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IAEA International Atomic Energy Agency

2237-3

Joint ICTP-IAEA Conference on Coping with Climate Change and Variability in Agriculture through Minimizing Soil Evaporation Wastage and Enhancing More Crops per Drop

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An introduction to forecasting systems components useful for crop yield prediction

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An introduction to forecasting systems components useful for crop yield prediction
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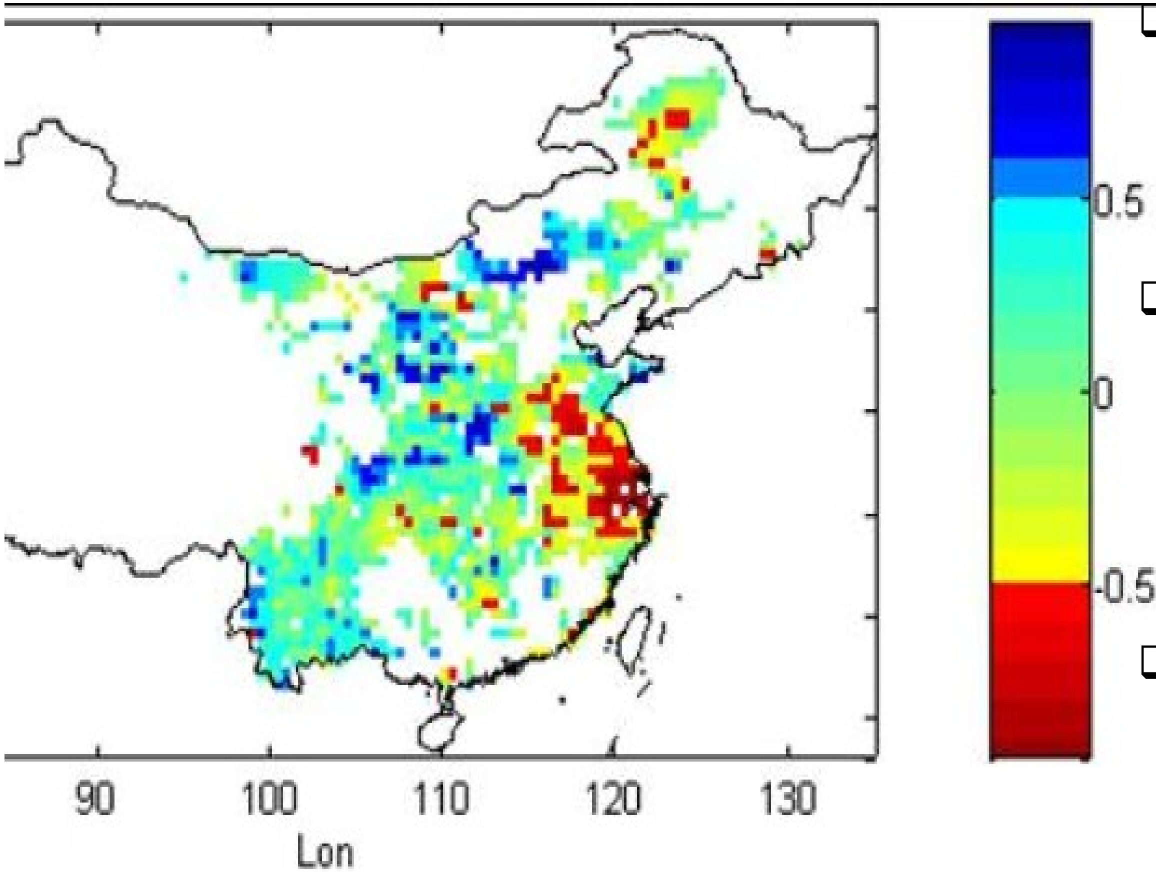
Talk is ECMWF and Africa-centric

1) Why use forecast model output?
2) Introduction to forecast models
3) Data Assimilation
4) Accounting for Uncertainty
5) Examples of predictable modes from short range to seasonal

Why are we interested in Weather Forecasts?

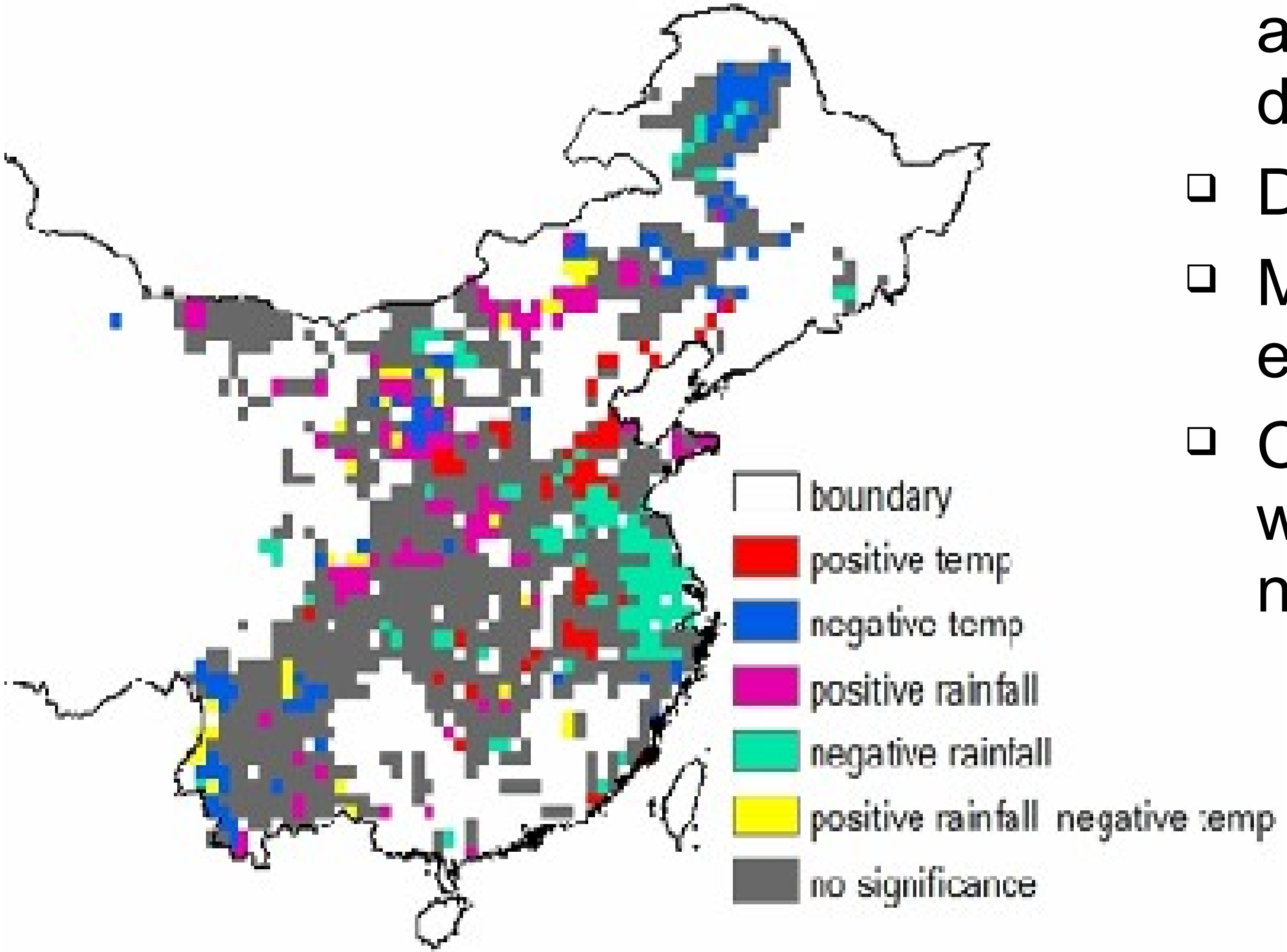
- Inter-annual variability of crop yield driven by a variety of factors
  - Socio-economic drivers of crop demand and production (war, migration, speculation)
  - Land use change
  - Governmental and NGO intervention programmes (fertilisers, technology subsidies).
  - Outbreak of pests, disease.
  - Climate variability and extreme events (floods, droughts, severe storms, fire)
- There are many interactions and feedbacks.
- Some of these are inherently predictable: weather

An example in China: correlation between rainfall and observed yield (1985-2000)



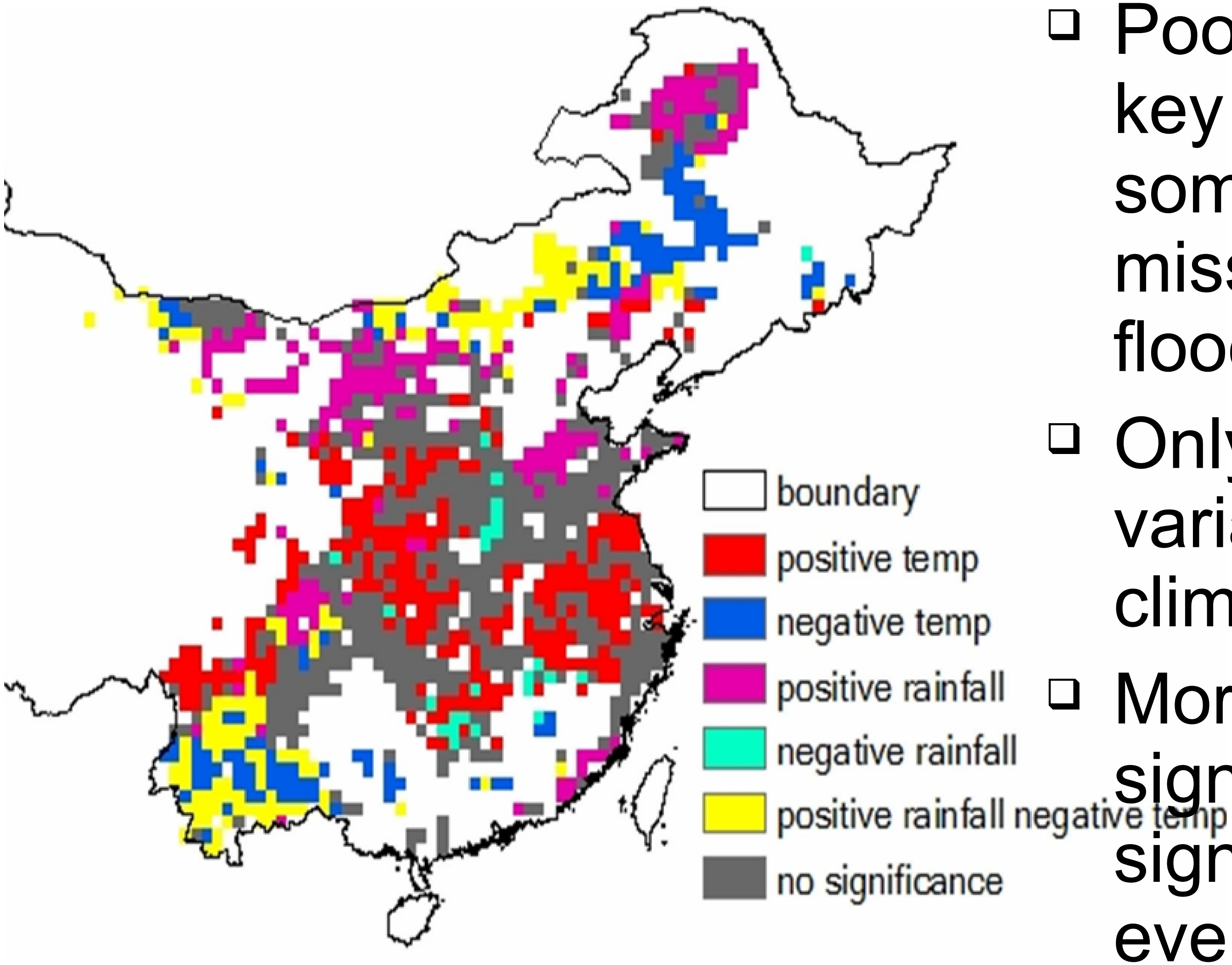
- Positive correlation in north west, rainfall limited.
- Negative in east where irrigation fraction is higher: Effect of flooding
- Significance?

Key significant correlations: observed yield with observed seasonal climate



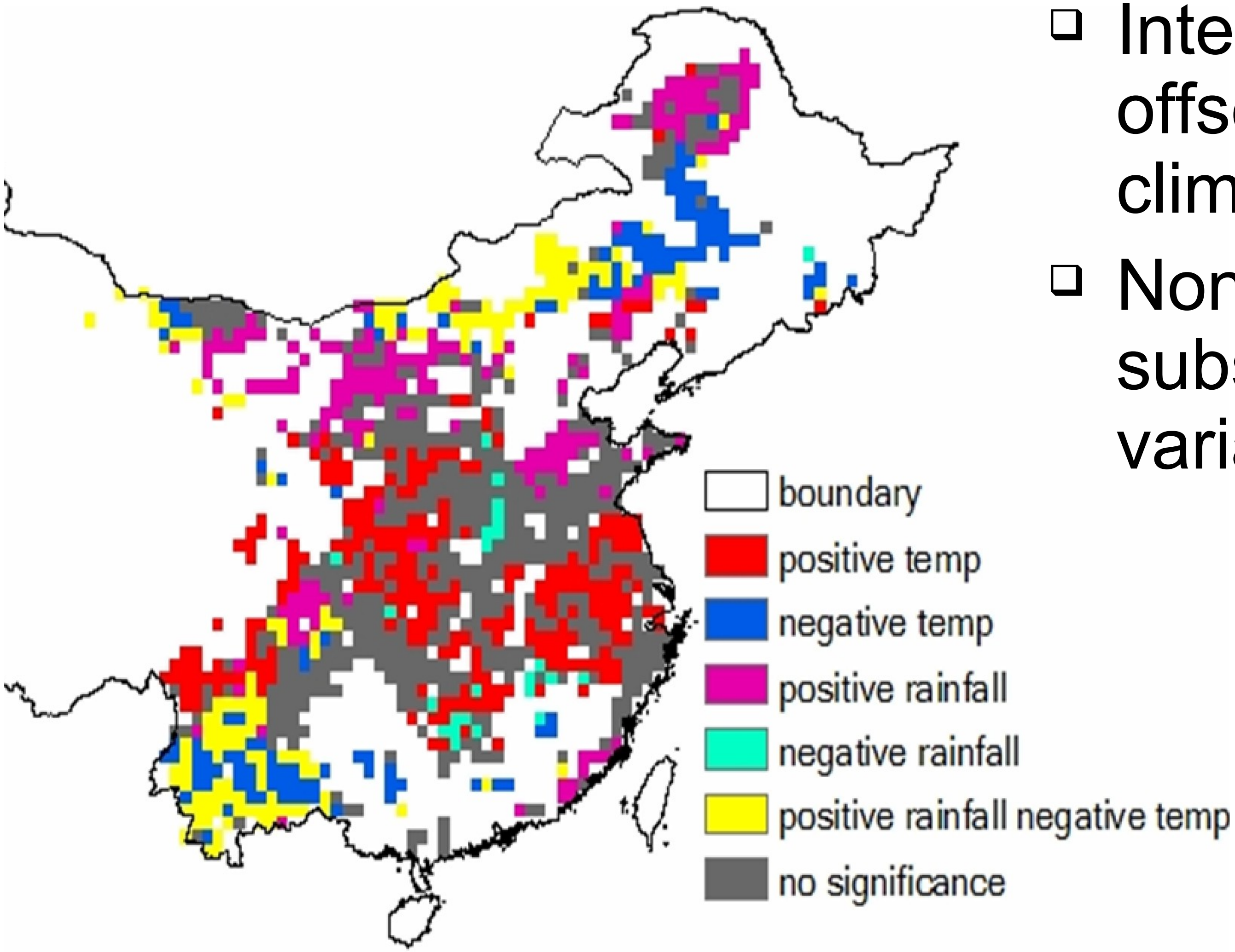
- Many areas have no apparent climate driver of yield- Why?
- Data uncertainty
- Management, pests etc confounding signal
- Crop yield relationship with climate is highly nonlinear!

Key significant correlations: GLAM yield



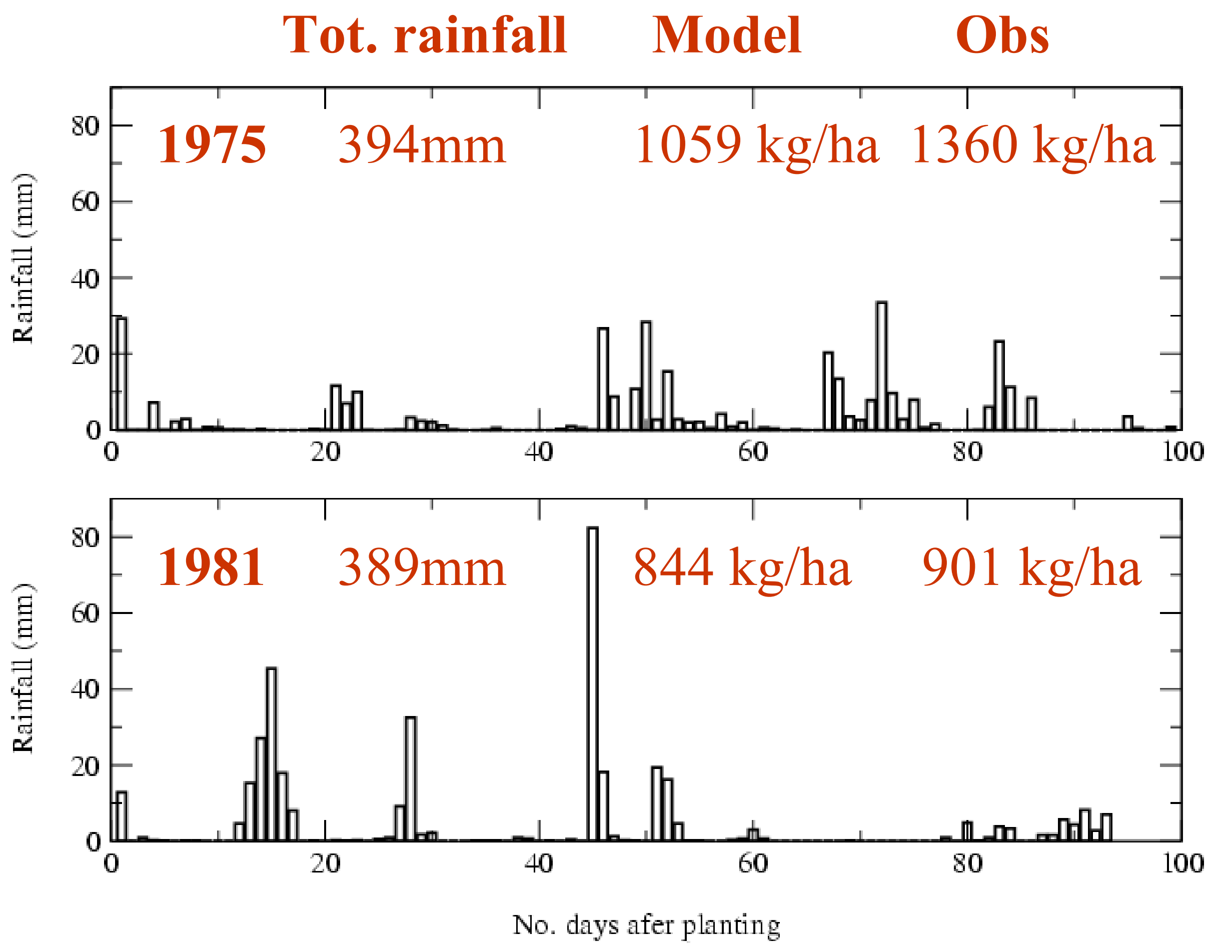
- Poor agreement with key relationships in some areas due to missing physics? e.g. flooding
- Only impact on yield variability here is climate.
- More robust climate signal, but still not significant everywhere - Why?

Key significant correlations: GLAM yield



- Interactions and offsets between climate variables
- Nonlinearity due to subseasonal climate variability.

Capturing the effect of intra-seasonal rainfall variability



- Seasonal total rainfall
- Co-incidence of stress with critical crop development stages
- Partitioning of precipitation into runoff, drainage and transpiration

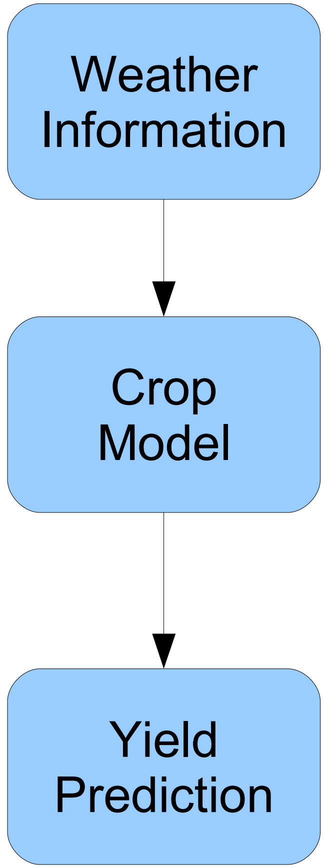
Challinor et al. (2004)

Yield monitoring and prediction

- Monitoring of yield statistics involves a delay
- Climate monitoring/forecasts may give enhanced lead-times
  - Monitoring of weather extremes for planning
  - Use of Crop Models may enable one predict year-to-year fluctuations
  - Statistical crop models
    - based on observed empirical relations
    - Simple and robust but require long data records
  - Dynamical models
    - Can model the plant growth explicitly
    - Require smaller datasets
    - Can represent strongly nonlinear relationship between crops and climate – including sub-seasonal variability

Climate information

- Crop models can be driven by relevant climate parameters
  - Temperature
  - Rainfall
  - Solar radiation
- These can be observations/reanalysis
  - Temperature and solar: model reanalysis, station data
  - Rainfall: Satellite AND station data
- Or they can be from forecast models to increase lead-time of predictions (potentially!



What are forecast models?

