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ABSTRACT

Study region: Ghana, West Africa, spanning strong hydroclimatic gradients from humid tropical forests in the south-west to savannah-dominated drylands in the north under the influence of the West African monsoon.
Study focus: This study evaluates a 1 km application of the Community Land Model version 5 (CLM5) in simulating land–atmosphere processes across Ghana. The model is driven by ERA5 meteorological forcing and uses MODIS land cover and SoilGrids soil properties. Simulations are evaluated against 23 soil moisture stations, four eddy covariance flux sites, streamflow from four catchments, and derived gross primary production (GPP).
New hydrological insights: CLM5 reproduces major spatial gradients and seasonal cycles of soil moisture, energy fluxes, GPP, and runoff, including wetter southwest conditions and a northward transition to more seasonal, water-limited regimes in Ghana. It captures wet season increases in latent heat flux and GPP and higher sensible heat flux during dry periods. However, systematic biases persist, including soil moisture overestimation, dry-season underestimation of GPP, and mixed latent and sensible heat flux errors across sites. Runoff simulations reproduce seasonality but underestimate streamflow and show weak agreement with observations. These limitations likely reflect uncertainties in precipitation forcing, soil hydraulic properties, vegetation representation, and simplified runoff processes. Overall, CLM5 demonstrates strong capability for representing regional land-surface dynamics in West Africa, but improvements in forcing data and process representations are needed to enhance performance in data-sparse tropical regions. The results support potential applications in hydrological assessment, agricultural planning, and climate resilience strategies.

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1. Introduction

Land surface models (LSMs) play a crucial role in simulating water, energy, and carbon exchange between the land surface and the atmosphere (Sy et al., 2017; Bonan, 2008; Sy and Quesada, 2020, Perugini et al., 2017). These models are widely used to study hydrological processes, energy fluxes, and vegetation dynamics, contributing to improved understanding of land-atmosphere interactions. Understanding these processes as they govern water, energy and carbon fluxes plays a vital role in resource management, agricultural planning, and climate adaptation strategies. Therefore, the demand for precise estimation and prediction of land surface processes is essential for mitigating risks associated with climate change and enhancing sustainable resource management. Accurately predicting these processes in West Africa is particularly important for addressing unique ecological challenges, such as deforestation, and promoting sustainable development (Sy et al., 2017).

Despite significant advancements in LSM development, their validation remains challenging, particularly in data-sparse regions such as Africa. The lack of comprehensive ground-based observations in many parts of the continent, including Ghana, has limited the verification of high-resolution LSM simulations, raising uncertainties in their applicability for regional studies. A growing body of research has employed LSMs to evaluate regional climate (Sy et al., 2017), extreme events (Sy and Quesada, 2020) and energy balances in various ecological settings (Quansah et al., 2017). However, in Ghana, where ground-based observations are often limited (Oduro et al., 2024), conceptual models are commonly used for catchment management, e.g. the Soil and Water Assessment Tool (SWAT) (Bair, 2014; Awotwi et al., 2019; Ampofo et al., 2021 Assefa et al., 2023). For instance, Assefa et al. (2023) applied SWAT in the Upper Offin sub-basin, where it successfully captured hydrological responses under baseline conditions. The model demonstrated reasonable performance in simulating flow dynamics, and it underscored the importance of calibrating parameters related to channel and groundwater flow. In addition, Guug et al. (2020) and Ampofo et al. (2021) applied SWAT in the Sheriguan and Black Volta catchments to analyse water availability and surface runoff. The latter study found that despite successful calibration of SWAT, forward modelling yielded unsatisfactory results (Nash-Sutcliffe efficiency of only -0.02) due to uncertainties in the data and the conceptual model design. At the regional scale, Achugbu et al. (2020) assessed the performance of multiple LSMs including Noah-MP and CLM4 coupled with the WRF model over West Africa, noting that there are only a few extensive studies on the sensitivity of regional climate models to different land surface schemes in the region, and that the impact of LSM choice on the West African Monsoon and land surface energy balance remains an important area of investigation. Their study further revealed that Noah-MP and CLM4 differ principally in their vegetation representation and parameterization of the soil water column, with CLM4 simulating higher latent heat fluxes while Noah-MP produces higher SM amounts. In another study by Pinnington et al. (2018), the Joint UK land Surface Simulator (JULES) was used over Ghana at a low resolution of 0.5° and calibrated through assimilation of SM observations. Their study emphasizes the importance of improved precipitation data to reduce bias in SM estimation. The results of these studies highlight the challenges of accurately modelling hydrological processes in data-sparse regions such as Ghana.

The Community Land Model Version 5 (CLM5) is a sophisticated land surface model that serves as the land component of the Community Earth System Model (CESM) for hydrological processes, vegetation dynamics, and energy balance (Lawrence et al., 2019; Yan et al., 2023). One of the significant advantages of CLM5 over its predecessors is its enhanced representation of SM dynamics and hydrological processes (Gao et al., 2021). Recent studies have demonstrated its capability in capturing hydrological and energy balance processes at various spatial scales. However, while CLM5 has been extensively tested in various regions (e.g. Boas et al., 2024; Dombrowski et al., 2022; Dombrowski et al., 2024), its application and validation in West Africa remains limited. Recently, Oloruntoba et al. (2025) applied CLM5 at a spatial resolution of 3 km over the African continent to assess the impact of using different atmospheric forcings and their temporal resolution, various soil texture information sources, and various upscaling strategies of soil texture on the model performance. The study revealed that the upscaling strategy of soil texture information only significantly influenced the simulation of runoff and SM dynamics in combination with high temporal resolution information of the atmospheric forcings. Additionally, the results emphasize the pronounced impact of atmospheric forcing data on the simulated actual evapotranspiration rates. In another study, Mehboob et al. (2020) coupled CLM4.5 with a regional climate model (REGCM4.3) to assess the potential effects of vegetation feedback on drought conditions in West Africa. Their model results indicated that when accounting for dynamic vegetation changes using the dynamic vegetation module of CLM, prolonged drought conditions are anticipated in both current and future climates across the Sahel region. Given the region's unique climatic conditions and land surface characteristics, evaluating the performance of CLM5 against in-situ measurements is critical for assessing its reliability in simulating land surface processes in this region. This study aims to address this gap by setting up and validating high-resolution (1 km) CLM5 simulations over Ghana using ERA5 meteorological reanalysis data and detailed land surface datasets, including topography, land use, and soil properties. Locally calibrated parameters, particularly those governing vegetation characteristics, soil hydraulic properties, and evapotranspiration processes have been shown to improve CLM5 performance in well-instrumented regions (Denager et al., 2023). Such calibration requires sufficient high-quality observational data, which remains a significant constraint across much of West Africa. Therefore, this study establishes a baseline evaluation of CLM5 using its default global parameter settings, allowing for a systematic assessment of the model's transferability to Ghana without regional tuning, and providing a foundation upon which future calibration efforts can build.

The study evaluates CLM5's ability to simulate SM, runoff, photosynthetic activity, and energy fluxes across Ghana using eddy covariance (EC) measurements from the WASCAL environmental research observatory. Notably, it incorporates data from two newly established stations, Janga and Mole Park, providing a unique opportunity to assess model performance in contrasting ecosystems across the savanna region of Ghana (Nadolski et al., 2024; Quansah et al., 2015; 2017; Berger et al., 2019). This work contributes to bridging observational gaps and improving land surface modelling in the region. Given Ghana's representative conditions for West Africa, this study also contributes to a broader understanding of the applicability of CLM5 in this part of Africa. This will help refine

LSM applications in data-limited regions and inform future efforts to improve model parameterizations for better representation of land surface processes in West Africa.

2. Materials and methods

2.1. Study area

The study domain covers Ghana and the southernmost part of Burkina Faso within longitudes from 3.5 W to 1.2 E and latitudes from 4.5 N to 12.2 N (see Fig. 1). The study area is characterised by diverse landscapes ranging from tropical forests to savannah grasslands, which are predominantly determined by the region's climatic zones (Yamba et al., 2023). The south-western part of Ghana is covered by tropical rainforests, with dense canopy and a high level of plant species diversity. In contrast, the northern part of the study area is characterised by a transition into the Guinea and Sudan savannah, which is dominated by grasses, shrubs, and scattered trees (Swaine, 1992).

As shown in Fig. 1c, forest areas are only found in the southwestern part of Ghana. The elevation of the terrain varies considerably across the region, from the low-lying coastal plains in the south to the hilly and mountainous areas in the central and northwestern parts, such as the Akwapim-Togo Range (see Fig. 1b). Tropical climate prevails in the region, with mean annual temperatures ranging from 24°C to 30°C. The southern, coastal regions tend to have more moderate temperatures due to the influence of the Atlantic Ocean, while the northern regions experience higher temperatures, particularly during the dry season. Seasonal temperature variations are driven by the movement of the Inter-Tropical Convergence Zone (ITCZ), which brings changes in wind patterns and solar radiation, affecting surface energy balances (Nicholson, 2018).

Rainfall patterns are highly seasonal and spatially variable. The southern forested areas experience bimodal rainfall with a major rainy season from April to June and a minor season from September to November with annual rainfall exceeding 1500 mm in some locations (Logah et al., 2021). In contrast, the northern savannah regions experience a unimodal rainfall regime, with most precipitation occurring between May and October, averaging around 800–1200 mm annually. The north is characterised by a prolonged dry season, with limited rainfall between November and March. During the dry season, runoff is predictably low, but it significantly increases in wetter periods like, JJA (June-July-August), and SON (September-October-November). This pattern aligns with seasonal trends in West Africa, where limited precipitation in dry months reduces surface runoff, while rainy periods lead to higher runoff (Roudier et al., 2014). Besides rainfall, factors such as topography, soil properties, and vegetation cover are crucial, especially in regions like the Ghana-Togo border and southwestern Ghana, where high clay content and elevation enhance runoff sensitivity.

2.2. Data Sources

2.2.1. Community land model forcing data

The Community Land Model version 5 (CLM5) relies on a variety of data sources to accurately simulate land surface processes. For this study, meteorological data, i.e. precipitation, air temperature and pressure, wind speed (U and V components), and incoming solar radiation are sourced from ERA5 ECMWF Reanalysis version 5 (Hersbach et al., 2020). Land cover data was obtained from the Moderate Resolution Imaging Spectroradiometer (MODIS), which was classified based on the International Geophere Biosphere Programme (IGBP) land cover classification system (Sulla-Menashe et al., 2019). Over Ghana, 13 different LULC categories were identified as indicated in Fig. 1b. Out of the 13 categories of LULC information, 9 which included some Plant Functional Type (PFT)

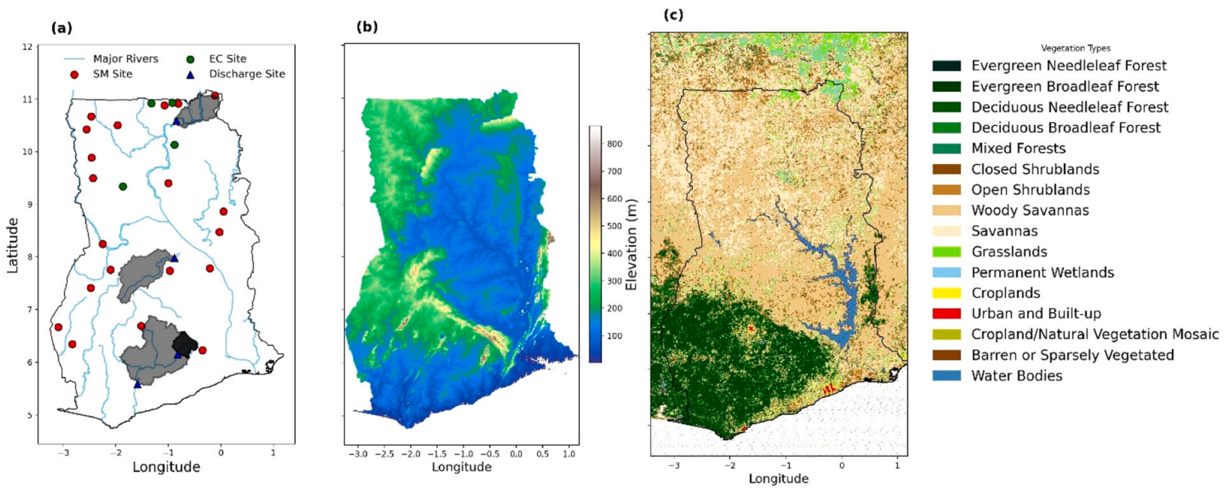

Fig. 1. Study domain showing various observational sites (a) and the 1 km Land Use Land Cover (LULC) information (b) over Ghana for MODIS. The catchment areas of the four runoff gauging stations are also presented in the left panel (highlighted in grey).

were matched with corresponding PFTs in CLM5. In the case of lacking vegetation types in CLM5 such as Savanna and Woody Savanna, two or more CLM5 PFTs are combined to represent the MODIS vegetation type. The numbers in Table 1 represent the fractional percentages of each PFT assigned to approximate MODIS vegetation types that do not have a direct equivalent in the CLM5 standard PFT library, ensuring a realistic representation of Ghana's vegetation cover within the model. Soil properties information, specifically sand and clay content from depths of 0–200 cm, is derived from the SoilGrids dataset (Poggio et al., 2021).

