ACC DAR Adapting to Climate Change in Coastal Dar es Salaam

SAPIENZA
UNIVERSITÀ DI ROMA

International Workshop

TOWARDS SCENARIOS FOR URBAN ADAPTATION PLANNING
Assessing seawater intrusion under climate and land cover changes in Dar es Salaam, Tanzania

HOMOGENEOUS & NON-HOMOGENEOUS HIDDEN MARKOV DOWNSCALING MODEL FOR PROJECTION OF HYDROCLIMATE CHANGES IN TANZANIA

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FRANCESCO CIOFFI , ALESSANDRO MONTI & UPMANU LALL

University of Rome "La Sapienza" & Columbia University (New York)

phone : +393407714932

Mail : francesco.cioffi@uniroma.it

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Objective

- ✓ to estimate the precipitation pattern changes under global warming scenarios in Der er Salam (Tanzania) coastal region

Framework

- ✓ Vulnerability, Resilience and Adaptation to climate change, i.e to quantify the impact, beyond the existing anthropic ones, of hydro-climatic changes on surface and deep water bodies (floods, droughts, salt intrusion,….)

Why is so difficult to evaluate changes in precipitation?

- ✓ To evaluate the effects of climate change on precipitation the main tools are **GCMs** (General Circulation Models)

- ✓ **GCMs** is supposed to represent almost well the large scale structure of meteorological variables but GCM's have poor spatial resolution (150x150 km) which does not allow to take into account local effects , as those due to orography . Since precipitation are affected by local orography, rainfall is poorly represented in GCM's; simulations are affected by strong biases.

- ✓ To overcome these drawbacks downscaling methods have been proposed

  - ❖ **Dynamic Downscaling Models** (DDM)
  - ❖ **Statistical Downscaling Models** (STM)

DDMs

- DDMs are based on RCMs (Regional Circulation Models)
- RCMs are supposed to improve the spatial resolution by using models on a limited region of Earth
- RMCs impose boundary conditions coming from CGMs
- RMCs require very powerful computers and long computational time
- Spatial resolution is better (25x25 Km) but still poorly in capturing local effects.
- Bias corrections are needed to fit observations.

SDMs

- SDMs try to find stochastic relationship between large scale atmospheric circulation (i.e meteorological variables which are supposed to be well simulated by GCMs or RCMs) and measured local rainfall characteristics (frequency and intensity).

SDMs VS DDMs

- ✓ SDMs do not require powerful computer
- ✓ SDMs are able to capture local effects by parameters of statistics
- ✓ a deterministic link is obtained between large scale atmospheric circulation and local phenomena

❖ **Among the existing SDMs, Homogeneous Markov Model (HMM) and Non-Homogeneous Markov Model (NHMM) appear to be the most promising since they are particularly efficient in the treatment of discrete variables like precipitations**

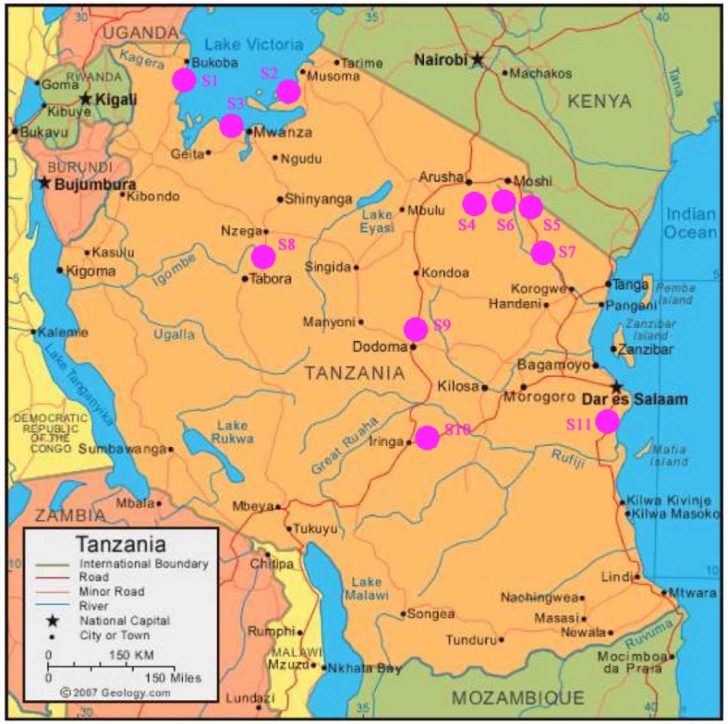
In the current presentation we explore the potentiality of **HMM** & **NHMM** to simulate the precipitation pattern in Tanzania and we show the proposed approach is able to:

- **capture the main characteristics of rainfall pattern typically occurring in East Africa**
- **identify the large scale atmospheric circulation patterns affecting local precipitations**
- **simulate with considerable accuracy frequency and intensity of precipitations in Tanzania region**

Data

Type;	Daily Rainfall Spells
N. of Stations;	11
Time Period;	from 1950 to 1990
Dataset;	KNMI Climate Explorer

Stations location in Tanzania (on Map)



Giuseppe Faldi, 2010. "Valutazione della vulnerabilità al cambiamento climatico delle comunità costiere di Dar es Salaam (Tanzania) rispetto al fenomeno dell'intrusione salina nella falda acquifera". Dissertation. (modified)

Stations location in Tanzania (data info)

	ON MAP	CODE/NAME	LATITUDE	LONGITUDE
1	S1	TZ000063729 BUKOBA	-1.33N	31.82E
2	S2	TZ000063733 MUSOMA	-1.50N	33.80E
3	S3	TZ000063756 MWANZA	-2.47N	32.92E
4	S4	TZ000063789 ARUSHA	-3.33N	36.63E
5	S5	TZ000063790 MOSHI	-3.35N	37.33E
6	S6	TZ000063791 KILIMANJARO_AIRPORT	-3.42N	37.07E
7	S7	TZ000063816 SAME	-4.08N	37.72E
8	S8	TZ000063832 TABORA_AIRPORT	-5.08N	32.83E
9	S9	TZ000063862 DODOMA	-6.17N	35.77E
10	S10	TZ000063887 IRINGA	-7.63N	35.77E
11	S11	TZ000063894 DAR_ES_SALAAM_AIRPC	-6.87N	39.20E

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Theory

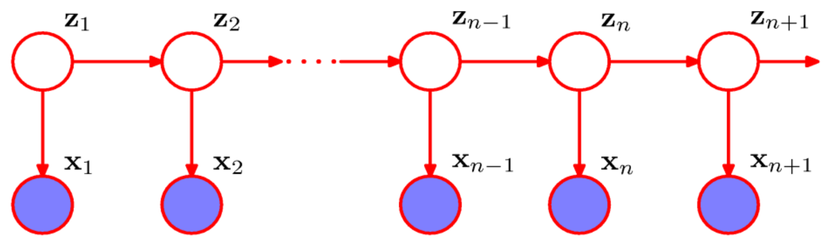
The **HMM** assumes that observations are generated from a mixture of distributions among which subjects move according to a hidden Markov chain, and that rainfall occurrence is governed by a few discrete states, with Markovian daily transitions between them. HMM used here follows the approach of the (Hughes and Guttorp, 1994) to model daily rainfall occurrence, while additionally modeling rainfall amounts (Robertson et al. 2004-2006).

In **NHMM** the transition probabilities are allowed to vary with time, and so it generalizes the homogeneous HMM. In particular for downscaling applications, the transition probabilities between states are allowed to vary as a function of external inputs (i.e. these variables, Xk,t, can influence the evolution of the weather states sequence, Z).

Legend:

Zn;	transition probabilities (no stationary) Hidden States
Un;	external inputs
Xn;	observed data
K;	the number of Hidden States
σ and ρ;	parameters to be estimated

Homogeneous Hidden Markov



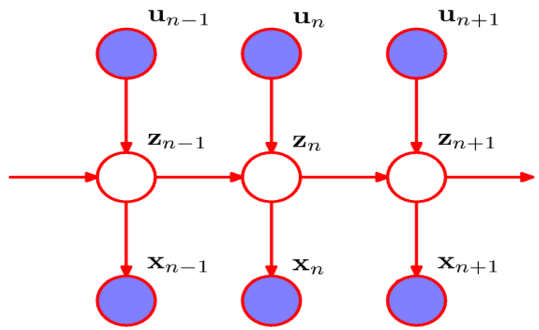
Markov Property $p(\mathbf{x}_n \mid \mathbf{x}_1, \ldots, \mathbf{x}_{n-1}) = p(\mathbf{x}_n \mid \mathbf{x}_{n-1})$

Conditional Indipendece Property $\mathbf{z}_{n+1} \perp \mathbf{z}_{n-1} \mid \mathbf{z}_n$

Joint probability distribuition

$$p(\mathbf{X},\mathbf{Z} \mid \Theta) = p(\mathbf{z}_1 \mid \pi)\left[\prod_{n=2}^{N} p(\mathbf{z}_n \mid \mathbf{z}_{n-1}, \mathbf{A})\right]\prod_{m=1}^{M} p(\mathbf{x}_m \mid \mathbf{z}_m, \theta)$$

Non-Homogeneous Hidden Markov



Conditional distribuition

$$p(z_n = j \mid z_{n-1} = j, \mathbf{u}_n = u) = \frac{\exp(\sigma_{ij} + \rho_j u)}{\sum_{k=1}^{K} \exp(\sigma_{ik} + \rho_k u)}$$

