The Usefulness of Gridded Climate Data Products in Characterizing Climate Variability and Assessing Crop Production

Working Paper No. 322

CGIAR Research Program on Climate Change, Agriculture and Food Security (CCAFS)

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Abstract

A sparse rain gauge network in dryland regions has been a major challenge for accessing high-quality observed data needed to understand variability and trends in climate. Gridded estimates of weather parameters produced through data assimilation algorithms that integrate satellite and irregularly distributed on-ground observations from multiple observing networks are a potential alternative. Questions remain about the application of such climate data sources for assessing climate variability and crop productivity. This study assessed the usefulness and limitations of gridded data from four different sources i.e. AgMERRA, CHIRPS, NASA Power, and TAMSAT in estimating climate impacts on crop productivity using Agricultural Production Systems Simulator (APSIM). The study used data for 11 locations from Africa and India. The agreement between these data sets and observed data both in the amount and distribution of rainfall was evaluated before and after bias correction statistically. A deviation of more than 100 mm per season was observed in 13%, 20%, 25%, and 40% of the seasons in CHIRPS, AgMERRA, NASA Power, and TAMSAT data sets respectively. The differences were reduced significantly when data sets were bias-corrected. The number of rainy days is better estimated by TAMSAT and CHIRPS with a deviation of 4% and 6% respectively while AgMERRA and NASA Power overestimated by 28% and 67% respectively. The influence of these differences on crop growth and productivity was estimated by simulating maize yields with APSIM. Simulated crop yields with all gridded data sets were poorly correlated with observed data. The normalized root-mean-square error (NRMSE) of maize yield simulated with observed and gridded data was <30% for two locations in the case of AgMERRA and CHIRPS and three locations in the case of NASA Power. The NRMSE was > 30% for all locations with TAMSAT data. When yields were simulated with data after bias correction using the linear scaling technique, results were slightly improved. The results of our study thus indicate that the gridded data sets are usefully applied for characterizing climate variability, i.e. trends and seasonality in rainfall, however their use in driving crop model simulations of smallholder farm level production should be carefully interpreted.

Keywords

Gridded data; climate change; climate variability; bias correction; APSIM.

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Contents

Acronyms

AgMERRA	AgMIP Modern-Era Retrospective Analysis for Research and Applications
APSIM	Agricultural Production Systems Simulator
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
FAO	Food and Agriculture Organization
LGP	Length of Growing Period
NASA POWER	National Aeronautics and Space Administration, Prediction of Worldwide Energy Resources
PET	Potential Evapotranspiration
TAMSAT	Tropical Applications of Meteorology using SATellite data and ground-based observations
WMO	World Meteorological Organization

1. Background

Drylands - defined as the areas with a length of growing period (LGP) ranging from 1 to 179 days (FAO, 2000) – are considered as the hotspots for vulnerability to climate variability and change. About 40% of the earth's surface is made up of drylands of which 72% is in the developing countries (UNEP, 2007). The percentage of the world's population living in these drylands was calculated to be about 38%, equivalent to 2.3 billion of today's global population of 6 billion (UNDP, 2011). They account for more than 70% of the cropped land in Africa (Morris, 2016) and about 60% of cropped land in India (Singh et al., 2004). The drylands are further divided into arid, semi-arid, and sub-humid areas based on the aridity index (ratio of annual precipitation to potential evapotranspiration or P/PET) varying between 0.05 and 0.65 (UNCCD, 2000). This excludes hyper-arid or desert areas with an aridity index of < 0.05 which has limited potential for agriculture, except the desert farming concept. Though drylands are intensively used for agricultural and pastoral activities, their production and productivity are constrained by the amount of moisture available and the magnitude of stress that the crop experiences during the growing period which varies significantly within and between the seasons. (Koohafkan, 2012). Analysis of 77 series of annual data on production and rainfall from various arid zones of the world by Le Houérou et al. (1988) had revealed that each mm of rain produces an average of 4 kg of above-ground dry matter per ha per year while variability in production is, on the average, 1·5 times greater than variability in rainfall. Hence, a good understanding of local climatic conditions is an important pre-requisite to assess the production potential and associated risks with farming in dryland areas.

Good quality long-term station data play a significant role in characterizing the climatic conditions and in assessing their suitability for agricultural, livestock, and forestry production (Sinclair and Pegram, 2005). Reliable and accurate information about the climatic conditions are an important basis for strategic planning and decision making in weather-sensitive sectors such as agriculture. For calculating a normal or average, the WMO Guide to Climatological Practices (WMO, 2011) recommends the use of data for 30 years consisting of data for at least 80% of the years and the period of missing data not exceeding three or more consecutive years. The availability of such long-term data is a major constraint in the case of dryland areas because of the limited number of gauging stations in these areas and concerns about the quality of the records maintained including data continuity. Africa has one of the very poor observational network systems of any continent and the same is reported to be deteriorating gradually (Washington et al., 2006, Dinku et al., 2011). WMO estimates that the network is eight times less dense than their recommended level of one station per 26,000 km^2 across Africa. The few stations that do exist are unevenly distributed and suffer from maintenance problems leaving much of the continent unmonitored (Washington et al., 2006).

Even though gauge measurements of weather stations are considered to be the gold standard for meteorological data, they also suffer from several constraints and deficiencies. These include measurement accuracy, incomplete areal coverage of sparsely populated areas such as drylands, and deficiencies in data quality (Kidd et al., 2017; Rana et al., 2015). Gridded estimates of weather parameters—produced through data assimilation algorithms that integrate irregularly distributed satellite and on-ground observations from multiple observational networks—are considered as one potential alternative to observed data since they provide coverage that is more spatially homogeneous and temporally complete (Sun et al., 2018, Xie and Arkin, 1996; Daly, 2006). While several such climate data sets of varying spatial and temporal resolution have already been constructed and applied in a substantial number of studies, the different data sets are not completely consistent (Tapiador et al., 2017). Studies carried out to assess the quality of these estimates have revealed considerable differences between these products and observed station data. Statistical comparison of observed data and various gridded data sets by Bandyopadhyay et al. (2018) have shown that the rainfall patterns in both amounts and frequencies are well captured by gridded data. However, the accuracy of these data sets was found to vary spatially and also by the type of gridded data product used (Zambrano et al., 2017). Rainfall estimates from many gridded data sources were found to correlate poorly with observed data especially on a daily scale (Sun et al., 2018). Most studies on quality assessment were carried out at a very coarse scale of global, continental, or regional (Daly et al., 2017, Kotlarski et al., 2014). The detailed source-specific assessment showed limitations in the representation of several weather patterns by reanalysis data sets partly due to problems with satellite information under specific cloud cover conditions (Häggmark, 2000; Bosilovich et al., 2008; Kidd et al., 2012).

Despite these problems gridded precipitation data products are often used as meteorological input for simulating various ecological processes including hydrological modeling exercises at landscape and regional level spatial scales (Nkiaka et al., 2017; Palazzi et al., 2013), to study the extreme events such as assessing the ability to reproduce flood events in Northern Italy (Mei et al. 2014; Nikolopoulos et al., 2013), to assess impacts of climate variability and change (Jones and Thornton, 2003) and to replace the missing values or fill the gaps in the station rainfall data which is one of the most common problems with observed station data at many locations (Meher and Das, 2019). Despite the mixed results from these studies, with some findings showing reasonably good results (Hadjikakou et al., 2011; Lauri et al., 2014) while others are less encouraging (Roth and Lemann, 2016), these studies have demonstrated the advantages and limitations of using these data products for different purposes.

Considering the sensitivity of dryland agriculture to variability and high variability in rainfall over spatial scales, the current study had an overall objective to evaluate four widely used gridded data sets for their ability to represent actual weather conditions at eleven locations in Africa and India. The hypothesis that we aimed to test is that gridded or derived climate data products can be used as valid surrogates, where ground-based measurements are unavailable or incomplete. This study uses four gridded weather data products, AgMERRA, CHIRPS, NASA Power, and TAMSAT, in various regions of Africa and India mainly focuses on answering three major questions. These include how well-gridded data sets capture the within and between the year variability in precipitation in different eco-regions, whether the accuracy of different data sets can be improved by the application of bias correction technique, and how useful these data sets are in simulating the growth and performance of different crops and cropping systems using system simulation model APSIM (**A**gricultural **P**roduction Systems **Sim**ulator) that uses daily climate parameters.

2. Methodology

The methodology adopted is aimed at better understanding the similarities and differences in the amount and distribution of rainfall from various gridded data sets and between the gridded data sets and observed station data. The rainfall from gridded data sets was initially compared with the observed data recorded at one of the locations that fall within the grid before and after bias correction of gridded data. This was followed by an evaluation of how these differences between gridded and observed data manifest in assessing the impacts of climate on the performance of agricultural systems.

2.1 Study locations

We have selected 11 dryland locations representing semi-arid and sub-humid dryland environments from India and Africa for this study. These environments are also described as water-stressed environments where the performance of agriculture and allied activities is highly dependent and sensitive to the amount and distribution of rainfall during the crop season. Five of these locations -three from India and two from Senegal in West Africa are located in the northern hemisphere and four locations, two each from Zimbabwe and Malawi in Southern Africa are in the southern hemisphere while the remaining two locations from Kenya in Eastern Africa are located near the equator (Table 1). These locations cover a latitudinal range from -20.5^0 in the south to 19.3^0 in the north and an altitudinal range from 14 to 1377 m above mean sea level (AMSL). The annual rainfall at these locations is at least 500 mm with maximum temperature varying between 25^{0}C and 42^{o}C and minimum temperature between 11^{o}C and 28^{0}C. Except for the two East African locations near the equator – Embu and Kambi Ya Mawe which have bimodal rainfall distribution, with rainy seasons from October to December and March to May– all other locations have a single rainfall season.

Table 1: Geographical locations selected for this study

Location	Country	Latitude (^{0})	Longitude (^{0})	Elevation (m)
Matopos	Zimbabwe	-20.506	28.435	1377
Masvingo	Zimbabwe	-20.064	30.828	1095
Chitedze	Malawi	-13.983	33.633	1149
Kasungu	Malawi	-13.035	33.484	1048
Kambi Ya Mawe	Kenya	-1.860	37.646	1145
Embu	Kenya	-0.531	37.451	1293
Kolda	Senegal	12.880	14.970	10
Kaffrine	Senegal	14.105	15.542	14
Anantapur	India	14.682	77.601	349
Patancheru	India	17.529	78.267	543
Parbhani	India	19.258	76.774	417

2.2 Data

The study used station data collected from local sources as reference data. Observed rainfall data for the period from 1983 to 2010 were collected and necessary quality assessments were carried out using WMO recommended procedures (WMO, 2019). Gridded data for temperature and precipitation for the same period were extracted for the grid cells in which selected weather station falls. The four selected gridded data products are AgMERRA (AgMIP Modern-Era Retrospective Analysis for Research and Applications) from National Aeronautics and Space Administration, Goddard Institute for Space Studies (Ruane et al., 2015), NASA Power from the NASA Langley Research Center POWER (Prediction Of Worldwide Energy Resources) Project (https://power.larc.nasa.gov/), CHIRPS (Climate Hazards Group InfraRed Precipitation with Station data) from the Climate Hazards Center, University of California, Santa Barbara (Funk et al., 2015) and TAMSAT (Tropical Applications of Meteorology using SATellite data and ground-based observations) from the University of Reading (Maidment et al. 2017). Table 2 below describes the gridded data used:

Table 2: Descriptions of the gridded datasets used in the study from 1983 to 2010.

