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Erin R. Stearns   Date

Poverty and neglected tropical diseases in Nigeria: a quantitative geospatial assessment at the sub-national level.

By

Erin R. Stearns

Degree to be awarded: MPH

Global Epidemiology Department

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Bachelor of Science

Miami University

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An abstract of
A thesis submitted to the Faculty of the Rollins School of Public Health of Emory University in partial fulfillment of the requirements for the degree of Master of Public Health in the Global Epidemiology Department

2016

Abstract

Poverty and neglected tropical diseases in Nigeria: a quantitative geospatial assessment at the sub-national level.

By Erin R. Stearns

Neglected tropical diseases (NTDs) and poverty are commonly associated in NTD literature despite not necessarily having quantifiable evidence of such an association. Quantifying the association at a sub-national level could lead to more informed and thus effective public health policy and disease intervention programming. **Objectives:** The objectives of this study were to spatially visualize and quantify the relationship between poverty and trachoma, lymphatic filiriasis (LF) and cumulative soil-transmitted helminth (STH) infection prevalence in Nigeria at the sub-national level. **Methods:** Poverty and NTD data were visualized using ArcMAP. ArcMAP was also employed to extract data from each spatial layer to tables then exported and analyzed in SAS. Multicollinearity was assessed for each model then multiple linear regression was performed for the association between poverty and LF and STH, while logistic regression was performed for poverty and trachoma. A two-sample t-test was also conducted for assessing the poverty-trachoma relationship. **Results:** A sub-national, geospatial assessment of the association between poverty and each NTD revealed positive estimates of association, however they were very imprecise and non-significant. The results of this analysis fail to reject the null hypothesis of no association between poverty and each NTD. **Conclusions:** There were many limitations to this analysis thus it is important not to interpret the results as confirmation of a null association. Limitations arose from incomplete and non-representative small area NTD data for Nigeria and highlighted the difficulties of performing spatial analysis in low-resource settings. These results also shed light on the importance of representative sub-national data for the investigation of intra-country variation in the relationship between poverty and NTD prevalence. Future work should include a reevaluation of the spatial infrastructure of NTD surveillance to include improved, temporally-relevant small area NTD surveillance. Improving small area NTD surveillance is necessary for characterizing, monitoring and intervening on NTD transmission.

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Table of Contents

1.1 Introduction

Neglected tropical diseases (NTDs) cause tremendous suffering, decrease quality of life, and are a considerable burden upon the population of those living in endemic countries. They affect more than a billion people worldwide. NTDs are considered 'diseases of poverty,' alongside HIV/AIDS, tuberculosis and malaria (May, 2007), though there is a dearth of quantified evidence to support the assertion. Literature supports the conclusion that NTDs and the poor health status of citizens limits economic development in most tropical countries (Bonds, Dobson, & Keenan, 2012). The World Health Organization (WHO), among others, saw an opportunity to make great strides forward in health equity and potentially economic development by targeting nine select NTDs for elimination (Savioli & Daumerie, 2012). The WHO created a plan in January 2012 for controlling and eliminating, or at least substantially reducing the burden of, NTDs globally by 2020(Savioli & Daumerie, 2012). The nine NTDs chosen were lymphatic filariasis, leprosy, human African trypanosomiasis, blinding trachoma, schistosomiasis, soil-transmitted helminthiasis, Chagas disease, visceral leishmaniasis and onchocerciasis.

NTDs have been labeled diseases of poverty from circumstantial observation that diseases such as trachoma do not exist where substantial socioeconomic progress has been made (Bailey, Downes, Downes, & Mabey, 1991). Past studies have quantified the relationship between trachoma and poverty, however, this has primarily been at the country-level and does not account for intra-country variation in disease burden, geography and population density. There is limited published evidence of an association between LF and poverty at a sub-national level, as well, despite substantial unfounded rhetoric (Molyneux & Nantulya, 2004). Support for the concept that trachoma and LF, as well as other NTDs, are diseases of poverty requires examination at a more detailed level (Frick, Hanson, & Jacobson, 2003).

It is possible that the relationship between poverty and poor health outcomes is bi-directional, thus determining the impact of one on the other is a persistent challenge in allocating aid and directing interventions. If health is a fundamental determinant of economic prosperity, then targeted interventions of the most burdensome diseases such as NTDs would be crucial to macroeconomic strategy for poor countries and appropriate targets for foreign financial aid (Bonds et al., 2012). Conversely, if after controlling for environmental factors, the impact of NTDs upon economic development is null, humanitarian conscience aside, then foreign aid may be better directed at bolstering economic infrastructure and institutions than targeting a reduction in NTD burden.

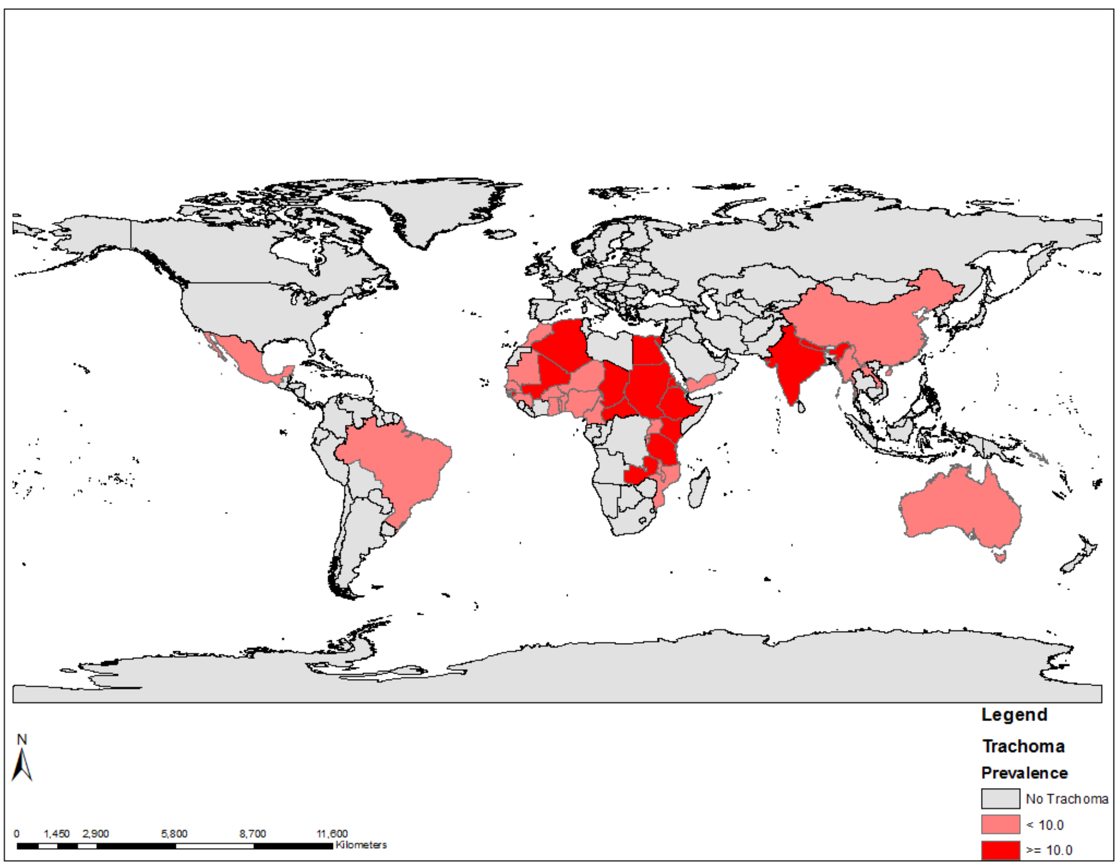
The first goal of the Sustainable Development Goals is to eradicate extreme poverty (subsistence on less than $1.25 per day) for all people everywhere by 2030. The WHO has goals of eliminating the nine aforementioned NTDs by 2020. Literature suggests the two global goals of eliminating poverty and NTDs are intimately intertwined although there is inadequate evidence demonstrating causal pathways highlighting the importance of epidemiological knowledge for informing future action. A sub-national, geospatial assessment of the relationship between poverty and the NTDs trachoma, lymphatic filariasis and soil-transmitted helminths and using robust high-resolution gridded poverty surfaces (Tatem, Gething, Pezzulo, Weiss, & Bhatt, 2014), controlling for appropriate covariates, will be conducted for Nigeria in this thesis.

1.2 Background of selected Neglected Tropical Diseases

1.2.1 Trachoma

Trachoma is a highly infectious disease caused by an organism called Chlamydia trachomatis and is transmitted through the discharge of an infected person's eyes. Trachoma can then be passed on by hands, clothing or by flies that land in the infected discharge and then land on other individuals. The World Health Organization (WHO) estimates six million people globally(Figure 1) are blind as a result of repeated trachoma infection and more than 150 million people are in need of treatment (World Health Organization, 2015c).

Figure 1. Global burden of trachoma (*NTD Mapping Tool Methods 2014*, 2014).



Clinical Manifestation

Trachoma initially strikes in childhood as itching, redness and pain in the eyes. Trachoma is recognizable by the requisite lesion, a trachomatous follicle, characteristically occurring in the upper tarsal conjunctiva, the mucous membrane that lines the inside of the eyelids and covers the front of the eye. The upper tarsal conjunctiva appears to have a rough texture upon examination (trachoma is Greek for “rough”) (Kasi, Gilani, Ahmad, & Janjua, 2004).

