S2S impacts on health

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With input from:

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QWeCI and HEALTHY FUTURES

Surveillance vs. Early Warning

- Surveillance systems are intended to detect disease outbreaks and measure and summarize data on such outbreaks as they occur
- Early warning systems are designed to alert the population and relevant authorities in advance about possible adverse conditions that could lead to a disease outbreak and to implement effective measures to reduce adverse health outcomes

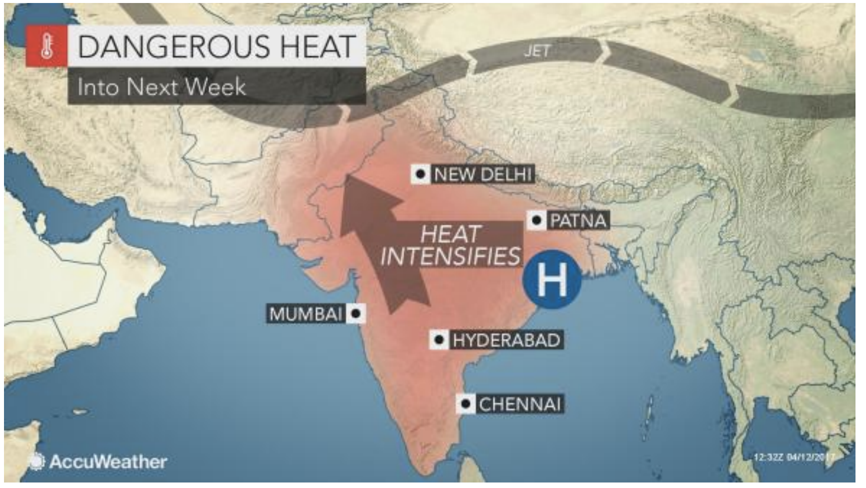
ICTP

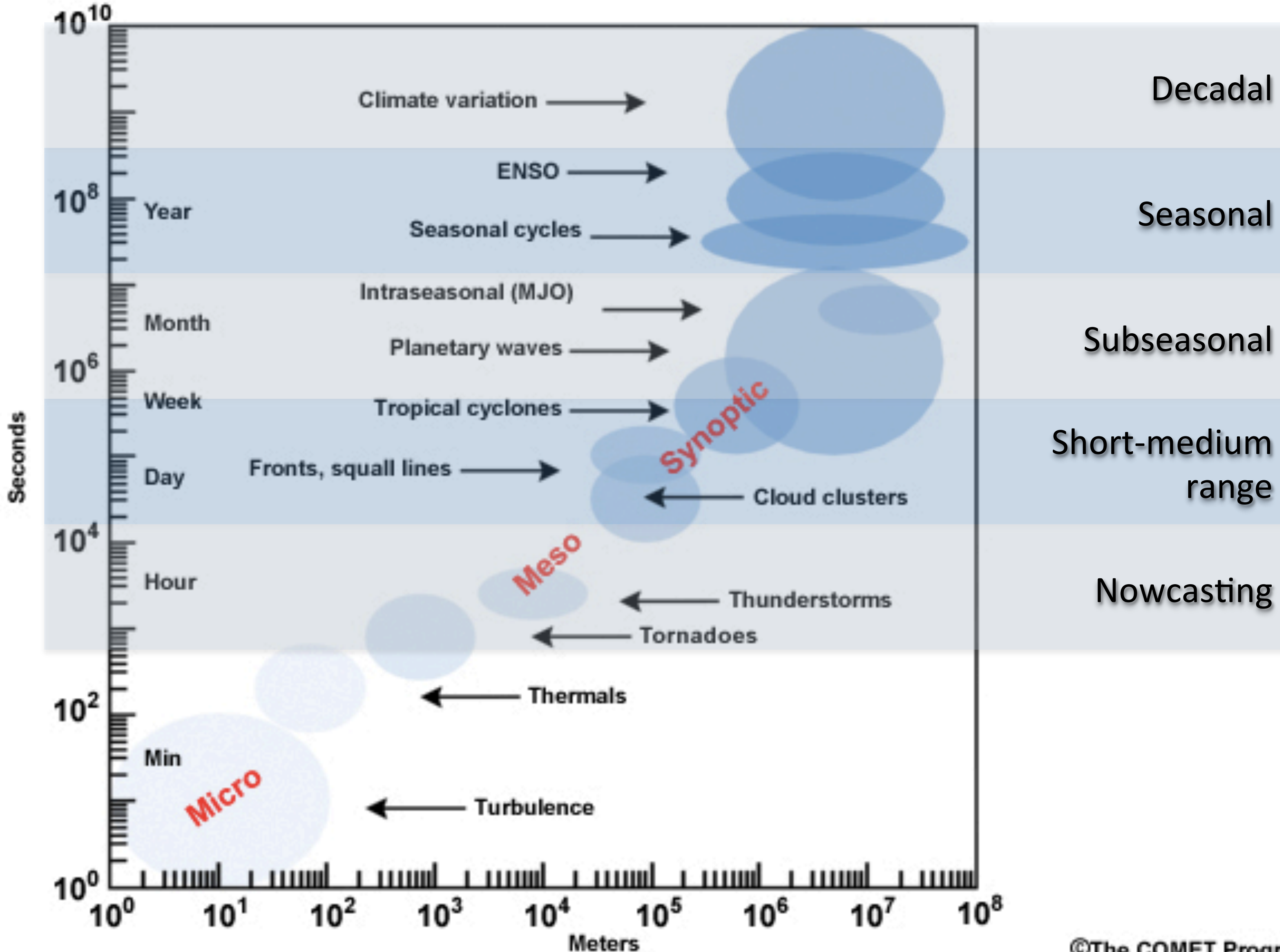
World Health Organization

Regional Office for South-East Asia

S2S applications in health

- S2S why?
  - Lead times and decisions
  - Complexity of hydrology, subseasonal variability
- Two case studies
  - heatwaves
  - VBD: malaria
- Where next?
  - S2S, NMME
  - Genetic algorithm calibration
  - Incorporating



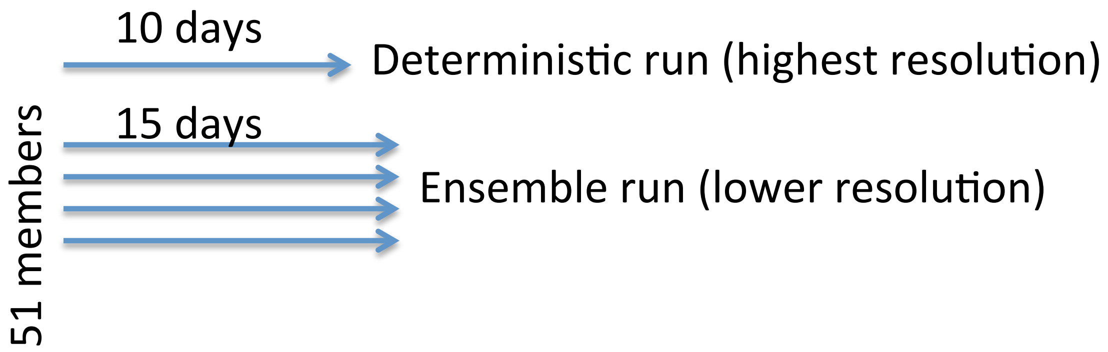


Decadal
Seasonal
Subseasonal
Short-medium range
Nowcasting
Climate variation
ENSO
Seasonal cycles
Intraseasonal (MJO)
Planetary waves
Tropical cyclones
Fronts, squall lines
Cloud clusters
Thunderstorms
Tornadoes
Thermals
Turbulence
Synoptic
Meso
Micro
Year
Month
Week
Day
Hour
Min
Seconds
Meters
10^{0}
10^{1}
10^{2}
10^{3}
10^{4}
10^{5}
10^{6}
10^{7}
10^{8}
10^{10}

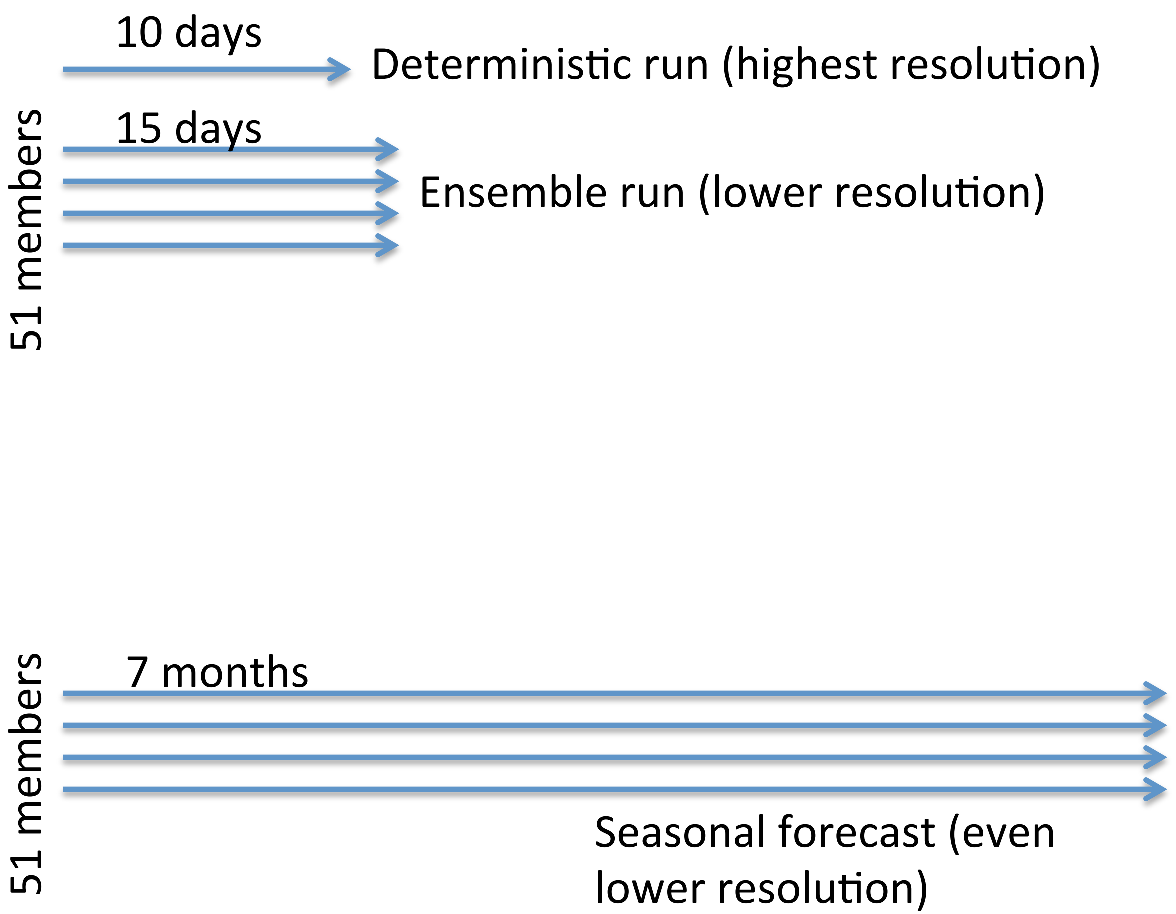
An introduction to forecast timescales
The ECMWF framework

10 days → Deterministic run

An introduction to S2S timescales: The ECMWF framework



An introduction to S2S timescales: The ECMWF framework



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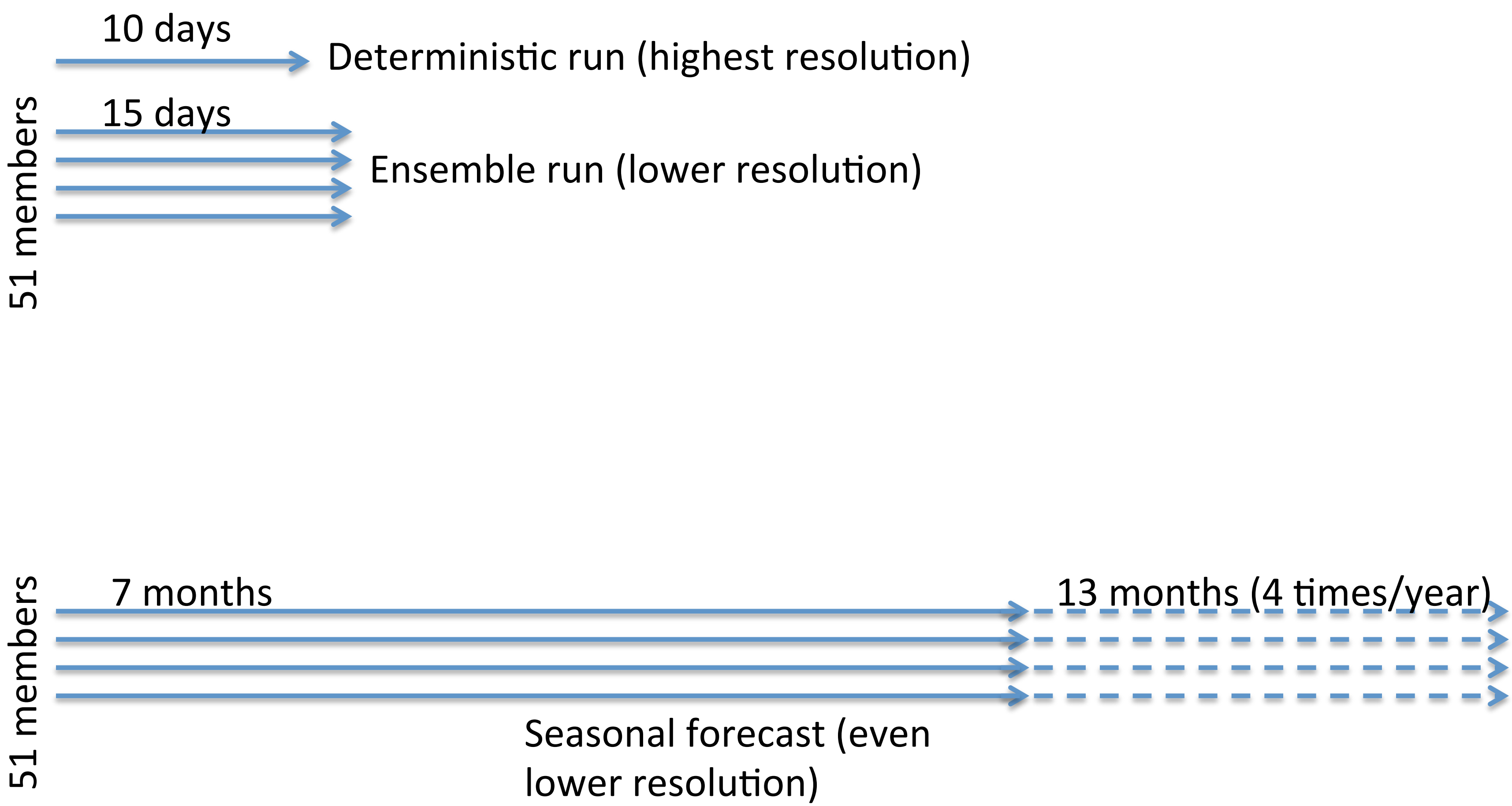

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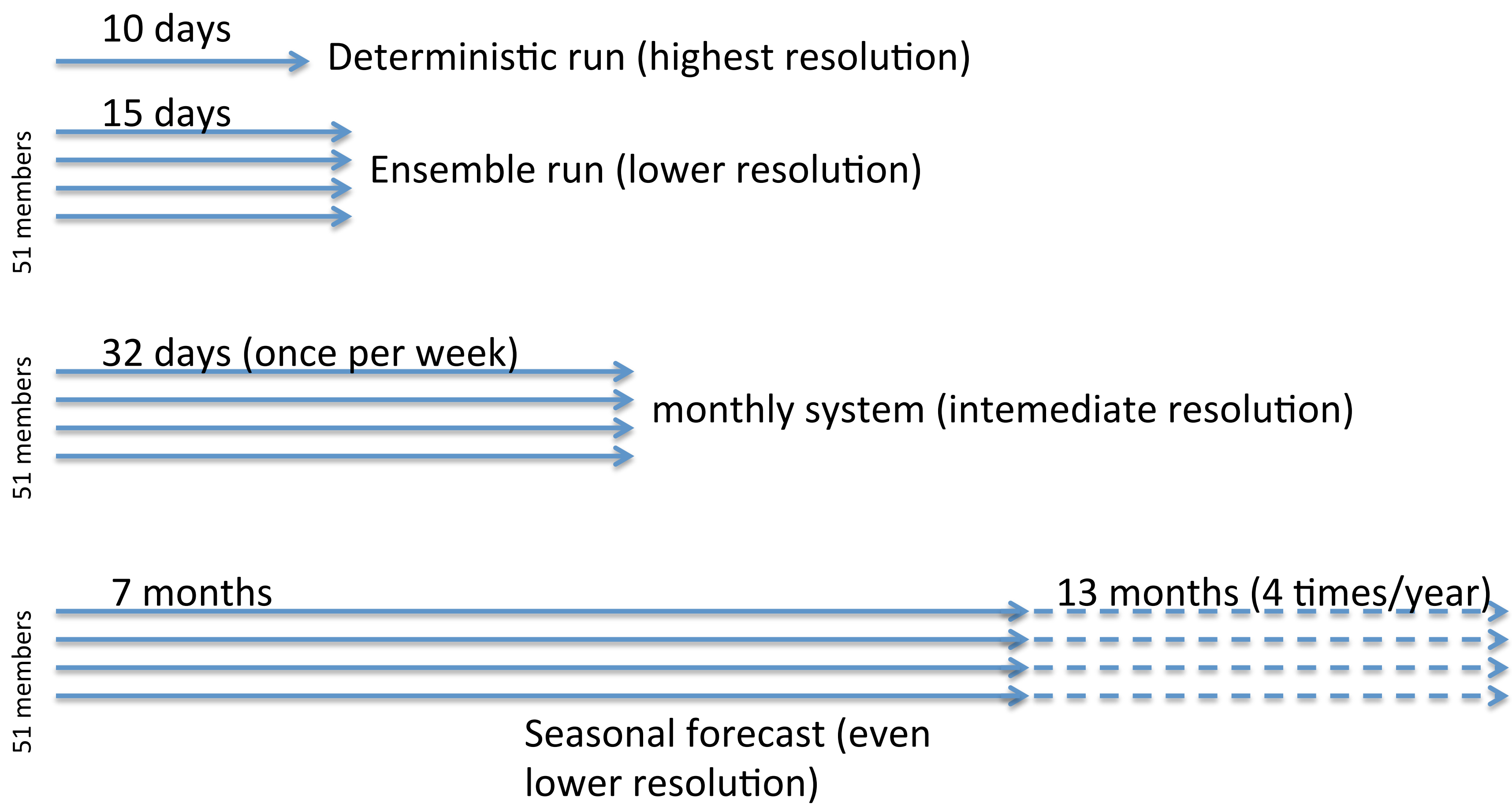
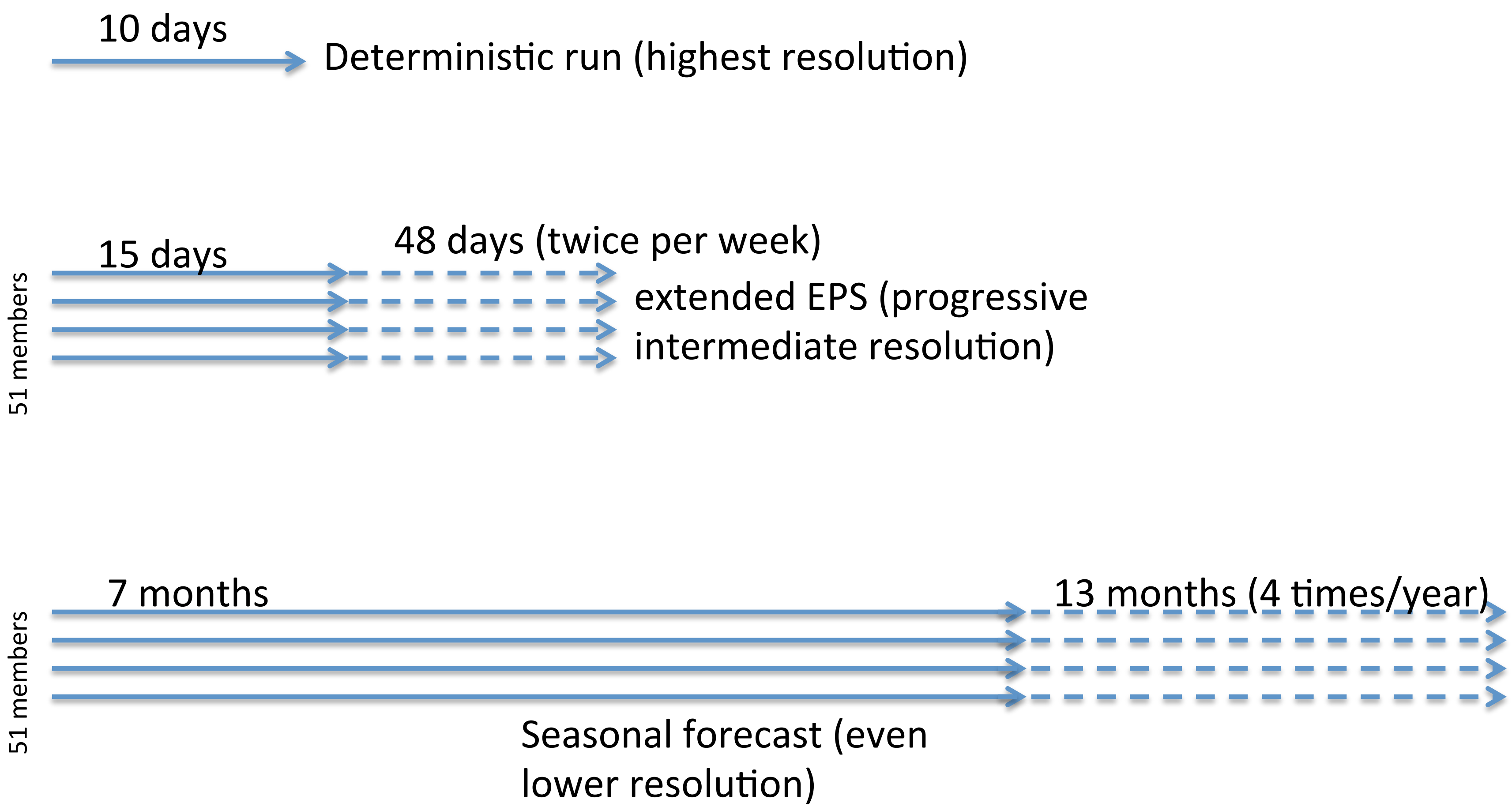


An introduction to S2S timescales: The ECMWF framework



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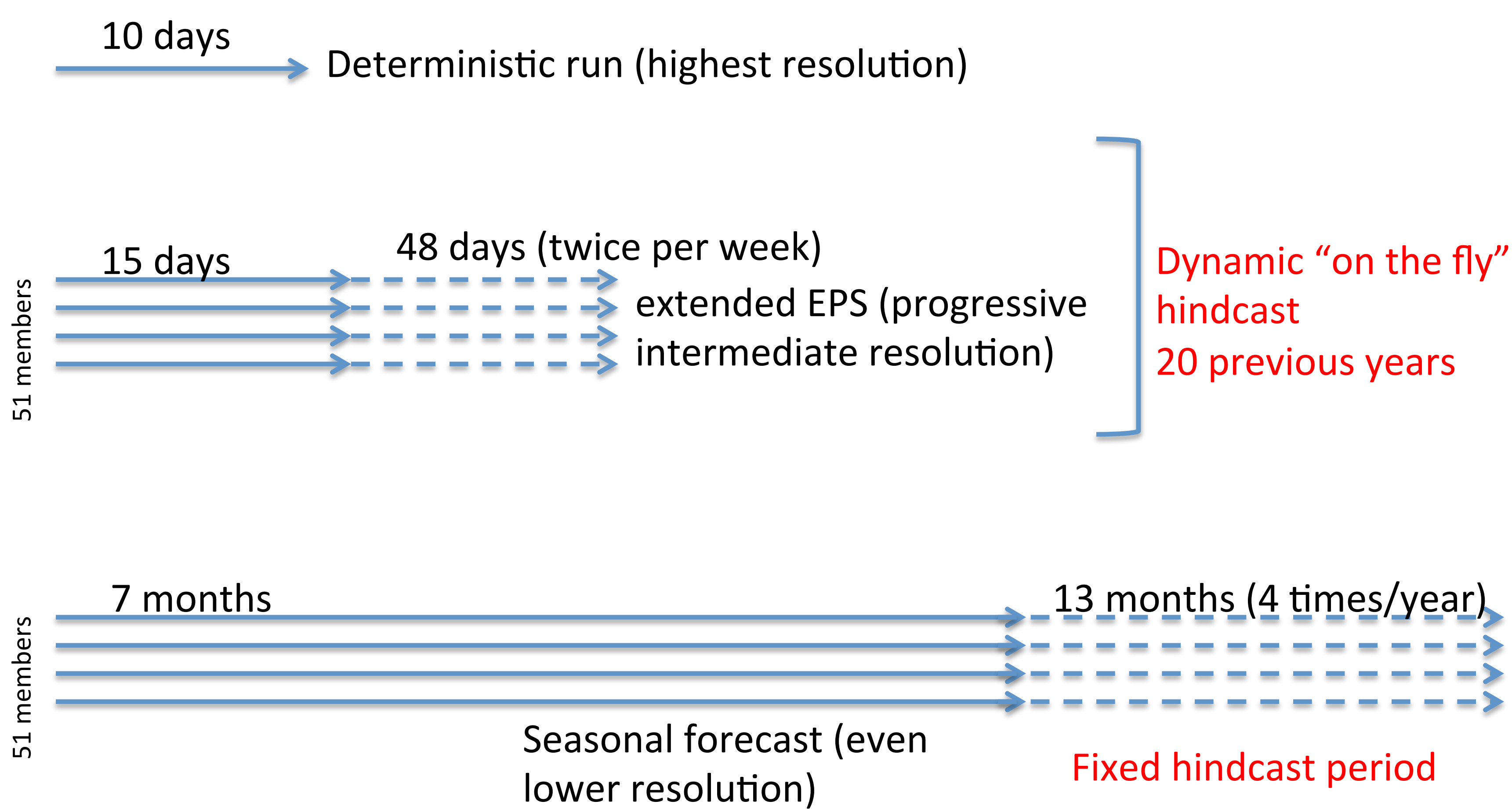
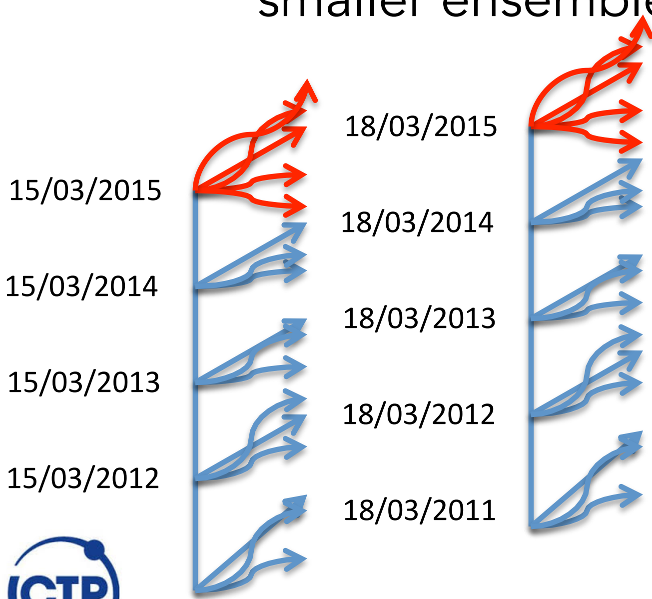
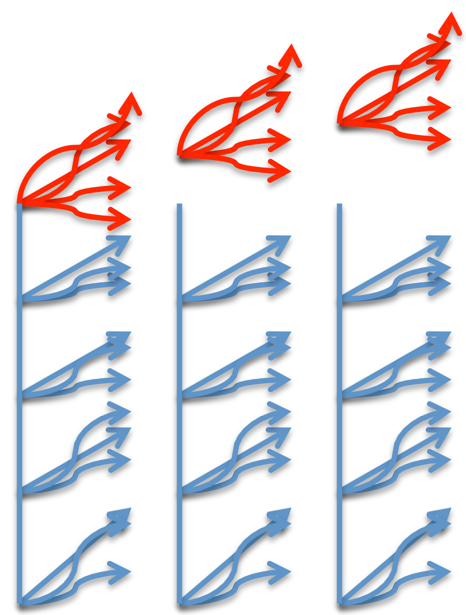


Hindcast Strategies

- "On the fly" – Each forecast is accompanied by a set of hindcasts starting on the same date for the previous N years
  - GOOD: same model version and set up
  - GOOD: Always same start date
  - BAD: Expensive to run, smaller ensemble sizes

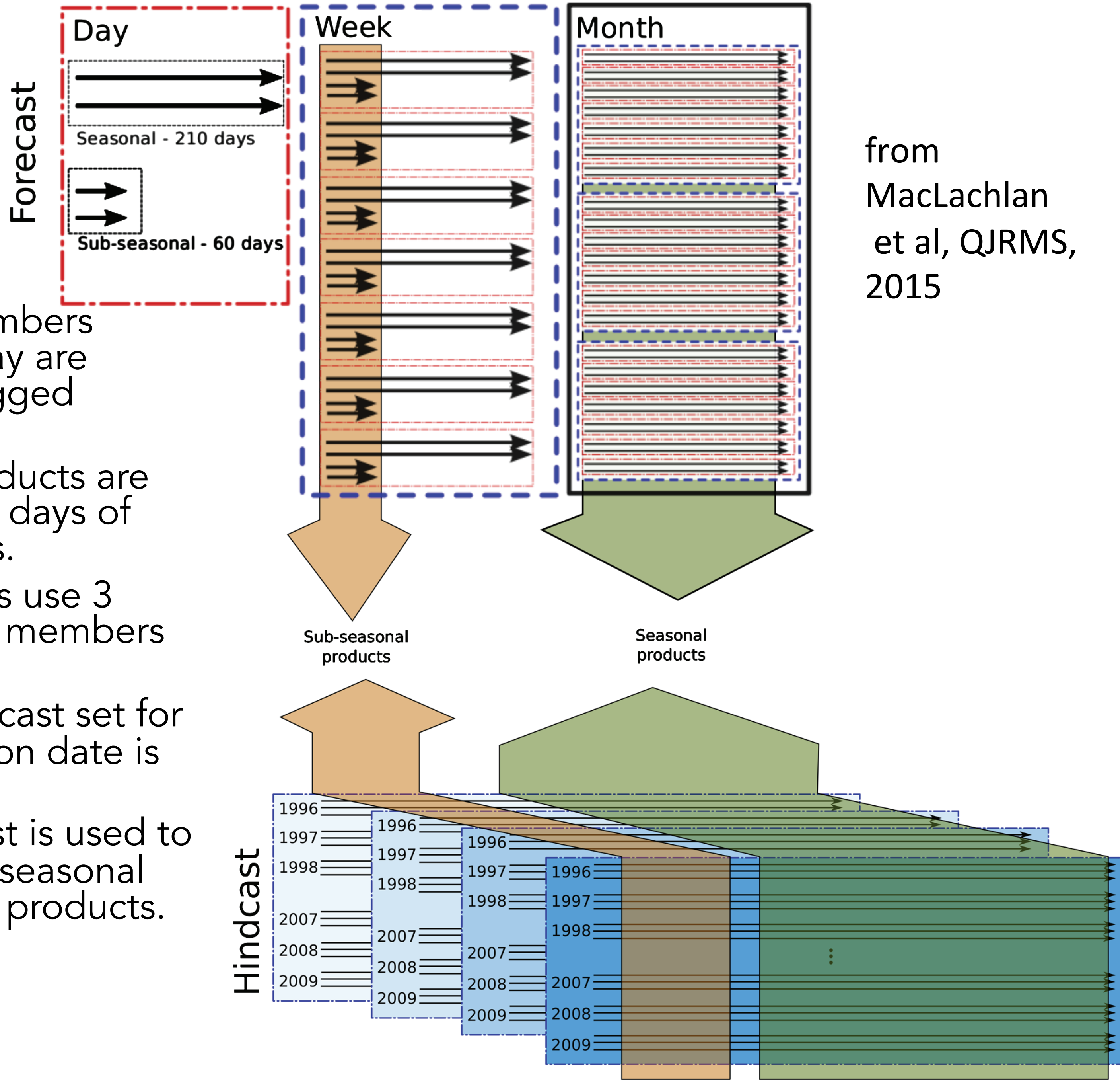


- "Fixed" – Hindcast data set run once for a particular model cycle
  - GOOD: Cheaper (if system not updated too frequently), larger ensemble sizes possible
  - BAD: Not always matching dates



The Met Office system

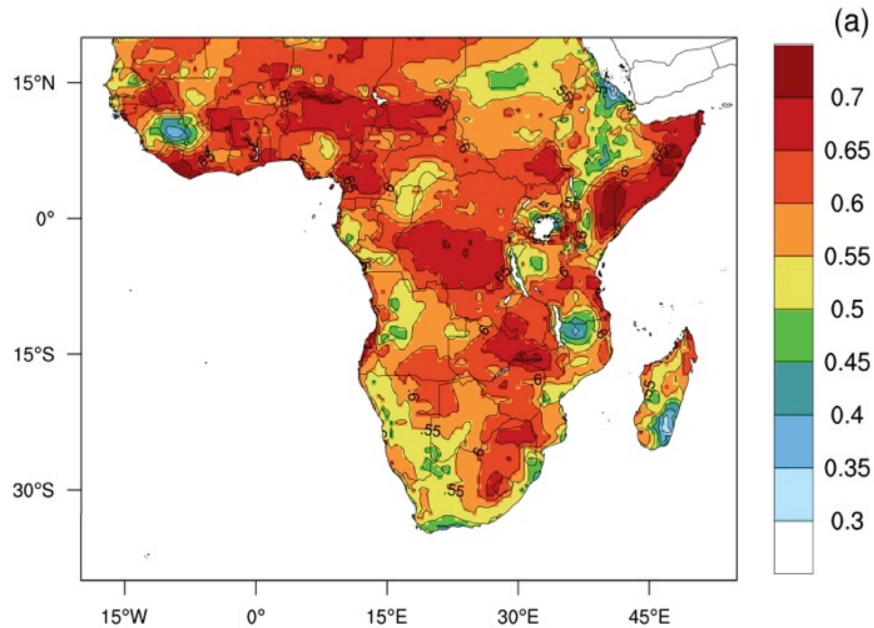
- Four forecast members initialized each day are combined in a lagged ensemble.
- Sub-seasonal products are generated from 7 days of forecast members.
- Seasonal products use 3 weeks of forecast members in the ensemble.
- Each week a hindcast set for a given initialization date is completed.
- The same hindcast is used to bias correct both seasonal and sub-seasonal products.