Data set	Resolution	Frequency	Parameter(s)
AgMERRA	0.25^0X0.25^0	Daily	*Rainfall, Min and Max temperatures, and solar radiation*
CHIRPS	0.05^0X0.05^0	Daily	*Rainfall*
NASA	0.5^0X0.5^0	Daily	*Rainfall, Min and Max temperatures, and solar radiation*
TAMSAT	0.0375^0X0.0375^0	Daily	*Rainfall*

2.3 Bias Correction

Precipitation data from gridded products are known to contain systematic biases relative to station data (Parkes et al., 2019) leading to either over or underestimation of the frequency and/or intensity of the observed precipitation values (Velasquez et al., 2020). An attempt was made to minimize these errors and reduce the differences between gridded and recorded observations using bias-correction techniques. Several bias correction methods from simple linear scaling methods to complex power transform and quantile mapping were considered and used to improve the match between observed and derived weather parameters. Comparative assessment of several bias correction techniques has indicated that simple bias correction methods such as linear scaling are as good as complex methods such as quantile mapping (Shrestha et al. 2017). In the present study, we employed the linear scaling technique which uses a scaling factor to correct the derived rainfall amounts (Hay et al., 2000). The advantage of this method is its simplicity and modest data requirements. In this method,

$$P_{model,corr} = P_{model} \times \frac{P_{obs,monthly\ mean}}{P_{model,monthly\ mean}}$$

Where, $P_{model,corr,}$ and P_{model} are corrected and uncorrected monthly rainfall amounts from the model; $P_{obs,\ monthly\ mean}$ and $P_{model,\ monthly\ mean}$ are the monthly mean observed and modelled rainfall amounts.

2.4 Error metrics

To assess the significance of differences between the observed and gridded data sets statistically, three different error metrics – Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), and the Normalized Root Mean Square Error (NRMSE) were used. Below is the mathematical formulation of the aforementioned error metrics:

$$\boldsymbol{MAPE} = \frac{1}{N}\sum_{i=1}^{N} \left| \frac{X_{obs,i} - X_{model,i}}{X_{obs,i}} \right| \times 100\%$$

Where, $X_{obs,i}$ is the actual value for the i^{th} year, and $X_{model,i}$ is the model derived value for the same year and N is the total number of observations.

$$\boldsymbol{R^2} = \left[\frac{N(\sum_{i=1}^{N} X_{obs,i}X_{model,i}) - (\sum_{i=1}^{N} X_{obs,i})(X_{model,i})}{\sqrt{\{N\sum_{i=1}^{N} X_{obs,i}^2 - (\sum_{i=1}^{N} X_{obs,i})^2\}\{N\sum_{i=1}^{N} X_{model,i}^2 - (\sum_{i=1}^{N} X_{model,i})^2\}}} \right]^2$$

Where, $X_{obs,i}$ is the actual value for the i^{th} year, and $X_{model,i}$ is the model derived value for the same year and N is the total number of observations.

$$\boldsymbol{NRMSE} = \frac{\boldsymbol{RMSE}}{X_{obs,mean}}$$

Whereby

$$\boldsymbol{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(X_{obs,i} - X_{model,i})^2}$$

Whereby $X_{obs,\ mean}$ is the mean of observed data. RMSE is often expressed as a percentage, where lower values indicate less variance better match.

These parameters were calculated for precipitation data before and after bias correction and maize yields simulated with them.

2.5 Simulation of crop growth and yield

One of the questions that this study was aimed to address is related to the usefulness of gridded data sets in estimating crop growth and performance. For this, we conducted a scenario analysis with system simulation model APSIM using maize as a test crop. APSIM is a widely used farming system model that simulates crop growth and development as a function of soil, climate, and management variables (Holzworth et al. 2014). APSIM has been widely tested in Africa and in India to simulate the performance of maize and other crops (Akinseye et al. 2017; Whitbread et al. 2010). In this study, APSIM (version 7.8r3867) was configured with maize and a standard soil profile with 91 mm PAWC, 0.52% organic carbon to 40 cm depth, and 100 cm rooting depth for all locations. The soil is a loamy sand and other parameters are set to match this texture. These include curve number to 85, U or first stage evaporation to 3.5, falling rate (Cona) or second stage evaporation to 6, diffusivity constant to 250, diffusivity slope to 22, and SWCON to 0.7. Simulations were conducted for 13 seasons at 11 locations and five climate data sets (AgMERRA, CHIRPS, NASA Power, TAMSAT, and Observed) in case of African locations and four in case of Indian locations (excludes TAMSAT) using a standard set of crop management practices. Maize sowing was triggered by a rainfall criterion which is set to 30 mm rainfall over three days during the month in which the rainy season starts. The maize cultivar Katumani which is well-calibrated to African locations is used with a plant population of 50,000 plants/ha. Other management practices used are one tillage with the disc before the sowing window starts and application of 40 kg N as urea N at the time of planting.

3. Results

The ability of AgMERRA, CHIRPS, NASA Power, and TAMSAT gridded rainfall data to replicate the trends and variability in observed rainfall recorded at a station located within the grid was assessed by comparing the gridded data with observed data directly and also by calculating three different statistical parameters to evaluate the level of significance of the observed differences. The analysis was carried out on all data sets before and after applying the bias correction.

3.1 Annual rainfall and seasonality

Initially, the data sets were assessed for their ability to capture the amount and distribution of rainfall at annual scales. The rainfall at the selected locations varied from about 550 mm at Matopos to 1250 mm at Embu and its coefficient of variation (CV) from 21.5% at Chitedze to 48.8% at Masvingo. The gridded data sets differed in their accuracy to estimate the amount of rainfall at these locations (Table 3). Among the four sources, CHIRPS performed slightly better with a ±10% difference between the estimate and measured station value for eight of the eleven stations compared to seven stations with AgMERRA and NASA power. In the case of TAMSAT, only four of the eight African locations are having rainfall within ±10% of the observed value. The variability in gridded annual rainfall, measured as the coefficient of variation (CV), for all locations is lower than that of the observed. At Masvingo in Zimbabwe, the CV of observed data is almost double to that measured with AgMERRA, CHIRPS and NASA Power estimates while for the Kasungu location in Malawi the difference is within the range of 1-5%. The estimates from gridded data sets were found to be better for locations in India and Senegal with lower altitudes (<1000 m above MSL) compared to those in Eastern and Southern Africa with higher altitudes (>1000 m).

Table 3: Observed station and gridded annual rainfall amounts (mm) and their coefficient of variation (% in parenthesis) at target locations from 1983-2010

Location	Station	AgMERRA	CHIRPS	NASA Power	TAMSAT
Matopos	551 (27.4)	573 (20.7)	540 (23.6)	562 (23.1)	512 (34.6)
Masvingo	706 (48.8)	600 (26.0)	541 (25.1)	651 (24.9)	489 (37.0)
Chitedze	1114 (21.5)	877 (18.1)	857 (18.2)	1108 (22.6)	918 (15.5)
Kasungu	769 (21.9)	841 (20.4)	1058 (15.9)	1058 (20.1)	702 (22.8)
Kambi Ya Mawe	580 (39.5)	783 (23.1)	567 (48.9)	626 (25.1)	492 (35.7)
Embu	1249 (26.6)	1125 (22.4)	1026 (23.3)	984 (20.4)	734 (37.6)
Kolda	1021 (24.2)	1078 (13.0)	1016 (15.8)	915 (22.5)	977 (14.1)
Kaffrine	587 (25.8)	580 (20.4)	564 (18.1)	638 (23.9)	540 (14.7)
Anantapur	587 (35.6)	724 (26.1)	575 (25.3)	603 (23.6)	-
Patancheru	933 (25.0)	963 (24.4)	840 (25.5)	872 (17.8)	-
Parbhani	976 (28.8)	944 (18.3)	924 (19.2)	976 (19.1)	-

Rainfall seasonality or temporal distribution of rainfall was evaluated by comparing monthly mean rainfall estimates from different sources with observed station data (Figure 1). Though there are differences in the amount of rain received in different months, all data sets represented the temporal distribution of rainfall through the year fairly well. Except for the two Kenya locations, Kambi Ya Mawe and Embu which experience bi-modal rainfall distribution, all other locations have uni-modal rainfall distribution. In the case of Southern African locations from Zimbabwe and Malawi, the rainy season starts in November and ends in March and for locations in India and Senegal, the rainy season starts in June and ends in September. At Kambi Ya Mawe and Embu, the first season also known as the long rain (LR) season starts in March and ends in May and the second season, or short rain (SR) season starts is from October to December. The rest of our analysis is focused on characterizing rainfall during the rainy season which is important for agricultural purposes.

