S2S applications: Monthly to seasonal forecasting of malaria in Africa

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UMSP: Uganda sentinel site data

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QWeCI and HEALTHY FUTURES

1. Overview of malaria
2. Modelling malaria
3. Predicting malaria

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

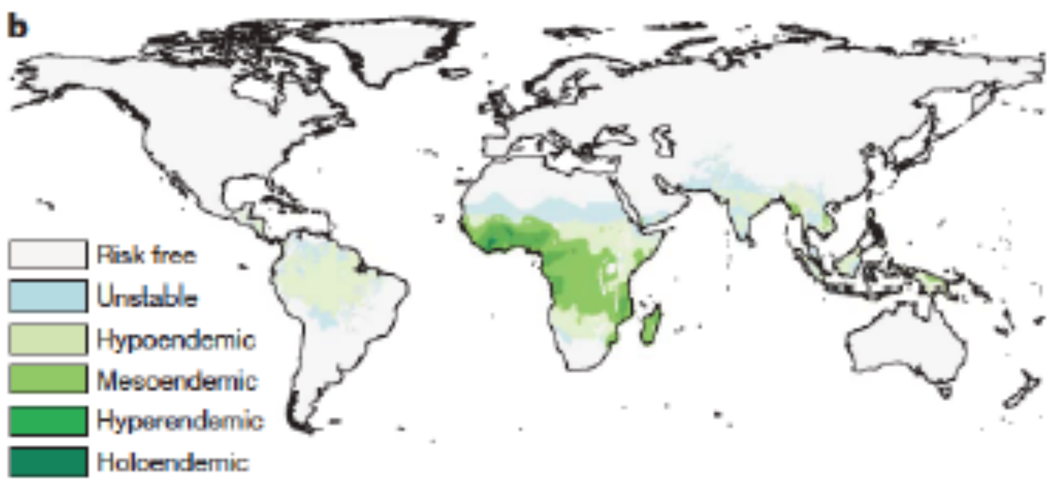
falciparum and vivax are the most widespread, their vector is the anopheles genus of mosquito (Fig. 1).

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.

Malaria endemicity definitions

Endemicity	PR	Definition
Holoendemic	0.75-1.0	all year round
Hyperendemic	0.5-0.75	all year with dry season pause
Mesoendemic	0.1-0.5	regular but seasonal transmission
hypoendemic	0-0.1	very intermittent transmission (Epidemics)



Malaria affects > 100 countries world-wide but 98% of the fatalities occur in 35 countries, 30 of which are in Africa

- 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.

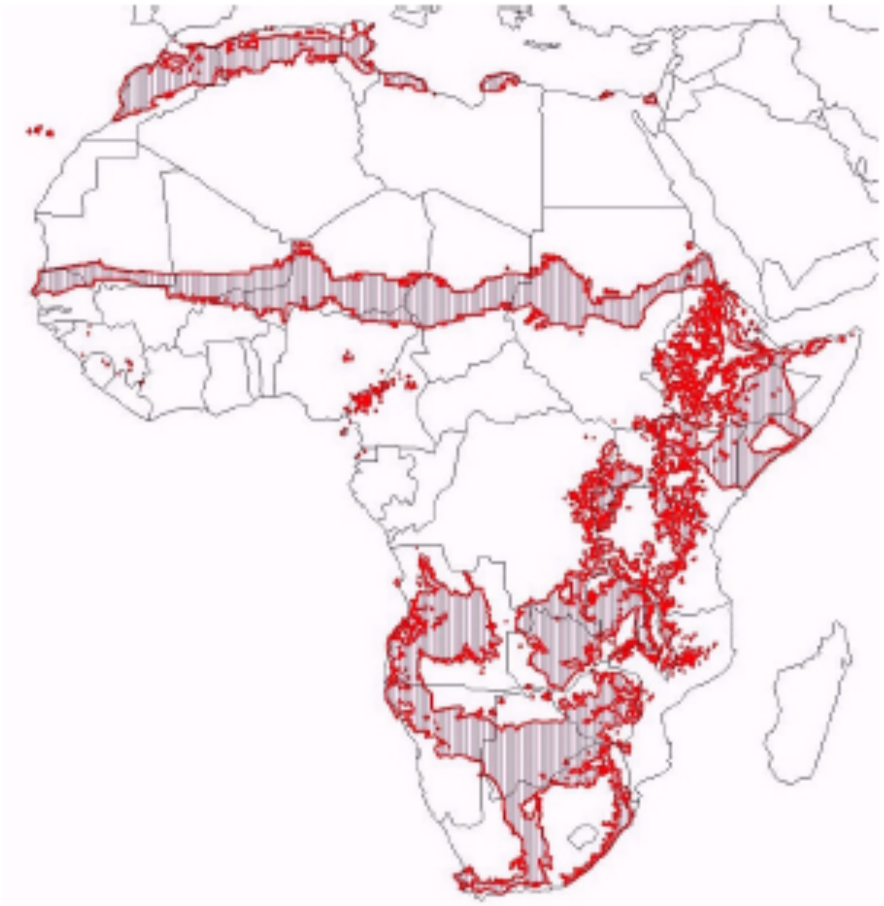
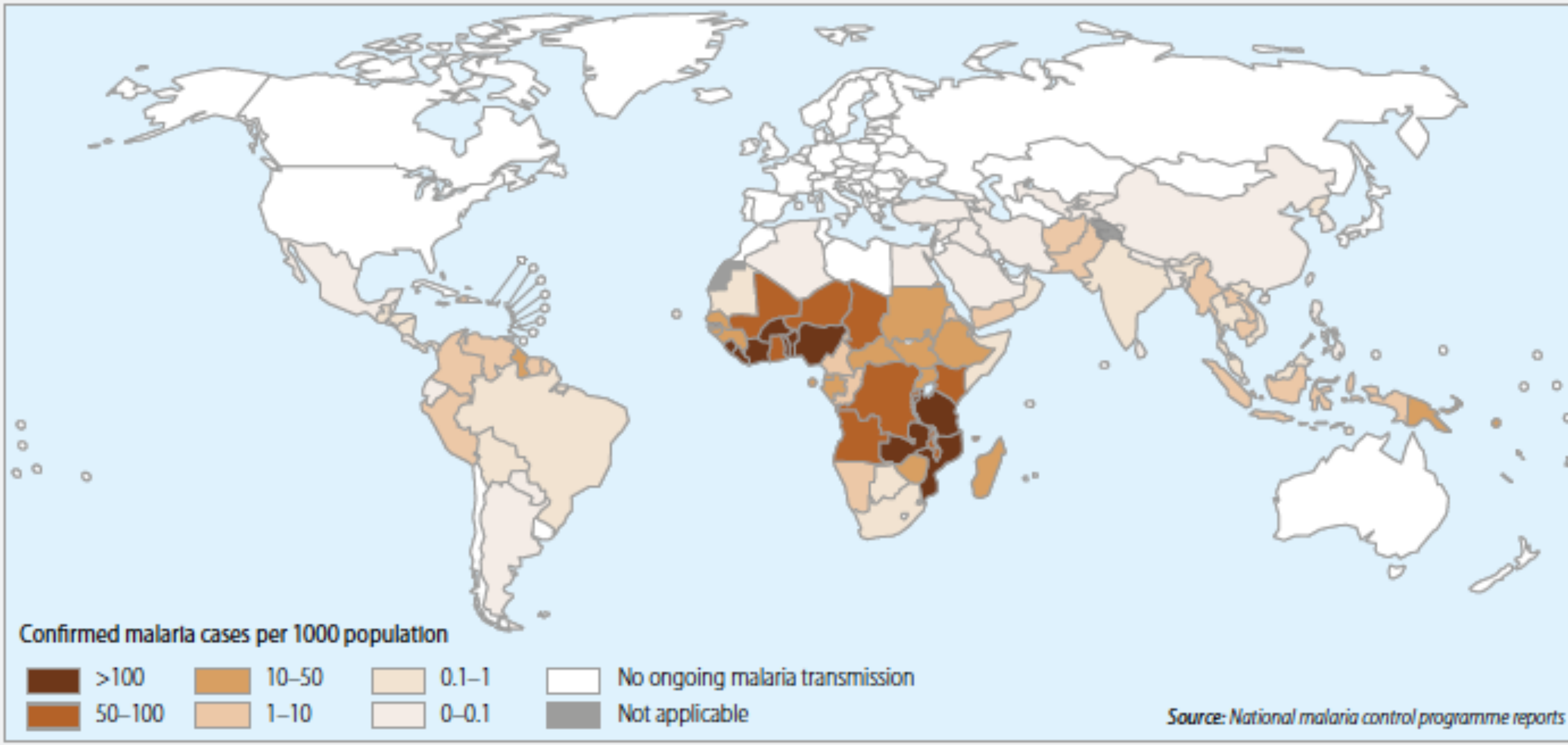


Figure: Malaria epidemic zones - from ?

World Malaria Report 2014

Figure 1.1 Countries with ongoing transmission of malaria, 2013



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$, targetted spending 5.1 US$

EIR

Generally the division between epidemic and endemic regions is governed by the force of infection.

entomological inoculation rate

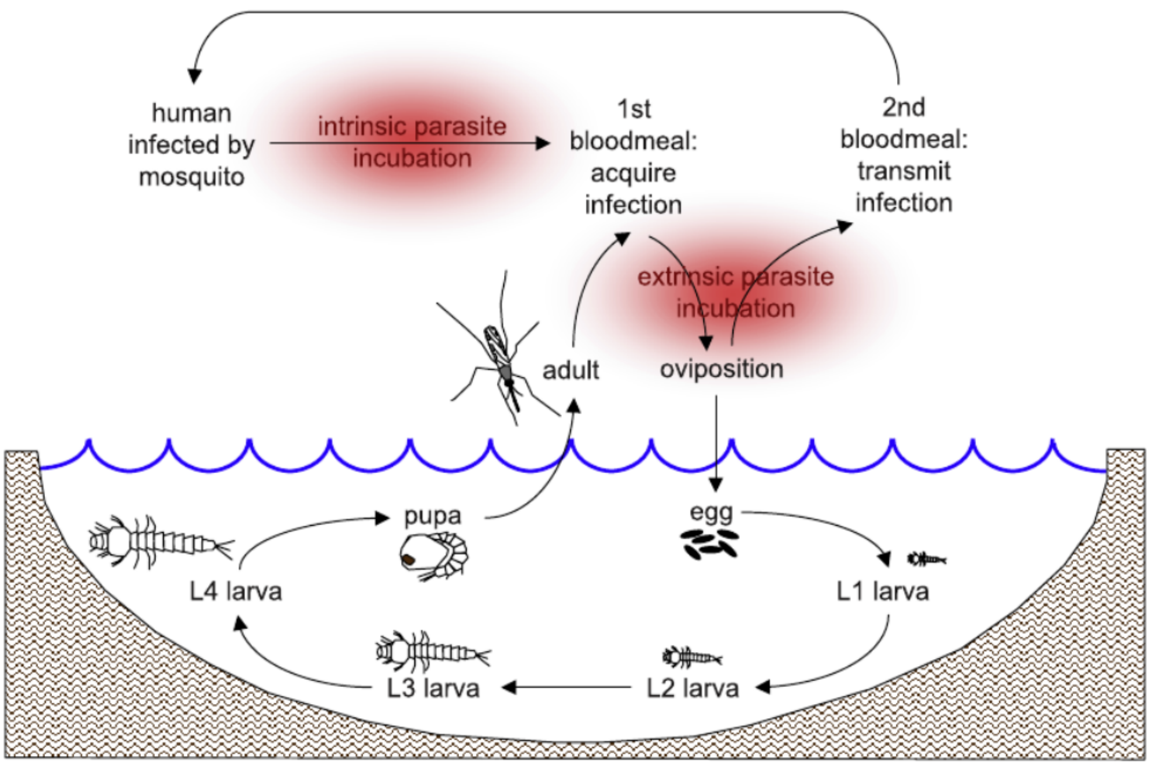
A good measure of the force of infection is the entomological inoculation rate (EIR) which is the number of infected bites per person per unit time.

An EIR of around 10 infected bites per year marks the division between epidemic and endemic areas.

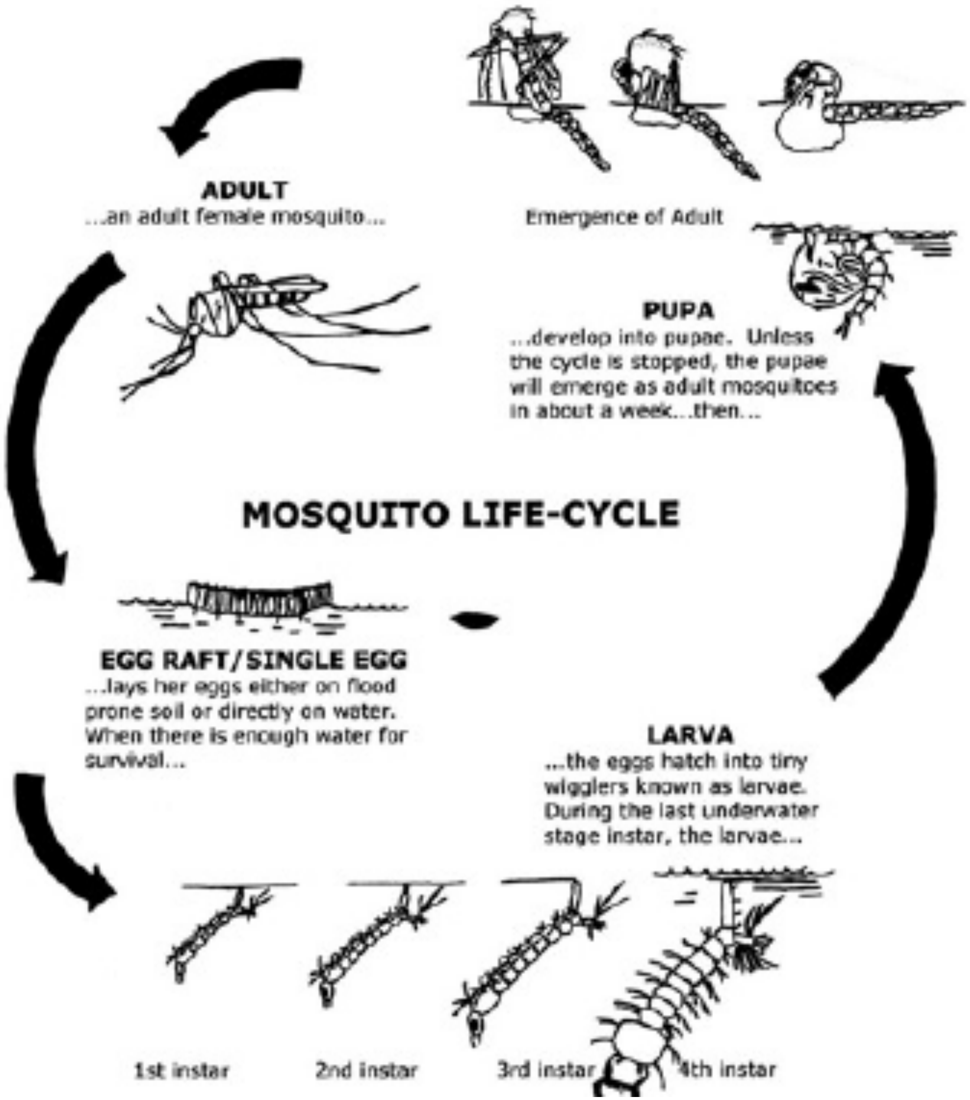
Climate drivers of malaria

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.



What came first: the mosquito or the egg?



As temperature increases

- Larvae development speeds up in warmer ponds
- Gonotrophic cycle: Eggs development in vector speeds up (Degree days concept)
- But high temperatures $> 39C$ kill vector
- And high water temperature $> 35C$ kill larvae

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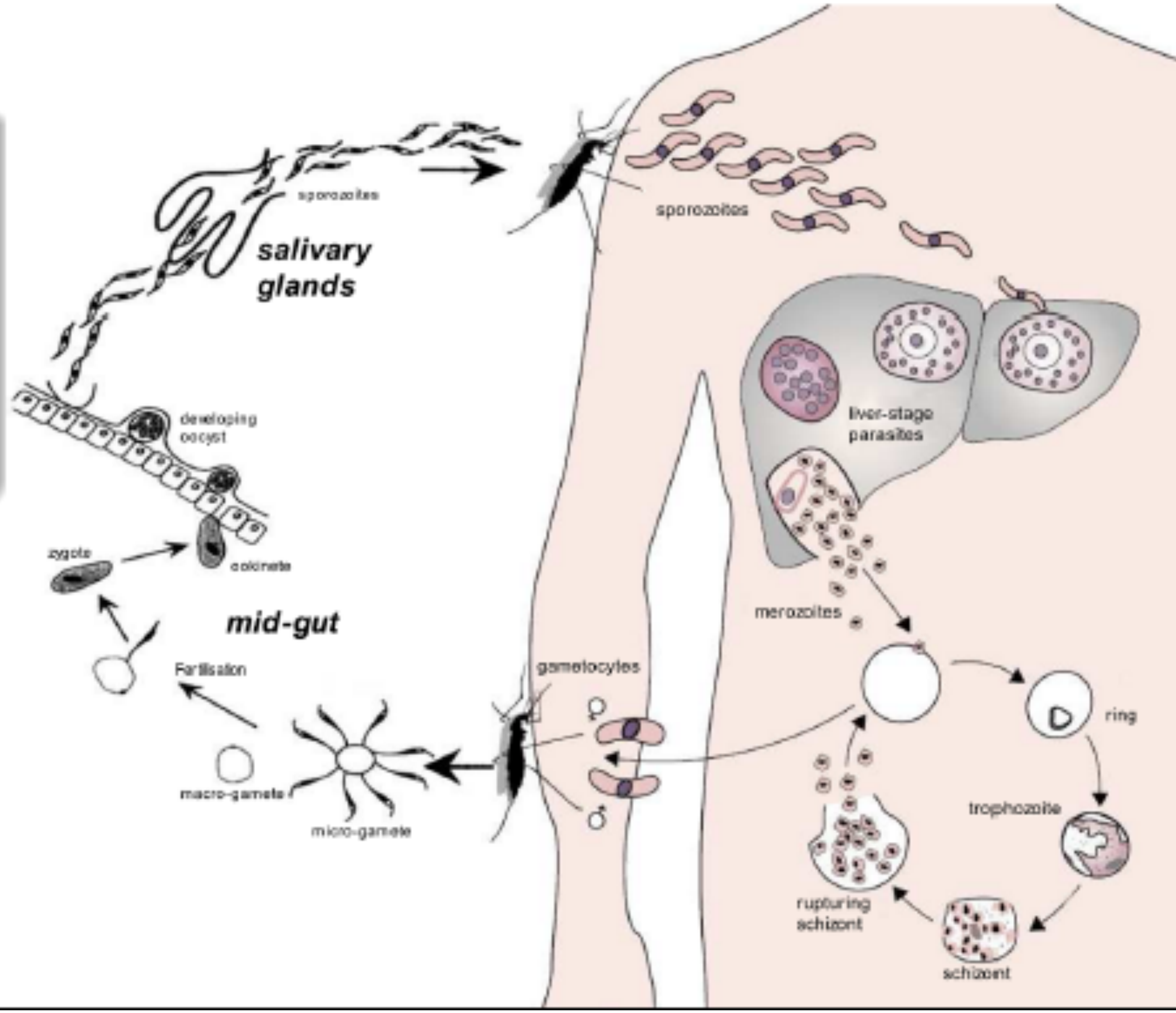
Cycle in host takes 10-26 days

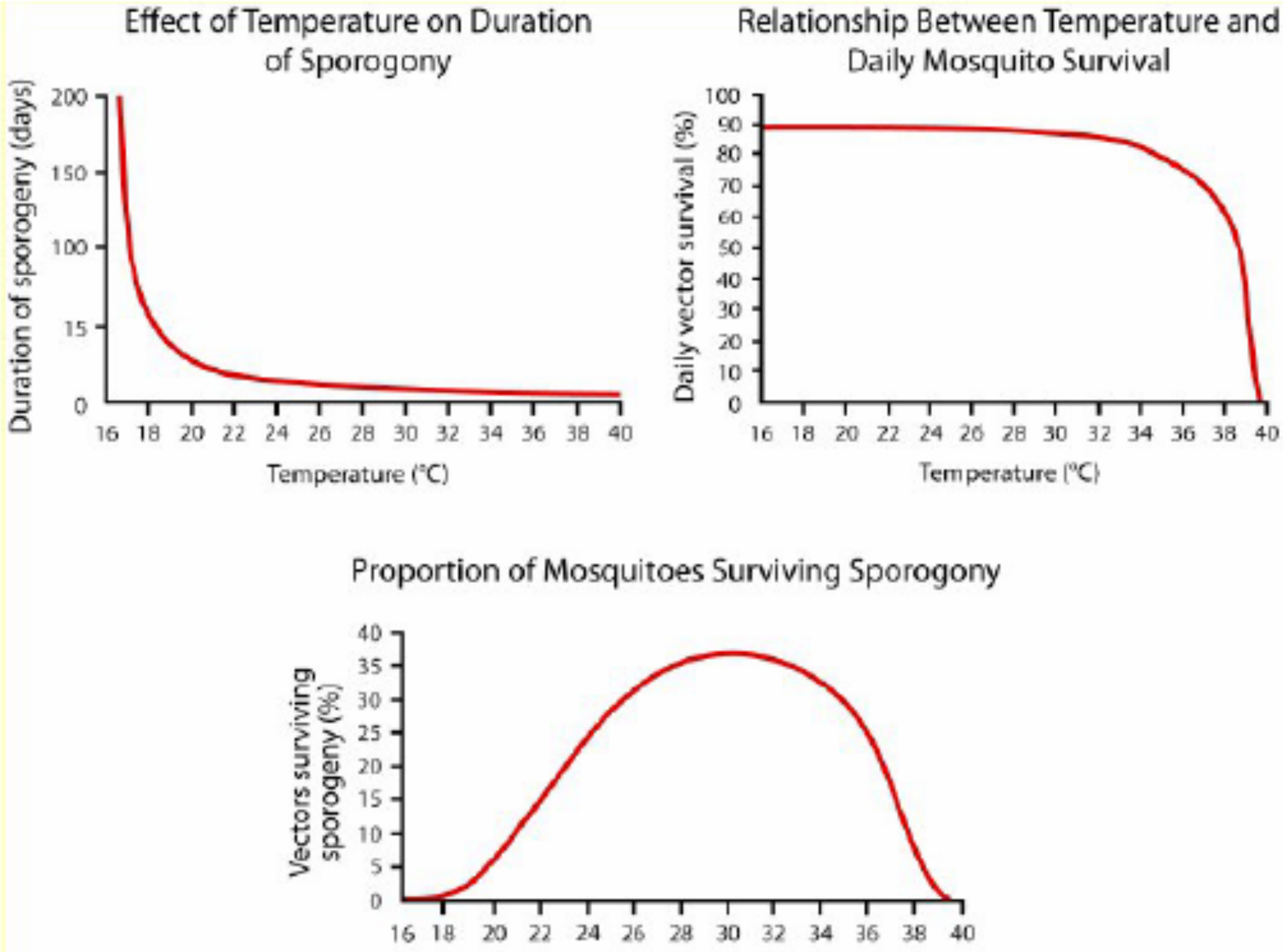
Sporogonic cycle

Cycle in vector is temperature dependent (threshold 16-18C, 111 degree days)

Not all bites on infective host or by infected vector lead to transmission (probability estimated at 20-30%)



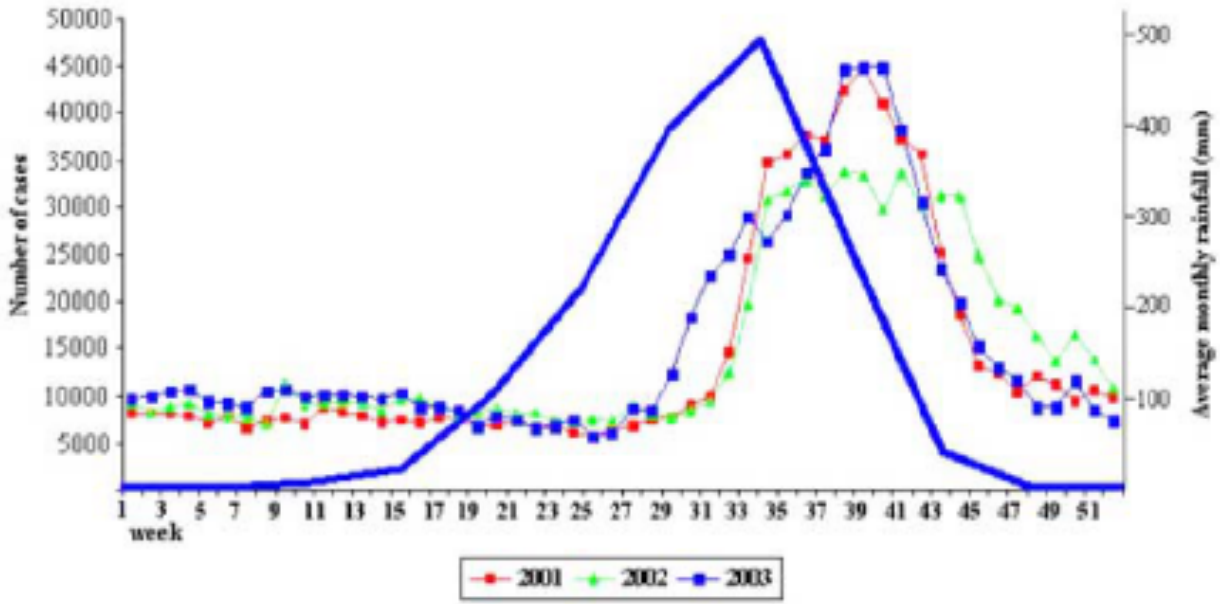
Sporogonic cycle



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)



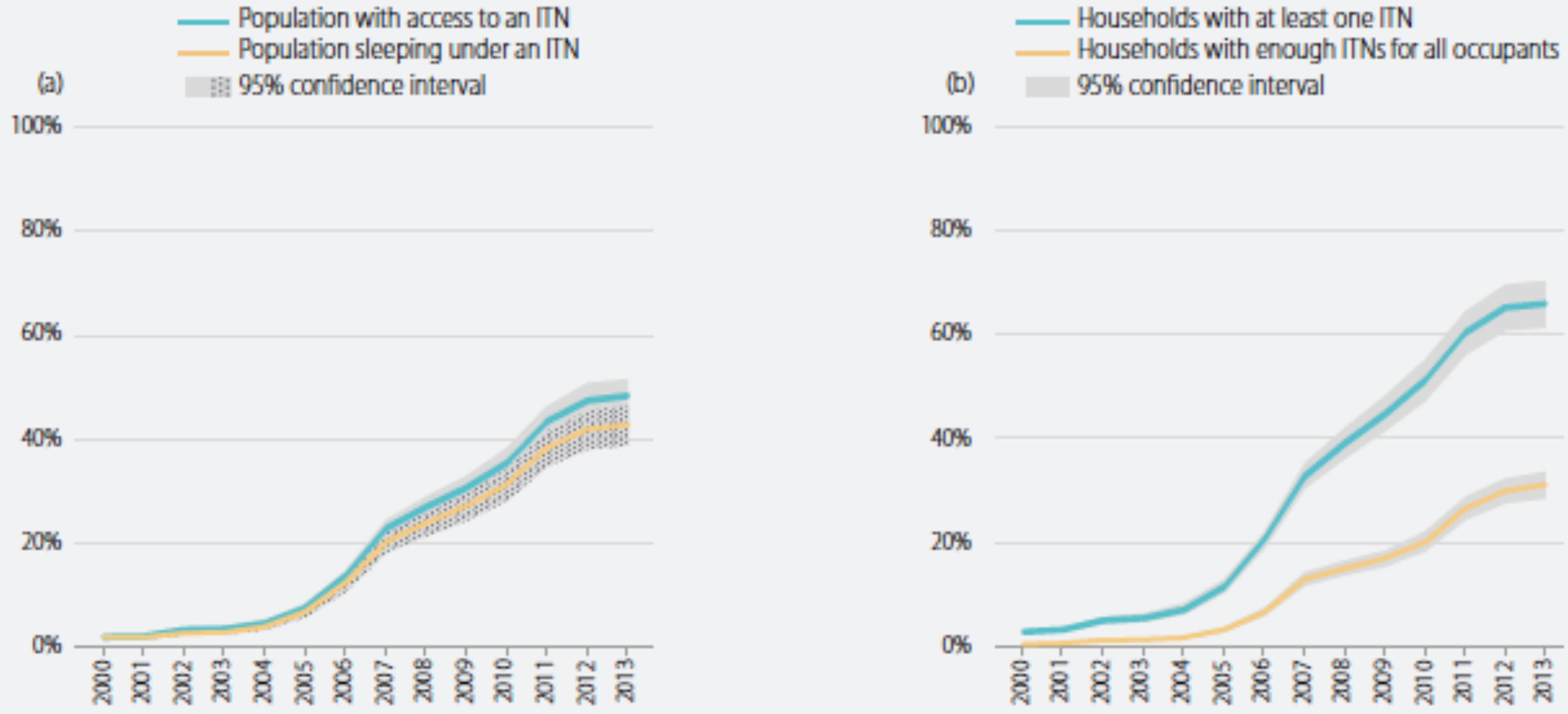
Blue - Rainfall
Dots - Malaria cases in 3 seasons

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

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

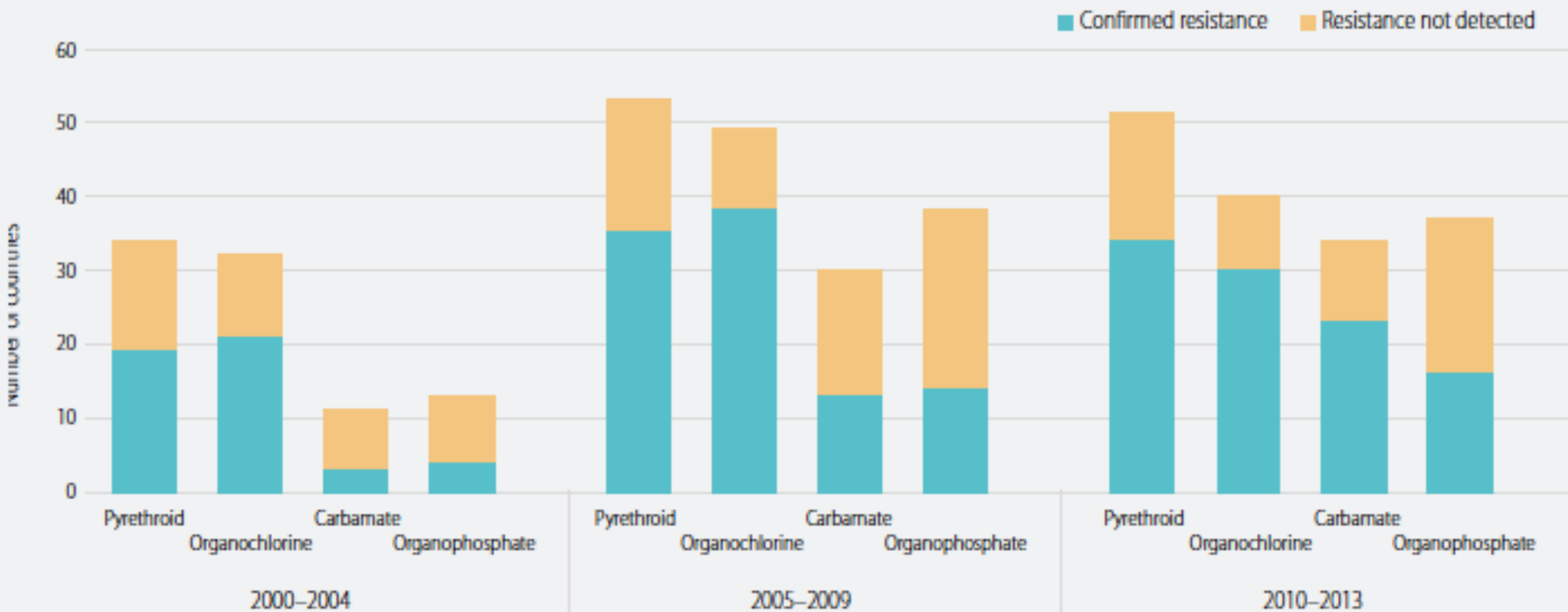


ITN, insecticide-treated mosquito net

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

Issue of insecticide resistence

Figure 3.9 Number of countries reporting insecticide resistance monitoring results, by insecticide class and years of monitoring activity



Source: *National malaria control programme reports, African Network for Vector Resistance, Malaria Atlas Project, President's Malaria Initiative, published literature*

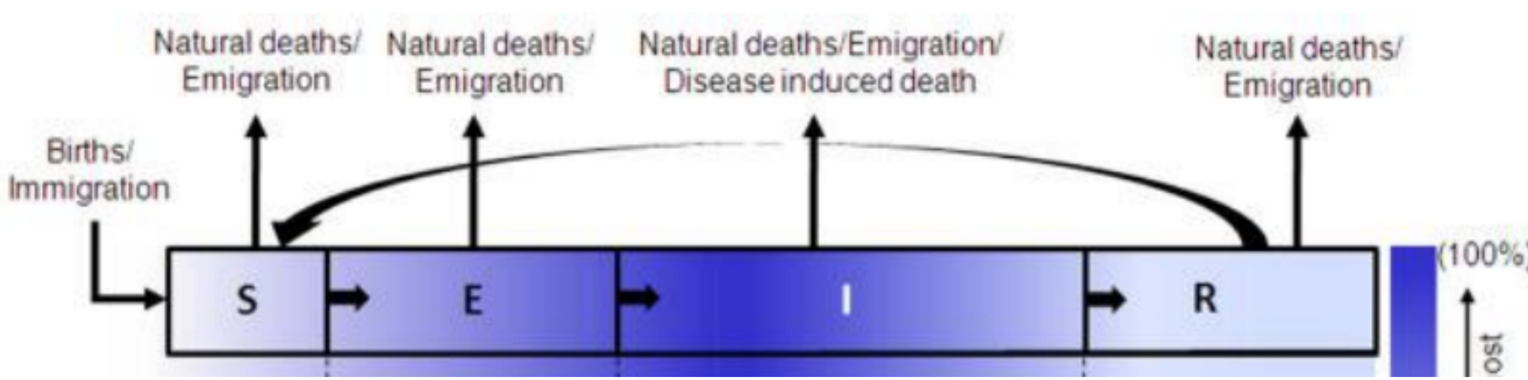
2. Modelling malaria: Some existing models for malaria that account for climate:

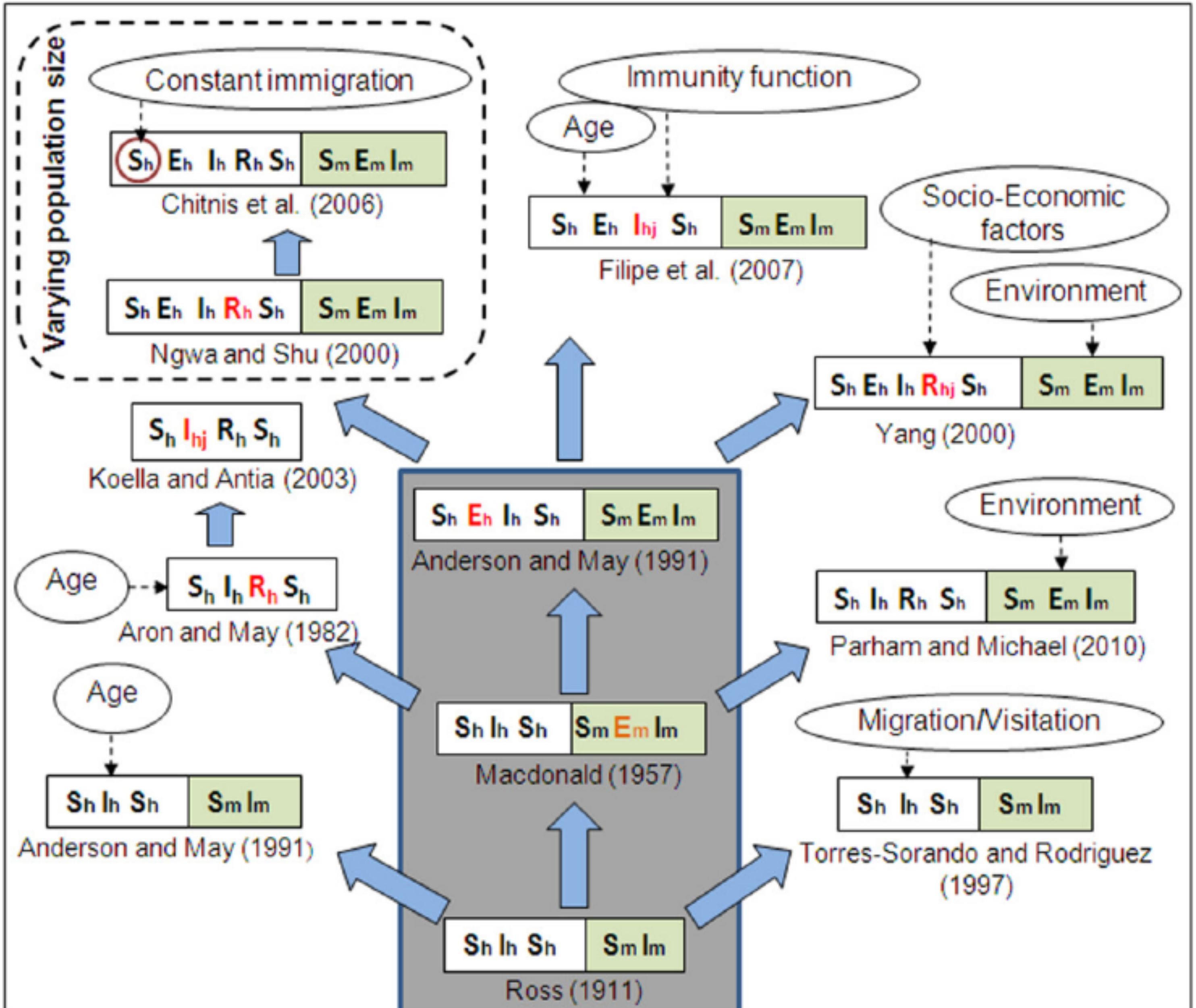
- MAP : Spatial Baysian statistical model that uses climate information as a predictor
- LMM: Spatial model driven by climate, vector density linked to rainfall and temperature impacts vector/ parasite lifecycles. Does not account for population density
- Dynamical SEIR approach that minimizes parameter settings to fit to health data for given location and incorporate rainfall and/or temperature
- planned: OPENMALARIA, in depth model of malaria interventions, runs at a single location and requires EIR measurement to set emergence rate

SEIR approach

Epidemiological compartment models focus on the disease transmission and progression in human populations, dividing human status into some or all of the following categories

S	fraction of host population that is **S**usceptible to infection
E	**Exposed** fraction of population individuals infected by pathogen, but not capable of passing it on to others during latent period
I	fraction of **I**nfectious individuals, who are capable of passing on transmission to others
R	**R**ecovered fraction that have acquired temporary or permanent immunity





Varying population size
Constant immigration
Sh Eh Ih Rh Sh Sm Em Im
Chitnis et al. (2006)
Sh Eh Ih Rh Sh Sm Em Im
Ngwa and Shu (2000)
Immunity function
Age
Sh Eh Ihj Sh Sm Em Im
Filipe et al. (2007)
Socio-Economic factors
Environment
Sh Eh Ih Rhj Sh Sm Em Im
Yang (2000)
Sh Ihj Rh Sh
Koella and Antia (2003)
Age
Sh Ih Rh Sh
Aron and May (1982)
Sh Eh Ih Sh Sm Em Im
Anderson and May (1991)
Environment
Sh Ih Rh Sh Sm Em Im
Parham and Michael (2010)
Sh Ih Sh Sm Em Im
Macdonald (1957)
Age
Sh Ih Sh Sm Im
Anderson and May (1991)
Migration/Visitation
Sh Ih Sh Sm Im
Torres-Sorando and Rodriguez (1997)
Sh Ih Sh Sm Im
Ross (1911)

VECTRI model

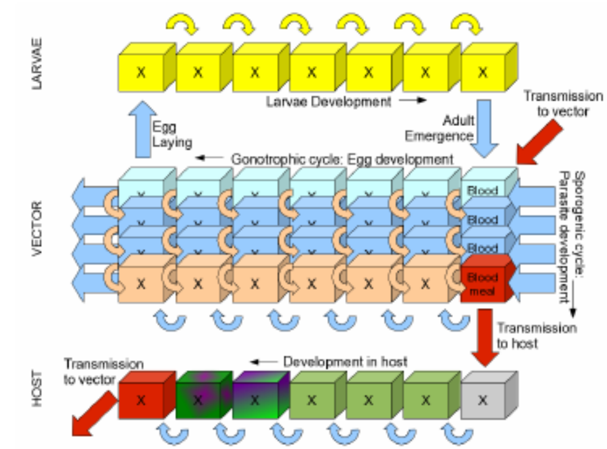
- Aim to build a spatial model for the climate impact on malaria transmission
  - Simple representation of surface hydrology
  - Explicit modelling of temperature impact on parasite/vector life cycles
  - Accounting for human population density
  - regional/continental scale with resolutions down to about 5km.
- Presently no/limited tuning of parameters for a location (postprocessing calibration?)

