### **Operational Short-Term Flood Forecasting for Bangladesh:**

### Application of ECMWF Ensemble Precipitation Forecasts

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### The Climate Forecast Applications Project CFAB



- Bangladesh at confluence of: Meghna, Brahmaputra and Ganges
- Limited upstream river discharge data provided to Bangladesh
- However, good quality border daily discharge measurements
   => utilize in forecasting

CFAB's GOAL: Provide operational upper catchment flood-stage discharge warning and precipitation forecasts at differing time-scales

# Overview: Short-term flood forecasting



- 1. Multi-Model Ensemble Discharge Forecasting: Combining Data-Based and Distributed Modeling Techniques
- 2. "Dressing" Precipitation-derived Discharge Ensembles with Model Error Estimates: "Truer" Discharge Probabilities
- 3. Conclusions, and Future Work

### **Ganges catchment-averaged ECMWF 51 member 1-10 day Precipitation Forecasts**

-- comparisons to the Global Precipitation Climatology Project (GPCP) precipitation estimates

- GPCP and CMORPH used as "truth"
- => used to calibrate models
- => initializes soil-moisture
- bias and spread corrections of ECMWF "catchmentaveraged" forecasts done similar to Hamill and Colucci, 1997

Average Daily Accumulated Rainfall Over the Ganges Daily GPCP Precipitation Estimates compared with 1 to 10-day Ensemble Forecasts, Days June 11 - October 15, 2003





#### 216hr ECMWF ensembles and GPCP (dashed) 240hr ECMWF ensembles and GPCP (dashed)



### Discharge Multi-Model-Ensemble

Krishnamurti (2001): combining (via regression) multiple NWP model outputs significantly improves weather forecasts => apply to 2 discharge models to generate 'multi-model-ensemble' discharge forecasts

#### Data-Based Modeling (Beven, 2002)

- -- Linear Store / Linear Transfer Function Approach.
- <u>Benefits</u>: recalibrate to specific conditions => ; maximizes data-assimilation (discharge measurements)
- <u>Drawbacks</u>: basin lumped model; limited slow time-scale response

### Distributed Model (US NWS River Forecast System)

- -- subcatchment gridded 2 soil-layer model
- Benefits: ET/soil-storage/water-balance explicitly modeled
- <u>Drawbacks</u>: Model recalibration and data-assimilation inflexible

## Discharge Multi-Model Ensemble (cont)

Multi-Model-Ensemble Approach:

• Rank models based on historic residual error using current model calibration and "observed" precipitation

•Regress models' historic discharges to minimize historic residuals with observed discharge

•To avoid over-calibration, evaluate resultant residuals using Akaike Information Criteria (AIC)

•If AIC minimized, use regression coefficients to generate "multi-model" forecast; otherwise use highest-ranked model => "win-win" situation!



## Multi-Model Ensemble Regression Coefficients

- DBM-TFM model (red)Distributed Model (blue)
- Significant catchment variation
- Coefficients vary with the forecast lead-time
- $\Rightarrow$  Representative of the
- $\Rightarrow$  each basin's hydrology
- ⇒ -- Ganges slower time-scale response
- $\Rightarrow$  -- Brahmaputra "flashier"



## Multi-Model Ensemble Forecasts

#### Results:

- -- show improvements
- -- but compromise timing (distributed) with amplitude (DBM)
  - => use of different error measure in selection process

#### Future:

- -- structure allows incorporating other models -- MMS/PRMS
- -- KNN technique to select based on current precipitation/discharge conditions



### <u>Combining Precipitation (Ensemble)</u> <u>Probability with Model Error:</u> <u>Forecasting "Truer" Discharge Probabilities</u>

### Rainfall Probability



### **Discharge Probability**



Above danger level probability 36% Greater than climatological seasonal risk?

### <u>A More Complete Discharge</u> <u>Probability Forecast</u>

<u>Step 1:</u> generate model error PDF (discharge model/rating curve/observed precipitation)
-- historically generate residual time series for each day's re-calibrated hydrologic model (multi-model) using <u>"observed"</u> precipitation
-- use K-Nearest-Neighbor (KNN) technique to select "nearest-neighbor" residuals (selection: values/slope/curvature)
-- use Mahalanobis Distance to weight and create model-error PDF



### Combining Model / Precipitation Error (cont)

Step 2: generate precipitation-ensemblegenerated discharge PDF

<u>Step 3:</u> combine model error PDF with the above to generate a "new-andimproved" more complete PDF for forecasting:



#### Brahmaputra Discharge

120

120



#### Ganges Discharge



#### <sup>Br</sup> Brahmaputra Flood Probability

#### June 15 - October 15, 2003 Obs (solid), 1-day 95%/50%/Ens Mean (dash) Obs (solid), 2-day 95%/50%/Ens Mean (dash) 1 day 2 day Q [10^4 m^3/s] Q [10^4 m^3/s] Ō Dav Day Obs (solid), 3-day 95%/50%/Ens Mean (dash) Obs (solid), 4-day 95%/50%/Ens Mean (dash) 4 day 3 day O [10^4 m/3/s] Day Day Obs (solid), 5-day 95%/50%/Ens Mean (dash) 95% 5 day O [10^4 m^3/s] 50%

Day

### Ganges Flood Probability



## **Danger Level Probabilities**



## Conclusions

Incorporated operationally into Bangladesh flood warning program
 Forecasts based on ECMWF 51-member forecasts and "observed" near-real-time precipitation estimates
 Shows good skill out to 5-7 days ("useful" skill out to 10-days)
 Extends Bangladeshi forecasts to 7-9 days

Future Work: combine ECMWF EPS precipitation with longer time-scale statistical-derived precipitation forecasts for a "seam-less" extension