RainCheck Africa: A Systematic Review and Meta-Analysis of Gridded Precipitation Dataset Performance at Continental Scale

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Abstract. Gridded rainfall products are indispensable for water resource management, agricultural monitoring, and disaster risk reduction across Africa, yet no systematic synthesis of their performance has been conducted. We present RainCheck Africa: a PRISMA-compliant systematic review and meta-analysis of 72 peer-reviewed studies published between 2015 and 2025 evaluating satellite, reanalysis, and merged products against ground observations across Africa, covering 1,749 metric observations across 148 locations and 154 product variants. Three findings emerge. First, correlation improves by 0.23 units from the daily to dekadal scale across all product families, confirming that gridded products are more reliable for climate monitoring and drought assessment than for daily event-based applications. Second, overestimation and underestimation co-occur in 90% and 87% of extraction entries respectively; this is not a contradiction but two expressions of the same intensity-dependent bias structure. Third, the daily Nash-Sutcliffe Efficiency of uncorrected products across 105 observations is centred near zero, meaning raw products applied directly to rainfall-runoff models perform no better than the long-term mean: bias correction is a prerequisite. Product performance is context-dependent. Reanalysis products are consistently outperformed and should not be used as primary rainfall inputs. CHIRPS v2.0 has the broadest validation base among global products; IMERG Final is the emerging standard for daily applications, though its corpus-level performance is concentrated in Ethiopian highland contexts and carries wide uncertainty elsewhere. Nine African Union member states have no validation study in the corpus, and the Congo Basin remains uncharacterised; this circularity can only be broken by expanded observation networks and open data-sharing.

1 Introduction

Rainfall is the primary driver of agricultural production, water availability, and livelihood security across Africa in a manner that sets the continent apart from any other inhabited region. An estimated 95% of African cropland is rain-fed (Bagiliko et al., 2025), meaning that interannual and sub-seasonal variability in precipitation translates almost directly into variability in food security, rural incomes, and household welfare. Droughts routinely displace millions and destabilise food systems across the Sahel, the Horn of Africa, and southern Africa; at the same time, flash floods and riverine inundation, events intensifying in frequency and severity under anthropogenic climate change, rank among the continent's deadliest natural hazards (Kikstra et al., 2022). In Ethiopia alone, climate extremes have driven widespread crop failure, forage and water shortages, livestock mortality in pastoralist communities, and a recurring need for emergency food aid averaging US$1.1 billion annually (Mera, 2018; Tola et al., 2025). Against this backdrop, accurate, timely, and spatially resolved precipitation information is not merely a scientific convenience: it is a prerequisite for effective water resources management, agricultural planning, disaster risk reduction, and climate adaptation across the continent (Dinku, 2020; Dinku et al., 2018).

Yet Africa's capacity to observe its own rainfall remains profoundly limited (Dinku, 2020). The continent's rain gauge network is the sparsest of any inhabited landmass, and it has been shrinking for decades. The number of African stations contributing to the Global Precipitation Climatology Centre (GPCC) full-data product has declined substantially since the 1980s (Dinku, 2020). Large areas of the Sahara, the Congo Basin, and the Horn of Africa contain fewer than one operational gauge per 10,000 km^2, far below the minimum densities recommended by the World Meteorological Organization for hydrological applications (Kidd et al., 2017). Where gauges do exist, they are unevenly distributed, concentrated in cities and towns along major transport corridors, leaving coverage weakest in rural and remote areas where livelihoods are most vulnerable to climatic variability (Dinku, 2020; Gebremicael et al., 2019). Even in Ethiopia, which operates one of Africa's comparatively denser networks with over 1,372 manual stations and approximately 300 automatic weather stations, significant gaps persist in lowland and conflict-affected regions, and data availability has been severely disrupted by security crises (Tola et al., 2025). Compounding the physical scarcity of observations is a pervasive institutional barrier: many African gauge records remain inaccessible to the international research community because of data-sharing restrictions and limited digitisation capacity (Dinku, 2019, 2020). The practical consequence is that ground-based observations alone cannot support the spatial and temporal resolution of rainfall monitoring that African decision-makers urgently require.

To bridge this observational gap, the remote sensing and climate modelling communities have developed a diverse portfolio of gridded rainfall datasets over the past two to three decades. These products provide spatially continuous precipitation estimates at resolutions ranging from 0.04° to 2.5° and at temporal frequencies from sub-hourly to monthly, covering periods extending in some cases back to 1981. They fall broadly into three categories. Satellite-based estimates infer rainfall indirectly from cloud-top brightness temperature observed by infrared (IR) sensors on geostationary platforms, or from hydrometeor emission and scattering signals measured by passive microwave (PMW) radiometers on low-Earth orbit satellites (Kidd and Huffman, 2011; Macharia et al., 2022). The most widely used global products in this family include TRMM Multi-Satellite Precipitation Analysis (TMPA), the Global Precipitation Measurement (GPM), Integrated Multi-satellitE Retrievals (IMERG), PERSIANN and its derivatives, CMORPH, and GSMaP; African-specific products TAMSAT and TARCAT exploit locale-specific IR calibrations (Maidment et al., 2017; Huffman et al., 2007; Joyce et al., 2004). Reanalysis datasets, principally ERA5 (ECMWF), MERRA-2 (NASA), and JRA-55, reconstruct the atmospheric state by assimilating diverse observations into numerical weather prediction models, yielding precipitation as a model-derived diagnostic (Hersbach et al., 2020). Merged or gauge-satellite products combine the spatial coverage of satellites with the accuracy of ground observations through statistical blending or bias-correction algorithms. CHIRPS, CPC RFE 2.0, ARC2, MSWEP, and GPCC are the most prominent, and have become workhorses for African climate monitoring and hydrological modelling (Funk et al., 2015; Satgé et al., 2020). The ENACTS initiative, developed at IRI Columbia and now operational across over 15 African countries, combines quality-controlled national station data with satellite estimates at 4 km resolution extending back to 1981 (Dinku et al., 2022; Tola et al., 2025).

Despite their utility, gridded precipitation products carry substantial and spatially heterogeneous uncertainties whose physical origins are now well understood. IR-based algorithms exploit cold cloud duration, assuming that colder, taller clouds produce more rainfall; this assumption fails systematically over coastal and mountainous regions where shallow warm clouds generate substantial precipitation that IR sensors cannot detect (Dinku, 2020; Dinku et al., 2011). PMW algorithms interact more directly with precipitation particles, but are constrained by coarse spatial resolution (10–50 km), limited overpass frequency, and surface emissivity ambiguities over land (Kidd and Huffman, 2011). Over arid and semi-arid zones, satellite retrieval algorithms are prone to systematic overestimation driven by sub-cloud evaporation of detected hydrometeors, desert aerosol effects, and surface emissivity patterns that mimic precipitation signatures, with false alarm ratios exceeding 90% reported over the driest parts of the Sahara (Dinku et al., 2010). Reanalysis products must parameterise deep convection at resolutions that smooth steep orographic gradients and are further compromised by the limited availability of assimilation data from Africa (Dinku, 2020; Diro et al., 2011). Merged products are constrained by the gauge networks they assimilate: the number of stations used in CHIRPS has declined drastically across most of Africa, potentially introducing temporal inhomogeneities that complicate trend analysis (Dinku, 2020). These fundamental retrieval characteristics explain why no single product consistently outperforms all others across the continent's heterogeneous climates, terrains, and rainfall regimes (Camberlin et al., 2019; Satgé et al., 2020).

Recognition of these uncertainties has prompted a rapidly growing body of validation research. Over the past decade, dozens of studies have evaluated gridded rainfall products against gauge observations across African countries and river basins, ranging from single-product assessments in individual watersheds to multi-product comparisons at continental scale. Dinku (2020) attempted to summarise the main validation results for selected satellite products but concluded that this was “a daunting task” because different authors used different validation approaches and different ways of presenting results, the spatial extent of validations varied widely, and results for the same product at the same location were sometimes inconsistent. This fragmentation means that practitioners in African water agencies, agricultural extension services, and disaster management authorities who seek guidance on which product to use for a given application must navigate a scattered and sometimes contradictory literature with no consolidated, evidence-based resource to support their decision-making.

This situation calls for a formal systematic synthesis. While earlier reviews have discussed satellite rainfall estimation in Africa (e.g., Dinku et al., 2018; Sun et al., 2018), none has undertaken a systematic review with standardised data extraction and meta-analysis across the full spectrum of satellite, reanalysis, and merged products evaluated against ground observations across the African continent. Dinku (2020) explicitly called for "a comprehensive validation of the main operational satellite products at a continental level" to overcome the challenges created by inconsistent evaluation approaches. The present study answers that call through a systematic review of 72 peer-reviewed studies following the PRISMA framework, supplemented by a quantitative meta-analysis of extracted performance metrics that enables pooled estimation of product accuracy and its moderating factors across products, regions, temporal scales, and applications. Our analysis is structured around five research questions:

1. What validation approaches and metrics are commonly used to evaluate gridded rainfall products in Africa?
2. Which products have been evaluated, and how do satellite-only, reanalysis, and merged datasets compare in terms of accuracy across regions and temporal scales?
3. What systematic error patterns (including biases, detection failures, and performance degradation at fine temporal scales) are consistently reported across the literature?
4. To what extent do performance limitations exhibit geographic specificity?
5. What are the key research gaps and priorities for improving gridded rainfall products for the modeling and planning of African water resources?

By consolidating and quantitatively synthesising insights from across this literature, this study makes three primary contributions. First, it provides the first meta-analytic assessment of gridded rainfall product performance across Africa, enabling pooled accuracy estimates with associated uncertainty and explicit modelling of the moderating roles of product type, geographic region, climate zone, and temporal aggregation scale. Second, it offers evidence-based, application-specific guidance for dataset selection across drought monitoring, flood forecasting, hydrological modelling, and climate trend analysis, translating an often-inaccessible scientific literature into practical decision support. Third, it maps the geographic and thematic gaps in existing validation evidence, identifying the observational and methodological investments most urgently needed to improve rainfall data quality across the continent. The remainder of this paper is organised as follows. Section 2 describes the systematic review methodology and meta-analysis framework. Section 3 presents the results. Section 4 discusses implications, practical recommendations, and research priorities. Section 5 concludes.

2 Methods

This study follows the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework across all phases: literature search, screening, eligibility assessment, data extraction, and quantitative synthesis (Figure 1). The quantitative synthesis applies two complementary approaches selected according to data density: subgroup pooling where sufficient comparable observations exist, and distribution characterisation elsewhere. This design was chosen in preference to a classical random-effects meta-analysis because the between-study heterogeneity in this literature, arising from differences in study region, gauge density, spatial aggregation approach, product version, and evaluation design, is so substantial that a single pooled effect size would carry very wide uncertainty and limited practical interpretability. Where pooling is performed, it is restricted to subgroups within which study designs are sufficiently comparable to support meaningful aggregation.

2.1 Literature Search

A systematic search was conducted across three bibliographic databases: Web of Science, Scopus and Google Scholar, executed in February 2025. The search strategy combined three thematic blocks using Boolean operators. The first block targeted gridded precipitation products using terms including “gridded rainfall”, “satellite rainfall”, “satellite precipitation”, “reanalysis precipitation”, “precipitation validation”, “rainfall assessment”, and the names of specific products (CHIRPS, TAMSAT, IMERG, TRMM, ERA5, PERSIANN, CMORPH, ARC2, RFE, MSWEP, and related variants). The second block targeted evaluation activities using terms including “validation”, “accuracy”, “bias”, “evaluation”, “verification”, and “comparative analysis”. The third block restricted results geographically using both continental terms (“Africa”, “sub-Saharan Africa”, “Horn of Africa”, “Sahel”, “Congo Basin”) and the names of all 55 African Union member states. Full search strings for each database are provided in Appendix A6. The initial searches returned 427 records from Web of Science and 228 from Scopus, yielding 655 candidate articles before deduplication. Google Scholar was searched iteratively to identify records missed by the indexed databases, and backward citation tracking of key review papers was performed to identify additional relevant studies.

2.2 Screening and Eligibility Assessment

After removing 179 duplicates, 476 unique records were screened at title and abstract level by reviewers. Five initial inclusion criteria were applied: (a) the study evaluates one or more named gridded rainfall products against ground-based observations; (b) the study area includes at least one African country or region; (c) the study reports quantitative validation statistics; (d) the study is published in English; and (e) the study validates rainfall specifically. Studies were excluded if they contained no comparison with surface observations ($n = 247$), were not Africa-focused ($n = 18$), reported no evaluation metrics ($n = 25$), did not validate rainfall ($n = 19$), or operated exclusively at temporal scales coarser than sub-monthly ($n = 38$). Of 129 records assessed at full-text stage, 57 were further excluded principally for lacking sub-monthly temporal evaluation. The final corpus comprised 72 peer-reviewed studies.

2.3 Data Extraction

A standardised extraction form was developed collaboratively by the research team and piloted on five studies before full deployment. For each eligible study, the following information was extracted:

- *Study-level metadata:* authors, publication year, DOI, study region and basin, African climate zone, validation period, and number of gauge stations used.
- *Products evaluated:* full product name and version, spatial and temporal resolution, product family (satellite-only, reanalysis, or merged), and whether gauge adjustment was applied.

