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Research paper

The use of CHIRPS satellite rainfall estimates for Pitman hydrological modelling in South Africa

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The Pitman model is widely used in South Africa for hydrological modelling and water resource management. For the model to assist with ongoing water management, it needs to use the most recent observed rainfall data, which has proved challenging over the past decade due to data scarcity. This research aimed at developing a CHIRPS (Climate Hazards Group Infrared Precipitation)–based Pitman model framework that instead uses satellite-derived rainfall estimates for the simulation of stream flows. The framework was developed and tested in Catchments G, B, V, and L, as case study catchments representative of the diverse hydroclimatic regions of South Africa. CHIRPS estimates (1981–2019), downloaded at a quaternary catchment scale for the study catchments, demonstrated a generally strong monthly correlation (R^2 > 0.7) with the WR2012 rainfall data. The satellite rainfall data (CHIRPS) were adjusted to correspond to the WR2012 rainfall data, and the Pitman model was set up and calibrated for the period 1981–2009, using the satellite rainfall data. Validation was done for the period 2010–2019. Calibration and validation were performed for 351 quaternary catchments in evaluating the suitability of using satellite data in modelling hydrological catchment responses. The simulated CHIRPS-based flows illustrated good similarity ($\Delta \leq 4\%$) to observed flows. Further, a goodness-of-fit assessment of CHIRPS-based flows using 8 hydrological indices at a ±15% threshold of acceptable error was performed. The results demonstrated 78%, 73%, and 80% suitability of simulated CHIRPS-based flows for Catchments B, V and G, respectively. Catchment L had 'suspect' results, with indices illustrating inadequate correspondence between observed and CHIRPS-based flows. Based on satisfactory performance of the developed CHIRPS-based Pitman model framework, complementary application of CHIRPS rainfall estimates with the declining available observed rainfall data for the simulation of observed flows in data-scarce South African catchments is recommended.

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INTRODUCTION

Informed management of water resources for a water-scarce country such as South Africa is important to protect its population from perennial water shortages occasioned by factors such as rainfall variability. Observed data are important for the monitoring and appraisal of water resources for management purposes. However, Tauro et al. (2018) observe a general global decline in gauge stations and the quality of available data. Pitman and Bailey (2021) reported a continuous decrease in the number of functional rain gauge stations in South Africa since 1970, resulting in a shortage of approximately 2 700 suitable rain gauge stations (Du Plessis and Kibii, 2021).

Hydrological modelling has made significant progress globally (Moges et al., 2020). The Pitman model (1973) (Pitman, 1973 in Hughes, 2013), widely used in South Africa, has also been continuously improved, with the latest version being the Water Resources Simulation Model (WRSM/Pitman) (Bailey and Pitman, 2016). Beven (2016) argues that, irrespective of the advancements made in hydrological models and modelling, observed data inadequacies continue to be a source of uncertainty in simulated flows. Kapangaziwiri et al. (2012) identifies the need to incorporate uncertainty estimation in models to quantify the level of confidence in results, for improved decision-making. Kapangaziwiri et al. (2012) highlights the use of ensemble predictions and/or indices of expected basin behaviour as suitable methods for uncertainty estimation in data-scarce regions such as South Africa. This research applies the latter approach (hydrological indices) for the assessment of goodness-of-fit of simulated CHIRPS-based flows.

The decline in quantity and quality of observed data, as well as limited accessibility, has resulted in researchers opting for remotely sensed (satellite) products that are often free of charge and readily available. Hughes (2013) recommends an increased use of satellite data, which is reiterated by Munch et al. (2013) and Hughes (2015), who highlight the increasing potential for the application of satellite data for hydrological modelling of data-scarce catchments. Subsequently, Hughes et al. (2020), Pitman and Bailey (2021), Kibii et al. (2021), Fikileni and Wolski (2022), and Kibii and Du Plessis (2024) have applied satellite data in their research, and obtained results that compare reasonably with observed data. Pitman and Bailey (2021) and Fikileni and Wolski (2022) report the ability of CHIRPS to adequately replicate WR2012 rainfall data while Kibii et al. (2021) and Kibii and Du Plessis (2024) report CHIRPS-based simulated flows to adequately compare to observed flows. These researchers all recommend further exploration of satellite data.

Dejuan and Kun (2016) point out that satellite data provide a promising alternative to observed data, with good spatio-temporal resolution while having global coverage. However, the ability of satellite data to provide an accurate temporal representation of observed data varies across regions (Watson et al., 2021). Rainfall is the primary variable influencing hydrological model outputs. The use of satellite data often compounds the already existing uncertainties associated with highly parameterised models such as the Pitman model. This necessitates the incorporation of uncertainty analysis in hydrological modelling. Further, the application of the outputs of hydrological modelling to real-life challenges is often accompanied by significant uncertainty (Montanari et al., 2013).

Kapangaziwiri et al. (2012), Ndzabandzaba and Hughes, (2017), Hughes et al. (2020), and Kabuya et al. (2020) have applied uncertainty analyses in hydrological studies in the South African region. These studies use hydrological indices as distinct signatures/identifiers of catchment dynamics for uncertainty assessments in constraining calibrated model outputs, ensuring model realism and hence improved confidence. The hydrological indices are based on a spatio-temporal average of time series (≥21 years with at least 5 years of continuous data, to cater for climatic and hydrological variability (Merz et al., 2009)), in order to filter out noise (Westerberg et al., 2016). The capability of a model's output to replicate multiple distinct hydrological indices thus illustrates its ability to represent the intended catchment dynamics (Fenicia et al., 2018), hence accurately simulating flows. This research thus applied hydrological indices for the assessment of suitability of simulated CHIRPS-based flows.

This research builds on the work of Kibii and Du Plessis (2023), who tested the applicability of CHIRPS-based Pitman modelling in the Berg catchment. In this study the research approach is extended to include various study catchments across South Africa, with different hydroclimatic conditions. It further builds on the work of Kapangaziwiri et al. (2012), which made use of hydrological indices (signatures) in constraining uncertainty in simulated flows. A ±15% threshold of acceptable model error is used to limit the acceptability of simulated flows. Westerberg et al. (2016) defined a maximum limit range of ±30–40%, Quesada-Montano et al. (2018) note a range of ±20%, while Ndzabandzaba and Hughes (2017) highlight a ±15–20% range. Taking note of the varied thresholds applied by researchers, this research applies a conservative ±15% in the assessment of goodness-of-fit for the CHIRPS-based flows. Where simulated flows are not within the ±15% threshold of acceptable error, the results were rejected and considered inconsistent with the observed catchment dynamics, as represented by the hydrological indices.

The management of water resources in South Africa is based on the databases produced by a series of studies funded by the Water Research Commission (WRC), of which 'WR2012' is the most recent (Bailey and Pitman, 2016). The initial study using the Pitman model was '1981', which was subsequently succeeded by 'WR90', 'WR2005' and then 'WR2012' (Bailey and Pitman, 2016). However, with the persistent challenge of a decline in observed data, updating the WR2012 database has proven to be difficult. In researching the applicability of CHIRPS for use in the Pitman model, Pitman and Bailey (2021) and Kibii and Du Plessis (2021) have noted that CHIRPS rainfall estimates have a high spatio-temporal resolution with near-present data that is freely available, and have hence recommended CHIRPS as a potential alternative to declining observed data for hydrological studies in South Africa. This research thus aimed to extend the work of Kibii and Du Plessis (2023) to further improve and test the use of the developed CHIRPS-based Pitman model framework in 4 major primary catchments (G, B, V, and L) of South Africa, as defined by Bailey and Pitman (2016) in 'WR2012'.

MATERIALS AND METHODS

Study area

South Africa is classified into 8 climatic zones (Rouault and Richard, 2004) that can be further categorised into 'summer', 'all year', and 'winter' rainfall regions. Bailey and Pitman (2016) used the 21 primary hydrological catchments, as delineated for South Africa in in their most recent WRC study (WR2012) for their Pitman modelling, as illustrated in Fig. 1a.

