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Stakeholder-informed mapping of climate change impacts on the water-energy-food-environment nexus in the Lake Victoria basin

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Abstract

The water-energy-food-environment (WEFE) nexus supports integrated, cross-sectoral analysis of socio-environmental challenges. Multiple nexus sectors in the Lake Victoria basin (LVB) already experience significant stress, and climate change will likely intensify these pressures. Current WEFE nexus tools remain relevant but do not use process-based modelling or stakeholder-driven indicator development. Without these components, it is difficult to account for local knowledge systems and priorities. They also miss key biophysical dynamics that shape historical and future conditions. This study introduces a new approach that uses participatory methods and process-based modelling to develop a stress-analysis tool for the LVB. Indicators selected by stakeholders were operationalised by soft-coupling an eco-hydrological and land management model with a lake-ecosystem model. This enabled quantitative analysis of 77% of high-priority indicators and improved existing WEFE methodologies. The framework assessed historical stress patterns, explored mid-century changes under two climate scenarios, and offers temporal and spatially explicit insights into future vulnerabilities. Our framework is transferable to data-scarce, transboundary systems and demonstrates the value of integrating participatory approaches with process-based modelling. Multiple stress hotspots already exist across the nexus in the LVB. Future projections show both intensification and expansion of stress hotspots that concentrate in densely populated, transboundary regions. Degradation of water quality, lake biodiversity, and agricultural productivity, combined with increased land degradation, will expose more people to important nexus stresses, rising from about 15.5 to up to 20.1 million under future scenarios. This underscores the need for regional cooperation and adaptation measures.

1. Introduction

The water-energy-food (WEF) nexus has emerged as a key framework for assessing complex socio-ecological challenges under accelerating global change pressures (Hirwa *et al* 2021, Yoon *et al* 2022). This integrated systems approach recognises that water, energy, and food resources are fundamentally interconnected, requiring coordinated management strategies that move beyond traditional sectoral approaches. However, the ecological foundation that provides essential support for all other nexus components remains systematically neglected in most nexus applications. This omission is especially problematic given that ecosystem degradation can cascade through multiple nexus components simultaneously, undermining the sustainability of water, energy, and food systems. Recognition of this limitation has driven the evolution from the WEF to the WEF-environment (WEFE) nexus, which explicitly incorporates environmental systems as a critical fourth pillar.

Approaches for WEFE nexus assessments have advanced considerably, with a growing diversity of tools combining indicator-based approaches and process-based models, and integrated frameworks exist. Hydro-environmental models, such as the Soil and Water Assessment tool (SWAT) (Arnold *et al* 2012), WEAP (Yates *et al* 2005), together with hydrodynamic and ecohydraulic models, can represent a range of environmental processes associated with the nexus. Some studies have applied these types of tools to explicitly represent environmental variables, including hydrological, hydrodynamic and sediment modelling (Schmitt *et al* 2018, Trung *et al* 2020), ecohydraulic modelling for fish habitat assessments (Kuriqi *et al* 2020), and assessments of floodplain connectivity and flow-regime changes on aquatic biodiversity (Angarita *et al* 2018), demonstrating the value of process-based approaches for nexus analyses. Moreover, energy-focused tools such as the low emissions analysis platform (Weap and Leap 2025), or the Model for Energy Supply Strategy Alternatives and their General Environmental Impact are commonly used in nexus assessments producing outputs related to the environmental pillar through proxies and indicators, though without mechanistically simulating underlying environmental processes. These types of tools can be combined within integrated frameworks such as CLEWS, DAFNE, and PRIMA (Schlemm *et al* 2024), which bring multiple sectoral tools under a common structure. On these modelling approaches, the level of process complexity required to represent depends on the study's purpose. For example, optimisation approaches for the design of management strategies and portfolios (Kasprzyk *et al* 2009, Hurford *et al* 2020) generally require simpler models to achieve computational efficiency, whereas assessments focusing on understanding dynamics from a limited set of scenarios (e.g. management, future climate) can benefit from more complex models that capture feedbacks across sectors in greater detail.

Despite considerable advances, WEFE nexus modelling still faces constraints that limit its policy relevance and scientific applicability. Most tools lack geo-spatial representation capabilities, even though WEFE resources have important spatial heterogeneity (Taguta *et al* 2022). Many assessments rely on static indicator-based assessments from national statistics rather than process-based representations of system dynamics (Simpson *et al* 2022). Even when process-based models are used, many studies examine only two or three nexus pillars rather than the full WEFE system. This is not inherently a limitation, as the appropriate scope depends on the study context, but it matters particularly in assessments of climate change, as shifts across water, energy, food, and ecosystems create complex trade-offs (Winemiller *et al* 2016) that partial analyses may miss. Following this, the food pillar is often overlooked in process-based approaches, even though fisheries and crop yields depend on the same hydrological and biogeochemical dynamics that these models aim to capture. Moreover, the environmental component, whether in standalone models or integrated frameworks, is often treated through proxies such as weighted usable area or habitat fragmentation, or through simplified indicators, rather than through mechanistic ecological models that represent trophic dynamics and feedbacks on biogeochemical cycles, meaning that certain variables associated with biodiversity or fisheries may remain neglected in most WEFE assessments. In that sense, the limited representation of the environmental pillar may also fail to capture the interests and priorities of stakeholders, who largely benefit from or depend on environmental resources.

The limited inclusion of stakeholders in WEFE nexus research further undermines the practical applicability of research outputs. Current approaches predominantly engage stakeholders only as end-users of technical information, rather than as co-designers of research priorities, indicator frameworks, and modelling approaches (Hoolohan *et al* 2018, Sušnik *et al* 2018). This top-down approach creates a fundamental disconnect between scientific outputs and local needs, limiting policy uptake and practical application. The growing emphasis on participatory modelling and co-production approaches in sustainability science offers a pathway to address these limitations by ensuring that scientific research responds to the actual needs, values, and priorities of stakeholders (Bielicki *et al* 2019, Schlemm *et al* 2024). However, stakeholder engagement remains limited in spatial WEFE nexus tools, such as the WEF Nexus Tool and PRIMA, with most failing to incorporate local priorities into indicator development or model design. This gap between scientific tools and local knowledge and priorities limits the capacity of nexus assessments to inform management decisions efficiently. Addressing this disconnect becomes increasingly urgent as climate change acts as an amplifier of WEFE vulnerabilities (Byers *et al* 2018), generating pressures that local communities experience most directly.

Climate risks compound through simultaneous impacts across multiple WEFE sectors, driven by the interwoven nature of the nexus, creating vulnerability hotspots where adaptive capacities can become overwhelmed. These WEFE nexus climate hotspots, defined as geographic areas experiencing high-magnitude, multi-sectoral climate impacts, require spatial identification to prioritise climate adaptation investments and target interventions such as nature-based solutions (NbS) (Rasul and Sharma 2016, Nhamo *et al* 2018), and to map vulnerability asymmetries among communities and sectors (Hoolohan *et al* 2018, Mendoza *et al* 2018).

East Africa exemplifies the complex WEFE nexus challenges facing tropical regions under climate change, with the Lake Victoria basin (LVB) representing a critical socio-ecological system undergoing rapid transformation (Williams *et al* 2015, Nyamweya *et al* 2023). The basin supports over 40 million people across five countries and faces accelerating environmental challenges, including eutrophication, decreased biodiversity and fisheries yield, widespread deforestation, variable crop yields, increased flooding events, drought, and reduced water quality (Olokotum *et al* 2020, Nyboer *et al* 2022, Pietroiusti *et al* 2024). Climate projections indicate intensifying thunderstorms, precipitation variability, and extreme events, with potential anthropogenic contributions to recent extreme flooding events (Ogega *et al* 2023, Pietroiusti *et al* 2024). The basin's high population density and growth rates intensify pressures on natural resources, while climate impacts in the continent are disproportionate and further enhance current issues associated with social inequities (Nyiwul 2021), making it an ideal case study for understanding climate-WEFE interactions in data-scarce transboundary contexts, where accounting for stakeholder priorities is a necessity.

This study addresses the limits of current WEFE approaches with the LVB as a case study. We aim to understand historical stress patterns prioritised by stakeholders and explore future conditions. Given the limited capacity from existing WEFE tools to address indicators associated with stakeholder priorities (Schlemm *et al* 2024), we developed and applied an integrated modelling framework where we coupled the: SWAT+(Arnold *et al* 2012, Bieger *et al* 2017) with the Atlantis lake ecosystem model: ATLANTIS (Fulton *et al* 2011), to simulate variables associated with prioritized indicators from previous stakeholder engagements in the basin, leading to a spatial evaluation of hydrological, agricultural, water quality and ecological processes. Our framework identifies multi-sectoral risk hotspots and reveals possible exposure patterns across the basin. This helps prioritise climate adaptation planning. We also examine how stakeholder-informed WEFE assessments can influence climate adaptation policy in transboundary contexts, such as the LVB. This is the first use of coupled eco-hydrological, land-management, and lake-ecosystem models for a spatially explicit WEFE nexus climate assessment, which represents a significant methodological advancement for participatory environmental modelling in this context.

2. Methods

2.1. Study area

The LVB spans 251 000 km^2 across Uganda, Kenya, Tanzania, Rwanda, and Burundi, encompassing Africa's largest lake, Lake Victoria (68 900 km^2), which feeds the Upper White Nile (figure 1). The basin exhibits diverse topography, from lowlands to mountains, with major tributaries including the Kagera, Simiyu, and Mara rivers that drain into Lake Victoria. The region experiences a bi-modal rainfall pattern with long rains (March–May), short rains (October–December), and a dry season (June–September) (Ogega *et al* 2023). Mean annual precipitation ranges from 1200 to 1400 mm, contributing up to 87% of Lake Victoria's water balance through direct precipitation and tributary inflow (Global Environment Facility *et al* 2016, USAID 2016). The basin is a biodiversity stronghold, supporting 651 freshwater species, including 234 native fish, 135 aquatic plants, and 50 freshwater molluscs (Van Soesbergen *et al* 2019). However, environmental pressures have intensified dramatically in recent decades; agricultural expansion increased from 35% to 65% of land area between 1985 and 2014, whilst indigenous forest coverage declined by 80%–95% over the same period (Katusiime *et al* 2023). These land changes have contributed to nutrient pollution, erosion, eutrophication, and declining biodiversity. Population growth rates of 2.2%–3.0% exceed the global average (0.9%) (World Bank 2022), with livelihoods heavily dependent on natural resources for subsistence agriculture, fisheries, and energy provision (Onyango and Opiyo 2021, Nyboer *et al* 2022).

