Historical climate impact attribution of changes in river flow and sediment loads at selected gauging stations in the Nile basin

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Abstract

The Nile basin is the second largest basin in Africa and one of the regions experiencing high climatic diversity with variability of precipitation and deteriorating water resources. As climate change is affecting most of the hydroclimatic variables across the world, this study assesses whether historical changes in river flow and sediment loads at selected gauges in the Nile basin can be attributed to climate change. An impact attribution approach is employed by constraining a process-based model with a set of factual and counterfactual climate forcing data for 69 years (1951–2019), from the impact attribution setup of the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP3a). To quantify the role of climate change, we use the non-parametric Mann-Kendall test to identify trends and calculate the differences in long-term mean annual river flow and sediment load simulations between a model setup using factual and counterfactual climate forcing data. Results for selected river stations in the Lake Victoria basin show reasonable evidence of a long-term historical increase in river flows (two stations) and sediment load (one station), largely attributed to changes in climate. In contrast, within the Blue Nile and Main Nile basins, there is a slight decrease of river flows at four selected stations under factual climate, which can be attributed to climate change, but no significant changes in sediment load (one station). These findings show spatial differences in the impacts of climate change on river flows and sediment load in the study area for the historical period.

1 Introduction

Long-term temporal changes in river flow and river sediment load regimes are key indicators of potential impacts of climate change. River flows and sediment loads represent an integrated response of all hydroclimatic processes acting upon a river basin (Hannaford 2015), and alterations of river flow and sediment regimes could have some profound

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impacts on water availability and water quality, respectively (Zhang et al. 2020). Historical hydroclimatic variables provide insights into how the magnitude, timing and seasonality of hydrological and water quality variables respond to climatic forcings (Jiang et al. 2017). According to Nyeko-Ogiramoi et al. (2013), the issue on climate variability and climate change relies heavily on the detection of trends in hydroclimatic variables. Consequently, there is burgeoning literature on the subject of trend detection in Africa mainly on hydrological variables (river flows) (e.g. Conway 2005; Ahmed et al. 2019) but limited literature on water quality variables like river sediment loads (Walling and Fang 2003). Yet, river sediment loads mostly from soil erosion, are considered an important measure of loss of soil nutrients, land degradation and transfer of pollutants from terrestrial to coastal and marine systems (Walling and Fang 2003). Notably, an increase in river sediment loads is often linked to high-intensity rainfall events, which, especially in semi-arid regions, are associated with considerable soil erosion (Baartman et al. 2012).

The attribution of long-term trends in hydrological or water quality variables to observed changes in climate enhances our understanding of natural systems' response to climate variation. Accordingly, climate change impact attribution studies are continuously emerging but with scarce studies in African river basins, mainly due to poor streamflow gauging networks and poor data quality (Do et al. 2017). However, Africa is considered a highly vulnerable region to climate change mainly due to its reliance on weather-related activities and low adaptive capacity (Degefu et al. 2019). Thus, there is a need to better understand the role of climate in historical patterns of hydrological and water quality regimes over the continent to inform adaptation measures.

In accordance with the framework of the IPCC WGII-AR6 Chap. 16 (O'Neill et al. 2022), climate impact attribution can be approached in two ways: (1) "impact attribution to climate change" and (2) "impact attribution to anthropogenic climate forcing". Approach (1) involves attributing the observed changes in a system's state to any long-term climate trend, regardless of its cause. In these studies, detrended (counterfactual) climate data is utilized as input for process-based models, such as hydrological models, to understand the behaviour of the system in the absence of climate change (Mengel et al. 2021). Subsequently, this behaviour is then compared with the observed or simulated system dynamics driven by observed or reanalysis climate data (e.g., Rikani et al. 2023). Conversely, approach (2) focuses on attributing the detected changes in a system solely to anthropogenically forced climate change, excluding changes driven by natural climate forcing (Ara Begum et al., 2022). In this case, two or more datasets of climate model ensemble runs, with and without greenhouse gas emissions, are used as inputs for process-based models and attribution is addressed by comparing the model outputs forced by these individual climate forcing agents (e.g., Gillett et al. 2021). For the purpose of this study, the first approach is employed.

To support climate impact studies, the Inter-Sectoral Impact Model Intercomparison Project (ISIMIP, Warszawski et al. 2014) provides factual and counterfactual climate forcing data (Lange 2019a; Mengel et al. 2021). Factual (reanalysis) climate forcing data is based on observationally constrained global meteorological data while counterfactual climate forcing data represents data in which the long-term change in climate (climate change signal) has been removed (Mengel et al. 2021). Following the ISIMIP3a simulation protocol of attribution of observed impacts (https://protocol.isimip.org/), an impact attribution study can be supported by utilizing both datasets as inputs into a process-based model, such as the Soil and Water Assessment Tool (SWAT+, Bieger et al. 2017), which facilitates a comparison

of the observed state of a system with its hypothetical, counterfactual state. One indication of a system's state being influenced by climate change is when significant trends appear in model simulations driven by factual climate data, but not in those forced by counterfactual climate data. However, to ensure the validity of this comparison, it is crucial to maintain consistency in observed human drivers such as land use changes and water management in both simulations (Mengel et al. 2021).

In this paper, we aim to investigate whether the historical long-term changes in river flow and sediment loads at selected gauges in the Nile basin over the period of 69 years (1951–2019) can be attributed to climate change. To achieve this, we utilize the SWAT + hydrological model, which has previously demonstrated success in simulating the response of river flows, water quality, and crop yields to various changes in climate, land use, and management practices in the Nile basin (Nkwasa et al. 2022a, b). Specifically, we compare the model simulations forced with factual climate data and those forced with counterfactual climate data. By exploring temporal and spatial linear trends of climate, river flows and sediment loads at selected gauges across the basin until 2019, we aim to understand the role of climate change in driving historical changes in river flows and sediment loads. Additionally, calculating the differences in long-term mean river flows and sediment loads of the model simulations forced with factual climate and those forced with the counterfactual climate enables us to assess relatively the degree to which climate change has influenced the historical changes in river flows and sediment loads at selected gauges.

Understanding linkages between historical climate patterns with the hydrological and water quality variables is crucial for climate adaptation planning and climate negotiations. For example, if climate change is largely driving the changes in river flows and sediment loads, then hydro-meteorologists need to assess the future trends of climate to adapt their water resources management strategies in a timely manner. However, it is important to highlight that this study's reliance on a limited number of gauging stations for river flow and sediment load, coupled with short time series for river sediment loads, brings about uncertainties when interpreting results to a broader basin context.