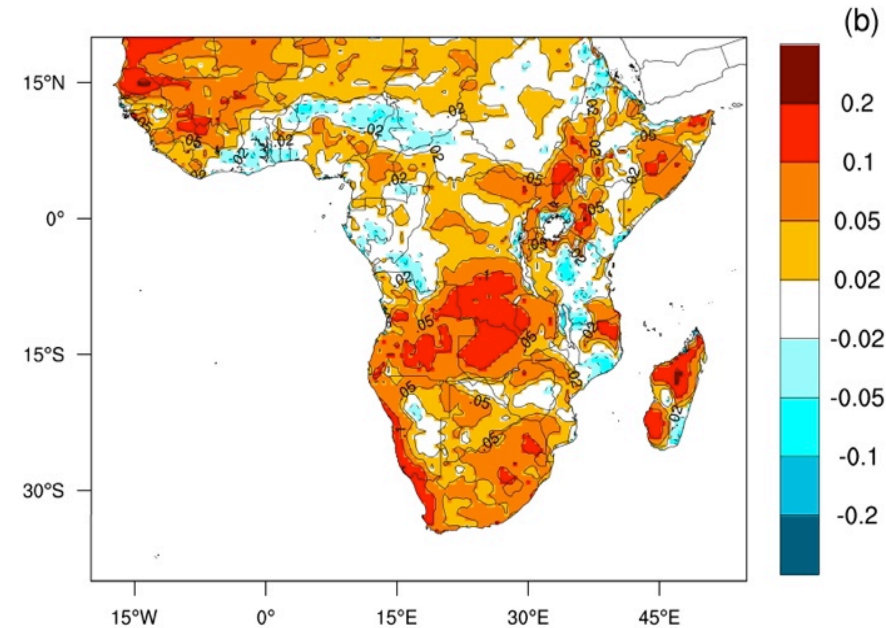
from MacLachlan et al, QJRMS, 2015

Improvement of 2 metre temperature correlation of S2S 5 member mean over 5 members of seasonal system

from Tompkins and Digiuseppe, JAMC, 2015

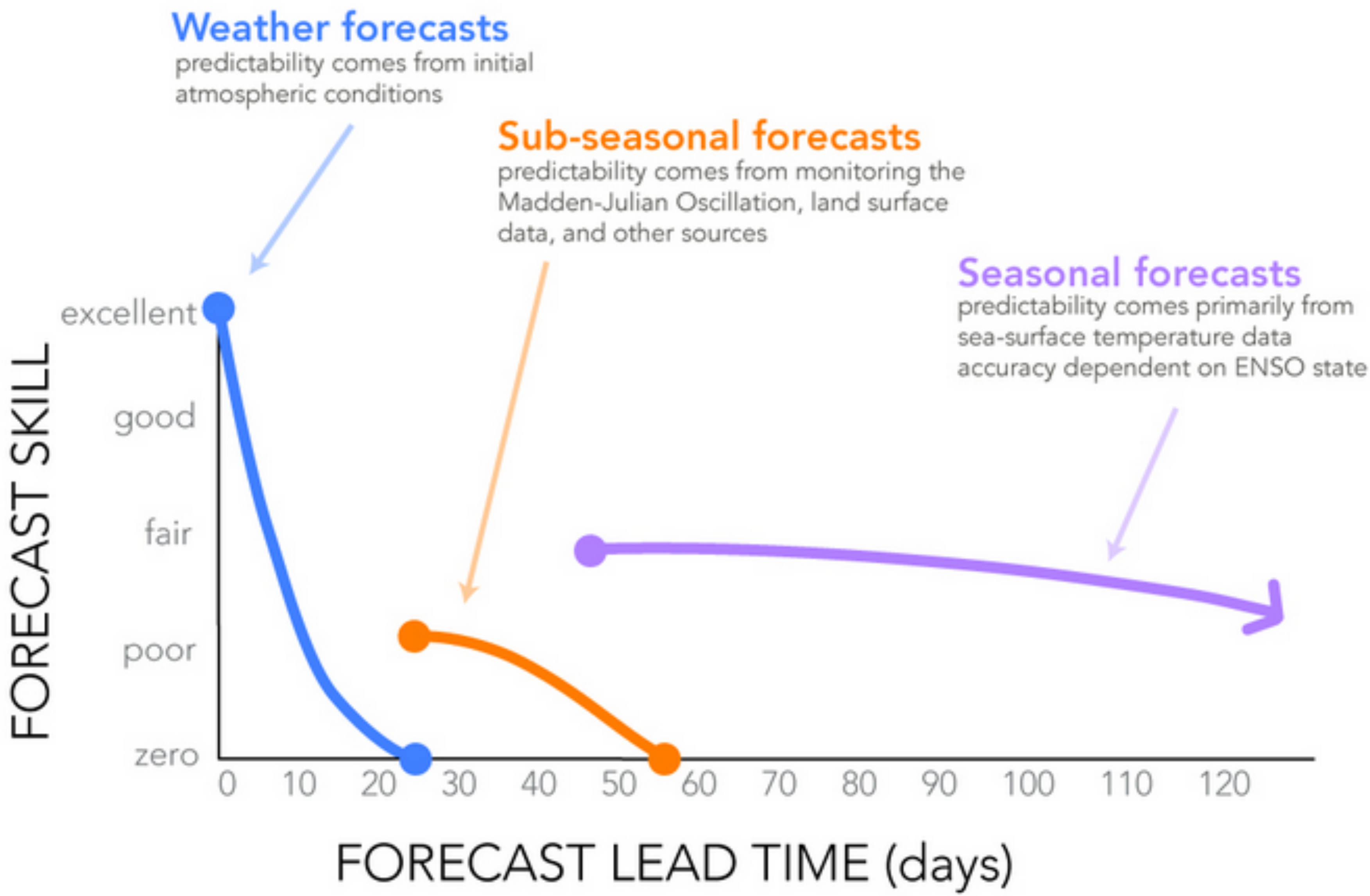


Correlation of day 1-32 T2m anomaly against ERA-Interim for 1994-2012 of Extended range EPS over Africa
12 start dates (First Thursday of each month)



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

1. Lead time advantage (more frequent updates) [~3 days here]
2. Model physics (more frequent updates)
3. Framework (higher resolution, different ocean initialization…)



Weather forecasts
predictability comes from initial atmospheric conditions
Sub-seasonal forecasts
predictability comes from monitoring the Madden-Julian Oscillation, land surface data, and other sources
Seasonal forecasts
predictability comes primarily from sea-surface temperature data
accuracy dependent on ENSO state
FORECAST SKILL
excellent
good
fair
poor
zero
0
10
20
30
40
50
60
70
80
90
100
110
120
FORECAST LEAD TIME (days)

Applications in health

- Many health outcomes are sensitive to climate as a factor
  - Nutrition (crop production, temperature and rainfall)
  - Heat waves (temperature, humidity, radiation)
  - Weather extremes (immediate danger)
  - Meningitis (dust, winds, rainfall)
  - Cholera (water temperatures, rainfall)
  - Vector-borne disease (vector/intermediate host and pathogen climate sensitivity)
- Lead time of information may or may not be useful for decision entry
  - Heat waves: immediate, useful
  - VBD, delay in outbreak relative to climate => longer leads, but still may not be adequate (e.g. Rift Valley Fever example)

Heat health decision-making across timescales

Red Cross Example - IRI

Develop action plans
Refresh medical training
Train media on appropriate messaging
Contingency planning for events
Supply routes for backup water & generators
Coordinate with utilities to ensure continued provision of energy

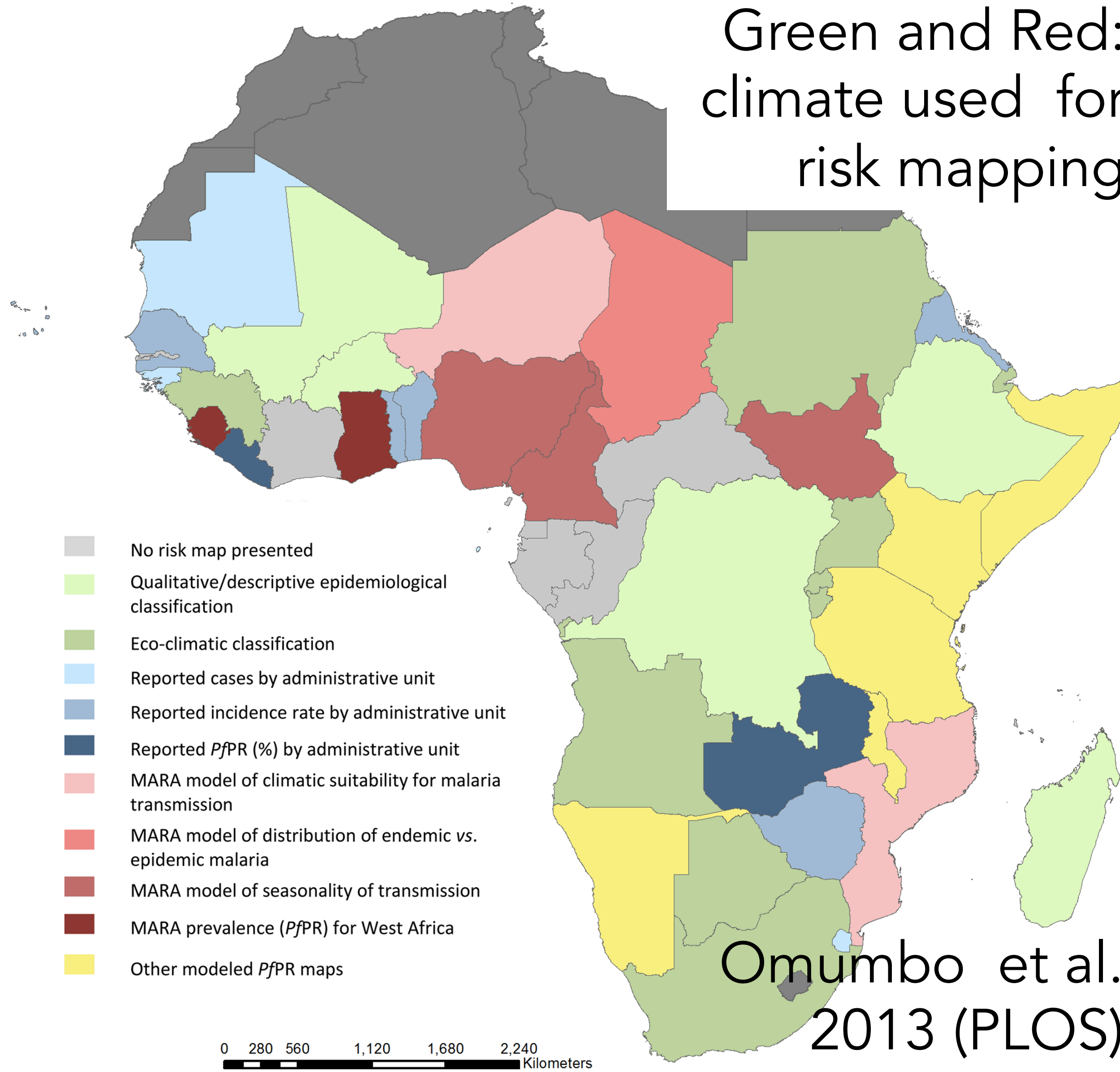
Monitor weather forecasts closely
Re-cap emergency action plans
Inform schools
Inform cooling centers
Reinforce coordination with disaster management personnel
Distribute appropriate advice through media
Procure emergency drinking water

Prepare utilities for increased power demand
Prepare to open cooling centers
Mass media public awareness campaign begins
Distribute emergency drinking water
Alert hospitals of increased demand
Reschedule hospital staff shifts
Check in on elderly people

Approaches to incorporating climate into health

- ❑ Mapping of mean risk or seasonality
- ❑ Forecasts of climate used:
  - directly
  - drive simple statistical models of health outcomes
  - drive complex dynamical models
- ❑ Mapping model outcome to health entry point a challenge

Green and Red: climate used for risk mapping



Omumbo et al. 2013 (PLOS)

Case study 1: Heat waves

1957 Europe


The Milwaukee Sentinel - Jul 9, 1957

Sentinel Photo by Ray Hunholz

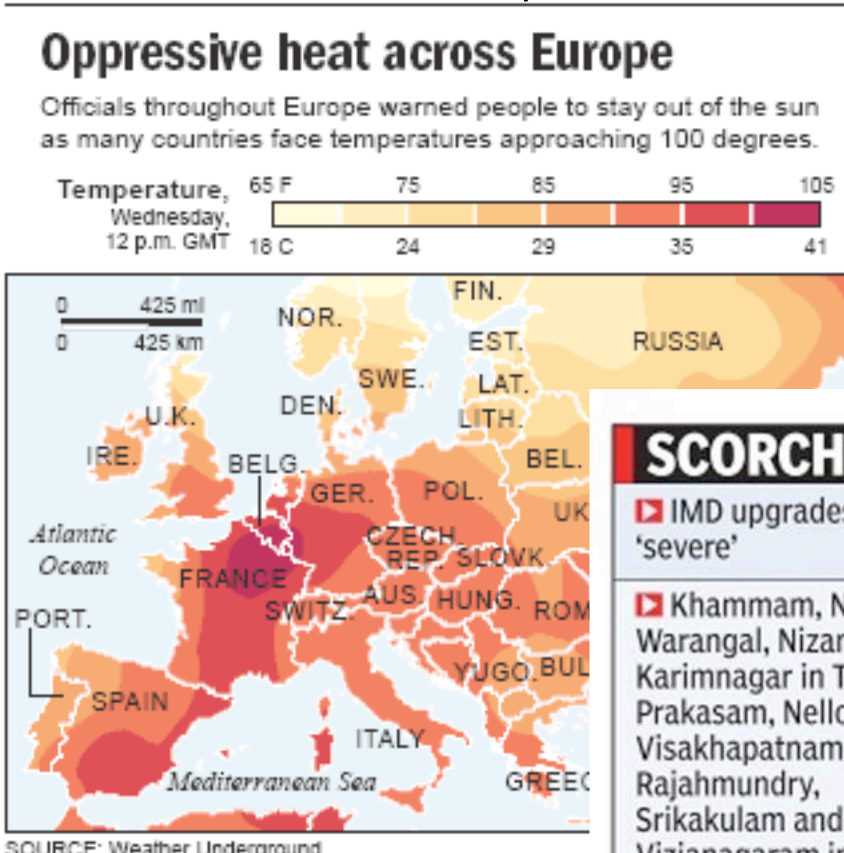
Europe Heat Wave Deaths Pass 200

ROME, July 8 (AP) Sweltering Europe counted more than 200 dead in July's torrid heat wave, but there were signs Monday of a slight cooling off.

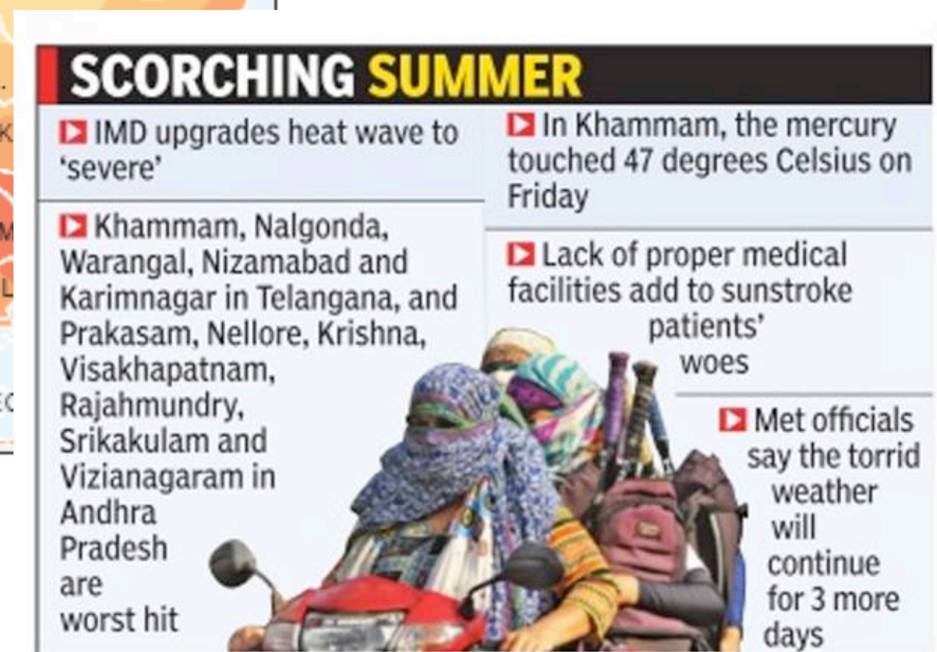
Britain, Norway and France all reported relief but in Italy, Switzerland, West Germany and Poland it was still hot and humid.

The heat wave had one of its most tragic chapters between dusk Sunday and dawn Monday in a home for the aged at Venice. There, 15 persons—10 of them in their 80s—died in the steaming night. Doctors said all were in weak condition but that 100-degree heat contributed to their deaths.

2003 Europe



2015 and 2016 India



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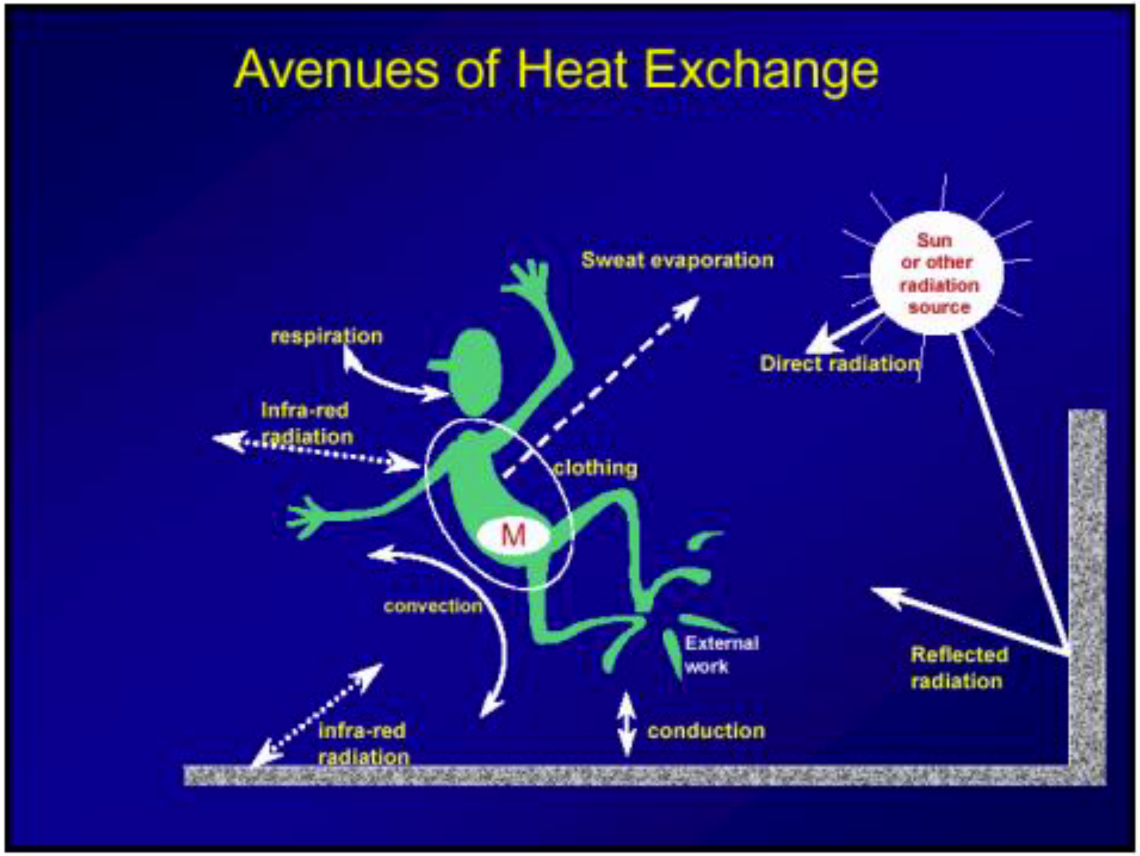
Heat stress is more than just temperature

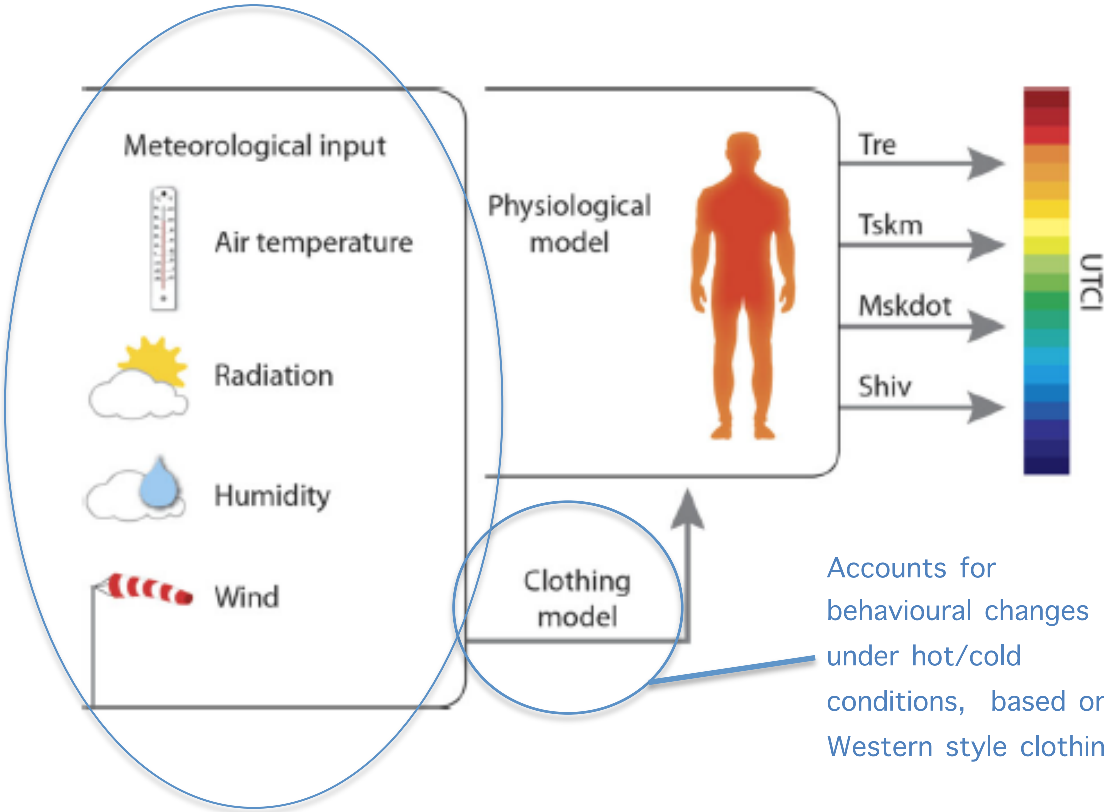


- TEMPERATURE
- HUMIDITY
- WIND
- SOLAR RADIATION

The human heat budget: energy in - energy out = energy gained

Heat budget models (e.g. German Weather Service)

Universal Climate Thermal Index (UTCI) model



Accounts for behavioural changes under hot/cold conditions, based on Western style clothing

\+ Most accurate description of heat stress on human body available

\- Demanding data inputs

\- Unfeasible on long lead times

\- Computationally demanding

Other examples of output from heat budget models:

- Standard Effective Temperature
- Predicted Mean Vote
- ***Perceived Temperature: German Weather Service***
- Physiological Equivalent Temperature
- ***Universal Thermal Climate Index (UTCI)***

Pappenberger et al (2015), In. J. Biometeorol.

