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Linking Earth Observation and Precipitation In-Situ Data in the Sirba River Basin in West Africa

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Abstract: Floods have caused substantial loss of life and economic damages in West Africa, with a marked increase of extremes over the past decades. These flood events are largely driven by frequent extreme local rainfall. The sparse meteorological stations in Burkina Faso contain data gaps that limit effective monitoring of rainfall. This study fills the gap by integrating satellite data with in-situ precipitation measurements. This study assesses spatio-temporal correlations between cloud coverage and reservoir surface water areas extracted from Sentinel-2 to in-situ rainfall historical data complemented with spatially explicit gridded meteorological products, including ERA5 and CHIRPS. In-situ precipitation shows a strong correlation with cloud coverage (Mean $r = 0.65$), better agreements with ERA5 ($r = 0.83$) and CHIRPS ($r = 0.91$), and a time-lagged correlation with surface water areas. A developed open-access app (Abraiz, 2026) provides insights for real-time dynamics of the cloud coverage, precipitation, and surface water area of reservoirs in the Sirba River basin with potential applicability in other data-scarce regions.

Keywords: Sentinel-2; cloud coverage; precipitation; surface water; spatio-temporal changes.

1 Introduction

The high discharge in the Sirba River (which flows through Burkina Faso and Niger before draining into the Niger River) is considered a major source of flooding in Niamey (Aich et al. 2014). Flooding in this region is primarily driven by extreme local rainfall events, which trigger flash (pluvial) floods (Miller et al. 2022). However, the rainfall measurement network in Burkina Faso is sparse and often characterized by significant data gaps, highlighting the need to integrate satellite-based rainfall datasets (Cannella et al. 2024). Moreover, extreme rainfall exhibits strong spatial and temporal variability across the studied area (Panthou et al. 2014), emphasizing the need for improved monitoring of precipitation patterns at larger spatial scales.

Gridded precipitation datasets provide a valuable complement to sparse ground-based observations. In particular, Climate Hazards Group InfraRed Precipitation with Stations (CHIRPS) and fifth generation of the European Centre for Medium-Range Weather Forecasts (ECMWF) reanalysis data (ERA5) have been shown to perform well in West Africa, offering improved rainfall estimation and filling gaps in rain gauge networks (Sategé et al. 2020). Moreover, ERA5 also provides sub-daily precipitation data and enhances rainfall monitoring (Hersbach et al. 2020). However, the spatial resolutions

(~5km for CHIRPS and ~11km for ERA5) of the above-mentioned gridded precipitation limit the fine scale monitoring of precipitation. In this study, we propose a fine-scale indirect monitoring of precipitation by linking it to cloud coverage.

The growing availability of satellite data, combined with cloud computing platforms such as Google Earth Engine (GEE), has significantly advanced the monitoring of global surface water dynamics (Donchyts et al. 2016). Small and medium-sized reservoirs are of particular interest due to their higher sensitivity to precipitation variability and rapid response behaviour (Donchyts et al. 2022). Several studies have demonstrated time-lagged relationships between precipitation and hydrological responses, particularly in reservoir storage dynamics (Piccarreta et al. 2026). However, the relationship between precipitation and surface water area spatio-temporal variations remains unexplored, especially in small and medium sized reservoirs within data-scarce regions, which are explored in this study.

In this study, we have investigated the correlations between in-situ precipitation complemented by ERA5 and CHIRPS measurements to cloud coverage and surface water areas of reservoirs. Cloud information is derived from Sentinel-2 imagery using cloud probability metadata, and we used a cloud fraction threshold of 30% to divide all pixels into a “clear-sky” and “cloudy” group. Surface water is mapped using the Modified Normalized Difference Water Index (MNDWI) (Tiepolo et al. 2025).

The novelties of this study are twofold: first, establishing a relationship between Sentinel-2 cloud coverage and in-situ precipitation measurements; and second, quantifying the links between precipitation and surface water dynamics in small and medium-sized reservoirs within the Sirba River basin. The study investigates three key relationships using multi-source, multi-temporal datasets: (1) Sentinel-2 cloud coverage and in-situ precipitation; (2) in-situ precipitation and gridded datasets (ERA5 and CHIRPS); and (3) in-situ precipitation and surface water area changes.

