Optimizing Reservoir Operations for Hydropower Production in Africa through the Use of Remote Sensing Data and Seasonal Climate Forecasts

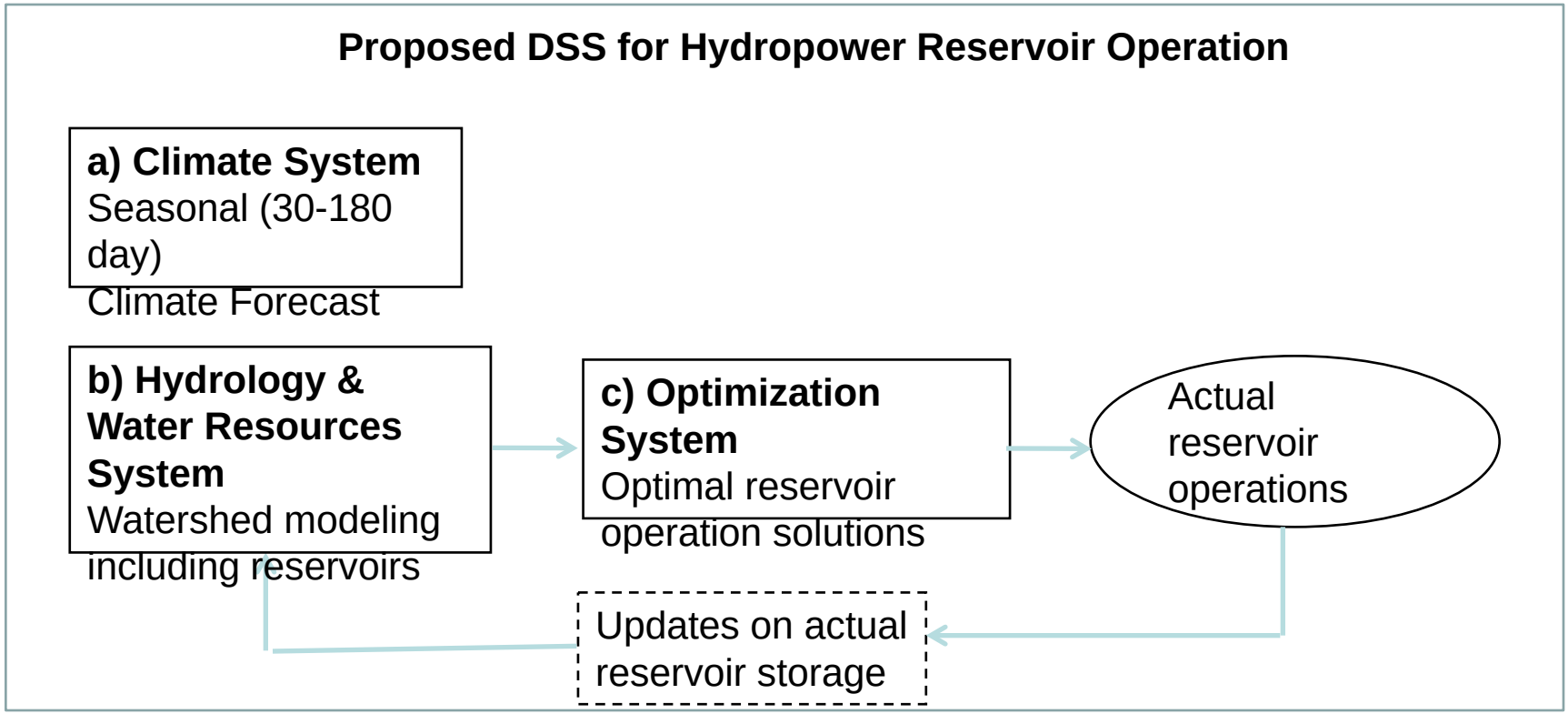
Team: Mekonnen Gebremichael (UCLA)
Thomas Hopson (NCAR)
Emily Riddle (NCAR)
Solomon Demissie (UCLA)
William Yeh (UCLA)
G. Robert Brakenridge (U. Colorado, Boulder)
Dan Collins (NOAA)
Dorita Rostkier-Edelstein (Israel Institute of Biological Research)
Jennifer Boehnert (NCAR)
Diriba Korecha (NMA)
Mebrate Tafesse (WWSDE)

End Users: Ethiopian Ministry of Water, Energy and Irrigation
Ethiopian Electric Power
Tanzania Electricity Company
National Meteorological Agency of Ethiopia

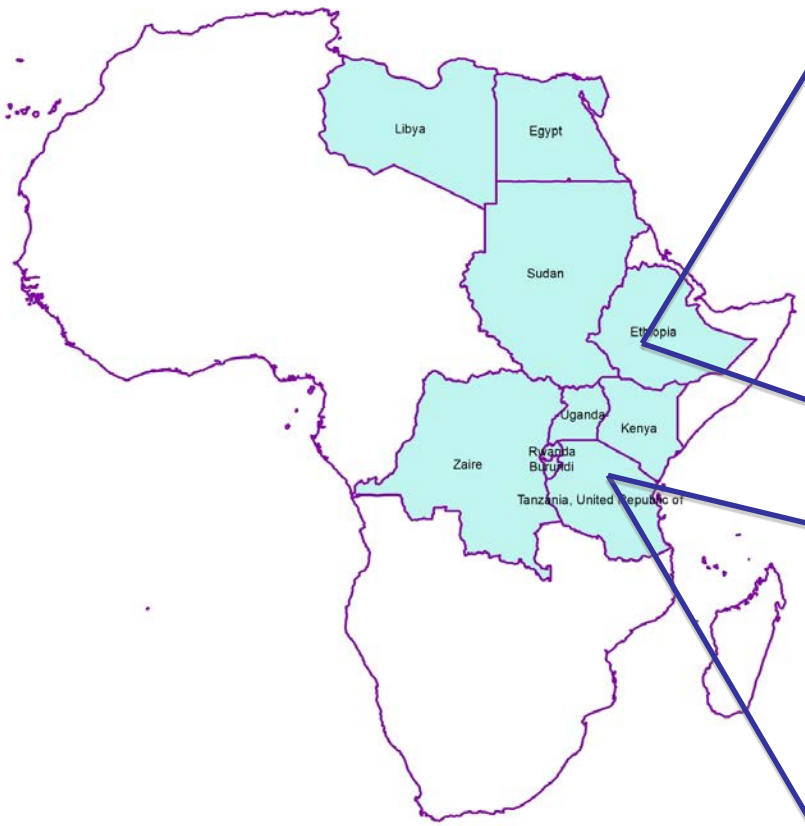
Objectives

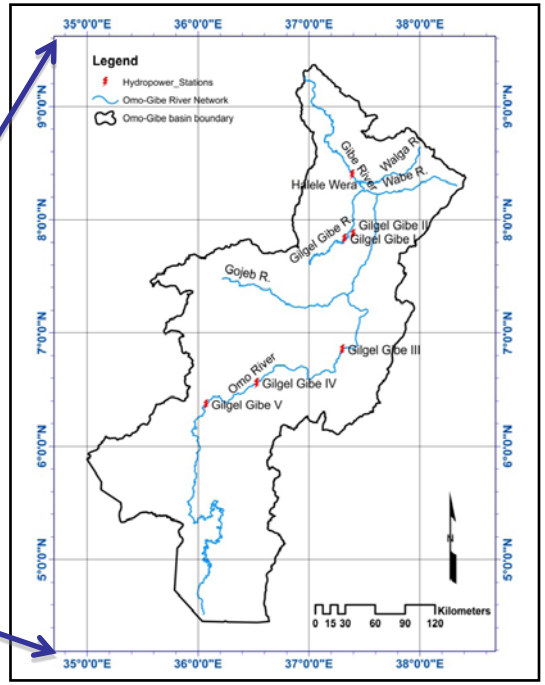
- To optimize reservoir operation for maximum hydropower production in Africa through the utilization of remote sensing data and seasonal climate forecasts in a DSS.

Main Components of DSS



Project Areas



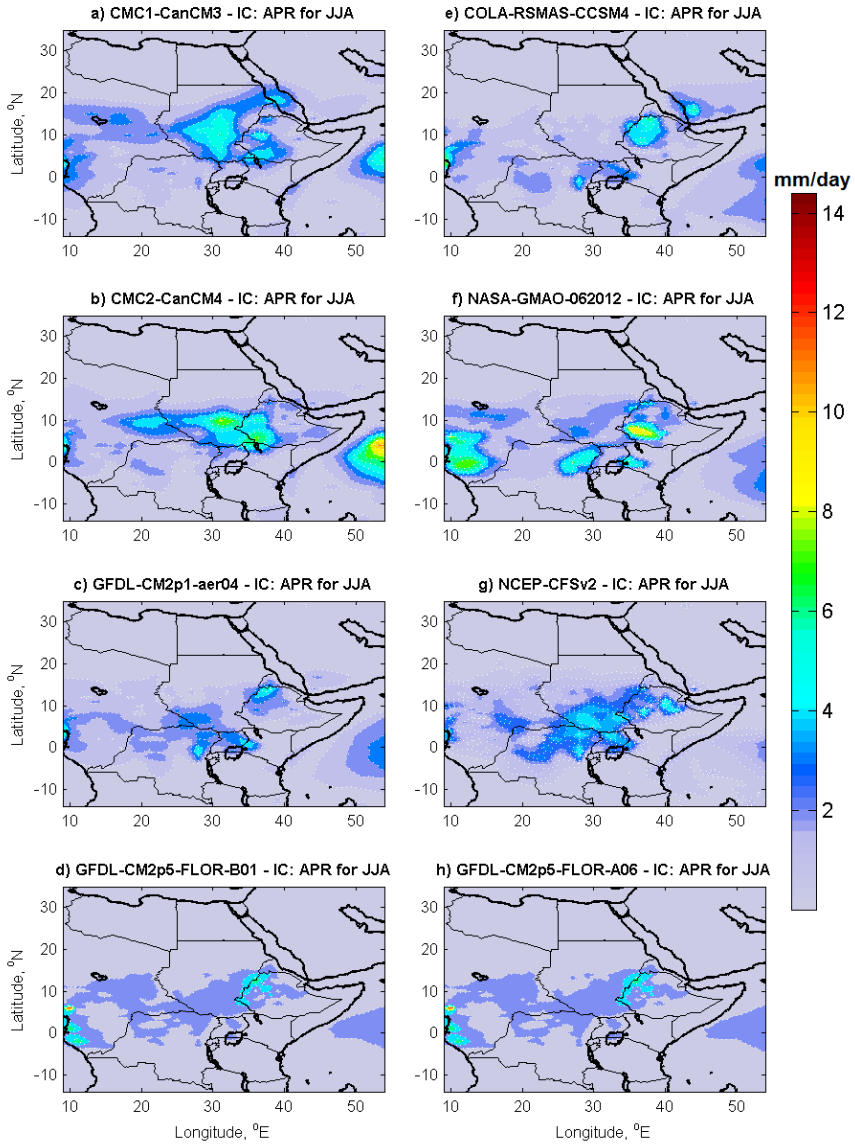


Omo-Gibe basin (Ethiopia): Gibe I, II, III, IV, V

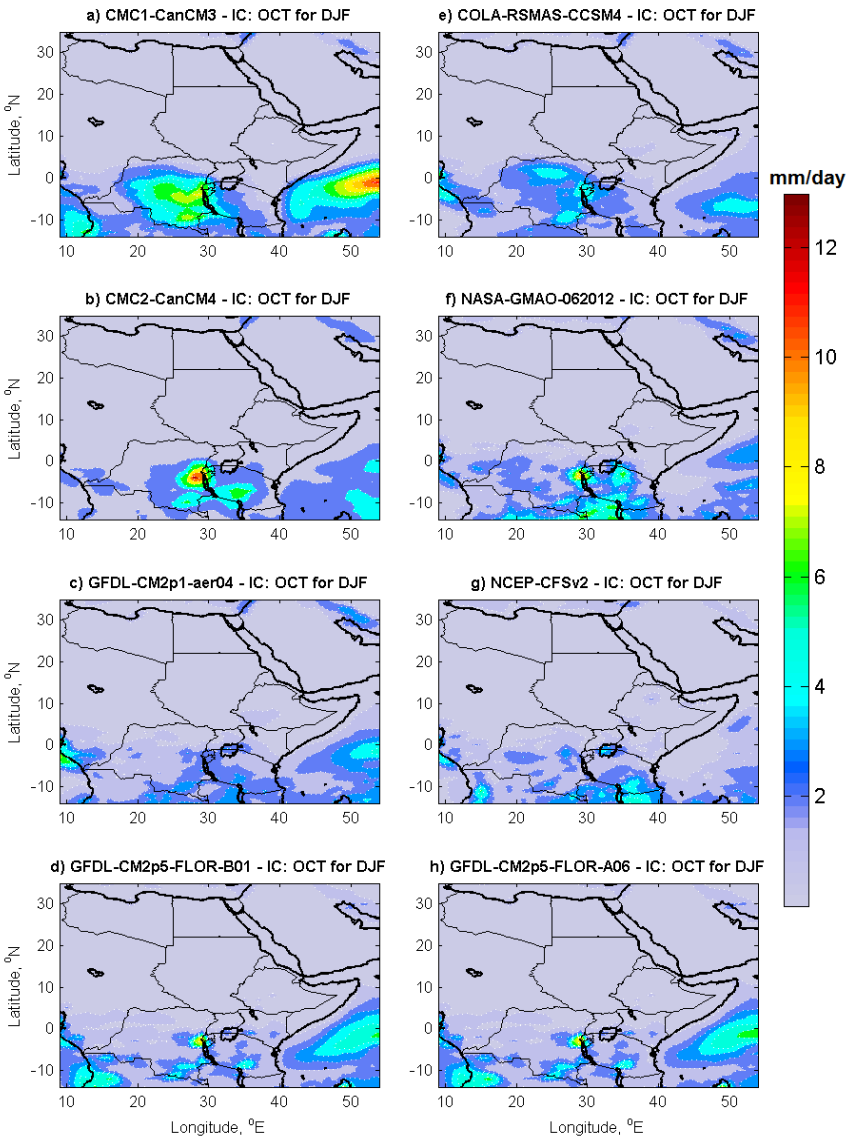
Pangani basin (Tanzania): Nyumba ya Mungu

