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Watershed Ecosystem Health and Macroinvertebrate Responses to Climate and Land Use Change in the Dinki Watershed, Ethiopia

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and Land Use Change in the Dinki Watershed, Ethiopia**

By:

Yared Worku Haile

June, 2026

Bahir Dar, Ethiopia

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**Watershed and Ecosystem Health and Macroinvertebrate Responses to
Climate and Land Use Change in the Dinki Watershed, Ethiopia**

By: Yared Worku Haile

**A PhD Dissertation Submitted to the College of Agriculture and
Environmental Sciences, Bahir Dar University, in the partial Fulfillment of
the Degree of Doctor of Philosophy in Aquatic and Wetland Ecosystem
Management**

Advisors:

Prof. Dr. Argaw Ambelu

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June, 2026

Bahir Dar, Ethiopia

Declaration

This is to certify that the thesis entitled “**Watershed Ecosystem Health and Macroinvertebrate Responses to Climate and Land Use Change in the Dinki Watershed, Ethiopia**”, submitted in partial fulfilment of the requirements for the degree of Doctor of Philosophy in **Aquatic and Wetland Ecosystem Management** in the College of Agriculture and Environmental Sciences, Department of Fisheries and Aquatic Science, Bahir Dar University, is a record of original work carried out by me and has never been submitted to this or any other institution to get any other degree or certificates. The assistance and help I received during the course of this investigation have been fully acknowledged.

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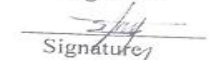
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I hereby certify that I have supervised, read, and evaluated this dissertation titled "Watershed Ecosystem Health and Macroinvertebrate Responses to Climate and Land Use Change in the Dinki Watershed, Ethiopia" by Yared Worku Haile, prepared under my guidance. I recommend that the thesis/dissertation be submitted for oral defense.

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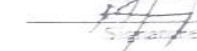
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Original Published Articles

- Worku, Y.,** Asmamaw, M., & Ambelu, A. (2026c). Impacts of land use/land cover change on ecosystem service values in the Dinki Watershed, central highlands of Ethiopia. *Scientific Reports*, 1-21. <https://doi.org/10.1038/s41598-026-44717-9>
- Worku, Y.,** Asmamaw, M., & Ambelu, A. (2026b). Development of a benthic macroinvertebrates-based multimetric index for assessing the ecological health of Ethiopian Highland streams. *Limnologia*, 117, 126321. <https://doi.org/10.1016/j.limno.2026.126321>.
- Worku, Y.,** Asmamaw, M., & Ambelu, A. (2026a). The potential of riparian vegetation to improve surface water quality: review paper. *Discover Applied Sciences*, 1-23. <https://doi.org/10.1007/s42452-026-08444-0>
- Worku, Y.,** Asmamaw, M., & Ambelu, A. (2026d). Macroinvertebrate-based assessment of spatial patterns in stream health across the Dinki Watershed , central highlands of Ethiopia. *Journal for Nature Conservation*, 94, 1–20. <https://doi.org/10.1016/j.jnc.2026.127363>
- Worku, Y.,** Asmamaw, M., Melese, D., & Ambelu, A. (2026E). Predicting habitat suitability of pollution - sensitive macroinvertebrates under climate change using climate and land use predictors in Ethiopia : an ensemble modeling approach. *Ecological Processes*, 15(80), 1–21. <https://doi.org/10.1186/s13717-026-00712-6>

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Worku, Y., Asmamaw, M., & Ambelu, A. Ecological Health Assessment of Streams Using Macroinvertebrates in the Dinki Watershed: A Comparative Study of Temporal Variation in Central Highlands of Ethiopia

Worku, Y., Asmamaw, M., & Ambelu, A. Climate Change Impacts on Headwater Streams: A Systematic Review of Hydrological Alterations, Biodiversity Responses, and Management Strategies

Abstract

Watersheds regulate hydrological processes, support biodiversity, and provide essential ecosystem services, but are increasingly affected by land-use change, climate variability, and human activities. In the Dinki Watershed of the central highlands of Ethiopia, agricultural expansion, habitat loss, and hydrological changes have increased pressure on watershed ecosystems, while information on biophysical characteristics, LULC dynamics, ecosystem services, climate variability, aquatic biodiversity, long-term ecological changes, and watershed management remains limited. Therefore, this study assessed watershed ecosystem health and macroinvertebrate responses to climate and land-use change by characterizing biophysical attributes, evaluating LULC changes and their effects on ecosystem services, examining spatial and temporal changes in macroinvertebrate communities and ecosystem health between 2016 and 2023, identifying key environmental drivers, and assessing potential future vulnerability. A comparative spatiotemporal research design was employed, with hydrological characteristics analyzed using ArcGIS 10.5, LULC dynamics from 1994 to 2023 assessed using supervised Support Vector Machine (SVM) classification, and ecosystem service values estimated by integrating remote-sensing outputs, global ecosystem evidence, and socioeconomic perceptions from key informant interviews (KIIs) and focus group discussions (FGDs) analyzed using QDA Miner Lite.

Climate variability was evaluated using 30 years of rainfall and temperature data from the Ethiopian Meteorology Institute and analyzed in Python, while soil physicochemical properties, including pH, EC, nutrients, texture, and bulk density, were obtained from EthioSIS and analyzed using R. Macroinvertebrates were sampled following South African guidelines, with 100 composite samples collected from 25 sites during wet and dry seasons in 2016 and 2023 and identified to family level. Ecological responses were assessed using paired t-tests, ANOVA, rmANOVA, and MANOVA, while community patterns were examined using PCA, NMDS, and RDA, and indicator taxa were identified using IndVal analysis. A multimetric index (MMI) was developed from 37 candidate metrics, with five core metrics selected through statistical screening and validation: %EOT, %Trichoptera, Hemiptera abundance, ASPT, and FBI. Pollution-sensitive taxa (Perlidae and Philopotamidae) were modeled using ensemble approaches, including BRT, RF, GLM, GAM, and MaxEnt, incorporating bioclimatic and LULC

predictors to project distributions for the 2050s and 2070s under SSP2-4.5 and SSP5-8.5 scenarios. Model performance was evaluated using AUC and TSS, and integrated analyses in R and Python examined relationships among climate variability, LULC change, hydrology, and macroinvertebrate biodiversity.

The result showed a complex stream network, consisting of 45 first-order, 9 second-order, and one third-order stream, and the Dinki River extended 30.35 km before joining the Awash River. The overall ecological improvement was reflected by the habitat visual assessment scores (HVAS), which improved from 10 in 2016 to 11-15 in 2023, considered as suboptimal, and the Ecosystem Health Index, which gradually increased from 1.40 in 2016 to 2.05 in 2023. The soils were mainly clay (70%) and black cotton soils (26%) and were very variable in chemical properties, such as iron (Fe) content (144.45mg/kg) and carbon/nitrogen (C/N) ratio (13.94). The hydrological analysis showed that the discharge increased significantly in the wet season ($p < 0.05$). From the long-term climate analysis, the annual rainfall ranged between 800 and 1000 mm, and the temperature was 18 to 21 °C.

LULC analysis showed that agriculture, grazing land, and water bodies continued to be dominant land use types. Cropland, however, decreased 22.54% from 1994 to 2023, with an increase in sparse vegetation, grazing land, and water bodies. Even though there were some reductions in agricultural lands and forest ecosystems, the ecosystem service value increased from US\$ 200.32 thousand in 1994 to US\$ 310.33 thousand in 2023. A total of 9,479 macroinvertebrates were recorded, with more abundant numbers (6526) recorded during the dry season in 2023. Pollution-sensitive taxa were related to forested streams with high oxygen levels, while tolerant taxa, such as Chironomidae, Gomphidae, and Tabanidae, were more abundant in degraded water bodies with high EC, TDS, and turbidity levels. Multivariate analyses (PCA, NMDS and RDA) showed good site separation along environmental gradients, reflecting environmental responses at intra- and inter-annual scales. Taxon-specific responses were observed, with increases of the Heptageniidae and Perlidae associated with an increase in vegetation, while Odonata decreased with an increase in temperature. The overall water quality enhanced as evidenced by the high value of ecological indices, EPT and EOT, and the Odonata index remained stable or decreased. The macroinvertebrate communities were impacted by both change in land use and climate variability, and cumulative impacts affecting the distribution of indicator sensitive taxa in the

Dinki watershed. The general linear model (GLM) results indicated that climate, particularly temperature, is a key determinant (especially for families Tabanidae and Dytiscidae), and combined effects with land use determined overall ecological patterns, with the Variation Partitioning Analysis (VPA) results indicating this. The developed MMI was found to be an effective discriminating index between reference and impacted sites, ranging from 10.22 (poor) to 22.43 (very good). The ensemble habitat suitability models for the Perlidae and Philopotamidae performed very well in terms of predictive performance (AUC and TSS), and they showed climate refuges in the Ethiopian highlands. The SSP5-8.5 scenario, however, suggested habitat losses of 50-59% by the 2070s, exposing a high sensitivity to climate and land use change.

The Ecosystem Health Index increased from 1.40 in 2016 to 2.05 in 2023, means the Dinki Watershed under recovering, though it is highly dependent on the continued changes in the environment. The results highlight the significance of prioritizing riparian vegetation restoration and protection of forested headwater streams in order to maintain a pollution-sensitive macroinvertebrate community. This will need a coordinated approach between watershed managers, regional environmental agencies, and communities. Continued ecological monitoring, based on the developed MMI, over a longer timeframe is acceptable, and climate-based habitat projections need to be improved for use in adaptive watershed management strategies.

Keywords: Climate variability, Watershed, Ecosystem service value, Ensemble modeling, Macroinvertebrate assemblages, Multimetric index, Spatiotemporal variation

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Acronyms and Abbreviations

ASPT	Average Score Per Taxon
BWMP	Biological Working Monitoring Party
CC	Climate Change
CCA	Canonical Correspondence Analysis
CS	Coefficient of Sensitivity
DCA	Detrended Correspondence Analysis
DEM	Digital Elevation Model
EMI	Ethiopian Metrological Institute
EPT	Ephemeroptera, Plecoptera, and Trichoptera
ESV	Ecosystem Service Values
ESVf	Ecosystem Service Values function
FBI	Family Biotic Index
FFG	Functional Feeding Group
FGDs	Focus Group Discussions
GCMs	Global Circulation Models
GIS	Geographic Information System
GPS	Global Positioning System
KII	Key Informant Interview
LU/LC	Land Use Land Cover
MMI	Multimetrix Index
MMK	Modified Mann-Kendall
NMDS	Non-metric Multidimensional Scale
IVs	Indicator Values
RCMs	Regional Climate Models
RDA	Redundancy Analysis
TN	Total Nitrogen
TP	Total Phosphorus
TDS	Total Dissolved Solids
USGS	United States Geological Services

CHAPTER 1: INTRODUCTION

1.1. Background

Ecosystems are formed through interactions between living organisms and their physical environments in the watershed (Islam, 2022). A watershed represents an integrated ecological unit that encompasses interconnected terrestrial and aquatic ecosystems and are essential for sustaining biodiversity, ecological processes, and human well-being (Hernández-Blanco *et al.*, 2022; Aamir *et al.*, 2025). Healthy ecosystems provide important services, including fertile soils for agriculture, forests for carbon cycling, climate regulation, and suitable air quality for respiration and clean freshwater for drinking and irrigation (Jamil *et al.*, 2024; Pedro *et al.*, 2024). Freshwater ecosystems like rivers, lakes, wetlands, and streams have been identified as highly valuable ecosystems, as they cover only 0.3% of the earth's surface but support almost 6% of the known species worldwide (Matomela *et al.*, 2021). Headwater streams play a particularly significant role in freshwater ecosystems as they support river networks and have a strong influence on ecological and hydrological processes downstream (Richardson, 2019).

The headwater streams, which are generally considered first-order streams (Jackson, 2021), are an important basis for river networks and make up most catchment systems (Lakew, 2020). They control downstream hydrology, help to maintain flows during droughts, mitigate flooding by retaining rainfall, and help to maintain nutrient cycling and sediment transport processes (Martin *et al.*, 2015; Richardson, 2019). Headwater ecosystems also offer habitat heterogeneity in terms of water chemistry, substrate composition, food availability, and riparian vegetations (Richardson, 2019; Dabessa *et al.*, 2021). Headwater streams are highly reliant on detrital organic matter that originates from riparian plants, which is an important source of energy for aquatic food webs and macroinvertebrate communities (Lee *et al.*, 2025). Therefore, these stream have indispensable roles in sustaining freshwater biodiversity, ecological integrity, and watershed functionality (Pedro *et al.*, 2024).

Freshwater ecosystems also drive local economies and sustain human livelihoods through various socio-economic benefits (Yirgu, 2022). They facilitate food production, irrigation, hydropower generation, domestic water supply, and sustainability of livelihoods (Atalay, 2018;

Nguyen *et al.*, 2018). The ecological role of relatively small streams within larger downstream rivers is often large, even in relatively small streams (Wohl *et al.*, 2015). From an economic perspective, the contribution of freshwater ecosystems to the global ecosystem service values is enormous, and the United States has an estimated value of 15.7 trillion USD in the United States watersheds, and South Carolina alone has an estimated value of 42 billion USD (Jackson, 2021). Therefore, it is not only vital to ensure the health of freshwater ecosystems for the conservation of biodiversity but also for long-term socioeconomic development and climate resilience (Teague *et al.*, 2020; Bekele *et al.*, 2024; Berhanu *et al.*, 2025).

Despite their ecological and socioeconomic significance, freshwater ecosystems are facing an increased threat from anthropogenic and environmental pressures (Dudgeon, 2019; Uwizye, 2020; Tampo *et al.*, 2021). These freshwater ecosystems face intense pressures, and approximately 1% of the world's freshwater surfaces and the 7.7 billion well-known species are declining due to anthropogenic and environmental threats (Uwizye, 2020; Tampo *et al.*, 2021). Anthropogenic pressures such as rapid population growth, urban expansion, agricultural intensification, deforestation, overgrazing, hydrological modification, and climate change have accelerated LULC changes, habitat degradation, erosion, sedimentation, and water quality deterioration in freshwater ecosystems (Yirgu, 2022; Venus *et al.*, 2022; Debie, 2024).

Pollution caused by the use of fertilizers, pesticides, and industrial effluents also disturbs the ecological processes and biodiversity within water bodies (Shiferaw *et al.*, 2021; Kuma *et al.*, 2022; Fida *et al.*, 2024). Climate change also another driver in precipitation patterns, rising temperatures, removal of riparian vegetation, deforestation, sedimentation (Cui *et al.*, 2022; Sripanya *et al.*, 2023; Worku *et al.*, 2026), more frequent floods and droughts, and changes to freshwater habitats and hydrological processes (Lohmann *et al.*, 2020; Asnake *et al.*, 2021). This is due to these cumulative pressures that have led to the extensive degradation of freshwater ecosystems and the significant loss of global biodiversity (Moniruzzaman *et al.*, 2021; Kengne *et al.*, 2022). Over half of the world's freshwater ecosystems are degraded and are essential for ecosystem services linked to safe drinking water, soil fertility, and climate regulation, which serve billions of people globally (Boretti & Rosa, 2019; Dudgeon, 2019). The main elements of these services are for both large and small watersheds (Marchioni *et al.*, 2025).

Climate warming also raises water temperature and evaporation, and changes flow patterns and hydrological connectivity (Lohmann *et al.*, 2020). These pressures pose risks to biodiversity, decrease ecological resilience, and weaken ecosystem services that underpin the livelihoods of the people (Kakouei *et al.*, 2020). Hence, the demand for integrated approaches in watershed management, which aim at an equilibrium between ecological protection and sustainable use of the resource, is growing (Kurthen *et al.*, 2020). Watershed characterization is becoming a vital tool in the understanding of ecosystem dynamics and to support sustainable land and water resource management (Woldeyohannes *et al.*, 2020; Hailelassie *et al.*, 2024; Sisay *et al.*, 2024).

Soils, vegetation, climate, hydrology, and biological communities are all interconnected and comprise watersheds as an integrated ecosystem (Argaw *et al.*, 2024). Knowing about these interactions can help elucidate drivers of degradation and inform management interventions to reduce degradation and improve outcomes (Okello *et al.*, 2024). Vegetation, soil properties, nutrient status, infiltration rate, biodiversity, and ecosystem functioning are significant indicators of watershed conditions that affect nutrient cycling, water infiltration, biodiversity, and ecosystem functioning, respectively (Teague *et al.*, 2020; Berhanu *et al.*, 2025). Soil properties such as organic carbon, nitrogen, and phosphorus influence infiltration, nutrient cycling, erosion, and sediment transport processes (Bekele *et al.*, 2024; Berhanu *et al.*, 2025), while vegetation cover stabilizes soils, regulates microclimate, improves groundwater recharge, and provides habitat for aquatic and terrestrial organisms (Gitima *et al.*, 2022). Because these ecological components are highly interconnected, alterations in land use and land cover (LULC) can substantially affect watershed processes like declining soil fertility and ecosystem functioning.

LULCs have a significant role in the watershed functionality, hydrological processes, soil stability, biodiversity, and ecosystem service provision (Ewunetu *et al.* 2021; Beshir *et al.*, 2023). Agricultural intensification and livelihood diversification, coupled with population growth, are among the socio-economic factors that drive land use and resource utilization, contributing to land use changes in the watershed (Beshir *et al.*, 2023; Tesfay *et al.*, 2023). From 1992 to 2018, the world lost about 241.5 million hectares of forest mainly because of the expansion of agriculture (Hu *et al.*, 2021; Sisay *et al.*, 2024). Hydrological degradation is often

reflected through increased runoff, nutrient enrichment, unstable flow regimes, and high sediment loads (Alkhadher *et al.*, 2025). Consequently, combining ecological assessment, field measurements, hydrological analysis, and remote sensing techniques has become increasingly important for watershed monitoring and climate-resilient management on freshwater (Hadeed *et al.*, 2024; Lausch *et al.*, 2024).

Freshwater streams are highly responsive to land use and climate change, making their ecological health a key indicator of watershed integrity (Bogardi *et al.*, 2020). Conventional physicochemical monitoring provides useful but short-term information, limited to the time and place of sampling, and cannot adequately capture long-term ecological integrity or biogeochemical alterations (Mishra *et al.*, 2023). In contrast, biological monitoring provides a more integrated and long-term or more holistic evaluation of freshwater ecosystem condition because aquatic organisms respond continuously to environmental stressors (Bogardi *et al.*, 2020).

Aquatic communities, particularly macroinvertebrates, are widely used for biomonitoring because they are cost-effective, easy to sample, ubiquitous, and exhibit diverse sensitivities to pollution, making them reliable indicators of ecological change (Asmamaw *et al.*, 2019; Sitotaw & Mengistou, 2021; Ko *et al.*, 2020). Taxonomic identification can be time-consuming and requires expertise (Feio *et al.*, 2021). Pollution-sensitive groups like Ephemeroptera, Plecoptera, and Trichoptera (EPT) are particularly valuable as indicators because they are sensitive to alterations in the habitat and degradation of water quality (Peng *et al.*, 2024) and respond quickly to changes in water quality even watersheds. Generally, streams with low anthropogenic impact have high diversity of sensitive taxa, while degraded streams have low diversity and higher abundance of tolerant taxa like Chironomidae and Oligochaeta (Ruaro *et al.*, 2020; Sitotaw & Mengistou, 2021; Worku *et al.*, 2026). Due to these reasons, macroinvertebrate-based bioassessment combined with physicochemical monitoring has emerged as one of the most effective methods to assess stream ecological health and provide information on environmental stressors (Zhu *et al.*, 2021; Sripanya *et al.*, 2023; Girma *et al.*, 2021; Tian *et al.*, 2024).

Previous studies have shown that disturbed watersheds are often dominated by pollution-tolerant taxa, while less-disturbed streams maintain higher proportions of sensitive EPT taxa (Assefa *et al.*, 2020; Akamagwuna *et al.*, 2024). For example, Azis & Abas (2021) reported higher macroinvertebrate diversity in less-disturbed upstream sections of the Langat River, Malaysia, whereas disturbed downstream sites were dominated by tolerant taxa such as *Limnodrilus* sp. Similarly, Zhang *et al.* (2025) found that agricultural areas in the Chesapeake Basin supported higher richness of sensitive Ephemeroptera, Plecoptera, and Trichoptera (EPT) taxa than urban sites. However, the combined effects of climate variability and land use change on pollution-sensitive macroinvertebrates remain insufficiently understood in Ethiopian headwater systems (cf. Carr *et al.*, 2019; Monbertrand *et al.*, 2019; Kakouei *et al.*, 2020; Khaliq *et al.*, 2024; Johnson *et al.*, 2024; Dahal *et al.*, 2025).

To improve biological assessment of freshwater ecosystems, MMIs are an effective bioassessment tool (Birk *et al.*, 2020), and have been developed globally to integrate multiple biological metrics into a single ecological assessment tool (Macedo *et al.*, 2016; Ruaro *et al.*, 2020). MMIs commonly combine metrics related to taxa richness, EPT composition, pollution tolerance, and functional feeding groups to evaluate ecological integrity comprehensively (Assefa *et al.*, 2023; Edegbene *et al.*, 2024). Although MMIs are widely applied in Europe and North America (Karr & Chu, 1997), locally calibrated indices remain limited in Africa and Ethiopia (Masese *et al.*, 2023; Joseph, 2023). Existing Ethiopian indices (ETHbios) might not represent all local environmental gradients and disturbances of watersheds (Lakew & Moog, 2015). Thus, the development of region-specific MMIs for Ethiopian highland streams is crucial for enhancing ecological assessment, water quality monitoring, and conservation of freshwater biodiversity (Alemneh *et al.*, 2019; Ghannem *et al.*, 2024; Shibeshi & Venkatesham, 2024).

In addition to ecological assessment, forecasting responses of sensitive taxa to altered environmental conditions is now a growing concern for freshwater conservation planning (King *et al.*, 2025; Yoezer *et al.*, 2026). LULC and climate changes are projected to significantly impact freshwater habitat suitability, hydrological connectivity, and ecological integrity (Breiner *et al.*, 2018; Lohmann *et al.*, 2020). The species that are sensitive, like Perlidae and Philopotamidae, are especially vulnerable due to their low ecological tolerance and requirement

for stable habitat conditions (Makumbe *et al.*, 2022). Species distribution models (SDMs) are powerful tools for predicting habitat suitability under future climate scenarios under the predictors of climate and land uses, particularly ensemble modeling approaches that combine algorithms like Random Forest, MaxEnt, Boosted Regression Trees, Generalized Linear Models, and Generalized Additive Models (Dormann *et al.*, 2018). These methods enable the identification of ecological habitats, the prediction of impacts on biodiversity, and adaptive watershed management and conservation planning (Ghannem *et al.*, 2024; Jamali *et al.*, 2024).

Many ecologically significant rivers and headwater streams in the Ethiopian highlands supply water resources, biodiversity, agriculture, and rural livelihoods (Lakew, 2020; Yirgu, 2022; Debie, 2024). But the exploitation of these freshwater systems is being threatened by various factors such as agricultural expansion, deforestation, overgrazing, population pressure, and climate variability (Shiferaw *et al.*, 2021; Kuma *et al.*, 2022; Fida *et al.*, 2024). The Dinki watershed in the central highlands of Ethiopia is a good example of such challenges. The watershed has experienced significant changes in hydrological processes, soil characteristics, habitat quality, and aquatic biodiversity due to intensive cultivation in steep slopes, degradation of vegetation, and climate change (Asmamaw *et al.*, 2020; Tesfay *et al.*, 2023; Derbib, 2025). The environmental pressures have also contributed to an increased erosion rate, diminished ecosystem services, and vulnerability of local communities and populations to climate-related disturbances (Mengist *et al.*, 2022; Elias & Biratu, 2022).

While several studies have been conducted on LULC dynamics, water quality, degradation of watersheds, and macroinvertebrate diversity in Ethiopia (Alemayehu *et al.*, 2019; Gitima *et al.*, 2022; Abuhay *et al.*, 2023; Sisay *et al.*, 2024). Limited studies have been conducted to link watershed characterization, macroinvertebrate bioassessment, climate variability, multimetric index development, and predictive habitat suitability modeling. In particular, there are gaps in how climate variability and land use change as predictors affect pollution-sensitive macroinvertebrates in headwater systems of Ethiopia, especially when combined it. In this context, this dissertation combined ecological, hydrological, physicochemical, climatic, and biological assessments to assess watershed ecosystem health in the Dinki watershed, central highlands of Ethiopia.

Specifically, the study aimed to characterize the ecological features of the watershed, assessing the LULC impacts on ecosystem services, investigating the spatiotemporal variation in pollution-sensitive macroinvertebrate assemblage from 2016 to 2023, examining the combined effects of climate variability and land use change on pollution-sensitive indicator species, developing and validating a region-specific benthic macroinvertebrate-based-MMI for Ethiopian highland streams, and predicting habitat suitability of pollution-sensitive macroinvertebrates based on current and future climate scenarios. The study presents scientific evidence through this integrated approach for sustainable watershed management, conservation of freshwater biodiversity, ecological monitoring, and climate-resilient environmental planning in Ethiopia.

1.2. Statement of the problem

Research Problem 1: The biophysical attributes and impacts of LULC change on the ecosystem service of the Dinki watershed are not well documented

Biophysical attributes of a watershed are an essential step for understanding natural resources and the factors that influence ecological processes and environmental sustainability (Girma *et al.*, 2025). There are several biophysical characteristics that are commonly used to describe a watershed, such as topography, soil types, hydrology, vegetation, LULC, climate variability, water resources, and biodiversity (Asefa *et al.*, 2020). Such features are valuable for evaluating both the availability and use of resources as well as management practices in a watershed (Danano *et al.*, 2025). Likewise, Ethiopian watersheds are crucial for controlling hydrological processes, provisioning ecosystem services, safeguarding biodiversity, and maintaining agricultural livelihoods (Bekele *et al.*, 2024; Berhanu *et al.*, 2025). These systems are, however, becoming more endangered due to anthropogenic pressures and landscape modification, which are causing environmental degradation (Alemneh *et al.*, 2017; Atalay, 2018).

Although the biophysical characterization of a watershed is crucial, many of Ethiopia's watersheds have not been fully characterized, especially with respect to their integration of topography, soil distribution, hydrology, river water quality, vegetation, climate variability, and biodiversity in a single watershed assessment (Alemneh *et al.*, 2017; Atalay, 2018; Tilahun *et al.*, 2021). Furthermore, there has been little research on understanding spatial and temporal changes in watershed ecosystem services due to LULC. Ahmed (2023), for example, characterized the

Medo watershed based on land use types, topography, soil types, and climate variability, but did not examine hydrology, river water quality, and the impacts of land use/land cover change on ecosystem services. Girma *et al.* (2025) also evaluated the Halaba watershed and mainly studied the topographic, LULC, soil types, and short-term climate variability components of the watershed ecosystem, with a lack of river water quality. The soil erosion hot spots, sediment transport, and hydrological processes were studied by using SWAT-based modeling in the Gilgel Abay watershed by Alebachew *et al.* (2025), with a lack of vegetation composition and water quality. Likewise, Belay & Ayalew (2021) focused on only the effects of land use and climate change on soil erosion in the Muga watershed. In general, several LULC changes have been widely studied in the Ethiopian highlands (Hassan *et al.*, 2016; Desta & Fetene, 2020; Tewabe & Fentahun, 2020; Mariye *et al.*, 2021; Ababu *et al.*, 2024; Mulu *et al.*, 2024).

Studies in other central Ethiopian highland watersheds have also concentrated on specific issues, such as soil erosion in the Urago micro-watershed (Endrias *et al.*, 2025), hydrological responses to combined LULC and climate change in the Finchaa catchment (Dibaba *et al.*, 2020), and the impacts of spatiotemporal LULC change on soil loss in the Zoa watershed (Gitima *et al.*, 2023). Similarly, Alemneh *et al.* (2017) examined the impacts of settlement expansion in the Choke Mountain catchment, while Asmamaw *et al.* (2020) focused on the climate change-induced shocks to vulnerable livelihood communities and demographic pressures in the Dinki watershed. These studies have generated valuable information; however, they mainly addressed specific or little attributes of watersheds rather than providing a comprehensive assessment of watershed biophysical attributes and ecosystem services. Therefore, the holistic watershed characterization remains limited in the central highlands of Ethiopia.

In addition, there are several studies that have quantitatively linked LULC dynamics with ecosystem service values (ESVs) over long time periods. For example, such assessments were conducted in the Munessa-Shashemene catchment (1973-2012) (Kindu *et al.*, 2016), Bilate-Alaba sub-watershed (1972-2017) (Godebo *et al.*, 2018), Guna Mountain watershed (1995-2020) (Belay *et al.*, 2022), Abaya-Chamo Basin (1985-2050) (Woldeyohannes, 2020), Bale Eco-region (1992-2022) (Hailelassie *et al.*, 2024), Chelimo Forest in Dendi District (1973-2015) (Tolessa *et al.*, 2017), Chacha watershed (1997-2021) (Tesfay *et al.*, 2023), Rib watershed in the Upper Blue

Nile Basin (2000-2020) (Anley *et al.*, 2022), Kaffa Zone (1986-2049) (Mengist *et al.*, 2022), and Gojeb watershed (1986-2016) (Shiferaw *et al.*, 2021). These studies demonstrated the importance of linking LULC dynamics with ecosystem service value changes. However, similar assessments have not been conducted in the Dinki watershed.

The Dinki watershed is experiencing increasing anthropogenic pressure from land conversion and settlement expansion in urban (zego) (Asmamaw *et al.*, 2020). Nevertheless, both comprehensive watershed characterization and assessment of ecosystem service responses to LULC change remain limited in the watershed. In particular, there is a lack of long-term assessments (1994-2023) that quantify multi-class LULC transitions and evaluate their implications for ecosystem service values. Consequently, the effects of landscape transformation on watershed functions, ecological integrity, and livelihood-supporting ecosystem services remain poorly understood. Therefore, the relationship between long-term LULC dynamics, watershed characteristics through biophysical attributes, and ecosystem service value response to LULC changes in the Dinki watershed remains insufficiently documented and requires further investigation.

Research Problem 2: The spatial, temporal, and seasonal variation of pollution-sensitive macroinvertebrates in the Dinki watershed is poorly understood.

Benthic macroinvertebrates such as Ephemeroptera, Plecoptera, and Trichoptera are widely recognized as reliable bioindicators of freshwater ecosystem health because of their sensitivity to changes in water quality, habitat conditions, and hydrological disturbances (Asmamaw *et al.*, 2020; Eshete, 2022; Ghannem *et al.*, 2024; Sitati *et al.*, 2024). Pollution-sensitive macroinvertebrates play a central ecological role in riffle and pool habitats of running-water ecosystems (Mehari *et al.*, 2014; Girma *et al.*, 2021; Tian *et al.*, 2024).

Several studies worldwide have investigated the spatial and temporal dynamics of macroinvertebrate communities. For example, a study in the Ganga River, India, examined the spatio-temporal variability of macroinvertebrate communities over three consecutive years (2020-2022) (Charan *et al.*, 2023). The study was useful in understanding community dynamics and how they relate to water quality, but a relatively short monitoring period was used, which

reduced the ability to assess long-term ecological trends and the watershed conditions. Likewise, macroinvertebrate communities were also studied in the Aras River (Turkey) in three seasons between 2014 and 2015 (Özbek *et al.*, 2025). While the study evaluated seasonal variations in community composition, it lacked long-term monitoring and comprehensive spatial-temporal comparisons. Likewise, a study in the Yangtze River, China, monitored macroinvertebrate assemblages for only one year (2021) and focused primarily on hydrological characteristics, with limited consideration of water chemistry variables (Zhou *et al.*, 2025). Consequently, the long-term responses of macroinvertebrate communities to environmental changes remain insufficiently understood and long-term studies are globally rare.

In Ethiopia, several studies have assessed macroinvertebrate communities and their application in freshwater biomonitoring. For instance, the Infranz River was monitored during wet and dry seasons from August 2010 to May 2011 using a limited set of physicochemical parameters (Mehari *et al.*, 2014). Other important studies include investigations of macroinvertebrate responses to hydrological disturbance in the Dinki Stream (Asmamaw *et al.*, 2019), studies in the Gilgel Abay River (Getnet *et al.*, 2022), environmental monitoring for headwater river management (Lakew, 2020), assessments in the Mekelle region (Teferi *et al.*, 2012), the Rift Valley region (Girma *et al.*, 2021), the Gilgel Gibe catchment (Gebrehiwot *et al.*, 2017), the Abay River (Fentaw *et al.*, 2024), and other Ethiopian rivers (Sitotaw & Mengistou, 2021). Although these studies have generated important baseline information, most were conducted over relatively short periods and were limited in their ability to evaluate long-term spatial, seasonal, and temporal patterns of macroinvertebrate communities. Meanwhile, Ethiopian headwater streams are increasingly exposed to agricultural runoff, deforestation, sedimentation, and riparian habitat degradation, all of which can alter aquatic community structure and ecosystem functioning (Tamire & Beneberu, 2022; Worku *et al.*, 2026). These growing anthropogenic pressures underscore the need for long-term ecological monitoring and assessment.

Despite their ecological importance, the spatial, seasonal, and interannual variation of pollution-sensitive macroinvertebrates in Ethiopian highland watersheds remains poorly understood. Study on Dinki watershed (2016) was done by (Asmamaw *et al.*, 2019, 2021). However, the long-term

information on these communities is lacking, particularly across upstream-downstream gradients and wet-dry seasonal cycles during 2016-2023. This knowledge gap limits the assessment of ecological condition, environmental change, and watershed health. Therefore, a long-term examination of pollution-sensitive macroinvertebrate dynamics in relation to physicochemical parameters is essential for effective monitoring and watershed conservation practices.

Research Problem 3: The combined impacts of LULC change and climate variability on macroinvertebrate indicator species remain poorly addressed

Macroinvertebrates are ecological indicators and constitute one of the basic parts of aquatic food webs (Özbek *et al.*, 2025). They are, however, very sensitive to anthropogenic activities and environmental changes, especially those resulting from climate variability and alteration of land use (Edegbene *et al.*, 2021; Getnet *et al.*, 2022). On a global level, freshwater biodiversity is now being increasingly driven by the interaction between land use change and climate variability, both of which affect the distribution of species (Tampo *et al.*, 2021).

Several international studies have focused on the overall effect or the effects of these drivers individually. For example, integrated analysis of climate and land use change has been carried out in South-east Queensland, Australia (Mantyka-Pringle *et al.*, 2014) and the Taizi River Basin in Northeast China (Li *et al.*, 2018), where both have been shown to have a significant impact on freshwater ecosystems. Previous studies have mainly focused on the impact of climate change, particularly on temperature changes for macroinvertebrates, such as Swiss rivers (Pfenninger, 2007; Bonacina *et al.*, 2023), the Jeziora river in the central part of Poland (Chattopadhyay & Sza, 2024), the Danube near Ingolstadt, in southern Germany (Pander *et al.*, 2022), across the country in Korea (Li *et al.*, 2013), and in Switzerland (Khaliq *et al.*, 2024). Also, rainfall-related research has been carried out in Gapyeong stream (Gun *et al.*, 2018), Dobong stream in South Korea (Bae & Park, 2019), and Lake Geneva in Switzerland (Monbertrand *et al.*, 2019).

In African highland regions, rising temperatures and increasing rainfall variability, combined with land degradation, are expected to intensify stress on freshwater ecosystems. For instance, studies focusing on land use impacts include those in the eastern highlands of Zimbabwe (Dalu *et al.*, 2021), the Upper Ewaso Ng'iro Basin in Kenya (Wachira *et al.*, 2026), and various

Ethiopian highland streams (Lakew & Moog, 2015a & 2015b; Lakew, 2020a & 2020b; Asmamaw *et al.*, 2020). Additional research has been conducted in the Abay (Blue Nile), Omo-Gibe, and Awash River basins (Getachew, 2023), as well as Sebata streams and rivers (Mezgebu *et al.*, 2019). Studies explicitly addressing climate-related impacts on stream temperature and hydrology remain limited, including work in Mekelle Town (Teferi *et al.*, 2013) and the Choke Mountain catchment (Alemneh *et al.*, 2017). However, most studies conducted in Ethiopia have focused on climate change or land use change separately from one another in the absence of interaction between them (Yesuph & Dagnew, 2019; Shiferaw *et al.*, 2021). This is an important knowledge gap in understanding the interaction between multiple stressors on freshwater ecosystems. The integrated research to link the responses of macroinvertebrate indicator species to long-term patterns of climate and LULC change with respect to environmental gradients is lacking in the Dinki watershed specifically.

Research Problem 4: There is no macroinvertebrate-based-MMI for assessing ecological health in the Dinki watershed.

The use of macroinvertebrate based-MMIs has been recognized as an effective way of assessing river ecological integrity that combines multiple biological metrics into a single assessment framework (Ruaro *et al.*, 2020; Sitotaw & Mengistou, 2021). These indices are rapid, reliable, and standardized methods used for the rapid assessment of aquatic ecosystem health and as a support to biomonitoring programs (Silva *et al.*, 2017; Majaneva *et al.*, 2024). The use and development of MMIs in Africa are still quite limited, although they are used in many parts of the world. Some notable examples are the South African Scoring System (SASS) (Dickens & Graham, 2002), the MMI developed for the river in Nigeria (Edegbene *et al.*, 2024), and the Kenya EPT Index (Shimba & Jonah, 2016).

Several bioassessment tools have been developed in Ethiopia, for example, the ETHbios index (Lakew & Moog, 2015), MMIs for selected river systems (Alemneh *et al.*, 2019; Tamire & Beneberu, 2022; Assefa *et al.*, 2023; Melaku *et al.*, 2023). Most of the indices, however, were designed from data gathered for only one season or one year, which might not reflect temporal change in macroinvertebrate communities. The ETHbios index, in particular, provides a valuable framework for assessing ecological conditions in Ethiopian highland streams. Nevertheless, as a

generalized national-level tool, it may not fully reflect the unique environmental characteristics, ecological gradients, and anthropogenic pressures of specific watersheds.

The watersheds have already been discussed by (Asmamaw *et al.*, 2019, 2020, 2021), and he was not involved in developing the MMIs for the Dinki watershed. Moreover, the 2023 and 2016 datasets of macroinvertebrates are available to create a robust time-based index. For this reason, this study is focused on developing and validating a benthic macroinvertebrate-based-MMI, which is site-specific for the headwater streams (using 2016 for validation and 2023 data for MMI development) of the Dinki watershed in the central Ethiopian highlands. This evidence has been developed with watershed management and decision-making in the study area in mind.

Research Problem 5: Pollution-sensitive taxa distribution model under climate scenarios using climate and land use predictors remain unknown in the Dinki watershed.

Predictive ecological modelling is now an important tool for estimating the impacts of environmental change on biodiversity, for conservation planning, and for predicting habitat suitability under different climate and land-use scenarios (Phillips *et al.*, 2006; Zhao & Boll, 2017; Elith, 2021; Tabor & Koch, 2021; Ahmed *et al.*, 2023). Species Distribution Models are useful in predicting current and future habitat suitability under changing climate and land-use conditions, such as using ensemble modelling that combines multiple SDM algorithms like Random Forest (RF), Boosted Regression Trees (BRT), Maximum Entropy (MaxEnt), Generalized Linear Models (GLM), and Generalized Additive Models (GAM) (Dormann *et al.*, 2018; Hao *et al.*, 2019; Makumbe *et al.*, 2022; Ghannem *et al.*, 2024). These models have been extensively used globally to predict range shifts and changes in habitat suitability under the influence of climate and land-use change, and have shown that terrestrial and aquatic species can be significantly affected by climate and land-use change on the geographical scale (Zhao & Boll, 2017; Elith, 2021).

Habitat suitability modelling has also been done for various animal and plant species in Ethiopia. These can include animals, such as the gelada (*Theropithecus gelada*) (Ahmed *et al.*, 2023), the endemic and endangered Ethiopian wolf (Berhanu *et al.*, 2022), from birds, the Breasted Lapwing (Aligaz *et al.*, 2024), and the fruit bats (*Rousettus aegyptiacus* and *Epomophorus*

labiatus) (Ahmed *et al.*, 2023). Furthermore, from plant species *Acacia decurrens* (Alemayehu *et al.*, 2024), *Parthenium hysterophorus* L. and *Salvia tiliifolia* Vahl (Melese *et al.*, 2025b), *Ekebergia capensis* Sparrm (Melese *et al.*, 2025c), *Bidens macroptera* (Hailegiorgis *et al.*, 2025), and *Commiphora africana* (Mekasha *et al.*, 2026). But no similar studies have been carried out for freshwater pollution-sensitive macroinvertebrate taxa.

In freshwater ecosystems, SDMs have become more popular to forecast possible future changes in macroinvertebrate communities in relation to climate and land-use change scenarios and to evaluate the regional suitability of habitats in Asia and Europe (Sami *et al.*, 2013; Kuemmerlen *et al.*, 2015; Sultana *et al.*, 2020). Most of the previous studies have been based on broad macroinvertebrate assemblages; however, except studied by Sultana *et al.* (2020), it has not focused on the specific indicator species that are sensitive to pollution. Moreover, there are limited studies that evaluate the future habitat suitability of pollution-sensitive macroinvertebrate species under a climate change scenario, and most of these studies are not conducted in Africa and are scarcely available in Ethiopia. To date, no study has examined the future distribution and habitat suitability of pollution-sensitive macroinvertebrate taxa (*Perlidae* and *Philopotamidae*) in the Dinki watershed using an ensemble modelling framework in a climate change scenario, which integrates climate and land-use as predictors. These sensitive species were selected due to their exhibit predictable responses to environmental stressors such as nutrient enrichment, sedimentation, and hydrological regime changes, making them reliable bioindicators for assessing the health of freshwater ecosystems (Kilonzo *et al.*, 2014; Ghannem *et al.*, 2024). This knowledge gap restricts the ability to develop effective approaches for freshwater conservation, a freshwater campaign, and adaptive approaches in watershed management under future climate and land use change scenarios.

Therefore, this PhD study seeks to fill these research gaps by evaluating the health status of the watershed ecosystems with ecosystem services impacted by LULC, inspecting the response of pollution sensitive macroinvertebrates to land use and climate variations, creating a multi-metric index for assessing the health condition of a watershed, and predicting the future habitat suitability of pollution sensitive macroinvertebrates under the conditions of land use change and

climate variability in Dinki watershed of the central highlands of Ethiopia using ensemble species distribution modeling techniques.

1.3. Significance of the study

This study provides important scientific evidence on the relationships between land-use/land-cover (LULC) change, climate variability, watershed health, and pollution-sensitive macroinvertebrates in the Central Highlands of Ethiopia. By integrating ecological monitoring, hydrological assessment, climate analysis, and ecosystem-service valuation, it improves understanding of how multiple environmental stressors interact and affect freshwater biodiversity in Ethiopian headwater streams.

The findings supply useful baseline data on pollutant-sensitive taxa, habitat conditions, and watershed characteristics that are essential for long-term ecological monitoring and for assessing climate-change impacts. They also reinforce the value of benthic macroinvertebrates as bioindicators of ecological health and environmental degradation in Ethiopian rivers. In addition, the results help identify vulnerable areas, project future habitat suitability under different climate scenarios, and support evidence-based watershed management and restoration planning. Linking LULC patterns with ecosystem-service valuation further contributes to sustainable land- and water-resource management and climate-adaptation strategies.

The outcomes of this research will be of practical use to policy makers, environmental protection agencies, watershed managers, conservation organizations, researchers, and local communities involved in the conservation and climate resilience of highland freshwater ecosystems. Overall, the study underscores the need for sustainable management practices to protect pollution-sensitive taxa and maintain the ecological integrity of Ethiopian highland streams.

1.4. Research questions

- What are the major biophysical attributes (topography, soils, hydrology, vegetation, biodiversity), and how have LULC changes influenced the ecosystem services of the Dinki watershed?

- Are there spatial and temporal patterns in pollution-sensitive macroinvertebrate assemblages within the Dinki watershed between 2016 and 2023?
- To what extent do LULC changes and climate variability influence the sensitive taxa macroinvertebrates in the Dinki watershed? evidence from 2016 and 2023 surveys.
- Which macroinvertebrate metrics are most effective indicators of stream ecological health for the development of MMI?
- What are the current and projected future suitable habitats for pollution-sensitive macroinvertebrates in the Ethiopian watershed based on the ensemble species distribution models?

1.5. Objectives

1.5.1. General objective

- To assess the watershed ecosystem health and macroinvertebrate responses to climate and land use change in the central highlands of Ethiopia with identifying of the key environmental drivers

1.5.2. Specific objectives

The specific objectives of this study were:

- To determine the biophysical attributes and effects of LULC changes on ecosystem services of Dinki Watershed
- To examine the spatiotemporal variation of pollution-sensitive macroinvertebrate assemblages across environmental gradients in the Dinki watershed between 2016 and 2023
- To evaluate the effects of long-term climate and LULC change on sensitive macroinvertebrate indicators: evidence from 2016 and 2023 surveys
- To develop a macroinvertebrate-based-MMI for assessing stream ecological health in Ethiopian highland streams
- To predict current and future habitat suitability of pollution-sensitive macroinvertebrates under climate scenario using land use and climate variability: an ensemble modeling approaches

1.6. Outline of the PhD Dissertation

The dissertation consisted of **Seven chapters**. These include: **Chapter One**, which is a general introduction and contains the background, statement of the problem, significance of the study, research questions, and research objectives along with the outline of the dissertation. **Chapter Two:** The literature reviewed in relation to the watershed ecosystems, freshwater biodiversity, LULC change, riparian vegetation, climate variability, freshwater ecosystem macroinvertebrate-based ecological assessment or MMI development, and predictive modeling approaches is summarized. **Chapter Three:** The materials and methods used in the study are described, which comprises the study area, study design, sampling technique, data collection, statistical analysis, development of indices, predictive modeling, and data quality assurance.

Chapter 4: The results of the study are presented and include watershed ecological characteristics, LULC, watershed hydrology, climate, soil, habitat quality, ecosystem services, macroinvertebrate assemblages, effects of climate and land-use change, development of the MMI, and habitat suitability modeling of pollution-sensitive macroinvertebrates under future climate scenarios. **Chapter Five:** The key results of the study are presented in relation to the previous study, and the ecological implications of the findings are discussed. **Chapter Six:** The general conclusions and recommendations based on the findings of the study are presented. The validity and generalizability of the study are then outlined in the final chapter, which is **Chapter 7**, along with methodological strengths and scientific novelty, limitations of the study, future research directions, and followed by references and annexes.

CHAPTER 2: LITERATURE REVIEW

2.1. Watershed ecosystems and their ecological importance

Watersheds are landscape units that integrate terrestrial and freshwater processes; their headwater components (commonly defined as first- and second-order streams, catchments <1 km² (Lakew, 2020a; Richardson & Dudgeon, 2022), or source reaches within a short distance of emergence) form the ecological backbone of river networks (Richardson & Dudgeon, 2022). Although definitions vary in the literature (e.g., distance-based, catchment-area, or stream-order criteria), headwater streams constitute the bulk of channel length in most basins and therefore disproportionately influence downstream hydrology, sediment and organic matter fluxes, and biodiversity (Richardson & Dudgeon, 2022). Moreover, headwaters originate anywhere that the surfacing of groundwater (e.g., springs, swales, etc.). Headwaters are surrounded by forest, but they can originate in alpine or subalpine areas (Di Cugno & Robinson, 2017), grasslands or savannahs (Larson *et al.*, 2013), or any other type of landscape. Headwaters can also be fabricated as the outflows of lakes, mires, and other wetlands, with special characteristics of their own (Stengård *et al.*, 2020). By this way of defining headwaters, a second or third-order stream would not be counted as a headwater stream, and we have encouraged this distinction where we refer to second and higher-order streams as “small streams”(Lakew, 2020a). Streams can be classified as exterior or most upland tributaries in river networks and typically considered to be 1st & 2nd order streams (stream orders), but it depends on the map (link magnitude) (Mengist *et al.*, 2022).

Highland watersheds deliver diverse ecosystem services, including provisioning (example, water for domestic use and irrigation), regulating (flow moderation, sediment trapping), supporting (nutrient cycling, primary production), and cultural (landscape values, local livelihoods) services (Wang *et al.*, 2021). Since these services rely on the integrity of headwater systems, changes in upland land use and flow regimes quickly affect downstream service provision (Yin *et al.*, 2022; Mengist *et al.*, 2022). Ecosystem functions also play multidimensional ecological, socio-cultural, and economic roles, making them vital for human well-being (Summers *et al.*, 2018; Mengist *et al.*, 2022). By definition, ecosystem services encompass all benefits humans derive from natural ecosystems (Shrestha *et al.*, 2019; Mengist *et al.*, 2022). However, these services are

significantly threatened by LULC (Msofe *et al.*, 2020). Global assessments have highlighted the magnitude of this loss, for example, between 1997 and 2011, LUCC-driven declines in ecosystem services were valued at \$4.3-20.2 trillion. On the Tibetan Plateau, the annual ecological value was estimated at \$151 billion, representing 17.68% of China's annual ecological value and 0.61% of the global freshwater value (Mengist *et al.*, 2022).

2.2. Freshwater macroinvertebrate

Benthic macroinvertebrates are one of the aquatic creatures to whom aquatic resources as a habitat. These are the bottom-dwelling invertebrates that lack a spine, are visible to the naked eye, and are retained in mesh size > 500 µm (Onyena, 2019). These macroinvertebrates can be found in sediment and accumulated leaves and in association with macrophytes between rocks, interacting with a wide range of environmental conditions (Patil, 2021). They can also be found in fast water areas of the stream (riffle), stick to rocks, and smooth, flowing water may have a flat shape to prevent being swept downstream. In slow-moving pools, many organisms have adapted to burrow inside the sediments or sometimes developed bulky cases to get protection from predators (Di Cugno & Robinson, 2017). The mayflies and caddisflies are important examples of benthic macroinvertebrates (Gutiérrez-Rial *et al.*, 2023). Moreover, these can be observed through a range of reactions from species presence/absence ratios to changes in the whole invertebrate community (Uwizeye, 2020). Macroinvertebrates are strongly related to local stressors such as chemical degradation, climate change, and riparian degradation because of their long life history and limited mobility (Uwizeye, 2020)

Although the use of macroinvertebrate communities in habitat assessment has different advantageous characteristics (Agboola *et al.*, 2019). These are their diversity (taxonomically and tropically), abundance, low mobility (good indicators of localized conditions), suitable lifespans, ability to show responses to a variety of pollution types and levels, ability to provide information about cumulative and synergistic pollution effects, ease, it signal ecological condition and cost-effective way, seen as time intensive, ease of identification to family-level, significance in food webs, and the significant amount of background information that is available on taxa in temperature (Zaghloul *et al.*, 2020). On this basis, the information provided to decision-makers for environmental conservation, their responses are used in indices to monitor freshwater

ecosystems for integrity, aiding in decision-making in management and remediation, which is accurate (Tampo *et al.*, 2021; Edegbene *et al.*, 2021). On top of this, bioindication has an added advantage as it may transcend informing policies and reach local communities (Uwizeye, 2020). This is evident particularly when the indicator organisms are charismatic, as they are more likely to be embraced in citizen science. This increases public participation in long-term monitoring. From macroinvertebrates, Plecoptera (stone fly) and odonatan species are sensitive pollution bioindicators in the headwater streams ecosystem. Both species are sensitive to stressors in both aquatic and terrestrial habitats. Dragonflies and Damselflies (they are Odonata) may provide insights into the effects of anthropogenic and climate factors on biodiversity (Villalobos-Jiménez *et al.*, 2016).

Plecoptera are a primitive and the most pollution-sensitive group of insects that can be found in flowing waters that are clean, well-oxygenated, and act as freshwater and terrestrial (Hamid & Rawi, 2017). Stoneflies (Plecoptera) are an ancient order of insects whose fossil record extends from 300 million years ago to the Pennsylvanian (DeWalt & Ower, 2019). According to Amiruddin and Suhaila (2020), tropical stoneflies have high diversity and comprise more than 2000 species worldwide. Similarly, Yanai (2022) orders Plecoptera, or stoneflies, a small group of hemimetabolous insects, which includes approximately 3900 extant, valid species placed in 16 families worldwide. Stoneflies utilize all stream sizes, inhabit high latitudes, and have evolved to complete their life cycles under a broad range of stream permanence conditions (DeWalt & Ower, 2019). Adults are almost exclusively terrestrial, and the highest species richness of stoneflies occurs in cool and cold water streams draining mountains of temperate latitudes, but considerable diversity occurs in high-quality, warm-water streams (Mo *et al.*, 2019).

Stoneflies provide services that meet at least three of these categories. Provisioning services from stoneflies, as a direct source of food for humans, is uncommon (Dudley & Williams, 2017). As provisioning services, stoneflies are essential, as a direct source of food for humans (Asia and Africa), wild fish, prey for other invertebrate and vertebrate predators in both the aquatic and terrestrial setting are common (DeWalt & Ower, 2019). As a regulating service, stoneflies perform and are used as indicators of water quality and as mediators of nutrient cycling and energy flow across the land-water interface. They are often the first insects to be lost from

freshwater systems after relatively minor nutrient enrichment, degradation of habitat, or changes in aquatic thermal regimes (Dudley & Williams, 2017). Cultural services provided by stoneflies are mostly recreational, involving trout fishing. Fishermen model both dry and wet artificial flies after stonefly nymphs and adults. They often examine the size and coloration of species available streamside to more accurately match the locally available nymphs and adults (DeWalt & Ower, 2019).

Therefore, stoneflies (Insecta: Plecoptera) generally provide ecosystem services as indicators of water quality, as food for predators, as mediators of energy flow and nutrient cycling, and through cultural services related to recreation and artistic creativity. Loss of shredder stoneflies from headwaters due to acid precipitation, climate change, or pesticide application could dramatically diminish the availability of fine organic matter, causing a cascade of losses of downstream invertebrate and vertebrate species that provide many other ecosystem services (Giersch *et al.*, 2017). Similarly, Cantonati *et al.* (2020) posted that many stonefly species are vulnerable or threatened with extinction due to increasing pollution of running waters (mainly from sewage, agricultural, and industrial waste), habitat fragmentation of streams, the alteration of water courses and their banks, and the narrow ecological requirements.

In a similar study, in Ethiopia, among many macroinvertebrate, the percentage of organisms belonging to Ephemeroptera, Plecoptera and Trichoptera (% EPT), Plecoptera was rarely found in the low land which is Gilgel Gibe watershed is located in south-western Ethiopia (Ambelu *et al.*, 2010). According to Newman *et al.* (2021), Plecoptera are restricted to the mountain and forested areas in the tropical region, like may be in Ethiopian highland streams, but it is affected due to the above-listed factors (Lakew & Moog, 2015). The presence of Plecoptera in the European region is being reduced due to the growth of organic water pollution and climate change, which is leading to the extinction of these species, which are associated with clean and cold streams (Amiruddin & Suhaila, 2020).

Odonates will also be chosen as bioindicators for the ecological integrity of the river corridor, since this taxon provides information on the conditions of their aquatic breeding sites, as well as on the surrounding terrestrial areas, due to its amphibiotic life cycle (Golfieri *et al.*, 2016). Odonates are also charismatic insects, and will potentially engage and promote citizen-based

monitoring (Uwizeye, 2020). Dragonflies meet the requirements of a good bioindicators because: (i) their ecology, taxonomy and geographical distribution is well known, at least in some geographic settings (e.g., in highland streams), (ii) they are sensitive and quickly react to alterations of their habitats, (iii) they have highly specific sets of habitat requirements, (iv) the number of species is suitable for assessment. As a result, some studies which was investigated in developed and undeveloped countries (Amiruddin & Suhaila, 2020). Because the adult odonates over benthic macroinvertebrate larvae are increasingly being demonstrated as efficient biological indicators.

Odonates reflect the impact of environmental change and act as proxies for both aquatic and terrestrial habitats (Cunningham-Minnick *et al.*, 2019). This is due to their amphibiotic life cycle, which means they live in aquatic habitats for part of their life development, and terrestrial habitats when they become adults (Uyizeye *et al.*, 2021). Their prolonged nymphal phase in aquatic habitats allows odonates to reflect the ecological integrity and habitat heterogeneity of bodies of water (Saxton *et al.*, 2021). The use of adult odonates in habitat assessment and monitoring is practical (Pires *et al.*, 2020). They are relatively easy to identify to the species level due to their morphologically distinctive traits between species. This maintains the accuracy in assessment results (Uyizeye *et al.*, 2021). Many other empirical and analytical studies suggest that a positive relationship between invertebrate assemblage and habitat characteristics or land use types becomes much clearer when invertebrates are analyzed to the species level. It has been suggested, therefore, that assessment metrics with a finer resolution, such as Odonate species, are the best approach (Siddig *et al.*, 2016). Furthermore, odonates can offer specific insights about the condition and structure of the aquatic and riparian vegetation types, such as short grasses, tall wetland grasses, and shrubs (Ekka *et al.*, 2020). Odonates can also be used in selecting habitats that need preservation. This process is usually done through “the complementarity approach. Therefore, the occurrence patterns in Plecoptera and Odonata assemblages should be useful due to both species to detect both terrestrial and freshwater habitat assessment (Golfieri *et al.*, 2016).

2.3. Land use land cover change and its impacts on river/stream health

LULC refers to the transformation of natural landscapes through human and natural activities such as agriculture, deforestation, urbanization, settlement expansion, and vegetation

modification (Ekka *et al.*, 2020). It is widely recognized as an important environmental issue because changes in land use patterns strongly influence watershed conditions, ecological processes, and freshwater ecosystem sustainability (Summers *et al.*, 2018; Yin *et al.*, 2022). In recent decades, rapid population growth and increasing demand for land resources have accelerated LULC changes, particularly in developing countries and tropical highland regions, resulting in growing pressure on watershed ecosystems (Wantzen *et al.*, 2019; Ekka *et al.*, 2020).

2.3.1. LULC-based assessment for the watershed status

LULC is one of the most factor which influencing the watershed ecosystem (Yin *et al.*, 2022) and alter the hydrological processes, sediment transport, nutrient dynamics, and habitat quality (Firmiano *et al.*, 2021; Mengist *et al.*, 2022). Agricultural expansion, deforestation, urbanization, and channel modification increase runoff, erosion, sedimentation, and nutrient enrichment while reducing riparian buffering capacity and ecological resilience (Ekka *et al.*, 2020; Aga & Shomre, 2024). In the Ethiopian highlands, rapid expansion of agriculture and settlements has contributed to declining water quality and ecological disturbances in major river basins (Tolessa *et al.*, 2017). Studies further show that forest-dominated catchments generally maintain better ecological conditions and macroinvertebrate integrity than agricultural and urbanized watersheds characterized by higher conductivity, phosphorus concentration, and tolerant taxa dominance (Asnake *et al.*, 2021; Abebe *et al.*, 2021).

2.3.2. Physicochemical and hydrological assessment of the aquatic ecosystem

Physicochemical and hydrological parameters are broadly used to assess and monitor the watershed status and the ecological conditions of freshwater systems (Fikadu, 2022; Babatunde *et al.*, 2024; Anand *et al.*, 2025). The main indicators of river water quality are nutrients (nitrate and phosphates), dissolved oxygen, pH, electrical conductivity, turbidity, and temperature, which help to determine pollution levels in rivers, streams, and wetlands (Bekele *et al.*, 2018; Asmamaw *et al.*, 2019). Thus, measurements effectively reflecting current environmental conditions, they are often recommended to be integrated with biological and habitat assessments for comprehensive watershed evaluation (Assefa *et al.*, 2023). On the other hand, the hydrological variables such as runoff, streamflow alteration, discharge, and sediment transport

have been providing important information about watershed functionality under climate variability and land-use changes (Riis *et al.*, 2020). Furthermore, the previous studies showed that intensively refined and urbanized catchments commonly exhibit elevated nutrient loads, sedimentation, and degraded water quality compared to forested watersheds (Kidane *et al.*, 2019; Getachew *et al.*, 2023).

2.3.3. *Biological monitoring using macroinvertebrates*

Macroinvertebrates are among the most biological indicators for assessing watershed and aquatic ecosystem health because they respond sensitively and rapidly to long-term changes in water quality and habitat conditions of the watersheds (Firmiano *et al.*, 2021). Pollution-sensitive taxa such as Ephemeroptera, Plecoptera, and Trichoptera (EPT) are generally associated with healthy river systems, whereas disturbed and polluted streams are dominated by tolerant groups, including Chironomidae and Tubifex (Getachew *et al.*, 2023). Biological metrics such as %EPT, Biomonitoring Working party (BMWP), Family Biotic index (FBI), Average Score Per taxon (ASPT), and diversity indices are widely applied to evaluate ecological integrity in freshwater ecosystems (Shigute *et al.*, 2022; Venkatesham, 2024; Worku *et al.*, 2026). Ethiopian studies from the Upper Awash, Blue Nile, Omo-Gibe, and Baro-Akobo basins reported significant reductions in sensitive taxa along agricultural and urban disturbance gradients (Assefa *et al.*, 2020; Sitotaw & Mengistou, 2021). For instance, as Sitotaw & Mengistou (2021) revealed that % EPT in Chacha river showed that decreased while the tolerant taxa were increased and dominance a under high nutrient and conductivity conditions.

2.3.4. *Habitat and ecosystem services assessment*

Habitat assessment of watershed approaches examines riparian vegetation, substrate composition, channel morphology, bank stability, and habitat complexity, all of which strongly influence aquatic biodiversity and ecosystem functioning (Mengist *et al.*, 2022). Ecosystem service assessments are also increasingly used to evaluate watershed health because they reflect both ecological integrity and human well-being (Shrestha *et al.*, 2019). Ecosystem services (provisioning, regulating, cultural, and supporting services) are closely linked to watershed conditions and human livelihoods (Summers *et al.*, 2018; Yin *et al.*, 2022). However, LULC changes significantly decrease the ecosystem service capacity through habitat degradation,

biodiversity loss, and hydrological alteration (Msofe *et al.*, 2020). Globally, ecosystem service losses associated with land conversion have been estimated at USD 4.3-20.2 trillion between 1997 and 2011 (Abebe *et al.*, 2021; Mengist *et al.*, 2022). In Ethiopia, continued LULC changes threaten ecologically and economically important river systems. Many ecologically and economically valuable river systems in Ethiopia, like the Awash Basin, are facing threats due to the continuation of LULC changes, which calls for integrated watershed management and ecosystem-based conservation strategies (Kidane *et al.*, 2019; Getachew *et al.*, 2023).

2.3.5. River /Stream health assessment and monitoring

Spatial and ecohydrological models are gaining more and more significance in the understanding of the various land use-hydrology-climate variability-water quality-biological communities interdependencies in watersheds (Granitto *et al.*, 2025; Dinca *et al.*, 2025). The mapping of LULC dynamics, watershed degradation, and ecological vulnerability at temporal and spatial scales is accomplished widely by using Geographic Information Systems (GIS), remote sensing, and spatial analyses (Leps & Samilauer, 2003). Further, multivariate statistical techniques (including Principal Component Analysis (PCA), Redundancy Analysis (RDA), Canonical Correspondence Analysis (CCA), Non-metric Multidimensional Scaling (NMDS), and Permutational Multivariate Analysis of Variance (PERMANOVA) are frequently employed to explore the relationship between macroinvertebrate assemblage and environmental variables (Ren *et al.*, 2023). There is also a trend to use ecohydrological models like SWAT to assess impacts of climate change, runoff dynamics, sediment transport, and future watershed conditions under various land management scenarios (Makumbe *et al.*, 2022; Ghannem *et al.*, 2024). The integrated approaches tools offer the best available scientific evidence for sustainable watershed restoration and management practices.

2.4. Riparian vegetation and stream Health

Riparian vegetation refers to the transitional interface between terrestrial and aquatic environments such as rivers, streams, and estuaries (Yang *et al.*, 2018; Riis *et al.*, 2020; Dinca *et al.*, 2025). Healthy riparian forests typically consist of large native trees with an understory of shrubs and grasses that create structurally diverse vegetation communities capable of supporting multiple ecological functions (Yang *et al.*, 2018; Marques *et al.*, 2021). These well-preserved

vegetation buffers are extremely important when it comes to water chemistry, floodplain stabilization, and protecting aquatic ecosystems downstream (Dunn *et al.* 2022; Liu *et al.*, 2023; Nsenga *et al.*, 2024).

Riparian vegetation also plays a role in controlling important hydrological and biogeochemical processes that affect the health and water quality of freshwater ecosystems (Riis *et al.*, 2020). Riparian vegetation also has the ability to act as a natural filter, preventing sediments, nutrients, and pollutants from entering aquatic ecosystems from surrounding land-use activities (Melese *et al.*, 2025; Worku *et al.*, 2026). Pollution reduction is achieved through the filtration of sediments, absorption of nutrients, and denitrification activities among other microbial processes in vegetated buffers that enhance the self-purification capacity of freshwater ecosystems (Dunn *et al.* 2022; Liu *et al.*, 2023; Nsenga *et al.*, 2024). In addition, riparian canopy shading helps to balance the water temperature and control the amount of dissolved oxygen, which are critical for the maintenance of aquatic organisms, such as fish and macroinvertebrates (Yang *et al.*, 2018; Melese *et al.*, 2025). The combined ecological roles of riparian vegetation contribute to ecosystem resilience and preserve the physicochemical and biological integrity of freshwater ecosystems (Yang *et al.*, 2018; Riis *et al.*, 2020).

2.4.1. Riparian vegetation degradation

Anthropogenic although riparian vegetations are important to maintain the local ecological web, they still face serious threats due to anthropogenic pressures like agricultural development, urbanization, industrial development, and climate change (Dai *et al.*, 2020). These activities have introduced contaminants into river systems via surface runoff, domestic wastewater, and industrial effluents, leading to poor water quality (Ren *et al.*, 2021; Hira *et al.*, 2023). This degradation or removal of riparian vegetation has a negative effect on these impacts and further reduces the pollutant input to the freshwater ecosystems by eliminating the naturally occurring filters (Granitto *et al.*, 2025; Dinca *et al.*, 2025). Streams are particularly vulnerable to sedimentation, nutrient enrichment, and disturbances to ecosystems that compromise ecosystem stability (Yang *et al.*, 2018; Hira *et al.*, 2023). Riparian plants help to anchor the stream's sides with their root systems and prevent erosion, which helps to limit the amount of sediment entering aquatic habitats (Fernandez *et al.*, 2021; Dai *et al.*, 2020). In the freshwater ecosystem, the loss

of riparian zones would increase sediment deposition, nutrient loading, and reduce biodiversity (Bojanowski & Orli, 2025). Agricultural land use can create adverse effects on macroinvertebrate diversity through reduced habitat complexity and altered water quality conditions (Marques *et al.*, 2021), which different research has shown can be counteracted by the riparian forests. Therefore, it is important to conserve and restore riparian vegetation to enhance aquatic biodiversity, macroinvertebrate assemblage, and freshwater ecosystem functioning.

2.5. Climate variability at highland watersheds

Freshwater ecosystem alteration is a significant consequence of climate change and climate variability, through changes in river flow regimes, thermal regimes, and stability of the freshwater ecosystem, which in turn affects the structure and functioning of the aquatic (Kakouei *et al.*, 2020). River ecosystems are closely tied to the atmosphere and temperature, and precipitation directly affects river hydrology, dissolved oxygen, and biological processes that support river food webs (Carr *et al.*, 2019). Furthermore, the impacts of climate change on ecosystems do not occur in isolation; they compound other stressors, including pollution (which affects the hydrology and thermal regimes), eutrophication, acidification, and biological invasion that lead to increased ecosystem vulnerability (Masese *et al.*, 2023; Edegbene *et al.*, 2024).

2.5.1. Climate-driven hydrological alterations

Climate variability impacts the hydrology and thermal regime of rivers via changes in the precipitation pattern and increases in air temperature related to altered streamflow, higher evaporation during dry seasons, and greater flood and drought frequency (Carr *et al.*, 2019; Bonacina *et al.*, 2022). These hydrological changes affect the continuity, stability, and physicochemical conditions (including dissolved oxygen) of aquatic ecosystems, which are fundamental for their functioning (Jin *et al.*, 2022). There is also a direct impact on the metabolic processes, life-cycle timing, and survival of ectotherms (birds, fish, insects, reptiles, and other invertebrates) to increased water temperature, which can result in changes to the composition of communities (Carr *et al.*, 2019; Monbertrand *et al.*, 2019).