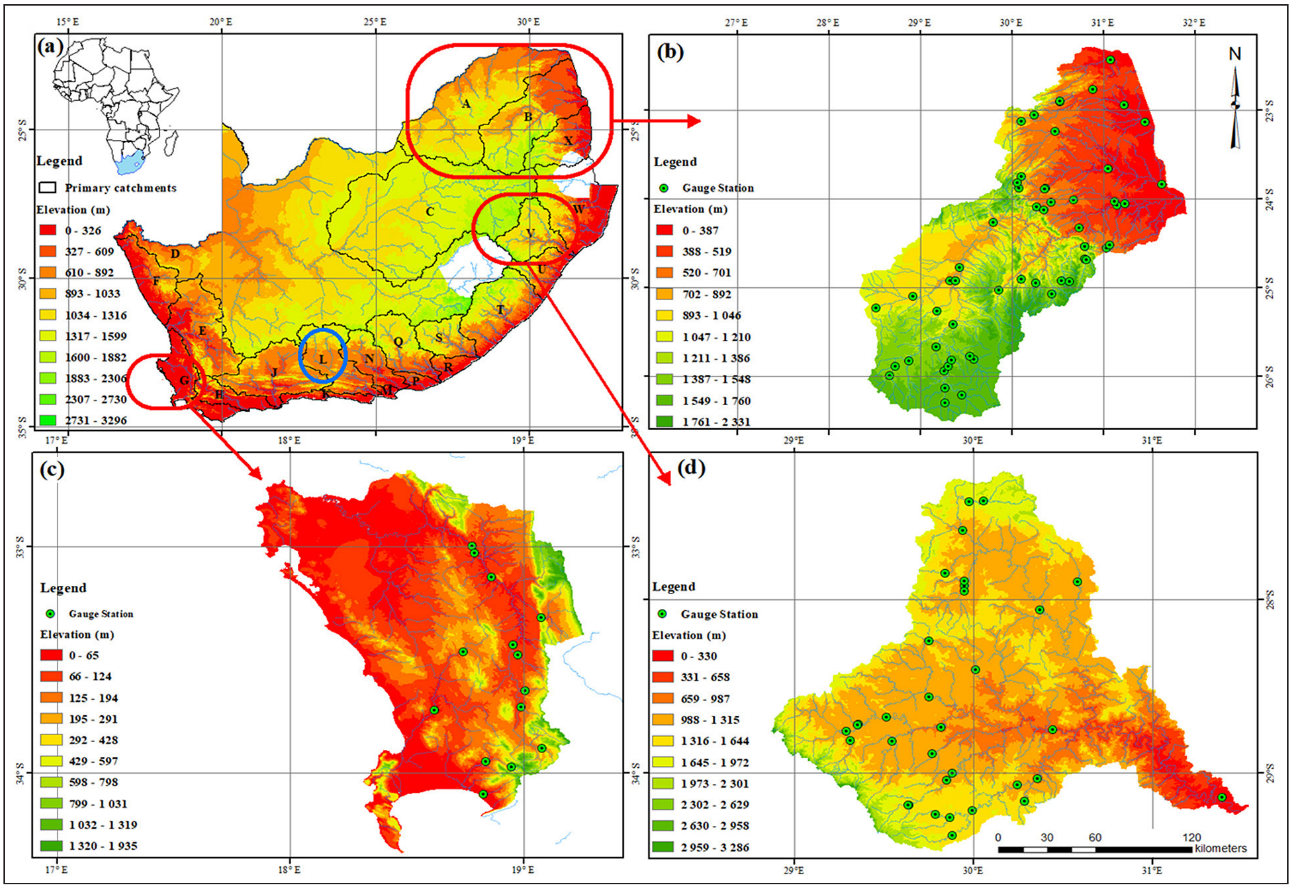

Figure 1. (a) The 21 primary catchments of South Africa (Bailey and Pitman, 2016), (b) Catchment B, (c) Catchment G, and (d) Catchment V

Based on the findings of Pitman and Bailey (2021) and Du Plessis and Kibii (2021), Catchments B, G, L, and V were selected for this research, as illustrated in Fig. 1. Du Plessis and Kibii (2021) observed CHIRPS to have a strong correlation ($R^2 \geq 0.5$) to observed monthly rainfall in Catchments B and V, while G and L have, on average, a lower correlation ($R^2 \leq 0.5$). Pitman and Bailey (2021) observed CHIRPS to be reliable across South Africa, with the exception of the winter rainfall region (Catchment G). Each of the study catchments has unique climatic conditions that influence the nature of rainfall received, thus affecting correspondence with CHIRPS.

Catchment B experiences the 'north-eastern interior' climate while Catchment V experiences the 'KwaZulu-Natal' climatic conditions. These climatic conditions are both characterised by summer rainfall with a January maximum of about 80–130 mm. However, the 'KwaZulu-Natal' climate is wetter compared to the north-eastern interior climate. Catchment G experiences the 'south-western Cape' climatic condition, characterised by winter rainfall with a June maximum of approximately 70 mm. Catchment L (Fig. 1, circled in blue) experiences the 'south coast' climate with an 'all year' rainfall, at an average of 30–40 mm/month (Rouault and Richard, 2004).

Pitman model

The Pitman model is a semi-distributed model that runs on either daily or monthly time steps (Hughes, 2013). The model has input data requirements of climate data (evaporation, rainfall), land cover/land use and water demand. Calibration of the model further requires observed streamflow data. The Pitman model uses modules (runoff, reservoir, irrigation, mine and channel) linked to each other by hydrological equations representing respective catchment processes. Catchment hydrological response is simulated by the conveyance of flow from one module to the next. This research used the monthly time-step Pitman model in simulating flows.

Data collection and analysis

The primary input requirements for the Pitman model for the period 1981–2009 were obtained from the WR2012 database (WR2012, 2024). Observed streamflow data for 2010–2019 was obtained from the Department of Water and Sanitation (DWS) database (DWS, 2024).

The WR2012 rainfall files are classified into rainfall zones made up of quaternary catchments with similar rainfall characteristics derived from shared rainfall stations. The mean annual precipitation (MAP) for each quaternary catchment is provided. Also provided is the monthly %MAP distribution for each rainfall zone that the model uses to generate monthly rainfall. The %MAP distribution was used to generate monthly rainfall time-series for quaternary catchments to be correlated with CHIRPS.

CHIRPS-based rainfall estimates at a daily timestep were obtained from the ClimateSERV database. Shapefiles for quaternary catchments were first created for uploading on the ClimateSERV database. CHIRPS daily rainfall estimates for the period of interest (1981–2019) were then queried and downloaded in Excel format. The process for obtaining and adjusting CHIRPS data is summarised into 4 steps as depicted in Fig. 2.

CHIRPS monthly time-series were prepared and correlated to the generated WR2012 monthly rainfall (based on gauged records from the South Africa Weather Service) for each quaternary catchment within the primary catchment. The correlation was done for the common period 1981–2009, where both datasets were available. The linear relationships between monthly CHIRPS and WR2012 rainfall, for each quaternary catchment, were obtained as adjustment (calibration) factors (Fig. 2, Step 2) and

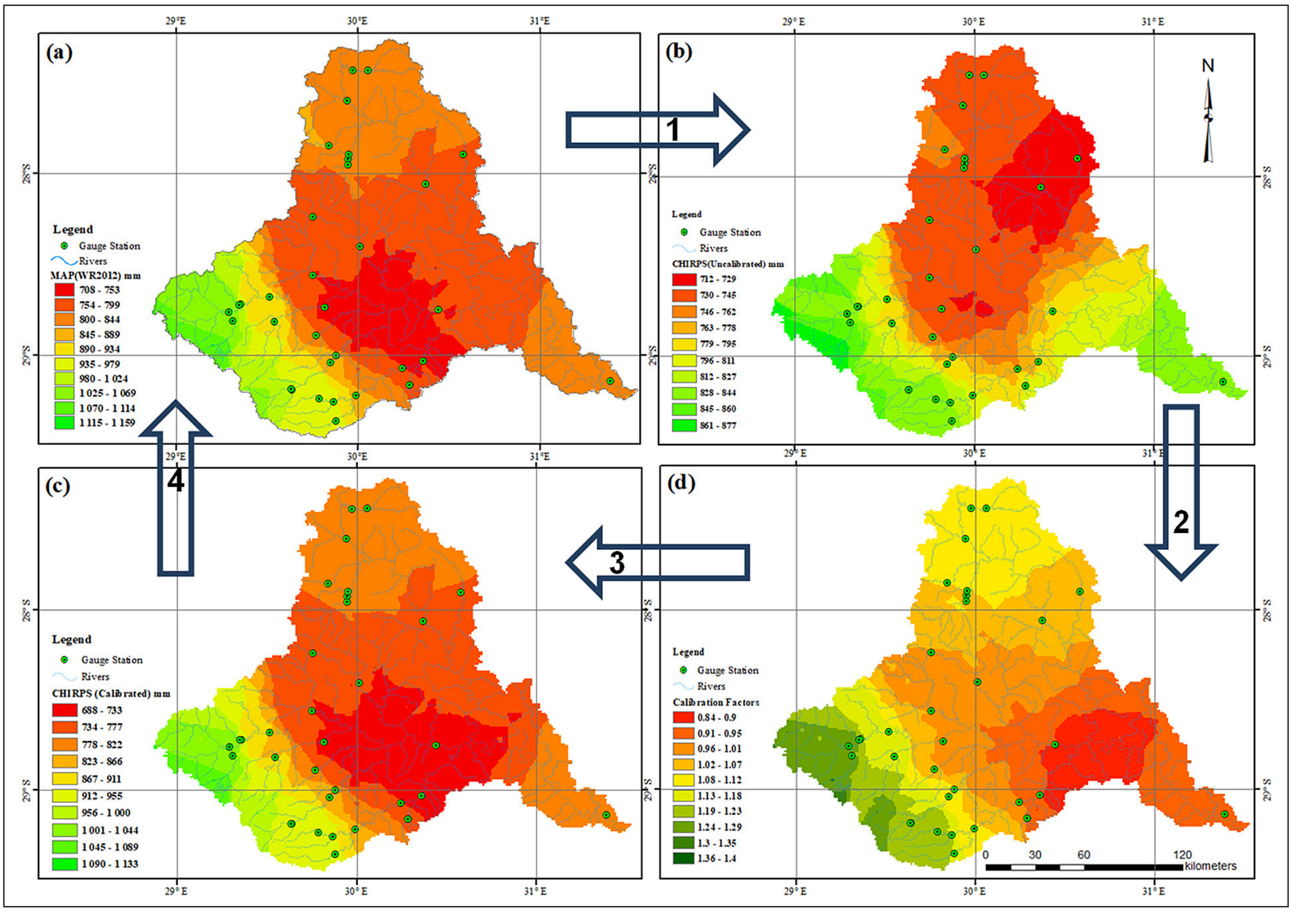

Figure 2. Process of adjusting CHIRPS rainfall estimates (Catchment V)

used to adjust CHIRPS estimates (Fig. 2, Step 3). The adjusted CHIRPS data were then checked to correspond to the WR2012 catchment rainfall time series. The MAPs for the two time-series were also compared for differences ≤ 10%. Figure 2, Step 4 is a spatial illustration of the MAP comparison.

The Pitman model uses a %MAP file to run model simulations. The adjusted CHIRPS data were then used in the preparation of the CHIRPS-based Pitman model run files.

Model setup and calibration

The Pitman model was set up for the respective quaternaries with areas of between 80 and 2 000 km^2 across all the study catchments in Catchments B, V, G and L. The model was set up using WR2012 and the adjusted CHIRPS rainfall data. The model was calibrated for the period 1981 to 2009. The calibrated model was then used to simulate flows for the validation period (2010–2019). The calibration and validation periods were determined based on a common window of data availability for CHIRPS and WR2012. For validation, observed updated flows from DWS (for the same gauging stations in WR2012) were used.