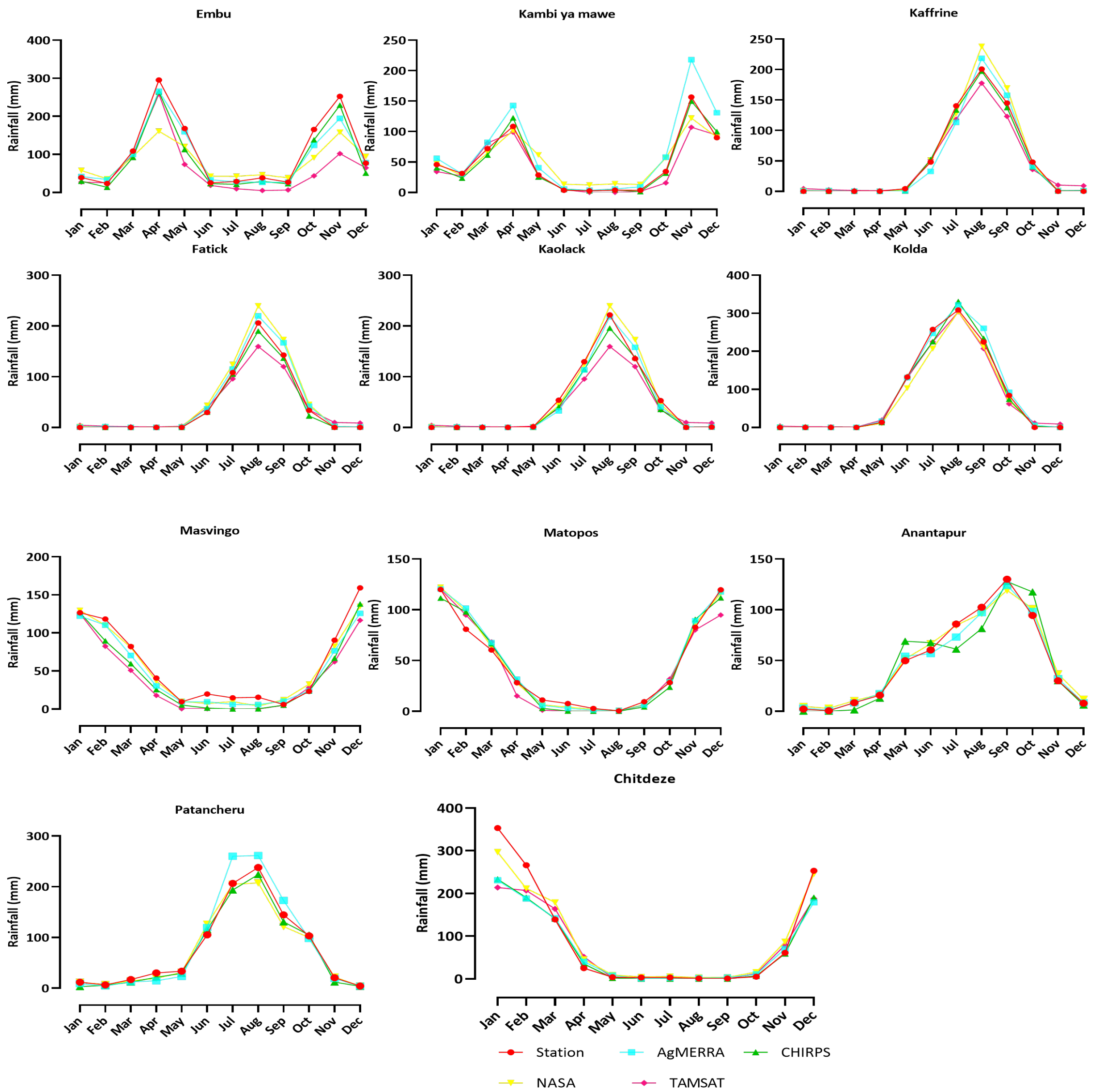

Figure 1: Distribution of average monthly rainfall (mm) estimates from different sources and observed data at study locations.

3.2 Crop seasonal rainfall

The duration and period of occurrence of the rainy season are different for different locations. The rainy season for the five locations in India and Senegal is of four-month duration from June to September. The four locations in Southern Africa experience a five-month-long rainy season starting from November while the two locations near the equator in Eastern Africa have two short seasons of three months each, one starting in March and the other in October. Hence, the analysis was done on rainfall totals of 13 seasons which are referred to as locations.

Seasonal rainfall amounts varied from about 209 mm during the LR season at Kambi Ya Mawe to about 1000 mm at Chitedze. The differences between the observed and gridded estimates of seasonal rainfall amounts are very similar to those found with annual rainfall (Table 3). This is expected since more than 80% of the annual rainfall occurs during the rainy season. CHIRPS, AgMERRA and NASA Power estimates were found to be better compared to the TAMSAT estimates by differing with observed rainfall by ±50 mm or ±10% for more than 50% of the locations. Major differences were observed at Chitedze and Embu locations where the difference between various estimates and observed is more than 100 mm or ±20%. Overall, the observed seasonal mean rainfall of 13 locations (582 mm) was overestimated by 1.0% by AgMERRA and underestimated by 7.3%, 4.2%, and 17.9% by CHIRPS, NASA Power, and TAMSAT data sets. Among the locations, the difference between the estimated and observed rainfall was found to be smaller for locations at a lower altitude (<500 masl) compared to those located at altitudes higher than 1000 masl.

Table 3: Observed and gridded estimates of mean seasonal rainfall (mm) and its coefficient of variation (% in parenthesis) at target locations.

Location	Mean seasonal Rainfall (mm)				
	Station	AgMERRA	CHIRPS	NASA Power	TAMSAT
Matopos-NDJFM	468 (36.8)	499 (28.1)	479 (29.2)	490 (29.2)	459 (41.6)
Masvingo-NDJFM	591 (44.4)	515 (34.0)	484 (31.2)	543 (28.3)	441 (45.3)
Chitdeze-DJFM	1005 (22.6)	741 (18.3)	757 (16.6)	935 (22.3)	778 (13.5)
Kasungu-NDJFM	725 (20.5)	798 (15.5)	742 (11.2)	975 (20.3)	681 (21.7)
Kambi Ya Mawe-MAM	209 (55.9)	266 (34.6)	209 (47.8)	228 (31.3)	208 (42.0)
Kambi Ya Mawe-OND	281 (45.5)	407 (35.6)	281 (66.3)	270 (42.1)	217 (66.3)
Embu-MAM	572 (35.4)	525 (25.6)	469 (28.5)	376 (29.5)	432 (44.2)
Embu-OND	495 (39.4)	396 (38.0)	418 (38.2)	344 (37.9)	211 (72.8)
Kolda-JJAS	920 (22.5)	960 (13.3)	924 (15.7)	826 (22.5)	866 (14.5)
Kaffrine-JJAS	534 (28.2)	522 (19.9)	520 (18.1)	586 (24.8)	471 (15.0)
Anantapur-JJAS	379 (52.9)	351 (38.5)	338 (33.3)	371 (33.9)	-
Patancheru-JJAS	709 (30.8)	771 (29.2)	642 (31.9)	665 (19.4)	-
Parbhani-JJAS	795 (30.9)	799 (19.4)	789 (20.3)	711 (18.1)	-

Note: Letters following the location name are the months of the rainy season and seasonal rainfall is the sum of rainfall during these months. In the case of locations in Southern Africa, seasonal rainfall is computed by adding the previous year's November and December rainfall and current year January to March rainfall. The locations in Kenya have two seasons.

Major differences were observed in the variability of seasonal rainfall. The CV of seasonal rainfall estimates from different sources except for TAMSAT was found to be lower compared to that with the observed data. In the case of TAMSAT, CV was found to be higher for six of the 10 African locations and the values are very high for rainfall during the SR season at Embu (73%) and Kambi Ya Mawe (66%). The observed all location mean maximum station rainfall (1036 mm) is higher than the AgMERRA, CHIRPS, NASA Power, and TAMSAT gridded estimates by 7.3%, 10.8%, 5.4%, and 16.4%, respectively (Figure 2). NASA Power and AgMERRA provided better estimates of maximum rainfall with an error of less than 10% compared to CHIRPS and TAMSAT which deviated by more than 10%. In the case of minimum rainfall (209 mm), estimates of TAMSAT and CHIRPS are close to the observed with a deviation of 0.4% and 0.1% while AgMERRA, and NASA Power estimates are higher by 27.3% and 9.4%, respectively. TAMSAT significantly overestimated the lower quartile rainfall by 42.9% while other data sets gave a close approximation of less than 10% deviation — AgMERRA 2.0%, CHIRPS: 4.0%, NASA Power: 9.7%. The upper quartile rainfall is approximated fairly well with all the data sets with the highest deviation being 9.8% recorded with TAMSAT. On average, the observed maximum rainfall is 5.6 times higher than the minimum rainfall. CHIRPS with a ratio of 5.9 is close to the observed while AgMERRA with a ratio of 4.2 and NASA power with a ratio of 4.4 underestimated the range. Overall, the estimates by CHIRPS and AgMERRA compared better with station data for most locations compared to NASA power and TAMSAT

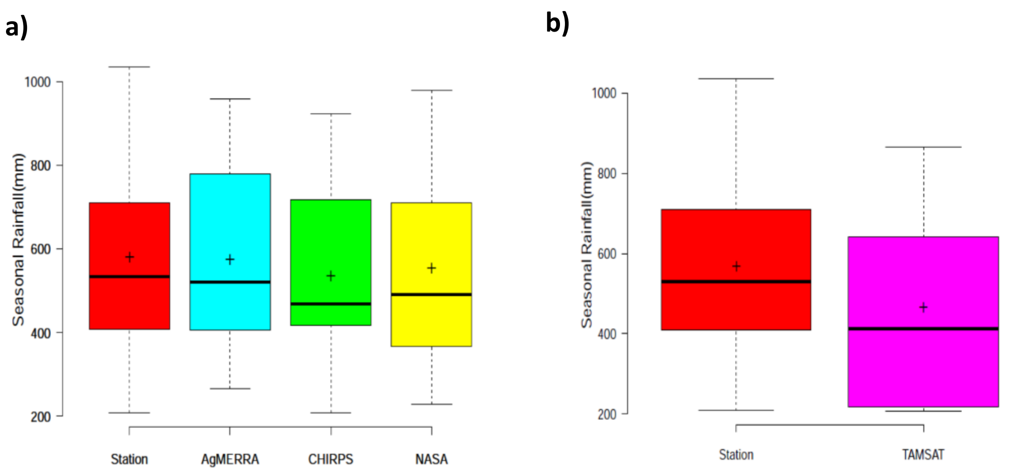

Figure 2: Distribution of mean seasonal rainfall of station data and estimates from AgMERRA, CHIRPS, and NASA Power (a), and TAMSAT (b). ***(TAMSAT data compares only African locations)***

3.2.1 Statistical evaluation of gridded data in characterizing rainfall amounts

Three types of error metrics were used to evaluate the ability of the gridded data sets in representing the seasonal rainfall amounts and their variability. The results from the same are presented in Appendix A and discussed in the below sections.

Mean Absolute Percentage Error (MAPE).

The MAPE values for different data sets used in this study are summarized in Table A1, A2, A3, and A4. We considered the MAPE value of less than 20% between the gridded and observed station data as an indicator of a good estimate of the seasonal rainfall amounts. AgMERRA with 54% of the locations and CHIRPS with 46% of the locations having MAPE values less than 20% performed better compared to NASA Power with 23% locations and TAMSAT with 20%. Albeit AgMERRA and CHIRPS data predicted the actual rainfall amount with higher accuracy at most locations compared to NASA Power and TAMSAT. NASA Power did extremely well in estimating rainfall at Chitedze, which is the wettest station with about 1000 mm rainfall during the season. The error tended to be low for stations located at lower altitudes compared to the ones located at higher altitudes.

Coefficient of Determination (R-Squared).

The correlation between observed and AgMERRA and CHIRPS gridded data sets was better compared to that with NASA Power and TAMSAT data sets. The R^2 values are greater than 0.5 for 62% of the locations with the AgMERRA dataset and 54% of the locations with the CHIRPS dataset. The best relationship with an R^2 of 0.85 was found between the observed and AgMERRA estimates for Anantapur, having a mean seasonal rainfall of 379 mm, and the estimates correlated poorly with an R^2 of 0.14 for Kaffrine with seasonal rainfall of 534 mm. Similarly, the CHIRPS dataset showed a strong correlation with an R^2 of 0.79 for Embu during SR season with a mean rainfall of 396 mm and correlated poorly with an R^2 of 0.29 for Kolda having a mean seasonal rainfall of 920 mm. Both AgMERRA and CHIRPS data sets recorded better R^2 values for the locations with a seasonal mean rainfall of less than 600 mm than those with more than 600 mm. Only 33% of the seasons in the TAMSAT dataset and 23% of the seasons in the NASA Power dataset had R^2 values greater than 0.5.

