ACC DAR Adapting to Climate Change in Coastal Dar es Salaam

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International Workshop

Mainstreaming climate change adaptation into urban development and environmental management plans and programs

Projecting Changes in Tanzania Rainfall for the 21st century: Scenarios, Downscaling & Analysis

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Outline

- Objective
- Framework
- Problems
- Data
- Methods: HMM & NHMM
- Selection of predictors for NHMM and interpretation of hidden states
- Model Calibration & Validation
- Projections of future rainfall patterns in Tanzania under global warming scenario RCP8.5 as simulated by CMCC-CMS CGM

Objective

✓ to estimate the precipitation pattern changes under global warming scenarios in Dar es Salaam (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,….)

Projecting Changes in Tanzania Rainfall for the 21st century: Scenarios, Downscaling & Analysis

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; rainfall 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, HIDDEN MARCOV MODEL (HMM) and NON-HOMOGENEOUS HIDDEN MARCOV MODEL (NHMM) appear to be the most promising since they are particularly efficient in the treatment of discrete variables like precipitations

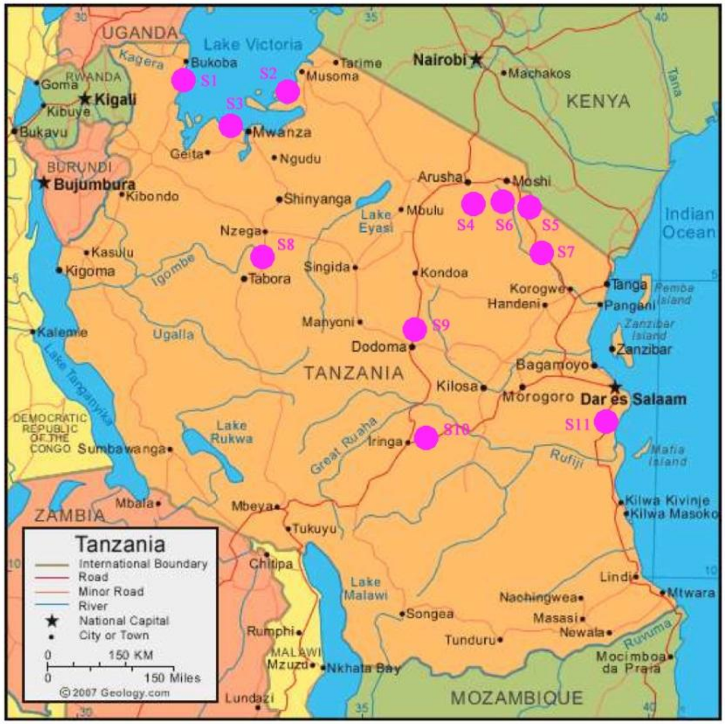
In the current presentation we explore the potentiality of **HMM** & **NHMM** to simulate the precipitation pattern in Tanzania and we show the proposed approach is able to:

- **capture the main characteristics seasonality of rainfall pattern typically happening 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**
- **predict future rainfall patterns in Tanzania under global warming scenarios from CMIP5 (Coupled Model Inter-comparison Project Phase 5)**

Data

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

Stations location in Tanzania (on Map)



Stations location in Tanzania (data info)

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

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)

Theory

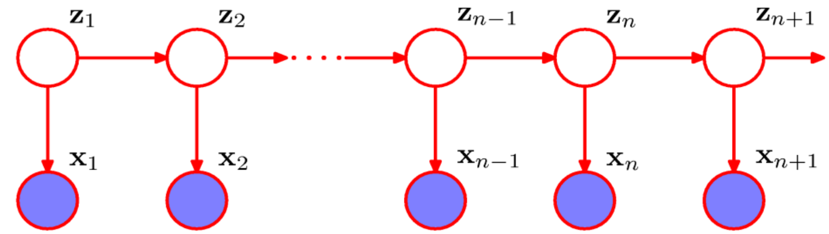
The **HMM** assumes that observations are generated from a mixture of distributions among which subjects move according to a hidden Markov chain, and that rainfall occurrence is governed by a few discrete states, with Markovian daily transitions between them. HMM used here follows the approach of the (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



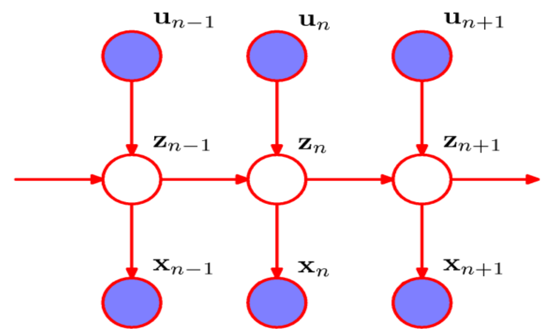
Markov Property $p(\mathbf{x_n}|\mathbf{x_1},\ldots,\mathbf{x}_{n-1}) = p(\mathbf{x_n}|\mathbf{x_{n-1}})$

Conditional Indipendece Property $\mathbf{z_{n+1}} \perp \mathbf{z_{n-1}} | \mathbf{z_n}$

Joint probability distribution

$$p(\mathbf{X},\mathbf{Z}|\Theta) = p(\mathbf{z_1}|\pi)\left[\prod_{n=2}^{N} p(\mathbf{z_n}|\mathbf{z_{n-1}},\mathbf{A})\right]\prod_{m=1}^{M} p(\mathbf{x}_m|\mathbf{z_m},\theta)$$

Non-Homogeneous Hidden Markov



Conditional distribuition

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

Joint probability distribuition

$$p(\mathbf{X},\mathbf{Z}|\Theta,\mathbf{U}) = p(\mathbf{z_1}|\pi,\mathbf{u_1})\left[\prod_{n=2}^{N} p(\mathbf{z_n}|\mathbf{z_{n-1}},\mathbf{u_n},\mathbf{A})\right]\prod_{m=1}^{M} p(\mathbf{x}_m|\mathbf{z_m},\theta)$$