2.2. Stakeholder-driven indicators

We based our analysis on prioritised indicators developed through stakeholder engagement in previous research conducted in the study area by Schlemm *et al* (2024). In that work, stakeholders across the LVB were identified through a nonprobability snowball sampling approach, where initial contacts progressively expanded the network of participants. The resulting group spanned a broad range of sectors and institutions, including national and local government agencies (e.g. Ministry of Water and Environment of Uganda), research centres and universities (e.g. University of Dar es Salaam, Lake Victoria Centre for Research and Development), farmer, fisher and water user associations (e.g. Association of Fishers and

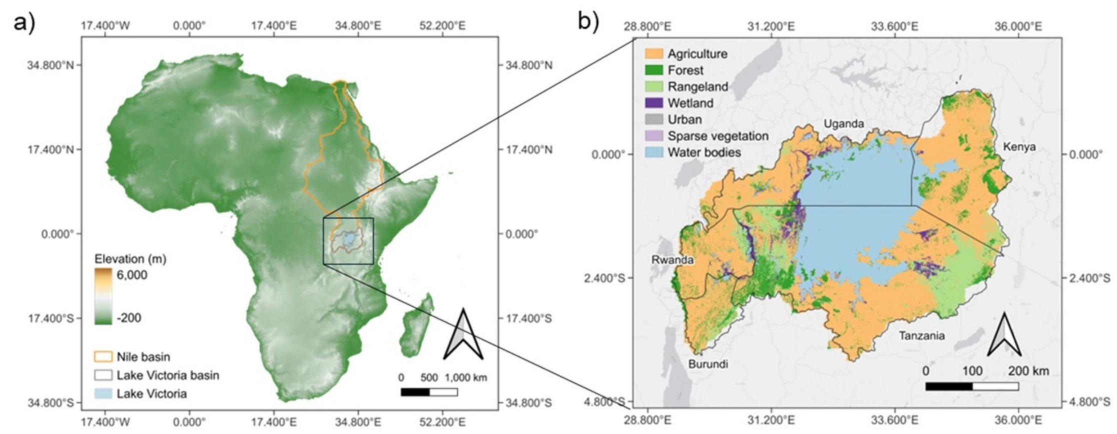

Figure 1. The Lake Victoria basin (a) position on the African continent; and (b) land use.

Lake Users of Uganda), tourism associations, water and energy service companies (e.g. Uganda Electricity Generation Company Limited), international cooperation agencies (e.g. Austrian Development Agency), and regional governance organisations (e.g. LVB Commission). Based on semi-structured, in-person interviews conducted between July 2022 and July 2023, divided into two sessions, several WEFE-related indicators were identified, along with the level of priority stakeholders give to them (figure 2). The level of priority was derived from the percentage of stakeholders who considered it a concern during the interviews. For a full list of identified stakeholders and further methodological details on the interview process and output processing, we refer the reader to the original study.

2.3. Integrated modelling framework

The framework uses a soft coupling between SWAT+ and ATLANTIS to provide a comprehensive representation of WEFE nexus interactions, with SWAT+ outputs at the landscape and river network levels used as inputs to drive ATLANTIS simulations. Then, the outputs of the soft coupling on the different components (figure 3) of the system were utilised to calculate WEFE nexus indicators. The model selection for our modelling framework was based on stakeholder-identified priorities and their heterogeneous nature, given the large variability among stakeholder groups in terms of their sectors of interest and spatial locations. The framework, through this model coupling, provides outputs for nine indicators related to water quantity, sediment yield, nutrient loading, crop and fisheries yield, aquatic biodiversity, land degradation, hydropower potential, and eutrophication.

With our framework, we are able to address 77 % of high-priority stakeholder-identified indicators, representing a substantial improvement over existing WEFE nexus tools, which typically address less than 33% of local priorities in the LVB, as identified by Schlemm *et al* (2024). Moreover, our framework treats the environmental pillar as a biophysical system by representing several underlying environmental processes, thereby allowing us to derive variables describing the system's state and underpinning the ecosystem services associated with that state.

2.4. The LVB SWAT+ model

The SWAT+ model is a widely utilised tool that can simulate streamflow, pollutant transport, and crop growth across different temporal and spatial scales and systems within a river basin, representing both processes at the landscape and river scales (Arnold *et al* 2012). It is a semi-distributed model with a structure based on hydrological response units (HRUs), landscape units, and sub-basins, in relation to terrestrial processes (e.g., surface runoff, erosion, nutrient leaching), and river reaches where routing of water and constituents occurs (Neitsch *et al* 2011, Bieger *et al* 2017, Nkwasa *et al* 2022). This study utilised outputs related to water quantity, water quality, and crop growth.

2.4.1. Model configuration

The SWAT+ model structure for the LVB was configured using mainly global datasets of topography, land use, crop distribution, and soil properties, provided in table 1, commonly used in SWAT+ applications. Agricultural land use areas were further detailed into four specific farming zones and their corresponding dominant crops following Adhikari *et al* (2015): 1) grain sorghum/millet for semi areas with 400–800 mm annual rainfall; 2) mixed maize for higher rainfall zones (800–1200 mm yr^{-1}) supporting diverse cropping systems; 3) cassava for areas with variable precipitation (600–1200 mm yr^{-1}) requiring

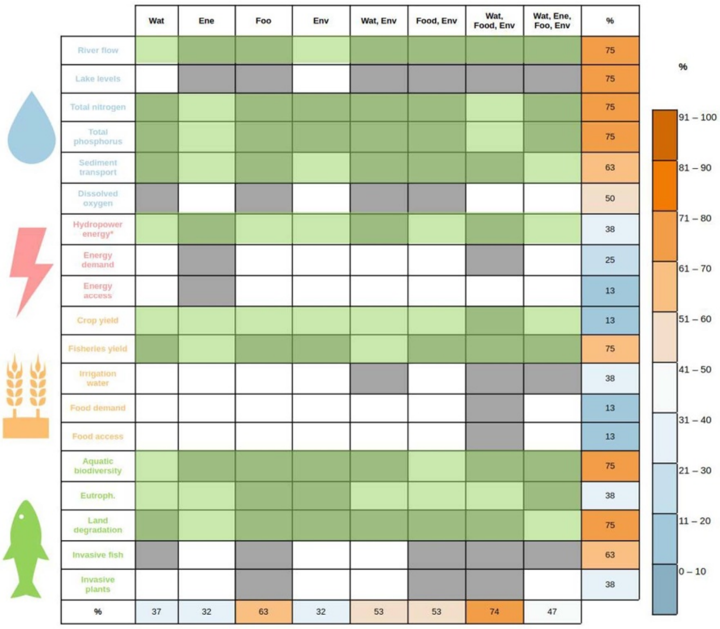

Figure 2. Stakeholder-developed WEFE indicators with those included in this study highlighted in green. Grey shading indicates that the concern relevant to the proposed WEFE nexus indicator was raised by the stakeholders, and white indicates that it was not. The final column shows the % of stakeholders which discussed a certain WEFE nexus indicator, whereas the final row shows the % of WEFE nexus indicators discussed by a particular group of stakeholders. Adapted from Schlemm *et al* (2024).

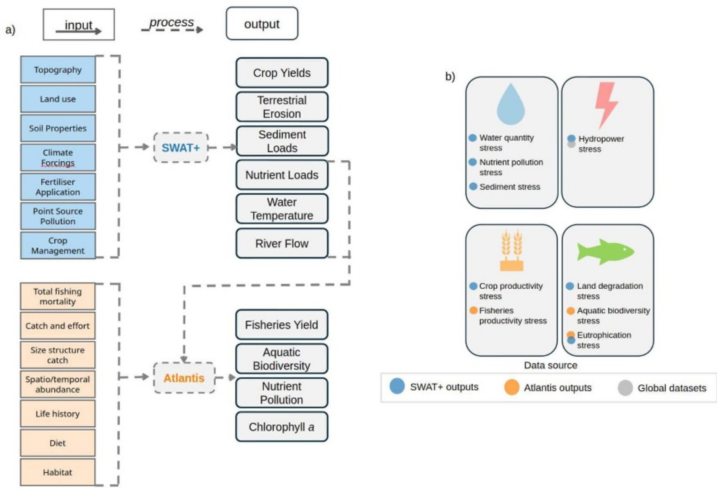

Figure 3. Integrated modelling framework showing SWAT+ — ATLANTIS coupling, (a) model inputs and outputs; (b) study WEFE indicators.

drought-tolerant crops; and 4) highland perennial banana for high-altitude regions with reliable rainfall (1200–2000 mm yr^{-1}) supporting banana and coffee systems. These areas were further subdivided into fractions to represent secondary crops such as beans, sweet potato, and coffee. In total, the model structure resulted in 20 000 HRUs, balancing computational efficiency and spatial detail.

By default, SWAT+ sets crop planting and harvest dates based on heat unit accumulation during the season (Neitsch *et al* 2011). However, on the LVB, the cropping season is highly dependent on water availability (Nkwasa *et al* 2022). To represent this, management schedules and decision tables were developed utilizing FAO crop calendars and regional crop yield data (FAO 2025, 2025b), accompanied by a verification based on evaluation of the leaf area index of agricultural HRUs against the seasonal rainfall patterns, to ensure that crop growth periods aligned with water availability; a common approach on tropical regions with rain-fed agriculture (Nkwasa *et al* 2022, Chawanda *et al* 2024). Since most of the area is rain-fed (Nyamweya *et al* 2023), no irrigation practices were included in the model.

Table 1. Global datasets used for SWAT+ model setup and calibration.

