



West African Reservoirs Exhibit Variable Sensitivity to Large-Scale Climate Patterns

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Abstract. Limited understanding of current trends in reservoir surface extent in West Africa and how large-scale climate patterns influence these dynamics challenges efforts to anticipate stress on water resources. To address this gap, we assessed reservoir sensitivity to large scale climate patterns across West Africa. We linked reservoir surface extent dynamics from 1985 to 2022 for 412 reservoirs with ten large-scale climate patterns represented by ten Sea Surface Temperature Anomaly (SSTA) indices, using supervised machine learning approaches and further analyzed the regional clustering in reservoirs responses. Most West African reservoirs, with significant trend, exhibit declining surface extent from 1985 to 2022 and respond primarily to combined Indo-Mediterranean-Atlantic climate signals rather than to single SSTA indices. Western Mediterranean Index (WMED) emerged as the dominant driver and is generally positively associated with reservoir surface extent, while the Eastern Mediterranean Index (EMED) showed contrasting effects. Secondary contributions were observed from Atlantic modes, particularly the Atlantic Multidecadal Oscillation (AMO) and the Atlantic Meridional Mode (AMM). Regression coefficients of SSTA indices vary widely across reservoirs, with limited significant spatial clustering, indicating variable sensitivity of reservoirs to large-scale climate patterns potentially shaped by local factors. This spatial heterogeneity further stressed the need to investigate its implication for adaptation strategies, as well as the effects of local management practices and unique reservoir configuration on reservoir sensitivity to large scale climate patterns.

1 Introduction

Ocean-atmosphere interactions shape the global climate system, particularly through variations in Sea Surface Temperature Anomalies (SSTAs), so-called oceanic oscillations (Zardi, 2024). These anomalies strongly influence the terrestrial hydrological cycle through their effects on the climate system (Dey and Döös, 2019; Wang et al., 2004). One of the primary



pathways through which SSTAs affect hydroclimate is their modulation of the Intertropical Convergence Zone (ITCZ) (Wang et al., 2004; Talib et al., 2020; Nogueria et al., 2024) . Shifts in the position or intensity of the ITCZ can generate substantial changes in precipitation patterns, altering monsoon systems, and triggering hydrometeorological anomalies across continents (Geen et al., 2020; Hari et al., 2020; Hakam et al., 2025). For instance, a northward displacement of the ITCZ may enhance rainfall in normally wet regions while inducing drier conditions further south (Fontaine et al., 2010; Hari et al., 2020; Wang et al., 2021).

SSTA indices originating from the Pacific, Atlantic, Indian Oceans, and the Mediterranean basin exert different and pronounced effects on water availability in West Africa by modulating moisture transport and rainfall intensity (Fontaine et al., 2010; Polo et al., 2011; Gaetani and Fontaine, 2013; Diatta and Fink, 2014; Preethi et al., 2015; Xue et al., 2016). The magnitude and direction of these effects are linked to the phase and physical mechanisms of each SSTA index. Warm phases of El Niño-Southern Oscillation (ENSO) and cool phases of the Pacific Decadal Oscillation (PDO) typically shift atmospheric circulation patterns, leading to reduced rainfall across the Sahel and parts of West Africa (Nguyen et al., 2021; Nooni et al., 2025). These effects are amplified during abnormally warming of Tropical Indian Ocean (TIO) (Yue et al., 2021), which weakens the Walker circulation by reducing the east–west surface pressure gradient across the Pacific (Tokinaga et al., 2012). In contrast, warm phases of the Atlantic Multidecadal Oscillation (AMO), associated with a northward shift of the ITCZ, enhance moisture transport from the Atlantic towards West Africa (Martin and Thorncroft, 2014; Hodson et al., 2022; Mohino et al., 2024), which increase summer monsoon rainfall (Mohino et al., 2024). Variability of the Mediterranean SSTAs i.e. the Western and Eastern Mediterranean modes (WMED, EMED), influence moisture transport to West Africa by different mechanisms (Fontaine et al., 2010; Gaetani et al., 2010; Polo et al., 2011; Gaetani and Fontaine, 2013). While warm phases of the WMED shift the monsoonal ascent northward (Fontaine et al., 2010; Gaetani et al., 2010), those of the EMED strengthen the southwesterly flow and weaken the climatological northeasterly winds (Fontaine et al., 2010; Gaetani and Fontaine, 2013). As WMED and EMED modify atmospheric circulation over different parts of North Africa, they affect rainfall patterns across West Africa differently. Recent observations (Zittis et al., 2022; Urdiales-Flores et al., 2023; Napolitano et al., 2025) reveal that the Mediterranean Sea, particularly its eastern part (EMED) (Zittis et al., 2022), has experienced pronounced and accelerated warming at rates significantly higher than the global average. This warming has contributed to more frequent and intense heatwaves, reduced precipitation, and increased drought conditions (Urdiales-Flores et al., 2023; Napolitano et al., 2025) that can severely affect water and ecosystems (Klaus et al., 2022).

By shaping moisture and rainfall distribution, SSTA indices directly affect the hydrological cycle in West Africa, particularly streamflow, infiltration, and evaporation (Wang et al., 2004; Dey and Döös, 2019; Chun et al., 2021; Hounkpè et al., 2025; Chen et al., 2026; Zhang et al., 2026). Consequently, water storage in reservoirs is affected, which are critical for climate-resilient water management and mitigation of hydrological extremes (Wheater and Gober, 2015; Zhang and Gu, 2023). Several thousand reservoirs have been constructed in West Africa to support food production, energy generation, and water security



65 (Abobi and Wolff, 2020; Cecchi et al., 2020; Lèye et al., 2021). However, reservoirs are highly sensitive to variability in the hydrological cycle which is itself modulated by SSTA indices (Oyerinde et al., 2016; Chun et al., 2021; Hou et al., 2022). This sensitivity may constrain the seasonal availability of reservoir water storage and increase exposure to both water scarcity and excess (Mateus and Tullos, 2017).

70 Despite the well-established climate-hydrology link, the specific response of reservoirs to different SSTA indices in West Africa remains unclear. Recent global studies report widespread declines in reservoir water storage (Wisser et al., 2013; Li et al., 2023; Yao et al., 2023; Simeone et al., 2024; Miao et al., 2025; Chandanpurkar et al., 2025), which has been linked to various anthropogenic and climatic factors (Marshall et al., 2012; Diawara et al., 2016; Giardino et al., 2018; Ni et al., 2018). Climate variability, strongly modulated by SSTAs, emerges as a major driver of reduced reservoir inflows (Hou et al., 2022). The influence of SSTA on reservoir water storage dynamics is further illustrated by Andam-Akorful et al. (2017) and Rodell
75 et al. (2024), who identified progressive changes in extreme hydrological conditions linked to ENSO variability. Similarly, Ndehedehe et al. (2018) highlighted the roles of ENSO and AMO in controlling soil moisture, thereby indirectly modifying reservoir water availability. Chun et al. (2021) and Mampo et al. (2025) demonstrated that multiple SSTA indices including coupled Pacific, Atlantic, Indian Ocean, and Mediterranean variability (ENSO, AMO, TIO, and EMED), exert a strong control on streamflow variability in West Africa. These findings suggest a potential importance of interacting large-scale climate
80 patterns in shaping reservoir behaviour across the region.

We address these knowledge gaps by examining how reservoir surface extent dynamics relate to large-scale climate patterns across West Africa. Specifically, we investigate two key research questions: (i) what are the current spatiotemporal patterns and trends in reservoir surface extent dynamics and how are they associated to the variability of SSTA indices variability? (ii) do reservoirs exhibit differential responses to distinct SSTA indices?

85 Based on the known physical mechanisms associated with SSTA indices, their hydroclimatic impacts, and observed global trends in reservoir water storage, we hypothesize that: (i) reservoir surface extent dynamics exhibit pronounced spatiotemporal variability in response to SSTA indices patterns; (ii) reservoir responses to SSTA indices in West Africa emerge from the combined influence of multiple interacting SSTA indices rather than from any single oceanic driver; (iii) coupled SSTA indices from the Pacific-Atlantic-Indian-Mediterranean indices exert strong and widespread influence on reservoir surface extent
90 dynamics; (iv) SSTA indices exert different mode-specific and spatially heterogeneous signals on reservoir surface extent variability.

This study advances knowledge of regional-scale trends in reservoir surface extent dynamics and provides a West Africa-wide assessment of reservoir sensitivity to major SSTA indices. Understanding the interactions between climate indices and reservoirs in West Africa is essential for developing more targeted adaptation strategies, improve monitoring efficiency, and
95 ultimately reduce uncertainty in hydroclimatic forecasting.



2 Methods

2.1 Study area

West Africa extends roughly from the equator to about 20°N and is characterized by strong climatic gradients operating from intraseasonal to multidecadal scales (Fig. 1). Three broad climatic zones are commonly described in the literature (Fink et al., 2017; Quenum et al., 2019; Ndao et al., 2020). From north to south, these include: (a) the Sahelian zone (~12.5° N), a semi-arid transition toward the Sahara Desert characterized by highly variable rainfall (approximately 150-600 mm yr⁻¹); (b) the Sudanian or savannah zone (9-12.5°N), a sub-humid region shaped by the West African Monsoon (WAM) and receiving about 200-1,000 mm yr⁻¹; and (c) the Guinean coastal zone (4-9°N), a humid tropical region experiencing a bimodal rainfall pattern linked to the seasonal migration of the Intertropical Discontinuity (ITD), with annual precipitation ranging from 1,600 to 2,000 mm. West Africa is drained by several major river systems, including the Niger, Senegal, Gambia, and Volta rivers. Over the past decades, national governments and development agencies have constructed several thousand reservoirs throughout the region. These reservoirs increase water storage, sustain hydropower generation, support irrigation, enhance food security, and contribute to livelihood diversification (Cecchi et al., 2009; FAO, 2016; Abobi and Wolff, 2020; Lèye et al., 2021). The elevation ranges from low-lying coastal plains in the south to the higher interior plateaus and uplands in the north and east, generally increasing toward the Sahel and parts of the Guinea Highlands (Appendix A, Fig. A1).

