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Modeling changes in nutrient retention ecosystem service using the InVEST-NDR model: A case study in the Gumara River of Lake Tana Basin, Ethiopia

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A R T I C L E I N F O

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A B S T R A C T

Aquatic ecosystems provide valuable ecosystem services (e.g., habitat for fisheries) to surrounding communities but environmental degradation can diminish the quality of these ecosystem services. The Lake Tana basin, including the Gumara River and its associated wetlands in Ethiopia, has experienced rapid environmental change in the last several decades. Changes in the export of nutrients from the uplands might contribute to the rapid degradation of aquatic ecosystem services due to the expansion of water hyacinths and declines in fish biodiversity and yields. We estimate how human modification and climate change have impacted watershed nutrient retention from 1986 to 2020. Here we (1) examine trends in surface water chemistry, watershed land use/land cover change, and flow alterations; (2) estimate the watershed nutrient delivery ratio (NDR), a metric of watershed nutrient retention, through time; and (3) examine how fishery yields and water hyacinth infestation in Lake Tana at the outlet of the Gumara River change during a period of rapid increase in nutrient export from the Gumara River. Estimates of the surface load and export of both phosphorus (P) and nitrogen (N) from the Gumara River watershed were approximately stable between 1986 and 2009, but from 2014 to 2020 exports increased by 69 % for P and 80 % for N. Potential factors driving this rapid increase include an expansion in irrigation for agriculture, land conversion to eucalyptus plantations, decreases in dry season flow, and an increase in mean annual precipitation since 2009. In addition, the increase in nutrient export from the Gumara River watershed coincides with a near extirpation of fish in the Gumara River and a ten-fold expansion of water hyacinth downstream in Lake Tana. Human activity and hydrological alteration in the Gumara River watershed have resulted in water quality changes, declines in fish populations, and the expansion of invasive species. Long-term monitoring and watershed modeling can help inform the management of regionally important aquatic ecosystems such as the Gumara River and Lake Tana.

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1. Introduction

Aquatic ecosystems have the potential to yield services essential to society, including food production, water purification, recreation opportunities, and conservation of genetic diversity (Costanza et al., 1997; Caro et al., 2020). Despite the importance of freshwater ecosystems for providing ecosystem services, routine monitoring of aquatic ecosystems is scarce, particularly in most regions undergoing rapid environmental degradation (Costanza et al., 2014; Costanza et al., 2017; Grizzetti et al., 2017; Hoyek et al., 2022). Pollution, climate change, invasive species, and habitat degradation are the primary challenges facing the conservation of aquatic ecosystems. In Ethiopia, the Lake Tana basin is economically and ecologically important to the region (Woldu, 2018; Wondie, 2018), but is facing declining fish populations (Dejen et al., 2017) and the expansion of invasive species like the water hyacinth (Dersseh et al., 2020). The Gumara River is one of the four largest tributaries of the Lake Tana basin with the spawning ground for migratory fish species and the highest fish diversity in the basin (Dejen and Vreven, 2019; Goshu et al., 2010; Ameha; and Assefa, 2002) that is also facing some of the greatest land use change and subsequently water quality degradation (Abebe et al., 2021). In this study, we investigate how land use and land cover (LULC) change in the Gumara River watershed over the last four decades has altered Gumara River watershed nutrient export to Lake Tana.

To inform decision-making in areas with relatively scarce monitoring, the Natural Capital Project (NCP) developed the Integrated Valuation of Ecosystem Services and Tradeoffs (InVEST) model to quantify and map the values of ecosystem services (Tallis et al., 2011; NCP, 2022). The InVEST model is a tool for exploring how changes in ecosystems can lead to changes in benefits that flow to people (NCP, 2022). The model can be used to address and quantify how land degradation affects water quality in river basins. The InVEST model relies on a digital elevation model (DEM), land cover and land use data, precipitation or runoff data, and discrete water chemistry data. These data are often available even in data-sparse regions such as the Lake Tana basin in Ethiopia. We used the InVEST model to investigate how nutrient loading and export from the Gumara River watershed changed over time. The InVEST model has been previously applied in different basins of Ethiopia to investigate (1) LULC dynamics related to changes and tradeoffs of ecosystem services in a coffee forest biosphere reserve (Abera et al., 2021), (2) the impact of landscape pattern changes on hydrological ecosystem services (Yohannes et al., 2021), (3) soil loss and sediment export to inform land management in data-scarce areas (Gashaw et al., 2021), (4) the ecosystem services of wetlands in a Lake Tana basin (Wondie, 2018), and (5) habitat risk assessment (Posner et al., 2016; Caro et al., 2020; Benra et al., 2021). However, the InVEST model has not previously been used to estimate watershed-scale nutrient retention from the Gumara River to Lake Tana.

Both anthropogenic activity and climate change impact the sustainable use of water resources in the Lake Tana Basin. Approximately 60 % of the Lake Tana Basin has historically experienced lower rainfall variability than the present-day (Abebe et al., 2017), and the entire Lake Tana Basin is predicted to experience increased precipitation under global climate change (Roth et al., 2018; Tigabu et al., 2020). Total annual precipitation in the Gumara River watershed slightly increased at a rate of 4 mm year^{-1} between 1981 to 2018 (Abebe et al., 2020). Despite this increase in precipitation, both low flows and high flows have decreased in the Gumara River (Abebe et al., 2020), as well as in the adjacent Gilgel Abbay (Enku et al., 2014) and Megech (Abebe and Kebede, 2017) Rivers in the Lake Tana Basin. These decreases in flow are attributed to the expansion of pump irrigation and the expansion of eucalyptus plantations (Abebe et al., 2020). Between 1986 to 2015, forested land cover in the Gumara River declined from 11 % to 5 %, and grassland cover declined from 18 % to 10 %, while cultivated land increased from 70 % to 82 % (Birhanu et al. (2019)). Beyond the Gumara River, cultivated land cover increased throughout the entire Lake Tana Basin between 1986–2013 (Abebe and Minale (2017). The expansion of cultivated land at the expense of forest land, shrubland, and grassland has increased the mean rate of soil erosion, sediment yield, surface runoff, mean wet season monthly flow, and mean annual stream flow while reducing the dry season average monthly flow, groundwater recharge, groundwater flow, and evapotranspiration in the last four decades since the 1980s (Tigabu et al., 2019; Negese, 2021). Moreover, land cover change from forest and grassland to cultivated land and bushland has been influencing the low flow or dry season flow of the catchment (Chakilu and Moges, 2017). These rapid changes in the land use and land cover, as well as the hydrology of the Lake Tana Basin, have potentially triggered changes in aquatic ecosystem services that the surrounding communities rely on.

Concurrent with land use change, water quality in the rivers, wetlands, and lake of the Lake Tana Basin has been deteriorating (Goshu et al., 2020; Dersseh et al., 2019a). Lake Tana used to be an oligotrophic lake (Wondie, 2010; Teshale et al., 2002; Wudneh, 1998; Nagelkerke and Sibbing, 1997) but its trophic status has changed gradually to mesotrophic or eutrophic; especially at river outlets which have experienced seasonal eutrophication because of nutrient loading (Dersseh et al., 2020; Goshu et al., 2017; Goshu et al., 2010). From 1999 to 2014, the turbidity of Lake Tana increased which has been attributed to the non-point source sediment and nutrient inflow to the lake with high erosion rates in the contributing Gumara watershed (Moges et al., 2017). In addition, high total phosphorus (P) concentrations at the outlets of rivers in Lake Tana have been linked to a greater occurrence of the nuisance water hyacinth (Dersseh et al. (2019b)). Observed increases in dissolved P concentrations that coincide with the expansion of water hyacinths in the lake is potentially caused by fertilizer use in a large potato growing area in the temperate part of the Gumara Watershed (Alemu et al., 2017). However, previous work has not shown the quantitative correlations between rates of watershed nutrient loading via human activity and nutrient export to Lake Tana.

