Applications of the EPS:Health

[and some simple suggestions on how to use the ECMWF toolbox]

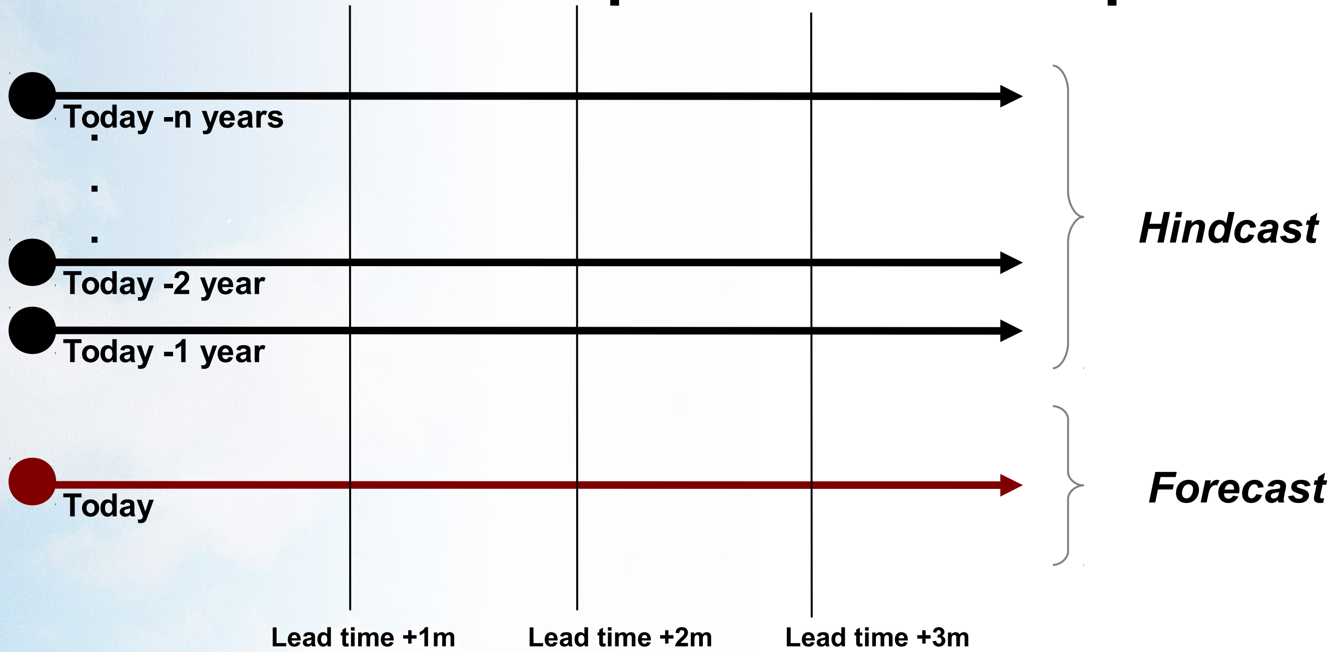
F. Di Giuseppe @ecmwf.int

Part I
How to correct model outputs at long time range so that they can be used for sectoral applications

Part II
The malaria early warning system developed for the Africa continent under the QWECI project

Hindcast -1

Hindcast/ Re-forecast: Forecast produced in the past



The monthly-varEPS has 20 years of hindcast (4 members)
The seasonal forecast (system-4) has 30 years of hindcast 1981-2011 (15 members)

Hindcast -2

Why at the monthly to seasonal time scale we need an hindcast [while at shorter leadtime an hindcast is not used]

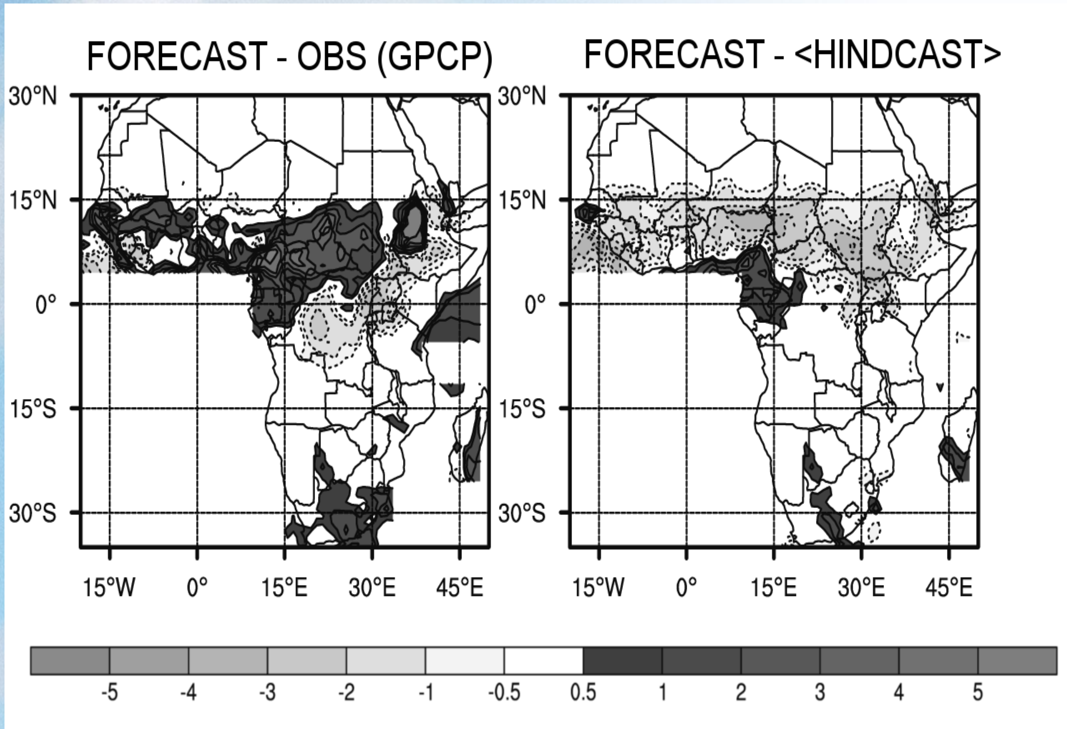
1 . At long lead times we have low predictability. Therefore forecast has to be intended to provide information in a <u>statistical sense</u> [such as positive/negative anomaly compared to a mean climate....] this is why an hindcast is provided.

2. The hindcast dataset provides the model climate needed to bias correct model outputs

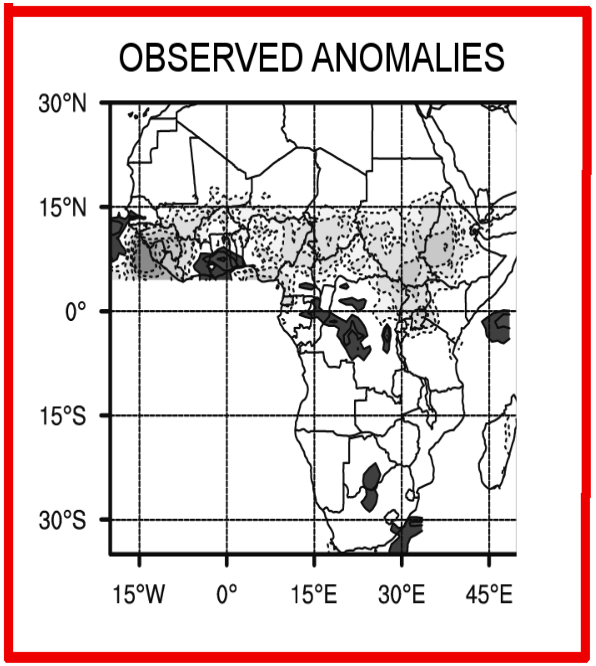
At very long lead times forecast errors are dominated by the model bias

Forecast for west Africa monsoon JJA 2006 [1 month lead-time]