The disease progresses over years as repeated infections cause fibrosis which results in scarring of the conjunctiva (scarring conjunctiva)(World Health Organization, 2015c). “In scarring conjunctiva, the upper eyelid is shortened and distorted (entropion) and the lashes abrade the eye (trichiasis),” (Kasi et al., 2004). Repeat infections lead to higher degrees of entropion and trichiasis and eventually cause blindness.

Environmental Risks

Chlamydia trachomatis flourishes in environments with overcrowding, water and sanitation accessibility issues, limited healthcare services and large populations of flies. Hot, dusty climates lend themselves to trachoma transmission as well.

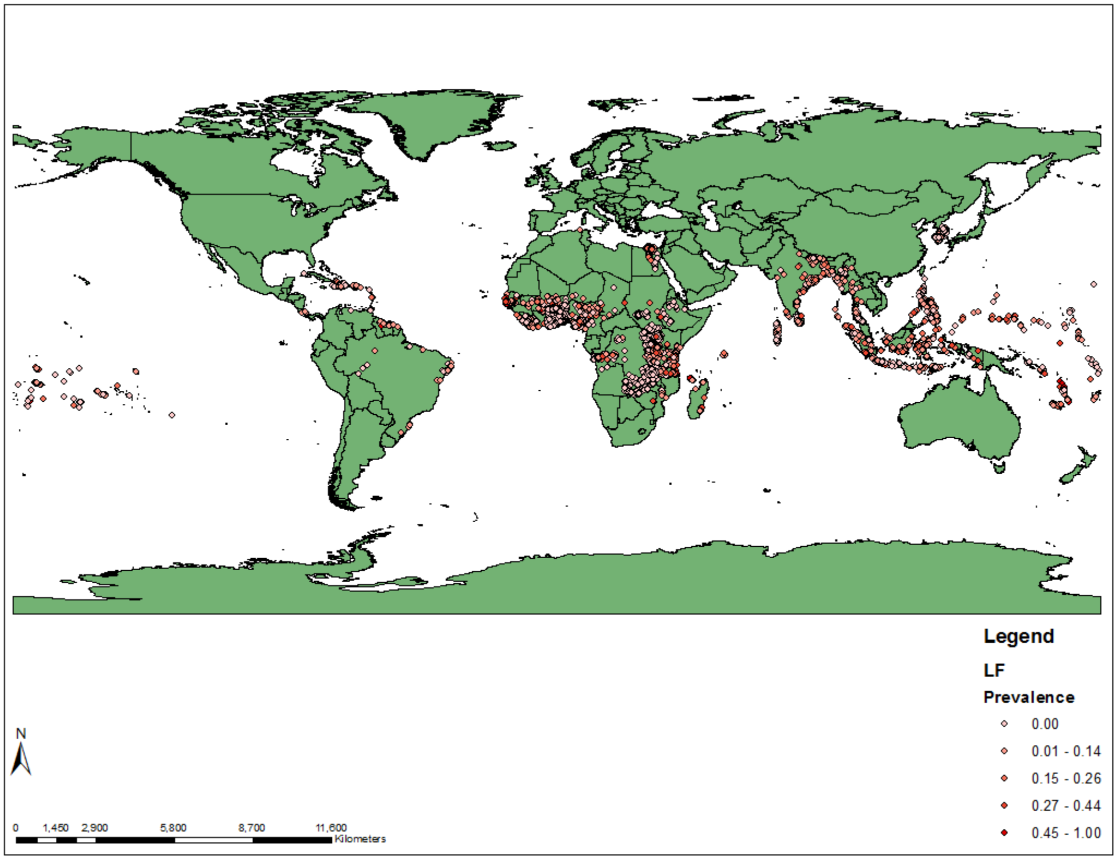
Recommended interventions

The “SAFE”(Surgery for trichiasis, Antibiotics to treat trachoma, Face washing, and Environmental improvements to curb transmission) strategy is recommended for limiting trachomatous blindness (Emerson, 2014). Improved sanitation and reduction of fly breeding sites are also recommended.

1.2.2 Lymphatic filariasis (LF)

LF is a mosquito vector-borne neglected tropical disease frequently referred to as elephantiasis. Like trachoma, infection usually occurs early in childhood. This initial infection causes hidden damage to the lymphatic system that manifests later in life. LF often exhibits itself as painful, disfiguring expressions that include lymphoedema, elephantiasis and scrotal swelling that lead to disability. LF co-infection with other parasites and infectious diseases is common and can lessen protective immune responses against malaria and tuberculosis as a result of its immune system suppression (Taylor, Hoerauf, & Bockarie, 2010). People living with LF suffer mental, social and financial loss contributing to stigma. Over 120 million people are infected with LF (Figure 2), with approximately 40 million experiencing disfigurement and disability (World Health Organization, 2015a).

Figure 2. Global burden of LF (*NTD Mapping Tool Methods 2014,* 2014).



Clinical Manifestation

Two of eight species of filarial nematodes that have human hosts are responsible for LF: *Wuchereria bancrofti* (accounts for approximately 90% of cases globally) and *Brugia malayi* (distribution restricted to Southeast Asia and accounts for remainder of cases). These filarial nematodes are transmitted by mosquitoes and produce long-term, chronic infection through suppression of host immunity. Adult-worm parasitism takes place in nests (lymphangiectasia) within the lymphatic vessels, most commonly in the extremities and male genitalia (Taylor et al., 2010). Adult worms can live an average of 6-8 years and produce millions of microfilariae (immature larvae) that circulate in the blood. Mosquitoes are infected with microfilariae by ingesting blood during a blood meal of an infected host. Microfilariae mature into infective larvae within the mosquito. The infected mosquito deposits the infective larvae on the skin of the host they are feeding on, where they can then enter the body. If the larvae enter the body, they move to the lymphatic vessels where they mature into adult worms and continue the cycle of transmission (World Health Organization, 2015a).

Environmental Risks

LF is transmitted by different species of mosquitoes and is primarily determined by geographic area. The *Culex* species is most common in urban and semi-urban areas, the *Anopheles* mostly in rural areas and *Aedes* principally in endemic islands in the Pacific Ocean. Environmental risks for LF are consistent with risk factors for mosquito colonies which include humidity, heat and moderate to high rainfall (Sabesan, Raju, Srividya, & Das, 2006).

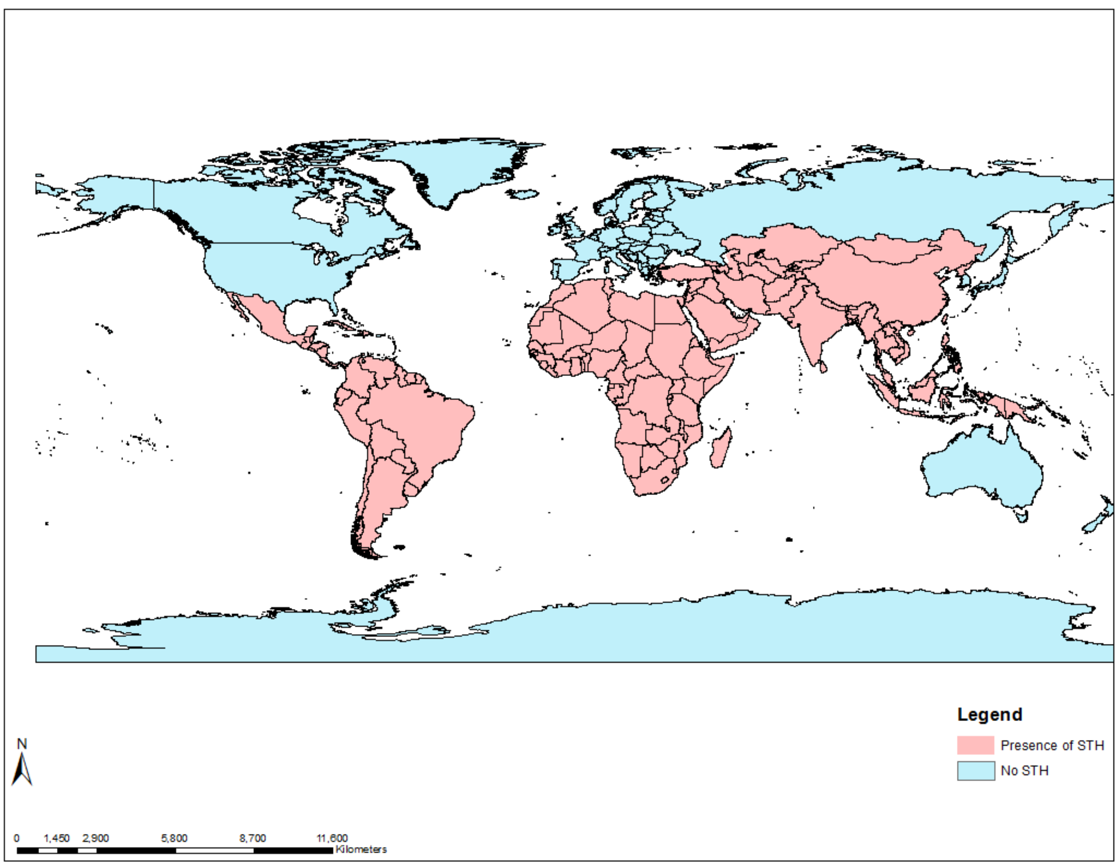
Recommended interventions

The global alliance to eliminate lymphatic filariasis launched in 2000 the Global Programme to Eliminate LF (GPELF) by 2020. The main objective of GPELF is to halt the cycle of transmission between mosquitoes and humans largely through preventive chemotherapy via mass drug administration of diethlycarbamazine or ivermectin combined with albendazole (Taylor et al., 2010). Vector-control interventions such as sleeping under bed nets and indoor residual spraying are also recommended approaches (World Health Organization, 2015a).