2.2.2. Validation data

This study employs a variety of observational data over Ghana, including SM, streamflow, and latent and sensible heat fluxes, to validate the model results. SM data were obtained for 23 stations in Ghana. Of these, two stations are part of the WASCAL CONCERT project (stations Kayoro and Gorigo), while the remaining stations were established by the TAHMO project (van de Giesen et al., 2014). The two WASCAL CONCERT stations also provided sensible and latent heat flux data from eddy covariance measurements (Table 2).

2.3. Method

2.3.1. Model description and setup

In this study, the land surface model simulations were carried out with the Community Land Model version 5 (CLM5) (Lawrence et al., 2019). CLM5 simulates the coupled terrestrial water, energy and biogeochemical cycles including land surface energy fluxes and vegetation states. CLM5 uses as input atmospheric forcings and soil and vegetation properties (Lawrence et al., 2020). The hydrological and biogeochemical processes are simulated on different sub-grid units within a grid cell that include (1) the land unit, which defines the land use category (e.g. forest, crops), (2) the column, which is represented by 20 soil and 5 rock layers and resolves state variables as well as water and energy fluxes in the soil, and (3) the patch level, which records land cover characteristics of plant functional types (PFTs) (e.g. deciduous forest, soybean). CLM5 is particularly well suited for modelling complicated terrain, such as that found in Ghana. For the CLM5 model setup over Ghana, all cropland areas were classified as Unmanaged Rainfed Crop, and the crop model was not activated. This configuration ensures that agricultural lands are represented without irrigation or active management while also excluding dynamic crop growth processes. By not activating the crop model, the simulation focuses on natural land-atmosphere interactions without accounting for phenological changes in crops. The one-dimensional multi-layer vertical water flow in the soil is simulated using a modified Richards equation (Dingman, 2015), in which the hydraulic parameters of the soil are derived from pedotransfer functions (Clapp and Hornberger, 1978; Cosby et al., 1984).

In this study, we used the Satellite Phenology Mode to run CLM5. Considering how initial conditions are critical to model performance (Lawrence et al., 2020; Yang et al., 2022), we ran an 80-year spin-up simulation using the available global GSWP3 v1 atmospheric forcing dataset from 1990 to 2000 at a three-hourly temporal and 0.5° spatial resolution to attain equilibrium of the water and energy fluxes. CLM5 was run at hourly intervals in a 1 km x 1 km grid cell architecture. Meteorological data served as the model's driving input for the period from 2000 to 2023, with derived soil and land use data from SoilGrids and MODIS replacing the default values for Ghana.

2.3.2. Model performance evaluation

The simulation results were compared against observations from local SM and eddy covariance stations to evaluate the CLM5 performance in simulating SM, latent and sensible heat fluxes, and runoff over Ghana. The evaluation of CLM5 runoff was conducted using the catchment area corresponding to the discharge station where streamflow data was obtained. Runoff data was extracted from the CLM5 output based on this catchment area. Since the CLM5 runoff was not routed, the total runoff for the extracted area was summed over the years and compared directly to observed streamflow measurements from the stations. This approach allowed for an assessment of how well the model-simulated runoff aligned with actual hydrological observations.

The Pearson correlation coefficient (r) was used to assess the strength of the linear relationship between the model simulations and observed values. A r value > 0.7 indicates a strong positive relationship in accordance with commonly used guideline ranges (Rehman et al., 2018). The Pearson's correlation was estimated for each variable as:

Table 1
Summary of MODIS LULC remapping on CLM5 PFTs.

MODIS Vegetation	CLM5 Plant Functional Type Combination
Broadleaf Evergreen Tree	Broadleaf Evergreen Tree-Tropical (BET)
Broadleaf Deciduous Tree	Broadleaf Deciduous Tree- Tropical (BDT)
Needleleaf Evergreen Tree	Needleleaf Evergreen Tree- Temperate (NET)
Grassland	C4 grass
Mixed Forest	BET (55%), BDT (25%), NET (20%)
Savannah	BET (20%) and C4 grass (80%)
Woody Savannah	BET (45%) and C4 grass (55%)
Closed Shrubland	Broadleaf deciduous shrub -Temperate (BDS) (45%) and BDT (55%)
Open Shrubland	BDS (30%) and C4 grass (70%)
Cropland	Unmanaged Rainfed Crop

Table 2
Basic site characteristics of the soil moisture stations over Ghana used for model validation.

Station	Longitude (°)	Latitude (°)	Elevation (m)	LC classification	Data availability
Gorigo	-0.92	10.93	222	Grassland	2020–2023
Kayoro	-1.32	10.92	286	Cropland	2020–2023
Janga	-0.89	10.13	130	Rice field	2022–2024
Mole Park	-1.87	9.34	160	Reserved forest	2023 – 2024
Bia SHTS Debiso	-3.08	6.67	228	Grassland	2019 – 2022
CRIG (Station 2)	-0.35	6.23	222	Mixed vegetation	2019 – 2022
Bongo SHS	-0.81	10.91	223	Cropland	2019 – 2022
CSIR-SARI, Tania	-2.46	9.89	348	Cropland	2019 – 2022
Atebubu SHS	-0.97	7.74	147	Cropland	2019 – 2022
Sacred Heart SHS	-2.48	7.41	359	Cropland	2019 – 2022
Notre Dame Seminary	-1.07	10.88	187	Cropland	2019–2022
Bui Power Authority	-2.25	8.25	171	Mixed vegetation	2019–2022
CSIR-SARI, Nyankpala	-1	9.4	191	Cropland	2019–2022
Kajaji SHS	-0.21	7.78	130	Shrubland	2019–2022
Walembelle Poly Clinic	-1.97	10.5	228	Cropland rainfed	2019–2022
Wenchi Methodist SHS	-2.1	7.76	322	Cropland rainfed	2019–2022
Gbewaa College of Edu.	-0.12	11.07	260	Cropland	2019–2022
Juaboso SHS	-2.83	6.35	172	Cropland	2019–2022
CRIG (Station 1)	-0.35	6.23	228	Mixed vegetation	2019–2022
Bimbilla SHS	0.05	8.86	195	Cropland	2019–2022
KNUST Farm	-1.52	6.69	274	Cropland	2019–2021
St.Johns RC JHS, Tuna	-2.44	9.49	319	Shrubland	2019–2022
Han SHS	-2.47	10.67	320	Cropland	2019–2022
Kpandai SHS	-0.03	8.48	215	Shrubland	2019–2022

$$r = \frac{\sum(x-\overline{x})(y-\overline{y})}{\sqrt{\sum(x-\overline{x})^2}\sqrt{\sum(y-\overline{y})^2}} \tag{1}$$

where x and y denote the variable of interest from observation and simulation, respectively. In addition, the root mean squared error (RMSE) and the unbiased root mean squared error (ubRMSE) were used to evaluate the performance of CLM5. The RMSE was calculated as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y-x)^2} \tag{2}$$

The RMSE measures the average magnitude of errors between CLM5 simulated and observed data which reflects both the variance and the bias of the errors, providing a direct measure of how far predictions deviate from observations. Lower RMSE values indicate a better fit between modelled and actual data. Unlike RMSE, which combines all sources of error, ubRMSE isolates the random error by subtracting the mean bias between the simulated and observed values before calculating the squared differences:

$$ubRMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[(y-\overline{y})-(x-\overline{x})]^2} \tag{3}$$

The ubRMSE quantifies errors that are independent of consistent over- or underestimations and thus provides insight into the model's ability to reproduce variability.

Additionally, the Kling-Gupta Efficiency (KGE) was employed to provide a comprehensive evaluation of model performance by considering correlation (r), variability, and bias in simulated data compared to observations Gupta et al. (2009):

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_{CLM5}}{\sigma_{obs}} - 1\right)^2 + \left(\frac{\mu_{CLM5}}{\mu_{obs}} - 1\right)^2} \tag{4}$$

where σ and μ represent the standard deviation and mean of the observed and CLM5 simulated variables. A KGE > 0.75 indicates a very good model performance (Houngnibo et al., 2023). The evaluation process involved pre-processing both model output and observed datasets to ensure consistency in time intervals. Following this, correlation coefficients were calculated for each variable, and KGE values were computed to assess overall model performance. This methodology offers a robust framework for understanding CLM5's capabilities in simulating hydrological processes in Ghana, allowing for informed conclusions about its applicability in regional hydrological modelling.

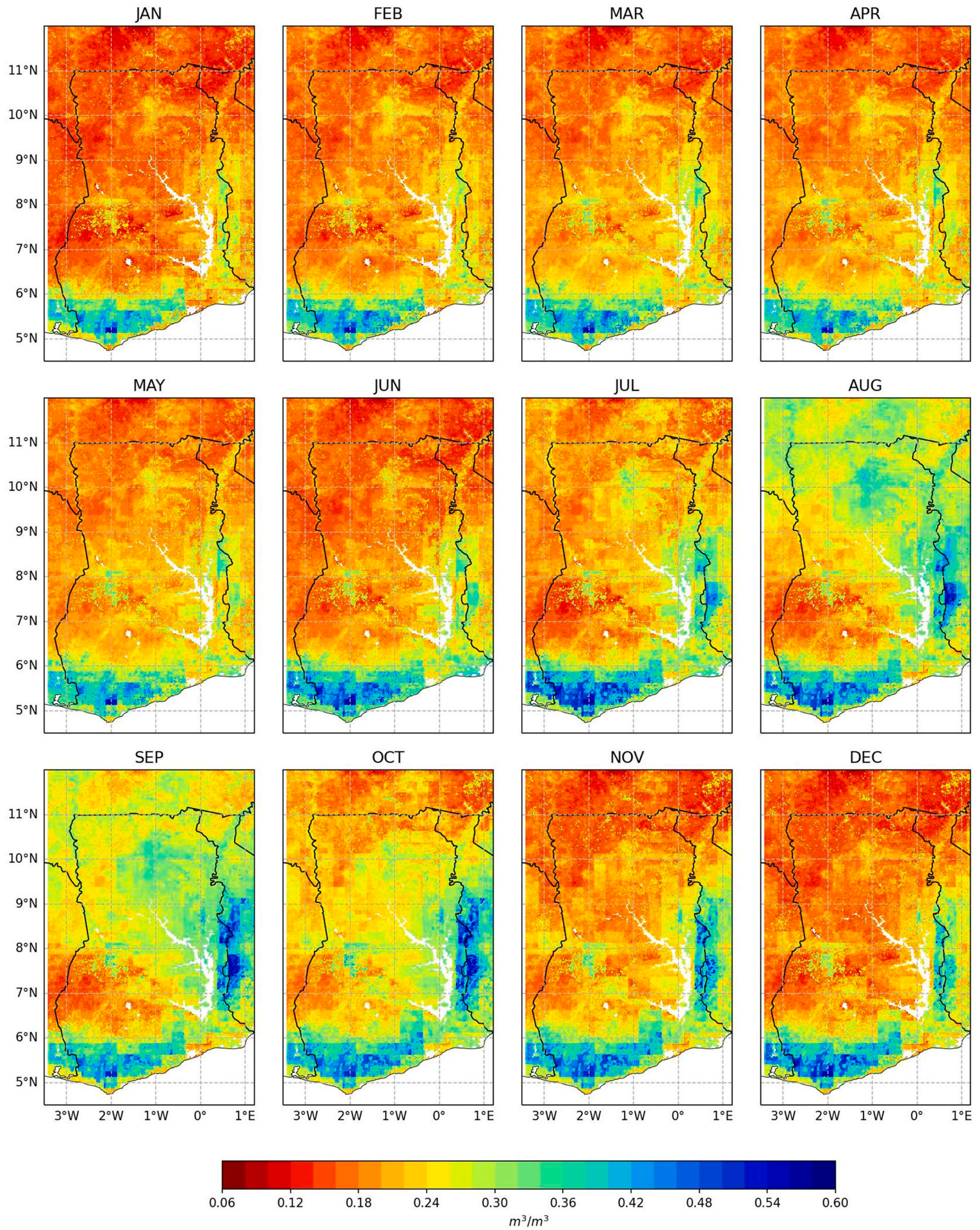

Fig. 2. Spatial distribution of CLM5 mean monthly soil moisture (0–6 cm) over Ghana from 2018 to 2023.