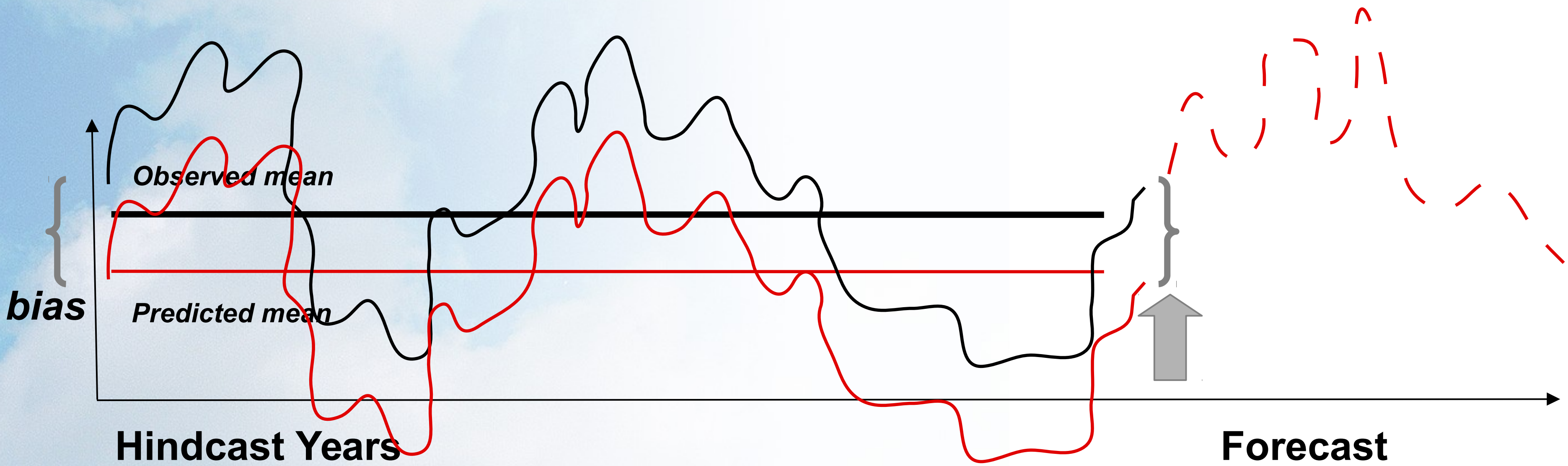
Model



GPCP dataset

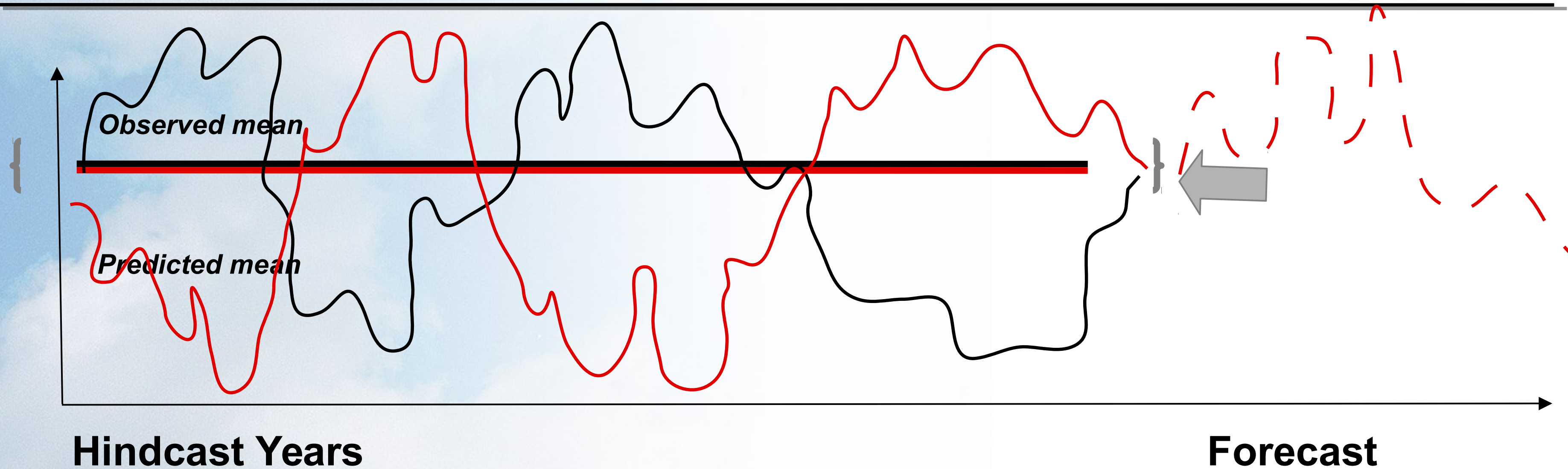


Model (climate) bias versus model skill - 1



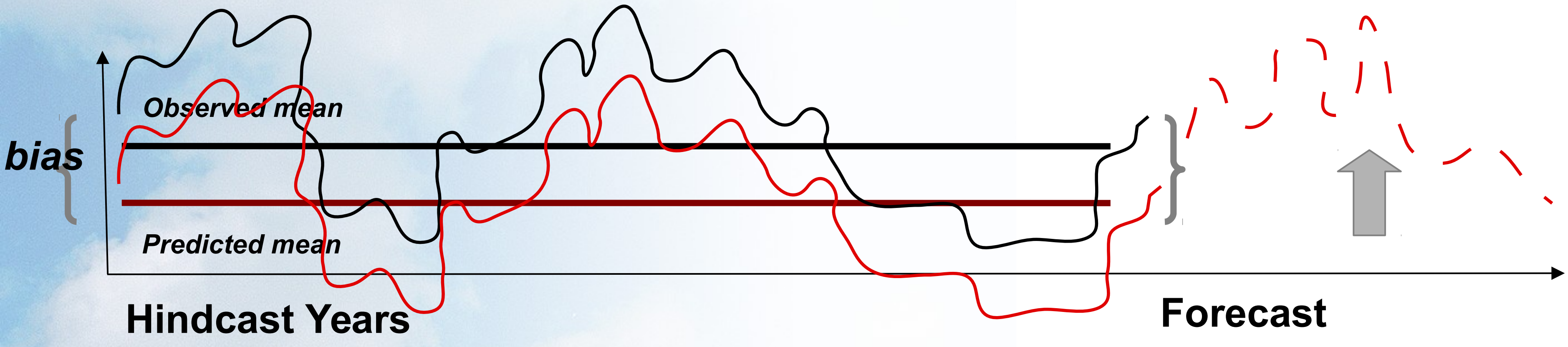
The 'climate' of the model is dry BUT the temporal variability is good (this means good model skills)
→ the predicted anomalies are good even if forecast fields are biased
→ a simple bias correction [i.e adding the mean bias] can improve the forecast fields

Model (climate) bias versus model skill - 2

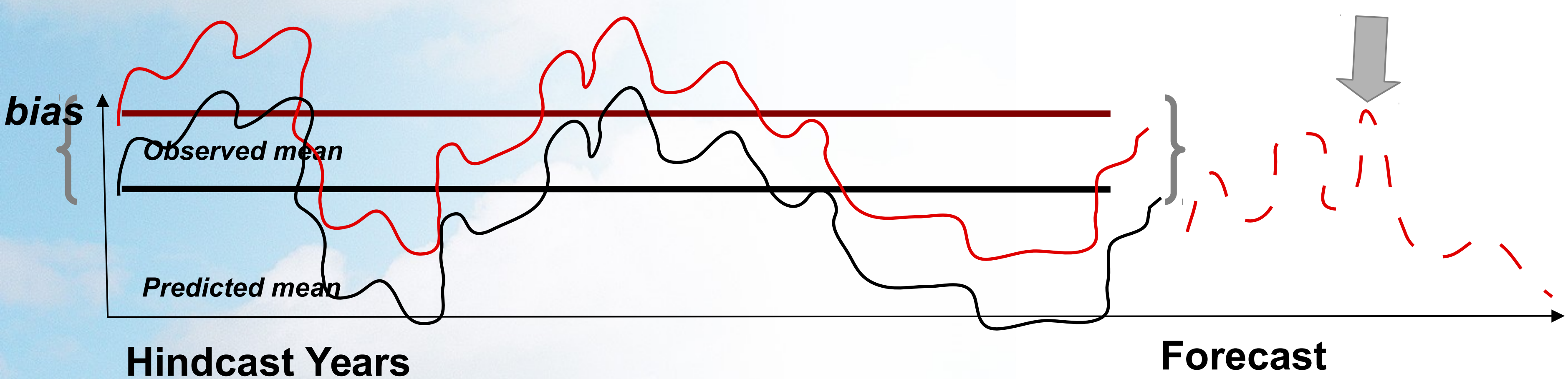


The 'climate' of the model is very good BUT the temporal variability is in anti-phase with the observations (bad model prediction skills)
→ the predicted anomaly are reversed respect to the observations!!
→ a simple (i.e. statistical) bias correction could NOT help to provide a good forecast

Lead time X



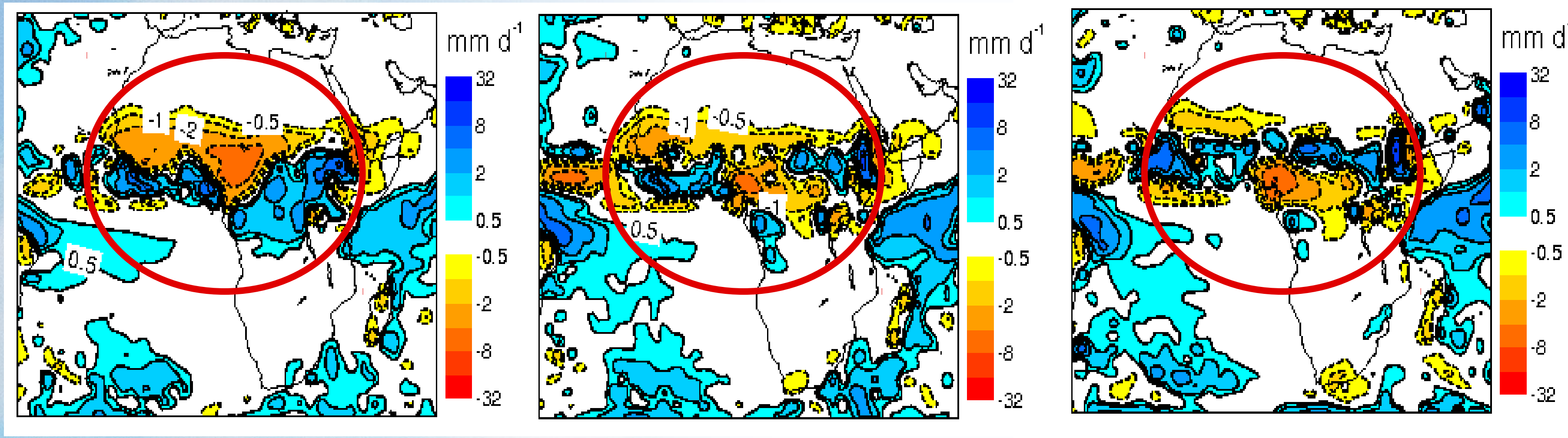
Lead time Y



Model drift example from cycle 35R1

Precipitation: Model- GPCP for different lead times

DAY-1 DAY-5 DAY-10



Amalgamation of day1, day 5 and day-10 lead times for JJA-2006

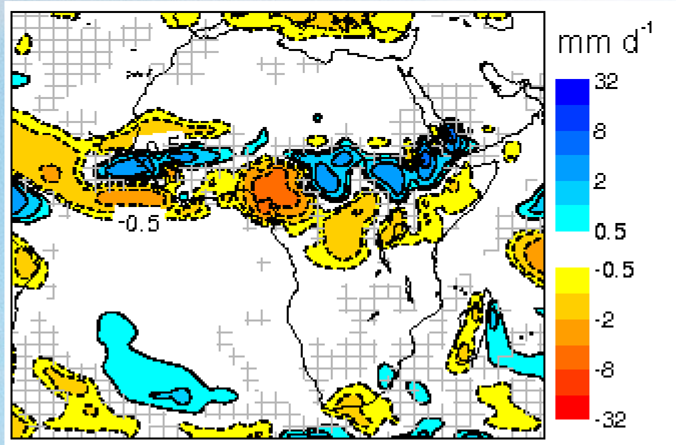
The southerly shift in the monsoon progression shifts northwards as a function of lead-time

Hindcast Upgrade

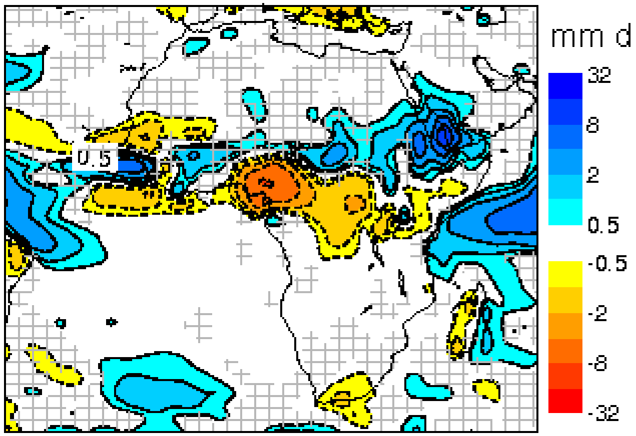
The hindcast for a given model has to be updated at each model cycle

1. An hindcast set needs to be calculated each time there is an upgrade of a model cycle since biases can change across new model releases.