Moreover, with broad-scale changes in LULC and water quality in the Lake Tana basin, rapid environmental change in both fisheries and the extent of the nuisance water hyacinth have been observed in the lake and its surrounding wetlands. Declines in the abundance of the commercially important Labeobarbus fish species have occurred in juveniles in pool habitats of the Gumara River (Dejen and Vreven, 2019) and in Lake Tana (Gebremedhin; et al., 2018; Dejen et al., 2017; Ameha; and Assefa, 2002; Ameha; et al., 2006). Degradation of breeding grounds of the Nile Tilapia and declines in the fish stock at the mouth of the Megech River that flows into Lake Tana and shorelines of the lake have also been reported (Wondie, 2018). Water hyacinth (Eichhornia crassipes) has also infested Lake Tana since 2011 (Wondie, 2012), its coverage continuing to escalate from 20 ha in 2012 to more than 50,000 ha in 2014 (Tewabe et al., 2017; Gebremedhin; et al., 2018; Dersseh et al., 2020). In addition, a recent assessment shows that close to one-third or more than 30 % of the shoreline of the north-eastern part of the lake is now invaded by water hyacinth (Worqlul et al., 2020). Total P concentrations are highest where water hyacinths are found in the northeastern part of the lake (Kebedew et al., 2020). Water conductivity, chlorophyll-a, total suspended solids, and total dissolved solids were significantly higher in habitats covered with water hyacinth suggesting that water hyacinth infestation has a negative impact on water quality and biotic communities (Gezie et al., 2018; Mucheye et al., 2022). Due to their rapid reproduction and the high capacity of water hyacinth to use nutrients, this species outcompetes the native aquatic plants and dramatically affects the biological and physical-chemical characteristics of Lake Tana (Gichuki et al., 2012; Patel, 2012; Gezie et al., 2018; Anteneh et al., 2015). Water hyacinth also affects the fish in the lake by restricting the growth of submersed macrophytes that are habitat to native fish and invertebrates as well as the associated communities that depend on them (Shewit et al., 2017; Tewabe et al., 2017).

Understanding the interactions between environmental change in the upland catchments of Lake Tana (i.e., the Gumara River watershed) and biotic and abiotic conditions in Lake Tana is important for predicting how aquatic ecosystem services will change in response to both climate and land use change in the future. Previous studies have mostly investigated either the lake or the catchment separately, and the source-sink relationships with regard to nutrients are not well understood (Getaneh et al., 2022). Hence, this study focuses on investigating which factors control nutrient retention and export from the Gumara watershed to Lake Tana. Here, nutrient retention is considered a supporting ecosystem service because it refers to the natural processes within an ecosystem that cycle and retain nutrients, which are essential for the functioning of all other ecosystem services, like primary production and food provision. We also characterize recent temporal trends in fish abundances in the Gumara River and water hyacinth expansion in Lake Tana and floodplain wetlands at the mouth of the Gumara River.

2. Methodology

2.1. Overarching conceptual framework of the research

We investigated the degree of human modification of the Gumara River watershed and climate variation as drivers of change in nutrient retention and export that impact ecosystem services-dependent livelihoods within a broader conceptual framework (Fig. 1) which included: A) controls on water quantity; B) controls on water quality; C) water quantity impact on livelihoods; and D) water quality impact on livelihoods. In this manuscript, we focus on water quality and connected livelihoods (B and D).

2.2. Description of the study area

The Gumara River starts at ~4000 m elevation in the Guna Mountains and drains a basin of 1376 km^2 ending in Lake Tana (Fig. 2). Two permanent wetlands at the edge of Lake Tana, Walala and Shesher, cover about 8 km^2 altogether, and many seasonal wetlands are found along the river. Both the permanent and seasonal wetlands are encroached by cultivation of Rice, Tef, and Maize. The Gumara River watershed in 2019, is dominated by cultivated agricultural land accounted for 83.08 %, followed by shrubland (12.79 %), while forest, grassland, and settlement accounted for 2.59 %, 1.36 %, and 0.18 %, respectively (Belay et al., 2024). The average annual precipitation is 1280 mm with 80 % of annual precipitation falling from June to the middle of September and mean annual temperature of 20°C (Abebe et al., 2017).

More than 500,000 people living in the area surrounding Lake Tana depend on fishery and other economic activities directly and indirectly related to Lake Tana and its surrounding wetlands (Getnet and Taw (2021), Dejen et al. (2017)). The most abundant fish family in Lake Tana, the Cyprinidae, is represented by four genera: Barbus, which has three species—*B. humilis, B. pleurograma*, and *B. tanapelagious*; Varicorhinus, which has one species— *V. beso*; the most common genus in the family, Labeobarbus, with 17 species that constitute a distinct species flock in Lake Tana; and Garra is represented by four species: *G. dembecha, G. tana, G. regressus*, and *G. small mouth* (Shitaw et al. (2018).

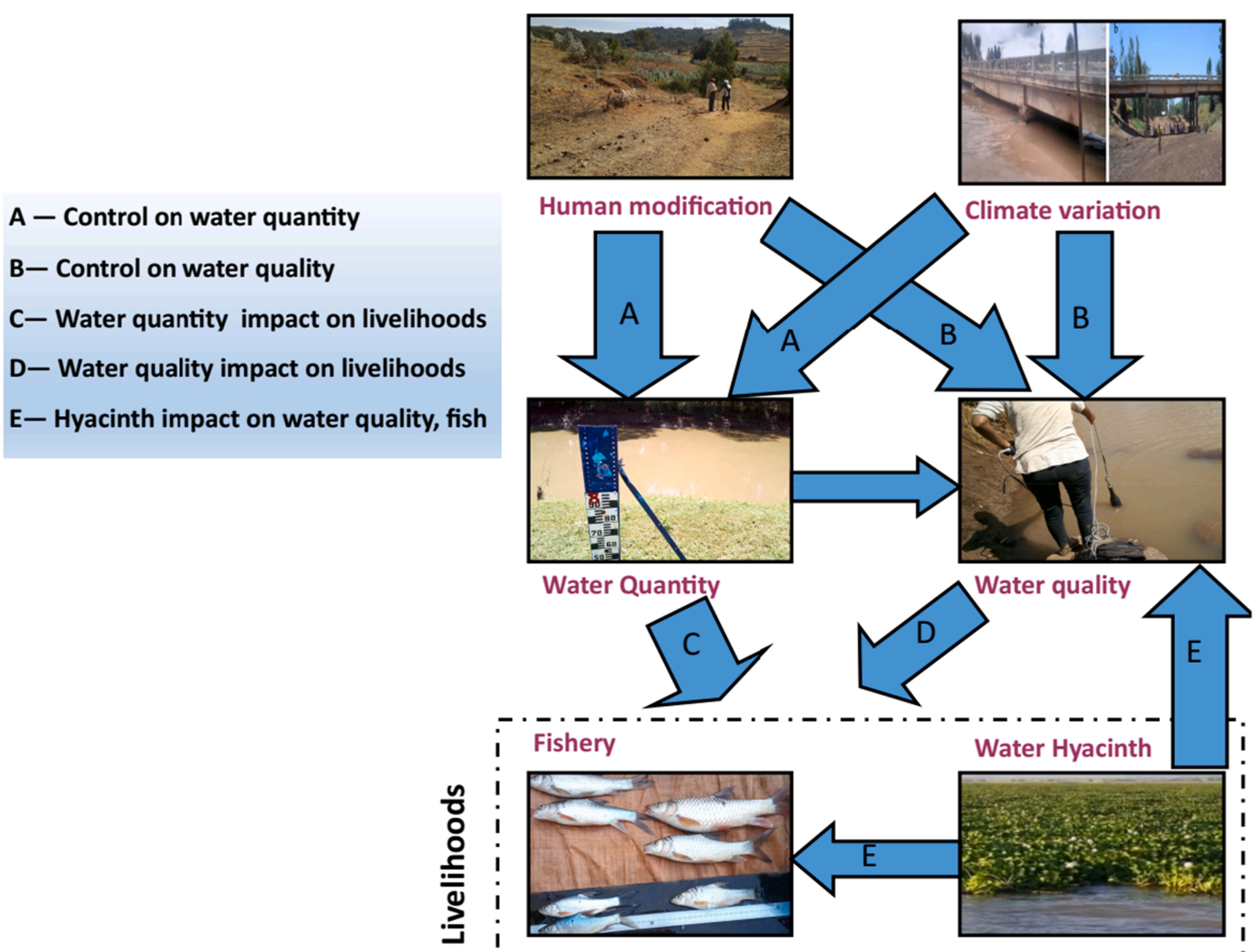

Fig. 1. Conceptual diagram linking human modification to changes in ecosystem services. Human modifications to landscapes through cultivation or urbanization as well as climate variability affect water quality and quantity, which can in turn impact fisheries and invasive species (i.e., water hyacinth).

