Use of GIS in Malaria Research: Three Case Studies

S. M. Niaz Arifin

April 20, 2010

Geographic information system (GIS)

- A GIS is a combination of maps (cartography) and database: a ***spatial database***
- A system that captures, stores, analyzes, manages, and presents data that are linked to location
- GIS applications are tools that allow users to create interactive queries, analyze spatial information, edit data, maps, and present the results of all these operations

- Three case studies:
  - MAP: the Malaria Atlas Project
  - Laos
  - Kenya

Case Study 1: MAP (the Malaria Atlas Project)

- MAP, the Malaria Atlas Project, develops global maps of malaria risk
- *Plasmodium falciparum* parasite rate (PfPR):
  - the proportion of the population found to carry asexual blood-stage parasites
  - related to the entomological inoculation rate (EIR), the number of bites on a person by sporozoite positive vectors at the steady state
  - follows a well-established pattern as a function of age and transmission intensity
  - rises during infancy and childhood, settles to a plateau in older children, and declines in adults as malaria immunity develops

A World Malaria Map: Plasmodium falciparum Endemicity in 2007
Simon I. Hay et al., PLoS Medicine, 2009.

Goals

Hay et al. 2009

- last global map of *P. falciparum* endemicity was published in 1968, and had some deficiencies
- this project describes the generation of a new global map of malaria endemicity
- **Malaria cartography**: an increasingly important tool for planning, implementing, and measuring the impact of malaria interventions worldwide
- the map provides an explicit geographical framework for monitoring and evaluation of the impact of the malaria control
- **Objective**: use a contemporary database of PfPR surveys to make a continuous, global, *P. falciparum* malaria endemicity surface for 2007

Methods

Hay et al. 2009

- PfPR surveys:
  - a total of 8,938 surveys were identified from 78 of the 87 *P. falciparum* malaria endemic countries
  - 7,953 passed data fidelity tests for inclusion into a global database of PfPR data
  - data age-standardized ($PfPR_{2\text{-}10}$)
- Used a predictive framework known as model-based geostatistics (MBG) for the spatial prediction of malaria endemicity

Hay et al. 2009

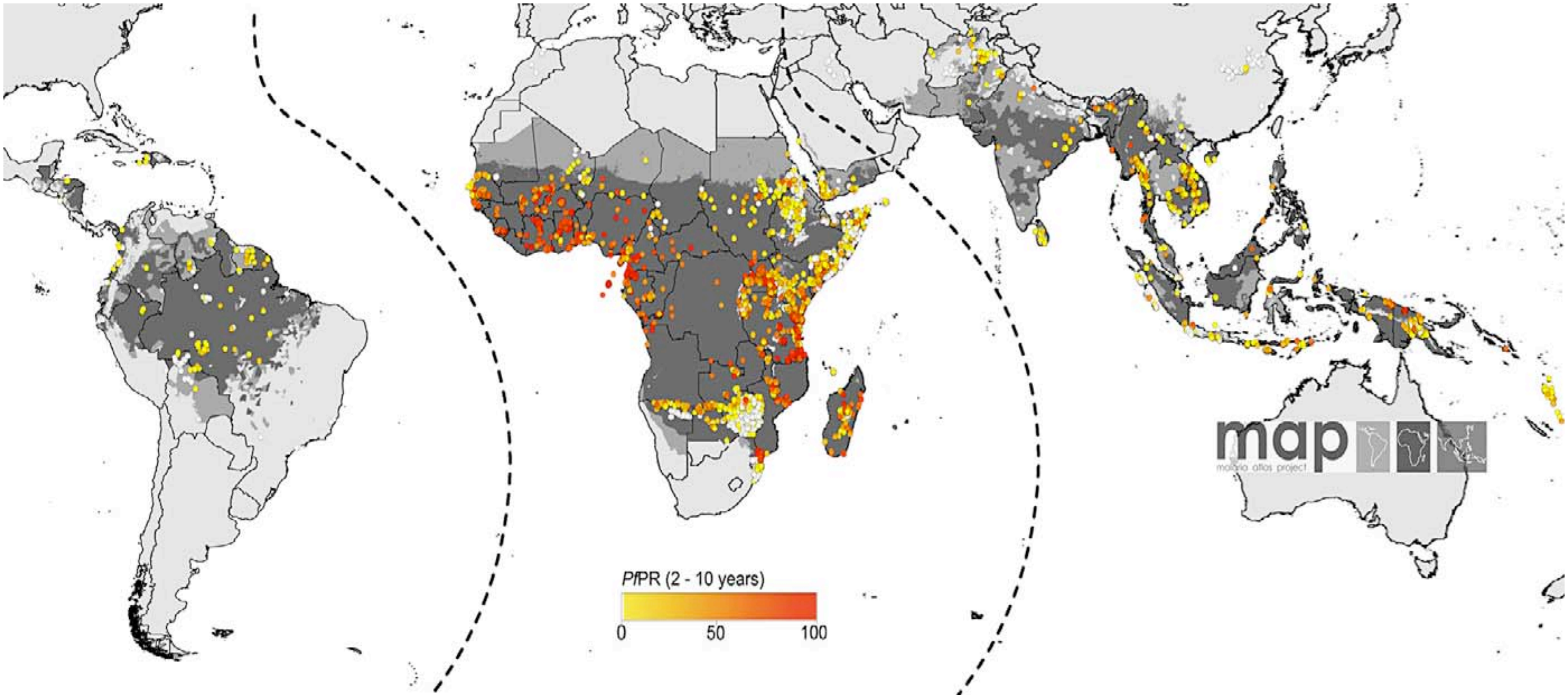


Figure: Spatial Limits of *P. falciparum* Malaria Risk Defined by PfAPI

- Areas defined as: **no risk** (light grey), **unstable risk** (medium grey), **stable risk** (dark grey)
- Shown as a **continuum** of yellow to red from 0%–100%
- Dataset was stratified into three major global regions:
    - the **Americas**, **Africa+** and **CSE Asia**

