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One third of African rivers fail to meet the 'good ambient water quality' nutrient targets

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ABSTRACT

The ambition of Sustainable Development Goal (SDG) target 6.3 is to improve global water quality by 2030. SDG indicator 6.3.2 monitors progress towards this target by assessing water bodies against 'good' ambient water quality criteria, with nutrients (nitrogen and phosphorus) as part of the key metrics. However, large data gaps present a fundamental challenge, especially for Africa on how to assess the progress being made with respect to both the current and desired future situations. Here, a continental water quality model for Africa is presented to simulate river sediment load, Total Nitrogen (TN) and Total Phosphorus (TP) loads and concentrations. Furthermore, critical areas and hotspots of TN and TP pollution are mapped for the period 2017 – 2019, in relation to the United Nations Environment Programme (UNEP) target thresholds used for the assessment of SDG indicator 6.3.2. Utilizing the UNEP's criteria, which designates a water body as having "good ambient water quality" if 80% or more of its monitored values meet their targets, it is estimated that 44 % and 15 % of African rivers fail to meet the set water quality thresholds for simulated TP and TN, respectively. When synthesizing data for both TP and TN, 34 % of the rivers do not qualify as having "good ambient water quality". Geographically, the most pronounced nutrient pollution hotspots were in North Africa, Niger River Delta, Nile River basin, Congo River basin and specific zones in Southern Africa. These areas correlate with regions characterized by high inputs of fertilizers, manure and wastewater discharge.

1. Introduction

Human activities are altering the natural state of freshwater ecosystems with frequent introduction of excessive organic matter, surplus nutrients, and synthetic chemicals such as pesticides and pharmaceuticals into these systems (Chapman and Sullivan, 2022). As a result, surface water pollution is one of the predominant environmental challenges of this century (Perrin et al., 2014). In particular, human disruptions to the natural cycles of nitrogen and phosphorus over the decades have made eutrophication a critical global threat to freshwater ecosystems (Camargo and Alonso, 2006). However, gauging the true extent of how impacted global freshwaters are by humans remains challenging (Chapman and Sullivan, 2022). This is simply because the quality of many freshwater bodies, especially in Africa, has not been, and remains, unmonitored (Damania et al., 2019).

Water quality is recognized in the Sustainable Development Agenda, influencing and interlinking with almost all Sustainable Development Goals (SDGs) (Miao et al., 2023). Of particular interest, SDG target 6.3 articulates the goals: " By 2030, improve water quality by reducing pollution, eliminating dumping and minimizing release of hazardous chemicals and materials, halving the proportion of untreated wastewater and substantially increasing recycling and safe reuse globally." To gauge the progress being made toward this goal, SDG Indicator 6.3.2 plays a pivotal role by tracking the percentage of water bodies that meet

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the targets of 'good' ambient water quality, where 'good' refers to a level of dissolved oxygen, salinity, nutrients (Total Nitrogen, TN and Total Phosphorus, TP) and acidification that does not damage ecosystem and human health. Evaluating this indicator involves comparing measured or simulated physio-chemical parameters such as TN and TP to a numerical concentration limit/benchmark that represents water of good ambient quality.

Despite the high ambitions of the SDGs for water quality, the first SDG 6 Synthesis Report released in 2018 suggests that the world is not on track to achieve the SDG 6 targets by 2030 (UN Water, 2018; Ortigara et al., 2018). One significant barrier is the lack of available and reliable national data for SDG 6 (Hakimdavar et al., 2020). There is a significant data gap globally, particularly in the Global South, presenting a fundamental challenge on how to assess the progress being made with respect to both the current and desired situations. Only 40 % of the indicators in the global SDGs data framework are accompanied by data in Africa (Lamizana and Zennaro, 2019). Out of the 75,000 water bodies reported in 2020, slightly more than 1.5 % were from the 20 poorest nations (UN Water, 2021). While there are more comprehensive data in developed countries, the United Nations Environment Programme's (UNEP's), Global Environment Monitoring System for Freshwater's (GEMS/Water) database (GEMStat) – a leading repository of in-situ freshwater quality measurements, often has fragmented and aged data, compromising their relevance in contemporary policy making and advocacy (Desbureaux et al., 2022). Consequently, addressing these data gaps becomes paramount to better understanding the location of hotspots, to determine trends, and to measure progress towards reaching SDG target 6.3 and improving water quality by 2030.

Physically-based water quality models, such as the Soil and Water Assessment Tool, SWAT+ (Bieger et al., 2017; Arnold et al., 2018), offer a promising avenue to bridge these data gaps. These models allow for simulations of pollutant emissions (point sources and nonpoint sources) and their movement in river networks, leveraging land use, climatic conditions, hydrology, and socio-economic data. Such models are particularly valuable in predicting water quality in regions with sparse data and in forecasting scenarios under uncertain future conditions (Wanders et al., 2019). Especially pertinent to the African context, where water quality data are sparse, these models can significantly improve the understanding of the hotspots and trends of water quality in Africa under multiple global change drivers.

In this study, a SWAT+water quality model is presented for Africa which can be used to simulate river sediment load, TN and TP loads and concentrations. All simulations are provided at a daily time step from 1951 to 2019 for 5644 river reaches in Africa. A 'river reach' is defined here as a simple cartographic unit, i.e., the line segment between two adjacent confluences, rather than a functional unit that encompasses specific ecosystem processes or habitats (Linke et al., 2019). Additionally, critical areas and hotspots of TN and TP are mapped in relation to the UNEP target thresholds used for the assessment of SDG indicator 6.3.2. This continental overview underscores the significance of minimizing nutrient release and transport, as it can substantially improve river water quality across certain regions on the continent especially in nutrient hotspot areas.

2. Materials and methods

2.1. SWAT+model description

SWAT+is an advanced version of the SWAT model, designed to provide improved flexibility in connecting spatial units and in depicting management operations (Bieger et al., 2017; Arnold et al., 2018). This semi-distributed model predicts hydrological processes, crop growth, sediment transport, and nutrient loads. It operates by segmenting hydrological basins into sub-basins and Hydrologic Response Units (HRUs), with each HRU representing areas with similar land use, soil, slope, and management practices (Neitsch et al., 2005). The model also differentiates between upland and lowland processes through landscape units (LSUs). SWAT+applies the hydrological water balance concept as the basic driver of all hydrological processes.