1.2.3 Soil-transmitted helminth (STH) Infections

STH infections are among the most widespread of chronic infections affecting humans globally (Brooker, Clements, & Bundy, 2006). They are transmitted by eggs present in human feces that contaminate soil in areas of poor sanitation. The four central nematode species that infect humans are the roundworm (*Ascaris lumbricoides)*, the whipworm (*Trichuris trichura)* and hookworms (*Necator americanus* and *Ancylostoma duodenale).* Over 1.5 billion people worldwide (Figure 3), approximately 24% of the global population, are infected with STH infections (World Health Organization, 2015b).

Figure 3. Global burden of STH infections (*NTD Mapping Tool Methods 2014*, 2014).



Clinical Manifestation

STH infection occurs through ingestion of eggs or penetration of skin by larvae. The parasite then lives in the host intestine and produces eggs that are passed through the feces and deposited in the environment. Adult worms can survive for several years and produce thousands of eggs each day (Brooker et al., 2006). Eggs passed in feces need roughly 3 weeks to mature in soil before becoming infectious. Eggs can remain infectious in the soil for several months dependent on presence of conducive environmental factors.

Symptom expression is dependent on concentration of worms within an individual. Higher concentrations can cause diarrhea, abdominal pain, weakness and impaired cognitive and physical development. Hookworms cause chronic intestinal blood loss that can result in anemia (World Health Organization, 2015b).

Environmental Risks

Environmental risks for STH infection include temperature, soil moisture and relative humidity. Areas with higher humidity are associated with faster development of eggs in soil to the infective stage, while lower humidity inhibits the egg from becoming infectious.

Recommended interventions

Periodic deworming to eliminate infecting worms, particularly among school-aged children, is a recommended strategy for curbing the proliferation of STH infections. School-aged children are particularly vulnerable to the developmental impediments caused by STH infection. Health education is also recommended as is improved sanitation to reduce soil contamination with infective eggs (World Health Organization, 2015b).

1.3 Trachoma, LF and STH infections and poverty

Trachoma no longer exists in areas that have experienced significant socioeconomic improvements. Changing the economic landscape of an area cannot be done in isolation of neighboring areas, whether that be a village or a country, nor can it be done quickly. It is a long, laborious process that the Sustainable Development Goals aim to pursue by eradicating extreme poverty (people living on less than $1.25/day) for all people everywhere by 2030 ("Sustainable Development Goals: 17 Goals to transform our world," 2015) . As a result, focus has historically been placed upon low-cost interventions such as behavior change education surrounding hygiene and water use (Bailey et al., 1991). A study in the Philippines found LF-endemic areas had a tendency of being the poorest at the provincial level and elimination of LF in these areas presents substantial potential to reduce poverty and health inequalities (Galvez Tan, 2003). One study used country-level per capita income from 2001 and LF endemicity data from 2000 to explore the association between LF and poverty. This study found that of 175 countries with available data, 73% (47/64) of low-income countries (per capita/annum < $746), 33% (24/72) of middle income countries (per capita/annum: $746-$9205), and 5% (2/39) of high income countries (per capita/annum > $9205) were LF endemic (Durrheim, Wynd, Liese, & Gyapong, 2004). A study in Brazil used advanced Bayesian geostatistical modeling, along with geographic information systems and remote sensing to visualize the distribution of relevant STH species in Brazil. Remotely sensed climatic factors and environmental variables as well as socioeconomic variables available from national databases were used as predictors. Results of fitting the model-based, spatially explicit risk maps revealed certain environmental covariates (precipitation and temperature) and socioeconomic covariates were strongly correlated with the spatial distribution of STH infection and thus acted as important predictors (Scholte et al., 2013).

Attaining development goals such as those set by the UN in September 2015 require critical examination of intra-country geographical disparities and inequities in health access, resource allocation, and financial capital (Tatem et al., 2014). Development indicators measured at the national level can often obscure crucial inequities at the sub-national level, particularly among the rural poor. A better understanding of the geographical variation of health, wealth and environmental factors at a subnational level will allow policy-makers to target interventions more effectively. A more thorough comprehension of the issues facing populations at varying levels within administrative boundaries will enable solutions to be tailored to address specific chasms in equity in a more efficient and effective manner.

Targeted health interventions to eliminate trachoma, LF and STH infections or direct, targeted economic improvement: which would have a greater impact upon the overall well-being of people most affected by both poverty and NTDs? This investigation aims to quantify and visualize the relationship between poverty and trachoma, LF, and STH infections in Nigeria at a sub-national level, controlling for relevant environmental covariates.

1.4 Utility of geospatial methods

Numerous previous studies have demonstrated place can, and oftentimes does, affect health outcomes (Diez-Roux et al., 1997; Pickett & Pearl, 2001; Shouls, Congdon, & Curtis, 1996; Waitzman & Smith, 1998). Geospatial methods allow examination of patterns and clusters that may not be identifiable using aspatial modeling. After a model is fit, model residuals reveal how well the model predicts the actual results. Explanatory variables are sought out to minimize model residuals and strengthen the predictive power of the model. Geospatial modeling allows further investigation into model residuals by incorporating space and heterogeneous features of space as potential explanatory variables that may not have already been accounted for using an aspatial model. Geospatial modeling is a valuable tool because it can provide further understanding of diagnostic and mechanistic aspects of etiologic research. It can be used to create suitability maps that identify areas most at risk for developing certain outcomes based upon various environmental inputs which may provide additional insight into explaining phenomena in deterministic terms. Geospatial modeling can identify areas most effected by a certain outcome and improve resource allocation for targeted preventative and control interventions (Kitron, 1998). This approach is particularly relevant in low resource settings (Khan et al., 2010). Geospatial methods result in improved knowledge, more effective targeting of interventions and more informed long-term planning.

2.1 Methods

Open source, publicly available data were exclusively used in this investigation. Trachoma, lymphatic filariasis and soil-transmitted helminth infection data comes from *NTDmap.org*, a mapping tool created in 2013 collaboratively between the Global Atlas of Helminth Infection at the London School of Hygiene and Tropical Medicine, Task Force for Global Health, International Trachoma Initiative, African Programme for Onchocerciasis Control, Mectizam Donation Program, and the International Coalition for Trachoma Control. The current version of the mapping tool was developed by SimSpatial GIS Consulting, LLC.

The poverty data came from the WorldPop project (http://www.worldpop.org.uk/). The WorldPop project began in October 2013 as a means of combining the AfriPop, AsiaPop and AmeriPop population mapping projects. The goal of the WorldPop project is to provide an open access collection of spatial demographic datasets for Central and South America, Africa and Asia to support development, disaster response and public health.

2.2 Data Sources

Five separate data sources were used to conduct this investigation. Details regarding each spatial layer can be seen below (Table 1).

Table 1. Summary table of all data layers used for analysis.

	Data Layer	Data source	Spatial data format	Spatial resolution/Area Unit
Exposure	Poverty	WorldPop (http://www.worldpop.org.uk/)	Raster	0.0083333 decimal degrees (30 arc-seconds, approximately 1km at the equator)
Outcome	Trachoma	NTD Mapping tool (http://www.ntdmap.org/)	Polygon	Local Government Area (LGA) unit
	Lymphatic filariasis		Point	
	Soil-transmitted helminths		Polygon	
Covariates	Temperature	WorldClim (http://www.worldclim.org/)	Raster	0.0083333 decimal degrees (30 arc-seconds, approximately 1km at the equator)
	Precipitation		Raster	
	Aridity	Consultative Group on International Agricultural Research - Consortium for Spatial Information (http://www.cgiar-csi.org/)	Raster	
	Land cover	European Space Agency (http://due.esrin.esa.int/page_globcover.php)	Raster	300 meters

2.2.1 Trachoma data

The trachoma spatial data are derived from population-based prevalence surveys (PBPS). Data were extracted from published and unpublished literature to ascertain cross-sectional epidemiological trachoma burden profiles dating as far back as 1980 and as a continuation of the work done by Smith et al., 2013 (Flueckiger et al., 2015).These data were then entered into a standardized database and mapped using geographical information systems (GIS) software. The goal was to collect the most up-to-date data possible to optimally inform control efforts (Smith et al., 2013). Survey data for Nigeria spanned the timeframe from 2003-2014.

The trachoma spatial data is dichotomized according to intervention guidelines and reveals whether or not trachomatous follicular (TF) prevalence in children ages 1-9 years old is higher or lower than 10% of that population. The 10% threshold is recommended by the WHO as a guideline for district level mass drug administration

(MDA) of antibiotics for trachoma treatment. TF is the first level of the trachoma grading system and represents the presence of five or more follicles greater than 0.5 millimeters in the upper tarsal conjunctiva.

The trachoma spatial data came as a shapefile at the local government area (LGA) administrative level with data represented as polygons.

2.2.2 Lymphatic filariasis (LF) data

LF spatial data were acquired through structured searches of published and unpublished literature, unpublished surveys, government and international archives, and through direct contact with researchers and program managers (Cano et al., 2014). The LF spatial data measures the prevalence of LF at a particular site. Inclusion criteria for creation of the LF prevalence map were if the data provided the number of people surveyed, the number of LF positive cases, the methodological details of diagnosis and details about the specific study site (*NTD Mapping Tool Methods 2014*, 2014). The LF spatial data came as a shapefile at the local government area (LGA) administrative level with data represented as points.