Solve the equations of motion on a discrete grid

Need to know
The initial conditions X(t)
And the forecast model dX/dt

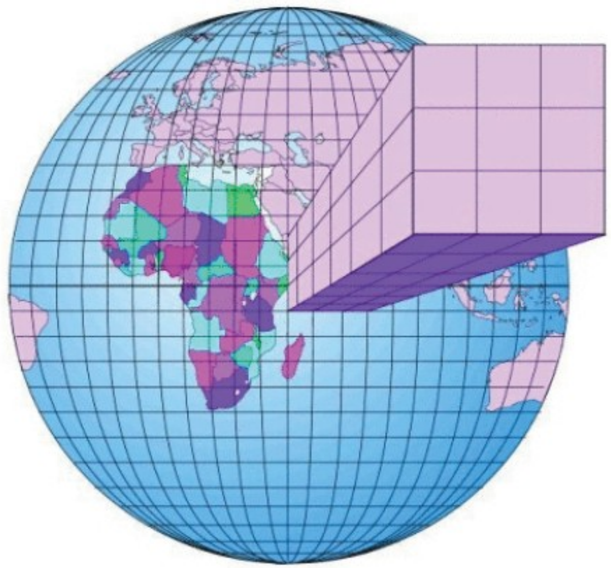
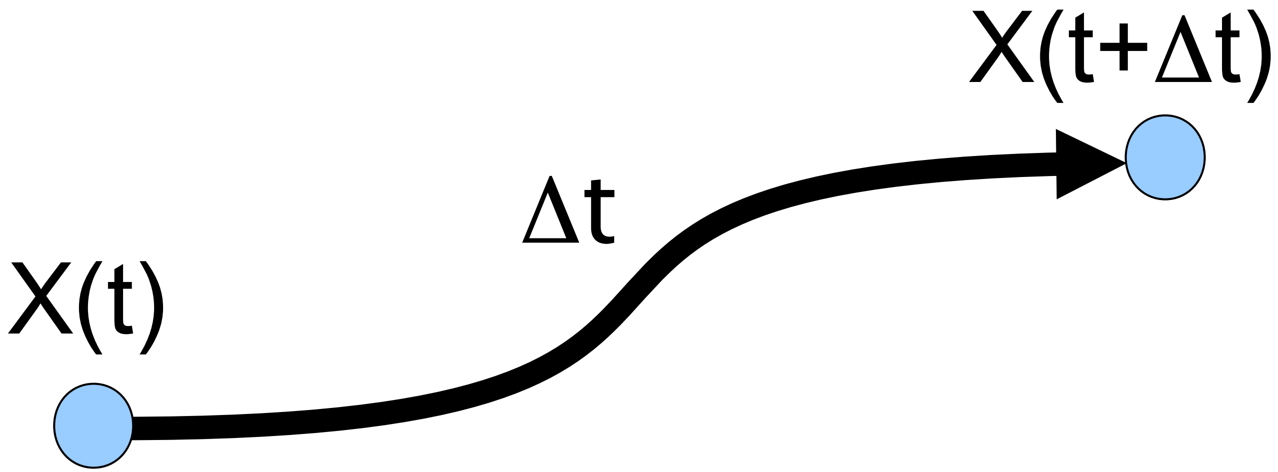


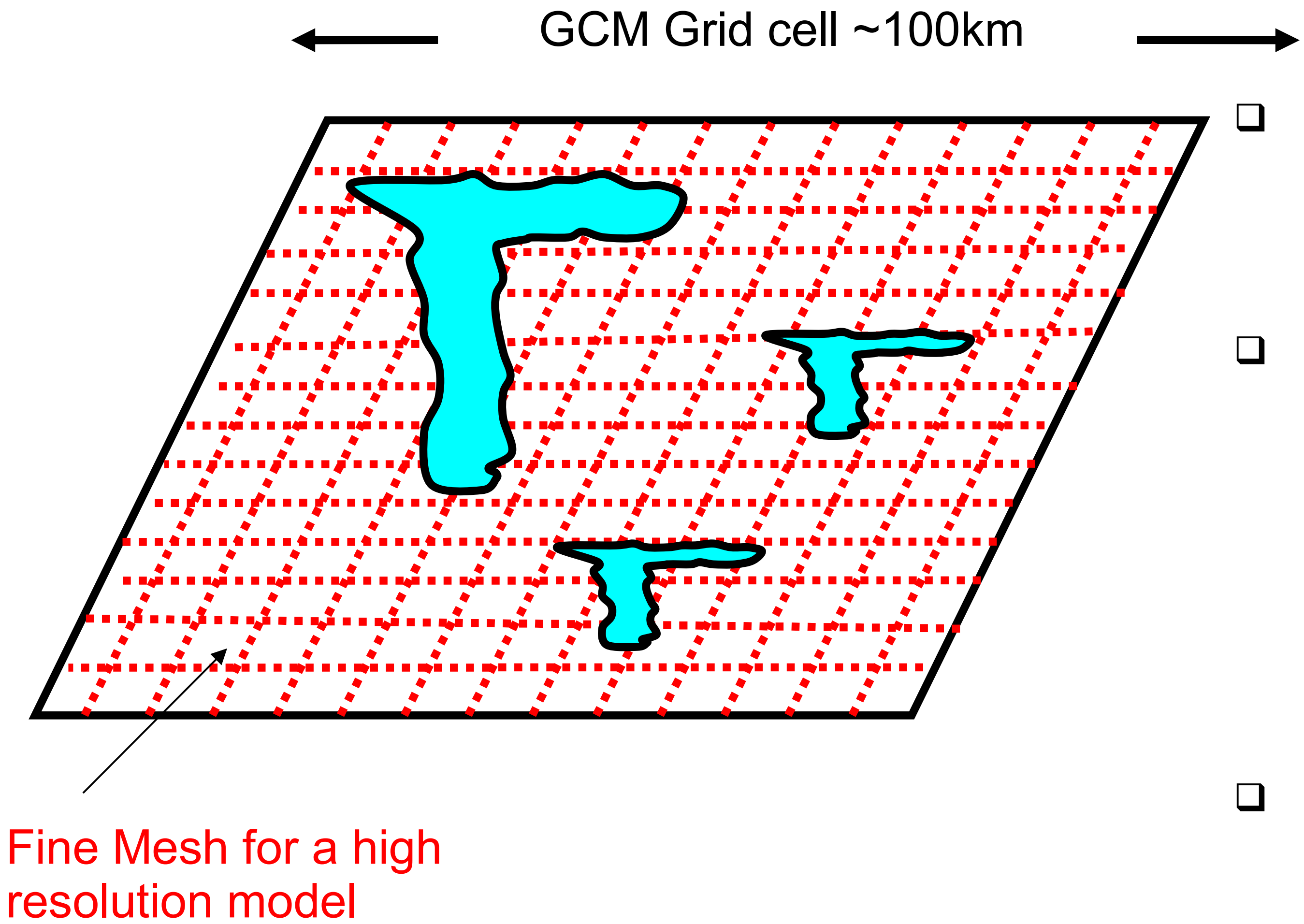
Figure: Schematic of a low resolution grid mesh for a global model.



How fine a mesh can we use to solve our equation set? It depends on many factors, the length of the integration, the power of the computer facility available, the efficiency and complexity of the numerical model.

But in general a global climate model that must run for many tens of years uses a horizontal mesh size of 100 to 300km, while global numerical weather prediction models that run for days to weeks use mesh sizes of 25 to 50km, with seasonal forecasts somewhere in between.

How big are convective clouds?



- Clouds occur on small spatial scales
- Their effect has to be "parametrized" (a simple toy model is inserted to account for their effect.
- These can be highly empirical and uncertain

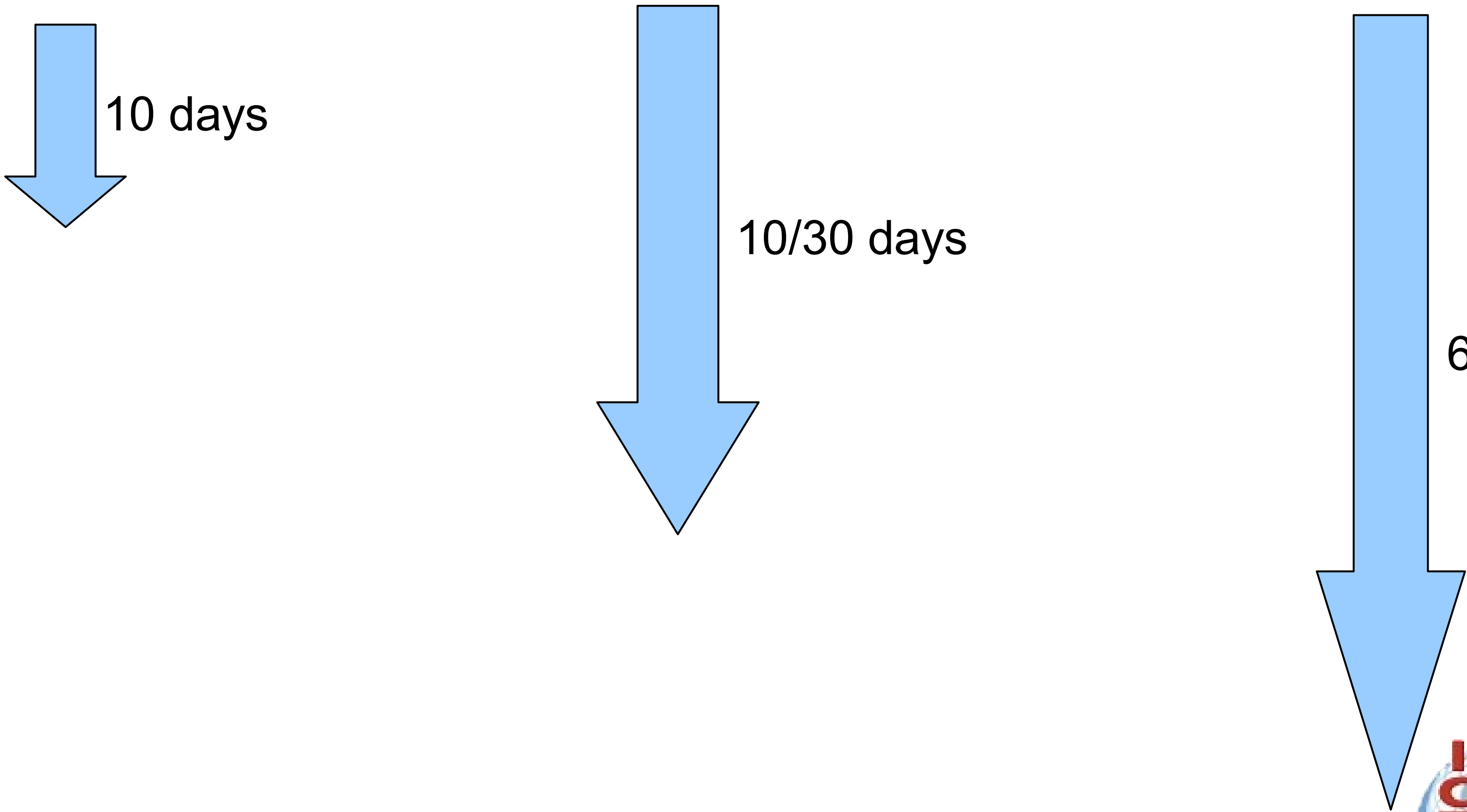
Thus models have error not only due to truncation error but also due to errors in model physics

Introduction to a typical system - ECMWF A different model system for different timescales:

T1279 (16km)
no ocean
single forecast

T613/319 (30-60km)
ocean>10days
ensemble

T159 (125km)
ocean
ensemble



The modelling systems are not identical. The seasonal forecast system is less frequently updated.

Operational Cycles and the Seasonal System

CYCLE	YEAR	NOTES
.		
.		
23R4	2000	System 2 (released 2002), ERA-40
24		
24R1		
24R2		
.		
.		
31R1	2006	System 3 (released March 2007), ERA Interim
31R2		
31R3		
.		
.		
35R1	2009	Current deterministic & VAREPS

- Seasonal system updated far less frequently
- ECMWF system becomes less seamless in time...

Why can't we run a single forecast system for the whole period-region of interest?

- Numerically too expensive: Perhaps want to use high resolution at for short range or over region of interest.
- Pragmatism: We all know models have errors, perhaps one model performs better for a region or timescale, another model better for seasonal timescale.
- Metrics: What does "better" actually mean? Not the case that a single system can maximize skill in all metrics.

May have different metrics that are considered important at different timescales and for different users.

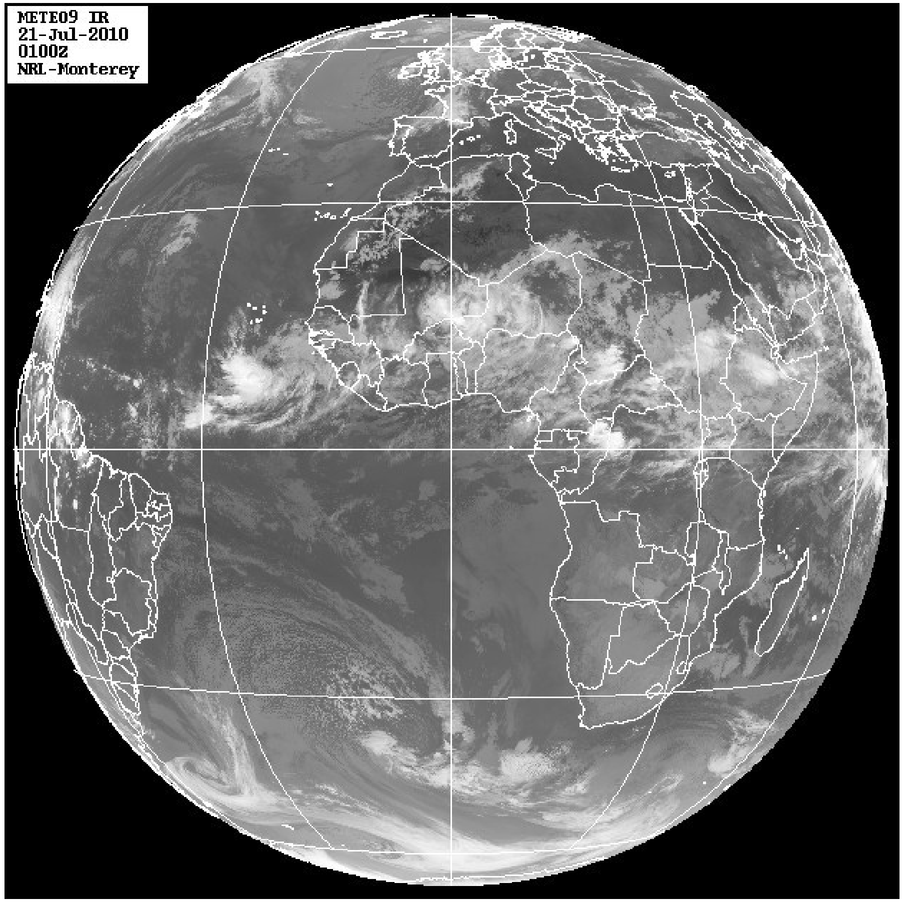
Modes/Aims of Predictability in the Tropics

- Nowcasting and shortrange: deterministic prediction of weather
  - convection, temperature, severe weather events…
- Medium to monthly range: Prediction of dynamical features
  - 3-10 days: African Easterly Waves, extra-tropical intrusions… (see lectures by Andreas Fink and Peter Knippertz)
  - 20-60 days: Madden Julian Oscillation
- Seasonal range: weather anomalies associated with sea surface temperature
- Annual to decadal: anomalies associated with ocean decadal modes and trends with

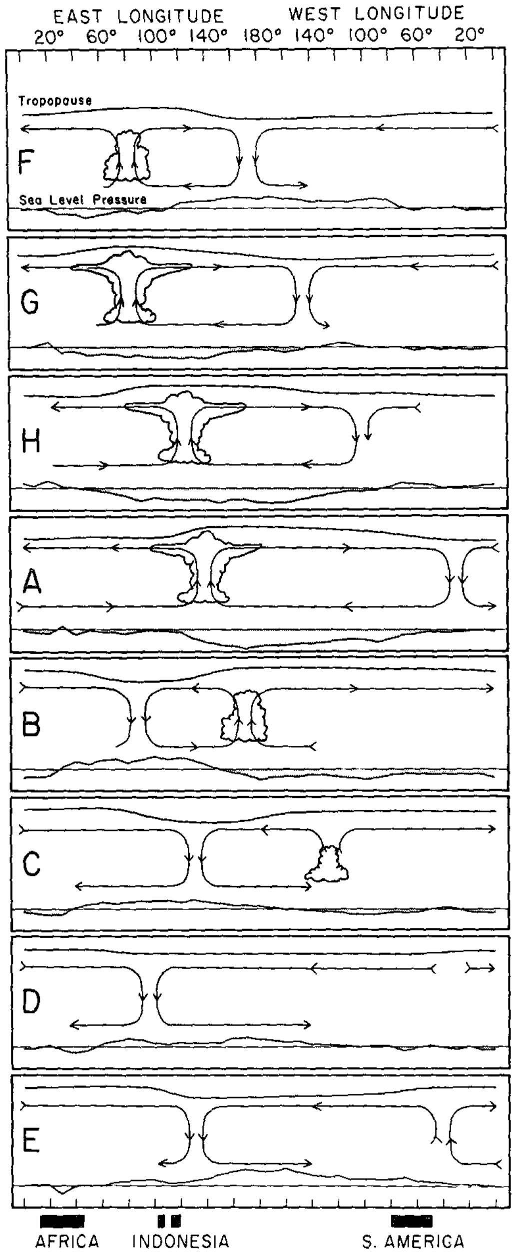
Nowcasting over various timescales

Just as “nowcasting” with satellite or radar involves the extrapolation of disturbances over the following few hours…

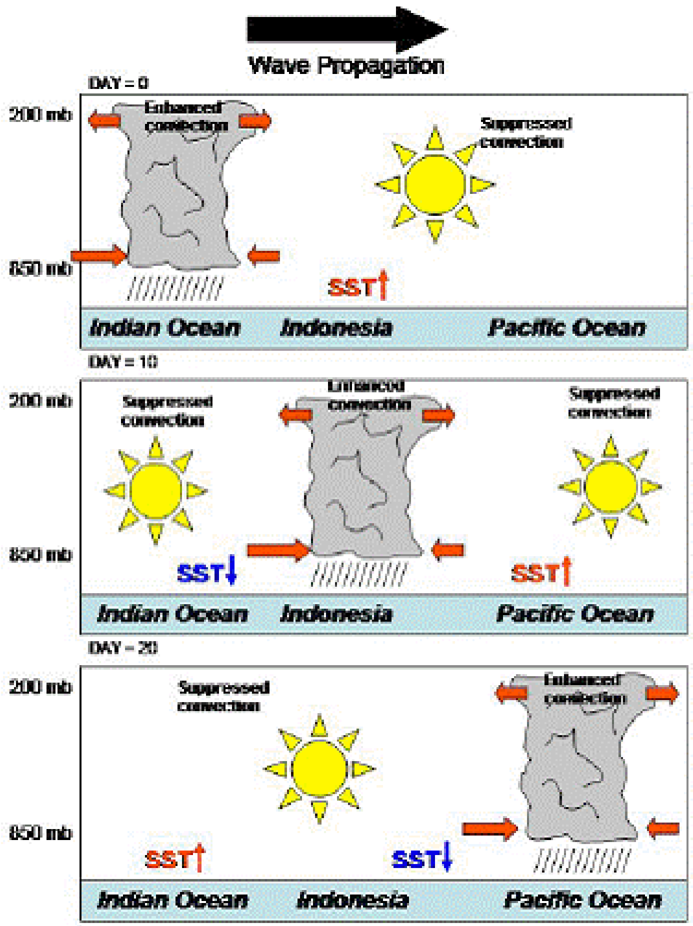
…modes of variability such as African Easterly Waves or the Madden Julian Oscillation can enhanced



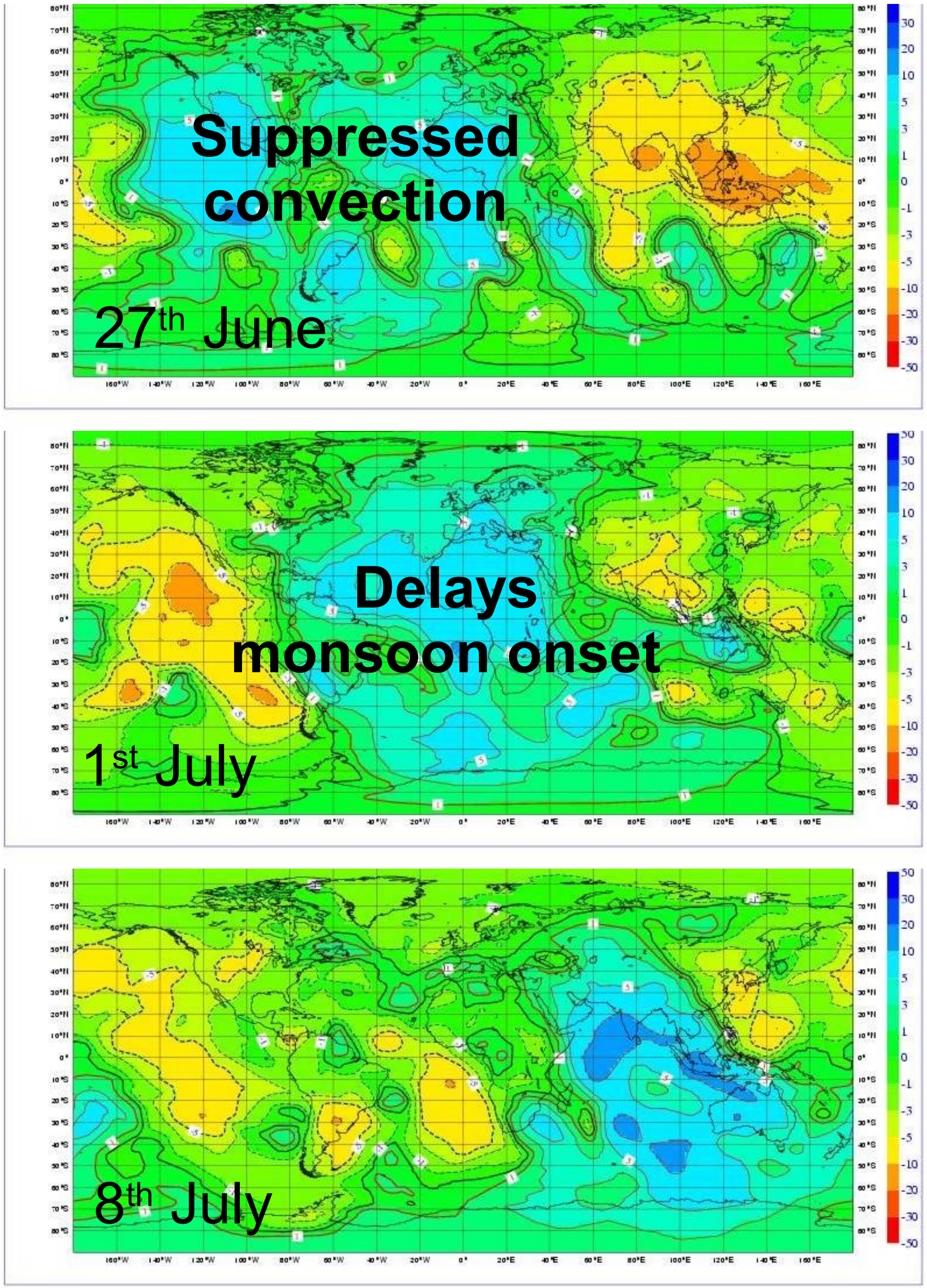
Madden-Julian Oscillation (MJO)