2 Materials and methods

2.1 Study area

The Nile basin (Fig. 1a) covers eleven countries including Burundi, Democratic Republic of Congo, Egypt, Ethiopia, Eritrea, Kenya, Rwanda, South Sudan, Sudan, Tanzania, and Uganda in North-eastern Africa, with a catchment area of about 3,489,000 km² (Nkwasa et al. 2022a). The hydrological processes of the Nile basin are characterized by high inter-annual variability, spatial differences in topography and climate, and river flows modified by natural features and water infrastructures (Siam and Eltahir 2017). The Nile basin has 10 major sub-basins: Blue Nile, Victoria Nile, White Nile, Tekeze-Atbara, Baro Akobbo Sobat, Bahr el Jebel, Lake Victoria, Lake Albert, Bahr el Ghazal and Main Nile (Fig. 1b). The Blue Nile contributes about 60% of the total flow of the Nile and is an important river basin for Eastern Nile countries while Tekeze-Atbara and Baro-Akobbo-Sobat contribute slightly less than 15% each (Beyene et al. 2010).
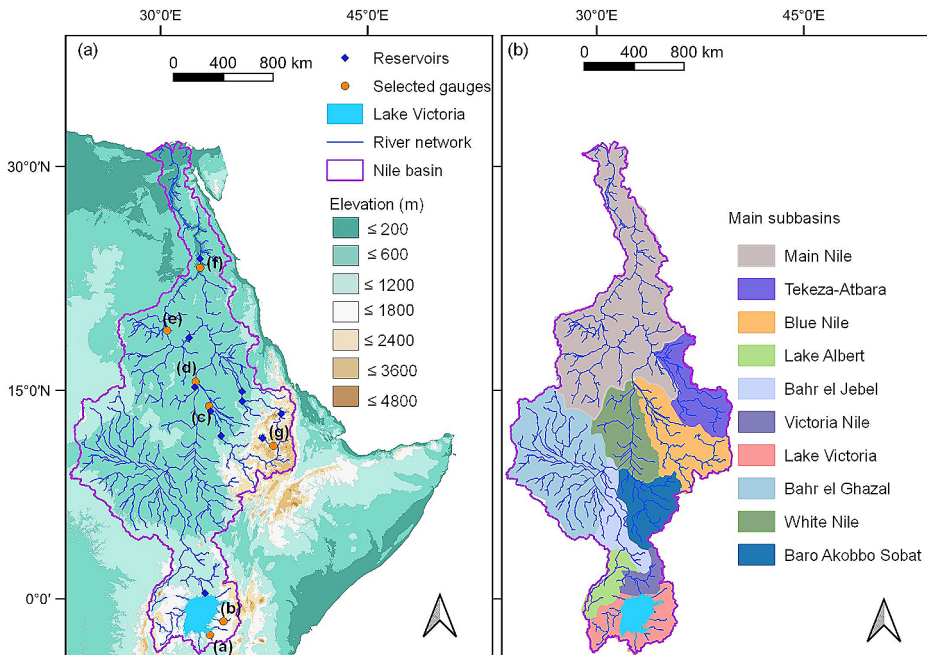
Fig. 1 (a) Selected gauge sites for attribution analysis and (b) main subbasins in the Nile basin (NBI 2017). River flow gauging sites: (a) Simiyu, (b) Mara mines, (c) Sennar, (d) Khartoum, (e) Dongola, (f) Aswan dam inflow. River sediment load sites: (a) Simiyu and (g) Kessie

The mean annual precipitation is heterogeneous across the basin with equatorial regions and the Ethiopian highlands receiving precipitation in excess of 1000 mm yr^{-1} while areas from northern Sudan and across all of Egypt receiving precipitation below 50 mm yr^{-1} (Onyutha et al. 2016). According to Siam and Eltahir (2017), climate change has enhanced the inter-annual variability of the Nile river flow. Thus, due to the diversity of climatic regions in the basin, this study focuses on seven different spatially distributed gauging sites (Fig. 1a) across some of the major subbasins.

2.2 SWAT + model description

SWAT+model is a completely restructured version of the SWAT model, which offers greater flexibility with watershed discretization, configuring and connecting spatial units in the representation of management operations as well as maintaining databases (Bieger et al. 2017; Arnold et al. 2018). In SWAT+, a basin is divided into sub-basins connected by a stream network, further divided into Land Scape Units (LSUs) and Hydrologic Response Units (HRUs). LSUs allow the separation of upland processes from wetlands while HRUs are areas of unique properties of land use, soil, slope class and management practices. The hydrological part of the model simulates a basin's hydrological cycle, based on the water balance equation, and calculates the surface runoff, evapotranspiration, percolation and return flow from each HRU (Neitsch et al. 2005). As for the sediment component, SWAT+uses the Modified Universal Soil Loss Equation (MUSLE; Williams 1975) to esti-

mate soil erosion and sediment yield at the HRU level. Sediment routing in the channel is controlled by both the degradation and deposition processes (Arnold et al. 1995). In this study, dynamic land use change is not considered. Temporal variations in erosion rates are attributed to changes in runoff intensity (replacing the rainfall energy factor), while spatial variability is influenced by differences in land use, runoff intensity, soil erodibility, crop cover, and topography, collectively impacting river sediment loads.

2.3 Datasets and model setup

The model for the Nile basin was setup using freely available global and regional datasets (Table 1). Of specific interest in this study is the climate forcing data (factual and counterfactual). The GSWP3-W5E5 reanalysis dataset, which has been bias-corrected (Lange 2019b) offers daily temporal resolution at 0.5° spatial resolution. It combines two products i.e. the W5E5 v2.0 product (Cucchi et al. 2020; Lange 2019a), covering 1979 to 2019 and the GSWP3 v1.09 product (Kim 2017) covering 1901–1978. Compared with the observed climate dataset used in the former ISIMIP protocol (ISIMIP2), GSWP3-W5E5 provides improved consistency among different variables (Boulange et al. 2023). Consequently, it is the recommended primary climate forcing dataset within the ISIMIP3a modelling protocol (https://protocol.isimip.org/). Simultaneously, the counterfactual climate dataset of GSWP3-W5E5 prepared using the ATTRICI (ATTRIbuting Climate Impacts) method (Mengel et al. 2021) was also employed. A detailed description of other input (geospatial)

