# *Quantifying Weather and Climate Impacts on Health in Developing Countries (QWeCI)*

**A Seventh Framework Programme Collaborative Project (SICA)**

13 partners from 9 countries

www.liv.ac.uk/QWeCI

Grant agreement 243964

## A statistical modelling approach to identify the importance of climate as a driver of malaria in Malawi

Rachel Lowe[1,3], James Chirombo[2], Adrian Tompkins[1], Xavier Rodo[3]

1. International Centre for Theoretical Physics (ICTP)
2. Ministry of Health, Lilongwe, Malawi
3. Catalan Institute for Climate Science (IC3)

rachel.lowe@ic3.cat

SEVENTH FRAMEWORK PROGRAMME

# Malaria in Malawi

- Malaria leading cause of morbidity/mortality (>6 million episodes per year), >85% *Plasmodium falciparum*.
- Direct costs: treatment. Indirect costs: workdays lost agriculture/industry, absenteeism school.
- RBM Objective: under 5 and pregnant women access to personal and community protective measures.
- National Malaria Control Programme established in 2002 to coordinate control measures.
  - Long lasting insecticide net (LLIN)- Over 5 million distributed in 2012 in a mass campaign
  - Effective case management (diagnosis and treatment of illness within 24 hours)
  - Access to intermittent preventive treatment (IPT) for pregnant women.

# Malaria transmission

- CLIMATE
- Temperature
- Precipitation
- Humidity

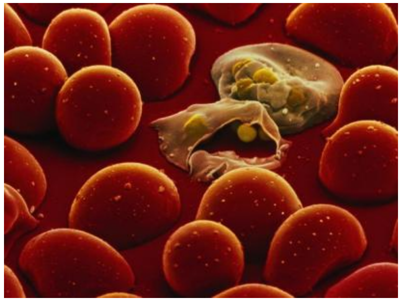
Mosquito biology and breeding sites

- NON-CLIMATE
- Urbanisation
- Poverty
- Level of education

Human vulnerability and vector habitat

Malawi tourism

CDC

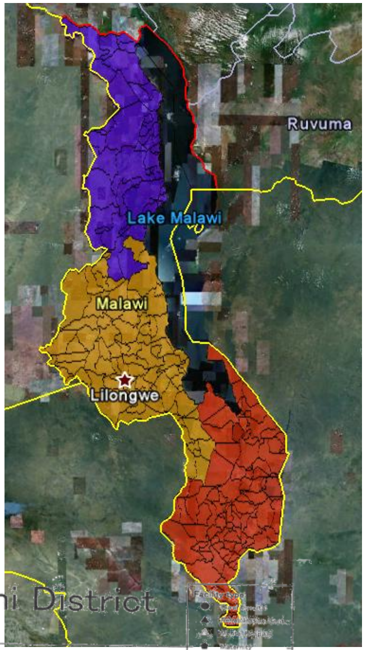


National Geographic

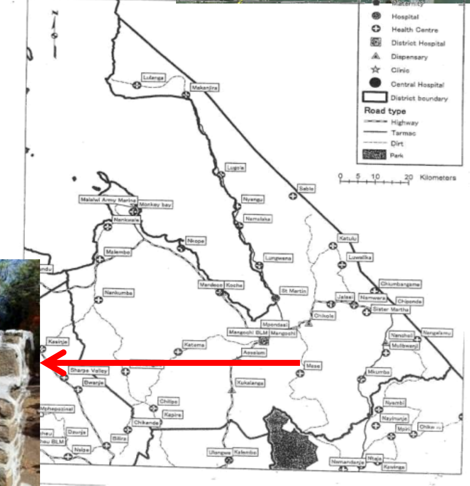
UNICEF

# Research questions

- To what extent can variations in malaria be accounted for by climate?
- Which non-climatic factors are important?
- Does inclusion of non-linear relationships between climate and the vector, captured by the dynamical model equations, improve model predictions in space and time?
- How can malaria early warnings be effectively disseminated to decision makers?