3. Results

3.1. Spatiotemporal soil moisture dynamics

Fig. 2 presents the simulated spatial distribution of mean monthly SM at a depth of 6 cm in Ghana.

The simulation reveals a considerable variability in SM levels in the simulated domain, ranging from 0.06 to 0.60 m^3m^{-3} . Notably, the southern region exhibits significantly wetter SM conditions compared to the central and northern part of Ghana. SM exhibits pronounced seasonal dynamics, with the soil typically being wetter from July to November. Throughout the year, the highest mean SM was simulated in south-west Ghana. Higher SM levels were also simulated in the transition zone along the Ghana-Togo border from

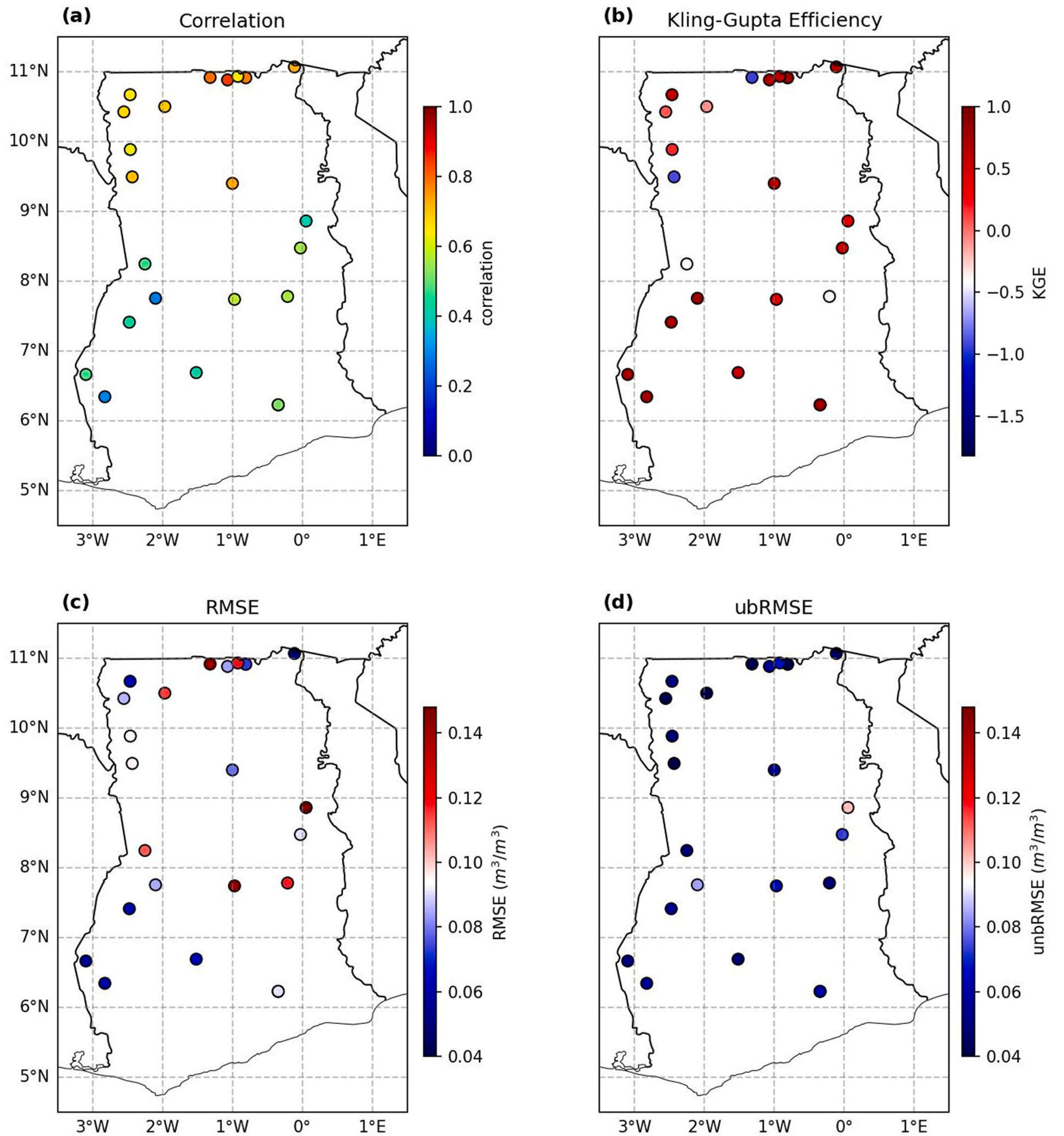

Fig. 3. Performance of CLM5 simulated SM compared to 23 TAHMO SM stations over Ghana using the Pearson's correlation (a), Kling-Gupta Efficiency (KGE) (b), root mean squared error (RMSE) (c) and the unbiased root mean squared error (ubRMSE) (d).

August to December.

The comparison of CLM5 simulated SM with the observations at 23 SM stations showed an overall good linear agreement ($0.3 < r < 0.95$) as indicated in Fig. 3a.

In contrast to the southern stations, the northern regions exhibited a stronger linear correlation. Specifically, the correlation values in northern Ghana, spanning latitudes 9° N to 11.5° N, ranged from 0.65 to 0.87. Notably, most stations in the south recorded correlation values below 0.6 with a lower correlation at the south-western corner of Ghana. The KGE results further underscore the performance differences between these two regions (Fig. 3b). In general, the KGE observed for all stations in Ghana ranged between −1.55 and 0.63. Here, the mean value is used as the benchmark for KGE (-0.41).

Based on this benchmark, two stations in the northern part of Ghana showed a KGE < -0.41. In contrast, higher KGE values were observed in the south-western part of Ghana with two stations within the transition belt presenting KGE values of near −0.41. These north-south disparities in model performance could be related to greater seasonal fluctuations in the northern region.

To further analyse this, the annual cycle of the simulated SM was examined and compared to the observations. Fig. 4 shows the annual cycle of SM data across the 23 TAHMO SM stations in Ghana revealing important insights into the seasonal hydrological dynamics of the region. The CLM5 SM closely aligns with observed patterns across various sites but exhibits consistently higher values. Fig. 4a-w illustrate that the simulated SM closely follows the rainfall distribution, varying from lower to higher latitudes (6.23° to 11.07° N). At the CRIG station (latitude 6.23°), a bimodal SM pattern is evident (Fig. 4a), which transitions into a unimodal pattern

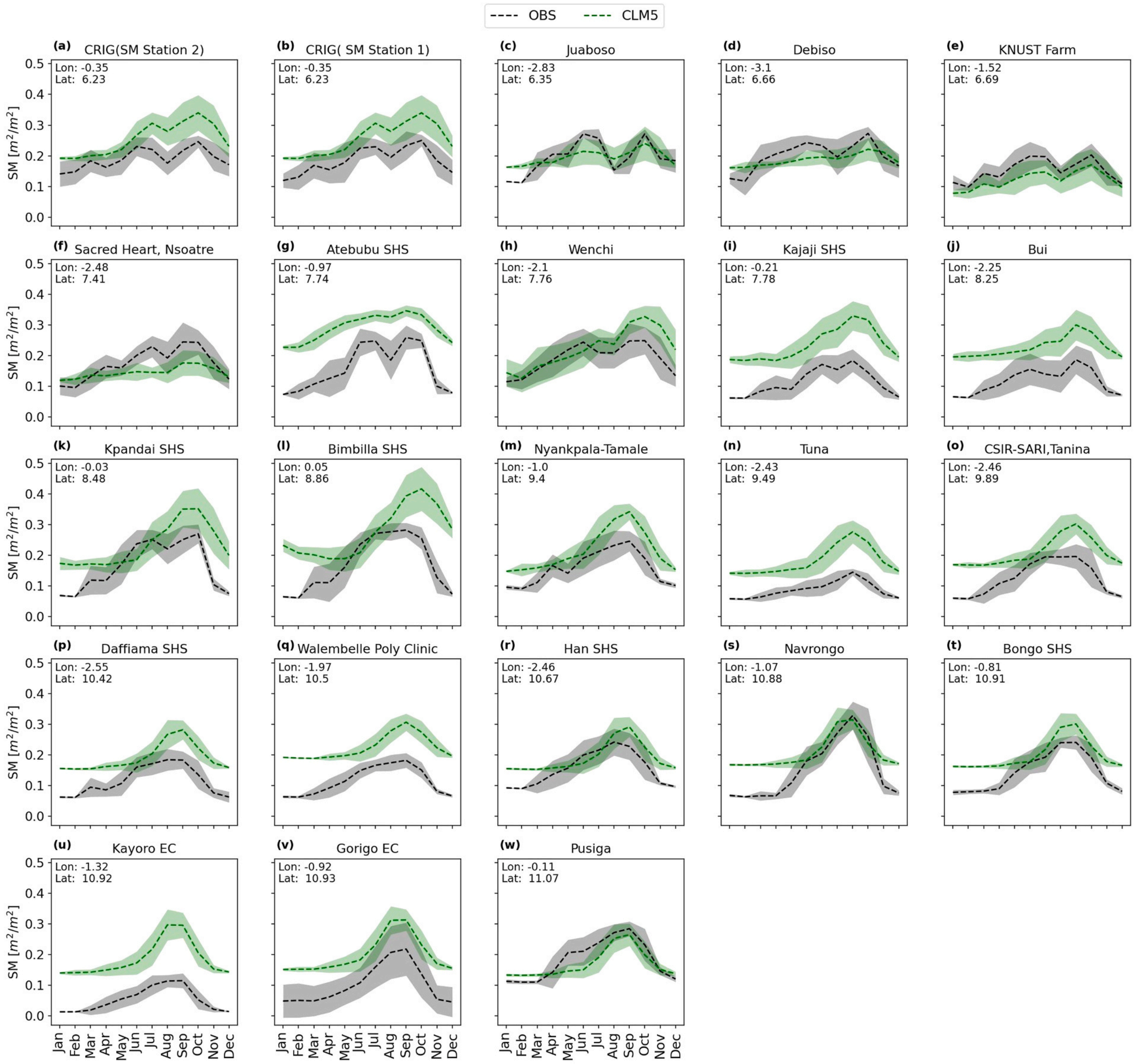

Fig. 4. Annual cycle of CLM5 simulated (green) and observed (black) soil moisture (0–6 cm) at 23 TAHMO SM stations over Ghana. The shaded region represents the standard deviation.

towards the northernmost station, Pusiga (latitude 11.07° N, Fig. 4w).

However, in most cases, CLM5 overestimates the observed SM contents (Fig. 4). Whereas most stations show only minimal fluctuations in SM during the dry season, both in the simulated and observed data, SM varies greatly at most stations during the rainy season.

3.2. Energy fluxes across different ecosystems in Ghana

The transfer of thermal energy between the soil, vegetation, and atmosphere, is closely linked to photosynthesis and overall plant growth and can thus serve as an indicator for ecosystem productivity.

