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A new workflow for estimating groundwater recharge in data-scarce environments

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ABSTRACT

This study proposes a novel workflow for estimating groundwater recharge in data-scarce environments, using the Densu Basin in Ghana as a case study. The method combines the water table fluctuation method (WTFM) and the soil water balance (SWB) approach, with a bias correction step applied to reconcile systematic differences between the two methods. Recharge estimates from both approaches revealed significant spatial and seasonal variability, with higher rates in the northern sectors characterized by favorable soil types (sandy clay loam and sandy clay) and extensive forest cover. The WTFM, applied from 2004 to 2009, yielded an average monthly recharge of 43.9 mm, while the SWB approach, covering 1960–2015, estimated a lower average of 33.7 mm. The June–July–August season (June–August) exhibited the highest recharge contribution. Bias correction of the SWB series using WTFM as reference substantially reduced systematic error, with linear scaling achieving the smallest mean bias and providing corrected recharge estimates ranging from 27 to 39 mm/month, increasing from the southern to the northern parts of the basin. The soil conservation service method estimated an annual runoff of 439 mm (26% of annual rainfall). The results highlight the influence of soil properties, land cover, and rainfall patterns on recharge dynamics and emphasize the need for adaptive, localized water management strategies to ensure long-term sustainability of groundwater resources in the Densu Basin.

Key words: Densu Basin, Ghana, groundwater recharge, SCS-CN, water balance, water table fluctuation method

HIGHLIGHTS

- Developed an integrated workflow combining WTFM and SWB to estimate recharge in the Densu Basin under data scarcity.
- Identified clear spatial and seasonal variability, with higher recharge in the north.
- Applied bias correction, with linear scaling nearly eliminating mean bias.
- Demonstrated improved recharge estimates to support groundwater management in data-limited regions.

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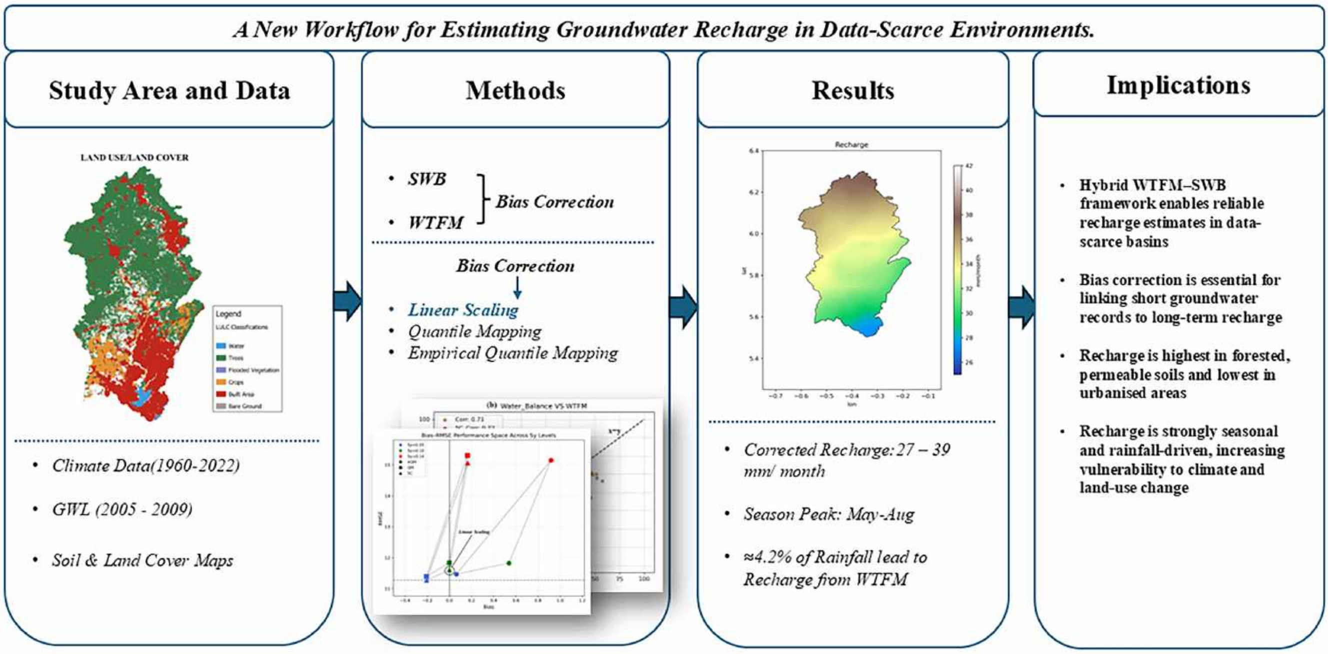
GRAPHICAL ABSTRACT



1. INTRODUCTION

A significant portion of Earth's freshwater is stored in groundwater reservoirs, supplying essential water resources to over two billion people worldwide (Famiglietti 2014). In regions like the Densu Basin in Ghana, groundwater is essential to meet the rising demand for clean water amid environmental pressures. Despite its relatively small size, the Densu Basin is one of Ghana's most heavily used water systems, with the river crossing numerous towns and providing water for over 200 communities (Duah *et al.* 2021). Population density around the basin ranges from 150 to 200 persons per square kilometer, which is significantly higher than the national average of 77 persons per square kilometer (Water Resources Commission 2007).

In addition to the challenges of high population density, the basin faces various environmental stresses, including climate change, urbanization, illegal mining, and inadequate agricultural and waste disposal practices. These factors collectively affect both the quality and the availability of water resources in the area (Adomako *et al.* 2011; Yidana *et al.* 2018). As surface water resources become increasingly compromised, groundwater has become a vital alternative, despite challenges in yield and accessibility (Daily Graphic 2001). This growing reliance on groundwater highlights the need for effective resource management to ensure the basin's long-term water security.

Estimating groundwater recharge, a key process for sustaining groundwater levels, is particularly complex in data-scarce regions of developing countries. These settings often lack the systems and capacity to acquire the high-resolution data needed for accurate recharge estimation. This limitation necessitates the development of innovative approaches that can work effectively with limited or incomplete datasets. Many traditional recharge estimation methods require extensive hydrological and geological data that are often unavailable or incomplete in such settings. Advanced models like MIKE SHE and MODFLOW, for instance, can provide detailed simulations but require substantial input data, which may be difficult to obtain in data-limited environments (Yidana *et al.* 2014). Other methods, such as the water table fluctuation method (WTFM) and chlorine mass balance techniques, similarly face limitations when reliable yield data are lacking (Duah *et al.* 2021).

Given these limitations, there is a pressing need for approaches that offer reliable recharge estimates with fewer data demands. The WTFM and soil water balance (SWB) approaches are two widely used methods, but both are challenging to apply in data-scarce regions. WTFM requires accurate groundwater level measurements and specific yield estimates, which are often sparse or unreliable. Likewise, the SWB approach depends on comprehensive data for precipitation,

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runoff, evapotranspiration, and soil moisture storage, which may be incomplete or unavailable. This study aims to address these challenges by comparing and combining the WTFM and SWB methods to improve groundwater recharge estimates in data-sparse environments. Specifically, it will apply the WTFM to bias-correct SWB estimates, thereby enhancing the accuracy of recharge predictions.

While bias correction is common in climate modeling, its use to reconcile groundwater recharge estimation methods remains limited. This study introduces bias correction techniques [linear scaling (LS), quantile mapping (QM), and empirical quantile mapping (EQM)] to align SWB outputs with water-table-based recharge estimates. This methodological transfer is particularly valuable in data-scarce environments, where neither method alone provides robust long-term estimates.

This study also aligns with the United Nations Sustainable Development Goal (SDG) 6, which emphasizes sustainable water management. By addressing groundwater recharge in data-scarce regions, this study contributes to a deeper understanding of water resources and supports the development of sustainable management practices. The objectives of this study are: (1) to assess the applicability and limitations of the WTFM and the SWB approach in estimating groundwater recharge; (2) to develop an integrated approach that combines the strengths of both WTFM and SWB to enhance the accuracy of recharge estimations; (3) to analyze groundwater recharge rates across multiple temporal scales to better understand seasonal and interannual recharge dynamics in the basin; and (4) to apply the developed methodology as a case study in the Densu Basin of Ghana to provide insights into groundwater management.

