ADDIS ABABA UNIVERSITY

SCHOOL OF GRADUATE STUDIES

DYNAMICS OF WATER QUALITY AND PUBLIC HEALTH RISKS IN THE CASE OF UPPER AWASH RIVER BASIN, ETHIOPIA

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A Thesis Submitted to the School of Graduate Studies of Addis Ababa University, Ethiopian Institute of Water Resources in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy in Water and Health (Water and Public Health)

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APPROVAL AND SIGNATURE SHEET

As PhD dissertation advisors, we hereby certify that we have read and evaluated this PhD thesis prepared under our guidance by Tesfa Aklilu Afework and ID number: GSR/1813/09, entitled "Dynamics of water quality and public health risks in the case of upper Awash River subbasin, Ethiopia". We recommend that it be submitted as fulfillment of the dissertation requirement.

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As members of the board of examiners of the final open research PhD thesis defense by " Tesfa Aklilu Afework and ID number: GSR/1813/09", have read and evaluated the PhD dissertation titled "Dynamics of water quality and public health risks in the case of upper Awash River subbasin, Ethiopia" and examined the candidate. Finally, I certify that the dissertation is accepted in partial fulfillment of the Degree of Doctor of Philosophy in Water and Public Health.

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DEDICATION

Dedicated to my late Grandfather, Ato Aklilu Afework, and Grandmother, W/ro Simegn Dessie, who instilled in me a passion for literacy, education, and patriotism for our country.

I am also dedicating this work to the visionary behind the national literacy campaign, which commenced with the first-round campaign on 8 July 1979. My educational journey began in 1983 as part of the short-range plan aimed at eliminating illiteracy and ensuring that all 7-year-old children had access to education by 1988. I started primary school at Mamamesk Primary School in September 1984, owing to these transformative efforts that not only impacted me but also enlightened millions of Ethiopians.

STATEMENT OF THE AUTHOR

By my signature below, I declare and affirm that this thesis is my own work. I have adhered to all ethical principles of scholarships in the preparation, data collection, data analysis, and completion of this dissertation. All scholarly material included in the dissertation has been appropriately cited and acknowledged. I confirm that I have referenced all the sources used in this document. Every effort has been made to avoid plagiarism in the preparation of this dissertation.

This dissertation is submitted in partial fulfillment of the requirements for a degree from the School of Graduate Studies at Addis Ababa University. The dissertation is deposited in the Addis Ababa University Library and is available to borrowers under the library's rules. I solely declare that this dissertation has not been submitted to any other institution anywhere for the award of any academic degree, diploma, or certificate.

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Date: 18/04/2025____

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ABBREVIATIONS

ANOVA: Analysis of variance

BMP: Best Management Practices

CCME-WQI: Canadian Council of Ministers of the Environment Water Quality Index

CHABs: Cyanobacterial Harmful Algal Bloom

COD: Chemical Oxygen Demand

DBPs: Disinfectant Byproducts

DO: Dissolved Oxygen

DOM: Dissolved Organic Matter

DTP: Dissolved Total Phosphorus

EDWS: Ethiopian Drinking Water Standard

EIA: The Environmental Impact Assessment

FAO: Food and Agriculture Organization of United Nation

GDP: Gross Domestic Products

GIS: Geographical Information System

GTP: Growth and Transformation Plan

HACCP: Hazard Analysis of Critical Control Point

EHDS: Ethiopian Health and demographic Survey

IWSM: Integrated Watershed Management

LMICs: Low- and Middle-Income Countries

MLR: Multiple Linear Regressions

MOWIE: Ministry of Water, Irrigation and Electricity

PCA: Principal Component Analysis,

SDG: United Nation’s Stainable Development Goal

TMDL: Total Maximum Daily load

TN: Total Nitrogen

USD: United State Dollar

WASH: Water, Sanitation and Hygiene

WHO: World Health Organization

WQI: Water Quality Index

WSP: Water Safety Plan

ABSTRACT

Introduction: Water quality issues are a major global concern, particularly in the upper Awash subbasin, where reports highlight both water quality problems and unmet water demands. As a critical socioeconomic and political center and a key water source for rural and urban residents, the subbasin is experiencing declining water quality due to rapid urbanization, industrialization, agriculture, and population growth. Efforts should focus on mitigating water pollution risks by addressing these factors. This study aims to address water quality issues and public health risks associated with drinking water consumption while narrowing existing gaps in understanding the cumulative effects of these factors on water quality and public health. Through the lens of watershed management, this study introduces new approaches to quantify public health risks, exposed populations, and vulnerable water supply schemes. It employs technologies such as GISs, statistical models, and risk characterization tailored to the local context, offering fresh insights to improve existing practices, water quality management, advocacy, and policy formulation.

Objective: To analyze the dynamics of water quality and public health risks in the Upper Awash Sub-River Basin, including mapping water pollution risks, characterizing temporal and spatial water quality distributions, identifying pollution sources, quantifying public health risks, and delineating protection zones to ensure the safety of water supply users, with the aim of informing effective management and mitigation strategies.

Methods: To achieve the objectives of this study, the DRASTIC model was employed along with the integration of the National WASH Inventory-2 (NWI-2) to identify vulnerable water schemes and conduct water source pollution risk (WSPR) mapping and water pollution indexing, including the estimation of exposed populations via the ArcGIS environment. Additionally, an artificial neural network (ANN) was utilized to predict the water quality index (WQI) from samples collected from 60 water supply schemes during dry and wet seasons, along with samples from 10 river water sampling stations across three seasons. Furthermore, Aquachem 2014.2, principal component analysis (PCA), and positive matrix factorization (PMF) models were applied to analyze 197 borehole samples, 70 surface water samples, and 60 water supply samples to identify water pollution sources. In accordance with the WHO guidelines, 120 water samples were collected from 60 drinking water supply schemes in both the dry and wet seasons, which are located in low and high water pollution risk (WPR) areas.

The concentrations of the target parameters were measured via instruments such as multiple meters, spectrophotometers, digital arsenators, and microbiological test kits. The assessment involved methods of hazard identification, exposure and dose–response analysis, and risk characterization, including hazard quotient (HQ), cancer risk (CR), hazard index (HI), and probability of infection.

Results: The findings reveal that 32.96% of the groundwater in the study area has low pollution risk, while 53.56% are at a moderate risk level, and 13.5% face high groundwater risk, with a model explanation of 67.8% (R^2 =0.678). In terms of surface water, 72.64% of the sites presented a low pollution risk, whereas 27.36% presented moderate to very high risks, including 4.82% at high and 3.7% at very high pollution levels, with water pollution index values exceeding 1 for all ten water quality monitoring sites during the dry season, indicating significant surface water pollution. The study estimates that 5.64%, 3.88%, and 2.30% of the population are exposed to high groundwater pollution risk (GWPR), surface water pollution risk (SWPR), and water source pollution risk (WSPR), respectively. Additionally, among the 2,864 water supply schemes analyzed, only 14.4% had a water safety plan, while 20.7% practiced water safety, and 6% reported the occurrence of waterborne diseases. Over 39.23% of the schemes were located in high vulnerability areas, with 12.32% in very high vulnerability areas and only 8% in low vulnerability areas, as validated by a model accuracy of 61.7%. Animal grazing (66.7%), agriculture (61.7%), and other human activities (40%) were identified as potential sources of water pollution in water supply systems. Na-HCO3 (65%) and Ca-HCO3 (32.5%) geogenic sources contributed to 64% of the drinking water pollutants, with 29% and 7% attributed to agricultural and anthropogenic sources, respectively. Significant variations in drinking water quality were observed between districts. The surface water parameters, such as total hardness, TDS, pH, F, Mg, chloride, and HCO3, varied significantly between the dry and wet seasons. The ANN model accurately predicted drinking WQI via five parameters (85% prediction accuracy and 94% overall accuracy) and surface water quality (95.1% accuracy) via four parameters. The Health Quotient (HQ) for nitrate exceeded unity (HQ>1) in the dry season for all groups, whereas a chromium HQ>1 was observed for women (1.1E+00) and children (1.4E+00) in the wet season in high Water Pollution Risk (WPR) areas. The risk of arsenic-related cancer exceeded 1 in 10,000 children in the dry season across all groups and for women and children in the wet season in high WPR areas. The cancer risk associated with chromium

exceeded 1 in 1000 people. Moreover, the Hazard Index (HI) was consistently above unity (HI>1) for most cases, and all daily and annual risks of *E. coli* infection were deemed unacceptable.

Conclusion and recommendations: WSPR modeling plays a crucial role in identifying vulnerabilities and pollution risks in new and existing water supply systems. Integrating various approaches and models, along with predicting populations exposed to health risks associated with water quality, emphasizes the importance of considering public health through a comprehensive approach. The demonstration of the integration of NWI-2 with vulnerability assessments along with the quantification of public health risks and identification of water pollution sources, contributes to solve water quality issues. This highlights the importance of implementing water source protection measures by all relevant authorities for the integration of WASH inventory in monitoring and evaluation systems, utilizing GIS technology, and adopting integrated watershed management practices. Specifically, recommendation for actions are

1. Comprehensive water source protection measures, including vulnerability assessments, water source pollution risk mapping, watershed management, and the application of water treatment technologies and sanitation measures at the source and point-of-use levels, should be implemented.
2. Waste disposal management should be enhanced, groundwater quality should be monitored, fertilizer use should be controlled, and the conservation of water sources via integrated watershed management should be promoted.
3. The enabling environment should be strengthened through policy formulation, regulatory frameworks, and community awareness initiatives to address pollution sources, integrate public health into water management, protect water resources, and institutionalize Water Safety Plans (WSPs). Furthermore, to fill evidence gaps, research on pollutant travel, assimilation, and land use priorities for accurate delineation should be undertaken.
4. Further research is needed on pollutant travel time, assimilation capacity, and land-use priorities to effectively delineate protection zones, along with policy analysis for identified risks and pollution sources.

Keywords: Cancer and noncancer risks, groundwater vulnerability index, delineation of protection zone, exposed population, water quality index, source contribution

CHAPTER 1: GENERAL INTRODUCTION

1.1. BACKGROUND AND JUSTIFICATION

The integrated watershed management (IWSM) approach addresses water issues for ecological, social, and economic development, as well as the interests of users. From a social perspective, IWSM reduces public health problems and improves overall health[1,2]. It relies on the management of watershed characteristics such as biophysical and socioeconomic features[3]. Consequently, most water quality parameters are influenced by watershed characteristics, including climate, spatial and seasonal changes, vegetation, geology, topography, and socioeconomic factors, which are major attributes affecting both water quality and quantity in watershed management [4,5]. IWSM aims to create and implement plans, programs, and projects that sustain and enhance watershed functions, benefiting the communities within the watershed boundary. The watershed boundary is the geographical limit of water drainage for a specific area, whereas the basin system represents the interconnected network of water bodies and channels that collect and convey water within that watershed.

In the basin system, hydrological events such as flooding and droughts, which are attributed to low water flow, affect the biological, physical, and chemical components of water quality. Changes in land use and land cover, such as soil erosion, deforestation, conversion of croplands and pastures, urban development, improper irrigation management, and reservoir seepage, contribute to water pollution and impact the water quality of the system [6–10]. Furthermore, anthropogenic activities, including rapid population growth, urbanization, increasing construction rates, discharge from industrial zones, and mining activities, are responsible for the deterioration of surface and groundwater quality [11–15].

On the other hand, watershed characteristics such as topography, hydrogeology, soil types, and the impervious surface area of the watershed are determinant factors in the protective capacity of the natural defense system for water quality [16,17]. Topographical features and aquifer media explain significant variations in water quality and facilitate the transportation of contaminants within the groundwater basin[5]. Hydrochemical variations in water quality are also controlled by geological, geochemical, and geomorphological factors. Generally, the qualities of surface water and groundwater are influenced by geological, physical-chemical, biological, and anthropogenic factors[18]. In this study, well-known factors are considered when mapping water supply pollution risks for risk reduction approaches.

In the study area, the upper Awash subbasin presents characteristics that are identified as contributing factors to the deterioration of water quality parameters. The subbasin is prone to water pollution due to these factors, and it is evident that the Awash River Basin, in general, is the most important but also the most polluted river basin in Ethiopia. Pollution is particularly severe in impacted areas[19–21]. The subbasin is home to millions of people, with numerous industrial corridors, varied settlement patterns, emerging towns, high population growth, rapid urbanization, extensive flower farms, loss of vegetation, soil erosion, and other significant factors [19,20,22,23]. In addition to these aggravating factors, major problems persist in the Awash Subriver Basin, including a lack of coordination, insufficient evidence, inadequate attention to source protection and monitoring, failure to incorporate water quality issues into water resource management, the absence of enforcement measures, and a disjointed institutional setup at the grassroots level[21,24–26].

In fact, to address deteriorating water quality, water resource protection is more effective than focusing solely on point-of-use interventions. Protecting water sources is more effective than treating contaminated water [27]. The World Health Organization's Water Safety Plan (WSP) approach is a source protection strategy that involves system assessment to characterize water quality and quantify associated risks[28]. This approach provides evidence-based risk management within integrated watershed management (IWSM) to address both point and nonpoint sources of water pollution.

Groundwater pollution risk is assessed by overlaying the DRASTIC vulnerability map with land use [29]. The DRASTIC model incorporates parameters such as depth to water, recharge, aquifer media, soil media, topography, impact of the vadose zone, and conductivity (hydraulic) of the aquifer[30]. On the other hand, surface water pollution risks are evaluated through analyses of topography, soil type, land use and land cover, and watercourse zones, which are used to establish surface water pollution risk maps[31]. Furthermore, water source pollution risk levels are determined by combining both surface and groundwater pollution risk maps, allowing estimation of the proportion of the population exposed to each risk class.

Consequently, this study aims to contribute evidence for risk reduction and source protection by mapping surface and groundwater pollution risks, predicting the proportion of the exposed population through pollution risk mapping, quantifying public health risks, identifying water pollution sources, and characterizing water quality in terms of temporal and spatial characteristics. This evidence can contribute to site-specific environmental impact assessments for new developments, risk management, the prioritization of pollution control measures on the basis of risk levels, the establishment of legal regulations, the incorporation of public health issues into integrated watershed management, appropriate resource allocation, and the delineation of protection zones. The Upper Awash River Basin plays a critical role in supporting various socioeconomic activities and ecosystems. The dynamic interactions between water quality and public health within this basin are of principal importance, considering the increasing pressures from urbanization, industrialization, and agricultural activities. Water quality in the Upper Awash River Basin is influenced by multiple factors, including point-source and nonpoint-source pollution, seasonal variations, and land-use changes. These factors can significantly impact the health and well-being of communities that rely on water resources from the basin for drinking, irrigation, and other purposes.

1.2. STATEMENT OF THE PROBLEM

Water quality degradation in the upper Awash subbasin poses significant public health and environmental risks. This study addresses critical gaps, including the lack of comprehensive pollution risk maps, ineffective protection zone delineation, poor characterization of pollution sources, and a limited understanding of water quality temporal–spatial dynamics and associated health risks, necessitating targeted interventions and advanced modeling techniques. The following are the research problems corresponding to each specific objective:

1. **Research Problem 1**: A comprehensive map that indicates pollution risks for both surface and groundwater sources across the Upper Awash subbasin is unavailable, hindering the ability to prioritize areas for intervention and protection.
2. **Research Problem 2**: Protection zones within the upper Awash River subbasin have not been delineated via vulnerability assessments and pollution risk factors, limiting effective water source protection strategies and interventions such as the Water Safety Plan and National WASH inventory.

3. **Research Problem 3**: The temporal and spatial distributions of water quality in the upper Awash subbasin have not been parameterized via advanced modeling techniques, leading to a lack of insight into seasonal and spatial variations in water quality parameters.
4. **Research Problem 4**: The pollution sources affecting water quality in the upper Awash River subbasin have not been fully identified or characterized, preventing mitigation efforts and comprehensive pollution management.
5. **Research Problem 5**: The public health risks associated with the consumption of drinking water in the upper Awash River subbasin are not well quantified, particularly in relation to specific water quality parameters, limiting the understanding of health implications for local populations for advocacy, regulatory frameworks and policy formulation.

The water supply plays a crucial role in promoting human health, sustaining ecosystems, and accelerating socioeconomic development worldwide. Despite its importance, the deterioration of water quality has emerged as a critical global concern [32]. The lack of a safe water supply and sanitation contributes to approximately 842,000 deaths annually in low- and middle-income countries [33]. The substantial costs associated with treating waterborne diseases highlight the urgent need for effective implementation of WASH (Water, Sanitation, and Hygiene) services, with potential annual savings exceeding 7.34 billion USD [34]. To address these problems, water resource protection is more effective than point-of-use interventions, which can avert 13,000 USD/DALY (Disability-Adjusted Life Year), whereas point-of-use water treatment may avert 20 USD/DALY[35]. However, water resource protection has received less investment, public attention, political commitments, and scientific support globally, especially in sub-Saharan countries[22,33].

In Ethiopia, water quality is boldly incorporated into water sector policies and strategies; however, water quality management is still not practiced effectively as needed. Approximately 86% of the population consumes drinking water that poses a risk of *E. coli* contamination, and 89% have access to water sources with high turbidity[36]. Evidence shows that the expansion of modern agricultural practices and the growth of livestock have serious implications for water quality[37]. Urbanization contributes to a high discharge of wastewater, with more than 92% being disposed of directly into the ecosystem, causing water pollution[38].

These factors, along with high population growth, industrialization, flower farms, loss of vegetation, soil erosion, and other significant factors, are assumed to be more prevalent in the study area [19,20,22,23]. The study area represents one of the most important but highly polluted river basins, exacerbated by the presence of Addis Ababa city and emerging cities with many industrial corridors (24). Additionally, issues such as lack of coordination, insufficient evidence, minimal attention to source protection and monitoring, failure to incorporate water quality issues into water resource management, absence of enforcement, and disjointed institutional setups at the grassroots level remain major challenges in the Awash Sub-River Basin [21,24–26].

All of these factors have negative impacts on public health and the ecosystem at large. However, there is a notable lack of significant evidence to address public health-related issues effectively within basin management through risk management and the development of applicable policies. Gaps in understanding the cumulative effects of these factors on water quality and public health over time remain under researched. Furthermore, comprehensive investigations of the interactions among watershed characteristics, water quality, and public health are lacking, particularly in this subbasin, which is not only the most important but also the most polluted and serves as the sociopolitical center of the country. This study introduces new approaches, such as integrating National WASH inventory results with groundwater vulnerability assessments to quantify public health risks and populations exposed to different water source risk levels, offering new insights to improve existing practices and technologies. Additionally, data on the effectiveness of current water protection measures and enforcement mechanisms are limited. To address this, this study proposes the use of GIS technology for delineating protection zones, incorporating the National WASH inventory results, to strengthen water quality management and protection.

1.3. RESEARCH QUESTIONS

1. Which areas within the upper Awash River subbasin have the highest potential for surface and groundwater contamination, and how can this contamination be effectively mapped?
2. Are there apparent spatial patterns or trends in the distribution of potential pollution risks across the upper Awash River subbasin?
3. How do key water quality parameters vary across the upper Awash River subbasin over time, particularly in relation to seasonal variations?

4. What are the primary factors influencing the temporal and spatial variations in water quality within the upper Awash River subbasin?
5. What are the primary sources of pollution impacting the water quality of the upper Awash River subbasin?
6. How can pollution within the upper Awash River subbasin be effectively traced back to its sources?
7. What is the potential health risk associated with consuming water from different areas within the upper Awash River subbasin?
8. Are certain populations within the Upper Awash River Sub-Basin more vulnerable to health risks due to water quality issues?
9. How does the consumption of water from different parts of the upper Awash River subbasin impact the health of local communities?

1.4. OBJECTIVES OF THE STUDY

1.4.1. GENERAL OBJECTIVE

- To determine the temporal and spatial patterns of water pollution and associated public health risks in the upper Awash sub-River Basin, innovative assessment tools and management strategies should be developed to address identified gaps and improve water quality and public health outcomes.

1.4.2. SPECIFIC OBJECTIVES

The specific objectives of this study are to:

- Develop a comprehensive map of surface and groundwater sources indicating pollution risks across the subbasin.
- Delineate protection zones within the upper Awash River subbasin on the basis of vulnerability assessments and pollution risk factors, providing a framework for water source protection and interventions.
- Parametrize water quality of the subbasin in terms of its temporal and spatial distributions via advanced modeling techniques.

- Identify and characterize the pollution sources affecting water quality within the upper Awash River subbasin.
- Quantify the public health risks associated with the consumption of drinking water in the upper Awash River subbasin and to link the water quality parameters.

1.5. SIGNIFICANCE OF THE STUDY

The Upper Awash subriver basin is home to millions of people and encompasses various industrial areas, diverse settlement patterns, rapid population growth, and rapid urbanization. It also hosts numerous economic activities that contribute to both point and nonpoint sources of water pollution. The subbasin includes the city government of Addis Ababa, the Oromia region, and small portions of the Amhara and South Nation Nationalities Regions. Approximately 65% of industries in the country are located in this subbasin. Maintaining good water quality and ensuring an adequate quantity of water are essential for this subbasin to support public health and achieve Sustainable Development Goal Six (SDG 6). However, achieving this goal requires a preventive approach rather than relying solely on water treatment and selective water testing for specific hazards. Water testing is time-consuming, and the volume of water tested is rarely statistically representative. Furthermore, water testing may not detect all changes and may not be available at all localities or at all times for all water quality parameters.

Therefore, this study identified areas vulnerable to water pollution risk; assessed exposure status to different hazards; quantified water pollution risk; and analyzed public health risk and exposure over time, locations, and types of water quality parameters at the subbasin level. This information is critical for monitoring water quality, predicting health risks, and implementing cost-effective risk management strategies. Additionally, the study aims to generate evidence that facilitates linking the water sector with the health sector through the application of integrated watershed management approaches.

In general, public health can be considered through the lens of Integrated Watershed Management as it enhances health and social-ecological resilience by examining watershed characteristics linked with water quality and public health. This study presents an innovative approach that goes beyond simple identification of vulnerable areas, provides real-time information to identify whether existing water supply schemes are located in vulnerable areas, and proposes the establishment of practical protection zones.

This research contributes by providing inputs for climate-resilient water safety planning, public health risk management, and environmental impact assessment while enhancing ecosystem protection services. It supports safeguarding surface water sources and groundwater aquifers and aligns with local and national integrated sustainable development efforts. The findings can be integrated into national WASH inventory systems, and the approach contributes to the WHO-UNICEF Joint Monitoring Program at an international level. Additionally, the study informs the amendment of regulations and helps define roles and responsibilities across relevant sectors for improved water resource management.

Understanding the dynamics of water quality problems and their associated public health risks is crucial for formulating policy options, strategies, and procedures. This research also emphasizes advocating for active stakeholder participation, resource allocation, and promoting healthy investments. This study provides scientific evidence and new insights for the scientific community in the emerging field of integrated watershed management, with a focus on public health. This includes methods for predicting exposed populations, integrating the national WASH inventory with vulnerable water supply schemes, and conducting subbasin-level public health risk assessments. This research explores the relationships between watershed characteristics and public health and identifies hazards leading to health effects via various analytical methods.

Overall, this research addresses critical scientific gaps and contributes to the understanding of the interactions among watershed characteristics, water quality, and public health in the Upper Awash Sub-River Basin, a region with high pollution and sociopolitical significance. By applying innovative approaches, such as GIS technology for mapping pollution risks, estimating exposed populations, and quantifying public health risks, this study aims to enhance watershed management practices and technologies. It also addresses the lack of comprehensive data on cumulative effects by integrating vulnerability assessments and protection zone delineation with the National WASH inventory and Water Safety Plan. Furthermore, applying artificial neural networks (ANNs) to predict the water quality index and using positive matrix factorization (PMF) for pollution source profiling will advance the understanding of water quality dynamics, improve monitoring, and support proactive source protection measures, ultimately benefiting public health and water source protection in the country's most polluted subbasin.

1.6. SCOPE OF THE STUDY

The scope of the study, "Dynamics of Water Quality and Public Health Risks in the Upper Awash River Basin, Ethiopia", referred to the boundaries and extent of the research in terms of its objectives, geographical coverage, and focus areas. The following are considerations for the scope of this study:

1. **Geographical Coverage:** This study specifically focused on the upper Awash River subbasin in Ethiopia, including key tributaries and surrounding areas within the subbasin.
2. **Water quality parameters**: This study assessed a range of water quality parameters, such as physical, chemical, and microbiological water quality parameters, on the basis of available data from different sources and sampling data.
3. **Public health risks:** The scope included examining public health risks associated with water quality parameters such as microbial infections, cancer, and noncancer risks.
4. **Temporal Considerations:** This study covered two seasons of sampling and more seasonal variations in the secondary data to consider the seasonal variations in water quality dynamics and public health risks within the subbasin.
5. **Methodology and Approach:** This study employed a mix of quantitative and qualitative methods, including a literature review, field surveys, water sampling, laboratory analysis, epidemiological studies, spatial analysis via geographic information systems (GIS), statistical analysis, and other methods, including positive matrix factorization (PMF).
6. **Engagement of sectoral authorities and stakeholders:** This study engaged diverse stakeholders, including local communities, government agencies, NGOs, and other relevant actors, to gain insights into water quality and public health. On the basis of these insights, the study recommends strategies for sustainable water management, capacity building, and future research directions. This study further explores the implications for water resource management and policy development to mitigate water quality issues and improve public health outcomes. Outputs from the study include research reports, academic publications, and presentations aimed at disseminating the findings and engaging stakeholders.

1.7. STRUCTURE OF THE DISSERTATION

This dissertation presents a comprehensive study on water quality and public health risks in the upper Awash River subbasin, Ethiopia. The research is organized into five chapters, each of which addresses specific aspects of water quality, public health risks and presentation strategies. The structure follows a logical sequence, building from establishing the research context, methods, results and conclusions:

CHAPTER 1 - INTRODUCTION: The introduction presents the research topic focused on water quality and public health risks in the upper Awash River subbasin, Ethiopia. This chapter outlines the problem statement of the study, highlights the research objectives to assess water pollution risks and associated public health risks, and emphasizes the importance of addressing these issues. The scope and limitations of the study are discussed.

CHAPTER 2 - LITERATURE REVIEW: The literature review chapter critically examines existing research and scholarly works related to water quality, public health risks, and pollution management in similar contexts. It synthesizes theoretical frameworks, models, and methodologies used in water quality assessment, water pollution risk assessment, and public health studies. By summarizing previous findings and identifying gaps in the literature, this chapter provides a comprehensive foundation for the current study's research approach and contributes to advancing knowledge in the field.

CHAPTER 3 - METHODS AND MATERIALS: Chapter 3 outlines the materials and methods used in this research. It begins with a description of the study area by detailing its geographic and hydrological characteristics. The data sources and model parameters are then discussed, followed by comprehensive procedures for spatial analysis. These include mapping groundwater and surface water pollution risks via geospatial tools and risk modeling techniques. Groundwater pollution is assessed on the basis of various factors, whereas surface water pollution risk is mapped via analysis of catchment area characteristics and other factors. Water quality analysis is conducted via methods such as the water quality index (WQI), artificial neural network (ANN), PMF model and principal component analysis (PCA). The risk assessment covers chemical and microbial risks, utilizing approaches such as hazard quotient, hazard index, and Monte Carlo simulation, while qualitative data are also collected and analyzed to ensure the achievement of the predefined objectives of this study.

CHAPTER 4 - RESULTS AND DISCUSSIONS: Chapter 4 presents the research results and discussion, focusing on water pollution risks and public health implications. It begins by validating the DRASTIC model and developing a water pollution index to assess groundwater and surface water pollution risks, followed by estimating the population exposed to these risks. The chapter also covers delineating water source protection zones, supported by linear regression analysis and the National Water, Sanitation, and Hygiene Inventory (NWI-2). Water quality dynamics are explored through microbial analysis, temporal and spatial variations, and predictions of water quality parameters. Pollution sources are identified via principal component analysis (PCA) and positive matrix factorization (PMF), and their contributions to water degradation are quantified. Public health risks are assessed, with a focus on noncancer, cancer, and microbial risks, which offers insights into the health impacts of water pollution in the study area.

CHAPTER 5 – GENERAL DISCUSSION, CONCLUSION, RECOMMENDATION, AND FUTURE WORKS: Chapter 5 provides the general discussion, conclusion, recommendations, and suggestions for future work. It summarizes the key findings of all the objectives of the study, highlighting the assessment of water pollution risks and public health implications while evaluating the effectiveness of models such as DRASTIC and PMF. Recommendations focus on improving water resource management, implementing pollution mitigation strategies, and developing stronger policy interventions to safeguard water quality. The chapter also outlines potential future research areas, such as refining water pollution risk models, advancing pollution source apportionment techniques, and further exploring the health impacts of water contamination.

CHAPTER 6: ANNEXES: Chapter 6 is structured its annexes, is designed to provide a comprehensive additional information on the study results. It includes a detailed examination of water quality parameters against established limits for both groundwater and surface water. Furthermore, the structure incorporates weighting and prioritizing relevant factors for water quality index analysis. The annex also presents statistical data on drinking water and surface water quality, supplemented by materials supporting the vulnerability analysis and the unstructured questionnaires used for qualitative data collection. This structure ensures this report provide detailed supplementary information, enhancing transparency and supporting the main findings.

CHAPTER 2: LITERATURE REVIEW

This chapter provides a comprehensive review of key studies, approaches, and knowledge gaps relevant to watershed characteristics and water quality parameters, with a particular focus on the upper Awash subbasin under study. Despite its sociopolitical significance, research on the combined impact of surface and groundwater sources in subbasins remains limited. This review explores new methodologies for assessing groundwater and surface water vulnerabilities, pollution risk modeling, and source protection zone delineation, highlighting innovative techniques for estimating the population exposed to contamination risks and vulnerable drinking water supply schemes. Additionally, it examines statistical models for water quality and risk analysis, narrowing knowledge gaps related to spatial, seasonal, and parameter-specific variations. Finally, this chapter explores the public health impacts of water quality, emphasizing the need for protection strategies and risk assessments to inform policy and advocacy efforts in mitigating public health risks associated with water pollution. Furthermore, the conceptual framework is summarized as follows to provide a structured approach to understanding the key concepts, relationships, and variables within this study. The detailed explanations of the literature review are depicted below.

2.1. CONCEPTUAL FRAMEWORK OF THE STUDY

The conceptual framework for this literature review is centered around the interconnectedness of watershed characteristics, water source vulnerability, and their impact on public health. The first focus is on watershed characteristics and water quality parameters, where peer-reviewed articles have comprehensively analyzed groundwater and surface water sources and their management. As a result, gaps are identified, which are particularly significant in the study of subbasins that are the most socio-politically important but highly polluted among basins in the country. By integrating water source vulnerability and pollution risk modeling**,** the framework explores methods such as groundwater vulnerability assessment, surface water vulnerability assessment, and the water quality index (WQI) to understand the status of water sources in the basin. Additionally, the delineation of source protection zones, particularly drinking water supply schemes based on national WASH inventory results, serves as a key method to estimate the population exposed to contamination risks, addressing the need for improved water source management and prevention of waterborne diseases.

