The Abdus Salam International Centre for Theoretical Physics

1956-19

Targeted Training Activity: Seasonal Predictability in Tropical Regions to be followed by Workshop on Multi-scale Predictions of the Asian and African Summer Monsoon

4 - 15 August 2008

Forecasting severe floods of the Brahmaputra and Ganges rivers.

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Operational Flood Forecasting for Bangladesh using ECMWF ensemble weather forecasts

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Peter Webster, Georgia Tech
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Climate Forecast Applications for Bangladesh (CFAB): USAID/CARE/ECMWF/FFWC/NASA/NOAA

Bangladesh Stakeholders: Bangladesh Meteorological Department, Bangladesh Water Development Board, Department of Agriculture Extension, Disaster Management Bureau, Institute of Water Modeling, Center for Environmental and Geographic Information Services, CARE-Bangladesh

Asia

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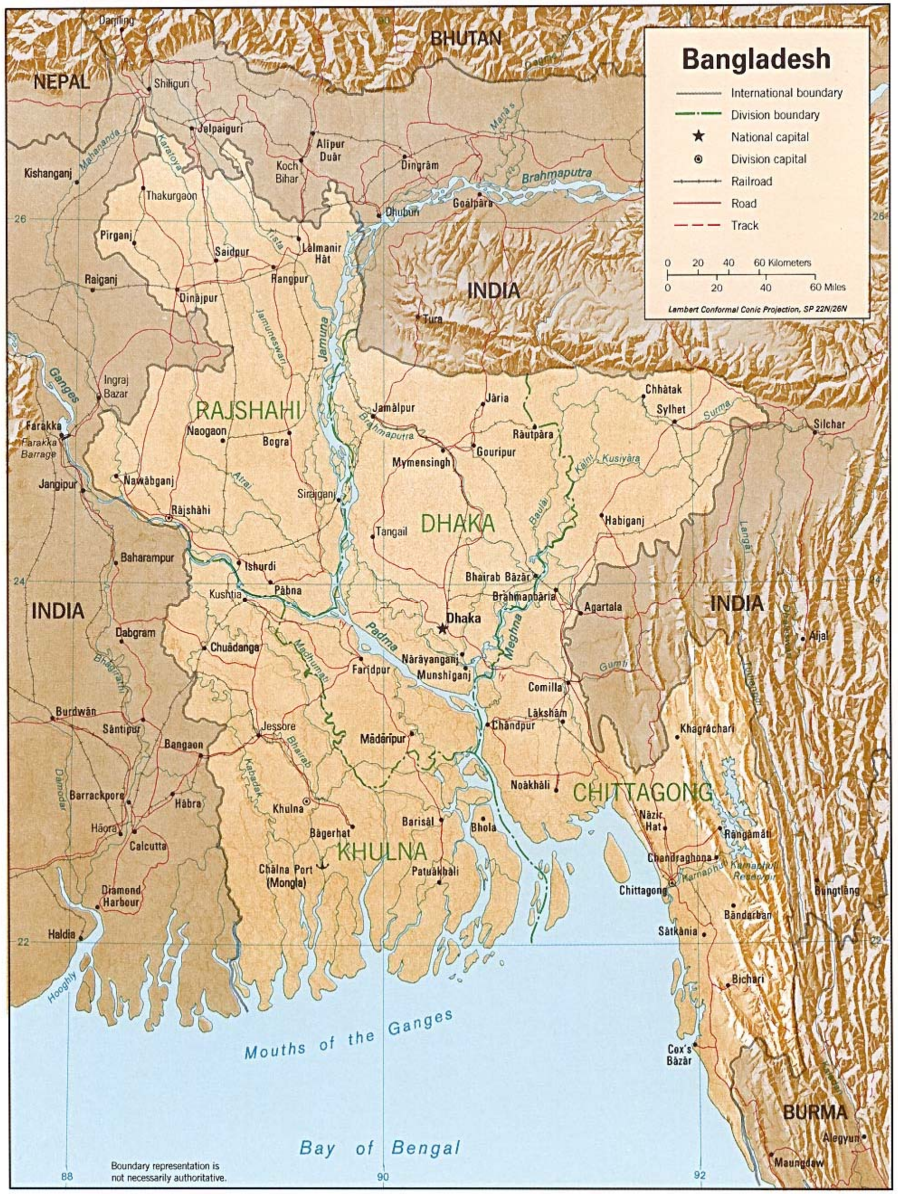

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Damaging Floods:

River Flooding

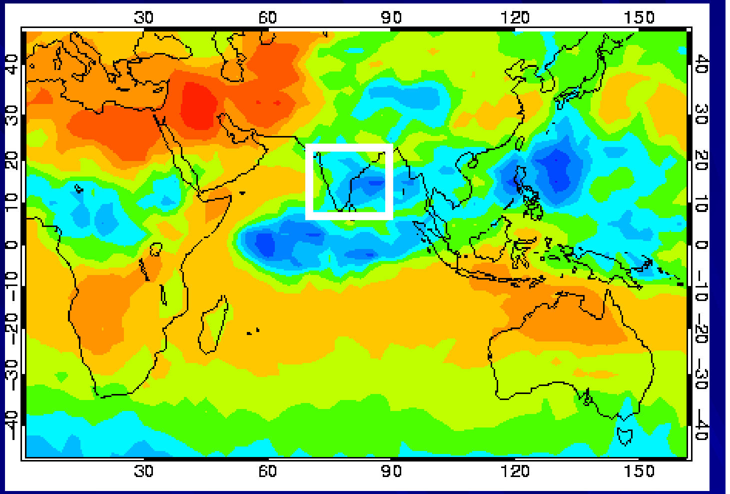
- **large peak or extended duration**
- **Affect agriculture: early floods in May, late floods in September**

Recent severe flooding: 1974, 1987, 1988, 1997, 1998, 2000, 2004, and 2007

- **1998: 60% of country inundated for 3 months, 1000 killed, 40 million homeless, 10-20% total food production**
- **2004: Brahmaputra floods killed 500 people, displaced 30 million, 40% of capitol city Dhaka under water**
- **2007: Brahmaputra floods displaced over 20 million**

(World Food Program)

Overview:
Bangladesh flood forecasting



I. CFAB History -- Sea-level impacts on flooding

II. 1-10 day Discharge Forecasting

1. precipitation forecast bias removal
2. multi-model river forecasting
3. accounting for all error: weather and hydrologic errors

III. 2007 Floods and Warning System Pilot Areas

IV. Verifying the ensemble spread-skill relationship

V. Calibrating ensemble forecasts with spread-skill information

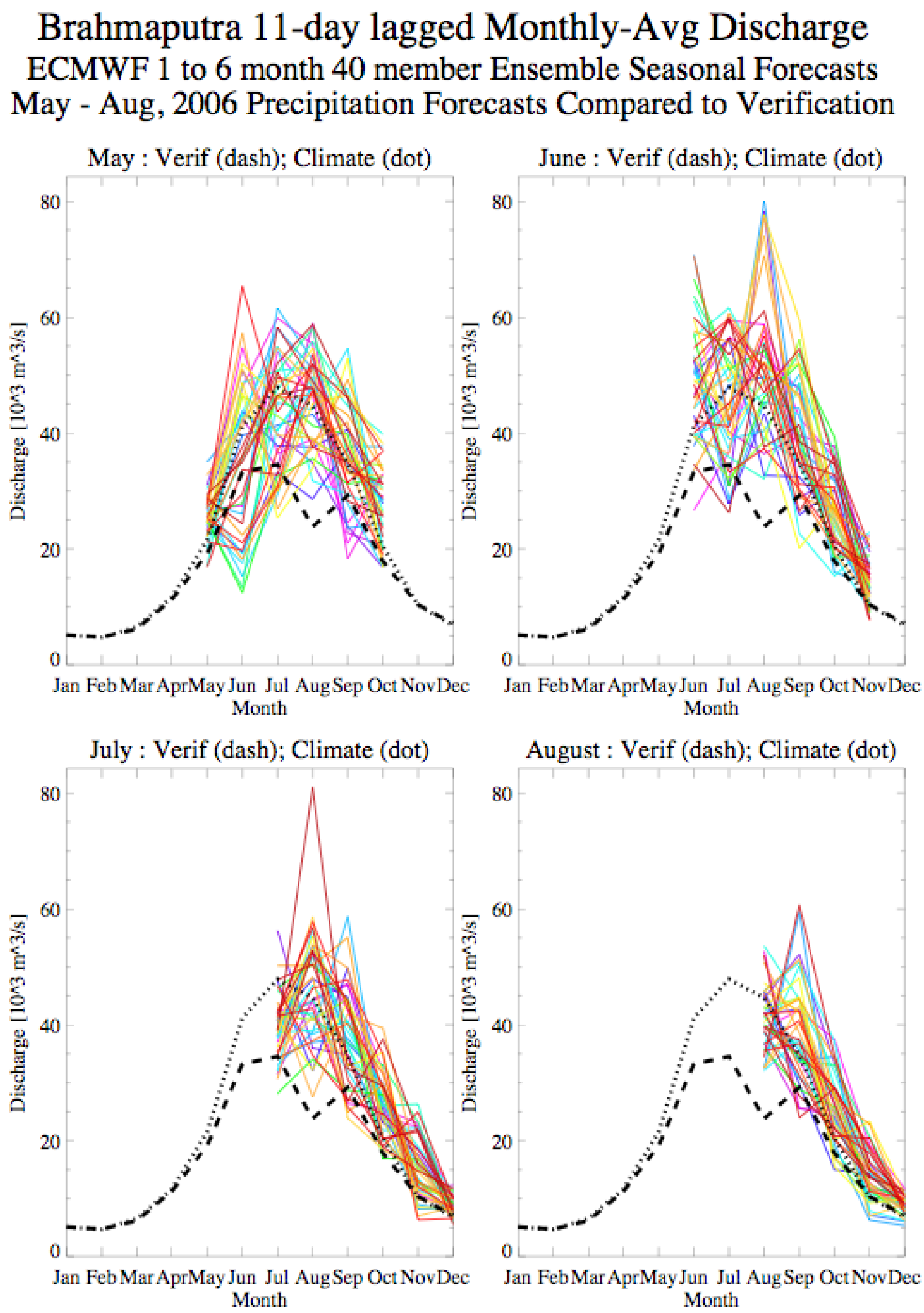
Three-Tier Overlapping Forecast System Developed for Bangladesh

SEASONAL OUTLOOK: “Broad brush” probabilistic forecast of rainfall and river discharge. Updated each month. Produced out to 6 months, currently most useful skill out 3 months

20-25 DAY FORECAST: Forecast of average 5-day rainfall and river discharge 3-4 weeks in advance. Updated every 5 days.

1-10 DAY FORECAST: Forecast of rainfall and precipitation in probabilistic form updated every day. Considerable skill out to 5-days. Moderate skill 5-10 days.

Seasonal Forecasts

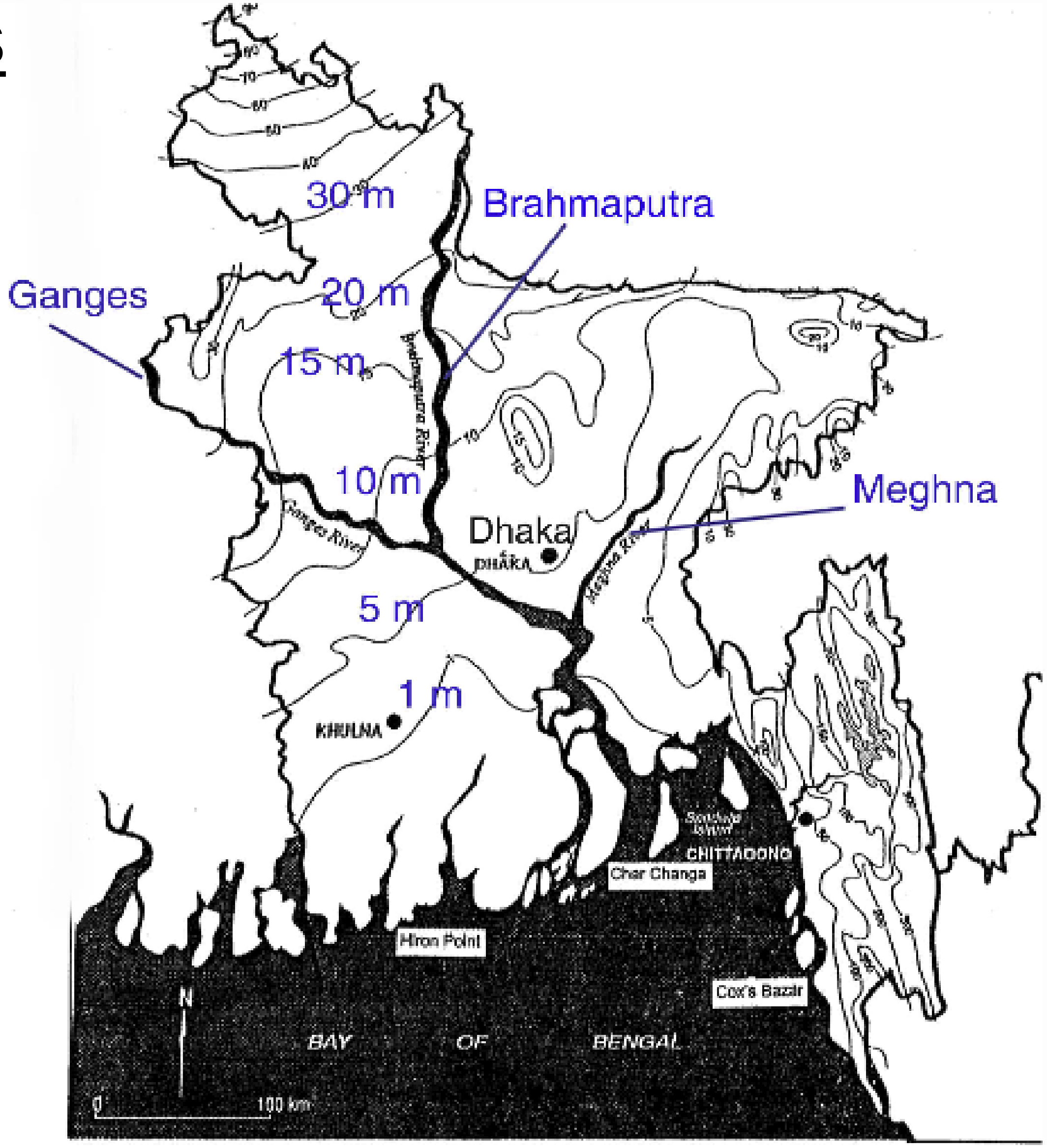


Topography of Bangladesh

Sea Level Impacts

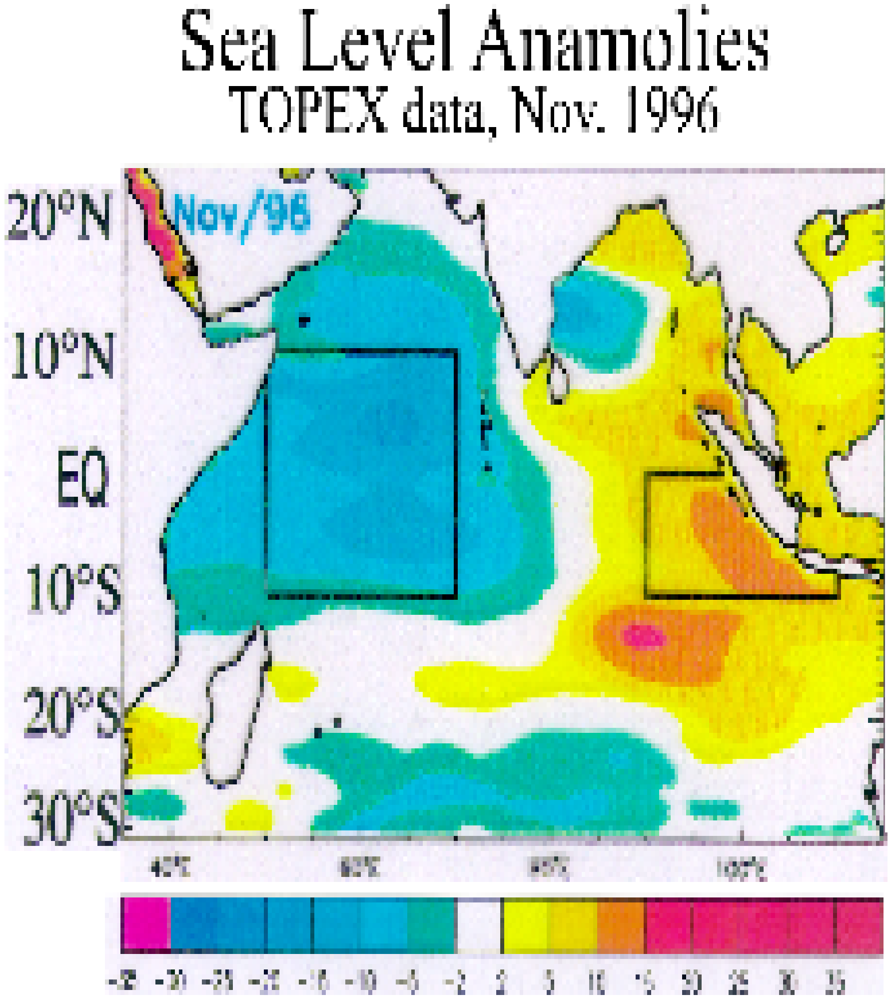
-Very flat topography

-Can changes in Bay of Bengal sea level height significantly affect river flooding over the whole country?

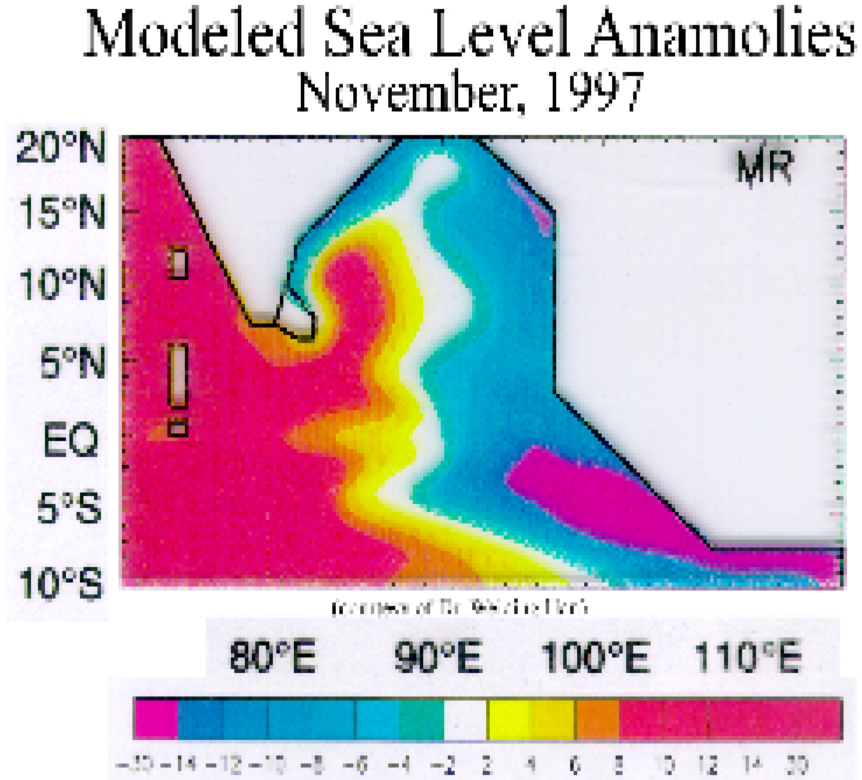


Ocean Dynamics Effecting Sea-Level in the Bay of Bengal

Indian Ocean Zonal Mode



Baroclinic Coastal Kelvin Wave



(results by Weiqing Han)

Sea Level Impacts

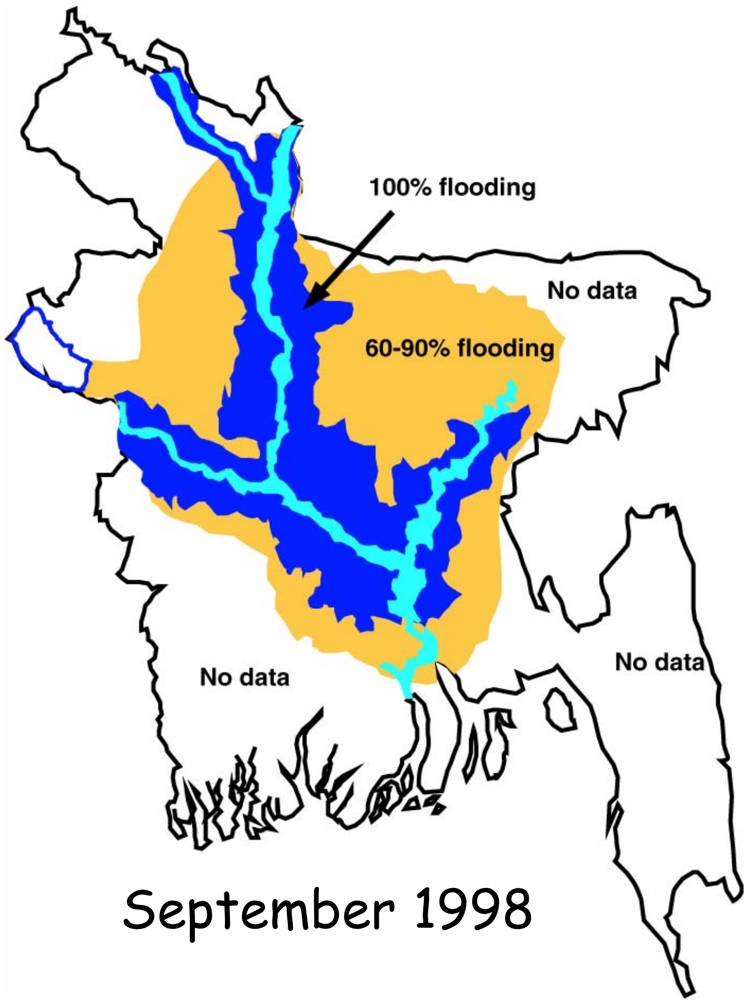
Calculation: linearize the depth-integrated Navier-Stokes equation about the "normal depth" D_n

Results: exponential decrease of sea-level impacts with e-folding length $D_n / (3S_0)$~150km

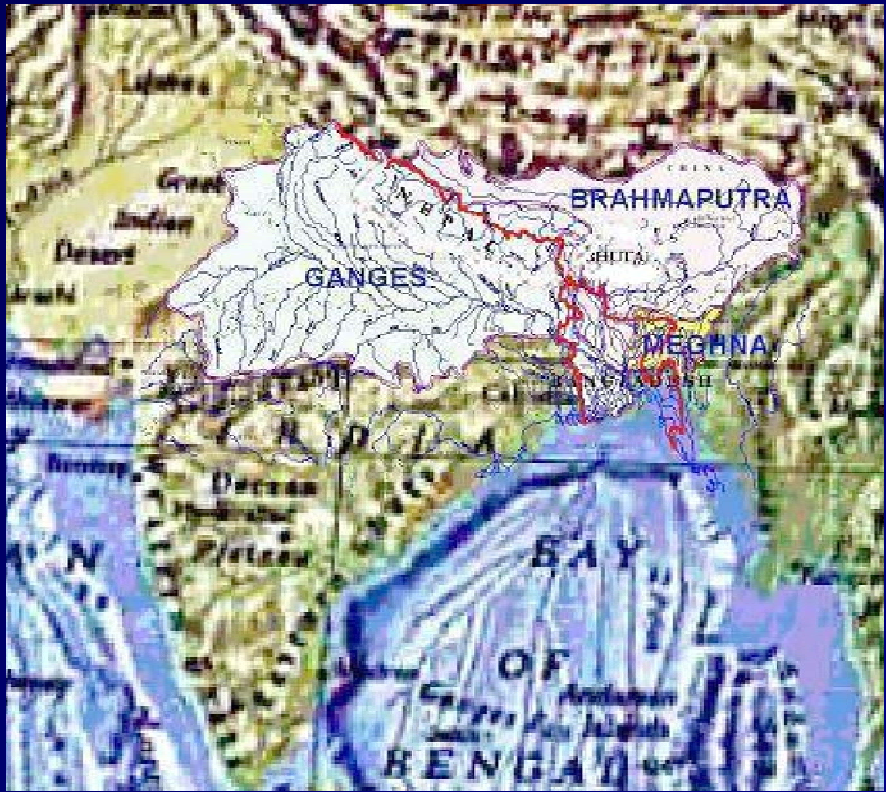
- Backwater effects limited to lower third of country and bounded by roughly 30cm
- Severe flood years affect whole country, with water depth variations of O(1m)

=> Look at precipitation-driven effects on flooding

disasterous flood year



CFAB Project: Improve flood warning lead time



<u>Problems</u>:

1. Limited warning of upstream river discharges

2. Precipitation forecasting in tropics difficult

<u>Good forecasting skill derived from:</u>

1. good data inputs: ECMWF weather forecasts, satellite rainfall
2. Large catchments => weather forecasting skill “integrates” over large spatial and temporal scales
3. Partnership with Bangladesh’s Flood Forecasting Warning Centre (FFWC) => daily border river readings used in data assimilation scheme

1) Rainfall Inputs

1) Rain gauge estimates: NOAA CPC and WMO GTS
   0.5 X 0.5 spatial resolution; 24h temporal resolution
   approximately 100 gauges reporting over combined catchment
   24hr reporting delay

2) Satellite-derived estimates: Global Precipitation Climatology Project (GPCP)
   0.25X0.25 spatial resolution; 3hr temporal resolution
   6hr reporting delay
   geostationary infrared "cold cloud top" estimates calibrated from SSM/I and TMI microwave instruments