THE EASTERN AFRICA POWER POOL

RMSE Forecast Skills at 2.5 months lead

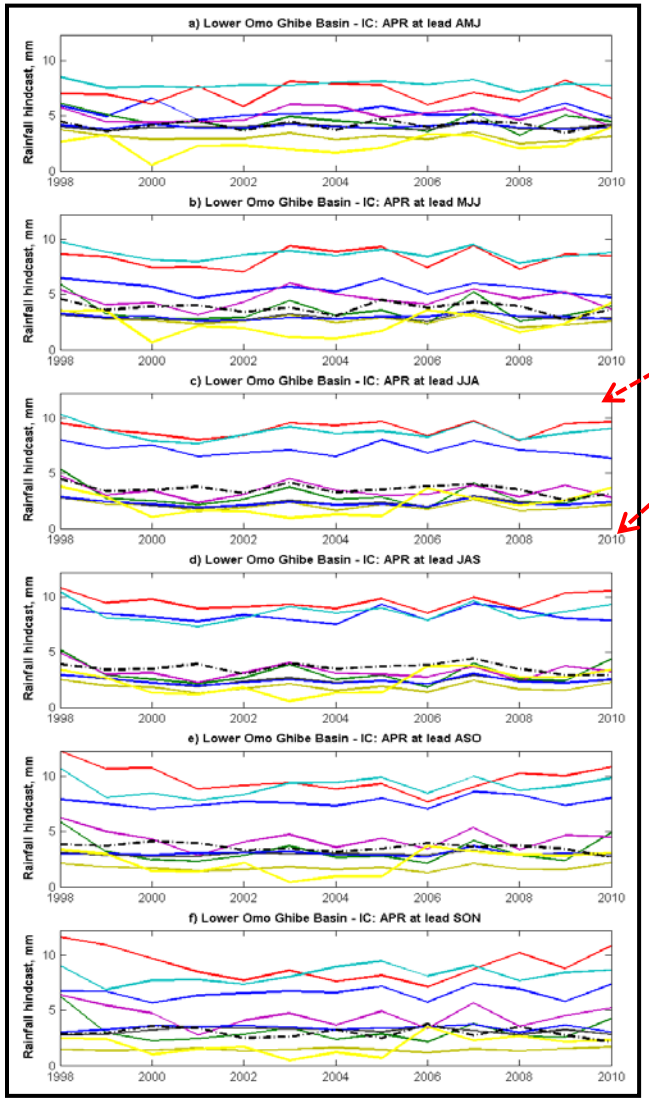


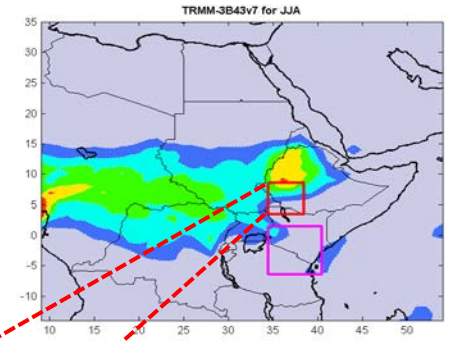
IC: APRIL for JJA

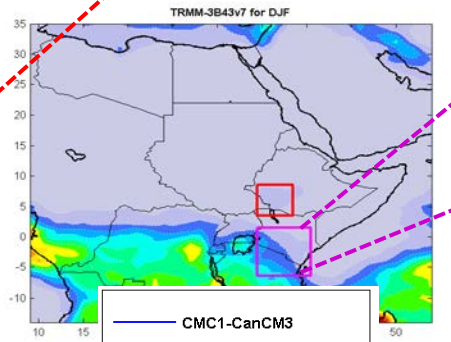


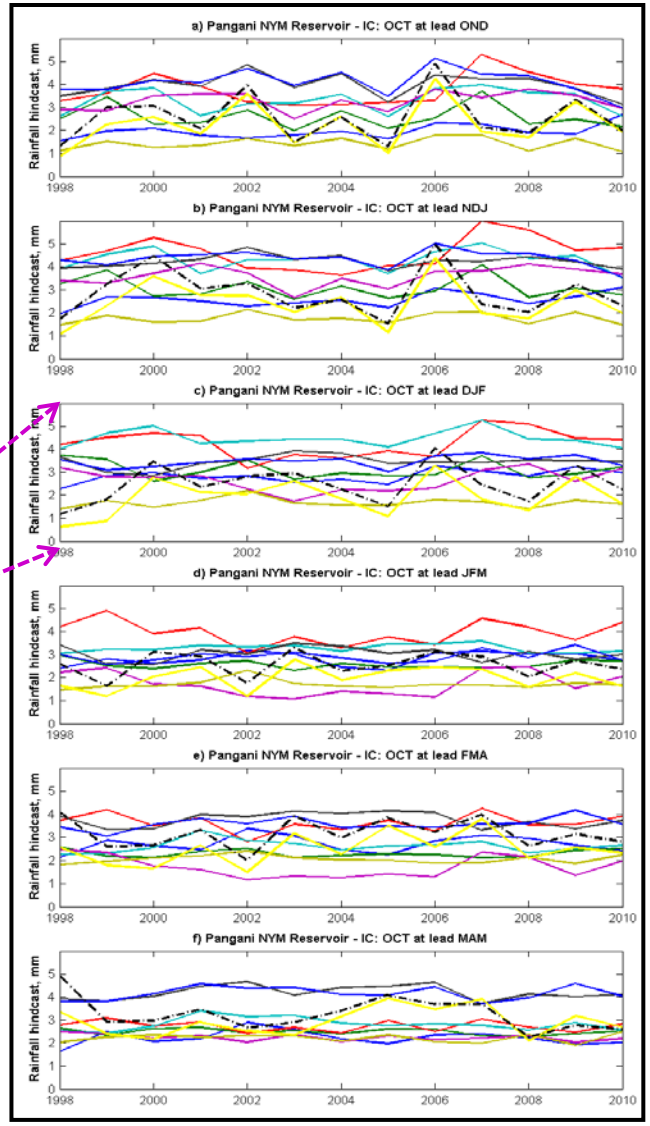
IC: OCTOBER for DJF

Seasonal Forecasts for Case Study Regions



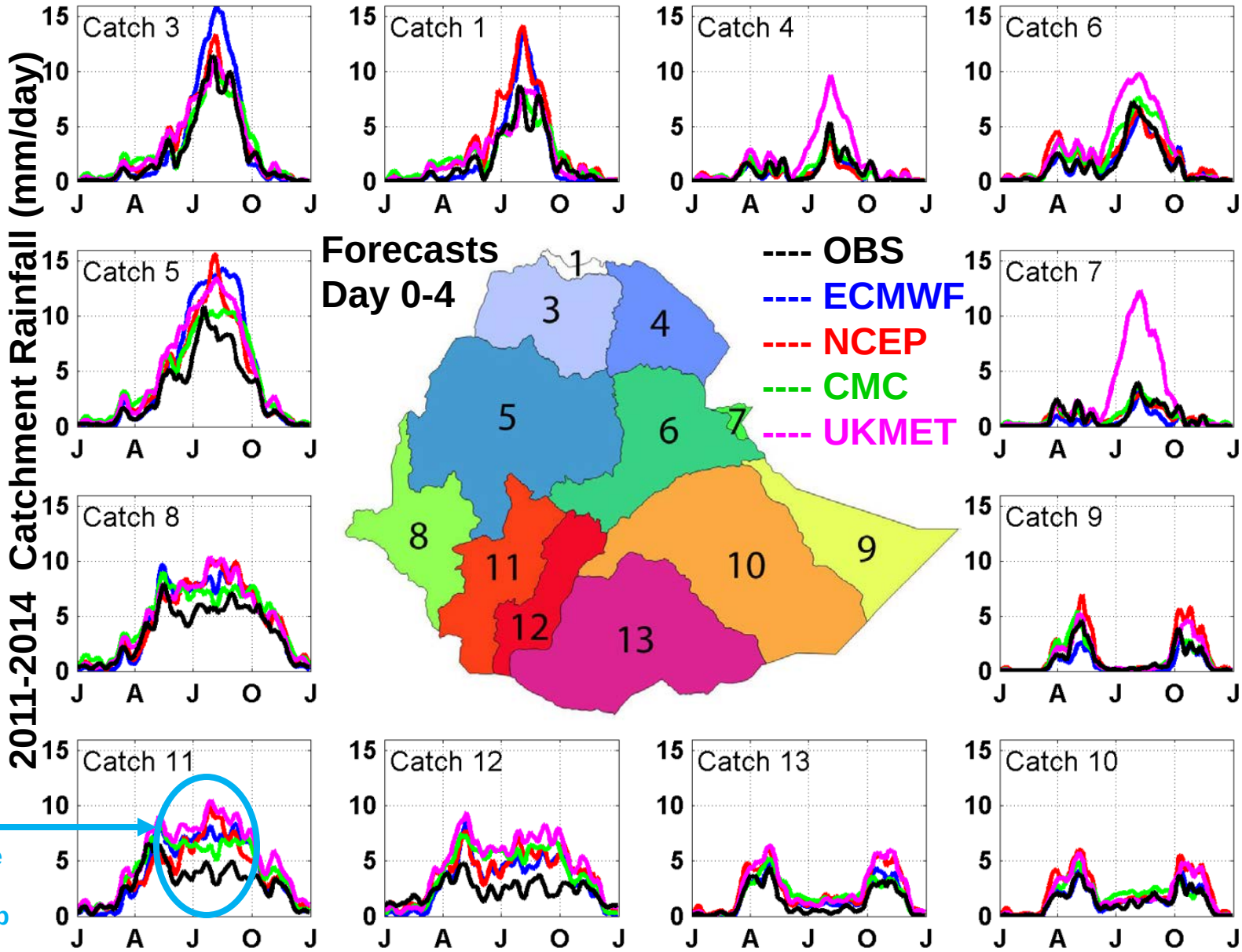






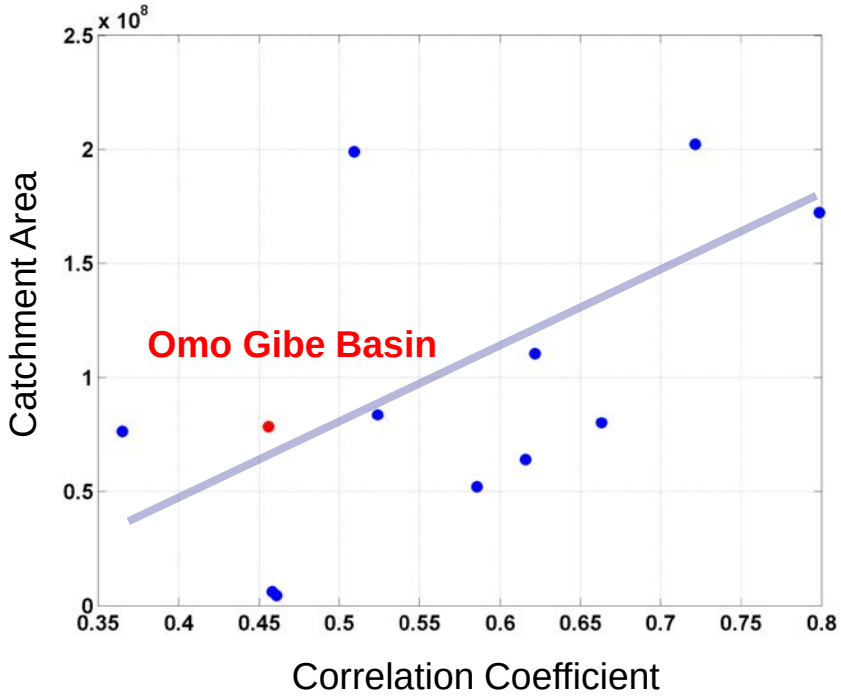
- CMC1-CanCM3
- COLA-RSMAS-CCSM4
- CMC2-CanCM4
- NASA-GMAO-062012
- GFDL-CM2p1-aer04
- NCEP-CFSv2
- GFDL-CM2p5-FLOR-B01
- GFDL-CM2p5-FLOR-A06
- CPC-CMAP-URD
- TRMM-3B43v7

