

# Simulating Climate Variability and Change for Central Asia Using a Nonhomogeneous Hidden Markov Model

S. Sellars<sup>1</sup>, A. Robertson<sup>2</sup>, T. Siegfried<sup>1</sup>

*1-The Columbia Water Center: Columbia University, 2-International Research Institute for Climate and Society, Palisades, NY*

## Introduction

We demonstrate one potential method of using a 8 - State, Nonhomogeneous Hidden Markov Model (NHMM) to stochastically generate two future 50 year precipitation series for 110 subcatchments in the Tien Shan region in Central Asia (60-80E, 40-50N).The first is a baseline scenario derived from TRMM Observations (2000-2009) and the second is a IPCC AR4 SRES A2 (2070-2099) experiment trend adjusted scenario.

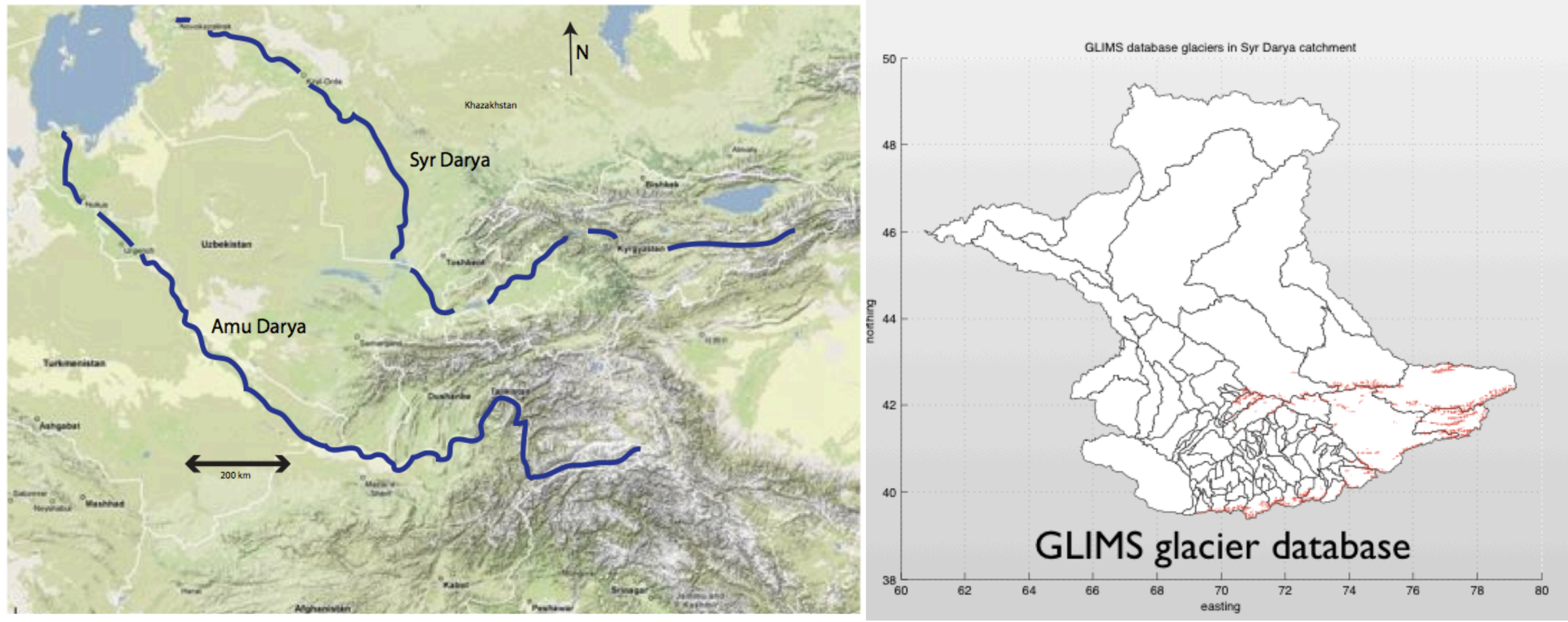


Figure 1: Central Asia:Tien Shan Region (60-80E, 40-50N) on the left and 110 subcatchments of the Tien Shan region on the right