# Malaria, demographic and socio-economic data

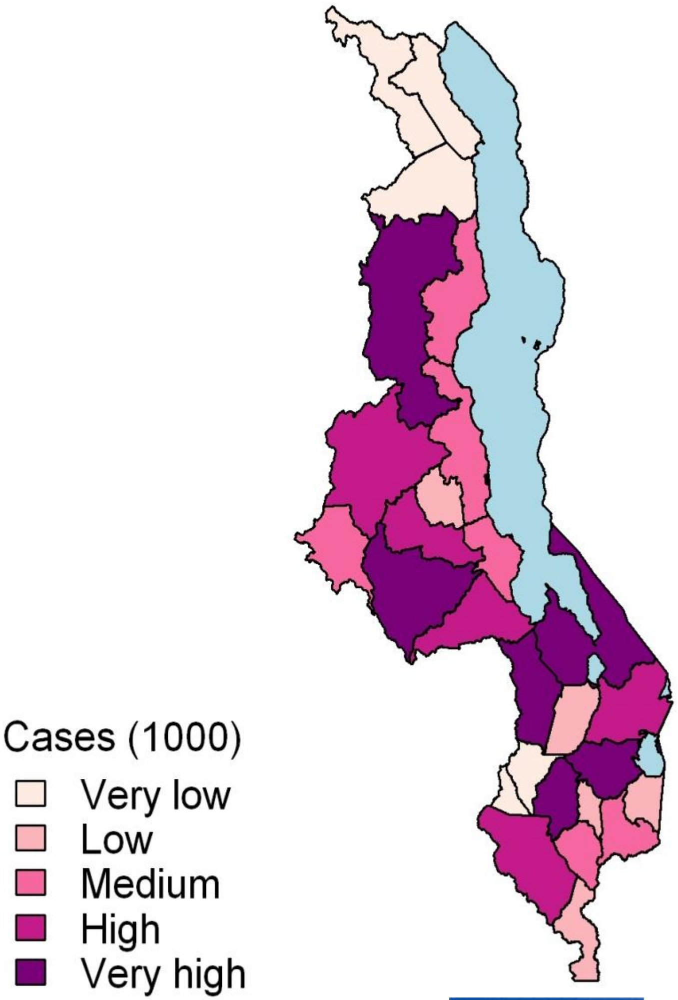
- Counts of malaria cases for under 5 and 5 years and over July 2004 – June 2011 (84 months).

- Annual population and density estimates.

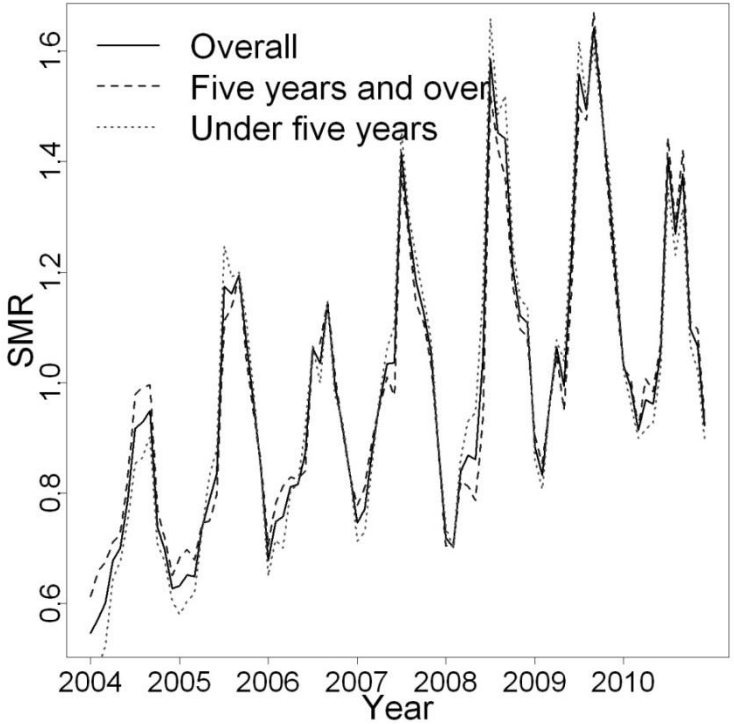
- Number of health facilities per 1000 population.

- Yearly estimates of ITN distribution for each district by different agencies: UNICEF, PMI

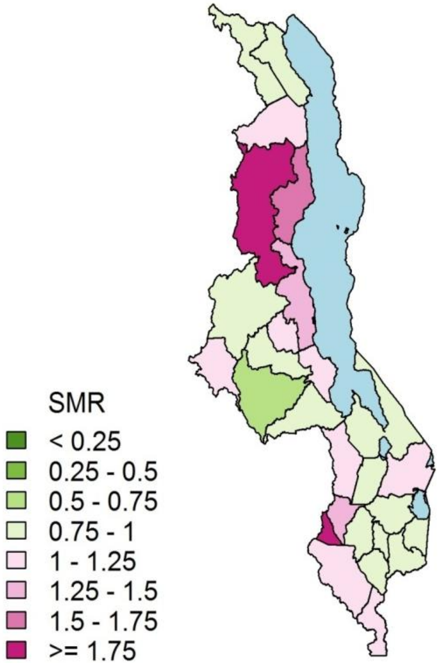
- Proportion of population in district
  - Urban areas
  - One room for sleeping
  - No toilet
  - Living in traditional housing
  - Literate
  - Do not attend school