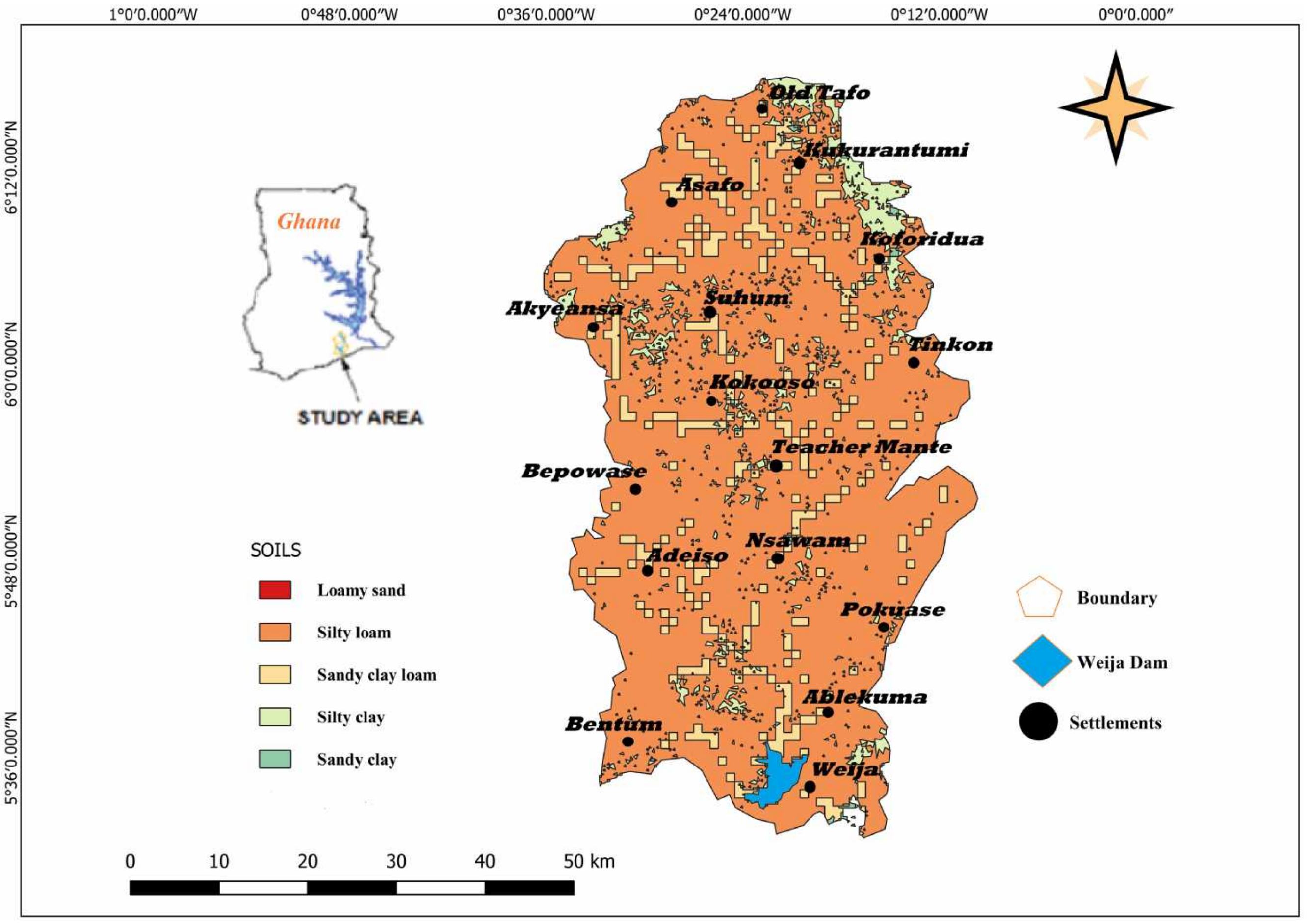

Figure 1 | Location map of Densu River Basin showing the soil types, Weija Dam, and major settlements.

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2. STUDY REGIONS

2.1. Geography, climate, and hydrogeology

The Densu River basin spans between latitude 5°30N–6°17N and longitude 0°10W–0°37W in the southern region of Ghana (Figure 1), covering a significant portion of three administrative regions: Greater, Eastern Accra, and Central. The basin encompasses an area of about 2,600 km^2 (Water Resources Commission 2007). Its catchment areas include the Gulf of Guinea to the south, where it empties into the sea, the Volta basin to the north, Odaw to the east, Ayensu and Okrudu to the west, and Birim to the northwest. There are over 200 communities in the basin, and their population density, which ranges from 150 to 200 people per square kilometer, is higher than the 77 people per km^2 that is the average for the country (Ghana Statistical Service 2000).

The basin's vegetation changes from wet semideciduous forest in the north to coastal savannah, grassland, and thicket in the south along the coast. The terrain is gently rolling, characterized by hills that contribute to the basin's picturesque landscape. Agriculture is the primary economic activity, encompassing crop cultivation, livestock farming, and fishing. Cultivated crops include cocoa, maize, vegetables, pineapples, and cocoyam.

The Densu Basin has two distinct climatic zones: a wet semiequatorial climate in the north and a relatively dry equatorial climate toward the southeastern coast (Duah *et al.* 2021). Both climates exhibit a bi-modal rainfall pattern with different intensities. This is mainly due to its location in the southern part of the country, where the northward and southward movement of the intertropical discontinuity (ITD) regulates the rainfall dynamics of the entire country. This movement results in a unimodal rainfall pattern in the north and bi-modal at the south of Ghana (Yamba 2010). The basin has two primary rainy seasons: the major rainy season from April to July, peaking in June, and the minor rainy season, less intense, occurring from September to November. The basin experiences a range of rainfall intensities, with 70% of the total falling between 40 and 120 mm/hour. The intensity of the rainfall also varies throughout the basin (Alfa *et al.* 2011).

Temperature in the basin generally remains elevated throughout the year, with an annual mean of 26.7 °C, peaking at 33 °C in February/March and declining to a minimum of 24 °C around July/August (see Figure S2). Monthly trend analysis (see Figure S2) of PET indicates that elevated levels occur in March (112 mm), preceding the onset of the rainy season. However, this trend diminishes as both major and minor rainfall seasons progress due to the northward shift of the ITD in early March (Osei *et al.* 2019).

The Densu River Basin is predominantly underlain by the Basement Complex, featuring a variety of Precambrian crystalline rocks and formations. The Birimian Supergroup, which occupies a significant portion of the northwestern basin, consists of Paleoproterozoic crystalline rocks, predominantly metamorphic and sedimentary in origin, including chlorite schists and amphibolites. These rocks were significantly altered by the Eburnean tectonothermal event, which caused extensive folding and metamorphism. In addition, Eburnean and Tamnean granitoids, which include aluminous varieties like 2-mica granites, dominate much of the basin's geology (Adomako *et al.* 2010; Duah *et al.* 2021; Akurugu *et al.* 2022).

2.2. Earlier studies on recharge in the Densu Basin

Understanding groundwater recharge processes in the Densu Basin is essential for sustainable water resource management, ecological preservation, and climate adaptation. Recharge estimation in the region has been approached using various methods, offering valuable insights into the basin's hydrogeological dynamics. However, challenges such as limited data availability and varying methodologies highlight the need for a comprehensive understanding of groundwater recharge patterns and rates.

For instance, Duah *et al.* (2021) estimated recharge using the WTFM and the chloride mass balance approach, relying on chloride and water level data from 10 monitoring wells. Their findings revealed seasonal and spatial variations in recharge, with a decreasing trend from north to south. They reported an average annual recharge of 70 mm using the chloride mass balance approach and 62 mm using the WTFM. Furthermore, the study highlighted that the combined groundwater use from commercial water producers, rural villages, and factories accounted for only 8% of the annual recharge.

Adomako *et al.* (2010) applied solute transport modeling and the approximate peak-shift method to estimate recharge rates in the Densu Basin. Using HYDRUS-1D, they analyzed the movement of stable water isotopes in the unsaturated zone at three sites with varying altitudes, geology, and vegetation. The study reported that groundwater recharge ranged between 94–182 and 110–250 mm annually, depending on the method used, equivalent to 7.2–13.9 and 8.4–19.1% of

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annual rainfall, respectively. Their results also indicated that evaporation significantly influenced the isotopic composition in the top 2–3 m of soil.

Alfa *et al.* (2011) utilized daily rainfall data as input to the physically based hydrological model MIKESHE to compute water balance and describe hydrological processes in the basin. They observed a pattern of increasing rainfall from downstream to upstream and estimated potential groundwater recharge between 120 and 153 mm annually, corresponding to 8–13% of annual rainfall. The study also projected a potential decline in infiltration due to increased rainfall intensity linked to climate change.

Yidana *et al.* (2014) employed MODFLOW to model the hydrogeological system of the basin under transient conditions, using data from monitoring wells, aquifers, and surface hydrology. They observed rainfall ranging from 900 to 1,600 mm annually, with recharge rates decreasing from 12% of annual precipitation in 2006 to 10.3% in 2008. The highest recharge occurred in the central granitic regions, while the lowest was observed in the northern eburnean plutonic suite. They cautioned that while the estimated recharge indicates potential for commercial groundwater development, the system is unsustainable under a scenario of annual abstraction increases of 20%.

Despite these efforts, most studies in the Densu Basin rely on individual methods, which introduce uncertainty in recharge estimates. Employing multiple techniques can mitigate these uncertainties, but numerical models often face challenges due to their labor-intensive nature and extensive data requirements.

3. DATASET AND METHODOLOGY

3.1. Data sources

Three primary datasets were used in this study: gridded climate data, groundwater level observations, and soil property information. Climate forcing variables, including precipitation, temperature, vapor pressure, and potential evapotranspiration, were obtained from the CRU TS v4.07 dataset at 0.5° spatial resolution for the period 1901–2022. These data were used to drive the SWB model. Actual evapotranspiration data used for calibration were obtained from the Ghana Meteorological Agency and subjected to quality control checks prior to use.

Groundwater level data were obtained from five monitoring boreholes equipped with automatic loggers and operated under a CSIR-WRI monitoring programme. Water levels were recorded at 6-hour intervals between 2005 and 2009 and processed into continuous time series. These observations were used to estimate recharge via the WTFM and to provide a reference series for bias correction. Table 1 summarizes the key characteristics of the groundwater dataset, including station coordinates, the number of valid observations, mean groundwater-level elevations, and the range of short-term fluctuations (Δh) derived from the irregular hourly sequences.

Soil properties required for SWB parameterization were extracted from the FAO data catalog (https://data.apps.fao.org/map/catalog/). Soil raster layers were taken from the FAO/UNESCO Soil Map of the World (https://www.fao.org/soils-portal/). Raster soil layers at 30 arc-second resolution were clipped to the basin and resampled to the model grid. Soil attributes from two depth intervals (0–30 and 30–100 cm) were averaged to represent the effective root zone depth. Additional details on soil classification are provided in the Supplementary Information.

3.2. Methodology

3.2.1. Data preprocessing

Due to the CRU TS dataset's inherent quality of having no missing values for any months or land cells, it serves as a reliable data source.

Table 1 | Summary of groundwater level observations used in the WTFM recharge estimation

Station	Lon	Lat	Obs	Mean elev. (m)	Δh_{min} (m)	Δh_{max} (m)
ADWUMAKO	−0.50	6.194	6,153	1,266.448	−318.6	304.8
KOJO ASHONG	−0.40	5.700	7,457	1,025.499	−249.9	252.1
NSAWAM	−0.30	5.800	5,377	1,368.896	−416.7	363.5
SUHUM	−0.30	6.040	5,370	1,601.538	−452.9	438.6
TAFO	−0.34	6.220	5,369	1,408.601	−97.1	95.0

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Groundwater levels were recorded at 6-hour intervals from 2004 to 2009 at five monitoring stations. The 2004 data series was incomplete for all stations except Kojo Ashong, with large gaps and irregular sampling that prevented reliable water-table fluctuation analysis. For consistency across stations, we therefore restricted the analysis to the common period October 2005 to June 2009. Missing and nonphysical values were removed because Δh calculations require consecutive valid measurements. Daily water-level changes (Δh) were computed from the cleaned 6-hourly series, after which both Δh and water levels were aggregated to monthly values to match the temporal resolution of the recharge estimates. Kojo Ashong station was excluded from the final analysis because the logger showed no meaningful day-to-day or month-to-month variation. Such behavior is inconsistent with natural water-table dynamics in the Densu Basin and suggests either logger malfunction or issues with sensor installation. Including this station would bias the recharge estimation toward unrealistically low variability, so it was removed from subsequent analyses. The remaining four stations provided 45 valid monthly observations suitable for WTFM-based recharge estimation.

