

Seasonal forecasting of malaria and a focus on Senegal

Malaria caused by the plasmodium parasite of which 6 species are known to infect man:

- P. falciparum
- P. Vivax
- P. Ovale (2)
- P. Malariae
- P. Knowlesi

falciparum and **vivax** are the most widespread, their vector is the anopheles genus of mosquito (Fig. 1).

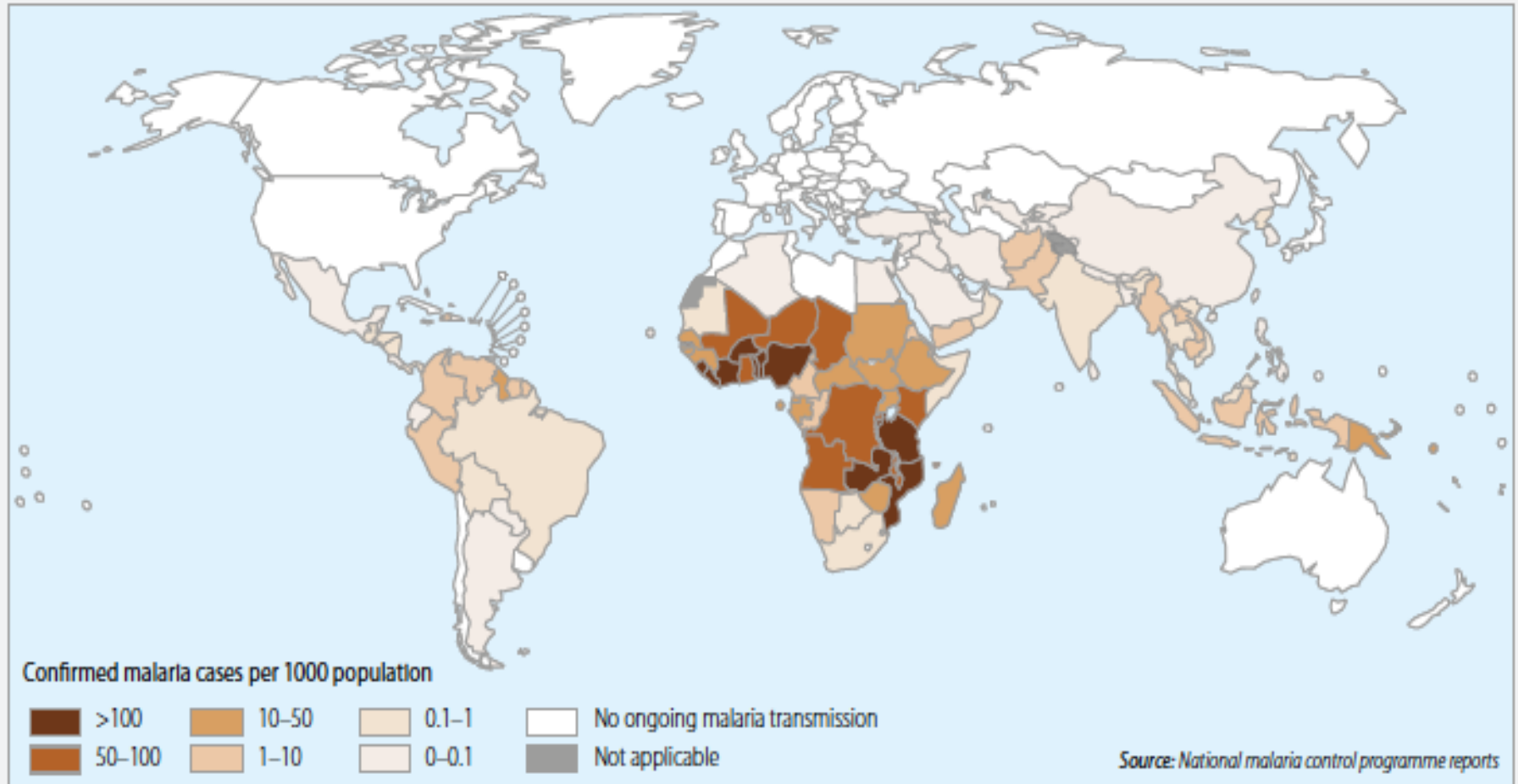


Figure: anopheles gambiae vector

Vivax can lie dormant in the liver for weeks to years and cause frequent relapses, while falciparum has wide-spread drug resistance and causes the most fatal cases due to the potential cerebral complications.

World Malaria Report 2014

Figure 1.1 Countries with ongoing transmission of malaria, 2013



- Epidemic regions are usually found on the transmission fringes and are associated with temperature and/or rainfall seasonality (Fig. 3).
- Epidemic areas - low immunity, whole population at risk - forecasts potentially very useful for early warning.
- Epidemic belt on the Sahel fridge is associated with rainfall variability, while cold temperatures reduce or eliminate malaria incidence at high altitudes over eastern Africa.

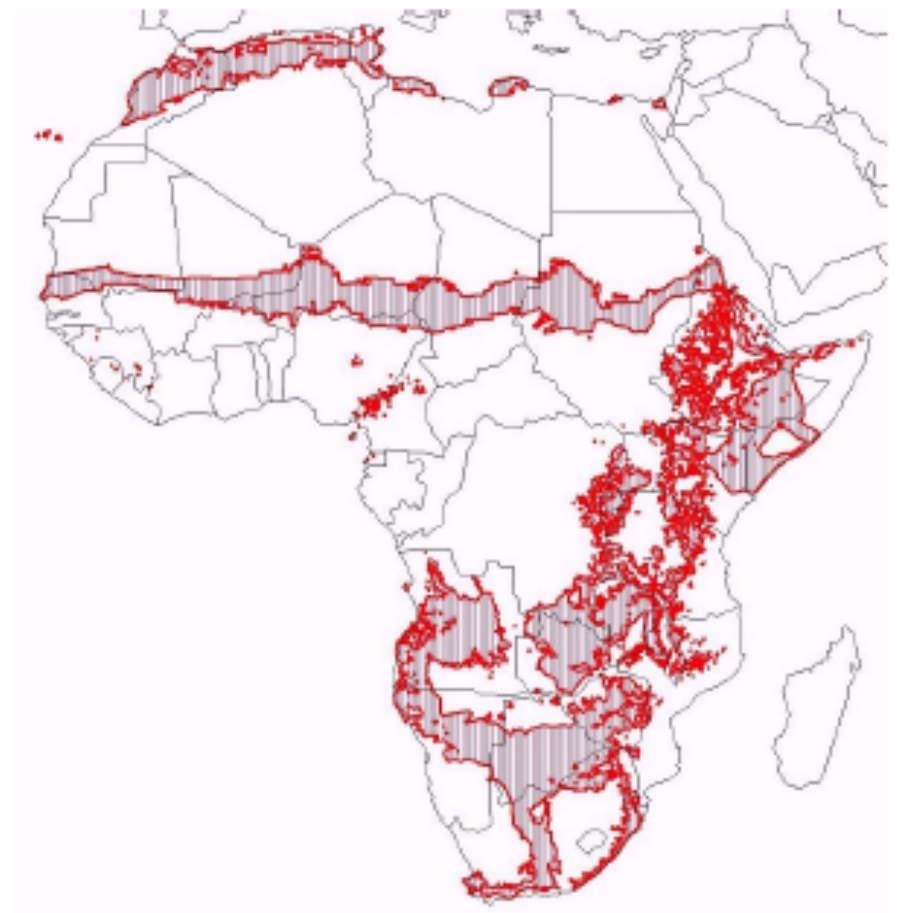


Figure: Malaria epidemic zones - from ?

Roll Back Malaria Summary

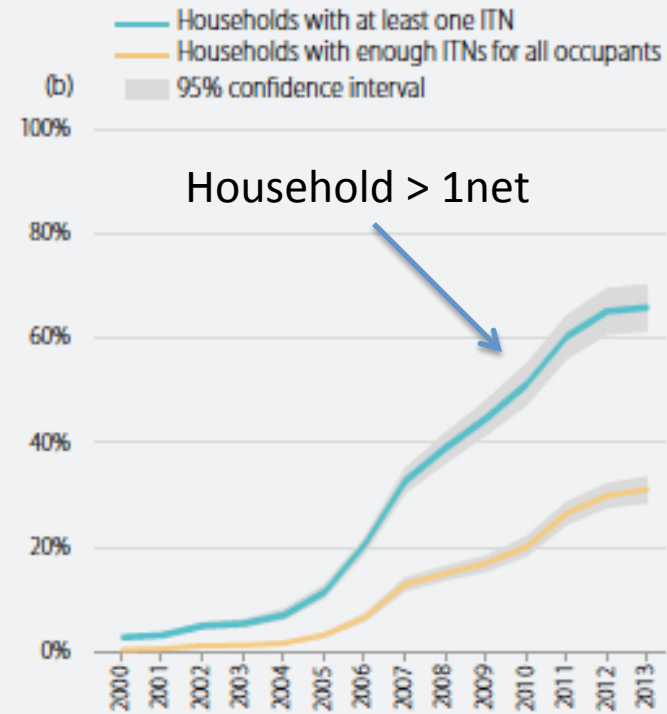
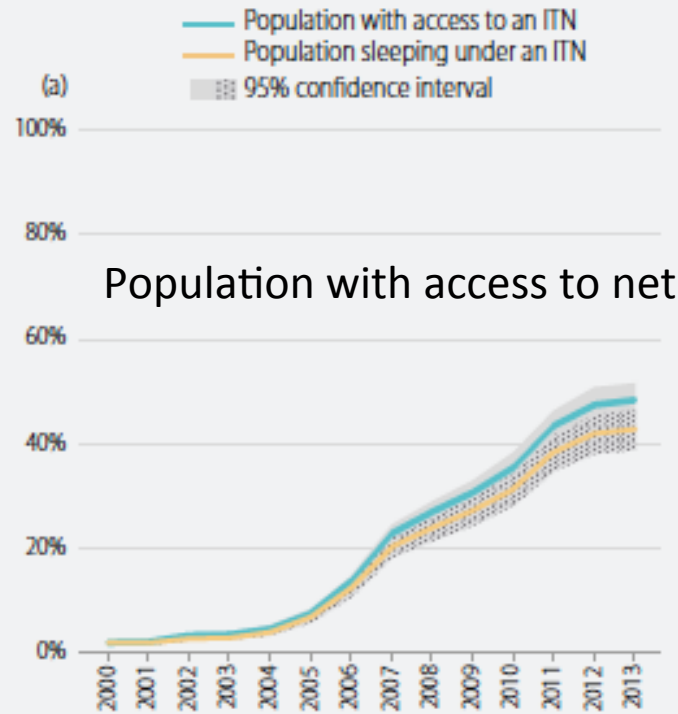
- ❑ Annual mortality 584,000 (367-755) – reduction of approximately 50%
- ❑ 49% of population at risk has at least one bednet in the household
- ❑ 70% of malaria patient could potentially be treated with ACT drug therapy in Africa, however only 26% of children with malaria received an ACT
- ❑ 2013 global spending on malaria 2.7 billion US\$, targetted spending 5.1 US\$

Fighting malaria

- Long-lasting Insecticide treated bednet (LLIN) distribution
- Indoor residual spraying (IRS)
- Improved diagnosis (RDT)
- Intermittent preventive treatment during pregnancy
- Environmental intervention (larvacide)
- Drug access (ACT)
- (Mass screen and treat)
- Housing improvements
- Healthcare infrastructure, training and access
- Land management
- Education
- Socio-economic development (the paddy paradox)

Increasing distribution and use of LLINs in Africa

Figure 3.1 a) Proportion of population with access to an ITN and proportion sleeping under an ITN, b) Proportion of households with at least one ITN and proportion of households with enough ITNs for all persons, sub-Saharan Africa, 2000–2013



ITN, insecticide-treated mosquito net

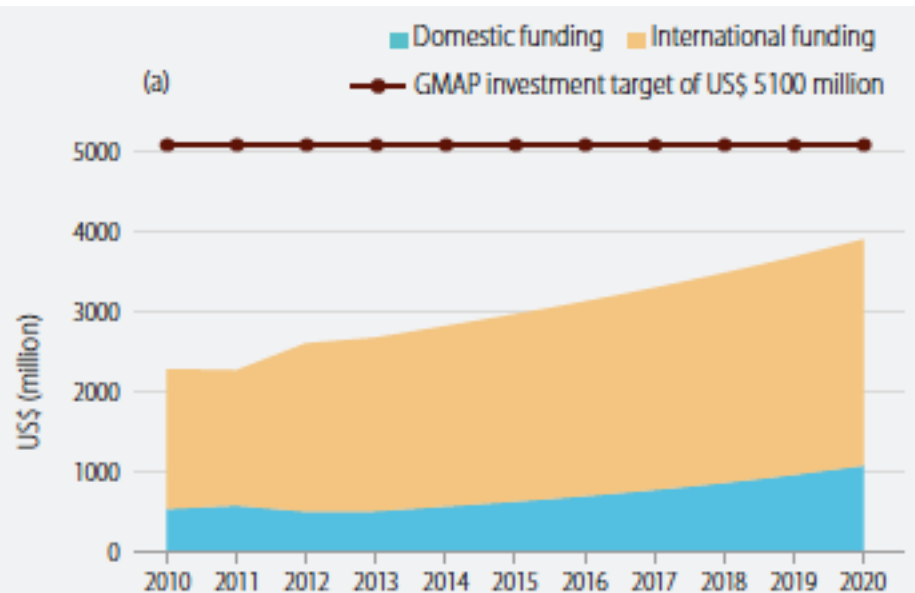
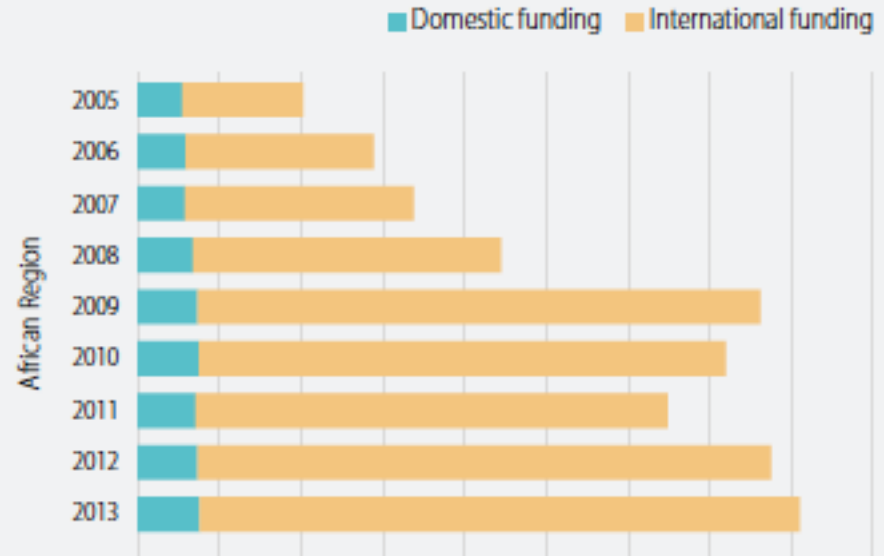
Source: ITN coverage model from the Malaria Atlas Project (based at the University of Oxford)