2.2.3 Soil-transmitted helminth (STH) infection data

STH spatial data was acquired through structured searches of electronic bibliographic databases as well as local archives and libraries and through direct contact with researchers. Inclusion criteria dictated that only cross-sectional prevalence surveys be used and excluded data based on hospital, clinic, post-intervention or sub-population surveys. There were no restrictions imposed based upon sample size or STH diagnostic method (*NTD Mapping Tool Methods 2014*, 2014).

The STH spatial data measures the cumulative prevalence of STH by including prevalence of infection with any STH species. The cumulative prevalence of STH was calculated by using a straightforward probabilistic model of combined infection, incorporating a correction factor to allow for non-independence between species, an approach used by previous researchers (de Silva & Hall, 2010). The cumulative prevalence of STH without a correction factor was calculated as $PHAT = H + A + T - (HA) - (AT) - (HT) + (HAT)$. H is the prevalence of hookworm infection, A the prevalence of *A. lumbricoides* and T the prevalence of *T. trichiura*. The slope of the line representing the difference between the observed and predicted cumulative prevalence of STH was 0.0596 and rounded to 0.06, which indicated that cumulative STH prevalence was overestimated by 0.06 for every 10% increase in prevalence (de Silva & Hall, 2010). The corrected cumulative prevalence of STH infection was then estimated as $PHAT \div 1.06$ (*NTD Mapping Tool Methods 2014*, 2014). The STH spatial data came as a shapefile at the local government area (LGA) administrative level with data represented as polygons.

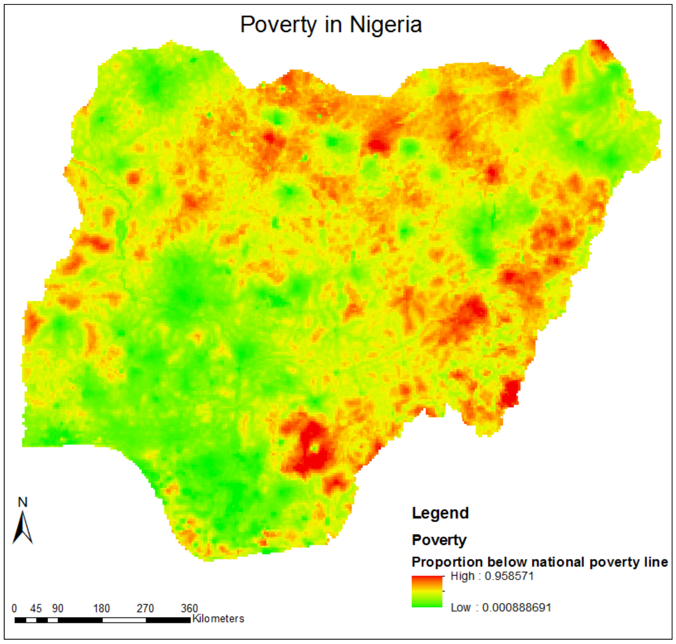
2.2.4 Poverty data

The poverty spatial data used to create this map were derived from Demographic and Health Survey (DHS) and Living Standards Measurement Survey (LSMS) variables. The poverty spatial data measures the proportion of residents living at or below the nationally set poverty level. These data were presented as an interpolated poverty surface at a spatial resolution of 30-arc seconds, or approximately 1 kilometer at the equator (Figure 4).

The poverty map was created using a novel spatial statistical methodology that produced high-resolution gridded poverty surfaces using data from the aforementioned sources. A Bayesian geostatistical modeling structure, following approaches built for the Malaria Atlas Project to create continuous contemporary surfaces (Gething et al., 2011), was employed to mine spatiotemporal relationships within the data, explore and utilize a broad array of covariates and manage uncertainties to produce robust output surfaces with confidence intervals (Tatem et al., 2014). This approach was applied to mapping consumption-based poverty metrics from 2010/2011 LSMS data for Nigeria.

WorldPop describes three elements critical to consumption-based poverty analysis: a welfare indicator to rank people within a population, an appropriate poverty line (in the case of Nigeria, a nationally set poverty line of $1.08 per capita per day was used instead of the internationally accepted line of $1.25 per capita per day), and a formula to combine individual welfare indicators into a single, aggregate poverty figure (Tatem et al., 2014). The consumption-based poverty measures used for the Nigeria poverty layer used household surveys that were part of the LSMS program. One of the goals of the LSMS is to improve household data quality to better measure and evaluate measures of households' standards of living and poverty status. The LSMS surveys collect a vast array of information on household expenditures on an item-by-item bases. This includes expenditures on food, tobacco, non-durable goods, semi-durable and durable goods and services, frequently purchased services and non-consumption expenditures (Male-Mukasa, 2010).

Figure 4. Interpolated poverty surface displaying proportion of population living below Nigerian national poverty line (Tatem et al., 2014).



2.2.5 Climatic and environmental data

The NTD burden in a country is unlikely the direct result of poverty alone (Durrheim et al., 2004). The poverty-NTD relationship could potentially be confounded or modified by environmental factors that may determine how hospitable an area is to economic prosperity and also conducive to vector breeding and survival. With this in mind, candidate variables were included in this investigation that will be described below.

2.2.5.1 Annual mean temperature and annual precipitation data

Annual mean temperature and annual precipitation data were obtained from the global climate data site, WorldClim (http://www.worldclim.org). Temperature data are in °C * 10, such that a value of 231 represents 23.1 °C. This allows for reduced file sizes and enables easier downloading. The unit used for the precipitation data is millimeters of rain annually. Input data were collected from various sources and restricted to the time period 1950-2000, where possible. Records were only used if they had at least 10 years of data to calculate mean values. Using an expanded time period from 1950-2000 significantly increased the number of records in certain areas (Hijmans, Cameron, Parra, Jones, & Jarvis, 2005). These data were presented as global interpolated climate surfaces at a spatial resolution of 30-arc seconds, or approximately 1 kilometer at the equator (Figures 5 and 6).

Figure 5. WorldClim mean annual temperature estimates for Nigeria. (Hijmans et al., 2005).

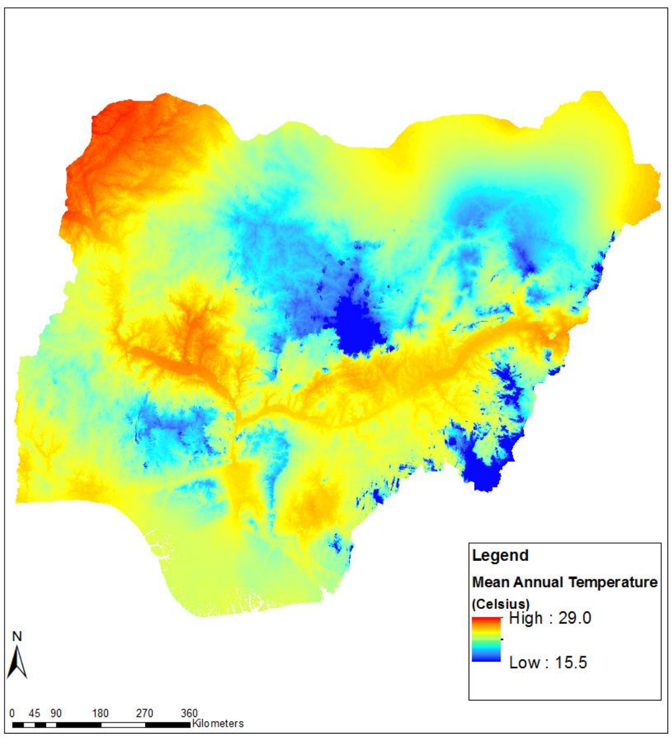
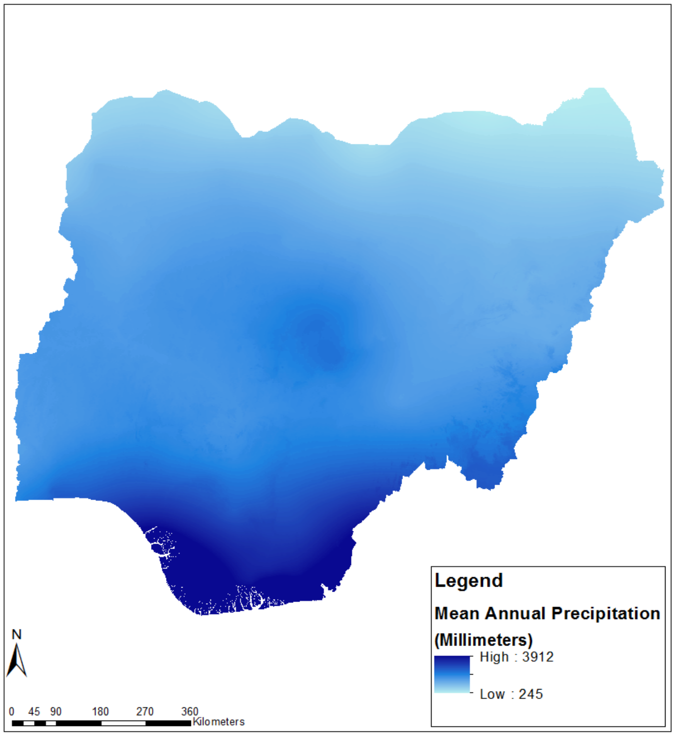


Figure 6. WorldClim mean annual precipitation estimates for Nigeria (Hijmans et al., 2005).



