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Satellite rainfall bias correction incorporating effects on simulated crop water requirements

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ABSTRACT

Satellite rainfall estimates (SRE) offer spatial-temporal rainfall representations in regions with limited ground-based gauge rainfall measurements. However, differences exist between SRE and gauge measured rainfall, which needs assessment and reduction. This study presents a method to correct errors in SRE to make their use in agro-hydrological applications and models meaningful. The main scientific objective is the determination of effective window sizes for SRE bias correction. To conclude on effective window sizes, the crop water requirement satisfaction index (WRSI) for gauged rainfall, uncorrected SRE and bias corrected SRE were estimated and propagation effects of SRE errors on respective WRSI estimates were assessed. WRSI indicates how much of the crop water needs are satisfied by rainfall. The Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) SRE was bias corrected using gauged rainfall data from 20 stations in the Lake Victoria basin of Kenya from 2012 to 2018. The results show that the error in WRSI can serve to determine effective window sizes for SRE bias correction rather than using SRE bias error itself. This proposed correction method resulted in improved estimates of WRSI.

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KEYWORDS
Bias correction; chirps; crop water requirement satisfaction index; satellite rainfall; bias correction windows

1. Introduction

In estimating water required by crops, it is essential to accurately estimate the soil water balance affected by rainfall and actual evapotranspiration. Rainfall, the main source of water in rainfed agriculture, affects soil water storage (Geneti 2019). Any error in rainfall data can affect crop water estimates and consequently crop growth (Vergopolan et al. 2021). Therefore, accurate rainfall data that represent key characteristics relevant for crop growth are necessary.

Rain gauges are used to record rainfall. However, Tapiador et al. (2017) highlighted challenges in obtaining data from these gauge networks to represent spatial-temporal rainfall. These challenges include complex terrain, inaccessible locations, geopolitical

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instabilities and uneven distribution of gauges. Infrared and microwave satellite sensors provide an opportunity to estimate rainfall from space. When reliable, these estimates can supplement or replace ground-based rainfall data in agro-hydrological studies (Mokhtari, Sharafati, and Raziei 2022; Pellarin et al. 2020).

Satellite rainfall estimates (SRE) provide rainfall data at fair spatial grid resolution (e.g. 5 km × 5 km) and daily or sub-daily temporal resolution (e.g. 15 min). However, these estimates are derived indirectly from sensed cloud properties such as brightness temperature. SRE are affected by systematic and random errors (Chen et al. 2021), causing misrepresentation of rainfall characteristics. The systematic error in SRE is commonly referred to as bias (Smith et al. 2006; Toté et al. 2015). Such rainfall misrepresentations can affect simulations of soil water required by crops. For example, Omondi et al. (2021) assessed the accuracy of four SRE products in representing the onset day, rainfall depth, dry spells and rainfall occurrence for different crop growth stages. The study used the crop water model in Instat+ 3.37 software, developed by the Statistical Services Centre (see https://www.ssc.rdg.ac.uk), to determine the crop water requirement satisfaction index (WRSI), which indicates how much of the water requirements for crop growth are satisfied by rainfall. WRSI can be interpreted as an index that shows soil water availability for crops. The results showed varying onset dates for wet season rains across four SRE products. These products performed well in periods of high rainfall, but their performance weakened as the cropping season progressed. SRE represented dry spells more accurately during early crop growth stages. The study recognized that errors in SRE should be reduced to improve SRE for agro-hydrological applications and models.

Bias correction is a method to reduce systematic errors of SRE. Studies focusing on soil water availability for crop growth have emphasized the need to correct for bias (Luetkemeier et al. 2018; Omondi et al. 2021). Bias correction seeks to improve representation and reliability of SRE by using statistical methods such as linear regression, Bayesian approaches (Kimani, Hoedjes, and Su 2018), mean bias correction (Chaudhary and Dhanya 2019), and distribution function matching (Mastrantonas et al. 2019). Gauged rainfall serves as the reference for assessing errors in SRE and its correction. Bias correction is common in hydrological modelling, and the time window sizes used are often fixed and short (less than 10 days) (Faghih, Brissette, and Sabeti 2022; Koshuma et al. 2021), as bias errors may impact simulation of high peak flows that develop over short periods of time (e.g. daily). While accumulation of SRE errors increases over short periods, they stabilize over longer periods as random errors compensate each other whereas systematic errors remain to reach the largest value over a certain period of time (Bhatti et al. 2016). Short bias correction windows of fixed size might not be effective to estimate requirements for crop growth as the effect of SRE bias is unknown and thus bias correction may be ineffective.

Different studies have tested the effectiveness of various bias correction window sizes. Shabalova, van Deursen, and Buishand (2003) used an 80-day window for SRE bias reduction. Leander and Adri Buishand (2007) applied a 65-day window to correct the standard deviation of SRE through a regression equation. Terink et al. (2010) highlighted that smaller window sizes could lead to correction of random errors instead of systematic errors. Habib et al. (2014) used a seven-day window to correct SRE bias. Following this approach, Bhatti et al. (2016) assessed the error magnitude between CMORPH and gauged rainfall using different sizes and showed that increases in the SRE error reduced when window sizes were increased. The study shows that errors levelled off for windows longer than 7 days, with minimal increases for windows larger than 15 days. The study distinguished between systematic errors (i.e. bias) and random errors. For windows larger than 15 days, errors did not increase much anymore as systematic errors were at its highest and the effects of random errors minimized as positive and negative errors compensated. For application in runoff modelling, the study proposed to adapt to 7 days windows with restrictions to apply correction for a minimum of five rainy days and at least 5 mm of rainfall. Gumindoga et al. (2019) adopted this methodology. Bias correction methods in these studies were meant for streamflow modelling to simulate quick catchment responses to rainfall causing high flows. The use of SRE in agricultural applications is underexplored. Similarly, bias correction applications in estimating WRSI for crop growth are rare, which should follow different principles as errors may not necessarily propagate to result in inaccurate soil water requirements, thereby affecting crop growth. A setback to the use of SRE in crop growth is that the size of a preferred window to effectively bias correct SRE meant for estimating WRSI remains undefined.

This study proposes and evaluates a method to correct bias in SRE by assessing its effects on WRSI. The proposed method aims to quantify how SRE bias contributes to WRSI errors and, consequently, crop growth. The WRSI is estimated using gauged rainfall, uncorrected SRE and corrected SRE. Specific objectives are to: (a) determine efficient bias correction window sizes based on assessing the effects of SRE bias on WRSI, (b) apply SRE bias correction and compare differences in WRSI for uncorrected and corrected SRE to assess the effects of SRE bias on WRSI, and (c) validate the proposed bias correction procedure. The novelty in this study is that error in WRSI due to SRE bias is used to determine window sizes for bias correction that can be of different sizes.

2. Materials and methods

2.1. Study area and rain gauge network

Twenty automated weather stations from the Lake Victoria basin of Kenya were selected for the study (Figure 1). The basin covers 43,368 km^2 between 2° 05′ 00″ S to 1° 20′ 00″ N and 33° 55′ 00″ E to 36° 05′ 00″ E. The elevation ranges from 1079 to 4318 m above sea level. Tropical rain forest characterizes the basin. Long rains occur from March to June and short rains from October to November, with intermittent dry spells in other months. The annual rainfall is 700–2000 mm (1987–2016) with a bi-modal distribution (Evans, Mukhovi, and Nyandega 2020). The region practices rainfed farming of mixed cereals as a staple food, sown from early February through March due to fluctuating rainfall patterns.