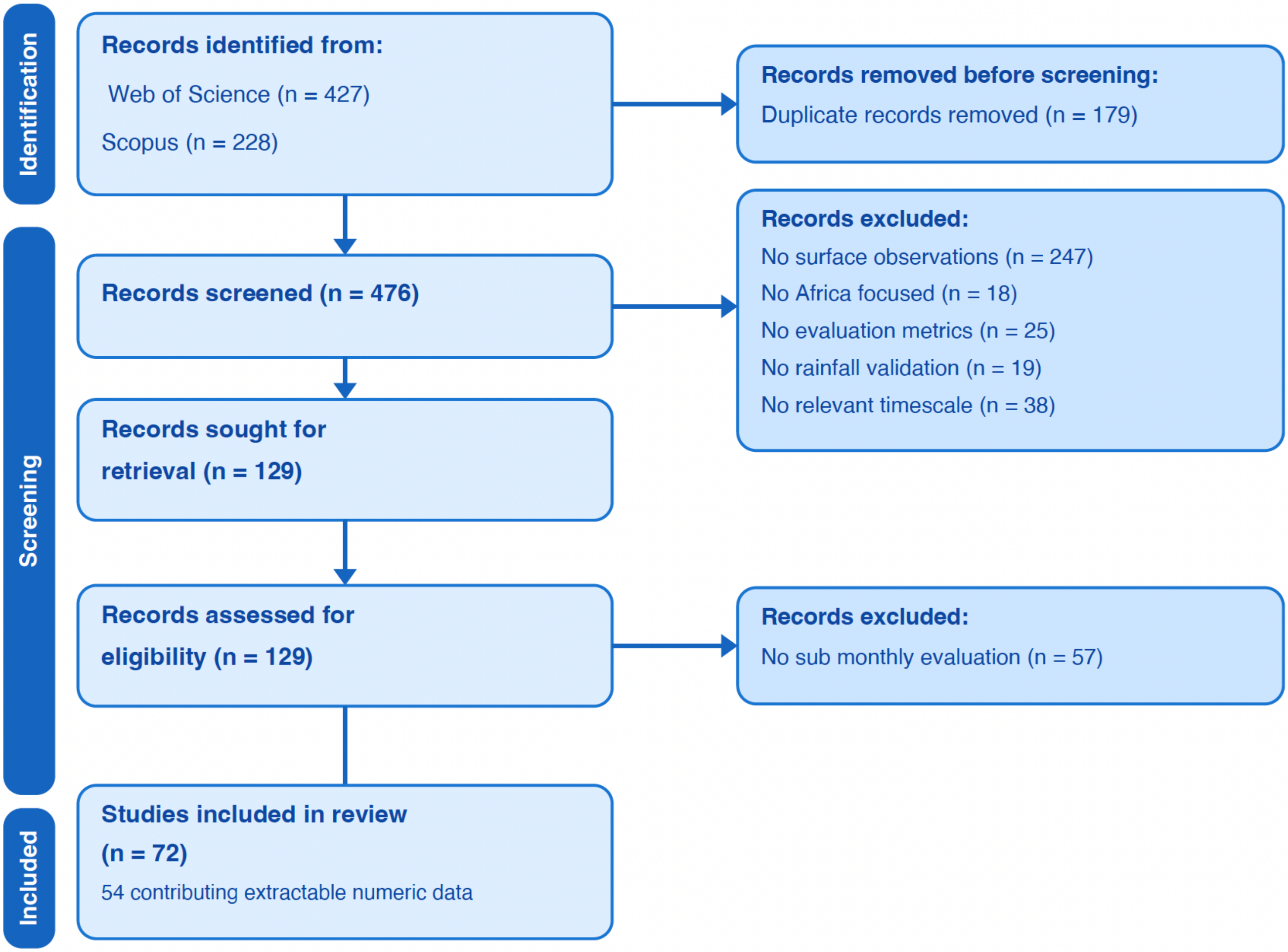

Figure 1. PRISMA flow diagram for the systematic literature search, screening, and eligibility assessment. Phase labels (Identification, Screening, Included) appear on the left sidebar; exclusion reasons with counts branch to the right at each stage. The single largest exclusion at full-text stage was absence of sub-monthly temporal evaluation

- *Validation methodology:* comparison approach (point-to-pixel or pixel-to-pixel), spatial aggregation strategy, and temporal scales evaluated (sub-daily, daily, pentadal, dekadal, monthly, seasonal, or annual).
- *Quantitative performance metrics:* all reported metric values extracted verbatim and recorded alongside their associated product, location, and temporal scale. Metrics extracted include Pearson correlation coefficient (CC), root mean square error (RMSE), mean absolute error (MAE), bias and percentage bias (PBIAS), Kling-Gupta Efficiency (KGE), Nash-Sutcliffe Efficiency (NSE), probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI).
- *Error pattern classification:* each study was coded for the presence or absence of six pre-defined error categories: (1) overestimation of rainfall amounts, (2) underestimation of rainfall amounts, (3) poor detection of heavy rainfall events, (4) underestimation in high-altitude areas, (5) orographic rainfall difficulty, and (6) weak performance at daily or sub-daily time steps.

2.4 Quantitative Synthesis

The extraction database contains 1,749 individual metric observations across 54 studies, 148 unique locations, and 154 product name variants spanning six temporal scales. Two complementary synthesis strategies were selected a priori and applied according to data density and comparability within each subgroup.

2.4.1 Product Harmonisation

The 154 unique product name strings in the extraction database reflect inconsistent naming conventions and version numbering across studies. Prior to synthesis, all product strings were harmonised to a canonical name-version scheme. For example, the strings "CHIRPS", "CHIRPSv2", "CHIRPS V2.0", "CHIRPS-V2", and "CHIRPS2" were all mapped to the canonical label CHIRPS. Products were then classified into four primary families: (1) satellite-only estimates, encompassing TRMM/TMPA, GPM IMERG and its early/late/final run variants, PERSIANN and its CDR/CCS/RT derivatives, CMORPH and its adjusted variants, GSMaP, TAMSAT/TARCAT, and SM2RAIN; (2) reanalysis products, encompassing ERA5, ERA5-Land, MERRA-2, JRA-55, CFSR, EWEMBI, and WFDEI variants;(3) merged encompassing CHIRPS, ARC2, RFE2, MSWEP, GPCC, and ENACTS ; and (4) gauge-adjusted products, including GPCC and PRISM. A complete list of canonical product names, version strings, periods of record, and study counts is provided in Table A1.

2.4.2 Subgroup Pooling

Subgroup pooling was applied where a metric-product combination had at least five independent daily-scale observations from distinct studies or gauge networks. These criteria were met for CC at the daily scale for 13 canonical products, with observation counts ranging from $n = 5$ to $n = 64$. Bias metrics at the daily scale met the threshold for 11 products.

For each qualifying subgroup, the median, interquartile range (IQR, 25th–75th percentile), and full range (minimum to maximum) were computed. The median was preferred over the mean as the measure of central tendency because the metric distributions are right-skewed and contain outliers driven by individual studies in topographically extreme or data-sparse settings. For CC, values were Fisher z-transformed prior to computing the median and IQR, then back-transformed to the correlation scale for reporting, to account for the bounded and asymmetric distribution of correlation coefficients near ± 1. Results are presented as box plots stratified by product and product family (Figures 6 and 7).

2.4.3 Distribution Characterisation

For metrics or temporal scales where observation counts per product were insufficient for subgroup pooling (fewer than five observations), distribution characterisation was used. This approach describes the range and central tendency of reported values across the full evidence base without attempting to attribute differences to specific moderators. Metrics treated in this way include NSE ($n = 105$ daily observations), KGE ($n = 77$), POD ($n = 151$), FAR ($n = 144$), and CSI ($n = 91$) at the daily scale, as well as all metrics at sub-daily and dekadal scales.

2.4.4 Evidence Matrix for Error Patterns

For the six error-pattern categories coded at study level, a structured evidence matrix was constructed tabulating the number and proportion of extraction entries reporting each pattern by product family, geographic region, and temporal scale. Patterns reported in more than 50% of entries within a subgroup are treated as consistent findings; patterns reported in 25–50% of entries are treated as emergent; and patterns reported in fewer than 25% of entries are noted but not emphasised.

2.5 Qualitative Synthesis

Alongside the quantitative synthesis, a structured qualitative synthesis was conducted to capture study findings that cannot be represented as extractable numeric values, including narrative descriptions of spatial error patterns, topography-performance interactions, and application-specific recommendations made by study authors. The qualitative synthesis employed a convergent-integrated design in which quantitative distribution findings and qualitative thematic patterns were developed in parallel and integrated in the Discussion. Geographic patterns in study coverage were mapped by attributing each extraction entry to the countries for which gauge data were used, allowing identification of regions where validation evidence is sparse relative to geographic extent (see Figure 3 and Supporting Information).

2.6 Software and Reproducibility

All quantitative analyses were conducted in Python. The full extraction database, analysis scripts, and reproducibility documentation are archived in a publicly accessible repository (Zenodo, DOI to be inserted upon acceptance) to enable verification and future updating of the synthesis. An interactive dashboard allowing practitioners to query product recommendations by country, application, and temporal scale is available at https://africlimate-research.github.io/RainCheckAfrica/ (see Figure 2).

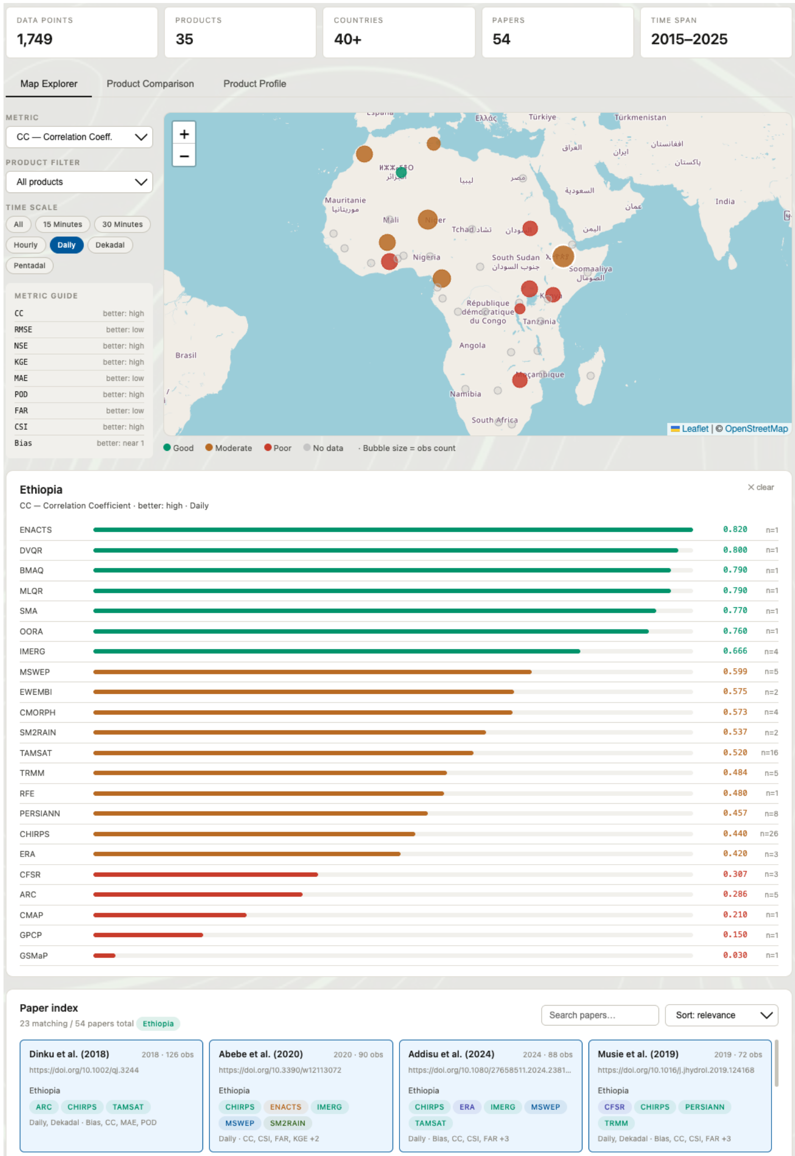

Figure 2. The RainCheck Africa interactive dashboard. The Map Explorer tab (shown) displays median correlations by country and product for a user-selected metric, product filter, and temporal scale. The Product Comparison and Product Profile tabs provide ranked bar charts and per-product summaries. Practitioners can filter by country, application domain, and temporal scale to retrieve evidence-based product guidance."

3 Results

The systematic review identified 72 peer-reviewed studies published between 2015 and 2025, yielding 54 data-extraction entries and 1,749 individual metric observations across 148 unique locations and 154 product name variants. All quantitative analyses are performed at the product parent level (e.g., CHIRPS, IMERG, TAMSAT, TRMM), aggregating across versions and regional variants to ensure sufficient observation counts for meaningful synthesis. Results are organised into five subsections: study and corpus characteristics (Section 3.1), validation approaches and metrics (Section 3.2), performance by temporal scale (Section 3.3), product-level performance at the daily scale (Section 3.4), and systematic error patterns with geographic distribution (Section 3.5).

3.1 Study and Corpus Characteristics

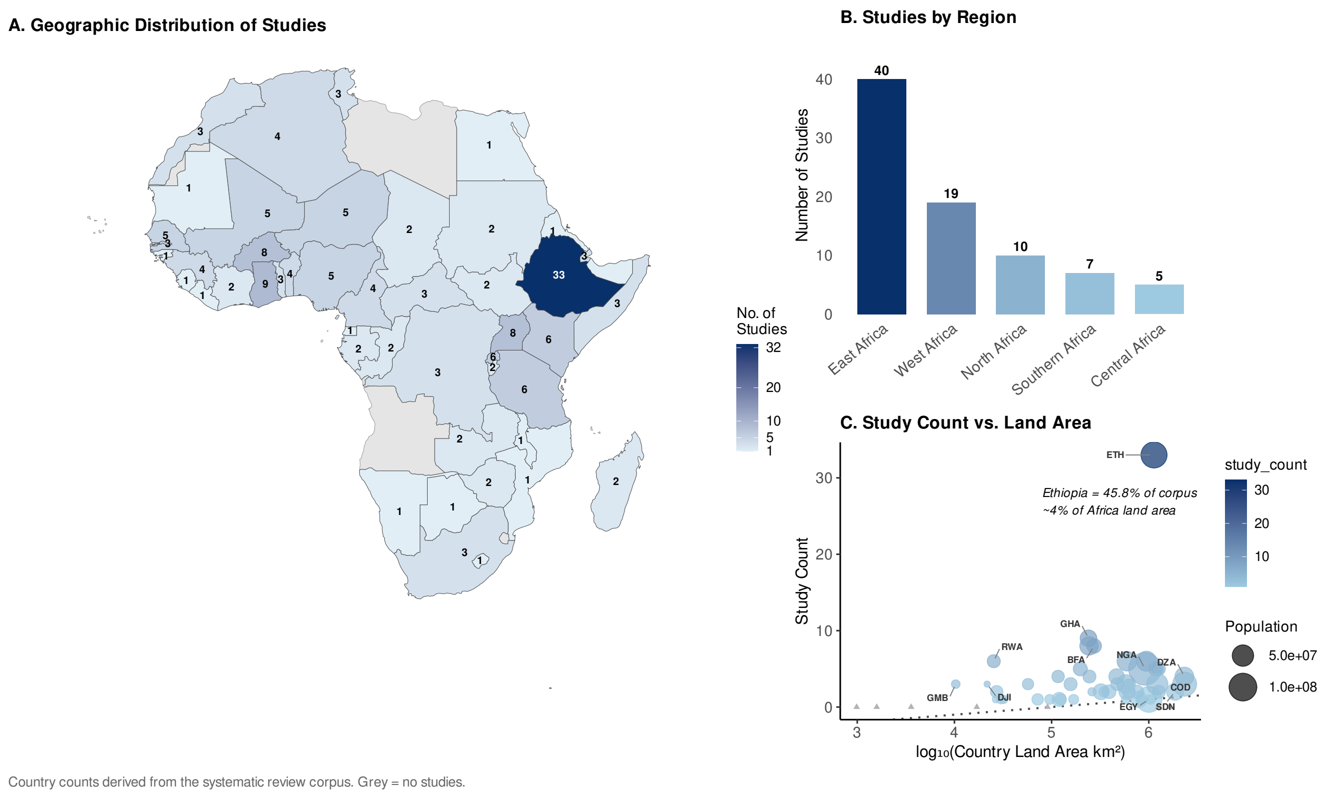

Figure 3. Geographic distribution of the 72 included studies. (A) Choropleth map: colour intensity (white to deep blue) proportional to study count per country; grey = zero studies. (B) Regional bar chart. (C) Study count versus log-transformed country land area; bubble size proportional to national population. The diagonal reference line marks proportional representation (one study per million km^2); countries above the line are over-represented relative to land area, those below under-represented. Countries with zero representation are listed in Table A2.