VECTRI key elements

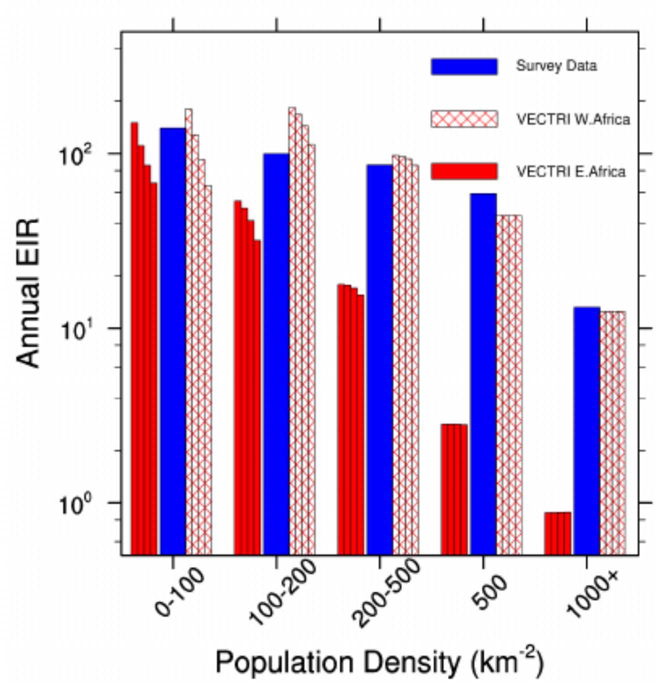
VECTRI

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

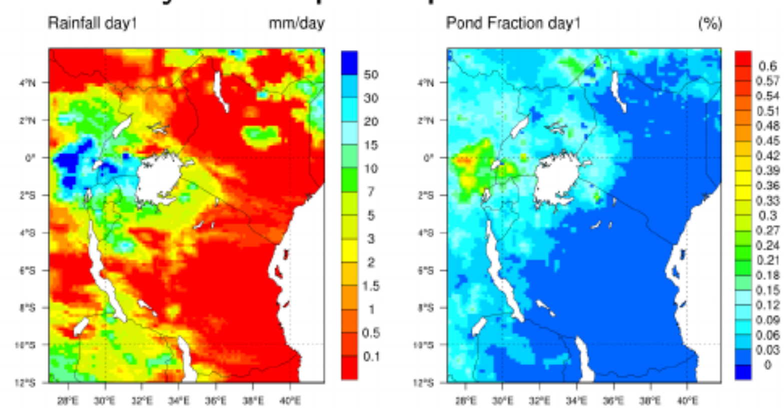
1. Bin-resolved parasite/vector lifecycles influenced by climate:



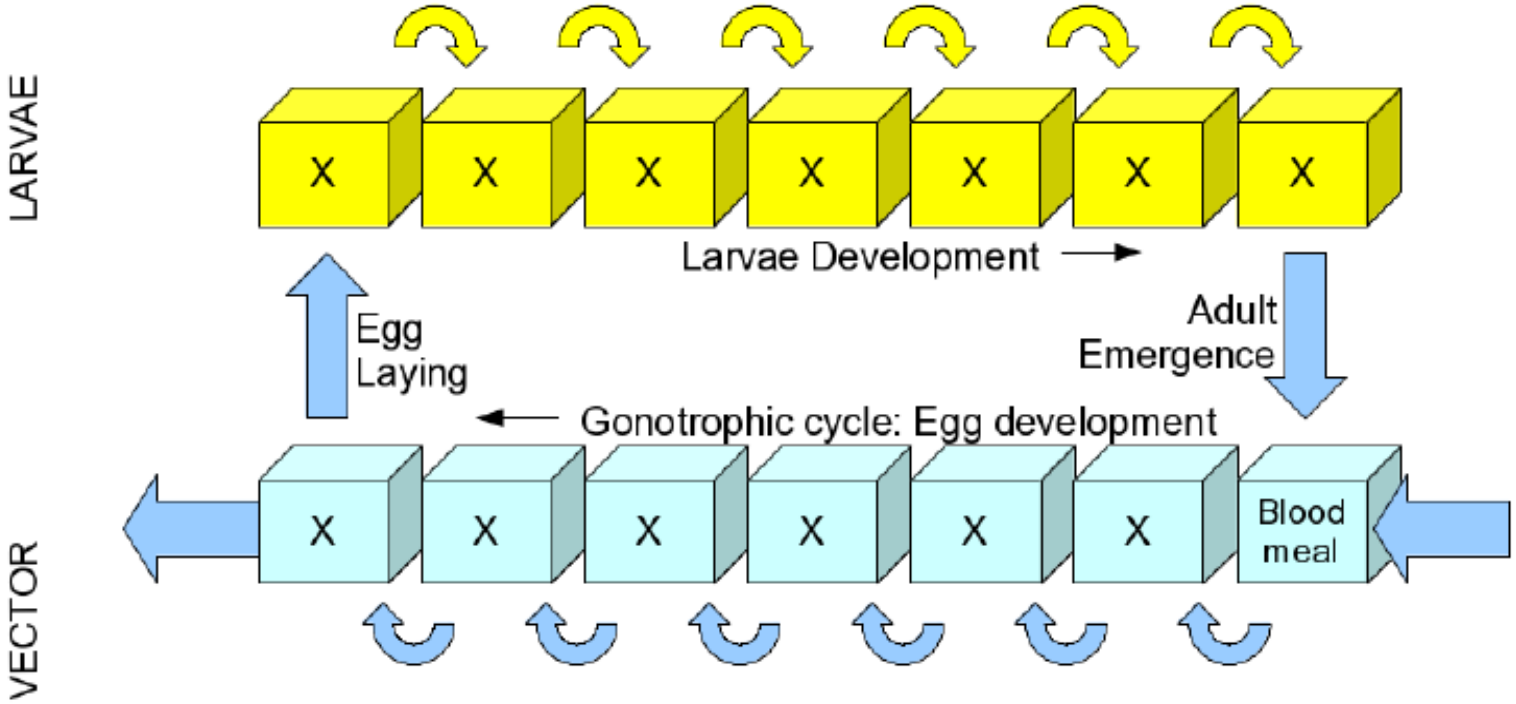
2. Accounts for population density



3. Dynamic pond parametrization

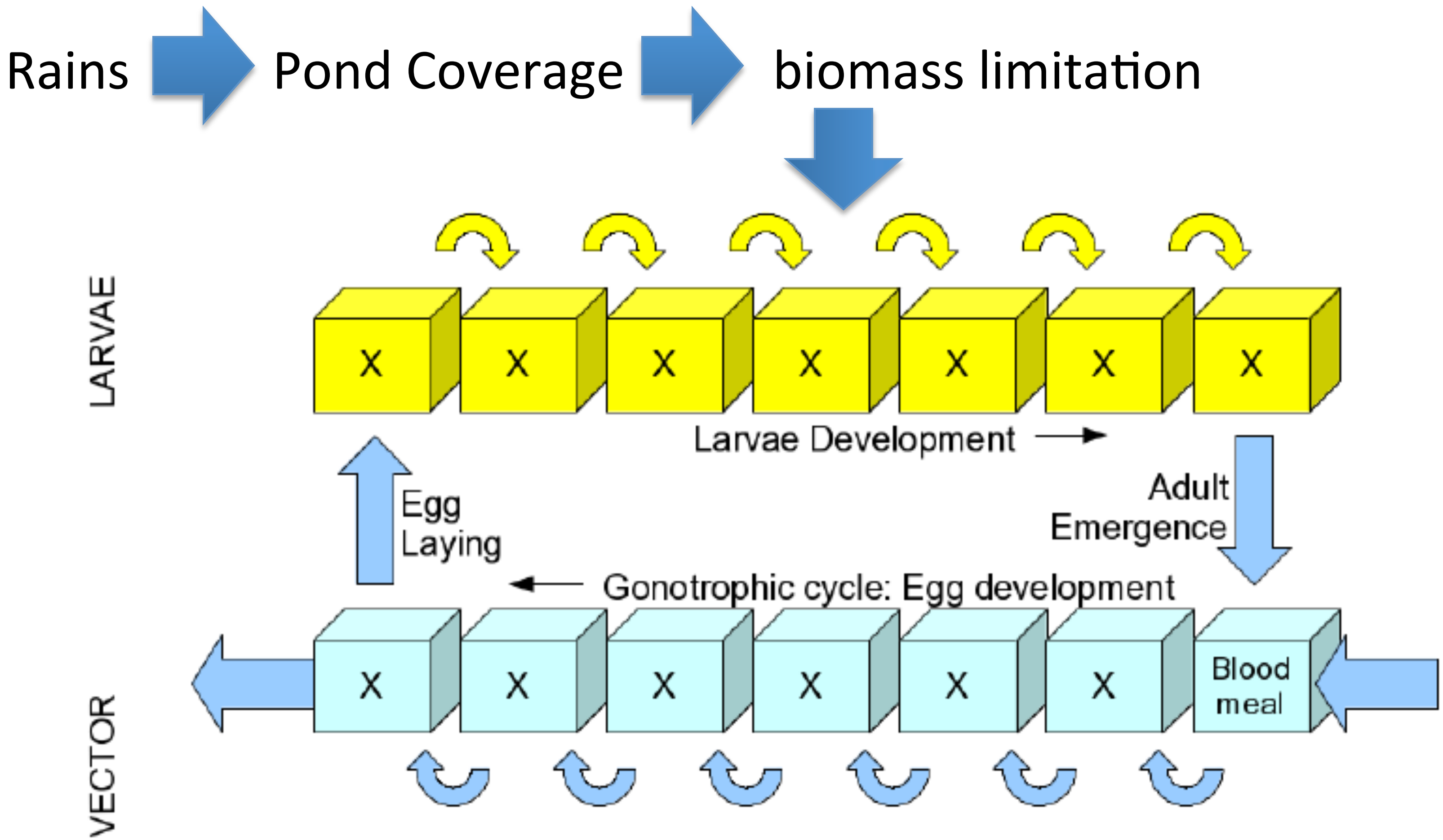


Basic larvae-adult vector lifecycle



Division into a series of boxes to represent delay between rains and vector spin up

Basic larvae-adult vector lifecycle



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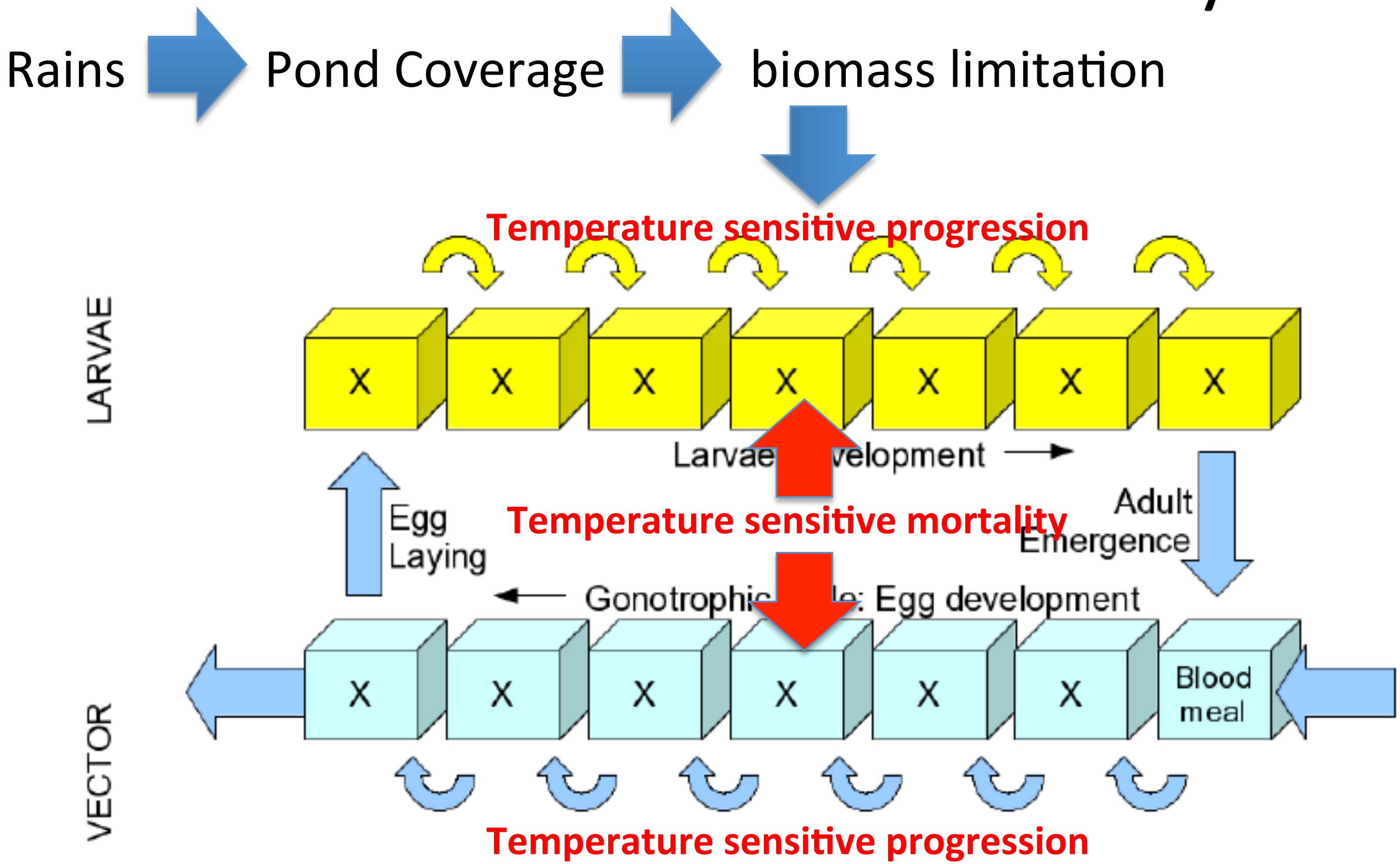
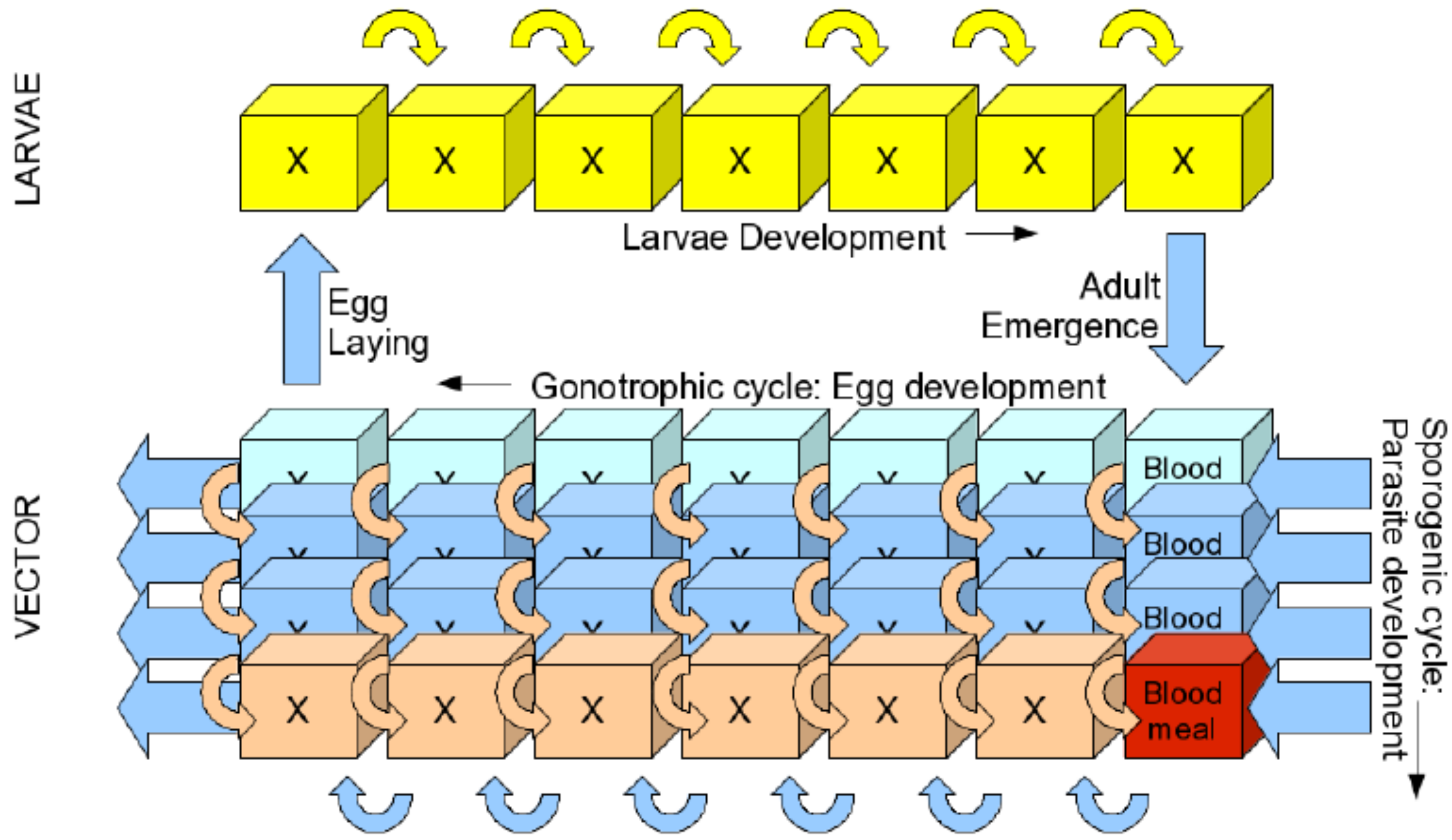
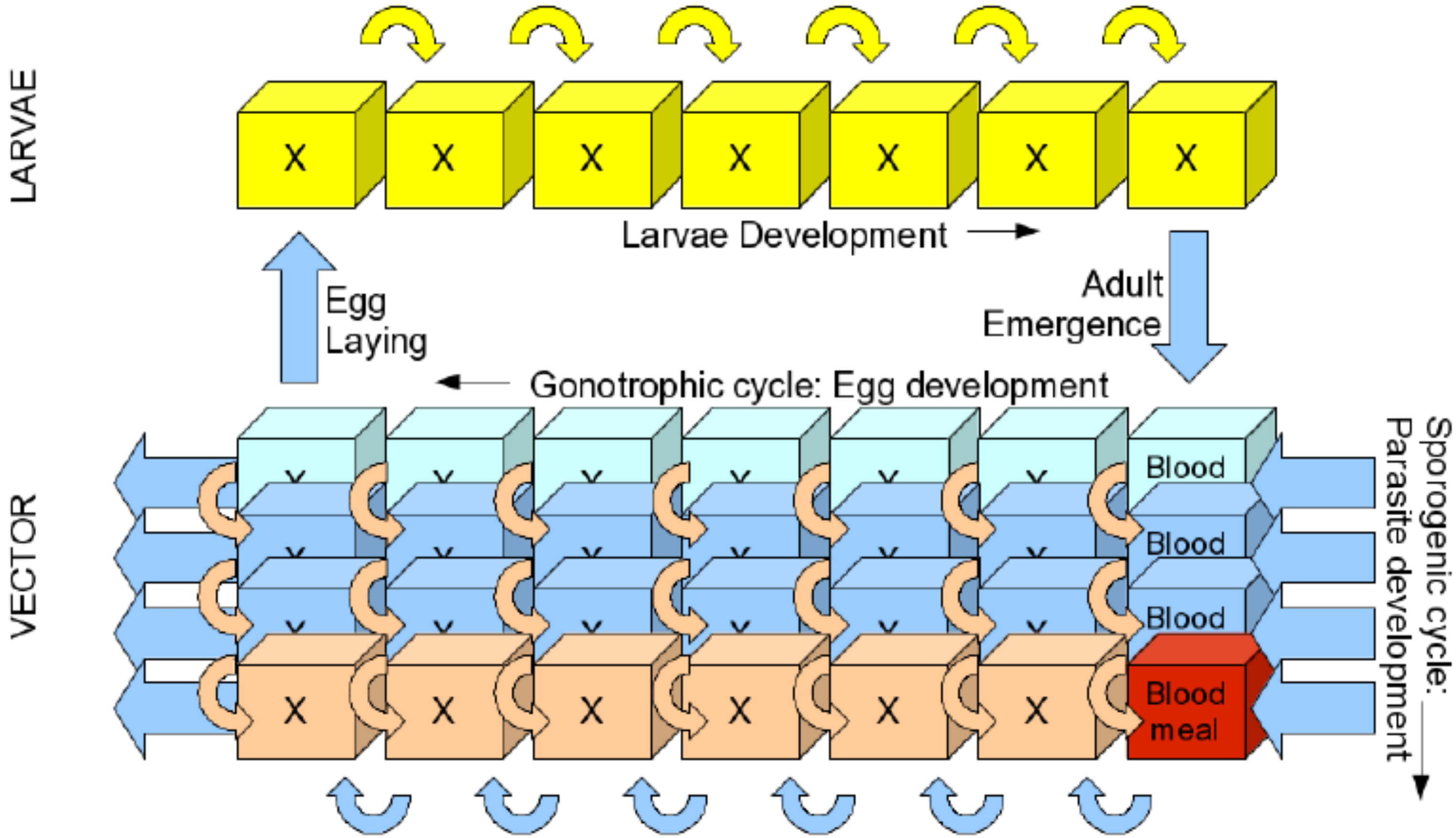


Division into a series of boxes to represent delay between rains and vector spin up

Add an additional vector dimension for parasite state

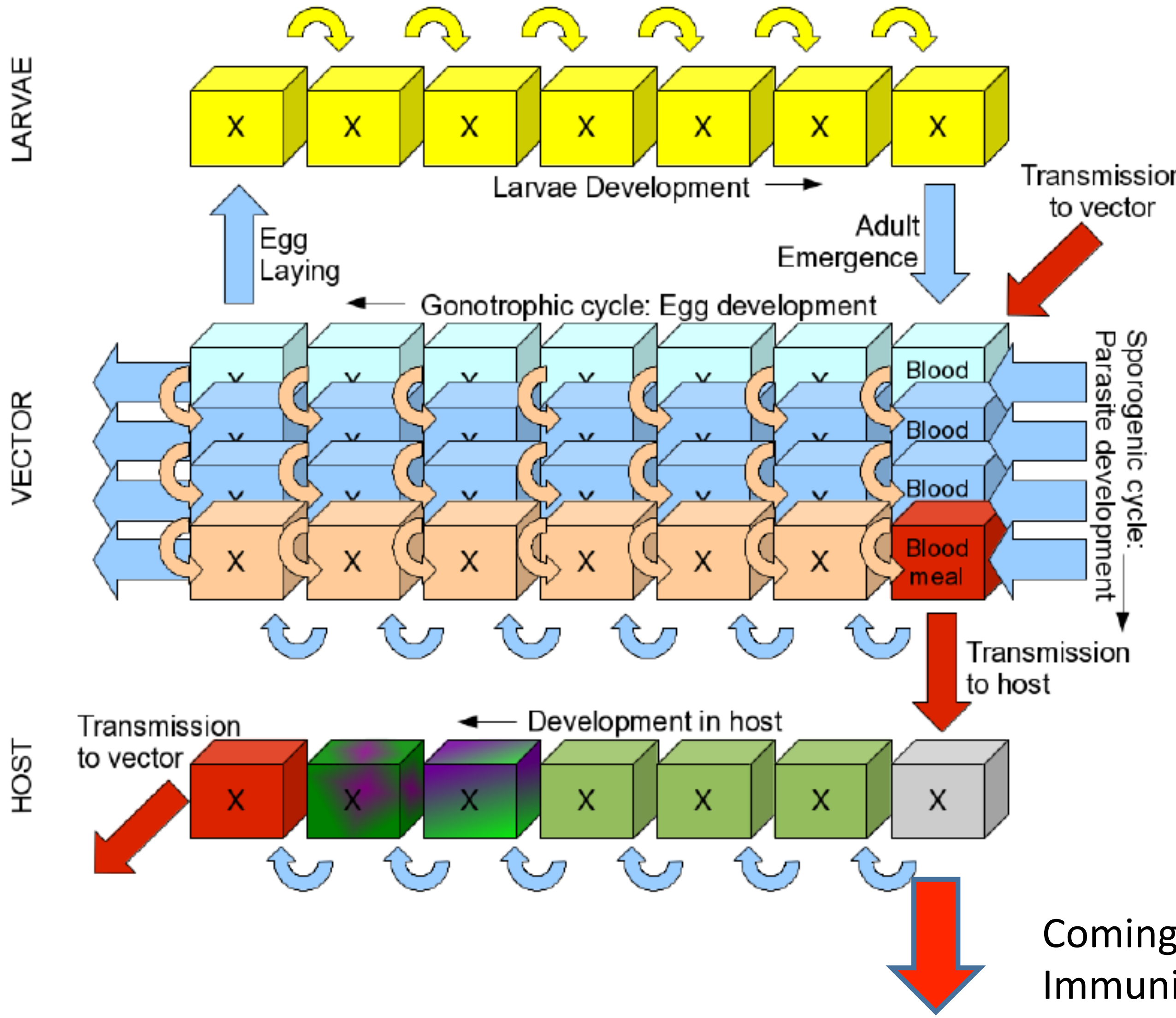


Add an additional vector dimension for parasite state



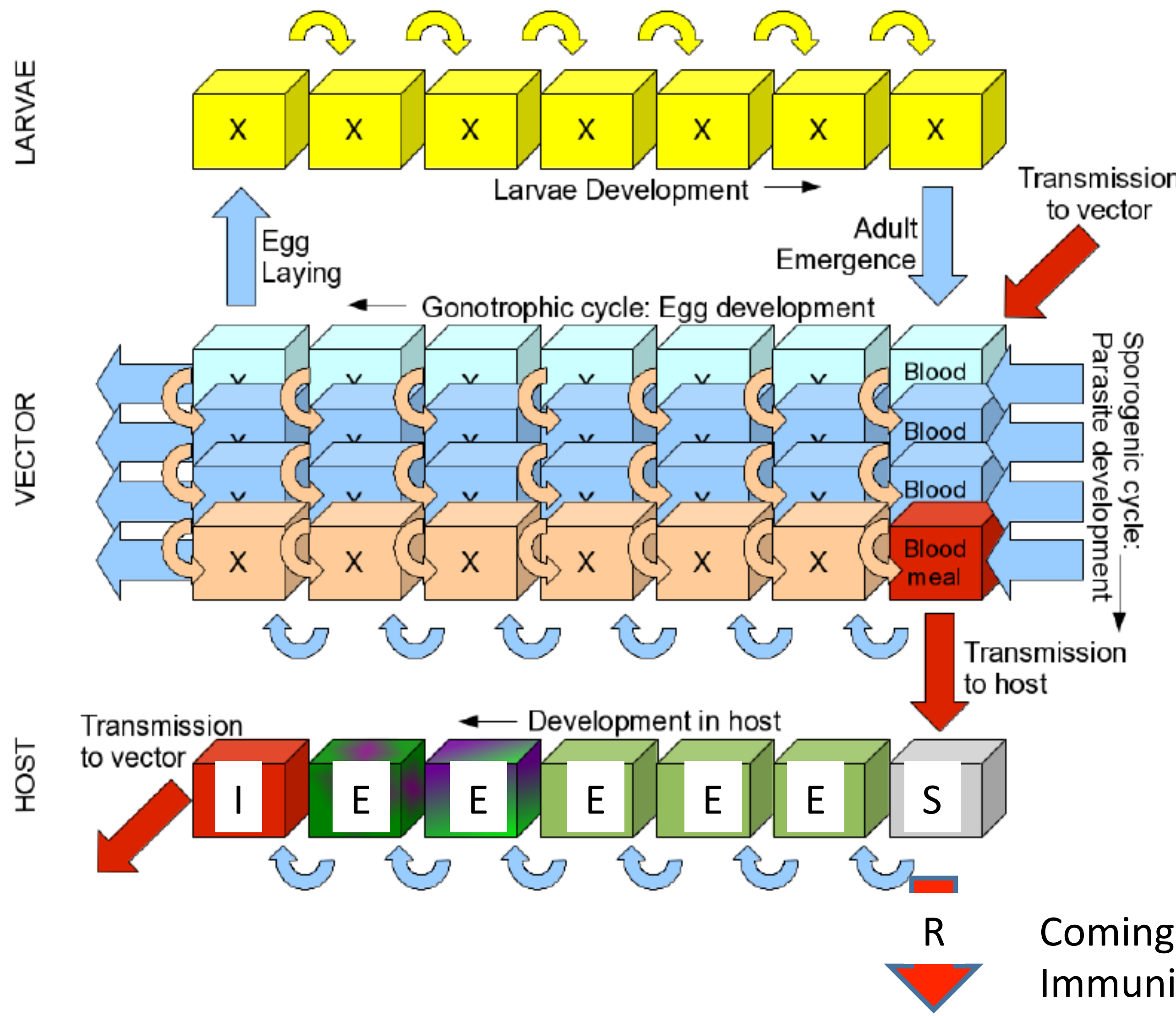
Temperature sensitive progression

And finally an additional array for the human state



Coming soon in v1.4.0: Immunity!

And finally an additional array for the human state



Coming soon in v1.4.0: Immunity!

Simple parameterizations...

Gonotrophic Cycle: egg development

The work of Detinova (1962) showed a degree day concept applied to egg development such that the fractional growth rate F is a linear function of temperature T:

$$F = K(T - T_{crit}) \tag{1}$$

- Threshold temperature for egg development T_{crit}=7.7C
- 37.1 degree days required for egg development ($K = 1/37.1\mathrm{K}^{-1}\ \mathrm{day}^{-1}$)

Given thresholds and rates are a function of relative humidity.
Uncertainty: differences between lab experiments, and differences to the field situation.

Uncertain parameterizations...