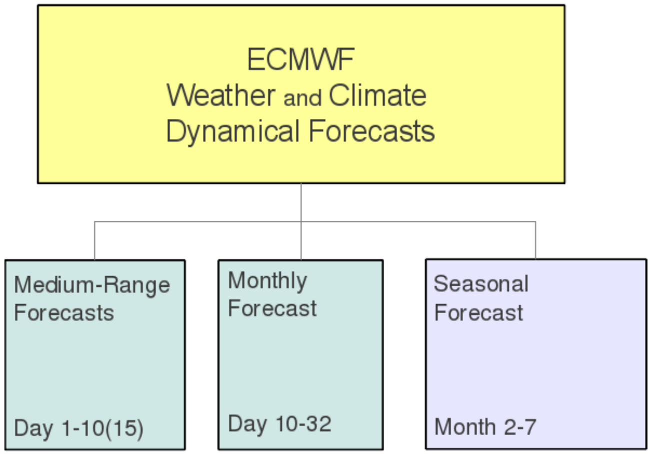
35R1



36R1



Model releases



Cycle	Year	NOTES
-		
23R4	2000	System2, ERA-40
24		
24R1		
24R2		
-		
-		
31R1	2006	System3, ERA-Interim
31R2		
-		
-		
36R3	2010	System4
-		
-		
38R1	2012	Current release

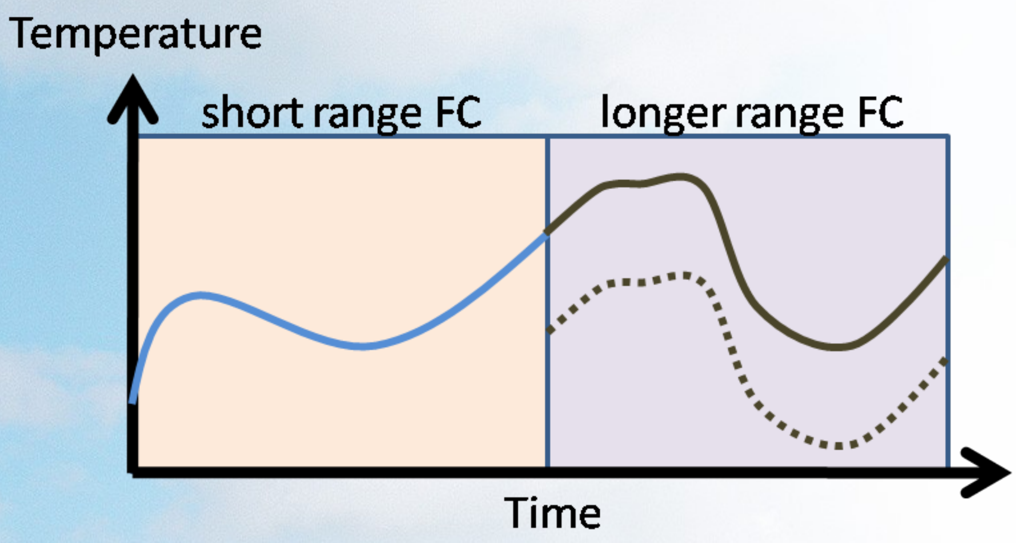
2-4 model cycle (CY) releases (R) every year for the Deterministic and the monthly.

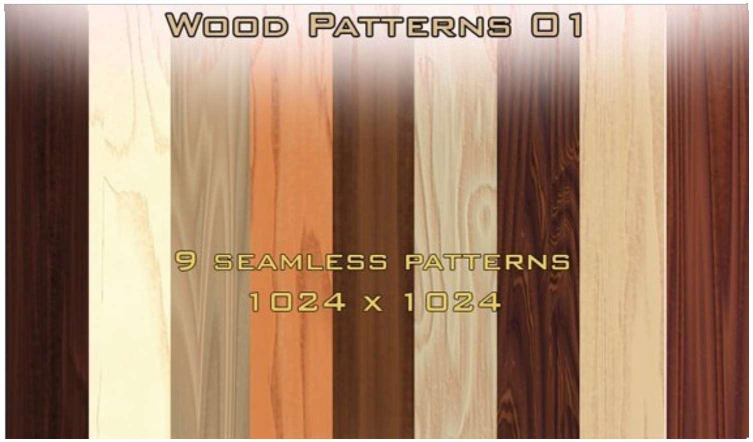
The seasonal forecast is released only each ~5 yr

Can we go from the short to the long range merging together all the systems?

This is what is called seamless forecasting

For many practical applications this would be an advantage … but a correction in time and space is required to concatenate different systems in a way transparent to the final user





ECMWF

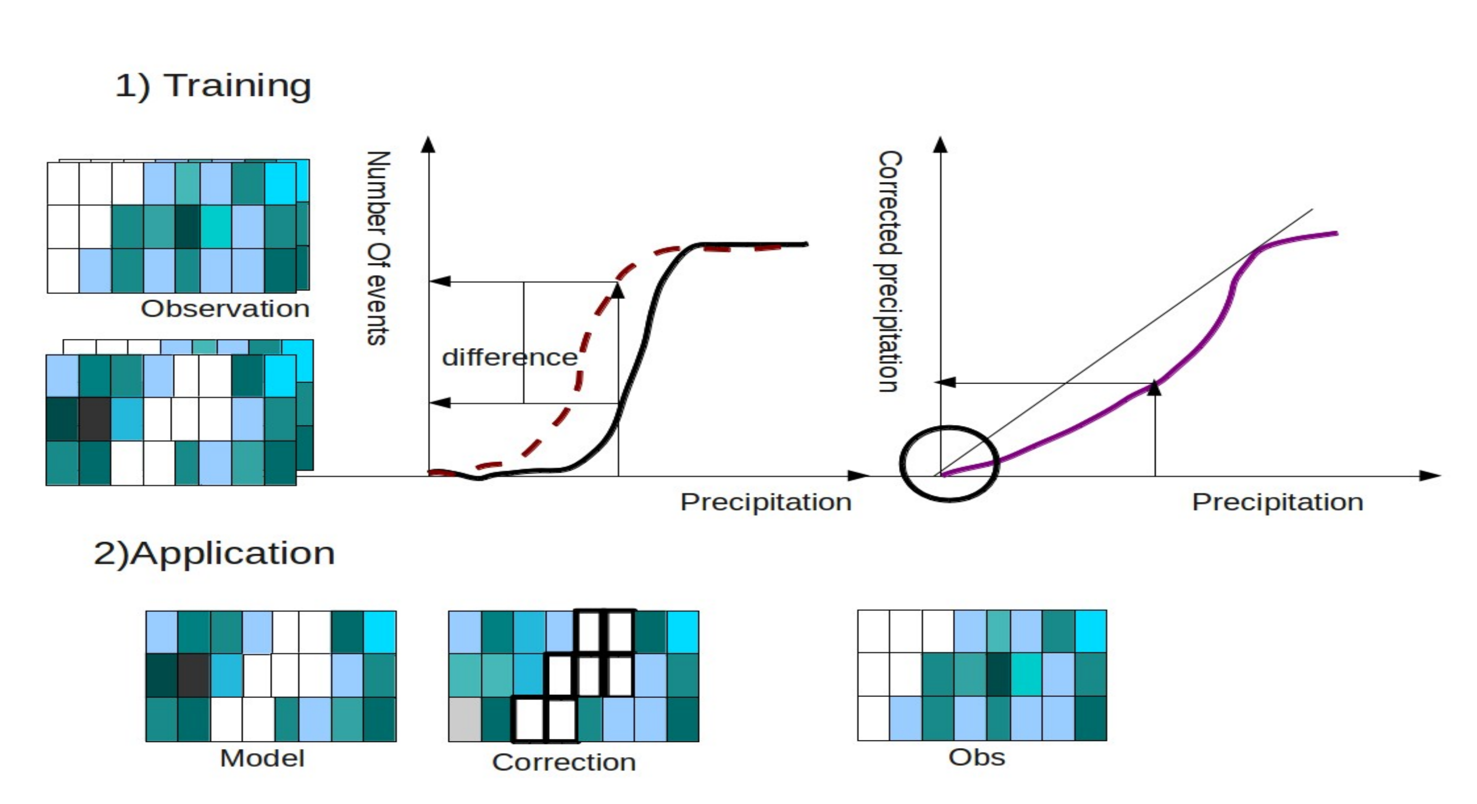
Bias correction techniques in three steps

1. Training dataset composed of simultaneous modelled and observed fields [I. e. long time series of precipitation from observations and hindacst]

2. Some sort of inferential method to match the distribution properties of the observation into the model [mean bias removal, quantile matching, more complex statistical decompositions, SVD, EOF]