Publication volume increased substantially across the review period: only 14 studies between 2015 and 2018, whereas 25 appeared in 2023–2025. The geographic distribution is highly concentrated (Figure 3). East Africa dominates with 40 studies, driven overwhelmingly by Ethiopia (33 studies, 46% of the corpus). West Africa contributes 19 studies concentrated in Ghana (9), Burkina Faso (8), Senegal (5), Nigeria (5), and Niger (6). North Africa provides 10 studies from Algeria (4), Tunisia (3), Morocco (3), and Egypt (1). Southern Africa contributes 7 studies and Central Africa only 5, with the Democratic Republic of Congo represented by a single study. Nine African Union member states have no representation in the corpus (4 mainland states, 5 island states); the full list is provided in Table A2.

The product evaluation landscape spans all three families (Figure 4). CHIRPS leads with 34 studies, followed by TAMSAT (19), PERSIANN-CDR (19), TRMM/TMPA (18), IMERG (15) and CMORPH (14). Reanalysis products appear as primary evaluation targets in 10 studies. The dominance of CHIRPS is important for interpreting synthesis statistics: pooled estimates for CHIRPS rest on the largest observation counts in the database, providing substantially more stable central estimates than IMERG or ERA5. A complete tabulation of product versions and study counts is provided in Table A1.

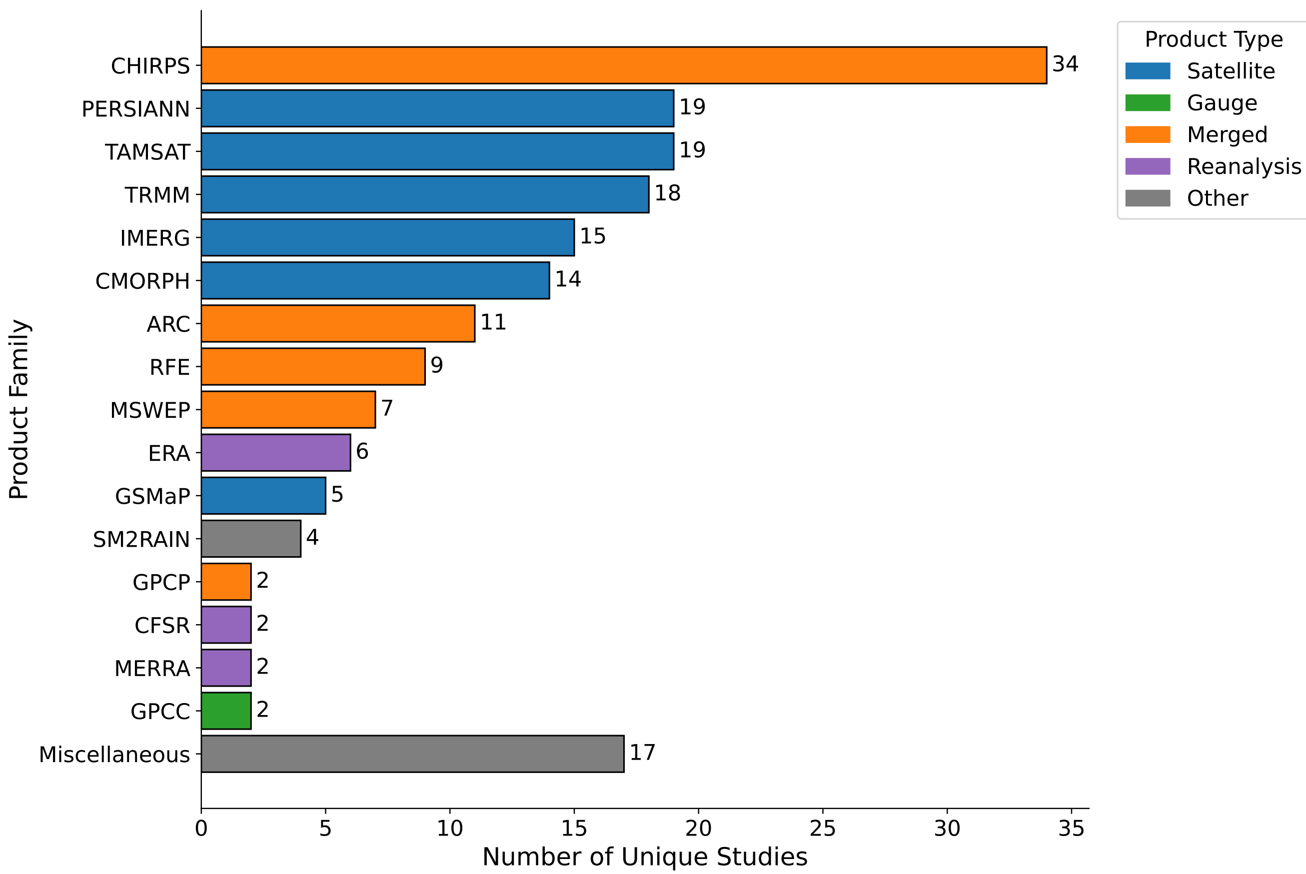

Figure 4. Number of unique studies evaluating each gridded rainfall product, ranked in descending order. Bars are colour-coded by product family. Study counts are annotated at the right of each bar. Products appearing in only a single study are grouped at the bottom.

3.2 Validation Approaches and Metrics

Point-to-pixel comparison was used in 61 of 72 studies (85%) with pixel-to-pixel comparison in only 9. The remaining two studies used both methods. Daily temporal scale evaluation was reported in 64 of 72 studies (89%), monthly in 51 (71%), seasonal in 20 (27%), annual in 23 (32%), dekadal in 13 (18%), pentadal in 5 (7%) studies and sub-daily in 15 (21%). Table 1 summarises metric frequency and synthesis database observation counts. Pearson correlation coefficient is the most widely reported metric (CC, 41 studies), followed by percentage bias (PBIAS, 33 studies), root mean square error (RMSE, 31 studies), probability of detection (POD, 28 studies), false alarm ratio (FAR, 24 studies), mean absolute error (MAE, 18 studies), critical success index (CSI, 16 studies), Nash-Sutcliffe Efficiency (NSE, 12 studies), and Kling-Gupta Efficiency (KGE, 6 studies).

Table 1. Validation metrics extracted across the included studies, ranked by frequency of use. Observation counts reflect all extractable numeric values across all products, regions, and temporal scales; daily-scale counts are shown separately in parentheses as these form the primary basis for subgroup pooling.

Metric	Studies (n)	Observations (n)
CC	41	399 (297 daily)
Bias / PBIAS	33	277 (188 daily)
RMSE	31	246 (188 daily)
POD	28	177 (151 daily)
FAR	24	173 (144 daily)
MAE	18	163 (94 daily)
NSE	12	114 (105 daily)
KGE	6	77 (77 daily)
CSI	16	111 (91 daily)

3.3 Performance by Temporal Scale

Figure 5 shows median CC and Bias, MAE, and RMSE across temporal scales from 30 minutes to dekadal, and confirms the most consistent quantitative finding in this corpus: a monotonic improvement in all performance metrics as temporal aggregation increases, reported in 52 of 72 extraction entries across all product families and regions.

At the sub-daily scale, satellite products at 30-minute resolution have a median CC of 0.235 (n = 4), with performance further degraded by retrieval timing mismatches (Bounab et al., 2025). At the daily scale, products show a median CC of 0.47 (IQR = 0.36–0.60, n = 297). At the dekadal scale, median CC rises to 0.70, representing gains of approximately +0.23.

The monotonic improvement in performance with extended timescales holds across all product families and are independent of geographic region, confirming that temporal aggregation is the single most reliable lever available to practitioners seeking to improve product skill without additional calibration data.

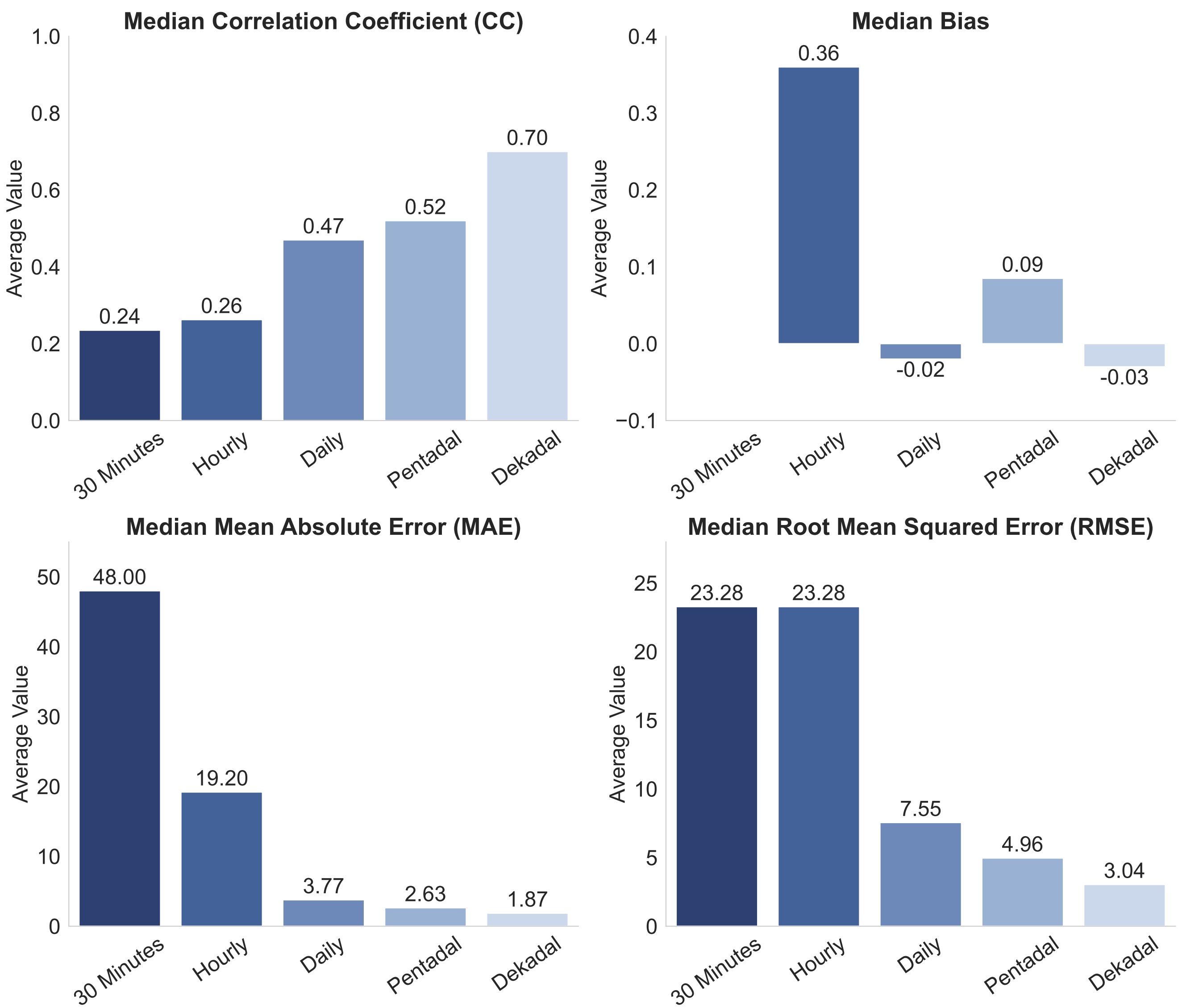

Figure 5. Validation metric values by temporal aggregation scale, restricted to scale–metric combinations with five or more observations. Four panels: (A) Median Correlation Coefficient (CC); (B) Bias; (C) Mean Absolute Error (MAE, mm per aggregation period); (D) Root Mean Square Error (RMSE, mm per aggregation period). Darker bars correspond to shorter aggregation periods; lighter bars to longer periods. Only scale–metric combinations with n≥5 observations are shown.

3.4 Product-Level Performance at the Daily Scale

All analyses in this section are conducted at the product parent level, grouping product versions and regional variants under their canonical parent name (e.g., TRMM 3B42, 3B42V7, and 3B42RT all analysed under TRMM; CHIRPS v2.0 and CHIRP analysed under CHIRPS). This approach ensures sufficient observation counts per product for meaningful distributional summaries.