# Standardised Morbidity Ratio (SMR)




- SMR ratio of observed to expected cases
- Excess risk when SMR>1

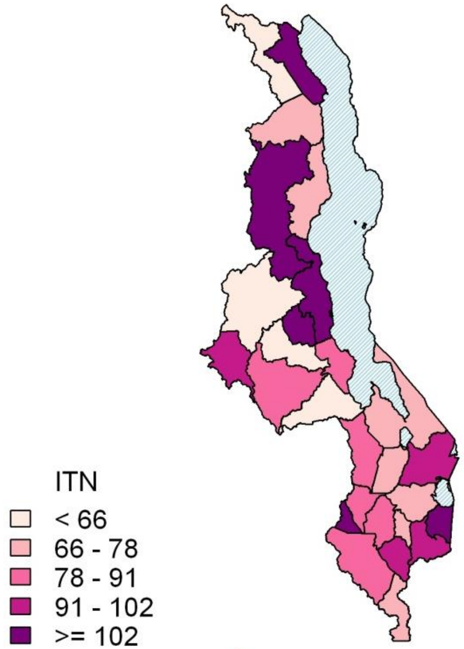


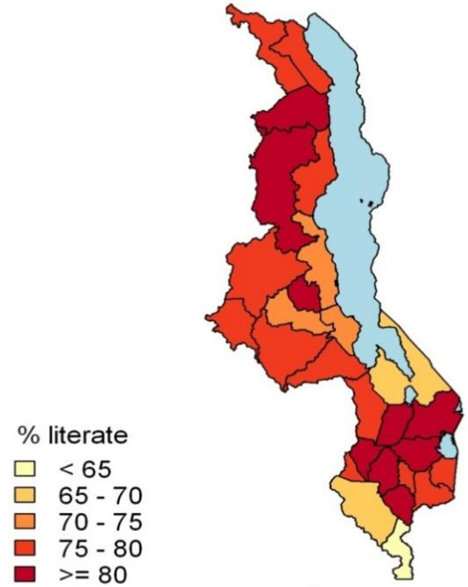

$$SMR_{st} = \frac{y_{st}}{e_{st}},$$

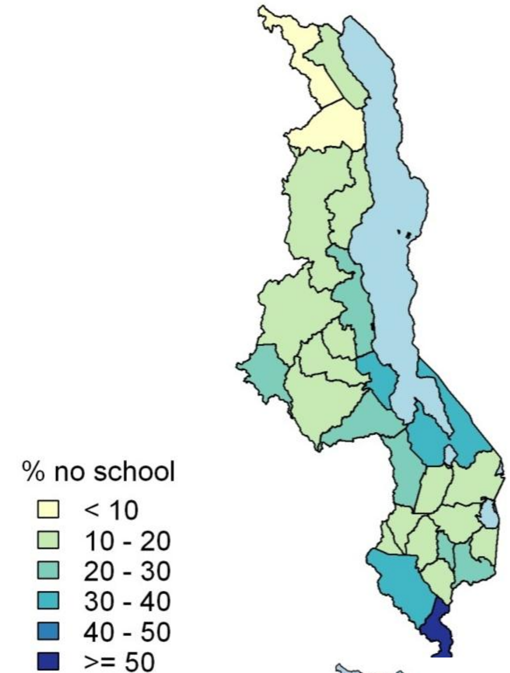
$$e_{st} = p_{st}\pi,$$

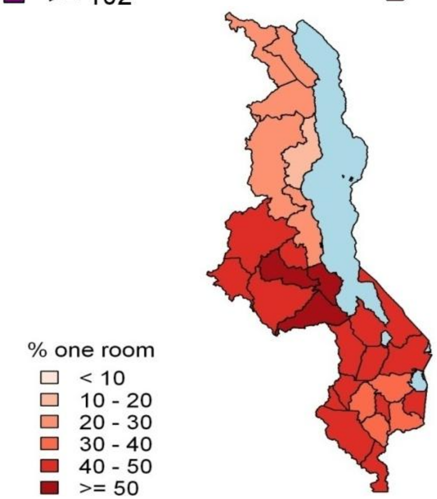
$$\pi = \frac{\sum y_{st}}{\sum p_{st}}.$$