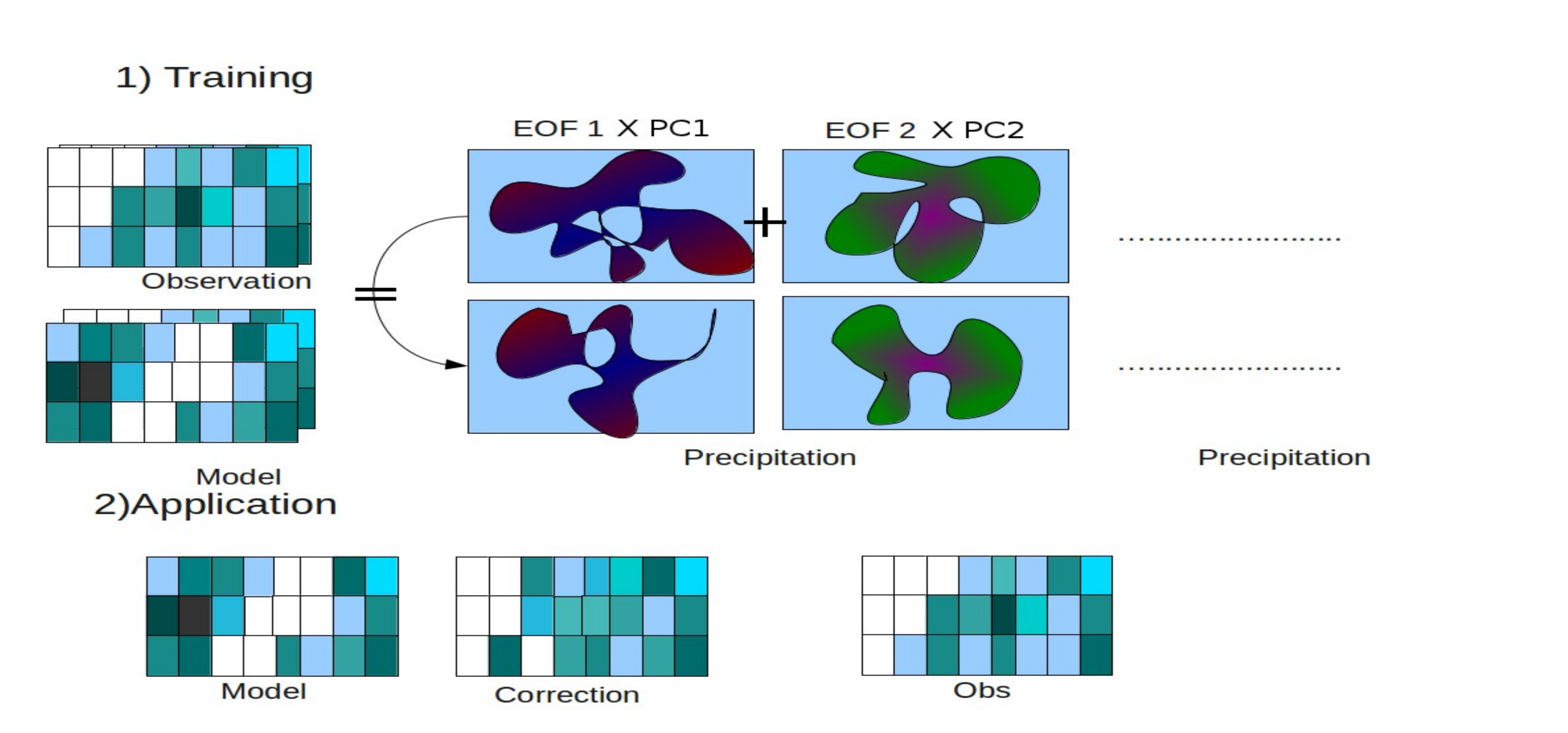
3. Application of the correction to the forecast

Point-wise methods



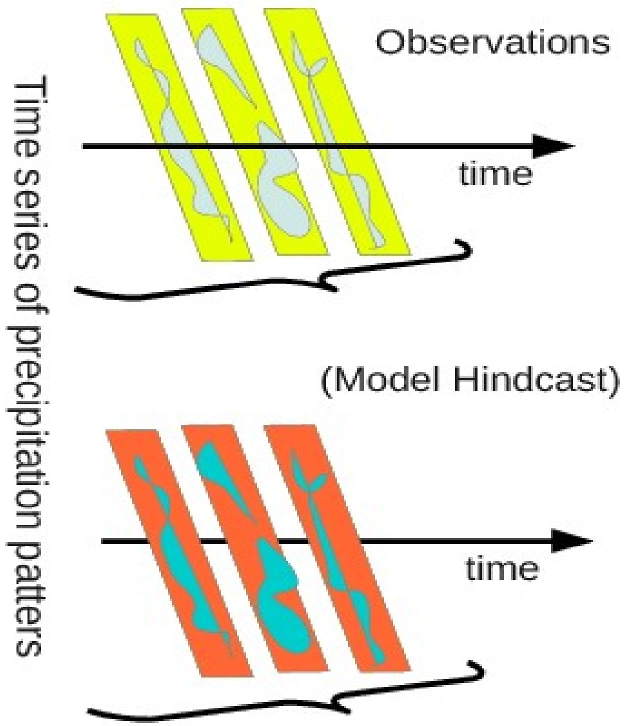
Point-wise methods are relatively simple to implement and can be used successfully to remove systematic model deficiencies in, say, the representation of the hydrological cycle, but do not account for spatially coherent signals. (Kolmogorov-Smirnov statistics).

Spatial Methods



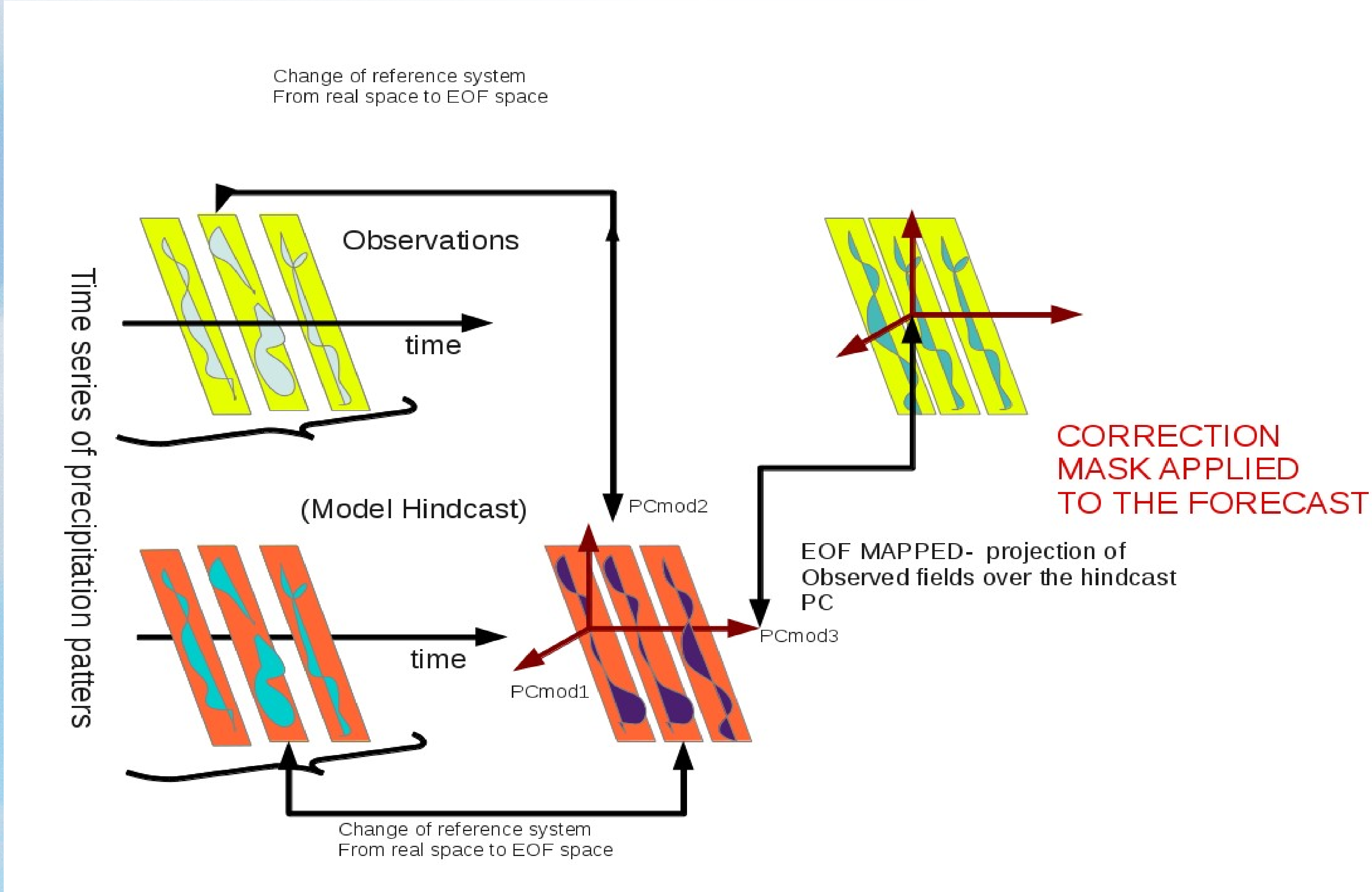
- Rely on a one-to-one mapping of model and observational modes. If the leading observational mode of variability in observations corresponds to the second order or lower mode in the model, or possibly a combination of modes, this will not be accounted for.
- For this reason techniques have only been applied to monthly rainfall average anomalies which are much more smooth and Gaussian then daily precipitation data.