The Pitman network files (consisting of runoff, irrigation, channel, reservoir (dam) and mine modules) for the study catchments, as published in WR2012, were set up and calibration done, following guidelines provided by Bailey and Pitman (2016). The difference (Δ) between simulated and observed mean annual runoff (MAR) was confirmed to be ≤4%. The mean log MAR, standard deviation, seasonality index and flow hydrographs were also considered during calibration. In the calibration process, the Pitman model calibration parameters were adjusted within the published range in WR2012 (Pitman and Bailey, 2016).

The Pitman model was thereafter set up using CHIRPS-based rain files and calibrated as described above. Upon satisfactory calibration, CHIRPS-based flows were simulated for the validation period of 2010–2019. During the validation period, land use and water demands were assumed to undergo insignificant changes. In the validation analysis, MAR and flow hydrograph (graphical) comparisons between observed DWS flows and simulated CHIRPS-based flows were done. Further, goodness-of-fit analyses using hydrological indices were conducted as illustrated in the next section.

Goodness-of-fit analysis using hydrological indices

A hydrological index is a unique identifier of a catchment's response, representing its input–output characteristics (Kapangaziwiri et al., 2012). Hydrological indices have the advantage of being model-independent while complementing simple model calibration procedures, leading to more desirable model outputs (Wagener and Monari, 2011). Euser et al. (2013) and Shaffi and Tolson (2015) note that hydrological indices provide for an assessment of a model's ability to simulate the different catchment hydrological responses.

This research considered data availability and quality in identifying suitable hydrological indices that are consistent (usable for a variety of catchments) and have discriminatory power (sensitive to process difference) (McMillan et al., 2017). The following 8 indices were selected: mean monthly runoff volume (MMQ); percentile flows expressed as a ratio to MMQ (Q_{10}/MMQ, Q_{50}/MMQ, Q_{90}/MMQ); the slope of MMQ (slope$_{MMQ}$); coefficient of variability of MMQ (CV$_{MMQ}$); runoff ratio (Q/P) and aridity index (PE/P) (Kibii and Du Plessis, 2023).

The MMQ and Q/P indices have been used to represent catchment water balance. The Q/P index further illustrates the transferability of rainfall to runoff as a measure of how well the water balance is simulated (Zhang et al., 2018). Q/P is related to PE/P through the Budyko (1974) curve, where a high PE/P is an indication of low potential runoff (Q/P) (Hobbins et al. 2017). Exceedance percentile flow indices represent high (Q_{10}), median (Q_{50}), and low (Q_{90}) flows, respectively, and were used in the characterisation of the flow duration curves. The slope$_{MMQ}$ index illustrates the slope of the flow duration curve, providing a measure of the variability of flows. Slope$_{MMQ}$ is however sensitive to zero and extremely low flows (Kabuya et al., 2022); hence CV$_{MMQ}$ was also used as a complementary indicator of flow variability.

This research defined a ±15% threshold of acceptance to limit the acceptability of simulated CHIRPS-based flows. Simulated flows were classified as 'good', 'suspect', or 'poor' based on the proportion of their hydrological indices that fell within the defined threshold of acceptance/error bounds. Simulated flows for which 6 or more of the 8 indices (i.e. at least 75% of the indices) were within 15% of the observed flow indices were classified as 'good'. Those with 4 to 5 indices within 15% of the observed were classified as 'suspect', and those with fewer than 4 indices (under 50% of indices) within the acceptable error range were classified as 'poor'. This approach was informed by findings of previous researchers (Beven and Freer, 2001; Hughes, 2016) indicating varying degrees of uncertainty in index values from observational data, due to uncertainties in these datasets (e.g. due to measurement errors, rating curves or other derivation processes, etc.), depending on signature type, with the highest ranging from ± 30–40% for high and low flows, and 10–20% for median and average flows (Westerberg et al., 2016).

RESULTS AND DISCUSSION

Adjustment of CHIRPS rainfall data

South Africa experiences a diverse range of climatic conditions and topography, which influences the nature, amount, and mechanism of rainfall formation. These have an influence on the relationship between observed rainfall and CHIRPS estimates.

CHIRPS-based catchment rainfall estimates were downloaded and validated through a process of correlation analysis. Calibration (adjustment) factors were obtained and used for CHIRPS adjustments. The correlation results for Catchments B, V, G and L are summarised in Fig. 3.

The correlation results illustrate a good relationship between CHIRPS estimates and WR2012 rainfall for all test catchments except L (having sections of the catchment with $R^2 < 0.5$). Catchment L (Fig. 3d) receives 'all year' rainfall due to the movement of warm moisture-laden air from the Indian Ocean along the southern coast. The frontal systems along the coastline tend to influence its rainfall formation mechanism, hence the low correlation between observed rainfall and CHIRPS (Dinku et al., 2018). The low correlation ($R^2 \leq 0.7$) over a large part of this catchment affects the performance of simulated flows, as will be illustrated later.

Catchments B and V experience summer rainfall and have a strong correlation to CHIRPS estimates. The correlation for these catchments was observed to increase from downstream to the high-altitude hinterland. The topography of these catchments (Fig. 1) influences the observed strong correlation, as highlighted by Duan et al. (2016). The correlation results for Catchment G were exceptional, at $0.9 \leq R^2 \leq 0.94$, in contrast to the observations of Du Plessis and Kibii (2021), in which CHIRPS estimates had a low correspondence to observed station data (SAWS) for the same region. However, the improved results are likely to be attributed to the use of catchment as opposed to station (point) rainfall data, as highlighted by Bailey and Pitman (2021). Fikileni and Wolski (2022) also note CHIRPS to be superior in replicating observed

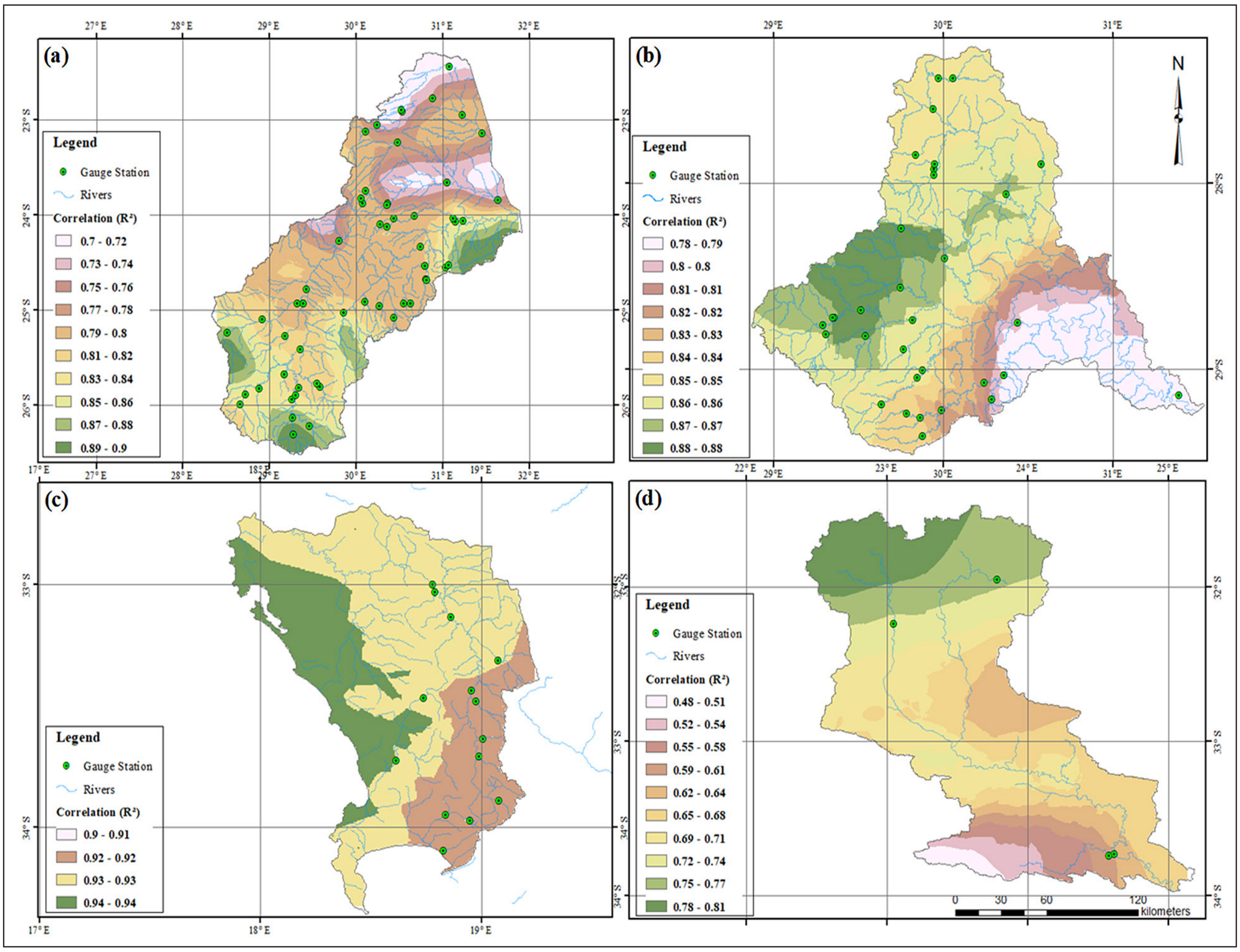

Figure 3. CHIRPS correlation (R^2) for Catchments (a) B, (b) V, (c) G and (d) L

catchment rainfall in comparison to point rainfall, as was used in Du Plessis and Kibii (2021). The process of obtaining catchment rainfall was likely to have taken into consideration the Western Cape's complex topography in obtaining rainfall zone data; hence the lower error values often attributed to the winter rainfall (Duan et al., 2016).