The second part of the framework incorporates statistical modeling for water quality and risk analysis**,** which provides a deeper understanding of the variations in water quality on the basis of location, season, and types of contaminants. This knowledge is critical for linking water quality with public health outcomes. With respect to information on water source vulnerability and pollution risk, the impact of water quality on public health connects the literature with the study's findings, emphasizing the importance of water source protection to mitigate health risk. Finally, the public health risk assessment component quantifies health risks by predicting cancer and noncancer risks, as well as infection probabilities, on the basis of water source vulnerability and pollution risk modeling results**.** This comprehensive approach informs advocacy and policy-making efforts to address water quality challenges and improve public health through the lens of integrated watershed management (See the diagram of conceptual framework in **Figure 1**)

2.2. WATERSHED CHARACTERISTICS AND WATER QUALITY PARAMETERS

A safe and adequate water supply is essential for health and development. The primary focus area of this study is dynamic water quality and public health risks. Water quality management involves a combination of methods, including protecting water sources from nonpoint and point source pollutants originating from the watershed at which water is harvested, managing water sources, monitoring treatment processes, and ensuring safe handling and storage at the household level.

Water quality refers to the chemical, physical, and biological characteristics of water. These characteristics are often referred to as water quality parameters or quality indicators of natural water bodies, drinking water, and discharged water[39]. Research findings support the variability of water quality parameters due to spatial and temporal situations as well as watershed characteristics. These characteristics significantly influence hydrological responses, the well-being of humans, and the ecosystem at large. These watershed characteristics include various biophysical and socioeconomic features, including climate, geology, physiography, soils, land use and land cover type, hydrology, and socioeconomic activities. For example, land use, land cover, and impervious surfaces are negatively correlated with water quality [3]. The dynamics of the Biliuhe Water Reservoir indicate that water quality deteriorates in summer and improves in winter, whereas water quality is better upstream than downstream[40].

It was confirmed that spatial and seasonal changes influence surface water quality in the Burio River in Costa Rica[4]. On the other hand, water quality parameters are highly dynamic during flooding, which is a significant hydrological event and is influenced by watershed characteristics. Particularly at the onset of flooding, pathogens and contaminants in floodwaters are nearly as concentrated as they are in sewers[41]. In the Songhua River Basin, human activities greatly influence water quality parameters because industries are located upstream, and these activities have been identified as major sources of pollution[12]. Collectively, water quality is affected by complex factors attributed to watershed characteristics such as climate, land use and cover, geology, topography, and socioeconomic conditions. For a detailed review, the following explanations highlight major factors with a high impact on water quality and public health. Understanding these factors will contribute to the prevention and control of water supply pollution.

Emissions of greenhouse gases can induce climate change. In the Northern Hemisphere, the period from 1983--2012 was the warmest in the last 1400 years. Projected surface temperatures over the 21st century indicate that extreme precipitation will become more intense, which has potential impacts on global water quality and public health[42]. In Ethiopia, climate change affects spring and summer rains. There has been an approximately 17.5% reduction in rainfall since the mid-1970s[43]. At the watershed scale, there has been a significant decline in rainfall from June to September in watersheds such as Baro-Akobo, Omo-Ghibe, Rift Valley, and the southern Blue Nile[44]. Floods and droughts are primary outcomes of climate change, impacting the biological, physical, and chemical parameters of water quality and potential risks to public health[45]. The evidence indicates that microbial risks are associated with weekly temperatures. Erratic, irregular, and severe rainfall events are also linked to the occurrence of microbial species[46]. Additionally, extreme temperatures and rainfall can increase the concentrations of dissolved organic matter, nutrients, pathogens, and toxins in water bodies. This can lead to the creation of disinfection byproducts in drinking water, accelerate the growth of pathogenic organisms, increase the probability of pathogen survival, and facilitate the transportation of coliform organisms through watershed storm events. For example, increased temperatures threaten waterborne diseases, particularly cholera, in Asia and South America[47]. This has led to an anticipated increase in the incidence of diarrheal disease worldwide[48]. Furthermore, higher water temperatures affect chemical reaction kinetics, resulting in water quality deterioration. Longer water residence times in rivers and lakes can lead to toxic algal blooms and reduced dissolved oxygen levels[49]. In general, during the rainy season, dead vegetation can cause changes in water color and taste and increase the presence of organic matter and bacteria in water bodies. In contrast, the dry season often results in higher dissolved salt and mineral concentrations. Seasonal effects such as floods and low flows negatively impact water quality. Dissolved oxygen levels in water can fluctuate within a day due to flow variability [50]. As a result, climate change, as part of a temporal assessment, was considered in this study by using different approaches.

The increased demand for agricultural land and subsequent forest loss resulted in the loss of 7 million hectares of forest per year from 2000--2010[51] in tropical countries. These losses affect water quality through soil erosion and sediment deposition in various water bodies, such as wetlands, ponds, lakes, streams, and rivers[6]. In 2009, approximately 11% of the world's land surface was used for crop production, accounting for 70% of all water withdrawn from aquifers, streams, and lakes. Additionally, 40% of irrigated areas now rely on groundwater [52]. These reports highlight how land use and cover changes impact freshwater quality and influence the prevention of infectious diseases. In Ethiopia, land use and land cover are significantly affected by land degradation, primarily due to rapid population growth, soil erosion, deforestation, and imbalanced crop and livestock production [8]. For example, agricultural lands and settlement areas increased from 57% to 75% by 2014, whereas woodlands decreased from 26.16% to 6.63% over 41 years. Additionally, two large-scale irrigation schemes located in the upper Awash River subbasin and the Blue Nile Basin have had different impacts on water quality [7]. The relationship between land use and river water quality has been analyzed in the Little Miami River watershed in the USA. Poor water quality was observed downstream, particularly in areas dominated by urban land use[10]. Water quality issues associated with pathogens have been linked to grazing animals, whereas animal production is associated with nitrogen and phosphorus pollution[53]. The impact of land use on water quality is also documented because of settlement areas and arable land in the upper Nisa catchment in the Czech Republic. The impacts of land use are significantly associated with water quality in river systems at different scales [54,55]. It is well known that deforestation and changes in cropland and pasture land result in the deterioration of water quality. On the other hand, forests provide improved water quality conditions; for example, in North America, forested watersheds are an important source of adequate quantities of high-quality water. Higher total nitrogen concentrations and electrical conductivity in streams are related to land use, which is dominated by pasture and narrower riparian forests [56,57]. All these reviewed documents provide strong evidence of land use–land cover, which is an influential factor for water quality improvement at the watershed level, particularly in the river basin in general.

Population growth, urbanization, industrialization, and mining significantly affect water quality. In Sri Lanka's Kelani River, a population density below 2375 people/km^2 satisfies the water quality standards at the watershed scale [11]. In 2015, Korea reported that moderately urbanized areas affect water quality, and when urban land exceeds 31.5% of watershed areas, broad management practices are needed to improve stream water quality [58]. Additionally, in 2017, increased rates of construction and industrialization influenced water quality in rural areas of Beijing[13]. Similarly, urbanization levels determine the spatial pattern of surface water quality in Shanghai [14]. Industrial wastewater effluents have led to pH fluctuations, microbial growth, and natural water purification in stream water, which are associated with industrial pollution[59]. In the Ona River and the Alaro River in Nigeria, higher levels of nitrate, chloride, total phosphorus, total solids, and oil and grease are present in industrial zones because of industrial discharges[60]. A study in Accra, Addis Ababa, and Hyderabad revealed that urban growth, wastewater production, and urban irrigation caused water pollution in downstream areas with public health risks[61]. In the southwestern Awetu-Kito River in Jimma town, Ethiopia, and in the Awetu-Kito River in Jimma town, the water quality of the river deteriorated due to industrial and population activities[62]. In Ethiopia, the textile and food industries are the primary pollutants, while agriculture, agricultural value added, and foreign direct investment help reduce pollution levels [63]. Overall, evidence suggests that population growth, urbanization, and industrialization impact surface and groundwater quality. In addition to the generation of evidence through research, sustainable water management, improved wastewater treatment, and pollution control measures are vital to mitigate these challenges and protect water quality for ecosystems and socioeconomic development.

The proportion of impervious surface area (PISA) should be considered during watershed planning to address water quality issues effectively, as it contributes significantly to degradation. A reduction in PISA by 10% is a crucial strategy for improving water quality[17]. This evidence suggests that slope influences downstream water quality by accelerating runoff. In Ile-Ife, Nigeria, the local topography was linked with waterborne diseases[64]. However, catchments with slopes steeper than 15 degrees are negatively correlated with major water ions due to multicollinearity in watershed characteristics [65]. On the other hand, fractured rock facilitates the transport of bacteria, silt, and various chemicals within groundwater basins. In southern Ontario, natural landscape features (such as slope) and silt–clay geology deposits have notable effects on water quality [66]. Arsenic occurrence in groundwater can be attributed to alluvial lacustrine deposits, volcanic activity, geothermal systems, and uranium and gold mining [67]. Water–rock interactions under specific temperatures, pressures, and chemical conditions influence parameters such as conductivity, pH, calcium, and bicarbonate, affecting fluoride dissolution from fluoride-rich minerals. An alkaline medium, high HCO_3 concentration, and moderate conductivity favor fluoride dissolution[68]. In Ethiopia, hydrochemical variations in water quality are determined by geological, geochemical, geomorphological, and climatological factors. Rift valley waters present high total dissolved solids with elevated levels of Na and HCO_3, whereas highland waters are fresh with lower ionic concentrations dominated by Ca, Mg, and HCO_3 ions [69]. In conclusion, topography and hydrogeology, which are factorized throughout this study as needed, greatly influence water quality parameters. Slope and geological deposits affect sediment transport and pollutant runoff. Geological formations determine the mineral contents of surface water and groundwater quality.

2.3. WATER SOURCE VULNERABILITY AND POLLUTION RISK MODELING

2.3.1. Groundwater vulnerability and pollution risk assessment

Groundwater quality is dependent on geological, physicochemical, biological, and anthropogenic factors. Groundwater pollution results from three fundamental mechanisms: physical processes such as advection, diffusion, dispersion, evaporation, infiltration, filtration, and volatilization; geochemical processes such as acid–base reactions, sorption–desorption, ion exchange, oxidation–reduction reactions, precipitation, dissolution, and surface complexation; and biochemical processes such as transpiration, bacterial respiration, decay, and cell synthesis. These interconnected processes emphasize the complexity of groundwater pollution[18]. For example, in Oke-afa, Oshodi Area of Lagos State, a municipal waste dumpsite[70]; in Yunnan, China, sewage effluent, agricultural fertilizer, and water–rock interactions in limestone and dolomite systems[71]; in central Morocco, evaporation, water–rock interactions, and geochemical processes[72]; and in Serbia, industrial, urban effluent, and agricultural activities[73].

The solution to groundwater problems is more expensive, making protection of groundwater sources before pollution is the most reliable approach. This involves considering all pollutants and potential actions within the catchment area; as a result, the concept of vulnerability assessment plays a crucial role in groundwater protection and in estimating the likelihood of environmental risk. The creation of groundwater vulnerability maps, which have been utilized for more than 30 years in developed nations, is a key tool for protection. These methods include DRASTIC, GOD, GLA, PI, COP, and EPIK. DRASTIC is the oldest and most frequently applied method[74]. It serves as an initial step in risk assessment, fortifying the defense of groundwater aquifers[75]. This model within integrated water resource management is categorized into three main categories: indexing and overlaying methods, logistic regression and process-based methods within statistical approaches, and numerical models[76].

Index-based methods such as DRASTIC, SINTACS, SEEPAGE, EPIK, HAZARD_PATHWAY-TARGET, GOD, AVI, PI, INDICATOR KRIGING, and hybrid methods such as ISIS are commonly used for groundwater vulnerability assessment. The DRASTIC and GOD methods are comparable in their ability to assess pollution risk[77]. Statistical methods play crucial roles in characterizing hydrochemical properties and identifying groundwater pollution sources. Piper trilinear diagrams, major ion ratios, and canonical correspondence analysis are used to study hydrochemical evolution, identify pollution sources, and assess groundwater composition[78]. Other statistical methods, such as Bayesian spatial analysis, principal component analysis (PCA), correlation analysis (CA), hierarchical cluster analysis (HCA), and R-Model factor analysis, are used to analyze hydrogeochemical characteristics, contamination, and factors influencing groundwater quality due to natural and anthropogenic impacts[79]. Regression discriminant analysis, likelihood ratio functions, and weights of evidence reveal relationships between contamination factors. However, extensive observed contamination data are often required for effective groundwater pollution risk assessment[80].

On the other hand, a comprehensive groundwater risk assessment model integrates contaminated source hazard (H), intrinsic vulnerability (V), and groundwater function value (F), which has been validated in Jilin city, China, to predict contamination probabilities and create groundwater pollution risk maps[81]. The GIS-based groundwater risk assessment model (GRAM) was used to evaluate hazard release, detection likelihood, consequences, and residual contamination risk from nitrate in the Kathmandu Valley, Nepal[82]. The groundwater risk index (GRI) can be used to identify and quantify the adverse effects of groundwater depletion. In the lower Liaohe River Plain, China, a relative risk model (RRM) combines indices for receptors, sources, exposure, and hazard analysis; generates environmental contamination probabilities and impact maps; and is validated via Monte Carlo analysis for ecological risk assessment [83]. A novel approach integrates parametric methods with a land use index to develop a robust "global risk index" for assessing groundwater vulnerability. For example, the groundwater risk assessment model (GRAM) in South Australia focuses on a "multibarrier" approach, identifying weak barriers, the likelihood of release, contaminant pathways, and consequences to inform risk management actions. This approach compares risk levels to total coliform detections to gauge groundwater quality[84]. In general, this study uses indexing methods, overlaying methods such as DRASTIC and GRAM, to achieve the predefined objectives to delineate groundwater vulnerability, map protection zones, and estimate the exposed population within the subbasin system.

The DRASTIC model, when applied with GIS, is effective for analyzing groundwater vulnerability and correlating it with nitrate concentration. Sensitivity analysis enhances the model's credibility by assessing parameter ratings and weights, reducing errors and uncertainties[31]. The model's assumptions include contaminant introduction at the surface, transport into groundwater by precipitation, water-like mobility, and an area size of 100 acres or larger[85]. The DRASTIC model assesses groundwater pollution potential on the basis of physical characteristics: depth to water, recharge (net), aquifer media, soil media, topography, impact of the vadose zone, and conductivity (hydraulic). It uses a numerical ranking system to quantify vulnerability, incorporating weights, ranges, and ratings for each parameter in the governing equation[30].

$$\textbf{DRASTIC Index} = \mathbf{Dr} * \mathbf{Dw} + \mathbf{Rr} * \mathbf{Rw} + \mathbf{Ar} * \mathbf{Aw} + \mathbf{Sr} * \mathbf{Sw} + \mathbf{Tr} * \mathbf{Tw} + \mathbf{Ir} * \mathbf{Iw} + \mathbf{Cr} * \mathbf{Cw}$$

Where:

- r = the rating for the parameter
- w = an assigned weight for the parameter
- The DRASTIC model encompasses seven key parameters that collectively assess groundwater vulnerability:

1. Depth to water table (D): This parameter measures the distance from the ground surface to the water table. A shallower water table indicates greater vulnerability to contamination, as it offers less opportunity for pollutant attenuation. The depth to the water table is determined via interpolation techniques applied to monitoring site data, particularly during the rainy season, when groundwater recharge is at its peak[86,87]
2. Effective Recharge (R): Effective recharge quantifies the amount of precipitation infiltrating from the Earth's surface into an aquifer. This process significantly contributes to aquifer vulnerability, as it transports surface pollutants downward. Recharge is calculated via hydrological models or field experiments on the basis of precipitation and evapotranspiration data. Different land surface types have varying recharge ratios, influencing the vulnerability rating assigned to each area [86].
3. Aquifer Media: This parameter refers to the geological formation that serves as a hydrogeological reservoir. The porosity, permeability, and transmissivity of the aquifer media influence groundwater flow and contaminant transpiration. The material types within the aquifer are classified into seven categories (e.g., karstic limestone to tuff) on the basis of their attenuation potential[85,88].
4. Impact of the Vadose Zone: The unsaturated zone, or vadose zone, lies between the ground surface and the water table. It plays a crucial role in pollutant attenuation before contaminants reach the groundwater reservoir. The impact of the vadose zone on vulnerability is determined by factors such as lithology, texture, and mineral composition[85,87,88].

5. **5.** Soil Type: The nature of the soil directly affects the transportation and retention of pollutants in the vadose zone. Different soil types have varying abilities to retain contaminants through processes such as sorption or biochemical reactions. The soil types are categorized into seven classes on the basis of their attenuation capacities[85,87,88].
6. **6.** Topography (T): Slope influences groundwater vulnerability by affecting precipitation rates and water displacement over the land surface. Areas with low slopes allow for greater infiltration and mixing with groundwater, whereas steeper slopes result in increased runoff and reduced infiltration, lowering contamination risk[85,87,88].
7. **7.** Hydraulic Conductivity: This parameter measures the ease of fluid flow through porous media within an aquifer. The hydraulic conductivity determines the rate at which contaminants move through groundwater[89]. The values for hydraulic conductivity are derived from groundwater flow models or aquifer media data and are grouped into four classes on the basis of their vulnerability implications[88,90].

The DRASTIC model assumes that contamination begins at the ground surface, enters the water table via rainfall percolation, and travels with water at the same rate. The application of these methods is limited to areas no greater than 100 acres with unconfined aquifers and excludes dominant pesticide pollutants. Combining DRASTIC with GIS produces vulnerability maps on the basis of index grades, which are useful for assessing groundwater pollution risk via hydrogeologic parameters and limited site-specific data[91,92]. Combining DRASTIC with GIS informs decision-makers about the importance of groundwater vulnerability assessment for environmental, economic, and social development [31]. The AHP-DRASTIC software package integrates the analytic hierarchy process (AHP) with GIS for specific aquifer vulnerability assessments, predicting contamination likelihoods on the basis of surface activities. Scholars suggest modifying the DRASTIC model via nitrate measurements to map groundwater vulnerability to agricultural nonpoint source pollution, which results in improved accuracy over that of the original method validated via Pearson correlation.

Scholars have also recommended that the modification of the DRASTIC model to map groundwater vulnerability to pollution via nitrate measurements in agricultural areas is better than the original method for nonpoint source pollution in agricultural areas, which has been confirmed by Pearson correlation [93]. On the other hand, an enhanced DRASTIC index incorporates hydrogeological factors such as multilayer vadose zones, preferential flow, and contaminant properties such as sorption and decay, justifying its integration into a GIS system[94]. This approach is utilized for site-specific environmental impact assessments, vulnerability assessments, and integrated water resource management. The study opts for the DRASTIC index with GIS due to its user-friendly nature without compromising the quality of the results. It considers geological, hydrological, and hydrogeological characteristics but is independent of the nature of contaminants. Key considerations include the advective travel time, quantity of contaminants reaching the target, and physical attenuation, such as dispersion or dilution during transport[85]. However, these methods suffer from subjectivity in assigning values and weights, oversimplification of complex relationships, and lack standardized validation. Specifically, for sub-Saharan countries, the DRASTIC model overlooks critical factors such as large water bodies, karst topography, diverse contaminant sources, and human activities. Vulnerability assessments in developing countries, such as those in Sub-Saharan Africa, face unique challenges due to limited hydrogeological data; difficulty in establishing context-specific assessment methods; and various political, social, and financial obstacles related to groundwater legislation, skilled personnel, funding, and policy frameworks.

On the other hand, groundwater vulnerability assessment and risk identification are fundamental aspects of integrated water resource management (IWRM) and are influenced by study purpose, scope, scale, data availability, time, cost, and beneficiaries. Vulnerability reflects groundwater sensitivity to contamination on the basis of aquifer characteristics. Groundwater vulnerability maps are critical for regulatory frameworks against pollution, resource allocation, intervention prioritization, monitoring, nitrate pollution prediction, delineation of protection zones, and pesticide risk evaluation. Combining vulnerability maps with land use and contamination sources aids legal resource management, policy guidance, and mineral system monitoring, benefiting decision-makers. [74,85,91,95,96]. Groundwater risk assessment involves quantifying the level of specific contaminants in groundwater systems on the basis of natural aquifer characteristics and potentially polluting activities. This assessment prioritizes risks to implement groundwater protection measures. Land use and cover are crucial parameters in risk assessment, reflecting human activities such as agriculture, urbanization, industry, and deforestation. The global risk index model uses standardized land use ratings and weights to create risk maps to assess hazard release likelihood, detection, consequences, and residual contamination risk. This study provides evidence linking water quality to land use for effective land management and urban planning, supporting efforts to protect groundwater resources. The limitations of this study include the reliance of the DRASTIC model on seven factors, which may overlook complex hydrogeological interactions determining groundwater vulnerability. The model may not adequately address site-specific conditions, such as the nature and intensity of contaminant sources. Additionally, confined aquifers are treated similarly to unconfined aquifers, and the study represents a single point in time without accounting for future changes in land use or climate. The use of WASH inventory data is constrained by the inherent limitations of secondary data sources. These limitations highlight the need for cautious interpretation and complementation with additional approaches to ensure a comprehensive assessment of water supply scheme vulnerability and protection zone delineation.

2.3.2. Surface water vulnerability assessment and Water Quality Index

Water quality analysis is vital for assessing water suitability for various purposes, such as drinking, recreation, and industry. This study focuses on analyzing drinking water at the subriver basin scale via methods such as the water quality index (WQI). The WQI categorizes water quality on the basis of parameters such as dissolved oxygen (DO), pH, coliforms, specific conductance, alkalinity, and chloride. Statistical techniques such as factor analysis help in parameter selection and weight assignment [97]. The WQI provides a numerical expression of water quality, aiding in pollution control and water management[98]. The Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) categorizes raw water quality on the basis of major ions, nutrients, turbidity, color, suspended solids, and trace metals. These assessments help in classifying river water quality and zoning for different uses, supporting water quality management efforts globally[99].

The WQI is applied to assess seasonal variations in water quality parameters. In the Warri River of Nigeria, a weighted mean index was used across nine parameters to demonstrate water quality trends[100]. The WQI is useful for assessing both surface and groundwater quality. For example, in the Thirumanimuttar subbasin, India, premonsoon samples exhibited poorer quality because of the leaching of ions, groundwater overexploitation, effluent discharge, and agricultural impacts. The WQI aids in identifying anthropogenic impacts and watershed pollution statuses[101]. In northwestern Madrid, Spain, a strong linear relationship was found between the

WQI and dissolved oxygen deficit. The WQI, integrated with GIS, evaluates drinking water quality by sorting it into good, poor, and very poor water qualities [102].

A systematic review of 50 water vulnerability assessment tools with 710 indicators revealed that holistic approaches to water resource management, particularly integrated water resource management (IWRM), emphasize social and institutional considerations such as adaptation, institutions, and governance [103]. GIS-based models analyze nonpoint source pollutants, generating pollution severity and risk maps that are used to assess surface water vulnerability and pollution risk. This approach was applied in the Al-Abrash Syrian coastal basin and West Central Côte d'Ivoire Anowa, integrating GIS overlay analysis and the analytic hierarchy process (AHP) via watershed characteristics such as soil type, slope, land use, drainage density, and runoff [104][105]. Additionally, the USGS (United States Geological Survey) method assesses water supply contamination risk on the basis of factors such as annual precipitation, slope, land cover, land use, and groundwater contributions [106]. Such assessments inform integrated land management, aiding in sediment, nutrient, and pesticide management in watersheds and subbasin protection zone delineation. Accordingly, in this study, surface water vulnerability and pollution risk were assessed via the aforementioned models by considering factors prevailing in the subbasin system that contribute to surface water pollution.

2.3.3. Delineation of source protection zones

Delineating source protection zones is crucial for safeguarding water quality by safeguarding recharge areas and enacting water source management legislation. This internationally applied approach prevents groundwater contamination from hazardous substances. Using GIS, three protection zones were delineated around water sources to identify vulnerable areas[105]. Surface water protection perimeters are established on the basis of vulnerability maps to minimize pollution risk [107]. In addition to wellhead and surface water intakes, source protection zones ensure water supply safety [108]. Groundwater vulnerability mapping and protection zone delineation are practiced in Jordan[109]. However, low-income countries such as Ethiopia need more attention in terms of water source protection amid anthropogenic threats and limited local land–water management integration [110].

Groundwater protection involves two key methods: groundwater vulnerability mapping and delineation of source protection zones. These methods identify risks from polluting activities and accidental pollutant release. Source protection zones aid catchment management by safeguarding areas around abstractions with poor water quality[111]. Areas with relatively high vulnerability index values need protection to manage aquifer recharge and prevent groundwater contamination[112]. Water source protection zones are delineated on the basis of vulnerability assessments, which involve immediate, inner, and outer protection zones[113]. This approach requires basic data, including public and private drinking water resource information; water quality analysis results; and hydrological, hydrogeological, and environmental isotope data[114].

Protection zones are established to prevent rapid contaminant ingress or wellhead damage, which are controlled by regulations to safeguard vulnerable aquifers and preserve groundwater quality for current and future use. The delineation of groundwater and surface water protection zones considers various factors, including proximity to contamination sources, drawdown in unconfined aquifers, flow velocity, assimilative capacity, flow boundaries, contaminant loading, and land use priorities[110]. Typically, three zones are delineated around wells: boreholes, springs, and intake structures or reservoirs.

1. Inner Protection Zone: This zone extends a minimum radius of 50 meters or a travel time of 50 days from any point below the water table to the water sources. The assumption of 50 days is that most pathogenic bacteria die within 40–60 days or more while traveling through groundwater[115]. Alternatively, in some countries, the Inner Protection Zone may consist of at least 25 meters upstream of the well (depending on the groundwater flow direction), 10 meters downstream, and 15 meters on each side, with fences and signposts indicating restrictions[114].
2. Outer Protection Zone: This zone requires a minimum radius of 250 meters or 500 meters, depending on the size of the abstraction or a travel time of 400 days. In certain areas, the buffers extend 2,000 meters upstream and 1,000 meters downstream of each production well, combined with an additional buffer of 350 meters[114].
3. Source Catchment Protection Zone: This zone encompasses the area around the water source where all groundwater recharge occurs, including the entire groundwater catchment of the well field. Within this zone, development, agricultural activities, industrial operations, and social activities are permitted but subject to specific regulatory controls[114].

Surface water source protection delineation involves integrating spatial analysis models with parameters such as slope, land use, soil type, drainage density, and runoff. These factors are prioritized, weighted, and incorporated into a geographic information system (GIS) to establish three protection zones around surface water [105].

1. Zone I (Immediate Protection Perimeter/Intake Zone): This zone extends within a radius of 100 m around the surface water to mitigate the risk of direct pollutant discharge. It includes a land strip expanding 5–30 m landward for up to 1000 m upstream (or 500 m for lake intakes) and 100 m downstream. For river intakes, the immediate protection perimeter is set at 200 m around the water intake to address vulnerability to pollution [108]. This zone may also incorporate a radius of 2000 m around lakes, covering water, islands, and coastal areas[105].
2. Zone II (close protection perimeter): This zone, which is determined on the basis of the water direction and its impact on surface water vulnerability, extends beyond Zone I. This zone allows for pollutant attenuation through dilution and dispersion within flowing water and the unsaturated and saturated zones. The close protection perimeter typically spans between 100 and 450 m around the surface water[116].
3. Zone III (Distant Protection Perimeter): This outermost zone accounts for diffuse pollution and covers the entire upstream catchment area, extending beyond Zone II. It serves as a guide for managing and protecting water intakes and informs land use planning, as it surrounds a large portion of the basin to address diffuse pollution sources affecting water quality[105].

This literature review highlights several gaps and challenges in the implementation of water safety plans (WSPs), which can play significant roles in source protection through standardized delineation of source protection zones. Despite the development of WSP guidelines and strategies by the Ministry of Water, Irrigation, and Energy (MOWIE) and regional water bureaus, these strategies have largely remained in the pilot phase since June 2018[117]. Climate-resilient WSP projects have been introduced in cities such as Addis Ababa and Adama, but widespread implementation of these projects remains limited[118]. Globally, WSPs face obstacles such as a lack of preventive culture, prioritization issues, and difficulties integrating WSPs into existing practices. Countries such as the United States and Uganda illustrate these challenges, with limited success in monitoring and managing WSPs and progress largely seen in high-income nations[119]. Additional challenges include insufficient institutionalization, inadequate catchment protection efforts through vulnerability assessment and zoning, and a lack of climate information, which have prompted the need for climate-resilient WSPs (CR-WSPs) with approaches and practices for appropriate demarcation of protection zones[120]. The absence of national source protection zoning guidelines and lack of specific evidence exacerbates these issues, as existing legal frameworks do not encompass comprehensive management of land around water sources or address contamination risks effectively. This study proposes the use of ArcGIS and national WASH inventory data to delineate water source protection zones, with the aim of enhancing WSP implementation by integrating it with a broader information management system within the One WASH national program.

The upper Awash subbasin is characterized by economic activity, pollution, and a dense population, and the significance of groundwater vulnerability maps in safeguarding groundwater sources cannot be overstated[121]. These maps can play crucial roles in establishing legal regulations, allocating resources wisely, prioritizing interventions, monitoring groundwater, and accurately predicting pollutant sources in drinking water supplies to delineate protection zones. Currently, there is no practical strategy or guideline for applying protection zones or integrating the national WASH inventory with new approaches to the ultimate use of the inventory database. This study presents an innovative approach that goes beyond simple identification of vulnerable areas. It provides real-time information on existing water supply schemes and proposes the establishment of practical protection zones. These zones can be integrated with the national WASH inventory, watershed management, water conservation, water safety plans (WSPs), and regulatory controls for evidence-based management. In conclusion, this study, by reviewing the strengths and limitations of this approach, delineates protection zones for both surface water and groundwater, which should be integrated with WASH programs and projects, such as the WASH inventory and water quality surveillance systems, to ensure water quality for drinking purposes and ecosystem health.

2.4. IMPACTS OF WATER QUALITY ON PUBLIC HEALTH

Around the world, the association between poor water quality and health has been documented for many years. Improved water quality is effective in preventing diarrhea and other water-related diseases. The prevalence of water-related diseases has been directly linked to the contamination of river water[122]. For example, in Nigeria, cholera, decracunculiasis, hepatitis, typhoid, and filariasis are attributed to poor drinking water quality[123]. In developing countries, evidence has shown that waterborne outbreaks are associated with poor water quality due to distribution network defects, wastewater backflow, and inadequate maintenance[124,125]. Waterborne diseases are typically caused by enteric pathogens transmitted via the fecal–oral route—organisms excreted in feces by infected individuals and then ingested through contaminated water or food [126]. Common causative agents of waterborne diseases include bacteria, viruses, and protozoa. Bacterial agents. Additionally, toxic chemicals and inorganic pollutants associated with diseases include arsenic, copper, fluoride, lead, and nitrate, whereas organic compounds found in drinking water, such as pesticides, chlordane, phenol, and trihalomethanes, can present health risks[127]. Cyanobacterial harmful algal blooms that produce toxins pose an increasing threat to drinking and recreational water, producing a variety of hepatotoxins, neurotoxins, and dermatoxins with short- and long-term effects[128].