2.5.2. Uncertainty and gaps in the understanding of the climate model

Climate models have proven to be a valuable tool for predicting ecological change, but there is a lot of uncertainty, especially in the regions with complex rainfall patterns (Adámek *et al.*, 2016;

Pyne & Poff, 2017) due to the variability between Global Climate Models (GCM), Regional Climate Models (RCM), and Emission scenarios (ESCs). These uncertainties affect predictions of hydrological regimes and biological responses, especially when relating macroinvertebrate dynamics to climatic factors (Asmamaw *et al.*, 2019). However, research on tropical highland watersheds, including Ethiopia, is still in its early stages, especially on the impacts of climate variability and land-use on macroinvertebrates. In addition, there is poor detection of climate-related trends due to the absence of long-term ecological data. Thus, integrated research that incorporates the variability of climatic conditions, land use changes, and macroinvertebrate responses is essential to enhance watershed management in Ethiopian headwater systems in the highlands.

2.5.3. Macroinvertebrate responses to climate variability

The macroinvertebrate (MI) communities have been responsive to the climate-induced changes in the stream condition, as reflected by the changes in diversity, abundance, and functional structure of the macroinvertebrate community (Chattopadhyay *et al.*, 2024). They are sensitive to environmental changes and are associated with low mobility, short life cycles, and high dependence on water quality and habitat stability, making them good bioindicators of environmentally driven changes in natural systems (Goulding *et al.*, 2021; Goenka, 2023; Bharti & Yeole, 2025). Empirical studies indicate that increasing temperature and decreasing runoff are both significant factors influencing the taxonomic shifts, distribution, and phenology of the species (Monbertrand *et al.*, 2019). This means that groups of macroinvertebrate pollution sensitive (such as Ephemeroptera, Plecoptera and Trichoptera, EPT) tend to be reduced under climatic stress and the other, less sensitive, fish groups tend to be increased. These ecological changes are consistently reflected by common biological indicators (e.g., %EPT, O/E ratios, total richness), which are a reflection of these climate-driven ecological changes (Goulding *et al.*, 2021). Persistent changes in macroinvertebrate communities over time are also documented in Europe and North America in association with temperature and precipitation changes (Jin *et al.*, 2022).

2.6. Macroinvertebrate Metrics in Ecological Assessment

2.6.1. Bioindication concept and ecological basis

One of the most commonly used ecology-related methods is called bioindication, which involves finding out how living things react to pollution and the changing of habitats and climate to check environmental conditions (Asif *et al.*, 2018; Ko *et al.*, 2020). Bioindicators are more reliable indicators for watershed health, as they integrate with a long-term effect of the watershed, unlike physicochemical measurements, which represent only the momentary conditions (Parmar *et al.*, 2016; Agboola *et al.*, 2019). Benthic macroinvertebrates are the most widely used aquatic bioindicators among aquatic organisms due to their high sensitivity to environmental stress, limited mobility, and their range of tolerance to pollution and habitat degradation (Uwizeye, 2020; Dabessa *et al.*, 2021). They are influenced by physical, chemical, and biological disturbances and are important tools for freshwater ecological monitoring (Ambelu, 2013; Villantes, 2015).

2.6.2. Macroinvertebrate Indices (MI)

The basic index used for assessing the status of aquatic ecosystems is MI on the basis of taxonomic composition, diversity, and functional feeding structure (Hamid & Rawi, 2017; De Walt, 2019; Worku *et al.*, 2026). The quality of stream and river conditions and community stabilities are reflected by taxonomic metrics such as total taxa richness, Ephemeroptera-Plecoptera-Trichoptera (EPT) richness, and diversity indices such as Shannon and Simpson (Golfieri *et al.*, 2016). Tolerance-based indices such as the Biological Monitoring Working Party (BMWP), Average Score Per Taxon (ASPT), and Family Biotic Index (FBI) are widely applied to assess organic pollution and water quality conditions (Hilsenhoff, 1988; Barbour *et al.*, 1996). The functional feeding groups and trait-based indicators further complement these metrics by describing ecosystem processes such as energy flow and ecological strategies of organisms (Mo *et al.*, 2019; Cantonati *et al.*, 2020). Together, these indices provide a detailed biological response to environmental stress and form the foundation of ecological assessment in freshwater systems (Cunningham-Minnick *et al.*, 2019; Uyizeye *et al.*, 2021).

2.6.3. Vegetation-Based Indices (VBI)

Vegetation-based indices assess the watershed health by evaluating riparian conditions that directly influence aquatic ecosystem conditions and their functioning (Wantzen *et al.*, 2019; Ekka *et al.*, 2020). Riparian vegetation is essential for regulating bank stability, sediment retention, nutrient cycling, shading, and thermal moderation of streams, thereby maintaining overall habitat quality and ecological integrity in freshwater systems (Ren *et al.*, 2021; Hira *et al.*, 2023; Worku *et al.*, 2026c). Degradation of riparian vegetation due to land-use intensification leads to increased erosion, habitat fragmentation, higher sediment and nutrient loading, and reduced ecological resilience of river systems (Mengist *et al.*, 2022; Abebe *et al.*, 2021). Accordingly, vegetation-based indicators such as riparian condition assessments, habitat quality indices, and canopy cover metrics are widely used to assess the land-water interactions and ecosystem degradation patterns (Barbour *et al.*, 1999). Healthy riparian vegetation is consistently associated with higher aquatic biodiversity and improved ecological status, whereas degraded vegetation zones correspond with reduced macroinvertebrate diversity and increased dominance of pollution-tolerant taxa (Assefa *et al.*, 2023; Getachew *et al.*, 2023).

2.6.4. Integrated Multimetric and Biotic Integrity Indices (MMI and CBM-IBI)

Multimetric indices integrate multiple biological metrics, including taxonomic richness, diversity, tolerance, and functional traits, into a single composite score representing overall ecological integrity (Barbour *et al.*, 1996; Hering *et al.*, 2006). This approach is more robust than individual metrics because it captures multiple dimensions of ecosystem condition and allows clear classification of ecological status (poor, moderate, good) (Agboola *et al.*, 2019; Mangadze *et al.*, 2019). MMIs calibrated to local reference conditions have been used successfully in river and stream systems in Africa and Ethiopia to detect ecological degradation due to land-use change and pollution (Worku *et al.*, 2026a; Assefa *et al.*, 2020). The Combined Biota-Based Multimetric Biotic Integrity Index (CBM-IBI) builds on this concept and combines macroinvertebrates and vegetation metrics into a single assessment system. It is also particularly suitable for complex highland watershed systems with multi-stressors (Lind *et al.*, 2019; Martínez-fern *et al.*, 2021; Worku *et al.*, 2026b).

2.6.5. Ethiopian Biotic Index (ETHBios)

The Ethiopian Biotic Index (ETHBios) is a macroinvertebrate-based water quality assessment tool developed locally, which will rate the water quality conditions of Ethiopian rivers based on locally adapted taxa sensitivity values (Lakew & Moog, 2015b). It was designed to address the shortcomings of using temperate zone-based indices like BMWP or ASPT without modification for tropical streams with higher elevations and different tolerances to various stressors. Ethiopia's water quality systems are characterized by the ecological condition of the river in terms of a composite water quality score derived from the tolerance scores assigned to the families of macroinvertebrate species in accordance with their organic pollution and habitat degradation sensitivity (Lakew & Moog, 2015b; Assefa *et al.*, 2020). Research has proven that ETHBios works well in discriminating between relatively undisturbed headwater streams and heavily disturbed agricultural or urban streams in the Ethiopian highlands. The current indices (such as ETHbios) provide useful general frameworks, but they are not comprehensive enough to fully represent the special hydrological, land-use, and bioclimatic conditions of the specific area Dinki watershed. The suitability of the site conditions requires a biological assessment tool that can be calibrated locally to provide an ecologically meaningful assessment. Hence, the specific MMI in the Dinki watershed was the focus of this study to help support resource management, conservation policy, and community-based monitoring in areas experiencing increasing water resource demand, such as the Ethiopian highlands.

2.7. Spatiotemporal dynamics in macroinvertebrate assemblages

Macroinvertebrate assemblages are highly variable in both space and time and are influenced by complex interactions among gradients in physicochemical conditions, habitat structure, hydrological regime, and land use (Beck *et al.*, 2020; Muluneh, 2021). Spatially, there is a significant variation between communities on river longitudinal gradients (from headwaters to downstream reaches) and across land use types, where increases in conductivity, nutrient concentrations and turbidity from agricultural and urban landscapes are accompanied by a decline of sensitive communities of EPT taxa, and by a predominance of tolerant taxa, such as Diptera and Oligochaeta, which proliferate (Tibebe *et al.*, 2022; Bogardi *et al.*, 2020; Assefa *et al.*, 2020). These patterns are also influenced by habitat heterogeneity, with riffle habitats, coarse

substrates, higher canopy cover, and increased flow variability promoting greater diversity and functional complexity than degraded or homogenized habitats (White *et al.*, 2017; Getachew *et al.*, 2023). Lentic systems (lakes) tend to have more organic deposition, more dominance by sediment-tolerant taxa, and slower water turnover than lotic river systems (rivers), which tend to be more sensitive to water and substrate variability and to exhibit greater spatial variation in assemblages (Ko *et al.*, 2020; Zhu *et al.*, 2021; Sripanya *et al.*, 2023).

Highland and lowland are also significantly different in their ecology (Alemneh *et al.*, 2017; Abebe *et al.*, 2021; Asmamaw *et al.*, 2021). Highland streams generally have higher proportions of sensitive taxa, high oxygen levels, and lower temperatures, and in less disturbed catchments (Mpumalanga *et al.*, 2024; Vasconcelos & Sacht, 2024). However, lowland rivers have generally been warmer, slower, and more nutrient-enriched, leading to an increased abundance of pollution-tolerant and intolerant taxa (Sripanya *et al.*, 2022; Tubi'c *et al.*, 2024). These differences are accentuated by the pressure on land-use, especially in the headwaters of the highlands, where there is high biodiversity value but which are also highly vulnerable to disturbance (Abebe *et al.*, 2021).

Macroinvertebrates show high seasonal variability, particularly in response to wet and dry season hydrological changes, with a strong relationship between seasonality and the communities of macroinvertebrates (Ambelu *et al.*, 2010; Mereta, 2013). Increased discharge and flood events in the wet season can affect the benthic habitat in a physical manner, leading to scouring and reduced abundance and temporary resetting of the community (Beyene & Shumetie, 2023; Edward, 2023; Mangadze *et al.*, 2019). Conversely, the dry season generally occurs with less flow, higher water temperature, and lower dissolved oxygen, creating more environmental stress and promoting more tolerant taxa that are able to withstand harsh conditions (Kuma *et al.*, 2022). This wet and dry seasonal difference is especially high in tropical highland systems like Ethiopia, where rainfall occurs in two distinct modes, resulting in strong seasonal variation in community composition (Fan *et al.*, 2015; Lemma *et al.*, 2024).

Over long temporal scales, interannual climate variability and progressive land-use change drive directional shifts in assemblage structure (Davidson & Finlayson, 2018; Badamfirooz *et al.*, 2022). Repeated disturbances often result in a transition from diverse, sensitive communities

toward simplified assemblages dominated by tolerant taxa, accompanied by reductions in functional feeding group diversity and overall ecological integrity (Alemneh *et al.*, 2017; Abebe *et al.*, 2021; Asmamaw *et al.*, 2021). These spatial and temporal dynamics across wet and dry seasons, highland and lowland gradients, and river-lake systems highlight the necessity of multi-seasonal and multi-habitat monitoring to accurately capture ecological change and disentangle the relative influence of land-use and climate variability on freshwater biodiversity (Gething, 2024; Mehari *et al.*, 2014). However, in the Ethiopian highland context, such spatio-temporal dynamics between 2016 and 2023 remain insufficiently studied, particularly in relation to combined land-use and climate variability effects on macroinvertebrate assemblages, which this study aims to address.

2.8. Predicting Habitat Suitability Under Climate Change Scenarios

Predictive modeling under a climate change scenario is crucial for forecasting the future habitat suitability and pollution-sensitive species responses in freshwater ecosystems. River systems provide critical ecosystem services but are increasingly threatened by land-use change, deforestation, agricultural expansion, and climate-driven hydrological alterations (Reid *et al.* 2019; Grill *et al.*, 2019). Climatic variables such as temperature increase and precipitation variability directly influence streamflow regimes, water quality, and habitat structure, leading to shifts in the distribution of pollution-sensitive macroinvertebrates such as Ephemeroptera, Plecoptera, and Trichoptera (Makumbe *et al.*, 2022; Ghannem *et al.*, 2024). Combinations of predictive models and ecological data can thus be used to identify vulnerable habitats early and to facilitate proactive conservation planning before irreversible ecological changes happen to the watersheds (Mantyka-Pringle *et al.*, 2014; Bojanowski & Orli, 2025).

2.8.1. Species Distribution Models for Habitat Suitability Prediction

Species distribution models (SDMs) are more powerful, particularly when used to predict habitat areas, and are commonly applied in order to project the potential distribution of a species, using the relationship between occurrence and environmental predictors (Tabor & Koch, 2021). These models, including the MaxEnt model, which is a probabilistic machine learning algorithm, are particularly used for SDM in the presence-only datasets, which are commonly used for all plant

and macro and micro species, particularly macroinvertebrate studies (Phillips *et al.*, 2006). SDMs combine climatic information (such as temperature and rainfall), hydrologic information, and land-use information to provide estimates of habitat suitability in both current and future climate conditions. SDMs have particular potential for freshwater ecosystems, where they can help to identify potential refugia for sensitive taxa and areas of high risk of biodiversity loss as a result of changing environmental conditions and climate change (Zhao & Boll, 2017; Bojanowski & Orli, 2025).

2.8.2. Machine Learning Algorithms

Some machine learning methods like Random Forest (RF) and Boosted Regression Trees (BRT), as well as other ensemble methods, are being widely used to predict freshwater biodiversity because of their high predictive power and the capacity to deal with complex nonlinear systems (Sami *et al.*, 2013; Kuemmerlen *et al.*, 2015; Sultana *et al.*, 2020). The main role of the RF is to overcome overfitting and stabilize predictions, and BRT is particularly good at minimizing the prediction error and capturing complex patterns (Yang *et al.*, 2016). Ensemble modeling is expected to enhance the reliability of prediction by reducing the uncertainty originating from the output of individual models, and thus integrating the performance of various algorithms (Dormann *et al.*, 2018; Hao *et al.*, 2019). They are especially valuable tools for synthesizing vast amounts of environmental data, such as climate projections, land-use change, and hydrological variables, to inform predictions of macroinvertebrate distribution patterns across various climate scenarios (Tabor & Koch, 2021). They contribute to comprehensive spatial mapping of ecological risk areas and can be used to prioritize conservation efforts in data-scarce areas like tropical highland watersheds (Hao *et al.*, 2019; Jamali *et al.*, 2024).

2.9. Conceptual framework

The conceptual framework has a multi-scale systemic approach, and the core biological indicator of ecological health is macroinvertebrate assemblage. It speculates that the macroinvertebrate structure is a result of the combined stress of climate variability (CV) (1994-2023) such as rainfall variability and temperature rise and LULC changes (agricultural expansion, settlement growth and forest loss) (Carr *et al.*, 2019; Monbertrand *et al.*, 2019). These drivers have an impact on the physicochemical parameters such as total nitrogen (TN), total phosphorous (TP),

dissolved oxygen (DO), water temperature (T_{water}) and discharge (Q) can create pressures on the watershed including soil erosion and riparian degradation, resulting in direct hydro-chemical and biological responses (Mantyka-Pringle *et al.*, 2014). Localized anthropogenic activities (sand mining, waste disposal, fertilizer application and water abstraction) further exacerbate the change in LULC and water-quality degradation. Mitigating factors include positive watershed interventions (reforestation, soil and water conservation, policy practices and community initiatives). The cumulative impacts of stressors are compared to restoration effects using a temporal comparative design (Baseline 2016 versus Resurvey 2023), assuming that community shifts observed are a result of the combination of climate, land-use, human pressures and interventions (Jonsson *et al.*, 2017). Overall, the framework illustrates how the long-term hydro-climatic and landscape changes interact with immediate anthropogenic disturbance and management response, to influence indicator taxa and ecological health, as measured by a multimetric index and species distribution modelling for sensitive taxa such as Plecoptera and Trichoptera (PT) (Fig. 1) (Scotti *et al.*, 2020).

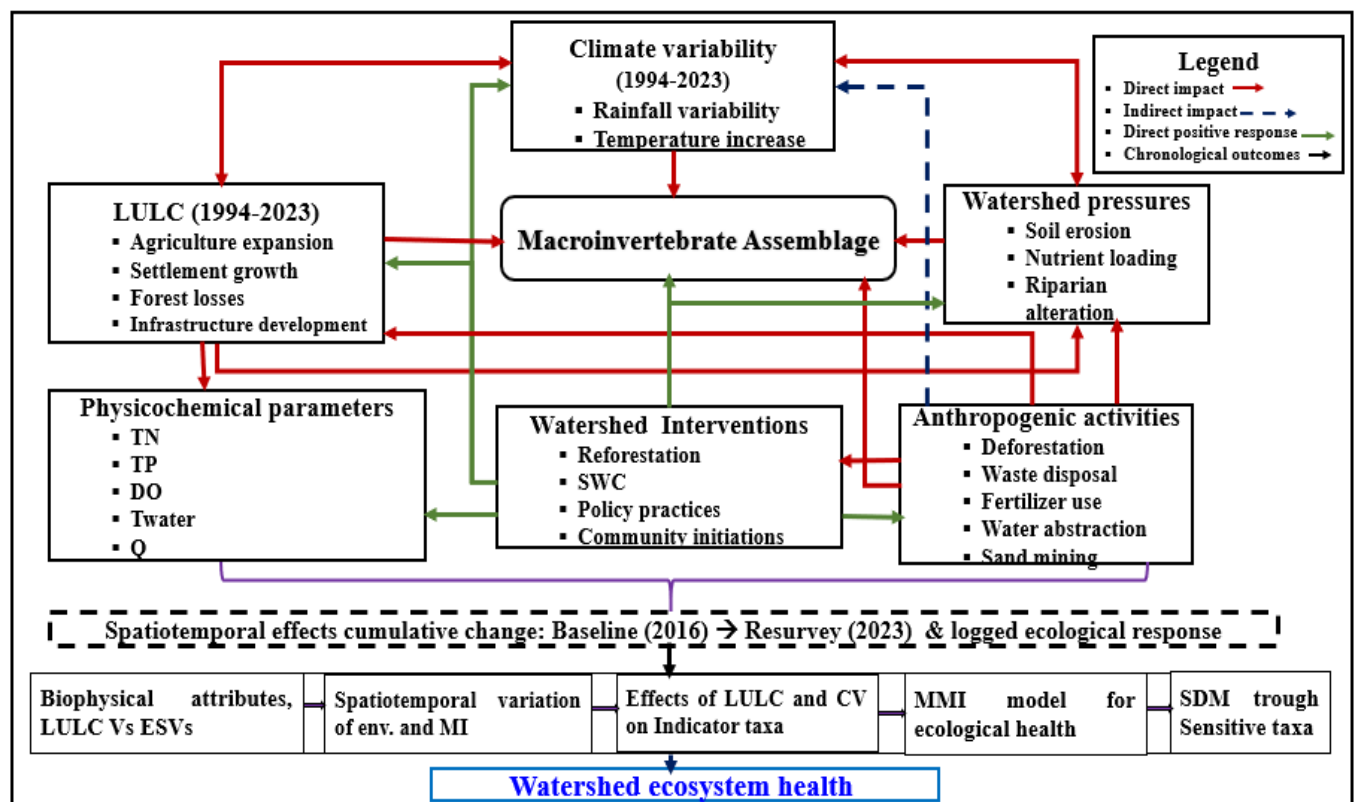


Figure 1.A conceptual framework of the key land-use land cover types, watershed pressures, water quality, and climate factors analysis was impacted on macroinvertebrate richness with their species distribution prediction model: ensemble approach.

CHAPTER 3: MATERIALS AND METHODS

3.1. Study area

The study Dinki watershed is conducted in Awash Sub-basin, located in Ankober District, Central Highlands of Ethiopia. The watershed includes four major sub-watersheds: Dinki, Hagere-Selam/Zego, Gedamoch, and Dense. Ankober's administrative center, Gorobela, is about 42 km east of Debre Berhan and 172 km north of Addis Ababa. Geographically, the watershed lies between 9°32'30"-9°42'30" N latitude and 39°41'0"-39°53'0" E longitude, with elevation ranging from about 1,257 m to 3,181 m above sea level (Worku *et al.*, 2026c). The area is dominated by rugged terrain, mainly hills and mountains, with smaller proportions of rocky and flat lands. In Ethiopia, most likely the watershed has a bimodal rainfall pattern, with a long dry/bega season from October to January, belg/spring/ small rains season (February-May), and a Kiremit/main rainy/wet season from June to September. Mean annual rainfall ranged from about 812 mm in 2012 to 900 mm in 2023, while mean annual temperature increased from about 17.5°C to 18.5°C during the study period (Worku *et al.*, 2026c) (Fig. 2).

Subsistence rain-fed agriculture integrated with livestock production is the dominant livelihood in the watershed. The Dense sub-catchment, located in the upper watershed, includes Lay-Gorobela, Mehal-Wonz, and Ememihret village associations and is partly bordered by the Dense Natural Forest. It is characterized by agricultural land, rural settlements, soil and water conservation structures, and small-scale tree plantations. The Gedamoch sub-catchment contains much of the Dense forest, while its lower part from Dense is used for agriculture, slight grazing, and settlement. It lies downstream of Mehal-Wonz and upstream of Zego, extending toward the northwestern part of Hagere-Selam. The area supports important native tree species, including

Podocarpus falcatus, *Hagenia abyssinica*, *Cordia africana*, *Olea africana*, *Ficus sur*, and *Juniperus procera*, and agroforestry practices are common.

The Hagere-Selam area borders the Ememihret mountain escarpment through the Gedamoch sub-catchment, but parts of the area are degraded by intensive agriculture, grazing, and settlement expansion. The Dinki sub-catchment is located downstream and includes the lower parts of Zego and Hagere-Selam. Traditional irrigation, agroforestry, fruit cultivation, and crop production are common. Major crops include barley, field pea, teff, wheat, horse bean, maize, and mung bean. Cultivated land is the dominant land-use type, although built-up areas, grazing lands, slight vegetation, and water bodies are also present. In general, Dinki watershed topographically (top to down) and level degradation (minimum-high): Dense, Gedamoch, Zego and Dinki, and level of degradation.

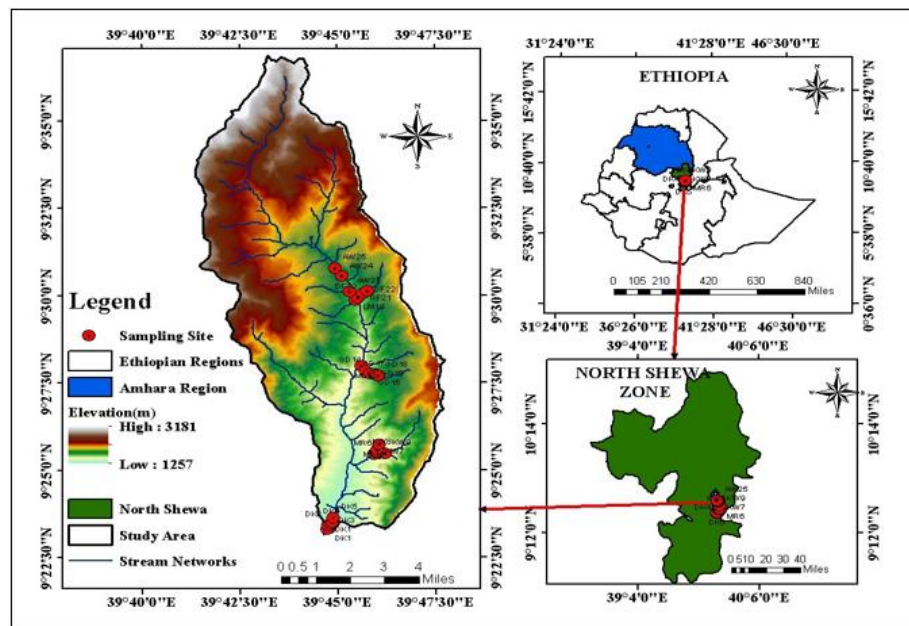


Figure 2. Dinki watershed is located in the Amhara region, North Shewa Zone.

3.2. Study design, Community perception, and Sampling techniques

A comparative cross-sectional study design was employed between December 2022 and June 2023 to assess spatial and temporal variations in water quality and macroinvertebrate assemblages between the 2016 and 2023 sampling periods. To ensure data comparability, the 2023 sampling locations were the same as those used in the 2016 study (Asmamaw *et al.*, 2019;

2021); this allowed for comparison of data. Site selection considered both the longitudinal gradient and the level of anthropogenic disturbance along the Dinki watershed. Accordingly, the Dense sub-catchment represented partly impacted upstream sites; Gedamoch served as the least impacted (Asmamaw *et al.*, 2019) area, Zego as moderately impacted, and Dinki as the most disturbed downstream site. Data were collected during both dry and wet seasons in each year to account for seasonal variability in water quality and biotic responses. Since the 2016 dataset included four seasonal samples, the summer

and wet seasons were merged to represent a single wet-season category, while dry-season data were directly compared between 2016 and 2023.

3.2.1. LULC and Watershed features

A comparative study design was employed to evaluate LULC dynamics and their relationship with watershed ecological conditions. The watershed was stratified into three agroecological sections: upper (cold/alpine), middle (dry-warm to cold), and lower (sub-moist warm). Historical LULC changes were assessed for the period 1994-2023, together with monitoring activities conducted during the project implementation period. Cloud-free Landsat and Sentinel-2A satellite images were downloaded from the USGS Earth Explorer platform (<https://earthexplorer.usgs.gov/>) for LULC analysis, while additional spatial data, including aerial photographs, terrestrial photographs, and topographic maps, were collected to support image interpretation and validation. Ground surveys and Google Earth imagery were used to collect training samples representing the major land cover classes. Supervised classification techniques were applied to classify the LULC types into six dominant categories: forested land, agricultural land, grazing land, slight vegetation land, water body and built-up land. Land use variables were quantified as percentage coverage within a 200 m buffer around stream segments using the Zonal Statistics tool in Hawth's Analysis Tools. LULC; in addition, a 30 m Digital Elevation Model (DEM) was used to determine flow-path directions and delineate the watershed into three sub-watersheds using the hydrology tools in ArcGIS version 10.5.

3.2.2. Meteorological Data

Meteorological data (rainfall and air temperature) were collected from the Ethiopian Meteorological Institute (EMI), local meteorological data and information stations. Records were

quality checked, homogenized, and gap-filled for 30 years (1994-2023) to evaluate and document climate variability and its effect on watershed processes, hydrology, and habitat conditions.

3.2.3. Soil data

Soil physical properties, including bulk density and texture, were derived from secondary sources. These data were obtained from the Ethiopian Soil Information System (EthioSIS), a raster-based dataset with 250 m spatial resolution generated from remote sensing products.

3.2.4. Environmental and Macroinvertebrate Sampling

The comparative study design was used to collect environmental and macroinvertebrate data based on their hydrologic disturbance events, following the prescription (Reid *et al.*, 2016). All 2023 sampling sites followed the sites established during the 2016 data collection, where the grid data were obtained from the authors upon permission (<https://repository.ju.edu.et/handle/123456789/9331>) for comparison. A Geographic Positioning System (GPS) was used to record the altitude and the coordinates of sampling sites. All streams in the Dinki watershed are sources of the ecological data for the biophysical (environmental and macroinvertebrate) data collection. Two sampling efforts were conducted, taking the season (dry and wet) and streamflow conditions into consideration. Hence, the dry period was extended from October to mid-May, stream flows were substantially reduced, and fragments of permanent pools were created, especially at the intermittent Hagere-Selam sites. The wet or summer period was extended from mid-May to the end of September, and during this period, a large volume of precipitation occurred, especially during sampling days on 26, 27, 28, and 29 June in 2016 and 2023.

As a result, the dry season data were collected from January to February and the wet season from May to June in the both 2016/2017 and 2022/2023 years of data collection. The wet and dry seasons in 2016 were measured at 0.03 and 0.01 m³/s and in 2023 measured at 0.88 m³/s and 0.36 m³/s respectively. The discharge (m³/s) was calculated following the velocity-area method by integrating mean depth (m), width (m), and current velocity (m/s) for both 2016 and 2023. The average stream discharge during these sampling periods was 0.03 m³/s and 0.45 m³/s 2016 and 2023, respectively. Streamflow velocity was calculated by averaging the time involved in a

floating object to travel a 1-m stream reach/distance from 3 trials on each reach (Barbour *et al.*, 1999). For the study of macroinvertebrate assemblage and MMI analyses, all taxa occurrence data are used while for SDM, occurrence data of the pollution sensitive families Perlidae/stoneflies/Plecoptera and Philopotamidae/caddisflies/Trichoptera are used from Ethiopian watersheds. The GPS coordinate points and species data were taken from registered databases and existing datasets for suitability prediction of habitats.

3.2.5. Habitat quality assessment

Habitat quality was assessed at each sampling station using the US-EPA Rapid Bioassessment Protocol (HABSCORE) (Barbour *et al.*, 1999) with visual estimates of key physical parameters. Physical habitat information was taken at each sampling site with a visual estimate measurement technique (Fig. 3). Assessment metrics included vegetation cover, riparian stability, epifaunal substrate, channel morphology, bank erosion, substrate diversity, flow regime, and instream cover. Habitat scoring was conducted during each sampling campaign to account for temporal variation caused by vegetation and flow changes. The 25 sampling sites across the Dinki watershed were classified into four distinct sub-catchments to evaluate spatial heterogeneity in habitat quality, physical impact, and hydrologic regime: Dinki (DK1–DK5), Zego (KM6–ML12), Gedamoch (MK13–GD18), and Dense (LM19–AW25). Dense (encompassing Lik-Marefiya [LM19], Denaf [DF20–DF22], and Ashewa [AW23–AW25]) occupies the upper watershed bordering the partially conserved Dense Natural Forest. This sub-catchment is characterized by intensive rain-fed agriculture and expanding rural settlements, exhibiting elevated agricultural land use, good pool substrate availability, moderate landslides, localized small-scale tree plantations, slight tree canopy removal, and moderate channel alterations alongside minor irrigation, waste dumping, and micro-scale extraction. Gedamoch (spanning Mentik-Gedamoch [MK13] and Gedamoch [GD14–GD18]) acts as a critical ecological area downstream of Mehal-Wonz and upstream of Zego. It encompasses well-protected native forest and agroforestry zones. Gedamoch demonstrated the lowest anthropogenic impact scores overall, featuring pristine permanent flow, minimal sedimentation, high pool substrate retention, very low tree removal, and suppressed physical disturbance relative to all other sub-catchments.

Moving into the mid-to-lower stream zones, Zego (including Kewot–Mesal [KM6], Kewot [KW7–KW9], and Mesal [ML10–ML12]) represents an intermediate landscape subject to moderate agricultural expansion, extensive livestock grazing, and intermittent flow regimes. Visual and habitat quality assessments in Zego revealed high sediment accumulation, minimal-to-moderate pool substrates, slight-to-medium riparian vegetation cover, moderate landslides, active smallholder irrigation, moderate tree plantation activity, and minor channel modifications. Dinki (DK1–DK5) occupies the lowermost reaches, integrating runoff from the upper catchments and Hagere-Selam escarpments. Dominated by traditional irrigation, fruit orchards, and croplands (teff, maize, barley, pulses, and mung bean), the Dinki sites exhibit moderate-to-high agricultural pressures, high sediment loading, degraded pool substrates, and sparse riparian canopy. However, channel stability remains largely unorganized at sites DK2 and DK3, with negligible channel alterations and localized tree plantations (e.g., DK3), despite pervasive grazing pressure and localized waste dumping.

In total, 25 sampling sites were examined across both years, with 50 pooled samples (dry and wet) collected in 2023 and an equivalent set from 2016, yielding 100 composite samples overall. Land use characteristics varied among sub-catchments. Dinki sites were dominated by irrigation-based agriculture and regenerated vegetation; Zego by grazing lands with intermittent flow; Gedamoch by well-protected forests with permanent flow; and Dense by degraded agricultural and settlement zones bordered by partially conserved forest. Such habitat assessments yielded a comprehensive understanding of how land use, flow regime, and ecological integrity intersect in the Dinki watershed.

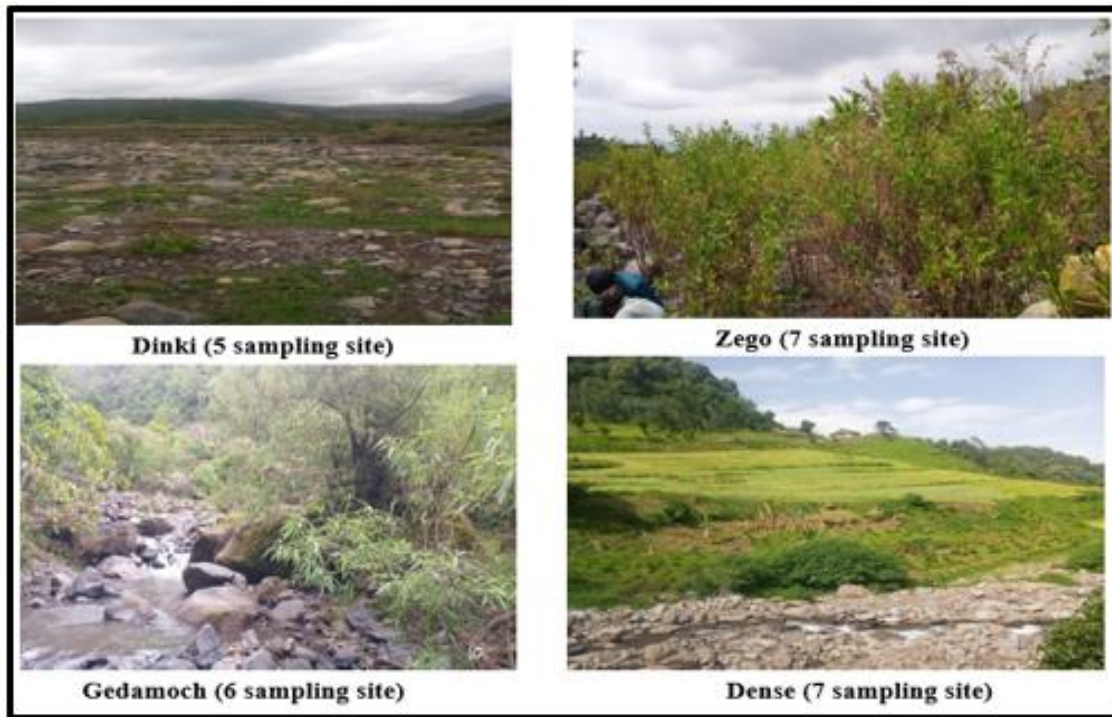


Figure 3. The current habitat of the Dinki watershed at each sampling site in 2023.

3.3. Data collection

3.3.1. Soil data collection

Physical and Chemical properties of soil were retrieved from the literature and databases. The physical properties of soil, like bulk density and texture, were collected from Ethiopian Soil Information System (EthioSIS), which is a raster (spatial grid) dataset with 250 and 250 resolutions, and the information was derived from satellite remote sensing.

3.3.2. Climate data collection

Meteorological data (annual rainfall data and max and min temperature) were collected. These meteorological stations were located within the study area (Dinki watershed) and contained the same missing data. The missing data was filled using the normal ratio method, and the double-mass curve method was used to check the data's consistency. Meteorological data preparation

and quality assurance: annual meteorological data of 30 years (1994-2023) collected from the Ethiopian Meteorological Institute (EMI). The missing data was computed by the linear regression method and filled before preparing as input for the Arc SWAT model. Then, the arranged data were saved in a comma-delimited format as required for the Arc SWAT model input.

For this study, gridded climate data (rainfall and temperature) and macroinvertebrate data were utilized. Climate datasets were sourced from the Enhancing National Climate Services Time Series (ENACT) database, which provides rainfall and temperature data with a spatial resolution of 4×4 km, spanning the period from 1994 to 2023 for 30 years. The ENACT rainfall dataset was developed by integrating quality-controlled meteorological station data with Tropical Applications of Meteorology Using Satellite (TAMSAT) rainfall estimates. Similarly, temperature data were derived by assimilating station temperature records with Moderate Resolution Imaging Spectroradiometer (MODIS) Land Surface Temperature (LST) estimates and a digital elevation model.

The Ethiopian Meteorological Institute (EMI) provided both ENACT rainfall and temperature data sets that are used for climate trend analysis in this study. These datasets provided a robust basis for examining long-term climatic trends and their potential impacts on macroinvertebrate populations. A detailed summary of the datasets employed in this study is presented in Table 1. The required data type and source are shown in Table 1 below, such as station data, grid data, satellite data, and DEM.

Table 1. Description of data type and source

No	Data type	Sources of Data	Spatial Resolution	Duration
1	Station Rainfall, Minimum and Maximum Temperature	EMI	Station level	1994-2023
2	Digital elevation model (DEM)	USGS	30m	-----
3	Enact data Rainfall, Maximum, and Minimum Temperature	EMI	4*4km	1994-2023

3.3.3. *Riparian vegetation data collection*

The main riparian vegetation data were collected through the bioassessment stream sheet during habitat quality assessment, direct field observations, key informant interviews (KIIs), focus group discussions (FGDs) and published literature in Dinki watershed.

3.3.4. *LULC and Topography data collection*

The Dinki watershed was divided into upper, middle and lower agroecological zones and historical LULC change (1994-2023) was assessed. Supervised classification and ground truth surveys were aided by cloud-free Landsat and Sentinel-2A data, DEM, topographic maps and aerial/terrestrial photos. The land use was classified as densely forested area, agricultural land, grazing land, built up, water body and slight vegetation land surfaces and percentage coverage was estimated in the stream buffers. River and stream habitats were further evaluated, integrating physical watershed characteristics with ecological conditions, with the US-EPA protocol. The watershed delineation (topography map) was acquired using the remote sensing and terrain modelling techniques, mainly Digital Elevation models (DEMs) were used. These are maps stored in a grid, with each pixel holding a particular geographic x, y coordinates and elevation value z.

3.3.4.1. *Data Acquisition or Dataset*

LULC changes for the periods 1994-2014 and 2014-2023 were assessed using Landsat satellite imagery. For 1994, the Landsat 5 TM imagery was used, and for 2014 and 2023, the Landsat 7 ETM+ imagery and Landsat 8 OLI imagery were used, respectively (Table 2). All satellite images were downloaded from the United States Geological Survey (USGS) Earth Explorer platform (<https://glovis.usgs.gov/>). The images were obtained as USGS collection 2 Level 2 surface reflectance products with 30 m spatial resolution. Image selection was based on the WRS-2 path (168-169) and row (53-54) coverage, and only dry season images captured from January to February with cloud cover less than 20% were used. The downloaded images were geometrically and topographically corrected before analysis. Image pre-processing, classification, change detection, post-processing, and LULC change analyses were conducted using ArcGIS version 10.3, while ArcGIS version 10.5 was used to estimate vegetation coverage

(km²) within the study area. In addition, relevant literature and records from the local Dinki Agriculture Bureau were reviewed to support vegetation coverage assessment.

Table 2. Landsat images in the present day.

Spacecraft	Sensor type	Data type	Acquisition date	Resolution (m)	Path/Raw
LANDSAT 5	TM	LITP	02-09-1994	30	168/053
LANDSAT 7	ETM+	LITP	02-09-2014	30	168/053
LANDSAT 7	ETM+	LITP	1994-2014	30	168/053
LANDSAT 8	OLI	LITP	02-03-2023	30	168/053
LANDSAT 8	OLI	LITP	2014-2023	30	168/053

3.3.5. Qualitative data collection

Qualitative data were collected to integrate local knowledge and socio-ecological information for assessing LULC change, watershed degradation, ecosystem service dynamics, and natural resource management practices in the Dinki watershed. The watershed was stratified into three agro-ecological zones: upper (cold/alpine), middle (dry-warm), and lower (sub-moist warm) zones to capture spatial variability in environmental conditions and community experiences.

Focus Group Discussions (FGDs): A total of 3 FGDs were conducted across the upper, middle and lower watershed, each involving 8-12 participants purposively selected from elders, women representatives, youth groups, development agents, kebele leaders, model farmers, extension workers, and local resource conservation groups to ensure diverse perspectives. The topics covered included drivers of LULC change, hydrological alteration (including drainage, ditching, and filling), habitat alteration (including tree cutting, grazing, and plantation development), ecosystem service alteration, and challenges to watershed conservation. The duration of each discussion was around 60-90 minutes, and some discussions lasted up to 2 hours.

Key informant interviews (KIIs): The 15 KIIs were conducted with community leaders, development agents, and knowledgeable farmers sampled using purposive and snowball sampling techniques. Interviews focused on land use pressures, degradation of watersheds, natural resources use, conservation practices, and changes in the availability of resources over time. The interviews were about 25-30 minutes in length, conducted in Amharic, and then translated into English for analysis.

Field observations: These were conducted concurrently to record the land management practices, economic activities, natural resource utilization, and ecological conditions of the watershed. Triangulation was used to increase the reliability of data by combining FGDs, KIIs, field observations, and the characterization of watersheds using remote sensing data, thus ensuring data consistency between community perceptions and biophysical data.

3.3.6. Environmental and Macroinvertebrate data collection

3.3.6.1. Physicochemical Parameters

Water quality measurements were conducted both spatially (Dinki, Zego, Gedamoch, and Dense) and temporally before macroinvertebrate sampling to avoid disturbance. The parameters measured included water temperature (°C), dissolved oxygen (DO; mg/L), electrical conductivity (EC; µS/cm), turbidity (NTU), and pH, which were analyzed onsite using a HACH HD401 multi-parameter portable instrument (HACH, Loveland, USA). Air temperature was measured using a mercury thermometer. The water samples (250 mL) were collected from each site for the analysis of total nitrogen (TN), nitrate-nitrogen (NO₃⁻), total phosphorus (TP), and orthophosphate (PO₄³⁻). Samples were transported to Addis Ababa Environmental Protection authority (AAEPA) and Addis Ababa University Limnology laboratories for nutrient analysis. These analyses were conducted to compare water quality parameters across spatial locations (Dense, Gedamoch, Zego, and Dinki) and between sampling years (2016 and 2023) to identify environmental changes. Furthermore, total suspended solids, phosphate, and nitrate-nitrogen were analyzed following standard procedures prescribed by the American Public Health Association (APHA, 2005) and the Hach method (Hach *et al.*, 1987).

Total suspended solids

Total suspended solids were filtered using 47 µm fiberglass and the gravimetric method (vacuum gas pump), and the measured volume of 100 mL was well mixed. Dried at 105°C for 1 hour in an oven and cooled in desiccators to balance temperature and weighed before and after.

$$\text{TSS (mg/L)} = \frac{(W_2 - W_1) * 1000,000 \text{ g/mL}}{V \text{ or } 100\text{mL}} \text{-----}$$

Eq1

The weight of the cleaned and dry filter before the filtration (W_1) (g), the weight of the filter plus dried residue after the filtration (W_2) (g), the volume of water sample filtered (V) (mL) and the conversion factor used to express the result in milligrams per liter (mg/L) are all needed.

Phosphate

The phosphorus (orthophosphate) was determined using the stannous chloride method. A blank solution is prepared in a similar way with distilled water (APHA, 2005). 4ml of ammonium molybdate and 0.5 ml (10 drops) of stannous chloride solution are added, then stoppered and mixed by inverting each flask six times. The samples were allowed to stand for 10 minutes, but were measured before 12 minutes using a DR 5000 spectrophotometer at 690 nm.

Nitrate nitrogen

Nitrate-nitrogen and orthophosphate-phosphate concentrations were analyzed at the Addis Ababa University Limnology Laboratory and AA-EPA Environmental Laboratory following standard methods (APHA, 2005). Nitrate-nitrogen was determined using the phenoldisulfonic acid method and measured using a DR5000 spectrophotometer at 410 nm. In addition, stream width, stream depth, and current velocity were measured in the field using a measuring tape and a flow meter, respectively.

3.3.6.2. *Macroinvertebrates' data collection*

Macroinvertebrate samples were collected from sites established for the 2016 data collection. Sampling was conducted across different land use types using a multihabitat approach that included bed substrate, macrophytes, overhanging vegetation, and other available microhabitats. A D-frame net (20 × 30 cm frame, 500 μ m mesh) was used for sampling in riffles and pools (Barbour *et al.*, 1999; Gabriels *et al.*, 2010) which was used for multihabitat (e.g., riffles, runs, pools, submerged vegetation, leaf packs, and coarse substrates where available). In each sampling reach, macroinvertebrates were collected along a 10 m stream stretch with an overall sampling effort of approximately 5 minutes for each side (10 minutes), covering all available habitats (Bouchard, 2012). In riffle habitats, the net was held against the current while the substrate was disturbed, whereas stream edge and vegetated areas were sampled by sweeping the bank and submerged vegetation (Lock *et al.*, 2011). Large stones were also lifted and washed

into the net to detach attached organisms. Samples from all microhabitats were combined into a single composite sample per reach. All samples were preserved in 70% ethanol and transported to the laboratory for analysis. In the Ethiopian Environment and Forest Research Institute (EEFRI) laboratory, macroinvertebrates specimen were sorted, counted, and identified to the family level using a stereomicroscope and standard taxonomic keys in accordance with the Rapid Bioassessment Protocols (Gerber & Gabriel, 2002). Sampling was conducted in both wet and dry seasons, with dry season sampling carried out in November-January 2022/23 and wet season sampling in June, following a consistent seasonal design applied in 2016.

3.4. Statistical Analysis

3.4.1. Soil data analysis

Soil texture area is calculated using the raster cell count and resolution, where the count represents the number of pixels classified under each soil type. The area is determined by multiplying the count by the square of the cell size, with a 250m × 250m resolution (Mcdonnell, 2014; Hengl *et al.*, 2017; Nielsen & Senent-aparicio, 2023). The formula used is:

Area = Count for each soil type × (250m × 250m). Then m² were converted into km² which is divided by one million.

Similarly, soil chemical properties analyzed in this study include nutrients such as nitrogen (N), phosphorus (P), calcium (Ca), and magnesium (Mg), along with the micronutrient iron (Fe). Soil acidity was assessed through pH, while electrical conductivity (EC) served as an indicator of salinity. Additionally, the carbon-to-nitrogen (C/N) ratio was examined to evaluate organic matter dynamics. Data were retrieved from the EthioSIS raster data and were changed into a polygon for final data usage. These datasets were used to obtain regional averages and ranges of soil properties for the watershed area. The current status of soil chemistry in the study sites was analyzed their multiple regression model in the R packages. The weighted mean formula we are using is standard in spatial soil analysis, which was obtained from the EthioSIS raster data when estimating chemical concentrations over a defined area, which is 160.90km². However, assuming equal area distribution for categories should be justified or supported by spatial data.

According to Hengl *et al.* (2004) and Lelago *et al.* (2016), the general formula for the weighted mean of spatial soil properties is:

$$X^- = \frac{\sum(Xi * Ai)}{\sum Ai} \text{-----Eq2}$$

Where: X^- = Weighted mean, Xi = Mean value of the soil property for category, Ai = Area of category, and $\sum Ai$ = Total watershed area.

Since the specific areas (Ai) for each category are unavailable, we assume that each category occupies an equal fraction/distribution of the total watershed area (Zhi *et al.*, 2014). This leads to a simplified formula:

$$X^- = \frac{\sum xi}{n} \text{-----Eq3}$$

Where: n = Number of phosphorus categories (5 in this case).

3.4.2. Climate data analysis

3.4.2.1. Homogeneity test

We employed several data analysis methods, including consistency checks of station data using the Climate Data Tool (CDT) and statistical techniques. Homogeneity tests and data adjustments followed the guidelines of Dinku *et al.* (2018) and Tizazu *et al.* (2024). In the case of climatic parameters (rainfall and temperature); the climate of Ankober is characterized by three distinct seasons: (Dry/Bega, Spring/Belg, and Wet /Kiremit) seasons, daily meteorological data were summarized at the monthly and seasonal levels (NMA, 2007; Gashaw *et al.*, 2023; Wubaye *et al.*, 2023). The purpose of this long time series was to identify climatic trends or seasonal variability which was relevant to agricultural planning and resource management.

Graphs and spatial maps were used to visualize temporal and geographic variations in rainfall and temperatures. Daily data were used to obtain monthly and seasonal mean temperatures and to determine the trends to assess climatic stability and fluctuations. Using ArcGIS and CDT, spatial distributions of rainfall and temperature were mapped to demonstrate the annual and seasonal variations in rainfall and temperature over the Ankober zone. Data interpretation was facilitated using visualization tools such as line charts, bar graphs, and spatial mapping, which

showed climatic dynamics. The methodology enabled a comprehensive analysis of long-term rainfall and temperature variations and their implications for climate resilience and sustainable development.

To ensure the quality and completeness of meteorological and macroinvertebrate data, a pre-processing was performed before analysis, and the performance of the models will rely on the quality of the input data (Alemayehu & Kabite, 2023). Seasonal climate trends were analyzed using the Mann-Kendall trend analysis method done in Python software, and time-series climate and macroinvertebrate analyses were performed in Microsoft Excel.

3.4.2.2. *Modified Mann-Kendall (MMK) trend test*

The Modified Mann-Kendall (MK) Trend Test is a non-parametric statistical test that is applied to identify an increasing or decreasing trend in a time series. A two-stage extension of the original Mann-Kendall test for detecting trends that incorporates autocorrelation and tied values to enhance the accuracy and power of the test. The test is widely used in hydrology, climatology, and environmental sciences, where data are not necessarily normally distributed.

In the analysis, chronological data like rainfall and temperature data were collected, and the data were ranked by magnitude. The association between the ranked data and time was then determined by Kendall's Tau. On this basis, the Modified MK statistic and its variance were calculated, and the Z-statistic was derived to identify whether trends were happening in a positive or negative direction and if they were significant. Positive Z values suggested increasing trends; negative Z values suggested decreasing trends, and higher Z values indicated more extreme trends. The calculated Z-value was compared with the values from statistical tables or software to determine the statistical significance.

The usefulness of trend analysis for environmental and climatic change detection over a long period of time. The MK test is especially well-suited to environmental data sets because there are no assumptions of normality. But autocorrelation of time series may cause the significance of trends to be exaggerated, which can affect the reliability of the trend detection. Hence, the Modified MK test has corrections for autocorrelation in order to make the analysis more reliable

and robust. This is a good way to measure long-term climatic and ecological changes in a complex data set.

The Mann-Kendall test statistic “S” is based on the comparison of all pairs of data points in the data time series. The difference for each pair is computed, S is increased for concordant pairs (positive difference), and decreased for discordant pairs (negative difference). The S value shows the direction and the strength of the trend; a positive S value indicates that the trend is going up, and a negative S value indicates that the trend is going down. The value of S is:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^n \text{sign}(T_j - T_i) \text{-----Eq4}$$

$$\text{Sign}(T_j - T_i) = \begin{cases} +1 & \text{if } T_j - T_i > 0 \\ 0 & \text{if } T_j - T_i = 0 \\ -1 & \text{if } T_j - T_i < 0 \end{cases}$$

where T_j and T_i are the annual values in j and i years, $j > i$, respectively (Alemayehu & Kabite, 2023; Evans, 2023).

The value of S is compared against the expected value for the null hypothesis of no trend, with the variance of S calculated under the assumption that there are no ties or autocorrelation.

The value of $|S|$ is directly compared to the theoretical S distribution calculated by Mann and Kendall if $n > 10$. It employs the two-tailed test. Accordingly, the H_0 is at a specific probability threshold discarded in favour of H_1 if the absolute value of S equals or exceeds a predetermined value $S_{\alpha/2}$, where $S_{\alpha/2}$ is the smallest S with the likelihood of being less than $\alpha/2$ in the absence of a trend. If the S value is positive, increasing trends of the data exist, while a negative S value shows decreasing trends of the dataset. Moreover, the statistic S is normally distributed with the mean and variance for $n \geq 10$ (Equation (4)).

The significance of the trend is tested using a Z-statistic, which is derived from the Mann-Kendall test statistic S. The Z-value is then used to compute the p-value, indicating whether the observed trend is statistically significant

at a chosen confidence level. Therefore, the significance of the trend is tested using a Z-statistic:

$$E(S) = 0$$

The variance (σ^2) for the S-statistic is defined by:

$$\sigma^2 = \frac{n(n-1)(2n+5) - \sum t_i(i-2)(2i+5)}{18} \text{-----Eq5}$$

where t_i denotes the number of ties to an extent i . The standard test statistic Z_S is calculated using equation (6).

$$Z_S = \frac{S}{\sigma} \text{ or } S > 0, 0 \text{ for } S = 0 \text{ and } \frac{S}{\sigma} < 0 \text{-----Eq6}$$

The Z_S (test statistic) is a measure of the significance of the trend. This test statistic is used to test the null hypothesis, H_0 . If $|Z_S|$ is greater than $Z_{\alpha/2}$, where α represents the chosen significance level (e.g., 5% with $Z_{0.025} = 1.96$), then the null hypothesis is invalid, implying that the trend is significant (Motiee & Mcbean, 2009; Shu *et al.*, 2024). A positive Z indicates an upward trend, while a negative Z indicates a downward trend. The p-value is used to assess the significance of the trend based on the Z value. If the p-value is below a chosen significance level (usually 0.05 or 0.01), the null hypothesis of no trend is rejected, meaning a significant trend exists. Trend magnitude (Sen's slope) is often used alongside the MK test to quantify the magnitude of the trend (i.e., how much the variable is increasing or decreasing per unit time).

3.4.3. Riparian vegetation data analysis

The analyses of riparian vegetation data were of a qualitative nature, with a narrative descriptive approach. Findings from the habitat quality assessment protocol were summarized and interpreted to characterize the condition of riparian vegetation, and to back up the interpretation of the findings.

3.4.4. LULC and Topography data analysis

3.4.4.1. Image Pre-processing

The main steps for image classification include selection of a suitable classification method, selection of training samples, image pre-processing, feature extraction, selection of a classification algorithm, post-classification processing, and accuracy assessment. Image classification is the stage of image analysis in which the multivariate quantitative measurement associated with each pixel is translated into a label from a pre-defined set (e.g., land use categories) (Hashim *et al.*, 2019). The multi-temporal images downloaded from the USGS free website are standard products that have been geometrically and radiometrically corrected by the

data providers. All the satellite images were geometrically corrected through ortho-rectified level. For this study, the spatial detail, original pixel size, and value for each image for specific bands are retained.

3.4.4.2. *Classification of Images and Change Detection*

Signatures were prepared based on the ground truth (GPS data) collected through field surveys, Google Earth, and Landsat images. As for the classification stage, a uniform pixel-based supervised (the most reliable and longest process) classification was applied to map the LULC classes. The maximum likelihood classifier tool of ArcGIS was used to classify images. The majority filter was applied to smooth the classification. Supervised classification was done by collecting training samples for LULC classes. Training areas were created accurately by polygon for each of the classes, and classification was performed using the Maximum Likelihood (ML) and Support Vector Machine (SVM) methods or algorithms. Both Maximum Likelihood (ML) and Support Vector Machine (SVM) classifiers were tested, and SVM consistently outperformed than ML based on preliminary accuracy assessments. SVM was therefore used for all LULC maps (1994, 2014, 2023), with post-classification filtering applied to reduce the salt-and-pepper effect. Based on the prior land cover information, field observations, and regional ecological characteristics, six major LULC classes were identified and analyzed, including: (i) agricultural crop land/agricultural land, (ii) sparse/slight vegetation, (iii) water bodies, (iv) Dense forest, (v) grazing land/grassland, and (vi) built-up areas. Descriptions of these classes are provided (Table 3).

3.4.4.3. *Accuracy Assessment*

The accuracy assessment was based on over 360 reference points obtained from Google Earth™, GPS, and Landsat images of historical land use (FAO, 2016) and the accuracy of the classifications. Three standard metrics were computed: overall accuracy, producer's accuracy, and user's accuracy, and the kappa coefficient (Eq. 7- 10) (Mathur & Foody, 2008). In total, over 360 reference points were used, which were derived from a mix of GPS-based field surveys, high-resolution Google Earth™ imagery, and historical Landsat data. These points were used independently to assess the reliability and robustness of the classification results. Standard equations were used to determine the accuracy metrics as described below:

$$OA = \frac{N_{correct}}{N_{total}} \times 100 \dots\dots\dots \text{Eq7}$$

Overall accuracy (OA) is equal to the number of correctly classified samples ($N_{correct}$) divided by the number of samples (N_{total}) times 100%

$$UA_i = \frac{N_i}{N_{row_i}} \times 100 \dots\dots\dots \text{Eq8}$$

Where UA_i is the user's accuracy (%) for class i , N_i is the number of correctly classified samples in class i (diagonal element of the confusion matrix), and N_{row} is the total number of samples classified in row i . Which represents the probability that a pixel classified as class i actually corresponds to that class on the ground, reflecting commission errors.

$$PA_i = \frac{N_{ii}}{N_{col_i}} \times 100 \dots\dots\dots \text{Eq9}$$

Where PA_i is the producer's accuracy (%) for class i , N_{ii} is the number of correctly classified samples in class i (diagonal element of the confusion matrix), and N_{col_i} is the total number of reference samples in that column.

The kappa coefficient reveals the difference between observed agreement and the agreement expected by chance, which was calculated by Eq. (10) (Kuma *et al.*, 2022).

$$k = \frac{P_o - P_e}{1 - P_e} \dots\dots\dots \text{Eq10}$$

The Kappa coefficient, k , indicates the degree of agreement observed (overall accuracy), P_o , and the degree of agreement expected by chance, P_e .

This one measures the chances of a reference pixel of type i being correctly classified, or omission errors. These accuracy measurements are used together to get a comprehensive quantitative assessment of the accuracy of the classification, which should enable the LULC maps to be used in further temporal change detection and ecological studies with confidence. Lastly, a set of thematic LULC maps was created in ArcGIS 10.5 for the years 1994, 2014, and 2023. The overall image classification procedure was illustrated in Fig. 2.

Table 3. Description of LULC classes in Dinki watershed adopted.

Land use	Descriptions
----------	--------------

types	
Agricultural land	Areas used for crop cultivation (teff, wheat, barley, bean, chickpea, etc.) and different Settlements(villages) associated with the cultivation fields
Built up	Includes urban, suburban, villages, and other man-made structures, i.e., roads
Dense forest	Land covered by trees higher than 5 m with > 10% canopy cover
Grazing land	Land covered with a mix of both small shrubs and grasses is commonly used for livestock grazing.
Slight vegetation	Three areas: park and playground, grassland, and vegetable land.
Water body	River, permanent open water, lakes, ponds, canals, and reservoirs. Permanent and seasonal wetland, low-lying areas, marshy land, mudflats, all cultivated areas, including urban areas

3.4.4.4. Post-Processing and LULC change analysis

After supervised classification, appropriate post-processing has been done. Majority analysis was applied to avoid minor, fragmented classification arrangements on the output map. The final classification was validated using Ground Control Points (GCPs) to ensure the accuracy of the classified LULC map. LULC change analysis was performed through pair-wise comparison and weighted overlay within the ArcGIS 10.5 environment. In order to analyze the land cover structural changes in the study area, Table 4 below, showing the area in hectares and percentage changes between the periods 1994-2014 (two periods of 20 years) and 2014-2023, was quantified for each LULC type (Worku *et al.*, 2026c). The absolute change in LULC of the three periods was obtained as the difference of the values of different times of the same category, while the percentage change was calculated by dividing it by the total area and multiplying by one hundred. Finally, the areal coverage, annual rate of change, change rate, and relative change were tabulated for each of the identified LULC types. The annual change rates were calculated using Eq.11.

$$\text{Rate of change (km}^{-2} \text{ year}^{-1}) = \frac{A_2 - A_1}{T_2 - T_1} \text{-----Eq11}$$

3.4.4.5. Determination of Ecosystem Service Values (ESVs)

The impacts of LULC changes on ecosystem service value (ESV) dynamics were evaluated using an integrated valuation approach based on updated ecosystem service value coefficients. In this regard, conservative estimation coefficients newly developed for the Ethiopian context

(Kindu *et al.*, 2016; Tesfay *et al.*, 2023) were used and verified with the local people and through community participation. These coefficients are based on a detailed knowledge of the landscape characteristics in Ethiopia and are based on additional appreciation work, mainly from the valuation database of the Economics of Ecosystems and Biodiversity (TEEB). The classified LULC outputs for 1994, 2014, and 2023 were used to quantify the ESVs of different land cover types within the Dinki Watershed. Each LULC class was systematically matched to corresponding biomes defined in the global ecosystem services and natural capital framework established by Costanza *et al.* (1997), Costanza *et al.* (2017), and Costanza (2020).

Furthermore, the biome equivalence was established based on vegetation structure, dominant land cover characteristics, and ecological functioning rather than strict global biome definitions. Dense forest areas in the watershed exhibit closed-canopy woody vegetation and were therefore matched with tropical forest biomes. Slight vegetation areas are dominated by shrubs and sparse woody cover and were classified as shrubland. Grazing lands are primarily herbaceous and were matched with grassland biomes, while water bodies correspond to lake and river systems. This approach follows previous ESV studies conducted in the Ethiopian highlands (Kindu *et al.*, 2016; Tesfay *et al.*, 2023) (Table 4).

Table 4. Updated estimation of LULC types, associated biomes, and ecosystem value coefficient on the study watershed (Tefay *et al.*, 2023).

LULC types	Equivalent Biome	Ecosystem service coefficient (US\$ ha ⁻¹ y ⁻¹)
Agricultural land	Crop land	225.56
Built up	Urban	0
Dense Forest	Tropical forest	986.69
Grazing land	Grass land	292.45
Sparse/slight vegetation	Shrub land	986.69
Water body	Lakes/rivers	8103.5

These LULC classes were then matched to biomes, and the total ecosystem service values (ESVs) for the watershed were estimated for each study period. ESVs were calculated every 10 years between 1994 and 2023, giving a sense of how ecosystem service provision has been changing over the past nearly 30 years, in terms of magnitude, direction, and drivers of change (Andualem & Debie, 2024). The following equations were used for valuation:

- (i) ESV of a specific land use/land cover category:

$$ESV_k = \sum (A_k * VC_k) \text{-----Eq12}$$

Where: ESV_k = Ecosystem's service value of land cover type k

A_k = Area (ha) of land cover type k

VC_k = Value coefficient (USD ha⁻¹ year⁻¹) for land cover type k

- (ii) Change in ecosystem service values between the two periods:

$$ESV \text{ change (\%)} = (ESV_{final \text{ year}} - ESV_{initial \text{ year}} / ESV_{initial \text{ year}}) * 100 \text{-----}$$

Eq13

3.4.4.6. Individual Ecosystem Value Determination

To calculate the total ecosystem service value (ESV), the values of 17 individual ecosystem services were first estimated using Equation 13. For each LULC class, the ESV was computed by multiplying the corresponding value coefficient by the total area (km²) of that LULC type. The total ESV of the watershed for each reference year was then obtained by summing the ESVs of all LULC classes. Changes in ESV over the study period (1994-2014, 2014-2023, and 1994-2023) were quantified using the formula outlined in Eq.14.

$$ESV_f = \sum (A_k * V_{fk}) \text{-----Eq14}$$

Where ESV_f = the estimated ecosystem service value of function f , A_k = the area (ha), and VC_{fk} = the value coefficient of function (US \$ ha⁻¹yr⁻¹) for LULC category k .

Furthermore, the sensitivity and robustness of the adopted value coefficients in the estimation of ESV were validated using the coefficients of sensitivity (CS). The CS of ESV was computed following Tesfay *et al.* (2023) as:

$$CS = \frac{VC_k * A_k}{ESV} \text{-----Eq15}$$

Where CS = Coefficient of Sensitivity, ESV = total estimated ESV coefficient value (US\$/ha⁻¹yr⁻¹) for LULC type k .

The coefficient of sensitivity (CS) is derived from the economic concept of elasticity and reflects the influence of the assigned value coefficient on the estimated ecosystem service value. When $CS < 1$, the estimated ecosystem value is considered inelastic with respect to the coefficient, indicating that the results are relatively robust and reliable (Tesfay *et al.*, 2023). Conversely,

when $CS > 1$, the ESV is elastic, demonstrating higher sensitivity to changes in the assigned value coefficient. If this is the case it's essential to be specific about the value coefficient, since the reliability of the estimated ESV depends on the value of the coefficient. As the CS values rise, the need for an accurate estimation of coefficients grows. The more the CS values, the more important the need to accurately estimate the coefficients becomes (Bera *et al.*, 2022; Tesfay *et al.*, 2023).

To quantify ESVs due to LULC changes, the study used a mix of global ecosystem service value (ESV) coefficient values (Costanza *et al.*, 1997; Costanza *et al.*, 2014; Costanza, 2020) and local or context-specific ESV coefficient values adapted for Ethiopia by Kindu *et al.* (2016). The result indicates that the application of these coefficients was done following the methods described by Kindu *et al.* (2016), Tesfay *et al.* (2023), and Tadesse *et al.* (2025).

Costanza *et al.* (1997) have mentioned that ecosystem service value coefficients don't exist for urban and desert regions. In developed countries, urban areas may have relatively high ESVs because of the recreational, cultural, and tourism services. However, ecosystem services in built-up areas in the Dinki Watershed are low, as there are no recreational areas, such as lake front developments, and no organized green space, nor any basic urban facilities like parking spaces. This would lead to ESVs being significantly overestimated in this local context if the US\$6,661 $\text{ha}^{-1} \text{yr}^{-1}$ coefficient recommended by Costanza *et al.* (2014) for urban land were used. As there are no context-specific categories for built-up areas in Ethiopia, the built-up LULC categories were excluded from ESV calculations in this study. The flow of the image classification and the process of creating a LULC map is illustrated in Fig. 4.

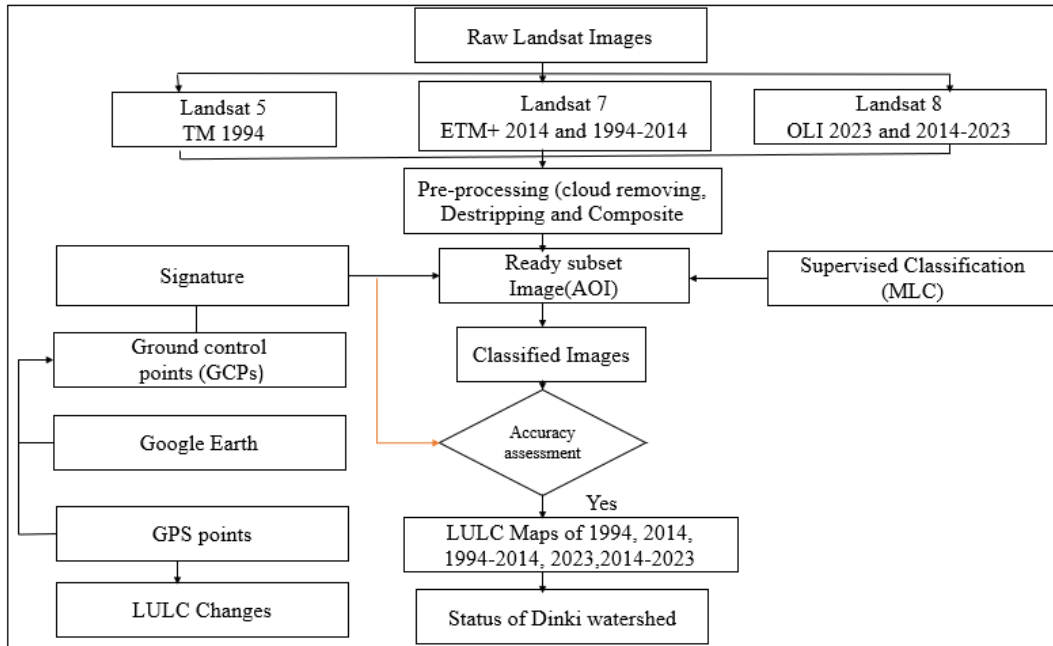


Figure 4. Flowchart illustrating the stepwise methodology employed in this study.