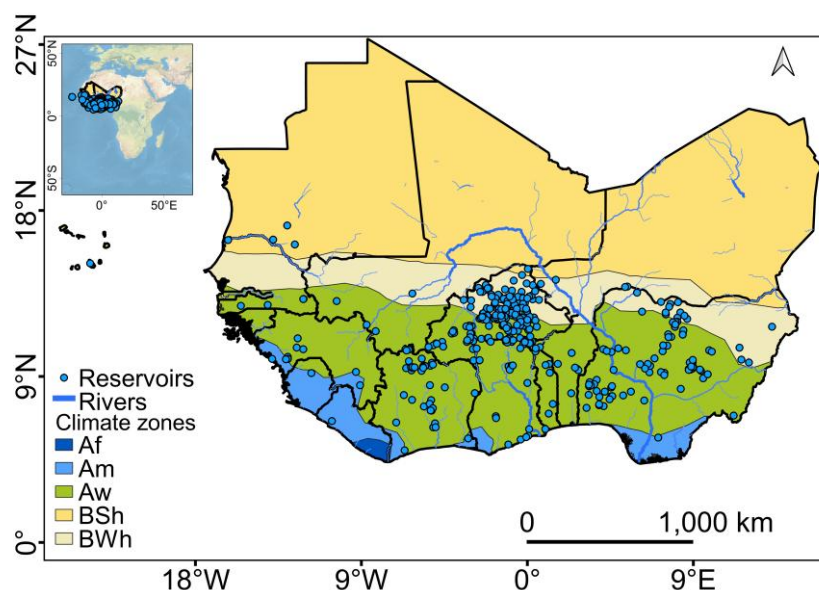
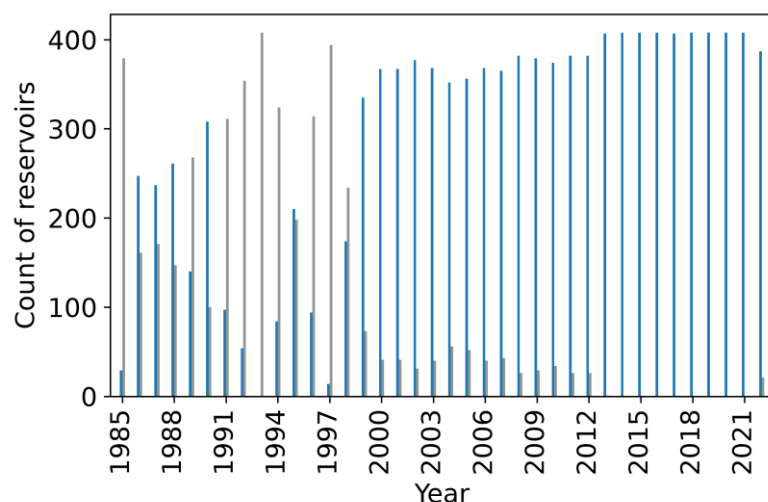


Figure 1: Spatial distribution of 412 reservoirs, and Köpen-Geiger climate zones (Beck et al., 2023) in West Africa. Af: Tropical wet (Equatorial), Am: Tropical monsoon, Aw: Tropical savannah, BSh: Warm desert, BWh: Warm semi-arid.



2.2 Reservoirs and climate indices data

115 We obtained monthly time series (1985-2022) of reservoir surface extent for 412 artificial reservoirs in West Africa with sizes ranging from approximately 0.005 to 1,118 km², from the Global Water Watch (GWW) platform (<https://www.globalwaterwatch.earth/map/>). GWW integrates multi-annual, multi-sensor satellite observations, specifically from Landsat and Sentinel, to monitor small (10-100 ha) and medium-sized (>100 ha) artificial reservoirs at the global scale. The dataset was validated against 768 daily *in-situ* water level and storage measurements (Donchyts et al., 2022). The dataset
120 was validated against observed reservoir surface extent data. Despite missing records (Fig. 2), the validation indicate that 67% of the reservoirs achieved a correlation coefficient (r^2) greater than 0.7 (Donchyts et al., 2022). This confirms that the dataset provides a robust proxy for reservoir storage dynamics.



125 **Figure 2: Annual number of West African reservoirs with and without an available surface extent record in the Global Water Watch (GWW) dataset from 1985 to 2022. For each year, blue bars represent the number of reservoirs with at least one surface extent observation, while grey bars represent the number of reservoirs with no surface extent observation during that year, among the 412 reservoirs considered. The reservoirs included in each category may vary from year to year.**

We used monthly time series of ten climate indices (SSTA indices) over 1985-2022 (Table 1). These climate indices are defined by distinct Sea Surface Temperature (SST) patterns representative of ocean regions that exert influence on Sahelian
130 hydroclimatic variability at interannual to decadal timescales (Fontaine et al., 2011; Rodriguez-Fonseca et al., 2011; Dieppois et al., 2015; Sidibe et al., 2019; Chun et al., 2021). The indices were derived from the Extended Reconstructed SST dataset, version 5 (ERSSTv5, Huang et al., 2017), and computed using Empirical Orthogonal Function (EOF) analysis (Chun et al., 2021). A key advantage of ERSSTv5 is its resilience to the cold biases introduced by satellite data assimilation in the late
135 twentieth century. In other SST datasets, these biases have been shown to suppress the magnitude of the global warming trend and to generate spurious decadal-scale negative anomalies (Reynolds et al., 2002).



Table 1: Details on the ten SSTA indices used for this study and representing key oceanic regions known to influence Sahelian hydroclimatic variability on interannual to decadal timescales (Chun et al., 2021).

Region	SSTA indices	Description	Reference
Global	Global Sea Surface Temperature (GT)	Weighted global SSTa (-70-70°N)	Trenberth and Shea (2006)
	Atlantic Niño (AtlNiño)	1st principal component (PC) of tropical Atlantic SSTa (-70-20°E, -30-30°N)	Chiang and Vimont (2004)
Atlantic	Atlantic Meridional Mode (AMM)	2nd PC of tropical Atlantic SSTa (-70-20°E, -30-30°N)	Chiang and Vimont (2004)
	Atlantic Multidecadal Oscillation (AMO)	Average SSTa for the North Atlantic (-80-0°E, 0-60°N)	Enfield et al. (2001) Trenberth and Shea (2006)
	Eastern Mediterranean (EMED)	Average SSTa for the East Mediterranean (15-36°E, 32-44°N)	Fontaine et al. (2011)
Mediterranean Sea	Western Mediterranean (WMED)	Average SSTa for the West Mediterranean (-6-15°E, 32-44°N)	Fontaine et al. (2011)
	El Niño-Southern Oscillation (ENSOpc)	1st PC of equatorial Pacific SSTa (110°E-95°W, -30-30°N)	Weller and Cai (2013)
Pacific	Interdecadal Pacific Oscillation (IPOpc)	1st PC of Pacific SSTa (100°E-70°W, -50-50°N)	Folland et al. (1999) Power et al. (1999)
	Pacific Decadal Oscillation (PDOpc)	1st EOF of North Pacific SSTa (100°E-100°W, 20-65°N)	Mantua et al. (1997)
Indian	Tropical Indian Ocean (TIO)	Average SSTa for the Tropical Indian Ocean (35-90°E, -24-24°N)	Mantua et al. (1997)

2.3 Data analysis

2.3.1 Variability and trends of reservoir surface extent and climate indices

We aggregated monthly reservoir surface extent and sea surface temperature anomaly (SSTA) data into annual time series and subsequently standardized them (Appendix B). Standardization was applied to ensure comparability between variables, enhance the detection of anomalies, reduce bias in statistical methods sensitive to variance, and enable consistent temporal comparisons (Jänicke et al., 2009; Roshan et al., 2021; Rawat et al., 2024). We analyzed the standardized anomaly index both spatially, along latitudinal and longitudinal gradients, and temporally at interannual and decadal scales of reservoir surface extent. The standardized SSTA indices (SSSTA) were primarily examined temporally. Positive and negative values in the standardized anomaly index of reservoir surface extent correspond to wetter-than-normal and drier-than-normal conditions, while these values indicate warmer and cooler ocean states for SSTA indices. This approach enabled the identification of wet and dry phases in reservoir surface extent dynamics and their correspondence with warm and cold phases of climate indices variability.



To detect long term monotonic trends in both standardized anomaly index of reservoir surface extent and SSSTA annual series, we applied the Modified Mann Kendall test (MMK; Appendix C; Hamed and Rao, 1998). The MMK test was selected for its robustness to non-normal data, missing observations, and serial correlation. It accounts for autocorrelation by adjusting the variance of the test statistic using the concept of effective sample size (Hamed and Rao, 1998).

155 2.3.2 Linking climate indices to reservoir surface extent dynamics

First, we evaluated multicollinearity among the SSTA indices using Pearson correlation analysis (Benesty et al., 2009). We then modelled annual reservoir surface extent anomalies using the standardized anomalies of the ten SSTA indices as predictors over the 38 year period from 1985 to 2022. As high collinearity among predictors can lead to overfitting or underfitting, reduce model interpretability through coefficient shrinkage, and weaken predictive stability (Mahdian et al., 2023; Chiabudini et al., 160 2020; Otse et al., 2025), we implemented three multivariate regression based machine learning approaches to reservoirs with at least twenty annual reservoir surface extent observations. 385 reservoirs met this requirement. The machine learning approaches were Ridge regression (Hoerl and Kennard, 1970), Elastic Net (Zou and Hastie, 2005; Giglio and Brown, 2018; Liu et al., 2018), and Partial Least Squares or PLS (Geladi and Kowalski, 1986; Pirouz, 2006). We systematically compared the performances of the machine learning approaches to identify the most robust and interpretable approach. A detailed 165 description of each approach is provided in the supporting file (Appendix D).

To further reduce overfitting risk and evaluate model robustness, we designed three experimental configurations based on different combinations of SSTA predictors. The first configuration (C1) included all ten SSTA indices simultaneously. The second configuration (C2) tested all possible combinations of two to eight SSTA indices to identify the optimal predictor subset for each reservoir. The third configuration (C3) used only low collinearity predictors and inputs filtered through 170 principal component analysis (PCA, Greenacre et al., 2022). We retained the number of components that explain at least 95 % of the total variance of the SSTA indices for each SSTA model of the third configuration (C3) for the PCA.

For each reservoir and each combination of SSTA indices, we implemented a consistent K-fold cross-validation framework (Jung, 2018). We randomly partitioned the dataset into K folds ($K = 5$), and models were iteratively trained on K-1 folds and tested on the remaining fold. We used *GridSearchCV* function in python (Shanthi and Chethan, 2023) to automatize the process 175 of hyperparameter (α , λ and the number of latent components) tuning. Testing R^2 and Root Mean Squared Error (RMSE) across folds were used to derive the overall mean R^2 , Standard deviation of testing R^2 (Std R^2), mean RMSE, and the number of reservoirs with positive predictive skill (testing $R^2 > 0$). We calculated an overfitting score from the average gap between scaled training and testing R^2 (train R^2 -testing R^2) within each fold. These fold-level gaps were then averaged across folds and reservoirs to obtain a method-level overfitting score. We selected the best-performing machine-learning approach using a 180 hierarchical set of criteria applied in the following strict order: the lowest overfitting score, the lowest RMSE, the highest mean



R^2 , and the highest number of positive R^2 values. Each subsequent criterion was considered only when the preceding criterion did not clearly distinguish between approaches.

We assessed the relative importance of each predictor, represented by the SSTA indices, for the three machine learning approaches using normalized absolute standardized regression coefficients (Grömping, 2015). This was to quantify the contribution of each climate index to reservoir surface extent dynamics. Although normalized absolute standardized coefficients do not provide a strict variance decomposition in the presence of correlated predictors, they offer a stable and model based indicator of predictor influence (Tonidandel and LeBreton, 2011; Grömping, 2015). For PLS, particularly, we obtained the relative importance by multiplying the loadings (weights assigned to the predictors when forming the latent components) of the predictors by their corresponding regression coefficients before standardizing them. Lastly, we averaged reservoir-level importance vectors for each method to produce the final variable-importance profiles used for comparisons.

2.3.3 Spatial dependence analysis of reservoirs sensitivity to climate indices

We define reservoir sensitivity to each climate index as the regression coefficient quantifying the contribution of the corresponding SSTA index to variations in reservoir surface extent. We assessed the spatial dependence (regional clustering) of reservoir sensitivity to each SSTA index using global and local Moran's I, which are widely used measures of spatial autocorrelation (Liu et al., 2020; Chen, 2023). For each SSTA index, we paired reservoir-level sensitivity coefficients (regression coefficients) with geographic coordinates and analyzed them separately. Spatial dependence was defined using row-standardized k-nearest-neighbours weight matrices ($k = 8$). We computed Global Moran's I through permutation tests (ESDA in Python; Anselin, 2019) to determine whether sensitivities exhibited significant spatial autocorrelation ($p < 0.05$). We then applied Local Moran's I (LISA) to identify the spatial arrangement of clusters and outliers. A high positive local Moran's I value indicates that a reservoir is surrounded by others with similar sensitivities (high-high (HH) or low-low (LL) clustering), while low or negative values reflect dissimilar neighbours (high-low (HL) or low-high (LH)). We classified each reservoir into HH (hot spots), LL (cold spots), and HL and LH (transitional outliers), or non-significant categories, and mapped these classifications to characterize the spatial patterns associated with each SSTA index.