Waterborne diseases are creating health challenges globally. There have been at least 325 reported water-associated outbreaks attributed to protozoan diseases worldwide, with *Giardia lamblia* and Cryptosporidium parvum accounting for the majority of these incidents[129]. In Northwest Nigeria, waterborne diseases are prevalent, particularly among children under 5 years of age, and are often associated with contaminated river water[122]. Similarly, in Italy, reports from 1998--2005 revealed that 40% of water-related disease outbreaks were linked to drinking water, and these outbreaks affected 76% of the country's regions[130]. The association between poor water quality and waterborne diseases is aggravated by factors such as low awareness, socioeconomic and cultural issues, environmental challenges, financial constraints and an inadequate community water supply [131]. Research conducted in southern Ethiopia, Derashe district, revealed that the occurrence of diarrheal disease was significantly linked to a lack of household water treatment, a reliance on unimproved water sources and poor sanitation services[132]. Similarly, findings from Jigjiga highlighted that handwashing practices, water sources and storage methods, liquid waste drainage systems and other sanitation factors are associated with waterborne diseases [133]. Additionally, research on Addis Ababa's Goffa, Kera, and Akaki farms revealed that the concentrations of trace metals such as Pb, Cd, Co, Cu, Mn, and Ni in irrigation water samples exceeded safety limits[134]. However, especially in developing countries, the impact of these outbreaks is likely underestimated because of unreliable surveillance and reporting systems as well as the production of evidence through the use of a viable research design.

Various worldwide studies have highlighted the importance of awareness of waterborne diseases for health professionals, government officials, and the general public to increase public health surveillance and response capabilities and improve prevention and control measures[135]. The lessons learned from waterborne disease outbreaks provide valuable insights into the public health impact of waterborne diseases and information for effective intervention strategies[136]. Systematic reviews confirmed that water quality improvements when combined with basic hygiene and environmental measures were effective in preventing diarrheal diseases[137]. Consequently, overall improvements in drinking water and sanitation contribute to decreased risks of diarrhea. There is a direct relationship between water-related diseases and water quality, which depends on watershed characteristics. This is supported by a cross-sectional study conducted in hilly tribal villages in India; villages with Integrated Watershed Management Programs had reduced water scarcity, increased access to toilets and better utilization of modern healthcare facilities, which indicates the vital role of watershed management in improving public health outcomes[138]. Therefore, this study contributes to justifying the relationship between water quality and public health by generating evidence to prevent risks originating from the overall subbasin system. A safe and adequate water supply reduces public health risks, and the methods demonstrated in this study can protect water sources, maintain water quality, and safeguard public health. By linking existing knowledge with new findings, this study addresses gaps related to watershed characteristics and water quality parameters in subbasins. It uses an integrated approach, considering both groundwater and surface water sources, emphasizing the subbasin's significance as one of the most polluted and socio-politically important areas in the country. Water source vulnerability and pollution risk modeling methods are innovative for estimating the population exposed to contamination risks in vulnerable areas. Additionally, the statistical model for water quality and risk analysis narrows knowledge gaps regarding spatial, seasonal, and parameter-specific variations, aiding in public health risk predictions. This study also quantifies public health risks, identifies vulnerable water supply schemes via national WASH inventory data, supports advocacy and policy formulation, and enhances programs such as climate-resilient water safety plans to minimize the impact of water quality on public health.

2.5. STATISTICAL MODEL FOR WATER QUALITY AND RISK ANALYSIS

Statistical methods play a critical role in water quality analysis, providing valuable tools for comparing variability across different locations, times, and conditions and predicting relationships between independent and dependent variables. Multivariate analysis methods are particularly useful for assessing associations between water quality and factors such as land use, forested areas, buffering zones, and catchment landscape characteristics within watershed systems[66].

Principal component analysis (PCA), analysis of variance (ANOVA), and regression analysis are widely used techniques in water quality analysis. Regression analysis, for example, helps identify sources of variation among water quality parameters. In studies conducted in regions such as the Jakara Basin (northwestern Nigeria) and Bhainsa village (India), regression analysis has explained water quality variations on the basis of specific parameters such as total solids and physicochemical components[139]. Similarly, in the Glomma River, Norway, factors affecting the presence of microbial pathogens in raw water were identified via regression analysis [140]. Before conducting regression analysis, it is essential to test assumptions and address constraints to ensure accurate modeling and prediction reliability. Various statistical transformations, such as linear, power, exponential, and logarithmic functions, can be applied to water quality data for analysis [141,142].

To estimate trends in water quality, analysts must consider factors such as trend hypotheses, data types (e.g., concentration or flux data), and data manipulation techniques for trend analysis[143]. Techniques such as the seasonal Kendall test and flow adjustment methods are used to identify and quantify changes in water quality over time, considering challenges such as nonnormal distribution, seasonality, missing values, and serial correlation[144]. Factor analysis (principal component) is a comprehensive method for analyzing water quality dynamics. For example, in the Songhua River Basin, changes in pollutant composition and hydrological variability were studied via PCA, revealing dominant impacts such as dissolution of secondary salts and anthropogenic influences[145]. Evidence shows that PCA and factor analysis (FA) effectively assess hydrogeochemical processes governing groundwater chemistry, aiding in water quality management and pollution source identification[146–151].

Among statistical analysis methods, Bayesian networks stand out for their flexibility in handling missing data and continuous real-time updates[152]. Statistical analyses are crucial for spatiotemporal surface water quality analysis, identifying variations in exposure to naturally occurring geogenic elements such as iodine, lithium, and strontium, which have beneficial effects on human health[149,153]. Methods suggest the use of different hydrogeochemical processes, such as weathering, ion exchange, and anthropogenic activities, to quantify exposure status and health risks, which can help predict water quality status[154]. Therefore, statistical models are essential tools for analyzing water quality parameters in this study. In conclusion, gaps in statistical modeling for water quality analysis, such as the limited application of advanced techniques such as machine learning for improved prediction accuracy and dynamic real-time analysis, exist. Existing models often fail to capture spatial and temporal variability and integrate health risk assessments comprehensively. Addressing these gaps through innovative methods could enhance water quality management and minimize public health risks due to deteriorated water quality.

2.6. PUBLIC HEALTH RISK ASSESSMENT

2.5.1. Public health risks and requirement of water source protection

Public health risk assessment is a key strategy for protecting public health by evaluating interventions to reduce risk factors and identify environmental risks in residential areas, workplaces, and food and water sources. This literature reviews water quality risks to public health within a watershed. Public health risk assessment involves identifying and quantifying the probability of specific risks within a range of uncertainty.

Source water protection is a vital strategy to ensure the safety of drinking water by employing a multibarrier approach across source water protection, water treatment, and distribution systems. The components of source protection include watershed delineation, management plans, vulnerability assessments, and inventories of land use and contaminants[155]. Implementation occurs at the watershed level, reflecting the diversity of municipal jurisdictions and water supply systems. The evidence highlights the need to address cumulative effects from multiple discharges and concentrations to minimize risks effectively[156]. Challenges in source water protection implementation stem from inadequate watershed monitoring capacity, insufficient awareness of protection needs and municipal responsibilities, conflicts over multiuse watersheds, and limited watershed planning and management[157]. Risk analysis is essential for protecting water sources and involves three main components: risk assessment, risk management, and risk communication[158]. The development of quantitative microbial risk assessment techniques has allowed the integration of microbiological criteria into hazard analysis critical control point (HACCP) systems to safeguard public health. It was initially implemented by the Icelandic waterworks in 1997. It has been adopted for managing water quality to ensure safe drinking water, enhance water quality, promote consumer accountability, and reduce waterborne hazards[159]. HACCP-based models have been used for water reuse in the food industry[160]. For example, in terms of groundwater supply, aquifer management is a critical control point (CCP), whereas coagulation, flocculation, sedimentation, filtration, and chemical disinfection serve as CCPs in the surface water supply. These points act as quality control points (QCPs) for ongoing monitoring and corrective actions to prevent recontamination of treated water sources[161]. Preventive risk management systems, refined through experiences with hazard analysis critical control points (HACCPs) in water utilities in the USA and Australia, have informed the development of water safety plans worldwide. Major approaches include the HACCP protocol, WHO Water Safety Plan, Bonn Charter, and Quantitative Microbial Risk Assessment (QMRA), facilitating contamination risk control, risk understanding, identification of critical control points, and integration into water supply operations[162]. The implementation of WSPs led to a significant reduction in diarrhea incidence and a 14% decrease in clinical diarrhea cases within the affected population. Moreover, water quality improvements were observed across most sampled locations following WSP implementation[163]. However, even in high-income countries with supportive environments for WSP implementation, failures in risk management have led to waterborne disease outbreaks.

According to the US EPA's guidelines on quantitative risk assessment, four key steps are involved. The first step is hazard identification, which determines whether exposure to a stressor can lead to specific adverse health effects, such as diseases, cancer, reproductive defects, or other harmful outcomes. This process involves understanding toxikinetics (how the body absorbs, distributes, metabolizes, and eliminates chemicals) and toxicodynamics (the effects of chemicals on the human body). The second step is a dose–response assessment, which estimates the likelihood and severity of adverse health effects in relation to the amount and condition of exposure to a chemical agent. The third step is exposure assessment, which examines the magnitude, frequency, and duration of exposure, considering the size, nature, and type of human populations exposed and addressing uncertainties. Exposure can be quantified via methods such as point-of-contact measurement, scenario evaluation, or reconstruction. The final step, risk characterization, integrates information from the preceding steps to synthesize an overall conclusion about the risk associated with the exposure scenario. This structured approach ensures a comprehensive evaluation of risks to inform effective risk management strategies.

Human exposure assessment employs various approaches, such as biological monitoring with biomarkers, epidemiology studies, and GIS techniques, to predict pollutant concentrations. A common limitation of exposure assessments is reliance on overly conservative assumptions and difficulty in accounting for highly exposed populations. Effective cumulative risk assessment for contaminated sites involves stages such as planning, exposure analysis, toxicity analysis, and risk characterization[164]. Microbial risk assessment uniquely requires consideration of pathogen growth and deactivation, known as predictive microbiology[165]. The literature suggests that probabilistic health risk assessments often utilize Monte Carlo analysis. Supplementary statistical methods such as ANOVA, fuzzy methods, and Bayesian methods can be integrated with two-dimensional Monte Carlo methods to identify controllable inputs and key uncertainties within the model. Bayesian probabilistic risk assessment is recognized as particularly suitable for conveying uncertainty information in risk assessments[166]. The outcomes of risk assessments provide insights into the probability of encountering a specific risk value within a specified range of uncertainty. In this probabilistic framework, all variables and parameters used in risk assessment are treated as distributions[167]. Monte Carlo and Bayesian models address most of the limitations by assessing uncertainty in parameters and estimating plausible exposure and risk levels. The Bayesian method outperforms the Monte Carlo method by integrating observational data and expert judgment to refine the occurrence probability. Accordingly, this study focuses on water quality-related health risks such as waterborne diseases, cancer, and noncarcinogenic chemicals. This study provides detailed methods for public health risk management and justifies the need for water source protection by sector authorities and stakeholders to improve public health in subbasin systems.

2.5.2. Public health risks and method of risk assessment

2.5.2.1.Chemical and Heavy metals

In this study, chemical risk and risk assessment methods were also included to predict the quantified risk level due to water quality parameters such as heavy metals. Heavy metals are dense or high-atomic-weight chemicals, such as cadmium, mercury, lead, and arsenic, identified by the WHO as major public health concerns. Other heavy metals include manganese, chromium, cobalt, nickel, copper, zinc, selenium, silver, and antimony[168]. From a public health perspective, heavy metals, including lead, mercury, cadmium, cobalt, nickel, iron, thallium, bismuth, and arsenic, are metals or semimetals with potential human or environmental toxicity. These metals occur naturally in the Earth's crust, but human activities can increase their concentration, allowing them to enter plant, animal, and human tissues via inhalation, ingestion, or handling. Lead, cadmium, mercury, and arsenic pose significant health threats, especially in less developed countries. Their harmful effects include oxidative and nitrative stress, depletion of antioxidants, damage to macromolecules, chromosomal abnormalities, altered gene expression, membrane damage, and disruption of protein structure[169].

Reports indicate that several African countries are exposed to heavy metals such as mercury, lead, cadmium, and arsenic. For example, at Ilesha gold mine sites in Nigeria, the levels of Fe, Ba, Mn, Pb, Cr, and Ni exceeded the recommended drinking water standards, with arsenic levels posing unacceptable risks for carcinogenic effects[170]. Northern Ghana has recorded levels of Hg, Pb, and Cd in drinking water that surpass the WHO limits, posing health risks to mining communities [171]. In Cairo, Egypt, health issues such as renal failure, liver cirrhosis, hair loss, and chronic anemia have been linked to heavy metal contamination in drinking water with Pb, Cd, Cu, Mo, Ni, and Cr [172]. Similarly, in Izmir, Turkey, trace metals, including arsenic, chromium, copper, manganese, nickel, and zinc, were found in water samples, with concerns over arsenic noncarcinogenic risks for 19% of the population [173]. The Euphrates River in Iraq has shown concentrations of Cd, Cu, Ni, Fe, Mn, and Cr that exceed the USEPA guidelines[174]. However, heavy metal concentrations in Kirkuk city, northern Iraq, were found to be lower than WHO-estimated levels[175]. Taiwan's Houjing River faces heavy metal contamination from industrial processes such as metal plating, plastic manufacturing, and semiconductor packaging [176]. In Ubon Ratchathani Province, Thailand, warmer climates increase susceptibility to noncarcinogenic and carcinogenic effects from heavy metal-contaminated groundwater because of increased daily drinking water intake[177]. The factors affecting metals in soils around Beijing reservoir watersheds include atmospheric deposition, land use, soil texture, type, and chemical parameters, which influence heavy metal residues and retention in soils[178]. Metal concentrations in organisms are relatively high near river inputs that are heavily impacted by human activities [179]. Monitoring point sources of heavy metals in water and sediments is crucial for mitigating the effects of industrial effluent and domestic sewage discharge[180].

Mercury (Hg), the most toxic heavy metal, enters the environment through agriculture, mining, incineration, and industrial wastewater discharge. The health effects of mercury include kidney damage and allergic reactions. Organic mercury (methyl mercury) can cause poisoning, nervous system damage, tremors, personality changes, and lung damage, with health impacts varying on the basis of its distribution in the body [181]. Lead, which is emitted from petrol and lead-based paints, affects children more severely because of their underdeveloped blood–brain barrier. Lead exposure causes memory deterioration, anemia, renal damage, and hemoglobin synthesis impairment. Lead toxicity presents a serious, irreversible health risk[169]**.** Arsenic, a widely distributed metalloid found in rock, soil, water, and air, leads to significant health risks through exposure via food and drinking water. Inorganic arsenic is typically found in groundwater, whereas organic forms are present in fish [181]. Natural sources include volcanic activity, rock weathering, and geothermal water, whereas anthropogenic sources such as smelting, fossil fuels, and industrial activities contribute to environmental contamination. Approximately 200 million people are exposed to arsenic through drinking water, leading to increased risks of skin cancer, liver and kidney cancers, and other health issues[169,181]. Acute exposure to inorganic arsenic can cause gastrointestinal symptoms and severe cardiovascular and nervous system disturbances. Long-term exposure is associated with bone marrow depression, neurological disorders, and increased mortality from specific cancers. Chronic exposure to arsenic is linked to cardiovascular diseases, developmental abnormalities, and various cancers, highlighting the profound health impacts of this toxic metalloid[182]. Cadmium sources include rechargeable nickel–cadmium batteries; waste products (which are rarely recycled); cigarettes; ores containing zinc, lead, and copper; phosphate fertilizers; industrial emissions; and sewage sludge used in farming. Exposure to cadmium occurs primarily through contaminated water used for irrigation. The health effects of cadmium include mainly kidney damage and bone effects such as fractures and skeletal damage (seen in diseases such as itai-itai or "ouch-ouch"), although evidence that it is a human carcinogen is weak[181].

The chemical risk assessment uses different terms. These terms include no observed adverse effect level (NOAEL), lowest observed adverse effect level (LOAEL), acceptable daily intake (ADI), oral slope factor (OSF), tolerable daily intake (TDI), RfD: reference dose, and others. The level of exposure or dose of a toxic agent resulting in no observable or statistically significant increase in adverse health effects is termed the no observed adverse effect level (NOAEL), whereas the highest dose that does not impact morphology, functional capacity, or other aspects of the test animal is the no observed effect level (NOEL). A selected no-effect level from toxicology studies is divided by a 'safety' or 'uncertainty' factor to account for uncertainties in extrapolating from animals to humans, variation within species, or uncertainty about the actual no-effect level, along with concerns about serious effects. Traditionally, the default safety factor has been assumed to be 100, comprising a factor of 10 for interspecies extrapolation. Safety factors consider interspecies and individual sensitivity variations in human consumers[183]. For example, the safety factors used in setting acceptable daily intakes (ADIs) for pesticides may not consistently align with toxicity severity, requiring further assessment. Oral slope factors (OSFs) quantitatively estimate the carcinogenic risk from chemical exposure via the oral route, with OSF data available from the United States Environmental Protection Agency's Integrated Risk Information System (IRIS) database[184].

Chemical risk assessment must consider potential dietary intake from drinking water, including residues in or on food. The 'Guideline Value' (or 'Action Level') often represents the analytical limit of detection for chemicals in water via modern assay methods. If chemicals or pesticides are detected in drinking water, water supply authorities should take action to identify and mitigate contamination sources. The health guideline value assumes that water intake contributes approximately 10% of the total daily intake from the diet. Therefore, the health guideline value can be calculated via the following formula.

$$\text{Health guideline value (mg/l)} = \frac{ADI\left(\frac{mg}{kg} * \frac{bw}{d}\right) xAverageweightofaperson(Kg)X10\%}{Avragewaterconsumptionperperson(\frac{l}{d})}$$

Where

The average body weight of an adult typically ranges from 60 to 70 kg, with an estimated maximum water consumption of 2 liters per day. The acceptable daily intake (ADI) is determined by applying a safety factor of 100 to the no observable adverse effect level (NOEL) obtained from toxicology studies in test animals (comprising a factor of 10 for interspecies variation and 10 for human variability) [183]. This safety factor accounts for uncertainties related to differences between animals and humans, as well as variability among individual humans and mechanisms of action [185]. The ADI calculation involves incorporating this safety margin to accommodate unknown variables when extrapolating from animal studies to humans, considering the significant heterogeneity within the human population.

$ADI = NOEL/Safety\ Factor\ (SF)$;

A 10-fold uncertainty factor is applied in noncancer risk assessments to accommodate potential interindividual variations in chemical fate within the body (kinetics) and the sensitivity of target organs (dynamics) [186]. An additional safety or uncertainty factor is used to account for the nature of toxicity in estimating acceptable daily intake (ADI) and tolerable daily intake (TDI) values. This extra factor is typically applied in cases involving the detection of carcinogenicity for nongenotoxic chemicals or teratogenicity, specifically triggered by the toxicity endpoint's no-observed-adverse-effect-level (NOAEL).

However, in many cases, the additional factor was applied when the NOAEL used to calculate the tolerable daily intake (TDI) was for an unrelated toxicity, sometimes observed in a different species. If a safety factor for the nature of toxicity is to be used, it should logically be applied to the toxicity's NOAEL that triggered its use; the TDI should be calculated for different toxicity endpoints using the appropriate total safety/uncertainty factor for each endpoint. The adopted TDI would then be the lowest of those calculated for different endpoints. Toxicity endpoints are given an extra factor for three reasons: carcinogenicity, teratogenicity, and a steep dose response when serious toxicity is detected just above the NOAEL (possibly reflecting concerns about the precision of the NOAEL rather than the toxicity itself). The use of an additional 'safety' factor for nongenotoxic carcinogens remains controversial and challenging to justify objectively. However, applying a subjective factor to animal carcinogens not proven genotoxic may be beneficial if it prevents the need for model dependent, quantitative low-dose risk estimation for effects likely to have a biological threshold[187].

In many instances, an additional factor was applied when the NOAEL used for calculating the tolerable daily intake (TDI) was related to an unrelated toxicity, sometimes observed in a different species. If a safety factor for toxicity is used, it should logically be applied to the NOAEL triggering its use; TDIs should be calculated for different toxicity endpoints using the appropriate total safety/uncertainty factor for each. The adopted TDI would then be the lowest of those calculated for different endpoints. Toxicity endpoints are given extra consideration for three reasons: carcinogenicity, teratogenicity, and a steep dose response when serious toxicity is detected just above the NOAEL. The application of an additional 'safety' factor for nongenotoxic carcinogens remains controversial; however, it may be beneficial in avoiding model dependent, low-dose risk estimation for effects likely having a biological threshold[188]. To calculate intakes, the following formula is used:

$$\mathrm{I} = \frac{CxIRxEFD}{BW} x \frac{1}{\mathrm{AT}}$$

Where:

- **I (Intake):** amount of chemical at the exchange boundary (mg/kg body weight - day).
- **AT (Average Time):** Denotes the period over which exposure is averaged, specific to the pathway. The noncarcinogenic effects are calculated as the exposure duration (ED) multiplied by 365 days per year (365 days/year). The determination of carcinogenic effects is based on a lifetime of 70 years (70 years × 365 days/year).
- **BW (body weight):** average body weight during the exposure period, measured in kilograms (kg). For adults, the average body weight (BW) is considered 70 kg. Note that age-specific values may be defined accordingly.
- **C (chemical concentration):** the average concentration of the chemical encountered over the exposure period (mg/L).
- **IR (contact rate):** Specifies the rate at which the contaminant medium is contacted per unit time, measured in liters per day (liters/day). The contact rate for adults is typically 2 liters/day (90th percentile) or 1.4 liters/day (average).
- **EFD (exposure frequency and duration): the** duration and frequency of exposure.

typically 365 days/year. The exposure duration (ED) represents the years of exposure, which is conventionally set as 70 years (lifetime).

Furthermore, during exposure assessment, it is crucial to evaluate consumer characteristics such as demographics, behaviors, knowledge, perceptions of hazards, and disease prevalence. The exposure duration is classified into acute, intermediate, and chronic categories. Acute exposures last 24 hours or less, subchronic exposures involve repeated exposures over more than 30 days up to approximately 10% of the human lifespan, and chronic exposures involve repeated exposures for more than approximately 10% of the human lifespan[189].

In the dose–response analysis phase, the toxicity of contaminants for both noncarcinogenic and carcinogenic effects (including pesticides, heavy metals, and other chemicals) is calculated by assessing the effects of these chemicals in relation to carcinogenic and noncarcinogenic outcomes. This step helps estimate the impact of exposure on the severity or likelihood of adverse effects in the general population. For noncarcinogenic effects, after chemical intake in the general population is calculated, a dose–response quantification model is applied via the reference dose (RfD) [188]. The RfD helps estimate daily exposure levels that pose minimal risk of adverse effects over a lifetime.

$$\mathrm{RfD} = \frac{NOAEL\ or\ LOAEL}{UF_1 x\ UF_2 \ldots x\ MF}$$

Where

- RfD: Reference dose (oral dose in units of mg/kg-day)
- NOAEL (No observed adverse effect level): The dose of a toxic agent that results in no observable or statistically significant increase in the frequency of adverse health effects.
- LOAEL (lowest observed adverse effect level): The lowest dose of a toxic agent that produces a statistically or biologically significant increase in the frequency of adverse health effects in the exposed population.
- UF1: Uncertainty factor (to account for variations)
- UF2: Uncertainty factor (to account for additional variations beyond UF1)
- MF: Modifying factor

Importantly, uncertainty factors (UFs) are typically multiples of 10, accounting for specific areas of uncertainty related to variation within the general population, including sensitive subpopulations and variations when extrapolating from animals to humans or among different species. The NOAEL is derived from subchronic studies rather than chronic studies, and the LOAEL is used when extrapolating from LOAELs to NOAELs. The modifying factor (MF) ranges from >0--10 and is used to account for qualitative professional assessments of additional uncertainties in critical studies on the basis of professional judgment. The default value for MF is one [188].

In this study, datasets from the USEPA's IRIS database are utilized. These sources are freely available for download, and if necessary, requests will be made by clearly stating their academic purposes. Risk characterization and modeling constitute the final phase of risk analysis, summarizing and confirming the risks identified throughout the risk assessment process. To perform such characterization, microbial quantitative risk models and chemical risk assessment models are applied to four categories of risk:

1) **Noncarcinogenic risk:** The hazard quotient (HQ) is used to characterize noncancer risk. HQ is interpreted as the ratio of the exposure level to the reference dose (RfD), indicating the potential for noncancer effects when this ratio exceeds one

$$Noncancer\ Hazard\ Quotient = E/RfD$$

where

I = Intake; the amount of chemical at the exchange boundary (mg/kg body weight – day)

RfD= reference Dose (mg/kg body weight – Day)

2) **Carcinogenic risk:** Based on the identification of hazards and quantified exposure considering the probability via Montcarlo simulation, the risk is calculated as

$$Risk = CDIxSF$$

where:

Risk: a unitless probability of an individual developing cancer
CDI: Chronic daily intake average over 70 years (mg/kg-day) and

SF: Slope factor (mg/kg-day) from the database.

3) **Against carcinogenic and** noncacinogenic risks: Drinking water samples include mixtures

of chemical water parameters categorized as carcinogenic or noncarcinogenic risks. To calculate the risk for each individual in the population, the following formula is used:

i. Cancer risk for multiple water quality parameters

$$Risk_{Total} = \sum Risk_i$$

where

RiskTotal=The probability of the total cancer risk

$Risk_i$= The risk estimated for the ith substance

ii. Noncancer risk for multiple water quality parameters

$$Hazard\ Index = \frac{I_1}{RfD_1} + \frac{I_2}{RfD_2} + ..$$

where

I_i= Exposure level for the ith toxicant

RfDi=Referencing Dose for the ith toxicant

On the other hand, even though pesticides are not included in this study, they have public health importance in both positive and negative aspects. Pesticides are used to control pests to improve agricultural production, but they present significant health risks. Pesticides, including herbicides, insecticides, and fungicides, are used to control pests and increase food production but pose significant health risks, including cancer, reproductive issues, and respiratory problems[190]. They also harm the environment, contaminating water, soil, and air. In countries such as Ethiopia, pesticide use has increased, particularly for cereal crops, necessitating effective regulatory policies [191]. Globally, pesticide impacts are concerning, with pollutants detected in U.S. water supplies[192]. Assessing pesticide risk involves evaluating environmental dispersion and toxicological properties, considering various criteria and methodologies.

2.5.2.2. Bacteriological Risks

Epidemiological analysis of waterborne diseases emphasizes the importance of risk assessment to identify needs and provide evidence for public health decision-makers. However, the occurrence, concentration, and distribution of waterborne pathogenic microorganisms are often underestimated because of inefficient recovery and detection methods[193]. Each pathogenic organism has a unique risk equation; for example, in the case of protozoa, an exponential dose–response model reflects reality more accurately:

$$p_i = 1 - e^{(-rN)}$$

where:

P_i: probability of an infection resulting from the ingestion of an average number of organisms.

N: average number of organisms within 2 liters of water per day.

r: the fraction of ingested microorganisms that survive to initiate host-specific infection; for example, Cryptosporidium, r=0.00467, and Giardia, r =0.01982[194].

Exposure risk assessments have revealed that watersheds protected from human activity produce 0.6--5 Giardia cysts per 100 liters, whereas surface waters produce 0.33--104 Giardia cysts per 100 liters. As a result, watershed management contributes to a reduction in microbial risk [195]. In addition, the use of a serological approach for the risk assessment of waterborne parasitic infections confirmed that laboratory serologic data were associated with patterns of parasite contamination in drinking water[196]. Simulation studies, such as the one conducted in Milwaukee in 1993, align with historical cryptosporidiosis outbreaks. Such simulations can be enough to evaluate public health strategies to detect and control waterborne gastrointestinal disease outbreaks[197].

Diarrheal diseases represent a leading cause of childhood morbidity and mortality globally. In 2015, an estimated 2.3 billion illnesses and 1.3 million deaths worldwide were attributed to diarrheal diseases, with a greater burden observed in developing countries than in developed countries[198]. Bacterial pathogens such as *Salmonella typhi*, *Campylobacter, Escherichia coli, Shigella, Vibrio, Staphylococcus aureus, Bacillus cereus, Clostridium difficile, Clostridium perfringens, and Yersinia*, along with viral pathogens such as *rotavirus, adenovirus, and caliciviruses*, as well as protozoal pathogens such as *Entamoeba histolytica, Giardia species, and Cryptosporidium,* are major causes of diarrheal diseases linked to water contamination[199]. Notably, *rotavirus, Cryptosporidium, Shigella, and enterotoxigenic Escherichia coli* account for most diarrhea cases. Enterotoxigenic *Escherichia coli* and *V. cholera* O1/O139 cause hospitalizations, whereas *Salmonella, Shigella, and E. histolytica* are frequently identified in outpatient wards[200]. In developing countries, the pathogen-specific burden of community-acquired diarrheal diseases reveals that *norovirus, rotavirus, Campylobacter, astrovirus, and Cryptosporidium* dominate during the first year of life, whereas *Campylobacter, norovirus GII, rotavirus, astrovirus, and Shigella* dominate during the second year[201].

The use of *E. coli* as an indicator for routine monitoring of drinking water is popular because of its presence exclusively in warm-blooded animal feces, making it an appropriate indicator of contamination in water supplies. *Escherichia coli* encompasses five pathotypes—Enterotoxigenic, enteropathogenic, Shiga toxin-producing *E. coli* (STEC), enteroinvasive, and enteroaggregative—indicating different forms of contamination[198]. In Ethiopia, enterotoxinogenic bacteria isolated from infants and children with acute gastrointestinal symptoms include *E. coli* as the predominant strain (38%), followed by Klebsiella, Enterobacter, Proteus, Citrobacter, Serratia, and Aeromonas[202]. However, in Hawassa town, southern Ethiopia, Campylobacter species were identified as the predominant etiology on the basis of fecal samples from children under five years of age with diarrhea[203].

This study focused on the risk of diarrheal diseases caused by *E. coli* spp., one of the most common etiological agents of diarrheal diseases, particularly in developing countries such as Ethiopia. Additionally, *E. coli* is easy to test for water quality, making it an indicator organism for water quality monitoring and surveillance[204]. Quantitative microbial risk assessment (QMRA) is gaining attention in different countries to establish risk-based regulations and standards to increase food and water safety[205]. As a result, the QMRA characterizes the microbial risks associated with drinking water in the Upper Awash River Basin on the basis of hazardous assessment results via watershed water quality and groundwater vulnerability models.