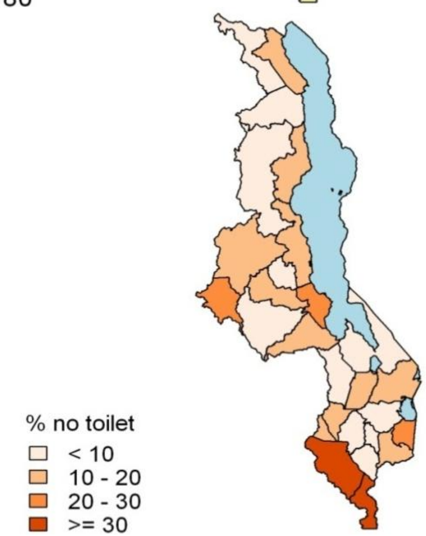
# Poverty indicators

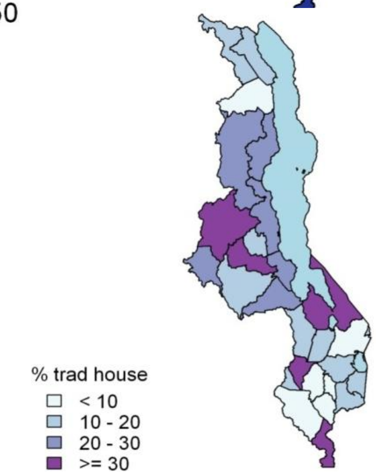


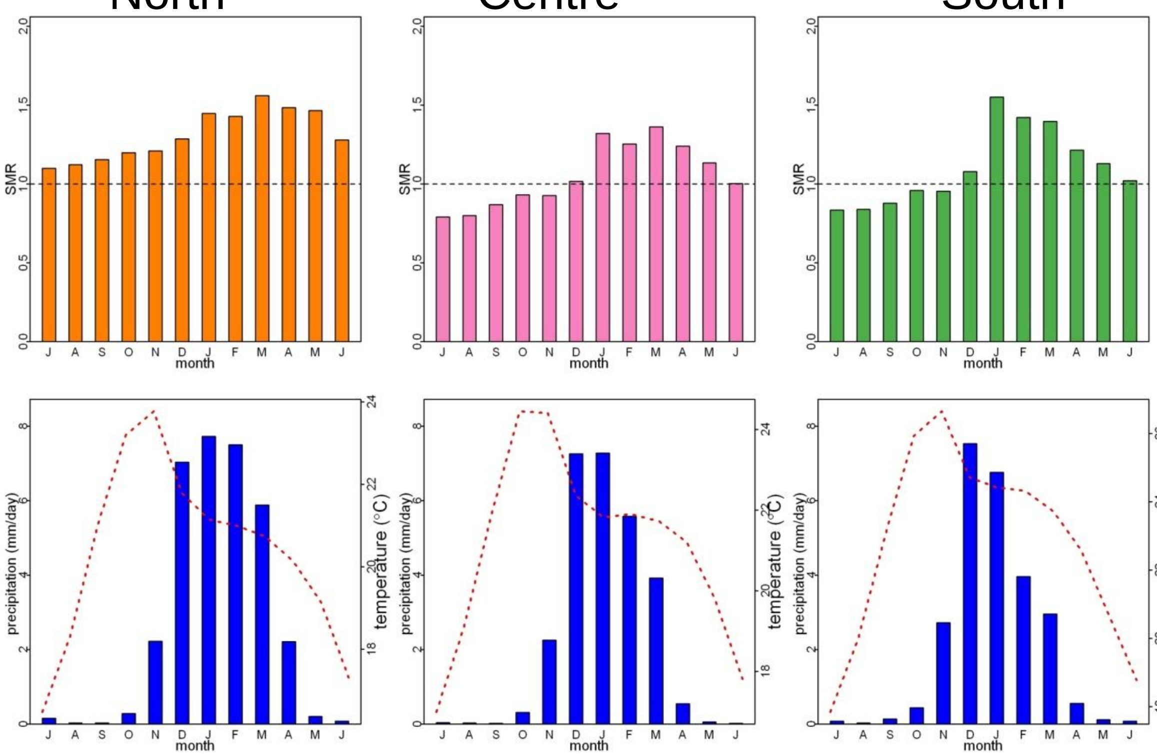



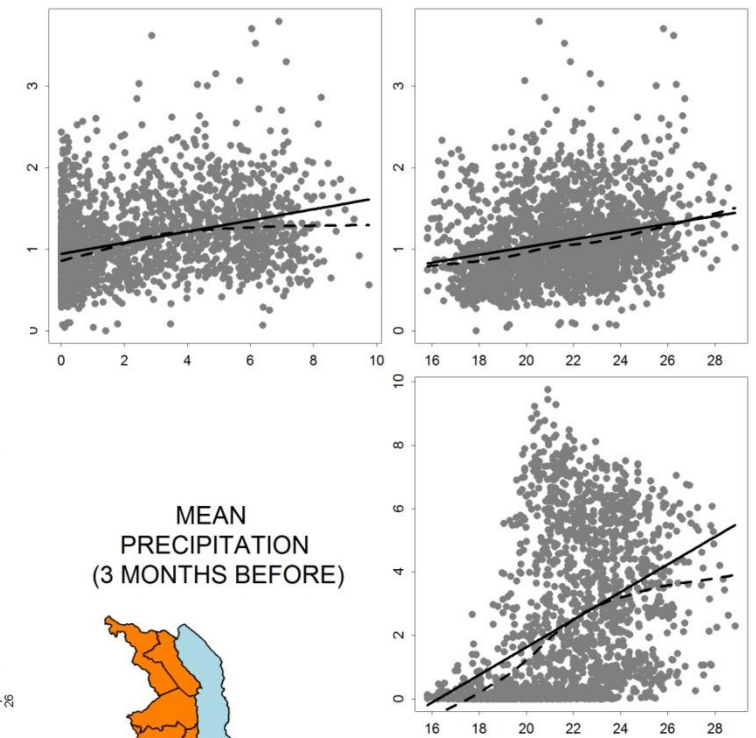



# Climate information

- CPC FEWS-Net rainfall estimates based on satellite and rain gauge data

- ERA-Interim Reanalysis temperature data




# Model framework

- Negative Binomial Generalised linear model framework used to test and select spatial, temporal variables, factors, interactions and polynomial terms.

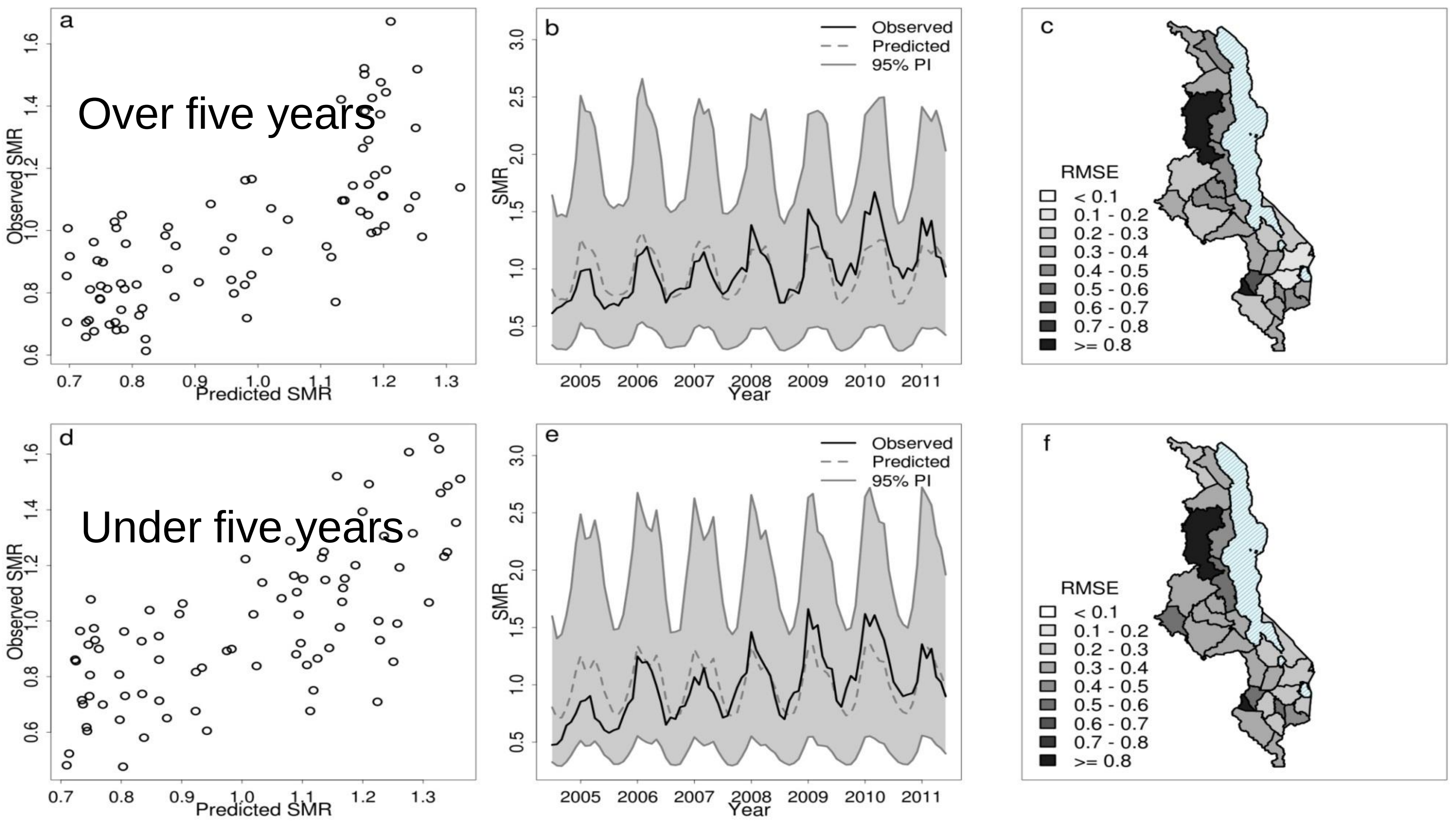
$$y_{stj} \sim NegBin(\mu_{stj}, \kappa)$$
$$\log \mu_{stj} = \log e_{stj} + \log \rho_{stj}$$

- Stepwise model selection using Akaike Information Criterion (AIC).
- **Categorical variables**: age group (under and over 5),region (north, central, south), zone (lowland, lake shore, highland and combinations), annual cycle.
- **Non-climate information**: Altitude, longitude and latitude (quadratic), demographic: urbanisation, population density, housing condition: one room for sleeping, no toilet, health facilities per population, education level.
- **Climate information**: temperature and precipitation (averaged over previous 3 months – precipitation: quadratic association).
- **Random effects:** account for unmeasured/unknown spatial heterogeneity and spatial correlation. Include auto-correlated annual cycle.