The daily rainfall observations from the 20 automated weather stations were provided by Agriculture and Climate Risk Enterprise Africa (https://acreafrica.com). The period of observation covered January 2012 to December 2018 making the time series well suited to achieve the objectives of this study. Rain gauges had few minor data gaps and were checked for consistency and completeness by Omondi et al. (2021).

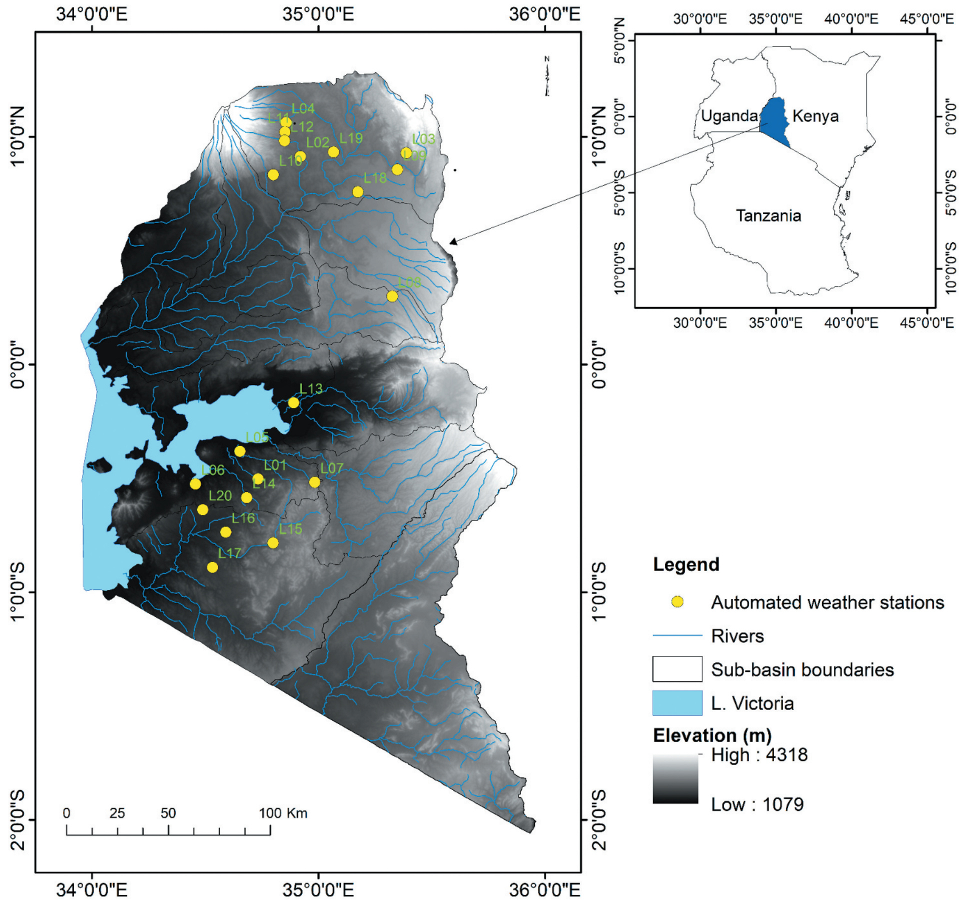

Figure 1. Distribution of 20 automated weather stations providing rain gauge measurements and other meteorological data for the study. Elevation is represented by a 30 m shuttle radar topography mission digital elevation model.

2.2. CHIRPS satellite rainfall

This study builds on the study of Omondi et al. (2021) where four SRE products were assessed for bias. The study concluded that the Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) product had the poorest performance because it falsely detected rainfall events, impacting the length of dry spells. This poor performance had a significant effect on estimated WRSI, making CHIRPS the focus of this study.

CHIRPS, a quasi-global infrared cold cloud duration-based rainfall product, combines satellite and ground station rainfall data for reliable drought monitoring (Funk et al. 2014; Gummadi et al. 2022). It has a spatial resolution of 0.05° and varies in temporal resolution from 6 h to 3 months. Omondi et al. (2021) used the latest CHIRPS Africa version 2.0 (https://data.chc.ucsb.edu/products) available at a daily time step and at a 0.05° spatial resolution.

2.3. Bias correction

2.3.1. WRSI estimation and SRE bias effects

WRSI served as a proxy to indicate soil water availability for crops in the bias correction method. WRSI compares actual evapotranspiration (AET) to the crop water requirement (WR) following Equation 1 (Frere and Popov 1986; McNally et al. 2015).

$$WRSI = \frac{AET}{WR} \times 100 \tag{1}$$

where *WRSI* is crop water requirement satisfaction index (%); *AET* is actual evapotranspiration (mm); *WR* is crop water requirement (mm).

To determine *WR*, potential evapotranspiration (PET) is required. The *PET* was estimated using the widely accepted FAO-56 Penman–Monteith method (Allen et al. 1998). The crop water requirement was then obtained by multiplying *PET* with crop coefficient (Kc) values according to Equation 2. *Kc* values, which adjust for crop water requirement per growth stage, were calculated for maize using the single *Kc* approach developed by Allen et al. (1998).

$$WR = PET \times Kc \tag{2}$$

The WRSI values for gauged rainfall $\left(P_g\right)$ and uncorrected SRE (P_s) were estimated using the crop water balance model in Instat+ 3.37 software. The Instat+ software was selected because of its modest data input requirements and its effective simulation of WRSI influenced by rainfall and *AET*. The model accounts for soil water-holding capacity (SWHC), which indicates the ability of a certain soil texture to physically hold water against the force of gravity. In the WRSI approach, SWHC is the maximum soil water storage available for crop growth. The SWHC data was obtained from the International Soil Reference and Information Centre (2004) soil and terrain database for Kenya version 2.0. The model estimates WRSI as affected by soil water stress, which can be caused by a water shortage or surplus for crop growth.

The WRSI value is 100 at the start of the cropping season, indicating that the soil water requirement for crops is fully satisfied without any drought stress (Senay and Verdin 2002). Any value lower than 80 signifies drought stress as shown in Table 1. As the cropping season progresses, drought may intensify due to changes in daily soil water storage resulting from rainfall and *AET*, that is estimated for gauged rainfall and SRE (Equation 3). *AET* represents soil water loss through crop evapotranspiration and is

Table 1. WRSI classification indicating the impact of drought stress on crop performance and how accumulated error in WRSI caused by the effects of accumulated SRE bias relate to a change of rainfall deficit classes.

WRSI	$\psi_{s,t}$	Rainfall deficit classes	Crop performance description
100–80	0–20	No water stress	Good
79–70	21–30	Mild	Satisfactory
69–60	31–40	Moderate	Average
59–50	41–50	Severe	Poor
<50	>50	Extreme	Total crop failure

estimated considering the crop available water derived from daily rainfall, soil water storage and *PET* that is its upper limit.

$$SW_t = SW_{t-1} + P - AET \tag{3}$$

where *SW* is soil water storage (mm), *P* is rainfall from respective rainfall data sources (mm) and *t* is time step. In case SW_t potentially could become larger than SWHC by high rainfall, then excess rainfall will be discarded to cause runoff.

