Stochastic Precipitation Generation for the Potomac River Basin Using Hidden Markov Models

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Outline

1. Background and Motivation
2. Methodology and Data
   - The Hidden Markov Model for Precipitation
   - Dataset and Model Parameters
   - Use of UMBC's High-Performance Computing Facility
3. Results
4. Conclusions

Background
The Potomac river basin

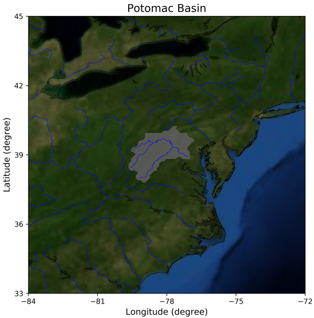

Figure: Extent of the Potomac river basin indicated by the gray shape; rivers are represented by blue lines.

- The Potomac river basin is located on the central region of the East Coast and provides water to much of that region
- Rainfall is one of the main sources of water for the basin
- Due to seasonal and inter-annual variations, modeling rainfall adequately is crucial when planning water allocation within the basin

Background

Statistical Modeling of Precipitation

- Generating ensembles for meteorological variables is common in climate studies and in the earth sciences, since physical based models are sensitive to initial conditions
- Most satellite data come with their share of measurement errors and errors stemming from data assimilation.
- Spatio-temporal modeling and synthetic generation of precipitation faces additional challenges since precipitation has a semi-continuous distribution, with a point mass at zero and a continuous distribution on $(0, \infty)$

Motivation

Synthetic Precipitation Generation under a Hidden Markov Model formulation

- **Precipitation Generators**: given existing data, they generate a synthetic time series of multi-site precipitation at a daily scale for long periods. Sites are often monitoring stations or points on a spatial grid
- We focus on the **Hidden Markov Models (HMM)** approach for daily precipitation generation and discuss its performance when working with Satellite Precipitation Estimates (SPEs)
- The three features of the daily data we want to replicate are long sequences, pairwise spatial correlations, and extreme events
- Usually, no model formulation can capture all features equally well

Outline

The Hidden Markov Model approach

The model follows Robertson et al. (2006)[2], which in turn is based on the work of Hughes and Guttorp (1994)[3]

- Precipitation is assumed to depend on a finite set of hidden (unobserved) weather states
- The hidden state model is first-order Markov, which captures temporal correlation
- Spatial correlation is also implicitly captured by the shared state
- Observed daily precipitation at each location is a ”noisy” version of the hidden shared weather state
- Conditional on the daily state, precipitation amounts at each location are modeled as independent and identical observations from a mixture of exponential distributions

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[2] Robertson et al. Subseasonal-to-interdecadal variability of the Australian monsoon over North Queensland. *Quarterly Journal of the Royal Meteorological Society*, 132:519-542, 2006.

[3] J.P. Hughes and P. Guttorp. Incorporating Spatial Dependence and Atmospheric Data in a Model of Precipitation. *Journal of Applied Meteorology*, 33:1503–1515, 1994.

Performance on weather station data

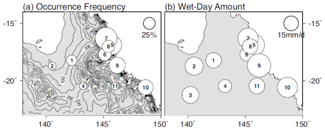

Figure: Weather stations used in Robertson (2006)

- There are no studies on HMM performance for gridded SPEs, or comparing it with the other widely used precipitation generator which is based on the Wilks method[4]
- We focus on modeling precipitation between July-September
- Our study uses daily IMERG V06[5] data from 2001-2018 over the 387 grid points of the Potomac basin
- After using grid search to find optimum parameters, a 4-state model using a mixture of 2 Gamma distributions was chosen based on BIC scores

[4] D.S. Wilks. Multisite generalization of a daily stochastic precipitation generation model. *Journal of Hydrology*, 210:1-4, pp. 178-191, 1998.

[5] https://disc.gsfc.nasa.gov/datasets/GPM_3IMERGDF_06/summary

Use of Taki Cluster

- Scripts for executing various elements of the HMM used `mpi4py` for parallelization in `Python 3.6.4`
- The python scripts for running the HMM used multiple nodes on the HPCF 2018 CPU cluster.
- The bulk of the statistical analysis and data generation based on the Gaussian copula was carried out in `R 3.6.3` using the `markovchain` package.
- Plots were produced via the `ggplot2` package in R.

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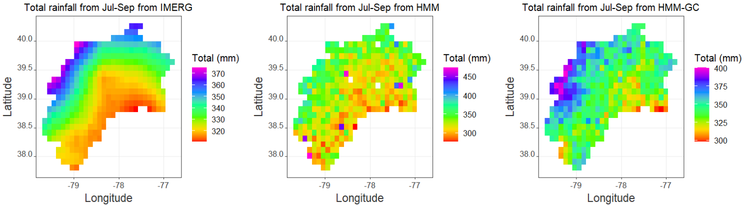
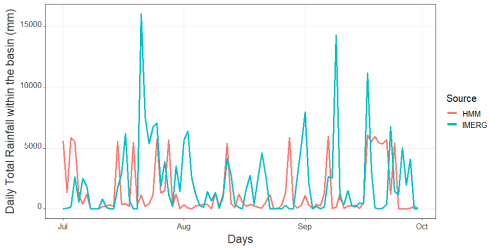
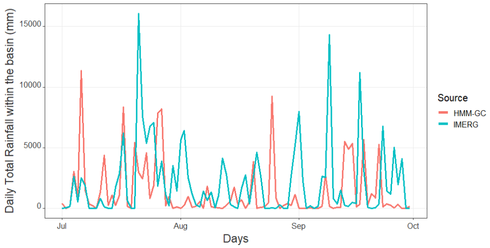
Spatial correlation visualization



