Remote Sensing in Health Assessment:

Using climate based classifications in assessing the vulnerability of schistosomiasis

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Abstract

Schistosomiasis is often endemic in rural hard to reach areas of the world, making ground control efforts difficult. Remote sensing is useful because of its ability to capture images over wide temporal and spatial scales, providing risk assessments at low cost. Initial predictive risk models were based off the ecological requirements of the disease's intermediary host, the snail. An attempt at creating a climatologically based risk map for Ghana is presented. The variables chosen were in close agreement with those used in the literature. The limitations of a regional model is its lack of sensitivity to the focality of schistosomiasis. It has been suggested that models can be refined by including factors of both hosts, snails and humans. Creating predictive models that fit an assortment of *Schistosoma,* snail species, and human factors, over both regional and local scales is necessary to understanding Schistosomiasis in Africa.

Schistosomiasis

Schistosomiasis is a preventable and curable disease, yet over 200 million people are infected and over 780 million are at risk. Transmission has been documented in over 78 countries, 90% of which are in Africa. A tropical parasitic disease is caused by blood flukes of the genus *Schistosoma*, of which the three main species affecting humans are *Schistosoma mansoni*, *S japonicum*, and *S haematobium*. Second only to malaria as the most devastating parasitic disease, it makes the World Health Organizations (WHOs) list of Neglected Tropical Diseases (NTDs).

In the epidemiological triangle, the trematode *Schistosoma,* often considered the agent . However, the difficulty with schistosomiasis is that it has two hosts, the human as well as the snail. As a result, transmission of the disease requires an interaction between snail habitat and human activity. Conditionality of snail population density is largely influenced by rain, vegetation and temperature. Looking at the accumulated rainfall as compared to schistosomiasis counts for 2013 allows us to visualize two of the major challenges in the spatial extent of this project: first, the necessary division between sub-Saharan versus Saharan climatology and second, the "schistosomiasis time lag."
These environmental constraints make schistosomiasis ideal for using spatial software in predicting prevalence.

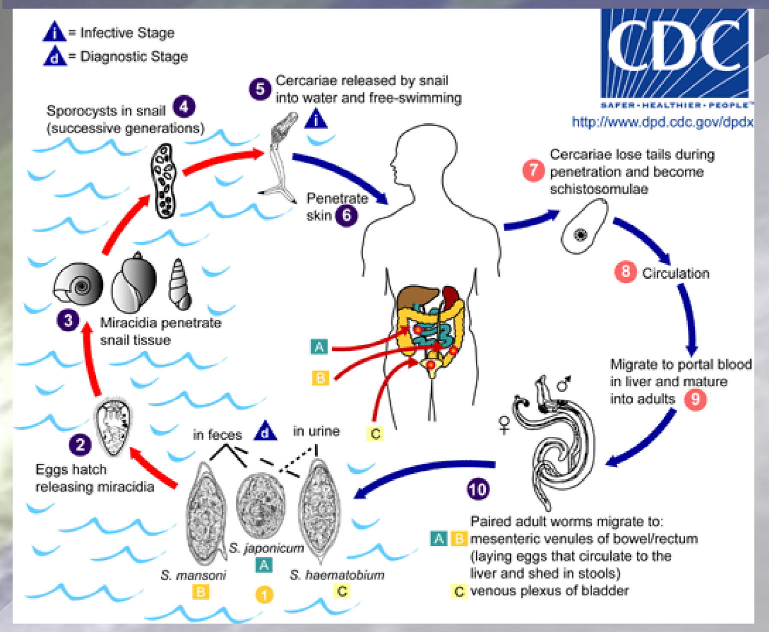


Figure 1: Ghana is located in Western Africa and has temporal nature of Saharan as well as sub-Saharan Africa