- Wave number 1-3 convectively-coupled eastward propagating (40-60 days) large-scale oscillation in the tropics

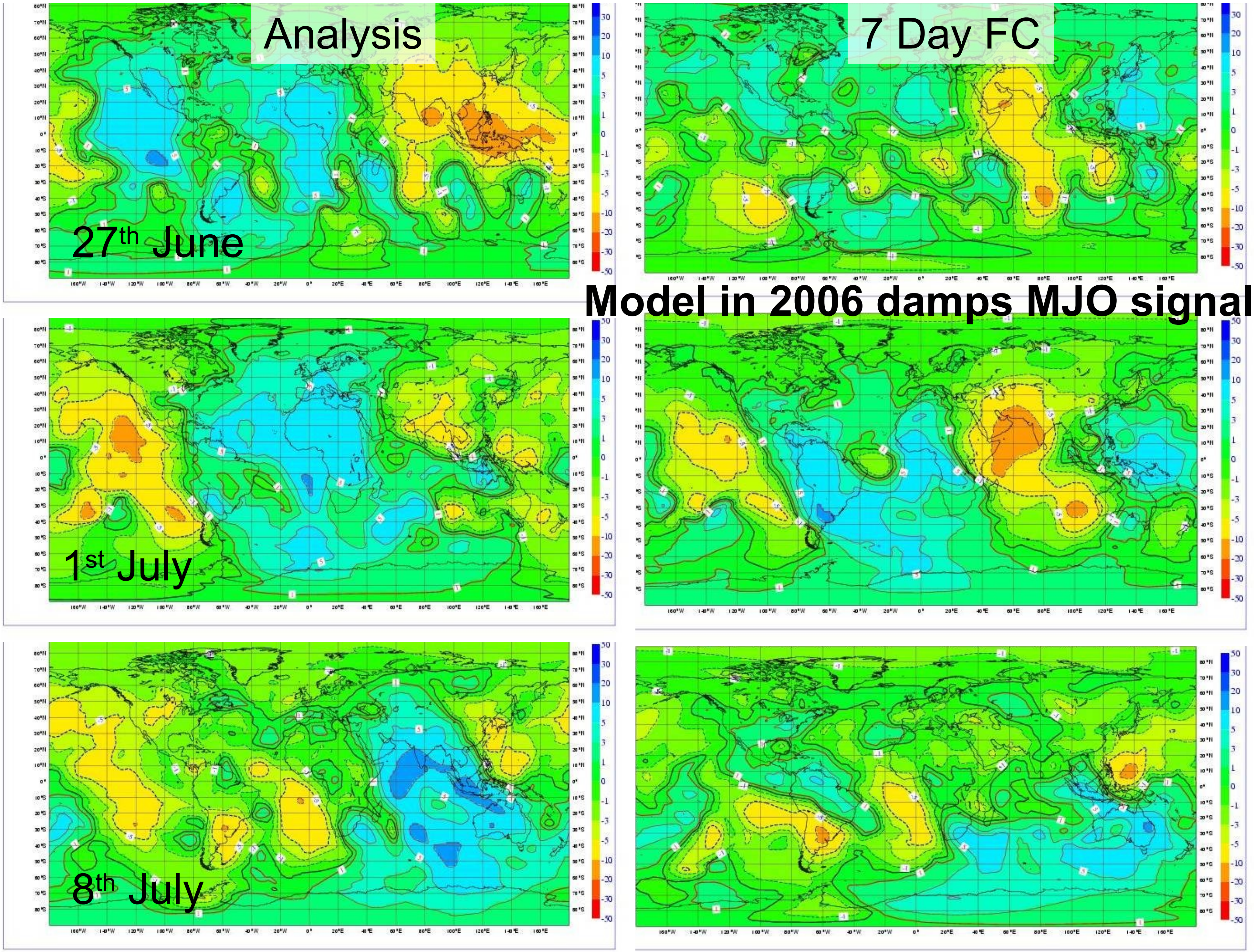


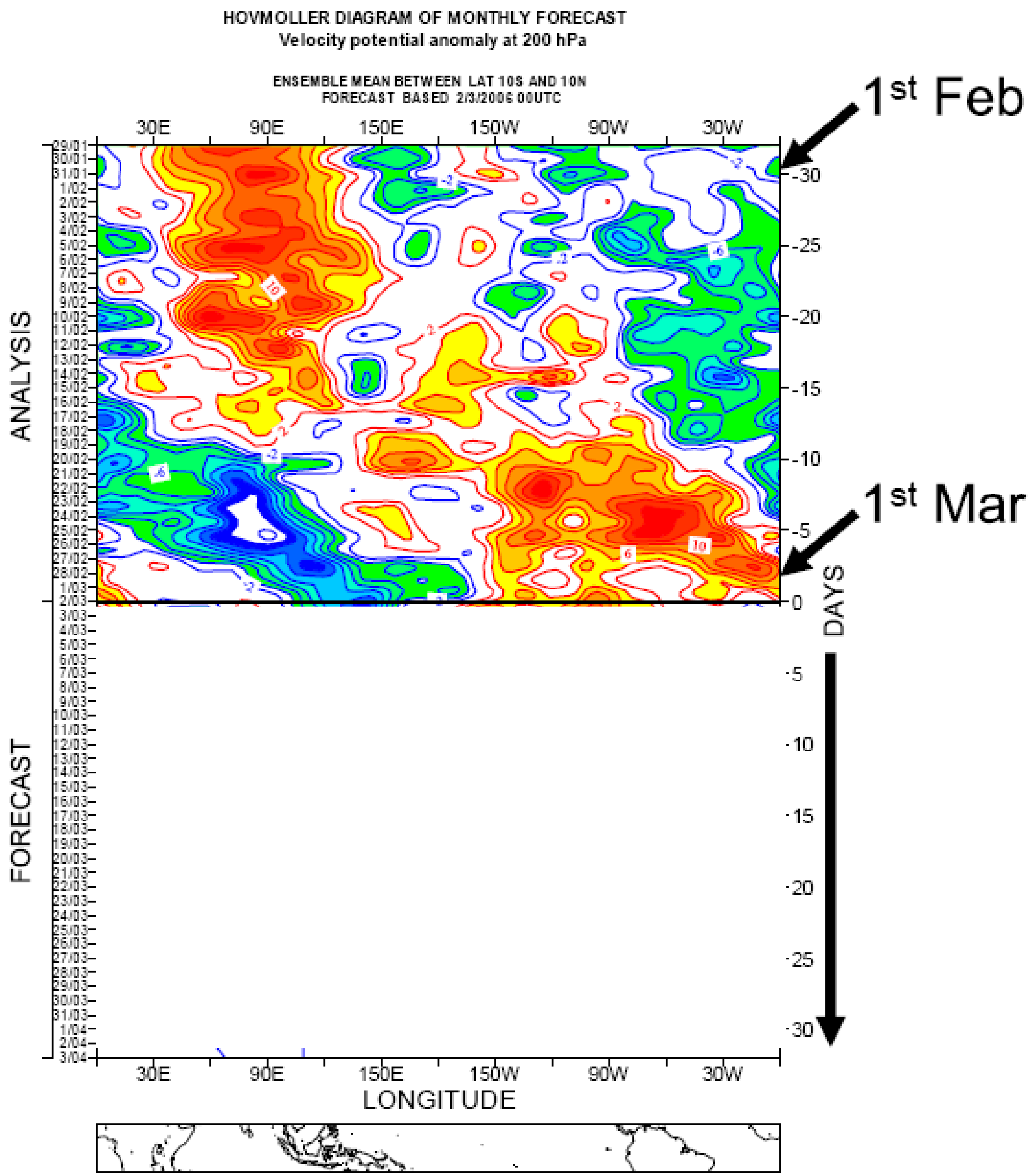
ECMWF Analysis of the 200 hPa Velocity potential Anomaly



Large-scale wave-number 1 pattern associated with an MJO event

Using this, ACMAD correctly predicted a late monsoon onset in 2006


Analysis
7 Day FC
27th June
Model in 2006 damps MJO signal
1st July
8th July

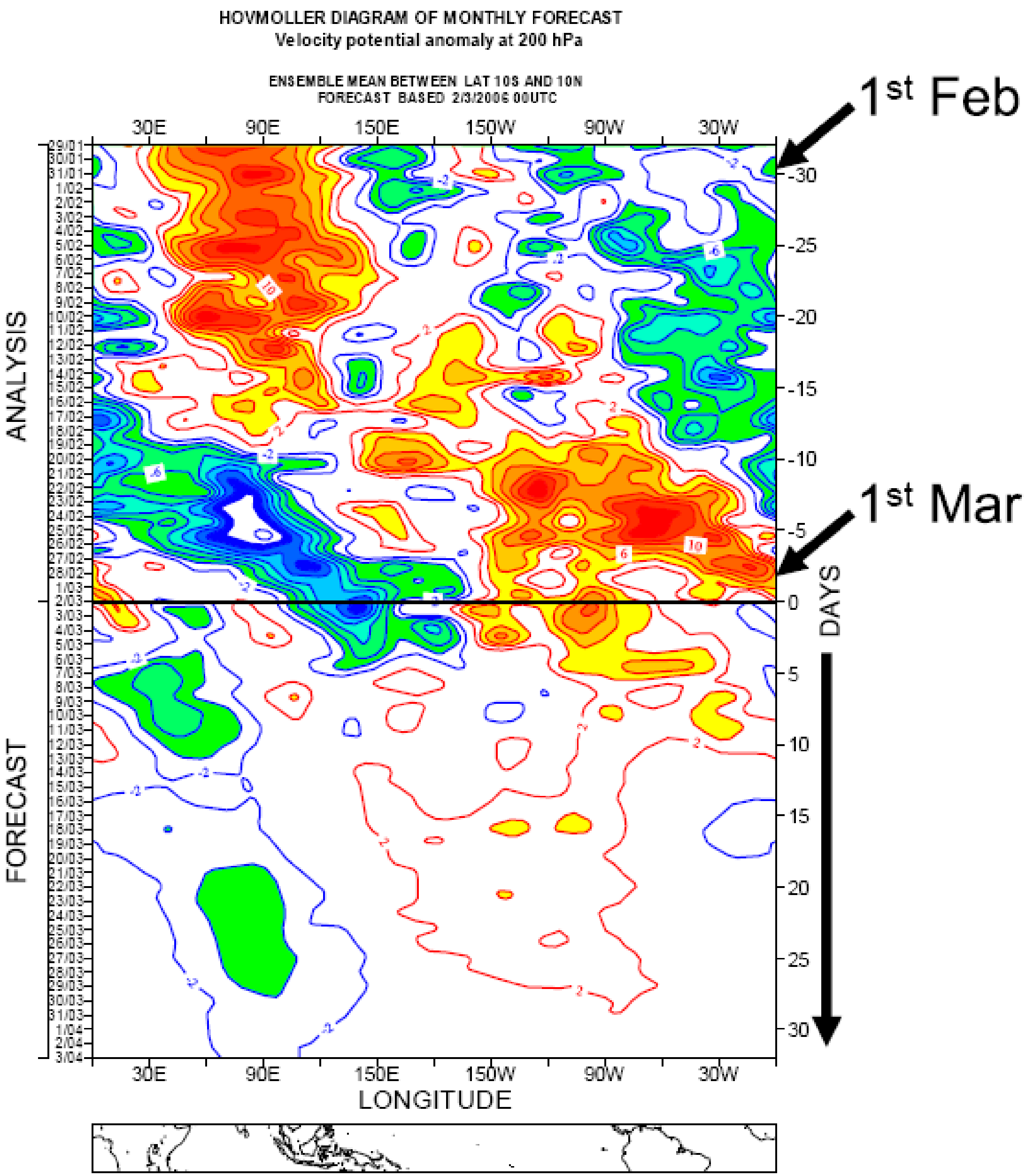


Typical MJO forecast at ECMWF

200hPa Velocity Potential Anomalies

February – March 2006

The top half of the plot monitors the preceding month using the analysis



Typical MJO forecast at ECMWF

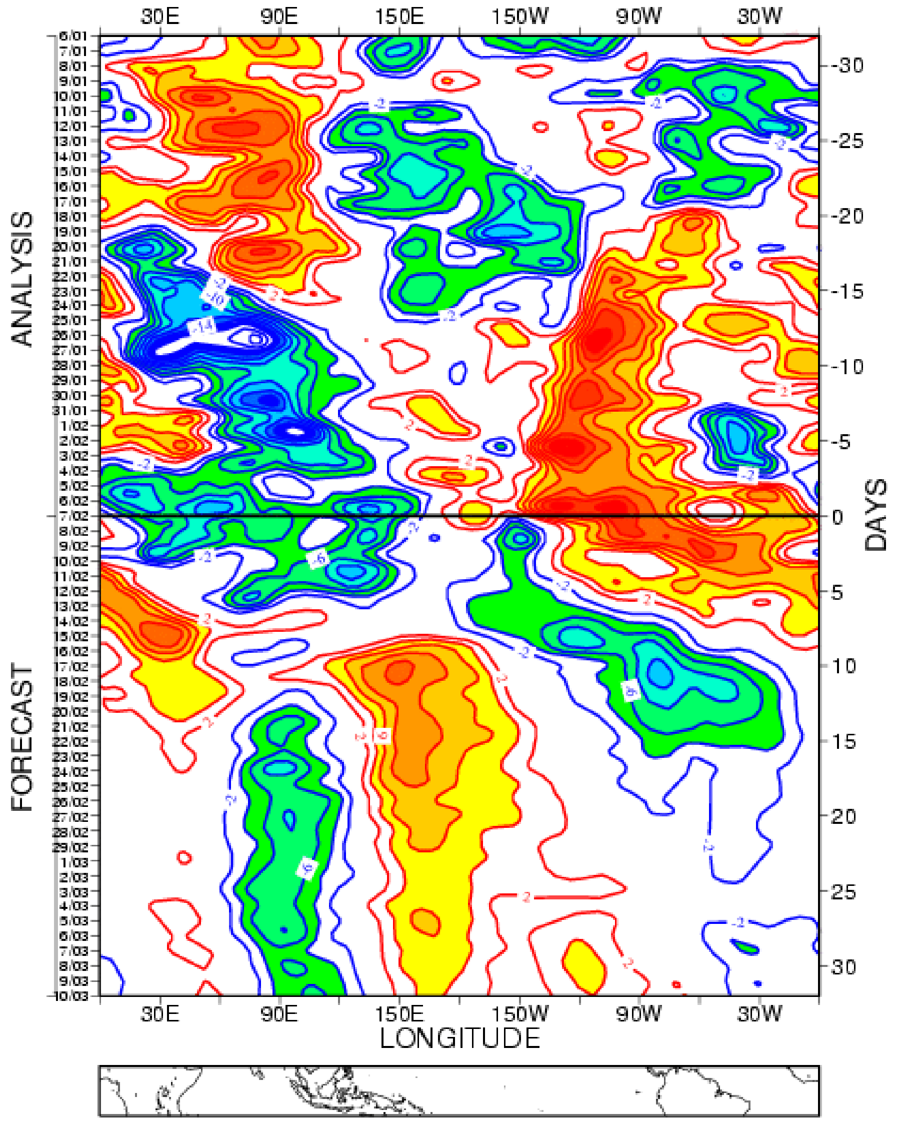
200hPa Velocity Potential Anomalies

February – March 2006

The top half of the plot monitors the preceding month using the analysis

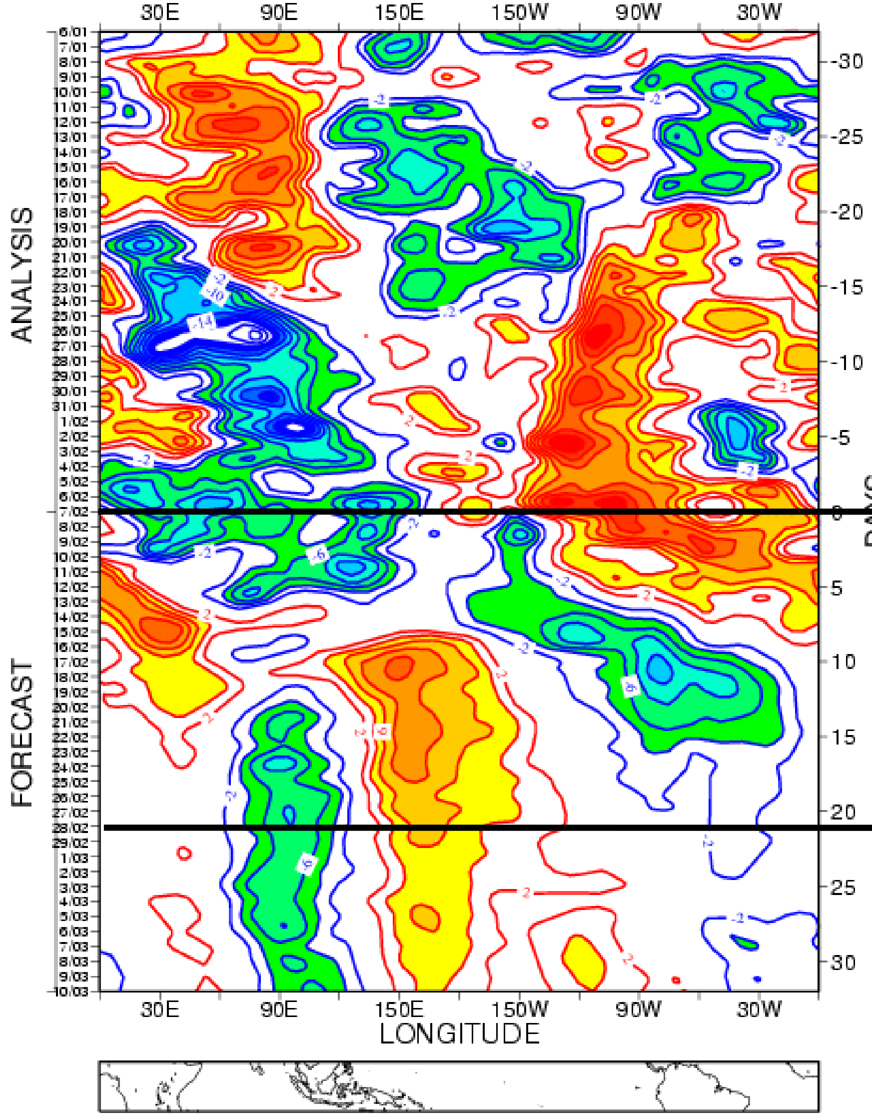
The lower half shows the monthly forecast using same model cycle as system 3

2008 – Cycle 32r3

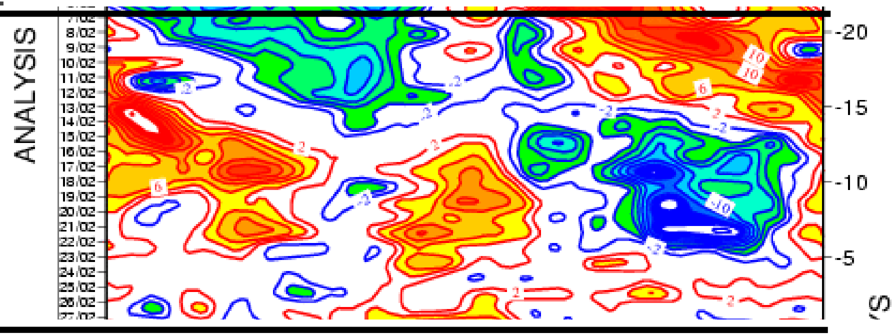


FC from 7/2

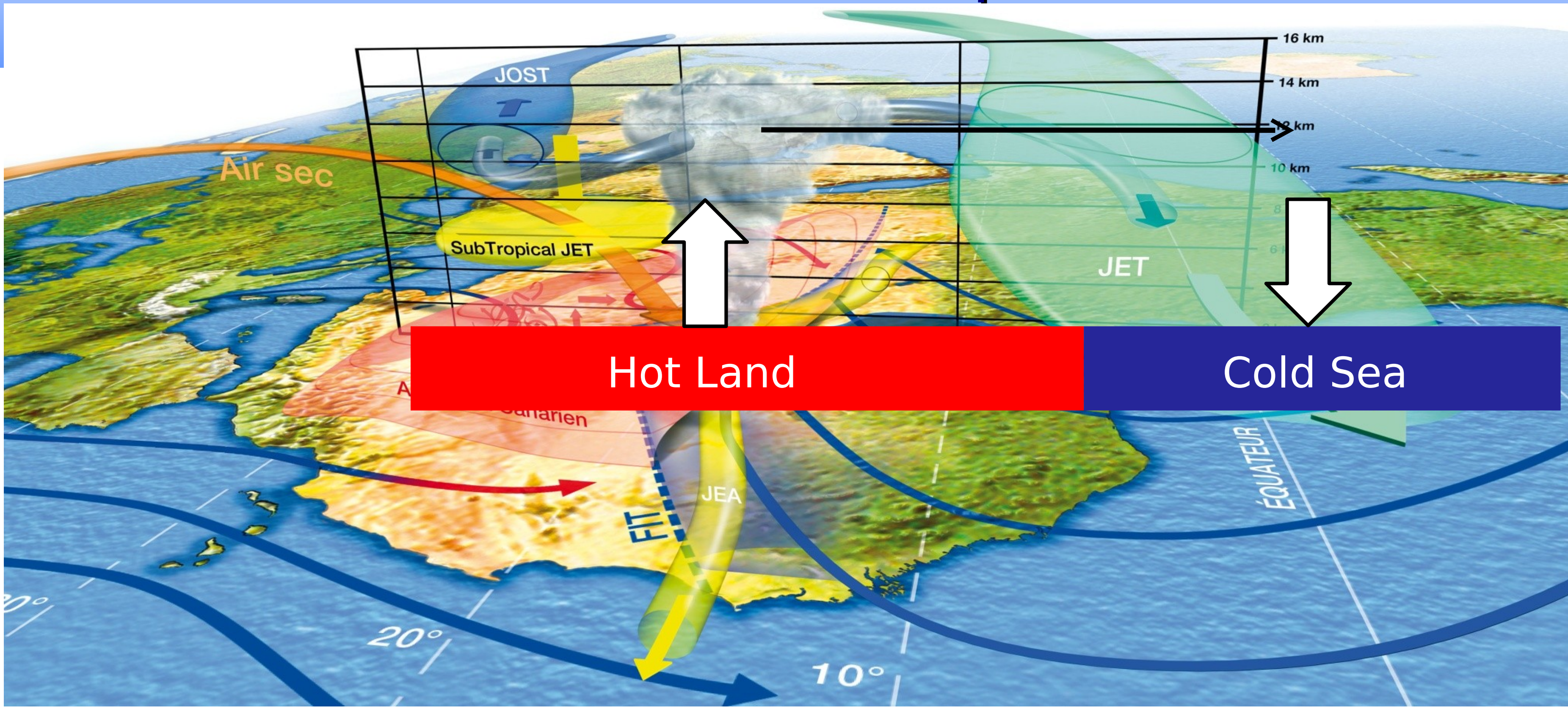
2008 – cycle 32r3



What actually happened:

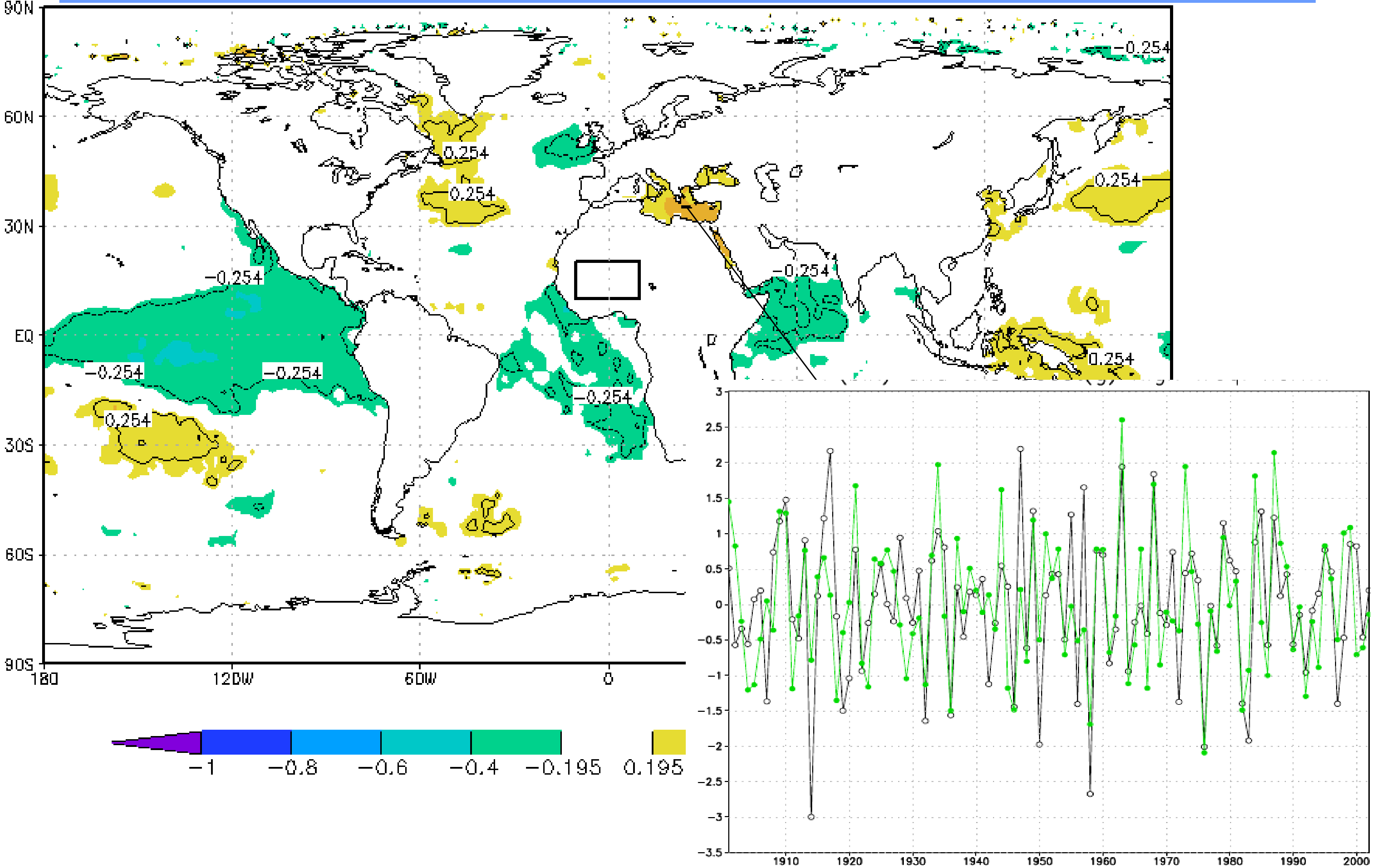


Seasonal timescales: SST impact on monsoon

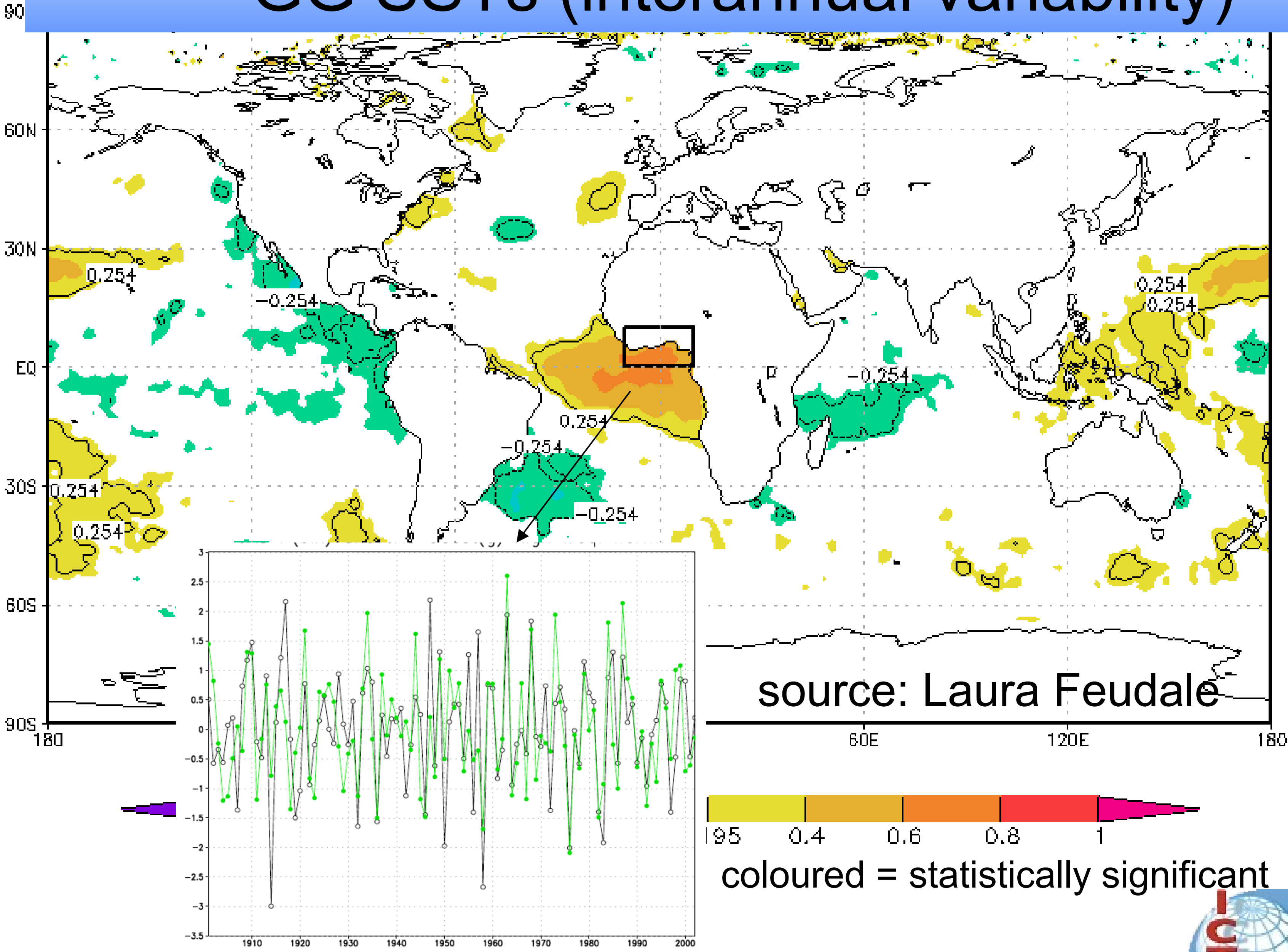


- Warm SSTs anomalies change land-sea contrast and can alter location and intensity of rainfall
- The thermal inertia of the ocean gives it a longer range "potential predictability" and thus also the monsoon rains

High freq (<10 years) correlations of SST with Sahel rainfall



Strong positive correction of boxed rainfall with GG SSTs (interannual variability)



source: Laura Feudale

coloured = statistically significant

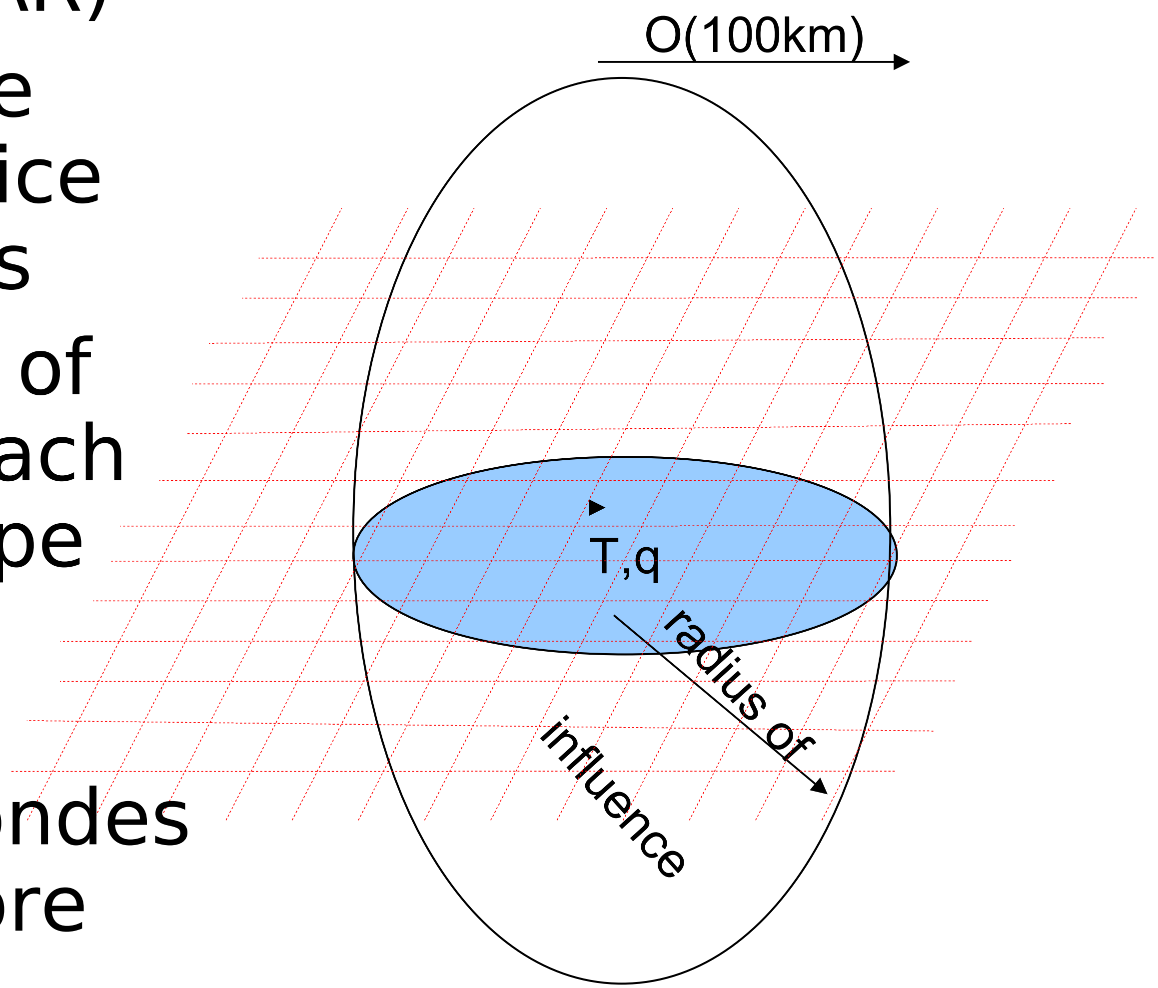
Initial Conditions

- Short range: Atmosphere is important
- Seasonal: Ocean is important

Data assimilation

- Aim:
  - To take a wide variety of parameters
  - from a wide variety of measurement platforms
  - with vastly different measurement densities
  - taking care to reject bad measurements
  - …and combine them into an assessment of the atmospheric state, that is near balance with the forecast model "climate"

- Methods range from very simple (nudging) to complex (4DVAR)
- 4DVAR now the method of choice in most centres
- Step 1: Radius of influence for each observation type needs to be defined.
- Sparse radiosondes have much more "weight" than satellite, can be a

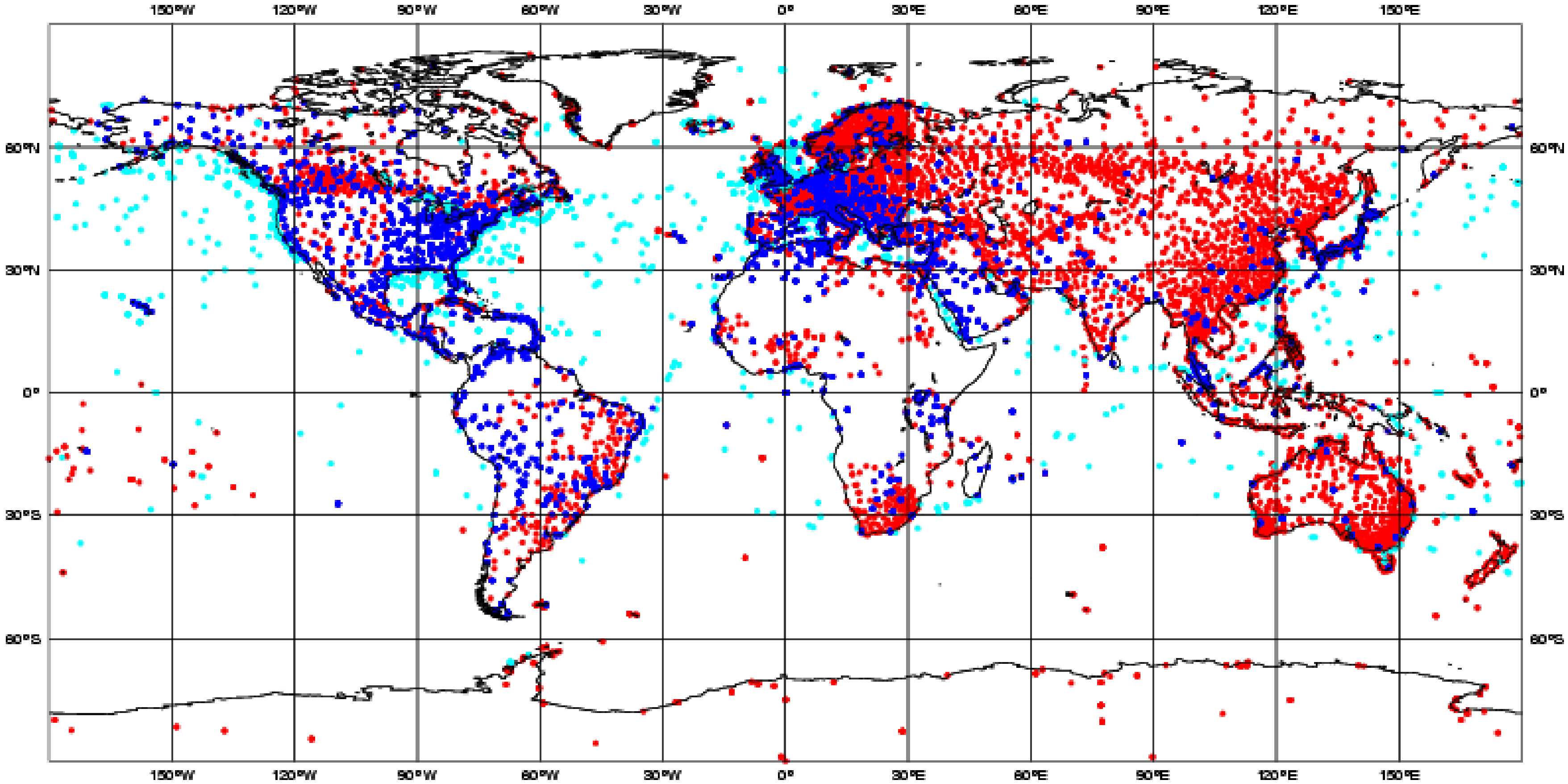


DATA USED: Pressure, humidity during day
SYNOP T,q also used for soil moisture analysis

Obs Type

16671 SYNOP   2524 SHIP   9818 METAR

ECMWF Data Coverage (All obs DA) - SYNOP/SHIP
21/JUL/2008; 00 UTC
Total number of obs = 29013



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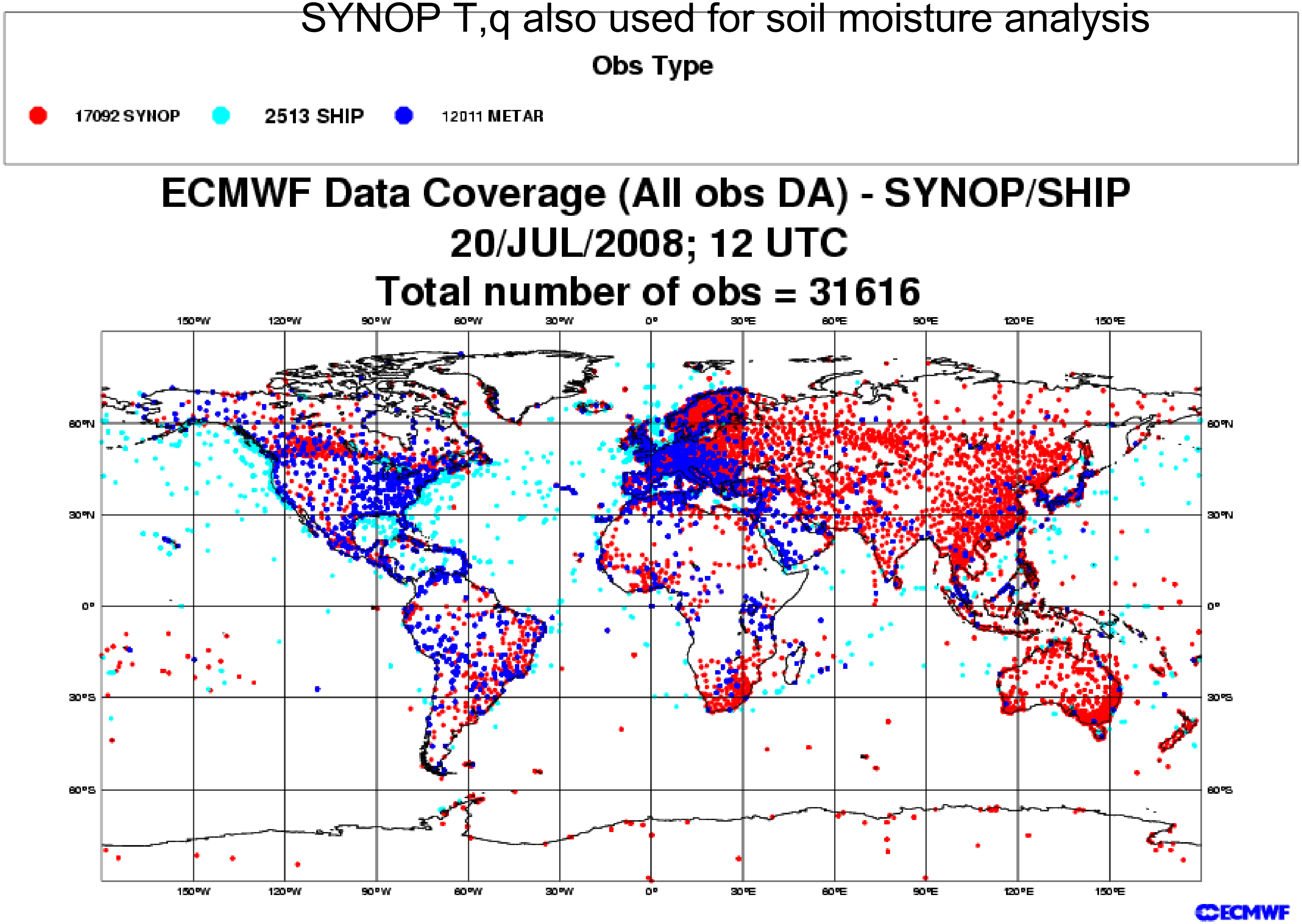
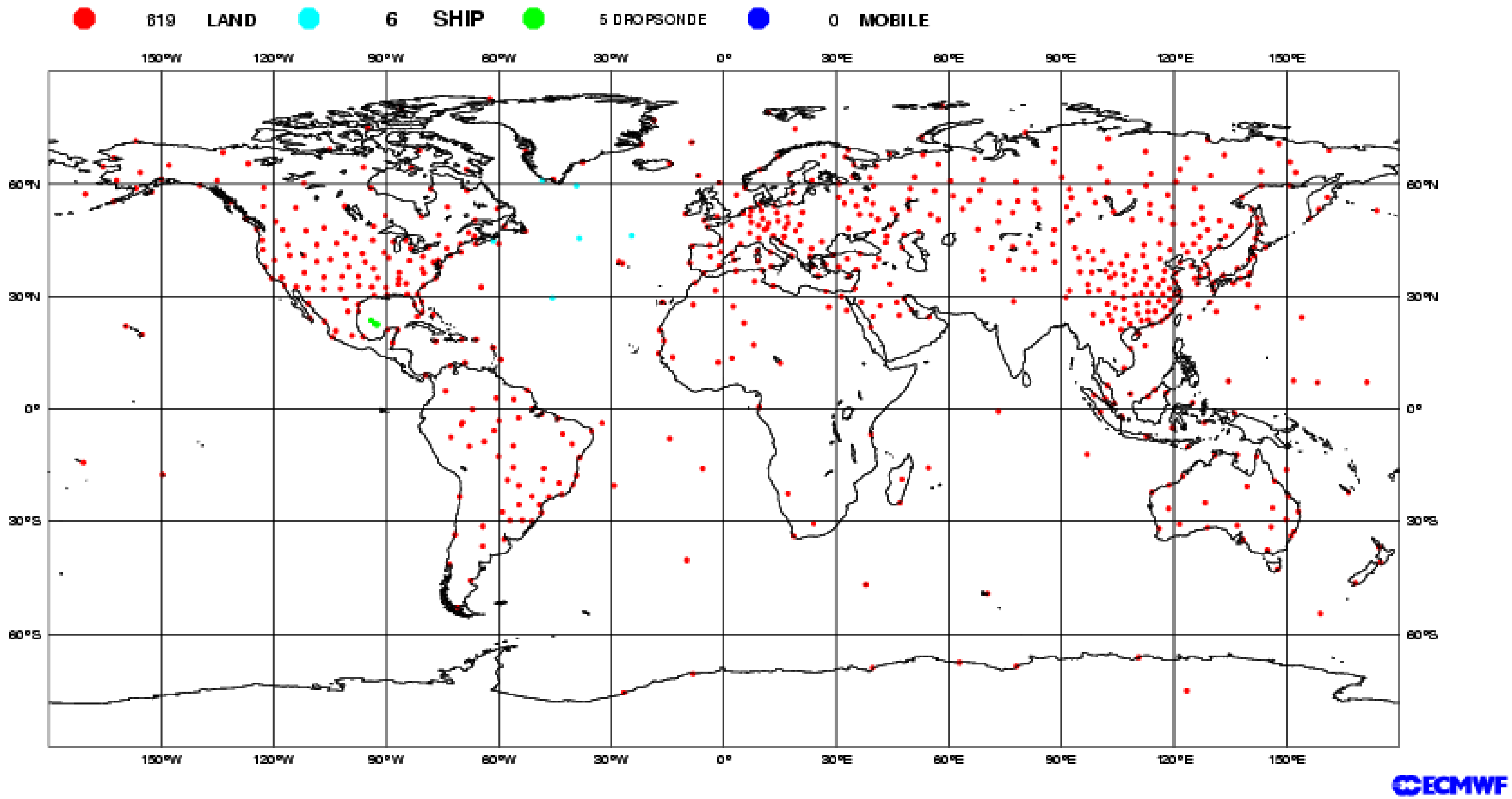