3.2.2. Bias correction

Recharge estimates from the SWB method differed systematically from those obtained using the WTFM. To reconcile these differences, three statistical bias correction techniques commonly used in climate model downscaling were applied: LS, QM, and EQM. The WTFM recharge series was used as the reference, while the SWB series provided the long-term recharge signal to be corrected. Methodological details of the bias correction procedures are provided in the Supplementary Information.

3.3. Water balance method

Groundwater recharge was estimated using an SWB framework driven by precipitation, evapotranspiration, and surface runoff. Surface runoff was estimated using the soil conservation service curve number (SCS-CN) method, while recharge was computed as the residual of the water balance. All formulations and parameter definitions are provided in the Supplementary Information.

3.4. WTFM

Groundwater recharge was estimated using the WTFM, based on observed changes in groundwater levels and a specific yield value derived from reported estimates for the Densu Basin (Duah *et al.* 2021). Recharge was calculated over the common observation period using groundwater-level records from the monitoring network. Mathematically, the WTFM is given in Equation (1) as

$$\text{Recharge} = \frac{\Delta h}{\Delta t} \times S_y \tag{1}$$

where

Recharge: estimated recharge (mm),
Δh: change in hydraulic head (depth),
Δt: period over which the change in hydraulic head occurs (time), and
S_y: specific yield of the aquifer (dimensionless).

Equation (1) is commonly utilized to apply the WTFM for estimating gross recharge. However, in this context, Δh no longer represents just the observed water table rise. Instead, it is adjusted to include both the observed rise and an empirical estimate of the net GW discharge. Equation (4) presents a modified form of the WTFM method, which considers net discharge. This modified approach was adopted from (Kotchoni *et al.* 2018):

$$h = h_{t-\Delta t} + \frac{R_t - D_t}{S_y} \tag{2}$$

$$S_y ht = S_y ht - \Delta t + R_t - D_t \tag{3}$$

$$R_t = S_y(h_t - h(t - \Delta t)) + D_t \tag{4}$$

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where

R_t: estimated recharge (mm),
Δh: change in hydraulic head (depth),
Δt: period over which the change in hydraulic head occurs (time),
S_y: specific yield of the aquifer (dimensionless), and
D_t: GW discharge through time.

In this study, Equation (4) was adopted in estimating the recharge from 4 monitoring boreholes in the Densu Basin.

3.5. GIS-based SCS-CN method for runoff estimation

Surface runoff was estimated using the SCS-CN method developed by the United States Department of Agriculture Soil Conservation Service (USDA-SCS). The method estimates direct runoff based on precipitation, land use/land cover, hydrological soil groups, and antecedent moisture conditions (Jasrotia *et al.* 2002). Normal antecedent moisture conditions (AMC-II) were adopted, consistent with the basin's bimodal rainfall regime. A GIS-based workflow was applied to derive spatial datasets of land use/land cover and hydrological soil groups. Land use data were obtained from the FAO map catalog, while soil data were derived from the FAO/UNESCO soil map. These datasets were processed using ArcGIS 10.8 and QGIS 3.28.15 to delineate hydrologically similar units and compute area-weighted curve numbers (CNs) for the basin. Detailed soil classification, CN assignment, and runoff computation equations are provided in the Supplementary Information.

4. RATIONALE FOR BIAS CORRECTION USING WTFM ESTIMATES

The SWB method, commonly used for estimating recharge and discharge rates, has limitations that can lead to inaccuracies. Specifically, it does not fully account for lateral flow, aquifer response time, or the complexity of evapotranspiration processes. It also simplifies soil moisture dynamics, which affects its precision. Although factors such as land cover and soil types were incorporated into runoff calculations, they were not directly included in the SWB water balance equation, which further restricts the method's accuracy.

To address these limitations, the study employed the WTFM as an observational benchmark for bias correction. WTFM provides recharge estimates directly from groundwater level fluctuations, making it a useful reference where high-frequency groundwater data are available. Unlike SWB, which offers basin-wide spatial coverage, WTFM estimates are point-based and sensitive to uncertainties in specific yield (see Figure 2 and Table 2) and local hydrogeological conditions. The two methods, therefore, complement each other: SWB provides spatially distributed recharge fields across the entire basin, while WTFM offers observation-based estimates that help constrain and correct the magnitude of SWB outputs. Due to data availability, WTFM estimates were only available from 2005 to 2009, so this period was used to derive the correction factor. Temporal variations between the SWB and WTFM estimates within this period were analyzed, yielding a relatively strong linear correlation of 0.71. The correlation was statistically significant ($p < 0.05$) (see Table 3), confirming that both methods captured similar temporal patterns despite differences in magnitude. However, the SWB method exhibited substantial overestimations and underestimations relative to WTFM, highlighting the need for bias correction.

To align SWB estimates more closely with WTFM recharge, three bias correction methods were applied: LS, QM, and EQM, as detailed in Section 3.2.2. Each method was evaluated for its ability to reduce discrepancies between SWB and WTFM. SWB recharge was extracted for 2004 to 2009, and all comparisons, bias values, and sensitivity results were based on this matched window. This approach follows the same principle used in climate studies, where bias correction is performed using overlapping periods between global climate models and local observations. A correction factor derived from the linear-scaling-adjusted SWB series (mean value 0.76) was then applied across the full SWB time series (2010–2015). Applying this factor to the basin-wide SWB outputs produced more reliable recharge estimates that are consistent with the observed groundwater-level response captured by WTFM. The workflow should be interpreted as bias-constrained estimation rather than full methodological integration.

Figure 3 summarizes the methodological workflow, illustrating how observation-based and model-based recharge estimates are integrated through bias correction.

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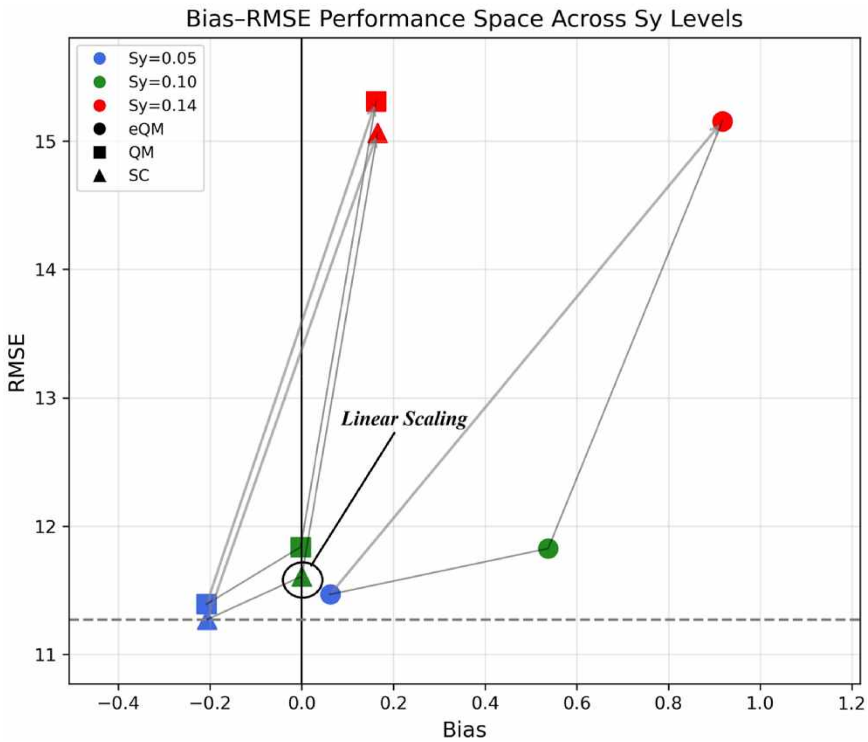

Figure 2 | Bias and RMSE for the three recharge methods across the three Sy levels. Points show eQM, QM, and SC at Sy 0.05, 0.10, and 0.14. Lines show how performance shifts with Sy.

Table 2 | Sensitivity of bias correction performance to specific yield (S_y)

Method and S_y	Bias	RMSE	RRMSE	MAE	Corr
eQM_corrected_0.05	6.21×10^{-2}	11.5	27.8	9.14	0.702
QM_corrected_0.05	-2.08×10^{-1}	11.4	27.6	9.11	0.706
SC_corrected_0.05	-2.07×10^{-1}	11.3	27.3	8.96	0.717
eQM_corrected_0.14	9.18×10^{-1}	15.2	36.7	12.2	0.702
QM_corrected_0.14	1.62×10^{-1}	15.3	37.0	12.3	0.706
SC_corrected_0.14	1.65×10^{-1}	15.1	36.5	12.8	0.717
eQM_corrected_0.10	5.38×10^{-1}	11.8	28.6	8.93	0.702
QM_corrected_0.10	-2.35×10^{-3}	11.8	28.6	9.00	0.706
SC_corrected_0.10	-7.89×10^{-17}	11.6	28.1	9.40	0.717

Table 3 | Performance of bias correction methods compared with WTFM recharge

Method	Bias	RMSE	RRMSE	MAE	Corr	*p*-value
scs_recharge_values	−16.4	40.4	97.7	34.1	0.717	2.94×10^{-8}
eQM_corrected	0.538	11.8	28.6	8.93	0.702	7.64×10^{-8}
QM_corrected	−0.00235	11.8	28.6	9.00	0.706	6.01×10^{-8}
SC_corrected	-7.89×10^{-17}	11.6	28.1	9.40	0.717	2.94×10^{-8}