Spatial Mapping developed at ECMWF step 1/3



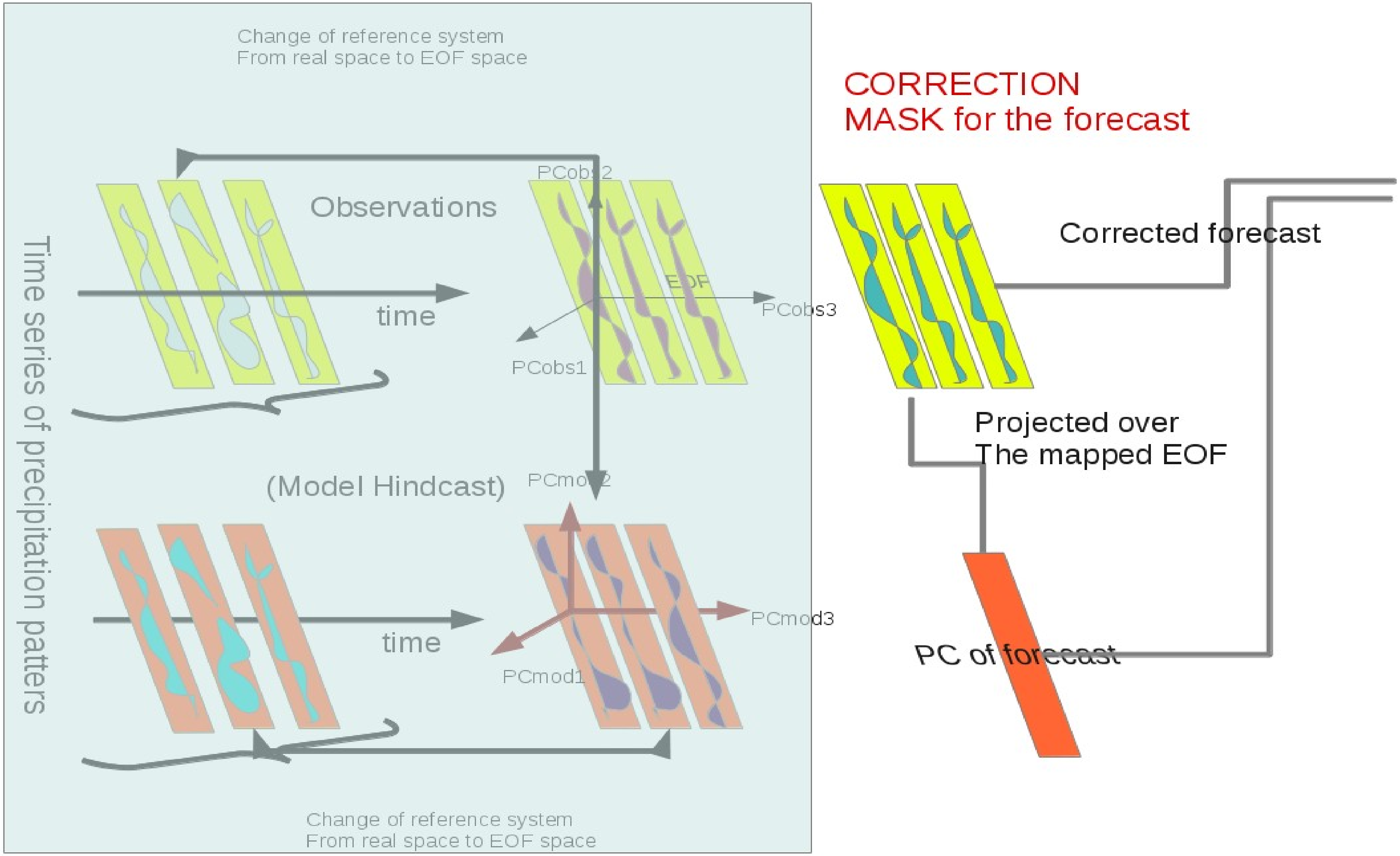
Di Giuseppe, F., Molteni, F. and Tompkins, A. M. (2013), A rainfall calibration methodology for impacts modelling based on spatial mapping. Q.J.R. Meteorol. Soc., 139: 1389–1401. doi: 10.1002/qj.2019

Spatial Mapping developed at ECMWF step 2/3



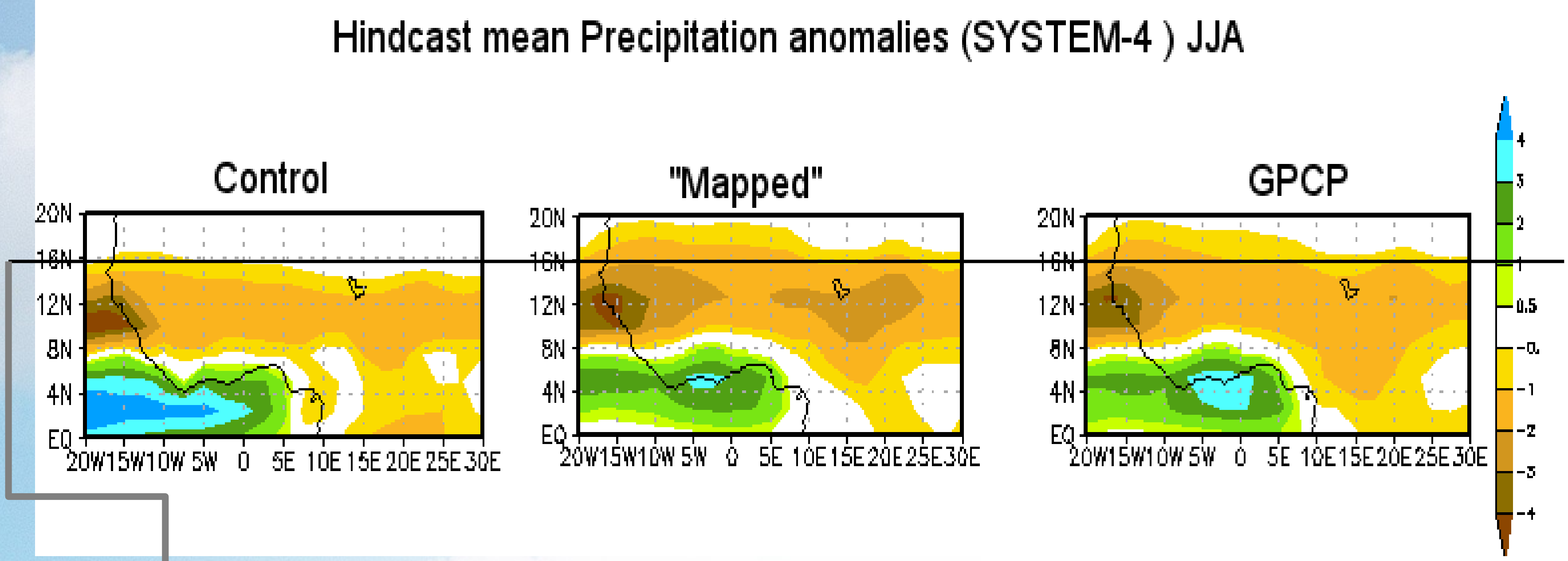
Di Giuseppe, F., Molteni, F. and Tompkins, A. M. (2013), A rainfall calibration methodology for impacts modelling based on spatial mapping. Q.J.R. Meteorol. Soc., 139: 1389–1401. doi: 10.1002/qj.2019

Spatial Mapping developed at ECMWF step 3/3



Di Giuseppe, F., Molteni, F. and Tompkins, A. M. (2013), A rainfall calibration methodology for impacts modelling based on spatial mapping. Q.J.R. Meteorol. Soc., 139: 1389–1401. doi: 10.1002/qj.2019

Precipitation correction



Known bias of southerly displacement of West African monsoon overall corrected

Conclusions -1

At long range forecast “calibration” is needed to remove model biases. The simplest form of bias-correction is to use the hindcast to calculate the model climate and compare it with an observational dataset .

Hindcast [I.e full forecast range] are needed because biases can change over **lead times.**

Calibration [here intended as bias correction] works ***only*** if model has 'climate bias' but predictive skills. Forecast skills can be improved only improving the model

Once the calibration is performed outputs at long range could be used to drive sectoral applications.

Part II
The malaria early warning system developed for the Africa continent under the QWECI project

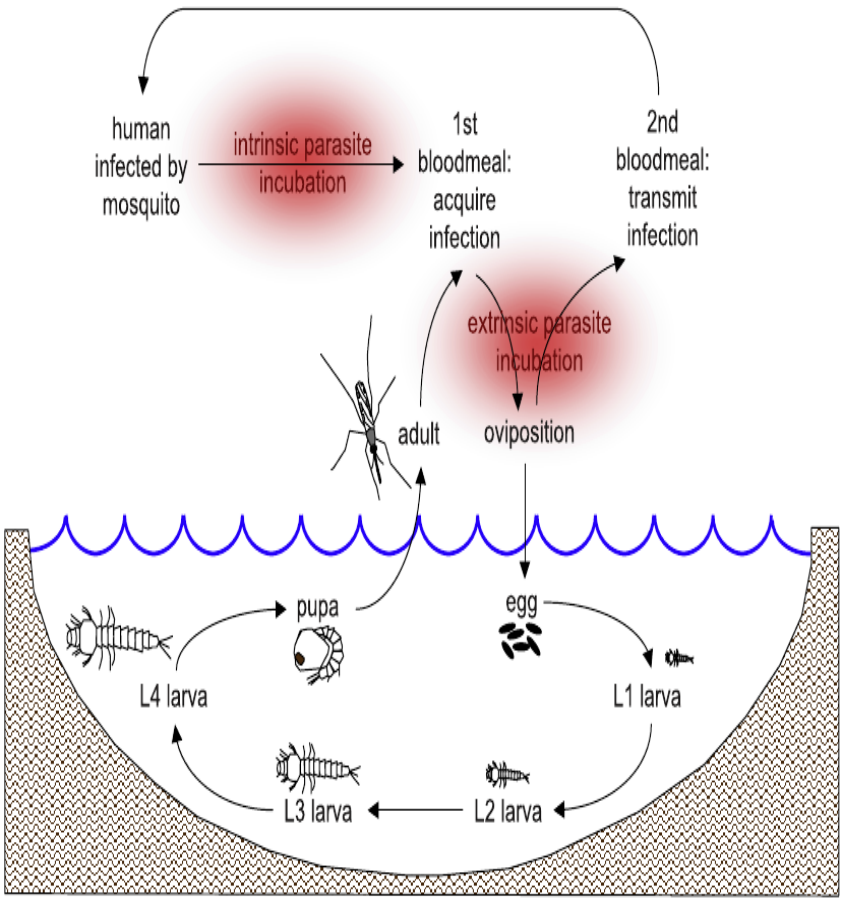
Malaria facts

Malaria parasites are from the genus Plasmodium. 4 species are known to infect humans. Two are wide-spread and particularly dangerous, falciparum and vivax. Vivax can lie dormant in the liver for weeks to years and cause frequent relapses, while faciparum has wide-spread drug resistance and causes the most fatal cases due to the potential cerebral complications.