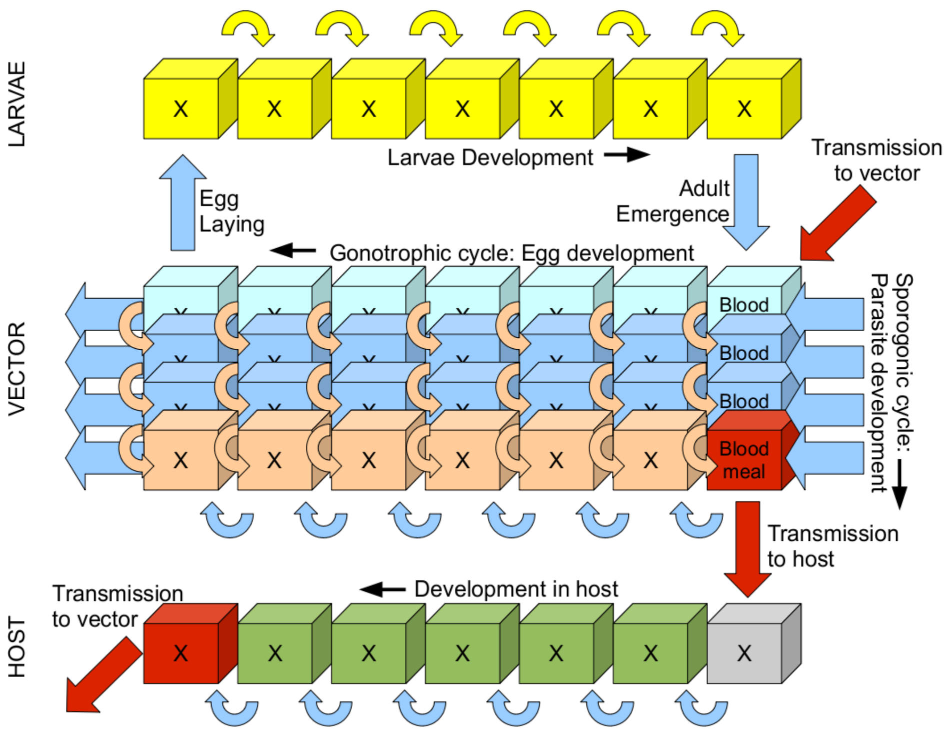
**WORK IN PROGRESS**

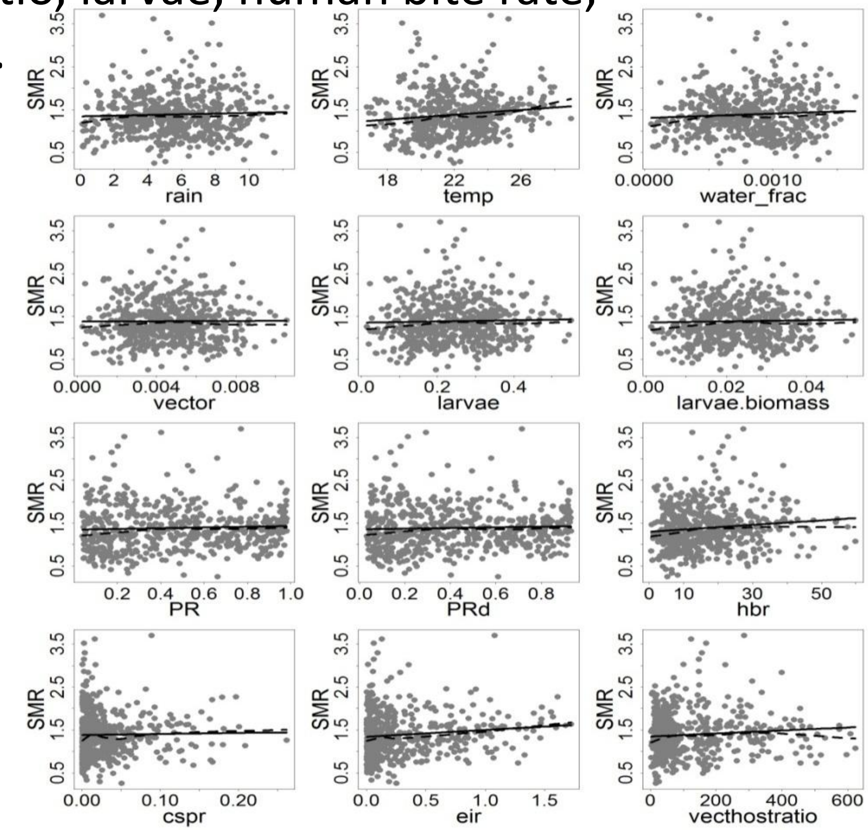
- **Dynamical model output**: vector density, larvae density, human bite ratio, proportion of infective vectors, Entomological Innoculation Rate, vector to host ratio