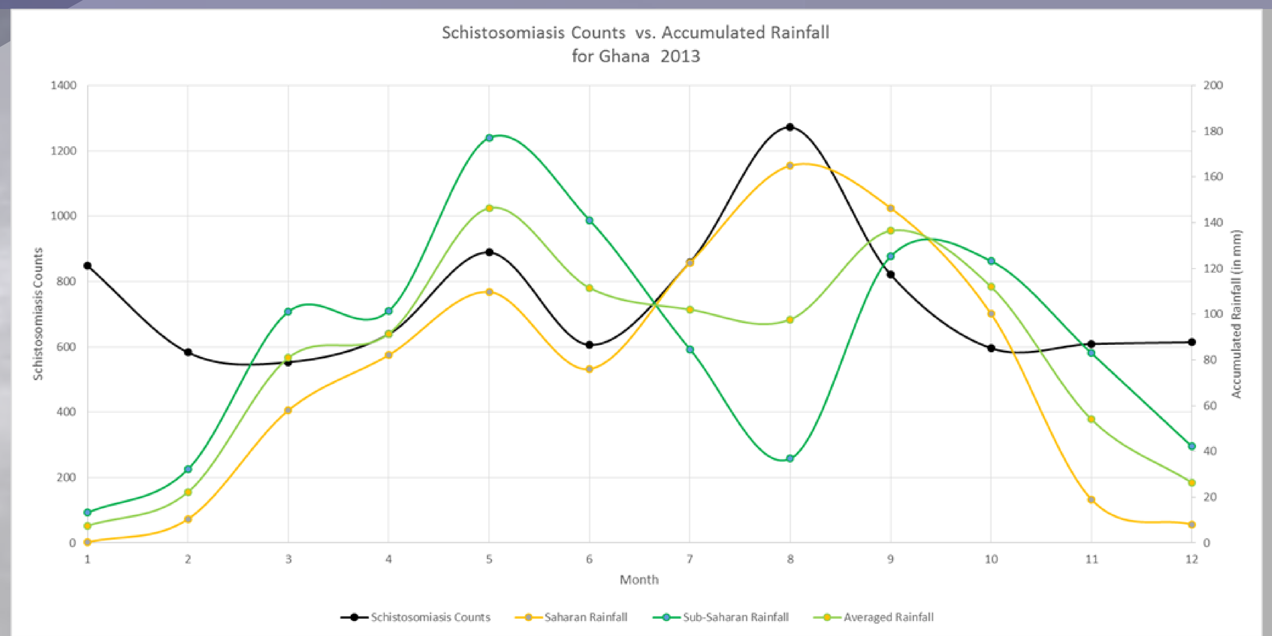
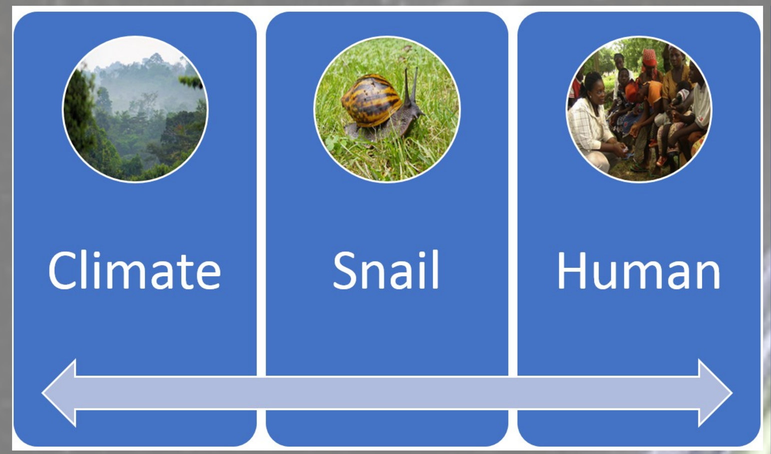


Figure 8: Schistosomiasis counts per person graphed in comparison to accumulated rain fall in mm, the latter is divided into sub-Saharan., Saharan, and average rainfall. 46 districts were included in Saharan and 124 were included in sub-Saharan Africa

By determining the seasonality of the disease, more spatially and temporally targeted preventative measures can be taken by health providers.

Model Refinement

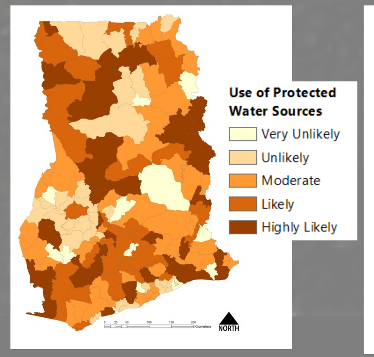
- Wind
- Temperature
- Diurnal
- Air, water, land, mud
- Length of dry season
- Rain
- Air