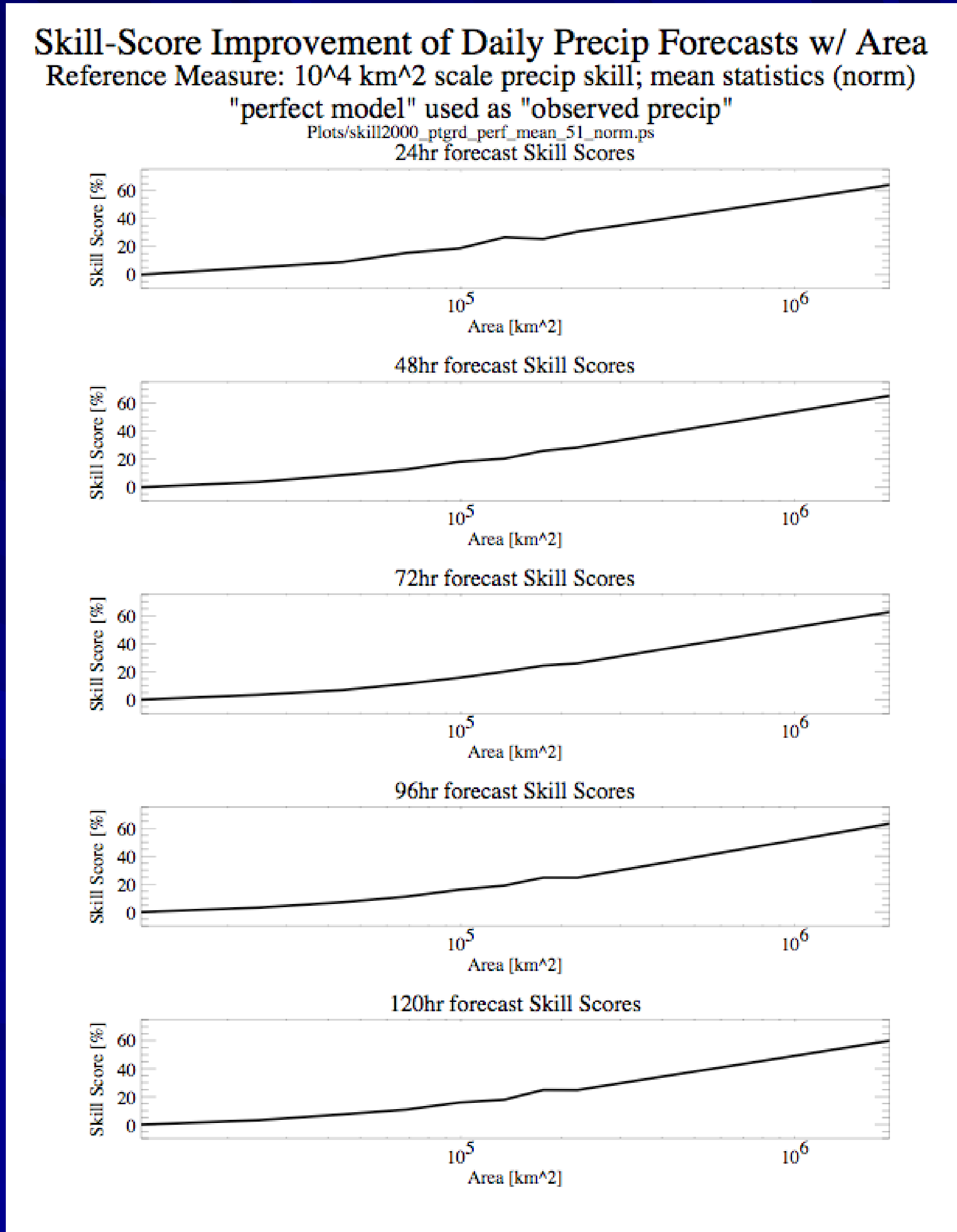
3) Satellite-derived estimates: NOAA CPC "CMORPH"
   0.25X0.25 spatial resolution; 3hr temporal resolution
   18hr reporting delay
   precipitation rain rates derived from microwave instruments (SSM/I, TMI, AMSU-B), but "cloud tracking" done using infrared satellites

4) Weather forecasts: ECMWF GCM 51-member ensemble weather forecasts at 1-day to 10-day forecast lead-times (nominal resolution about 1degree)

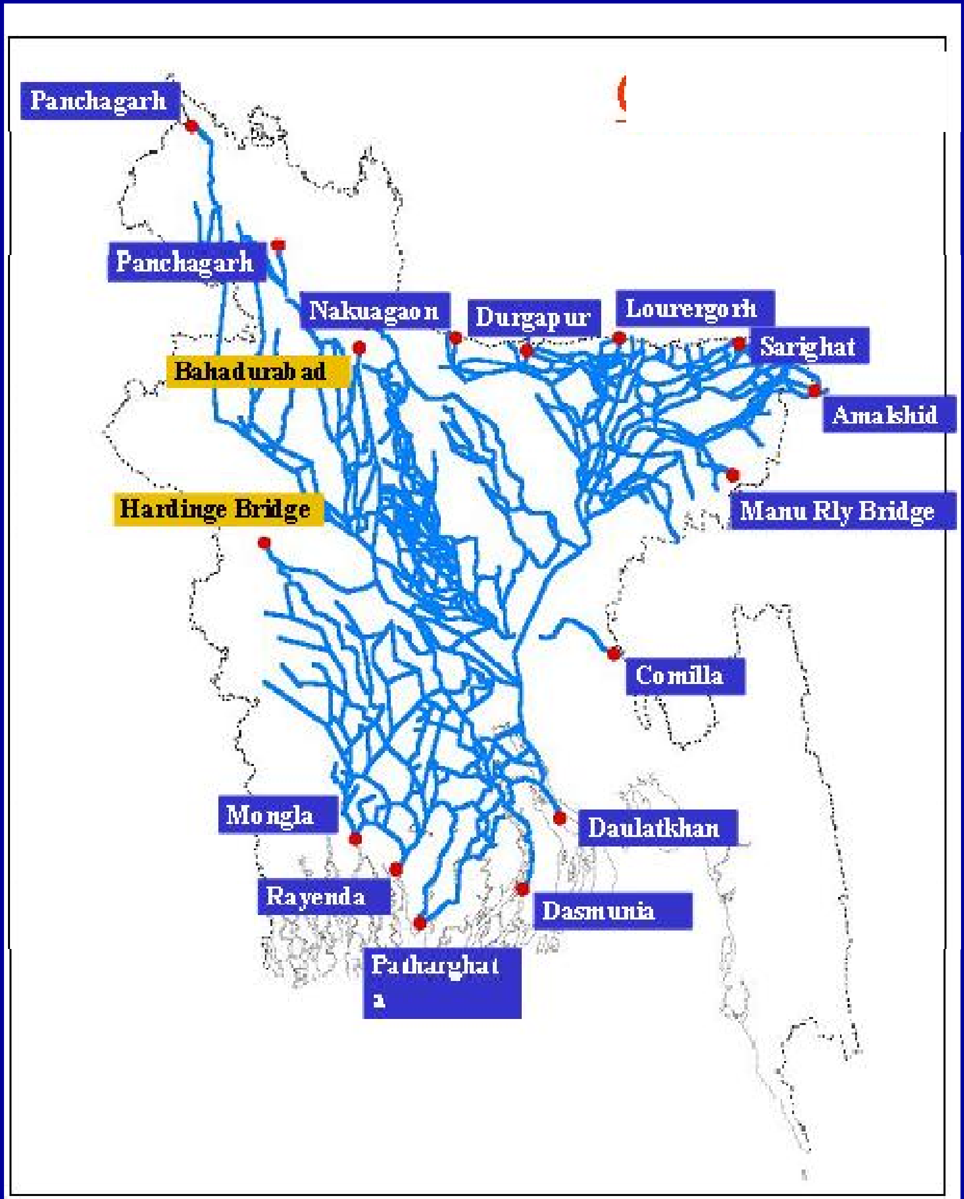
2) Spatial Scale

-- Increase in forecast skill (RMS error) with increasing spatial scale

-- Logarithmic increase



Merged FFWC-CFAB Hydraulic Model Schematic



Primary forecast boundary conditions shown in gold:

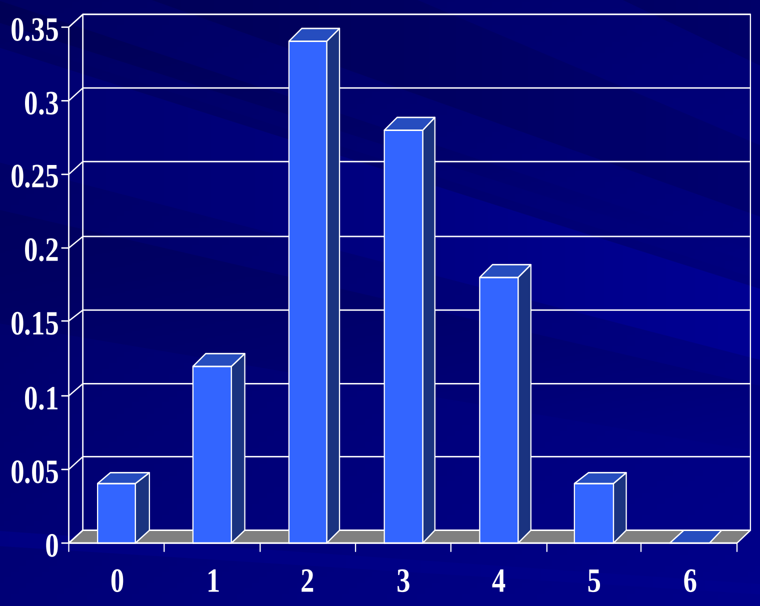
Ganges at Hardinge Bridge

Brahmaputra at Bahadurabad

<u>3) Benefit:</u> FFWC daily river discharge observations used in forecast data assimilation scheme (Auto-Regressive Integrated Moving Average model [ARIMA] approach)

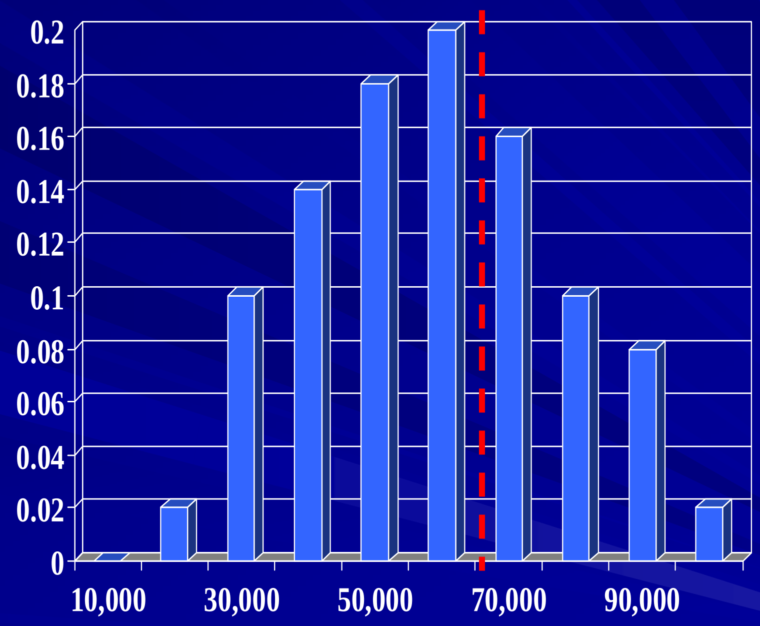
Transforming (Ensemble) Rainfall into (Probabilistic) River Flow Forecasts

Rainfall Probability



Rainfall [mm]

Discharge Probability

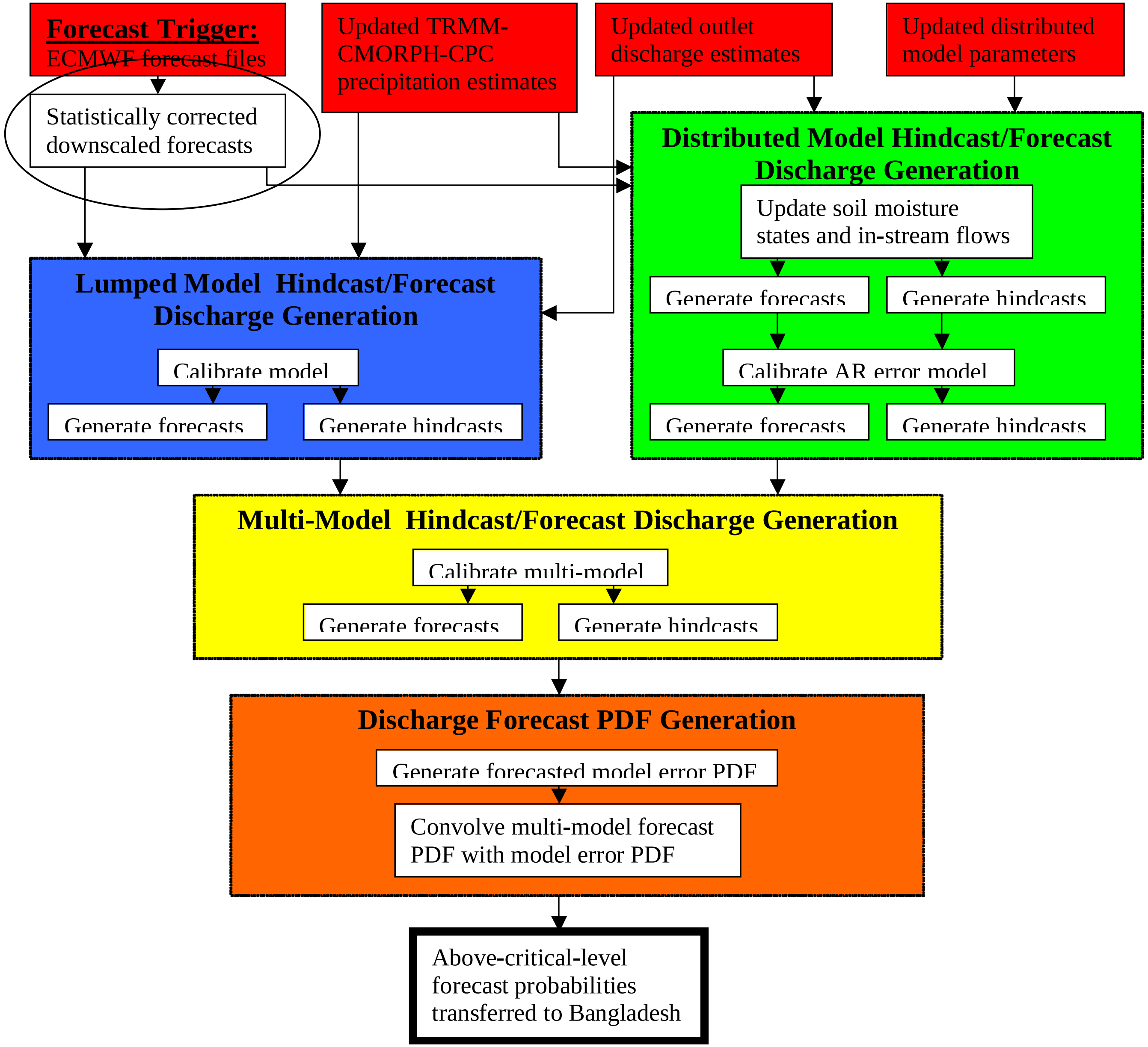


Discharge [m^3/s]

Above danger level probability 36%

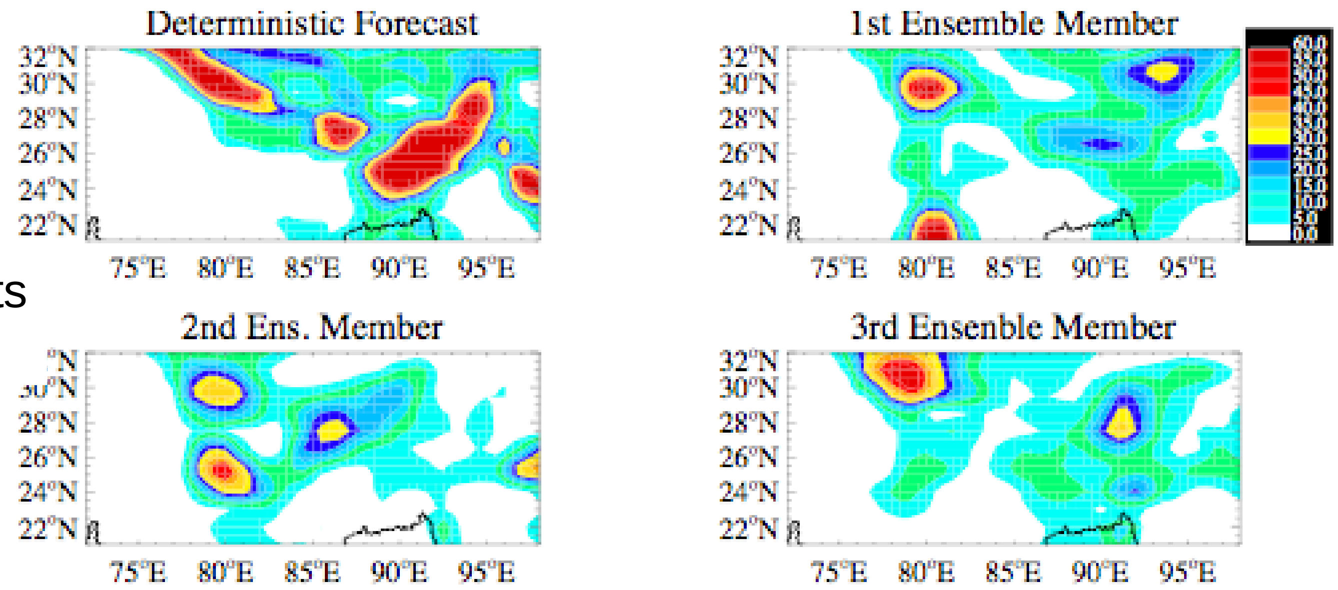
Greater than climatological seasonal risk?

Daily Operational Flood Forecasting Sequence



ECMWF 51-member Ensemble Precipitation Forecasts

5 Day Lead-time Forecasts
=> Lots of variability



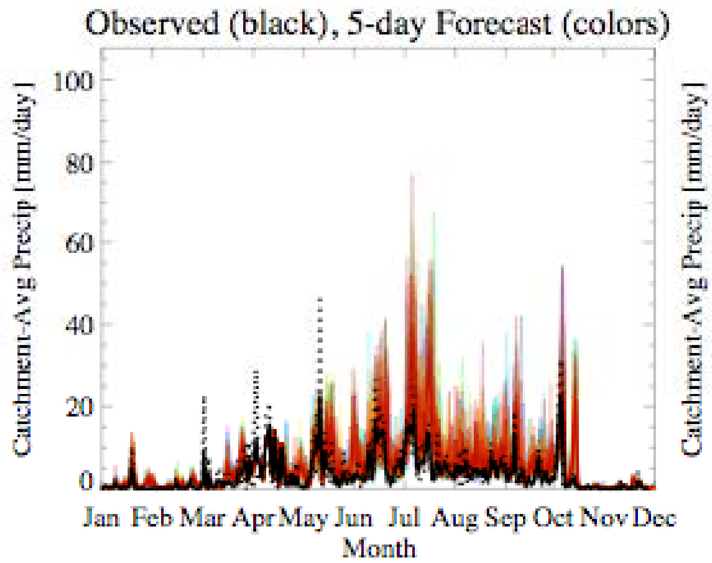
<u>2004 Brahmaputra Catchment-averaged Forecasts</u>

-black line satellite observations

-colored lines ensemble forecasts

⇒Basic structure of catchment rainfall similar for both forecasts and observations

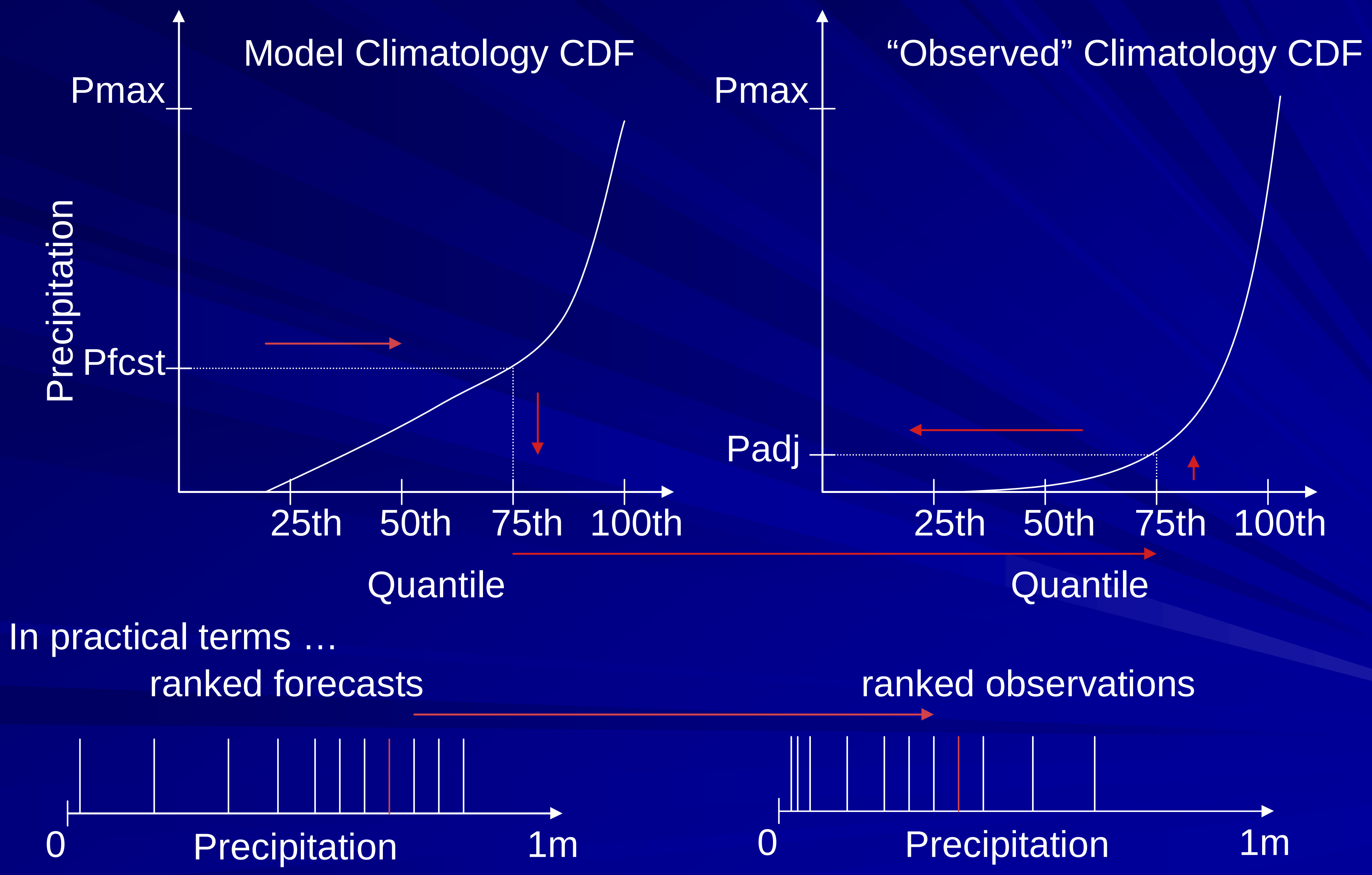
⇒But large relative over-bias in forecasts



Forecast Bias Adjustment

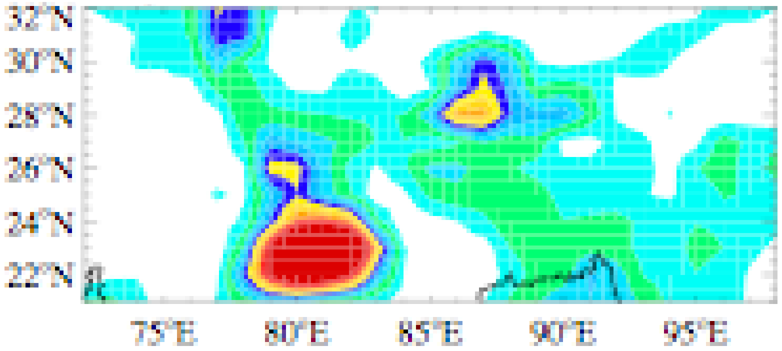
-done independently for each forecast grid

(bias-correct the whole PDF, not just the median)