SWAT+estimates sediment yield using the Modified Universal Soil Loss Equation (MUSLE) for each HRU, improving prediction accuracy by utilizing surface runoff and peak flow rate data (Neitsch et al., 2005). The channel sediment routing equation is based on Bagnold's sediment transport equation (Bagnold, 1977), which considers sediment load entering the channel to either deposit excess sediment or re-entrain sediment through channel erosion. Plant growth in the model is simulated at the HRU level using the simplified version of the EPIC growth model (Neitsch et al., 2011). Management operations that control the plant growth cycle, timing of fertilizer and manure, irrigation application and removal of plant biomass can be scheduled through either calendar days or heat units (Nkwasa et al., 2022a). The model simulates nitrogen (N) and phosphorus (P) nutrient cycles, tracking multiple inorganic and organic forms of both elements. Mineralization, decomposition, and immobilization are key aspects of both cycles. Nitrogen migration and transformation are calculated considering water volume and soil nitrate concentration, while organic N and P transport with sediment is predicted based on topsoil concentrations, sediment yield, and an enrichment ratio. From the land phase, nutrients can be introduced into the channel and transported downstream through surface runoff and lateral subsurface flow (Neitsch et al., 2011).

In-stream nutrient dynamics are simulated using the kinetic routines from the QUAL2E in-stream water quality model (Brown and Barnwell, 1987). The model tracks nutrients dissolved in the stream and nutrients sorbed to the sediment. Dissolved nutrients are transported with the water while those sorbed to the sediment are allowed to be deposited with sediment on the channel bed. For more details on nutrient processes in the SWAT+model, refer to the SWAT documentation (Arnold et al., 1998; Neitsch et al., 2011).

2.2. Global datasets used in the study

The water quality model for Africa was constructed and evaluated using the freely available global datasets listed in Table 1.

2.3. Model setup

The modelling process was organized in the following way: First, the default SWAT+model (revision 60.5) was set up for Africa 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; Nkwasa et al., 2024a). Decision tables enable the user to model intricate sets of rules and their subsequent actions by allowing users to add conditions for scheduling management (Nkwasa et al., 2022b). Secondly, the model was calibrated and validated using observed river discharge data, observed river TN and TP concentrations, and river sediment loads.

For the nonpoint sources of pollution, the model applies workflows similar to Nkwasa et al. (2022c), where crop phenology (plant and harvest days) and crop management (irrigation, N and P fertilizer and manure application rates) were extracted from the global datasets for both rainfed and irrigated areas (HRUs), while N atmospheric deposition was extracted for all HRUs in Africa. The point source (PS) input data to each subbasin was extracted from Beusen et al. (2022). However, the input data for point sources was in the form of TN and TP loads, whilst SWAT requires inputs for different forms of N and P. Ratios were established for organically bound N to inorganic NH_3 and NH_4 at 0.25:0.75, while ratios for organic phosphate to orthophosphate were set at 0.25:0.75 (Rossle and Pretorius, 2001; Pagilla et al., 2008; Gu et al., 2011; Hoxha et al., 2022). The ratios primarily capture raw and/or primary effluent speciation ratios. This assumption was made because in large cities across sub-Saharan Africa, on average, over 80 % of wastewater remains untreated. It is either released into the soil through on-

Table 1
Global datasets used for the modelling process.

Global Datasets	Resolution Temporal	Spatial	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)
Climate (precipitation, temperature, windspeed, solar radiation and relative humidity)	Daily	0.5°	GSWP3-W5E5 (Mengel et al., 2021; Dirmeyer et al., 2006;' Kim, 2017)
Irrigated areas	–	0.083°	Food and Agriculture Organization (FAO; Siebert et al., 2013)
Plant and harvest dates	–	0.5°	Global Gridded Crop Model Intercomparison (GGCMI; Jägermeyr et al., 2021)
Fertilizer use rate (N and P)	Yearly	0.5°	(Hurtt et al., 2020; Lu and Tian, 2017)
Manure use rate (N and P)	Yearly	0.5°	(Potter et al., 2010)
Atmospheric N deposition	Monthly	0.5°	ISIMIP (https://www.isimip.org; Tian et al., 2018)
Point source (wastewater discharge)	5 –year	0.5°	(Beusen et al., 2022)
Observed river discharge	Monthly	River gauge	Global Runoff Data Centre (GRDC; https://grdc.bafg.de)
Observed river TN and TP concentrations	Daily	River gauge	Global Freshwater Quality Database (GEMStat; https://gemstat.org/)
Observed/reported river sediment load	Annual average	River gauge	Literature search

site sanitation systems or directly discharged into rivers and lakes (Nyenje et al., 2010).

2.4. Model calibration and validation

For the hydrological component, model calibration and validation were performed in Chawanda et al. (2024). To summarize, a Hydrologic Mass Balance Calibration (HMBC) procedure (Chawanda et al., 2020) was employed to calibrate the model against long-term annual average water balance components. Six 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 component using previous SWAT literature. The statistical indicator Nash-Sutcliffe Efficiency (NSE) (Moriasi et al., 2015) calculated based on monthly data was used to assess the model performance. After calibration, 96 out of 154 gauging stations achieved a monthly NSE>0, with 50 gauging stations having NSE>0.5 at the river outlets (Online resource, Fig. A1, Chawanda et al., 2024). Low model performance was observed at gauging stations that were downstream of reservoirs, which was expected as a lack of data on dam management contributes to a poor simulation of river flows through reservoirs (Chawanda et al., 2024). This also has implications for nutrient retention and transformation, particularly phosphorus and sediment-bound nitrogen. For more details on the hydrological calibration, validation, and application of this model, refer to Chawanda et al. (2024).

Calibrating water quality variables, such as river sediment loads and nutrient loads (TN and TP), presents significant challenges due to limited in-situ and modelling data, especially in Africa (Nkwasa et al., 2024b). To address this, a regionalization procedure was followed for improving large scale soil erosion (Nkwasa et al., 2022c; Nkwasa et al., 2024a) and river sediment loads were calibrated by adjusting the bedload coefficient for 18 rivers (Online resource, Fig. A2) to ensure comparability between simulations and observed annual averages. The bedload coefficient determines the amount of incoming sediment in a river that settles as bedload (Neitsch et al., 2005). Concerning reservoir sedimentation, an annual trap efficiency of 79 % was determined for all reservoirs, except for the Aswan High Dam, where the rate was set at 98 % (Eizel-Din et al., 2010). However, it is important to recognize that the trap efficiency of a reservoir declines gradually over time as its capacity is reduced due to sediment accumulation (Nkwasa et al., 2024a).