Forecasting

malaria

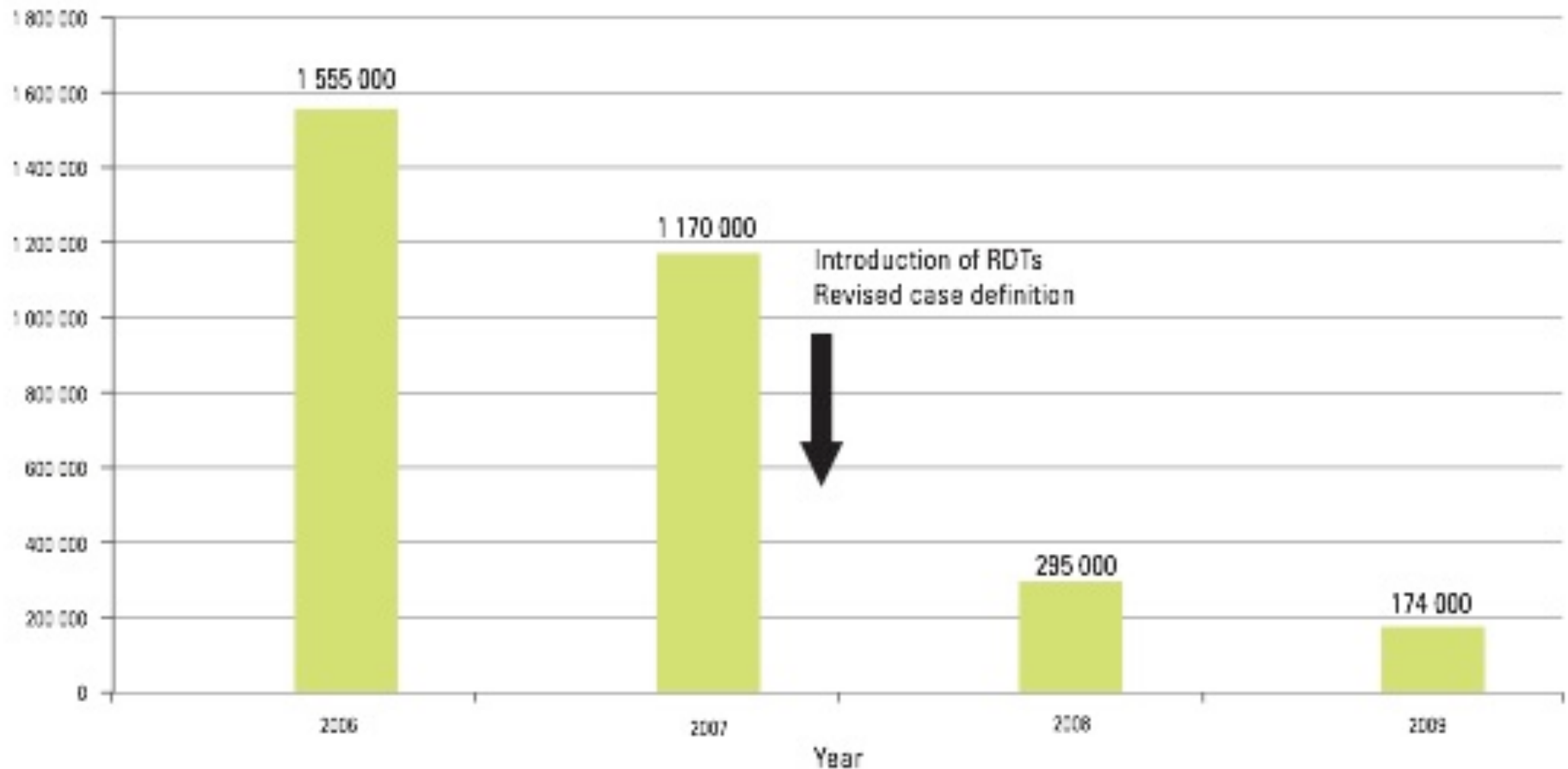
- ❑ Gains have been made through scale-up of interventions since 2010 - RBM estimates 50% reduction in mortality and > 4million lives saved
- ❑ Global spending has flattened – will future spending projections be maintained?
- ❑ Climate information may allow cost-effective prioritization of intervention and investment strategies over a range of timescales (months to decades)

Figure 2.2 Trends in domestic and international funding in the WHO African Region and other WHO regions, 2005–2013



Malaria trends in Senegal (RBM2010)

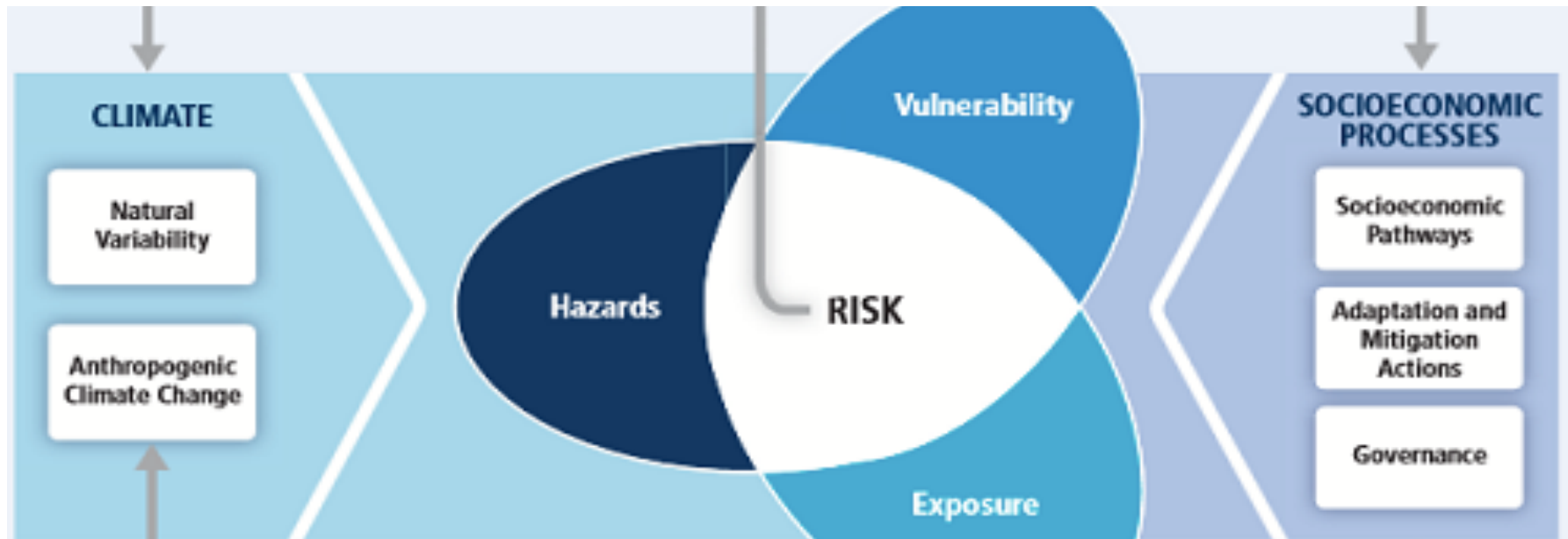
- Impact of interventions and improved diagnostics



Source: NMCP, 2010.

Prevalence in Senegal in 2010 (RBM)



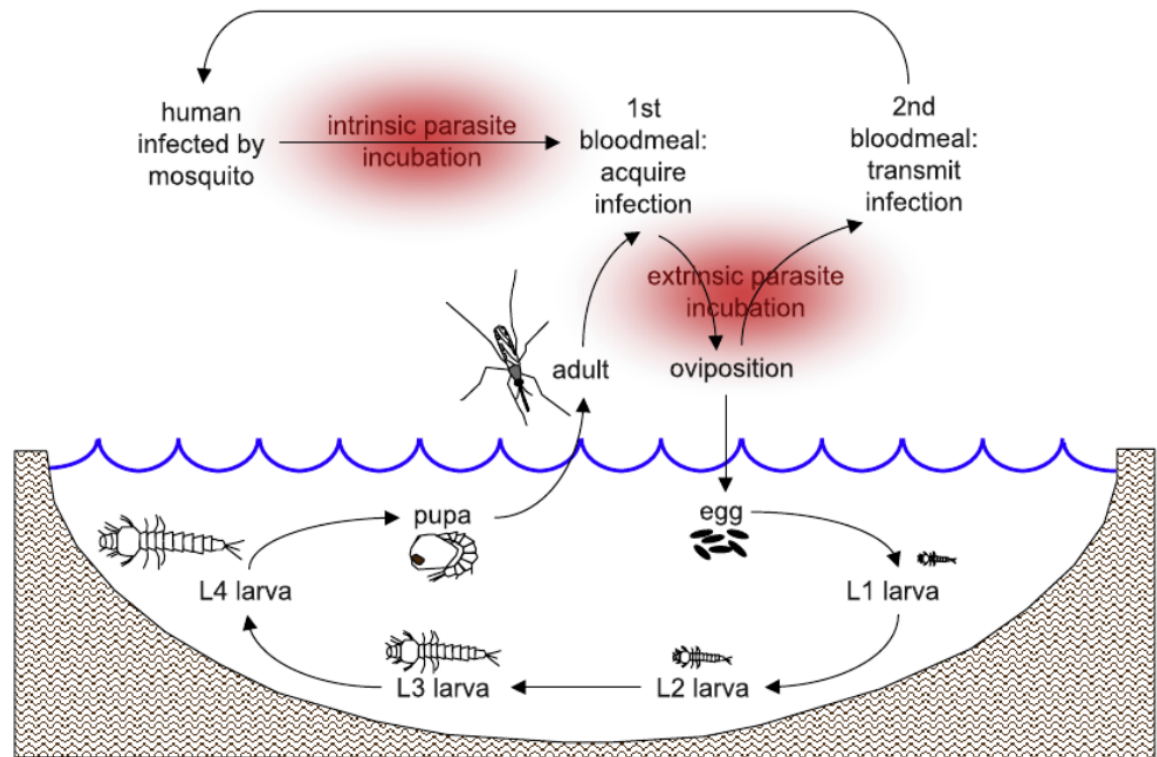


- ❑ Paradigm of surveillance and reaction for epidemical diseases
- ❑ Planning for endemic diseases on regular seasonal framework
- ❑ Longer term planning is on 5-10 year timeframe
- ❑ Some countries are integrating climate and health in their NAPA plans 2030-2040.

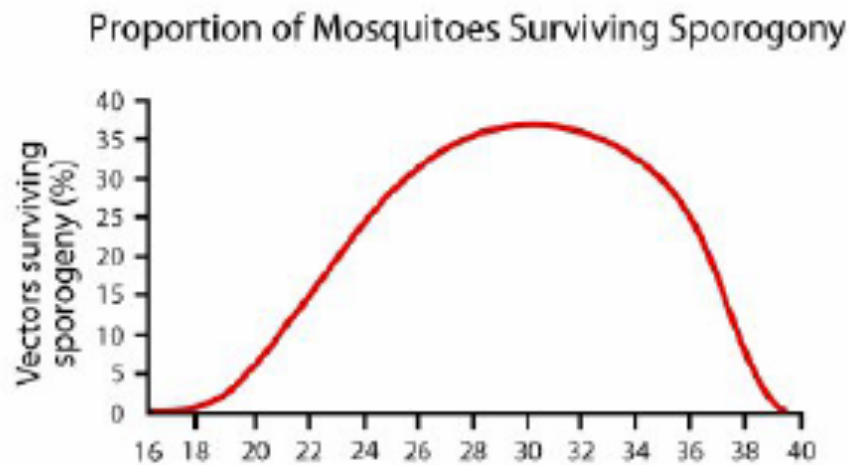
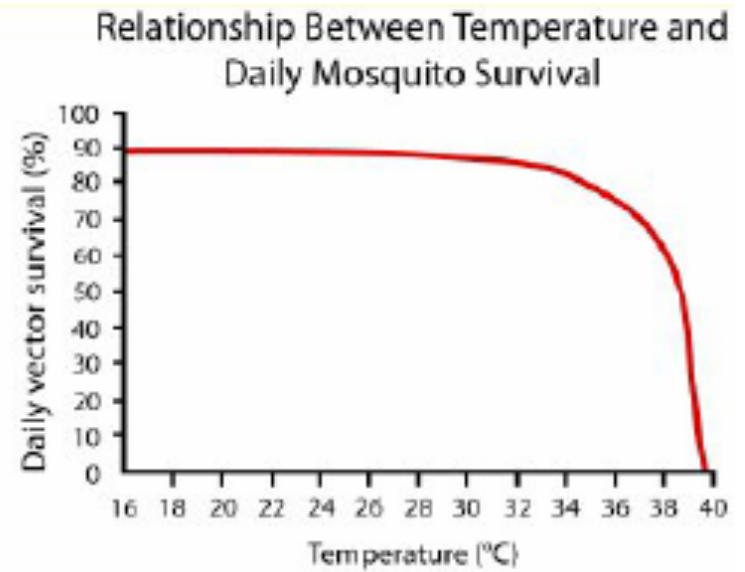
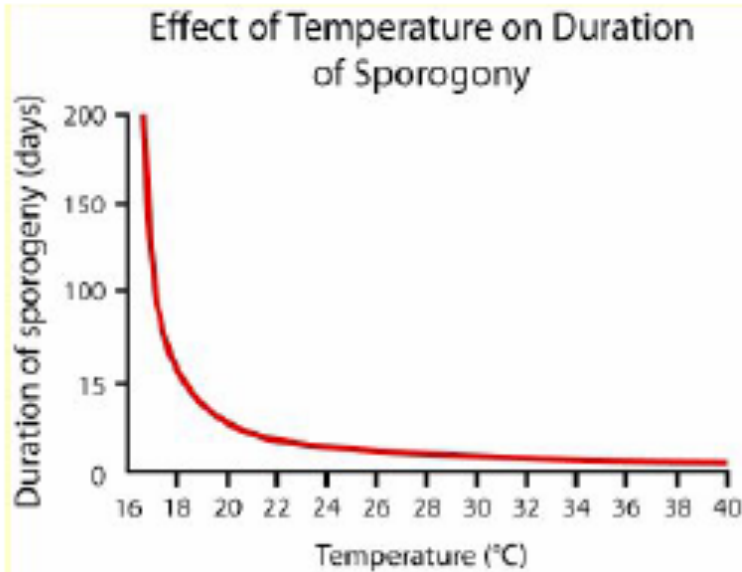
Climate drivers of malaria

Climate predictions could be used to map climate-related transmission **hazard** while recognising that other factors contribute to changes in disease hazard and vulnerability.

- **Rainfall** : provides breeding sites for larvae.
- **Temperature**: larvae growth, vector survival, egg development in vector, parasite development in vector.



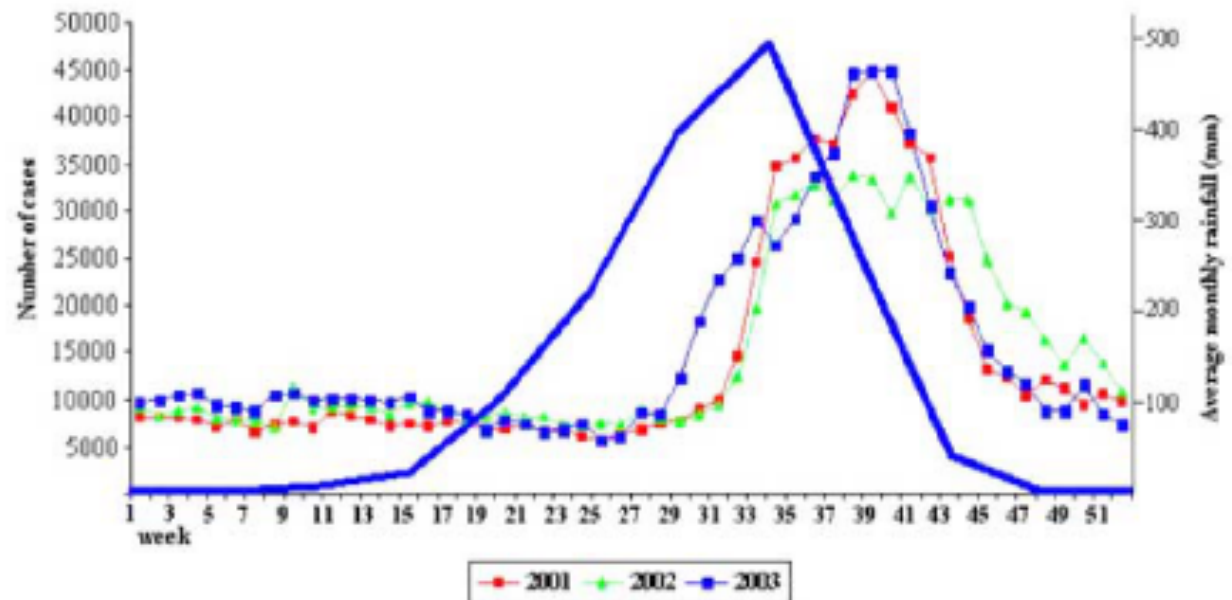
Sporogonic cycle



Rainfall

- Water required for breeding.
- Anopheles Gambiae prefers natural sunlit puddles.
- highly nonlinear relationship

Example from village in SW Niger from Bomblies et al. (2008)



Blue - Rainfall

Dots - Malaria cases in 3 seasons

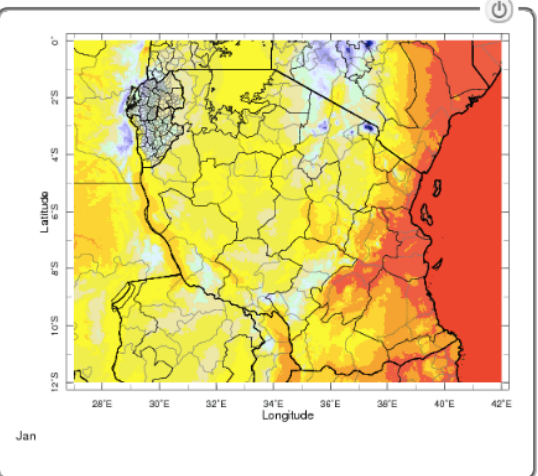
Enhanced National Climate Services (ENACTS) Tanzania

1983 to 2010

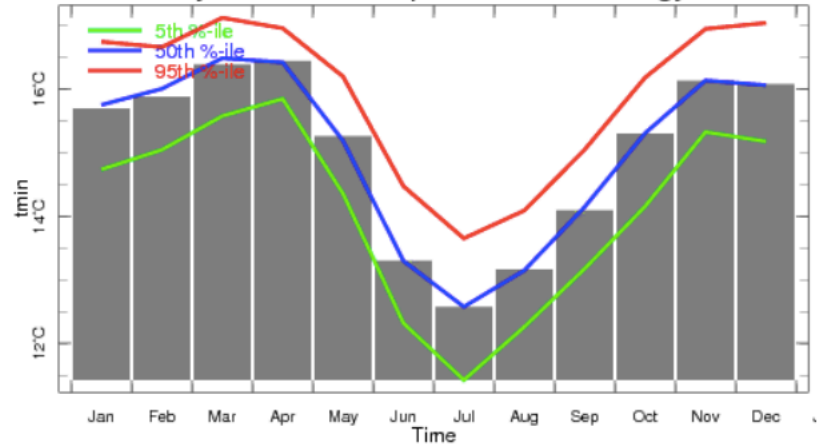
Monthly Climate Analysis

This Maproom provides information on the mean climate at any given point or at national and sub-national levels.