Seasonal cycles and bias in extended range forecasts (2011-2015)



Large positive biases over the Omo Gibe basin in June - Sep

Skill in extended range forecasts

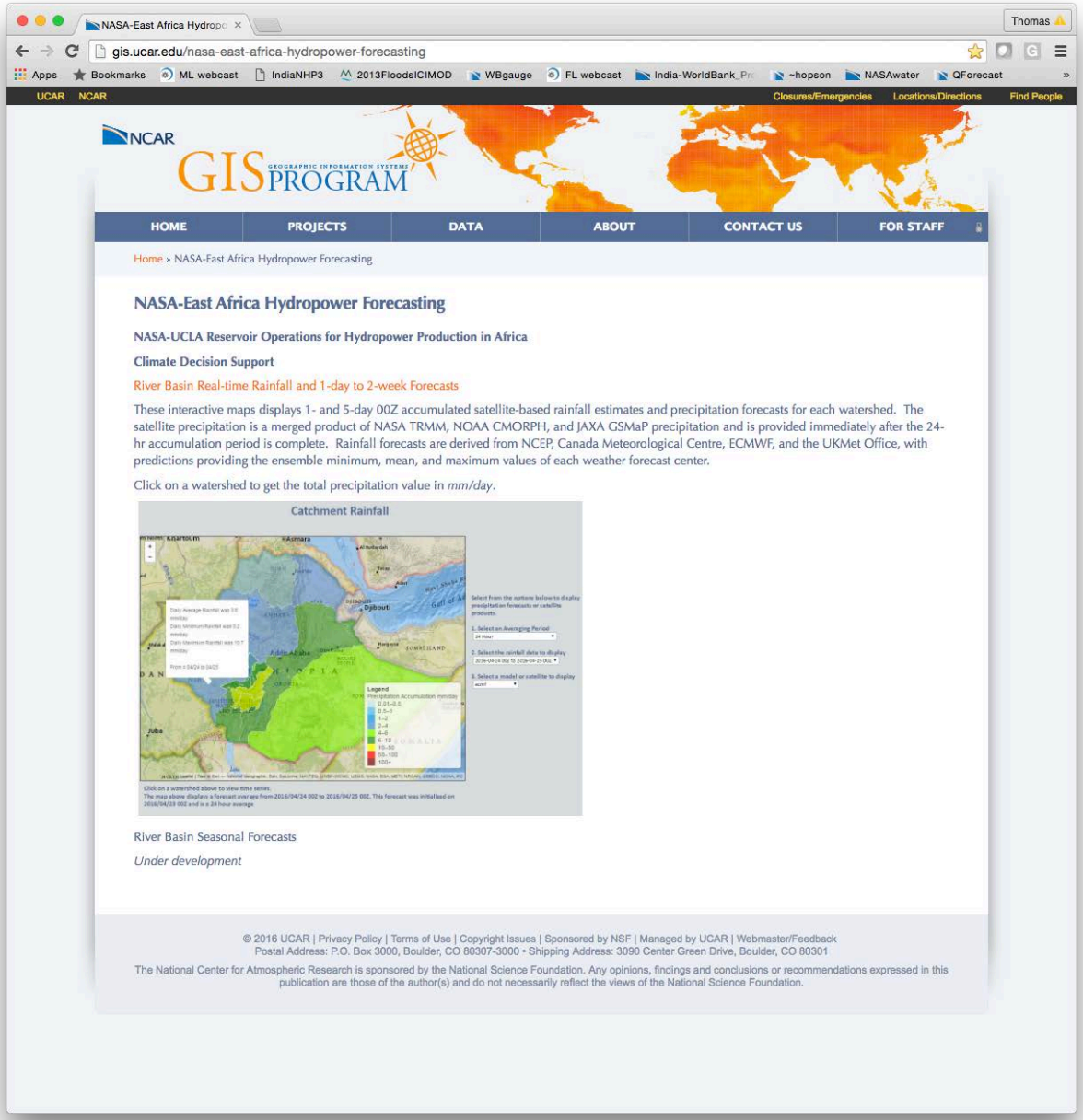


Relationship between catchment area and anomaly correlation skill Day 0, ECMWF forecast

Reservoir Operations for Hydropower Production in Africa

Real-time Climate Decision Support Web Tool

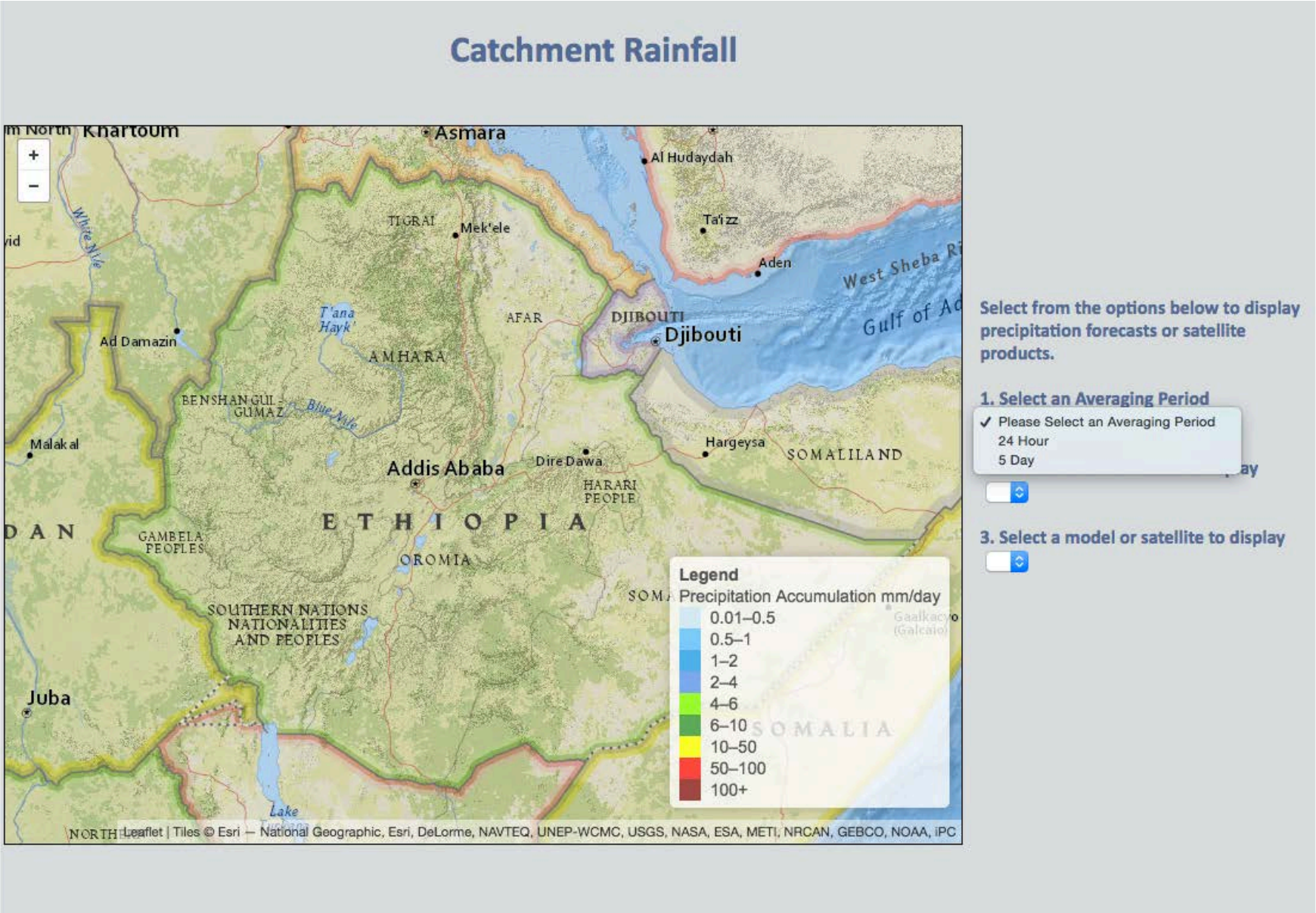
For catchment-based precipitation forecasts:
-- short-range (daily),
-- mid-range (5- to 15-day), -
- seasonal (1- to 6-months)



http://gis.ucar.edu/nasa-east-africa-hydropower-forecasting

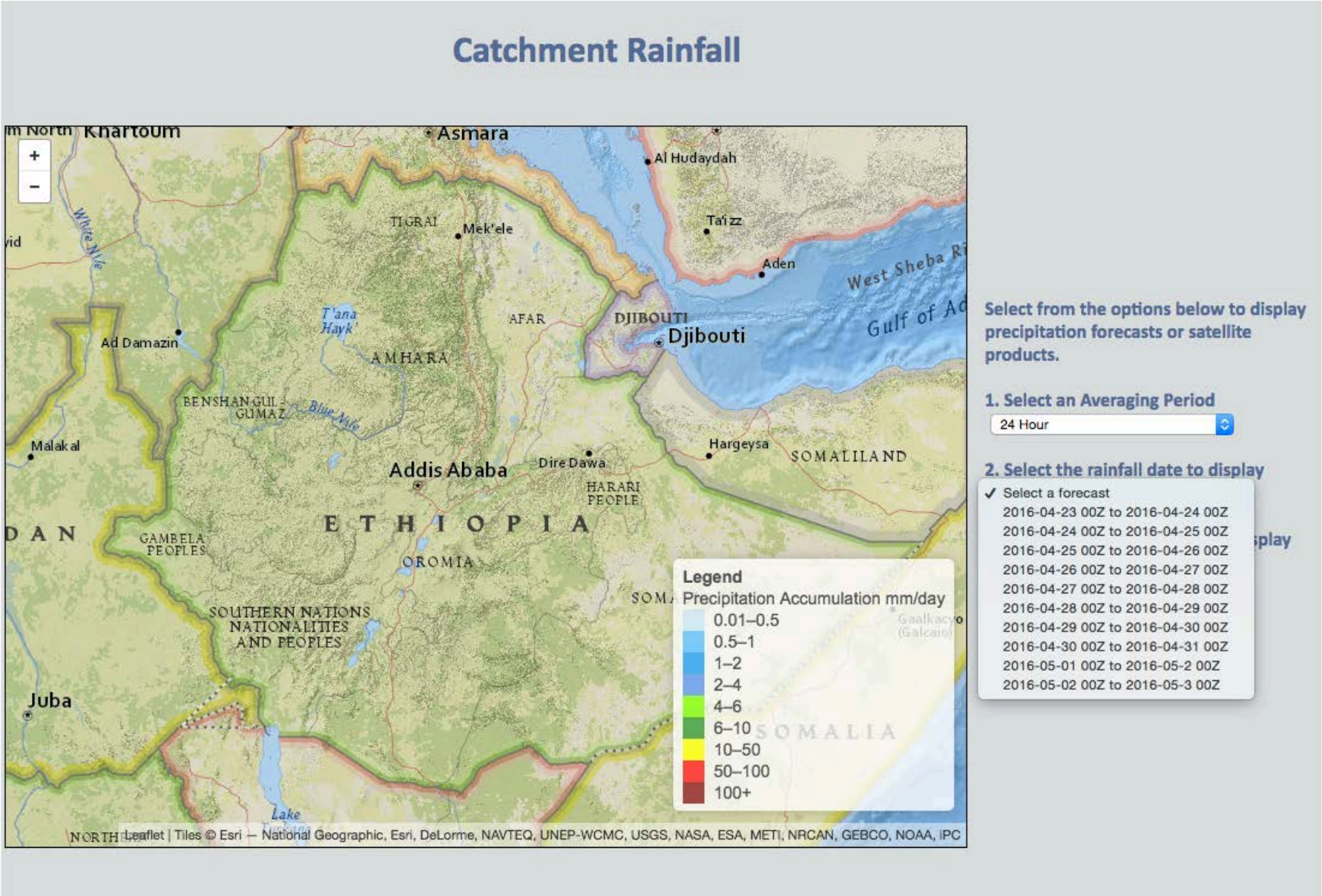
Reservoir Operations for Hydropower Production in Africa