In addition, simulated continental soil erosion estimates were compared with previous estimates from global soil erosion models. For TN and TP river concentrations, 18 and 20 gauging stations were calibrated, respectively, with more than 85 % of gauges located in South African rivers. Evaluation was performed using statistical indicators: NSE, percent bias (PBIAS), and a coefficient of determination (R^2). Calibration was focused on nutrient balance parameters, specifically, N and P plant uptake distribution, N and P percolation coefficient, P availability index, and organic N enrichment ratio. Validation efforts also included comparing the TN and TP river loads with previous estimates from global nutrient models and comparing simulated nutrient balance with other existing studies (Online resource, Table A1 and Table A2).

2.5. Mapping towards SDG indicator 6.3.2 for nutrient targets

Evaluating the SDG indicator 6.3.2 involves comparing measured or simulated physio-chemical parameters such as TN and TP to a numerical concentration criterion/benchmark that represents good ambient water quality. We used the optional UNEP target thresholds set for TN and TP in rivers at 0.7 mg/L and 0.02 mg/L, respectively (Warner, 2020; UN Water, 2021). These target thresholds serve as provisional targets in countries where national ambient water quality standards have not yet been established. Since national thresholds were unavailable for many countries in Africa, we applied these optional UNEP thresholds across the continent in our analysis. They act as a foundation for nations aiming to set new targets as they gather more localized data. To classify whether a water body is of "good ambient water quality" or not, a target threshold is applied where 80 % or more of monitoring values must meet their benchmark targets (Warner, 2020; UN Water, 2021). UNEP utilizes the preceding three years' data to calculate the indicator for each reporting year.

In this analysis, in line with the UNEP assessment method for the SDG indicator 6.3.2, the indicator is determined for the reporting year, 2020. This is assessed by examining the proportion of daily simulated values from the preceding three years (2017 – 2019) that fall below target thresholds for both TN and TP. This percentage reflects the nutrient water quality status, indicating the percentage compliance in achieving the target thresholds. If the compliance percentage is 80 % or more, then the water quality is classified as "good ambient water quality". To provide a holistic view, a combined percentage compliance is computed by examining the proportion of daily simulated values that fall below target thresholds for both simulated TN and TP concentration values in one single pool. For example, all TN and TP measurements are individually assessed against their respective targets, resulting in a series of ones (met target) and zeros (did not meet target) for all daily simulated values of a river reach. An 80 percent compliance threshold is then applied to this data to determine whether a water body has "good ambient water quality" or not. The continental indicator score and river basin score are also calculated for chosen major river basins by computing the average compliance across the river bodies at both continental and river basin levels (Online resource, Fig. A3). This consolidated indicator score aligns with UNEP's approach of classifying water quality for the SDG indicator 6.3.2 (Warner, 2020).

Initially, the percentage compliance for South Africa is computed using both simulated and observed values to assess model consistency with available observed data. South Africa is chosen due to the availability of observed TN and TP river concentration data. This assessment is then extended to the continental scale of Africa using simulated values for the reporting year of 2020. Additionally, the percentage compliance for the reporting year of 2013 (based on preceding years 2010 – 2012) is calculated and the difference between the two reporting years is analysed to evaluate changes in compliance percentages (target threshold achievements) over time in the recent decade of simulation. A change was deemed significant if it exceeded ± 5 %.

3. Results

3.1. Model evaluations

3.1.1. Soil erosion and river sediment load evaluation

The current study estimates a continental soil erosion rate of 3.57 t ha^{-1} yr^{-1} (Fig. 1) simulated between 2010 and 2019. These findings align with similar estimates reported in other global studies. For instance, Borrelli et al. (2017) estimated soil erosion rates in Africa to have risen from 3.51 to 3.88 t ha^{-1} yr^{-1} between 2001 and 2012. Furthermore, Yang et al. (2003) estimated continental soil erosion rates ranging from 3.8 to 4.4 t ha^{-1} yr^{-1} from the 1900 s to the 1980 s. The simulated long term annual average river sediment loads in the model across the continent were comparable to the reported ranges of observations (Online resource, Table A3) after calibration. River sediment loads affect TP and TN levels through the transport of nutrient-bound particles.

3.1.2. TN and TP evaluation

The evaluation periods for the TN and TP gauging stations (Fig. 2) corresponded to data available for any period within 1982 to 2017. Out of the stations that are used in the monthly river TN and TP concentration calibration, more than 75 % achieved an NSE>0.35 (Fig. 2), PBIAS ≤ ± 30 % and R^2 > 0.3, (Figs. 2 – 4), showing a satisfactory performance (Moriasi et al., 2015) with good seasonality, particularly given the data scarcity in Africa. The validation efforts further show that the continental estimates of river sediment export to coastal waters (long-term averages of 3.1 Tg N/yr and 1.2 Tg P/yr for 1980 – 2019) align with the ranges estimated by previous continental to global studies (4 – 7.7 Tg N/yr and 1 – 1.5 Tg P/yr) (Yasin et al., 2010; Mayorga et al., 2010; Seitzinger et al., 2005). Additionally, a comparative analysis for

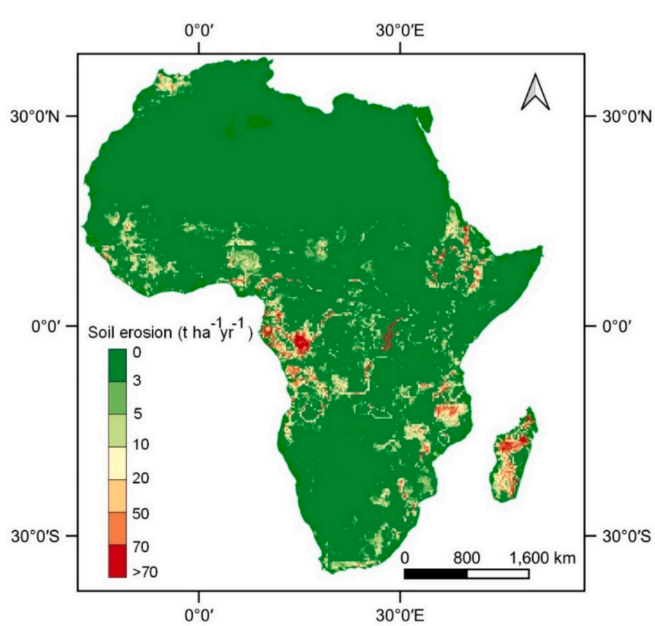

Fig. 1. African continental annual average rates of soil displacement by water erosion for the recent decade (2010 – 2019).

nutrient balance (Online Resource, Table A1) and nutrient export for four of Africa's major rivers (Online Resource, Table A2) was conducted, showing similar magnitudes of nutrient fluxes. The model was deliberately not fine tuned to avoid over parametrization using observations from mostly South African rivers (Fig. 2), which is a key limitation in scalability of the model. Further improvement of model performance requires a sensitivity analysis and more data time series representing other regions in Africa. However, the limited availability of data poses a significant challenge for both the development and evaluation of large-scale water quality models. Importantly, this modelling framework allows for calibration with localized water quality data as it becomes available. While initial data might be centred around South Africa, the model's framework allows for incorporating local data into the model to improve performance in specific areas.