Having obtained satisfactory correlation results, the relationships between CHIRPS and WR2012 catchment rainfall were used to adjust CHIRPS estimates. The adjusted CHIRPS data were then compared to the WR2012 catchment rainfall through ground-truthing. While the adjustment process is illustrated spatially in Fig. 2, the results have also been illustrated in Figs 4, 5 and 6, for ease of comparison between the WR2012 rainfall and CHIRPS.

The WR2012 rainfall (MAP) for Catchment V ranges from 708–1 159 mm (Fig. 2a), compared to the CHIRPS MAP of 712–877 mm (Fig. 2b), suggesting an underestimation by satellite data. The spatial distribution was also slightly different. However, due to the observed strong correlation (Fig. 3d) and using the obtained calibration (adjustment) factors (Fig. 2c), CHIRPS was adjusted to have a similar distribution to the WR2012 rainfall. Nonetheless, the underestimation of low rainfall by CHIRPS downstream in the catchment did not improve (Fig. 2d, i.e., WR2012 845–859 mm, unadjusted CHIRPS 828–844 mm, adjusted CHIRPS 778–822 mm).

Though the correlation for a large portion of Catchment L was poor (Fig. 3a), CHIRPS MAP was observed to give only a slight overestimation in the low MAP quaternaries within Catchment L. The spatial distribution of CHIRPS and WR2012 rainfall was however different, as illustrated in Fig. 4a and 4b. Applying calibration (adjustment) factors (Fig. 4d), the overestimation by CHIRPS was reduced (Fig. 4c). However, the spatial distribution of CHIRPS did not improve to correspond to WR2012 rainfall, which is likely to be attributed to the low correlation.

The WR2012 catchment rainfall for Catchment B ranges from 476–1 021 mm (Fig. 5a), while the downloaded CHIRPS estimates range from 445–964 mm (Fig. 5b). This observation suggests an overall underestimation by CHIRPS with slight differences in spatial distribution. However, using the obtained calibration (adjustment) factors (Fig. 5d), CHIRPS was adjusted to correspond to the WR2012 catchment rainfall amount and distribution (Fig. 5c).

The WR2012 rainfall (MAP) for Catchment G ranges from 219–1 331 mm (Fig. 6a), and from 313–792 mm for CHIRPS (Fig. 6b). This observation suggests that CHIRPS underestimates high MAP areas while overestimating low MAP areas. This corroborates with the observation of Bailey and Pitman (2021) that CHIRPS underestimates high rainfall amounts while overestimating low winter rainfall as also observed by Dinku et al. (2018). The spatial distribution is also slightly different. Using calibration (adjustment) factors (Fig. 6d), CHIRPS data were adjusted to have an almost similar amount and distribution to the observed catchment rainfall (Fig. 6c).

Having obtained adjusted CHIRPS data for all the study catchments, Pitman rain files were prepared for each of the rainfall zones in the respective study areas. This process involved conversion of the adjusted CHIRPS monthly rainfall into percentage MAP files, and putting them into the required format (RAN-file) to be used in the Pitman model.