Select an averaging length …



Reservoir Operations for Hydropower Production in Africa

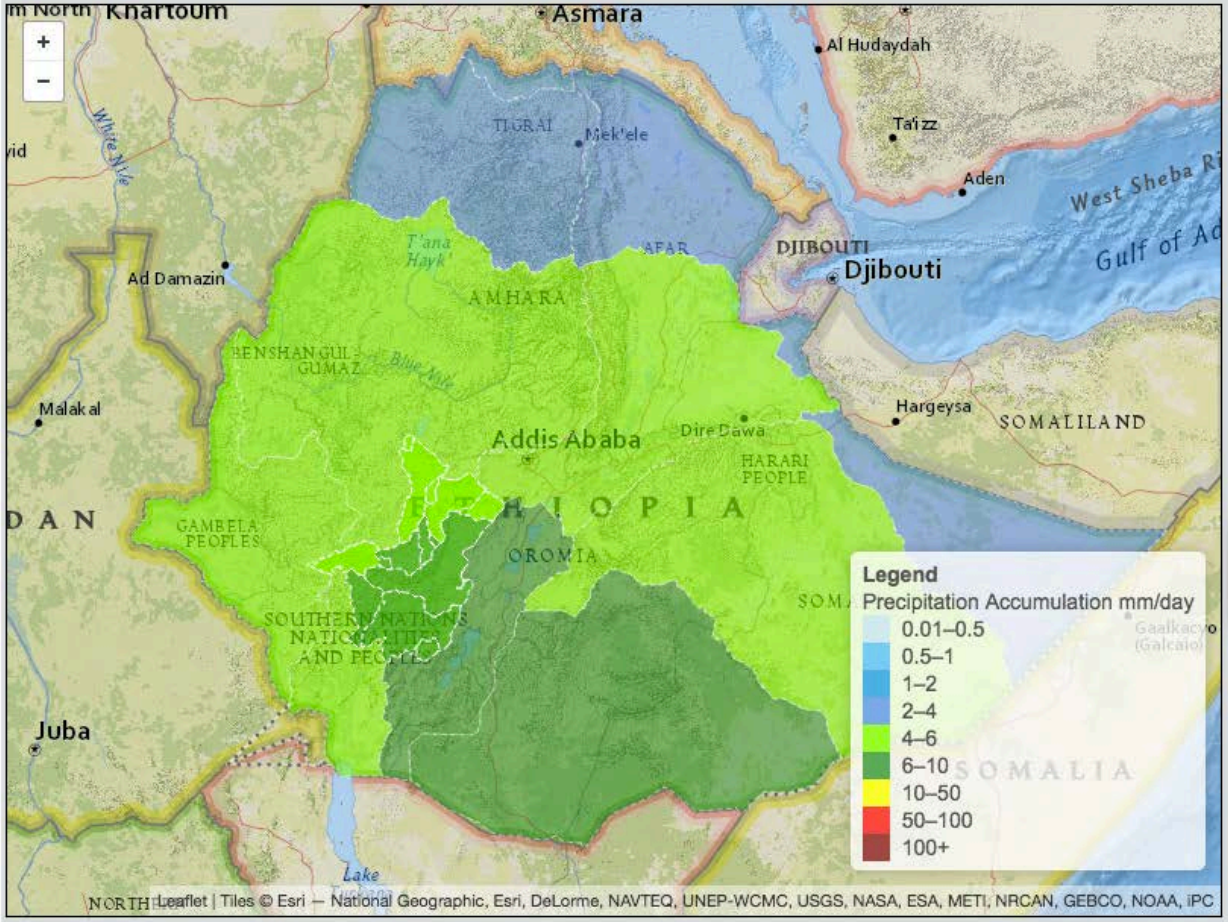
Select a forecasting window …



Reservoir Operations for Hydropower Production in Africa

Select a weather center or satellite product …

Catchment Rainfall



Select from the options below to display precipitation forecasts or satellite products.

1. Select an Averaging Period

24 Hour

2. Select the rainfall date to display

2016-04-29 00Z to 2016-04-30 00Z

r satellite to display

Select a forecast
✓ cwao
ecmf
egrr

Click on a watershed above to view time series.
The map above displays a forecast average from 2016/04/29 00Z to 2016/04/30 00Z. This forecast was initialized on 2016/04/23 00Z and is a 24 hour average

Reservoir Operations for Hydropower Production in Africa

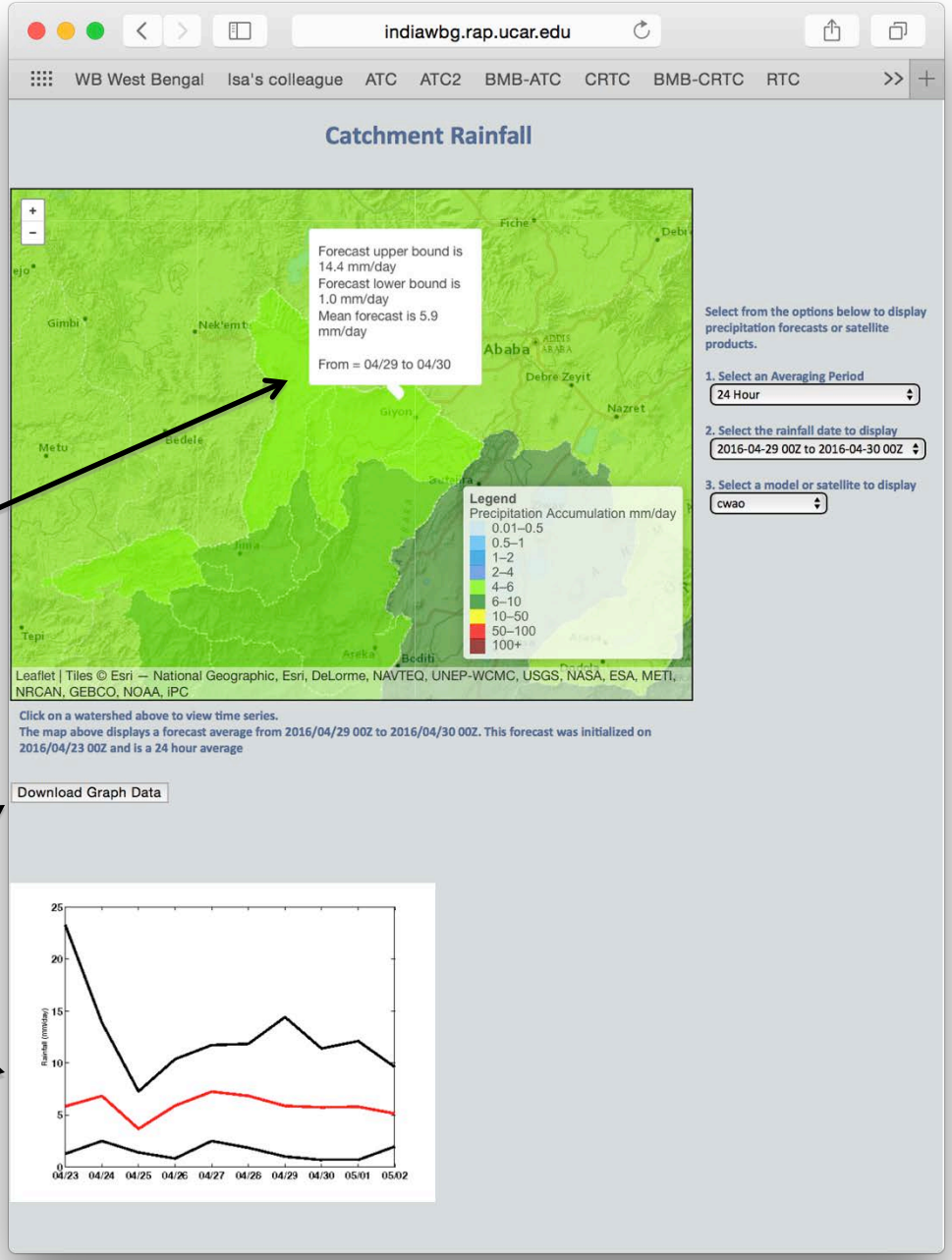
Real-time Climate Decision Support Web Tool

Pop-up windows provide:

-- basin-integrated ensemble min, mean, max values

-- basin most recent past and forecasted time-series (ensemble mean red min/max **black**)

-- downloadable data files for user community



Next Steps

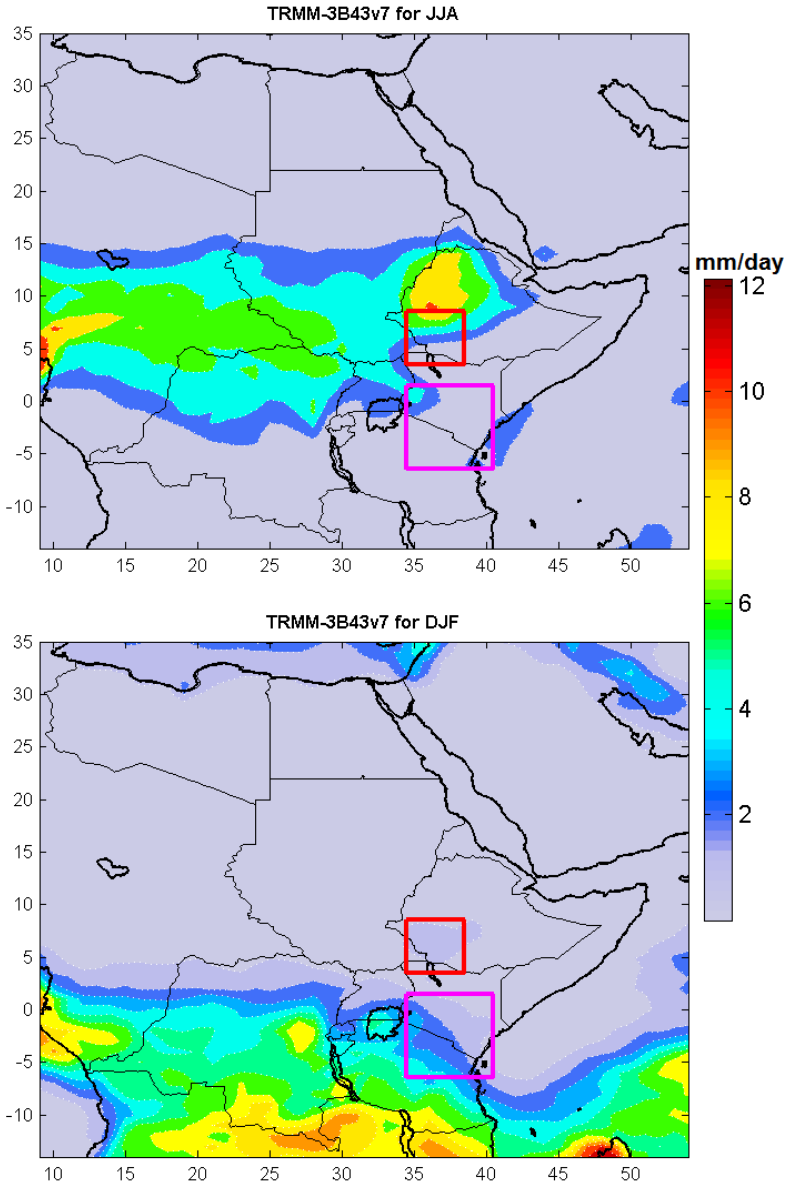
- Climate forecast improvement and spatial downscaling
- Hydrologic forecasting
- Optimization
- DSS software integration

Acknowledgement

NASA ROSES Applied Sciences Program – Water Resources Application.