Resort to simple heat indices

HWD	Definition	Heatwave days	Reference and note[a]
1	The daily maximum temperature ≥35°C (about top 1%) for 3 or more consecutive days	6	Hansen et al. 2008[6]
2	The daily maximum temperature of more than 5 consecutive days exceeds the average maximum temperature by 5°C, the normal period being 1961–1990	10	Frich et al. 2002[13]
3	The heat index (maximum temperature + relative humidity) is expected to reach 40.6°C with a minimum temperature not below 26.7°C as a period of at least 48 h	3	Robinson 2001[10]
4	The daily maximum temperature would be equal to or greater than 35°C (about top 1%) for at least consecutive 2 days	20	Extended from HWD1
5	The daily maximum temperature would be equal to or greater than 37°C (about top 0.5%) for at least consecutive 2 days	7	Extended from HWD4
6	The top 2.5% (≥33.59°C) of daily maximum temperatures for a continuous 2 days period	49	Extended from HWDs4 & 5
7	The top 2.5% (≥33.59°C) of daily maximum temperatures for a continuous 3 days period	27	Extended from HWD6
8	The top 5% (≥32.65°C) of daily maximum temperatures for a continuous 3 days period	93	Extended from HWD6
9	The top 5% (≥32.65°C) of daily maximum temperatures for a continuous 4 days period	57	Extended from HWD6
10	The top 5% (≥32.65°C) of daily maximum temperatures for a continuous 5 days period	37	Extended from HWD6

[a]The first three definitions were widely used in the literature and the remainder (HWDs 4–10) were extended definitions developed for this study.

doi:10.1371/journal.pone.0012155.t001

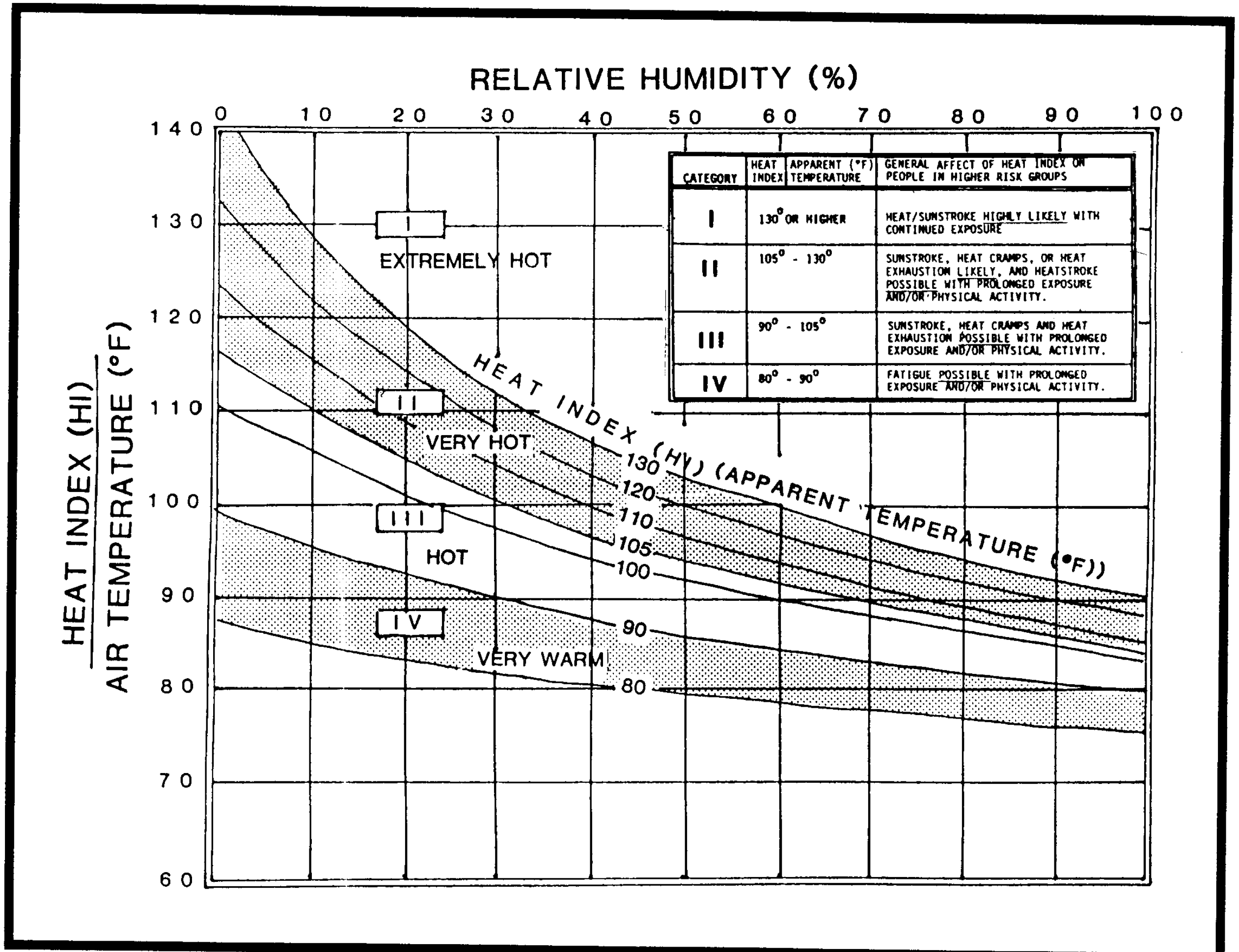
A bewildering array of heat indices

Tong et al. 2010 PLOS 1

The "feels-like" temperature

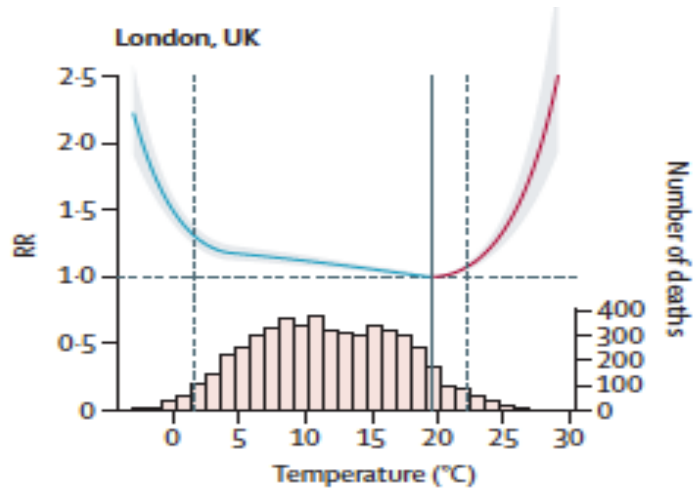
Apparent temperature tells us what the temperature *feels like,* summarising several effects into one HOT & HUMID: 30C could feel more like 35C

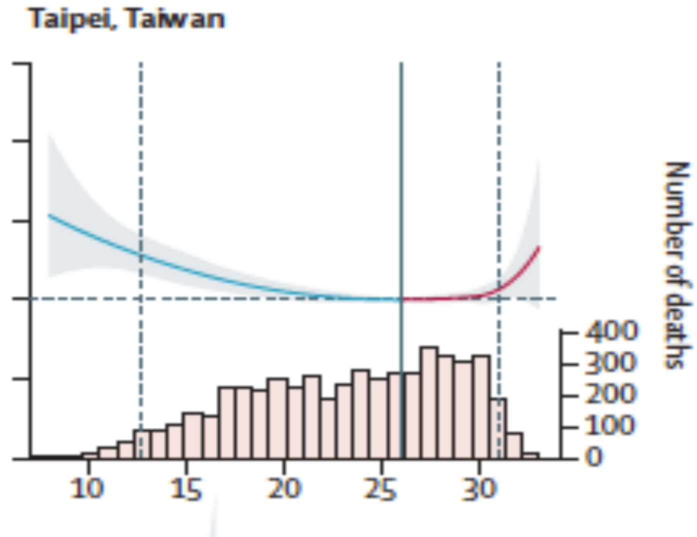
- HOT & WINDY: 30C could feel more like 27C

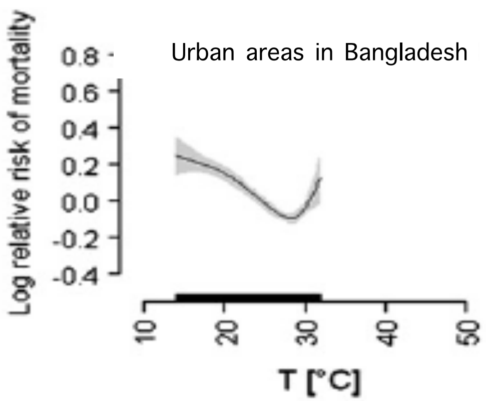


Setting the warning thresholds

Regional differences and seasonal, short-term acclimatization







Critical temperatures for increased mortality vary significantly among different regions

London & Taipei: Gasparrini et al, Lancet 2015 | Bangladesh: Burkart et al (2011)

Setting the warning thresholds

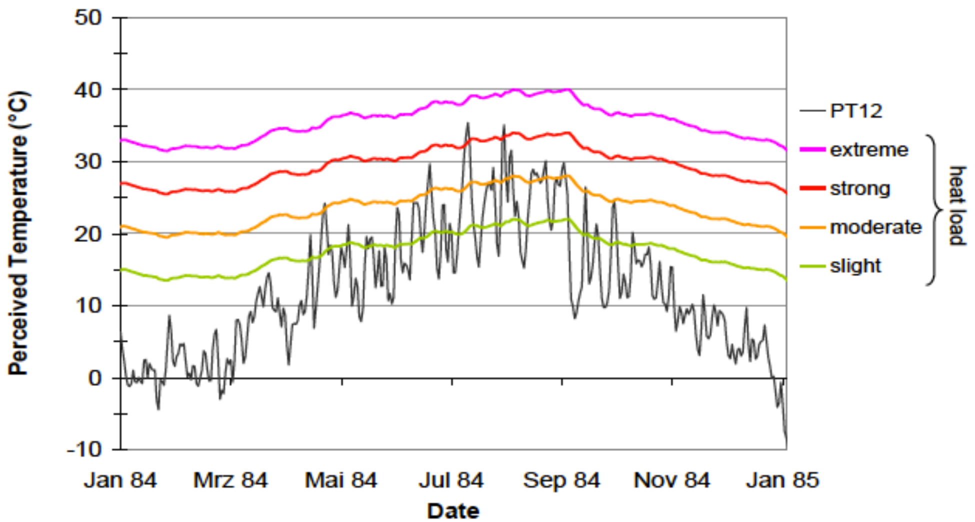
Short-term acclimitisation

After several days to weeks of hot conditions, we *temporarily* adapt and feel the heat less

GERMANY'S HeRATE SYSTEM

HeRATE is used to modify warning threshc for any heat index according to its deviati from the value over the last 30 days

- ✓ No need to impose a seasonal cycle in thresholds
- ✓ Can be used in all climates because it relies on local data



Heat health threshold warning levels (colours) and observed perceived temperatures (black) in 1984

Germany: WHO/WMO (2015)

Setting the warning thresholds

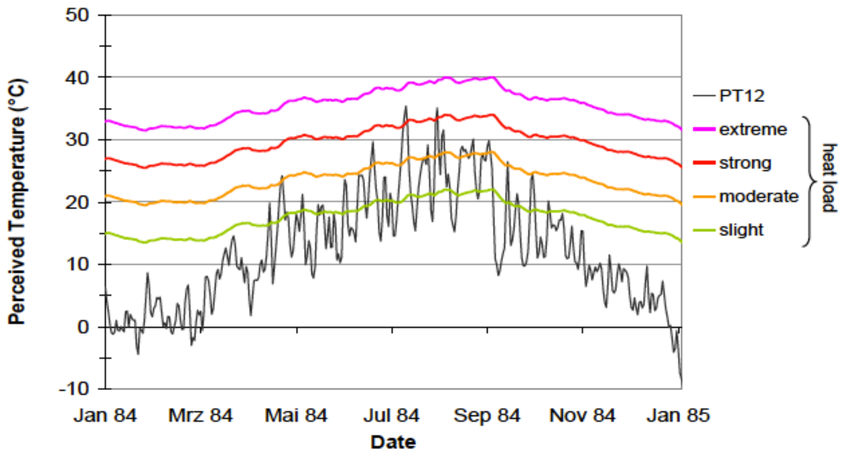
Short-term acclimitisation

After several days to weeks of hot conditions, we *temporarily* adapt and feel the heat less

WAYS TO ACCOUNT FOR ACCLIMITISATION

Express thermal index or temperature as deviation from

a) Climatology
b) Previous 30 days



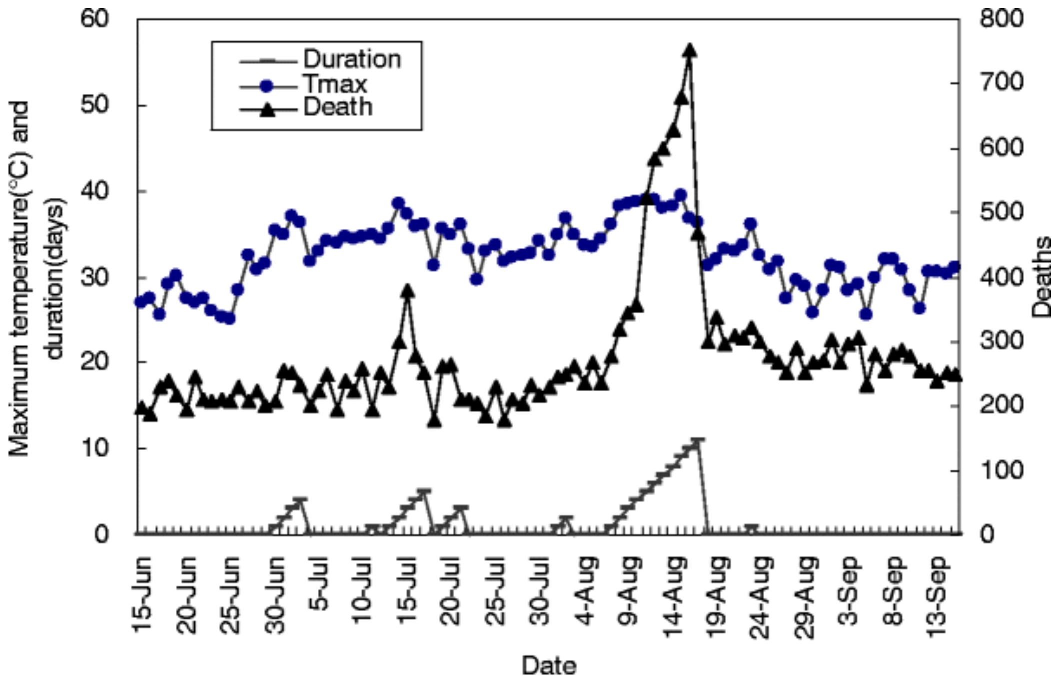
Heat health threshold warning levels (colours) and observed perceived temperatures (black) in 1984

Germany: WHO/WMO (2015)

Setting the warning thresholds

Heat wave duration

Longer heat waves can cause particularly high death rates



SHANGHAI 1998

MORTALITY CAN INCREASE NON-LINEARLY WITH HEAT WAVE DURATION…

Tan et al (2006), Int. J. Biometeorol.

Most places use simple temperatures to measure heat stress

Some use thermal indices to accounting for other variables (humidity, wind speed etc.)

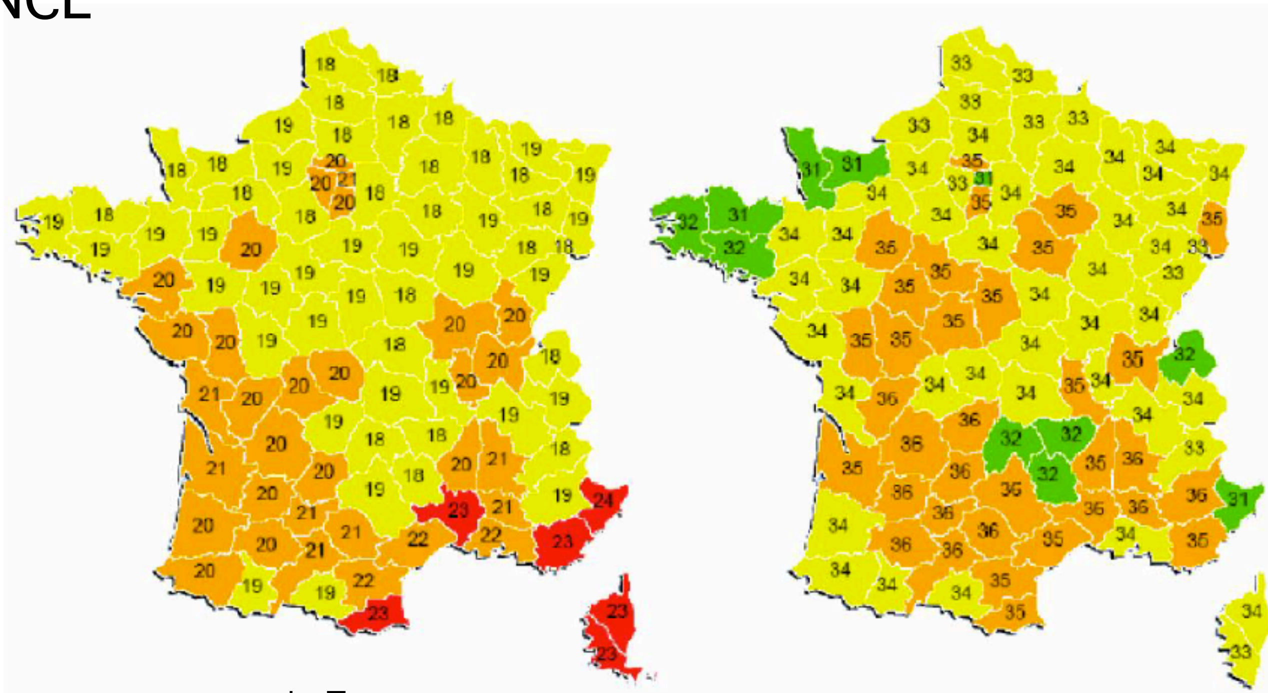
Most places consider the duration of a heat event

Most places relate the warning system to historical mortality data

Country	Threshold	Thresholds based on historical mortality	Excess mortality forecast	Duration of heat event included	Seasonality or adaptation included	Regionally variable thresholds	Human expertise
Australia (Queensland)	*AT*			2 days		✓	✓
Belarus	*T*						
Belgium	*Tmax/Tmin/*Ozone			3 days			
Canada (Toronto region)	Airmass	✓	✓	✓	✓	✓	✓
Canada (Montreal)	*Tmax/Tmin*			✓			
Canada (all others)	*Humidex*			✓			
China (Hong Kong)	*NET*						
China (Shanghai)	Airmass	✓	✓	✓	✓		✓
France	*Tmax/Tmin*	✓		3 days		✓	✓
Germany	*PT*			2 days	✓	✓	✓
Greece	*Tmax*			✓			
Hungary (Budapest only)	*Tmean*	✓					
Italy	Airmass/*Tapp*	✓	✓	✓	✓	✓	
Republic of Korea	Airmass	✓	✓	✓	✓	✓	✓
Republic of Korea (Seoul*)	Airmass	✓	✓	✓	✓	✓	✓
Latvia	*Tmax*			✓			
Netherlands	*Tmax*			✓			
Poland	*Tmax/Tmin*						
Portugal	*Tmax*	✓	✓	✓		✓	✓
Romania	*ITU*						
Slovenia	Forecaster						✓
Spain	*Tmax/Tmin*	✓				✓	✓
Switzerland	*HI*						
United Kingdom (England and Wales)	*Tmax/Tmin*			✓		✓	
USA (synoptic**)	Airmass	✓	✓	✓	✓	✓	✓
USA (all others)	*HI*			2 days		✓	✓

An example heat early warning system

FRANCE



min T max T

- Meteo-France forecast 3 day running average min and max temperatures for each region
- Thresholds applied for min and max temperature are values associated with 50% increase in mortality in urban and 100% in rural areas
- Other information, some qualitative, is also taken account of before issuing a warning: air pollution, public or sporting events

An example heat early warning system

AHMEDABAD

7 day *Early warning system from Georgia Tech*

Monday 02 June 2014 - ORANGE ALERT LEVEL

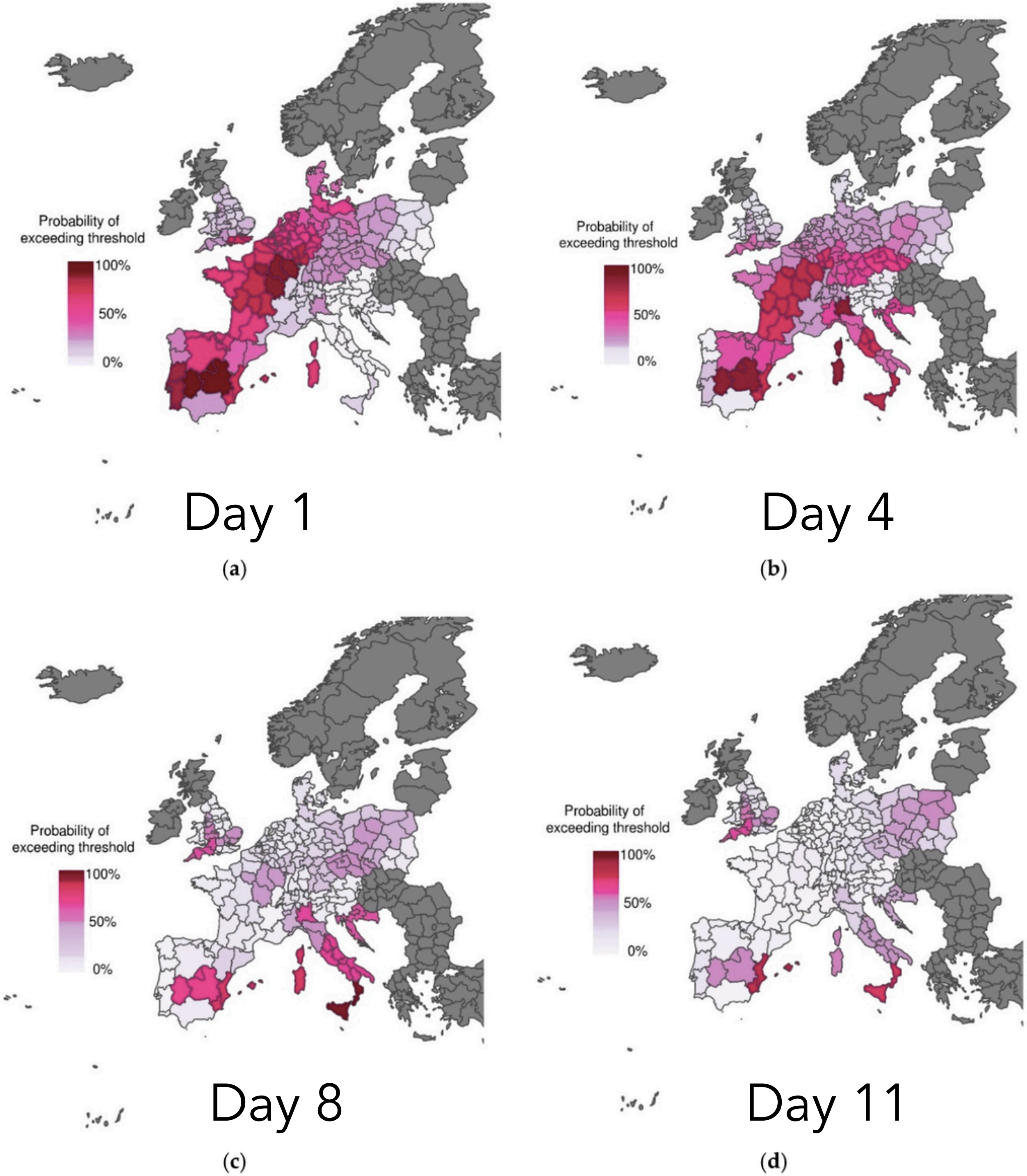
Current Forecast (Created 01-Jun)	02-Jun	03-Jun	04-Jun	05-Jun	06-Jun	07-Jun	08-Jun
Alert Level	Orange	Red	Red	Red	Orange	Orange	Orange
Likelihood of Crossing Threshold	High	High	High	High	High	High	Med
Maximum Temp (+/- 1 SD)	44.3°C (42.9-45.5)	46.1°C (44.7-47.5)	46.4°C (45.1-47.6)	45.8°C (44.0-47.4)	44.3°C (42.7-45.9)	43.8°C (42.6-45.2)	43.5°C (42.1-45.0)
Probability of "Safe Day"	0%	0%	0%	0%	0%	0%	0%
Probability of "Hot Day"	5%	0%	0%	2%	6%	18%	33%
Probability of "Very Hot Day"	75%	16%	2%	16%	67%	71%	59%
Probability of "Extreme Heat Day"	20%	84%	98%	82%	27%	12%	8%

Alert Levels:	Safe <41°C	Hot 41°C - 42.9°C	Very Hot 43°C - 44.9°C	Extreme Heat ≥45°C

Likelihood of Crossing Threshold
High>75% Med 50-75% Low<50%

Lowe et al. 2016

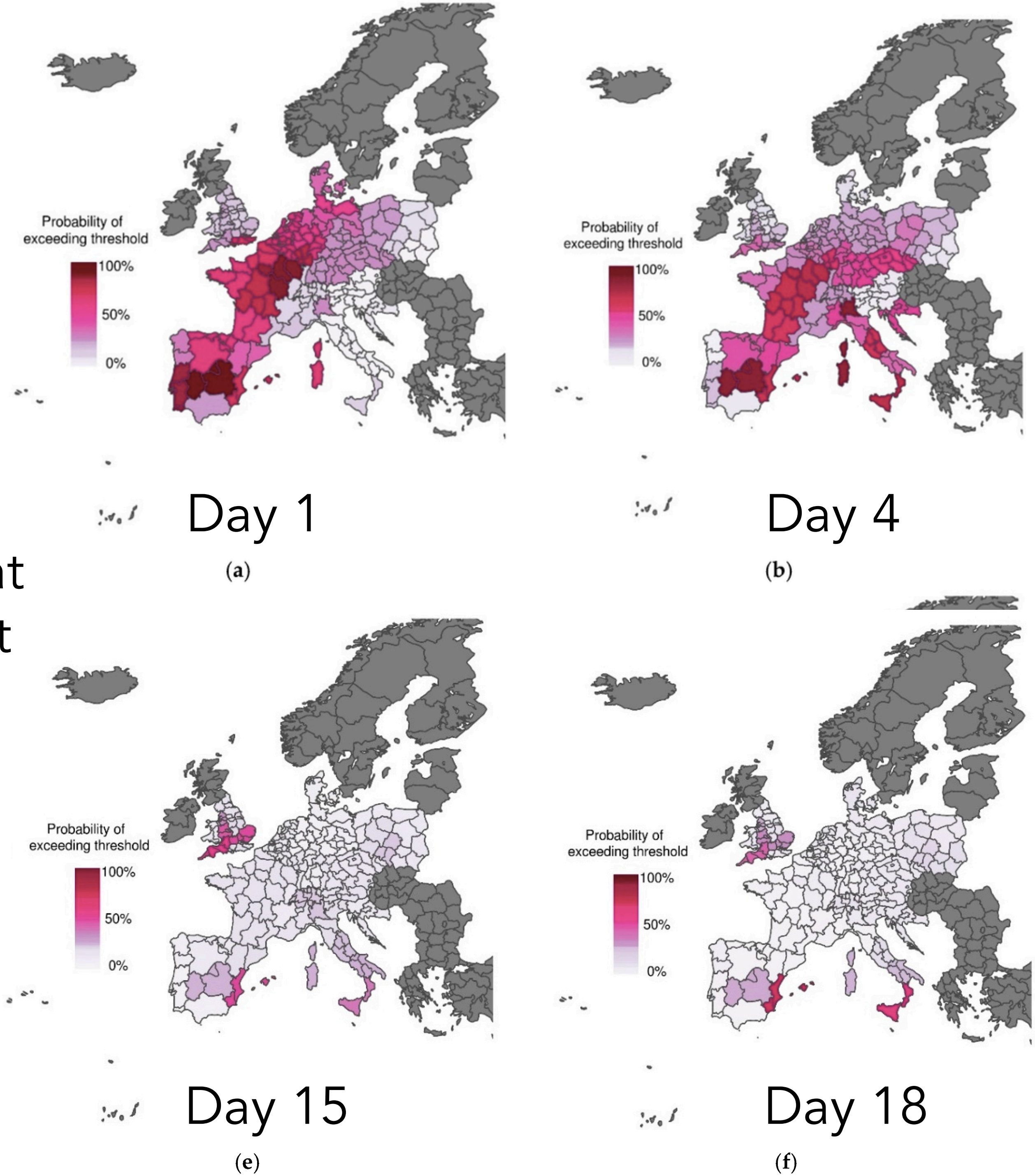
probability of exceeding 75th percentile (daily) using S2S forecasts from ECMWF



Lowe et al. 2016

probability of exceeding 75th percentile (daily) using S2S forecasts from ECMWF

Still using S2S systemat daily timescale without temporal integration



CASE STUDY 2: History of malaria early warning systems

- 1908 Epidemic in India (1 million deaths) Gill 1921, 1923 statistical model based on climate, used operationally throughout 1920-40s
- Interest in MEWS waned during 50/60s elimination efforts
- Malaria global rebound in 70s/80s
- Research Interest accelerated after the ENSO related outbreaks in 98/99

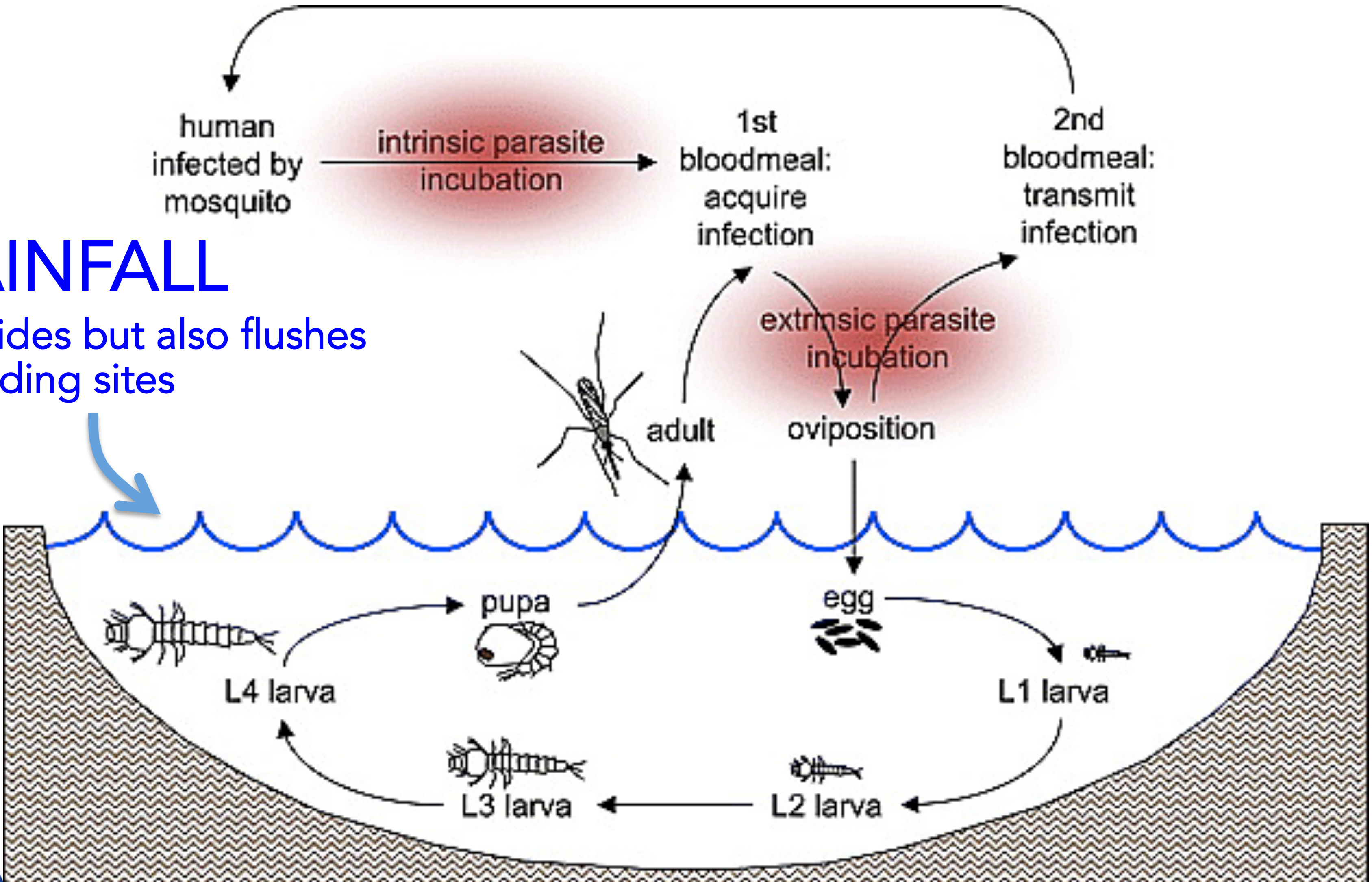
TEMPERATURE

Warmer temperatures speed up parasite, larvae and egg development

High temperature impact mortality of vector (adult and larvae)

RAINFALL

Provides but also flushes breeding sites



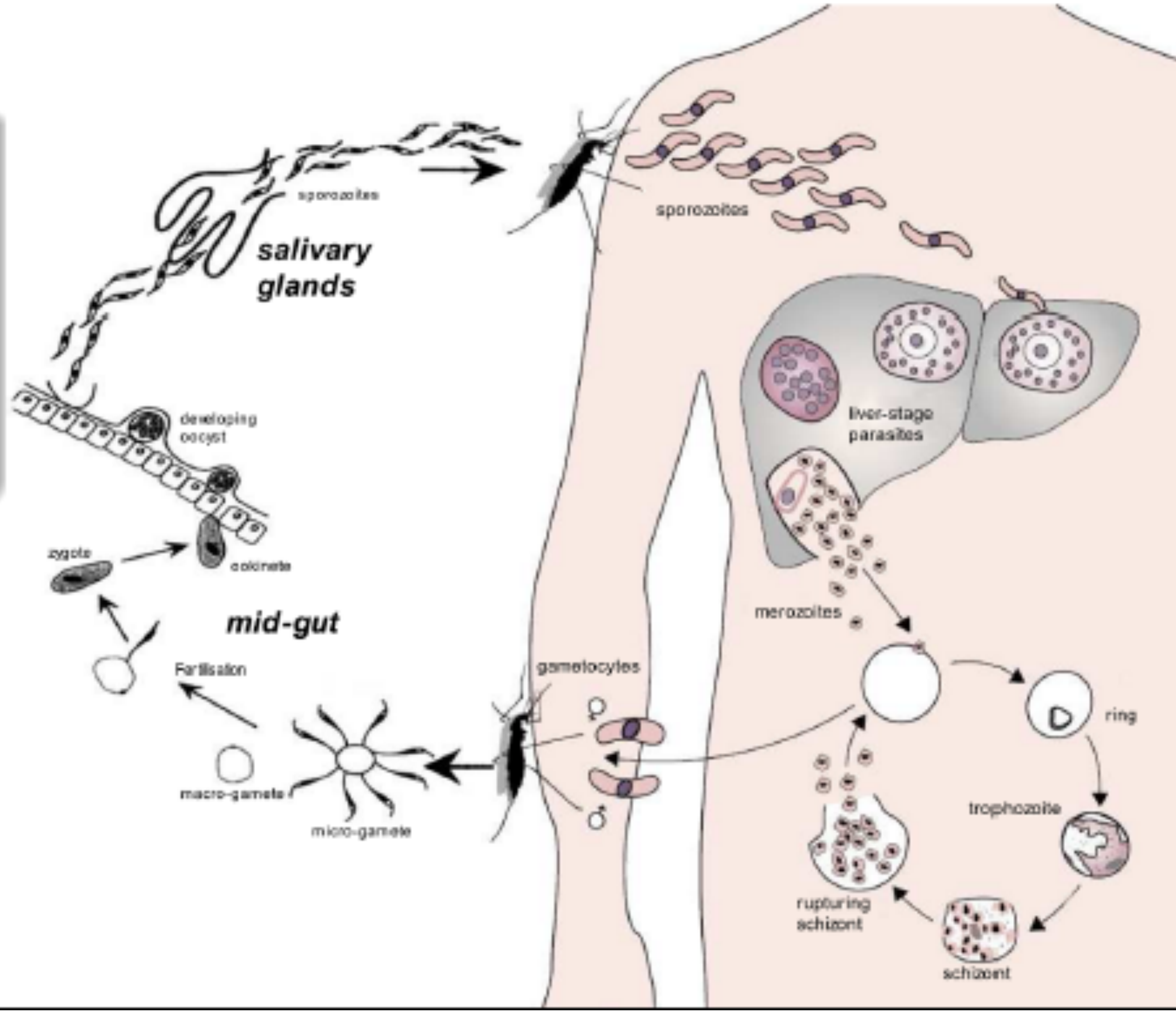
Bomblies et al.

