

A PICSA Fit-For-Purpose Validation of Satellite Rainfall Products in Zambia



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Introduction

Rainfall estimation from satellite data is of great importance, especially in areas where gauge stations are absent or sparse. However, most of the satellite-based precipitation estimation products rely on the relationship between cloud-top brightness temperature and actual rainfall, assuming that precipitation originates from convective clouds with cold tops. This assumption fails to work for precipitation that originates from warm clouds. It also overestimates rainfall for areas with cold cloud tops, which includes mistaking non-precipitating cirrus as rainy. Another issue of these products is that their rainfall estimates are areal averages that suffer from biases due to complex terrain leading to the underestimation of extreme rainfall events. This work does a fit-for-purpose validation of five satellite-based rainfall estimation products in Zambia for use in the Participatory Integrated Climate Services for Agriculture (PICSA).

How Station Rain Gauge Data and Satellite Data Differ



Bias Correction

We corrected the biases in the satellite estimates using the local intensity scaling (LOCI) by [1] as defined below:

$$s_m = \frac{mean(x_i | x_i \ge T_m^x) - T_m^x}{mean(y_i | y_i \ge T_m^y) - T_m^y},$$
(2)

where x_i are the daily station values, y_i are the daily satellite values for month m, T_m^y is the rain day threshold of the satellite data in month m calculated such that the long-term proportion of rain days for the satellite is the same as the station with rain day threshold $T_m^x = 0.85$ in accordance with [2]. Finally, the bias-corrected satellite values y'_i are obtained by,

$$y'_i = \begin{cases} 0, & \text{if } y_i \leq T_m^y \\ T_m^x + s_m(y_i - T_m^y), & \text{otherwise} \end{cases}$$

(3)

Figure 1. Point vs Pixel Rainfall Data

Study Area and Station Data





Figure 4. Gauge vs product estimates vs bias-corrected estimates - rain day frequency (rain days/year)

PICSA INDICATORS

- The start of season: The first occasion from 15th November that gets 20 mm or more rainfall in 3 consecutive days which is not followed by a dry spell of 10 days or more in the next 30 days ([2]). • The End of Season: This is defined as the first occasion from the last rainfall of 10 mm or more
- with empty water balance. The water holding capacity was taken to be 120 mm and evaporation was taken to be 5 mm per day.

Figure 2. Zambia stations

Satellite-Based Rainfall Estimation Products

Product	Inputs	Coverage		Period	Spatial Res.	Temporal Res.
CHIRPS	Satellite + gauge merge	Global	1983	- present	0.05°	Daily
CHIRP	Satellite	Global	1983 -	- present	0.05°	Daily
TAMSAT	Satellite + gauge calibration	Africa	1983 -	- Present	0.0375°	Daily
ERA5	Reanalysis	Global	1983 -	- present	0.25 °	Hourly
AGERA5	ERA5	Global	1983	- present	0.1°	Daily

Table 1. Details of 5 satellite-based rainfall estimation products used

Seasonality

We fitted a zero-order Markov Chain model with three harmonics to study the seasonality of rain day frequency. It is written mathematically as:

$$y(t) = \beta_0 + \sum_{i=1}^{k} (A_i \cos(\frac{2\pi i t}{p}) + B_i \sin(\frac{2\pi i t}{p})) + \epsilon,$$
(1)

where k is the number of harmonics, p is the period, t is the time (day of year), β_0 , A_i and B_i are parameters to be estimated, and ϵ is the error term.

Results on PICSA Indicators: Start of the season



Figure 5. Gauge vs ERA5 estimates vs ERA5 bias-corrected estimates - start of the season (day of year)

Conclusion and Recommendation

Conclusion

The results show that the products in their current form are likely unsuitable as a replacement for station rain-gauge-recorded data on PICSA indicators such as the start of the season. However, if they are adjusted with a bias-correction method such as the Local Intensity Scaling (LOCI) method, they may be suitable for calculating overall risks on these indicators.



Figure 3. Gauge and ERA5 estimated rain day frequency (rain days/year) at various thresholds

Recommendation

Further work is needed to make them suitable for detecting the PICSA indicators, such as the start of the season dates, on individual years.

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References

[1] Jürg Schmidli, Christoph Frei, and Pier Luigi Vidale.

Downscaling from GCM precipitation: a benchmark for dynamical and statistical downscaling methods. International Journal of Climatology, 26(5):679–689, 2006.

[2] R. D. STERN and P. J. M. COOPER.

ASSESSING CLIMATE RISK AND CLIMATE CHANGE USING RAINFALL DATA - a CASE STUDY FROM ZAMBIA. Experimental Agriculture, 47(2):241–266, March 2011.