Normalized Root Mean Square Error (NRMSE).

We considered the NRMSE value of less than 0.2 as an indicator for better agreement between the gridded and observed data with fewer error residuals. All estimates performed poorly when this criterion is applied (Appendix A). NASA power performed relatively better with NRMSE values of less than 0.2 for 38% of the locations and less than 0.4 for 85% of the locations. The next best was the AgMERRA estimates with 15% of the locations having less than 0.2 and 85% of the seasons having less than 0.4 NRMSE values. No major difference was observed between CHIRPS and TAMSAT with only one location (<10% of the locations) recording an NRMSE value of less than 0.2 and about 60% of the locations recording less than 0.4.

3.2.2 ***Gridded data Performance in Characterizing Rainfall Frequencies***

The rainfall frequency or the number of rainy days and its variability is a good indicator of the distribution of rainfall wet and dry spells during a season. Rainy days are computed by counting the number of days on which daily rainfall amount is equivalent to or more than 2 mm. In general, the gridded data sets overestimated the number of rainy days compared to the actual number of rainy days recorded at the station (Figure 4). Across all stations, the average number of rainy days recorded is 37.6 whereas the predicted number of rain days varied from 40.5 with CHIRPS to 62.8 with NASA Power. With an estimate of 41.2 rainy days, TAMSAT is very close to CHIRPS estimate while AgMERRA is slightly higher with 48.2 days. Hence, both CHIRPS and TAMSAT gave better estimates of the number of rainy days with a deviation of less than 10% while AgMERRA overestimated them by 28% and NASA Power by 67%.

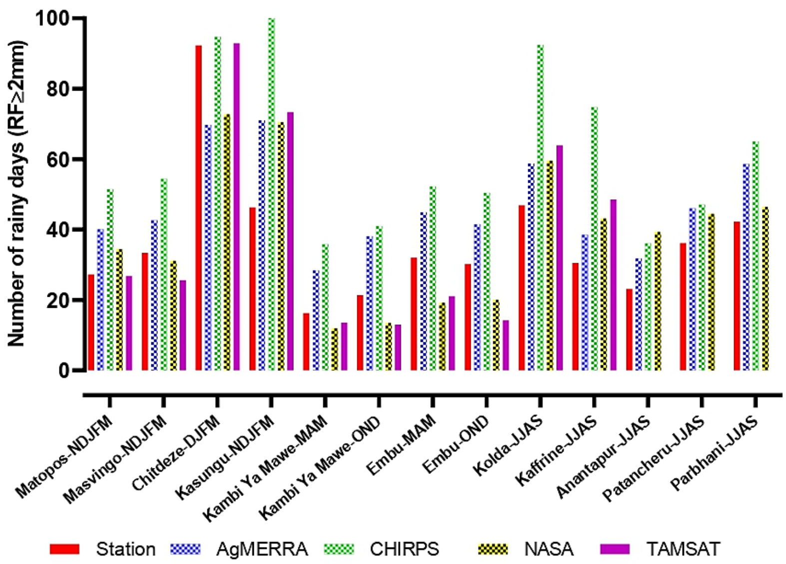

Figure 4: Number of rain days in a season recorded at the station and those estimated by AgMERRA, CHIRPS, NASA Power, and TAMSAT data sets

However, major differences were observed at the individual station level (Figure 4). For example, at Kasungu the number of rainy days was overestimated by more than 50% by all data sets with the biggest difference of more than 100% was observed with NASA Power. The best performing data sets of CHIRPS and AgMERRA showed different trends. While AgMERRA overestimated the rainy days by 25-78% for all stations except for Chitedze, the CHIRPS dataset underestimated the rainy days for six seasons and overestimated for seven seasons. NASA Power overestimated the rainy days for all seasons and the overestimate varied from 145% at Kafrine to 10% at Parbhani. TAMSAT overestimated the rainy days for five of the ten locations and underestimated for the remaining five locations. Both CHIRPS and TAMSAT underestimated the rainy days during both LR and SR seasons at Kampi Ya Mawe and Embu, which are located at the equator.

3.2.3 Probability of Exceedance in Seasonal Rainfall

The ability of the gridded data sets in capturing the uncertainty associated with seasonal rainfall was evaluated by constructing and comparing the probability of exceedance charts. For this, the locations are grouped into three depending on the amount of rainfall received during the season. The first group included locations with <500 mm rainfall, second group locations with > 500mm <750mm, and the third one include stations with >750 mm rainfall. The results below describe the trends for one of the locations within the group but the same applies to all locations in the group. The selected locations to represent different groups are Embu-OND for locations with less than 500mm, Kasungu for the group with > 500mm <750mm, and Chitdeze for the group with >750 mm rainfall during the season.

Locations with mean seasonal rainfall < 500 mm

The probability distribution of seasonal rainfall estimates from the gridded and observed station data are presented in figure 5. The charts indicate that the probability of getting a certain amount of rainfall is always lower with gridded data compared to that with observed data. For example, the probability to get 400 mm rainfall at this location is 10% with TAMSAT, 23% with NASA Power, and 45% with CHIRPS and AgMERRA data sets compared to 68% with observed data. The distribution of rainfall estimates from AgMERRA and CHIRPS data sets is very similar while the distribution of TAMSAT estimates is very different compared to the other data sets.

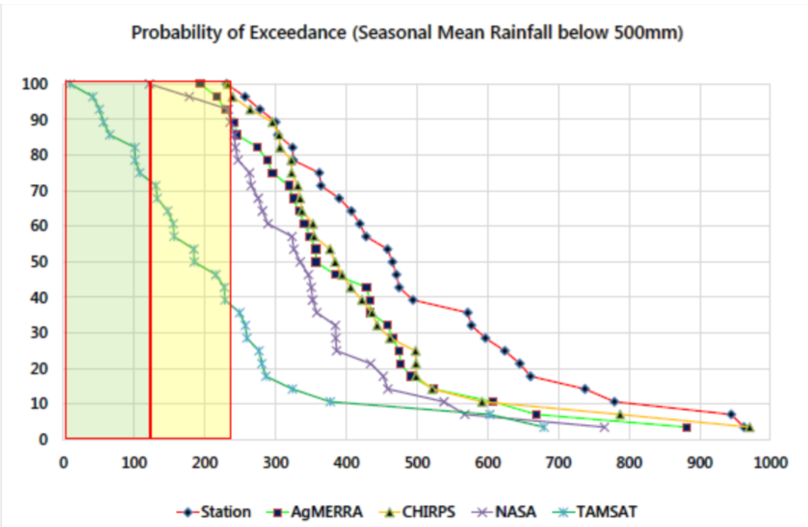

Figure 5: Probability of exceedance of seasonal rainfall estimates by AgMERRA, CHIPRS, NASA Power and TAMSAT for locations with less than 500 mm along with observed station data.

Locations with mean seasonal rainfall > 500 and < 750 mm

The probability distribution of mean seasonal rainfall at locations with >500 mm and <750 mm rainfall is very different compared to the <500 mm seasonal rainfall locations. The probability to get a certain amount of seasonal rainfall is higher with NASA power and low with TAMSAT estimates (Figure 6). The other two data sets, AgMERRA and CHIRPS have trends very similar to the observed data up to 700 mm beyond which AgMERRA estimates showed higher probability compared to observed and CHIRPS estimates.

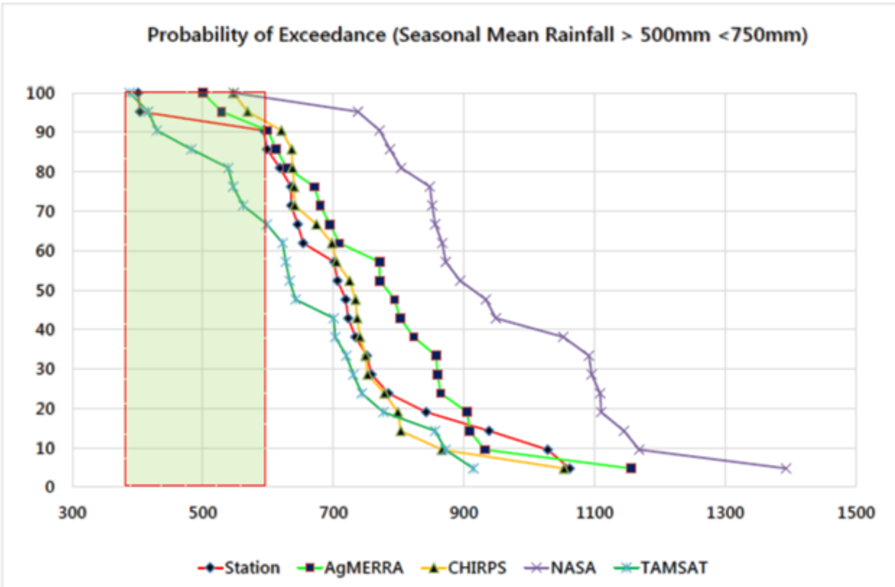

Figure 6: Probability of exceedance of seasonal rainfall estimates by AgMERRA, CHIRPS, NASA Power, and TAMSAT data sets for locations with >500 and <750 mm rainfall along with observed station data.

Locations with mean seasonal rainfall >750 mm

The probability distribution of rainfall in this group of locations is somewhat similar to the <500 mm group with observed station data showing higher probabilities (Figure 7). However, the trend with NASA Power estimates was found to be very close to the observed dataset while the remaining three are very similar but significantly different from the observed. For example, the probability to get 750 mm rainfall at these locations is 52% with AgMERRA, 61% with CHIRPS, and 70% with TAMSAT compared to 89% with observed and NASA Power data sets. Though NASA Power and observed data sets have similar trends up to 900 mm, NASA Power underestimated the rainfall between 900 and 1200 mm. According to the trends, the probability to get 1200 mm rainfall with NASA Power is 25% which is half of what the observed dataset is indicating. The highest amount of rainfall recorded is 1500 mm which is also the estimate by NASA Power. However, the maximum amount of rainfall in the AgMERRA, CHIRPS, and TAMSAT estimates is close to 1000 mm.

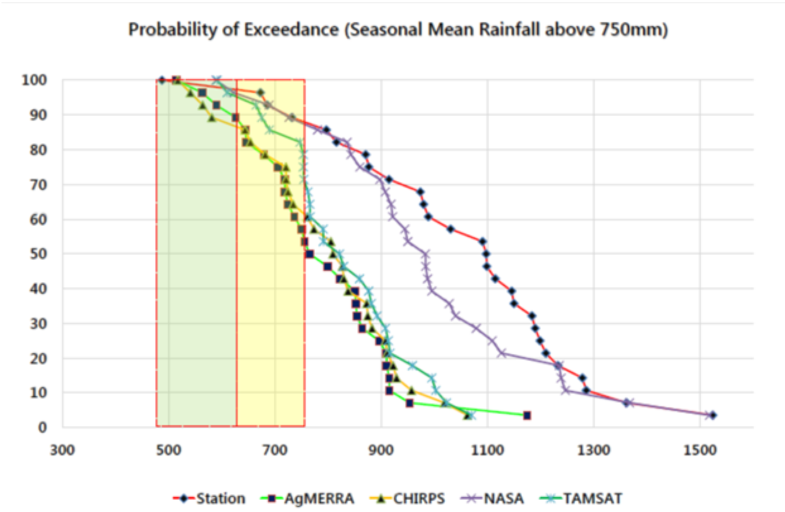

Figure 7: Probability of exceedance of mean seasonal rainfall estimates by AgMERRA, CHIPRS, NASA Power, and TAMSAT data sets for locations with more than 750 mm along with observed station data.