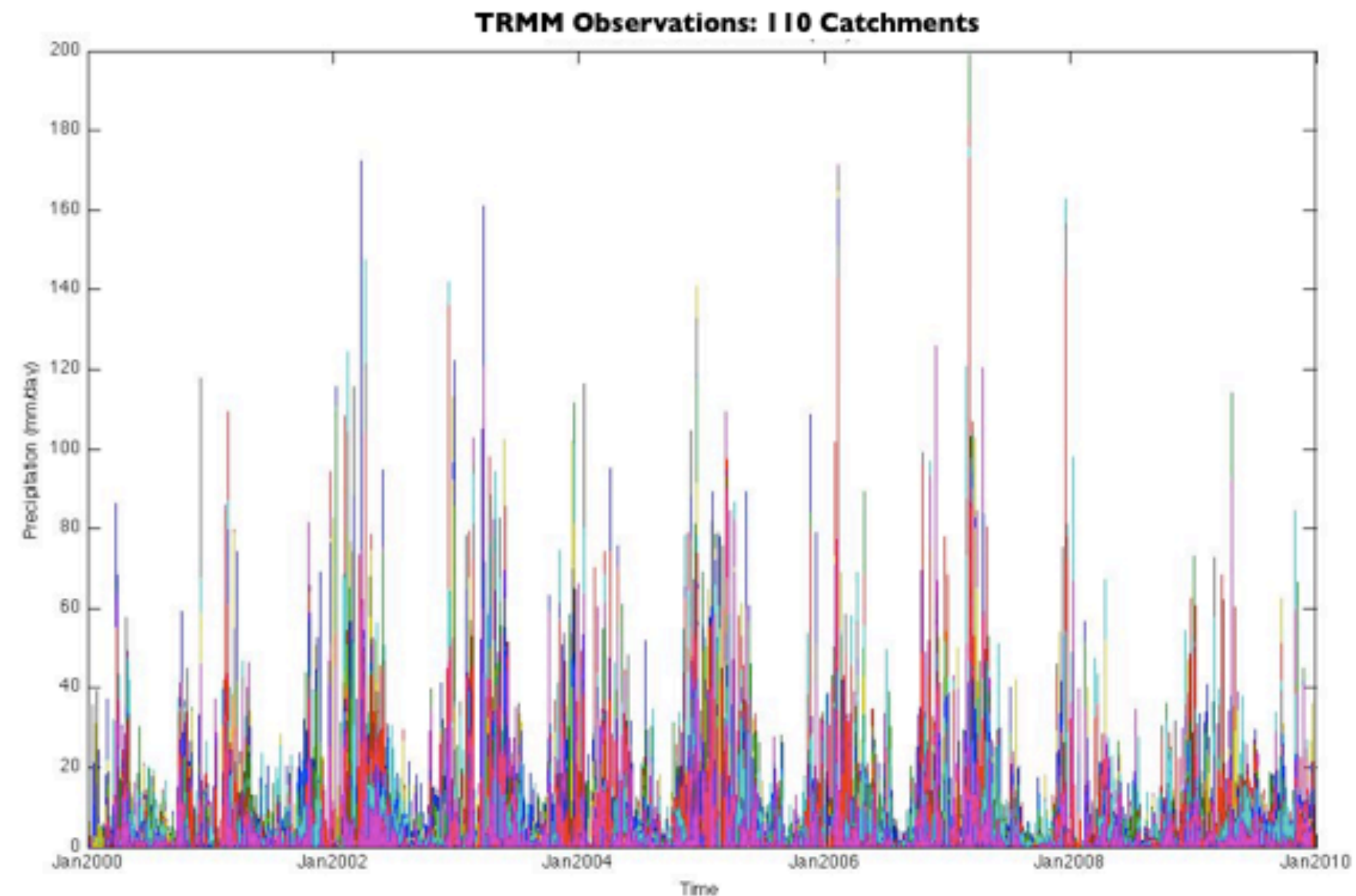


Figure 2: 110 subcatchment precipitation averages from TRMM

## Data Sources

Tropical Rainfall Measuring Mission (TRMM)\* / WCRP CMIP3 IPCC AR4 Monthly, GCM data, Multi-Model Dataset Archive at PCMDI\*