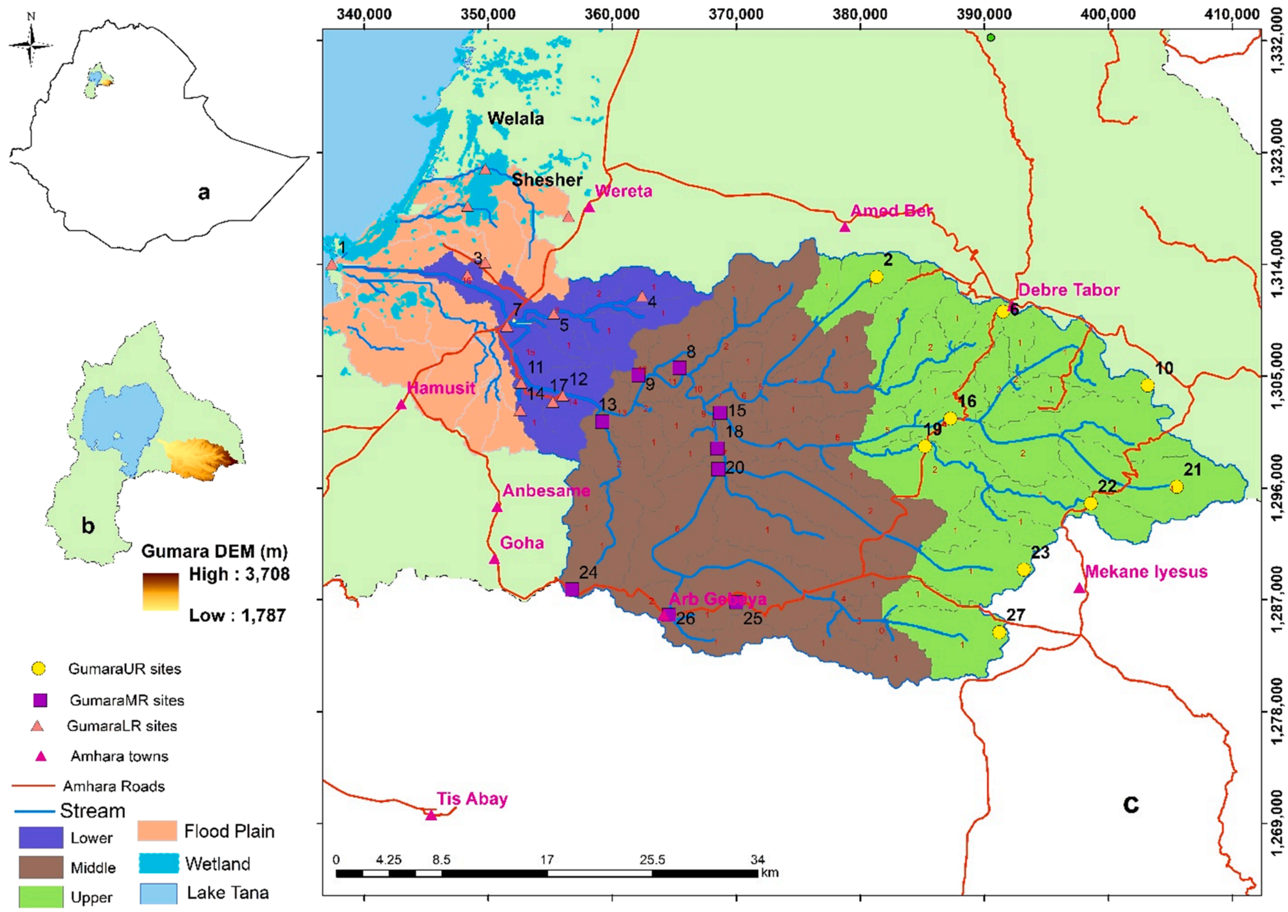

Fig. 2. Location of the Gumara River in (a) Ethiopia, (b) the Lake Tana Basin, and (c) the Gumara watershed divided into three reaches (lower in blue, middle in brown, and upper in light green) with sampling sites (1 to 27), and associated flood plain wetlands (Welala and Shesher); map adapted from (Abebe et al., 2020, 2021). The numbers indicate the different sampling sites in three reaches of the Gumara River watershed, and the Welala and Shesher wetlands. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

2.3. InVEST – NDR model

We used multiple biophysical inputs to apply the nutrient delivery ratio (NDR) model of InVEST (NCP, 2022) to estimate nutrient export of both nitrogen (N) and phosphorus (P) at the same time (Table 1). The NDR model uses a simple mass balance approach, describing the movement of a mass of nutrients through space representing the long-term, steady-state flow of nutrients through empirical relationships (NCP, 2022). Sources of phosphorus (P) and nitrogen (N) across the landscape, also called nutrient loads, are determined based on a LULC map and associated loading rates. Nutrient loads can then be divided into sediment-bound and dissolved parts, which are transported through surface and subsurface flow, respectively. In the second step, delivery factors are computed for each pixel based on the properties of pixels belonging to the same flow path (slope and retention efficiency of the land use). At the watershed/sub-watershed outlet, the nutrient export is computed as the sum of the pixel-level contributions.

Table 1
InVEST model inputs.

S. N.	Data type	Description	Source
1	River flow, 1986-2020	discharge in m^3s^{-1}	SWAT model result (Abebe et al., 2021)
2	Precipitation, 1981-now	0.25^0, resampled to 30m	CHIRPS, https://climexp.knmi.nl/start.cgi
3	Land use/cover, 1986- 2020	30 m	Own Image classification
4	DEM SRTM, 2000	30 m	(GLOVIS, 2016)
5	Water quality	30 sub-basins/ sites	Samples collected in March 2020 (Abebe et al., 2021)
6	Irrigation (pump)	Gumara catchment	Collected using ODKCollect App (https://ona.io)
7	Fertilizer application	Gumara farmlands, Kg/ha	Goshu et al. (2020)

2.4. Model inputs and data collection

The inputs to the NDR analysis included (1) a digital elevation model (DEM) of 30 m resolution from Shuttle Radar Thematic Mapper (SRTM) downloaded from the USGS Global Visualization Viewer (GloVis) (GLOVIS, 2016), (2) LULC data generated using the Google Earth Engine (GEE) cloud computing platform (Zhao et al., 2021), (3) runoff estimates from the Soil and Water Assessment Tool (Arnold et al., 2012) ecohydrological model (Arnold et al., 2012), and watershed boundaries (Table 1).

We used a random forest image classification algorithm to identify LULC types between 1986 and 2020 for every five years; i.e. 1986, 1991, 1995, 1999, 2004, 2009, 2014, 2020 (Supplementary Material – Data-InVEST.zip) based on a ground-truthed dataset (Thanh Noi and Kappas, 2018). We collected ground-truthing information for 7 major land cover types in the Gumara watershed including floodplain wetlands during the dry season in 2019 for image classification. In general, a total of 2651 signatures of LULC types were collected. Water bodies and towns were selected directly on the image displayed on GEE platform. We did LULC change detection using the image difference tool in the ERDAS IMAGINE

2015 software (Nelson and Khorram, 2018). Clusters of Pixels of the same class from the 'before' image (example 1986) that had more than a 10 % change in one cover type of the 'after' image (example 1991) named 'Increase' or 'Decrease', changes less than 10 % named 'some--increase' or 'some-decrease', and the rest named 'Unchanged'.