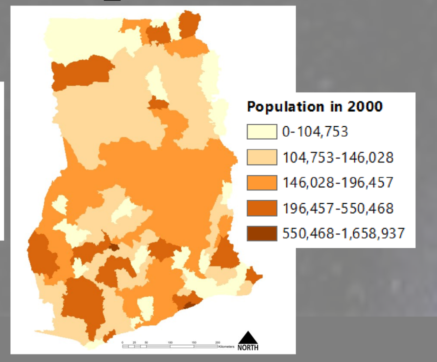


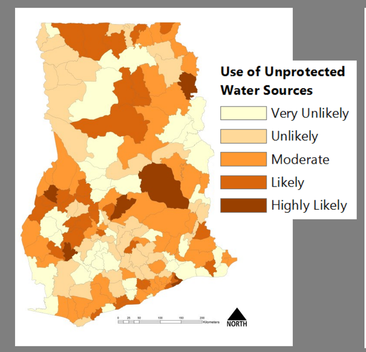
- Proximity to protected versus unprotected water sources
- Standard of living
- Education
- Accessibility of health facilities
- Population density
- Water, sanitation and hygiene facilities and practices

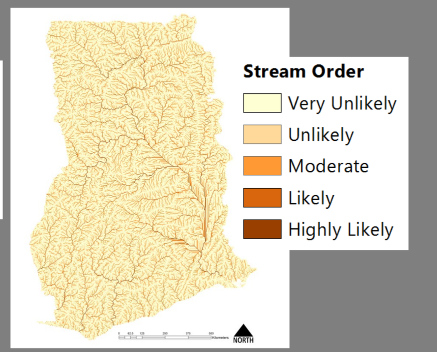
- Relocation due to stress
- Water depth variance
- Burying into mud
- Susceptibility
- Differences between species
- Multiple species in same

GIS Examples





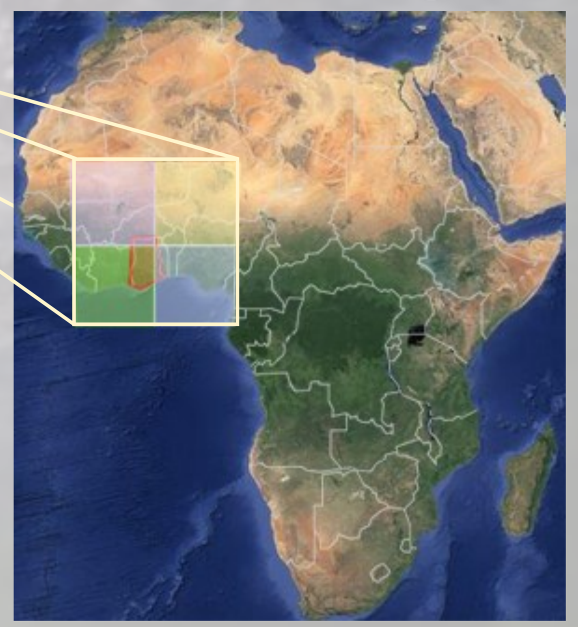




Recommendations

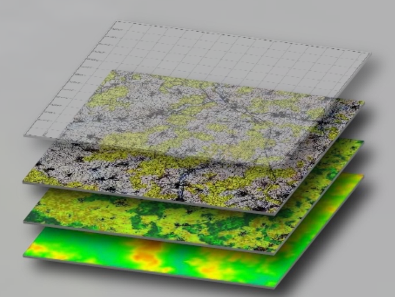
Climatic models were a good start to predictive risk assessment models, but in order to capture the focality of Schistosomiasis models need to be able to go from national to regional to local scales. There are many refinements that can be made to the variables in use already, and arguments for more to be added. The most valuable addition at this stage would be human in addition to snail. Much of the human factors are available though GIS, making a RS-GIS combination desirable. As further refinements can be made, models will increase in the accuracy of prediction and become an invaluable source of information in the furthering of control efforts.