# Model predictions: space and time



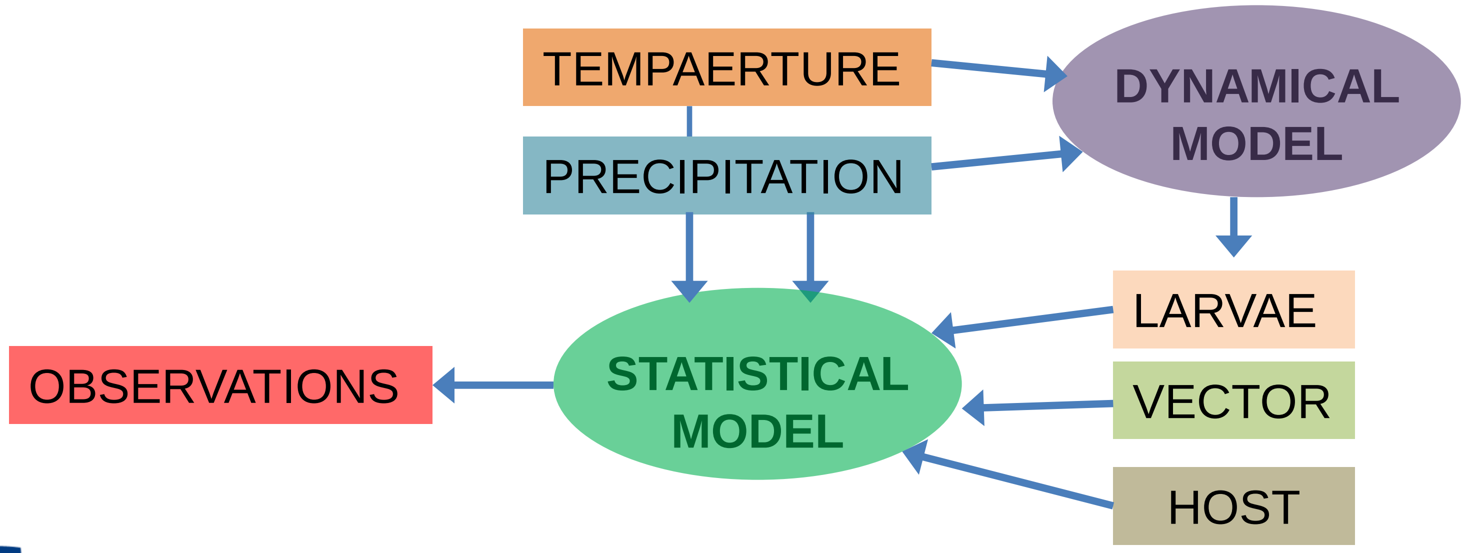
- VECTRI: VECToR-borne disease community model of ICTP.
- Incorporation of VECTRI output into model framework. Does this better represent climate influence on *Anopheles* mosquitoes than raw climate data?
- Model output: water fraction, vector-host ratio, larvae, human bite rate, parasite ratio, Entomological Inoculation Rate,…



Does the use of a physically based non-linear operator for climate information improve model?

| Model | AIC | $R^2_{ad}$ |
|---|---|---|
| non-climate | 82501 | 0.395 |
| +climate | 82450 | 0.402 |
| +dynamical | 82434 | 0.404 |
| combined | 82384 | 0.411 |