Cycle in host takes 10-26 days

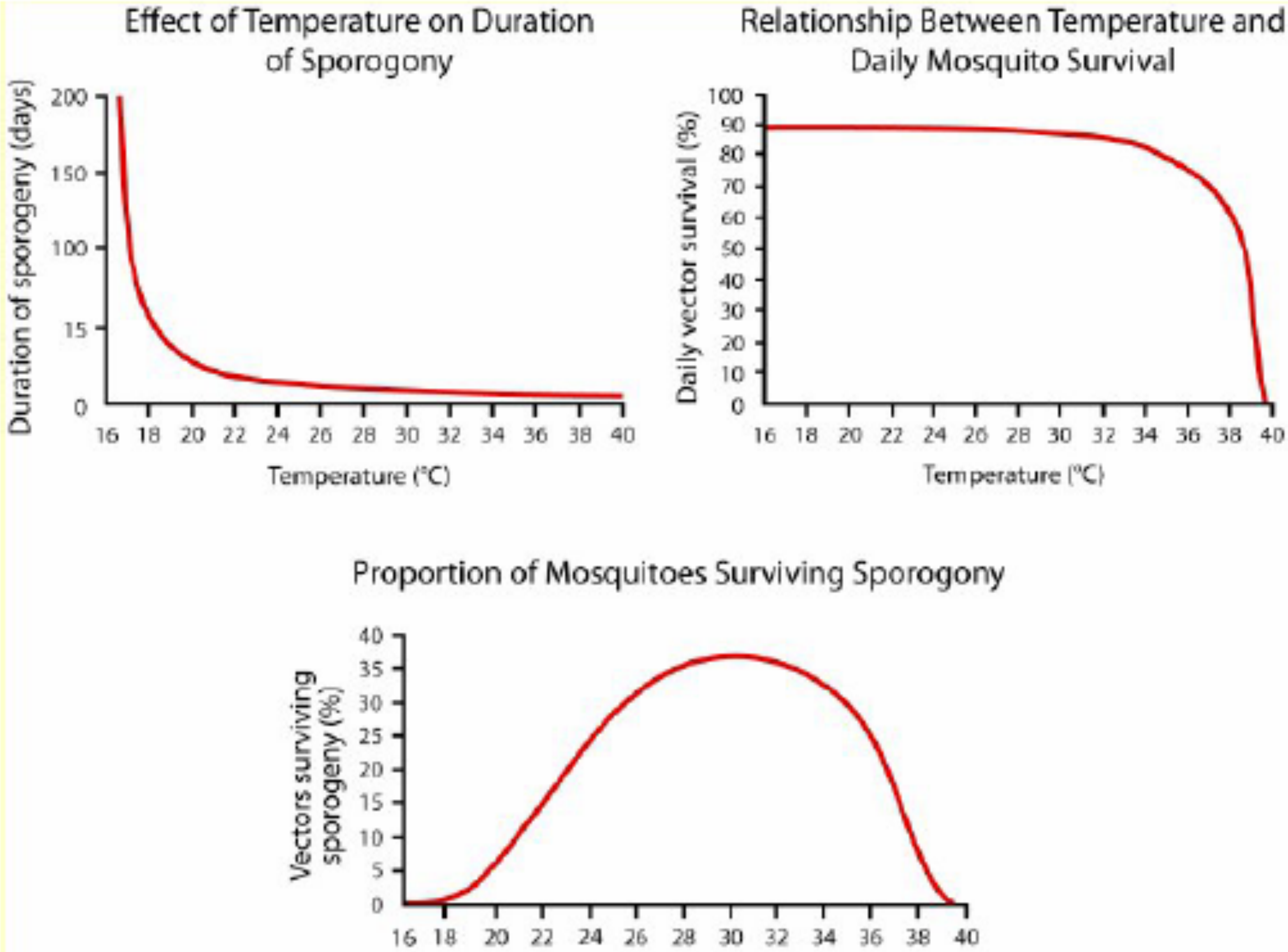
Sporogonic cycle

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

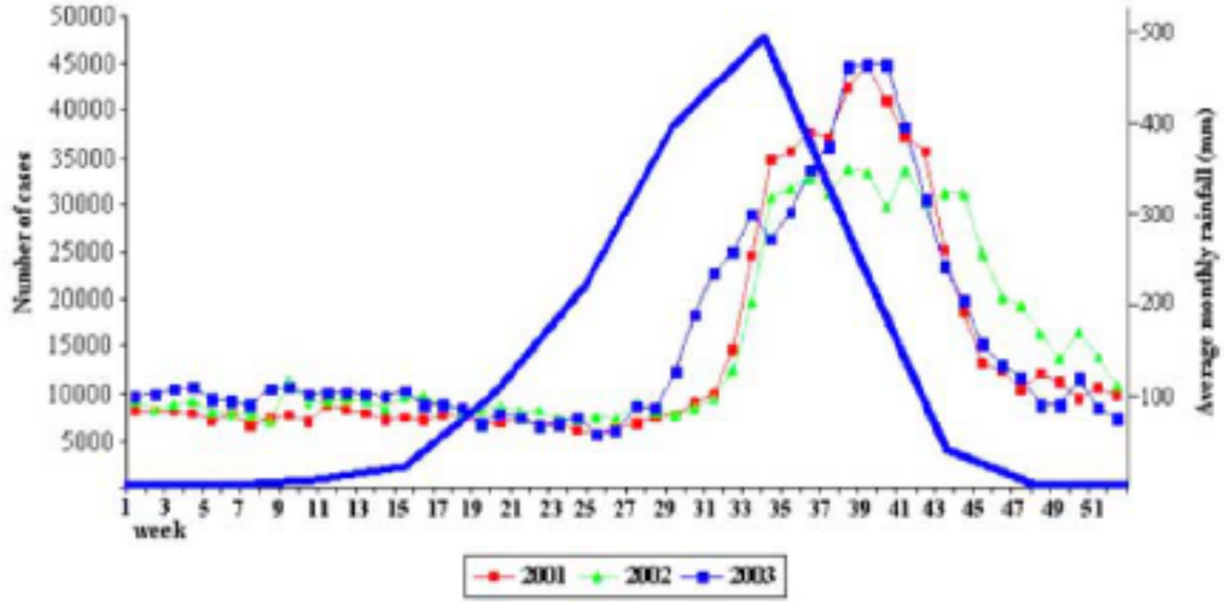


Craig et al 1999

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)

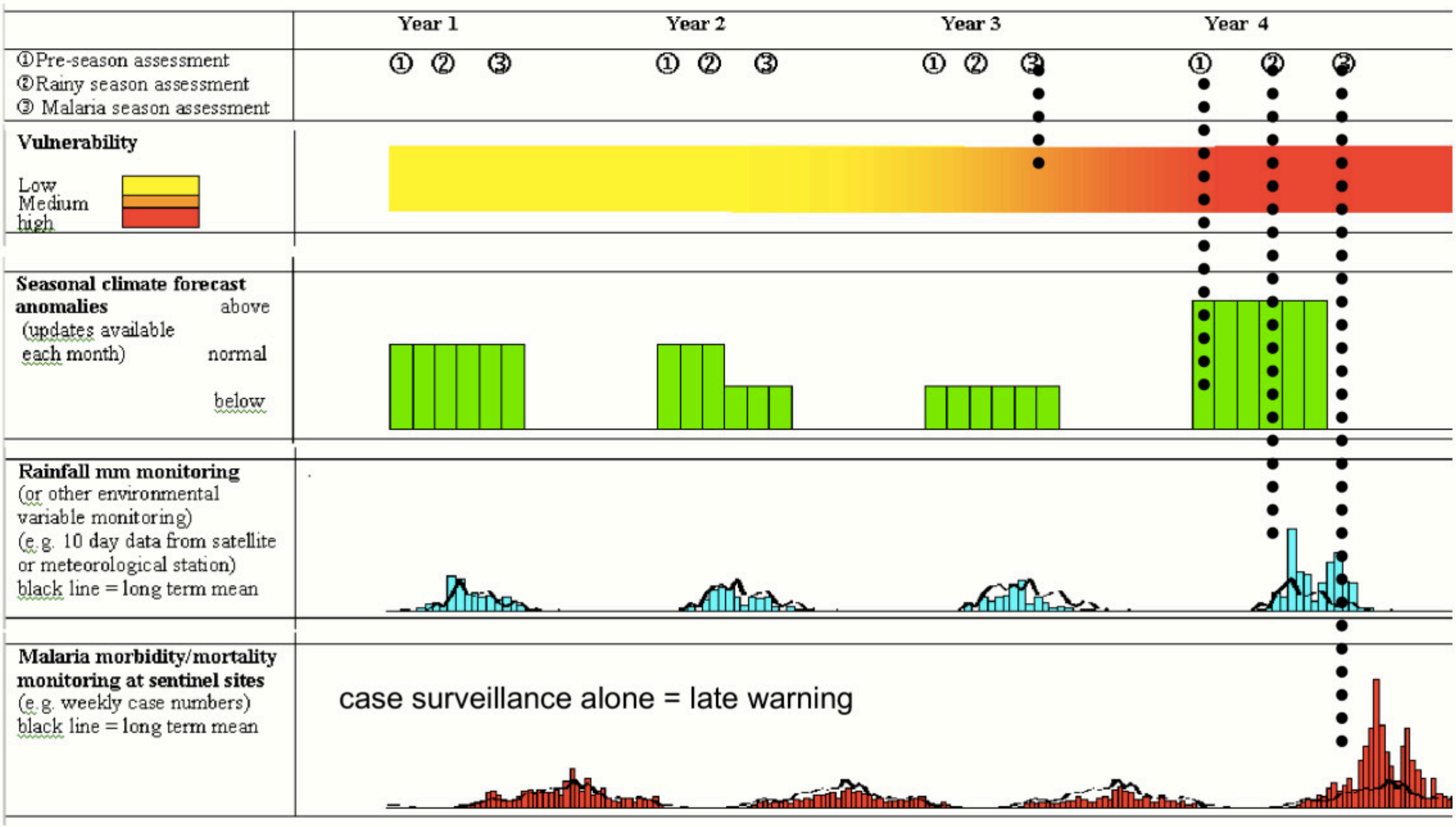


Blue - Rainfall
Dots - Malaria cases in 3 seasons

Rainfall monitoring can give 1 to 2 month early warning – S2S would aim to EXTEND this by 1 to 2 months

ICTP

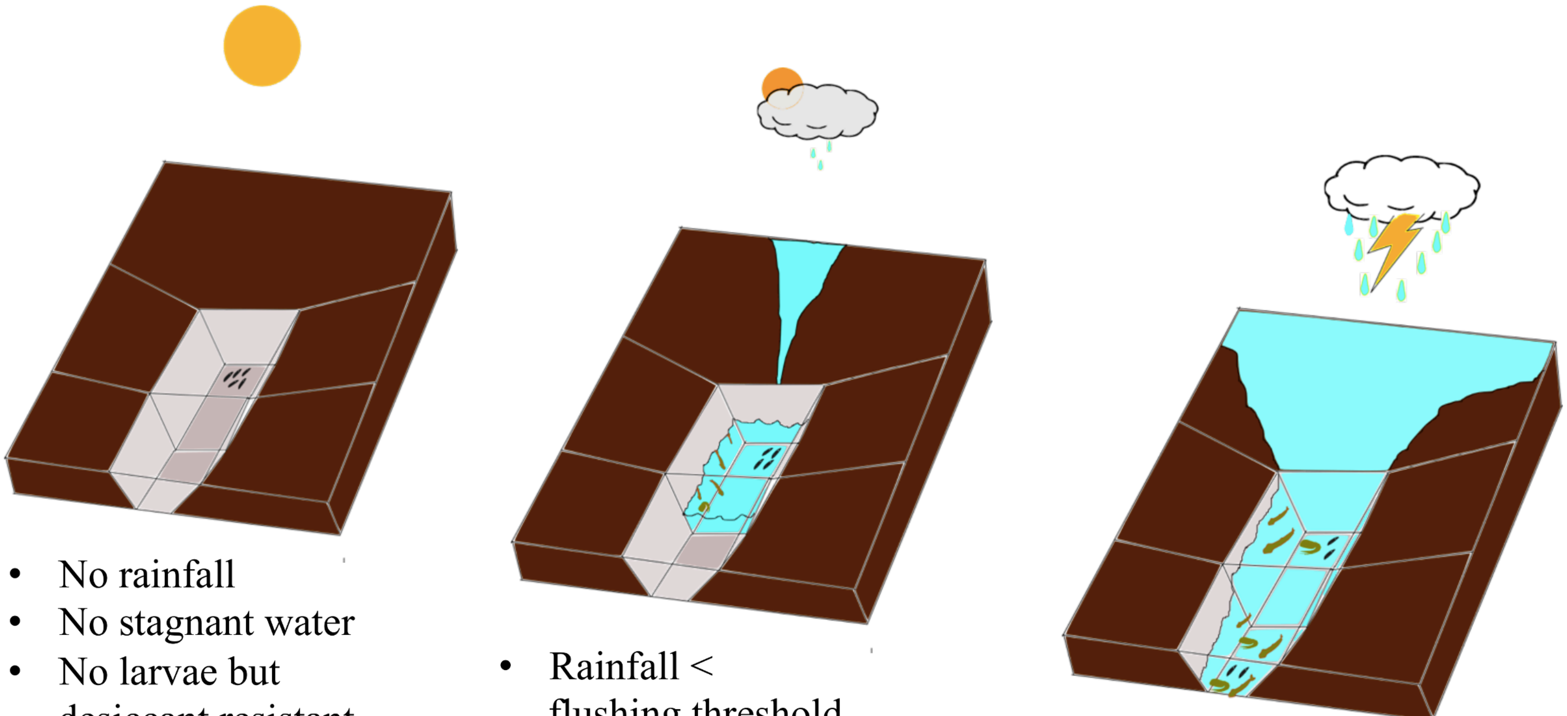
Seasonal forecasting used to extend early warning



DaSilva et al. 2004, Malaria Journal

FLUSHING

- Stage 1 larvae can be flushed by intense rainfall (Paaijmans et al. 2007)
- Implies that transmission related to sub-seasonal rainfall variability (implications for seasonal forecasting potential)



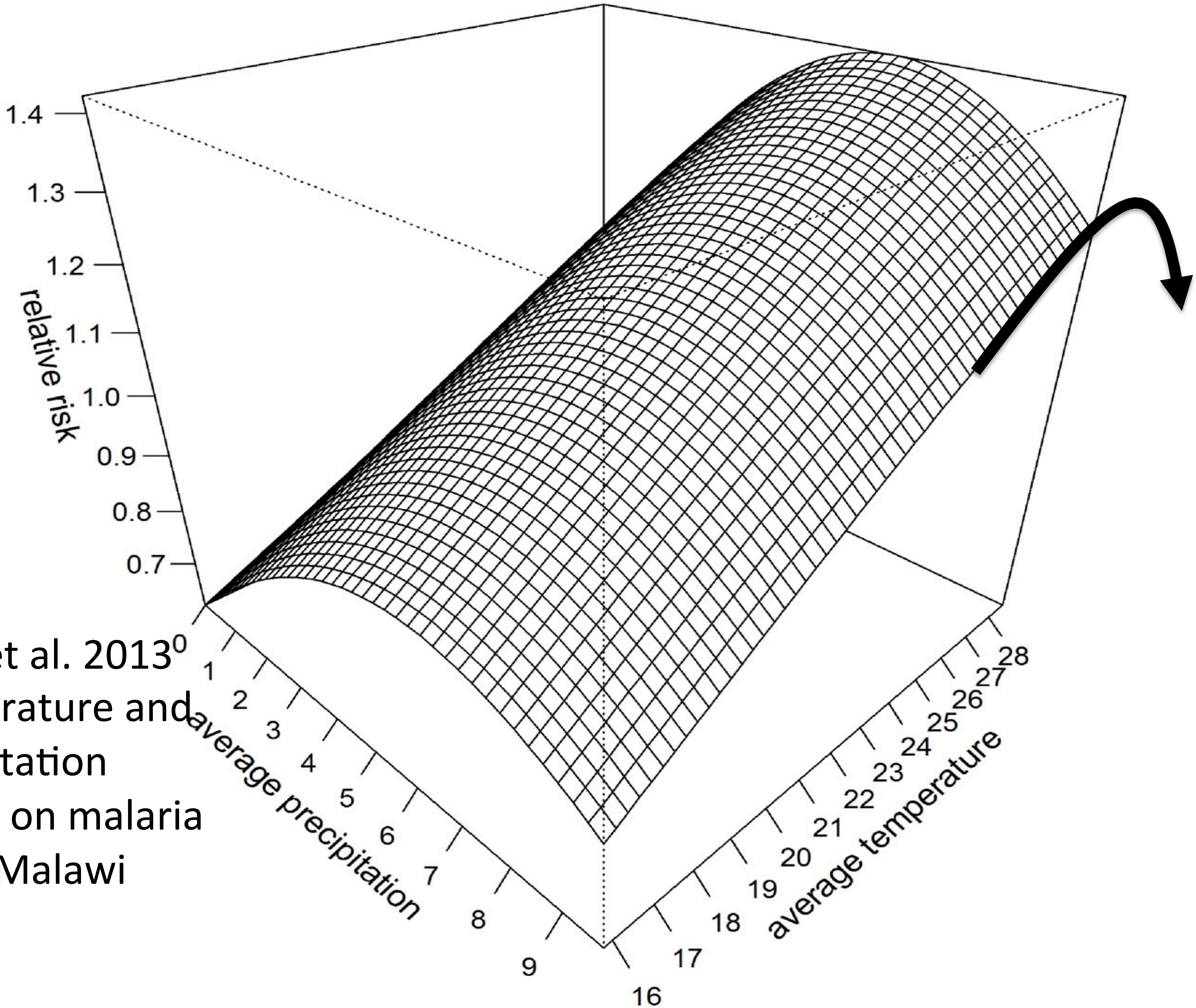
- No rainfall
- No stagnant water
- No larvae but desiccant resistant eggs

- Rainfall < flushing threshold
- Breeding of dengue vector
- No Flushing of larvae

- Rainfall > drainage threshold
- Flushing of aquatic stages

Seidahmed and Eltahir (2016)

Rainfall flushing of the dengue vector *Aedes aegypti*



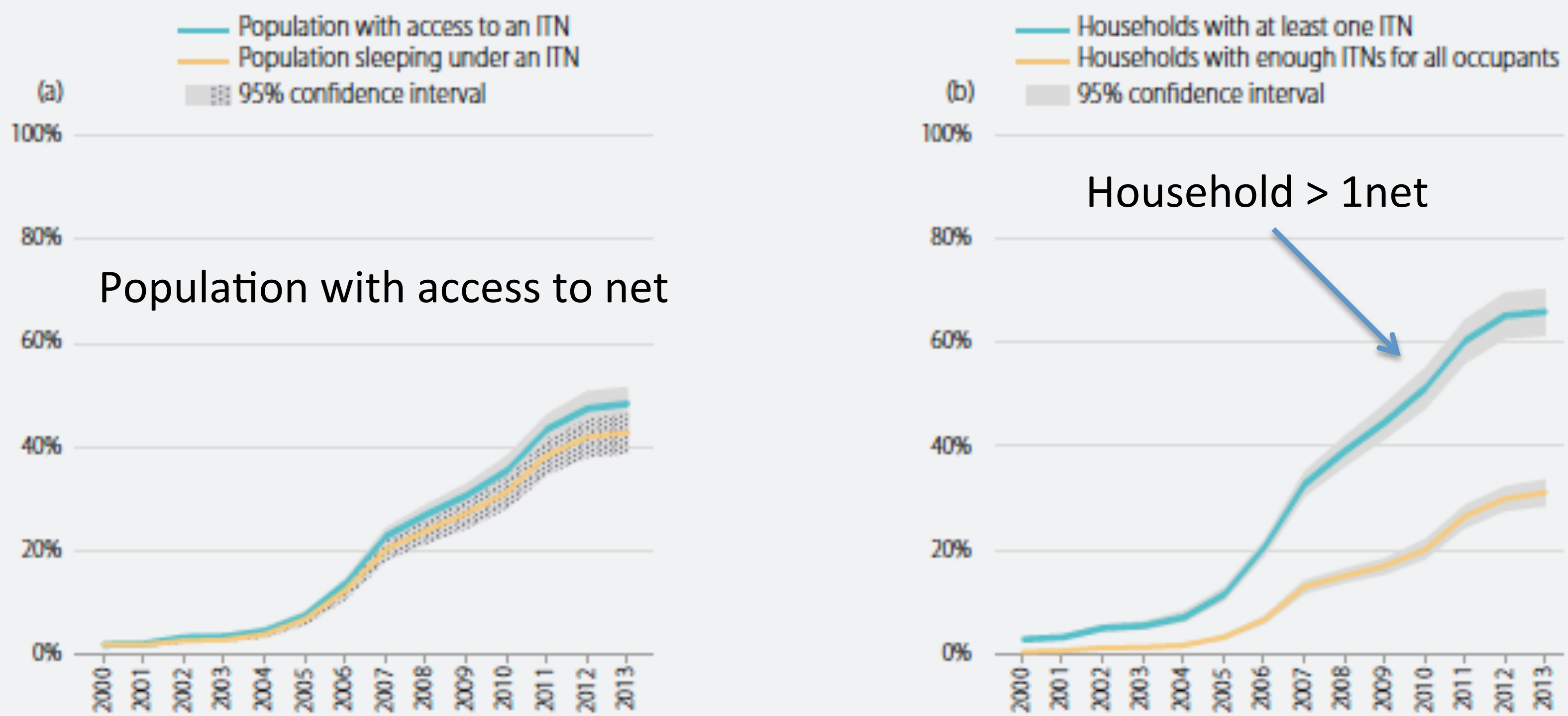
Lowe et al. 2013
Temperature and precipitation impact on malaria risk in Malawi

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

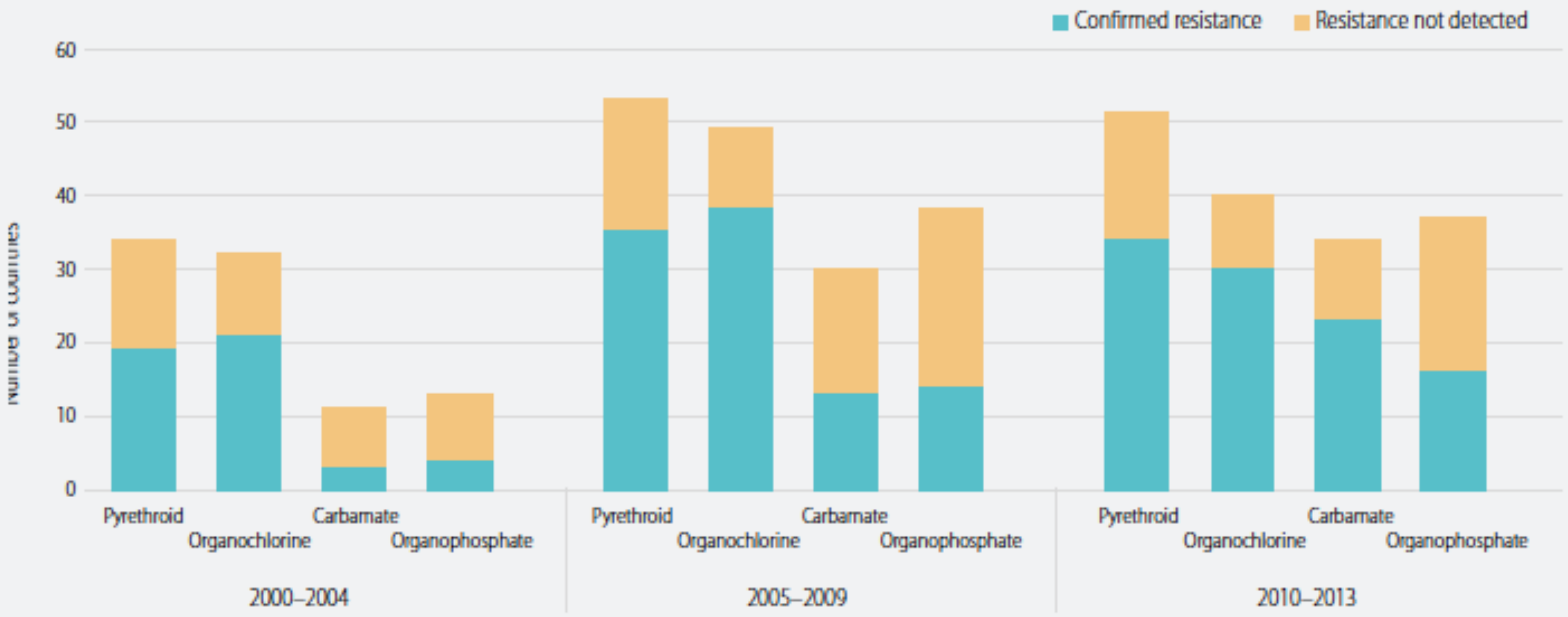


ITN, insecticide-treated mosquito net

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

Issue of insecticide resistence

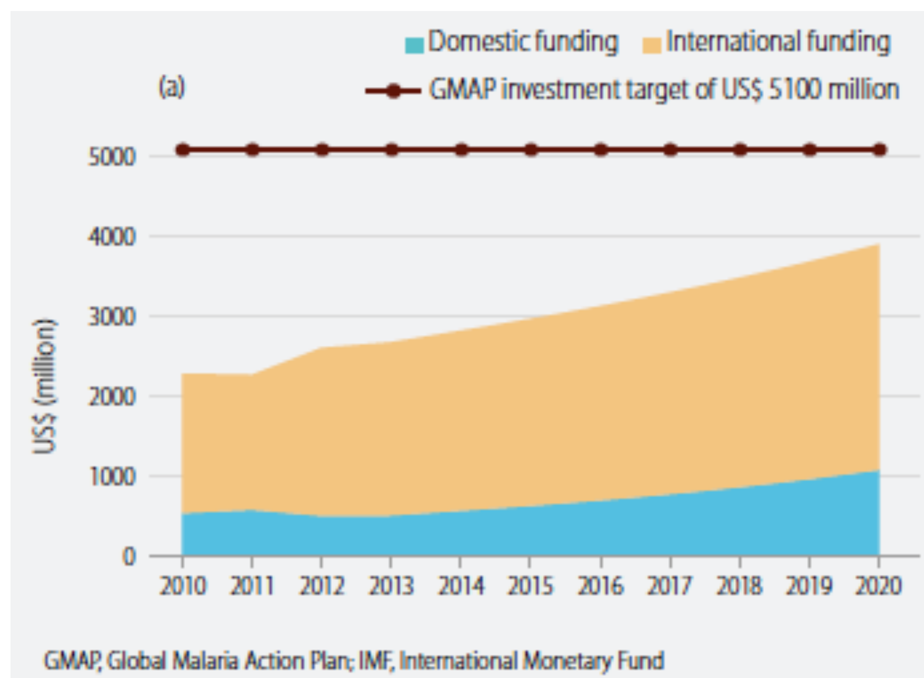
Figure 3.9 Number of countries reporting insecticide resistance monitoring results, by insecticide class and years of monitoring activity



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

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)

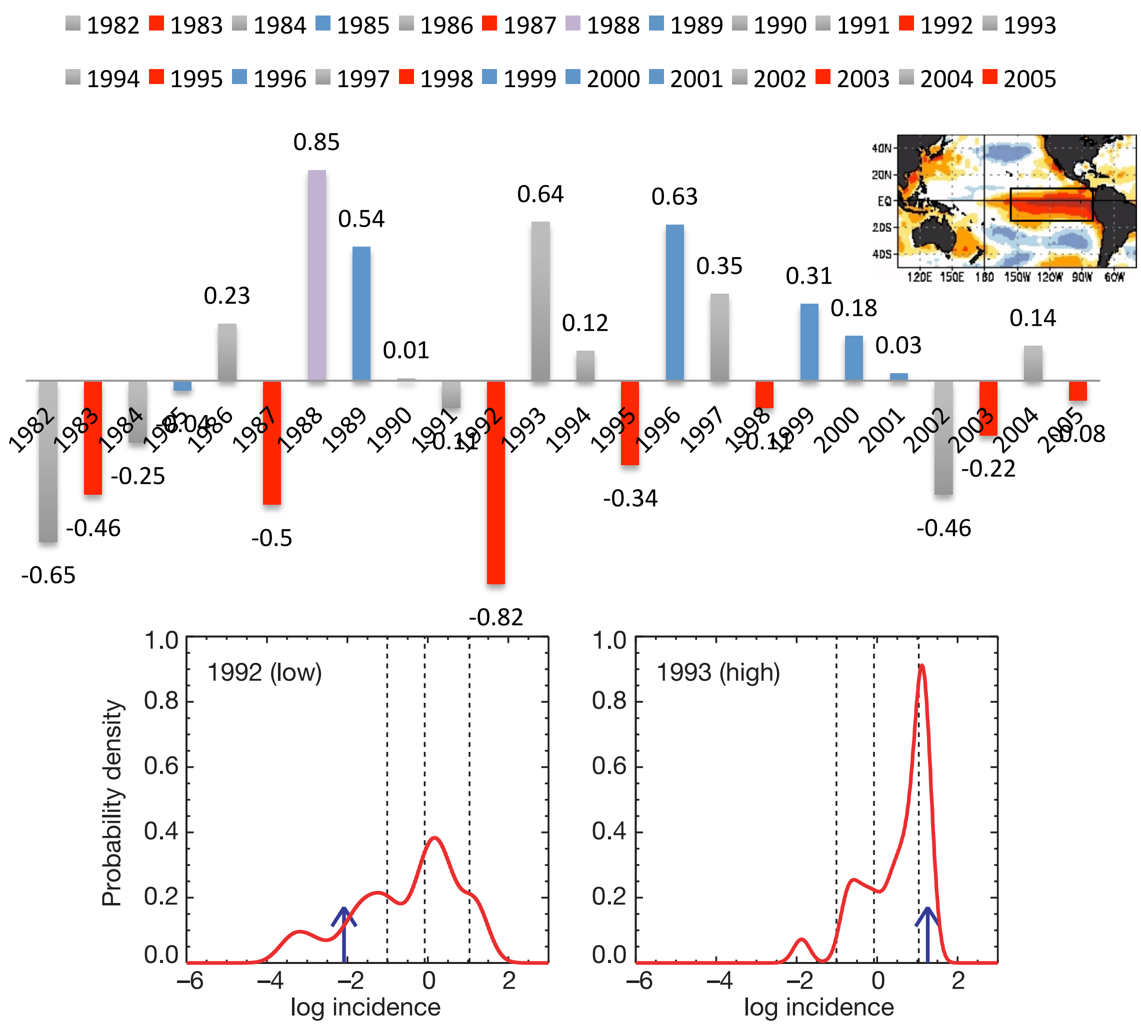


ICTP

Towards 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).
- Rainfall observations used to drive calibrated SEIR model for 4 month lead time in India (Laneri et al. 2010), but no seasonality allowed.