Laboratory:	Country:	Model:
Canadian Centre for Climate Modeling	Canada	CGCM3.1(T47)
Centre National de Recherches Météorologiques	France	CNRM-CM3
CSIRO Atmospheric Research	Australia	CSIRO-Mk3.0
Max Planck Institute for Meteorology	Germany	ECHAM5/MPI-OM
CSIRO Atmospheric Research	Australia	CSIRO-Mk3.5
University of Bonn, KMA	Germany / Korea	ECHO-G
Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.0
Geophysical Fluid Dynamics Laboratory	USA	GFDL-CM2.1
NASA / Goddard Institute for Space Studies	USA	GISS-ER
Istituto Nazionale di Geofisica e Vulcanologia	Italy	INGV-SXG
Institute for Numerical Mathematics	Russia	INM-CM3.0
Institute Pierre Simon Laplace	France	IPSL-CM4
Center for Climate System Research	Japan	MIROC3.2(medres)
Meteorological Research Institute	Japan	MRI-CGCM2.3.2
National Center for Atmospheric Research	USA	CCSM3
National Center for Atmospheric Research	USA	PCM1
Hadley Centre for Climate Prediction and Research	UK	UKMO-HadCM3
Hadley Centre for Climate Prediction and Research	UK	UKMO-HadGEM1

Table 1:WCRP-CMIP3 IPCCAR4 GCM Models, highlighted models were used in the final analysis

## Methodology

### NHMM - Description

The NHMM fits a single model to the 110 subcatchment observed rainfall records.The NHMM introduces a small number discrete rainfall states. Each state has a precipitation distribution for each location. Using a mixture model approach for each of the 110 subcatchments, a Delta function represents wet/dry days and a mixture of one or two exponentials or gammas to represent the rainfall distribution on wet days. In a NHMM a “predictor” or “input” is introduced to modulate the transition probabilities between states as seen in Figure 3.