3 Results

3.1 Analysing variability and trends of reservoir surface extent under climate indices

Reservoir surface extent and the SSTA indices show strong interannual and decadal variability, expressed as high-frequency alternating positive and negative values of standardized anomalies (Fig. 3). SSTA indices originating from the same ocean generally exhibit similar change over time, although Mediterranean indices (EMED and WMED) occasionally show contrasting patterns.



210 Interannual variability of the SSTA indices clusters into three periods: 1985-1999, 2000-2009, and 2010-2022 (Fig. 3a, b). The first period was characterized by large anomalies and ended with a pronounced warm phase of WMED in 1999. Variability was generally weaker during 2000-2009, although several Atlantic indices shifted toward positive phases. The period from 2010 to 2022 was marked by renewed and more pronounced anomalies and ended with a warm phase of EMED in 2022.

Reservoir surface extent followed a different temporal pattern, with two main periods separated around 1999 (Fig. 3a, b). The
215 period before 1999 showed pronounced fluctuations and culminated in widespread wetter-than-normal reservoir conditions in 1999. The second period is dominated by muted variability after 1999, although reservoir conditions continued to fluctuate. This second period ended with widespread drier-than-normal conditions in 2022.

At the decadal scale, reservoir surface extent shifted from predominantly dry conditions in 1985-1994 to slightly wet conditions in 1995-2004, then gradually trend back toward dry conditions in 2005-2014 and 2015-2022. The SSTA indices displayed
220 contrasting decadal patterns, particularly between the Pacific and Atlantic indices, while WMED has a consistent monotonic change from a cold to a warmer state.

Spatially, the magnitude of both interannual and decadal anomalies varied among reservoirs. Nevertheless, many reservoirs displayed anomalies of the same sign during the same years, indicating broad regional synchrony (Fig. 3a-d). Coherent clusters of negative decadal anomalies occurred particularly between 11°N and 17°N and between 2°W and 1.5°E during 1985-1994
225 and 2015-2022. Reservoirs at lower latitudes and in the western and eastern parts of the region more often showed positive departures.

Regarding long-term change, WMED exhibits the strongest upward trend and is the only index with a statistically significant trend from 1985 to 2022 ($p < 0.05$; Fig. 4a). This result corroborates with WMED monotonic transition toward warmer conditions at the decadal scale. Among reservoirs with statistically significant trends, 70 % showed declining surface extent
230 (Fig. 4b). These trends did not form clear spatial clusters, although most reservoirs are located within the Sudano-Sahelian belt.

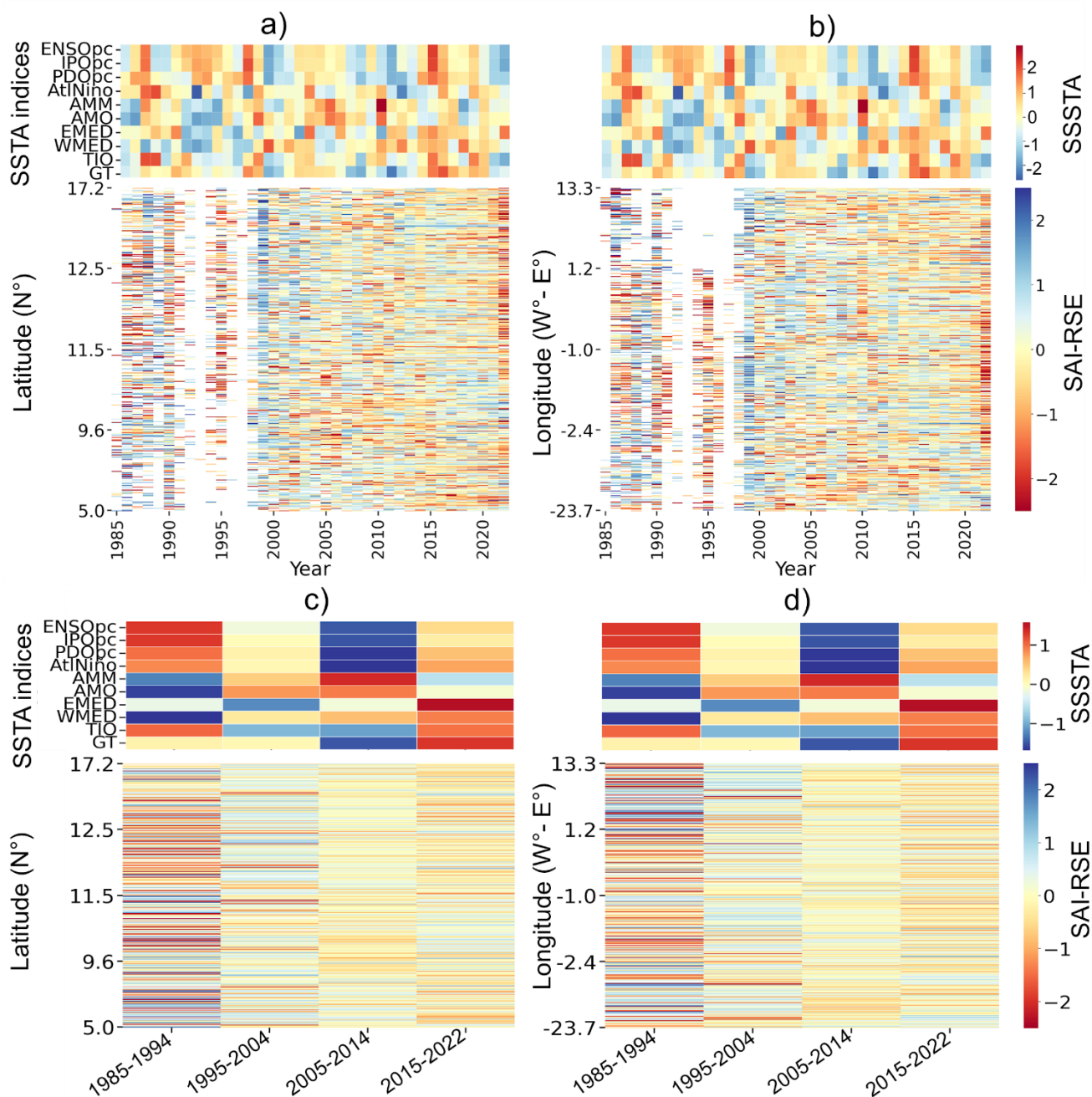


Figure 3: (a) Interannual variability of the Standardized Anomaly Index (SAI) of SSTA indices (SSSTA), and latitudinal and interannual variability of the Standardized Anomaly Index of reservoir surface extent (SAI-RSE); (b) Interannual variability of the SSSTA, and longitudinal and interannual variability of SAI-RSE; (c) Decadal variability of SSSTA, and latitudinal and decadal variability of SAI-RSE; (d) Decadal variability of SSSTA, and longitudinal and decadal variability of SAI-RSE. ENSOpc: El Niño-Southern Oscillation (1st PC), IPOpc: Interdecadal Pacific Oscillation (1st PC), PDOpc: Pacific Decadal Oscillation (1st Principal Component), AtlNiño: Atlantic Niño, AMM: Atlantic Meridional Mode, AMO: Atlantic Multidecadal Oscillation, EMED: Eastern Mediterranean, WMED: Western Mediterranean, TIO: Tropical Indian Ocean, GT: Global Temperature.

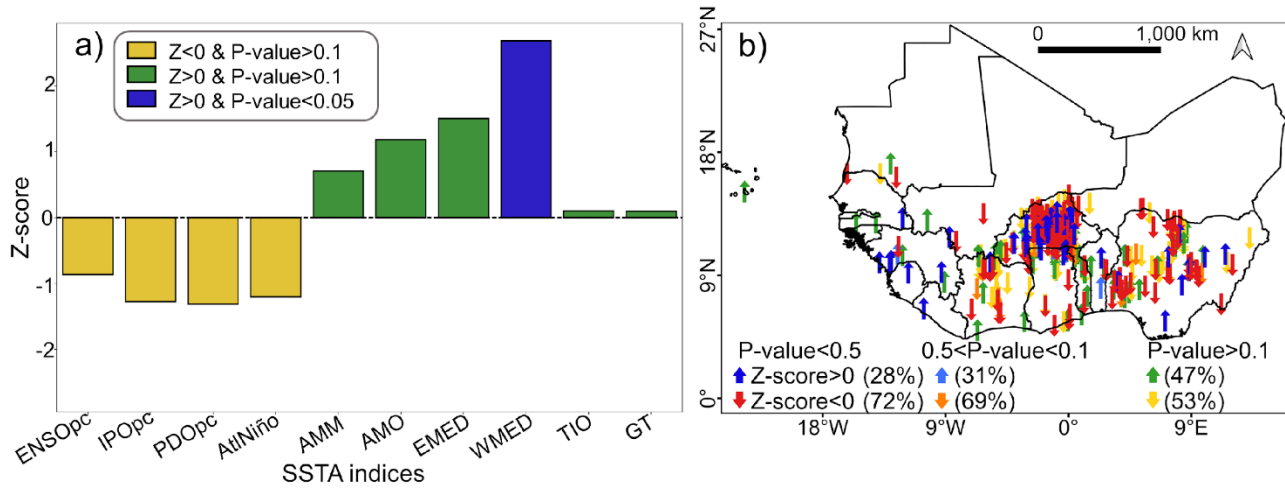


Figure 4: (a) Z-score and P-values of the Modified Mann-Kendall (MMK) analysis of SSTA indices; (b) Z-score and P-values of the MMK analysis of Standardized Anomaly Index of reservoir surface extent (SAI-RSE) dynamics.

3.2 Multicollinearity, models performance and relative importance

245 The SSTA indices from the same ocean basin share generally high variance with key exceptions. The Mediterranean indices (WMED and EMED) show low correlation with each other (Fig. 5), and the AtlNiño displays weak correlation with the other Atlantic indices (AMM and AMO).

The performance metrics of each model and the estimated relative importance of each SSTA indices vary systematically across machine learning approaches and experimental configurations (Table 2, Fig. 6). The PLS models implemented with low
250 multicollinearity SSTA indices and PCA filtered inputs (C3) demonstrate strong generalizability and stable out of sample predictive performance (Table 2). However, their predictive skill was low to moderate and varied spatially (Appendix E, Fig. E1 and E2).

Across all configurations, WMED is consistently the most critical predictor for reservoir surface extent dynamics, followed by the Atlantic modes (AMO and AMM) and EMED (Fig. 6). Contrary, Pacific indices (ENSOpc, IPOpc, PDOpc) consistently
255 show the lowest relative importances, with almost no predictive power.

Table 2: Performance metrics of the supervised machine learning methods (Ridge, Elastic Net and PLS). The texts in red indicate the best machine learning approach with its performance metrics.