Malaria vector The malaria parasite is spread by the anopheles genus of mosquito :

Malaria is constrained by weather/climate conditions

- **Rainfall** : provides breeding sites for larvae.
- **Temperature**: larvae growth, vector survival, egg development in vector, parasite development in vector (plasmodium falciparum/ plasmodium vivax).
- **Relative Humidity**: dessication of vector.
- **Wind**: Advection of vector, strong winds reduce CO2



schematic of transmission cycle from Bomblies WATER RESOURCES RESEARCH 2008

Other factors that influence the geographical extension of malaria

Factors that can reduce the disease range:

1)land use changes (drainage)
2)interventions (bed nets, spraying, treatment)
3) socio-economic factors (access to health facilities, behaviour, poverty)
4)predators, competition and dispersion limits

Factors that can increase the disease range:

land use changes (clearance of papyrus brings host closer to vector; papyrus produces chemical that limits larvae development)

NEWS

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WHO highlights disease from unhealthy environments

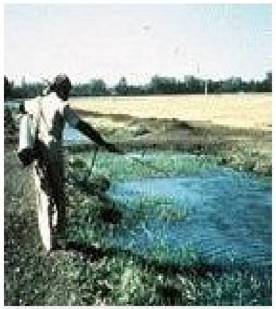
Sophie Hebden

19 June 2006 | EN | 中文

Unhealthy environments cause nearly one-third of all death and disease in developing countries, according to a report released on Friday (16 June) by the World Health Organization.

The report, a review of literature and surveys from over 100 experts, shows that Africans are most vulnerable to death, illness and disability caused by unsafe drinking water, poor hygiene, and other environmental factors.

In West Africa and parts of North Africa 350-500 deaths per 100,000 people are caused by

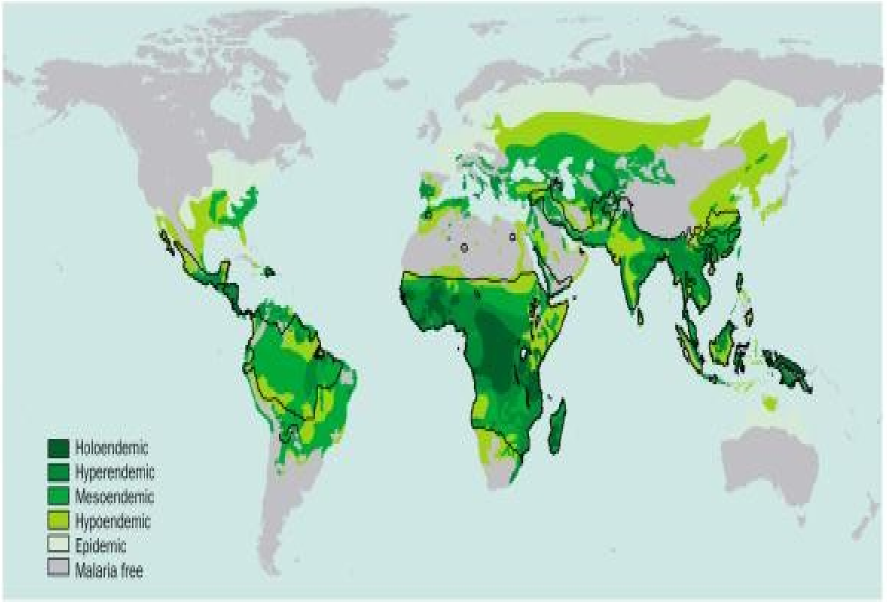


Spraying bodies of water to kill the larvae of mosquitoes that pass malaria to humans through their bites
WHO/TDR/Bahar

Headline extracted from the World Health Organization Report 'Preventing disease through healthy environments'

Malaria distribution since pre-intervention

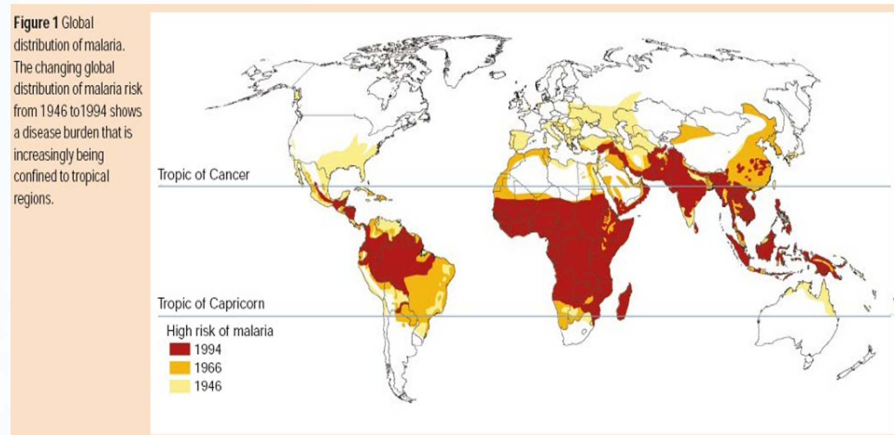
Graphical collection of maps from various sources. Areas of high and
low risk were merged throughout to establish all-cause malaria transmission limits. Each map was then overlaid to create a single global distribution map of malaria risk which
illustrates range changes through time.



Hay, S. I., C. A. Guerra, A. J. Tatem, A. M. Noor, and R. W. Snow, 2004: The global distribution and population at risk of malaria: past, present, and future. The Lancet Infectious Diseases, 4, 327-336.

Malaria distribution after intervention

Global distribution of malaria. The changing global distribution of malaria risk from 1946 to 1994 shows a disease burden that is increasingly being confined to tropical regions (Fig. 1 in Sachs and Malaney 2002).



Sachs, J., and P. Malaney, 2002: The economic and social burden of malaria. Nature, 415, 680-685

" The global distribution of per-capita gross domestic product shows a striking correlation between malaria and poverty, and malaria-endemic countries also have lower rates of economic growth"

Approaches to Modelling Malaria

Statistical model

Relate predictor to climate and non-climate disease drivers

1. Can include poorly understood drivers (e.g. poverty/interventions) easily
2.Can be simple and fast to implement
3. Needs (long/wide) training dataset in target area (transferable?)
4.Care required to avoid overfitting data
5.Trial/error required to determine best model
6. Not easy (but possible) to include sub-seasonal information

Dynamical model

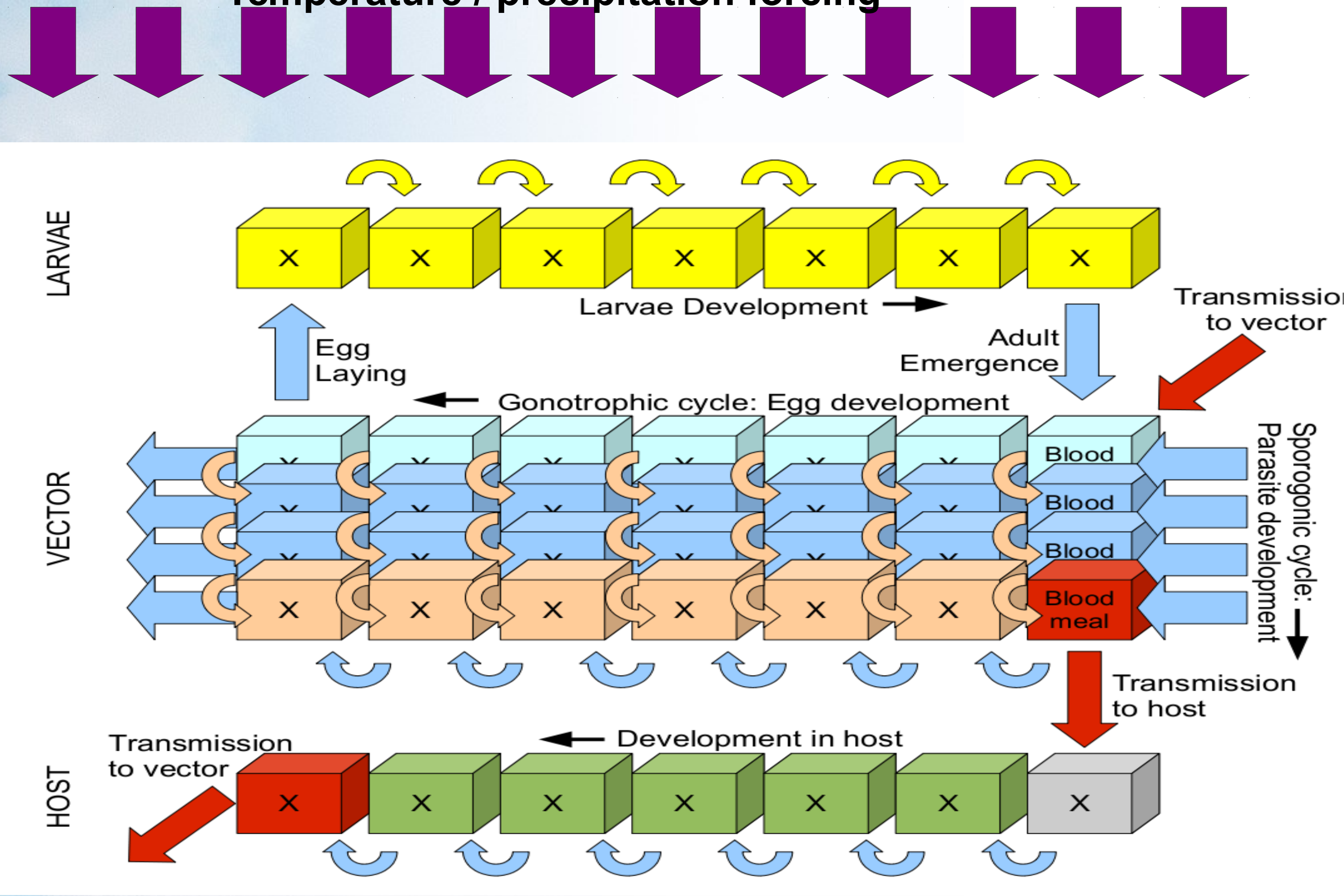
Solve equations describing the vector/parasite cycle where equations are mostly derived from controlled lab (or field) studies

1.Can account for sub-seasonal variability of climate drivers
2. More transferable from one location to another
3. More difficult to account for confounding factors?
4. Good data/understanding required for accurate model, tuning still required for poorly specified parameters.