Detrended SST anomalies (blue - La Nina and red = El Nino – both = purple)

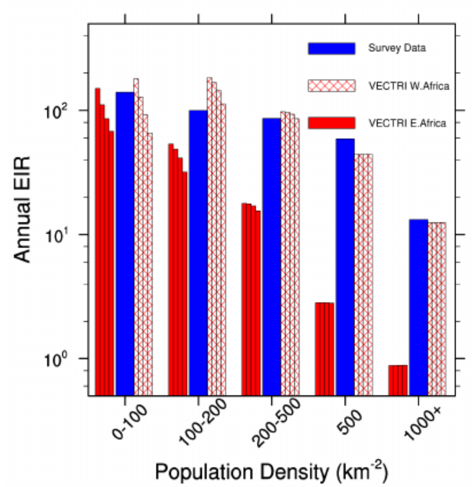


VECTRI malaria model

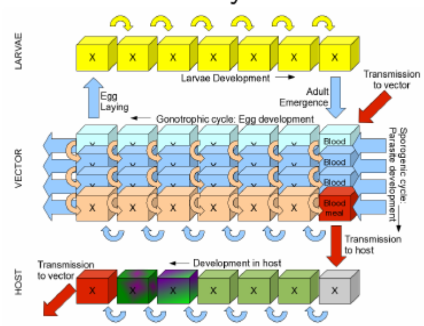
VECTRI

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

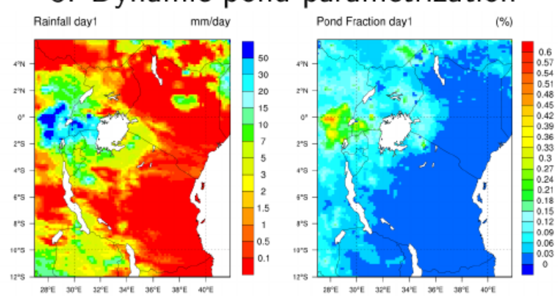
2. Accounts for population density



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

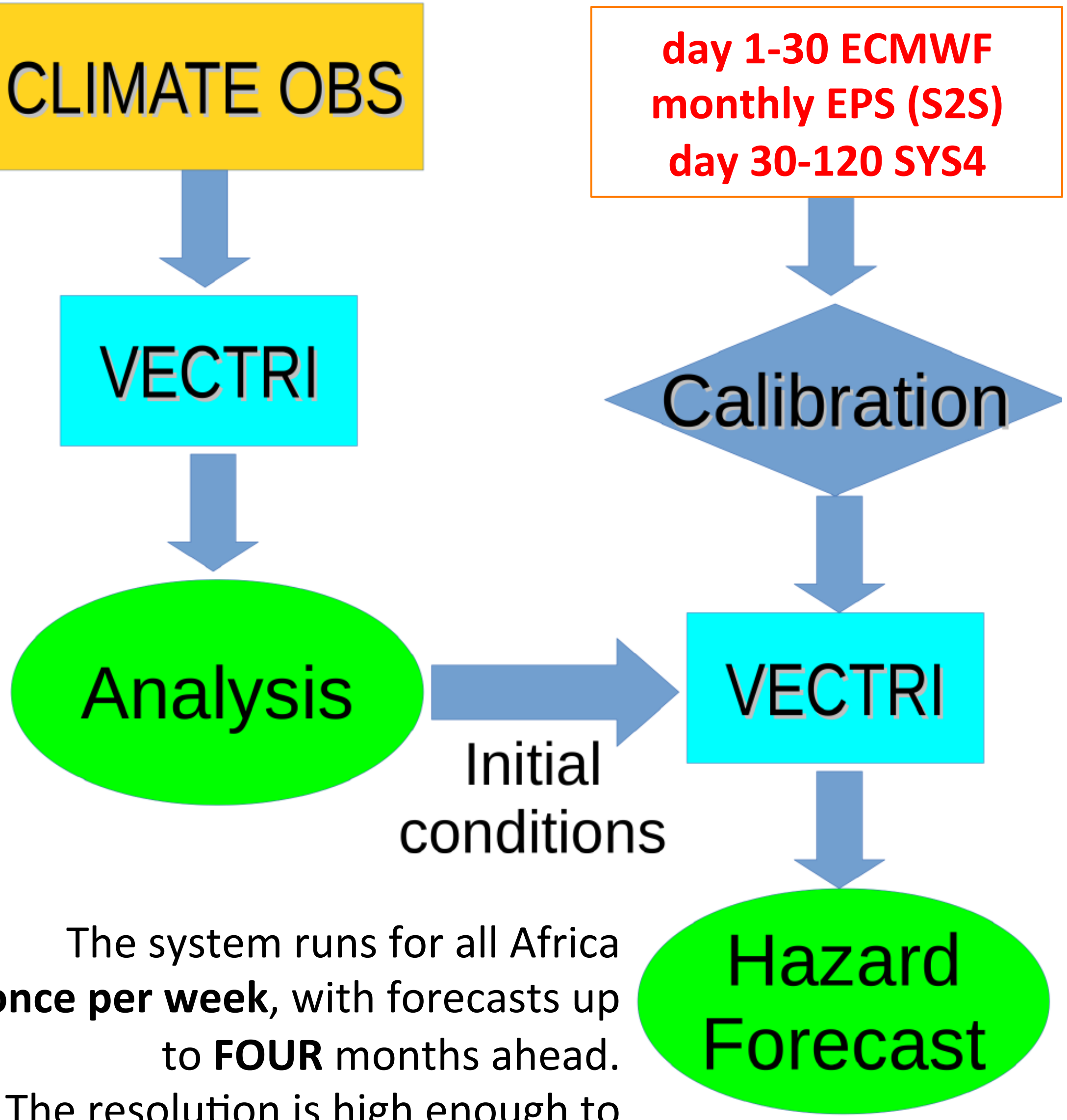


3. Dynamic pond parametrization



- ❑ 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

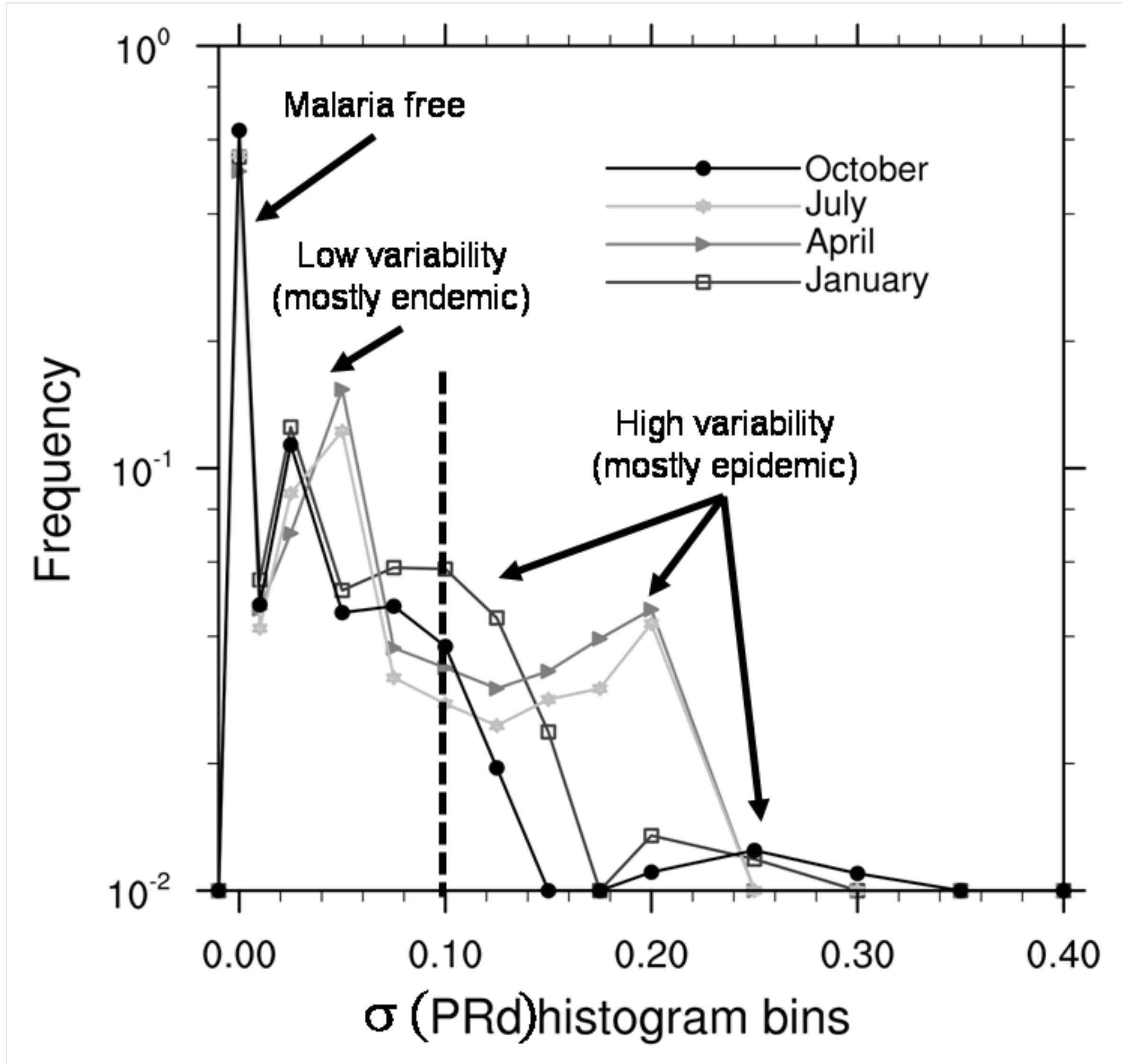
Climate observations are used to create an analysis of entomological and epidemiological conditions in order to initialize the malaria forecasts using the ICTP dynamical malaria model VECTRI (Tompkins and Ermert, 2013).



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**

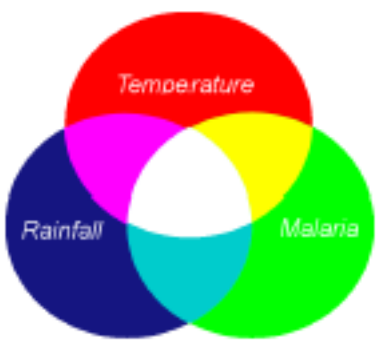
mask areas where climate is not key for driving variability.

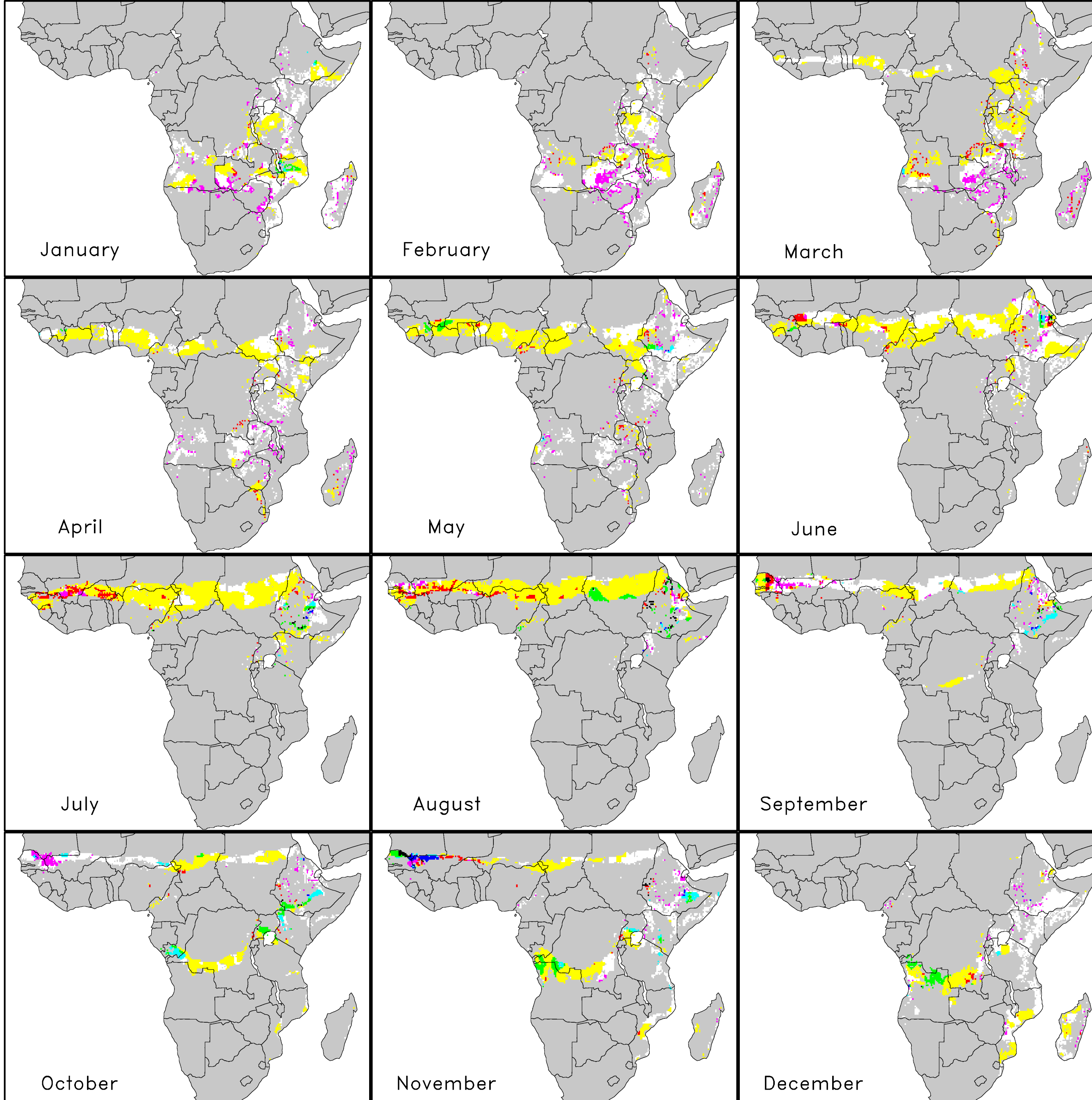
Interannual standard deviation of prevalence simulated by VECTRI driven by ERA Interim temperature and rainfall



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

Only focussing on high variability areas

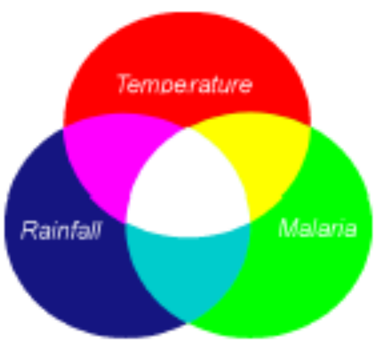


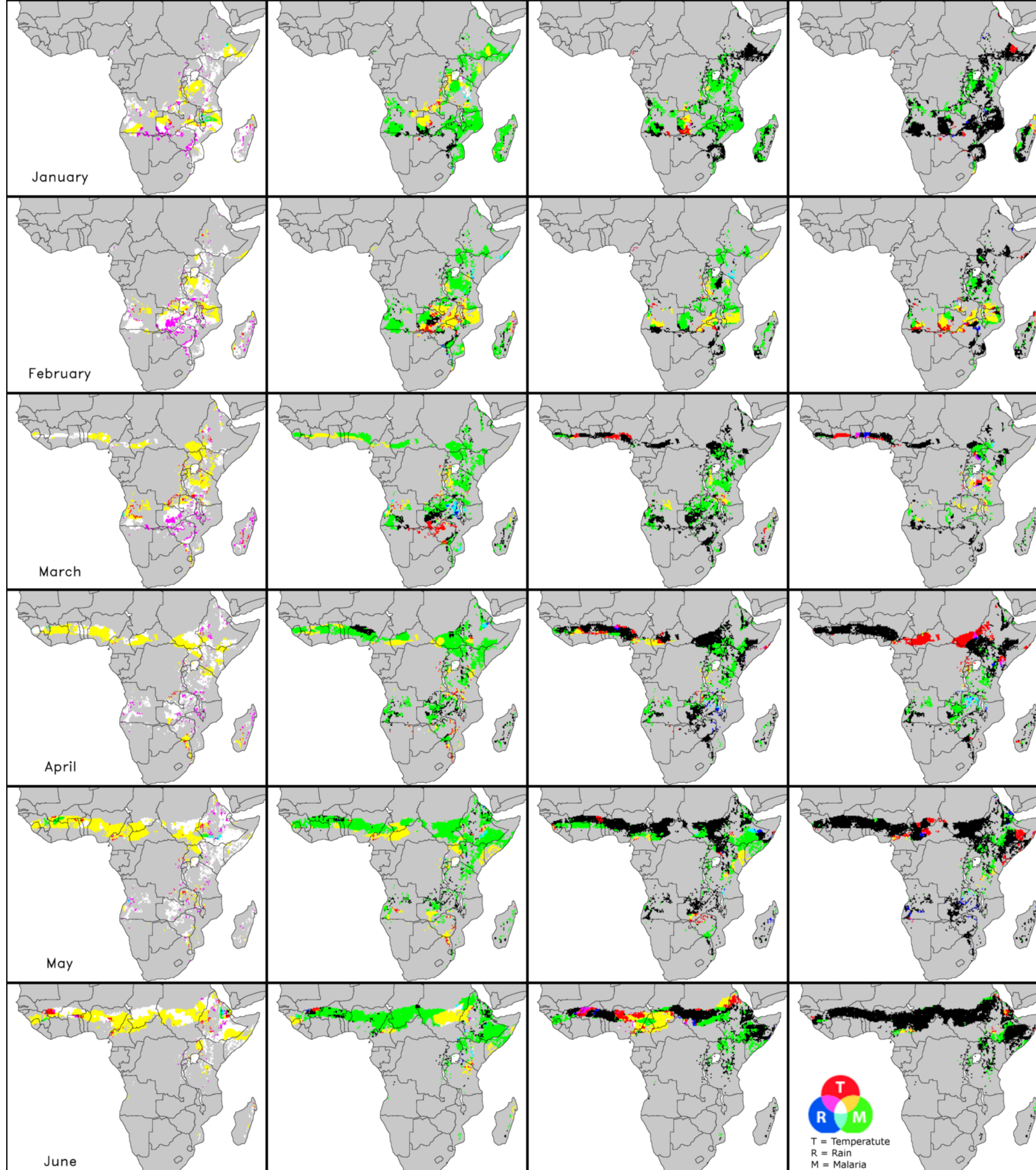


Lead 1-4 statistical skill

Only focussing on high variability areas

Malaria skill out to m3-4

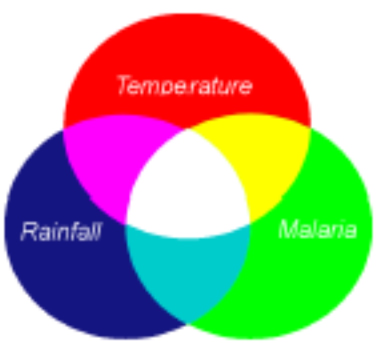




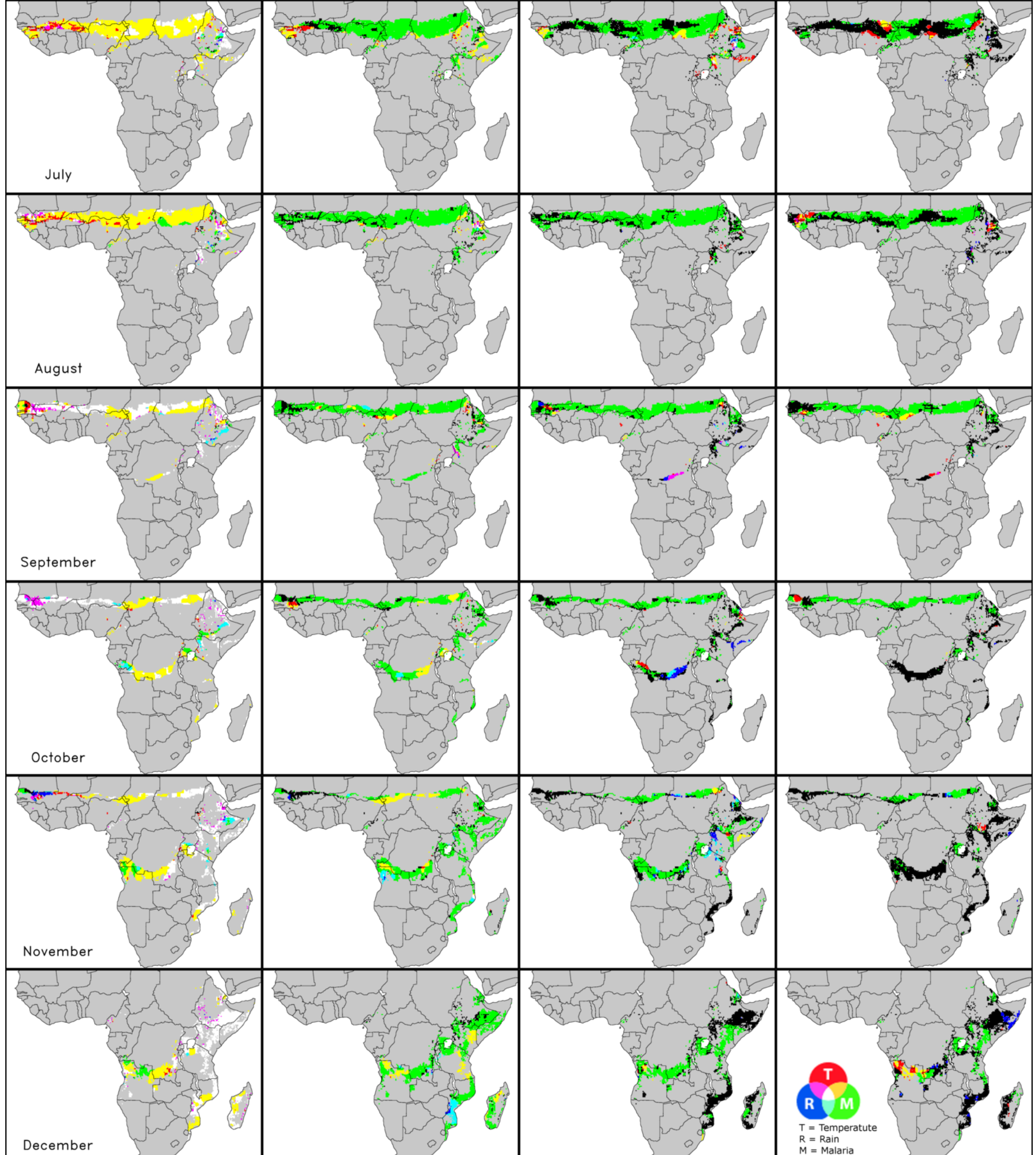
Lead 1-4 statistical skill

Only focussing on high variability areas

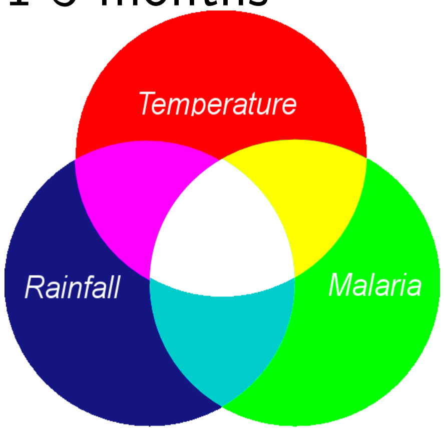
Malaria skill out to m3-4



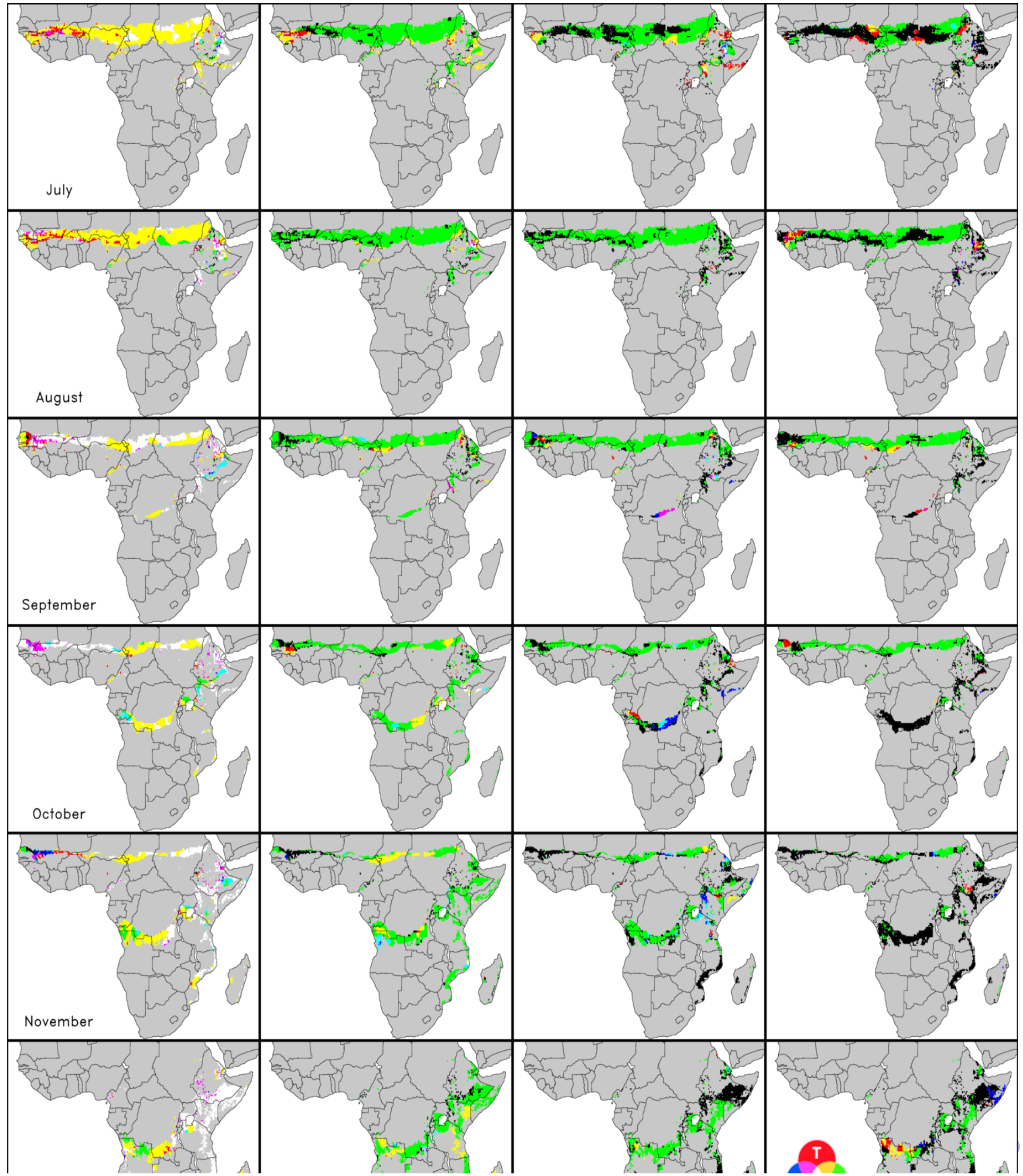
ICTP



Skill in predicting temperature, rainfall and malaria PR at lead 1-3 months



Malaria skill in m2 and 3 derives from climate forecast in m1 and the analysis.