Dataset	Resolution	Source
Digital elevation model (DEM)	300 m (Resampled)	Shutter radar topography mission (SRTM), OpenTopography (2013)
Land use map (1990)	300 m	ESA (2017)
Soil map and properties	250 m	Fischer *et al* (2008)
Climate forcings (precipitation, temperature, wind speed, solar radiation, and relative humidity)	0.5°	Lange *et al* (2025)
Atmospheric nitrogen deposition	0.5°	Büchner and Reyer (2022)
Point source pollution data	0.5°	Beusen *et al* (2022)
Fertiliser application area	0.5°	Volkholz and Ostberg (2022)
Crop regions	—	Adhikari *et al* (2015)
Crop calendar	—	FAO (2025, 2025b)
Streamflow	Monthly	Global runoff data centre (GRDC)
River sediment load	Monthly	van Griensven *et al* (2013)

Regarding pollution sources, wastewater discharge (i.e. point source of nitrogen and phosphorus) was derived from Beusen *et al* (2022), given the lack of local monitoring data and the suitability of this globally consistent framework, which accounts for wastewater return flows and nutrient emissions across multiple sectors. This dataset provides yearly riverine loads of total nitrogen (TN) and total phosphorus (TP), while SWAT+ requires organic and inorganic constituents. To address this, a 0.25:0.75 ratio was used for TN (i.e. NH_3:NH_4), and for TP (i.e. organic phosphate and ortho-phosphate), following Gu *et al* (2011) and Nkwasa *et al* (2024). This ratio applies to raw and/or primary effluent data, which is relevant to the LVB, where most wastewater remains untreated (Jones *et al* 2021).

Climate forcings were obtained from the ISIMIP 3A GSWP3-W5E5 dataset (Lange *et al* 2025), which provides bias-corrected daily data for precipitation, temperature, wind speed, solar radiation, and relative humidity at 0.5° resolution, on a daily time step. The choice of this dataset was mainly motivated by it is temporal coverage which coincides with observations for calibration, while it has been used in similar large-scale studies in the region (Nkwasa *et al* 2022, 2024, Chawanda *et al* 2024), where it proved sufficient to achieve adequate model performance, and provides consistency when transferring to GCM-driven scenario simulations, which operate on the same grid resolution. Following this, we used data from ISIMIP 3A (Büchner and Reyer 2022) for historical atmospheric nitrogen deposition on a monthly time step. Similarly, an important component of agricultural management and a source of diffuse pollution is fertiliser application, which was also represented in the model through management schedules using application dates and rates from ISIMIP 3A N-fertiliser data (Volkholz and Ostberg 2022) for agricultural HRUs.

2.4.2. Model calibration and validation

The model was set up to run for the period 1975–1990, splitting into a calibration (1980–1985) and validation (1986–1990) period, with a warm-up period of 5 years (1975–1979). Streamflow was evaluated at 7 stations with monthly data availability from the GRDC database (portal.grdc.bafg.de), while monthly river sediment load was calibrated at one station using publicly available data (van Griensven *et al* 2013). A global parameter sensitivity analysis was performed using the latin hypercube sampling method in the SWAT+ Toolbox. Then, automatic streamflow calibration was performed, followed by calibration of river sediment load. To this end, a Python-based calibration framework for large basins in SWAT+ that relies on the covariance matrix adaptation evolution strategy (ES) was developed and applied.

Calibration of streamflow was performed using a zonal approach, dividing the LVB into three regions: east, south-west, and north-west. This definition resulted from the sensitivity analysis, which allowed grouping streamflow stations with similar parameter sensitivity and hydrological behaviour. In that sense, a multi-site calibration was performed, assigning an equal weight to all stations within a calibration zone. For river sediment load, since only one station was available, a single-site calibration was performed. The objective function for automatic calibration was the Kling–Gupta efficiency (KGE), whilst Nash–Sutcliffe efficiency, percent bias (PBIAS), and the coefficient of determination (R^2) were used for a comprehensive model evaluation. Given the complexity of the system and lack of local datasets for model configuration, a target of KGE $>$ 0.3 and PBIAS $<=$ 25 % on average, across all zones and stations, was set. Overall, satisfactory performance was achieved for this study. Moreover, yearly crop yields were compared with historical data from FAO STAT to ensure a realistic representation of agricultural productivity (For more details on the calibration and validation process, see supplementary material).

2.4.3. Future climate scenarios

Climate scenarios were set following the ISIMIP 3B protocol (i.e. future climate impacts). This included atmospheric forcings from five bias-corrected GCMs (GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, UKESM1-0-LL), as well as anthropogenic forcings (i.e. fertiliser application and point sources), under two scenarios based on shared socio-economic pathways (SSPs) and representative concentration pathways combinations; SSP1-2.6 and SSP5-8.5, for mid-century projection (2050–2080). The timeline was chosen to align with regional planning frameworks and to increase local policy relevance. Climate data from these GCMs were used as input to the calibrated SWAT+ model, following an ensemble approach that captures inter-model uncertainty in climate projections whilst providing scenarios for low- and high-emission pathways. Moreover, a historical reference period (1980–2010) was simulated using the ensemble approach with the forcings from the five GCMs. Overall, we performed 15 model runs, 5 historical and 10 for mid-century SSP1-2.6 and SSP5-8.5.

2.5. The Lake Victoria ATLANTIS ecosystem model

The ATLANTIS model is a spatially explicit, three-dimensional model capable of simulating the relationships between environmental processes and the distribution and abundance of aquatic organisms. Through the simulation of biogeochemical, physical, and ecological processes, the model provides outputs related to trophic chain dynamics, fisheries yield, and nutrient cycling in the water column (Fulton *et al* 2004a, 2004b), which are useful for deriving indicators for our framework for Lake Victoria.

The Atlantis fisheries model for Lake Victoria consists of 12 spatial polygons representing distinct ecological zones and 34 biological groups (17 fish, 1 bird, 1 reptile, 9 invertebrates, and 6 primary producer groups) developed specifically for Lake Victoria fisheries assessment. The model can represent trophic interactions, capturing dynamics from reptiles and birds, large fish species such as the Nile Perch, down to planktivorous species and primary producers. Trophic interactions and environmental variables determine biogeochemical cycling in the lake's water column, allowing assessment of nutrient concentrations and chlorophyll-a, as well as species abundance and fish catch. The model was validated for fish catch and chlorophyll-a, showing satisfactory performance in both spatial and temporal representation (see Nyamweya *et al* (2016) and Nyamweya *et al* (2017) for further details on model setup, parametrisation, and calibration).

2.5.1. Soft coupling methodology

The outputs from SWAT+ (figure 2) on a monthly time step were used as inputs for the ATLANTIS model. SWAT+ provided a time series of streamflow, water temperature, and TN loads for the river network, which were then processed and correctly formatted as ATLANTIS inputs, accounting for the inlets to Lake Victoria. Following the ensemble approach for future climate scenario analysis, this model was run for the historical baseline, SSP1-2.6, and SSP5-8.5 scenarios, for each GCM in the ensemble.

2.6. WEFE indicator analysis

Following established methodologies for multi-sectoral risk assessment (Byers *et al* 2018), we linked outputs produced by the modelling framework to 9 stakeholder driven indicators (table 2). These stress indicators span the following WEFE dimensions: 1) water availability and quality; 2) energy security through hydropower potential; 3) food security through terrestrial and aquatic production; and 4) environmental integrity through biodiversity and ecosystem health measures.

The stress indicators were aggregated into a 5 km × 5 km grid to assess them within and across sectors. This means some cells may correspond to the lake, a river reach, or the landscape; in some cases, they overlap both river and landscape. Therefore, not all cells account for all indicators; only those that correspond to the component of the system they overlay do. Three assessments were performed for future climate scenarios: relative changes in stress, stress categorisation based on thresholds, and population exposure, using ensemble results of the stress indicators. For relative changes or stress threshold analysis, sectoral values were calculated as the mean of available component indicators, and the overall WEFE value was calculated as the mean of the sectoral values; all sectors were equally weighted. Results were analysed beyond the ensemble mean alone. For relative analyses, we used the ensemble mean, along with the 17th (P_{17}) and 83rd (P_{83}) percentiles, to estimate both percentage changes and Δ-stress, thereby accounting for uncertainty arising from the GCM forcing. For categorical analyses, WEFE stress indicators were calculated at the sectoral and overall levels using both the ensemble mean and individual GCM

Table 2. WEFE nexus indicators, their model sources; S:SWAT+, A:ATLANTIS, and stakeholder priority.

WEFE dimension	Indicator	Output variable	Units
Water	Water quantity	Monthly streamflow (S)	$m^3 s^{-1}$
	Sediment	Monthly sediment load (S)	$t\ month^{-1}$
	Nutrient pollution	Monthly N and P loads (S) and Yearly mean dissolved Kjeldahl N (TKN) load (A)	$t\ month^{-1}$ and $mg\ L^{-1}$
Energy	Hydropower potential	Monthly streamflow (S) + Dam data	—
Food	Crop productivity	Yearly crop yield (S)	$kg\ ha^{-1}$
	Fisheries productivity	Yearly fish catch (A)	tons
Environment	Aquatic biodiversity	Mean yearly shannon index (A)	—
	Eutrophication	Mean yearly chlorophyll-a (A)	$mg\ L^{-1}$
	Land degradation	Mean yearly landscape Erosion (S)	$t\ ha^{-1}$

outputs, from which we assessed spatial inter-model agreement. Exposed population to WEFE stresses was similarly estimated per GCM, with the mean, P_{17}, and P_{83} calculated across estimates to characterise exposure uncertainty.

2.6.1. Relative impacts

Relative climate-induced stress changes were calculated as percentage changes and change in relative stress (Δ-stress). Percentage changes were calculated as:

$$\text{change}\,(\%) = 100 \cdot \left(\frac{\text{val}_{\text{fut}} - \text{val}_{\text{his}}}{\text{val}_{\text{his}}}\right) \tag{1}$$

where val_{fut} and val_{his} are the future and historical long-term means of the indicator values. The maximum and minimum were limited to $\pm 200\%$ to prevent extreme outliers dominating visualisations while preserving the direction and magnitude of change (Nkwasa *et al* 2022). Values were excluded where historical values fell below the 5th percentile to avoid division by near-zero values, which can produce misleading percentage changes.

