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Assessment of combined nutrients and pesticides grey water footprint in a sub-Saharan African lake catchment

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ABSTRACT

Water scarcity and pollution are pressing challenges in agricultural catchments. This study quantified the Grey Water Footprint (GWF) of nutrients and pesticide residues in the Lake Naivasha catchment, Kenya, and assessed spatial patterns of pollution stress. Mean daily discharge ranged from 0.03 ± 0.01 m^3 s^{-1} at Little Gilgil (G2) to 2.95 ± 1.78 m^3 s^{-1} at Malewa Highway Bridge (M5). The highest nutrient-related GWF was recorded for total phosphorus at Karati (K1), $5.3 \times 10^6 \pm 1.6 \times 10^6$ mm^3 $year^{-1}$, while the lowest values were observed at the downstream Malewa sites (M4 and M5). For pesticides, cyclodienes peaked at K1 with values ranging from $1.59 \times 10^5 \pm 3.52 \times 10^4$ mm^3 $year^{-1}$ for dieldrin to 81.9 ± 32.7 mm^3 $year^{-1}$ for methoxychlor, while DDT and HCH groups ranged from 0.34 ± 0.08 mm^3 $year^{-1}$ for γ-HCH at Malewa to $3.80 \times 10^6 \pm 1.67 \times 10^6$ mm^3 $year^{-1}$ for pp-DDT at Karati. The Integrated Grey Water Footprint (IGWF) showed that pesticides dominated pollution stress at most sites, except Karati where phosphorus loads were highest. Grey Water Stress (GWS) exceeded unity (>1) at Karati, indicating that pollutant loads surpassed the river's assimilative capacity, while other sites remained below capacity, ranging from 2 to 4 % at Malewa (M1) to 10–20 % at Little Gilgil (G2). These findings highlight pollution hotspots in low-flow sub-catchments, driven by intensive farming and settlements, and underscore the urgent need for integrated water quality standards and advanced monitoring strategies to safeguard aquatic ecosystems and promote sustainable water management in sub-Saharan Africa.

1. Introduction

Water scarcity and pollution are critical global challenges, particularly in areas where agriculture relies heavily on the application of nutrients and pesticides (Holden, 2018). The Lake Naivasha catchment in Kenya is a prime example, as it sustains one of the country's most important horticultural zones while also providing vital ecosystem services and freshwater to surrounding communities (Kirui, 2006; Masso et al., 2017). Hence, assessing the grey water footprint of these contaminants is crucial for sustainable water resource management and the preservation of the Lake Naivasha ecosystem (Walker et al., 2019).

The Lake Naivasha catchment in the Kenyan Rift Valley, encompasses various land uses, including agriculture, horticulture, livestock farming, tourism, and urban settlements (Kuiper and Gemählich, 2017; Mekonnen et al., 2012; Waithaka et al., 2017; Willy et al., 2014). This catchment is known for its high agricultural productivity, particularly in floriculture and vegetable production, which heavily rely on the application of nutrients and pesticides (Kirui, 2006). The catchment also supports a rich diversity of flora and fauna, including numerous endemic and migratory species (Obegi et al., 2021).

Nutrients, such as nitrogen and phosphorus, are essential for crop growth and productivity. However, excessive application or improper management of these are a major cause of water pollution through surface runoff and sub-surface leaching leading to eutrophication, harmful algal blooms, and oxygen depletion that threaten aquatic organisms and drinking water quality (Phillips et al., 2017). Pesticides, including herbicides, insecticides, and fungicides, are commonly used to control pests and diseases in agricultural practices but they pose toxicological risks to aquatic invertebrates, fish, and beneficial soil microorganisms, as well as risks of bioaccumulation and persistence in

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sediments and food webs (Smalling et al., 2013). Together, these agrochemicals compromise water quality, biodiversity, and human health in agro-ecosystems (Jayaraj et al., 2016; Mahmood et al., 2016).

The concept of Grey Water Footprint (GWF) is defined as the water volume that is required in a catchment to assimilate the load of a pollutant in a water body and is based on the comparison between expected natural background concentrations and existing ambient water quality standards (Liu et al., 2017). GWF provides a measure that supports identification of risk and recommended actions to reduce water pollution (Franke et al., 2013). The Integrated Grey Water Footprint (IGWF) considers the GWF affecting water resources from multiple contaminants (Mekonnen and Hoekstra, 2015).

Our study uses Grey Water Stress (GWS) as a metric to identify the extent of water pollution. Identified by Liu et al. (2017), the GWS was