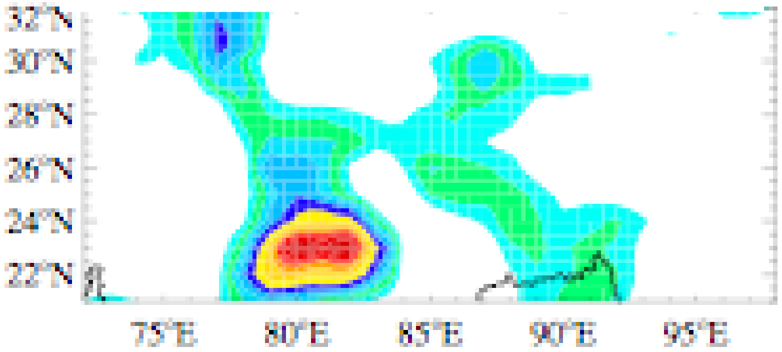


Bias-corrected Precipitation Forecasts

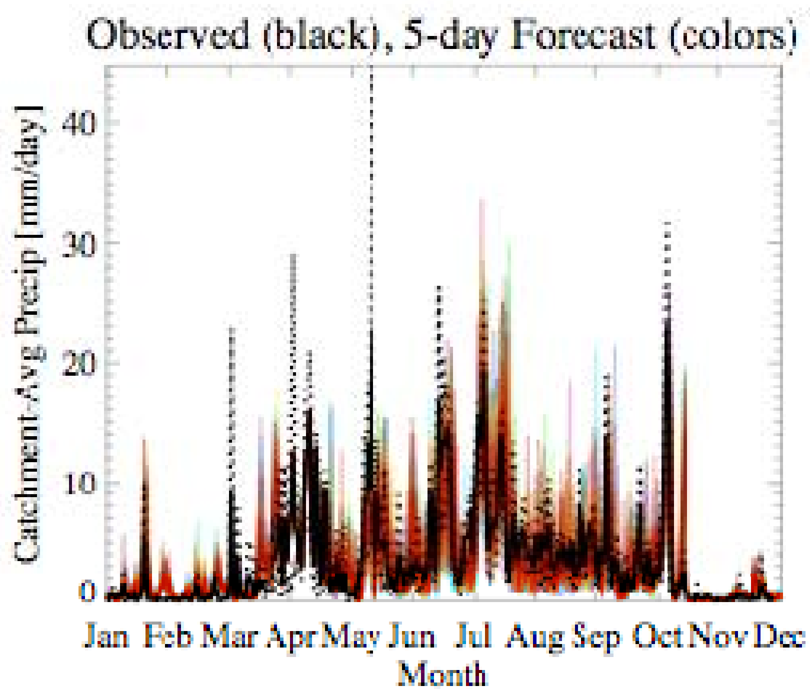
Original Forecast



Corrected Forecast



Brahmaputra Corrected Forecasts

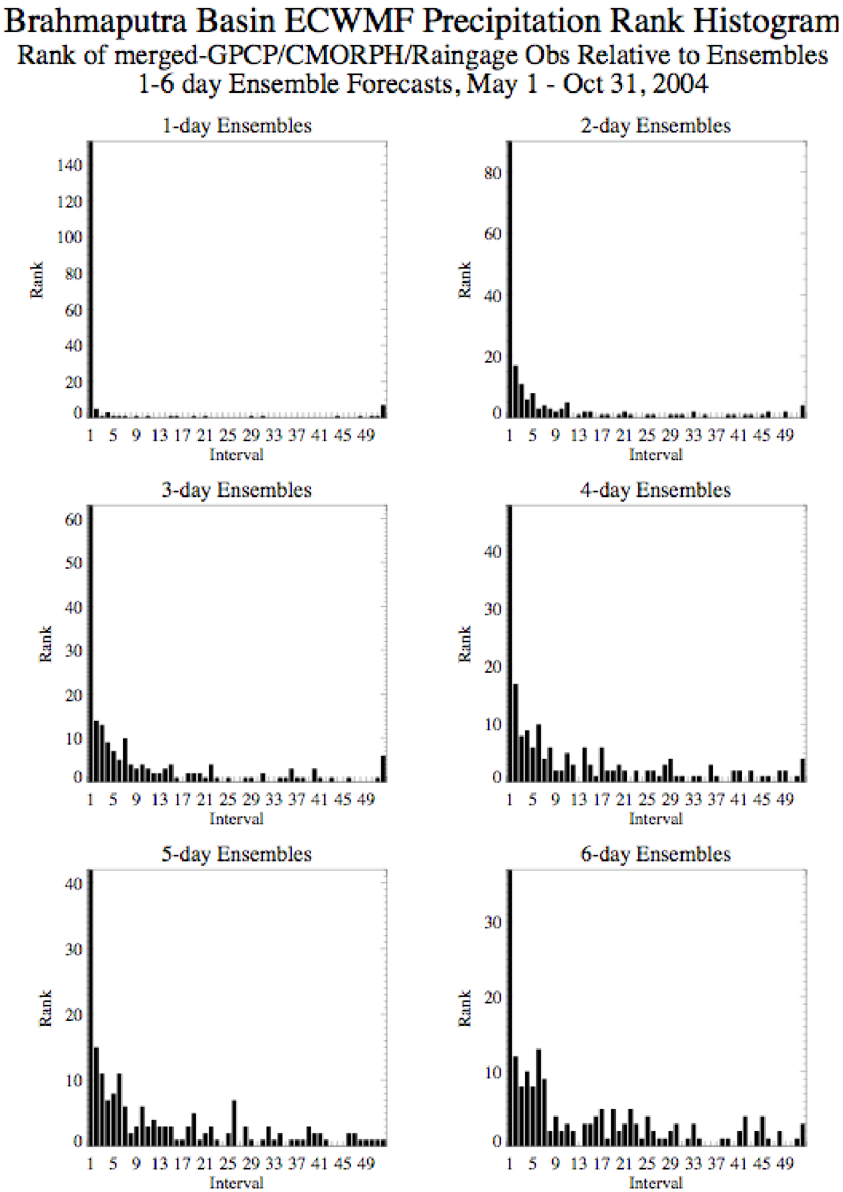


=> Now observed precipitation within the "ensemble bundle"

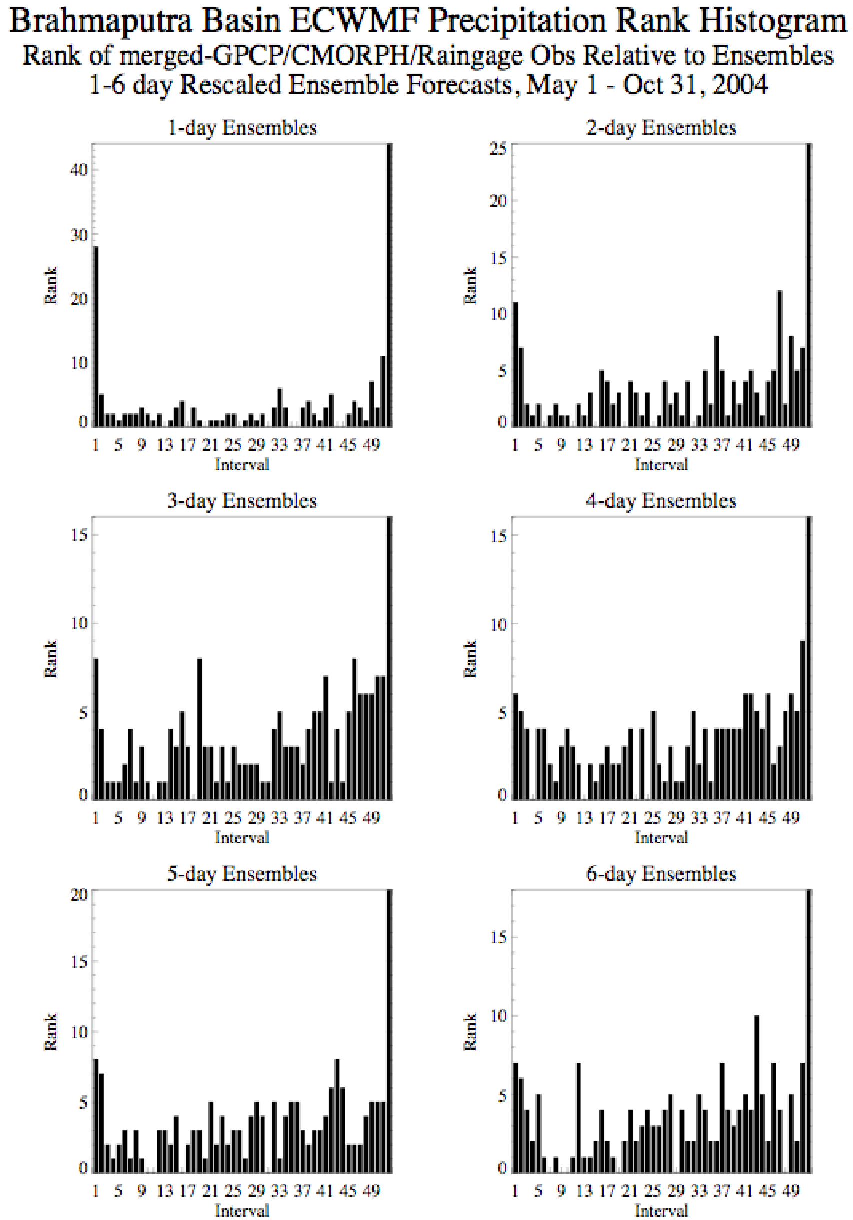
Rank Histogram Comparisons

(better but not perfect!)

Original



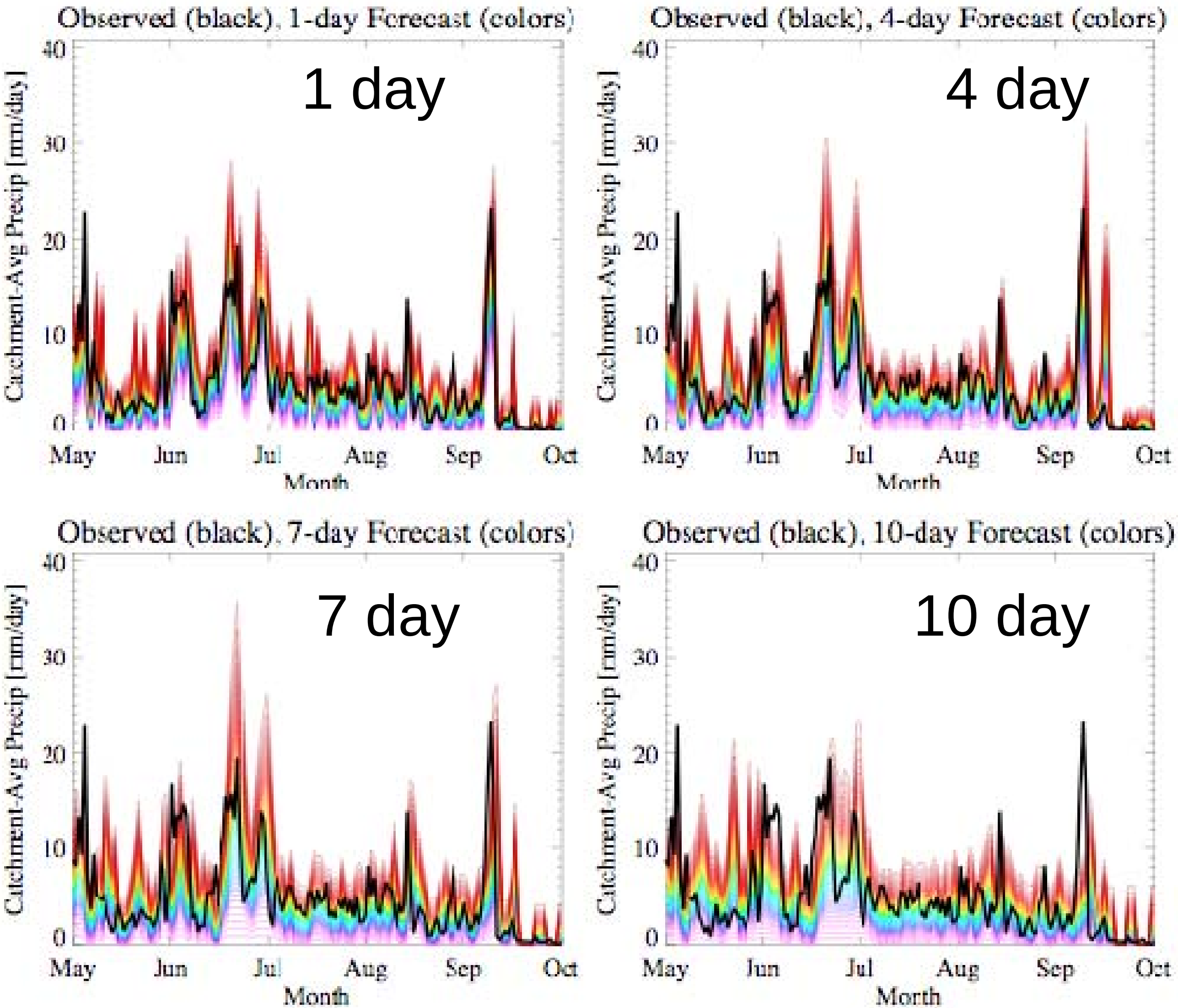
Adjusted



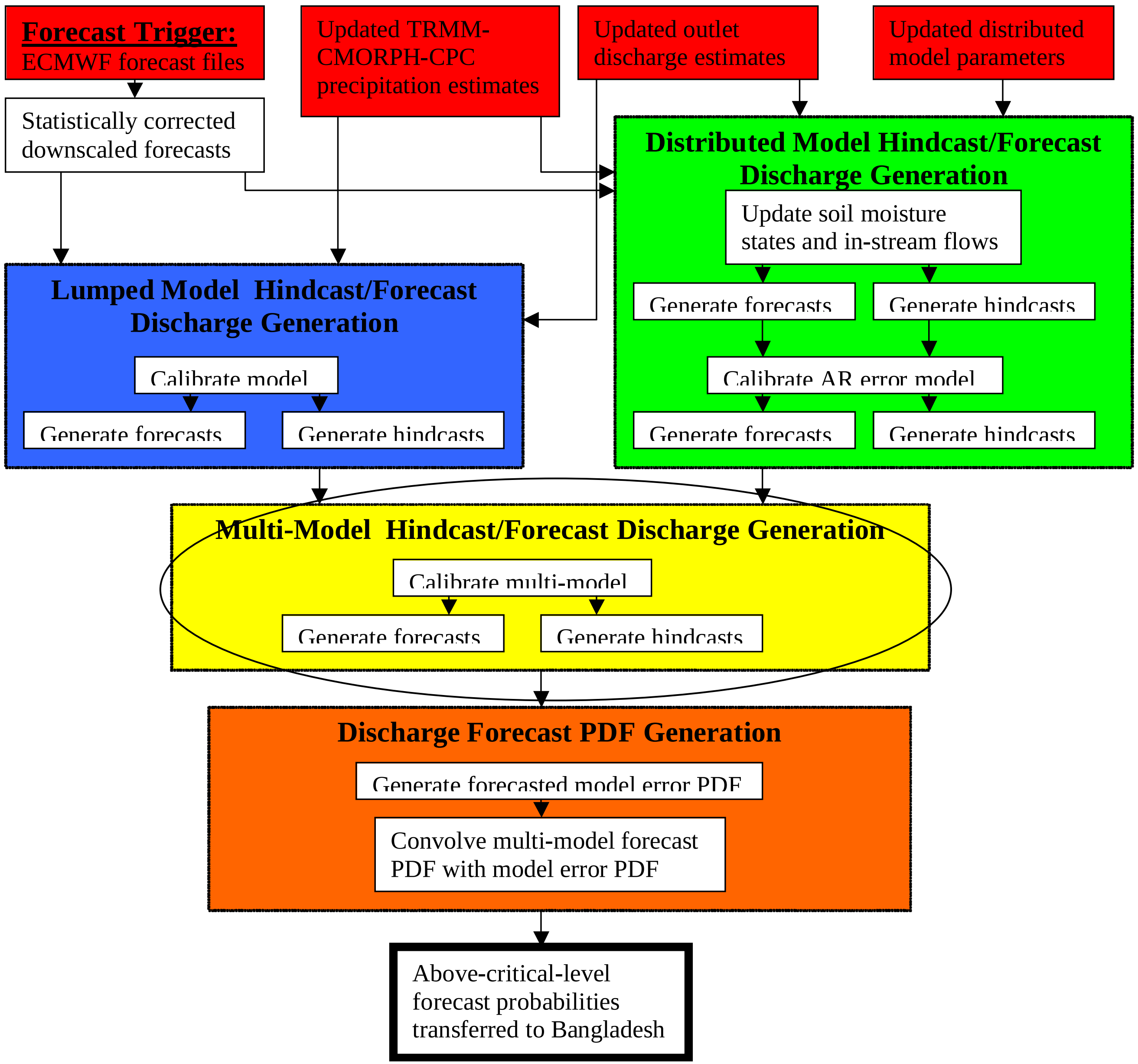
<u>Quantile Regression approach</u>:maintaining skill no worse than "persistence" for non-Gaussian PDF's

(ECMWF Brahmaputra catchment Precipitation)

- "Multi-model" statistical approach applied to NCAR's WRF mesoscale ensemble forecasts

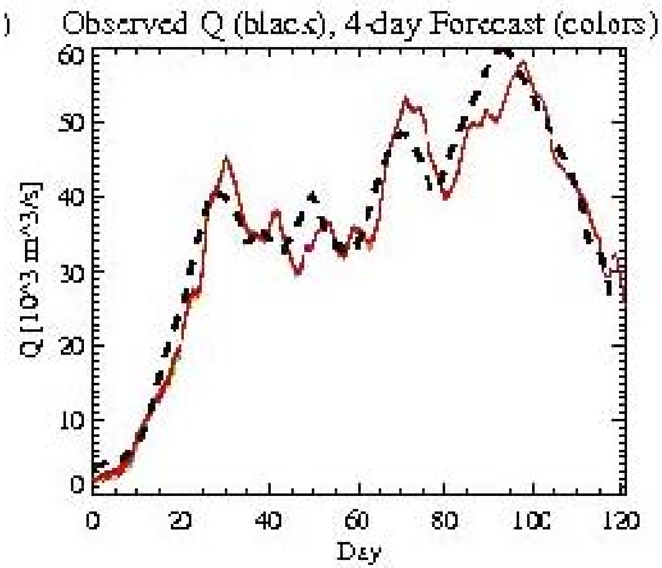


Daily Operational Flood Forecasting Sequence

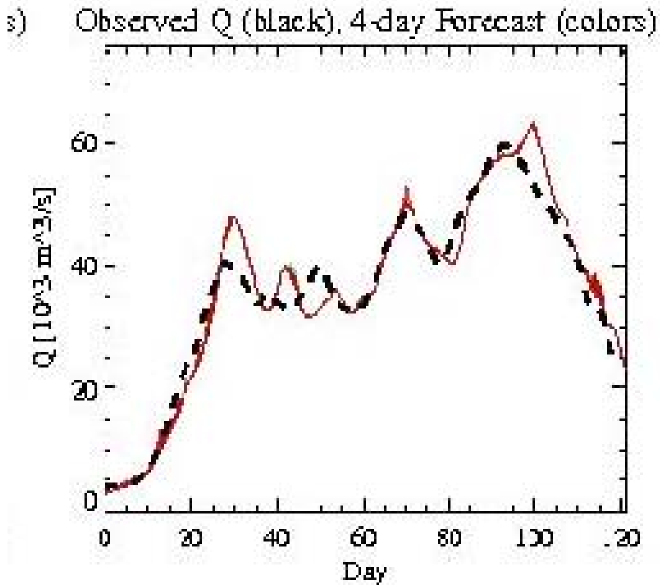


2003 Model Comparisons for the Ganges (4-day lead-time)

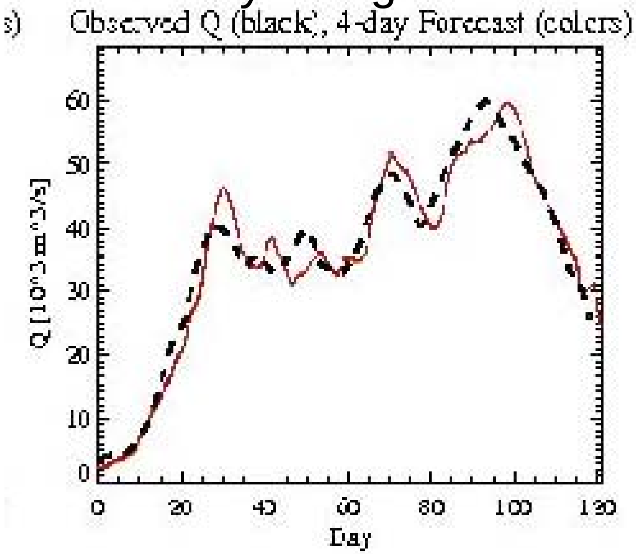
hydrologic lumped model



hydrologic distributed model



Resultant Hydrologic multi-model



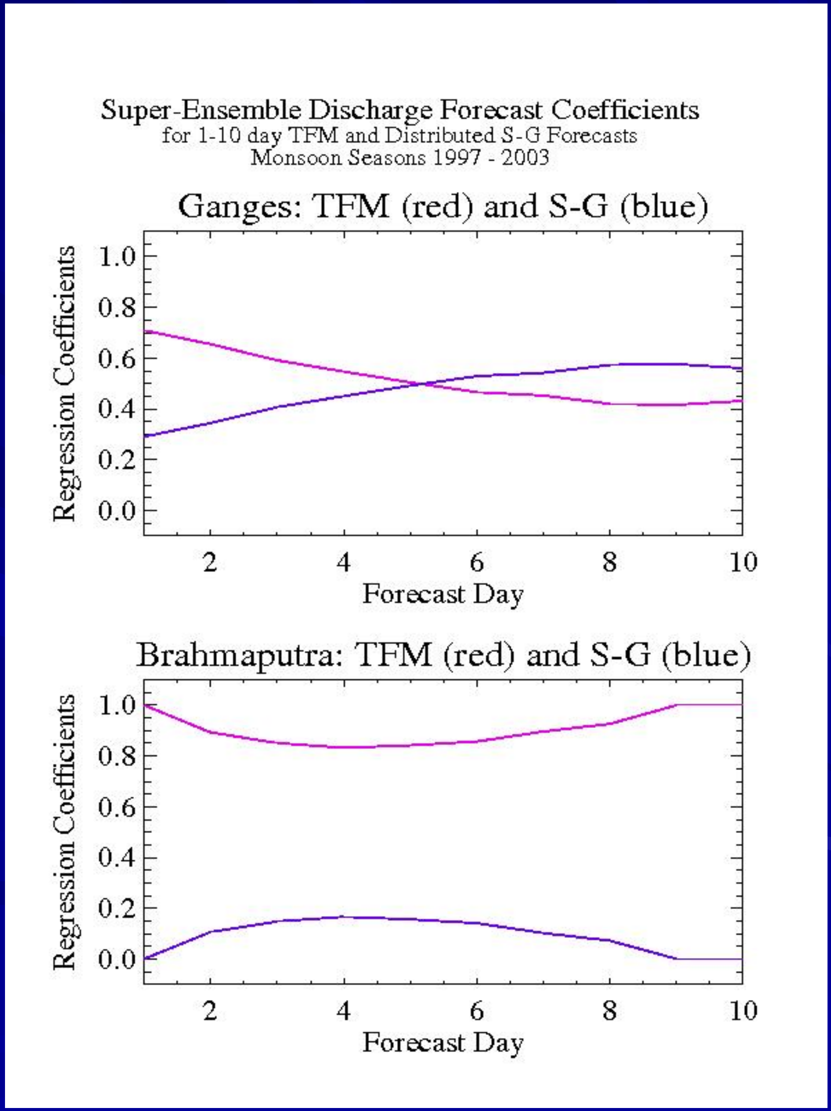
Multi-Model Forecast Regression Coefficients

- Lumped model (red)
- Distributed model (blue)

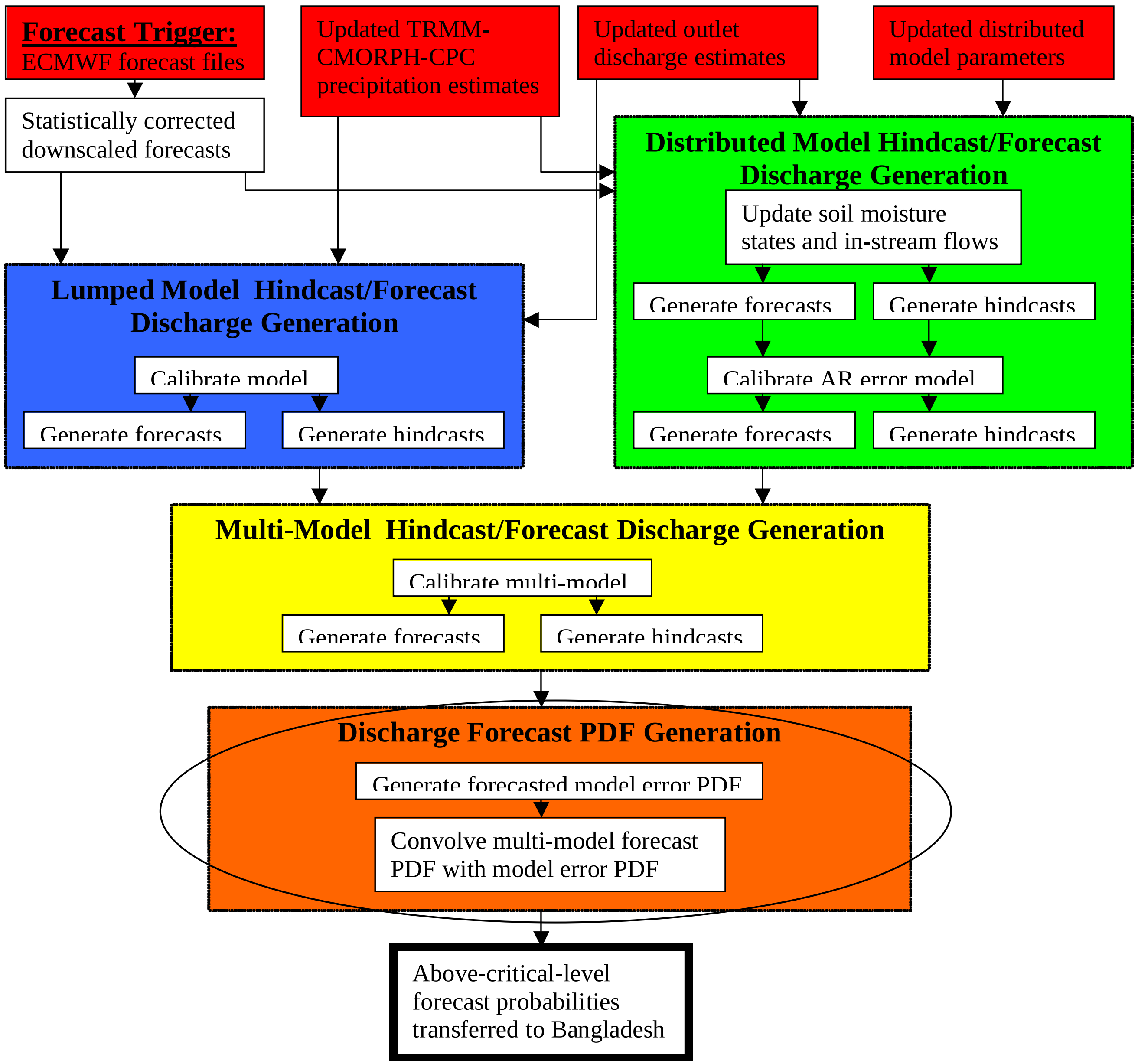
- Significant catchment variation
- Coefficients vary with the forecast lead-time
- Representative of the each basin's hydrology

-- Ganges slower time-scale response

-- Brahmaputra "flashier"