Method	Mean R^2	Std R^2	Mean RMSE	Number of positive R^2	Mean overfitting score	Total Models
C1: Models with 10 SSTA indices as predictors						
Ridge	0.098	0.17	1.67	385	1.4	385
Elastic Net	0.08	0.16	1.65	107	1.4	385
PLS	0.27	0.16	1.45	385	2.74	385
C2: Models with optimal SSTA indices subsets						



Method	Mean R^2	Std R^2	Mean RMSE	Number of positive R^2	Mean overfitting score	Total Models
Ridge	-0.75	2.35	0.87	93	53.51	385
Elastic Net	-0.77	2.39	0.87	87	51.17	385
PLS	-0.77	2.43	0.87	90	45.91	385
C3: Models with low multicollinearity SSTA indices + PCA-filtered						
Ridge	-0.72	3	1.42	61	43.18	385
Elastic Net	-0.64	2.14	1.41	32	45.32	385
PLS	0.3	0.13	1.45	385	0	385

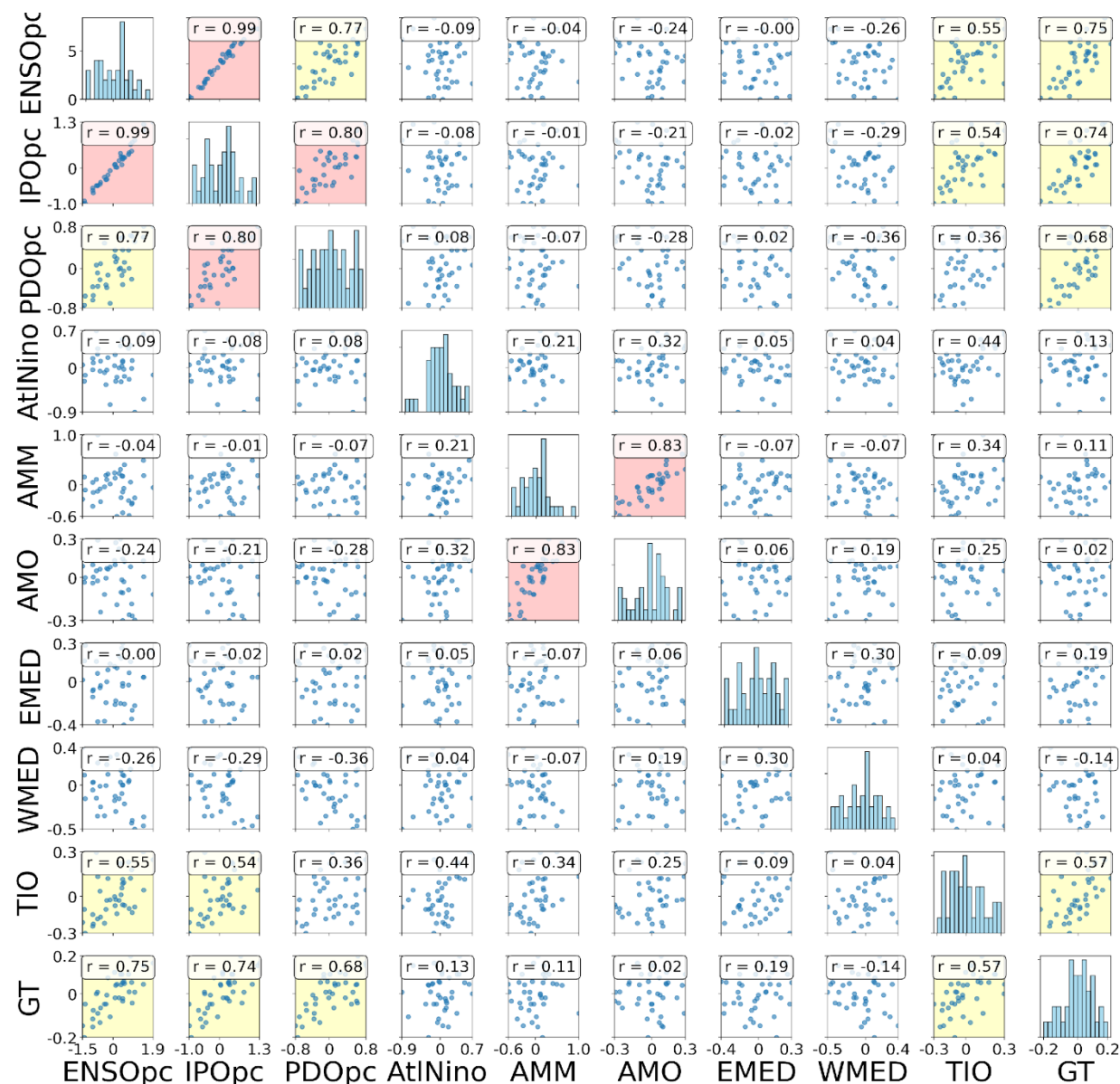


Figure 5: Pearson correlation matrix of the ten SSTA indices. Red background panels indicate high correlations ($|r| > 0.8$), yellow background panels indicate moderate correlations ($|r| > 0.5$), and diagonal histograms show the distributions of each SSTA index. ENSOpc: El Niño-Southern Oscillation (1st PC), IPOpc: Interdecadal Pacific Oscillation (1st PC), PDOpc: Pacific Decadal Oscillation (1st Principal Component), AtINiño: Atlantic Niño, AMM: Atlantic Meridional Mode, AMO: Atlantic Multidecadal Oscillation, EMED: Eastern Mediterranean, WMED: Western Mediterranean, TIO: Tropical Indian Ocean, GT: Global Temperature.

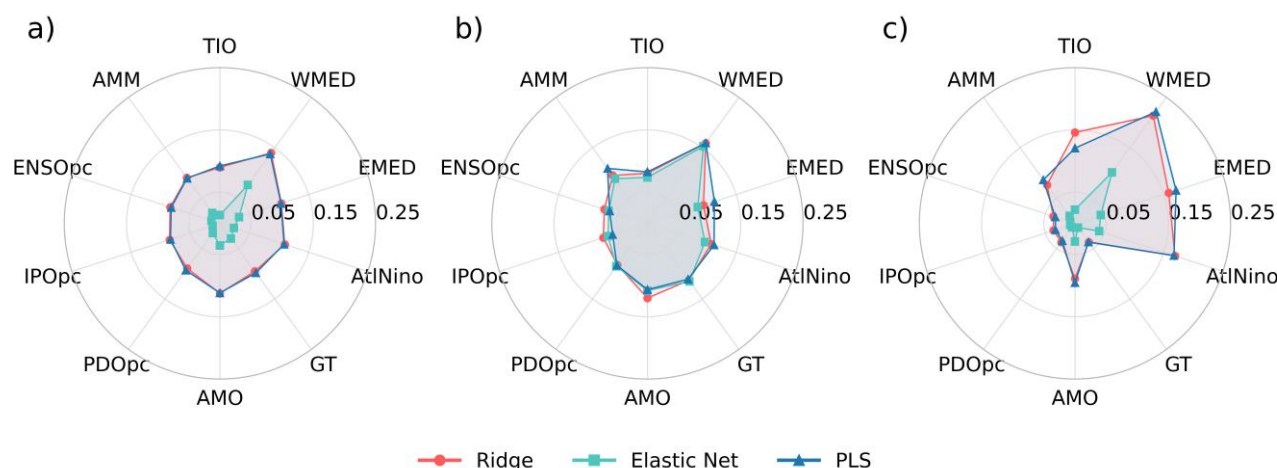


Figure 6: Mean relative importance of each SSTA index for each supervised machine learning method and each experimental configurations: (a) models with all ten SSTA indices per reservoir, (b) models fitted with optimal predictor subsets for each reservoir, (c) models fitted with low-collinearity predictors and PCA-filtered inputs. ENSOpc: El Niño-Southern Oscillation (1st PC), IPOpc: Interdecadal Pacific Oscillation (1st PC), PDOpc: Pacific Decadal Oscillation (1st Principal Component), AtlNiño: Atlantic Niño, AMM: Atlantic Meridional Mode, AMO: Atlantic Multidecadal Oscillation, EMED: Eastern Mediterranean, WMED: Western Mediterranean, TIO: Tropical Indian Ocean, GT: Global Temperature.

3.3 Climate indices-reservoir surface extent relationships: analysis from the best model

The SSTA indices influence reservoir surface extent dynamics to some degree, but their prevalence and direction differ markedly. The Indian (TIO), Mediterranean (WMED and EMED) and Atlantic (AtlNiño) indices stand out as the most pervasive modes of influence (Fig. 7 and 8). The Pacific, and other Atlantic modes (AMM and AMO) as well as the global ocean temperature (GT) affect fewer reservoirs. SSTA indices exhibit both positive and negative associations with reservoir surface extent dynamics.

Based on the dominant direction of their influence, the SSTA indices can be grouped into three categories. The first group includes indices that are more frequently associated with positive reservoir surface extent dynamics (TIO, WMED, AtlNiño, AMO, and IPOpc). The second group comprises indices that are more often linked to negative reservoir surface extent dynamics (EMED, AMM, and PDOpc). The third group exhibits a highly mixed relationship with no clear dominant direction of influence (ENSOpc and GT). This categorization highlights the opposite impact direction of the Mediterranean indices (WMED and EMED) for most of the reservoirs despite their pronounced relationships with reservoir surface extent anomalies (Fig. 8).

Furthermore, SSTA indices influence reservoir surface extent anomalies in a synergistic way (Fig. 9). The combinations that include Indo-Mediterranean-Atlantic (e.g., TIO, WMED, EMED, AtlNiño, and AMO) appear very frequently and therefore tend to dominate. However, all the SSTA combinations are associated to moderate mean R^2 regardless the frequency of appearance.

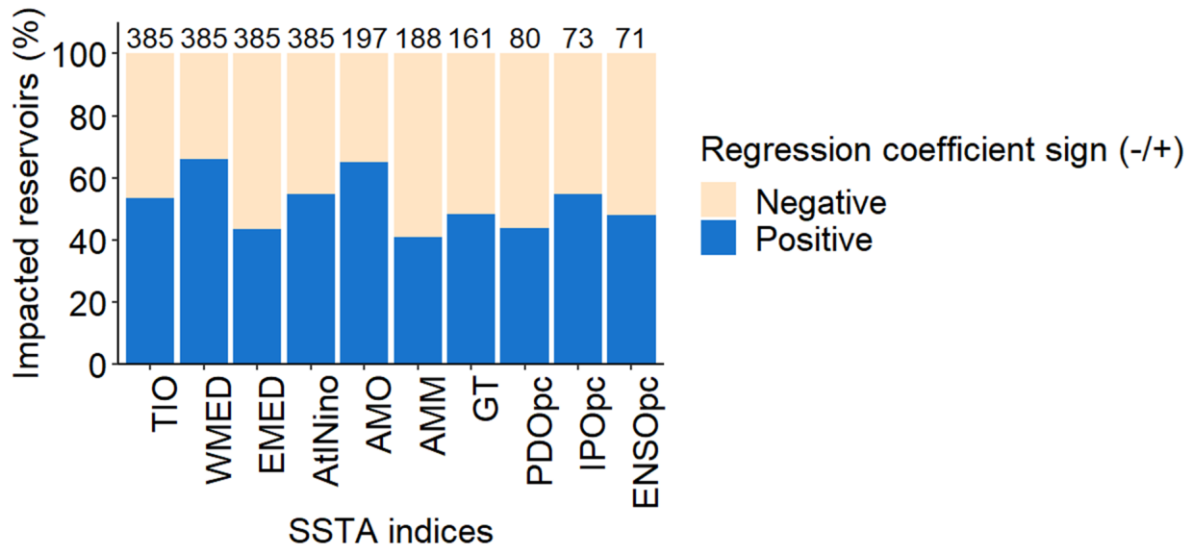


Figure 7: Percentage and total number of reservoirs negatively and/or positively influenced by each SSTA index. ENSOpc: El Niño-Southern Oscillation (1st PC), IPOpc: Interdecadal Pacific Oscillation (1st PC), PDOpc: Pacific Decadal Oscillation (1st Principal Component), AtlNiño: Atlantic Niño, AMM: Atlantic Meridional Mode, AMO: Atlantic Multidecadal Oscillation, EMED: Eastern Mediterranean, WMED: Western Mediterranean, TIO: Tropical Indian Ocean, GT: Global Temperature.