3.4.1 Correlation Coefficient

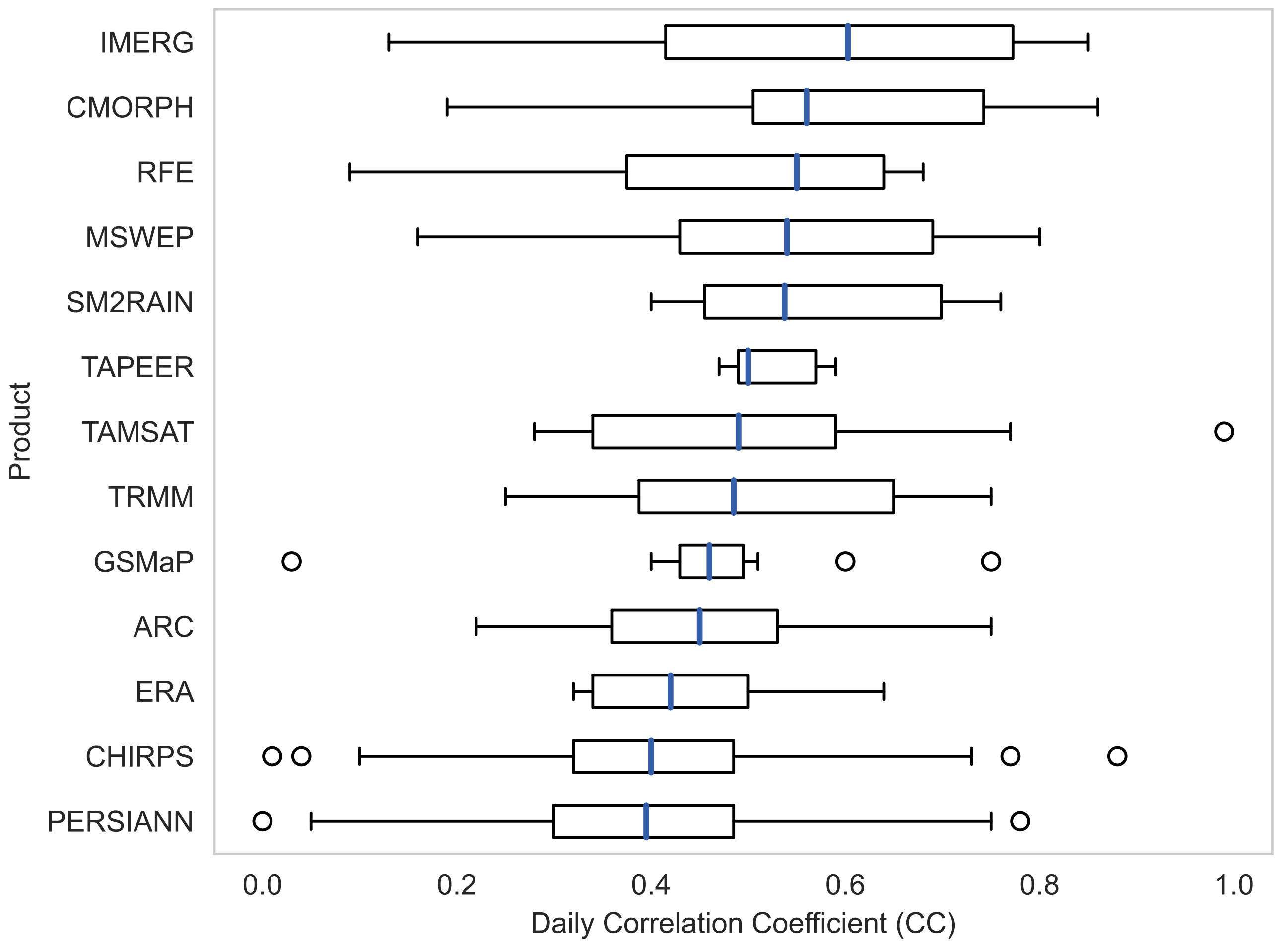

Figure 6. Daily Pearson correlation coefficient distributions for all products with n≥5 observations, ranked by median (descending). Box = IQR; centre line = median; whiskers = full range; circles = individual outliers. Observation counts (n) are annotated at the right of each row. The vertical dashed line at CC = 0.5 marks a commonly used acceptable-performance threshold.

Figure 6 presents box plots of daily CC for the 13 product parents with five or more observations in the synthesis database, ordered by median pooled correlation. The distributional statistics for each product; IQR, range, and observation count are reported in the figure caption; text discussion is confined to directional comparisons.

Three broad tiers are visible from the box plot. A higher-performing tier comprises IMERG and CMORPH, whose boxes sit clearly to the right of other products. A middle tier includes RFE, MSWEP, SM2RAIN, TAPEER, TAMSAT, TRMM, GSMaP, and ARC, all of which show broadly overlapping distributions with substantial spread. A lower-performing tier includes ERA, CHIRPS, and PERSIANN, whose median values fall below the CC $= 0.5$ reference line, though their distributions extend well into the acceptable range in specific study contexts. All products show wide IQRs, typically spanning 0.15-0.30 correlation units confirming that local context determines reported accuracy as strongly as product algorithm.

Two important caveats apply to this tier ordering. First, CHIRPS, with 64 daily CC observations spanning 12 countries, provides the most geographically stable central estimate in the corpus; its wide distributional range reflects genuine context-dependence rather than sampling variability. IMERG, by contrast, rests on only 14 daily CC observations in the corpus, the majority of which derive from Ethiopian highland studies where gauge density is comparatively high and product performance is well-supported (Taye et al., 2023; Zargar et al., 2025; Abebe et al., 2020). The sensitivity analysis in Table A3 shows that IMERG's median CC drops substantially when Ethiopian studies are excluded, indicating that its upper-tier position reflects an evidence concentration rather than a continent-wide performance advantage. Users in non-Ethiopian contexts should treat IMERG's corpus-level estimate with caution and seek local validation before operational deployment. Second, the tier ordering is not sharp: the upper and lower bounds of adjacent-tier products overlap considerably, meaning that in any given geographic context a nominally lower-tier product can outperform a nominally higher-tier one.

3.4.2 Detection Skill: POD and FAR

Figure 7 presents daily POD against FAR for all product parents with five or more observations, exposing the detection-false-alarm trade-off. TAPEER achieves the highest POD in the corpus but at the cost of very high FAR, meaning nearly half of all detected events are false alarms. PERSIANN similarly shows high POD with high FAR. MSWEP shows the most favourable overall detection profile, high POD combined with the lowest FAR among multi-observation products.

3.4.3 Bias: The Dual-Bias Pattern

Daily bias distributions for 10 product parents with five or more observations confirm that no product is characterised by a single consistent bias direction across all study contexts (Figure 8). The key finding is that nearly all products exhibit dual polarity: the same product overestimates in some contexts and underestimates in others. PERSIANN shows the widest spread and the strongest tendency toward positive bias, with an extreme upper outlier attributable to documented severe overestimation in an arid Sudan zone where sub-cloud evaporation eliminates rainfall before it reaches the surface (Siddig et al., 2022). The extreme negative outliers for CHIRPS and IMERG represent underestimation in the Abbay highlands where retrieval algorithms do not capture orographic enhancement (Taye et al., 2023). GSMaP and MSWEP show the smallest absolute median biases in the corpus. The intensity-dependent mechanism underlying this dual-bias pattern is examined in Section 4.4.

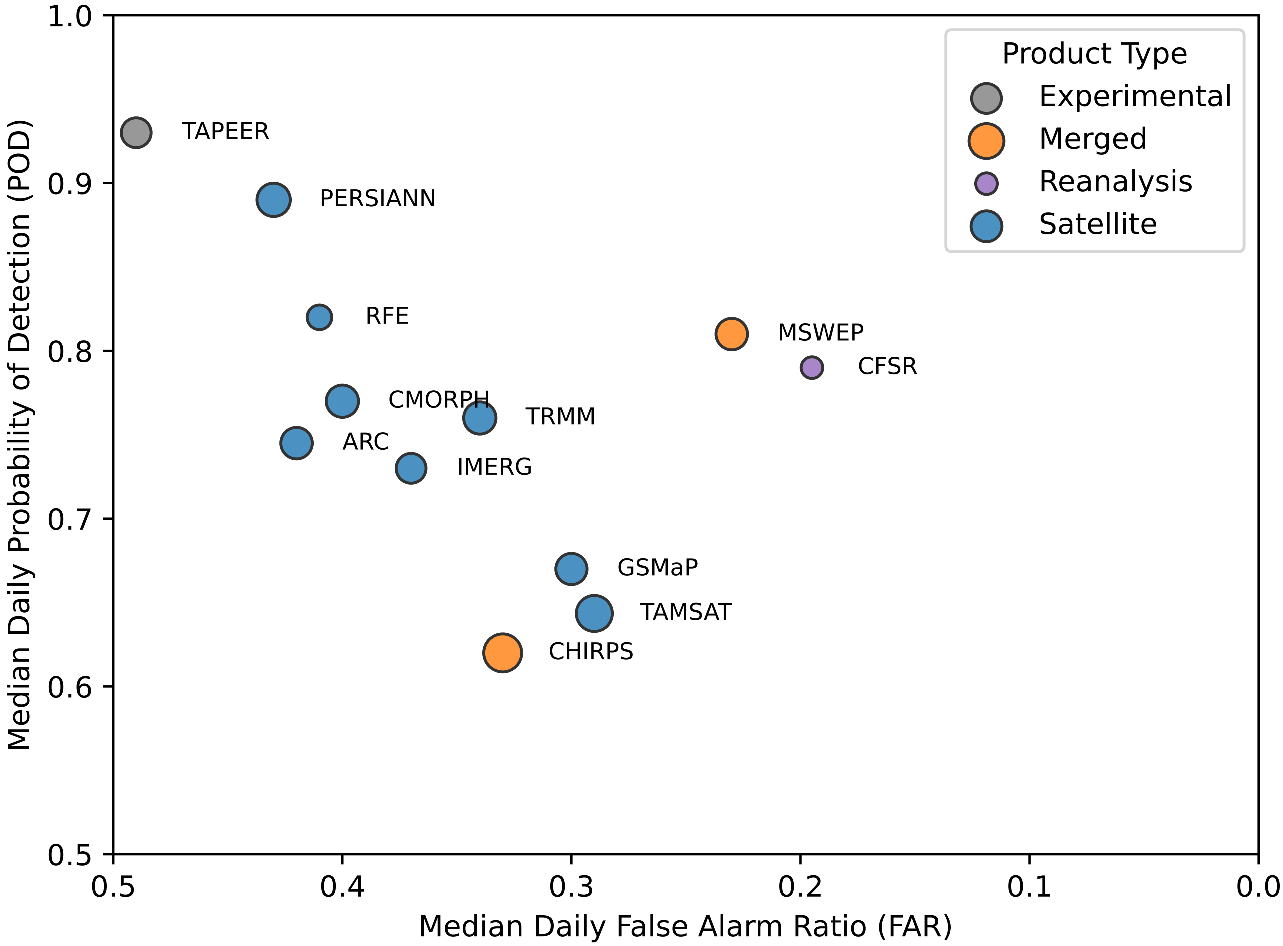

Figure 7. Median daily probability of detection (POD) versus median daily false alarm ratio (FAR) for products with ≥ 5 observations, colour-coded by product family (see legend). The FAR axis is inverted so that the upper-right corner represents the optimal profile (high POD, low FAR). Point size is proportional to observation count. Products nearest the upper-right corner offer the best detection skill relative to false alarms.

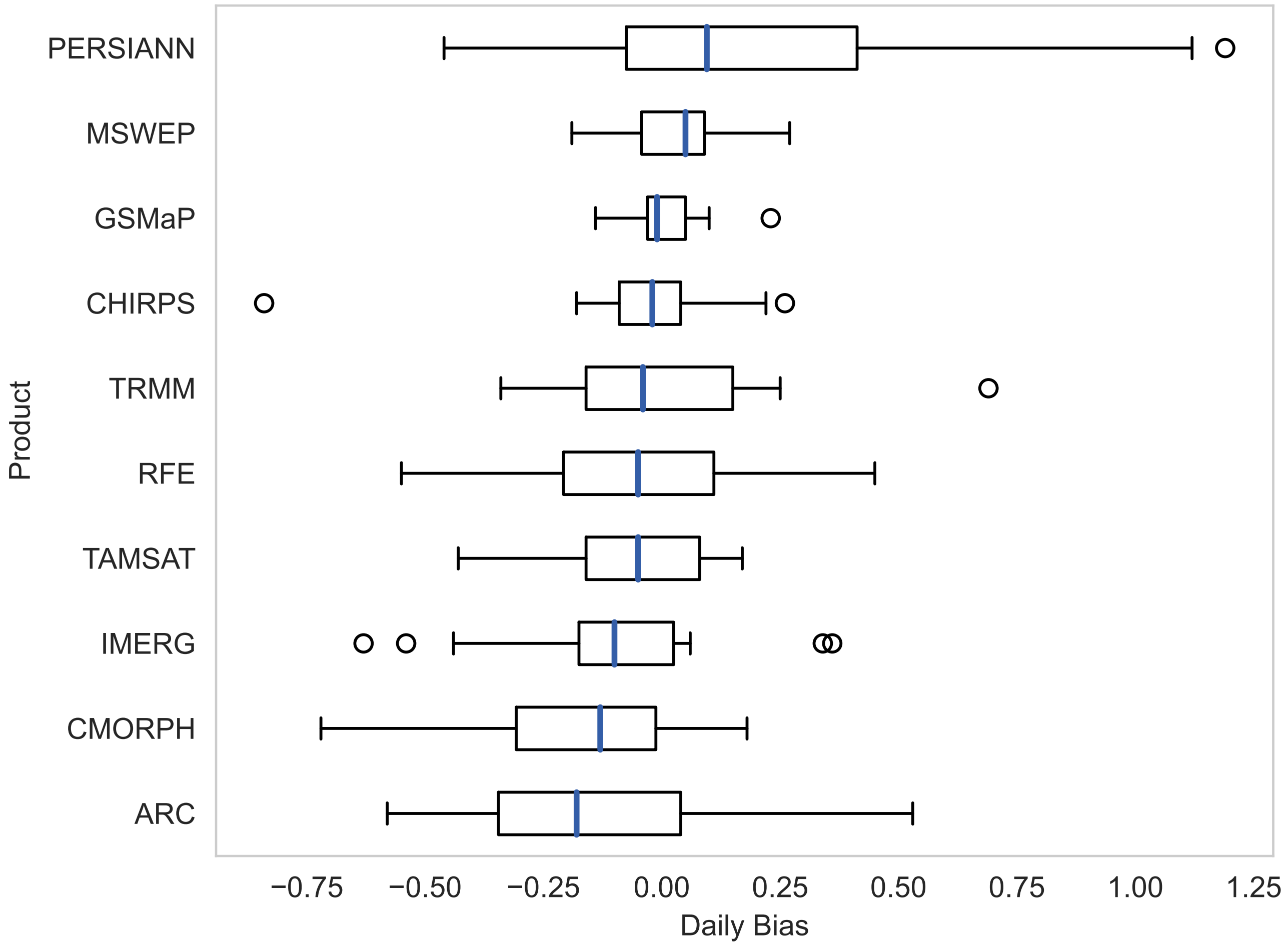

Figure 8. Daily bias distributions for the 10 most frequently evaluated products, ranked by median. Horizontal box-and-whisker plot: box = IQR; whiskers = 1.5×IQR; individual outliers plotted as points. Bias is expressed as a dimensionless ratio (observed as reference): values above zero indicate overestimation; values below zero indicate underestimation. The near-universal overlap of each product's distribution across zero illustrates the dual-bias pattern documented in Section 4.4.

In the Gumera watershed, CHIRPS v2, TAMSAT v3.1, and PERSIANN-CDR all overestimated the lowest daily rainfall amounts while underestimating the highest (Tsegaye Mersha and Mekuriaw, 2025). In Burkina Faso, all seven daily products simultaneously underestimated rainfall amounts while overestimating occurrence frequency (Dembélé and Zwart, 2016). In the Upper Blue Nile, CHIRPS overestimated light rainfall occurrence while underestimation dominated at higher intensities (Tessema et al., 2020).