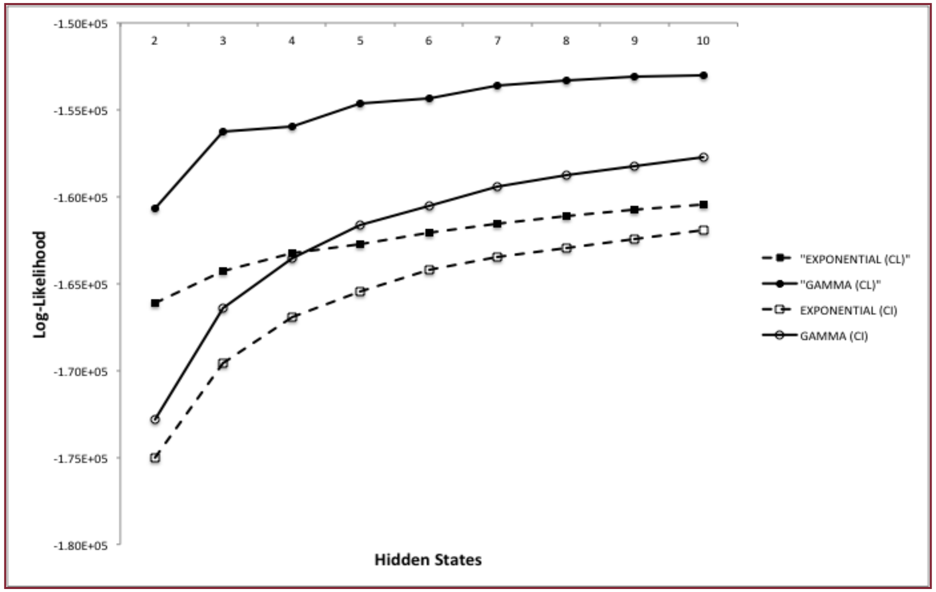
Chow Liu (CL) VS Conditional Independence (CI)

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.

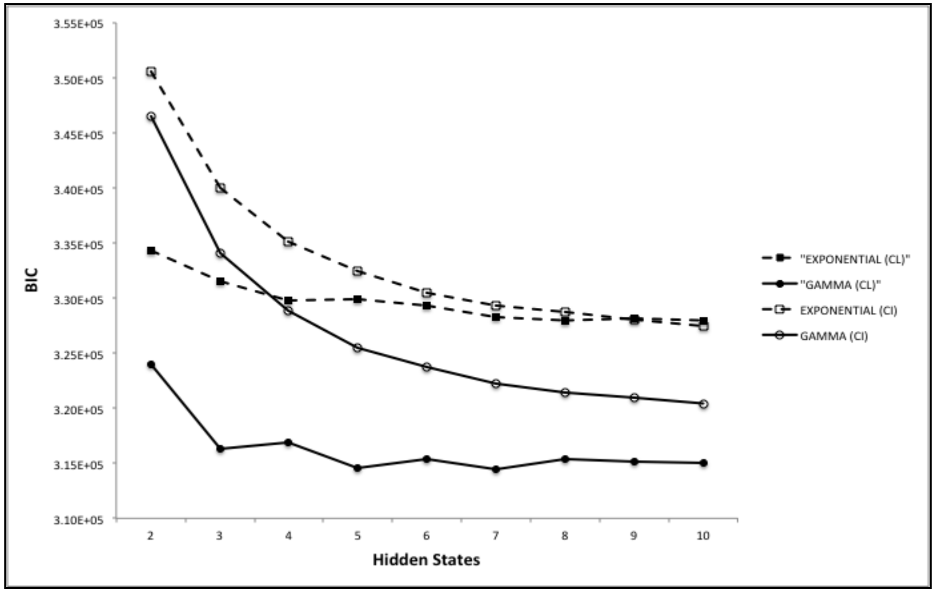
The Table represents data from CL / Gamma & CI / Gamma for 5 Hidden States

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

Log-Likelihood

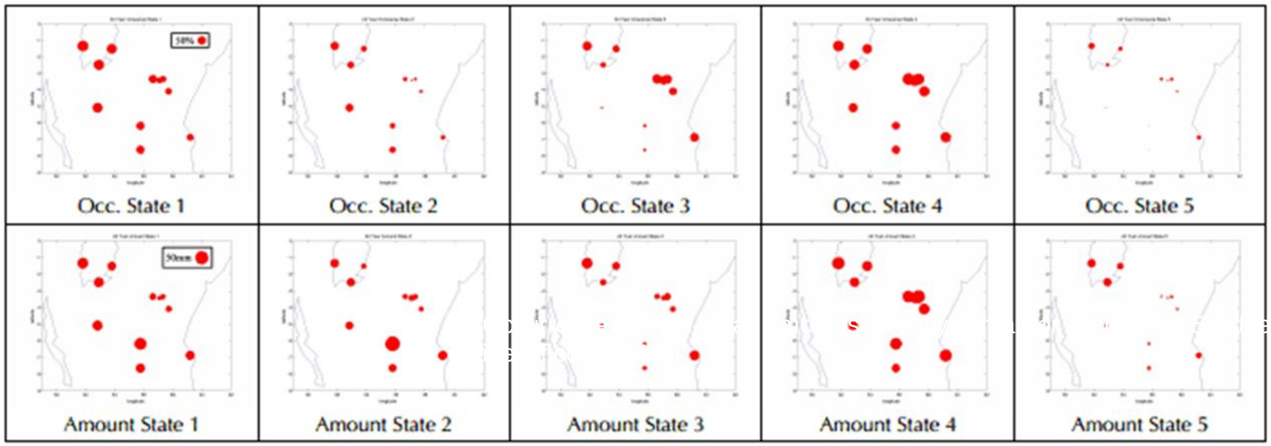


BIC

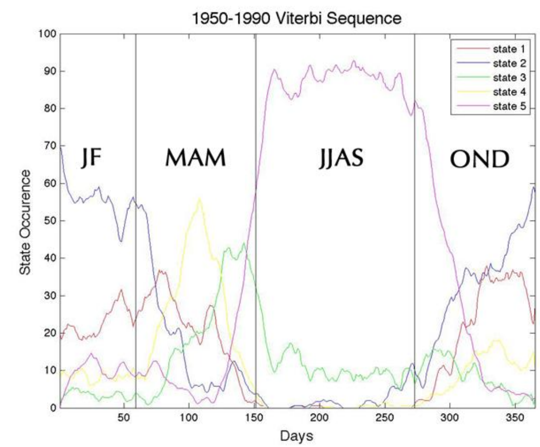


HIDDEN STATES OF DAILY RAINFALL OCCURRENCE AND AMOUNT

In global warming scenarios, seasonal shifts due to large scale atmospheric circulation changes have to be considered. The NHMM is consequently applied to the daily data for the full year without seasonality assumptions. "Seasonality" is identified by the variables that determine the atmospheric circulation patterns and their rainfall implications.