3.3 Impact of Bias Correction on Gridded Data

Considering the significant differences between observed and gridded data sets, efforts were made to explore the possibility to reduce the errors and improve the match between observed and gridded data sets using the bias correction approach. While several bias correction techniques are available, we used the simple linear scaling technique which is extensively used to correct the biases in the climate predictions by General Circulation Models (GCM).

3.3.1 Rainfall distribution after bias correction

The seasonal rainfall amounts from gridded data improved significantly and matched well with observed data after bias correction (Figure 8). The mean, minimum, maximum, lower, and upper quartile values of seasonal rainfall values from all gridded data sets matched well with the observed data after bias correction.

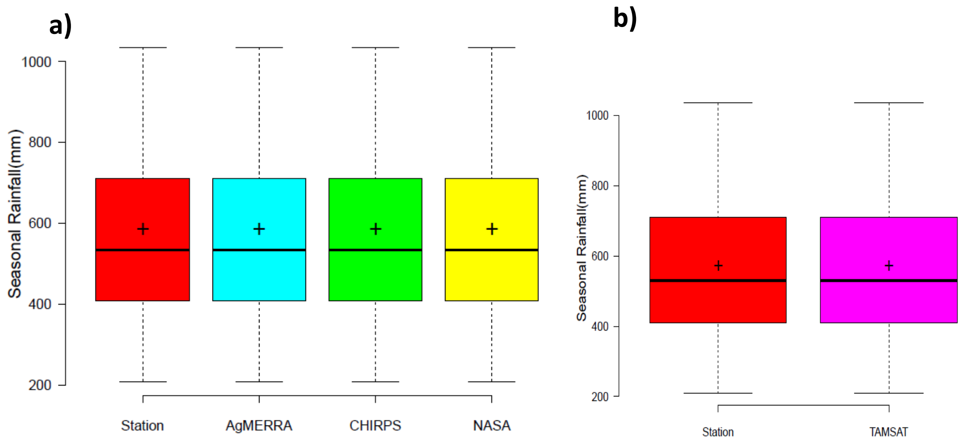

Figure 8: Comparison of box-plot distributions of observed and AgMERRA, CHIRPS, and NASA Power (a), and observed and TAMSAT gridded estimates (b) after bias correction. TAMSAT values compare only African locations.

The improved match between the observed and gridded data sets is also reflected in the various statistical indices computed. After bias correction, the number of locations with less than 20% MAPE values increased to 69% with both AgMERRA and CHIRPS estimates —a significant improvement compared to 54% and 46% before bias correction. Similar improvements were also observed with NASA Power from 23% to 38% and with TAMSAT from 20% to 30%. Overall, the number of locations with less than 20% MAPE increased by 16% with bias correction.

However, the coefficient of determination (R^2) has shown very little improvement with AgMERRA and NASA Power data sets and deteriorated marginally with CHIRPS and TAMSAT data sets with bias correction (Figure 9). The number of seasons with R^2 value greater than 0.5 increased from 8 to 9 or from 62 to 69% with AgMERRA and from 3 to 4 or 23 to 31% with NASA Power data sets after bias correction while the same was declined from 7 to 6 in case of CHIRPS and from 3 to 2 in case of TAMSAT.

The average difference in the NRMSE values between the observed and gridded data sets has shown a small decline in the error residuals with bias correction (Appendix A). The biggest improvement was observed with estimates by AgMERRA which recorded an increase in the number of locations with an NRMSE value of less than 0.2 from 2 to 6 or from 15 to 46%. With CHIRPS, NASA Power and TAMSAT data set a marginal improvement of about 8% was observed over the uncorrected data. The NRMSE values for all seasons with the AgMERRA dataset are below 0.4. The same is true with the CHIRPS dataset except for the two seasons at Kambi Ya Mawe location in Kenya.

3.3.2 Rainfall frequencies after bias correction

Since the linear scaling method adjusts the daily rainfall by a factor, any changes to the number of rainy days are due to the change in daily rainfall amount after the correction. The daily rainfall amount increases when a correction factor of more than one is used and decreases if the correction factor is less than one. In general, no major change in the number of rain days (days with ≥2 mm) was noted in any of the gridded data sets with bias correction.

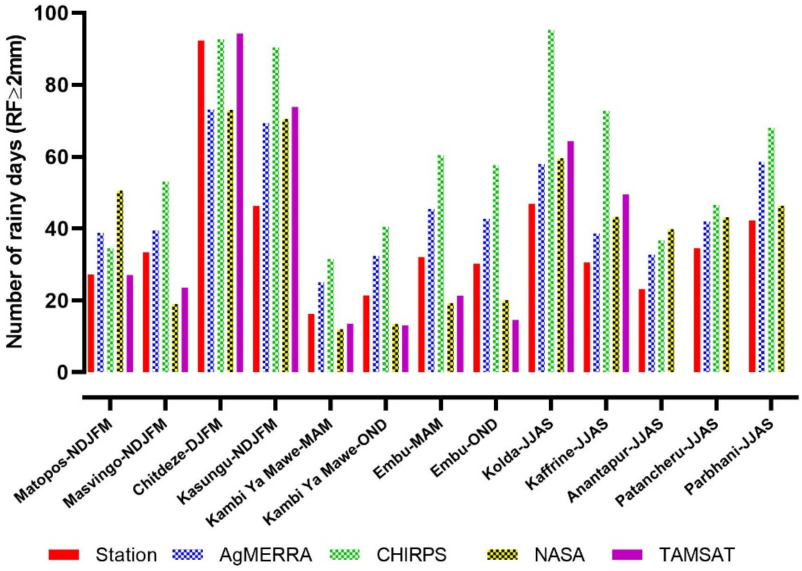

Figure 10: Number of rain days in a season recorded at the station and those estimated by AgMERRA, CHIRPS, NASA Power, and TAMSAT data sets after bias correction.

3.3.3 Probability of exceedance in seasonal rainfall after bias correction

Probability of exceedance charts were compared to assess the changes in the distribution of frequency of occurring different rainfall amounts after bias correction. Significant improvement was observed in the frequency distribution of seasonal rainfall estimates by AgMERRA, CHIRPS and NASA Power gridded data sets for locations with less than 500 mm rainfall and matched well with the trends from observed station data (Figure 11). All the three data sets estimated fairly well the upper and lower limits and also the distribution. Though improvement was also observed with TAMSAT estimates, it underestimated the lower and overestimated the upper end values. While the range of seasonal rainfall varied from about 200 to 1100 mm with other data sets including observed station data, in case of TAMSAT it varied from about 50 to 1600 mm. The TAMSAT trend matched better with the observed trend between 400 and 980 mm after bias correction. Overall, there is a significant improvement in the probability distribution of rainfall which matched well with the observed trend after bias correction for locations with a seasonal rainfall amount of below 500 mm.

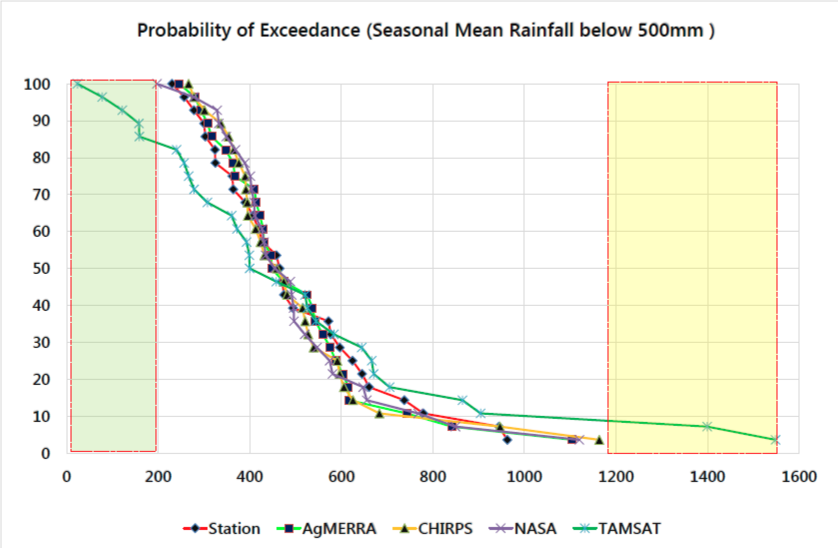

Figure 11: Probability of exceedance of bias-corrected seasonal rainfall estimates by AgMERRA, CHIPRS, NASA Power, and TAMSAT for locations with less than 500 mm

For the locations with mean seasonal rainfall of >500 and <750 mm, the probability distribution of seasonal rainfall from all gridded data sets matched well with the observed distribution after bias correction (Figure 12). Significant improvement was observed in the case of NASA Power which overestimated and TAMSAT which underestimated the seasonal rainfall before bias correction.

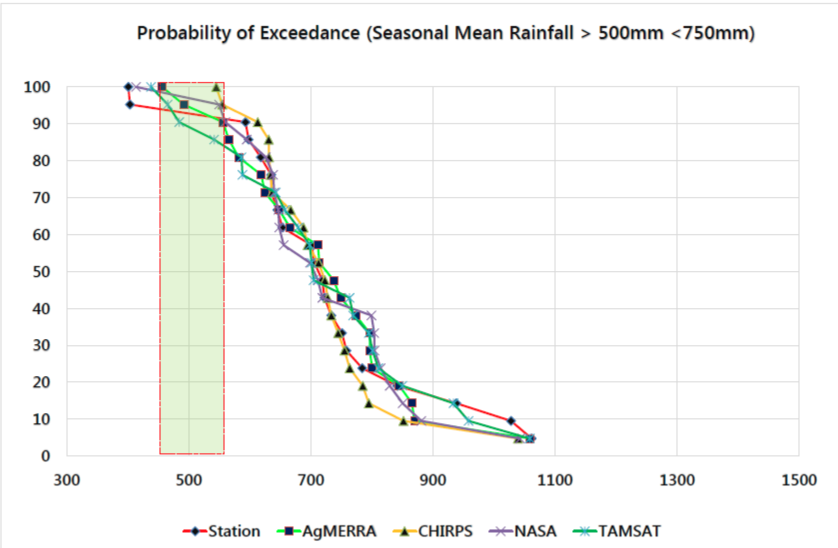

Figure 12: Probability of exceedance of bias-corrected seasonal rainfall estimates by AgMERRA, CHIPRS, NASA Power, and TAMSAT for locations with >500 and <750 mm.