3.4.4 Hydrological Performance: NSE and KGE

Daily NSE is the single most operationally diagnostic metric in the corpus and its distribution is stark (Figure 9). Across 105 daily NSE observations, the distribution spans from an extreme negative outlier (TRMM applied in the Upper and Central Breede, South Africa (Suleman et al., 2020)) to a maximum near 0.82, with the vast majority of uncorrected-product values concentrated just below zero. By product family: satellite products show a median near zero with a wide lower tail; merged products show a slightly negative median with a similar spread; and the two reanalysis observations both fall substantially below zero. Bias-corrected, merged, and ML-enhanced product variants show clearly elevated NSE values, demonstrating the transformation achievable through post-processing. Daily CC is highly correlated with daily NSE across the observations in the database (Figure 9B). A substantial fraction of product-study observations show CC above 0.5 which is conventionally considered acceptable, while simultaneously producing negative NSE, meaning the product performs worse as a hydrological model input than the long-term mean.

KGE distributions (Figure 10) show greater separation between products than NSE. Among products with multiple observations, IMERG consistently occupies the upper portion of the KGE distribution, followed by TAMSAT3 and MSWEP, while CHIRPS shows a lower central value.

3.5 Systematic Error Patterns and Geographic Distribution

3.5.1 Error Pattern Frequency

Table 2 and Figure 11 present the frequency of the six pre-defined error categories across the 72 extraction entries. Overestimation (90%) and underestimation (87%) are near-universal, reflecting the dual-bias signature documented in Section 3.4. Weak daily performance (70%) is consistent across the corpus. Poor heavy-rainfall detection (61%) and orographic difficulty (48%) are less universal but still represent majority findings. High-altitude underestimation (37%) is an emergent pattern.

3.5.2 Regional Distribution of Error Patterns

Error patterns are not uniformly distributed across African regions (Figure 11). East Africa ($n = 41$ entries) shows the highest rates of orographic difficulty (66%) and high-altitude underestimation (51%), consistent with the Ethiopian highlands and East African Rift escarpments dominating that regional evidence base (Gebremicael et al., 2019; Ehsan Bhuiyan et al., 2019; Addisu et al., 2024; Taye et al., 2023; Ahmed et al., 2024). West Africa ($n = 17$) shows 100% overestimation reporting, with 82% studies documenting underestimation and low rates of orographic (13%) and high-altitude (12%) patterns, reflecting

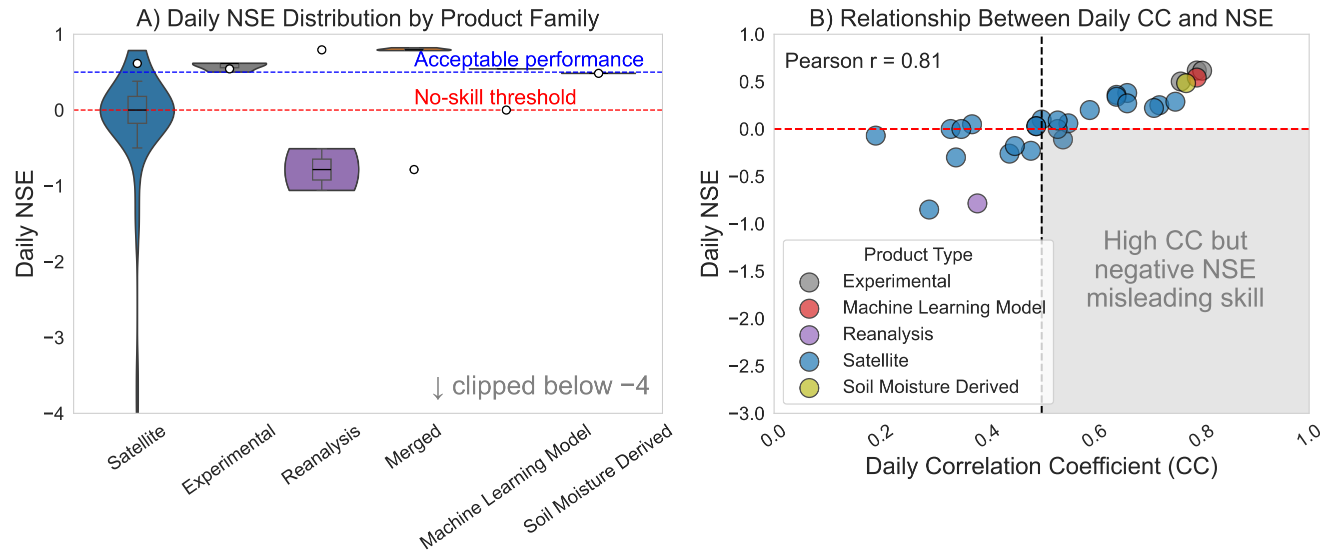

Figure 9. Panel A: Violin plot of daily NSE by product family across 105 observations. Each violin shows the kernel density of the distribution; the inner box spans the IQR; the white dot marks the median. The y-axis is clipped at -4 (break symbol shown); values below this threshold are plotted at the clip boundary. Dashed reference lines mark the no-skill threshold (NSE = 0, red) and the acceptable-performance threshold (NSE = 0.5, blue). Panel B: Scatter plot of daily CC versus daily NSE for the same 105 observations, coloured by product family. The shaded grey region (high CC, negative NSE) highlights observations where correlation appears acceptable but hydrological skill is below no-skill.

Table 2. Error pattern frequency across 72 extraction entries. Multiple patterns per entry are permitted; absence of code indicates the study did not report on that pattern. Classification thresholds: consistent finding ($> 50\%$), emergent finding (25–50%).

Error pattern	n	**%**	**Classification**
Overestimation of rainfall amounts	65	90	Consistent
Underestimation of rainfall amounts	63	87	Consistent
Weak daily performance	51	70	Consistent
Poor heavy-rainfall detection	44	61	Consistent
Orographic rainfall difficulty	35	48	Emergent
High-altitude underestimation	27	37	Emergent

the predominantly flat Sahelian context (Satgé et al., 2020; Dembélé and Zwart, 2016; Datti et al., 2024; Goudiaby et al., 2024). North Africa ($n = 10$) shows lower rates across all categories, partly because Mediterranean and arid rainfall regimes produce qualitatively different error types (Tramblay et al., 2019; Guermazi et al., 2019). Southern Africa ($n = 5$) distinctively

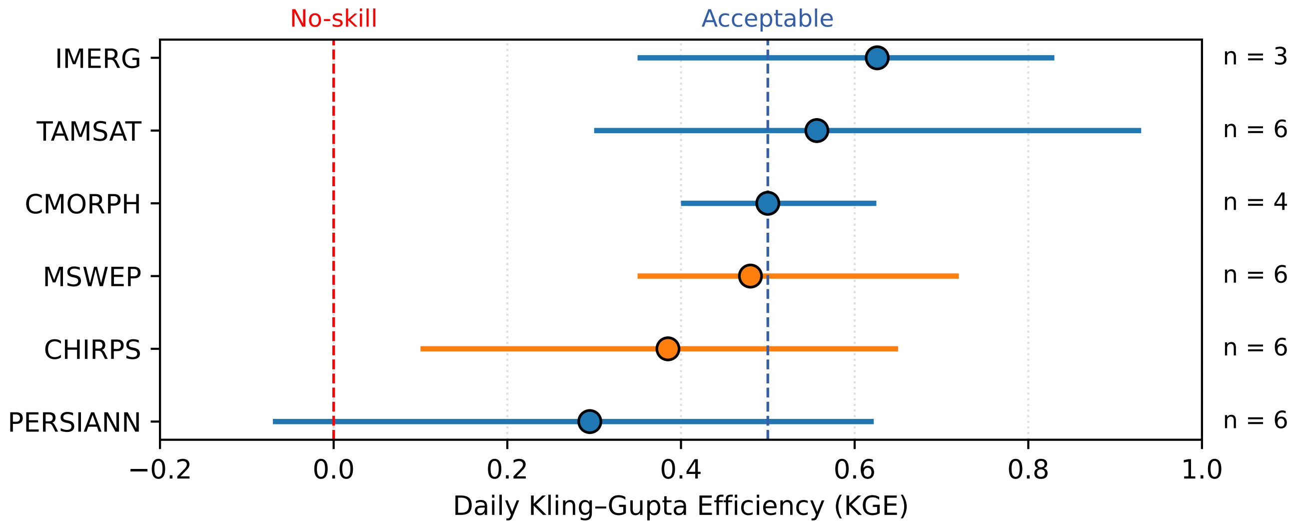

Figure 10. Daily Kling-Gupta Efficiency (KGE) for the six products with n $\geq$ 3 observations, ranked by median (descending). Filled circle = median; horizontal bar = full observed range; n annotated at right. Colour indicates product family: blue = satellite-only (IMERG, TAMSAT, CMORPH, PERSIANN); orange = merged (MSWEP, CHIRPS). Vertical dashed lines mark the no-skill threshold (KGE = 0, red) and the acceptable-performance threshold (KGE = 0.5, blue). All values are from raw, uncorrected products.

shows 100% weak-daily-performance, while heavy-rain detection failure (20%) and orographic difficulty (20%) are notably lower than East Africa (Lekula et al., 2018; Suleman et al., 2020; Ndemere et al., 2024; du Plessis and Kibii, 2021). Central Africa and continental assessments ($n = 2$ including entries from the Congo Basin) show 100% rates across all six categories (Camberlin et al., 2019), consistent with the known difficulty of all products in equatorial high-rainfall environments, but this figure rests on only two entries and must be interpreted with caution.

3.5.3 Detection Skill Across Rainfall Intensity Classes

The 44 entries reporting poor heavy-rainfall detection reflect a consistent pattern of detection skill deteriorating with increasing rainfall intensity threshold. TARCAT gave zero contribution for rainfall intensities exceeding 300 mm month^{-1} in Burkina Faso (Dembélé and Zwart, 2016). In Ghana and Uganda, all products failed to detect intermediate (10–20 mm day^{-1}) and large-threshold events ($>$ 30 mm day^{-1}) (Boluwade, 2020). In the Upper Blue Nile, no product could capture rainfall above the 95th percentile (Abebe et al., 2020). In the Lake Ziway Basin, CHIRPS achieved POD of only 22% and CSI of 12% above a 10 mm day^{-1} threshold (Musie et al., 2019).

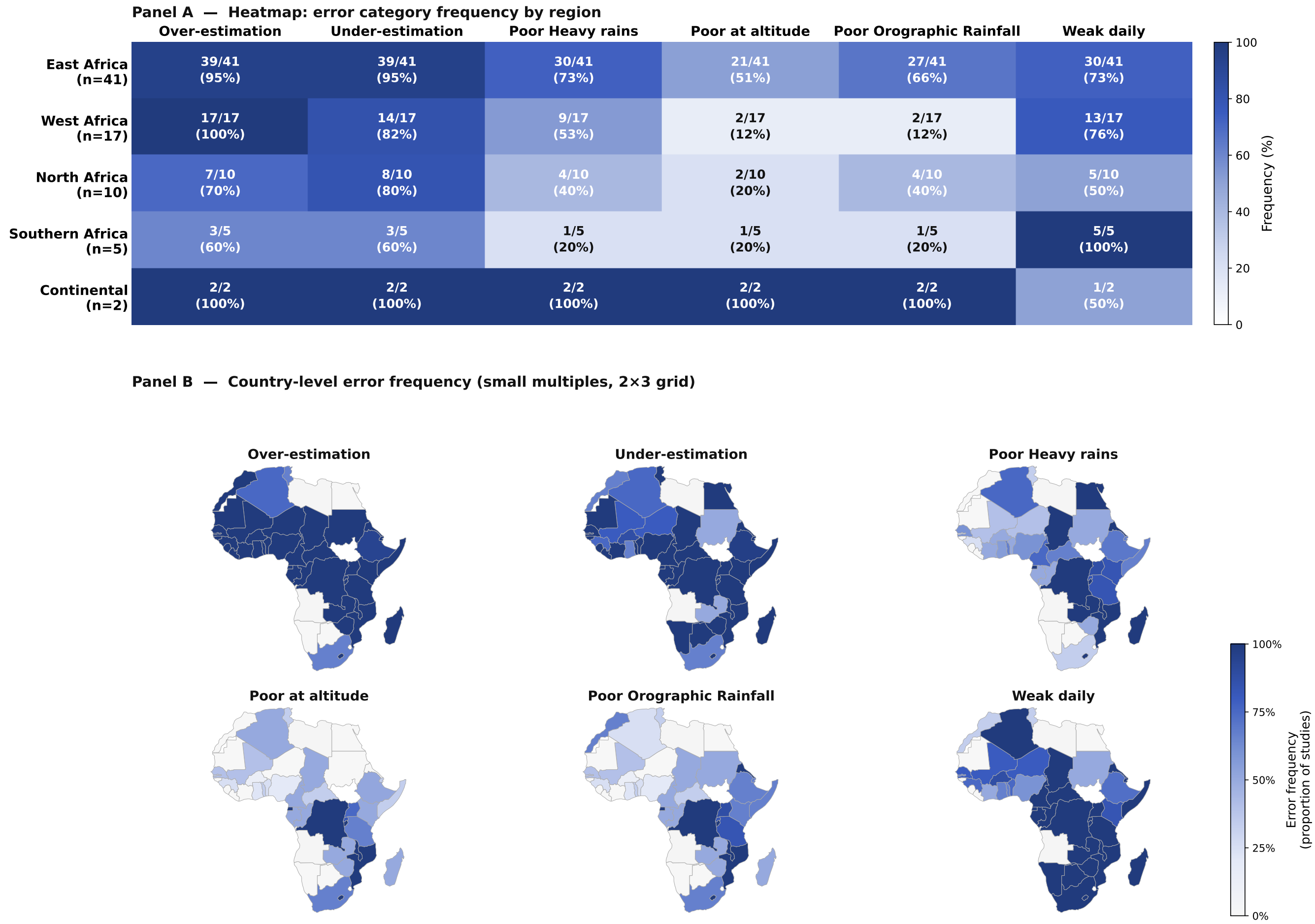

Figure 11. Panel A: Heatmap of error-category frequency by region. Rows = five regions; columns = six error categories. Cell colour intensity is proportional to the percentage of extraction entries within that region reporting the pattern; exact percentages are annotated in each cell. Panel B: Multiple choropleth maps of Africa, one per error category, with country-level shading proportional to the frequency of that pattern in studies from each country. Studies validating in more than one region are counted in each; regional n therefore sum to 75, not the 72 included studies

3.5.4 Evidence Gaps in the Validation Literature

Figure 3 maps validation study density against country representation, revealing the extreme geographic concentration of the evidence base. Ethiopia accounts for 46% of all studies despite covering 3.6% of Africa's land area. The DRC, covering 2.3 million km^2, has only a single study in the corpus. Seven AU member states have zero representation (Table A2). The distribution is fundamentally shaped by gauge network availability: countries with operational gauge networks and strong meteorological institutions are represented; those without are not. This circularity where products are most needed where data are scarcest and least evaluated constitutes the most important structural limitation of the existing validation evidence base.