Table 1 Data description and sources used in this study

Data type	Resolution	Source
Digital Elevation Model (DEM)	90 m	Shutter Radar Topography Mission (SRTM; Farr et al. 2007)
Land use	0.25 °	Harmonized land use (LUH2; Hurtt et al. 2020)
Soil	250 m	Africa Soil Information Service (AFSIS; Hengl et al. 2015)
Factual and counterfactual climate forcing (ISIMIP3a)	0.5 °	GSWP3-W5E5 (Dirmeyer et al. 2006; Kim et al. 2017; Lange 2019a; Cucchi et al. 2020)
Crop phenology	0.5 °	Waha et al. (2020)
Irrigated areas	0.083 °	Food and Agriculture Organization (FAO; Siebert et al. 2013)
Elemental Nitrogen and fertilizer	0.5 °	Hurtt et al. (2020) and Lu and Tian (2017)
River discharge	monthly	Global Runoff Data Centre (GRDC; http://grdc.bafg.de)
River sediment load	monthly	Ali et al. (2014) and van Griensven et al. (2013)
Reservoir data	-	Global Reservoir and Dam (GRanD) database (Lehner et al. 2011)
Evapotranspiration (ET)	250 m	FAO Water Productivity Open-access portal (WaPOR; https://wapor.apps.fao.org)

and evaluation (river flow and sediment load) data as listed in Table 1 is available in Section A.1 of the online resource material.

The modelling process was organized in the following way: First, the default SWAT + model (revision 60.5) was set up for the whole Nile basin, with factual climate forcing data in a QGIS – QSWAT interface and run from 1951 to 2019, with reservoirs and crop management practices implemented using decision tables (Nkwasa et al. 2020, 2022c). Ten major reservoirs (Owen falls, Tekeze, Tana, Roseries, Sennar, Rumela, Khashm el Gibra, Jebel aulia, Merowe, and Aswan dam) were implemented in the model using decision tables (Chawanda et al. 2020), generalized according to their purpose (Online resource, Table A1), using reservoir functions (release rates and target volumes) described in Wu et al. (2020). Decision tables enable the user to model intricate sets of rules and their subsequent actions by allowing them to add conditions for scheduling management (Arnold et al. 2018). The land use was kept static using a land use map for 1980. However, crop management (planting dates, harvest dates, fertilization and irrigation practices) was implemented using the workflows described in Nkwasa et al. (2022b).

Secondly, the model was calibrated and validated using observed river discharge data from GRDC, for eighteen gauging stations (Online resource A, Fig. A2 – A4) and river sediment load data from literature sources for 2 gauging stations (Fig. 2). Finally, the structure and parameterization of the calibrated hydrological model were held constant while being forced with counterfactual climate forcing data. This approach works with the assumption that the calibrated and validated SWAT + model in the factual climate performs robustly also with the counterfactual climate input data.

2.4 Model calibration and validation (river flow and sediment load)

The present study's calibration and validation of river flow and sediment load expands upon the Nile basin model calibrated in Nkwasa et al. (2022a) by incorporating additional gauging stations and reservoirs into the modelling framework. The calibration of river flow at eighteen gauging sites (Online resource, Fig. A2) was conducted using the Hydrological Mass Balance Calibration (HMBC) approach to calibrate the water balance components for all the subbasins, as outlined in Nkwasa et al. (2022a). Notably, a significant portion of the observed river discharge data in the GRDC database for the Nile basin predates 1985, with the majority ending before that year. For stations with more than five years of observed data, the dataset was divided into two subsets, facilitating coverage for both the calibration
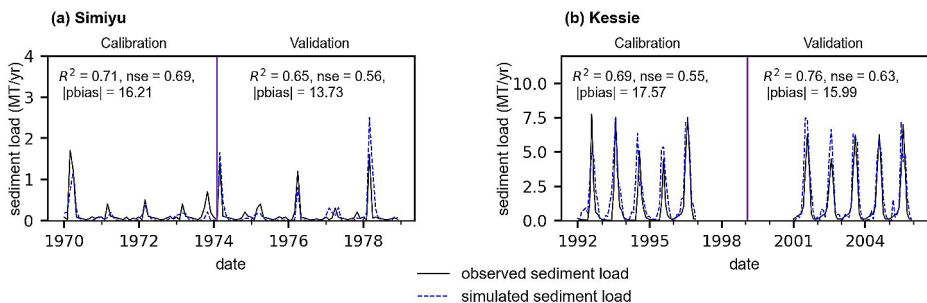

Fig. 2 Comparison of monthly simulated and observed river sediment load at selected sediment load gauge sites (Fig. 1a)

and validation periods. Five model parameters: curve number, soil evaporation compensation factor, plant uptake compensation factor, baseflow alpha factor and slope length for lateral subsurface flow were selected for calibration based on their influence on the water balance components using previous SWAT literature (https://swat.tamu.edu/publications/calibrationvalidation-publications/).

The model performance of monthly river flow (Online resource, Fig. A3 and Fig. A4) across the eighteen gauges ranged from unsatisfactory to very good performance based on statistical indicators of Nash-Sutcliffe Efficiency (NSE), percent bias (PBIAS) and coefficient of determination (R^2) (Moriasi et al., 2015). Most of the very good performance was achieved for gauges in the Blue Nile basin and the Main Nile basin stations (Online resource, Fig. A3) while most of the stations in the White Nile (Online resource, Fig. A4), did not achieve a satisfactory performance. This unsatisfactory performance in the White Nile could mainly be attributed to the lack of detailed wetlands/swamp representation in the model due to incomplete wetland-river interactions in the current version of the SWAT+model, which subsequently has implications for sediment modelling in this part of the basin. Among the gauging stations, six stations for river flow (Table 2) that had at least a satisfactory statistical performance (Moriasi et al., 2015) of NSE$\geq$0.5, PBIAS$\leq\pm$15% and $R^2\geq$0.6 were further selected for the subsequent flow attribution analysis.

Calibration of water quality variables e.g. river sediment loads is very difficult in quantitative terms as in-situ data and modelling data are lacking in Africa. Building upon the simulation of soil erosion and sediment processes of this case study conducted in Nkwasa et al. (2022a) and further summarized in Section A.4.2 of the online resource material, temporal calibration and validation of river sediment load was done at monthly time step for only two gauging sites (Fig. 2) i.e. Kessie and Simiyu stations. The observed river sediment load data for these stations were obtained from existing literature studies, specifically Ali et al. (2014) for the Kessie station and van Griensven et al. (2013) for the Simiyu station. These studies detail the derivation of monthly sediment loads from sediment rating curves of catchment outlets. Calibration was conducted at the Kessie station from 1992 to 1997 and validation from 2001 to 2006, while at the Simiyu station, calibration spanned from 1970 to 1974, with validation from 1975 to 1978. Calibration of sediment parameters involved adjusting the Modified Universal Soil Loss Parameters (MUSLE) parameters as described in Nkwasa et al. (2022a) and the bedload coefficient manually. The bedload coefficient determines the amount of incoming sediments in a river that settles as bedload. These two gauging stations were further selected for analysis in this study (Table 2) owing to the satisfactory statistical performance (NSE$\geq$0.45, PBIAS$\leq\pm$20%, R2$\geq$0.4).