Significant improvement was also observed in the probability distribution of seasonal rainfall at the locations having >750 mm with bias correction (Figure 13). Before bias correction, all data sets except for NASA power underestimated the probability of getting rainfall. While the data sets matched with the observed in the overall trend, some differences were observed in the estimates of lower and upper limits. The observed minimum rainfall is lower compared to the estimate by all gridded data sets. The observed maximum rainfall is similar to that estimated by NASA Power and AgMERRA but higher than that estimated by CHIRPS and TAMSAT.

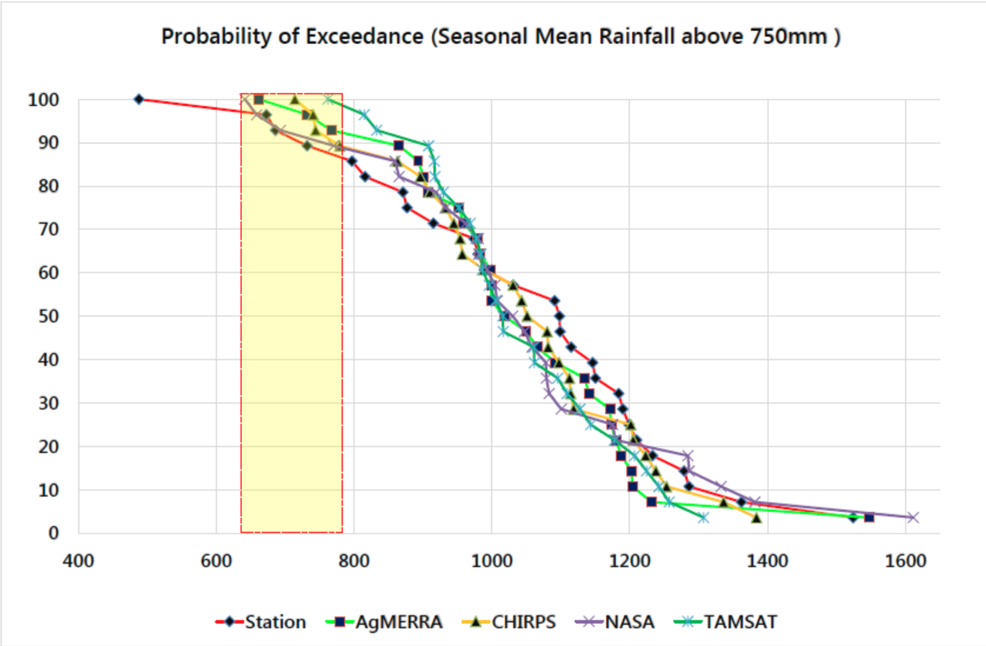

Figure 13: Probability of exceedance of bias-corrected seasonal rainfall estimates by AgMERRA, CHIPRS, NASA Power, and TAMSAT for locations with >750 mm rainfall.

3.4 Impact of Gridded Data on Crop Productivity

Considering the differences between the gridded and observed data sets in estimating the amount of rainfall and the number of rainy days, an assessment was carried out to examine how these differences translate into differences in crop growth and yield. In this assessment, we used a soil whose plant available water content and organic matter content were set to represent the conditions that are common to the majority of the smallholder farms in these areas. The profile used in the simulations has a plant available water capacity of 90 mm to one-meter depth and organic carbon content of 0.5% in the top layer. One tillage operation was preceded the sowing operation and 40 kg N was applied at the time of sowing. Simulations were carried out with all the climate data sets with and without bias correction and crop yields were analyzed to capture the differences. We used maize as a test crop because of its sensitivity to soil moisture stress and also because of its widespread cultivation in almost all the target locations.

3.4.1 Simulated maize yield with different climate data sets

The mean yields were slightly overestimated when simulated with AgMERRA, CHIRPS, and TAMSAT data sets and underestimated with NASA Power data compared to the 1964 kg/ha yield simulated with observed station data (Figure 14). Simulated yields are higher by 12% with TAMSAT, 11.8% with AgMERRA, and 5% with CHIRPS while the yields are lower by 18% with NASA Power compared to those obtained with observed data. The difference between the mean yield with AgMERRA and observed data was found to be >± 250 kg/ha for 54% of the locations and >± 500 kg/ha for 39% of the locations. In the case of CHIRPS, the locations with a difference of >± 250 kg/ha are 23% and those with >± 500 kg/ha are 46%. Among the locations, the highest difference of about 1300 kg/ha was observed at Embu during the LR season, and the lowest difference of <100 kg/ha was observed at Matopos with both AgMERRA and CHIRPS datasets. Though the difference in grain yield simulated with AgMERRA and observed climate data for Embu is very high, the difference in the mean season rainfall is less than 50 mm. This is attributed to the lower variability in gridded rainfall compared to the observed rainfall (Table 3). The lower difference in the yield at Matopos is in order with the difference in seasonal rainfall and its variability at this location. The erratic nature of rainfall distribution in NASA Power contributed significantly to the variability in crop productivity including the complete failure of the crop in some seasons.

The box plots indicate a better match between CHIRPS and station data compared to AgMERRA which has higher mode and upper and lower quartile values (Figure 14). The lower and upper quartile mean yields are overestimated by 3.0% and 8.9% with CHIRPS climate input and by 15.9% and 16.0% with AgMERRA climate input. NASA Power underestimated the lower quartile mean yield by 8.9% but the upper quartile mean yield with a deviation of 0.05% is very similar to that simulated with observed. TAMSAT underestimated the lower quartile mean yield by 5.6% while overestimated the upper quartile mean yield by 10.1%. Thus, the percentage deviation in minimum, maximum, lower and upper quartile yields is less than 20% with the gridded climate data except for minimum and lower quartile yields with NASA Power, which are higher by more than 20%. With CHIRPS, the percentage deviation is lower in the minimum and lower quartile yields but higher in the upper quartile and maximum yield. This implies that low yields simulated with CHIRPS had lower dispersion as compared to that with the observed climate. Yields simulated with AgMERRA climate input had a higher deviation in the minimum and lower quartile yields than in the maximum and upper quartile yields indicating higher dispersion in the lower yields compared to that in higher yields. In the case of TAMSAT data, both smaller and larger yield values had similar dispersion and in the case of NASA Power greater dispersion was observed in the lower yields.

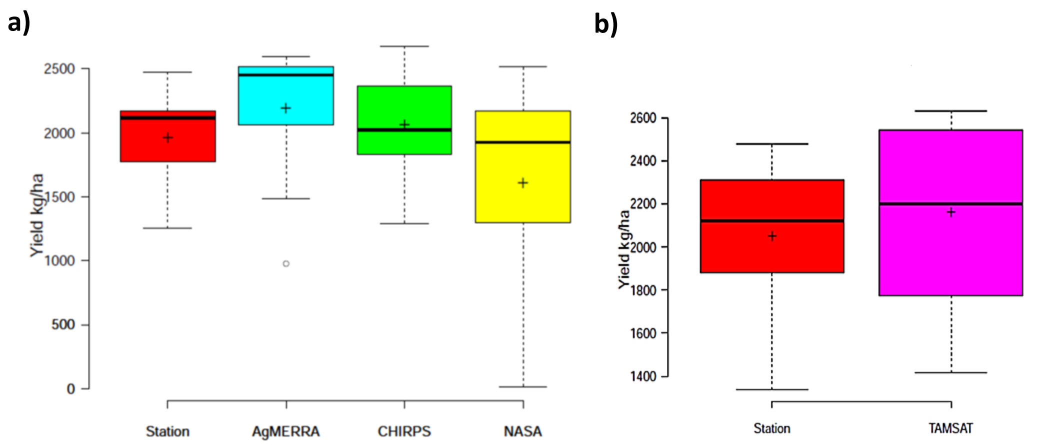

Figure 14: Box-plot distribution of simulated maize yields with observed, Ag-MERRA, CHIRPS, and NASA Power gridded climate data for all locations (a) and with TAMSAT for African locations (b).

3.4.2 Statistical assessment of differences in maize yield

Mean Absolute Percentage Error (MAPE).

The poor performance of gridded data sets is evident with MAPE values often exceeding 100% at many locations (Appendix B). The MAPE of simulated maize yields is less than 20% with AgMERRA, CHIRPS, and NASA Power data sets for 13% of the locations and with TAMSAT for 33% of the locations. MAPE values of less than 30% were observed for 54% locations with AgMERRA, 31% locations with CHIRPS, and NASA Power, and 50% locations with TAMSAT.

Coefficient of determination (R-Squared).

Maize yields simulated with gridded climate data sets correlated very poorly with those simulated using observed data (Appendix B). Only at Kasungu, the R^2 value exceeded 0.5 with AgMERRA, CHIRPS, and TAMSAT climate estimates. The R^2 is always less than 0.5 with yields simulated for other locations. Yields simulated with NASA Power data are very poorly correlated with observed data for all the locations.

Normalized root mean squared error (NRMSE)

The NRMSE values of maize yields ranged from less than 0.1 to more than 1.0 at different locations with different climate data sets (Appendix B). Values of less than 0.3 were observed for only 30% of the locations when maize yields were simulated with AgMERRA, CHIRPS, NASA Power, and TAMSAT climate data products. Among the locations, higher values were observed for drier locations of Anantapur, Matopos, and LR and SR seasons at Kampi Ya Mawe. NRMSE values of more than one were found for Anantapur with AgMERRA and CHIRPS data sets and Matopos and Kambi Ya Mawe with NASA Power, implying a large deviation from the yield simulated with observed data.

Overall, significant differences were observed in the maize yields simulated with gridded climate data and those simulated with station recorded data. The yields are overestimated by most gridded data sets for most locations. This is partly due to the differences in the amount of rainfall received during the crop season and partly due to the differences in rainfall distribution as reflected by the differences number of rainy days which are higher with gridded data.

3.4.3 Effect of bias correction

Maize yields simulated with bias-corrected climate data sets has shown a small reduction in the dispersion (Figure 16) and are closer to the yields simulated with observed climate. The difference between the mean yields simulated with observed data and bias-corrected AgMERRA data was reduced to 4.2% from 11.8% before bias correction. In the other three data sets i.e. CHIRPS, NASA, and TAMSAT, the improvement was less than one percent. The bias-corrected gridded climate data sets overestimated both maximum and upper quartile yields. However, the estimated maximum maize yield is 1.0 to 1.5% lower compared to those obtained with uncorrected climate data sets. Similarly, a reduction of about 4.0 to 5.0% was observed in the upper quartile values of the yields with bias correction. The difference in minimum yields was also reduced by up to 9% when bias-corrected data was used in the simulations but no improvement was observed in the lower quartile yields. The results indicate that bias correction has helped in reducing the errors in the upper quartile values compared to the yields in the lower quartile.