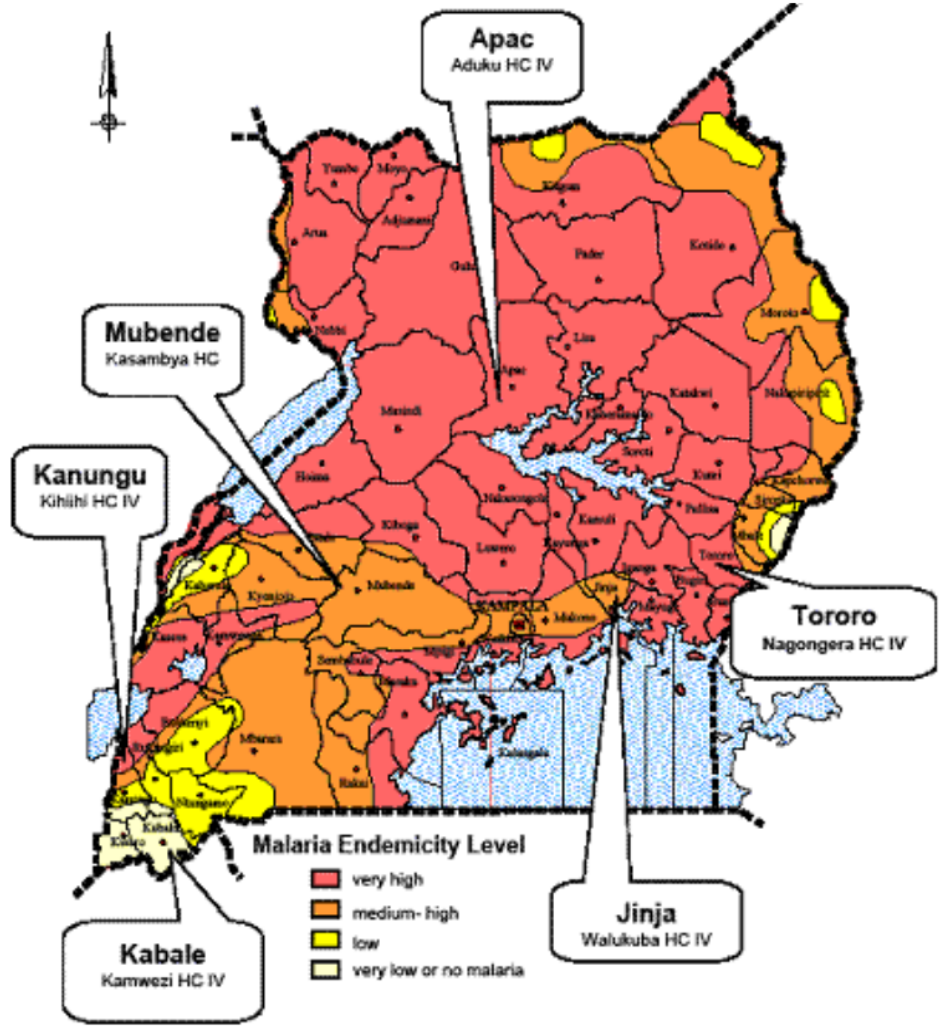
Uganda analysis

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

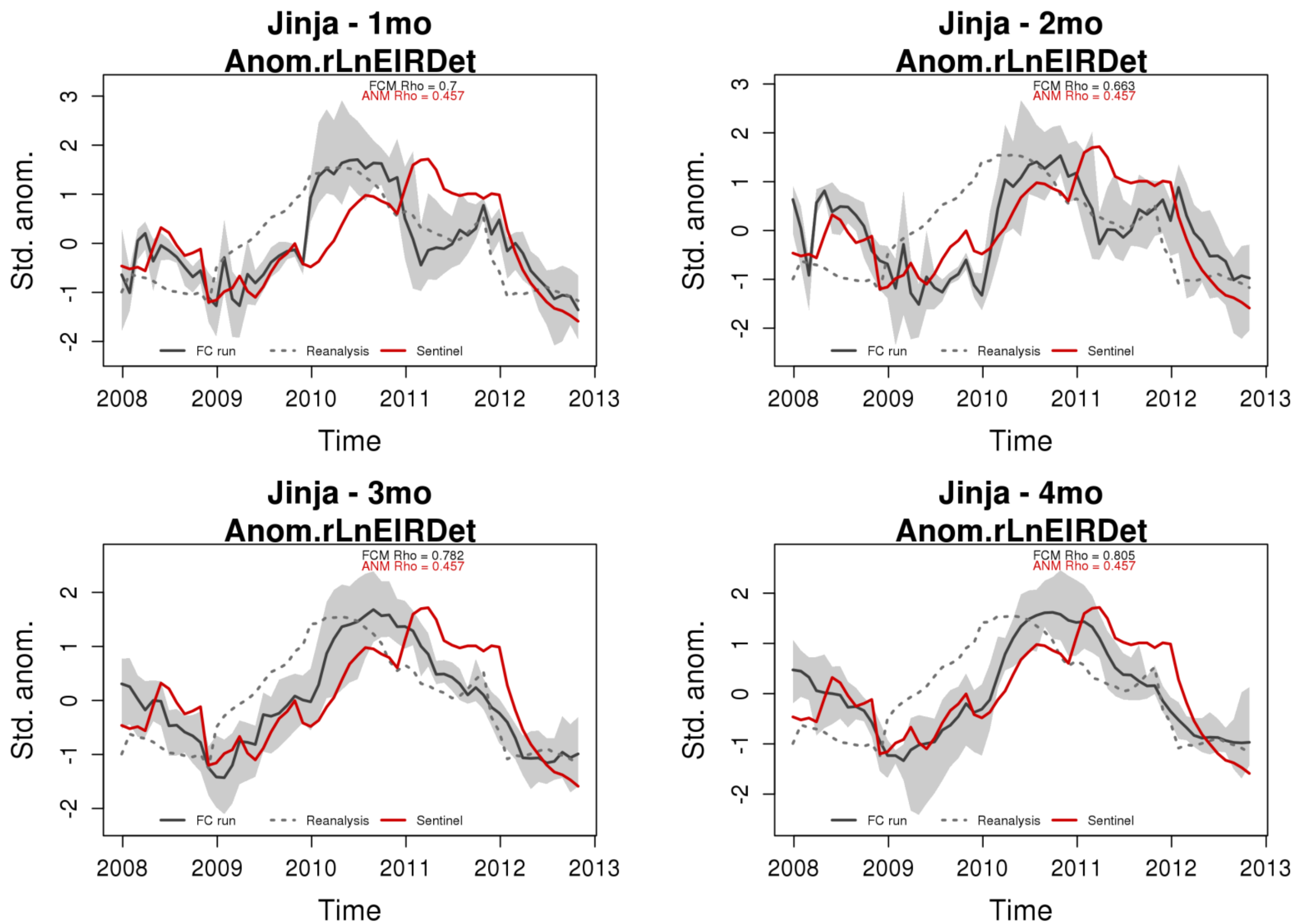
Red line: normalized **confirmed** cases

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

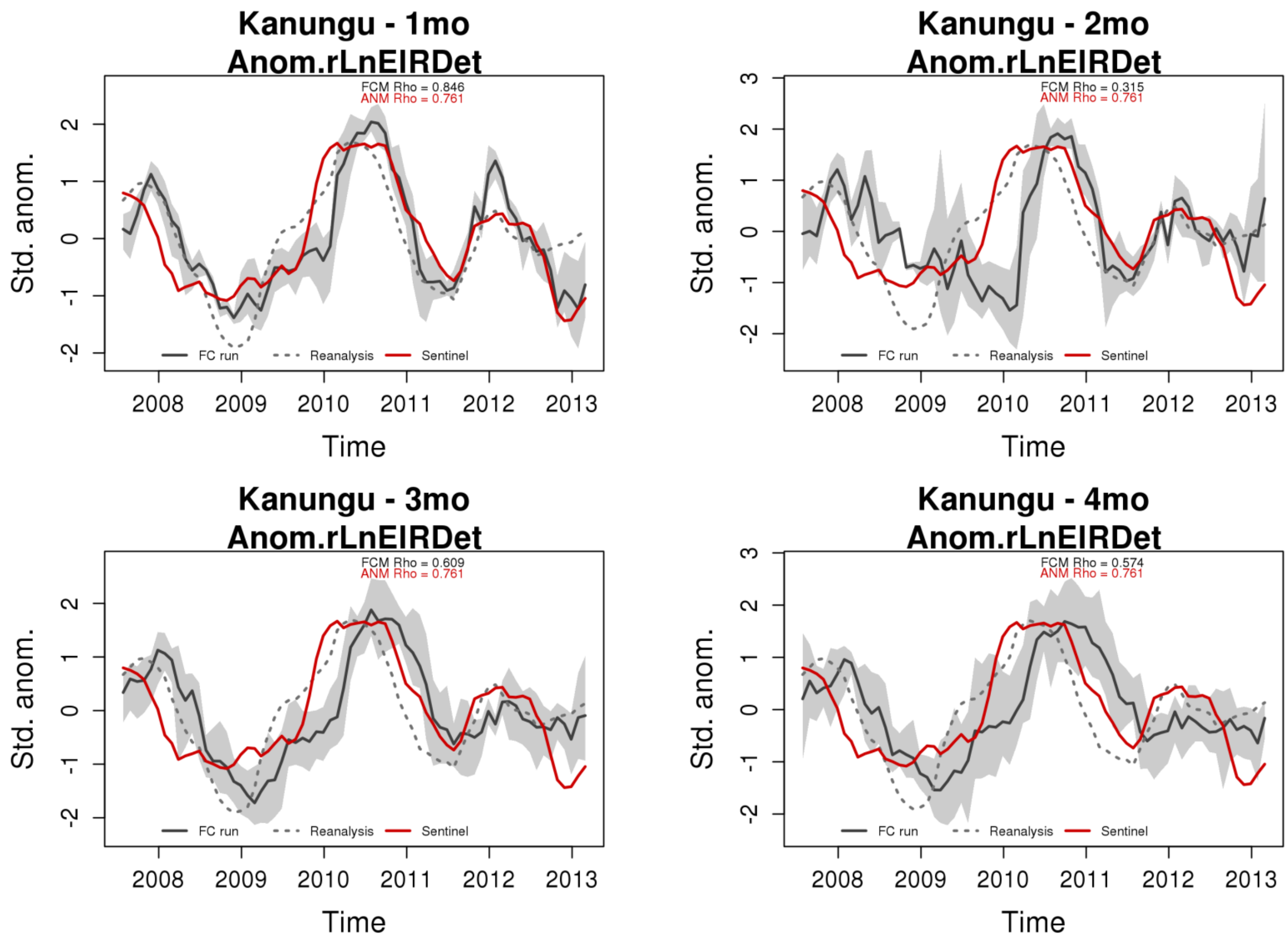
Red line: normalized **confirmed** cases

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

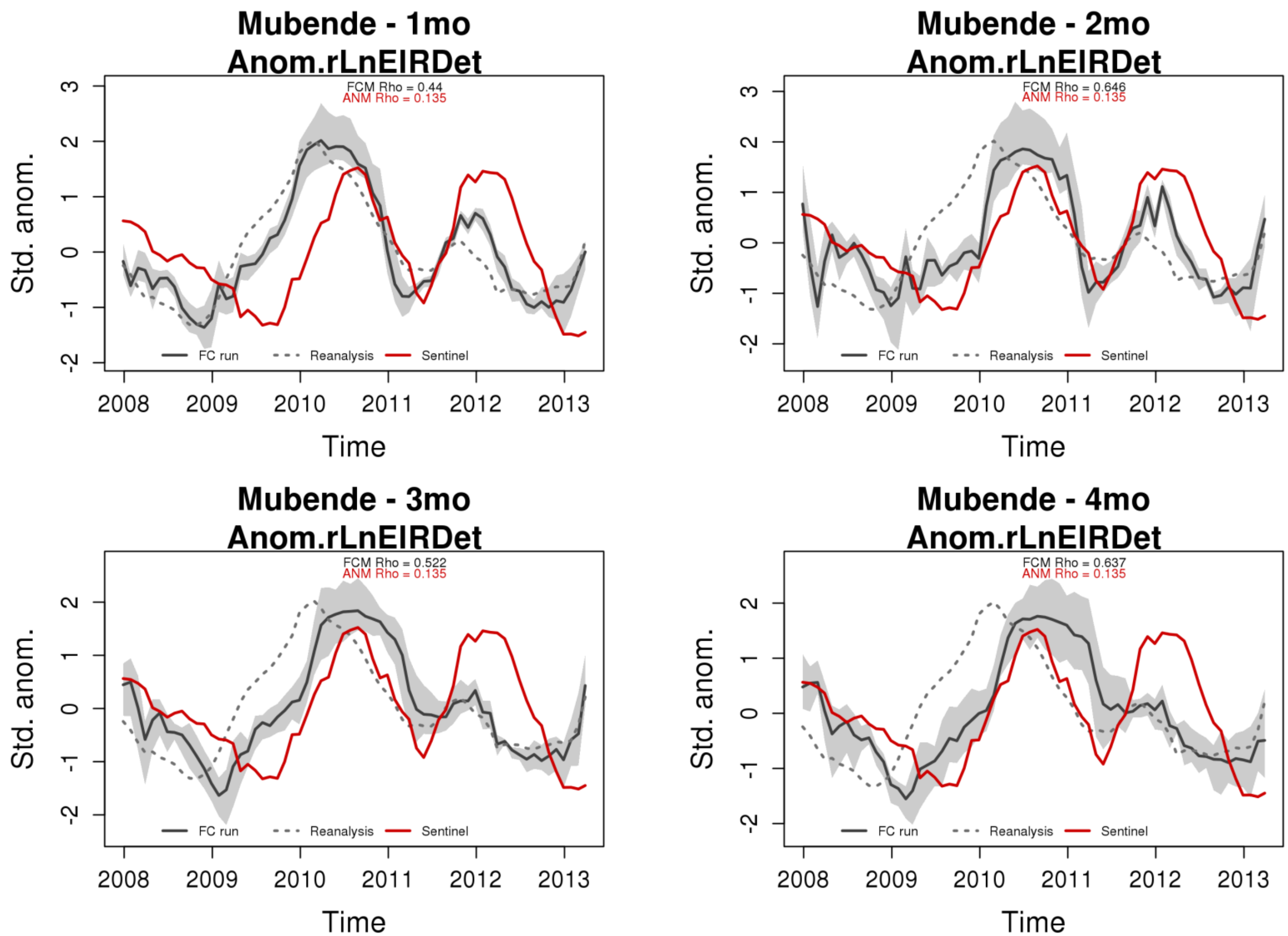
Red line: normalized **confirmed** cases

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

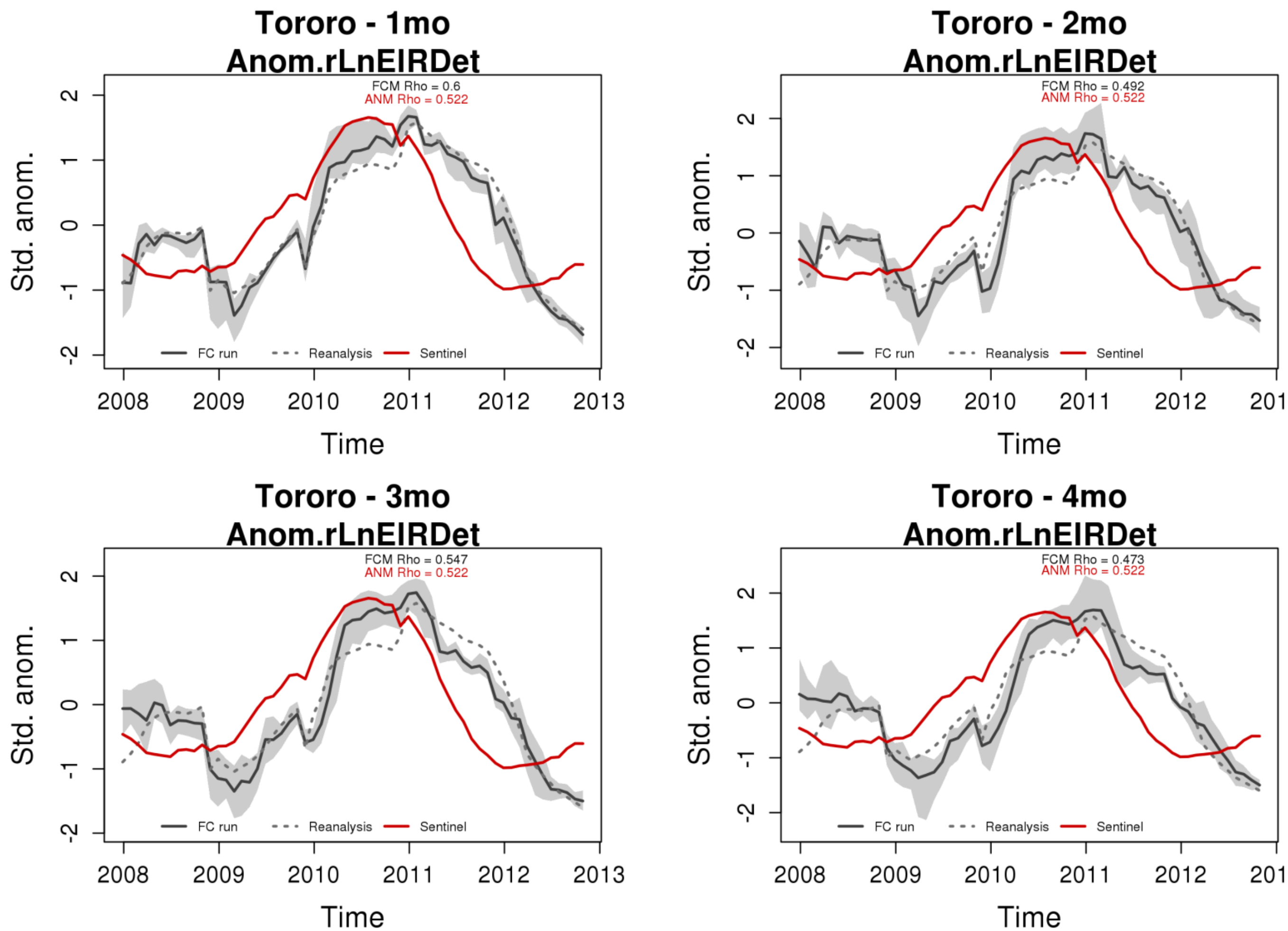
Red line: normalized **confirmed** cases

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



Sample results again MoH district data

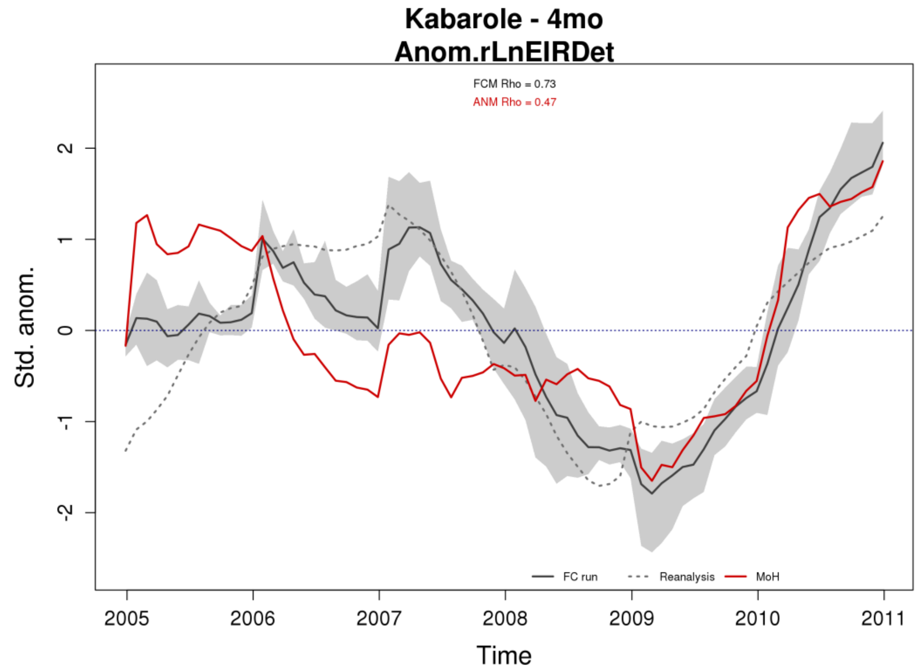
Red line: normalized **suspected** cases

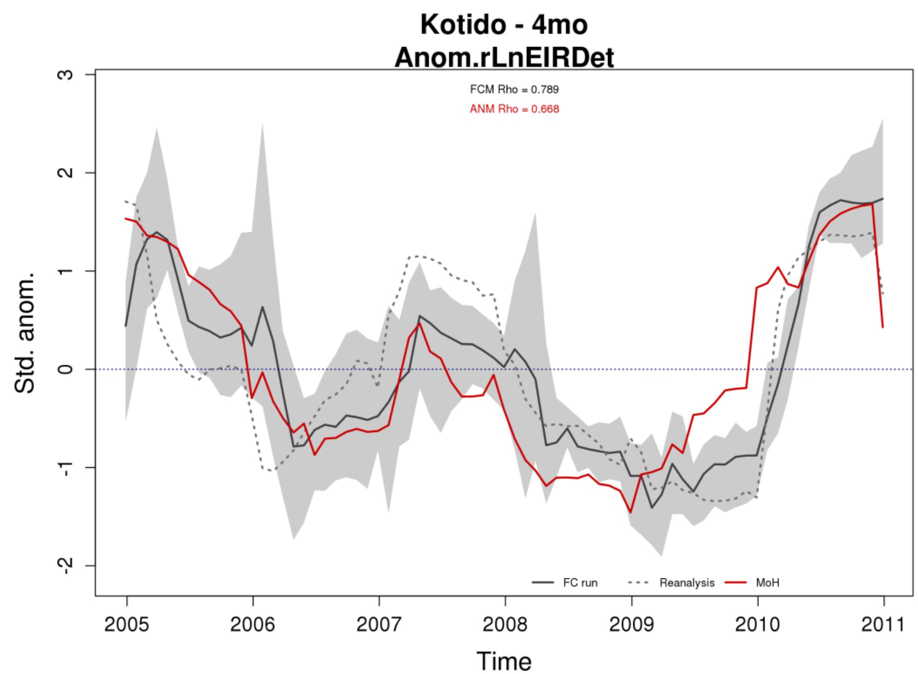
Black Line: normalized malaria forecast

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

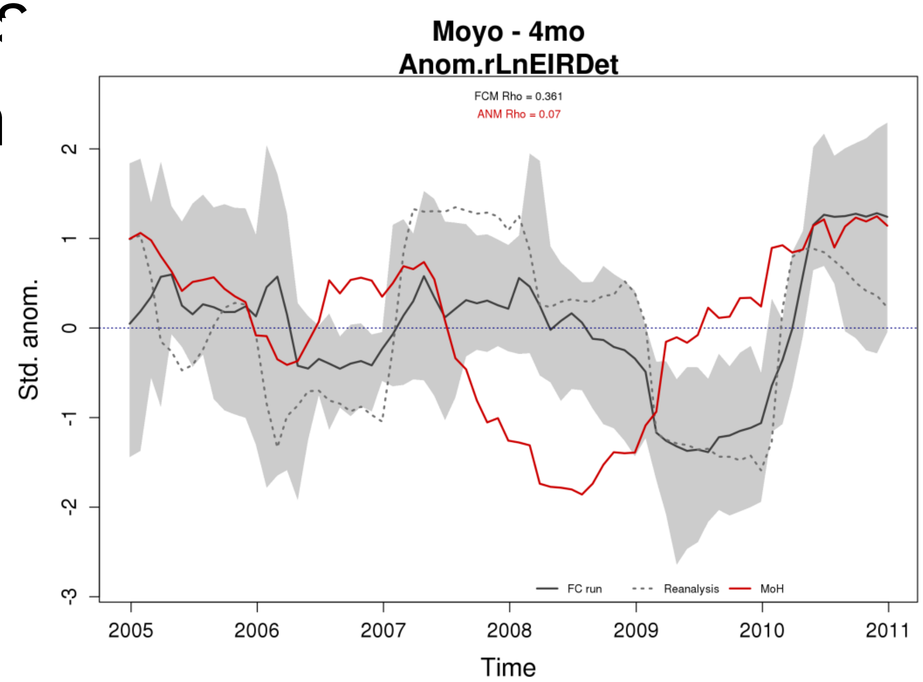
Red line: normalized **suspected** cases

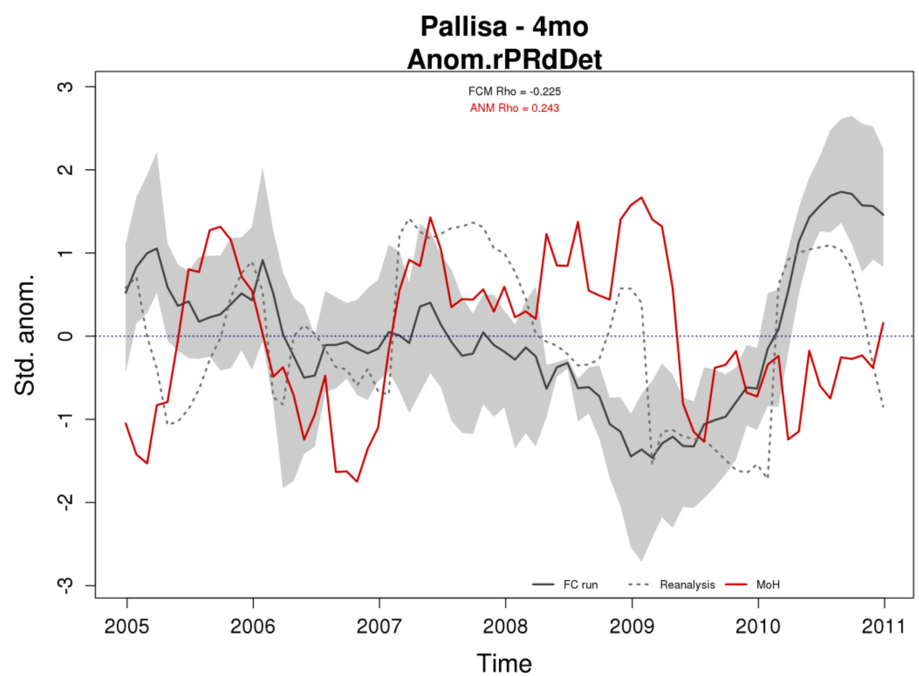
Black Line: normalized malaria forecast

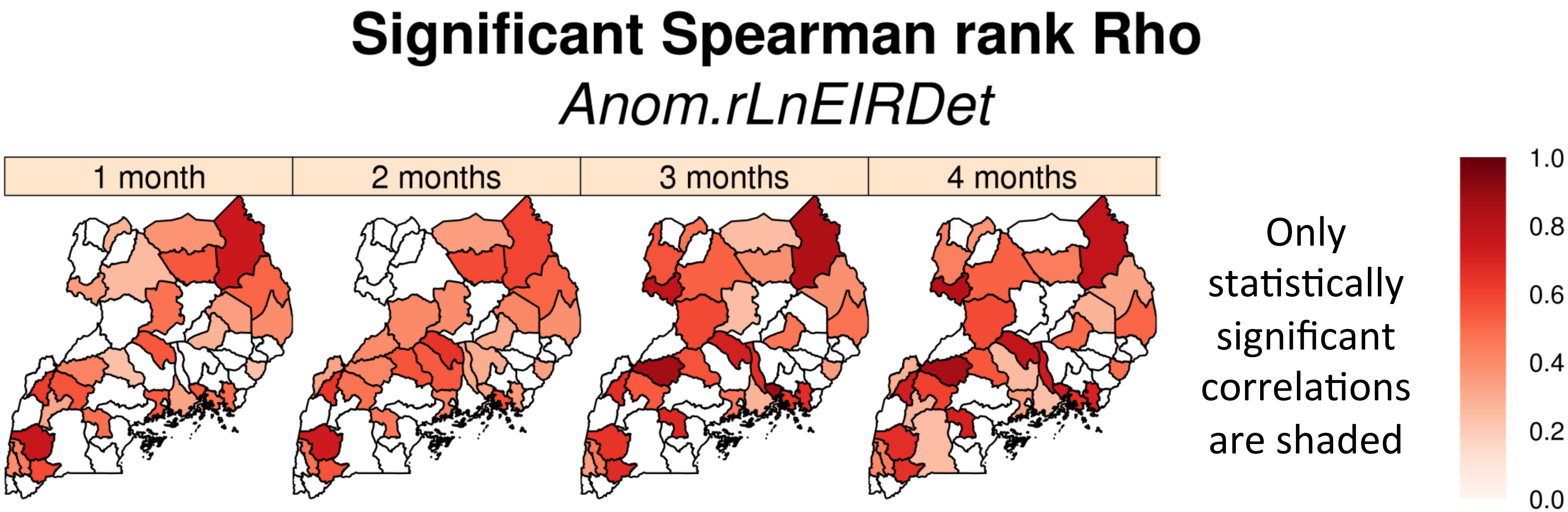
Grey shading: range of the 5 forecasts

Dash lined: the malaria initial conditions

Four panels: the four levels of advance warning

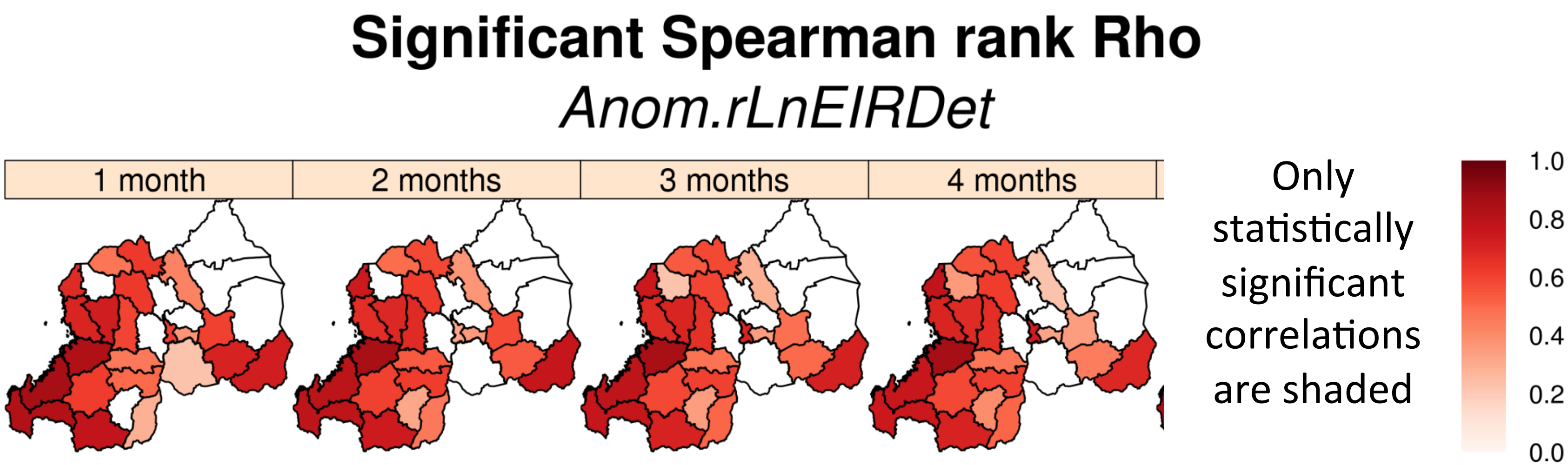






- Over half the districts have significant skill (95% level), despite uncertainties in the weather forecasting system, the malaria model and the health data

What about Rwanda?