Authors used a thin-plate smoothing spline algorithm employed by a specific software package (ANUSPLIN) to create the interpolated surfaces (Hijmans et al., 2005). The advantages of using these interpolated climate surfaces over others are the high spatial resolution, more weather stations used than in other data analyses, better elevation data and availability of information about spatial patterns of uncertainty. Surface uncertainty was quantified by mapping weather station density, weather station elevation bias, and elevation variation. Spatial patterns of uncertainty are influenced by weather station density (Figures 7 and 8), elevation bias in the weather stations (Figure 9) and elevation within grid cells (Figure 10). Uncertainty is highest in mountainous and poorly sampled areas (Hijmans et al., 2005). Weather station density for precipitation data reveals the highest uncertainty in central Nigeria while highest uncertainty for mean temperature appears to be northern Nigeria. Elevation bias and within grid cell variation in elevation do not appear to be issues of uncertainty in Nigeria.

Figure 7. Locations of weather stations from which data was used in the precipitation interpolations (47,554 stations) (Hijmans et al., 2005).

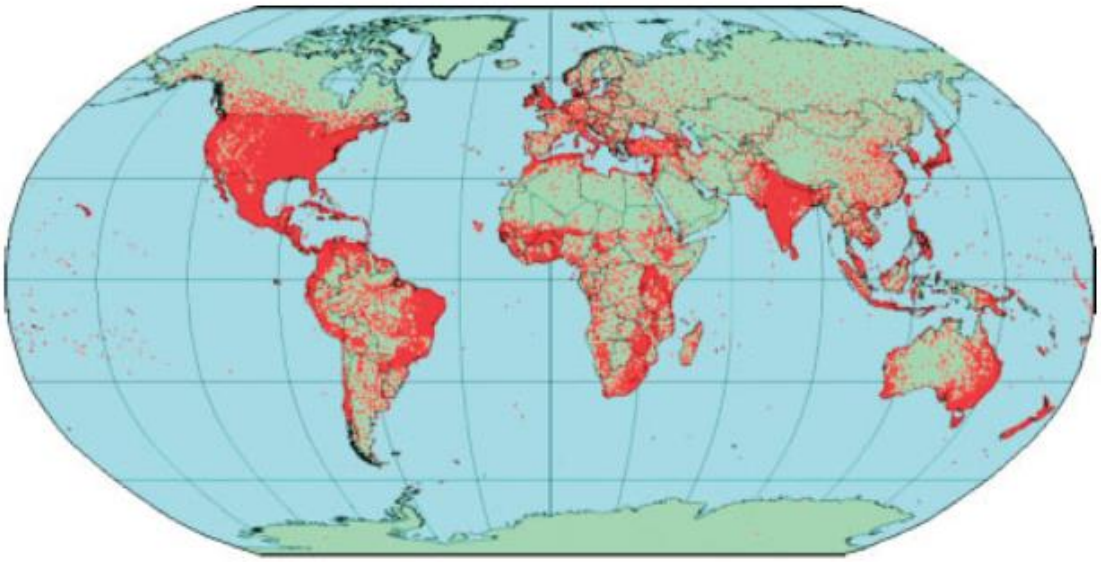


Figure 8. Locations of weather stations from which data was used in the mean temperature interpolations (24,542 stations) (Hijmans et al., 2005).

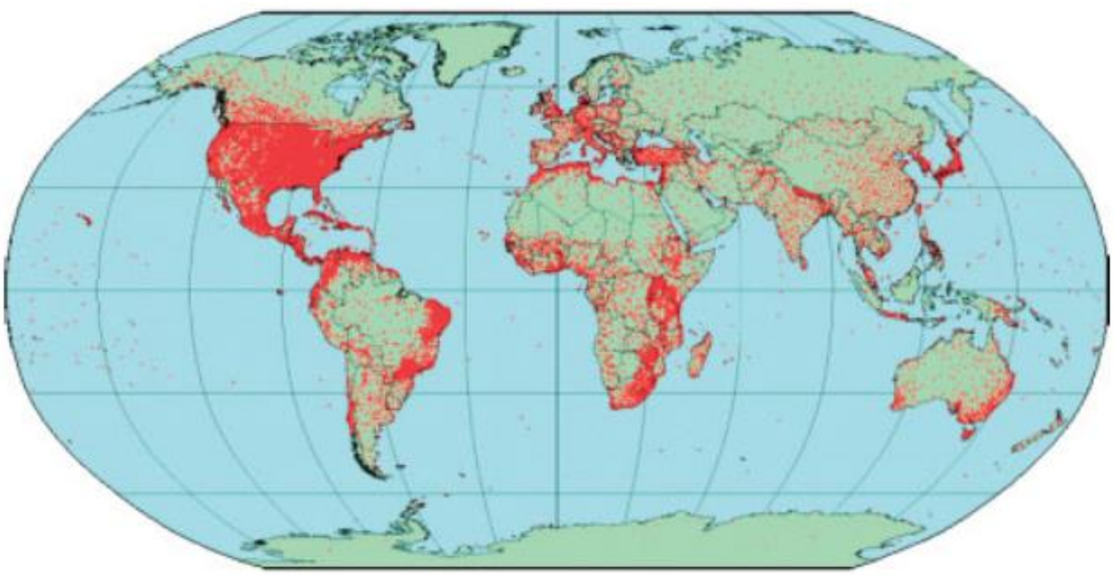


Figure 9. Elevation bias in rainfall stations, here defined as the mean elevation in a 2-degree grid cell minus that of the stations in that cell (Hijmans et al., 2005).

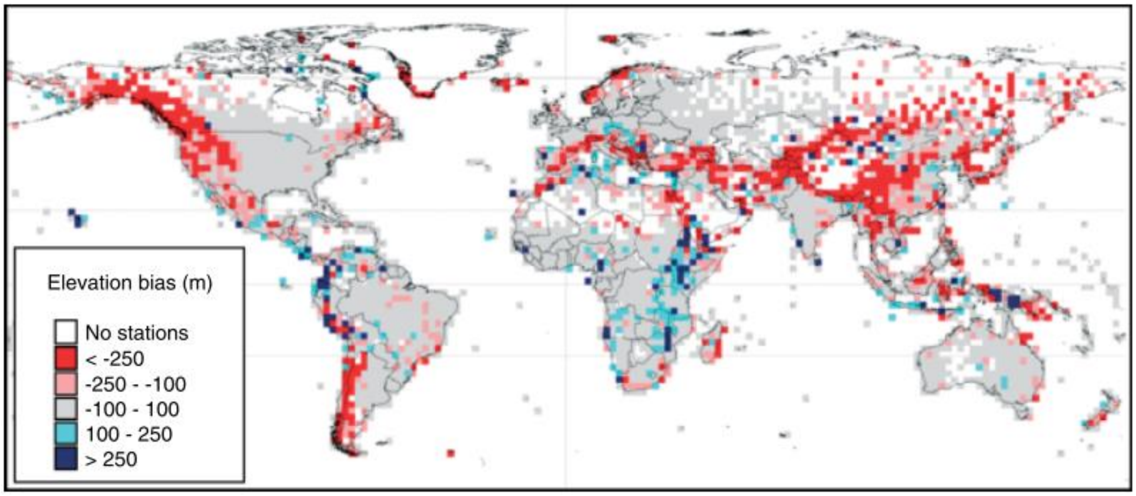
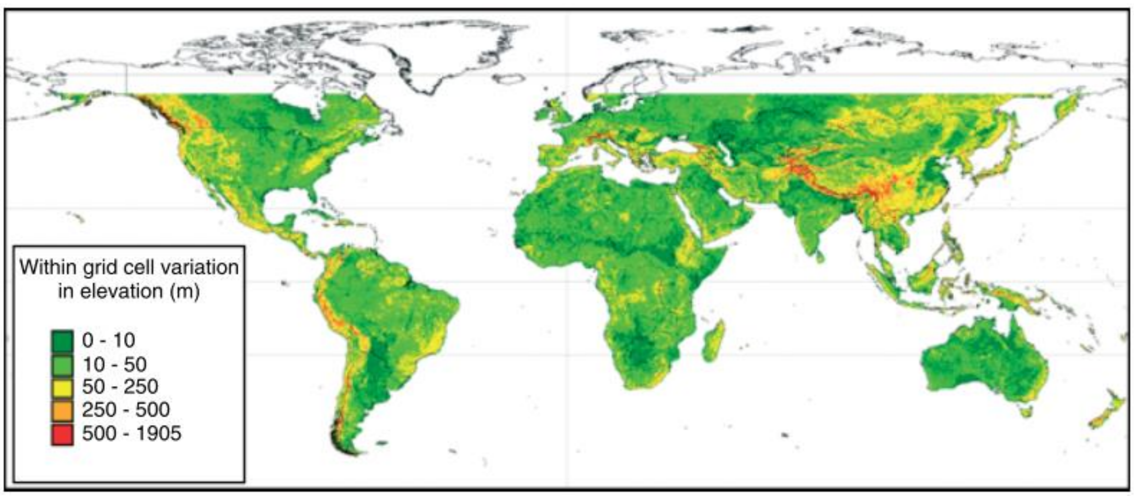


Figure 10. Elevation within grid cell variation. The elevation range of 3 arc s (~90 m) resolution elevation data within a 30 arc s (~1 km) grid cell, for areas where Shuttle Radar Topography Mission (SRTM) data was available (Hijmans et al., 2005).