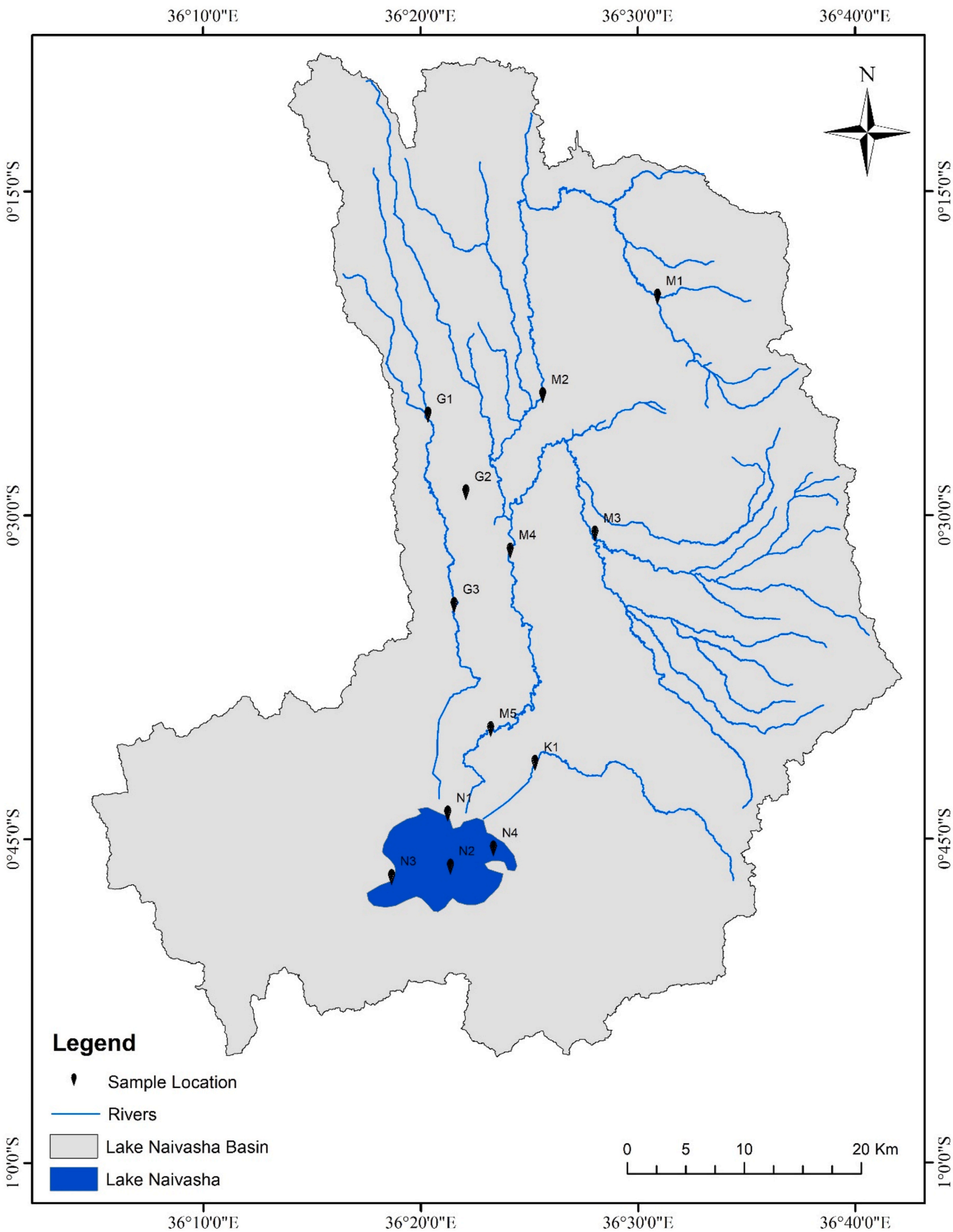

Fig. 1. Lake Naivasha catchment with sampling sites. Gilgil River (G1 - Kahuho, G2 - Little Gilgil, G3 - Gilgil Highway). Malewa River (M1 – Wanjohi, M2 – upper Malewa, M3 – Turasha, M4 – Malewa Bush ventures, M5 – Malewa Highway site). Karati River (K1 – Karati Highway site). The lake sites (N1 – River Mouth, N2 – Mid-lake, N3 – Hippo Point, N4 – Crescent).

designed to estimate the assimilative capacity of a water body under pressure from the GWF (Liu et al., 2017). It standardizes the potential pollution through critical dilution volumes to provide a single score for potential contamination at a spatially defined spatial scale (Ridoutt and Pfister, 2013). The GWS has similarities with the Agricultural Water Stress Index (AWSI) as applied by Xinchun et al. (2017), except that while the AWSI focuses on the ratio for irrigation water demand, the GWS focuses on the ratio for water pollution status. The application of a GWF is predicated on the idea that a GWS less than 1 indicates that the water volume at a site can dilute the contaminants to within legally published water quality standards, while a GWS of more than 1 indicates the need for remedial measures to reach acceptable water quality standards (Wang et al., 2021).

The interpretation of the GWS indicator is highly dependent legally published water quality standards and for what purpose the water from the ecosystem will be used (Liu et al., 2017). For instance, drinking water quality standards are more stringent compared with those set for effluent monitoring (WASREB, 2008). The GWF approach has been used to assess the GWF of pharmaceuticals (Wöhler et al., 2020), thermoelectric power plants (Chini et al., 2020), pesticides in cultivated soils (Vale et al., 2019; Vale et al., 2019), pesticides from industrial park development (Dong et al., 2021), and different sizes of wastewater treatment plants (WWTP) (Ansorge et al., 2020). However, to our knowledge, only one study has considered the determination of GWF by combining nutrients and pesticide pollution in IGWF assessment (Miglietta et al., 2017).

While previous studies (Ansorge et al., 2020; Chini et al., 2020; Dong et al., 2021; Martínez-Alcalá et al., 2018; Miglietta et al., 2017; Wöhler et al., 2020) have explored the grey water footprint of either nutrients or pesticides separately, a combined footprint allows for an assessment of synergistic or cumulative impact (Traas et al., 2004). Our study assesses the combined nutrients (nitrogen and phosphorus) and pesticides (organochlorines) grey water footprint in the Lake Naivasha catchment. The focus of nitrogen and phosphorus is because they are the most common components of inorganic fertilisers used in intensified agricultural production systems (Maberly et al., 2020). Additionally, our study explores GWF associated with organochlorine pesticides (such as DDT, cyclodienes and HCH) owing to their persistent nature in the environment. DDT has been banned for agricultural use, but still used for pest control and reported in environmental samples (Onyango et al., 2015). The objectives of the study were to quantify the amount of water required to assimilate nutrients and pesticides from agriculture within the catchment and the spatial distribution of the integrated grey water footprint. This was used to identify hotspots of pollution based on the GWS.

2. Methods

2.1. Study area

This study was carried out within the 3346 km^2 Lake Naivasha catchment, Kenya (Fig. 1). The Gilgil and Malewa Rivers drain into Lake Naivasha from the North and North-Eastern side of the catchment, and the Karati River drains from the East (Clarke, 1990). Both surface and ground waters in the catchment are heavily exploited for irrigated horticultural farming, capture fisheries, tourism and wildlife, drinking, recreation and the generation of geothermal electricity. The catchment has a semi-arid climate characterized by mean monthly temperatures of 16 °C–18 °C (Odongo, 2016), and a bimodal rainfall distribution with long rains typically from April to May/June and short rains from October to November (Ase et al., 1986). The data for this study were collected between April and August, during the long rainfall season of 2015 and 2016.

2.2. Site selection

Nine sampling stations were selected along the rivers Malewa, Gilgil and Karati, and four in Lake Naivasha (Fig. 1). The Wanjohi (M1) and upper Malewa (M2) sites are in the upper reaches of the Malewa River, while Malewa Bush Ventures (M4) is in the mid-reaches, and Malewa Highway (M5) is in the lower reaches. The Turasha site (M3) is a tributary to the Malewa River running from the North-East before entering the Turasha Dam. Kahuho site (G1) is in the upper part of the Gilgil River, while Little Gilgil site (G2) is a tributary to the main channel. The Gilgil Highway site (G3) is situated in the lower part of the catchment below the Gilgil dam. The only site along the Karati River– the Karati Highway Bridge site (K1), is in the lower reaches of the river. The Lake Naivasha sites comprise the River Mouth site (N1) where the Gilgil and the Malewa rivers enter the lake, the Mid-lake site (N2) intended to capture the conditions of the lake as a whole, the Hippo Point site (N3), where there was minimal visible impact along the South-Western lake shore area, and the Crescent site (N4) on the North-East of the lake, close to the farms on the shores of the lake (Fig. 1).