Uncertainty of observations: vector survival

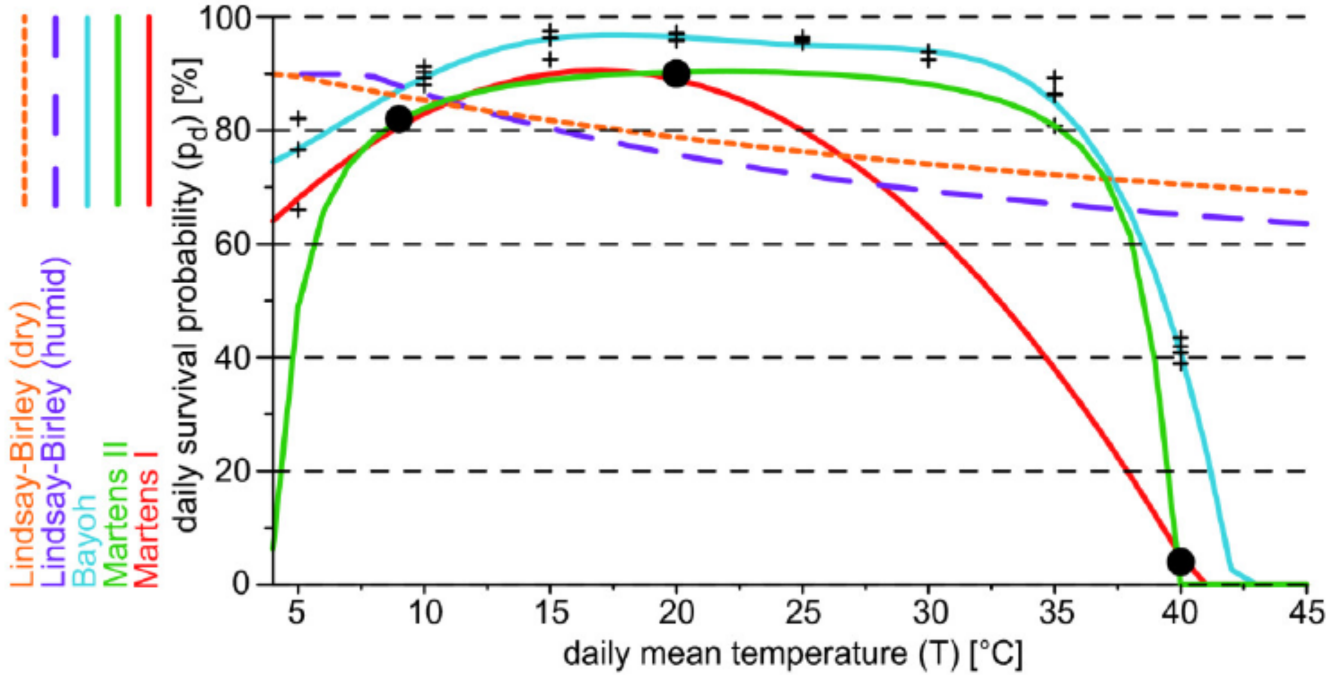
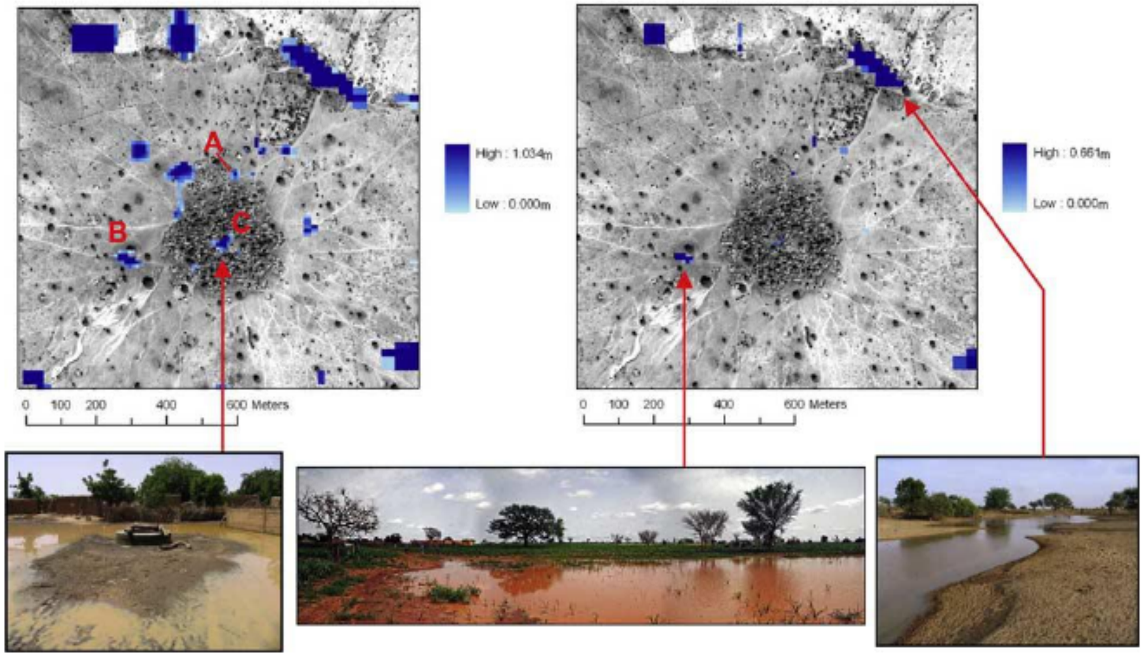


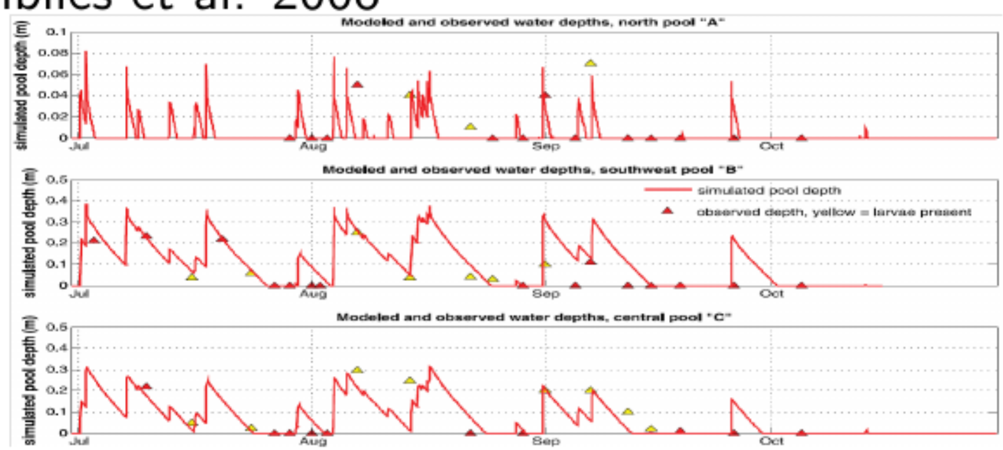
Figure: Graph of temperature dependency of vector daily survival rates

highest uncertainty: surface hydrology

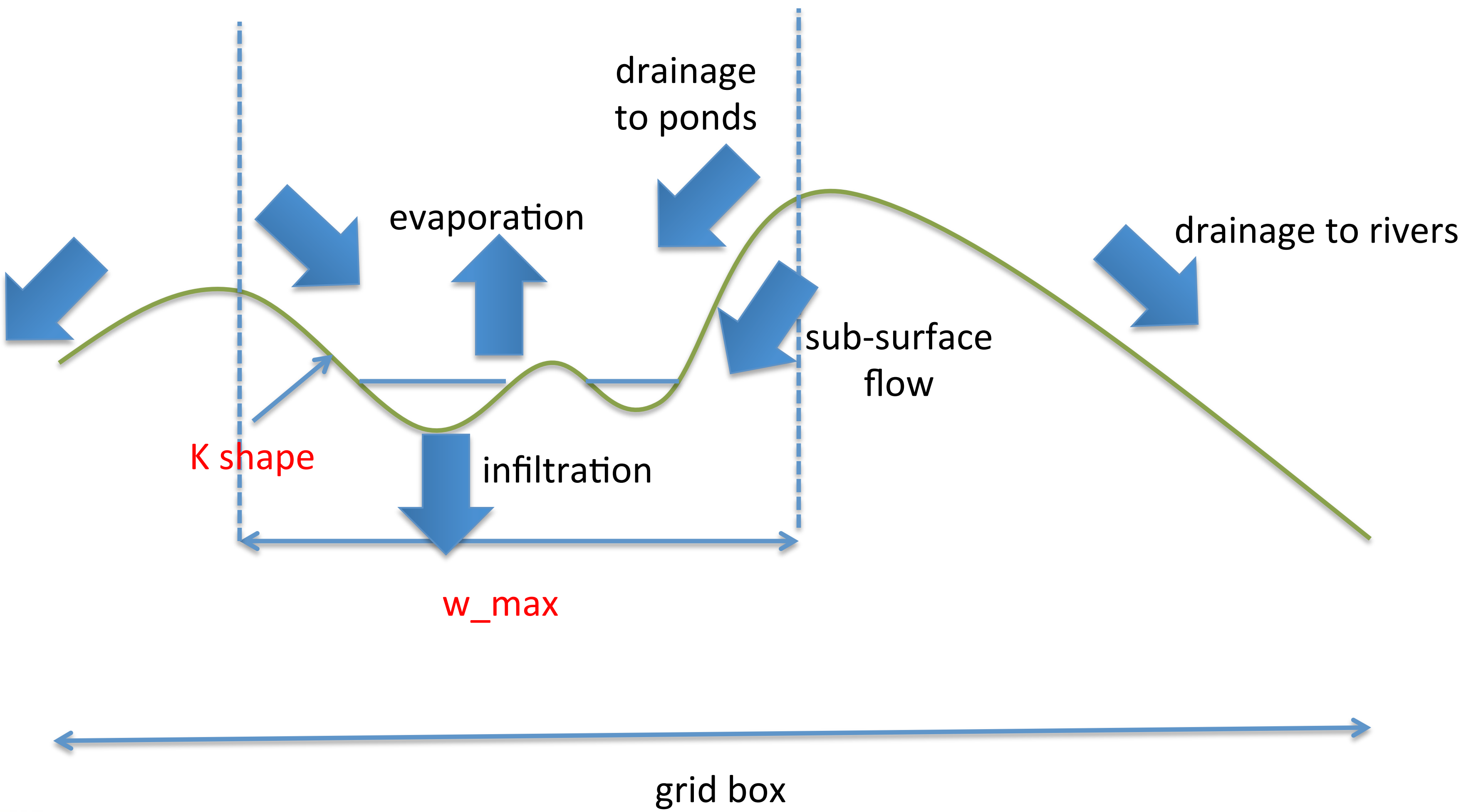


Modelled pond behaviour - However the aggregated effect of these small water bodies could be represented by a pond parametrization in a coarser scale model

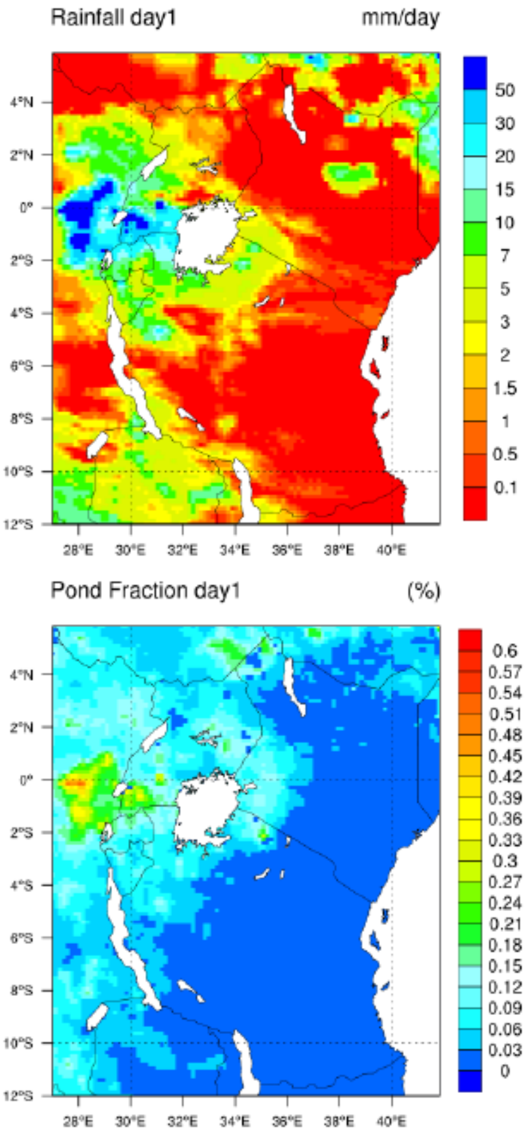
Bomblies et al. 2008



Schematic of simple hydrology



Surface Hydrology



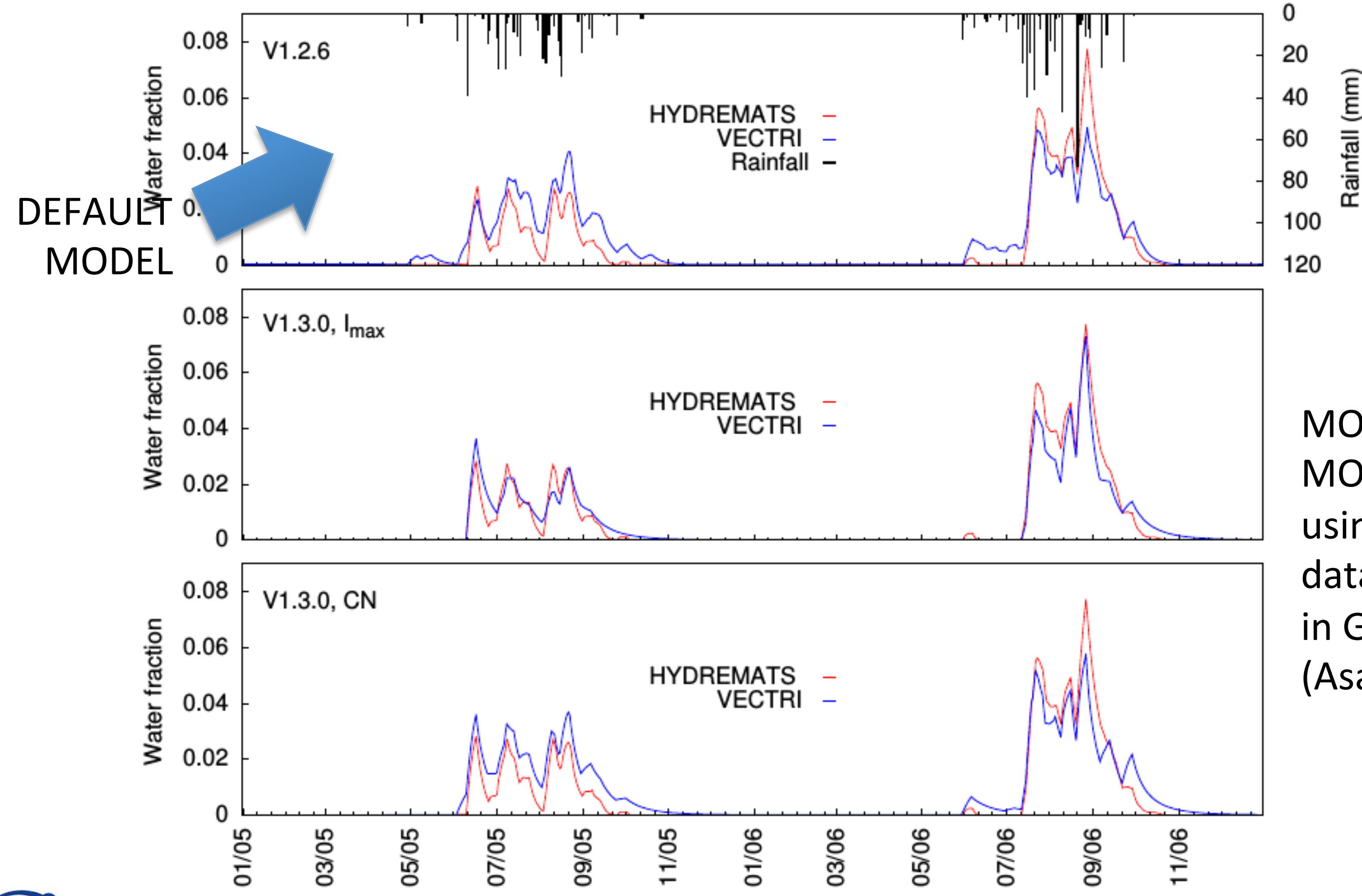
Breeding sites are divided into a permanent breeding fractions plus a temporary 'pond' fraction $w = w_0 + w_{pond}$. A competition factor limits larvae biomass to 300 mg m^{-2}, while intense rainfall flushes out larvae.

The rate of change of fractional pond coverage w_{pond} is given by

$$\frac{dw_{pond}}{dt} = K_w \left(P(w_{max} - w_{pond}) - w_{pond}(E + I) \right). \quad (2)$$

- P is the precipitation rate
- K_w is related to the aggregate pond geometry
- I Infiltration rate
- E Evaporation rate
- w_{max} Collection area = Maximum coverage (overflow losses)

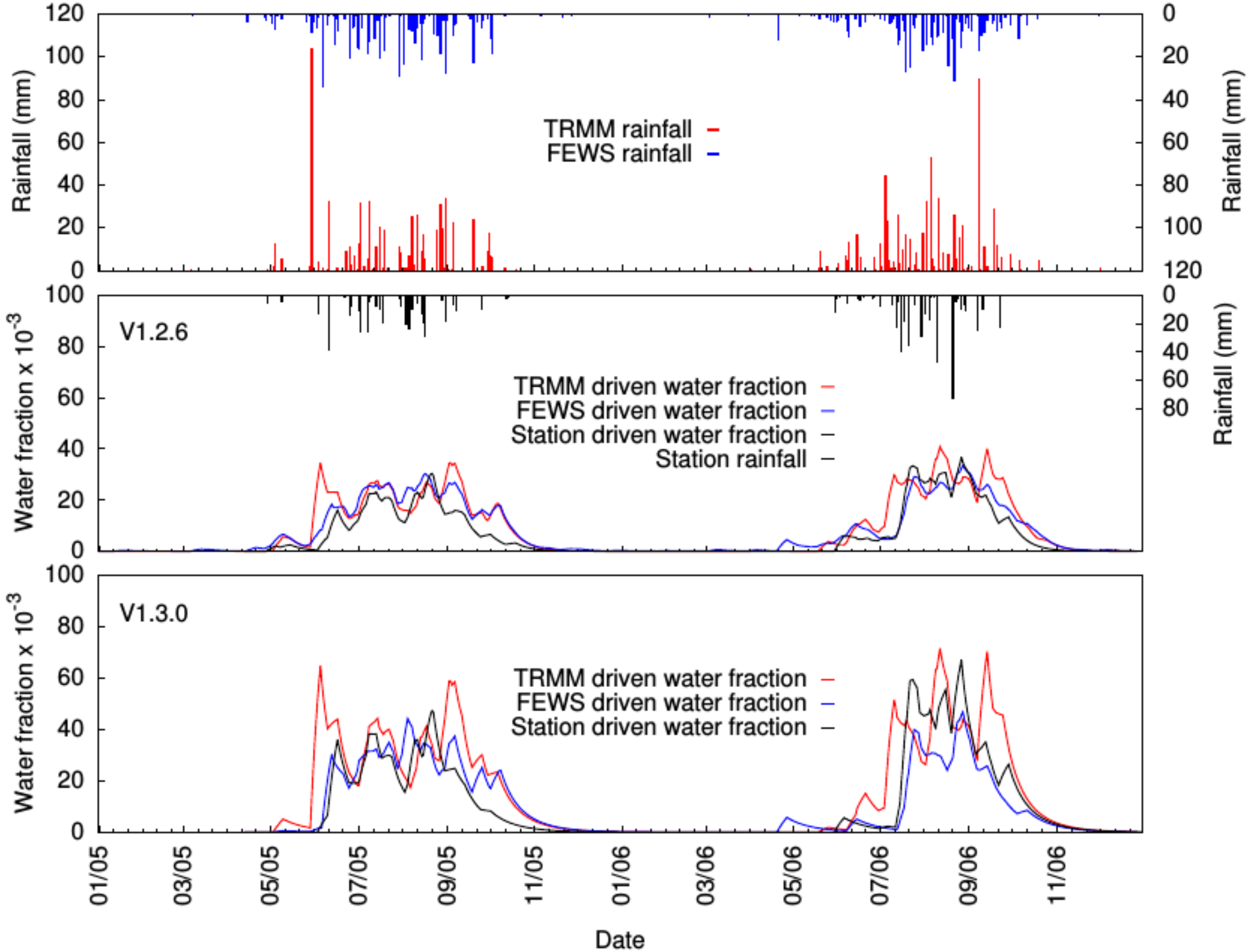
Evaluation with 10m (not km!) resolution model at the village scale in Niger.



MODIFIED MODEL using in situ pond data from Kumasi in Ghana (Asare PhD)

Ernest O Asare, Adrian M Tompkins and Arne Bomblies, 2015: Evaluation of a breeding site availability model for malaria vectors using explicit pond-resolving surface hydrology simulations (just about to be) submitted

FEWS rainfall gives similar results to the station, while TRMM performs less well



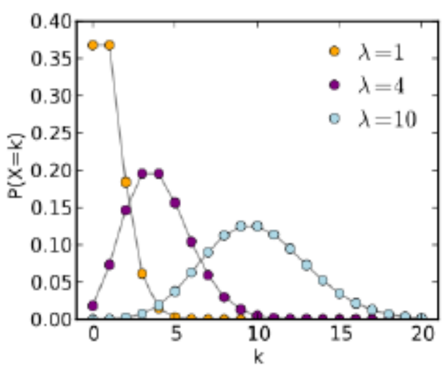
Population Density

- Mean number of bites per human $B = V_b/D$ biting vectors density/population density
- Assume random distribution (all people equal)
- bednet (BN) use can be accounted for.
- single-bite malaria transmission probability is integrated over Poisson distribution to give transmission probability

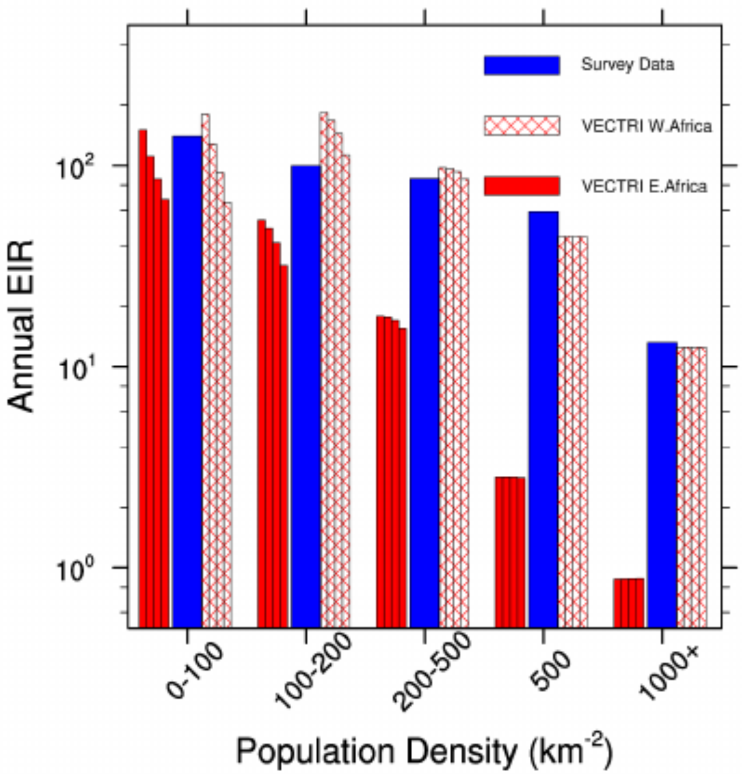
$$P_{vh} = (1 - P_{bednet}) \sum_{n=1}^{\infty} G_{B*}(n) P^n_{v_i h} \qquad (3)$$

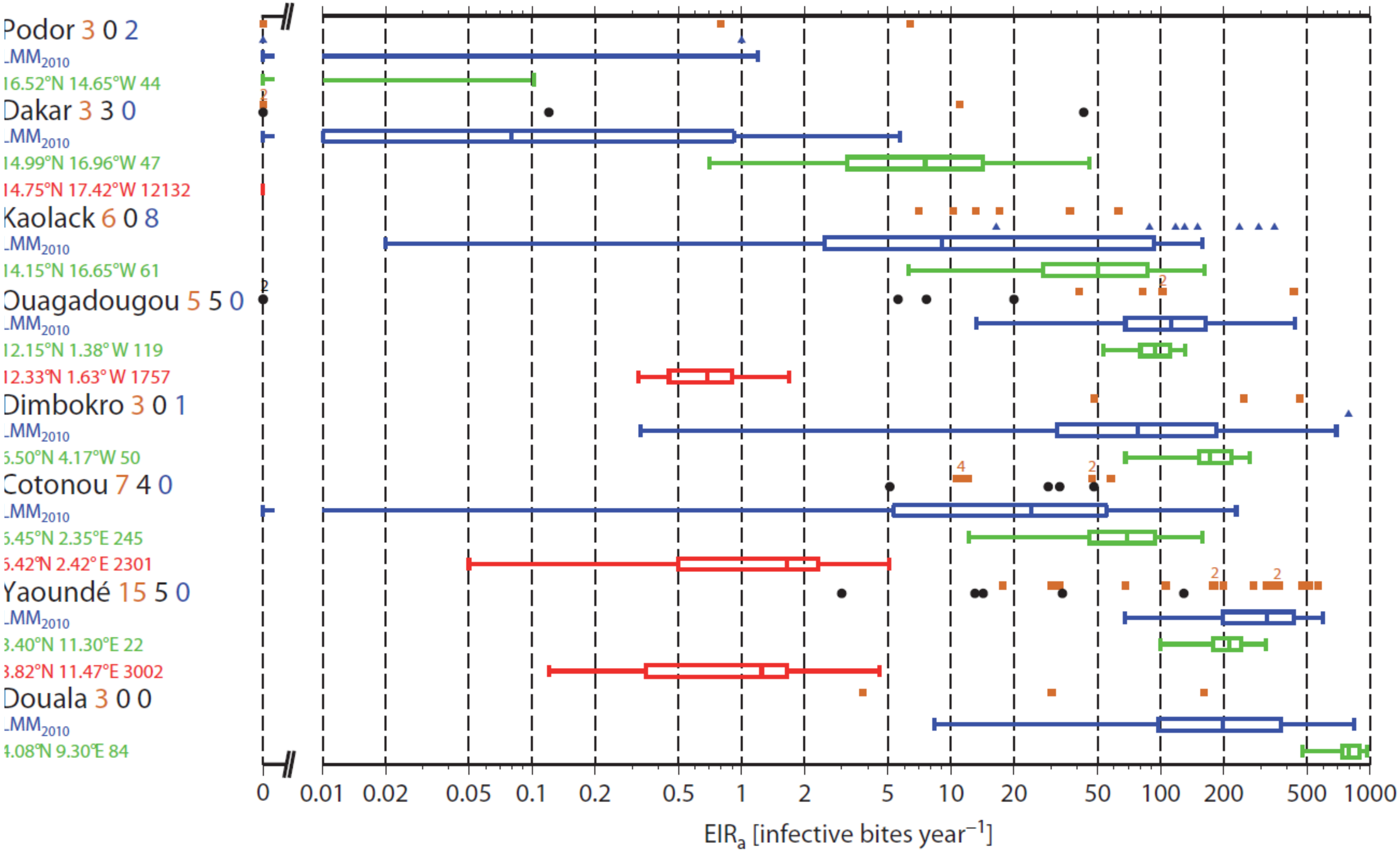
where G_B is the Poisson distribution for a mean bite rate B^*

Poisson distributions:



VECTRI EIR compared to survey data:

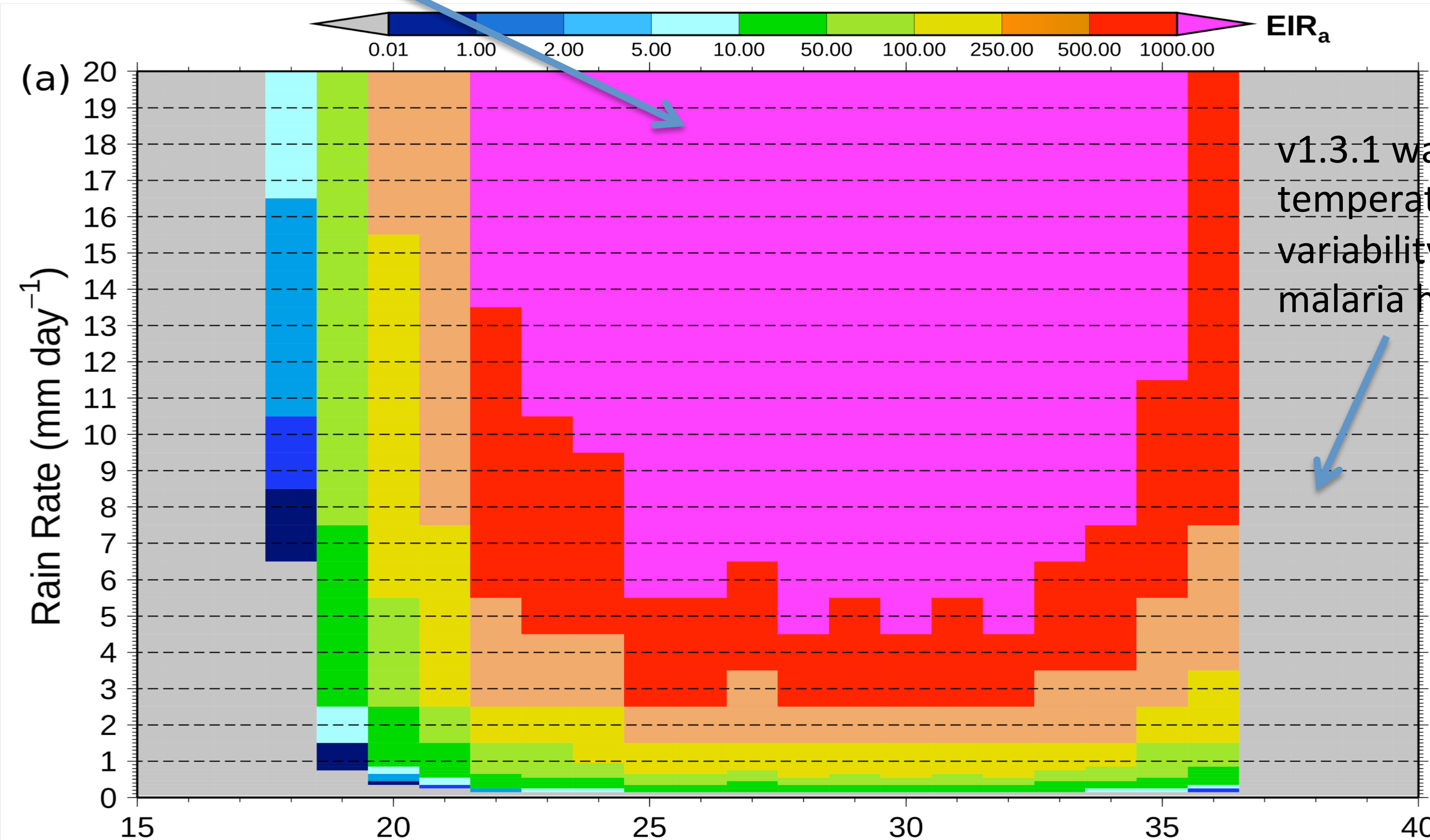




Symbols represent field campaign measurements.
Brown square: urban location
black dots: rural location (non-zero)

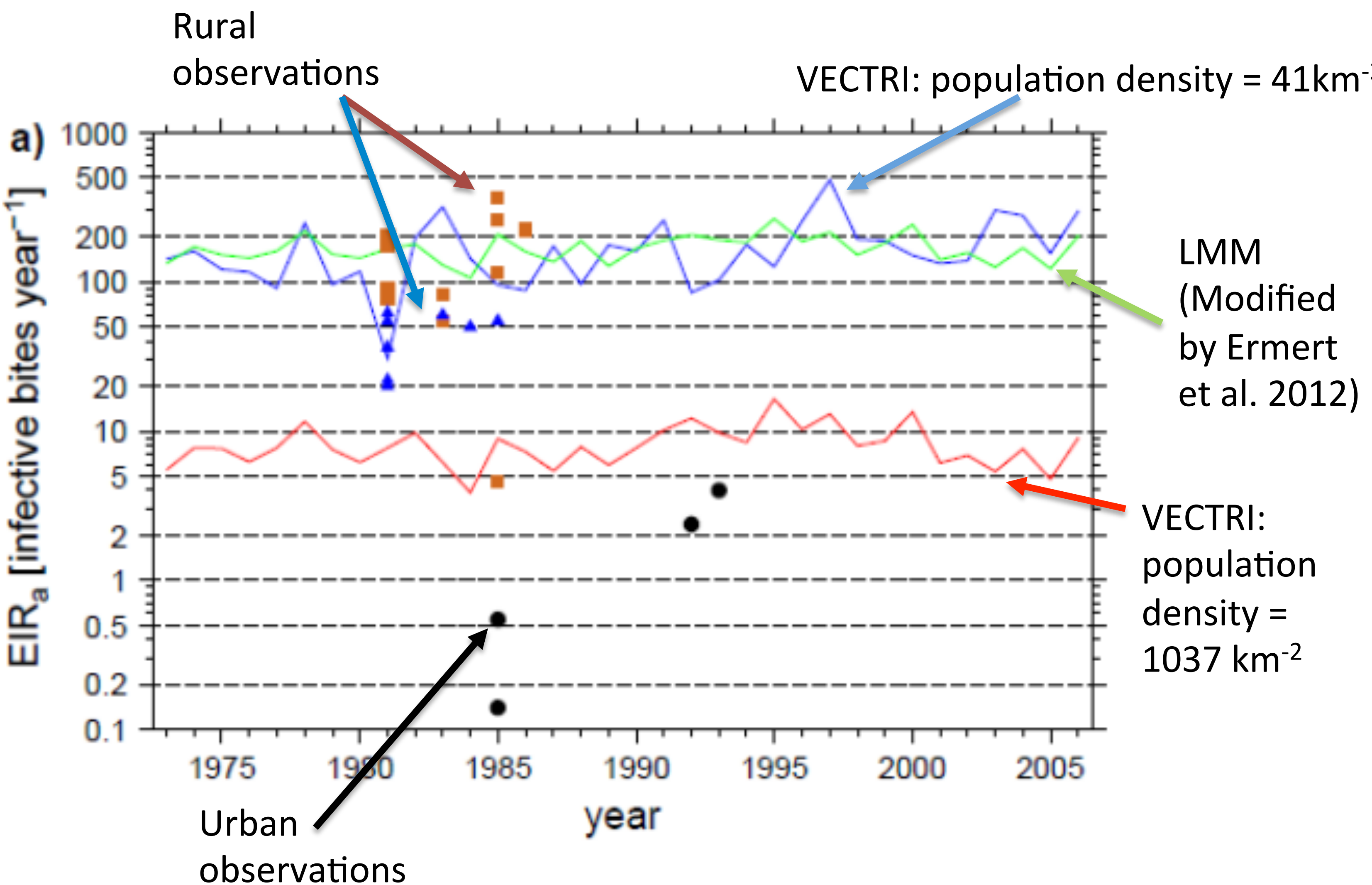
Equilibrium EIR for VECTRI v1.2.6

v1.3.1 flushing now reduces EIR here

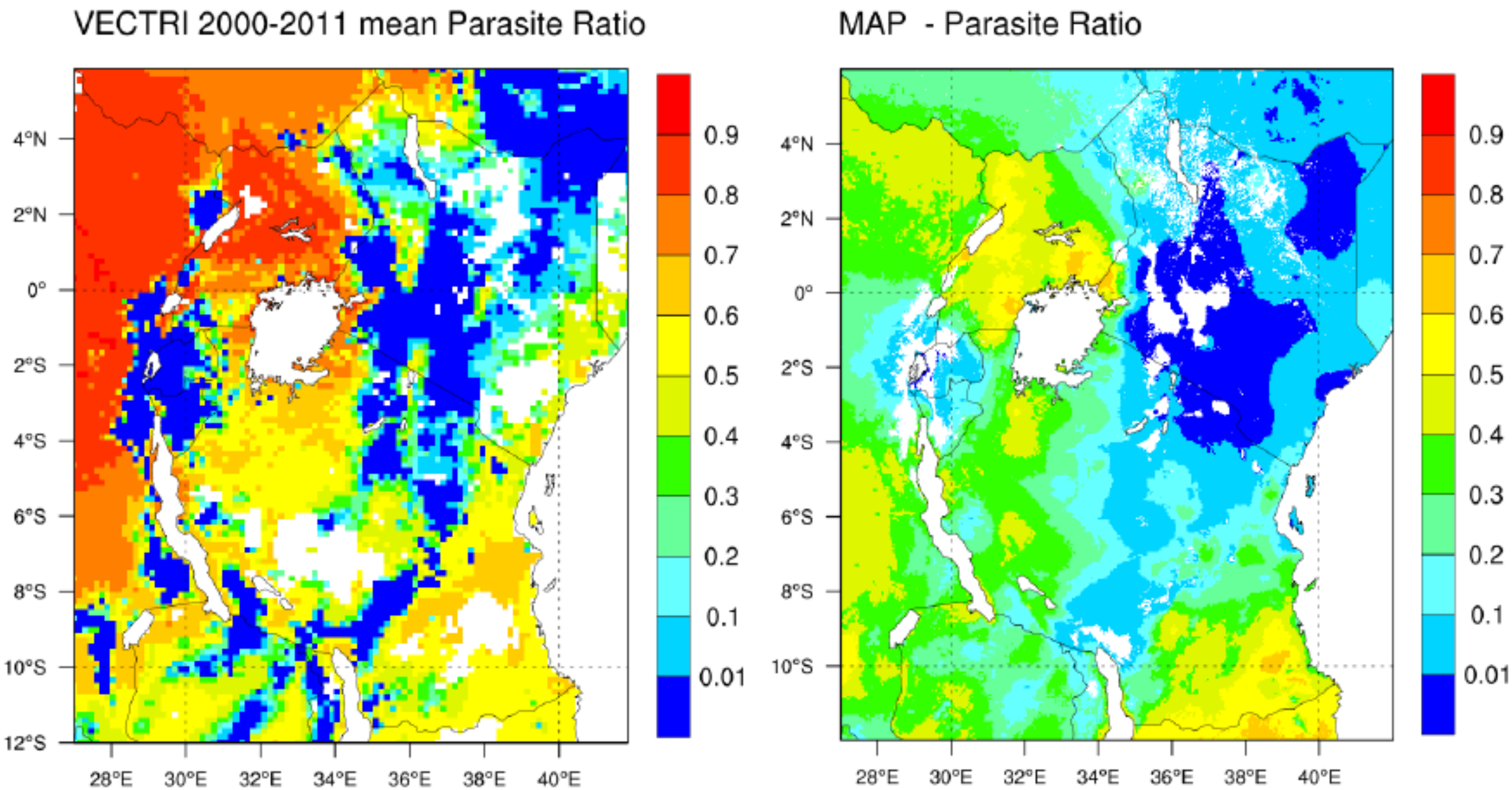


v1.3.1 water temperature variability permits malaria here

Effect of population density: Bobo Dioulasso



Comparison of v1.2.6 against MAP_{2010}



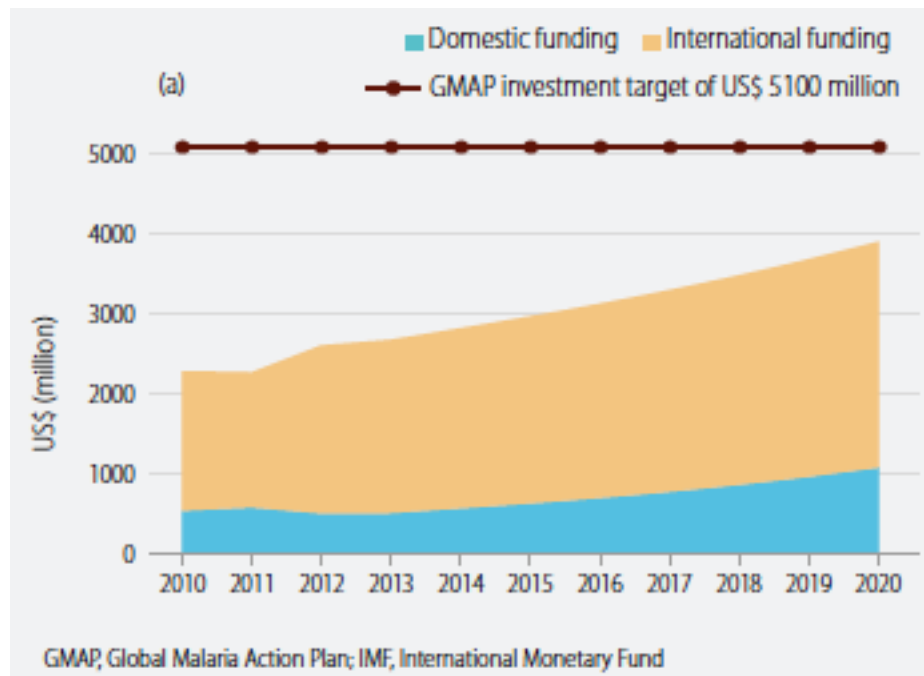
- Spatial variability driven by topography
- MAP implicitly accounts for interventions