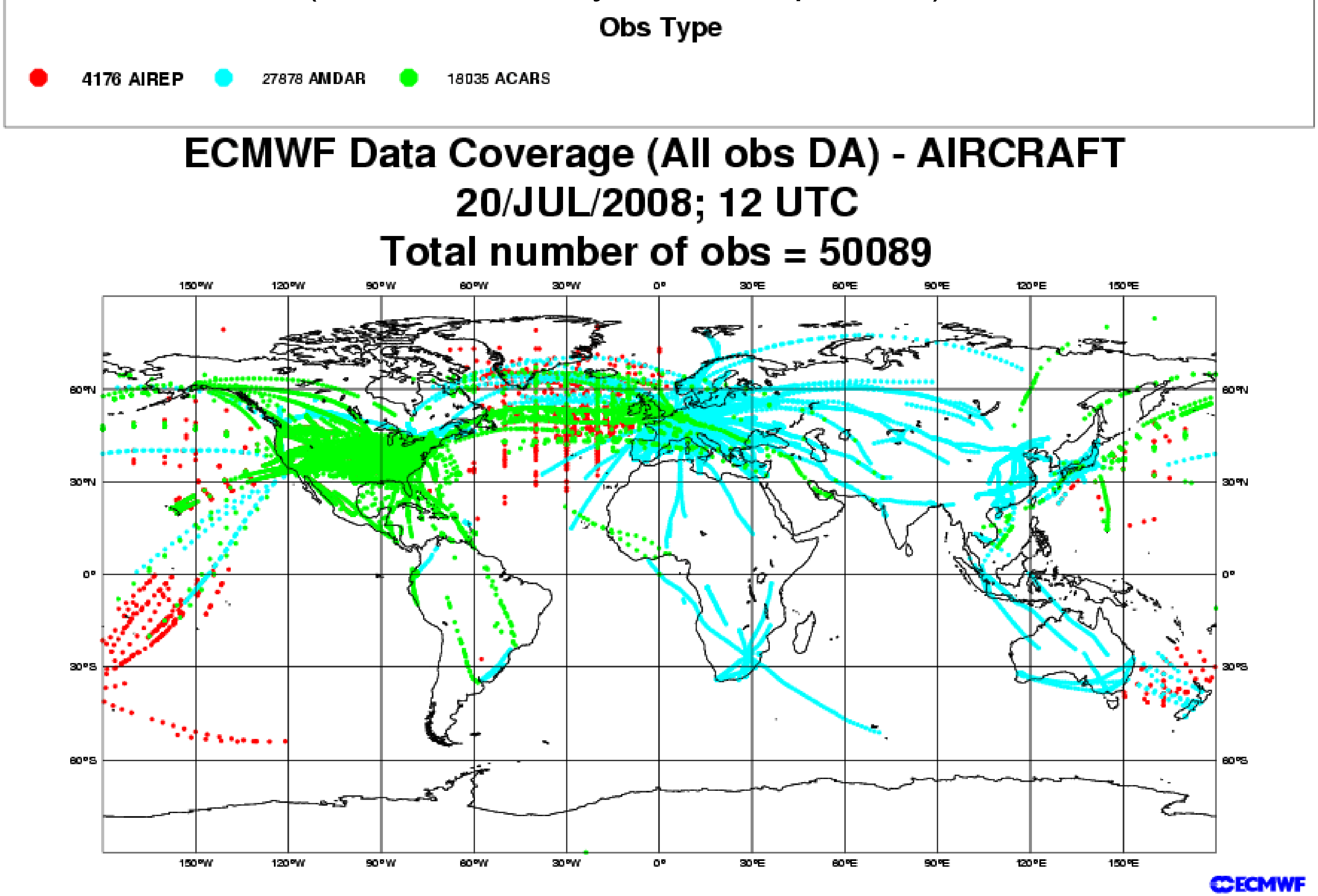
ECMWF Data Coverage (All obs DA) - TEMP
29/JUN/2010; 12 UTC
Total number of obs = 630

RADIOSONDE: profiles of T,q,u,v – very important

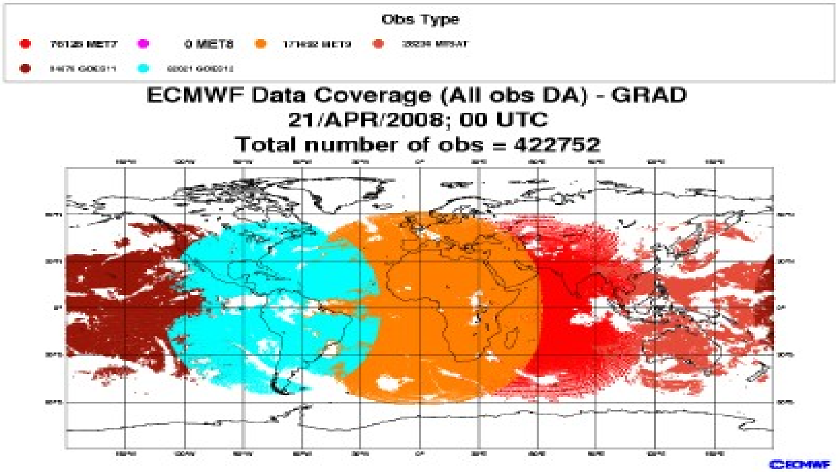


DATA USED: Temperature, winds

(mozaic humidity research product)

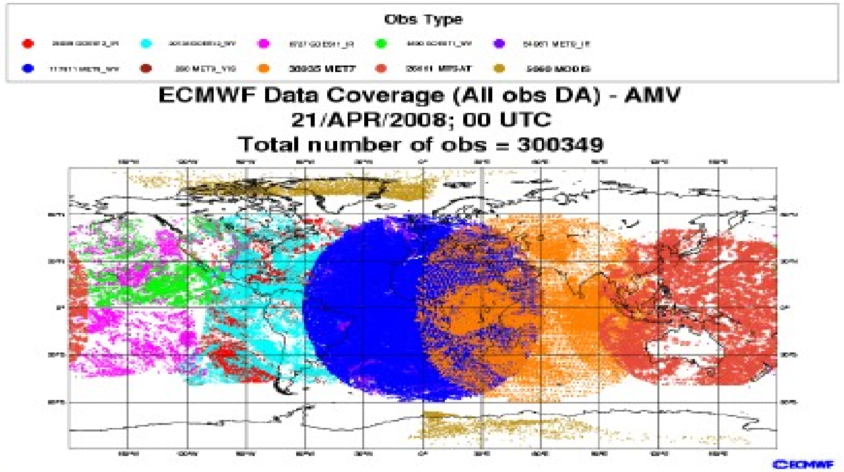


Clear-sky radiances



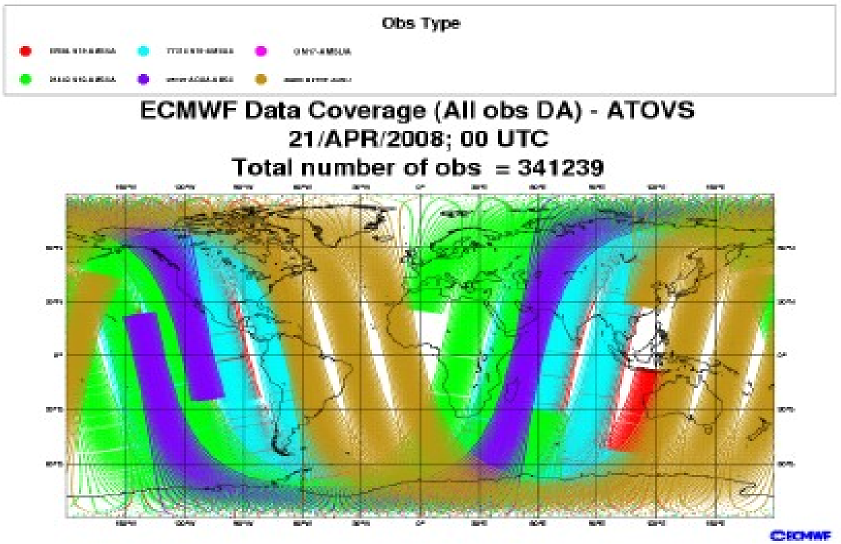
GOES-W GOES-E Met-9 Met-7 MTSAT-1R

Atmospheric Motion Vectors

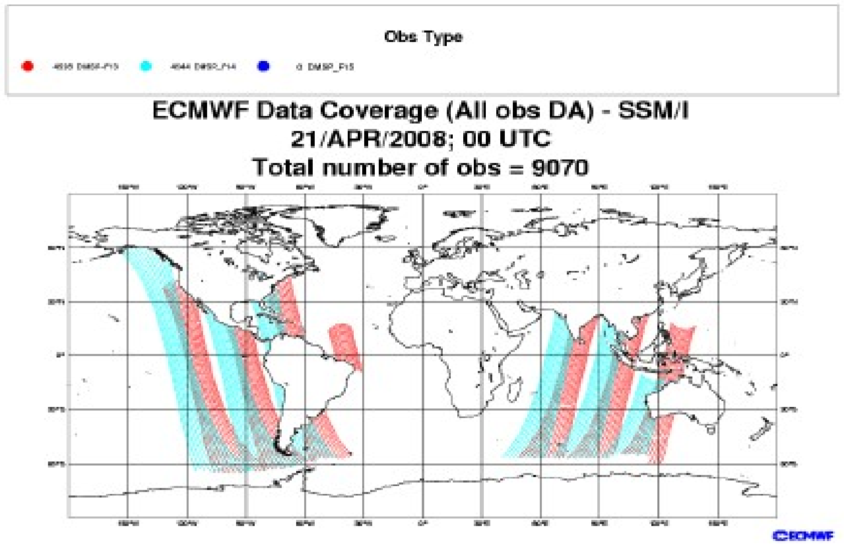


GOES-W GOES Met-9 Met-7 MTSAT-1R

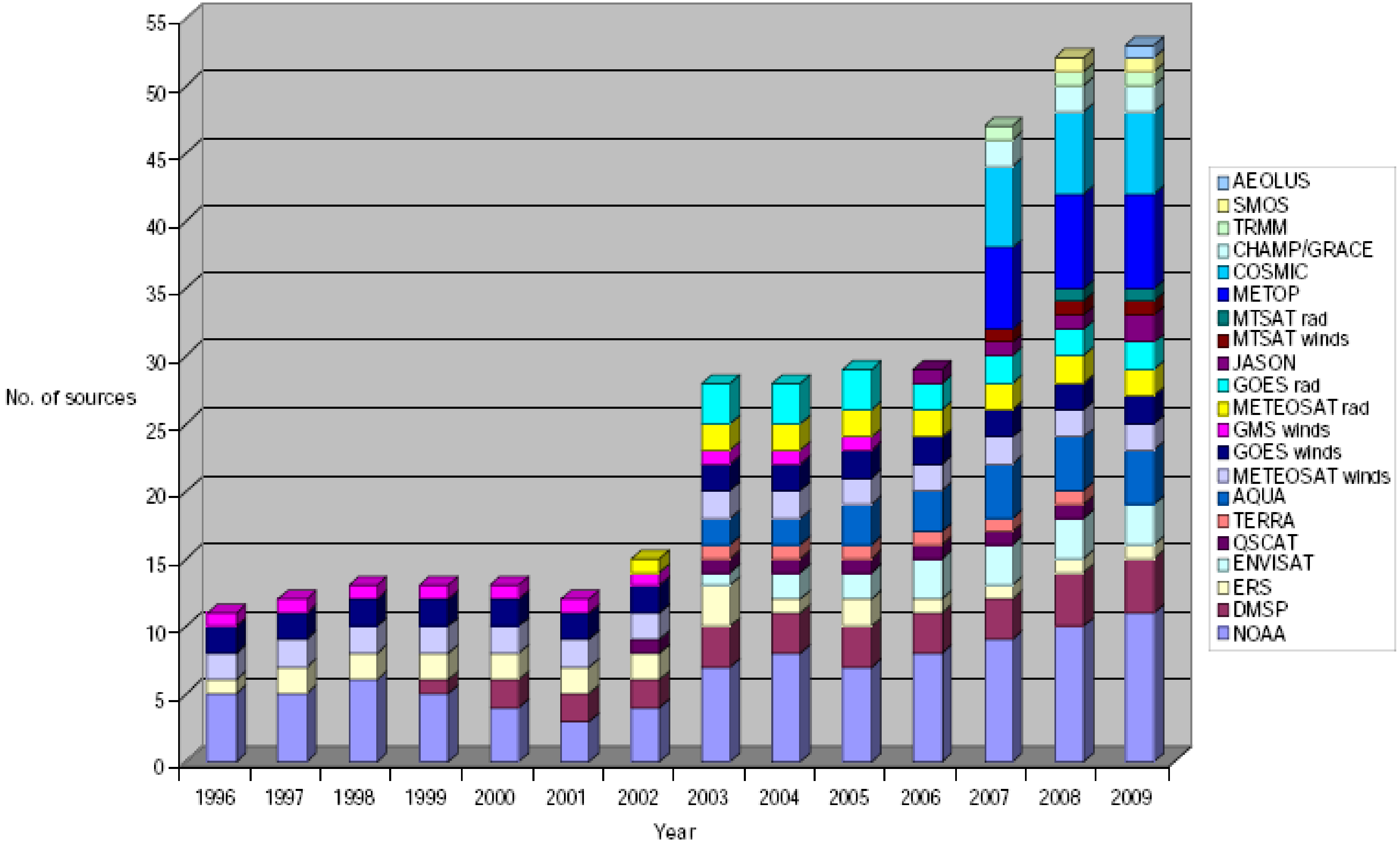
AMSU-A



SSM/I



Satellite data sources in 2007+



Large increase in satellite data

Problems with Satellite Data

- Lack of information concerning atmosphere vertical structure
  - Improving with latest generation multi-frequency instruments
- Lack of information near surface due to uncertainty concerning surface properties
- Lack of absolute information
  - In fact model used to calibrate satellite esp. if no overlap between missions
  - In any case need to correct satellite to model otherwise assimilation system is not sensitive to regional anomalies
  - Implies that only conventional data “pegs” the analysis: hence very important!

Some common misconceptions

- Very little information concerning clouds or precipitation is directly assimilated into the model
- Clouds in the analysis are a model product from the model physics, their location/properties determined by temperature, humidity and dynamics.
- Thus the parameters most important for crop modelling – temperature, solar radiation and precipitation are all heavily influence by the model physics even in the analysis

Re-analysis data

- Many of the forecast system updates modify the data assimilation data
  - Changes to bias correction
  - New observation types
  - Improvements to the assimilation techniques
- Thus reanalyses are conducted to use the modern system for the past.
- Also improved due to recovery of observations not available realtime
- Disadvantage: lower resolution
- NOTE: ERA-40 is from the 2000 system and does not perform well in the tropics for thermodynamic variables

Ocean Data Assimilation Systems

- Ocean analysis systems have tended to be simpler than their atmospheric counterparts, mostly using optimal interpolation (less variables measured).
- Until recently there was a lack of data outside of Pacific Ocean and especially concerning sub-surface information

Ocean analysis

Vidard et al.
MWR 2007

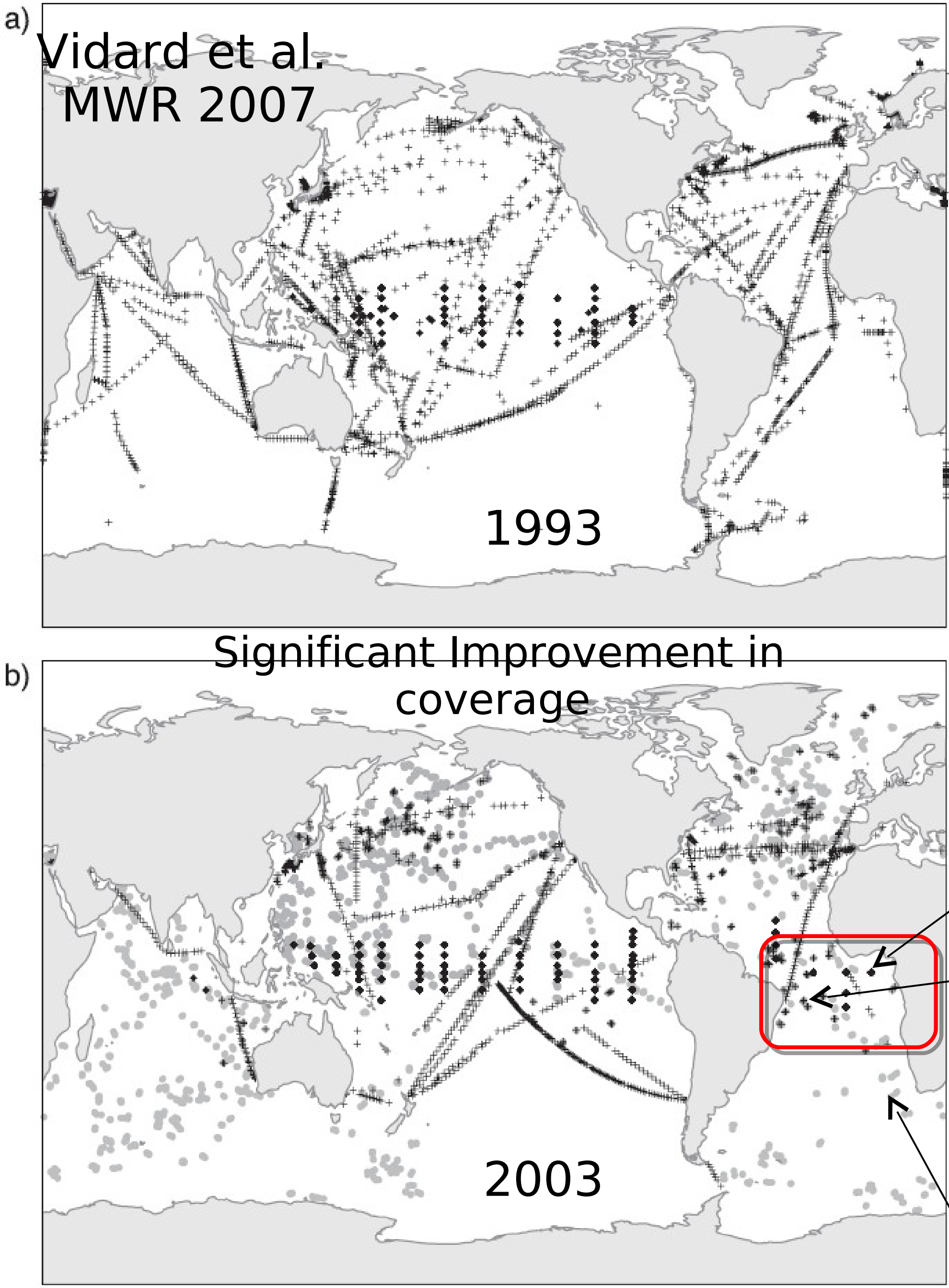
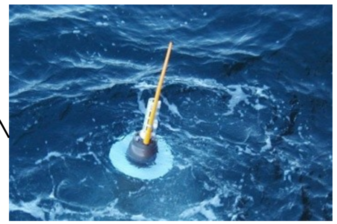


Figure 1: *In situ* observation coverage for a) March 1993 and b) March 2003. Diamonds represent moorings, black crosses XBTs and grey circles Argo floats.