The single-hit dose–response model is commonly used in QMRA methods. The single-hit beta-Poisson model$P_i\ (d/\alpha,\beta)$ is a special case of the generalized model with $K_{min} = 1$ (which implies,$r *= 1$)[206]However, developing this QMRA model is time-consuming, requires substantial data, and requires extensive modeling expertise. In the reviewed article, exponential, exact beta–Poisson models and approximate beta–Poisson dose–response models are described for QMRA.

- Exponential dose–response model:$p_i(d) = 1 - \exp(-rd)$
- The exact beta–Poisson model:$p_i(d) = 1 - 1F_1(\alpha, \alpha + \beta, -d)$
- Approximate beta–Poisson dose–response model: $P_i = 1 - (1 + \frac{d}{\beta})^{-\alpha}$

The approximate beta–Poisson model was selected in this study because it has a fixed value of α for sufficiently large values of β, i.e., if α< 1 and β> 1. If α<< β and β>>1. This model is an accurate approximation of the exact beta-Poisson dose–response model. To estimate the probability of a valid use of the model, parameter estimates are used as a rule of thumb: $\hat{\alpha}$ and $\hat{\beta}$. That is, $\hat{\beta} > (22\hat{\alpha})^{0.5} for\ 0.02 < \hat{\alpha} < 2$; for example, $p_r(0 < r < 1|\hat{\alpha}, \hat{\beta}) > 0.99$). Therefore, for valid application, the approximate beta–Poisson dose–response model is a widely accepted and user-friendly formula: $Pi(D) = \mathbf{1 - (1 + D)/\beta)^{-\alpha}}$ [207].

Where Pi (D): the probability of infection; D=mean dose; β = 1.78E+6; and α = 0.1778 for *E. coli* (pathogenic strain). In addition, the annual microbial infection probability was calculated as $\boldsymbol{P = 1 - (1 - Pinf)^n}$, where P (annual and seasonal infection probability), Pinf (the probability of infection for a single exposure to a dose D of *E. coli*) and n (the frequency of exposure- 365 days/year)[208]

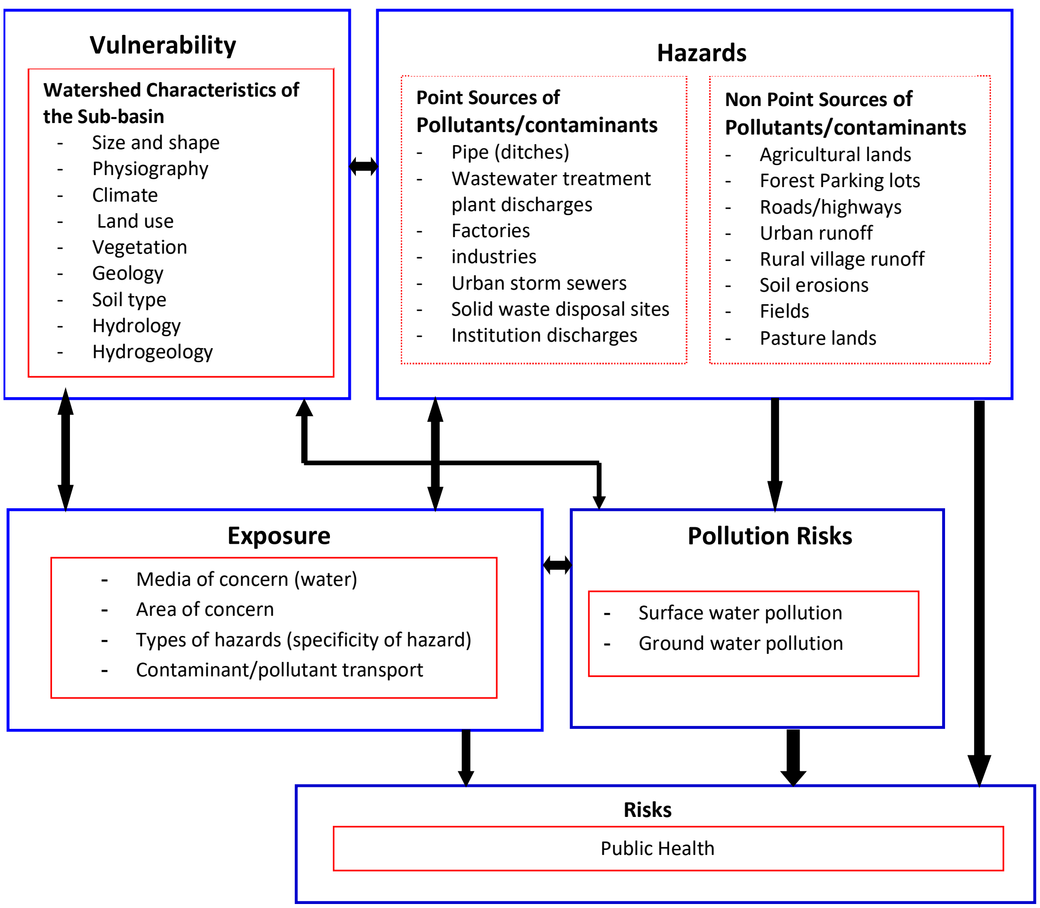


Figure 1: Conceptual Framework

CHAPTER 3: MATERIALS AND METHODS

3.1. STUDY AREA

Ethiopia has twelve river basins, including the Awash River Basin. It is subdivided into basins. The uppermost subbasin is the upper Awash River subbasin, which is the focus of this study. It began at Ginchi 80 km west of Addis Ababa and ended at Koka Dam, with a total length of 220 km. It is one of four basin parts with 11,442 ^{km2} (6 9.9%). It is situated between approximately 8°12'59.39"N to 9°18'00.64"N latitude and 37°06'41.73"E to 39°16'53.09"E longitude. It has a high altitude of 3000 m above mean sea level and a low altitude of 1500 m above mean sea level. It travels approximately 200 km until it reaches Koka Reservoir. The Akaki, Holeta, Berga, and Legedadi Rivers are the four primary tributaries of the subbasin.

The primary land use–land cover of the subbasin comprises 93.2% cultivated agricultural land, grassland, and shrubland, whereas the remaining 6.8% is characterized by other land cover types, such as forestland and rural and town settlements [209].

The wet period is between June and September, and the dry period is between October and February. The hottest month is May, and the coldest months are November and December. The mean annual temperatures range from 20.8 °C to 29 °C at Koka[210]. The rainfall distribution is mostly unimodal and is usually controlled by the movement of the intertropical convergence zone[211]. The annual maximum daily rainfall varies from 62 to 37 mm. The subbasin has an average annual rainfall of 1052 mm, with variations ranging from 400 mm to 1900 mm per year[212].

According to a 2007 survey by the Central Statistical Agency (CSA 2007), 14.9 million people live in the Awash River Basin as an entire area, and more than 65% (9,7 million) of this population lives in the Upper Awash subbasin, which is composed of 4,415,324 rural people and 5.3 million urban people. The subbasin has population densities ranging from 110--270 persons per km^2.

The subbasin includes the city government of Addis Ababa, the Oromia region, and small portions of the Amhara and South Nation Nationalities Regions. It includes many urban residents with industrial, agricultural, and other socioeconomic activities. Approximately 65% of industries in the country are located in this subbasin[213]. Moreover, the Awash Basin accommodates 48 to 70% of the country's existing large-scale irrigated agriculture. Within the subbasin, a combined total of existing and potential large-scale irrigated land covers 33,900 hectares, constituting 22.4% of the entire Awash Basin[214]. The subbasin includes the city government of Addis Ababa, the Oromia region, and small portions of the Amhara and South Nation Nationalities Regions.

The upper wash subbasin is a critical area affected by various factors that contribute to extensive contamination. These include sewage and industrial runoff, rapid urbanization, deforestation-driven sedimentation, and agricultural runoff carrying nutrients from fertilizers and organic waste. Additionally, land use changes exacerbate pollution. The subbasin hosts numerous irrigation projects, industries, and water sources for rural and urban areas, including Addis Ababa and Adama. Its central location and role in Ethiopia's socioeconomic progress, combined with the challenges posed by pollution, urbanization, and industrialization, make it a prime study area for safeguarding ecosystems and communities. The specific locations of the study area and sample site for both the drinking water and surface water are illustrated in Figure 1 below.

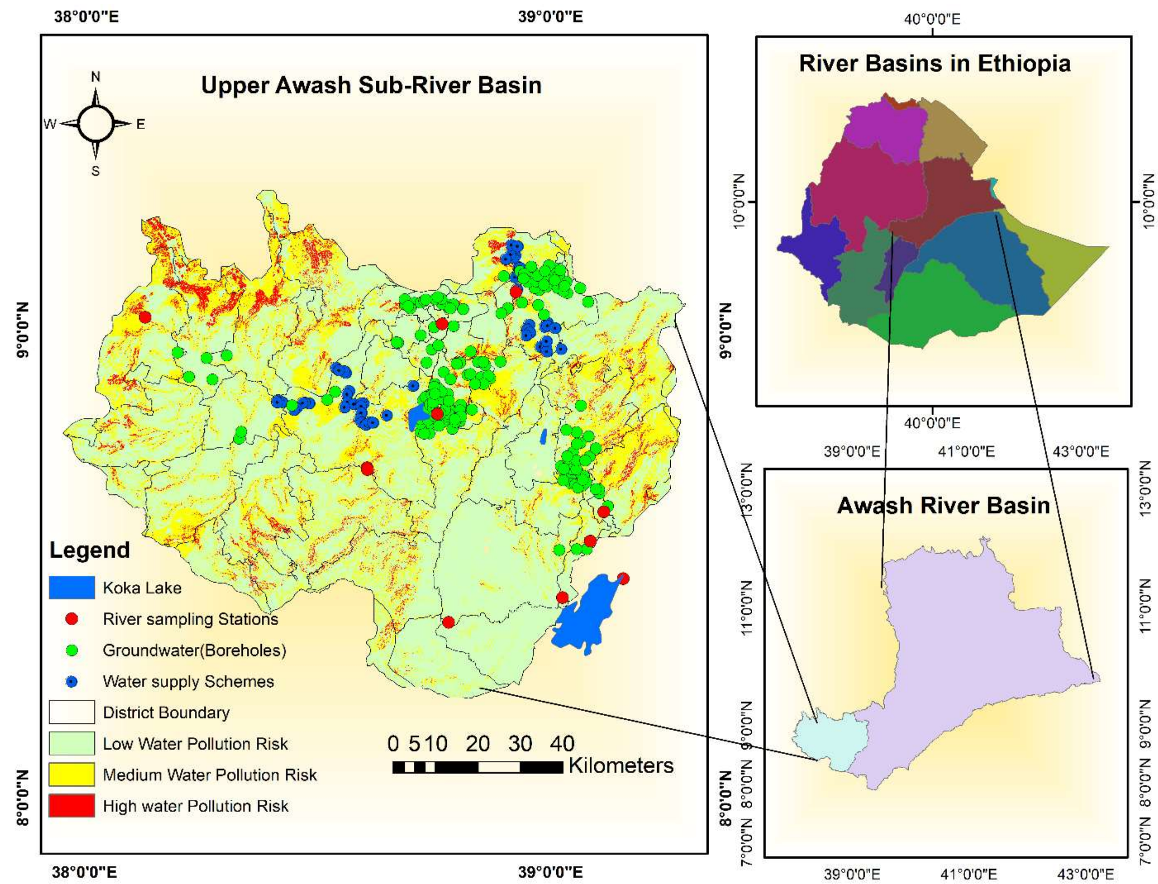


Figure 2: Map of Ethiopia showing the study area

3.2. DATA SOURCES AND MODEL PARAMETERS

Various parameters were utilized from different sources to map WSPR. Access to government sources involved acquiring data through official letters, whereas data from websites, such as satellite images, were obtained through the registration and login process. The depth to the water table (D), effective recharge (R), aquifer media (A), soil type (S), topography (T), impact of the vadose zone (I), hydraulic conductivity (C), and land use land cover (LULC) data were obtained from the Ministry of Water and Energy (MOWE). Data on population and settlement maps are sourced from the Water and Land Resource Centre (WLRC) of Addis Ababa University[215,216], whereas information for effective recharge (R) was gathered from the National Metrology Authority (Rainfall data) and MOD16A3GF v006 (MODIS/Terra Net Evapotranspiration Gap-Filled Yearly L4 Global 500 m SIN Grid) [217]. Additionally, the Awash River Basin Office provides data on land use land cover (LULC). This comprehensive dataset from various sources enables a thorough analysis of parameters in the study area to map the WSPR and estimate the proportion of the exposed population.

3.3. PROCEDURE AND SPATIAL ANALYSIS

In this study, geographic information system (GIS)-based analysis was employed, and ArcGIS Version 10.7 was used to map the pollution risk. The process involved overlay analysis of various parameters and estimation of the proportion of the population exposed to these risks.

Figure 3 provides a visual representation of the outlined procedure. The subsequent sections provide detailed information for a more in-depth understanding of the methodology and analysis.

3.3.1. Mapping Groundwater Pollution Risk

An overlay analysis using the DRASTIC model index and the land use index was conducted to assess the risk of groundwater pollution. **Table 1** describes the overall DRASTIC and land use index rating and weight values. A detailed description of each factor is also depicted below.

1. **Depth to water table (D)**: The interpolation technique was employed to create a raster map of the water table using the static water depth of 851 boreholes. This method is widely used for vulnerability assessments of groundwater. The weights for the parameter and the rate values for each class, as outlined, were determined under the guidelines of the DRASTIC model [86,87].

2. **Effective Recharge (R):** The calculation of effective recharge involves the use of input data such as precipitation, evapotranspiration, and land use/land cover data. To generate the annual precipitation map, 30 years of rainfall data from 13 gauging stations were collected and processed via the Thiessen polygon method within the ArcMap toolbox. Annual evapotranspiration and land use land cover raster data were analyzed via map algebra within the ArcMap Spatial Analyst extension tool. It was applied to process these raster maps via equation (1). The recharge ratios of the Built areas are lower than those of the other areas (0.20), suggesting limited permeability and greater surface runoff. Forested areas, on the other hand, demonstrate a higher recharge ratio of 0.73, indicating greater water infiltration and groundwater recharge. Similarly, open fields and lawns display an acceptable recharge ratio of 0.75. Agricultural fields, with variations in soil type, have recharge ratios of 0.60 for clayey soils and 0.70 for sandy soils. These ratios provide valuable insights into the potential impact of land use characteristics on groundwater recharge within the study area. The resulting recharge output raster underwent adjustments in rates and weights to make it suitable for overlay analysis[218].

$$\mathbf{R = (Annual\ PPT - Annual\ ET) X\ Recharge\ ratio} \qquad (1)$$

Where:

R- Effective Recharge;

Annual PPT- Annual precipitation;

Annual ET- annual evapotranspiration.

3. **Aquifer media (A):** the geological shape file was transformed into a geological raster map via the ArcGIS environment to facilitate overlay analysis. Rates were assigned for each class, and the weight for this parameter was determined on the basis of certain criteria
4. **Impact of Vadose Zone (I):** As described in the aquifer media, geological map attributes are applied for the estimation of the impact of the vadose zone. The rating classes and weights for the impact of the vadose zone are used.
5. **Soil type (S):** The soil type map was prepared on the basis of the soil texture map. The rating value of the soil type can range from 10 to 1 for the seven categories of soil type and a weight of 2 for the soil type parameter.

6. **Topography (T):** The slope map was prepared from a digital elevation map. Slope values can be grouped into seven classes, and the rating value ranges from 1--10.
7. **Hydraulic Conductivity (C):** its raster map is prepared on the basis of the geological nature of the aquifer of the subbasin, as it is possible to use information on aquifer media in the absence of unavailable hydraulic conductivity data. The estimated hydraulic conductivity was used to provide a rating for each geological material[219].
8. **Land use land cover (LULC):** The land use index (LUI) is calculated via equation (2), and the weight for land use and land cover is 5.

$$\mathbf{LUI = Lr * Lw} \qquad (2)$$

Where

- LUI: Land use index;
- Lr: Land use rating;
- Lw: Land use weight

DRASTIC modeling: The simulation of DRASTIC modeling was conducted via spatial analyst extension. This tool, specifically the spatial analyst tool in ArcGIS, enables the processing of various digital map layers to delineate vulnerable zones by calculating the vulnerability index and analyzing the spatial variability of groundwater vulnerability [86]. Each DRASTIC parameter and other digital geospatial dataset for the model were created via collected shape file formats within the ArcGIS environment. Vector formats were converted into raster formats, and weights and rates were assigned to the parameters. By employing a raster calculator and Lookup syntax in the ArcGIS 10.7 environment, overlay analysis of the parameters was performed to generate DRASTIC and the land use index (LUI) via equations (2) and (3). The DRASTIC map product has been categorized into four classes to interpret vulnerability levels: low vulnerability, with values less than 109; moderate vulnerability, ranging from 109--138; high vulnerability, between 138--166; and very high vulnerability, with values above 166, as derived from the processed raster map.

$$\mathbf{DIV = Dr * Dw + Rr * Rw + Ar * Aw + Sr * Sw + Tr * Tw + Ir * Iw + Cr * Cw} \qquad (3)$$

Where:
DIV= DRASTIC index value
r = rating for the parameter

w = given weight for the parameter

D: Depth to groundwater

R: Net Recharge

A: Aquifer media

S: Soil media

T: Topography (slope)

I: Vadose Zone

C: Hydraulic Conductivity of the aquifer

Table 1: DRASTIC and land use index ratings and weight values.

Rating	Depth of water table(m) W= 5	Net Recharge (mm/y) W= 4	Aquifer Media, W=3	Soil Media W=2	Topography (%), W=1	Impact of Vadose Zone W=5	Hydraulic Conductivity (GPD/ft2) W= 3	LULC categories (weight =5)
10	0.0 -1.5		Karst Limestone	Thin or absent, gravel	0-2	Karst Limestone	>2000	Croplands
09	1.5 - 4.5	>250	Basalt	Sandstone & volcanic	2-6	Basalt		Built-up areas
08		180-250	Sand & Gravel	Peat		Sand and Gravel	1000-2000	Urban areas
07	4.5 - 9		Massive Sandstone and limestone	Shrinking/aggregate clay/alluvium		Gravel, sand		Nonirrigated field crops
06		100-180	Bedded sandstone and lime stone	Sandy loam, schist, sand, karst volcanic		Limestone, Sandstone, Sand and Gravel with Silt & clay	700-1000	
05	9 -15		Glacial	loam	6-12			
04			Weathered Metamorphic /igneous	Silt loam		Metamorphic/ igneous	300-700	Grassland/scrublands
03	15 - 23	50-100	Metamorphic /Igneous	Clay loam	12-18	Shale		Water bodies
02	23 - 31		Massive Shale				100-300	
01	>31	0.0-50		Nonshrink & unaggregated clay	>18	Silt/Clay	1-100	Bare areas/uncultivated Forest/tree/

Groundwater Pollution Risk Index: the final GWPR map was generated via a map algebra function that combines the DRASTIC value index and the land use index (LUI) via Equation

(4). The GWPR index values from the resulting raster map were further classified into four risk classes: low, moderate, high, and very high. The GWPR classes are defined by total index values, which are categorized into four levels. A total index value below 165 corresponds to the low-risk class, whereas values ranging from 166 to 207 fall into the moderate-risk category. The high-risk class encompasses total index values between 208 and 249, and any value exceeding 270 is classified as very high risk. This classification system is a valuable tool for assessing and categorizing the severity of groundwater pollution risk, providing a clear and concise framework for understanding and managing groundwater quality within the study area.

$$\mathbf{GWPRI} = \mathbf{DVI} + \mathbf{LUI} \qquad (4)$$

Where:

GWPR: groundwater pollution risk index;

DVI: DRASTIC Value Index

LUI: Land use index

3.3.2. Surface Water pollution risk

The prediction of SWPR involves a combination of four parameters based on equation (5). These parameters, namely, the soil type, slope, land use/land cover and watercourse raster maps, were assigned weights on the basis of findings from similar studies[220]. The nature of each parameter was analyzed via the ArcGIS toolbox. The soil type, land use/land cover, and slope were processed to obtain rated raster maps for subsequent analysis. Furthermore, the watercourse parameter was derived via the multiple-ring buffer tool, following a series of steps utilizing the hydrology tool from digital elevation model (DEM) data. The streams were then classified into four buffering rings or zones, as outlined in **Table 2**, who specified the parameters and their rates for surface water pollution risk estimation[221].

Table 2: Class and rate of each SWPR factor

S/N	Soil type		Slope (%)		Land use		Watercourse (W) [in m]	
	Class	Rate	Class	Rate	Class	Rate	Class	Rate
1	Clays	5	>14	30	Agriculture (Cropland)	20	Zone 1 (0–50)	10
2	Silts/fine sand	4	11–14	21	Barren land	8	Zone 2 (50–200)	6
3	Sands	3	8–10	13	Settlements/ Urban areas	6	Zone 3 (200-1000)	3
4	Organic matter	3	5–7	8	Shrub/bush/ Woodland	4	Zone 4 (>1000)	0
5	Gravels/hard rock	2	3–4	4	Grassland	2		
			1–2	2	Forests	1		
			0	1	Water body	1		

The equation for the production of the final SWPR map is described as follows:

$$\boldsymbol{SWPR = K * S * W * U} \tag{5}$$

Where:

SWPR: Surface water pollution risk

K: Soil type (Texture)

S: Slope in percent

W: Watercourse (Buffer)

U: Land Use

The final overlay analysis classified the data into four risk classes according to the mean values of the product and standard deviation[222]. The low-risk class corresponds to total index values below the mean, whereas the moderate-risk class includes values from the mean to one standard deviation above the mean (mean plus 1 SD). The high-risk class encompasses total index values falling between the mean and two standard deviations above the mean (mean plus 2SD). Finally, the very high-risk class comprises values greater than the mean plus three standard deviations (mean plus 3SD). This classification system, which is based on the mean and standard deviation, provides a concise and quantitative framework for assessing different levels of risk, offering a standardized approach to understanding the GWPR within the study area.

3.3.3. Water pollution Risk modeling

Within the ArcGIS framework, contamination risks for both groundwater and surface water were assessed to determine water-source pollution risks (Figure 2). The matrix addition resulted in the creation of eight classes on the raster map, which were subsequently categorized into three risk levels: low, with values of 2 and 3; moderate, with values of 4 and 5; and high, with values of 6, 7, and 8.

3.3.4. Exposed Population Analysis

In the ArcGIS environment, the population map was generated via the raster layer of the 2016 population density model. The population density raster specific to the upper Awash subbasin was extracted through masking. To estimate the exposed population in the zones of the GWPR, SWPR, and WSPR maps, the Zonal Statistics (Spatial Analyst) tool of the ArcGIS environment was employed. This tool calculates statistics, summarizes the values of a raster within the zone of another raster and reports them as a table. Accordingly, the values of the population density raster map within the zones defined by the three aforementioned raster (GWPR, SWPR, and WSPR) maps were used **(Figure 2)**. Further calculations, involving the proportion or absolute number of people exposed to water pollution risks or residing in different statuses of water pollution risks, were carried out via Microsoft Excel 2016.

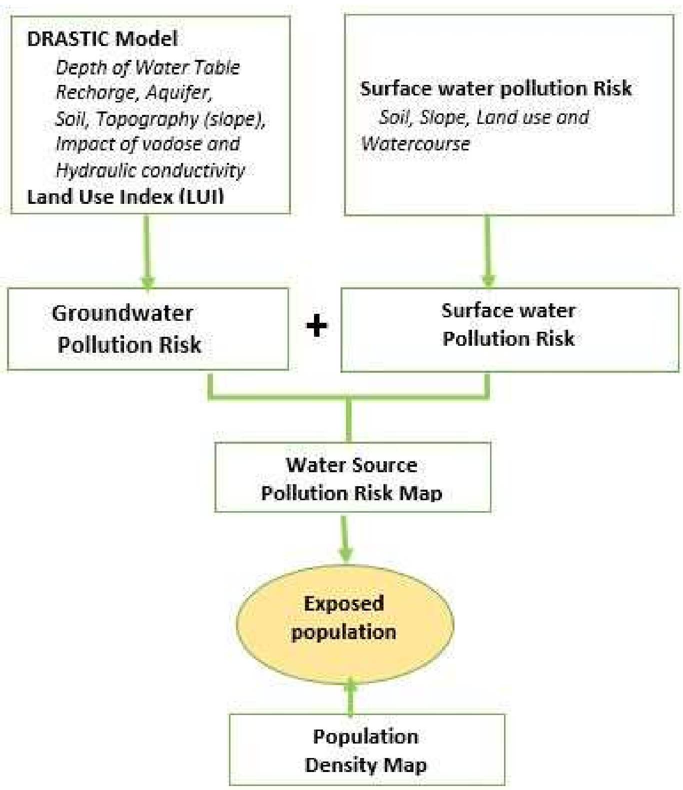


Figure 3: Procedures of ArcGIS operation for different analyses

3.3.5. Model Validation

The validation process utilized nitrate concentrations and raster values, with nitrate chosen because of its contaminant nature in groundwater [86]. Raster values were extracted from the DRASTIC model-generated map and linked with point data from 851 boreholes via the Extract Raster Values to Point tool in ArcGIS. This generated new data for simple regression analysis, validating the model against the ground truth. SPSS version 25 facilitated the statistical analysis and compared the raster values with the observed nitrate concentrations. The nitrate concentration served as the dependent variable, whereas raster values were considered independent [Equation (6)]. The assumptions of normality, linearity, homoscedasticity and independence for linear regression analysis were satisfied. The model's goodness of fit was assessed through the coefficient of determination (R-square). It signifies the proportion of total variation in the dependent variable explained by variations in the independent variable. The remaining percentage reflects unexplained variations in nitrate concentration attributed to factors not considered in the DRASTIC value index.

$$Y_i = \beta_o + \beta_1 X_i \; + \; \varepsilon_i \tag{6}$$

where Y_i is the dependent variable (nitrate concentration, mg/l), β_o is the population intercept, β_1 is the population slope coefficient, Xi is the independent variable (raster values) and ε_i is a random error term.

In addition, the model was validated via linear regression analysis of model output (DRASTIC index) values extracted from the product map (extraction – extract values to points) and the observed nitrate concentrations from 60 drinking water samples collected in 2 districts of the study area. The R2 was predicted from the relationship between the dependent variable (NO3) and independent variable (DRASTIC index value) with the assumption that if there was valid groundwater vulnerability, the index value increased proportionally to the concentration of nitrate with a significant R^2. The nitrate concentration is used for validating the DRASTIC model and assessing the accuracy of its predictions, as it is a common indicator of groundwater contamination, particularly from agricultural sources such as fertilizers[121,223].

3.3.6. National Water, Sanitation and Hygiene (WASH) Inventory

Spatial point data of 2,864 water supply schemes located in the subbasin were extracted from the National WASH Inventory-2 (NWI-2) database of the Ministry of Water and Energy (MOWE) to analyze the vulnerability of water supply schemes. The National WASH inventory is a key component of the comprehensive One WASH National Program (OWNP) monitoring and evaluation system used to achieve the Sustainable Development Goal (SDG-6), which was implemented nationwide in March 2019 to generate information to improve service levels[224]. The NWI-2 database was established as an online mobile data collection platform through the management of the MOWE. NWI-2 point data were processed in the ArcGIS environment. Ten percent of the scheme data were not extracted from the downloaded file due to errors and were excluded from the analysis. Additionally, users of boreholes in urban areas were excluded, as the data for water supply systems in urban areas are limited in terms of user data and need further analysis.

3.3.7. Delineation of the Water Source Protection Zone

The delineation of the groundwater protection zone was performed via overlay analysis of the resulting DRASTIC model map with National WASH Inventory point data **Figure 4**. Accordingly, with the use of the ring-buffering tool in the ArcGIS environment, the following three zones are established for wells, boreholes, springs, springs, and water intake structures. The groundwater source protection zones include 1) the Inner Protection Zone, which has a minimum radius of 50 m [115]; 2) the Outer Protection Zone, which has a radius of 500 m [114]; and the Catchment Protection Zone, which is the area around the water source within which all the groundwater recharges. It includes the entire groundwater catchment of the well field[114]. Source protection areas were produced for the upper Awash River subbasin. The resulting map is then overlain with simple maps of the inner and outer source protection areas to delineate the vulnerability of both the inner and the outer source protection areas. This map is the basis for defining the level of protection to be implemented for each area[115].

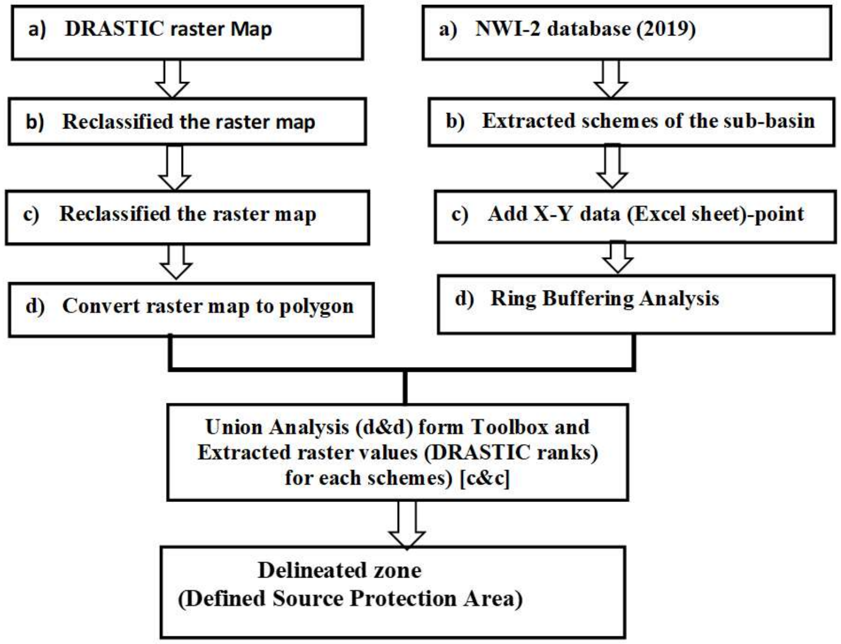


Figure 4: Procedures of source protection area delineation

3.3.8. Water pollution index

In this research, the methodology incorporates the use of a water pollution index to comprehensively evaluate the overall health of a water body within a subbasin. The Nemerow pollution index is specifically employed to assess the degree of surface water pollution, both as a quantitative measure and as a validation tool for broader water source pollution risk (WSPR) assessment. Surface water data, which were systematically collected in 2021 from ten river water sampling stations located within the subbasin, were obtained through the Ministry of Water and Energy (MOWE) for monitoring surface water quality. The collected dataset was prepared for analysis via MS Excel 2016 software via Equation (7). A comprehensive data management process resulted, including checks for missing data, treatments for outliers, and general data cleaning procedures. The average values for both the dry and wet seasons were subsequently computed for further analysis and interpretation.

$$\boldsymbol{WPI} = \sqrt{\frac{[(\frac{1}{N})\sum(\frac{Ci}{Si})]^2 + [\mathbf{Max}(\frac{Ci}{Si})]^2}{2}} \tag{7}$$

Where

WPI: Water Pollution Index.