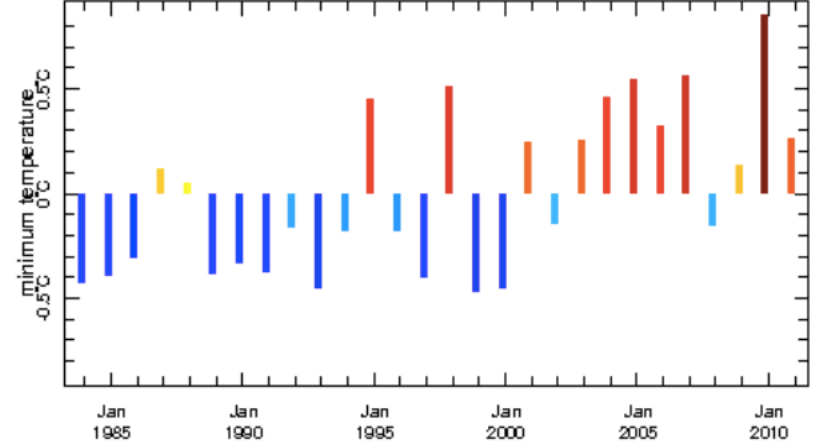
This tool allows the user to construct maps of monthly mean climate variables: rainfall, maximum temperature and minimum temperature. The default map shows average precipitation for January over the whole country. Clicking on the map would generate graphs showing monthly climatologies as well as over 30-year time series of monthly anomalies for the selected season.



Monthly Minimum Temperature Climatology



Yearly Seasonal Min Temperature Anomalies



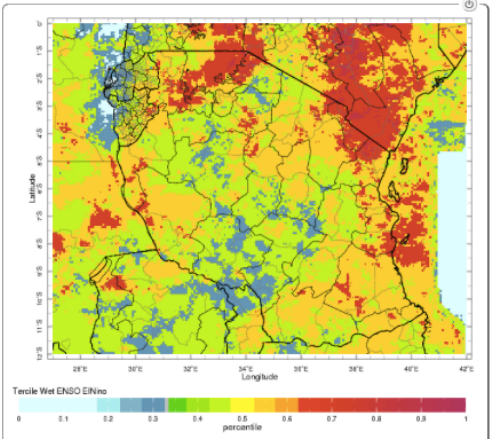
Probability of Monthly Averages (in a Season) Rainfall Tercile Conditioned on ENSO

This map shows the historical probability (given in percentile) of seasonal average monthly rainfall falling within the upper (wet), middle (normal), or bottom (dry) one-third ("tercile") of the 1983-2010 historical distribution in the country given the state of ENSO (El Niño, Neutral, La Niña) during that same season.

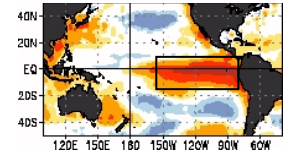
Here, the ENSO state for each season is determined by the seasonal average of the NINO3.4 SST index. If the seasonal average NINO3.4 SST index is in the top (bottom) 25% of the historical distribution for the season, the ENSO state is classified as El Niño (La Niña). The ENSO state is Neutral if the NINO3.4 index falls between the 25th and 75th percentiles of the historical distribution. Use the controls on the page to select the season, rainfall tercile category of interest, and ENSO state.

Clicking on the map will then display, for the selected point, yearly seasonal rainfall averages time series. The color of the bars depict what ENSO phase it was that year, and the horizontal lines show the historical terciles limits. This allows to quickly picture what years fell into what ENSO Phase and into what Rainfall Tercile category.

NB: This is not a forecast. It is based just on historical observations of rainfall and SST. However, it would be a good tool for exploring the efface of different ENSO phases on seasonal rainfall.



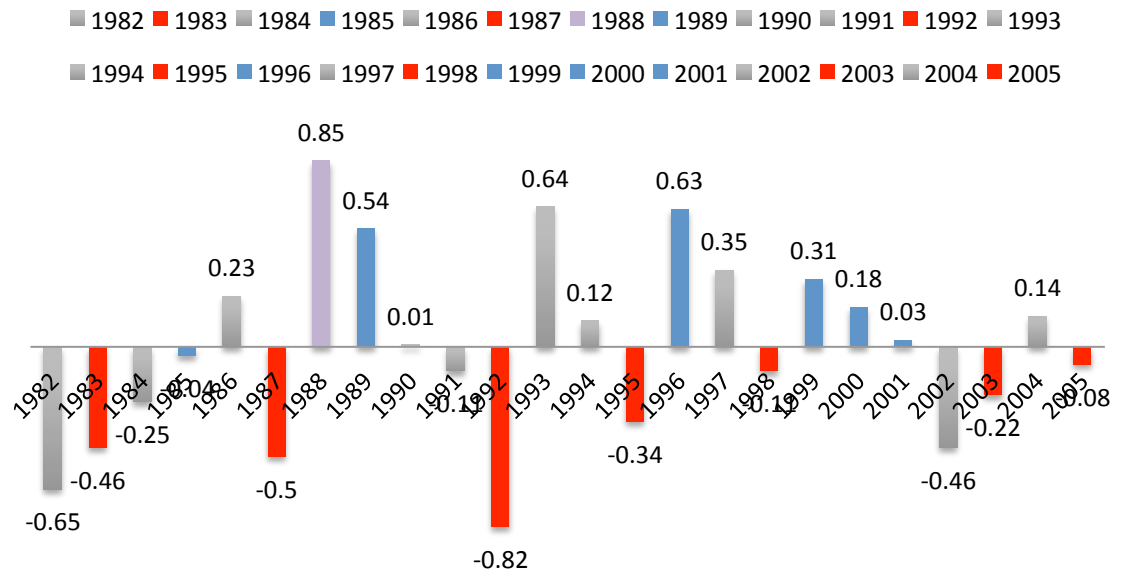
Towards Dynamical MEWS



□ Early example of a research platform: DEMETR forecasts used to drive a simple statistical model in Botswana (Thomson et al. 2006)

□ LMM model has been used in potential skill investigations (tier 2) in Africa and India (e.g. Jones et al. 2010, 2012).

Detrended malaria incidence anomalies in Botswana associated with ENSO (blue - La Nina and red = El Nino – both = purple)



from M Thomson (IRI)

Modelling malaria: Some existing models for malaria that account for climate:

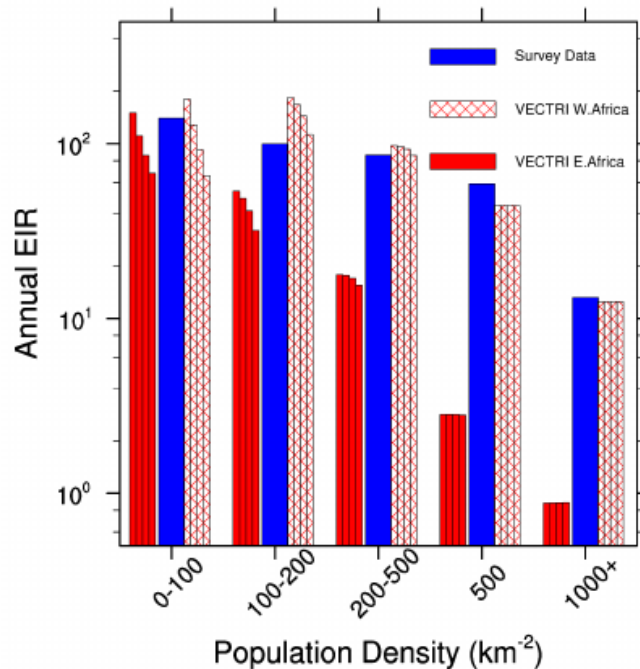
- ❑ **MAP** : Spatial Bayesian statistical model that uses climate information as one of several predictors
- ❑ **Dynamical SEIR** approach that minimizes parameter settings to fit to health data for given location and incorporate rainfall and/or temperature (Laneri et al. 2010)
- ❑ **LMM**: Spatial model driven by climate, vector density linked to rainfall and temperature impacts vector/parasite lifecycles (Hoshen and Morse 2004)
- ❑ **VECTRI**: Accounts for population density, surface hydrology, immunity with genetic-based calibration algorithm (Tompkins and Ermert 2013)

VECTRI malaria model key elements

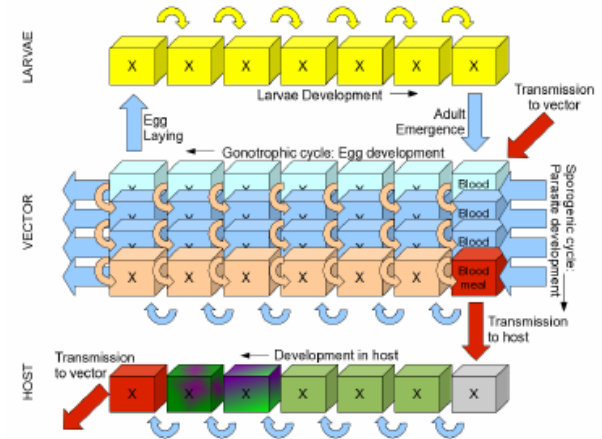
VECTRI

A new large-scale dynamical malaria model running at high spatial resolutions.

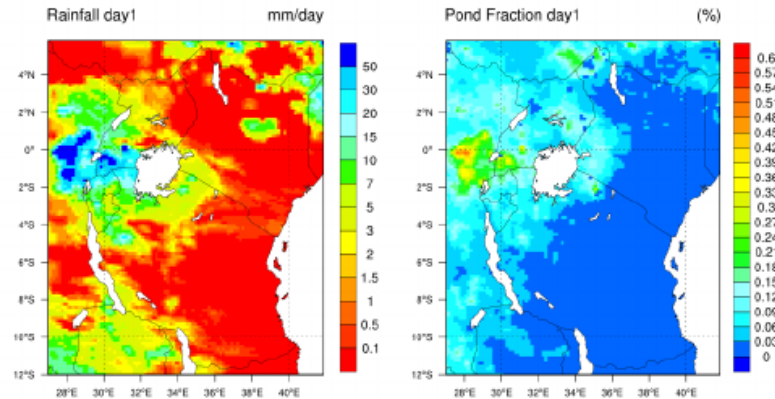
2. Accounts for population density



1. Bin-resolved parasite/vector lifecycles influenced by climate:



3. Dynamic pond parametrization

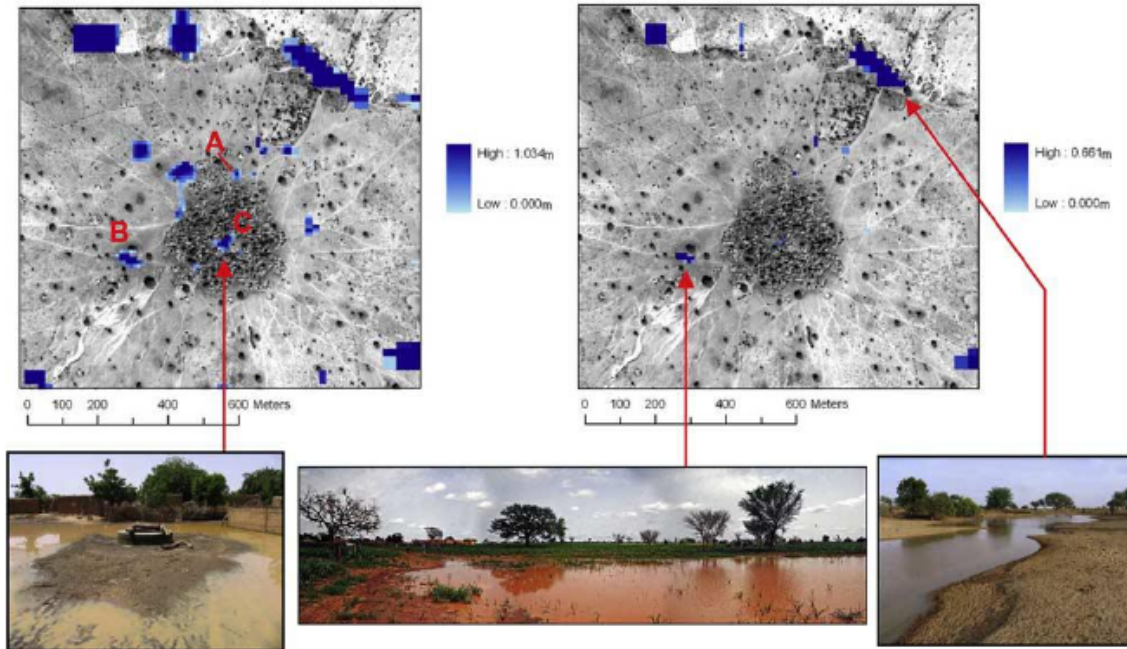


only gridded model accounting for climate that is open source

www.ictp.it/~tompkins/vectri

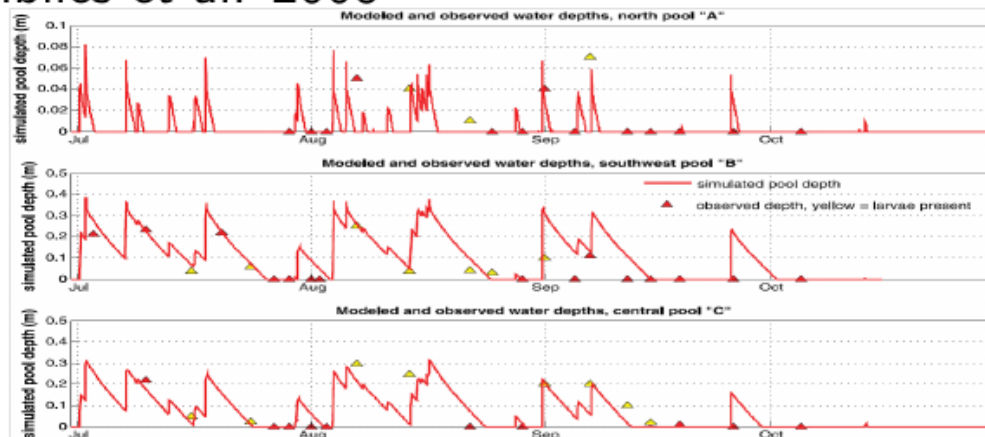


highest uncertainty: surface hydrology



Modelled pond behaviour - **However** the aggregated effect of these small water bodies could be represented by a **pond parametrization** in a coarser scale model