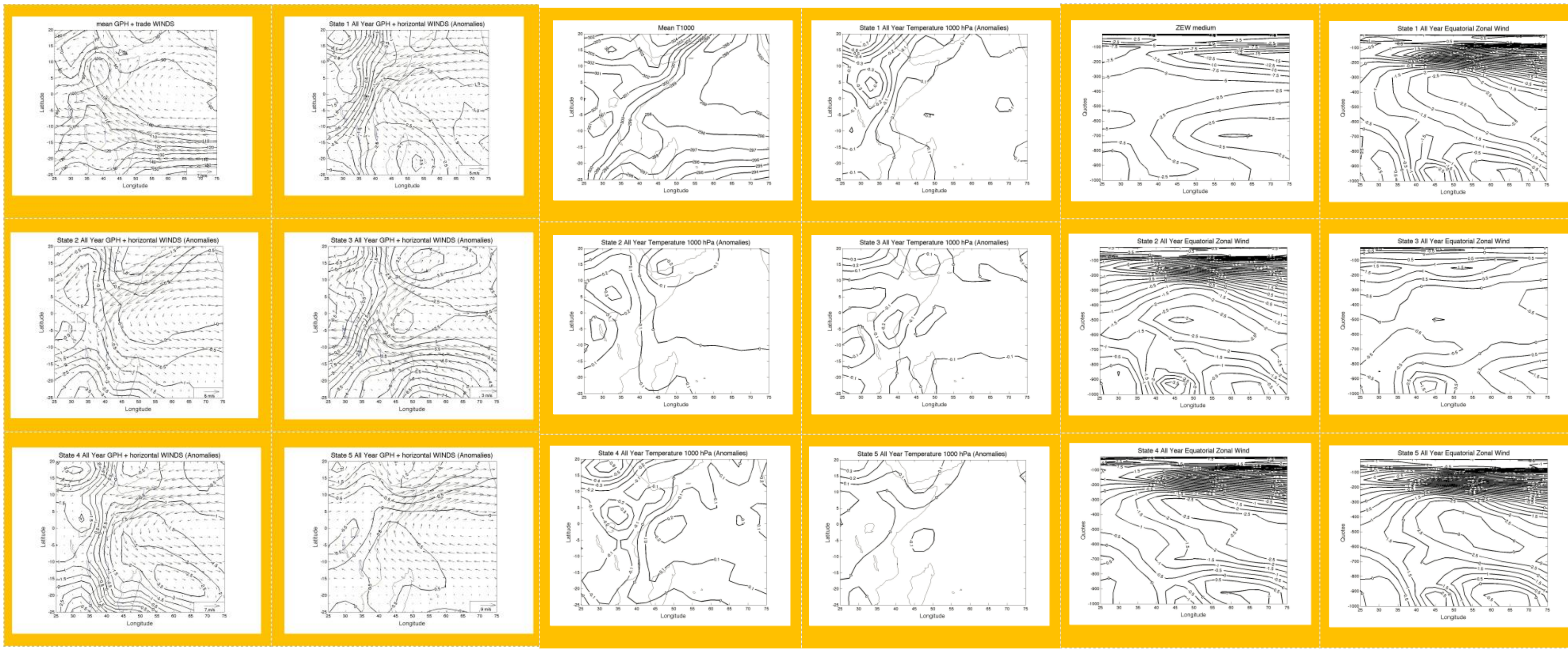
Occurrence and the mean amounts of daily rainfall for each of the 5 hidden states identified by HMM



Seasonality of the daily frequency of the hidden states (averaged over 1950-1990)

State 1 : wet homogeneous	**Dominant in the current Winter / early Spring, from November to April**
State 2 : wet inhomogeneous	**Significantly persists in winter and completely disappears from June to September**
State 3 : wet inhomogeneous	**Occurrence probability peaks in May. Low occurrence in the dry season**
State 4 : Very wet homogeneous	**Its occurrence is maxima in April with a minor intense peak in November**
State 5 : very dry homogeneous	**Representative of the of dry season : from June to September is the dominant state**

HIDDEN STATES PHYSICAL INTERPRETATION & SELECTION OF PREDICTORS (25S to 25N; 25E to 75N) (Reanalysis data from IRI Library – NOAA-NCAR)



GEO-POTENTIAL HEIGHT at 1000 hPa and Vector WIND at 850 hPa

TEMPERATURE at 1000 hPa

ZONAL WINDS from 10 to 1000 hPa captured at 27N Latitude

- ✓ Calculation of the averaged composite of each variables, from the daily fields corresponding to a particular state of the HMM "Viterbi" sequence
- ✓ Comparative analysis of the composite fields for each hidden state for meaningful physical interpretation.
- ✓ Dimension reduction for each field using Principal Component Analysis (PCA)