Hay et al. 2009

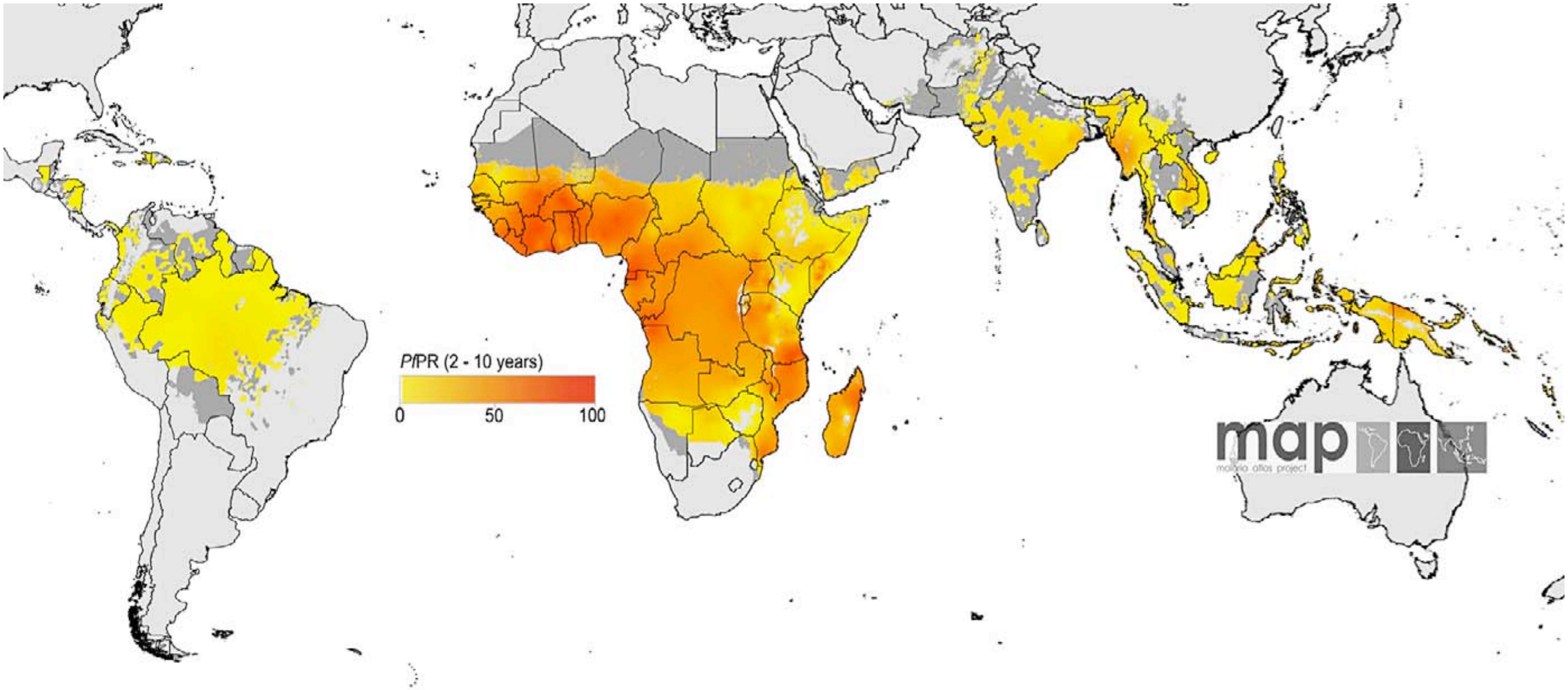


Figure: The continuous predicted surface of *P. falciparum* malaria endemicity

- The model-based point estimates of the annual mean $PfPR_{2\text{-}10}$ for 2007 within the stable spatial limits of *P. falciparum* malaria transmission
- Displayed as a continuum of yellow to red from 0%-100%
- The rest of land area was defined as unstable risk (medium grey areas) or no risk (light grey areas)

From spatial Limits to the continuous predicted surface

- Geostatistical algorithms were used to generate continuous maps by predicting values at unsampled locations
- The confidence attached at a given unsampled location depended on:
  - the distribution of survey points around that location,
  - the number of people sampled in each survey etc.
- An MBG (model-based geostatistics) approach was implemented in a Bayesian statistical framework
- Because data were collected at different times throughout 1985-2008, it was important to extend the spatial-only geostatistical approach to a space-time framework

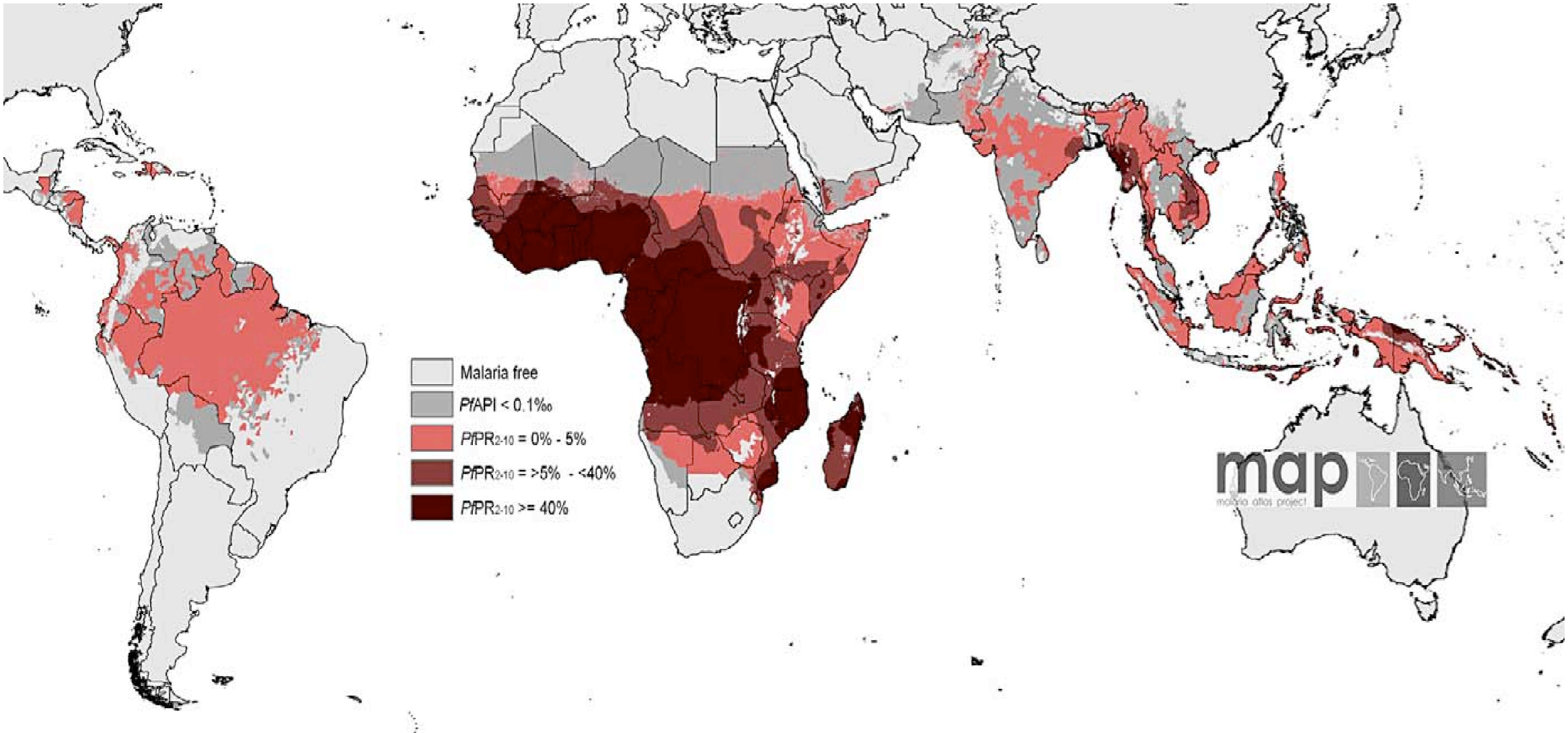


Figure: Spatial Distribution of PfPR2-10 Predictions Stratified by Endemicity Class

- Categorized as **low risk** ($PfPR_{2-10}$ <= 5%, light red), **intermediate risk** ($PfPR_{2-10}$ > 5% to < 40%, medium red), and **high risk** ($PfPR_{2-10}$ >= 40%, dark red)
- The map shows the class to which $PfPR_{2-10}$ has the highest predicted probability of membership