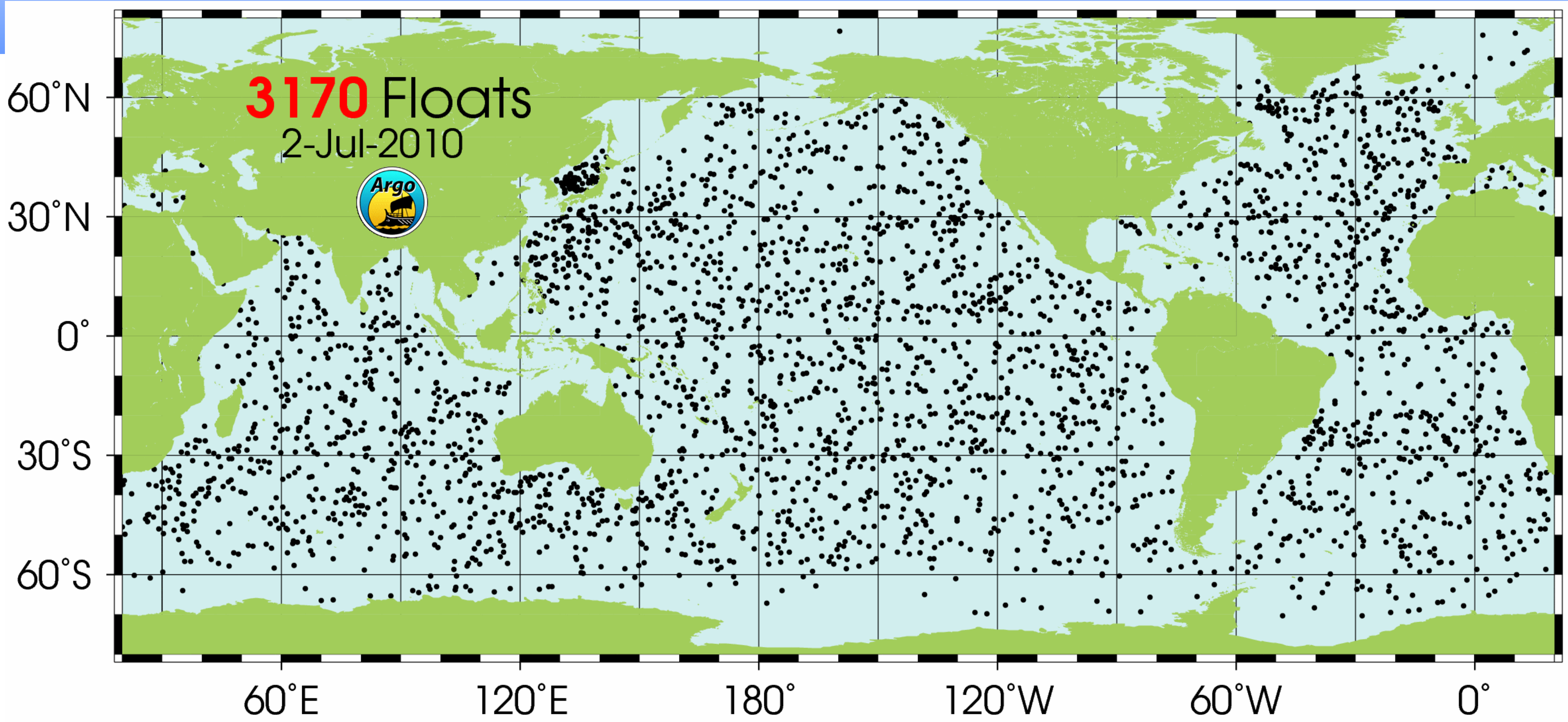
TAO/Triton mooring arrays: wind speed and direction, air temperature, relative humidity and sea surface temperature) and subsurface temperatures

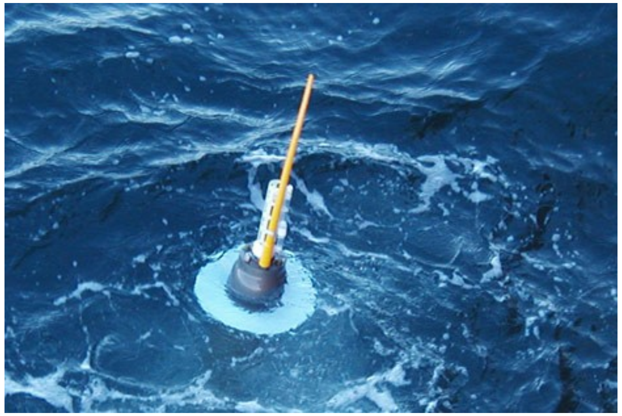
XBT: Expendable bathythermograph measurements of water temperatures at depths within the ocean

Argo Float



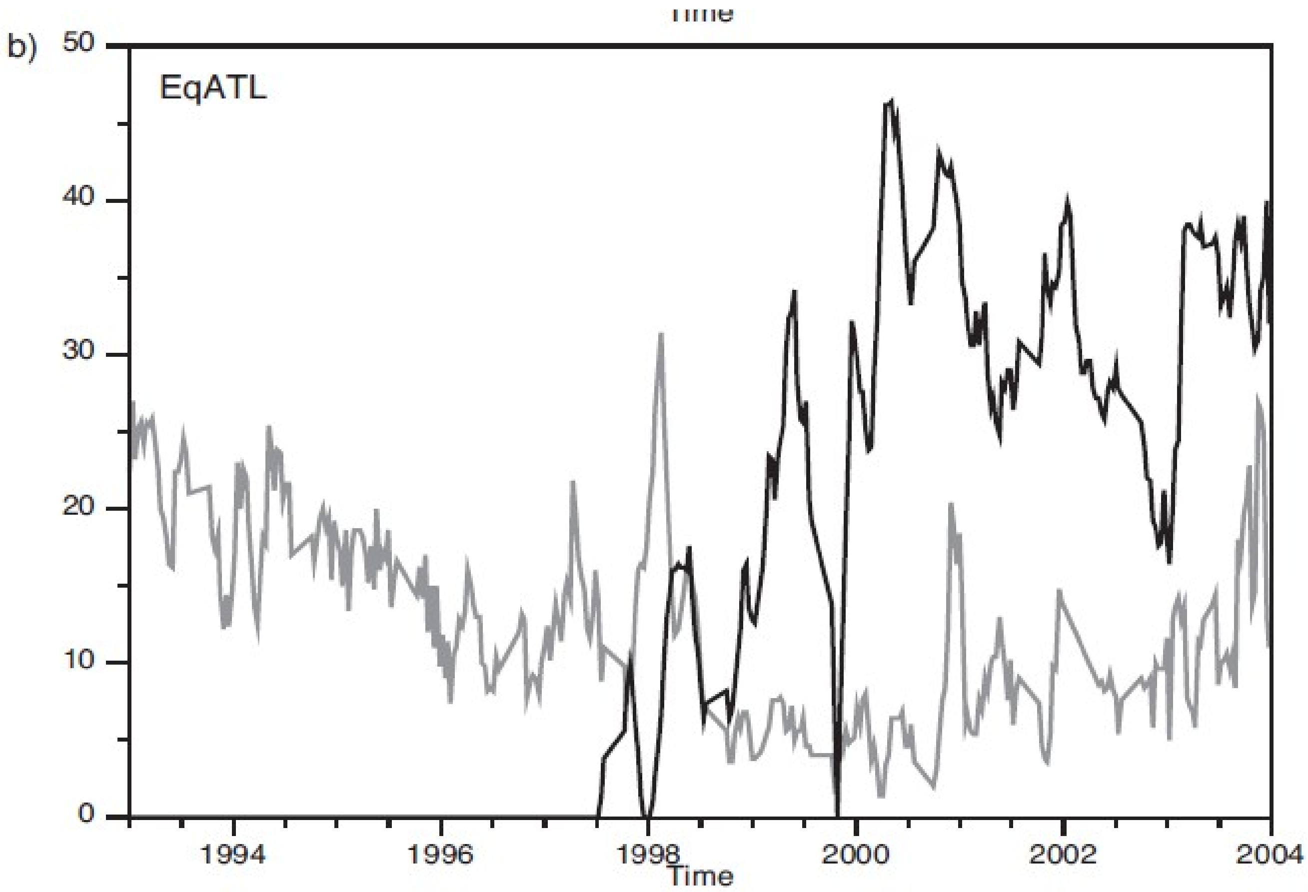
ARGO coverage as of July 2010





Argo is a global array of 3,000 free-drifting profiling floats that measures the temperature and salinity of the upper 2000 m of the ocean

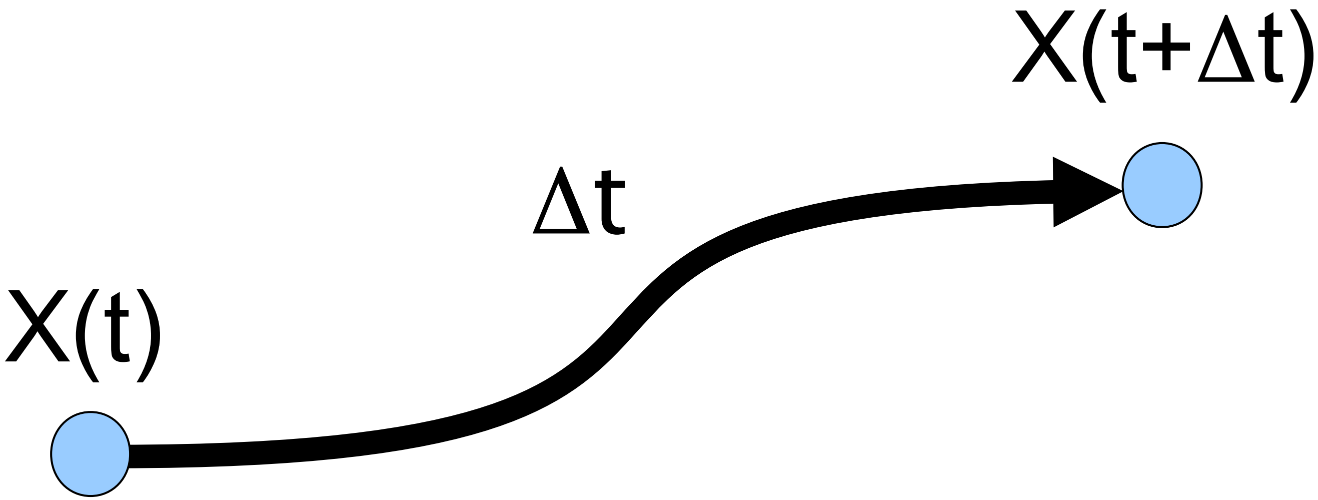
Increases in Atlantic data since the mid-1990s



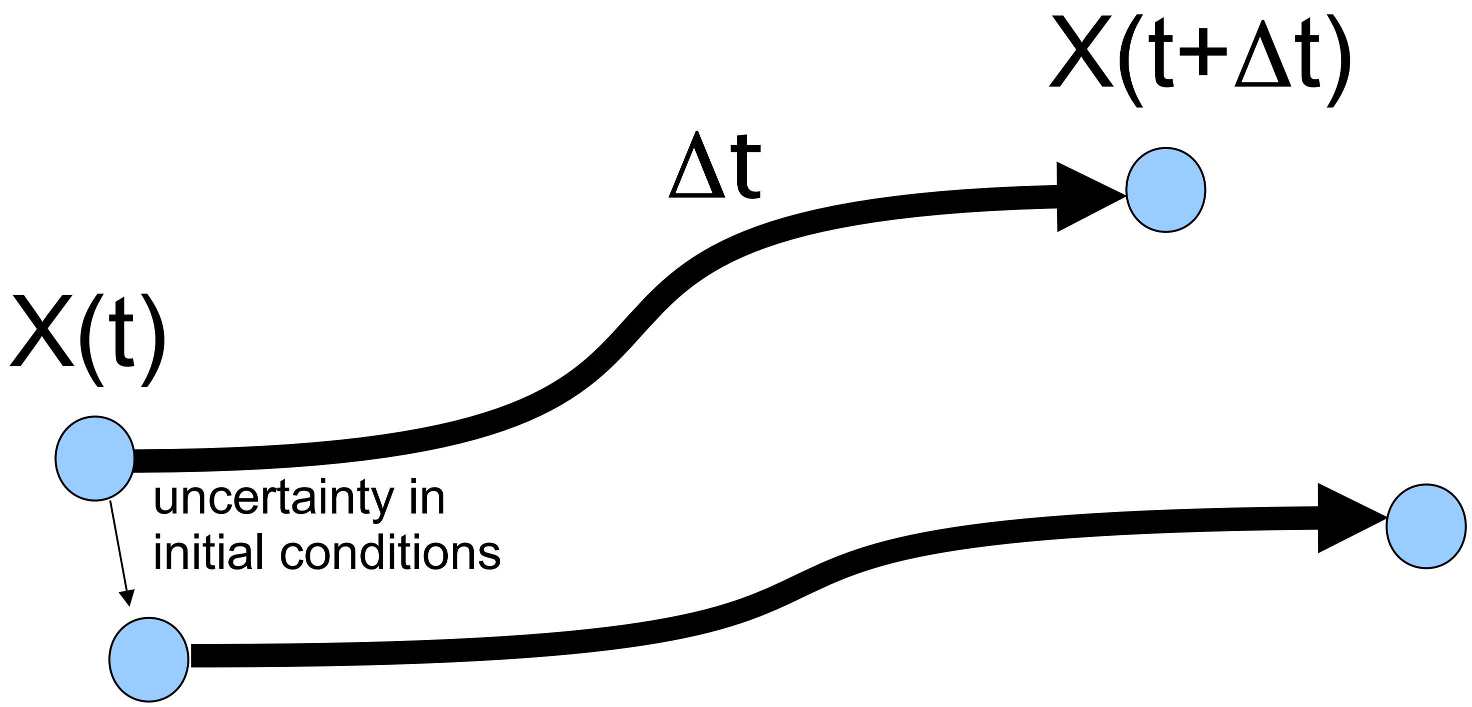
Vidard et al. MWR 2007

Figure 2: Number of observations at 175m in a 10-day period as a function of time from Jan 1993 to Dec 2003 for two key regions: a) Niño3 and b) the equatorial Atlantic. The grey curve indicates XBT measurements and the black curve the number of moorings. The regions are shown in fig 3

Accounting for Uncertainty
In numerical weather prediction the two main causes are...?

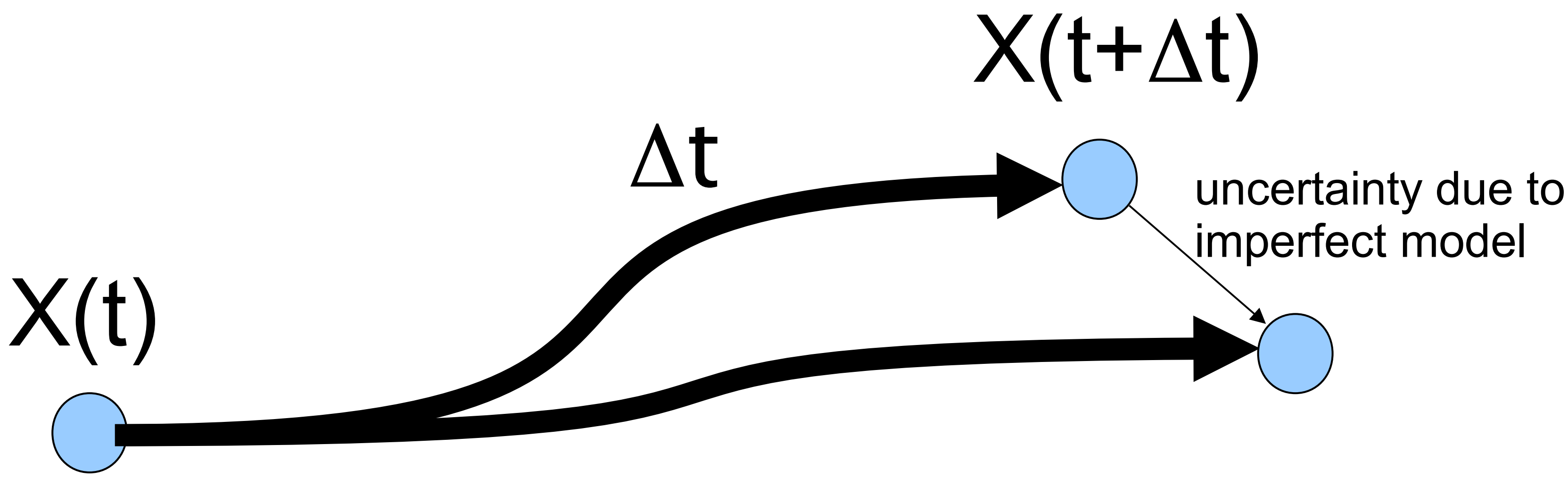


i. Uncertainty in initial conditions

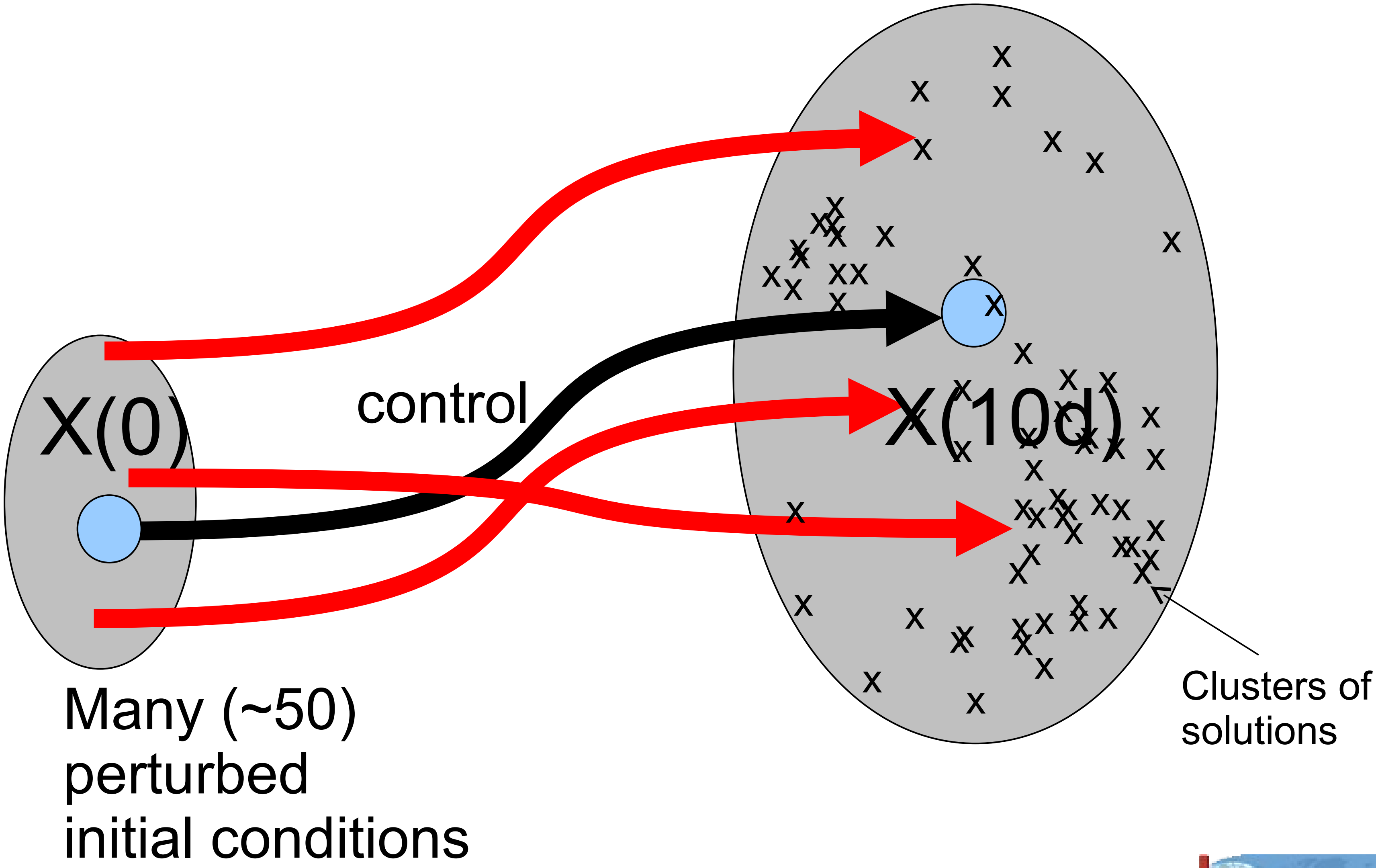


"Butterfly Effect"

ii. Imperfect model



Account for this
1. perturbing initial conditions
2. perturbing the forecast model physics

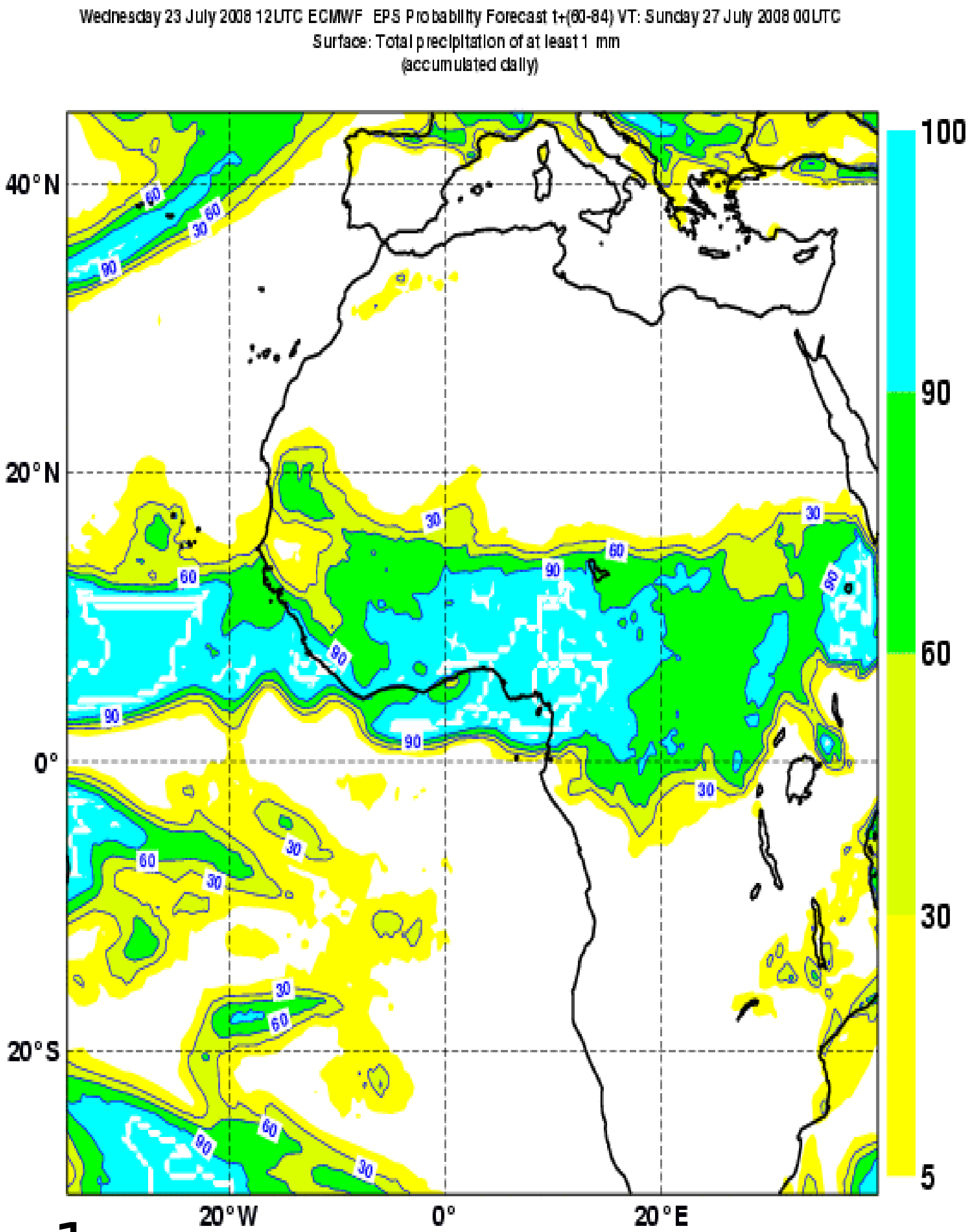


Perturbations to initial conditions

- Perturbations have to lead to solutions that encompass uncertainty
- Have to be done in a clever way as we can not run millions of forecasts!
- ECMWF uses singular vector technique to identify fastest growing modes (for a specific energy metric) for a specific target area at a specific lead time of 48 hours
- NOTE: Method is Linear!!!
- Processes in Tropics highly nonlinear.