2.3. Nutrients and pesticides concentration data

The study measured the nutrients (nitrate-nitrogen, ammonium-nitrogen and total phosphorus); and organochlorine pesticide (OCP) residues (α-HCH (CAS RN: 319-85-6), γ-HCH (CAS RN: 58-89-9), Heptachlor (CAS RN: 76-44-8), Aldrin (CAS RN: 309-00-2), pp-DDE (CAS RN: 72-55-9), Endrin (CAS RN: 72-20-8), Dieldrin (CAS RN: 60-57-1), pp-DDD (CAS RN: 72-54-8), pp-DDT (CAS RN: 50-29-3) and Methoxychlor (CAS RN: 72-43-5)). Data for the concentrations were drawn from Onyango et al. (2024a).

In Onyango et al. (2024a), water samples were collected monthly (April–August 2015) from rivers and the lake, using composite surface grabs for rivers and depth-integrated Schindler sampler grabs for the lake. Nutrient samples were stored in polythene bottles and analyzed at Egerton University for total nitrogen (micro-Kjeldahl method), total phosphorus (persulphate digestion with ascorbic acid method), and total suspended solids (gravimetric method). Pesticide samples were stored in amber glass bottles, extracted via liquid–liquid extraction following DIN EN ISO standards, and analyzed at the University of Nairobi using gas chromatography–mass spectrometry (Thermo Scientific DSQ™ with PTV LV injector). Quality assurance included blanks, spiked recoveries (70–95 %), and calibration standards, with detection limits ranging from 0.0011 to 0.0036 μg/L, ensuring robust measurement of nutrient and pesticide contamination in the catchment (Onyango et al., 2024a).

2.4. Determination of discharge

The discharge (Q in m^3/s) was measured using the area-velocity method following Gore and Banning (2017) as a product of the average velocity (V m/s) and the cross-sectional area (XA in m^2) at the site. To estimate the daily discharge (Q_e in $m^3.day^{-1}$) for the sites, daily flow measurements for the sampling period were acquired from the Lake Naivasha Water Resources Authority (WRA) for three discharge measuring stations. Using regression analysis between the measured discharge and the flow measurements from the WRA, the daily discharge for the sampling period (122 days) was estimated as:

$$Q_e = c + m \times Q_{dm}$$

where:

$\boldsymbol{Q_e}$ is the estimated daily discharge; $\boldsymbol{c}$ is the regression intercept; $\boldsymbol{m}$ is the regression coefficient; and $\boldsymbol{Q_{dm}}$ is the daily flow measurement from the current study

2.5. Daily nutrients and pesticides concentration estimation

The nutrient and pesticide residue concentrations were converted from $mg.L^{-1}$ to $kg.m^{-3}$, to standardize the volumetric measurements with discharge estimates at the sites. Subsequently, the daily concentrations (*Conc* in $kg.m^{-3}$) of the nutrients and pesticide residues were estimated as a regression between the discharges determined at the sampling site and day, and the measured concentration. The daily concentrations were estimated as:

$$Conc_e = c + m \times Q_i$$

where:

> $\boldsymbol{Conc_e}$ is the estimated daily concentration; $\boldsymbol{c}$ is the regression intercept; $\boldsymbol{m}$ is the regression coefficient; and $\boldsymbol{Q_i}$ is the discharge determined at the sampling site and day in the current study.

Only regression models with $R^2 > 0.35$ were retained, as they explained at least one-third of the variance in concentration–discharge relationships. For contaminants where the regression fit was weaker ($R^2 \leq 0.35$), arithmetic means were used instead to avoid misleading extrapolations. While $R^2 > 0.35$ offers a minimal threshold for model acceptance, environmental data often have limited frequency, making regression fits weak, thus a need to use alternative models, such as averages or stratified models (Pohle et al., 2021). The total daily load (L in $kg.day^{-1}$) at a site for the nutrients and pesticides were calculated as a product of estimated concentration ($Conc_e$ in $kg.m^{-3}$) and discharge (Q_e in $m^3.day^{-1}$), while the annual discharge was estimated as the sum of the daily discharge in the year. The annual loads per site extrapolated as a sum of the estimated daily loads L (in kg) for the year.

2.6. GWF calculations

The GWF was calculated after Franke et al. (2013):

$$GWF_i\left(m^3.year^{-1}\right) = \frac{L\left(kg.year^{-1}\right)}{C_{Max}\left(kg.m^{-3}\right) - C_{Nat}\left(kg.m^{-3}\right)}$$

where GWF_i is the grey water footprint for pollutant i in m^3 per year; L is the load of the pollutant i in kg per year; C_{Max} is the maximum allowable concentration of pollutant i in $kg.m^{-3}$, and C_{Nat} is the natural background concentration of pollutant i in $kg.m^{-3}$.

The maximum allowable concentrations and the natural background concentrations for measured pollutants of potential harm in the surface waters of the Lake Naivasha catchment are presented in Table 1, as derived from multiple sources. The nutrients or pesticides contaminants with the highest GWF, are considered critical contaminants for the site, and need urgent attention for reducing environmental risks to the water quality.

Since the study considered multiple contaminants, the IGWF approach was applied to determine the total GWF following the method by Liu et al. (2017):

$$IGWF\left(m^3.year^{-1}\right) = Max\left(GWF_i, \ldots .GWF_n\right)$$

Where *IGWF* is the total GWF for a sub-catchment in $m^3.year^{-1}$, which is determined by choosing the highest mean GWF at a site derived from single pollutants GWF for i to n. A total of 13 GWF_i were determined for the pesticide and nutrients contaminants.

The Grey Water Stress (GWS) was calculated as a ratio between the IGWF $\left(m^3.year^{-1}\right)$ and the discharge Q $\left(m^3.year^{-1}\right)$.

$$GWS = \frac{IGWF\left(m^3.year^{-1}\right)}{Q\left(m^3.year^{-1}\right)}$$

GWS <1 means that the water body still has excess assimilative capacity to accommodate more pollutants; GWS = 1 means all the assimilative capacity is used up; and GWS >1 means that the pollution level has exceeded the assimilative capacity and that the water pollution is thus unsustainable (Wang et al., 2021). The higher the GWS, the poorer the water quality.

Table 1
Maximum allowable concentrations and natural background concentrations used in the study.