Fig. 5 illustrates the mean seasonal distribution of sensible (Fig. 5a–d) and latent (Fig. 5e–h) heat fluxes across Ghana (Fig. 6).

During the dry seasons (DJF and MAM), when compared to observed measurements, CLM5 simulations show higher sensible heat fluxes across most parts of Ghana, except in the south-western region, where distinctively lower values are observed (Fig. 5a and b). In contrast, latent heat fluxes exhibit an opposite pattern, with higher values in the south-western region during the dry season. The analysis of surface heat fluxes over Ghana revealed distinct spatial patterns in both latent and sensible heat fluxes.

Simulated latent heat flux (LE) ranged from 23 to 160 Wm^{-2}, with higher values concentrated in the south-western corner and along the Ghana-Togo border, gradually decreasing northward. Interestingly, the coastal region in southern Ghana, exhibited LH fluxes comparable to those in the northern regions (see Fig. 5a). In contrast, the H fluxes, which varied between −11 and 123 Wm^{-2}, showed an inverse pattern, with higher H fluxes in the northern parts of Ghana and lower H fluxes in the southwest and in the border areas of Togo. The observed LE and H fluxes from four EC stations (i.e. Gorigo, Kayoro, Janga, and Mole Park) were used to assess CLM5 performance with regard to energy exchanges over Ghana and to identify discrepancies with the observed temporal patterns of LE and SH. Fig. 3 presents the simulated and observed LE and H fluxes at four eddy covariance (EC) stations.

For the analysis period, CLM5 captured the seasonal dynamics of latent heat flux (LE) and sensible heat flux (H) at Gorigo but showed a consistent underestimation of LE and overestimation of H. Overall, LE was underestimated by 21.89 Wm^{-2}, while H was overestimated by −18.35 Wm^{-2}. This pattern persisted across seasons, with dry-season biases of 12.98 Wm^{-2} for LE and −11.31 Wm^{-2} for H, and wet-season biases of 28.18 Wm^{-2} for LE and −23.32 Wm^{-2} for H. A similar pattern was observed at Kayoro, where CLM5 successfully captured the seasonal variations in LE and H, though with consistent biases. Overall, LE was underestimated by 3.17 Wm^{-2}, while H was overestimated by −20.93 Wm^{-2}. During the dry season, LE was underestimated by 2.98 Wm^{-2}, while H was overestimated by −15.90 Wm^{-2}. In the wet season, the biases were 3.37 Wm^{-2} for LE and −20.93 Wm^{-2} for H.

On the other hand, at the Janga and Mole EC stations, CLM5 overestimated both latent heat flux (LE) and sensible heat flux (H),

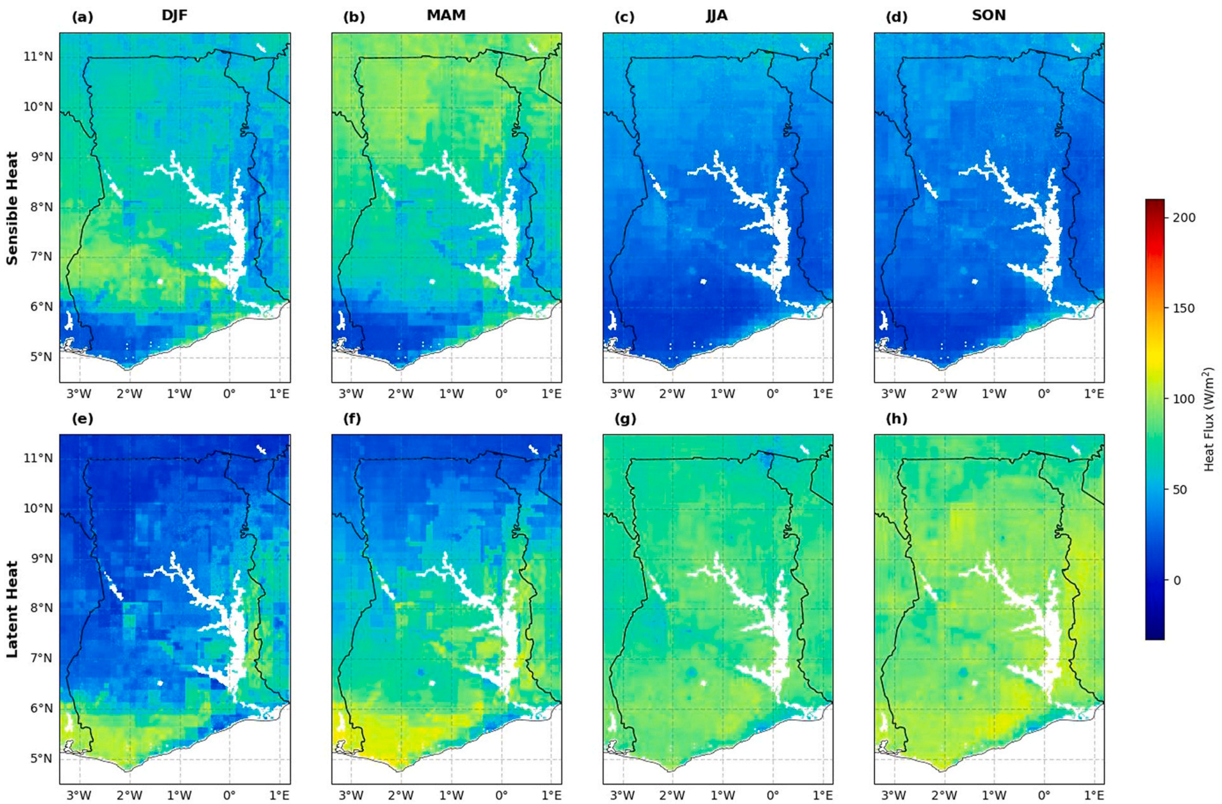

Fig. 5. Simulated mean seasonal distribution of sensible (a-d) and latent (e-h) heat fluxes over Ghana from 2020 to 2023.

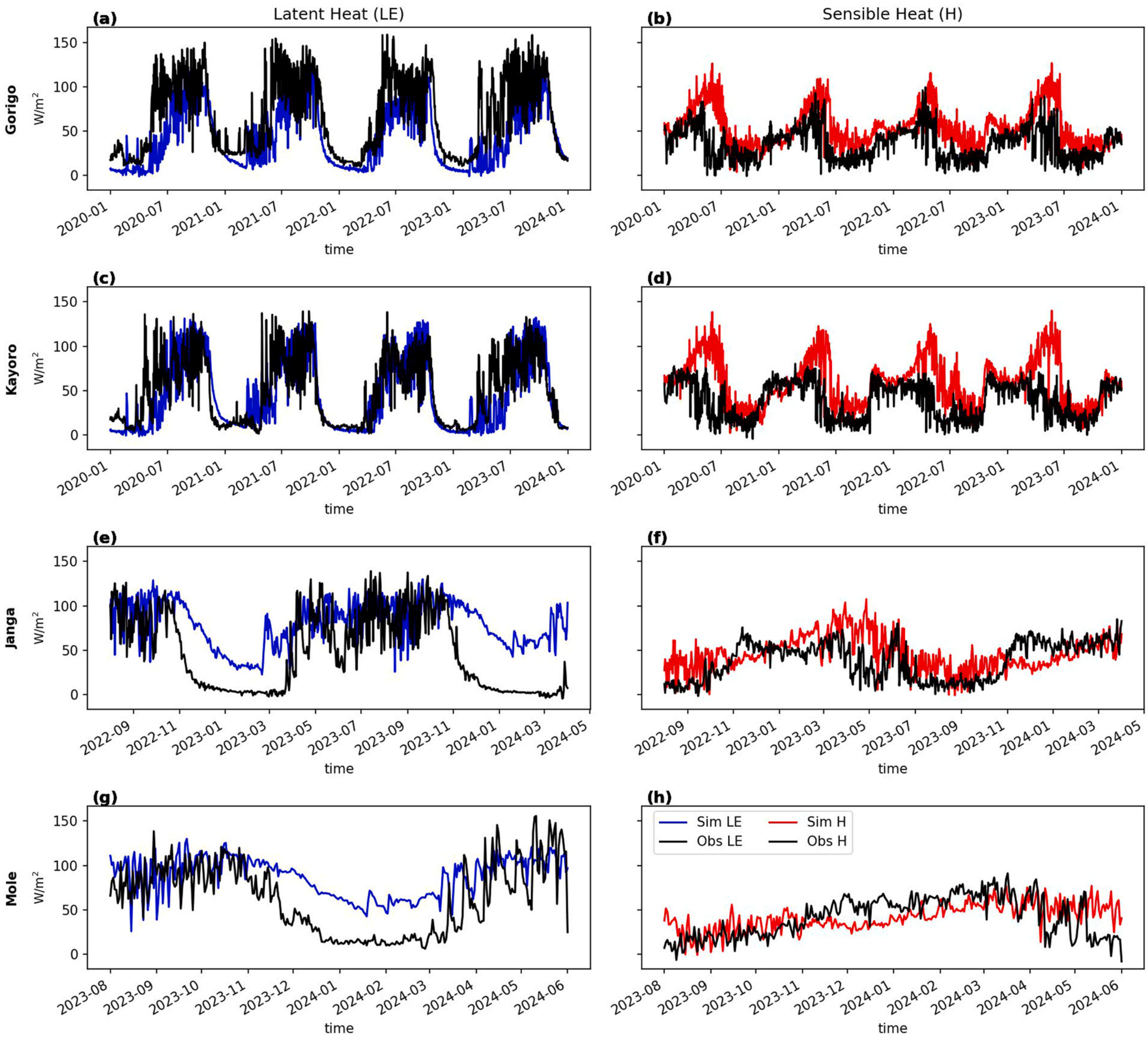

Fig. 6. Comparison of simulated daily latent fluxes (left column) and sensible heat fluxes (right column) against observations from four eddy covariance stations (rows). Observed latent and sensible heat fluxes are denoted by black lines, while simulated latent and sensible heat fluxes are denoted by blue and red solid lines, respectively.

while successfully capturing the seasonal dynamics. At Janga, CLM5 exhibited an overall overestimation, with biases of −9.83 Wm^{-2} for LE and −12.06 Wm^{-2} for H. Seasonally, LE was consistently overestimated in both the dry (-9.41 Wm^{-2}) and wet (-10.16 Wm^{-2}) seasons, while H was overestimated during the dry season (-11.36 Wm^{-2}) and in the wet season (-12.62 Wm^{-2}). At Mole, CLM5 showed a general overestimation of LE (-21.11 Wm^{-2}), with the highest bias during the dry season (-38.14 Wm^{-2}) and a smaller bias in the wet season (-9.53 Wm^{-2}). H, however, was underestimated in the dry season (9.96 Wm^{-2}) but later overestimated in the wet season (-9.39 Wm^{-2}), leading to a minor overall bias (-1.56 Wm^{-2}). Further analysis comparing the four radiation components (incoming and outgoing shortwave and longwave) from the model and the observation from the various sites revealed some significant biases and poor linear agreements as indicated in Fig. A1 in the Appendix.