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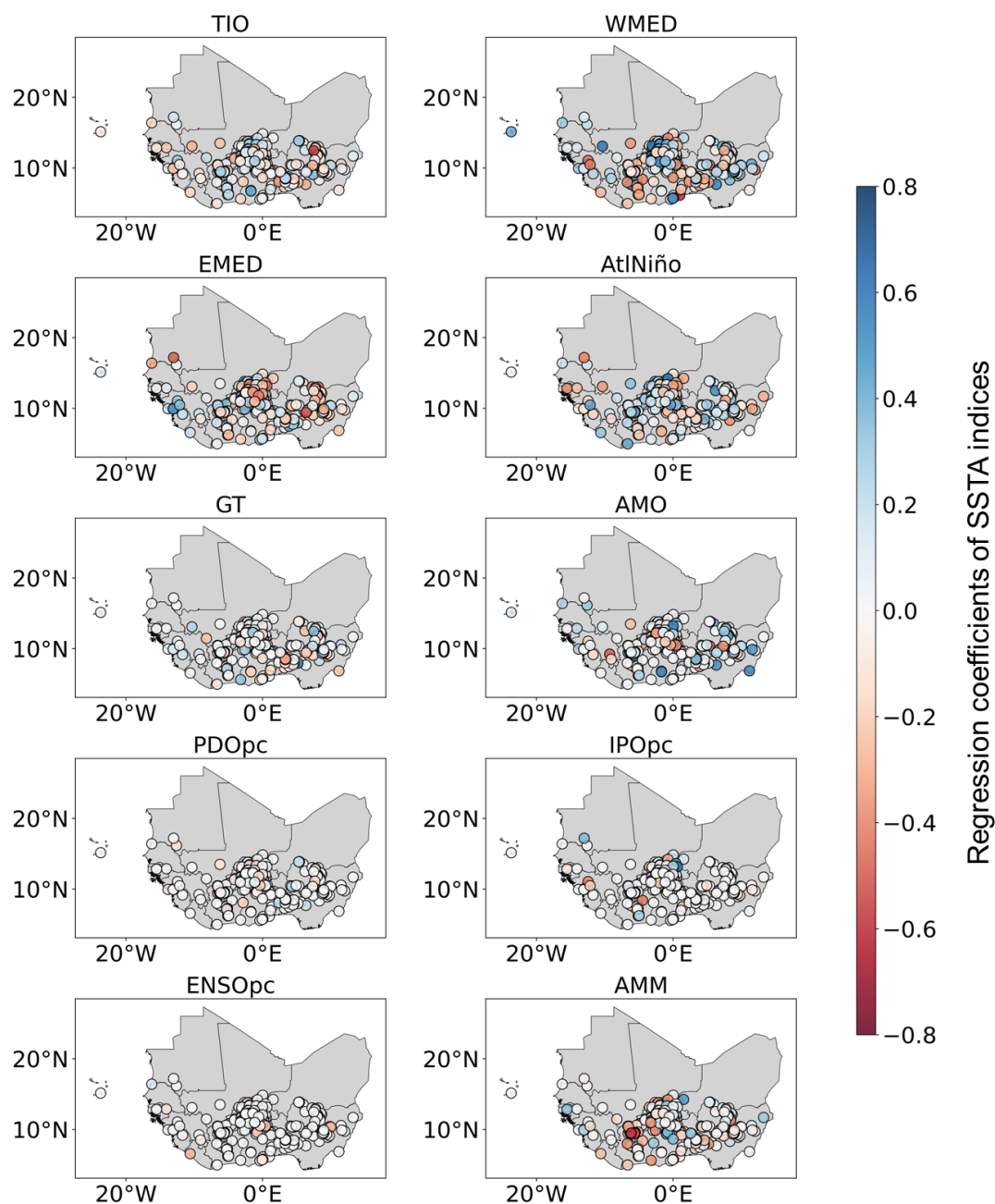


Figure 8: Spatial distribution of the regression coefficients of each SSTA index across West Africa. These regression coefficients represent the sensitivity of reservoirs to each SSTA index. ENSOpc: El Niño-Southern Oscillation (1st PC), IPOpc: Interdecadal Pacific Oscillation (1st PC), PDOpc: Pacific Decadal Oscillation (1st Principal Component), AtlNiño: Atlantic Niño, AMM: Atlantic Meridional Mode, AMO: Atlantic Multidecadal Oscillation, EMED: Eastern Mediterranean, WMED: Western Mediterranean, TIO: Tropical Indian Ocean, GT: Global Temperature.

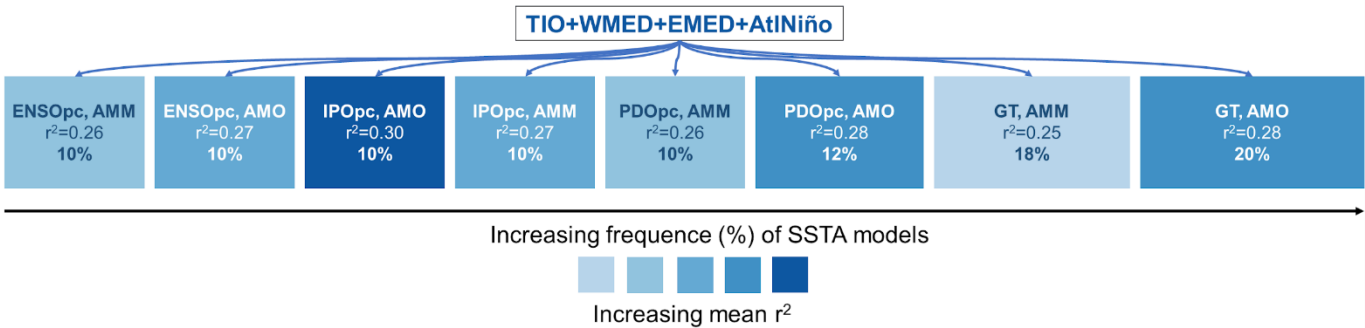


Figure 9: Frequency and Mean r^2 of SSTA Index Combinations Influencing West African Reservoirs. Bar widths represent frequency (%), and the colormap indicates mean r^2 values. ENSOpc: El Niño-Southern Oscillation (1st PC), IPOpc: Interdecadal Pacific Oscillation (1st PC), PDOpc: Pacific Decadal Oscillation (1st Principal Component), AtlNiño: Atlantic Niño, AMM: Atlantic Meridional Mode, AMO: Atlantic Multidecadal Oscillation, EMED: Eastern Mediterranean, WMED: Western Mediterranean, TIO: Tropical Indian Ocean, GT: Global Temperature.

3.4 Regional clustering in reservoir responses to climate indices

Despite the statistically significant spatial autocorrelation of reservoir sensitivity to several SSTA indices (Fig. 10a), the sensitivity of most reservoirs does not form spatially coherent clusters across large portions of the region (Fig. 10b). The spatial organization of reservoir sensitivity varies across SSTA indices and comprised hot spot (HH), cold spot (LL), and transitional outlier (HL and LH) clusters that are generally confined to specific sub regions. This is particularly evident for the Mediterranean indices (WMED and EMED) and IPOpc. Cold spot clusters of WMED are concentrated from the Guinean coastal zone to the Sudanian region, while its hot spot clusters occur farther north, especially in the central Sahelian zone. This distribution reflects a clear south to north gradient in reservoir sensitivity. In contrast, EMED shows hot spot clusters extending from the southwestern Sudanian zone to the western Sahelian zone, whereas cold spot clusters are mainly located in the central and eastern Sahelian regions, indicating a west to east gradient. For IPOpc, cold spot clusters extend from the western Sudanian to the western Sahelian zone, while only a few hot spot clusters appear in the central Sahelian zone.

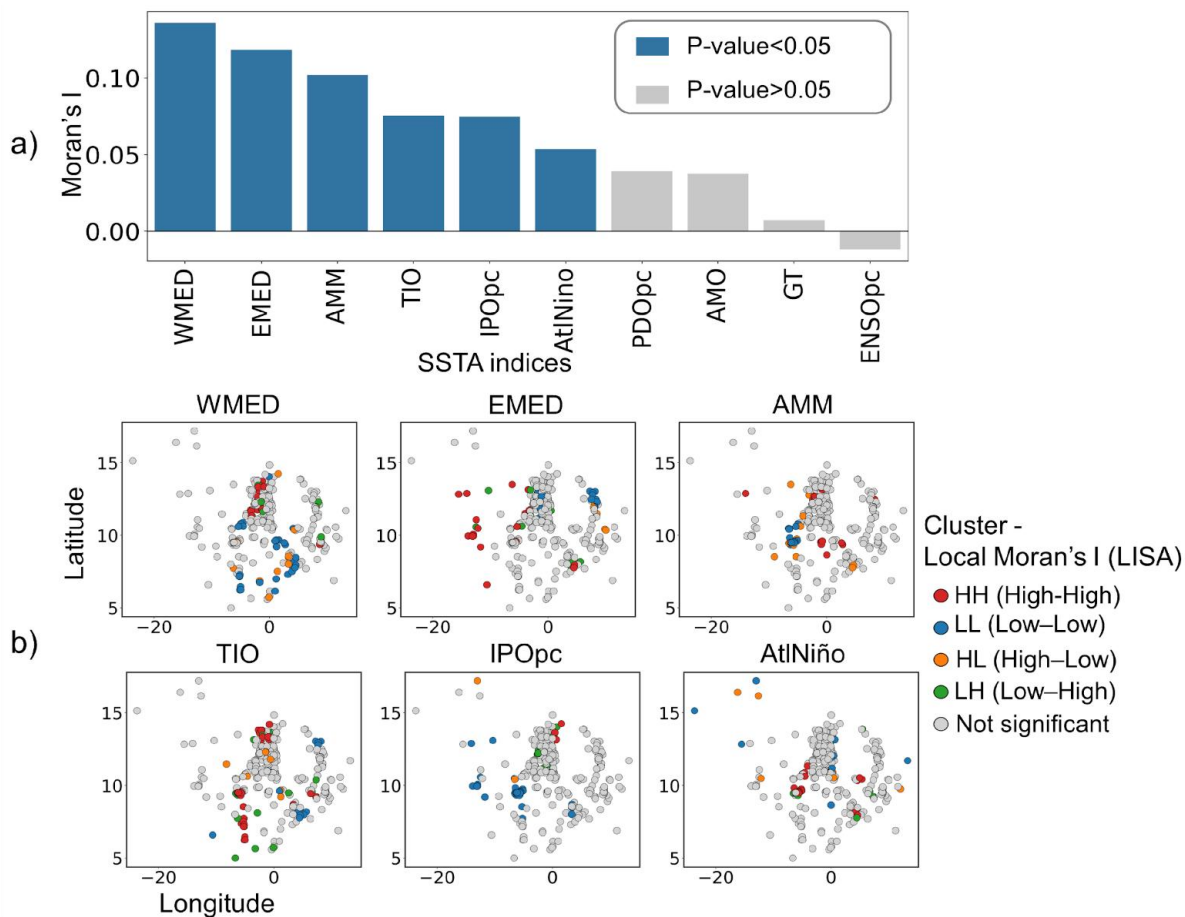


Figure 10: Regional clustering of reservoir sensitivity to SSTA indices in West Africa: (a) Global Moran's I of SSTA indices with their statistical significance; (b) Local Moran's I (LISA) of SSTA indices with significant Global Moran's I. ENSOpc: El Niño-Southern Oscillation (1st PC), IPOpc: Interdecadal Pacific Oscillation (1st PC), PDOpc: Pacific Decadal Oscillation (1st Principal Component), AtlNiño: Atlantic Niño, AMM: Atlantic Meridional Mode, AMO: Atlantic Multidecadal Oscillation, EMED: Eastern Mediterranean, WMED: Western Mediterranean, TIO: Tropical Indian Ocean, GT: Global Temperature