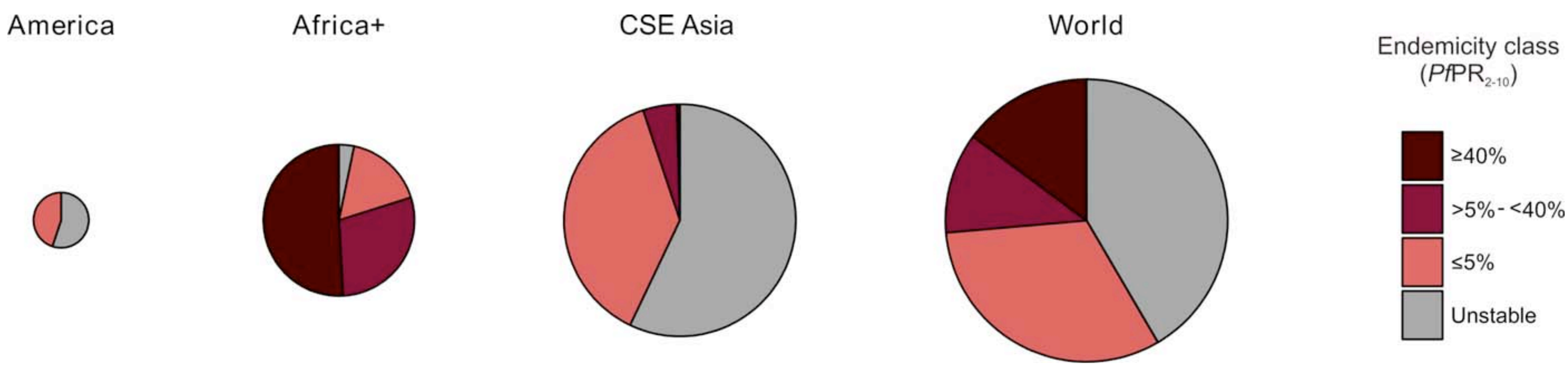


Figure: Pie Charts Showing the Populations At Risk (PAR) of *P. falciparum* Malaria in 2007

- The charts, scaled proportionally to the total population at risk, show the proportion of the population living in each predicted $PfPR_{2-10}$ endemicity classes
- *"The world is substantially less malarious than would be predicted from the inspection of historical maps, both through a shrinking of the spatial limits and through a reduction in endemicity"*
- Of the ~1.4 billion people exposed to stable malaria risk in 2007, ~0.8 billion live in *extremely low* malaria endemicity with $PfPR_{2-10}$ <= 5%
    - CSE Asia (~80%), Africa+ (~15%), and America (~5%)

Summary

Hay et al. 2009

- This cartographic resource will help countries determine their needs and serve as a baseline to monitor and evaluate progress towards interventional goals
- Mapped surfaces made available in public domain
- The MAP team anticipate providing annual updates of this *P. falciparum* global malaria endemicity map and the accompanying PfPR database

Case Study 2: Laos

- Using GIS maps to malaria control monitoring: intervention coverage and health outcome in distal villages of Khammouane province, **Laos**
- GIS mapping allows:
  - visualization of field survey results,
  - essential information in targeting limited financial and human resources for malaria control
  - easy to use maps: outputted as *html* so could be viewed with any standard browser

Geographic information system (GIS) maps and malaria control monitoring: intervention coverage and health outcome in distal villages of Khammouane province, Laos
Shirayama et al., Malaria Journal, 2009.

Shirayama et al. 2009

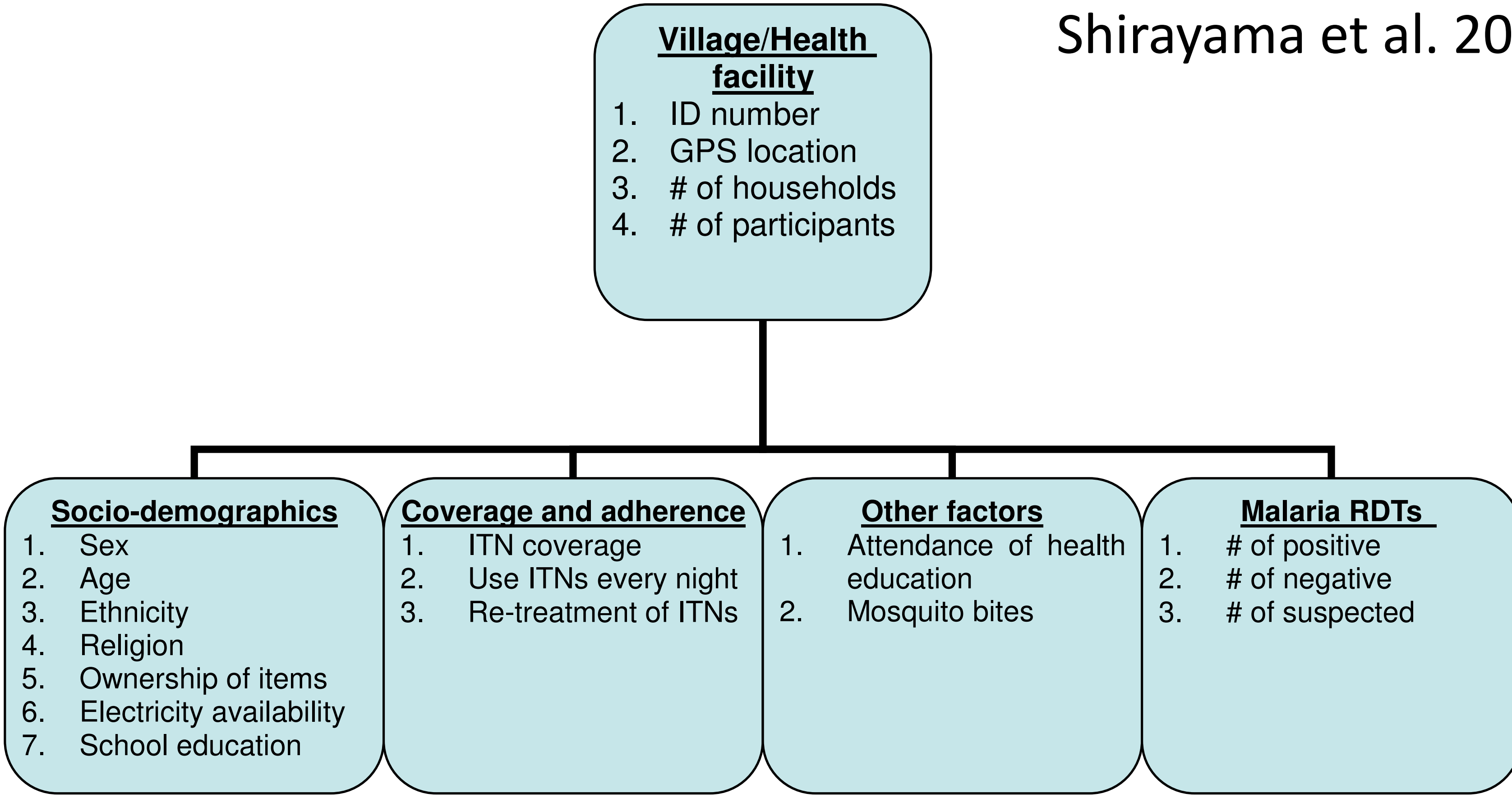


Figure: Components of GIS

- Data were collected through questionnaire interviews and malaria RDTs (rapid diagnostic tests) at each household
- **1711** study participants, **403** households