2.3.2. Determining bias correction windows

To minimize the effects of SRE bias on WRSI estimates, an effective bias correction procedure and a properly defined correction window size is needed. The proposed bias correction method in this study uses window sizes based on a predefined threshold value in WRSI error due to SRE bias. This threshold signifies a misrepresentation of water available for crops due to SRE bias. The following outlines the steps of the proposed bias correction method, as shown in Figure 2.

(1) A threshold value in WRSI error due to SRE bias, β (see Equation (4)), is pre-defined.

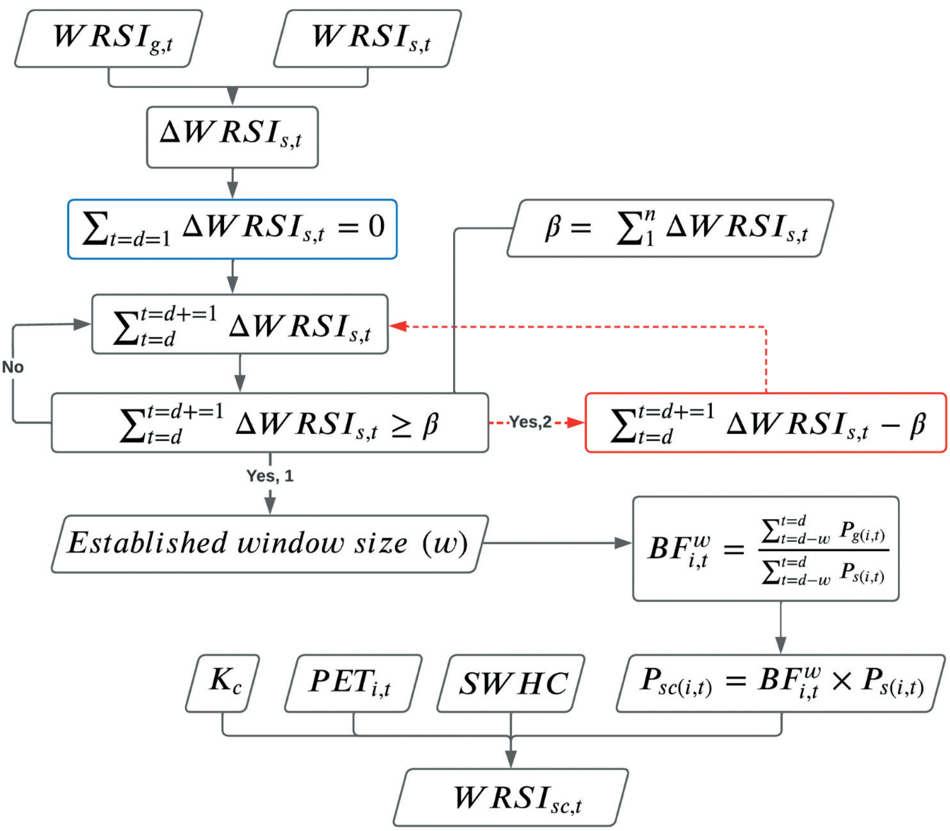

Figure 2. Flowchart showing the bias correction procedure.

$$\beta = \sum_{1}^{n} \left(WRSI_{s,t} - WRSI_{g,t} \right) \tag{4}$$

where β is a pre-defined threshold in WRSI error attributed to SRE bias, n marks a period of unknown size in days over which β is reached, subscripts g and s represent gauged and uncorrected SRE rainfall inputs, respectively.

(2) Throughout the cropping season, daily WRSI is estimated using P_g and P_s as described in section 2.3.1.

(3) Each day, the WRSI difference between WRSI estimated using gauged rainfall $\left(WRSI_g\right)$ and uncorrected SRE $(WRSI_s)$ is updated over a time window of undefined size and denoted as $\Delta WRSI_{s,t}$.

(4) With the progression of the cropping season, the daily $\Delta WRSI_{s,t}$ estimated in (3) is aggregated and denoted as $\psi_{s,t}$ in Equation 5, to signify WRSI error due to SRE bias.

$$\psi_{s,t} = \sum_{t=d}^{t=w} \left(WRSI_{s,t} - WRSI_{g,t} \right) \tag{5}$$

where t is the time step (in days) over a time window of unknown size w; and d is the onset day number for the time window.

(5) When the $\psi_{s,t}$ exceeds β, a bias correction window of variable size (w) is established. The β denotes threshold for $\psi_{s,t}$ at which SRE needs to be corrected as $\Delta WRSI_{s,t}$ becomes too large due to SRE bias to affect simulated crop growth.

(6) A rainfall bias correction factor (BF), that applies to all days of the correction window established in (5), is then calculated from the start to the end of the window based on Equation 6.

$$BF^{w}_{i,t} = \frac{\sum_{t=d-w}^{t=d} P_{g(i,t)}}{\sum_{t=d-w}^{t=d} P_{s(i,t)}} \tag{6}$$

where i represents rain gauge/pixel location and w is the bias correction window size (in days).

(7) The calculated rainfall bias correction factor is then multiplied with the corresponding P_s using Equation (7) to obtain the bias corrected SRE (P_{sc}) for the day number of the correction window.

$$P_{sc(i,t)} = BF^{w}_{i,t} \times P_{s(i,t)} \tag{7}$$

where P_{sc} represents bias corrected SRE (mm d^{-1}) at rain gauge/pixel location i.

(8) The $\psi_{s,t}$ is tracked over consecutive time steps until β is reached to mark the start of a preceding correction window.

Whereas a threshold value for $\psi_{s,t}$ can be pre-defined, the period to reach it is undefined due to the unknown daily SRE bias. Consequently, $\Delta WRSI_{s,t}$ values influence the size of the bias correction window. In the bias correction method, the size of the first correction window is determined by initiating $\psi_{s,t}$ to zero at the onset of the window. For all subsequent window sizes, $\psi_{s,t}$ at the start of a window is adjusted to the difference between β and $\psi_{s,t}$ of the preceding window to ensure consistency throughout the rainfall bias correction windows.

2.4. Evaluation indices

Since β is subject to SRE bias, its effectiveness in determining bias correction window sizes was tested. Values of β were varied from 0.5 to 50% in 0.5% increments. The selection of β was based on the principle that rainfall misrepresentation beyond a certain percentage has an effect on WRSI that could lead to (incorrect) loss of crop performance and eventually to (incorrect) failure if not timely corrected (see Table 1).

The relative bias was used to evaluate the effectiveness of β values. Relative bias in WRSI, denoted as RB^{s}_{wrsi} for uncorrected SRE and RB^{sc}_{wrsi} for corrected SRE, was determined using estimated WRSI from gauged rainfall as reference (Equation 8 and Equation 9). Relative bias was selected because it is a normalized measure where effects of systematic differences $\left(WRSI_{s,t} - WRSI_{g,t}\right)$ are indicated with reference to $WRSI_{g,t}$. The relative bias ranges from -∞ to ∞ with an optimal value of zero indicating no systematic differences (Smith et al. 2006).

$$RB^{s}_{WRSI} = \frac{\sum_{t=1}^{N}\left(WRSI_{s,t} - WRSI_{g,t}\right)}{\sum_{t=1}^{N} WRSI_{g,t}} \times 100\% \tag{8}$$

$$RB^{sc}_{WRSI} = \frac{\sum_{t=1}^{N}\left(WRSI_{sc,t} - WRSI_{g,t}\right)}{\sum_{t=1}^{N} WRSI_{g,t}} \times 100\% \tag{9}$$

where N is the duration of the cropping season (days) and $WRSI_{sc}$ is WRSI estimated using P_{sc}.