N: number of water quality parameters considered.

Ci: concentration of the i^{th} parameter in the water sample.

Si: standard or permissible limit for the i^{th} parameter.

Max: maximum concentration

The index has six categories, each with a different range of numbers: no pollution (up to 0.5), clean (0.5--0.7), warm (0.7--1.0), polluted (1.0--2.0), medium pollution (2.0--3.0), and severe pollution (above 3.0). The index can be used to evaluate the ecological condition and health risk of a water body and to suggest ways to improve water quality.

3.4. WATER QUALITY ANALYSIS

3.4.1. Water Quality Index (WQI)

Each of the 15 water quality parameters was assigned different weights on a scale of 1 for the least effect on water quality and 5 for the greatest effect on water quality. Weights are determined on the basis of their importance to overall water quality and primary health effects concerning drinking water quality with the support of the literature (Annex 1). The relative weight (Wi) is computed via Equation 8:

$$\mathbf{Wi = wi / \sum_{i=1}^{n} wi} \qquad (8)$$

Where:

Wi: relative weight, wi: weight of each parameter, and n: number of parameters.

The quality rating (qi) for each parameter (equation 9) is assigned by dividing its concentration in each water sample by its limit values and multiplying the result by 100:

$$\boldsymbol{qi = \frac{Ci}{Si} x\ 100} \qquad (9)$$

Where:

qi: quality rating, Ci: concentration of each chemical parameter in each water sample in mg/L, and Si: drinking water standard for each chemical parameter in milligrams per liter

To calculate the WQI, the SIi value is determined as

$$\boldsymbol{SI_i = Wixqi};\ \mathbf{WQI = \sum_{i=1}^{n} SI_i} \qquad (10)$$

Where:

SIi: subindex of the i^{th} parameter, qi: quality rating based on the concentration of the i^{th} parameter (equation 10).

The computed WQI values are classified into five categories: 50 excellent water qualities; 50–100 good water qualities; 100–200 poor water qualities; 200–300 very poor water qualities; and < 300 unsuitable for drinking, which indicates that the water quality falls below acceptable standards for human consumption and leads to health risks if consumed without treatment. The classification is determined through scientific analysis and consultation with experts in the field of water quality to establish regulatory standards and ecological health guidelines and characterize water quality[102].

3.4.2. Parametric and Non parametric test

The parameters and nonparameter tests were accomplished **via** IBM SPSS version 25. **A** parametric test of one-way ANOVA was used to estimate the means of the concentrations of water quality parameters and WQI changes due to seasons of the year (wet and dry seasons) and locations (2 districts). Assumptions and tests for ANOVA were conducted, including assessments for normality, homogeneity, and treatment of outliers and missing data. Parameters that did not fit the normality test were transformed by a common logarithmic function. When the assumption and tests fail, nonparametric tests (independent samples Mann–Whitney U test) are applied to identify water quality changes due to independent factors that influence water quality parameters. Statistical measurements such as relative error, the sum of square error, residual analysis, and coefficient of variation/determination, a p value of 0.05, and 95% confidence intervals were used to determine statistical significance.

3.4.3. Artificial Neural Network (ANN) analysis:

A multilayer perceptron of the ANN type was applied via IBM SPSS version 25. In this statistical model, the ANN analysis uses WQI as the dependent variable and predictor variable, which are all water quality parameters and are plugged in covariate (scale) space in both drinking water and river water samples. The dependent variables and covariates were rescaled via a standardized method to improve network training. The partition dataset was prepared separately to assign 70% training and 30% testing datasets. Two hidden layers were used to decrease complexity and computational demands. A hyperbolic tangent activation function for the hidden layers and an identity activation function for the output function with the automatic computation of a number of units were used. Batch types of training and scaled conjugate gradients of the optimization algorithm were applied to estimate the synaptic weights. The evaluation of the model summary included an examination of the sum of squares error and relative errors, a comparison of the predicted values with the observed values, and an assessment of the residuals by the predicted values. Furthermore, an analysis of the importance of the independent variables was conducted. Additionally, the results were validated via linear regression analysis.

3.4.4. Geochemistry of ground and surface water

Using AquaChem 2014.2 software, analysis and plot visualization of the water quality data were performed to evaluate the geochemistry of the groundwater and surface water types. Guidelines were applied during software execution. To illustrate the data on water quality, analysis tools, including Piper plotting and the calculation of water facies, were used[225]. The amount of each cation and anion contributing to the overall concentration of ions in the solution, expressed as equivalents per liter, was used to determine the different types of water. Short and long water types were computed in this calculation. The cations and anions with the highest equivalent concentrations are combined to determine the short water type, and concentrations of 10% - 20% contributions are combined to determine the long water type. More than 10% of an ion is considered dominant.

3.4.5. Principal Component Analysis (PCA)

Principal component analysis (PCA) was conducted via SPSS version 25 to reduce the dimensionality of the dataset while retaining as much variance as possible. The process begins by standardizing the data to ensure comparability across variables, followed by computing the covariance matrix to examine the relationships between variables. Eigenvalues were calculated to determine the significance of each principal component. On the basis of these findings, the most important components were selected, and varimax rotation was used to improve interpretability. The analysis helped identify the number of pollution sources and their associated contaminants.

3.4.6. PMF Model

3.4.6.1. Sanitary survey

At the time of sample collection, a sanitary survey of the water supply system was performed via a predetermined checklist, and probable sources of pollution were identified. The survey was used to identify the source of water pollution as well as inputs for the source contribution and source profile analyses. These results were used to determine the origin of water supply pollution sources and help to fix the number of factors for the PMF model.

3.4.6.2. Analyze Input Data

This receptor model considers 120 water supply plans, 208 borehole samples, and 230 surface water samples. The outliers and missing values were handled in accordance with the reference's recommended procedure[226]. For data entry, a dataset with 20% uncertainty (analytical and sampling error) was generated along with concentrations with nonzero and negative values. Input files were submitted to the model and contained information such as different species, concentration values, sampling IDs, and dates. Significant parameters were determined by analyzing the input data statistics after the prepared data had been uploaded. These statistics included classifications (strong, weak, and bad), the signal-to-noise ratio, minimax, percentiles, concentration scatter plots, and time series graphs. Records of species correlations were made to monitor species with comparable source types[227].

3.4.6.3. Base Model

1. The concentration scatter plot of the pollutants, the findings of the sanitary survey, the hydrochemistry water types, the features of the parameter, and the literature were all used to determine the number of components. For establishing source profiles, and contributions, runs have been carried out using the recommended 20 base runs.
2. **A**fter base runs**,** minimum Q (robust) and converged solutions were identified for goodness-of-fit parameter as per equation (11)[226,228].

$$\mathbf{Q} = \sum_{i=1}^{n} \sum_{j=1}^{m} \left[\frac{x_{ij} - \sum_{k}^{p} g_{ik} f_{ki}}{\mu_{ij}} \right]^2 \tag{11}$$

Where:

Q: [Q (true) is the goodness-of-fit parameter calculated including all points and Q (robust) is the goodness-of-fit parameter calculated excluding points not fit by the model]

x_{ij}: the j_{th} species concentration measured in the i_{th} sample,

g_{ik}: the species contribution of the kth source to the i_{th} sample,

f_{kj}: the j_{th} species fraction from the kth source,

e_{ij}: the residual for each sample/species, and

p: the total number of independent sources

μ: uncertainties

3. Examining the Q/Qexp graphs, the factor fingerprints, the rotating G-space plots, and the factor contributions were examined. These methods were used to check the model's fit: observed/predicted scatter plot, profiles/contributions, and residual analysis. Using a rotatable tool for further investigation, the problem of the non-uniqueness of solutions was addressed.
4. In order to discover error estimates of Bootstraps (BS) for random error, Displacement method (DISP) for rotational ambiguity, and BS-DISP for both random error and rotational ambiguity, 100 BS runs were used to check the mapping proportion between bootstraps and factors.
5. Rotational Tool Application (Fpeak Runs): Following the basic run, Fpeak runs and an evaluation of the Fpeak data were conducted.

3.5. WATER QUALITY DATA SOURCE, SAMPLING AND TESTING

Data on surface and groundwater quality were sourced from the Ministry of Water and Energy (MOWE) and the Awash Basin Authority. Surface water quality was monitored at ten sampling stations from September 2011 to December 2021, while groundwater quality data were collected from boreholes during pumping tests starting in April 2021. To verify these findings, 60 samples were collected from Sebeta-Hawas and Bereh Districts during both dry and wet seasons; these samples represented various water supply systems: 37 shallow wells (nine hand-dug), five boreholes, four protected springs, and five unprotected springs. The average values for water quality were calculated over three seasons on the basis of four months of data. For drinking water, 120 samples were taken, with 60 collected during the dry and wet seasons. The number of samples was chosen on the basis of the requirements of minimal sample size for statistical analysis[229]. Various methods were applied to prepare the raw data for analysis, including checking for missing values and treating outliers, ensuring robust data quality for the study.

The exact sampling locations were identified by overlaying the WPR map onto the National WASH Inventory (NWI-2) database via the ArcGIS environment[230]. Adequate equipment and materials were prepared, and representative water samples were collected, documented, and handled according to the quality assurance protocols of the WHO. Furthermore, to ensure data integrity, rigorous measures such as aseptic equipment sterilization, blank measurements, and duplicate analysis were employed. The number of samples was calculated by applying the minimal sample size requirements for statistical analysis[229]. The types of water quality indicators chosen for analysis were determined on the basis of their public health significance and regular occurrence in these locations.

A Thermo Scientific star A 325 pH/ISE meter was used to measure Tem (C^{o}), TDS (mg/l), and EC (S/cm) onsite[231]. Calibration was performed before these targeted parameters were measured according to the user's manual. A Palintest 7100 Photometer was used to examine water quality parameters such as Fe (mg/l), Mn (mg/l), F (mg/l), Cr(VI) (mg/l), As (/l), NO_2 (mg/l), NO3 (mg/l), NH_3 (mg/l), $SO_4{}^2$ (mg/l), Mg (mg/l), Ca (mg/l), and alkalinity (mg/l)[232]. In accordance with the user's manual, reagents in tablet form designated for the Palintest Photometer 7100 device were employed for these parameters. Calibration and validation were performed by the manufacturer, and specific dates and intervals were verified in accordance with the provided documentation of the manufacturer. Arsenic was also analyzed via a portable digital arsenator[233]. Upon reaching zero, any key was pressed to retrieve the result, revealing the arsenic concentration in parts per billion (ppb). An Aquasafe WSL25 Plus microbiological test kit was used for microbial testing and analysis [234]. The membrane filter technique specified in the American Public Health Association's (APHA) Standard Methods for the Examination of Water and Wastewater was used. *Total Coliform (TC)* and *Escherichia coli (E. coli)* in Water Detected by Membrane Filtration and Simultaneous Detection (M-broth). The bacteriological sampling procedures, such as cleaning, disinfection with alcohol and the use of an appropriate amount of water in the sample bottle, filtering, incubation and reading after 48 hours and calculation, were performed in accordance with the sampling guidelines. The number of colony forming units (CFUs) for each bacterial strain was calculated via equations (12) and (13).

A 100mL sample was filtered and incubated at 37°C for 24 hours. Finally, using the following formula, record the red and blue colonies as *TC* forms and the blue colonies as *E.coli* and report as *E. coli* or *TC* per 100 mL of drinking water[235].

$$\boldsymbol{E.coli/100\mathrm{mL}} = \frac{\boldsymbol{Numberofbluecolonies}}{\boldsymbol{Volumeofsamplefiltered\ (mL)}}\ \boldsymbol{x\ 100} \tag{12}$$

$$\boldsymbol{TC/100\mathrm{mL}} = \frac{\boldsymbol{Numberoffluorescentcolonies+Number\ ofblue,non-fluorescentcolonies(ifany)}}{\boldsymbol{Volumeofsamplefiltered\ (mL)}}\ \boldsymbol{x\ 100} \tag{13}$$

3.6. RISK ASSESSMENT PROCEDURE AND ASSUMPTIONS

3.6.1. Chemical Risk Assessment

i. **Hazard identification**: A review of the literature was conducted to determine the chemical risks to the water supply that can potentially cause toxicity. *E. coli* was assessed, as it is one of the most prevalent etiological agents for diarrheal disease and an indicator organism for risk-based regulation[205].

ii. **Dose–Response**: Arsenic, chromium (VI), fluoride, nitrate, nitrite, and iron reference dose (RfD) (mg/kg-day) and slope factors of chromium and arsenic were retrieved from the USEPA's IRIS database and other sources. (**Table 3**) [236].

Table 3: Parameter reference dose (RfD) for risk quantification for the oral exposure route

No	Parameters	Some of the health effects (Hazards)	RfD	Slope factor and Age Dependent Adjustment Factor (ADAFs)	Ref.
1	Arsenic	Hyperpigmentation, keratosis, and possible vascular complications	3 x 10-4 mg/kg-day	CSF: 1.5 ADAFs: 3 (for <16 years of age) ADAFs:1 (>16 years)	[236]
2	Chromium (VI)	None reported	3 x 10-3 mg/kg-day	CSF: 0.5 ADAFs: 3 (for <16 years of age) ADAFs:1 (>16 years)	[236]
3	Fluoride	Dental fluorosis	6 x 10 -2 mg/kg-day		[236]
4	Nitrate	Methemoglobinemia	1.6 mg/kg-day		[236]
5	Nitrite	Methemoglobinemia	1 x 10 -1 mg/kg-day		[236]
6	Iron	Gastrointestinal toxicity	7X10-1 mg/kg/day		[236]

iii. **Exposure assessment:** Chemicals in drinking water are calculated in this step on the basis of their concentrations, frequency of occurrence, and duration of exposure to drinking water. The laboratory results of six water quality measures and the assumptions indicated in the following table were used to calculate daily chronic intakes for each group (**Table 4**) [188].

To calculate intake,

$$\mathbf{I} = \frac{CxIRxEFxED}{BW} x \frac{1}{\mathbf{AT}} \tag{14}$$

where:

I: Daily Chronic Intake

C: Average concentration (mg/l)

IR: Contaminant medium ingested per day (L/d)

EF: Exposure frequency per year (days/year)

ED: Exposure duration, lifetime (year).

AT: Average time (days)

BW: Average body weight

Table 4: Sources for the calculation of Daily Chronic Intake exposure

Exposure parameter and description		Unit	Value	Ref.
I	Daily Chronic Intake	mg/kg/d		
AT	The period over which exposure is averaged	day	365	[188,189]
BW	Average body weight over the exposure period	kg		
	Men (>15 Years)	kg	(56.4, 15.95)	[237]
	Women (>15 Years)	kg	(51.8, 14.96)	[237]
	Child <15 years	kg	23	[188,189]
C	Average concentration ingested over the exposure period	mg/L	-	-
IR	Contaminant medium ingested per day	L/d		
	Men (>15 Years)	L/d	2	[188,189]
	Women (>15 Years)	L/d	2	[188,189]
	Child <15 years	L/d	1.4	[188,189]
EF	Exposure frequency per year	days/y	25,550.00	[189]
ED	Exposure duration (lifetime).	y	70	[189]

3.6.2. Chemical Risk Characterization

The cancer, noncarcinogenic, and aggregated risks of the parameters were characterized. The hazard quotient (HQ) (Equation 3) was used to assess noncancer risk. If the HQ is greater than one, it is taken as a potential noncancer effect from exposure. This signifies that if the exposure concentration exceeds the reference dose (RfD)/threshold level, the likelihood of noncancer risk is significant.

$$\textbf{Hazard Quotient} = \frac{\mathbf{I}}{\mathbf{RfD}} \tag{15}$$

where

I: Daily chronic intake, mg/kg body weight – day (Equation -2)

RfD: Reference Dose, mg/kg body weight – day (Equation- 1)

The hazard quotient (HQ) (Equation-15) was used to assess noncancer risk. If the HQ is greater than one, it is taken as a potential noncancer effect from exposure. This signifies that if the exposure concentration exceeds the reference dose (RfD) threshold level, the likelihood of noncancer risk is significant. To interpret the risk data, if it is less than 1.00E-06 (1 in 1,000,000 people), it is considered safe; if it is between 1.00E-04 and 1.00E-06, it is considered satisfactory; and if it is greater than 1.00E-04, it is considered unacceptable carcinogenic risk.[238].

$$\textbf{Risk} = \textbf{IxSFxADAFs} \tag{16}$$

where:

- Risk: a unitless probability of an individual developing cancer
- I: Chronic daily intake average over exposure years (mg/kg-day)
- SF: Slope factor (mg/kg-day) and
- ADAFs: Age-dependent adjustment factors

On the basis of Equation (17), the hazard index (HI) and the six HQs were summed to estimate the cumulative noncarcinogenic risk for numerous water quality indicators. A satisfactory HI result is less than one (HI <1), as in HQ. [239].

$$\textbf{Hazard Index} = \frac{\mathbf{F}}{\mathbf{RfD_F}} + \frac{\mathbf{NO2}}{\mathbf{RfD_{NO2}}} + \frac{\mathbf{Fe}}{\mathbf{RfD}_{Fe}} + \frac{\mathbf{Cr}}{\mathbf{RfD_{Cr}}} + \frac{\mathbf{NO3}}{\mathbf{RfD_{NO3}}} + \frac{\mathbf{As}}{\mathbf{RfD_{As}}} \tag{17}$$

where

I: Exposure level for the specified toxicant

RfD: Reference dose for the specified toxicant

3.6.3. Monte Carlo simulation for chemical risk analysis

A Monte Carlo simulation was performed to make statistical inferences from the sample statistics. The probabilities of exposure and risk were calculated for stratified areas with high WPRs. The analysis was carried out with Microsoft Excel 2016 and SPSS version 25. The concentrations of parameters such as F, NO_2, Fe, Cr(VI), As, and NO_3 with the sample mean, standard deviation, and 95% confidence intervals were determined via a random number generator (RNG) with 10,000 iterations under the assumption of a normal distribution. The values were entered into the daily chronic intake calculation. The technique ensures that the output risk distributions converge and are stable. This two-dimensional Monte Carlo analysis was performed to meet the criteria for probabilistic risk assessment[240].

3.6.4. Microbial risk analysis

1. **Microbial exposure analysis**: The amount of contaminant water ingested per person per day is 2 liters, and the microbiological exposure frequency is 90 days per year for the rainy season, 275 days per year for the dry season, and 365 days per year for the annual average. It is assumed that daily drinking water consumption is the route of exposure, that the population has equal susceptibility to diseases, and that secondary infection by pathogens is ignored[188,189].
2. **Microbial dose–response analysis**: Microbial dose–response analysis was performed via an approximate beta-Poisson model (Equation 18) [207].

$$\boldsymbol{Pi(D) = 1 - (1 + D)/\beta)^{-\alpha}} \tag{18}$$

Where: Pi (D) is the probability of infection; D is the mean dose; and β = 1.78E+6 and α = 0.1778 for *E. coli* (pathogenic strain). On the basis of the literature, 8% of the CFUs of *E. coli* identified in the drinking water supply are estimated to be pathogenic *E. coli*[241]. In addition, the annual microbial infection probability (equation (19)) was calculated as

$$\boldsymbol{P = 1 - (1 - Pinf)^{n}} \tag{19}$$

where P (annual and seasonal infection probability), Pinf (the probability of infection for a single exposure to a dose D of *E. coli*) and n (the frequency of exposure- 365 days/year)[208]

3. **Microbial risk characterization**: This characterization uses the WHO criterion for the daily risk of infection (1 in 10,000,000) and the annual infection risk (1 in 10,000 people) [242].
4. **Monte Carlo simulation**: The simulation was carried out with the help of Microsoft Excel 2016 random number generation (RNG). This method produced random numbers with a normal distribution for the *E. coli* dose/2 liters of water and 10,000 iterations on the basis of the sample mean and standard deviation of the microbial dose. SPSS version 25 was used to examine the dataset and determine potential hazards (mean and standard deviation with 95% CI).

3.7. QUALITATIVE DATA COLLECTION AND ANALYSIS

Focus group discussions (FGDs) were held with five MOWE professionals working on the WSP. The experts discussed the subject matter (thematic area) on the basis of their knowledge, experiences, and what is happening in the MOWEs related to the WSP. Source protection and zoning (buffering) are accomplished with the assistance of field reports, training reports, workshop reports, and annual performance reports. A structured questionnaire (Supplementary material) was used to manage the focus discussion, which was moderated by the primary investigator. The questionnaire includes the enabling environment for WSP at the national and local levels, current and implemented significant WSP activities, and implementation gaps with remedial strategies, such as idea development for policy and decision-makers. Thematic analysis was used to analyze the acquired data on the water source protection themes.

CHAPTER 4: RESULTS AND DISCUSSION

3.1. WATER POLLUTION RISKS AND ESTIM EXPOSED POPULATION

This study aims to map water pollution risks in the upper Awash River subbasin and predict the number of exposed populations via ArcGIS. This research provides evidence for effective risk reduction and source protection strategies for water quality, land, and urban management. The following sections analyze and describe various factors influencing water quality at the watershed scale.

3.1.1. Validation of DRASTIC Model

Model validation is a crucial step in evaluating the model results. As a result, in the model validation via linear regression, assumptions of normality, linearity, homoscedasticity, and independence were checked via visual inspection of graphs and tests; for example, the Durbin–Watson test (1.7) is in the acceptable range of 1.5--2.5, which indicates independence between the targeted variables.

Table 5: Results of linear regression analysis for mode validation

Descriptive Statistics	**Variables**	**N**	**Mean**	**Std. D**		
	Nitrate (mg/l)	851	8.30	11.19		
	Index value	851	136.86	24.98		
Model Summary	**R^2**	**F Change**	**df1**	**df2**	**Sig.**	**Durbin-Watson**
	0.678	1788.845	1	849	0.000	1.711
ANOVA		**Sum of Squares**	**df**	**Mean Square**	**F**	**Sig.**
	Regression	72156.86	1	72156.86	1788.85	0.000
	Residual	34246.22	849	40.34		
	Total	106403.08	850			
Coefficients	**Unstandardized**	**t**	**Sig.**	**95.0% CI for B**		
	B			**Lower Bound**	**Upper Bound**	
	- 42.185	-34.771	0.000	-44.566	-39.80	
	0.369	42.295	0.000	0.352	0.386	

The model summary reveals that 67.8% of the variance in the dependent variable, nitrate concentration, is explained by the independent variable, raster values of the DRASTIC index. The significant P value in the ANOVA table (P<0.001) ensures that the regression model better predicts the dependent variable than chance. The coefficients table provides values for equation (1) to predict nitrate concentrations from raster values. Within the 95% confidence interval for B, the intercept is -42.19, and the slope is 0.37, indicating that the parameter value for the slope of the regression line is between 0.352 and 0.39. The validation process using nitrate concentrations in the DRASTIC model confirmed its effectiveness in assessing water pollution risk. Nitrate concentrations exceeding 2 mg/l are attributed to human activities, revealing a strong association with pollution risk indices explained by 67.8%[243]. The validation produced a predictable model; for every one unit increase in the groundwater vulnerability index, the nitrate concentration increased by 0.37 units. Consequently, the DRASTIC model's input parameters are validated and accepted[244]. On the other hand, correlations were observed between the cropland percentage, temperature, and precipitation, with negative impacts on the nitrate concentration[245]. Positive correlations were found between the nitrate concentration in the vadose zone and increased groundwater depth due to denitrification processes[246,247]. Nitrate sources in groundwater, whether natural or anthropogenic, contribute to varying concentrations of nitrate[248]. This study aligns with a report from the Awash River Basin, indicating elevated nitrate concentrations in the upper Awash River subbasin compared with other catchments, verifying the study's mean concentration of 8.30 mg/l[249].

3.1.2. Water pollution Index

In the calculation of the water pollution index (WPI), fifteen water quality parameters were considered. The analysis revealed notable variations in the mean values of these parameters between the wet and dry seasons. Specifically, during the dry season, nine parameters (TDS, pH, TH, Ca, Mg, HCO3, F, NO3 and Cl) presented relatively high mean values, whereas six parameters (Na, K, Fe, Mn, NO2, and SO4) presented elevated mean values during the wet season (Supplementary #1).

The computed WPI values for the dry season exceeded 1 for all ten monitoring sites, indicating surface water pollution. Among these sites, two were categorized as polluted (1.0--2.0), three as medium pollution levels (2.0--3.0), and five as severe pollution levels (above 3.0) (**Table 6**). These findings highlight the urgent need for remedial measures to increase water quality, emphasizing the importance of addressing ecological conditions and mitigating health risks associated with river water in the targeted subbasin.

Table 6: Water pollution indices of ten river water quality monitoring stations.

S/N	Water Quality Monitoring Station	Seasons of the year	
		Dry season	Wet Season
1	Koka	1.78	1.26
2	Zeway	2.50	1.47
3	Modjo	3.86	1.24
4	Ginchi	1.39	2.21
5	Great Akakie	2.43	1.39
6	After Abasamuel	4.98	0.78
7	Legedadi	1.70	0.85
8	Melkakunter	3.23	1.31
9	Little Akakie	4.96	0.94
10	Ombolie	2.17	3.68

This research, which employs the WPI in various locations, provides valuable insights into diverse water quality conditions and concerns across ecosystems. In Greek rivers and lakes, studies have revealed moderate to high pollution levels, emphasizing the urgent need for environmental intervention [250]. Similarly, the WPI demonstrates a significant correlation between pollutant concentration and water quality management, offering crucial insights for prioritizing effective management measures[251]. In Basrah Marshes, Iraq, undesirable physicochemical parameters result in elevated water pollution index values, categorizing the water as not clean and highlighting critical environmental challenges[252]. Investigations in the Yangtze River and Yellow River Basins in China underscore the complex impact of increased pollution, with variations observed between basins and seasonal influences on agricultural pollution[253]. The correlation between the water pollution index and the incidence of diarrhea in children under five years of age in the coastal area of Semarang city, Indonesia, underscores the critical health implications of water quality, emphasizing the necessity for comprehensive water quality management [254].

In contrast, the Alaknanda River in Uttarakhand, India, consistently maintains good water quality conditions throughout the year, as evidenced by the WPI[251]. Similarly, an investigation of the Heilongtan Reservoir in China revealed stable water quality over three years, with minimal temporal and spatial changes, implying effective water quality management practices [255]. In the Dramaga Campus in Indonesia, the use of a pollution index suggests a favorable water quality status[256]. Despite exhibiting low pollution levels, the Ganges River in Bangladesh highlights the importance of implementing proper management and monitoring strategies for sustainable use [257]. Finally, the evaluation of Lugu Lake in China, which employs the Nemerow pollution index and single-factor pollution index methods, consistently indicates good water quality conditions over three years, indicating effective environmental management[258].

In general, this study and others conducted globally demonstrate the utility of the WPI in assessing water pollution status. The WPI serves as a valuable tool for enhancing water quality and mitigating the adverse effects of water pollution. For example, evaluations of groundwater quality in China, Indonesia, and Egypt, which incorporate pollution indices such as the Nemerow and DRASTIC models, have revealed the complex influences of pollutants and aquifer vulnerability. These assessments offer crucial insights for sustainable groundwater management[259]. The utilization of the WPI for groundwater vulnerability mapping in Datong city, China, emphasizes the importance of integrated approaches in evaluating groundwater quality, especially in regions with limited data[260].

3.1.3. Ground Water Pollution Risk

In the designated subbasin, an integrated approach combining the DRASTIC model and land use index is employed to predict groundwater pollution risk. This model, developed from governing equations and a weighting system involving eight parameters through overlay analysis, provides a comprehensive assessment that facilitates the prioritization of groundwater protection measures[230]. It effectively captures the impacts of human activities such as agriculture, urban planning, industrial development, and deforestation/afforestation on water quality. The method uses standardized land use ratings and weights to generate risk maps, which are then interpreted on the basis of four classes of risk levels. As a result, approximately 32.96% of the subbasins fall into the low GWPR category, whereas 53.56% are classified as having a moderate risk level (Figure 3). Furthermore, more than 13.5% of the subbasin is identified as having a high groundwater risk level (**Table 7**). This approach provides valuable insights for targeted intervention and management strategies to mitigate groundwater pollution.

Table 7: Groundwater pollution risk level of the upper Awash subbasin

S/N	Risk Levels	Area (m^2)	%
1	Low Risk (77-165 value)	3528673200	32.96
2	Moderate (166-207 value)	5734532700	53.56
3	High Risk (207 – 249 values)	1440726300	13.46
4	Very High Risk (249-256 values)	3491100	0.03
	Total	10707423300	100

Groundwater quality is subject to the influence of geological, physicochemical, biological, and anthropogenic factors. Notable anthropogenic contributors include municipal waste dumpsites, sewage effluent, and agricultural fertilizers. Hydrogeochemical characterization, water–rock interactions, and mixing of water through geochemical processes are hydrogeological factors that contribute to groundwater pollution[71]. The DRASTIC model is rooted in the physical characteristics affecting groundwater pollution potential. These physical characteristics include depth to water, net recharge, aquifer media, soil media, topography, impact of the vadose zone, and hydraulic conductivity of the aquifer[30].

The depth of the water table plays a crucial role in the infiltration of pollutants within the unsaturated zone of the aquifer, with shallower depths indicating increased vulnerability to contaminants. The recharge process facilitates the transport of surface pollutants into the subsurface. Higher net recharge in the aquifer corresponds to an increased likelihood of contaminating the water table[86]. It is influenced by precipitation, evapotranspiration, and land use characteristics, resulting in variable recharge ratios. A precipitation raster map was generated via interpolated data from 13 meteorological stations over a 30-year period. The evidence indicates that a significant proportion of groundwater recharge in the Middle Blue Nile Basin contributes to the storage of aquifer systems in the Upper Awash Basin[261]. The aquifer medium serves as a subsurface water storage unit and facilitates the transport of contaminants within it, with the speed of transportation being determined by the aquifer type[85,88]. In areas where the aquifer system has low retardation and filter percolating fluid capacity, it becomes highly vulnerable to surface contamination[262]. In addition to vulnerability characteristics, the types and loads of contaminants play influential roles in groundwater pollution, ultimately influencing the choice of protective measures[263]. In the southern part, the upper and lower regional basaltic aquifers combine to form an unconfined regional aquifer system, whereas the lower and upper systems are separated by a regional aquiclude, resulting in confined aquifers in the northern and central parts of the subbasin[264]. On the other hand, the Vadose Zone serves as the connector in the hydrologic cycle between the surface component and groundwater and is influenced by factors such as texture, mineral composition, grain size, and fracturing [85,87,88]. It acts as a protective zone for groundwater and is the region between the ground surface and the water table aquifer media. The impact of stormwater infiltration systems on groundwater is contingent on the thickness of the vadose zone, as distinct biogeochemical processes occur within it. Parameters such as water transit time and water saturation in the vadose zone are crucial for bacterial transfer associated with infiltration[265].