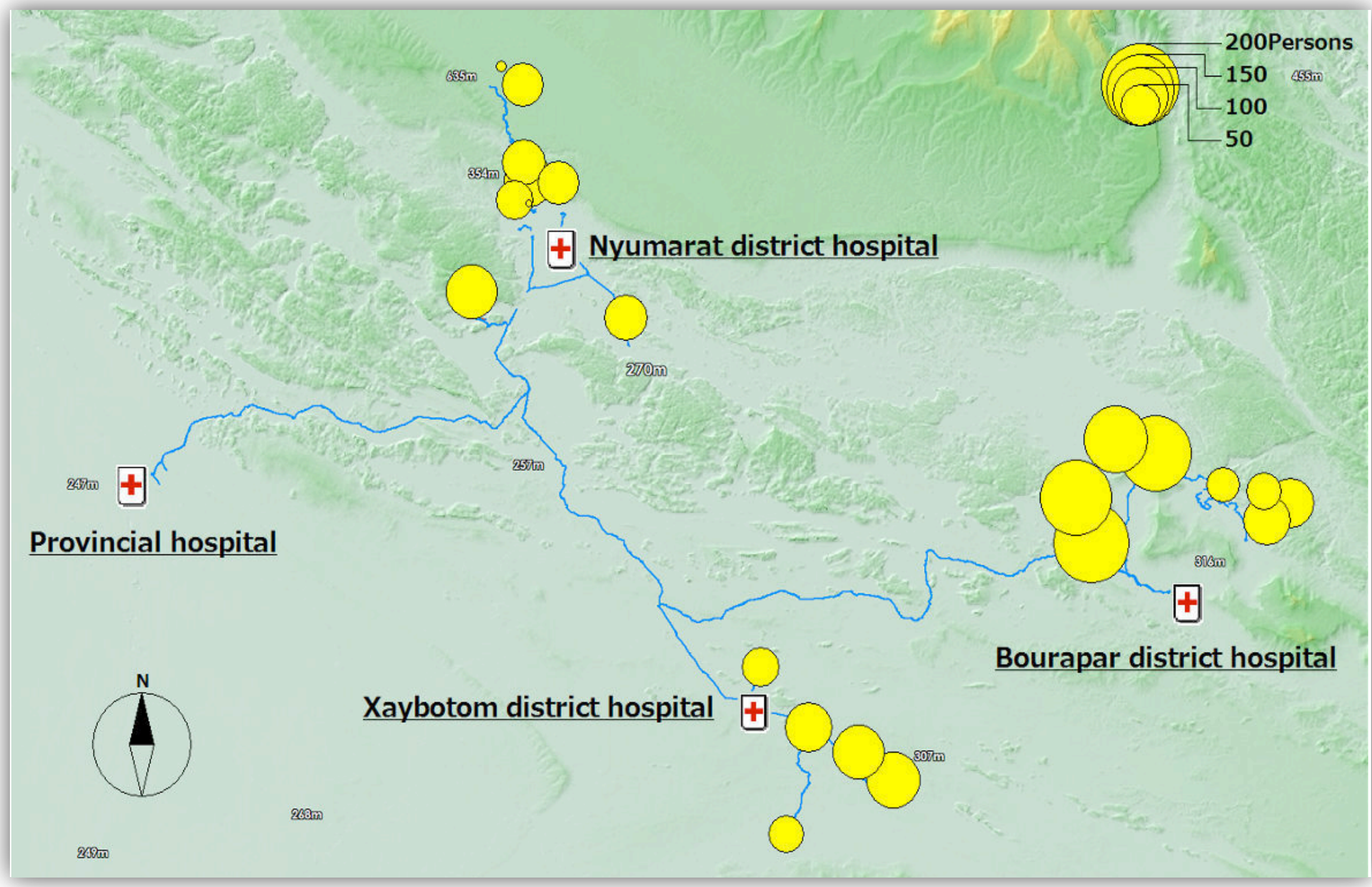


Figure: Number of the study participants in each site.

- The provincial hospital and three district hospitals are shown as red cross icons
- Blue lines represent the Track, the study team's path of travel
- Other socio-demographic characteristic, i.e., sex, age, ethnicity, religion, school education etc., can also be outputted to a map

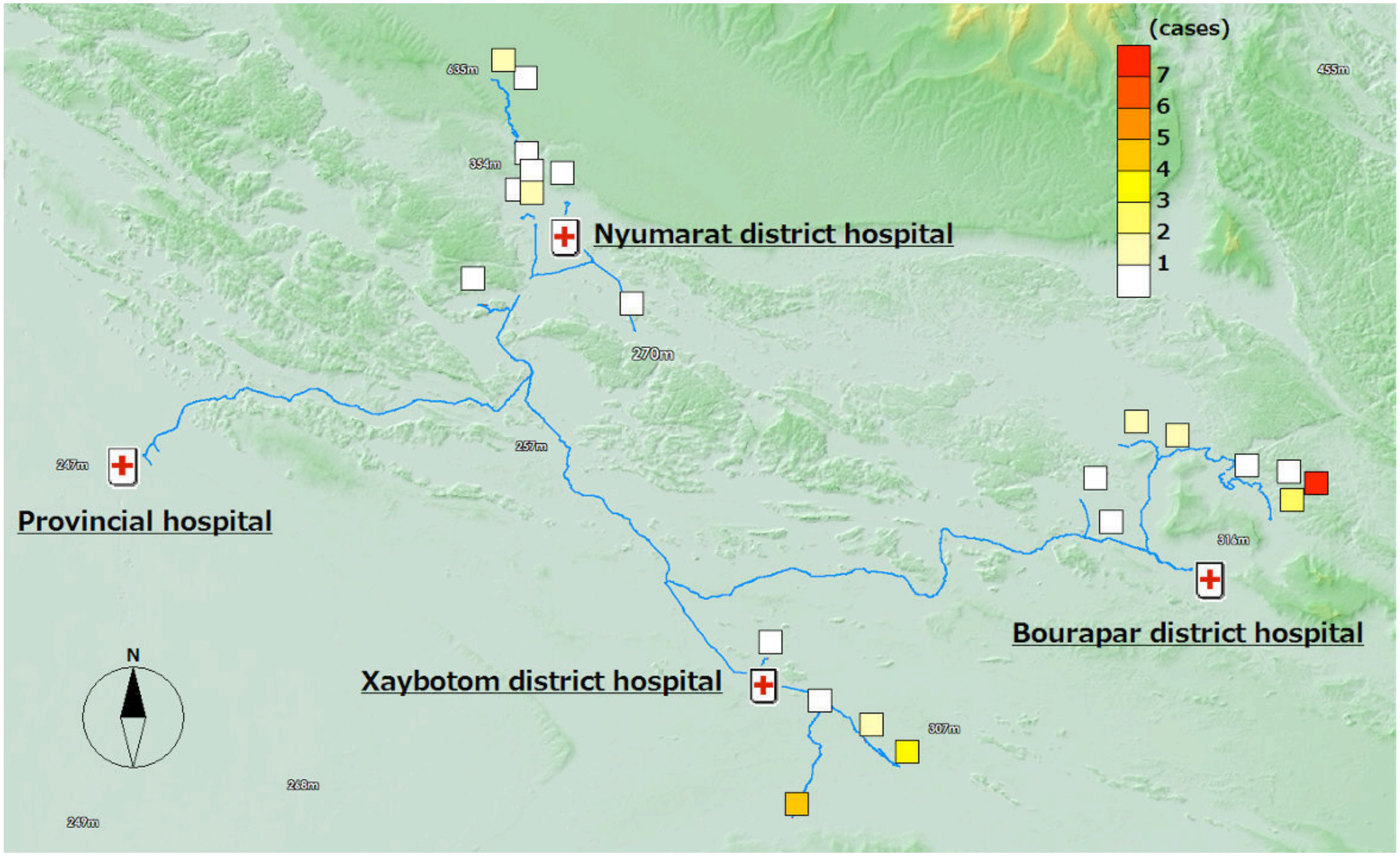


Figure: Malaria health outcome: 21 positive and suspected cases.

