linkages. Some researchers for example have produced district-based risk maps when in fact disease risk distribution may not be for the whole district. For some researchers, inability to collect, analyze and interpret environmental and health data that form the major part of the GIS system are some of the setbacks. It is also proposed that the usefulness of the GIS based models be scrutinized by the assessment of their spatial limits, predictive performance and practical application in the field [12].

Therefore, it is imperative that African countries invest enough time into understanding these emerging technologies and how they can be applied to solving some public health problems [46]. This implies that in each emerging technologies and if proved to be beneficial, there is need to develop capacities in those areas by supporting applied local research and also strengthen cooperation among researchers and stakeholders.

Moving forward, there is need to conduct localized research in the areas designated as high-risk areas to determine factors that may be putting the populations at risk apart from climatic and environmental factors only. The probability of risk maps should be used further to estimate the actual populations at risk in Zambia. Studies are needed on the potential impact of climate change on schistosomiasis in Zambia. Biology of the snails unique to Zambia in the transmission of schistosomiasis must be given priority. There is also need to collect more and uniform data on which the models can be built and developed.

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CONFLICT OF INTEREST

There is no conflict of interest in this research.

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