We used a nutrient runoff proxy raster representing the spatial variability in runoff potential (i.e. runoff at Hydrologic Response Unit or HRU level) generated in SWAT+ model output for the Gumara River between 1986 and 2020 every 5 years (i.e. 1986, 1991, 1995, 1999, 2004, 2009, 2014 and 2020; according to Reckhow et al. (1980)). We also delineated a watershed boundary shapefile of the Gumara River basin from the DEM data. Then, we aggregated biophysical data for the NDR model using existing literature (Table 2). We used crop coefficient (Kc) values for crops, forest areas and water bodies from Descheemaeker et al. (2011).

To calibrate the NDR model, we used nutrient data from water samples collected in March 2020 from thirty sites (Abebe et al., 2021) (Fig. 2) . Total Phosphorus (TP), and Total Nitrogen (TN) were measured from water samples following standard methodologies (APHA, 1997) at the Bureau of Water, Irrigation and Electric (BoWIE) laboratory in Ethiopia. We estimated the extent of irrigation practice in the Gumara catchment using the ODKCollect android App by development agents working in the watershed and analyzed and mapped in OnaData (Ona Systems, Inc.). To determine trends in TN and TP loading, we used fertilizer application rate estimates from secondary sources (Goshu et al., 2020) and published data (Abebe et al., 2021).

2.5. NDR Model setup and analysis

To run the NDR model, we set the parameters according to the InVEST User's Guide (NCP, 2022) and extracted parameters values from published literature relevant to the study area (Table 2; Abera et al. (2021); Yohannes et al. (2021); Rashid et al. (2013); Descheemaeker et al. (2011); Shenkut et al. (2013); farmwest.com (2021); Hurni (1985); Zerihun et al. (2018); and Wischmeier and Smith (1978)) The default subsurface retention efficiency was 0.8, the default subsurface critical length was 200 m, the threshold flow accumulation was 1000 for a 30 m resolution DEM, and the Borselli k parameter value was 2 (Yang et al., 2019).

2.5.1. Surface water quality

2.5.1.1. Nutrient Loads. We derived load values for each LULC class from available information on fertilizer application rates and livestock waste, human waste, biological N_2 fixation and atmospheric N deposition in the Gumara watershed. The biophysical properties the inputs required for NDR analysis using the InVEST model in the Gumara watershed for each year were synthesized from multiple sources including data collected as part of this project (Goshu et al., 2020; Yang et al., 2019; Harder et al., 2019; Zerihun et al., 2018; Harper, 2016; Rashid et al., 2013; Hurni, 1985; Wischmeier and Smith, 1978; ENBSAP, 2005).

The LULC-based loads defined above are averages for the region, but each pixel's contribution will depend on the amount of runoff transporting nutrients (Endreny and Wood, 2003; Heathwaite et al., 2005). As a simple approximation, the loads can be modified as follows (NCP, 2022) (Eqn. 1):

$$M_i = l_i \times RPI_i \quad (1)$$

where M is the modified load for each pixel i, l is the loading estimate based on the values in Table 2, and RPI is the runoff potential index, defined as (Eqn. 2):

$$RPI_i = \frac{RP_i}{RP_{av}} \quad (2)$$

where RP_i is the nutrient runoff proxy for runoff on each pixel i and RP_r is the average runoff potential over the raster.

Because phosphorus particles are usually sediment-bound and less likely to be transported via subsurface flow (NCP, 2022), The ratio between these two types of nutrient sources is given by the parameter 'proportion_subsurface_n' which quantifies the ratio of dissolved nutrients over the total amount of nutrients. For a pixel i (Eqn. 3):

$$L_{surf,i} = (1 - S_i) \times M_i \quad (3)$$

where L_{surf} is the total surface load for each pixel i, S is the proportion of subsurface loading, and M is as described in Equation 1. However, in this study, the proportion of subsurface nutrient flow is assumed to be zero, eg. proportion_subsurface_n is 0, meaning that all nutrients are reaching

Table 2
Gumara watershed biophysical properties and nutrients input level.

Land use type (model code)	The universal soil loss equation cover-factor	Universal soil loss equation management factor	Phosphorus load, kg/ha/year	Nitrogen load, kg/ha/year	Retention efficiency of p/n	Critical length to retain p/n	Root depth	Kc, crop coefficient	Vegetation presence
Farm village (2)	0.99[a]	0.33 [c]	26[d,e,f,g]	167 [d,e,f,g]	0.26[h]	15 [i]	2000 [j]	0.675 [j]	0
Grazing land (5)	0.01[b]	1 [c]	5.45 [d,e,f,g]	138 [d,e,f,g]	0.6 [h]	30 [i]	2000 [k]	1 [k]	1
Farmland (3)	0.25 [b]	0.14 [c]	26 [d,e,f,g]	28.73 [d,e,f,g]	0.48 [h]	15 [i]	1000 [l]	1.15 [l]	1
Forest (1)	0.01 [b]	1 [c]	5.5 [d,e,f,g]	138 [d,e,f,g]	0.8 [h]	20 [i]	3500 [l]	1.025 [l]	1
Waterbody (6)	0 [b]	1 [c]	1 [d,e,f,g]	12 [d,e,f,g]	0.4 [h]	15 [i]	10 [l]	0.9 [l]	0
Woodland (4)	0.15 [b]	1 [c]	1 [d,e,f,g]	12 [d,e,f,g]	0.6 [h]	20 [i]	3500 [j]	0.675 [j]	1
Wetland (0)	0 [b]	1 [c]	26 [d,e,f,g]	167 [d,e,f,g]	0.6 [h]	15 [i]	10 [j]	0.9 [j]	0

Note:
[a] Hurni, 1985.
[b] Zerihun et al., 2018.
[c] Wischmeier&Smith, 1978.
[d] Rashid et al., 2013,
[e] Goshu et al., 2020,
[f] Harder et al., 2019,
[g] Harper, 2016.
[h] Yang et al., 2019.
[i] NCP, 2022.
[j] Descheemaeker et al., 2011.
[k] Shenkut et al., 2013.
[l] https://farmwest.com/climate/calculator-information/et/crop-coefficients/.p/n-Phosphorus/nitrogen; Kc-crop coefficient.

the stream via surface flow.

2.5.1.2. Nutrient Delivery. Nutrient delivery is based on the concept of the nutrient delivery ratio (NDR), an approach inspired by the concept of a sediment delivery ratio (Vigiak et al., 2012). To simplify the assumptions in the model, for this study we omit subsurface flow.

Surface NDR

The surface NDR is the product of a delivery factor, representing the ability of downstream pixels to transport nutrient without retention, and a topographic index, representing the position on the landscape (NCP, 2022). For a pixel I (Eqn. 4):

$$\mathbf{NDR_i} = \mathbf{NDR_{o,i}}\left(1 + \mathbf{exp}\left(\frac{IC_0 + IC_i}{k}\right)\right)^{-1} \tag{4}$$

Where, IC_0 and k are calibration parameters, IC_i is an index of connectivity which is a topographic index, and NDR_0,i is the proportion of nutrient that is not retained by downstream pixels (irrespective of the position of the pixel on the landscape). The value of IC_0 is set to $IC_0=(IC_{max}+IC_{min})/2$. This imposes that the sigmoid function relating NDR to IC is centered on the median of the IC distribution, hence that the maximum IC value gives NDR = NDR_{max}. k is set to a default value of 2 based on Sediment Delivery Ratio (SDR) model theory (Borselli et al., 2008); it is an empirical factor that represents local topography. Below details on the computation of each factor is provided. NDR_0,i is based on the maximum retention efficiency of the land between a pixel and the stream (downslope path), (Eqn. 5):

$$\mathbf{NDR_{0,i}} = 1 - \mathbf{eff_i} \tag{5}$$

IC, the index of connectivity, represents the hydrological connectivity, i.e. how likely nutrient on a pixel is likely to reach the stream. In this model, IC is a function of topography only (NCP, 2022) (Eqn. 6):

$$\mathbf{IC} = \mathbf{log}_{10}\left(\frac{\mathbf{Dup}}{\mathbf{Ddn}}\right) \tag{6}$$

Where D_{up} (Eqn. 7),

$$\mathbf{D_{up}} = \mathbf{S_{av}}\sqrt{A} \tag{7}$$

And, D_{dn} (Eqn. 8),

$$\mathbf{D_{dn}} = \sum_i \frac{di}{Si} \tag{8}$$

where D_{up} is the area upslope of each pixel, S_{av} is the average slope gradient of the upslope contributing area (m/m), A is the upslope contributing area (m^2); D_{dn} is the flow path between the pixel and the nearest stream, d_i is the length of the flow path along the i^{th} cell according to the steepest downslope direction (m), and S_i is the slope gradient of the i^{th} cell, respectively.