- 12 *P. falciparum* malaria positive cases were detected by RDTs (rapid diagnostic tests), nine more false-negative cases suspected
- Almost all of the 12 cases were detected in the distal (**remote**) villages (which need a road trip by car, and three hours by boat on the flooded river during the rainy season)
- Villages with best access to district hospital, central part of the district, were malaria-free

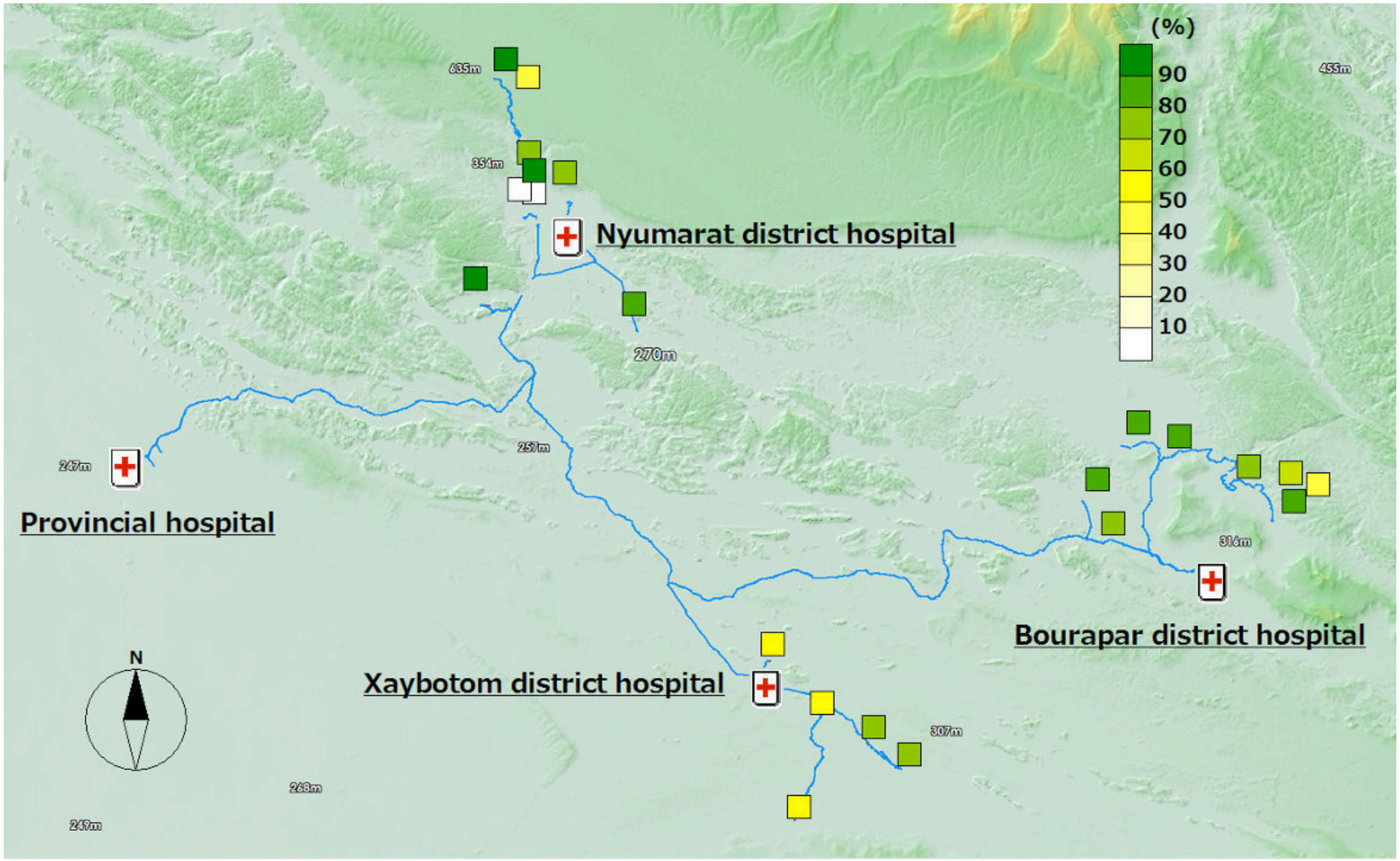


Figure: ITN (insecticide-treated nets) coverage.

- Recommended: number of persons who share the same ITN should be smaller than ***three***
- In **76.7%** (309/403) of households, the recommended intervention coverage was achieved, with a range in each village of 42.9-100%

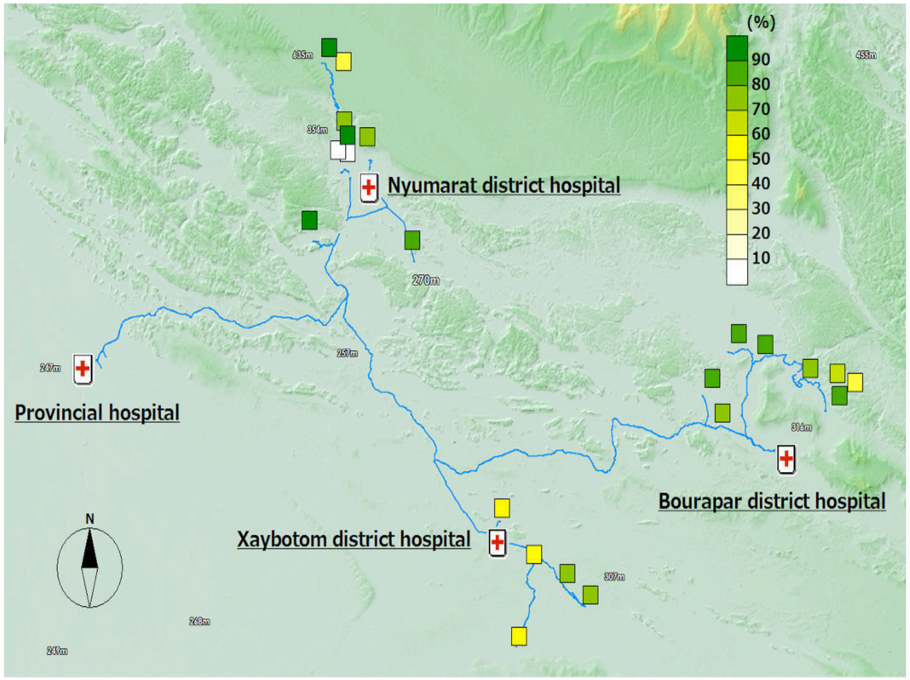


Figure (left): Proportion of people who reported getting mosquito bites often

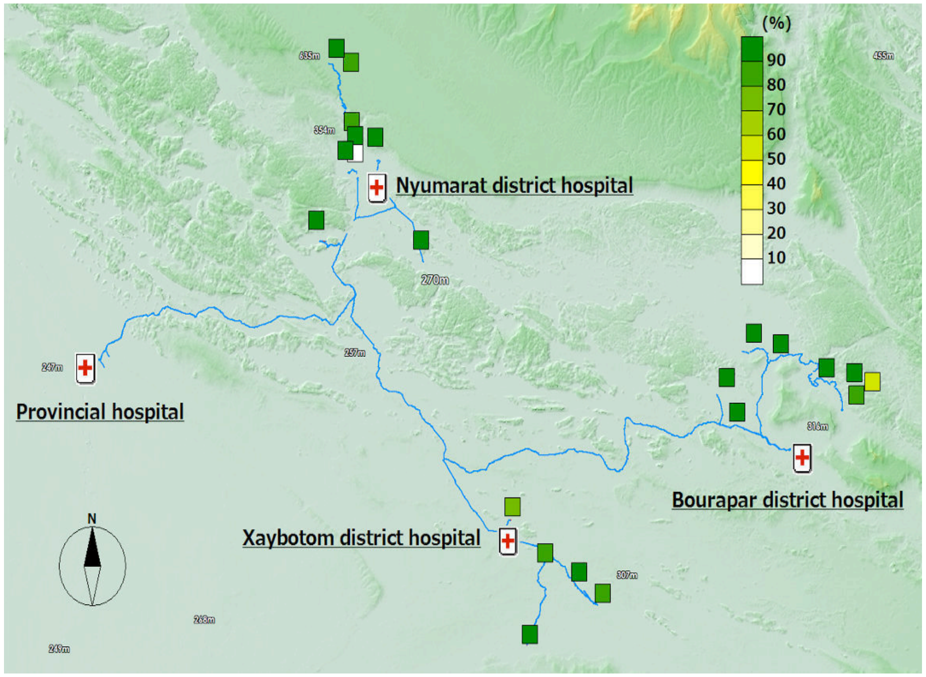


Figure (right): Proportion of people who sleep under nets every night

Summary

- GIS maps visually indicated the ***uneven distribution of intervention coverage and health outcome*** within one province
- Highlighted where malaria cases occurred, as well as villages with lower coverage of ITNs or lower adherence to the intervention
- Based on the data and the maps, ***feedback*** was given to decision-makers and local health staff
- Helped with ***prioritizing*** malaria control activity under ***limited*** financial and human resources