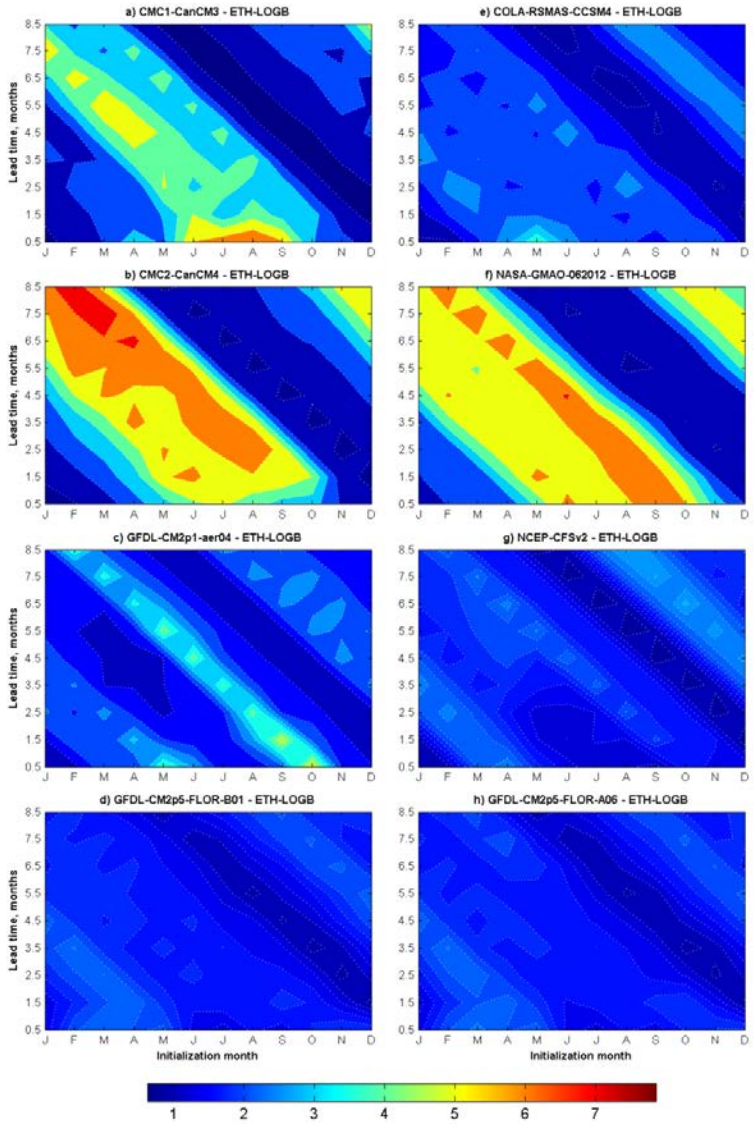
Backup Slides

Evaluation and Improvement of Seasonal Forecasts

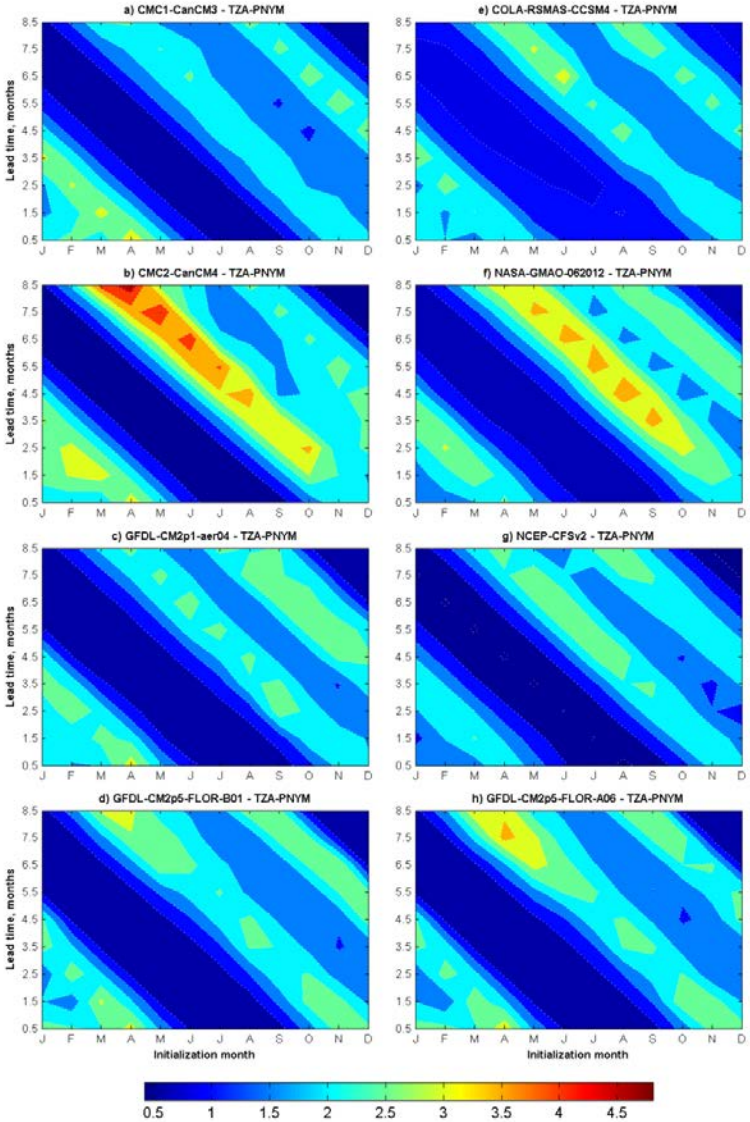


- Seasonal forecasts from 8 NMME models (each with10-24 ensemble sizes, 0.5-11.5 months of lead time, and monthly initializations for 1982-2010)
- The CPC Unified rain gauge and TRMM merged rainfall are used for validation
- The project domain is the East Africa Power Pool region (the left map extent)
- Two case study regions are used for time series comparison:
  - Omo Ghibe basin region, Ethiopia
  - Pangani basin region, Tanzania
- Validation of seasonal forecasts
- Combination of models' forecasts
- Spatial downscaling and bias correction

RMSE Forecast Skills for Initializations and Leads



Lower Omo Ghibe Basin



Pangani NYM Basin

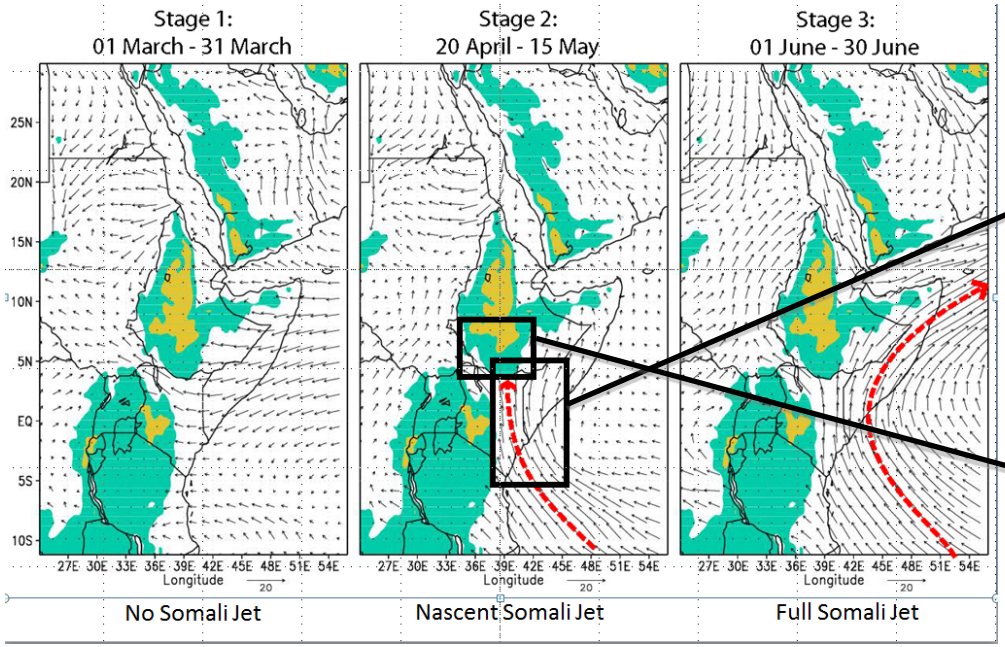
Geophysical Dynamics and forecast challenges:

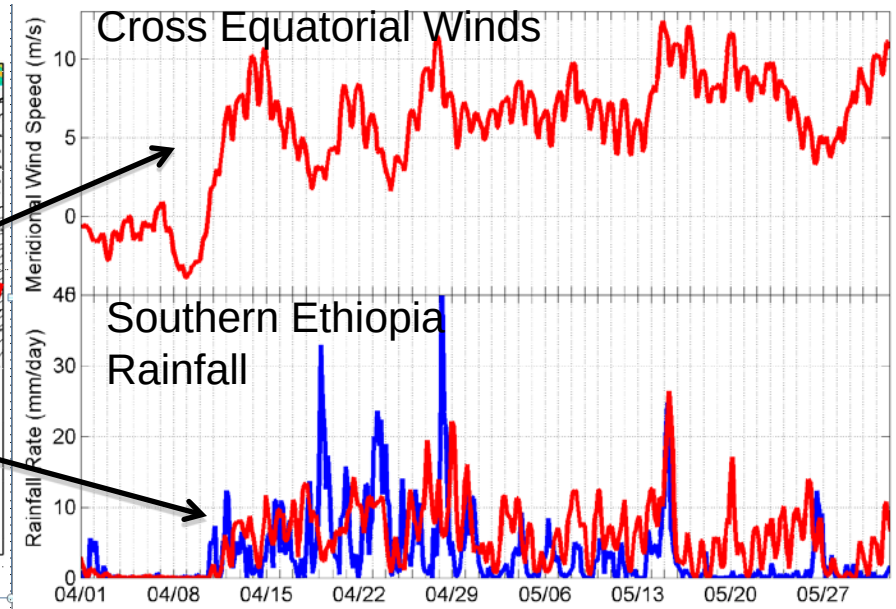
-Complex topography and interactions between ITCZ and monsoon flows make for complicated spatial patterns.

-Varying seasonal cycles and drivers of precipitation even in neighboring catchments.

-Not a lot of spatial coherence in the inter-annual variability of precipitation, especially during the spring (MAM) season

-Timing of onset of the rainy season in March-May may be related to the





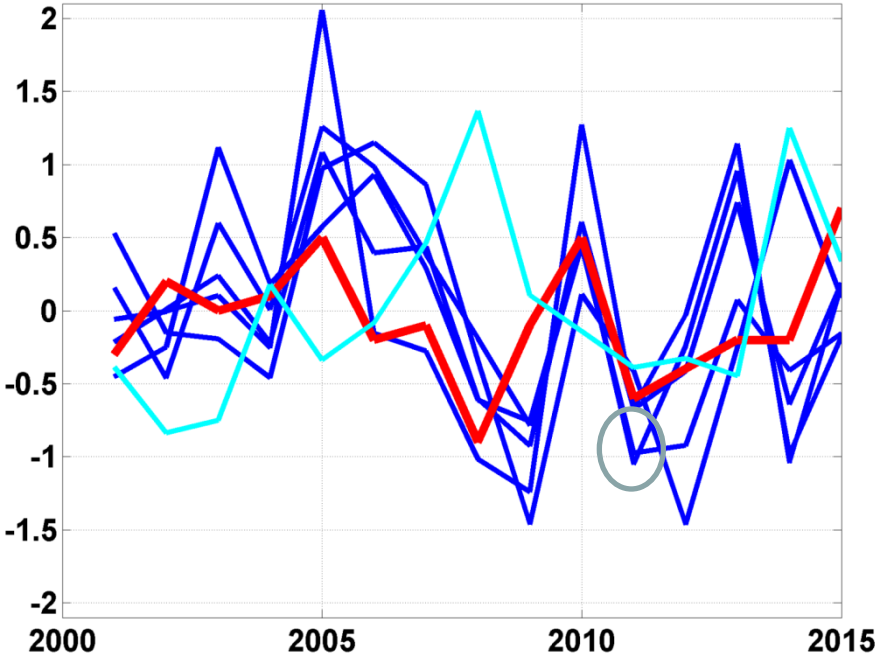
Simulation of rainy season onset in 2003