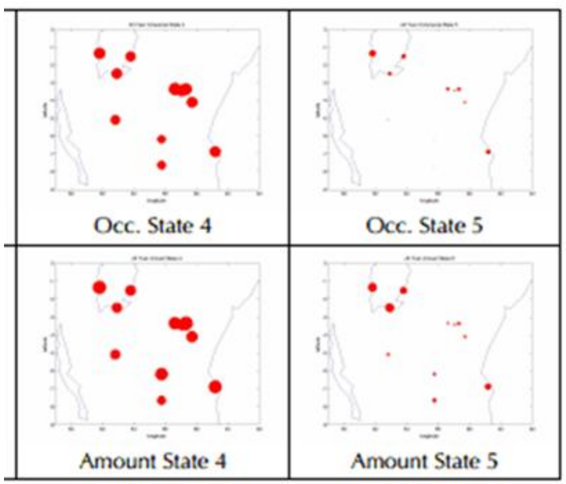
Wet states vs dry ones

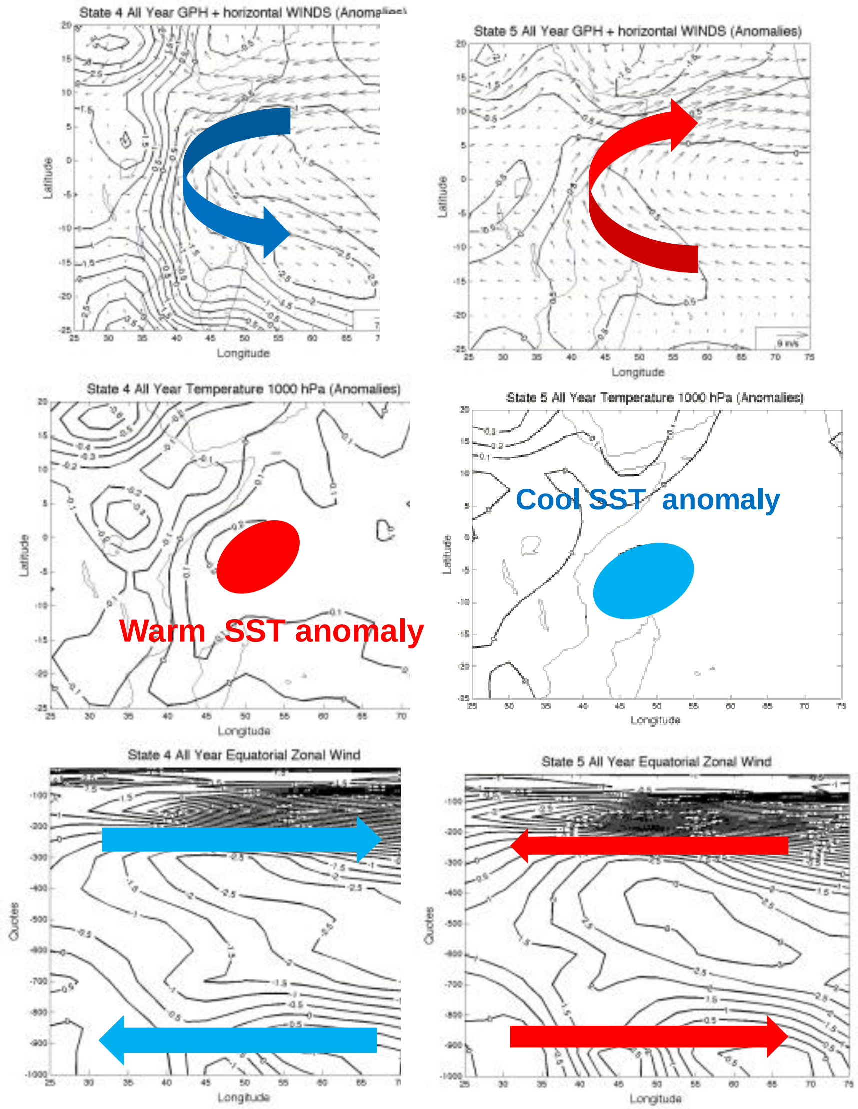
State 4. Very Wet Homogeneous

- western Indian Ocean sea surface temperature warmer than the east one,
- easterly wind anomalies across the Indian Ocean strongly directed against east Africa with all moisture associated with them

State 5. Very Dry Homogeneous

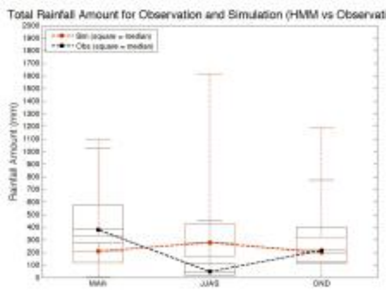
- cooler temperatures in the Western Indian Ocean relative to the East are related to easterly winds
- less rain over East Africa





HMM & NHMM CALIBRATION (1950-1980) & VALIDATION (1981-1990)

Data refer to the average value on all the stations, (a) HMM; (b) NHMM with PCAs from geo-potential height composite fields; (c) NHMM with PCAs from geo-potential height and temperature composite fields; (d) NHMM with PCAs from composite fields of geo-potential height, temperature and zonal and meridional winds
(validation period 1981-1990)



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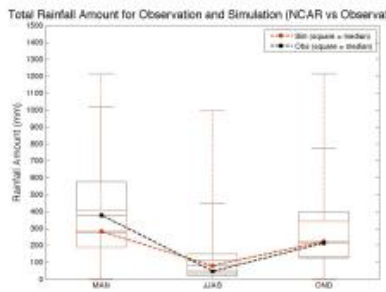

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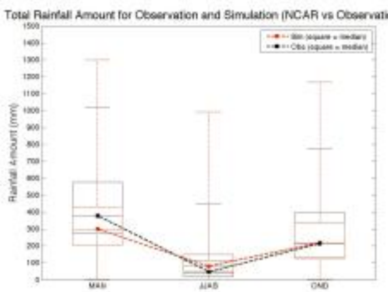

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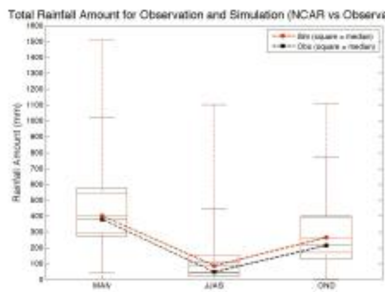
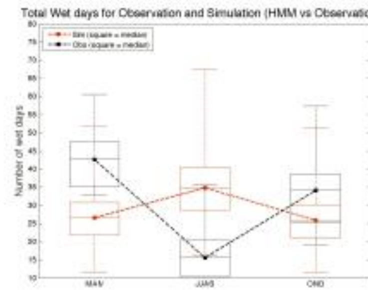
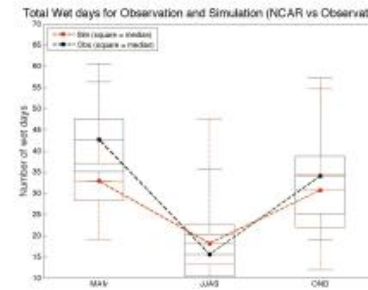


(d)

Total Seasonal Rainfall Amount



(a)



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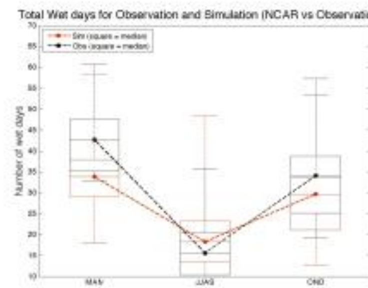

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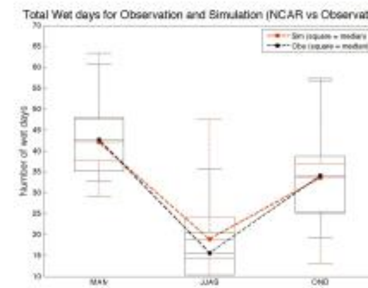
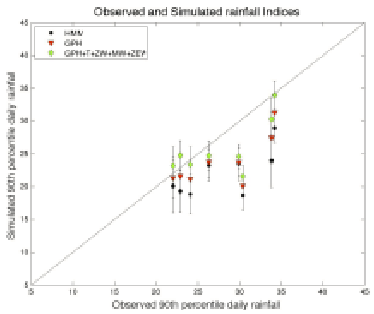