In addition, the effect of P_{sc} on the estimated crop water requirement was assessed using the relative bias, RMSE and the Pearson linear correlation coefficient (R). RMSE indicates differences in rainfall estimates between P_g and P_s, and P_{sc}, and WRSI values between $WRSI_g$ and $WRSI_s$ and WRSI corresponding to P_{sc} (denoted as $WRSI_{sc}$). Smaller RMSE values indicate better performance. The correlation coefficient R was used to assess the agreement between rainfall estimates as well as WRSI values.

2.5. Cross validation

To validate the proposed bias correction method, cross-validation assessment was implemented. The commonly used 'leave-one-out' cross-validation technique recommended by the World Meteorological Organization standardized verification system was selected (Acharya et al. 2013). This method involves withholding one gauge station from the network of available stations and designating it as a validation station. The location is assumed to be ungauged i.e. without observation time series of gauged rainfall. By spatial interpolation of bias factors from the remaining stations, the bias factor at the withheld station is estimated. For validation analysis, this procedure was repeated for all gauge stations and all-time steps. Interpolated bias factors at respective stations were subsequently compared to the original ones. This study resorted to the use of the most widely used inverse distance weighting interpolation (IDW) method that uses the concept of distance weighting. The spatially interpolated bias factors follow Equation 10 and Equation 11. The method assumes that observation points at short distances from the ungauged grid cell are more similar as compared to more distant points (Maleika 2020).

This study adopted a radius of influence of 40 km by considering the density and spatial distribution of stations in the northeast and central regions. Barrios et al. (2018) described the radius of influence in IDW interpolation as the spatial extent around the unknown station within which nearby known stations are used for interpolation. Given the 40 km radius, a minimum of 8 stations contributed to the interpolated bias correction values. To weigh the effect of the distance of a station to the grid point to be interpolated, this study adopted a distance weighting factor of 2 that is commonly applied in daily rainfall interpolation studies (e.g. Dirks et al. 1998; Ly, Charles, and Degré 2011). Such weighting factor ensures that the estimated values are influenced not only by a few nearby stations with respective bias correction values but also proportionally by stations at larger distances.

$$BF_{k,t} = \sum_{i=1}^{M} z_i BF_{i,t} \tag{10}$$

$$z_i = \frac{d_i^{-\propto}}{\sum_{i=1}^{M} d_i^{-\propto}} \tag{11}$$

where $BF_{k,t}$ represents the interpolated bias factor for a grid cell (k) at a daily time step; $BF_{i,t}$ is the bias factor of the i^{th} rain gauge station, M is the number of rain gauge stations used in the interpolation, z_i is the weight of each rain gauge station and $\propto$ is the distance weighting factor.

3. Results and discussion

3.1. Propagation effects of SRE bias on WRSI

The relation between β and the relative bias for corrected SRE $\left(RB_p^{sc}\right)$ is illustrated in Figure 3. As β starts at the smallest value of 0.5%, RB_p^{sc} rapidly decreases. However, this rapid decrease in RB_p^{sc} stabilizes after a certain β. This suggests the insensitivity and ineffectiveness of increasing the size of bias correction windows. Comparative analyses show that RB_p^{sc} is consistently lower than RB_p^{s}. This decrease in rainfall bias after correction means that the proposed SRE bias correction method reduces systematic differences between P_g and P_s.

Figure 3 also illustrates the relationship between β and RB_{wrsi}^{sc}. It also shows the relative bias for uncorrected SRE $\left(RB_p^{s}\right)$ and the associated relative bias in WRSI $\left(RB_{wrsi}^{s}\right)$ to indicate contribution of SRE bias on WRSI. The consistently lower values of RB_{wrsi}^{sc} compared to RB_{wrsi}^{s} highlights the effectiveness of bias correction. The SRE bias is corrected such that when corrected SRE is used for estimating WRSI, the calculated crop water needs can more closely correspond with those determined using gauged rainfall.

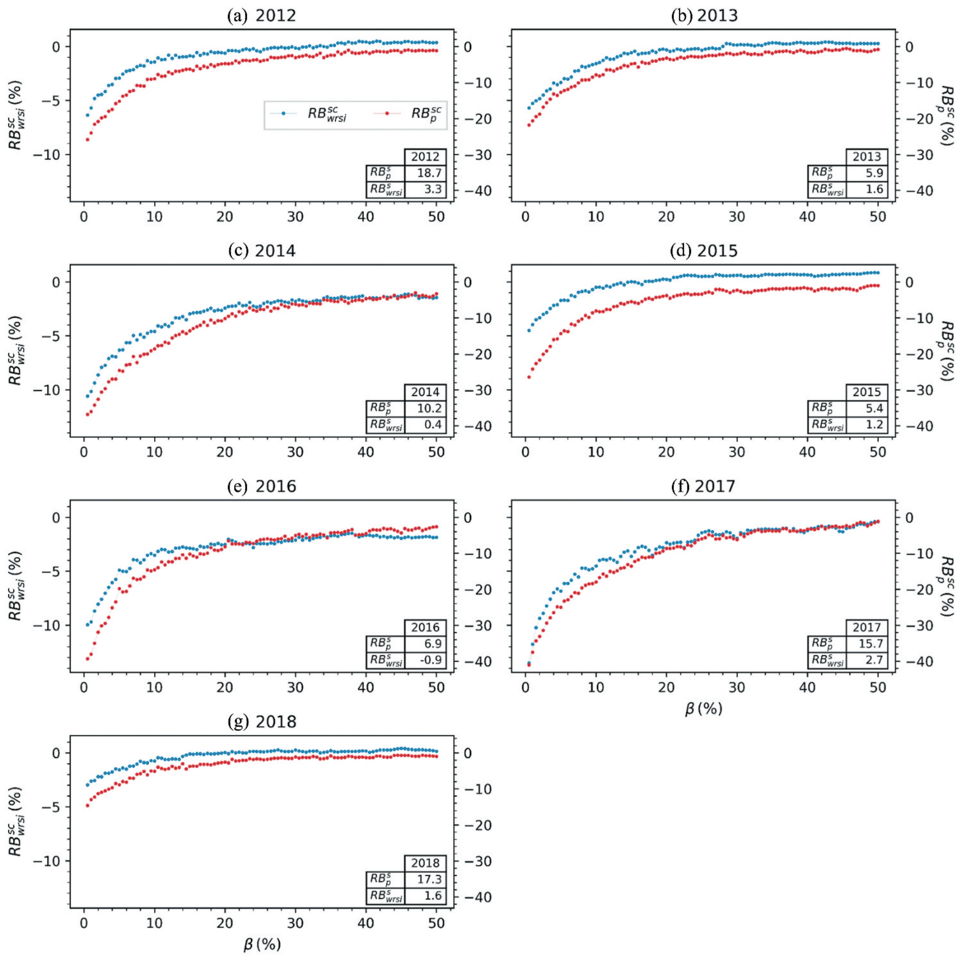

Figure 3. The relationship between β and relative bias values across the 20 rain gauge stations (2012–2018). RB^{sc}_p in red and RB^{sc}_{wrsi} in blue. The sub-set tables indicate RB^s_p and RB^s_{wrsi} calculated over all days of the cropping season.