The VECTRI malaria model

he most recent models divides the categories into many sub-categories, or bins, or order to try and odel delays in e.g. adult emergence, and have been applied to spatial modelling

Temperature / precipitation forcing



Schematic of the the dynamic malaria model VECTRI (Tompkins and Ermert Journal of Malaria 2012) Freely available at http://users.ictp.it/~tompkins/vectri/

What do we want to know from a Malaria forecasting system?

Endemic Areas [high immunity, mortality mainly in <5years] potential prediction of seasonal onset.

Epidemic Areas [low immunity, mortality across all age groups] prediction of outbreaks

Decadal timescales: potential shift of epidemic areas to higher altitudes (e.g. Pascual et al Proc. Natl. Acad. Sci. USA), and changing epidemic and endemic patterns.

The epidemic belt on the edge of the Sahara is associated with lack of rainfall, while cold temperatures reduce or eliminate malaria incidence at high altitudes over eastern Africa from Contribution of Working Group II to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change, 2007

Why can we develop a Malaria Early Warning System (MEWS) now?

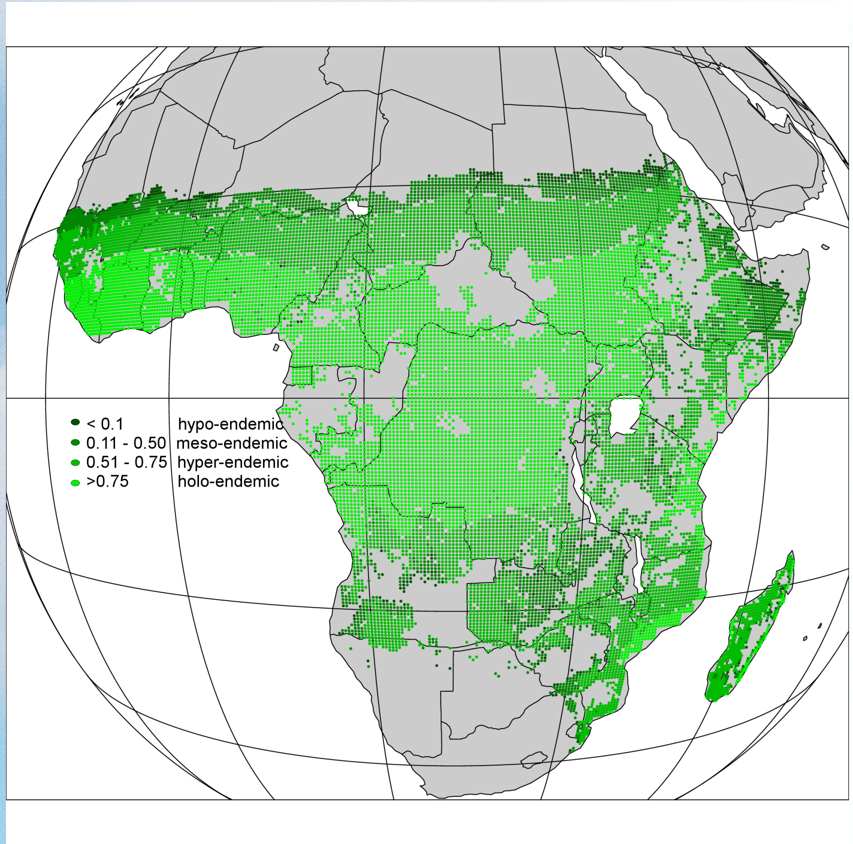
Malaria is a very old disease. Fossils of mosquitoes 30 millions years old show that the vector for malaria was present well before the earliest history of man.

(1)Several African nations have implemented improved health monitoring systems over the last decade, which in combination with malaria detection kits, has greatly improved health data for evaluation

(2)Latest generation seasonal forecast systems are now starting to exhibit skill in temperature and precipitation with lead times of one or two months and beyond.

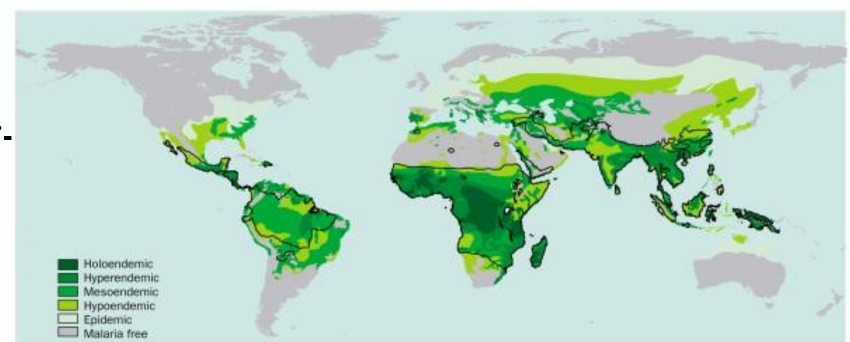
(3)Improved understanding of malaria transmission had lead to better dynamical malaria modelling systems capable of modelling the disease transmission on a regional scale.

MEWS evaluation

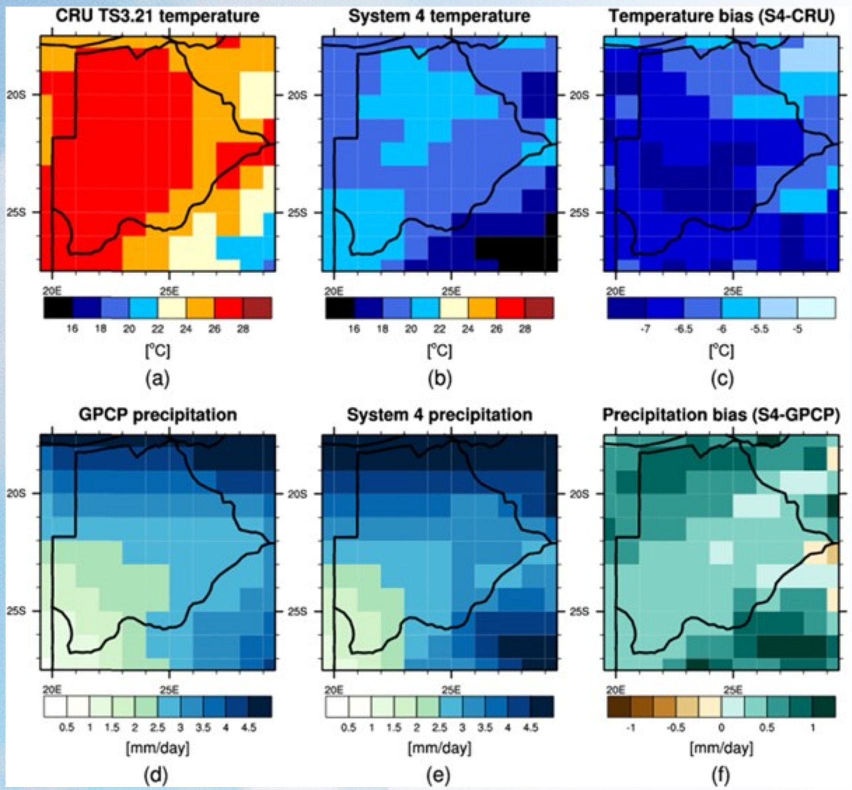


(Comparison with Hay et al. Lancet Infect Dis. 2004 Jun;4(6):327-36. The global distribution and population at risk of malaria: past, present, and future. (readapted from Lebedew AW, editor. Itogi Nauki: Medicinskaja Geografija. Academy of Sciences, USSR; Moscow: 1968. pp. 25-146)

The model only accounts for CLIMATE and POPULATION DENSITY. It does not (yet!) account for interventions, (e.g. bed nets, spraying) immunity or treatment which all reduce PR. Migration is also ignored. Note: model does not run when population is < 1 km-2

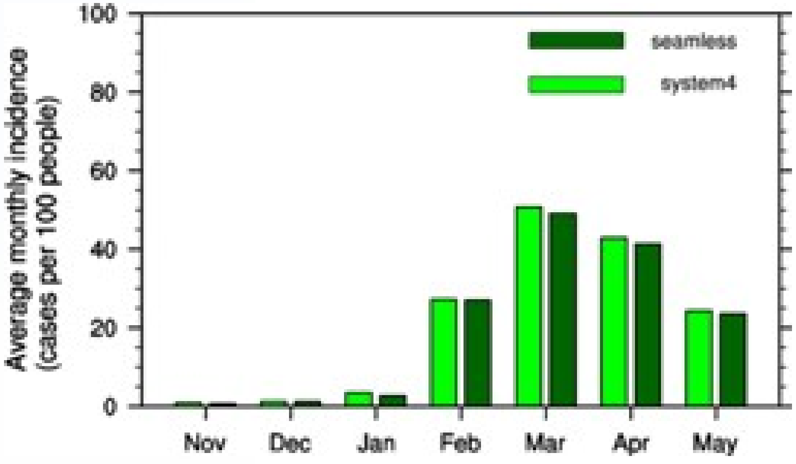


The importance of the calibration



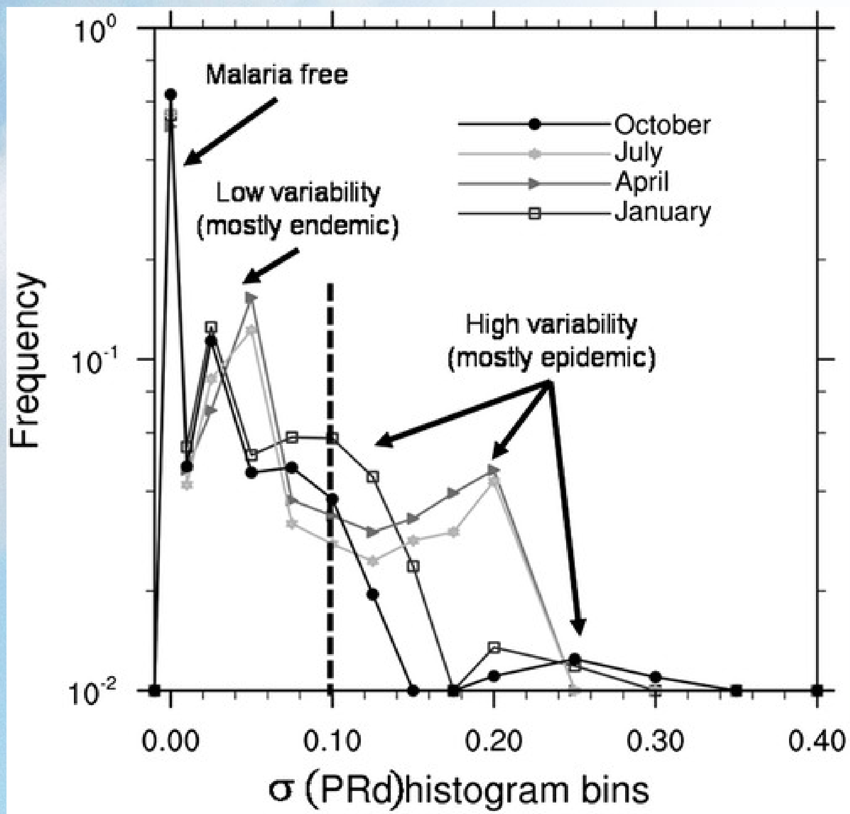
Bias in temperature and precipitation over Botwana