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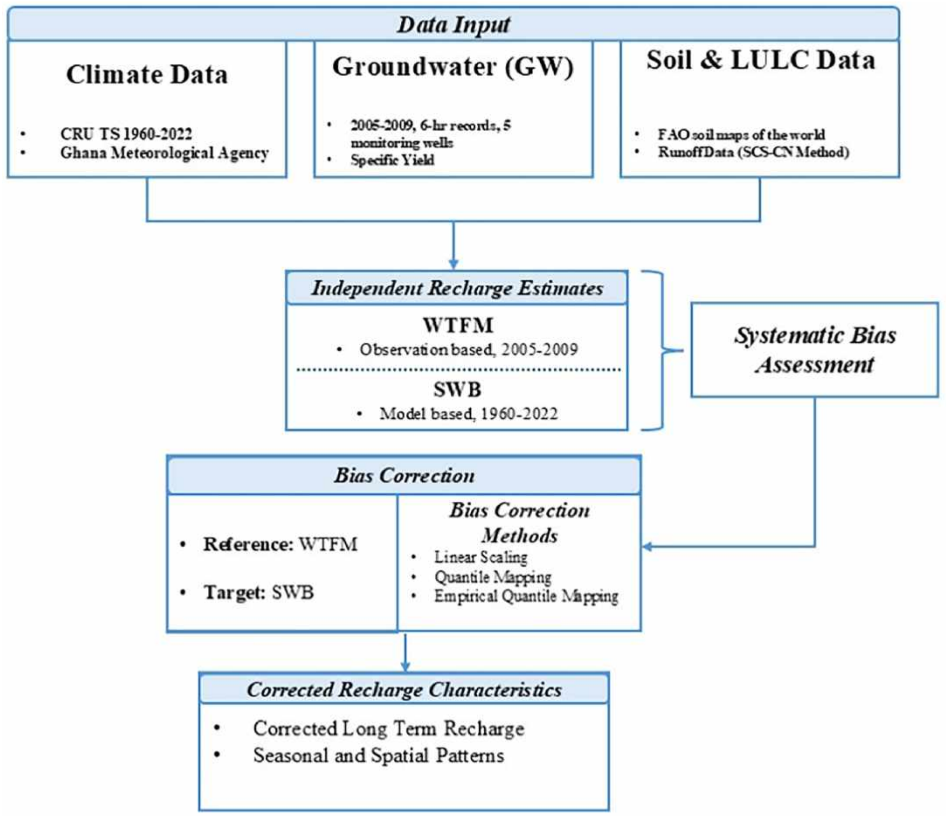

Figure 3 | Methodological framework illustrating the integration of observation-based and model-based groundwater recharge estimation. Recharge is first estimated independently using the WTFM and an SWB approach. Systematic differences between the two estimates are reconciled through bias correction using LS, QM, and EQM. The corrected SWB series is subsequently used to analyse long-term groundwater recharge variability.

5. VALIDATION METRICS

To evaluate the performance of the bias correction between the WTFM and SWB methods, five statistical metrics were used: correlation coefficient (*r*), bias, Root Mean Square Error (RMSE), Relative Root Mean Square Error (RRMSE), and Mean Absolute Error (MAE). These metrics provided a quantitative assessment of the accuracy and reliability of each method in estimating recharge rates. Details of these methods are provided in the Supplementary Information.

6. RESULTS AND DISCUSSION

6.1. Independent recharge estimates

6.1.1. Recharge estimates from the WTFM

Natural groundwater recharge estimated using the WTFM from 2005 to 2009 exhibits a clear seasonal pattern across all monitoring locations. Positive recharge occurs predominantly during the rainy months (May–August), while discharge dominates during the dry season (December–March), indicating a strong dependence of recharge on precipitation. Mean recharge rates vary substantially among locations, with Suhum recording the highest mean recharge (72 mm/month) and Adwumako the lowest (25.9 mm/month) (Figure 4). The highest monthly recharge (72 mm/month) was observed in the middle sector of the basin, and the lowest (25.9 mm/month) was recorded in the northern sector, depicting an increasing trend in recharge magnitude from north to south. This pattern is consistent with findings by Yidana *et al.* (2014). Correlation analysis between recharge and precipitation shows a strong relationship at Tafo ($r = 0.82$), moderate correlations at Suhum ($r = 0.56$) and Adwumako ($r = 0.60$), and a weaker relationship at Nsawam ($r = 0.45$). These differences indicate that recharge response is influenced not only by rainfall magnitude but also by local soil properties, land cover,

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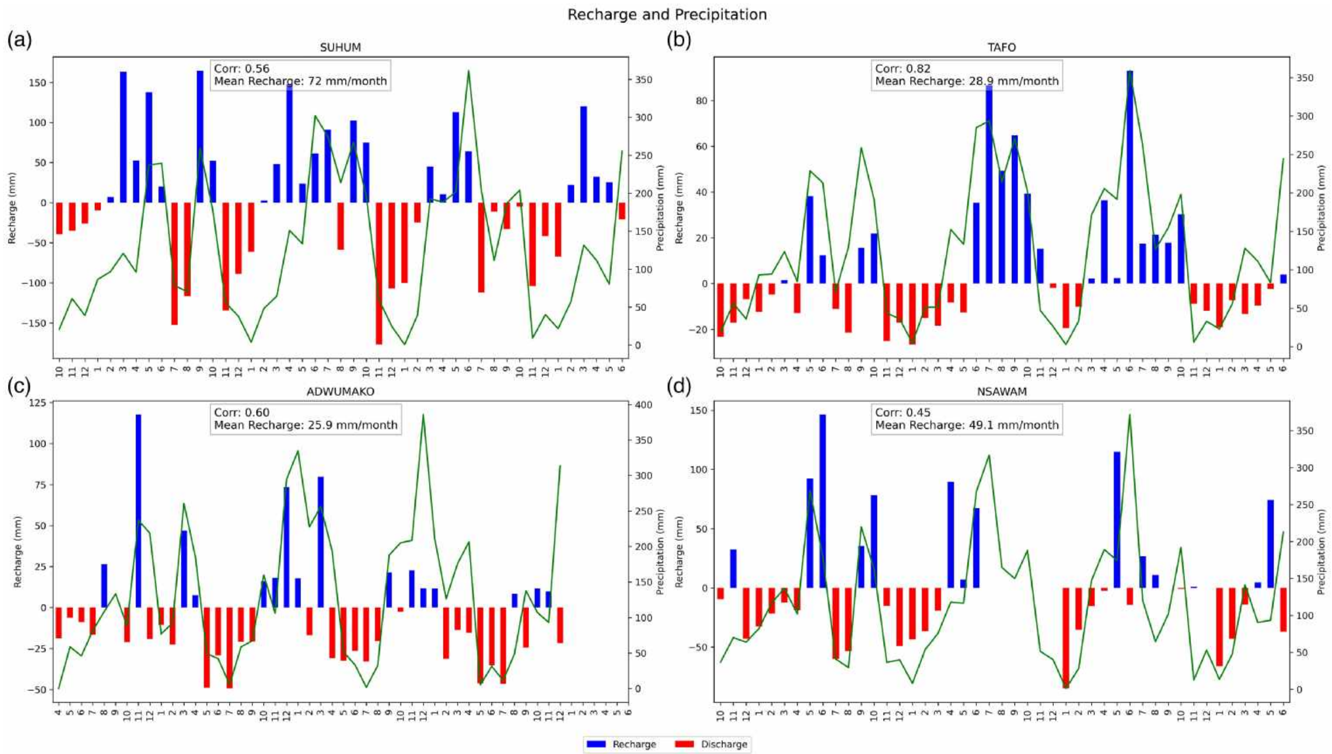

Figure 4 | Temporal variation of GW levels and rainfall (2005–2009) at Suhum, Nsawam, Adwumako, and Tafo in the Densu Basin. Red bars represent discharge, blue bars indicate recharge, and the green line depicts monthly rainfall variations. Rainfall magnitudes are shown on the twinned *x*-axis.

evapotranspiration, and aquifer characteristics (Li *et al.* 2014; Appels *et al.* 2015). Cross-correlation analysis (Figure S5) confirms a rapid recharge response to rainfall, with the highest correlation (0.65) occurring at zero lag.

Recharge estimates were calculated using a specific yield (S_y) of 0.10, based on reported values for the Densu Basin (Duah *et al.* 2021). Sensitivity analysis using S_y values of 0.05, 0.10, and 0.14 shows that increasing S_y to 0.14 substantially degrades bias-correction performance, with RMSE increasing from approximately 11.3–11.8 to 15.1–15.3 mm and RRMSE from about 27–29 to 36–37%, accompanied by a strong positive bias (Table 2 and Figure 2). While $S_y = 0.05$ and $S_y = 0.10$ yield similar RMSE values, $S_y = 0.05$ introduces systematic underestimation, whereas $S_y = 0.10$ produces near-zero bias for the linear-scaling correction. Based on this trade-off, $S_y = 0.10$ was retained as the preferred value, with $S_y = 0.05$ and $S_y = 0.14$ treated as uncertainty bounds.

Spatial differences in recharge are strongly influenced by local soil properties and land cover. Higher recharge rates observed at Suhum and Nsawam are associated with sandy clay loam and sandy clay soils and dense forest cover, which promote infiltration by reducing the impact of raindrops on the soil surface, minimizing soil compaction, and improving soil structure through root systems (Jost *et al.* 2012; Kercheva *et al.* 2019). In contrast, Adwumako, characterized by silty loam soils with lower infiltration capacity and higher runoff potential, exhibits consistently lower recharge (see Figure 5(a)). WTFM-based recharge represents approximately 4.26% of annual rainfall across the basin. This low percentage highlights the limited proportion of rainfall contributing to aquifer replenishment, emphasizing the need for sustainable water resource management strategies to address potential groundwater scarcity, especially in areas with high water demand or during prolonged dry seasons.