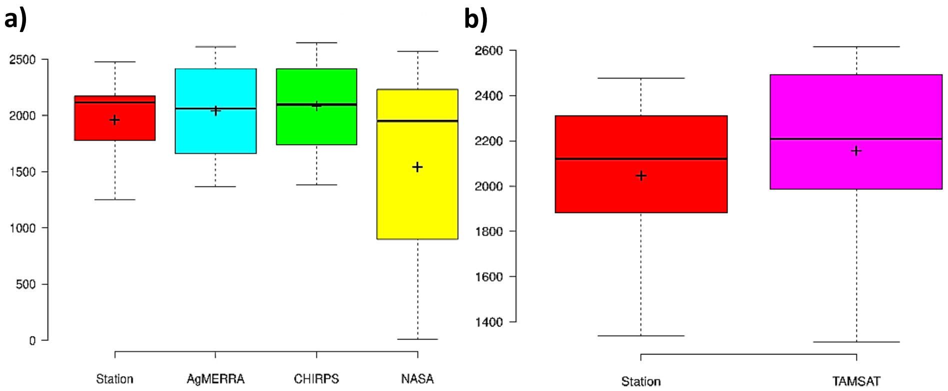

Figure 16: **Box-plot distributions of maize yields simulated with observed and bias-corrected Ag-MERRA, CHIRPS, and NASA Power for all locations (a) and with TAMSAT for African locations (b).**

The effect of bias correction on simulated yields was also evaluated using the three statistical indices that were used for maize yields simulated with bias uncorrected data.

Mean Absolute Percentage Error (MAPE).

Though most MAPE values are more than 20%, the bias correction has contributed positively to the reduction in the errors. The number of locations with a MAPE value of less than 20% increased from 13% to 31% of the locations with AgMERRA and from 13% to 23% with CHIRPS. No improvement was observed with TAMSAT while a small reduction was observed with NASA Power after bias correction.

Coefficient of Determination (R-Squared).

No improvement was observed in the correlation of maize yields simulated with observed data and bias-corrected gridded data sets. Most R^2 values indicate a poor correlation with values ranging between 0.1 and 0.4. Higher correlations were observed only for Kasungu and Chitedze locations which are also high rainfall locations.

Normalized Root Mean Square Error (NRMSE).

The NRMSE values computed for yields simulated with bias-corrected gridded data are lower compared to those obtained with simulations using uncorrected data. About 31% of the locations have an NRMSE value of less than 0.3 when yields were simulated with bias-corrected AgMERRA, CHIRPS, and NASA Power data sets compared to 23% before the correction. In the case of TAMSAT, the number of locations with less than 0.3 NRMSE value increased to 40% from 30% before correction. The number of observations with NRMSE values greater than one was also reduced with bias correction of gridded climate data.

4. Discussion

Good quality precipitation data is not only crucial to understand the trends and variability in the climatic conditions but is also important for efficient management of agriculture, water, and other natural resources which are highly sensitive to climate variability (Sarojini et al., 2016). Though, gauge measurements provide high-quality estimates of rainfall and other weather parameters, their availability and access to available data is a major constraint especially in the sparsely populated areas such as drylands. As an alternative to gauge data, various large-scale climate data sets with varying Spatio-temporal resolutions have been developed which help in overcoming the above constraints by providing more homogenous spatial and temporal coverage for most areas across the globe (Kidd and Levizzani, 2011; Xie et al., 2003). Some of these data sets are now operationally available and are increasingly used in agriculture and related fields. This study made a comprehensive assessment of four commonly used gridded precipitation estimates and quantified the discrepancies in the precipitation estimates at seasonal timescale. The four data sets evaluated are AgMERRA, CHIRPS, NASA Power, and TAMSAT. These data sets vary in their spatial resolution from 0.04^0 X 0.04^0 with TAMSAT to 0.5^0 X 0.5^0 with NASA Power. A total of 11 locations with good quality historical observations lying between the latitudes -20.506^0 in the south and 19.258^0 in the north were selected for this study. The focus is on trends and variability in crop season rainfall which varied from about 200 to 1000 mm.

The comparison of gridded rainfall amounts with observed station level data has yielded mixed results. AgMERRA and CHIRPS estimates have matched better with the observed rainfall compared to NASA Power and TAMSAT. However, large deviations ranging from -250 to 250 mm were observed for some locations. Similar differences were also observed between observed and gridded data sets for seasonal rainfall. All data sets predicted the monthly rainfall distribution and seasonality fairly well. Several studies have noted such discrepancies between the observed values and gridded estimates (Sun et al., 2018). This is attributed to several factors that included the reanalysis method combining observations and a numerical model (Bandhopadhyay et al., 2018), spatial and temporal distribution and density of the observed data (Taylor, 2001), time of the year with higher differences during JJA and MAM seasons compared to other seasons (Sun et al., 2018) and local orographic influences (Prakash et al., 2015). Among the four datasets compared in this study, the deviations from observed were found to be highest with TAMSAT which is based on high-resolution thermal-infrared observations and the disaggregation of 10 and 5 days rainfall estimates to a daily time-step using daily cold cloud duration. Similar discrepancies with TAMSAT were also noted by Maidment et al., (2017) in their assessment of daily estimates using ground-based observations from Mozambique, Niger, Nigeria, Uganda, and Zambia. Our assessment further indicates that the match between observed and gridded data sets is better for locations with lower elevations and poor for locations with higher elevations and also for the locations near the equator. A review of Global Precipitation Data Sets by Sun et al. (2018) has also highlighted the difficulties in estimating the annual and seasonal rainfall amounts in complex mountain areas, northern Africa, and some high-latitude regions due to differences in the number and spatial coverage of surface stations, the satellite algorithms and the data assimilation models used in various estimates.

Another important parameter that we evaluated is the rainfall frequency or the number of rainy days which is extremely important for assessing the agricultural impacts of climate. Major differences were observed between the rainy days recorded at the station and those estimated by various gridded data sets. Among the data sets, rainy days estimated by NASA Power are always higher and for some locations, they are more than double the recorded observations. At the daily scale, gridded data sets overestimated the low rainfall events (with <5 mm/day) and underestimated the high rainfall events with more than 20 mm/day (Ayoub et al., 2020). This lead to more number of rainy days and better distribution of rain during the season. This is one potential limitation in using the gridded climate data sets for estimating the growth and performance of different crops because of its influence in altering the magnitude and distribution of stress that the crops experience. This discrepancy is less with AgMERRA and CHIRPS datasets compared to NASA Power and TAMSAT. This is more likely due to the smoothening effect of the interpolating technique used in converting the station observations to gridded data sets that cover the entire land area (Hegerl et al., 2015; Sun, Miao, et al., 2014). Generally, interpolation smooths the extreme values and affects long-term trends, especially in regions with limited observations.

Bias correction using a simple linear scaling method, a technique extensively used to correct the systematic biases in the climate predictions by General Circulation Models, has improved the match between the observed and corrected rainfall amounts. After the bias correction, the annual and seasonal rainfall amounts were found to be very similar to the observed values (Li, W., et al., 2019; Yeggina, S., et al., 2020) However, statistical properties of the corrected data have shown marginal improvement. In this study, we used three statistics MAPE, $R^{2,}$ and NRMSE to quantify the variability between the datasets and observed. MAPE is a measure of prediction accuracy, R^2 indicates how well-observed outcomes are replicated by the model, and NRMSE which aggregates the magnitudes of the errors into a single measure (Shrestha M., et al., 2017). All the three statistical indices have indicated that AgMERRA and CHIRPS estimates have lower errors compared to those of NASA Power and TAMSAT, before bias correction. These indices have improved marginally, by about 5-10% after bias correction.

The probability of exceedance charts is extensively used to assess the risks and opportunities associated with rainfall in agriculture and other sectors (Nathan, R., et al., 2016) The results from the analysis of the probability of exceedance to assess the discrepancy between the observed and gridded data sets have indicated major differences in the way gridded data compared with observed data in low, medium and high rainfall locations. While the gridded data underestimated the probability of occurrence of different rainfall amounts in low and high rainfall locations, a fairly good match was observed in the case of medium rainfall locations. These over and underestimates in the probability to get rainfall alters the risk profile of the locations with a significant impact on decision making especially for locations having a mean seasonal rainfall of less than 500 mm. In these locations, the climate is the main source of risk, and risk-averse farmers tend to opt for low-risk farming practices which may not help in capitalizing the opportunities offered by good seasons. Bias correction of gridded data sets has reduced the errors and made the probability distribution charts of gridded data sets comparable with observed data. Similar results were reported in the study by Luo, M. et al. (2018) and thus evidenced the benefits of bias correction of gridded products.

Though fairly good assessment of the amount of rainfall and its frequency distribution is possible with bias-corrected gridded climate data products at a seasonal scale, the mismatch in the number of rainy days and distribution of rainfall at daily time steps is expected to affect the accuracy of crop models in predicting crop growth and yields. This was assessed by simulating maize yields with APSIM using both bias-corrected and uncorrected climate data sets. The results indicated that the yields simulated with gridded climate data products tend to be higher compared to the ones simulated with observed data as it has been found by Van Wart, J., et al. (2013) and Mourtzinis, S., et al. (2016). Though the differences in the mean yields simulated by observed and gridded climate data are less than 20%, the statistical indices indicate a very poor relationship between them. A better correlation was observed for Kasungu and Chitedze locations which are high rainfall locations. This indicates that the poor relations in the yields are mainly due to the differences in the amount and distribution of rainfall which in the case of gridded data sets is more uniformly distributed compared to the observed. Bias correction has not yielded any major change in the trends.

Our work has established that discrepancies exist in the amount and distribution of rainfall estimated by different products and those observed at the station. Several studies indicate that it is difficult to attribute these differences to any specific factor (Gampe and Walton and Hall 2018; Beck et al. 2018). This may be partly because gridded climate product generation is a complex process and there are limitations in understanding the same. Hence, these uncertainties remain until new knowledge emerges. Though there is no single product that is superior to others, the AgMERRA and CHIRPS data sets were found to be giving better estimates compared to NASA Power and TAMSAT data sets. It is more appropriate to assess these products based on the specific application for which the data set is used since different applications need different levels of accuracy (Quintero et al. 2016; Beck et al. 2017; Laiti et al. 2018).

5. Conclusions

This study seeks to explore and highlight the differences across gridded climate data products and understand how they influence the performance of climate-sensitive systems such as agriculture. This research assumes importance because, in the absence of availability of good quality gauge data, researchers and extension agents are increasingly using these data sets to assess the impacts of climate variability and change on agricultural systems by overlooking their potentials and limitations. Available gridded data sets are developed using the state of the art models and algorithms and by integrating ground observations and satellite recorded imageries in multiple wavelengths. The advantages of these estimates include adequate spatial and temporal resolution with coverage extending to un-gauged regions. The disadvantages are that these are not direct measurements and are subject to errors especially in areas where rainfall is controlled by the local orography and inability of IR retrievals to capture light precipitation events.