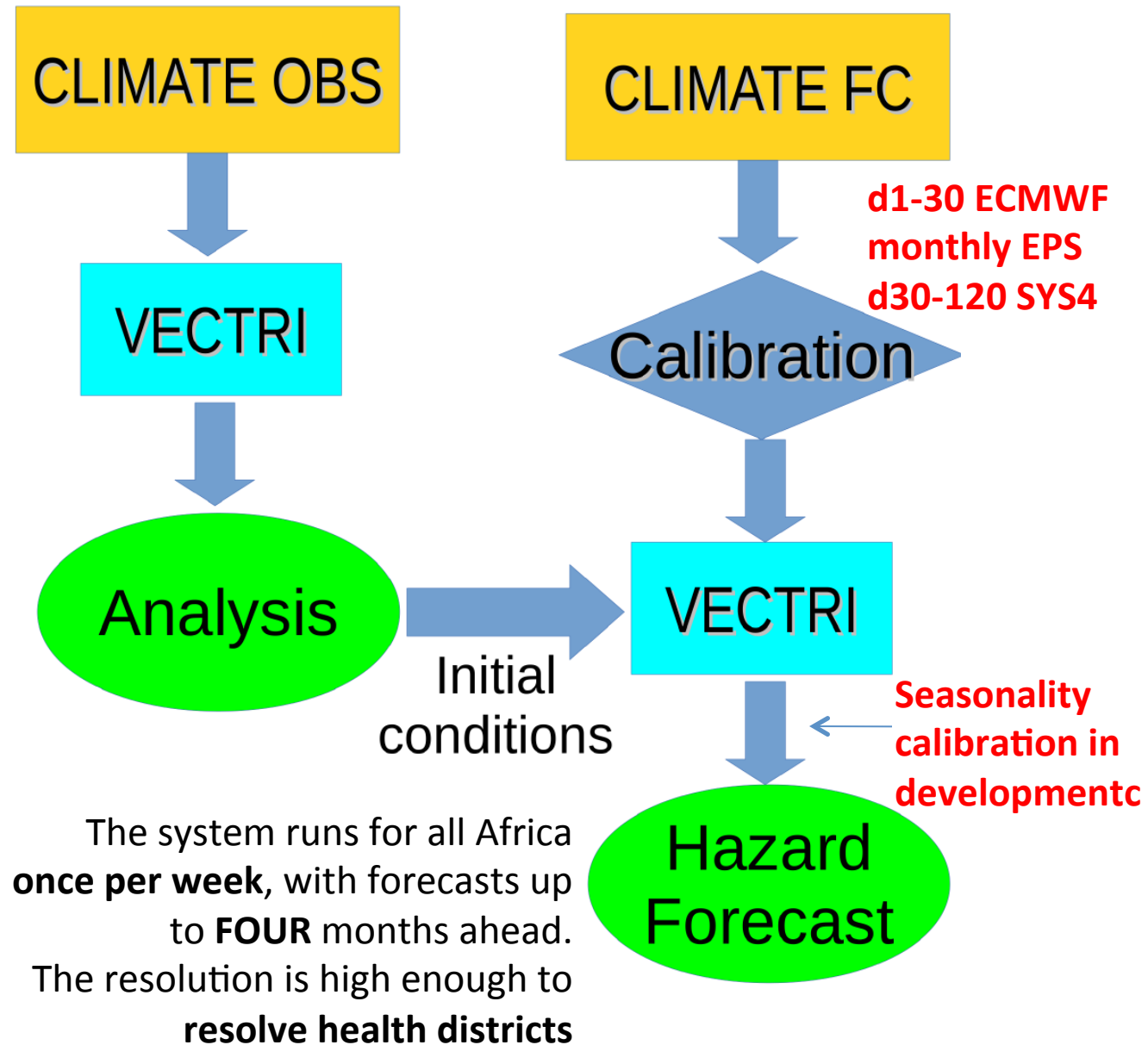
Bomblies et al. 2008



Use of VECTRI

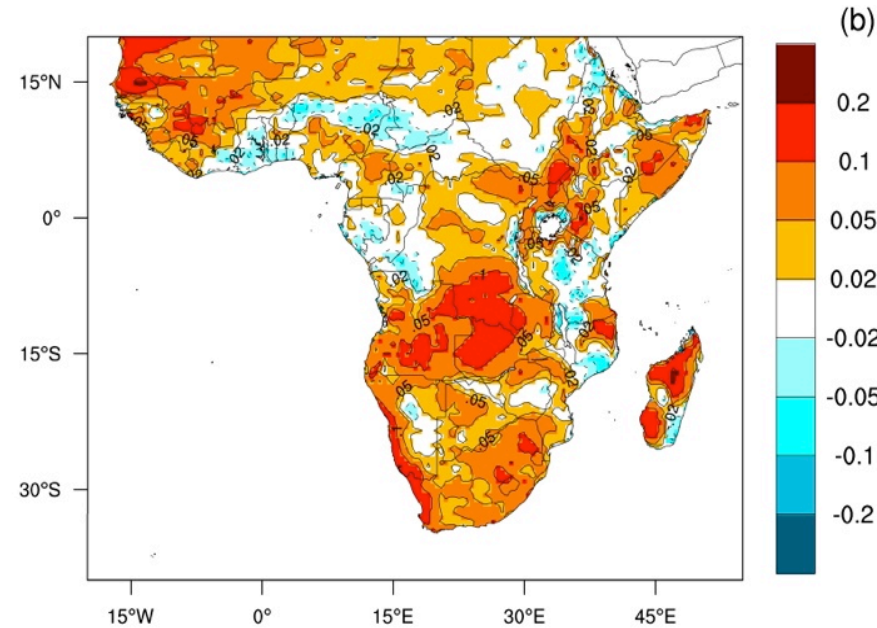
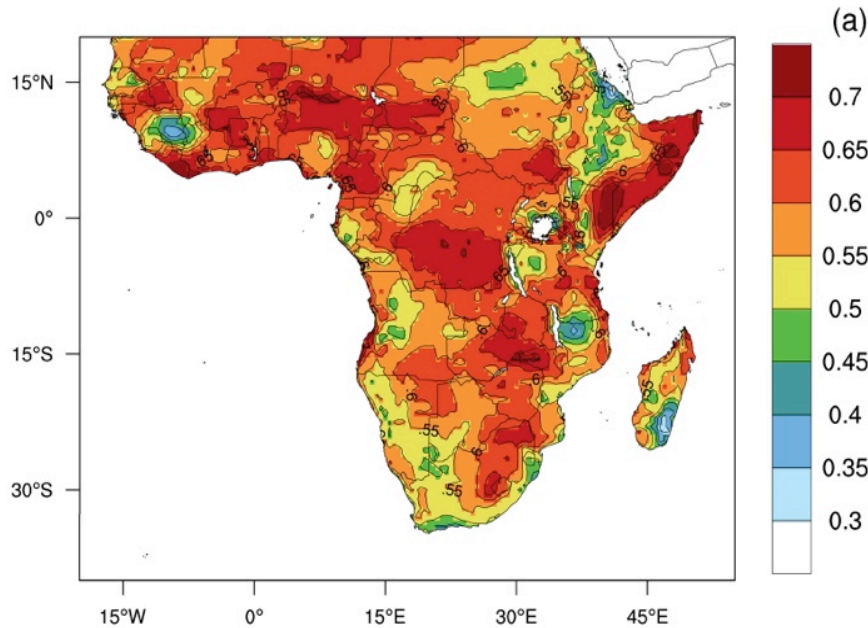
- ❑ Seasonal forecasting in Africa: case study of Rwanda and Uganda
- ❑ Historical simulations: Could past climate variability explain transmission variations in 1920s-1960?
- ❑ Multimodel climate change impact: ISIMIP
- ❑ Land use change indirect impact on malaria transmission
- ❑ Uncertainty of malaria transmission models: Stochastic integrations for Kericho

Climate observations are used to create an analysis of entomological and epidemiological conditions in order to initialize the malaria forecasts using the ICTP dynamical malaria model VECTRI (Tompkins and Ermert, 2013).



Where do these gains in skill come from?

from Tompkins and DiGiuseppe, JAMC, 2015



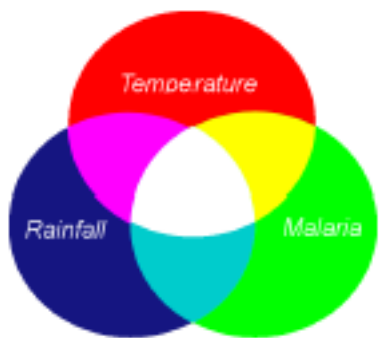
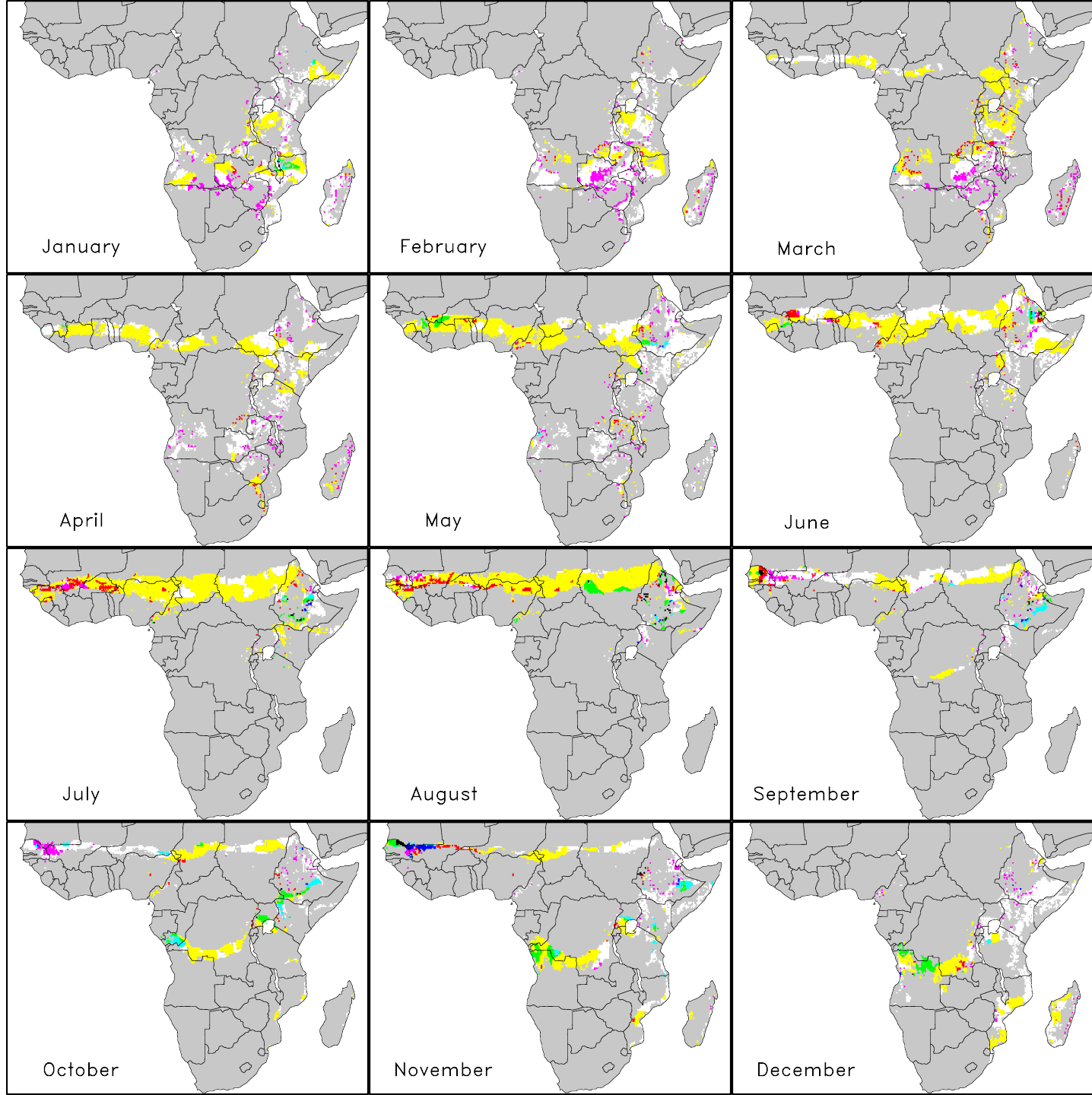
Correlation of day 1-32 T2m anomaly against ERA-Interim for 1994-2012 of Extended range EPS over Africa
12 start dates (First Thursday of each month)

Increase in correlation relative to the exact same days predicted by the most recent seasonal forecast system

Where does this skill advantage come from?

Lead 1
statistical skill
comparing
forecast to
analysis (TIER
2)

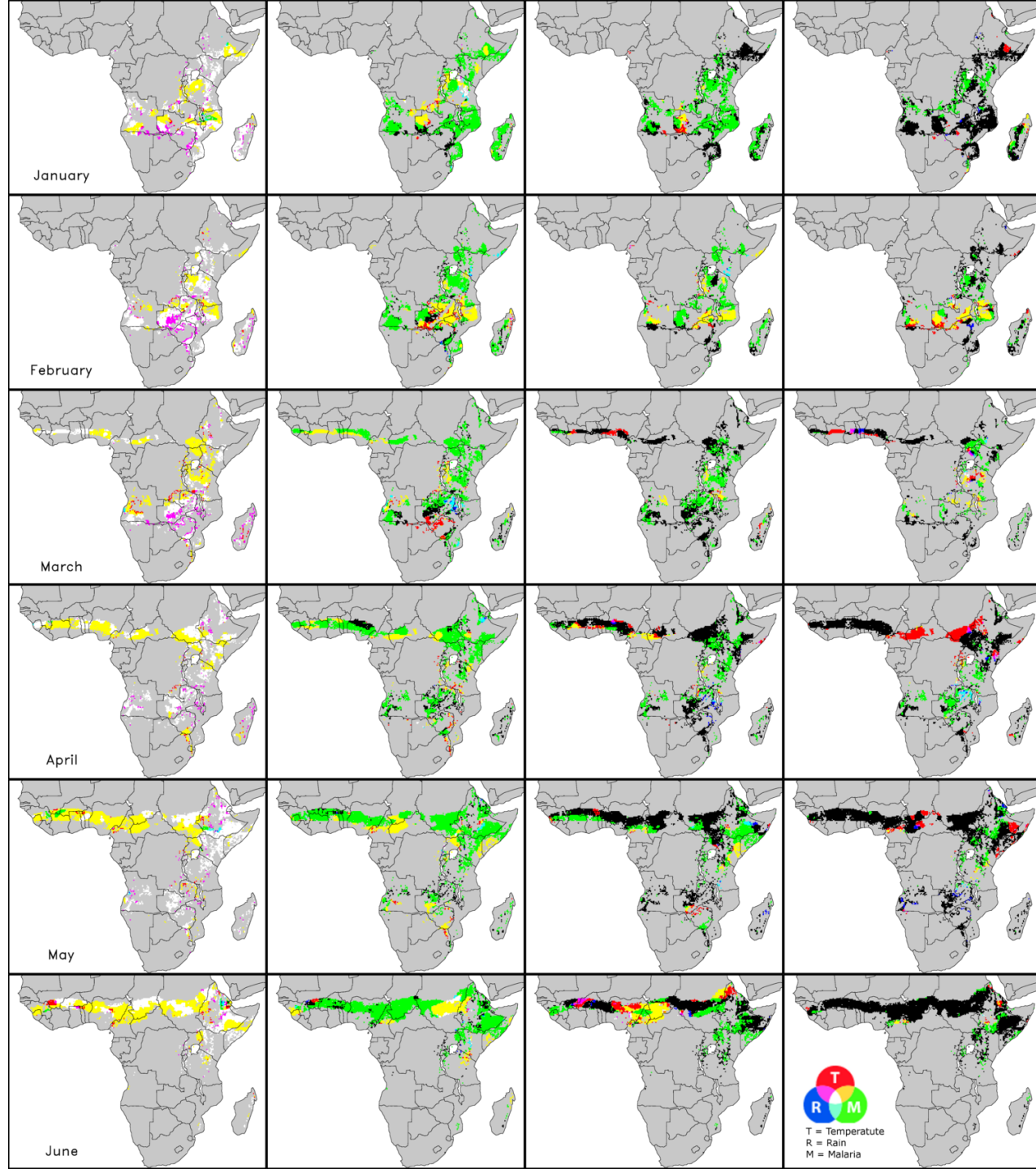
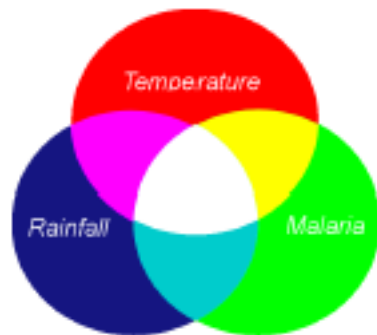
Only focussing
on high
variability areas