Summary

- Malaria cases were detected in the ***distal*** villages, while the villages with best access were malaria-free
- They demonstrated that ***malaria did not vanish, but remained unevenly distributed within districts***

Case Study 3: Kenya

- **Objective**: to develop a GIS-based model that establishes the relationship between malaria incident rates and its underlying environmental factors using maximum likelihood estimation method
- The model would help:
  - decision-makers involved in policy, planning & prevention of malaria
  - to select intervention procedures such as supplying insecticide-treated nets, drugs & draining of standing water
  - to provide information on not only *where* but also *when* malaria are most likely to occur

Understanding Malaria Incident Rates in Kenya using GIS-Based Multivariate Spatial Econometric Models
Mohamed Ismael Ahmed, Master's Project,
School of Economic, Political & Policy Sciences, University of Texas at Dallas

Ahmed 2007

Data source

- Environmental data: downloaded from the International Livestock Research Institutes' website
- Malaria incident data: from the KEMRI-Welcome Trust Research Program, the Kenya government's Ministry of Health (MOH) etc.

Ahmed 2007

Variables

- The model starts with one dependent variable (rate) & seven independent environmental variables:
  - mean daily rainfall,
  - mean maximum daily temperature,
  - elevation,
  - soil pH,
  - population density,
  - percentage tree cover &
  - a dummy variable for the presence of large water bodies (1 if present, 0 otherwise)

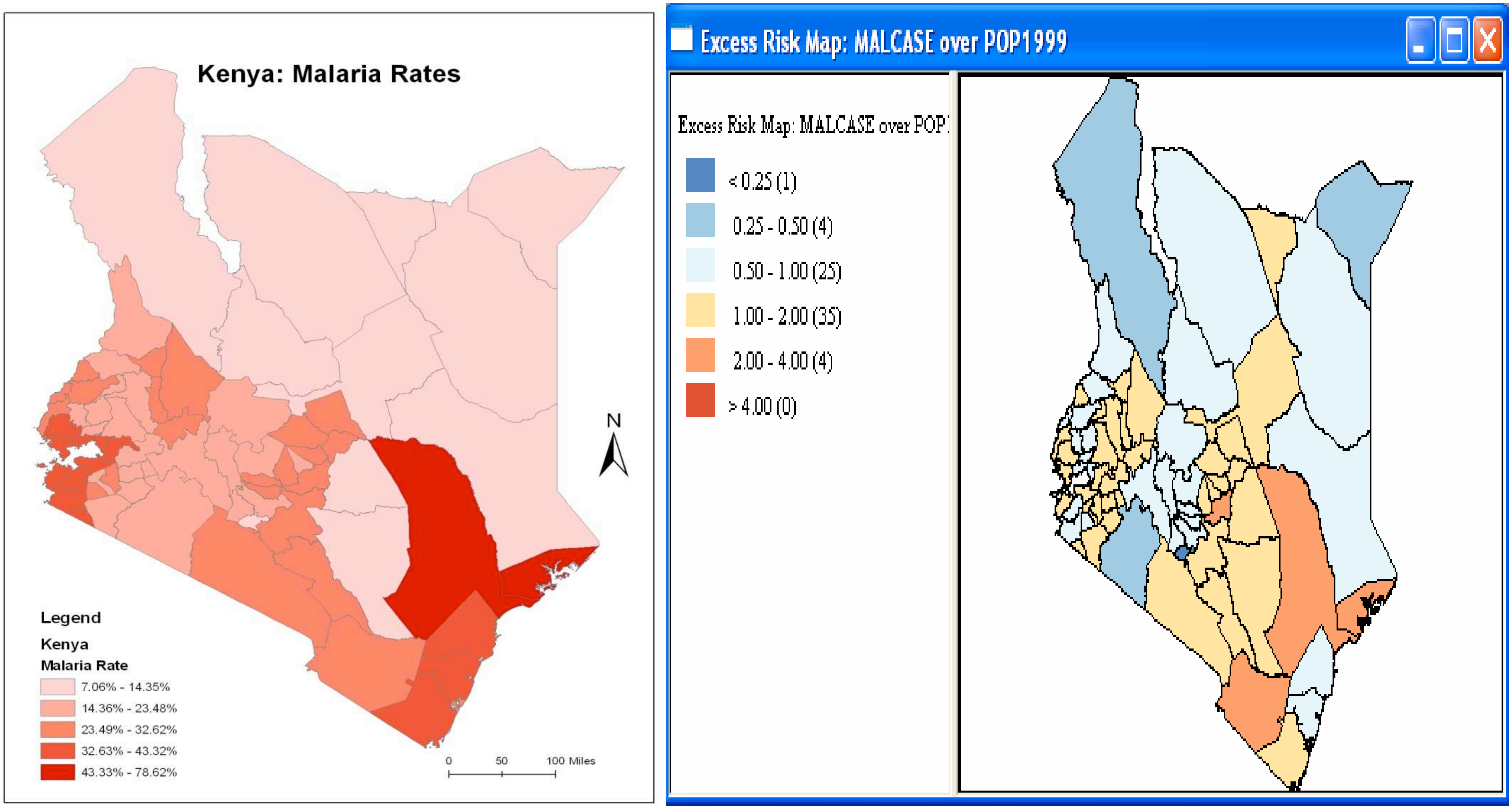


Figure: Malaria incidence rate (dependent variable)