Joint probability distribuition

$$p(\mathbf{X},\mathbf{Z} \mid \Theta, \mathbf{U}) = p(\mathbf{z}_1 \mid \pi, \mathbf{u}_1)\left[\prod_{n=2}^{N} p(\mathbf{z}_n \mid \mathbf{z}_{n-1}, \mathbf{u}_n, \mathbf{A})\right]\prod_{m=1}^{M} p(\mathbf{x}_m \mid \mathbf{z}_m, \theta)$$

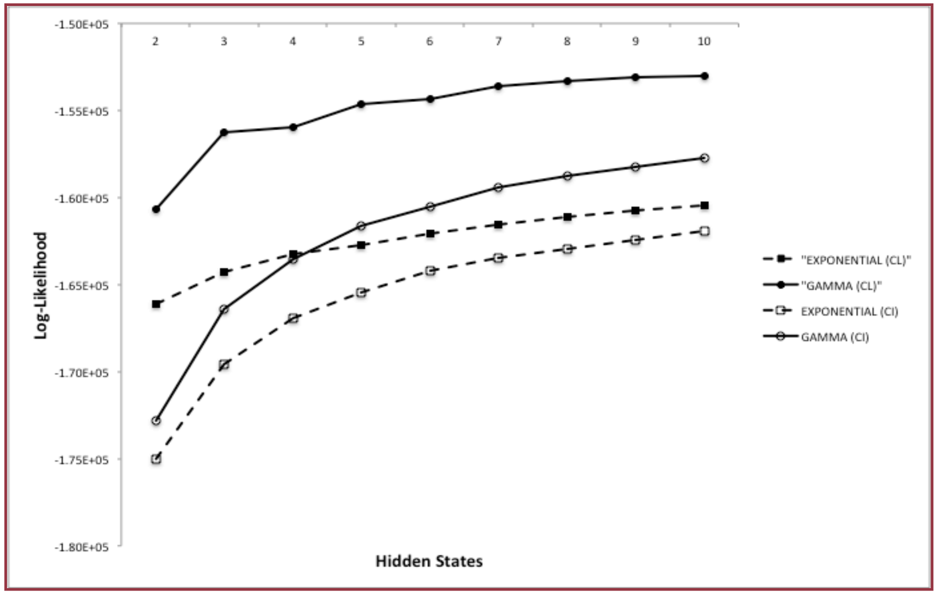
Chow Liu (CL) VS Conditional Independence (CI)

The comparison between **CL** and **CI** is made calculating, for **Hidden States** from 2 to 10 and for two different Density Probability Functions (**Gamma and Exponential**), the Bayesian Information Criterion (BIC) and the Log-Likelihood. All analysis is annually run for 1950-1990 period considering 11 Rainfall Stations.

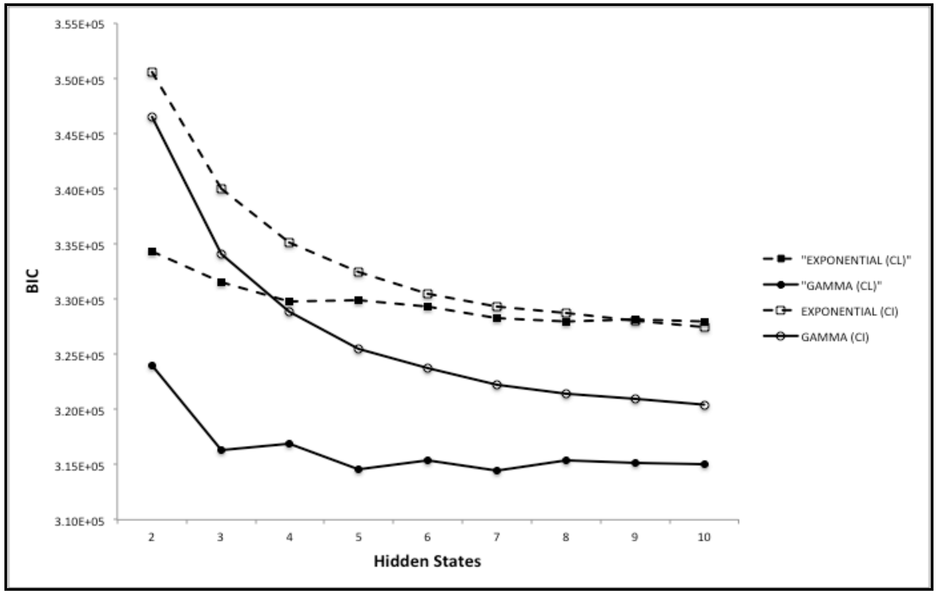
The Table represents data from CL / Gamma & CI / Gamma for 5 Hidden States

	HMM-CL		HMM-CI	
	Log-Likelihood	BIC	Log-Likelihood	BIC
1950-1990	-154632	314541	-161622	325533

Log-Likelihood



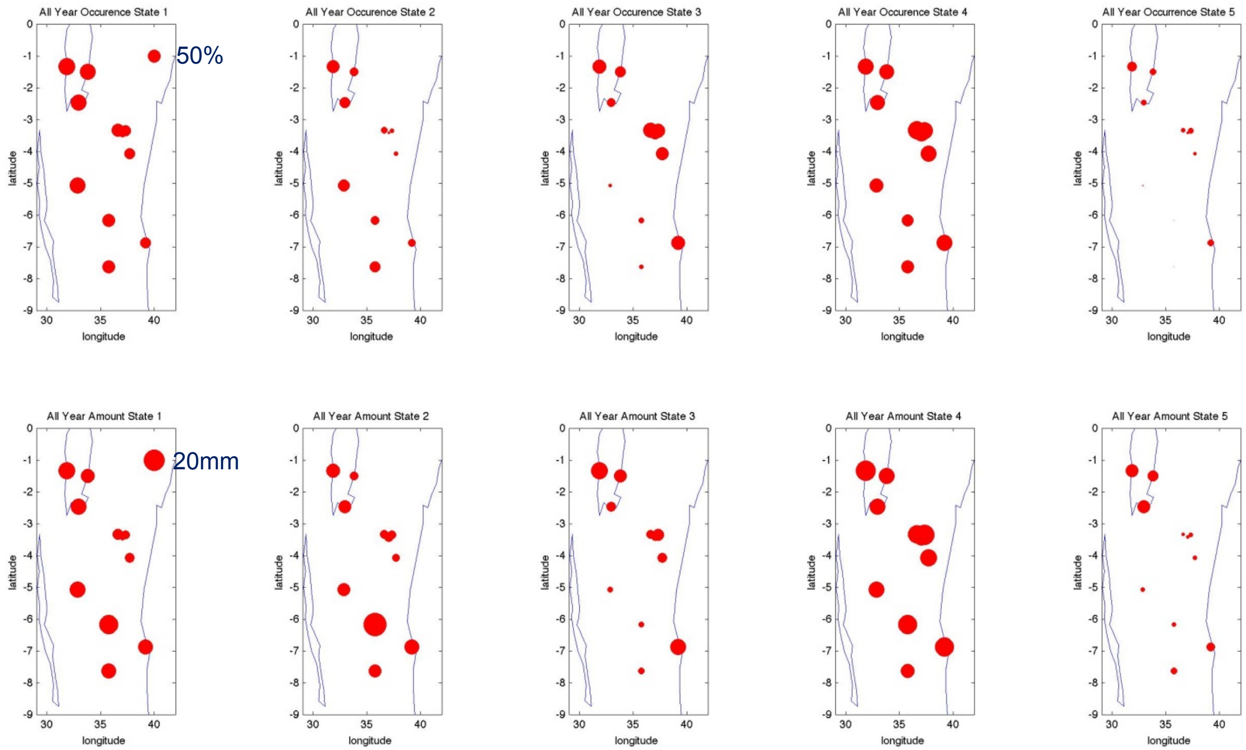
BIC

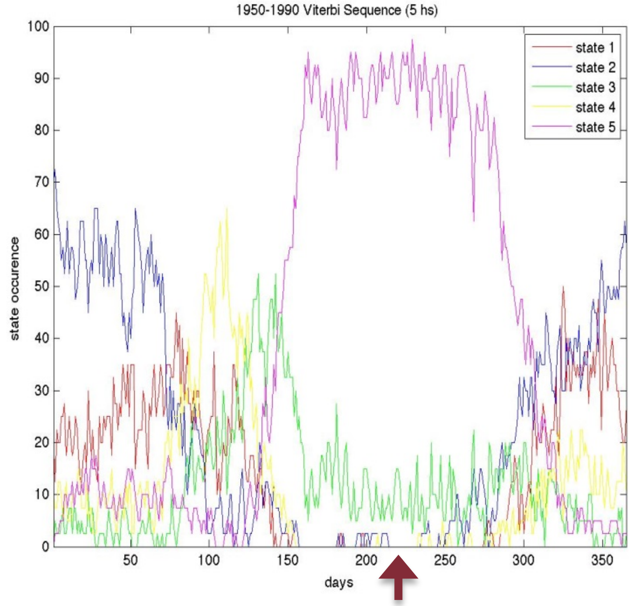


Five Hidden States for Annual period

"**Occurrence**" and the mean "**Amounts**" of days receiving greater than zero rainfall calculated from the parameters of the Gamma distribution (Annual period from 1950 to 1990 for 11 stations in Tanzania).

The **Hidden State** could be physically read as a particular rainfall pattern the can sudden in the area. (see the legend)





The figure above represents the State Occurrence during year. There are significant seasonal variations during the year typically occurring in East Africa.