There are various possible explanations for the poor performance at some stations (Figs. 2 – 4). First, the model might not accurately represent the observed peaks, particularly if the monthly aggregate derived from the measurements is overestimated due to a limited number of observations within the month. Second, the input data resolution of 0.5° for TN and TP sources may not be sufficiently detailed for smaller rivers, especially when considering point sources that release TN and TP loads at specific locations. Factors that might contribute to model uncertainties, include; watershed processes not incorporated into the model (e.g., wind erosion, wetland processes), human interventions (e.g., water transfers, farm management affecting water quality), and the quality of other input data. In large watershed applications, these types of uncertainties might account for some prediction errors. However, as highlighted by UNEP (2016), large scale water quality models aim to provide reliable estimates that capture the broader trends, seasonality, and hotspots. Overall, there is a strong agreement between simulated and observed concentration ranges (Fig. 3 and Fig. 4), underscoring the model's ability to simulate concentrations within the correct concentration range displaying pronounced seasonality in the process.

3.2. Mapping TN and TP hotspots using SDG indicator 6.3.2

3.2.1. A South African case study

The UNEP criteria to determine "good ambient water quality" requires 80 % or more of the monitoring values to be within set target thresholds. In this case, model simulated values were utilized instead of measured values to evaluate the compliance against the set target threshold. The consistency between daily observed and model simulated TN and TP concentration values was assessed for selected South African rivers considering the reporting year 2020 (Fig. 5). Among the 28 river gauging stations with daily data available during the selected period (2017 – 2019), 21 rivers attained the same compliance percentage ranges (target threshold achievements) for simulated TN as in the observed data (Fig. 5a and Fig. 5b, respectively), while 25 rivers achieved corresponding compliance percentage ranges for simulated TP as in the observed data (Fig. 5c and Fig. 5d, respectively). Overall, the model closely aligns with observed values, achieving a high similar river classification rate (i.e., 75 % and 89 % for TN and TP, respectively).

For TN in the selected time period, all selected rivers achieved less than 60 % of the target threshold (0.7 mg/L), which does not qualify as "good ambient water quality" for TN. In contrast, for TP, 26 rivers (92 %) achieved more than 80 % of the target threshold (0.02 mg/L), thus, qualifying as possessing "good ambient water quality" for TP for the selected period.

3.2.2. Continental perspective on TN and TP hotspots for reporting year 2020

Scaling SDG indicator 6.3.2 analysis to the continental scale, simulated daily time series data from 2017 to 2019 are analysed for reporting year 2020 by applying the UNEP criteria to determine "good ambient water quality" that requires 80 % or more of the monitoring values to be within set thresholds. Throughout this period, the majority of African

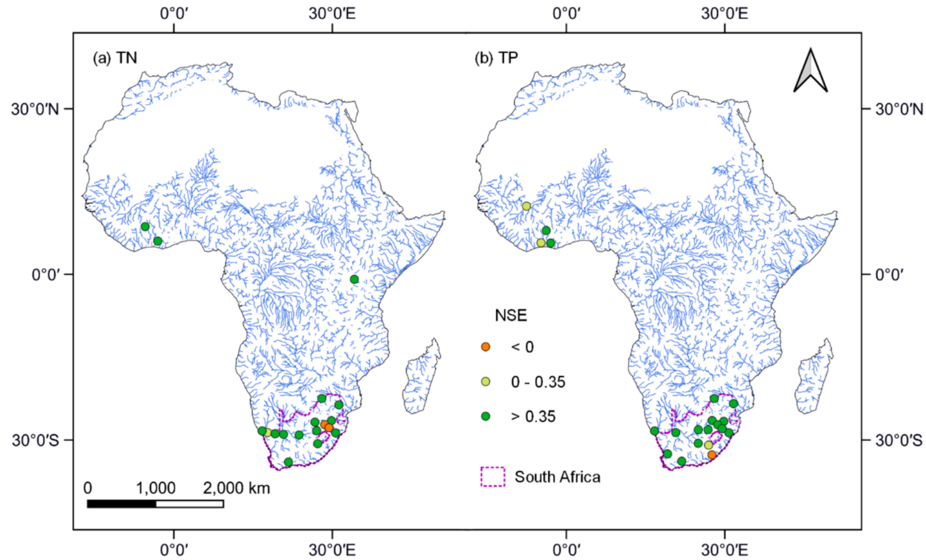

Fig. 2. Monthly NSE values for (a) TN and (b) TP river gauging stations across the SWAT+Africa Model.

rivers exhibited TN concentrations within the target threshold (0.7 mg/L), with just 15 % of the rivers falling short of achieving a compliance percentage of 80 % or higher (Fig. 6a). In contrast, there was a significant number of rivers having lower compliance rates in achieving UNEP target thresholds of TP concentration (0.02 mg/L), with 44 % of the rivers registering compliance percentages of less than 80 % (Fig. 6b).

When considering both TN and TP together (Fig. 6c), 34 % of the rivers did not achieve a compliance percentage of 80 % or higher. Thus, 44 % and 15 % of the rivers do not meet the quality targets for TP and TN, respectively, while 34 % of the rivers do not qualify as having "good ambient water quality" when considering TN and TP parameters combined. Looking at the average compliance across the continent gives an indicator score of 61 % while across river basins shows ranges from 19 % to 78 %, with the lowest indicator score obtained in the Sebou River basin and the highest in Senegal River basin (Online resource, Fig. A3).

3.2.3. Change in compliance percentages between the 2020 and 2013 reporting years

A comparison between two reporting years, 2020 and 2013 (Fig. 7), for the direction of changes in compliance percentages (target threshold achievement) reveals spatially different directions of change. Here, a positive change in a river indicates an improvement in meeting target thresholds, whereas a negative change suggests a decline in meeting these thresholds. For TN (Fig. 7a), 8 % of rivers had a significant positive change, while 4 % experienced a significant negative change. The majority of rivers (88 %) underwent relatively minor changes or remained stable over the years.