Additionally, it suggests that the effectiveness of the bias correction window size can be assessed across different β values.

The graphs for both RB^{sc}_p and RB^{sc}_{wrsi} start from large negative values and gradually decrease to small values as β increases. This implies that SRE bias consistently impact simulated WRSI. For β values where the bias correction resulted in P_{sc} smaller than P_g, it caused a negative difference in rainfall, denoted as $-\Delta P_{sc,t}$. This leads to smaller soil water availability for crops, causing a negative difference in simulated WRSI since $WRSI_{sc}$ is less than $WRSI_g$ (i.e. $-\Delta WRSI_{sc,t}$).

Graphs show a few cases where RB^{sc}_p and RB^{sc}_{wrsi} at a succeeding β become larger than those at a preceding β. This means that the succeeding β results in $-\Delta P_{sc,t}$ that leads to a smaller $WRSI_{sc}$ compared to those obtained using a preceding β value. This can happen because β is subject to SRE bias and thus the window size. So, when β increases, the size of the respective $\psi_{s,t}$ windows also increase.

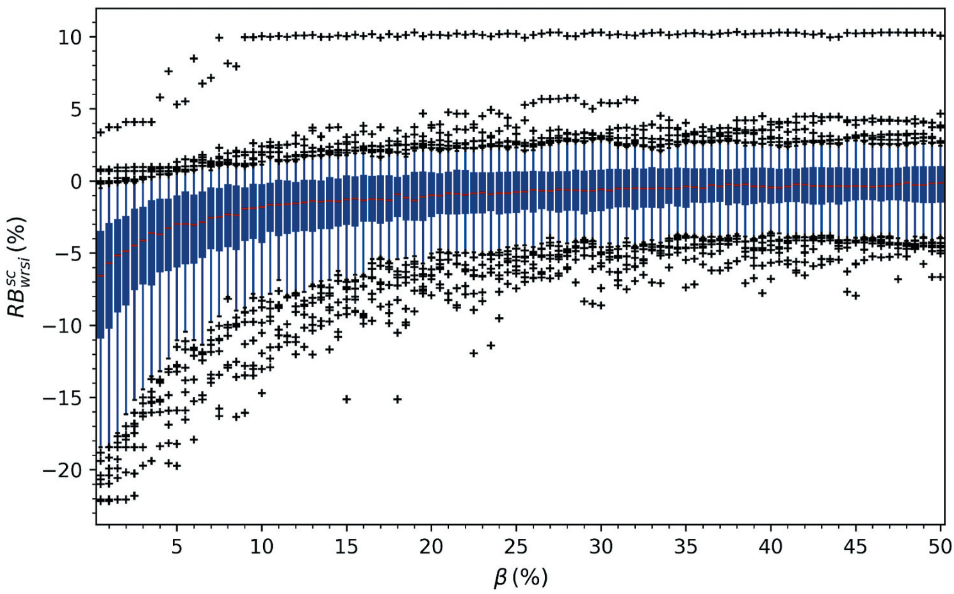

Figure 4. Box whisker plots representing the relationship between β and RB^{sc}_{wrsi}. A single box-whisker represents a series of seven cropping seasons (2012–2018) from 20 rain gauge stations in the Lake Victoria basin. The red horizontal line inside the box represents the median (50th percentile), the top and bottom boundary of the box represents the 25th and 75th percentiles, while the whiskers indicate the extreme values (5% and 95%) excluding outliers. The black crosses show the outliers. RB^{sc}_{wrsi} lower than zero indicate that the β value results in smaller P_{sc} than P_g to cause a negative difference in rainfall that propagates to cause a negative difference in simulated WRSI.

Consequently, the daily variations of differences in rainfall inputs (i.e. P_g and P_s), whether positive or negative, might not immediately affect WRSI estimates to trigger bias correction. Instead, these effects are sustained until the pre-defined β is reached.

3.2. Bias correction window sizes

Figure 4 shows box-whisker plots for each β for daily RB^{sc}_{wrsi} for seven cropping seasons (2012–2018) from 20 rain gauge stations.

The graph shows that the spread of RB^{sc}_{wrsi} narrows as β increases. Large spread of RB^{sc}_{wrsi} is shown for β values lower than 6%. This pattern is consistent during cropping seasons with low and high rainfall in 2014 and 2012 (Figure 5). The spread decreases notably beyond a β of 11% for cropping season with low rainfall and 5% for cropping season with high rainfall. At the lowest β of 0.5%, the median of RB^{sc}_{wrsi} starts from the largest negative value and gradually reduces when β increases (see also Figure 6 shows the effectiveness of the bias correction method for β values at various rain gauge stations). This suggests that bias correction becomes more effective at larger β values. When β exceeds 20%, RB^{sc}_{wrsi} shows minor, steady decrease, resulting in less fluctuation of $\Delta WRSI_{sc,t}$. This indicates that as β progressively becomes larger, the effects of SRE bias on WRSI do not substantially increase. The graphs show that RB^{sc}_{wrsi} was lower for most β values. This suggest that bias