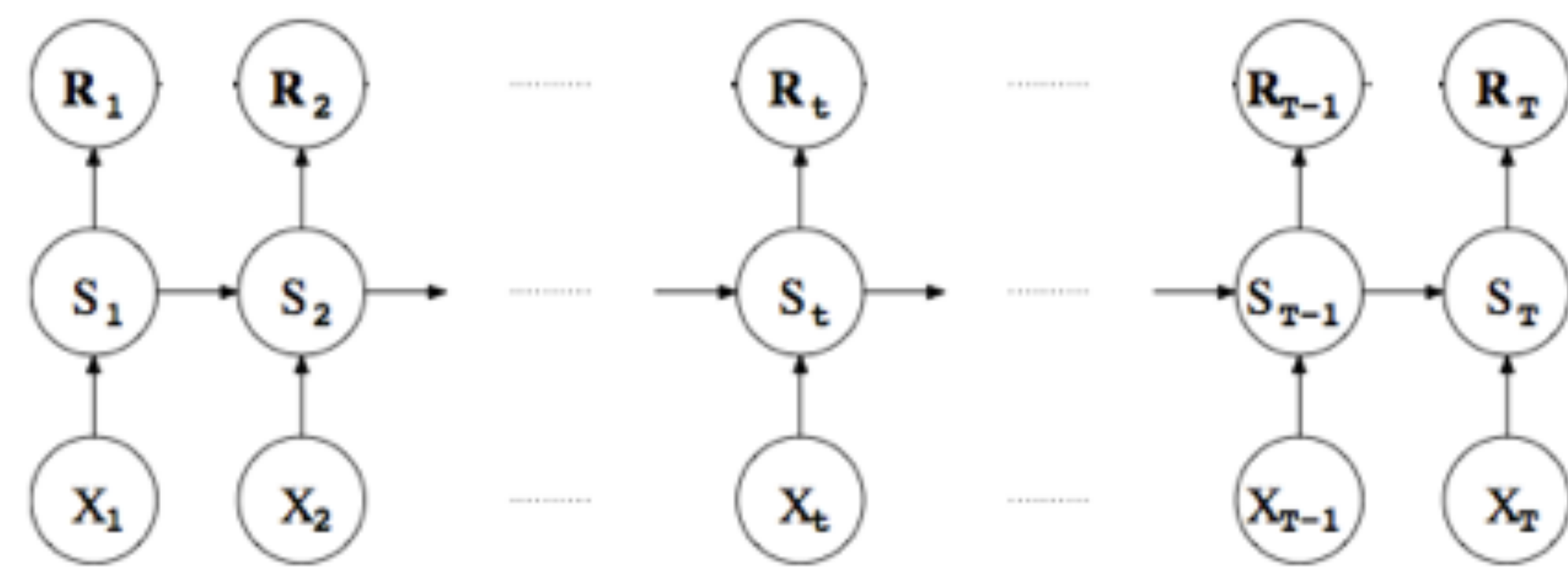


Figure 3: Representation of the Nonhomogeneous Hidden Markov Model. X is the predictor used by the NHMM, S is the state which is influenced by the predictor and R is the rainfall

### Step 1 - Baseline Scenario - Derived from TRMM:

**Input (Baseline Predictor):** 1)TRMM Daily Averaged Observations (2000-2009) for the Tien Shan region, 2) Apply Low Pass Filter (60 Days), 3) Interpolated daily values, 4) Repeat to 10 years, 5) Standardize

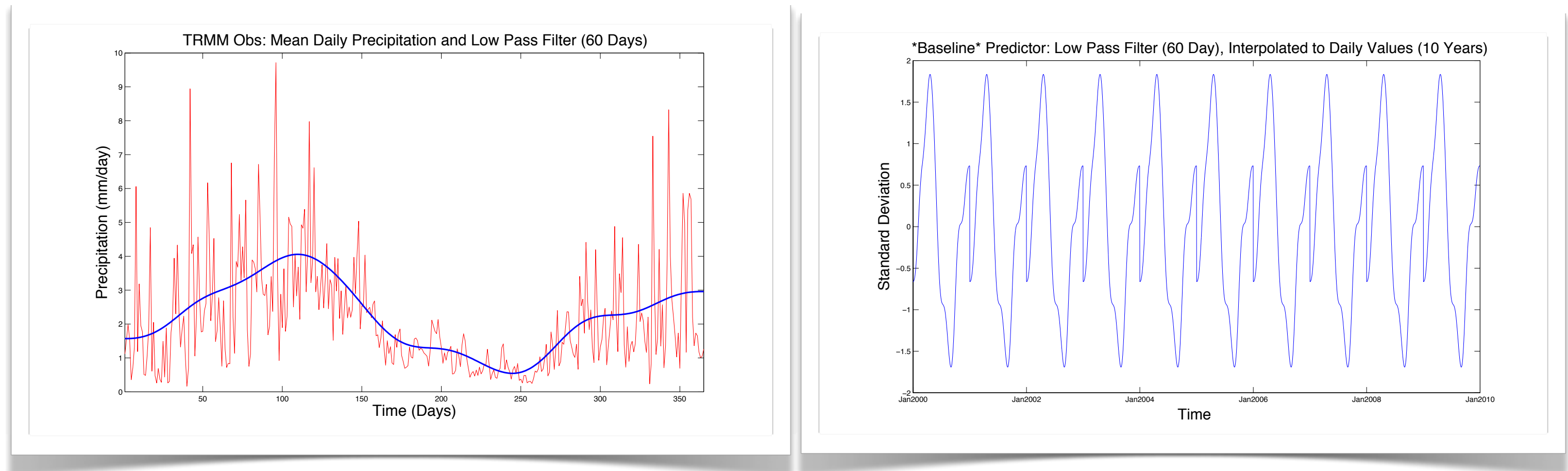


Figure 4: TRMM daily precipitation average for the Tien Shan region (Red) with a 60 day low-pass filter (Blue) on the left and the 60 day low-pass filter repeated 10 years on the right.

### Step 2a - GCM Trend Extraction:

WCRP-CMIP3 IPCC AR4 GCM **Monthly** data (60-80E, 40-50N):

- 20th Century Experiment (20C3M: 1950-1999), 18 Models (56 runs)
- SRES A2 Experiments (SRESA2: 2070-2099), 18 Models (37 runs)

First we define the mean monthly cycle (average values for each month of the year) for the TRMM observations and the GCM 20C3M runs.