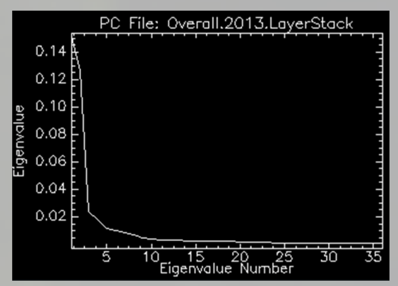
Satellite Images



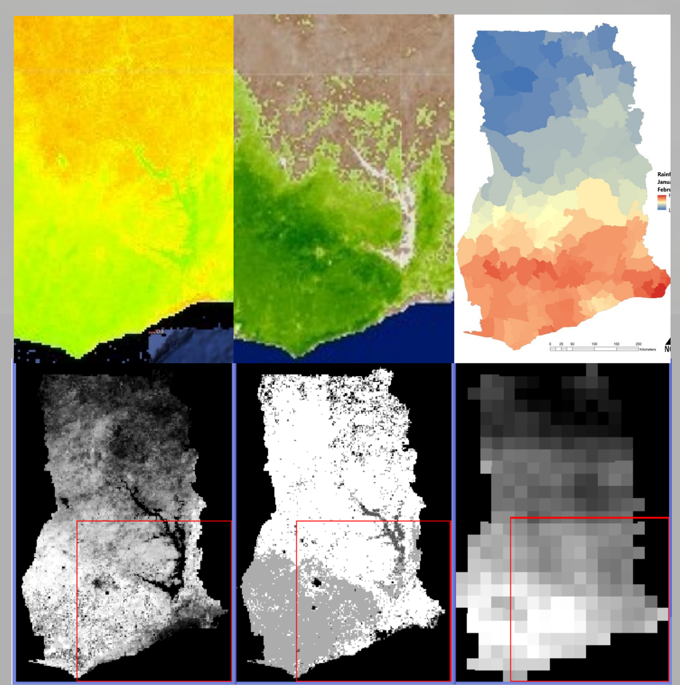
Processing Steps

1. Mosaic
2. Georeference
3. Resize
4. Mask
   i. Water
   ii. Border
5. Layer Stack
6. Principal Component Analysis
7. Classification
   i. Unsupervised
   Ii. Supervised
8. Post Classification
10. GIS statistical analysis
11. Compare to health data



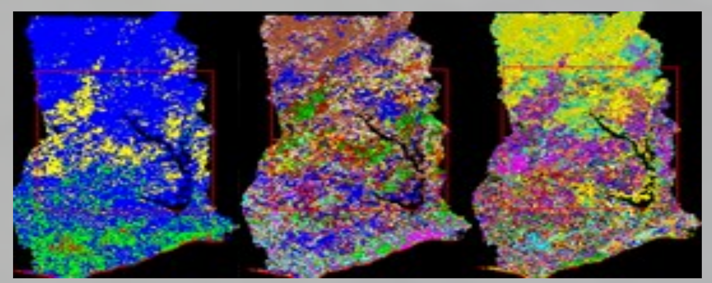


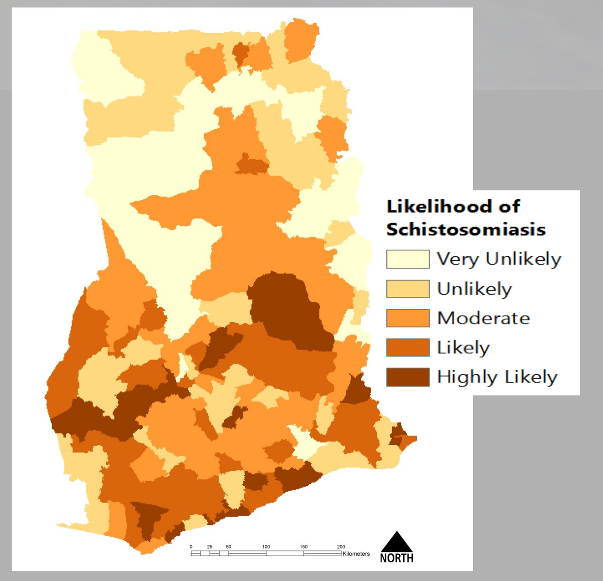
Satellite Sensor Products



Top: Color Coded Images
Bottom: Black and White Masked Images

Classification Results





Interpolated Schistosomiasis 2013

Discussion

Each column seen to the left is a step in the process of making a climatology based predictive risk model for Ghana. This model utilized the satellite Aqua and Terra and the MODIS sensor. Ghana was positioned in such a way as to require four images stitched together to make one complete image of Ghana. The sensor had a variety of "products" of which we used surface temperature, normalized difference vegetation index (NDVI), and accumulated rainfall. Each of these products were taken for every month of 2013, and then resized to Ghana's exact border shape and water features. These were then grouped together, in a process called layer stacking. Once combined, principal component analysis (PCA) was applied to extract the most important information and place it into layers of descending importance. The important layers have the highest peak as seen in the graph to the left. In this way only the first and most important layers were selected while the remaining "noise" discarded. These underwent a process called classification, to group together the most similar areas of the PCA composites. These grouped areas can be compared to the health data for comparison.