4 Discussion

4.1 Consistent variability and trends in reservoir surface extent and climate indices

We observed pronounced interannual and decadal variability in both SSTA indices and reservoir surface extent, underscoring the complex and dynamic coupling between oceanic conditions and terrestrial hydrological systems in West Africa. The frequent alternation between wetter and drier-than-normal reservoir conditions may reflect reservoir responses to variability of SSTA indices. This relationship can be explained by the influence of oceanic conditions on atmospheric moisture transport and rainfall. Ni et al. (2018), for example, attributed variations in continental water storage to ocean-to-land moisture transport, which drives rainfall over land. This mechanism is also consistent with the high hydroclimatic seasonality of West Africa,



where rainfall and hydrological variability associated with the meridional migration of the ITCZ are strongly modulated by
335 oceanic processes (Talib et al., 2020; Nogueria et al., 2024).

The interannual variability characterized by three periods for the SSTA indices and two periods for reservoir surface extent
dynamics coincide with intense large-scale climate events, particularly ENSO (El Niño/La Niña) and AtlNiño. ENSO and
AtlNiño modulate the Walker and Hadley circulations and have been linked to widespread hydrological extremes in West
Africa during the study period (1985-2022) (Power and Smith, 2007; Freitas et al., 2017; Oliveira et al., 2018; Trombini et al.,
340 2025). Weak or strong El Niño / La Niña (ENSO) strongly alter atmospheric and oceanic dynamics, through feedback loops
involving wind, rainfall, and ocean temperatures (Vialard et al., 2025). ENSO effect on atmospheric and oceanic dynamics
was further demonstrated in Zu et al. (2024) that showed that weakened La Niña conditions lead to reduced westerly winds
over the Indian Ocean, thereby making TIO formation harder.

The effects of SSTA variability on reservoir surface extent are more evident at the decadal scale where reservoir surface extent
345 anomalies shift from predominantly negative to slightly positive, then a gradual return to negative anomalies. The persistent
effects of SSTA indices on reservoirs may emerge clearly over decades. Wang et al. (2004) provide evidences that the SSTA
indices influence large-scale atmospheric circulation patterns resulting in atmospheric teleconnections. These teleconnections
control rainfall, evaporation, and moisture transport over long periods. When SSTA indices remain in a particular phase or
recur frequently, they result in multi-year wet or dry conditions (dos Santos et al., 2025; Hakam et al., 2025). As a result,
350 reservoirs, which are linked to other hydrological systems, exhibit a persistent and retain the cumulative effects of these climate
signals.

The decadal pattern of reservoir surface extent anomalies, also, aligns with documented decadal swings in Sahelian and Guinea
Coast rainfall recovery after the 1980s drought followed by partial waning (Sanogo et al., 2015; Nicholson et al., 2018). Crétat
et al. (2024) attributed these hydroclimatic shifts to coupled Pacific-Atlantic-Mediterranean teleconnections. This is supported
355 by the opposite-sign decadal behaviour between Pacific and Atlantic indices that we observed. Cool phases of IPO/PDO often
co-occur with Atlantic warmth that enhances the West African monsoon thereby increases rainfall, whereas the opposite
configuration tends to suppress it (Hong et al., 2022; Crétat et al., 2024).

The reservoir surface extent variability and the contrasting behaviour of WMED and EMED around 1999 and 2022 is
consistent with the Mediterranean configurations described by Fontaine et al. (2010). Indeed, warm WMED phases enhance
360 convection over the Gulf of Guinea, favouring wetter conditions across West Africa. Contrarily, warm EMED anomalies tend
to weaken moisture inflow to northern basins, promoting drier conditions. The coincidence of extreme positive WMED and
near-neutral EMED in 1999 with widespread positive reservoir surface extent anomalies, and their reversal in 2022 with
widespread dryness, reinforces the notion of a regionally differentiated Mediterranean control on Sahelian rainfall and, by
extension, reservoir storage.



365 WMED decadal pattern (monotonic warming) is in line with its significant annual upward trend ($p < 0.05$). Previous studies
(Pastor et al., 2019; Kubin et al., 2023) have attributed the rising temperatures in the WMED to global warming, increasing
atmospheric heat, and changes in regional circulation which have substantial impacts on water cycles. Regarding the long-
term trends in reservoir surface extent anomalies, nearly half of the reservoirs exhibit statistically significant trends, with more
frequent downward trajectories. This pattern is consistent with widespread declines in global water storage, increased
370 evaporative demand, growing water use, sedimentation, and potential declines or shifts in rainfall seasonality (Marshall et al.,
2012; Diawara et al., 2016; Giardino et al., 2018; Yao et al., 2023)

4.2 Model's interpretability and relative importance of climate indices

Decorrelating the SSTA indices through PCA enhances the performance of PLS. PLS benefits from dimensionality reduction
as its latent components capture shared variance more effectively once multicollinearity is reduced (Angel and McCabe, 2022).
375 This aligns with (Moresco et al., 2017), who showed that appropriate variable selection improves PLS performance. Using
PCA-filtered, low-collinearity predictors therefore offers a simple and effective way to produce more stable and interpretable
PLS models. Additionally, the PLS models performance with zero overfitting confirm their strong generalizability, supporting
their suitability for predicting the effects of SSTA indices on reservoir surface extent at the interannual timescale.

Across all experimental configurations, WMED consistently emerges as the most influential index, indicating that its
380 hydroclimatic signal remains both strong and uniquely informative even after multicollinearity is reduced. The recurring
importance of Atlantic indices such as AMM and AMO behind WMED suggests that Atlantic variability plays a secondary
but still meaningful role in modulating reservoir surface extent.

4.3 Individual and combined effects of climate indices

The heterogeneous but structured influence of SSTA indices on reservoir surface extent dynamics highlights the combined
385 effect of multiple oceans on ocean-hydrology teleconnections in West Africa. Although all SSTA indices exert some degree
of control, the prevalence, direction, and strength of their effects differ markedly among reservoirs and oceans. The Indo-
Mediterranean-Atlantic indices (TIO, WMED, EMED, and AtlNiño) emerge as the most pervasive influences, suggesting that
variability within these oceans exerts a dominant role in modulating water balance in reservoirs. This finding aligns with
numerous previous studies (Gaetani et al., 2010; Chun et al., 2021; Prabhu and Arya, 2025; Zheng et al., 2025) that showed
390 the strong relationship between these indices and the climate and hydrology of West Africa. This relationship is not only
related to the role of these indices within large-scale atmospheric circulations such as the Walker and Hadley cells and the
monsoon flow, but also to their close proximity to the region. Several studies show that areas located nearer to oscillation
sources experience more pronounced climatic effects due to stronger teleconnections and enhanced local interactions. For
example, ENSO affects Indonesia more directly when it is active in the eastern Pacific (Kurniadi et al., 2021), and Kelvin
395 waves strongly influence rainfall in Southeast Asia (Ferrett et al., 2020). In such cases, closer coupling leads to larger shifts in



weather patterns and more frequent extreme events, such as floods and droughts. Similarly, the proximity of these SSTA indices to West Africa allows them to directly control temperature and pressure gradients that drive regional winds. They also regulate low-level moisture transport into the monsoon system. As a result, their influence on the region is rapid and experiences little atmospheric damping. In contrast, the Pacific indices (PDOpc, IPOpc, ENSOpc) affect fewer reservoirs and exhibit highly mixed relationships, implying that their influence is more spatially heterogeneous and likely transmitted indirectly through global-scale atmospheric circulation (He et al., 2025; D'Arrigo and Wilson, 2006).

The particular positive widespread association of TIO with reservoir surface extent anomalies aligns with previous findings linking Indo-Pacific SST variability to monsoon intensity and moisture transport over the African continent (Preethi et al., 2015). Positive TIO anomalies are often associated with enhanced convection over the western Indian Ocean and strengthened West African monsoon circulation (Mohino et al., 2011), which can lead to wetter conditions and expanded reservoir surfaces. Similarly, the prominence of the Mediterranean indices underscores the growing recognition of the Mediterranean indices as a key modulator of Sahelian hydroclimate (Fontaine et al., 2010). Furthermore, unlike EMED, WMED is more often positively associated with reservoir surface extent, confirming that these indices generally affect reservoir water availability differently as their contrasting phases shift the monsoon in opposite directions. Previous studies showed that the Mediterranean indices, particularly EMED is warming faster than the global average (Zittis et al., 2022; Urdiales-Flores et al., 2023; Napolitano et al., 2025). This suggests an accelerated and substantial decline in reservoir water availability as the EMED index is more often negatively correlated with reservoir surface extent in the region.

The Atlantic indices display mixed but interpretable signals. AtlNiño and AMO maintain moderate yet spatially consistent associations with reservoir surface extent variability, supporting their role in controlling interannual rainfall fluctuations via modulation of the Atlantic zonal SST gradient (Okonkwo, 2014; Nkiaka and Tume, 2025). The more frequent positive linkage between AMO and reservoir surface extent compared to AtlNiño and AMM suggests that multi-decadal Atlantic warming phases generally favour wetter conditions and increased water availability. Martin and Thorncroft (2014) indicated that during warm AMO phases, North Atlantic sea surface temperatures (SSTs) rise, leading to a northward shift of the ITCZ. This shifts the rainy belt over the Sahel, increasing total summer rainfall.

The joint influence of multiple SSTA indices, particularly combinations spanning the Indo-Mediterranean-Atlantic domains, shows that reservoirs respond not to single SSTA index forcing but to compound teleconnection structures. This is consistent with previous studies (Chun et al., 2021; Mampo et al., 2025), which similarly identify coupled Indo-Mediterranean-Atlantic indices as dominant climatic controls on streamflow and drought variability. These combined effects likely reflect the co-evolution of large-scale climate patterns that regulate atmospheric moisture transport and precipitation over West Africa.



425 4.4 Spatially uneven effects of climate indices

Reservoir sensitivities to several SSTA indices exhibit a statistically significant spatial organization, forming identifiable cold and hot spot clusters. This indicates that the influence of these indices on regional hydroclimate and reservoir surface extent dynamics is not uniform; instead, certain subregions respond more strongly or weaklier in a coherent way. Importantly, the cluster locations differ among indices, meaning that each SSTA index leaves a distinct spatial “footprint” and interacts with
430 regional climate and geography in its own way.