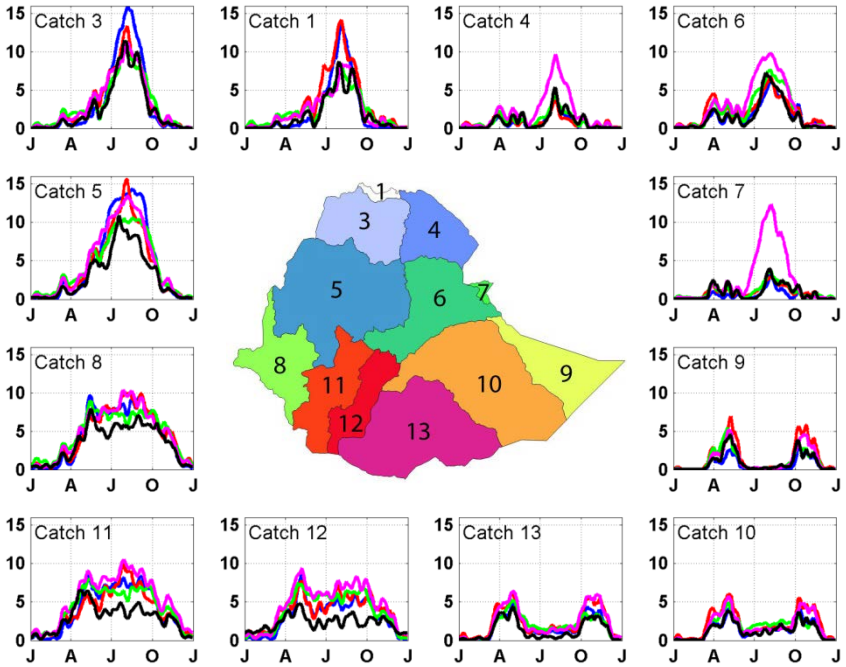
MAM

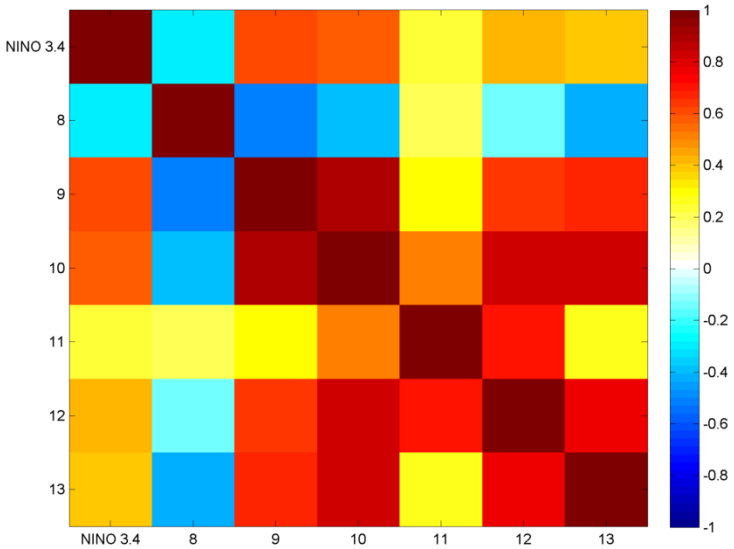
Red: ENSO 3.4 SST anom

Cyan: Catchment 8 precip anom

Blue : Catchments 9-13 precip anom







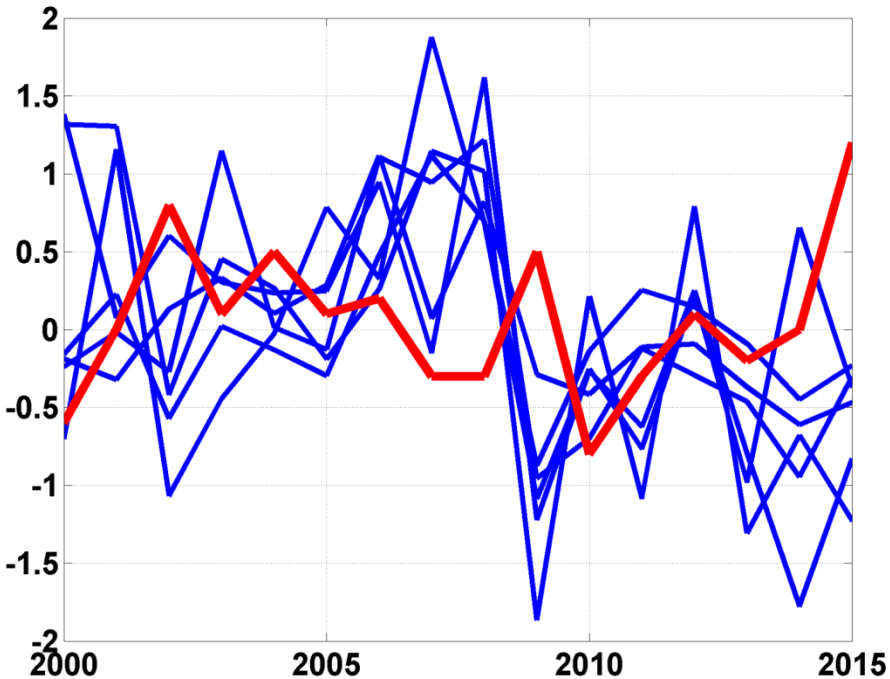
Correlations between catchments 8-11 and NINO 3.4

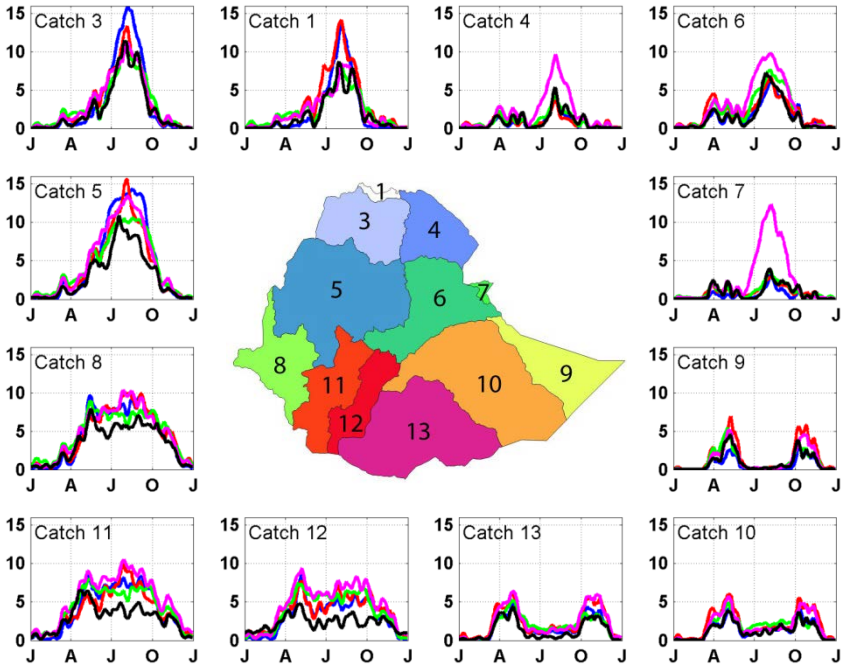
8	9	10	11	12	13
-0.29	0.61	0.59	0.24	0.42	0.39

JJA

Red: ENSO 3.4 SST anom

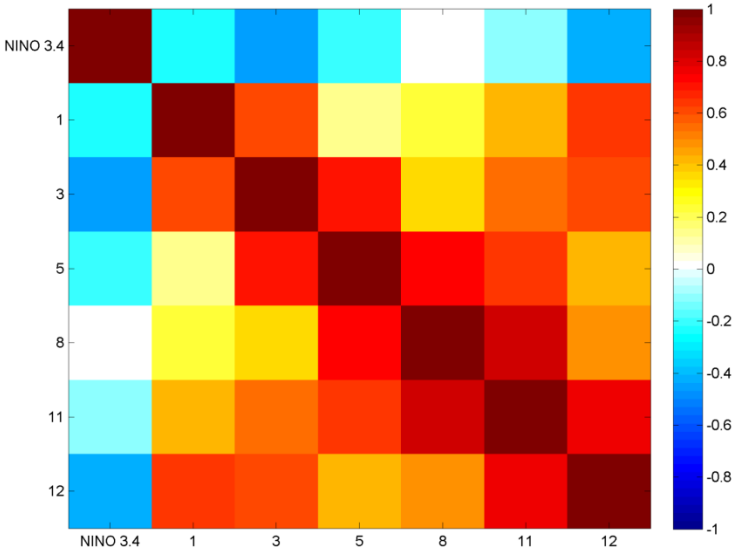
Blue : Catchments 1,3,5,8,11,12 precip anc





Correlations between catchments 8-11 and NINO 3.4

1	3	5	8	11	12
-0.23	-0.45	-0.21	0.00	-0.10	-0.41

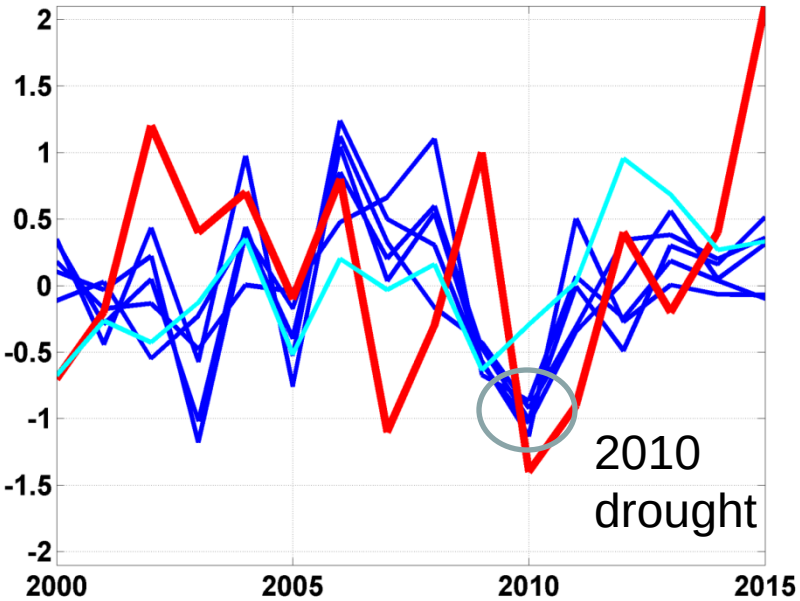


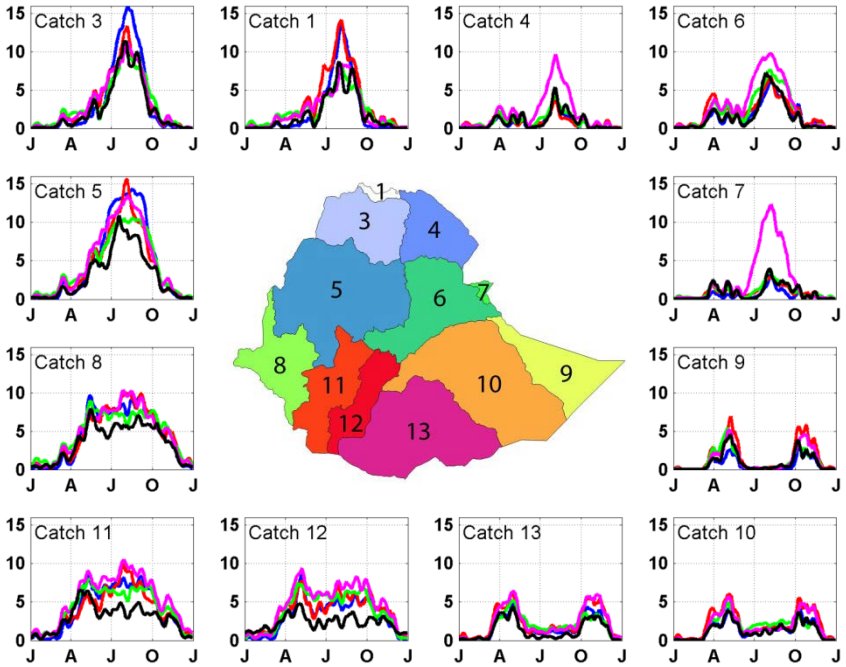
SON

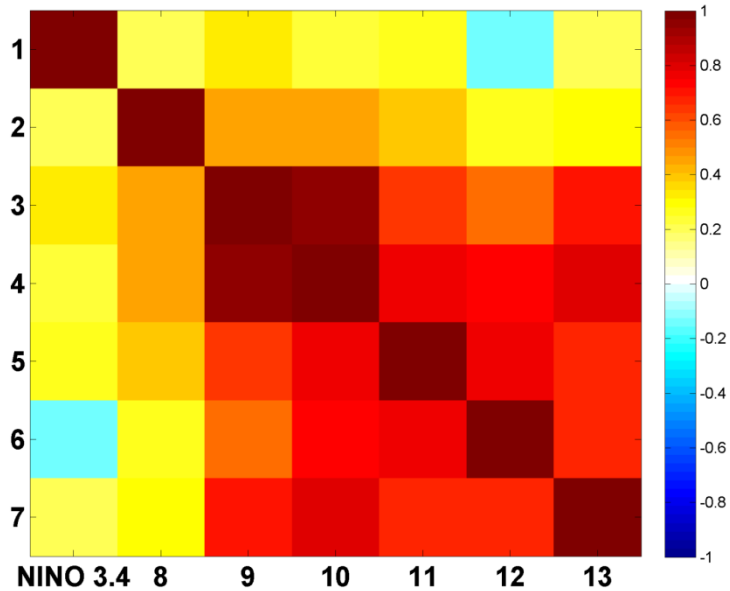
Red: ENSO 3.4 SST anom

Cyan: Catchment 8 precip anom

Blue : Catchments 9-13 precip anom







Correlations between catchments 8-11 and NINO 3.4

8	9	10	11	12	13
0.19	0.34	0.23	0.26	-0.14	0.21

Summary of ENSO teleconnections from my dissertation literature review (needs to be updated!):

Summer (JJAS) rainfall in northern Ethiopia / Eritrea negatively correlated with ENSO
Beltrando and Camberlin, 1993; Camberlin, 1995; Gissila et al., 2004; Segele and Lamb, 2005; Korecha and Barnston, 2007;