6.1.2. SWB

Water balance-based approaches are advantageous because they are simple to implement and rely on readily available data, such as rainfall, runoff, and water levels, and account for all water entering the system (Lerner 1990). The basic components of the water balance for a basin include inflows and outflows. Precipitation is the primary inflow, while the main outflows

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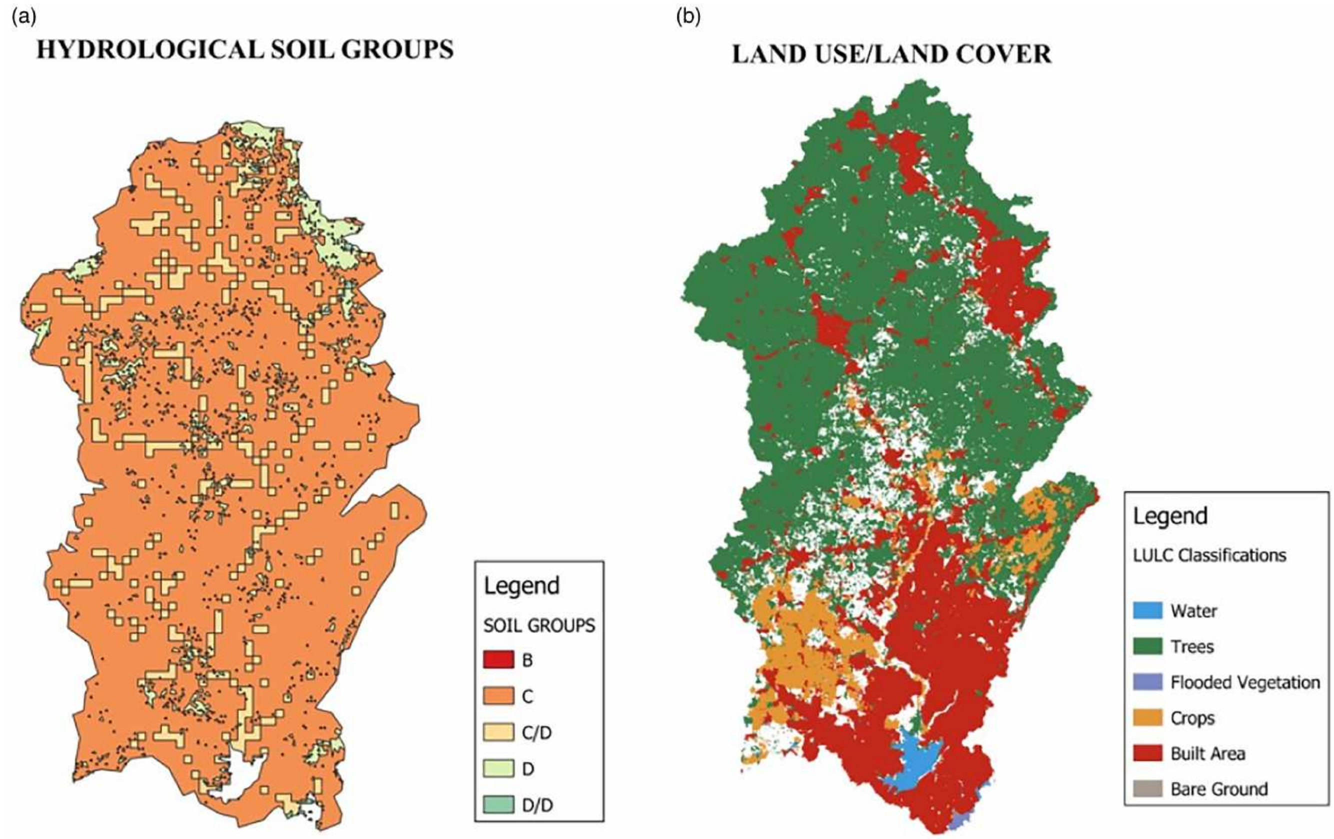

Figure 5 | Soil and land use/land cover maps.

are runoff, evapotranspiration, and interception losses. Before estimating recharge using SWB (see Equation (10) in the Supplementary Information), the important components are first identified and assessed separately. The SCS method was employed to estimate runoff.

6.1.2.1. SCS runoff estimate

6.1.2.1.1. Soil and land use/land cover. To accurately estimate runoff using the SCS method, specific input data, particularly in raster format, are required for hydrologic and land use characteristics. This method relies on the classification of HSG and land use/land cover, which directly influence runoff potential and infiltration rates across the basin. The soil and land use/land cover raster was fed into ArcMap 10.8 for classification and map creation.

The study area comprised hydrologic soil Groups B, C, and D, as illustrated in Figure 5(a). These HSGs represent soils with moderate to high runoff potential, with Group B having moderately low potential and Group D having the highest. The predominance of Group C soils, indicating moderate infiltration capacity, suggests a balance between runoff generation and GW recharge in the basin. This classification is important for understanding the potential for recharge under various land cover types and climatic conditions.

Similarly, the LULC map (Figure 5(b)) highlights six key classifications: water, built area, crops, flooded vegetation, trees, and bare ground. Notably, tree cover, depicted in green, is the dominant land cover type, accounting for roughly 65% of the basin. This extensive vegetative cover, particularly in the northern parts, plays a crucial role in stabilizing the soil, reducing surface runoff, and promoting GW recharge (Kim & Jackson 2012). In contrast, the southern sector of the basin is more urbanized, with built-up areas contributing to increased impervious surfaces, reduced infiltration, and higher flood risks.

6.1.2.1.2. Overlayed soil and land use/land cover analysis. Overlaying the maps was achieved using QGIS Desktop 3.28.15, employing the CN generator function. This tool classifies the layer based on soil type and land use classifications across the basin. During the classification process, a lookup table was uploaded, which assigns the CN for each classification. A

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summary of the lookup table is provided in Table S2. The weighted area average function in QGIS was employed to calculate the weighted CN value over the entire basin (see Equation (4) in the Supplementary Information). The CN is a dimensionless parameter ranging from 1 (indicating minimal runoff) to 100 (indicating maximum runoff). It was calculated based on HSG classifications and land use/land cover patterns. Figure 6 depicts the overlaid map generated. Table 4 provides a summary of all the parameters computed.

6.1.2.1.3. Surface runoff depth analysis. Using the adjusted CN and monthly rainfall data over the basin, surface runoff was calculated using Equation (1) under the SCS-CN Runoff Computation section in the Supplementary Information. The annual runoff, defined as the portion of rainfall that flows over the land surface into streams and rivers, was calculated to be 439 mm, accounting for approximately 26% of the total annual rainfall over the basin. To assess the accuracy of the estimated runoff, it was compared to the monthly mean discharge data from the Ayensu River spanning 1980 to 2006 within the basin. Figure 7 provides the relationship between the calculated runoff and river discharge. The figure reveals a positive correlation (0.55) between the calculated runoff and river discharge, indicating that as runoff increases, river discharge also

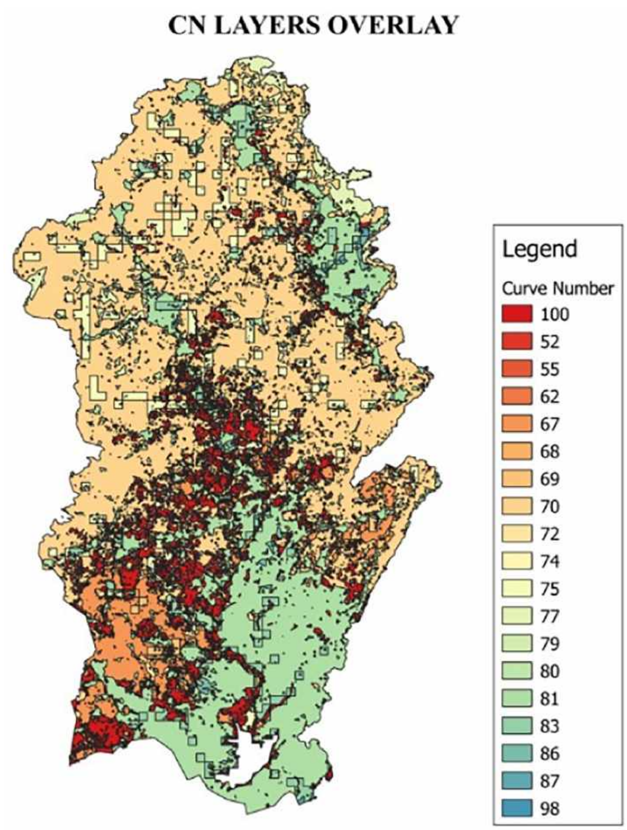

Figure 6 | SCS Curve number for the Densu Basin based on soil and landuse/cover maps.

Table 4 | Weighted curve number, soil retention parameter and initial abstraction, and the adjusted curve number of the Densu Basin

Parameters	Computed values
Weighted curve number	74
Soil retention parameter (S), mm	89.2
Initial abstraction (I_a), mm	17.8

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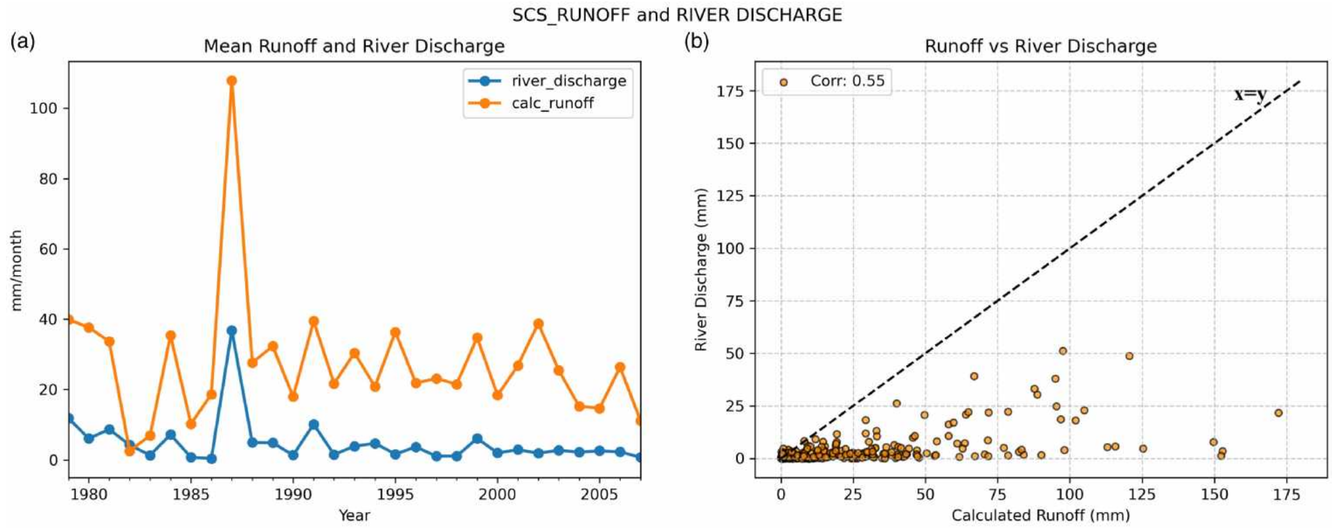

Figure 7 | Comparison between the mean SCS-calculated runoff (orange line) and river discharge (blue line) over time (a) and their correlation (b), where the scatter points represent the relationship between calculated runoff and river discharge, with the $x = y$ line.

increases. The phase difference observed between the calculated runoff and river discharge suggests that changes in runoff do not immediately result in corresponding changes in river discharge. This delay likely reflects the effects of processes such as infiltration and evapotranspiration, where some of the runoff water is either absorbed into the soil or lost to the atmosphere before reaching the river. The difference in calculated runoff and observed discharge can also be attributed to these hydrological factors. For instance, Darko *et al.* (2003) reported that while a significant portion of rainfall in the basin is lost to evapotranspiration (44.8%), another portion contributes to soil moisture and GW recharge (33.3%), reducing the volume of water available for direct river discharge. This explains why not all of the calculated runoff translates immediately into streamflow, as part of the water cycle diverts into these processes before contributing to river discharge.