The upslope contributing area and downslope flow path are delineated with a Multiple-Flow Direction algorithm (NCP, 2022). To avoid infinite values for IC, slope values (S) are forced to a minimum of 0.005 m/m if they occur to be less than this threshold, based on the DEM (Cavalli et al., 2013).

2.5.1.3. Nutrient export modeling. Nutrient export from each pixel i is calculated as the product of the load and the NDR (NCP, 2022), (Eqn. 9):

$$E_i = \left(L_{surf,i} \times NDR_i\right) \tag{9}$$

where the surface export E for each pixel i is the product of the surface load L and the nutrient delivery ratio NDR.

Total nutrient at the outlet of each user-defined watershed is the sum of the contributions from all pixels within that watershed, (Eqn. 10):

$$\mathbf{X_{exptot}} = \sum_i X_{expi} \tag{10}$$

2.5.1.4. Model Calibration and Uncertainty. We calibrated the NDR model simulated nutrient export from the Gumara River watershed according to Redhead et al. (2018) using an automatic calibration software. Automatic calibration was done using the Optimization Software Toolkit for Research Involving Computational Heuristics (OSTRICH) with a Dynamically Dimensioned Search (DDS) optimization algorithm (Matott, 2017). OSTRICH is a model-independent multi-algorithm optimization and parameter estimation program that can be configured with any modeling program that uses text-based input and output file formats. In this study, DDS was used to minimize statistical error metrics (PBIAS and NSE) between predicted and observed data for total Nitrogen (Tolson and Shoemaker, 2007). We developed a series of python scripts and batch files and implemented them to automate the process of: 1) extracting, computing, and exporting model output values at observation points; 2) to compute model performance values for each model run; and 3) to connect NDR with OSTRICH through InVEST's Python API (Fig. S1). The flow accumulation and Borselli k parameters are calibration parameters used considering parameter value with ranges of 100 to 1000 for flow accumulation and 2 to 100 for k. The parameter selection and ranges were chosen based on the manual for NDR model (NCP, 2022). We used total nitrogen and total phosphorus observations from 2020 for 27 sub-watersheds of the larger Gumara watershed to calibrate the model. Then, we estimated model uncertainty for the multi-site calibration using 100 simulations of a combination of the two calibration parameters, K and F_{acc}, generated using a Latin hyper cube sampling (Abbaspour et al., 2007; Abbaspour et al., 2004). A *p-factor*, which is the percentage of measured data bracketed by the 95 % prediction uncertainty (95PPU), and *r-factor*, which is the average thickness of the 95PPU band divided by the standard deviation of the measured data, are calculated to estimate the degree of uncertainty. The 95PPU is calculated at the 2.5 % and 97.5 % levels of the cumulative distribution of an output variable obtained through Latin hypercube sampling.

2.6. Irrigation expansion

To understand the extent of irrigation pumps which divert water from the Gumara river network, we collected irrigation pump measurements from March to April 2021 in the Gumara River and connected flood plains irrigated lands (Supplementary Information in Excel sheet; Gumara_Pumpdata_Apr2021.xlsx and Fig. S2, InVEST-modeling_on_GumaraRiver_supplementalMaterial20241209.docx). We mapped a total of 674 irrigation sites in the Gumara River catchment. Some pumps were individual pumps and some were grouped (up to 40 pumps in 100 meters distance) in one location as well as other structures for water extraction (Fig. S2).

2.7. Trends in fish abundance and water hyacinth extent

To examine trends in fish abundances as well as water hyacinth extent during a period of estimated increasing nutrient export from the Gumara River watershed, we first collated data on fish abundance estimates from Abebe et al. (2021) and water hyacinth extent from Derseh et al. (2019a, 2020). We then determined the direction and magnitude of trends using a Mann Kendall (MK) trend test. All analyses were done in R version 4.2.2. (Team, 2023).

3. Results and Discussion

3.1. Trends: Human modification

3.1.1. Land use and land cover change

The land use/cover of Gumara Watershed between 1986 and 2020 showed a decline in wetlands by 23 %, water bodies by 28 %, farm villages by 31 %, and farmland by 11 % (Fig. S3). Whereas, forest cover increased by 14 %, woodland by 148 %, and grassland by 84 %. The change detection found a 12 % decrease and a 15 % increase in any of the LULC classes but 73 % remained unchanged between 1986 and 2020 (Fig. 3). The highest proportion of unchanged area was existing farmland (67 % or 101,398 ha; Fig. S3b). As observed in the field, the proportion of farmland in the watershed increased because of the expansion of irrigated lands and the increase in forest cover was due to conversion from cultivated lands to eucalyptus plantations. This finding suggests that the mass mobilization of the public for soil and water conservation efforts and afforestation beginning in 2016 is attributable to the increase in eucalyptus plantations (Abi et al., 2019), Eucalyptus plantations have significantly altered the regional hydrology, including causing declines in baseflow during the dry season (Enku et al., 2020; Chanie et al., 2013). However, this forest vegetation increase did not occur along riparian areas of the river Thalweg, which instead had a significant decline (Abebe et al., 2021). Such reductions in riparian buffer vegetation may decrease the nutrient retention capacity of the riparian zone (Weigelhofer et al., 2012; Walton et al., 2020).

3.1.2. Irrigation expansion

In 2021, we observed 132 river diversions, 2 dams, 11 spring diversions, 164 groundwater pumping locations, 356 river pumping locations, and 9 hand-fetching irrigation practices with a total of 674 irrigation sites. There were 4259 irrigation pumps, with ~65 % used to pump river water (2804 pumps) and the remaining pumps (1455 pumps) used for groundwater pumping (Fig. S2). The river pumps can pump 30 m^3/hr from 4 to 24 hours per day. When averaged to 8 hours of pumping per day, the daily river pumping capacity is approximately 240 m^3/day (see Fig. S4 for specification).

Irrigation in the Gumara River watershed started in 1997 with 25 pumps on hundreds of hectares with an agricultural extension program of district agriculture offices (Abebe et al., 2020). The area being irrigated during the dry season (March-April) in 2021 has reached 3171 ha, representing a 10-fold increase. In 2021, these agricultural lands include 26 % of maize, 9 % of teff, 3 % of garlic, 1 % of pepper, 2 % of tomatoes, 17 % of potatoes, 41 % of onion, and 1 % fruit trees (Fig. S5). Due to this trend of water extraction, it has become challenging to maintain the dry season flow necessary for riparian and aquatic ecosystem conservation (Abebe et al., 2020).

3.1.3. Fertilization on agricultural lands - a synthesis from other studies

In a 2014 household sample survey on fertilizer application by ADSWE (2014), out of 287 farmers growing different crops in the Gumara catchment in 2014, 19.5 % of the farmers applied no fertilizer, 39 % of the farmers applied 10 to 25 Kg/ha, 22 % of the farmers applied between 25 to 50 Kg/ha, 15 % of the farmers applied 56 to 100 Kg/ha and only 5 % of the farmers used more than 101 Kg/ha. Across all farmers, the mean fertilizer application rate was 32 Kg/ha (Fig. S6a). According to Goshu et al. (2020), based on their study in the Lake Tana basin in 2017, the fertilizer application in the major catchments of Lake Tana reached 28.73 Kg/ha, agreeing closely with the average found by ADSWE (2014). In another survey of 10 Kebeles (the lowest administrative boundary in this region) clustered according to agro-climatic zones in 2019, the application of fertilizer in the Gumara Catchment ranged from 0 to 336 Kg/ha with an average rate of 196 kg/ha (Schuurman, 2021). Fertilizer application was highest (close to the research recommendation of 200 kg/ha (Tamene et al. 2017)) in the middle and lower reaches of the Gumara catchment (Fig. S6b). This fertilizer application rate is still lower than the 200 kg/ha minimum recommendations in Ethiopia (Tamene et al., 2017).