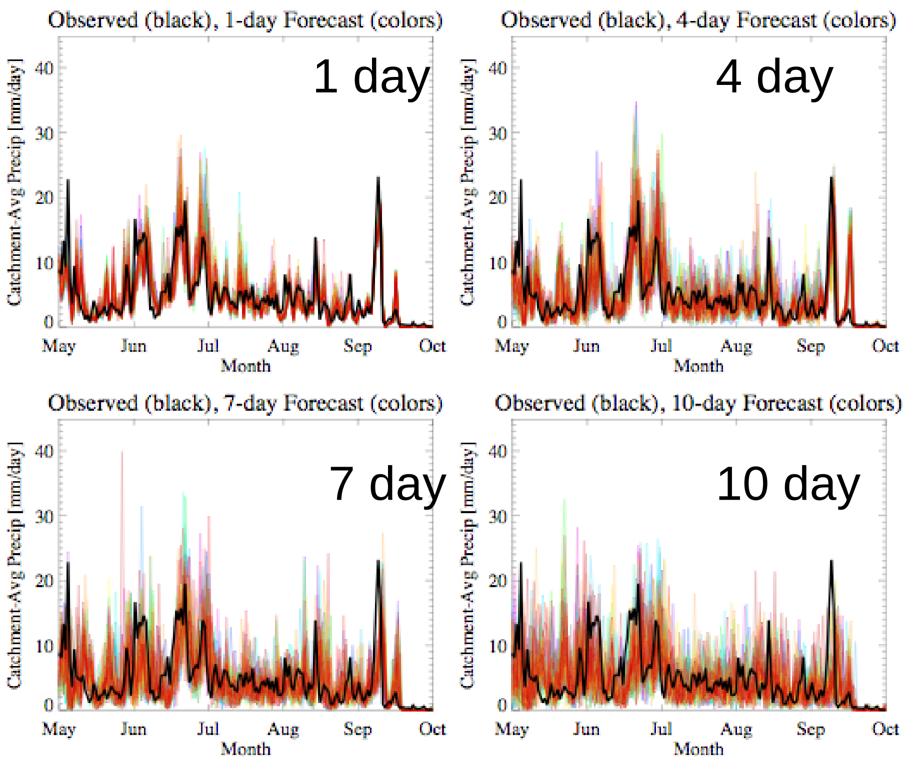


Daily Operational Flood Forecasting Sequence

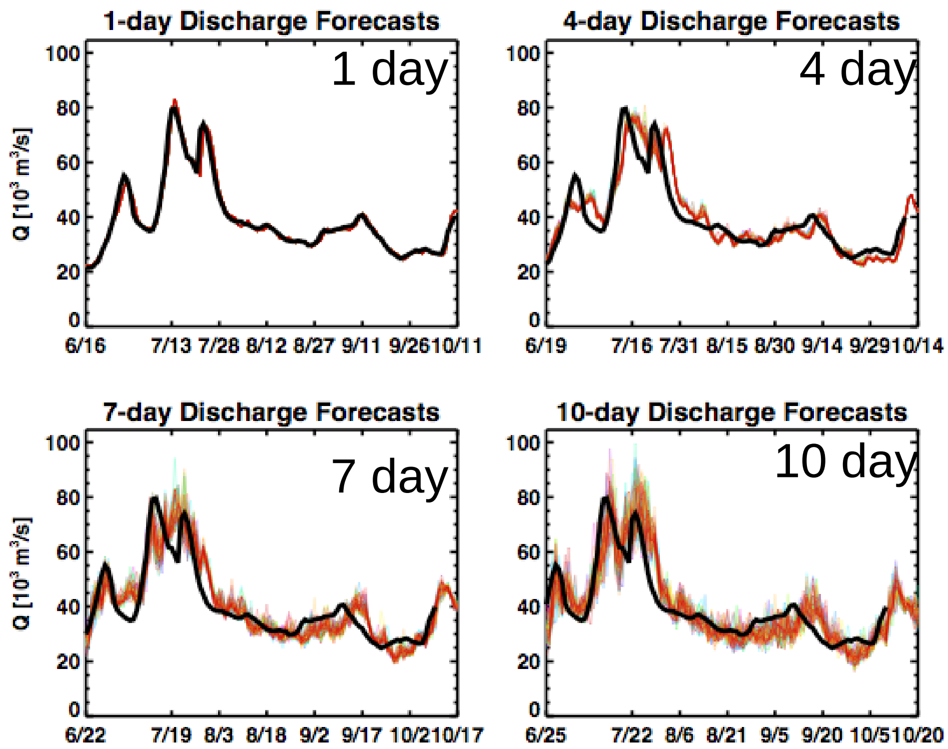


Significance of Weather Forecast Uncertainty
Discharge Forecasts

Precipitation Forecasts

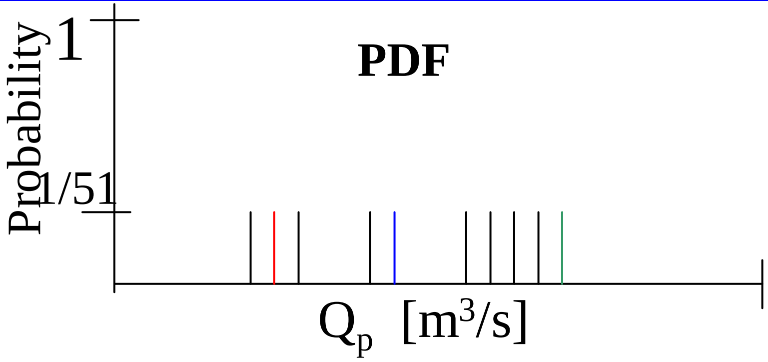


Discharge Forecasts

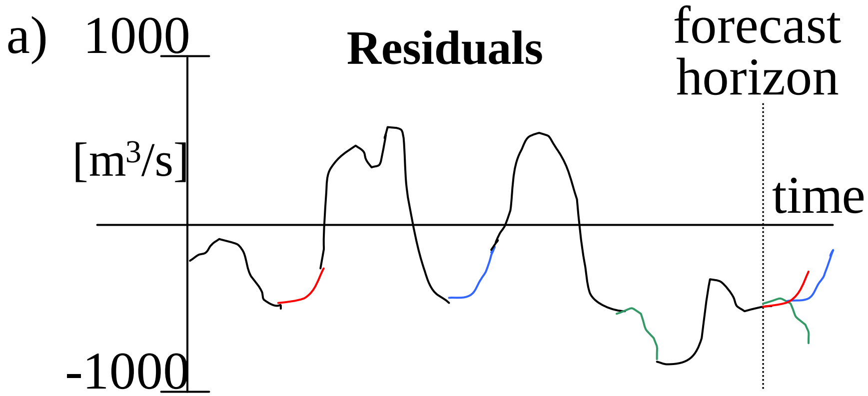


Producing a Reliable Probabilistic Discharge Forecast

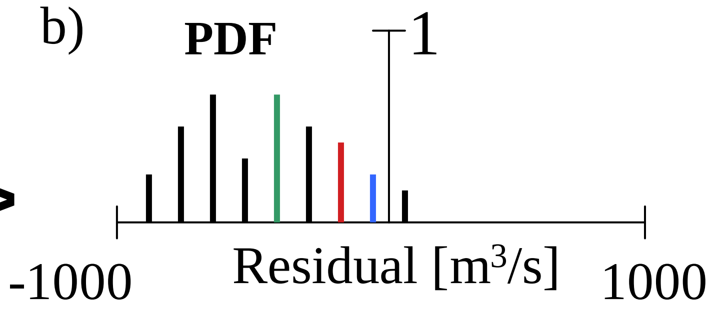
Step 1: generate discharge ensembles from precipitation forecast ensembles (Q_p):



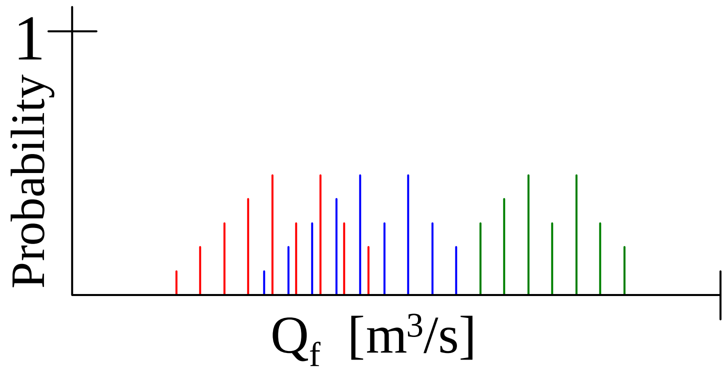
Step 2: a) generate multi-model hindcast error time-series using precip estimates; b) conditionally sample and weight to produce empirical forecasted error PDF:



=>



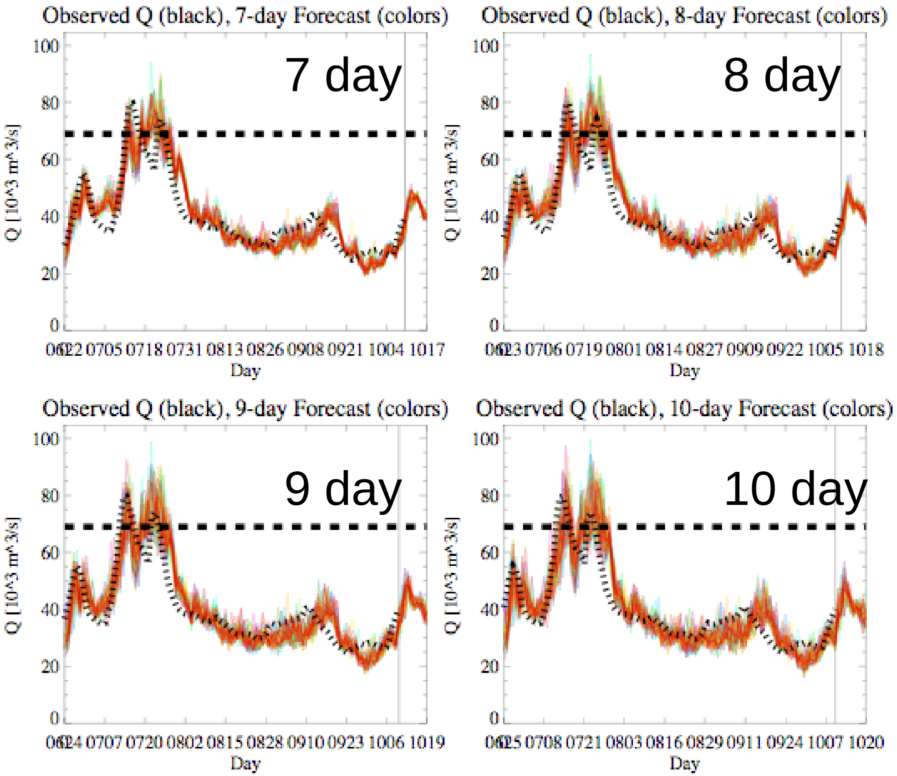
Step 3: combine both uncertainty PDF's to generate a "new-and-improved" more complete PDF for forecasting (Q_f):



Significance of Weather Forecast Uncertainty Discharge Forecasts

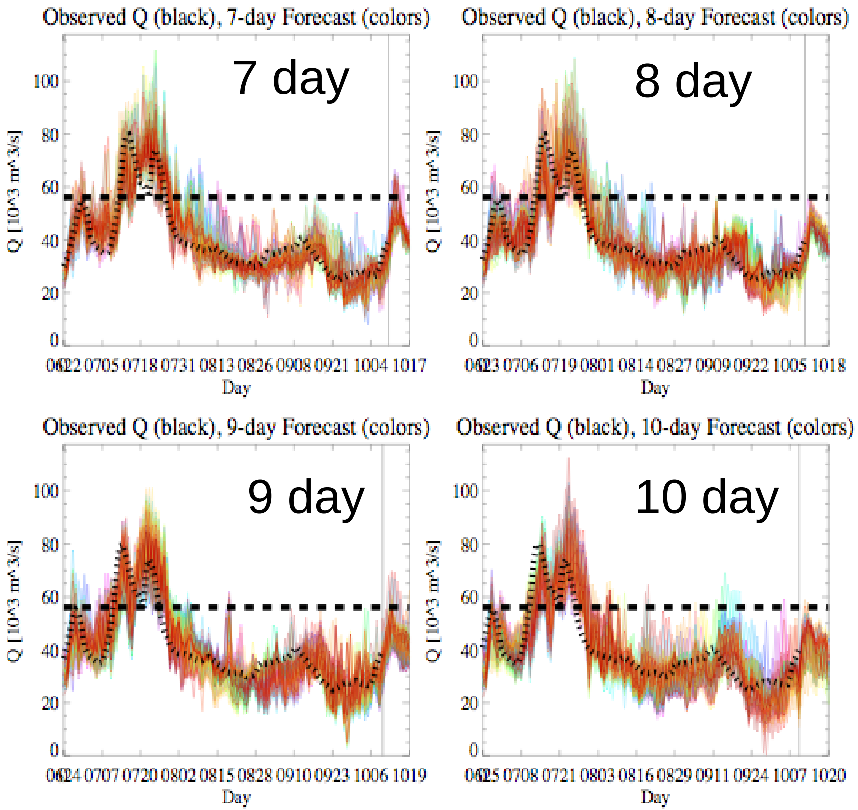
2004 Brahmaputra Discharge Forecast Ensembles

Multi-Model Brahmaputra Discharge Forecasts
7-10 day using ECMWF Precipitation Forecasts
Forecasts Initialized June 15, 2004 - October 10, 2004



Corrected Forecast Ensembles

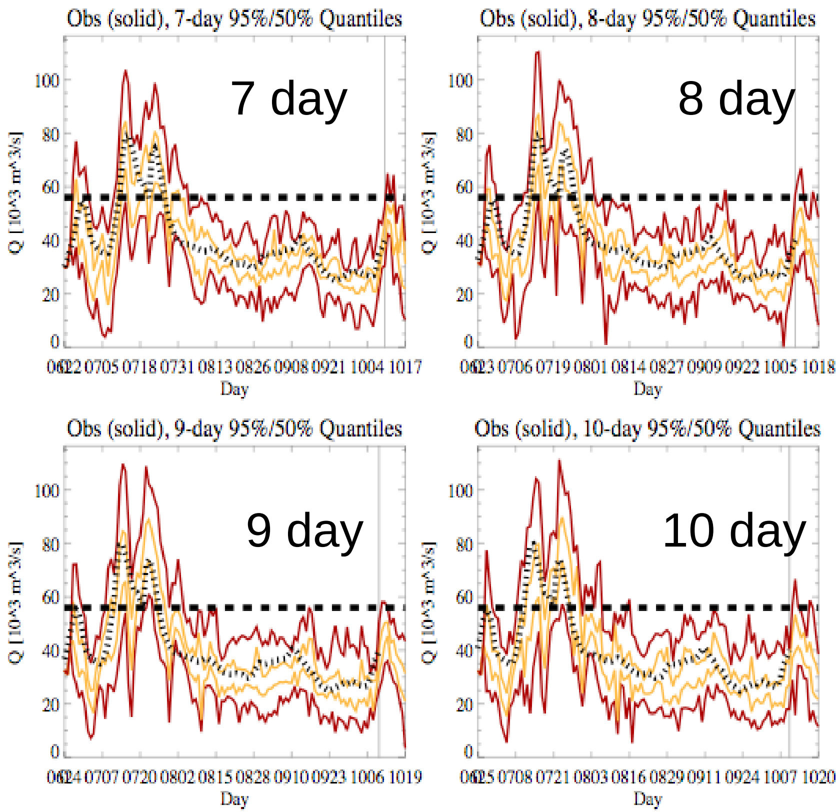
Super-Ensemble Brahmaputra Discharge Forecasts
7-10 day using ECMWF Precipitation Forecasts
Forecasts Initialized June 15 - October 10, 2004



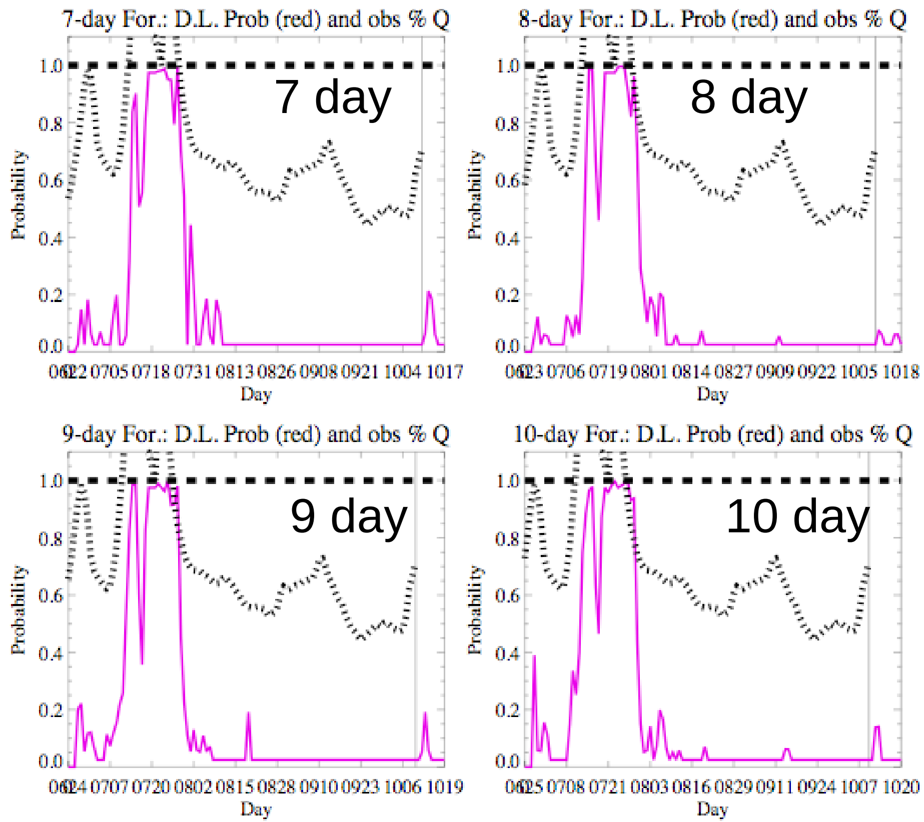
2004 Brahmaputra Forecast Results

Confidence Intervals

50% 95%

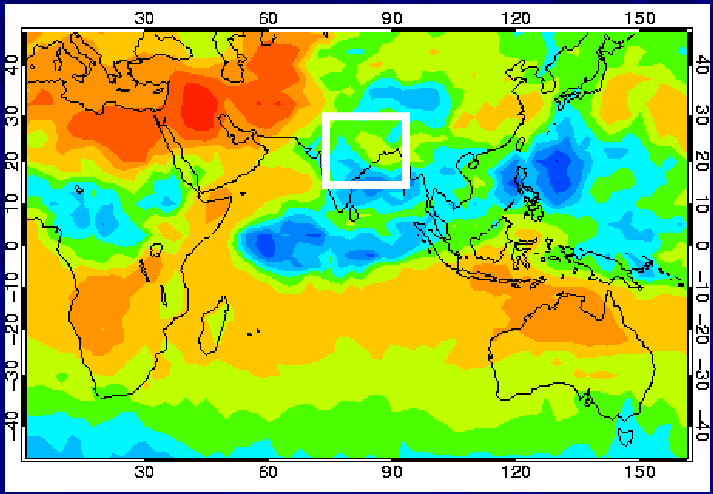


Above-Critical-Level Cumulative Probability



Overview:

Bangladesh flood forecasting

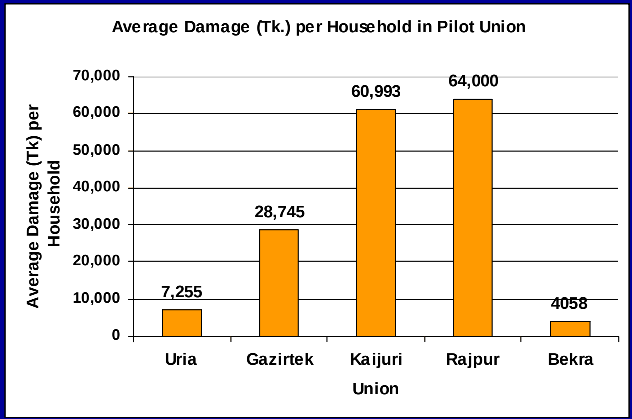


I. CFAB History -- sea-level backwater effects

II. 1-10 day Discharge Forecasting
  1. precipitation forecast bias removal
  2. multi-model river forecasting
  3. accounting for all error: weather and hydrologic errors

III. 2007 Floods and Warning System Pilot Areas

Five Pilot Sites chosen in 2006 consultation workshops based on biophysical, social criteria:



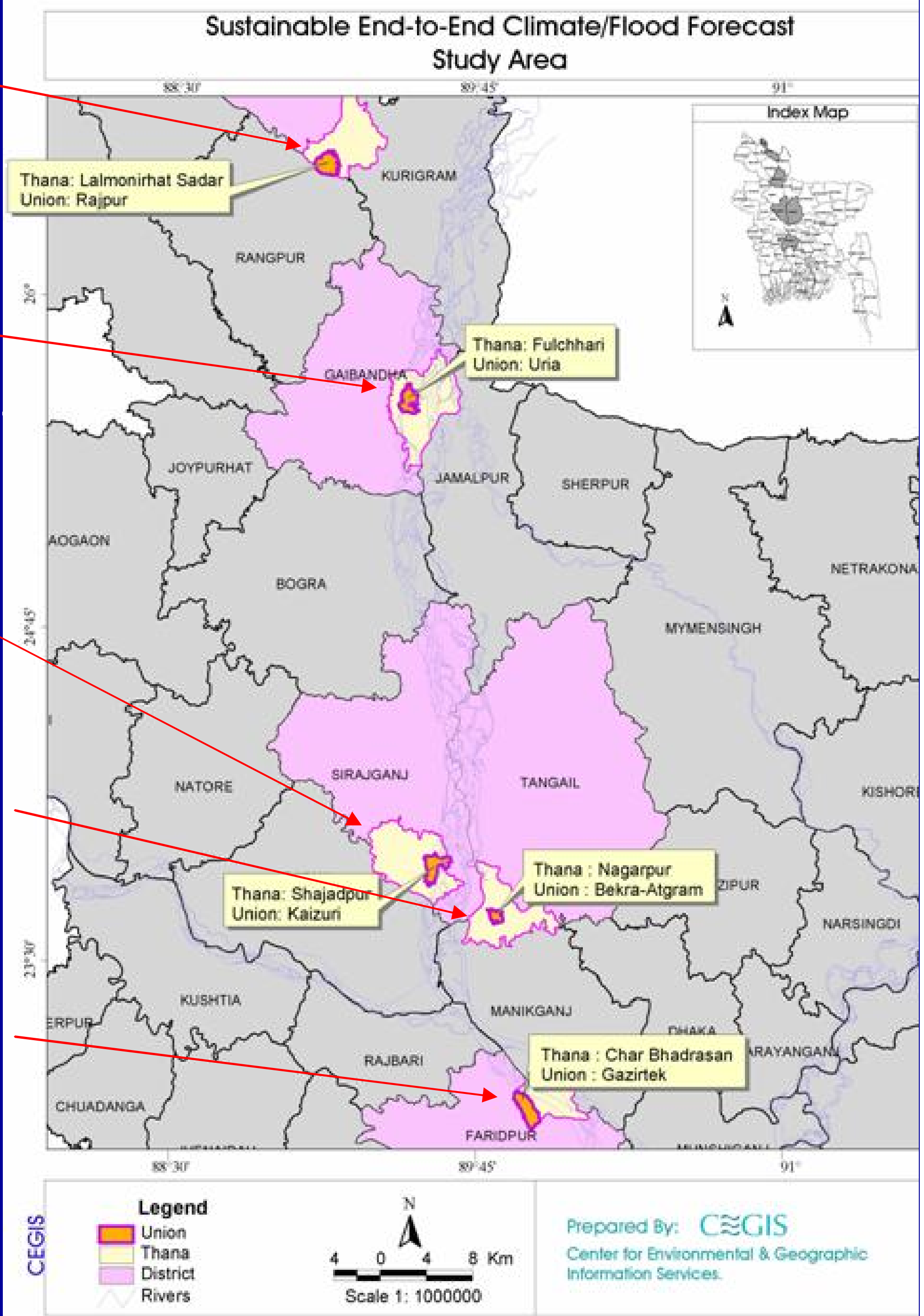
Rajpur Union
-- 16 sq km
-- 16,000 pop

Uria Union
-- 23 sq km
-- 14,000 pop.

Kaijuri Union
-- 45 sq km
-- 53,000 pop

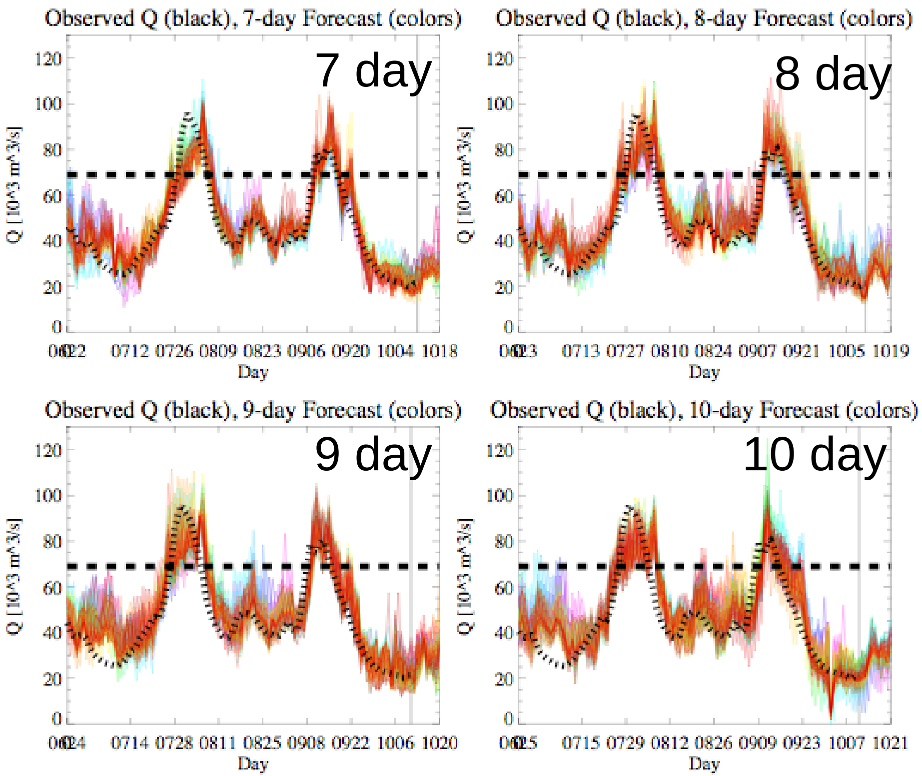
Bhekra Union
-- 11 sq km
-- 9,000 pop.

Gazirtek Union
-- 32 sq km
-- 23,000 pop.