Imperfect model: Stochastic Physics

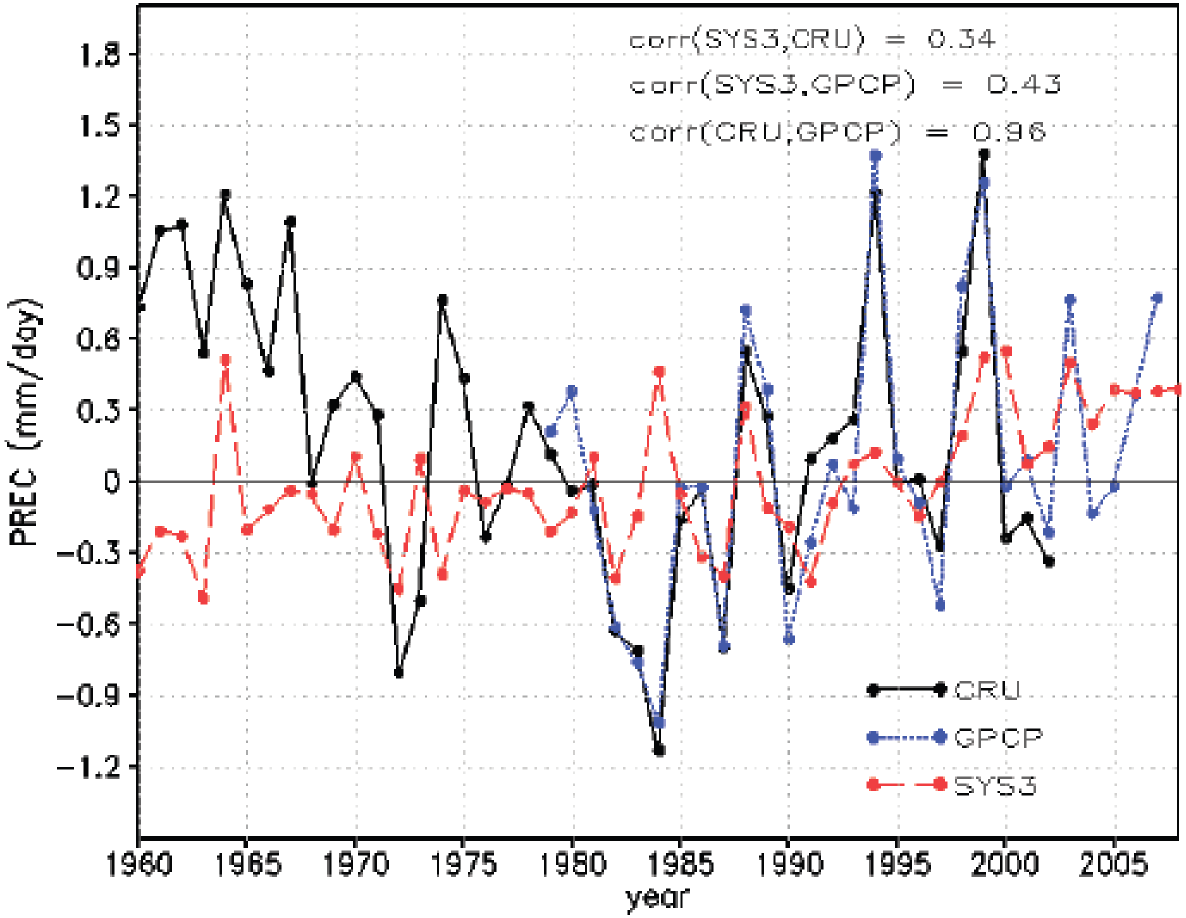
- Uncertainty in model parametrizations taken into account using stochastic physics
- Tendencies (from radiation, clouds, gravity wave drag, turbulence and convection) are multiplied by C in [0.5, 1.5]
- In the tropics the convection perturbations dominate



Probability of rain exceeding 1 mm

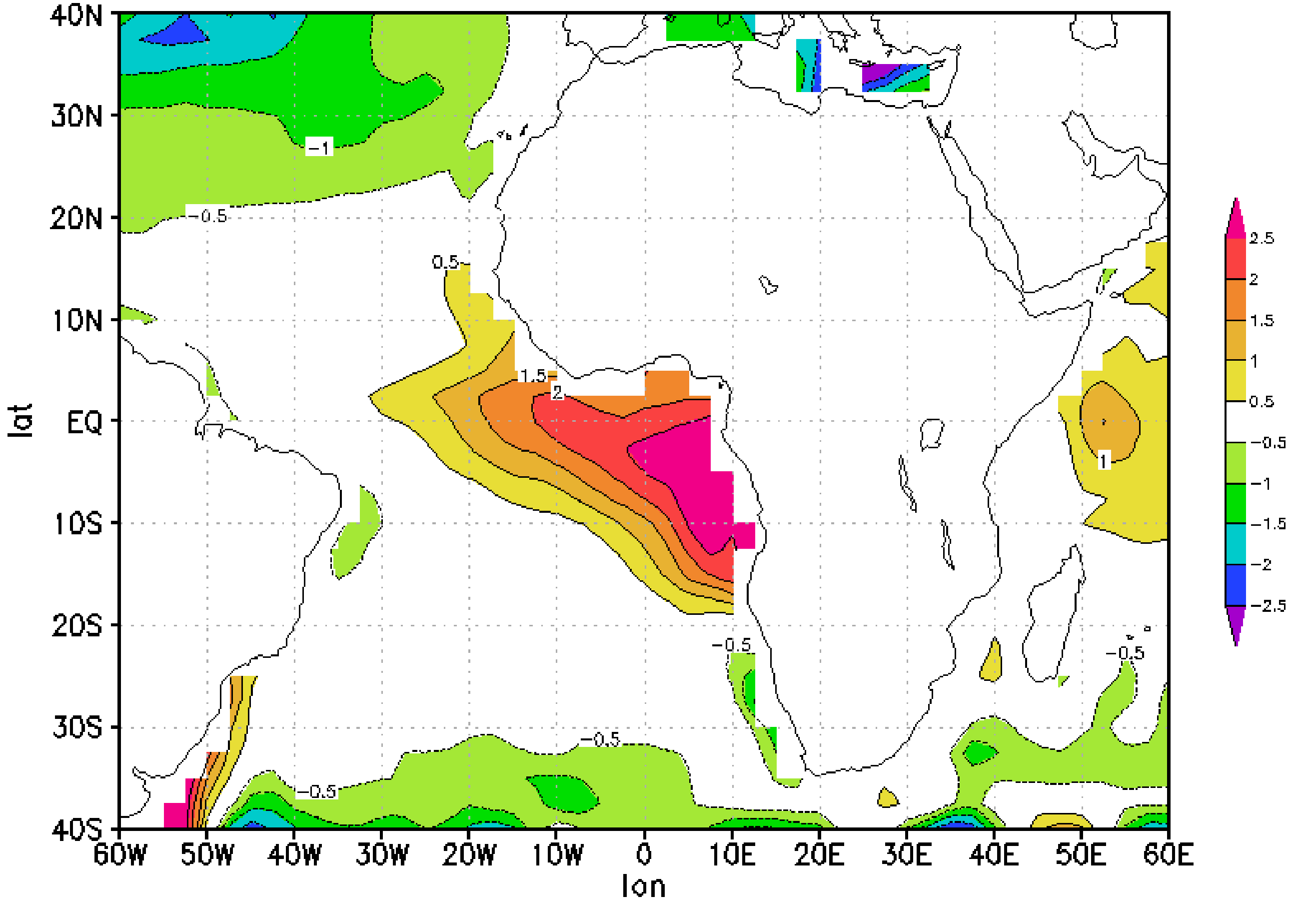
Examples: Skill of seasonal system over the Sahel steadily improving due to ocean observation network

Anomaly prediction



But still a lot of room for improvement!

SST biases

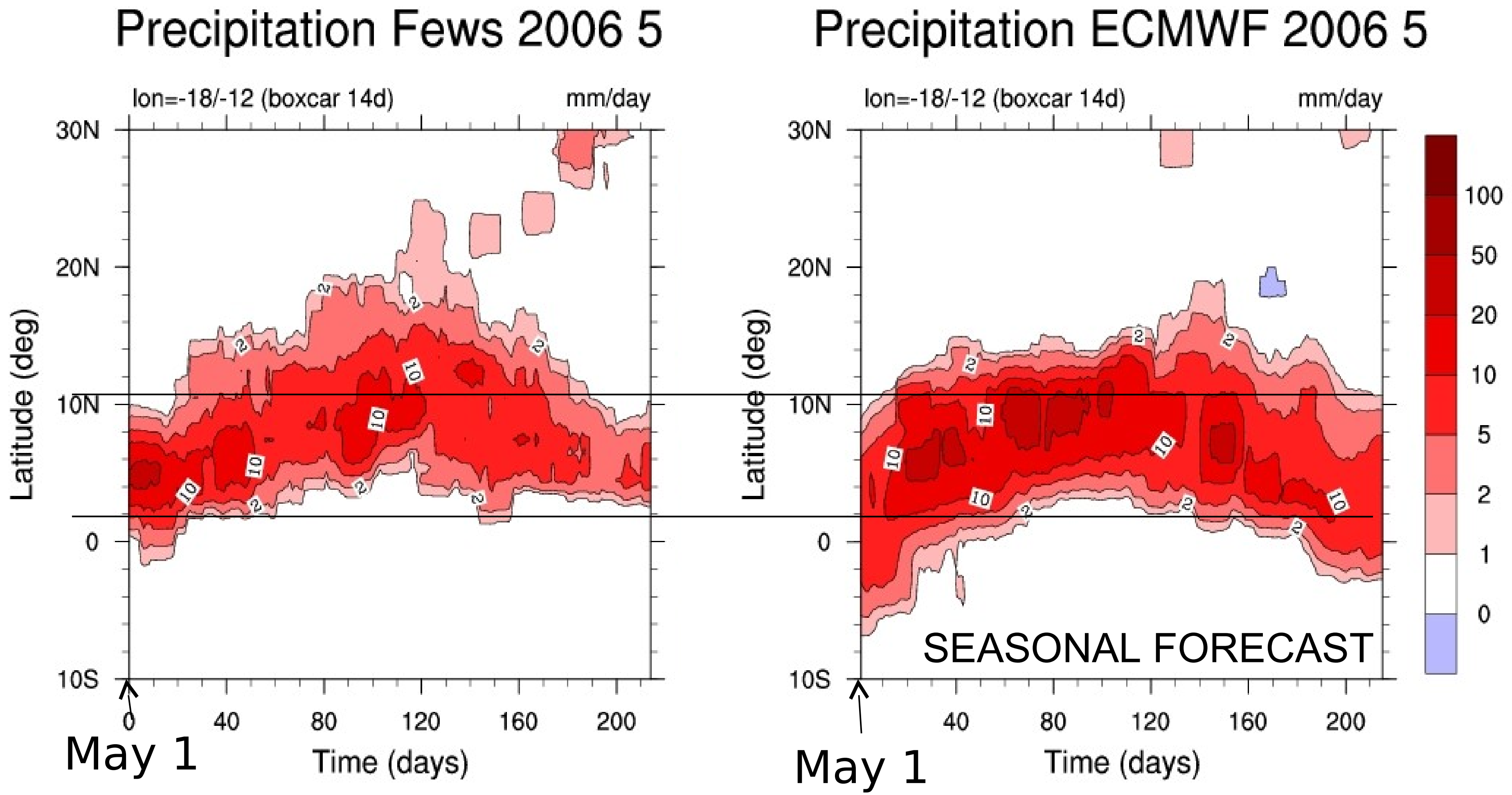


Mean JAS SST bias of ECMWF sys3 from 1st May

Strong warm bias in Atlantic

Predictive skill is also poor here for JAS, little better than persistence

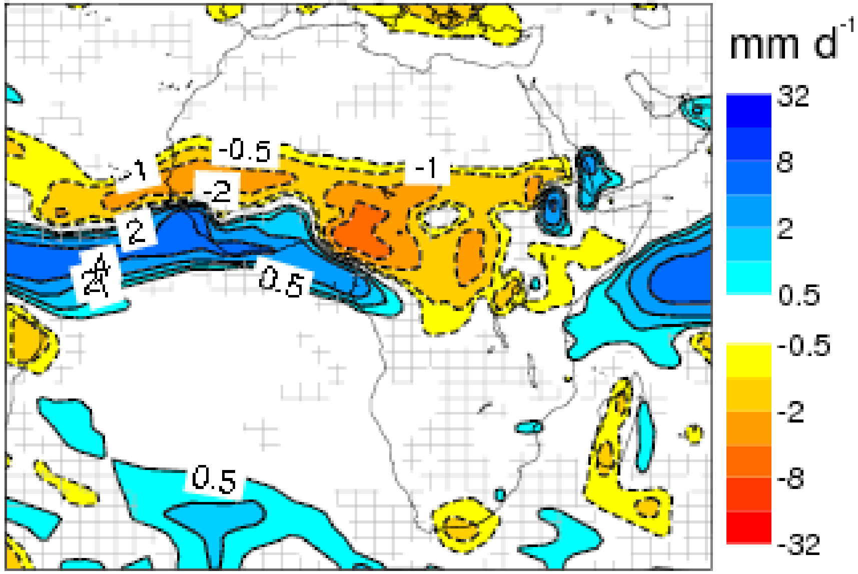
Comparison of Rainfall with FEWS centred on Senegal



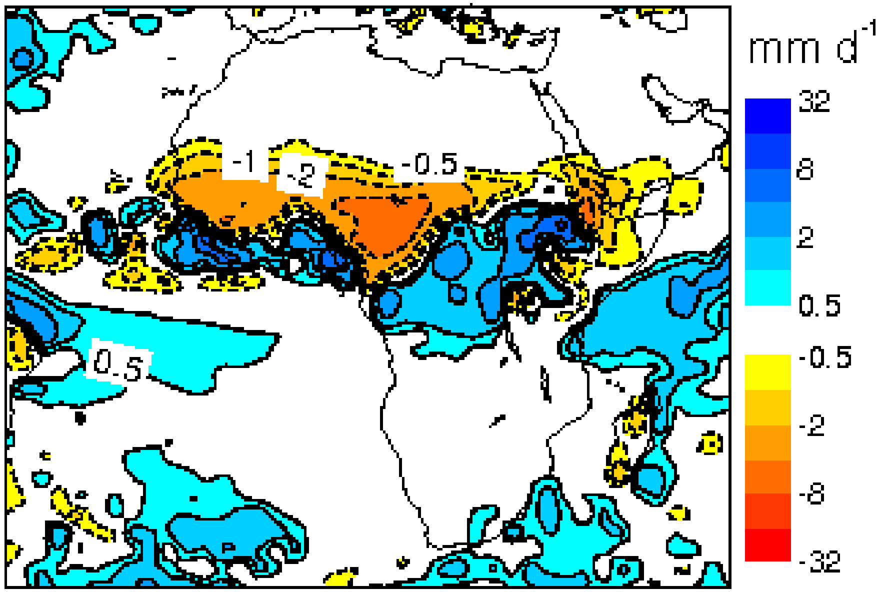
RAINFALL too far south in model climate

Biases in short range and seasonal systems both show general southerly shift of JAS rainfall

Seasonal Forecast rainfall bias



Average of many one day forecasts
Forecast Day 1 bias



Similar looking biases may have different causes

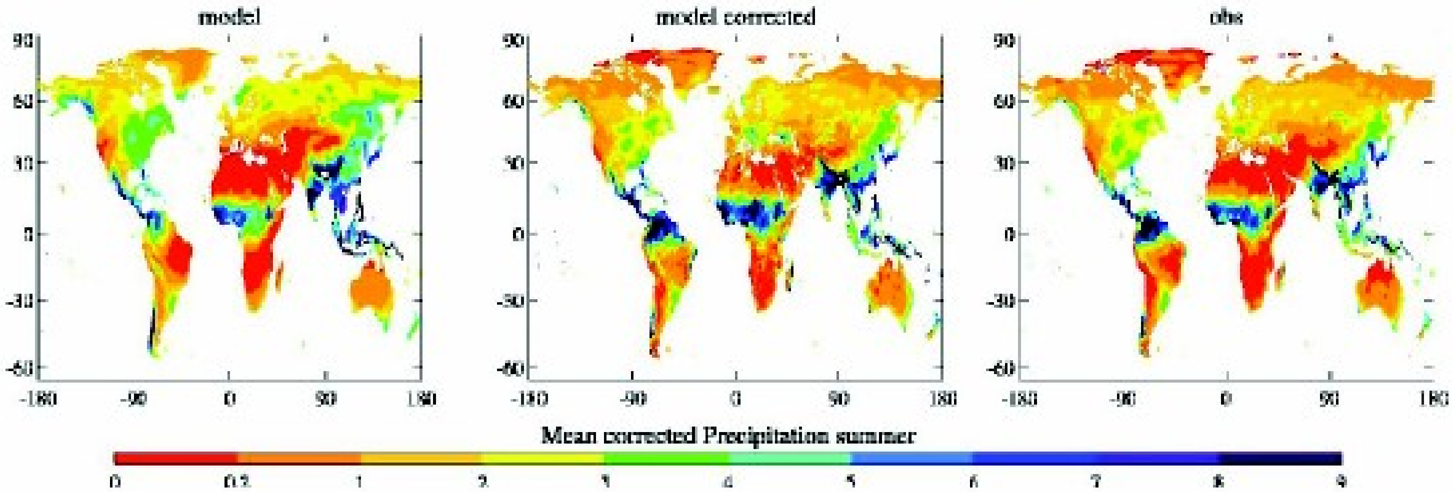
Bias Correction

- Errors in models imply bias correction is necessary
- Work at ICTP focuses on point-wise (CDF) and spatial pattern based (EOF) techniques

Statistical Correction Example: bias correction of rainfall

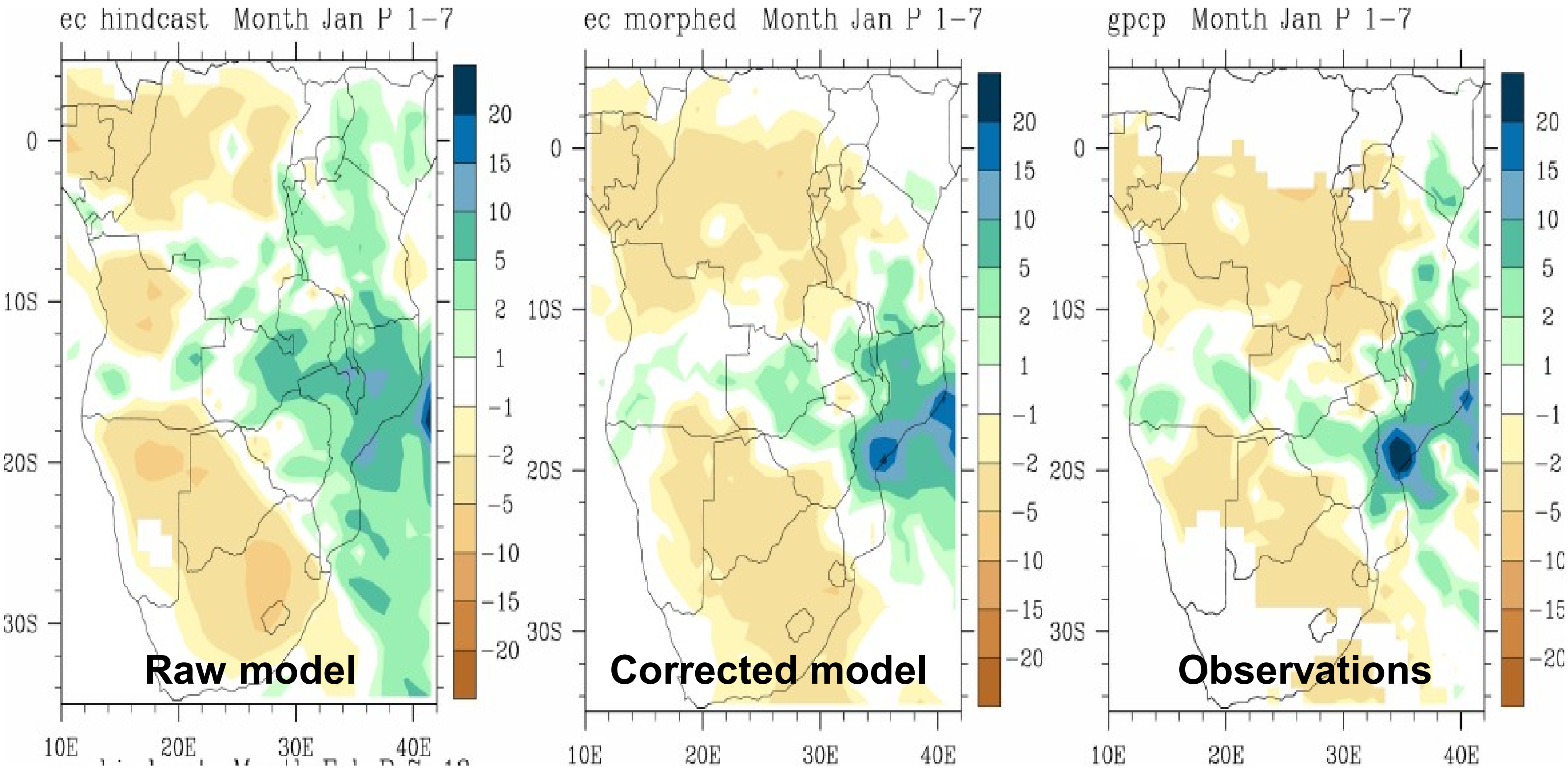
Cumulative distribution frequency (CDF) matching developed by C. Piani for WATCH