No.	Pollutant	CAS Number	Maximum Allowable concentration ($\mu g.L^{-1}$)	Natural background concentration ($\mu g.L^{-1}$)	
				Documented	Estimated
Nutrients					
1	Nitrate-Nitrogen	14797-55-8	13000[b]	100[c]	94.58 [d]
2	Ammonium-Nitrogen	7664-41-7	16[b]	15[c]	8.03 [d]
3	Total Phosphorus	7723-14-0	100[b]	10[c]	76.07 [d]
Pesticides					
1	Aldrin	309-00-2	0.004[b]	0 [c]	0.10 [d]
2	Dieldrin	60-57-1	0.004[b]	0 [c]	0.04 [d]
3	Endrin	72-20-8	0.0023[b]	0 [c]	0.17 [d]
4	Heptachlor	76-44-8	0.0038[a]	0 [c]	0.02 [d]
5	Methoxychlor	72-43-5	40[a]	0 [c]	0.15 [d]
6	pp-DDD	72-54-8	0.0003[a]	0 [c]	0.04 [d]
7	pp-DDE	72-55-9	0.0002[a]	0 [c]	0.03 [d]
8	pp-DDT	50-29-3	0.001[a]	0 [c]	0.10 [d]
9	α-HCH*	319-84-6	0.0026[a]	0 [c]	0.03 [d]
10	γ-HCH	58-89-9	0.95[a]	0 [c]	0.12 [d]

[a] US-EPA (2014) – *US National Recommended Water Quality Criteria - Aquatic Life Criteria.*
[b] Canadian Council of Minister of the Environment (2007)
[c] Franke et al. (2013).
[d] These are estimated mean concentrations of the receiving water body (Lake Naivasha sites – N1, N2, N3, N4).

2.7. Data analysis

Mean, standard deviation (S.D.), and standard error (S.E.) were calculated to summarize variability in discharge and Grey Water Footprint (GWF) across sites and contaminant groups. Linear regression analysis was applied to establish concentration–discharge relationships, with regression coefficients, intercepts, and coefficients of determination (R^2) reported to assess model explanatory power. Correlation analysis was also conducted to assess the relationship between discharge and GWF, highlighting the negative relationship between increasing discharge and declining pollutant loads downstream.

Graphical outputs, including bar plots and comparative site figures, were generated to visualize GWF, Integrated Grey Water Footprint (IGWF), and Grey Water Stress (GWS) values. Statistical computations and figure generation were performed using R statistical software (version 4.5.0) (R Core Team, 2025) with the packages stats and (R Core Team, 2025), ggplot2 (Wickham, 2016). Microsoft Excel (Microsoft Corporation, 2016) was used for initial data organization and calculation of basic descriptive statistics. All analyses were carried out using site-level datasets aggregated over the sampling period.

3. Results

3.1. Discharge (Q) measurements

The values of Grey Water Footprint (GWF) rely largely on the discharge recorded at a site. In this study (Table 2), the lowest discharge was recorded at Little Gilgil (G2), and the highest discharge at Malewa

Table 2
Mean daily discharge measurements at the Lake Naivasha catchment sampling sites, for the 2015–2016 sampling period.

Site		Observed Main land use in the sub-catchment	Mean daily discharge ± S.D. ($m^3.s^{-1}$)		
Gilgil River					
G1	Located in the upper reaches of the Gilgil River catchment	Smallholder, Natural vegetation	0.35	±	0.51
G2	On tributary to the main river, in the mid-reaches of the sub-catchment.	Settlement, livestock ranch	0.03	±	0.01
G3	Site on the lower reaches of the catchment below the Gilgil Dam, along the main highway	Settlement, intensive farming	0.74	±	0.67
Karati River					
K1	Site along the Karati River–the Karati Highway Bridge site (K1), is on the lower reaches of the river, along the main highway	Settlement, intensive farming	0.39	±	0.55
Malewa River					
M1	Located in the upper reaches of the sub-catchment	Smallholder, Natural vegetation	0.11	±	0.04
M2	Site on the upper reaches of the sub-catchment	Small holder	0.45	±	0.27
M3	On a tributary to the main river, in the mid reaches of the sub-catchment	Extensive farming	1.20	±	1.31
M4	Site on the mid-reaches of the sub-catchment, below the Turasha Dam	Extensive farming, livestock ranches	1.81	±	1.05
M5	Located on the lower reaches of the sub-catchment, along the main highway	Extensive & intensive farming, settlement	2.95	±	1.78

Highway Bridge (M5).

The discharge data reveal clear spatial variability across the Lake Naivasha catchment, with the lowest flows recorded at Little Gilgil (G2; 0.03 ± 0.01 m^3 s^{-1}) in a settlement and livestock-dominated tributary, and the highest at the Malewa Highway Bridge (M5; 2.95 ± 1.78 m^3 s^{-1}) where extensive upstream inputs converge. The Gilgil River sites exhibited moderate flows, increasing downstream with intensification of farming and settlement, while the Karati River maintained relatively low discharge (0.39 ± 0.55 m^3 s^{-1}), making it particularly vulnerable to pollution accumulation due to limited dilution capacity. In contrast, the Malewa River displayed a strong upstream–downstream gradient, from low-flow smallholder-dominated reaches (M1; 0.11 ± 0.04 m^3 s^{-1}) to high-flow mixed-use downstream sites, highlighting both the hydrological scaling effect and the influence of diverse land uses on river discharge.

3.2. Grey water footprint in Lake Naivasha catchment

The GWF results are presented in Figs. 2–4. The highest GWF associated with nutrient contamination ($5.3 \times 10^6 \pm 1.6 \times 10^6$ $mm^3.Year^{-1}$) was total phosphorus at the Karati River highway (K1) site, which also recorded the highest GWF for nitrate and ammonium. The Little Gilgil site (G2) along Gilgil River had the second highest nitrate and ammonium GWF, while the Turasha site (M3) showed the second highest total phosphorus GWF. On the other hand, the lower reaches of the Malewa River (M4 and M5) had the lowest GWF with respect to nutrients. In general, GWF declined from upstream to downstream. There was a negative correlation between GWF, and discharge measured among the sites, with a reduction of GWF with increase in discharge, downstream.

Total phosphorus consistently dominated, contributing more than an order of magnitude higher GWF compared with nitrate-N and ammonium-N at all sites, particularly at Karati (K1), where phosphorus reached above 1.0×10^7 mm^3 $year^{-1}$, nearly three orders of magnitude higher than the nitrogen species. Correlation analysis revealed a strong negative relationship between mean discharge and GWF ($r = -0.72$, $p < 0.05$), confirming that higher flows in the Malewa downstream sites (M4, M5) are associated with significantly reduced pollutant footprints due to enhanced dilution capacity. Variance among replicates (demonstrated by error bars) was smallest at low-flow tributaries (G2, M1), where flow and load conditions were more stable, and highest at K1 and M3, indicating temporal variability linked to both rainfall events and land use activities. Comparisons across contaminant groups further indicate that phosphorus loads are disproportionately influential in determining overall nutrient stress, while nitrate and ammonium contributions, though lower in magnitude, reflect diffuse pollution inputs from settlements and livestock ranching (notably at G2). These patterns highlight that sub-catchments with low discharge and intensive farming exert the greatest water quality pressure, whereas high-discharge reaches provide greater assimilative capacity.