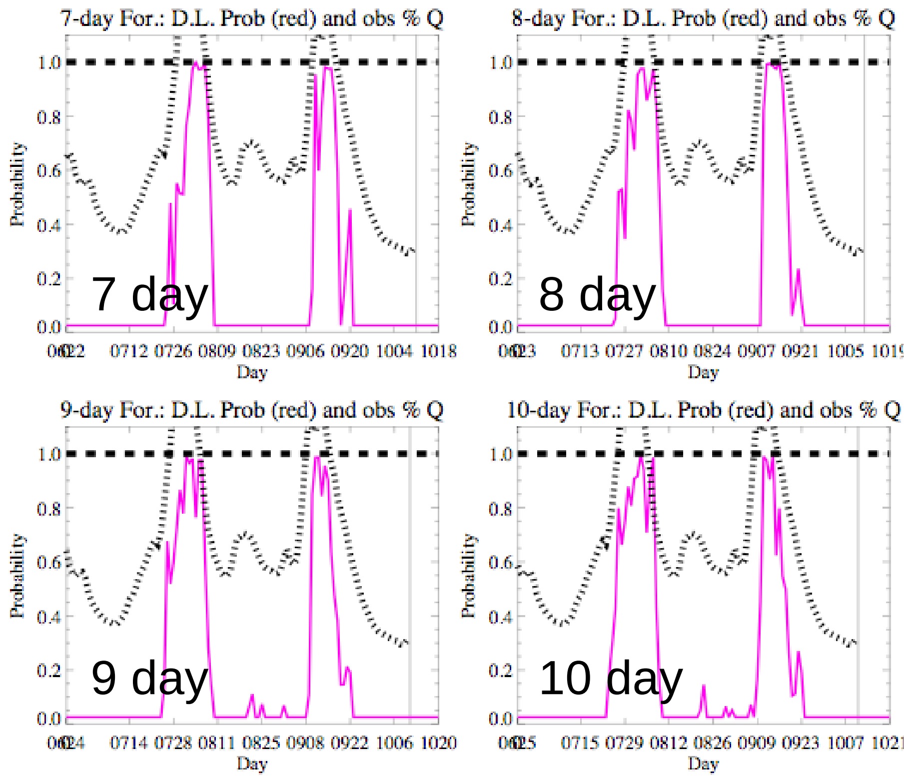


2007 Brahmaputra Ensemble Forecasts and Danger Level Probabilities

7-10 day Ensemble Forecasts



7-10 day Danger Levels

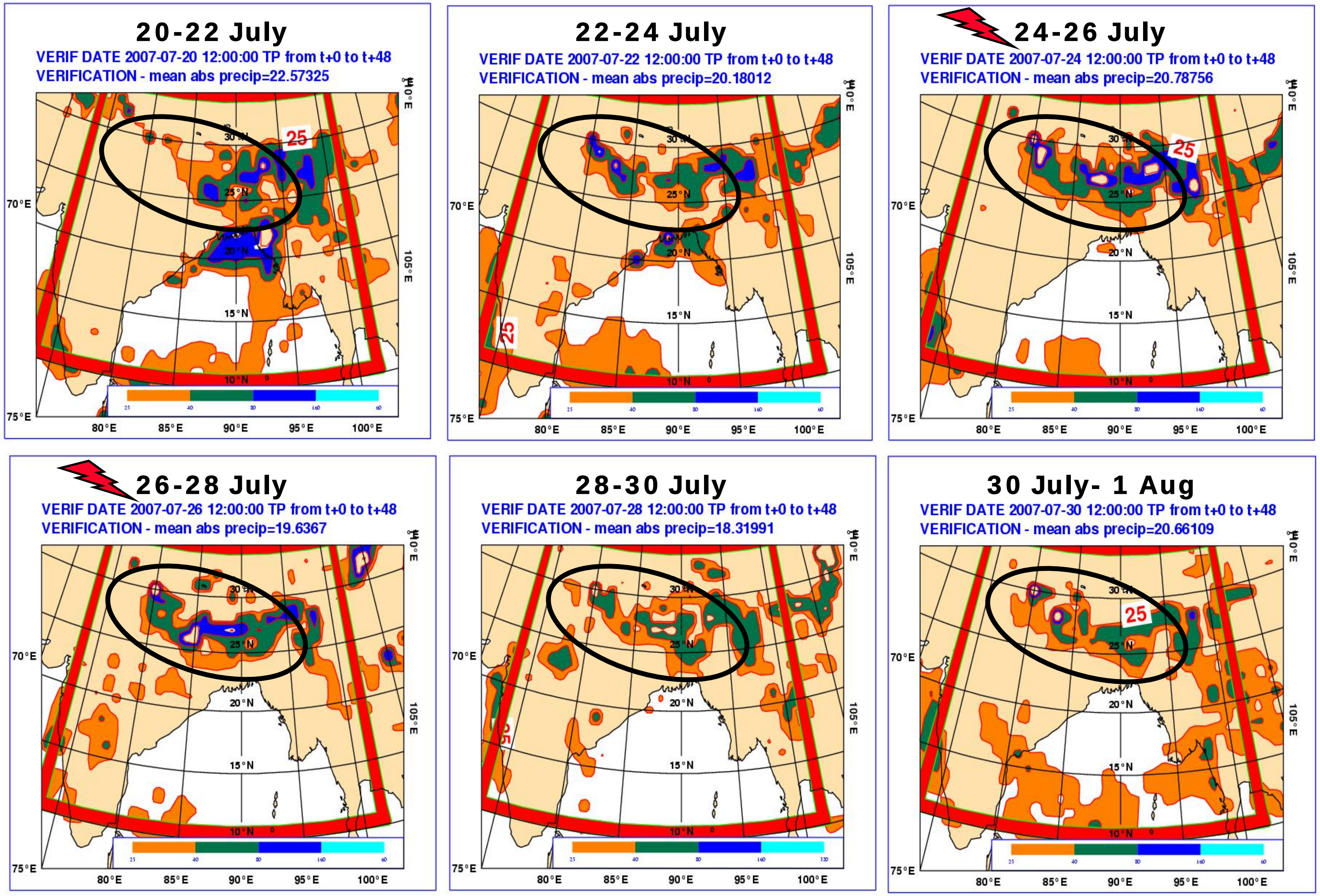


5.2 July/August 2007 floods in Bangladesh

"Seven people had died and thousands have been forced to leave their homes in Bangladesh because of worsening floods. Officials said that nearly half a million people remained marooned in seven flood-hit districts in the country's north west and in the south." (8 August 2007, from *http://news.bbc.co.uk*).

5.2 July/August 2007: floods in Bangladesh

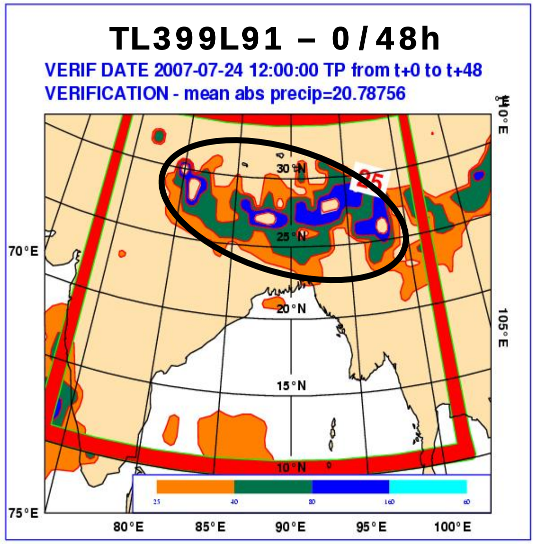
The floods were linked to intense precip towards the end of July, especially from 24 to 28 July.

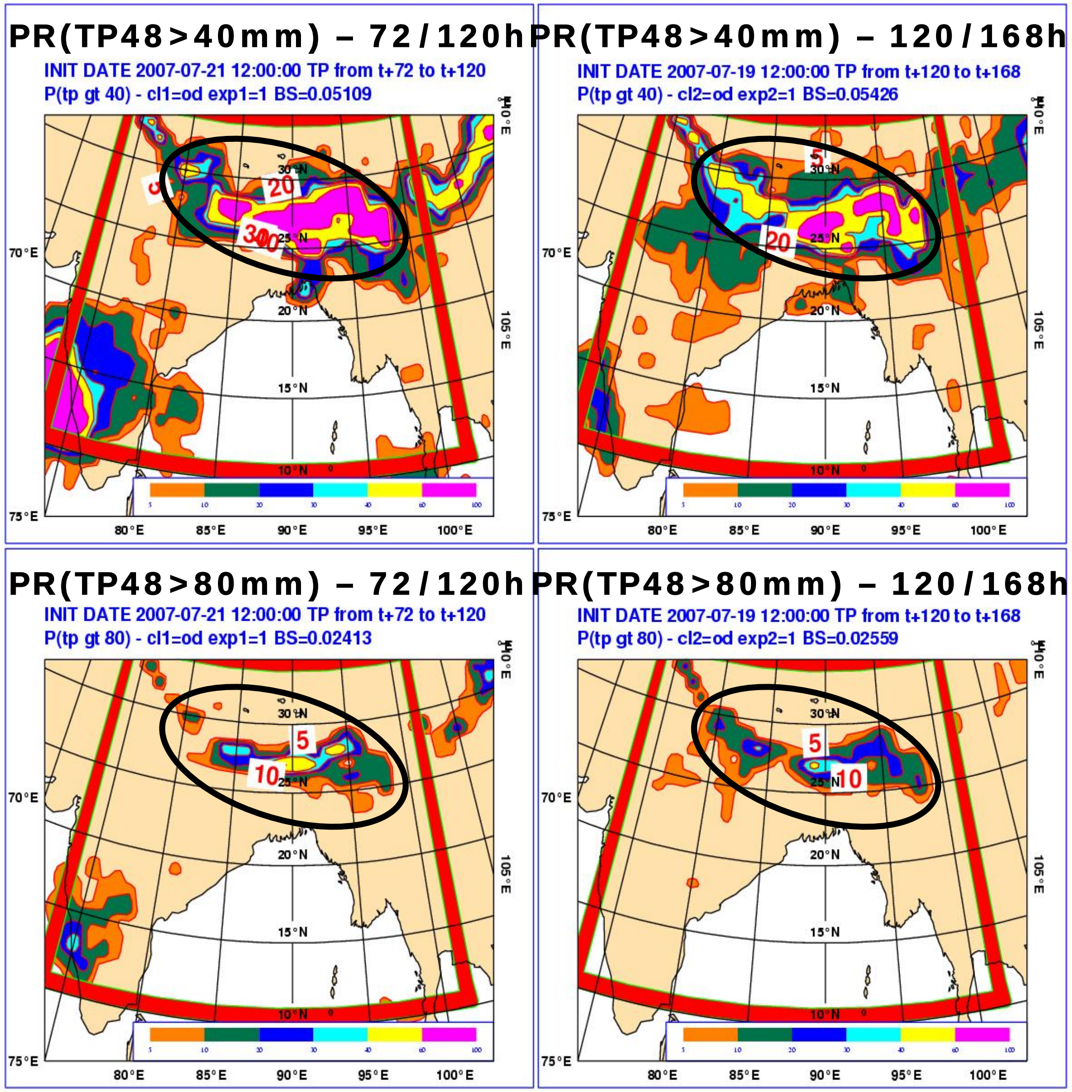


5.2 2007 floods in Bangladesh – fcs for 24/07-26/07

The right figure shows the 72/120h (left) and the 120/168h (right) fc probabilities of 48h-accumulated rainfall in excess of 40 (top) and 80 (bottom) mm (CI 5/10/20/30/40/60/110%).

The left 1-panel figure shows a 0/48h TL399L91 forecast (CI 25/40/80/160/320mm).



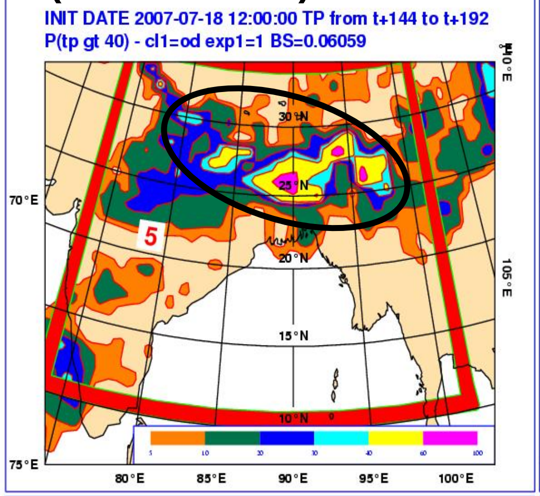


5.2 2007 floods in Bangladesh – fcs for 24/07-26/07

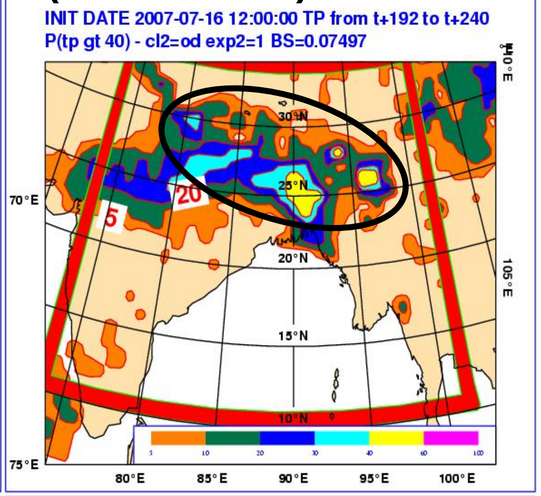
The right figure shows the 144/192h (left) and 192/240h (right) fc probabilities of 48h-accumulated rainfall in excess of 40 (top) and 80 (bottom) mm (CI 5/10/20/30/40/60/110%).

The left 1-panel figure shows a 0/48h TL399L91 forecast (CI 25/40/80/160/320mm).

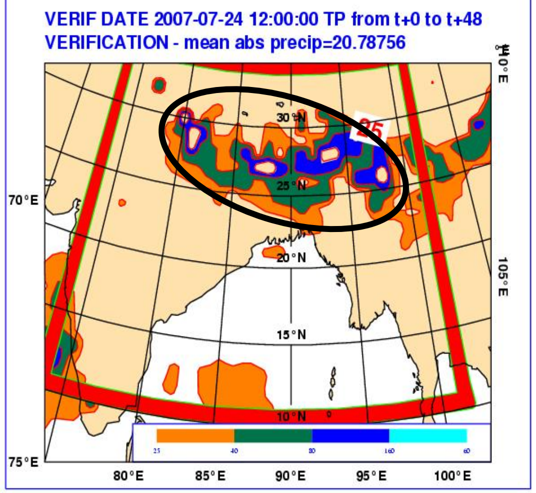
PR(TP48>40mm) – 144/192h



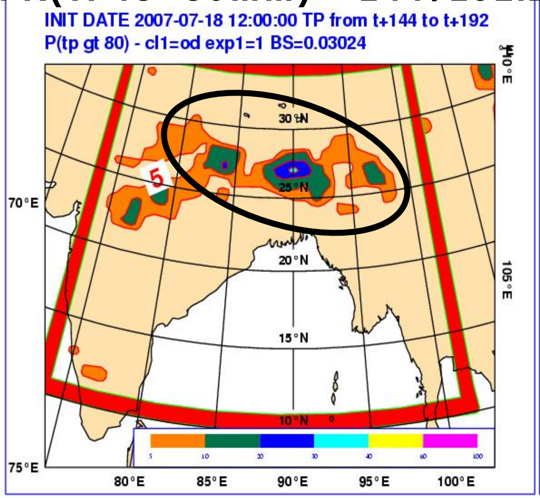
PR(TP48>40mm) – 192/240h



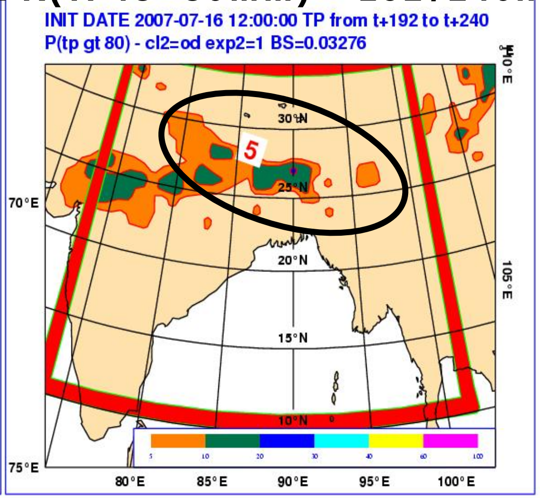
TL399L91 – 0/48h



PR(TP48>80mm) – 144/192h



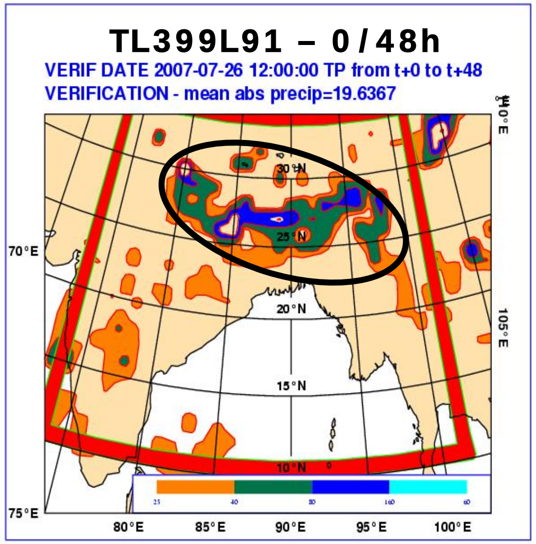
PR(TP48>80mm) – 192/240h

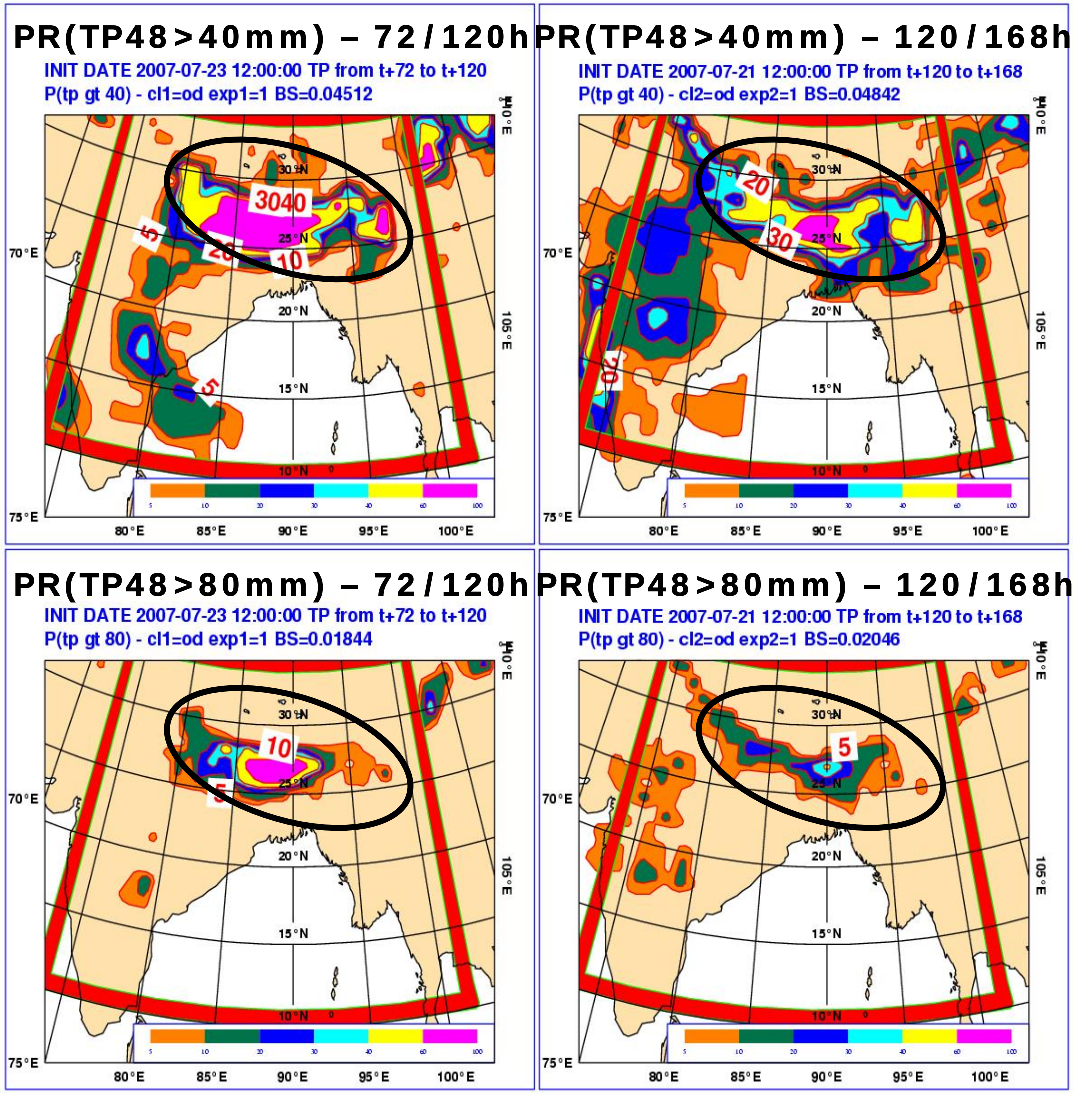


5.2 2007 floods in Bangladesh – fcs for 26/07-28/07

The right figure shows the 72/120h (left) and the 120/168h (right) fc probabilities of 48h-accumulated rainfall in excess of 40 (top) and 80 (bottom) mm (CI 5/10/20/30/40/60/110%).

The left 1-panel figure shows a 0/48h TL399L91 forecast (CI 25/40/80/160/320mm).



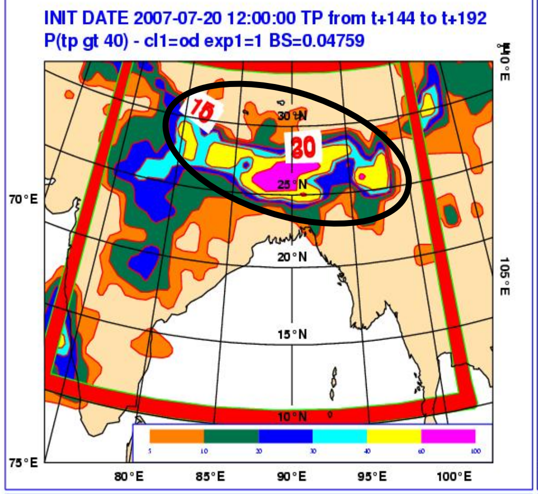


5.2 2007 floods in Bangladesh – fcs for 26/07-28/07

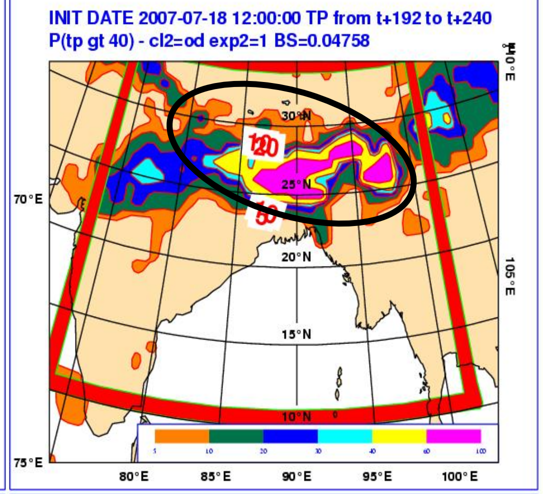
The right figure shows the 144/192h (left) and 192/240h (right) fc probabilities of 48h-accumulated rainfall in excess of 40 (top) and 80 (bottom) mm (CI 5/10/20/30/40/60/110%).

The left 1-panel figure shows a 0/48h TL399L91 forecast (CI 25/40/80/160/320mm).