3.2. Climate Variations

3.2.1. Precipitation

The historical precipitation over the Gumara River catchment between 1981 to 2020 has an average areal value of 1345 mm/year (StDev=133.4 mm) with a minimum value of 1054 mm/year in 2009, and a maximum value of 1632.5 mm/year in 2019 (KNMI climate

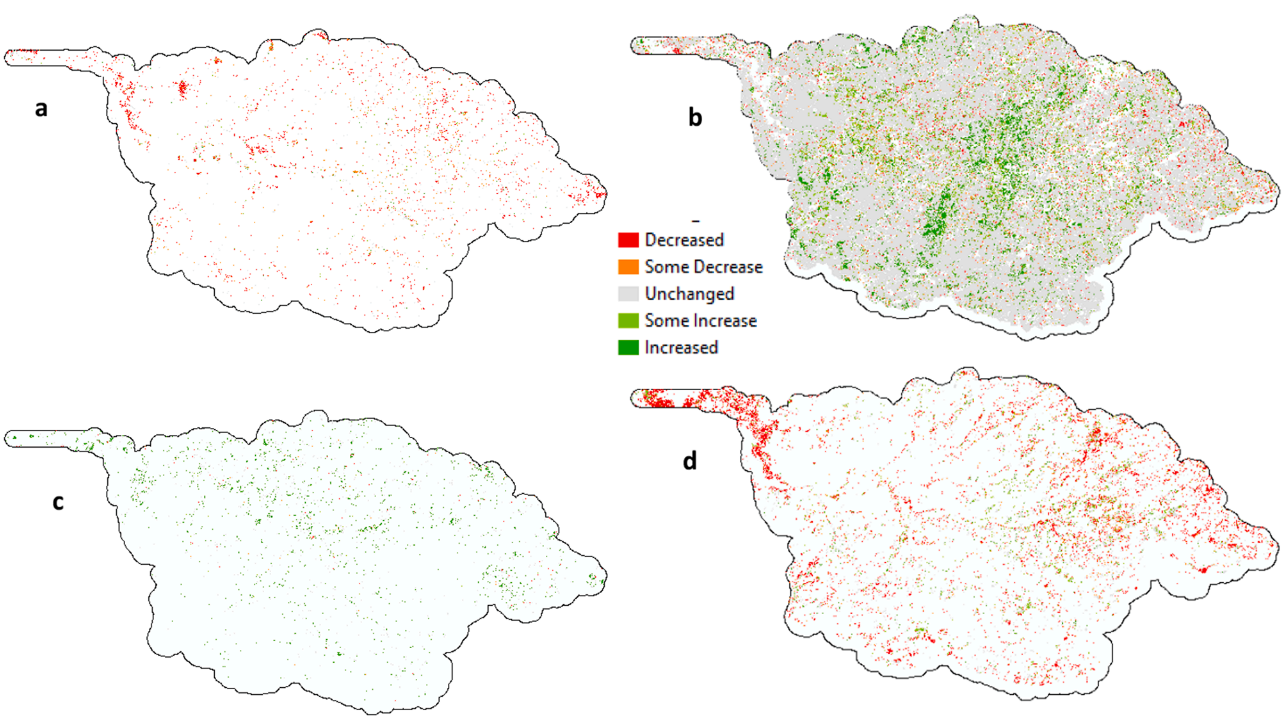

Fig. 3. Land cover/use change detection between 1986 and 2020 in the Gumara Watershed. Change detection is shown for a) wetlands, b) farmland, c) grazing land and d) forest land. Note: areas ‘decreased’ are those in which any land cover class has shrunk by more than 10 % from their original coverage and ‘increased’ areas are those expanded by more than 10 % from their original coverage.

explorer: https://climexp.knmi.nl). The areal average precipitation in the Gumara River showed an increase at a rate of 5 mm/year between 1981 to 2020 ($p < 0.05$; Fig. S7a). There was a sudden increase in the amount of annual precipitation starting in 2009, with a non-significant ($p > 0.1$), but increasing rate of 22 mm/year.

3.2.2. *Flow alteration–a synthesis of previous studies*

The historical flow of the Gumara River showed declines in both low and high flow (Abebe et al., 2020). Minimum daily low flows decreased from 1.55 $m^3 s^{-1}$ in 1973 to 0.16 $m^3 s^{-1}$ in 2018 and seasonal (90-day) mean low flows decreased from 4.88 $m^3 s^{-1}$ in 1973 to 2.04 $m^3 s^{-1}$ in 2018 (Fig. S7b). Maximum daily flows also decreased over the same period, with daily maximum flows decreasing from 335 $m^3 s^{-1}$ in 1973 to 266 $m^3 s^{-1}$ in 2018 but seasonal (90-day) mean daily maximum flows stayed approximately the same at 188 $m^3 s^{-1}$ in 1973 to 185 $m^3 s^{-1}$ in 2018 (Abebe et al., 2020) (Fig. S7c). The daily maximum flow is a good indicator of changes in the magnitude of peak flooding which is an important component of the natural flow regimes of rivers (Poff et al., 1997). Large floods in the Gumara River watershed are important for inundating wetlands near Lake Tana (Abebe et al., 2020). Decreasing the magnitude of flooding has the potential to result in early disconnection of the wetlands from Lake Tana and the Gumara River which could interrupt fish migration.

3.3. *Input data synthesis and InVEST model calibration*

3.3.1. *Input data synthesis*

Nutrient loading and other biophysical properties varied among land use types in the Gumara River watershed (Table 2). Nitrogen loading was estimated to be 116 kg/ha/year from animal manure, 29 kg/ kg/ha/ year from synthetic fertilizer, 10 kg/ha/year from human waste, 9 kg/ ha/year from biological N_2 fixation, and 3 kg/ha/year from atmospheric N deposition (Goshu et al., 2020) (Table 2). Phosphorus loading was estimated to be 20.65 kg/ha/year from fertilizer, 3.23 kg/ha/year from animal manure, and 2.22 kg/ha/year from human waste.