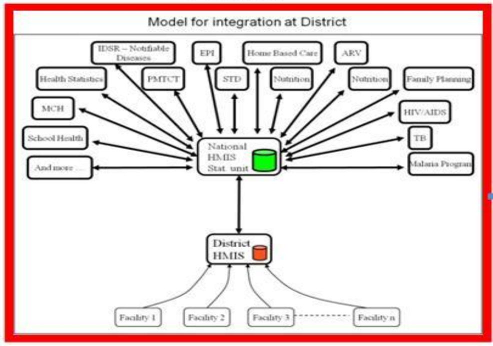


**TRAINING**


**RURAL CLINIC**

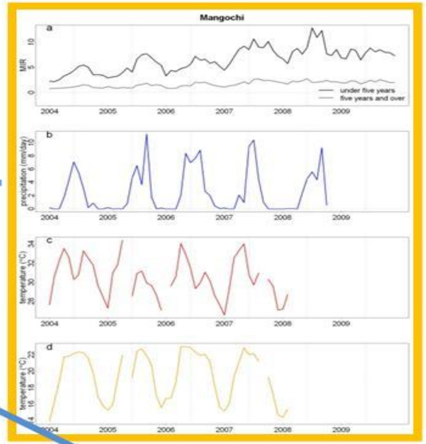
**WIFI LONG LINK**

**DHIS**

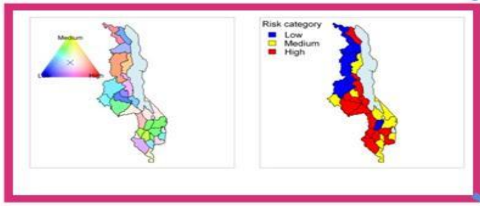


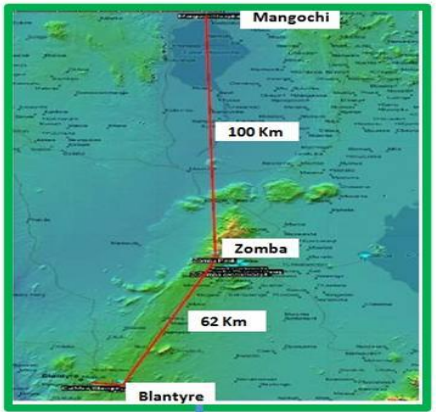

**NEW TECHNOLOGY**
VOIP
WEATHER SENSORS

**DATA ANALYSIS**




**MODEL FRAMEWORK**





**HEALTH FACILITIES**


**CHALLENGES**
RELIABILITY OF LINK
FUEL SHORTAGES
SPEED OF DATA TRANSFER

**MINISTRY OF HEALTH**

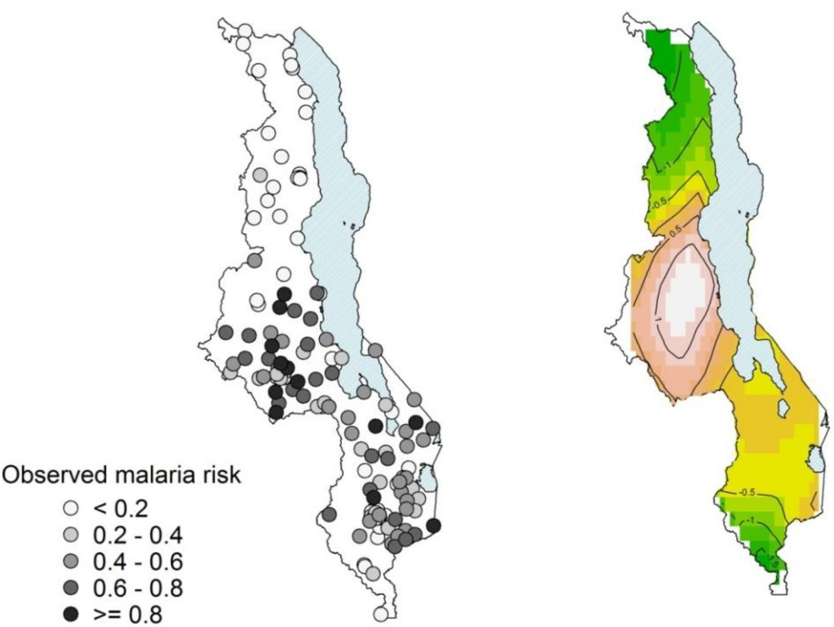
# A platform to integrate climate information and rural telemedicine

UNIVERSITY OF LIVERPOOL

# Geostatistical analysis of household malaria risk in Malawi

UNIVERSITY OF MALAWI

- MSc thesis James Chirombo, Ministry of Health.
- 2010 Malaria indicator survey data, malaria status of child determined by RDTs.
- Statistical analysis Bayesian structured additive logistic regression model. Response: Probability of testing +ve.




- Important to account for non-linear effects and spatial autocorrelation.
- Risk map aid targeted interventions.

# Conclusions

- Climate significant predictor of malaria in space and time, explains very small % inter-annual variability.
- Important consider other spatio-temporal factors that influence malaria.
- By adopting a Bayesian model framework, random effects included in the model to account for unobserved/unmeasured factors that result in latent structure/correlation. Help identify important drivers of malaria.

# Further work

- Continue test usefulness dynamical model output in statistical models to capture non-linear effects of climate on the vector and disease.
- Extent to which climate forecasts extend predictive lead time.
- Integrate ensemble of QWeCI disease models to predict malaria.
- Test model framework more fully in other locations.

*Thank you*

*Asante Sana*