Furthermore, in this study, the valuation coefficients developed by Costanza *et al.* (1997) were adopted, as they provide a comprehensive framework for 16 major biomes and 17 ecosystem services. The modified coefficients used in this analysis, which account for local conditions, are presented in Table 5.

Table 5. Ecosystem service functions and their corresponding value coefficients (adopted from Costanza *et al.*, 1997).

*ESV coefficients (US\$ ha⁻¹ yr⁻¹) modified by ^a(Kindu *et al.*, 2016), and ^b(Tesfay *et al.*, 2023)

3.4.5. Qualitative data analysis

All qualitative data obtained from FGDs, KIIs, and field observations were transcribed, translated into English, coded, and thematically analyzed using QDA Miner Lite software

		Ecosystem service value of each LULC type (USD ha ⁻¹ year ⁻¹)					
Ecosystem services category	Ecosystem services functions	Agricultural crop land (ACL)	Built up (BP)	Dense Forest (DF)	Grazing land (GL)	Slight vegetation (SV)	Water body (WB)
Provisioning services	Water supply			8		8	2117
	Food production	187.56 ^a		32	117.45	32	41
	Raw material			51.24 ^a		51.24 ^a	
	Genetic resources			41		41	
Regulating services	Water Regulation			6 ^a	3 ^a	6 ^a	5445 ^a
	Wastewater regulation			136 ^a	87	136 ^a	431.5
	Erosion control			245	29	245	
	Climate regulation			223 ^{a&b}		22 ^{a&b}	
	Biological control	24			23		
	Gas regulation			13.68 ^a	7 ^a	13.68 ^a	
	Disturbance regulation			5 ^a		5 ^a	
Supporting services	Nutrient cycling			184.4 ^b		184.4 ^a	
	Pollination	14		7.27 ^{a&b}	25 ^a	7.27 ^a	
	Soil formation			10 ^a	1 ^a	10 ^a	
	Habitat/refugia			17.3		17.3	
Cultural services	Recreation		0	4.8		4.8	69
	Cultural			2		2	
Total		225.56	0	986.69	292.45	986.69	8103.5

following the procedures described by Ugwu *et al.* (2023). The analysis was structured thematically by grouping the responses into major thematic categories of LULC change, degradation of watersheds, ecosystem services, natural resource management practices, and community adaptation strategies.

Thematic coding was used to detect patterns, relationships, and local perceptions of change in the environment and use of resources in the watershed. Information generated from FGDs, KIIs, and field observations was cross-checked to improve the consistency and reliability of interpretation. The qualitative findings were further integrated with remote sensing-based watershed characterization to provide a comprehensive understanding of the socio-ecological dynamics of the Dinki watershed.

Local perceptions regarding ecosystem service changes and the magnitude of forest cover change were assessed using the physical habitat assessment protocol of Barbour *et al.* (1999) and the forest cover classification ranges proposed by Solomon *et al.* (2018), supplemented by community knowledge. Based on these approaches, forest cover conditions were categorized into four classes: major change (poor condition), moderate change (marginal condition), slight change (suboptimal condition), and stable or no significant change (optimal condition) (Table 6).

Table 6. Classification of forest cover in the Dinki watershed with associated indicators.

Classification	Range	Criteria/Indicators	Reference
Major Change	0-5	Areas without visibility or data	(Barbour <i>et al.</i> , 1999 and Solomon <i>et al.</i> , 2018)
Moderate Change	6-10	Minimal or negligible variation in forest cover (<10% change)	(Barbour <i>et al.</i> , 1999 and Solomon <i>et al.</i> , 2018)
Slight Change	11-15	Noticeable but not drastic changes in forest density (10-30%)	(Barbour <i>et al.</i> , 1999 and Solomon <i>et al.</i> , 2018)
No view	16-20	Significant forest loss (>30%)	(Barbour <i>et al.</i> , 1999 and Solomon <i>et al.</i> , 2018)

Changes were categorized as: major change= poor; moderate change= marginal; no change= suboptimal; and no view= optimal.

3.4.6. Environmental and Macroinvertebrate Data Analysis

Descriptive statistics were employed to analyze variables based on their numeric counts, percentages, means, standard deviations, and standard errors to present the distribution of macroinvertebrate assemblages and associated environmental variables. Bivariate correlations and multicollinearity tests were used to screen the environmental variables contributing to the community structure of macroinvertebrates. Scatterplots with trend lines were generated to visualize significant correlations, such as between nutrient levels and EPT richness. The macroinvertebrate family-level richness (taxa richness), Shannon-Wiener index, and density (individuals) were calculated for each sampling site, sampling season (dry and wet), and sampling period (2016 and 2023). Biodiversity was computed with the richness index (S) measures the number of taxa present, Simpson index diversity (1-D) (Simpson, 1949)

emphasizes dominance and evenness, and Shannon-Wiener index (H') (Shannon, 1948), integrates both taxon richness and relative abundance. The biological indices were calculated using formula (16)-(19).

$$\text{Shannon – Weiner diversity index } H = - \sum_i^n \frac{n_i}{n} \ln \frac{n_i}{n} \quad (\text{Shannon, 1948}) \quad (16)$$

$$\text{Gibson's evenness } E = e^H / S \quad (\text{Pielou, 1966}) \quad (17)$$

$$\text{Simpson dominance index } D = 1 - \sum_i^n \frac{n_i(n_i-1)}{N(N-1)} \quad (\text{Simpson, 1949}) \quad (18)$$

$$\text{Margalef's richness index } d = (S - 1) / \ln(n) \quad (\text{Margalef, 1968}) \quad (19)$$

Where n_i is the number of individuals of taxon i ; n is the total number of individuals; $\ln$ is the natural logarithm; S is the number of taxa; e is the natural logarithm equal to 2.718. The total number and abundance of the most sensitive taxa (Ephemeroptera, Plecoptera, Trichoptera) were calculated to obtain a comprehensive understanding of stream health and water quality of streams (Penrose, 1996; Hamid *et al.*, 2017).

To identify an ecologically important species for the season, an indicator species analysis based on the Indicator Value (IndVal) method was performed in each sampling season and year. The indicator value (IndVal) of a species is the product of its fidelity (frequency) and its relative abundance ($\times 100$) in each season, where the value ranges from 0 (no indication) to 100 (perfect indication). A species in the cluster with a higher indicator value than other species was considered an ideal indicator species for that cluster (Dufrene & Legendre, 1997). The statistical significance of the mean indicator value of each species was tested using a one-way analysis of variance (ANOVA).

Physical habitat information was taken at each sampling site with a visual estimation measurement technique. The US-EPA rapid bio-assessment protocol (HABSCORE) (Barbour *et al.*, 1999) was used to assess the habitat status of the sampling sites of selected tributaries of the Dinki watershed catchment area. During each sampling campaign, the habitat status was assessed, as the habitat metrics are temporarily variable due to variation in riparian vegetation cover, riverbank stability, epifaunal substrate, substrate composition (sand, gravel, bedrock), in-stream cover, channel morphology, bank erosion, riparian zone, pool/glide, riffle/run, depth,

gradient, and channel flow regime/flow velocity. Twelve habitat components were quantitatively assessed, with each parameter scored on a scale of 0-20, resulting in a total score of 240. This score was then standardized to a 100-point scale, and the average value was calculated across 25 sampling sites for both 2016 and 2023. The percentile habitat score was classified as excellent ($\geq 95\%$), very good (85-94%), good (75-84%), fair (60-74%), poor (50-59%), and very poor ($\leq 49\%$) (Barbour *et al.*, 1999). Similarly, ten impact assessment components were evaluated per sampling site, each scored from 0 to 100. The total score was standardized to a 100-point scale and averaged across 25 sampling sites for both years. The percentile impact score was categorized as high ($\geq 75\%$), medium ($\geq 50\%$), and low ($\leq 49\%$) (Barbour *et al.*, 1999).

The indicator species were selected through past software for trend analysis in relation to 30 years of land use types and climate variability. Therefore, for the fulfilment of effects of long-term climate and land use change on pollution sensitive macroinvertebrate indicators: a comparative analysis of 2016 and 2023 survey objective, we identified 32 families, 14 orders, and 7 indices that were commonly found in the years 2016 and 2023 at the Dinki watershed study site. These were analyzed using past software to determine the IndVal (%) species for pristine, degraded/impacted, and minimally impacted sites. Based on the species and orders identified at different sites, the past software selected specific indicator families to assess ecological health and water quality.

A paired t-test analysis was computed to explain the mean variation in environmental and macroinvertebrate variables between the dry (January to May) and wet (June to September) seasons in each sampling period. Likewise, the mean differences between environmental variables and macroinvertebrate assemblages between sampling periods (2016 and 2023) were computed by a repeated measures Analysis of Variance (Romanova) model (Kuryło & Smaga, 2024). One-way ANOVA (to detect overall site differences) followed by Tukey's post-hoc test (to pinpoint specific pairwise site differences). All tests were carried out using the IBM Statistical Product and Service Solutions package (IBM SPSS ver. 23, 2015), PAST software version 2, and the R-vegan packages.

3.4.7. *Environmental predictor modeling of indicator taxa analysis*

Relationships between selected indicator variables and environment predictor variables (temperature, rainfall, and agricultural land use) were evaluated using General Linear Models (GLMs). Each taxon was fitted separately with a model, and GLM was calculated through:

$$Y_i = \beta_0 + \beta_1 \text{Temp}_i + \beta_2 \text{Rain}_i + \beta_3 \text{LU}_i + \varepsilon_i \text{-----Eq20}$$

Where Y_i = abundance of a given macroinvertebrate taxon, β_0 = intercept; β_1 , β_2 , β_3 = regression coefficients (estimates); Temp_i , Rain_i , LU_i = predictor variables, ε_i = error term

Likewise, Variation Partitioning Analysis (VPA) was used to assess the independent and shared influence of climate and land-use variables on the variation in indicator taxa. The total explained variation was divided into four parts:

$$R^2_{\text{Total}} = [a] + [b] + [c] + [d] \text{-----Eq21}$$

Where, Adjusted R^2 = values were used for the number of predictors and sample size (25 stations * 2 years * 2 seasons, $n = 100$): [a] variation explained by climate variables only, [b] variation explained by land use variables only, [c] shared variation between climate and land use, and [d] unexplained variation (residuals).

3.4.8. *Multivariate data analysis*

A multivariate data analysis was used to determine the relationships among macroinvertebrate assemblages, between sampling sites, and environmental variables. Canoco and R software (vegan package) were used to perform the analysis. Using decorana(), detrended correspondence analysis (DCA) was applied first to determine the gradient length, which suggested a short gradient and called for linear ordination methods. Principal component analysis (PCA) and redundancy analysis (RDA) were thus used to provide a summary of environmental variables and to relate macroinvertebrate assemblage to environmental gradients. Redundancy analysis (RDA) was also used to investigate the relationships between indicator taxa of macroinvertebrates and environmental variables (land use, temperature, and rainfall). Species data were Hellinger transformed, and significance was assessed by permutation tests (999 permutations) in R (vegan package). PCA was performed in both CANOCO and R (functions

rda() from vegan and prcomp() from stats), and RDA was used in both platforms to relate the species abundance data with physicochemical variables (Leps & Samilauer, 2003) and sites. To visualize similarities among sampling sites, non-metric multidimensional scaling (NMDS) was performed in R using metaMDS (). Bray-Curtis dissimilarity (vegdist ()) was used. In all analyses, the abundance of macroinvertebrates and physicochemical variables was used, and species data were decostand() before ordination (Ren *et al.*, 2023).

Scoring macroinvertebrate taxa for MMI development was done using environmental sensitivity. Mann-Whitney U tests (wilcox.test()) and Spearman correlation (cor.test()) were used to screen the candidate metrics. Ecological indices were created by decostanding selected metrics (scaled 0-1) and then amalgamating them. All analyses were conducted in R, and visualization was done using ggplot2. The ensemble modelling approach was used for species distribution modelling. Pollution-sensitive macroinvertebrate taxa, Plecoptera and Trichoptera, were used as occurrence data, and land use and climate were used as predictors in the analysis. Climate scenario data from 2070 were used to make future projections to infer the likely distribution shift of these taxa under future environmental conditions. Modelling, analysis, and visualization were carried out in R with appropriate modelling packages and spatial mapping packages.

3.5. Index development analysis

3.5.1. Ecological Health Indicator Index Model

The present study was carried out in order to determine the ecological health of the Dinki watershed by calculating the ecological health indicator (EHI) in two stages, in 2016 and 2023. Several ecological indices (i.e., diversity indices like Simpson's Index, Shannon's Diversity Index, equitability indices like Evenness, and physicochemical parameters, like pH, dissolved oxygen, temperature) were used to derive the EHI. The indices were employed to measure the biodiversity and the equitability of species populations. Water quality parameters such as DO, pH, and temperature were measured and analyzed for their influence on stream health.

According to Burkhard (2018), to compute the Ecological Health Indicator (EHI), the diversity indices and water quality parameters were weighted and combined using the following formula:

$$EHI = \frac{(Simpson_1-D + Shannon_H + Evenness)}{3} * \frac{(DO * pH)}{Temperature} \text{-----Eq22}$$

Where: Simpson_1-D is the inverse of Simpson's index (1-D1 / D1-D), Shannon is the Shannon Diversity Index, Evenness is the Evenness Index, DO is the Dissolved Oxygen level, pH is the pH level of the stream, and Temperature is the water temperature.

The EHI is a combination of Shannon, Simpson_1-D, Evenness, DO, pH, and Temperature, a stream health measurement. The EHI of the Dinki watershed has been calculated for two time points (2016 and 2023). The Shannon and Simpson_1-D measure the biodiversity, and the Evenness shows the balance of the species. DO and pH are water quality parameters, and oxygen solubility and organism metabolism are affected by temperature. They provide a wide but easily understood view of an ecologically "healthy" state.

The formula is used to create a composite index using data from both biodiversity and water quality to provide a general assessment of stream health. Additionally, the EHI with LULC incorporated land use changes (agriculture, vegetation, water bodies, etc.) into the formula to assess how land use alterations affected the ecological health of the watershed. For this, the following equation was used:

$$EHI_{with_LULC} = EHI * (1 + \frac{\sum LULC_Each\ area}{Total_area}) \text{-----Eq23}$$

Where LULC_ each area refers to the area of specific land use types (agricultural land, dense forests, water bodies, built up, grazing land, and slight vegetation), and total area is the total area of the watershed. The results were compared between 2016 and 2023 to assess trends in ecological health over time.

The fraction $\frac{\sum LULC\ each\ area}{Total\ area}$ represents the proportion of land use types. Then, for computing the rate percentage change in the Ecological Health Indicator (EHI) between 2016 and 2023 using the formula:

$$Percentage\ Change\ EHI = \left(\frac{EHI\ in\ 2023 - EHI\ in\ 2016}{EHI\ in\ 2016} \right) * 100 \text{-----Eq24}$$

The results on ecological improvement were compared with respect to land use dynamics in a

temporal sense. As revealed by Burkhard (2018), when the level of EHI is zero in percent (%), the EHI was divided into five categories; 0-20% (worst health state), 20-40% (bad health state), 40-60% (middle health state), 60-80% (good health state), and 80-100% (best health state).

3.5.2. Multimetric index development

3.5.2.1. Sample Site Selection

The preliminary survey was conducted in September 2016 to communicate with local experts and administrative bodies, observe Dinki watershed landscapes, and select sampling sites (Asmamaw *et al.*, 2021). Field surveys were the most suitable method to achieve these 2023 goals. This approach allowed us to map sampling sites and collect all the necessary data for the study. To develop the 2023 MMI for the Dinki watershed, we first classified each site as either reference or impacted based on ecological conditions, and then validated the index using 2016 data (Silva *et al.*, 2017; Alemneh *et al.*, 2019; Kuma *et al.*, 2022). The referenced site condition is commonly defined as a site with minimal human disturbance within a given ecoregion, as described by several authors (Barbour *et al.*, 1996; Silva *et al.*, 2017). However, in tropical East African countries, there are no standardized thresholds to identify reference sites. These sites can be designated either by conducting preliminary assessments of environmental variables and field surveys before sampling (Edegbene *et al.*, 2025) or by using a post-sampling evaluation based on biological and environmental characteristics (Mereta *et al.*, 2013).

Stream sites were defined as less impaired sites based on the land use categories and level of anthropogenic disturbance (Odabaşı *et al.*, 2022), including land use intensity, local habitat, alteration, due to natural and anthropogenic factors and hydrological modification. These anthropogenic disturbances were carefully scored during each sampling event based on the scoring criteria (Table 7). According to Alemneh *et al.* (2019), each site was given a score from zero to five based on the degree of human activity. The higher the score, the indiscernible/less was the human impact on the stream site. Hence, the study sites were categorized into three human impact classes on the basis of the level of disturbances (Wang *et al.*, 1998; Chen *et al.*, 2017; Alemneh *et al.*, 2019; Agra *et al.*, 2021; Li *et al.*, 2022). Sites with an average impact score of ≤ 1 were highly impacted (impaired sites), and sites with an average score of ≥ 4 to 5 were less impacted (referenced). The remaining study sites had a moderate human impact with

an average score between 1 and 4. The use of least disturbed and most disturbed sites comparison is essential in MMI development (Bolding *et al.*, 2020). A total of 25 unique sampling physical sites were selected across the Dinki watershed along a gradient of anthropogenic disturbance. Each site was sampled during both dry and wet seasons, with seasonal observations treated as repeated measurements rather than independent samples. Anthropogenic disturbance was assessed using ten habitat-related indicators scored from 1 (very high impact) to 5 (no discernible impact). Site habitat quality was expressed as a percentage similarity to reference conditions, calculated as the site score divided by the mean reference score and multiplied by 100. Sites were classified as excellent (>90%), good (75-88%), fair (60-73%), or poor (<58%) habitat quality (Barbour *et al.*, 1999). Based on pooled seasonal information on habitat condition (HVAS), land use, and physicochemical parameters, sites were finally categorized as reference (n = 7) or impacted (n = 18). These validation sites were chosen based on their accessibility and their representativeness of reference and impacted conditions. GIS and GPS tools (Magellan® SporTrak Pro) were used to measure site-to-site distances, altitude, and the total catchment area of the study region.

Table 7. Scoring criteria used in the selection of reference sites in the headwater streams of western Ethiopian highlands Modified from (Barbour *et al.*, 1999; Wang *et al.*, 1998; Alemneh *et al.*, 2019).

Disturbance	No or less disturbed	Moderately disturbed	Highly disturbed
Land use intensity			
Farming/Agriculture	No farming, or farming > 100m from the stream	Farming in 50–100 m from the stream	Farming, including a buffer of the streams
Urban influence	No urban influence > 500m	No urban influence < 300–500m	No urban influence < 300m
Settlement	No settlement around streams or settlement > 300m	Settlement within 300 m	Settlement within < 300 m
Grazing	Minimal grazing < 10%	Medium grazing 10–50%	Intensive grazing > 50%
Local habitat alteration			
Riparian vegetation removal	Less riparian vegetation removal, < 10%	Medium riparian vegetation removal, 10–50%	High riparian vegetation removal > 50%
Influence Erosion	No erosion or minimal erosion > 100m	No erosion within 100m	No erosion < 10m
Influence of geographical/landslide change	No landslide or minimal landslide > 100m	Landslide 10m - 100m from the stream channel	Landslide next to the stream channel
Irrigation	No irrigation or irrigation > 200m	Irrigation within 100–200 m	Irrigation within < 100m
Hydrological modification			
Influence of the dam or weir	No Weirs in the sampling site or weirs within > 100m	Weirs within 100 m of the sampling site	Weirs within < 50m from the sampling site
Influence on instream diversion	No stream diversions > 100m	Stream diversion within 100 m of the sampling site	Diversion within < 50m from the sampling site
Extractive industry/sand/gravel dredging	No or less sand/gravel extraction < 10%	Medium activities of sand dredging 10–50%	Intensive use of sand/gravel > 50%
Physical and Chemical			
Point source pollution	No or < 10% point source pollution	Medium pollution: 10–50% pollution	High pollution > 50%
Non-point source pollution	No or < 10% point source pollution	Medium or 10–50% non-point source pollution	Intensive or > 50% non-point source pollution

3.5.2.2. Metric screening, scoring, and statistical analysis

Candidate Metric Selection

A total of 37 candidate metrics (Table 3) representing various aspects of the macroinvertebrate community were selected based on literature (Barbour *et al.*, 1996; Lakew & Moog, 2015; Moges *et al.*, 2016; Getachew *et al.*, 2023). These metrics included a variety of biodiversity indices such as richness, Shannon diversity, evenness, number of individuals, dominance (D-1), Simpson diversity (1-D), abundance, Brillouin, Menhinick, and Equitability. J, Fisher's alpha, Berger-Parker, and Chao-1. Moreover, the proportional composition of macroinvertebrate orders and Functional Feeding Groups (FFGs). In addition, compositional indices (e.g., EPT, EOT, ECT, ET), biotic indices (FBI, BMWP, ASPT), and counts of major taxonomic groups (Trichoptera, Plecoptera, Diptera, Hemiptera, Decapoda) were included. Tolerance-based metrics, such as the percentage of intolerant, moderately tolerant, and tolerant taxa with the total number of Taxa for each site, ratios like Baetidae to Ephemeroptera, and relative abundance, were also incorporated and measured to comprehensively capture the ecological status of the study sites (n = 25). Normality of candidate metrics was tested using normal probability plots and the Kolmogorov-Smirnov test; all metrics were non-normally distributed, so non-parametric tests were applied. The metrics showing significant differences ($p < 0.05$) between reference and impacted sites were retained for MMI development, following established bioassessment protocols (Karr *et al.*, 1986; Barbour *et al.*, 1996; Alemneh *et al.*, 2019).

Testing Discriminatory Power

24 Core metrics were initially screened for their capacity to distinguish reference from impaired sites using Mann-Whitney U tests ($p < 0.05$) and analysis of inter-quartile (IQ) overlap in box-and-whisker plots (Raburu *et al.*, 2009; Ghimire *et al.*, 2022). Seasonal data were pooled per site for this assessment. To validate preliminary metric selection, the 2023 scoring formula was applied to 2016 site-level data, and site scores were compared between reference and impacted sites using a Mann-Whitney U test on the site (n=25).

Redundancy Analysis

Spearman correlation analysis was performed to examine redundancy among the selected metrics. Pairs of metrics with $r_s \geq 0.70$ and $p < 0.05$ were considered redundant. In such cases, the metric showing stronger correlations with environmental variables (pH, H₂AS, DO, T_{water}, and Turbidity) and greater practical utility for monitoring highland streams was retained (Barbour *et al.*, 1996).

Final Metric Selection and Scoring

Metrics were further evaluated using inter-quartile overlaps in box-and-whisker plots, considering both the direction (up and down) and magnitude of responses to increasing disturbance (Ghimire *et al.*, 2022). Threshold ranges were scenically derived from Box-and-Whisker plots of site-level core metric values from reference sites using the 2023 dataset. Scores were then assigned according to these thresholds: metrics indicative of reference conditions received a score of 5, intermediate conditions a score of 3, and the greatest deviation from reference conditions a score of 1 (Raburu *et al.*, 2009; Ghimire *et al.*, 2022). The final MMI for each site was calculated by summing the scores of five selected core metrics. Pooled seasonal data from the same sites were used to generate site-level MMI scores for ecological classification (Assefa *et al.*, 2023; Sripanya *et al.*, 2023).

3.5.2.3. MMI Validation

To assess the discriminatory power of the developed MMI, the final 2023 scoring formula was applied to the 2016 season and site-level data. Site scores were then compared between reference and impacted sites using a Mann-Whitney U test to evaluate the index's ability to distinguish between healthy and degraded conditions.

3.5.2.4. Multivariate data analysis

The multivariate data analysis was presented in section 3.4.4 of chapter three.

3.5.2.5. Conceptual flow chart

The development of the multimetric index followed a stepwise screening procedure (Fig 5). Initially, candidate metrics were selected based on ecological relevance and expected response to anthropogenic disturbance. Metrics were then statistically evaluated for discriminatory power between reference and impacted sites using the Mann-Whitney U-test. Redundant metrics were removed based on correlation analysis. Remaining metrics were further screened using box-and-

whisker plots to confirm clear separation between site classes. The final selected metrics were validated using independent 2016 site-level data and subsequently integrated to develop MMI.

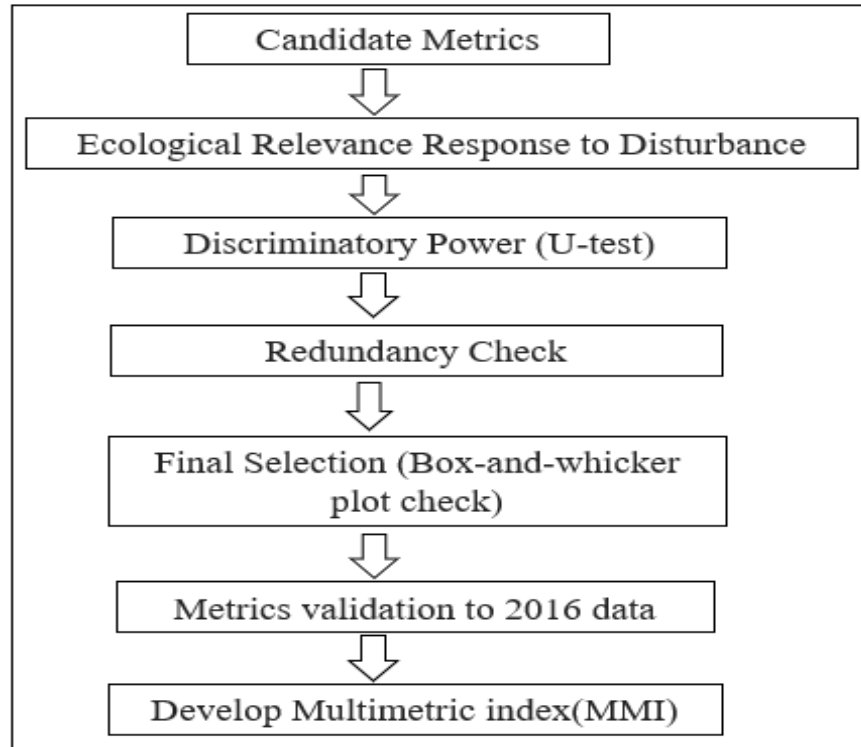


Figure 5. The conceptual flowchart for multimetric index development.

3.5.3. *Ensemble species distribution model*

3.5.3.1. *Species Occurrence Data*

Ethiopia is the richest country in biodiversity across both terrestrial and aquatic ecosystems (Asefa *et al.*, 2020; Regassa, 2024), with freshwater habitats hosting sensitive macroinvertebrate species widely distributed across its basins. The pollution-sensitive families Perlidae (Plecoptera) and Philopotamidae (Trichoptera) are concentrated in highland streams, where they serve as strong bioindicators of clean, fast-flowing, and well-oxygenated rivers (Assefa *et al.*, 2020; Orozco and Ocasio, 2023). These families were selected for ecological modeling due to their high sensitivity to disturbance, reliable presence in undisturbed habitats, ecological roles as functional feeding group representatives, and the availability of sufficient data for model calibration and validation (Sripanya *et al.*, 2023). Occurrence records were obtained from three sources (Table 8; Fig. 3), and 76 records for Perlidae and 72 records for Philopotamidae were

used to model their species distribution independently (Annex IX). Spatial rarefaction was applied to occurrence records from field surveys, GBIF, and published literature using SDM Toolbox v2.6 in ArcGIS 10.8 (Brown, 2014; Guisan *et al.*, 2017; Aligaz *et al.*, 2024) to limit the number of occurrences to a maximum of 1 per 1 km². This spatial thinning is especially relevant for aquatic species which are strongly affected by the distribution of river flow, and can show clumped distributions along river networks, with an increase of the model performance if this is not taken into account.

A spatial resolution of 1 km was also chosen because it was important to maintain consistency between the datasets for various environments (Domisch *et al.*, 2015). All spatial analysis was done using the HydroSHEDS database (Lehner *et al.*, 2013), which was created from the SRTM Digital Elevation Model (Lehner *et al.*, 2008). The product was available with higher resolution (~500 m), but the 1 km resolution product was used to match the spatial resolution of the environmental predictors used for the riverine and stream conditions (Lehner *et al.*, 2013). This harmonization reduces scale mismatch and uncertainty in the data integration of multi-source environmental layers, and enables spatial filtering of occurrence data to align with the resolution of the predictor space used in the species distribution models (Dendoncker *et al.*, 2006).

The increased number of records in Oromia and Amhara is probably not only a result of varying sampling intensity, but also due to the biogeographic structure of Ethiopia's freshwater ecosystems. Much of the Ethiopian lakes, along with most river and stream networks, are very densely populated with aquatic habitats. Hydrological syntheses indicate that Oromia accounts for ~40-50% of surface water bodies, while Amhara contributes ~20-30%, mainly due to Lake Tana and the Blue Nile headwaters; other regions collectively account for ~30-40% (Bekele *et al.*, 2007; Evans *et al.*, 2012). Therefore, the occurrence records were compiled from multiple complementary sources, including field surveys, the GBIF, and peer-reviewed literature. This multi-source integration was used to minimize sampling gaps and reduce single-source bias in species occurrence data.

Table 8. Species occurrences were collected from three different data sources along with the Ethiopian river basins.

Data sources	Species name	No of presence	References
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		data	
Field survey		15	Dinki Watershed, Ankober Woreda
GBIF		2	<u>GBIF: https://www.gbif.org</u>
Published literatures	Perlidae	59	A total of 59 study sites with recorded coordinates were used across Ethiopia, with 75% of the data concentrated in central regions, particularly Oromia and Amhara (Alemneh <i>et al.</i> , 2019; Lakew, 2020; Getenet <i>et al.</i> , 2022; Asefa <i>et al.</i> , 2023; Worku <i>et al.</i> , 2026).
Total		76	
Field survey		14	Dinki Watershed, Ankober Woreda
GBIF		1	<u>GBIF: https://www.gbif.org</u>
Published literatures	Philopotamidae	57	A total of 57 study sites with recorded coordinates were used across Ethiopia, with 75% of the data concentrated in central regions, particularly Oromia and Amhara (Alemneh <i>et al.</i> , 2019; Lakew, 2020; Abebe <i>et al.</i> , 2021; Getenet <i>et al.</i> , 2022; Asefa <i>et al.</i> , 2023; Worku <i>et al.</i> , 2026a)
Total		72	

Note: GBIF indicates Global Biodiversity Information Facility

3.5.3.2. *Environmental variables*

Twenty environmental variables were used to model the distribution of pollution-sensitive macroinvertebrates (Perlidae and Philopotamidae), comprising 19 bioclimatic variables and land cover predictors. The bioclimatic variables were obtained from <https://www.worldclim.org/data/index.html> or WorldClim version 2.1 at a spatial resolution of 30 arc-seconds (~1 km²) (Fick & Hijmans, 2017). Topographic attributes were derived from the Shuttle Radar Topography Mission (SRTM) digital elevation model (Jarvis *et al.*, 2008), while ecoregion data were obtained from Olson *et al.* (2001). The global land cover map was obtained from the Copernicus Climate Change Service (<https://cds.climate.copernicus.eu/>), which describes the land surface into 22 classes, defined using the United Nations Food and Agriculture Organization's (UN FAO). The Land Cover Classification System (LCCS) includes cropland, broad-leaved evergreen forest, broad-leaved deciduous forest, shrubland, grassland, urban areas, bare lands, and water bodies. These variables were used to generate current baseline (1970-2000) predictions and future projections for 2050 (2041-2060) and 2070 (2061-2080), using the HadGEM2-ES global circulation model (GCM) developed by the UK Met Office Hadley Centre under two Shared Socioeconomic Pathways (SSPs): an intermediate pathway (SSP2-4.5) and a high-emissions scenario (SSP2-8.5).

Multicollinearity of climatic predictors was analyzed in R 4.1.2 using the usdm package, retaining variables with $|r| < 0.7$ and $VIF < 10$ (Eyre *et al.*, 2022; Guisan, 2017), and only non-collinear variables were used in MaxEnt modeling (Phillips *et al.*, 2006; Phillips *et al.*, 2017). LULC was incorporated as a static predictor and held constant in future projections due to the lack of reliable and spatially explicit future datasets; therefore, projections represent climate-driven habitat suitability under a fixed land-use background (Table 9). Initially, we included 20 continuous environmental variables, which were evaluated for multicollinearity using the VIF procedure. The categorical variable (land use) was excluded from the VIF analysis due to its non-continuous nature. Among the predictors, 9 variables showed collinearity problems, leaving 9 variables for use in the model (Table 9). After selecting the non-collinear continuous variables, the land use variable was added to the final set of predictors, which was then used for model prediction (Melese *et al.*, 2025). For the development of future scenarios, two Shared Socioeconomic Pathways (SSP2-4.5 represents intermediate greenhouse gas emission, where CO₂ emissions are projected to remain near current levels until 2050 before declining, and SSP2-8.5 represents a high-emission scenario associated with greater challenges for mitigation) (Adhikari *et al.*, 2023). Therefore, in total, 10 environmental variables were selected and used to model suitable habitat distributions for Perlidae and Philopotamidae (Table 9).

Table 9. Environmental variables retained for modeling and their Variance Inflation Factor (VIF) Values After Multicollinearity Analysis.

No	Variables	Code	Units	VIF1	VIF2
1	Isothermality (BIO2/BIO7) ($\times 100$)	BIO3	%	6.57	7.22
2	Temperature seasonality	BIO4	$^{\circ}\text{C}$	7.09	7.63
3	Temperature annual range	BIO7	$^{\circ}\text{C}$	2.09	2.10
4	Mean Temperature of Driest Quarter	BIO9	$^{\circ}\text{C}$	3.52	3.51
5	Precipitation of Wettest Month	BIO13	mm	6.68	6.72
6	Precipitation of Driest Month	BIO14	mm	2.74	2.77
7	Precipitation seasonality	BIO15	mm	2.97	3.01
8	Precipitation of the warmest quarter	BIO18	mm	2.38	2.28
9	Precipitation of the coldest quarter	BIO19	mm	4.00	3.84
10	Land use Land cover (Categorical)	LULC	---	---	---

VIF1- Variance Inflation factor of Perlidae; VIF2-Variance Inflation Factor of Philopotamidae

3.5.3.3. *Model fitting and evaluation*

A species prediction and distribution model was conducted using an ensemble model with various algorithms, categorized into two groups: classical regression techniques and machine learning approaches (Rooper *et al.*, 2016; Elith, 2017). According to Melese *et al.*, (2025), who reported and cited the following authors, we applied two regression algorithms, such as Generalized Linear Models (GLM) and Generalized Additive Models (GAM) and three machine learning algorithms Boosted Regression Trees (BRT), Random Forests (RF) and Maximum Entropy Model (MaxEnt) to enhance predictive performance (Santini *et al.*, 2021). These algorithms (Table 10) are widely used in research and species conservation (Zhang & Li, 2017) for their strong predictive accuracy (Hailegiorgis *et al.*, 2025; Melese *et al.*, 2025).

Models were fitted and implemented in R using the *dismo* and *ensemble* packages. The *dismo* package offers implementations of several species' distribution models, including an R interface to the maxent model, as well as native implementations of Bioclim and Domain. It also has functions to support the use of Boosted Regression Trees. The package vignette (available through vignette ('SDM', package = *dismo*) is a good place to begin. Additionally, *dismo* provides facilities to sample background points, 10-fold sub-sampling, and to evaluate models with various metrics such as AUC. The same set of functions can be applied to other SDM methods, such as GLM, GAM, and Random Forest (Phillips *et al.*, 2009). This comprehensive approach enabled us to identify the key environmental drivers of the species' distribution for both present and future scenarios (Eyre *et al.*, 2022).

Before model development, both default and optimized parameter settings (including background point generation, iterations, learning rate, feature types, and number of trees) were evaluated to improve model reliability (Melese *et al.*, 2025). Species distribution models were implemented using the SDM R package in R, following Naimi and Araujo (2016), which supports ensemble modeling across multiple algorithms, with algorithm-specific settings applied. For GLM, forward and backward model selection procedures were applied with linear and quadratic terms, while GAMs incorporated nonparametric smooth functions to account for nonlinear relationships. For BRT and RF, 2,500 and 500 trees were grown, respectively (Thuiller *et al.*, 2009; Elith, 2021). MaxEnt was run with 1,000 background points and up to 5,000 iterations. For each statistical model (BRT, RF, GLM, GAM, and MaxEnt), ten-fold sub-

sampling with 10 replications was applied, and the data were split into 70% for calibration and 30% for evaluation (Phillips *et al.*, 2006; Wang *et al.*, 2022; Ahmed *et al.*, 2023).

Because of the absence of data, 10,000 random background points were generated across the study area with the sdm R package function gRandom. For the consistency of the models, these points were used as background data in MaxEnt and as pseudo-absences for algorithms that needed absence data. To create ensemble predictions, the model predictions were averaged using the True Skill Statistic (TSS) of individual models, which is a widely used metric to increase the accuracy of a model prediction and reduce the uncertainty when creating ensemble predictions (Dormann *et al.*, 2018).

Table 10. Results from predictive models based on machine learning (BRT, RF, and MaxEnt) and regression (GAM and GLM) approaches are presented, including a short description and a few references to the literature about using these models to model the distribution of pollution-sensitive macroinvertebrates.

Algorithms	Descriptions
Boosted Regression Trees (BRT)	Methods using a limited number of trees improve predictive performance, handle multiple predictors with high accuracy (Gu <i>et al.</i> , 2019), and construct models through iterative gradient boosting (Melese <i>et al.</i> , 2025).
Random Forest (RF)	An effective method for predicting species occurrence data (Abdi, 2019), it is relatively insensitive to parameter tuning (Freeman <i>et al.</i> , 2015) and reduces overfitting by randomly selecting variables to build multiple classification trees (Jin <i>et al.</i> , 2016).
Maximum Entropy Modeling (MaxEnt)	It performs well with small sample sizes (Perkins-Taylor & Frey, 2020), is designed for presence-only species data (Phillips <i>et al.</i> , 2006), and can build complex models based on occurrence records and user-defined settings (Elith <i>et al.</i> , 2008).
Generalized Linear Model (GLM)	It can be used to study non-linear relationships and can be used in ecological studies (Bunce, 2000). Generalizes ordinary least squares regression to use parametric functions (such as linear or polynomial) to model the relationship between predictor responses
Generalized Additive Model (GAM)	It is commonly used regression model in ecological research for handling non-normal distributions (Ravindra <i>et al.</i> , 2019).

3.5.3.4. Model Validation and Mapping

The receiver operating characteristic (ROC) curve (Annex VIII, both Perlidae and Philopotamidae), the area under the curve (AUC), and threshold-based metrics such as True Skill Statistic (TSS), sensitivity, and specificity (Allouche *et al.*, 2006) were used to evaluate the model performance. AUC values range from 0 to 1, where 0.5 indicates random prediction, 0.7–0.8 fair performance, 0.8–0.9 good performance, and values above 0.9 excellent discrimination. TSS ranges from –1 to +1, with 1 indicating perfect agreement, 0 representing random performance, and values above 0.6 generally considered reliable. Negative TSS values indicate performance worse than random classification (Bahn and McGill, 2012). Moreover, models with the ROC curve are a graphical plot of sensitivity (true positive rate) against 1-specificity (false positive rate), illustrating the model’s ability to distinguish suitable from unsuitable habitats (Alemayehu *et al.*, 2024) for both Perlidae and Philopotamidae (Annex III). Because of the continuous nature of the results, the optimal threshold for species occurrence was established after creating a predictive map. Maximizing the sum of sensitivity and specificity ($\max(se + sp)$) determines the threshold that optimally balances accurate predictions for both the presence and absence of the species. Therefore, the models with $AUC > 0.86$ and $TSS > 0.6$ were also retained for ensemble weighting. The weighted mean ensemble approach was used, where weights were assigned to individual models based on their predictive performance.

Ensemble maps were generated by multiplying each grid cell by its respective weight and summing across models. Future projections were produced under two climate scenarios (SSP2-4.5 and SSP5-8.5) for the 2050s and 2070s. Predicted distributions were analyzed for range shifts, habitat loss and gain, and remain suitable, using the range size function in R software version 4.3.3 and spatial overlays in ArcGIS 10.8. This framework enabled us to identify the most influential environmental predictors and quantify potential changes in suitable habitats for the target families (Perlididae and Philopotamidae).

3.6. Ethical consideration

The current PhD dissertation, entitled Watershed Ecosystem Health Assessment and Predictive Modeling of Pollution-Sensitive Macroinvertebrate Responses to Climate and Land Use Change in the Dinki Watershed, Central Highlands of Ethiopia, was to be conducted in Ankober District,

North Shewa Zone, and Amhara Regional State. The study aims to assess the watershed ecosystem health status and predictive modeling of pollution-sensitive macroinvertebrate responses to land uses and climate change in the Dinki watershed. In effect, water quality parameters, macroinvertebrate assemblages, household survey, and long-term climatic data were collected following standard procedures. Standard and validated protocols from credible literature were adopted to critically maintain the validity and generalizability of the PhD dissertation.

In this regard, an ethics statement was received from the Institute of Review Board (IRB), College of Agriculture & Environmental Sciences, Bahir Dar University, and submitted to the Ankober District administration office. A participatory rural appraisal through key informant interviews, focus group discussions, and household surveys was conducted after an oral consent was obtained from individual participants. Furthermore, participants were informed that the current information is kept confidential, solely used for PhD dissertation purposes, and they are able to withdraw when they want to do so.

The climatic and associated data were obtained from the National Meteorological Agency (NMA), soil data from the Agriculture Transformation Agency (ATA), and LULC data from Landsat and extracted from the Google Earth image following standard procedures. The macroinvertebrate and water samples were collected in replicates, and all instruments to be used in the Lab and field were calibrated before analysis. The physicochemical and biophysical data collection procedures followed the rapid bio-assessment protocols developed for streams and wadeable waters. Moreover, protocols from international standards were used to allow adequate time for both the qualitative and biophysical data collection. Furthermore, critical safety rules were applied to all personnel working in the lab and field. Despite the fact that the current research does not consider threatened species, appropriate precaution measures were applied to protect the environment in the protected areas during field sampling.

3.7. Data quality assurance

All-important data quality control under each activity were measured, like method calibration, evaluation of watershed characteristics, climate change, water quality index, composition of invertebrate for performing of data analysis, determination of method detection level, daily assessment of limitation, and the existence of limitation of counting invertebrates or other

problems were to perform based on the standard method for the assessment of abundance of biodiversity in streams under different land uses.

3.8. Operational Definition

3.8.1. *Bio-indication*

The simplification and interpretation of ecological information to understand the state, quality, and disturbance level of an ecosystem.

3.8.2. *Climate variability*

Natural climate fluctuations occurring over seasonal to millennial time scales, driven by internal climate system processes.

3.8.3. *Ensemble species distribution model:*

A process that combines the spatial information from multiple species distribution models. Combining multiple SDMs to improve the accuracy, robustness, and uncertainty reduction of the species distribution modelling under environmental and climatic scenarios.

3.8.4. *Functional feeding group (FFG)*

The way the aquatic macroinvertebrates are classified into feeding groups (shredders, collectors, scrapers, grazers, and predators).

3.8.5. *Modified Mann-Kendall (MMK) test*

Non-parametric statistical technique for detecting a trend in a time series data that is robust to the presence of autocorrelation.

3.8.6. *Multimeric Index (MMI)*

A composite biological index that reflects biological integrity, ecological condition, and water quality of aquatic systems based on several biological parameters.

3.8.7. *Spatio-temporal variation*

Space and time variability, which is a representation of environmental processes, climate influences, and anthropogenic impacts.

3.8.8. *Watershed characterization*

A detailed account of the biophysical, hydrological, climatic, soil, and land use characteristics of a watershed that support watershed assessment and management.

3.9. Dissemination of Results

This dissertation will be disseminated in several ways to both academic and non-academic audiences. Academically, the results will be presented in national and international conferences, workshops, and seminars in the department and published in peer-reviewed reputable journals of

environmental/aquatic sciences. The key findings and recommendations will also be shared with relevant local government departments, research institutions, and organizations working in the community to facilitate evidence-informed actions and sustainable resource management. Key messages will also be translated into simplified formats (e.g., policy briefs, posters, and community awareness materials) and shared with local stakeholders, practitioners, and community members directly impacted by the environmental issues in the study area.

CHAPTER 4: RESULTS

4.1. Biophysical attributes and effects of LULC changes on ecosystem services in Dinki Watershed

4.1.1. Physical and Geomorphological Characterization

4.1.1.1. Watershed Delineation

The map provides information on the Dinki watershed, which has an area of 160.90 km² (Dense, Gedamoch, Zego and Dinki sub watershed) and an elevation range of 1,257-3,187 masl. The Digital Elevation Model (DEM) at 20 x 20 m resolution shows the topography of the watershed, with higher topography in the northwest and lower topography in the southeast. The watershed boundary (WS-Boundary) is the outer boundary of the watershed enclosing the stream network, where the main perennial stream, Dinki River, extends 30.35km, which finally drains into the Awash River (Fig. 6a). Moreover, the stream network analysis of the Dinki watershed shows a hierarchical arrangement of streams: 45 first-order streams and 9 second-order streams, and one single third-order stream (Table 11). First-order streams dominate the watershed, and there are 20.493 km of these, 10.918 km of second-order streams, and 1.343 km of third-order stream. The number of streams decreases as the order increases, which is typical of a dendritic drainage pattern, a natural merging pattern. Given the relatively short stream lengths at all orders, this indicates a steep landscape in which water is moving rapidly, which can affect sediment transport and watershed hydrodynamics (Fig.6b).

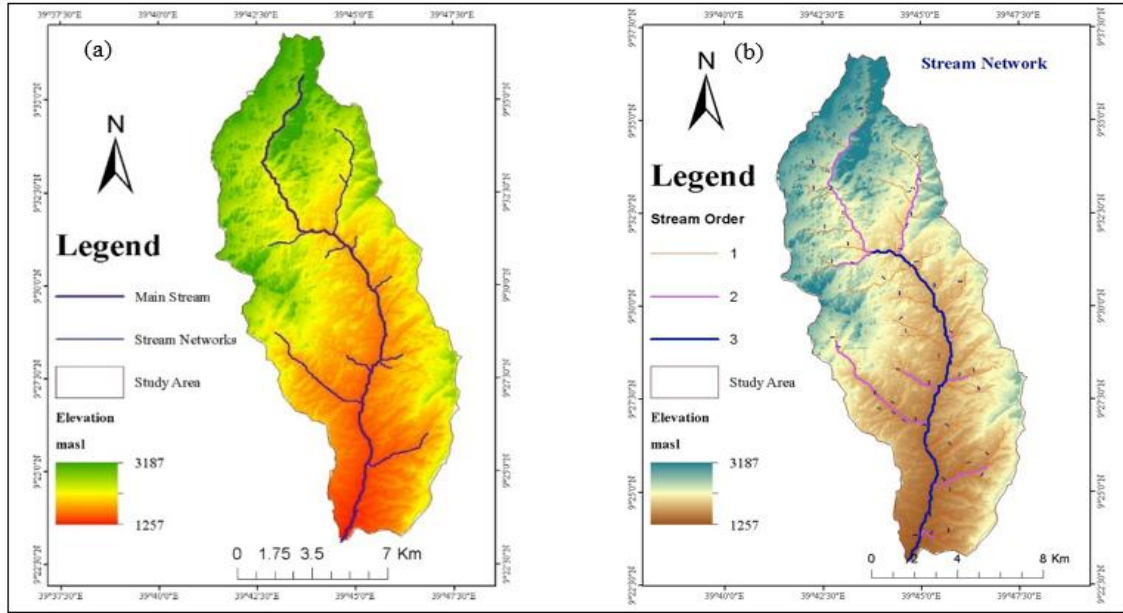


Figure 6. (a) Delineation of the watershed with the streamflow network and corresponding elevations, and (b) Stream order of the Dinki watershed with the streamflow network and corresponding elevations.

Table 11: Stream order and connection in Dinki watershed

Stream Order	No of Streams	Average Stream length	Sum Stream length(km)
1	45	0.455	20.493
2	9	1.213	10.918
3	1	1.343	1.343

4.1.2. Status of Habitat Assessment between 2016 and 2023

The Dinki watershed was identified using habitat assessment scores and impact assessments based on Barbour's 1999 standard classification. The status of watersheds in the Dinki region was evaluated in 2016 and 2023 using Habitat and Visual Assessment Scores (HVAS) and Impact Assessments (IA). The watershed name of our study site is the Dinki Watershed. In this watershed, there is one specific study site called Dinki, the outlet of this watershed. The outlet is named for the watershed. Significant habitat quality and impact changes were identified in the assessment of the Dinki watershed conducted from 2016 to 2023.

The highest IA value was observed at Zego (45.71%) and Dinki (39.71%) sites in 2016 (Asmamaw *et al.*, 2019), which falls within the category of near to medium impact. Gedamoch (15.50%) was the least impacted site, with little disturbance. Similarly, in 2023, Zego (43.60%)

and Dinki (32.44%) were still in the near to medium impact class, as was Gedamoch (10.83%) in 2016 (Asmamaw *et al.*, 2019) which indicates slight improvement in habitats over time, though slight. Gedamoch (65.21%) and Zego (60.06%) had the highest mean scores in 2016 and were both classified in the 'fair' (60-74%) habitat condition class. This trend continued in 2023 with 'fair' conditions still present for Gedamoch (70.21%) and Zego (61.93%) with marginal improvements in comparison to the 2016 period (Fig. 8). The mean HVAS has risen from 52 ± 10.81 (rated 'poor') in 2016 to new 62 ± 14.76 (rated 'fair') in 2023, suggesting a generally better watershed habitat condition in 2023 (Fig. 7).

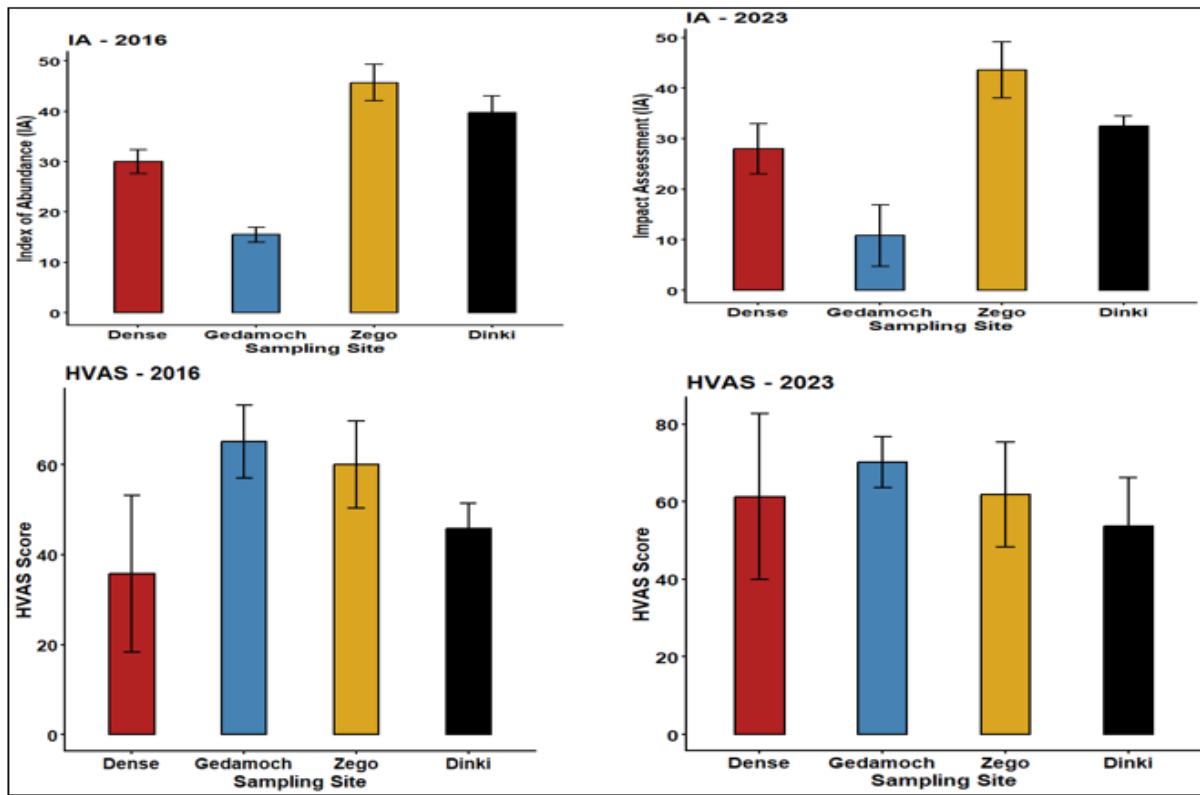


Figure 7. Identify the status of the Dinki watershed by Impact Assessment (IA) (a) for 2016 (Asmamaw *et al.*, 2019) and (b) for 2023, and Habitat and Visual Assessment Score (HVAS) (c) for 2016 and (d) for 2023. IA (%) rated as: High = $\geq 75\%$, Medium = $\geq 50\%$, Low = $\leq 49\%$; HVAS (%) rated as excellent ($\geq 95\%$); very good (85-94%); good (75-84%); fair (60-74%); poor (50-59%) and very poor ($\leq 49\%$). Or on the other hand: HVAS= Habitat visual assessment score: Optimal=16-20 or 161-200, Suboptimal= 11-15 or 121-160, Marginal=6-10 or 60-120, and poor= 1-5 or 0-59.

4.1.3. Soil and Geology

4.1.3.1. Soil Type

According to Nigatu (2014), the Dinki watershed consists of two primary soil types: clay soil, which includes brownish (31%), grey (28%), and red (11%) variations, collectively covering 70% of the total area, and black cotton soil, which accounts for 26% of the land in Ankober Woreda. The remaining 4% consists of other soil types. However, in contrast, the current analysis with ArcMap classified the dominant soil types in the Dinki watershed as clay loam (70%), clay (26%), and loam (4%) (Fig. 8). Similarly, a report from the local agricultural bureau identifies two main soil categories: brown/clay soil, covering 87.5% of the area, and black cotton soil, making up 12.75%. The different classifications suggest some differences in soil characterization, with GIS-based soil mapping offering a finer spatial scale of representation, and literature and local reports focusing on larger soil groupings.

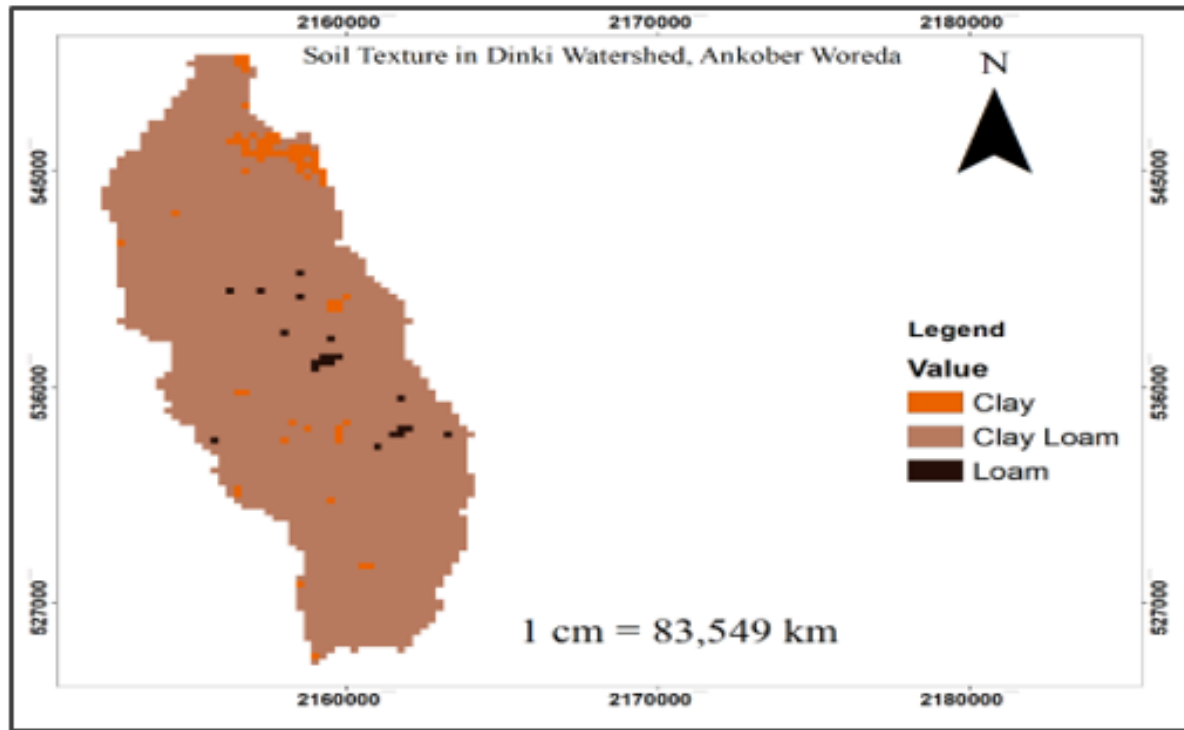


Figure 8. Soil texture in the Dinki watershed

4.1.3.2. Soil physical and chemical properties of Dinki watershed: Spatial trend analysis

Soil physical properties were determined for the Dinki watershed using texture (Fig. 8) and bulk density ranging from 905 to 1360 kg/m³ (or 0.91-1.36 g/cm³), averaging to 1.12 g/cm³, from the EthioSIS database. Furthermore, soil texture was computed with the R package, and by applying the $\text{Area} = \text{Count} \times (250 \times 250)$ formula, the area coverage for clay (Count = 69) is 4.31 km² ($69 \times 250 \times 250$), for clay loam (Count = 2,488) is 155.50 km² ($2,488 \times 250 \times 250$), and for loam (Count = 21) is 1.31 km² ($21 \times 250 \times 250$). Furthermore, the multiple linear regression (MLR) model was used to assess the effect of the most important soil chemical properties on phosphorus (P) and nitrogen (N) availability in the Dinki watershed, which covers 160.90 km². The soil chemical properties collected from the EthioSIS database revealed that there were variations between soil types in the Dinki watershed (Table 12). The soil pH had a range between 6.80 and 7.20, with an average of 7.05, which is near neutral. Phosphorus (P) showed the highest range (13.03-58.77 mg/kg; average = 26.46 mg/kg; standard deviation = 17.59) while electrical conductivity (EC) showed very low range (0.16 $\mu\text{S}/\text{cm}$). The results from the t-tests showed that all soil chemical characteristics were statistically significant ($p < 0.05$).

Table 12. The soil chemical properties of Dinki watershed were estimated by min, max, mean, STDEV, Standard error, t-value, and P-value.

Soil Variable	Min	Max	Mean	STDEV	Std. Error	t value	P-value
pH	6.80	7.20	7.05	0.16	0.07	98.99	0.001
Fe (mg/kg)	25	30	28	1.90	0.85	32.88	0.001
C/N ratio	10.8	17.18	12.33	2.98	1.33	9.25	0.001
Ca (mg/kg)	71.13	86.87	78.86	5.89	2.64	29.93	0.001
EC ($\mu\text{S}/\text{cm}$)	0.08	0.29	0.16	0.08	0.04	4.4	0.001
Mg (mg/kg)	7.68	17.88	12.43	3.84	1.72	7.25	0.000
N (mg/kg)	0.05	0.67	0.29	0.24	0.11	2.66	0.005
P (mg/kg)	13.03	58.77	26.46	17.59	7.87	3.87	0.001

Diagnostic plots (Fig. 9) indicated a lack of linearity, heteroscedasticity, and some deviations from normality, with high leverage points affecting the estimates. For nitrogen (N), weak predictive power was observed ($t = 2.66$, $p = 0.005$). The residual standard error (RSE) for Phosphorous (P) the model was high (17.59), which shows that there are limitations in the model

and that it will be necessary to refine the model to gain more understanding about the nutrient availability predictions. Nevertheless, the model is scientifically acceptable ($R^2 = 0.624$) since it explains a great deal of the variation in P levels and provides a list of critical predictors. To complete its refinement, however, it will be necessary to overcome the remaining complexities and make it even more reliable for wider applications. Residuals vs Fitted determines the linearity of the independent and dependent variable. Normal Q-Q is used to determine if the residuals are normally distributed. Scale-Location tests the homoscedasticity (that is whether the variance is constant) of the residuals. The Residuals vs. Leverages plot helps identify observations that could have an impact on the regression model that is not proportionate.

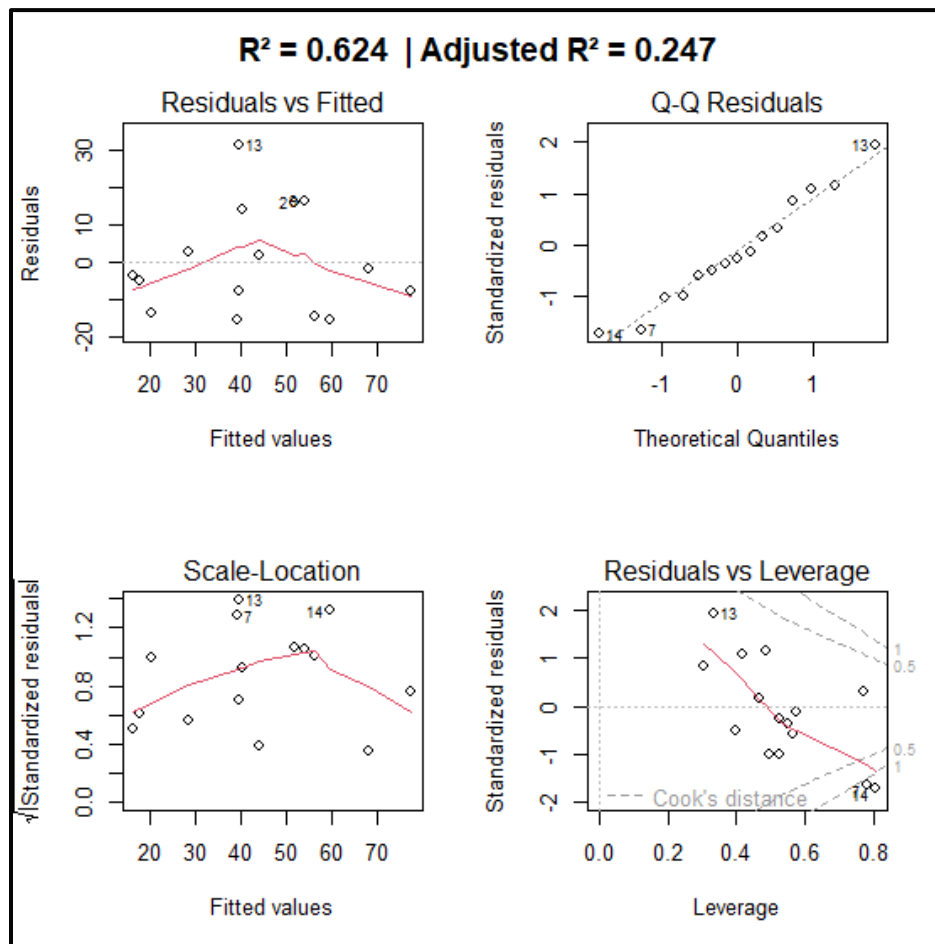


Figure 9. Diagnostic plots assessing the Multiple regression model fit for soil chemical properties of the Dinki watershed derived from EthioSIS data and extracted using ArcGIS, and include Residuals vs. Fitted (top-left), Normal Q-Q plot (top-right), Scale-Location plot (bottom-left),

and Residuals vs. Leverage (bottom-right), used to detect potential outliers and assess model validity.

4.1.4. Hydrological Characterization: spatial and temporal comparison

The one-way Anova (for spatial) paired t-test (for temporal) variation of surface water hydrology and water quality results indicate significant spatial differences in surface water hydrology across study sites in 2016 and 2023. Significant spatial and temporal variations were observed in habitat and physicochemical parameters across the study sites. However, the detailed results and interpretations are presented in Chapter four under ‘spatial and temporal Variations in Environmental and Physicochemical Parameters’ (Table 20 & 22) respectively.

4.1.5. Climate (rainfall and temperature) pattern

Rainfall during the 2016-2023 period ranged from 800 mm to 1,000 mm per year, with significant decreases in 2016 and 2020; the Kiremit season had similar trends, with greater amounts in 2019, but less than 600 mm in drier years. The Belg season was fairly consistent, with generally less than 250 mm of rain, with a few ups and downs in 2018 and 2022, while the Bega season consistently had the lowest amounts of rain, often below 100 mm (Fig. 10a). The trends in the annual temperature, however, are clear, marked by an increase in temperature after 2017, with the temperatures after this year exceeding 19°C. The Kiremit season had the largest variations, with highest temperatures above 21°C in the years of 2015 and 2019 followed by stable temperatures above 19°C, and the Belg season had temperatures greater than 20°C since 2018. The Bega season is the coolest but there is a steady rise from about 16°C in 2016 to almost 18°C in 2023 (Fig. 10b).

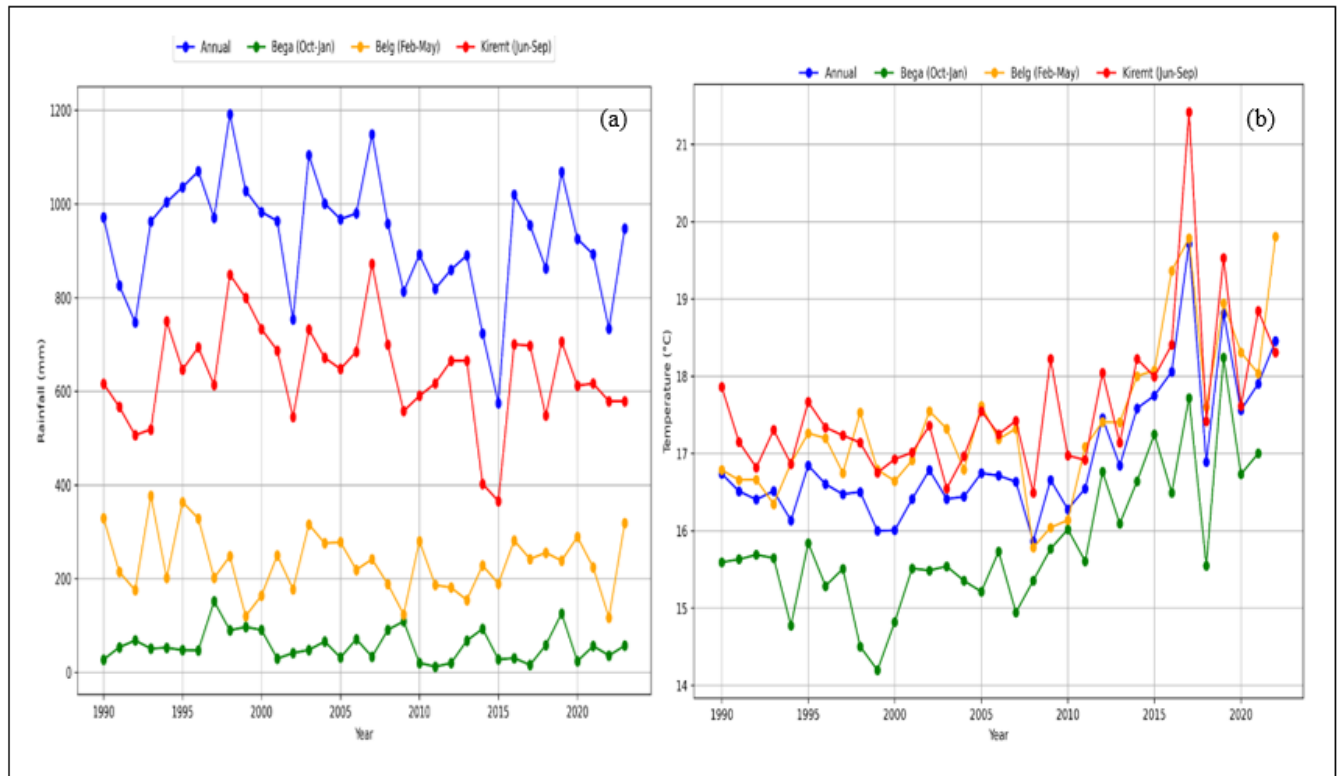


Figure 10. The annual and seasonal patterns of rainfall (a) and temperature (b) in Ankober region.