Relative stress indicators were calculated by normalising the variables to a common 0–1 scale using historical baseline percentile-based scaling:

$$\text{Norm}_{\text{var}} = \frac{\text{value} - p5}{p95 - p5} \tag{2}$$

or

$$\text{Norm}_{\text{var}} = 1 - \frac{\text{value} - p5}{p95 - p5} \tag{3}$$

where value is the long-term mean of the indicator (historical or future), and $p5$ and $p95$ represent the 5th and 95th percentiles of the historical time series.

This approach allows for the analysis of possible changes in the distribution of indicators when based on long-term means: a value of 0.5 indicates that the indicator's time series resembles a normal distribution, while a higher normalised value indicates a skew towards high indicator values, and vice versa. This allows for capturing the influence of extreme events and interannual and seasonal variations. In the case of indicators where a skewed distribution towards higher values is seen as undesired (i.e. nutrient pollution, sediment load, erosion and chlorophyll-a), equation (2) was used, and equation (3) was used for the indicators where the opposite is true. For all indicators, a higher normalised value indicates a skew towards an undesired direction.

Change in relative stress (Δ-stress) was calculated as the difference between future and historical normalised stress values:

$$\Delta\text{Stress} = \text{Norm}_{\text{Future}} - \text{Norm}_{\text{Historical}} \tag{4}$$

where $\text{Norm}_{\text{Future}}$ and $\text{Norm}_{\text{Historical}}$ are the normalised stress values for future and historical periods, respectively. This provides a dimensionless measure of stress change, where an increase represents higher stress, and a decrease the opposite.

2.6.2. Stress categorisation

The stress threshold analysis methodology converts model outputs to standardised 0–3 stress scales, where 0 represents optimal WEFE resource availability and quality, and 3 represents severe stress or scarcity (Byers *et al* 2018). Thresholds were established by combining a literature review, historical data analysis, and environmental standards specific to riverine and lacustrine systems, with preference given to empirically derived thresholds when sufficient observed data were available (see supplementary material).

2.6.3. Population exposure

Population exposure to WEFE stress was quantified using population data from the LandScan dataset (Lebakula *et al* 2025) at 1 km resolution, later aggregated to the 5 km analysis grid. For each stress category (low: 1; moderate: 2; high: 3), we calculated: total population exposed in each category; country-level exposure statistics; and changes in exposure between current and future scenarios.

2.6.4. Temporal framework

The analysis employed different temporal assessments:

- Current WEFE stress (1980–2010): baseline period stress levels.
- Future WEFE stress (2050–2080): climate change-induced stress levels for mid-century scenarios.
- Change in relative (2.6.1) and categorised (2.6.2) WEFE stress from baseline period to mid-century future scenarios.

This enabled an assessment of current vulnerabilities, future climate risks, and an analysis of the magnitude and direction of expected changes, providing comprehensive information for adaptation planning.

3. Results

3.1. Relative climate change impacts on the WEFE nexus

Relative climate percentage impacts reveal substantial changes across most of the basin, with intensity and extent generally greater under SSP5-8.5 (table 3 and figure 5). These percentage changes reflect raw variable responses without stress classifications; they indicate the magnitude of climate-driven system changes, yet their beneficial or detrimental nature is not immediately clear. Unless otherwise stated, the following ranges reflect ensemble mean values for SSP1-2.6 and SSP5-8.5, respectively: The patterns are driven by substantial increases in river flow (17%–37%), river sediment load (25%–62%), and soil erosion (34%–78%), followed by increases in nitrogen load in both riverine (7%–16%) and lacustrine (2%–8%) water bodies, however a tendency of reduction on TP load in the river was found (2%–4%). Agricultural productivity sees mild increases in crop yield (4%–8%); however, fish catch is expected to decrease significantly (35%–33%) in the lake. Hydropower potential is expected to increase overall, consistent with higher river flows. In Lake Victoria, chlorophyll-a concentrations are expected to increase (4%–13%), while aquatic biodiversity is expected to increase under SSP1-2.6 (19%) but decrease significantly under SSP5-8.5 (35%).

The uncertainty across the ensemble of simulations, expressed as the P_{17}-P_{83} range, varies considerably across indicators and scenarios (table 3, figure 4). In terms of relative change compared to the historical baseline, the most uncertain variable under SSP1-2.6 is the Shannon Index (6%–53%), while river flow (8%–25%), fish catch (−49 to −22%), erosion (24%–40%), and sediment load (15%–33%) show moderate ranges. Under SSP5-8.5, river flow (10%–58%), erosion (46%–95%), and sediment load (32%–81%) show the widest spread, indicating significant inter-model variability. GFDL-ESM4 projects changes in river flow and hydropower potential that disagree in direction with the remaining ensemble members, MPI-ESM1.2 shows opposing signals for TP load and the Shannon Index, and MRI-ESM2 diverges from the ensemble on crop yield under SSP1-2.6. Notably, uncertainty generally increases from SSP1-2.6 to SSP5-8.5; this is quite visible for flow, sediment load, and erosion. This is particularly evident in figure 4, where UKESM1 consistently projects the largest changes across flow, sediment load, and erosion under SSP5-8.5, often falling well outside the P_{17}–P_{83} range, indicating it as a consistent outlier driving the upper tail of the uncertainty range. In contrast, GFDL-ESM4 and MRI-ESM2 tend to cluster closer to the ensemble mean across most indicators. For the Shannon Index, model disagreement is particularly pronounced under SSP1-2.6, with some simulations projecting negligible changes, and others

Table 3. Summary of relative change (%) for ensemble mean and P_{17}-P_{83} range on WEFE Nexus indicators.

WEFE dimension	Indicator	SSP1-2.6 (%)	SSP5-8.5 (%)
Water	Water Quantity	17 (8–25)	37 (10–58)
	Sediment Load	25 (15–33)	62 (32–81)
	Nutrients (N load rivers)	7 (5–9)	16 (12–21)
	Nutrients (TKN load lake)	2 (1–3)	8 (6–10)
	Nutrients (P load rivers)	−2 (−3 to 1)	−4 (−8 to −1)
Energy	Hydropower Potential	9 (0–18)	23 (8–35)
Food	Crop Yield	4 (0–8)	8 (6–10)
	Fisheries Yield	−35 (−49 to −22)	−33 (−43 to −25)
Environment	Aquatic biodiversity	19 (6–53)	−35 (−48 to −22)
	Eutrophication	4 (<1)	13 (10–15)
	Land degradation	34 (24–40)	78 (46–95)

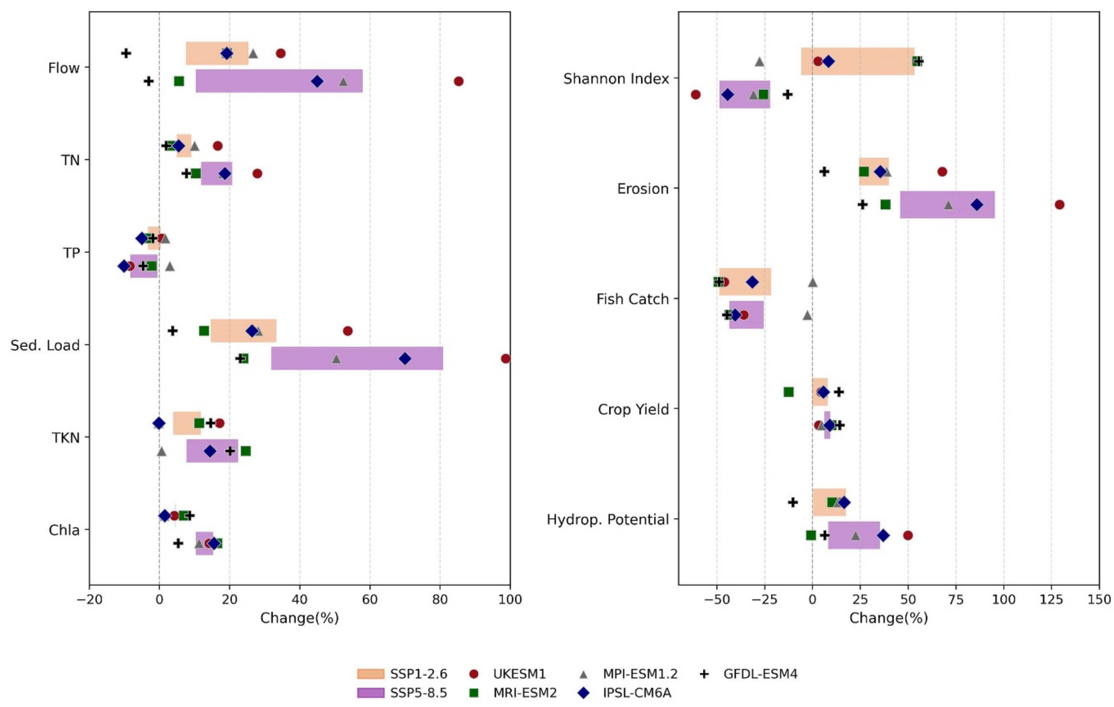

Figure 4. Average relative change values per indicator across the basin per GCM and P_{17}–P_{83} range of the ensemble for both future scenarios.

significant increases or moderate reductions, reflecting important uncertainty in the biodiversity indicator under this scenario. Nutrient and food-related indicators, as well as chlorophyll-a, show a generally lower range. Hydropower potential, which largely depends on streamflow, inherits its uncertainty, particularly under SSP5-8.5, though with a lower range.