The regional distribution of cold and hot spot clusters of WMED, EMED, and IPOpc was particularly clear. The spatial patterns observed for WMED and EMED align well with established Mediterranean-West Africa teleconnection mechanisms in (Rowell, 2003; Gaetani et al., 2010; Polo et al., 2011; Gaetani and Fontaine, 2013; Fontaine et al., 2010). The evidence shows that warm anomalies in WMED enhance deep convection over the Gulf of Guinea, strengthen low-level moisture advection,
435 and shift the monsoonal ascent northward. This northward influence explains why WMED exhibits cold spots clusters in the Guinea Coast-Sudanian zone and hotspot clusters concentrated in the central Sahel, forming a clear south-north gradient. In contrast, EMED SST variability primarily forces atmospheric circulation over North Africa, producing asymmetric impacts on the monsoon accompanied by enhanced southwesterly flow and weakened northeasterly climatological wind. This mechanism is consistent with the west-east gradient in our results regarding the EMED index, where hot spot clusters extend
440 from the southwestern Sudanian to the western Sahel, while cold spot clusters are confined to the central and eastern Sahel. For IPOpc, Villamayor (2020) demonstrated that its atmospheric mechanism involves anomalous Walker circulation patterns that induce subsidence over the Sahel, suppressing convection and reducing rainfall. This aligns with our findings, where IPOpc shows mostly cold spot clusters across the western Sudanian-western Sahel region and only a few hot spot clusters in the central Sahel. These spatial patterns reflect the fact that IPO-related subsidence most strongly affects the core Sahel, while
445 western West Africa remains less responsive due to the dominance of Atlantic rather than Indo-Pacific variability.

Overall, the presence of cold and hot spot clusters suggests areas where monsoon rainfall variability is strongly coupled to ocean forcing (e.g., parts of the central and eastern Sahel), contrasted with areas where hydrological behaviour is more driven by local processes or human modification. This is evident in the coherent decadal-anomaly clusters around 11-17°N and 2°W-1.5°E during 1985-1994 and 2015-2022. Matching the core Sudano-Sahel belt, rainfall in this region is particularly sensitive
450 to SST variability in nearby SSTA indices (Sultan and Gaetani, 2016; Sawadogo et al., 2024; Rauch et al., 2025). Meanwhile, coherent anomalies at southern latitudes and farther western or eastern longitudes highlight spatial gradients in teleconnection strength, as well as orographic and land-surface feedbacks that further shape runoff and storage (Gnann et al., 2025).

Reservoir sensitivities to PDOpc, AMO, GT, and ENSOpc are not statistically significant and appear more spatially diffuse. Their influence may simply be weaklier organized at the scale of the reservoir network or modulated by local factors that
455 obscure regional coherence. This is consistent with the predominance of non-significant local Moran’s I values and with the



modest-to-moderate R^2 values obtained from SSTA-based models. They indicate that, while multiple ocean SSTs configurations capture broad regional tendencies, local hydrological and anthropogenic processes may remain major determinants of reservoir behaviour that need to be investigated.

5 Conclusions

460 The insights gained from this regional assessment of reservoir responses to variability in large scale climate indices across West Africa lead to the following conclusions:

(i) Reservoir surface extent exhibits pronounced interannual and decadal variability. Reservoir surface extent dynamics closely track the phases of SSTA indices, indicating a coupling between oceanic conditions and reservoir water storage in West Africa. Among the indices, WMED shows the strongest and only statistically significant long-term increase over 1985-2022. Of the
465 reservoirs exhibiting significant long-term trends, about 70 % display declining surface extent alongside spatially heterogeneous hydrological changes across the region.

(ii) Reservoirs respond primarily to combined teleconnection signals rather than to individual climate indices. However, our initial expectation of the widespread effect of the Pacific-Atlantic-Indian-Mediterranean indices on reservoir surface extent dynamics is not supported. The coupled Indo-Mediterranean-Atlantic indices (TIO, WMED, EMED, AtlNiño, and AMO),
470 exert the strongest and most widespread influence on reservoir surface extent variability. AMM and Pacific indices (PDOpc, IPOpc, ENSOpc) show weaker and more spatially mixed effects. WMED index emerges as the most dominant influence and is generally associated with positive reservoir surface extent anomalies, whereas EMED more often shows negative effects. This highlight contrasting Mediterranean influences on reservoir surface extent dynamics.

(iii) The influence of SSTA indices on reservoir surface extent is both mode-specific and spatially heterogeneous. Significant
475 spatial clustering of reservoir sensitivity reveals coherent hot and cold spot regions, indicating that certain subregions respond more strongly than others. This spatial structure is particularly evident for Mediterranean indices. WMED exhibits a clear south-north gradient (cold-hot spots), while EMED displays a west-east gradient (hot-cold spots). The reservoirs show spatially diffuse responses to SSTA indices, suggesting that local factors could play an important role in modulating reservoir sensitivity to SSTA indices and limiting regional coherence.

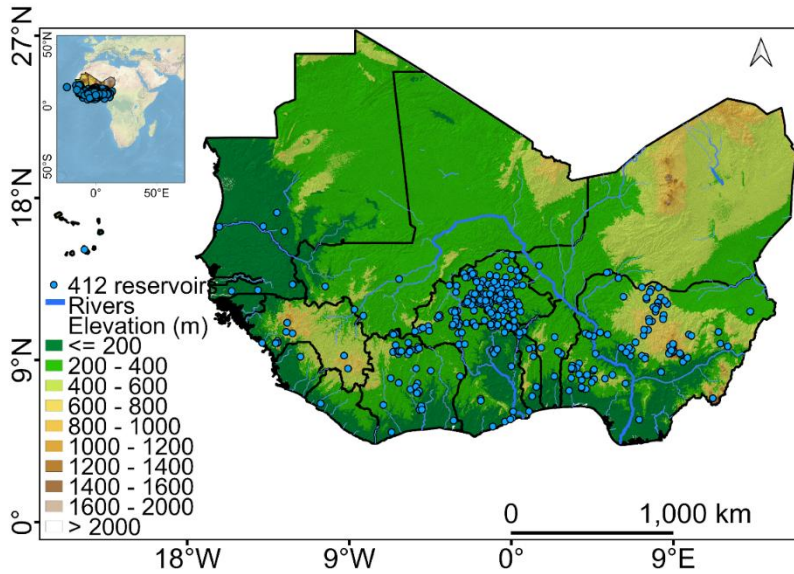
480 Future research should investigate the effects of local human and environmental factors, such as watershed and reservoir characteristics, land use, and dam operation practices, on reservoir sensitivity to SSTA indices. Additionally, large-scale climate drivers with local reservoir attributes and management practices should be integrated to improve predictive capability and mechanistic understanding of reservoir surface extent dynamics. In particular, coupled climate-hydrology modelling approaches (Larsen et al., 2016; Pathiraja et al., 2016; Ning et al., 2019) offer strong potential to incorporate physical processes,



485 address spatial heterogeneity, and account for nonstationarity by extending analysis from historical variability to future climate projections.

Appendix A: Topography of West Africa

West Africa topography is characterized by a wide range of elevations. The elevation ranges from low-lying coastal plains in the south to the higher interior plateaus and uplands in the north and east.



490

Figure A1: The topography map of West Africa showing the spatial distribution of reservoirs across elevation ranges. This map supplements the regional context provided in the study area description.

Appendix B: Standardized Anomaly Index (SAI) calculation

To analyze the spatiotemporal variability, we first standardized reservoir surface extent and the SSTA indices (Jänicke et al., 2009; Roshan et al., 2021; Rawat et al., 2024). The SAI was calculated as:

495

$$SAI_t = \frac{S_t - \underline{S}_{ref}}{\sigma_{ref}} \quad (B1)$$

where SAI_t is the Standardized Anomaly Index of reservoir surface extent or SSTA index at time t , S_t is reservoir surface extent or SSTA index at time t , $\underline{S}_{ref}$ is mean surface extent or SSTA over the reference period (1985-2022), and σ_{ref} is the corresponding standard deviation.



500 Appendix C: Modified Mann Kendall (MMK) test

The MMK (Hamed and Rao, 1998) is an extension of the non-parametric Mann-Kendall (MK) test. The original MK test assumes independence in the time series; when serial correlation is present in the data, the power of statistical tests can be reduced by overestimating the statistical significance of trends (Hamed and Rao, 1998). The MMK test addresses this by adjusting the variance of the test statistic using the concept of effective sample size. The effective sample size is calculated as:

$$505 \quad n^* = \frac{n}{1 + 2 \sum_{k=1}^{n-1} \left(1 - \frac{k}{n}\right) \rho_k} \quad (C1)$$

where n represents the length of the time series and ρ_k , the autocorrelation at lag k .

The adjusted variance of the Mann-Kendall statistic is then:

$$\text{Var}^*(S) = \text{Var}(S) \times \frac{n^*}{n} \quad (C2)$$

510 where $\text{Var}(S)$ is the variance of the Mann-Kendall statistic under the assumption of independence, n^* is the effective sample size, and n is the actual sample size.

The standardized test statistic is computed as:

$$Z = \begin{cases} \frac{S-1}{\sqrt{\text{Var}^*(S)}}, & \text{if } S > 0 \\ 0, & \text{if } S = 0 \\ \frac{S+1}{\sqrt{\text{Var}^*(S)}}, & \text{if } S < 0 \end{cases} \quad (C3)$$

where S is Mann-Kendall statistic, and $\text{Var}^*(S)$ is the variance corrected for autocorrelation.

515 A positive value of Z indicates an increasing trend, while a negative value indicates a decreasing trend. In this study, we assessed the statistical significance at $p\text{-value} \leq 0.05$.

Appendix D: Supervised machine learning models

Ridge regression

520 Ridge regression, also known as Tikhonov regularization estimates coefficients by minimizing the penalized least-squares function and can be summarized as follow (Hoerl and Kennard, 1970): given $X \in R^{n \times p}$, the standardized predictor (climate indices) matrix, where n is the number of observations and p is the number of predictors; $Y \in R^n$, the response vector (in this study, standardized reservoir surface extent index); $\beta \in R^p$ the vector of regression coefficients to be estimated; $\alpha \geq 0$ the regularization (shrinkage) parameter controlling the strength of the penalty; and I_p , the $p \times p$ identity matrix.

The ridge estimator $\hat{\beta}_{ridge}$ is obtained by minimizing the penalized least-squares loss function:

$$\hat{\beta}_{ridge} = \arg \arg\{\|Y - X\beta\|_2^2 + \alpha\beta_2^2\} \quad (D1)$$

525 Where $\|Y - X\beta\|_2^2 = (Y - X\beta)^T(Y - X\beta)$ represents the residual sum of squares, and $\|\beta\|_2^2 = \beta^T\beta$ is the squared magnitude of the coefficient vector.



The analytical solution to this optimization problem is given by:

$$\hat{\beta}_{ridge} = (X^T X + \alpha I_p)^{-1} X^T Y \quad (D2)$$

Here, the term αI_p ensures numerical stability by inflating the diagonal elements of $X^T X$, thus reducing the impact of
530 multicollinearity among predictors. Larger values of α result in greater coefficient shrinkage toward zero, reducing model
variance at the cost of a small bias. It effectively mitigates multicollinearity and stabilizes model estimates but does not perform
variable selection, retaining all predictors regardless of their significance (Hoerl and Kennard, 1970; Ölmez and Yağanoğlu,
2023).