Hydraulic conductivity quantifies the ease with which a fluid moves through the pore space of an aquifer, determining the potential movement of contaminants in saturated media through the interconnectivity of voids within the aquifer. A higher hydraulic conductivity rate indicates greater vulnerability of the aquifer to groundwater pollutants[89]. Various physicochemical processes of the soil, such as sorption, ionic exchange, oxidation, or biological activity, affect the transportation of pollutants and serve as the primary defense against contaminants entering groundwater. The soil type parameter is mapped via a digital soil texture map and assessed for its ability to retain pollutants of seven classes [85,87,88]. A gentle slope facilitates the movement of pollutants from the ground surface to the groundwater, whereas areas with steeper slopes tend to generate more runoff, reducing the infiltration of contaminants into the groundwater[85,87,88]. Additionally, land use and land cover on the ground surface are significant factors affected by land degradation, which, in turn, has repercussions on water quality [8]. Activities such as soil erosion, sediment deposition in water bodies, deforestation, and changes in cropland and pastures contribute to the deterioration of water quality[6]. Furthermore, inadequate irrigation management and reservoir seepage can result in the contamination of groundwater quality[7].

Deteriorated water quality is evident downstream and is influenced primarily by dominant urban land use and point source water pollution[10]. Various anthropogenic factors, including high livestock density, grazing animals, pasture production, and other land use activities, significantly contribute to water quality issues[57,266]. Within the subbasin, there is a noticeable trend of increased cropland utilization and urban expansion, which contrasts with the inadequate maintenance of vegetation cover. Land use and cover changes have led to substantial fluctuations in streamflow and sediment yield [267]. Accelerated deforestation rates, population growth, urbanization, and cropland expansion have adversely impacted both available water resources and the stipulated water quality parameters[268]. These findings emphasize the imperative for future land use and cover improvements, emphasizing the necessity of developing effective basin management strategies.

Addressing groundwater pollution is challenging, necessitating the safeguarding of groundwater sources by implementing risk reduction measures within the watershed management framework. Key solutions involve delineating groundwater vulnerability and mapping protection zones. This approach serves to minimize the probability of hazard release, mitigate the consequences of hazards, reduce residual risks of groundwater contamination, and identify the weakest barriers for effective risk management[84]. Evidence from subbasin areas underscores the influence of geogenic processes and anthropogenic activities, such as urban sewage and fertilizer use, on groundwater chemistry in the study area[269]. Notably, in addition to land use, the risk of water contamination may be attributed to poor construction and casing corrosion. This underscores the need to design risk management actions that consider well designs and operational practices. By combining the vulnerability index with the land use characteristics of the area, it becomes possible to rank groundwater pollution risk through the spatial distributions of vulnerability and risk. This ranking serves as a foundation for implementing measures aimed at the protection, restoration, and integrated management of groundwater resources[270]. The prioritization of vulnerability areas within the subbasin facilitates focused groundwater monitoring and the prevention of groundwater contamination. Additionally, GWPR mapping functions as a valuable decision-making tool, supporting hydrogeological conceptualization and the decision-making process in water resource management.

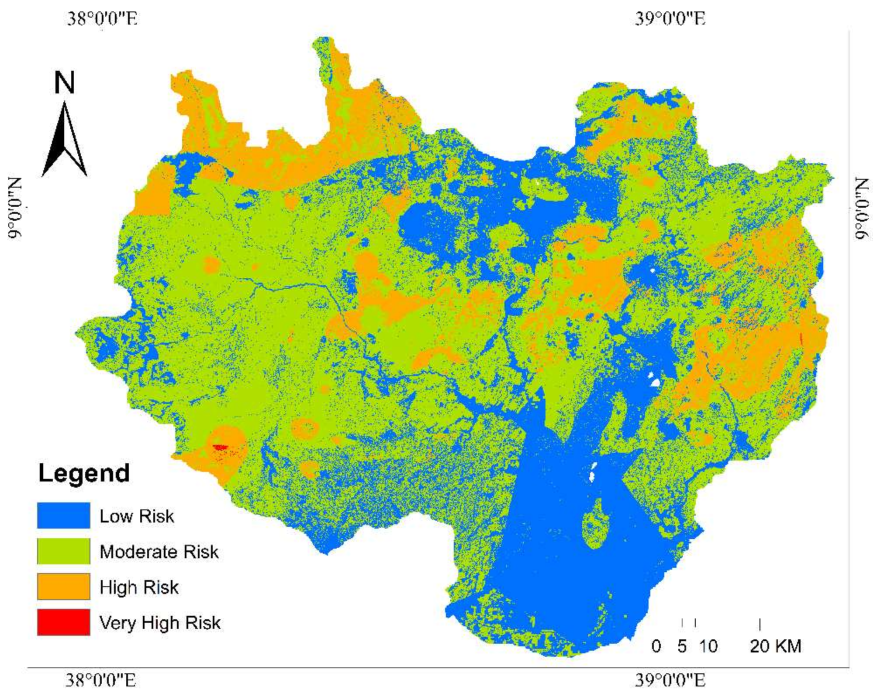


Figure 5: Map of the GWPR in the upper Awash subbasin

Research indicates moderate vulnerability to groundwater pollution from pesticide use due to their rapid dissolution and penetration into groundwater. In Lahore, Pakistan, the model highlighted high vulnerability in land use, development, industrial, and agricultural areas compared with settlements[31]. The Haouz aquifer in Morocco has the ability to differentiate between vertical vulnerability (vadose zone) and contamination susceptibility (saturated zone)[73]. In India, the DRASTIC model demonstrated a strong correlation with nitrate levels, which is particularly suitable for assessing agricultural nonpoint source pollution. Groundwater pollutants encompass biological, inorganic, and organic categories, originating from various sources, such as municipal waste dumps (Lagos, Nigeria) [70]; hydrogeochemical characteristics (Janah Plain, Iran)[71]; sewage, fertilizer, and water–rock interactions (Nandong karst system, China); evaporation; water–rock interactions; water mixing (Central Morocco) [72]; and industrial, urban effluent, and agricultural activities (Serbia) [73]. Overall, these findings underscore the effectiveness of the DRASTIC model in evaluating groundwater vulnerability and pinpointing areas at risk from diverse pollution sources. Recognizing these vulnerabilities is vital for implementing robust water resource management and protection strategies. Therefore, the application of this model, which assesses groundwater vulnerability to pollution on the basis of hydrogeologic parameters without extensive site-specific pollution data, has emerged as a cost-effective method to identify areas necessitating further investigation, such as risk assessment studies..

3.1.4. Surface Water pollution Risk

SWPR modeling is crucial for safeguarding water bodies. This involves ArcGIS overlay analysis, which considers watershed characteristics that influence water quality parameters. Some models rate these characteristics to assess the risk of potential contamination to water supplies. In the subbasin, integrated models manage land, sedimentation, and nutrients, assisting in delineating protection zones. The incorporation of a geographical information system enhances SWPR modeling, enabling the creation of watershed-scale risk maps for nonpoint source pollution. Notably, this approach can be regularly updated in response to observed parameter changes[271].

Table 8: Surface water pollution risk level of the upperwash subbasin

S/N	Risk Levels	Area (m^2)	Percentage (%)
1	Low Risk (3- 780 value)	7,798,175,100.00	72.64
2	Moderate (780-2170 value)	2,022,706,800.00	18.84
3	High Risk (2170-3560 values)	517,353,300.00	4.82
4	Very High Risk (3560 -30000 values)	396,855,000.00	3.70
	Total	10,735,090.200	100

Following this model approach, the study affirms that only 72.64% of the subbasins present a low SWPR level (Figure 4). In contrast, 27.36% of the subbasin comprises areas with more than moderate risk, with approximately 4.82% classified as high pollution risk and 3.7% classified as very high pollution risk (**Table 8**). Notably, a study conducted in Ethiopia assessing surface water risk indicated a low to negligible acute human risk associated with surface water consumption[272]. However, in contrast, the concentrations of selected nutrients and heavy metals were found to be consistent among the sampling sites along the streams of the subbasin, which was attributed to pollution from catchment nutrient sources[20].

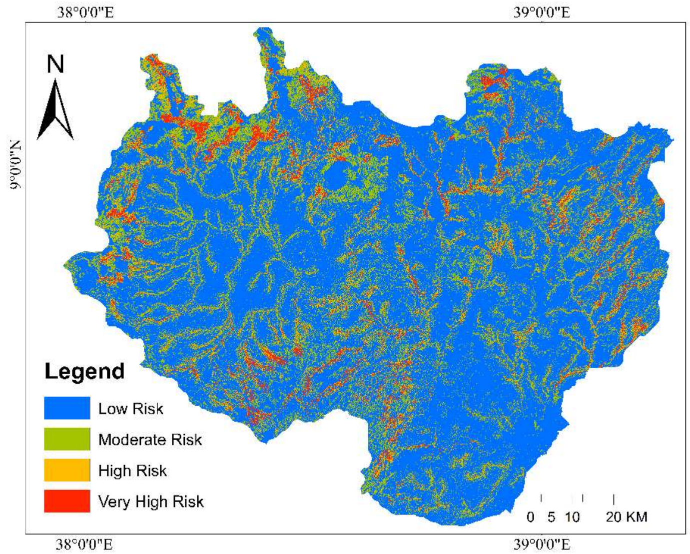


Figure 6: Surface water pollution risk in the upper wash subbasin

3.1.5. Water Source Pollution Risks

Water pollution is characterized by the presence of excessive amounts of pollutants in water to the extent that it becomes unsuitable for drinking, bathing, cooking, or other purposes [273]. The evidence highlights four major pollution sources: industries, mining and related activities, mixed sources (geogenic and anthropogenic), and fertilizer application[274]. In this study, separately modeled groundwater and surface-water pollution risk maps were integrated to create unified risk rating maps through a matrix addition operation within the ArcGIS environment. Consequently, the product map delineates seven risk classes, which are further reclassified into three classes. According to Table 10, the subbasin area is classified as having 68.1% low risk, 27.5% moderate risk, or 4.4% high risk for water source pollution (Table 10) and (Figure 7).

Table 9: Water source (ground and surface) pollution risk level, upperwash subbasin

S/N	Risk Levels	Area (m^2)	Percentage (%)	Remark (Matrix addition of values)
1	Risk Level 2	3,092,021,100.00	28.8774	1,1&1,1
2	Risk Level 3	4,199,048,100.00	39.2162	1,2 & 2,1
3	Risk Level 4	2,159,873,100.00	20.1717	2,2; 2,2; 3, 1 & 1, 2
4	Risk Level 5	783,423,900.00	7.3166	2,3;3,2 and 1,4
5	Risk Level 6	367,049,700.00	3.4280	4,2; 2,4; 3,3 & 3,3
6	Risk Level 7	105,939,000.00	0.9894	3,4 & 4,3
7	Risk Level 8	68,400.00	0.0006	4,4 & 4,4
		10,707,423,300.00	100.0000	

In the study area, evidence suggests that the combined use of surface water and groundwater could increase the water supply and alleviate stresses on groundwater resources. To implement this approach effectively, understanding SWPR is crucial for addressing water quality issues. This also supports a source protection strategy to prevent contaminants from entering surface waters, aquifers, or groundwater recharge areas. However, in the subbasin, integrated water resources management (IWRM) principles and economic development plans were not implemented because equity and the environment were considered[275].

Table 10: Reclassified WPR levels, upperwash subbasin

S/N	Risk Levels	Area (m^2)	%	Remark (classification of values)
1	Low Risk	7,291,069,200.00	68.1	1,2 & 3
2	Moderate Risk	2,943,297,000.00	27.5	4 & 5
3	High Risk	473,057,100.00	4.4	6,7 & 8
	Total	10,707,423,300.00	100	

Therefore, this study advocates the application of a multiple-barrier approach, which identifies critical sites for contaminant entry into the drinking water supply system[276]. This involves a risk management system by developing a water safety plan approach, which can help control contamination risks, comprehend the risks associated with the process, and identify critical control points to integrate within water supply operations[277].

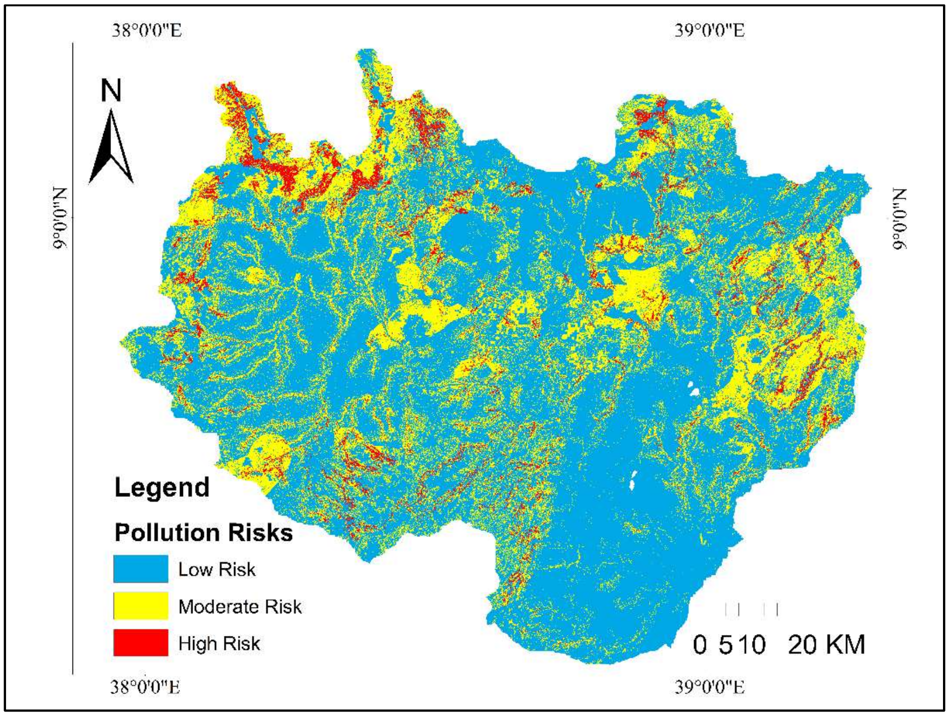


Figure 7: Water source pollution risk in the upperwash subbasin

3.1.6. Exposed Population for water pollution risks

The estimation of the population residing in WPR areas was conducted by utilizing population density maps (number of persons per square kilometer, 2016 CSA) and a WPR map. This was achieved through the ArcGIS zonal statistic method within the tool sets. The results revealed that 82.52% of the population (3,663,891 persons) resides in areas characterized by low water pollution risk, whereas more than 17.47% live in moderately risk-prone areas. Notably, a greater proportion of individuals are exposed to more than moderate risk when considering both groundwater and surface water pollution risks. Estimates of 5.64%, 3.88% and 2.30% of the population were exposed to high GWPR, SWPR and WSPR, respectively (Table 11) and (Figure 8). Importantly, water supplied from defined moderate- and high-risk areas may serve as a water source for individuals residing in low-risk areas. Therefore, in addition to predicting water source risks, tracking drinking water supply sources with respect to the WPR product map is imperative for comprehensive water quality management within the watershed system.

In Ethiopia, high rural population density is correlated with smaller farm sizes and increased fertilizer use per hectare, potentially leading to water pollution if fertilizer application is not managed wisely[278]. The assessment of heavy metals in the surface water of the Awash Basin emphasizes the need for measures to reduce pollution risk in accordance with basin standards[279]. Severe surface water quality impairment is observed in the upper Awash basin, where more than 90% of Addis Ababa's industries discharge untreated waste into nearby waterways[280]. The heavy metal evaluation index indicates elevated levels of Fe, Mn, and Cr in groundwater, posing a serious threat to the exposed population[281]. Water pollution in Ethiopia is a major concern for public health and water security, stemming from human activities and weak enforcement, with a limited understanding of the effectiveness of policies and institutional frameworks in addressing pollution [282].

Table 11: Exposed population and water pollution risk levels in the upper wash subbasin

S/N	Risk Level	GWPR level		SWPR level		WPR (combined)	
		Population	%	Population	%	Population	%
1	Low	2483266	55.93	3,603,915	81.11	3663891	82.52
2	Moderate	1706278	38.43	548,731	12.35	673680	15.17
3	High risk	250248	5.64	172,305	3.88	102018	2.30
4	Very High Risk	245	0.01	118,484	2.67	-	-
		4,440,037	100	4,443,435	100	4,439,589	100

Studies on human health risks due to water pollution highlight the scientific understanding required for the biological, chemical, and physical processes controlling contaminant movement, with consequences varying on the basis of factors such as composition, exposure duration, and pollutant concentration[283].

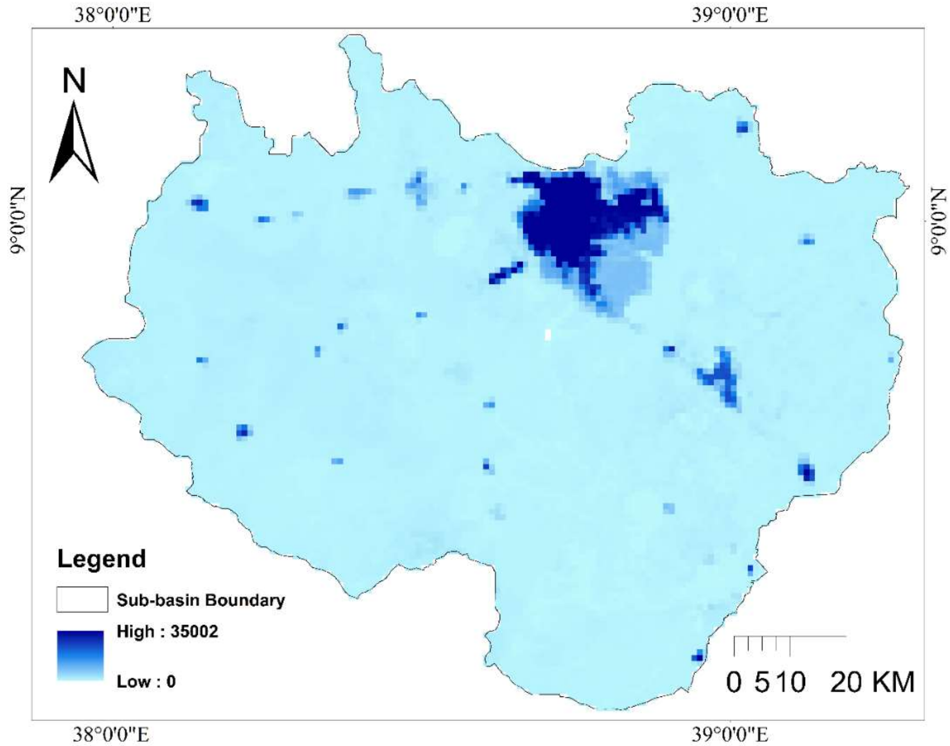


Figure 8: Population density (number of people/km2), upper wash subbasin

Research on the impacts of land use and population density on seasonal surface water quality suggests that urban land is a dominant factor influencing pollutants in highly urbanized regions, with the relationship being weak, as pollutants primarily come from point sources[284]. By the late twentieth century, population growth was causing increasing constraints on land, water, and other natural resources in many areas[285]. Changing land use and population density are identified as factors that degrade water quality in the lower Mekong Basin and are associated with agriculture, urbanization, and population density [286]. Assessment of the effects of population exposure on water pollution is crucial, as it directly affects public health by helping to understand and mitigate the risks associated with contaminated water sources. Identifying areas with high exposure allows for targeted interventions, aiding in the prevention of waterborne diseases and ensuring environmental justice by addressing vulnerabilities in specific communities. Moreover, it facilitates regulatory compliance, guiding policymakers to enforce measures that improve water quality and protect public health. Efficient resource allocation is enabled by prioritizing interventions in areas most at risk, whereas community awareness and empowerment are fostered through sharing assessment results, enabling informed decision-making. Ultimately, population exposure assessments contribute to the development of sustainable water management strategies, addressing immediate pollution concerns and laying the foundation for long-term water quality improvement and resource preservation for future generations.

3.2. PROTECTION ZONE DELINEATION

3.2.1. Description of NWI-2

As a component of the national WASH monitoring and evaluation system, the first National WASH Inventory (NWI-1) was created in 2011. The results were obtained in March 2013 by the Water and Energy Minister to track the progress of the Millennium Development Goals (MDGs)[287]. More than 92,000 rural water supply systems, 1,600 small town water supply systems, 50,000 institutions and 12 million households were included in the first NWI census [288]. The second National WASH Inventory (NWI-2) was conducted in March 2019 to assess the effects of drinking water supply schemes on physical status, beneficiaries at the scheme level according to government standards, service delivery performance, management status, sanitary conditions, and other relevant parameters for monitoring and evaluating the WASH program, such as hygiene practices and sanitation facility functionality. In this study, approximately 2,864 drinking water supply schemes (408 of which are nonfunctional) were extracted from the national database. More than 1,010 (35%) shallow wells, 1,032 (36%) hand-dug wells, 604 (21%) boreholes, 206 (7%) springs, and 10 (0.35%) various types of drinking water supply schemes were inventoried in the subbasin.

Table 12: Distribution of drinking water supply schemes in the upper Awash subbasin, NWI-2.

S/N	Types of drinking Water Supply Schemes	Scheme Location		Functional Status of Schemes				Total	
				Functional		Not functional			
		Rural	Urban	# of Schemes	# of Users	# of Schemes	# of Users	Total # of Scheme	# of Users
1	Shallow well	1004	6	914	309,050	96	22,664	1,010	331,714
2	Hand dug well	1022	10	854	101,010	178	11,297	1,032	112,307
3	Borehole	177	427	510	25,143	93	1,064	604	26,207
4	Spring source	203	3	166	34,723	39	12,564	206	47,287
5	Other	10	0	8	508	2		10	508
	Grand Total	**2416**	**446**	**2,454**	**470,434**	**408**	**47,589**	**2,864**	**518,023**

shows that the density of water supply schemes is concentrated in the western part of the subbasin, whereas the central part of the subbasin in the southern direction of Addis Ababa has fewer water supply schemes.

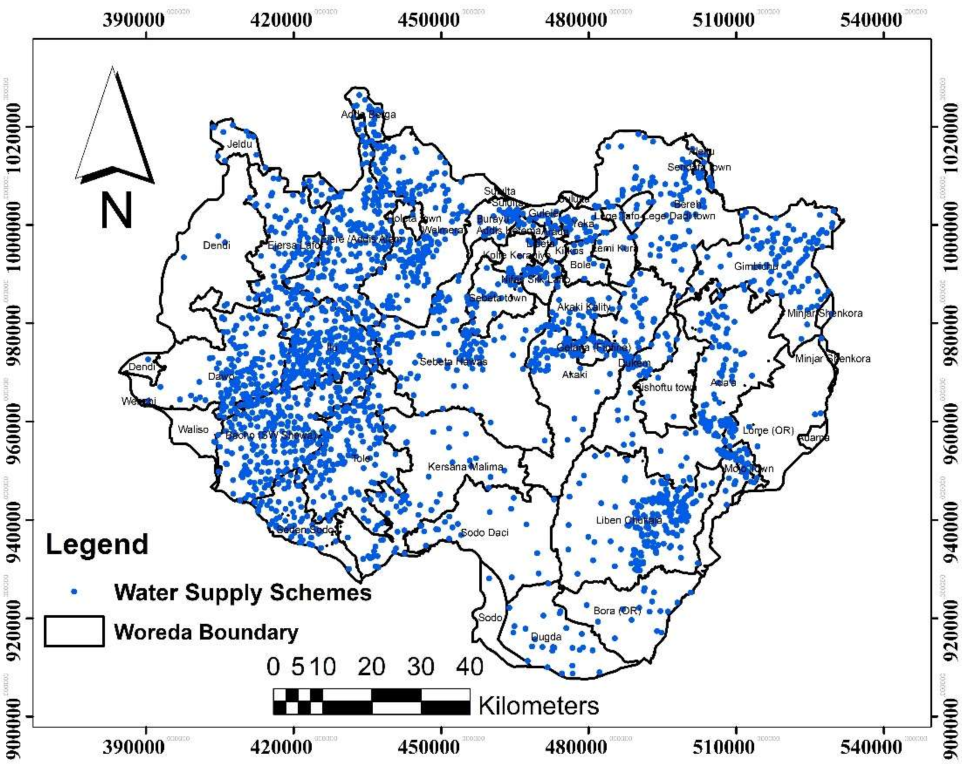


Figure 9: Map of the water supply scheme distribution in the Upper Awash Sub-River Basin

The findings showed that among the 2,864 inventoried water supply schemes, 14.4% (413) had a water safety plan, 20.7% (594) implemented water safety practices, and 6% (174) reported the incidence of waterborne diseases in the past year. The sanitary conditions of the water supply scheme sources were 12.2% bad, 71.1% fair, and 16.6% good. According to the NWI-2 guidelines, a "good" sanitary situation indicates a clean source free of pollution or contamination. "Fair" indicates a clean source but with room for improvement. "Bad" indicates a dirty source exposed to pollution or contamination (Table 2).

Overlapping data from the NWI-2 results and vulnerability assessment revealed that a number of schemes require immediate attention for source protection because of their locations in extremely vulnerable areas and poor management of water supply schemes. In addition to poor water safety standards and sanitary conditions, the risk of pollution or contamination further increases if the source is located in a sensitive groundwater aquifer. To safeguard these schemes, establishing a fixed radius around the source can be an appropriate strategy for both microbiological protection and the creation of a surveillance zone[289]. Thus, integrating the delineation method with NWI-2 can facilitate groundwater recharge and delineate activity-free zones around water sources[112]. This integration not only improves the effectiveness of WASH monitoring in Ethiopia but also provides valuable insights for the international Joint Monitoring Program (JMP) to consider source protection issues in its WASH monitoring system[290].

Table 13: Water safety plan; safety practice; incidence of waterborne diseases; sanitary situation of water supply sources; NWI-2

S/N	Indicators		Yes		No		Do not know		Total
1	Water Safety Plan		413	14.4	2,446	85.4	5	0.2	2,864
2	Water Safety Practices		594	20.7	2,266	79.1	4	0.1	2,864
3	Waterborne Disease		174	6.1	2,683	93.7	6	0.2	2,863
4	Sanitary Situation	Bad	349	12.2	2,515	87.8		-	2,864
		Fair	2,037	71.1	827	28.9		-	2,864
		Good	475	16.6	2,389	83.4		-	2,864

3.2.2. The situation of WSP at the national level.

Expert discussions revealed that the MOWE has a National WSP Technical Working Group (N-WSP-TWG). This group comprises representatives from the Ministries of Health, Water and Energy, the Environmental Protection Agency, the National Meteorology Agency, the Ministry of Agriculture, and other relevant sectors. . The experts highlighted major ongoing WSP activities such as capacity building, development of working documents, pilot-level risk and vulnerability assessments, supportive supervision and review meetings, coordination of WSP implementations, and identification of research topics. They also explained the purposes of WSP and the responsibilities of the MOWE at the national level.

The discussion, along with the supplementary materials, revealed that comprehensive water supply risk assessment and risk-based management have not received significant attention since the fifth WASH Multistakeholders meeting in November 2012. MOWIEs and regional water bureaus have been piloting methods, building capacity, and risk assessment since then, and WSP guidelines and a strategy framework have been developed; however, implementation has remained in a pilot phase since June 2018. As a result, the strategy and guidelines have not been fully implemented. However, capacity-building interventions targeting 20 urban water utilities and 11 rural water utilities for the development and implementation of WSPs for existing water delivery systems are estimated to benefit almost 2,113,567 people. As part of those efforts, climate-resilient WSP projects were piloted in the Addis Ababa and Adama city water supply systems to practice WSP and provide attention to the impact of climate on drinking water supply schemes[118]. A review of the literature revealed that WSP was in its pilot phase in China at the time, and full-scale implementation only began in 2018[117]. Challenges to effective WSP implementation exist globally. In the United States, for example, a lack of preventive culture, prioritization, leadership, and difficulty integrating WSPs into existing practices hinder progress. [291]. Similarly, WSP monitoring, verification, and management in Uganda have not been entirely successful, with the exception of system assessment and improvement[119]. However, progress has been made in high-income countries under the OECD (Organization for Economic Cooperation and Development). This is evident in the creation of an enabling environment through guidelines, regulations, tools, and resources, public health support, and context-specific evidence[120]

In addition to the identified best practices, several challenges hinder traditional WSP implementation. These challenges include a lack of institutionalization, limited efforts for catchment protection, a neglect of sanitation safety planning, and the unavailability of climate information. These limitations necessitate the development of climate-resilient WSPs (CR-WSPs). Furthermore, owing to challenges such as the COVID-19 pandemic, country instability, organizational reform, limited stakeholder engagement and stakeholder commitments, the implementation of the CR-WSP has not progressed well. An additional challenge identified by technical experts is the absence of national source protection zoning or delineation guidelines, except for existing CR-WSP implementation guidelines for urban and rural water supply systems. The requirements of legal restrictions further complicate this issue. Water sector responsibilities are limited and do not include the management and administration of land around the water source, development activities within the catchment zones, or the removal of hazards/contamination risks from source to point of use. Additionally, there is a lack of evidence and established practices for source protection zoning. These findings address these gaps by demonstrating how to delineate water source protection zones in the upper Awash River subbasin via ArcGIS and national WASH inventory data. This approach can strengthen national water safety plan implementation by integrating program implementation and an information management system within the One WASH national program

3.2.3. Linear regression analysis

The analysis of water quality data revealed an average nitrite concentration of 0.15 mg/L, ranging from 0.02 mg/L to 0.31 mg/L (with a 95% confidence interval). Similarly, the average nitrate concentration was 24.98 mg/L, ranging from 17.72 mg/L to 32.25 mg/L (with a 95% confidence interval) (Table 14). These parameters are crucial for assessing water safety and environmental impact, especially considering the health risks associated with elevated nitrate concentrations. Nitrate contamination is more commonly associated with agricultural practices, including the use of fertilizers and manure. Further evaluation of nitrate levels, although variable, is needed, especially considering the potential health risks associated with chronic exposure to high nitrate concentrations.

Table 14: Descriptive statistics of nitrate and nitrite in drinking water

S/N	Water Quality Parameters	Mean	95% CI for Mean		Std. D	Min	Max
			Lower Bound	Upper Bound			
1	Nitrite(NO_2) mg/L	0.15	0.02	0.31	0.91	0.01	8.00
2	Nitrate(NO_3) mg/L	24.98	17.72	32.25	40.19	0.08	300.00

In addition to the public health significance of nitrate, various scholars have suggested that nitrate concentrations can be used to validate different models, such as the DRASTIC model. High nitrate levels often indicate agricultural runoff, sewage contamination, or other forms of pollution that can affect groundwater quality[121,223,292]. As a result, relationships between the vulnerability indices and nitrate concentrations were established, and the fluctuations were described by R^2 values of 61.7%. This suggests that variations in nitrate concentration are correlated with vulnerability index values. The validation method also yielded a predictable model; if the groundwater vulnerability index increased by one unit, the nitrate content increased by 2 times (P value<< 0.05) (Table 15). Therefore, in accordance with these validation results, the DRASTIC model input parameters are acceptable[85,293].