Bias correction developed for ECHAM model output using CRU rainfall data from the 1960s and applied to the 1990s:

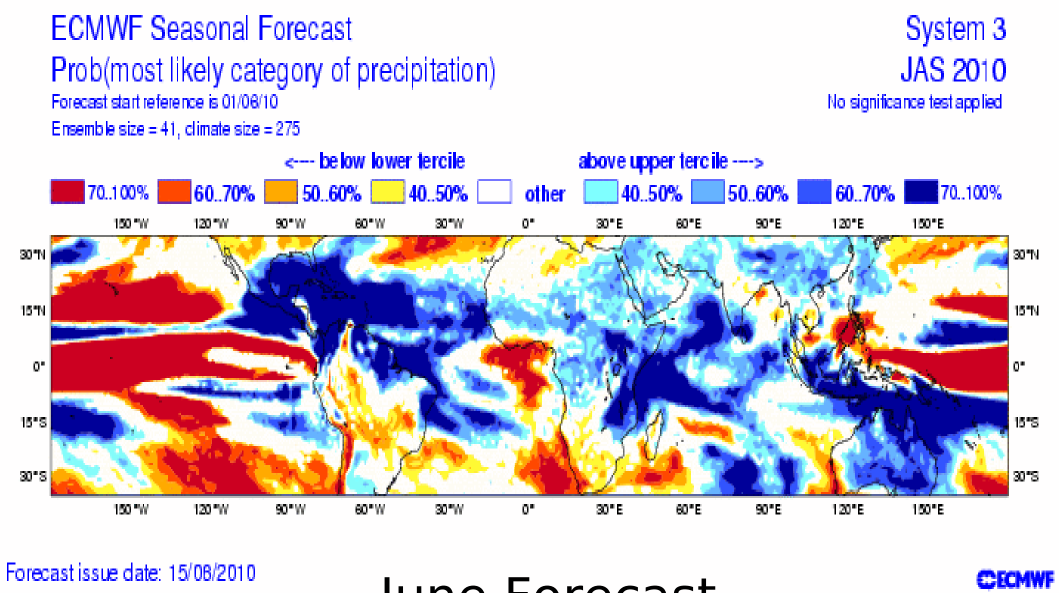


Spatial bases techniques

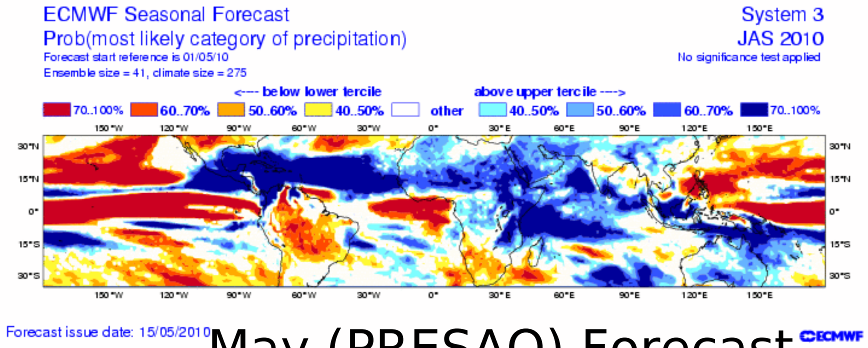
- EOF based correction technique developed with ECMWF for monthly forecast



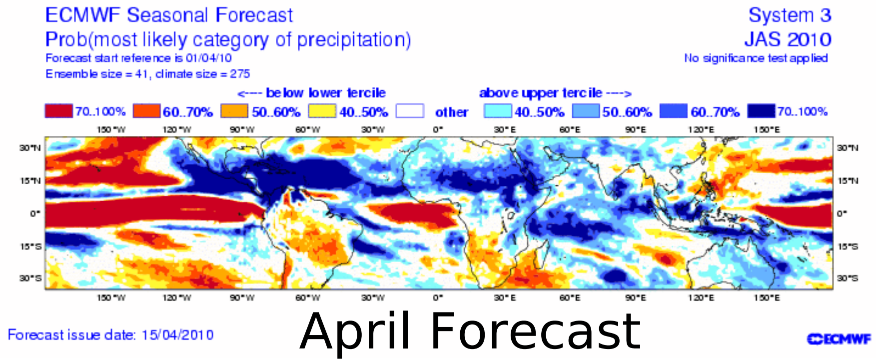
2010 seasonal forecasts: ECMWF



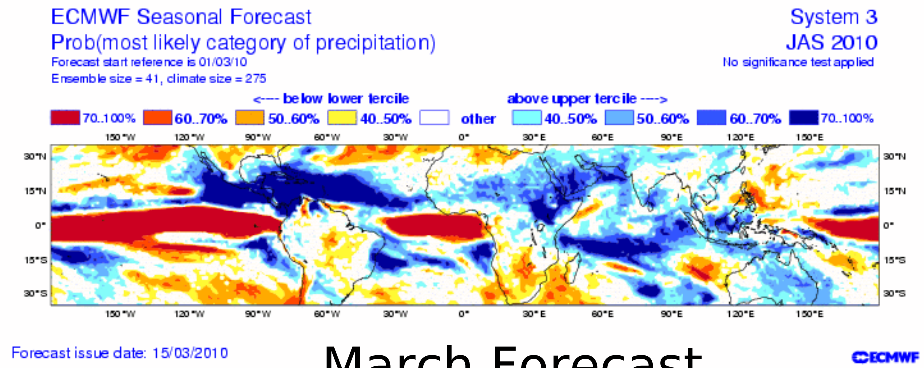
June Forecast



May (PRESAO) Forecast

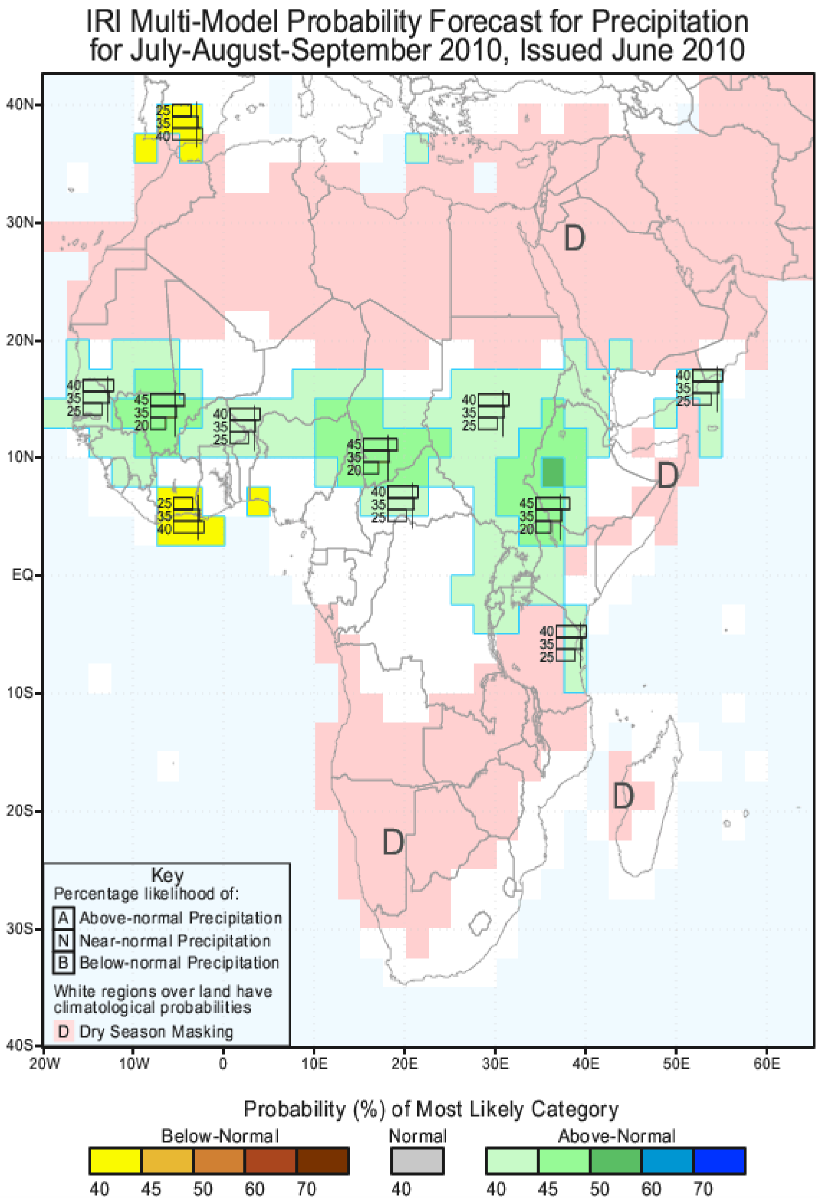


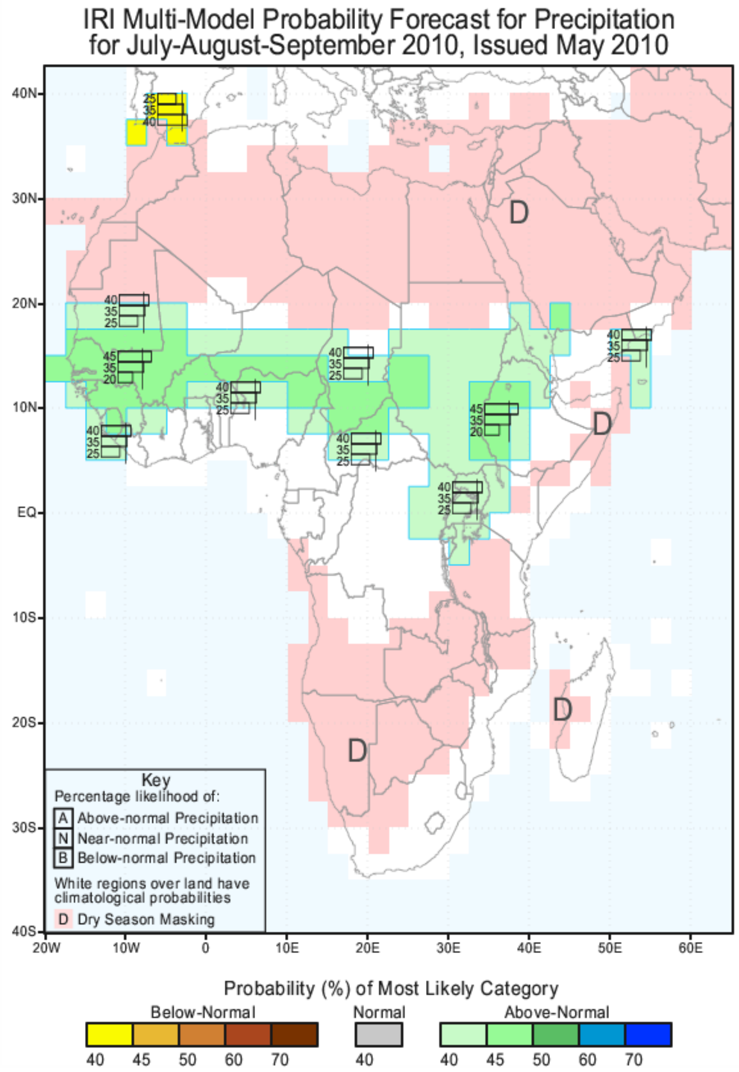
April Forecast



March Forecast

IRI


IRI Multi-Model Probability Forecast for Precipitation
for July-August-September 2010, Issued June 2010
D
Key
Percentage likelihood of:
A Above-normal Precipitation
N Near-normal Precipitation
B Below-normal Precipitation
White regions over land have climatological probabilities
D Dry Season Masking
40N 30N 20N 10N EQ 10S 20S 30S 40S
20W 10W 0 10E 20E 30E 40E 50E 60E
Probability (%) of Most Likely Category
Below-Normal
Normal
Above-Normal
40 45 50 60 70
40
40 45 50 60 70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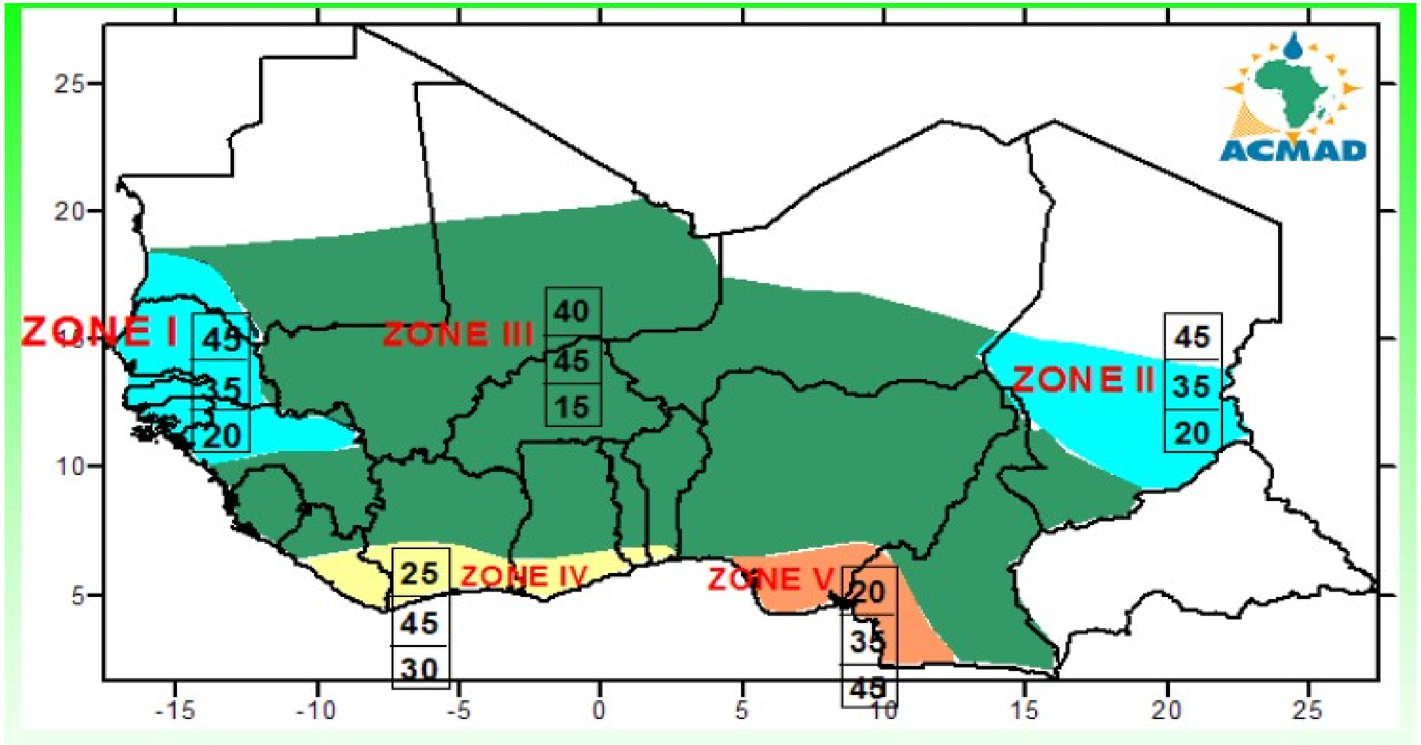
Probability (%) of Most Likely Category
Below-Normal
Normal
Above-Normal
40 45 50 60 70
40
40 45 50 60 70

2010 seasonal forecasts: ACMAD consensus forecast

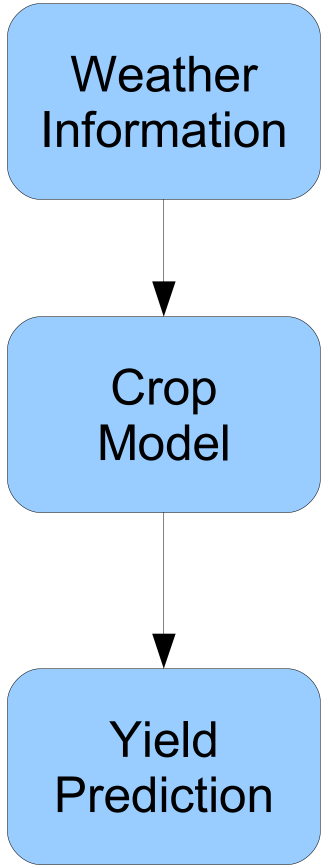


- Difficult to use directly for crop yield forecasting
- One new method at Reading is to use a spatial weather generator which is driven to match these statistics (Greatrex nd Grimes 2011)

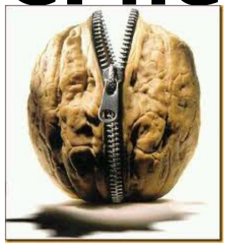
In July 2010:
Will there be flooding in the Sahel in 2010?

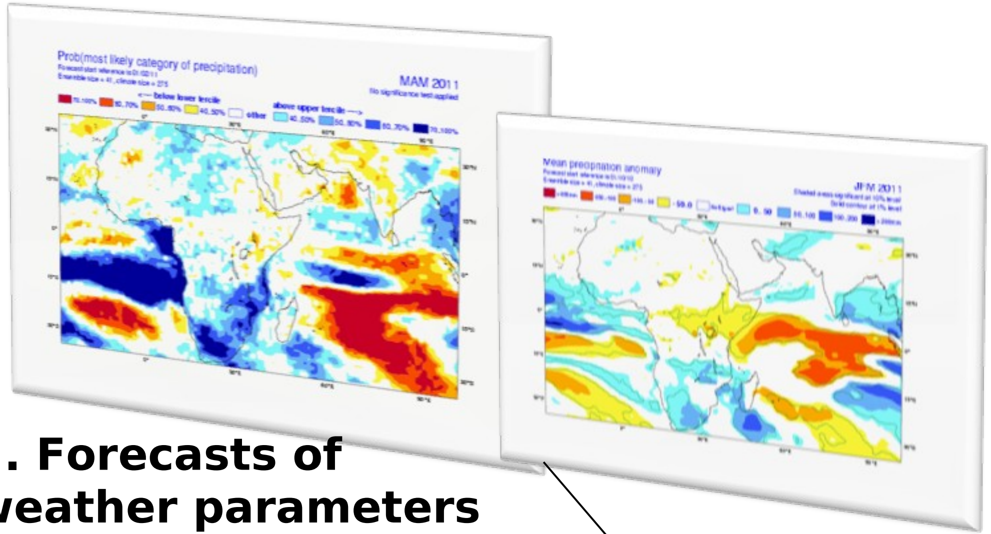
Summary

- Forecast models show potential to be used in a model cascade to provide crop yield predictions
- Predictability at different timescales derives from diverse phenomena
  - Atmospheric initialization important for weekly timescales
  - Ocean for monthy to seasonal timescales
- Examples in Africa show that bias correction of model output required for impacts modelling
- Sanai's talk will outline work with the crop modelling component GLAM

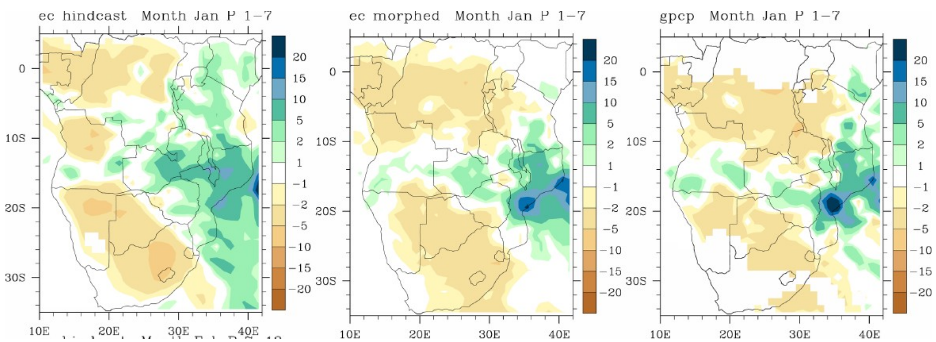


CONCEPT in a NUTSHELL QWeCI health

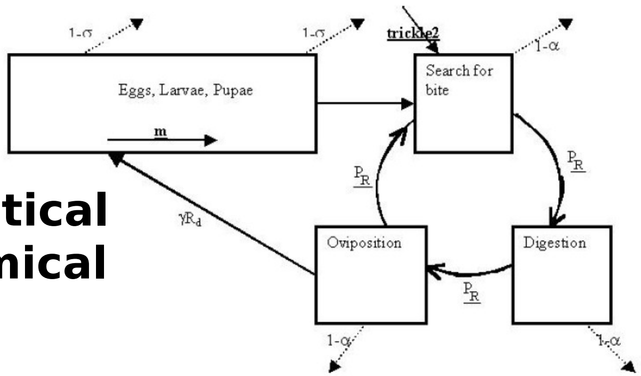




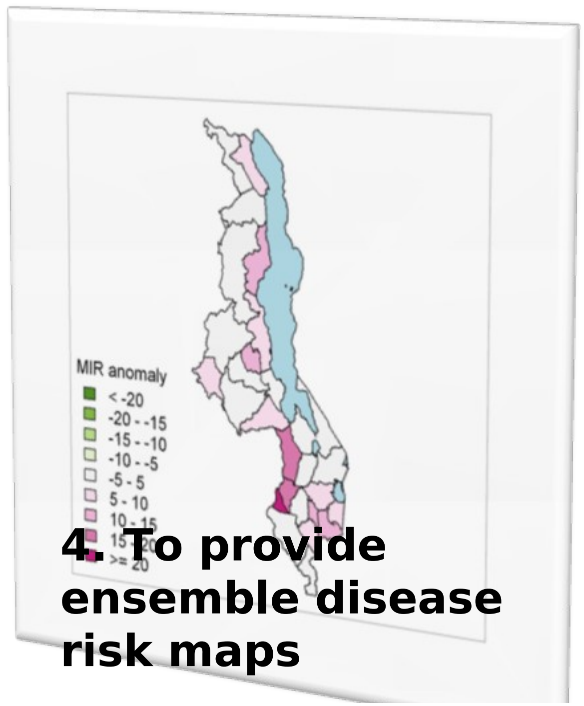
. Forecasts of weather parameters



2. Biases corrected statistically and/or dynamically



3. Fed into statistical (ICTP) and dynamical



4. To provide ensemble disease risk maps