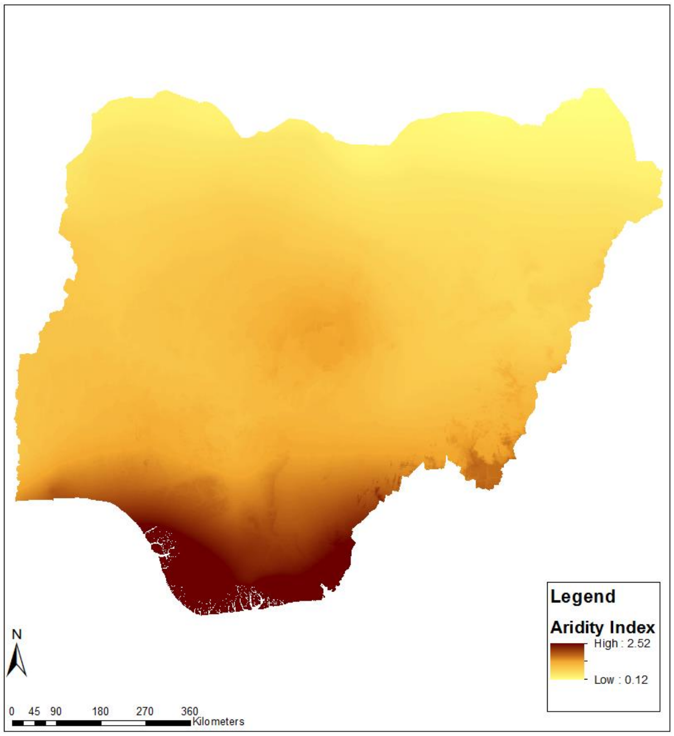
2.2.5.2 Aridity index

The aridity index map shows moisture availability for potential growth of reference vegetation ignoring the impact of soil condition to absorb and retain water (Figure 11). The aridity index value is higher for more humid environments and lower for more arid environments. Precipitation and temperature data were obtained from the

WorldClim dataset and mean annual evapotranspiration (MAE) was estimated based upon modelling of evapotranspiration (PET) (Robert J. Zomer, Trabucco, Bossio, & Verchot, 2008). The aridity index was created by the Consultative Group on International Agricultural Research - Consortium for Spatial Information (CGIAR-CSI). This index is at a resolution of 30-arc seconds, or approximately 1 kilometer at the equator. Aridity is typically expressed as a function of precipitation, PET and temperature (R J Zomer, Trabucco, Van Straaten, & Bossio, 2006). The aridity index is used to calculate precipitation deficit over the ability of the atmosphere to remove water through evapo-transpiration processes (Robert J. Zomer et al., 2008). The equation used to calculate and map the aridity index is:

$$Aridity\ Index\ (AI) = \frac{Mean\ annual\ precipitation\ (MAP)}{Mean\ annual\ evapotranspiration\ (MAE)}$$

Figure 11. Authors calculated an aridity index (AI) for the world. The aridity map for Africa is shown below. Note that higher AI and darker color represents more humid conditions and lower AI and lighter colors represents higher aridity (Hijmans et al., 2005).



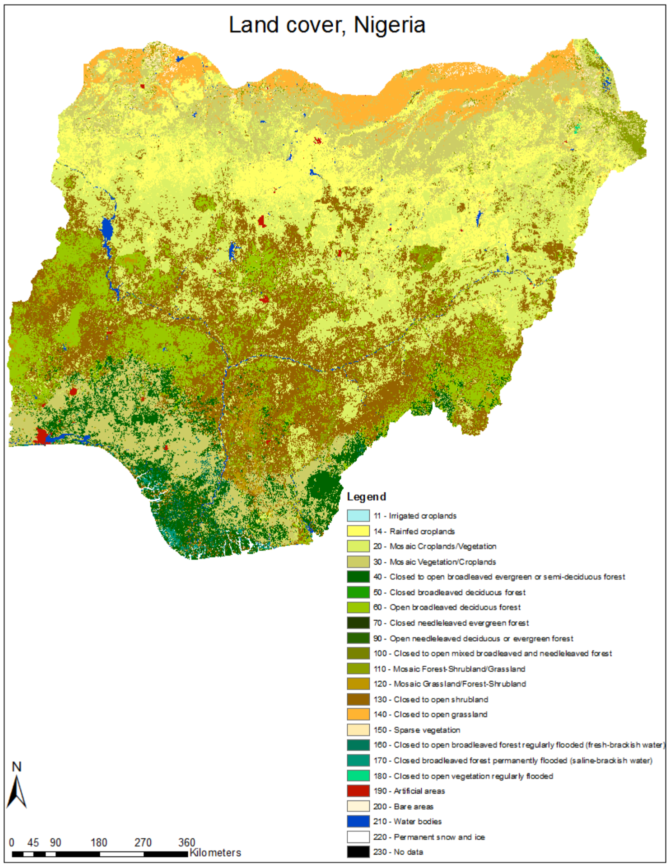
2.2.5.3 Land cover

Land cover data was obtained from the European Space Agency (ESA) GlobCover project. The land cover map counts 22 land cover classes defined with the United Nations (UN) Land Cover Classification System (LCCS) (Figure 12). This data is at a 300 meter resolution.

Aboard the ESA Environmental Satellite (ENVISAT), launched into orbit in 2002, is a wide field-of-view imaging spectrometer measuring the solar radiation reflected by the Earth in 15 spectral bands. This device is called MERIS. MERIS is able to achieve global coverage in 3 days (Defourny, Bogaert, Kalogirou, & Perez, 2011). The land cover map created by the GlobCover project uses data from MERIS to classify areas into 22 different classes. For trachoma, LF and STH cumulative prevalence data, only 10 classes were present in relevant sites. The 10 different classes were grouped into 6 classes for analysis. Artificial surfaces/urban areas were used as the referent group. Rain fed croplands maintained their own group while mosaic croplands/vegetation and mosaic vegetation/croplands were merged into one group. Closed to open broadleaved evergreen and semi-deciduous forest and open broadleaved deciduous forest were merged into one group. Mosaic forest-shrub land/grassland, mosaic grassland/forest-shrub land and closed to open shrub land were merged into one group. Closed broadleaved forest permanently flooded (saline-brackish water) maintained its' own group for LF analysis. For STH infection and trachoma analysis, the sixth group was closed to open grassland.

Land cover is being considered as a candidate confounder of the poverty-trachoma association as previous studies have found land cover, urban surfaces in particular, meaningfully associated with trachoma distribution (Clements et al., 2010; Smith et al., 2015). Land cover acts as a potential confounder of the poverty-STH association because soil moisture is known to influence the development and survival of STH ova and larvae (Brooker et al., 2006) and may also affect poverty by influencing the success of crops and desirability of an area to inhabit. Land covers also acts as a potential confounder of the poverty-LF association because land cover has been found to be an important predictor of LF distribution. Croplands and grasslands in particular have been associated with high probabilities of LF infection (Mwase et al., 2014).

Figure 12. ESA GlobCover layer, Nigeria (Defourny et al., 2011).



2.3 Statistical analysis

Appropriate spatial data was identified and obtained then brought into ArcMap for visualization and data extraction. Each poverty-NTD analysis project was created in ArcMap using a gridded poverty surface overlaid with disease prevalence data for each NTD: trachoma, lymphatic filiriasis (LF) and soil-transmitted helminth infections (STH). Covariates associated with each disease as identified in the literature were also brought into each project to best isolate the relationship between poverty and each NTD.

Analysis of the poverty-trachoma association began with polygon data containing a binary indicator revealing whether or not trachomatous follicular (TF) prevalence in children ages 1-9 years old is higher or lower than 10% of that population contained within that LGA unit. The poverty layer was then overlaid with the trachoma layer. Data was extracted from the poverty layer to the same areal units as the trachoma data using the zonal statistics as a table tool to assign the mean poverty value for the same areas as trachoma polygons. The covariate data (temperature, rainfall, aridity and land cover) were layered on top of the trachoma data to capture the environmental attributes of each areal unit with trachoma data using the zonal statistics as a table tool again. Trachoma data, poverty pertaining to each polygon, and environmental attributes were merged into a table and exported. This exported table was imported into SAS and analyzed.

Analysis of the poverty-LF association began with point data of LF prevalence at a particular site. The poverty layer was then overlaid with the LF prevalence point data. Data was extracted from the poverty layer at the same locations as the LF prevalence points. The covariate data (temperature, rainfall, aridity and land cover) were layered on top of the LF prevalence point data to capture the environmental attributes of each site with LF prevalence data. LF prevalence data, poverty pertaining to each point, and environmental attributes were merged into a table and exported. This exported table was imported into SAS and analyzed.

Analysis of the poverty-STH infection association began with polygon data containing the cumulative prevalence of STH infections within that areal unit. The poverty layer was then overlaid with the STH layer. Data was extracted from the poverty layer to the same areal units as the cumulative prevalence of STH infections data using the zonal statistics as a table tool to assign the mean poverty value for the same areas as STH cumulative prevalence polygons. The covariate data (temperature, rainfall, aridity and land cover) were layered on top of the STH cumulative prevalence data to capture the environmental attributes of each areal unit with STH prevalence data using the zonal statistics as a table tool again. STH cumulative prevalence data, poverty pertaining to each polygon, and environmental attributes were merged into a table and exported. This exported table was imported into SAS and analyzed.