2.5 Statistical and trend analyses

The non-parametric Mann-Kendall (MK, Mann 1945; Kendall 1948) test has been widely used for trend tests as it does not require the data to be normally distributed. The only requirement is that the data should be independent. However, the effect of serial correlation should be eliminated as it increases the chance for a significant trend. In this study we adopt a modified MK test that applies a trend free pre-whitening procedure (Hamed 2009) to account for the effect of serial correlation in the timeseries. The process involves using the ordinary least-square method to estimate both the slope trend and the autocorrelation coefficient at the same time, followed by the correction of bias in the correlation coefficient.

Table 2 Overview of the selected river flow and sediment load gauges (Fig. 1a) used in the attribution analysis

Gauge name and location (Fig. 1)	Drainage area (km²)	Data period		Variable	Reservoirs implemented upstream	Criteria of model evaluation (NSE/PBIAS/R²)	
		Calibration	Validation			Calibration	Validation
(a) Simiyu	6093	1970–1983	1984–1996	flow	-	0.53/7.75/0.69	0.59/9.51/0.71
		1970–1974	1975–1978	Sediment load	-	0.69/16.21/0.71	0.56/13.73/0.65
(b) Mara mines	15,000	1970–1974	1975–1979	flow	-	0.69/12.97/0.76	0.80/8.87/0.87
(c) Sennar	202,960	1952–1967	1968–1982	flow	Sennar, Roseries, Lake Tana - char achara weir	0.73/13.71/0.77	0.63/9.71/0.73
(d) Khartoum	325,000	1952–1967	1968–1982	flow	Sennar, Roseries, Lake Tana - charachara weir	0.71/8.40/0.77	0.64/10.13/0.71
(e) Dongola	2,694,000	1952–1968	1969–1984	flow	Merowe, Jebel Aulia, Owen falls, Tekeze, Rumela, Khashm el Gibra, Sennar, Roseries, Lake Tana - charachara weir	0.51/9.63/0.71	0.55/10.02/0.80
(f) Aswan inflow	2,849,000	1971–1984	1985–1997	flow	Merowe, Jebel Aulia, Owen falls, Tekeze, Rumela, Sennar, Roseries; Lake Tana - charachara weir, Khashm el Gibra	0.77/13.12/0.82	0.83/12.48/0.87
(g) Kessie	65,784	1976–1980	-	flow	Lake Tana - charachara weir	0.54/19.9/0.72	-
		1992–1997	2001–2005	Sediment load		0.55/17.57/0.69	0.63/15.99/0.76

Trends were examined for climate data indices (annual precipitation, 95th percentile of daily precipitation), hydrological data index (mean annual daily flow) and water quality index (annual sediment load). Then, the significance of trends was determined at the significance level of 5%. The non-parametric Sen's approach (Sen 1968) was used to calculate the slope of the detected trends. The trend analysis of river flows and sediment loads in this study only focuses on the annual timeseries rather than the intra-annual characteristics of hydrographs e.g., peak flows and low flow conditions.

2.6 Impact attribution to climate change

A comparison between model simulations with factual and counterfactual climate forcing data sets was made to allow for attribution of long-term changes of model outputs (river flows and sediment loads) to climate change. The historical impact of climate change is calculated as the percentage difference between the model simulations (Eq. 1).

$$CC_i = \left(\frac{S_o - S_c}{S_c} \right) x100 \ (1)$$

Where; CC_i is the historical impact of climate change (%), S_c is the annual average model output of simulations forced with counterfactual climate data, S_o is the annual average model output of simulations forced with factual climate data.

3 Results

3.1 Climate analysis (Trends)

3.1.1 Trend analysis of the factual annual and the 95th percentile precipitation

In the Nile basin (Fig. 3a), the result of the statistical trend analysis revealed that on the annual scale, factual precipitation had significantly ($\rho < 0.05$) increased and decreased in 42% and 7% of the basin area respectively, with the annual precipitation increasing at a mean rate of 0.8 mm yr^{-1} and decreasing at a mean rate of 1 mm yr^{-1} (Fig. 3c) during the historical period (1951–2019), in different parts of the river basin. At a local scale, the Lake Victoria basin predominantly showed statistically significant increasing trends (69% of the basin), implying that this basin had largely become wetter in the last 69 years while the Blue Nile basin showed a mixture of increasing and decreasing annual precipitation trends in 38% and 11% of the basin respectively. The strongest rate of increase in precipitation of up to 4.5 mm yr^{-1} was found in the headwaters of the Lake Victoria basin, while the largest decrease up to -6.0 mm yr^{-1} was found in Ethiopia (south of the Blue Nile basin) where the highest amount of precipitation in the Nile basin occurs.