4.1.6. Ecological Characterization

4.1.6.1. Riparian vegetation

The riparian buffer zone vegetation of the Dinki watershed is found to have spatial variations among different macro-level zones. The dominant species of Dinki are: *Maytenus senegalensis*, *Ehretia cymosa*, *Ficus sur*, *Juniperus procera*, *Acacia Senegal*, *Croton macrostachyus*, and *Persea americana*. The vegetation of Zego includes *Aloe vera*, *Dodonaea viscosa*, *Maesa lanceolata*, *Acacia saligna*, *Acacia senegal*, *Rosa abyssinica*, and grasses. Gedamoch has a wide variety of riparian plants such as *Podocarpus falcatus* (*P. gracilior*), *Olea europaea subsp. cuspidata* (*Olea africana*), *Carissa spinarum* (*C. edulis*), *Croton macrostachyus*, *Rosa abyssinica*, *Prunus africana*, *Maesa lanceolata*, and *Aloe vera*. The major species of Dense are *Discopodium penninervum*, *Eucalyptus globulus*, *Cyathea manniana*, and *Salix mucronata* (*S. subserrata*). Although there is a general decrease in Dense Forest growth, these riparian species are important in maintaining ecological stability, regulating hydrology, and providing support for

biodiversity in the watershed. Though much of the area has been altered, key informants and focus group discussions suggest that natural vegetation in locations like Girar Meda, Zego, Mehal Wonz, Chifa, Koren, and King Minilk Bete Mengist are beginning to recover. There was a significant loss of forest cover, from 14.5% in 1984 to 4.8% in 2022 (66.67% of the forest area has been lost), which is still a major environmental concern and is largely due to the expansion of agriculture and population pressure.

4.1.6.2. Watershed land use/land cover dynamics and distribution

The final land use land cover maps for the Dink watershed in the years 1994, 2014, and 2023 were presented in Fig.11. The analysis and classification of the periods 1994-2014 and 2014-2023 reveal that the Dink watershed experienced significant LULC changes. The Dinki watershed spans a total area of 160.90 km² in both 2014~16 and 2023. Land use classification for both years identified six major types: agricultural land (AC), built-up areas (BP), Dense Forest (DF), grazing land (GL), slight vegetation (SV), and water bodies (WB). The classification result was tested using a confusion matrix. To perform the confusion matrix, training samples were needed. Between the first and 2nd image, twenty years' time interval (years), and between the second and 3rd image, were taken ten years' time interval in total of 30 years' time interval (for this chapter, we used 8 years land cover dynamics, which means 2014~2016 and 2023). The rates of temporal LULC change in the Dinki watershed during the period 1994-2014~16 -2023 are summarized in Table 13. The land use composition in 2014, which closely resembles that of 2016 when river water quality was sampled, remained unchanged over this period. The dominant land use types in 2014 included agricultural land (67.71 km²), slight vegetation (40.18 km²), and water bodies (27.34 km²), collectively accounting for 84.04% of the total area. Grazing land was minimal, covering only 0.44 km². By 2023, agricultural crop land (43.10 km²), slight vegetation (46.18 km²), and water bodies (29.25 km²) also remained dominant, making up 73.67% of the watershed. However, agricultural land experienced a significant decline, decreasing from 67.71 km² in 2014 to 43.10 km² in 2023 a loss of 24.12 km² (Fig. 11, 12 and 13).

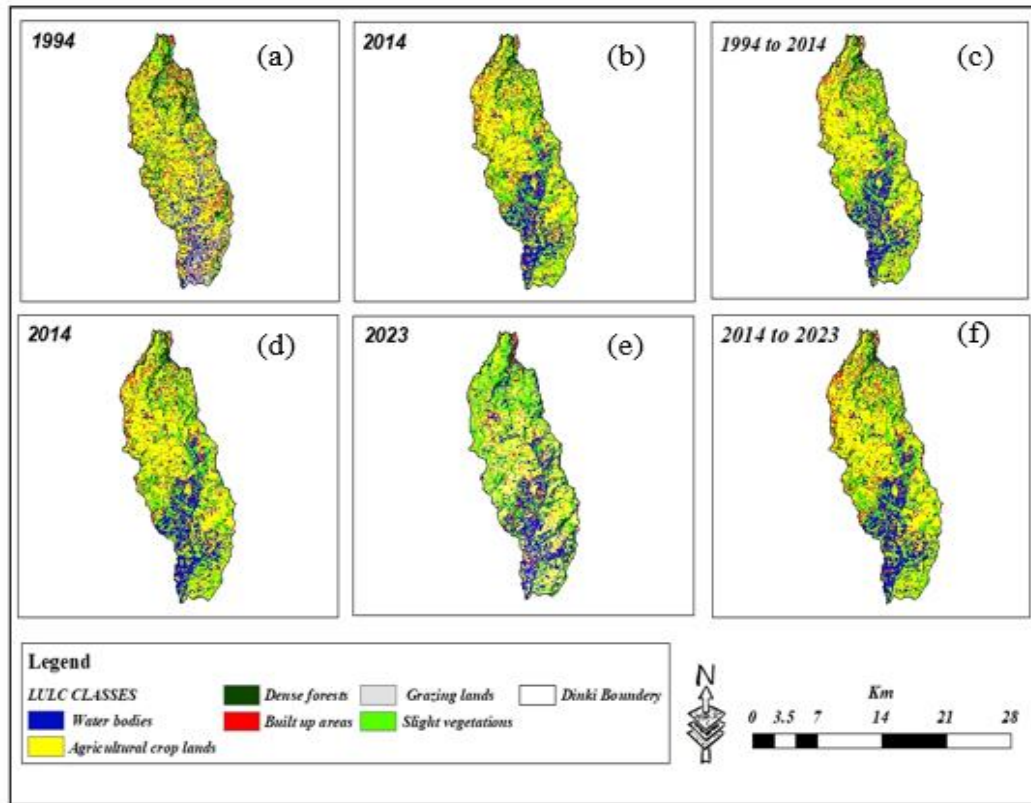


Figure 11. Spatial distribution of LULC classes in the Dinki Watershed for 1994, 2014, and 2023, and the corresponding LULC changes for 1994-2014 and 2014-2023. The maps illustrate the spatial patterns and transitions among agricultural land, slight vegetation, Dense forests, grazing land, built-up areas, and water bodies over the study period. The maps were created using ArcGIS Desktop 10.5 (Esri, <https://www.esri.com>) from raster layers generated in R (version 4.3.3; R Core Team, <https://www.r-project.org/>). NB: Agricultural cropland is replaced by agricultural land in the text.

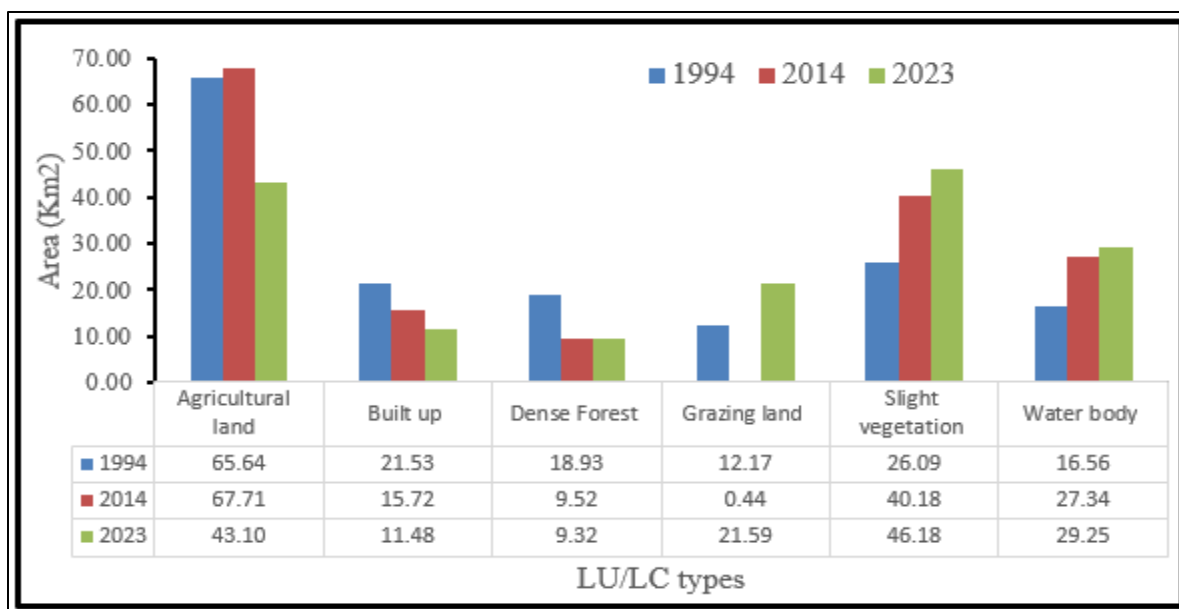


Figure 12. Classified land use/cover types in the study area in a table form; source: own study

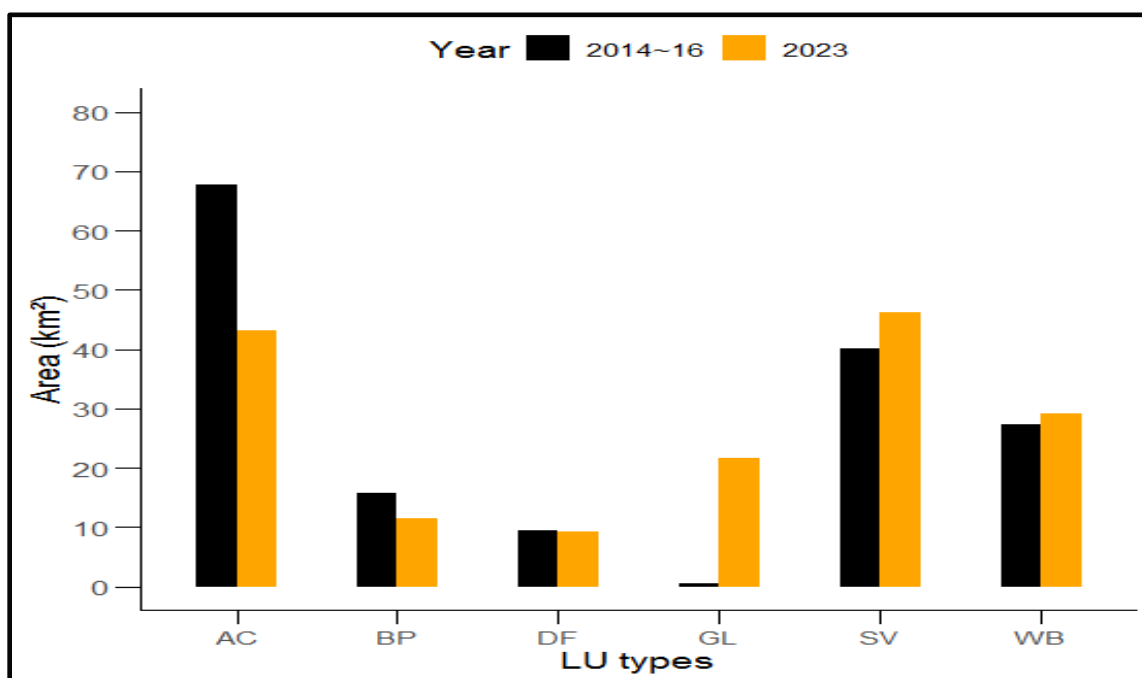


Figure 13. The types of land use in the Dinki watershed: agricultural land (AC), Built up (BP), Dense Forest (DF), Grazing land (GL), Slight vegetation (SV), Water body (WB).

Trends in Agricultural land in Dinki Watershed over 1994-2023

As the land use land cover change matrix between period 1 (1994 and 2014) indicated (Table 13 and Fig. 11C), the dominant LULC type, which is agricultural land, increased from 40% (65.64 km²) in 1994 to 42% (67.71 km²) in 2014. Although the agricultural land showed in the beginning study year, almost 40% (13.48 km²) of the area was converted into a water body, followed by built-up areas with an unchanged value of 32.93 km² and a changed value of 32.71 km² to different land use types. The observed increase (67.71 km²) in the first period (1994-2014) was due to the transformation of 9.77% (15.72 km²) of built-up, 5.92% (9.52 km²) Dense Forest, and 0.27% (0.44 km²) of grazing land into agricultural land (Table 13). However, the agricultural land showed an alarming decrease in the second period (from 2014 to 2023), which means it directly converted from 42% (67.71 km²) to 26.78% (43.10 km²), with a rate of 4.61km² declination. The rate of agricultural land decline has been 1.47 km² per year between 1994 and 2023 and 22.54 km² per year over the 30 years.

Dynamics of slight vegetation in the Dinki Watershed (1994-2023)

Next to the agricultural cropland, the slight vegetation covered the largest part of the Dinki Watershed landscape in all of the analysis periods. Even though the coverage of the slightly vegetated land in the Dinki Watershed was very small compared to the agricultural land, it showed a continuously significant increase. The largest vegetation coverage was recorded in 2023, which is 28.70% (46.18 km²), followed by 25% (40.18 km²) in 2014, and the smallest was computed in 1994, which is 16% (26.09 km²). The area under slight vegetation cover showed an alarming increase over the period under study, with the rate of expansion of 0.67km² per annum (Table 13, 14, 15, and Fig. 11C).

Decline of Dense Forest Land and Grazing Land in the Dinki Watershed (1994-2023)

Dense forest cover exhibited a continuous decline throughout the study period. In 1994, approximately 12% (19 km²) of the watershed was covered by Dense forest; by 2014, this had sharply decreased to 5.92% (9.52 km²), and by 2023, it further declined slightly to 5.79% (9.32 km²) (Table 13). Whereas grazing land was a major land cover type in the Dinki Watershed, particularly during the most recent period. Its largest extent was recorded in 2023, covering 26.78% (43.10 km²) of the watershed, followed by 7.56% (12.17 km²) in 1994, while the

smallest coverage was observed in 2014 at only 0.27% (0.44 km²). Among all LULC classes, grazing land exhibited the most pronounced expansion between 1994 and 2023, increasing at an average rate of 1.03 km² per year (Table 13 and Fig. 11). The exceptionally low grazing-land extent in 2014 reflects its highly fragmented and degraded condition, which also contributed to reduced class-level accuracy (Table 13) due to partial spectral overlap with slight vegetation and cropland, whereas the substantial expansion and improved class separability observed in 2023 confirm a genuine land-use transition rather than classification confusion.

Expansion of water bodies in Dinki Watershed (1994-2023)

Next to the grazing land covered water body, which is the headwater, is the largest part of the Dinki Watershed landscape in 2023 of the analysis periods, and also the most extensive coverage in 2014, next to slight vegetation. The largest water body coverage was recorded in 2023, which is 18.88% (29.25 km²). Over the 1994-2023 period, water bodies exhibited a moderate increase, expanding at an average rate of 0.42 km² per year (Table 13; Fig.11), and the observed expansion may be attributed to improved water resource management, natural recovery processes, and local restoration initiatives. According to seasonal and climatic variability, which can enhance water retention, this likely contributed to the gradual increase. Collectively, these factors explain the progressive growth in water body and headwater stream coverage over the past three decades.

Table 13. Temporal dynamics (1994-2023) of land use/land cover change in the Dinki Watershed (1994-2023).

LULC Class	Area						Net change (%)			Rate of change (km ² y ⁻¹)		
	1994		2014		2023		1994-	2014-	1994-	1994-	2014-	1994-
	Km ²	%	Km ²	%	Km ²	%	2014	2023	2023	2014	2023	2023
AL	65.64	40.79	67.71	42.08	43.10	26.78	2.07	-24.61	-22.54	0.04	-0.51	-1.30
BP	21.53	13.38	15.72	9.77	11.48	7.13	-5.81	-4.24	-10.05	-0.12	-0.09	-0.48
DF	18.93	11.76	9.52	5.92	9.32	5.79	-9.41	-0.20	-9.61	-0.19	0.00	-0.44
GL	12.17	7.56	0.44	0.27	21.59	13.41	-11.73	21.15	9.42	-0.24	0.44	0.04
SV	26.09	16.21	40.18	24.97	46.18	28.70	14.09	5.99	20.09	0.29	0.12	0.09

WB	16.56	10.29	27.34	16.99	29.25	18.18	10.78	1.91	12.69	0.22	0.04	0.05
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*P<0.01, per annual year (AY⁻¹), LULC, Agricultural Cropland (ACL), Built-Up Areas (BP), Dense Forest (DF), Grazing Land (GL), Slight Vegetation (SV), and Water Body (WB).

LULC Change Matrix of the Dinki Watershed (1994-2014)

The data reflects the LULC changes from 1994 to 2014, showing significant shifts in various classes. Agricultural land (AL) experienced a slight increase (+2.07 km²), indicating its stability and sustained usage over the years. On the other hand, slight vegetation (SV) and water bodies (WB) saw notable expansions (+14.09 km² and +10.78 km², respectively), highlighting potential restoration or land management efforts. These trends emphasize the dynamic nature of land use and the need for targeted policies to balance development and conservation (Table 14 and Fig. 11C).

Table 14. LULC change matrix between 1994 and 2014

year		2014						
	LU/LC Class	ACL	BP	DF	GL	SV	WB	GT
1994	Agricultural land	32.93	10.20	0.37	0.19	8.47	13.48	65.64
	Built up	11.78	2.97	0.44	0.11	3.66	2.57	21.53
	Dense Forest	3.19	0.48	6.30	0.02	8.57	0.37	18.93
	Grazing land	4.12	0.03	0.96	0.00	5.73	1.33	12.17
	Slight vegetation	12.69	1.22	1.42	0.10	9.37	1.29	26.09
	Water body	3.01	0.82	0.03	0.01	4.38	8.30	16.56
	Total	67.71	15.72	9.52	0.44	40.18	27.34	160.91
Area change (km²)		2.07	-5.81	-9.41	-11.73	14.09	10.78	-
Annual change rate (km²)		0.10	-0.29	-0.47	-0.59	0.70	0.54	-

ACL=agricultural cropland; BP=built-up areas; DF= Dense forest; GL=grazing land; SP=sparse vegetation; WB=water bodies, GT= Grand total

Land use land cover matrix of the Dinki Watershed (2014-2023)

Agricultural land (ACL) declined drastically, from 67.71 km² in 2014 to 43.10 km² in 2023, a reduction of -24.12 km², likely due to land conversion for other uses. Slight vegetation (SV) increased slightly, from 40.18 km² to 46.18 km² (+6.00 km²), reflecting a modest recovery or expansion. Similarly, water bodies (WB) experienced a small increase, from 27.34 km² to 29.25

km² (+1.91 km²), suggesting better water resource management (Table 15 and Fig 11f). These changes illustrate a shift in land use priorities, with notable losses in agricultural land balanced by minor gains in vegetation and water bodies.

Table 15. LULC change matrix between 2014 and 2023

Year		2023						
2014	LU/LC Classes	ACL	BP	DF	GL	SV	WB	GT
	Agricultural land	27.62	3.69	1.51	15.10	13.39	6.40	67.71
	Built up	5.75	2.08	0.04	1.67	4.57	1.60	15.71
	Dense Forest	0.32	0.18	4.51	0.09	3.21	1.21	9.52
	Grazing land	0.04	0.02	0.00	0.17	0.04	0.03	0.44
	Slight vegetation	21.49	1.24	3.11	1.56	21.49	7.77	40.18
	Water body	3.46	4.27	0.15	2.99	3.46	12.23	27.34
	Total (GT)	43.10	11.48	9.32	21.59	46.18	29.25	160.90
Area Change (km²)		-24.62	-4.23	-0.20	21.15	6.00	1.91	-
Annual change rate (km²)		-2.46	-0.42	-0.02	2.11	0.60	0.19	-

4.1.7. Status and Dynamics of Ecosystem Services in Dinki Watershed (1994- 2023)

4.1.7.1. Accuracy Assessment

Accuracy assessment was conducted using an error (confusion) matrix to evaluate the reliability of the image classifications. Overall classification accuracy increased progressively from 86.1% in 1994 to 91.67% in 2014 and further to 94.4% in 2023, indicating a consistent improvement in classification performance over time. Correspondingly, the Kappa coefficients rose from 0.83 (1994) to 0.90 (2014) and 0.93 (2023), all exceeding the 0.80 threshold and demonstrating strong agreement between the classified maps and reference data (Table 16). Furthermore, the decrease in built-up areas near Zego reflects local population shifts, while the increase in water bodies results from intermittent dry-season rainfall. High classification accuracies (user accuracies 100% for built-up and water bodies) confirm these trends are reliable and not due to misclassification.

Table 16. Accuracy assessment (%) of the LULC maps (1994-2023).

LU/LC Class	1994		2014		2023	
	Producer	User	Producer	User	Producer	User
Agricultural land	100.0	100	100.00	100.0	100.0	100.0
Built up (BP)	85.71	100	81.71	100.0	78.21	100.0
Dense Forest (GL)	63.64	100	77.78	100.0	87.5	87.50
Grazing land (SV)	100.0	80	20.00	55.5	83.33	100.0
Sparse vegetation (SV)	100.0	20	100.0	66.67	100.0	85.71
Water body (WB)	98.00	100	100.0	100.0	100.0	100.0
Overall accuracy	86.11		91.67		94.44	
Kappa Coefficient	0.830		0.900		0.930	

PA= Producer accuracy (%), UA= User accuracy (%), OA = Overall accuracy (%), KC= Kappa coefficient

4.1.7.2. *Estimated Ecosystem Service Values*

The estimation of ecosystem service values (ESVs) for each LULC category was conducted using Eq. 6. In 1994, the dominant contributors to ecosystem services were water bodies (US\$134.15 thousand), sparse vegetation (US\$25.74 thousand), Dense forest (US\$18.68 thousand), and agricultural cropland (US\$18.17 thousand). Across all LULC types, ESVs ranged from US\$3.56 thousand for grazing land, the lowest, to US\$134.15 thousand for water bodies, the highest (Table 17). In 2014 and 2023, water bodies continued to provide the highest ESV, valued at US\$221.54 thousand and US\$237.00 thousand, respectively. Sparse vegetation also exhibited an increase in ESV, rising to US\$39.65 thousand in 2014 and US\$45.56 thousand in 2023, reflecting incremental gains over time. Over the 1994-2023 period, water bodies contributed most significantly to total ESV, increasing from 16.77% to 29.62%, a gain of more than 10%. Sparse vegetation followed, increasing moderately from 3.22% to 5.69%, while grazing land ranked third. Agricultural cropland consistently recorded the lowest ESV throughout the study period.

Table 17. Estimated ESVs by LULC Category in the Dinki Watershed between 1994 and 2023

LU classes	ESV (US\$ 10 ³)					
	1994	%	2014	%	2023	%
Agricultural crop land	18.17	2.27	18.74	2.34	12.60	1.58
Built up	0.00	0.00	0.00	0.00	0.00	0.00
Dense Forest	18.68	2.33	9.39	1.17	9.19	1.15
Grazing land	3.56	0.44	0.13	0.02	5.97	0.75

Sparse vegetation	25.74	3.22	39.65	4.96	45.56	5.69
Water body	134.17	16.77	221.54	27.69	237.00	29.62
Total	200.32	25.04	289.46	36.18/+89/	310.33	+110/38.79/

ESV=ecosystem service value; %= percent change

4.1.7.3. Dynamics of Individual and Total Ecosystem Services in Dinki Watershed (1994-2023)

The trends of individual ecosystem service value functions (ESVf) over the entire study period (1994-2023) indicated a general upward trend in the overall value. The most prominent ecosystem services were water regulation (US\$399.33 thousand), water supply (US\$156.05 thousand), water treatment (US\$56.84 thousand), erosion regulation (US\$38.42 thousand), nutrient cycling (US\$27.70 thousand), genetic resources (US\$6.35 thousand), recreation (US\$5.77 thousand), and climate regulation (US\$2.44 thousand), among the 17 ecosystem services assessed. Water regulation and water supply had the highest individual values during 1994-2023.

The services that consistently decreased throughout the study period were food production (US\$43.01 thousand), raw materials (US\$15.64 thousand), and soil formation (US\$2.65 thousand), while the lowest values of cultural services (US\$6.07 thousand) were observed in 1994 and 2023. All other ecosystem services showed an upward trend, possibly due to decreasing anthropogenic pressures on the watershed and less intensity of landscape management actions, such as the Green Legacy actions, that reduced landscape disturbance and improved ecosystem services.

In total, an ESV of US\$767.49 was delivered by the Dinki Watershed in the four main categories. 2023 recorded the highest total ESV (US\$297.96 thousand). Regulating services contributed the most (US\$502.03 thousand), followed by provisioning services (US\$221.04 thousand), supporting services (US\$38.35 thousand), and cultural services (US\$6.07 thousand) during 1994-2023 (Table 18). Increased regulating services were primarily linked to the improvement in land use through the reduction of degraded areas and the increase in sparse vegetation from the watershed management interventions, including the Green Legacy projects, which significantly increased the overall ecosystem service value. Natural habitat, including

Wof-Washa Forest, which is important for climate regulation and other major ecosystem functions, is essential for providing a variety of ecosystem services and must be preserved in terms of integrity and extent to ensure their long-term provision.

Table 18. Estimated ecosystem service values (ESV) and their changes by LULC types between 1994 and 2023 (US\$ thousand).

Ecosystem Services	ESV Change (US\$ thousands)			Total ESV (US\$ thousands)	ESV change (US\$ thousands)	Proportion (%)
	1994	2014	2023			
Provisioning services						
Water supply	35.41	58.28	62.36	156.05	26.95	76.09
Food production	18.20	17.96	15.69	50.85	-2.51	-23.84
Raw materials	5.93	6.02	3.95	15.64	-1.98	-30.34
Genetic resources	2.05	2.04	2.28	6.35	0.23	11.65
Subtotal	61.59	84.29	84.27	228.88	22.68	33.56
Regulating services						
Water regulation	90.46	149.16	159.71	399.33	138.49	76.55
Water treatment	14.33	18.59	23.92	56.84	19.18	66.95
Erosion regulation	13.38	14.69	17.45	45.52	6.93	33.43
Biological control	2.86	1.64	1.51	5.00	-0.69	-18.64
Gas regulation	0.70	0.68	1.06	2.44	0.72	51.33
Subtotal	121.73	184.77	203.64	509.14	164.63	69.33
Supporting Services						
Disturbance regulation	0.23	0.25	0.28	0.75	0.10	23.27
Nutrient cycling	10.30	12.67	12.83	34.80	3.86	24.27
Pollination	1.55	1.32	1.78	4.65	0.47	15.01
Soil formation	2.70	3.09	4.19	8.90	-1.90	-60.43
Habitat/refugia	0.78	0.86	0.96	2.60	0.36	23.27
Subtotal	15.56	18.18	20.04	51.70	2.89	11.65
Cultural services						
Recreation	1.36	2.12	2.28	5.77	1.85	68.15
Cultural	0.09	0.10	0.11	0.30	0.04	23.27
Sub total	1.45	2.22	2.40	6.07	1.89	65.36
Total	200.32	289.46	310.33	800.11	213.58	59.86

4.1.7.4. Dynamics of Ecosystem Service Values in the Dinki Watershed (1994-2023)

Overall, the analysis of the ecosystem service value (ESV) indicated a significant rise for the three assessment periods: 1994-2014, 2014-2023, and the study period (1994-2023). Total ESV for the first period (1994-2014) rose by some US\$89.14 thousand, which represents 40.51% of the baseline value in the year 1994. Agricultural land, Dense forest, and grazing land, however, experienced a decrease in ESVs of US\$0.57 thousand, 9.28 thousand, and 3.43 thousand, respectively. Total ESV increased by a further US\$20.87 thousand (or 9.49%) during the second period (2014-2023). The total ESV rose by US\$119.01 thousand (50%) over the entire study period (1994-2023), which is 10% more than it did in the first period.

Except for agricultural land, Dense forest, and built-up land, all other land-use categories exhibited notable increases in ESVs throughout the study period (Fig.15). Grazing land in particular recorded a significant rise of approximately US\$19.82 thousand. Similarly, sparse vegetation and water bodies increased by about US\$19.82 thousand and US\$102.82 thousand, respectively, relative to their values in 1994-2014 (Fig.14).

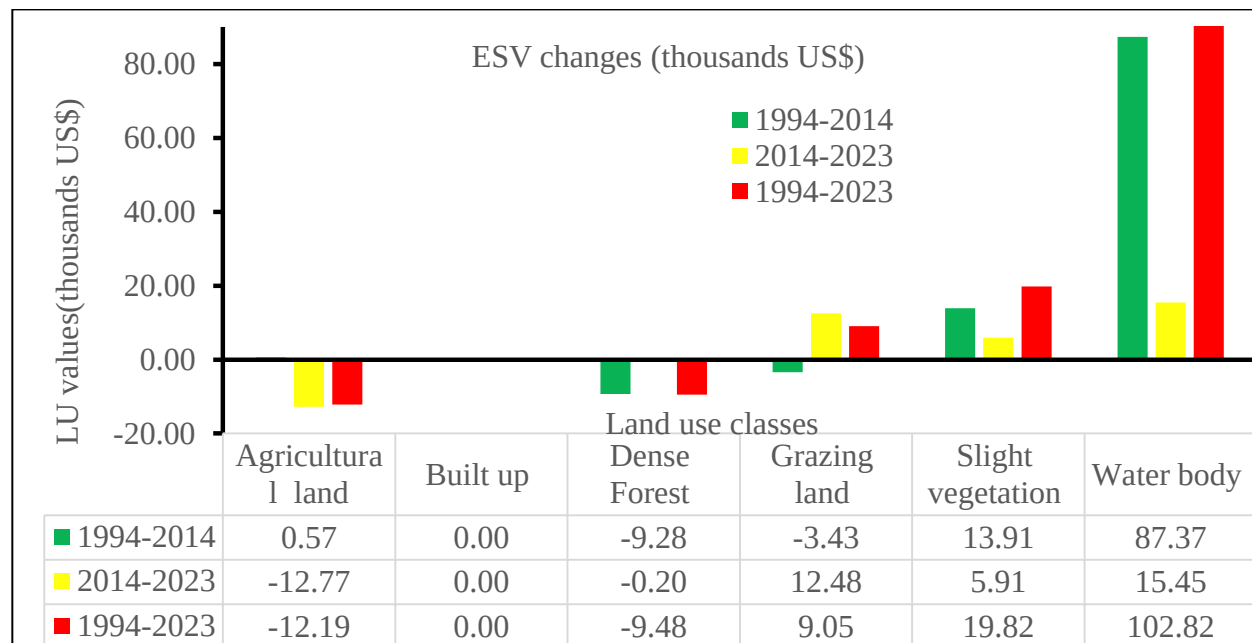


Figure 14. Spatial distribution of ecosystem service values (ESVs) in US\$/km²/year across the study landscape for the years 1994, 2014, and 2023.

4.1.7.5. Impact of LULC Changes on Ecosystem Service Values

The changes in ecosystem services value were also quite different for each LULC type, with their distinct contributions to the area covered and ESVs during the study periods (Fig.15). The overall trend was that agricultural land (AL), built-up areas (BA), and Dense forest (DF) decreased at different rates and consistently. Specifically, the area of agricultural land decreased by over 20 km² from around 40.79% of the landscape in 1994 to 15.41% in 2023. Other built-up areas also went down from approximately 13.38% to 7.13%, and Dense forest from 11.76% to 5.79% during the period. Even with these decreases in the area, the total ESV of the watershed did not show any significant decrease, but rather showed a significant increase. For instance, the ESV associated with water bodies increased from 10.29% in 1994 to 18.18% in 2023. Similarly, the ESV of sparse vegetation increased from 3.22% to 4.96%, and the ESV of grazing lands grew from 0.44% to 1.58% during the study period.

There were some significant increases, such as for water bodies, which rose from 10.29% in 1994 to 18.18% in 2023. Similarly, there were positive trends observed for ESV in sparse vegetation with an increase from 3.22% to 4.96%, and sparse grazing land with an increase from 0.44% to 1.58%. The major contributor to the overall increase in ESVs throughout the study area was the expansion of water bodies and the absence of vegetation. They contributed significantly to the increase of net total ESVs by US\$110.01 thousand from 1994 to 2023, which amounted to an ESV increase of US\$134.17 thousand and US\$237 thousand, respectively.

Agricultural land, on the other hand, showed a negative trend in area, with its ESV falling from US\$18.17 thousand (2.27%) in 1994 to US\$5.97 thousand (0.75%) in 2023. However, when expressed in relative terms, the contribution of agricultural land ESV to the total markedly increased from 25.04% in 1994 to 38.79% in 2023, suggesting that the value of ecosystem services per unit area intensified despite the reduction in cropland extent. Overall, the observed trends in ESVs resulting from LULC dynamics remained consistent with estimates derived using the global value coefficients.

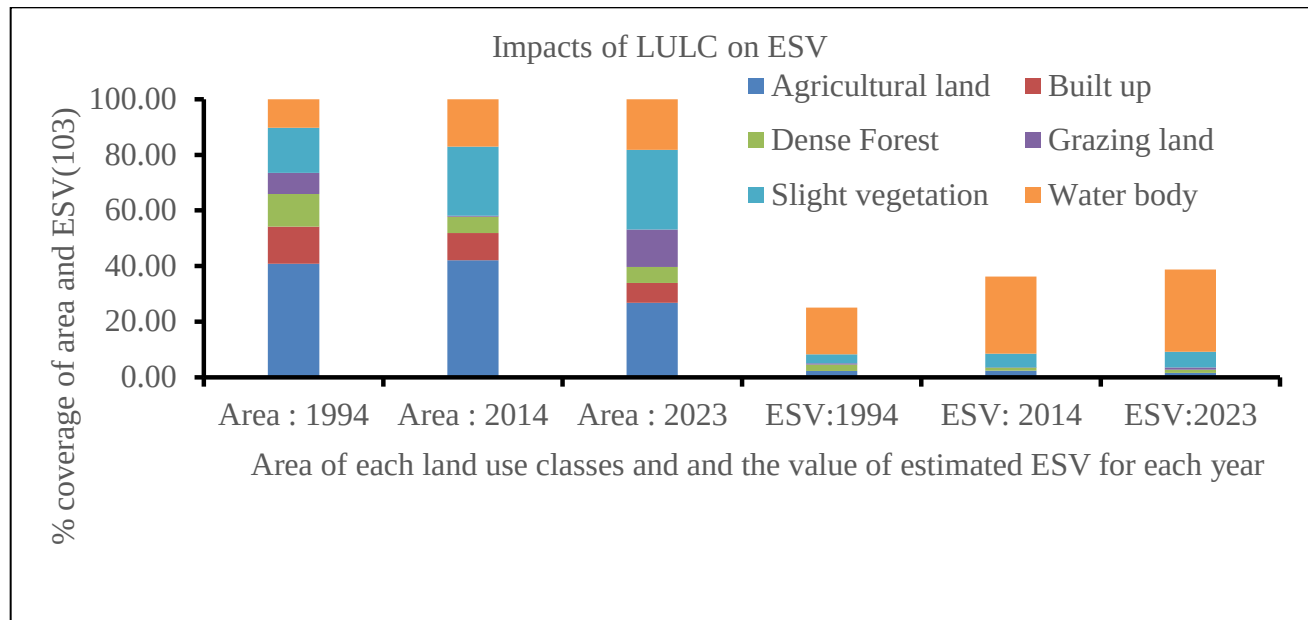


Figure 15. Impacts of LULC changes on ecosystem service values across the study periods.

4.1.7.6. Sensitivity Analysis of Ecosystem Service Values

The coefficient of sensitivity (CS) was below one for all LULC types except water bodies and sparse vegetation, indicating that the estimated ecosystem service values (ESVs) were generally inelastic and less sensitive to changes in conservation value coefficients (Fig. 16). Water bodies had the highest CS values, indicating the highest influence on total ESVs, while agricultural land had the lowest CS value (0.19), which means it had the least influence on the provision of ecosystem services because of its decreasing coverage. The ecological importance of these areas of sparse vegetation and water bodies was highlighted by their consistently high CS values throughout the study period and their sensitivity to valuation changes.

The values of CS for grazing land were variable over time, and Dense forest and agricultural land experienced gradual decreases. Some LULC types showed very strong effects on total ecosystem service provision, with the maximum CS value reached at 1.67 (Fig. 16). The sensitivity analysis has been performed and confirms the robustness and validity of the valuation methods used in the Dinki Watershed, because of the CS values below one, which means that the estimates of ESV are reliable and inelastic.

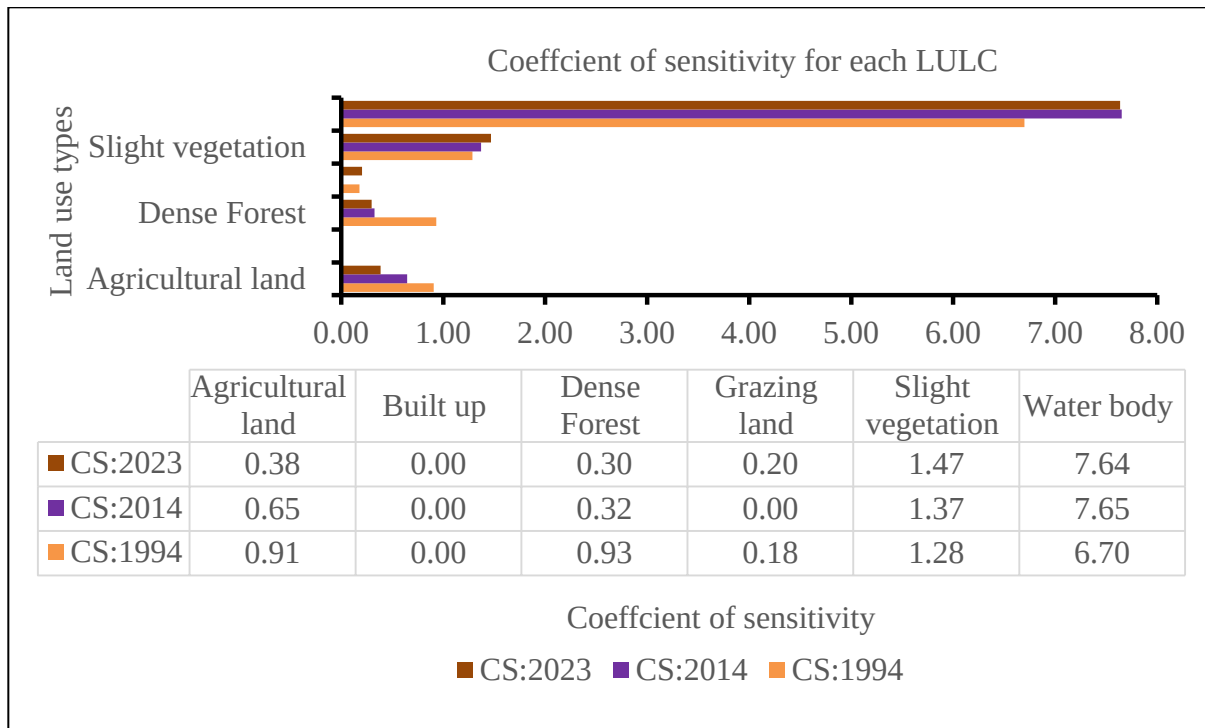


Figure 16. Coefficient of sensitivity (CS) of ecosystem service values for each LULC type from 1994 to 2023.

4.1.8. Community Perceptions of LULC Changes

Key informants and FGD participants demonstrated strong knowledge of the Dinki Watershed. The most frequently discussed themes were watershed characteristics (15.6% of codes; 46.7% of cases) and trends in watershed status (16.9% of codes; and mentioned 66.7% of cases), reflecting recognition of changes such as expanding water bodies and declining agricultural practices. Degraded areas were mentioned less frequently (3.9% of codes; 20% of cases), partly due to the influence of Green Legacy initiatives that shifted attention toward ecosystem service improvement. Concerns about watershed management coordination accounted for 9.1% of codes (40% of cases), while solutions to driving forces of change emerged as a major theme (18.2% of codes; 60% of cases) (Table 19). Overall, local perceptions closely aligned with the biophysical evidence from remote sensing. As shown in Table 19, 46.7% of households recalled that the watershed was previously dominated by agricultural croplands. Currently, 66.7% of respondents observed declining farmland and increasing vegetation and stream/rivers. Participants also emphasized long-

term declines in forests, grazing lands, and shrublands. These perceptions from KIIs and FGDs are consistent with the LULC changes detected through satellite image classification (Table 11-15; Fig. 11).

Table 19. Key Themes Identified in the Dinki Watershed

Theme category	Code	Count	% of codes	Cases	% Cases
Characterization of the Dinki watershed	Characterization (Th 1)	12	15.6	7	46.7
Benefits of Dinki Watershed	Ecosystem service (Th 2)	17	22.1	7	46.7
Trends in the status of Dinki Watershed	Trends (Th 3)	13	16.9	10	66.7
Driving force for Dinki Watershed	Causes (Th 4)	11	14.3	7	46.7
More Degraded area	Vulnerable (Th 5)	3	3.9	3	20
Status of Coordination	Coordination (Th 6)	7	9.1	6	40
Solutions	Solutions for driving forces (Th 7)	14	18.2	9	60

Serv.=Services; Th=Theme. Codes: number of times a particular code or category was used in all the text segments. % of codes: percentage of coding references that are of a particular code or category. Cases: number of different sources (e.g., interviews, FGDs, participants) where the code can be found at least once. % of cases: percentage of total cases in which the code is identified.

4.1.8.1. Local Communities' Perceptions of LULC Changes and Key Drivers Over Time

Indicators of ecosystem service changes in the Dinki Watershed, such as forest cover, agricultural land, grazing land, stream water, and vegetation products, were identified through key informant interviews and focus group discussions. The findings were also supported by GIS-based land use classification, which showed a significant reduction in forest area from 19km² in 1994 to 9.32km² in 2023. This finding is also aligned with local perceptions, as both participants in the KIIS and FGD noted significant decreases in forests over time. Respondents noted that, aside from initiatives introduced in the past two years, no major reforestation or plantation efforts have been undertaken since the Derg regime. The drivers of forest degradation identified included household demand for

construction materials, clearing to deter crop-raiding by apes and monkeys, historical agricultural expansion, and increased grazing pressure associated with rising cattle populations. Other land use categories like agricultural crop land have declined in recent years, while water bodies have expanded slightly, a change attributed partly to the intensification of irrigation in the lower catchments of the watershed (Fig.17).

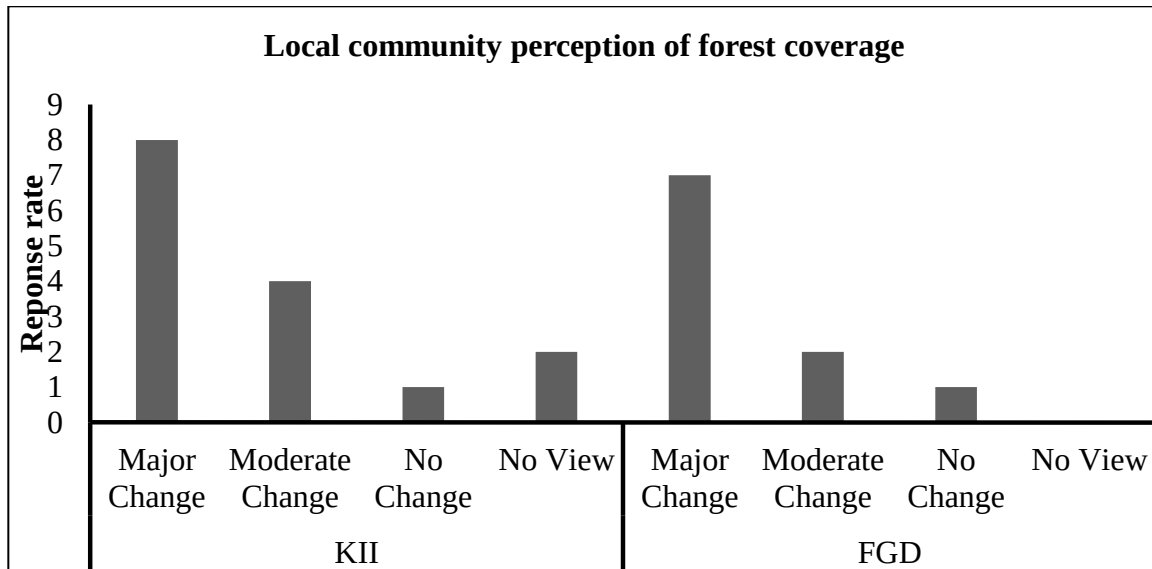


Figure 17. Local Community Perceptions of LULC Changes from 1994 to 2023

4.1.9. Ecological Health Index (EHI) model

The analysis of the EHI model index for the years 2016 and 2023 reveals a significant difference between the two years, with an increase in the EHI from 1.40 in 2016 to 2.05 in 2023. The statistical significance of this difference is supported by a p-value of 0.02, indicating a 98% confidence level in the observed trend. Additionally, the R^2 value of 0.85 suggests that 85% of the variation in the EHI model index can be explained by the factors considered, demonstrating a strong correlation between land use and ecological health in the study area. Furthermore, the percentage change in EHI from 2016 (1.40) to 2023 (2.05) is 46.43%, while the percentage change in EHI with LULC is 25.00% (Fig. 18). This discovery reinforces how land use can affect environmental health and the need to consider these elements when evaluating ecosystems in the future.

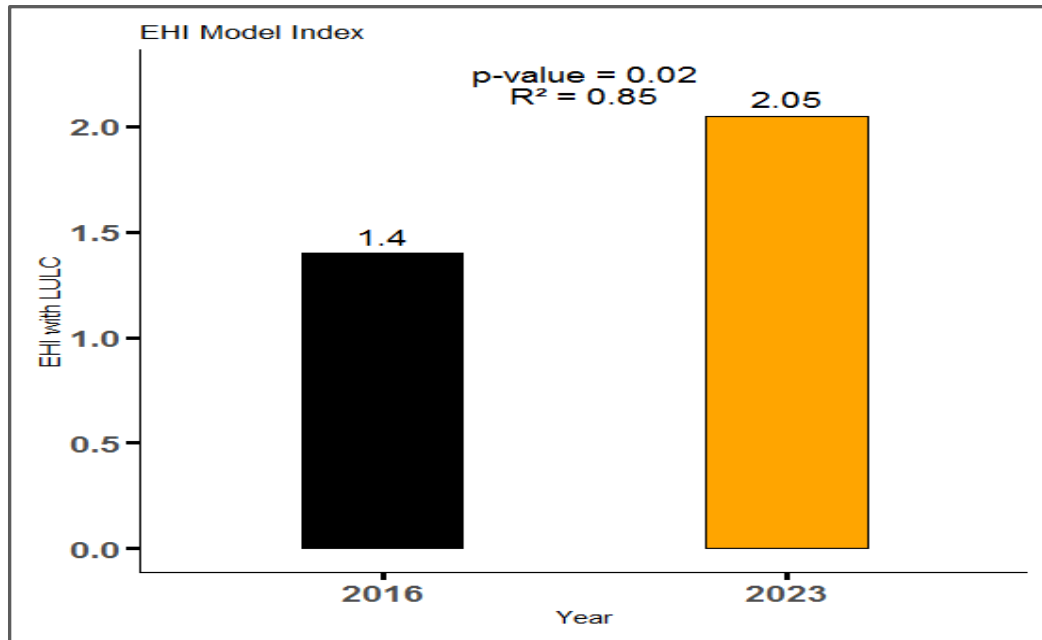


Figure 18. Ecosystem health indicator for Dinki watershed

4.2. Spatiotemporal Variation in Sensitive Macroinvertebrate Assemblages in the Dinki Watershed

4.2.1. The spatial variations of environmental and Physicochemical parameters

The PCA for the 2016 sampling period revealed that Axis 1 explained 29% of the variance ($R^2 = 0.09$), while Axis 2 accounted for 21.2% ($R^2 = 0.09$). Most of the variables were primarily related to the Gedamoch sites (MK13 - GD18) and Dense sites (DF21 - DF22). In contrast, impacted sites like Dinki (DK1-DK5) and Zego (MR6, KW7-KW9) were mainly linked with EC, Twater, and DO. Nutrient-related variables (PO_4^{3-} , NO_3^- , TP, and Turbidity) were more closely associated with Zego (ML10-ML12) and Dense (AW24) (Asmamaw *et al.*, 2019). In 2023, PCA results showed that Axis 1 explained 33.1% ($R^2 = 0.09$) and Axis 2 explained 27.3% ($R^2 = 0.08$) of the variance. Environmental variables such as HVAS, Discharge(Q), and DO were associated with the reference site Gedamoch (MK13-GD18) and sites undergoing rehabilitation in the Dense region (LM19-DF25). Meanwhile, other variables, specifically nutrients (PO_4^{3-} , NO_3^- , TN, TP), EC, and Twater, were strongly associated with Dinki (DK1-DK5) and Zego (MR6-ML12) sites (Figure 18). Habitat visual assessment score (HVAS) and discharge (Q) were contributing to the macroinvertebrate abundance and diversity (Fig. 19).

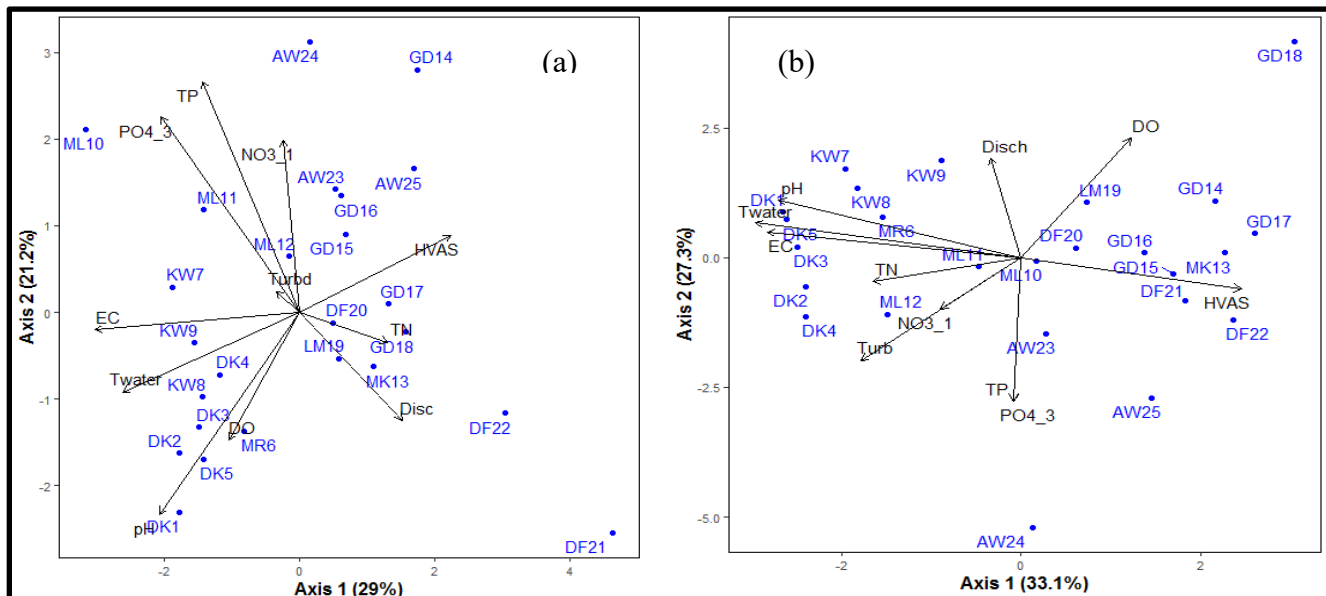


Figure 19. The principal component analysis (PCA) environmental-sample biplot in Dinki watershed headwater streams, Ethiopia. The environmental parameters (black arrow) and sampling points were represented in blue points in 2016 (a) and 2023 (b).

On the other hand, the one-way ANOVA result showed that, in 2016 (Asmamaw *et al.*, 2019), the environmental variables such as HVAS, water temperature, electrical conductivity, and discharge showed significant differences among the sampling sites. HVAS and water temperature varied significantly ($p < 0.05$), electrical conductivity showed a stronger difference ($p < 0.01$), while discharge exhibited the most significant variation across sites ($p < 0.001$) (Table 20).

Whereas in 2023, the one-way ANOVA result showed that there were significant differences observed among sites for HVAS, pH, dissolved oxygen, water temperature, electrical conductivity, and discharge. HVAS and dissolved oxygen showed moderate variation ($p < 0.05$), while pH and electrical conductivity exhibited stronger differences ($p < 0.01$). Water temperature and discharge demonstrated the most significant variation across sites ($p < 0.001$), reflecting clear spatial heterogeneity in habitat condition, ionic concentration, thermal regime, and flow characteristics within the watershed (Table 20).

Table 20. Spatial variations in water physicochemical parameters by mean values $\pm$ standard deviation in the 2016 and 2023 sampling sites computed using a one-way ANOVA (Asmamaw *et al.*, 2019).

Year	Study Sites	HVAS	pH	DO (mg/L)	Twater	Tur. (NTU)	EC (μ S/cm)	TN (mg/L)	TP (mg/l)	Disc. (m^3/s)
2016	Dinki	3.89 $\pm$ 0.23	7.58 $\pm$ 0.13	7.92 $\pm$ 0.14	20.42 $\pm$ 1.11	6.55 $\pm$ 2.82	293.50 $\pm$ 60.21	20.94 $\pm$ 5.49	0.95 $\pm$ 0.22	0.04 $\pm$ 0.01
	Zego	6.33 $\pm$ 1.54	7.29 $\pm$ 0.48	7.29 $\pm$ 0.78	21.38 $\pm$ 1.16	2.67 $\pm$ 0.78	368.23 $\pm$ 74.50	22.54 $\pm$ 11.05	1.24 $\pm$ 0.51	0.01 $\pm$ 0.01
	Gedamoch	11.84 $\pm$ 3.48	6.96 $\pm$ 0.41	7.64 $\pm$ 0.24	17.67 $\pm$ 1.29	3.99 $\pm$ 1.86	211.65 $\pm$ 67.69	21.48 $\pm$ 5.42	1.27 $\pm$ 0.71	0.04 $\pm$ 0.01
	Dense	7.68 $\pm$ 1.73	6.91 $\pm$ 0.40	6.90 $\pm$ 0.43	18.92 $\pm$ 1.72	6.10 $\pm$ 3.35	139.66 $\pm$ 41.12	27.57 $\pm$ 18.18	1.12 $\pm$ 0.73	0.03 $\pm$ 0.01
	F-value	5.94*	2.21	1.08	4.45*	5.71	7.96**	1.25	1.13	16.57***
2023	Dinki	7.47 $\pm$ 2.60	8.17 $\pm$ 0.12	8.49 $\pm$ 1.00	24.45 $\pm$ 0.87	44.06 $\pm$ 32.08	330.60 $\pm$ 44.06	4.45 $\pm$ 2.98	0.26 $\pm$ 0.21	0.88 $\pm$ 1.07
	Zego	10.64 $\pm$ 3.89	8.03 $\pm$ 0.17	10.06 $\pm$ 1.28	19.49 $\pm$ 1.67	38.47 $\pm$ 53.71	204.59 $\pm$ 30.03	4.91 $\pm$ 5.80	0.18 $\pm$ 0.14	0.37 $\pm$ 0.54
	Gedamoch	13.15 $\pm$ 1.77	7.69 $\pm$ 0.18	18.20 $\pm$ 11.21	15.92 $\pm$ 0.54	19.66 $\pm$ 3.68	134.25 $\pm$ 11.78	5.64 $\pm$ 4.16	0.19 $\pm$ 0.14	0.40 $\pm$ 0.34
	Dense	11.30 $\pm$ 4.52	7.59 $\pm$ 0.22	8.48 $\pm$ 2.74	15.91 $\pm$ 1.29	20.15 $\pm$ 4.65	121.14 $\pm$ 30.33	5.56 $\pm$ 3.14	0.31 $\pm$ 0.36	0.17 $\pm$ 0.17
	F-value	3.57*	11.35**	3.13*	178.26***	2.45	9.02**	0.74	0.3	19.45***

* $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$

Furthermore, on the other analysis, the results of the repeated measures ANOVA (rmANOVA) revealed that the mean values of approximately 97% of the environmental variables were statistically significant ($p < 0.001$) between the sampling sites in the years 2016 and 2023. Notably, HVAS, pH, dissolved oxygen, water temperature, turbidity, electrical conductivity, NO_3^- , TP, PO_4^{3-} , and discharge exhibited highly significant spatial differences ($p < 0.001$). Total nitrogen (TN) also varied significantly between sites across years ($p < 0.01$). These findings highlight strong spatial variability in the physicochemical characteristics of the Dinki watershed (Table 21).

Table 21. rmANOVA Summary statistics of environmental variables in the sampling sites of 2016 (Asmamaw *et al.*, 2019) and 2023.

Year	Study Site	Environment										
		HVAS	pH	DO (mg/L)	Twater	Tur. (NTU)	EC ($\mu\text{S}/\text{cm}$)	TN (mg/L)	NO_3^{-1} (mg/L)	TP (mg/L)	PO_4^{-3} (mg/L)	Disc. (m^3/s)
2016	Dinki	3.88±0.23	7.58±0.13	1.73±0.14	0.42±0.11	0.55±0.83	171.73±15.59	20.94±5.48	2.63±1.30	0.95±0.21	1.06±0.40	0.03±0.01
	Zego	6.33±1.54	7.29±0.48	1.71±0.78	0.39±0.05	0.67±0.87	167.57±30.88	22.54±11.05	3.32±1.08	1.24±0.51	1.20±0.49	0.01±0.01
	Gedamoch	11.84±3.48	6.95±0.41	1.84±0.24	0.38±0.29	0.59±0.88	122.65±45.36	21.48±5.42	1.95±0.74	1.17±0.40	1.08±0.70	0.03±0.01
	Dense	7.68±1.73	6.91±0.40	0.90±0.43	0.31±0.06	0.10±3.35	77.40±17.54	27.56±18.19	2.67±0.83	1.12±0.74	0.94±0.59	0.03±0.07
2023	Dinki	7.47±2.59	4.45±2.98	1.07±0.34	0.29±0.36	0.95±1.10	293.5±60.22	8.02±0.12	1.49±0.99	112.39±25.93	19.49±1.67	0.88±0.81
	Zego	10.64±3.89	4.91±5.79	0.62±0.45	0.19±0.14	0.53±0.42	204.59±30.03	8.17±0.17	2.06±1.28	143.53±28.78	15.91±1.29	0.36±0.65
	Gedamoch	13.15±4.77	5.63±4.16	1.87±0.41	0.17±0.14	0.57±0.43	134.25±11.78	7.69±0.17	1.20±2.1	127.93±18.00	15.91±0.55	0.40±0.08
	Dense	11.30±4.52	5.55±3.13	1.28±0.17	0.27±0.21	0.81±0.64	121.14±30.34	7.59±0.22	1.48±2.73	105.38±34.91	24.45±0.87	0.37±0.21
F-Value		118.7***	84.16***	147.46***	107.41***	135.46***	163.05***	38.24**	82.77***	65.63***	42.22***	3.77**

* $P < 0.05$, ** $P < 0.01$, *** $P < 0.001$, 2016 data were collected from (Asmamaw *et al.*, 2019, 2021)

4.2.2. Temporal variations in Environmental and physicochemical parameters

The results of the paired test showed that physicochemical parameters, such as turbidity, pH, total nitrogen (TN), nitrate (NO_3^{-1}), and total phosphorus (TP), were statistically significant ($P < 0.0001$) between the dry and wet seasons in the 2016 sampling periods. Likewise, pH, water temperature (Twater), TN, NO_3^{-1} , and stream discharge were statistically significant ($P < 0.0001$) between the dry and wet seasons in the 2023 sampling periods (Table 22). Likewise, there were statistically significant ($p < 0.05$) variations in almost all environmental variables between the 2016 and 2023 wet and dry sampling seasons (Appendix I), indicating considerable temporal variations in environmental parameters.

Table 22. Paired t-test results of environmental variables by mean values $\pm$ Standard deviation between the dry and wet sampling seasons in both the 2016 and 2023 sampling years.

Variables	2016_dry	2016_Wet	t-value	2023_dry	2023_Wet	t-value
HVAS	7.91 $\pm$ 1.76	6.96 $\pm$ 1.73	1.92	11.2 $\pm$ 3.01	11.57 $\pm$ 3.38	-0.41
pH	6.87 $\pm$ 0.32	7.51 $\pm$ 0.39	-6.34***	7.73 $\pm$ 0.15	8.00 $\pm$ 0.19	-5.58***
DO (mg/L)	7.42 $\pm$ 0.40	7.46 $\pm$ 1.34	-0.14	8.66 $\pm$ 1.63	13.96 $\pm$ 14.48	-1.82
Twater	19.33 $\pm$ 1.30	19.87 $\pm$ 1.91	-1.17	18.45 $\pm$ 1.02	19.43 $\pm$ 1.17	-3.16***
Tur. (NTU)	20.41 $\pm$ 2.49	14.49 $\pm$ 2.49	8.41***	24.11 $\pm$ 37.88	19.06 $\pm$ 9.19	0.65
EC (μ S/cm)	262.26 $\pm$ 59.32	262.81 $\pm$ 54.37	-0.03	182.06 $\pm$ 27.80	194.68 $\pm$ 38.39	-1.33
TN (mg/L)	16.21 $\pm$ 13.55	30.06 $\pm$ 6.52	-4.60***	10.17 $\pm$ 7.99	0.10 $\pm$ 0.05	6.30***
NO ₃ ⁻¹ (mg/L)	5.78 $\pm$ 2.39	0.52 $\pm$ 0.08	10.99***	1.99 $\pm$ 0.56	0.36 $\pm$ 0.13	14.18***
TP (mg/L)	0.69 $\pm$ 0.39	1.6 $\pm$ 0.69	-5.74***	0.31 $\pm$ 0.34	0.16 $\pm$ 0.08	2.15**
PO ₄ ⁻³ (mg/L)	0.98 $\pm$ 0.48	1.16 $\pm$ 0.54	-1.25	0.16 $\pm$ 0.95	0.48 $\pm$ 0.25	-1.63
Disc. (m ³ /s)	0.03 $\pm$ 0.01	0.03 $\pm$ 0.01	0.00	0.02 $\pm$ 0.16	0.71 $\pm$ 0.89	-3.82***

***P<0.001, **P<0.05; **Note:** 2016 environmental data were sourced from (Asmamaw *et al.*, 2019 & 2021).

On the other hand, the results of the repeated measure Analysis of Variance (rmANOVA) indicated that all environmental variables were statistically significant ($p<0.05$) in the 2016 and 2023 sampling periods (Table 23), indicating Interannual variation in environmental parameters. The mean values of variables such as HVAS, DO, and discharge showed improvements in 2023 over the 2016 sampling periods. Whereas the mean values of water temperature, electrical conductivity, and most nutrients were lower in 2023 than in the 2016 sampling periods. However, it might be the impact of rainfall-induced surface runoff occurring a few days before the sampling periods in 2023 that might have caused an increased turbidity value, unlike other environmental parameters.

Table 23. Repeated measure ANOVA of environmental variables by mean values $\pm$ Standard deviation between the 2016 and 2023 sampling periods.

Interannual variation in environmental variables			
Environment metrics	2016	2023	F-value
HVAS	7.43 $\pm$ 1.74	11.39 $\pm$ 3.19	14.84***
pH	7.19 $\pm$ 0.36	7.87 $\pm$ 0.17	10.52***
DO (mg/L)	7.44 $\pm$ 0.40	11.31 $\pm$ 6.55	18.43***
Twater	19.60 $\pm$ 1.32	18.94 $\pm$ 1.09	13.43***
Tur. (NTU)	4.82 $\pm$ 2.20	30.58 $\pm$ 23.53	16.93***

EC ($\mu\text{S}/\text{cm}$)	262.53 $\pm$ 56.84	188.37 $\pm$ 33.09	20.83***
TN (mg/L)	23.13 $\pm$ 10.03	5.16 $\pm$ 4.02	4.78**
NO ₃ ⁻¹ (mg/L)	3.15 $\pm$ 1.24	1.18 $\pm$ 0.35	10.35***
TP (mg/L)	1.15 $\pm$ 0.54	0.23 $\pm$ 0.21	8.2***
PO ₄ ⁻³ (mg/L)	1.07 $\pm$ 0.55	0.72 $\pm$ 0.65	5.28***
Disc. (m ³ /s)	0.03 $\pm$ 0.01	0.45 $\pm$ 0.53	1.22**

P<0.01, *P<0.001; **Note:** 2016 environmental data were sourced from (Asmamaw *et al.*, 2019 & 2021).

The spatial variation in habitat condition was quantitatively evaluated using the Habitat Visual Assessment Score (HVAS) and Impact Assessment (IA) techniques (Fig. 6). The detailed result of the spatial variation of the Dinki watershed status is stated under chapter four (4.1.2).

The temporal variation in habitat condition was quantitatively assessed based on the habitat visual assessment score and Impact Assessment techniques. The results indicated that the values of the Impact assessment were slightly decreased from 31 $\pm$ 15.44 in 2016 to 29 $\pm$ 14.7 in 2023, suggesting a tendency of habitat improvements in the 2023 sampling period. Likewise, the mean overall value of the HVAS showed improvement from 52 $\pm$ 25.08 in 2016 (Asmamaw *et al.*, 2019 & 2021), which is rated as poor, to 62 $\pm$ 31.40 in 2023, which is rated as fair habitat conditions (Fig. 20), indicating a slight improvement in watershed conditions in the 2023 sampling period.

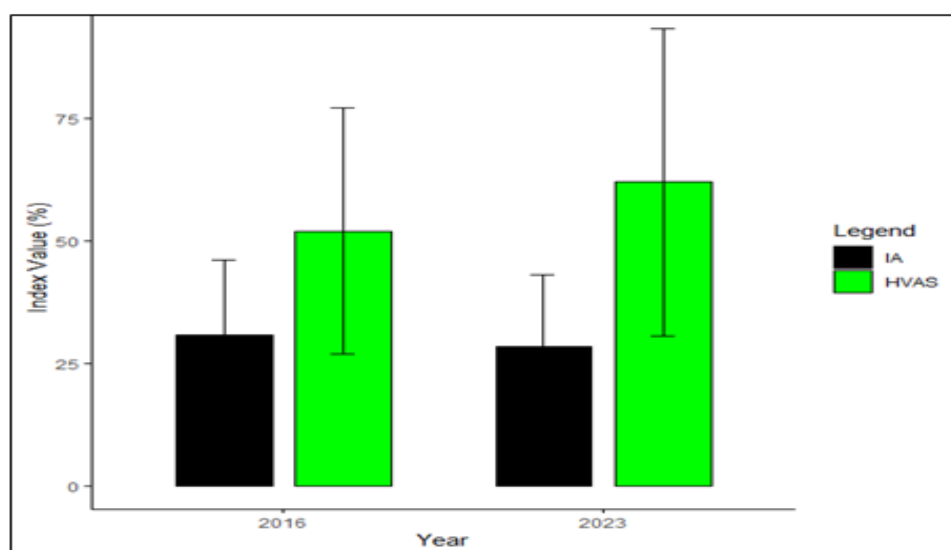


Figure 20. Interannual Variation in Dinki Watershed based on the Impact Assessment (IA) and Habitat and Visual Assessment Score (HVAS). HVAS (%) rated as excellent ($\geq 95\%$); very good

(85-94%); good (75-84%); fair (60-74%); poor (50-59%) and very poor ($\leq 49\%$); IA (%) rated as: High = $\geq 75\%$, Medium = $\geq 50\%$, Low = $\leq 49\%$.