For TP (Fig. 7b), 7 % of rivers displayed a significant positive change, whereas 12 % showed a significant negative change. Similarly, the majority of rivers (81 %) saw little to no change over the reporting years. Combining both TN and TP (Fig. 7c), 7 % and 5 % experienced significant positive and negative changes respectively. These changes, although seemingly small gain significance when considering the broader context as they represent changes in a fraction of the 5644 rivers in Africa.

4. Discussion and limitations

4.1. 1 contextualizing the results within the broader landscape of research across the continent

The current findings offer comprehensive insight into the water quality of 5644 rivers and hotspots spanning the African continent. Geographically, the most pronounced nutrient hotspots were identified in North Africa and West Africa (mainly, the Niger Delta) (Fig. 6c – 6d). The Niger Delta in the Niger River basin (Fig. 6d) presents a less optimistic status, with most rivers having fewer values within the target thresholds, as corroborated by the recent UN Water (2021) progress report. This degradation can be traced back to a surge in human activities leading to excessive nutrient influx, as noted by Nafagha-Lawal et al. (2022). The simulation findings for North Africa show similar patterns to the observations made by Perrin et al. (2014). They demonstrated that the Sebou River basin (Fig. 6d and Fig. A2) in North Africa consistently records TP concentrations that surpass the Moroccan environmental quality targets of levels at 0.3 mg/L for TP. Other significant nutrient hotspot regions included select parts of southern Africa, and the Nile River basin (Fig. 6a – 6d). In the Nile River basin, high nutrient concentrations have been reported in previous studies (Hussien et al., 2021; Hasaballah et al., 2019; Abdel-Satar, 2005), while in southern Africa, Villiers and Thiart (2007) highlighted rivers, particularly in the Orange River basin (Fig. 6d), showing conditions of dissolved inorganic phosphates exceeding 0.02 mg/L throughout the year.

In West Africa, the results from the Senegal River basin (Fig. 6d) mirror findings by Mbaye et al. (2016), who reported that concentrations are still relatively low in the basin, indicating low human impact. The Congo River basin (Fig. 6d), representing a significant chunk of Africa's freshwater, shows that most rivers achieve 60 – 80 % of the values below the UNEP target thresholds (Fig. 6a – 6c), in line with the UN Water (2021) report. However, water quality studies in the Congo River basin remain *terra incognita* (Meybeck, 2005), except a few studies that have been made upstream in the basin e.g., in Lake Kivu, studies that have reported contradicting nutrient statuses of low (Bagalwa et al., 2015) and high (Bisimwa et al., 2022) concentrations compared to the United Nations Economic Commission for Europe (UNECE, 1994) and World Health Organization (WHO, 2011) standards.

Overall, rivers not achieving target thresholds (low compliance percentages) correlate with regions characterized by high fertilizer and manure use (Online resource, Fig. A4) and high wastewater discharge loads (Online resource, Fig. A5), particularly in North Africa, the Niger River delta, Nile River basin, Congo River basin and southern Africa. These sources of nutrient pollution have also been documented by Perrin et al. (2014) in North Africa, Hussien et al. (2021) and Abdel-Satar (2005) in the Nile River basin, and Villiers and Thiart (2007) in southern Africa. This means that reducing nutrient use and loss will have a great positive impact on water quality in Africa. Therefore, implementing targeted strategies for efficient fertilizer application and wastewater

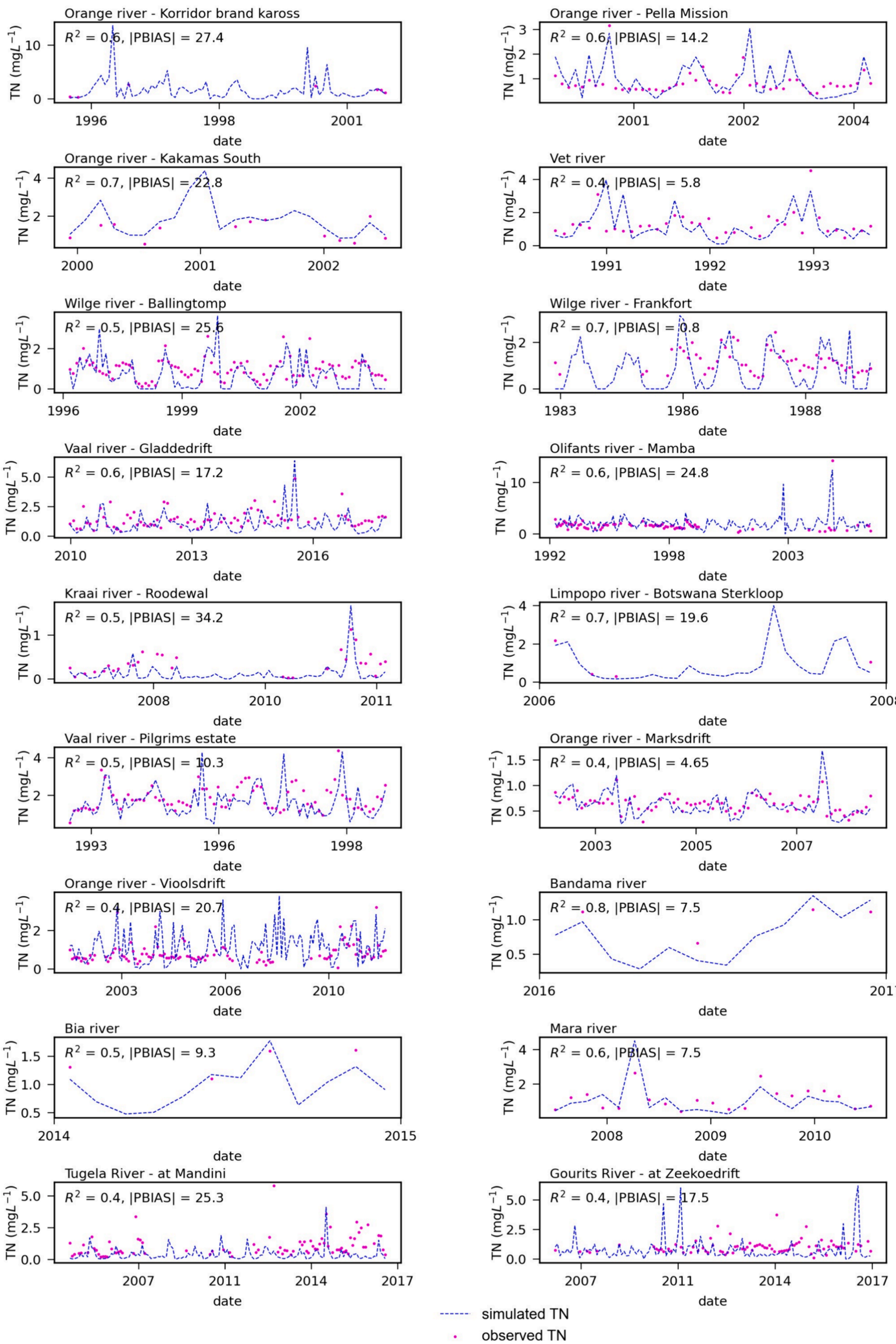

Fig. 3. Monthly simulated and observed river TN concentrations at selected gauging stations in Africa.