Results show that most indicators exhibit significant spatial variation in their changes across future scenarios (figure 5). Water quantity is expected to increase overall in the basin, with the southern and eastern regions (Isonga, Magogo, Simiyu, and Mara River Basins) presenting the greatest changes, particularly under SSP5-8.5. For nutrient loads, there is high heterogeneity under SSP1-2.6, while there are consistent and significant increases overall under SSP5-8.5, especially in those locations where streamflow also increases. Nitrogen loads increase overall in the lake, a logical response to overall increases in the basin, but important changes are more concentrated in the Winam Gulf and southwestern sections of the lake, which is the result of increased pollution, namely wastewater, from cities near the coasts (e.g. Kisumu, Kenya). Erosion and Sediment yield logically follow similar patterns: significant erosion increases overall in the east, west, and north-east of the basin, followed by increases in sediment load,

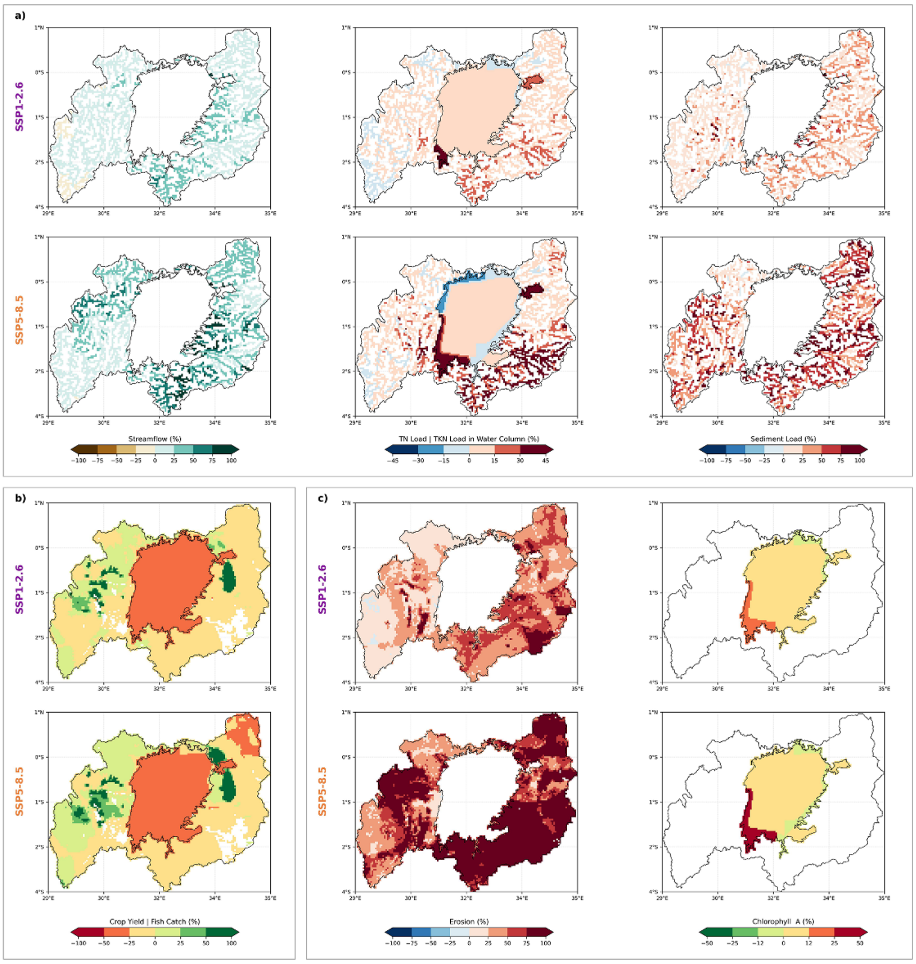

Figure 5. Percentage change for future scenarios in selected indicators with important spatial variability for the (a) water sector, (b) food sector and (c) environment sector.

which are much more intense under SSP5-8.5, particularly in the east, with no single region showing any reduction, highlighting land degradation as the dominant component in terms of relative changes.

There are some differences between the east and most of the west of the LVB in the food sector. Overall, crop yields decrease in the south and east, where grain and root crops are mainly cultivated, while the high-perennial-crop region in the north-west and near the Winam Gulf sees significant increases. This is an expected response to higher water quantity. The spatial variability in food indicators shows that the average change (table 3) is not necessarily representative, as significant increases occur in only small regions, while reductions have a larger extent. This is especially the case for scenario SSP5-8.5, where drastic decreases are expected in the northeastern region, where corn is the main crop. In contrast, overall reductions in fish catch dominate the lake's food sector. chlorophyll-a is expected to increase across most sections of the lake, with the largest changes projected in the southwestern section, as other processes leading to eutrophication intensify in the basin.

Inter-model variability shows a spatial distribution (figure 6) in which, in general, locations with higher uncertainty coincide with those of large projected changes for scenario SSP5-8.5, while for scenario SSP1-2.6, the uncertainty is overall moderate across the basin. As established before, streamflow, sediment yield, and erosion exhibit high inter-model variability under SSP5-8.5, and this uncertainty is spatially concentrated in the same southern and eastern regions where projected changes are largest. In Lake Victoria, moderate to high inter-model variability is observed in the southern sections and the Winam Gulf for both scenarios. Interestingly, in the Winan Gulf area, external TN inputs from the landscape show less inter-model variability, whereas sediment load shows greater variability. There is a similar situation in the southern and western bay areas, where TKN variability is moderate, but chlorophyll-a variability tends to be high. However, the Emin Pasha Gulf, which shows consistent increases in chlorophyll-a and TKN on the southern section of the lake, does not exhibit high uncertainty.

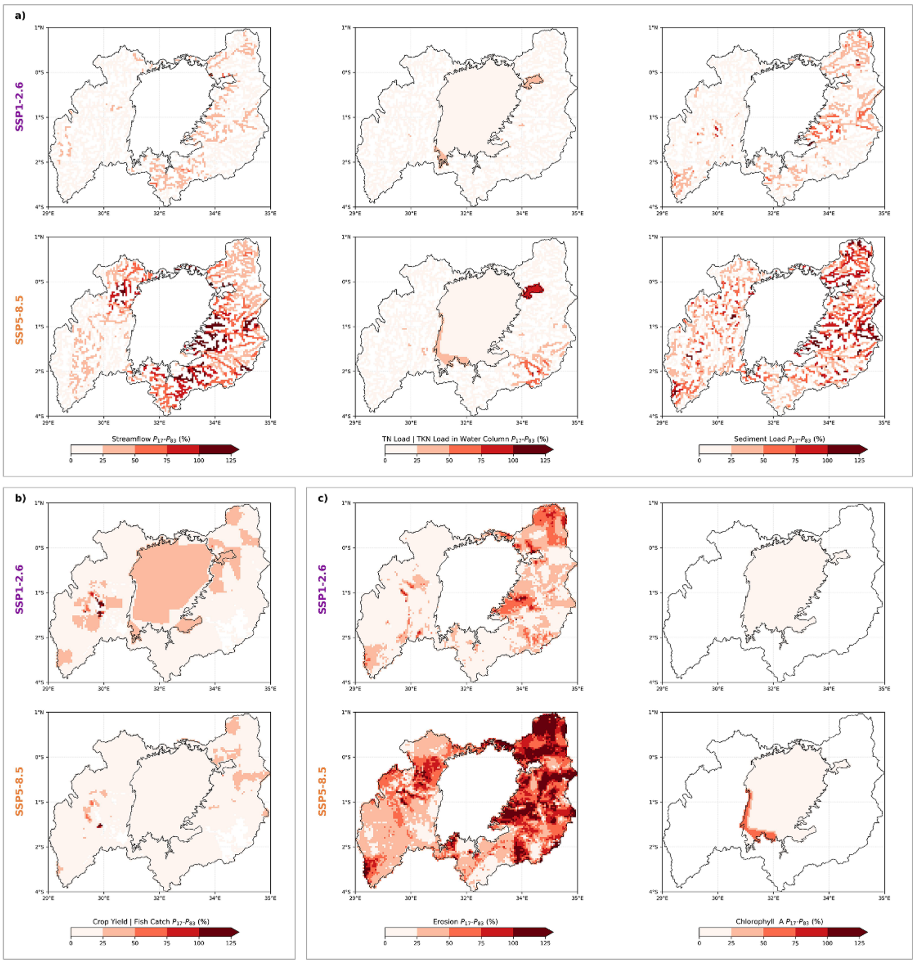

Figure 6. Difference on relative percentage change between P_{17} and P_{83} values of the ensemble for selected indicators with significant spatial variability.

Projections based on the ensemble mean suggest shifts in normalised WEFE indicators towards an undesired direction across the LVB (figure 7), affecting regions in all countries within it. Highlighting the complex and non-linear responses of the system to different levels of climate change, much higher stress changes are expected in the east and parts of the south, south-west and overall in Lake Victoria under SSP5-8.5, compared to SSP1-2.6. On the landscape, 88% of the area shows a positive Δ-stress value under SSP1-2.6 and SSP5-8.5, mainly driven by significant increases in erosion sediment load, with only some regions that, due to higher crop yields, see a reduction in stress (i.e. negative Δ-stress). Significant increases in stress (+0.25) occur in only 2% of the basin under SSP1-2.6, but increase to 37% under SSP5-8.5, concentrating on the eastern side of the basin. Areas of significant increase in stress align with those where a coupling of increased land and water quality degradation occurs. These results indicate the potential for more frequent or more intense extreme hydrological events, as well as years with low crop yields in the basin's landscape.

Lake Victoria shows overall positive values on the aggregated Δ-stress analysis across all indicators, which is largely driven by significant decreases in fish catch, and increases in chlorophyll-a concentrations and TKN load (table 2 and figure 5). It is also important to consider individual indicators in greater detail; fish catch dynamics depend on the species, for which in some cases, such as the Nile Perch, increases are expected in the future, while the total opposite occurs for the Silver cyprinid, which largely drives the reduction in total catch (see supplementary materials). These complex dynamics and the differences among species drive differential responses to each scenario in terms of biodiversity and the presence of primary producers.