Lead 1-4
statistical skill

Only focussing
on high
variability
areas

Malaria skill
out to m3-4



T
R
M

T = Temperature
R = Rain
M = Malaria

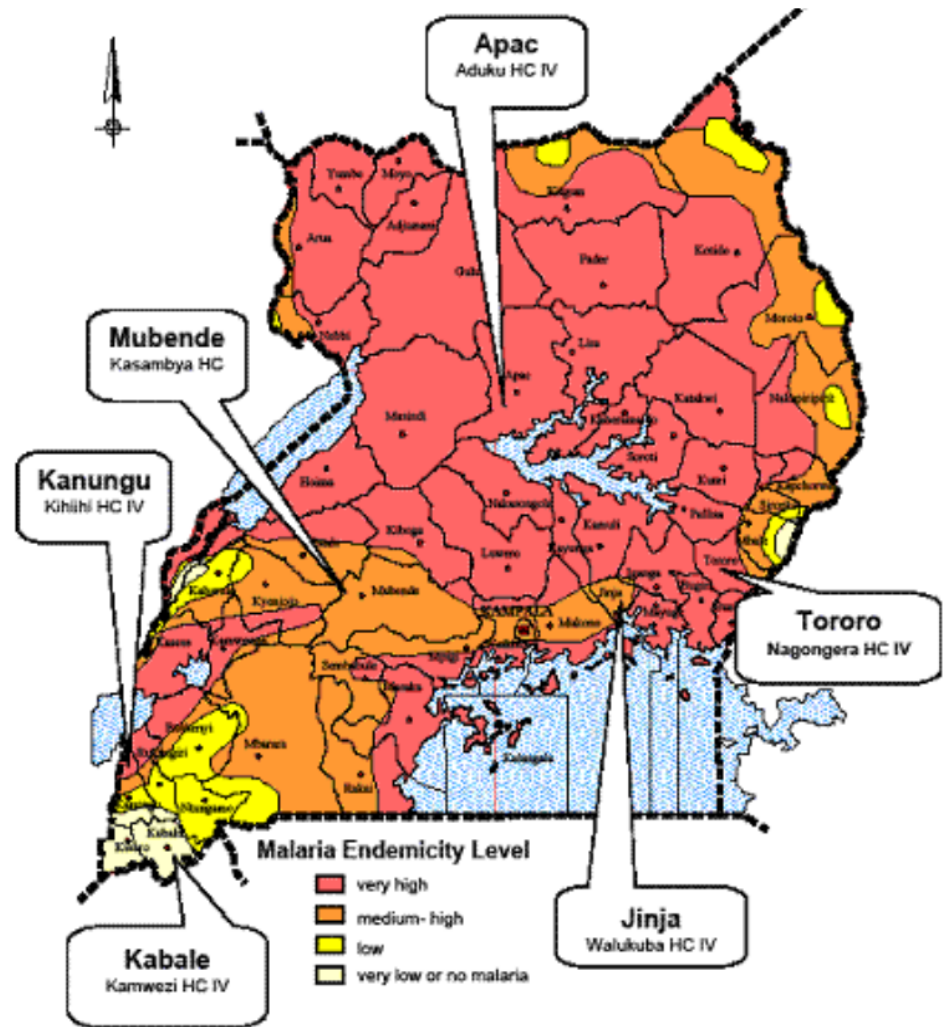
Uganda analysis

We present a preliminary evaluation of the normalized logarithm of the entomological inoculation rate, $\ln(\text{EIR})$, from

- Malaria Analysis system
- Malaria Forecast system from 1 to 4 months ahead

Comparing to observed malaria cases.

- MoH district data suspected cases 2002-2010
- UMSP confirmed cases from 6 sentinel sites 2006/09-2013



Results for Jinja Sentinel Site

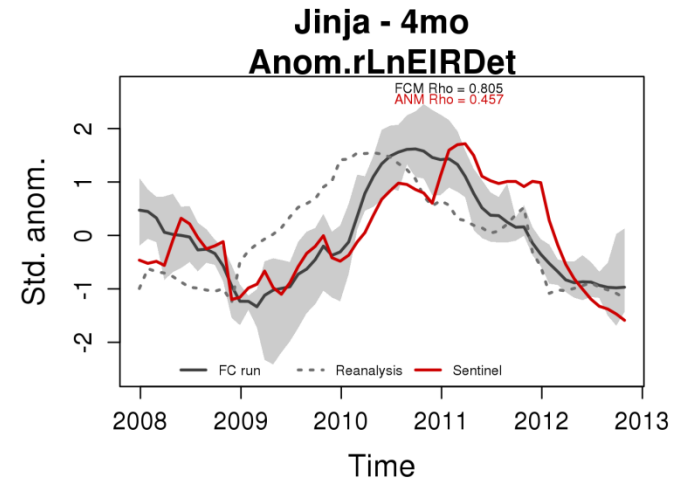
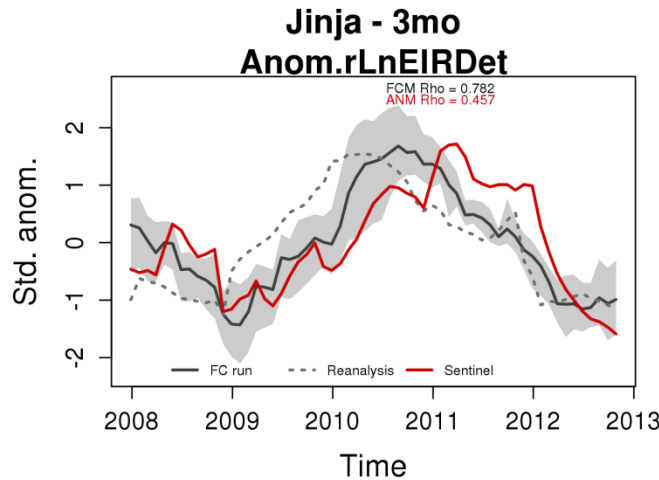
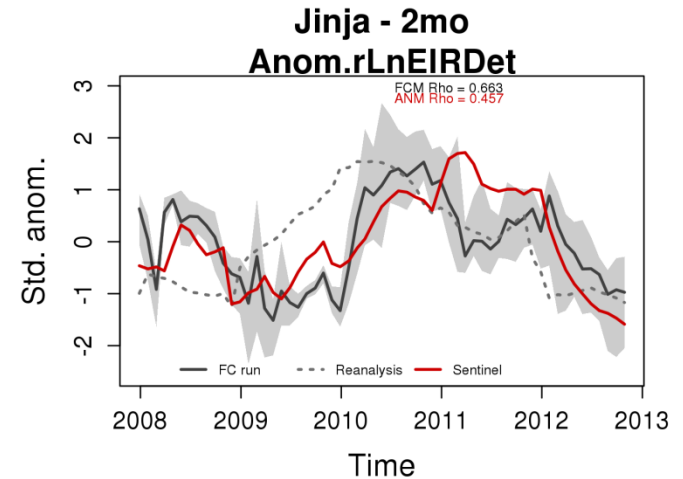
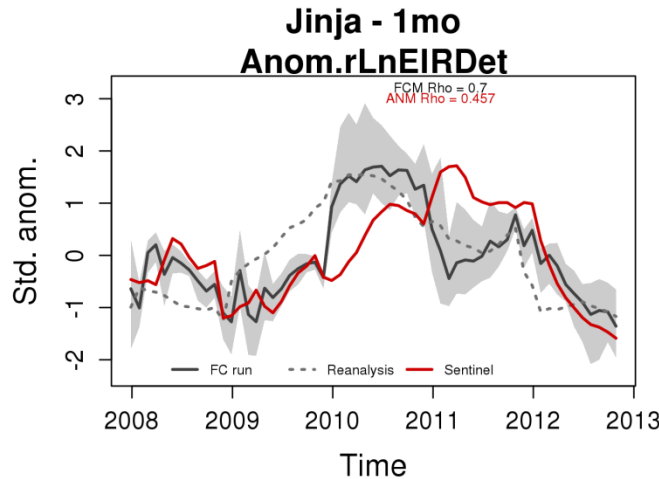
Red line: normalized confirmed cases

Black Line: normalized malaria forecast (ln(EIR) – no immunity in model yet)

Grey shading: range of the 5 forecasts

Dash lined: the malaria initial conditions

Four panels: the four levels of advance warning



Results for Kanungu Sentinel Site

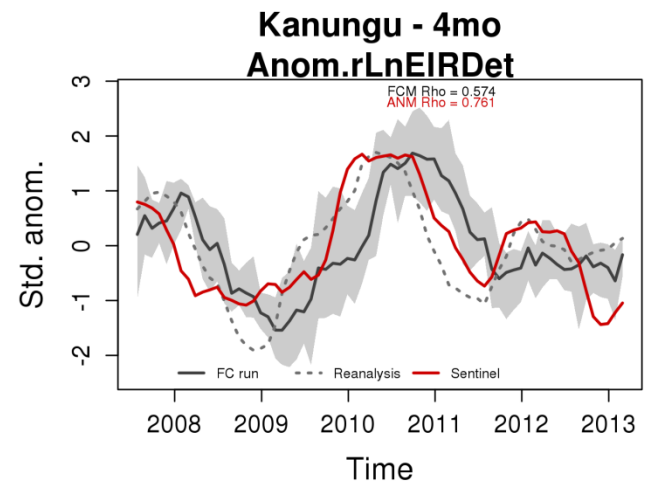
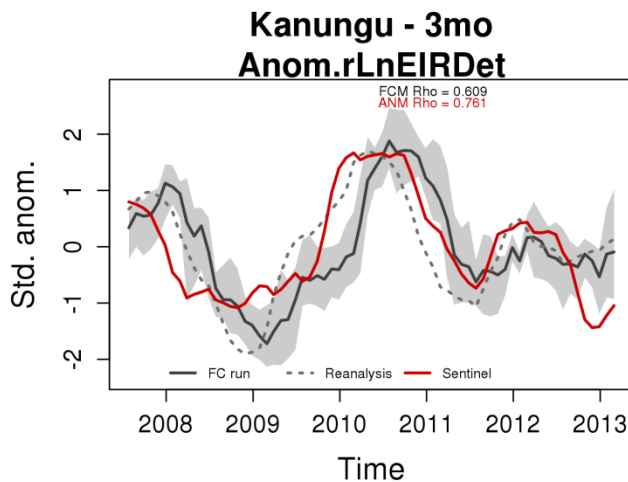
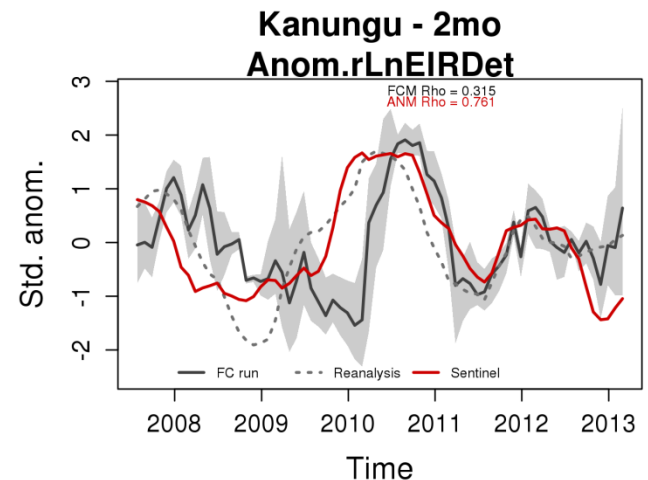
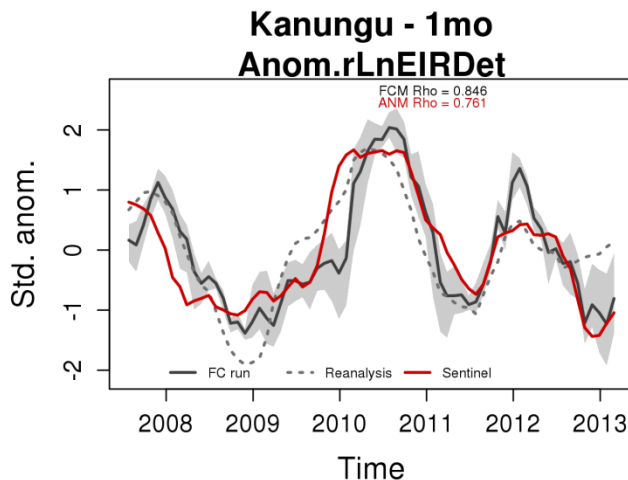
Red line: normalized confirmed cases

Black Line: normalized malaria forecast

Grey shading: range of the 5 forecasts

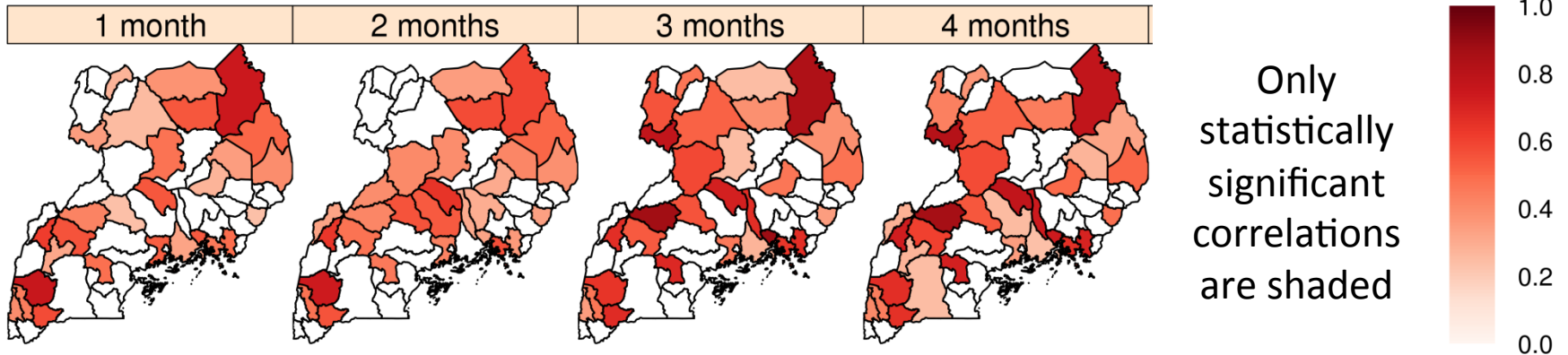
Dash lined: the malaria initial conditions

Four panels: the four levels of advance warning



Significant Spearman rank Rho

Anom.rLnEIRDet



- ❑ Over half the districts have significant skill (95% level), despite uncertainties in the weather forecasting system, the malaria model and the health data
- ❑ but non-monotonicity of lead time vs skill highlights short data series

Open Questions?

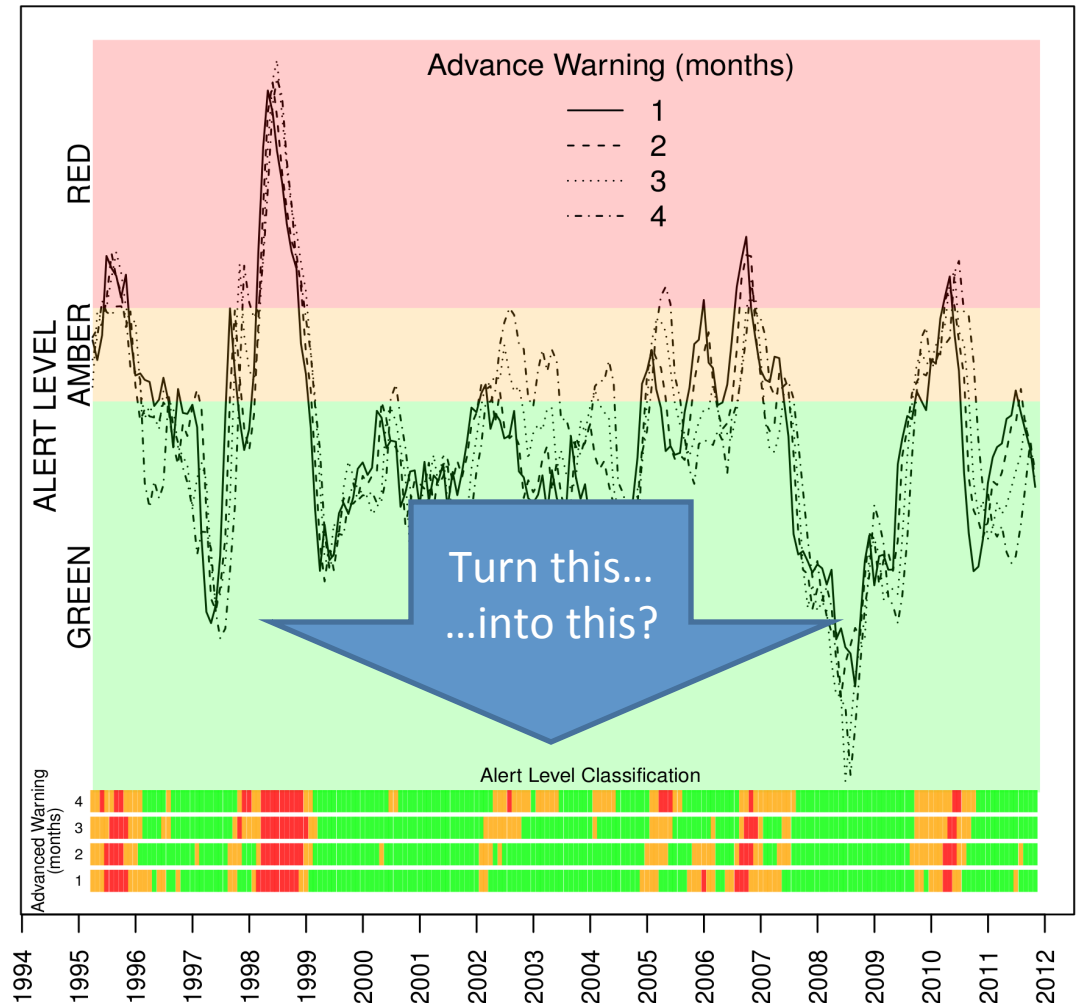
- How best to develop a usable system? -
What is the best format to provide information?
- How best to incorporate vulnerability assessments?
- Are four months adequate for key decision processes?
- Which process would streamline the integration of climate information into policy?
- How best to communicate uncertainty?