(d)

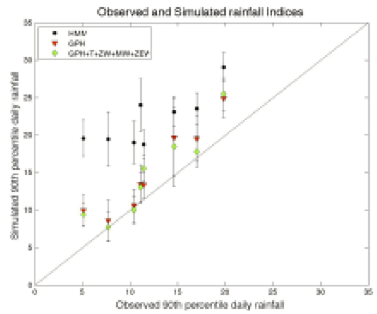
Total Seasonal Wet Days

HMM & NHMM CALIBRATION & VALIDATION

Data refer to single stations, (a) MAM; (b) JJAS; (c) OND



(a)



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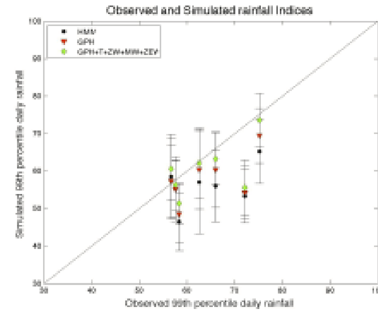
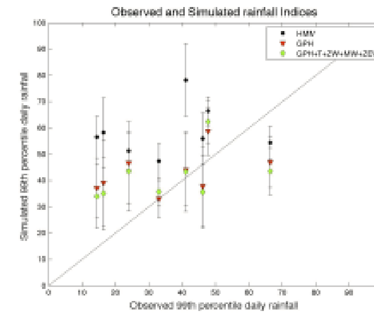


(a)



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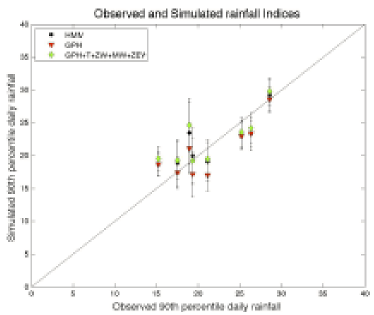

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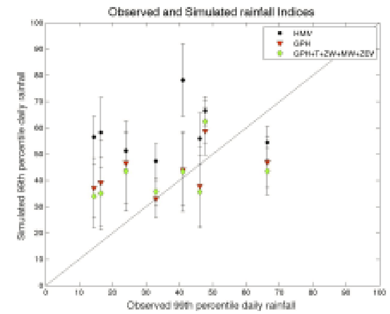
Rainfall 90th percentile from observations compared to those from NHMM with predictors from reanalysis (1981-1990).



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Rainfall 99th percentile from observations compared to those from NHMM with predictors from reanalysis (1981-1990).

The calibration (1950-1980) and validation (1981-1990) tests, for different predictor combinations, reveal the effectiveness of the NHMM for the conditional simulation of the rainfall occurrence and amount statistics including the extreme values

PROJECTING CHANGES IN TANZANIA RAINFALL FOR THE 21ST CENTURY

- **In order to predict (by using NHMM) future rainfall patterns for Tanzania under 21st century global warming scenarios we apply:**

- 1. **a selection criteria to choose between different GCMs from CMIP5 (Coupled Model Inter-comparison Project Phase 5). (Karl et al, 2009)**

- **2. Variance correction of the PC's for the best GCM to match the scales of the corresponding PC's for the observations.**

GCMs from CMIP5 (Coupled Model Inter-comparison Project Phase 5)

- **We considered the two most cited models from Lawrence Livermore National Laboratory (U.S. Department of Energy) internet site: the CanESM2 Model (Chylek et al., 2011) and a variant of the second most cited model (MPI-ESM-LR), the CMCC-CMS Model. The CMCC-CMS (Centro Mediterraneo sui Cambiamenti Climatici) integrates the following models: ECHAM5 for atmosphere. (Roeckner et al. 2006), OASIS3 for ocean (Valcke et al., 2006, 012), and OPA8.2/LIM for ocean/sea ice interaction (Madec et al., 1999)**

- **For each of the NHMM predictors, a systematic analysis of the basic statistics (seasonal mean, variance, skew, variance and serial correlation) and the spatial pattern was performed for the PCs from the two candidate GCMs for each variable in the NHMM developed with re-analysis atmospheric fields**

Variance correction of the best GCM's predictors

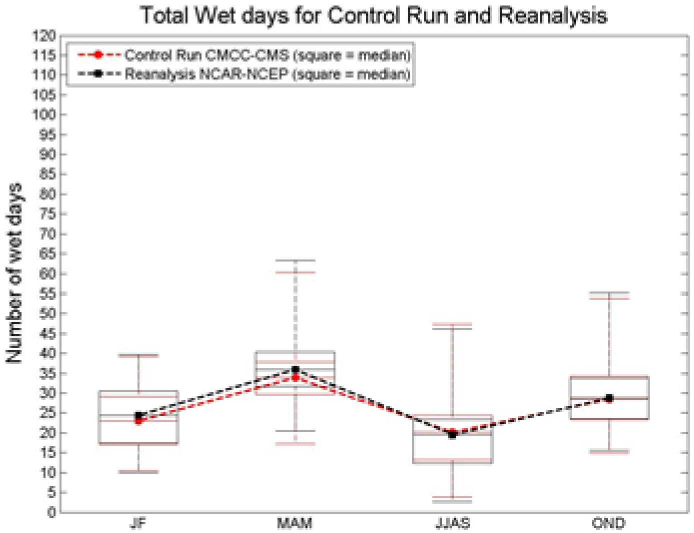
- **The CMCC-CMS model best matches the main features - temporal trend and the spatial pattern- of the main meteorological variables which have been used in the NHMM application.**

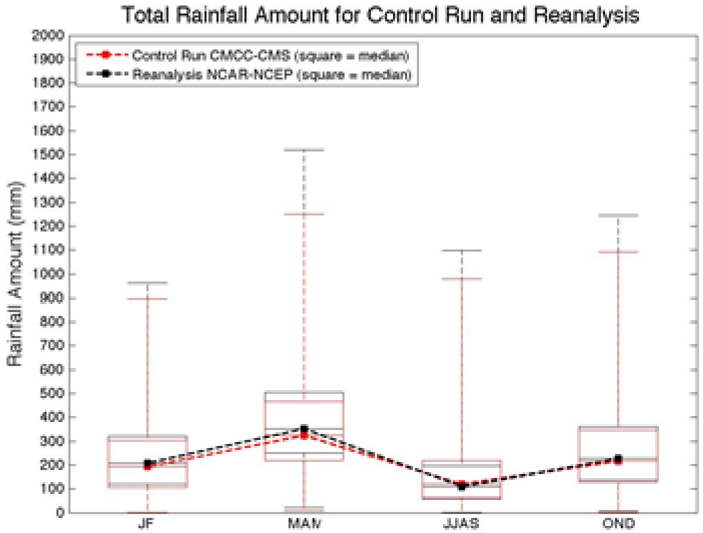
- **Let PC_{jt}^{M20} represent the time series of the j^{th} predictor considered for the NHMM, and PC_{jt}^{O20} represent the corresponding time series for the observations, over the 20th century control run of CMCC-CMS.**