Table 15: Results of linear regression analysis of the DRASTIC index values and NO3 concentrations.

S/N	Parameters	Values	t	Sig.	95.0% CI	
					Lower Bound	Upper Bound
1	DRASTIC Value Intercept (constant)	-241.43	12.50	0.000	-279.7	-203.2
2	Unstandardized Coefficients of B	2.036	13.9	0.000	1.7	2.3
3	Adjusted R Square (Model Summary)	61.7%				

3.2.4. Delineation of the Water Source Protection Zone

This study revealed that more than 39.23% (1,124) of the 2,864 water supply schemes were located in highly vulnerable areas, with an additional 12.32% (353) in very highly vulnerable areas. Conversely, only 8% (229) of the schemes were located in low vulnerability areas. This vulnerability translates to user exposure, as 55.30% (286,403) of users depend on water sources in highly vulnerable areas (Table 16). These findings highlight the critical need for source protection zone delineation in subbasins. This method, one of the most widely used approaches for maintaining water quality, involves mapping groundwater vulnerability and delineating zones around water sources to prevent pollution. [294]. This study employed a GIS environment to conduct groundwater vulnerability mapping and protection zone delineation. Using the ring buffer approach in the ArcGIS toolbox, all the extracted water supply schemes were designated as inner (50 m), immediate (500 m), and outer (entire water catchment) zones[115] (Figure 10). The most effective way to limit the risk of water resource pollution is to divide the region around a water source into three protection zones and determine the protection perimeters on the basis of the vulnerability map [105,107]. The methods for source protection zoning include fixed radius, flow system mapping, analytical modeling, and numerical modeling. In general, a fixed radius is the most effective of these methods. This can be put into practice to safeguard water supply schemes from contamination, but more complex aquifers and more vulnerable water supply schemes require robust methods[295]. For example, when there is low vulnerability, the fixed radius approach can be used, but when there is high vulnerability, the isochrone method and the groundwater vulnerability mapping method should be used to characterize aquifer properties [296]. Fixed radius and groundwater vulnerability mapping were used in this study to integrate the national WASH inventory results for a synergetic approach. This form of protection is equally crucial to the wellhead, sanitary seal surrounding the well casing, and surface water intake. In the upper Awash Subbasin, this source protection zone can be used to help with watershed management problems in areas near abstractions where there is a risk of water pollution and vulnerability to pollution[108].

Table 16: Groundwater vulnerability level and distribution of drinking water supply schemes

S /N	Types of Schemes	Groundwater Vulnerability level					
		No Data	Low Vulnerable	Moderate Vulnerable	High Vulnerable	Very High Vulnerable	Grand Total
1	Shallow well		16	374	516	104	1,010
2	Hand dug well		83	401	374	174	1,032
3	Borehole	2	125	281	178	18	604
4	Spring Source	2	4	94	52	55	207
5	Dug well			5	1		6
6	Other types		1		3	2	6
Total (Number)		3	229	1,155	1,124	353	2,865
Total (%)		0.14	8.0	40.31	39.23	12.32	100
Users (Number)			5,745	225,875	230,244	56,159	518,023
Users (%)			1.11	43.60	44.45	10.84	100

On the other hand, a high groundwater vulnerability index indicates that the sensitive zone influencing aquifer recharge should be defined as a groundwater protection zone or pollution-free zone for managing groundwater sources. These areas must be safeguarded from point and nonpoint sources of water pollution since the subbasin is at the country's center, including the capital city, and is affected by significant pollution risks caused by population, industrialization, urbanization, and intense agricultural activities ([112].

There are numerous examples of groundwater vulnerability mapping and groundwater protection zone delineation in various parts of the world[109]. However, in low-income nations such as Ethiopia, where there is a lack of institutional capacity to integrate land and water management at the local level, water source protection has not received enough attention, in addition to concerns arising from anthropogenic activities[110]. Therefore, these results encourage relevant authorities to standardize source protection delineation, particularly for the Upper Awash River subbasin. This can be achieved by developing protection policies, establishing regulatory controls on waste disposal, managing sites, planning land use with consideration for compensation to account for the growth of zoned areas, and coordinating stakeholders for integrated watershed management.

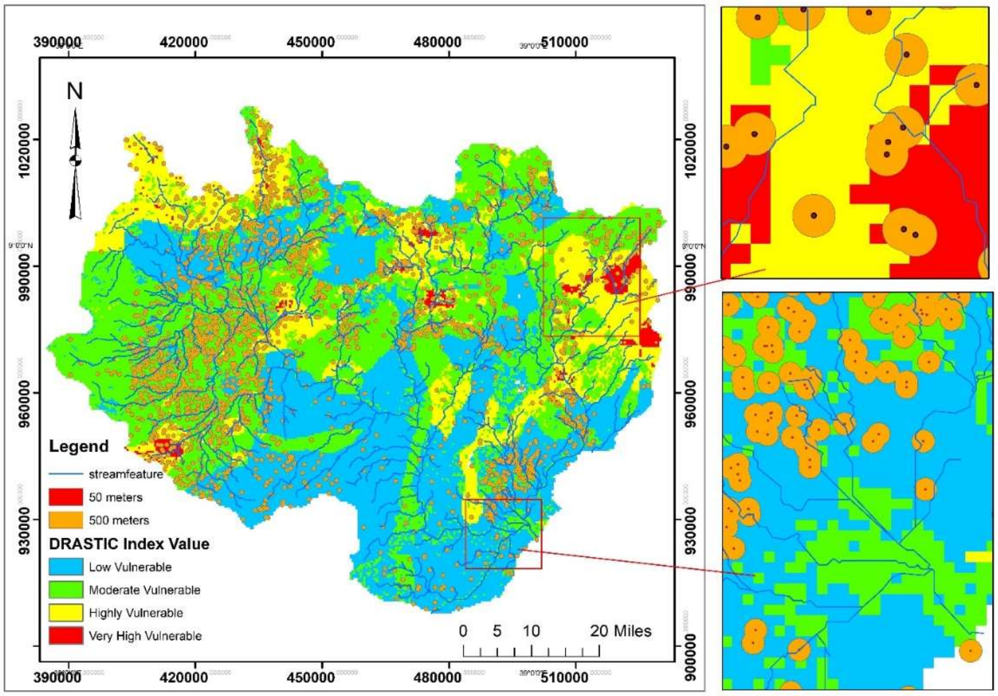


Figure 10: Delineated zones for groundwater source protection

The construction of new water sources and the maintenance of existing water supply sources can benefit from such protective techniques. Responsible authorities and users should establish bylaws to restrict the boundaries of the protection zone after delineation, define types of waste disposal, manage sites, select sites in relation to aquifer vulnerability status, and prioritize water safety when developing land use and cover analysis. Examples of managing land use and human activities in protection zones include restricting polluting activities, planning land use, establishing regulatory frameworks, taking into account the characteristics of the protected zone, and compensating or providing other forms of financial support to current land users impacted by changes. Vulnerability assessments are used for long-term planning of groundwater resource safeguarding, corresponding to the system assessment concept in building a water safety plan. It is possible to define action levels to provide the necessary protection for drinking water sources. By classifying vulnerability status in terms of protection requirements, it is possible to define action levels that provide the necessary protection for drinking water sources. Including these factors in a water safety plan (WSP) helps to communicate their significance for meeting quality standards and facilitates the management of a drinking water catchment.

3.3. WATER QUALITY DYNAMICS

3.3.1. Microbial Water Quality Analysis

The results of this study indicated that 11.7% (7) of the samples collected in the dry season and 40% (24) of those collected in the wet season were free from contamination, suggesting that there was no risk of contamination. However, the wet season had a greater mean dose of *E. coli* per 100 mL (18>14 CFU/100 mL) than did the dry season. Compared with the Bereh District samples, the Sebeta-Hawas District samples had more *E. coli* (17>15 CFU/100 mL). In terms of risk levels, approximately 47% (28) of the schemes in the dry season and 20% (12) in the wet season presented low risks (1--10 *E. coli*), whereas 41.7% (25) of the schemes in the dry season and 40% (24) in the wet season presented medium risk levels (11--100 *E. coli*) (Table 17).

Table 17: Distribution of Microbial Water Quality Parameters

S/N	Water Supply Scheme Level	*E.coli*/100 ml Risk Level						Total		Mean doses (CFU/100 ml)
		No Risk		Low Risk		Medium Risk				
		No	%	No	%	No	%	No	%	
	Dry Season									TC = 46 *E.coli* =14
1	Borehole	2	3.3	1	1.7	2	3.33	5	8.33	
2	Hand Dug Well	1	1.7	2	3.3	6	10.00	9	15.	
3	Protected Spring	1	1.7	3	5.0	0	0.00	4	6.67	
4	Shallow Well	3	5.0	21	35.0	13	21.67	37	61.7	
5	Unprotected Source	0	0	1	1.7	4	6.67	5	8.33	
	Total	**7**	**11.7**	**28**	**46.7**	**25**	**41.7**	**60**	**100**	
	Wet Season									TC = 88 *E.coli* =18
1	Borehole	2	3.33	1	1.67	2	3.33	5	8.33	
2	Hand Dug Well	1	1.67	3	5.00	5	8.33	9	15	
3	Protected Spring	2	3.33	1	1.7	1	1.7	4	6.7	
4	Shallow Well	18	30.0	7	11.67	12	20.00	37	61.7	
5	Unprotected Source	1	1.67	0	0.00	4	6.67	5	8.33	
	Total	**24**	**40.0**	**12**	**20.0**	**24**	**40.00**	**60**	**100**	
	Districts									
1	Bereh District	21	35.0	9	15.0	30	50	60	100	TC = 56, *E.coli* =15
2	Sebeta-Hawas District	10	16.7	20	33.3	30	50	60	100	TC = 78, *E.coli* =17
	Total	31	26.0	29	24.00	60	50	120	100	

In the southern part of the upper Awash subbasin, Wondogenet District presented similar findings, with fecal coliform bacteria detected in 25% of the water supply schemes[297]. These findings are similar to those of the 2016 national survey report, where only 14% of the population accessed water from low-risk sources[36]. In some areas in Canada, peak contamination of water supply wells by *E. coli* occurred in July, and a later peak for total coliforms occurred in September, suggesting a temporal association with groundwater quality[298]. Microbial contamination is often slightly more prevalent during the dry season than during the wet season. However, the mean doses of total coliform bacteria and *E. coli* per 100 mL were higher in the wet season than in the dry season. In addition, the distribution of *E. coli* between districts was similar in the medium-risk category, but the Sebeta-Hawas District had a high mean dose of microbial organisms per 100 mL. Evidence shows that the microbial distributions of microbial pathogenic organisms depend on geographical areas and seasons of the year[299]. These findings may serve as robust evidence for public health when planning and developing intervention programs. On the other hand, among the water supply systems, 5% (3) of the shallow wells during the dry season and 30% (18) of them during the wet season have no risk, which means that 95% and 70% of the schemes have low and greater risks in the dry and wet seasons, respectively. The depth of groundwater sources plays a pivotal role in contamination levels, with shallower wells correlating with higher incidences of childhood diarrhea than deeper wells do[300]. This finding aligns with a peer-reviewed paper from low- and middle-income countries, which reported a positive association between *E. coli* or thermotolerant coliform bacteria (TTC) and unimproved water sources and a negative association with improved water sources[301].

In general, total coliform bacteria are crucial indicators of microbial contamination in drinking water supplies, originating primarily from warm-blooded animal sources, including humans. Its detection in drinking water signifies contamination with microbes, including highly infectious *E. coli* O157:H7, which has been linked to waterborne outbreaks worldwide, resulting in significant morbidity and mortality[302]. Moreover, among the total number of *E. coli* bacteria detected, five pathogenic strains are significant: enterotoxigenic, enteropathogenic, Shiga toxin-producing, enteroinvasive, and enteroaggregative strains[198]. These harmful strains of *E. coli* are estimated to make up 8% of the *E. coli* [303]. In Ethiopia, numerous enteropathogenic *E. coli* serotypes have been identified in infants and children displaying acute gastrointestinal symptoms[202]. Systematic review articles have also highlighted the emergence of enterotoxigenic and enteroaggregative *E. coli* diarrheal cases in the United States[304]. Hospitalization data indicate that enterotoxigenic *E. coli* and *V. cholerae* O1/O139 are the primary causes. In outpatient settings, Salmonella spp., Shigella spp., and *E. histolytica* are commonly isolated pathogens[200].

In addition, the scatter plot shows the correlation of *E. coli* with total coliform bacteria (R^2= 57% and P<0.001; correlation coefficient = 62.4% according to Kendall's tau-b nonparametric test, P<0.001) (Figure 11). This finding was supported by an article that explained the single linear relationship between *E. coli* and total coliform bacteria[305]. Even if *E. coli* is sorted into a total coliform bacterial group, the positive association may be due to the presence of familiar sources.

In summary, bacterial contamination in water supply schemes often emerges from septic and sewage discharge, issues such as leaching of human waste and animal manure and defects in the construction and maintenance of water supply infrastructure. To mitigate these contaminants, communities should adopt household water treatment technologies at the point of use. Additionally, local governments should implement appropriate sanitation programs and integrated watershed management strategies that account for seasonal variations and site-specific factors within the subbasin**.**

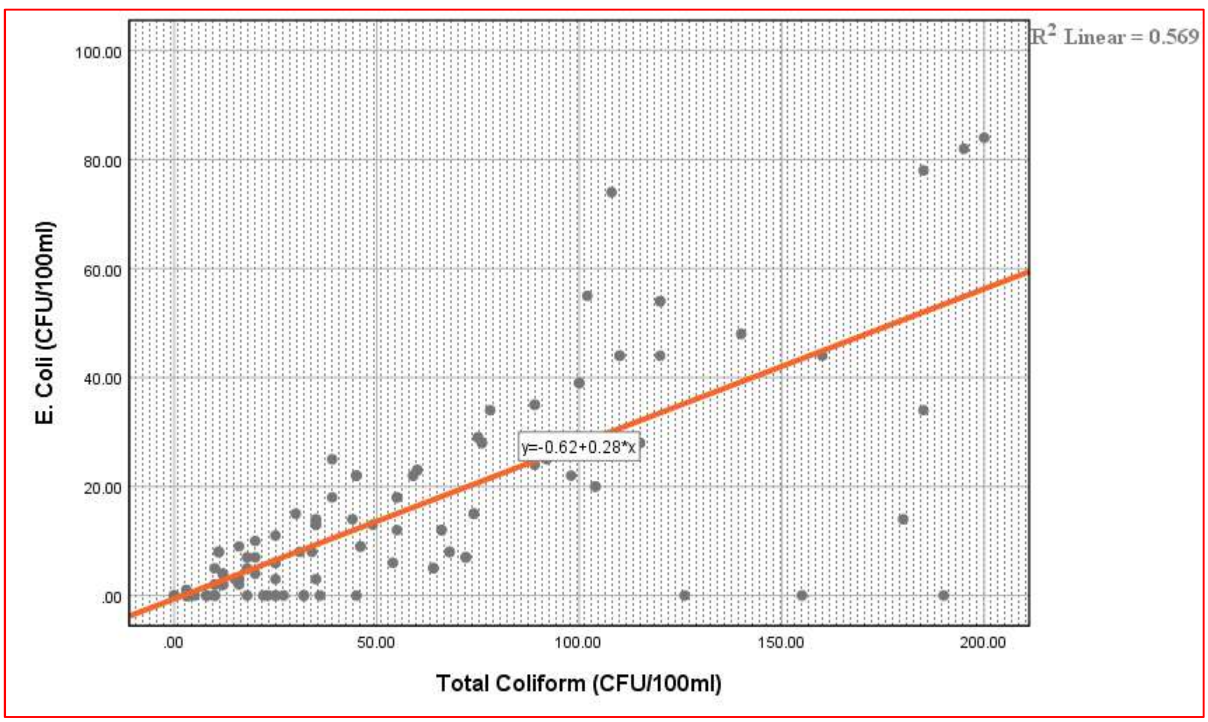


Figure 11: Scatter plot of *E. coli* with *total coliform* bacteria.

3.3.2. Status of Water Quality of the sub-basin

The findings of this study indicated that the drinking water quality was classified as excellent, sound, or poor in 13.3% (16), 75.8% (91), or 9.2% (11) of the drinking water supply samples, respectively (Table 18) refer to Table 3). Similarly, for surface water, the results revealed that the water quality was excellent, good, poor, and very low at 10% (3), 43% (13), 30% (9), and 17% (5) of the sites, respectively (Table 19). A better water quality index was identified in the wet season (more than 90%) than in the dry season (88.3%). This could be due to the deeper entry of contaminants into the ground and the dilution effects on contaminants during the rainy season. In contrast, contaminants spread toward the well from the surrounding aquifer during the dry season. In contrast, the Sebeta-Hawas District had many drinking water schemes (27%) with poor water quality compared with the Bereh District (17.6%). On the other hand, except for Koka and Legedadi, 47% (14) of the samples from eight sampling sites had poor and extremely poor WQIs, with 30% (9) and 16.7% (5), respectively. Approximately 70% (7) of the samples from wet months, such as June, July, August, and September (JJAS), presented better water quality than did those from the other two seasons of the year (Table 19). There is ample evidence that water supply contaminants, including heavy metals, are found in subbasins in accordance with the WHO guidelines[306]. These findings are confirmed by evidence collected in the subbasin, which revealed that the concentration of surface water contaminants in the Kebena River was higher during the dry season than during the wet season[307]. This is due to decreased water flow discharge along the main Awash River in the dry season with high concentrations of contaminants and dilution effects during the rainy season. The assessment of water quality over different seasons revealed notable variations. Water quality was deemed poor in March and June, in contrast with the medium to good classification observed in July and September, particularly at the La Vega dam. This temporal fluctuation stresses the dynamic nature of water quality parameters and highlights the influence of seasonal factors on water quality dynamics[308].

In the Tigris River Basin, notable variations in WQI values were observed across different months. Specifically, the winter and spring months presented the highest WQI values, indicating better water quality during these seasons than during the dry season[309]. In West Bengal, India, seasonal variations in water quality, influenced by elevated concentrations of iron and chloride, result in higher WQI values during the premonsoon period, indicating predominantly good water quality, whereas during the postmonsoon period, water quality declines due to decreased precipitation[310].

Table 18: Water quality indices of the drinking water quality in the upper Awash subbasin.

S/N	Water Quality Classes	Seasonal WQI values(Bereh District)				Seasonal WQI values (Sebeta-Hawas District)				Seasonal WQI values(both districts)				Total Samples	
		Dry		Wet		Dry		Wet		Dry		Wet			
		No	%	No	%	No	%	No	%	No	%	No	%	No	%
1	Excellent water	7	23.3	0	0.0	4	13.3	5	16.7	11	18.3	5	8.3	16	13.3
2	Good Water	22	73.3	26	86.7	20	66.7	23	76.7	42	70.0	49	81.7	91	75.8
3	Poor Water	1	3.3	3	10.0	5	16.7	2	6.7	6	10.0	5	8.3	11	9.2
4	Very Poor Water	0	0.0	1	3.3	1	0.0	0	0.0	1	1.7	1	1.7	2	1.7
	Total	30		30	100	30	100	30	100	60	100	60	100	120	100

However, there was minimal disparity in water quality between the dry and wet seasons due to engineering controls implemented on the rivers, which effectively mitigated seasonality in water quality. This attenuation of seasonal variations highlights the efficacy of these engineering interventions in stabilizing water quality parameters throughout the year[311].

Table 19: Water quality index classes at each sampling station and season of the year

S/N	Description	Water Quality Index class								
		Excellent water		Good water		Poor water		Very poor		Total
		No	%	No	%	No	%	No	%	
A	**Surface water sampling stations**									
1	Koka	2	67%	1	8%	0	0%	0	0%	3
2	Ombolie	0	0%	1	8%	0	0%	2	40%	3
3	Zeway	0	0%	2	15%	1	11%	0	0%	3
4	Modjo	0	0%	1	8%	1	11%	1	20%	3
5	Ginchi	0	0%	1	8%	2	22%	0	0%	3
6	Great Akaki	0	0%	2	15%	1	11%	0	0%	3
7	After-Abasamuel Lake	0	0%	2	15%	1	11%	0	0%	3
8	Legedadi	1	33%	2	15%	0	0%	0	0%	3
9	Melkakun	0	0%	1	8%	2	22%	0	0%	3
10	Little-Akaki	0	0%	0	0%	1	11%	2	40%	3
	Total	3		13		9		5		30
	%	10%		43%		30%		17%		
B	**Annual seasons**									
1	JJAS (Jul-Jun-Aug-Sep)	1	33%	6	46%	2	22%	1	20%	10
2	ONDJ(Oct-Nov-Dec-Jan)	2	67%	2	15%	4	44%	2	40%	10
3	FMAM(Feb-Mar-Apr-May)	0	0%	5	38%	3	33%	2	40%	10
	Total	3	100%	13	100%	9	100%	5	100%	30
	%	10%		43%		30%		17%		100%

Conversely, water quality across different geographical regions reveals significant variations in spatial and temporal patterns. In the Awash River in Ethiopia and the Tigris River in Iraq, fluctuations in water quality indices indicate overall deteriorated conditions, with recommendations for interventions such as wastewater treatment plants, sanitation interventions, and stormwater management strategies[312]. Conversely, groundwater from the southern Voltaian Formation is highly acceptable drinking water, with the majority of samples falling within excellent and good categories[313]. However, spatial disparities are evident in the Aksu River basin in southwestern Turkey, with areas exhibiting both good and poor water quality conditions[102]. In Paris Park, a strong correlation between the WQI and dissolved oxygen deficit highlights the impact of climatic conditions on water quality parameters [101]. Moreover, the Euphrates River has diverse water quality levels, ranging from good to poor, and is influenced by domestic sewage and industrial effluent pollution [314]. Poor water quality is caused by impacted places such as agricultural activities, industrial areas, urban settlements along the Awash River's course, and indiscriminate disposal of waste into the river without treatment[24]. To enhance water quality assessment, it is recommended that extensive data be consolidated into a single value or index, such as the WQI. Therefore, since these findings consolidate water quality data from various parameters into a meaningful indicator, they emphasize the importance of targeted measures to mitigate contamination sources. Overall, integrating long-term water quality assessment via the WQI into national surveillance and monitoring programs can aid in pinpointing both point and nonpoint sources of pollution. This approach can support water supply and sanitation programs and integrate watershed management efforts via national water, sanitation, and hygiene (WASH) inventories, serving as a crucial component of the water sector information management system.

3.3.3. Temporal and spatial variations of water quality

.One-way analysis of variance was used to evaluate the temporal and spatial changes in the drinking water supply and surface water quality. The normality test, homogeneity of variance, and other assumptions and tests were executed before performing the ANOVA. Accordingly, this study confirmed that there was a significant difference in the mean WQI values of drinking water between Bereh district (mean= 55.54, SD=13.46) and Sebeta Hawas Districts (mean = 64.05, SD=15.69), $F(1, 118) = 9.31$, $P<0.003$. However, the mean WQI values did not differ significantly between the dry and wet seasons (Table 20).

Table 20: Temporal and spatial variations in the WQI for the drinking water supply

Test of Homogeneity of Variances					
	Levene Statistic	df1	df2	Sig.	
Bereh and Sebeta-Hawas	0.944	1	118	0.333	
Dry and wet seasons	0.002	1	118	0.966	
ANOVA					
Dry and wet seasons	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	0.010	1	0.010	0.815	0.368
Within Groups	1.442	118	0.012		
Total	1.452	119			
Bereh and Sebeta-Hawas Districts					
Between Groups	0.106	1	0.106	9.312	0.003
Within Groups	1.346	118	0.011		
Total	**1.452**	**119**			

Alternatively, a nonparametric test revealed significant differences in the mean values of the parameters between the dry and wet seasons and between districts. As a result, fourteen parameters (TDS, pH, Na, K, TH, F, Cr, NO_2, NO_3, HCO_3, SO_4, Akl, As, and EC) presented variable mean values due to spatial variability between the Bereh and Sebeta-Hawas districts. Additionally, eleven drinking water quality parameters (Na, Fe, Mn, F, Cr, NO_3, CO_3, HCO_3, NH_3, Alk, and As) presented variations in their mean values across the dry and wet seasons throughout the year (Supplementary No. 1.4).

For the surface water sampling stations, the ANOVA findings show that the mean values of the given surface water parameters varied significantly with the dry and rainy seasons of the year (Table 21). The statistical results of the ANOVA for the surface water parameters are summarized as total hardness (mean=145.8, SD=164.5, F(2,27), P<0.003), total dissolved solids (mean=318.7, SD=194.4, F(2,27), P<0.004), pH (mean=7.2, SD=0.51, F(2,27), P<0.001), magnesium (mean=21.05, SD=24.8, F(2,27), P<0.015), chloride (mean=64.23, SD=47.03, F(2,27), P<0.021), and bicarbonate (mean=282.5, SD=181.90, F(2,27), P<0.004). As a result, the post hoc tests revealed that the mean values of TDS, Mg, and HCO_3 differed between the rainy season (JJAS) and the dry and middle-dry seasons (ONDJ and FMAM). Nevertheless, there was no difference between the ONDJ and FAMA seasons (Supplementary material No. 2.4). Furthermore, the mean values of the pH and chloride parameters differed significantly between the rainy (JJAS) and mid-dry (FAMA) seasons.

Table 21: Temporal variation in surface water quality across seasons of the year

S/N	Surface Water Parameters		Sum of Squares	df	Mean Square	F	Sig.
1	Total Hardness (TH)	Between Groups	41946.67	2	20973.333	7.208	0.003
		Within Groups	78557.50	27	2909.537		
		Total	120504.17	29			
2	Total Dissolved Solids(TDS)	Between Groups	0.826	2	0.413	6.703	0.004
		Within Groups	1.664	27	0.062		
		Total	2.490	29			
3	pH	Between Groups	0.017	2	0.008	24.311	0.000
		Within Groups	0.009	27	0.000		
		Total	0.026	29			
4	Magnesium (Mg)	Between Groups	1.584	2	0.792	4.903	0.015
		Within Groups	4.362	27	0.162		
		Total	5.946	29			
5	Chloride(Cl)	Between Groups	3.536	2	1.768	4.494	0.021
		Within Groups	10.62	27	0.393		
		Total	14.16	29			
6	Bicarbonate (HCO_3)	Between Groups	0.76	2	0.380	6.824	0.004
		Within Groups	1.50	27	0.056		
		Total	2.26	29			

The findings of this study reveal a significant disparity in the mean WQI values of drinking water between the Bereh district and Sebeta-Hawas districts, which are situated east and southwest of the capital city of Addis Ababa, respectively. Research has indicated that the WQI reflects seasonal fluctuations, often highlighting poor classifications during the dry season[315]. However, the variance in WQI concerning seasonal changes within the subbasin remains relatively unexplored, with insufficient evidence either supporting or disproving this finding. Other studies have demonstrated that water quality exhibits significant temporal and spatial variability, with many characteristics being subject to climatic influences [316,317]. Floods and droughts induced by climate change are the main impacts of climate change and influence the biological, physical, and chemical aspects of water quality, eventually placing public health at risk. Furthermore, the disparity between the mean value of the WQI and other parameters may be due to inherent vulnerability and ground pollution risks, which are influenced by various factors, such as the aquifer, vadose zone, topography, hydraulic conductivity, depth of the water table, groundwater recharge, soil type, and land use/land cover. Additionally, geological, physicochemical, biological, and anthropogenic factors all impact groundwater quality[30]. This result suggested that variability in the mean concentration of drinking water quality parameters concerning sampling sites initiates site-specific intervention. These findings inform the action of drinking water quality monitoring and surveillance activities.

Conversely, the results of the ANOVA for surface water parameters reveal significant variations in the mean values of total hardness, total dissolved solids, pH, magnesium, chloride, and bicarbonate between the dry and rainy seasons. Similarly, in this study, the mean concentrations of parameters such as TDS, Cl, and SO_4 were variable during the wet season, and these differences resulted in the deterioration of Awash River water quality via temporal variations[318]. The authors predicted that a major increase in farmland, urban areas, and industrialization would have an impact on surface water quality in this subbasin[319]. However, the ANOVA results indicated no significant differences in the mean WQI values across the seasons. This finding contrasts with evidence suggesting notable variations in the WQI between the dry and wet seasons[320]. Water quality variability was dramatically identified from the upper to lower regions of the river basin; for example, TDS, TH, and Cl concentrations decreased throughout the dry season[318]. However, a case study report from Mizan-Aman town in Southwest Ethiopia revealed that the physicochemical and bacteriological properties of the water were greater in the wet season than in the dry season[321].

In general, in other parts of the world, such as China's Sabarmati River, spatial and temporal changes in the mean concentration of surface water quality parameters were observed as the concentrations of different parameters increased from upstream to downstream[322]. Similarly, parameters such as pH, TDS, TH, and Ca have been documented in India for seasonal fluctuations[323]. These changes in characteristics were caused by urbanization and agricultural practices in the upper stream and along the river. Furthermore, land use and land cover patterns were identified as aggravating factors for quality deterioration. As a result, considering spatial and temporal variations, land use land management through integrated watershed management and riverine protection should be implemented to ensure sustainable land use practices and river water management

3.3.4. Prediction of the Water Quality parameters

Among the twelve drinking water quality parameters modeled by the ANN, the first five parameters, i.e., Fe, Cr, Mn, K, and NO_3, were associated with values ranging from 10% to 25% of the model's relevance. These parameters contributed approximately 85% of the WQI, whereas the remaining seven parameters contributed 15% of the WQI (Table 22). This ANN model predicted and validated the drinking water WQI with an accuracy of 94% (coefficient of determination, R^2 = 94%) or with 5.6% relative error for testing and 6.6% for training simulation. Additionally, the ANN of surface water demonstrated that the WQI could be predicted by four water quality parameters with 95.1% model fitting accuracy, 1.1% relative error in training simulations, and 9.8% error in testing simulations. According to Table 22, F, SO_4, K, and Na were important at 33.2%, 25.1%, 22%, and 19.8%, respectively, and their contributions to the model are explained. Using two hidden layers, the model structure predicts one output (WQI) (Figure 12).

These findings highlight the use of multilayer perceptron (MLP) artificial neural networks (ANNs) for water quality management. MLP ANNs have been utilized for environmental and water resource modeling since the 1990s, with feedforward networks being the preferred architecture owing to their documented efficacy across numerous cases[324]. Scholars have emphasized the efficacy of ANNs in predicting and classifying water quality characteristics, noting their superiority over multilinear regression models in this regard[325]. ANNs function similarly to the human brain, operating within the body's nervous system. In the modern era, ANNs play a crucial role in artificial intelligence systems, representing the functions of neurons and synapses. They excel in predicting and modeling complex linkages, patterns, and nonlinear correlations, working with diverse data forms, handling errors in data, extracting features from datasets, and rapid data processing.