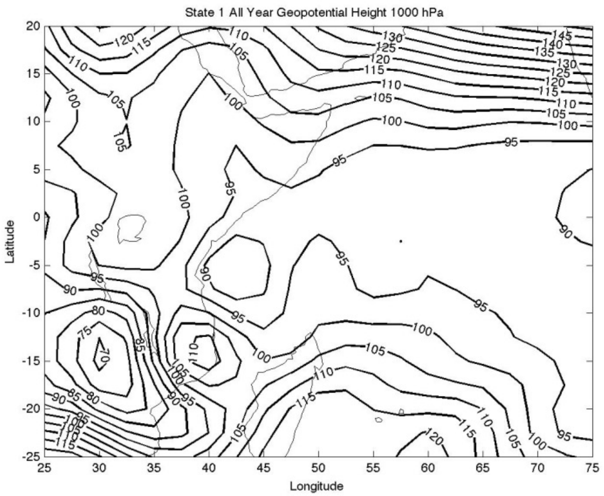
Legend

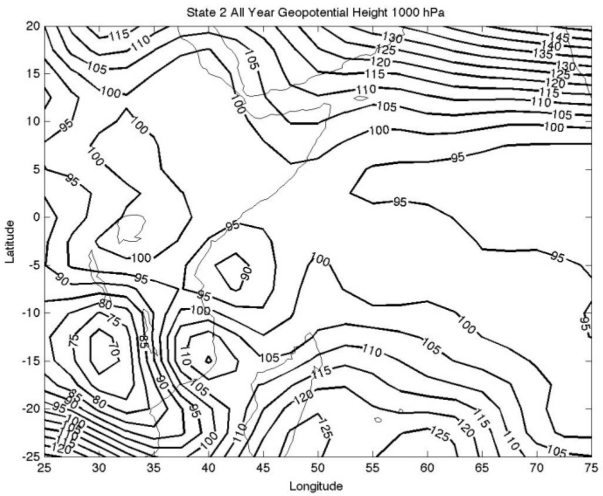
State 1:
Wet Homogeneous
State 2:
Coastal Wet Non-Homogeneous
State 3:
Inland Wet Non-Homogeneous
State 4:
Very Wet Homogeneous
State 5:
Dry Homogeneous

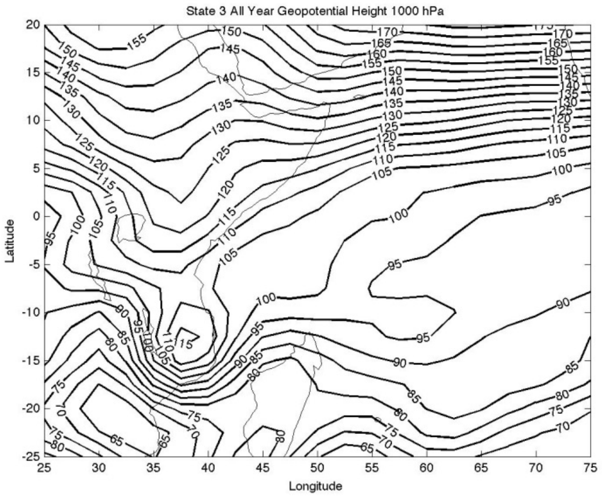
Interpretation of the HMM States and Choosing Predictor/s

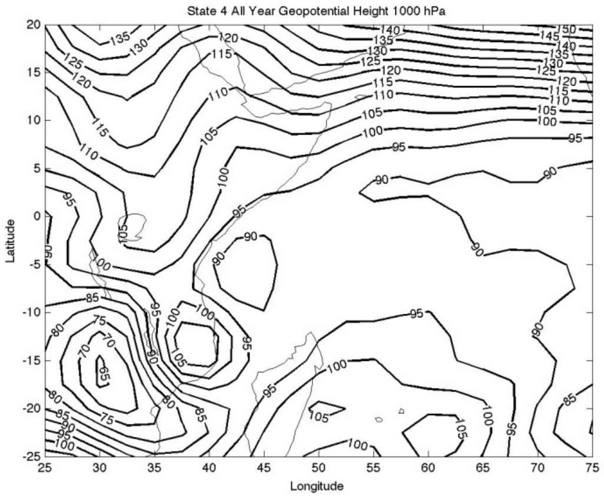
GPH at 1000 hPa

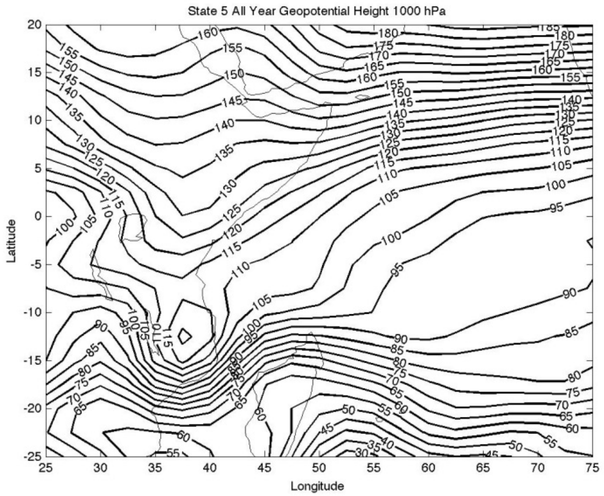
The Rainfall States provide a **diagnostic of Large Scale Weather Conditions**. Composites fields, with respect to the Annual climatological mean of the days assigned to each state, are obtained for Geo-potential Height (GPH), Temperature (T) at 1000 hPa, Meridional Winds (MW) at 850 hPa, Zonal Winds (ZW) at 850 hPa and Zonal Equator Winds (ZEW) . These fields show that GPH,T, ZW, ZEW, MW and their appropriate combinations can be used as predictors in NHMM.







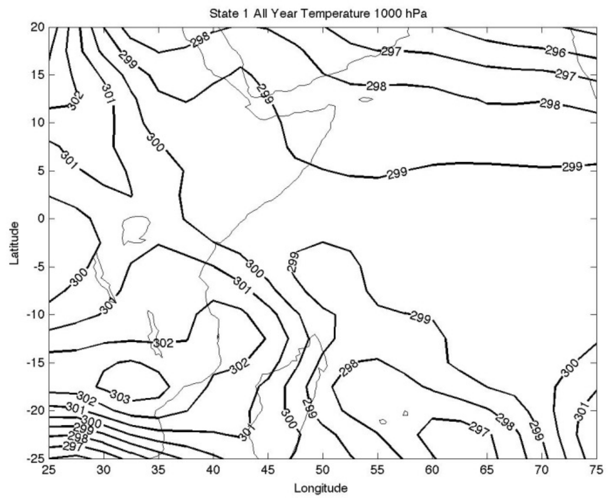


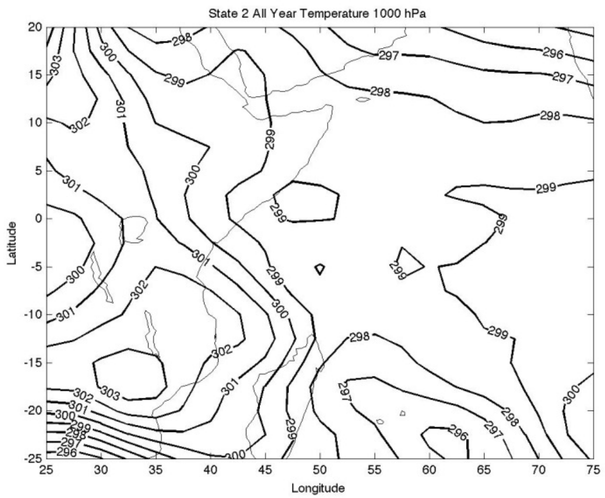


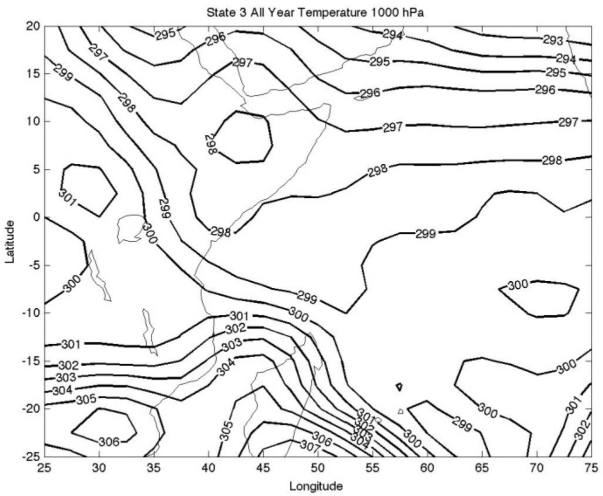
Interpretation of the HMM States and Choosing Predictor/s

