

# Monitoring drought conditions and their uncertainties in areas with sparse precipitation data.

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## Evaluation of different datasets in Africa

### Overview

#### Objective

Evaluate the uncertainties due to sample size associated with the estimation of the Standardized Precipitation Index (SPI) and their impact on the possible level of confidence in drought monitoring in Africa using high spatial resolution but short time series (TRMM).

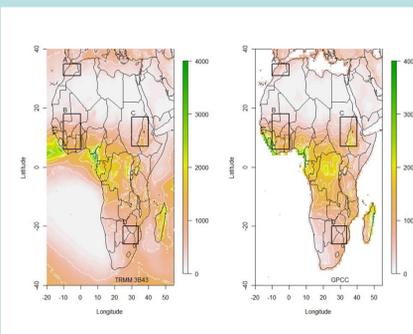


Figure: Annual mean precipitation for TRMM 3b43 and GPCC dataset and African regions used in this analysis.

#### Datasets and case studies

Tropical Rainfall Measuring Mission (TRMM) satellite monthly rainfall product 3B43 and the Global Precipitation Climatology Centre (GPCC) gridded precipitation dataset were analyzed,

Four case in Africa (Oum er-Rbia (A), Niger (B), Eastern Nile (C), and Limpopo (D) ) as well as at continental level were studied.

### Parameter estimation (Bootstrap)

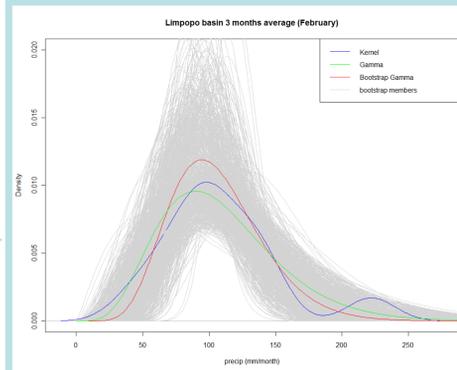


Figure shows the empirical distribution of the 3 month averaged precipitation at Limpopo basin.

A non-parametric resampling bootstrap approach was used in order to assess the sampling bias and uncertainties associated with SPI estimation,

Kernel, Gamma and unbiased Gamma distribution using a bootstrap technique were tested. The results show that the unbiased estimation fits better (lower K-S distance) compared with the other approaches.

The results also show the distribution estimation and the family of distributions associated with the bootstrap resampling. It is shown that the bootstrap members vary widely, but the mode is in general well represented by the majority of those.

### Parameter estimation (Continental scale)

At Pan-African level, the spatial distribution of the unbiased shape and scales parameters of the Gamma distribution using 3-monthly averaged TRMM precipitation data are shown. This estimation shows a regional consistency and is in agreement with the findings by Husak et al. (2007) using the CHARM dataset.

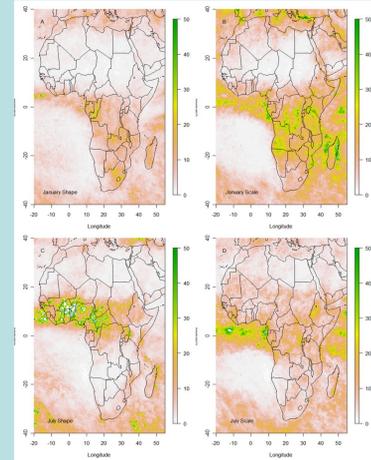
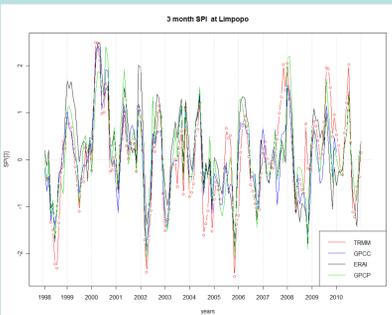


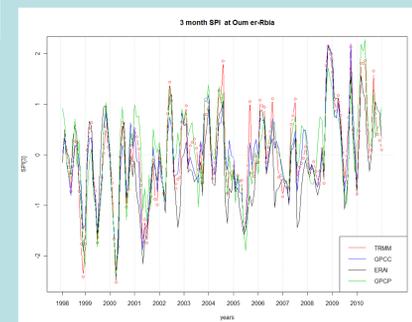
Figure: Shape and Scale parameters for January and July using unbiased estimation of parameters.

Large shape values tend to follow the Inter-tropical Convergence Zone (ITCZ) through each of the monthly maps. The areas with higher scale parameter are mainly observed in the poleward borders of the ITCZ where the rainfall could be more variable.

### SPI-3 Comparison



Comparing SPI calculated from different datasets, it is observed that TRMM tends to overestimate peaks compared with GPCC information. This means that the main source of error is due to the estimation of tails of the distribution.



The agreement between datasets is good for most of the regions ( $r > 0.60$ ), but with higher differences in mountainous regions.

Figures: 3-month SPI time series calculated using different datasets and baselines.

### SPI-3 Comparison + Confidence intervals

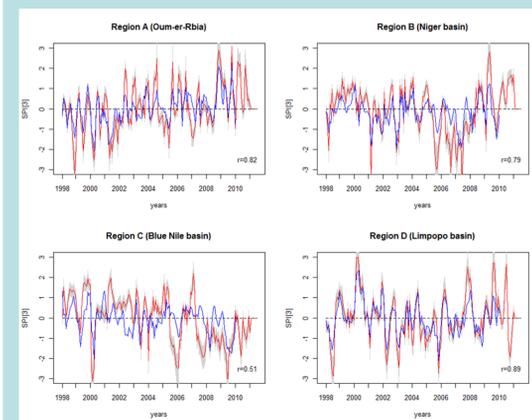


Figure: 3-month SPI time series calculated using 12 year TRMM (red) and 50 year GPCC datasets (blue) and C.I. (lightgrey).

However, while TRMM overestimates the peaks, it is observed that the GPCC estimation is within the TRMM estimation confidence intervals most of the time.

The biggest differences are observed for the Niger basin and the Blue Nile basin, region with the most complex orography. These regions have the lowest station density per grid with up to 75% of pixels without any ground observation for the GPCC dataset.

This means that more in-situ data are needed in order to improve the GPCC precipitation datasets and the TRMM calibration as well.

### Conclusion

A non-parametric resampling bootstrap approach was used in order to assess the sampling uncertainties associated with SPI estimation in terms of confidence bands.

Higher discrepancies in SPI estimations are shown in mountainous areas and areas with low in situ station density. This kind of approach could be used to improve monitoring rainfall conditions in three ways:

- First, to obtain an unbiased estimation of the Gamma parameters in order to obtain a better estimation that could contain errors due to the record length of dataset.
- Secondly, to prepare decision makers providing the measurement of uncertainties associated with the datasets to better understand in which situations this tool is more reliable.
- Finally, this type of approach could allow some forecast applications. For instance, it is possible to use the distribution information for each member of the bootstrap as initial conditions to develop drought scenarios.