3.3. Comparison of GPP dynamics in CLM5 and observational data

Gross Primary Production (GPP) is a critical component of the carbon cycle, reflecting the rate of carbon uptake by vegetation through photosynthesis. Fig. 7 reveals the seasonal mean of GPP over Ghana showing a distinct spatial and seasonal variation from CLM5 simulation. During the dry seasons (DJF and MAM), GPP values are generally lower across the country, reflecting reduced photosynthetic activity as indicated in Fig. 7a and b. However, the south-western part of Ghana stands out, showing higher simulated GPP values during these periods. As the year transitions into the wet season, GPP values show a notable increase across Ghana (see

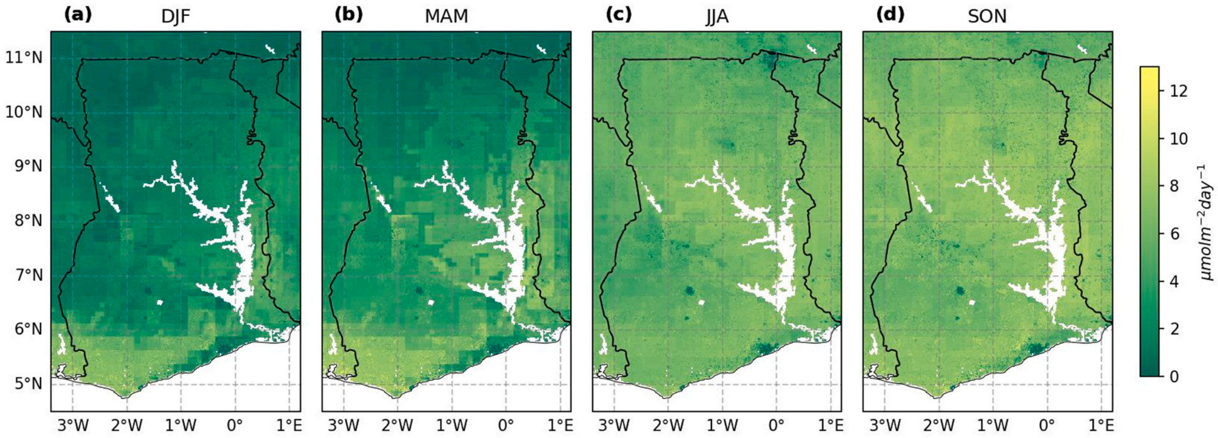

Fig. 7. Mean seasonal distribution of CLM5-simulated gross primary production (GPP) over Ghana between 2020 – 2024.

Fig. 7c and d). The rise in GPP highlights the seasonal dynamics of ecosystem productivity and the dependence of GPP on water and nutrient availability. To evaluate the performance of CLM5 in simulating GPP, we compared the CLM5 output with observed daily GPP data from four EC stations. Note that the GPP for each EC station was estimated using the ReddyProc online tool (Wutzler et al., 2018) which partitioned the station's net ecosystem exchange into GPP and ecosystem respiration.

Fig. 7 illustrates the daily dynamics of GPP at these stations, highlighting the temporal variability in both the CLM5 and the observed GPP data. Note that the vegetation of CLM5 at these stations is slightly different from the actual vegetation cover; the grassland vegetation of the Gorigo site was correctly represented on the CLM5 surface file, Kayoro cropland was misrepresented with grassland, as well as the rice field of the Janga station. The Mole national park which is a forest reserve was represented with a mixture of 45% broadleaf evergreen tropical trees and 55% grassland (Fig. 8).

The results observed for all four EC stations revealed that CLM5 captured closely the seasonal dynamics of photosynthetic activity. Generally, a good linear agreement ($r > 0.75$) was observed for all EC stations with a slight overestimation of GPP by CLM5 at Gorigo ($bias = -0.003$ μmolm^{-2}day^{-1}), Kayoro ($bias = -0.867$ μmolm^{-2}day^{-1}) and Janga ($bias = -1.323$ μmolm^{-2}day^{-1}). The simulated GPP at Mole national park on the other hand, was underestimated compared to the observed values ($bias = 0.308$ μmolm^{2} day^{-1}). However, during dry season at each station, there was little to no variability in photosynthetic activity when compared to the observations from the stations (see months January to May in Fig. 9). During the dry season, CLM5 simulated GPP showed a lower correlation ($r < 0.3$) at all stations. Note that the uncertainties from partitioning and gap filling may also account for the biases observed during the dry season resulting at times in negative values of GPP. Conversely, CLM5 showed a good agreement in simulating GPP during the wet season for all stations ($0.6 < r < 0.7$) except of the Mole National Park ($r < 0.3$).

3.4. Discharge and runoff dynamics in CLM5 simulations

The seasonal distribution of surface runoff (QOVER) simulated by CLM5 over Ghana reveals distinct spatial and temporal variations as indicated in Fig. 9. During the DJF season, surface runoff is relatively low across most of Ghana, except in the lower south-western region where slightly higher runoff values are observed. As the season transitions into MAM (March-April-May), JJA, and SON, surface runoff increases across Ghana. Notable hotspots of runoff emerge along the Ghana-Togo border and the lower south-western part of the country, where consistently higher values are recorded than in the rest of the region. Also indicated is a patch area around the Lake Volta where simulated surface runoff was close to zero visible in all seasons. These areas are observed to be the low land areas in Ghana (see Fig. 1c).

Generally, the surface runoff regime can be divided in three distinct zones of Ghana: the northern zone, the transition zone, and the southern zone (Figure A4). The north shows a unimodal surface runoff pattern while the southern zone depicts a bimodal pattern. Among these three zones, the transitional zone produces less runoff than both the southern and northern zones, with the southern zone having the highest runoff levels throughout the year. Furthermore, we compared the observed runoff data from four gauging stations with the accumulated runoff data generated by the CLM5 model within the corresponding catchment areas: Twifo Praso (catchment area: 12,938 km^2), Kade (catchment area: 1650 km^2) in the southern part of Ghana, Pwalugu (catchment area: 3748 km^2) in the north and Prang (catchment area: 6428 km^2) in the transition region of Ghana (Fig. 1). Fig. 10 shows a comparison of simulated annual surface runoff with observed runoff in terms of correlation coefficient, root mean squared error, and bias for each site.

Overall, the CLM5 model's performance is poor across all sites. At Twifo Praso, there's almost no correlation between the observed and simulated data. Kade shows a negative correlation, suggesting an inverse relationship. Prang also shows very weak correlation. Pwalugu displays the worst performance, with a low correlation, high RMSE, and substantial bias, indicating significant underestimation (Obs - CLM5$_{sim}$). The CLM5 model generally underestimates discharge and fails to accurately capture the patterns of observed discharge at these locations.

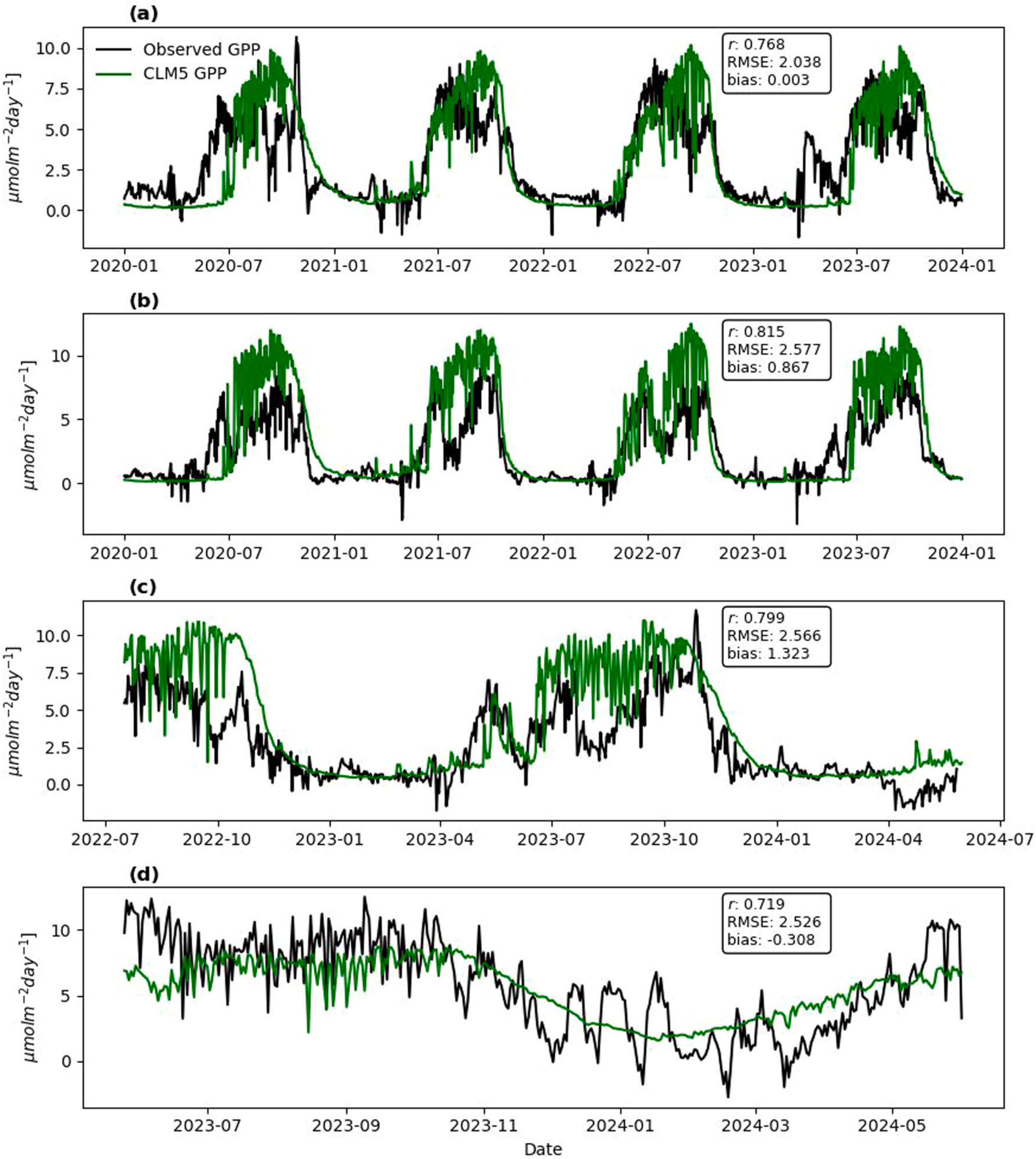

Fig. 8. Comparison of simulated (green lines) and observed (black lines) daily dynamics of gross primary production (GPP) at the Gorigo (a), Kayoro (b), Janga (c) and Mole Park (d) eddy covariance stations.

4. Discussion

4.1. Performance of CLM5 in predicting soil moisture dynamics

The simulation of mean monthly SM revealed a significant spatial variability across Ghana. The spatial and temporal pattern of CLM5 SM conforms to the weather patterns observed in the region (Boamah et al., 2024). This pattern reflects the influence of seasonal rainfall events, which can lead to rapid fluctuations in SM content which is observed by both stations and CLM5-simulated SM although some positive biases were observed. This suggests that CLM5 reasonably represents local hydrological patterns, which can support agricultural planning and water resource management, especially in regions with variable rainfall if further adjustments are carried out to reduce biases. Notably, in our study, the northern part of Ghana shows stronger seasonal variation in CLM5-estimated SM

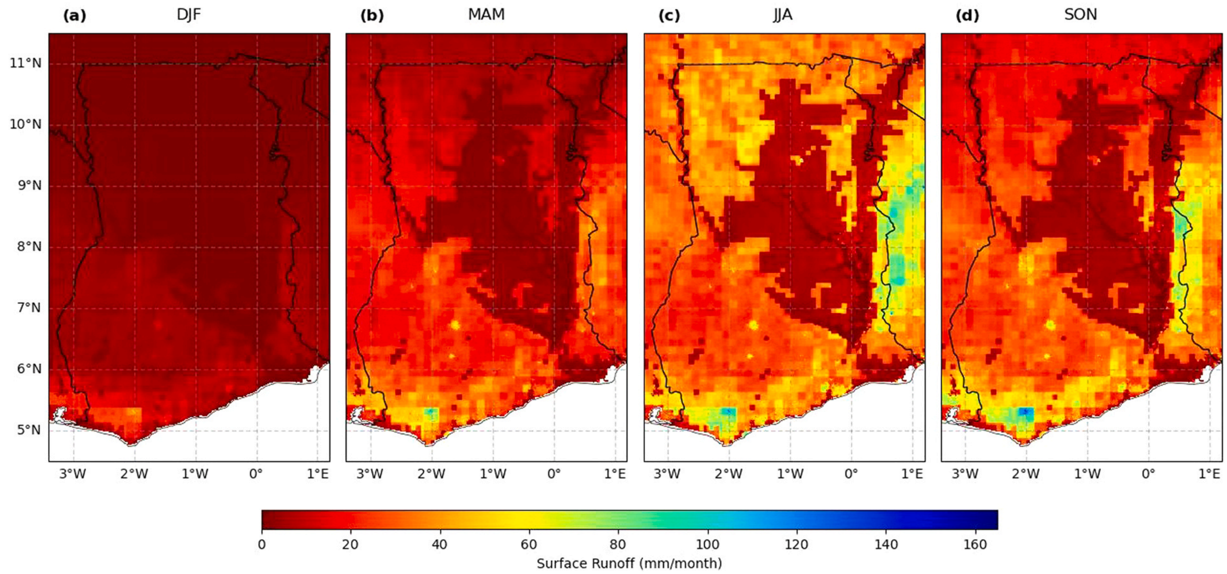

Fig. 9. Seasonal variation of simulated surface runoff over Ghana between 2000 and 2012.

compared to other studies (Abagale and Tetteh, 2011; Pinnington et al., 2018) as well as station measurements. Furthermore, the south-western parts of Ghana exhibit consistently higher SM levels, suggesting the influence of localized factors such as proximity to water bodies or variations in vegetation cover (Pinnington et al., 2018).