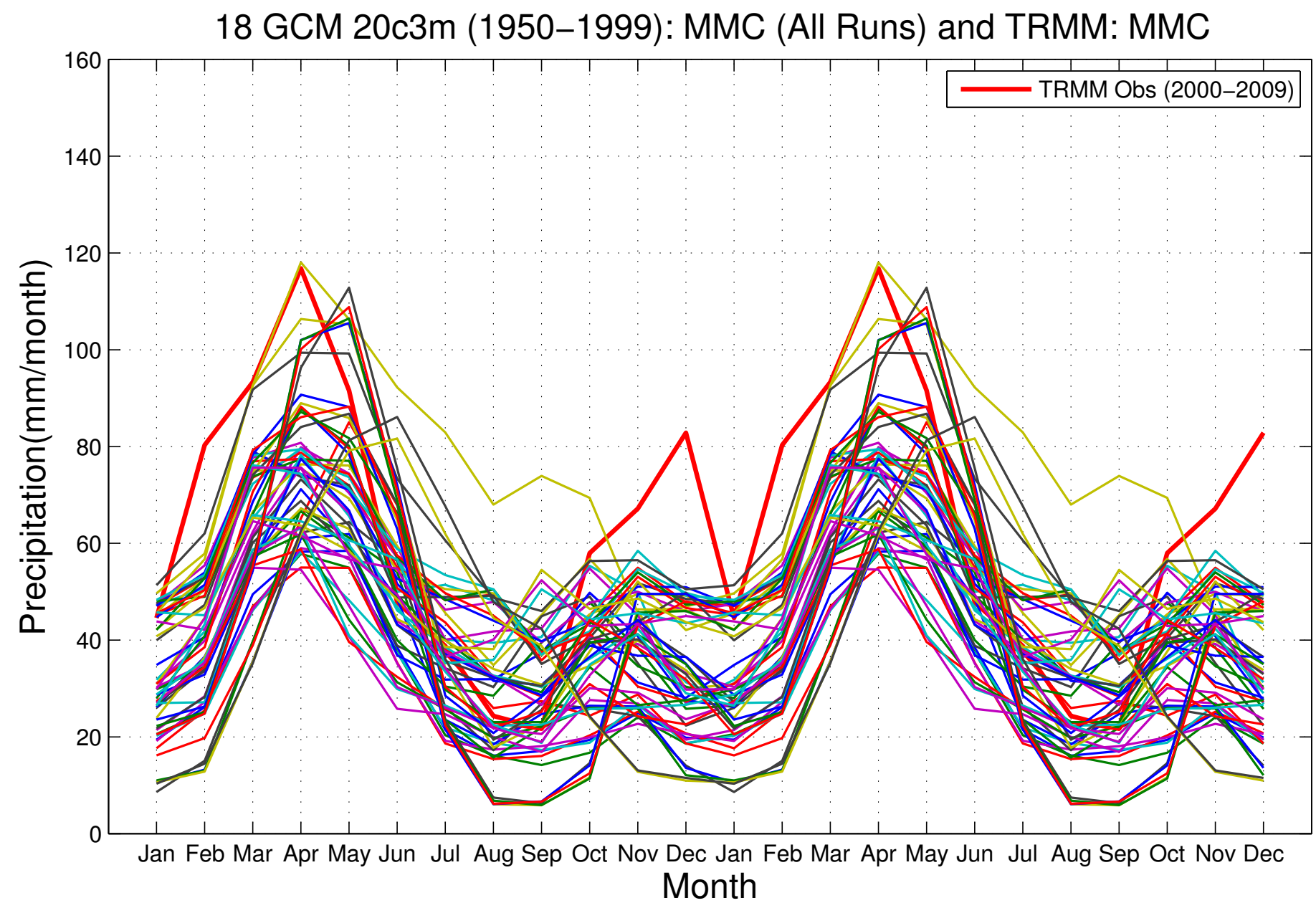


Figure 6: Representation of the NHMM methodology

We then average delta values for all SRES A2 model runs. Next we interpolate to daily values and multiply the daily delta values by the baseline predictor deriving the “delta adjusted” predictor (Eq. 2).