6.2. Systematic bias and bias correction performance

6.2.1. Seasonal and soil influences on recharge estimation and method agreement

Figure 8 shows the cluster classification of recharge estimates from the WTFM and the SWB method, providing insights into recharge processes and the agreement between the two methods across Suhum, Tafo, Adwumako, and Nsawam. The seasonal distribution of the recharge clusters (see Figure S6) highlights the influence of soil properties, vegetative cover, and climatic conditions during the transition seasons: March–April–May (MAM) (premonsoon) and September–October–November (SON) (postmonsoon), as well as during the monsoon [June–July–August (JJA)] and dry season [December–January–February (DJF)].

In Suhum, the light blue clusters (SWB negative, WTFM positive) were present in MAM and DJF, with greater prominence in MAM (see Figure S6). During MAM, high evapotranspiration reduces soil moisture levels, leading SWB to estimate negative recharge. However, Suhum's sandy clay loam and sandy clay soils (Figure 5(a)) support delayed infiltration, which WTFM captures as positive recharge. During JJA and SON, light red clusters (WTFM negative, SWB positive) occurred, with a stronger presence in JJA. The intense rainfall during JJA saturates the soil, causing runoff and limiting infiltration to the groundwater table. SWB interprets the surplus of water as recharge, while WTFM records a minimal response to the groundwater table due to delayed percolation.

In Tafo, deep blue clusters dominated across MAM, JJA, and SON, with their strongest presence in JJA (see Figure S6). This indicates strong agreement between the two methods, facilitated by Tafo's sandy clay soils (Figure 5(a)), which have high infiltration capacity. The small number of light clusters across seasons suggests that both methods consistently capture recharge processes without significant temporal lags or runoff effects. During MAM and SON, the soils quickly translate rainfall into groundwater recharge, leading to alignment between WTFM and SWB.

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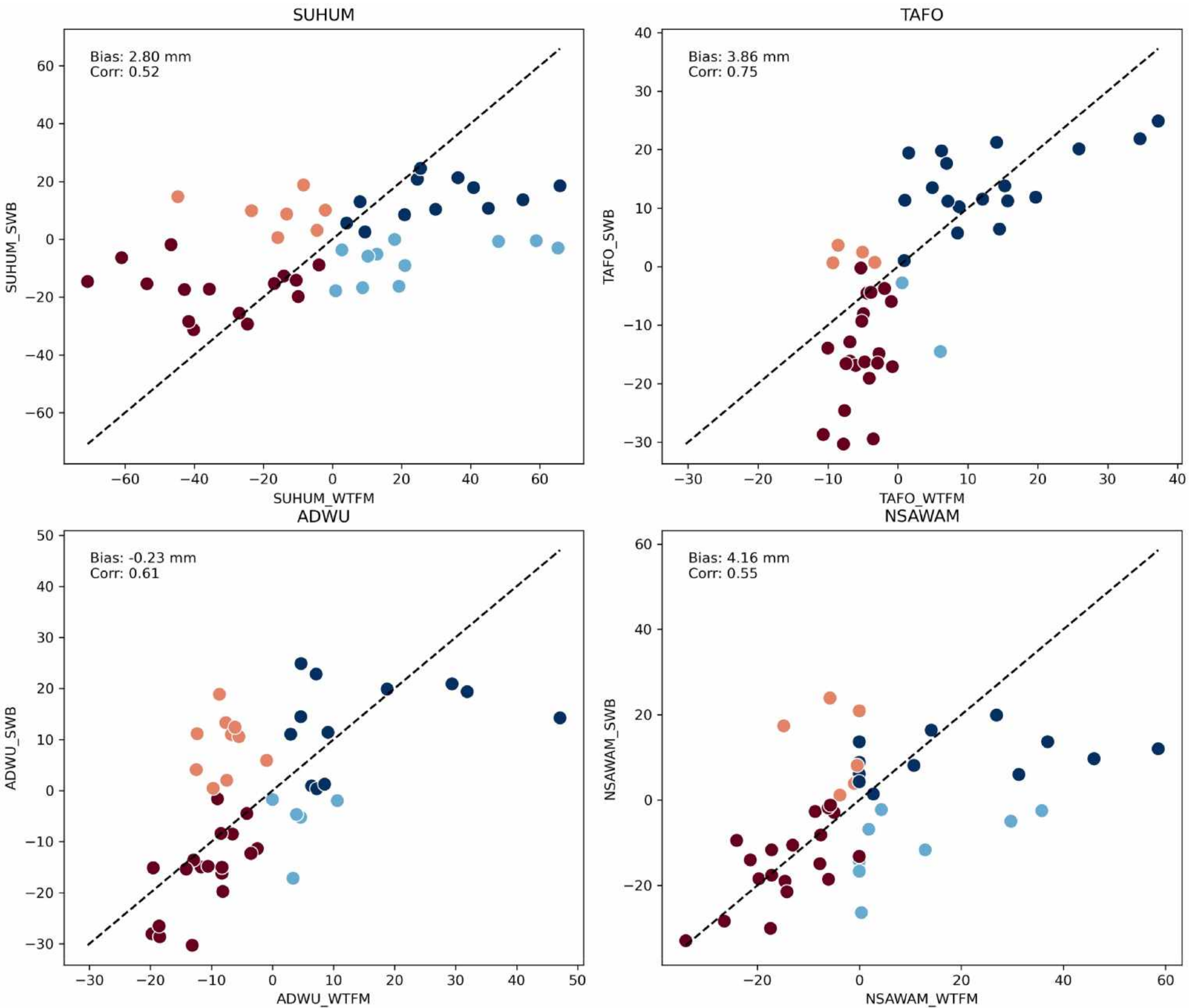

Figure 8 | Scatter plot of recharge estimates from the WTFM and the SWB method for Suhum, Tafo, Adwumako, and Nsawam. The clusters are color-coded as follows: −2 (deep red): both methods yield negative recharge; −1 (light red): WTFM negative and SWB positive; 1 (light blue): WTFM positive and SWB negative; 2 (deep blue): both methods yield positive recharge. The plot illustrates the agreement and disagreement between the two methods, influenced by soil properties, seasonal rainfall, and aquifer dynamics.

In Adwumako, light red clusters were frequent in JJA and SON (see Figure S6) due to the dominance of silty loam soils (Figure 5(a)), which have low infiltration capacities and promote surface runoff. SWB often overestimates recharge in these seasons by interpreting water surpluses at the surface as recharge, while WTFM captures the minimal groundwater response. The absence of light blue clusters during SON indicates that the soils do not support delayed recharge, even during periods of residual moisture from the monsoon. During DJF, deep red clusters highlight consistent groundwater discharge and limited soil moisture availability.

In Nsawam, the light blue clusters were dominant during MAM and SON but were present across all seasons (see Figure S6). In MAM, high evapotranspiration reduces soil moisture levels, leading SWB to estimate negative recharge, while WTFM captures delayed infiltration through the sandy clay loam soils (Figure 5(a)). During SON, residual monsoonal moisture supports continued percolation, leading to positive recharge captured by WTFM. Light red clusters in JJA reflect intense rainfall and surface saturation, which limit infiltration and cause SWB to overestimate recharge relative to WTFM.

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6.2.2. Bias correction performance and method comparison

Figure 9 compares the uncorrected SWB recharge estimates with the WTFM reference series over the common observation period. Although the two methods showed a correlation of 0.717, the uncorrected SWB estimates had a mean bias of −16.4 mm, an RMSE of 40.4 mm, an RRMSE of 97.7%, and an MAE of 34.1 mm. The correlation indicates that the two methods captured broadly similar temporal variations, while the large error values show substantial differences in recharge magnitude. These discrepancies provided the basis for applying bias correction. The corrected SWB estimates were subsequently evaluated against the WTFM recharge series. All three bias correction methods substantially reduced the systematic errors, as shown in Figure 10. Linear scaling, labelled SC_corrected in the analysis, produced the lowest RMSE of 11.6 mm and the lowest RRMSE of 28.1%. It also retained the highest correlation of 0.717 and reduced the mean bias to approximately zero (−7.89 × 10−17 mm). This relationship was statistically significant ($p < 10^{-7}$). The QM and eQM methods produced RMSE values of 11.8 mm and correlation coefficients of 0.706 and 0.702, respectively, with p-values below 10−7. Although eQM produced the lowest MAE of 8.93 mm, linear scaling provided the strongest overall balance between bias, RMSE, relative error, and correlation. Table 3 summarises the complete performance statistics. The three methods reduced the magnitude errors while retaining the main temporal variations represented by the WTFM series.