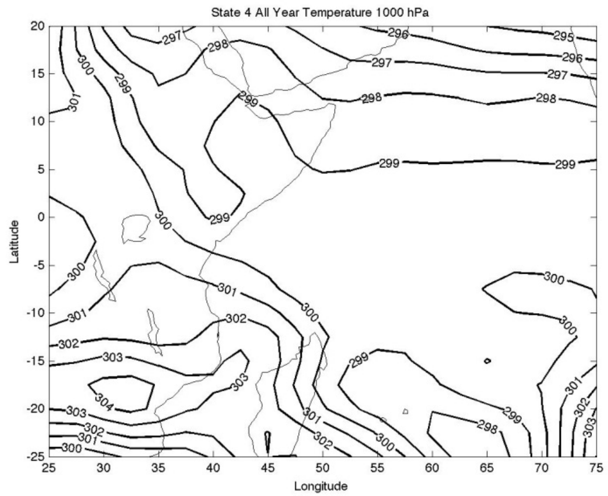
T at 1000 hPa

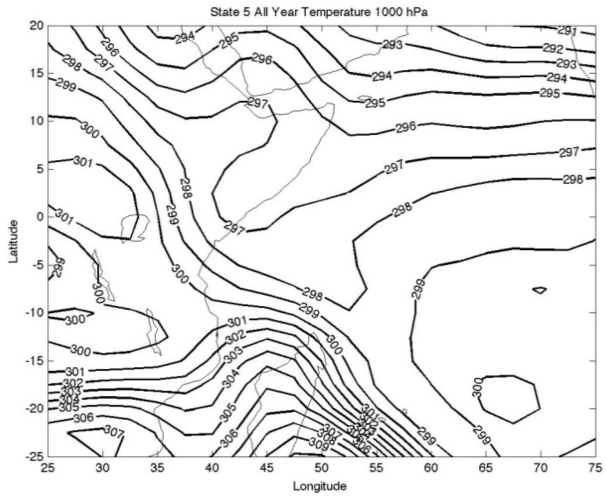
The Rainfall States provide a **diagnostic of Large Scale Weather Conditions**. Composites fields, with respect to the Annual climatological mean of the days assigned to each state, are obtained for Geo-potential Height (GPH), Temperature (T) at 1000 hPa, Meridional Winds (MW) at 850 hPa, Zonal Winds (ZW) at 850 hPa and Zonal Equator Winds (ZEW) . These fields show that GPH,T, ZW, ZEW, MW and their appropriate combinations can be used as predictors in NHMM.







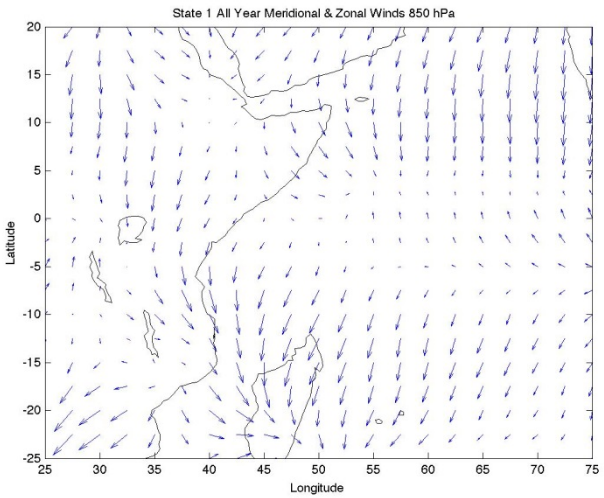


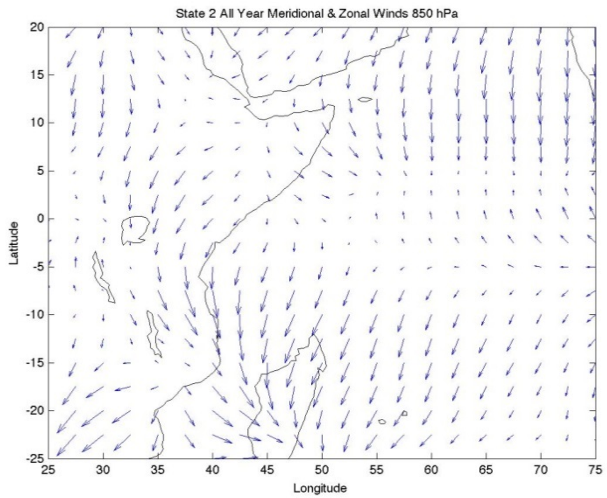


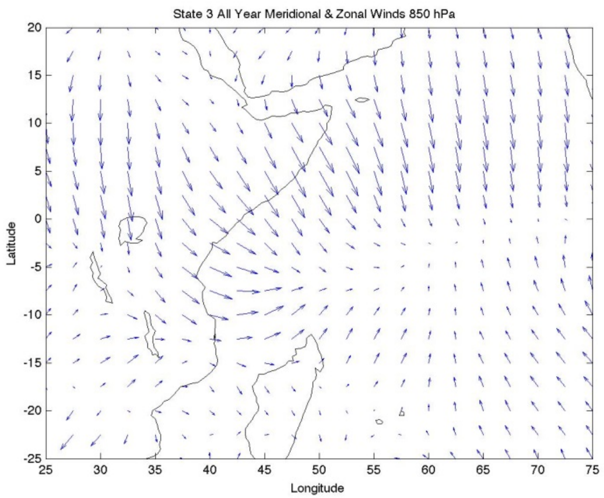
Interpretation of the HMM States and Choosing Predictor/s

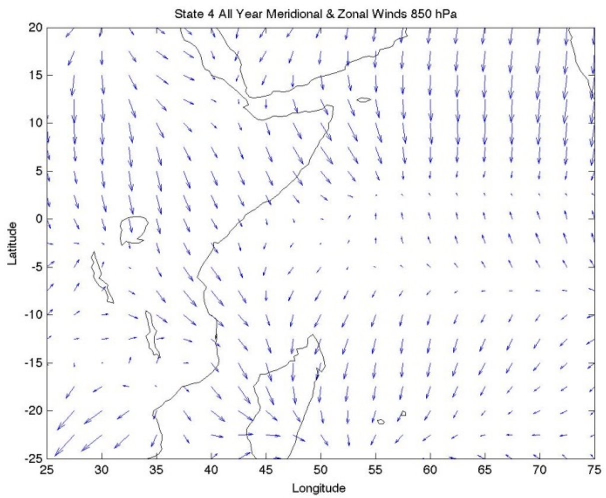
MW & ZW at 850 hPa

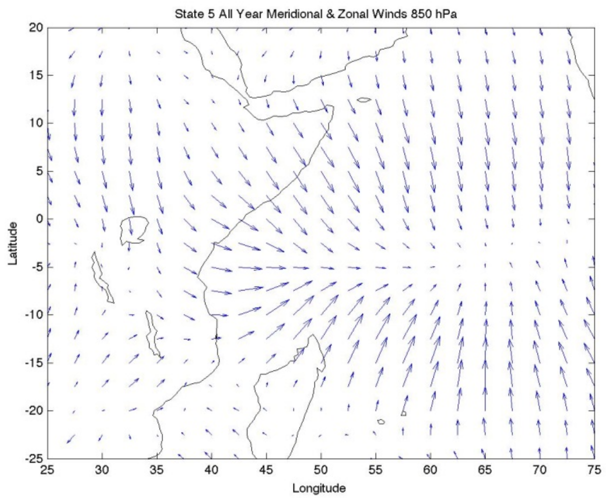
The Rainfall States provide a **diagnostic of Large Scale Weather Conditions**. Composites fields, with respect to the Annual climatological mean of the days assigned to each state, are obtained for Geo-potential Height (GPH), Temperature (T) at 1000 hPa, Meridional Winds (MW) at 850 hPa, Zonal Winds (ZW) at 850 hPa and Zonal Equator Winds (ZEW) . These fields show that GPH,T, ZW, ZEW, MW and their appropriate combinations can be used as predictors in NHMM.







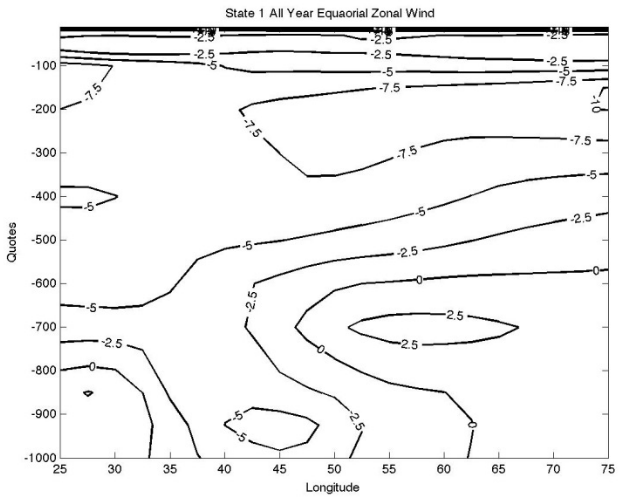


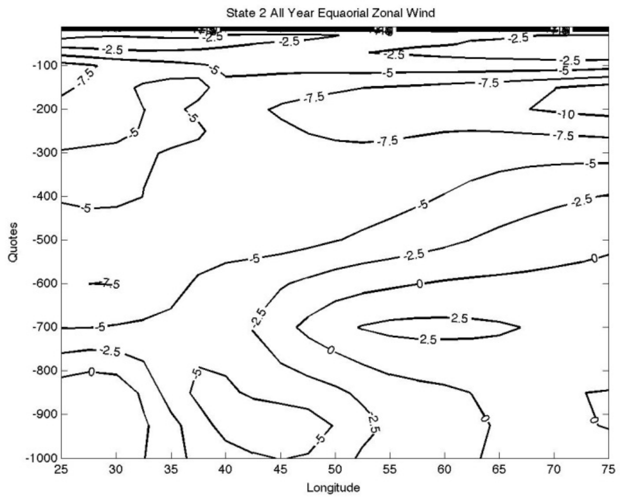


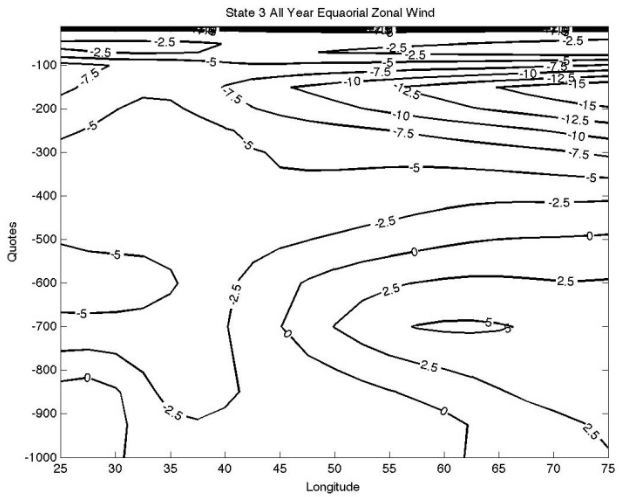
Interpretation of the HMM States and Choosing Predictor/s