2 Materials and methods

The Sirba River catchment covers an area of about 39,138 km² and has a length of around 906 km flowing through Burkina Faso and Niger before joining the Niger River (Tamagnone et al. 2019). It is the largest tributary of the Niger River in Niger. The Sirba River basin is comprised of three tributaries: Faga (320 km), Koulouko (300 km) and Yali (140 km), which merge into one near the Niger-Burkina

Faso border before flowing downstream (146 km) into the Niger river.

Daily in-situ precipitation historical data were collected from 10 meteorological stations installed at 10 different locations (shown in Figure 6 and listed in Table 3) across the Sirba River catchment and are considered for the analysis. This in-situ data was made available by the local meteorological departments from Burkina Faso and Niger from 1960 to 2022.

In order to correlate precipitation to hydrological responses, the analysis includes 41 small and medium-sized reservoirs inside the Sirba River basin having surface areas greater than 10 hectares (Donchyts et al. 2022). These water bodies were compiled from the four global water datasets including global in-situ data for lakes and reservoirs from Copernicus, global reservoir dam dataset from World Bank, OpenStreetMap and global surface water explorer from the European Commission Joint Research Centre (JRC). The studied area is shown in (Figure 6).

To ensure spatial and temporal consistency, CHIRPS data were resampled to 11 km to match the coarser ERA5 resolution. Given the different temporal coverages of the datasets—ERA5 (from 1951), CHIRPS (from 1981), and in-situ observations (1981–2022)—the analysis was limited to the common overlapping period from 1 January 1981 (the date when CHIRPS dataset become available) to 31 December 2022 (latest available in-situ precipitation observation date). The daily and hourly data were aggregated into monthly totals and mean annual precipitation values were computed for all years (1981–2022). Hydrological years were defined to account for seasonal variability, with the wet season considered from June to September and the dry season from October to May for all years, following established literature for the study area (Tamagnone et al. 2019).

Cloud coverage and surface water areas of waterbodies

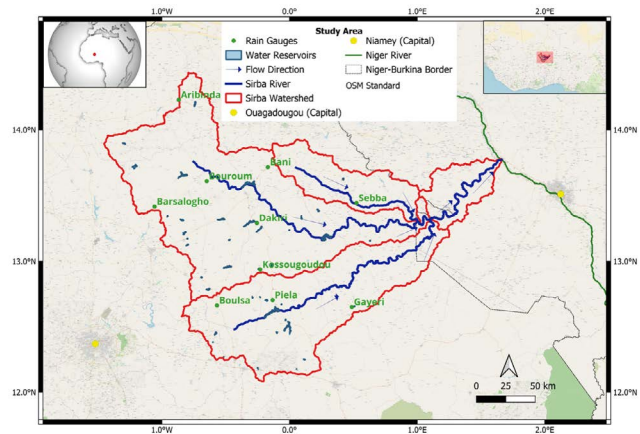


Figure 6. Study area including the Sirba River (in dark blue) and its watershed (in red) with arrows showing the river flow direction, the green points show the locations of the meteorological stations where in-situ precipitation data was available, and 41 small and medium water bodies (in light blue) with surface area greater than 10 hectares included in analysis.

were derived from the cloudy pixel percentage metadata from surface reflectance Sentinel-2 (S2) images. Cloud coverage was extracted every 5 days (temporal resolution of S2) starting from 28 March 2017 (first date when S2 became available in GEE) until the latest available in-situ precipitation observation (31 December 2022) in order to correlate it with in-situ precipitation data and mean values were calculated every month. The surface area of 41 reservoirs within the watershed of the Sirba River was extracted from the Modified Normalized Difference Water Index (MNDWI) given by equation (1) using S2 image classification and were correlated with in-situ precipitation monthly aggregated data. Where ρ_{Green} and ρ_{SWIR} are the surface reflectance of green and shortwave infrared bands (SWIR) of Sentinel-2 images respectively.

$$MNDWI = (\rho_{Green} - \rho_{SWIR}) / (\rho_{Green} + \rho_{SWIR}) \quad (1)$$