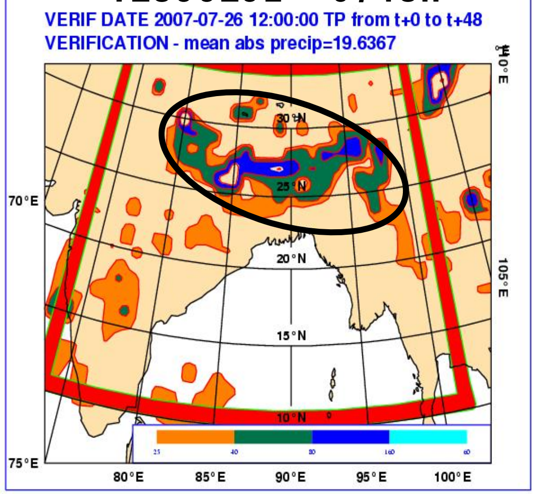
PR(TP48>40mm) – 144/192h



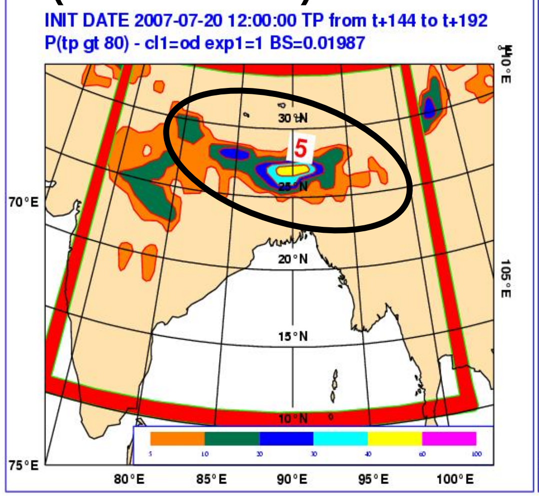
PR(TP48>40mm) – 192/240h



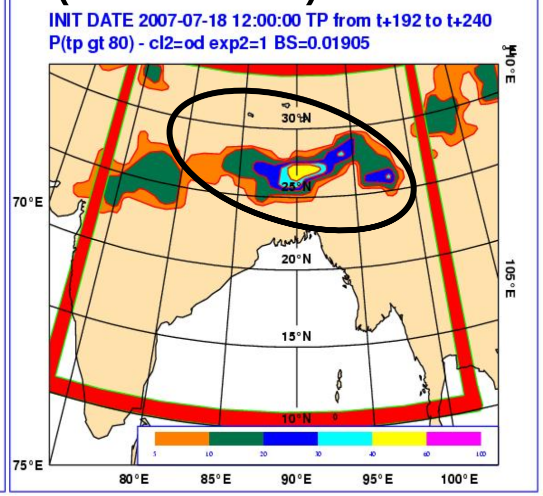
TL399L91 – 0/48h



PR(TP48>80mm) – 144/192h



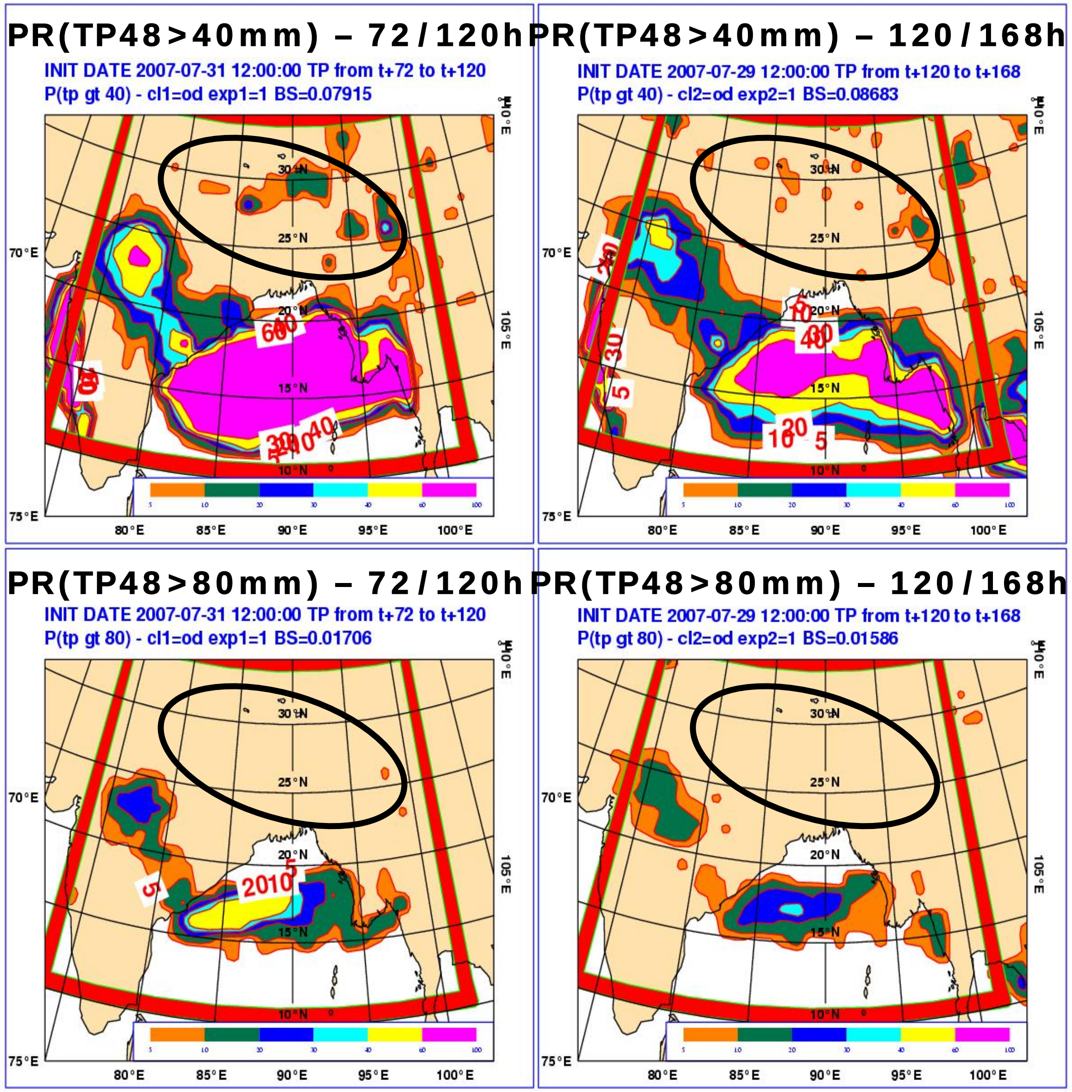
PR(TP48>80mm) – 192/240h

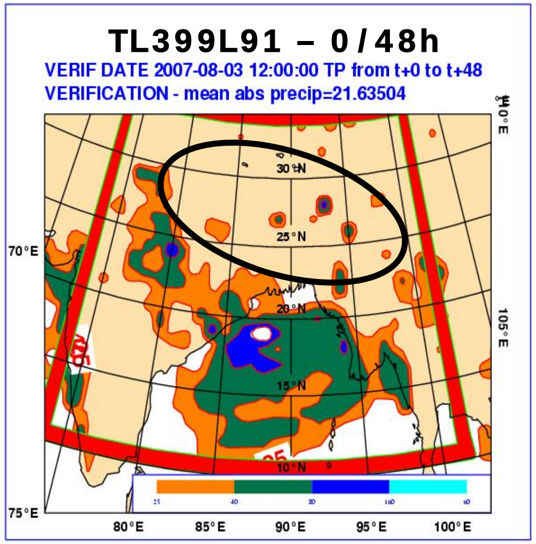


5.2 2007 floods in Bangladesh – fcs for 03/08-05/08

The right figure shows the 72/120h (left) and the 120/168h (right) fc probabilities of 48h-accumulated rainfall in excess of 40 (top) and 80 (bottom) mm (CI 5/10/20/30/40/60/110%).

The left 1-panel figure shows a 0/48h TL399L91 forecast (CI 25/40/80/160/320mm).





Response of National Institutions for 2007 flood forecasts

- Flood Forecasting and Warning Center (FFWC) incorporated the CFAB forecasts to produce water level forecasts for many locations along Brahmaputra and Ganges well in advance

- National level Disaster Emergency Response Group prepared emergency response plans, logistics for preparedness and relief in advance

Response of local institutions for 2007 flood forecasts

- Local project partners used community vulnerability maps to assess the risk of flooding

- Local NGOs and CBOs mobilise boats to rescue people and livestock from the “char” areas

Selvaraju (ADPC)

Community level decision responses for 2007 flood forecasts (High lands)

- Protected homestead vegetables by creating adequate drainage facilities

- Livestock was protected in high lands with additional dry fodder (paddy straw)

- Early harvesting of B.aman rice and jute anticipating floods in Gaibandha and Sirajganj, respectively.

Selvaraju (ADPC)

Community level decision responses for 2007 flood forecasts (Low lands)

- Secured cattle, poultry birds, homestead vegetables, protected fishery by putting nets in advance

- Planed to evacuate and identified high grounds with adequate communication and sanitation facilities

Community level decision responses for 2007 flood forecasts (Low lands)

"… on 25th July we started communicating the information to as many people as possible … especially those people living in river islands ("chars")..."

"On the 28th and 29th, meetings were organized in villages near Rangpur … they perceived that the river water level would fall, but our forecasts showed a rising trend…[with] significant chance of overflow and breaches [of weak] embankments ... We engaged … an evacuation plan urgently"

"We communicated the forecast to another pilot union … on July 26th … to mobilize resources for evacuation ... All the six villages in the union were later flooded to a height of 4-6 feet on July 29th… about 35% of the people in the union were evacuated in advance."

"The communities in Rajpur Union … were able to use the forecast for … mobilizing food, safe drinking water for a week to 10 days, protecting their … rice seedlings, fishing nets, and … fish pods."

Conclusions

- 2003: CFAB forecast went operational
- 2004:
  -- Forecasts fully-automated
  -- CFAB became an entity of Bangladesh government
  -- forecasted severe Brahmaputra flooding event
- 2006:
  -- Forecasts incorporated into operational FFWC model
  -- 5 pilot study dissemination areas trained
- 2007: 5 pilot areas warned many days in-advance during two severe flooding events

Future Work

- Dartmouth FloodWatch Program river discharge estimates assimilated for improved river routing

- Fully-automated forecasting scheme relying on global inputs (ECMWF forecasts, satellite rainfall) rapidly and cost-effectively applied to other river basins with in-country capacity building


Thank You!

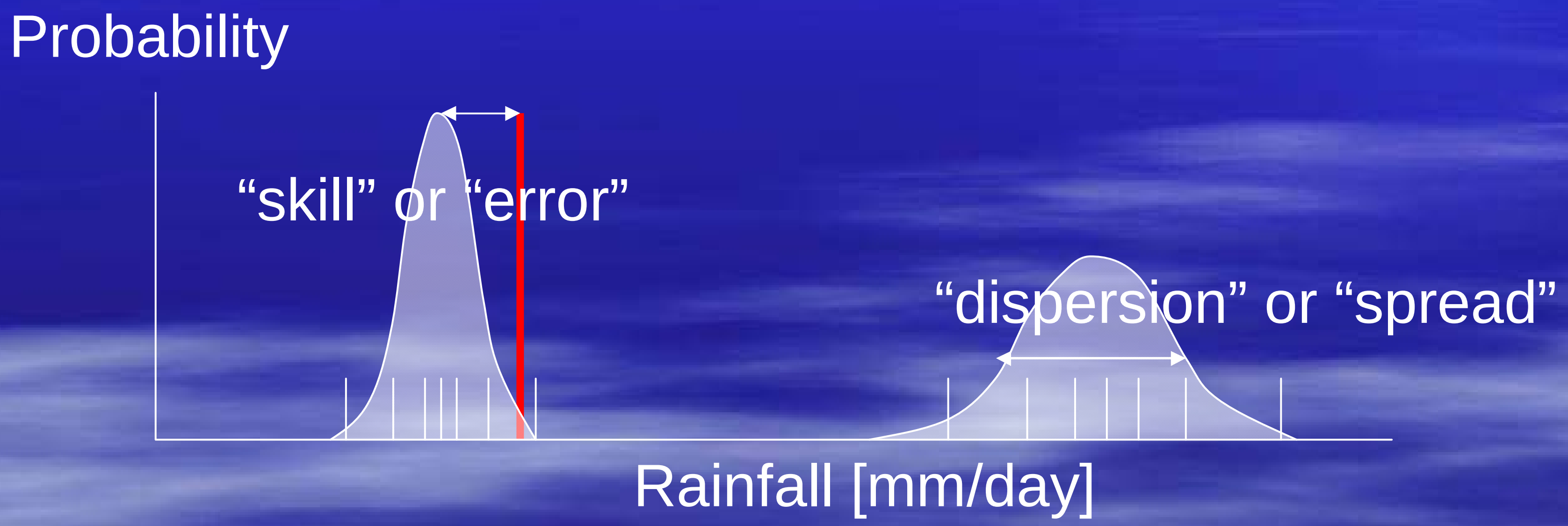
Verifying the Relationship between Ensemble Forecast Spread and Skill

Tom Hopson ASP-RAL, NCAR

Motivation for generating ensemble forecasts:

1) Greater accuracy of ensemble mean forecast (half the error variance of single forecast)
2) Likelihood of extremes
3) Non-Gaussian forecast PDF's
4) Ensemble spread as a representation of forecast uncertainty

Ensemble “Spread” or “Dispersion” Forecast “Skill” or “Error”



ECMWF Brahmaputra catchment Precipitation Forecasts vs TRMM/CMORPH/CDC-GTS Rain gauge Estimates

<u>Points:</u>

-- ensemble dispersion increases with forecast lead-time

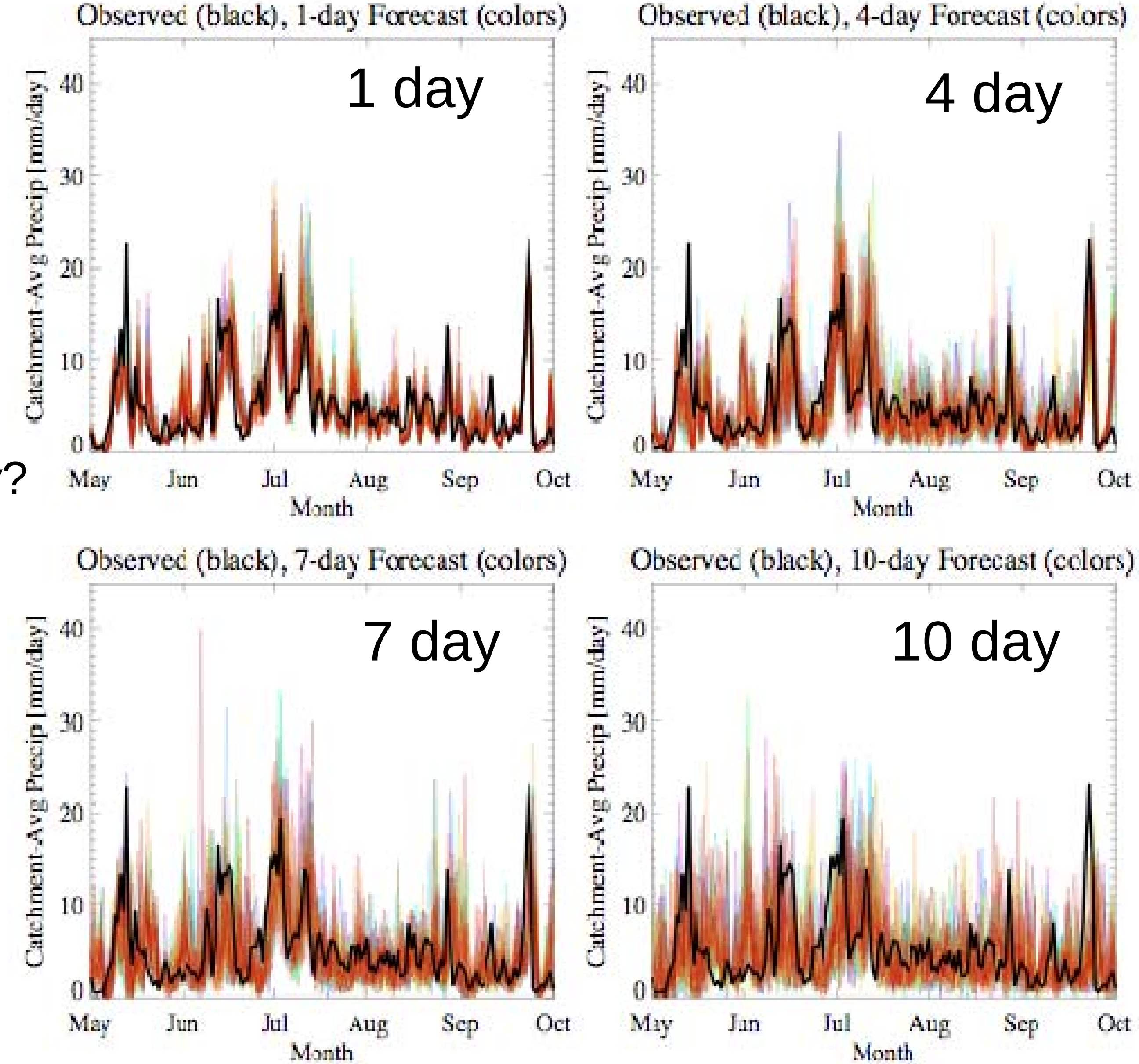
-- dispersion variability within each lead-time

-- Provide information about forecast certainty?

<u>How to Verify?</u>

-- rank histogram? No. (Hamill, 2001)

-- ensemble spread-forecast error correlation?



Overview -- Useful Ways to Measure Ensemble Forecast System's Spread-Skill Relationship:

- Spread-Skill Correlation misleading (Houtekamer, 1993; Whitaker and Loughe, 1998)
- Propose 3 options

  1) "normalized" spread-skill correlation

  2) "binned" spread-skill correlation

  3) "binned" rank histogram
- Considerations:

  -- sufficient variance of the forecast spread? (outperforms ensemble mean forecast dressed with error climatology?)

  -- outperform heteroscedastic error model?

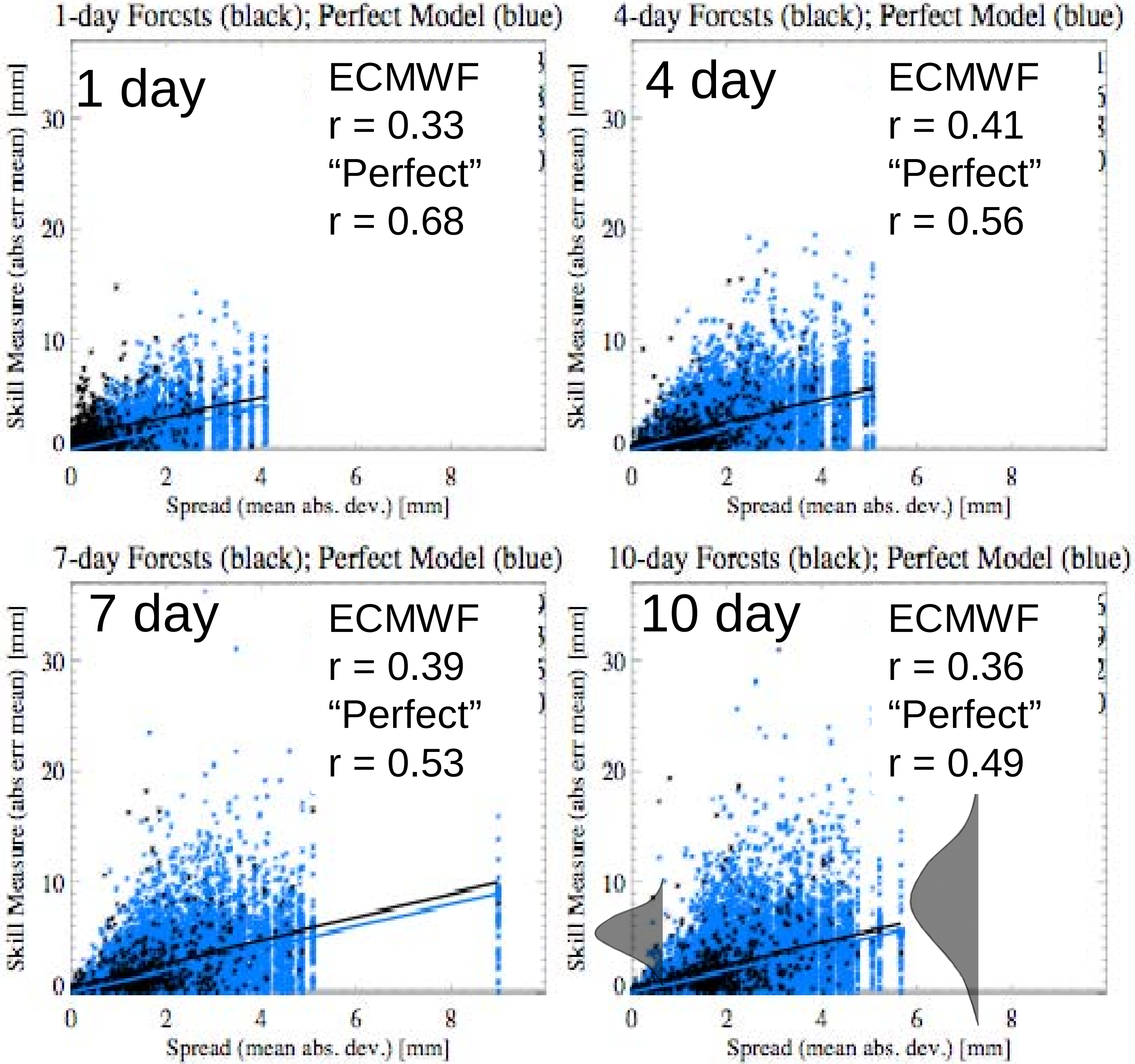
  -- account for observation uncertainty and under-sampling

Naturally Paired Spread-skill measures:

- Set I:
  - Error measures:
    - absolute error of the ensemble mean forecast
    - absolute error of a single ensemble member
  - Spread measures:
    - ensemble standard deviation
    - mean absolute difference of the ensembles about the ensemble mean
- Set II (squared moments):
  - Error measures:
    - square error of the ensemble mean forecast
    - square error of a single ensemble member
  - Spread measures:
    - ensemble variance

Spread-Skill Correlation …

- ECMWF spread-skill (black) correlation << 1
- Even "perfect model" (blue) correlation << 1 and varies with forecast lead-time



Limits on the spread-skill Correlation for a "Perfect" Model

Governing ratio, g:

(s = ensemble spread: variance, standard deviation, etc.)

$$g = \frac{\langle s \rangle^2}{\langle s^2 \rangle} = \frac{\langle s \rangle^2}{\langle s \rangle^2 + \mathrm{var}(s)}$$

Limits:

Set I

$$g \to 1, \quad r \to 0$$

$$g \to 0, \quad r \to \sqrt{2/\pi}$$

Set II

$$g \to 1, \quad r \to 0$$

$$g \to 0, \quad r \to \sqrt{1/3}$$

What's the Point?
-- correlation depends on how spread-skill defined
-- depends on stability properties of the system being modeled
-- even in "perfect" conditions, correlation much less than 1.0

How can you assess whether a forecast model's varying ensemble spread has utility?

- Positive correlation? Provides an indication, but how close to a "perfect model".
- Uniform rank histogram? No guarantee.

1) One option -- "normalize" away the system's stability dependence via a skill-score:

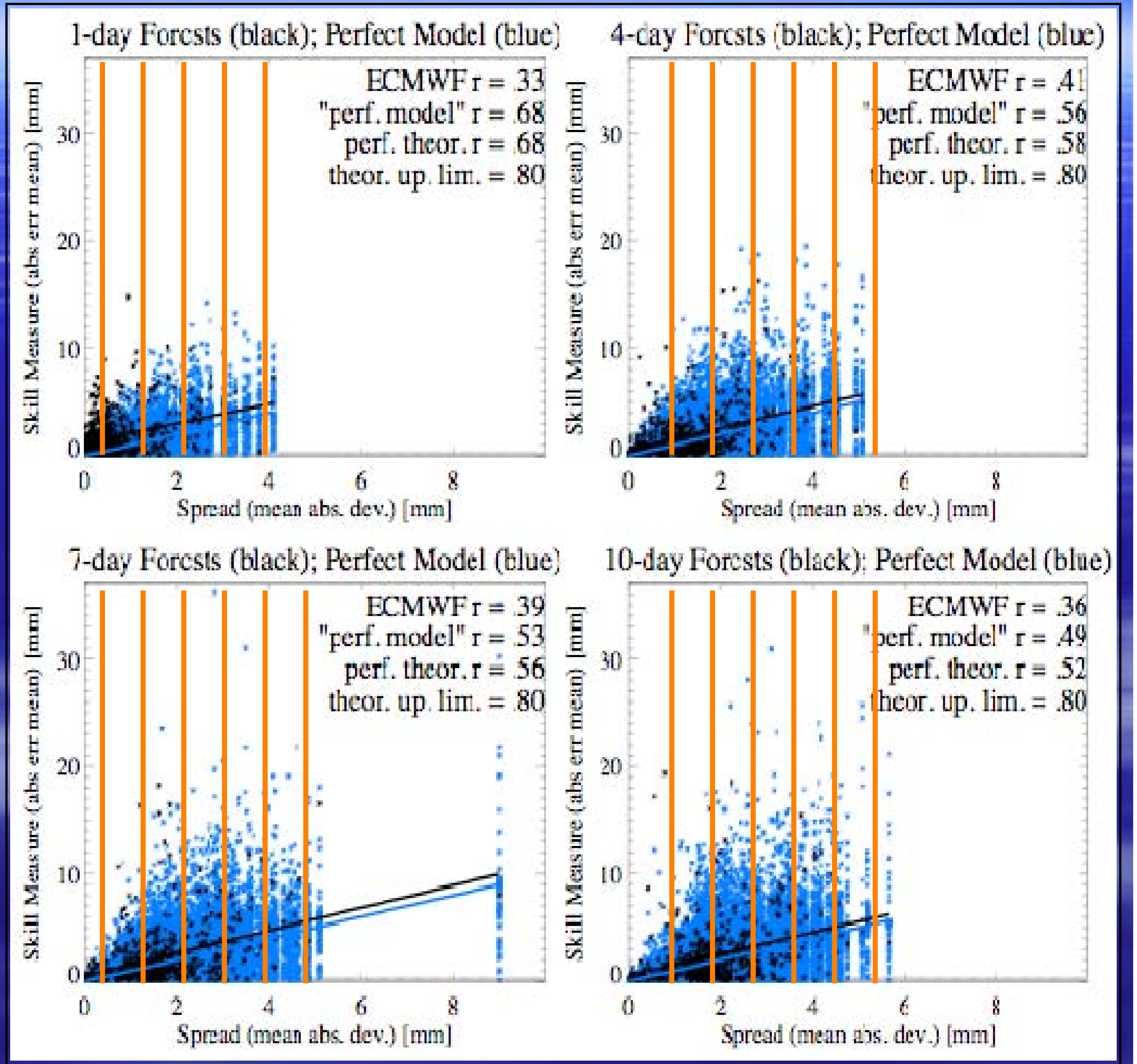
$$SS_r = \frac{r_{frcst} - r_{ref}}{r_{perf} - r_{ref}} X100\%$$

two other options …

Assign dispersion bins, then:

2) Average the error values in each bin, then correlate

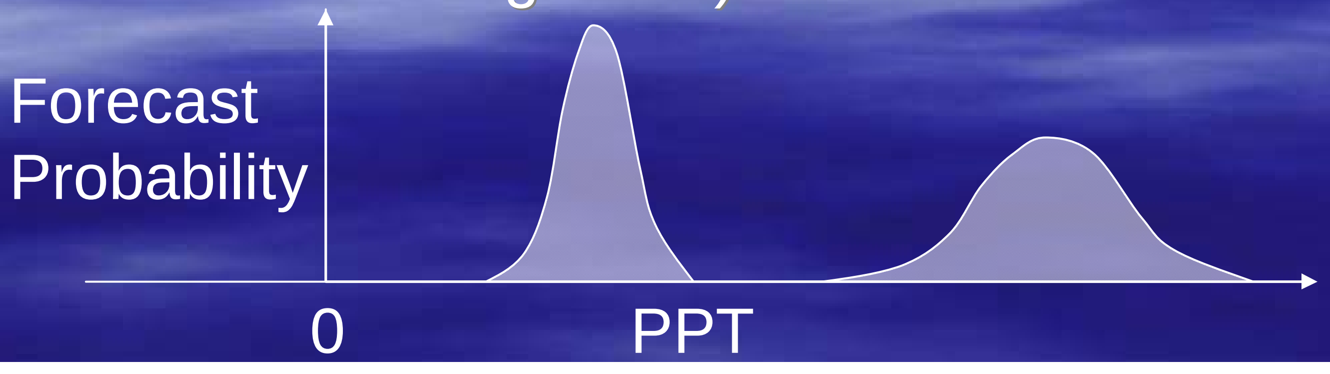
3) Calculate individual rank histograms for each bin, convert to a scalar measure