4 Discussion

This systematic review and meta-analysis of 72 studies evaluating gridded precipitation datasets across Africa has produced a rich evidence base that extends well beyond cataloguing which products perform best where. The synthesis reveals consistent structural patterns in product error, explains those patterns through the physical mechanisms of satellite retrieval, and identifies the specific investments, in observation infrastructure, algorithmic development, and methodological standardisation, that would most improve rainfall data quality across the continent. The following discussion integrates these threads into themes that collectively constitute our answer to the question: what do these 72 studies, taken together, tell us about the current reliability and future improvement of gridded rainfall products for African water resource science and practice?

4.1 The Primacy of Context: Why No Single Global Product Dominates

The most robust conclusion of this review is that no single global gridded rainfall product consistently outperforms all others across Africa's diverse climates, terrains, and applications, with two important exceptions. Reanalysis products (ERA5, MERRA-2, and related variants) are consistently outperformed by satellite and merged products across the corpus; they are not a competitive choice for primary rainfall estimation in Africa. Within the remaining space of global satellite and merged products, however, no clear universal winner exists (Satgé et al., 2020; Waberi et al., 2023; Omay et al., 2025; Camberlin et al., 2019). Product rankings shift systematically across at least four dimensions: geographic region, temporal aggregation scale, rainfall intensity class, and intended application.

Geographically, CHIRPS v2.0 emerged as the most broadly recommended product in the corpus, appearing as the top or joint-top recommendation in studies spanning Ethiopia (Gebremicael et al., 2019; Musie et al., 2019; Reda et al., 2022; Zargar et al., 2025; Ayele et al., 2024; Bayissa et al., 2017; Tsegaye Mersha and Mekuriaw, 2025; Ahmed et al., 2024), Nigeria (Datti et al., 2024), the Sahel (Abera et al., 2016), and several continental assessments. Yet CHIRPS was not universally superior: it underestimated extreme return levels in Senegal (Diedhiou et al., 2024), and showed poor daily detection skill in multiple Ethiopian agro-ecological zones where MSWEP v2.8 and TAMSAT v3.1 outperformed it (Addisu et al., 2024). These divergences reflect that CHIRPS's strengths (gauge incorporation, long record from 1981, 0.05° resolution, stable monthly bias) are most advantageous for monthly-to-seasonal climate monitoring, while its limitations (infrared-based daily retrieval, light-rain overestimation, declining gauge inputs) become apparent at daily and sub-daily scales or in regions with sparse gauge networks.

Temporally, the improvement in product skill from daily to dekadal or monthly aggregation is so consistent, reported in 52 of 72 extraction entries (72%), that it constitutes a general rule of thumb for African applications (Figure 5). This scale-dependence has direct operational consequences: gridded products are appropriate for monthly climate monitoring and seasonal drought assessment, but daily applications (flood forecasting, event analysis, crop-model forcing, etc.) require either bias correction, multi-product ensemble approaches, or supplementary ground data.

This multi-dimensional context-dependence is not a counsel of despair. Within the global satellite and merged product space, it is an invitation to move beyond the question "which product is best?" toward the question "best for what, where, and at what time scale?" The practical guidance in Table 3 is framed around these anchors, and we expand on them in Section 4.10 below.

4.2 CHIRPS, IMERG, and the Evolving Product Landscape

Two products stand out from the synthesis as most broadly useful for African applications, albeit for different reasons and at different scales. CHIRPS v2.0 is the most frequently recommended product in the review, spanning the widest range of countries and applications. Its strengths derive from the combination of satellite infrared observations with station data, a long record extending back to 1981, and a fine spatial resolution of 0.05°. In Ethiopia, CHIRPS was recommended for drought monitoring (Bayissa et al., 2017; Weldegerima and Gebresilassie, 2025), streamflow simulation (Musie et al., 2019; Reda et al., 2022; Ayele et al., 2024), and rainfall estimation in highland areas where it showed relatively robust performance compared to ERA5 (Ahmed et al., 2024). In Nigeria, it emerged as the best satellite rainfall estimate overall (Datti et al., 2024). Across the transboundary Medjerda Basin in northwest Africa, CHIRPS outperformed PERSIANN-CDR for hydrological modelling (Guermazi et al., 2019). However, CHIRPS carries documented limitations. It overestimates light rainfall at daily scales, producing too many rainy days (Dembélé and Zwart, 2016; Tsegaye Mersha and Mekuriaw, 2025). The number of stations used in CHIRPS's gauge-incorporation step has been declining drastically across most of Africa (Dinku, 2020), meaning that the temporal homogeneity of the product is not guaranteed and trend analysis based on CHIRPS should be approached with caution.

GPM IMERG represents the next generation of satellite precipitation estimation and is increasingly recommended for daily-scale and event-based applications. IMERG Final Run was identified as the most recommended product for the central highlands of the Abbay Basin (Taye et al., 2023), performed comparably to CHIRPS in the Blue Nile for daily hydrological modelling (IMERG NSE $= 0.80$; CHIRPS NSE $= 0.81$ in validation) (Zargar et al., 2025), was the consistently optimal product in Burkina Faso (Yonaba et al., 2024), provided a better approximation of extreme return levels than CHIRPS in Senegal (Diedhiou et al., 2024), and was a strong performer across the IGAD region (Waberi et al., 2023). However, IMERG's advantages must be qualified by the geographic concentration documented in Section 3.4: its corpus-level ranking is substantially driven by Ethiopian highland evaluations, and its performance in less-studied regions, the Congo Basin, the Saharan margins, and southern Africa remains poorly constrained. IMERG is also not without limitations: it failed to capture rapid convective peaks at sub-daily scales in Senegal (Diedhiou et al., 2024) and Ghana (Agyekum et al., 2023), it overestimates in some regions

(Ageet et al., 2022), and its record begins only in 2000, making it unsuitable for long-term trend analysis without combination with earlier satellite records.

Beyond these two headline products, several others retain important operational niches. MSWEP v2.2/v2.8 was recommended for daily rainfall studies in Ethiopia (Addisu et al., 2024) and drought monitoring in West Africa (Houngnibo et al., 2023). TAMSAT v3.1 retains important roles for daily estimation in Ethiopia (Addisu et al., 2024) and long-term variability characterisation (Houngnibo et al., 2023) owing to its locale-specific calibration and homogeneous long record from 1983. RFE v2.0 shows strong daily detection skill in the Sahel (Dembélé and Zwart, 2016; Goudiaby et al., 2024; Goshime et al., 2019) and the Kalahari (Lekula et al., 2018).

4.3 The Limitations of Reanalysis Products for African Rainfall

A consistent finding across the review is that reanalysis products (ERA5, MERRA-2, EWEMBI, PGF, WFDEI variants, and JRA-55) are generally outperformed by satellite-based and merged products for rainfall estimation in Africa. ERA5 underestimated extreme rainfall events in Ghana (Agyekum et al., 2023) and performed particularly poorly at elevations between 2,000 and 3,500 m in Ethiopia (Ahmed et al., 2024). Across West Africa, reanalysis products presented among the lowest statistical scores at the daily time step (Satgé et al., 2020). These limitations are fundamentally rooted in the parameterisation of deep convection in global numerical weather prediction models at resolutions that smooth steep orographic gradients and underestimate peak intensities. Nonetheless, reanalysis products have specific roles where their advantages are relevant, including applications requiring multi-variable inputs (crop modelling, evapotranspiration estimation, energy balance studies) and as one component of multi-source ensemble products like MSWEP. The recommendation from this review is therefore not to exclude reanalysis products categorically, but to use them as ancillary inputs rather than primary rainfall sources, and never to use them as the sole reference for validation.

4.4 The Dual-Bias Signature

The co-occurrence of overestimation and underestimation within the same product (across different rainfall intensity classes, seasons, and geographic subregions) is one of the most important structural findings of this review. At the continental scale, overestimation was reported in 90% of extraction entries and underestimation in 87%, near-identical frequencies that reflect the fact that the dual-bias pattern operates at the product level: the same product overestimates in some contexts and underestimates in others. Satellite retrieval algorithms are tuned to detect precipitation using cloud-top temperature thresholds or ice-scattering signatures. These detection mechanisms systematically generate false positives for light events: cold cirrus clouds misidentified as precipitating systems, cold highland plateaux triggering IR thresholds, and low-emissivity surfaces generating apparent PMW scattering. The result is an excess of detected rainy days and overestimation of the frequency distribution at low rainfall intensities. The same retrieval physics simultaneously fails at the upper end of the intensity distribution: spatially compact convective cores whose peak rain rates may exceed 100 mm h^{-1} over areas of 1–10 km^2 are smoothed across pixels of 25–2,500 km^2, dramatically diluting the peak.

This intensity-dependent bias reversal was explicitly documented in the Gumera watershed (Tsegaye Mersha and Mekuriaw, 2025), in the Upper Blue Nile basin (Tessema et al., 2020), and in Burkina Faso where all seven daily products simultaneously underestimated rainfall amounts while overestimating occurrence frequency (Dembélé and Zwart, 2016). The practical implication is that blanket characterisations of any product as “wet-biased” or “dry-biased” are misleading. The correct framing is that products are *intensity-biased*: they have a variance deficit that overestimates the frequency of light events while underestimating the magnitude of heavy ones. Intensity-stratified correction, quantile mapping, or statistical downscaling approaches that explicitly reconstruct the upper tail of the intensity distribution are needed to address this fundamental limitation (Ehsan Bhuiyan et al., 2019; Bhatti et al., 2016; Tessema et al., 2020; Haile et al., 2015).

4.5 The Essential Role of Bias Correction

The distribution of daily NSE values across 105 observations, with the vast majority of uncorrected-product values clustered near zero and a long negative tail (Figure 9), makes the case for bias correction more compellingly than any narrative argument. Raw, uncorrected gridded products applied directly as inputs to daily rainfall-runoff models produce hydrological simulations that, on average, perform no better than using the long-term mean as a predictor. Multiple studies demonstrated that bias correction transforms near-zero or negative NSE into acceptable performance. In eastern Zimbabwe, CHIRPS, CMORPH, PERSIANN-CCS, and PDIR-Now were all deemed unacceptable raw for hydrological modelling (Ndemere et al., 2024). In the Upper Omo-Gibe Basin, Ethiopia, bias correction was crucial for obtaining acceptable SWAT-model simulations from CMORPH and TRMM (Koshuma et al., 2021). In the Lake Ziway Basin, CHIRPS achieved daily SWAT calibration NSE of 0.59–0.60 and validation NSE of 0.51–0.55 in the Ketar and Meki watersheds (Musie et al., 2019).

The latency-accuracy trade-off presents a practical challenge for real-time flood forecasting. Bias correction, however, is not a panacea. It requires representative gauge data for calibration, precisely what is lacking in much of Africa. For hydrological applications requiring accurate simulation of flood peaks and drought durations, intensity-aware correction methods such as quantile mapping are strongly preferred over simple scaling (Ehsan Bhuiyan et al., 2019; Bhatti et al., 2016; Tessema et al., 2020).

4.6 The Persistent Challenge of Orographic Terrain

The Ethiopian highlands, the Atlas Mountains, the East African Rift escarpments, the Cameroon Highlands, and the Drakensberg all featured in this review as areas of systematically degraded product performance. Twenty-seven extraction entries (37%) reported high-altitude underestimation and 35 (48%) reported orographic rainfall difficulty. The magnitude of the orographic challenge is substantial: CMap PBIAS reached up to -75% at altitudes above 3,000 m a.s.l. in Ethiopia, while CHIRPS and TRMM 3B42 remained within $\pm 25\%$ at the same elevation (Gebremicael et al., 2019); ERA5 performed particularly poorly between 2,000 and 3,500 m (Ahmed et al., 2024); and in Morocco, products that performed adequately in flat zones showed PBIAS of 50% in rain-shadow areas (Gadouali and Messouli, 2020).

The underlying causes are dual. On the windward side of mountains, shallow warm-topped clouds generate orographic rainfall through low-level lifting that cannot be detected by IR algorithms and is underestimated by PMW algorithms. This warm-rain mechanism is the primary driver of high-altitude underestimation in Ethiopia, Kenya, Tanzania, and the Atlantic-facing slopes of West and Central Africa. On the lee side, warm dry air descending from orographic barriers evaporates most precipitation before it reaches the surface (virga), but IR sensors observing cloud-top temperatures see the same cold clouds on both sides of the ridge. This is the primary driver of rain-shadow overestimation in Morocco, Algeria, and the Eastern Rift of Ethiopia. A machine-learning blending approach evaluated across multiple regions, including the Blue Nile, demonstrated that incorporating topographic and land-surface predictors significantly reduced both systematic and random error (Ehsan Bhuiyan et al., 2019), the most promising algorithmic direction identified in the corpus for orographic contexts.

4.7 The Untapped Potential of Multi-Product Ensembles

An under utilised but highly promising strategy that emerges from this review is the simultaneous use of multiple products rather than selection of a single best dataset. In Djibouti, requiring consensus among CHIRPS, IMERG, MSWEP, and RFE before declaring a rain event substantially improved true-positive detection compared to any individual product, though false alarms remained a limitation in dry seasons (Waberi et al., 2023). In Ethiopia (Gilgel-Abay watershed, Blue Nile basin), a neural network ensemble improved low-performing individual products by up to 17.5% (Gichamo et al., 2023) in hydrological simulation NSE. For practitioners, the immediate recommendation is pragmatic: do not rely on a single product for critical applications. For drought monitoring, corroborate the primary product (CHIRPS or TAMSAT) with a second independent source (RFE or MSWEP). For flood forecasting, run hydrological models with at least two rainfall inputs and treat the spread of streamflow predictions as a measure of rainfall uncertainty. For agricultural early warning, require agreement between at least two products before issuing a planting recommendation based on monsoon onset.

4.8 The Critical Need for Expanded Ground Observations

A theme that runs through virtually every study in this review is that the utility of gridded precipitation products in Africa is fundamentally constrained by the sparsity, decline, and inaccessibility of ground-based observation networks. This constraint operates simultaneously at two levels: it limits the quality of the products themselves, and it limits our ability to assess that quality through independent validation. The ENACTS programme's performance advantage over global products (Abebe et al., 2020) is directly attributable to its use of quality-controlled national gauge data at 4 km resolution: it demonstrates the performance ceiling that global products could achieve if comparable national station datasets were universally available.

The geographic concentration documented in Figure 3 reflects this circularity directly: the studies exist where the gauges are. Product performance in the Congo Basin, the Sahara margins, highland Madagascar, and rural Angola remains essentially uncharacterised because there are no gauge records with which to validate against. The most promising complementary approaches for expanding observational coverage include community and citizen-science rain gauge networks (e.g., TAHMO), soil-moisture-based rainfall retrieval using the SM2RAIN algorithm (Abebe et al., 2020; Goshime et al., 2019), X-band weather radar deployment in strategic highland and coastal locations, and national meteorological service capacity-building programmes. Critically, data sharing must improve. The ENACTS programme, which operates by supporting national meteorological services to produce and use their own data rather than exporting it to external institutions, provides a model for building this capacity within African institutions.