Data exploration was conducted and cleaned accordingly in SAS. In the LF analysis, observations that were along the Nigerian national border had missing data issues with the poverty and mean temperature data. If poverty or temperature data were missing, the observation was removed. Trachoma was a binary outcome (trachomatous follicular (TF) prevalence in children ages 1-9 years old higher or lower than 10%), while LF and STH were both continuous measures of prevalence. LF and STH values were both right skewed so values were log-transformed for analysis. A basic correlation assessment was conducted to investigate the relationship between poverty and each NTD.

Simple linear regression as well as multiple linear regression models were run for both LF and STH. Multicollinearity tests were run to eliminate variables that may threaten the validity of the measure of association. Multicollinearity was assessed by examining the condition indices (CNI > 30) and proportion of variance values (>0.5). Once candidate variables were selected, an all-possible subsets, backwards elimination approach was employed to evaluate whether or not variables appeared to be confounders of the poverty-NTD association. Variables were considered confounders if they modified the relationship between poverty and each NTD by more than 10% in either direction. If variables did not appear to be confounders, they were dropped from the model as they did not have a meaningful effect upon the poverty-NTD association.

A two-sample t-test was conducted for trachoma comparing poverty at survey sites with trachoma prevalence above 10 to sites with trachoma prevalence below 10. Logistic regression was then used to incorporate covariates.

3.1 Results

Table 2. Correlation analysis (Pearson correlation coefficient) between poverty and each NTD, controlling for annual temperature, annual rainfall, land cover and aridity.

NTD	Poverty
LF	0.05
p-value	0.44
STH	-0.21
p-value	0.12

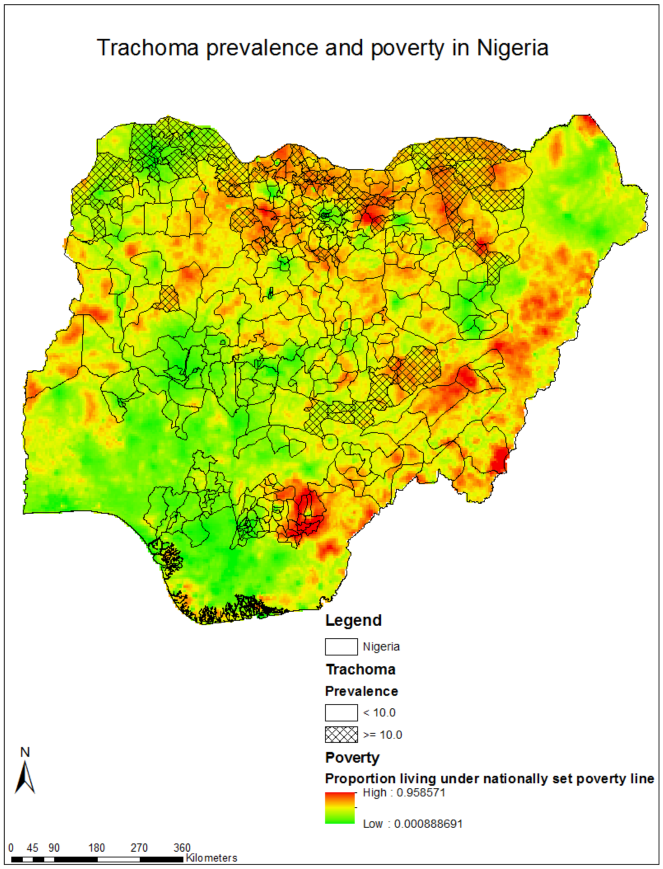
Table 3. Final models and corresponding association between poverty and each NTD.

NTD	Final Model	$\boldsymbol{\beta_{Poverty}}$	95% CI	p-value (α=0.05)
Trachoma	$P(Trachoma > 10\% \mid Poverty,\ Aridity) = \frac{1}{1 + e^{-(\beta_0 + \beta_1 Poverty + \beta_2 Aridity)}}$	0.5582 **OR** = 1.748	-0.3946-1.5111 **OR:** (0.674-4.532)	0.2509
LF	$LF\ prevalence = \beta_0 + \beta_1 Poverty + \beta_2 Aridity$	0.85276	-0.3198-2.0253	0.0832
STH	$STH\ prevalence = \beta_0 + \beta_1 Poverty + \beta_2 Aridity + \beta_3 Mean\ temperature + \beta_4 Land\ cover$	0.01666	-1.205-1.2384	0.9759

3.2 Trachoma and poverty

A basic visualization of trachoma and poverty does not present an obvious relationship between the two factors (Figure 13).

Figure 13. Trachoma prevalence (*NTD Mapping Tool Methods 2014*, 2014) and proportion of people living below the nationally set poverty line, Nigeria. (Tatem et al., 2014).



A two-sample t-test conducted revealed that the proportion of people living below the national Nigerian poverty line in areas with more than 10% of the population infected with trachoma are significantly different from poverty in areas with less than 10% of the population infected with trachoma (Table 4).

Table 4. Mean poverty in areas of trachoma prevalence above or below the threshold of 10% and examination of the difference using a two-sample t-test.

	<10% Prevalence	**>=10% Prevalence**	**Two-sample t-test p-value**
Mean poverty	0.41 (0.38−0.44)	0.53 (0.43−0.62)	0.0228

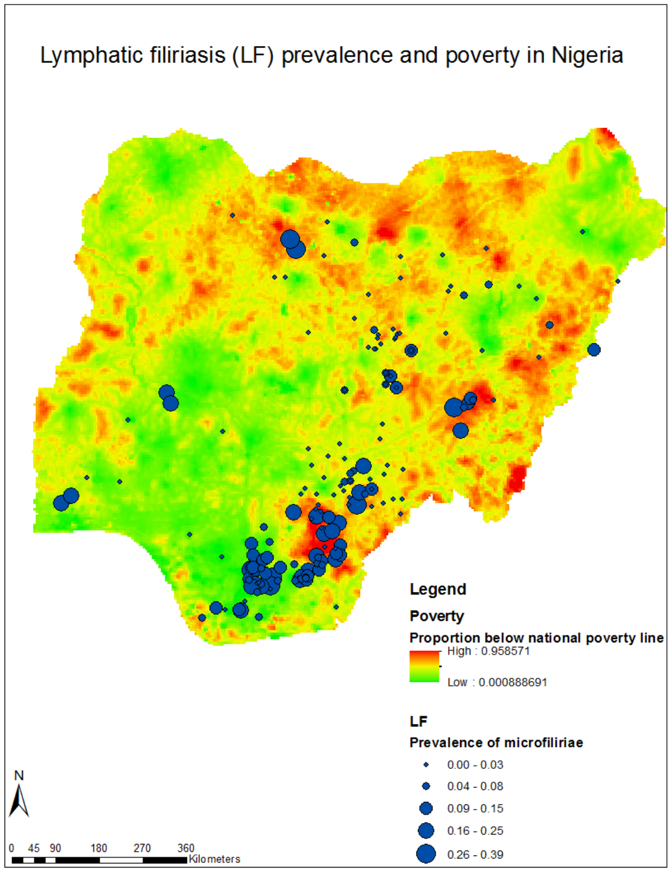
A multicollinearity assessment of candidate variables revealed collinearity between the intercept and mean temperature. Dropping mean temperature revealed collinearity between annual precipitation and the aridity index. Dropping annual precipitation from the model resolved the collinearity issue and multicollinearity problems desisted.

All possible subsets, backwards elimination was then employed to find the most unbiased estimate of the poverty-NTD association. The aridity index was identified as a confounder of the poverty-trachoma association. As a result, the final model controlled for the confounding effect of the aridity index. The final logistic regression model (Table 3) estimated an imprecise and non-significant odds ratio for poverty and trachoma (OR = 1.75, 95% CI: 0.67−4.53). These results, however imprecise, suggest that holding aridity constant, the odds of trachoma prevalence being greater than or equal to 10% in a particular area increase by 17% for a contrast of communities at the 75th versus the 25th percentile of poverty.

3.3 Lymphatic filiriasis (LF) and poverty

Visualization of LF and poverty shows potential clustering of LF in areas of high poverty, particularly in the south-central, north-central and eastern areas of Nigeria (Figure 14).

Figure 14. Lymphatic filiriasis (LF) prevalence (*NTD Mapping Tool Methods 2014*, 2014) and proportion of people living below the nationally set poverty line, Nigeria. (Tatem et al., 2014).



A Pearson correlation analysis controlling for all covariates did not reveal a statistically meaningful relationship between LF prevalence and poverty in Nigeria (Table 2).

