Assessing Crop Yield Variability Using Meteorological Drought Indices for Agricultural Drought Monitoring in Botswana

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EXTENDED METHODOLOGY AND RESULTS

S1. Validation of CHIRPS and CHIRTS data

CHIRPS satellite rainfall estimates validated against observed gauge measurements over 6 stations, namely Francistown, Kasane, Mahalapyes, Maun, Shakawe and Sir Seretse Khama (SSKA) displayed strong correlation and statistical agreement. The correlation ranged from 0.81 to 0.89. The CHIRPS dataset proved reliable for capturing well, rainfall variations which are useful for drought monitoring.

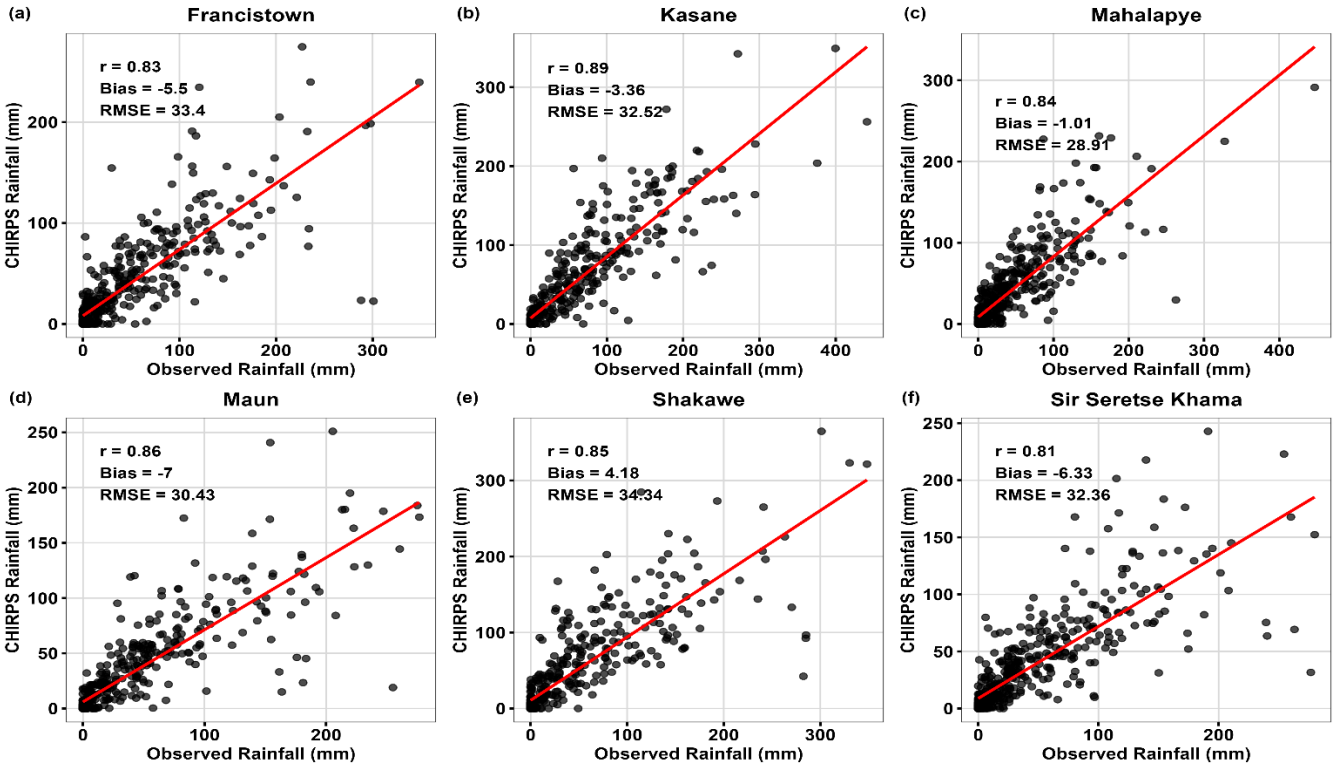


Figure S1. Panel plots showing CHIRPS validation against gauge observed rainfall data (1984 - 2024) in Botswana**.** BIAS (mm) and RMSE (mm) for n = 6 stations.