Similar trend patterns were observed in the 95th percentile of the daily precipitation (Fig. 3b and d). However, the mean increasing (0.02 mm yr^{-1}) and decreasing (-0.03 mm yr^{-1}) rates of the 95th percentile precipitation in the Nile basin were much lower than for annual precipitation. The strongest rates of increase and decrease of the 95th percentile precipitation (up to ± 0.15 mm yr^{-1}) were found in Ethiopia. It's essential to acknowledge
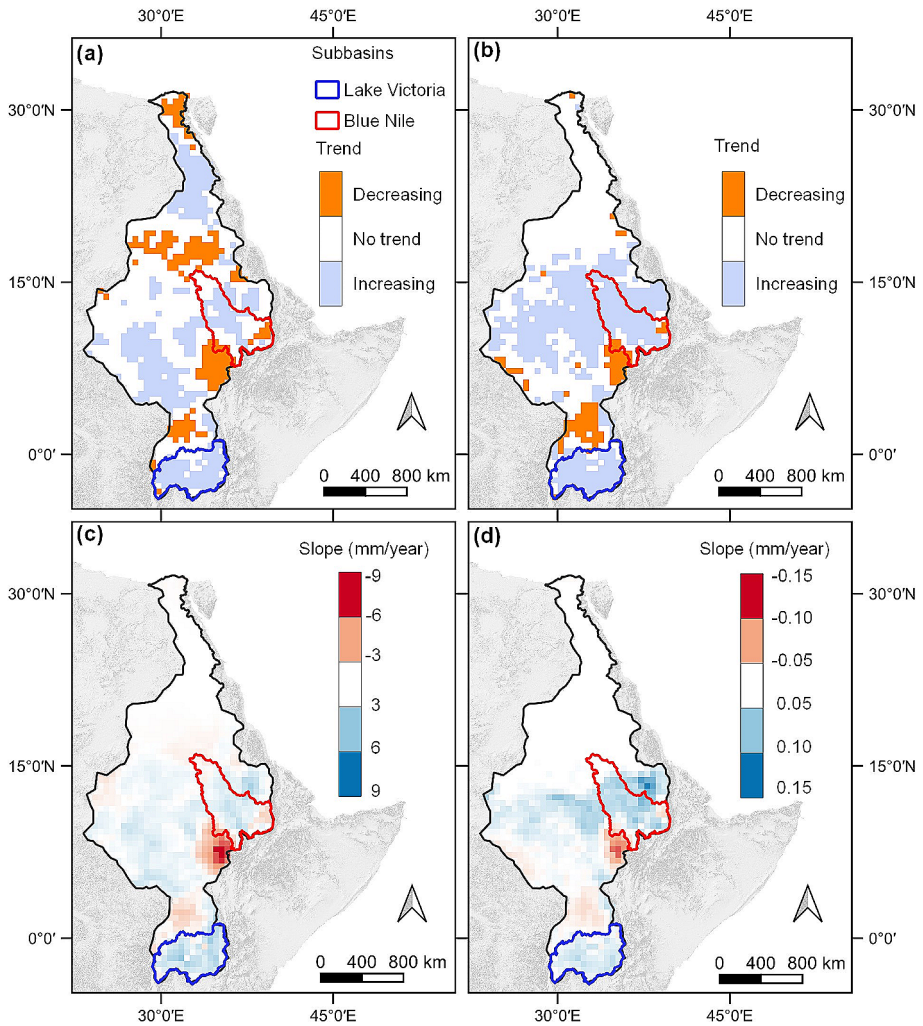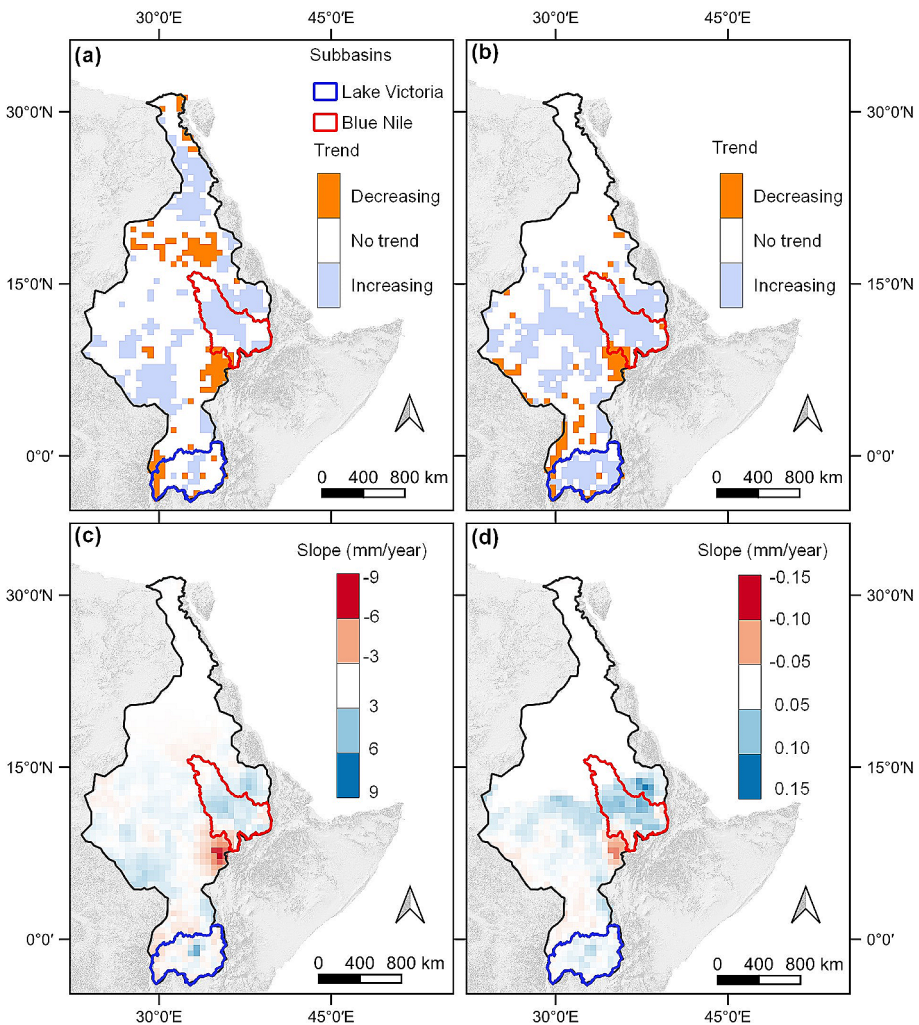
Fig. 3 Spatial distribution of the trend (1951–2019) in factual; (a) annual precipitation and (b) 95th percentile of daily precipitation; spatial distribution of the slope in factual; (c) annual precipitation and (d) 95th percentile of daily precipitation

that there was significant spatial variability among the factual climate trends, and for a large portion of the basin (51%), the trend test statistics did not show any statistically significant results ($\rho < 0.05$).

3.1.2 Trend analysis of the counterfactual annual and 95th percentile precipitation

With the counterfactual precipitation, the result of the statistical trend analysis showed that at the annual timestep (Fig. 4a), precipitation significantly ($\rho < 0.05$) increased and decreased in 29% and 6% of the basin area respectively. 65% of the basin area had non-significant

($\rho < 0.05$) trends. The basin mean precipitation increase rate was 0.7 mm yr^{-1} while the mean decreasing rate was 0.6 mm year^{-1} during the historical period (Fig. 4c). The strongest rate of increase in precipitation of up to 6.1 mm yr^{-1} was found in the headwaters of the Lake Victoria basin, while the strongest decrease up to -9.0 mm yr^{-1} in Ethiopia. Comparable trend patterns were observed in the 95th percentile of daily counterfactual precipitation (Fig. 4b and d) as in the counterfactual annual precipitation, though with considerably reduced slopes. It is important to acknowledge that while we observe some trends in the counterfactual precipitation data over a 69-year period, these trends are expected to be close to zero when calculated for the entire dataset covering the period 1901–2019.