4.9 Toward Standardised Validation Frameworks

The methodological heterogeneity of the reviewed studies (wide variation in metrics used, temporal scales reported, gauge network characteristics, and comparison approaches) represents a structural barrier to cumulative knowledge production in this field. Building on the comprehensive validation framework articulated by Dinku (2020) and the metric diversity documented in this review, we recommend that future African rainfall validation studies adopt a minimum reporting standard comprising: (1) CC and PBIAS at all temporal scales evaluated; (2) RMSE or NRMSE for quantitative error magnitude; (3) POD and FAR at a standard detection threshold of 1 mm day^{-1}; (4) KGE for any study with hydrological application; (5) intensity-stratified analysis reporting bias and POD separately for light rain (< 1 mm day^{-1}), moderate rain (1–10 mm day^{-1}), and heavy rain (> 10 mm day^{-1}); and (6) explicit reporting of the comparison approach, the number and spatial distribution of gauge stations used, and the period of record.

4.10 Practical Guidance for Users

Table 3 distils evidence-based guidance by application domain, drawn from the collective evidence of 72 studies across 29 African countries. No recommendation is unconditional: every preferred product is specified for a particular temporal scale, geographic context, and operational purpose.

For monthly climate monitoring and seasonal drought assessment, CHIRPS v2.0 is the safest first choice across most African regions, supported by the broadest evidence base in the corpus. It should be supplemented with TAMSAT v3.1 or RFE v2.0 for corroboration, particularly in West Africa and the Sahel.

For daily rainfall estimation and event detection, GPM IMERG Final Run is the emerging standard, particularly in regions with complex terrain where its improved PMW sampling from the DPR-guided constellation offers advantages over pure IR-dependent products. In the Sahel and West Africa, RFE v2.0 and ARC2 v2.0 retain strong daily detection skill and may outperform IMERG in specific contexts (Dembélé and Zwart, 2016; Goudiaby et al., 2024; Houngnibo et al., 2023). TAMSAT v3.1 and MSWEP v2.8 are jointly recommended for daily estimation in Ethiopia (Abay Basin) (Addisu et al., 2024).

For hydrological modelling and streamflow simulation, no product should be applied raw. Bias correction calibrated to local gauge climatology is non-negotiable, as the daily NSE distribution for uncorrected products demonstrates. Intensity-stratified quantile mapping is preferred over simple mean bias correction for applications requiring accurate simulation of flood peaks.

For climate trend analysis, TAMSAT v3.1, MSWEP v2.2, and ARC2 provide long time series with algorithms that remain consistent across their full periods of record (Houngnibo et al., 2023). Any trend detected in a satellite record should be corroborated across at least two independent datasets and tested for homogeneity before attribution to climate change.

Table 3. Evidence-based product selection guidance by application domain, geographic context, and temporal scale, derived from the systematic review of 72 peer-reviewed studies. No recommendation is unconditional; every preferred product is specified for a particular temporal scale, geographic context, and operational purpose. †Bias correction is mandatory for all hydrological modelling applications regardless of product choice. ‡For data-sparse regions (Congo Basin, Saharan margins) no product has been adequately validated; a multi-product ensemble is the only defensible operational approach.

Application domain	**Recommended product(s)**	**Region / context**	**Notes**
Drought monitoring	CHIRPS v2.0 (primary); RFE v2.0/ARC2 (Sahel); TAMSAT v3.1 (West & East Africa)	Pan-African; strongest evidence for Ethiopia, Sahel, and West Africa	Account for CHIRPS light-rain overestimation bias in day-count drought indices. (Abebe et al., 2020; Dembélé and Zwart, 2016; Weldegerima and Gebresilassie, 2025; Bayissa et al., 2017; Houngnibo et al., 2023)
Flood forecasting & hydrological event detection	Multi-product consensus: CHIRPS + IMERG + MSWEP + RFE (most robust); Single product: IMERG Final (preferred)	Pan-African; strong evidence for Djibouti, Senegal	IMERG performance estimates are Ethiopia-concentrated; verify locally before deployment. (Waberi et al., 2023; Diedhiou et al., 2024)
Hydrological modelling (streamflow simulation)†	IMERG Final (highest KGE; complex terrain); TAMSAT v3.1 (Ethiopia); CHIRPS v2.0 (broad); RFE v2.0 (West Africa); ENACTS* (KGE = 0.75)	East Africa: strong evidence; West/Southern Africa: limited evidence; Central Africa: insufficient data‡	Bias correction mandatory. Quantile mapping preferred over mean scaling. (Musie et al., 2019; Abebe et al., 2020; Reda et al., 2022; Zargar et al., 2025; Ayele et al., 2024)
Daily rainfall estimation & event detection	IMERG Final (complex terrain; extreme events); MSWEP v2.8 (Ethiopia); TAMSAT v3.1 (East Africa highlands); GSMaP/GSMaP_wGauge (continental); RFE v2.0/ARC2 (Sahel)	Complex terrain: IMERG; Highland East Africa: TAMSAT; Sahel/flat: RFE or ARC2	Wide uncertainty for IMERG outside Ethiopia. (Goudiaby et al., 2024; Addisu et al., 2024; Taye et al., 2023; Zargar et al., 2025; Waberi et al., 2023)
Climate trend analysis & long-term variability	TAMSAT v3.1 (preferred; stable since 1983); MSWEP v2.2 (consistent weights); CHIRP (ungauged; greater temporal homogeneity than CHIRPS)	Africa-wide; best algorithm stability: TAMSAT and MSWEP	Corroborate any detected trend across ≥ 2 independent datasets; test for homogeneity before attributing to climate change. (Houngnibo et al., 2023; Funk et al., 2015)
Agricultural monitoring, onset/cessation & crop-model forcing	CHIRPS v2.0 (seasonal totals; East Africa); RFE v2.0/ARC2 (Sahel onset); TAMSAT v3.1 (daily; East Africa); MSWEP v2.2 (daily forcing; Ethiopia)	Sahel: RFE, ARC2; East Africa: CHIRPS, TAMSAT; West Africa: CHIRPS, MSWEP	Require agreement between ≥ 2 products before triggering planting advisories. (Dinku et al., 2018; Goudiaby et al., 2024; Abdallah et al., 2024; Weldegerima and Gebresilassie, 2025; Bayissa et al., 2017; Houngnibo et al., 2023)
Monthly climate monitoring & seasonal assessment	CHIRPS v2.0 (broadest evidence base); TAMSAT v3.1 (corroboration); RFE v2.0 (Sahel);	Pan-African; CHIRPS has the largest validation evidence base of any product (34 studies)	Dekadal aggregation substantially more reliable than daily. (Dinku et al., 2018; Weldegerima and Gebresilassie, 2025; Bayissa et al., 2017; Houngnibo et al., 2023)
Sub-daily & urban flash-flood estimation	IMERG (sub-hourly; best available); CMORPH sub-daily; GSMaP sub-hourly. *No product adequately validated at this scale across Africa*	Very limited evidence: only 9 studies, 64 observations continent-wide	IMERG initiated storm events earlier than observed in Ghana (Agyekum et al., 2023); in Senegal, IMERG captured early rainfall but missed the event's peak intensity (Diedhiou et al., 2024). Validate locally before operational use.
Data-sparse regions (Congo Basin, Saharan margins)‡	No product adequately validated; multi-product ensemble recommended (IMERG + CHIRPS + MSWEP minimum)	Central Africa (DRC, CAR); North: Sahara margins, Libya; Southern: Angola, Namibia	Daily and interannual skill drops sharply in the Congo Basin; ARC and TARCAT show near-zero interannual skill in central DRC (Camberlin et al., 2019). Bias correction impossible without gauge data.

4.11 Limitations of This Review

Several limitations of the present synthesis should be acknowledged. First, the geographic concentration of the evidence base (with Ethiopia contributing 46% of all studies) means that our pooled statistics are heavily influenced by East African results. Second, metric heterogeneity across studies constrains the quantitative synthesis; the small sample sizes for some products, particularly IMERG ($n = 14$ daily CC observations, majority from Ethiopia) mean that pooled estimates carry substantial uncertainty. Third, publication bias is a potential concern in any systematic review: studies finding that products perform poorly may be published less readily than those finding acceptable performance. Fourth, this review covers the period up to early 2025 and does not include the most recent generation of machine-learning-based precipitation products.

4.12 Ethiopia Sensitivity Analysis

Given that Ethiopia contributes 46% of the corpus, we conducted a sensitivity analysis examining how the exclusion of Ethiopian studies affects the daily CC distribution across products. At the overall level, the Fisher z-transformed median daily CC shifts by less than 0.02 correlation units when Ethiopian studies are excluded, indicating that the overall temporal aggregation finding is robust to this concentration. At the product level, IMERG shows a pronounced shift; its median CC drops substantially when Ethiopian studies are excluded, indicating that its advantage in this corpus reflects the concentration of its evaluations in Ethiopia's well-monitored highland context, and that its performance in less-studied regions is less well constrained. CHIRPS and TAMSAT show negligible shifts, consistent with their broader geographic evaluation bases. This sensitivity analysis is presented as two-panel box plots in Figure A2, with full summary statistics in Table A3.

4.13 Research Priorities for the Next Decade.

Synthesising the evidence gaps and thematic themes from this review, we identify five research priorities that would most improve the reliability and utility of gridded rainfall products for African water resource applications over the next decade.

Priority 1: Sub-daily validation at continental scale. The near-absence of sub-daily validation (only 9 studies, 64 observations, no systematic coverage) is the most critical knowledge gap relative to operational need. Coordinated sub-daily validation campaigns using TAHMO and national AWS networks, benchmarked against IMERG, CMORPH, and GSMaP sub-hourly products would transform our understanding of these products' operational viability.

Priority 2: Central Africa validation initiative. The Congo Basin and surrounding Central African countries are the most important unvalidated region in the global rainfall dataset. A dedicated validation programme, combining TAHMO station deployment, national meteorological service partnerships, and retrospective gauge data digitisation would fill the most critical geographic gap in the evidence base.

Priority 3: Machine-learning product development for African contexts. Several studies in this corpus demonstrated that ML approaches substantially outperform their inputs (Gichamo et al., 2023; Ehsan Bhuiyan et al., 2019; Estébanez-Camarena et al., 2023). Systematic development and independent validation of ML-based blending approaches trained on African gauge data, with explicit attention to data-sparse regions and orographic contexts, represents the most promising near-term algorithmic direction.

Priority 4: Long-term homogeneity assessment for trend analysis. The continent-wide use of CHIRPS, PERSIANN-CDR, and TAMSAT for climate trend analysis has proceeded without a systematic assessment of temporal homogeneity in these products. Formal change-point detection analysis applied to the full records of major products, benchmarked against homogeneity-tested national gauge archives, is urgently needed.

Priority 5: Conflict and disruption impacts on product quality. Security issues in northern Ethiopia have caused outages at meteorological stations, with station records becoming unavailable for multi-year periods during times of instability (Tadesse et al., 2024). This points to a broader uncharacterised risk: in conflict-affected regions across Africa, ongoing instability may be simultaneously degrading observational capacity while increasing the operational demand for satellite rainfall products, though this remains largely uninvestigated.

5 Conclusion

This systematic review and quantitative synthesis of 72 peer-reviewed studies was designed to answer a question that practitioners across African water agencies, meteorological services, and food security programmes face daily: which gridded rainfall product should I use, and how much should I trust it? The answer the evidence compels is not a ranking table but a principle, performance is determined more by context than by product. Reanalysis products are consistently the lowest performers in the corpus and should not be used as primary rainfall sources. Within the remaining global product space, no single option leads across all regions and applications. CHIRPS is the most broadly validated product in the literature, but TAMSAT v3 and IMERG outperform it at the daily scale in multiple contexts (Addisu et al., 2024; Zargar et al., 2025; Taye et al., 2023); RFE2 and ARC2 are more reliable than CHIRPS in the Sahelian detection task (Dembélé and Zwart, 2016; Goudiaby et al., 2024; Houngnibo et al., 2023). IMERG's relatively strong corpus-level performance should be interpreted cautiously: most of its daily CC observations derive from Ethiopian highland contexts, and its performance advantage shrinks substantially when those studies are excluded (Table A3). Its current upper-tier ranking reflects a validation evidence gap outside Ethiopia as much as a genuine continent-wide performance advantage. The practical consequence is that product selection should be preceded by local validation rather than continental reputation, and unconditional reliance on any single product (however widely used) carries real operational risk.

Three quantitative findings from the meta-analysis deserve to be stated plainly because they have direct implications for how gridded rainfall data are currently used across the continent. First, the daily NSE distribution of uncorrected products across 105 observations is centered near zero, meaning that raw satellite and reanalysis products applied directly to rainfall-runoff models perform no better, on average, than using the long-term mean as a predictor. Bias correction is not a refinement; it is a prerequisite. Second, correlation improves substantially from the daily scale to the dekadal scale across the corpus a gain in the order of 0.23 correlation units that reflects the averaging out of random retrieval timing errors, and that makes gridded products substantially more reliable for monthly climate monitoring and drought assessment than for daily event-based applications. Third, overestimation and underestimation co-occur in 90% and 87% of studies respectively. This is not a contradiction but two expressions of the same intensity-dependent bias structure: products overestimate the frequency of light rainfall while underestimating the magnitude of heavy events. Bias correction methods that do not account for this intensity structure will leave the most operationally consequential errors such as underestimation of flood-generating events largely unaddressed (Ehsan Bhuiyan et al., 2019; Bhatti et al., 2016; Tsegaye Mersha and Mekuriaw, 2025; Tessema et al., 2020).

Three investments would do more than any other to improve the reliability of gridded rainfall data for African water resource applications. The first is expanded and shared ground observation: the gauge scarcity that motivates the use of satellite products is simultaneously the primary constraint on their calibration and validation. This is a circularity that can only be broken by deploying more stations particularly in the Congo Basin, the Saharan margins, and highland Madagascar and by removing institutional barriers that keep existing African gauge records inaccessible to the international community (Dinku, 2019; Satgé et al., 2020; Ramahaimandimby et al., 2022; Camberlin et al., 2019). The second is adoption of multi-product ensemble strategies: the partial independence of error structures across product families means that combining IR-based, PMW-based, and gauge-adjusted products can cancel errors that persist in any individual product, as the Djibouti consensus experiment demonstrated (Waberi et al., 2023). The third is methodological standardisation: the metric heterogeneity across the 72 studies in this corpus prevented more definitive quantitative conclusions than the data volume would otherwise support. A minimum reporting standard including CC, PBIAS, RMSE, POD and FAR at 1 mm day^{-1}, and KGE for hydrological applications, reported at both daily and monthly scales with intensity-stratified analysis would make the next generation of African validation studies directly comparable and cumulative in a way the current literature is not (Waberi et al., 2023; Addisu et al., 2024; Omay et al., 2025).