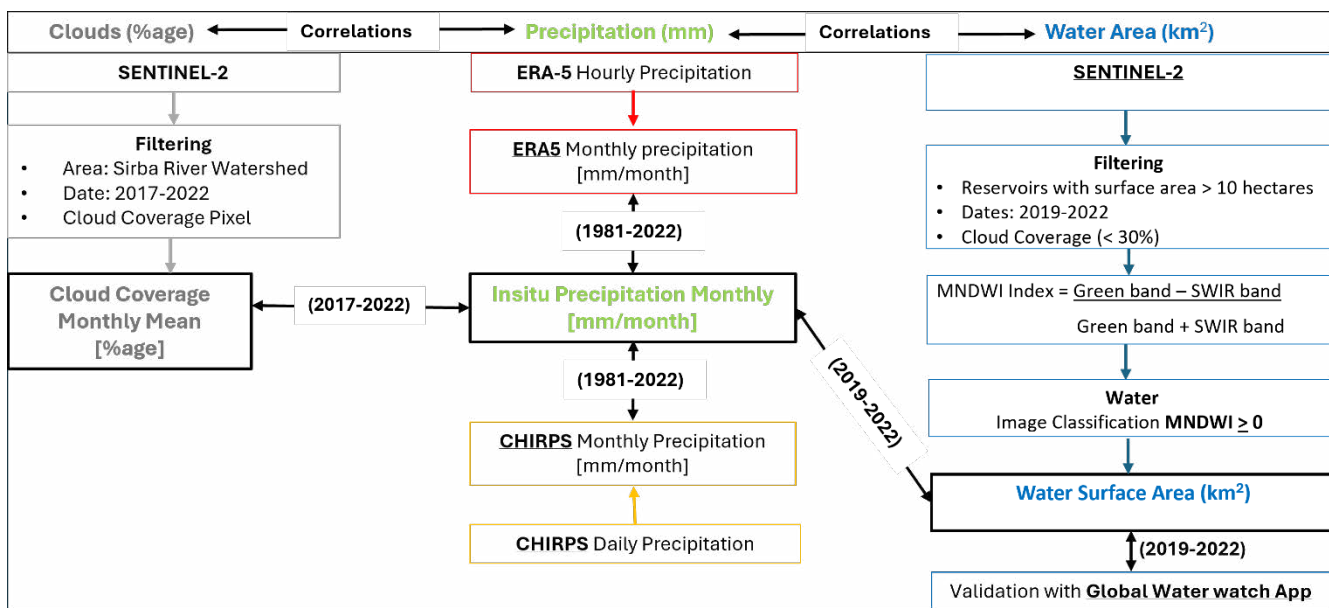


Figure 7. Methodology and workflow adopted to correlate cloud coverage, three types of precipitation (in-situ, ERA5 and CHIRPS) and surface water area extraction in overlapping time period depending on datasets availability, where correlations are represented by double-headed arrows investigated in the common time period in which all the datasets were available.

Depending on data availability and to ensure temporal consistency, correlations between cloud coverage and in-situ precipitation (2017–2022), in-situ precipitation and gridded precipitation datasets (1981–2022), and in-situ precipitation and reservoir’s surface areas (2019–2022) were assessed using the Pearson correlation coefficient (r) over their respective overlapping periods following the workflow shown in (Figure 7). Lastly, The MNDWI-derived maximum water extents were validated with the Global Water Watch app for all the water reservoirs from 1st January 2019 (depending on the availability of surface area time series of water bodies from Global Water Watch app) until latest available in-situ precipitation observation.

3 Results

Overall, in-situ precipitation shows the strongest temporal correlations with gridded precipitation datasets (ERA5 and CHIRPS), followed by cloud coverage, while the weakest relationship was observed with surface water areas. To ensure comparability despite differing dataset lengths, correlation analyses were performed over their respective overlapping periods (2017–2022 for cloud-related analysis, 1981–2022 for precipitation datasets, and 2019–2022 for surface water dynamics). The monthly cloud coverage shows a strong positive correlation (mean $r = 0.65$) with in-situ precipitation especially in peak precipitation periods with a peak correlation of $r = 0.88$ in 2019. Over the 6 years period (2017–2022) analysed, CHIRPS overestimated the precipitation (except 2017) while ERA5 underestimated the precipitation consistently compared with in-situ precipitation (Figure 8).