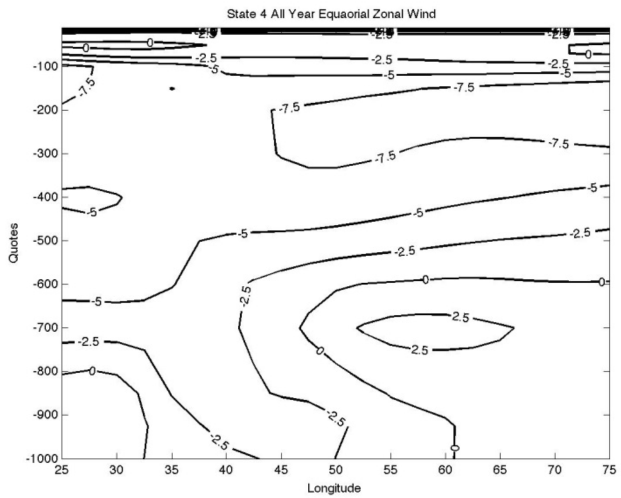
ZEW from 10 to 1000 hPa

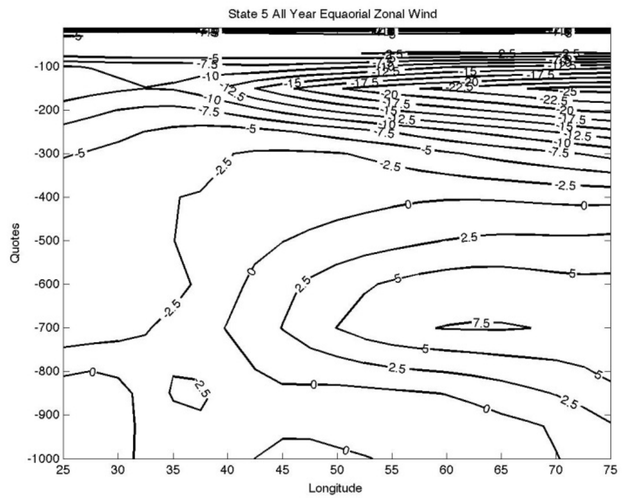
The Rainfall States provide a **diagnostic of Large Scale Weather Conditions**. Composites fields, with respect to the Annual climatological mean of the days assigned to each state, are obtained for Geo-potential Height (GPH), Temperature (T) at 1000 hPa, Meridional Winds (MW) at 850 hPa, Zonal Winds (ZW) at 850 hPa and Zonal Equator Winds (ZEW) . These fields show that GPH,T, ZW, ZEW, MW and their appropriate combinations can be used as predictors in NHMM.











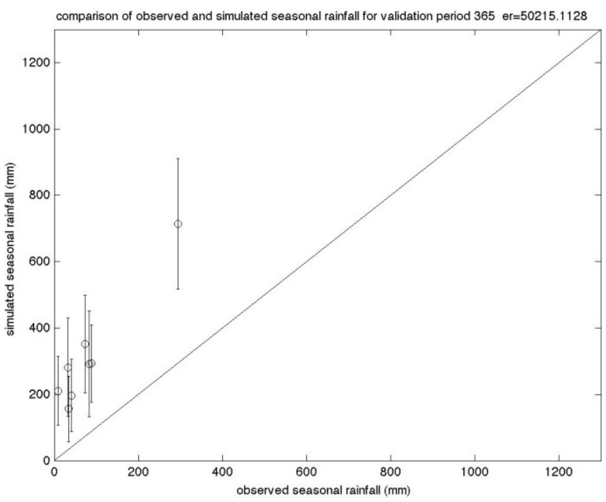
Validation & Calibration

30 years as “Learn” phase and 10 years as “Simulation” along all year.
HMM represents a basement in comparing with predictors obtained from NHMM elaborations.

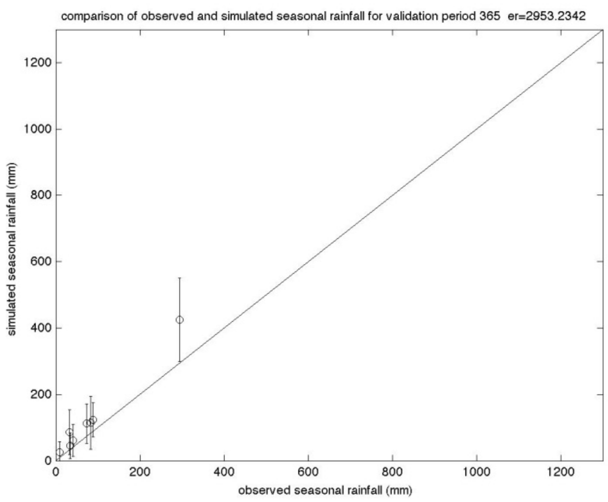
Total Amount Seasonal Rainfall

Dry Season – (JJAS)

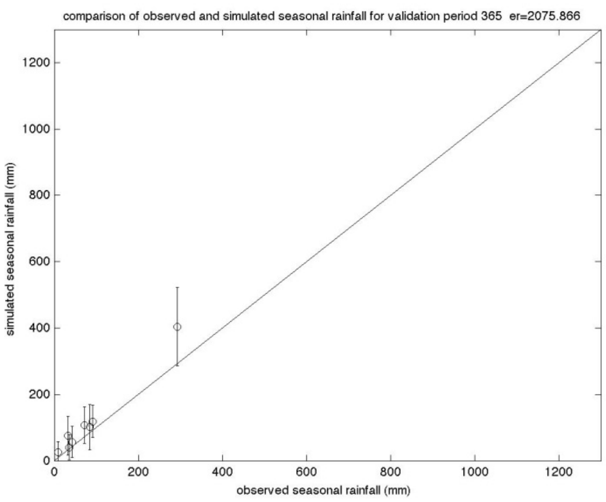
HMM



NHMM – T&GPH



NHMM – T&GPH&ZEW

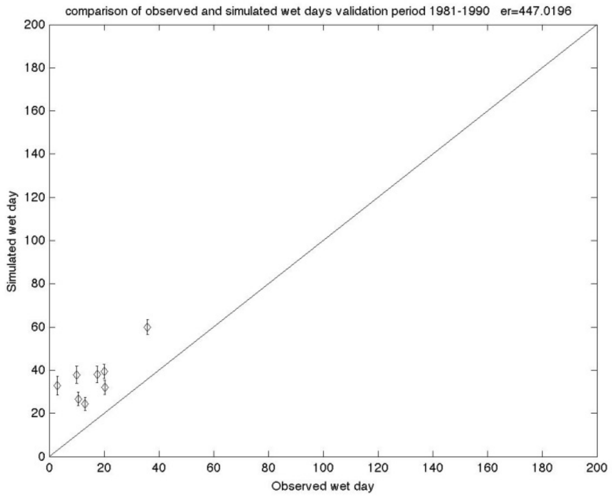


Calibration & Validation

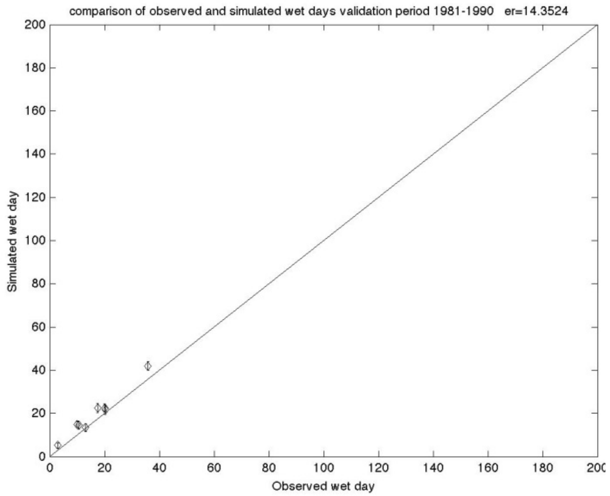
30 years as "Calibration" phase and 10 years as "Validation" ones along all year.
Significant rainfall statistical indices calculated from HMM and NHMM simulations are compared

Total Wet Days   Dry Season – (JJAS)