- **Then the 21st century corrected predictor for the NHMM is:**

$$PC_{jt}^{M1'} = PC_{jt}^{M21} * s(PC_{jt}^{O20}) / s(PC_{jt}^{M20})$$

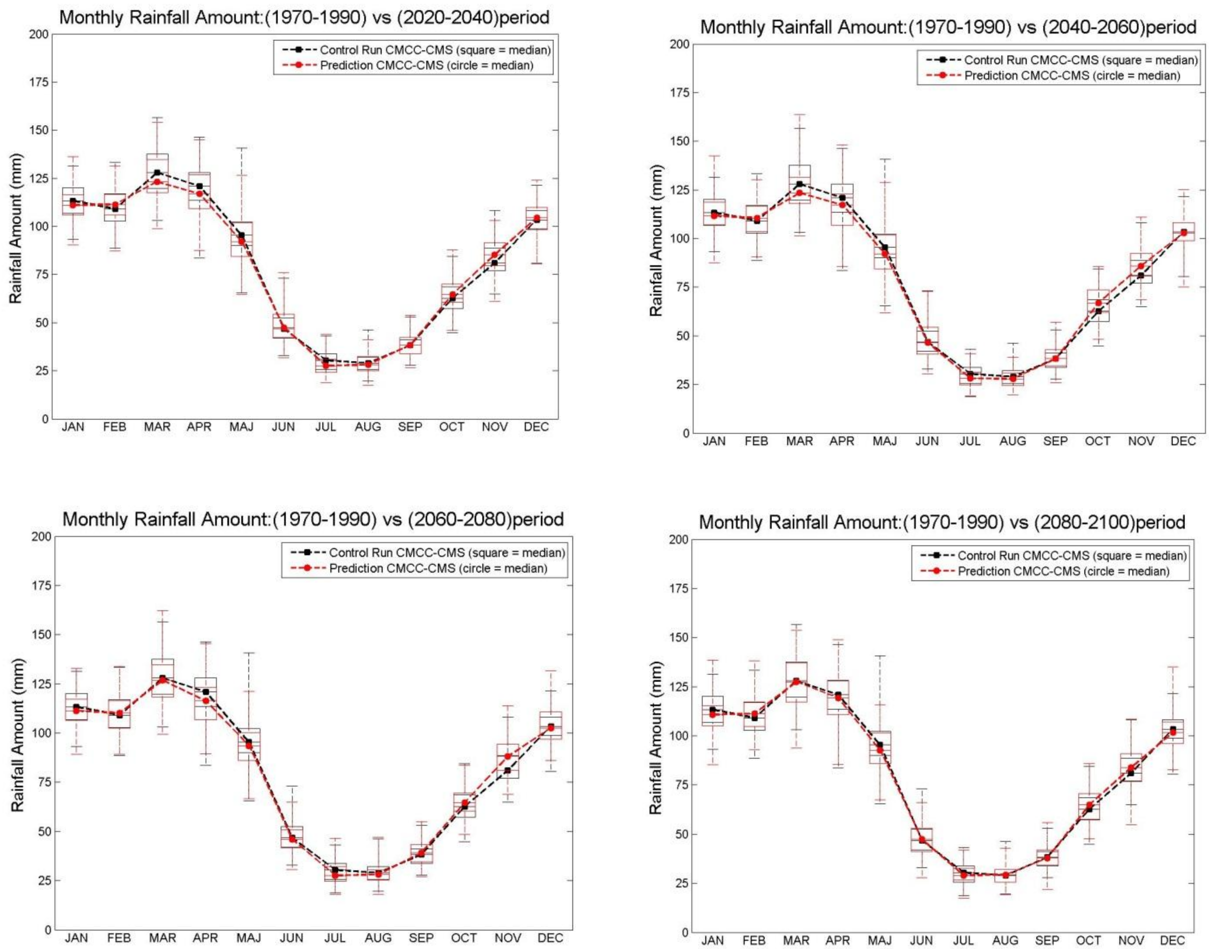
Validation of variance correction of the best GCM's predictors





Comparison , for 1950-1990, between the Seasonal Total Rain Amount and Wet days as obtained by using predictors from Reanalysis (NCAR-NCEP) and from Control Historical Run (CMCC-CMS) .

Projections of the future rainfall patterns in Tanzania under global warming scenario RCP8.5 (CMCC-CMS CGM)

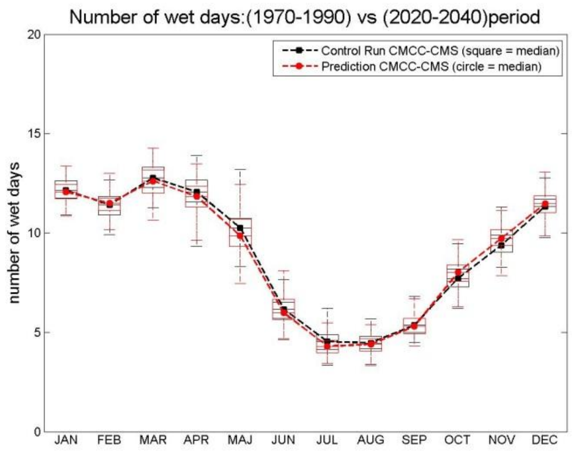


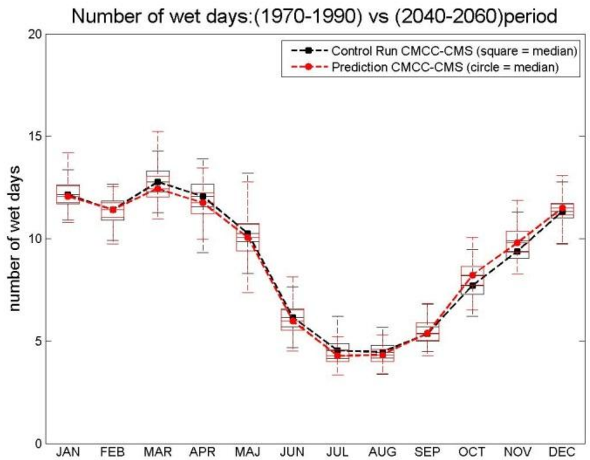
Slight decrement of monthly rainfall amount in MAM and JJAS