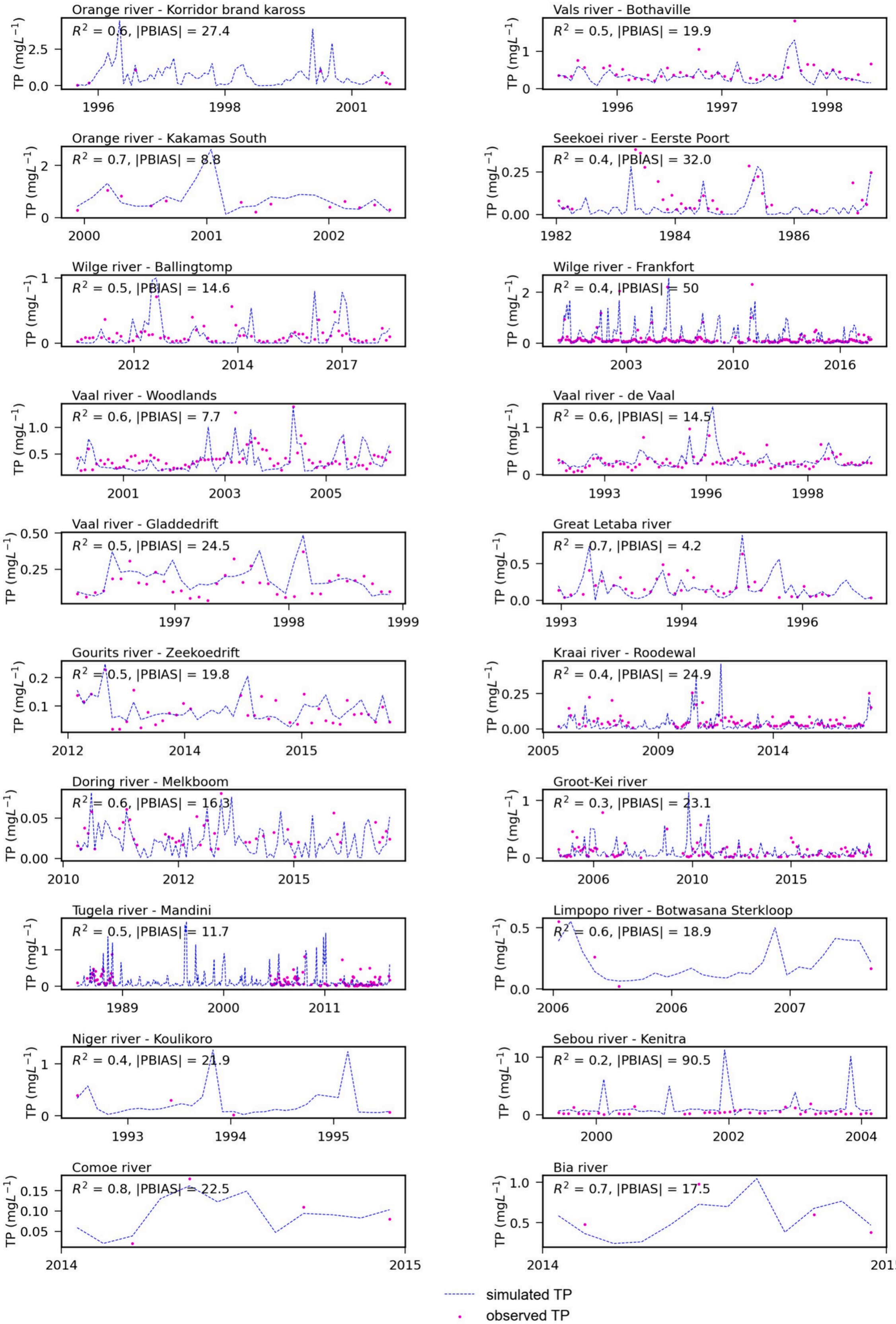

Fig. 4. Monthly simulated and observed river TP concentrations at selected gauging stations in Africa.

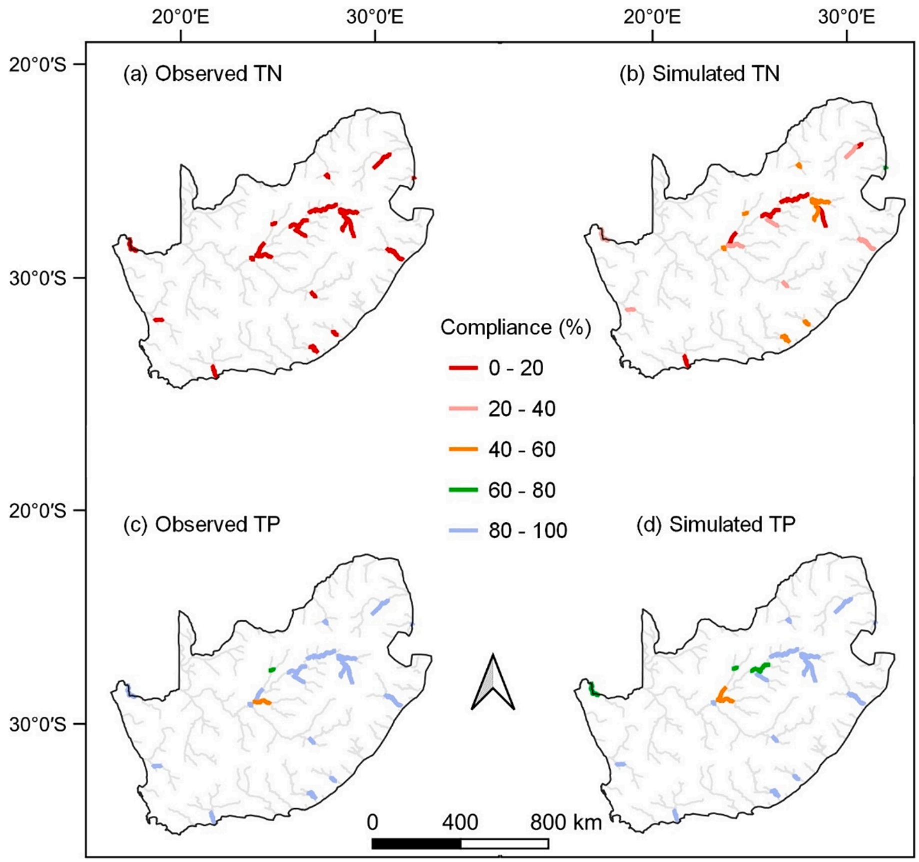

Fig. 5. Proportion of daily (a) Observed TN, (b) Simulated TN, (c) Observed TP, and (d) Simulated TP values between 2017 and 2019, within target thresholds (compliance percentage) for selected South African rivers.