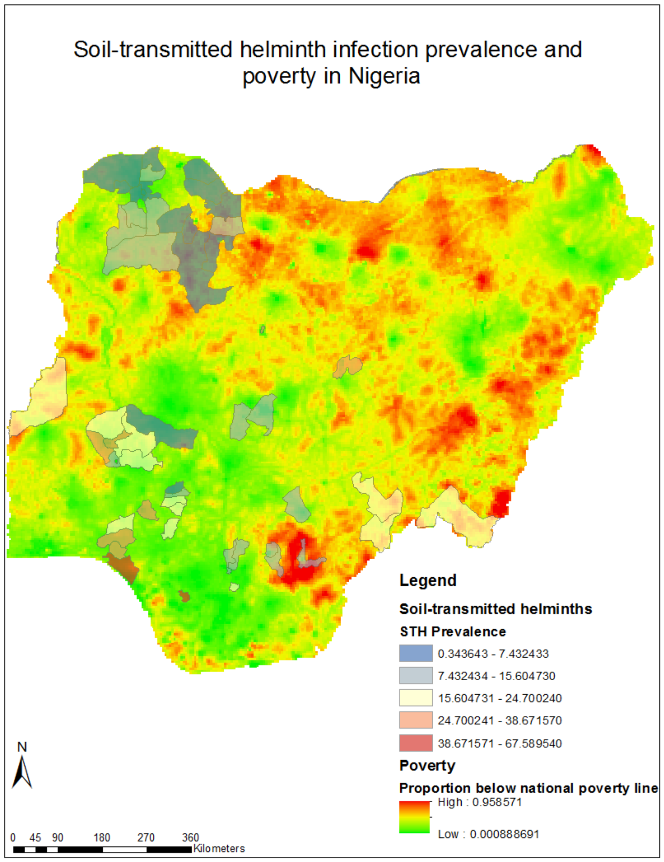
A multicollinearity assessment of candidate variables revealed collinearity between annual precipitation and the aridity index. Dropping annual precipitation resolved the collinearity issue with the aridity index, however this gave rise to a collinearity issue between the intercept and mean temperature. Dropping mean temperature resolved the collinearity issue and multicollinearity problems desisted.

All possible subsets, backwards elimination was then employed to find the most unbiased estimate of the poverty-LF association. The aridity index was identified as a confounder of the poverty-LF association. As a result, the final model controlled for the confounding effect of the aridity index. This final model did not find a significant relationship between poverty and LF ($\beta_1 = 0.85$, 95% CI:-0.32−2.03). These findings, though imprecise, suggest that holding aridity constant, the change in log-prevalence of LF is 0.24 for a contrast of communities at the 75th versus the 25th percentile of poverty.

3.4 Soil-transmitted helminth infections (STH) and poverty

A basic visualization of STH infection prevalence and poverty does not present an obvious relationship between the two factors (Figure 15).

Figure 15. Soil-transmitted helminth infection prevalence (*NTD Mapping Tool Methods 2014*, 2014) and proportion of people living below the nationally set poverty line, Nigeria. (Tatem et al., 2014).



A Pearson correlation analysis controlling for all covariates did not reveal a statistically meaningful relationship between cumulative STH infection prevalence and poverty in Nigeria (Table 2).

A multicollinearity assessment of candidate variables revealed collinearity between annual precipitation and the aridity index. Dropping annual precipitation resolved the collinearity issue with the aridity index and multicollinearity problems desisted.

All possible subsets, backwards elimination was then employed to find the most unbiased estimate of the poverty-STH association. The aridity index, mean annual temperature and land cover were identified as confounders of the poverty-STH association. As a result, the final model controlled for the confounding effects of the aridity index, mean annual temperature and land cover. This final model did not find a meaningful relationship between poverty and STH infection prevalence ($\beta_1 = 0.02$, 95% CI:-1.21−1.24). These findings, though imprecise, suggest that holding aridity, mean annual temperature, and land cover constant, the change in log-prevalence of STH cumulative prevalence is 0.005 for a contrast of communities at the 75th versus the 25th percentile of poverty.

4.1 Discussion

Sub-national, geospatial assessments of the relationship between poverty and trachoma, lymphatic filariasis and soil-transmitted helminths, controlling for appropriate and available covariates as prior literature informed, revealed positive estimates of poverty-NTD associations. These estimates, however, were gravely imprecise and non-significant. These findings are important for the NTD elimination community to consider and invest additional resources into further research and collection of NTD data that is representative of within country heterogeneity. The results of this analysis fail to reject the null hypothesis of no association between poverty and each NTD however these results should not be misinterpreted as confirmation of null associations. Although literature suggests there is a meaningful association between poverty and trachoma (Jansen et al., 2007), these findings are at a national level and do not consider intra-country variation which is important information for cost-effective and impactful targeting of interventions (Muhammad et al., 2014).

Annual rainfall, annual mean temperature, aridity and land cover were chosen as covariates for investigating the relationship between each disease and poverty based upon past research and were included to better isolate the relationship between poverty and each disease. Literature has found that vector-borne and parasitic diseases, including neglected tropical diseases, are influenced by both socioeconomic factors such as poverty and environmental factors (Bonds et al., 2012; Dasgupta, 1997; Deaton, 2003). Thus theoretically, controlling for environmental factors that are predictors of each NTD, the poverty-NTD association estimates should be closer to their true values.

Quantifying the relationship between poverty and NTDs is difficult because of the potential bi-directional nature of poverty and poor health outcomes and also because of the challenge in isolating this effect from environmental factors that may be associated with each outcome. While eliminating NTDs may reduce poverty, sustained elimination requires improvements in living conditions that require significant funding (Savioli & Daumerie, 2012). With both extreme poverty eradication and NTD elimination on the global agenda, poverty alleviation may provide an environment more conducive to the sustained elimination of NTDs.

NTDs affect some of the world's most vulnerable populations and further research is needed to assess the burden and most strongly associated, modifiable variables (Bhaumik et al., 2015). There is currently a paucity of evidence in support of the assumption that NTD burden reduction will in turn lead to poverty reduction. This is problematic for strategic planning for both Sustainable Development Goals implementation as well as the NTD Roadmap project (Savioli & Daumerie, 2012). As emphasized earlier, sustained elimination of NTDs requires a substantial financial commitment. If the NTD Roadmap project funnels funding towards interventions that target NTDs alone and achieves elimination without consideration of health system strengthening or economic development, resurgence of disease is entirely plausible. Conversely, if the action plan for achieving the first goal of the SDGs examines an economic gradient alone and does not account for disease burden, people may not experience the improvement in overall well-being that is sought by this first goal. It is for these reasons that it is important to assess and quantify, in a meaningful way, the relationship between poverty and NTDs.

4.2 Limitations

As stated above, positive estimates of association between poverty and trachoma, LF and STH were found, however these estimates were very imprecise and likely attributable to low power. Incomplete small area outcome data and potential measurement issues with exposure data as well as covariate data compromised statistical power for analyses. Data used in this analysis did not appear representative of the trachoma, LF and STH burden for the entirety of Nigeria. This is in part a result of different disease mapping strategies and also of data-sharing. In particular, the cumulative STH infection prevalence layer dataset was considerably truncated by missing and unavailable data. LF prevalence points were not randomly distributed throughout the country. The lack of representative outcome data greatly limits the ability of spatial analysis to capture within-country heterogeneity of the outcome, exposure and covariates.

Another potential limitation of this thesis is the use of the most up to date data in the trachoma prevalence layer. From a measurement quality perspective, the most up to date data may not be informative nor adequate. If trachoma prevalence is relatively constant through time, then it may not be problematic. However if there is substantial variation over time, then older data may derail the relevance of any seemingly meaningful results. Related to this issue of temporal variation, another limitation of this thesis is that it is looking at cross-sectional data of processes that are likely longitudinal. This thesis provides a snapshot of the poverty-NTD relationships, however transmission may change seasonally, environmental suitability may vary over time, and the covariates precipitation, temperature and aridity potentially vary on a daily basis. Accounting for temporal variability in future studies would improve estimates of the poverty-NTD association.

The use of geostatistically generated raster layers for poverty and all covariates in this thesis assumed absolute spatial certainty of estimates which is unrealistic and a limitation of the findings reported here. In future analyses, incorporating the spatial uncertainty introduced by each layer would improve estimates and paint a more informative landscape of the associations being examined.

This investigation was carried out using only open-source, publicly available data. Data-sharing is valuable and vital to fostering collaborative research efforts to alleviate the world from biological and societal burdens, however, open-source data does come with unique challenges, as well. Bringing in data from multiple different sources makes analysis, particularly geospatial analysis, challenging as one has to consider various factors that may affect analysis such as spatial resolution, projection and data type.

4.3 Public Health Implications and Conclusions

Most find it intuitively plausible that the effects of poverty on overall health are deleterious (Deaton, 2003). However it is also plausible that the effects of poor health lead to poorer economic outcomes. Determining the impact of poverty on NTD prevalence or vice versa is an enduring challenge in aid distribution and intervention programs. A geospatial assessment of the relationship between poverty and NTD prevalence at a sub-national level, accounting for potential confounders and assuming representative data, could provide valuable insight for policy-makers and public health strategists. Areas most affected by either outcome could be appropriately targeted with interventions, funding allocation could be better informed, and surveillance could be strengthened.

NTDs have been labeled diseases of poverty from conjectural observation of coincident presence of both poverty and NTDs and also by coincident absence. The few studies that have quantified the relationship between poverty and NTDs have primarily been at the country-level and did not account for intra-country variation in disease burden, geography and population density. The country level analysis is not useful in practical application because the areal unit is too large to be informative. Quantifying the association between poverty and NTDs is useful for public health policy and interventions at a sub-national, small area level.

The results of this study highlight the importance of representative sub-national data for the investigation of intra-country variation in the relationship between poverty and NTD prevalence. Future work should include a reevaluation of the spatial infrastructure of NTD surveillance to include improved, temporally-relevant small area NTD surveillance. Improving small area NTD surveillance is necessary for characterizing, monitoring and intervening on NTD transmission.

NTDs contribute to increased morbidity and decreased quality of life. Poverty has similarly detrimental effects. NTDs and poverty affect more than a billion people worldwide and weigh heavily on the global humanitarian conscience. To alleviate the burden of one may aid in mitigating the other, however, this cannot simply be assumed. A more complete, small area understanding of the relationship between poverty and NTDs is essential for informing policy and interventions to lessen the global burden of both poverty and NTDs.

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