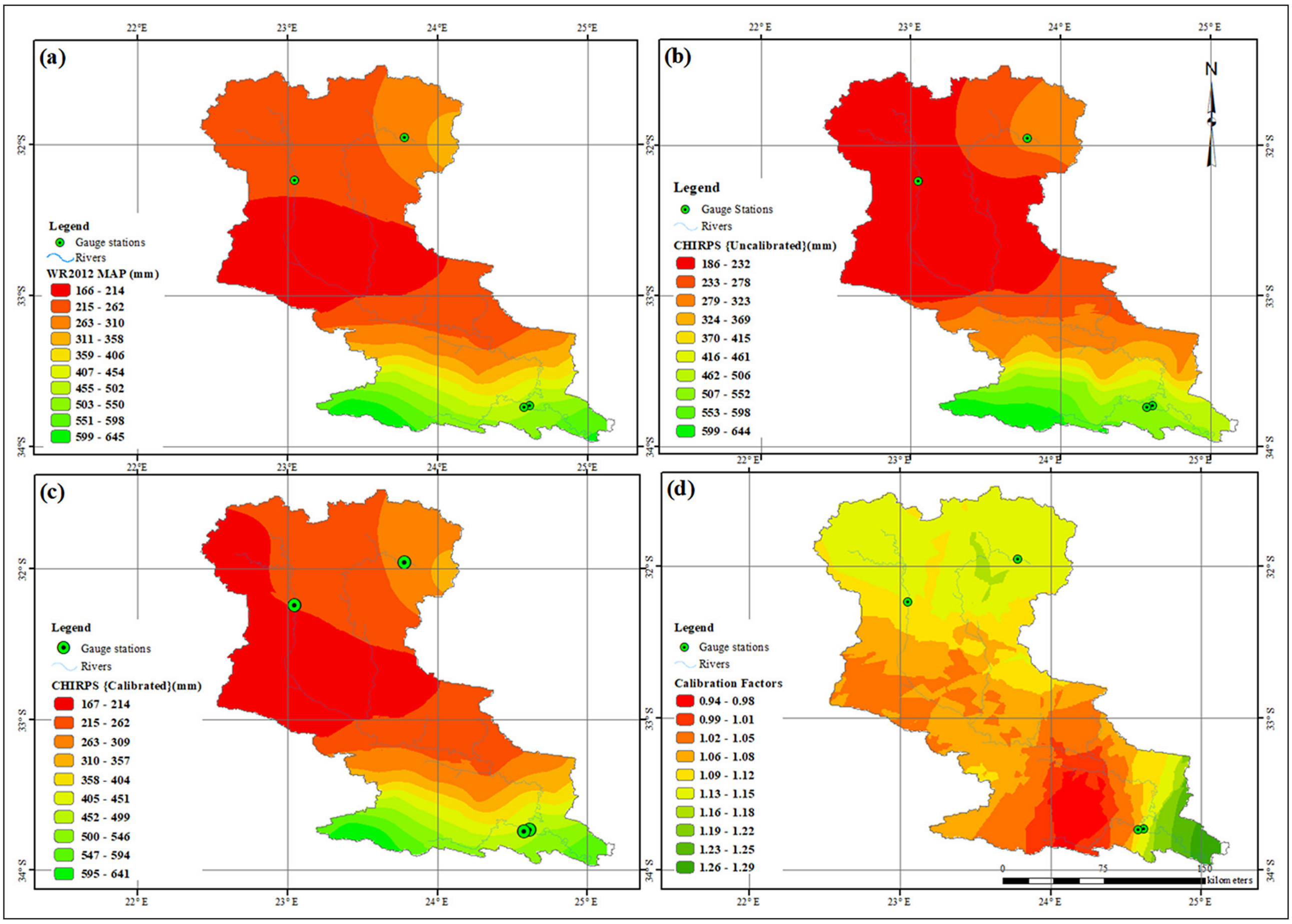

Figure 4. CHIRPS adjustment summary for Catchment L

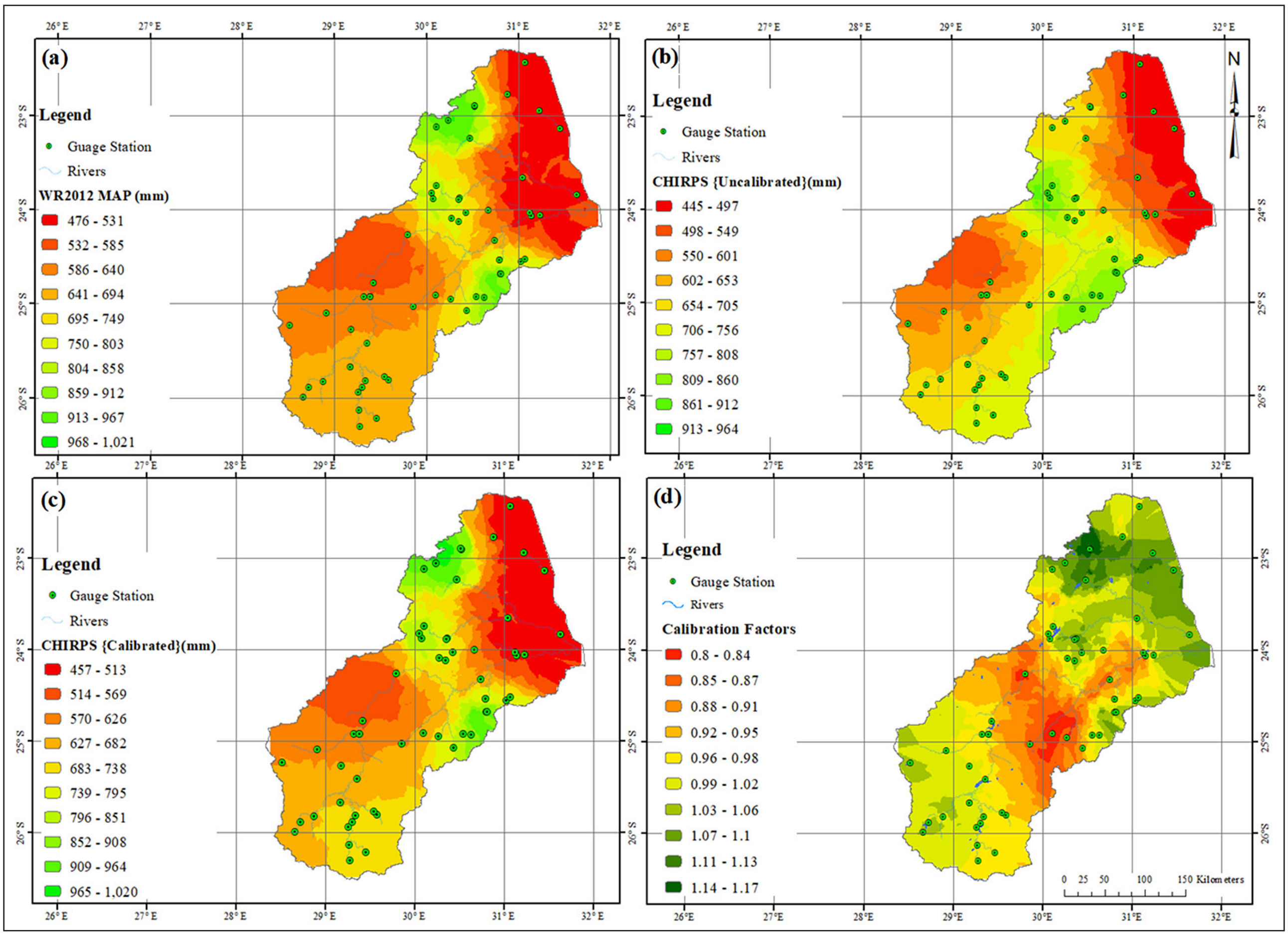

Figure 5. CHIRPS adjustment summary for Catchment B

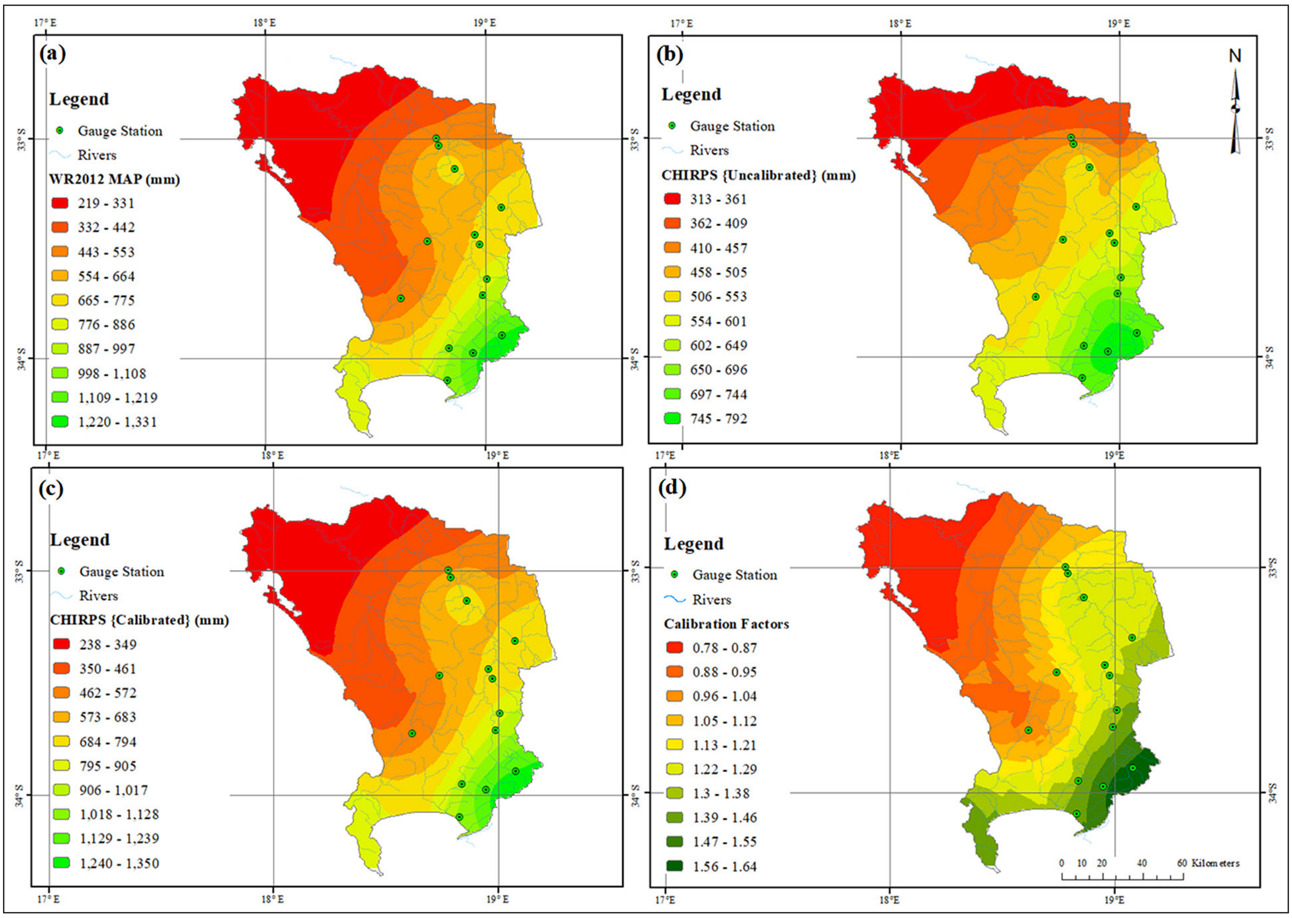

Figure 6. CHIRPS adjustment summary for Catchment G

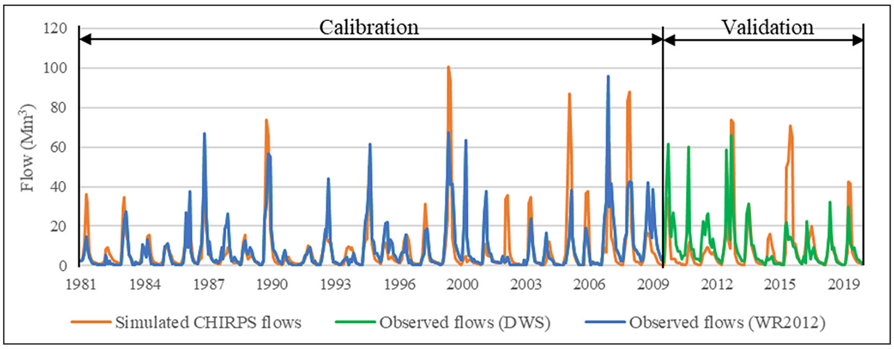

Figure 7. Monthly hydrograph for Gauge B4H003

Calibration and validation of Pitman model

Having prepared Pitman rainfall files from CHIRPS data, the model was set up and calibrated for 4 Catchments (L, B, G and V). A calibration period of 1981–2009 was selected based on a common window of CHIRPS and observed (WR2012) data availability. CHIRPS data are only available from 1981 to the near-present, while the WR2012 data are only available up to 2009. Also, some of the observed flow data were for a short period, having gaps of more than 5 years, and some were classified by DWS to be outliers or have extremely low to zero annual flows. Although such data were used for calibration where no alternative existed, the results obtained were considered of low confidence as they are unrepresentative. This situation rendered some gauged catchments effectively unusable. For example; Catchment L had 4-gauge stations – 2 were outliers, 1 had near-zero annual flows, while the remaining gauge had only 4 years (1981–1984) of observed data within the defined calibration period (1981–2009). This rendered the results for Catchment L 'suspect', as will be illustrated.

In performing calibration, the Pitman model parameters were adjusted based on input data to arrive at a satisfactory calibration (Bailey and Pitman, 2016). However, in some cases where the MAP was too low, the model was unable to simulate adequate flows, as observed by Pitman and Bailey (2021). This was common among quaternary catchments with more downstream sub-catchments. An upstream underestimation of MAR due to low input MAP resulted in downstream catchments underestimating observed MAR. Watson et al. (2021) attribute this phenomenon to large systematic impacts that headwater catchments have on the overall simulated flows. Having satisfactorily calibrated the gauge stations, validation was done where DWS data were available for the period 2010–2019, using flow hydrographs as illustrated by Fig. 7. Although MAR was considered in the validation analysis, the graphical comparison using flow hydrographs was key, due to observed flow data limitations.

In the calibration analysis, all gauge stations in each catchment with data within the defined calibration period (1981–2009) were considered, but downstream gauges were considered more representative, as the flows thereof are inclusive of upstream sub-catchments. Watson et al. (2021) note that while headwater catchments have a large impact on the overall modelled streamflow, downstream catchments are more important, especially for low flows. The observed, WR2012, and CHIRPS-based cumulative flows for these gauges are summarised in Table 1.

Generally, the CHIRPS-based flows had good correspondence to observed flows. This was illustrated by simulated flows for 67 gauge stations (70%) having a ≤4% difference to the observed flows. This observation demonstrates the utility of CHIRPS estimates as a suitable alternative to the WR2012 catchment rainfall in Pitman modelling.

The CHIRPS-based simulated flows were further assessed for goodness-of-fit using hydrological indices, in order to evaluate their suitability.