The P_{17}–P_{83} for Δ-stress range reveals important spatial variability in inter-model agreement (figure 7). Under SSP1-2.6, the western basin shows moderate inter-model variability, though in some sections the sign of delta stress is opposite, given that most models project modest changes, and in some cases, in opposite directions. However, the magnitudes remain low throughout. The eastern basin shows

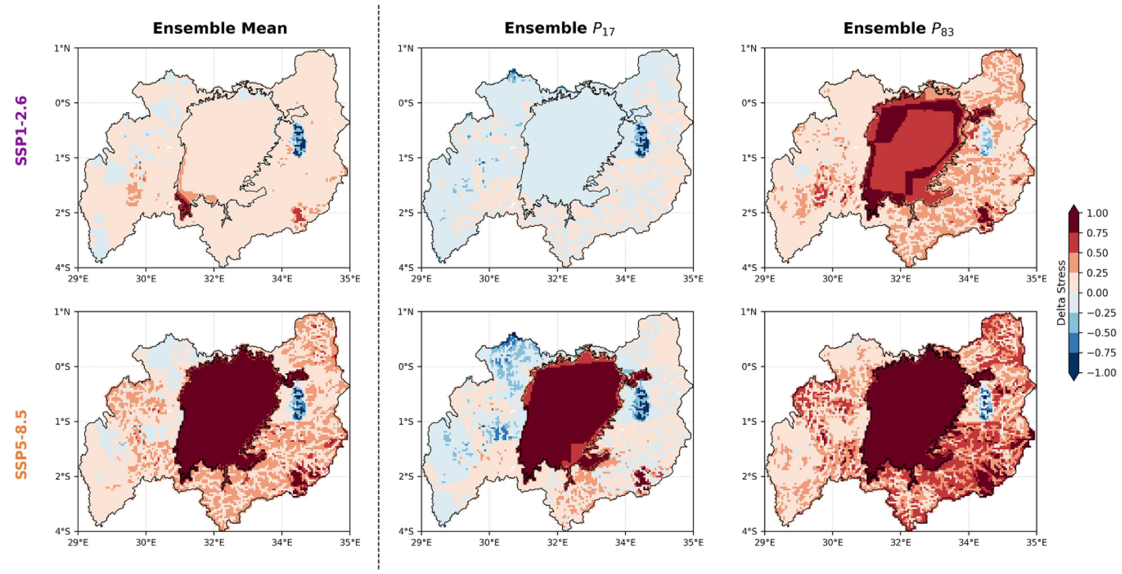

Figure 7. Relative WEFE nexus Δ-stress across climate scenarios by using the mean value, P_{17}, and P_{83} of indicators across the ensemble.

some clusters with high variability, but elsewhere there is agreement on low to moderate positive Δ-stress, and one region south of the Winan Gulf shows strong agreement on negative Δ-stress driven by crop yield increases. For Lake Victoria, the P_{17}–P_{83} range is considerable under SSP1-2.6, with the exception of the Emin Pasha Gulf, where both percentiles agree on positive Δ-stress. Under SSP5-8.5, inter-model agreement improves in the eastern basin and over the lake, though localised clusters of high uncertainty persist. Overall, the ensemble mean Δ-stress is broadly representative, yet the lake's variability under SSP1-2.6 warrants assessing individual indicators (figures 5 and S6, supplementary materials), as they exhibit important signals that are not captured by the aggregated WEFE Δ-stress.

3.2. Categorised climate change impacts on the WEFE nexus

Historically, stress hotspots occurred predominantly in western Kenya, parts of Tanzania, and northern Burundi (figure 8), driven primarily by degraded water quality, land degradation, and low crop yields in grain-crop agricultural regions. WEFE stresses classified as moderate and above currently affect 17% of the basin, with important variations across sectors.

Water stress shows the greatest spatial extent, with 35% of the basin area categorised as with moderate or higher stress. This is mainly due to high sediment loads, followed by elevated nutrient concentrations in the rivers and the lake. The environment sector follows, with 30% of the area classified as having moderate or higher stress, reflecting soil erosion rates exceeding 40 tonnes ha^{-1} yr^{-1} in severely affected areas and high chlorophyll-a levels in several sections of the lake. Food stress hotspots cover 22% of the basin's area, predominantly in the north-east and parts of the central basin, mainly where grain crops are cultivated, followed by fish catch stresses in the southern section of the lake and the Winam Gulf. Energy stress remains spatially limited, primarily concentrated in northern Rwanda, where hydropower facilities face seasonal flow constraints, limiting hydropower potential.

Climate change alters the spatial distribution and intensity of WEFE stress across the basin for mid-century projections (figure 8). Under both scenarios, the fraction of the basin with moderate to high WEFE stress increases from 17% (historical) to 31% under SSP1-2.6 and 36% under SSP5-8.5, resulting in increases of 82% and 110% in area, respectively. The largest expansion occurs in the lake, as reduced fish catch increases food stress in the central lake and Winam Gulf. On the landscape, some expansion occurs in agricultural areas in the north-east of the basin and near the southern lake shore, also related to increased food stress.

The dominant sector in terms of stress category shows significant spatial variability across the landscape and the lake, and important transitions are expected in future scenarios. Historically, the environment sector dominates in most parts of the lake, except the Winam Gulf and the southern shores, where low fish catch drives food stress (figure 5). However, in future scenarios, food stress plays a dominant role in WEFE stress in the lake, whereas environmental stress becomes dominant along the southeastern shore under SSP5-8.5, due to biodiversity loss. Food stress dominates the north-east, where low crop

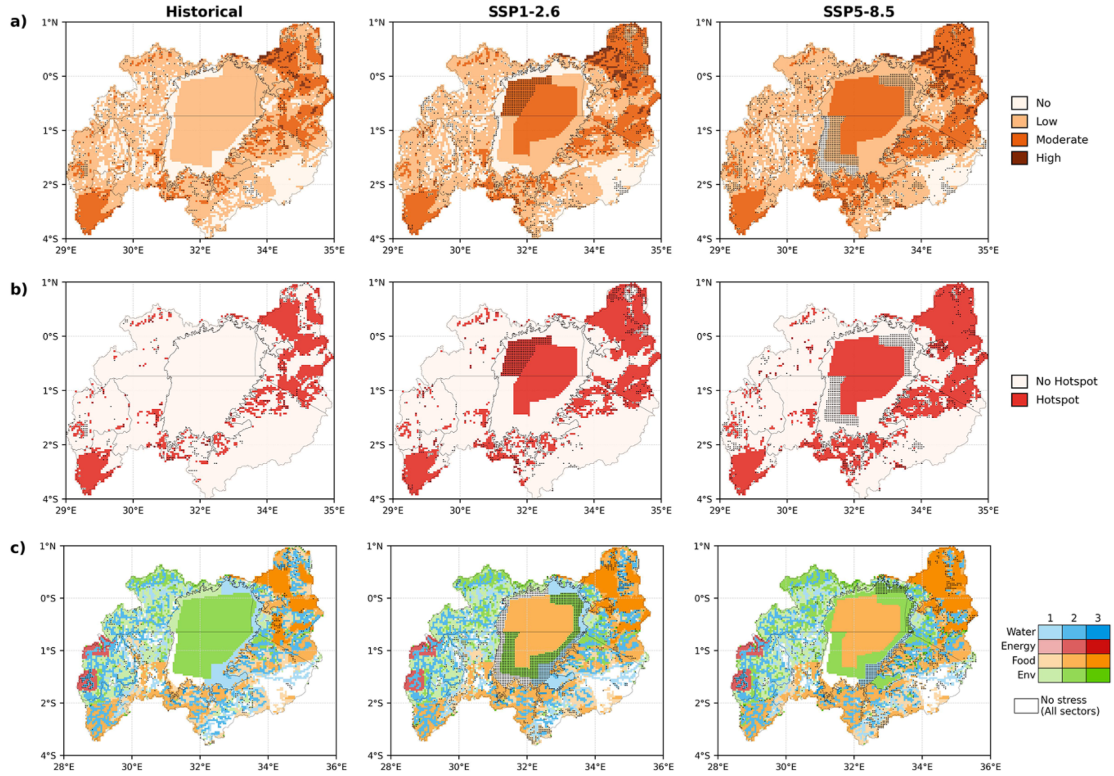

Figure 8. Ensemble stress threshold analysis of the WEFE nexus showing: (a) stress category; (b) hotspot areas (moderate or higher) (c) dominant WEFE sector and its stress category. Stippled areas indicate where simulations driven by 3 GCMs or less agree on the category.

yields occur in areas where mainly corn and sorghum are cultivated. The environmental sector dominates overall in the western basin, due to high erosion rates, while some sections of Rwanda show energy stress due to reduced hydropower potential in some facilities. Many water bodies across the basin show moderate or higher water sector stress, with the water sector as the dominant sector, particularly in areas where land degradation is important, and large agricultural areas exist, as fertiliser application and erosion degrade water quality.

Inter-model agreement on stress categories is considerably higher than on relative changes. For the historical baseline, all five GCMs agree on the stress category in 85% of the basin area, and on the dominant sector in 90% of the area. Agreement decreases for future scenarios, yet remains strong: under SSP1-2.6, all five models agree on the stress category and dominant sector in about 55% of the area, with a majority of three or more models agreeing across virtually the entire basin. Under SSP5-8.5, full agreement occurs in 55% of the area for the stress category and increases notably to 67% for the dominant sector. Cases where only two models agree are negligible across all scenarios (<1%), indicating that even in areas of lower agreement, a majority consensus is maintained. Spatially, areas of reduced agreement (i.e. 3 out of 5 GCMs) are concentrated in the lake and in scattered clusters in the eastern and southern landscape (stippled areas in figure 8), coinciding with locations of previously identified indicator uncertainty. In the lake, some disagreement arises over the dominant sector: the ensemble identifies the environment or water sector as dominant, but individual models occasionally identify food stress as dominant, driven by uncertainty in fisheries yield, particularly under SSP1-2.6. Overall, based on the majority consensus, the ensemble mean results are quite representative of the entire ensemble when looking at the stress category.