Spatial representativeness presents an inherent challenge in the validation of land surface model simulations, as point-scale observations reflect localised soil and vegetation conditions that may differ from the aggregated conditions represented across a model grid cell. This mismatch is particularly relevant in heterogeneous landscapes such as Ghana, where soil properties and land cover can vary considerably over short distances. A pixel-to-station aggregation approach would have helped reduce this uncertainty; however, the sparsity of the observational network in Ghana makes it unlikely that two or more stations fall within the same 1 km model grid cell, rendering this approach impractical. To complement the site-level evaluation and address this spatial limitation, Fig. A4 presents a pixel-wise evaluation of CLM5 surface soil moisture against SMAP retrievals. Correlation coefficients are moderate to high across most of the domain (Fig. A4a), indicating that CLM5 reproduces observed temporal variability reasonably well. A systematic dry bias dominates the central and northern regions, while a wet bias is evident along the southern coast (Fig. A4b). Elevated RMSE values in the south (Fig. A4c) coincide with areas of dense vegetation, where both model parameterization and satellite retrievals are subject to greater uncertainty. These results demonstrate the value of SMAP as an independent validation dataset and highlight the potential of remote sensing products for broader land surface model evaluation in data-sparse regions.

While CLM5 provides valuable insights into SM dynamics, there are also biases in the simulations compared to observed SM that need to be considered, as also suggested in previous studies. Beyond spatial representativeness, biases in CLM5 simulations can also arise from model parameterisation. For instance, a study conducted in the Huai River Basin found that CLM5 significantly overestimated SM in the shallow soil layer (0–5 cm), with relative biases reaching up to 0.161 m^3m^{-3}, primarily due to systematic biases in model parameterization (Wang et al., 2024). This is particularly relevant to the present study, as the CLM5 parameters governing soil water retention, drainage, and transpiration including the saturated hydraulic conductivity and Medlyn stomatal slope rely on global default values that may not adequately represent Ghana's diverse soil and vegetation conditions (Ma and Wang, 2022). Additionally, research in Northwest China indicated that the model overestimated interception and underestimated evapotranspiration during the growth period, leading to an overall overestimation of soil water content (Zhang et al., 2023). Furthermore, a sensitivity analysis highlighted positive biases in SM estimates due to uncertainty in key soil-texture-related parameters (Ma and Wang, 2022), which is likely true for our study as well, given the reliance on SoilGrids data with limited regional specificity. The SoilGrids system relies on a large dataset of soil profiles, with approximately 240,000 locations globally. However, in Africa, including Ghana, the data is much less dense. For instance, the Africa Soil Information System (AfSIS) utilized around 28,000 sampling locations to create soil property maps at a 250 m resolution (Kempen et al., 2015). The influence of atmospheric forcing data, especially rainfall, on SM estimates is crucial since it introduces uncertainties that can affect the accuracy of the simulation. In this context, the ERA5 rainfall product has been shown to have a positive precipitation bias when compared to observations (see Fig. A1). Conversely, CHIRPS has been found to perform better than ERA5 in various evaluations. Specifically, studies have demonstrated that CHIRPS consistently outperforms ERA5 in detecting high-intensity rainfall events and provides a more accurate representation of rainfall variability across different landscapes (Atiah et al., 2020; Ahmed et al., 2024). These compounding factors, namely the positive precipitation bias in ERA5 forcing

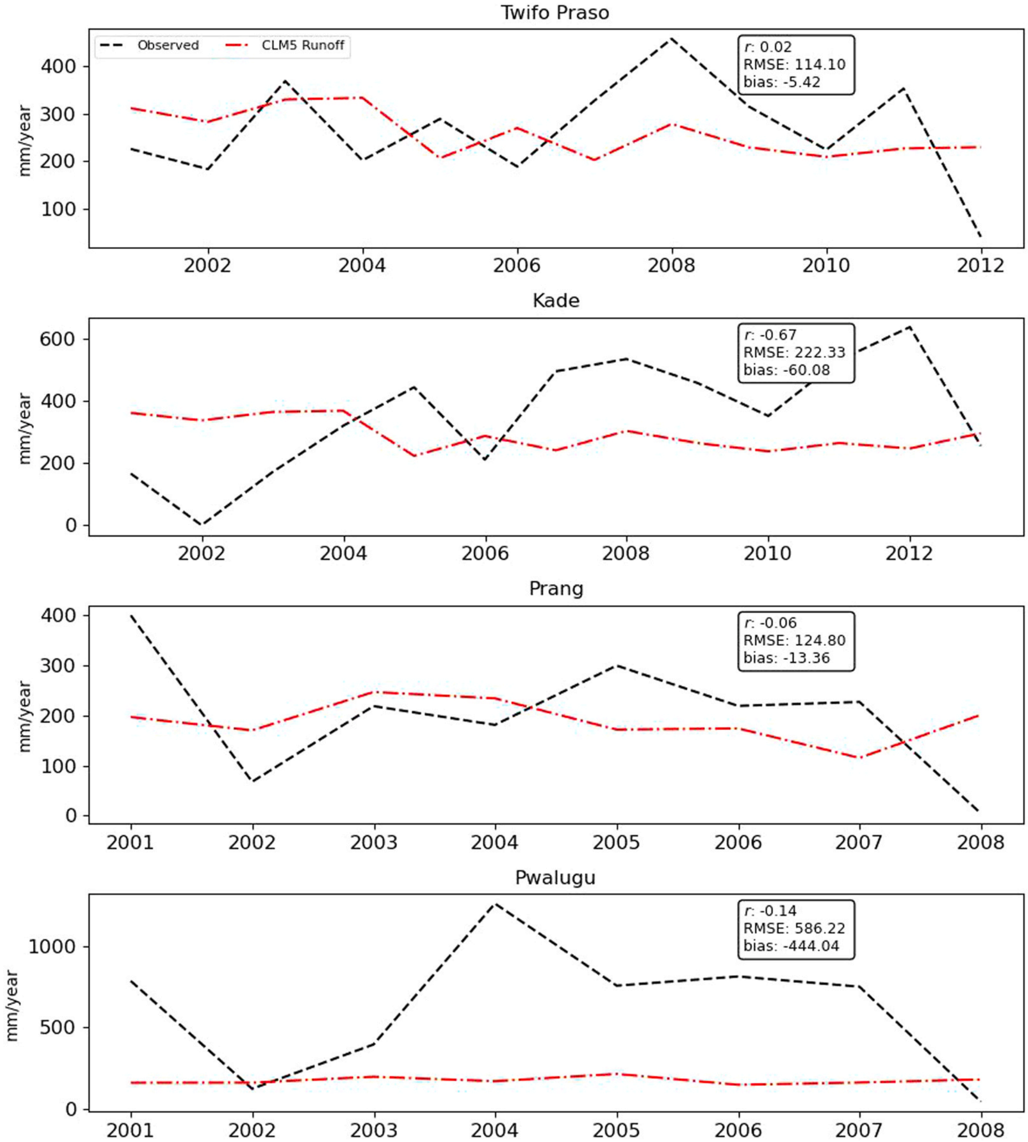

Fig. 10. Comparison of simulated annual surface runoff with observed runoff at the Twifo Praso, Kade, Prang and Pwalugu gauging stations.

data, the reliance on global default soil hydraulic parameters that may not adequately represent Ghana's conditions, the limited regional specificity of SoilGrids input data, and the tendency of CLM5 to overestimate interception while underestimating evapotranspiration, provide a plausible explanation for the systematic overestimation of SM observed across most sites. Since each of these biases acts in the same direction, their combined effect is likely to push simulated SM consistently above observed values, as reflected in Fig. 4.

4.2. Performance of CLM5 in predicting latent and sensible heat fluxes

The results from CLM5 simulations of latent and sensible heat fluxes over Ghana revealed distinct spatial patterns, consistent with known regional climatic variations as indicated in Fig. 5. The spatial variation in latent heat flux across Ghana is significantly influenced by vegetation cover, SM, and regional climatic conditions. In the south-western part of the country, dense forests and higher rainfall contribute to increased evapotranspiration, resulting in higher latent heat flux compared to the drier northern regions. This is supported by studies utilizing the SEBAL model, which estimates evapotranspiration based on satellite data, revealing areas with abundant vegetation and moisture which experience greater energy fluxes (Salifu, Agyare, 2012). Additionally, the tropical rainforest climate in the southwest results in high evapotranspiration rates, while topographic variations create microclimates that further enhance moisture retention and heat exchange processes (Dore, 2005). Consequently, the stark contrast between the humid southwest and the arid north leads to significant spatial differences in latent heat flux across Ghana, which is well represented in the simulations, as Fig. 5 illustrates higher latent heat fluxes in the south compared to the north.

Despite the overall good performance of CLM5 in representing turbulent fluxes, comparisons with data from four EC stations revealed notable discrepancies. It is important to acknowledge the inherent scale mismatch between point-based eddy covariance observations and grid-based model outputs at 1 km resolution. Eddy covariance flux footprints typically extend from a few hundred meters to over one kilometre (Kljun et al., 2015), only partially overlapping with the model grid, and sub-grid heterogeneity in vegetation cover and SM can produce simulated fluxes that deviate from tower measurements even when broader patterns are well captured. Comparisons should therefore be interpreted primarily in terms of temporal dynamics and seasonal patterns rather than exact magnitude agreement. The model generally overestimated sensible heat flux (H) with biases at Gorigo (-18.35 Wm^{-2}), Kayoro (-20.93 Wm^{-2}), Janga (-12.06 Wm^{-2}) and Mole Park (-1.56 Wm^{-2}). For latent heat flux (*LE*), the model generally showed underestimation with biases at Gorigo (21.89 Wm^{-2}) and Kayoro (3.17 Wm^{-2}), while at Janga (9.83 Wm^{-2}) and Mole (21.11 Wm^{-2}) CLM5 showed overestimation. Our results agree with previous studies in other regions using CLM5 (Ma et al., 2023). CLM5 shows stronger correlations with observed LE and H during the wet season due to its effective simulation of hydrological processes under high precipitation conditions (Ma and Wang, 2022; Li et al., 2024). However, its performance declines in dry periods due to challenges in simulating evapotranspiration and SM retention. Biases in LE and H fluxes can be linked to biases in SM, which implies that improving SM will have a significant impact on surface energy flow simulations. As highlighted by Zhang et al. (2023), CLM5 may overestimate or underestimate SM, affecting the accuracy of simulated heat fluxes. These discrepancies can be partly attributed to biased input forcing radiation data strongly influences net radiation, which in turn affects the partitioning of energy into turbulent fluxes (latent and sensible heat), contributing to the observed over- and underestimations. For instance, at Mole national park, our analysis revealed that the incoming shortwave radiation (SWin) used to force CLM5 was underestimated by more than 100 Wm^{-2} when compared to EC station measurements. This large bias in incoming radiation input likely explains the underestimation of modelled energy fluxes at this site, highlighting also issues in model input rather than structural or parameter-related model errors. Again, potential misrepresentation of land cover characteristics such as vegetation type or spatial heterogeneity can contribute to discrepancies in energy flux simulations. Structural mismatches between modelled and actual land cover types may alter evapotranspiration rates (MingYue et al., 2022) and surface energy dynamics, amplifying errors from biased forcing data. Similarly, surface heterogeneity in land cover generates mesoscale atmospheric responses that traditional eddy covariance methods struggle to resolve, creating energy balance closure issues in measurements. These findings underscore the importance of accurately representing land cover types and their spatial distribution to improve energy flux modelling.