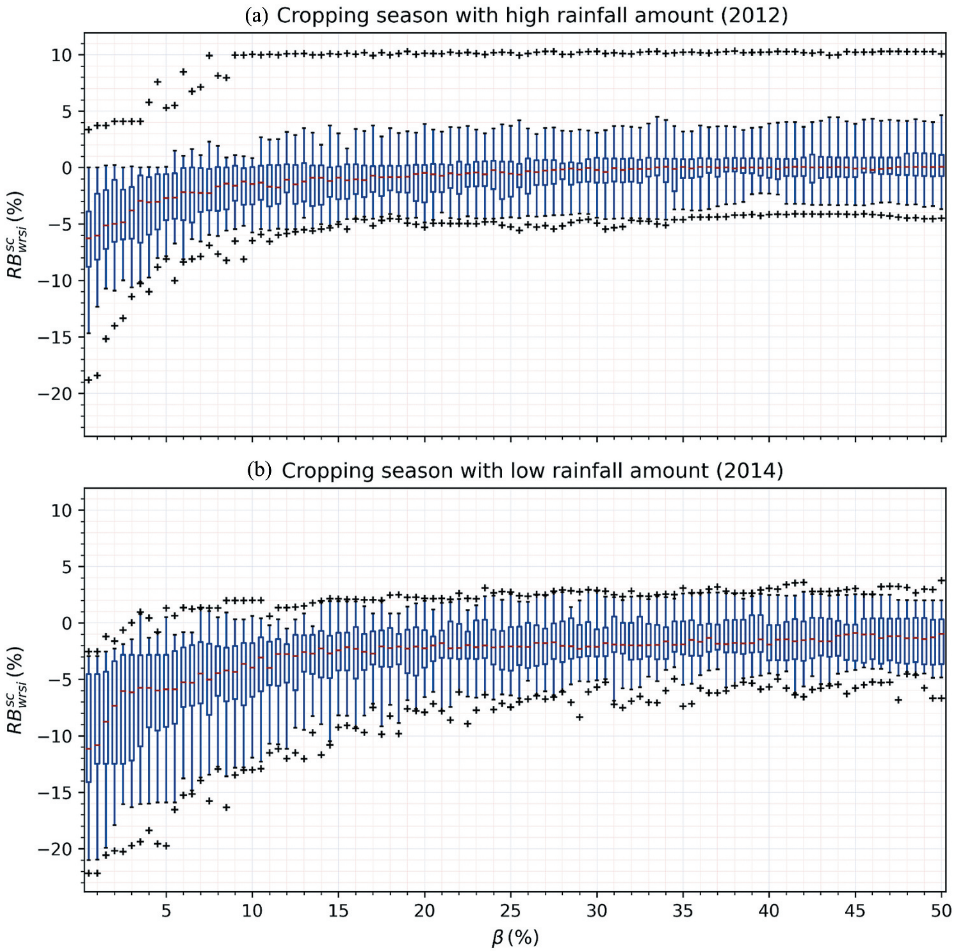

Figure 5. Representation of the relationship between β and RB^{sc}_{wrsi} for cropping seasons with (a) high and (b) low rainfall across 20 rain gauge stations in the Lake Victoria basin. Box-whisker plot representation is the same as in Figure 4.

correction based on window sizes defined by the respective β values result in $-\Delta P_{sc,t}$ to cause $-\Delta WRSI_{sc,t}$.

Table 2 indicates that an effective β, defined in this study as a value where RB^{sc}_{wrsi} is close to zero and stabilizes at an inflection point, depends on the cropping season and rain gauge location. The effective β might also vary subject to different climatic characteristics. Figure 4 reveals that the spread of RB^{sc}_{wrsi} starts to decrease at β values beyond 23.5%. Therefore, a β of 23.5% is selected as effective for determining the bias correction window sizes. A β value exceeding 23.5% signals incorrect representation of water required by crops due to SRE bias, and that bias correction is desirable. A larger β would require larger $\psi_{s,t}$ to initiate SRE bias correction. This could occur from large daily SRE bias over a short period or from accumulation of small daily SRE bias over extended periods. Omondi et al. (2021) demonstrated that it is more likely to encounter large SRE bias at later crop growth stages when rainfall events are

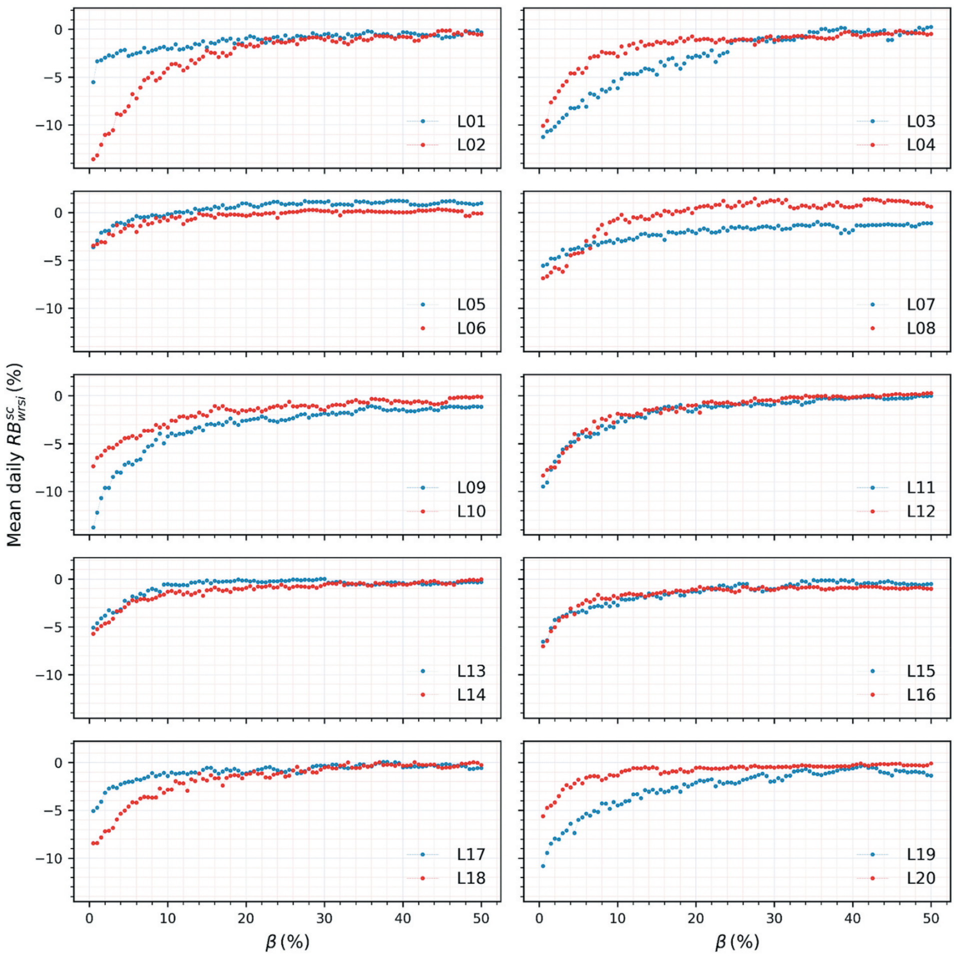

Figure 6. Relationship between β and mean daily RB^{sc}_{wrsi} for individual rain gauge stations (L1-L20) for seven cropping seasons (2012–2018) with gauged rainfall as reference.

Table 2. Effective β values (in %) for determining bias correction window sizes across the 20 rain gauge stations and corresponding relative bias in WRSI for corrected SRE (in %) for the 2012–2018 cropping seasons.

SID	β	$RB_{sc,\beta}$	SID	β	$RB_{sc,\beta}$	SID	β	$RB_{sc,\beta}$	SID	β	$RB_{sc,\beta}$
L01	24	−0,8	L06	21	−0,1	L11	18	−1	L16	20,5	−1,1
L02	22,5	−0,1	L07	24,5	−1,5	L12	21	−0.55	L17	15,5	−0,75
L03	25	−1	L08	21.5	0,65	L13	15	−0,1	L18	21	−0,95
L04	18	−0,8	L09	18	−2,25	L14	20,5	−0,7	L19	22	−1,75
L05	23,5	1,15	L10	21.5	−1,25	L15	22	−0,9	L20	20	−0,6

more frequent to satisfy water requirements for growth. While a large β can be effective in accounting for systematic errors, it might not be suitable to timely correct for incorrect representation of soil water for crops due to SRE bias. Conversely, a small β suggests a smaller $\psi_{s,t}$, implying that a much shorter bias correction window size is required.