4.2.3. Spatial Variation in macroinvertebrate composition

A total of 9479 individual macroinvertebrates belonging to four phyla, eight classes, 22 orders, and 107 families were identified in the 2016 (Asmamaw *et al.*, 2019) and 2023 sampling periods from representative habitat types of study sites. In 2016, 15 orders encountered Diptera was the dominant taxa group with the relative abundance 28.91%, followed by Ephemeroptera 22% and Coleoptera 12% in each site. Similarly, in 2023-year 18 orders were encountered. Ephemeroptera was the dominant taxonomic group with a relative 51%, followed by Diptera 18% and Trichoptera 13% (Table 22). In 2016, Gedamoch exhibited the highest macroinvertebrate abundance, contributing 41.38% of the total, followed by Zego (22%). However, by 2023, Gedamoch contribution increased significantly to 52%, while Zego also showed improvement, rising to 23%. Conversely, Dinki experienced a notable decline, from 20% to 11%, indicating possible environmental stress such as habitat degradation, pollution (turbidity), or hydrological alterations (like road construction in Dinki sub watershed). Dense, with minimal variation (16% in 2016 to 18% in 2023), remained the least diverse site, with some improvements (Appendix I). In general, however, Gedamoch site (13%) and 36% followed by Zego (7%) and 13.5 % of macroinvertebrate composition were recorded in both the 2016 and 2023 sampling periods, respectively (Fig. 21 & 22; Annex I).

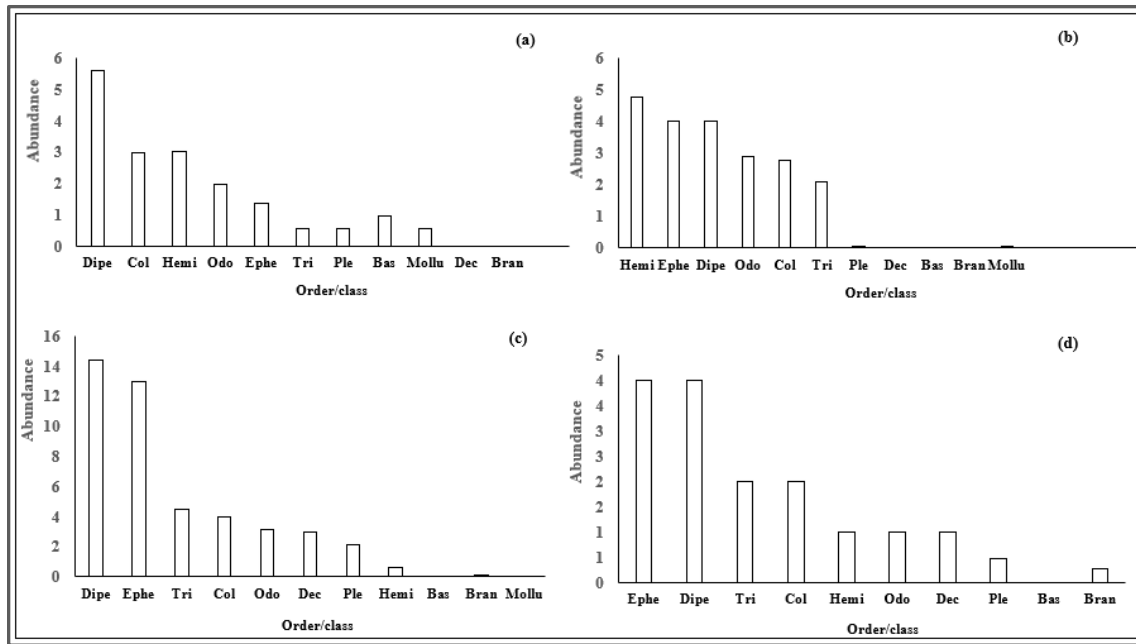


Figure 21. Taxonomic composition of macroinvertebrate assemblages and relative abundance in 2016 of (a) Dinki, (b) Zego, (C) Gedamoch, and (b) Dense sampling periods in Dinki watershed headwater streams.

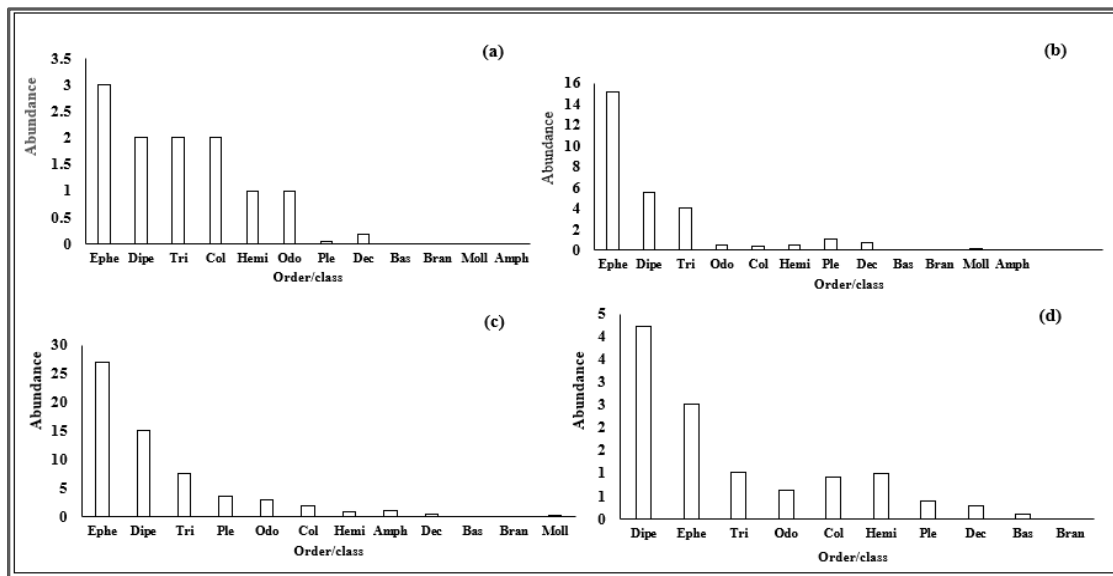


Figure 22. Taxonomic composition of macroinvertebrate assemblages and relative abundance in 2023 of (a) Dinki, (b) Zego, (C) Gedamoch, and (b) Dense sampling periods in Dinki watershed headwater streams. Indication: Ephemero=Ephemeroptera, Dipte= Diptera, Tri=Trichoptera,

Pleco=Plecoptera, Odo= Odonata, Col= Coleoptera, Hemi= Hemiptera, Amph= Amphipoda, Bas= Basommatophora, Bran= Dec= Decapoda, Mollu= Mollusca, Branchiob=Branchiobdellida and Arthyncho= Anthynchobdellida.

The results of one-way ANOVA indicated significant spatial variations in macroinvertebrate assemblages across the study sites in the Dinki watershed. In 2016 (Asmamaw *et al.*, 2019), spatial variation was evident, with Ephemeroptera ($F = 8.54$, $p < 0.001$), Trichoptera ($F = 3.76$, $p = 0.05$), and Diptera ($F = 6.23$, $p = 0.02$) showing significantly higher abundance at Gedamoch compared to Dinki, Zego, and Dense. This indicates that there were relatively better water quality and habitat conditions at Gedamoch, providing a more favorable environment for pollution-sensitive taxa. The lower numbers of these groups for Dense and Zego, however, might suggest that some environmental pressures like sedimentation, organic pollution, and hydrological alterations are impacting their distribution.

Likewise, in 2023, the abundance of Ephemeroptera ($F = 5.62$, $p < 0.001$), Trichoptera ($F = 1.76$, $p < 0.05$), Plecoptera ($F=3.12$, $p < 0.05$), and Diptera ($F = 2.85$, $p < 0.05$) was higher at Gedamoch, further confirming the ecological stability of this site while serving as a reference for the others. Others, however, including Coleoptera ($p = 0.36$) and Hemiptera ($p = 0.23$), showed a spatial variation that was not significant enough to be attributed to large-scale environmental variation, and may reflect a microhabitat preference at the site level. The presence of Decapoda ($F = 4.10$, $p = 0.01$) in Gedamoch and their infrequent occurrence in other sites also shows the importance of habitat stability in macroinvertebrate distribution. It is noteworthy that Annelida and Pelecypoda were found at a few locations, indicating that they are either rare in these streams naturally or sensitive to local disturbances. Overall, the observed spatial patterns suggest that pollution-sensitive taxa tend to be more abundant in Gedamoch than in Dinki, Zego and Dense, indicating different levels of environmental stress in these different zones (Table 24).

Table 24. Descriptive statistics of the composition and distribution of macroinvertebrate assemblages in spatial variation of two years (2016 and 2023) in Dinki watershed headwater streams, computed with one-way ANOVA. Represented in mean value $\pm$ standard error, minimum, and maximum values in the study site

Order	2016					2023				
	Dinki	Zego	Gedamoch	Dense	F-value	Dinki	Zego	Gedamoch	Dense	F-value
Odonata	5.80±4.18 (2-9)	6.14±3.82 (1-10)	7.75±2.25(5-10)	2.64±2.58 (0-7)	4.32**	6.80±4.64 (3-13)	2.36±2.84 (0-8)	14.92±13.27 (4-39)	1.79 ±2.02 (1-6)	2.47**
Ephemero	3.90±4.35 (1-12)	8.4±7.13 (2-23)	32±14.24 (10-39)	7.86±4.20 (2-16)	8.54***	31.90±27.22 (18-22)	53.00±16.33 (37-79)	152.33±70.84 (53-257)	32.79±17.17 (10-61)	5.62***
Coleoptera	16.60±6.61 (10-28)	5.86±4.84 (0-15)	2.41±4.47 (0-12)	5.14±6.03 (1-18)	2.25	5.21±4.89 (3-14)	5.14±2.55 (0-7)	8.08±8.11 (1-22)	8.00±9.22 (0-26)	1.23
Trichoptera	1.60±0.96 (1-3)	4.36±5.96 (1-17)	11.08±6.43 (6-23)	4.93±4.04 (1-11)	3.76**	11.30±4.92 (6-18)	11.36±6.33 (1-23)	37.17±20.04 (12-67)	10.79±7.76 (6-28)	1.76**
Plecoptera	3.08±0.14 (1-7)	0.14±0.38 (0-1)	5.25±4.63 (1-13)	0.93±1.43 (0-32)	1.13	0.00±0.00 (0-4)	1.07±1.74 (0-4)	18.50±21.15 (0-59)	1.71±2.71 (0-8)	3.12**
Diptera	16.60±8.06 (6-28)	9.07±9.91 (4-31)	35.5±8.76 (27-50)	9.00±6.99 (1-213)	6.23**	12.30±12.30 (1-31)	19.64±6.26 (12-28)	40.25±14.58 (23-55)	22.43±18.28 (4-58)	2.85**
Hemiptera	8.90±8.25 (1-20)	10.07±4.83 (4-17)	1.42±2.13 (0-6)	1.86±2.41 (0-9)	2.74	0.10±0.22 (0-1)	1.00±1.20 (0-3)	0.00±0.00 (0-2)	0.21±0.27 (0-2)	1.56
Decapoda	0.00±0.00	0.00±0.00 (0-3)	7.25±5.72 (2-16)	1.64±1.95 (0-44)	5.94**	1.00±2.24 (0-5)	1.43±1.90 (0-10)	1.67±1.13 (1-4)	1.43±1.59 (0-4)	4.1**
Annelida	2.90±4.59 (0-11)	0.00±0.00	0.00±0.00	0.00±0.00	5.93	0.10±0.22 (0-1)	0.21±0.36 (0-1)	0.50±0.45 (0-1)	0.93±1.43 (0-7)	2.14
Pelecypod	0.00±0.00	0.00±0.00	0.33±0.82 (0-2)	0.00±0.00	3.41**	0.00±0.00	0.00±0.00	0.67±1.08 (0-1)	0.00±0.00	1.89
Mollusca	3.00±5.66 (0-13)	0.14±0.38 (0-1)	0.00±0.00	0.00±0.00	0.41	0.00±0.00	4.00±0.18 (0-1)	1.67±3.03 (0-8)	0.29±0.57 (0-2)	6.72***

p<0.05; *p<0.001, 2016 data were sourced from (Asmamaw *et al.*, 2019)

Macroinvertebrate assemblages exhibited notable spatial variation across sampling sites in the Dinki watershed for both 2016 and 2023, as analyzed using R software. Among all sites, Gedamoch consistently supported the highest macroinvertebrate abundance in across both sampling years. Post-hoc Tukey HSD ANOVA (Table 25) further confirmed that Gedamoch had significantly higher abundance than both Dense (p < 0.05) and Dinki (p < 0.05), while other pairwise comparisons did not yield statistically significant differences (p > 0.05).

Table 25. Pairwise comparisons of macroinvertebrate abundance across sites in 2016 and 2023 with 95% Confidence Intervals

Site	diff	95% confidence interval		P-value
		lower	upper	
Dinki- Dense	0.92	-24.65	26.49	0.99
Gedamoch-Dense	21.67	-3.90	47.24	0.01
Zego-Dense	1.52	-24.04	27.10	0.99
Gedamoch-Dinki	20.74	-4.83	46.32	0.04
Dinki-Zego	0.61	-24.97	26.18	0.99
Zego-Gedamoch	-20.14	-45.71	5.43	0.06

4.2.4. Changes in Macroinvertebrate Composition: Temporal

A total of 9479 macroinvertebrates were identified in the 2016 (Asmamaw *et al.*, 2019 & 2021) and 2023 sampling periods. Of which about 37.93% (3095 individuals) and 67.35 % (6384 individuals) were obtained in the wet and dry seasons, respectively. Similarly, 37.93 % (1120 individuals) and 62.07 % (1833 individuals) were collected in the wet and dry seasons of the 2016 sampling year, respectively. Likewise, 30.26% (1975 individuals) and 69.74% (4551 individuals) were collected in wet and dry seasons during the 2023 sampling period, respectively. The majority of the assemblages were composed of Arthropods (92 %), followed by Annelida (4%) and Mollusca (3.4%). Among the insect orders, Diptera (29%), Ephemeroptera (23%), and Coleoptera (13%) were the most dominant in 2016, whereas Ephemeroptera (50%), Diptera (18%), and Trichoptera (13%) were dominant in the 2023 sampling period. In general, however, Ephemeroptera (37%) and Diptera (24%) were the most dominant orders in both the 2016 and 2023 sampling periods (Fig. 23; Annex I).

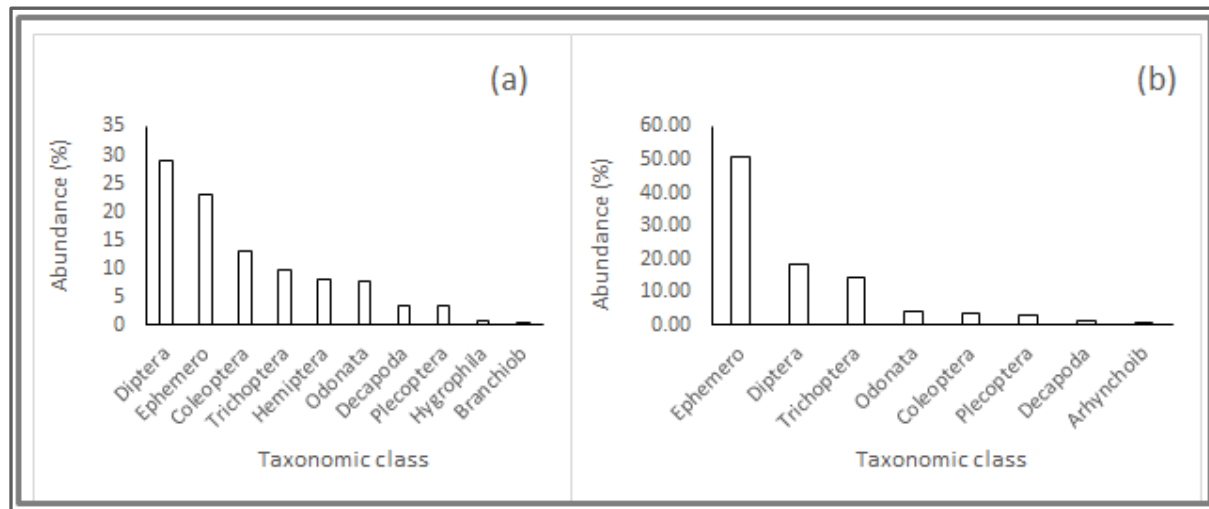


Figure 23. Taxonomic composition of macroinvertebrate assemblages and relative abundance in 2016 (a) and 2023 (b) sampling periods in Dinki watershed headwater streams. Indication: *Ephemero*=*Ephemeroptera*, *Branchiob*=*Branchiobdellida* and *Arthyncho*= *Anthynchobdellida*.

The paired test results showed that most macroinvertebrate assemblages, including the Ephemeroptera-Plecoptera-Trichoptera and Odonata taxa, varied ($p < 0.05$) between seasons, indicating seasonal variation in assemblages. For instance, the Odonata taxa were statistically

significant ($P < 0.05$) between the dry and wet seasons in the 2016 sampling periods (Asmamaw *et al.*, 2019 & 2021). Similarly, the Ephemeroptera, Trichoptera, and Odonata were statistically significant between the dry and wet seasons in the 2023 sampling periods (Table 26). Besides, the paired-test results revealed that some macroinvertebrates, like the Ephemeroptera taxa abundance, statistically varied between the dry ($t = -4.15$) and wet ($t = -4.27$) seasons of the 2016 and 2023 sampling periods. Likewise, Trichoptera taxa abundance statistically varied between the dry ($t = -3.33$) seasons of 2016 and 2023. While Plecoptera showed a moderate rise in the dry season ($t = -1.63$). Odonata remained stable with no significant changes, suggesting consistent environmental conditions. Coleoptera exhibited no change in the dry season but declined in the wet season ($t = 1.54$), possibly due to environmental stress. Overall, these results indicated a habitat improvement, especially for Ephemeroptera and Trichoptera. The mean values $\pm$ standard deviation of the macroinvertebrate assemblages in each season and sampling year are presented in Appendix II.

Table 26. Paired t-test results of macroinvertebrate composition by mean values $\pm$ Standard deviation between the dry and wet sampling seasons of the 2016 and 2023 sampling periods.

	Year_ season Functional Indices	Statics	95% CI		t- value
		Mean $\pm$ SD	lower vs upper	Upper	
Paired_1	2016_dry: Ephe	13.76 $\pm$ 15.34	-7.68	10.64	0.32
	2016_wet: Ephe	12.28 $\pm$ 16.85			
Paired_2	2016_dry: Trico	1.72 $\pm$ 3.81	-2.98	6.26	0.30
	2016_wet: Trico	2.00 $\pm$ 3.95			
Paired_3	2016_dry: Pleco	6.4 $\pm$ 26.52	-2.49	1.93	-0.26
	2016_wet: Pleco	4.76 $\pm$ 5.49			
Paired_4	2016_dry: Odo	10.4 $\pm$ 7.22	6.91	12.77	6.75****
	2016_wet: Odo	0.56 $\pm$ 0.92			
Paired_5	2016_dry: Coleo	6.00 $\pm$ 8.74	-8.05	4.13	-0.64
	2016_wet: Coleo	7.96 $\pm$ 12.36			
Paired_6	2023_dry: Ephe	88.08 $\pm$ 99.60	-0.71	85.19	1.98**
	2023_wet: Ephe	45.84 $\pm$ 38.59			
Paired_7	2023_dry: Trico	9.12 $\pm$ 23.14	5.79	30.53	2.95****
	2023_wet: Trico	1.32 $\pm$ 2.85			
Paired_8	2023_dry: Pleco	26.52 $\pm$ 28.98	-1.58	17.18	1.67
	2023_wet: Pleco	8.36 $\pm$ 10.29			
Paired_9	2023_dry: Odo	10.60 $\pm$ 14.80	2.85	15.15	2.94****
	2023_wet: Odo	1.60 $\pm$ 3.88			
Paired_10	2023_dry: Coleo	7.64 $\pm$ 10.66	-0.81	8.97	1.68
	2023_wet: Coleo	3.56 $\pm$ 5.83			

*** $P < 0.001$ ** $P < 0.05$; **Note:** 2016 macroinvertebrates data were sourced from (Asmamaw *et al.*, 2019 & 2021).

The results of the repeated measures ANOVA revealed significant temporal variation in macroinvertebrate assemblages between the 2016 and 2023 sampling periods. Specifically, the Ephemeroptera, Plecoptera, Trichoptera (EPT), and Ephemeroptera, Odonata, Trichoptera (EOT) indices showed strong year-to-year differences ($p < 0.01$). The most sensitive taxa, like the Ephemeroptera Plecoptera Trichoptera (EPT), Ephemeroptera Coleoptera Trichoptera (ECT), Ephemeroptera Odonata Trichoptera (EOT), Ephemeroptera-Trichoptera (ET), and Ephemeroptera, showed significant variations ($p < 0.001$) between sampling periods, where higher values were recorded during the dry periods (Annex IV), indicating seasonal and interannual variation in macroinvertebrate distribution and abundance.

The majority of macroinvertebrate assemblages showed variations during the dry and wet seasons as well as between the 2016 and 2023 sampling periods. For instance, the Ephemeroptera, Trichoptera, and Diptera were higher in the 2023 sampling period, whereas the Coleoptera and Hemiptera showed a reduction in their abundance in the 2023 sampling period. While Branchiobdellida, Araneae, and Pelecypoda were not reported in the 2023 sampling, the Lepidoptera, Veneroida, Amphipoda, and Megaloptera, which were not reported during 2016, were recorded in the 2023 sampling periods (Annex III). In general, however, the majority of assemblages persisted across the 2016 and 2023 sampling periods. In contrast, ET and Trichoptera displayed greater variability. Furthermore, variations in macroinvertebrate taxa between sampling years were also confirmed by the Pearson correlation matrix (Annex IV), highlighting varying relationships among macroinvertebrate families across years.

On the other hand, spatially and temporally, the natural clustering of sampling sites along the species composition gradient was computed with non-metric multidimensional scaling analysis. The NMDS results in the 2016 sampling showed (Fig 24a) that NMDS 1 explained 69.34% ($R = 0.64$) and NMDS 2 explained 7.56% ($R = 0.13$) of the variance, with a stress value of 0.116. Species such as *Trichoptera*, *Ephemeroptera*, *Decapoda*, and *Diptera* were primarily associated with reference sites, including GD14-GD18 and MK13. Impacted sites like DK4 and DF20, on the

other hand, were strongly linked to taxa such as *Annelida*, Mollusca, and *Coleoptera* (Asmamaw *et al.*, 2019).

In 2023 (Fig 24b), NMDS1 accounted for 77.14% ($R = 0.87$) and NMDS2 for 11.81% ($R = 0.18$) with a stress value of 0.228. Dominant species such as *Decapoda*, *Hemiptera*, and *Coleoptera* were associated with impacted sites, including DF21, DF22, DK4, and DK5. Reference and relatively less impacted sites, such as GD14-GD18, MK13, and LM19, clustered together and showed stronger associations with *Trichoptera*, *Ephemeroptera*, Plecoptera, Diptera, EPT, EOT, ECT, and ET. The observed shifts from 2016 to 2023 indicate reorganization in species assemblages, reflecting differences in site conditions and biological communities over time (Fig. 24).

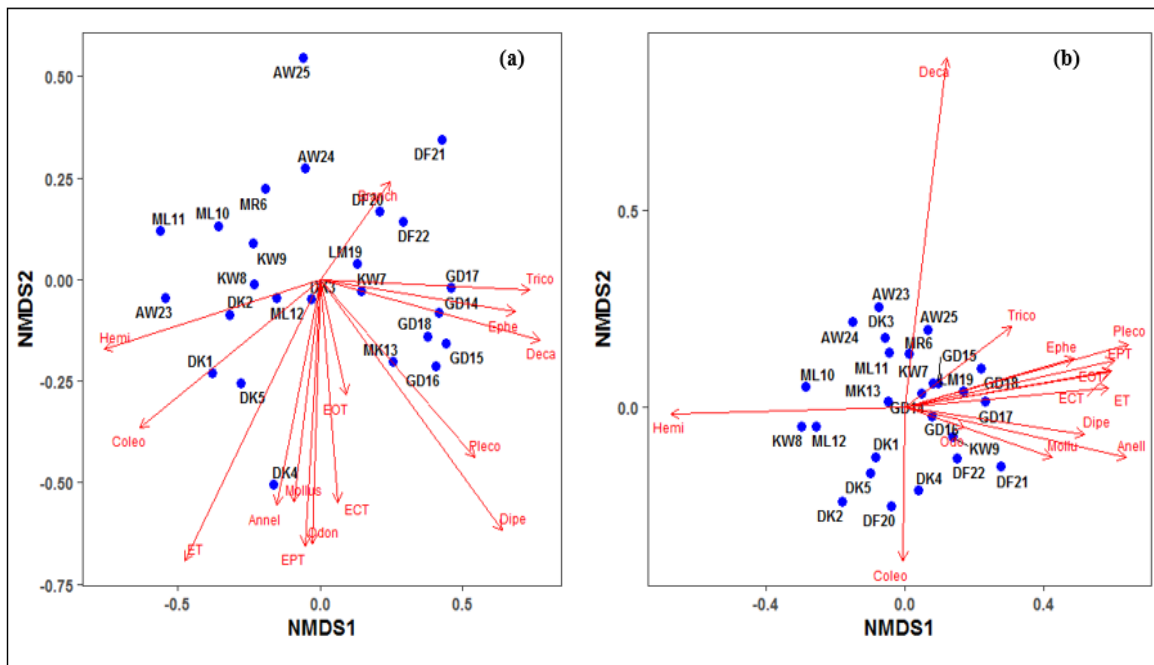


Figure 24. A non-metric Multidimensional Scaling (NMDS) biplot showing ordination of sampling sites and associated with sensitive taxa using similarity index of Euclidean distance collected in 2016 (a) (Asmamaw *et al.*, 2019) and 2023 (b) sampling sites.

Furthermore, the Principal Component Analysis (PCA) showed that Axis 1 and Axis 2 explained 48.7% and 10.5% of the total variance in macroinvertebrate assemblages during the 2016 sampling period (Asmamaw *et al.*, 2019), respectively, accounting for 59.2% of the overall variation. This means there is a high species gradient between sites. Positive correlation was observed with the

reference site, Gedamoch (MK13-GD18), and negative correlation was obtained for Zego (MR6, KW7, ML9-ML11) and Dense (AW23, AW25) sites with respect to Axis 1. Taxa such as Tabanidae, Tricorythidae, Chironomidae, Gyrinidae, Caenidae, and Gomphidae, located in the upper left quadrant, were positively associated with Dinki sites (DK1-DK5, ML12), suggesting a preference for more degraded habitats. In contrast, more sensitive taxa like Heptagenidae, Aeshnidae, Perlidae, and Tipulidae, found in the upper right quadrant, were positively associated with the Gedamoch site, indicating less impacted conditions (Fig. 25A).

Similarly, in 2023, Axis 1 and Axis 2 explained 52.0% and 16.3% of the variance, respectively, together accounting for 68.3% of the total variation. Axis 1 was positively correlated with Gedamoch (GD14, GD17, and GD18) and Dense (LM19) sites but negatively associated with Dinki (DK1-DK5) and Zego (KW7-KW9, and ML10, ML12). Axis 2 was positively associated with Gedamoch (GD15, GD16) and Zego (MR6) and negatively correlated with Dense (DF20-DF21, AW23-AW25) (Fig. 25B). Sensitive taxa such as Perlidae, Heptagenidae, and Aeshnidae remained dominant in the upper right quadrant, reflecting their association with the relatively undisturbed Gedamoch site. In contrast, tolerant taxa such as Tabanidae, Gyrinidae, and Gomphidae were more associated with degraded sites like Dinki, typically occupying the lower left quadrant. Overall, tolerant groups such as Chironomidae, Tipulidae, and Tabanidae consistently showed strong associations with impacted habitats. The full names of the taxa and orders in Fig 25 are presented in Annex II.

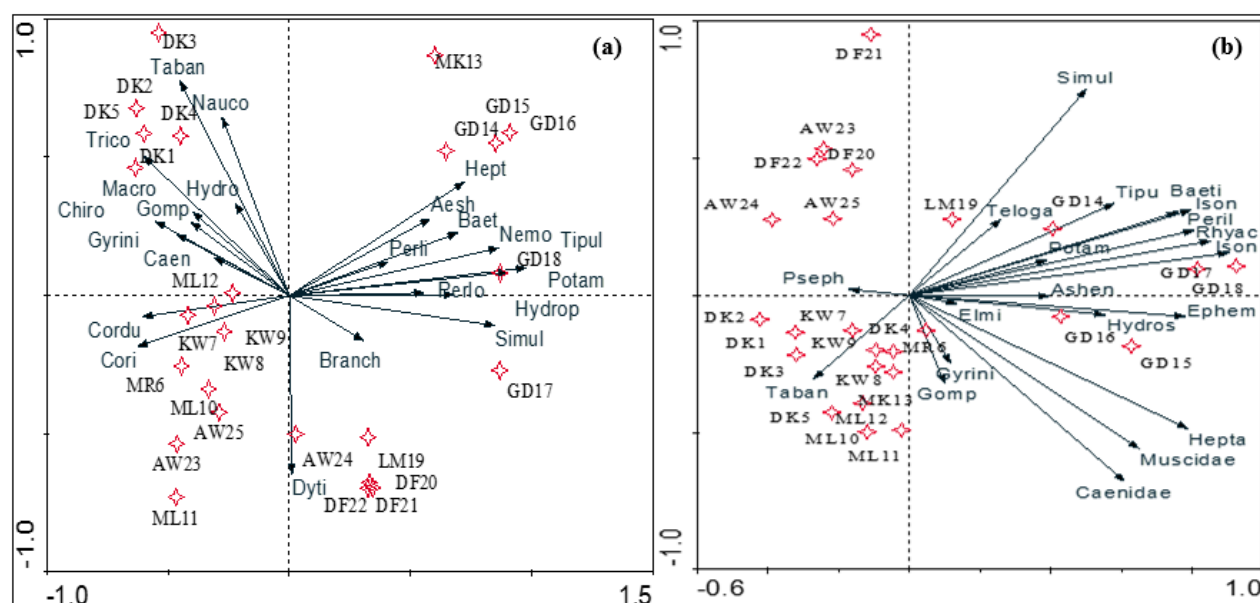


Figure 25. Principal component analysis biplot showing the ordination of macroinvertebrate families and sampling sites in 2016 (A) (Asmamaw *et al.*, 2019) and 2023 (B).

Furthermore, the Redundancy Analysis (RDA) revealed (both spatially and temporally) that the first two axes explained 55.3% (45.7 + 9.6) variation in species data during the 2016 sampling period (Asmamaw *et al.*, 2019 & 2021). Axis 1 was positively associated with DO, discharge, TP, and nitrate NO_3^- but negatively correlated with water temperature; whereas axis 2 was negatively correlated with TN and HVAS and positively correlated with EC, phosphates, and turbidity (Fig. 26A). The Monte Carlo permutation tests revealed a statistical significance of all canonical axes ($F=3.25$, $p<0.05$) at 499 permutations. In the 2016 sampling periods (Asmamaw *et al.*, 2019 & 2021), taxa like Tabanidae, Naucoridae, Chironomidae, Gyrinidae, Tricorythidae, etc., which inhabit the upper left quadrant (DK3, DK4, DK5), are positively correlated with EC, turbidity, and elevated pH, indicating a preference for degraded habitat conditions. Whereas Taxa like Heptagenidae, Aeshnidae, Perlidae, Tipulidae, etc. are inhabitants of the Gedamoch sites (upper right quadrant) and are positively correlated with DO and discharge, suggesting a preference for oxygenating stream water conditions. Hence, these sites are forested and fully shaded, where higher dissolved and elevated nutrient (TN, TP) levels might have been driven by natural hydrological and ecological processes, not necessarily pollution, suggesting dynamic, nutrient-exporting but still nearly pristine ecosystems.

Likewise, the first two axes explained 89.5% (42.9 +46.6) variations in species data in the 2023 sampling periods (Fig. 26b). Axis 1 was positively correlated with DO and HVAS but negatively correlated with nutrients (TP & TP), water temperature, and EC; whereas axis 2 was positively associated with nitrates, TP, and TN but negatively correlated with discharge and turbidity. The Monte Carlo permutation tests revealed a statistical significance of all canonical axes ($F = 6.17$, $p < 0.05$) at 499 permutations, indicating a promising relationship between the distribution of macroinvertebrate taxa and the environmental variables in the 2016 and 2023 sampling periods.

In the 2023 sampling periods, still the most sensitive taxa, such as Perlidae, Heptagenidae, Aeshnidae, etc., were inhabitants of the Gedamoch sites (upper right quadrant), where DO and HVAS were strong gradients; whereas taxa such as Tabanidae, Gyrinidae, Gomphidae, Elmidae, etc., which prefer degraded water, were inhabitants of the Dinki sites (lower left quadrant). Therefore, more tolerant groups like Chironomidae, Tipulidae, Tabanidae, etc., are pulled toward degraded sites, which are still associated with elevated EC and turbidity in both the 2016 (Asmamaw *et al.*, 2019 & 2021) and 2023 sampling periods, suggesting tolerance to degraded water quality conditions. Some sensitive taxa, such as Heptagenidae, Aeshnidae, Perlidae, etc., remain associated with cleaner sites, which are correlated with higher DO but nutrients possibly sourced from active nutrient cycling rather than anthropogenic activities. In both years, DO and HVAS strongly influenced species distribution, with sensitive taxa such as Heptagenidae and Aeshnidae positively correlated with these variables.

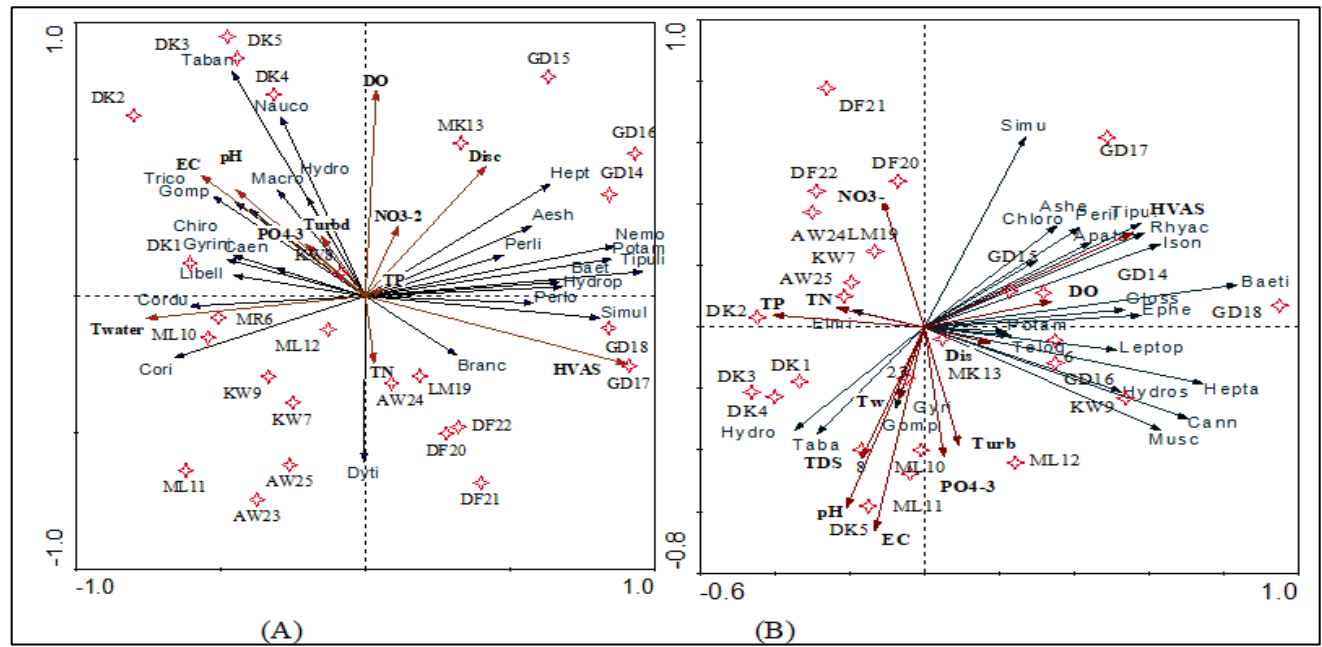


Figure 26. Redundancy Analysis triplots showing the ordination of macroinvertebrate families, sampling sites, and environmental variables in 2016 (A) and 2023 (B). Arrows indicate the direction and strength of environmental gradients.

4.2.5. Spatial variation in macroinvertebrate structures

A multivariate analysis of variance (MANOVA) through Box and Whicker plot indication was conducted to assess differences in macroinvertebrate structure, specifically taxa abundance, richness, and diversity, across the study sites: Dinki, Zego, Gedamoch, and Dense. The analysis revealed a statistically significant multivariate difference among sites (Wilks' Lambda = 0.002, $F = 49.5$, $p = 0.02$), indicating that abundance, richness, dominance, diversity/Shannon_H, and evenness varied notably across locations. Data from 2016 and 2023 showed that species richness, species density, and species diversity were significantly different between the four sites ($p < 0.05$), but not dominance or evenness. In 2016 (Asmamaw *et al.*, 2019), Gedamoch exhibited the highest mean richness (21.33 ± 5.42) and density (209 ± 62.74), whereas Dense recorded the lowest density (70.14 ± 30.12). The ecological improvements continued with increasing richness (32.50 ± 9.25) and density (502.50 ± 176.13) by 2023, which indicates higher resilience or habitat quality. In both years, notably, species richness ($F = 4.05^{**}$, 2016; $F = 6.17^{**}$, 2023) and density ($F = 10.86^{***}$, 2016; $F = 6.95^{***}$, 2023) were significantly different among the sites; habitat conditions

and local site characteristics affected the structure of the macroinvertebrate community. These results indicate that Gedamoch is a relatively undisturbed site, whereas Dinki, Zego, and Dense are more disturbed sites, further supporting the presence of an ecological gradient within the watershed (Fig. 27).

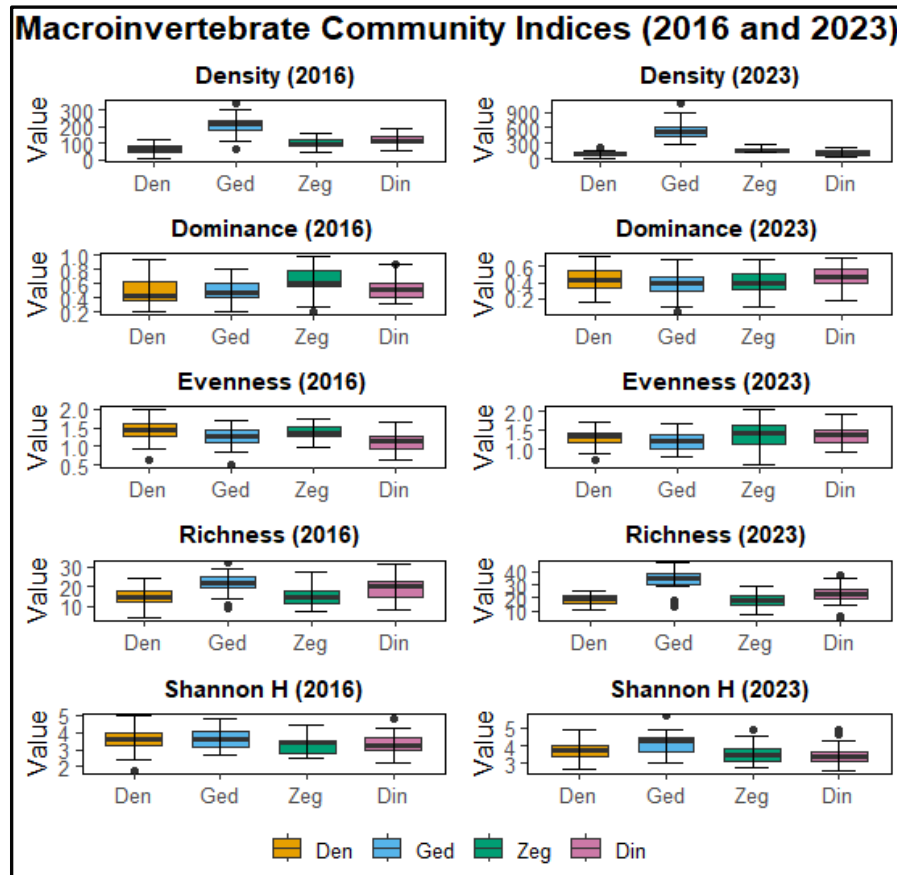


Figure 27. Box and whisker plot of spatial variation in macroinvertebrate indices (One-way Anova) by the mean-value $\pm$ standard deviation (SD) in parentheses. Indication: Richness₁₆ ($F=4.05^{**}$), Density₁₆ ($F=10.86^{***}$), Shannon_H₁₆ ($F=3.12^{**}$), Evenness e^H/S_{16} ($F=1.37^{**}$), Richness₂₃ ($F=6.17^{**}$), Density₂₃ ($F=6.95^{***}$), Dominance₂₃ ($F=0.5^{**}$). ($^{**}P<0.01$; $^{***}P<0.00$).

Furthermore, from the above-mentioned boxplot analysis of ecological indices based on 2016 data at all sites, Dense, Gedamoch, Zego, and Dinki, it is observed that there is a clear spatial gradient with the highest medians recorded at Gedamoch for EPT richness, EOT richness, ECT richness,

taxa richness, and Shannon diversity, while Dinki recorded the lowest values. By 2023, all sites, especially Dense and Zego, exhibited upward shifts in the medians of EPT/EOT/ECT and Shannon_H, with Zego's richness distribution moving from ~8 in 2016 to ~14 in 2023 and Dense improving from ~8 to ~10; Gedamoch remained high and even gained in richness and diversity, while Dinki showed modest gains in Shannon diversity and evenness. Together, these boxplot shifts indicate a clear overall improvement in macroinvertebrate community health over the seven-year period, with the greatest recovery at Dense and Zego, Gedamoch retaining its reference site status, and Dinki beginning to recover from more degraded conditions (Fig.28).

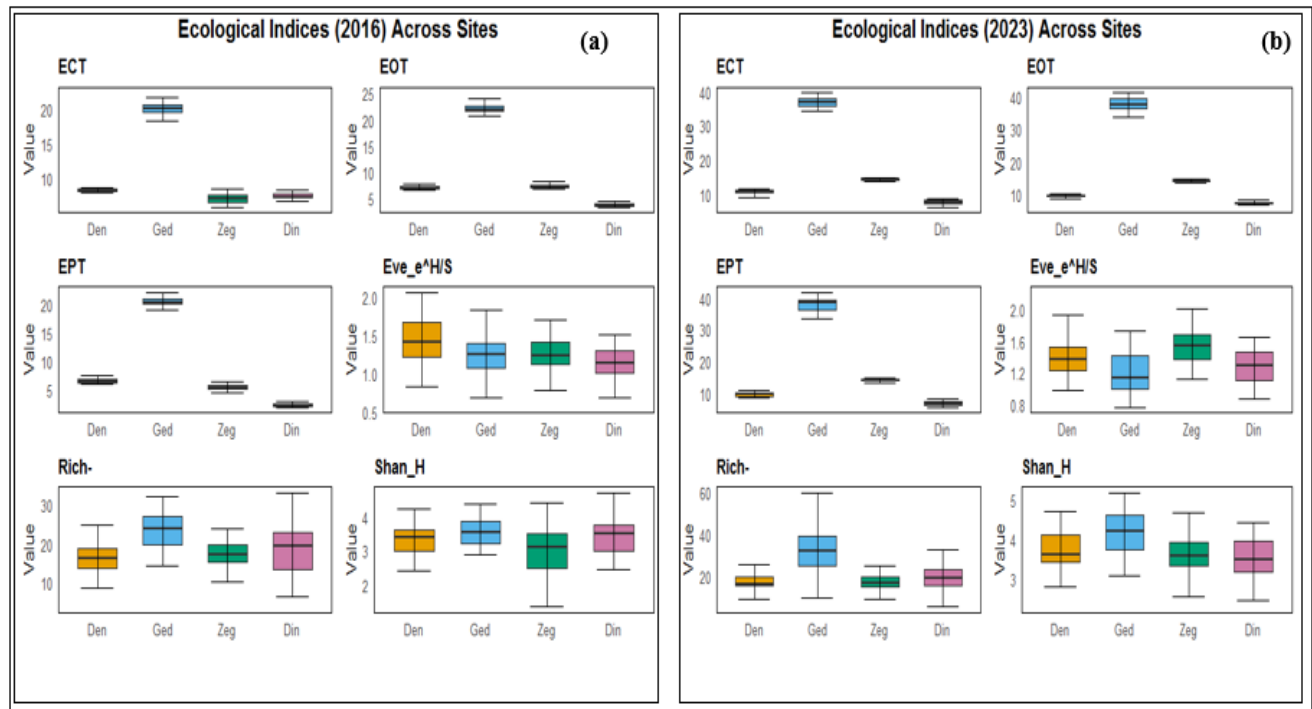


Figure 28. Box-and-whisker plots of each of the six selected metrics used to discriminate between reference and impaired sites for 2016 (a) and 2023 (b) Box-and-whisker plots of each of the six selected metrics used to discriminate between reference (Ged = Gedamoch) and impaired sites (Din = Dinki, Zeg = Zego, and Den = Dense) for 2016 (a) and 2023 (b). Small black squares represent median numbers, boxes represent interquartile ranges (25 & 75% percentiles), and range bars show maximum and minimum values (EOT = Ephemeroptera, Odonata, Trichoptera; EPT = Ephemeroptera, Plecoptera, Trichoptera, ECT= Ephemeroptera, Coleoptera, Trichoptera, ET= Ephemeroptera, Trichoptera, Ephem= Ephemeroptera, Odonata= Odonata).

4.2.6. Macroinvertebrate distribution in spatial context based on functional feeding group

In the Dinki watershed, macroinvertebrate distributions assessed in 2016 (Asmamaw *et al.*, 2019) and 2023 showed notable changes in Functional Feeding Groups (FFGs), indicating ecological improvement. All FFGs showed gains between the two years in all areas except Snowdrop, indicating better functioning of the ecosystems. The trophic structure and prey availability improved such that the predator (Pred) proportion rose from 10-12% in 2016 (Fig. 30a) to 23-32% in 2023 (Fig 30b), being highest at Gedamoch. This was also reflected in the increase in Collector-Gatherers (CG), which was more pronounced at Dense and Gedamoch, suggesting a greater input of organic matter. Shredders/Scrapers (Sh/SR) and Collector-Filterers (CF) were both low in abundance at sites, and both experienced significant increases, possibly related to the improvement of riparian vegetation and water quality. Scrapers (SC) showed significant growth at Zego and Gedamoch. Overall, the observed FFG shifts indicate improved habitat conditions and functional ecosystem recovery, especially at the reference site, Gedamoch (Fig. 29).

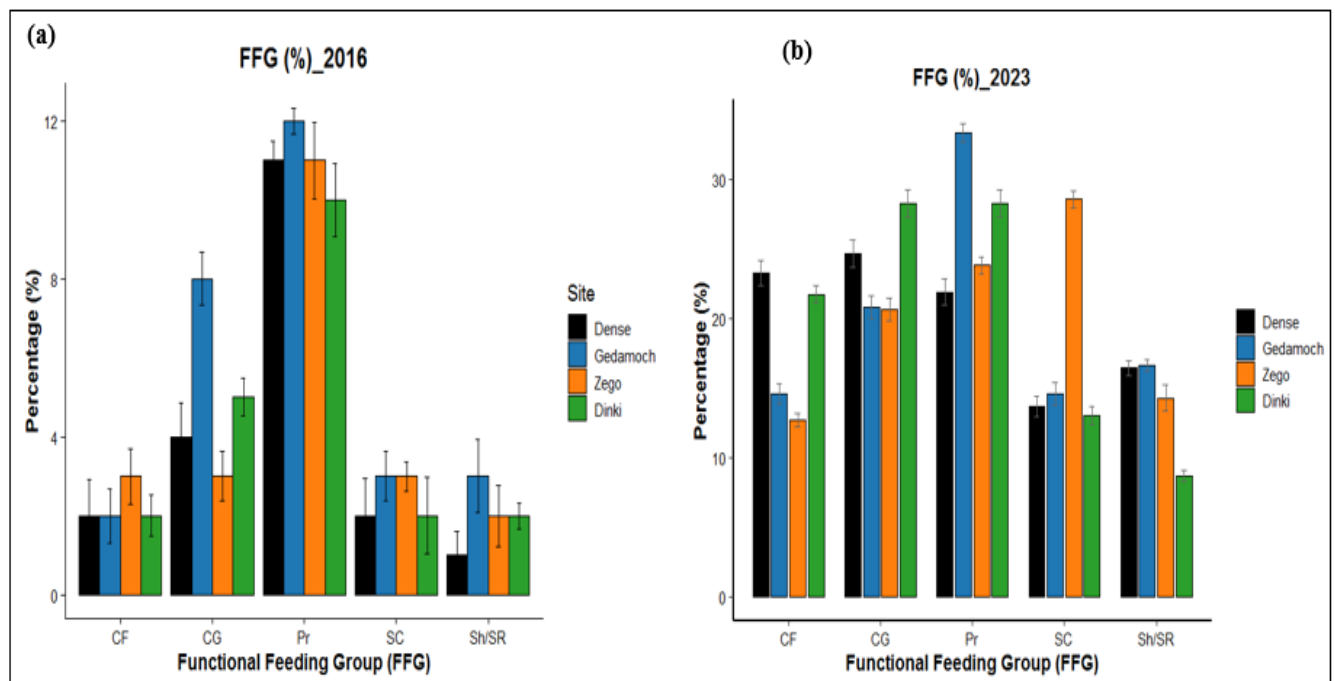


Figure 29. Functional feeding group of Macroinvertebrate taxon across sites in the years 2016 and 2023.

4.2.7. Changes in macroinvertebrate structures and Biodiversity Indices: Temporally

The results of the paired test showed that a minority of macroinvertebrate structures (Indi, and Sim_1-D) and key indicator groups (biodiversity indices, like EOT and Odonata) showed statistically significant ($p < 0.05$) variation between seasons in both sampling periods (Table 27). Except for the taxa evenness, the mean values of taxa richness, abundance, EOT, and Odonata were higher in the dry season during the 2016 sampling period. Likewise, except for Taxa_S and Evenness_e^H/S, the mean values of all other macroinvertebrate structures and key indicator groups were higher in the dry sampling periods in the 2023 sampling period. However, there were no statistically significant differences in mean values of Ephemeroptera, ET, ECT, EPT, and Shannon index between the dry and wet sampling seasons during the 2016 sampling. Likewise, the mean value of the taxa richness between the dry and wet seasons was not significant during the 2023 sampling period (Table 27).

Table 27. Seasonal variations in macroinvertebrate structures and biodiversity indices by mean values $\pm$ standard deviation in both the 2016 and 2023 dry and wet seasons computed using a paired t-test.

Indices	2016_dry	2016_wet	t-value	2023_dry	2023_wet	t-value
Taxa_S	9.9 $\pm$ 2.9	8.2 $\pm$ 3.0	2.0**	13.8 $\pm$ 6.7	11.3 $\pm$ 5.5	1.5*
Ind	73.3 $\pm$ 45.2	44.8 $\pm$ 26.5	2.7***	182.0 $\pm$ 165.6	79.0 $\pm$ 54.9	2.9***
Domi_D	0.3 $\pm$ 0.1	0.3 $\pm$ 0.1	0.3*	0.2 $\pm$ 0.1	0.3 $\pm$ 0.1	-3.81***
Sim_1-D	0.7 $\pm$ 0.1	0.8 $\pm$ 0.2	0.2*	0.8 $\pm$ 0.1	0.7 $\pm$ 0.1	3.5***
Shan_H	1.7 $\pm$ 0.3	1.7 $\pm$ 0.5	0.6*	2.1 $\pm$ 0.4	1.7 $\pm$ 0.4	3.5***
Even_e^H/S	0.6 $\pm$ 0.1	0.7 $\pm$ 0.2	-1.92**	0.7 $\pm$ 0.1	0.6 $\pm$ 0.1	2.6**
EPT	42.9 $\pm$ 37.6	37.1 $\pm$ 27.9	0.6*	115.4 $\pm$ 83.4	39.7 $\pm$ 27.9	-4.3***
EOT	63.7 $\pm$ 30.4	36.7 $\pm$ 30.4	3.1***	116.0 $\pm$ 83.4	52.1 $\pm$ 32.2	-3.6***
ECT	46.3 $\pm$ 33.3	31.1 $\pm$ 34.7	1.6*	254.7 $\pm$ 85.3	120.8 $\pm$ 85.3	5.6***
ET	59.7 $\pm$ 41.9	46.1 $\pm$ 32.7	1.3*	280.5 $\pm$ 114.7	109.0 $\pm$ 68.4	8.2***
Ephemeroptera	86.0 $\pm$ 83.6	76.0 $\pm$ 69.2	0.5*	250.5 $\pm$ 88.4	108.5 $\pm$ 78.0	2.3***
Odonata	65.0 $\pm$ 27.1	3.5 $\pm$ 1.3	11.4***	66.3 $\pm$ 64.1	10.0 $\pm$ 7.8	4.4***

*** $p < 0.001$, ** $P < 0.05$, * $P > 0.05$; Indication: Ind= Individual, Domi_D= Dominance_D, Sim_1-D= Simpson_1-D, Shan_H= Shannon_H, Even_e^H/S= Evenness_e^H/S. **Note:** 2016 diversity indices, composition indices, and order data were sourced from (Asmamaw *et al.*, 2019 & 2021).

The results of the descriptive statistics and the repeated measures ANOVA (rmANOVA) comparing macroinvertebrate structures and biodiversity indices in both sampling years reveal

significant ($p < 0.05$) differences, where higher mean values were recorded in the 2023 sampling period. For instance, the total abundance, taxa richness, EPT indices, ECT, ET, and Ephemeroptera showed higher mean values in 2023 over the 2016 sampling periods (Table 28). This could be associated with the fact that improvement in ecological conditions of certain sites of the Dinki headwater streams might have contributed to improvements in most macroinvertebrate structures and biodiversity indices, including the most sensitive taxa like the Ephemeroptera and EPT indices in recent periods.

Table 28. Interannual variations in macroinvertebrate structures and Biodiversity indices (key indicator groups) by mean values $\pm$ standard deviation computed using a repeated measure Analysis of Variance (rmANOVA).

Indices	2016	2023	F-value
Taxa_S	9.0 $\pm$ 2.9	12.6 $\pm$ 6.1	11.5***
Individual	59.1 $\pm$ 35.9	130.51 $\pm$ 110.3	27.2***
Dominance_D	0.3 $\pm$ 0.13	0.2 $\pm$ 0.1	0.6*
Simpson_1-D	0.8 $\pm$ 0.2	0.8 $\pm$ 0.1	0.7*
Shannon_H	1.7 $\pm$ 0.4	1.9 $\pm$ 0.4	0.8*
Evenness_e^H/S	0.6 $\pm$ 0.2	0.6 $\pm$ 0.1	0.3*
EPT	40.0 $\pm$ 32.7	77.5 $\pm$ 55.7	9.1***
EOT	50.2 $\pm$ 30.4	84.0 $\pm$ 57.8	0.2***
ECT	38.7 $\pm$ 34.0	187.8 $\pm$ 85.3	49.8***
ET	52.8 $\pm$ 37.3	194.8 $\pm$ 91.5	86.9***
Ephemeroptera	81.0 $\pm$ 76.4	179.5 $\pm$ 83.2	70.4***
Odonata	34.6 $\pm$ 14.2	38.1 $\pm$ 35.9	0.0*

*** $p < 0.001$, ** $P < 0.05$, * $P > 0.05$; **Note:** 2016 diversity indices, composition indices, and order data were sourced from (Asmamaw *et al.*, 2019 & 2021).

Furthermore, the boxplot analysis reveals significant changes across twelve ecological metrics. Specifically, macroinvertebrate taxa richness (Taxa_S), individual abundance, and diversity indices (Shannon_H and Simpson_1D) were notably higher in 2023 than in 2016, suggesting a general improvement in ecological conditions. In 2023, the interquartile range and median of Taxa_S and Ind were always higher, suggesting greater diversity and abundance of macroinvertebrates. Likewise, the reduced spread for certain metrics, such as Simpson_1D, points to enhanced community stability and evenness in 2023. Similarly, the key indicator groups, such as EOT, EPT, ECT, and ET, also showed higher values in 2023, suggesting the trend of improved macroinvertebrate assemblages. These findings suggest that habitat quality and environmental

conditions have likely improved in 2023 over the 2016 sampling periods, resulting in higher mean values of macroinvertebrate structures and key indicator groups, including the sensitive EPT indices (Fig. 30).

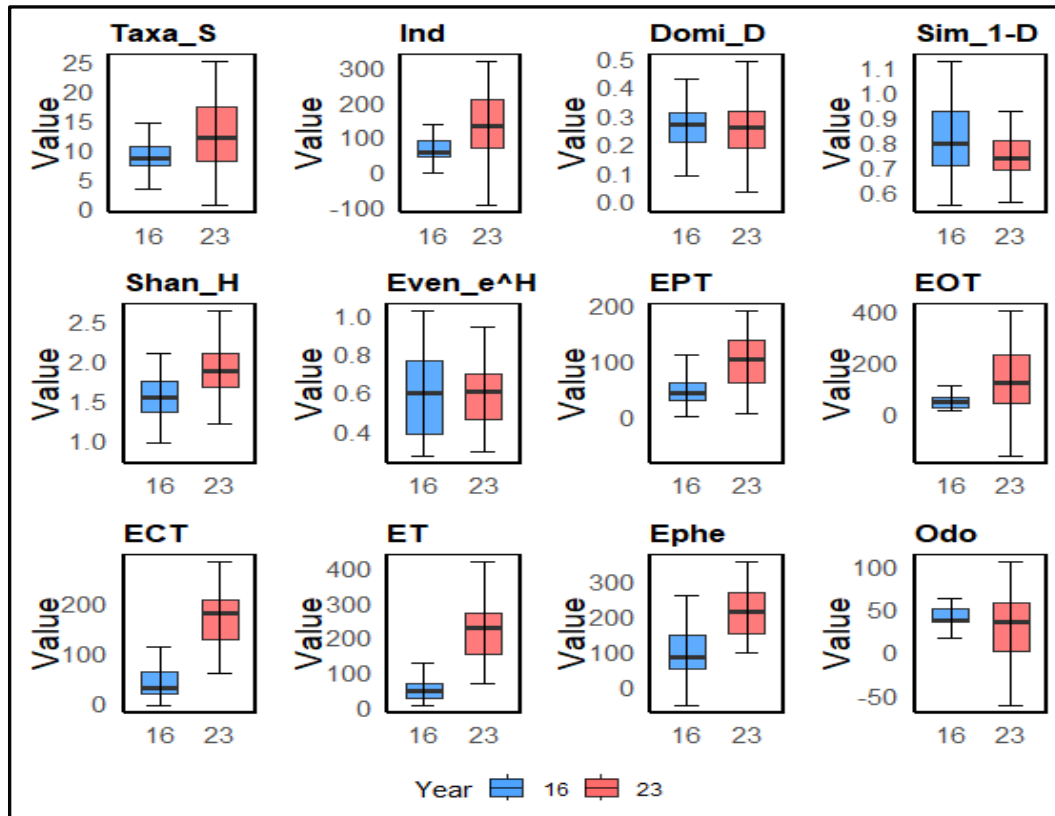


Figure 30. Boxplot comparison of biodiversity indices, including Taxa richness, individual abundance, diversity (Simpson's 1-D, Shannon_H), dominance, evenness, and key indicator groups (EPT, EOT, ECT, ET, Ephemeroptera, Odonata, Trichoptera) between the 2016 and 2023 sampling periods, reflecting shifts in biodiversity and ecosystem stability over time. Note: 2016 diversity indices, composition indices, and order data were sourced from (Asmamaw *et al.*, 2019 & 2021).

4.2.8. Variations in Indicator Taxa

In terms of Indicator Species Analysis (ISA) in season (dry and wet), the taxa Philopotamidae (IndVal=32.63), Perlodidae (IndVal=28.34), and Perlidae (IndVal=17.72) were indicators of the dry period in 2016 due to their abundances. The taxon Philopotamidae was an indicator (IndVal=32.63) of the dry period of 2016 year but had a lower abundance in the wet or summer

season of 2016. Whereas the taxa Hydropsychidae (IndVal 36.10), Dytiscidae (IndVal=35.26), and Taeniopterygidae (IndVal=35.26) were indicators of high flow or summer in the year 2016 due to their abundances. Furthermore, Gomphidae (InVal=40.89), Heptagenidae (IndVal=36.3), Pteronarchyidae (IndVal=31.87), and Tabanidae (InVal=24.13) were in the list of top abundant taxa as well as indicators of the dry or normal flow period in 2023. Moreover, Gomphidae (IndVal=73.77), Aeshnidae (IndVal=37.67), and Perlodidae (34.34) were the top recorded due to their abundance in the higher flow season or summer season of 2023. In addition to these, in the dry and wet seasons of 2016 and 2023 years Lymnaeidae, Chloroperlidae, Codulegastridae, and Scirtidae were recorded with list values of (3.7, 10.37, 9.57, 9.87), respectively. From all sites and two consecutive annual years, Gomphidae (IndVal= 73.77) was recorded under the wet season of 2023, with a high value, which indicated a significant indicator species. All these assemblages with $\text{IndVal} \geq 25$ were statistically significant ($p < 0.001$) and assumed to be strong indicators of the respective season within the years (Annex V).

4.3. Effects of Long-Term Climate and Land-Use Change on Sensitive Macroinvertebrate Indicators: A Comparative Analysis of 2016 and 2023 Surveys

4.3.1. *Macroinvertebrate indicator taxa at the family level*

The indicator species were selected through past software for trend analysis in relation to 30 years of land use types and climate variability. At the Dinki site, Tabanidae (Diptera; horseflies) were selected, suggesting habitats that support aquatic and semi-aquatic insects. At the Zego site, Dytiscidae (Coleoptera; predaceous diving beetles) and Heptageniidae (Ephemeroptera; mayflies) were identified, both commonly associated with clean, well-oxygenated waters, indicating relatively good water quality. The stoneflies (Plecoptera: Perlidae) and caddisflies (Trichoptera: Philopotamidae) were chosen at the Gedamoch site. These pollution-sensitive families are widely used as bioindicators, suggesting the importance of water quality monitoring at this site. For the Dense site, Aeshnidae (Odonata; dragonflies) was identified, indicating well-vegetated and relatively stable aquatic habitats. Overall, the selected families reflect varying ecological conditions, water quality, and habitat characteristics across the study sites (Fig. 31).

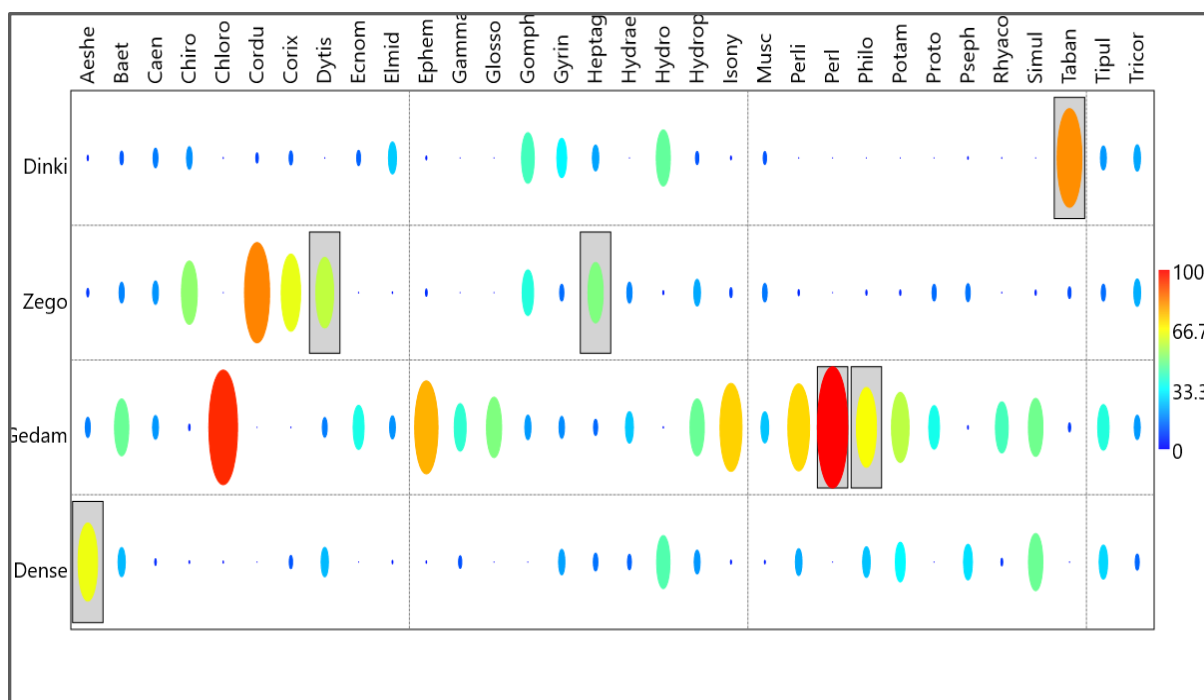


Figure 31. Indicator taxa along study sites in the study years of 2016 and 2023. * *Aeshe* = *Aeshnidae*, *Baet* = *Baetidae*, *Caen* = *Caenidae*, *Chiro* = *Chironomidae*, *Chloro* = *Chloroperlidae*, *Cordu* = *Corduliidae*, *Corix* = *Corixidae*, *Dytis* = *Dytiscidae*, *Ecnom* = *Ecnomidae*, *Elmid* = *Elmidae*, *Ephem* = *Ephemerellidae*, *Gamma* = *Gammaridae*, *Glosso* = *Glossosomatidae*, *Gomph* = *Gomphidae*, *Gyrin* = *Gyrinidae*, *Heptag* = *Heptagenidae*, *Hydrae* = *Hydraenidae*, *Hydro* = *Hydrophilidae*, *Hydrop* = *Hydropsychidae*, *Isony* = *Isonychidae*, *Musc* = *Muscidae*, *Perli* = *Perlidae*, *Perl* = *Perlodidae*, *Philo* = *Philopotamidae*, *Potam* = *Potamonautidae*, *Proto* = *Protoneuridae*, *Pseph* = *Psephenidae*, *Rhyaco* = *Rhyacophilidae*, *Simul* = *Simuliidae*, *Taban* = *Tabanidae*, *Tipul* = *Tipuliidae*, *Tricor* = *Tricorythidae*

4.3.2. Land Use/Land Cover dynamics

The final land use land cover maps for the Dinki watershed in the years 1994, 2014~16, and 2023 were presented in Fig. 10. The detailed explanation was stated under Chapter 4 in Subsection 4.3.6.2. In 1994, 2014~16, and 2023, the top three dominant LULC types were agricultural crop land, slightly vegetation, and water body, which were more dominant and averagely covered by 51.64km², 37.48 km², and 24.38 km² of the total area, respectively, and significantly different

($p < 0.01$) (see Fig. 11 and Table 13). However, for this chapter, we used only the 2014 and 2023 land use type areas.

4.3.3. Climate dynamics of Ankober

4.3.3.1. Mean monthly rainfall and temperature of the Ankober zone

The mean monthly rainfall (30 years, 1994-2023) for Ankober shows that there is a distinct variation in rainfall from season to season. During the dry season (December to February), there are few rainfall events with very little rain, especially in December when rainy days are 5.83 mm of rain. The rain starts to increase slowly from March, which is the onset of the rainy season; the rain is significant during April and May, reaching a peak of 94.48 mm during April. This is followed by a significant increase in rain during July and August, the wettest months of the year, with July having recorded 250.02mm and August 256.61mm (Fig. 32). Following this maximum, the rains reduce again during September and October, and are observed to be less during November and December when the rainy season is said to be ending. This trend shows that the rainfall distribution is bimodal in the year, with a peak during the rainy season of July-August and another during the rainy season of April-May.

On the other hand, with its three seasons, Ankober's mean monthly temperature is typical for Ethiopia. The Bega season (October to January) is cooler with average temperatures of 15.62°C to 16.34°C. During the Belg season (February to May), the temperatures slowly rise from 16.21°C in February to 17.86°C in May. During the Kiremit season (June to September), the long rainy season, temperatures remain relatively constant, reaching a high of 18.34°C in June, and decreasing a little in July and August (Fig. 32). This climate pattern shows that Ankober has relatively mild and stable temperatures, which are influenced by altitude and seasonality of precipitation.