$$\delta = \frac{SRESA2(run)}{20C3M(ensemble)} \quad (1)$$

$$\text{Delta Adjusted} = \delta * \text{Baseline} \quad (2)$$

### Step 2b - GCM Delta Adjusted Scenario:

**\*Input (Delta Adjusted Predictor):**1) TRMM Daily Averaged Observations, 2) Low Pass Filter (60 Days), 3) Delta Adjusted (Monthly, SRES A2, 2070-2099), 4) interpolated daily values, 5) Repeat to 10 years, 6) Standardize

### Step 3 - Predictor Comparison:

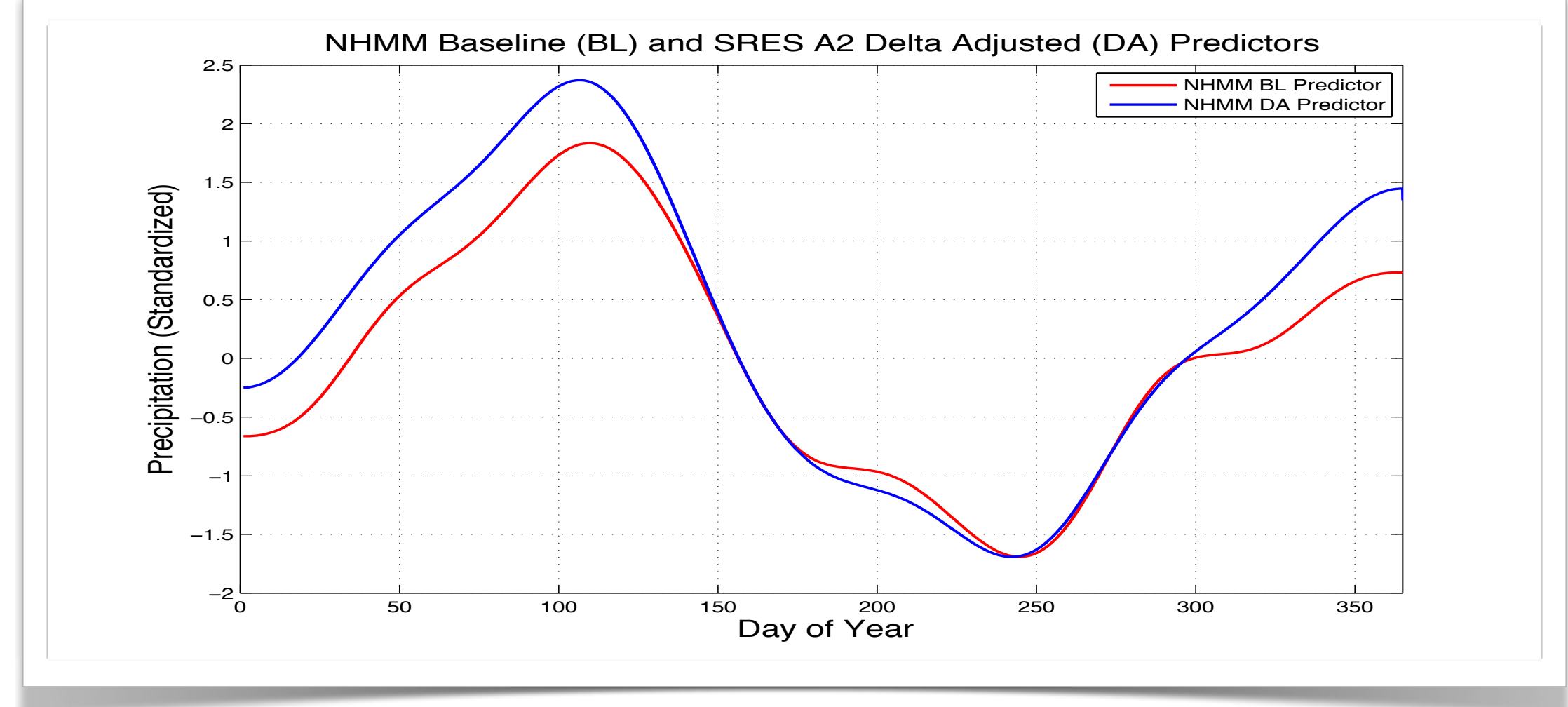


Figure 5: Comparison of predictors for training the NHMM.The baseline predictor is in red and the delta adjusted predictor is in blue.