Table 1. Streamflow gauges and simulated flows

No.	Gauge	Years	Cumulative flows (Mm^3)				
			(1) Observed	(2) WR2012-Flows	3 CHIRPS-Flows	(2-1/1) WR2012 %Δ	(3-1/1) CHIRPS %Δ
1	B8R001	1981–2009	1 342	1 488	1 301	11%	−3%
2	B8H014	1981–2009	912	986	876	8%	−4%
3	B8R003	1981–2009	573	576	559	0%	−2%
4	B8R005	1981–2002	2 626	2 790	2 445	6%	−7%
5	B8H009	1981–2009	2 853	2 853	3 075	0%	8%
6	B8H010	1981–2009	1 787	1 790	1 638	0%	−8%
7	B8H017	1981–1998	1 922	1 922	2 055	0%	7%
8	B8H008	1981–1998	2 622	2 680	2 715	2%	4%
9	B8H033	1986–1996*	374	407	359	9%	−4%
10	B8H018	2000–2009*	1 577	1 577	1 540	0%	−2%
11	B9H004	1984–2009	434	434	388	0%	−11%
12	B9H003	1984–2009	1 713	1 981	1 705	16%	0%
13	A9R001	1981–2009	300	285	312	−5%	4%
14	A9H007	1981–1998	144	144	149	0%	4%
15	A9H002	1981–1998	414	414	440	0%	6%
16	A9H003	1981–2009	582	582	539	0%	−7%
17	A9H012	1988–2009	6 246	5 924	6 011	−5%	−4%
18	A9H013_A	1981–1998*	1 145	1 120	1 012	−2%	−12%
19	A9H013_B	2004–2009*	540	540	826	0%	53%
20	B3R001	1981–2009	976	976	970	0%	−1%
21	B3R005	1984–2009	1 124	1 137	1 073	1%	−5%
22	B3H021	1989–2009	871	825	914	−5%	5%
23	B3H001	1981–2004	10 984	11 318	11 425	3%	4%
24	B3H007	1981–2009	838	938	759	12%	−9%
25	B4H003	1981–2009	2 972	3 064	2 836	3%	−5%
26	B4H009	1981–2009	484	488	480	1%	−1%
27	B4H010	1981–2009	1 830	1 859	1 769	2%	−3%
28	B4H021	1981–2009	608	608	571	0%	−6%
29	B5R002	1987–2007	10 455	11 887	11 886	14%	14%
30	B5H002	1981–2009	16 576	16 576	15 319	0%	−8%
31	B6H001	1981–2009	4 253	4 509	4 183	6%	−2%
32	B6H003	1981–2009	1 221	1 260	1 205	3%	−1%
33	B6R001	1981–2009	456	451	455	−1%	0%
34	B6H006	1981–2004	65	64	67	−2%	3%
35	B6R003	1981–2004	7 143	7 288	7 290	2%	2%
36	B7H009	1981–1997*	13 813	13 812	13 705	0%	-1%
37	B7R002	1981–2004	28 343	27 223	27 958	−4%	−1%
38	B7H002	1981–2009	245	247	246	1%	1%
39	B7H010	1981–2009	594	624	596	5%	0%
40	B7H014	1981–2009	290	290	305	0%	5%
41	B7H008	1981–1998*	443	443	468	0%	6%
42	B7H019	1988–2009	1 371	1 386	1 361	1%	−1%
43	B7H015	1987–2009	35 032	35 032	35 507	0%	1%
44	B7H004	1981–1998*	390	398	384	2%	−2%
45	B7R001	1981–2000	511	511	496	0%	−3%
46	B1H018	1989–2009	1 180	1 180	1 164	0%	−1%

NB: *Short period of analysis; hence considered 'suspect'

Table 1. Streamflow gauges and simulated flows

No.	Gauge	Years	Cumulative flows (Mm³)				
			(1) Observed	(2) WR2012-Flows	3 CHIRPS-Flows	(2-1/1) WR2012 %Δ	(3-1/1) CHIRPS %Δ
47	B1H005	1981–2005	4 211	4 476	4 277	6%	2%
48	B1H017	1989–2009	725	696	690	−4%	−5%
49	B1H021	1990–2009	1 454	1 615	1 496	11%	3%
50	B1H004	1981–2009	976	1 089	936	12%	−4%
51	B1H019	1990–2009	129	134	123	4%	−4%
52	B1R001	1981–2004	3 398	3 497	3 432	3%	1%
53	B1H002	1981–2009	322	344	293	7%	−9%
54	B1H012	1981–2009	1 520	1 580	1 501	4%	−1%
55	B1R002	1981–2009	1 727	1 695	1 647	−2%	−5%
56	B2H007	1985–2009	330	334	315	1%	−5%
57	B2R001	1981–2004	1 059	1 087	1 064	3%	0%
58	B2H014	1990–2009	1 191	1 228	1 154	3%	−3%
59	B3R002	1981–2009	15 300	17 125	16 226	12%	6%
60	V1R002	1981–2009	18 251	17 882	17 872	−2%	−2%
61	V1H031	1981–2003	266	266	245	0%	−8%
62	V1H041	1981–2009	5 574	5 604	5 538	1%	−1%
63	V1H026	1981–2009	11 890	11 890	11 857	0%	0%
64	V1R001	1981–2009	13 619	13 855	13 661	2%	0%
65	V1H038	1981–2008	6 165	5 975	6 260	−3%	2%
66	V1H010	1981–2009	6 472	6 472	6 674	0%	3%
67	V1H001	1981–2009	20 239	20 952	20 726	4%	2%
68	V1H009	1981–2009	532	557	504	5%	−5%
69	V6H002	1981–2009	43 148	44 608	43 635	3%	1%
70	V2H005	1981–2009	2 900	2 900	2 739	0%	−6%
71	V2H006	1981–2009	1 688	1 637	1 535	−3%	−9%
72	V2H007	1981–2009	824	824	773	0%	−6%
73	V2H002	1981–2009	6 655	6 669	6 672	0%	0%
74	V2H004	1981–2009	8 234	8 131	8 096	−1%	−2%
75	V2H016	1983–2009	664	654	677	−1%	2%
76	V3H010	1981–2009	13 196	13 075	12 997	−1%	−2%
77	V3R001	1981–2009	2 906	2 906	3 047	0%	5%
78	V3H009	1981–2009	587	579	607	−1%	4%
79	V3H007	1981–2009	963	913	825	−5%	−14%
80	V5H002	1981–2009	56 148	56 148	56 189	0%	0%
81	V6H006	1981–2009	308	308	319	0%	3%
82	V6H004	1981–2009	1 722	1 722	1 663	0%	−3%
83	V7H017	1981–2009	2 580	2 580	2 451	0%	−5%
84	V7H016	1981–2009	892	892	879	0%	−1%
85	V7R001	1981–2009	4 319	4 319	4 113	0%	−5%
86	V7H012	1981–2009	623	623	623	0%	0%
87	G1H003	1981–2009	769	834	776	8%	1%
88	G1H020	1981–2009	10 090	9 676	9 705	−4%	−4%
89	G1H037	1981–1991*	283	283	282	0%	−1%
90	G1H041	1981–2009	778	718	761	−8%	−2%
91	G1H036	1981–2009	12 356	12 541	12 393	1%	0%
92	G1H008	1981–2009	2 143	2 280	2 080	6%	−3%
93	G1H013	1981–2009	17 785	15 778	18 275	−11%	3%
94	G1R003	1981–2009	17 872	17 017	18 578	−5%	4%
95	G1H031	1981–2009	17 271	17 271	17 263	0%	0%
96	G2H012	1981–2009	369	370	355	0%	−4%
97	G2H042	1998–2009*	571	571	560	0%	−2%
98	G2H005	1981–2009	571	686	584	20%	2%
99	G2H020	1981–2009	1 227	1 163	1 239	−5%	1%
100	G2H044	2004–2009*	256	276	261	8%	2%
101	L2H003	1981–1991*	180	182	185	1%	3%
102	LH7006	1981–2009	1 502	1 959	1 483	30%	−1%
103	L8R001	1981–2009	3 999	4 001	3 982	0%	0%
104	L9R001	1981–2009	494	514	510	4%	3%

NB: *Short period of analysis; hence considered ‘suspect’

Hydrological indices

The accuracy of a model's simulation of observed flow characteristics is influenced by the availability of a precise spatiotemporal distribution of rainfall within a catchment area (Watson et al., 2021). Rainfall thus serves as the primary source of uncertainty in simulated flows, as highlighted by Sun et al. (2017). Eight hydrological indices were identified in this research to uniquely characterise dynamic catchment responses. The acceptability (goodness-of-fit) of simulated flows was assessed based on how well the simulated flows were able to closely reproduce these indices.

Using a defined ±15% error threshold, gauges that were able to reproduce each of the defined 8 indices were categorised as either 'good', 'suspect', or 'poor', respectively (Kibii and Du Plessis, 2023). This analysis was performed for all the gauge stations, and the results were summarised and spatially illustrated in Fig. 8 (Catchment B), Fig. 9 (Catchment V) and Fig. 10 (Catchment G).

Catchment B consists of 173 quaternary catchments. A total of 134 (78%) quaternary catchments illustrated a 'good' performance of CHIRPS-based flows, while the remaining quaternaries had 11% 'suspect' and 11% 'poor' performance. The catchments experiencing 'poor' performance of CHIRPS-based flows were mainly located in the high-altitude areas (Fig. 1) having high runoff ratios. The high runoff ratios were attributed to steep slopes often resulting in faster catchment response processes, increasing the likelihood of gauging errors associated with high flows and flashy runoff behaviours (McMillan et al., 2012). The 'suspect' catchments were observed to be areas having slight differences in CHIRPS estimates compared to observed rainfall (Fig. 5), hence the disparity between the WR2012 and CHIRPS-based flows. Generally, CHIRPS-based flows performed well for Catchment B.

Catchment V has a total of 86 quaternary catchments. Sixty-three quaternary catchments (73%) have 'good' CHIRPS-based flows, with 5% 'suspect' and 22% 'poor'. This is a generally high-altitude catchment draining into the ocean, and experiencing the KwaZulu-Natal climate. The poor-performing CHIRPS-based flows were attributed to steep upstream topography generating flashy flows into secondary streams, hence highly variable flows with high uncertainties. Downstream the flows in primary rivers stabilise, becoming more predictable, thus CHIRPS-based flows perform well.

Catchment G consists of approximately 35 quaternary catchments. This catchment has a complex topography and experiences winter rainfall, making it difficult for CHIRPS to estimate observed rainfall accurately. However, 80% of the quaternary catchments had 'good', 14% 'suspect', and 6% 'poor' CHIRPS-based flows. This observation contrasts the findings of Pitman and Bailey (2021) and Du Plessis and Kibii (2021) that CHIRPS underestimates winter rainfall, thus resulting in poor flow estimates. The 'suspect' catchments were next to the ocean, which affects satellite data estimation by CHIRPS, hence the 'suspect' flows. Also, mountainous and hilly catchments experience orographic effects which tend to produce high rainfall gradients making it difficult for CHIRPS to estimate observed rainfall (McMillan et al., 2012). The resulting CHIRPS-based flows thus tend to have high error levels. G21A is a dry catchment with CHIRPS underestimating rainfall, hence 'poor' flows.