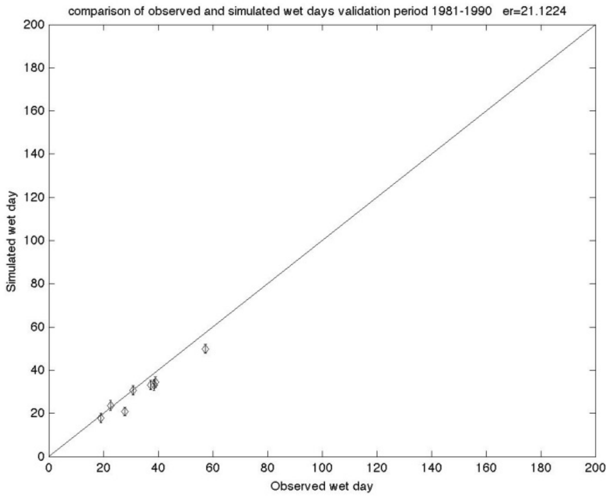
HMM



NHMM – T&GPH



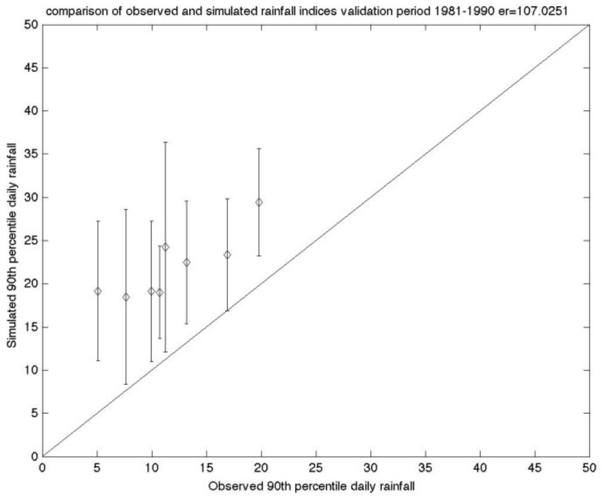
NHMM – T&GPH&ZEW



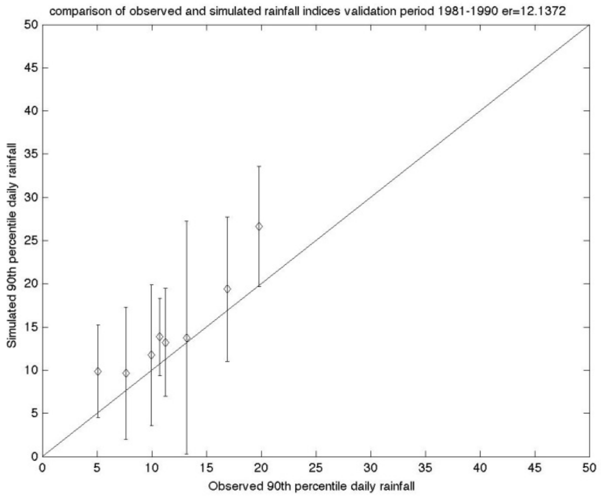
Validation & Calibration

90th Percentile — Dry Season – (JJAS)

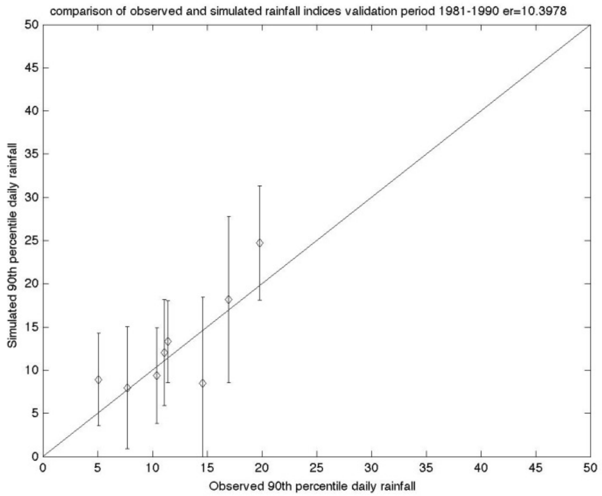
HMM



NHMM – T&GPH



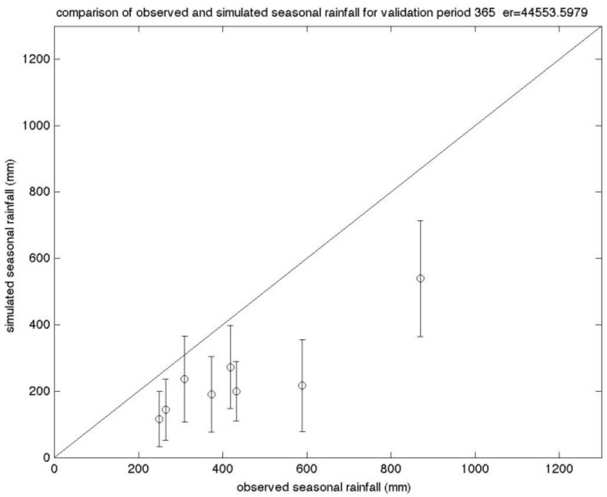
NHMM – T&GPH&ZEW



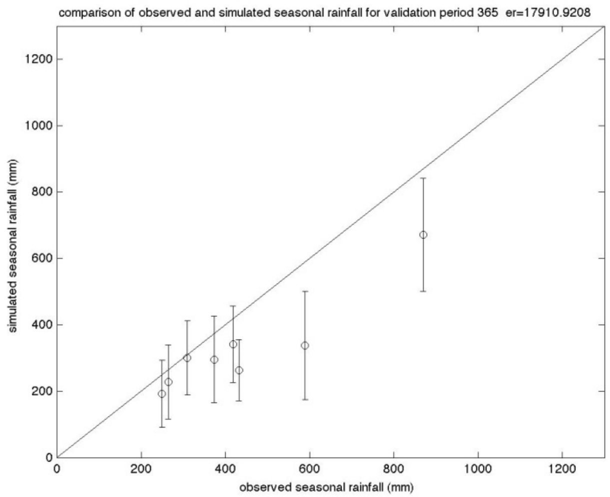
Validation & Calibration

Total Amount Seasonal Rainfall Wet Season – (MAM)

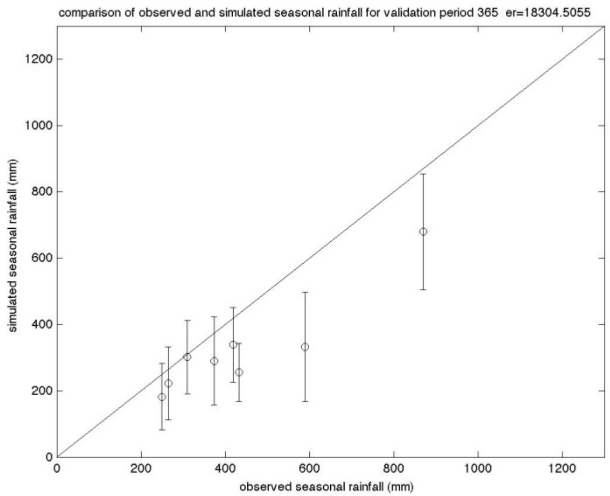
HMM



NHMM – T&GPH



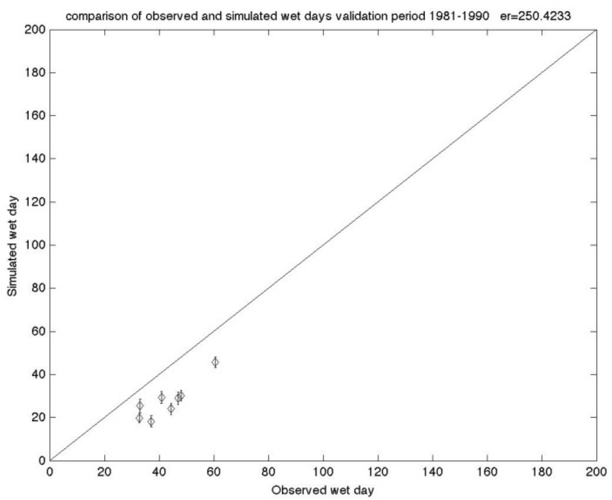
NHMM – T&GPH&ZEW



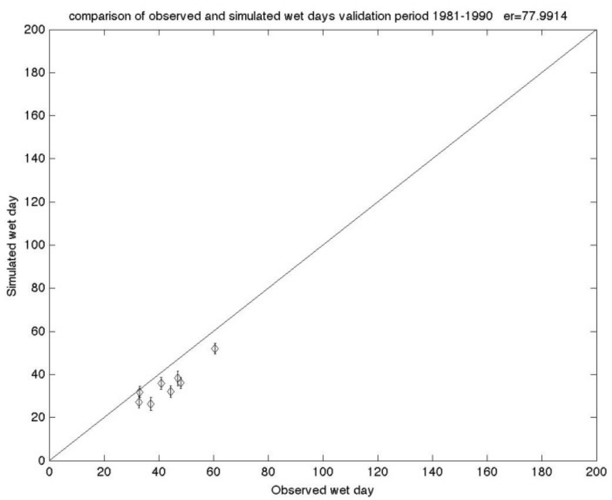
Validation & Calibration

Total Wet Days   Wet Season – (MAM)