Skill Score approach

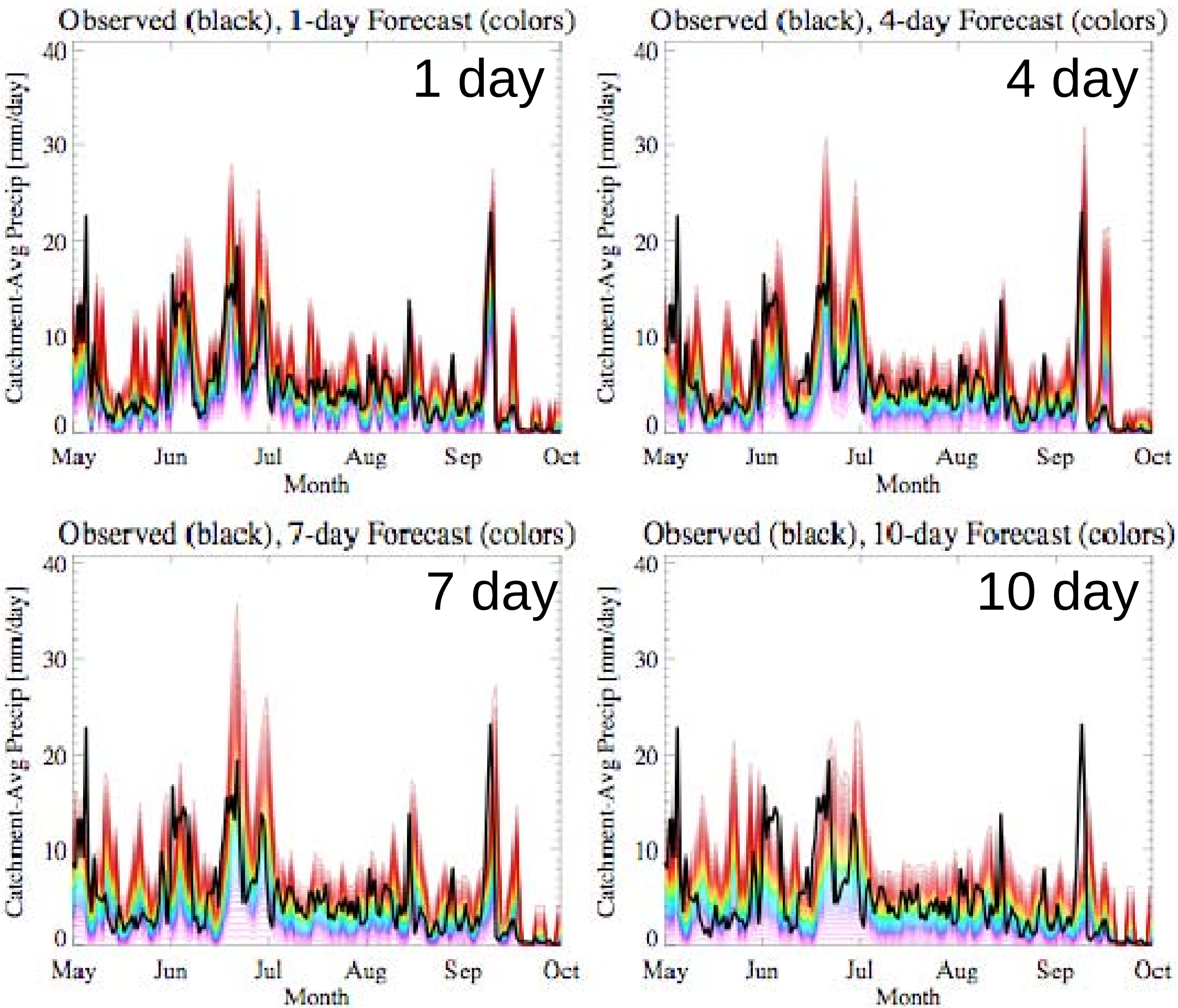
$$SS_r = \frac{r_{frcst} - r_{ref}}{r_{perf} - r_{ref}} X100\%$$

- r_{perf} -- randomly choose one ensemble member as verification
- r_{ref} -- three options:
  1) constant "climatological" error distribution (r --> 0)
  2) "no-skill" -- randomly chosen verification
  3) heteroscedastic model (forecast error dependent on forecast magnitude)

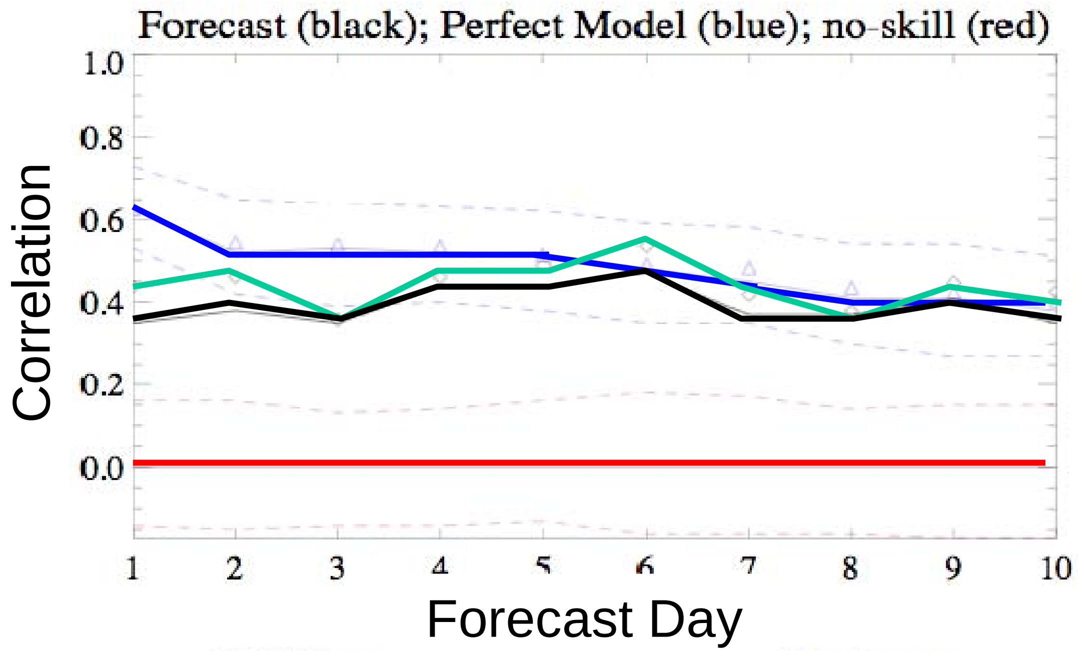


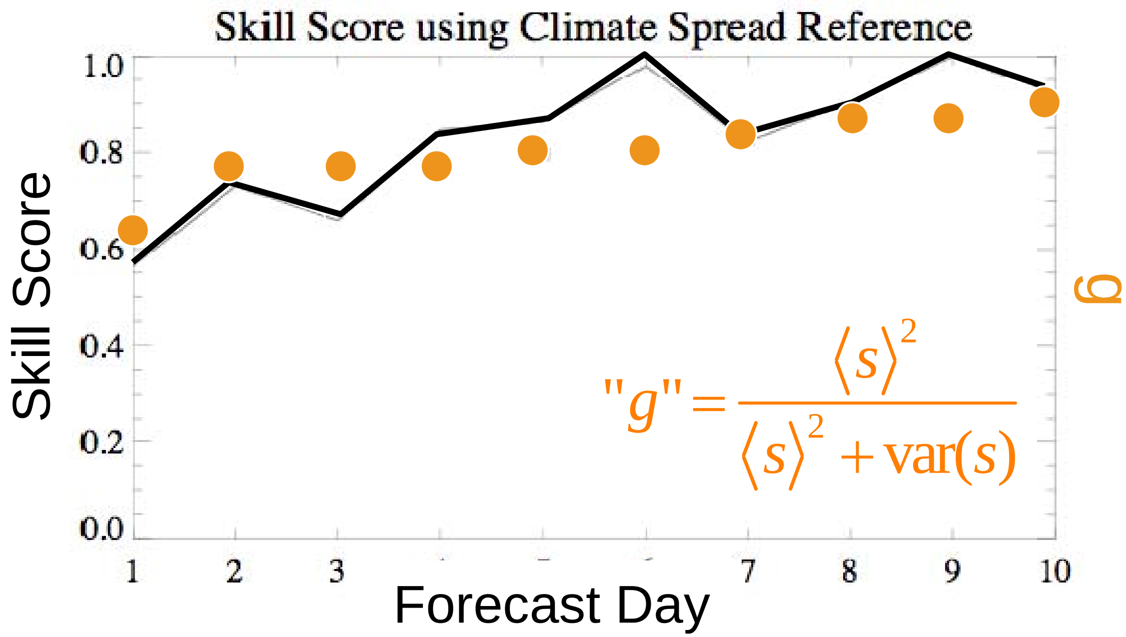
<u>Heteroscedastic Error model</u> dressing the Ensemble Mean Forecast (ECMWF Brahmaputra catchment Precipitation)

- From fit heteroscedastic error model, ensembles can be generated (temporally uncorrelated for clarity)



Option 1: “Normalized” Spread-skill Correlation

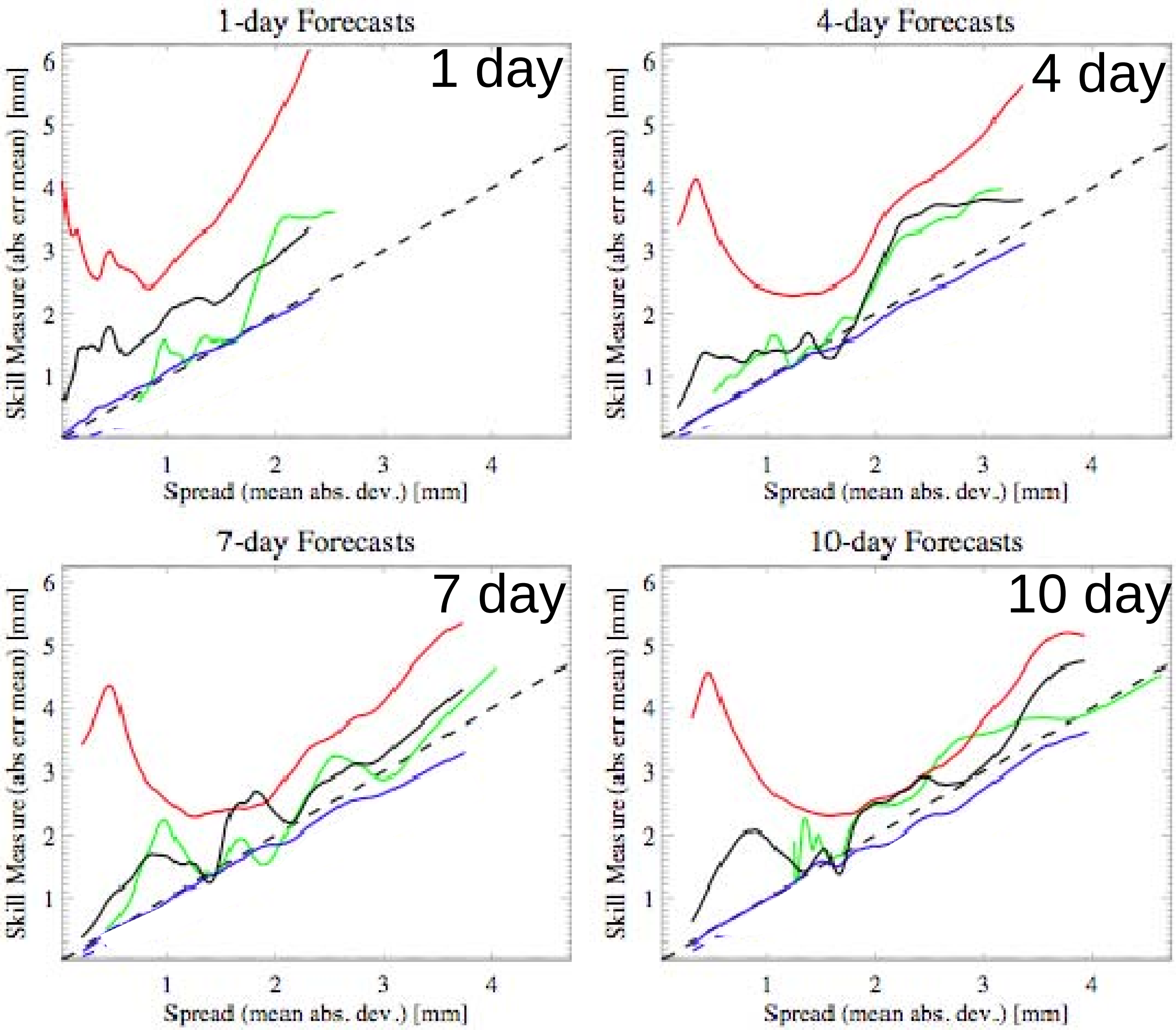




- Operational Forecast spread-skill approaches “perfect model”
- However, heteroscedastic model outperforms

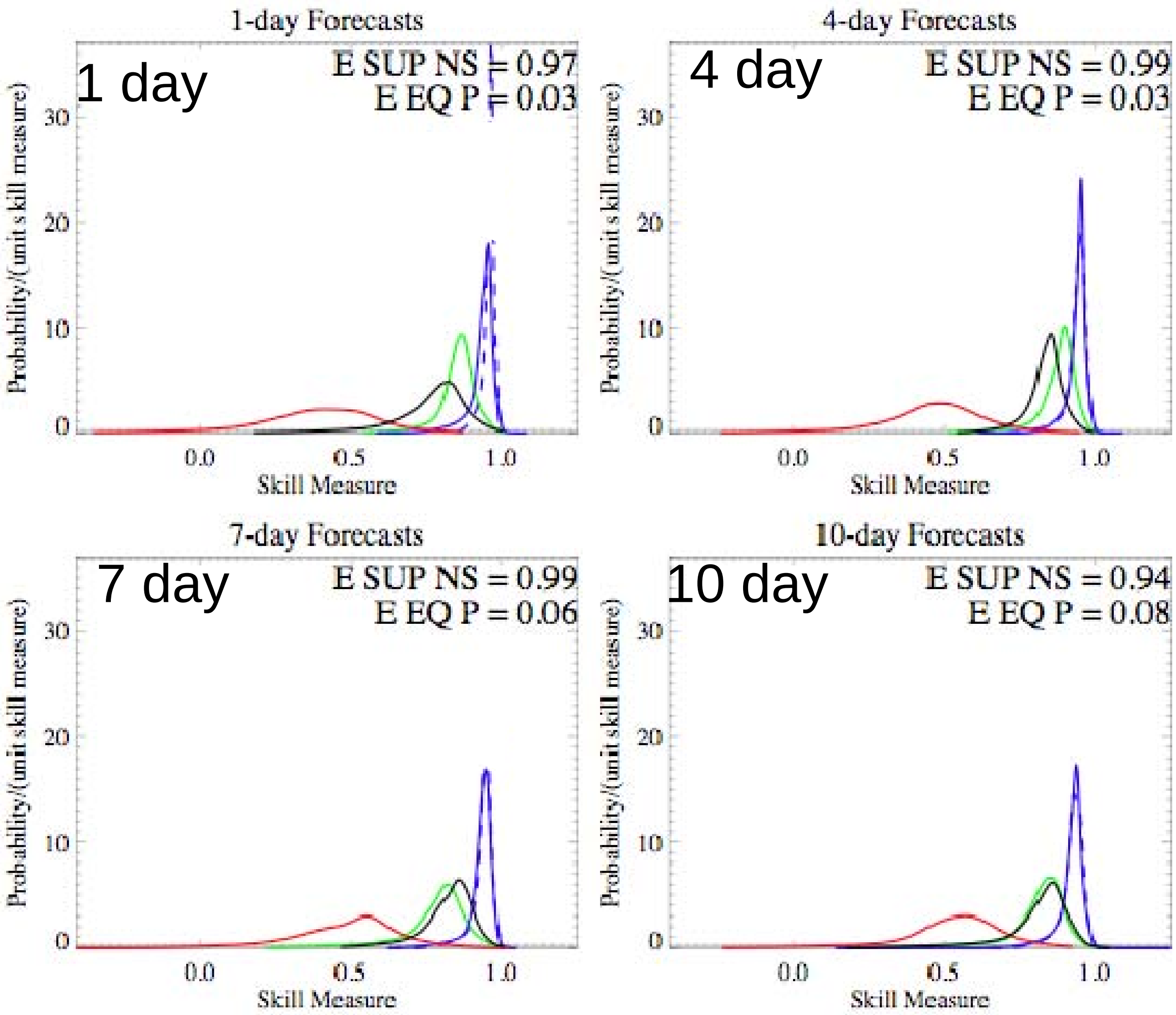
- Skill-scores show utility in forecast ensemble dispersion improves with forecast lead-time
- However, “governing ratio” shows utility diminishing with lead-time

Option 2: "binned" Spread-skill Correlation



- "perfect model" (blue) approaches perfect correlation
- "no-skill" model (red) has expected under-dispersive "U-shape"
- ECMWF forecasts (black) generally under-dispersive, improving with lead-time
- Heteroscedastic model (green) slightly better(worse) than ECMWF forecasts for short(long) lead-times

Option 2: PDF's of "binned" spread-skill correlations -- accounting for sampling and verification uncertainty



- "perfect model" (blue) PDF peaked near 1.0 for all lead-times
- "no-skill" model (red) PDF has broad range of values
- ECMWF forecast PDF (black) overlaps both "perfect" and "no-skill" PDF's
- Heteroscedastic model (green) slightly better(worse) than ECMWF forecasts for short(long) lead-times

Conclusions

- Spread-skill correlation can be misleading measure of utility of ensemble dispersion
  - Dependent on “stability” properties of environmental system
- 3 alternatives:

  1) “normalized” (skill-score) spread-skill correlation

  2) “binned” spread-skill correlation

  3) “binned” rank histogram
- ratio of moments of “spread” distribution also indicates utility

  -- if ratio --> 1.0, fixed “climatological” error distribution may provide a far cheaper estimate of forecast error
- Truer test of utility of forecast dispersion is a comparison with a heteroscedastic error model => a statistical error model may be superior (and cheaper)
- Important to account for observation and sampling uncertainties when doing a verification

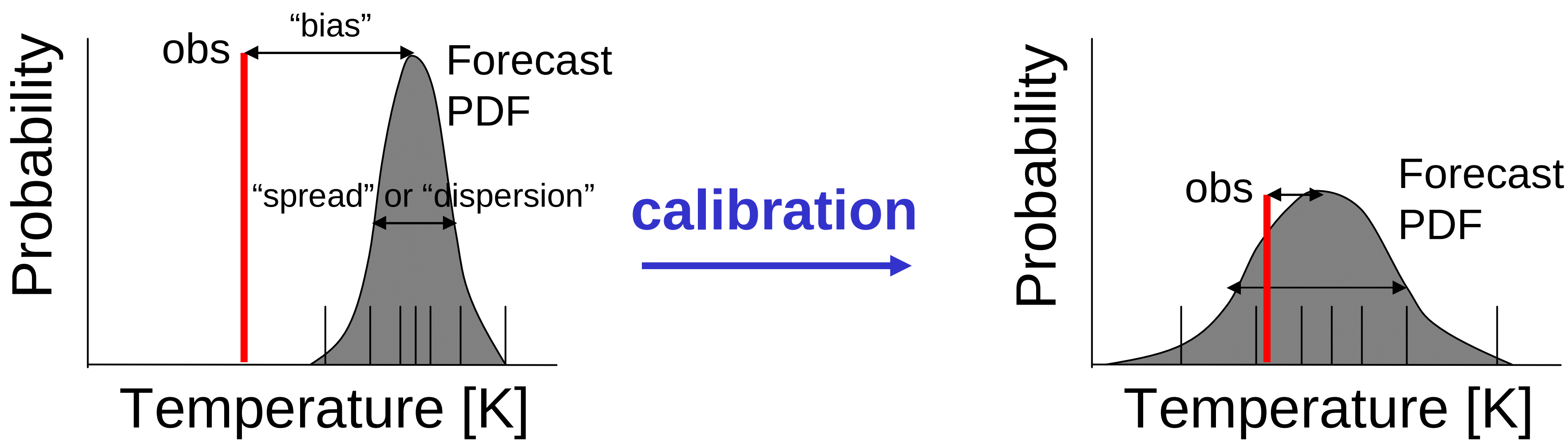
For more information and publications: hopson@ucar.edu

Motivation for Generating Ensemble Forecasts

1) Greater accuracy of ensemble mean forecast (half the error variance of single forecast)
2) Likelihood of extremes
3) Non-Gaussian forecast PDF's
4) Ensemble spread as a representation of forecast uncertainty

=> All rely on forecasts being calibrated

What do we mean by “calibration” or “post-processing”?



<u>Post-processing has corrected:</u>

- the “on average” bias
- as well as under-representation of the 2nd moment of the empirical forecast PDF (i.e. corrected its “dispersion” or “spread”)

Proper Ensemble Forecast Post-processing is expensive

- Proper calibration requires multiple years of hindcast generation

⇒Requiring significant allocation of computational resources, along with scientific manpower investment

Begs the question: Do the gains justify such expense?

Specific Benefits of Post-Processing

Improvements in:

- statistical accuracy, bias, and, reliability

- Correcting basic forecast statistics (increasing user “trust”)

- discrimination and sharpness

- Increasing “information content”; in many cases, gains equivalent to years of NWP model development!

⇒Relatively inexpensive!

(cont) Benefits of Post-Processing

NCAR

Essential for tailoring to local application:

- NWP provides spatially- and temporally-averaged gridded forecast output

=> Applying gridded forecasts to point locations requires location specific calibration to account for spatial- and temporal- variability (=> increasing ensemble dispersion)

What are we doing …

Working with NOAA Reforecast Data Set for algorithm development:

- Developed post-processing procedure for temperature (applicable to other weather variables)

- Introduce Quantile Regression

  - powerful under-utilized approach in atmospheric applications

- Other more-standard approaches (i.e. Logistic Regression) employed under Quantile Regression framework

Results of this study applied to 30 member HPC operational ensemble forecasts, available in 6 - 12 months

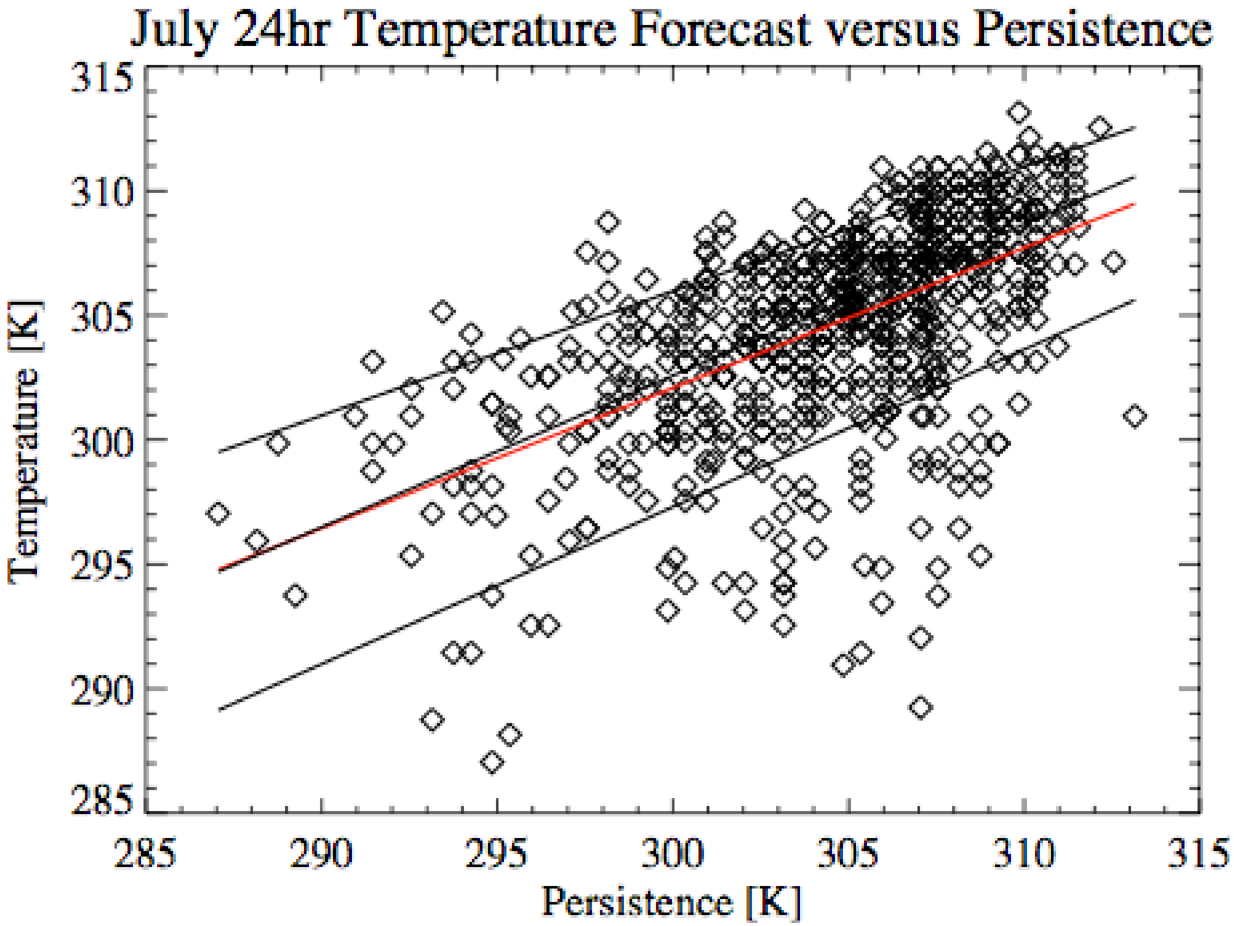
Ensemble reforecast and observations

(Hamill, Whitaker, Wei 2004: MWR)

- 1979-2001 15-member 24hr ensemble forecasts (MRF ca. 1998; bred modes)
- Conditional climatology for winter and summer:
  - include forecasts valid 15 Jan/July +/- 15 days
- persistence is obs valid at initialization

Surface temperature observations at Salt Lake City (KSLC) valid 00 UTC (4 PM LST)

Example of Quantile Regression (QR)