The cyclodienes (Fig. 3) including aldrin, dieldrin, endrin and methoxychlor recorded the highest GWF at River Karati site (K1), ranging between $1.59 \times 10^5 \pm 3.52 \times 10^4$ mm^3 $year^{-1}$ for dieldrin to 81.9 $\pm$ 32.70 mm^3 $year^{-1}$ for methoxychlor. The highest GWF for heptachlor was recorded at the Little Gilgil (G2) site, while the lowest GWF for the cyclodienes was recorded in the lower reaches of River Malewa.

The GWF values of cyclodiene pesticides (aldrin, dieldrin, endrin, heptachlor, and methoxychlor) varied substantially across sites, with the highest footprints observed at Karati (K1) and Little Gilgil (G2), and the lowest consistently in the downstream Malewa sites (M4, M5). Among the compounds, aldrin, endrin, and heptachlor displayed the highest mean GWF values across most sites, often exceeding 10^3–10^4 mm^3

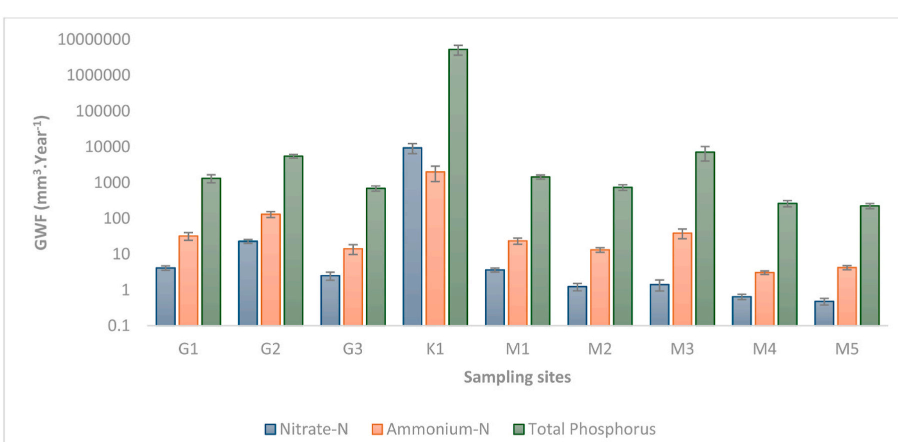

Fig. 2. Calculated Grey Water Footprint (mean ± S.E. $mm^3.year^{-1}$) of nutrients at the sampling sites in the Lake Naivasha catchment.

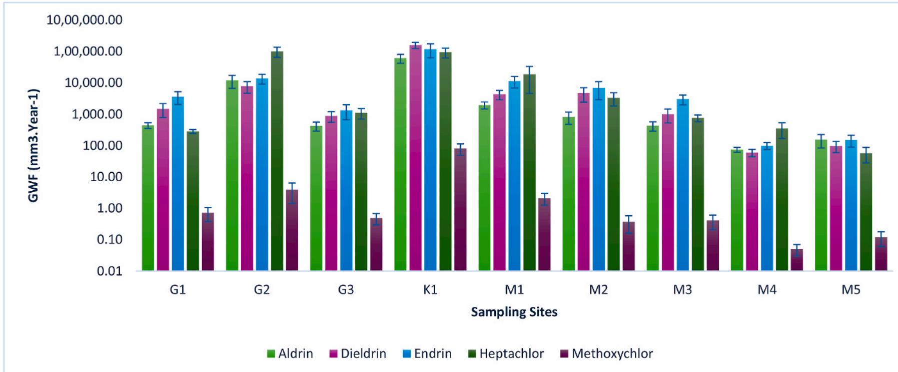

Fig. 3. Calculated grey water footprint in $mm^3.year^{-1}$ (Mean ± S.E.) among sites for cyclodienes organochlorine pesticide group.

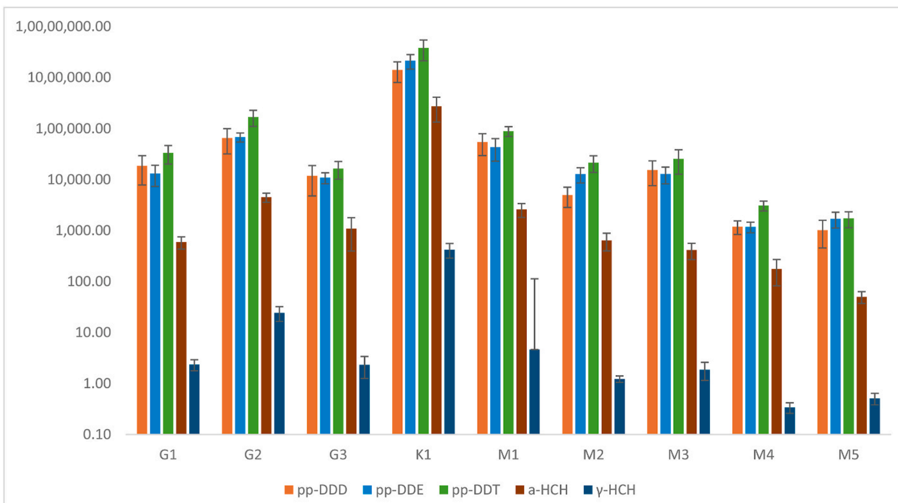

Fig. 4. Calculated Grey Water Footprint in $mm^3.year^{-1}$ (Mean ± Standard error of mean) among sites for the DDT and HCH organochlorine pesticide groups.

$year^{-1}$, while methoxychlor consistently recorded the lowest, often below 10^1 mm^3 $year^{-1}$. At K1, mean GWF values for aldrin, endrin, and heptachlor exceeded 10^5 mm^3 $year^{-1}$, confirming the site's critical hotspot status. Error bars indicate greater variability at G2 and K1, suggesting temporal fluctuations in pesticide loading, likely linked to seasonal runoff from surrounding agricultural lands. In contrast, the relatively stable error ranges at downstream Malewa sites (M4, M5) suggest more consistent dilution capacity and lower inputs of pesticides. Correlation analysis across sites revealed a negative association between discharge and pesticide GWF ($r = -0.68$, $p < 0.05$), similar to the nutrient patterns, confirming that low-flow tributaries (e.g., G2, K1) face disproportionate pesticide-related stress. Comparatively, cyclodienes pesticide GWF values were often of the same order of magnitude as nutrient footprints at the most polluted sites, underscoring that cyclodienes pesticide residues, despite lower absolute concentrations, exert a significant pressure due to strict water quality thresholds.

The GWF with respect to the DDT and HCH OCP groups indicate that GWF ranged from 0.34 ± 0.08 $mm^3.Year^{-1}$ for γ -HCH in lower reaches of the Malewa River to $3.80 \times 10^6 \pm 1.67 \times 10^6$ mm^3 $year^{-1}$ for *pp*-DDT in the Karati River site (Fig. 4).