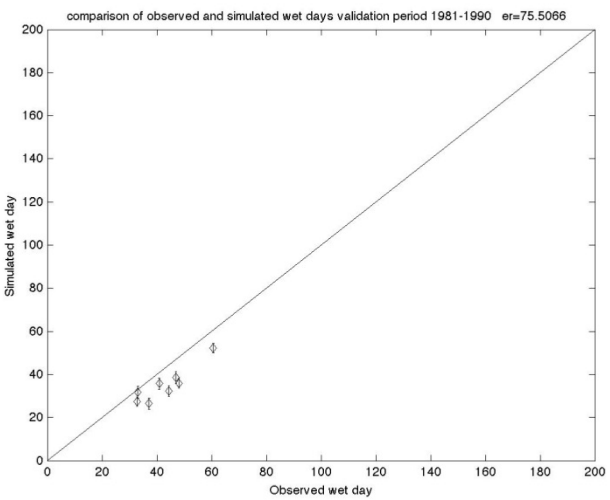
HMM



NHMM – T&GPH



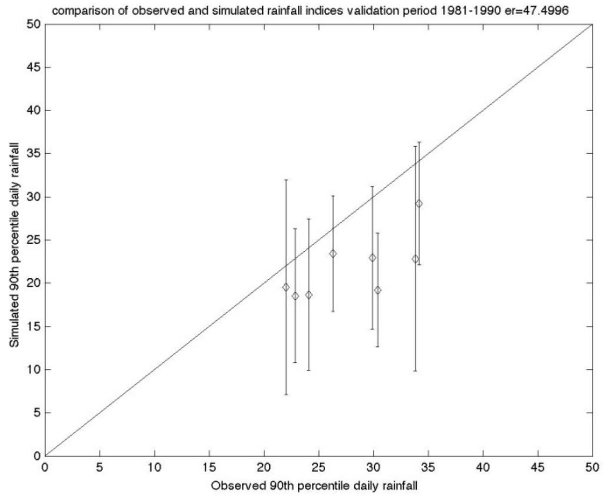
NHMM – T&GPH&ZEW



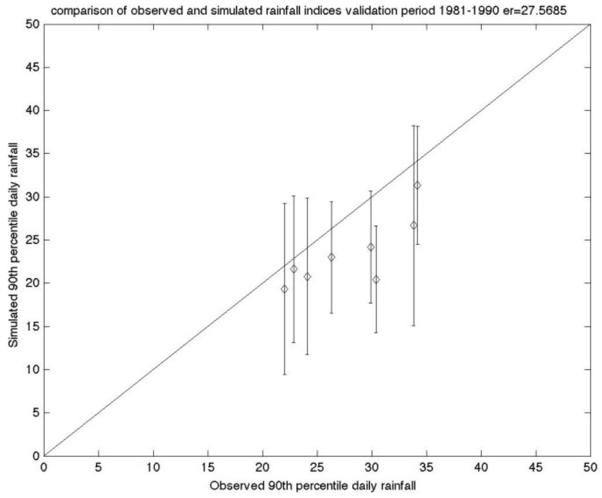
Validation & Calibration

90th Percentile Wet Season – (MAM)

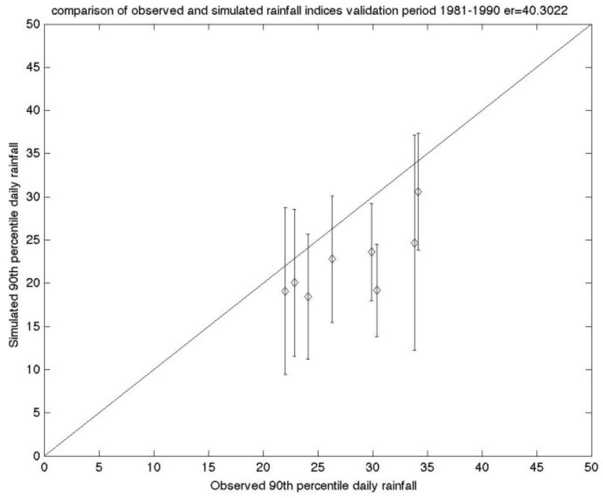
HMM



NHMM – T&GPH



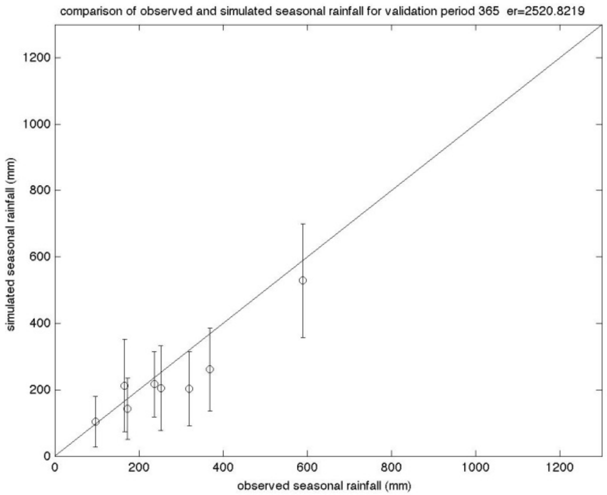
NHMM – T&GPH&ZEW



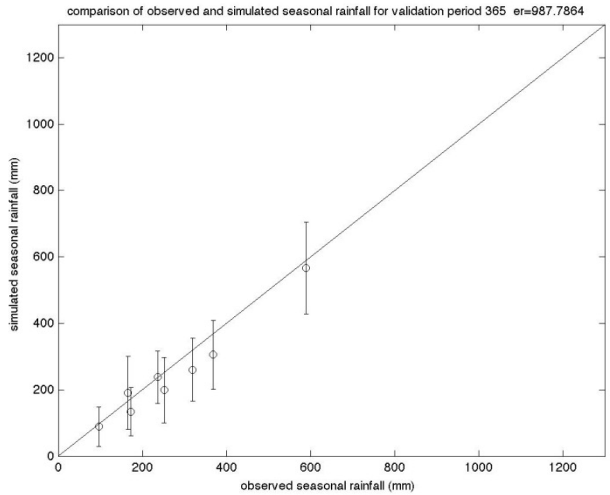
Validation & Calibration

Total Amount Seasonal Rainfall   Wet&Dry Season – (OND)

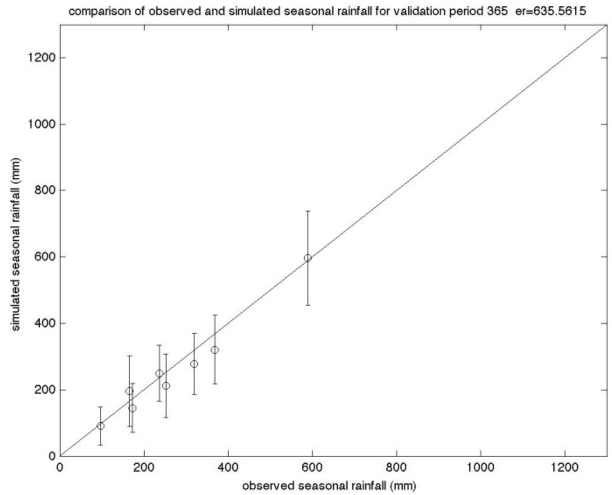
HMM



NHMM – T&GPH



NHMM – T&GPH&ZEW

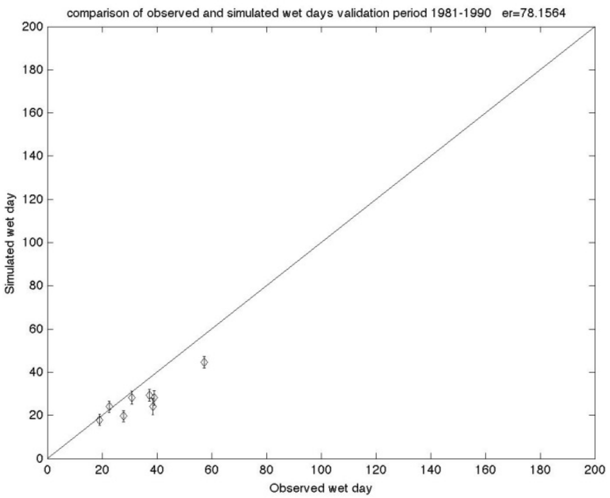


Validation & Calibration

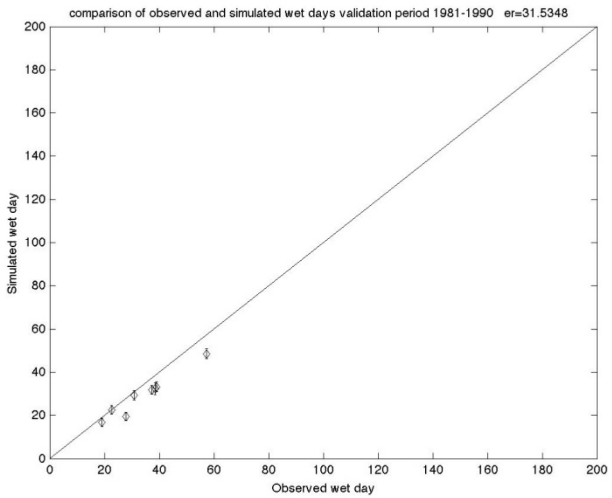
Total Wet Days

Wet&Dry Season – (OND)