Only statistically significant correlations are shaded

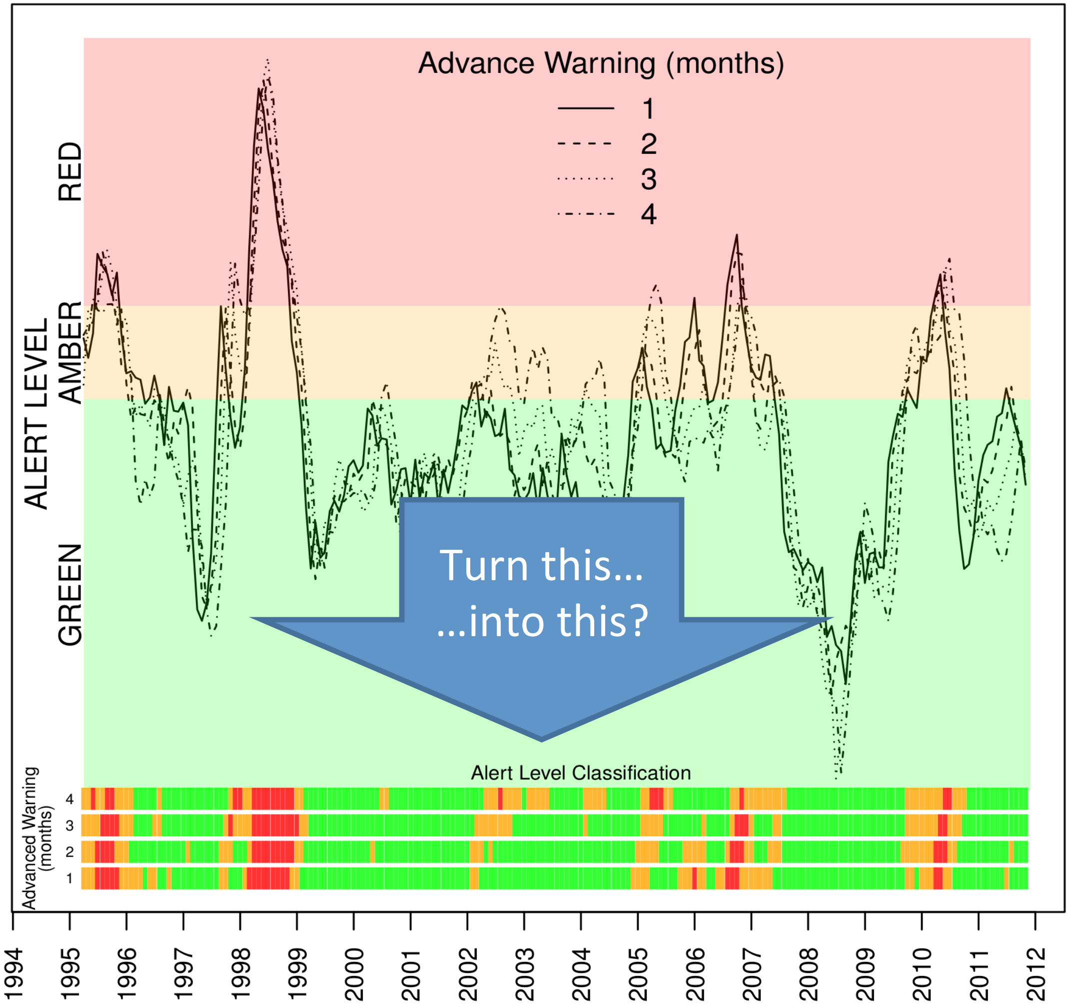
The majority of the districts are also significantly skilful, although model performs less well in regions where transmission is higher (e.g. East)

What is the decision entry point?

Does this really mean anything to anyone?

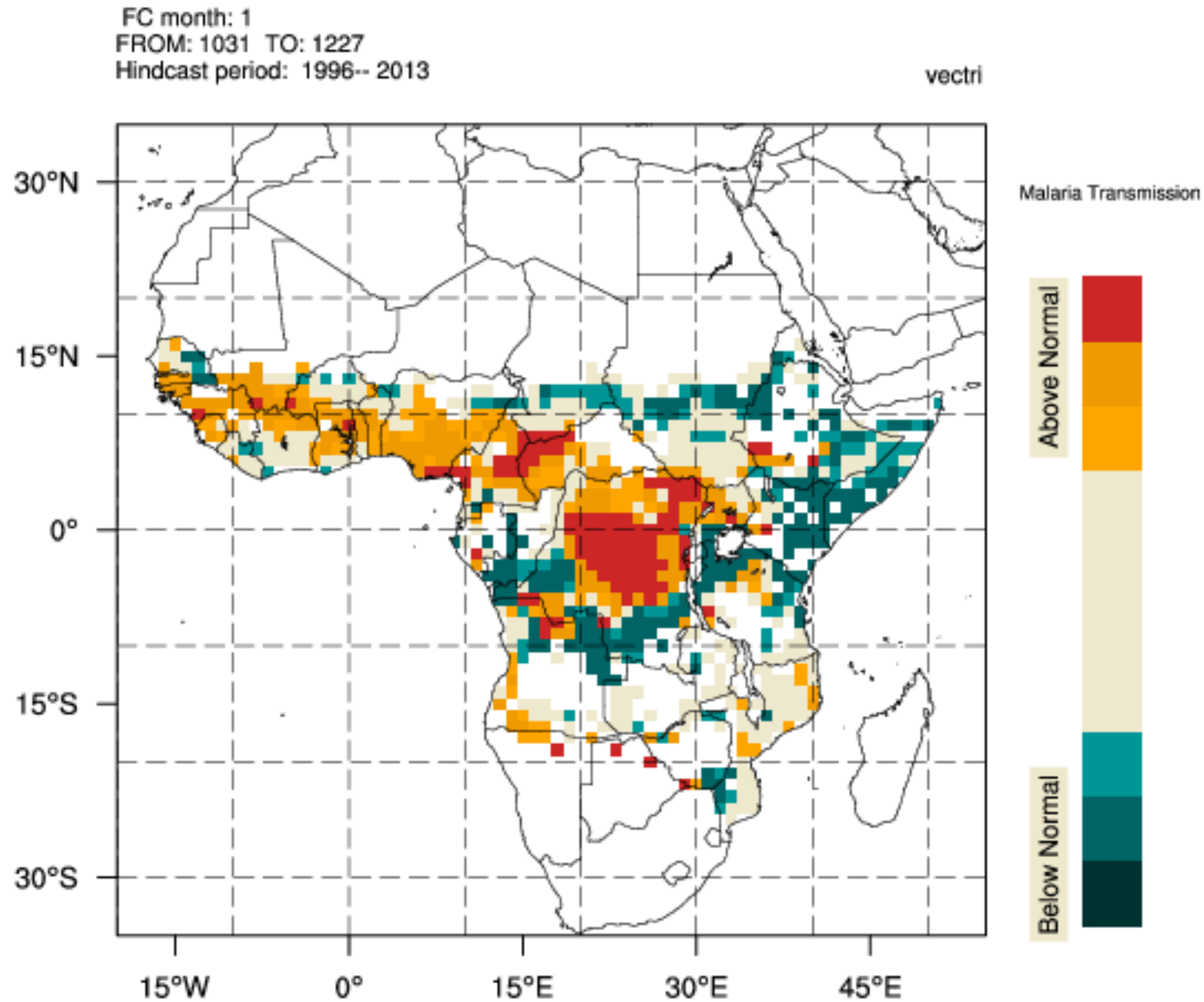
Do terciles relate to real health policy decisions? Doubtful…

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



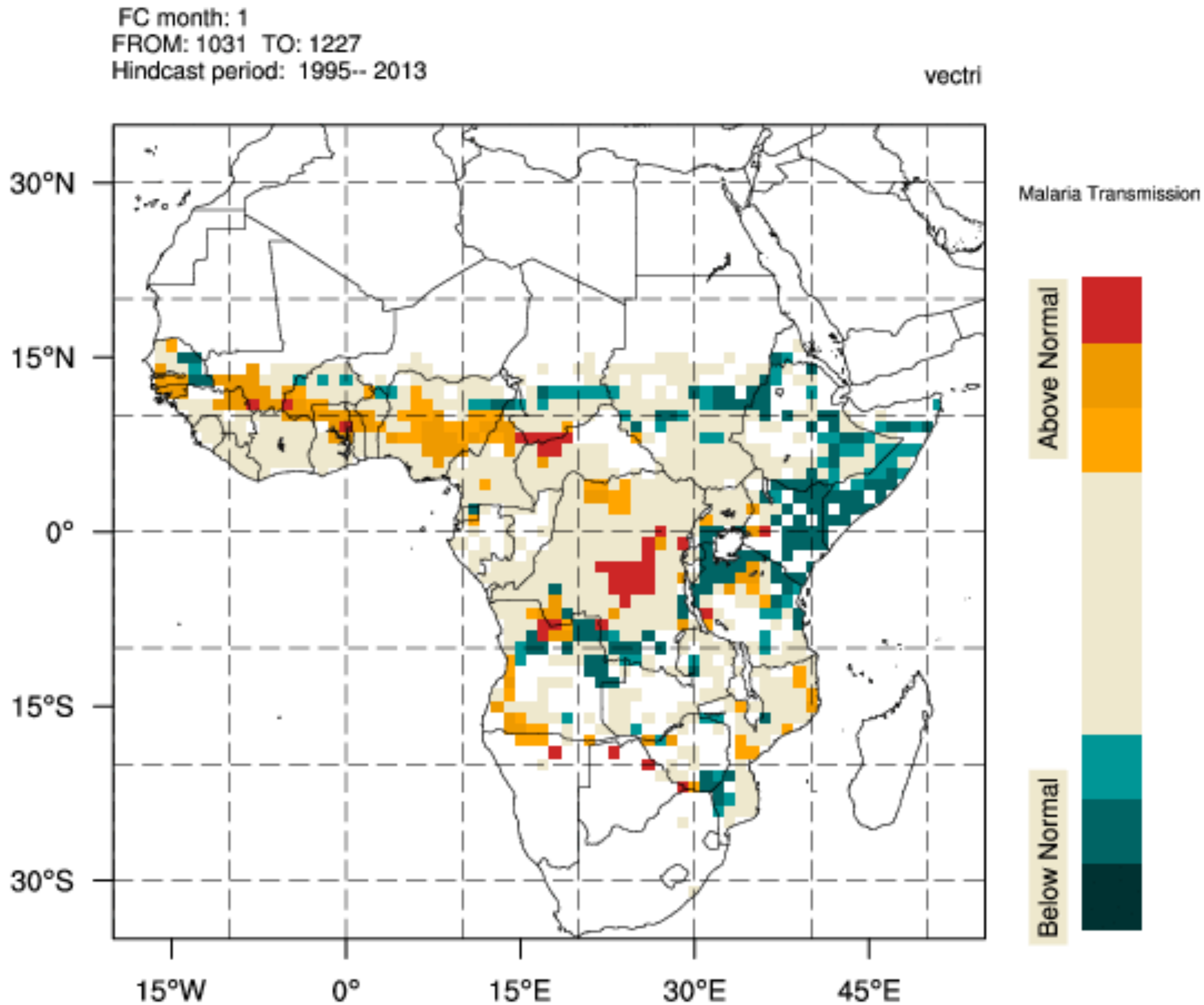
Tercile-based online pilot

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!/

A simple economic assessment

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

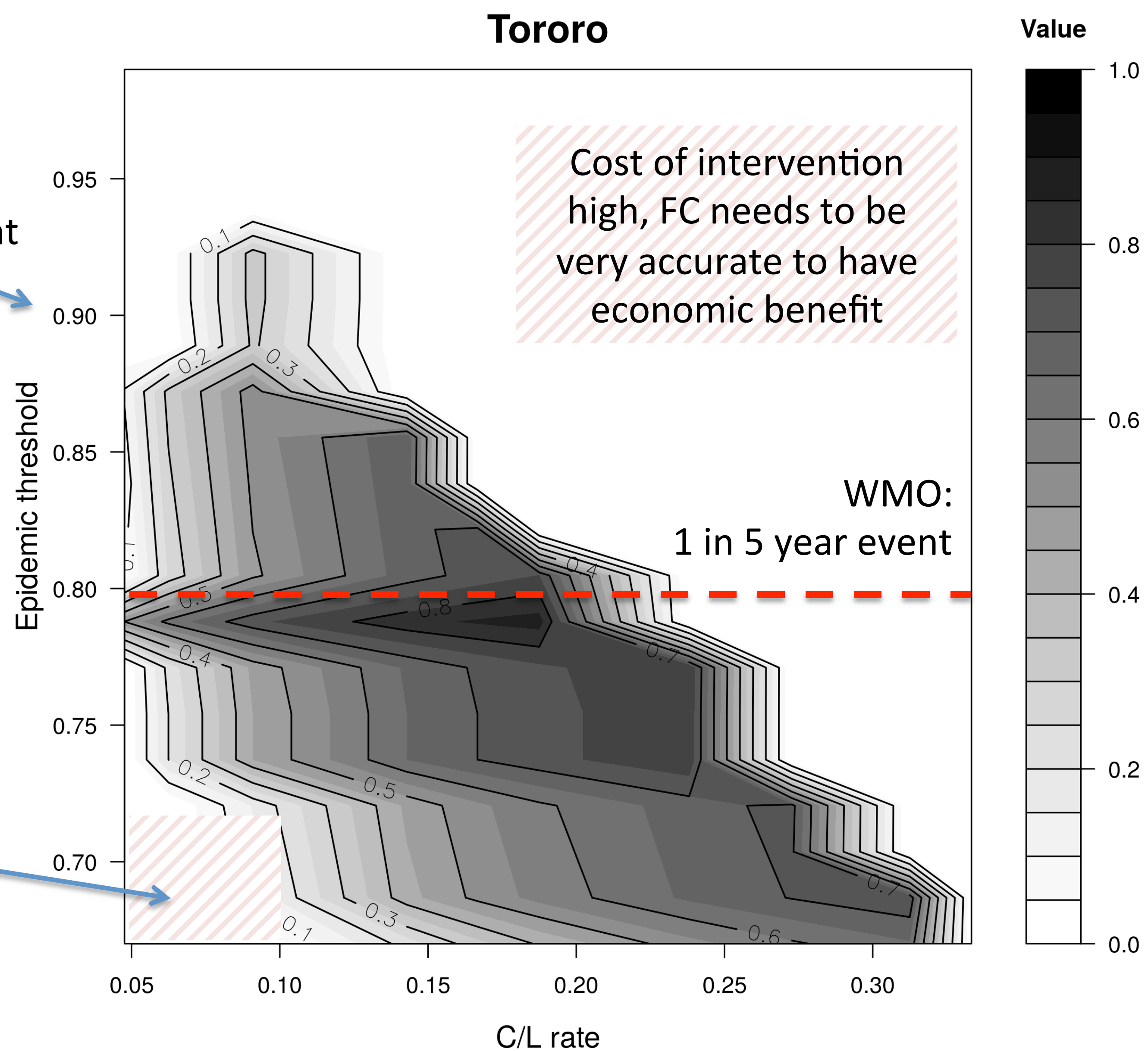
For a given event threshold examine past forecasts and see whether the forecast has a net benefit

C=Cost of intervention

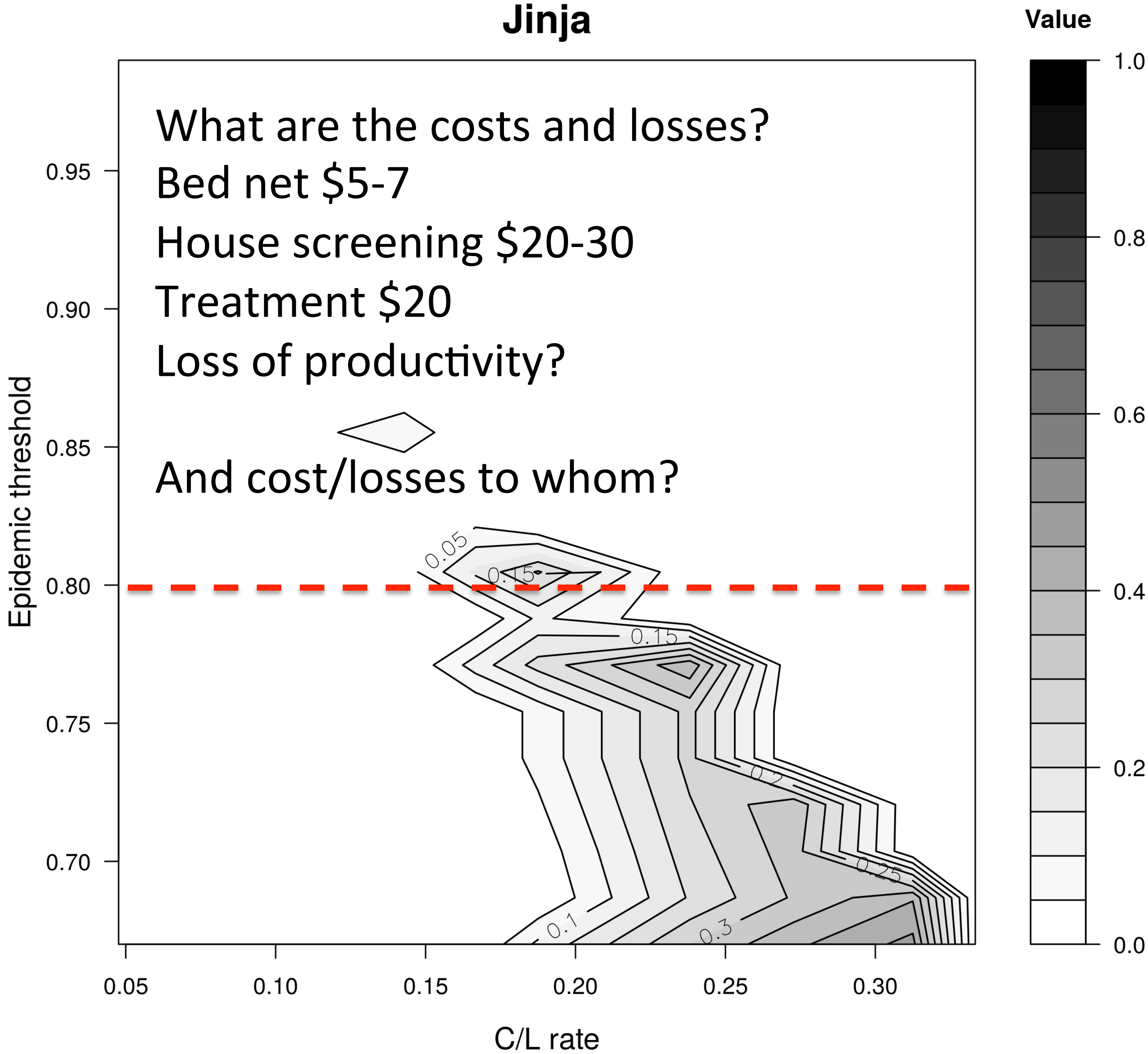
L=Loss if event is not prevented

Cost-Loss analysis

1 in 10 year event



Cost of intervention low, just intervene all the time!



What are the costs and losses?

Bed net $5-7

House screening $20-30

Treatment $20

Loss of productivity?

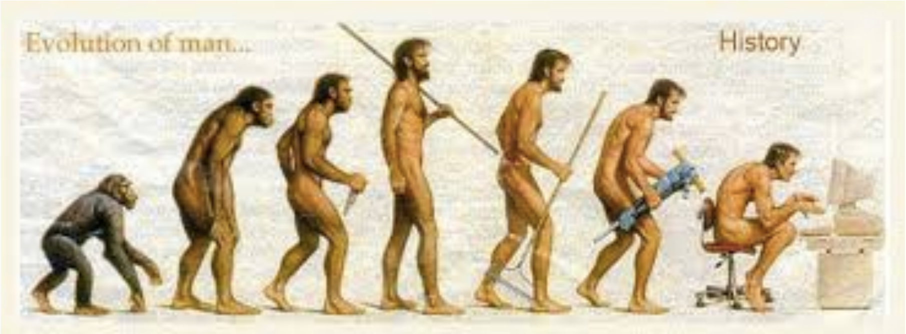
And cost/losses to whom?

Sometimes pragmatism enters into early warning systems

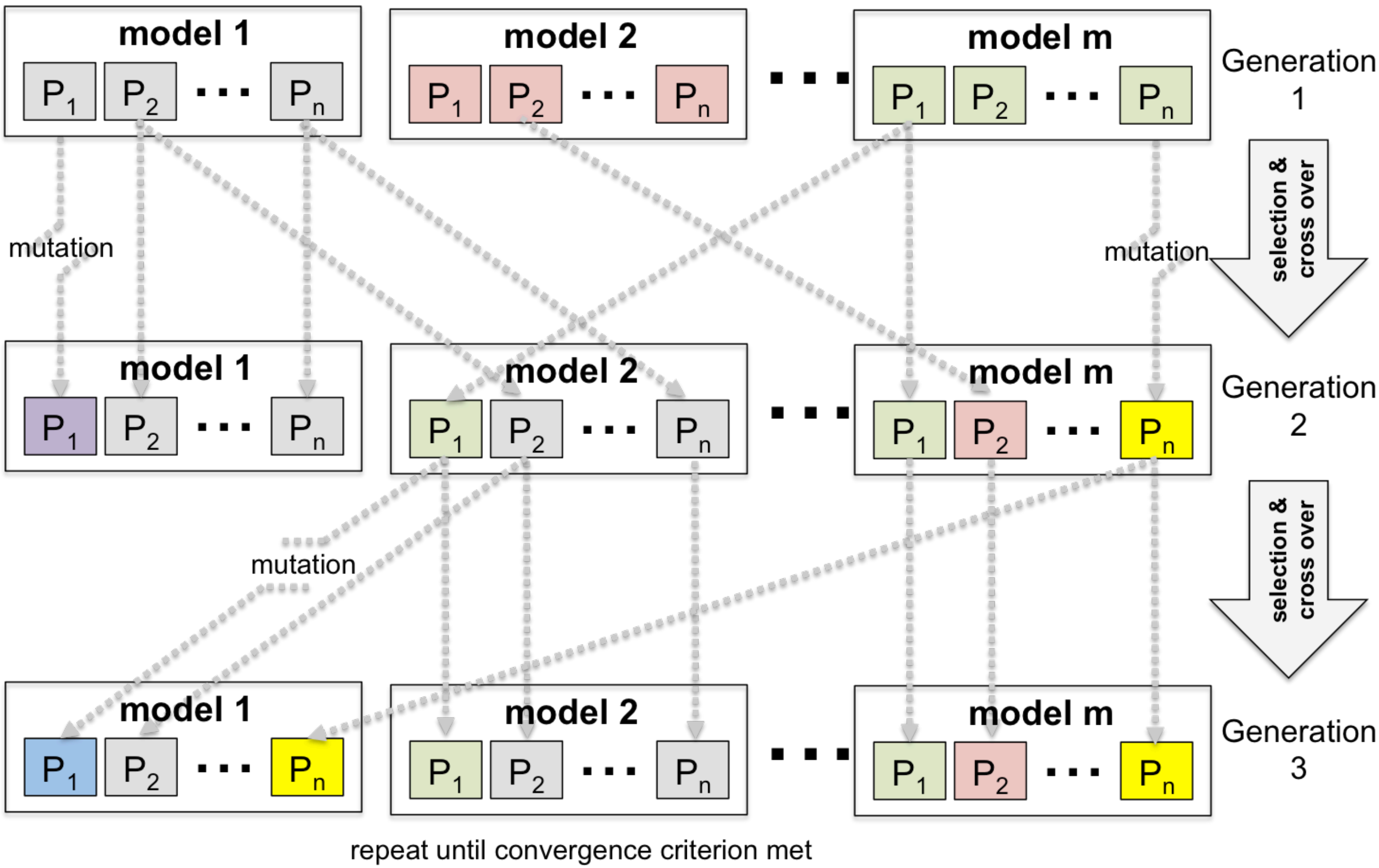
	Event occurs	No Event
Warning Given	Prepared	Loss cost warning (cost borne by others?) but legal action possible (e.g. lost tourism)
No warning	Sued for damages	Everyone Happy

ICTP

(Soft) Constraint Genetic Algorithm for Ensemble Prediction Model Parameter Setting



- ❑ Genetic algorithms used for a large variety of problems
- ❑ Can be used for model parameter calibration - "tuning"
- ❑ Advantages:
  - Simple, no adjoint required
  - Framework suited to existing ensemble approaches
  - Can handle highly nonlinear, discontinuous problems



- Method based on evolution:
  - Ensemble of models with different parameter settings
  - Metric for their fitness determines their ability to pass parameters to child generation
  - mutation of parameters to search parameter space

Despite a century of progress in understanding how climate impacts health and numerous demonstration projects, operational uptake is limited

- Resource allocation - justification of missed events – need for effective local-scale district health structures to identify local vulnerabilities.
- Demonstrate the need according to the setting
  - e.g. malaria: endemic, highland epidemic, disease elimination phase, assessing the efficacy of programmes and guiding surveillance
- Difficulty in evaluating the EWS in real time if not a direct impact (heatwaves, floods), accounting for confounding factors
- Access and use of climate information
  - S2S/Copernicus/NMME improvements
  - Training and workshop events
- Complexity and heterogeneity of impacts models (relative to climate)
- Difficulty to understand decision entry points for health – and the rigid, "top-down" nature of resource allocation determined by international agencies and funding bodies

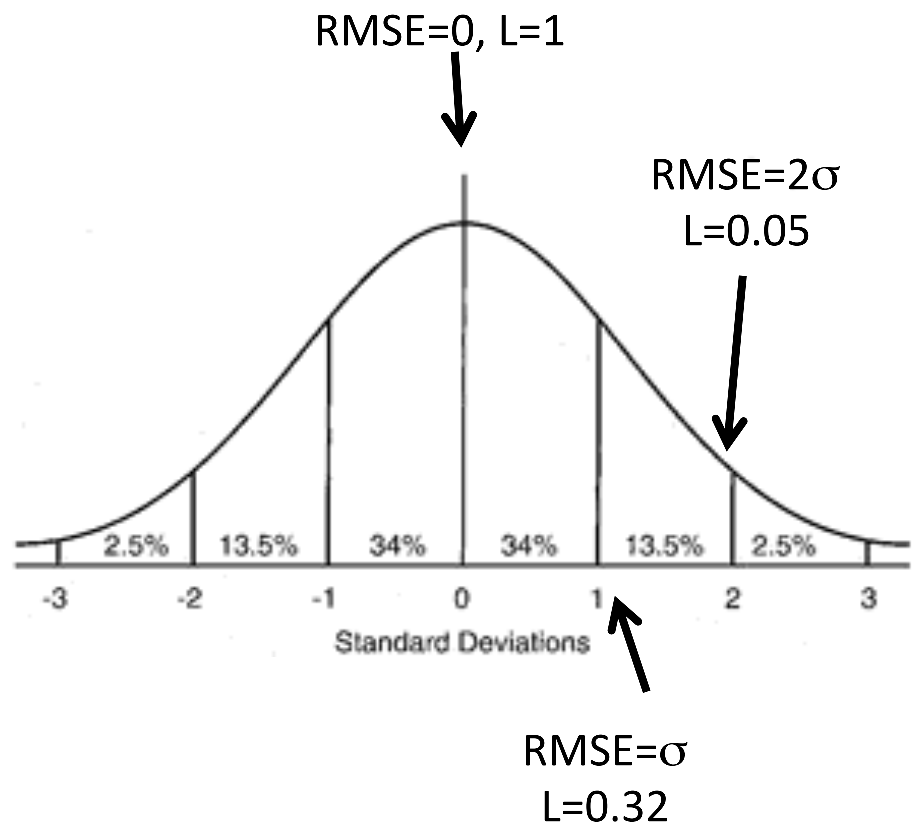
ICTP

New book 2018: THE GAP BETWEEN WEATHER AND CLIMATE FORECASTING: SUB-SEASONAL TO SEASONAL PREDICTION Eds: Andrew Robertson and Frederic Vitart.

Likelihood functional form

(defines the probability of a model becoming a parent)

- Could be based on r^2 or RMSE
- To minimize RMSE (equivalent to minimizing log-likelihood for a Gaussian variable) a sharp function such as L~1/RMSE produces a precise solution.
- But… preferable to account for observational uncertainty
- Assume observational errors are Gaussian in nature (usually possible to perform a variable transformation)
- Allows multiple metrics to be easily combined
- Produces "flat" penalty function once RMSE is within observational error.