Fig. 4 Spatial distribution of the trend (1951–2019) in counterfactual; (a) annual precipitation and (b) 95th percentile of daily precipitation; spatial distribution of the slope in counterfactual; (c) annual precipitation and (d) 95th percentile of daily precipitation

3.2 Impact attribution of changes in river flow and sediment load

3.2.1 Flow simulations with factual and counterfactual climate forcing

Figure 5 displays the timeseries of annual river flow from 1951 to 2019 at six selected hydrological stations located within the Nile basin. The model simulations using factual climate forcing data indicated that the annual flow trends in the Lake Victoria basin at Simiyu (Fig. 5a) and Mara mines (Fig. 5b) stations were statistically significantly increasing, with rates of change of 0.08 m^3 s^{-1} yr^{-1} and 0.24 m^3 s^{-1} yr^{-1}, respectively. On the other hand, the stations in the Blue Nile basin at Sennar (Fig. 5c), Khartoum (Fig. 5d), and the Main Nile stations at Dongola (Fig. 5e) and Aswan dam inflow (Fig. 5f) showed significant decreasing trends in river flows, with rates of change ranging from -2.13 m^3 s^{-1} yr^{-1} to -8.77 m^3 s^{-1} yr^{-1} in simulations using factual climate data. The trends of river flows in model simulations, driven by factual climate data at specific gauge stations, exhibited consistency with the spatial trends of factual precipitation throughout the drainage basins, except in the case
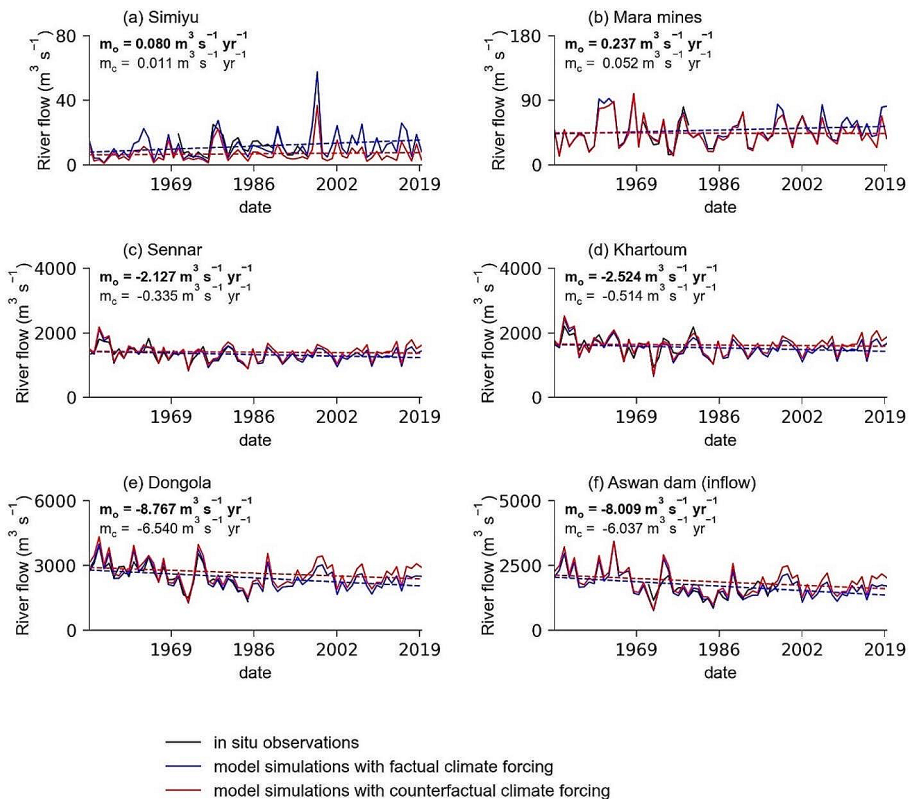

Fig. 5 Model simulations of mean annual daily river flow smoothed by a 5- year running mean (figures ordered upstream to downstream). Dotted lines represent the MK trend lines for respective datasets. Bold values denote trends significant at $\rho<0.05$ level. m_o and m_c are slopes for model simulations forced with factual and counterfactual climate forcing data respectively

of the gauges in the Blue Nile and Main Nile basins where no statistically significant trends in precipitation were found (Online resource, Fig. A1).

Contrary to the predominantly increasing precipitation trends observed in most parts of the Blue Nile basin (38%), the river flow trends mainly exhibited a decrease. This opposing trend can be partially attributed to the human interventions implemented upstream of the gauge stations, such as reservoirs (Table 2), which alter the flow regimes. Additionally, the opposing trend could be a result of the decrease in rainfall in the catchment defined at gauge Kessie (the orange region in the east of the Blue Nile catchment in Fig. 3a). Quantitatively, a reduction of precipitation to a certain percentage in the Kessie catchment would have a larger impact (due to higher annual rainfall) than the same percentage in increase in the downstream parts, e.g. at Sennar (where annual rainfall is much lower) (Online resource, Fig. A7). The analysis of model simulations forced with counterfactual climate data revealed similar trends in the annual river flow as the model simulations forced with factual climate data, albeit with reduced magnitudes and lacking statistical significance at all selected stations.

Table 3 indicates that climate change has resulted in a long-term increase of river flows at Simiyu (53.4%) and Mara mines (10.9%) stations located in the headwaters o the Lake Victoria basin over the simulation period, as demonstrated by the differences between model simulations that utilize factual and counterfactual climate data. Conversely, climate change has resulted in a decrease in the long-term mean annual river flow at all selected stations in the Blue Nile and Main Nile basins. The magnitude of the percentage decrease ranges from −5.0% to −8.8% over the simulation period. These findings highlight the spatial disparity in the historical impact of climate change on river flows in the basin.