Elastic Net regression

535 Elastic Net combines the penalties of lasso (L1) and ridge (L2) regressions and the estimator is obtained by minimizing the
following penalized least-squares function (Giglio and Brown, 2018; Liu et al., 2018; Zou and Hastie, 2005):

$$\hat{\beta}_{EN} = \arg \min_{\beta} \|y - X\beta\|_2^2 + \alpha[(1 - \lambda)\|\beta\|_2^2 + \lambda\|\beta\|_1] \quad (D3)$$

Where $\|\beta\|_2^2 = \sum_{j=1}^p \beta_j^2$ is the L₂-norm (ridge) penalty, which shrinks coefficients toward zero but retains all predictors;
 $\|\beta\|_1 = \sum_{j=1}^p |\beta_j|$ is the L₁-norm (lasso) penalty, which can drive some coefficients exactly to zero, performing variable
540 selection; α is the regularization parameter, and $\lambda \in [0, 1]$ is the elasticity parameter controlling the balance between L₁ and L₂
penalties ($\lambda = 1$ corresponds to pure lasso, $\lambda = 0$ corresponds to pure ridge).

This hybrid approach enables both shrinkage and variable selection, improving performance where the number of predictors
exceeds the number of observations and also when predictors are correlated (Braak, 2009; Qannari and Hanafi, 2005), though
it requires careful tuning of two hyperparameters (α and λ) increasing search complexity.

545 Partial Least Square (PLS) regression

Unlike the two previous regression methods, PLS decomposes the predictor matrix X and the response vector (or matrix) Y as
follows (Geladi and Kowalski, 1986; Pirouz, 2006):

$$X = TP^T + E \quad (D4)$$

and

$$550 Y = UQ^T + F \quad (D5)$$

where $T \in R^{n \times L}$ is the score matrix containing L latent components (or projections) extracted from X ; $P \in R^{p \times L}$ is the loading
matrix linking the original predictors to the latent components; $U \in R^{n \times L}$ and $Q \in R^{1 \times L}$ are the corresponding score and
loading matrices for Y ; E and F are the residual matrices of X and Y respectively; and L denotes the number of latent
components retained in the model, typically determined by cross-validation to minimize prediction error.



555 PLS identifies latent components by maximizing the covariance between the predictor scores T and response scores U , under the constraint that the extracted components are orthogonal. Once the latent variables are obtained, the regression model is expressed as:

$$\hat{Y} = XB_{PLS} + b_0 \quad (D6)$$

560 Where $B_{PLS} = W(P^T W)^{-1} Q^T$ is the matrix of regression coefficients, W is the weight matrix linking X to the latent scores T , b_0 and is the intercept term.

PLS regression is particularly suitable for datasets with multicollinear or high-dimensional predictors or when predictors exceed the sample size, yet the interpretability of individual predictors is reduced and overfitting can occur if too many components are retained (Camacho and Saccenti, 2018; Cook and Forzani, 2020).

Appendix E: Goodness-of-fit of best SSTA prediction models (PLS-C3)

565 The explained variance ($R^2 = 0.01-0.64$) indicates that SSTA forcing alone accounts for only a modest to moderate portion of the year-to-year variability in reservoir surface extent (**Figure E1**). RMSE values are generally low to moderate and span several orders of magnitude, confirming that reservoirs differ markedly in their anomaly amplitudes (**Figure E2**). However, the models show negligible bias ($MBE \approx 0$) and residuals are centred around zero (**Figure E1 c and E2 b, d, f, h, j, l**).

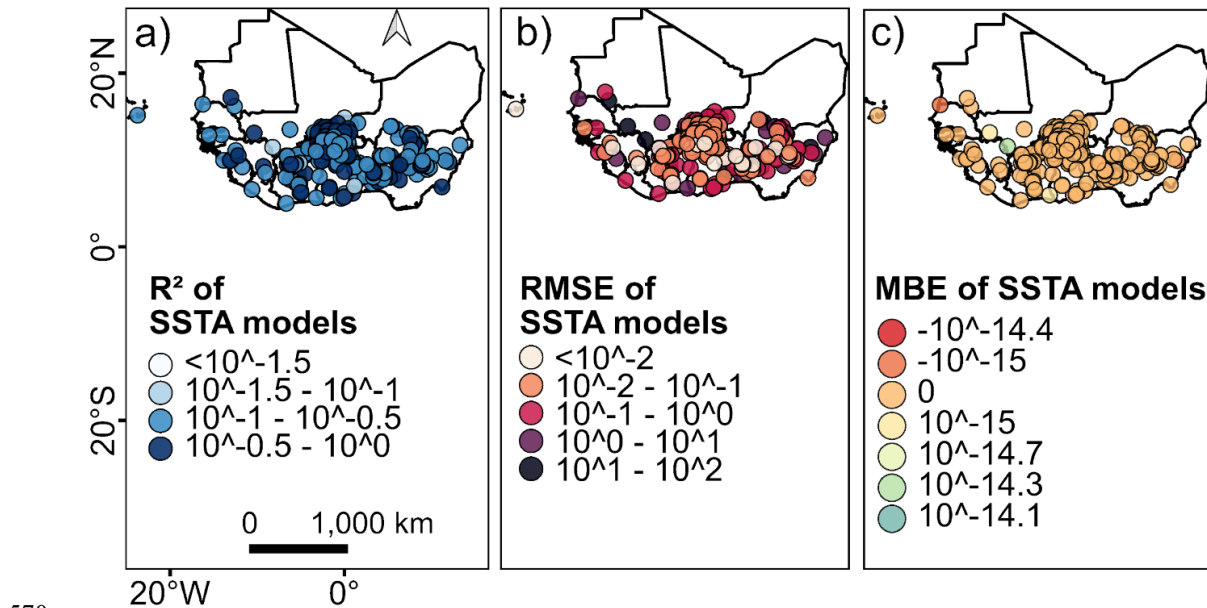


Figure E1: Spatial distribution of the mean R^2 , RMSE, and MBE of the best SSTA-based models (PLS-C 3) over West Africa.

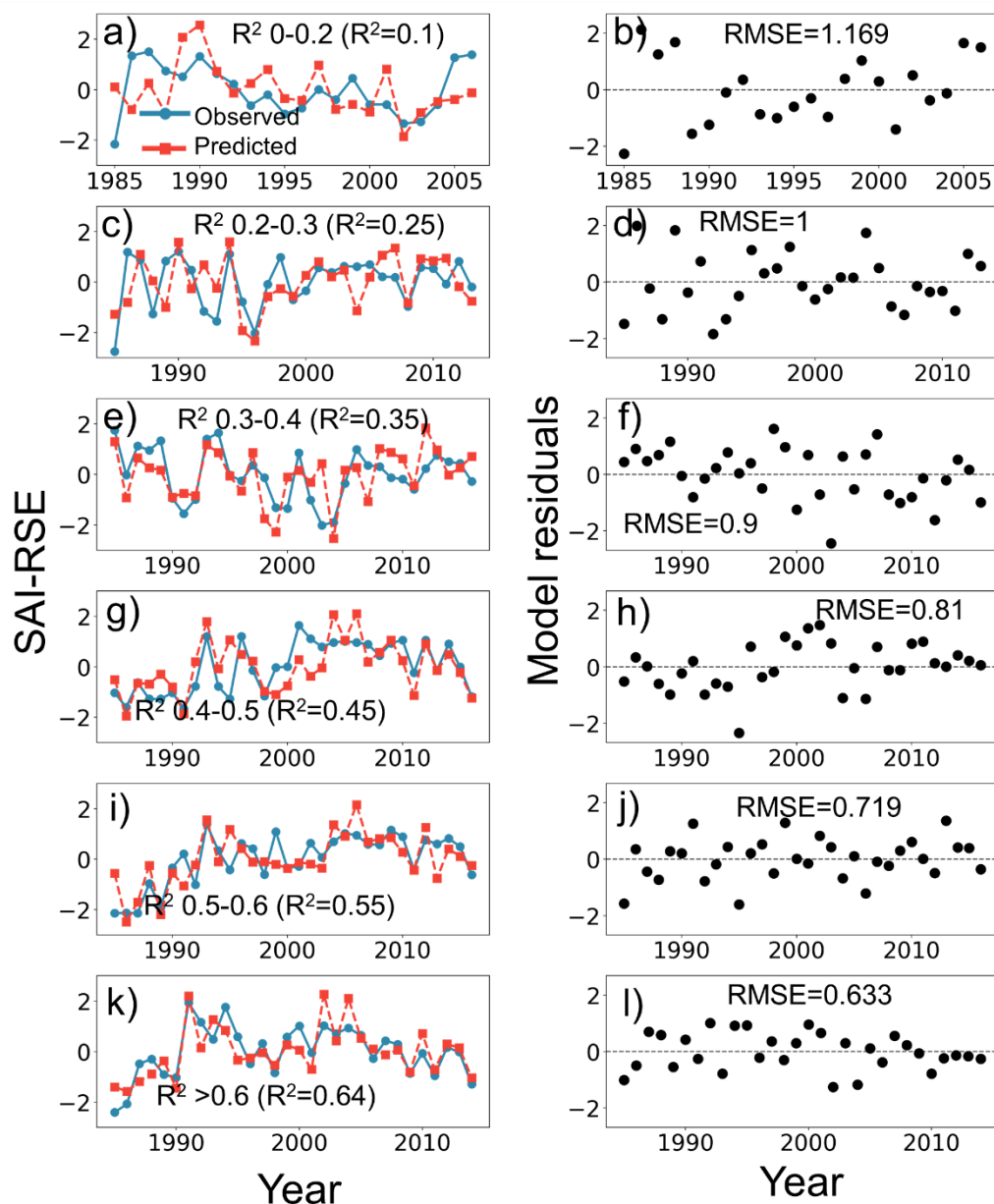


Figure E2: Comparison of observed and predicted standardized anomaly index of reservoir surface extent (SAI-RSE) time series and corresponding model residuals across increasing model performance classes defined by R^2 intervals. Panels (a, c, e, g, i, k) show observed and predicted SAI-RSE values, while panels (b, d, f, h, j, l) present the corresponding residuals for each class.

575



Code and data availability

The time series of reservoir surface extent that we used in the study are publicly available on the Global Water Watch (GWW) platform (Donchyts et al., 2022) via <https://www.globalwaterwatch.earth/map/>. Long-term observational SST datasets, i.e., ERSST.v5 (Huang et al., 2017) are available at <https://climexp.knmi.nl>.

580 The code used for data processing and analysis in this study was developed in Python and is publicly available on https://github.com/valerykouassivk-wq/SSTA-WA_Reservoirs-Python-Notebooks.

Author contributions

585 All authors contributed to the conception and design of the study. Valery Bessely Stanislas Kouassi and Kwok Pan Chun collected and organized the datasets. Valery Bessely Stanislas Kouassi and Julian Klaus designed the methodological framework. Valery Bessely Stanislas Kouassi and Blé Anouma Florest Yao developed the data processing codes, carried out the analyzes, and prepared the first draft of the manuscript. Albert Elikplim Agbenorhevi, Gneneyougo Emile Soro, Kwok Pan Chun, Albert Bi Tié Goula, Nelly Carine Kelome-Ahouangnivo, and Julian Klaus provided critical feedback on earlier versions
590 of the manuscript. All authors reviewed and approved the final version of the manuscript.

Competing interests

The authors declare that they have no conflict of interest.

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