### Step 4 - NHMM Training and Simulation:

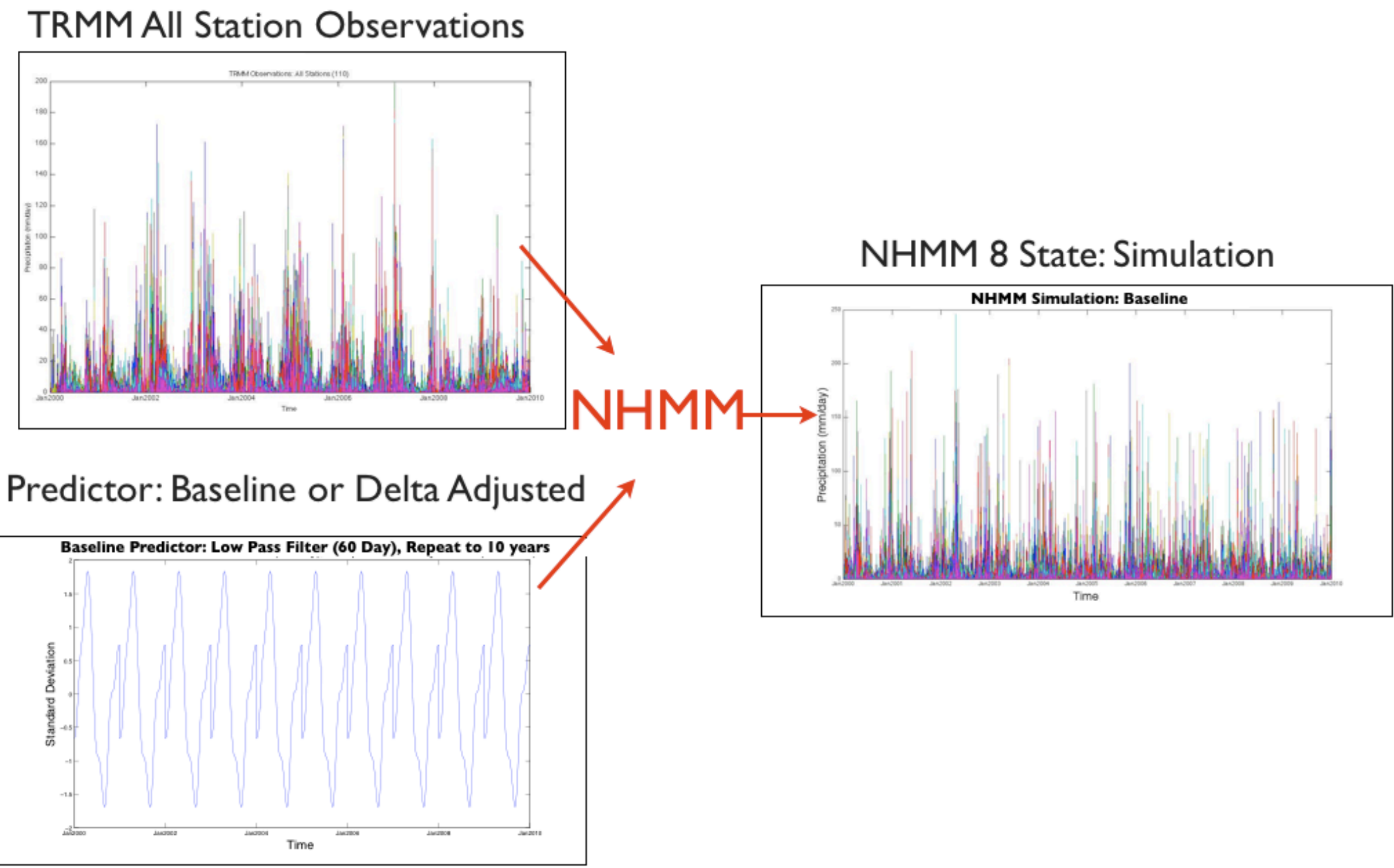


Figure 6: Representation of the NHMM methodology

## Results

### NHMM Simulations: 1) Baseline Simulation 2) GCM Delta Adjusted

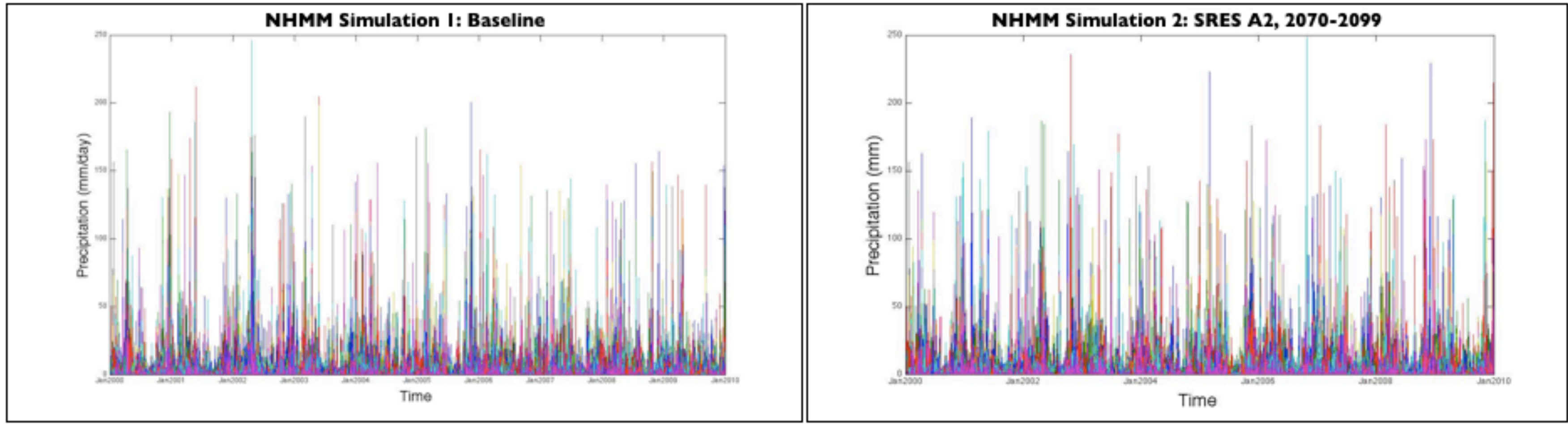


Figure 7:Two NHMM simulations, baseline on the left and delta adjusted on the right

NHMM results were satisfactory and seasonal shifts in precipitation were captured as well as the GCM shifts in future mean monthly cycle.

## Conclusion

We demonstrate the ability of NHMM to represent precipitation at the regional level.We also developed one potential method of incorporating regional GCM information into this model framework. NHMM can be seen as useful tool for simulating stochastic precipitation for hydrological model and reservoir operating rules testing.The stochastic nature of precipitation is represented in this methodology, but some problems did arise. Extreme precipitation events seem to not be well represented and further research is needed.

## References

MVNHMM toolbox developed by Dr. Sergey Kirshner (<http://iri.columbia.edu/climate/forecast/stochasticTools/index.html#hmm>). Dissertation: Kishner S. (2005). Modeling of Multivariate Time Series Using Hidden Markov