3.2.2 Sediment load simulations with factual and counterfactual climate forcing

As a result of limited in-situ river sediment load data, the attribution analysis was only conducted for two stations in the Nile basin, despite the short timeseries available for those stations. The annual river sediment load trends at selected stations (Fig. 6) mirror the river

Table 3 Differences (in %) in mean annual river discharge and river sediment load at selected stations between model simulations forced with factual and counterfactual climate data

Long-term mean annual change, CC_i, % change (Factual – counterfactual model simulations)			
(a) River flows			
Stations	Earlier 30 year cycle (1960–1989)	Recent 30 year cycle (1990–2019)	Total simulation period (1951–2019)
Simiyu	33.1%	77.9%	53.4%
Mara mines	4.4%	15.9%	10.9%
Sennar	–3.0	–7.9%	–5.2%
Khartoum	–2.9	–8.0%	–5.0%
Dongola	–5.8	–11.3%	–7.9%
Aswan dam (inflow)	-6.1	–12.4%	–8.8%
(b) Sediment load			
Stations	Earlier 30 year cycle (1960–1989)	Recent 30 year cycle (1990–2019)	Total simulation period (1951–2019)
Simiyu	37.6%	82.3%	59.4%
Kessie	–3.4	–7.3%	–5.1%

flow trends observed at Simiyu station (Fig. 5a) and Kessie station (Online resource, Fig. A6) within their respective river basins. Specifically, annual river sediment loads at Simiyu station (Fig. 6a) in the Lake Victoria basin significantly increased with climate change, while in the Blue Nile basin at Kessie station, annual river sediment loads decreased with climate change (Fig. 6b). However, the sediment load trends at Kessie station were not statistically significant with a small difference in the rates of sediment load decrease between the two model simulations.

Table 3 shows that climate change has led to a long-term mean annual sediment load increase of 59.4% at Simiyu station over the simulation period (1951–2019). Comparison between the earlier and recent multi-decadal 30-year cycles (Table 3) reveals an acceleration in the impact of climate change on river flows and sediment load during the recent cycle. This highlights that the effects of climate change on hydrological variables and water quality could be amplified if this trend persists in the future.

4 Discussion

4.1 Linking historical climatic trends to river flows and sediment loads

This study demonstrates that changes in climate have had a significant impact on river flows at six reference stations throughout the Nile basin. Simulated sediment loads were only significantly impacted at one of the two stations. Selected gauges in the headwaters of the Lake Victoria basin have experienced a trend towards wetter conditions, which is directly reflected in the river flows (two gauges) and sediment loads (one gauge). Additionally, the trend of increasing river flow could be likely attributed to climate change, due to the significant positive trend seen in factual simulations but not in counterfactual simulations. Moreover, the long-term mean annual river flows and sediment loads are consistently higher in model simulations forced with factual climate data than in those forced by counterfactual climate data within the Lake Victoria basin. The increasing trend in river sediment load at Simiyu station corresponds with the increasing trends in annual and 95th percentile of daily precipitation (Online Resource, Fig. A1) which increases the risk of soil erosion and subsequent sediment load. Given the strong association between high-intensity precipitation and
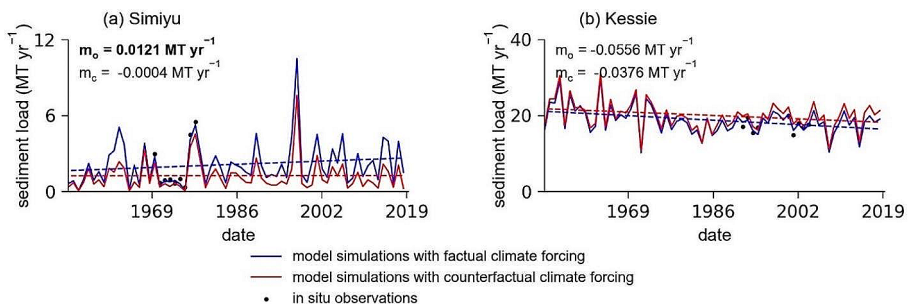

Fig. 6 Model simulations of annual river sediment load. Dotted lines represent the MK trend lines for respective datasets. Bold values denote trends significant at $\rho < 0.05$ level. m_o and m_c are slopes for model simulations with factual and counterfactual climate data respectively

severe soil erosion, the Lake Victoria basin is increasingly vulnerable to soil erosion and river sediment loads. It is likely that the result from the Simiyu and Mara mines gauging stations apply to other rivers in the Lake Victoria basin that experienced similar precipitation trends.

The increasing wetter trends of precipitation and 95th percentile precipitation in the Lake Victoria basin have implications for increased risks of flood and decreased water quality if the positive trends in river flows and sediment loads persist in the near or mid-term future. Increased risks of soil erosion and subsequent river sediment loads can easily result in accelerated sedimentation rates of water systems (reservoirs and river channels) as well as ecological problems related to sediment-fixed nutrients. Our results are in agreement with studies (Conway 2005; Onyutha et al. 2016; Ekolu et al. 2022) that reported a prolonged increase in annual precipitation over the 20th century within the Lake Victoria basin, resulting in a rapid and sustained rise in the lake levels and river flows. In addition, Nyeko-Ogiramoi et al. (2013) found evidence of the presence of increasing trends in river flow extremes in the Lake Victoria basin, however, no attribution analysis was carried out.

In contrast to the findings obtained in the Lake Victoria basin, our analysis at selected stations of the Blue Nile and the Main Nile basins suggests that these areas exhibit a comparatively smaller impact of climate change on river flows and sediment loads mainly due to the smaller magnitudes of changes in mean annual precipitation in the historical climate. This is shown by the similarity in the trend directions and smaller difference in trend slopes between model simulations forced with factual and counterfactual climate data. Furthermore, the differences in the long-term mean annual river flows and sediment loads of model simulations with factual and counterfactual climate forcing data were relatively small. Hence, the effect of climate change on river flows and sediment loads in selected gauges of the Blue Nile and Main Nile basins is less prominent. However, in the Blue Nile basin, the effects might be attributed to greater spatial heterogeneity. As a result, especially downstream of Kessie station, the overall magnitude of changes is likely minimal because positive and negative trends of precipitation counterbalance each other to some degree.

Although the Main Nile integrates both the Blue Nile and the White Nile river flows, the former contributes more than 60% to the river flows at Dongola station. The disparity between the contributions of the Blue Nile and the White Nile may explain the similarity of the trends at both the Blue Nile and the Main Nile selected discharge sites. Our results in the Blue Nile basin agree with previous studies (Seleshi and Camberlin 2006; Taye and Willems 2012) that found it difficult to identify signatures of climate change in the Blue Nile basin on either precipitation or river flow extremes. According to Sene et al. 2001, the progressive decline in river flows within the Blue Nile from the mid-1960s to early 1990s could partly be explained by increased water usages in this period, showing that factors other than climate change are likely influencing the trends of river flows downstream of the basin. Nevertheless, considering the 30 year cycles analysis and given that precipitation is projected to increase by most GCMs (Almazroui et al. 2020) within the basin, especially in the Ethiopian highlands and the Lake Victoria basin up to the end of the 21st century, the climate change signal should be expected to be more pronounced in river flows and increased risks of soil erosion leading to high sediment load trends with future climate.