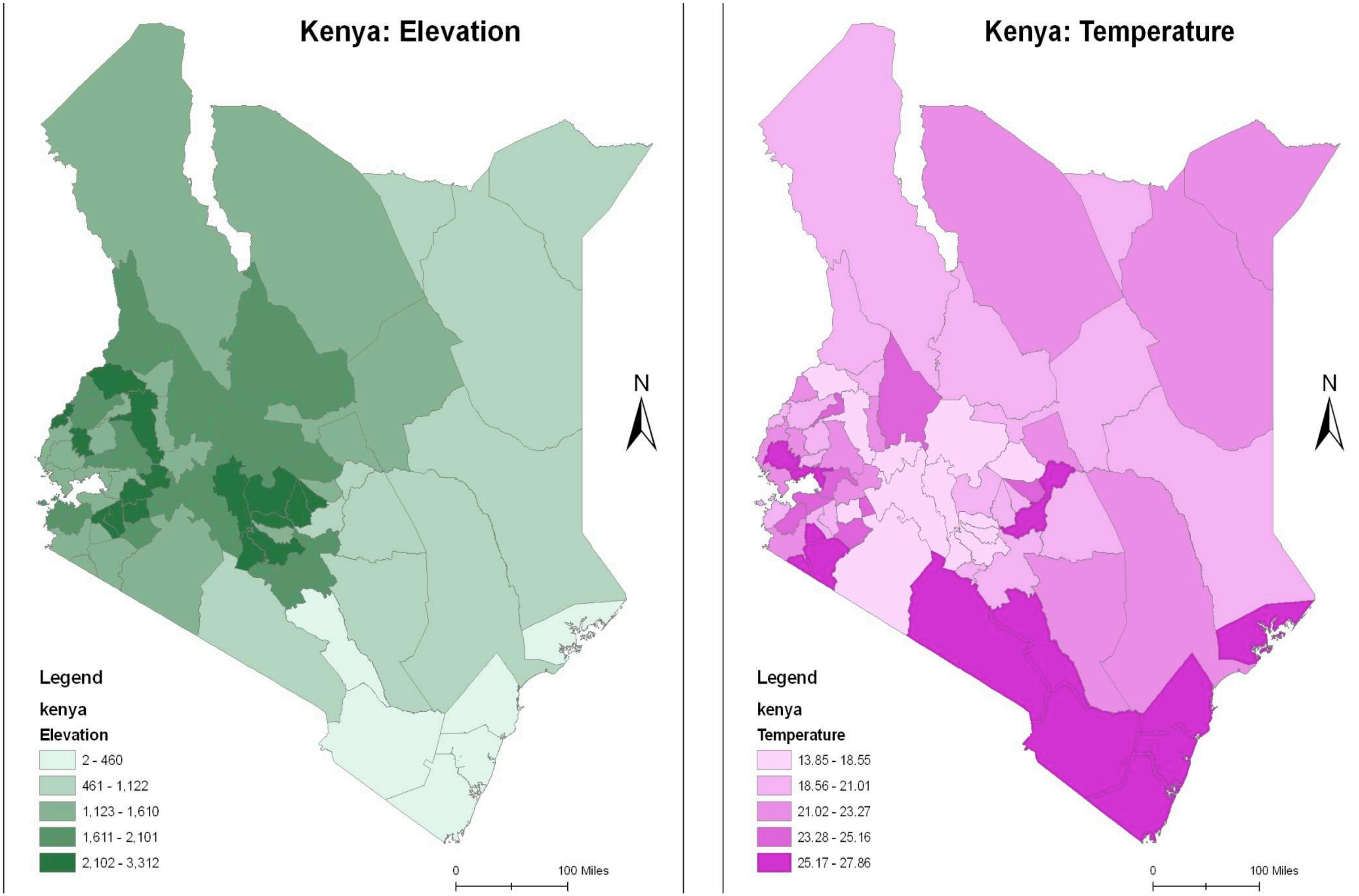
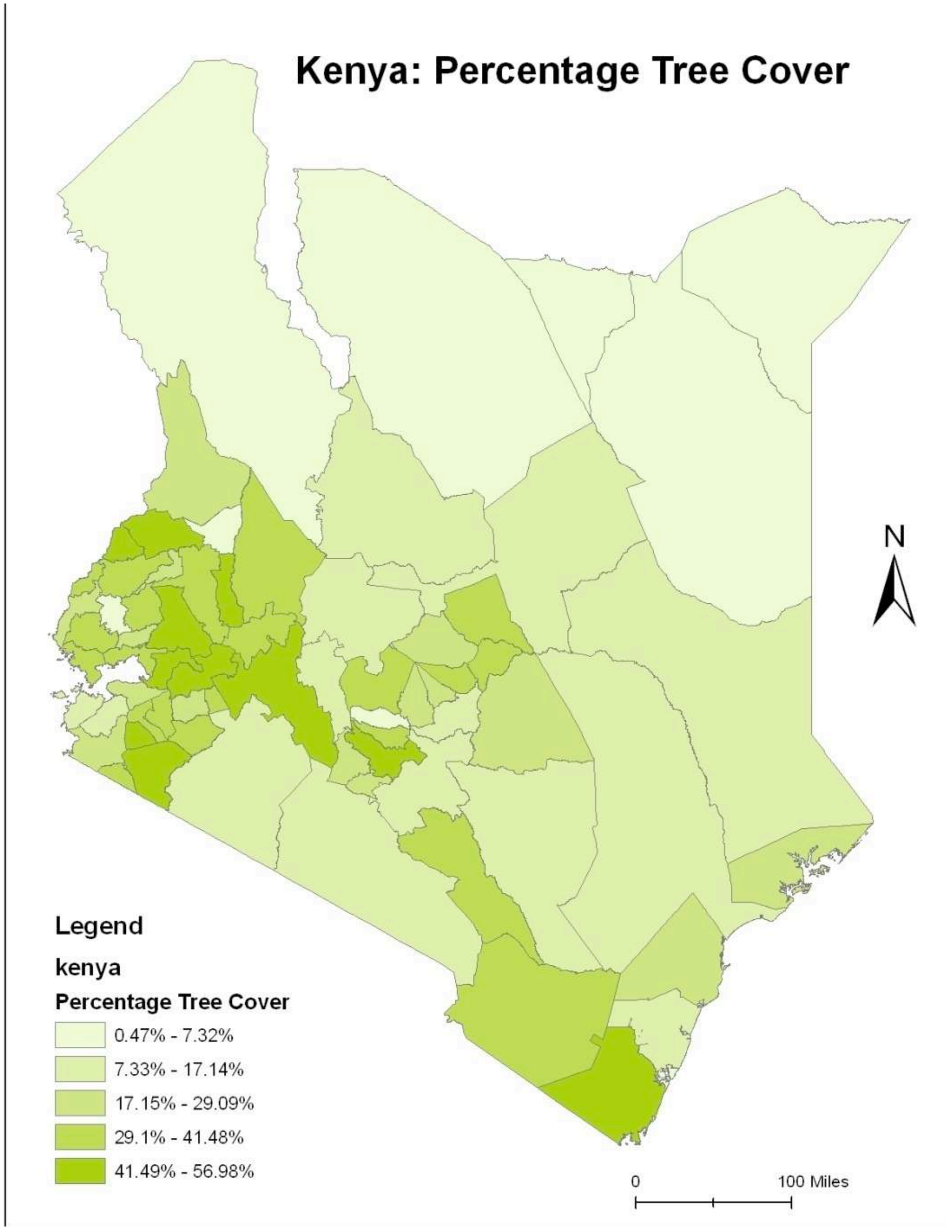