Attempt to convert Forecast to a simple alert level

Does this really mean anything to anyone?

Do terciles relate to real health policy decisions?
Doubtful...

We are currently attempting to turn this into a realistic cost-loss analysis for Uganda



A simple economic assessment

	Event occurs	No Event
Action taken	Hit C	False Alarm C
Action not taken	Miss L	

For a given event threshold
examine past forecasts and see
whether the forecast has a
net benefit

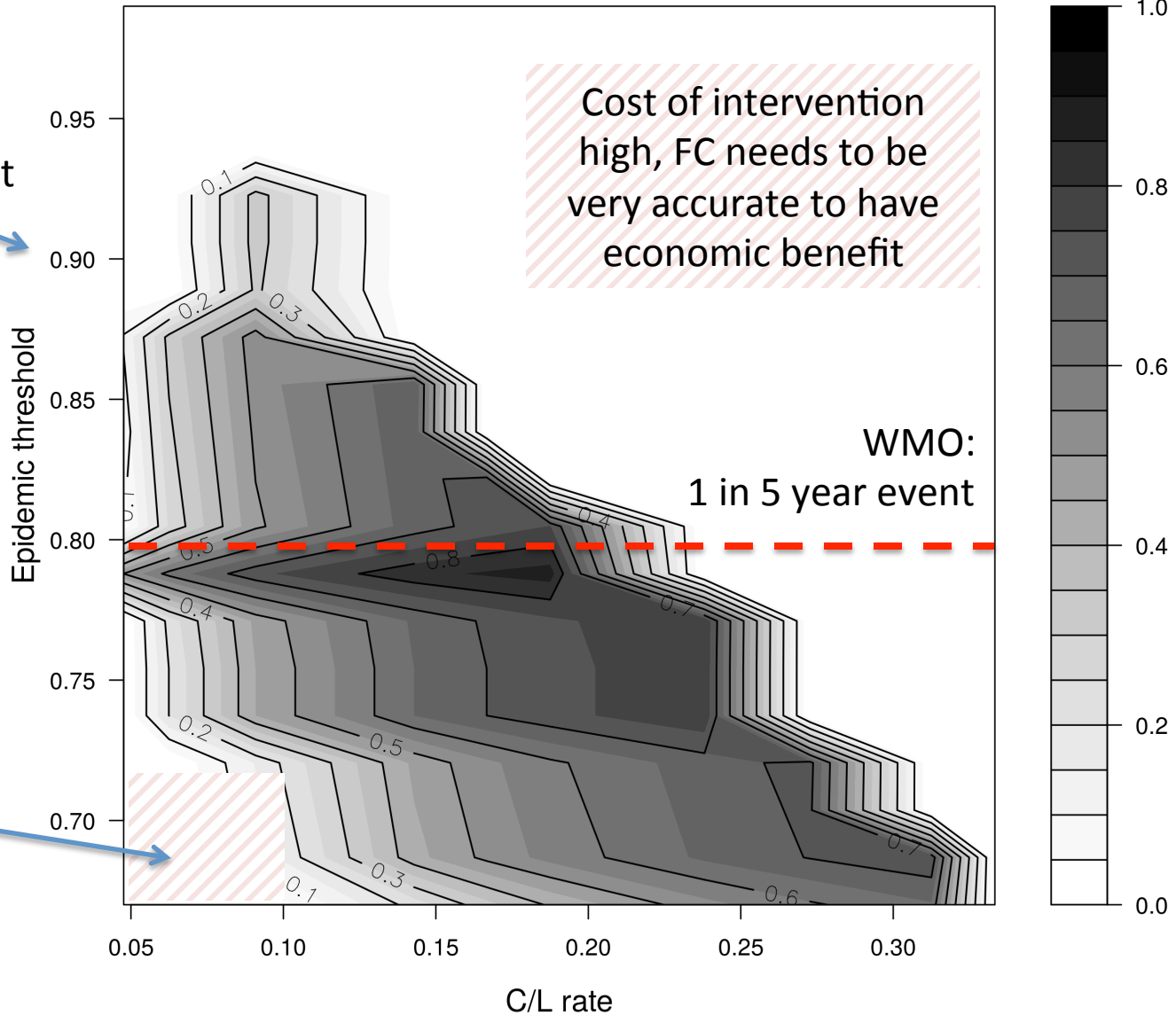
C=Cost of intervention

L=Loss if event is not prevented

Cost-Loss analysis

Tororo

Value



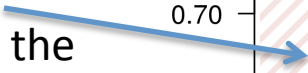
1 in 10 year event



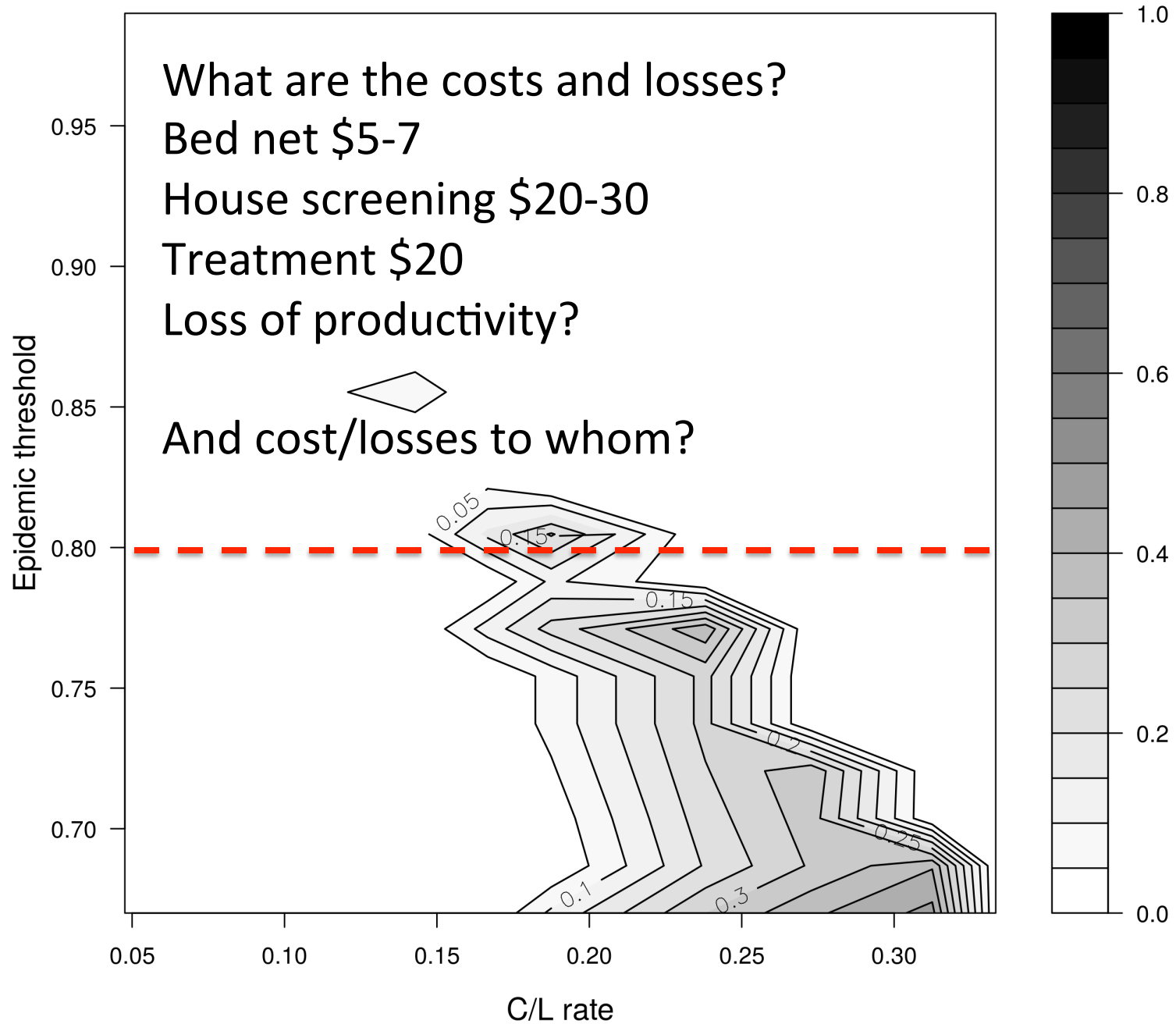
Cost of intervention high, FC needs to be very accurate to have economic benefit

WMO: 1 in 5 year event

Cost of intervention low, just intervene all the time!