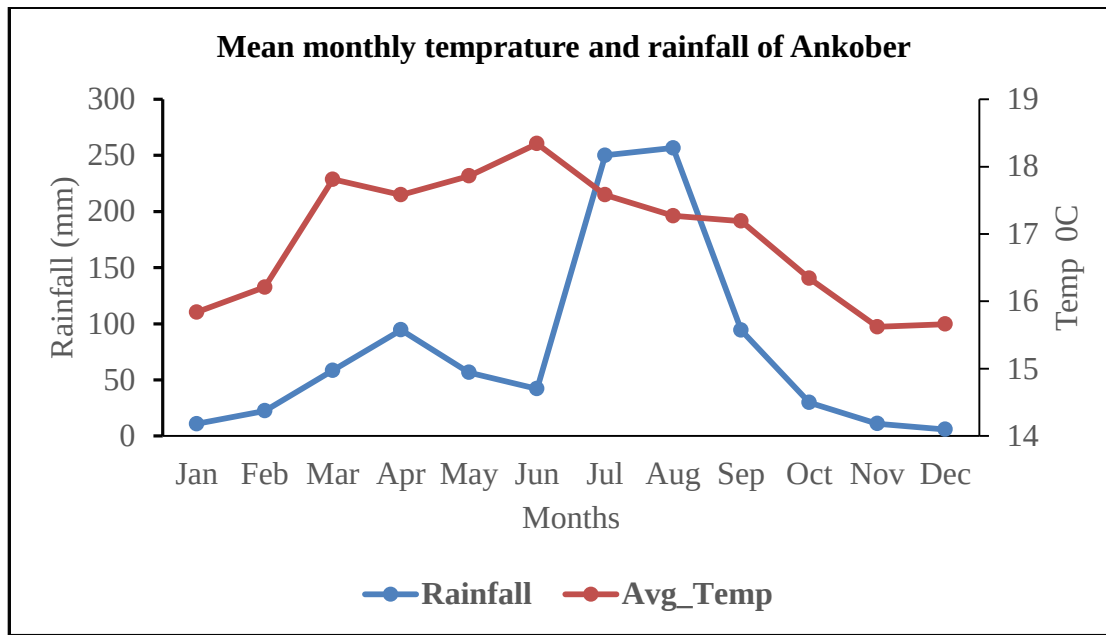


Figure 32. Mean monthly rainfall and temperature of Ankober (1994-2023).

4.3.3.2. Mean rainfall and temperature spatial distribution

The spatial distribution of mean annual rainfall (Fig. 33) indicated that the mean annual rainfall (Panel a) ranges from 500 mm to 1300 mm, with the highest values in the northeast and the lowest values in the southwest, which are affected by topography and climate. Reliable estimates of precipitation for the Bega season (Panel b, October-January) indicate the lowest levels (32-88 mm), although there is some extra rainfall in the southeast. There is moderate rainfall (180-270 mm) during the Belg season (February-May), and it is beneficial for agriculture, with higher precipitation in the north and in the central areas (Panel c). The Kiremit season (Panel d, June-September) provides the highest amounts of rainfall (320-960 mm), which is essential for water supplies and agriculture, especially in the northeast. These seasonal differences underscore the importance of the Kiremit season in the annual precipitation, which is crucial for water resource management and climate resilience.

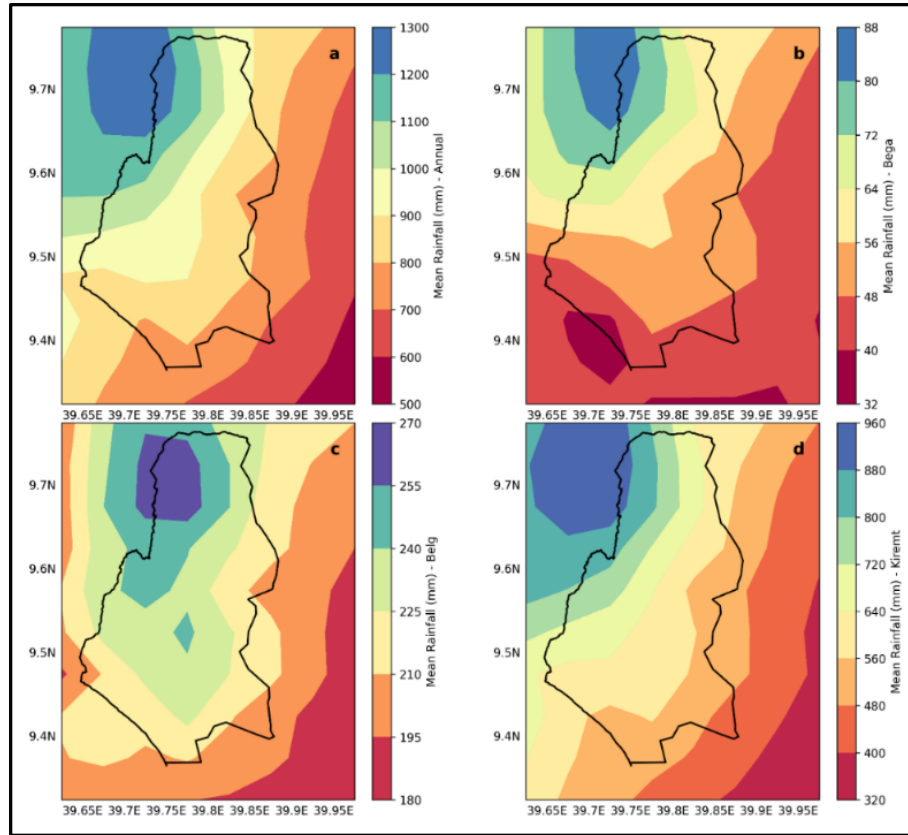


Figure 33. Mean Annual (a), Bega (b), Belg (c), and Kiremit (d) rainfall distribution.

The spatial distribution of mean temperature for three seasons is shown in Figure 34. The annual season(a) had the highest temperatures (19°C to 24°C) in the southeast. In the Bega season (Panel b), temperatures are below average, ranging from 10.5°C to 19°C, with cooler regions in the northwest. The Belg season (Panel c) has moderate temperatures ranging from 12°C to 21°C, with the south-eastern areas being warmer. The Kiremit season (Panel d) has the lowest temperature range from 10.5°C to 18°C, and the coolest areas are in the northwest. These variations indicate the difference in temperature between seasons (and places) due to both the seasonal variations and the altitude.

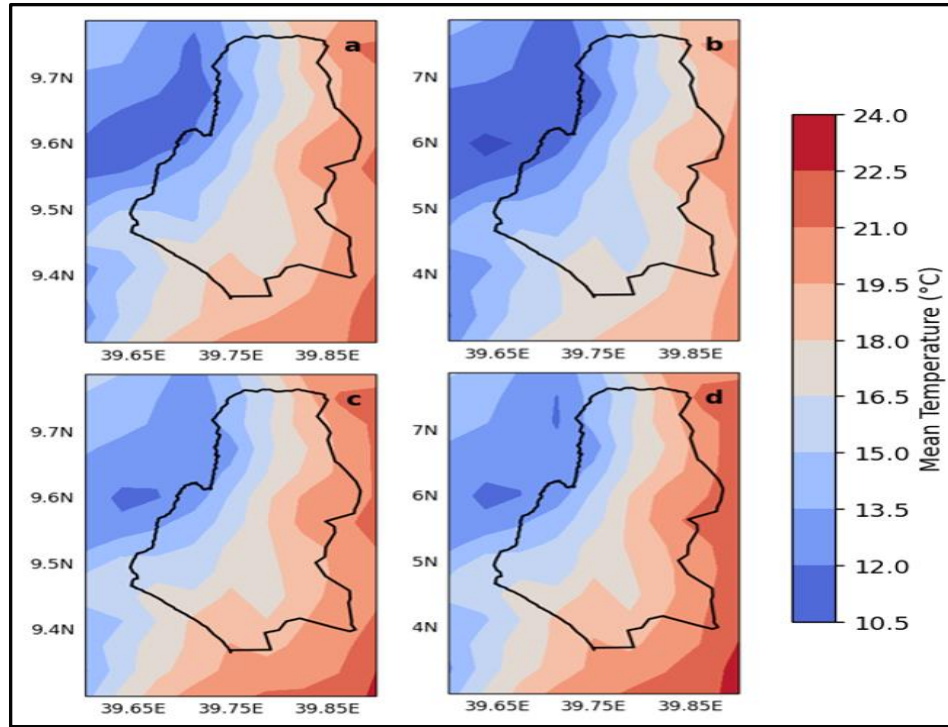


Figure 34. Mean Annual (a), Bega (b), Belg (c), and Kiremit (d) Temperature distribution.

4.3.3.3. Trend for Rainfall

There are several libraries in Python (such as Mann-Kendall) that can be used to implement the MK test using Python, along with custom implementations to account for autocorrelation. The graph shows the trend of annual and seasonal rainfall (Bega, Belg, Kiremt seasons) over the years, showing variations in the distribution of rainfall in the seasons and years (Fig. 10). The annual rainfall (blue line) is at its highest around the early 1990s and the mid-2000s, with more than 1,100 mm, and is at its lowest around 2015 and 2020 at around 800 mm. This indicates major variations, including a considerable drop in the most recent years.

The Kiremit season (red line), which accounts for the biggest percentage of rainfall, is similar and shows the highest rainfall around the early 1990s and mid-2000s (600–800 mm), and the lowest around 2015 (below 500 mm) (already stated in Figure 10a for annual rainfall). The Belg season (yellow line) has moderate amounts of rainfall with values above 300 mm occurring in some years, for example, 1996, while below 200 mm rainfall occurs from 2010 onward. The Bega season (green line) has the lowest level of rainfall, which is generally less than 100 mm, but with some

minor peaks around 1997 and 2007. In general, the bulk of the rainfall occurs in the Kiremit season, and the Bega season is the driest, with interannual variations for all seasons.

4.3.3.4. Mann- Kendall trend Rainfall Test

The p-value (0.013) is less than 0.05 and indicates that there is a statistically significant decreasing trend in rainfall for the annual period. This will enable us to reject the null hypothesis and conclude that there is a significant long-term decrease in rainfall. The negative Tau value (-0.242) suggests that the rainfall is negatively correlated and moderately. However, no significant trend is seen for rainfall during the Bega season ($p = 0.390$, $Z = -0.859$). The p-value is high, indicating that the trend observed is not statistically significant, and no definite trend of decrease or increase can be identified. The negative Tau value (-0.109) suggests a slight downward trend, but not significant enough to be considered.

In the same way, another significant trend can't be observed for the Belg season, since the p-value is greater than 0.05 ($p = 0.202$, $Z = -1.277$). The weak decreasing trend indicated by the negative Tau value (-0.110) is not statistically significant. There is also no significant trend in the Kiremit season, known as the main rainy season ($p = 0.366$, $Z = -0.904$). The negative Tau value (-0.106) indicates a weak and not significant downtrend. Overall, the only discernible trend is the decrease in annual rainfall, with moderate, but non-statistically significant, decreases seen in rainfall for the Bega, Belg, and Kiremt seasons (Table 29).

Table 29. The result of Mann Kendall trend test for rainfall of Ankober.

Season	P-value	z	S	tau
Annual	0.013233	-2.47744	-128	-0.24242
Bega	0.39008	-0.85947	-54	-0.10887
Belg	0.201668	-1.27681	-58	-0.10985
Kiremt	0.366174	-0.90366	-56	-0.10606

4.3.3.5. Trend for Temperature

The graph illustrates annual and seasonal temperature patterns (Bega, Belg, and Kiremt seasons) over time, revealing changes in temperature distribution across years and seasons (Fig. 10). Annual

temperature (blue line) shows a general upward trend, with lower temperatures observed in the early 1990s (around 16°C) and higher values exceeding 19°C in recent years, particularly after 2015. This indicates a gradual warming trend over time.

The Kiremit season (red line) generally records the highest temperatures among the seasons, peaking above 21°C in the years around 2015, while lower values are observed in the early 1990s (below 18°C). The Belg season (yellow line) follows a similar upward trajectory, with temperatures rising from approximately 17°C in the early 1990s to over 20°C after 2010. The Bega season (green line) consistently records the lowest temperatures, starting from below 15°C in the early 1990s and gradually increasing to around 17°C in recent years. Overall, all seasons exhibit a noticeable warming trend, with Kiremt being the warmest season and Bega the coolest. This reflects a clear pattern of temperature increase across all seasons over the observed period.

4.3.3.6. Mann-Kendall trend temperature test

The time series of annual temperature shows a statistically significant upward trend ($p = 0.0021$, $Z = 3.08$) and a moderately strong positive correlation ($\text{Tau} = 0.481$) between temperature and time. This is a validation of the recent warming trend in the annual mean temperature for the period of observation. Likewise, the temperature exhibits a significant increasing trend during the Bega season ($p = 0.0049$, $Z = 2.81$) and a moderate positive correlation with time ($\text{Tau} = 0.456$). The results indicate that temperatures have also been increasing gradually during the Bega season.

The Belg season shows the strongest statistically significant increasing trend ($p = 0.0000286$, $Z = 4.18$) and has the largest Tau value (0.513), which reflects a very high positive correlation between time and temperature, hence, the most significant warming for this season. There is also a significant rising trend in temperature during the Kiremit season ($p = 0.0139$, $Z = 2.46$), and a moderate positive relationship is found with a Tau value of 0.362 (Table 30). The results indicate a statistically significant increase in temperature in all seasons (Annual, Bega, Belg, and Kiremit), with the highest temperature increase being seen in the Belg season. The steady increase in temperature highlights a significant temperature change over the years.

Table 30. Result of the Mann-Kendall trend test for the average temperature of Ankober

Season	P-value	z	S	tau
Annual	0.002097	3.076158	254	0.481061
Bega	0.00493	2.811586	226	0.455645
Belg	2.86E-05	4.183994	271	0.513258
Kiremit	0.0139	2.459845	191	0.361742

4.3.4. Relationship between land use types and climate variability with pollution-sensitive macroinvertebrates

4.3.4.1.LULC VS Sensitive taxa: Annual-based trends

The LULC dynamics at the watersheds scale (160.91 km²) were also highly dynamic between 2016 and 2023, with a decrease in both AL (46.12 km²) and BP (4.24 km²) and an increase in GL (42.66 km²), in SV (5.99 km²) and in WB (1.91 km²), with a slight variation in the coverage of Dense forest (DF) (Table 4). Looking at these recent changes from a long-term perspective (1993-2023) showed that there has been an accumulation of land-use changes that affect habitat conditions. The families Heptageniidae and Perlidae taxa were significantly lower in 2016 compared with the 2023 (137 to 655; and 11 to 88, respectively), indicating better habitat quality, while Philopotamidae was significantly lower across land-cover types (110 to 54), and Aeshnidae and Dytiscidae were moderately higher across land-cover types (3 to 8 and 7 to 18, respectively). This has to be exceptional because some taxa like Baetidae live in both impacted and pristine site. So, the result was not to generalize. The results of these patterns indicate that LULC change patterns over the short term (2016-2023) and over the longer term (1993-2023) influence the structure of macroinvertebrate communities, and thus call for sustainable watershed management to sustain biodiversity and ecosystem functions in the Dinki watershed (Fig. 35).

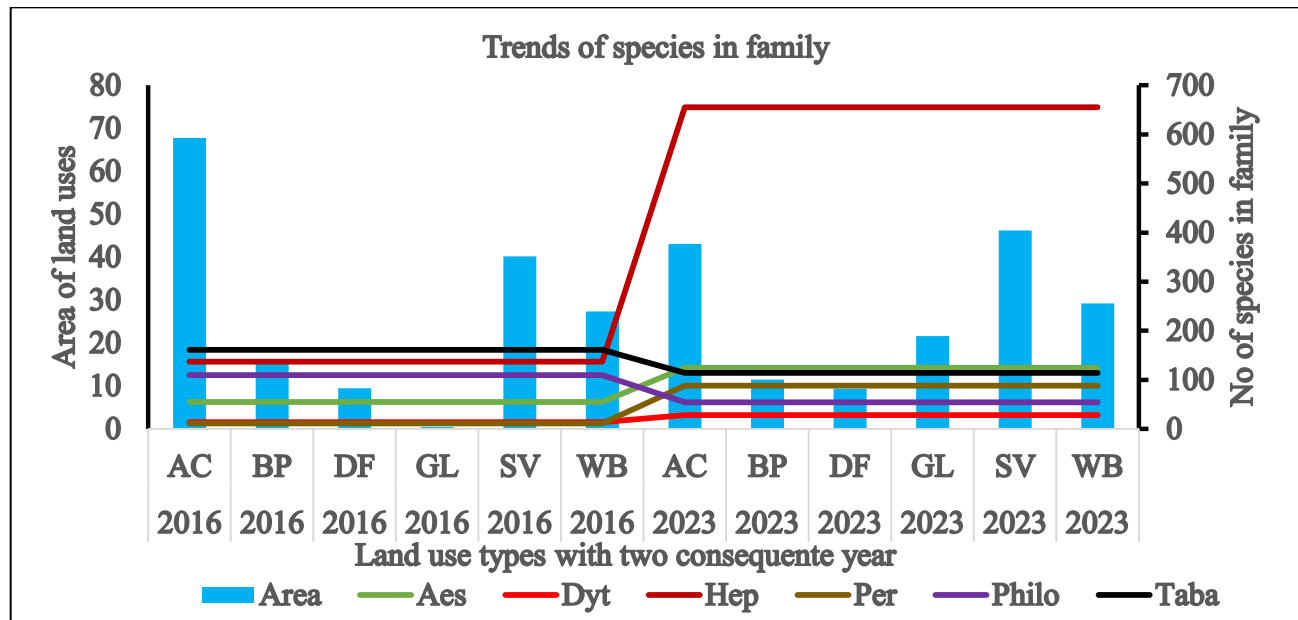


Figure 35. Watershed-level trends (160.91 km²) of LULC areas (bars) and total macroinvertebrate abundance for 2016 and 2023, illustrating concurrent changes in land use and species composition.

4.3.4.2. Trends in rainfall with sensitive taxa

Macroinvertebrate taxa composition was affected by rainfall fluctuations in 2016-2023, with significant shifts in species composition, particularly at stations. While rainfall decreased in Dinki (291.53 mm to 261.81 mm), it increased significantly in Zego (310.30 mm to 315.74 mm), Gedamoch (301.26 mm to 352.01 mm), and Dense (272.70 mm to 352.01 mm). The most significant increase was found in Heptageniidae, with a notable increase in Gedamoch (8.58 to 34.58) and Zego (0.93 to 14.14), indicating a trend towards better conditions as rainfall levels rise. The sensitive species were also Aeshnidae, which rose in Zego (0.50 to 2.43) and Gedamoch (4.33 to 7.83), but actually disappeared in Dinki and Zego. The number of Philopotamidae was moderate at all stations except at Zego, where it dropped by 84%, and at Gedamoch, where it dropped by 84.3%, indicating negative rainfall changes. The number of Tabanidae showed a marked decline at all stations, which dropped by 13%, with the most severe declines at Gedamoch (2.58 to 0.25) and Zego (1.29 to 0.36). The differential responses to rainfall variation of the macroinvertebrate families are indicated by these trends, where Heptageniidae increases with higher rainfall, and Tabanidae decreases with higher rainfall (Fig. 36).

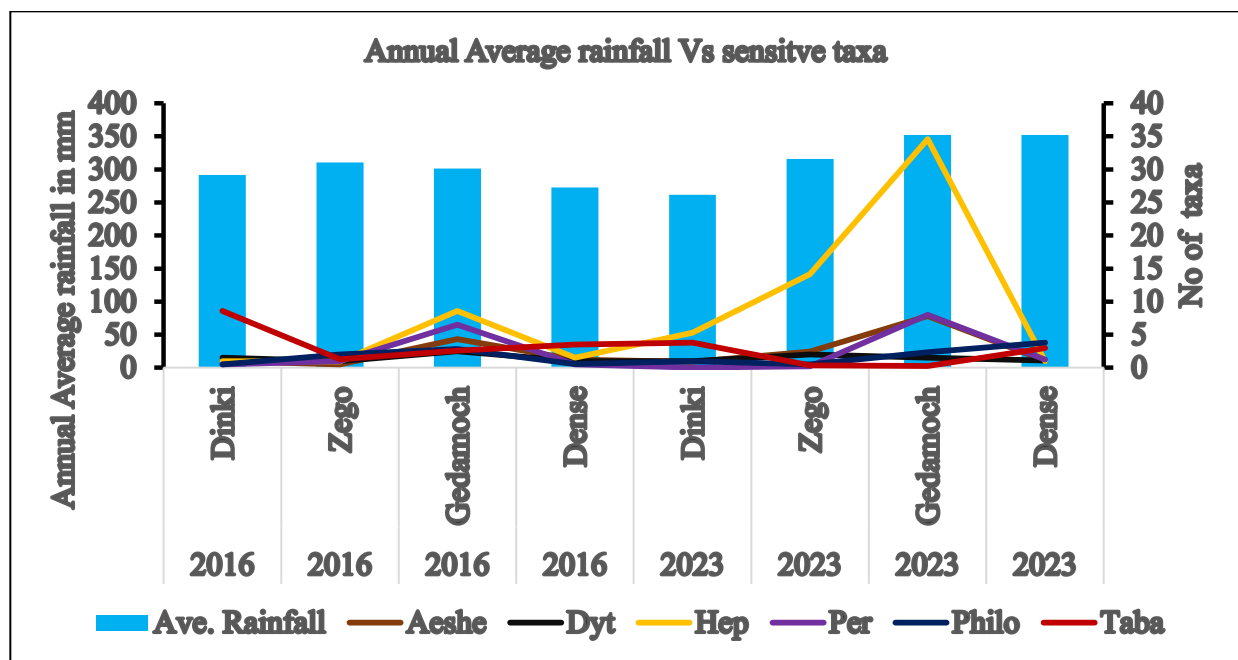


Figure 36. Trends of sensitive taxa along with the annual rainfall situation.

4.3.4.3. Temperature VS Sensitive taxa

4.3.4.3.1. Annual-based trend

There were clear changes in family species composition at stations from 2016 to 2023 when related to annual average temperature changes. A slight drop in temperature (from 20.54 to 19.54) was observed in Dinki, with significant fluctuations in species, such as an increase in Heptageniidae from 1.00 to 5.30, whereas other species, like Aeshnidae, Dytiscidae, and Perlidae, decreased. The temperature dropped slightly from 19.26°C to 19.16°C at Zego, with increases at Aeshnidae (0.50 to 2.43) and Dytiscidae (1.00 to 2.00) and a significant rise at Hep (0.93 to 14.14). In the case of Gedamoch, the temperature drop was more noticeable from 19.59°C to 18.71°C; its increase in Hep (8.58 to 34.58) and Aeshnidae (4.33 to 7.83) was more conspicuous, while Tabanidae had reduced from 2.58 to 0.25. Dense also saw a slight drop in temperature from 19.59°C to 18.71°C, but with moderate changes in species composition, notably in Tabanidae (from 3.50 to 2.96) and Hep (from 1.50 to 1.00). The patterns suggest that temperature variation played a role in the distribution and abundance of species for each station (Fig. 37).

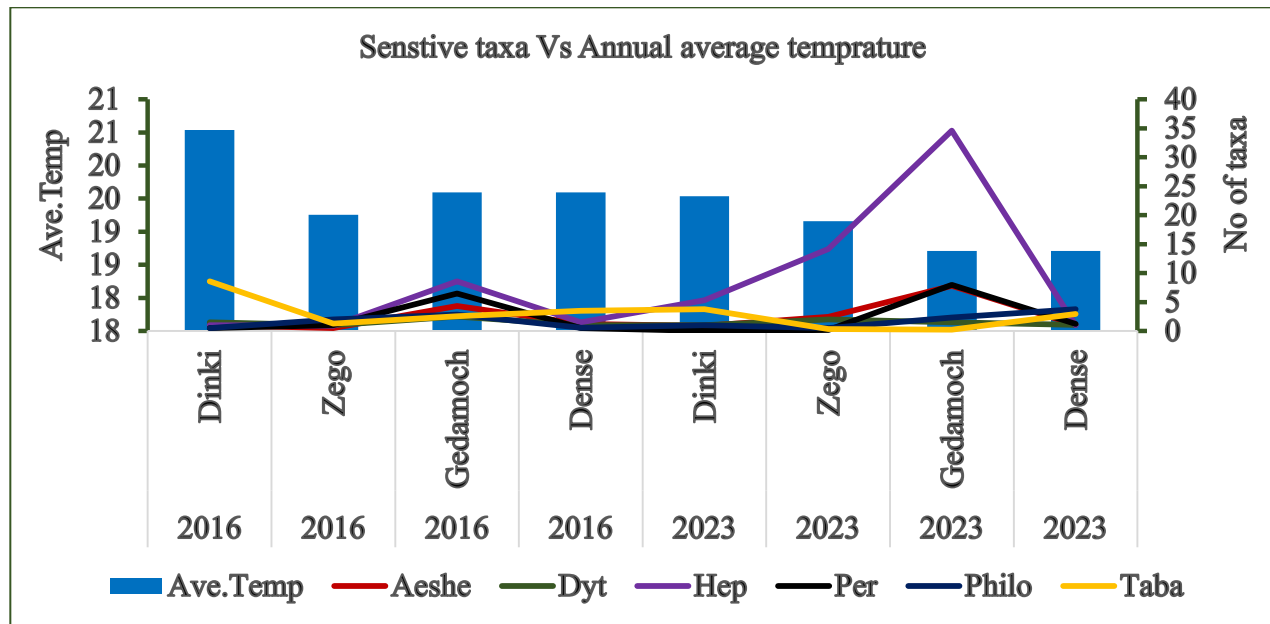


Figure 37. Trends of macroinvertebrate in family level along with the annual average temperature.

In addition, land-use and climate effects were found on the RDA based on macroinvertebrates in the watersheds of Dinki (Fig. 38). A comparison of 2016 sites with 2023 sites showed that sites in 2016 clustered separately, indicating temporal changes. Increased grazing land (GL) and shrub/vegetation (SV) as habitat improvements in 2023 were linked to sensitive families Heptagenidae (Hep) and Perlidae (Per), respectively, while higher agriculture (AC) and built-up areas (BP) in 2016 were linked to Philopotamidae, respectively. Aeshnidae and tolerant taxa (Tabanidae) were found to be more tolerant of the warmer, drier sites, while Heptagenidae and Perlidae were more favored by cooler, wetter sites (Ged-23, Den-23). The patterns further suggest both long-term changes due to land-use and short-term fluctuations due to climate, which reinforces the usefulness of macroinvertebrates as indicators of watershed health.

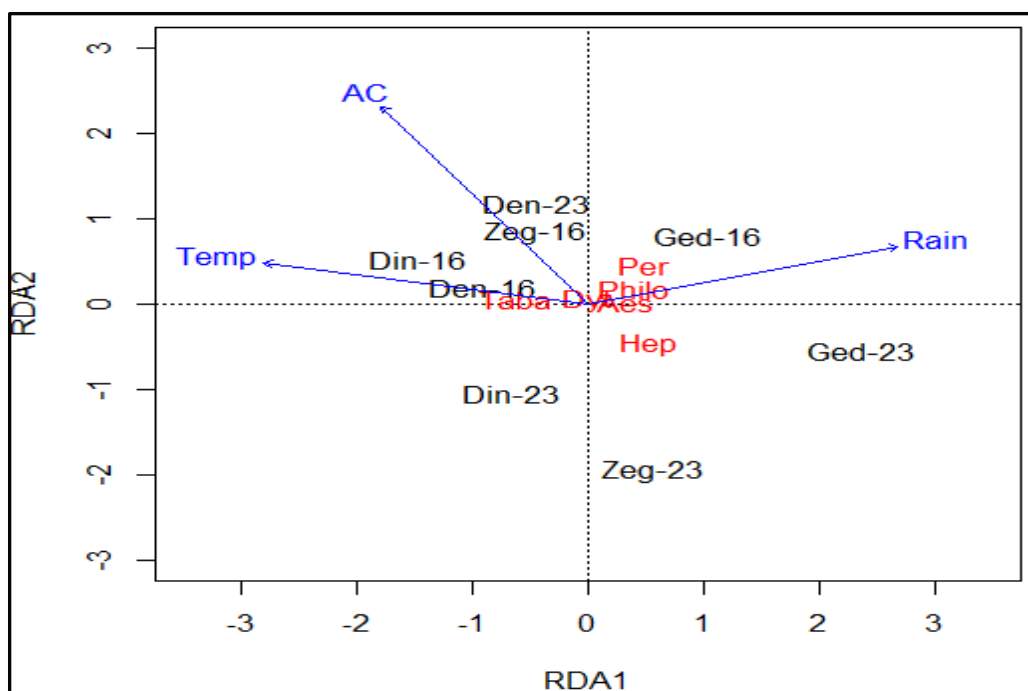


Figure 38. RDA of six macroinvertebrate taxa and environmental variables (LU types, temperature, rainfall) at four Dinki watershed sites (2016 & 2023).

Conversely, GLM results (Table 31) show that the pollution-sensitive macroinvertebrates were not significantly affected by climatic variables, apart from Tabanidae and Dytiscidae, both of which were significantly affected by temperature. The positive coefficient suggests that increasing temperature enhances the abundance of this taxon. In addition, other taxa (Aeshnidae, Heptagenidae, Perlidae, and Philopotamidae) showed highly significant relationships with temperature, rainfall, or land uses (LUs), indicating strong or variable sensitivity under the current dataset. The limited significance across taxa suggests that climate effects are taxa-specific, while most macroinvertebrates are more strongly regulated by combined environmental and habitat conditions rather than single predictors.

Table 31. Generalized Linear Model (GLM) results showing the effects of temperature, rainfall, and land use on pollution-sensitive macroinvertebrate taxa.

Indicator Taxa	Variable	Estimate	P-value	Significance	Interpretation
Aeshnidae	Temperature	-0.71	0.56	0.00	Highly Significant
	Rainfall	0.26	0.00	0.00	Highly Significant

	Land use	0.01	-0.04	0.00	Highly Significant
Dytiscidae	Temperature	-0.20	-0.10	0.05	Weak Significant
	Rainfall	0.09	0.00	0.71	Non-Significant
	Land use	0.03	-0.02	0.23	Non-Significant
Heptagenidae	Temperature	-5.74	0.03	0.77	Non-Significant
	Rainfall	0.64	0.00	0.00	Highly Significant
	Land use	-0.41	-0.06	0.00	Highly Significant
Perlidae	Temperature	-1.52	0.93	0.05	Highly Significant
	Rainfall	0.08	0.02	0.00	Highly Significant
	Land use	-0.02	-0.06	0.00	Highly Significant
Philopotamidae	Temperature	-0.23	0.44	0.01	Highly Significant
	Rainfall	0.06	0.01	0.00	Highly Significant
	Land use	0.01	0.03	0.00	Highly Significant
Tabanidae	Temperature	12.53	0.02	0.04	Highly Significant
	Rainfall	-1.02	-0.03	0.00	Highly Significant
	Land uses	-0.50	0.06	0.06	Highly Significant

Similarly, the VPR (Table 32) indicated that the climate variables separately explained 19.72% of the variation in macroinvertebrates, and land use had a slight independent contribution (1.95%). Climate and land use, however, have a fairly large shared fraction (6.84%), suggesting interactive effects between these two factors in shaping species distribution. There is also a high degree of unexplained variability, indicating that other local factors (such as microhabitat, substrate, or other unmeasured physico-chemical factors) are also important to macroinvertebrate distribution.

Table 32. Variation Partitioning Analysis (VPA) results indicate the magnitude of predictors or factors which affects indicator or taxa.

Fraction	Adj_R2	Percent (%)	Interpretation
Climate	0.1972	19.72	Strong independent climate effect
Land use	0.0195	1.95	Very weak independent effect
Shared	0.0684	6.84	Joint climate-land use effect
Residual	0.7149	71.49	Unexplained variation

4.4. Development of a Benthic Macroinvertebrate-based-MMI for Assessing the Ecological Health of Ethiopian Highland Streams

4.4.1. Selecting potential metrics

The 2023 data set was used to calculate the macroinvertebrate-based-MMI, and the 2016 data set was held back for validation. The reference and impacted sites in the Dinki watershed were determined based on the approach of James *et al.* (1986). Candidate metrics were selected based on their ecological relevance, interpretability, and sensitivity to anthropogenic disturbances. Based on the data from 50 composite sampling sites during the 2016 sampling period, 36 sites were classified as impacted, while 14 sites served as reference sites in both the dry and wet seasons for validation. Similarly, during the 2023 sampling period, 36 (72%) sites were again identified as impacted, and 14 (28%) were categorized as reference sites for MMI development. Overall, out of the 100 composite sites sampled across both years (25 sites $\times$ 2 seasons $\times$ 2 years), 72 were categorized as highly impaired, while the remaining 28 were classified as moderately or less impaired. Furthermore, based on the criteria stated in (Annex VI), of the 50 samples used for development of the index (using 2023 data), 36 (72%) were considered as impacted sites and the remaining 14 (28%) samples as the reference site. This pH, H₂SO₄, DO, T_{water} (water temperature), and Turbidity environmental variables were clearly differentiated between the referenced site with impacted sites (Annex VI). These data were newly used for developing the MMI and validating it through 2016 macroinvertebrate community data. The reason why was that there was a significant difference between 2016 and 2023 in discriminating between the impacted and referenced sites.

According to macroinvertebrate composition, a total of 107 families were identified across both years, with 63 families recorded in 2016 and 77 families in 2023. A total of 37 potential metrics were selected for initial screening (Table 33), all derived from macroinvertebrate assemblages. These included a variety of biodiversity indices such as richness, Shannon diversity, evenness, number of individuals, dominance (D-1), Simpson diversity (1-D), abundance, Brillouin, Menhinick, and Equitability. J, Fisher's alpha, Berger-Parker, and Chao-1. Moreover, the proportional composition of macroinvertebrate orders and Functional Feeding Groups (FFGs). In addition, compositional indices (e.g., EPT, EOT, ECT, ET), biotic indices (FBI, BMWP, ASPT),

and counts of major taxonomic groups (Trichoptera, Plecoptera, Diptera, Hemiptera, Decapoda) were included. Tolerance-based metrics, such as the percentage of intolerant, moderately tolerant, and tolerant taxa with the total number of Taxa for each site, ratios like Baetidae to Ephemeroptera, and relative abundance, were also incorporated and measured to comprehensively capture the ecological status of the study sites (Table 33).

Following preliminary screening based upon disturbance-response patterns and Mann-Whitney U-tests, 24 metrics were found to be significantly different ($p < 0.05$) between the reference and impacted sites and were retained for further evaluation (Table 33). These metrics had repeatable trends of either increasing or decreasing that indicate their sensitivity or tolerance to the stress gradient from relatively pristine (Gedamoch) to more impacted (Dinki, Zego, and Dense). For each metric, a statistical analysis was performed with the U-test, and significant differences ($p < 0.05$) were found between the reference and disturbed sites. The U test was selected due to the non-normal distribution of the data, a common issue in ecological assessments. Following established protocols (Barbour *et al.*, 1996; Karr *et al.*, 1986), metrics with p-values below 0.05 were considered reliable indicators of ecological impairment and were incorporated into the final development of the MMI.

Table 33. Potential metrics with their description and responses to increasing environmental disturbances, and the Mann-Whitney U test.

Metrics	Description of metrics	Response to disturbance	U-test	P-value	Testing criteria
%EPT	Total abundance of Ephemeroptera, Plecoptera, and Trichoptera in the Dinki watershed	Decrease	45	0.01	Yes
% EOT	Total abundance of Ephemeroptera, Odonata, and Trichoptera in the Dinki watershed	Decrease	50	0.04	Yes
%ECT	Total abundance of Ephemeroptera, Coleoptera, and Trichoptera in the Dinki watershed	Decrease	39	0.13	No
%ET	Total abundance of Ephemeroptera and	Decrease	33	0.006	Yes

%Ephem	Tricoptera in the Dinki watershed Total abundance of Ephemeroptera in the Dinki watershed	Decrease	27	0.0003	Yes
%Odonata	Total abundance of Odonata in the Dinki watershed	Decrease	60	0.0001	Yes
%Trico	Total abundance of Tricoptera in the Dinki watershed	Decrease	54	0.001	Yes
%Into. /No of taxa	Abundance of intolerant species /# of taxa in the Dinki watershed	Increase	47	0.02	Yes
% Mode. /No of taxa	Abundance of moderate species/taxa in the Dinki watershed	Increase	52	0.008	Yes
% Tole. /No of taxa	Abundance of tolerance species /# of taxa in the Dinki watershed	Increase	36	0.09	No
% Shredder	Abundance of shredder feeding group	Decrease	20	0.41	No
% Predator	Abundance of predator feeding group	Increase	30	0.08	No
% Scraper	Abundance of scraper feeding group	Decrease	29	0.03	Yes
% Gather/Collector	An abundance of Gatherer/Collector feeding groups	Increase	18	0.22	No
% Filterer/Collector	An abundance of Gatherer/Collector feeding groups	Increase	55	0.0007	Yes
Individuals	Total abundance of the family	Decrease	42	0.01	Yes
Simpson_1-D	$D = \sum_{i=1}^S \frac{1}{P_i^2}$, where, P_i , proportion of individuals in the i^{th} species; s , # of species	Decrease	23	0.06	No
Shannon_H	$H' = - \sum_{i=1}^s p_i \ln p_i$	Decrease	24	0.05	Yes
Evenness_e^H/S	$J = \frac{H'}{H_{max}}$	Decrease	38	0.11	No
Brillouin	$H = \frac{\ln N! - \sum \ln n_i!}{N}$	Decrease	40	0.07	No
Menhinick	$D = \frac{S}{\sqrt{N}}$	Decrease	35	0.013	Yes
Margalef	$DM = \frac{S-1}{\ln(N)}$	Decrease	32	0.02	Yes
Equitability_J	$J = \frac{H'}{\ln(S)}$	Decrease	37	0.08	No
Fisher_alpha	Log-series model estimates species richness.	Decrease	29	0.03	Yes

Berger-Parker	Dominance is measured by the most abundant.	Increase	18	0.22	No
Chao-1	Estimates unseen species from rares	Increase	52	0.0007	Yes
FBI	Family Biotic Index	Increase	22	0.004	Yes
BMWP	Biological Monitoring Working Party	Decrease	15	0.18	No
ASPT	Average Score Per Taxa	Decrease	12	0.006	Yes
Tricoptera	≠ of Tricoptera	Decrease	44	0.009	Yes
Plecoptera	≠ of Plecoptera	Decrease	46	0.006	Yes
Diptera	≠ of Diptera	Increase	48	0.005	Yes
Hemiptera	≠ of Hemiptera	Increase	41	0.03	Yes
Decapoda	≠ of Decapoda	Increase	39	0.04	Yes
Annelida	≠ of Annelida	Increase	50	0.01	Yes
RM	Relative abundance	Increase	34	0.08	No
Beat/Ephe	≠ Baetidae/≠ Ephemeroptera	Decrease	28	0.04	Yes

Note: * U-test is a significant difference at $p < 0.05$

4.4.2. Redundant Analysis and the Scoring Criteria of the Core Metrics

Twenty-four metrics primarily met the response-to-disturbance and U-test criteria (Table 33). These metrics were further evaluated using the Spearman (r_s) test to assess their sensitivity to human disturbance (Annex VII). As a result, 21 metrics of the 24 metrics were found to be redundant, so they were removed. For instance, the percentage of Ephemeroptera-Plecoptera-Tricoptera (%EPT) metrics is redundant with the percentage of Ephemeroptera-Odonata-Tricoptera (% EOT; $r_s=0.99$), percentage of Ephemeroptera-Tricoptera (%ET; $r_s= 0.99$), percentage of Ephemeroptera (% Ephe; $r_s=0.93$), and Individual ($r_s=0.86$). Furthermore, the percentage of Ephemeroptera-Odonata-Tricoptera (% EOT) metric is redundant with the percentage of Ephemeroptera-Tricoptera (%ET; $r_s=0.99$), percentage of Ephemeroptera (% Ephe; $r_s= 0.93$), and Individual (Idnv; $r_s=0.86$). percentage of Ephemeroptera-Tricoptera (%ET) was redundant with percentage of Ephemeroptera (%Ephe; $r_s=0.93$) and Individual (Indi; $r_s=0.88$). Likewise, the percentage of Tricoptera (% Trico) metric was redundant with Tricoptera (Trico; $r_s=0.83$). Similarly, the Individual (Indi) metric was highly correlated with Diptera (Dip; $r_s=0.85$). While Menhinick (Menh) metric was also redundant with Margalef (Marg; $r_s=0.84$), Fisher_alpha (Fish alp; $r_s=0.91$), and with Chao-1 ($r_s=0.76$). On the other hand, Margalef metric was redundant with Fisher_alpha (Fis-alp; $r_s= 0.97$), Chao-1 ($r_s=0.96$), and Plecoptera (pleco; $r_s=0.76$). Moreover, Fisher_alpha (Fish_alp) metric was redundant with Chao-1 (cha; $r_s=0.92$) and Plecoptera ($r_s=0.74$).

The chao-1 metric was redundant with Plecoptera (Pleco; $r_s=0.71$). Then the ASPT metrics were highly correlated with Tricoptera (Trico; $r_s=0.80$) and the FBI metrics were highly correlated with Hemiptera (Hem; $r_s=0.98$). Hence, the initial selection process identified EPT, ET, Ephemeroptera, Individual, Tricoptera, Margalef, Fisher alpha, Chao-1, and Plecoptera as redundant metrics. As a result, only six metrics with Spearman's $\rho>0.70$ and a significant P-value were chosen as the final metrics. These include %EOT, %Trichoptera, Diptera, Hemiptera, Average Score Per Taxon (ASPT), and Family Biotic Index (FBI).

On the other hand, to verify, using box-and-whisker plots eliminated Diptera. As shown in the figure. 39d, the box-and-whisker plot for Diptera couldn't effectively differentiate between referenced and impacted sites. This resulted in the selection of five core metrics, such as %EOT, %Trichoptera, Hemiptera, ASPT, and FBI, to develop the biota index. Therefore, only five core metrics were selected for developing the biotic index. Box-and-whisker plots of these five-core metrics (Fig. 39 a, b, c, e, and f) clearly illustrate their ability to differentiate between reference and impacted sites, reflecting distinct characteristics of macroinvertebrate communities in the Dinki watershed.

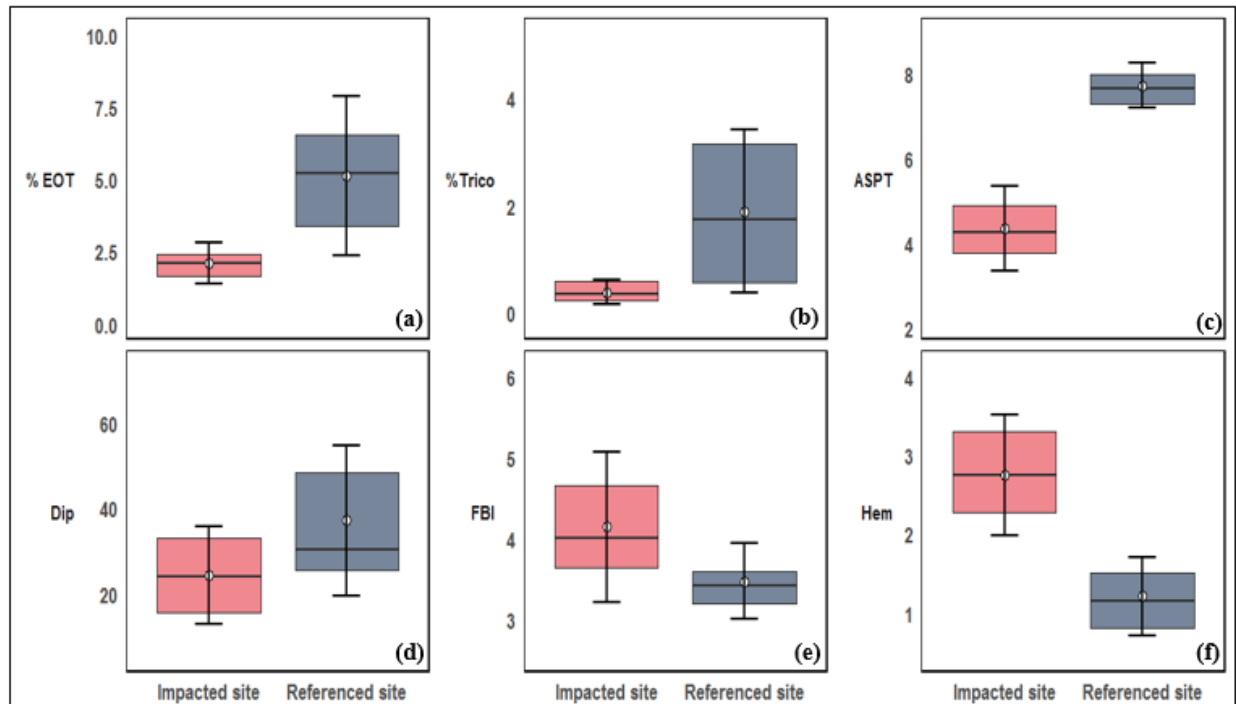


Figure 39. The box- and-whisker plots of the six-core metrics (a, b, c, e and f) and an inefficient (d) metric for discriminating the impaired from referenced watershed sites with their medians (at about the middle/bottom bolded line of each large box), the 25th and 75th quartiles of the bottom and top of the large box, respectively, and whiskers (representing the value outside of the 25th and 75th quartiles). Note: Dip= Diptera, Hem= Hemiptera

Furthermore, to simplify while assigning scores (Table 34), direct values of the core metrics (integers, percentages, or cover abundance) were used to create the box-and-whisker plots (Fig. 40). Unfortunately, there were no extreme values observed in the box plots except for %EOT and ASPT, that much not make interpretation sense to be as difficult. Therefore, no need for the values of the metrics to be transformed using $(\log_{10}(x + 1))$. This finding aligns with studies from Ethiopia (Alemneh *et al.*, 2019), which demonstrated the development of macroinvertebrate-based biotic integrity tools using metrics from the macroinvertebrate community.

Table 34. The five-core metrics, their threshold values, and scoring criteria, adapted from Karr *et al.* (1986) trisection method. Scores are assigned based on the current data distribution: 1 indicates severe impairment, 3 indicates intermediate conditions, and 5 reflects the reference site conditions.

Selected metrics	Threshold/box plot values					Scoring criteria		
	Min	25%	Median	75%	Max	5	3	1
% EOT	2.60	3.00	5.00	6.00	7.60	≥ 6.00	2.6-5.99	< 2.60
%Tricoptera	0.30	0.40	2.00	3.25	3.75	≥ 1.00	0.30-1.00	< 0.30
ASPT	7.11	7.12	7.90	8.00	8.50	≥ 7.13	7.11-7.12	< 7.13
FBI	3.00	3.25	3.50	3.75	4.00	≤ 3.00	3-3.75	> 3.75
Hemiptera	0.75	0.90	1.25	1.50	1.75	≤ 0.20	0.2-0.75	> 0.75

Note: Min = Minimum, Max = Maximum, 25% and 75% = the 25th and 75th quartile values of each box plot diagram for each metric, respectively.

4.4.3. Correlation of core metrics with environmental variables for their efficiency validation

We selected five core metrics and assessed their associations with river water physicochemical parameters across the Dinki River and its tributaries (Dinki, Zego, Gedamoch, and Dense streams). The analysis, aimed at validating the effectiveness of the metrics in distinguishing between

impacted and reference sites (Table 35), used Spearman's rank correlation coefficients (r_s). For instance, % EOT showed strong positive correlations with pH ($r_s = 0.42$, $p < 0.05$), DO ($r_s = 0.47$, $p < 0.05$), and HVAS ($r_s = 0.52$, $p < 0.01$), and strong negative correlations with water temperature ($r_s = -0.45$), EC ($r_s = -0.40$, both at $p < 0.05$), turbidity ($r_s = -0.61$), and TN ($r_s = -0.64$, both at $p < 0.01$). Similarly, % Trichoptera was positively correlated with DO ($r_s = 0.39$, $p < 0.05$). FBI was also positively correlated with TN ($r_s = 0.47$) and NO_3^- ($r_s = 0.46$) at $p < 0.05$. ASPT showed strong positive correlations with HVAS ($r_s = 0.52$) and DO ($r_s = 0.61$, both at $p < 0.001$), while negatively correlated with Twater ($r_s = -0.51$), EC ($r_s = -0.53$), TN ($r_s = -0.52$, all at $p < 0.01$), and NO_3^- ($r_s = -0.46$, $p < 0.05$). Hemiptera abundance was negatively correlated with DO ($r_s = -0.39$) and positively with turbidity ($r_s = 0.35$, both at $p < 0.05$). Finally, the newly developed MMI has also positively correlated with HVAS ($r_s = 0.54$; $p < 0.01$), DO ($r_s = 0.47$), and Discharge ($r_s = 0.40$) at $p < 0.05$ and negatively correlated with pH ($r_s = -0.46$), at $p < 0.05$.

Table 35. The Spearman's rho of core metrics and Dinki River water physicochemical parameters for validating their efficiency.

Core metrics	River water physicochemical parameters									
	pH	HVAS	DO	Twater	Turb	EC	TN	NO_3^-	TP	Discharge
%EOT	-0.42*	.523**	.465*	-.452*	-.610**	-.404*	-.639**	-.269	.053	.010
%Trico	-.305	.370	.396*	-.391	-.218	-.287	-.394	-.181	-.146	.125
FBI	.202	-.388	-.220	.095	.159	.098	.471*	.458*	-.240	-.341
ASPT	-.382	.522**	.606**	-.552**	-.512**	-.531**	-.521**	-.462*	-.105	.057
Hem	.221	-.222	-.397*	.352	.240	.319	.237	.232	-.137	-.032
MMI	-.464*	.544**	.466*	-.371	-.297	-.360	.288	.163	.370	.402*

Note: * correlation is significant at $p < 0.05$, ** correlation is significant at $p < 0.01$ (2-tailed) ($n = 50$)

4.4.4. Validation of core metrics with 2016 candidate metrics

The strengths of 2023's five core metrics, which were selected from the recent data, have been assessed using 2016 candidate metrics. The analysis, aimed at testing the effectiveness of the metrics in distinguishing between impacted and referenced sites (Table 36), used Spearman's rank correlation coefficients (r_s). For instance, core metrics % EOT was strongly positive correlations with %EOT ($r_s = 0.52$, $p < 0.05$), % Ephemeroptera ($r_s = 0.42$; $p < 0.05$), %Tricoptera ($r_s = 0.50$, $p < 0.05$), ASPT ($r_s = 0.48$; $p < 0.05$), Plecoptera ($r_s = 0.46$; $p < 0.05$), Hemiptera ($r_s = 0.44$; $p < 0.05$), %EPT ($r_s = 0.52$; $p < 0.01$), % ET ($r_s = 0.51$; $p < 0.01$) and % Intolerant/Taxa ($r_s = 0.53$; $p < 0.01$) and negative correlation with % Moderate/Taxa ($r_s = -0.44$; $p < 0.05$). Similarly, % Trichoptera was positively correlated with Intolerant/Taxa ($r_s = 0.57$; $p < 0.01$),

Individual ($r_s=0.53$; $P<0.01$), Menhinick ($r_s= 0.51$; $P<0.01$), and Relative Abundance (RA) ($r_s=0.55$; $p<0.01$). and negatively correlation with Moderate/Taxa ($r_s= -0.61$; $p<0.01$). FBI was also positively correlated with Individual ($r_s = 0.62$; $P<0.01$) and RA ($r_s = 0.64$) at $p < 0.01$. ASPT showed strong positive correlations with %EPT ($r_s = 0.68$), %EOT ($r_s=0.64$), %ET ($r_s=0.65$), %Ephe ($r_s=0.65$), Indi ($r_s=0.55$), Pleco ($r_s = 0.54$), RA ($r_s = 0.53$), and negatively correlated with % of Mode/Ta ($r_s=-0.59$), all at $p < 0.01$. Hemiptera abundance was positively correlated with RA ($r_s = 0.52$) and negatively with ASPT ($r_s = 0.53$, both at $p < 0.01$).

Table 36. Spearman's rank-order correlation coefficients (rs) validate the efficiency of the 2023 core metrics using the 2016 candidate metrics.

Core metrics	2016 Candidate for validation																									
	%EPT	%EOT	%ET	%Ephe	%Odo	%Trico	%In./Ta	%Mo/Ta	%SC	%FC	Indi	H	Menc	Marg	Fish_alp	Cha-1	FBI	ASPT	Trico	Pleco	Dip	Hemi	Decap	Anell	RA	Be/Ep
%EOT	.52**	.49*	.51**	.42*	.00	.50*	.53**	-.44*	.05	.25	.33	.34	-.07	.22	.09	.15	.10	.48*	-.01	.46*	-.09	.44*	-.23	.22	.30	-.35
%Trico	.41*	.50*	.36	.45*	.37	.18	.57**	-.61**	-.38	.01	.53**	.01	.51**	-.14	-.37	.04	.09	.45*	.08	.16	.21	.46*	-.07	.16	.55**	.04
FBI	-.27	-.21	-.28	-.28	-.40*	-.15	-.15	.02	.47*	.03	.62**	.39	.20	-.35	-.03	-.37	.34	-.34	.19	-.13	-.35	-.47*	.13	-.07	.64**	.13
ASPT	.68**	.64**	.65**	.65**	.33	.52**	.41*	-.59**	.27	.26	.55**	.27	-.30	.15	-.09	.18	.15	1.0**	.07	.54**	.26	.44*	-.13	-.21	.53**	.11
Hem	-.43*	-.47*	-.48*	-.38	-.34	-.26	-.16	.24	.28	.03	-.49*	-.16	.28	-.16	.13	-.29	-.29	-.53**	-.07	-.14	-.23	-.31	.11	-.21	.52**	-.17

* Significant results of rs at 0.05, ** significant results of rs at 0.01 (2-tailed), n=100 samples (2016 and 2023 data)

Note: %EPT= percentage of Ephemeroptera-Odonata-Tricoptera, %EOT= Percentage of Ephemeroptera-Odonata-Tricoptera, %ET=percentage of Ephemeroptera-Tricoptera , %Ephe= percentage of Ephemeroptera, %Odonata=Percentage of Odonata, %Trico=percentage of Tricoptera, %In./Ta= %Intolerant/No of taxa, % Mo/Ta= %Moderately/No of taxa, %SC= Percentage of Scraper, %FC= Percentage of Filterer/Collector, Indi= Individuals, H= Shannon_H, Menc=Menhinick, Marg= Margalef, Fish_alp= Fisher_alpha, Cha-1= Chao-1, FBI= Family Biotic Index, ASPT= Average Score Per Taxon, Trico= Tricoptera, Pleco= Plecoptera, Dip= Diptera, Hemi= Hemiptera, Decap= Decapoda, Anell= Annelida, RA= Relative abundance, Be/Ep= Baetidae/Ephemeroptera.

4.4.5. *Developing MMI and its Validation*

This study developed a MMI specifically for headwater streams in the Dinki watershed, based on metrics derived from macroinvertebrate communities. The final MMI was constructed through a systematic selection process that evaluated each metric's sensitivity to stress in the Dinki watershed. This evaluation involved statistical analyses, including U-tests and Spearman rank correlations, complemented by visual inspection of box-and-whisker plots. The trisection scoring method (Table 37) was applied to assign sensitivity values (5, 3, or 1) (Karr & Chu, 1997) to each core metric, with the scoring thresholds established from box-and-whisker plots (Fig. 41). Using these criteria, all data from the Dinki watershed reference sites (Gedamoch and one site each from Zego and Dense) and impacted sites (Dinki, Zego, and Dense) were scored for each core metric. Average values for each metric were then computed by pooling data from 18 plots at impacted sites and seven plots at reference sites. The final MMI score was calculated as the sum of the average scores for the five-core metrics. The minimum observed MMI sum for the impacted sites was 10.22, while the maximum for the reference sites was 22.43. The theoretical range of MMI scores spans from 5 (the sum of minimum scores for all metrics at highly impacted sites) to 25 (the sum of maximum scores at the least impacted sites). Based on this range, the MMI was categorized into five condition classes: 25-21 as Very Good, 20-17 as Good, 16-13 as Fair, 12-9 as Poor, and 8-5 as Very Poor. According to these categories (Table 37), the reference sites in the Dinki watershed fell within the " Very Good" class, while the impacted sites were categorized as "Poor."

Table 37. The score categories of the newly developed MMI and their corresponding biological integrity and impairment status.

MMI value group	Biological integrity status of sites	Watershed has fallen in each group	Impairment condition of sites
25-21	Very good	Referenced site	The least impacted site
20-17	Good	No watershed under this group	Slightly impacted site
16-13	Fair	No watershed under this group	Moderately impacted site
12-9	Poor	Impacted site	less severely impacted site
8-5	Very poor	No watershed under this group	Severely impacted site

Primary, the newly developed MMI was also validated for its efficiency using U-test and p-value, Spearman's r, box plots, RDA, and for its efficiency in discriminating impacted and referenced sites as shown in Table 3-4 and Figure 2-3, respectively. Next, the effectiveness of MMI was evaluated using RDA (Fig. 40). The RDA helps visualize the relationships between core metrics, MMI, river physicochemical parameters, and impacted and referenced sites by extracting basic information and plotting it on the X-axis (RDA1) and the Y-axis (RDA2). In this context, the RDA RDA1 and RDA2 were explained, 68.7% explained 27% respectively, and were used to validate the core metrics and the final MMI. The correlation matrix of the RDA (Fig. 40 and Table 4) showed that the majority of environmental variables were negatively correlated with core metrics and MMI except HVAS, DO, and Discharge.

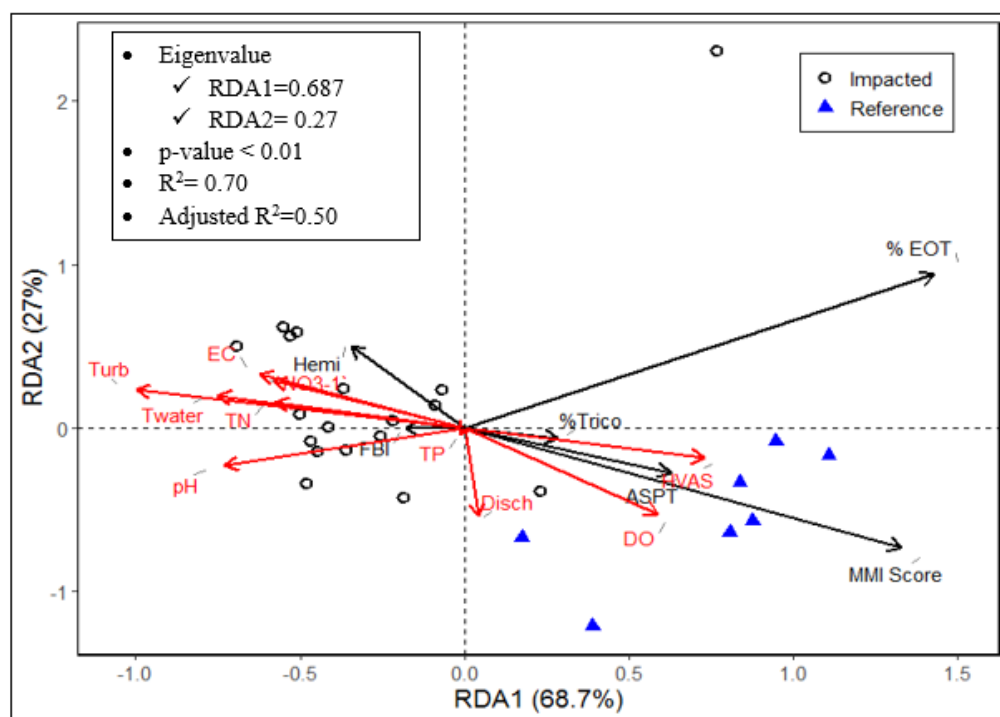


Figure 40. RDA diagram illustrating the correlation of core metrics, MMI, and the sampling plots with river physicochemical parameters using the RDA 1-and 2- axes.

Lastly, the efficiency of MMI in separating impacted from unimpaired sites was validated using two box plots (Fig. 41). The non-overlapping box plots of the two sites demonstrated the distinction between the poorly impaired sites and very good sites. The validation revealed that sites initially classified as reference sites were categorized as having less impacted habitat

conditions, while the majority of sites originally considered as impaired were categorized as having moderately to highly impacted habitat conditions in combined (Fig. 41). Fourth, a U-test confirmed the strength of the MMI, revealing a statistically significant difference ($p < 0.001$) between the two sites (Fig. 41). Results from the MMI scores clearly discriminate between impacted and reference sites in the Dinki watershed. The scores are lower (mean $\pm$ 95% CI: 8.9-11.5) for impacted sites, reflecting poor ecological conditions, and higher (mean $\pm$ 95% CI: 18.4-22.5) for reference sites, indicating good ecological conditions. The 95% confidence intervals for both site types overlap only slightly, supporting the conclusion that there is a significant difference between the two site types. This visualization is effective in communicating the distribution of site scores as well as the separation of the sites as a group, as a means of illustrating differences in ecological health throughout the watershed.

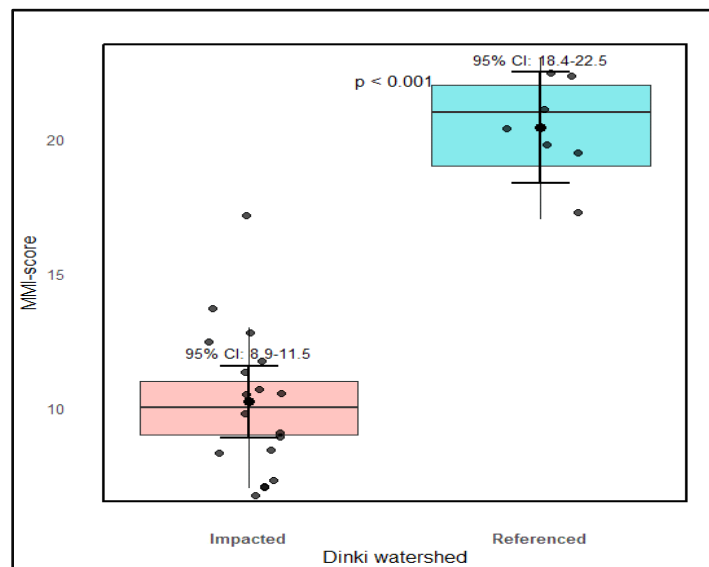


Figure 41. Box-and-whisker plots of MMI scores for headwater streams at different sites.

The plots show the 25th to 75th percentiles (boxes), median values (lines), and whiskers representing the maximum and minimum MMI values. Significant variation ($P < 0.001$) was observed between impacted and reference sites. MMI scores were calculated per season and pooled by site category. A significant difference was observed between reference and impacted sites (Mann-Whitney U-test, $P < 0.001$). Mean MMI difference between reference and impacted sites = 12.2 (95% CI: 8.7–15.7), indicating a substantial separation in ecological integrity.

4.5. Predicting Habitat Suitability of Pollution-Sensitive Macroinvertebrates under Climate Change Using Climate and Land Use Predictors in Ethiopia: An Ensemble Modeling Approach

4.5.1. Model performance and variable importance

The mean model performance demonstrated high evaluation metric values, with AUC, TSS, Sensitivity, and Specificity all indicating strong discrimination between suitable and unsuitable habitats. We generated probability maps using the weighted mean values from the ensemble predictions for Perlidae and Philopotamidae, based on the averaged outputs of multiple modeling statistical test models. Across all SDM Algorithms (BRT, RF) and Statistical test models (GLM, GAM, and MaxEnt), the highest values were recorded for AUC and specificity, while the lowest performances were observed in TSS and sensitivity for some cases. Overall, for both sensitive taxa, the habitat suitability predicted by the weighted ensemble model showed robust discrimination, achieving an AUC of 0.88 for both species and TSS of 0.64 for Perlidae and 0.67 for Philopotamidae (Table 38). The SD (<0.1) also indicates that there is consistency between metrics and good performance.

Table 38. Evaluating metrics using weighted mean ensemble predictions of habitat suitability for Perlidae and Philopotamidae.

Species	Evaluation metrics	BRT	RF	GLM	GAM	MaxEnt	SD	Ensemble
Perlidae	AUC	0.89	0.88	0.87	0.86	0.88	0.01	0.88
	TSS	0.67	0.64	0.65	0.62	0.62	0.02	0.64
	Sensitivity	0.59	0.67	0.63	0.58	0.64	0.04	0.62
	Specificity	0.83	0.75	0.74	0.77	0.75	0.04	0.77
Philopotamidae	AUC	0.90	0.90	0.85	0.88	0.89	0.02	0.88
	TSS	0.60	0.70	0.67	0.69	0.70	0.04	0.67
	Sensitivity	0.61	0.66	0.67	0.58	0.66	0.04	0.63
	Specificity	0.82	0.77	0.71	0.80	0.74	0.04	0.77

Furthermore, the results indicate that the key environmental factors likely to influence the future distribution and habitat suitability of Perlidae are the mean temperature of the driest quarter (BIO9) (32.35%), LULC (16.17%), precipitation of the driest month (BIO14) (13.48%), and precipitation of the coldest quarter (BIO19) (10.78%). The other environmental predictors have relatively the same contribution to Perlidae prediction. For Philopotamidae, the most influential

variables are mean temperature of the driest quarter (19.55%), temperature annual range (BIO7) (16.62%), Isothermality ($BIO2/BIO7 \times 100$) (BIO3) (16.32%), and current LULC as predictor (10.26%) (Fig. 42).

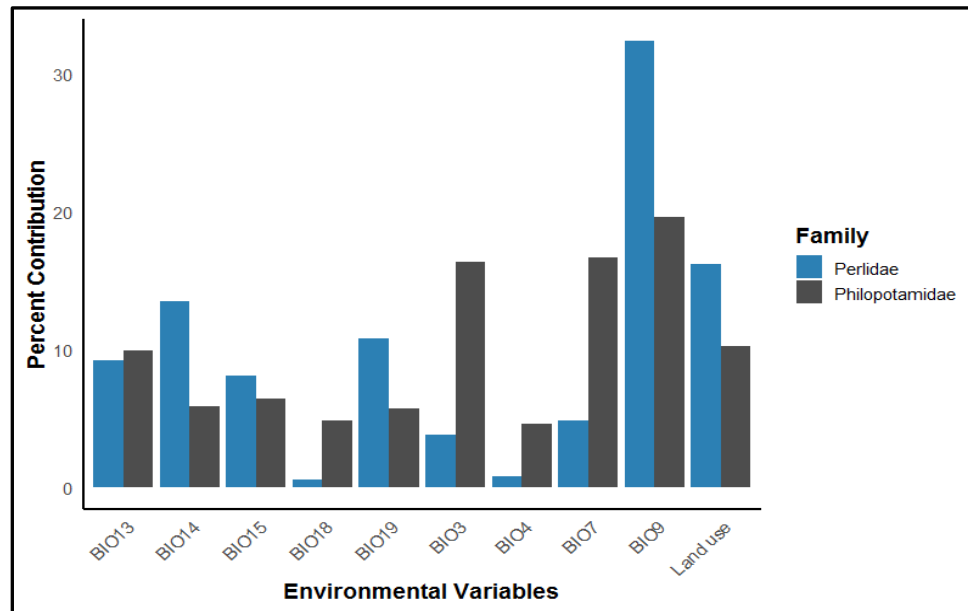


Figure 42. Projected suitable habitat areas for Perlidae and Philopotamidae based on ensemble modeling outputs under current and future environmental conditions

4.5.2. The Current habitats of Perlidae and Philopotamidae

The ensemble modeling prediction showed that, from the present climate, most of the Ethiopian highlands currently have suitable habitats for the Perlidae family with an area of 77,430.18 km² which is about 14.91% of the total water bodies area of Ethiopia (519,278 km²) (Fig. 43). Regarding Philopotamidae, suitable habitat for this species is about 92,448.14km² (17.80%) of the total area of the Ethiopian water bodies (519,278 km²) (Fig. 45). The suitable areas for both sensitive families were mainly located in the Awash (main rivers: Akaki, Meki, Katar, Mille, Dinki, Kesem, Gibe and Gojeb), Abay (main rivers: Didessa, Beles, Dabus, Gumara, Rib, Muger, Jamma and Kesem), and Shebelle (main rivers: Erer, Fafen, Jerer and Wabe) watershed while the less suitable habitat was recorded in Tekeze (main river: Kwale), Denkel (main river: Logiya), Baro (main river: Gilo), Omo (main river: Mago) and Genalle (main river: Weyib), which stream water quality, temperature and flow regimes favor Perlidae and Philopotamidae.