Use of VECTRI

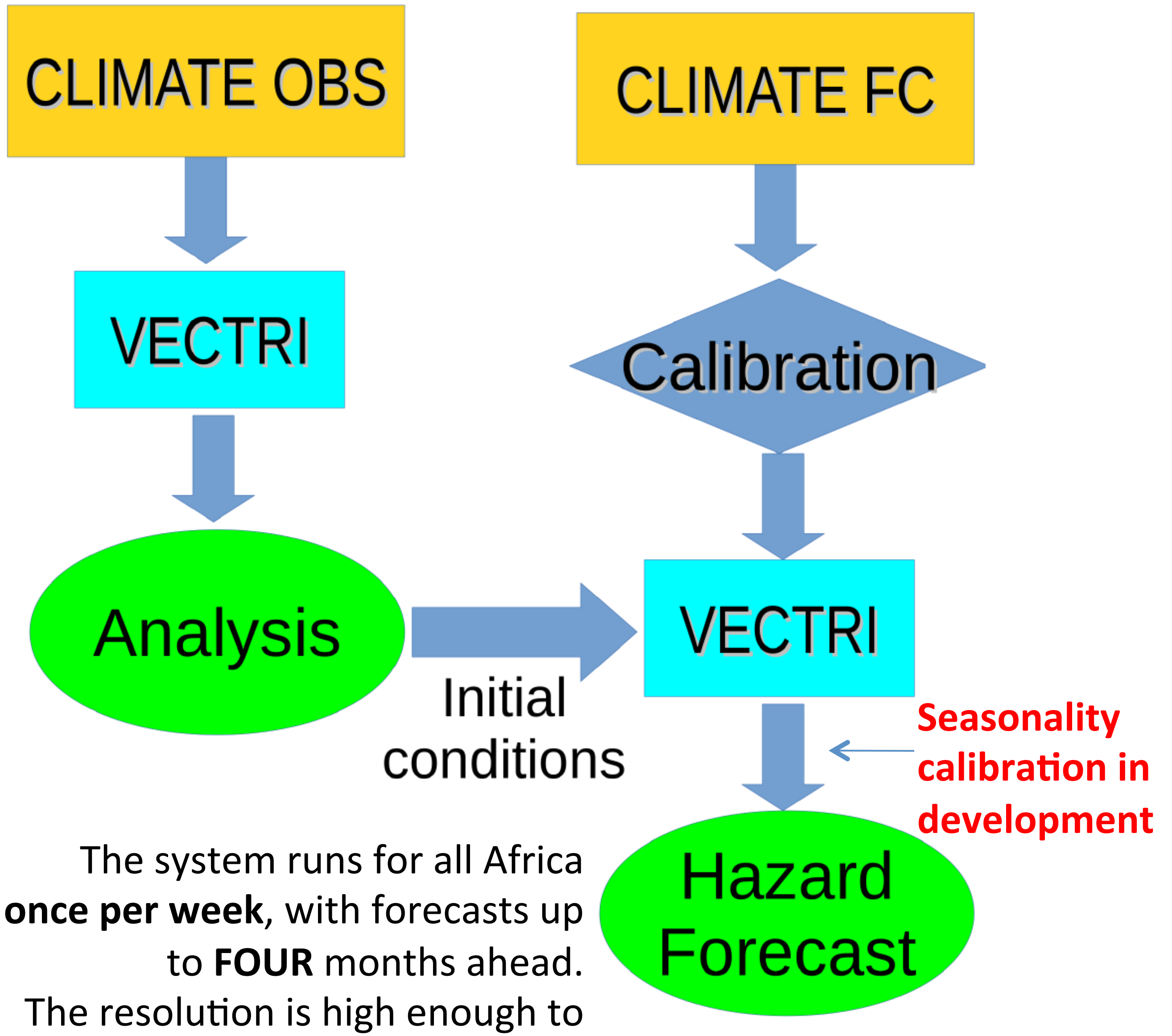
- Seasonal forecasting in Africa: case study of Rwanda and Uganda
- Historical simulations: Could past climate variability explain transmission variations in 1920s-1960?
- Multimodel climate change impact: ISIMIP
- Land use change indirect impact on malaria transmission
- Uncertainty of malaria transmission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

3. 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)



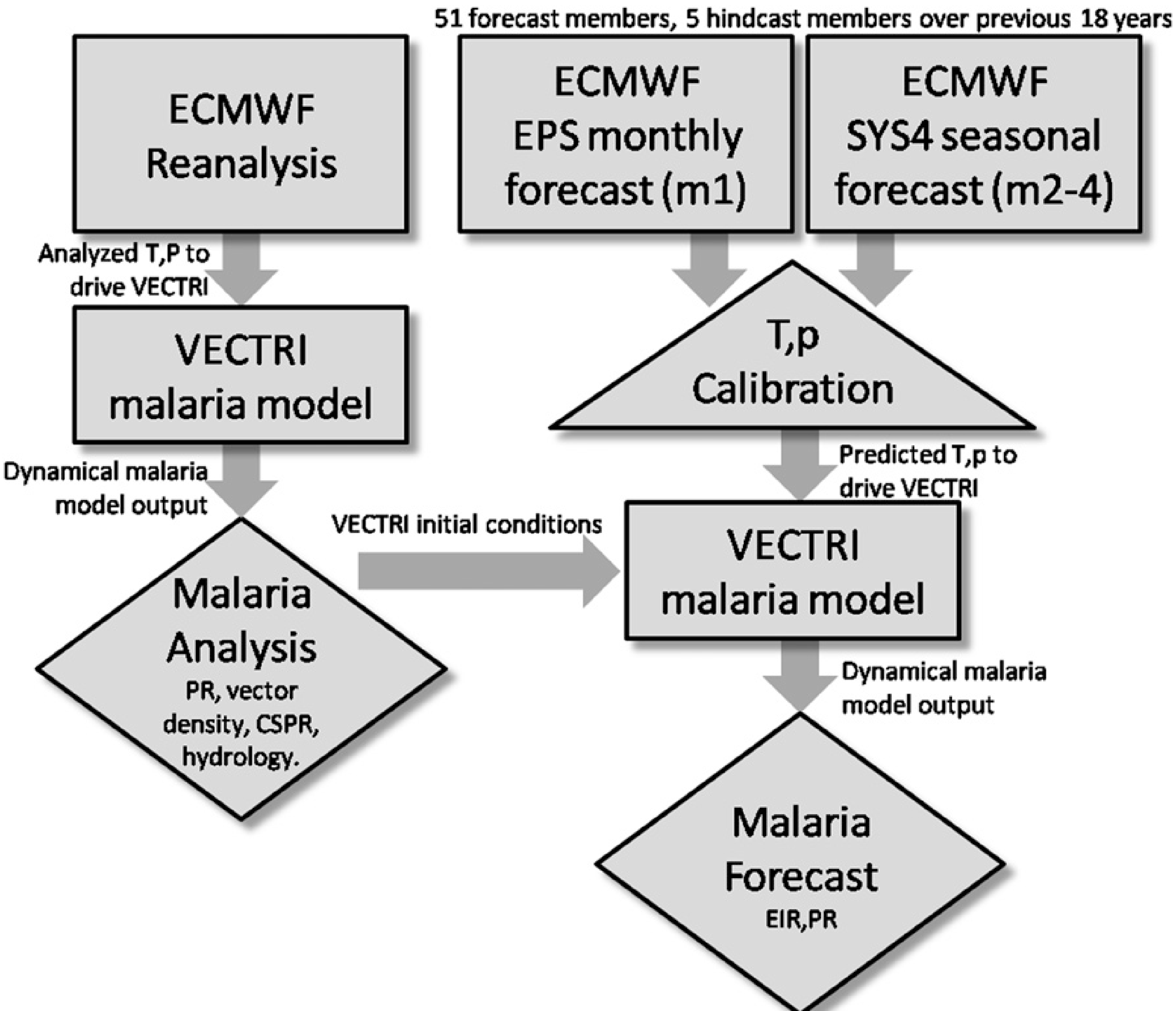
Climate observations are used to create an analysis of entomological and epidemiological conditions in order to initialize the malaria forecasts using the ICTP dynamical malaria model VECTRI (Tompkins and Ermert, 2013).



The system runs for all Africa **once per week**, with forecasts up to **FOUR** months ahead. The resolution is high enough to **resolve health districts**

ICTP

Seamless systems? Combining EPS and seasonal timescales



Tompkins and Di Giuseppe JAMC 2015

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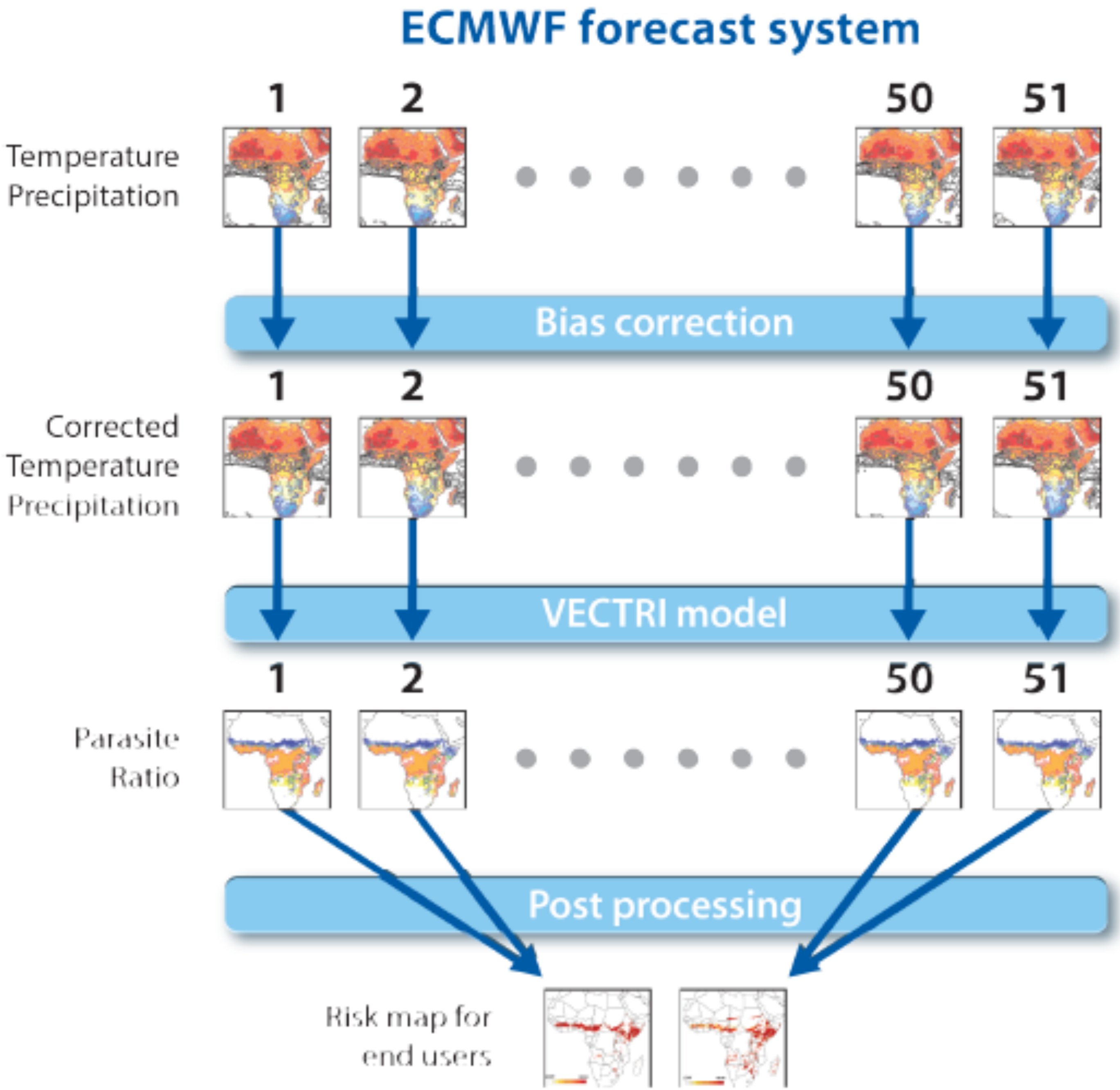
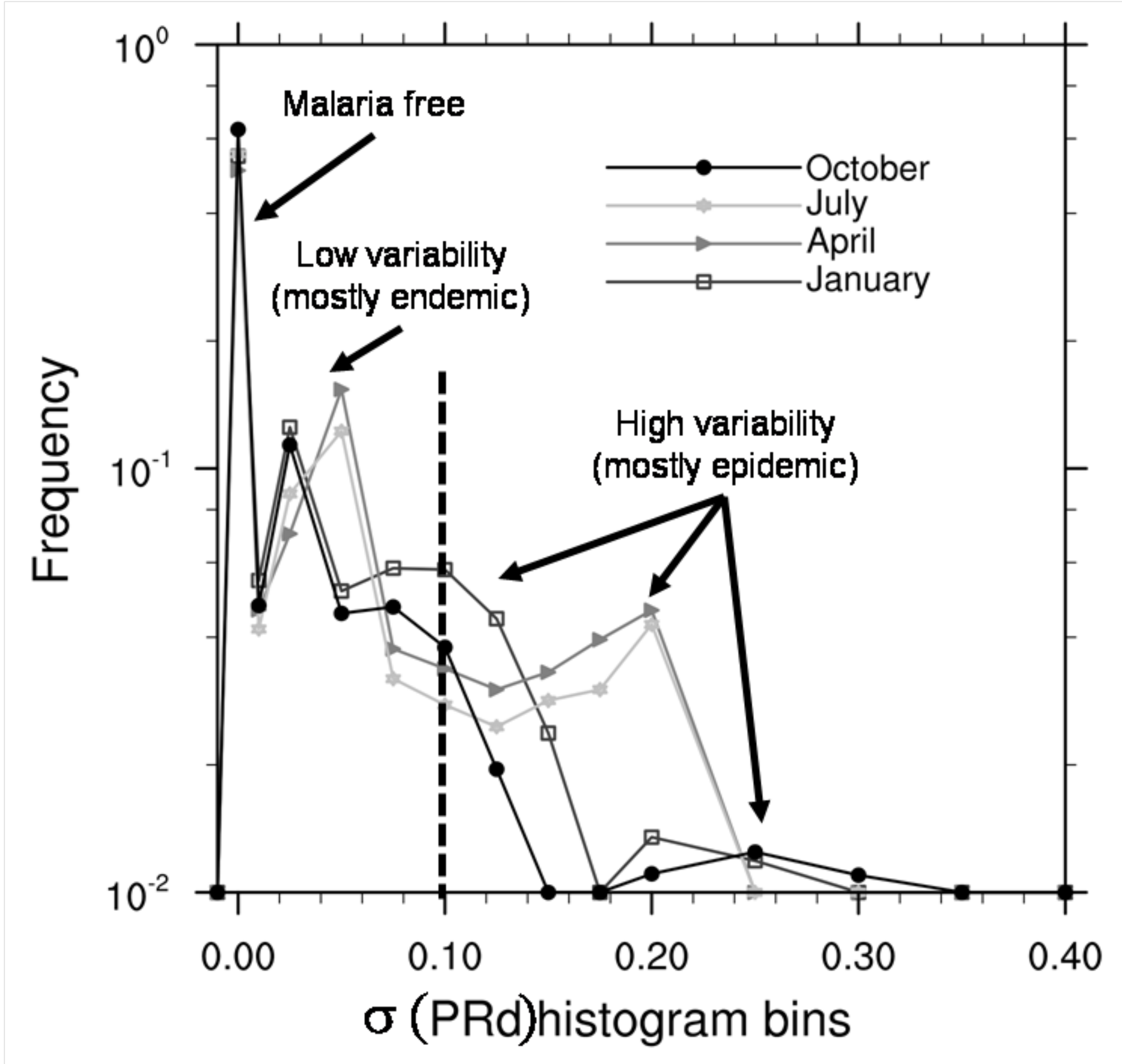

ECMWF forecast system
1
2
50
51
Temperature
Precipitation
Bias correction
1
2
50
51
Corrected
Temperature
Precipitation
VECTRI model
1
2
50
51
Parasite
Ratio
Post processing
Risk map for
end users

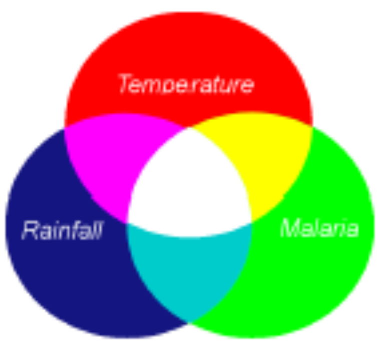
May want to mask areas where climate is not key for driving variability.

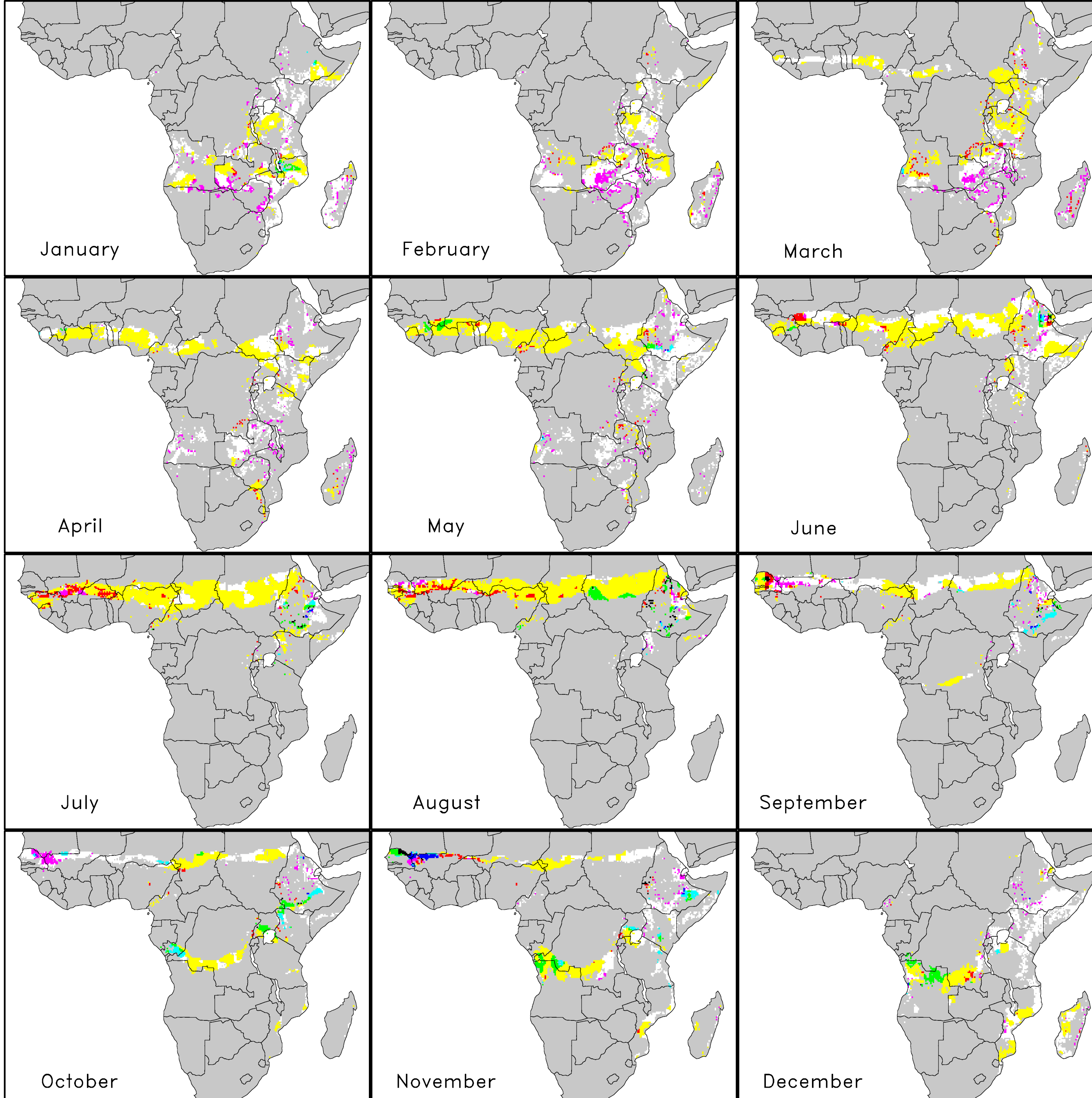
Interannual standard deviation of prevalence simulated by VECTRI driven by ERA Interim temperature and rainfall



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

Only focussing on high variability areas



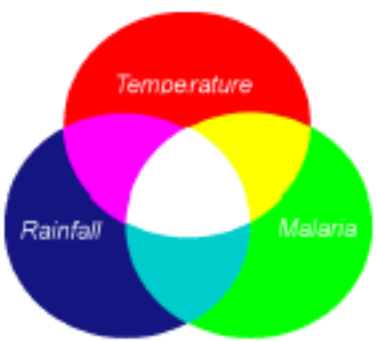


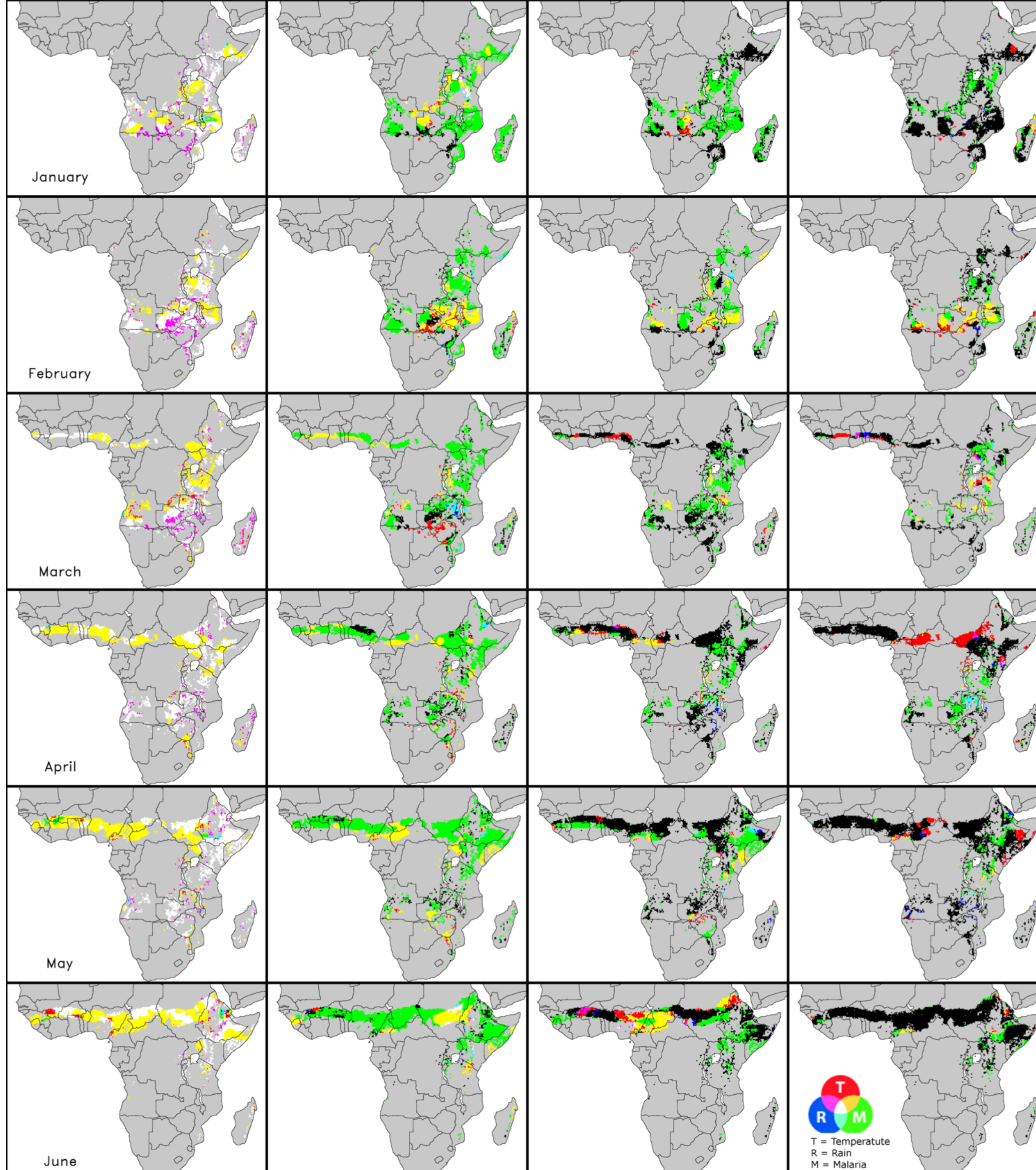
ICTP

Lead 1-4
statistical skill

Only focussing on high variability areas

Malaria skill out to m3-4





Lead 1-4 statistical skill

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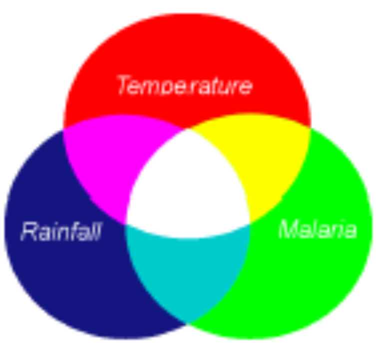
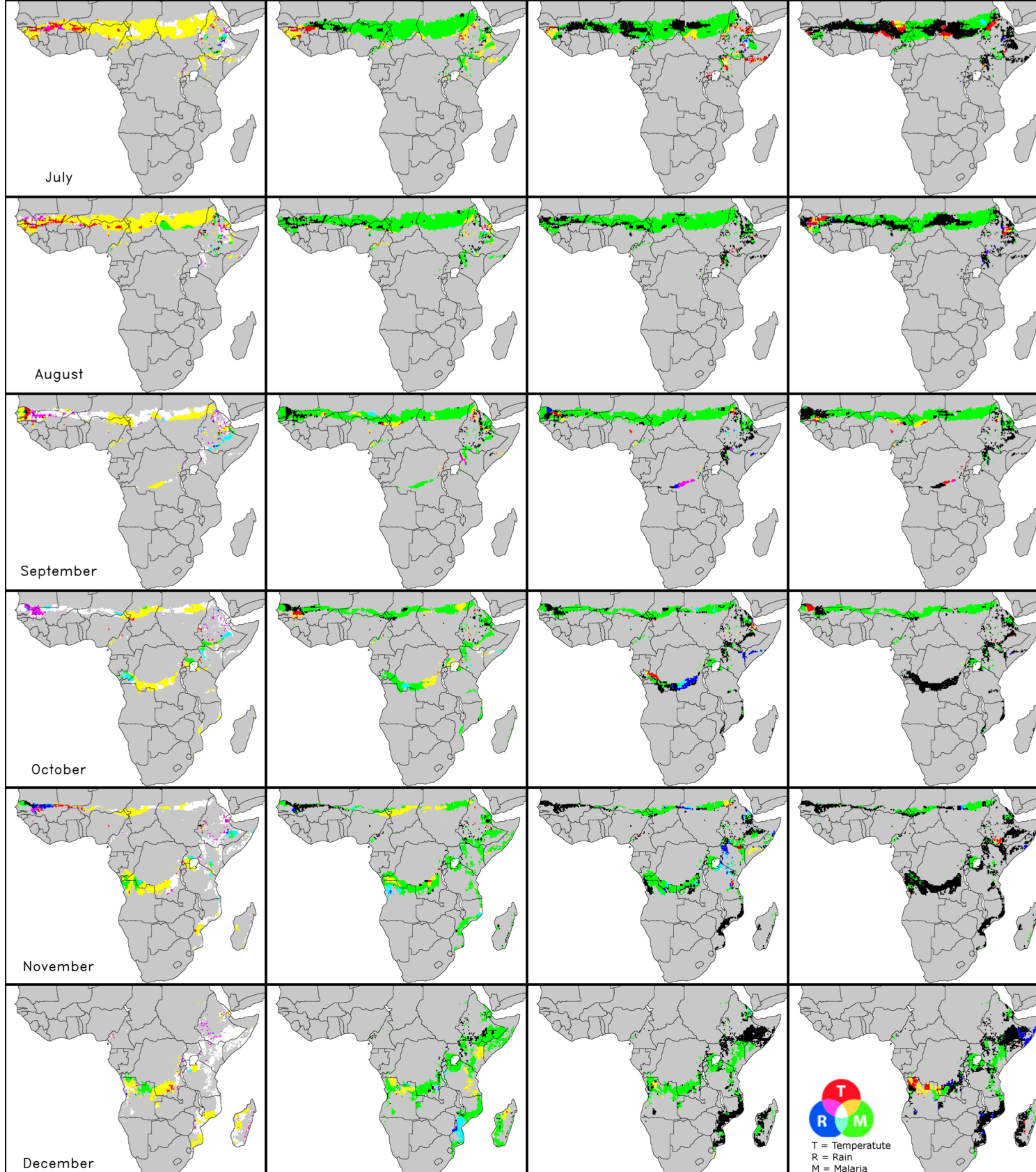
Malaria skill out to m3-4





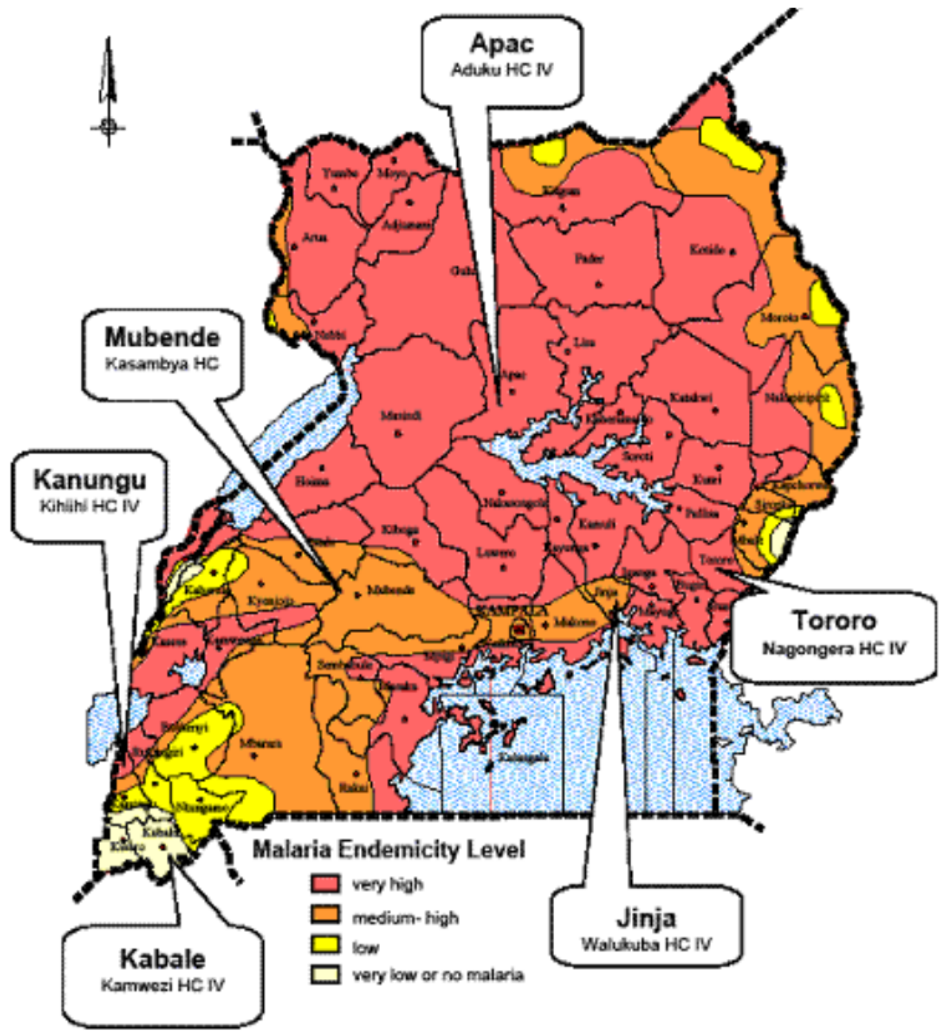
Uganda analysis

We present a preliminary evaluation of the normalized logarithm of the entomological inoculation rate, ln(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