The curated extraction database underlying the quantitative meta-analysis in this work with 1,749 metric observations across 54 studies, 148 locations, and 154 product variants is archived in a publicly accessible repository (Zenodo, DOI to be inserted upon acceptance) alongside all analysis scripts. An interactive dashboard allowing practitioners to query product recommendations by country, application, and temporal scale is available at https://africlimate-research.github.io/RainCheckAfrica/. Ultimately, the stakes of getting this right are not just technical, an estimated 95% of African cropland is rain-fed; droughts and floods driven by the continent's highly variable rainfall regime affect hundreds of millions of people annually. Improving the accuracy, reliability, and accessibility of gridded rainfall data through the product improvements, observational investments and methodological advances that this review identifies is one of the most direct contributions that the atmospheric and hydrological sciences can make to climate resilience across Africa.

Data Availability

The full extraction database (1,749 metric observations) is archived on GitHub (https://github.com/africlimate-research/RainCheckAfrica/tree/main). The interactive dashboard is available at (https://africlimate-research.github.io/RainCheckAfrica/) and allows practitioners to query product recommendations by country, application, and temporal scale.

Competing Interests

The authors declare that they have no conflict of interest.

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Appendix A: Supplementary tables, figures, and text

This appendix provides supporting tables, figures, and text referenced from the main text: the canonical product inventory (Table A1), African Union member states absent from the corpus (Table A2), the Ethiopia sensitivity analysis (Table A3 and Figure A2), corpus characteristics by publication year (Figure A1), the literature search strings (Appendix A6), and the extraction form field definitions (Appendix A7). All quantitative analyses are performed at the PRODUCT_PARENT level as described in Section 2.4.1 of the main text.

A1 Canonical product inventory

Table A1 lists all product parents appearing in the synthesis database with their canonical version strings and product family. Products were harmonised from 154 unique name strings to canonical labels as described in Section 2.4.1.

Table A1. Canonical product inventory. The 154 raw name strings in the extraction database were harmonised to 35 parent products prior to synthesis.

Parent	Family	Canonical version labels
ARC	Merged	ARC, ARC V2, FEWS-ARC V2
CFSR	Reanalysis	CFSR
CHIRPS	Merged	CHIRPS, CHIRPS V2, CHIRPS V8
CMAP	Merged	CMAP
CMORPH	Satellite	CMORPH, CMORPH ADJ, CMORPH CDR, CMORPH RAW, CMORPH-BLD v.1, CMORPH-CRT v.1, CMORPH-RAW v.1, CMORPH.CPC, CMORPH27, CMORPH8, CMORPH - HBV, CMORPH - HEC-HMS, CMORPH - SWAT
CPC	Gauge	CPC V1
ENACTS	Merged	ENACTS
ERA	Reanalysis	ERA5, ERA INTERIM
EWEMBI	Reanalysis	EWEMBI
GPCC	Gauge	GPCC
GPCP	Merged	GPCP, GPCP 1DD
GSMaP	Satellite	GSMAP, GSMAP WGAUGE, GSMAP MVK+, GSMAP ADJ V6, GSMAP NRT, GSMAP RT V6
IMERG	Satellite	IMERG, GPM, GPM IMERG-E, IMERG EARLY, IMERG LATE, IMERG FINAL, IMERG V6, IMERG-E, IMERG-F-0.18, IMERG-F-0.258
JRA	Reanalysis	JRA-55, JRA-55 Adj
MERRA	Reanalysis	MERRA V2
MSG	Satellite	MSG-SEVIRI
MSWEP	Merged	MSWEP, MSWEP V1, MSWEP V2, MSWEP V2.2, MSWEP V2.8
PERSIANN	Satellite	PERSIANN, PERSIANN CDR, PERSIANN CCS, PERSIANN-RT, PERSIANN-Adj, PERSIANN PDIR
RFE	Merged	RFE, RFE V2, RFE V3, FEWS-RFE V2
SM2RAIN	Other	SM2RAIN, SM2RAIN-ASCAT1.1, SM2R-CCI
TAMSAT	Satellite	TAMSAT, TAMSAT V2, TAMSAT V3, TAMSAT V3.1, TAMSAT-025, TARCAT
TAPEER	Satellite	TAPEER
TRMM	Satellite	3B42, 3B42 (V7), 3B42RT, 3B42V7, TRMM, TRMM 3B42, TRMM 3B42 V7, TRMM-Adj, TRMM-Raw, TMPA, TMPA 3B42 V7, TMPA RT, TMPA ResV, TMPA ADJ V7, TMPA-RT 3B42RT v7, 3B42 - HBV, 3B42 - HEC-HMS, 3B42 - SWAT, 3B42RT - HBV, 3B42RT - HEC-HMS, 3B42RT - SWAT
WFDEI	Reanalysis	WFDEI
BMAQ	Other	BMAQ
DVQR	Other	DVQR
FUSION	Other	FUSION
GAUGE	Other	GAUGE, Rain gauge
MLPET	Other	MLPET (K-fold), MLPET (Leave-one-region-out)
MLQR	Other	MLQR
OORA	Other	OORA
PRISM	Other	PRISM
RIVERWATCH	Other	RiverWatch3 discharge
SATRAN	Other	SATRAN
SMA	Other	SMA

A2 African Union member states absent from the corpus

Table A2 lists the 9 AU member states with no peer-reviewed validation study in the corpus. Referenced in Section 3.1 and Figure 3 of the main text.

Table A2: AU member states absent from the RainCheck Africa corpus ($n = 9$).

Country	Region	Type
Angola	Southern Africa	Mainland
Eswatini	Southern Africa	Mainland
Libya	North Africa	Mainland
Sahrawi Republic	North Africa	Mainland
Cabo Verde	West Africa	Island
Comoros	East Africa	Island
Mauritius	Southern Africa	Island
São Tomé & Príncipe	Central Africa	Island
Seychelles	East Africa	Island

A3 Ethiopia sensitivity analysis

Table A3 presents daily CC statistics for the five products with the most observations, computed on (a) all studies and (b) studies excluding Ethiopia. Supports Sections 3.4.1 and 4.12 of the main text.

Table A3: Sensitivity of daily CC estimates to Ethiopia corpus dominance (n≥10). ΔCC = median (excl. ETH) − median (all). IMERG shows the largest shift, confirming its upper-tier position in main text Figure 6 reflects an evidence concentration, not a continent-wide advantage.

Product	**All** (n)	**CC (all)**	**Excl. ETH** (n)	**CC (excl.)**	Δ**CC**
CHIRPS	59	0.400	27	0.390	−0.010
PERSIANN	40	0.395	32	0.395	0.000
TAMSAT	37	0.490	15	0.490	0.000
CMORPH	26	0.560	18	0.535	−0.025
TRMM	26	0.485	17	0.480	−0.005
ARC	21	0.450	16	0.505	0.055
IMERG	14	0.602	6	0.410	**−0.193**

A4 Corpus characteristics: publication years

Figure A1 presents the temporal distribution of the 72 peer-reviewed studies included in this review by publication year, spanning 2015 to 2025.

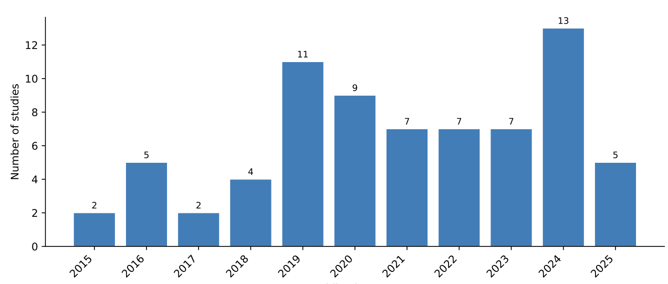

Figure A1. Distribution of the 72 included studies by publication year (2015–2025). Numbers above bars indicate study counts per year. The corpus spans eleven years, with peak publication activity in 2023 and sustained output from 2019 onward, reflecting the growing validation literature following the release of IMERG and CHIRPS v2.0.

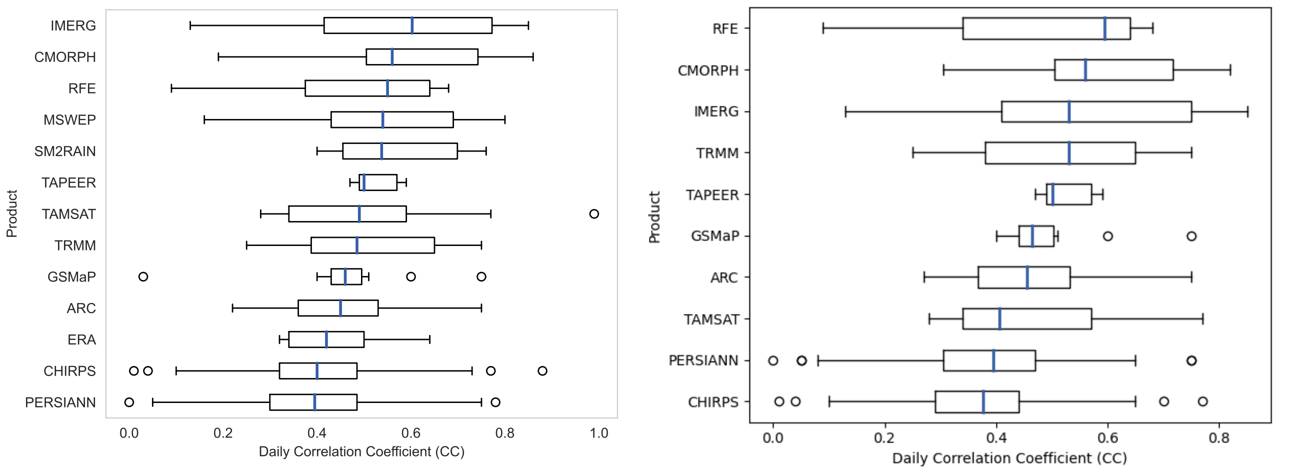

Figure A2. Sensitivity of daily CC distributions to Ethiopia corpus dominance. **Left panel**: all 72 studies (same as Figure 6 in the main text). **Right panel**: excluding Ethiopian studies (n per product in Table A3).

A5 Ethiopia sensitivity: daily CC box plots

Ethiopia contributes 33 studies (46% of the corpus) and has a comparatively dense gauge network for East Africa, particularly in the Blue Nile, Awash, and Rift Valley basins. The analysis shows overall corpus statistics are robust to Ethiopia exclusion. At product level, IMERG shows the largest sensitivity ($\Delta = -0.19$), consistent with its 14 daily CC observations being concentrated in Ethiopian highland studies. This indicates an evidence gap, not a performance failure outside Ethiopia. This finding reinforces Research Priority 2 in Section 4.13 of the main text.

A6 Literature search strings

A6.1 Web of Science

```
(TS=("gridded rainfall" OR "satellite rainfall" OR "satellite
precipitation" OR "reanalysis precipitation" OR "CHIRPS" OR
"TAMSAT" OR "IMERG" OR "TRMM" OR "ERA5" OR "PERSIANN" OR
"CMORPH" OR "ARC2" OR "RFE" OR "MSWEP" OR "GPCC" OR "GSMaP"
OR "SM2RAIN" OR "TARCAT" OR "ENACTS" OR "precipitation
validation" OR "rainfall assessment"))
AND
(TS=("validation" OR "accuracy" OR "bias" OR "evaluation" OR
"verification" OR "comparative analysis"))
AND
```

```
(TS=("Africa" OR "sub-Saharan Africa" OR "Horn of Africa" OR
"Sahel" OR "Congo Basin" OR "Ethiopia" OR "Nigeria" OR "Ghana"
OR "Kenya" OR "Tanzania" OR "Uganda" OR "Rwanda" OR "South
Sudan" OR "Sudan" OR "Egypt" OR "Libya" OR "Tunisia" OR
"Algeria" OR "Morocco" OR "Mauritania" OR "Mali" OR "Niger" OR
"Chad" OR "Senegal" OR "Gambia" OR "Guinea" OR "Burkina Faso"
OR "Benin" OR "Togo" OR "Cameroon" OR "Congo" OR "Democratic
Republic of Congo" OR "Angola" OR "Zambia" OR "Zimbabwe" OR
"Mozambique" OR "Malawi" OR "Botswana" OR "Namibia" OR
"South Africa" OR "Madagascar" OR "West Africa" OR
"East Africa" OR "North Africa" OR "Southern Africa" OR
"Central Africa"))
```

A6.2 Scopus

Equivalent string using `TITLE-ABS-KEY` field specification. Total records: 228 before duplicate removal.

A6.3 Google Scholar

Iterative searches for gap-filling. Backward citation tracking performed from key review papers.

A7 Extraction form field definitions and inter-rater reliability

The standardised extraction form comprised the following fields, applied consistently across all 72 included studies.

Table A4: Extraction form field definitions.

Field	**Definition and coding rules**
`PAPER_ID`	Unique numeric ID assigned at screening
`YEAR`	Publication year (integer)
`LOCATION`	Study location, basin, or watershed
`COUNTRY`	ISO country names for which gauge data were used
`PRODUCT`	Raw product name string as reported
`PRODUCT_PARENT`	Canonical parent name after harmonisation (e.g., all CHIRPS variants → "CHIRPS")
`PRODUCT_VERSION`	Specific version string

Continued...

Field	Definition and coding rules
PRODUCT_TYPE	Satellite, Merged, Reanalysis, Gauge, SM-Derived, ML-Model, Experimental
TIME_SCALE	Sub-daily, Daily, Pentadal, Dekadal, Monthly, Seasonal, Annual
METRIC	CC, RMSE, MAE, Bias, PBIAS, NSE, KGE, POD, FAR, CSI
VALUE	Numeric value verbatim from study
CORRECT_VALUE	Corrected value (transcription errors)
CORRECT_METRIC	Corrected metric type if ambiguous
FIGURE WITH DATA	Figure/table number in source paper
REVIEWER	Reviewer initials
Error pattern codes (0 = not reported, 1 = reported)	
OVEREST	Evidence of Overestimation of rainfall
UNDEREST	Evidence of Underestimation of rainfall
WEAK_DAILY	Evidence of Weak performance at daily/sub-daily time steps
HEAVY_FAIL	Evidence of Poor detection of heavy rainfall events
OROG	Evidence of Orographic rainfall difficulty
HIGH_ALT	Evidence of High-altitude underestimation
Synth	General Synthesis and Key Conclusions.

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