4.3. Performance of CLM5 in predicting GPP dynamics

The observed lower GPP values during the dry seasons (December-February and March-May) across Ghana align with expectations, as reduced moisture availability typically limits photosynthetic activity. This aligns with previous studies indicating that GPP is highly sensitive to water availability, as lower moisture levels can significantly limit photosynthesis (Liao et al., 2023; Zhang et al., 2023). However, the south-western region of Ghana exhibits higher GPP during these dry periods, suggesting localized factors such as dense vegetation cover or microclimatic conditions that may enhance photosynthetic rates despite overall dry conditions. Studies have highlighted the systemic challenges in modelling canopy-atmosphere interactions, particularly in complex tropical ecosystems and heterogeneous canopies (Song et al., 2020; Dombrowski et al., 2022). This observation is crucial as it points to the heterogeneity within Ghana's ecosystems and indicates that certain areas may be more resilient to climatic fluctuations than others. The transition into the wet season brings a marked increase in GPP across the country, reflecting enhanced photosynthetic activity driven by improved water and nutrient availability. This seasonal dynamic is vital for understanding ecosystem productivity and its implications for carbon cycling in tropical regions (Zhang-Zheng et al., 2024).

To assess the performance of the CLM5 model in simulating GPP, we compared its outputs with observed data from four eddy covariance (EC) stations. The model successfully captured the seasonal dynamics of GPP. However, the CLM5 predictions for GPP during the dry season showed a correlation below 0.3 for all stations. This discrepancy indicates that, while CLM5 can capture general trends in GPP, its performance is limited under conditions of limited SM, when photosynthetic activity is usually reduced. Conversely, during the wet season, the model's performance improved significantly (correlation values between 0.6 and 0.7), except for Mole national park where it performed poorly ($r = 0.21$). These findings suggest that while CLM5 is a robust tool for simulating GPP during favourable conditions, it requires further calibration to accurately predict GPP during periods of drought.

CLM5 calculates stomatal conductance using the Medlyn stomatal conductance model. Key parameters within this model, such as g_1, which relates stomatal conductance to net leaf photosynthesis and vapor pressure deficit, could be calibrated. Studies have shown that g_1 exhibits species-specific variations and sensitivity to CO_2, and accounting for this can significantly affect evapotranspiration estimates (Franks et al., 2018). Other studies also highlight the underperformance of CLM5 GPP during drought periods and even between different plant functional types (Umair et al., 2020; Poppe Terán et al., 2025). The discrepancies noted at specific EC stations can be attributed to differences in vegetation representation within CLM5. For instance, grassland was incorrectly represented at Kayoro cropland and Janga rice field stations, while Gorigo's grassland was accurately depicted. These misrepresentations likely contributed to the model's challenges in capturing the true dynamics of GPP at these locations. Note that tower-based gross primary productivity (GPP) is an indirectly derived quantity obtained through partitioning of net ecosystem exchange (NEE), which introduces inherent methodological uncertainties. On the other hand CLM5 applies uniform plant functional types (PFTs) across 1 km grid cells, inadequately resolving the fine-scale vegetation mosaics prevalent in Ghana's savanna ecosystems and thereby contributing spatial representativeness errors. These uncertainties in both measurements and model parameterization highlights that GPP discrepancies arise from a combination of observational limitations and structural simplifications, rather than model deficiencies alone.

4.4. Performance of CLM5 in predicting yearly runoff

Our study identified significant limitations in the ability of CLM5 to reproduce yearly runoff observed at four gauging stations in Ghana with different catchment areas (indicated in Fig. 1a). While CLM5 was able to capture the seasonal trends, there are significant discrepancies between simulated and observed runoff data (Fig. 9). This suggests that CLM5 does not adequately capture the hydrological dynamics in these regions, particularly regarding the contribution of subsurface runoff, which is only rudimentarily considered in the model. CLM5 uses the TOPMODEL approach to simulate runoff, which considers the generation of surface runoff and subsurface runoff in a very simplistic way (Niu et al., 2005). Surface runoff is computed based on the excess saturation mechanism and subsurface runoff is assumed when saturated conditions occur in the soil column. Thus, these model structural uncertainties of CLM5 may have led to inaccuracies in the modelling of the runoff. In addition, the accuracy of the SoilGrids data for Ghana may be limited. As the soil hydraulic properties have a strong influence on the simulation of infiltration processes, these inaccuracies could have led to an underestimation of the infiltration excess and thus insufficient surface runoff generation. These aspects should be investigated in future studies with more detailed information on soil properties.

CLM5 is also equipped with a river routing module for runoff simulations (Jin et al., 2022). However, since the simulations were carried out on a monthly time scale in this study, it was assumed that the runoff would be able to move from the farthest point to the discharge measurement stations. Therefore, the flow routing module was switched off and it was assumed that the total runoff over the entire catchment area can be used for comparison with the runoff observations. It is possible that this assumption was not entirely adequate, especially for the smaller catchments. This needs to be further investigated in future studies. Furthermore, each catchment presented unique runoff patterns as they differ in catchment size, rainfall pattern and land use and cover (Pilgrim et al., 1982; Chen et al., 2020), where more localized catchments often experience intensified runoff responses to rainfall events due to short response time, high runoff coefficient, and more responsive hydrological processes, compared to larger basins with complex hydrological pathways and longer response times to rainfall. This highlights the importance of spatial scale in runoff modelling and the need for site-specific calibration for accurately representing runoff patterns in the diverse climatic zones of Ghana.

5. Conclusions

The study provides a comprehensive evaluation of the Community Land Model Version 5 (CLM5) in simulating key hydrological and biophysical processes over Ghana, highlighting both strengths and limitations. Generally, the CLM5 model reproduced the spatial and temporal dynamics of water, energy, and gross primary productivity (GPP) well, demonstrating its ability to capture key land-surface processes driven by rainfall characteristics over Ghana, despite some observed uncertainties. Discrepancies in SM such as the observed wet biases may be associated with deficiencies in soil texture information (Soilgrid), radiation and precipitation data used as forcing.

Furthermore, key findings from this study indicate that during the wet season, CLM5 exhibited significant variability and biases in simulating turbulent fluxes (i.e. sensible and latent heat flux) as well as GPP ($RMSE < 3$ μmolm^{-2} day^{-1} and $r >= 0.75$) across Ghana. However, despite these biases, the model demonstrated a stronger linear agreement with observations in the wet season compared to the dry season, implying a relatively improved performance in capturing seasonal variations when SM and vegetation activity are at their peak. However, discrepancies were noted during the dry season, where GPP values were consistently underestimated across all EC stations. This is inconsistent with overestimated dry season SM. This may be due to the model misrepresenting stomatal closure or root water uptake dynamics, leading to lower GPP despite sufficient SM. These discrepancies highlight challenges in simulating evapotranspiration and SM retention. Improved SM simulations and better representation of vegetation would likely improve predictions of energy fluxes (Strebel et al., 2024).

CLM5 showed persistent limitations in simulating Ghana's annual runoff patterns across four catchments, despite capturing seasonal discharge trends. Structural deficiencies in its TOPMODEL-based runoff scheme, which considers surface runoff and subsurface runoff in a rudimentary manner, likely contributed to the lack of agreement with the observations. Further reasons for these deficits could be soil-hydraulic inaccuracies due to the imprecise SoilGrids data for Africa and the neglect of the river routing module. Improvements in hydrologic performance may also be achieved by incorporating higher-resolution and bias-corrected precipitation datasets such as CHIRPS, which better capture spatial and temporal rainfall variability critical for surface runoff and groundwater recharge dynamics.

The results demonstrate that CLM5 provides valuable insights into hydrological and biophysical processes across Ghana. Across all validated variables, the scale mismatch between point-scale observations and the 1 km model grid remains an inherent limitation of this study. Point-scale measurements reflect localised conditions that may not fully represent grid-cell-average behaviour, and this discrepancy likely contributed to some of the model-observation differences reported. The sparsity of monitoring stations across Ghana further constrained the validation approach, limiting the ability to aggregate observations at the grid-cell scale. However, key biases in SM, turbulent fluxes, and runoff highlight the need for targeted improvements in parameterization, vegetation representation, soil properties information and improved atmospheric forcing data. Addressing these challenges will further enhance the model's reliability and its regional suitability for characterizing agricultural water resource management and ecosystem functions in data-limited regions.

CRediT authorship contribution statement

P. Davies: Writing – original draft, Methodology, Formal analysis, Conceptualization; **O. Dombrowski:** Writing – review & editing, Methodology, Investigation, Conceptualization; **R. Baatz:** Writing – review & editing; **H.J. Hendricks Franssen:** Writing – review & editing; **S. Guug:** Writing – review & editing, Data curation; **S. Sy:** Writing – review & editing; **J. Bliefernicht:** Writing – review & editing; **E. Quansah:** Writing – review & editing; **L.K. Amekudzi:** Writing – review & editing, Supervision; **H. Kunstmann:** Writing – review & editing, Funding acquisition; **H.R. Bogena:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Conceptualization.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Heye Reemt Bogena reports financial support and article publishing charges were provided by Forschungszentrum Jülich Institute of Bio- and Geosciences Agrosphere 3. Heye Reemt Bogena reports a relationship with Forschungszentrum Jülich Institute of Bio- and Geosciences Agrosphere 3 that includes: employment. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A

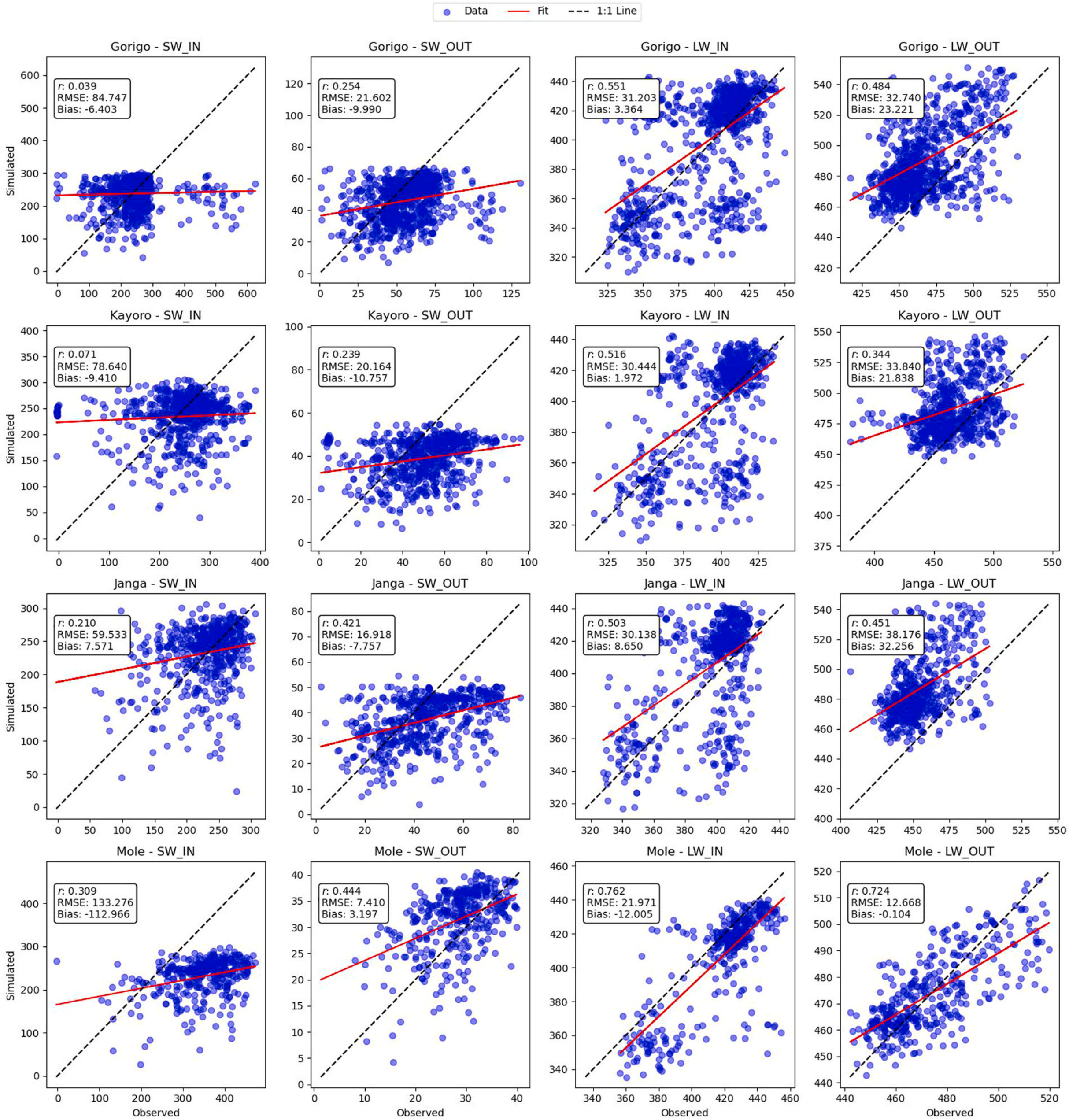

Figure A1. Scatter plots of the four observed radiation components compared to the simulated components for the various EC stations