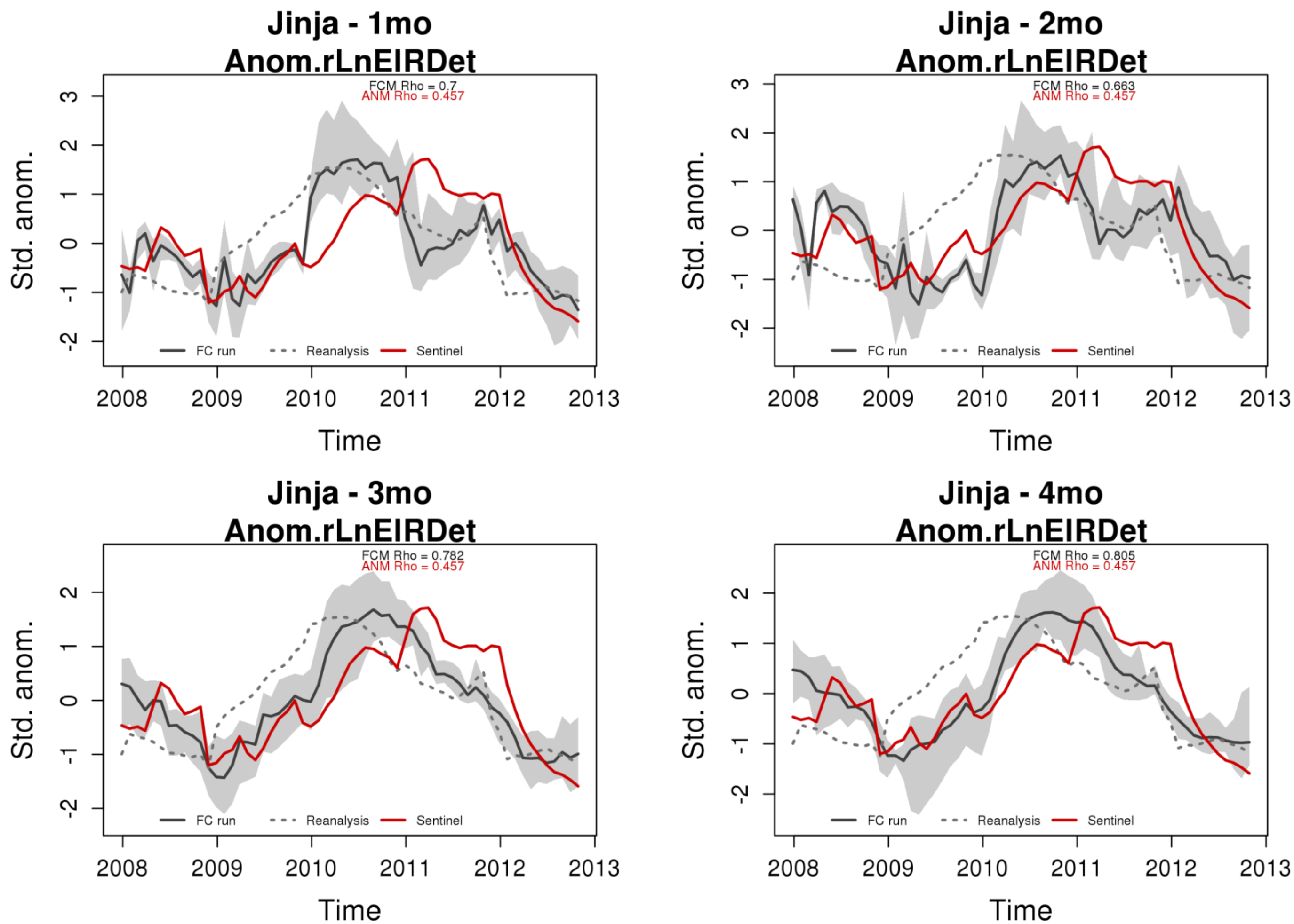
Red line: normalized **confirmed** cases

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

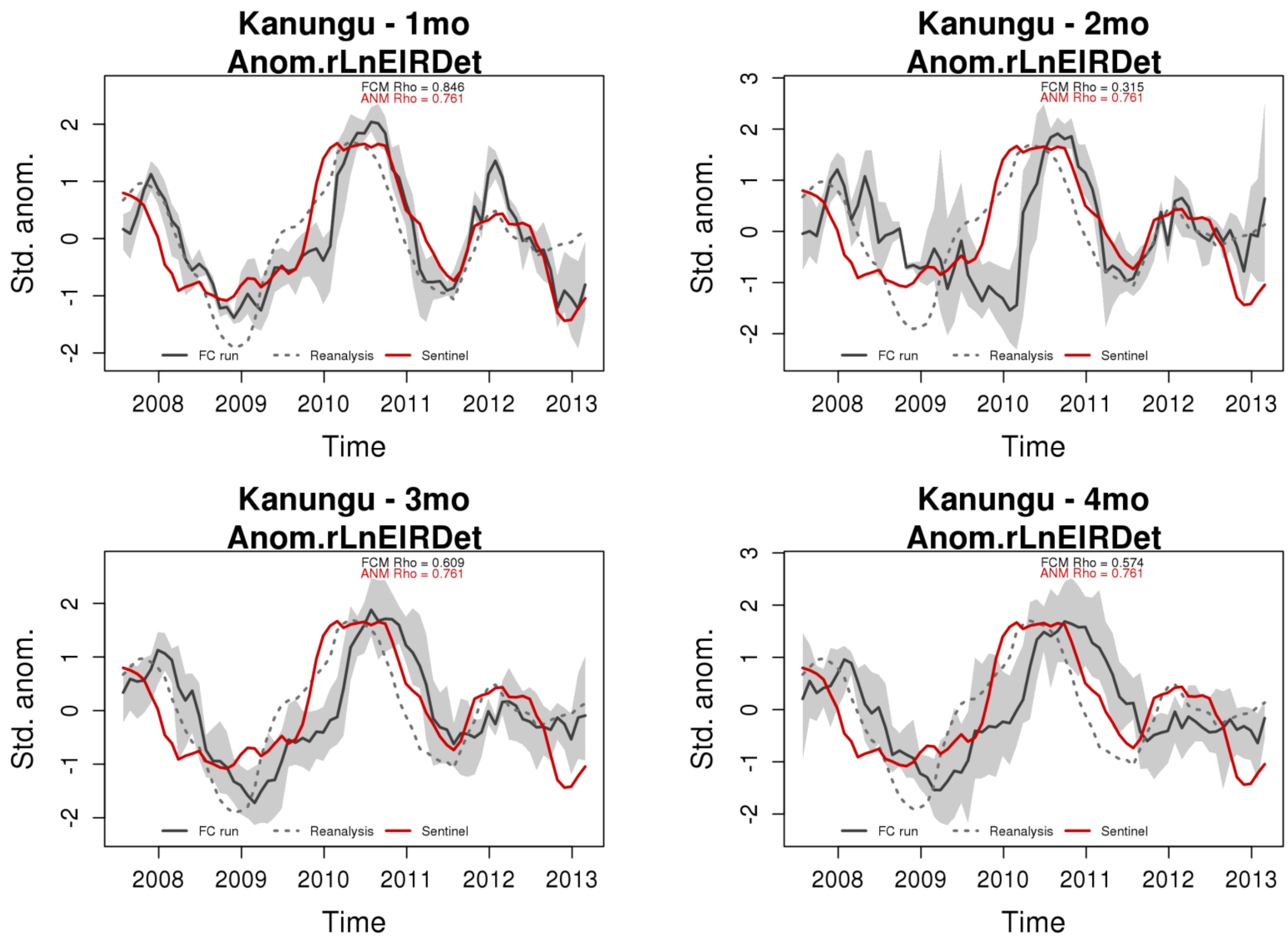
Red line: normalized **confirmed** cases

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



Results for Mubende Sentinel Site

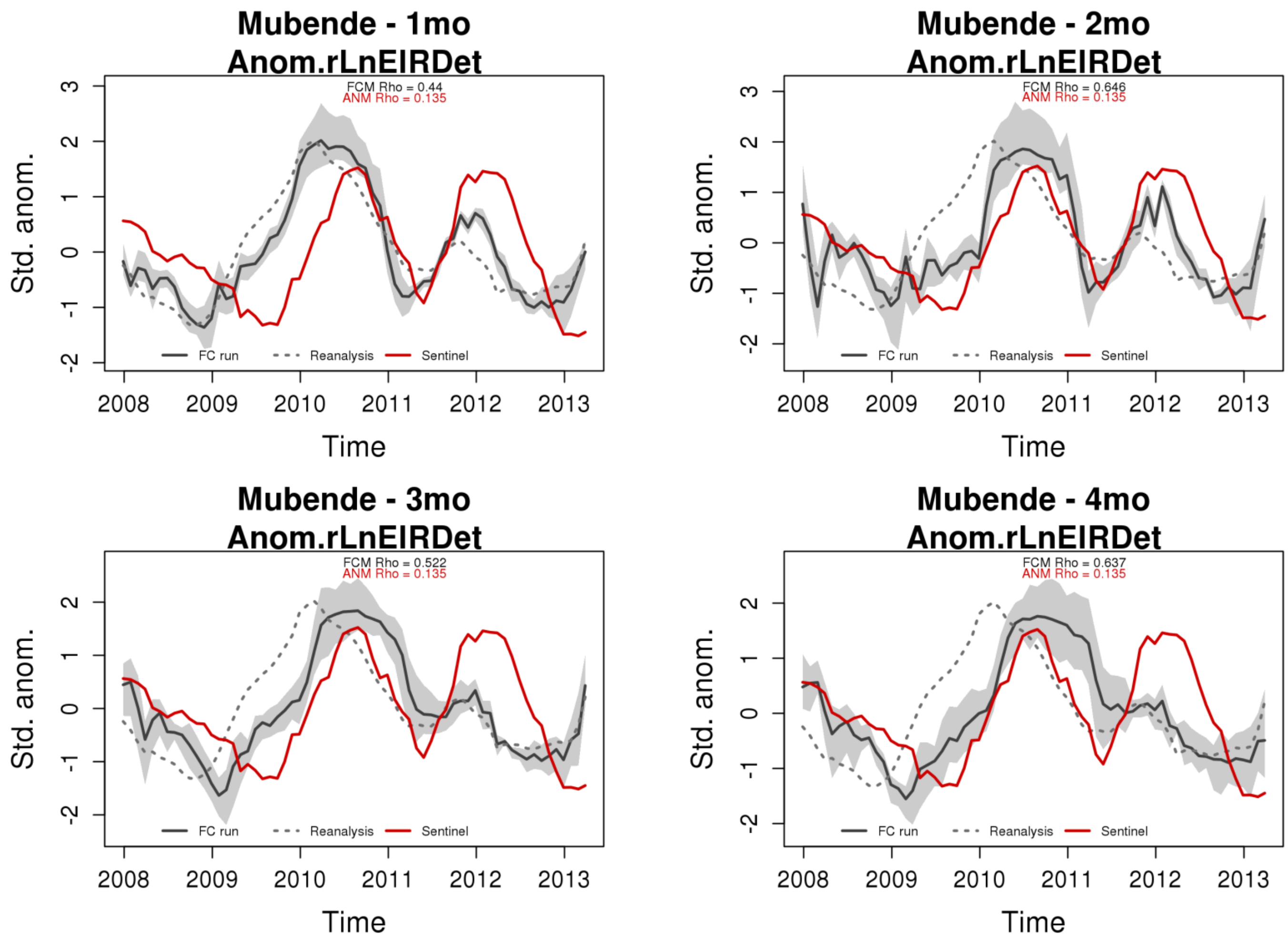
Red line: normalized **confirmed** cases

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



Results for Tororo Sentinel Site

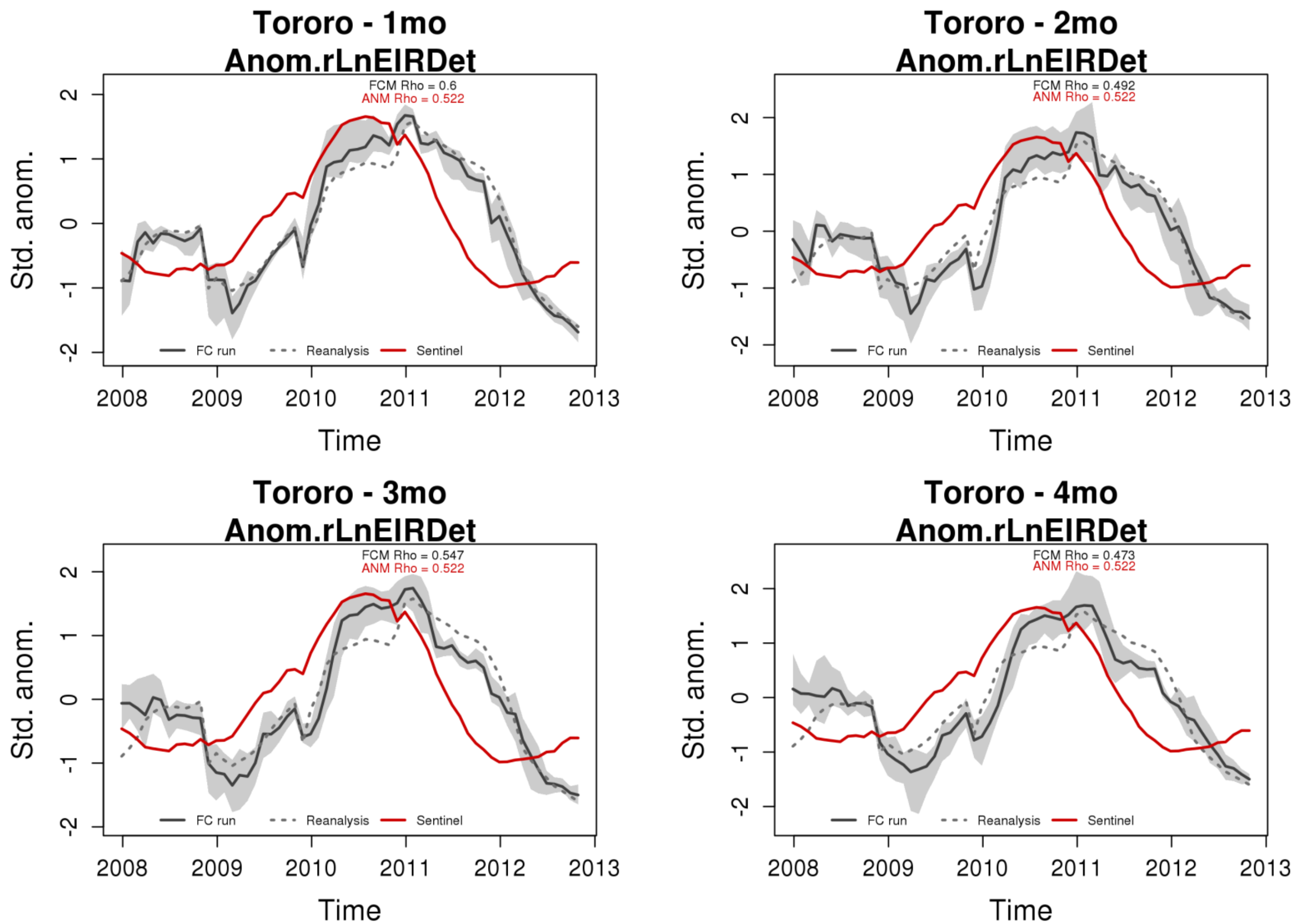
Red line: normalized **confirmed** cases

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



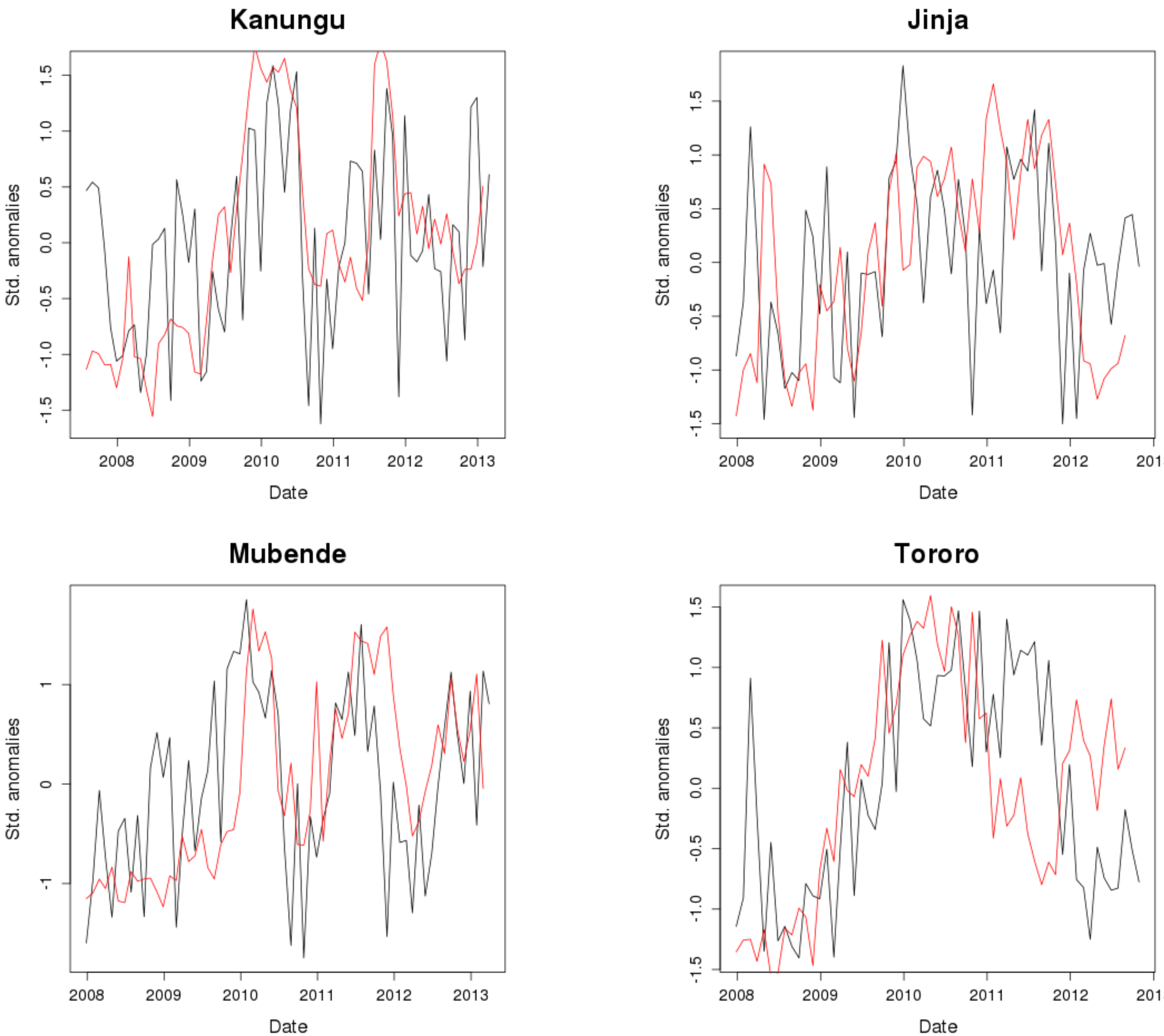
Summary of the sentinel site analysis

- The forecast for 5/6 sentinel sites is potentially statistically skillful four months in advance
- The exception is Kabale which is too cold to support malaria in the model.
- This is the first ever demonstration of a skillful malaria forecasting system based on a coupled dynamical system, and at the sub-national scale
- But! Heavily smoothed data due to poor sub-seasonality match to data – not useful in present format.

This is what the comparison looks like on a monthly timescale: lead 1

red=model forecast at month 1 lead time

black = sentinel data

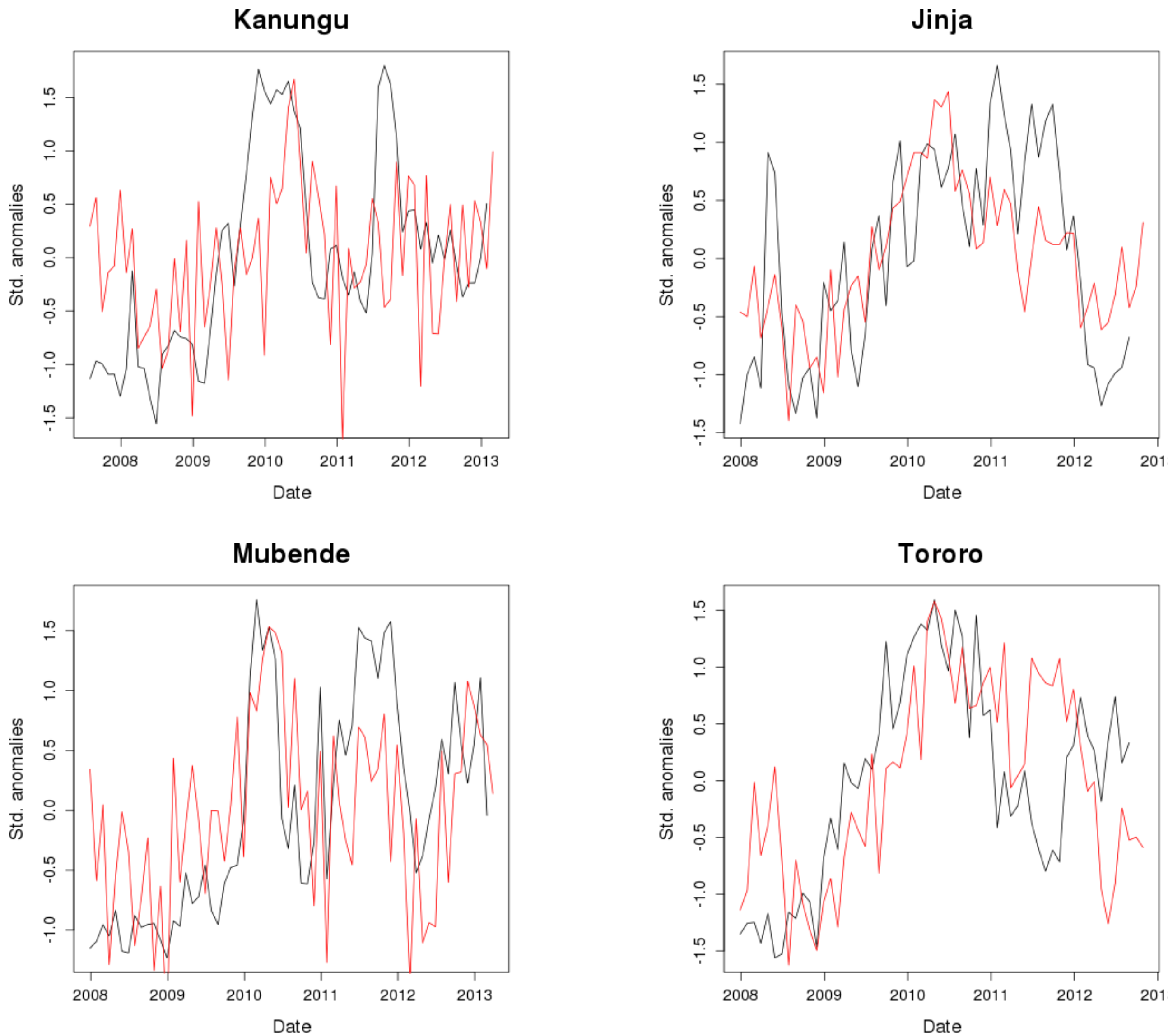


- Individual monthly predictions can be very wrong
- In some locations, model is out of phase by months

This is what the comparison looks like on a monthly timescale: lead 4

red=model forecast at month 4 lead time

black = sentinel data



- Individual monthly predictions can be very wrong
- In some locations, model is out of phase by months

Sample results again MoH district data

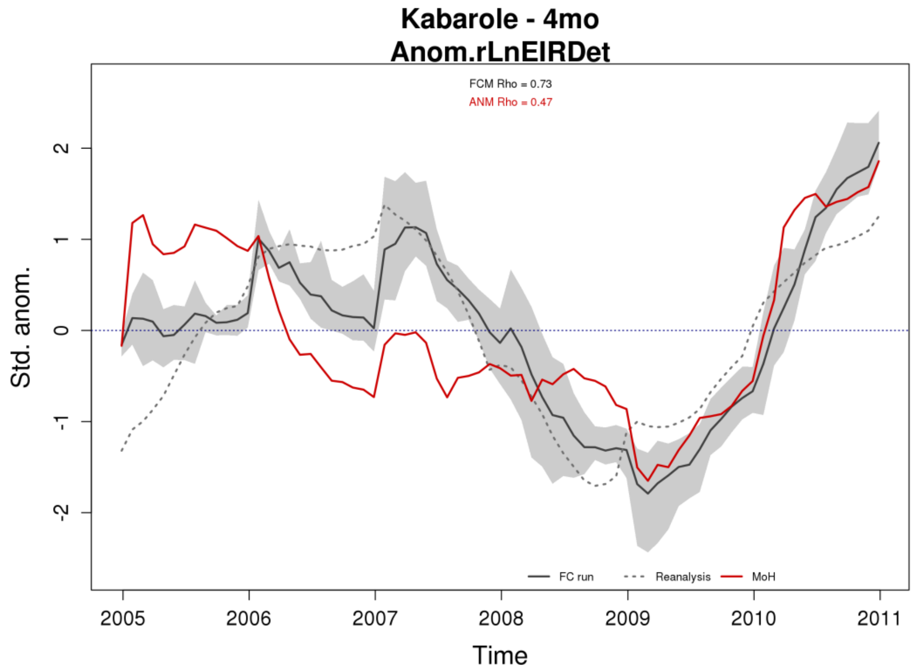
Red line: normalized **suspected** cases

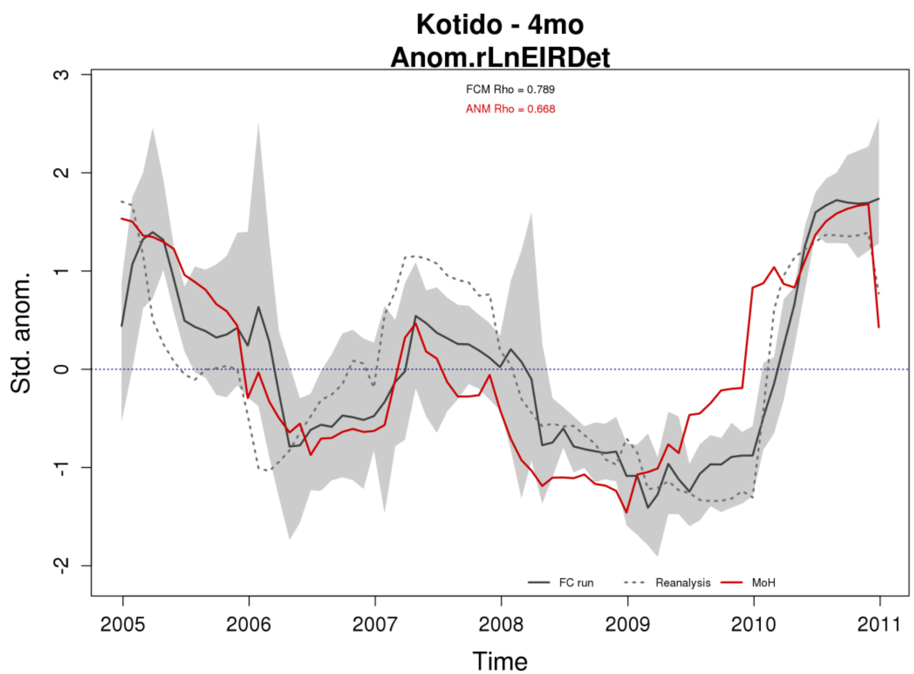
Black Line: normalized malaria forecast

Grey shading: **range** of the 5 forecasts

Dash lined: the malaria initial conditions

Four panels: the four levels of advance warning





In a number of districts there is no correlation

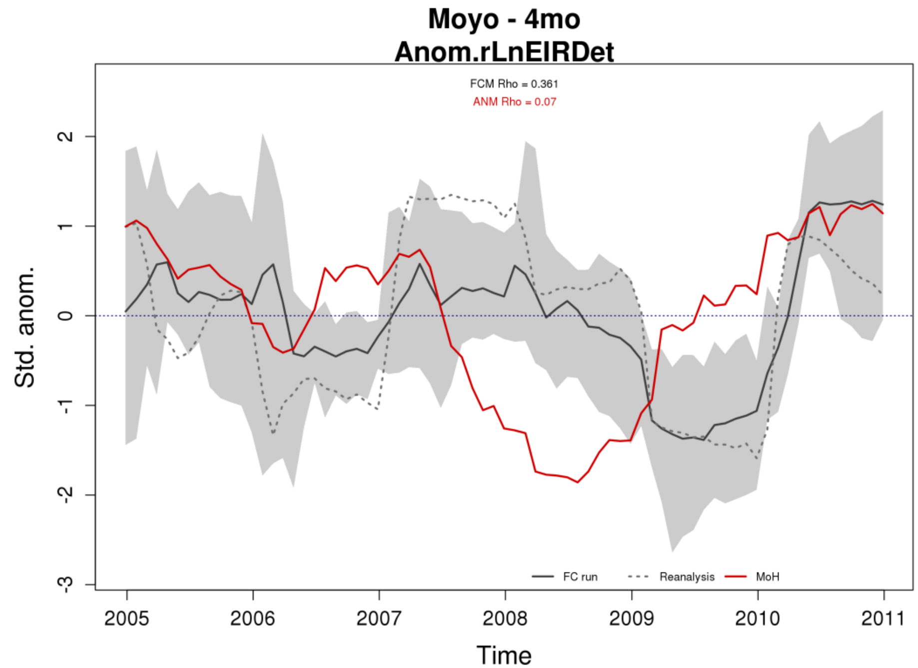
Red line: normalized **suspected** cases

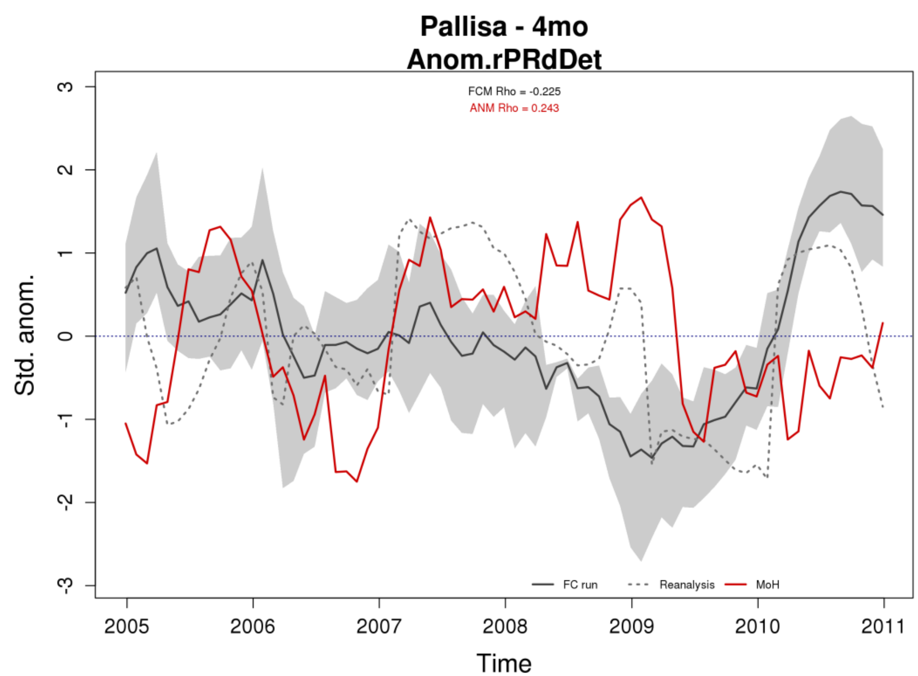
Black Line: normalized malaria forecast

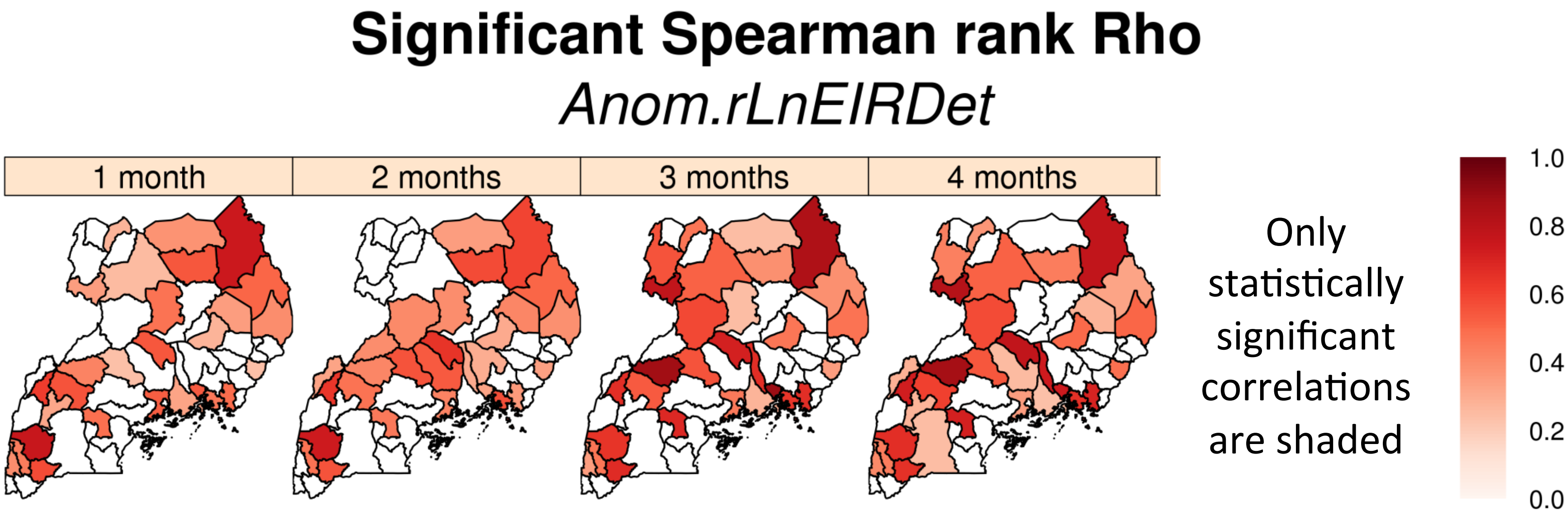
Grey shading: **range** of the 5 forecasts

Dash lined: the malaria initial conditions

Four panels: the four levels of advance warning

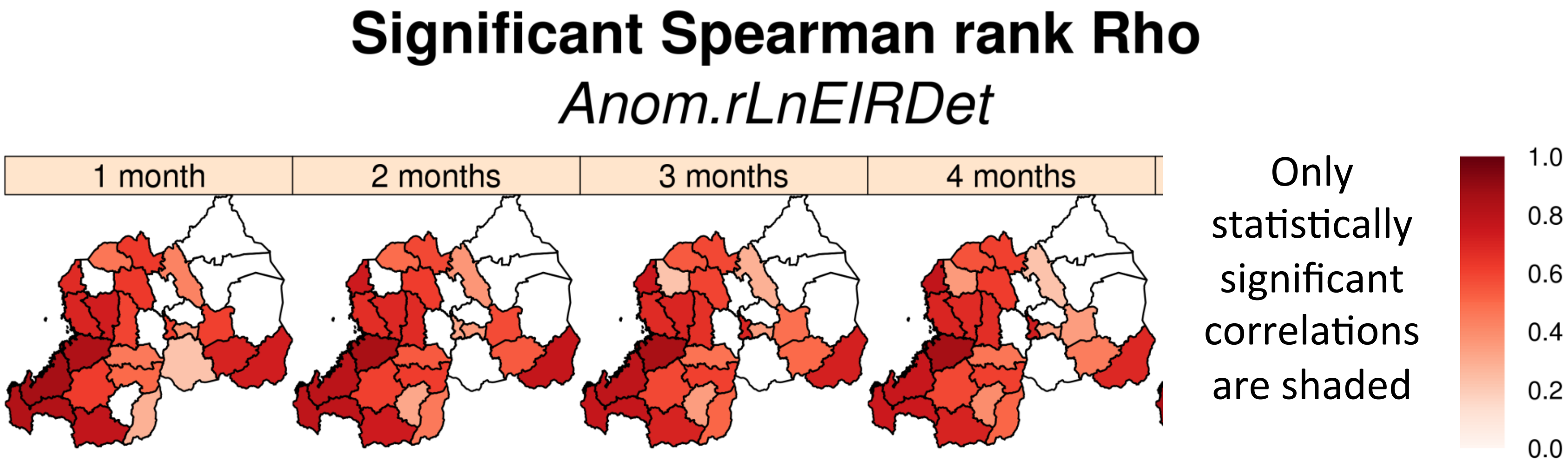






- Over half the districts have significant skill (95% level), despite uncertainties in the weather forecasting system, the malaria model and the health data

What about Rwanda?



The majority of the districts are also significantly skilful, although model performs less well in regions where transmission is higher (e.g. East)

Where are we?

- Pilot malaria forecast system produces forecasts at the district scale.
- Despite climate forecast, malaria model and health data uncertainties, statistical skill in Uganda in over half the districts four months in advance.
- ***Timeseries are heavily smoothed:***
  - ***Forecast system is skillful for year to year variability***
  - ***Monthly level predictions look a lot worse due to seasonality***
  - ***EOF-based district-level calibration for seasonality under development, based on Di Giuseppe et al. QJRMS 2013***
  - ***This is required for system to be used operationally***
- This is just the starting point!
  - Model and data will improve in time
  - More models added (LMM and EUROSIP)

Open Questions?