Catchment L had 'poor' simulated flows. The poor results for this catchment were attributed to several factors: Firstly, the region experiences an 'all year' rainfall, which CHIRPS was unable to estimate accurately due to the nature of the rainfall formation mechanisms, that is, influenced by the warm Indian Ocean currents (Dinku et al., 2018). Also, the catchment had poor gauge station density with only a single usable gauge (L3H001) that had data up to 1984. Upon using Gauges L8R001 & LH7006 (outliers) and L2H003 (with low to zero annual flows) for calibration, the results were bound to be poor, characterised by high uncertainty. The results for this catchment were therefore considered to be of low confidence (dubious) and were not illustrated spatially.

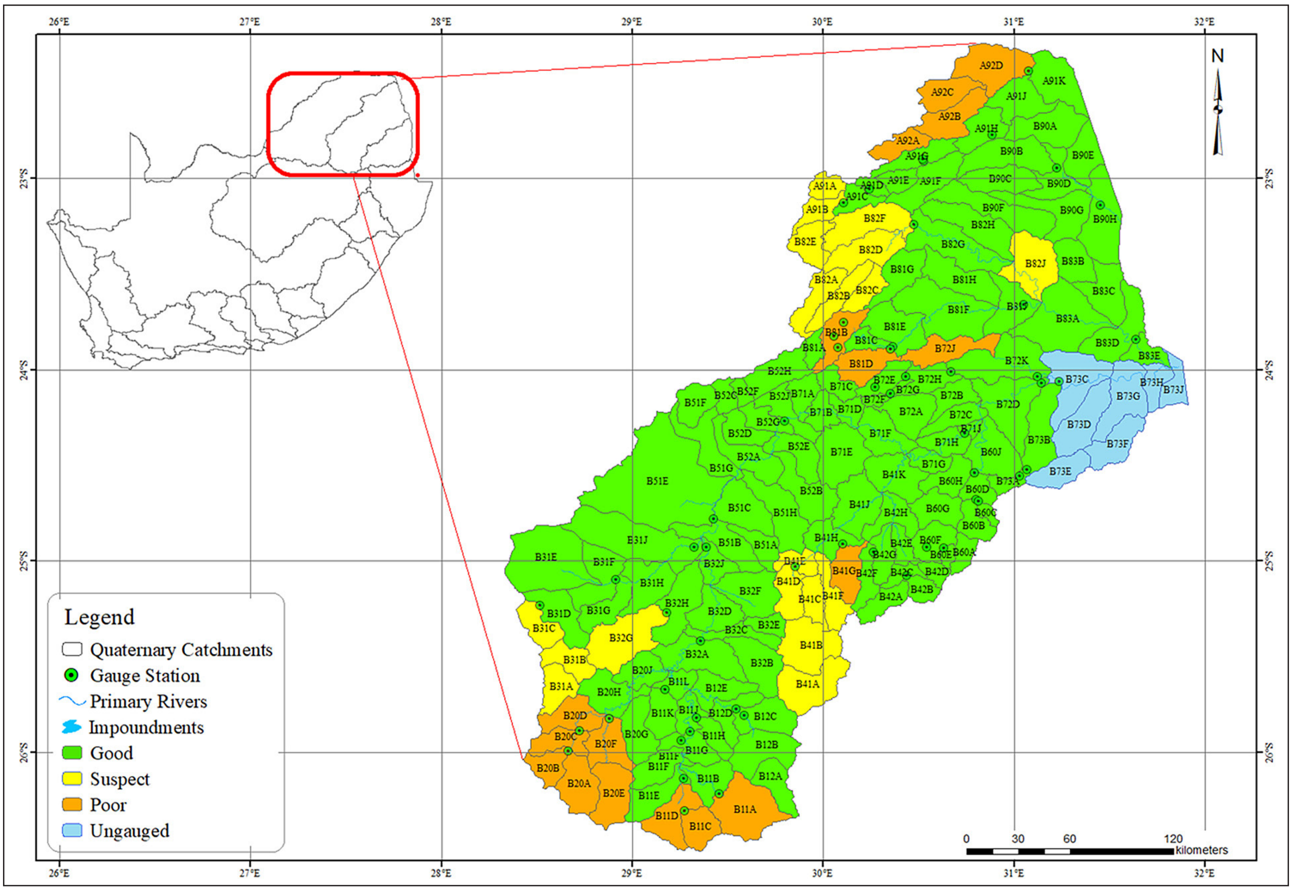

Figure 8. Performance of CHIRPS-based flows for Catchment B

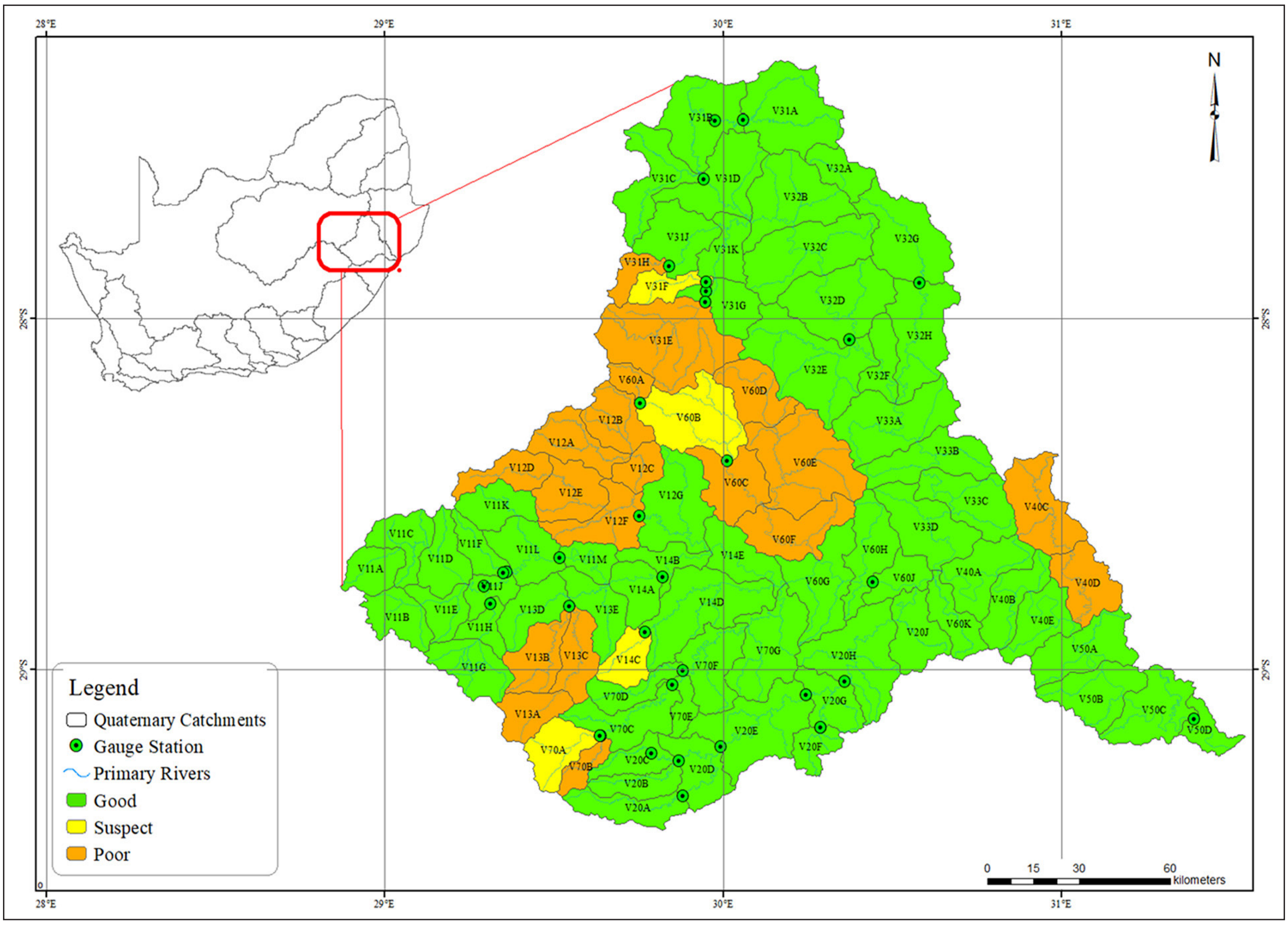

Figure 9. Performance of CHIRPS-based flows for Catchment V

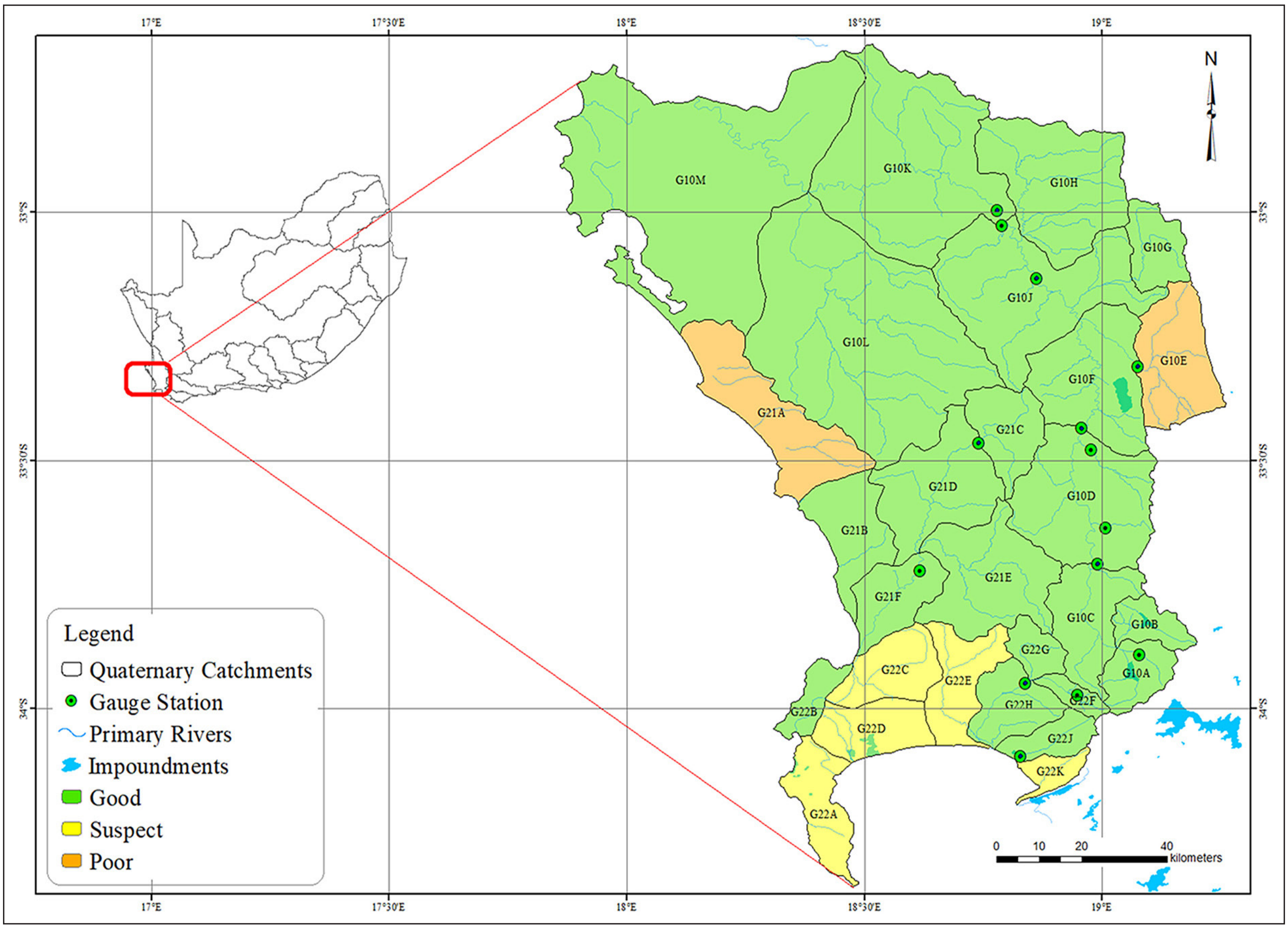

Figure 10. Performance of CHIRPS-based flows for Catchment G (Kibii and Du Plessis, 2023)

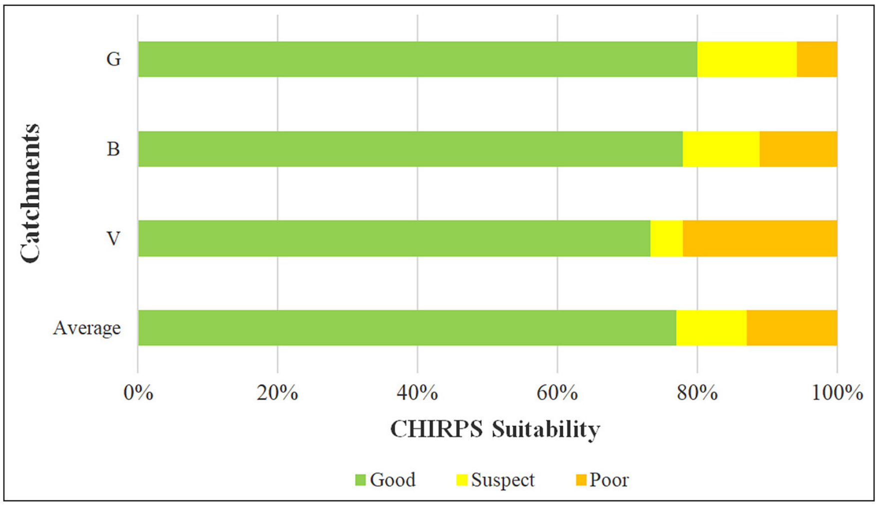

Figure 11. Summary of CHIRPS-based flow performance across selected South African catchments

CHIRPS-based flows were simulated for a total of 351 quaternary catchments in 4 catchments (L, B, G and V). Only Catchment L had high error simulated flows, but the results were considered of low confidence, due to the poor quality of gauge station data used. Taking into consideration the results for Catchments G, B and V, CHIRPS-based flows had an average of 77% suitability. These results illustrate CHIRPS rainfall estimates to be a highly suitable alternative to the WR2012 rainfall data in Pitman modelling for South Africa. A summary of the performance of CHIRPS-based flows for this research is shown in Fig. 11.

CONCLUSION

This research aimed at further developing and testing the CHIRPS-based Pitman model framework across South Africa, by understanding the impact of using adjusted CHIRPS data in simulating catchment hydrological responses while assessing the goodness-of-fit. Goodness-of-fit analyses using hydrological indices targeted increasing confidence in decisions made based on CHIRPS-based flows by reducing the associated risks. Finally, this research aimed at generating knowledge on the possibility of using alternative data in simulating reliable flows for data-scarce regions of South Africa.

The Pitman model is widely used for water resource management in South Africa. Observing a continuous declining trend in workable observed data, this research identified CHIRPS rainfall estimates as a suitable complementary alternative, based on the findings of previous researchers such as Pitman and Bailey (2021) and Du Plessis and Kibii (2021). To achieve the aims of this research, study catchments in Primary Catchments B, V, G and L, representing the varied hydroclimatic regions of South Africa, were selected.

CHIRPS data were downloaded, and correlation was done to the WR2012 catchment rainfall data. The correlation analysis illustrated a strong correlation, of $R^2 > 0.7$, in all of the study catchments except Catchment L, which had some sub-catchments with $R^2 \leq 0.5$. The low correlation in Catchment L was attributed to frontal systems along the coastline which influence the nature and amount of rainfall, hence the low correspondence with CHIRPS, as observed by Dinku et al. (2018). The strong correlation in the summer rainfall regions (B and V) complements the findings of Duan et al. (2016), while the observed strong correlation in the winter rainfall region, represented here by Catchment G, contrasts the observations of Du Plessis and Kibii (2021).

The relationship between CHIRPS and WR2012 catchment rainfall was used as a calibration factor for the adjustment of CHIRPS. Although the CHIRPS adjustment period was relatively short (29 years) compared to the timespan of WR2012 rainfall data (> 100 years), this research observed CHIRPS to demonstrate a strong correlation with observed data ($R^2 > 0.7$) in the majority of the study catchments. While gauge station density continues to decline, this research highlights the strong correlation results (and developed calibration factors) as a demonstration of the robustness of CHIRPS in replicating observed (WR2012) rainfall during wet and dry seasonal cycles experienced within a climate.