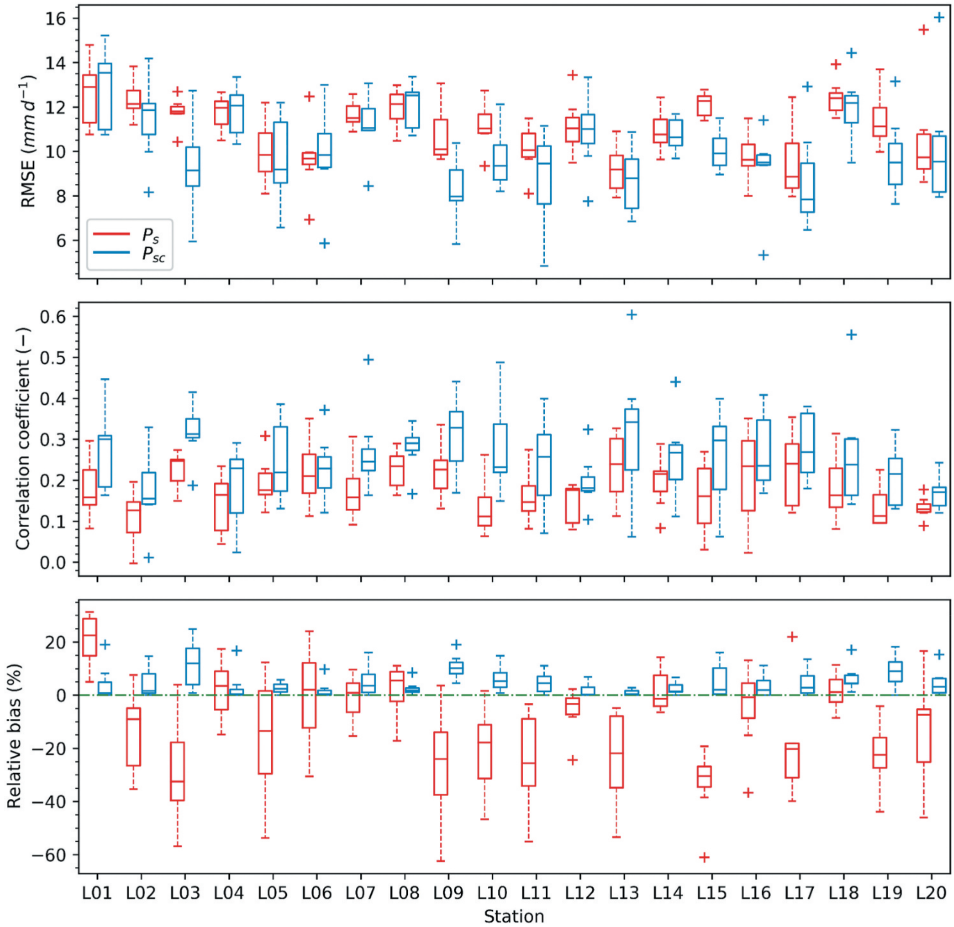

Figure 7. Comparison between daily uncorrected SRE and bias corrected SRE at various rain gauge stations using root mean squared error (RMSE), Pearson correlation coefficient and relative bias. The indicators are calculated using gauged rainfall as reference. Each rain gauge station has seven cropping seasons (2012–2018). Box-whisker plot representation is the same as in Figure 4. The x-axis denotes the rain gauge station. The green dotted line indicates the optimal value of the relative bias.

However, very small β values might be overly sensitive to random errors in SRE, as shown in Terink et al. (2010). When corrected SRE obtained using a small β are used to estimate $WRSI_{sc}$, effects of random errors in SRE could potentially contribute to a poor representation of water required for crop growth, leading to a large spread and rapid decreases of RB^{sc}_{wrsi} as shown in Figures 4 and 5.

3.3. Effects of bias corrected SRE on WRSI

Figure 7 shows how well P_s and P_{sc} align with P_g, when using bias correction with a β of 23.5%. The box-whisker plots represent data from seven cropping seasons across various rain gauge stations. These plots show the distributions of RMSE, relative bias and R for P_s and P_{sc} calculated using P_g as reference.

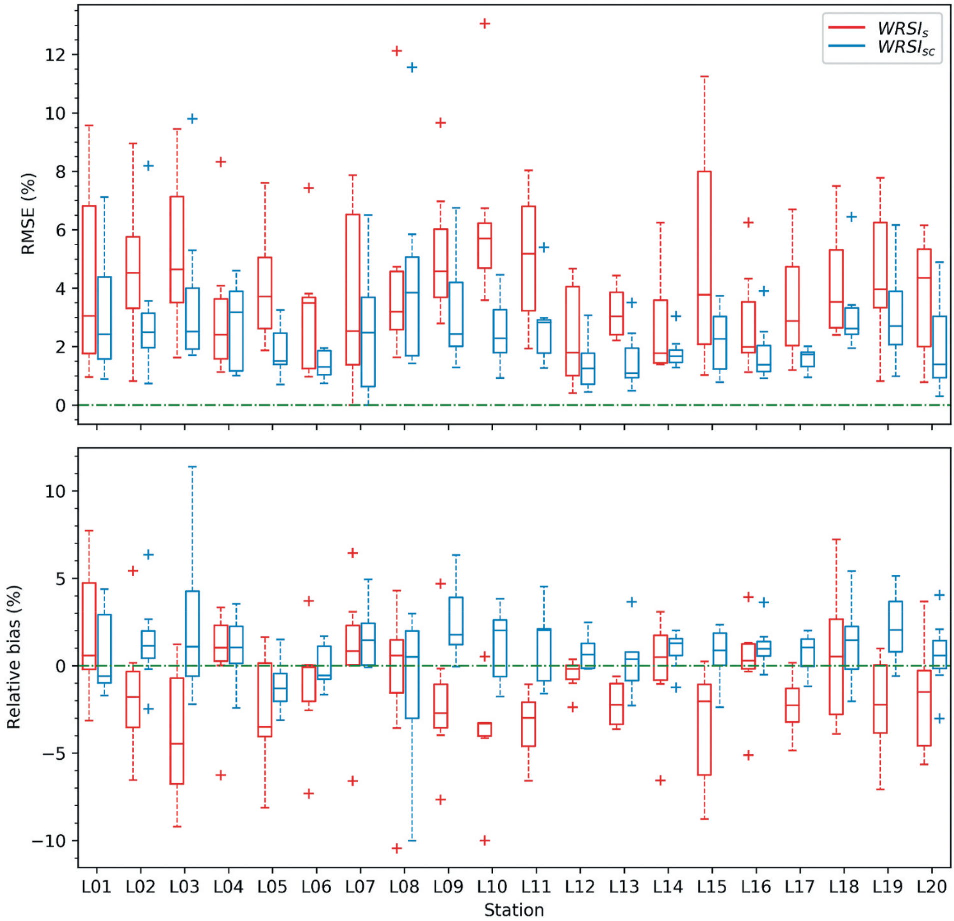

Figure 8. Box whisker plots of root mean squared error (RMSE) and relative bias illustrating how well $WRSI_s$ and $WRSI_{sc}$ align with $WRSI_g$. Each rain gauge station has seven cropping seasons (2012–2018). Box-whisker plot representation is the same as in Figure 4. The x-axis denotes the rain gauge station. The green dotted lines indicate the optimal value of RMSE and relative bias.

Generally, P_{sc} has a higher median value of R than P_s, indicating better agreement with P_g when bias correction is applied with a β of 23.5%. The largest increase in correlation is shown for L13, where R is 0.3 and 0.6 for P_s and P_{sc}, respectively. Extreme 5% values for P_{sc} are consistently higher than for P_s across all stations, except L04 and L13. The spread of relative bias values is consistently smaller for P_{sc} than for P_s. The figure shows that RB_p^{sc} is generally positive but below 25%, unlike the large negative biases in P_s reaching −60%. The median value of the relative bias for P_{sc} is closer to zero than for P_s across all stations except for L07, L16 and L18. Additionally, P_{sc} showed consistently lower RMSE median values than for P_s across all stations except for L01, L04, L06 and L08. Although P_{sc} had a larger spread of RMSE than for P_s, the spread is associated with smaller RMSE values.