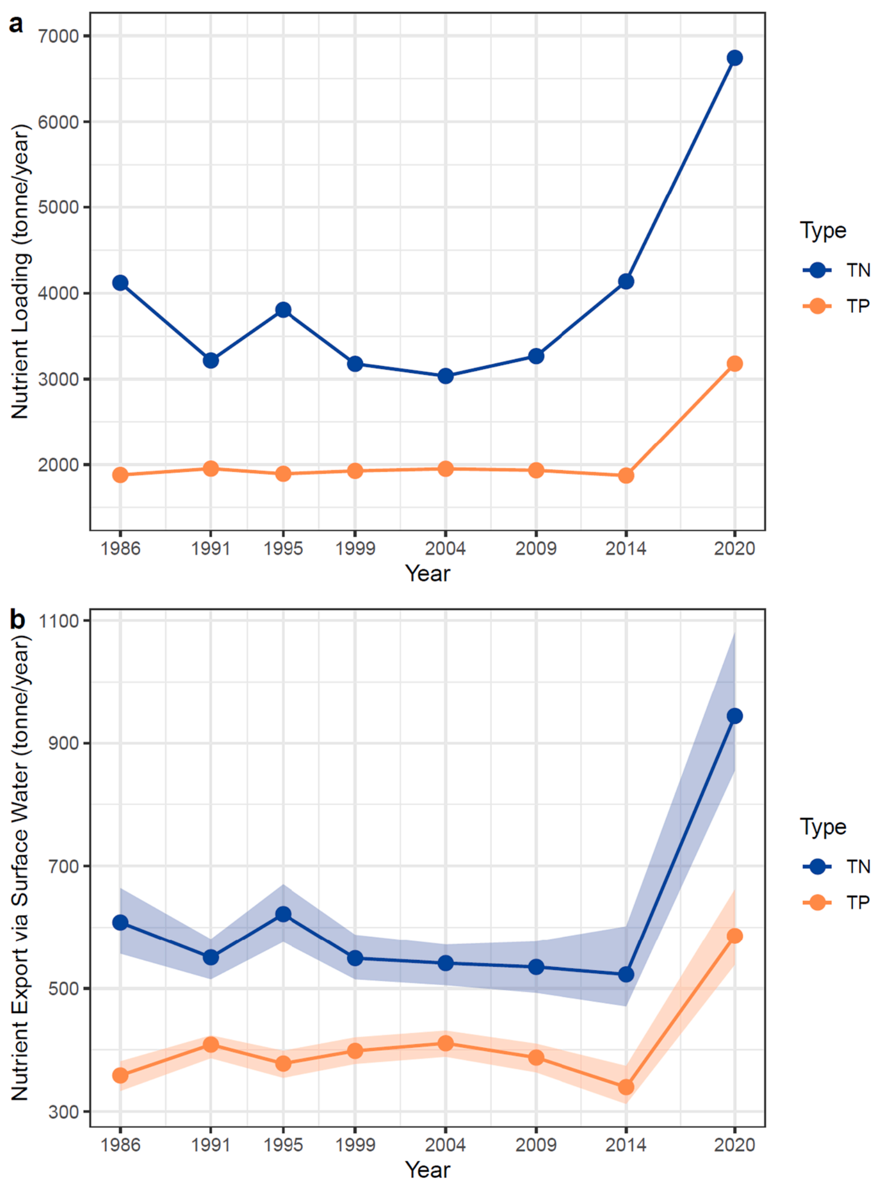

Fig. 4. Gumara watershed total nitrogen (TN; shown in blue) and total phosphorus (TP; shown in orange) surface loading (panel a) and TN and TP export via surface water (panel b) in tonne per year between 1986 and 2020. Surface loading estimates were calculated from Table 2, while nutrient export from the Gumara watershed via surface water was estimated using model calibration. Points in panel b represent the 50th quantile of calibration estimates, while the ribbon represents the confidence intervals (2.5 % & 97.5 %). (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

3.3.2. Calibration results

The InVEST model estimated surface loading and export of both phosphorus and nitrogen found to be stable between 1986 and 2009 but then increased between 2014 and 2020 (an increase of 67 % for P and 76 % for N; Table S1 and Fig. 4) for the default scenario. Whereas, the calibration of nitrogen export (Total Nitrogen, TN) on 27 sites has high performance with NSE = 0.88, R^2 = 0.94, PBias = -25.4, and RSR = 0.345. Alongside, phosphorus calibration performance was NSE = 0.413, R^2 = 0.48, PBias = 36.2, and RSR = 0.766. Correspondingly, the uncertainty for TN and TP found p-factor of 0.4 and 0.2; and r-factor of 0.2 and 0.2 respectively (Table S2, Fig. 4).

3.4. Spatio-temporal trends of water quality–InVEST model outputs

3.4.1. Temporal variation in nutrient surface export

The calibrated N export in the Gumara watershed of Lake Tana exhibited an increase between 1986 and 2020 from 38.45 kg/year to 64.0 kg/year (Fig. 5). Similarly, phosphorus export showed an increase between 1986 and 2020 from 6.45 kg/year to 9.96 kg/year (Fig. 5). Specifically, a higher increase was depicted in the years between 2014 and 2020; i.e. an increase of 69 % for P and 80 % for N. The overall Mann Kendal trend test was found significant for both TN and TP at *p*-value = 0.0008366.

3.4.2. Spatial variation in nutrient surface export

The highest N and P export values can be observed in channels and on riparian zones; the highest export being downstream close to the watershed outlet (Fig. 5). Besides, the nutrient export was higher close to channels in 1986 and it has expanded to the catchment in 2020. And, the highest decrease in land cover/use was observed where higher export for both Nitrogen and Phosphorus were exhibited (see Fig. 3, section 3.1.1.).

3.5. Relationships of water quality to ecosystem services

3.5.1. Spatio-temporal relationships between water quality and fish production

Data compiled from Ameha; and Assefa (2002), Mengistu et al. (2017a) showed that the commercial fishery catch in the Lake Tana basin between 1993 to 2013 increased from 393,000 Kg to 9,980,000 Kg per annum (Fig. S9). The fish abundance observed in multiple research efforts declined from 53 individual fish in 2014 to a single fish by 2020 indicating that fish abundances in the Gumara River have declined (Fig. S9; $p < 0.05$). The result is in line with a study by Abebe et al. (2021) which found that the fish species abundance decline is attributed to illegal fishing integrated with the water quality deterioration and flow alterations (Abebe et al., 2021; Dejen et al., 2017). Although it is believed that Lake Tana has more fish production potential than this (Wondie, 2010), and in recent years the water quality deterioration has likely harmed the fish diversity and abundance (Fig. 6 and Table S3). It is unclear how much water quality degradation is causing declines in fish abundance because there has been a simultaneous alarming increase in illegal fishery activity in which fishing is not regulated for gillnet size and material standard that might be exacerbating declines in fish abundances (Dejen et al., 2017; Mengistu et al., 2017b).

3.5.2. Spatio-temporal relationships between water quality and water hyacinth expansion

The invasive weed water hyacinth, first seen in Lake Tana in 2011, is showing rapid expansion, especially in the northeastern part of the lake (Dersseh et al., 2020; Tewabe et al., 2017). Water hyacinth extent in Lake Tana during the wet season increased in cover from 278.3 ha to

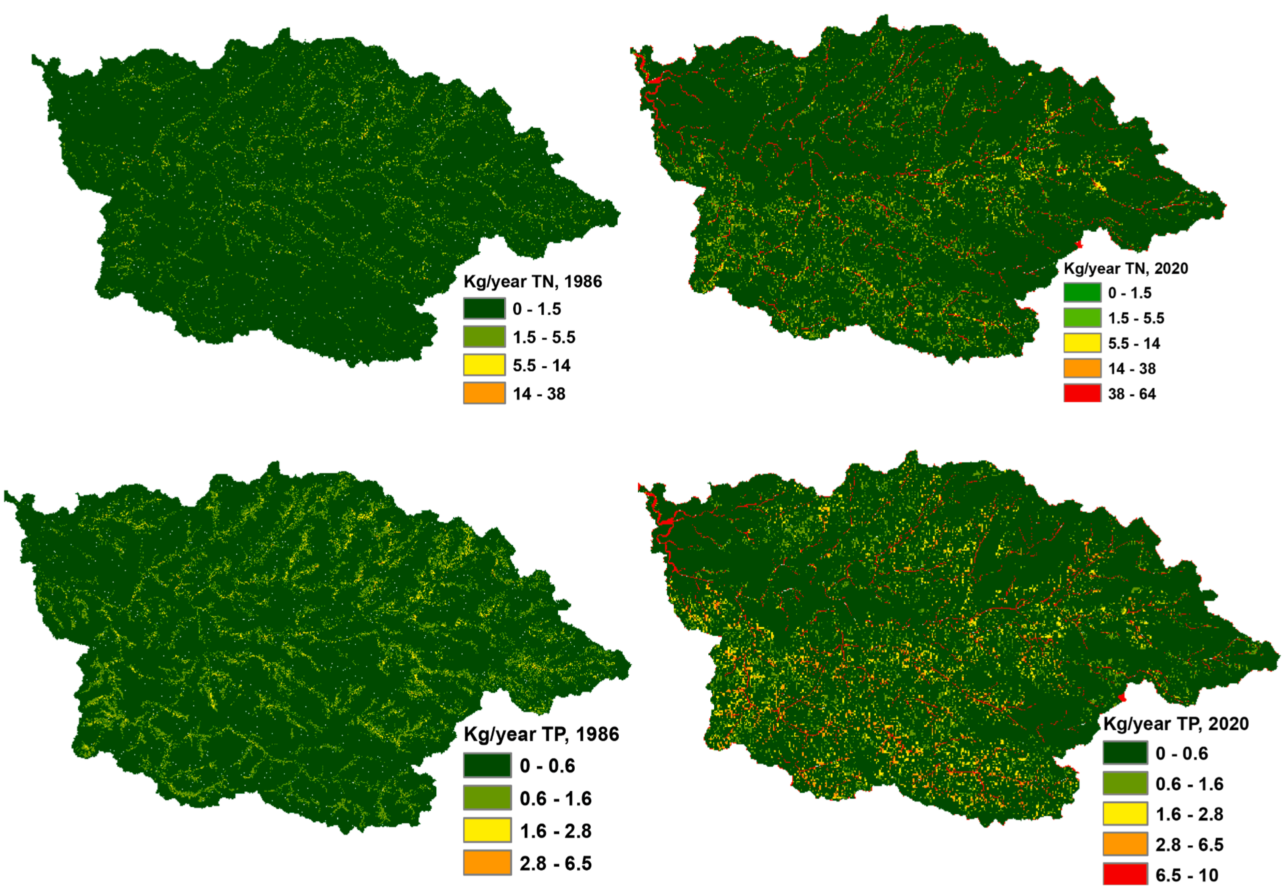

Fig. 5. Nitrogen and Phosphorus export in the Gumara watershed between 1986 and 2020.