Over the longer period of 42 years (1981–2022) Pearson’s correlation coefficient (r), Mean Error (ME), and Mean Absolute Error (MAE) indicate that both ERA5 and CHIRPS exhibit predominantly negative ME, reflecting an overall underestimation of precipitation by gridded precipitation datasets relative to in-situ measurements. However, CHIRPS demonstrates better agreement with in-situ observations (mean $r = 0.91$) in terms of r and biases (ME and MAE) compared to ERA5 (mean $r = 0.83$) across all ten meteorological stations as shown in (Figure 9) and with r and MAE summarized in Table 3.

Moreover, maximum surface area extracted from the Sentinel-2 using MNDWI index showed a strong agreement with Global Water Watch. When comparing 41 max areas of reservoirs inside the Sirba River watershed showed a Root Mean Square Error (RMSE) of around 0.32 km². But the surface water area correlation with in-situ precipitation remains the weakest (mean $r = 0.05$).

4 Discussion

The strong correlation between cloud coverage and mean in-situ precipitation measurements for all ten stations (mean $r = 0.65$, reaching up to $r = 0.88$ in 2019) suggests that atmospheric cloud conditions captured by Sentinel-2 can serve as a reliable proxy for rainfall seasonality in data-scarce regions. Although CHIRPS performs better statistically, both datasets exhibit systematic biases that should be corrected before hydrological applications in the study region.

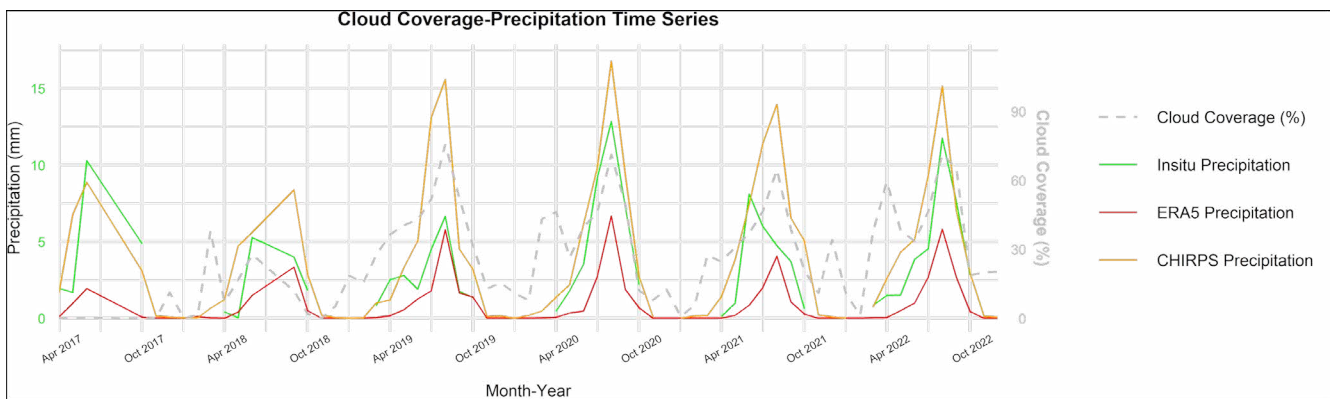


Figure 8. Monthly time series of S2-derived cloud coverage (in dotted grey line), In-situ precipitation (green), ERA5 precipitation (in red) and CHIRPS precipitation (orange).