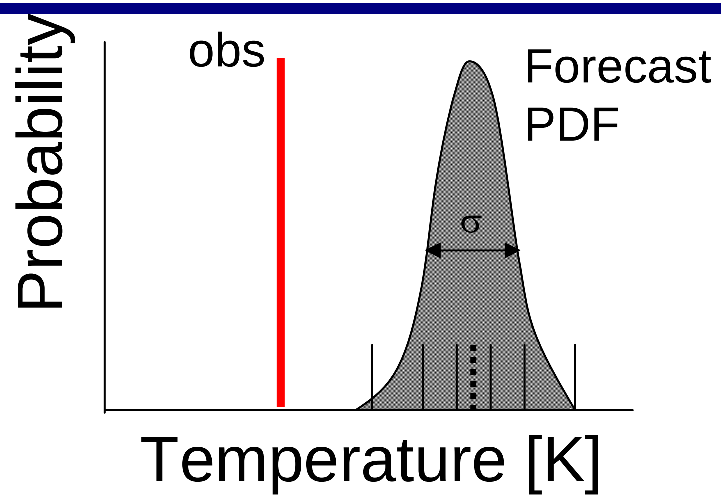


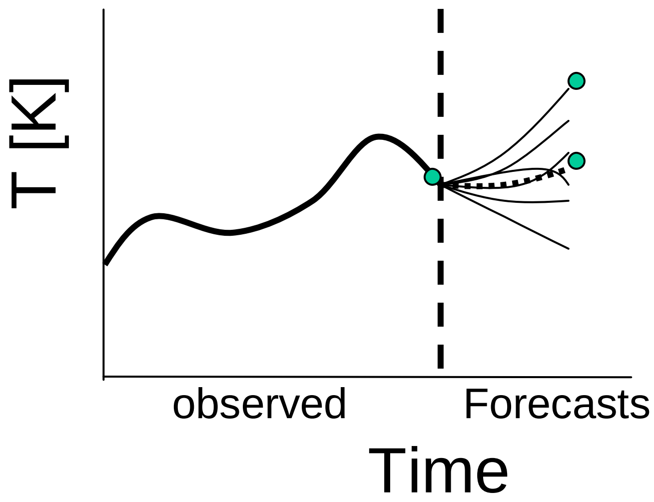
Our application

Fitting T quantiles using QR conditioned on:

1) Reforecast ens
2) ensemble mean
3) ensemble median
4) ensemble stdev
5) Persistence
6) Log Reg quantile

Calibration Procedure





1) Fit Logistic Regression (LR) ensembles
   - Calibrate CDF over prescribed set of climatological quantiles
   - For each forecast: resample 15 member ensemble set

<u>For each quantile:</u>

2) Perform a "climatological" fit to the data

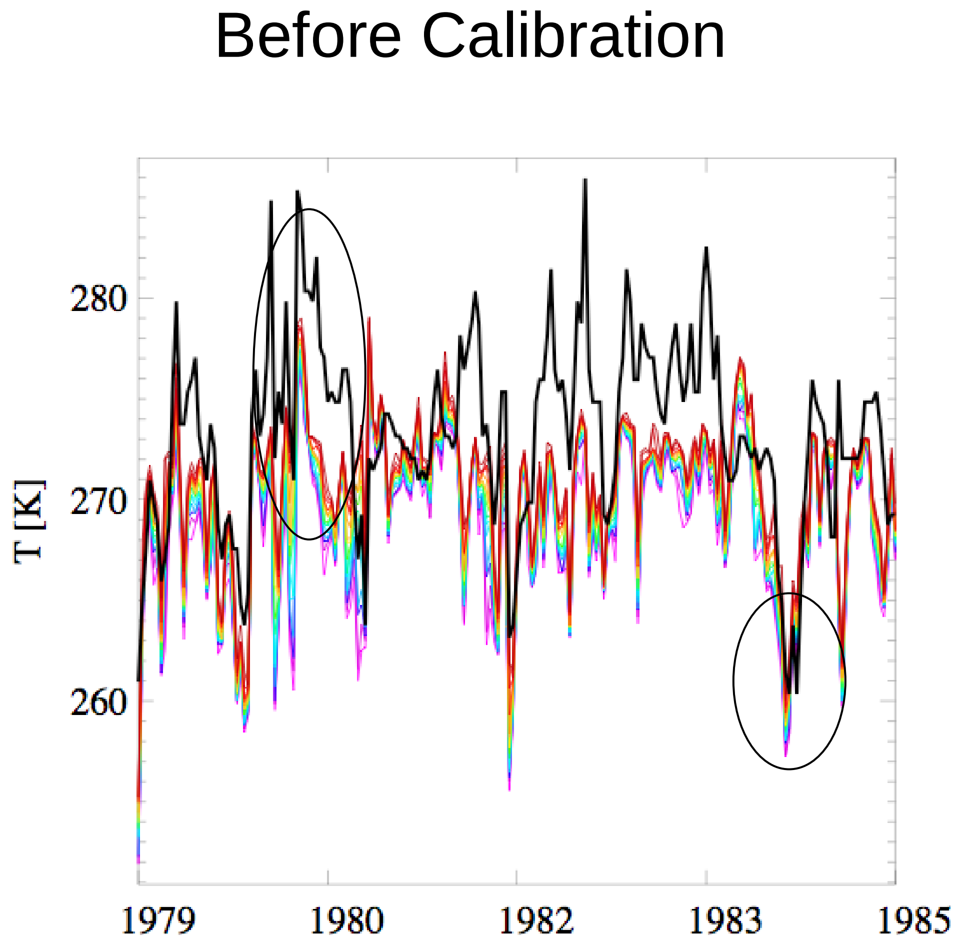
3) Starting with full regressor set, iteratively select best subset using "step-wise cross-validation"

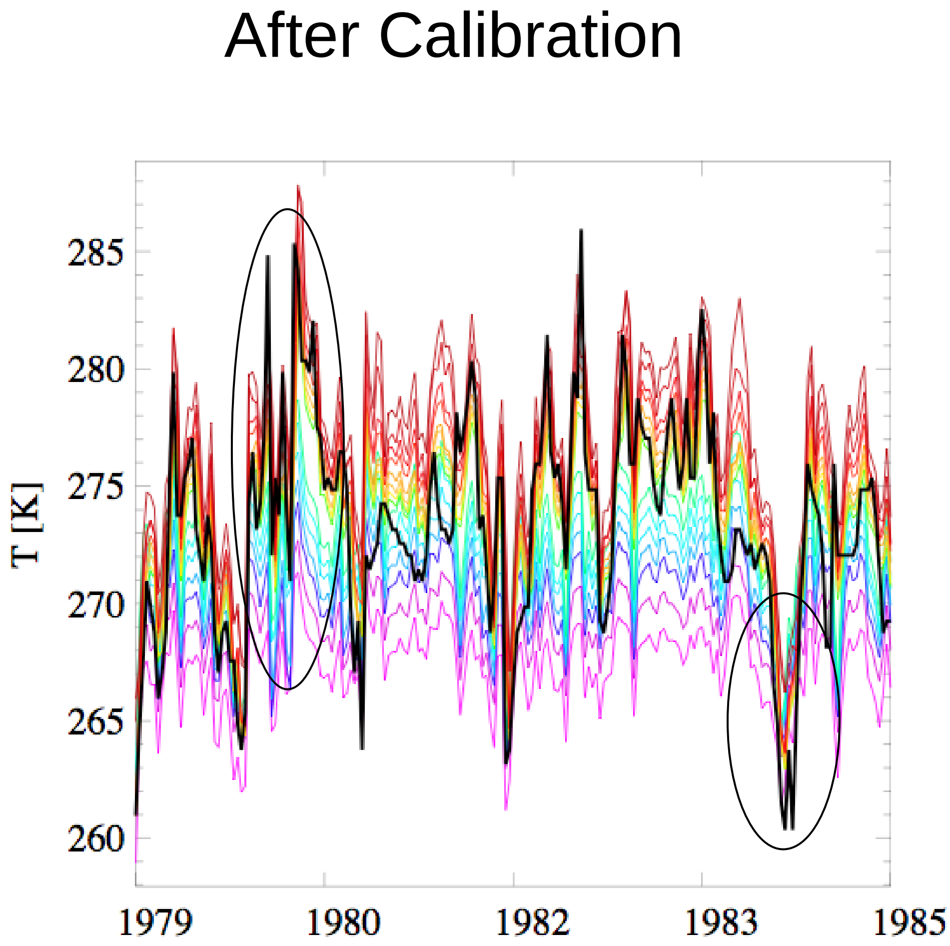
   - Fitting done using QR
   - Selection done by:
     a) Minimizing QR cost function
     b) Satisfying the binomial distribution

(2nd pass: segregate forecasts into differing ranges of ensemble dispersion, and refit models)

Regressors for each quantile: 1) reforecast ensemble 2) ens mean 3) ens median 4) ens stdev 5) persistence 6) logistic regression quantile

Example: January *T*

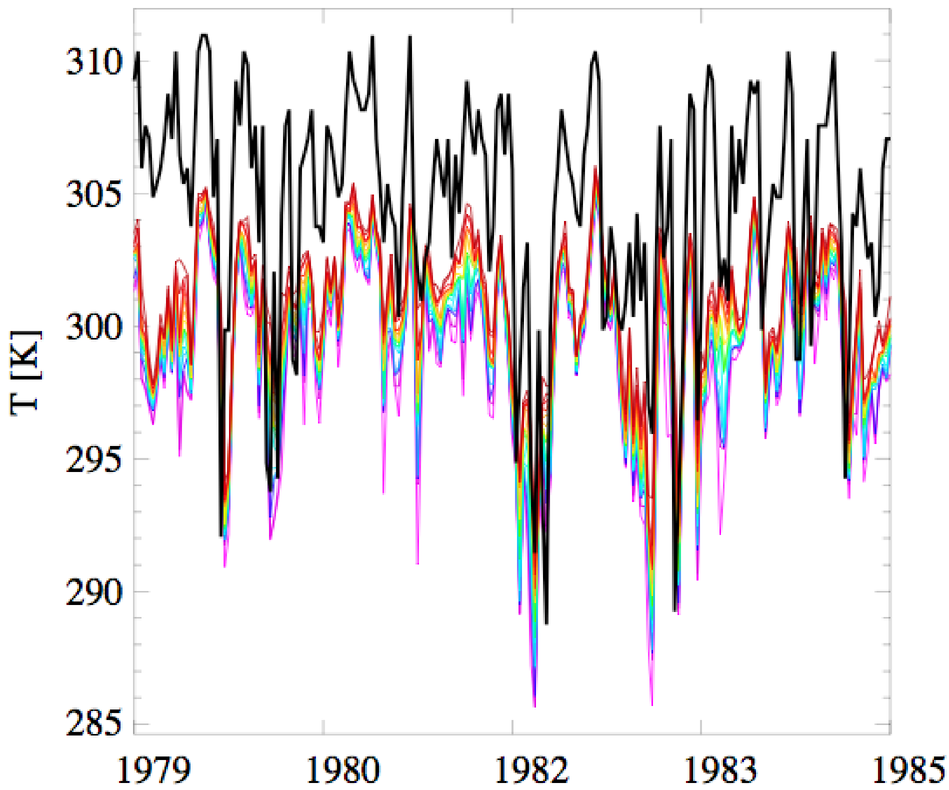




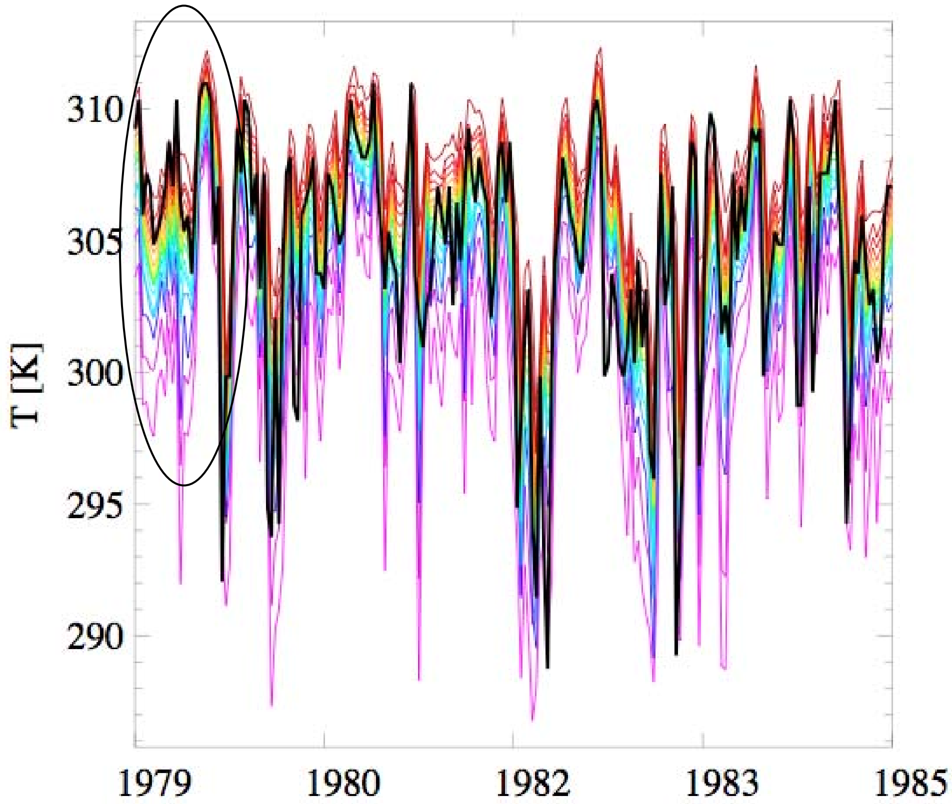
Black curve shows observations; colors are ensemble

Example: July *T*

Before Calibration

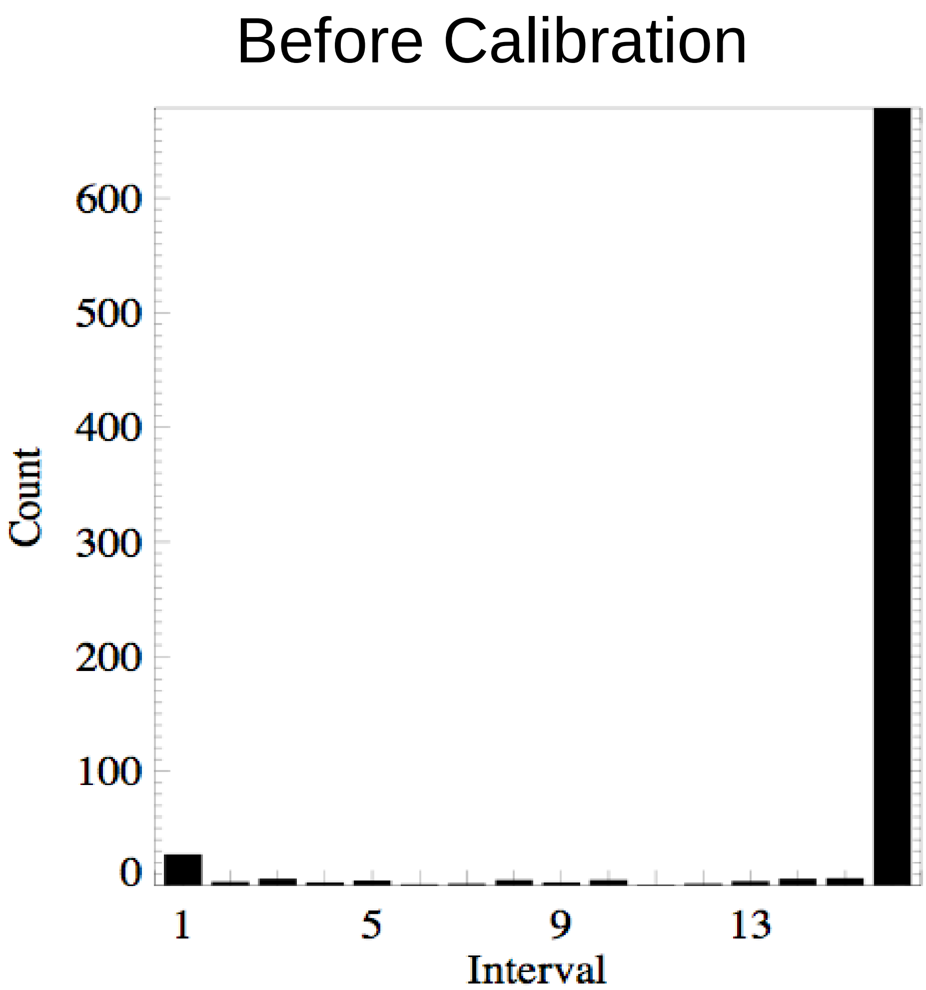


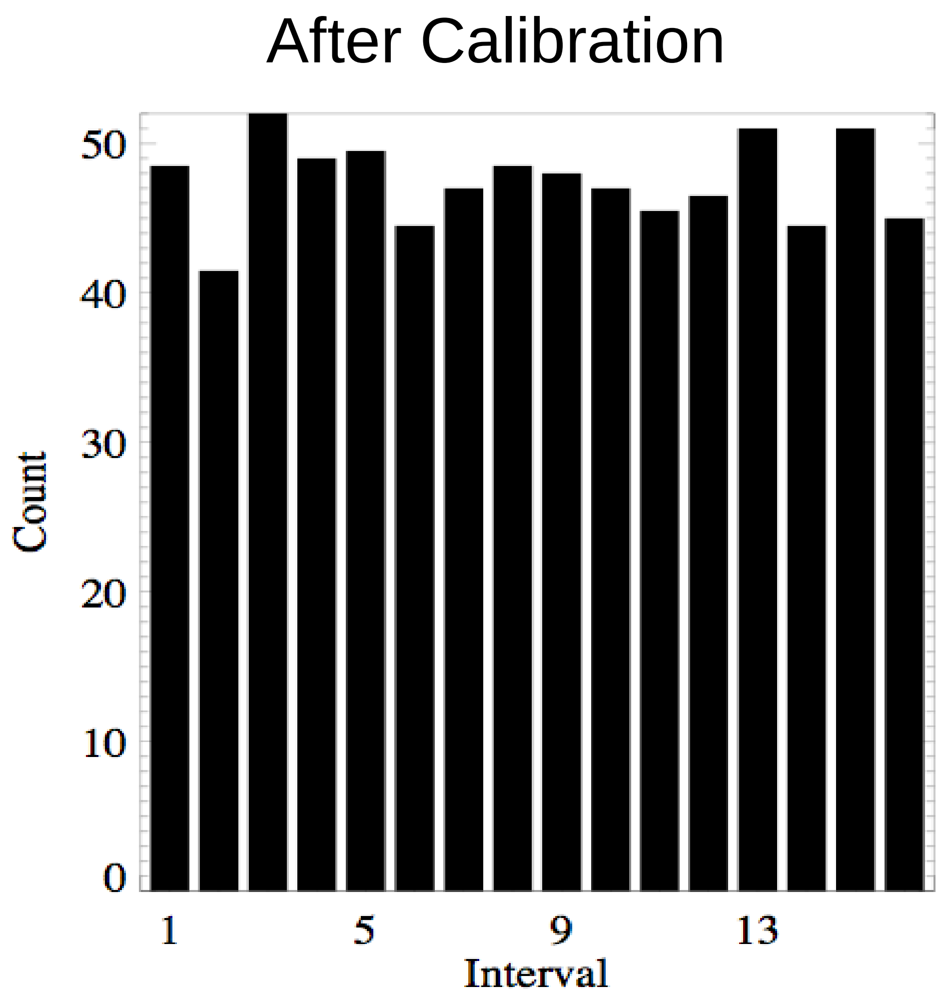
After Calibration



Black curve shows observations; colors are ensemble

Example: July *T*





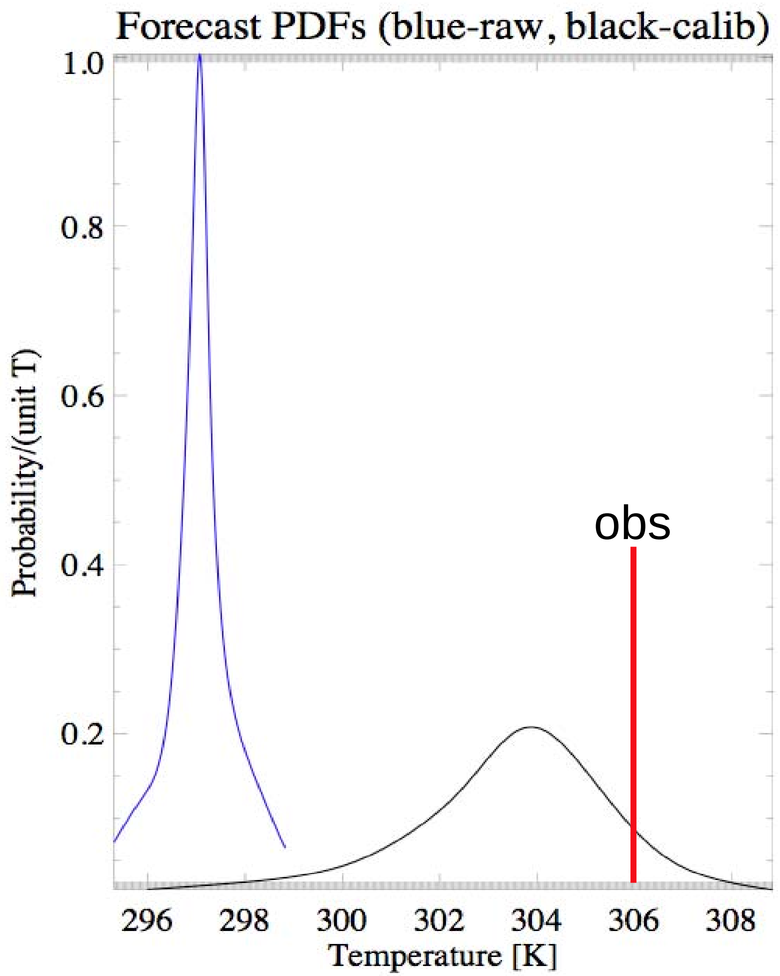
After quantile regression, rank histograms uniform

Raw versus Calibrated PDF's

Blue is "raw" ensemble
Black is calibrated ensemble
Red is the observed value

Notice: significant change in both "bias" and dispersion of final PDF

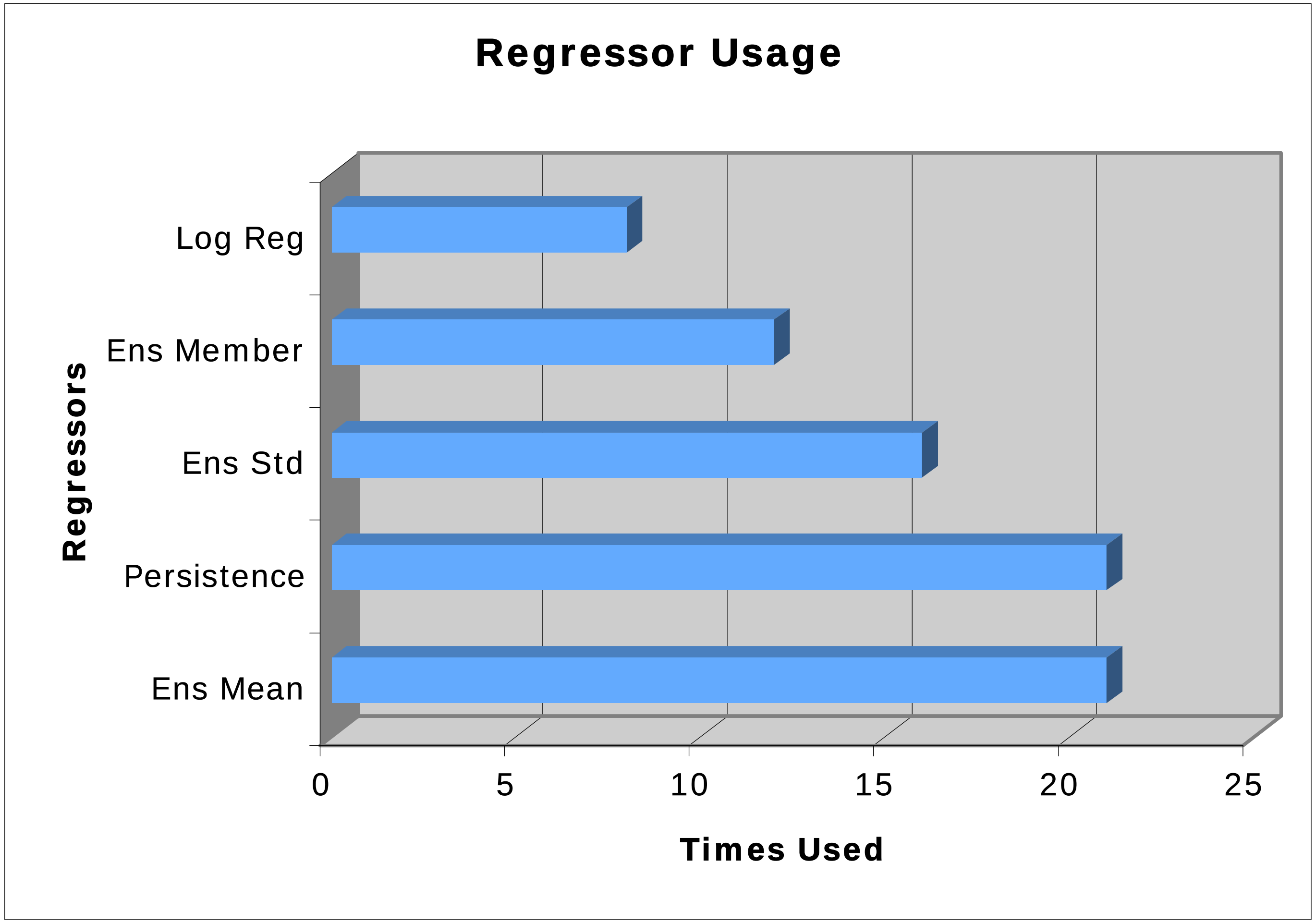
(also notice PDF asymmetries)



Results

Optimal regressor set varies, depending on:

- The quantile
- The season



Summary (to-date)

- Quantile regression provides a powerful framework for improving the whole (potentially non-gaussian) PDF of an ensemble forecast

- This framework provides an umbrella to blend together multiple statistical correction approaches (logistic regression, etc.) as well as multiple regressors (non-NWP)

- As well, “step-wise cross-validation” calibration provides a method to ensure forecast skill greater than climatology, persistence, and logistic regression (for a variety of cost functions)

- As shown here, significant improvements made to the forecast’s ability to represent its own potential forecast error:

  – More uniform rank histogram

  – guaranteeing utility in the ensemble dispersion (=> more spread, more uncertainty)