treatment is crucial in Africa to address the high nutrient concentrations especially for TP. Furthermore, different climatic patterns in different regions could influence the nutrient concentration levels. For example, arid conditions in North Africa with low precipitation amounts (Online resource, Fig. A6), limit dilution capabilities, further exacerbating concentration levels. Thus, a better understanding of the climate impacts and the natural purification processes in African rivers will help implement actions and steps aimed at improving water quality.

4.2. SDG 6.3.2 indicator outlook

The current study shows that TP concentrations are especially concerning, as they persistently fail to meet the “good ambient water quality” status in a majority (44 %) of African rivers during the simulation period, as compared to TN concentrations that fail to meet the status in 15 % of the rivers. This alarming pattern aligns with a recent UNEP report, which finds that among various water quality metrics, both TN and more noticeably, TP frequently miss their set benchmarks (UN Water, 2021). These simulated concentration patterns result from a complex interplay of factors including loadings from point and nonpoint sources, the dilution capacity of streams, and in-stream decay processes. It’s important to highlight that these continental-wide UNEP targets for SDG indicator 6.3.2 might overlook the natural diversity of different water bodies, potentially compromising the water quality of some rivers. On the other hand, while these thresholds provide a general guideline, some environments might require even stricter nutrient concentration limits to preserve downstream ecosystems (Dodds and Welch, 2000). Examining the shifts from the previous reporting year, a nuanced outlook is observed, revealing both positive and negative changes. These results underscore the necessity for targeted strategies in specific areas to prevent the exacerbation of nutrient hotspots. However, future analyses should consider examining long-term trends in adherence to “good ambient water quality” status over multiple years, rather than focusing solely on changes between two reporting periods. This approach would provide a more comprehensive understanding of water quality performance over time.

When considering the combined TN and TP threshold achievements, this study showed that about a third of the rivers in Africa do not meet the “good ambient water quality” status. However, the approach of combining the threshold percentages from only two parameters into a binary result of “good or not good ambient water quality” is a weakness as TN and TP are only two of the five core parameters (Warner, 2020). Future work is recommended to integrate other recommended UNEP core reporting parameters (salinity, oxygen, and acidification) with the current TN and TP datasets for a holistic SDG 6.3.2 assessment. Furthermore, relying solely on UNEP’s core water quality parameters might not be sufficient, especially without considering emerging water quality threats, such as pharmaceuticals and microplastics (Guppy et al., 2019). For instance, for emerging contaminants such as antiretroviral and antimalarial drugs that are rarely detected in the Western world, occurrence patterns in Africa reveal concentrations up to $> 100 \ \mu g \ L^{-1}$ (K’oreje et al., 2020), which are of toxicity concern for both ecosystems and humans. Currently, UNEP has a level 2 reporting scheme that allows for the incorporation of any other water quality parameters such as pathogens, and biological and physio-chemical parameters in the SDG indicator 6.3.2 reporting (Warner, 2023).

The calculation of the SDG 6.3.2 using a ballpark of available observed data could have a level of uncertainty given that the data may not be available daily but rather seasonally. This can bias the indicator towards specific seasons, as opposed to utilizing simulated daily data that covers all seasons. Additionally, relying solely on a limited number of gauge stations, as seen in the case of South Africa (Fig. 5) with data

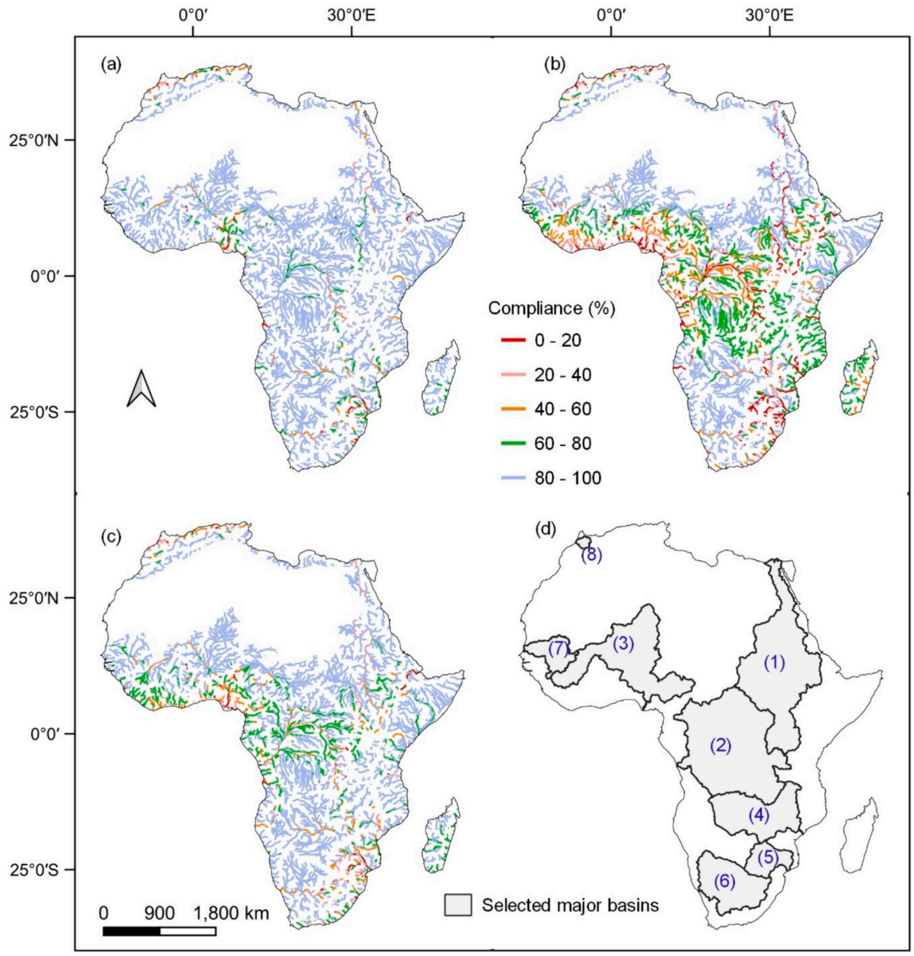

Fig. 6. Proportion of simulated values between 2010 and 2019 within target thresholds (compliance percentage) for (a) TN, (b) TP and (c) Nutrient indicator (combined TN and TP indicators). (d) Selected major basins – (1) Nile, (2) Congo, (3) Niger, (4) Zambezi, (5) Limpopo, (6) Orange, (7) Senegal, and (8) Sebou. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

from only twenty eight gauge stations for 2017 – 2019, may not provide a comprehensive nationwide assessment. Thus, complementing the measured data with modelled results, which offer consistent spatial and temporal resolution and coverage, would provide a more comprehensive nationwide picture.