Despite a basin average warming trend of 0.04 °C/yr (Online resource, Fig. A8), our analysis suggests that impacts of climate change on river flow and sediment load trends are currently more pronounced solely at selected gauging sites within the Lake Victoria basin.

In contrast, there is still a lesser impact of climate change on trends in river flows and river sediment load at selected gauges in the Blue Nile and the Main Nile basins. This suggests that factors such as dynamic land use changes, not accounted for in this study could have a more significant impact on the trends in river flows and sediment load than climate change. Furthermore, despite the implementation of reservoirs, a generalized reservoir management approach was employed, introducing uncertainties that could also impact the trends of river flows and sediment load. Ahmed et al. (2019) demonstrated a direct link between human activities such as dam construction and irrigation schemes in upstream countries of the Nile basin, and changes in river flow regimes in downstream countries. Within a global perspective, Dethier et al. (2022) argue that variations in suspended sediment fluxes of large rivers (basin area > 1000 km^2) throughout history have not been primarily caused by climate change, specifically precipitation fluctuations. Rather, human activities have been identified as the primary driver of these alterations. Therefore, we need to focus more attention on anthropogenic management activities rather than solely on climate change to effectively attribute historical changes in hydrologic and water quality variables.

Considering that the Nile basin has experienced strong intensification and expansion of agricultural management (Siderius et al. 2016), temporal evolution of land use and land cover (LULC) changes in the basin require increased attention in climate impact studies. We will address this topic in future analyses. It is noteworthy that the methodology employed in this study for determining climate impacts does not account for the attribution of such impacts to either anthropogenic climate forcing (pertaining to human-induced climate change) or natural forcing agents (inherent to natural climate variability). Subsequent research in the basin is necessary to fully comprehend the influence of anthropogenic climate change, which will require the application of different attribution methods.

4.2 Limitations

This study focused on seven discharge sites (Fig. 1a) that capture some of the main subbasins and different climatic zones in the Nile basin (i.e. Lake Victoria, Blue Nile and Main Nile subbasins), however, our results may not correspond to trend changes seen at other local sites. Trend analyses of other gauging sites or for other data periods may show different magnitudes and trend signs depending on the data period and gauging site considered. Additionally, this study focused on a gradual trend yet a change in timeseries may occur abruptly or may take a cyclic form or a combination of both (Nyeko-Ogiramoi et al. 2013). Such changes may also affect the overall statistical properties of the timeseries.

Another limitation to this study is the sparse and poor-quality records of river flow and sediment loads (Nkwasa et al. 2022a), making a proper model validation challenging for some stations. For instance, the inadequate spatial coverage of in-situ data, particularly in regards to river sediment loads, limited our ability to perform an evaluation of river sediment loads for more gauges in the basin. Additionally, the insufficient record length of observed river flows and sediment prevented the application of a proper trend detection, given that majority of the data ends before 1985. These constraint in spatial coverage and record length of in-situ data limits the validity of our findings. Similarly, the absence of specific reservoir operation data led to generalized reservoir management based on purpose, potentially introducing uncertainties in model simulations due to variable local release conditions. The climate data, with its coarse 0.5^0 resolution, reportedly underestimates daily

maximum precipitation due to its inability to capture localized rainfall events, leading to underestimations of rainfall erosivity (Chen et al. 2022). Therefore, there is a pressing need to acquire long-term, high-resolution datasets of meteorological variables, hydrological variables, water quality variables and reservoir management operations, in order to enhance the precision of climate impact attribution studies. In addition, the use of only one set of factual and counterfactual data limited the quantification of climate data uncertainty to the uncertainty in attribution. Hence, future studies are recommended to utilize a range of factual and counterfactual climate datasets to quantify the uncertainty in climate data. Presently, ISIMIP3a provides five additional datasets, which enable such an extended study allowing for an assessment of uncertainties related to climate data.

While our primary objective was to build a model incorporating the key physical processes affecting hydrological processes and sediment transport within the Nile basin, our current model does not account for the Grand Ethiopian Renaissance Dam (GERD) and lacks representation of dynamic land use changes. The GERD was excluded due to the ongoing filling of the reservoir that has a timeline of 5–15 years depending on the not yet agreed upon trilateral policy agreement between Ethiopia, Egypt and Sudan (Liersch et al. 2017). However, it would be important for future modelling studies involving climate change impacts to incorporate the GERD as the reservoir is expected to influence river flows and the ecosystems downstream in the Nile basin (Sterl et al. 2021). The absence of dynamic land use data introduces uncertainties in our model simulations, particularly regarding soil erosion estimates for regions in the basin that have experienced significant land use and land cover changes. Lastly, our model has certain structural limitations, such as the lack of representation of wetland-river interactions, which precluded the accurate depiction of land features like swamps and wetlands that play a vital role in water retention and sediment trapping. This could partly explain the poor performance of the model in the White Nile (Online resource, Fig. A4) that is covered largely by the Sudd swamp. Thus, continuous improvements in the model's structure and physical representation of processes, especially in the domain of sediment modelling are recommended.

5 Conclusion

This study provides valuable insights into the impacts of climate change on river flows and sediment loads for selected gauges in the Lake Victoria, the Blue Nile and the Main Nile subbasins. The headwaters of the White Nile, particularly the Lake Victoria basin, have experienced a trend towards wetter conditions, which is likely contributing to an increase in river flows at two gauging stations and heightening the risk of soil erosion, thereby intensifying sediment loads at one station. These trends are likely attributed to climate change, as evidenced by the positive statistically significant trends seen in simulations forced with factual climate data compared to counterfactual simulations. In contrast, selected gauges in the Blue Nile and Main Nile basins show decreasing trends in river flows and sediment loads, with a comparatively smaller impact of climate change. This minor impact is primarily due to the smaller magnitudes of changes in mean annual precipitation in these regions. However, the study acknowledges certain limitations, including the focus on a limited number of discharge sites and the potential for different trend changes at other locations. The sparse and poor-quality records of river flow and sediment loads, as well as the lack

of long-term, high-resolution datasets, further constrain the validity and precision of the findings. Thus, future research should aim to incorporate a wider range of gauging sites, longer data records, and improved model structures to enhance the understanding of climate change impacts on hydrological and water quality variables in the Nile basin. Nevertheless, the findings of this study can provide valuable insights for climate negotiations, attributing damages due to climate change, and shaping adaptation strategies for specific subbasins within the Nile basin, given the changing climate.

Declarations

Competing interests The authors declare that they have no conflict of interest.

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