Sectoral analysis reveals high variability and transitions across the LVB, highlighting the spatially heterogeneous nature of these changes, which are not necessarily captured by simple aggregation, hence the importance of a spatially explicit assessment. Area-fraction analysis by sector and region further clarifies vulnerability patterns (figure 9). The distribution of stress categories evolves differently across sectors and regions. Water stress remains similar to historical conditions in most regions, with some increases in intensity, particularly in the west. However, it is clear that water stress already affects most of the basin and will continue to do so in the future. Similarly, stressed fraction is close to 100% in most regions for the environment sector, with the north-east and north-west facing intensification of stress, rather than

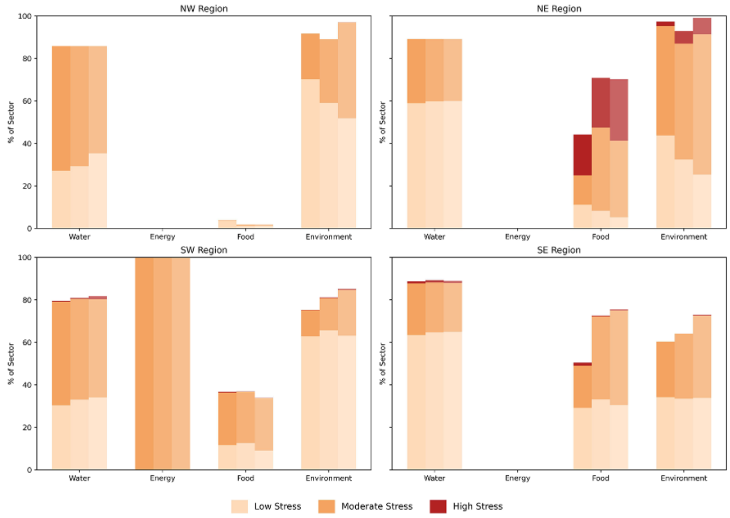

Figure 9. Regional area fraction per stress class and WEFE sector, based on ensemble mean values (left = historical, middle = SSP1-2.6, right = SSP5-8.5).

expansion, with moderate or high categories gaining more area. The food sector shows significant expansion of stressed areas in the east, mainly due to reductions in the productivity of grain crops in those regions, particularly in the north-east, where the high stress fraction is important. Stress in the energy sector is present only in the south-west region, mainly due to low hydropower potential at Rwandan facilities, which is expected to remain similar across future scenarios.

3.3. Changes in population exposure to WEFE stress

Important dynamics in human vulnerability to multi-sectoral climate risks were found. Historical conditions expose approximately 15.5 million people to moderate and high WEFE stress, increasing to 17.8 million under SSP1-2.6 (14% increase) and 20.1 million under SSP5-8.5 (30% increase). Country-level analysis (figure 10) reveals differential patterns of vulnerability. Kenya faces substantial overall exposure, driven by high population density, where important climate impacts occur in parts of the eastern basin. All countries experience a slight reduction in the proportion not exposed to stress, naturally transitioning towards stress categories. Kenya is expected to face reductions in low-stress exposure for future scenarios. However, this translates mainly into increases in moderate and higher stress exposure, indicating a dominant process of intensification (i.e. a transition towards higher stress categories). Tanzania follows a similar pattern to Kenya, only for SSP5-8.5; under SSP1-2.6, there is expansion of low-stress areas as well as intensification towards higher categories. Uganda shows no significant changes under SSP1-2.6, but significant expansion of low-stress areas occurs under SSP5-8.5, increasing the exposed population. Burundi and Rwanda show stable situations where the exposure remains similar to historical conditions.

Exposure uncertainty for the non-exposed fraction is low, whereas it is higher in the stressed categories for some countries, where uncertainty primarily reflects interchange between low and moderate or higher stress classifications rather than disagreement on the direction of change (figure 10). Kenya shows variability in low- and high-stress exposure in both future scenarios, consistent with the observed indicator uncertainty for future changes in the eastern basin, while Rwanda shows notable uncertainty across both scenarios due to hydropower potential near the boundary between low and moderate stress categories. Overall, the ensemble mean is broadly representative, while the direction of change for future scenarios is generally consistent.

Although aggregated WEFE stress exposure revealed important impacts, country-level exposure analysis by sector (figure 11) provides the full picture, with differing dynamics across categories. In the low-stress category, environmental stresses dominate across all countries, followed by food stresses in Kenya and Tanzania. Exposure to moderate stress in Kenya is widespread across the environment, water, and food sectors, highlighting the significant challenges in the region due to degraded water quality, land degradation, and low food productivity. Similar patterns of exposure in this category are found in Tanzania and Burundi, though with lower magnitudes. In Rwanda, the energy sector takes a more predominant role than the food sector in other countries.

Kenya faces the highest exposure to high stress, mainly in the food sector, followed by environmental stress. This is a clear result of the low food productivity in the north-east of the basin, which is expected

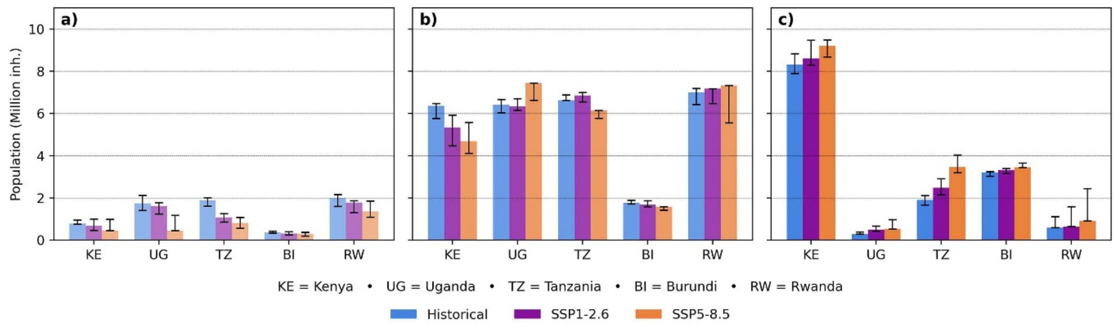

Figure 10. Historical and future projected population exposure to WEFE Nexus stresses by country, for (a) no stress, (b) low stress, and (c) moderate or higher stress. Error bars indicate the range between P_{17} and P_{83} of the ensemble.

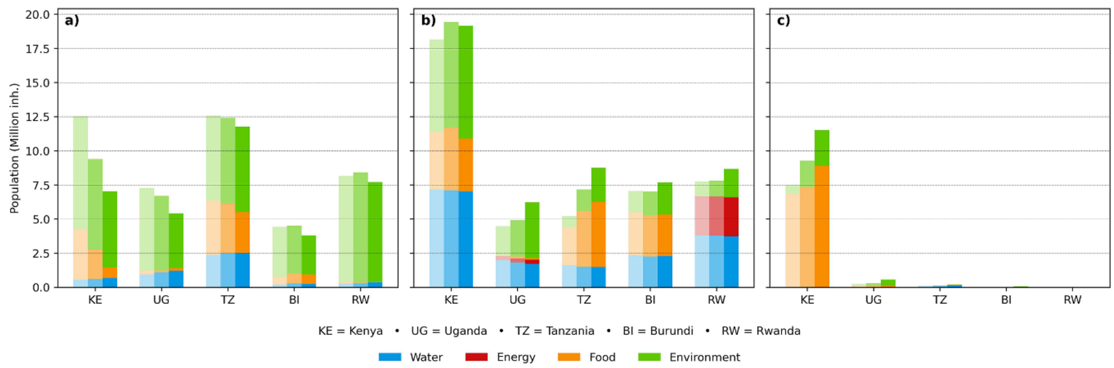

Figure 11. Historical and future projected population exposure to sectoral stresses by country, based on ensemble mean values, for (a) low stress, (b) moderate, and (c) high stress (left = historical, middle = SSP1-2.6, right = SSP5-8.5).

to worsen in the future. Exposure levels in the environment and food sectors are expected to increase further under future climate scenarios, particularly in Kenya and Tanzania. On the other hand, water stress exposure remains relatively stable across all countries, reflecting the already high levels of water stress in the basin and is not expected to change significantly in future scenarios.

4. Discussion

This study addresses critical gaps in WEFE nexus climate assessments by operationalising stakeholder-developed indicators to identify climate change impact hotspots in the LVB. Our findings reveal complex patterns of climate vulnerability that challenge traditional sectoral approaches to adaptation planning, underscoring the need for multi-sectoral and transboundary strategies (Van Noordwijk *et al* 2018). The coupling of process-based models and integration of empirically derived thresholds provides novel insights into the spatial dynamics of multi-sectoral climate risks in transboundary lake systems, whilst the stakeholder-informed framework ensures policy relevance and local applicability.

4.1. Advancing stakeholder-informed WEFE Nexus assessments

Our coupled modelling framework successfully operationalised 77% of stakeholder-developed priority indicators in the LVB, which represents an improvement over existing integrated WEFE tools (Schlemm *et al* 2024). A key methodological contribution lies in the explicit representation of environmental processes through the coupling of SWAT+ and ATLANTIS: while SWAT+ captures a wide range of landscape-scale processes across the water, food, and energy sectors, ATLANTIS provides a mechanistic representation of lake ecosystem dynamics, including trophic interactions, fisheries yield, and aquatic biodiversity. Together, this represents a novel level of process detail in WEFE nexus assessments, where the environmental dimension has rarely been represented through coupled mechanistic models of this complexity. The representation of water quality, land degradation, eutrophication, biodiversity, and food productivity addresses critical gaps in existing tools, achieving a more holistic assessment of interconnected systems.

Furthermore, the spatially explicit and multi-sectoral nature of our framework directly responds to the heterogeneous priorities identified through stakeholder engagement. Since stakeholder concerns vary by sector and location, our ability to provide spatially differentiated information across WEFE sectors ensures that results are actionable and relevant at the scale at which decisions are actually made. The participatory approach thus not only shapes the scientific focus of the assessment but also ensures that outputs feed back to stakeholders in a form that matches their spatial and sectoral needs (Sušnik *et al* 2018). Our approach demonstrates how participatory processes can bridge the theory-application gap (Liu *et al* 2017, Tye *et al* 2022, Ali and Acquaye 2024), and provides further evidence for the importance of cross-sectoral and cross-disciplinary research on the WEFE nexus (Bréthaut *et al* 2019, Ghodsvali *et al* 2019).