Slight increase of monthly rainfall amount in OND

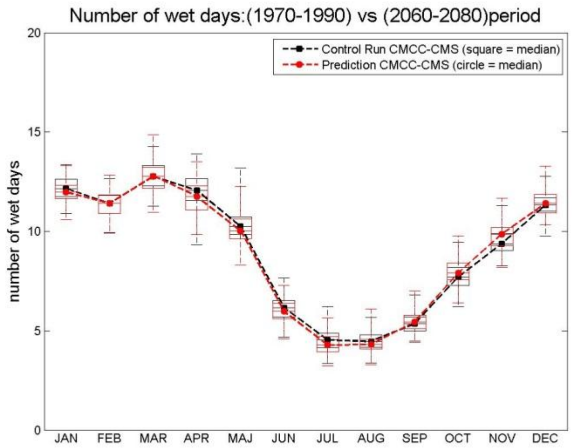
Comparison between the Monthly Rainfall Amount for the period (1970-1990) and for the different twenties(2020-2040), (2040-2060),(2060-2080),(2080-2100)

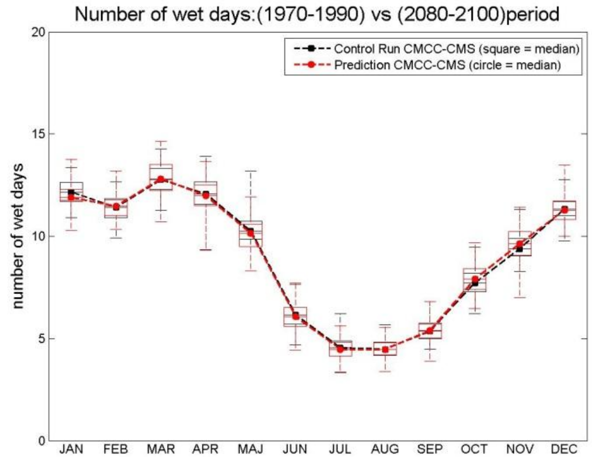
Projections of the future rainfall patterns in Tanzania under global warming scenario RCP8.5 (CMCC-CMS CGM)





Decrement of number of wet days in MAM and JJAS

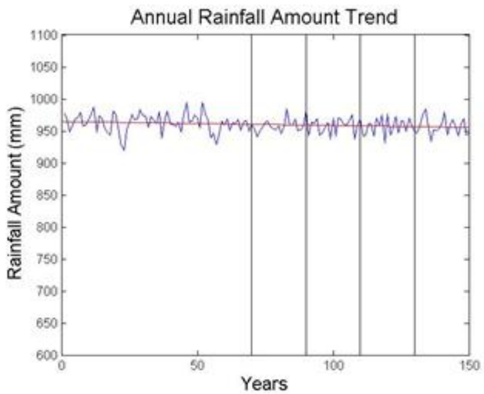




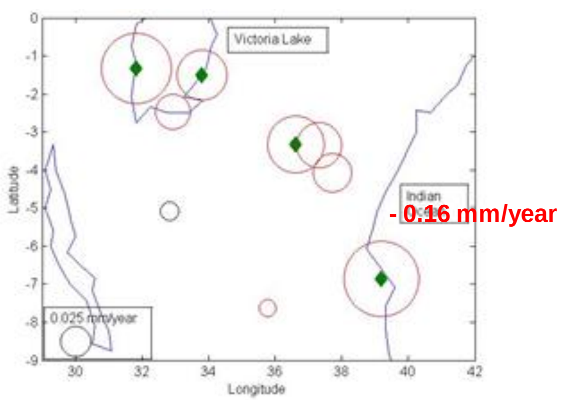
Increase of number of wet days in OND

Comparison between the Monthly Wet Days for the period (1970-1990) and for the different twenties(2020-2040), (2040-2060),(2060-2080),(2080-2100)

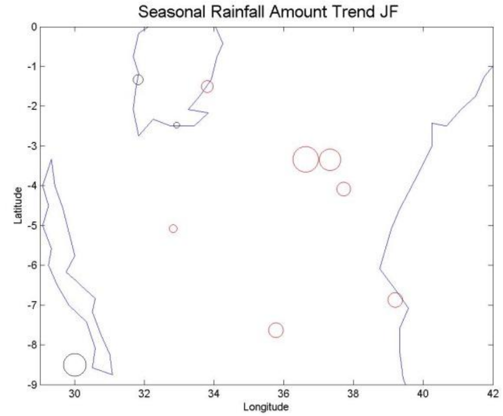
Projections of the future rainfall patterns in Tanzania under global warming scenario RCP8.5 (CMCC-CMS CGM)

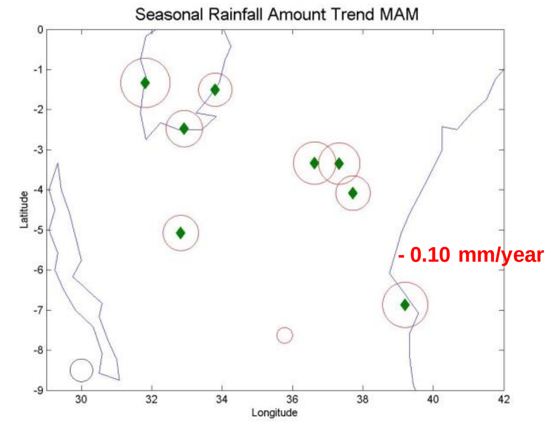


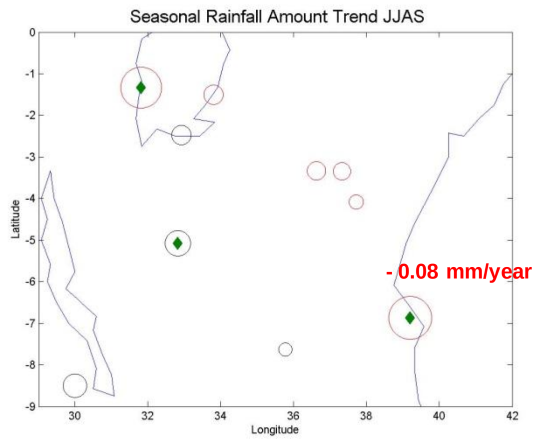
Annual Rainfall Amount Trend for the ensemble of stations