The gridded data sets used in this study have shown significant differences in estimating climatic conditions at different locations. All the data sets predicted the dry and wet periods well at all locations but differed in estimating the amount and frequency of rainfall. AgMERRA and CHIRPS performed better in estimating rainfall while CHIRPS and TAMSAT performed better in estimating rainy days. Bias correction helped in reducing the discrepancies in the amount of rainfall but not in the rainy days. Among the factors that influenced the reliability of the estimates are latitude and elevation of the location and amount of rainfall that the location receives. However, no clear trend is observed. Our results show that the gridded data sets should be used carefully after proper validation with observed data and after bias correction. There are differences in the ability of these products to represent the actual weather conditions. While the seasonal and monthly amounts and their probabilities are well replicated by these data sets, there are limitations with the data at a daily time step. The use of gridded data sets for applications such as crop growth and performance should be done carefully since the distribution of rainfall plays an important role in these assessments. Considering the diversity in the products available, a systematic analysis of individual products or product components would help in defining location and application-specific benchmarks for acceptable performance.

6. References

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7. Appendices

Appendix A: Statistical evaluation of gridded data in characterizing rainfall amounts

Table A1: Error metric values i.e. MAPE, R^2, and NMRE in the seasonal mean rainfall between observed station data AgMERRA data set before and after bias correction.

	AgMERRA before bias correction			AgMERRA after bias correction		
Location	MAPE (%)	R^2	NMRE	MAPE (%)	R^2	NMRE
Matopos	16.99	0.59	0.21	17.21	0.56	0.21
Masvingo	22.57	0.42	0.36	28.68	0.57	0.24
Chitdeze	34.74	0.43	0.30	14.86	0.43	0.17
Kasungu	14.17	0.51	0.18	12.8	0.49	0.17
Kambi Ya Mawe-LR	31.74	0.5	0.48	33.4	0.52	0.38
Kambi Ya Mawe-SR	34.70	0.33	0.63	31.85	0.33	0.38
Embu-LR	17.41	0.67	0.22	14.51	0.67	0.20
Embu-SR	26.91	0.76	0.28	14.05	0.76	0.19
Kolda	10.11	0.64	0.15	9.32	0.63	0.14
Kaffrine	28.12	0.14	0.33	27.84	0.17	0.33
Anantapur	19.06	0.85	0.25	17.78	0.86	0.22
Patancheru	19.36	0.71	0.24	14.84	0.68	0.19
Parbhan	16.73	0.56	0.20	16.47	0.58	0.20

Table A2: Error metric values i.e. MAPE, R^2, and NMRE in the seasonal mean rainfall between observed station data CHIRPS data set before and after bias correction.

	CHIRPS before bias correction			CHIRPS after bias correction		
Location	MAPE (%)	R^2	NMRE	MAPE (%)	R^2	NMRE
Matopos	15.92	0.67	0.23	19.8	0.47	0.23
Masvingo	30.70	0.44	0.41	43.62	0.45	0.27
Chitdeze	34.94	0.42	0.17	13.44	0.45	0.17
Kasungu	10.67	0.65	0.42	10.38	0.65	0.14
Kambi Ya Mawe-LR	43.67	0.48	0.48	46.91	0.48	0.41
Kambi Ya Mawe-SR	69.31	0.39	0.41	66.95	0.39	0.51
Embu-LR	25.23	0.76	0.43	13.54	0.78	0.17
Embu-SR	22.63	0.79	0.39	12.7	0.8	0.18
Kolda	14.39	0.29	0.23	14.47	0.28	0.19
Kaffrine	11.58	0.57	0.32	11.72	0.56	0.19
Anantapur	31.43	0.62	0.26	27.59	0.62	0.33
Patancheru	15.47	0.67	0.21	17.02	0.6	0.20
Parbhan	17.18	0.44	0.26	16.98	0.45	0.22

Table A3: Error metric values i.e. MAPE, R^2, and NMRE in the seasonal mean rainfall between observed station data NASA Power data set before and after bias correction.

	NASA Power before bias correction			NASA Power after bias correction		
Location	MAPE (%)	R^2	NMRE	MAPE (%)	R^2	NMRE
Matopos	18.83	0.5	0.18	16.69	0.64	0.19
Masvingo	30.84	0.17	0.37	33.93	0.45	0.26
Chitdeze	16.51	0.49	0.29	14.66	0.49	0.17
Kasungu	26.66	0.22	0.14	18.60	0.23	0.22
Kambi Ya Mawe-LR	38.62	0.29	0.41	37.71	0.41	0.42
Kambi Ya Mawe-SR	37.05	0.28	0.51	35.48	0.27	0.42
Embu-LR	54.78	0.48	0.26	20.03	0.5	0.25
Embu-SR	48.95	0.59	0.24	20.77	0.56	0.27
Kolda	23.04	0.27	0.19	20.13	0.25	0.22
Kaffrine	27.65	0.14	0.19	26.47	0.14	0.29
Anantapur	21.01	0.84	0.36	20.43	0.84	0.25
Patancheru	16.55	0.62	0.19	14.32	0.59	0.21
Parbhan	21.62	0.43	0.23	17.45	0.46	0.22

Table A4: Error metric values i.e. MAPE, R^2, and NMRE in the seasonal mean rainfall between observed station data TAMSAT data set before and after bias correction.

	TAMSAT before bias correction			TAMSAT after bias correction		
Location	MAPE (%)	R^2	NMRE	MAPE (%)	R^2	NMRE
Matopos	31.8	0.51	0.28	28.33	0.46	0.30
Masvingo	59.91	0.25	0.47	34.17	0.43	0.26
Chitdeze	30.69	0.16	0.29	17.71	0.16	0.21
Kasungu	23.19	0.22	0.24	21.08	0.21	0.23
Kambi Ya Mawe-LR	37.04	0.43	0.42	37.04	0.45	0.41
Kambi Ya Mawe-SR	75.75	0.08	0.61	61.46	0.07	0.68
Embu-LR	52.79	0.63	0.33	30.93	0.65	0.27
Embu-SR	87.86	0.4	0.65	52.33	0.39	0.56
Kolda	14.35	0.43	0.18	13.07	0.43	0.17
Kaffrine	18.04	0.57	0.23	15.23	0.56	0.19

Appendix B: Statistical assessment of differences in maize yield

Table B1: Error metric values i.e. MAPE, R^2, and NMRE in the seasonal mean rainfall between observed station data AgMERRA data set before and after bias correction.

	AgMERRA before bias correction			AgMERRA after bias correction		
Location	MAPE (%)	R^2	NMRE	MAPE (%)	R^2	NMRE
Matopos	61.42	0.25	0.63	58.96	0.25	0.66
Masvingo	27.64	0.31	0.43	25.37	0.13	0.77
Chitdeze	29.74	0.26	0.52	23.47	0.33	0.38
Kasungu	12.61	0.66	0.16	13.69	0.67	0.17
Kambi Ya Mawe-LR	93.56	0.28	0.70	39.81	0.37	0.50
Kambi Ya Mawe-SR	41.72	0.18	0.51	46.21	0.42	0.43
Embu-LR	22.52	0.09	0.32	14.83	0.5	0.22
Embu-SR	23.82	0.02	0.33	13.68	0.35	0.22
Kolda	12.33	0.08	0.17	12.41	0.16	0.18
Kaffrine	21.82	0.03	0.42	25.32	0.16	0.38
Anantapur	55.5	0.03	1.26	65.08	0.27	0.87
Patancheru	102.1	0.03	0.10	94.34	0.14	0.47
Parbhan	49.12	0.22	0.05	52.95	0.17	0.47

Table B2: Error metric values i.e. MAPE, R^2, and NMRE in the seasonal mean rainfall between observed station data CHIRPS data set before and after bias correction.

	CHIRPS before bias correction			CHIRPS after bias correction		
Location	MAPE (%)	R^2	NMRE	MAPE (%)	R^2	NMRE
Matopos	56.47	0.28	0.61	59.33	0.32	0.62
Masvingo	35.3	0.15	0.47	37.98	0.14	0.65
Chitdeze	28.25	0.40	0.47	23.14	0.47	0.32
Kasungu	10.25	0.54	0.16	14.87	0.58	0.18
Kambi Ya Mawe-LR	38.34	0.10	0.62	34.04	0.36	0.58
Kambi Ya Mawe-SR	92.61	0.05	0.58	89.77	0.29	0.57
Embu-LR	90.85	0.01	0.58	20.28	0.14	0.29
Embu-SR	115.23	0.04	0.58	16.91	0.16	0,25
Kolda	11.85	0.13	0.18	12.38	0.16	0.18
Kaffrine	21.4	0.03	0.40	20.25	0.18	0.41
Anantapur	52.54	0.07	1.03	52.48	0.15	1.13
Patancheru	88.61	0.01	0.04	78.31	0.15	0.43
Parbhan	72.53	0.38	0.42	62.90	0.39	0.41

Table B3: Error metric values i.e. MAPE, R^2, and NMRE in the seasonal mean rainfall between observed station data NASA Power data set before and after bias correction.

	NASA Power before bias correction			NASA Power after bias correction		
Location	MAPE (%)	R^2	NMRE	MAPE (%)	R^2	NMRE
Matopos	110.25	0.12	1.13	86.23	0.16	1.14
Masvingo	40.12	0.23	0.5	43.23	0.12	0.63
Chitdeze	26.79	0.40	0.36	24.04	0.52	0.28
Kasungu	19.96	0.47	0.22	21.15	0.21	0.28
Kambi Ya Mawe-LR	112.4	0.01	1.48	102.44	0.11	1.55
Kambi Ya Mawe-SR	114.2	0.11	1.07	114.35	0.37	1.15
Embu-LR	43.25	0.01	0.56	27.99	0.34	0.29
Embu-SR	96.24	0.10	0.58	53.73	0.14	0.37
Kolda	12.43	0.39	0.15	11.36	0.25	0.16
Kaffrine	27.44	0.07	0.38	32.34	0.12	0.37
Anantapur	106.25	0.18	0.84	99.14	0.18	0.87
Patancheru	47.96	0.01	0.02	47.96	0.12	0.44
Parbhan	40.24	0.16	0.46	40.24	0.16	0.46

Table B4: Error metric values i.e. MAPE, R^2, and NMRE in the seasonal mean rainfall between observed station data TAMSAT data set before and after bias correction.

	TAMSAT before bias correction			TAMSAT after bias correction		
Location	MAPE (%)	R^2	NMRE	MAPE (%)	R^2	NMRE
Matopos	69.32	0.04	0.78	67.23	0.15	0.70
Masvingo	116.25	0.10	0.67	58.72	0.11	0.61
Chitdeze	29.8	0.40	0.51	24.47	0.41	0.33
Kasungu	13.53	0.52	0.20	14.29	0.6	0.19
Kambi Ya Mawe-LR	39.15	0.15	0.67	31.90	0.29	0.58
Kambi Ya Mawe-SR	103.23	0.34	0.49	50.31	0.29	0.46
Embu-LR	18.75	0.46	0.24	18.84	0.28	0.25
Embu-SR	51.4	0.17	0.46	49.35	0.2	0.29
Kolda	11.12	0.13	0.17	12.08	0.17	0.18
Kaffrine	27.56	0.01	0.41	21.74	0.1	0.38

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