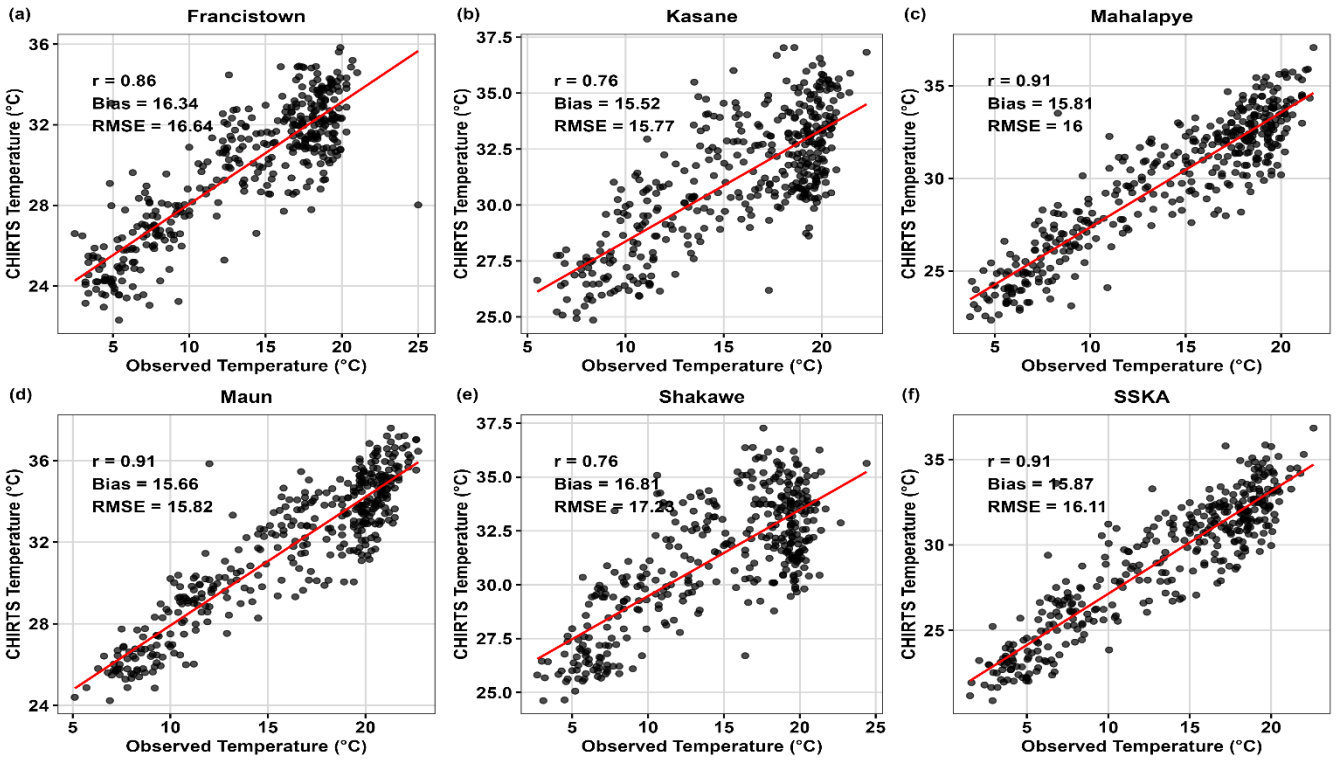


Figure S2. CHIRTS (maximum temperature) validation with station-observed maximum temperature data in Botswana. BIAS (°C) and RMSE (°C) for n = 6 stations.

Figure S2 shows contrast between CHIRTS monthly maximum temperature estimates with observed station data across the aforementioned areas, demonstrating good performance with over the regions with correlation coefficients ranging from 0.76 to 0.86. Mahalapye, Maun, SSKA and Francistown showed high correlations, suggesting that CHIRTS is much effective in capturing temperature variations in these regions.