Effects of correcting SRE on WRSI are shown in Figure 8. Comparing $WRSI_s$ and $WRSI_{sc}$ with $WRSI_g$ as reference, $WRSI_{sc}$ generally has a smaller spread in RMSE than $WRSI_s$ for all except stations L04 and L08. This spread of RMSE values for $WRSI_{sc}$ is skewed towards zero.

Similarly, the median values of RMSE for $WRSI_{sc}$ are consistently lower than for $WRSI_s$, with the largest reduction in RMSE for $WRSI_{sc}$ being 3.5% at station L10 after correction.

These findings suggest that, after applying SRE bias correction using a β of 23.5%, P_{sc} agrees better with P_g than P_s does. However, some differences still remain between P_{sc} and P_g, as shown by Luetkemeier et al. (2018) as well. Analysis of RB^{s}_{wrsi} and RB^{sc}_{wrsi} reveals a high variability in WRSI values estimated using both P_s and P_{sc} rainfall data. However, $WRSI_{sc}$ consistently shows a smaller spread than $WRSI_s$. The majority of box-whisker plots show RB^{sc}_{wrsi} values between −3% and 6.5%, indicating that while P_{sc} might overestimate WRSI, bias correction reduces rainfall misrepresentation by SRE, as evident from the negative values in $WRSI_s$. The smaller spread in RMSE and consistently lower median RMSE values for $WRSI_{sc}$ suggest that the bias correction was effective to simulate $WRSI_{sc}$ closer to $WRSI_g$ than $WRSI_s$.

3.4. Cross-validation results

Figure 9 presents box-whisker plots of both IDW interpolated and original bias factors for each withheld rain gauge station across seven cropping seasons. The comparison serves to validate the proposed bias correction method in this study. The graph indicates a large spread of whiskers in both lower and upper quantiles for all stations except for the original bias factors at L06 and L12. This spread in the IDW interpolated bias factors can be due to spatial variability in rainfall at stations used for interpolation.

For most rain gauge stations (except L01 through L04, L06, L12 and L18), the median values of interpolated bias factors are slightly higher than the original ones. The boxplots show comparable interquartile ranges between interpolated and original bias factors across most stations, indicating similar performance of the proposed bias correction method. As such, these validation results indicate that

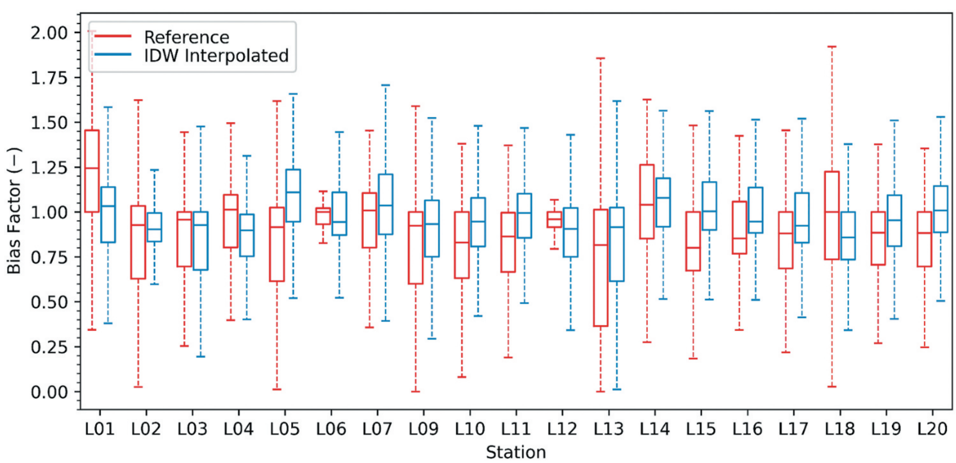

Figure 9. Box-whisker plots showing the distribution of interpolated and original bias factors at withheld cross-validation stations across 19 rain gauge stations. A single box-whisker represents a series of seven cropping seasons (2012–2018) for a specific rain gauge station. Box-whisker plot representation is the same as in Figure 4. The x-axis denotes the rain gauge station. L08 has been omitted because no station was nearby to be used for interpolation.

the proposed method can be applied at locations where rain gauge data is missing. The cross-validation results also depend on the applied IDW interpolation technique and the spatial distribution of available stations used for interpolation. This study did not further evaluate how changes in the specified radius of influence within the IDW method affect the number of stations used for interpolation, nor did it assess the impact of different distance weighting factors in the IDW method. As such, it is uncertain whether changing settings for the IDW interpolation algorithm or selecting a different interpolation method could improve cross-validation results. Aspects of interpolation need careful consideration before application in cross-validation approaches but assessing these aspects is not within the scope of this study.

This study was a first attempt to demonstrate the performance of the proposed SRE bias correction method using CHIRPS data for Lake Victoria basin. The method improves on existing SRE bias correction methods by estimating variable window sizes for bias correction, determined based on SRE error propagation analysis to affect water requirement estimates as a proxy for soil water availability for crops. This contrasts with the common approaches in SRE bias correction that use windows of fixed and short length (less than 10 days). This study shows that short windows are not meaningful to effectively estimate water requirements for crop growth as the effect of SRE bias on WRSI is very small. The proposed method improves rainfall representation by SRE and their applicability in agro-hydrological studies. The proposed bias correction method is straightforward and easy to implement, but high-quality gauge data is essential to assess SRE bias contribution. The study emphasizes the importance of SRE bias analysis for timely identification and correction, so that SRE products can serve to supplement or replace ground-based rainfall data in agro-hydrological studies. While this study focuses on CHIRPS, further testing with other SRE products across geographical areas and climates is necessary. The crop water model in Instat+ software proved to be effective in simulating WRSI and demonstrated the impact of SRE bias on soil water availability. This study recommends further investigations using more advanced physics-based crop growth models like AquaCrop (Steduto et al. 2009). The primary application of the proposed method is to reduce errors in SRE estimates, thereby improving their suitability for agro-hydrological applications and models.

4. Conclusions

This study proposed and evaluated a bias correction method to correct bias in satellite rainfall estimates (SRE) by assessing its effects on the crop water requirement satisfaction index (WRSI). WRSI served as a proxy to indicate soil water availability that drives crop growth. WRSI values for gauged rainfall, uncorrected SRE and bias corrected SRE were estimated using the crop water balance model in Instat+ software. The error in WRSI due to SRE bias was used to determine window sizes for bias correction that vary in size subject to attribution of SRE bias to affect WRSI. This study shows that: (a) SRE bias attributes to WRSI errors, (b) the spread of remaining errors in corrected SRE and related WRSI gradually reduces when pre-defined threshold in WRSI error attributed to SRE biases (β) increases, (c) increase in β causes a change in size of the bias correction window, and indicates that β is influenced by the daily SRE bias. A β of 23.5% was found to be effective in defining SRE bias correction windows, (d) rainfall representation by SRE improved after bias correction, leading to improved WRSI estimates using a β of 23.5%, and (e) the cross-validation results on IDW interpolated bias factors fairly compared to original ones, both in terms of median values and interquartile ranges. Results of cross validation suggest the applicability of the proposed bias correction method to correct for SRE bias at ungauged locations in the study.

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