4.5.3. *Future projection and range extent under climate change scenarios*

As compared to the current predicted range, the future projections indicated (Fig. 43) for 2050 show an increase in Perlidae to about 111,450.67 km² (21.5%), mainly in the central highlands of Ethiopia, with Awash and Abay watershed, the Dinki watershed, which is projected to be primarily suitable (Fig. 42 and 43). In this scenario, however, an estimated 18,091.42 km² (23.36%) will be unsuitable or lost habitats (Table 39, Fig. 44). The suitable habitat is expected to decline dramatically in the highlands to 57,339.12 km² (11.0%) under the worst-case scenario (SSP5-8.5), reflecting increased habitat fragmentation (Figs. 42 and 44). In this case, about 39,140.89 km² (50.50%) of the habitat is expected to be destroyed (Fig. 47 and Table 39). For Perlidae, the moderate scenario also had a net increase in species range size projections; 43.93 % for 2050 and 8.05 % for 2070 (Table 39). Furthermore, most habitat losses will be recorded in the northern highlands, especially in Tigray, Amhara north, and parts of the southern Rift valley region, under the 2050 and 2070 scenarios. In addition, in the future range size, the suitable habitat area for Perlidae is projected to decrease by about 26% (Fig. 47 and Table 39) under the worst climate scenario (SSP5-8.5, 2070). Lastly, in the eastern and southeastern parts (Somali and Afar), predictions of unsuitable (grey) conditions remain (Fig. 45 and Table 39). This is the typical pattern of the ecological preference of Perlidae for highland, cooler environments, which are generally missing here.

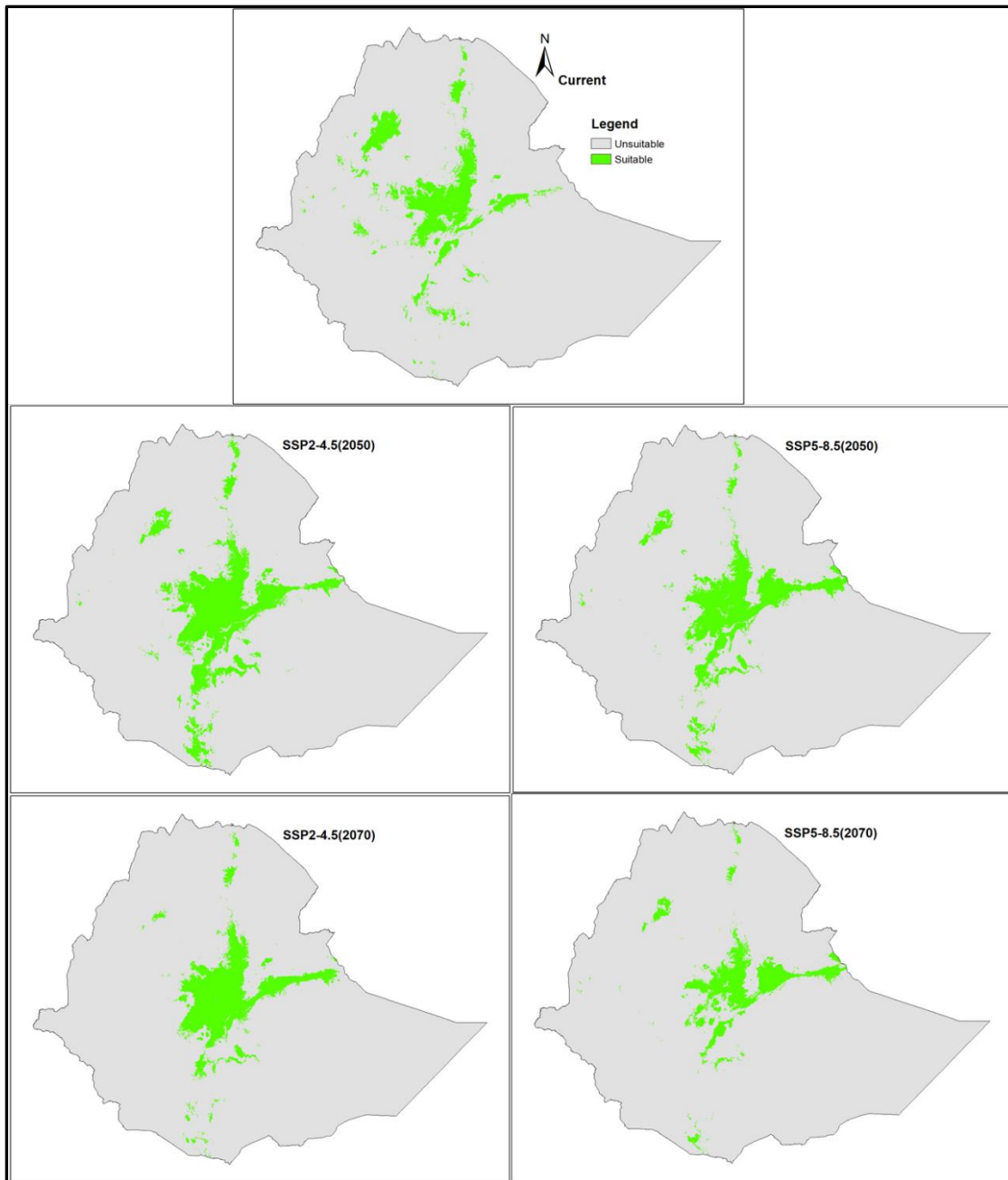


Figure 43. Predicted spatial distribution of suitable habitats for Perlidae under current and projected future climate, (the top map) and projected future climate conditions (intermediate scenario on 2050 and worst scenario 2050) (the middle map), and (intermediate scenario on 2070 and worst scenario 2070) (the bottom map), based on ensemble species distribution models.

The SSP2-4.5 scenario suggests a decline in suitable habitat area for Philopotamidae in 2050 compared to the present day, while the SSP5-8.5 scenario shows a decline as large as or greater than the present day. Under the SSP2-4.5 scenario, suitable habitat will shrink to 73,809.56km², a 20.16% loss of suitable area compared to current extent, and will be located in the central highland of Ethiopia (Fig. 42), while under the SSP5-8.5 scenario, suitable habitat will shrink to 73,821.81km² (20.15% loss of suitable area compared to the current extent) in the central highland of Ethiopia (Figure 50). In this case, under the worst scenario (SSP5- 8.5 (2050), 31,965.82 km² (34.58%) of the area is expected to become lost (Fig. 46 and Table 39). Under the worst scenario 54,424 km² (58.87%) suitable is expected to be lost in 2070, mainly in Tigray, Northern Amhara, and Parts of the southern Rift valley (Fig. 47 and Table 39). Similarly, under SSP5-8.5 (2070), the suitable habitat area for Philopotamidae is projected to decline by ~51%, from 92,448.14 km² to 45,195.73 km² (Fig 44 & Table 44). The result regarding future range size (Fig. 46 and Table 39), under the worst climate scenario (SSP5-8.5, 2070), the suitable habitat size of Philopotamidae is expected to decline from 92,448.14 km² to 45,195.73 km², which is about 51% (Fig. 47 and Table 39). Moreover, the central Ethiopian highlands (including the Dinki watershed through Oromia, Amhara, and a little into the southern highlands) are expected to support Philopotamidae. In contrast, the east and southeast (Somali and Afar) are expected to continue as unsuitable because Philopotamidae prefers cooler, humid highlands. In general, the losses are expected to be severe in the northern areas, and limited new suitable habitats will emerge in the eastern areas, leading to the need for targeted conservation actions in both the moderate (SSP2-4.5) and high (SSP5-8.5) emissions scenarios.

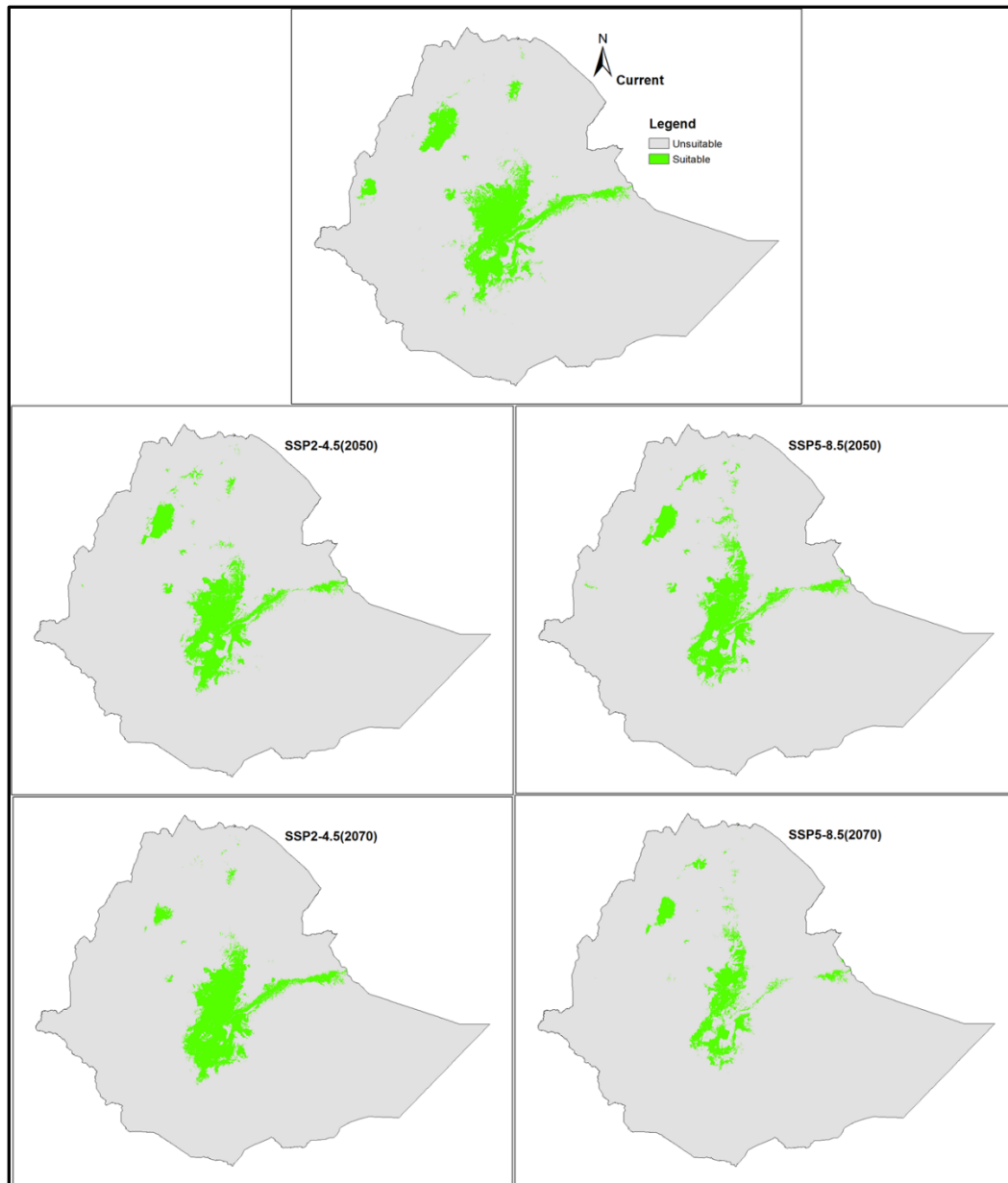


Figure 44. Projected changes in habitat suitability for Philopotamidae based on the intersection of current distributions with future climate scenarios. The first two maps show overlaps between current suitable habitats and 2050s projections under SSP2-4.5 (moderate emissions) and SSP5-8.5 (high emissions) scenarios. The latter two maps illustrate overlaps with 2070s projections under the same scenarios, highlighting areas of habitat persistence, loss, or expansion. The color was indicated: green colour = remain suitable; Red = loss; Blue = gain; and Gray = remain unsuitable.

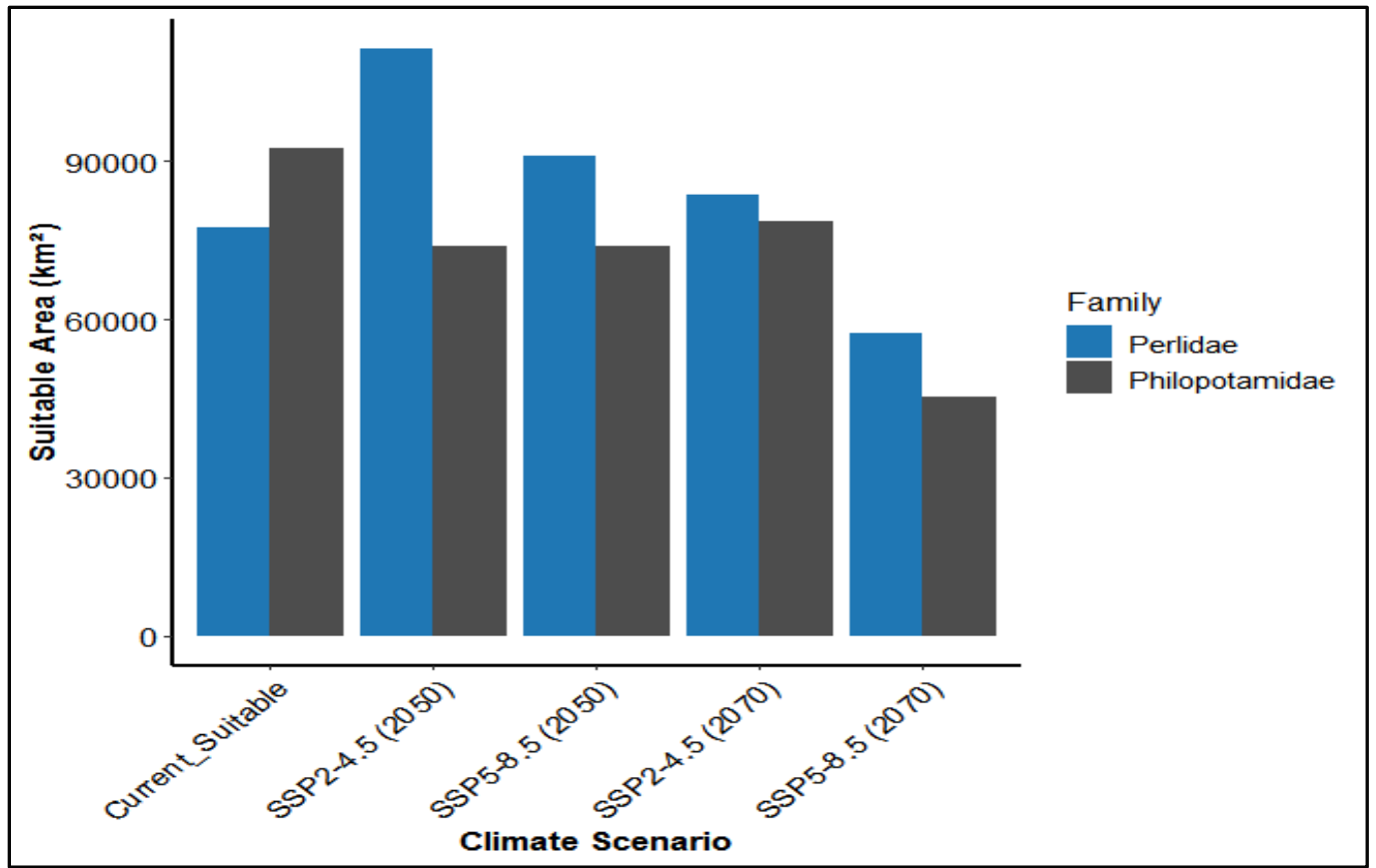


Figure 45: Projected suitable habitat areas for Perlidae and Philopotamidae based on ensemble modeling outputs under current and future environmental conditions.

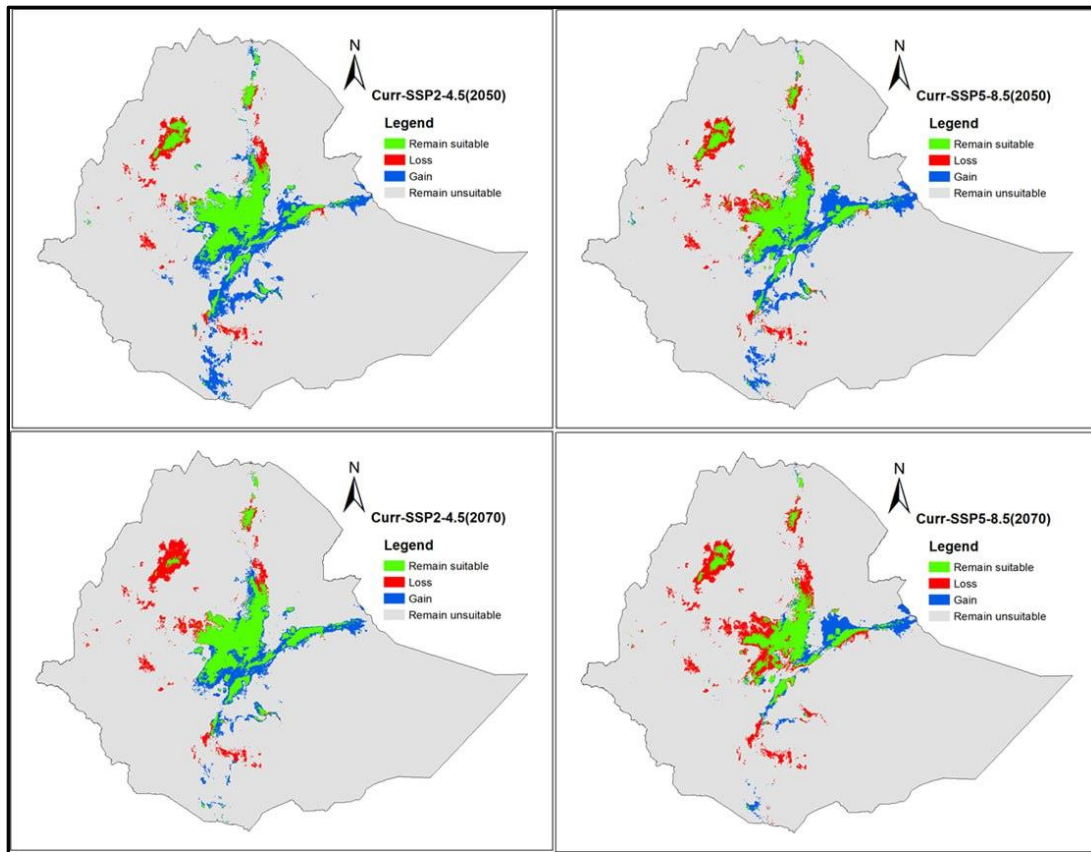


Figure 46. Projected habitat suitability changes for Perlidae based on the intersection of current distributions with future climate scenarios. The first two maps show overlaps between current suitable habitats and 2050s projections under SSP2-4.5 (moderate emissions) and SSP5-8.5 (high emissions) (Fig. 47). The last two maps present similar intersections with 2070s projections, illustrating potential habitat persistence, loss, or expansion under changing climate conditions. The color was indicated: green colour=remain suitable; Red=loss; Blue= gain, and Gray=Remain unsuitable.

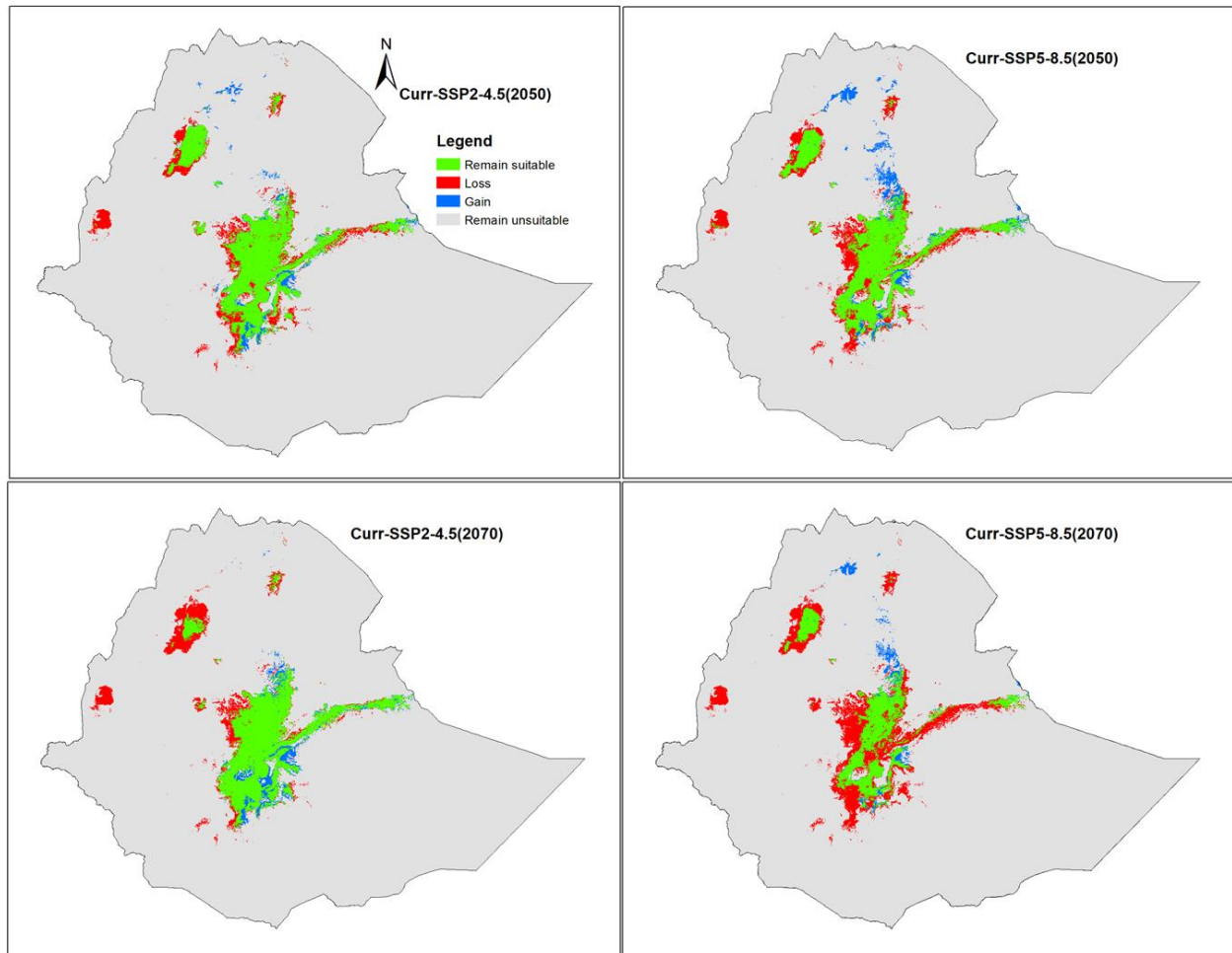


Figure 47. Projected changes in habitat suitability for Philopotamidae based on the intersection of current distributions with future climate scenarios. The first two maps show overlaps between current suitable habitats and 2050s projections under SSP2-4.5 (moderate emissions) and SSP5-8.5 (high emissions) scenarios. The latter two maps illustrate overlaps with 2070s projections under the same scenarios, highlighting areas of habitat persistence, loss, or expansion. The colour was indicated: green colour = remain suitable; red = loss; blue = gain, and gray = remain unsuitable.

Table 39. Ensemble model results showing changes in the spatial distribution of Perlidae and Philopotamidae under each climate scenario, based on weighted mean probability (WM) estimates.

Species	Scenarios	Loss km ²	remain suitable km ²	Gain Km ²	% loss	% gain	Species range change (%)	Current range size Km ²	Future range size Km ²
Perlidae	SSP2-4.5 (2050)	18091.42	59338.46	52106.51	23.36	67.30	43.94	77429.88	111444.97
	SSP5- 8.5 (2050)	25520.82	51909.04	39084.82	32.96	50.48	17.52	77429.86	90993.86
	SSP2-4.5 (2070)	24963.02	52466.59	31197.16	32.24	40.29	8.05	77429.61	83663.75
	SSP5-8.5 (2070)	39140.89	38288.96	19043.39	50.55	24.59	25.96	77429.85	57332.35
Philopotamidae	SSP2-4.5 (2050)	26387.11	66061.03	7748.53	28.54	8.38	20.16	92448.14	73809.56
	SSP5- 8.5 (2050)	31965.82	60481.99	13339.82	34.58	14.43	20.15	92447.80	73821.81
	SSP2-4.5 (2070)	25102.00	67346.14	11221.07	27.15	12.14	15.01	92448.14	78567.22
	SSP5-8.5 (2070)	54424.38	38023.46	7172.28	58.87	7.76	51.11	92447.84	45195.73

CHAPTER 5: DISCUSSION

5.1. The biophysical attributes and Effects of LULC on Ecosystem Service in Dinki Watershed

The results of this study indicated significant hydrology, soil, vegetation, and ecosystem health interactions and significant changes of ecological and LULC status in the Dinki Watershed from 1994 to 2023. The watershed area is 160.90 km², with high elevation areas in the Northwest and a 30.35 km perennial stream flowing into the Awash River. The first-order streams dominate and are highly hydrologically sensitive and play a significant role in the regulation of runoff and base flow. Consistent hydrological characteristics have been observed in other parts of Awash Basin (Gedefaw *et al.*, 2018; Takele & Kebede, 2018; Teklu *et al.*, 2019; Negussu, 2021).

Based on the watershed characterization results, physicochemical parameters, habitat conditions, and macroinvertebrate assemblage showed significant temporal and spatial changes in the ecological status of the Dinki watershed from 2016 to 2023. Habitat quality and impact assessments showed notable improvement in the Dinki and Zego sub-watersheds between 2016 and 2023, mainly due to soil and water conservation (SWC) practices such as soil and stone bunds. This means there was recovering stage on 2023 in Dinki watershed. Spatially, impact assessment of Gedamoch was the lowest (15.50% in 2016 and 10.83% in 2023) rate of ecological stability, with the highest HVAS (65.21% to 70.21%). In contrast, Dinki and Zego were more affected (IA > 30%) by the runoff, livestock grazing, and irrigation activities (Tognetti *et al.*, 2017; Pablo *et al.*, 2021; Bekele *et al.*, 2024). The measures resulted in the reduction of runoff, erosion, and nutrient loss, and increased productivity of the land (Teshome *et al.*, 2022). A similar result was noted in the Debre Mawi watershed after implementing conservation measures (Dagnew *et al.*, 2015), which increases watershed rehabilitation with vegetation coverage.

In contrast, there was a medium impact in some areas of Dense and Zego sub-watersheds because of a higher rate of agricultural expansion, deforestation, and low level of enforcement of conservation measures which led to more severe impact on runoff and habitat degradation (Tilahun, 2021; Bireda, 2024). Community-based conservation and sustainable land use are still

needed (Mosissa *et al.*, 2019). In this context, the recently implemented Climate Investment Funds (CIF) restoration project promotes restoration on a large scale that involves afforestation, reforestation, and water conservation (Park *et al.*, 2024; Government of Namibia, 2025).

The Gedamoch sub-catchment is predominantly in Dense forest with downstream areas for settlement, agriculture, and grazing. There is still some conservation of indigenous tree species (*Podocarpus falcatus*, *Hagenia abyssinica*, *Juniperus procera*), and agroforestry practices were common. Vegetation cover was heavily degraded in 2016 but slightly improved in 2023 with less land used for agriculture and settlements (Tilahun, 2021). Likewise, irrigation and agroforestry and livelihoods based on ecosystems are practiced at downstream Dinki sites. Crop-wise distribution is related to the elevation, with barley and field pea being grown at higher elevations, and maize at lower elevations. Although agricultural land is the most dominant land use, forests, grasslands, built-up areas, and water bodies are still present, highlighting the need for ongoing SWC activities to maintain agro-ecosystems and minimize degradation (Asmamaw *et al.*, 2021).

The watershed also has good-quality soils, which promote plant growth and ecosystem sustainability. Clay loam (70%) and clay (26%) are dominating soil types, with clay soils having brownish, grey, and red variants covering roughly 87.5% of the watershed (Nigatu, 2014). The low bulk density (1.12 g/cm³) means that it possesses good porosity and infiltration capacity (He *et al.*, 2016; Gurmu, 2019). The pH of the soil ranged from neutral to slightly alkaline (6.80-7.20), and there was a lot of variability in pH and iron content in the soil (Rabot *et al.*, 2023). Microbial activity, nutrient cycling, and vegetation recovery were promoted by moderate iron concentration, balanced C/N ratio, and adequate macronutrients (He *et al.*, 2016; Liu *et al.*, 2020). Minimal salinity stress was also confirmed by low electrical conductivity levels (Ostrowska, 2017). There was positive feedback in overall soil fertility and vegetation recovery, which improved soil stability and resilience of the watershed (Lelago *et al.*, 2016; Hua *et al.*, 2021). Surprisingly, this situation was observed in the study site, Dinki watershed. In addition, the diagnostic statistical soil regression model showed that there was a weak individual explanatory predictive power of the N and P. This may be attributed to the influence of interacting factors like climate, vegetation structure, microbial activity, and topographic variation (Hua *et al.*, 2021). Spatial variability in soil nutrients is often regulated by several environmental

factors, not just nutrient concentrations, and has been reported in recent studies (Hall *et al.*, 2024; Liang *et al.*, 2024).

Substantial recovery was also seen between 2016 and 2023 in terms of hydrological and water quality analysis, which also showed significant ecological recovery. Higher pH, dissolved oxygen (DO), turbidity, and discharge were measured at Dinki in 2016, and higher temperature and electrical conductivity (EC) were measured at Zego. In 2023, the habitat quality scores for Gedamoch were higher than those for the other variables, as were DO, total nitrogen, and total phosphorus. The higher discharge observed in the dry season in 2023 was accompanied by higher DO and pH, which may be correlated with improved canopy and root systems (Meseret, 2020). In addition, the vegetation cover in 2016 was 24.97% while it reached 28.70% in 2023, which is similar to the results from the Kebena watershed (Asnake *et al.*, 2021). Seasonal pattern revealed that discharge, DO, and pH increased during the dry season of 2023, which could be related to the enhanced canopy and root system (Meseret, 2020).

The nutrient decline observed in 2023 may result from increased macroinvertebrate competition, as species composition rose from 32.65% in 2016 to 67.35% in 2023 (Fentaw *et al.*, 2024). At the same time, positive water quality improvements were observed, including reduced water temperature, EC, TN, and TP, suggesting effective nutrient attenuation, likely from soil and water conservation interventions, as supported by studies in central highland catchments (Herano *et al.*, 2025). These shifts corresponded with higher macroinvertebrate counts and diversity, consistent with regional studies linking reduced nutrient loading to improved stream biotic integrity (Lakew, 2022; Mendoza *et al.*, 2025). Increased macroinvertebrate composition and regenerating indigenous vegetation further reflected ecological recovery and successful conservation efforts (Daniel, 2023; Hake, 2024). Despite substantial forest loss since 1984, community-based reforestation and indigenous management practices have restored parts of the watershed (Asmamaw *et al.*, 2021; Dieng *et al.*, 2023). Overall, the inclusion of indigenous knowledge and modern conservation practices increased the resilience and functioning of watersheds.

In Ankober, the climate pattern was shown from 2016 to 2023. Spatially, the increased rainfall of 800-1,000 mm is contrasted with low, but variable rainfall in the eastern (Rift Valley slope) and

southwestern areas. The topography of Ankober woreda is the main control for this pattern, as well as the movement of the Intertropical Convergence Zone (Asmaa *et al.*, 2020). Temperatures have clearly warmed from 2016 to 2023 during both wet (Kiremit) and dry (Bega) seasons. Temperatures during this period rose from approximately 19°C to above 20°C in the wet season and from approximately 16°C to nearly 18°C in Bega during the same period, which aligns with the observed general warming in Ethiopia during the same period (Asmamaw *et al.*, 2021; Dieng *et al.*, 2023). On the other hand, the Dinki watershed has been characterized by different vegetation, but commonly by *Aloe vera*, *Dodonaea viscosa*, *Maesa lanceolata*, *Acacia saligna*, *Acacia senegal*, *Rosa abyssinica*, *Podocarpus falcatus* (*P. gracilior*), *Olea europaea subsp. cuspidata* (*Olea africana*), *Carissa spinarum* (*C. edulis*), *Croton macrostachyus*, *Rosa abyssinica*, *Prunus africana*, *Maesa lanceolata*, and *Aloe vera* (Lulekal *et al.*, 2013).

Furthermore, six main classes of land use were identified through LULC analysis: agricultural land, built-up areas, Dense forest, grazing land, slight vegetation, and water bodies. There were significant time trends ($p < 0.01$) from 1994 to 2023. Until 2014, agricultural land dominated, but has decreased significantly since that time, mostly through conversion to low-density vegetation and plantation forest, and grazing land. Similar findings have been found in the Fagita-Lekoma (Belay & Ayalew, 2021) and Chacha watersheds (Endalew & Anteneh, 2022; Tesfay *et al.*, 2023; Ababu *et al.*, 2024). Natural regeneration and SWC activities were not the only drivers of slight vegetation increase (12.48%) over the study period, but also agricultural activities and unmanaged grazing had an impact on degradation (Taye *et al.*, 2023; Mulu *et al.*, 2024; Alemayehu *et al.*, 2025; Shibabaw & Wondimneh, 2025). The loss of forest cover between 2004 and 2022 was 66.67%, a forest cover reduction similar to the deforestation trend observed throughout Ethiopia and East Africa (Debebe *et al.*, 2023; Ojoatre *et al.*, 2023).

The proportion of Dense forest decreased significantly from 12% (19 km²) in 1994 to 5.79% (9.32 km²) in 2023, primarily due to changes in LULC, such as conversion to cropland and grazing land as well as population numbers and enforcement (Lulekal *et al.*, 2013). Ankober District saw further depletion of forests due to population growth from 2007 to 2022. This pattern of deforestation was also observed in other regions of Ethiopia, including Arise, Oromia/North Shewa, and also in northwestern Addis Ababa regions (Debebe *et al.*, 2023;

Ojoatre *et al.*, 2023). Plantation expansion also contributed to LULC changes, as degraded cropland was increasingly converted into *Acacia decurrens* and *Eucalyptus* plantations (Tesfay *et al.*, 2023; Mulu *et al.*, 2024). The communities also recognized grazing and fuelwood extraction, along with infrastructure development, as significant forces behind forest conversion. Grazing land increased considerably during 1994-2023, primarily from agricultural land and to a lesser extent Dense forest. This shift was fueled by rising demand for livestock products and population growth, especially in the Zego area. Returning degraded agricultural lands to grazing lands was common because it required a lot of work and was expensive for the farmer to do (Mulu *et al.*, 2024). Variations in this pattern have been observed in other parts of Ethiopia where grazing land management is thought to play a role in food security and poverty alleviation (Viana *et al.*, 2022; Tadesse, 2025).

Significant spatiotemporal variations in ecosystem functions were found in the Ecosystem Service Value (ESV) assessment (Costanza *et al.*, 2014; Costanza *et al.*, 2017; Kindu *et al.*, 2016; Costanza, 2020; Tesfay *et al.*, 2023). The study estimated the total ESV using locally adapted valuation coefficients and high-resolution LULC maps to rise from US\$200.32 thousand in 1994 to US\$310.33 thousand in 2023 (Worku *et al.*, 2026c). Water bodies had the highest ecosystem service value, followed by sparse vegetation, cropland, Dense forest, and grazing land. Increased water bodies and vegetation cover greatly improved water regulation, erosion control, and climate regulation services. The same results are found in Rib and Bilate catchments (Anley *et al.*, 2022; Kuma *et al.*, 2022; Camerin, 2024). The land converted from Dense forest and cropland slightly reduced their values, while the value of both sparse vegetation and grazing land increased, which stabilized the ecosystem value (Wang *et al.*, 2021).

The regulating services were the most important of the 17 ecosystem services assessed, followed by provisioning, supporting, and cultural services. The amount of regulation of services increased significantly from 1994 to 2023, as a result of the improvement of vegetation cover and hydrological regulation. The sensitivity analysis showed that ESV estimates were robust ($CS < 1$). The scholars (Yesuph & Dagne, 2019; Asmamaw *et al.*, 2020; Mariye *et al.*, 2021) identified population pressure, deforestation, traditional farming, and grazing as the major drivers of LULC change through focus group discussions and key informant interviews.

However, soil fertility restoration and integrated conservation practices, agroforestry, and local knowledge significantly contributed in ecological restoration and better soil fertility (Asmamaw *et al.*, 2020; Wayesa *et al.*, 2022; Viana *et al.*, 2022; Dieng *et al.*, 2023; Tadesse *et al.*, 2025).

The Ecological Health Index (EHI) improved significantly from 1.40 in 2016 to 2.05 in 2023, representing a 46.43% increase ($p = 0.02$, $R^2 = 0.85$). This enhancement is a combined effect of the re-growth of vegetation, less agricultural pressure, and better land management. Similar findings by Burkhard (2018), Ye *et al.* (2023), and Tamire and Beneberu (2022) show that reforestation and sustainable land management enhance ecosystem integrity (Han *et al.*, 2024; Moreno-Casasola, 2022). The results further demonstrate that integrating land use, soil, water, and biodiversity indicators in EHI modeling provides valuable guidance for sustainable watershed management and long-term ecological monitoring in the Dinki watershed (Yee *et al.*, 2021; Liu *et al.*, 2023; Moreno-Casasola, 2022). Therefore, these watershed-scale ecological characteristics collectively established the environmental foundation that shaped subsequent variations in stream physicochemical conditions, habitat quality, macroinvertebrate assemblages, and ecological integrity (Lakew, 2022; Mendoza *et al.*, 2025) across the Dinki watershed.

5.2. Spatiotemporal Variation in Pollution-Sensitive Macroinvertebrates in Dinki Watershed

River water quality in the Dinki watershed exhibited significant spatial and temporal variations between 2016 and 2023 due to the combined effects of land use change, management interventions, and hydrological dynamics. Multivariate analyses in 2016 (Asmamaw *et al.*, 2019) showed that nutrient-related parameters such as phosphate (PO_4^{3-}), nitrate (NO_3^-), total phosphorus (TP), electrical conductivity (EC), and water temperature were strongly associated with impacted sites (Dinki and Zego). These sites supported fewer and less diverse macroinvertebrates, consistent with studies reporting that nutrient enrichment and elevated temperature reduce sensitive taxa in tropical rivers (Xueyan *et al.*, 2022) and Assegide *et al.*, 2022). In contrast, the reference site (Gedamoch) and relatively less disturbed parts of Dense were associated with higher habitat visual assessment scores (HVAS), and discharge (Q), supporting more diverse assemblages (Urban, 2023; Banda *et al.*, 2023).

The higher variance explained by PCA axis 1 (in 2023, 33.1% compared to 29% in 2016) meant that the physicochemical conditions were improved. Increased HVAS and dissolved oxygen (DO) were observed in Dense areas, which also had positive responses to soil and water conservation interventions, consistent with restoration results reported by Mekuria *et al.* (2018) and Sinclair *et al.* (2024). These relationships add to the confidence of macroinvertebrates as an ecological health indicator (Keddari *et al.*, 2024; Zhou *et al.*, 2024).

On the spatial variations in water physicochemical parameters: HVAS, DO, and discharge showed significant differences among the sampling sites in both 2016 and 2023. This may be due to variability in habitat quality, thermal conditions, ionic concentration, and flow characteristics within the watershed (Tognetti *et al.*, 2017; Pablo *et al.*, 2021; Bekele *et al.*, 2024). The downstream Dinki experienced higher sedimentation and turbidity, which is consistent with prior studies on disturbed river systems (Johnson, 2019; Liu *et al.*, 2023; Lee *et al.*, 2025). Seasonal differences were also significant ($p < 0.0001$), with turbidity, TN, and TP higher in the dry season as a result of sediment resuspension and rain events that are infrequent enough to cause nutrients to be mobilized (Kleinman *et al.*, 2017; Chowdhuri & Gupta, 2023; Nordling *et al.*, 2024). The 2023 improvement in DO, discharge, and HVAS was related to the enhancement of the ecosystem's resilience due to vegetation regeneration and soil-water conservation practices (Bentsi-enchill *et al.*, 2022). However, there was a significant increase in turbidity (4.82 ± 2.20 NTU to 30.58 ± 23.53 NTU, $p < 0.001$), which was attributed to pre-sampling rainfall and bank erosion as observed in the Crocodile River (Vasconcelos & Sacht, 2024). Although there are general improvements, Dinki is still sensitive to deposition of sediment, low levels of dissolved oxygen, and dominance of tolerant taxa (Sripanya *et al.*, 2022; Tubi'c *et al.*, 2024).

Surprisingly, there was higher turbidity in 2023 recorded this might be could relate to increased sediment mobilization and/or runoff from the watershed, with heavy rainfall just before sampling at the Dinki sub-watershed outlet possibly driving mobilization (Nordling *et al.*, 2024). The decrease in EC could be due to dilution from increased runoff and freshwater inputs that lead to a decrease in concentration of dissolved ions. Reduced nutrient concentrations may be due to dilution, sedimentation and riparian vegetation uptake, and biological uptake by aquatic organisms (including macroinvertebrates) (Vasconcelos & Sacht, 2024). Overall, nutrient

decline, high DO, and good HVAS show that there is an ongoing recovery of the ecosystem with local management efforts.

The outcomes of the ANOVA and rmANOVA confirmed that most of the physicochemical variables had significant changes ($p < 0.05$) during the period, indicating the positive impacts of the watershed management practices. The results for both sites (Gedamoch and Dinki) in 2023 suggest that anthropogenic disturbance is reduced and habitat is better, as evidenced by the higher HVAS scores. The higher HVAS at both sites in 2023 indicate an absence of anthropogenic disturbance and better habitat conditions (Asmamaw *et al.*, 2019; Wang *et al.*, 2022). A possible link between lower water temperature at Gedamoch and higher water temperature at Dinki may be due to differences in riparian canopy cover and stream shading (Sisay *et al.*, 2023; Fentaw, 2024). Furthermore, higher turbidity and EC also contribute to the increased temperature. The rising trend in EC of Dinki can be attributed to the enhanced catchment's runoff and human activities, while the relatively stable trend at Gedamoch indicates less catchment disturbance and more stable hydrological conditions (Chapra & Camacho, 2021). The decrease in TN and NO_3^- seems to be related to better land management practices, whereas the increase in TP and PO_4^{3-} may be due to land erosion and sediment inputs caused by the construction of the workstation (Monbertrand *et al.*, 2019; Firmiano *et al.*, 2021).

Temporally, from all river water parameters, turbidity, electrical conductivity (EC), and discharge (Q) showed interannual increasing trends. For example, turbidity significantly increased ($p < 0.001$) between 2016 and 2023. This increase is likely due to surface soil erosion occurring approximately fifteen days before the 2023 sampling period, which affected turbidity more than other water quality parameters. Similar observations were reported in the Crocodile River system, where sudden rainfall-induced events increased sediment transport and turbidity (Mpumalanga *et al.*, 2024 & Vasconcelos & Sacht, 2024). Elevated sedimentation caused by higher wet-season discharge can lead to habitat instability, favoring more tolerant organisms such as Chironomidae (Johnson, 2019; Liu *et al.*, 2023 & Lee *et al.*, 2025). Interestingly, turbidity and EC did not always increase together in this study. Zego, Gedamoch, and Dense showed lower turbidity and EC, whereas Dinki recorded higher turbidity with a slight EC increase due to road construction and external watershed inputs. These conditions reduce

dissolved oxygen availability and create unsuitable habitats for many macroinvertebrates, particularly pollution-sensitive taxa such as Ephemeroptera and Trichoptera (Sripanya *et al.*, 2022 & Tubi'c *et al.*, 2024).

Water quality changes and management improvements were reflected in strong spatial and temporal variation in macroinvertebrate assemblages or composition (Orozco-González & Ocasio-Torres, 2023). In both study years, 9,479 taxa representing 22 orders and 107 families were recorded. The families with the most significant numbers were Diptera (29%) and Ephemeroptera (23%) in 2016, while the Ephemeroptera increased to 50% and Diptera decreased to 18% in 2023. Gedamoch had the highest overall abundance (42% in 2016, 52% in 2023), followed by Zego, Dinki, and Dense. The abundance of sensitive taxa (Ephemeroptera, Plecoptera, and Trichoptera) indicated better ecological conditions (Nguyen *et al.*, 2014) compared to some tolerant taxa (Coleoptera: Dytiscidae and Hydrophilidae and Hemiptera: Corixidae and Belostomatidae), which decreased (Goulding *et al.*, 2021).

Significant differences in the data were detected between the sites by the use of ANOVA ($p < 0.05$). Gedamoch was found to have a higher abundance of Ephemeroptera, Trichoptera, and Plecoptera, which are associated with ecological stability (Getachew *et al.*, 2023; Lubanga *et al.*, 2021), while Dinki and Dense had a higher abundance of tolerant taxa associated with sedimentation and organic enrichment. The same observation was made in the Mara River and the Upper Awash Basin, where EPT taxa were found to dominate at less disturbed sites (Matomela *et al.*, 2021). For the EPT, EOT, and ET indices, significant differences were found between 2016 and 2023 ($p < 0.001$) when using paired t-tests and rmANOVA. The results showed that the sensitive taxa increased and the tolerant groups decreased, reflecting good watershed management and food computations. There was also a seasonal difference, with the dry season having the highest counts of Ephemeroptera and Trichoptera, while the wet season had the highest counts of Coleoptera, which was attributed to turbidity increases in the wet season (Herbst *et al.*, 2018; Tubi & Koh, 2025). Similarly, the paired t-test showed that the Odonata taxa were statistically significant ($P < 0.05$) between the dry and wet seasons in the 2016 sampling periods (Asmamaw *et al.*, 2019 & 2021). Whereas the Ephemeroptera, Trichoptera, and Odonata were statistically significant between the dry and wet seasons in the 2023 sampling

periods, the results presented here show that macroinvertebrates are sensitive to hydrological and climatic changes (Sultana *et al.*, 2020; Chattopadhyay & Swiatek, 2024).

The results of an NMDS ordination showed obvious spatial and temporal differences in the macroinvertebrate assemblage throughout the Dinki watershed. Spatially, the reference sites (Gedamoch and partially Dense) were grouped with sensitive taxa, while the impacted sites (Dinki and Zego) were grouped with tolerant taxa like Chironomidae and Tabanidae. In 2016, mainly Gedamoch was correlated with the Trichoptera, Ephemeroptera, Decapoda, Diptera, and in 2023, sensitive groups such as the Trichoptera, Ephemeroptera, Plecoptera, EPT, EOT, ECT, and ET were correlated with reference conditions, which were associated with higher DO and lower nutrients. The ecological separation and community structure along NMDS Axis 1 were higher in 2023 (77.14%) than in 2016 (69.34%) when considering the temporal component. These differences are due to increased discrimination of site conditions in the direction of the NMDS gradient. The same trend was observed in the Paraná and Taizi rivers (Ambelu *et al.*, 2013; Alemneh *et al.*, 2017; Gezie *et al.*, 2023; Tampo *et al.*, 2021).

The PCA further showed distinct zonation of the macroinvertebrate assemblage. In 2016, reference (Gedamoch) and impacted (Dinki and Zego) sites were separated by Axis 1 (29.6%) and 2 (18.2%). The sensitive taxa (Heptagenidae, Aeshnidae, Perlidae, and Tipulidae) were grouped with Gedamoch, which was higher in 2023, with the top differentiation being in Axis 1, and this was reflected by better environmental quality in Gedamoch and Dense, with sensitive taxa expanding. Measurable habitat improvements and ecological recovery were found to be associated with higher DO, HVAS, and discharge, whereas EC, turbidity, and nutrients (TP and NO_3^-) were associated with the tolerant groups. This result were similar result with Asmamaw *et al.* (2019); Keddari *et al.* (2024) and Zhou *et al.* (2024).

In addition to the two broad categories used by the previous authors, RDA also differentiated the sites based on the presence of forest cover, settlement-agricultural (Dense), slightly vegetated-agricultural (Zego), and degraded (Dinki). Sensitive taxa (Heptagenidae, Aeshnidae, Perlidae) were strongly associated with forested sites with higher DO and HVAS but lower TP, TN, and NO_3^- . Degraded sites, on the other hand, were significantly ($P < 0.001$) correlated with high pH, EC, PO_4^{3-} , and turbidity, and were preferred by tolerant taxa like Tabanidae and Chironomidae.

Similar trends, in 2023, the sensitive taxa (Hydropsychidae, Elmidae, and Perlidae) all increased and correlated positively with higher DO, HVAS, and discharge, which suggests an improvement in the ecological status. The same was seen in the Dinki River (Asmamaw *et al.*, 2019 & 2021) and the Taizi River in China (Li *et al.*, 2018).

The ordination patterns were more dispersed in 2016, suggesting less optimal environmental conditions at impacted sites, while by 2023, the species distribution pattern was more structured, which suggests ecological recovery. Higher densities of sensitive insects (e.g., Ephemeroptera, Trichoptera, Plecoptera) were found in reference sites, and tolerant insects (e.g., Diptera, Odonata) continued to be found in disturbed sites. The better structural integrity of macroinvertebrate communities was observed with the improvement in physicochemical conditions and anthropogenic pressure, which is an indication of ecosystem resilience and macroinvertebrates' bioindicator potential (Gebrehiwot *et al.*, 2017; Makumbe *et al.*, 2022; Mulatu *et al.*, 2024).

The boxplot analysis also revealed that ecological indices had significantly improved between the years 2016 and 2023 at all sites ($p < 0.001$). There was a significant increase in the metrics, including EPT, EOT, ECT richness, and Shannon diversity, especially at Dense and Zego, where the median values were nearly doubled. The Shannon diversity and evenness index values of Dinki had improved moderately, while the Shannon diversity and evenness index values of Gedamoch remained high, indicating its status as a reference site. An increase in diversity and a decrease in dominance are signs of improved habitat quality, due to the recovery of riparian vegetation and management of the watershed (Gebrehiwot *et al.*, 2017; Mulatu *et al.*, 2024; Girma *et al.*, 2021; Beyene & Shumetie, 2023). Additionally, spatial variation of macroinvertebrates indices: richness and density showed significant differences ($P < 0.05$) among sites, suggesting habitat quality is an important factor in structuring communities in the Dinki watershed. Higher richness and density at Gedamoch indicate higher ecological conditions and lower disturbance, while lower values at Dinki, Zego, and Dense indicate higher environmental stress. Past studies have demonstrated that macroinvertebrate diversity is related to better habitat quality and lower anthropogenic impacts (Asmamaw *et al.*, 2019; Wang *et al.*, 2022)

Similarly, there were inter-site and inter-year differences in functional feeding groups (FFGs). Dinki and Zego were dominated by collector-gatherers and filterers, indicative of fine sediment buildup and organic enrichment, while Gedamoch had more shredders and scrapers in the presence of coarse organic material and periphyton stability. Predator increased especially at Gedamoch due to more provide food abundant (Gezie *et al.*, 2023). The patterns are consistent with the findings of Ambelu *et al.* (2010, 2013), Alemneh *et al.* (2017); Gezie *et al.* (2023), which indicate that the composition of FFG is influenced by the riparian vegetation and habitat structure. The observed rise in the population of shredders and scrapers in 2023 indicates habitat recovery due to regrowth of vegetation and stabilization of substrates (Mekuria *et al.*, 2018; Banda *et al.*, 2023).

Several species were found to be strongly correlated with specific habitats and physicochemical conditions through indicator species analysis. Tolerant taxa (Chironomidae, Simuliidae, and Culicidae) predominated impacted sites in 2016, while sensitive taxa such as Heptageniidae, Hydropsychidae, and Elmidae became significant indicators of improved water quality at Gedamoch and Dense in 2023. The shift from tolerant to sensitive taxa evidences significant water quality and habitat condition improvement (Johnston & Cunjak, 1999; Jesus & Monteiro, 2022; Fair *et al.*, 2023; Masese *et al.*, 2023; Edward, 2023; Espinar-Herranz *et al.*, 2025). The overall trend of the structural and compositional shifts in macroinvertebrate communities from 2016 to 2023 has been a positive one, indicative of continued soil and water conservation efforts. The observed recovery and resilience of the Dinki watershed, as reflected by increased abundance of sensitive taxa, improved DO, and improved HVAS, all point to land use change and climate-driven environmental conditions having counteracting effects on the structure of the local macroinvertebrate community. These biological changes suggest that the land use change and the climate-induced environmental factors had interacting effects that strongly regulated macroinvertebrate community structure.

5.3. Effects of Long-Term Climate and Land-Use Change on Sensitive Macroinvertebrates Indicators: A Comparative Analysis of 2016 and 2023 Surveys

The findings of this study reveal strong interactions between climate variability, LULC change, and the distribution of pollution-sensitive macroinvertebrates in the Dinki watershed from 1994 to 2023, indicating clear ecological shifts. Based on Ketema *et al.* (2020) and Wolde *et al.* (2021), six major LU classes were identified: agricultural land, built-up area, Dense forest, grazing land, slight vegetation, and water body. Agricultural land, slight vegetation, and water bodies were the dominant land-cover types, covering average areas of 51.64 km², 37.48 km², and 24.38 km², respectively, with significant differences ($p < 0.01$). Similar findings by Wolde *et al.* (2021) in the Gidabo watershed, East African Rift Valley showed that LULC changes (agroforestry, bare land, and grassland/slight vegetation) significantly affected hydrological processes and indicator species distribution.

The 30-year climate analysis of Ankober Woreda showed strong seasonal and spatial variability in rainfall and temperature. Rainfall peaked during July and August, while the dry season (December-February) received minimal rainfall. Temperature varied with altitude and season, consistent with Ethiopian highland climatic patterns (GFDRR, 2011), which reports highland rainfall varying from 0 to 4000 mm annually and temperatures from 16°C (Dega) to 50°C (Qola) based on elevation. Ankober is located between climatic zones of Weyna Dega, Dega, and Wurch climatic zones with an altitude range of 1650-3200 m. This study supports findings from Wollo (Esayas *et al.*, 2018; Adane & Asmerom, 2025) and Konso (Adane, 2025), which indicate that local topography plays a significant role in rainfall variability. Seasonal rainfall was dominated by Kiremit (June-September), which plays a major role in sustaining hydrological processes and water availability. These patterns agree with findings from northwestern Ethiopia and the Upper Erer Sub-basin, emphasizing the dominant role of Kiremit rainfall in sustaining water availability and climate resilience (Getaneh *et al.*, 2024; Seleshi, 2024; Getaneh *et al.*, 2024; Seleshi, 2024).

Trend analysis indicated no significant long-term change in annual rainfall due to natural climatic variability, whereas annual temperature showed a significant increasing trend. Similar

studies using the Modified Mann-Kendall test reported increasing trends in annual and Belg rainfall, with decreasing Kiremit rainfall (Abie & Tulu, 2022). Mann-Kendall approaches have also been widely applied for climate trend detection in Ethiopia (Bojago, 2025). The statistically significant decline in annual rainfall ($p = 0.013$, $Z = -2.477$) partly agrees with previous Ethiopian studies reporting mixed rainfall trends and declining normalized difference vegetation index (NDVI) values in some regions (Tesfaw, 2024; Teshome *et al.*, 2022; Alemayehu & Kabite, 2023). However, Dagnachew *et al.* (2020) reported a significant decrease in NDVI trends in the Gojeb catchment.

The spatial and seasonal distribution of temperature also exhibited significant variations with altitude and climate; with the highest temperatures recorded in the Belg season (9°C-24°C) and the lowest temperatures in the Kiremit season in the northwestern highlands, which is in line with the earlier studies conducted in Ethiopia (Hailu, 2020; Zegeye *et al.*, 2022). The same spatial and temporal variability has been widely reported throughout Ethiopia, with the interaction between topography and climate influencing temperature variability (Berihun *et al.*, 2023; Nebebe *et al.*, 2024; Aniye *et al.*, 2025). Significant warming trends in temperature were confirmed by Mann-Kendall in seasonal and annual values, particularly in the Belg season. The results are consistent with the research that has been conducted on the relationship between the recent warming trend in Ethiopia and climate change, where Asrat and Simane (2018), Gebrechorkos *et al.* (2019), and Yimer *et al.* (2024) all supported the conditions.

These environmental changes were reflected in the changes in macroinvertebrate assemblages, which were observed between 2016 and 2023. The rise in grazing land, slight vegetation, and water bodies indicates better habitat conditions and water quality with Heptagenidae and Perlidae (Stoyanova, 2014; Posthuma *et al.*, 2019). On the other hand, there was a decrease in Philopotamidae, which can be attributed to nutrient enrichment, siltation, and hydrological disturbances (Bonacina *et al.*, 2023; Pimentel *et al.*, 2020). Aeshnidae and Dytiscidae showed positive trends in almost all of the LULC types, reflecting the overall ecological improvement because they hunt other aquatic invertebrates/predators (Mereta *et al.*, 2021).

Macroinvertebrates were also impacted by rainfall variability from 2016 to 2023. The latter showed a preference for wetter habitats, Heptagenidae increasing from 8.58 to 34.58 in

Gedamoch and 0.93 to 14.14 in Zego, as found in Pedreros *et al.* (2020). Increased rainfall was found to increase habitat suitability for sensitive macroinvertebrates in similar studies (Jones *et al.*, 2021). Perlidae and Tabanidae, however, showed a decrease in numbers at several stations, which was attributed to the lack of sufficient water and hydrological instability (McCaffrey, 2021; Sowa & Krodkiewska, 2020; Asmamaw *et al.*, 2019; Edegbene *et al.*, 2025). Family composition was also affected by temperature variations. In Dinki, the abundance of Heptagenidae increased with a slight decrease in temperature, whereas Aeshnidae, Dytiscidae, and Perlidae decreased, suggesting that they were sensitive to the colder water (DeWalt & Ower, 2019; Pedreros *et al.*, 2020).

RDA results demonstrated that long-term LULC transformations and climate variability jointly shaped macroinvertebrate community structure in the Dinki watershed. Sensitive taxa responded not only to current environmental conditions but also to cumulative land-use changes and climatic shifts. Similar findings were reported by Masese *et al.* (2023), Edward (2023), Bohn *et al.* (2024), and Espinar-Herranz *et al.* (2025). The GLM analysis further showed that both Tabanidae and Dytiscidae responded significantly to temperature, likely due to the physiological sensitivity of ectothermic insects to warming conditions, which is thermal tolerance (Shah *et al.*, 2020). Furthermore, these taxa in response to temperature reflect their greater mobility and opportunistic feeding habits, which enable them to adjust quickly to temperature changes (Bonacina *et al.*, 2023). In contrast, other taxa (Aeshnidae, Heptagenidae, Perlidae, and Philopotamidae) responded significantly to microclimatic and land-use variables, indicating that their abundances are more strongly controlled by local habitat modifications and environmental shifts (Bonacina *et al.*, 2023). Similarly, VPA results indicated that climate contributed slightly more than land use, although their combined effects strongly influenced macroinvertebrate distribution (Zhang *et al.*, 2025). Overall, the interaction of climate variability, hydrological change, and land-use transformation provides a strong ecological basis for developing a Benthic Macroinvertebrate-based-MMI for the Dinki watershed.

5.4. Development of Benthic Macroinvertebrate-based Multimetric Index

The development of a benthic macroinvertebrate-based-MMI demonstrated its utility in assessing ecological health in headwater streams within the Dinki watershed. From macroinvertebrate

assemblages, 37 candidate metrics were initially selected and screened based on their responses to human disturbance gradients and Mann–Whitney U-tests, resulting in the retention of 24 statistically significant metrics. The selected metrics showed consistent directional responses along the disturbance gradient from relatively pristine streams such as Gedamoch to more impacted sites such as Dinki and Zego. The use of non-parametric U-tests was appropriate because macroinvertebrate and environmental datasets commonly exhibit non-normal distributions in ecological studies (Barbour *et al.*, 1996; Karr *et al.*, 1986; Gabriels *et al.*, 2010; Jun *et al.*, 2012; Moges *et al.*, 2016; Zewudu *et al.*, 2022; Odabaşı *et al.*, 2022; koyuncuoğlu *et al.*, 2023).

Subsequent analyses using Spearman correlation, Redundancy Analysis (RDA), boxplots, and U-tests effectively distinguished impacted from reference sites (Mereta *et al.*, 2013; Lakew & Moog, 2015; Alemneh *et al.*, 2019; Assefa *et al.*, 2023). The initial screening identified six final metrics, namely %EOT, %Trichoptera, Diptera, Hemiptera, ASPT, and FBI. However, box-and-whisker plot analysis revealed that Diptera could not effectively discriminate between reference and impacted sites and was therefore excluded. Ultimately, five core metrics (%EOT, %Trichoptera, Hemiptera, ASPT, and FBI) were selected for developing the final MMI. These metrics consistently reflected variations in community composition and environmental gradients, confirming their strong discriminatory capacity and ecological sensitivity. Some similar findings have been reported in Ethiopia (Lakew & Moog, 2015; Moges *et al.*, 2016; Getachew *et al.*, 2023; Alemneh *et al.*, 2019), Brazil (Macedo *et al.*, 2016), and Rio de Janeiro State (De Oliveira *et al.*, 2019), where macroinvertebrate-based multimetric tools have been able to capture ecological degradation gradients with success.

The final MMI was derived with a trisection scoring system, which gave scores of 5, 3, or 1 to each of the core metrics, based on their sensitivity to disturbance. The resulting MMI scores were theoretically between 5 (highly degraded condition) and 25 (least disturbed condition). Ecological condition classes were determined based on values observed and are classified as Very Good (25–21), Good (20–17), Fair (16–13), Poor (12–9), and Very Poor (8–5). The majority of the affected sites were categorized as “Poor,” while reference sites were mostly classified as “Very Good,” which means that the ecological condition of impacted streams was generally poor

(Odabaşı *et al.*, 2022; koyuncuoğlu *et al.*, 2023). In addition, validation with the 2016 candidate metrics showed that the selected core metrics were able to represent ecological conditions consistently over the years/hydrological seasons, which further increased the confidence in the developed MMI for long-term biomonitoring applications. As Jun *et al.* (2012); Moges *et al.* (2016); Alemneh *et al.* (2019); Zewudu *et al.* (2022) found similar strong correlations between core and candidate metrics in studies conducted in Turkey, Ethiopia, and Korea, respectively.

The efficacy of the developed MMI was additionally confirmed with RDA analysis, boxplots, and U-tests. The first two axes accounted for 68.7% and 27% of the variability, respectively, and were good at partitioning reference and impacted sites by environmental conditions and macroinvertebrate metrics (Saad, 2020). The MMI and sensitive metrics were negatively associated with most environmental stressors, while DO, discharge, and habitat quality were positively associated. The box plots indicated very little overlap between reference and impacted sites, and the U-test indicated that there were highly significant differences between the two groups ($p < 0.001$). The results also showed that the MMI scores were consistently lower in impacted sites compared to the reference sites, and that the index was able to discriminate ecological conditions within the watershed, as found by Jun *et al.* (2012), Alemneh *et al.* (2019), and Zewudu *et al.* (2022).

The MMI that has been developed is generally a strong and locally modified instrument to assess ecological health in headwater streams of Ethiopia (Chen *et al.*, 2014; Musonge *et al.*, 2019). The present MMI was developed in a specific manner according to the ecological conditions and disturbance gradients found in the Dinki watershed, whereas ETHbios (Lakew & Moog, 2015) was designed to be a general index for Ethiopian rivers. One of the greatest assets of the study was the ability to combine dry- and wet-season data from two years (2016 and 2023), providing better temporal reliability and stability of the selected metrics and the greater applicability of the index for long-term biomonitoring and watershed management. The MMI not only captures the impacts of LULC and climate variability, but it also offers a replicable framework for ecological monitoring in Ethiopian highlands. The present index is effective; however, it does not incorporate flora metrics, and it is recommended that the index be enhanced in the future to incorporate macroinvertebrate and riparian vegetation data to increase the ecological

representativeness and assessment accuracy. This integrative approach is important as it helps water bodies downstream of rivers and lakes that affect nutrient cycles, water quality, and overall watershed health (Posthuma *et al.*, 2019; Mereta *et al.*, 2021). The developed indices did a good job of describing current ecological conditions, but future climate change scenarios based on climate and land use predictors could significantly affect the suitability of habitats and long-term ecosystem stability.

5.5. Predicting Habitat Suitability of Pollution-Sensitive Macroinvertebrates

Finally, an ensemble modeling of habitat suitability for Perlidae and Philopotamidae under current and future climate scenarios highlighted both immediate and projected risks to these pollution-sensitive taxa under SSP2-4.5 and SSP5-8.5 climate scenarios. The averaged evaluation metrics showed high discriminatory power between suitable and unsuitable habitats. The mean AUC (0.88 for both taxa) and TSS values (0.64 for Perlidae and 0.67 for Philopotamidae) indicated strong model performance and were consistent with previous studies that recognized AUC and TSS as reliable indicators of predictive accuracy (Manel *et al.*, 2001; Allouche *et al.*, 2006; Thuiller *et al.*, 2009; Meller *et al.*, 2014). Ensemble modeling also reduced model uncertainty and improved prediction robustness, leading to more reliable species distribution projections (Kaky *et al.*, 2020).

The study further identified key environmental variables shaping the distribution and habitat suitability of Perlidae and Philopotamidae. Mean temperature of the driest quarter was the dominant predictor for both taxa, while current LULC also significantly influenced habitat suitability (Gezie *et al.*, 2023). The annual range additionally affected the Philopotamidae distribution. These results indicate the important influence of temperature-related factors, specifically during dry periods, on habitat suitability for pollution-sensitive taxa (Bonacina *et al.*, 2023). Interactions between climatic stressors and land use changes may further intensify habitat fragmentation and reduce suitable microhabitats for sensitive macroinvertebrates (Feng *et al.*, 2025).

Both climatic conditions and LULC significantly affected the distribution of the two macroinvertebrate families (Wagenhoff *et al.*, 2012; Machuca-Sepúlveda *et al.*, 2024). However, temperature and precipitation-related variables had a strong influence on Perlidae, while

temperature variables had a strong influence on Philopotamidae. The above taxa are very sensitive to environmental pollution and climatic extremes, especially changing temperature and precipitation (Abdul-Nabi *et al.*, 2025). Perlidae larvae are found in fast-flowing riffles and streams of good quality water; Philopotamidae larvae are found in streams with a stable flow, and where organic material is available, they construct nets and feed on them (Dean & Bunn, 1989; Cranston & Gullan, 2009). Consequently, increasing temperature, altered precipitation patterns, drought frequency, and flow instability can disrupt feeding efficiency, larval development, and habitat suitability for both taxa (Mantyka-Pringle *et al.*, 2014; López-López *et al.*, 2019; Gutiérrez-Rial *et al.*, 2023).

Anthropogenic pressures associated with LULC change, together with climate stressors, may simultaneously alter the geographic ranges of sensitive macroinvertebrates (Lakew and Moog, 2015; Tampo *et al.*, 2021; Liu *et al.*, 2023; Gutiérrez-Rial *et al.*, 2023; Gücker *et al.*, 2024). Loss of riparian vegetation due to agricultural expansion and human settlement reduces stream shading, increases sedimentation, and decreases dissolved oxygen availability (Isasi Bea, 2020). These environmental changes may reduce prey availability for predatory Perlidae, while increased sedimentation and unstable flow conditions can clog the filtering nets of Philopotamidae, thereby decreasing the survival and distribution of both taxa under worsening climatic conditions (Du *et al.*, 2025).

Under current climatic conditions, approximately 14.91% and 17.80% of Ethiopia's central and southwestern highlands were predicted to be suitable habitats for Perlidae and Philopotamidae, respectively. These areas, particularly within the Awash, Abay, and Shebelle watersheds, are characterized by relatively cooler temperatures, perennial streams, sustained rainfall, and well-oxygenated waters that support pollution-sensitive taxa (Getnet *et al.*, 2022). The predicted habitat suitability maps indicated that highly suitable habitats were concentrated mainly in the central highlands, extending into western and marginal southern highlands. These results are consistent with previous studies conducted in Ethiopian highland rivers (Assefa *et al.*, 2020). These pollution-sensitive taxa are widely recognized as indicators of river water quality, responding strongly to variations in dissolved oxygen, river temperature, nutrient status, and substrate composition (Worku & Ambelu, 2018; Masese *et al.*, 2023).