ICTP

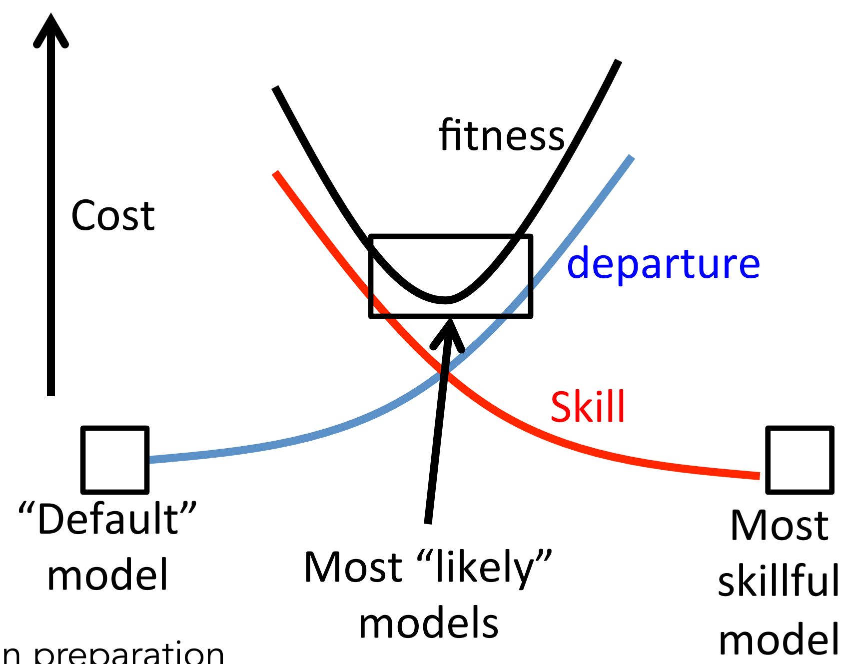
A soft constraint

- GA has been applied to a wide range of problems
- However, the dimensionality of the problem is often very high
- Introduce concept of soft constraint, penalty for departures of parameters around their default values
- Advantages:
  - Reduction of dimensionality (search essential in a N-sphere)
  - Allow the prior uncertainty of each parameter to be accounted for, preventing unreasonable parameter settings
- Not the optimum system in terms of skill but best compromise solution within the realm of assessed uncertainty (flat cost minimum).

$$\mathcal{L} = \eta \underbrace{P(C_s)}_{skill} \underbrace{\prod_{i=1}^{n} P(K_i)}_{constraint}$$

Assume parameter uncertainty is Gaussian

$$K_i \sim \mathcal{N}(K_{i0}, K_{i,\sigma}^2)$$

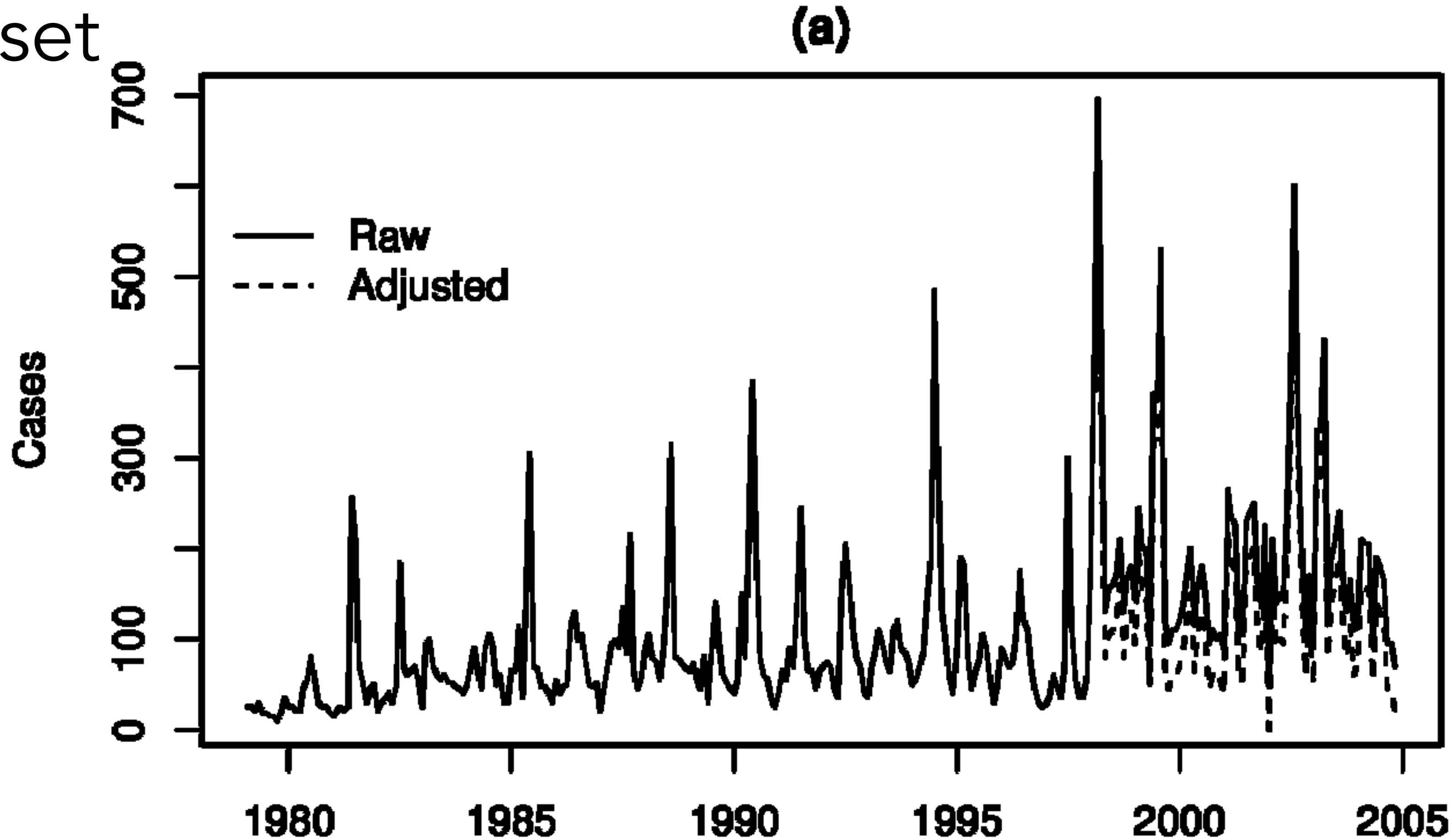


Tompkins QJRMS in preparation

Test for the Kenyan Highlands

(Tompkins and Thomson 2017)

- Tea Estate cases 1979-2005
- Minor Adjustment applied to "correct" offset

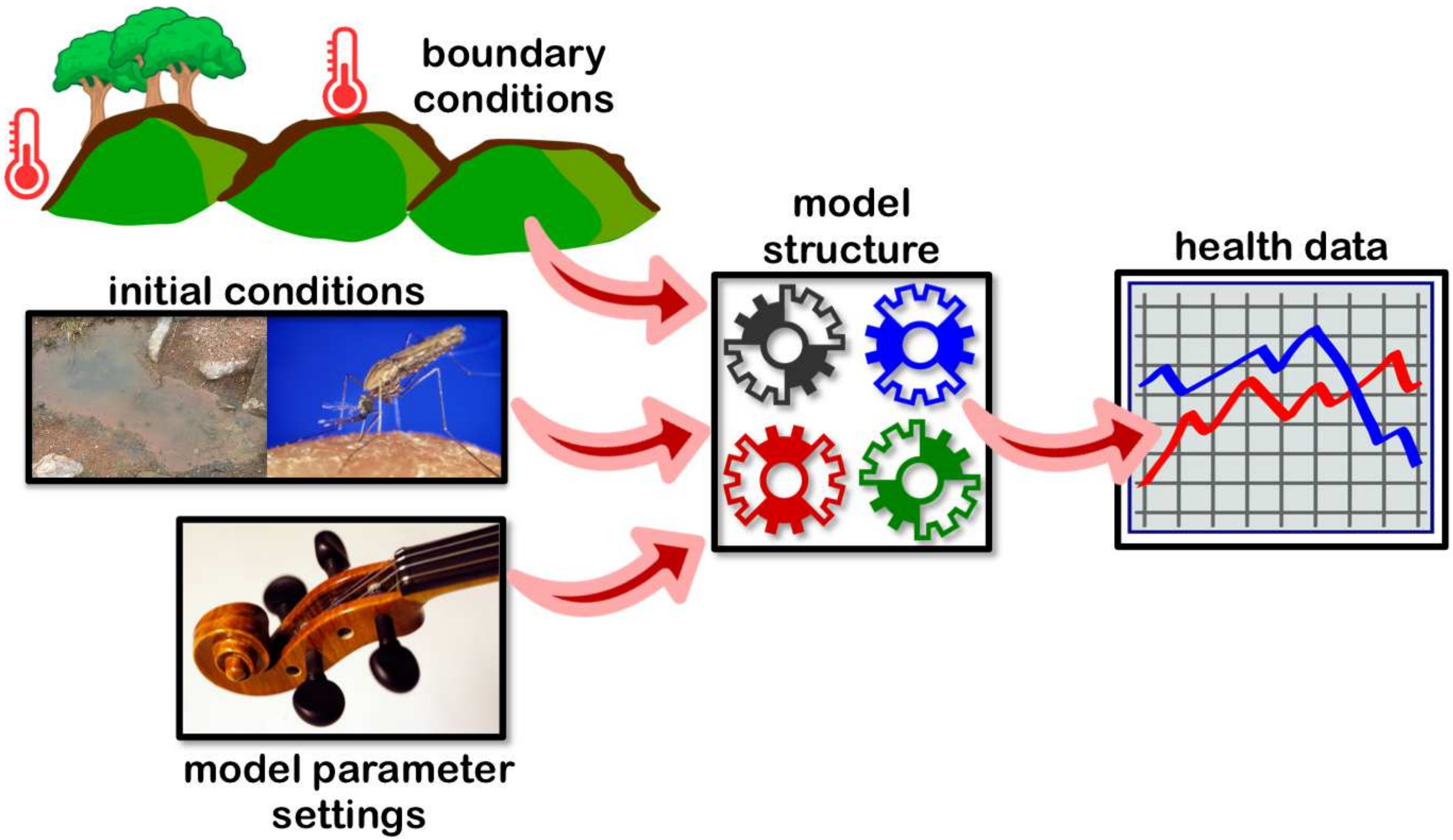


Tompkins and Thomson 2016 (NIH report)

ICTP

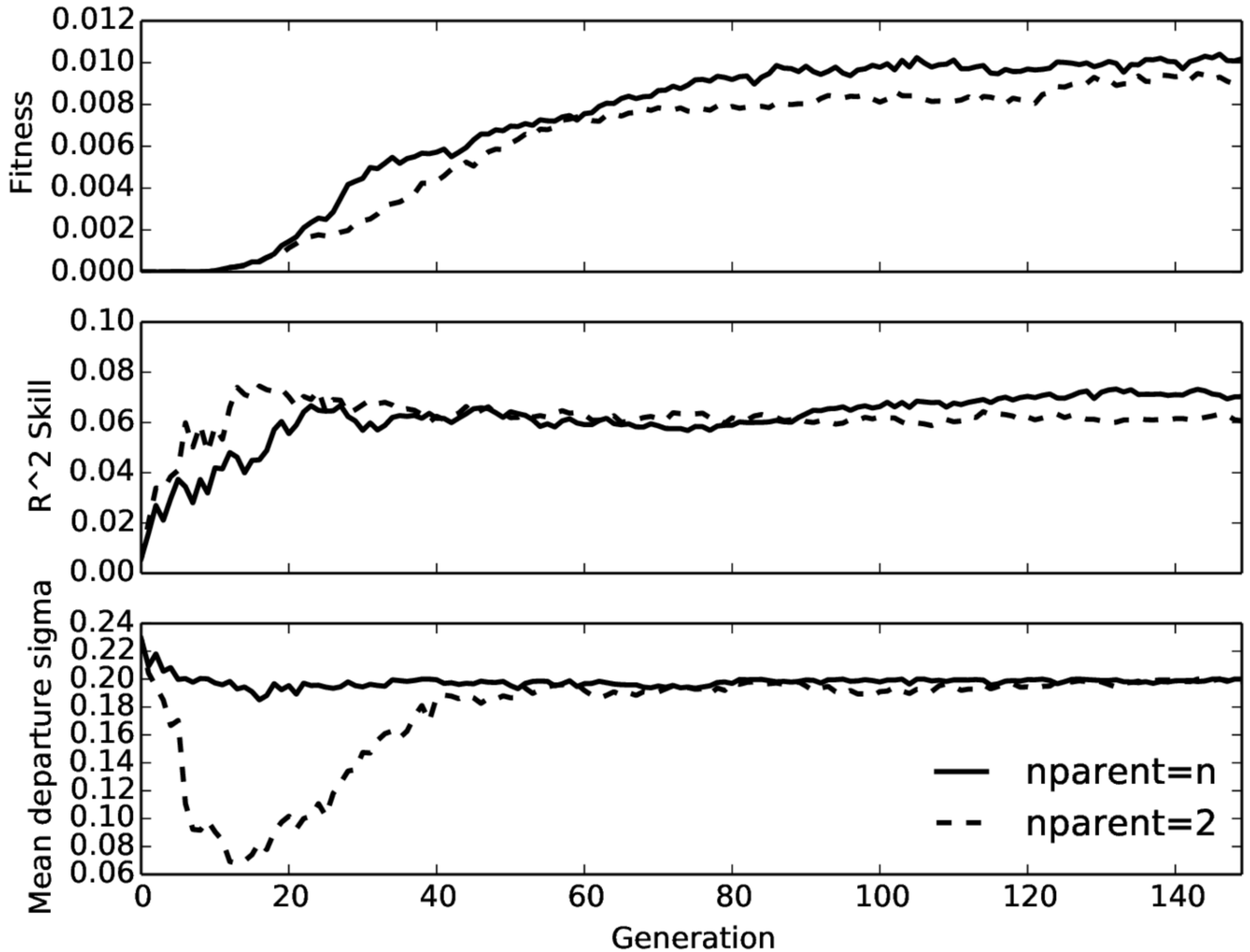
What are we calibrating?

- ❑Climate inputs
- ❑Model structure and parameter settings

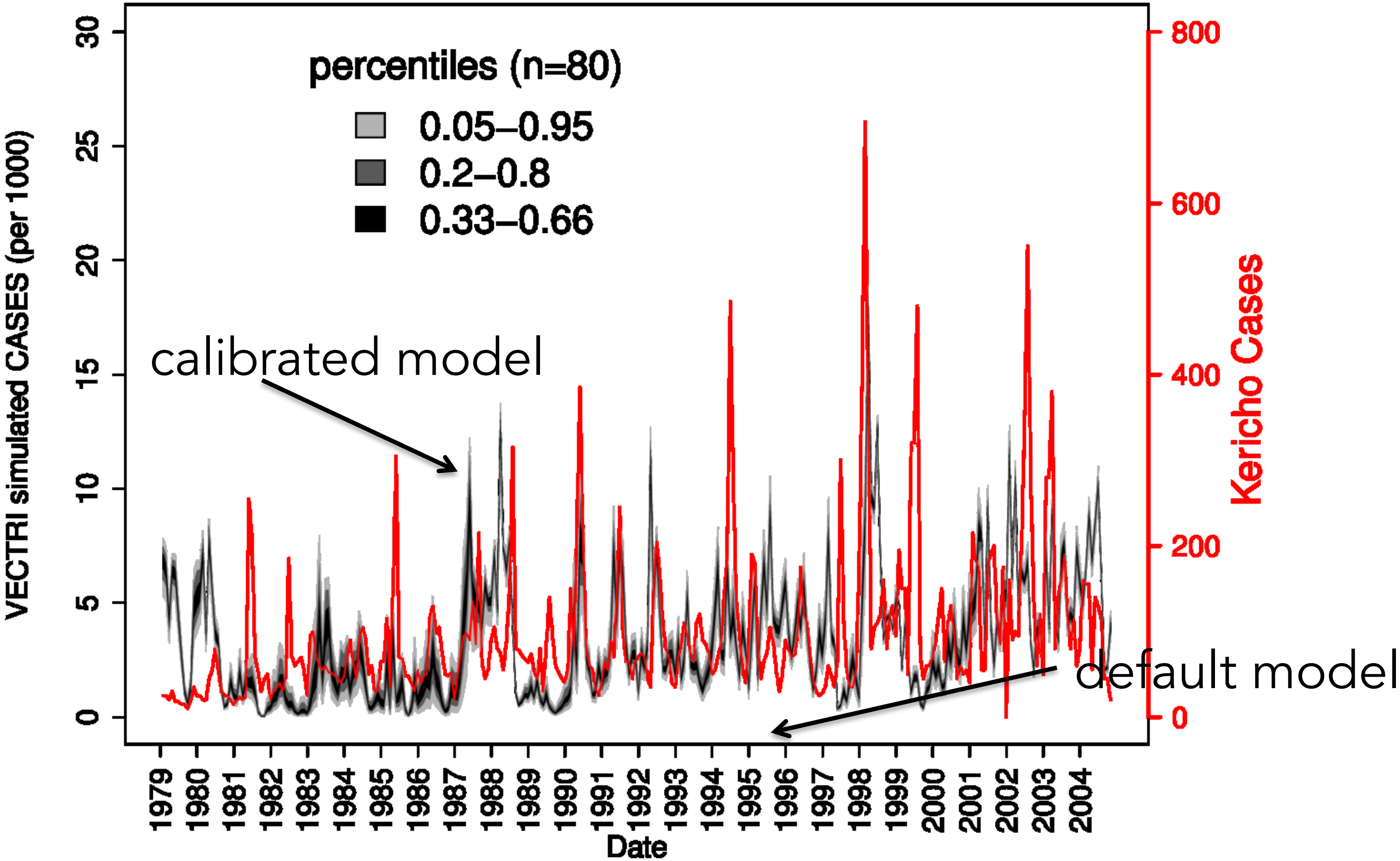


Adjustment

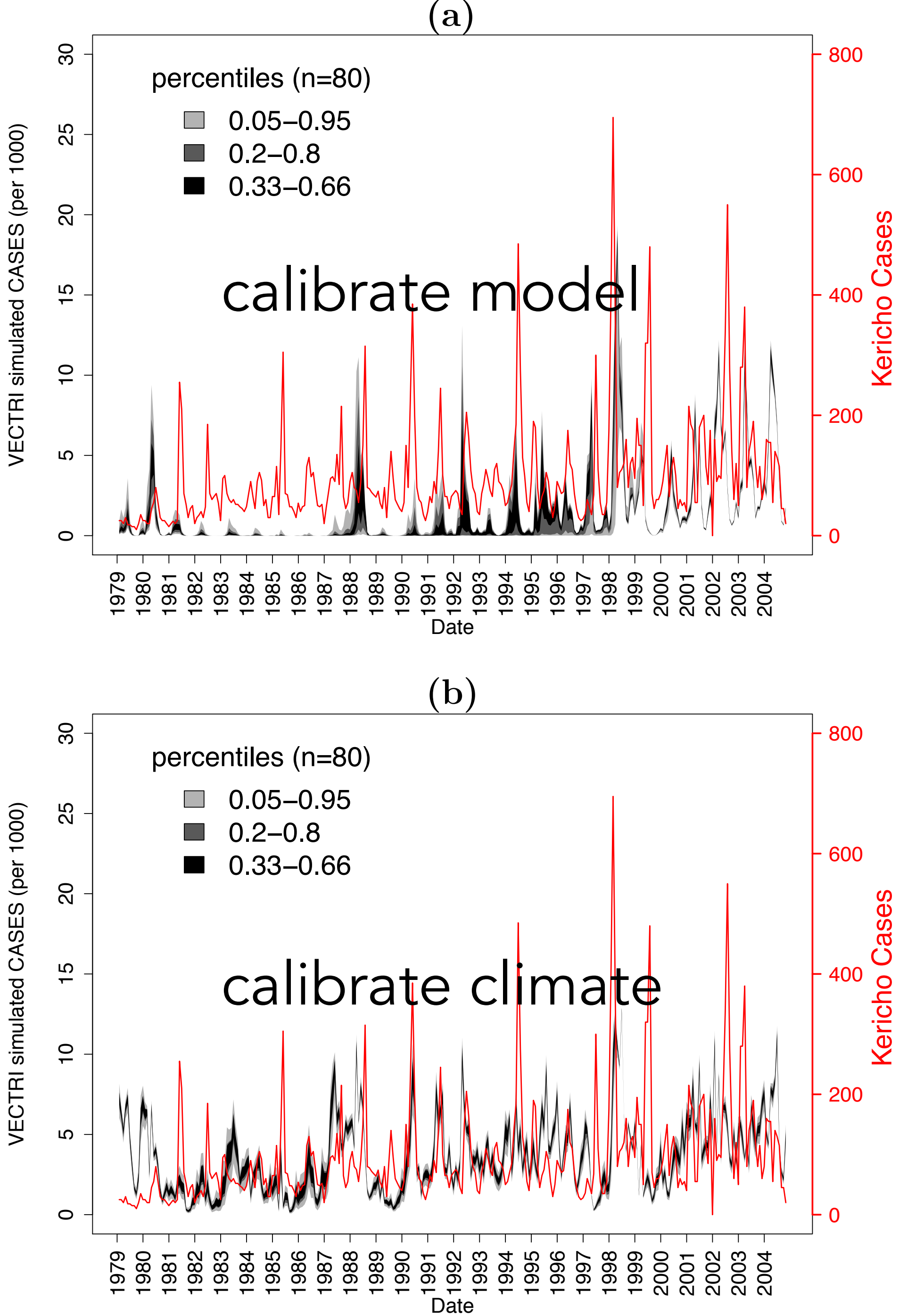
- About 60 generations required to reach equilibrium
- 18 model parameters calibrate
- 3 climate factors calibrated
  - Temperature offset
  - Temperature trend
  - Rainfall scaling



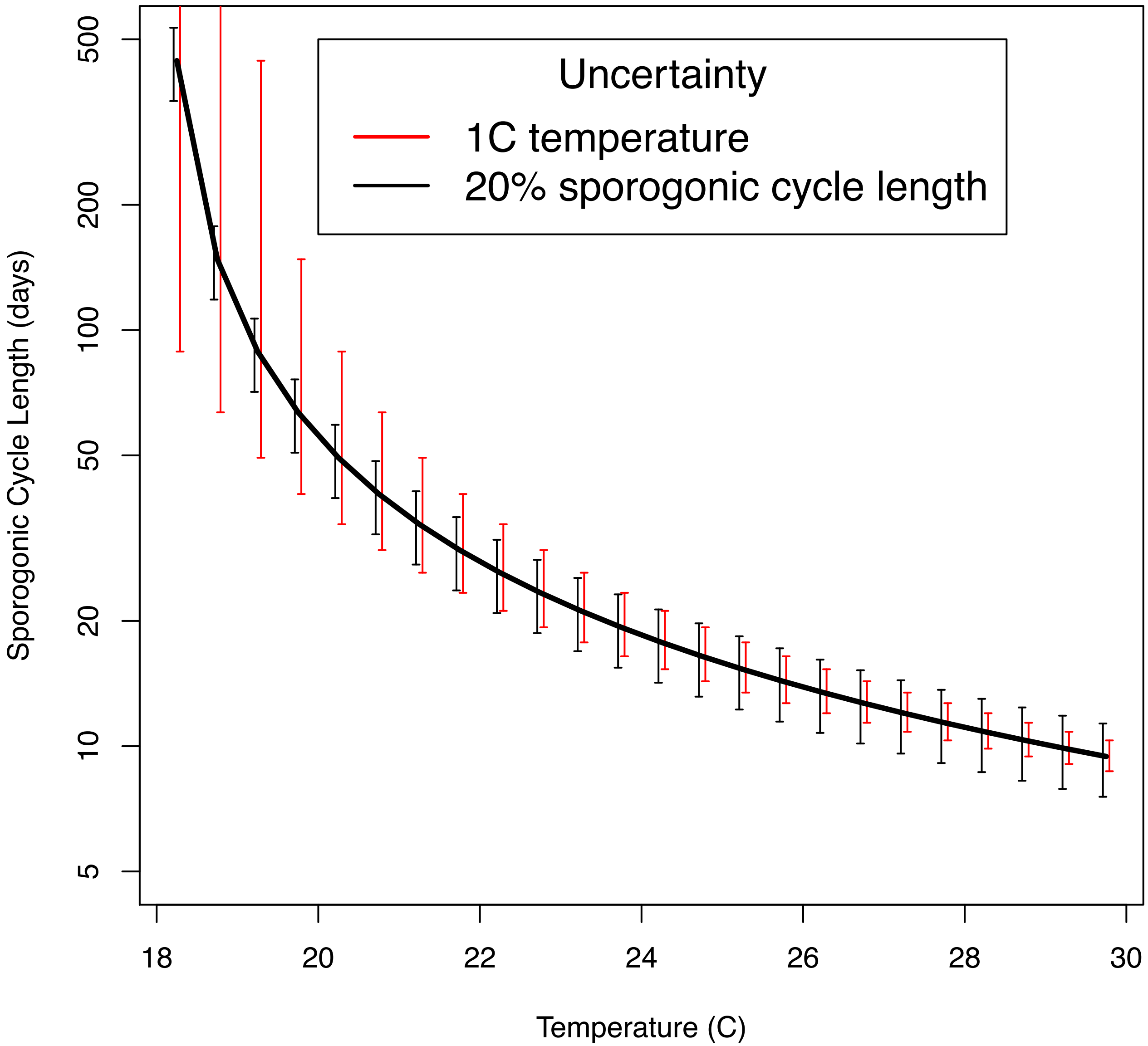
final calibration



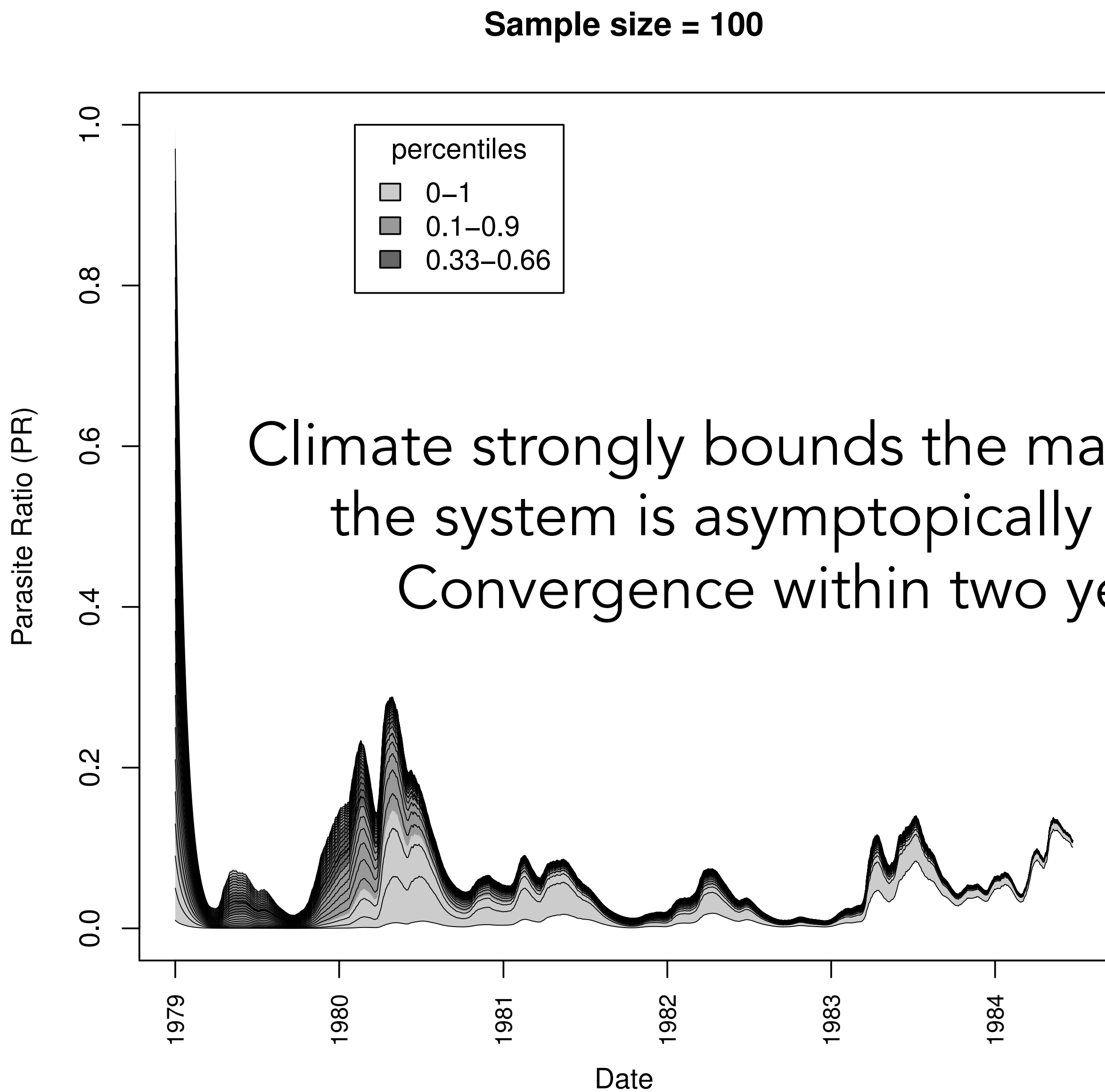
Model uncertainty less important than climate sensitivity IN THIS LOCATION



Sporogonic cycle versus temperature uncertainty



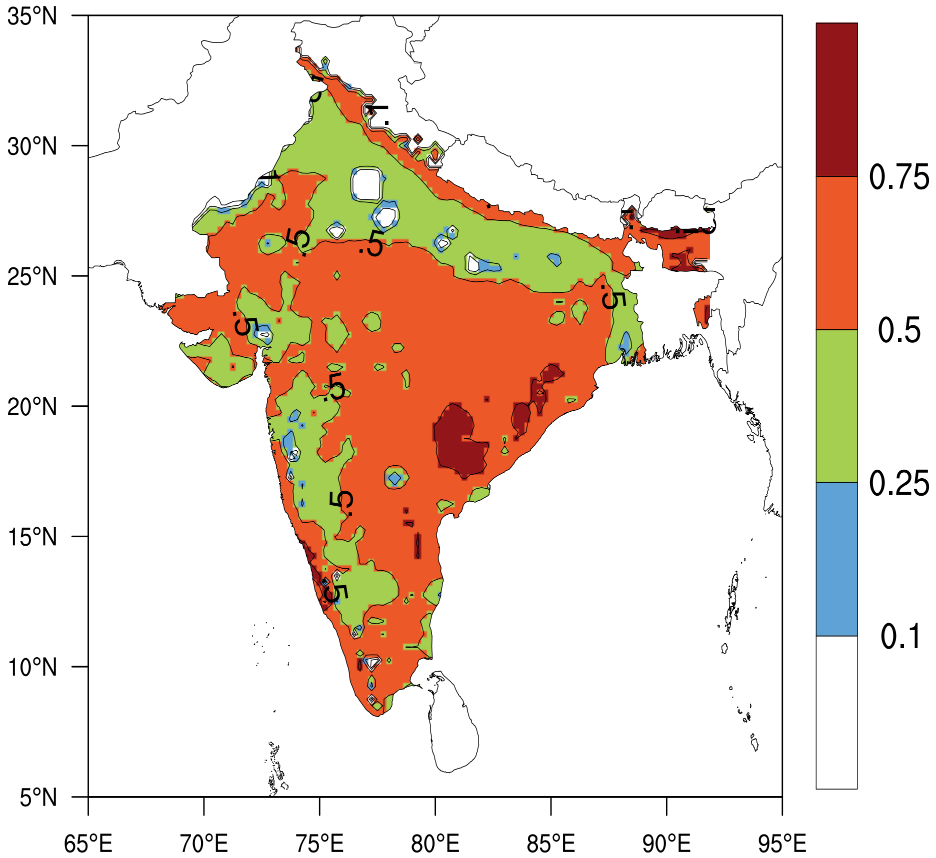
Initial Condition uncertainty



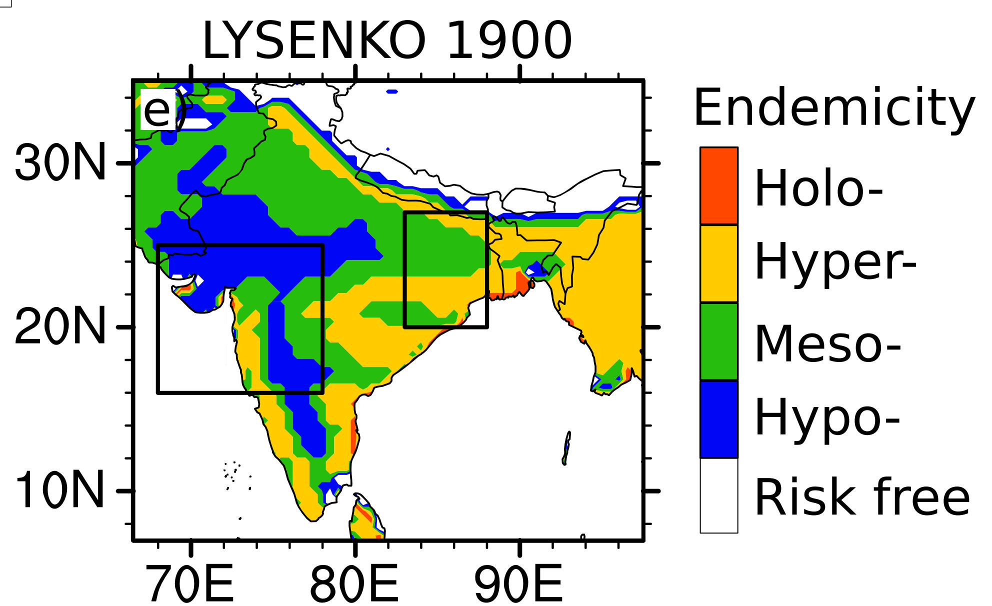
Climate strongly bounds the malaria, and the system is asymptopically stable
Convergence within two years

Figure 13. Evolution of PRd for an ensemble of 100 model integrations that differ only in their initial conditions of PRd, equispaced between 0.01 and 1.0. The ensemble mean is also plotted.

VECTRI parasite ratio v1.4-6



Assuming this class equivalence parasite ratio too high



Upcoming developments

- Rewrite for parallel code v1.5
- Improvements in surface hydrology for permanent water bodies
- Calibration code in main release
- Improved immunity model v1.5
- Interventions? Potentially by coupling to OPENMALARIA in a two-stage modelling process.
- Population migration by coupling to agent-based population model WISDOM v2.0
- GUI front end?

total trips to elsewhere in Senegal from Mobile phones