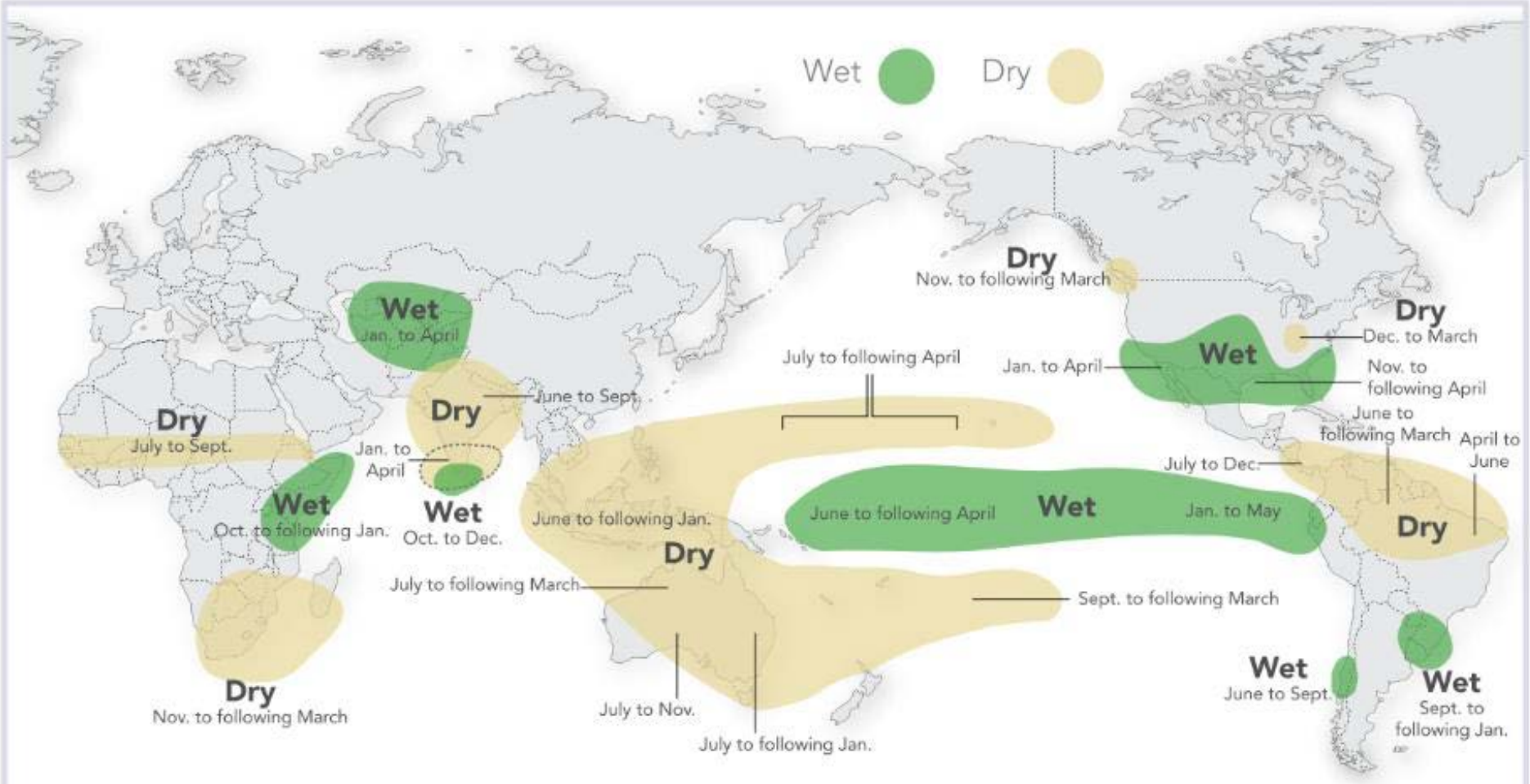
Fall (ON) rainfall in southern GHA positively correlated with ENSO and IOD
Ogallo, 1998; Hastenrath et al, 1993; Indeje et al, 2000; Mutai and Ward, 2000

Spring (MAM) rainfall is more complicated and there is not a lot of coherence in interannual variability between different regions and between the beginning and end of the season. If anything, though, there does appear to be a weak negative correlation with ENSO. Camberlin and Philippon, 2002; Indeje et al., 2000; Camberlin and Okoola 2003; Diro et al, 2008

I'm currently putting together a more comprehensive list of more recent studies.

El Niño and Rainfall

El Niño conditions in the tropical Pacific are known to shift rainfall patterns in many different parts of the world. Although they vary somewhat from one El Niño to the next, the strongest shifts remain fairly consistent in the regions and seasons shown on the map below.



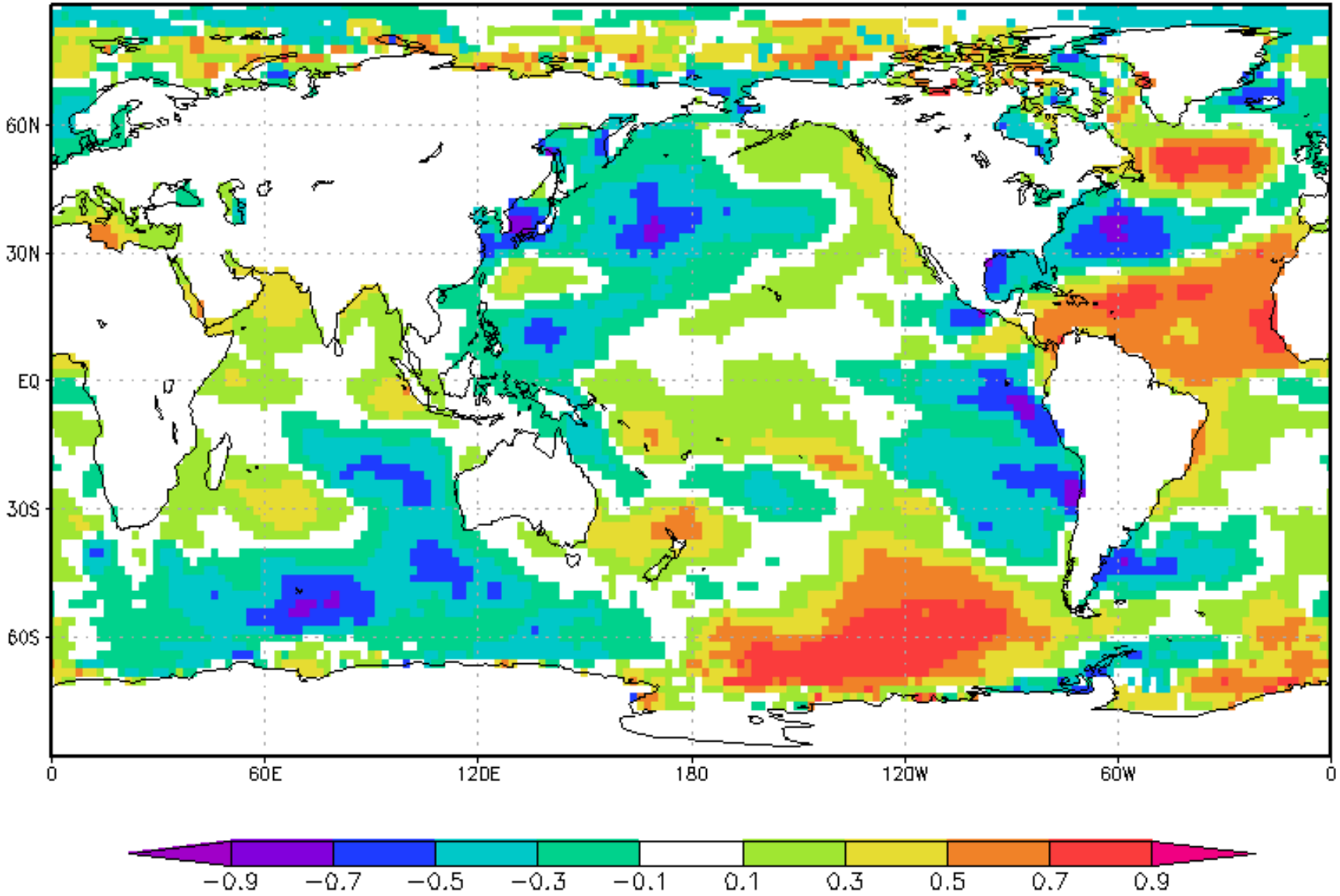
For more information on El Niño and La Niña; go to: http://iri.columbia.edu/enso/

Sources:
1. Ropelewski, C. F.; and M. S. Halpert, 1987. Global and regional scale precipitation patterns associated with the El Nino Southern Oscillation. Mon. Wea. Rev., 115, 1606-1626;
2. Mason and Goddard, 2001. Probabilistic precipitation anomalies associated with ENSO. Bull. Am. Meteorol. Soc. 82, 619-638

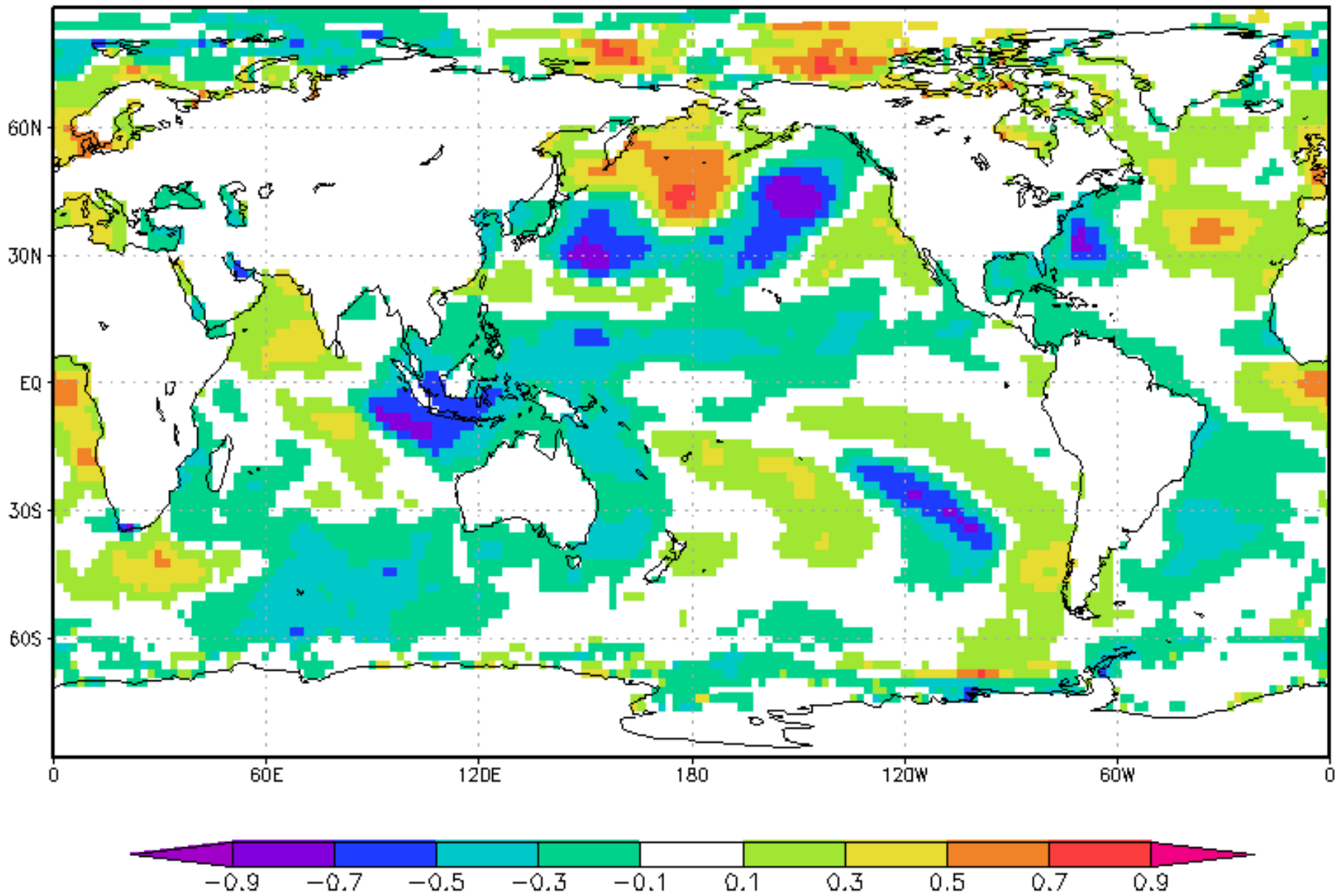
International Research Institute for Climate and Society