After adjustment, CHIRPS and WR2012 rainfall were compared. Similar to the findings of Dinku et al. (2018), CHIRPS was observed to overestimate rainfall in the relatively low rainfall areas in Catchment V and Catchment L, while underestimating rainfall in the wetter areas of Catchment B. In Catchment G, CHIRPS underestimates observed rainfall. Tote et al. (2015) highlight that satellite sensors detect proxy variables and utilise their relationship with measured rainfall to generate CHIRPS estimates. Low cloud cover, ice, and snow cover associated with winter rainfall often tend to interfere with satellite signals (Tian et al., 2007). The low cloud cover, and sometimes snow, in high altitude regions of Catchment G, would likely result in satellite estimation errors and hence the observed CHIRPS underestimations in Catchment G.

The adjusted CHIRPS data were then used to run the Pitman model for the calibration (1981–2009) and validation (2010–2019) periods. At least 69% of the gauges (72 of 104) had a ≤4% difference between observed and simulated CHIRPS-based flows. These results illustrate that CHIRPS performs well in simulating observed flows. Further, this research proceeded to assess the goodness-of-fit for CHIRPS-based flows using hydrological indices.

Hydrological indices are identifiers of a catchment's hydrological response (Kapangaziwiri et al., 2012). Whereas the Pitman model has structural inadequacies in representing the real-life complex runoff processes, rainfall data (CHIRPS for this case) were considered to be the primary source of uncertainty (Beven and Westerberg, 2011). Eight hydrological indices (MMQ, Q_{10}/MMQ, Q_{50}/MMQ, Q_{90}/MMQ, slope$_{MMQ}$, CV$_{MMQ}$, Q/P and PE/P) were identified and used to characterise catchment hydrological responses. Where CHIRPS-based flows were able to adequately replicate these indices within a defined ±15% error threshold, the flows were deemed suitable. Where these indices were not within the defined threshold of acceptable error, simulated flows were considered highly uncertain ('poor') and hence unreliable for decision-making. This analysis was performed for all of the study catchments.

Generally, the results illustrated a 77% suitability for CHIRPS-based flows across the South African catchments. CHIRPS-based flows for high-altitude areas with steep slopes were observed to be either 'poor' or 'suspect'. These 'poor' and 'suspect' performances are attributed to high mountains receiving orographic rainfall characterised by steep rainfall gradients that CHIRPS estimates are unable to accurately approximate (McMillan et al., 2012), hence the high error levels. Mountainous areas have steep slopes and shallow soils and tend to receive a lot of precipitation with low evapotranspiration (Markovich et al., 2021). These conditions result in faster catchment response systems with flashy flows, associated with errors and high uncertainties (McMillan et al., 2012). These high uncertainties in mountainous areas, mostly in the headwaters, present a direct conflict with their hydrologic significance as water towers (McMillan et al., 2012). The poor performance of CHIRPS-based flows for Catchment L was attributed to rainfall mechanisms and the unavailability of suitable gauges for analysis.

In conclusion, this research found CHIRPS rainfall estimates to be a suitable complementary alternative to the declining observed catchment rainfall in simulating hydrological responses across South Africa using the Pitman model.

DECLARATION OF COMPETING INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

JK Kibii: conceptualisation, methodology, analysis and writing original draft. JA Du Plessis: conceptualisation, methodology, review and editing.

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