4.2. Climate change: a heterogeneous amplifier of WEFE vulnerabilities in the LVB

Our findings reveal heterogeneous impacts of climate change on existing WEFE vulnerabilities, with significant variations across sectors, regions, and scenarios, demonstrating the non-linear nature of future climate risks on the WEFE nexus in line with global assessments (Byers *et al* 2018). Uncertainty in these projections deserves explicit consideration. Inter-model spread is significant for several indicators and varies per scenario, consistent with findings across Africa, where climate projections show disagreement depending on the choice of climate model (Diallo *et al* 2012). Aggregated metrics such as WEFE Δ-stress should therefore be interpreted alongside individual indicators, as ensemble averages may mask important variability. Notably, uncertainty differs between the landscape and the lake, and models that agree on landscape indicators do not necessarily agree on lake indicators. Landscape uncertainty is largely precipitation-driven, given the inter-model variability on indicators highly sensitive to surface runoff, whereas lake processes are more influenced by temperature and internal ecological dynamics, resulting in cases such as chlorophyll-a uncertainty not aligning with terrestrial nitrogen load uncertainty. When relative changes are translated into stress categories, however, model agreement is substantially increased, as categorical thresholds smooth out differences in magnitude, likely providing a more robust basis for adaptation planning.

Regarding impacts, the food and environment sectors are among the most affected, as they depend on changing rainfall and temperature patterns. Crop yield declines of up to 50% are projected in many regions, consistent with other studies on global warming impacts on agriculture in Sub-Saharan Africa (Thornton *et al* 2011, Hummel *et al* 2018), with grain crop regions most affected (Adhikari *et al* 2015, Stuch *et al* 2021). The water sector exhibits complex, spatially heterogeneous responses, with some areas benefiting from increased availability while others experience water quality degradation, a pattern documented across East Africa (Roegner *et al* 2020, Chawanda *et al* 2024, Nkwasa *et al* 2024). In the lake, climate change projections reveal divergent responses across species and scenarios. Under SSP1-2.6, more moderate conditions support a relatively balanced species community, favouring biodiversity. Under SSP5-8.5, harsher, more extreme conditions drive the collapse of sensitive endemic species such as haplochromines and cyprinids (figure S8, supplementary materials), threatening biodiversity (Marshall 2018, Nyboer *et al* 2022, Syanya *et al* 2023), while tolerant species thrive, sustaining fisheries yields similar to scenario SSP1-2.6. This mechanism explains the opposing directions of the Shannon Index across scenarios, whereas fish catch remains similar. Increasing chlorophyll-a concentrations under both scenarios further exacerbate documented eutrophication trends (Njagi *et al* 2022), compounding pressures on already stressed lake ecosystems.

The emergence and expansion of stress hotspots under future scenarios create significant challenges for adaptation planning, particularly in already-stressed areas such as western Kenya, northern Burundi, and the Kenya–Tanzania border, where high population density and compounding multi-sector vulnerabilities amplify climate risks (Kogo *et al* 2021, Kondowe *et al* 2022, Onyango and Opiyo 2022).

4.3. Population exposure and transboundary adaptation challenges

Climate impacts concentrate in specific hotspots, such as the Kisumu–Kakamega region and upstream basins in Kenya, northern Burundi, the Mara basin, and the Mwanza region in Tanzania. Identifying sectoral challenges in these areas provides critical guidance for prioritising adaptation investments, particularly given the clear correspondence between high population densities and identified hotspots. Although inter-model uncertainty exists in future projections, it does not undermine prioritisation, as the largest source of disagreement lies in the interchange between low and moderate or higher stress categories rather than in the direction of change. The population already exposed to stress is substantial, and this exposure is projected to increase, if not intensify, under future scenarios.

Population growth and resource demand will undoubtedly exacerbate pressures (Juma *et al* 2014, Kundu *et al* 2017) where stress changes are expected. Moreover, areas of documented WEFE-development-conservation conflicts correspond with our identified WEFE nexus hotspots, particularly in the transboundary context, which highlights the need for integrated socio-ecological approaches (Schlemm *et al* 2025). Moreover, exposure levels align with broader global inequities, where the poorest populations face higher exposure to climate impacts while contributing the least to greenhouse gas emissions (Mody and Pattillo 2004, Hallegatte and Rozenberg 2017).

The transboundary nature of many identified hotspots presents both coordination challenges and opportunities for regional cooperation. It is clear that climate impacts cascade across national boundaries and, in many cases, are accompanied by disparities in country-level exposure. Our findings provide scientific support for initiatives of transboundary organisations such as the Nile Basin Initiative and the Lake Victoria Commission.

4.4. Policy implications and adaptation recommendations

Priority interventions should focus on identified hotspots where multi-sector risks increase under climate change, especially where they coincide with densely populated areas. Western Kenya, northern Burundi, the Kenya–Tanzania border, and the southern lake shore regions emerge as the highest-priority regions in the LVB. Here, adaptation requires integrated approaches that combine water quality and land degradation management, sustainable agriculture, and ecosystem restoration. Moreover, many upstream stresses are translated into Lake Victoria, which is an essential resource for millions in the LVB (Njiru *et al* 2008).

Acknowledging uncertainty is not an impediment to action but rather a call for adaptive, flexible planning frameworks. Approaches such as the Climate Risk Informed Decision Analysis (Mendoza *et al* 2018) are specifically designed for contexts of deep uncertainty. Given the inter-model variability identified in this study, particularly for the high-impact scenario SSP5-8.5, such frameworks are especially relevant for the LVB, where the consequences of poor adaptation strategies could be severe for millions of people.

NbS are well aligned with the adaptive principle, as their inherent flexibility and co-benefits make them robust across a range of climate futures (Cohen-Shacham *et al* 2016). In that sense, soil erosion hotspots call for forest restoration, agroforestry, and riparian buffers (Van Noordwijk *et al* 2018, Muchane *et al* 2020), while lake-shore pollution highlights the need for wetland restoration (Schlemm *et al* 2025). The success of NbS implementations, however, depends on social equity, local participation, and supportive policy and institutional frameworks (Forest Peoples Programme 2020, Kooijman *et al* 2021, Mabon *et al* 2022), where the importance of equitable local inclusion in adaptation initiatives cannot be understated, given the documented patterns of historical exclusion and marginalisation within the region (Leach *et al* 2018, Odero and Odenyo 2022).

Finally, investments in regional monitoring networks and data accessibility frameworks represent a fundamental need for integrated basin management, requiring coordinated efforts to enhance both data generation capacity and institutional mechanisms that ensure data accessibility, which reduces blind spots. Improved monitoring and data sharing would strengthen model accuracy, reduce uncertainty in climate projections, and enhance the reliability of adaptation planning tools across the basin.

4.5. Limitations and future directions

Despite offering a novel operationalisation of the WEFE nexus, our study faces several limitations. Key drivers such as land-use changes and socio-economic dynamics were excluded, despite remaining important drivers of WEFE stress alongside climate change (Chawanda *et al* 2024). Moreover, the reliance on coarse global datasets for climate forcing, while positive for reproducibility, may constrain model accuracy compared to cases with abundant local data. Additionally, aquaculture was not explicitly accounted for in the modelling framework, despite its important role in LVB fisheries (Nyakeya *et al* 2022, Okechi *et al* 2022). Although hydropower production impacts were included, dam infrastructure was not explicitly modelled. This is relevant given that river fragmentation and flow regulation by dams can produce further feedbacks within the WEFE nexus (Angarita *et al* 2018, Kuriqi *et al* 2020). Finally, the study lacks consideration of resource quality, demand, access, and adaptive capacity, which is particularly relevant given evidence that fishing communities face constrained capacity to respond to environmental changes (Nyboer *et al* 2022).

Future research should prioritise: 1) climate change assessments incorporating land-use and socio-economic drivers; 2) incorporation of resource quality, demand, access, and environmental justice perspectives; 3) analysis of extreme and compound events; 4) expanded model coupling or ensembles; 5) coordination with local institutions for in-situ measurements; 6) inclusion of aquaculture within fisheries; 7) evaluation of NbS impacts on the WEFE nexus; 8) analysis of governance and policy coordination for climate adaptation.

5. Conclusion

This study demonstrates the feasibility and value of stakeholder-informed, process-based modelling for WEFE nexus climate assessment in transboundary lake systems. By coupling SWAT+ and ATLANTIS, we operationalised 77% of stakeholder-developed priority indicators, achieving a level of process detail in the environmental dimension rarely achieved in WEFE nexus assessments. The spatially explicit, multi-sectoral framework directly responds to the heterogeneous sectoral and spatial priorities identified through stakeholder engagement, ensuring that outputs are actionable at the scale at which adaptation decisions are made.

Our findings reveal that climate change acts as a heterogeneous amplifier of existing WEFE vulnerabilities, with the moderate or higher stress area fraction increasing from 17% historically to 31% under SSP1-2.6 and 36% under SSP5-8.5, exposing up to 20.1 million people to multi-sectoral climate risks. Climate impacts show pronounced sectoral and spatial differences, with water flows and erosion intensifying significantly, crop yields declining in grain-crop regions, and lake ecosystem stress increasing across scenarios. Inter-model uncertainty is substantial for relative changes, particularly under SSP5-8.5, but is considerably reduced when results are expressed as stress categories, which provide a more robust basis for adaptation planning and should be the preferred lens for decision-making under uncertainty.

Critical stress hotspots emerge in western Kenya, northern Burundi, and the Kenya–Tanzania border, where multi-sector risks coincide with high population densities, requiring coordinated transboundary responses. Acknowledging future uncertainty as inherent, adaptation strategies should prioritise flexible, robust measures that remain effective across a range of plausible futures. Effective adaptation further requires institutional mechanisms that can coordinate actions across sectors and borders, supported by scientific assessments that capture the full complexity of multi-sectoral climate risks. By demonstrating how stakeholder-informed, process-based modelling can deliver such assessments in a data-scarce transboundary context, this study provides a template for similar applications in similar systems.

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Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.17978928. Data will be available from 31 January 2026.

The scripts used in this study for post-processing, analysis, and figure generation, are available from https://github.com/jopator/WEFE-LVB-climateChange under the MIT licence. The version used to generate the results presented in this paper is archived on Zenodo under DOI: https://doi.org/10.5281/zenodo.19207670 (Teran 2026). Given the large size of the raw model input files, they cannot be stored on an online repository, but they are avaialable upon request. All external global datasets referenced in this study are publicly available from their respective repositories, as cited in the manuscript.

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