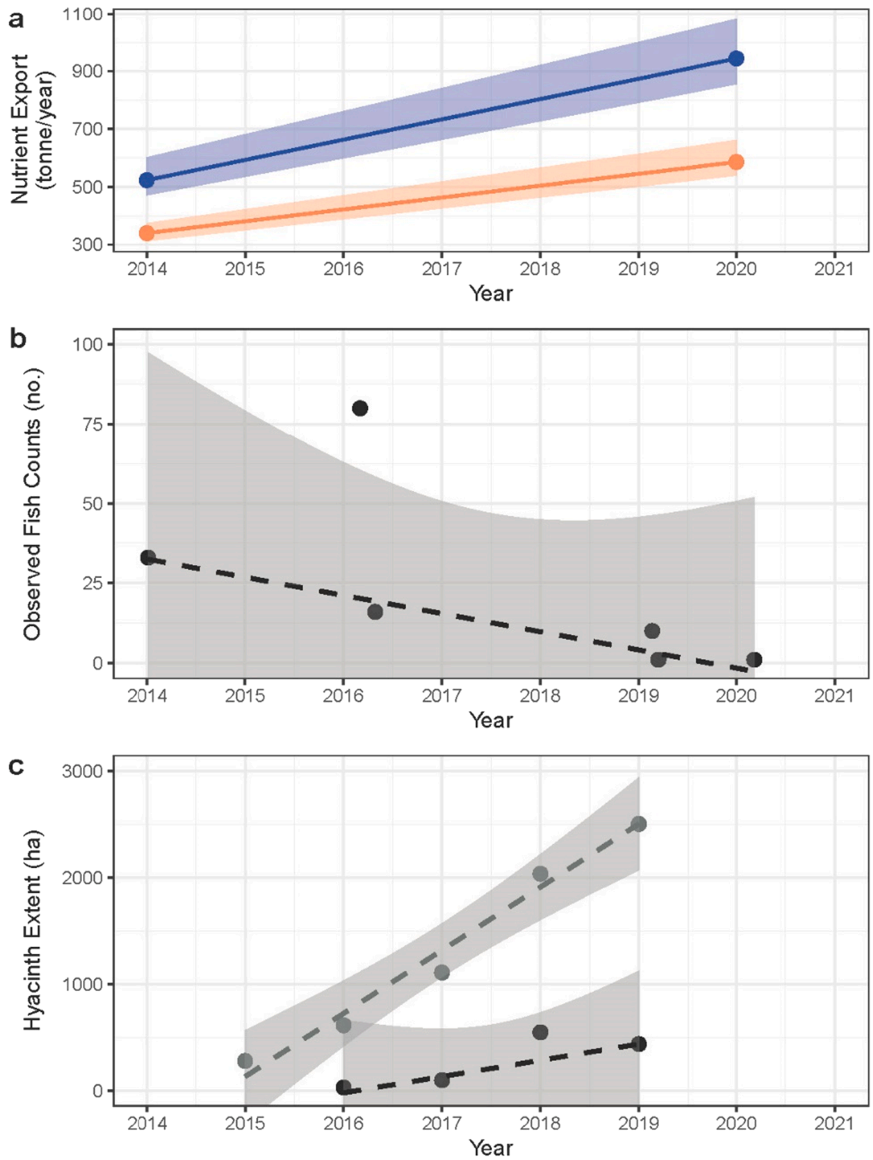

Fig. 6. Trends in dry season fish abundance (Panel b) and water hyacinth extent (Panel c) between the estimates of nutrient export (total nitrogen (TN) shown in blue; total phosphorus (TP) shown in orange) in 2014 and 2020 (Panel a) in the Gumara River of Lake Tana Basin. The trend lines in panels b and c are Theil-Sen slopes ($p < 0.1$) estimated using the 'mblm' package in R (Komsta, 2019). As both nitrogen and phosphorus nutrient export from the Gumara River increased from 2014 to 2020, fish abundance declined (Panel b) and water hyacinth extent (data adapted from Dersseh et al. (2020)) increased both during the wet (rainy) season shown in grey and during the dry season shown in black.

2504.5 ha between 2015 and 2019 (Dersseh et al., 2020). Water hyacinth extent also increased during the dry season when it has a generally lower extent. Together these increases in the invasive weeds are likely also contributing to declines in fish abundance and other aquatic ecosystem services.

4. Conclusion

Based on these results, several interconnected trends and their implications can be drawn for the Gumara River watershed and Lake Tana basin. The decline in wetlands, water bodies, farm villages, and farmland coupled with the significant expansion of irrigation activities since 1997 suggest a shift towards intensified agricultural practices in the region. This expansion may have contributed to alterations in hydrologic and ecosystem processes in the Gumara river watershed. The highest fertilizer application in the middle and lower reaches of the Gumara catchment, combined with the increase in nutrient export, particularly phosphorus and nitrogen, indicates potential concerns regarding water quality and ecosystem health. Over the time that nutrient export increased the most (2014–2020), fish species abundance declined dramatically, suggesting a negative impact on aquatic biodiversity. A concurrent increase in areal average precipitation contrasts with the observed drops in the historical flow of the Gumara River, highlighting potential impacts of land use changes and water management practices on river flow that may affect water availability, flow dynamics, and ecosystem functioning.

The decline in fish abundance in the Gumara River coupled with the significant increase in water hyacinth cover in Lake Tana, underscores the ecological consequences of altered land use and nutrient loading on aquatic ecosystems. The rapid expansion of water hyacinth during a period of increased nutrient export further suggests that nutrient enrichment downstream of the Gumara River could be a driver of invasive species expansion. Despite the substantial increase in commercial fishery catch in the Lake Tana basin over the last several decades, the decline in fish abundance in the Gumara River suggests potential localized impacts on fish populations, which may have broader implications for ecosystem resilience and fisheries sustainability. In conclusion, the observed trends indicate complex interactions between land use changes, agricultural practices, hydrological dynamics, nutrient loading, and ecological responses in the Gumara River watershed and Lake Tana basin. Addressing these challenges will require integrated and sustainable management strategies that consider the interconnectedness of socio-economic development and environmental conservation goals.

CRediT authorship contribution statement

Wubneh B. Abebe: Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Minychl G. Dersseh:** Writing – review & editing, Data curation. **Goraw Goshu:** Writing – review & editing, Data curation. **Wuletawu Abera:** Writing – review & editing, Validation, Supervision, Software, Resources, Methodology, Funding acquisition, Conceptualization. **Edo Abraham:** Writing – review & editing, Funding acquisition, Conceptualization. **Muluneh A. Mekonnen:** Writing – review & editing, Validation, Software, Methodology, Formal analysis, Data curation. **Nicola Fohrer:** Writing – review & editing, Methodology, Conceptualization. **Seifu A. Tilahun:** Writing – review & editing, Supervision, Methodology, Conceptualization. **Michael E. McClain:** Writing – review & editing, Supervision, Conceptualization. **William A. Payne:** Writing – review & editing, Supervision, Resources, Project administration, Methodology, Funding acquisition, Conceptualization. **Joanna R. Blaszczak:** Writing – review & editing, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, 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.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.ecohyd.2025.01.001.

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