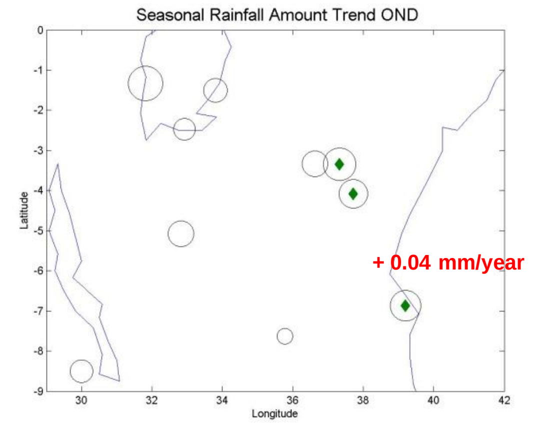


Annual Rainfall Amount Trend for each station: black circle = positive; red circle = negative; diamond = significant trend at 5%



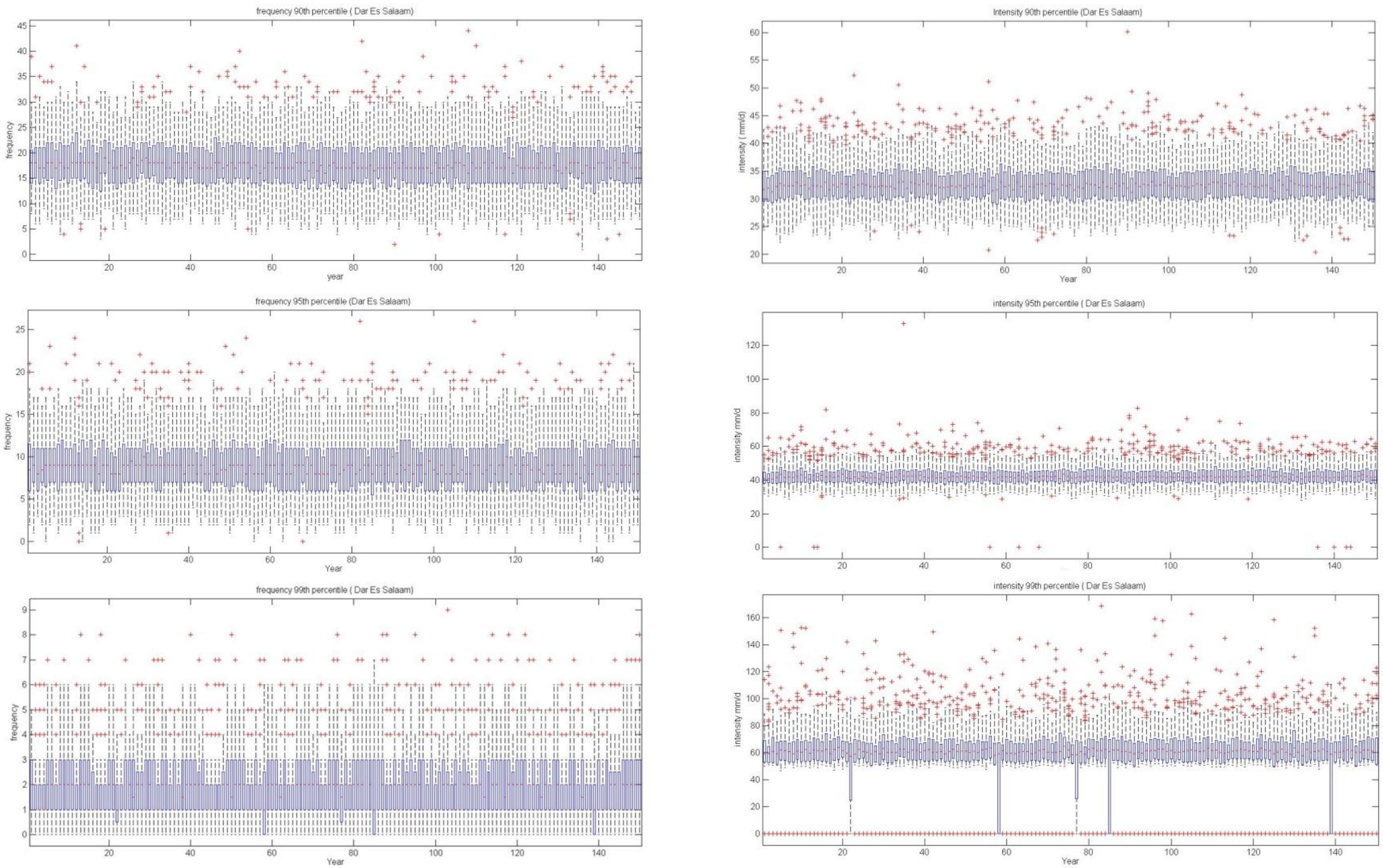






Seasonal Rainfall Amount Trend for each station: black circle = positive; red circle = negative; diamond = significant trend at 5%

Projections of the future rainfall patterns in Tanzania under global warming scenario RCP8.5 (CMCC-CMS CGM) (Rainfall extremes in Dar Es Salaam)



Slight Increasing trends in frequency and intensity of extreme rainfall, but no statistically significant (at 5%) in Dar Es Salaam and other Tanzania gages

Frequency $f_{jt} = \sum_{i=1} I(P_{ijt} > P_j^*)$

Intensity $r_{jt} = (\sum_{i=1} I(P_{ijt} > P_j^*)P_{ijt}) / f_{jt}$

Conclusions

- Typical precipitation patterns over Tanzania, by using HMM-CI and NHMM, are well reproduced by identifying the main characteristics of large scale climatology affecting Tanzania rainfall (as described by GPH1000 (SLP), together with T1000 (SST) and EZW)

- Under the RCP8.5 scenario , the NHMM downscaled future projections for Tanzania show :

  - (1) An slight decrement in the number of wet days and seasonal rainfall amount in MAM and JJAS, except OND; globally a reduction of annual total rainfall amount;

  - (2) even if trends are not statistically significant (at 5%) frequency and intensity of extreme rainfall as identified by 90th,95th and 99th percentiles events intensify

- In the future, the tendency to a reduction of available water resources together with the growing anthropic pressure, could dramatically impact on social and economical development of Dar Es Salaam area. Furthermore, the increase in frequency and intensity of flooding events, as a consequence of rainfall extremes, can not be excluded

- In this contest, any future planning activity has to consider as central the issue of a correct and sustainable water management.

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