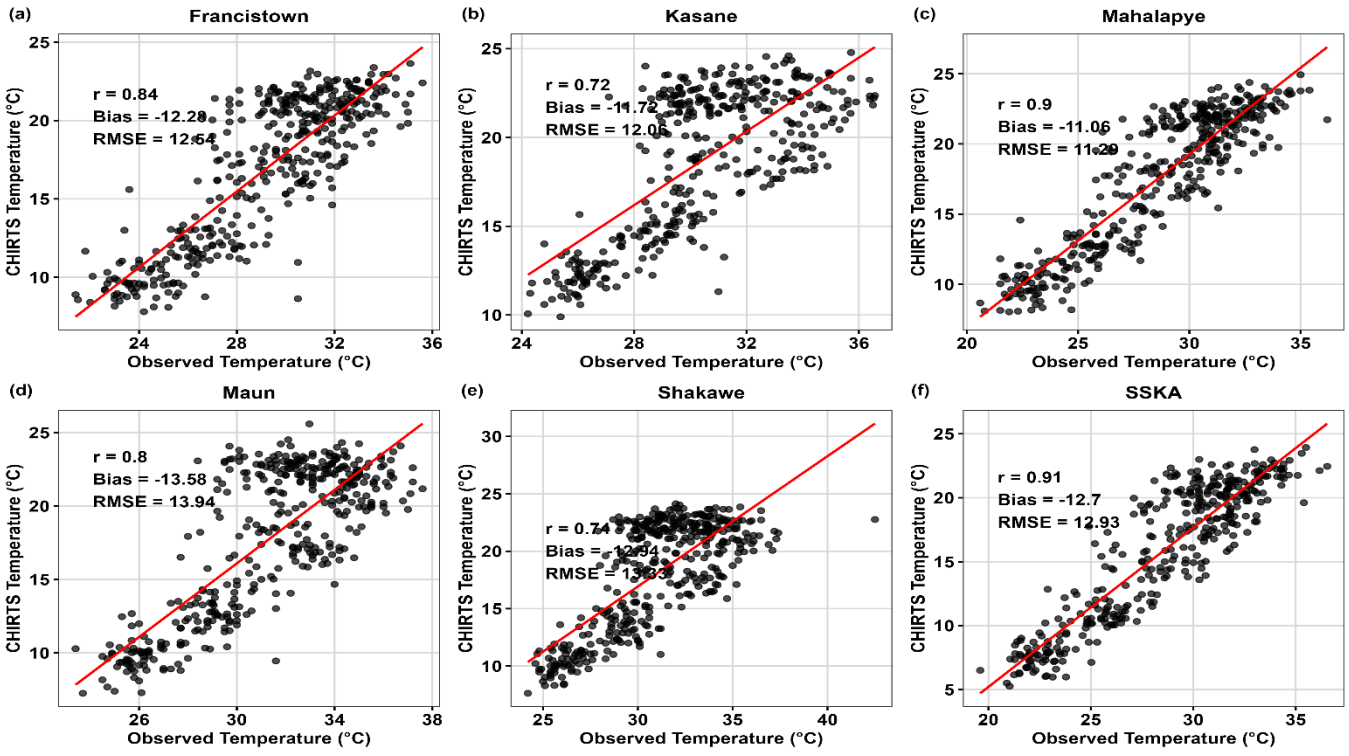


Figure S3. CHIRTS (minimum temperature) validation with station-observed maximum temperature data in Botswana. BIAS (°C) and RMSE (°C) for n = 6 stations.

Similarly Figure S3 also showed strong positive correlations ranging between 0.72 and 0.91. The highest performance appeared across the previously Mahalapye, Maun, Francistown and SSKA.

S2. Time series

Mean monthly drought index values were computed at each grid station across Botswana. For each month t, a national mean index value was then obtained by spatially averaging across all locations:

$$DI_t^{nat} = \frac{1}{N}\sum_{i=1}^{N} DI_{i,t} \quad \text{(S1)}$$

where, DI_t is the drought index at month t and N is the number of stations.

S3. Questionnaire - location description

Gaborone: The setting is characterised by preserved indigenous vegetation, with minimal commercial agriculture and dispersed fertile fields within or surrounding the local communities of Tlokweng, Mogoditshane, Mmopane, Metsemotlhabe and Gabane [98]. The city is situated in the southern region of the country, adjacent to the South African border and is the nation's principal administrative and commercial hub [99].

Tsabong: Leeming et al. (2001) noted that Tsabong (a large town), is located 27 km northwest of the Botswana/South Africa border and 575 kilometres southwest of Gaborone. The town is found in the Kgalagadi District of Botswana which possesses diverse wilderness characteristics, including sparse vegetation, woods, and white pans adjacent to sand dunes and grasslands (Saarinen et al., 2012).

Palapye: One of the important villages in Botswana (and now developing into a town), situated along the Lotsane River, in the central part of the country (Bafitlhile and Oladele, 2015). It is one of the most rapidly developing towns in Botswana (Statistics Botswana, 2015), with a semiarid climate characterised by an average annual precipitation. Rainfall distribution is influenced by orographic effect as the town is located between the Matepilepi Hills to the northwest and the Tswapong Hills to the southeast (Akinyemi, 2017).

Francistown: Francistown is the second most populous city in Botswana and serves as a transit hub for passengers to Kasane, Gaborone, Maun, Zimbabwe, South Africa, Zambia, and Namibia (Ketshabile, 2012). This is a semi-arid area that receives the most rainfall during the rainy season. Subsistence farming predominates in the nearby villages whilst small-scale commercial farming is also practiced.

S4. Results and discussion

S4.1. Evaluating skill assessment of the indices

With the use of raw detection metrics (Table S1*)*, SPEI1, SPEI3, SPI1 and SPI3 proved to have the highest performance. They recorded a POD of 100.00% with 0 misses and hit counts between 29 and 32 as well as false alarms ranging between 5 and 12. The POFD was also

100.00% across them with low false alarm rates of 14.71 to 27.27 range, highlighting that their sensitivity to detect historical droughts is strong. SPEI6 and SPI6, followed closely with 1 miss amongst each and POD being 96.55 % and 96.88 % respectively, which suggests that their performance can be reliable in drought detection. On the contrary SPEI12 and SPI12 had increased misses and false alarms with POD values of 86.21 % and 84.38 % respectively, showing reduced performance. The results indicate that shorter time scales 1 and 3 in particular, are more responsive and precise in detecting drought events as compared to longer time scale indices.