Figure: Elevation & Mean maximum daily temperature



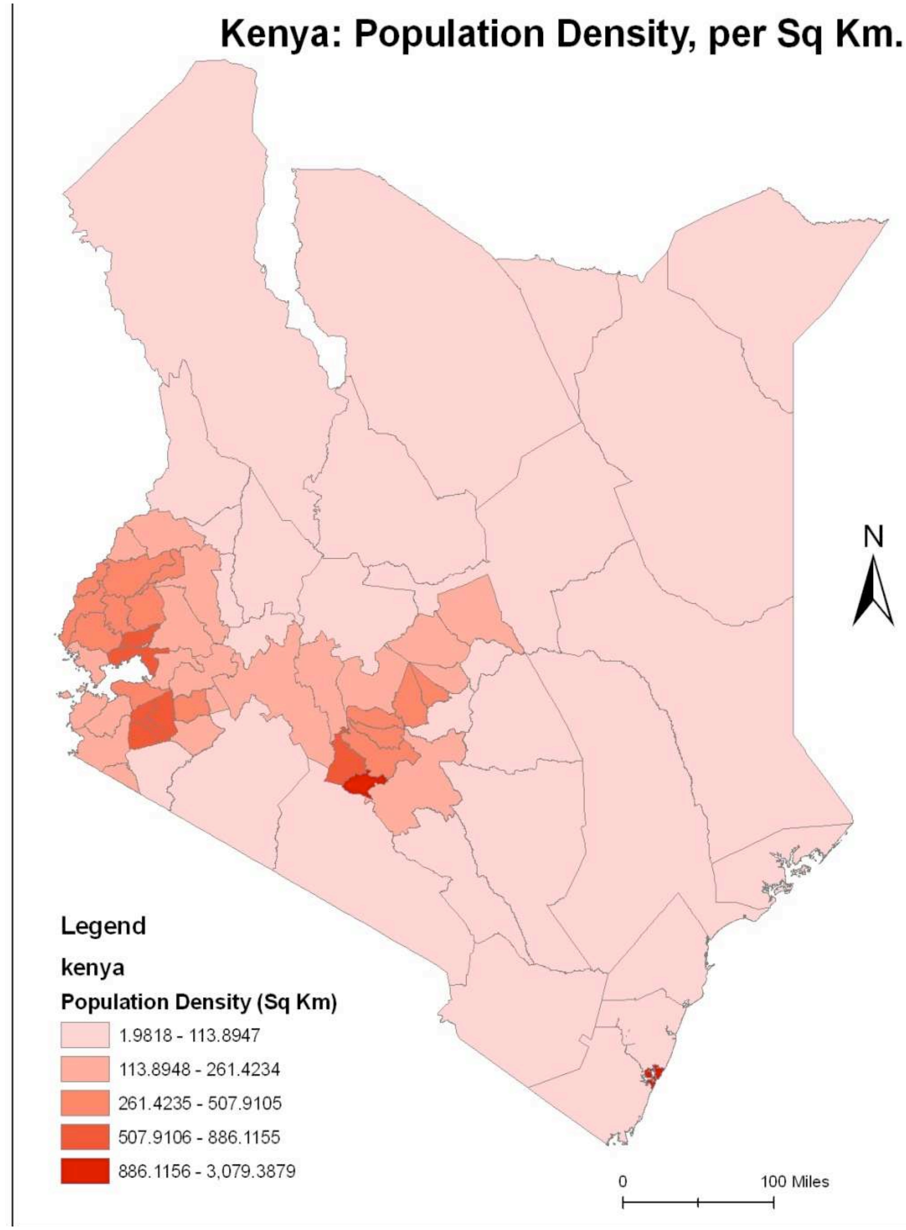


Figure: Percentage tree cover & Population density

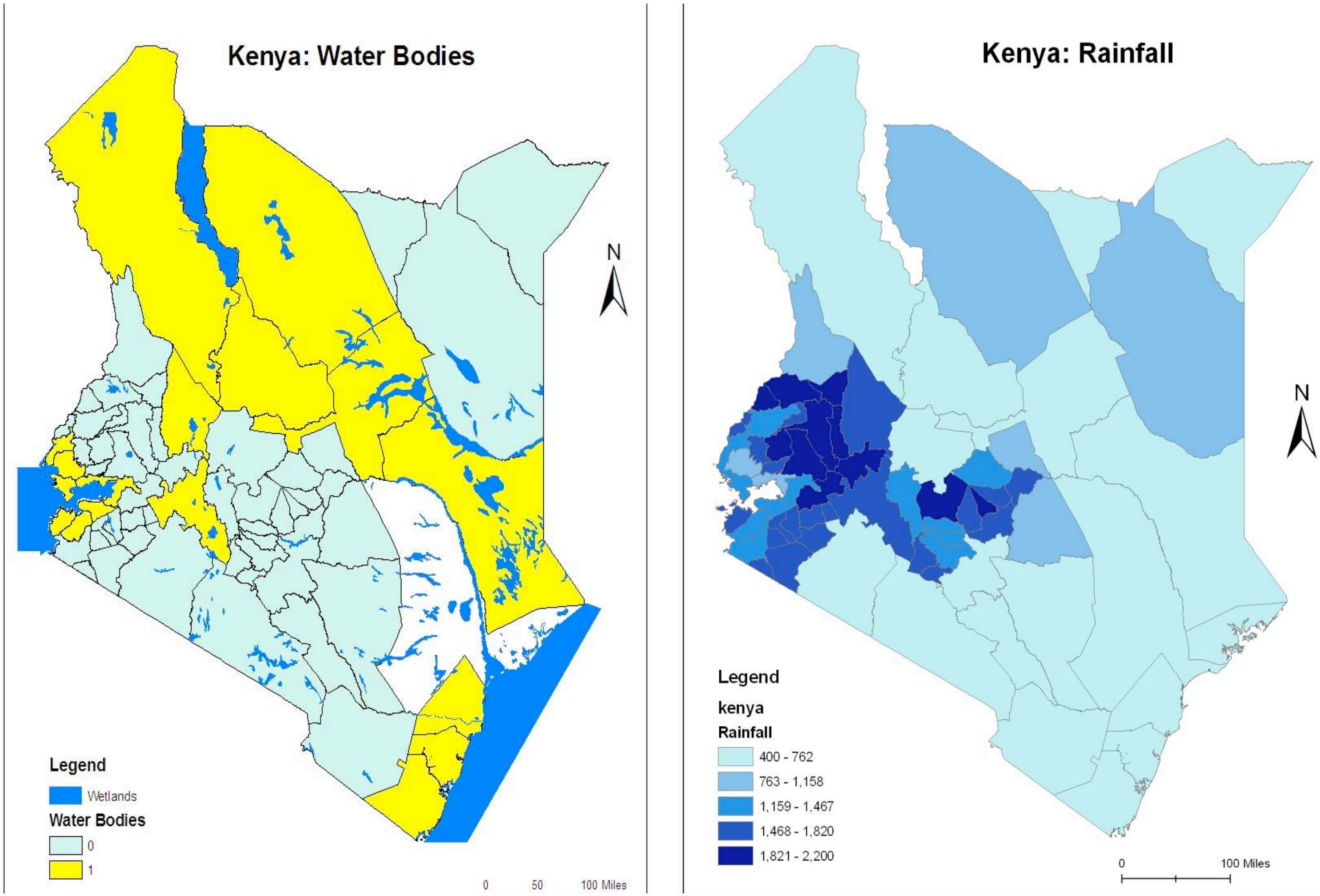


Figure: Water bodies (1 if present, 0 otherwise) **& Mean daily rainfall**

Ahmed 2007

Methods

- The environmental layers are overlaid (intersected) with malaria incident cases
- Created common layer is then summarized using averages of each field of interest
- A new '**rate**' field is added into the created layer
- The study covers 69 districts in the country
- The malaria incident rate is then calculated by dividing each district's malaria incident cases by its respective total population
- After creating one GIS-layer of Kenya containing all the fields, the layer is linked with the spatial regression methodology using GoeoDA, Spatial Econometrics Toolboxes & R

Summary

Ahmed 2007

Four questions answered:

1. Which top 10 districts suffer from highest malaria risks?

   Bondo, Homa Bay, Kisumu, Kuria, Migori, Nyando, Rachuonyo, Siaya, Suba & Kilifi

2. Are spatial autocorrelation effects present? *Yes*

3. Which model best describes the data (OLS, spatial lag or spatial error)?

   Both spatial models are significant improvements from the OLS model; the best fit for the data was given by the *spatial error* model

4. Based on the, which environmental factors are the most significant predictors of malaria incident rates?

   Mean daily rainfall,

   Elevation,

   Mean maximum daily temperature &

   Water bodies