The current habitat suitability predictions provide an important baseline for future conservation planning in Ethiopian highland rivers. Suitable habitats for both taxa occurred within and outside their historically suitable ranges, indicating potential range shifts under changing climatic and land use conditions (Eady, 2011; Tampo *et al.*, 2021). Since Perlidae and Philopotamidae are widely recognized as indicators of river ecological quality, their projected distribution changes may reflect broader alterations in freshwater ecosystem health (Canobbio *et al.*, 2009; Worku & Ambelu, 2018; Masese *et al.*, 2023).

Future climate projections suggested substantial changes in habitat suitability and spatial distribution for both taxa. Perlidae suitability was projected to slightly increase in some central highland areas under moderate climate conditions by 2050, potentially due to favorable temperature and precipitation conditions that support their physiology and reproduction (Prenda & Gallardo-Mayenco, 1999; Timoner *et al.*, 2021). However, in the SSP2-4.5 and SSP5-8.5 scenarios, about 23.36% and 50.55% of the suitable habitats were projected to be lost by 2070, respectively. Changes in climate, like higher temperatures, irregular precipitation, and stream fluctuations, may help cause stream degradation and habitat (Li *et al.*, 2024; Espinar-Herranz *et al.*, 2025).

Likewise, Philopotamidae were expected to lose about 34.58% and 58.87% of their suitable habitat under SSP2-4.5 and SSP5-8.5 scenarios, respectively, in 2050 and 2070. Decreased habitat suitability was linked to the increase in sediment loads, flow instability, and changes in organic matter availability that directly impact their filtering-net feeding strategy (Doerschlag, 2020; Li *et al.*, 2024). The future habitat suitability for Philopotamidae was expected to be around 58.87% less than the current situation, especially under the high warming scenario. These sensitive taxa may be subject to increased temperature (stress) and/or changes in precipitation patterns and increased frequency of extreme climatic events, which could push them beyond their physiological tolerance limits (Mantyka-Pringle *et al.*, 2014; Pedreros *et al.*, 2020).

The projected future distributions suggested shifts in suitable habitats to the north and to elevated areas, both of which would follow cooler and well-oxygenated refuges under the changing thermal and hydrological conditions, for both taxa (Wagle *et al.*, 2020; Dai *et al.*, 2021). Conservation recommendations, however, should be made with caution, as there are some differences in the response of the macroinvertebrate taxa to climate and habitat changes (Guisan

et al., 2017). The protection of pollution-sensitive aquatic insects is still necessary because of their significant ecological values in freshwater biodiversity, organic matter decomposition, nutrient cycling, etc (Goenka, 2023; Bharti & Yeole, 2025). Riparian restoration, land use control, and climate-smart watershed management are conservation strategies that can contribute to maintaining appropriate habitats in the face of future environmental change. It is also important to conduct long-term ecological monitoring and adaptive management to enhance the effectiveness of conservation (Mantyka-Pringle *et al.*, 2014).

Ensemble modelling was used to reduce the uncertainty in prediction, but there is still the limitation of depending on a single global climate model (GCM). However, local environmental stressors (LE) were not adequately included in future projections, even though they are important for sensitive taxa (SOR 2017; Mohammed *et al.*, 2022; Fernández *et al.*, 2023). To enhance the understanding of how macroinvertebrate species react to climate change and land use change and to facilitate targeted conservation planning, future studies should incorporate local-scale environmental variables, habitat fragmentation, and ecological interactions (Gál *et al.*, 2019).

CHAPTER 6: CONCLUSION AND RECOMMENDATIONS

6.1. Conclusion

This study integrates LULC changes, hydrology, water quality, habitat condition, macroinvertebrate community structure, and climate change impacts to help assess the general health and resilience of this watershed as a whole. In each analysis, a clear trend emerges, where the combined influence of land-use and climate variability, which dictate the quality of water, the integrity of the habitat, and the biological response, significantly influences watershed conditions.

The watershed had slightly change on LULC throughout the last thirty years (1994-2023), with cropland being added first, then removed over time; and vegetation cover, grazing land, and water bodies being added over time. Both of these changes can be attributed to human and land use pressures and to the positive impacts of conservation interventions. Increased implementation of soil and water conservation measures such as reforestation, soil bunds, terraces, and vegetation buffers have led to decreased soil erosion, increased vegetation cover, stabilized runoffs and decreased sediment and nutrient loading to streams. The overall ecosystem

service conditions have thus improved, though there are still places in the watershed where agricultural pressure continues to be a challenge.

Water quality conditions and habitat conditions have improved, especially from 2016 to 2023, in the context of improved land management. Dissolved oxygen increased, and turbidity and nutrient concentrations decreased, suggesting a general trend toward ecological recovery. Improvement in environmental conditions correlates well with improved habitat quality and minimizing disturbance at managed sites. Biological assessments with benthic macroinvertebrates corroborated these trends: There were increases in families and taxa that are pollution sensitive, including families such as Heptagenidae and Perlidae, and order such as Ephemeroptera, Plecoptera, and Trichoptera. Pollution-tolerant taxa and families decreased. Multivariate analyses additionally showed that the environmental quality of the habitats and the nutrient levels are also important factors in determining the macroinvertebrate community composition, revealing a strong relationship between environmental changes and responses.

A second refinement of the assessment framework was the development of a benthic macroinvertebrate-based MMI that effectively distinguished impacted from reference sites. This is evidence of the suitability of highland headwater streams in Ethiopia to determine ecological health by using macroinvertebrates as bioindicators. The absence of indicator plants, however, underscores the need to further develop with more integrated biotic indices, which incorporate measures of aquatic fauna and riparian vegetation together.

Climate and land-use change analyses also showed that ecosystem responses to local management are a function of the greater climate variability. The climate scenarios identified from habitat suitability modeling suggested a decrease in suitable habitats for pollution-sensitive macroinvertebrates, with shifts occurring, especially under the high emission scenarios. An increase in precipitation will lead to improvements in habitat in some areas, whereas temperature increases will be expected to have adverse effects on species distribution and community structure. It is better to see how different these effects are, and how it illustrates resilience and vulnerability of aquatic biodiversity in the face of changing environmental conditions. Finally, the study validates the use of macroinvertebrate-based assessments for developing a framework

of watershed health and management when combined with hydrological, physicochemical, and land use data. The findings also offer a solid scientific underpinning to create eco-monitoring tools and enhance conservation plans for Ethiopian highland headwater ecosystems.

6.2. Recommendations

Based on the results of this study, the following focus areas are suggested for improving watershed sustainability and ecosystem integrity through targeted interventions.

- The valuation of ecosystem services should be incorporated in the planning and decision-making processes of the watersheds. The study indicated that water bodies and vegetation-related land-use classes were the highest ecosystem service values and had played a significant role in enhancing the ecosystem health, thus future interventions to land-use should be oriented towards these ecosystem service land covers. This should be taken by the Amhara Regional Planning and Development Bureau and the watershed management offices.
- Watershed monitoring programs should consider habitat quality (HVAS) and stream discharge as important indicators. These variables were found to be the most significant factors affecting macroinvertebrate abundance and diversity in streams, and they are important indicators of ecological degradation and restoration success. This action will be continuously and regularly monitored to enhance the watershed's sustainability. This recommendation should be implemented by the universities, research institutes, the Environmental Protection Authority, and the Awash Basin Development Office.
- Long-term ecological monitoring should incorporate the use of biological indicators in conjunction with climate and land-use data. The changes in environmental conditions were also associated with changes in the pollution-sensitive macroinvertebrate assemblages, highlighting the sensitivity of aquatic ecosystems to combined climatic and land-use pressures, with significant differences noted between the 2016 and 2023 surveys. This recommendation will also need to have detailed investigation in the future. Therefore, the Ethiopian Meteorological Institute, the Plan Commission (on Climate issues), the Environmental Protection Authority, and the Basin Development Authorities are recommended to take up this recommendation.

- This study has developed a Macroinvertebrate Multimetric Index (MMI) that can be used as a standardized tool for assessing ecological health in Ethiopian highland streams. The index is able to effectively distinguish sites at varying disturbance levels and offers a scientifically sound & cost-efficient way to biomonitoring, assess restoration, and manage environmental resources. However, this index needs to have an updated version and make continuous monitoring for substantial uses and the river water protection, etc. Therefore, the Universities, Aquatic ecosystem research institutions, Environmental Protection Authority should be the main decision makers in this recommendation.
- Conservation and watershed management plans should consider habitat suitability maps created with the ensemble model. The model was able to successfully identify areas likely to remain suitable for pollution-sensitive taxa under future climate scenarios, thereby giving a scientific basis to prioritize conservation actions and to protect climate-suitable areas. It is recommended that the Ethiopian Biodiversity Institute, Environmental Protection Authority, and Ministry of Water and Energy implement this.

CHAPTER 7: VALIDITY, STUDY STRENGTH/NOVILITY, LIMITATION, FUTURE PROSPECTS

7.1. Validity and Generalizability

Reliability of this study is supported by the use of structured and standardized data collection methods and standardized analytical procedures at both temporal (1994 to 2023) and spatial (25 sampling locations) levels in the Dinki watershed. Calibrated instruments, standardized macroinvertebrate sampling methods, and cross-validation of LULC classification with high-resolution satellite imagery and field verification were used to ensure internal validity. Combining long-term climatic, hydrological, and biological data increased the confidence of causal inference of the relationships between land use change, climate variability, and macroinvertebrate distribution patterns. Global approaches, such as family-level bioindicator analysis and ecosystem service valuation (ESV) frameworks, were adopted to enhance external validity and generalizability of the results, and are easily transferable to other Ethiopian highlands and similar tropical watersheds with similar biophysical and socio-ecological conditions. This is achieved through the use of standard methods and procedures, clear data

handling, and sound statistical tests and validation (e.g., p-values, R² statistics) that guarantee the study's results are trustworthy and generalizable, thus offering a solid base for future studies in watershed and biodiversity management.

7.2. Methodological Strengths/Scientific Novelty

This study's methodological merits are its multidisciplinary and integrative design, which incorporates hydrological, physicochemical, soil, land use/land cover, macroinvertebrate, and predictive modeling methods in a comprehensive watershed health assessment. One of the most important scientific innovative in this dissertation is the development of an integrated watershed ecological health framework that brings together climate variability, hydrology, land use dynamics, habitat condition, macroinvertebrate assemblages, and ecosystem services into a single analytical platform. Incorporating long-term (30-year) climate data and multi-seasonal field surveys in 2016 and 2023 added to the temporal reliability, and spatial replication at 100 sampling sites (25 sampling sites x 2 seasons x 2 years (2016 and 2023)) also contributed to the ecological representativeness. The study also provides a unique long-term comparative ecological dataset for Ethiopian highland watersheds, allowing for a strong assessment of changes in the watersheds over time and strengthening understanding of the watershed resilience in the face of combining climatic and anthropogenic stressors. Paired t-tests, repeated-measures ANOVA (rmANOVA), Indicator Value (IndVal) analysis, Non-metric Multidimensional Scaling (NMDS), and Redundancy Analysis (RDA) were applied to elucidate species-environment relationships and were systematically used. Another major novelty is the development and application of a novel MMI specifically adapted to Ethiopian highland streams that has been developed as a scientifically sound indicator to assess ecological health and biomonitoring in data-deficient areas. A MMI was developed, further enhancing the accuracy and robustness of biological assessments. In addition, ensemble habitat suitability modelling under future climate scenarios showed high predictive performance, which in turn, increased the generalizability of the outcomes to other Ethiopian highland watersheds under similar environmental stress. The dissertation also contributes to the use of ensemble habitat suitability modeling for pollution-sensitive macroinvertebrates in the context of future climate, which provides an innovative future climate-based prediction tool for conservation and adaptation planning of freshwater biodiversity

in Ethiopia. In addition, incorporating ecosystem service assessment into ecological health indicators is an added value in the linkage of ecological science and sustainable watershed management and decision-making for ecosystem services.

7.3. Research limitations

However, there are several drawbacks recognized in these strengths and scientific novelty. First, macroinvertebrate identification was done to the family level based on the South African guidelines, which may lessen the taxonomic resolution and sensitivity in an ecological health evaluation. Second, LULC analysis relied on supervised classification of satellite imagery; although they have been field-validated, there remains uncertainty, particularly with regard to distinguishing grazing land from sparsely vegetated areas. Furthermore, in 2016 there was lack of biophysical attributes, spatiotemporal variation comparison, effects of land use and climate change on indicator taxa, lack of development of MMI and lack on the species distribution model (SDM). Third, although fewer than 10,000 macroinvertebrate individuals were analyzed, increasing the sample size to approximately 10,000 individuals for both the 2016 and 2023 sampling periods would provide greater statistical robustness. Fourth, long-term climate data enhanced temporal reliability, but fine-scale temporal analyses were limited by the lack of continuous long-term biological and hydrological data. Lastly, predictive models had good predictive skill, but failed to explicitly consider future land use and water quality scenarios, which constricted their ability to represent the full suite of ecological feedback mechanisms.

7.4. Future Prospects

Future research and management should be directed towards augmenting long-term ecological resilience, based on the current results:

- Designing adaptive watershed management frameworks in explicit consideration of climate variability, LULC change, and socio-ecological feedback.
- Identification of sensitive macroinvertebrates to the genus level to improve biomonitoring and ecological assessments.
- Assessing the socio-economic, demographic, and policy factors influencing LULC transitions.

- Development of a climate change, land use and river water quality-driven ensemble-based habitat suitability modelling to predict suitable habitats for pollution-sensitive taxa and inform climate-sensitive conservation planning.
- Enhancing the contributions of the community to the stewardship of the ecosystem, in the context of the ecological restoration programme and sustainable use of small-scale irrigation systems, in line with the national initiatives like Green Legacy and extrapolate to other watershed.

Collectively, these strategies will help to improve the resilience of freshwater biodiversity, ecological integrity, and the provision of key ecosystem services to local communities in the Dinki watershed and other highland ecosystems.

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Annexes

Annex I. The average composition and abundance of macroinvertebrate assemblages in each sampling sites (Dinki, Zego, Gedamoch and Dense) and years (2016 and 2023) in Dinki watershed headwater streams, computed.

Order	Family	2016				2023				F
		Dinki	Zego	Gedamoch	Dense	Dinki	Zego	Gedamoch	Dense	
Amphipoda	Gammaridae	0.00	0.00	0.00	0.00	0.00	0.00	32.00	5.00	1.450
Araneae	Pisauridae	0.00	2.00	2.00	0.00	0.00	0.00	0.00	0.00	3.00**
Arhynchobdellida	Hirudinae	0.50	1.00	1.00	0.00	28.00	101.00	189.00	9.50	3.96**
Basommatophora	Ancylidae	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.50	1.000
Branchiobdellida	Branchiobdellidae	0.00	0.00	1.50	5.00	0.00	0.00	0.00	0.00	1.900
Coleoptera	Carabidae	1.50	1.50	0.00	0.00	0.00	0.00	0.00	0.00	3.00**
Coleoptera	Dytiscidae	0.00	0.50	0.00	6.50	0.00	0.00	3.00	4.00	0.000
Coleoptera	Elmidae	0.00	0.00	0.00	0.00	18.00	1.00	13.00	2.00	4.15**
Coleoptera	Gyrinidae	24.50	29.50	10.50	20.50	0.00	0.00	0.00	0.00	27.80***

Coleoptera	Haliphidae	0.00	0.50	0.00	0.00	0.00	4.00	6.00	1.00	3.60**
Coleoptera	Helodidae	0.00	0.00	0.00	0.00	9.50	0.00	8.50	1.50	4.09**
Coleoptera	Hydraenidae	0.00	0.00	0.00	0.50	0.00	0.00	1.00	0.00	0.200
Coleoptera	Hydrophilidae	3.50	0.00	0.50	1.00	0.00	0.00	0.00	2.00	0.660
Coleoptera	Hygrobiidae	0.00	1.00	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Coleoptera	Psephenidae	0.00	0.00	0.00	0.00	1.50	10.00	2.00	19.50	3.81**
Coleoptera	psephenus	0.00	0.00	0.00	0.00	0.50	0.50	0.00	0.00	-
Coleoptera	Scirtidae	0.00	0.00	0.50	1.00	0.00	0.00	0.00	0.00	2.45*
Cycloneritida	Nertidae	6.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Decapoda	Potamonautidae	0.00	0.00	43.50	11.50	1.00	11.50	13.50	10.50	0.190
Decapoda	Protoneuridae	0.00	0.00	0.00	0.00	0.00	3.50	9.00	0.00	2.16*
Diptera	Anthericidae	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Diptera	Anthomyiidae	0.00	2.00	0.00	1.00	0.00	0.00	0.00	0.00	2.45*
Diptera	Atherilidae	0.00	0.00	0.00	0.00	0.00	0.00	3.00	1.50	2.45*
Diptera	Ceratopogonidae	0.00	0.00	0.50	4.50	0.00	0.00	0.00	0.00	1.320
Diptera	Chironomidae	28.00	28.00	2.00	3.50	0.00	2.00	2.00	0.00	3.86**
Diptera	Dixidae	0.00	0.00	0.00	0.50	0.00	0.00	4.50	1.00	1.350
Diptera	Ehydriidae	0.00	0.00	0.00	0.00	0.00	2.00	0.00	0.00	1.000
Diptera	Limoniinae	0.00	0.50	1.50	0.50	0.00	0.00	0.00	0.00	3.95**
Diptera	Muscidae	1.00	0.00	0.00	0.00	17.50	52.50	87.00	11.00	5.66**
Diptera	Pediciidae	0.00	0.00	0.50	0.50	0.00	0.00	0.00	0.00	3.00**
Diptera	Pschomidae	0.00	0.00	0.00	0.00	1.00	0.50	0.00	0.00	2.45*
Diptera	Psychiodidae	0.00	0.00	0.50	0.00	2.00	7.50	0.00	0.00	1.600
Diptera	Simuliidae	0.50	12.00	45.00	24.00	0.00	2.00	61.00	73.00	0.400
Diptera	Tabanidae	63.50	10.00	9.50	0.00	51.00	3.50	1.00	1.50	0.120
Diptera	Tipuliidae	0.00	7.00	177.00	39.50	4.00	66.00	86.00	68.50	0.000
Ephemeroptera	Ephemeridae	0.00	0.00	0.00	0.00	0.00	0.00	10.00	0.00	1.000
Ephemeroptera	Isonychidae	0.00	0.00	0.00	0.00	4.00	3.50	168.50	17.00	1.440
Ephemeroptera	Leptophlebiidae	0.00	0.00	0.50	0.00	0.00	11.00	12.00	0.00	2.86*
Ephemeroptera	Oligoneuridae	0.00	0.00	0.00	0.00	0.00	10.00	2.50	0.00	1.740
Ephemeroptera	prospistomatidae	0.00	0.00	0.00	0.00	0.00	0.00	2.50	0.00	-
Ephemeroptera	Telagenidae	0.00	0.00	0.00	0.00	0.50	1.00	0.00	0.00	2.45**
Ephemeroptera	Teloganodidae	0.00	0.00	0.00	0.00	3.50	10.00	19.50	16.50	12.10***
Ephemeroptera	Baetidae	11.00	35.50	113.00	39.00	93.50	119.00	295.50	177.50	5.91**
Ephemeroptera	Caenidae	10.00	0.00	0.00	6.50	32.00	100.50	102.00	8.00	5.50**
Ephemeroptera	Ephemerellidae	0.00	0.00	0.50	0.00	6.00	10.50	65.50	3.50	2.07*
Ephemeroptera	Heptagenidae	0.50	5.50	60.50	2.00	0.00	0.00	4.50	1.00	1.170
Ephemeroptera	Tricorythidae	50.00	25.50	12.00	12.00	0.00	0.50	11.00	3.50	5.15**
Haplotaxida	Annelidae	0.00	0.00	0.00	0.00	0.50	0.00	0.00	6.50	1.210
Hemiptera	Belostomatidae	1.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Hemiptera	Cicadollidae	0.00	1.50	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Hemiptera	Corixidae	25.50	67.00	1.50	11.50	0.00	1.50	0.00	0.50	3.22**
Hemiptera	Gerridae	0.00	0.00	0.00	0.50	0.00	5.50	6.00	0.00	2.72*
Hemiptera	Naucoridae	20.00	2.00	7.00	0.00	0.00	0.00	0.00	0.00	2.60*
Hemiptera	Nepidae	0.50	0.00	0.00	0.50	0.00	0.50	0.00	0.50	0.000
Hemiptera	Veliidae	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.00	3.00**
Isopoda	Asellidae	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.00	1.000
Lepidoptera	Pyalidae	0.00	0.00	0.00	0.00	2.50	4.00	1.50	0.00	5.65**
Lymnaeida	Lymnaeidae	1.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Lymnaeida	Lymnocyidae	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Megaloptera	Corydalidae	0.00	0.00	0.00	0.00	0.00	0.00	0.00	2.00	1.000

Mulusca	Mollusca	0.00	0.00	0.00	0.00	0.00	0.00	10.00	0.00	1.000
Odonata	Aeshnidae	2.00	0.00	18.00	7.50	2.00	13.00	40.00	7.50	0.880
Odonata	Chlorocyphidae	0.00	0.00	0.00	0.00	0.50	0.00	25.50	0.00	1.050
Odonata	Coenagrionidae	1.00	1.00	0.00	0.00	0.00	0.00	1.00	0.00	0.430
Odonata	Cordulegastridae	3.50	0.00	0.00	0.00	0.00	0.50	0.00	0.50	0.500
Odonata	Corduliidea	5.00	22.00	0.00	0.00	0.00	2.00	0.00	0.00	1.420
Odonata	Gomphidae	12.00	26.00	2.50	0.00	19.00	3.00	13.00	0.00	0.040
Odonata	Lestidae	0.00	0.00	0.00	0.00	0.00	0.00	9.00	0.00	1.000
Odonata	Libellulidae	1.50	3.50	0.00	0.00	0.00	0.00	1.00	0.00	1.330
Odonata	Macromiidae	4.00	4.50	0.00	0.00	0.00	0.00	0.00	0.00	2.98*
Oligochaeta	Oligochaeta	0.00	0.00	0.00	0.00	0.00	0.50	0.00	2.50	1.590
Orthoptera	Gryllidae	0.00	0.00	1.00	4.00	0.00	0.00	0.00	2.00	0.490
Plecoptera	Capniidae	0.00	0.00	0.50	0.00	0.00	0.00	5.00	0.00	0.800
Plecoptera	Chloroperlidae	0.00	0.00	0.50	1.00	0.00	0.00	0.00	0.00	2.45*
Plecoptera	Leuctridae	0.00	0.00	0.00	0.00	0.00	0.00	5.50	0.50	1.260
Plecoptera	Nemouridae	0.00	0.00	19.00	3.00	0.00	0.00	5.00	0.00	0.810
Plecoptera	Notonemouridae	0.00	0.00	0.00	0.00	0.00	2.50	5.50	0.00	2.34*
Plecoptera	Peltoperlidae	0.00	0.00	0.00	0.00	0.00	0.00	14.50	0.00	1.000
Plecoptera	Perlidae	0.50	1.00	3.50	0.50	0.00	1.50	32.00	10.50	1.690
Plecoptera	Perlodidae	0.00	0.00	7.00	0.00	0.00	0.00	18.00	0.00	0.320
Plecoptera	Petronarcyidae	0.00	0.00	0.00	0.00	0.00	0.00	4.00	0.00	1.000
Plecoptera	Planorbidae	10.50	0.00	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Plecoptera	Pteronarchyidae	0.00	0.00	1.00	0.50	0.00	0.00	0.00	0.00	2.45*
Plecoptera	Taeniopterygidae	0.00	0.00	0.00	1.50	0.00	0.00	0.00	1.00	0.080
Trichoptera	Apatanidae	0.00	0.00	0.00	0.00	0.00	0.00	29.50	0.00	1.000
Trichoptera	Brachycentridae	0.00	0.00	0.00	0.50	0.00	0.00	1.50	1.00	1.600
Trichoptera	Ecnomidae	0.00	0.00	0.00	0.00	9.50	0.50	27.00	0.00	2.150
Trichoptera	Goeridae	0.00	0.00	0.00	0.00	0.00	0.00	19.50	0.00	1.000
Trichoptera	Hydropsychidae	7.50	30.50	62.00	32.50	0.00	0.00	0.00	0.00	8.79***
Trichoptera	Hydroptilidae	0.50	0.00	0.50	0.00	6.00	1.50	0.00	8.00	3.72**
Trichoptera	Limnephidae	0.00	0.00	0.00	0.50	0.00	0.00	0.00	0.00	1.000
Trichoptera	Philopotamidae	0.00	0.00	3.00	1.00	0.00	1.50	5.00	5.50	1.750
Trichoptera	Pisuliidae	0.00	0.00	0.00	0.00	0.00	0.00	1.50	0.00	1.000
Trichoptera	Polycentropodidae	0.00	0.00	0.00	0.00	1.50	0.00	0.00	0.00	1.000
Trichoptera	Psychomyiidae	0.00	0.50	0.00	0.00	0.00	0.00	0.00	0.00	1.000
Trichoptera	Rhyacophilidae	0.00	0.00	0.50	0.00	44.00	72.00	156.50	59.00	10.80***
Trichoptera	Rhyacophilidae	0.00	0.00	0.00	0.00	0.50	0.50	30.00	4.50	1.560
Trichoptera	Sericostomatidae	0.00	0.00	0.00	1.00	0.00	0.00	0.00	0.00	1.000
Trombidiformes	Hydrachnidae	0.00	0.00	0.00	0.00	0.00	1.50	7.00	6.50	4.53**
Turbellaria	Turbellaria	0.00	0.00	0.00	0.00	0.00	2.00	0.50	0.00	1.740
Unionidae	Unionidae	0.00	0.00	0.00	0.00	0.00	1.00	0.00	0.00	1.000
Veneridae	Corbiculidae	0.00	0.00	1.00	0.00	0.00	0.00	4.00	0.00	0.530
Total Average		297.50	322.50	611.00	245.50	360.50	648.50	1693.50	560.50	

***p <0.001; **p <0.01; *p < 0.05.

Annex II. The composition and abundance of macroinvertebrate assemblages in each sampling season and years in Dinki watershed headwater streams, computed with paired t-test. Represented in mean value $\pm$ standard error, minimum and maximum values in parenthesis.

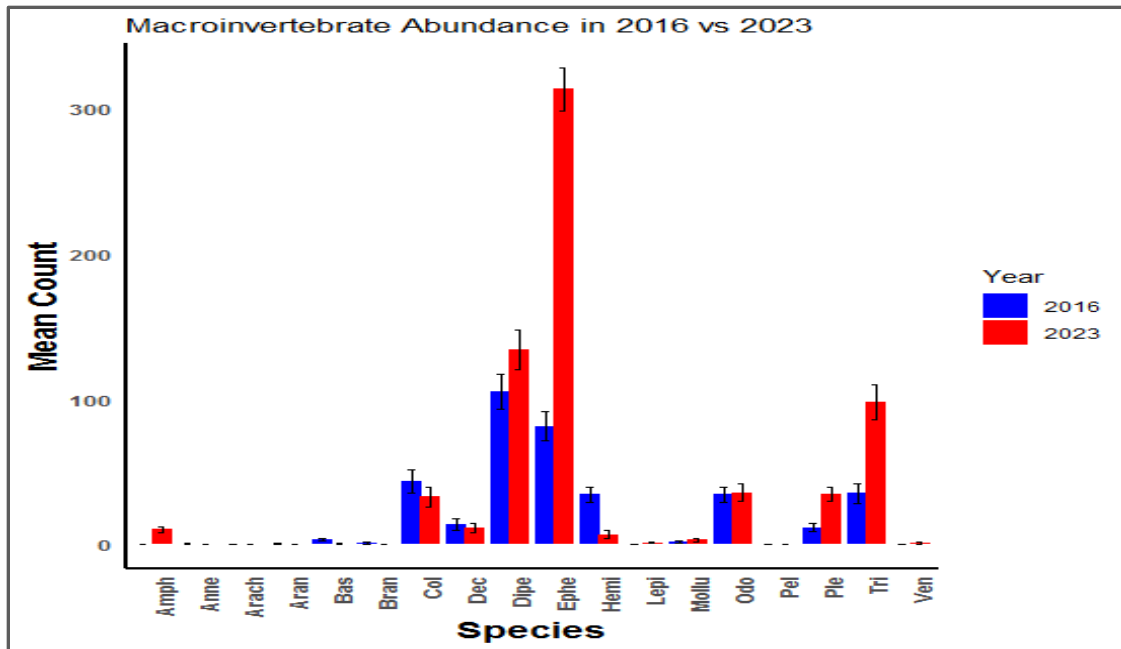
2016- Dry						2016-Wet				2023-Dry		2023-Wet	
Order	Invertebrate	Mean	F	Mean	F	Mean	F	Mean	F	Mean	F	Mean	F
Amphipoda	Gammaridae	0	1.00	0	1.00	1.8±7.20(0.35)	19.09***	0.08±0.40(0-2)	10.96				
Annelida	Ologochaeta	0	1.00	0	1.00	0.96±4.00(0-20)	15.98***	0.08±0.28(0-1)	3.13				
	Hirudinae	0.17±0.56(0-2)	1.43	0.04±0.20(0-1)	0.17	0.32±1.14(0-5)	3.89	0.88±1.69(0-8)	0.02				
Araneae	Pisauridae	0.25±0.53(0-2)	47.36***	0.08±0.40(0-2)	24.76***	0.6±2.12(0-10)	1.79	0.00	1.00				
Branchiobdellida	Branchiobdellidae	0.38±1.10(0-5)	13.44	0.04±0.2	26.39***	0.00	1.00	0	1.00				
Coleoptera	Amphipoda	0	1	0	1	0.12±0.60(0-3)	10.49***	0.00	1.00				
	Ancylidae	0	1	0	1	0.52±2.06(0-10)	6.76**	0.00	1.00				
	Carabidae	0.13±0.45(0-2)	0.16	0.12±0.60(0-3)	0.23	0	1.00	0.00	1.00				
	Dytiscidae	0.33±0.64(0-2)	0.05	0.2±0.50(0-2)	1.47	0.56±1.33(0-5)	4.56**	0.00	1.00				
	Elmidae	0	1.00	0	1.00	2.08±4.88(0-21)	6.65**	0.64±1.04(0-3)	0.28				
	Gyrinidae	5.63±9.12(0-25)	1.68	0.72±1.67(0-6)	11.84***	1.4±3.70(0-15)	16.99***	0.16±0.55(0-2)	9.0**				
	Haliphidae	0.00	1.00	0.04±0.20(0-1)	4.92**	0	1.00	0.00	1.00				
	Helodidae	0.00	1.00	0	1.00	0.28±1.40(0-70)	8.04**	0.08±0.40(0-2)	4.60*				
	Hydraenidae	0.04±0.20(0-1)	1.88	0.00	1.00	0.28±1.06(0-5)	3.19	0.2±0.58(0-2)	3.55				
	Hydrophilidae	0.13±0.45(0-2)	0.53	0.28±0.74(0-3)	3.28	0	1.00	0.72±3.01(0-15)	22.03**				
	Hygrobiidae	0.00	1.00	0.08±0.28(0-1)	12.84***	21.4±22.2(0-100)	2.48	0	1.00				
	Polycentropodidae	0	1.00	0	1.00	0.12±0.60(0-3)	0.27	0.00	1.00				
	psephenidae	0.00	1.00	0.00	1.00	1.08±4.99(0-25)	0.76	1.4±3.10(0-11)	5.33**				
	psephenus	0.00	1.00	0.00	1.00	0.16±0.80(0-4)	13.73***	0.00	1**				
	Psychomyiidae	0.00	1.00	0.04±0.20(0-1)	6.57**	0.2±1(0-5)	24.97***	0.08±0.28(0-1)	22.01**				
Decapoda	Decapoda	0	1.00	0	1.00	0.4±2(0-10)	1.47**	0.00	1.00				
	Potamonautidae	3.08±6.37(0-27)	1.45	1±1.89(0-6)	0.81	0	1.00	0.72±1.43(0-6)	13.16**				
Deptera	Anthomyiidae	0.17±0.48(0-2)	6.58	0.04±0.20(0-1)	24.72***	0.00	1.00	0	1.00				
	Anthericidae	0.00	1.00	0.04±0.20	0.00	0	1.00	0	16.05**				
	Athericidae	0.00	1.00	0.00	1.00	0.00	1.00	0.24±0.66(0-3)	1**				
	Ceratopogonidae	0.38±1.84(0-15)	9.30**	0.04±0.2(0-1)	1.26	0.00	1.00	0.00	1.00				
	Chironomidae	2.38±10.81(0-53)	14.21***	2.7±4.3(0-16)	15.09***	0.00	1.00	0.16±0.55(0-2)	0.00				
	Dixidae	0.04±0.20(0-	9.59*	0.00	1.00	0.00	0.02	0.16±0.37(0-	19.21*				

		1)	*					-1)	**
	Ehydridae	0	1.00	0	1.00	0.16±0.80(0-4)	9.68***	0.00	1.00
	Limoniinae	0.21±0.66(0-3)	3.48*	0.00	1*	0	1.00	0	1.00
	Muscridae	0	1.00	0.00	1.00	0.8±3.12(0-15)	9.21*	0.00	1.00
	Pediciidae	0.04±0.20(0-1)	5.59	0.04±0.20(0-1)	0.86	1±5(0-25)	20.69***	0	1.00
	Psychodidae	0.04±0.20(0-1)	1.15	0.00	1.00	0.08±0.28(0-1)	8.35*	0.00	0.08
	Tabanidae	3.79±5.64(0-20)	1.69	1.48±3.48(0-14)	4.61*	1.68±4.58(0-20)	14.42***	2.88±6.35(0-24)	7.67**
	Tipuliidae	13.25±22.39(0-68)	7.67*	3.2±3.71(0-11)	21.41**	9.24±0.83(0-23)	0.83	8.72±8.72(0-25)	15.64***
Ephemeroptera	Atherilidae	0	1	0	1	0.12	0.01	0.04±0.20(0-1)	0.20
	Baetidae	7.17±11.42(0-56)	16.97	8.4±12.71(0-57)	0.67	30.76±34.18(0-145)	2.17	24.5±25.9(0-96)	1.75
	Caenidae	0.62±1.47(0-6)	1.90	0.6±3(0-15)	***	15.12±18.55(0-57)	2.39	4.28±05.81(0-20)	6.06
	Ephemerellidae	0.00	1.00	0.04±0.20(0-1)	2.66	3.24±7.57(0-35)	24.13***	3.6±8.91(0-36)	43.48
	Ephemeridae	0	1.00	0	1.00	0.8±4(0-20)	15.52***	0.00	0.01
	Heptageniidae	3.58±7.67(0-32)	5.64*	1.24±2.44(0-6)	6.38*	25.6±28.71(0-102)	36.31***	1.48±1.94(0-7)	32.47**
	Hydrachnidae	0.00	0.00	0.00	0.00	0.08±0.40(0-2)	12.33***	0.00	0.02
	Isonychidae	0	1.00	0	1.00	0	1.00	4.32±9.84(0-45)	29.25**
	Leptophlebiidae	0	1.00	0	1.00	4.72±11.73(0-45)	22.70***	0.04±0.20(0-45)	3.45
	Oligoneuridae	0	1.00	0	1.00	0.44±1.39(0-5)	4.72*	0.04±0.20(0-1)	8.18**
	prospistomatidae	0	1.00	0	1.00	1.8±2.72(0-10)	18.12***	0.00	1.00
	Telagenidae	0.00	1.00	0.00	1.00	0.12±0.44(0-2)	8.49*	0.00	0.79
	Teloganodidae	0.00	1.00	0.00	1.00	2.4±6.44(0-30)	6.37*	1.56±4.53(0-22)	2.99
	Tricorythidae	2.96±4.99(0-13)	5.28*	3.6±6.5(0-24)	1.40	0.8±3.43(0-17)	2.24	0.4±1.41(0-7)	8.08**
Gastropoda	Hydrobiidae	0	1.00	0	1.00	0.00	1.00	0.08±0.40(0-2)	1.51
	Belostomatidae	0.00	1.00	0.12±0.33(0-1)	18.89***	0.00	1.00	0	1.00
	Cicadollidae	0.00	1*	0.12±0.60(0-3)	5.65*	0.00	1.00	0.00	1.00
	Corixidae	7.88±10.58(0-32)	1.34	0.56±1.78(0-4)	13.43***	0.12±0.60(0-3)	16.92***	0.04±0.20(0-1)	11.89**
	Gerridae	0.00	1.00	0.04±0.20(0-1)	1.60	0.4±1.38(0-5)	22.65***	0.04±0.20(0-1)	38.67**
	Naucoridae	2.13±4.66(0-19)	0.16	0.24±0.91(0-3)	0.91	12.32±13.19(0-50)	16.1**	0.00	1.00
	Nepidae	0.04±0.20(0-1)	0.44	0.04±0.20(0-1)	2.63	0.4±1.50(0-7)	1.12	0.04±0.20(0-1)	0.81
	Veliidae	0.00	1.00	0.00	1.00	0	1.00	0.08±0.28(0-1)	2.99
Lepidoptera	Pyracidae	0.00	1.00	0.00	1.00	0.76±2.24(0-	13.52	0.00	0.08**

						10)	***		
						0.32±1.14(0-5)	4.28*	0.12±0.44(0-2)	21.68**
Megaloptera	Pyrilidae	0.00	1.00	0.00	1.00				
	Corydalidae	0.00	1.00	0.00	1.00	0.00	1.00	0.08±0.40(0-2)	1.49
	Lymnaeidae	0.08±0.41(0-2)	3.70*	0.00	1.00	0	1.00	0.00	1.00
Mollusca	Lymnocyidae	0.04±0.20(0-1)	0.01	0.00	1.00	0	1.00	0	1.00
	Mulusca	0	1.00	0.00	1.00	0	1.00	0.00	0.38
	Nertidae	0.54±2.65(0-13)	10.49***	0.00	1*	0.04±0.20(0-1)	2.45	0.00	0.01
	Aeshnidae	2±3.28(0-10)	2.01	0.16±0.47(0-2)	0.01	1.08±3.16(0-12)	3.06	0.68±2.12(0-10)	2.75
	Codulegastridae	0	1.00	0	1.00	0.04±0.20(0-1)	9.57**	0	1.00
	Coenagrionidae	0.17±0.38(0-53)	3.83	0.00	1.00	0.08±0.40(0-2)	2.16	0.00	1.00
	Corduliidae	2.25±3.8(0-16)	24.77***	0.45±0.9(0-4)	1.00*	0.16±0.80(0-22.50)	22.50***	0.00	1.00
	Codulegastridae	0.25±1.03(0-5)	0.21	0.00	1.00		1.00	0.04±0.20(0-1)	0.08
Odonata	Gomphidae	1.38	1.38	0.00	1.00	2.76±6.75(0-25)	40.89***	0.04±0.20(0-1)	73.77**
	Lestidae	0	1.00	0	1.00	1.8±3.97(0-15)	19.01***	0.08±0.40(0-2)	11.39**
	Libellulidae	0.33±0.76(0-3)	0.73	0.08±0.40(0-2)	1.65	0.2±1(0-5)	3.63	0.04±0.20(0-1)	20.97**
	Macromiidae	0.71±1.97(0-9)	7.45*	0.00	1.00	0	1.00	0.00	1.00
	Parecenominidae	0	1.00	0	1.00	0.36±1.80(0-9)	15.40***	0	1.00
	Protoneuridae	0.00	1.00	0.00	1.00	0.2±1.00(0-5)	0.50	0.04±0.20(0-1)	21.96**
	Simuliidae	3.21±5.19(0-18)	0.11	2.64±4.80(0-21)	2.56	1.32±3.36(0-13)	4.14*	3.04±5.62(0-23)	9.87**
				0.4±1.63(0-2)	2.04				
Orthoptera	Gryllidae	0.00	1.00			0	1.00	0	1.00
Pelecypoda	Corbiculidae	0.08±0.41(0-2)	3.39*	0.00	1.00	0.32±1.14	3.07	0.00	1.00
Planorbidae	Planorbidae	0.88±4.08(0-20)	2.56	0.00	1.00	0.12±0.60(0-3)	16.88***	0.00	1.00
	Capniidae	0.04±0.20(0-1)	4.32	0.00	1.00	0.36±1.25(0-5)	0.15	0.04±0.20(0-1)	1.56
	Chloroperlidae	0.08±0.41(0-2)	6.49*	0.04±0.20(0-1)	10.37***	0	1.00	0.00	1.00
	Leuctridae	0	1.00	0	1.00	0.64±1.75(0-7)	10.66***	0.08±0.28(0-1)	0.13
	Nemouridae	0.13±0.45(0-2)	7.69*	0.64±0.25(0-6)	0.25	0	1.00	0.00	0.92
Plecoptera	Notonemouridae	0	1.00	0	1.00	0	1.00	0.2±0.58(0-2)	10.10**
	Peltroperlidae	0	1.00	0	1.00	0.12±0.60(0-3)	3.03	0.16±0.47(0-2)	7.04**
	Perlidae	0.25±0.85(0-4)	17.72***	0.16±0.47(0-1)	4.79*	0	1.00	0.84±1.99(0-8)	34.34**
	Perlodidae	0.58±2.08(0-10)	28.34***	0.00	1**	2.68	31.87***	0.72±2.39(0-10)	8.12**
	Petronarcyid	0	0.00	0.00	1.00	0	1.00	0.00	0.42*

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	Pteronarchyidae	0.13±0.45(0-2)	11.86***	0.00	1*	0	1.00	0.00	1.00
	Scirtidae	0.00	1.00	0.12±0.33(0-1)	35.26***	7.84±19.42(0-85)	21.60***	0	1.00
	Taeniopterygidae	0.00	1.00	0.12±0.12(0-3)	35.26***	0.08±0.40(0-2)	2.32**	0.00	1.00
Trichoptera	Annelidae	0	1	0	1	2.32±5.76(0-22)	13.58***	0.04±0.20(0-1)	2.20
	Apatanidae	0	1	0	1	4.32	19.71***	0.04±0.20(0-1)	15.45**
	Chlorocyphidae	0	1.00	0	1.00	1.88±5.09(0-22)	2.25	0.2±0.65(0-3)	0.07
	Ecnomidae	0	1.00	0	1.00	0.72±2.21(0-10)	0.50	2.24±9.09(0-45)	6.56**
	Brachycentridae	0.00	1.00	0.04±0.20(0-1)	0.89	0.2±0.65(0-3)	0.78	0.00	1.00
	Glossosomatidae	0.00	1.00	0	1.00	1.56±(4.57(0-21)	9.88**	0.00	1.00
	Goeridae	0.00	1.00	0	1.00	0.16±0.47(0-2)	0.16	0.00	0.11
	Hydroptilidae	0.08±0.28(0-1)	0.08	0.00	1.00	0.52±1.16(0-4)	0.32	0	1.00
	Hydropsychidae	6.21±10.23(0-42)	8.32**	3.5±4.2(0-18)	36.10***	0	1.00	5.16±	17.33**
	Muscidae	0.00	1.00	0.08±0.28(0-1)	27.29***	0	1.00	1.12±4.03(0-20)	1.75
	Philopotamidae	0.21±0.59(0-2)	32.63***	0.12±0.44(0-2)	16.89**	0.28±0.98(0-4)	7.16*	0.36±0.95(0-4)	6.32**
	Phryganiidae	0.00	1.00	0.00	1*	0	1.00	0.00	1.00
	Pschomidae	0.00	1.00	0.00	1.00	0.96±3.26(0-15)	20.39***	0.00	1.00
	Rhyacophilidae	0.00	1.00	0.00	1.00	0	1.00	1.52±3(0-12)	16.61**
Turbellaria	Turbellaria	0.00	1.00	0.00	1.00	0.2±0.82(0-4)	15.37***	0.00	1.00
Unionida	Unionidae	0.00	1.00	0.00	1.00	0	1.00	0.04±0.20(0-1)	1.15

***p<0.001, **p<0.01, *p<0.05



Annex III. The average total summary statistics trends of macroinvertebrate orders across sampling seasons in the Dinki watershed for the years 2016 and 2023 .* Indication: Odon= Odonata, Ephe= Ephemeroptera, Col= Coleoptera, Tri= Trichoptera, Ple= Plecoptera, Dip= Diptera, Hemi= Hemiptera, Dec= Decapoda, Bas= Basommatophora, Bran= Branchiobdellida, Aran= Araneae, Lepi= Lepidoptera, Pel= Pelecypoda, Olig= Oligochaeta, Ven= Veneroida, Anne= Annelida, Mollu=Mollusca, Amph=Amphipoda, Arach= Arachnida, Mega= Megaloptera, Neot= Neotaenioglossa, Unio= Unionoida. Note: 2016 macroinvertebrates data were sourced from (Asmamaw *et al.*, 2019 & 2021).

Annex IV. The Pearson correlation matrix of R software comparing the years 2023 and 2016 reveals varying relationships between different macroinvertebrate families across the two years.

2023- 2016	Odon	Ephem	Coleo	Trico	Pleco	Dipte	Hemip	Decap	Annel	Branch	Araneae	Pelec	Mollu	Arachn	Nemat	Orthop
Odon	0	-0.33	-0.63	-0.49	-0.37	-0.22	0.14	0.24	0.03	-0.15	-0.20	-0.31	-0.88	0.12	-0.52	0.36
Ephem	0.11	0	0.57	-0.02	-0.08	-0.08	-0.02	0.73	-0.03	-0.18	0.00	-0.01	-0.48	-0.21	-0.05	-0.19
Coleo	0.50	0.72	0	0.81	-0.01	0.25	-0.22	0.06	-0.01	-0.39	0.61	0.27	0.14	0.10	-0.49	-0.21
Trico	0.26	0.01	0.81	0	-0.16	-0.19	-0.01	0.80	0.04	-0.12	-0.05	-0.07	-0.30	-0.28	0.07	-0.18
Pleco	0.23	0.01	0.57	0.09	0	-0.01	0.22	0.91	-0.12	-0.51	-0.21	-0.03	-0.83	0.16	0.15	-0.26
Dipte	-0.02	-0.11	0.27	0.02	-0.13	0	-0.14	0.25	-0.19	-0.27	-0.19	-0.03	-0.85	-0.18	0.26	0.01
Hemip	-0.16	0.25	-0.07	0.28	0.40	0.12	0	0.23	-0.38	0.04	0.15	0.14	0.40	-0.29	0.62	-0.01
Decap	-0.35	-1.11	0.31	-1.04	-0.93	-0.52	0.46	0	0.06	0.16	0.07	0.88	-0.09	0.07	-0.01	0.12
Annel	-0.09	0.19	-0.16	0.30	0.00	-0.08	0.09	0.23	0	-0.07	0.01	-0.02	0.48	0.06	0.07	-0.13
Branch	0.13	-0.19	-0.09	-0.42	-0.32	-0.08	0.33	-0.19	0.17	0	-0.43	-0.57	-0.24	-0.06	0.21	0.58
Araneae	0.04	-0.26	0.63	-0.21	0.03	0.05	0.24	-0.36	0.23	-0.16	0	-0.07	-0.30	-0.05	-0.34	0.19
Pleco	0.13	-0.04	0.69	0.03	0.02	-0.12	0.35	-1.03	0.14	-0.32	-0.14	0	-0.64	-0.02	0.22	-0.37
Mollu	0.65	1.28	-0.43	1.43	1.02	0.73	-0.46	0.14	-0.71	0.05	1.02	1.22	0	-0.10	0.18	0.31
Arachn	-0.15	-0.01	0.14	-0.07	0.33	0.08	0.05	0.23	0.18	0.17	-0.02	0.14	0.08	0	0.83	-0.16
Nemat	-0.59	0.08	-0.22	0.12	0.32	0.35	-0.68	0.19	0.19	0.33	-0.35	0.27	0.23	-0.91	0	-0.33
Orthop	0.54	0.09	0.06	0.01	0.17	0.28	0.28	-0.15	0.12	-0.76	0.22	0.28	0.58	0.10	0.95	0

*Ephem= Ephemeroptera, Odon= Odonata, Coleo= Coleoptera, Trico= Tricoptera, Pleco= Plecoptera, Dipte= Diptera, Hempi=Hemiptera, Decap= Decapoda, Annel= Annelidae= Branch= Branchiobdellida, Pelecypod, Mollu= Mollusca, Arachn= Arachnidae, Nemat= Nematoda, Orthop= Orthopter. **Note:** 2016 macroinvertebrates data were sourced from (Asmamaw *et al.*, 2019 & 2021).

Annex V. The Indicator Species Analysis (ISA) results show the indicator taxa and indicator values (IVs) during the Dry and Wet season events. Significant values of ≥ 10 IV was considered.

Indicator taxon	Indicator values (%) in Winter/Dry and Summer/wet-two years 2016 and 2023			
	Dry-2016	Wet-2016	Dry-2023	Wet-2023
Gammaridae			19.09***	
Pisauridae		24.76***		
Branchiobdellidae		26.39***		
Gyrinidae		11.84***	16.99***	
Hydraenidae			12.33***	
Hygrobidae		12.84***		17.33***
Psephenidae			20.39***	
Psychomyiidae				21.68***
Athericidae				16.05***
Chironomidae	14.21***	15.09***		
Dixidae				19.21***
Limoniinae				20.97***
Psychodidae			13.73***	
Anthomyiidae		24.72***		
Tabanidae			24.13***	
Tipuliidae		21.41***		
Caenidae				
Ephemerellidae		15.29***	21.60***	
Heptagenidae			36.31***	32.47***
Leptophlebiidae				29.25***
Oligoneuridae				10.10***
prospistomatidae				13.16***
Tricorythidae				15.64***
Belostomatidae		18.89***		
Corixidae		13.43***	16.92***	11.89***
Aeshnidae				38.67***
Pyralidae			13.52***	
Lymnaeidae	3.70**			
Nertidae	10.49***			

Codulegastridae			9.57***	
Corduliidea			22.50***	
Gomphidae			40.89***	73.77***
Lestidae			22.70***	
Libellulidae			10.66***	
Parecenominae			15.98***	
Protoneuridae			18.12***	
Simuliidae				16.61***
Chloroperlidae		10.37***		
Leuctridae			19.01***	11.39***
Nemouridae			16.1***	
Peltroperlidae			15.40***	
Perlidae	21.72***		23.69***	
Perlodidae	28.34***			34.34***
Pteronarchyidae			31.87***	22.01***
Dytiscidae		35.26***		9.87***
Taeniopterygidae		35.26***	14.42***	
Annelidae				
Apatanidae				15.45***
Glossosomatidae			9.88***	
Taeniopterygidae			14.42***	
Annelidae			13.58***	
Apatanidae			19.71***	
Hydroptilidae				22.03***
Hydropsychidae	8.32***	36.10***		
Muscidae		27.29***		
Philopotamidae	32.63***	16.89***		
Phryganiidae				16.88***
Pschomidae				21.96***
Unionidae			15.37***	

*** Significant at $p < 0.001$, **Note:** 2016 macroinvertebrate data were sourced from (Asmamaw *et al.*, 2019 & 2021).

Annex VI. Water quality parameters and environmental conditions of the reference and impaired sites used to develop the Multimetric Macroinvertebrate Index, p-values, associated with the Mann-Whitney U test for testing the difference of the given parameters among referenced and impacted sites. P-value lower than 0.05 were considered significant (HVAS= habitat visual assessment score, DO= dissolved oxygen, T_{water}= temperature in river, EC= Electrical conductivity, TN= total Nitrogen, TP= Total phosphorous, NO₃⁻¹ = Nitrate, TP= Total Phosphorus, PO₄⁻³= phosphate.

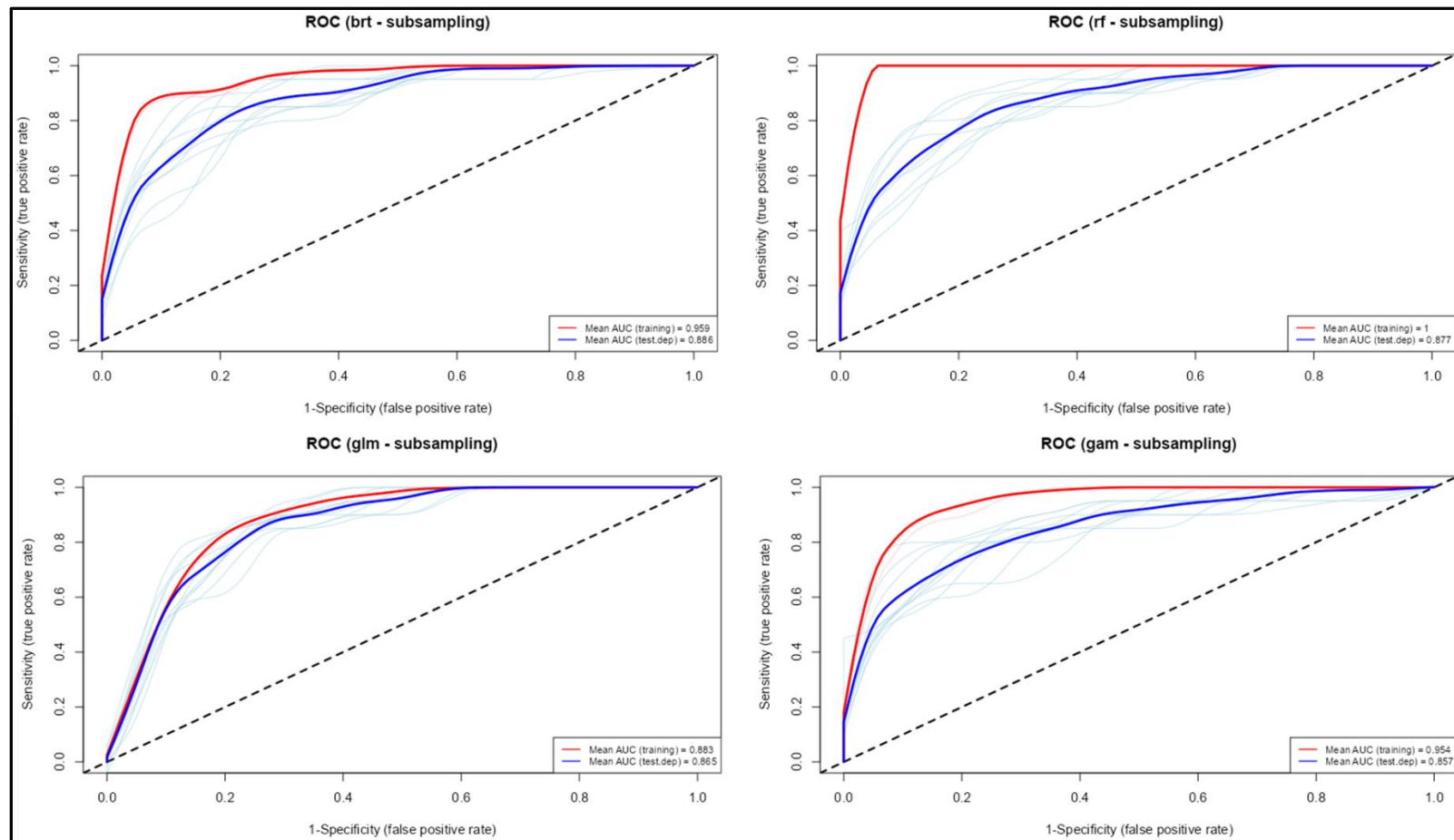
Water quality parameter	Referenced sample Mean±SD N=14	Impacted samples Mean±SD N=36	P-value
pH	7.71±0.18	7.91±0.29	0.005
HVAS	27.90±8.31	21.29±7.57	0.005
DO	18.91±20.68	8.74±1.68	0.020
T _{water}	15.87±1.20	19.69±3.53	0.001
Turbidity	14.50±7.60	38.60±34.81	0.002
EC	131±31.42	202.001±74.24	0.001
TN	5.64±3.27	3.96±5.59	0.200
NO ₃ ⁻¹	1.28±0.45	0.92±0.58	0.010
TP	0.24±0.23	0.22±0.12	0.700
PO ₄ ⁻³	0.08±0.07	0.07±0.04	0.500
Discharge	0.45±0.62	0.34±0.25	0.010

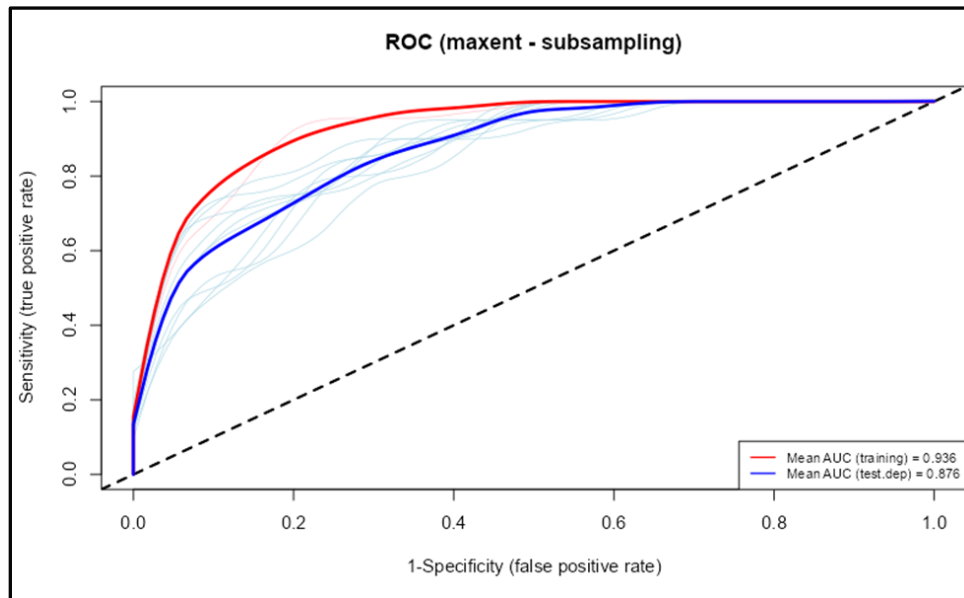
Annex VI. The spearman rank-order correlation coefficient(r_s) among the selected metrics to remove redundant metrics.

Metrics	%EPT	%EOT	%ET	%Ephem	%Odonata	%Trico	%Into/ taxa	%Mod. tax	%Scrap	Indi	Simp_1D	Menh	Marga	Fish alp	Chao1	FBI	ASPT	Trico	Pleco	Dip	Hem	Deca	Anel	Be/Ep.
%EPT	1																							

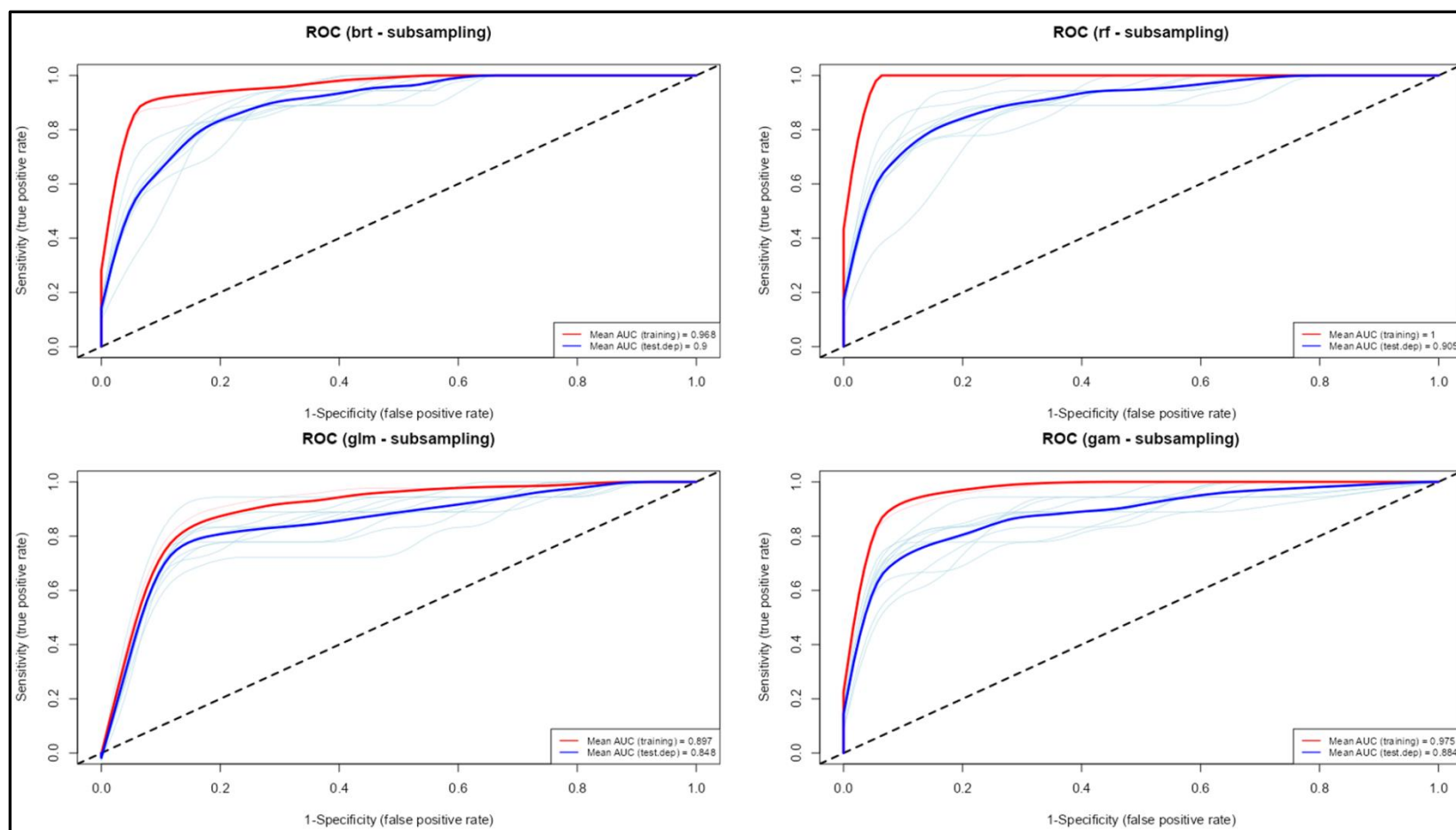
*Note: * Significant results of r_s at 0.05, ** significant results of r_s at 0.01 (2-tailed), n=50 samples, FBI= Family biotic index, ASPT= Average Score Per Taxon and the full names of the candidate metrics' abbreviations are provided in Table 33*

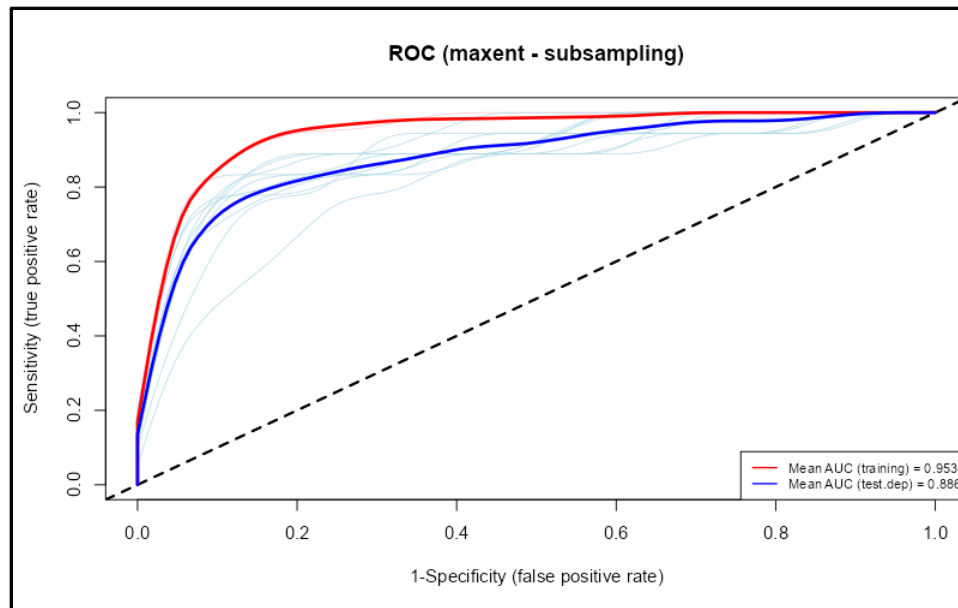
Annex VIII: ROC curves, generated using ten-fold bootstrap replication across five algorithms and statistical test models (MaxEnt, BRT, RF, GLM, GAM), were used to assess Perlidae and Philopotamidae distribution.



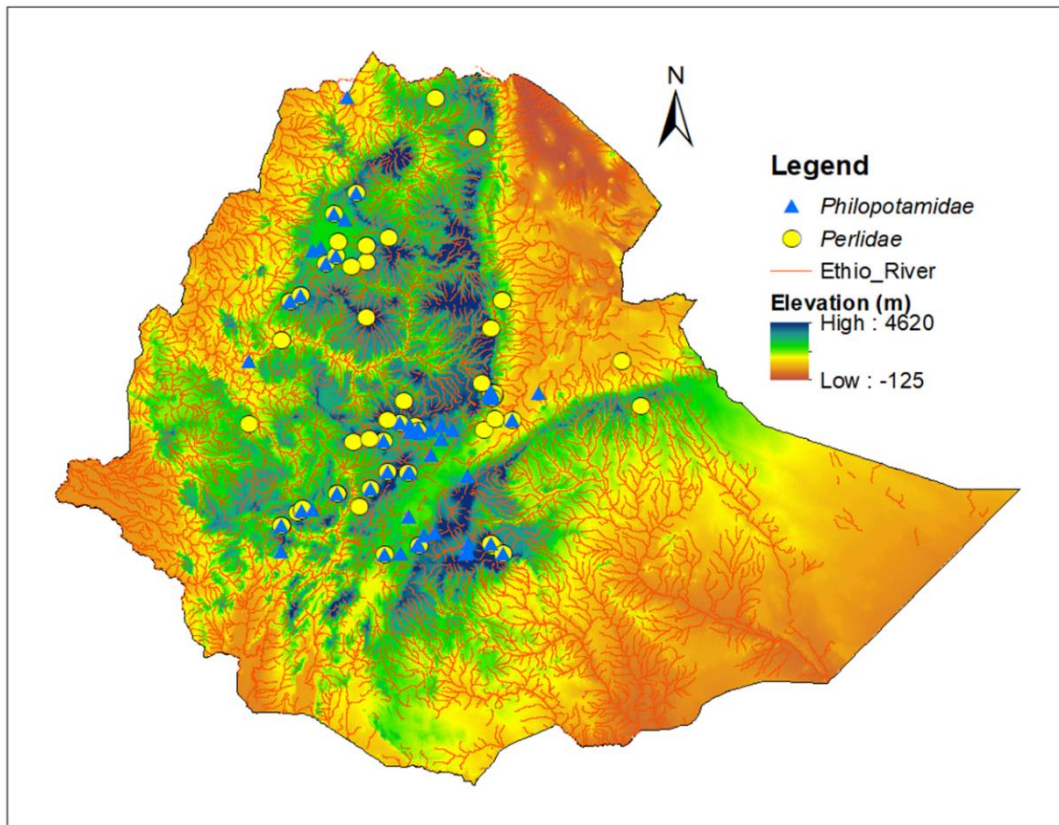


ROC curves, generated using ten-fold bootstrap replication across five algorithms and statistical test models (MaxEnt, BRT, RF, GLM, GAM), were used to assess *Perlidae* distribution. The y-axis shows sensitivity and the x-axis 1-specificity, reflecting classification accuracy. Smoothed red and blue curves represent mean AUC values for training and testing datasets, based on 70% training and 30% testing. Curves nearer the top-left corner indicate stronger model performance





Receiver Operating Characteristic (ROC) curves, generated using ten-fold bootstrap replication across five algorithms and statistical test models (MaxEnt, BRT, RF, GLM, GAM), were used to evaluate Philopotamidae distribution. The y-axis shows sensitivity (true positive rate) and the x-axis 1-specificity (false positive rate). Smoothed red and blue curves represent mean AUC values for training and testing datasets, based on 70% training and 30% testing. Curves closer to the top-left corner indicate higher model performance.



Annex IX. Map showing the spatial distribution of Perlidae (yellow circles) and Philopotamidae (pink stars) across elevation gradients in Ethiopia which is located in the Horn of Africa between 3°-15° N latitude and 33°- 48° E longitude.