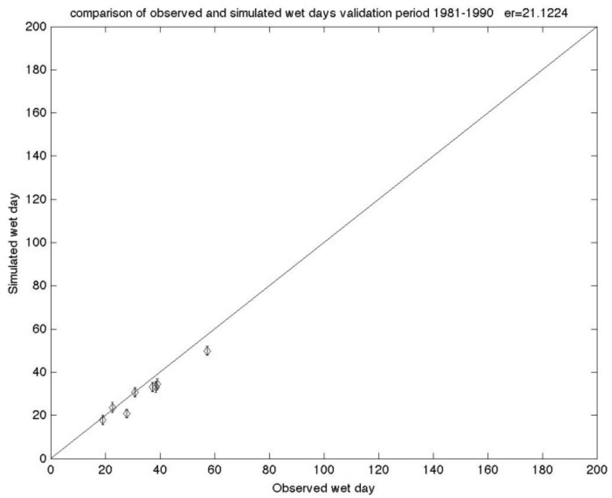
HMM



NHMM – T&GPH



NHMM – T&GPH&ZEW

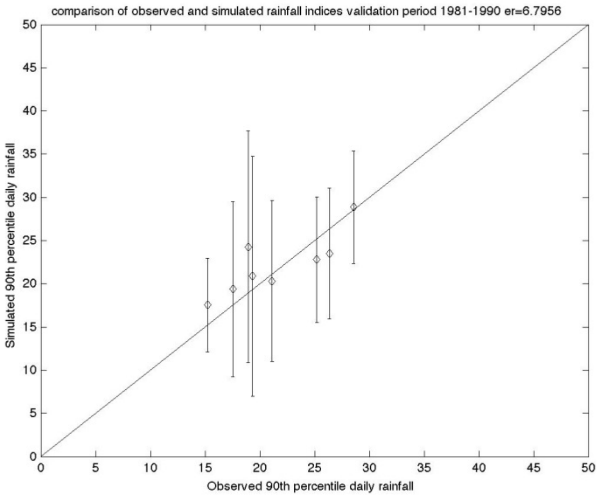


Validation & Calibration

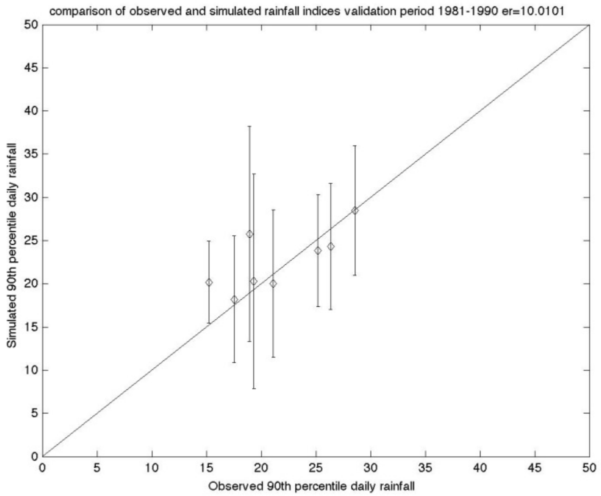
90th Percentile

Wet&Dry Season – (OND)

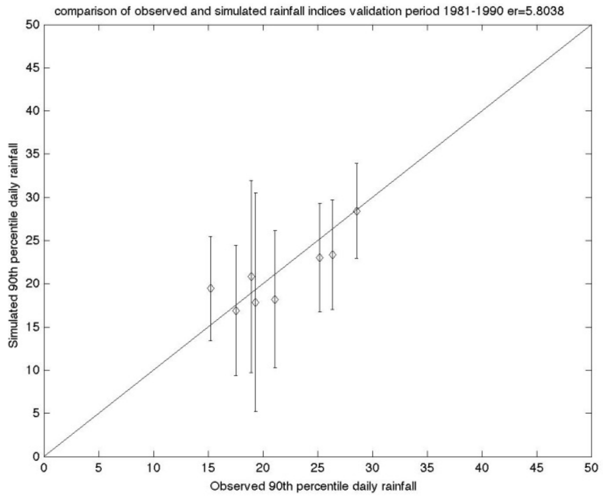
HMM



NHMM – T&GPH



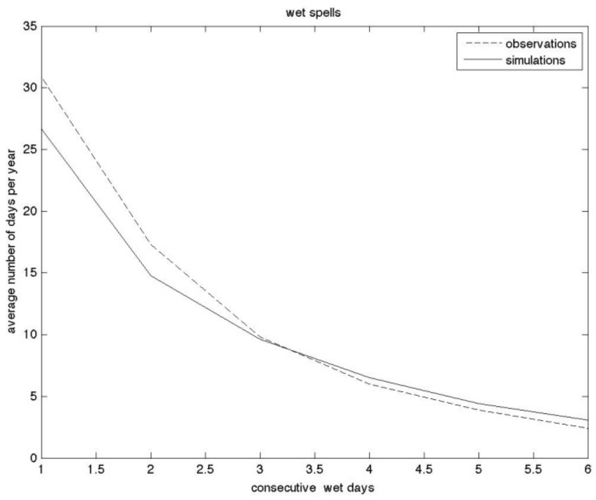
NHMM – T&GPH&ZEW



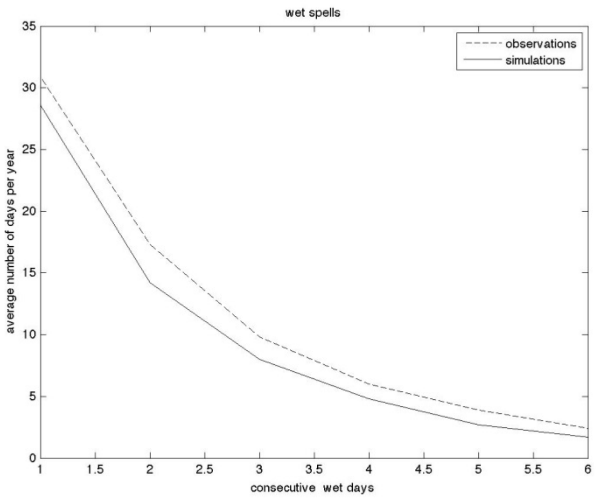
Validation & Calibration

Rainfall Spell S4 Wet Season – (MAM)

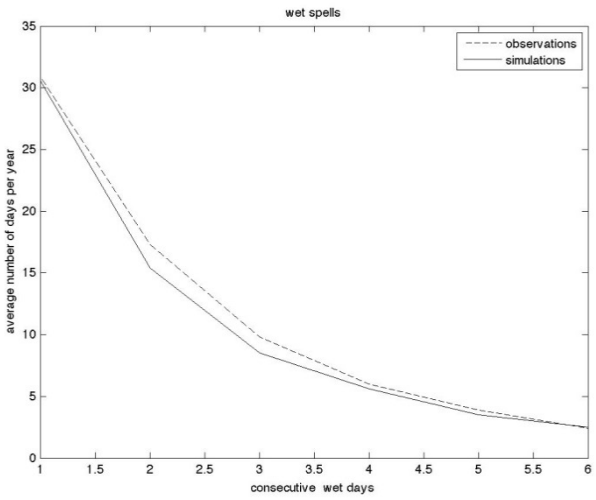
HMM



NHMM – T&GPH



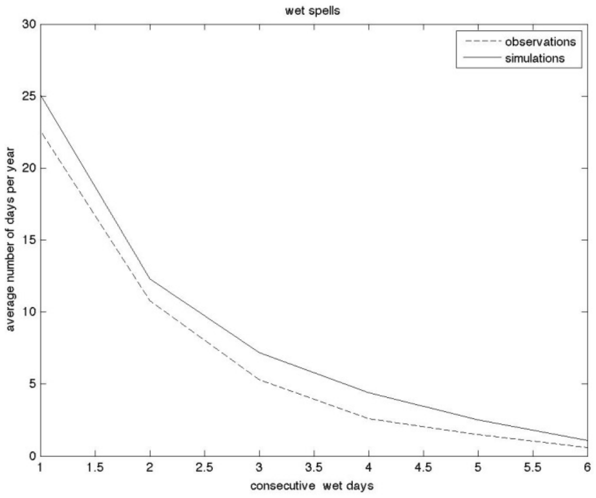
NHMM – T&GPH&ZEW



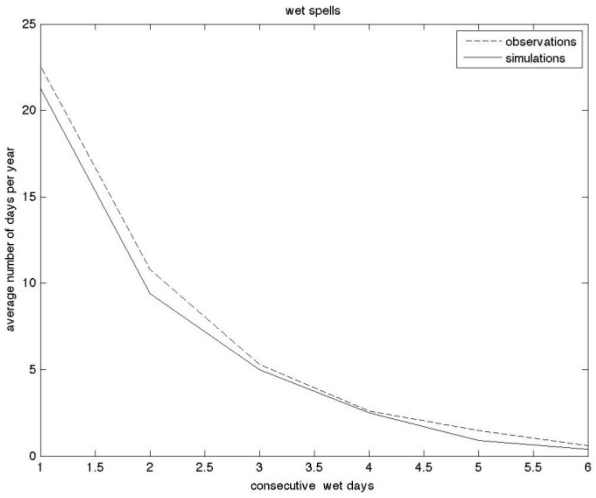
Validation & Calibration

Rainfall Spell S4 Wet Season – (MAM)

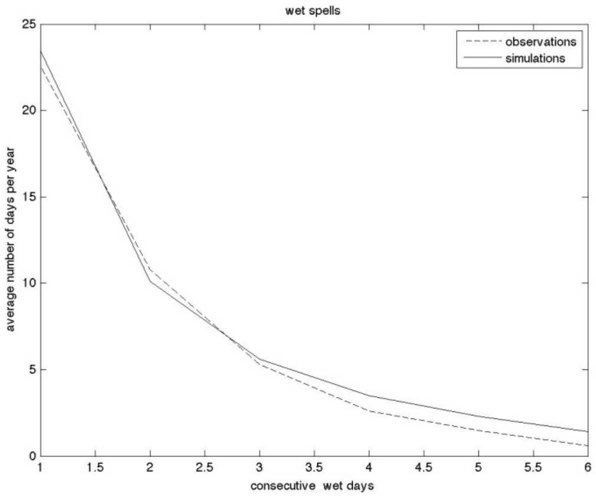
HMM



NHMM – T&GPH



NHMM – T&GPH&ZEW



Conclusions

- the annual precipitation pattern over Tanzania, by using HMM-CI, is reasonably well reproduced
- Physically significant 5 Weather States have been well identified by using HMM-CI
- GPH1000 (SLP), together with T1000 (SST) and EZW resulted to be the best candidate as predictors
- NHMM improves simulation results if compared with simple HMM well capturing the seasonal trend of precipitation in East Africa
- Work is in progress to analyze different future global warming scenarios (CMIP5 dataset)

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