/climatesociety @climatesociety

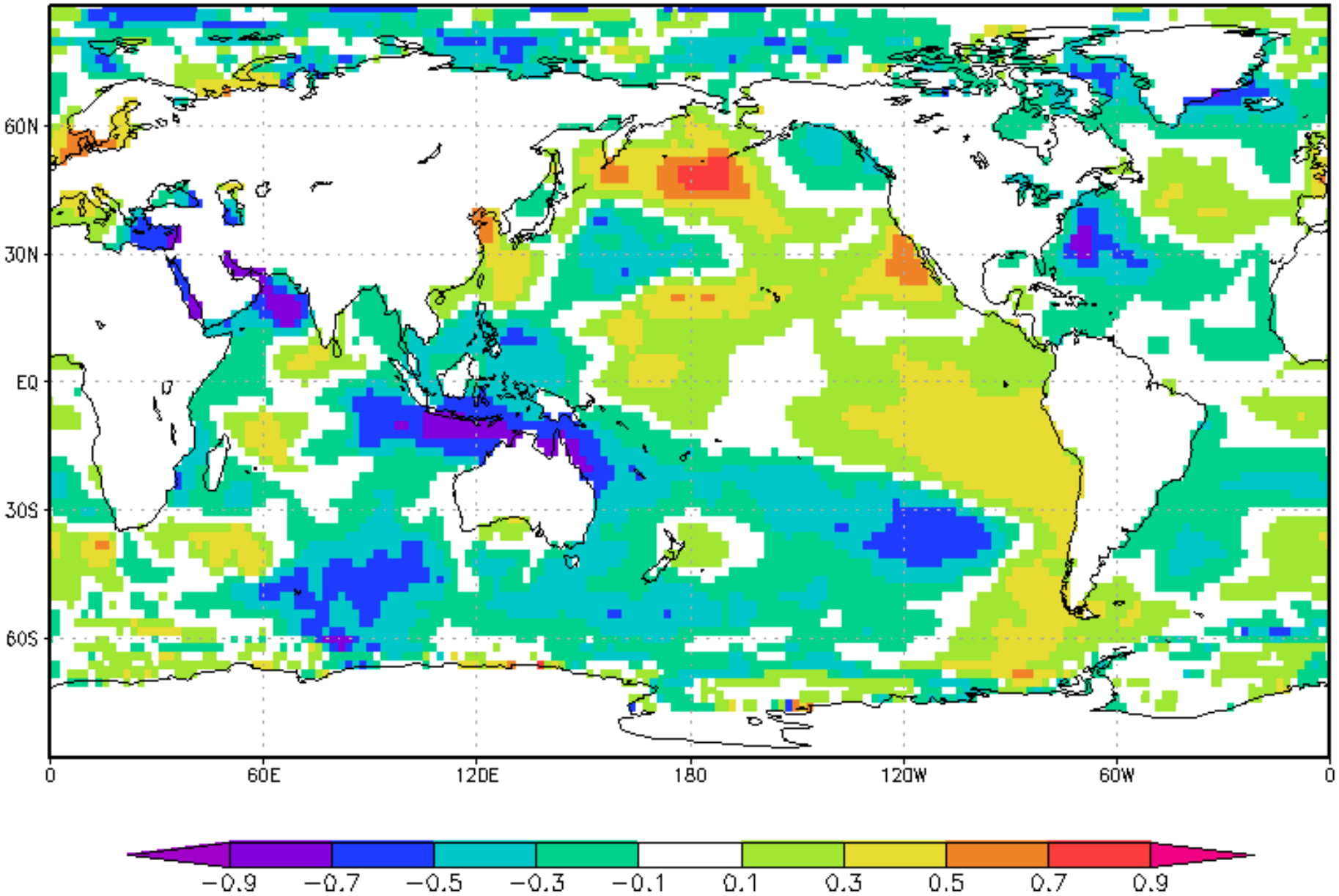
2001-2015 :Correlation of MAM SSTs with MAM Omo-Gibe basin rainfall
R= -0.17 Nino 3.4 vs. Omo-Gibe MAM precip



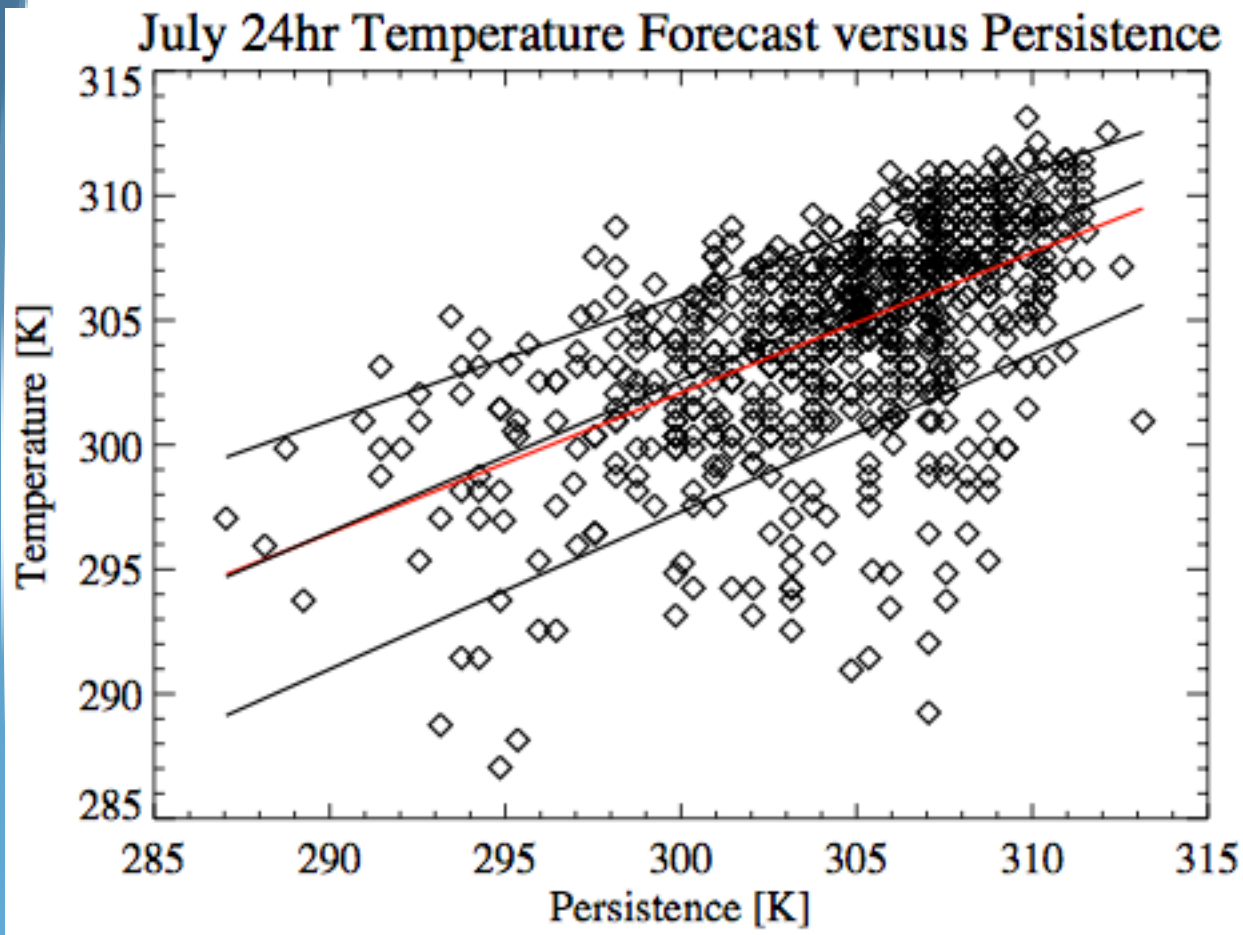
2000-2015: Correlation of JJA SSTs with JJA Omo-Gibe basin rainfall
R= -0.08 Nino 3.4 vs. Omo-Gibe JJA precip



2000-2015: Correlation of SON SSTs with SON Omo-Gibe basin rainfall
R=0.25 Nino 3.4 vs. Omo-Gibe SON precip



Example of Quantile Regression (QR)



Our application

Fitting T quantiles using QR conditioned on:

1) Ranked forecast ens

2) ensemble mean

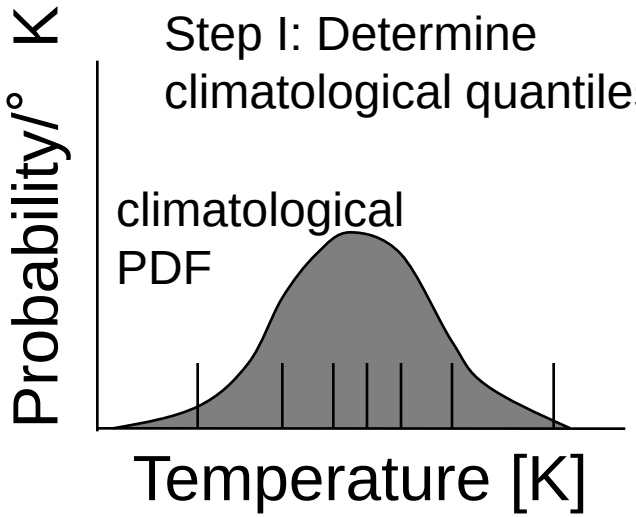
3) ensemble median

4) ensemble stdev

5) Persistence

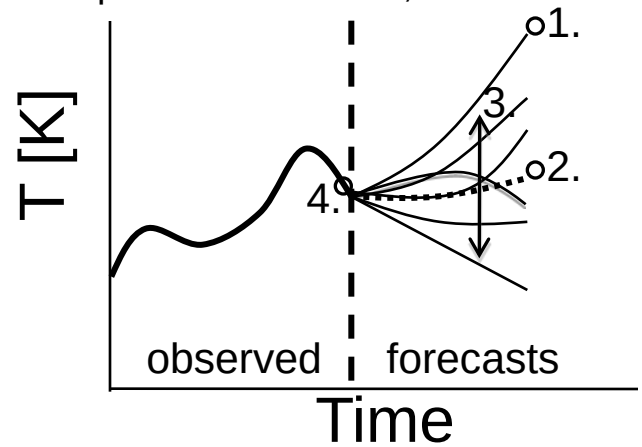
Hopson and Hacker 201

Step I: Determine climatological quantiles



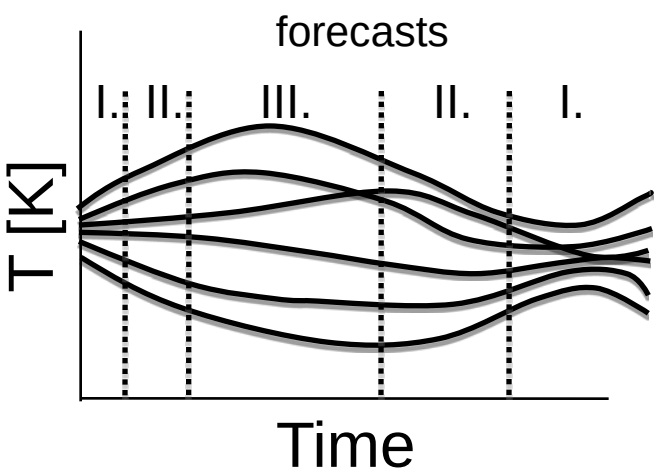
Step 2: For each quan, use forward step-wise cross-validation to select best regress set

Selection requires: a) min QR cost function,
b) binomial distrib at 95% confidence
If requirements not met, retain climatological "prior"

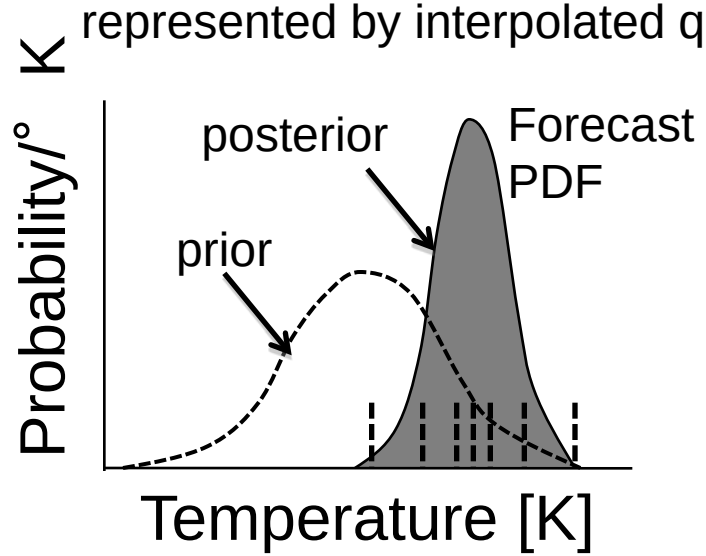


Regressor set:
1. reforecast ens
2. ens mean
3. ens stdev
4. persistence
5. LR quantile (not shown)

Step 3: segregate forecasts based on ens dispersion; refit models (Step 2) for each range



Final result: "sharper" posterior PDF represented by interpolated quans



Hopson and Hacker 201