The Grey Water Footprint (GWF) of DDT and HCH compounds (pp-DDD, pp-DDE, pp-DDT, α-HCH, γ-HCH) exhibited substantial spatial variation across the catchment. The Karati River site (K1) recorded the highest values, with pp-DDT exceeding 10^6 mm^3 $year^{-1}$, making it the dominant contaminant at this hotspot. Similarly elevated GWF values were observed at G2 (Little Gilgil), where both pp-DDT and pp-DDE contributed significantly, while the lowest values across the dataset were consistently associated with γ-HCH, often below 10^1 mm^3 $year^{-1}$ at downstream Malewa sites (M4, M5).

The study showed considerable variability at K1 and M1, suggesting temporal fluctuations in pesticide loading, likely linked to episodic runoff events and agricultural practices. By contrast, downstream Malewa sites (M4, M5) showed smaller variability and consistently lower GWF values, highlighting their greater dilution capacity. Statistical comparison across compounds shows that pp-DDT contributed disproportionately to total pesticide-related GWF, often by two orders of magnitude more than γ-HCH, emphasizing the persistence and low water quality thresholds associated with organochlorine pesticides. Correlation analysis confirmed a negative association between discharge and pesticide GWF ($r = -0.70$, $p < 0.05$), mirroring nutrient results, and underscoring that low-flow tributaries are more vulnerable to pesticide stress.

3.3. Integrated grey water footprint and grey water stress

The IGWF was determined as the maximum GWF per site (Fig. 5). The IGWF results show pronounced spatial variability across the catchment, with the Karati River site (K1) recording the highest footprint (>10^6 mm^3 $year^{-1}$), more than an order of magnitude greater than all other sites.

Elevated IGWF values were also observed at Little Gilgil (G2) and Gilgil downstream (G3), indicating that low-flow tributaries are hotspots of contamination. In contrast, the Malewa River sites (M4, M5) exhibited the lowest IGWF values, consistently below 10^3–10^4 mm^3

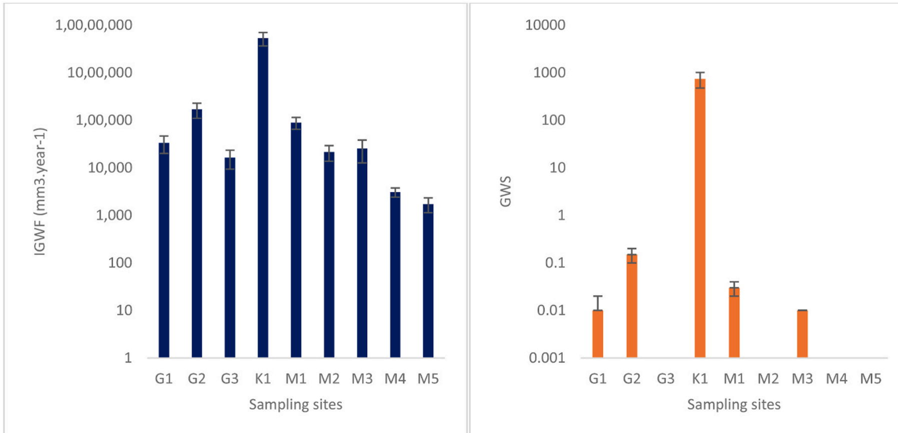

Fig. 5. Integrated Grey Water Footprint (IGWF) in mm3.year-1 and grey water stress (GWS) at sampling sites in the Lake Naivasha catchment.

year^{-1}, reflecting the high discharge and dilution capacity downstream. Lower within site variations, was an indication of stable pollutant dominance patterns, with IGWF strongly influenced by pp-DDT at most sites and by phosphorus at K1.

The GWS index further highlights the critical role of assimilative capacity in shaping water quality stress. At K1, GWS values exceeded 10^2–10^3, far above the threshold of 1, indicating that pollutant loads there surpass the river's dilution capacity and pose severe water quality stress. G2 also showed moderate stress, with GWS between 0.1 and 0.2, suggesting that 10–20 % of the assimilative capacity is already in use. By contrast, all other sites – including M1, M3, M4, and M5 – recorded GWS values below 0.05, indicating very low relative stress levels. The negative correlation between discharge and GWS ($r = -0.75$, $p < 0.01$) confirms that higher-flow systems provide greater resilience against pollutant pressures, while low-flow tributaries are disproportionately vulnerable.

4. Discussion

4.1. Grey water footprint in Lake Naivasha catchment

The Grey Water Footprint (GWF) has increasingly been applied as a quantitative indicator of water quality deterioration arising from human activities such as wastewater discharge (Martínez-Alcalá et al., 2018), crop production (Lovarelli et al., 2016), and urban settlements (Tian et al., 2019). Its application across diverse resource types - ranging from industrial effluents to groundwater and geothermal waters - demonstrates both the versatility of the methodology and the importance of adapting it to specific contaminant profiles and hydrological conditions. For instance, studies on industrial wastewater have shown that seasonal fluctuations (paint industry) and treatment efficiencies (dairy and dye industries) directly affect GWF values, underscoring the role of pollutant variability and technological interventions in shaping water quality impacts (Yapicioğlu, 2019; P. Yapıcıoğlu, 2020; P. S. Yapıcıoğlu, 2019). Similarly, applications to groundwater and geothermal resources reveal the influence of natural recharge dynamics and geochemical baselines, demonstrating that GWF outcomes are not only pollutant-driven but also hydrologically constrained (Yapicioğlu and Yeşilnacar, 2021; P. Yapıcıoğlu and Yeşilnacar, 2022).

In the present study, GWF was applied to agricultural catchments in sub-Saharan Africa, with a focus on Lake Naivasha. The results revealed clear spatial variability driven by discharge regimes. The Malewa River, characterized by perennial higher flows (Clarke, 1990), consistently exhibited lower GWF values relative to the Karati and Gilgil Rivers. This reflects the dilution effect of higher discharge, a trend also documented in broader hydrological studies where increases in flow reduce pollutant concentration per unit volume (Rice and Westerhoff, 2017; Turunen et al., 2020). However, flow variability can also mobilize pollutants during storm events, as highlighted by Outram et al. (2016), making seasonal hydrology a critical driver of grey water outcomes. Comparable findings in industrial contexts - for example, seasonal fluctuations in the GWF of a paint industry wastewater treatment plant (Yapicioğlu, 2019) - demonstrate that temporal variability is a cross-sectoral determinant of water quality stress.