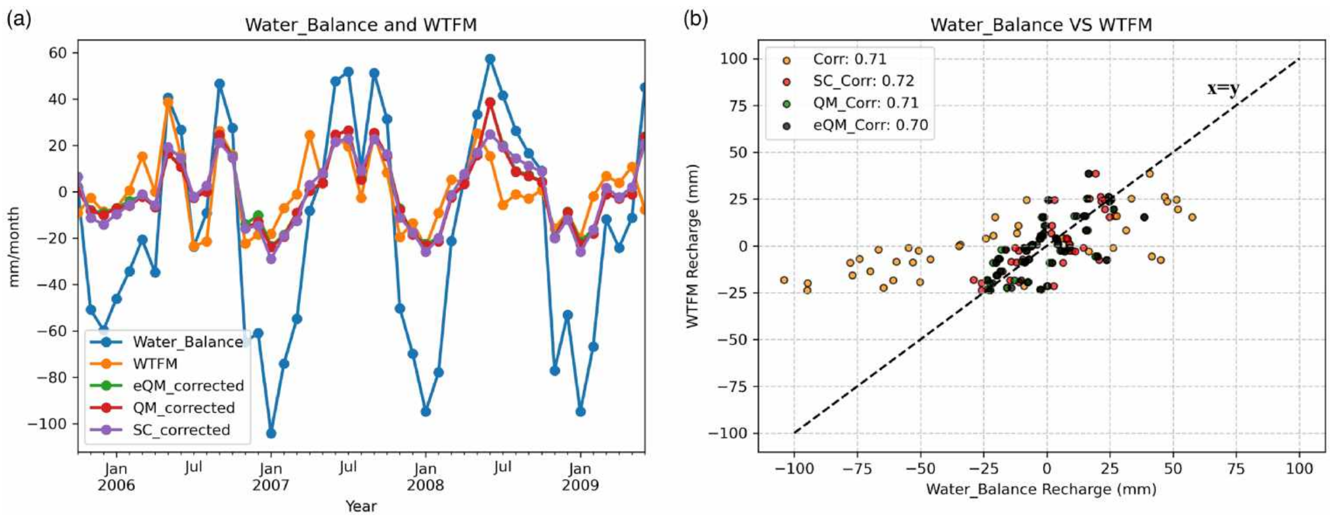

Figure 9 | Temporal variation between the Water balance and the WTFM estimates before corrections.

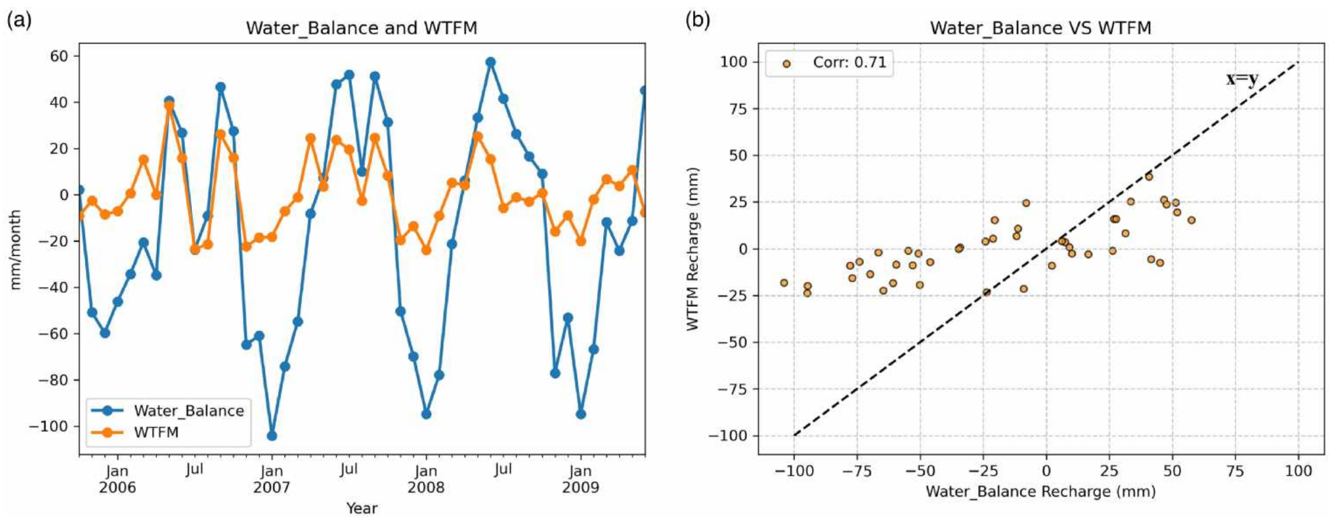

Figure 10 | Corrected temporal variation between the Water balance and the WTFM estimates.

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The performance of linear scaling likely reflects three factors. First, the discrepancy between the SWB and WTFM estimates was primarily associated with their mean magnitudes rather than their temporal patterns or distributional shapes. A mean-based adjustment was therefore well suited to correcting the dominant error. Second, the calibration record contained only 45 monthly observations. Distribution-based methods such as QM and eQM generally require longer records to estimate the tails of a distribution reliably. With a short calibration series, empirical quantiles become less stable (Lafon *et al.* 2013). Linear scaling relies mainly on differences in mean values and is therefore less sensitive to the limited sample size. Previous studies have similarly found that linear scaling performs well when the dominant model error is a mean shift and the calibration record is short (Thrasher *et al.* 2012; Shrestha *et al.* 2017). Third, the SWB method already represented the broad seasonal cycle of recharge, but misrepresented its magnitude, particularly during wet months. Linear scaling adjusted this magnitude while retaining the seasonal pattern. Following calibration, the mean linear-scaling correction factor of 0.76 was applied to the full SWB recharge field. Figure 10 shows the improved agreement between the corrected SWB estimates and the WTFM reference series during the overlapping period. The correction factor was then extended to the long-term SWB estimates to support the analysis of temporal and spatial recharge variability across the basin. Because the correction was derived from a short groundwater record at four monitoring locations, the resulting estimates should be interpreted as bias-constrained recharge estimates rather than as independently validated basin-wide observations. To partly address the risk of circularity associated with calibrating and evaluating the correction against the same reference data, a split-sample test was performed. Data from 2005 to 2008 were used for calibration, while data from 2009 were reserved for validation. This test produced a correction factor of 0.63 and substantially reduced the bias across all four monitoring locations, as reported in the Supplementary Information. The single-year validation period limits the strength of the independent assessment, but the results provide additional evidence that linear scaling improves the agreement between the SWB and WTFM recharge estimates.

6.3. Corrected recharge characteristics

6.3.1. Spatial characteristics and controls of bias-corrected recharge

Figure 11 shows the spatial distribution of the bias-corrected mean monthly groundwater recharge across the basin. Recharge rates range from approximately 27 to 39 mm/month, with uncertainty bounds implied by the bias-correction performance. RMSE values of 11–12 mm and relative errors of about 28% indicate an effective uncertainty of roughly ±10 mm at the monthly scale. This uncertainty reflects the combined effects of rainfall and evapotranspiration uncertainty, sparse groundwater observations, and limitations inherent in the bias-correction procedure.

A clear spatial gradient is evident, with higher recharge concentrated in the northern part of the basin and lower recharge in the south. This pattern has also been observed in several other studies conducted in the basin (Water Resources Commission 2007; Adomako *et al.* 2010; Alfa *et al.* 2011; Duah *et al.* 2021). Pixel-level correlation analysis (see Figure S9) indicates that recharge in the northern zone is moderately positively correlated with soil permeability and forest cover, with correlation coefficients ranging between about 0.15 and 0.45. These areas are characterized by permeable soils and dense vegetation, which promote infiltration and reduce surface runoff. Forest cover enhances soil structure and macroporosity, facilitating deeper percolation, although evapotranspiration and soil moisture feedbacks limit the strength of simple linear relationships (Scanlon *et al.* 2002; Healy 2010). As a result, correlations remain moderate despite the clear influence of vegetation and soil properties.

The central part of the basin exhibits weaker and more variable correlations, typically between 0.10 and 0.20. This zone corresponds to a transition from forested areas to cropland and mixed land use. In these areas, recharge is influenced by interacting factors such as variable rooting depth, tillage practices, and soil moisture conditions, which introduce nonlinear controls and weaken pixel-wise linear associations (Scanlon *et al.* 2002; Gilbert *et al.* 2025). This complexity explains the reduced coherence between recharge and individual surface characteristics in the central basin.

In contrast, the southern sector shows consistently negative correlations, ranging from approximately −0.55 to −0.30. These areas are dominated by settlements and compacted soils, where impervious surfaces and engineered drainage systems restrict infiltration and enhance surface runoff. The stronger negative signal reflects the more uniform impact of urbanisation on recharge processes, compared with the heterogeneous land-use patterns in the central basin (Kim & Jackson 2012; Maxwell & Condon 2016). The correlation patterns align with the spatial distribution of land cover shown in Figure 5(b).

Finally, the bias-corrected SWB estimates indicate that groundwater recharge represents approximately 11.61–24.68% of annual rainfall, which ranges from about 800 to 1,700 mm/year across the basin. Runoff estimates derived from the SCS

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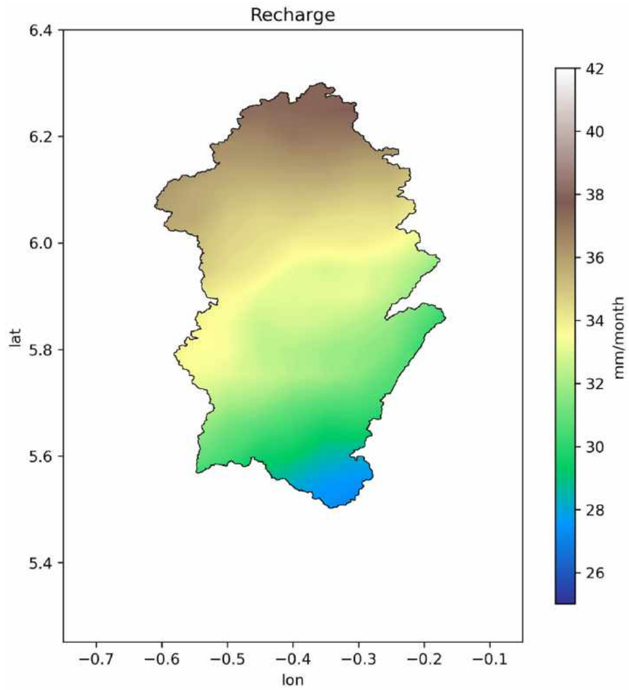

Figure 11 | Corrected spatial distribution of mean monthly GW recharge in the Densu Basin.

method suggest an annual runoff depth of about 439 mm, corresponding to roughly 26% of rainfall. This relatively high runoff fraction, particularly in urbanized southern areas, reduces the volume of water available for infiltration and helps explain the lower recharge rates observed there. The combined spatial patterns of recharge magnitude and correlation strength support the interpretation that land cover, soil properties, and urban development exert strong control on groundwater recharge distribution across the basin.