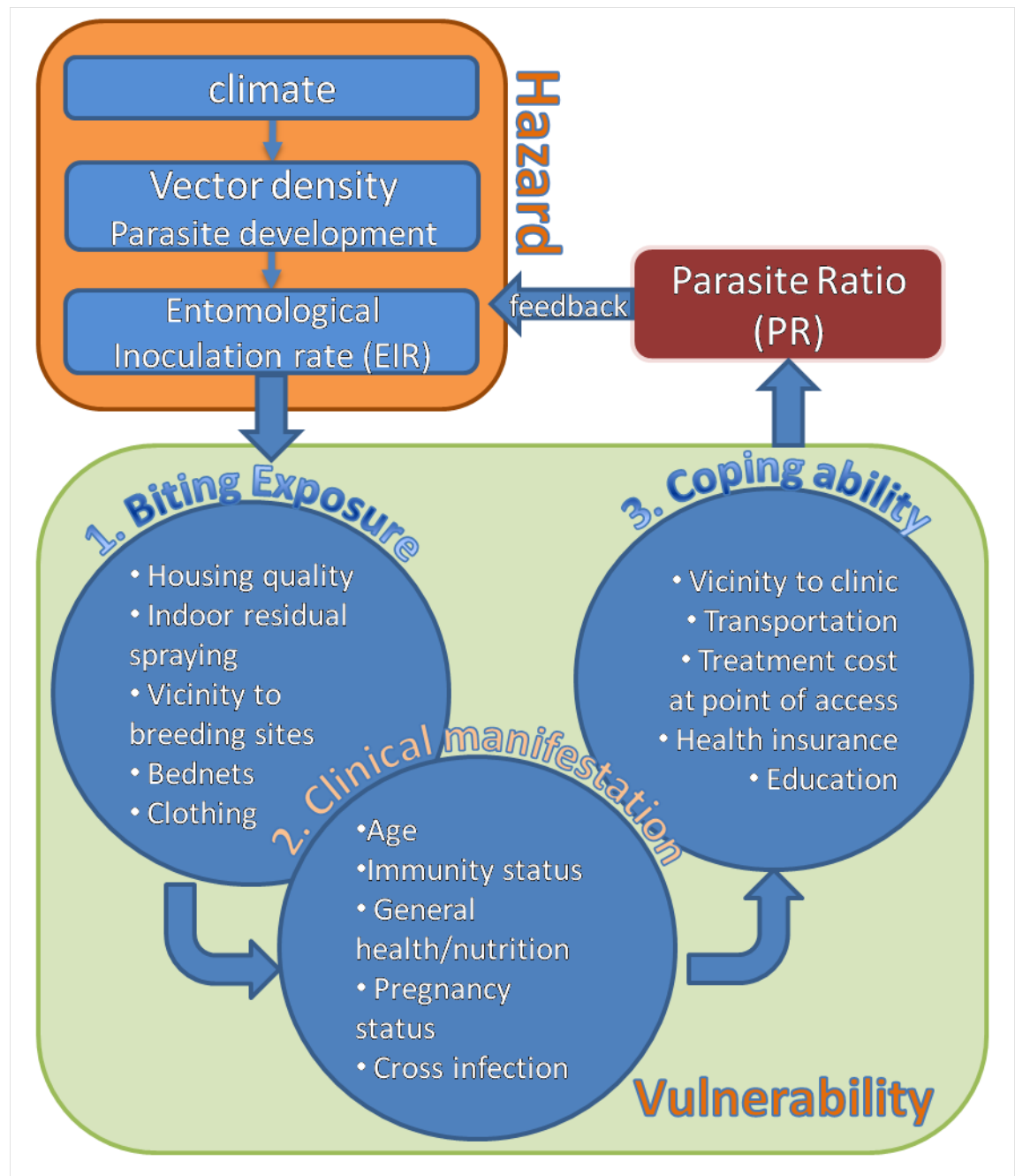


Jinja

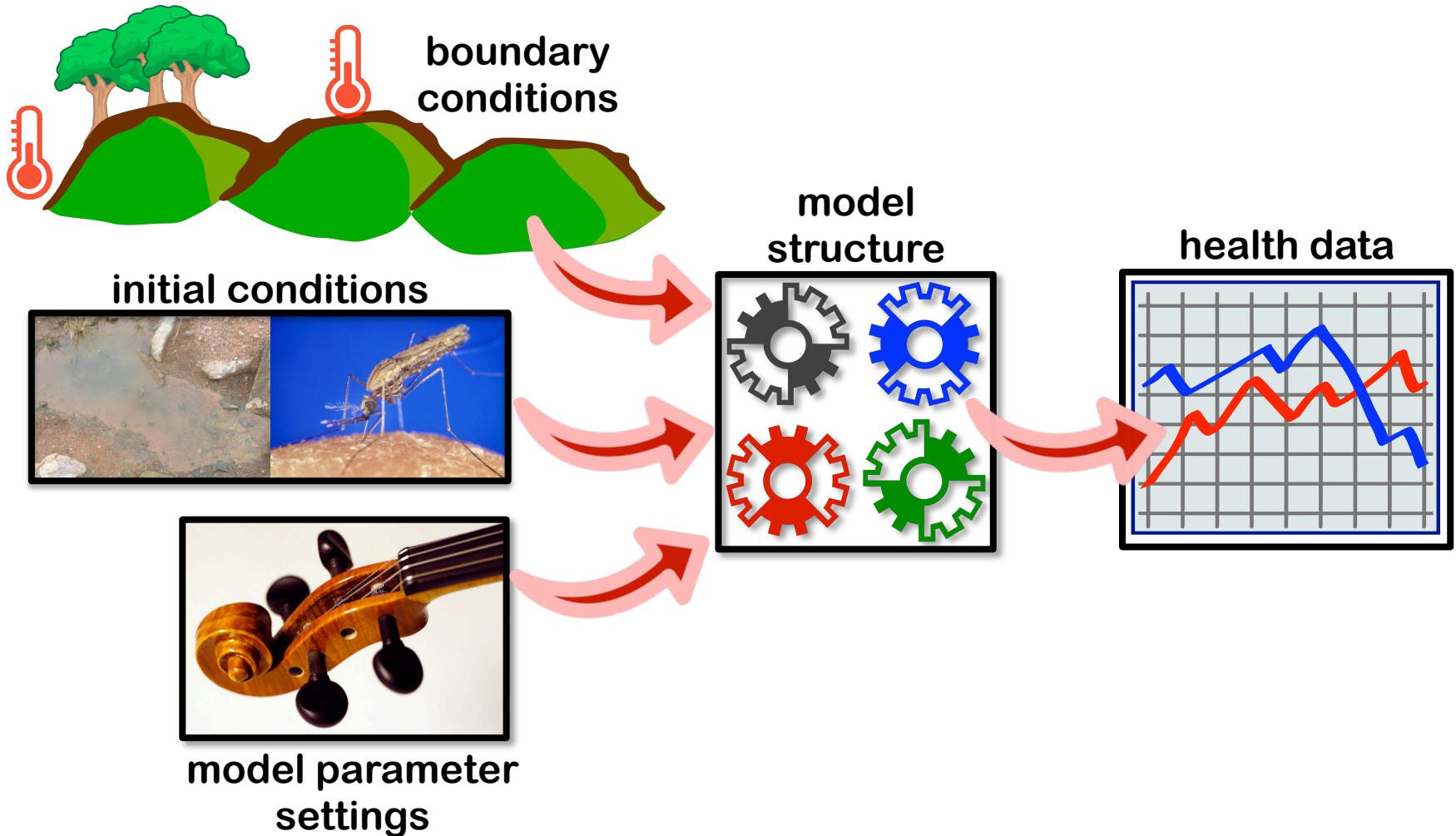


Vulnerability mapping for intervention planning

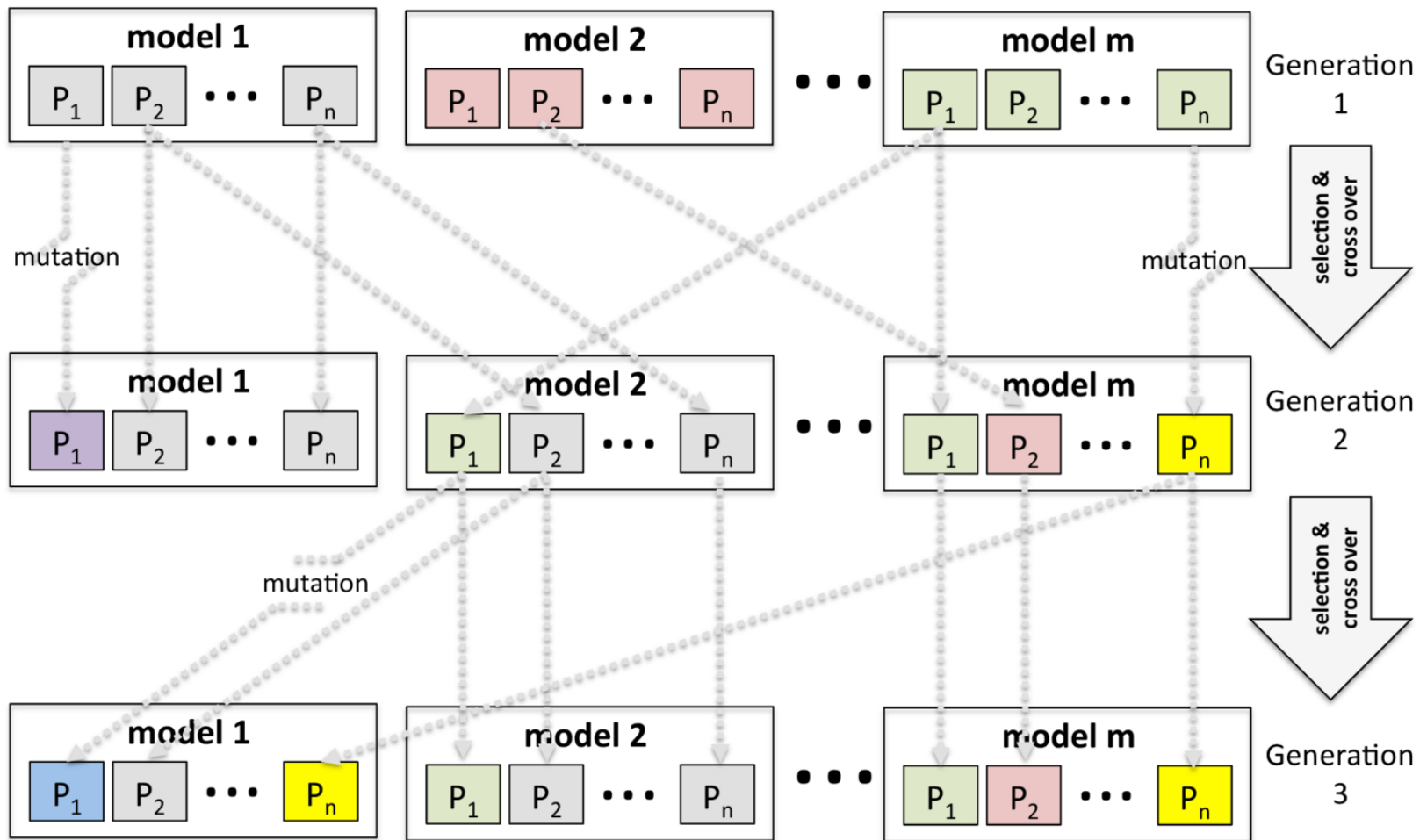
- ❑ Unlike many applications, system has strong feedback
- ❑ Vulnerability factors may need to be incorporated into modelling framework



Uncertainty in malaria simulations



Using a calibration technique to assess which is more important: climate or malaria model uncertainty



repeat until convergence criterion met

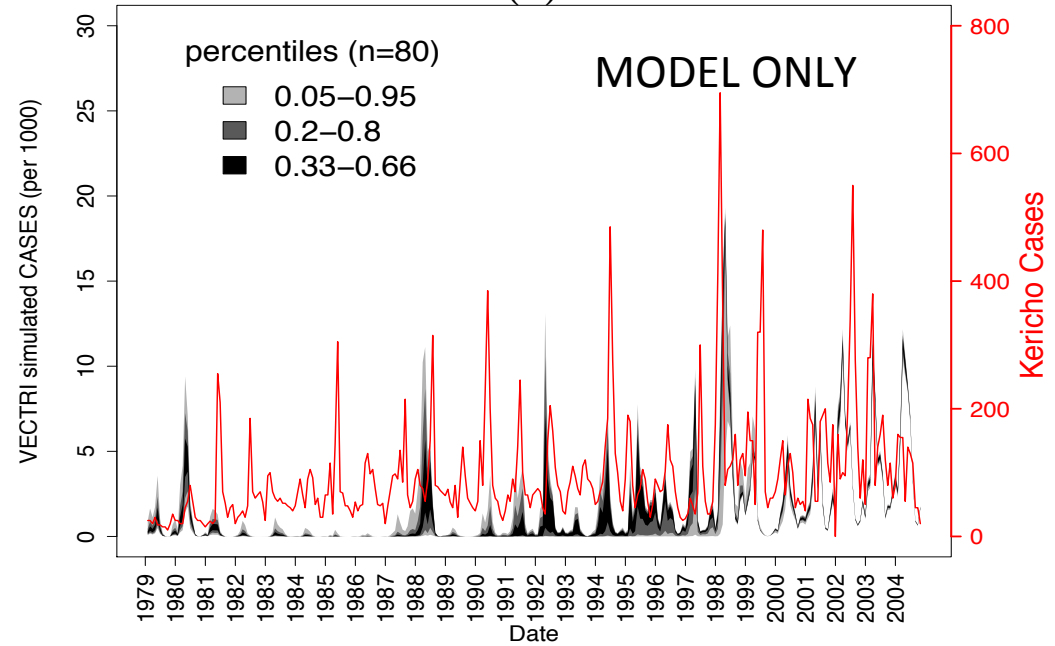
Method

- ❑ 80 ensemble members 1983-2004 integrations for Kericho plantation in Kenya highlands.
- ❑ 17 model parameters perturbed (Immunity, Hydrology, Temperature thresholds and gonotrophic/sporogonic degree day cycle lengths)
- ❑ 4 climate parameters perturbed
 - Water temperature
 - Air temperature offset and trend
 - Rainfall scale factor
- ❑ Mutation rate size and frequency decrease over time
- ❑ No mutation protection of superfit individuals
- ❑ "Constrained" GA, all parameters have a departure cost function that depends on the assessed uncertainty (re. 1D VAR)
- ❑ (NOTE: Ideal approach for ECMWF EPS tuning!)

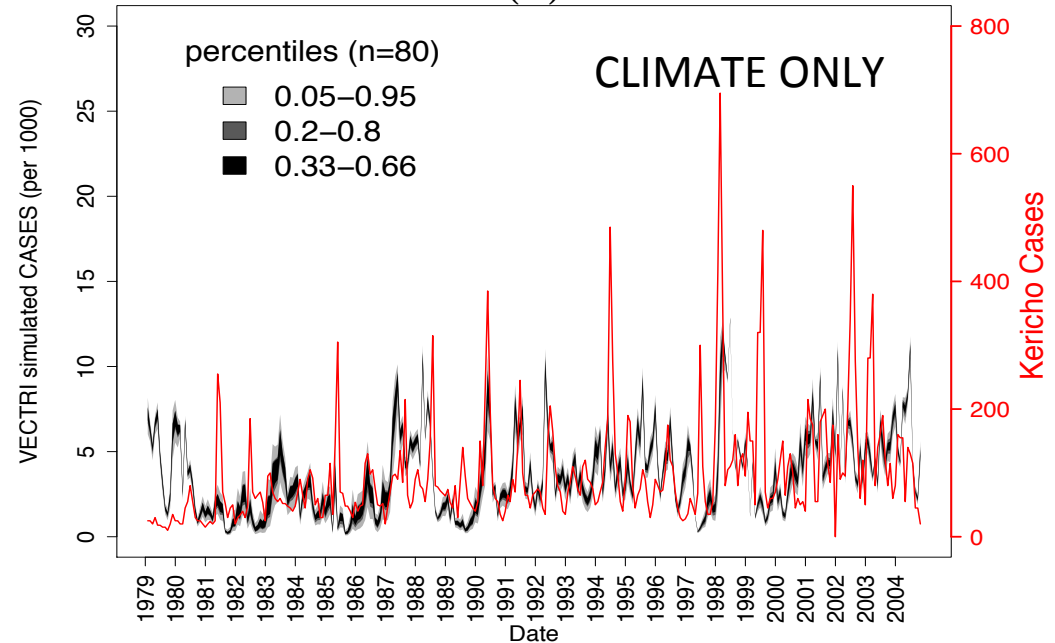
❑ Default model simulates NO transmission in this highland location in Kenya

❑ Despite the wide range of models parameters perturbed, adjusting the driving temperature data by $\sim 2\text{K}$ is adequate to produce "good" fit.

(a)

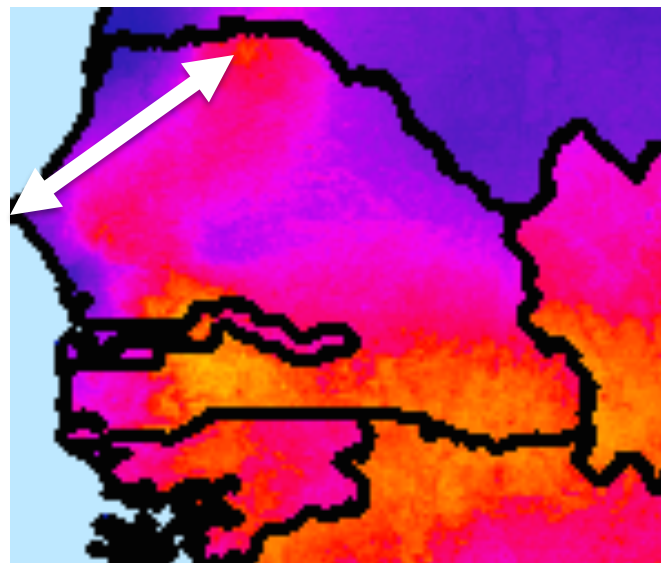


(b)

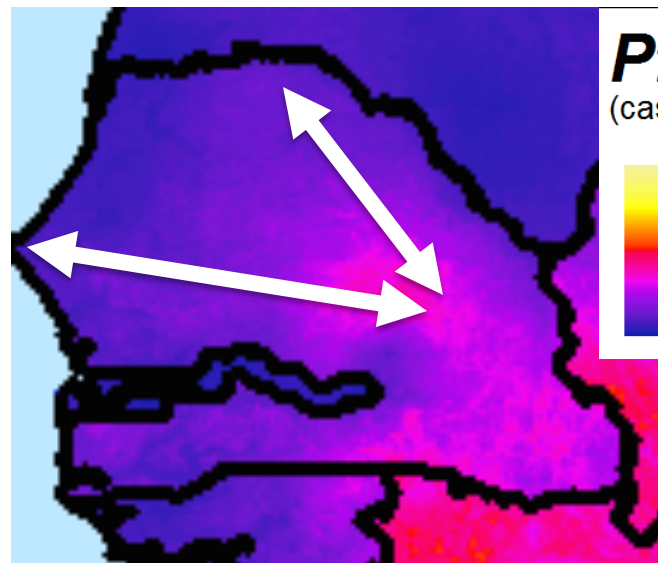


Movement of people?

- Cyclic Migration important if occurring in regions of high malaria prevalence gradients (e.g. N/S in Senegal)



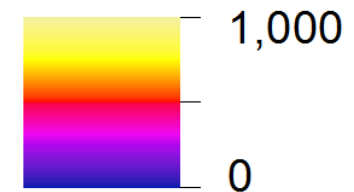
2000



2010

***Pf* Incidence Rate**

(cases per 1,000 people per annum)



MAP (Oxford)
Statistical model
incorporating
incidence data

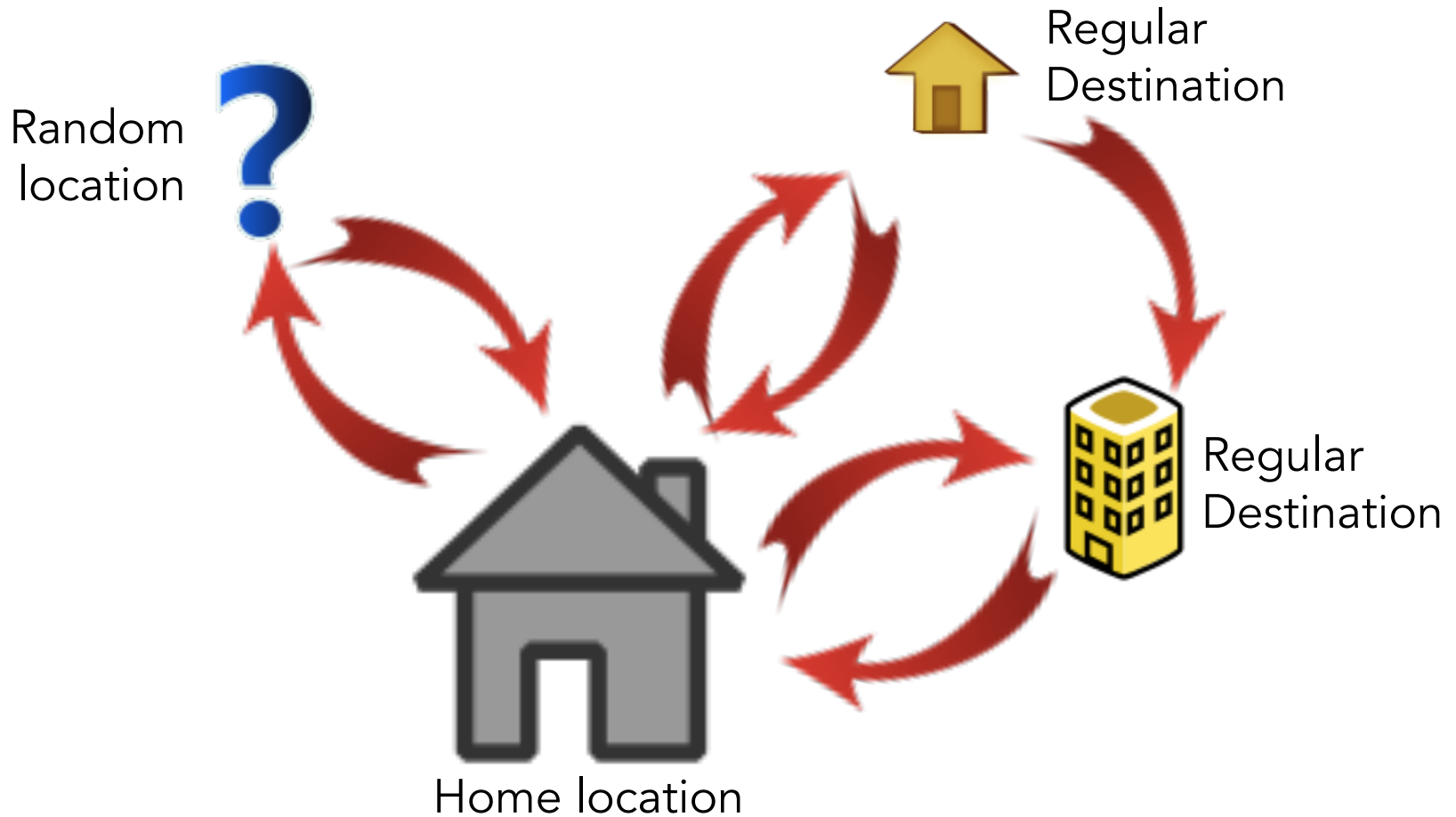
Analysis for Senegal

Tompkins and McCreesh GeoSpatial Health 2015

- ❑ Use of 2nd phase of the Data for development (D4D) challenge project (de Montjoye et al. 2014)
- ❑ We track 18384 anonymous people to coarse-scale arrondissement level for one year (data resolution is to address privacy concerns – ethical committee approved)
- ❑ The focus is on **journeys that result in overnight stays**, since evenings and night is when transmission predominantly occurs.