5. Conclusion

Overall, this study serves the dual purpose of addressing the research gap in regional to continental modelling of river nutrient water quality in Africa and mapping nutrient river hotspots according to the SDG indicator 6.3.2. The findings of this research provide baseline information on the water quality (sediment load, TN, and TP) of African rivers at high temporal and spatial resolution, and how the concentrations change over time and space. This information sets the stage for further exploration into the spatial and seasonal river nutrient changes in Africa. In the SDG context, this study shows that 34 % of the rivers in Africa do not qualify as having “good ambient water quality”, with the most pronounced nutrient hotspots identified in North Africa, the Niger Delta in West Africa, Congo River basin, Nile River basin and specific zones in southern Africa. These findings, along with the generated data augment the GEMStat database, offering a tool to monitor SDG target 6.3 progress and project potential outcomes by 2030, especially in areas where little or no information are available on whether water quality is suitable to support sustainable development, despite its fundamental importance. The significance of this research extends beyond the realm of water quality modelling. It holds relevance for the broader scientific community, offering essential methodological approaches and valuable data that can influence policies related to water resources management. For instance, by highlighting areas that do not qualify as having “good ambient water quality,” our results provide insights for national policy and decision makers to prioritize remediation efforts, develop targeted policies, interventions, and regulatory frameworks to improve water quality. However, the study acknowledges certain limitations, such as the reliance on a limited number of water quality observations (specifically TN, TP, and sediment concentrations and loads), the lack of detailed dam management operations, and the use of mostly global datasets for the modelling framework. Therefore, future research should aim to incorporate a broader range of local measurement observations, longer data records and improved model structures to enhance the robustness of water quality modelling in Africa.

6. Code availability

The codes used in this study are available open-access through a GitHub repository (https://github.com/VUB-HYDR/2023_Nkwasa_et_al).

CRediT authorship contribution statement

Albert Nkwasa: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal

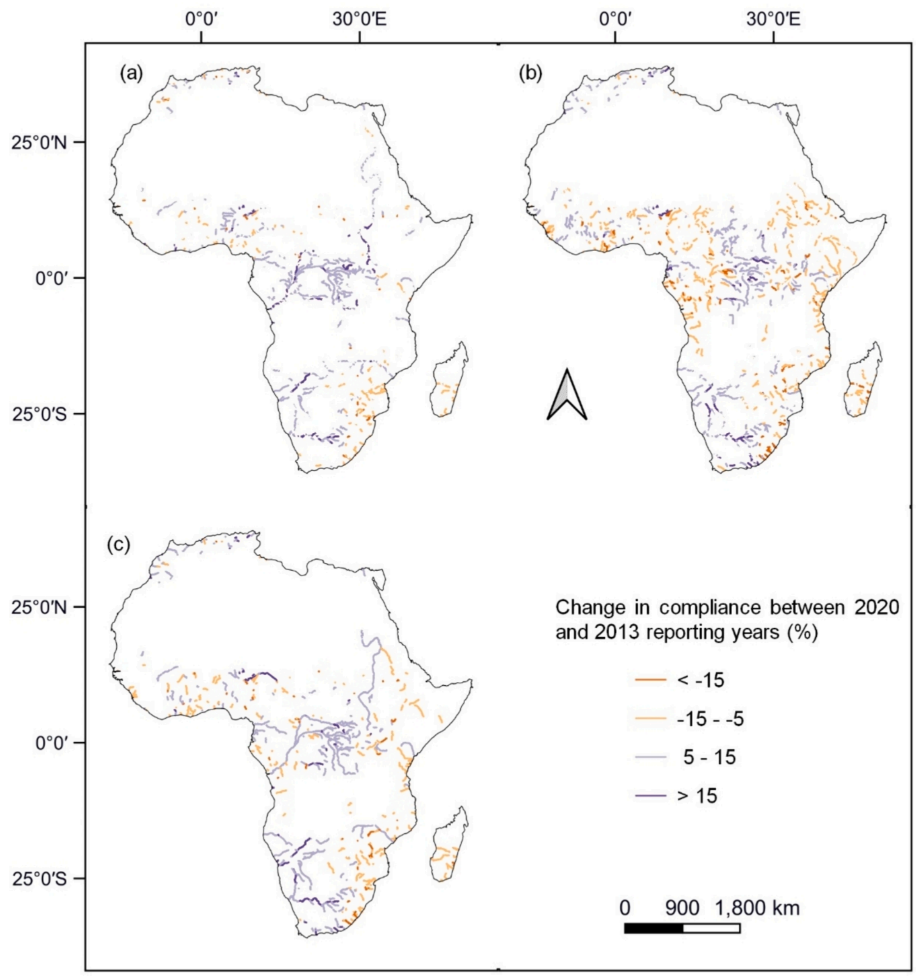

Fig. 7. Change in percentage compliance between 2020 and 2013 reporting years for (a) TN, (b) TP, and (c) the combined TN and TP indicator. Only changes that are fall outside the range of −5 to + 5 are shown. A positive change signifies an improvement while a negative change signifies a decline in achieving target thresholds.

analysis, Data curation, Conceptualization. **Celray James Chawanda:** Writing – review & editing, Validation, Methodology, Formal analysis. **Maria Theresa Nakkazi:** Writing – review & editing, Visualization, Formal analysis. **Ting Tang:** Writing – review & editing, Methodology, Investigation. **Steven J. Eisenreich:** Writing – review & editing, Methodology, Conceptualization. **Stuart Warner:** Writing – review & editing, Validation, Methodology. **Ann van Griensven:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The water quality model simulations of river sediment loads, and TN and TP loads and concentrations for Africa are available at https://doi.org/10.5281/zenodo.13254969.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.112544.

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