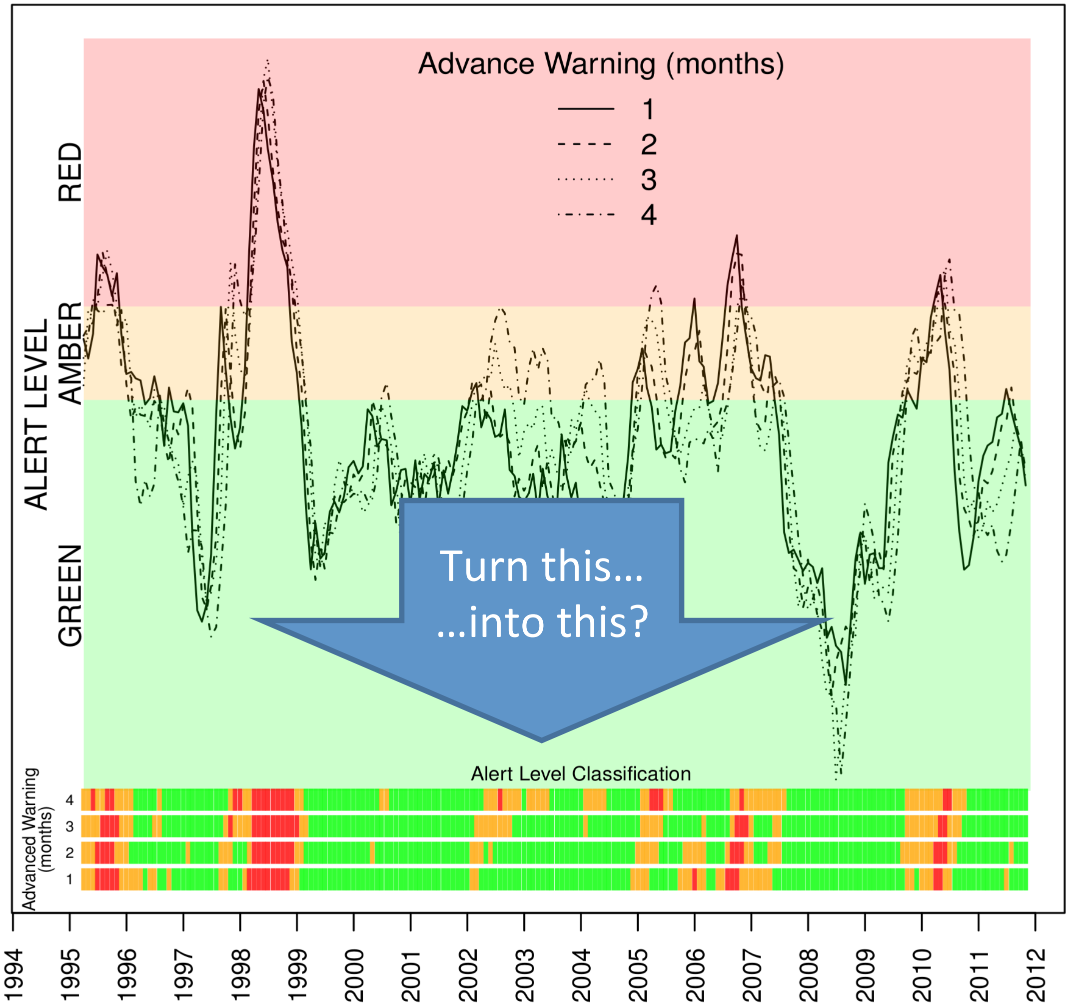
- ❑ How best to develop a usable system?
- ❑ How best to incorporate vulnerability assessments?
- ❑ Are four months adequate for key decision processes?
- ❑ What is the best format to provide information?

Clumsy attempt to boil down Forecast information

Does this really mean anything to anyone?

Do terciles relate to real health policy decisions? Doubtful…

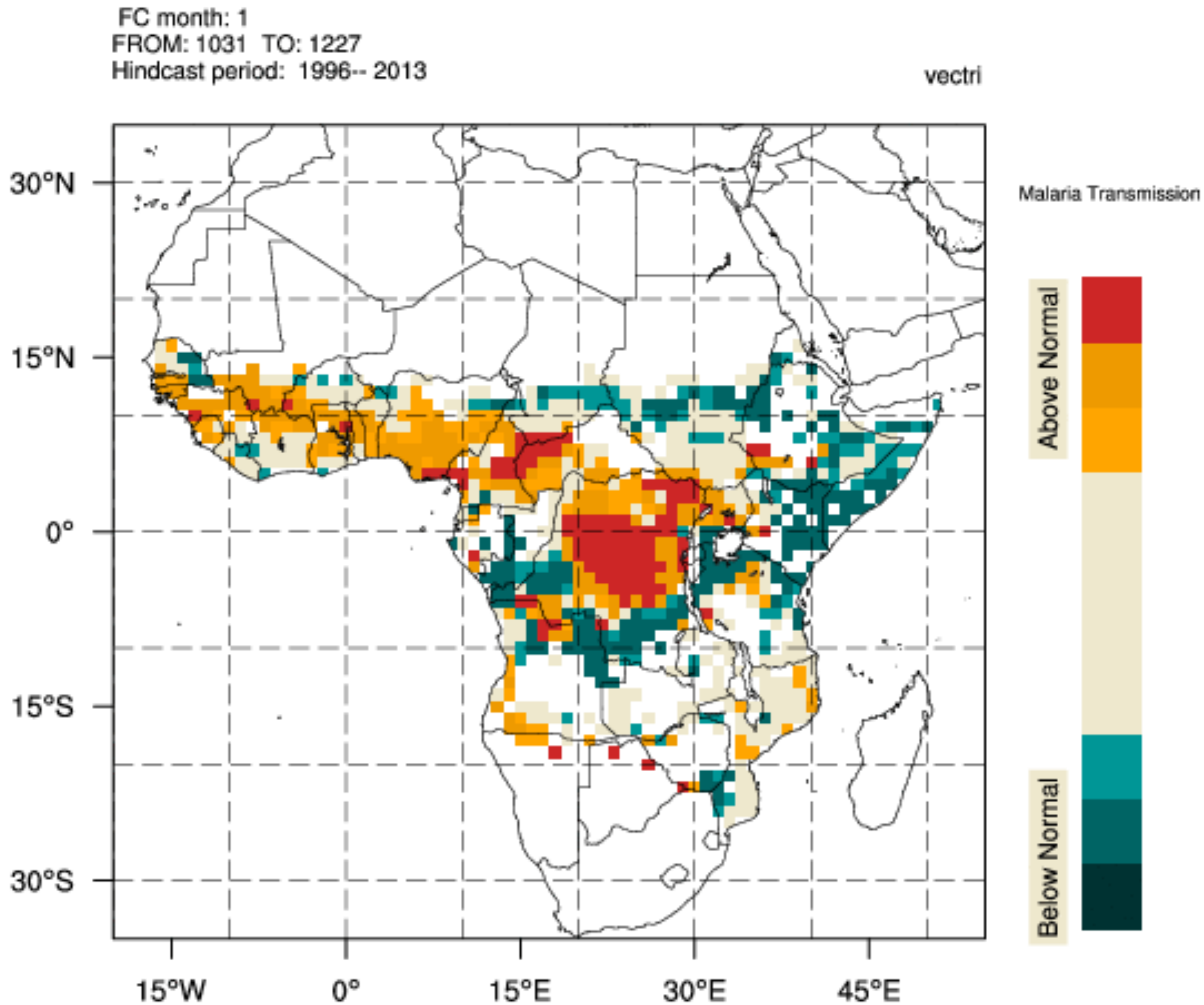
We are currently attempting to turn this into a realistic cost-loss analysis for Uganda



ICTP

Tercile-based online pilot

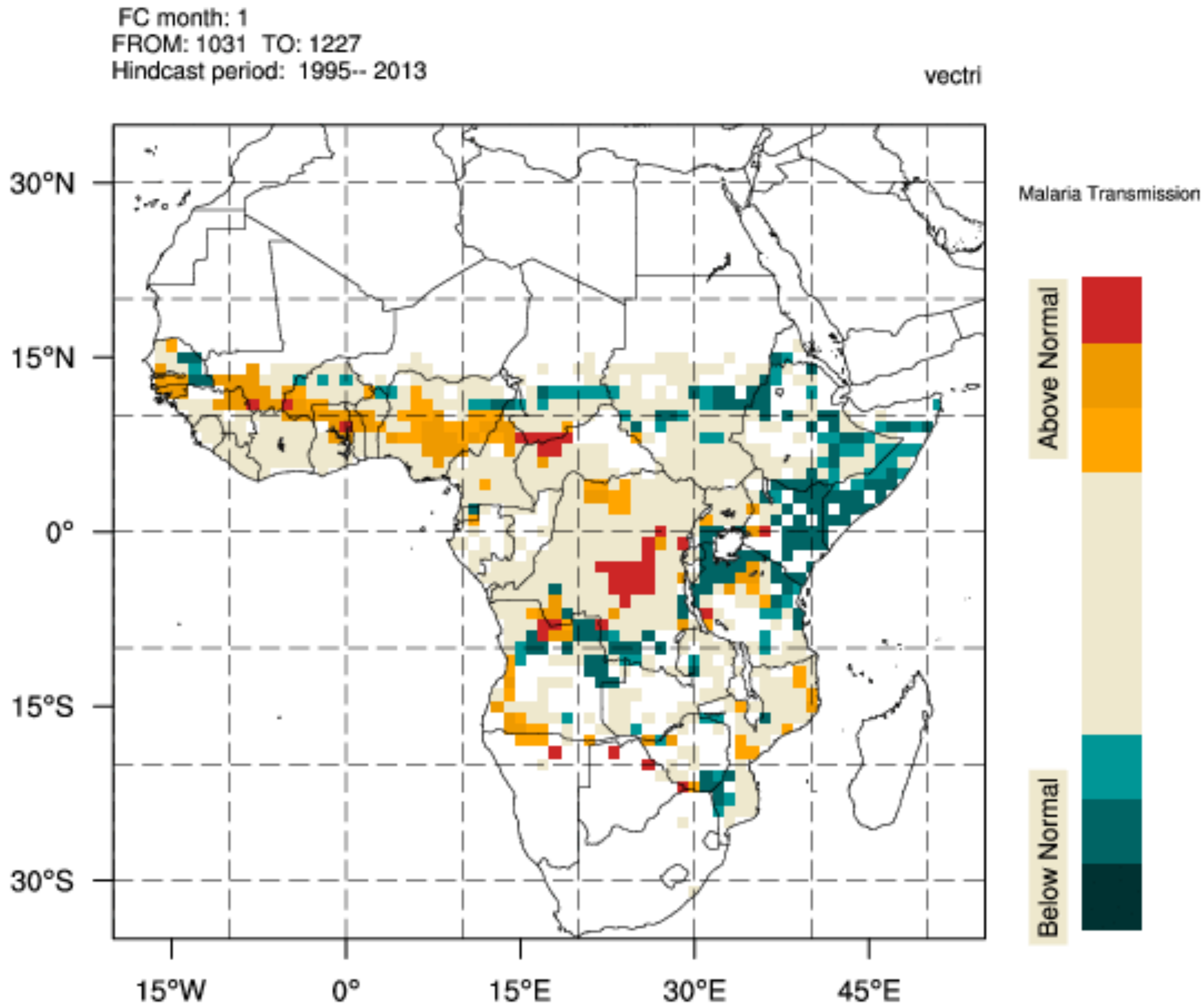
No masking for areas where climate is not a major driver



http://nwmstest.ecmwf.int/products/forecasts/d/inspect/catalog/research/qweci/malaria_fc/malaria_tercile!vectri!calibrated!Africa!unmasked!month4!20141030!/

Tercile-based online pilot

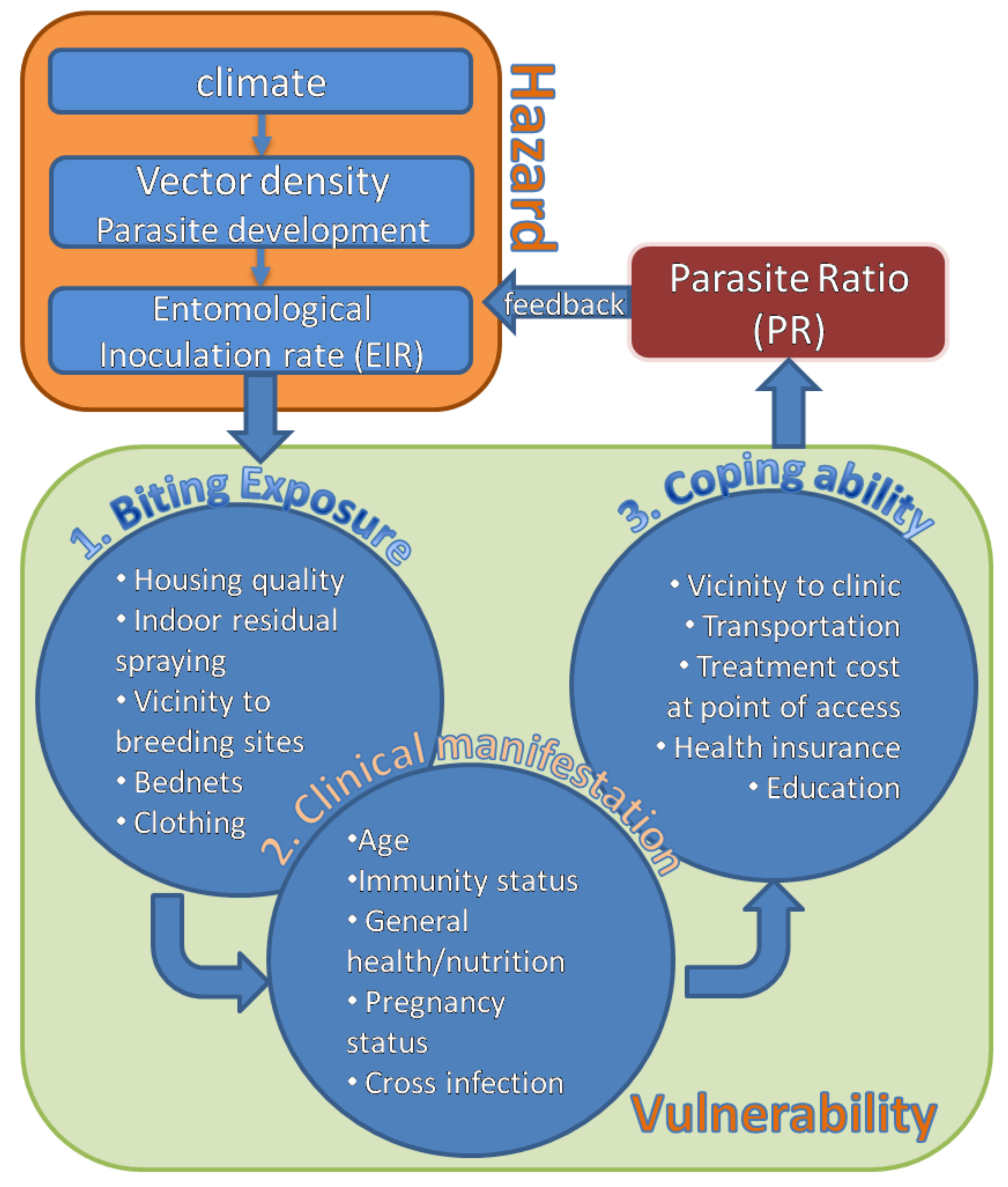
Masking for areas where climate is not a major driver



http://nwmstest.ecmwf.int/products/forecasts/d/inspect/catalog/research/qweci/malaria_fc/malaria_tercile!vectri!calibrated!Africa!unmasked!month4!20141030!/

Vulnerability mapping for intervention planning

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



ICTP

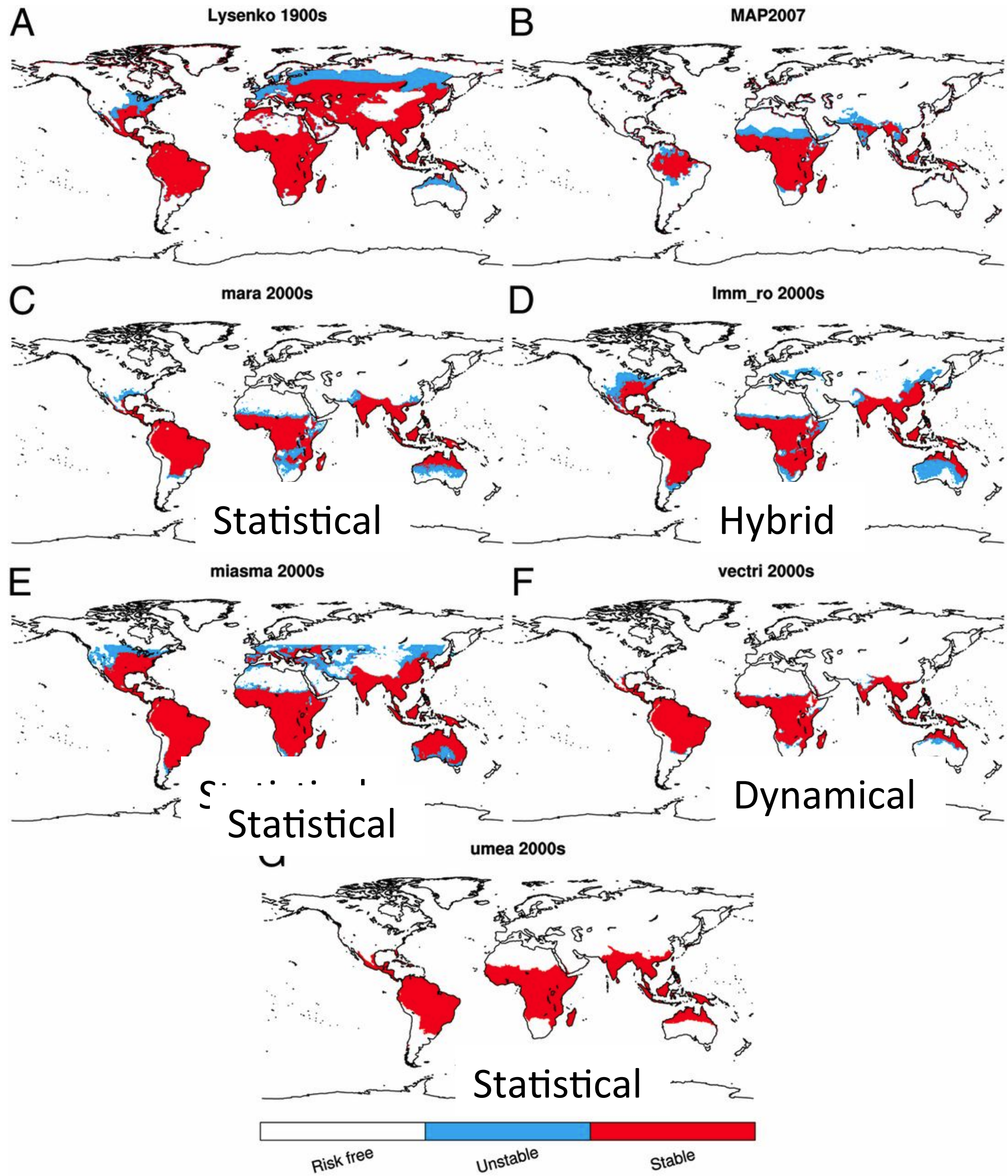
Summary

- ❑ VECTRI model for spatial simulations of malaria
  - open source available on gitlab.com
  - Key focus is on climate drivers of malaria
- ❑ No "fitting step - However, some parameters (particularly hydrology) are poorly constrained.
  - Potential for data assimilation? model fitting...
  - Data requirements? Which data to fit to spatially?
- ❑ A model is a tool...
  - Potential use for seasonal forecasting – post-FC calibration and/or parameter fitting still required.
  - Has also been used to understand potential impact of climate and environment on transmission
  - Key message is to assess uncertainty carefully...

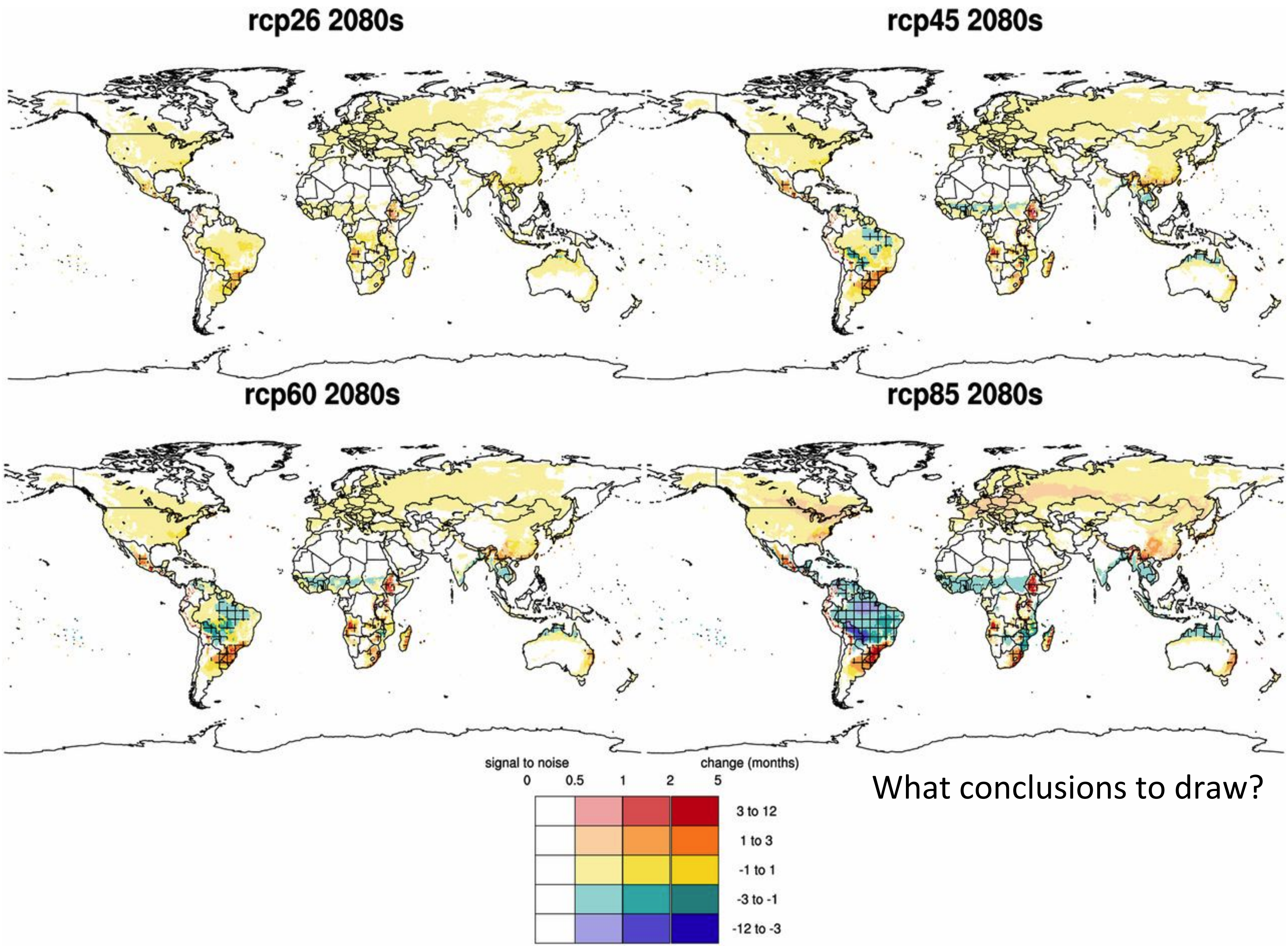
Climate change impact on malaria

ISIMIP – the first malaria model intercomparison

Caminade et al. 2014 (PNAS) – investigates impact of climate change on malaria transmission with multi-model ensemble



Large uncertainty due to malaria model



What conclusions to draw?

Extension within HEALTHY FUTURES

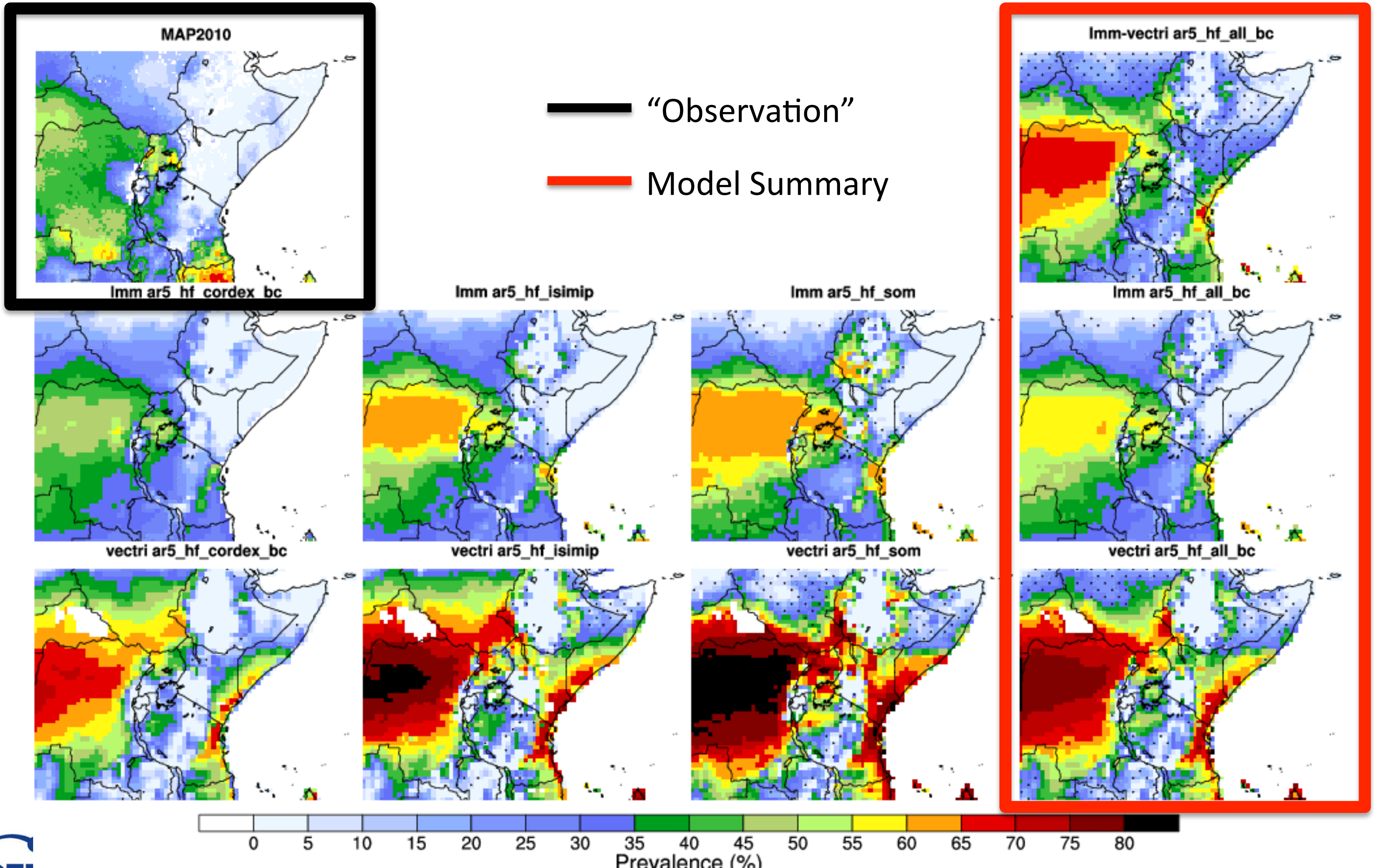
Environmental drivers: Temperature & Rainfall

Stream	No. of GCMs/ RCMs	Scenarios	Grid Size (°)	Timespan
SOM	10	rcp4p5, rcp8p5	0.5 x 0.5	1960-2099
ISI-MIP*	5	rcp2p6, rcp4p5 rcp6p0, rcp8p5	0.5 x 0.5	1951-2099
CORDEX	8	rcp4p5, rcp8p5	0.44 x 0.44	1951-2100

- Comparable: grid, scenarios, timespan (1980-2099)
- LMM/VECTRI: 46 simulations

slide from Joe Leedale (Liverpool)

LMM & VECTRI evaluation – Pr. & MAP$_{2010}$



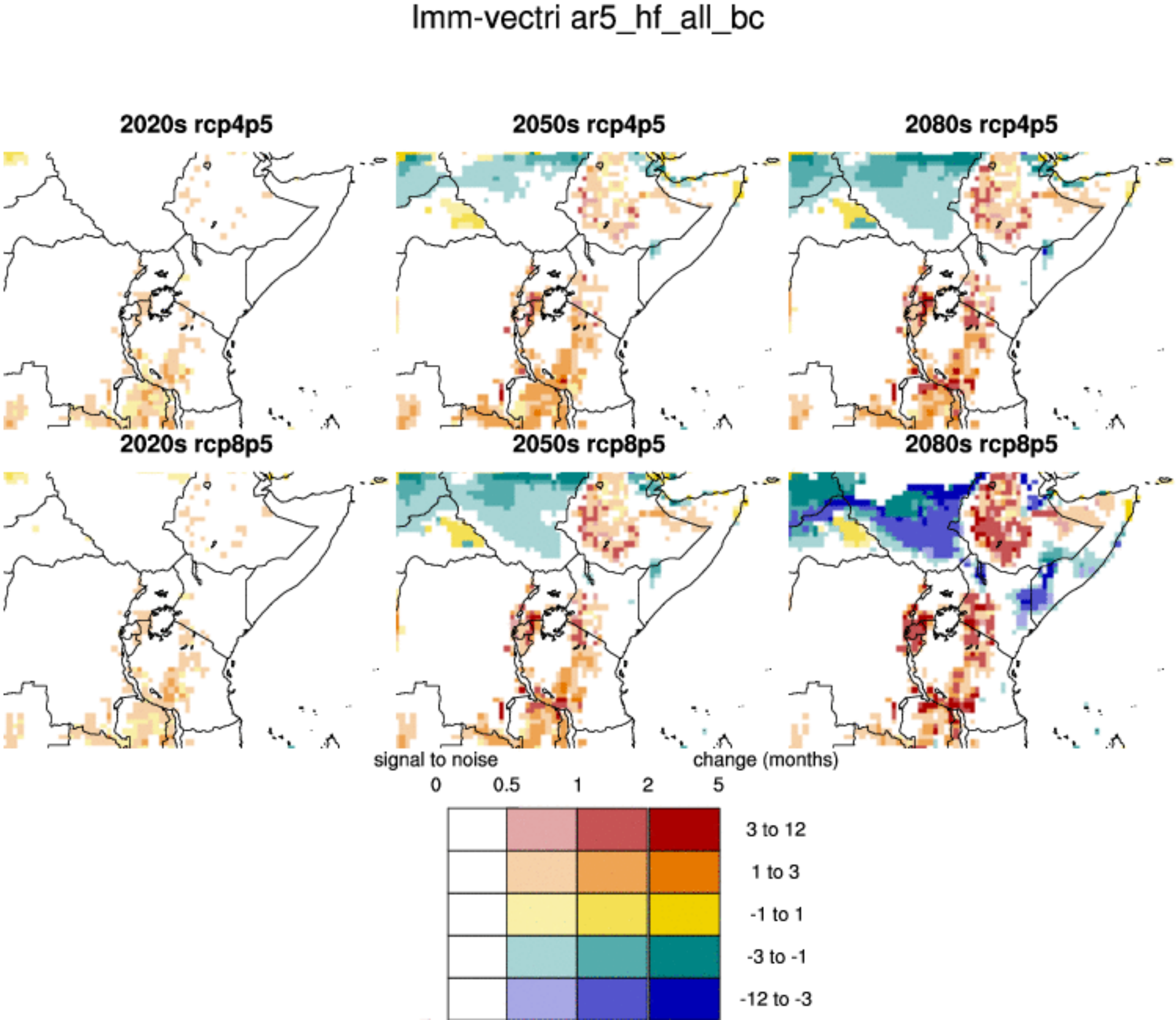
LMM prevalence saturates at 75%. VECTRI model more "binary"

LMM-VECTRI results – Future Scenarios (LTS)

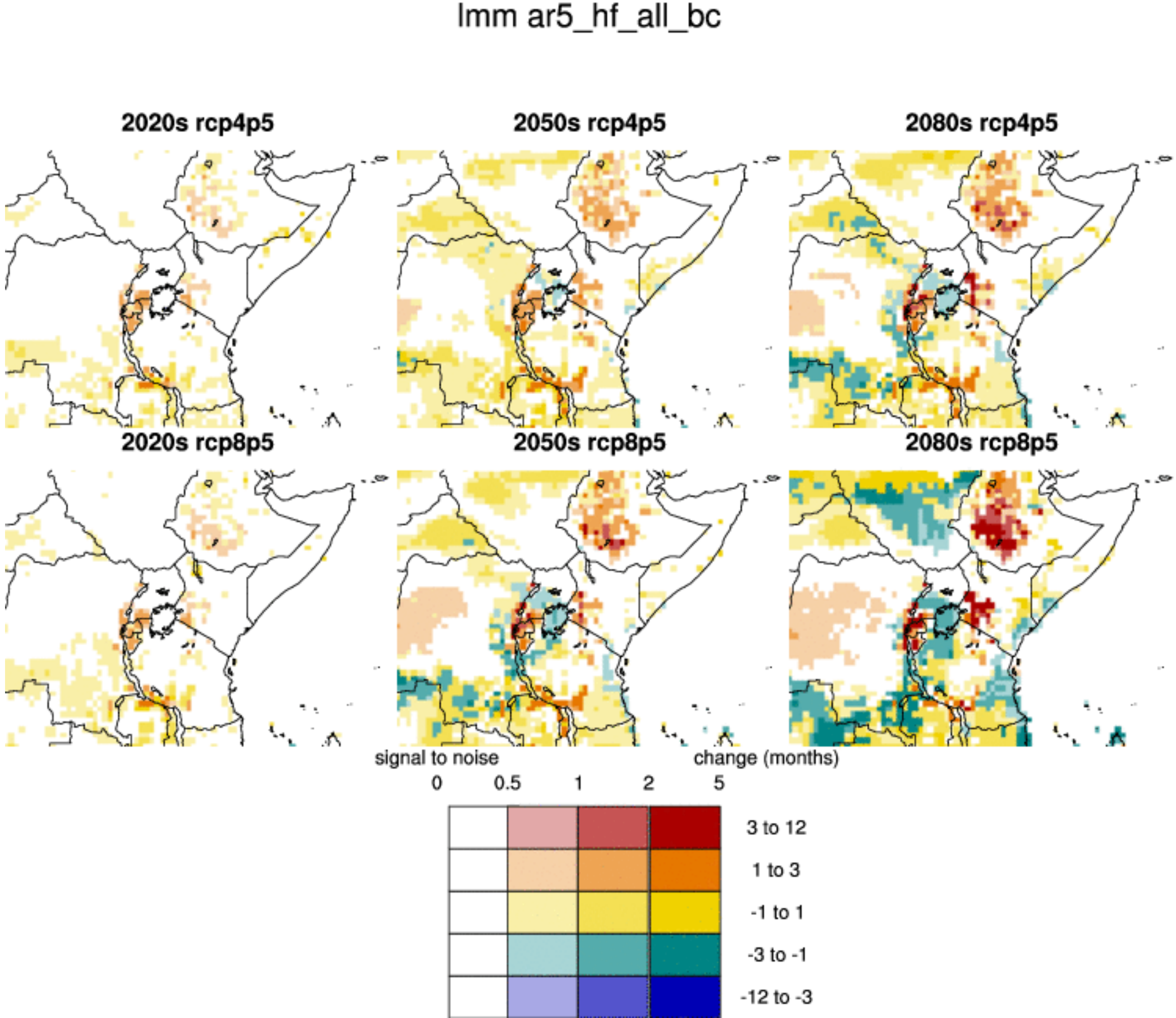
Mostly temperature driven signal

Malaria moves to higher altitudes

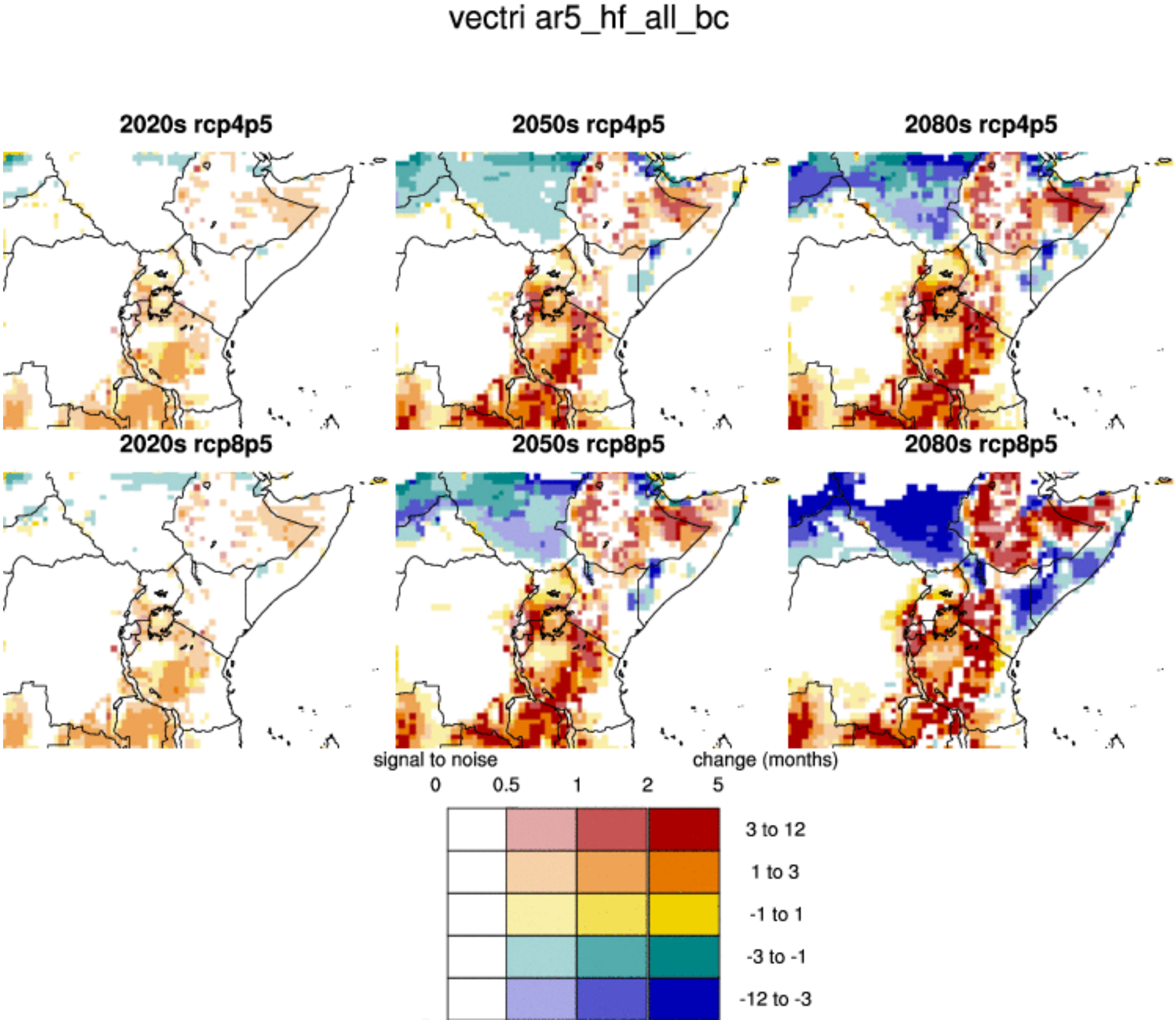
Requires representati of human migration in a dynamical model