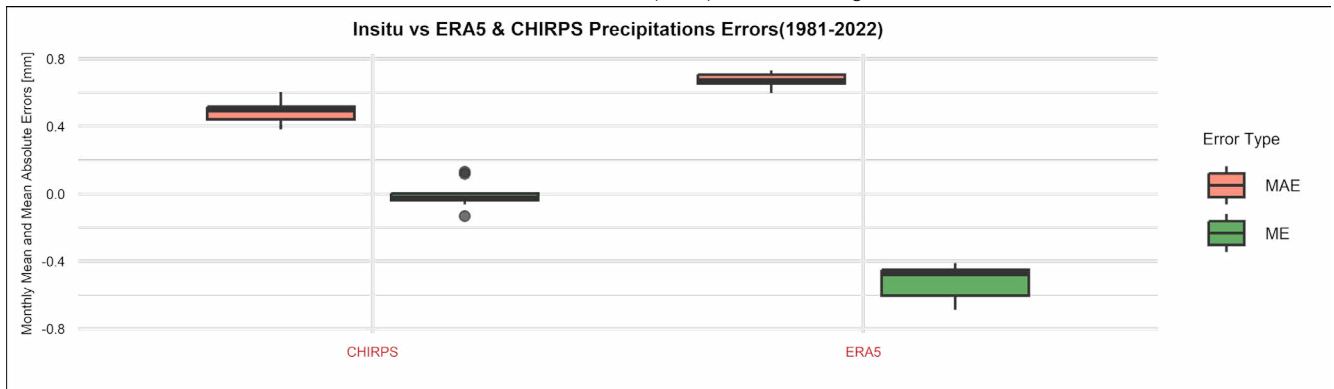


Figure 9. Mean Errors (ME) and Mean Absolute Errors (MAE) of CHIRPS and ERA5 aggregated monthly and compared relative to in-situ precipitation on monthly scale from 1981-2022.

Table 3. Summary of Pearson correlation coefficients (r) between cloud coverage (CC), in-situ precipitation (IP), and surface area (SA), along with Mean Absolute Errors (MAE) for ERA5 and CHIRPS across stations.

CC vs IP		IP vs SA	CC= Cloud coverage, IP= In-situ Precipitation, SA= Surface Area r = Pearson correlation Coefficient, MAE= Mean Absolute Errors, - (Years not analysed)									
Year	r	r	Stations	r	r	MAE	MAE	Stations	r	r	MAE	MAE
			Sr No. Location	ERA5 vs IP	IP vs CHIRPS	ERA5 vs IP	IP vs CHIRPS	Sr No. Location	ERA5 vs IP	IP vs CHIRPS	ERA5 vs IP	IP vs CHIRPS
2017	0.47	-										
2018	0.55	-	1.Aribinda	0.83	0.91	0.59	0.38	6.Dakiri	0.84	0.91	0.65	0.5
2019	0.88	0.40	2.Bani	0.83	0.91	0.65	0.42	7.Gayeri	0.73	0.75	0.92	0.6
2020	0.75	-0.21	3.Barsalogho	0.84	0.91	0.73	0.51	8.Kossougoudou	0.86	0.95	0.68	0.4
2021	0.6	-0.02	4.Boulsa	0.84	0.92	0.79	0.52	9.Piela	0.85	0.91	0.71	0.51
2022	0.67	0.03	5.Bouroum	0.83	0.92	0.79	0.5	10.Sebba	0.83	0.91	0.77	0.47
Mean	0.65	0.05	-	-	-	-	-	Mean	0.83	0.91	0.73	0.48

In contrast, the weakest relationship ($r = 0.05$) between surface area compared with the in-situ precipitation reflects the complex and non-linear response of reservoirs.

The sub-daily analysis is limited by the recent availability of Sentinel-2 data (2017) and temporal resolution (5 days) restricting the long historical analysis of cloud coverage and surface water area in contrast to daily precipitation data. Moreover, although the three aforementioned correlations were carried out in different temporal windows, additional analysis (not shown) indicated similar results for common temporal window (2019-2022), supporting the robustness of the findings despite dataset limitations.

5 Conclusions

The purpose of this study was to investigate three types of correlations (1) cloud coverage of Sentinel-2 to in-situ precipitation; (2) in-situ precipitation to gridded precipitation datasets; and (3) in-situ precipitation to reservoirs surface water area dynamics with the goal to correlate atmospheric conditions to hydrological responses. Firstly, there exists a very strong correlation between Sentinel-2 derived cloud coverage and precipitation (mean $r = 0.65$), especially in the periods of peak rainfall events in data-scarce regions (Figure 8).

Secondly, gridded precipitation datasets (CHIRPS and ERA5) show good agreement with in-situ precipitation (mean $r = 0.91$ and mean $r = 0.84$ respectively) but tend to underestimate rainfall (Figure 9) highlighting the importance to integrating in-situ precipitation measurements for accurate meteorological models. Thirdly, the correlation between precipitation and surface water area is weak ($r = 0.05$), indicating that reservoir dynamics are influenced by multiple hydrological and environmental factors beyond precipitation alone. We recommend investigating these processes in future research projects.

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