Beyond hydrology, the type and distribution of contaminants proved equally decisive. In most sub-catchments in this study, pesticide residues were the dominant drivers of elevated GWF, reflecting their persistence, toxicity, and diffuse input pathways. This aligns with evidence from other contexts where persistent organochlorine compounds, even at trace levels, produced disproportionately high GWF values due to stringent water quality standards (Jayaraj et al., 2016; Mahmood et al., 2016). By contrast, in the Karati River, nutrients – particularly total phosphorus – were the most critical contaminants, resulting in the highest GWF recorded in the catchment. This mirrors patterns observed in dairy wastewater treatment systems, where nutrient-rich effluents dominate GWF calculations when treatment efficiency is insufficient (P. S. Yapıcıoğlu, 2019). Similarly, in geothermal and groundwater studies, naturally high concentrations of certain ions or limited recharge capacity determined the pollutant group most responsible for driving GWF (Yapicioğlu and Yeşilnacar, 2021; P. Yapıcıoğlu and Yeşilnacar, 2022).

The comparative role of nutrients and pesticides in shaping GWF is therefore context-dependent. Nutrients, particularly nitrogen and phosphorus, are more mobile and linked to eutrophication risks, often showing higher GWF in areas with intensive fertilizer use and livestock runoff. Pesticides, although less abundant in absolute concentration, frequently yield higher GWF values because acceptable water quality thresholds are extremely low, amplifying their footprint even at trace levels. In Lake Naivasha, this distinction was evident: phosphorus was dominant in low-flow agricultural sub-catchments such as Karati, while pesticides were the principal contributors in Gilgil and other tributaries, underscoring the need for differentiated management strategies.

These findings reinforce the value of adopting an Integrated Grey Water Footprint (IGWF) approach (Hoekstra et al., 2017; Liu et al., 2017). As such, identifying site-specific and contaminant-specific drivers of water stress, IGWF allows practitioners to prioritize interventions where they are most urgently needed. For instance, phosphorus reduction through best nutrient management practices should be targeted in Karati, while pesticide surveillance and runoff mitigation are more critical in Gilgil. The literature further supports this differentiated strategy: Monte Carlo simulation approaches applied to dye industry effluents demonstrated that accounting for uncertainty and reuse options can substantially reduce GWF (P. Yapıcıoğlu, 2020), while groundwater studies highlight the need to consider recharge dynamics in shaping sustainable thresholds (P. Yapıcıoğlu and Yeşilnacar, 2022).

The Lake Naivasha case study demonstrates that both hydrological context and contaminant type determine grey water outcomes. When compared with industrial, groundwater, and geothermal applications globally, the findings here underscore the necessity of integrating pollutant-specific management with hydrological realities. This not only enhances the scientific robustness of GWF assessments but also strengthens their applicability as decision-support tools for sustainable water resource management in sub-Saharan agricultural catchments.

4.2. Integrated grey water footprint in Lake Naivasha catchment

This study is the first in Lake Naivasha catchment to apply GWF analysis based on field measurements. A previous GWF analysis conducted by Mekonnen et al. (2012) employed spatial data, nitrogen leaching coefficients, and fertilizer application rates to derive a GWF estimate of approximately 13 mm^3 $year^{-1}$ for the catchment. Within the catchment, the upper region was found to have a GWF of 5 mm^3 $year^{-1}$ (39 %), while the commercial farms on the southeastern side of the lake exhibited a GWF of approximately 8 mm^3 $year^{-1}$ (61 %). In comparison with Mekonnen et al.'s (2012) calculation of the GWF for the upper catchment, the IGWF among the sites in the present study demonstrated a notably higher magnitude, reaching up to 5.3×10^6 mm^3 $year^{-1}$. The a ssessment conducted by Mekonnen et al. (2012) did not, however, consider pesticides as active components. Relying solely on nutrient-based GWF underestimates the overall pollution effect in agriculturally intensified catchments.

When evaluating the GWF in agricultural catchments, the IGWF framework is preferred due to its incorporation of multiple contaminants. Historically, the management of contaminants in surface waters within the Lake Naivasha catchment has relied largely on estimations of pollution loads derived from individual contaminants such as nutrients only or pesticides only contamination (Abbasi et al., 2019; Abbasi and Mannaerts, 2018; Kitaka, 2000; Stoof-Leichsenring et al., 2011). The present study introduces a more comprehensive assessment by considering cumulative and worst-case (highest GWF) contamination scenarios.

4.3. Grey water stress in Lake Naivasha catchment

The highest calculated GWS of 744 in this study show a significant increase compared with the value of 0.06 reported by Mekonnen et al. (2012). Mekonnen et al. (2012) employed spatial resolution data at a 5 by 5 arc minute scale, rather than direct in-situ measurements, explaining the potential difference. Nonetheless, this previous calculation serves as a valuable reference point, particularly in the upper reaches of the catchment. The substantial disparity in the GWS values suggests a notable escalation of water stress within the catchment between 2012 and 2015.

The findings strongly underscore the pressing need for improved management of agricultural expansion as argued by Onyango et al. (2024a,b) and to incorporate combined nutrient and pesticide loads in designing appropriate environmental measures. Water stress in such systems is commonly driven by climatic variability and droughts that reduce available water resources (Rockström et al., 2009), intensive irrigation withdrawals for agriculture that exceed sustainable limits (Mekonnen and Hoekstra, 2025), and diffuse pollution from nutrients and pesticides that degrade water quality and reduce assimilative capacity (van Vliet et al., 2017). This necessity for enhanced management aligns with long-standing recognition of similar challenges in catchments within sub-Saharan Africa (SSA) (Le et al., 2017; MEMR, 2012; Mohamad Ibrahim et al., 2019). However, further data on chemical contamination is necessary to refine the GWS approach and safeguard surface waters in agricultural catchments across sub-Saharan Africa. The inherent variability in upstream and downstream discharge complicates comparisons of GWS values across different sites, as the dynamic nature of water flow and quality can lead to misleading conclusions if not accounted for properly.

GWF analysis emphasizes the need to allocate water for pollution assimilation, not just for consumption and agricultural utilisation. This emphasizes the need for integrated catchment management (Stewardson et al., 2017), allowing for a balance between the anthropogenic (i.e. agricultural) expansion in the catchment and ecosystem needs. It provides a useful means for integrating landscape management and a framework for stakeholders' collaboration. GWS therefore provides policy support for mitigating potential water pollution.

4.4. Water resources management

GWF assessment addresses both problems of water quality and water quantity into a single measurable unit, from which local and governmental stakeholders can decide on relevant water quality standards. The integrated Grey Water Footprint (IGWF) and Grey Water Stress (GWS) indices reveal site-specific vulnerabilities. Karati (K1) was the only site where GWS exceeded 1, indicating that pollution loads surpassed the river's assimilative capacity, while other sites such as Malewa (M1, M4, M5) remained below thresholds. This differentiation highlights the need for site-specific management measures. For example, stricter controls on fertilizer application and livestock runoff are essential for K1 and G2, while monitoring and early warning systems should be emphasized in high-flow Malewa sites to ensure that assimilative capacity is not compromised in the future. This study uses the Kenya, USA EPA and CCME standards for protection of aquatic life to demonstrate the current extent of pollution in the surface waters of the Lake Naivasha catchment. The local stakeholders can refine their ambitions in terms of local beneficial use with management and policy efforts differentiated by the common pollutants (Hughes and Mallory, 2009), while considering corporation among stakeholders (He et al., 2020). Managing the extent of pollution in an agricultural catchment requires three main considerations based on the GWS findings: development of data-driven policy and management decisions, cooperation of stakeholders in the management of the GWS, and facilitated dialogues among stakeholders (Naiman et al., 2005; Stewardson et al., 2017).