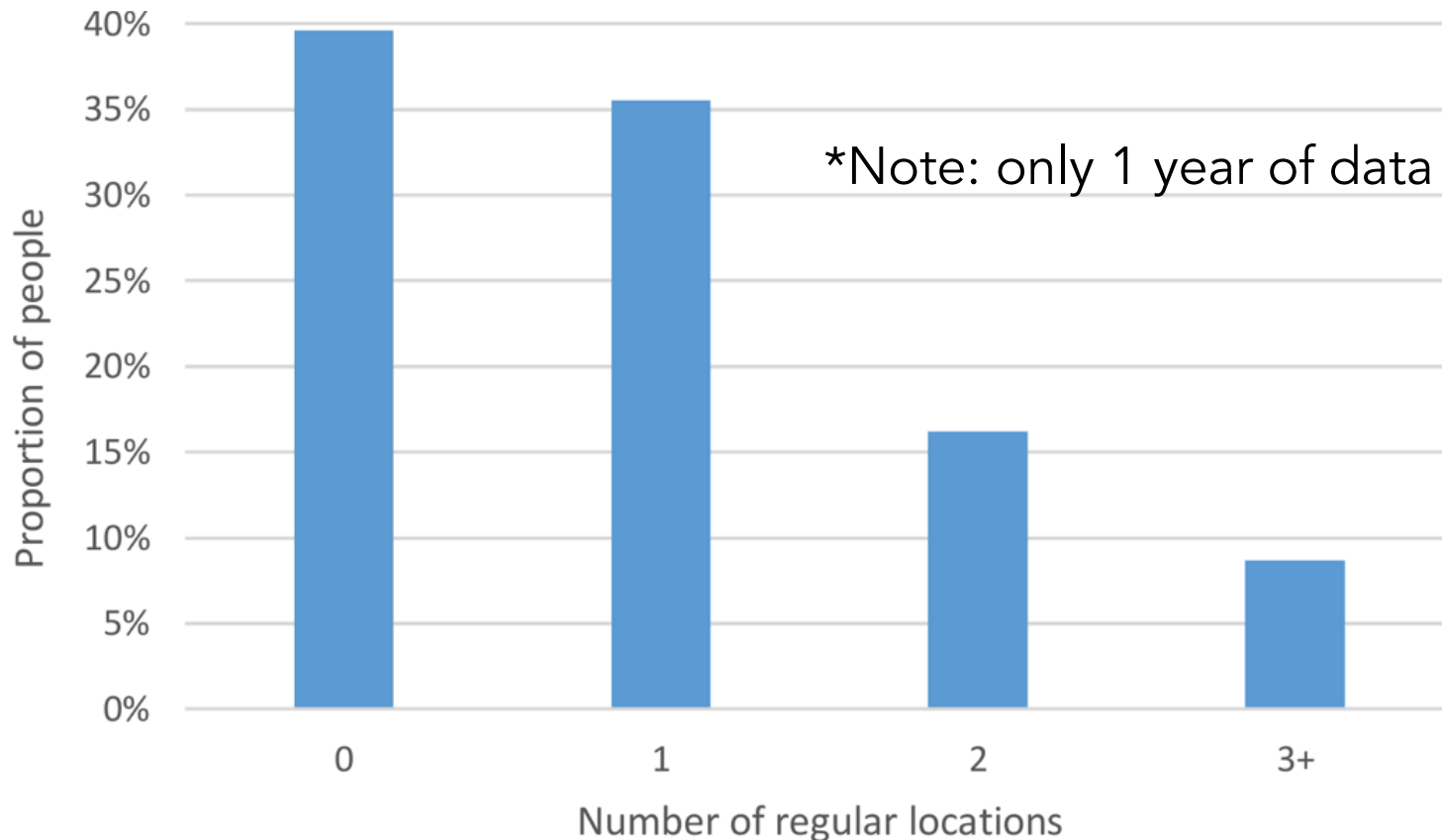
Migration analysis basis



Identify home location, regular destinations and probabilities of a journey

Number of regular destinations

- ❑ 60% of people regularly move to 1 or more regular destinations
- ❑ <10% have 3 or more regular destinations*



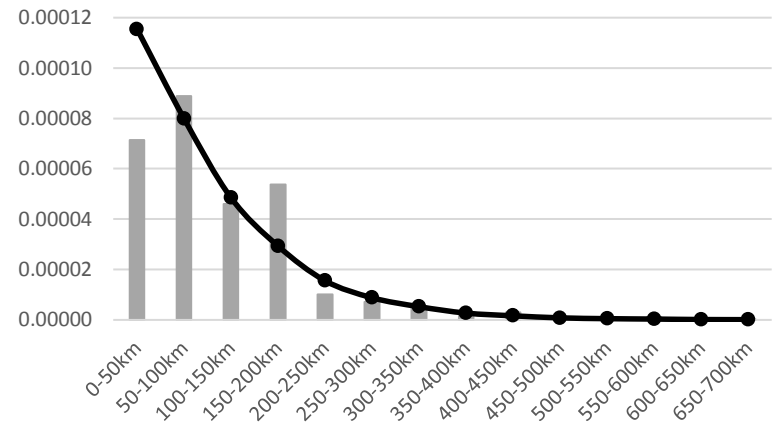
Probability of overnight stay as a function of distance

❑ Overnight stay probability peaks for a journey of 60 to 70 km.

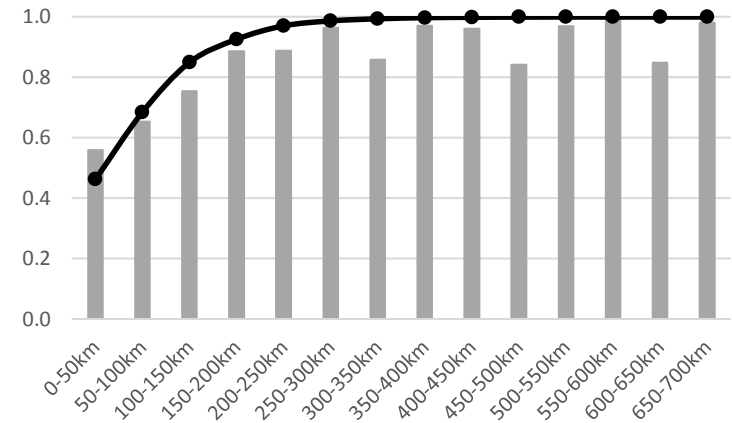
❑ Caveats:

- Distances are "crow-fly" distances (future use resistance maps)
- Analysis method excludes internal flights
- Distance functions do not account for population density

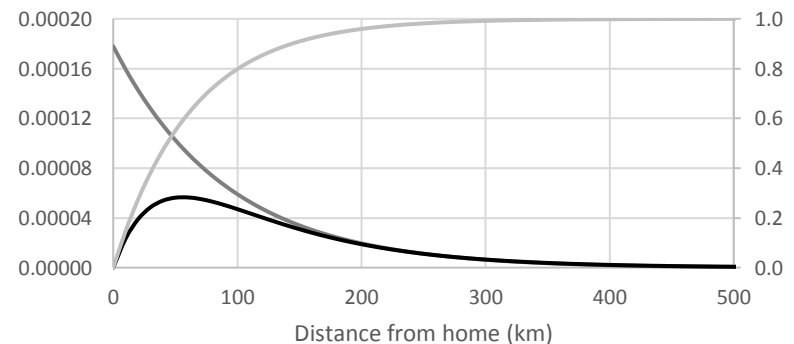
a) Probability of trip/day by distance



b) Probability that trip included night away, by distance

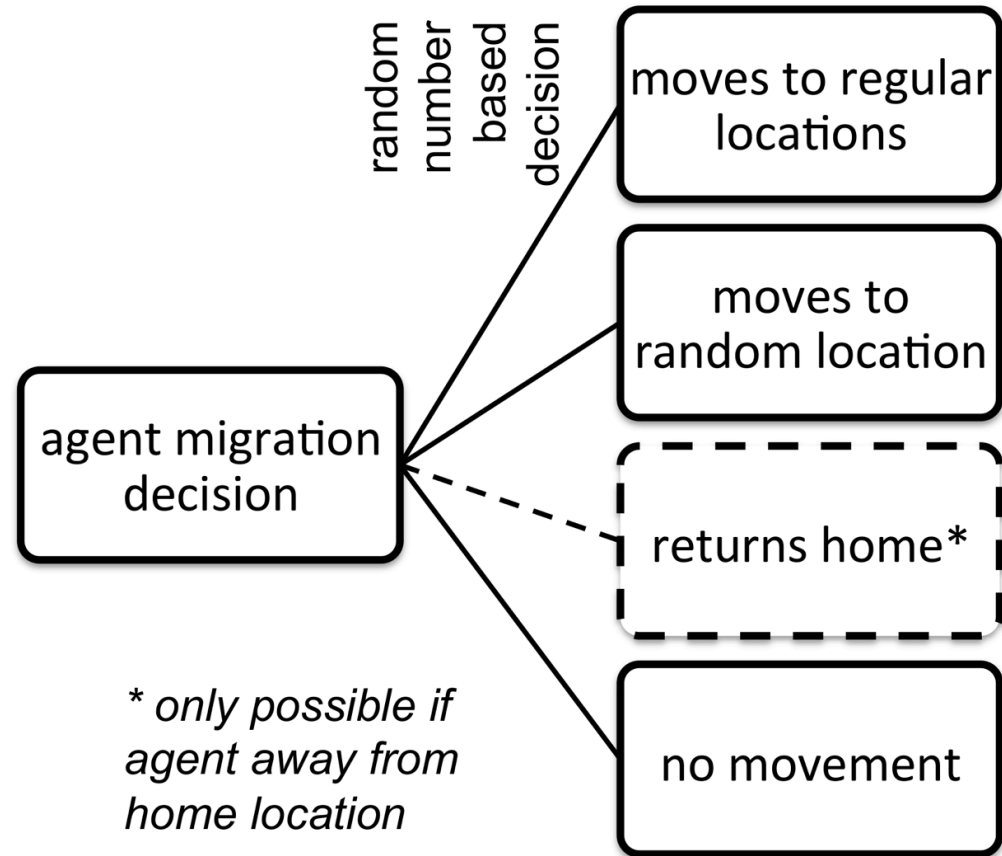


c) Fitted relationships

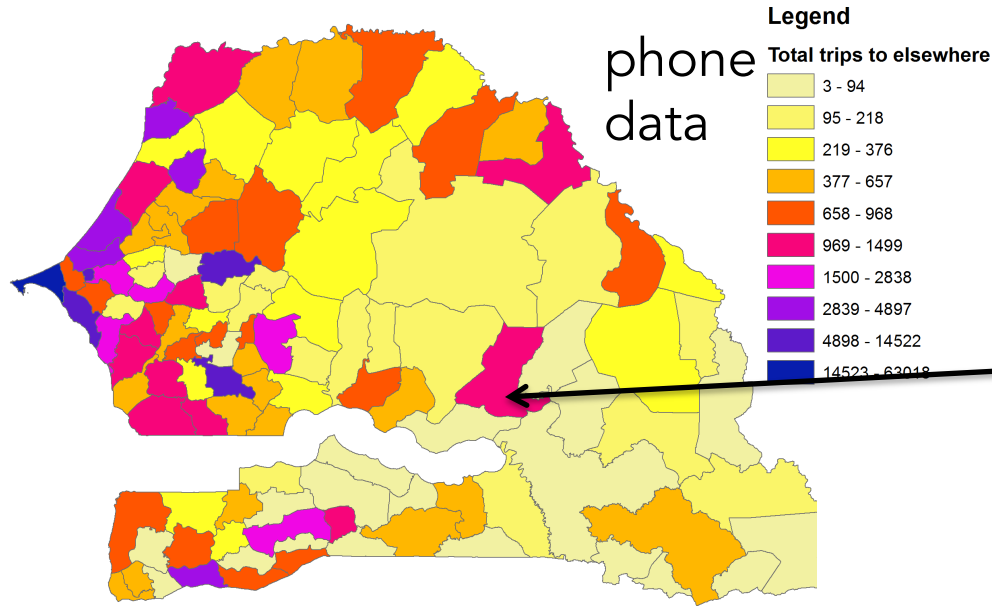


An agent-based migration model

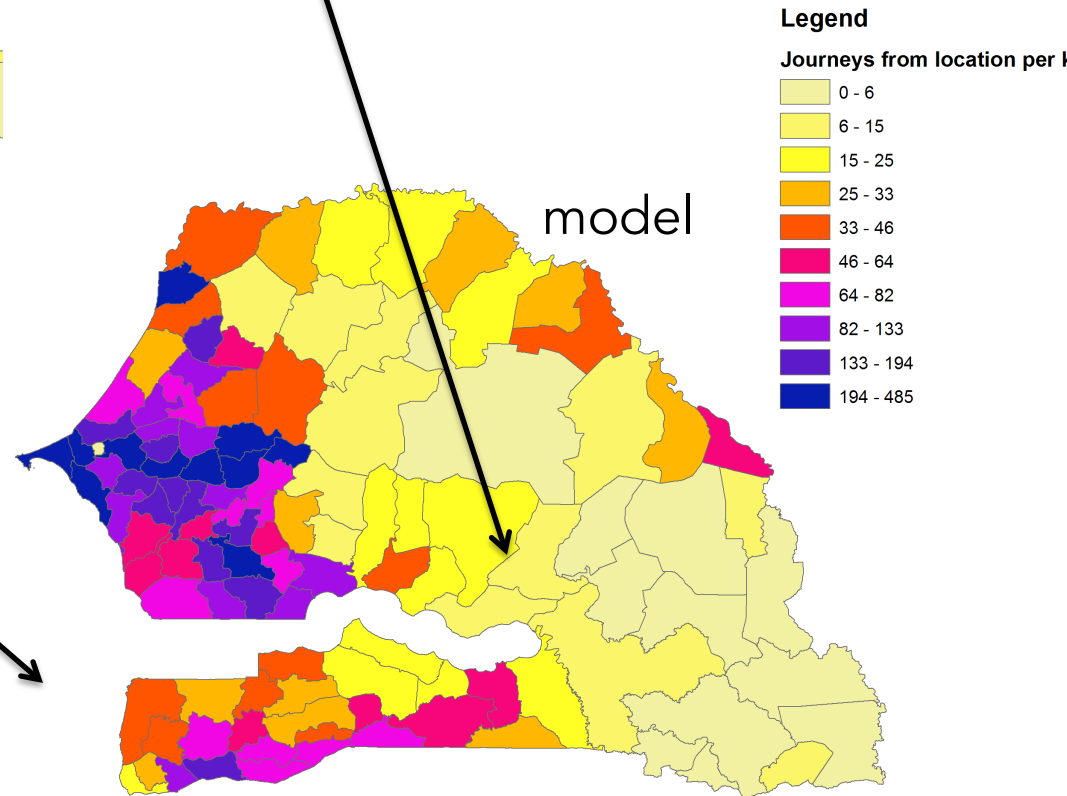
- ❑ 2.5 million agents distributed on regular 5km resolution grid, their "home" location
- ❑ Agent represent over 100 people in urban areas, less than half a person in rural areas
- ❑ Define set of "regular" destinations according to data-fitted gravity model
- ❑ Movements according to stochastic decisions (no economic model yet) based on gravity model
- ❑ Runs one year in 6 minutes on MAC laptop!



Quantile based comparison



Tambacounda
Need to sub-sample
distance probabilities as a
function of population
density



Movement to/from
Casamance overestimated –
need for resistance maps to
account for journey difficulty



Open Questions?

- How best to develop a usable system? -
What is the best format to provide information?
- How best to incorporate vulnerability assessments?
- Are four months adequate for key decision processes?
- Which process would streamline the integration of climate information into policy?
- How best to communicate uncertainty?