The uncalibrated temperatures generally remain below the sporogonic temperature threshold (18 °C), preventing parasite development within the mosquito vector as simulated by the model. Therefore without bias correction the malaria model would predict no cases



Demonstration of successful malaria forecasts for Botswana using an operational seasonal climate model Dave A MacLeod, Anne Jones, Francesca Di Giuseppe , Cyril Caminade, and Andrew P Morse 2015 Environ. Res. Lett.doi:10.1088/1748-9326/10/4/044005

Definition of epidemic and endemic regions

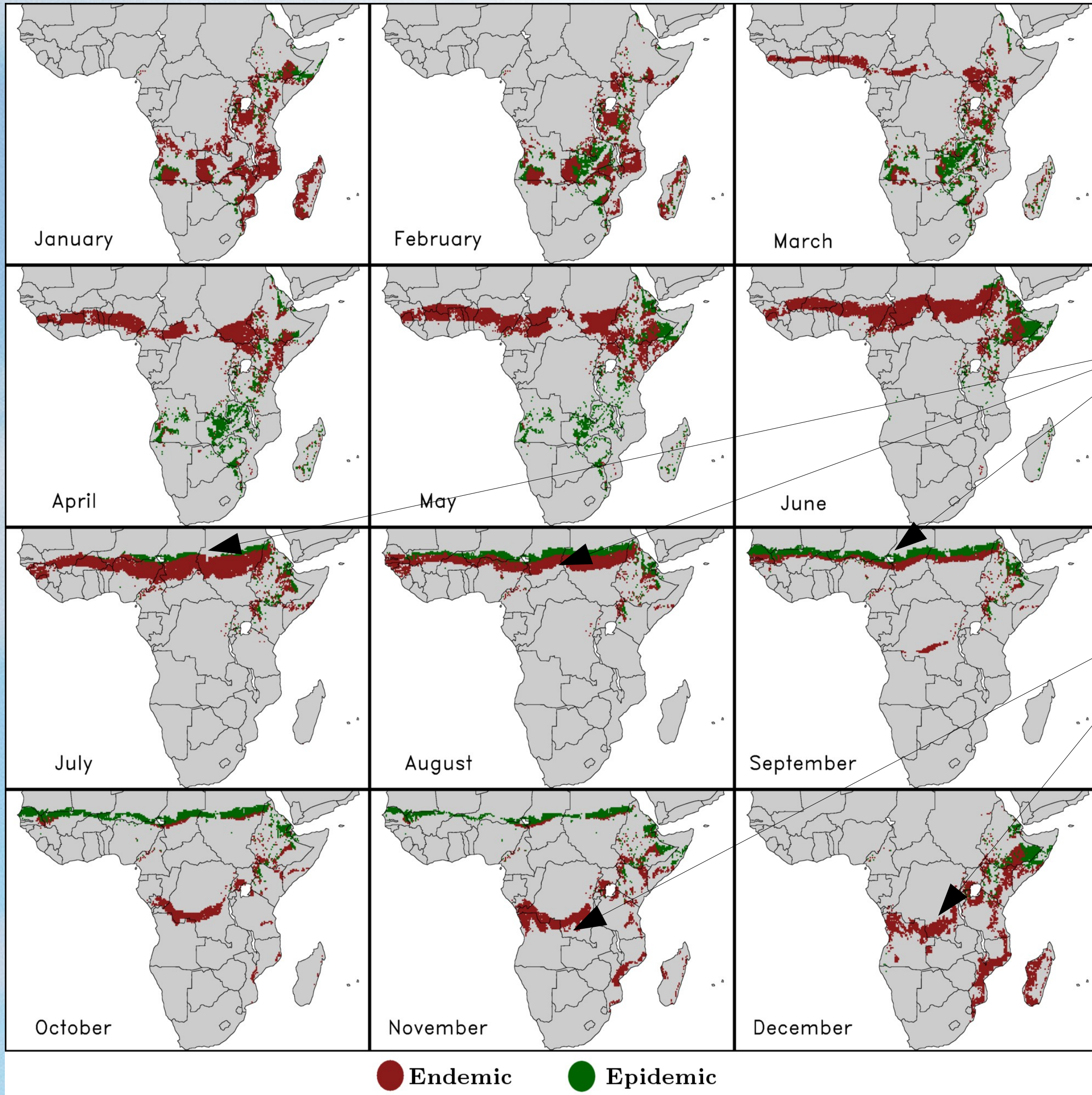


Epidemic/Endemic areas with predictable information

Predictable areas are defined by looking at the time variance of the number of cases (~ln(EIR)) over 30 years of re-analysis runs.

Small variances (< 0.10) defines **endemic areas**. High variance for the malaria transmission (> 0.10) define **epidemic area** where useful information can arise from a MEWS.

MEWS useful predictable information

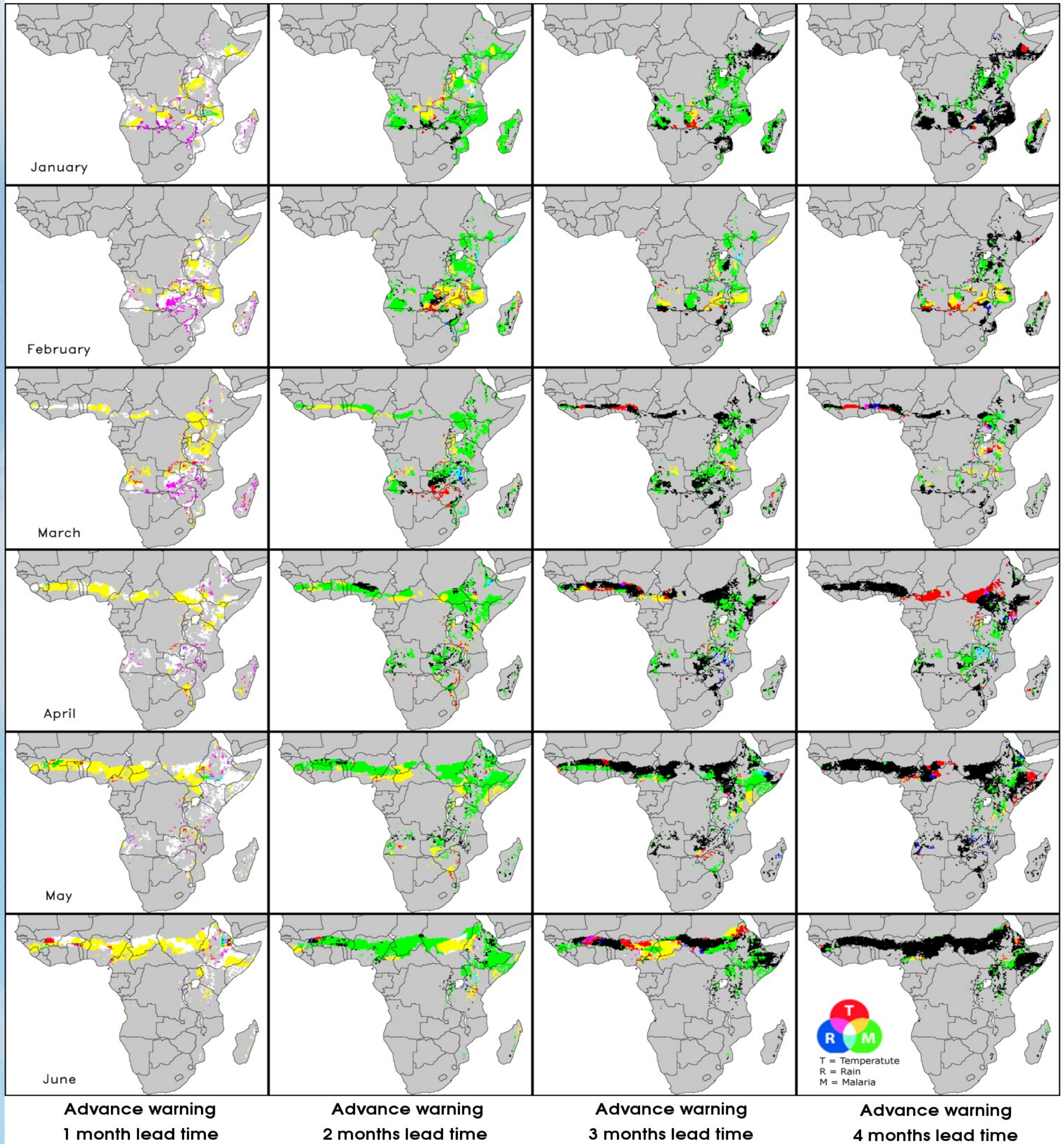


Epidemic/Endemic areas with predictable information

In the sahel the variability is due to the rain annula cycle (West Africa Monsoon)

In the highlands malaria variability is due to the temperature annual cycle

Malaria forecast: predictability



T = Temperatute
R = Rain
M = Malaria

Conclusions -2

We have seen the example of a prototype malaria early warning system.

The meteorological inputs from the long-range forecast of ECMWF required rainfall and temperature calibration before they could be used to drive the dynamical malaria models.

In this preliminary validation stage the system has been tested against reanalysis runs (i.e. in the “model world!”) showing reasonable results compared to early studies

The system will be tested over Malawi, Uganda and Rwanda with ministry of health partners from the QWeCI and HEALTHY FUTURES projects.