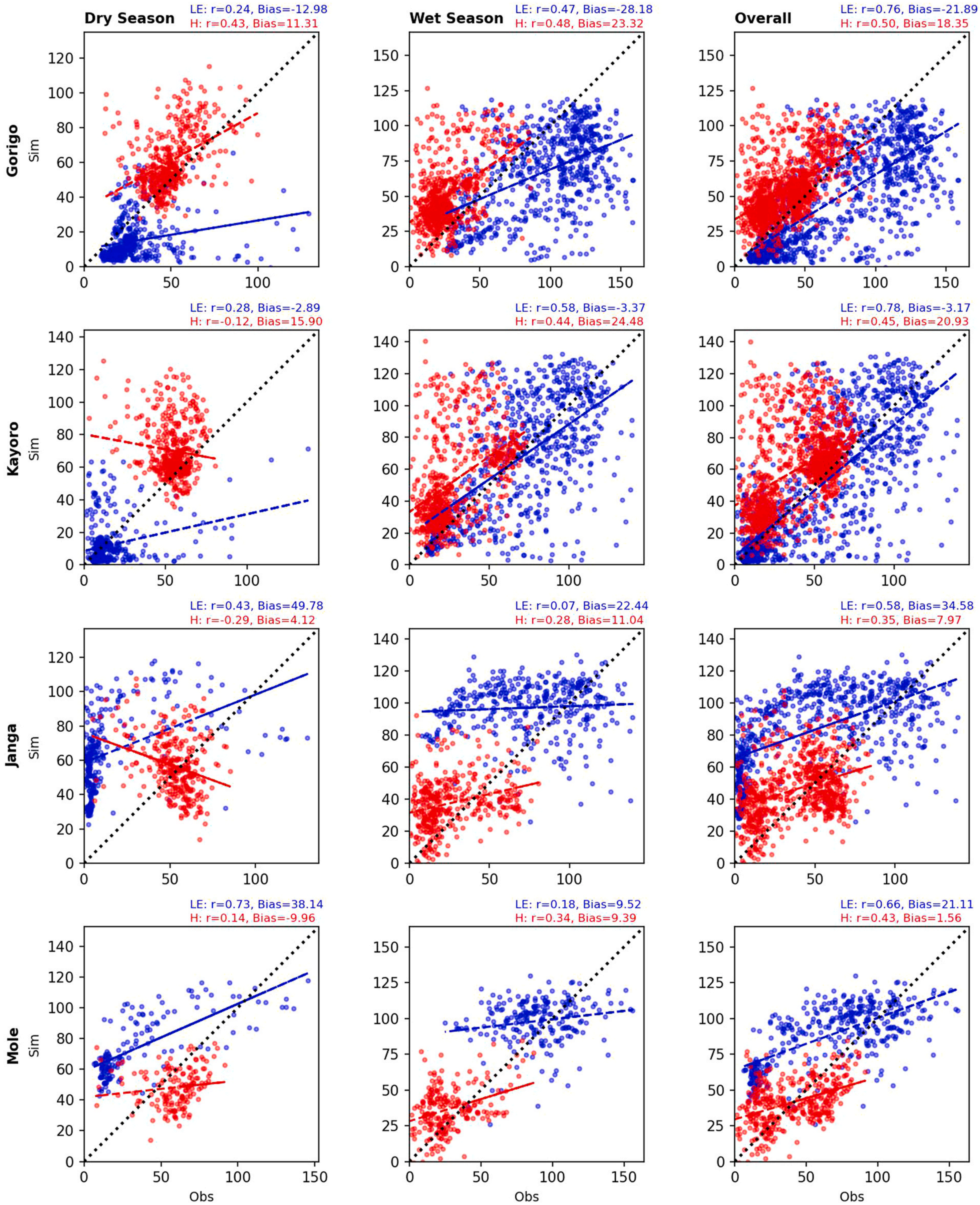

Figure A2. Scatter plots of the observed against simulated latent and sensible heat fluxes divided into dry and wet periods and for the entire period

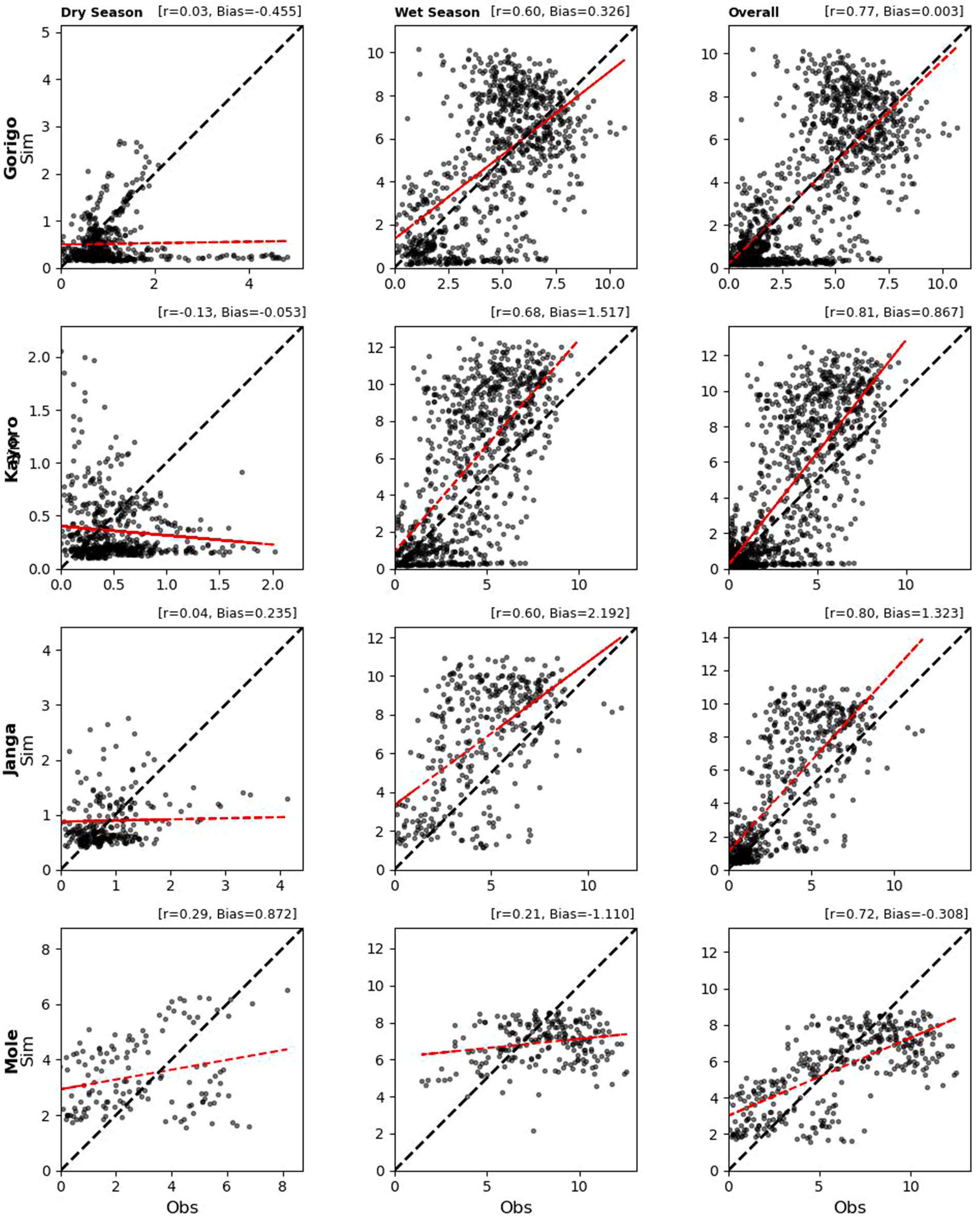

Figure A3. Scatter plots of the observed against simulated GPP divided into dry and wet periods and for the entire period

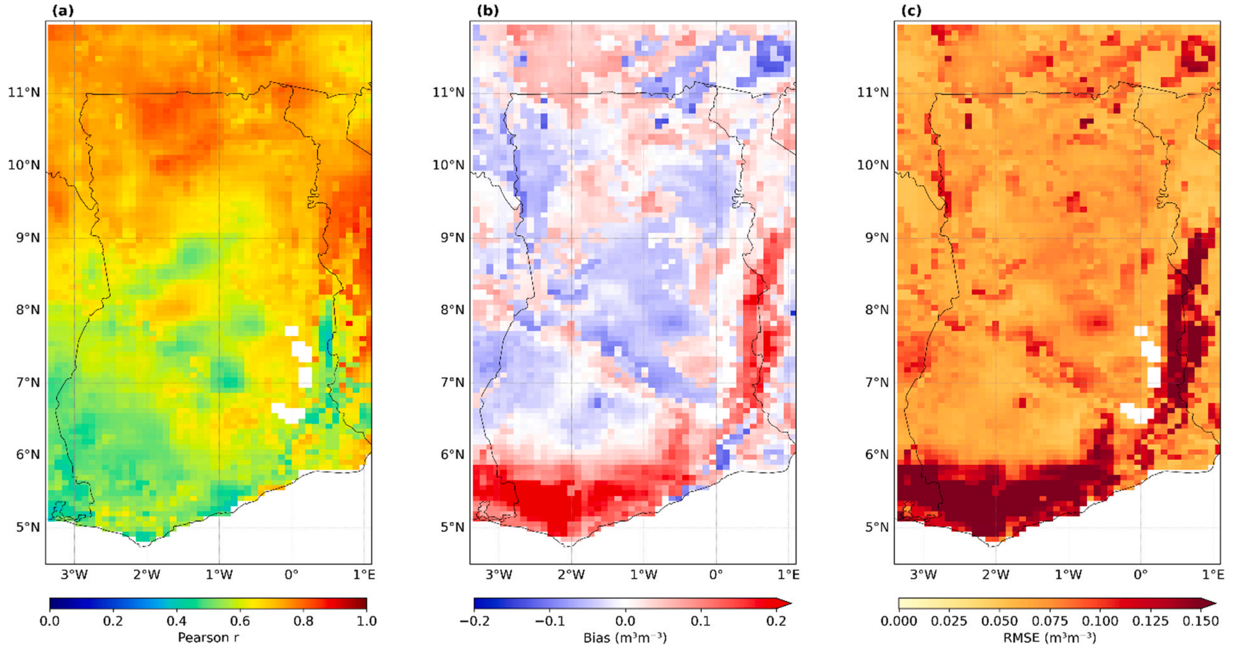

Figure A4. Spatial distribution of statistical metrics comparing CLM5-simulated and SMAP-observed surface soil moisture over Ghana. (a) Pearson correlation coefficient (r), (b) mean bias (CLM5 minus SMAP, m^3 m^{-3}), and (c) root mean square error (RMSE, m^3 m^{-3})

Appendix B. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.ejrh.2026.103573.

Data Availability

Data will be made available on request.

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