At a policy level, these results highlight gaps in existing frameworks. Kenya's *Masterplan for Conservation and Sustainable Management of Water Catchment Areas in Kenya* (MEMR, 2012) emphasizes conservation and sustainable use but lacks enforceable standards for water quality. The present findings support the call for integrated water quality standards that account for both nutrient and pesticide loads, building on frameworks such as the Canadian Council of Ministers of the Environment (CCME) water quality guidelines and the USEPA criteria for aquatic life protection. As others have argued, the Grey Water Footprint approach is valuable for linking water quantity and quality into a single metric, enabling stakeholders to make data-driven, site-specific management decisions (Hoekstra et al., 2017; Naiman et al., 2005).The catchment management options proposed in this paper resonate with those of the Masterplan, including the need for scientific evidence in policy decisions, and multi-stakeholder platforms. The Masterplan is an example in how catchment management measures ignore the need for water quality standards that integrate multiple pollutants, and the failure to adapt the standards to the changing agricultural landscapes while also ensuring the protection of aquatic life.

Importantly, the identification of hotspots such as Karati (K1) provides an opportunity for targeted interventions. As such, the findings of the study highlight the usefulness of establishing water quality standards that encompass multiple pollutants and can adapt to the changing agricultural landscape in the catchment (Onyango et al., 2024a). The standards will be instrumental in regulating combined pollutant levels, protecting aquatic life, and guiding management decisions with a focus on long-term sustainability (Onyango et al., 2024a). Environmental agencies (such as WRA and NEMA, together with research institutions, can collaborate to develop scientifically sound water quality standards that align with the specific needs and challenges of the catchment area.

These agencies and authorities can use assessments such as the GWF estimate to understand catchment water usage and guide the development of sustainable water resource management practices.

Further, the findings from this study demonstrates the need for strengthened monitoring practices for key pollutants, such as nutrients and organochlorine pesticide residues, using advanced techniques like passive sampling to enhance the accuracy of assessments (Abbasi et al., 2019; Abbasi and Mannaerts, 2018) monitoring will provide real-time data on combined and mixed pollutant levels, facilitating early detection of combined contamination and enabling prompt mitigation measures to be implemented. Focusing on sites with higher GWS, such as Karati Highway Bridge (K1) as established in this study, will ensure targeted monitoring of pollutant sources and concentrations.

5. Conclusion

This study is original in integrating nutrient and pesticide Grey Water Footprints (GWF) within a single framework for an agricultural catchment in sub-Saharan Africa, using the Integrated Grey Water Footprint (IGWF) approach. Unlike most prior studies that examine pollutants separately, this work combines both groups to reflect real-world multi-contaminant pressures. It relies on field-based measurements of discharge and pollutant concentrations, enhancing empirical robustness compared to model-only assessments. The analysis demonstrates, for the first time in Lake Naivasha, that Grey Water Stress (GWS) exceeds assimilative capacity in low-flow tributaries, providing novel insights into pollution hotspots and management priorities.

The study demonstrates the utility of the Grey Water Footprint (GWF) as an integrative indicator of water quality–quantity interactions in agricultural catchments, with application to the Lake Naivasha basin in Kenya. Results show that GWF is strongly mediated by hydrological conditions: low-flow tributaries such as Karati and Little Gilgil exhibited the highest nutrient and pesticide footprints, while high-flow sites along the Malewa River had greater dilution capacity and correspondingly lower footprints. The Integrated Grey Water Footprint (IGWF) and Grey Water Stress (GWS) indices revealed critical hotspots, notably at Karati where assimilative capacity was exceeded, underscoring the vulnerability of low-discharge systems under intensive land use. These outcomes highlight the need for water quality standards that incorporate multiple pollutants, and for improved monitoring systems capable of capturing both nutrient and pesticide dynamics under variable flow regimes. Essentially, site-specific interventions -nutrient load reductions in intensive farming zones, targeted pesticide surveillance in vulnerable tributaries, and sustained protection of high-flow reaches - should be prioritized. Embedding such approaches within Kenya's Vision 2030 and the African Union's Agenda 2063 frameworks would strengthen catchment resilience, safeguard aquatic ecosystems, and advance integrated water resources management in rapidly transforming agricultural landscapes of sub-Saharan Africa.

This study acknowledges several limitations and assumptions. The estimation of daily pollutant concentrations and discharges was based on regression models, where only equations with $R^2 > 0.35$ were applied; weaker fits were substituted with arithmetic means, assuming temporal homogeneity and potentially underestimating episodic peaks. Sampling was restricted to April–August (2015–2016), limiting seasonal representativeness, particularly during dry periods when pollutant concentrations may intensify. Natural background concentrations were derived from secondary sources and maximum allowable concentrations from international guidelines, introducing regulatory and contextual assumptions. Furthermore, the Integrated Grey Water Footprint (IGWF) approach emphasized the dominant single contaminant per site, without accounting for additive or synergistic effects of multiple pollutants. At the same time, steady-state conditions were assumed for pollutant inputs and discharge, although the Lake Naivasha catchment is highly dynamic and influenced by climatic variability and land-use change.

Future research should address these limitations by incorporating high-frequency and multi-seasonal monitoring to better capture pollutant dynamics during both wet and dry periods. The use of continuous sensors and passive samplers would improve detection of episodic spikes and provide a more representative picture of nutrient and pesticide fluctuations. Expanding the dataset to include long-term site-specific background concentrations (Cnat) and adopting context-specific water quality thresholds would reduce reliance on generalized standards and improve the accuracy of GWF calculations. Further, applying multi-pollutant modeling approaches would allow for assessment of additive and synergistic effects, thereby overcoming the constraints of the IGWF single-contaminant assumption. Integrating hydrological-climate models could also help simulate the impacts of climate variability and land-use change on assimilative capacity. Essentially, coupling GWF analysis with socioeconomic assessments of agricultural practices and policy interventions would support the design of targeted, evidence-based management strategies for sustainable catchment governance.

CRediT authorship contribution statement

Joel Onyango: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **John P. Simaika:** Writing – review & editing, Writing – original draft, Supervision. **Nzula Kitaka:** Writing – review & editing, Supervision. **Kenneth Irvine:** Writing – review & editing, Supervision, 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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Data availability

All the data used are included in the paper

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