LMM results – Future Scenarios (LTS)



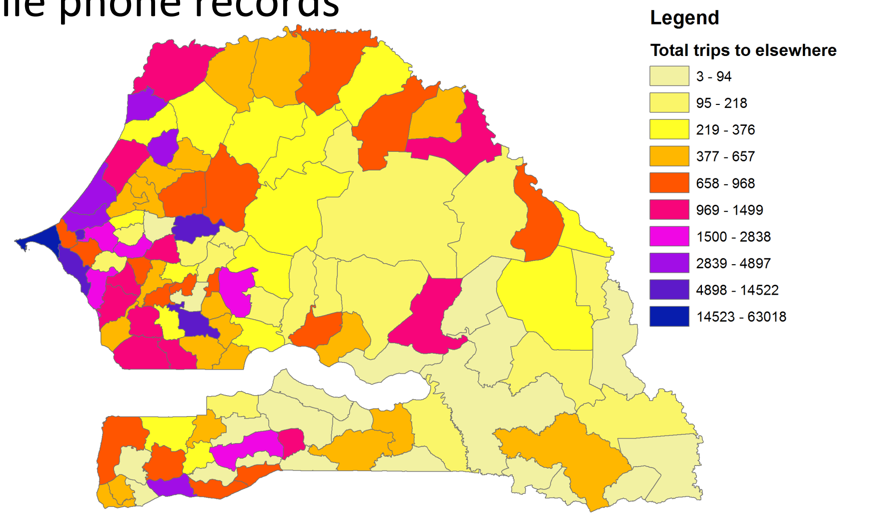
VECTRI results – Future Scenarios (LTS)



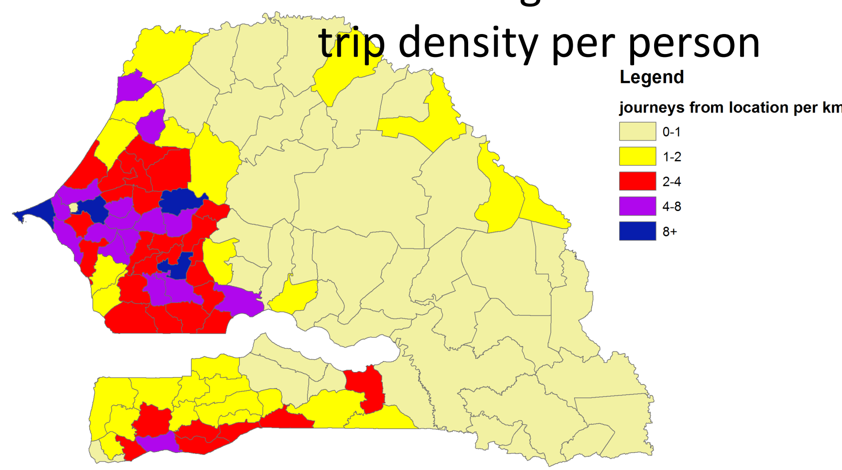
Upcoming developments after v1.3.4

- ❑ rewrite for parallel code
- ❑ Improvements in surface hydrology
- ❑ Simple immunity model v1.4.0
- ❑ Interventions? Potentially by coupling to OPENMALARIA in a two-stage modelling process.
- ❑ Population migration by coupling to agent-based population model WISDOM

total trips to elsewhere, from ~20K mobile phone records



WISDOM v1.0 beta
3 million agents
trip density per person



ICTP

2. Direct Impacts of LUC on malaria

(deliverable for EUFP7 HEALTHY FUTURES project)

- LUC "direct" impacts:
  - Increased pooling sites in disturbed land (farms, mines…)
  - Greater incidence of sunlight due to canopy and vegetation reduction, higher occupancy by key vectors
  - Closer vector-host contact
  - Reduced vulnerability of population due to socio-economic development from LUC ("paddies paradox")
  - While there have been attempts to quantify some of the above in field studies (e.g. Mungu et al.2009 and others, Ijumba and Lindsay, 2001) they remain poorly understood and **qualitative**.
- LUC "indirect" impact via climate...

Indirect impacts of LUC of malaria

- Indirect effect:
  LUC -> climate -> disease transmission
- Examples: Lindblade et al. 2000 (Uganda), Mungu et al. 2005 (Kenya), Afrane et al. 2008 Kenya) all cite LUC leading to higher temperatures and increasing transmission hazard
- Small sample studies come with caveats!

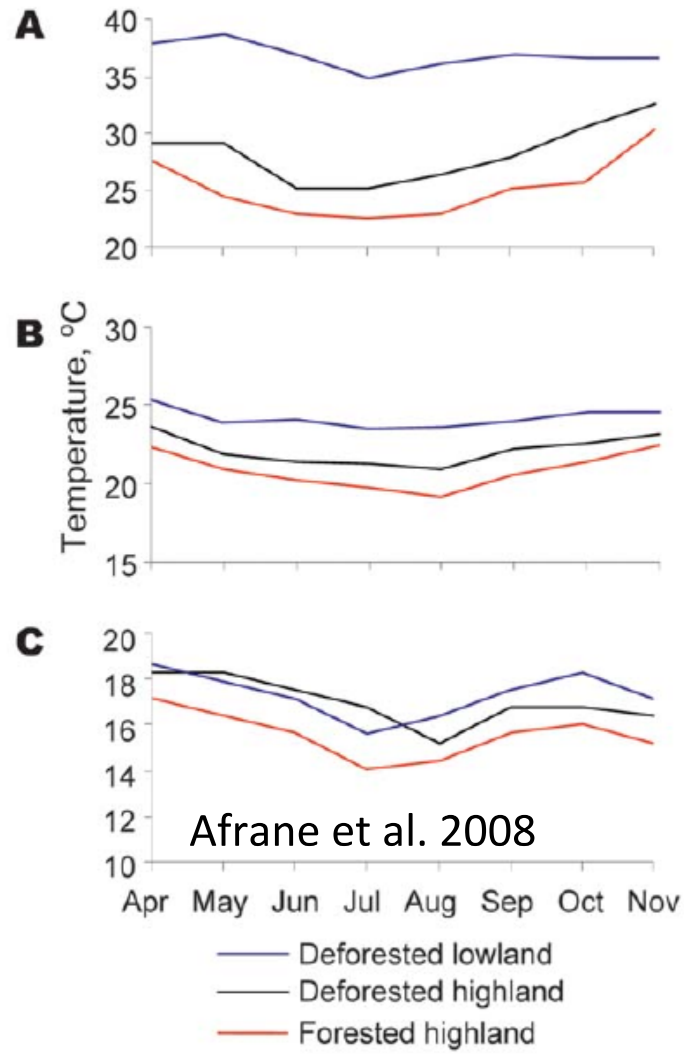
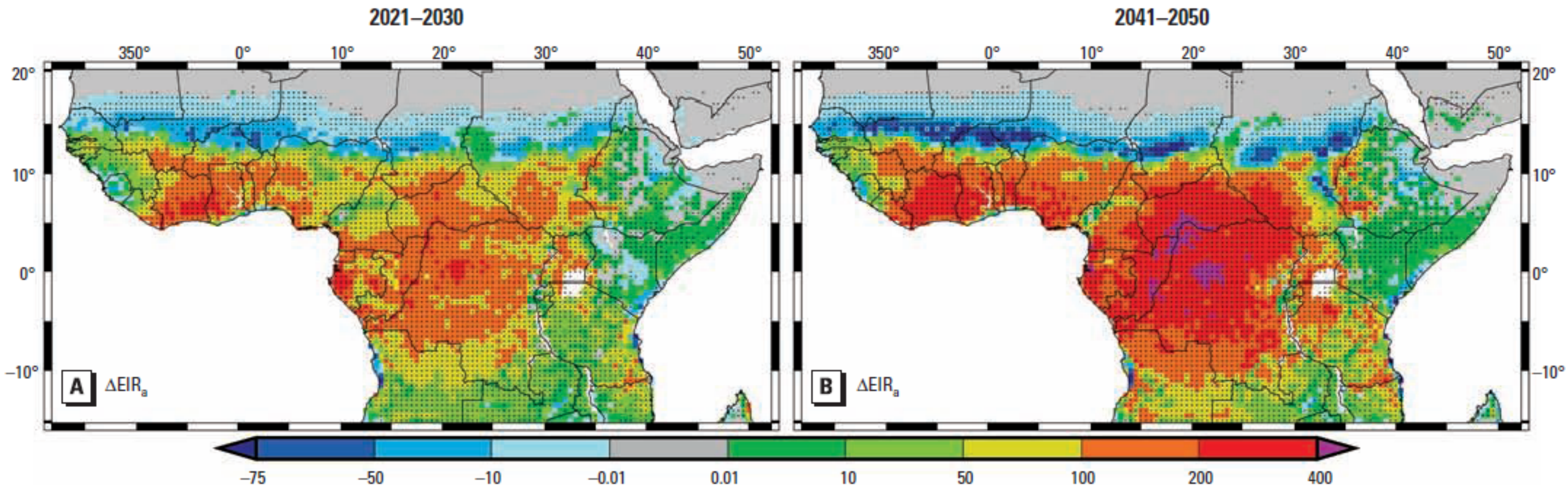


Figure 1. Monthly average value of daily maximum (A), mean (B), and minimum (C) indoor temperatures in forested and deforested areas in western Kenyan highland (Kakamega) and deforested lowland (Kisian), April–November 2005.

LUC indirect impact on malaria

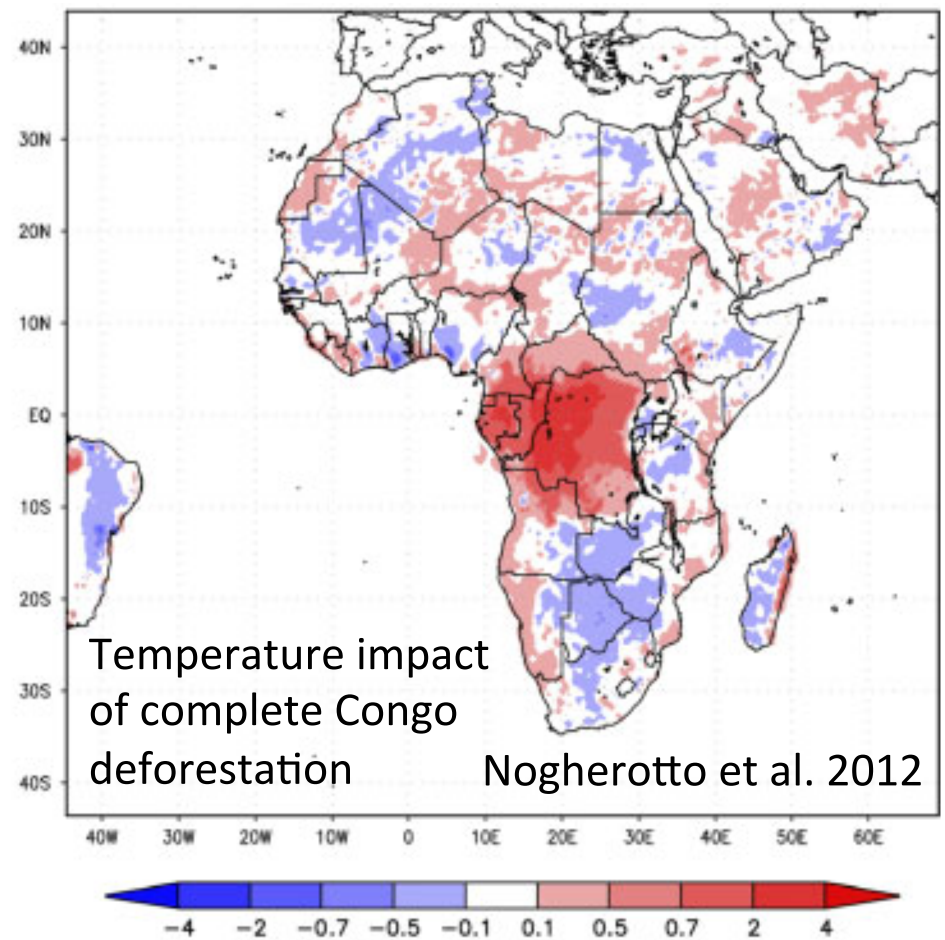


- ❑ Ermert et al. 2012 used a regional climate model to study climate and LUC impact on malaria.
- ❑ Uncertainty Caveats:
  - Use of a single climate model
  - No separation of climate from LUC impact
- ❑ Aim here: to further this work using a climate model ensemble with and without LUC to isolate its impact

ICTP

LUC impact on climate

- Large samples of studies from 1990-present that demonstrate significant (non) local impact of LUC (often deforestation) on temperature and rainfall, both globally and regionally.
- Often strong disagreement between models even for a particular region
- Many studies idealized: step-function complete deforestation



Land use change in CMIP5

- The IPCC 5th assessment report included an optional experiment to investigate anthropogenic LUC impact on climate
- RCP2p6 and RCP8p5
- Limited ensemble sizes from 1 to 3 members

Complex chain to GCM

Impact Assessment Models
rcp2p6 4p5 6p0 8p5

Anthropogenic LUC conversions

HYDE 3.1 model

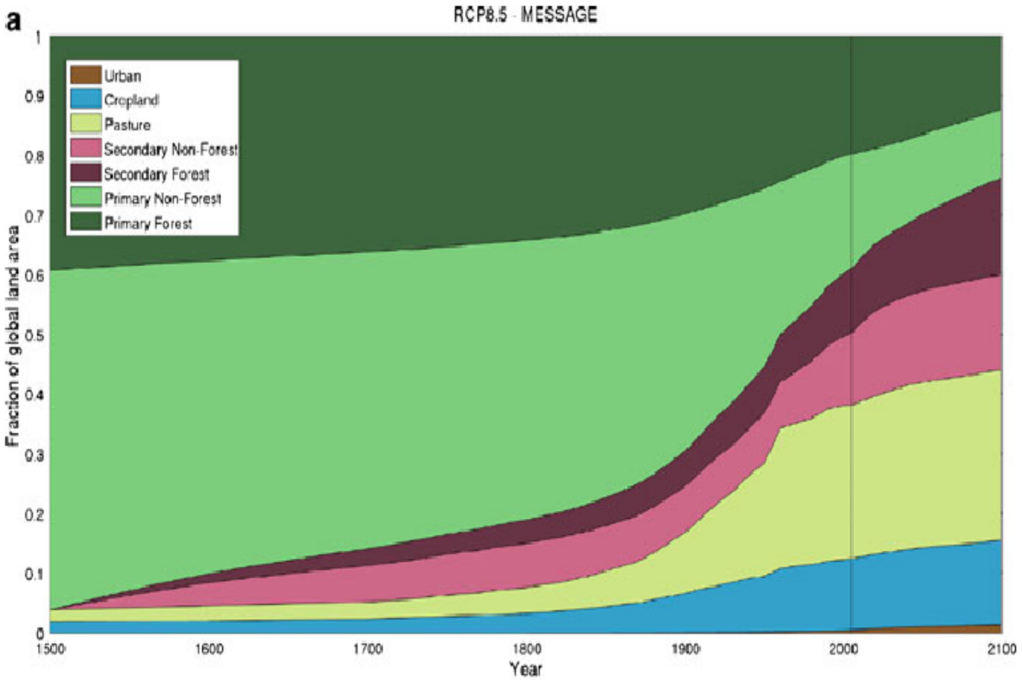
5 broad LU classes

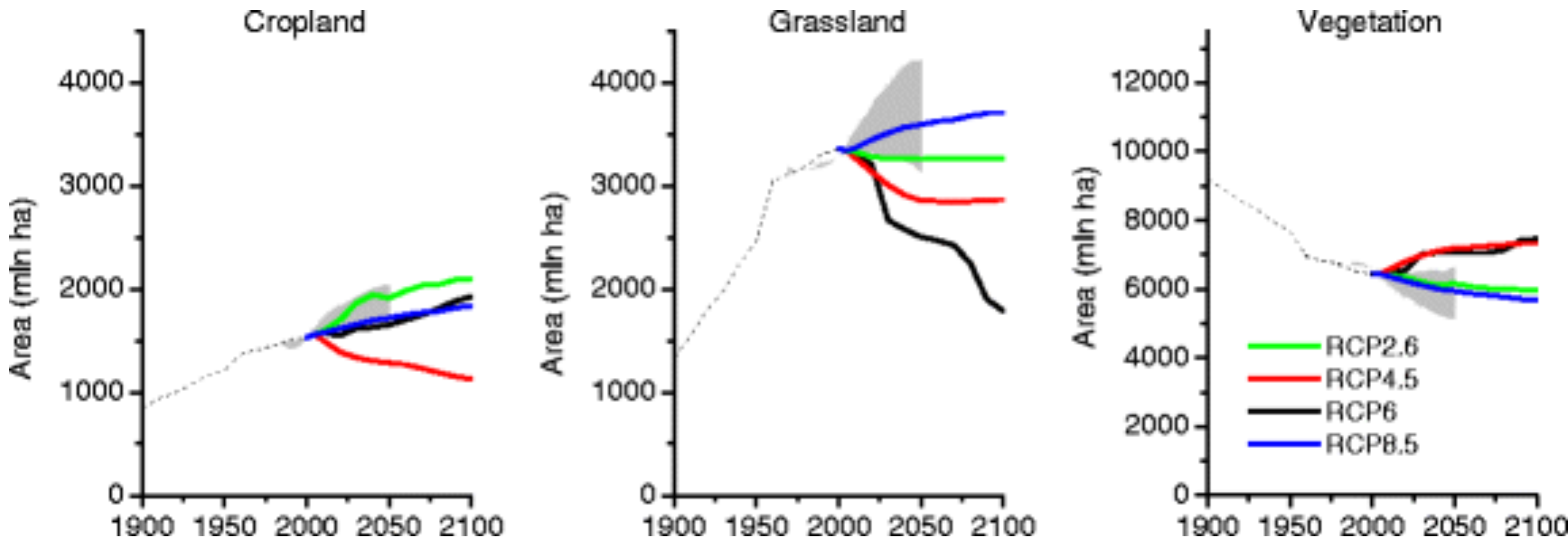
Land surface models:
CTEM, Orchidee, SEIB-DGVM, JSBACH, MOSES+TRIFFID

N PFT classes. Offline, complicated for dynamic vegetation model

Climate Models: IPSL(1), MPI(2), MIROC(1), CanESM (3), (HADGEM missing)

- RCP2p6 and 8p5 are surprisingly similar due to high use of biofuels needed to respect 2p6 Wm^{-2}

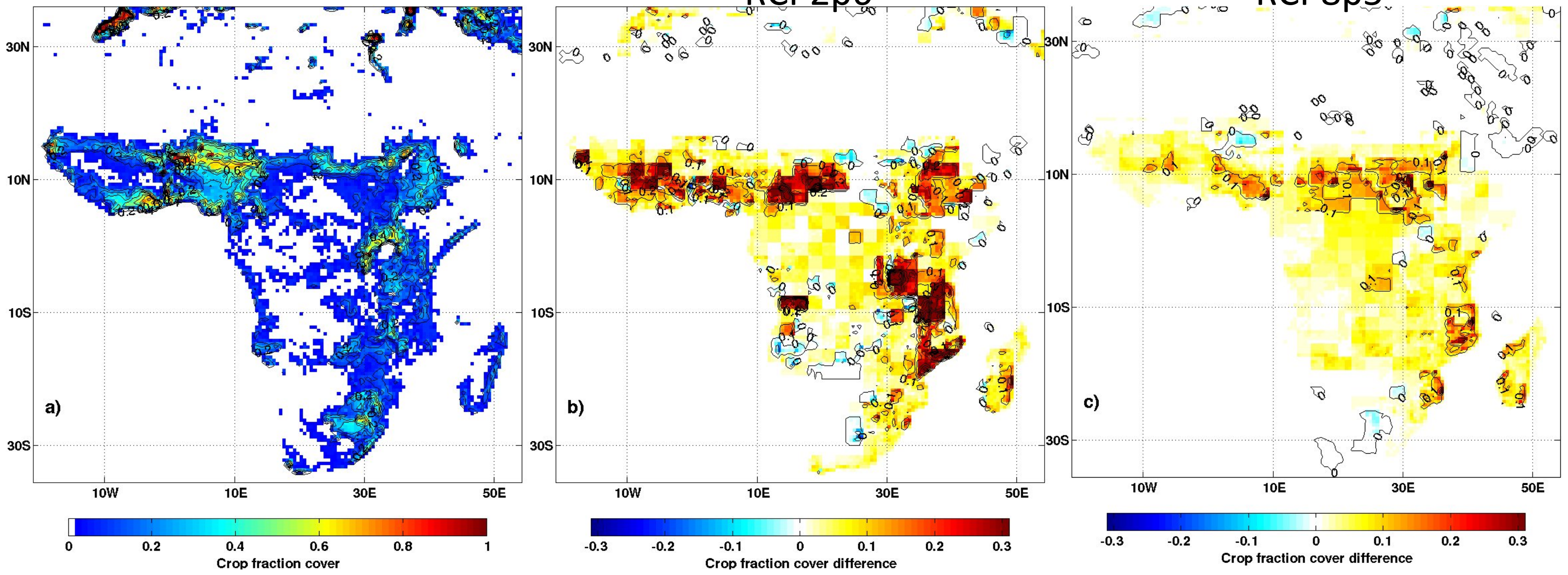




2. LUC example example (using CLM)

RCP2p6 actually has one of the greatest deforestation rates due to high use of biofuels.

RCP2p6 RCP8p5



LUC impact on T2m

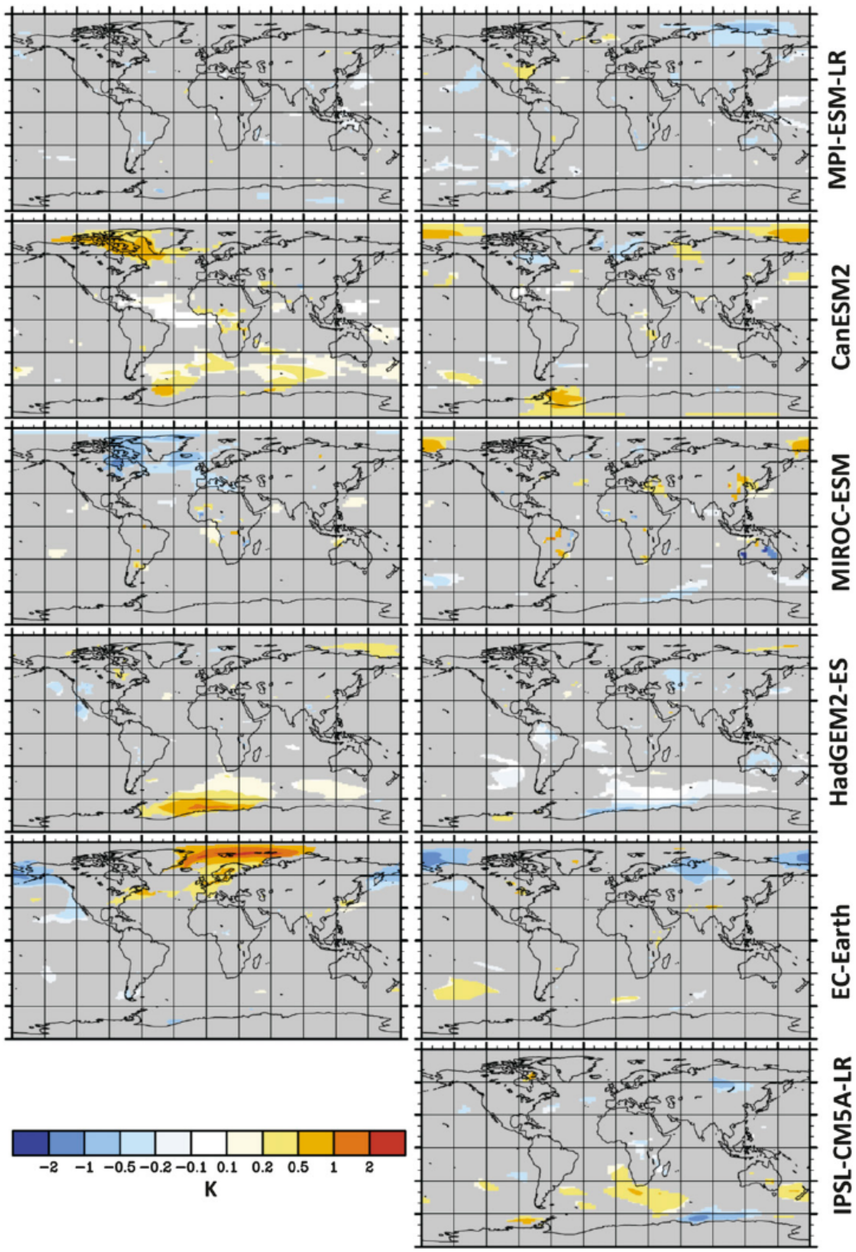
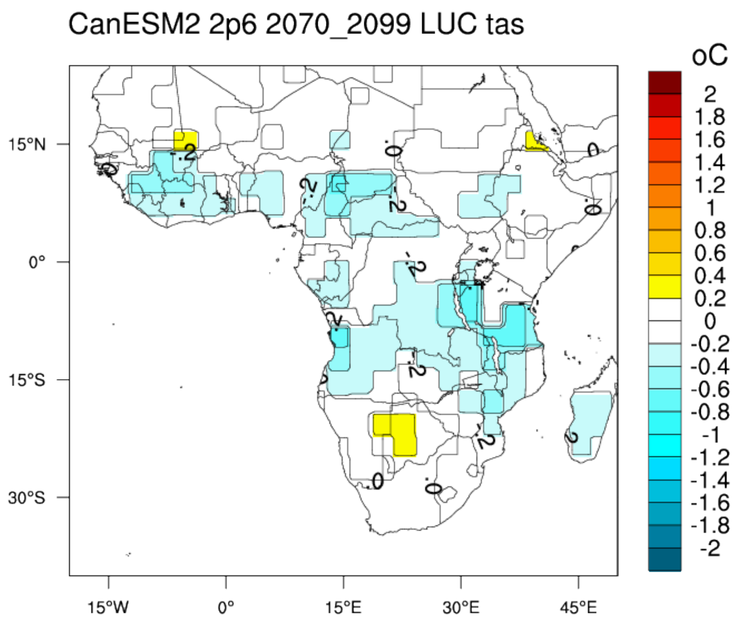
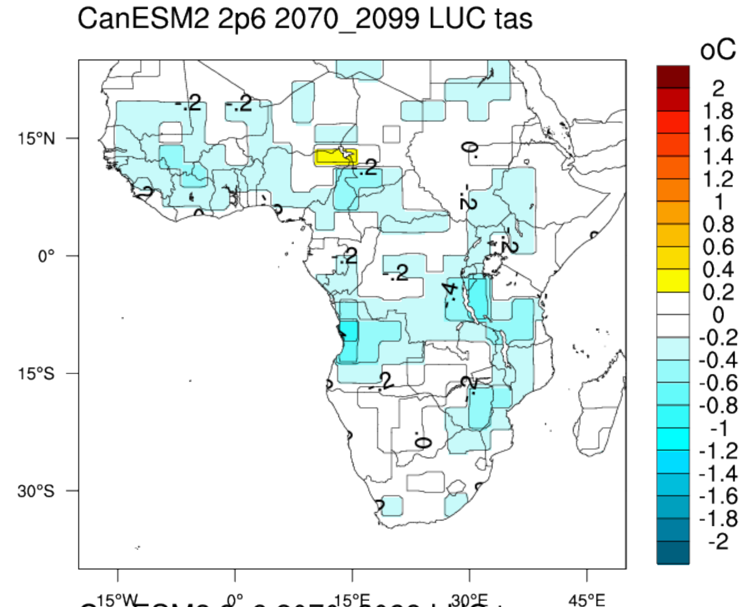


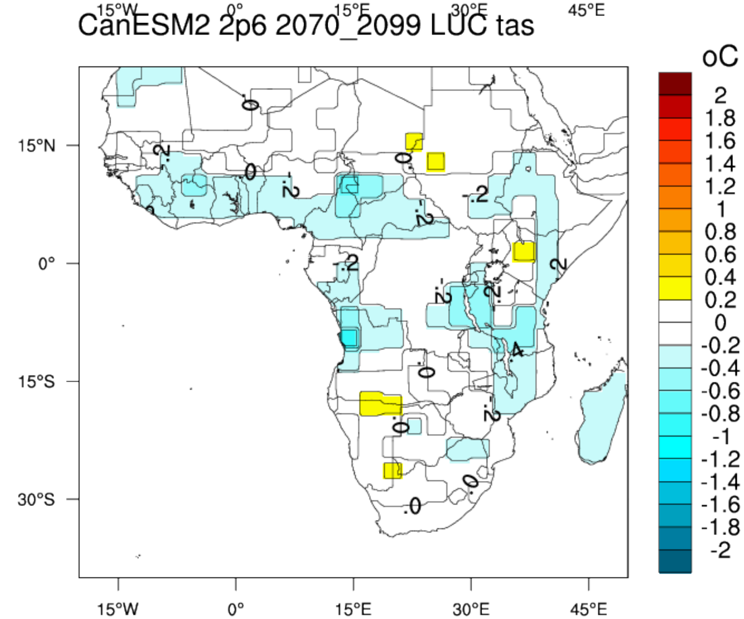
FIG. 5. Maps of difference in mean annual near-surface air temperature (K) between ensemble averages of the (top)–(bottom) RCP and LUCID simulations for (left) RCP2.6 and (right) RCP8.5 scenarios. The differences are averaged for years 2071–2100; only statistically significant changes ($p < 0.05$) are plotted.

- Brovkin et al. (2012) almost no impact on temperature is apparent, but:
  - 30 years is too short for small ensemble sizes (1-3), would sample multi-decadal variability.
  - Statistical significance testing appears possibly flawed (awaiting email follow up from author on how this was conducted with one member).