Models, Robertson, A.W., S. Kirshner, and P. Smyth, 2004: Downscaling of daily rainfall occurrence over Northeast Brazil using a Hidden Markov Model, J. Climate, 17, 4407-4424.G. J. Huffman, The TRMM multi-satellite precipitation analysis (tmpra): Quasi-global, multiyear, combined- sensor precipitation estimates at fine scales, Journal of Hydrometeorology, 8:38–55, 2007, Mehl, G.A., C. Covey, T. Delworth, M. Latif, B. McAvaney, J. F.B. Mitchell, R. J. Stouffer, and K. E. Taylor, 2007: The WCRP CMIP3 multi-model dataset: A new era in climate change research, Bulletin of the American Meteorological Society, 88, 1383–1394, 2007, **Acknowledgements:** We acknowledge Dr. Padraic Smyth and Scott Triggis at the Center for Machine Learning and Intelligent Systems, University of California, Irvine for their contributions to this research. The IRI is supported through a grant from the U.S. National Atmospheric and Ocean Administration. We acknowledge the modeling groups, the Program for Climate Model Diagnosis and Intercomparison (PCMDI) and the WCRP's Working Group on Coupled Modelling (WGCM) for their roles in making available the WCRP CMIP3 multi-model dataset. Support of this dataset is provided by the Office of Science, U.S. Department of Energy.