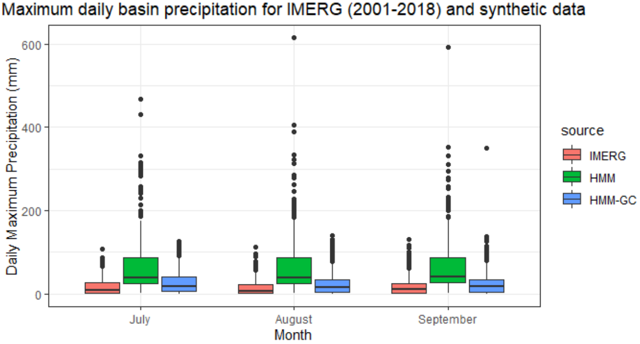
- Visualization comparing how both HMM and HMM-GC capture spatial correlation of the IMERG data
- HMM-GC displays significant improvement over HMM.

Comparision between HMM and HMM-GC



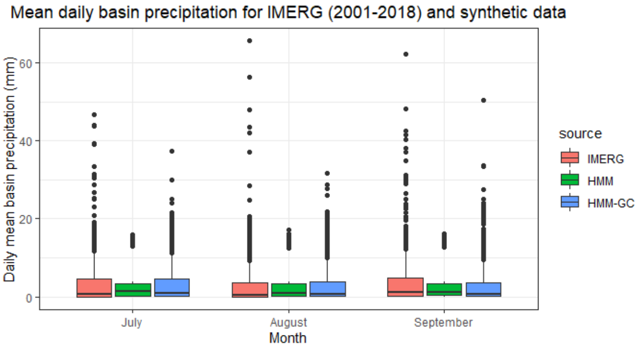


Maximum daily precipitation



- HMM overestimates maximum precipitation across the basin
- HMM-GC captures daily maximums much better than HMM

Mean daily precipitation



- Both HMM and HMM-GC have similar distributions for mean
- The key difference is the tail values corresponding to high precipitation at all locations, where the HMM-GC does a much better job

Scatterplot of the proportion of dry days per month

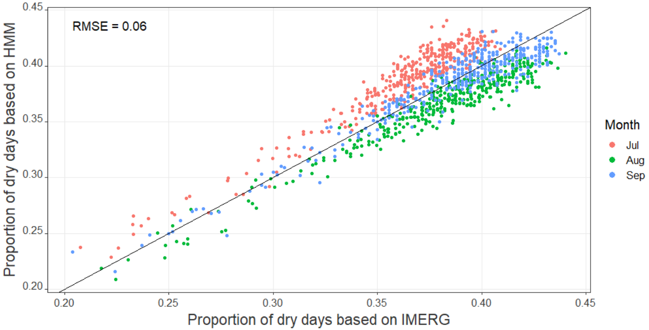


Figure: Scatterplot of the mean proportion of dry days per month at each grid point based on historical IMERG data (2001-2018) compared with means computed over 100 years of synthetic HMM-GC data

- Each point of synthetic represents an average taken over 100 years
- July is overestimated while August is underestimated.
- Low RMSE indicates that the model captures the number of monthly precipitation occurrences at each location

Scatterplot of the mean precipitation per month

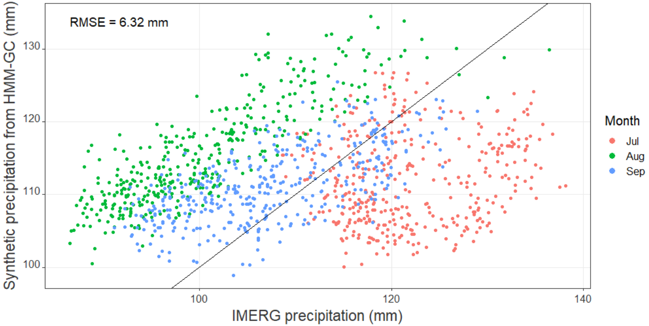


Figure: Scatterplot of the mean precipitation per month at each grid point based on historical IMERG data (2001-2018) compared with means computed over 100 years of synthetic HMM-GC data

- Each point representative of a 100 year mean worth of synthetic data at location
- August overestimated and July underestimated.
- Low RMSE indicates that the precipitation amounts are generally modeled by the HMM-GC

Conclusions

HMM

- Captures general precipitation events over long periods of time
- Fails to capture spatial correlation between locations adequately
- Can replicate extreme precipitation events at individual locations, but not spatially consistent

HMM-GC

- Captures general precipitation events over long periods of time
- Significantly improved spatial correlation in synthetic data
- Spatially consistent replication of heavy precipitation events

- HMM-GC improves the HMM's ability to capture long sequences, pairwise spatial correlations, and extreme events.
- The replication of spatial correlation can be further improved.
- The variation in the scatter plots signifies that there is information in the IMERG data that the HMM-GC fails to capture.