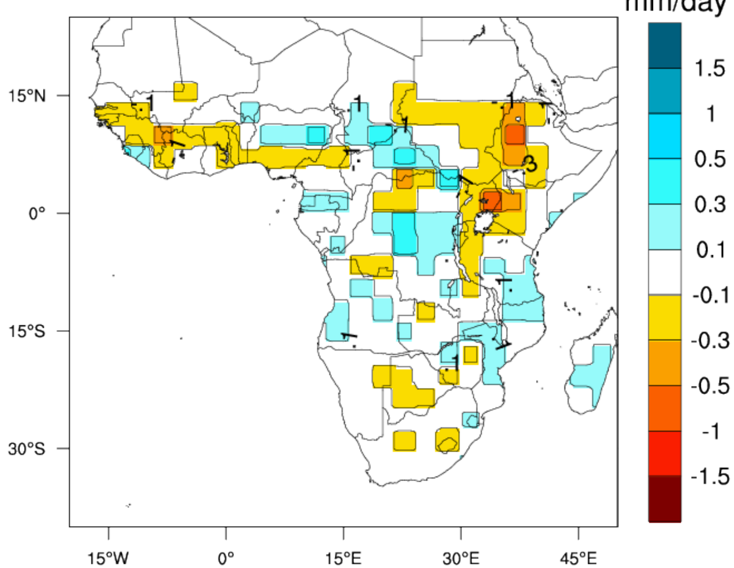
2070-2099 temperature – 3 member ensemble



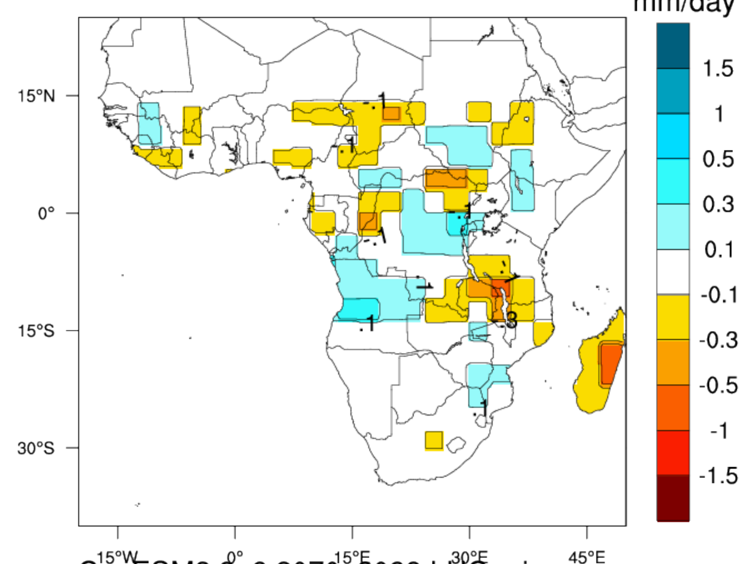




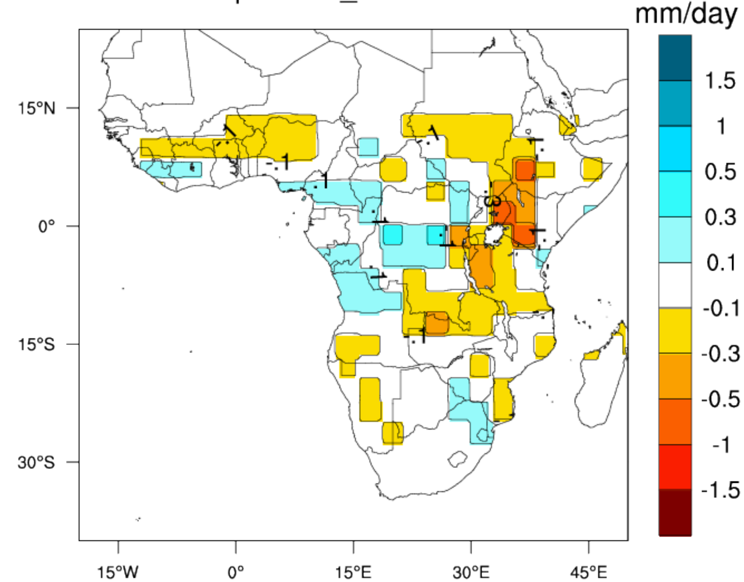
CanESM2 2p6 2070_2099 LUC rain



CanESM2 2p6 2070_2099 LUC rain



CanESM2 2p6 2070_2099 LUC rain



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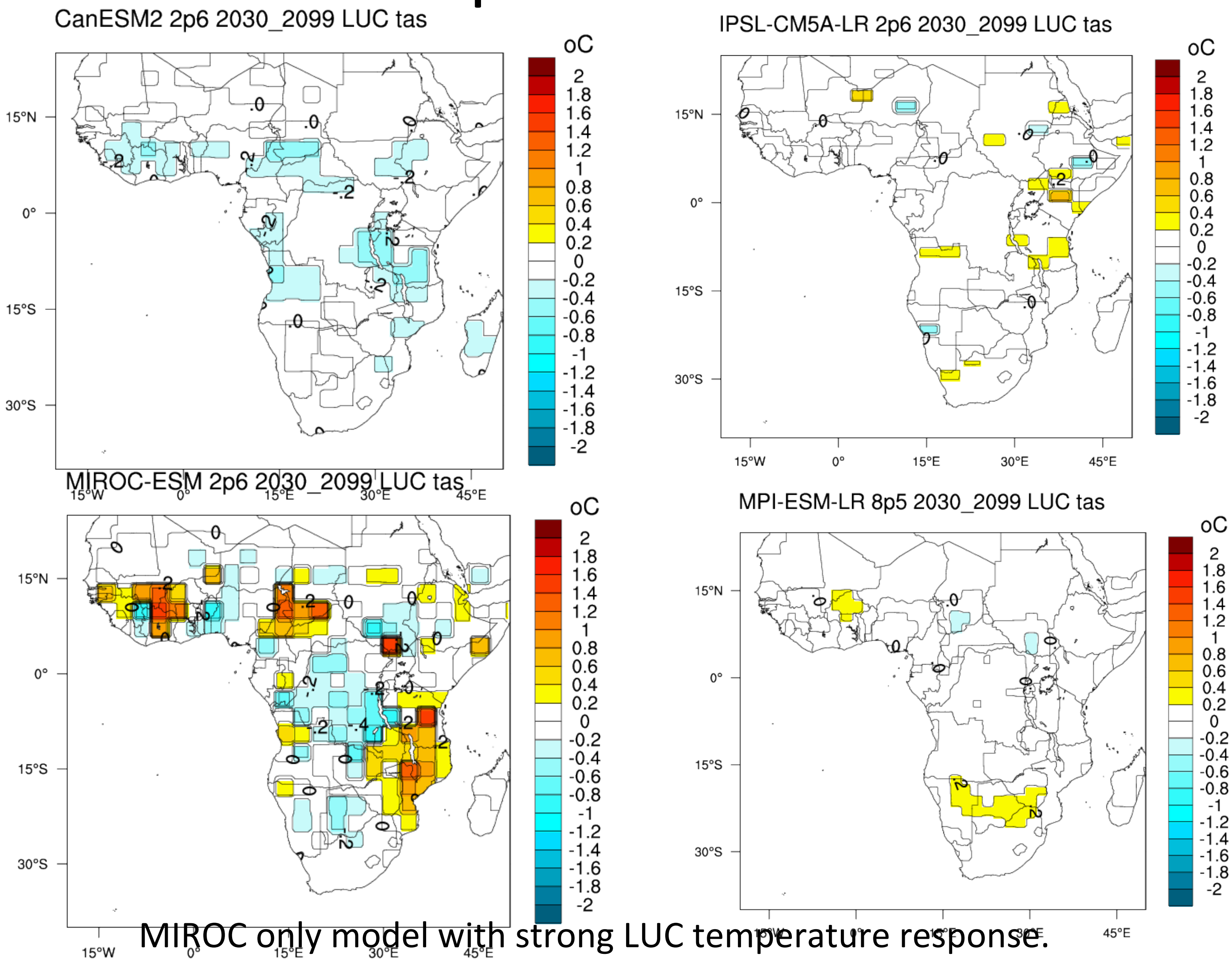
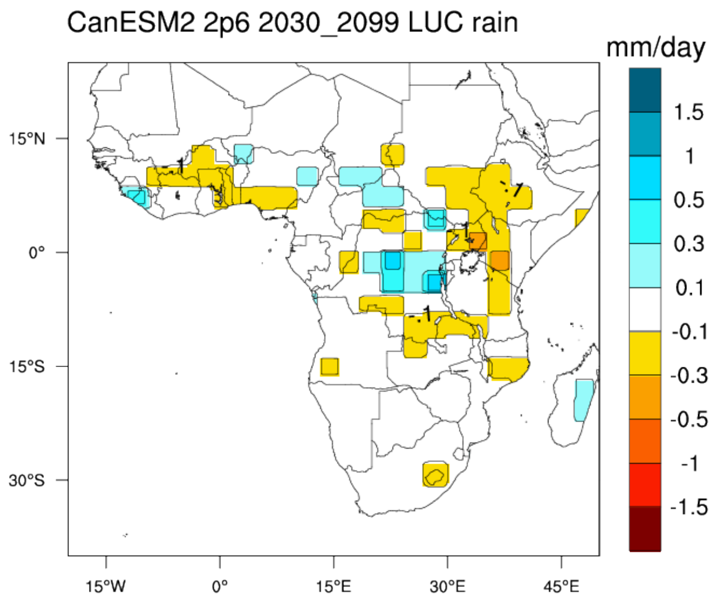
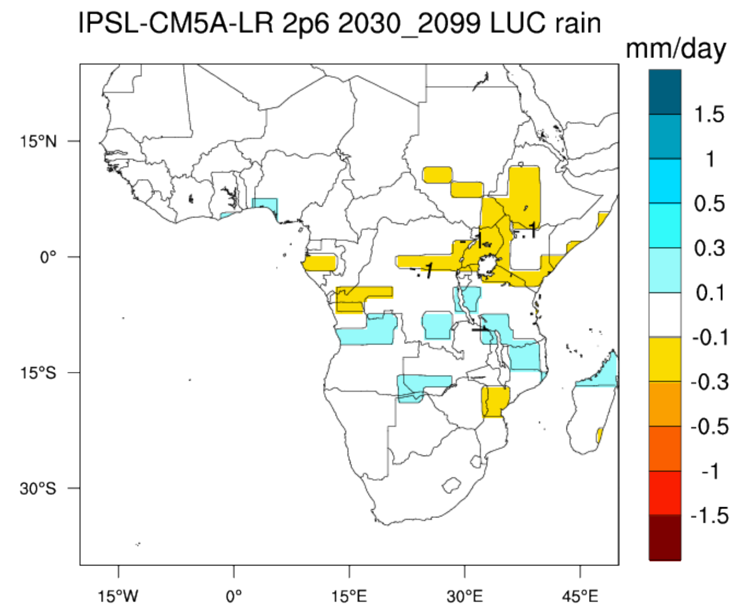
70 year averages: rcp2p6 Temperature impact of LUC

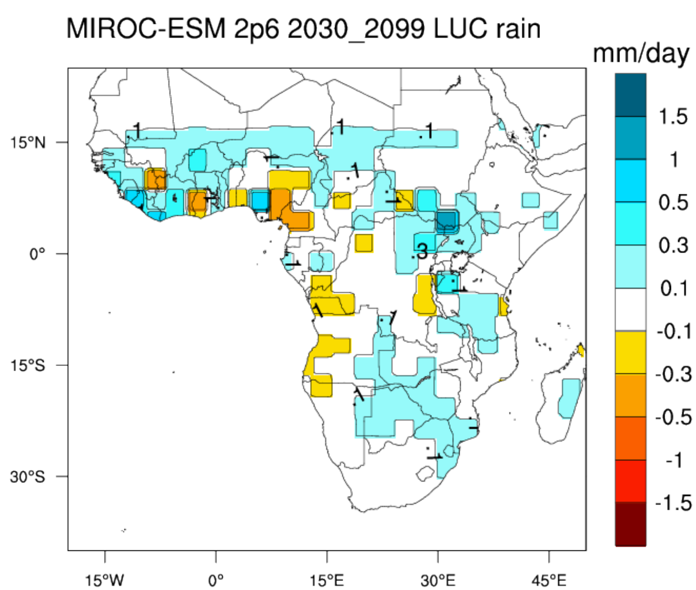


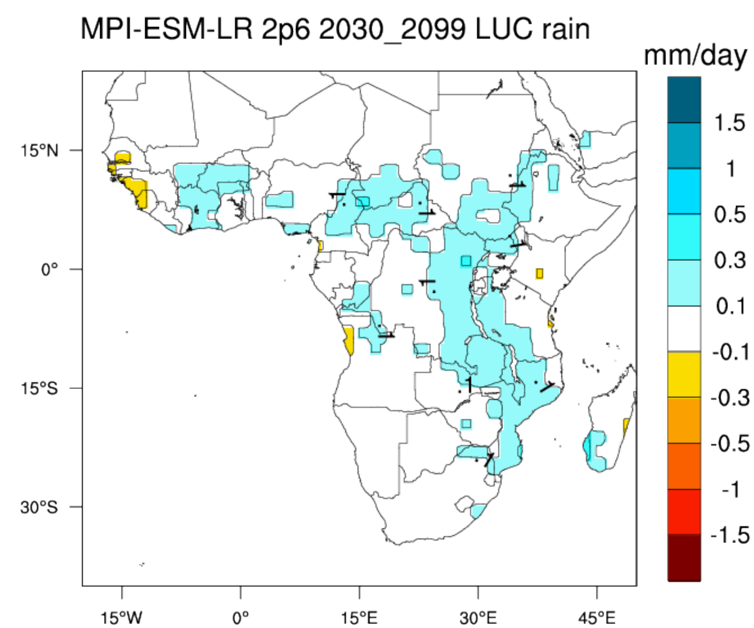
MIROC only model with strong LUC temperature response.

70 year averages: Precipitation









ICTP

Experimental set up

- 4 climate models, 2 RCPs, with/without LUC
- Simple bias correction of T2m using ERAI (1979-2005) or CRU (1960-2005) against “historical” run.
- Temperature and rainfall used to drive the VECTRI model with population fixed at 2010 values.
- Integrations to 2100.
- Preliminary results from one ensemble member only, thus take 2030-2100 averages. **No stats tests conducted.**

Complex chain to GCM

Impact Assessment Models
rcp2p6 4p5 6p0 8p5

Anthropogenic LUC conversions

HYDE 3.1 model

5 broad LU classes

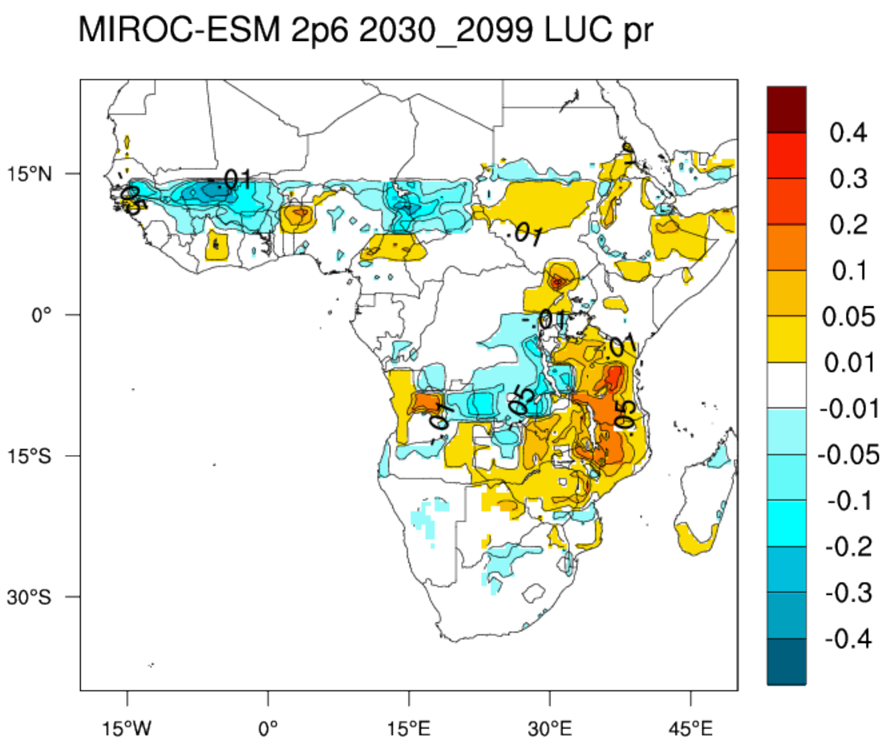
Land surface models:
CTEM, Orchidee, SEIB-DGVM, JSBACH, MOSES+TRIFFID

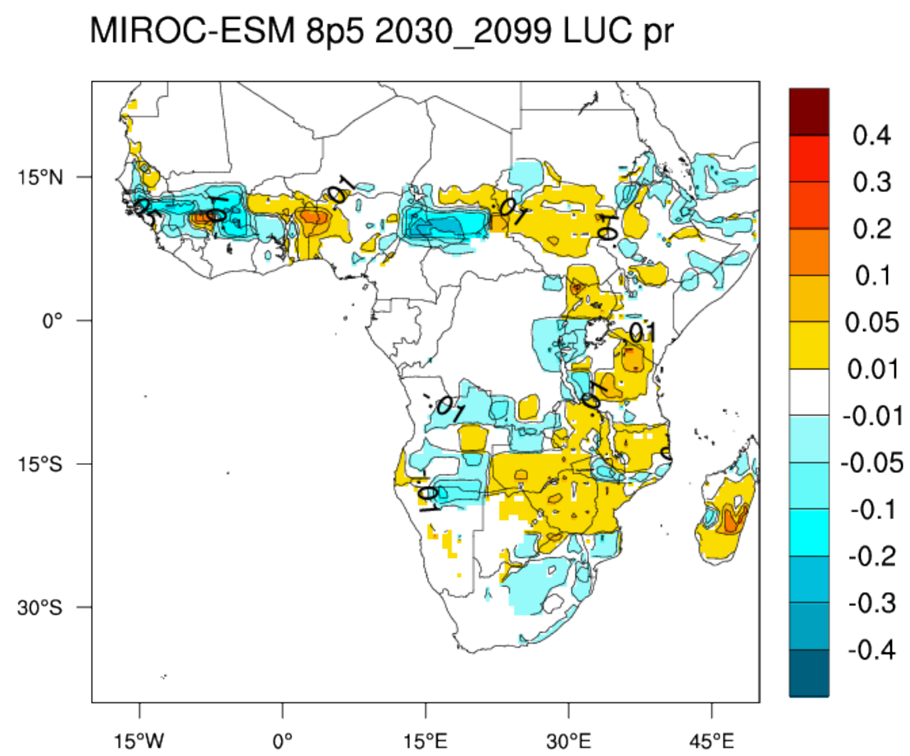
N PFT classes. Offline, complicated for dynamic vegetation model

Climate Models: IPSL(1), MPI(2), MIROC(1), CanESM (3), (HADGEM missing)

VECTRI

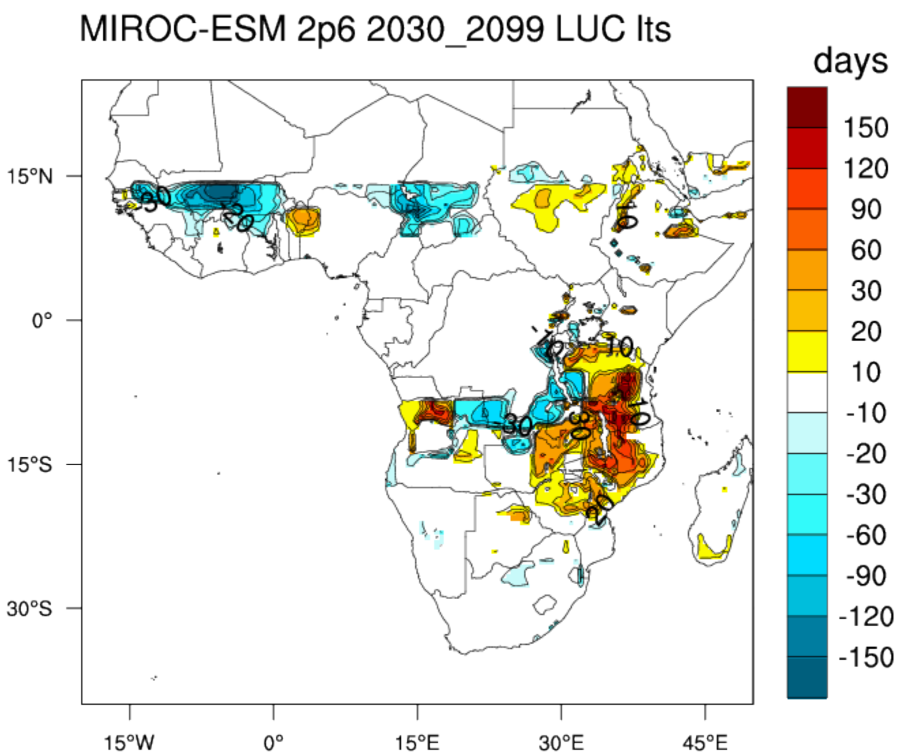
Malaria PR/LTS – MIROC

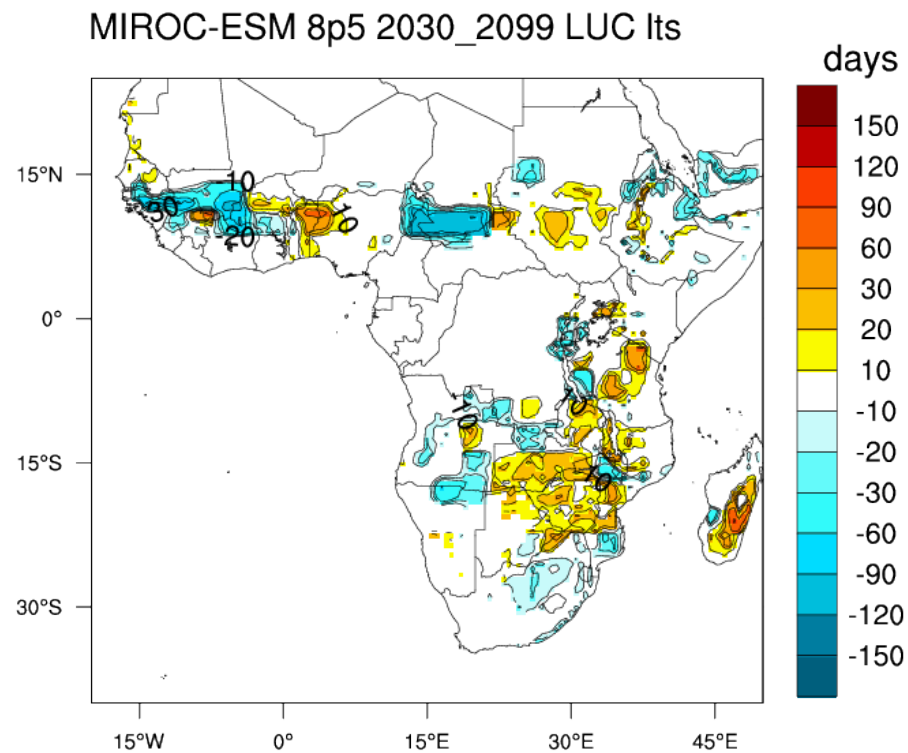




- Changes in prelevance directly correspond to areas of most land use change
- Only MIROC gives a signal – changes are insignificant for other three GCMs
- Conclusion: High uncertainty... need for larger ensembles

Malaria length of transmission season





Only MIROC gives a signal – changes are insignificant for other three GCMs

4. Project with IRI: Uncertainty in models, stochastic runs for Kericho.

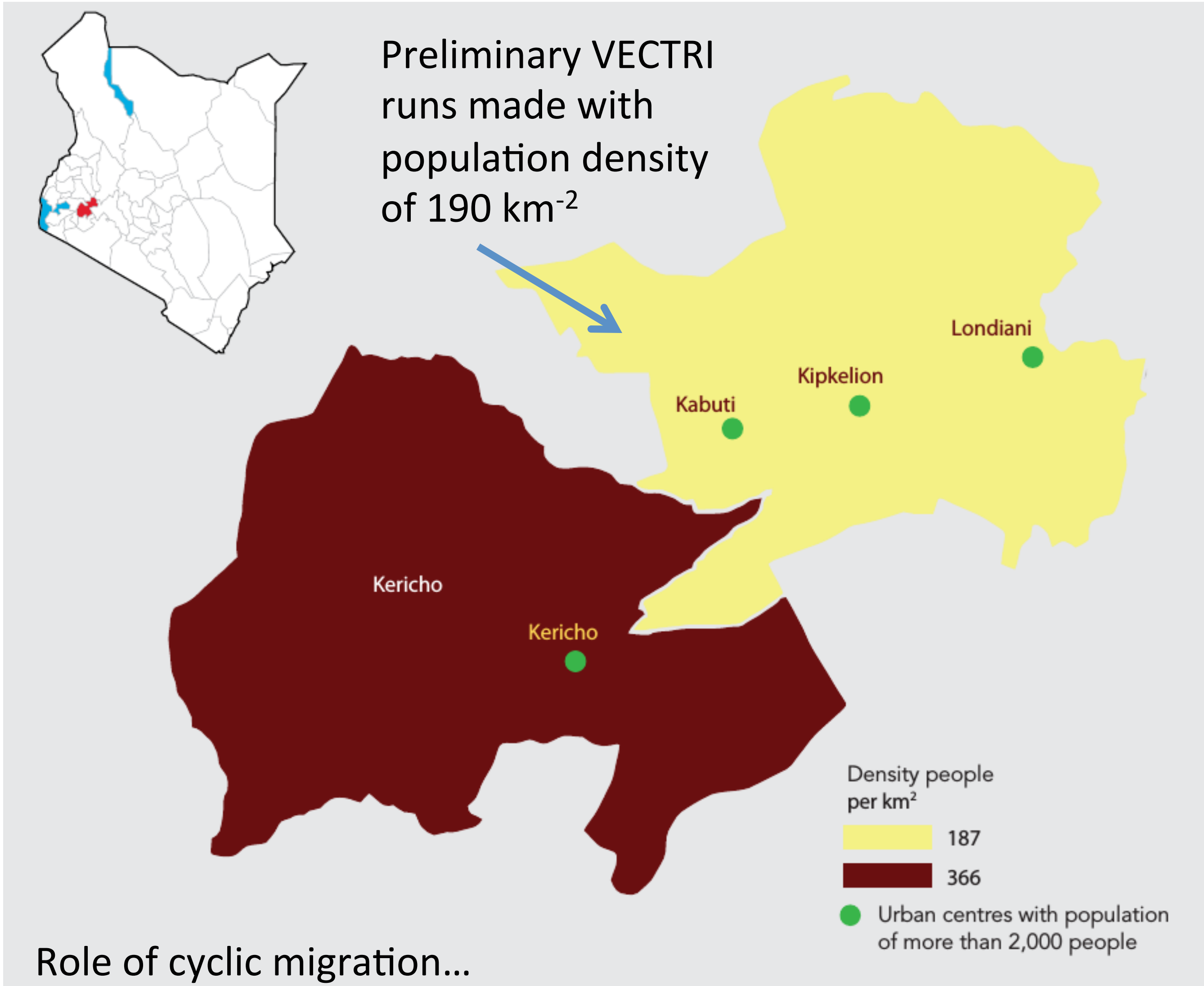
- VECTRI model run for Kericho town coordinates
  - Temperature: Era-Interim adjusted for height
  - Rainfall: nearest grid-point from RFE2, ARC2 and TRMM 3B42
- Perturbations made to one parameter at a time
- Magnitude of perturbations *mostly* +/- 20/40%

Perturbed values around default

nsurvival_scheme	"1"
neggmn	"36 48 72 84"
rlarv_flushmin	"0.32 0.48"
rlarv_flushtau	"12 16 24 28"
rbeta_indoor	"0.3 0.4 0.6 0.7"
rbiocapacity	"180 240 360 420"
rlarvsurv	"0.9 0.91 0.93 0.94"
rwaterperm_default	"1.e-05 1.e-04"
rwaterfrac_max	"0.12 0.16 0.24 0.28 "
rwaterfrac_evap126	"150 200 300 350"
rwater_tempoffset	"-0.5 0 1.0 1.5"
rhostclear	"30 40 60 70"
dsporo	"89 133"
rtsporo	"15.0 15.5 16.5 17.0"
rpthost2vect	"0.1 0.15 0.25 0.3"
rptvect2host	"0.2 0.25 0.35 0.4"
dgono	"29.7 44.52"

ICTP

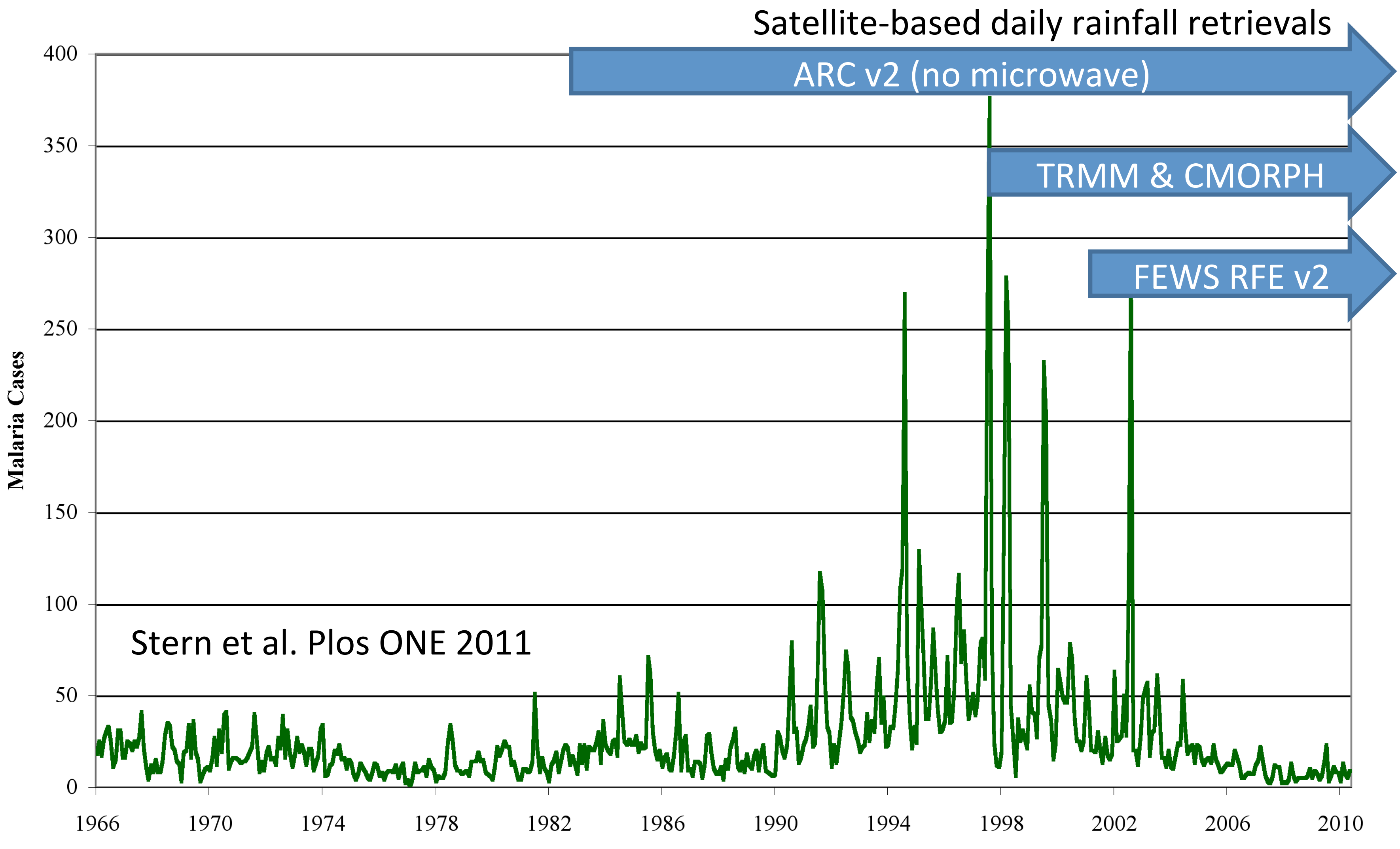
Kericho county



Preliminary VECTRI runs made with population density of 190 km^{-2}

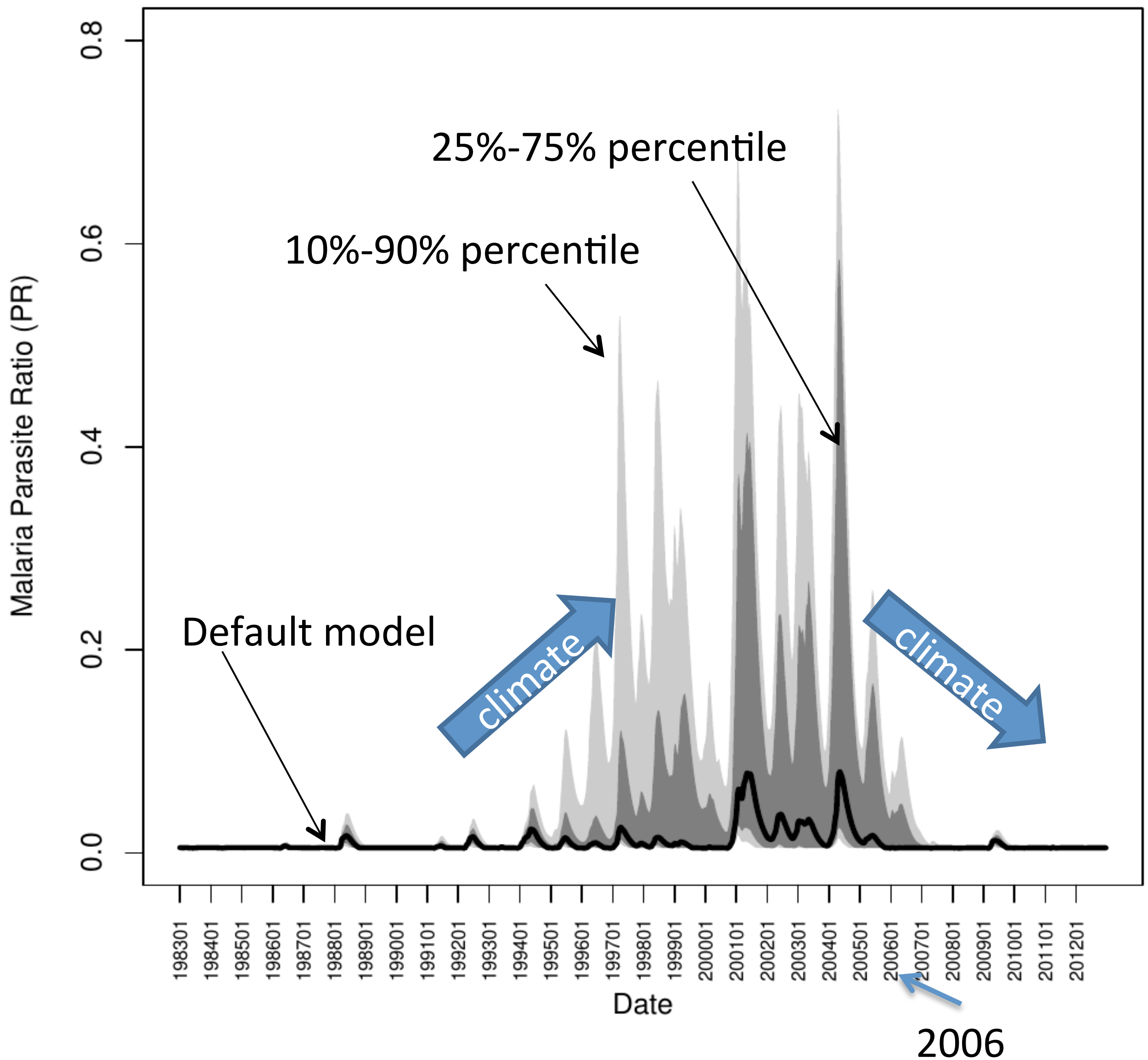
Role of cyclic migration…

Observed Cases for Kericho…



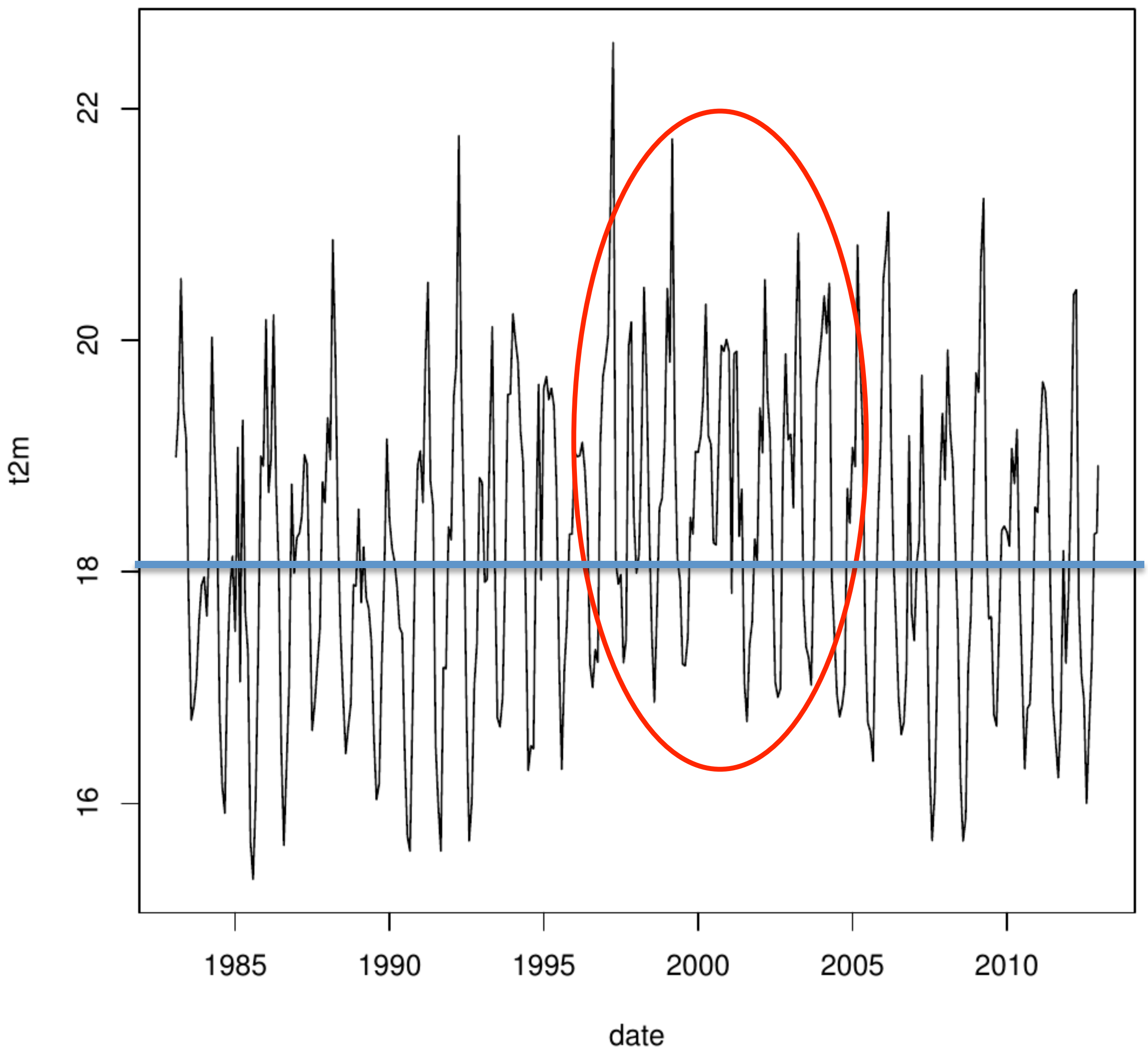
Simulations using FEWS ARC2

- Large uncertainty associated with the model – close to transmission limits
- Model indicates transmission would cease around 2006/2007 simply due to climate variability



Highlights importance of accounting for climate when assessing controls

Monthly Temperature from ERAI



Period around 2000, mean above 18C, coldest months much warmer than usual