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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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 hydroclimatic 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)**

<table>
<thead>
<tr>
<th>ON MAP</th>
<th>CODE/NAME</th>
<th>LATITUDE</th>
<th>LONGITUDE</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>S1 TZ000063729 BUKOBA</td>
<td>-1.33N</td>
<td>31.82E</td>
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<tr>
<td>2</td>
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<td>-6.17N</td>
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<td>10</td>
<td>S10 TZ000063887 IRINGA</td>
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<td>S11 TZ000063894 DAR_ES_SALAAM_AIRPC</td>
<td>-6.87N</td>
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</table>

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:

- \( Z_n \); transition probabilities (no stationary) Hidden States
- \( U_n \); external inputs
- \( X_n \); observed data
- \( K \); the number of Hidden States
- \( \sigma \) and \( \rho \); parameters to be estimated

\[
p(X_n | x_1, K, x_{n-1}) = p(x_n | x_{n-1})
\]

**Markov Property**

\[
z_{n+1} \perp z_{n-1} | z_n
\]

**Conditional Independence Property**

\[
p(X, Z | \Theta) = p(z_1 | \pi) \prod_{n=2}^{N} p(z_n | z_{n-1}, A) \prod_{n=1}^{M} p(X_m | z_m, \Theta)
\]

**Joint probability distribution**

\[
p(z_n = j | z_{n-1} = j, u_n = u) = \frac{\exp(\sigma_j + \rho_j u)}{\sum_{k} \exp(\sigma_k + \rho_k u)}
\]

**Conditional distribution**

\[
p(x, z, \Theta, U) = p(z_1 | \pi, u_1) \prod_{n=2}^{N} p(z_n | z_{n-1}, u_n, A) \prod_{m=1}^{M} p(x_m | z_m, \Theta)
\]

**Joint probability distribution**
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

<table>
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<tr>
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“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 that 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

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.

GPH at 1000 hPa
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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

homogeneous & non-homogeneous hidden markov downscaling model for projection of hydroclimate changes in tanzania

Date: 20-04-2013
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)

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<tr>
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Validation & Calibration

90th Percentile

Dry Season – (JJAS)

HMM

NHMM – T&GPH

NHMM – T&GPH&ZEW

homogeneous & non-homogeneous hidden markov downscaling model for projection of hydroclimate changes in tanzania

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Validation & Calibration

Total Amount Seasonal Rainfall

Wet Season – (MAM)

HMM

NHMM – T&GPH

NHMM – T&GPH&ZEW

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Validation & Calibration

Total Wet Days

Wet Season – (MAM)

HMM

NHMM – T&GPH

NHMM – T&GPH&ZEW

homogeneous & non-homogeneous hidden markov downscaling model for projection of hydroclimate changes in tanzania
Validation & Calibration

90th Percentile

Wet Season – (MAM)

HMM

NHMM – T&GPH

NHMM – T&GPH&ZEW

homogeneous & non-homogeneous hidden markov downscaling model for projection of hydroclimate changes in tanzania

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Validation & Calibration

Total Amount Seasonal Rainfall

Wet&Dry Season – (OND)

**HMM**

**NHMM – T&GPH**

**NHMM – T&GPH&ZEW**

- Comparison of observed and simulated seasonal rainfall for validation period 365 (en=2520 0219)
- Comparison of observed and simulated seasonal rainfall for validation period 365 (en=487 3864)
- Comparison of observed and simulated seasonal rainfall for validation period 365 (en=403 5615)
Validation & Calibration

Total Wet Days

Wet&Dry Season – (OND)

HMM

NHMM – T&GPH

NHMM – T&GPH&ZEW

homogeneous & non-homogeneous hidden markov downscaling model for projection of hydroclimate changes in tanzania

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Validation & Calibration

90th Percentile

HMM

NHMM – T&GPH

NHMM – T&GPH&ZEW

Wet&Dry Season – (OND)

Date: 20-04-2013
Validation & Calibration

Rainfall Spell S4

Wet Season – (MAM)

HMM

NHMM – T&GPH

NHMM – T&GPH&ZEW

homogeneous & non-homogeneous hidden markov downscaling model for projection of hydroclimate changes in tanzania

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Validation & Calibration

Rainfall Spell S4

Wet Season – (MAM)

HMM

NHMM – T&GPH

NHMM – T&GPH&ZEW

homogeneous & non-homogeneous hidden markov downscaling model for projection of hydroclimate changes in tanzania

Date : 20-04-2013
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)
References