Table S1. Skill assessment results from the performance metrics according to A (hits), C (misses), FM (false alarms), Cn (correct negatives), POD (probability of detection), POFD (probability of false detection), FAR (false alarm ratio) and d (Euclidean distance).

Index	A	C	FM	C_n	POD	POFD	FAR	d
SPEI-1	29	0	5	0	100.0	100.0	14.7	100.0
SPEI-3	29	0	5	0	100.0	100.0	14.7	100.0
SPEI-6	28	1	5	0	96.6	100.0	15.2	100.1
SPEI-12	25	4	4	1	86.2	80.0	13.8	81.2
SPI-1	32	0	12	0	100.0	100.0	27.3	100.0
SPI-3	32	0	12	0	100.0	100.0	27.3	100.0
SPI-6	31	1	12	0	96.9	100.0	28.0	100.1
SPI-12	27	5	9	3	84.4	75.0	25.0	76.6
STCI-1	29	0	5	0	100.0	100.0	14.7	100.0
STCI-3	27	2	5	0	93.1	100.0	15.6	100.2
STCI-6	12	17	1	4	43.4	20.0	7.7	61.9
STCI-12	0	29	0	5	0.0	0.0	NA	100.0

S4.2. Correlation results

To further support this (Figure S4), shows the Pearson correlation coefficients between SPI, SPEI and STCI. There was a moderate to high correlation between SPI and SPEI indicating that although they are normally sensitive to short term precipitation deviations, the temperature implications highlighted by SPEI introduces some distinction. Strong coherence is observed between SPI-1 and all SPEI (1- to 12-month) timescales (0.90, 0.84, 0.84 and 0.85 respectively), as well as SPI-3 and SPEI-3 (0.63). This suggests that both SPI and SPEI could be used together for drought monitoring, considering timescales that showed slightly a lower correlation which implies that their information in capturing drought signals may be combined.

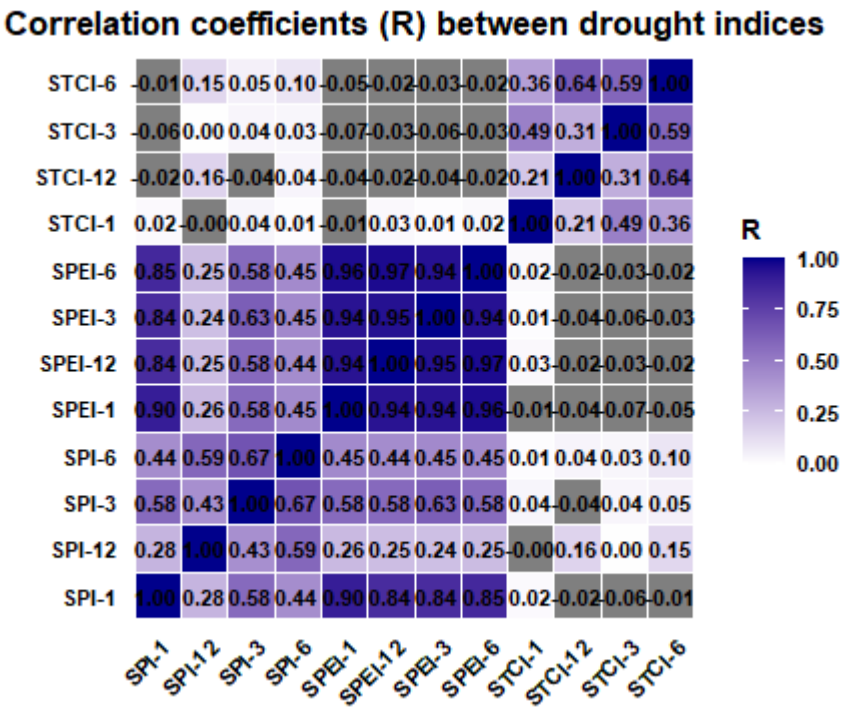


Figure S4. SPI, SPEI and STCI correlation coefficients (r) for the 1-, 3-, 6-, and 12- month timescales.

Contrastingly, STCI demonstrated weak association with both SPI and SPEI. Its variation may not always be in line with the precipitation derived drought indices since it is driven by temperature, highlighting heat stress. Nevertheless, a moderate correlation appeared at the 3, 6 and 12-month timescales which may be attributed to the combined effect of drought with increasing thermal stress, affecting agricultural production in Botswana's semi-arid climate. The findings underscore the importance of employing several indicators of drought in Botswana.