6.3.2. Seasonal recharge estimates in the Densu Basin

The recharge patterns reveal distinct seasonal variations throughout the basin, reflecting the influence of seasonal climatic factors on GW dynamics (DJF, MAM, JJA, and SON) (see Figure S4).

The DJF and MAM seasons exhibited relatively low recharge rates, typically not exceeding 10 mm/month. These seasons correspond to the dry periods in the region, where reduced rainfall and higher evapotranspiration rates limit the amount of water available for infiltration into the GW system. In contrast, the JJA season exhibited the highest recharge rates, often exceeding 30 mm/month. This period coincides with the peak of the monsoon season, characterized by heavy and sustained rainfall, which significantly enhances GW recharge. The abundant precipitation during this time replenishes soil moisture and increases the water table, facilitating greater infiltration and recharge. The SON season also showed elevated recharge rates, though they were generally lower than those observed in JJA. This suggests a gradual decline in recharge as the monsoon season wanes, but sufficient rainfall persists to sustain relatively high levels of GW replenishment.

The spatial distribution of recharge during the peak seasons (JJA and SON) is notably heterogeneous, with areas of both high and low recharge rates. The northern and eastern sectors of the basin consistently exhibited higher recharge values compared to the southern and western regions. This spatial variation likely reflects differences in local factors such as soil types, land cover, and precipitation patterns (see Figures 5(a) and 5(b)). For instance, regions with more permeable soils and denser vegetation may experience higher recharge due to increased infiltration capacity, while areas with less favorable conditions may see reduced recharge rates.

The seasonal pattern is shown in Figure 12, which presents the climatological monthly mean recharge. All discharge periods were set to zero to reflect net recharge conditions. Recharge peaks during JJA and remains near zero from December to March. The full spatial monthly distribution is available in Figure S4.

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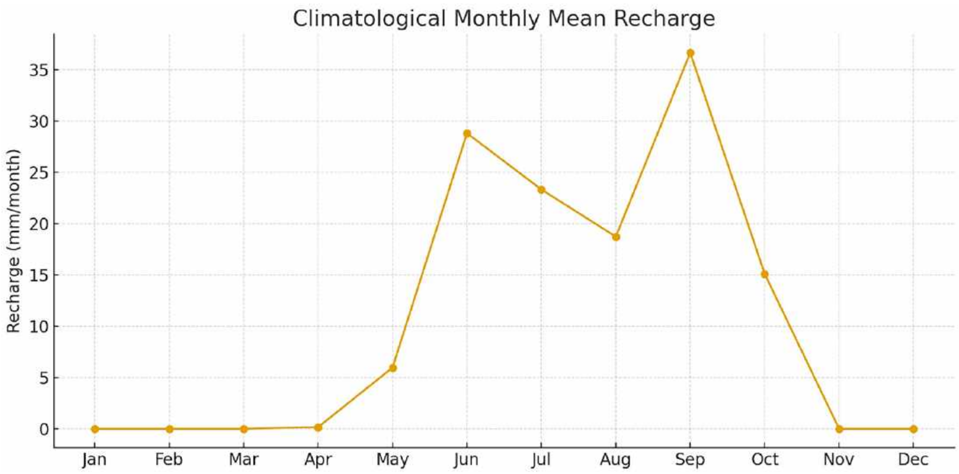

Figure 12 | Climatological monthly mean recharge for the Densu Basin. Values represent the basin-average recharge from 1960 to 2015. All discharge periods were set to zero. The plot shows a clear peak during JJA and near-zero recharge from December to March.

6.4. Groundwater sustainability assessment

The estimated annual groundwater recharge in the Densu Basin, based on the bias-corrected SWB method, represents approximately 11.61–24.68% of the annual rainfall, which varies between 800 and 1,700 mm/year. This recharge estimate translates into an annual recharge range of around 92.88–419.56 mm, indicating a strong reliance on rainfall patterns for groundwater replenishment. The variability in recharge suggests that groundwater availability is closely linked to seasonal and inter-annual rainfall fluctuations, which in turn are affected by climate conditions across the basin. This variability highlights that groundwater recharge is not consistently sustained throughout the year, leading to potential shortages during periods of lower rainfall.

A recent study by Duah *et al.* (2021) estimated annual groundwater abstraction in the basin at approximately 6,116,390 m^3. When comparing this abstraction rate with recharge rates from the SWB model, it becomes evident that sustainability in groundwater use is highly sensitive to annual rainfall patterns. In years with higher rainfall, where recharge values approach the upper range of approximately 24.68%, the recharge volumes may match or even exceed the abstraction rate, suggesting that groundwater use could remain sustainable under these conditions. However, in drier years, where recharge drops closer to 11.61% of annual rainfall, the volume of replenished groundwater may not fully compensate for the abstraction, leading to a potential groundwater deficit. This dependency on annual rainfall variability points to a risk of periodic shortages and potential depletion, especially as climate variability could further affect rainfall patterns in the region.

The findings highlight the importance of monitoring and managing groundwater use in the Densu Basin to avoid over-extraction, particularly during dry spells when recharge levels are insufficient to meet extraction demands. Continuous high abstraction rates without sufficient recharge could lead to a decline in groundwater levels, reducing not only the available quantity of groundwater but also potentially affecting its quality over time due to factors such as increased salinity or contamination from nearby sources. Such a trend would pose a significant threat to groundwater sustainability, especially as population growth and development increase the demand for water resources in the basin.

The spatial distribution of recharge has direct implications for groundwater management in the basin. Higher recharge in the northern areas suggests that abstraction in this zone should be guided by regular monitoring to avoid localized drawdown, while the limited recharge in the southern urbanized corridor indicates a higher vulnerability to stress. The concentration of settlements in this part of the basin reduces infiltration and increases surface runoff, which lowers the long-term potential for natural replenishment. As urban expansion continues, the imbalance between withdrawal and recharge in the southern zone is likely to grow, highlighting the need for careful siting of new wells and stricter allocation controls.

These results highlight the need for adaptive groundwater management practices in the basin. Implementing regulated extraction limits and actively monitoring groundwater levels can help mitigate the risk of over-extraction. Furthermore,

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enhancing recharge through techniques like managed aquifer recharge (MAR) during wet seasons could help increase groundwater reserves. Additionally, incorporating demand management strategies, such as water conservation practices and the promotion of alternative sources like rainwater harvesting, could reduce dependency on groundwater during dry periods, contributing to the basin's long-term water security.

7. LIMITATIONS OF THE STUDY

Some limitations should be acknowledged. Bias correction of SWB estimates relied on groundwater-level data from five boreholes over a relatively short period (2005–2009), reflecting limited monitoring coverage in the Densu Basin and introducing uncertainty when extrapolating results across the full basin. The WTFM reference estimates also assumed a uniform specific yield of 0.10, which simplifies analysis but does not capture spatial variability in aquifer storage properties that can influence water-table responses.

Uncertainty is also associated with the SCS-CN runoff estimates, as a uniform AMC-II condition was applied despite known spatial and temporal variation in antecedent soil moisture. Additional uncertainty arises from input datasets used in the SWB model, including rainfall and evapotranspiration fields affected by measurement and interpolation errors, as well as soil and land-cover rasters subject to classification uncertainty and coarse spatial resolution.

Human influences on recharge, such as groundwater abstraction, small-scale irrigation, land modification, and surface-water regulation, were not explicitly represented due to the absence of consistent basin-wide datasets. These limitations reflect data availability rather than shortcomings of the workflow and highlight the broader challenges of recharge estimation in data-scarce basins. Future application of the framework across additional aquifer systems and improved monitoring networks would help further evaluate its robustness.

8. CONCLUSION

This study evaluated groundwater recharge in the Densu Basin using a hybrid framework that integrates the WTFM with a SWB approach. Linking short-term observation-based recharge estimates with long-term model simulations through bias correction improves the reliability of recharge assessment under limited data availability. The results provide a clearer understanding of recharge variability across the basin and strengthen the evidence base for groundwater management in data-scarce settings.

1. Validation against WTFM shows that the hybrid workflow reproduces both the magnitude and seasonal behavior of groundwater recharge, while the bias-correction step reduces model error without distorting the temporal structure of the signal. These results demonstrate that reliable recharge estimates can be obtained under limited monitoring conditions by combining short groundwater-level records with a process-based SWB model. Given the wider availability of rainfall, soil, and land-cover data compared with long-term groundwater observations in West Africa, the workflow provides a practical template for recharge assessment in similar data-scarce basins.
2. Bias correction of SWB recharge estimates using WTFM as a reference significantly improved model agreement, with LS providing the most consistent performance among the tested methods. The resulting correction factor of 0.76 reduced systematic discrepancies and supports the use of bias-corrected SWB estimates for long-term recharge assessment in data-scarce environments.
3. Recharge estimates indicate that the basin can generally support current groundwater abstraction during wetter periods, but that natural recharge may not fully compensate for extraction in drier years. Projected increases in temperature and changes in rainfall characteristics are likely to exacerbate these vulnerabilities by reducing infiltration and increasing runoff. Adaptive management strategies, including controlled abstraction, MAR, and improved water-use efficiency, will be critical for sustaining groundwater resources under future climate stress.
4. Future studies should integrate additional independent datasets to further constrain recharge estimates. Remote sensing soil moisture can help track infiltration dynamics, GRACE-derived storage changes can provide basin-scale evidence of long-term groundwater trends, and isotope data can improve understanding of recharge sources and response times. Incorporating these datasets would enhance confidence in recharge assessment and support more robust groundwater management decisions.

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DATA AVAILABILITY STATEMENT

All relevant data are included in the paper or its Supplementary Information.

CONFLICT OF INTEREST

The authors declare there is no conflict.

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