Consequently, the MLP-ANN included an input layer with 20 parameters, two hidden layers, and an output layer such as WQI (Figure 12). Behind the scenes, the input layers (signal) are converted to neurons in the first hidden layer, and these neurons are transformed into an output signal that is transferred to the next layer by the application of complex nonlinear functions[326]. The conclusions of this study are strengthened by similar findings that advocate minimizing the number of factors and avoiding excessively complex calculations, thereby facilitating the generation of a single value for water quality management at the water source level. This study identified significant predictors of water quality along with their importance for public health. The WQI can be predicted, for example, to reduce difficult calculation processes and laboratory fatigues[327]; TDS, EC, and turbidity can be used for river water quality management[328];

dissolved oxygen (DO) can be used to reduce the health of river water[329]; and the river water WQI can be estimated to identify the acceptable water quality level.

Table 22: Model summary and independent variable importance for total dissolved solids (TDS)

Model Summary (R^2=94%)	Training	Sum of Squares Error	2.739
		Relative Error	0.066
		Training Time	0:00:00.00
	Testing	Sum of Squares Error	0.684
		Relative Error	0.056
Independent Variable Importance	Water Quality Parameters	Importance	Normalized Importance
	Iron(Fe)	0.252	100.0%
	Chromium(Cr)	0.249	98.6%
	Manganese(Mn)	0.127	50.1%
	Potassium(K)	0.121	48.0%
	Nitrate(NO_3)	0.099	38.4%
	Calcium (Ca)	0.034	13.5%
	Sodium(Na)	0.029	11.4%
	Total Dissolved Solids(TDS)	0.021	8.5%
	Bicarbonate(HCO_3)	0.021	8.4%
	Sulfate(SO_4)	0.018	7.2%
	Fluoride(F)	0.017	6.8%
	Magnesium(Mg)	0.013	5.0%
	Total	1.00	

Additionally, predictions of nitrate, manganese, sodium, potassium, pH, conductivity, oxidability, and total suspended solids (TSS) from different water quality input parameters; WQIs from TDS, EC, pH, SO_4, HCO_3, Cl, Ca, Mg, and Na input parameters; and other parameters have been reported. These studies have demonstrated the successful application of ANNs in modeling WQI, achieving a remarkable R^2 value [324,330–332]. The ANN model was used to predict parameters for water quality management in lakes, reservoirs, ponds, rivers, and streams[333]. However, limited evidence exists regarding the application of artificial neural networks (ANNs) to predict WQI in the study area, aside from a few studies conducted in the Little Akaki River within the upper Awash subbasin.

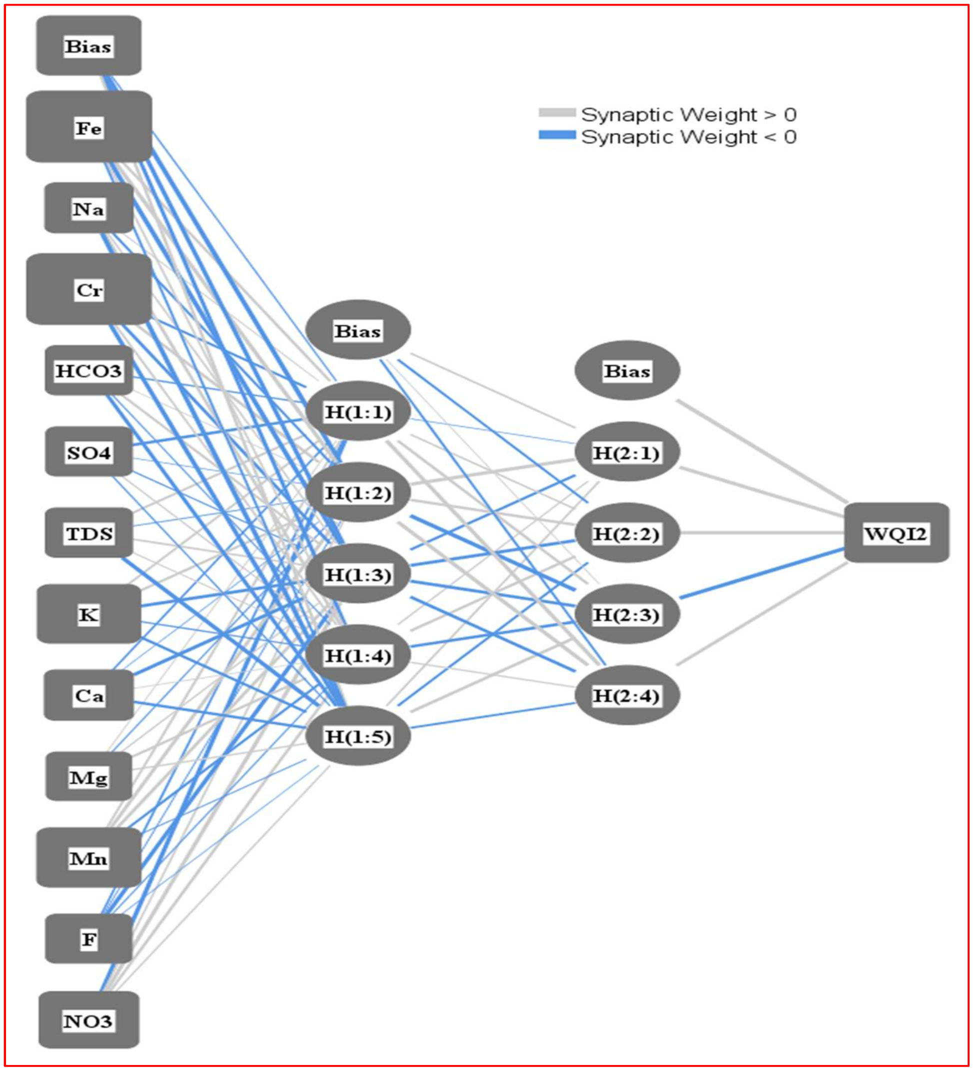


Figure 12: Two-hidden-layer architecture of the MPL-ANN for drinking WQI

Various studies have extensively utilized the ANN approach to predict WQI and other parameters across regions and water bodies. In the Mathura River Basin, the predicted dissolved oxygen (DO) values[329]; in the Shivganga River Basin in India, the WQI values are predicted across different seasons[334]. In Feitsui Reservoir, Taiwan, an ANN was applied for predicting WQI via the cascade network[335]. On the other hand, ANN models have been found to outperform linear regression models in accurately describing the behavior of water quality parameters, with basis function neural networks, mainly radial basis function (RBF) networks, emerging as highly accurate and reliable tools for processing large amounts of nonlinear data[336]. Overall, the use of ANN in predicting WQI offers significant advantages in computational efficiency, cost-effectiveness, and time savings compared with traditional methods, indicating its potential for widespread application in water quality monitoring and management.

Table 23: Model summary and independent variable importance of the WQI

<table>
<tr><td rowspan="5">Model Summary (R^2= 95.1%)</td><td rowspan="3">Training</td><td>Sum of Squares Error</td><td>0.102</td></tr>
<tr><td>Relative Error</td><td>0.011</td></tr>
<tr><td>Training Time</td><td>0:00:00.00</td></tr>
<tr><td rowspan="2">Testing</td><td>Sum of Squares Error</td><td>0.949</td></tr>
<tr><td>Relative Error</td><td>0.098</td></tr>
<tr><td></td><td></td><td>Importance</td><td>Normalized Importance</td></tr>
<tr><td rowspan="4">Independent Variable Importance</td><td>Potassium(K)</td><td>0.332</td><td>100.0%</td></tr>
<tr><td>Fluoride(F)</td><td>0.251</td><td>75.5%</td></tr>
<tr><td>Sulfate(SO_4)</td><td>0.220</td><td>66.2%</td></tr>
<tr><td>Sodium(Na)</td><td>0.198</td><td>59.6%</td></tr>
</table>

In conclusion, this study emphasizes simplifying water quality assessment by using ANN modeling to develop a comprehensive WQI based on significant input variables. This approach enables effective monitoring and classification of water quality as good, medium, or low, which is crucial for drinking water safety plans and multibarrier strategies. The application of the ANN model in the upper Awash subbasin offers practical solutions, reducing the need for extensive laboratory investigations and complex calculations. Moreover, it facilitates the prediction of WQI based on land use and watershed management, allowing proactive measures to mitigate pollution and safeguard riverine ecosystems. This approach holds promise for similar watershed features. It can contribute to ongoing efforts, such as the National Rapid Assessment of Drinking Water Quality at the country level, the Ethiopia Socioeconomic Survey, and the National WASH Inventory, in monitoring and managing water quality, ensuring the safety of both humans and aquatic life through early detection and effective pollution control measures.

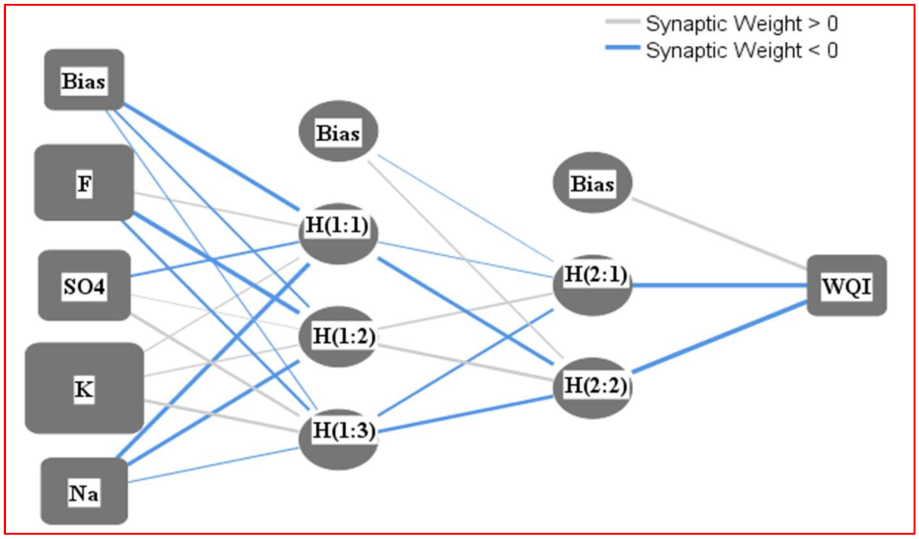


Figure 13: Two-hidden-layer architecture of the ANN for assessing surface water quality

3.4. SOURCES OF WATER POLLUTION AND SOURCE PROFILE

3.4.1. Sanitary Survey

Sanitary assessment is crucial for pinpointing the main contributors, hazardous circumstances, and contamination routes of water sources[303]. A sanitary survey revealed that agricultural activities were a potential cause of pollution for 61.7% (37) of the water supply schemes; 40% (24) of the schemes were located under settlement and human activities, and 66.7% (40) of the drinking water supply schemes were located in proximity to animal entrances (grazing) (**Table 24**) Schemes exposed to agricultural contaminants such as pesticides, chemical fertilizers, and livestock grazing, and the chance of pollution was greater. Additionally, pollutants from both urban and rural populations, as well as those from natural sources such as weather conditions, sources of air pollution, and geological formations, contribute to the contamination of water supplies [337–341]. However, industrial wastewater (effluents) was not observed during the assessment. The high-risk scores of survey results are directly proportional to pollutant loads related to land use [342]. Sanitary conditions are associated with water quality, the availability of coliform bacteria, biological oxygen demand, phosphate, turbidity and the pH of the water supply[343].

Sanitary assessment is a useful tool for water management in urban and suburban areas of tropical, developing countries[344]. However, it may not capture all types of hazards or time variabilities, and it is based on expert judgment [303]. Therefore, it is important to use practical measures, such as source protection techniques, to prevent pollutants from human activities, settlements, and agricultural operations, including grazing practices, from polluting water supplies.

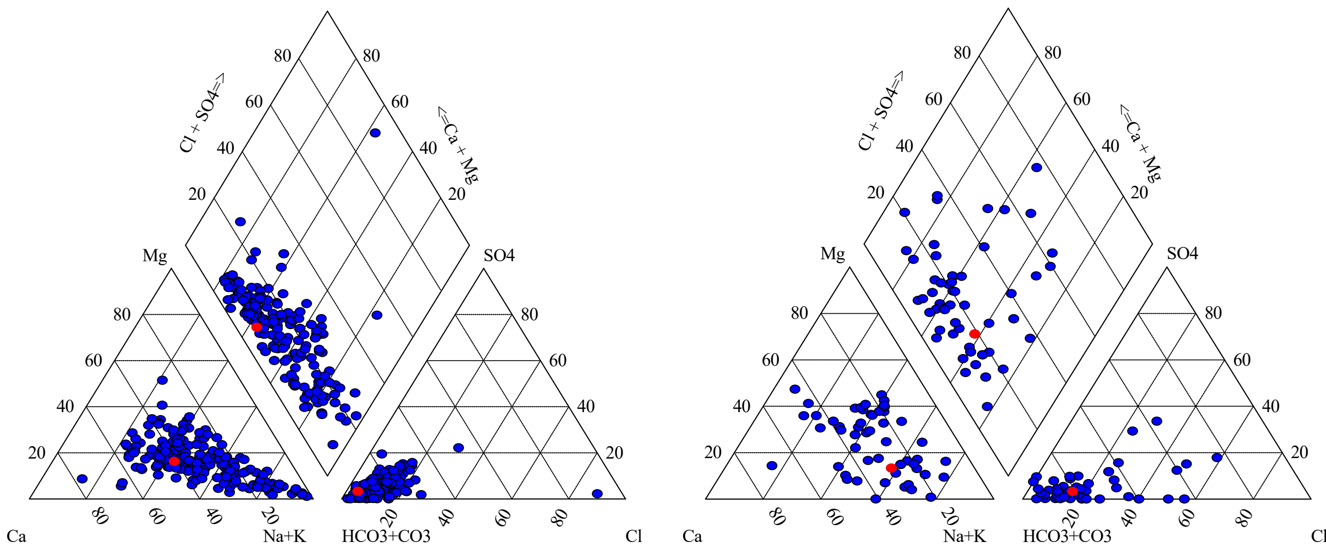
Table 24: Potential sources of pollution in the drinking water in the sampled areas.

S/N	Types of Water Supply Schemes	Sample size (n)	Agriculture (fertilizer & pesticides)		Upstream Settlement and human activities around the scheme		Animal entrance (grazing practices)	
			No	%	No	%	No	%
1	Borehole (BH)	5	2	40	0	0	4	80
2	Shallow well (SW)	37	22	59.45	14	37.8	20	54
3	Hand dug well(HDW)	9	7	77.8	6	66.7	8	89
4	Protected Developed Spring (SPD)	4	1	25	1	25	4	100
5	River intake	1	1	100	1	100	1	100
6	Unprotected well	4	4	100	2	50	3	100
	Total	60	37	61.7	24	40	40	66.7

3.4.2. Hydrochemistry water type

The most dominant water types were identified in the process of hydrochemical water type calculation. Na-HCO3 (65%), Ca-HCO3 (32.5%), Mg-HCO3 (2.03%) and Ca-Cl (0.51%) are recognized in groundwater. Water types such as Na-CO3 (35%), Na-HCO3 (13.3%), Ca-CO3 (11.7%), Ca-HCO3 (8.3%), Mg-CO3 (6.7%), Na-Cl (6.7%), Na-SO4 (3.3%), Mg-Cl (3.3%) and Ca-Cl (1.7%) were observed in the surface water.The water type calculation revealed that groundwater has four water types, whereas eleven water types were identified in surface water samples in the subbasin. This indicated that surface water has a greater source of contaminants than does groundwater

The factors that control the hydrochemistry of different types of water include rock–water interactions, evaporation, carbonate dissolution, carbon dioxide outgassing, acid volcanic heating, cation exchange, and anthropogenic activities. More than 65% of the water in the groundwater was Na-HCO3, according to the hydrochemical analysis of the findings. Ion exchange occurring simultaneously with silicate and carbonate dissolution may cause water to be of the Na-HCO3 type. The main source of the low calcium content in the Na-HCO3 water was cation exchange[345].



a) Groundwater hydrochemistry water type

b) Surface water hydrochemistry water

Figure 14: Geochemistry of water types of groundwater (a) and surface water (b)

Sometimes, the groundwater distribution of microorganisms in the presence of minerals can lead to the availability of sodium bicarbonate in groundwater because the production of carbon dioxide at depth can produce HCO3 and the precipitation of calcium and magnesium, which results in the maintenance of the creation of a sodium-dominant water type. High concentrations of bicarbonate lead to increases in pH, which may cause dissolution of organic matter and the precipitation of calcium and magnesium.

On the other hand, sodium carbonate and sodium bicarbonate made up 35% and 13.3%, respectively, of the water types in the surface water samples. The presence of rock–water interactions, dissolved silica, bicarbonate chemical characteristics, and microbial and anthropogenic activities contribute to a relatively large fraction of sodium carbonate[346]. Furthermore, the presence of basalt and sodium clays in areas where water is recharged from limestone, sandstone, and other aquifers plays an important role in the genesis of sodium bicarbonate.

Table 25: Proportion of chemical water types of groundwater and surface water

S/N	Water Type	Surface Water sampling Sites		Groundwater sampling sites	
		No	%	No	%
1	Ca-Cl	1	1.7	1	0.51
2	Ca-CO3	7	11.7	0	0
3	Ca-HCO3	5	8.3	64	32.49
4	Mg-Cl	2	3.3	0	0
5	Mg-CO3	4	6.7	0	0
6	Mg-HCO3	6	10.0	4	2.03
7	Na-Cl	4	6.7	0	0
9	Na-CO3	21	35.0	0	0
10	Na-HCO3	8	13.3	128	64.97
11	Na-SO4	2	3.3	0	0
Total Sampling sites		**60**	**100**	**197**	**100.0**

Silicate weathering is the most common chemical weathering technique used to create bicarbonate[347]. On the other hand, 32.5% of the groundwater types were Ca-HCO3. Evaporation is the second type of water in the system, and calcium tends to be retained in calcium-bearing minerals[348]. The key processes that contribute to the chemical composition of groundwater are dissolution, dedolomitization, and ion exchange reactions[349].

Finally, the surface water (river water) contained low proportions of Ca-CO3, Ca-HCO3, Mg-CO3, Na-Cl, Na-SO4, Mg-Cl, and Ca-Cl water types. In the Awash basin, which is part of this study area, cations and anions in groundwater are present in the following order: Na>>Ca>Mg>K and HCO3>>Cl>SO4 >NO3->CO2.[350] and surface water Na>>Ca>K>Mg and HCO3>> SO4 >Cl>> NO3 [350]. These dominant hydrochemical facies are associated with rock–water interactions, cation exchange, leaching, and evaporation[351].

3.4.3. Principal Component Analysis (PCA)

The results of the PCA of the five cases of water quality data are summarized in **Table 26**. Bartlett's test of sphericity revealed that all of the results' assumptions and tests were statistically significant (<0.05), indicating that PCA may be used to categorize enormous amounts of data into sources of water pollutants. Furthermore, the Kaiser–Meyer–Olkin (KMO) assumption of an acceptable sample size was met for factor analysis because it is greater than 0.68 in all five cases.

Table 26: Tests and assumptions for principal component analysis (PCA)

S/N	Test and assumptions		Groundwater	Surface Water in the dry season	Surface Water in the wet season	Sample schemes in the dry season	Sampled schemes in wet seasons
1	Kaiser–Meyer–Olkin **(KMO)**		0.682	0.753	0.693	0.696	0.706
2	Bartlett's Test	Sig.	0.000	0.000		0.000	0.000

Rotation sums of squared loadings (RSSLs) of groundwater quality data with 15 parameters revealed that four sources of pollution account for 63.5% of the total variance, with values greater than unity. The first source of pollutants (component 1) included total hardness, calcium, magnesium, fluoride, and nitrate; the second source of pollutants (component 2) included sodium, potassium, chloride, bicarbonate, and sulfate; the third source of pollutants (component 3) included phosphate and alkalinity; and the fourth source of pollutants (component 4) included iron and nitrite (**Table 27**). Ten parameters ranged from 60% to 90% variation, and each was explained throughout the four components.

The results suggested that the first component of the PCA is the agricultural source, as the factor loadings of total hardness, calcium, magnesium, fluoride, and nitrate are greater than those of the other components. The presence of calcium and magnesium in a component with total hardness is common because the hardness of groundwater is affected by calcium and magnesium. The presence of fluoride and nitrate in agricultural sources may be due to the passing of agricultural fertilizers to groundwater as contaminants[352]. Groundwater nitrate contamination is caused by organic and chemical fertilizers and manuring land and pastures[353]. The second component may be due to anthropogenic sources, such as sodium, potassium, chloride, bicarbonate, and sulfate, which are contaminants originating from anthropogenic activities, such as the discharge of domestic wastes, animal wastes, and organic wastes near groundwater boreholes. The variabilities of phosphate (51%) and alkalinity (75%) were captured in the four components, which were the dominant species in the third component. These results may be due to natural rock interactions. In addition, iron and nitrite also dominated the fourth component, which may have originated from natural occurrences. However, some of the elements in the component may not actually be manifested, as variations in iron (33%), fluoride (33%), sulfate (41%), nitrate (30%), and phosphate (51%) in the four sources of pollutants (components) did not provide sufficient evidence.

Table 27: PCA results of groundwater quality.

S/N	Parameters	Communalities (Extraction)	Sources (factor components)			
			Source 1	Source 2	Source 3	Source 4
1	TDS	0.89	0.247	0.888	0.197	0.042
2	Sodium	0.80	-0.451	0.759	0.129	0.078
3	Potassium	0.62	0.138	0.708	-0.287	-0.145
4	Total Hardness	0.90	0.939	0.124	-0.035	-0.021
5	Calcium	0.76	0.866	0.066	-0.057	-0.040
6	Magnesium	0.71	0.825	0.165	-0.043	-0.014
7	Iron	0.33	-0.395	0.098	0.008	0.405
8	Fluoride	0.33	-0.510	0.243	0.091	-0.002
9	Chloride	0.65	-0.323	0.711	0.189	0.004
10	Nitrite	0.76	0.114	-0.024	-0.011	0.866
11	Nitrate	0.30	0.542	-0.070	0.000	0.050
12	Bicarbonate	0.80	0.416	0.746	0.258	0.003
13	Sulfate	0.41	-0.082	0.597	-0.211	-0.007
14	Phosphate	0.51	-0.007	0.242	0.552	-0.385
15	Alkalinity	0.76	-0.134	-0.088	0.848	0.104
Rotation Sums of Squared Loadings		Total	3.619	3.472	1.324	1.106
		% of Variance	24.128	23.144	8.826	7.374
		Cumulative %	24.128	47.272	56.098	63.472

Six components were identified in each season for surface water samples that were likely sources of pollution due to substantial correlations within the component. The surface water in the wet season, the variation in all 18 parameters except ammonia, was explained by more than 50% of the six components. Generally, the six components explained approximately 70.62% of the variance accounting for each component after rotation. As per **Table 28**, Source 1 (TDS, total hardness, chloride, alkalinity, bicarbonate, and sulfate), Source 2 (sodium, potassium, calcium, and carbonate), Source 3 (ammonia, magnesium, nitrite, and nitrate), Source 4 (iron and phosphate), Source 5 (manganese), and Source 6 (fluoride) were assumed to be surface water contaminants.

Among the surface water samples collected during the dry season, component 1 (TDS, total hardness, calcium, alkalinity, and bicarbonate); component 2 (sodium, potassium, calcium, and carbonate); component 3 (ammonia, magnesium, nitrite, and nitrate); component 4 (iron and phosphate); component 5 (chloride); and component 6 (carbonate and sulfate) were grouped via

PCA. The extracted communalities revealed that 60% - 82% of the variation in 18 parameters explained the variability of the six components (sources). These six components explained 70.50% of the variance in the overall data when the eigenvalue (**Table 28**) was considered. On the basis of the unity eigenvalue, the number of sources or components in the eigenvalue, the number of sources or components in surface water is greater than that in groundwater. This suggested that the source of pollutants was greater in surface water than in groundwater because the risk of exposure to water pollution is greater due to flooding and direct discharge of wastewater and solid waste into surface water.

Table 28: Surface water sample in the wet season, rotation sums of squared loadings

S/N	Water Quality Parameters	Communalities	Sources (factor components, wet season)						Sources (factor components, dry season)						
			Sour.1	Sour.2	Sour.3	Sour.4	Sour.5	Sour.6	Communalities	Sour.1	Sour.2	Sour.3	Sour.4	Sour.5	Sour.6
1	TDS	0.78	0.62	0.16	0.03	-0.58	-0.08	0.18	0.60	0.67	0.08	-0.10	-0.32	0.17	0.10
2	Ammonia	0.50	0.32	0.11	0.47	0.38	0.12	0.12	0.57	0.13	0.19	0.53	0.47	-0.04	0.06
3	Sodium	0.79	0.11	0.85	0.04	0.20	0.07	-0.08	0.81	0.20	0.78	0.37	-0.01	0.04	0.15
4	Potassium	0.78	0.10	0.83	0.14	-0.08	-0.18	-0.15	0.76	0.11	0.86	0.00	0.06	-0.01	-0.06
5	Total Hardness	0.65	0.59	0.48	0.01	0.02	0.20	0.17	0.78	0.79	0.27	0.24	-0.13	0.04	0.06
6	Calcium	0.62	0.38	0.61	0.23	0.08	0.06	0.20	0.67	0.66	0.34	0.06	0.21	0.03	-0.27
7	Magnesium	0.73	0.04	-0.10	0.73	0.21	0.16	0.33	0.67	0.35	0.09	0.51	0.17	0.47	-0.18
8	Iron	0.60	-0.13	0.21	0.13	0.69	-0.21	-0.01	0.60	0.16	0.33	0.21	0.63	-0.16	0.09
9	Manganese	0.67	0.10	0.01	0.06	0.04	0.81	-0.06	0.75	0.00	0.09	0.84	0.17	-0.03	0.09
10	Fluoride	0.87	0.13	-0.03	0.03	-0.03	-0.02	0.92	0.65	0.01	0.51	0.04	0.34	0.46	0.23
11	Chloride	0.66	0.60	0.03	0.45	0.28	-0.14	0.07	0.80	0.20	0.02	0.06	-0.02	0.87	0.03
12	Nitrite	0.72	0.18	0.24	0.79	0.09	-0.05	-0.01	0.73	0.01	0.04	0.11	0.83	0.18	0.00
13	Nitrate	0.69	-0.04	0.12	0.71	-0.20	0.09	-0.36	0.56	0.25	0.63	0.05	0.09	0.02	-0.30
14	Alkalinity	0.86	0.85	0.21	0.07	-0.04	0.29	0.10	0.82	0.85	0.15	0.24	-0.06	0.10	-0.04
15	Carbonate	0.65	0.09	0.52	0.34	-0.26	0.43	0.10	0.80	0.51	0.07	0.24	-0.04	0.13	-0.67
16	Bicarbonate	0.77	0.71	0.13	0.44	0.05	0.21	0.09	0.73	0.73	0.07	-0.18	0.29	0.18	0.20
17	Sulfate	0.70	0.64	0.05	0.11	-0.16	-0.43	-0.24	0.70	0.37	0.04	0.15	0.09	0.09	0.74
18	Phosphate	0.66	0.16	-0.08	0.04	0.67	0.41	0.08	0.69	0.08	0.19	0.65	0.03	0.44	-0.17
Total			3.1	2.5	3.1	2.5	2.5	1.7		3.5	2.4	2.1	1.7	1.5	1.4
% of Variance			17.4	14.0	13.9	9.6	8.	7.4		19.4	13.5	11.7	9.7	8.6	7.6
Cumulative %			17.4	31.3	45.2	54.76	63.2	70.62		19.4	32.9	44.6	54.3	62.9	70.5

On the other hand, the 2nd components, with the exception of calcium, sodium, potassium, and carbonates, were observed in both seasons, whereas the 3rd component species, such as ammonia, magnesium, nitrite, and nitrate, and the 4th component species, such as iron and phosphate, in both seasons were similar, which can indicate that the sources of these contaminants may not change due to the seasons of the year. However, chloride and sulfate were under component 1 in the dry season but were under components 5 and 6 in the wet season. This difference may be due to the presence of seasonal variations in the sources of water pollution.

In the case of drinking water samples, the PCAs of components 1 (alkalinity, bicarbonate, and carbonate), 2 (TDS, fluoride, total hardness, and magnesium), 3 (sulfate, calcium, and nitrate), and 4 (manganese) were sorted to indicate the source of pollutants on the basis of the assumption that correlated parameters can originate from similar sources. The PCA communalities revealed that the four components explained 66% to 99% of the variation in 11 parameters. Considering RSSL, the four components with eigenvalues greater than one explain more than 85% of the variance in the water quality data (**Table 29**).

Table 29: PCA, rotated component matrix of drinking water quality in the dry and wet seasons.

S/N	Water Quality Parameters	Component in dry season					Component in wet season				
		Com.	Sour.1	Sour.2	Sour.3	Sour.4	Com	Sour.1	Sour.2	Sour.3	Sour.4
1	TDS	0.82	0.581	0.633	0.283	0.025	0.77	0.748	-0.228	0.394	0.004
2	Fluoride	0.66	0.300	0.517	-0.426	-0.34	0.67	0.239	0.569	0.521	0.115
3	Manganese	0.97	0.072	-0.02	0.114	0.974	0.83	-0.017	-0.062	-0.057	0.909
4	Sulfate	0.69	-0.024	0.099	0.823	0.079	0.62	0.305	0.111	0.674	-0.255
5	Alkalinity	0.99	0.970	0.216	0.008	0.033	0.90	0.895	0.308	-0.072	-0.077
6	Bicarbonate	0.98	0.971	0.197	0.005	-0.00	0.81	0.778	0.455	-0.024	-0.047
7	Carbonate	0.99	0.968	0.225	0.004	0.019	0.91	0.899	0.301	-0.074	-0.069
8	Calcium	0.80	0.475	0.336	0.682	0.009	0.78	0.860	-0.176	-0.102	-0.001
9	Total Hardness	0.89	0.468	0.759	0.279	0.115	0.78	0.828	-0.127	0.207	-0.178
10	Nitrate	0.67	-0.026	-0.43	0.688	0.110	0.68	-0.259	-0.421	0.358	0.554
11	Magnesium	0.94	0.173	0.941	-0.139	-0.06	0.80	0.362	0.143	-0.749	-0.294
12	Iron						0.52	-0.063	0.688	0.134	-0.156
13	Chromium						0.47	0.042	0.662	-0.151	-0.060
Total			3.731	2.575	1.986	1.107		4.55	1.94	1.68	1.40
% of Variance			33.92	23.41	18.06	10.07		35.02	14.93	12.91	10.54
Cumulative %			33.92	57.32	75.40	85.45		35.02	49.95	62.86	73.40

Drinking water supply samples from the wet season were grouped into four components: component 1 (TDS, alkalinity, bicarbonate, carbonate, calcium, total hardness); component 2 (fluoride, iron, and chromium); component 3 (sulfate and magnesium); and component 4 (manganese and nitrate). Except for the iron and chromium parameters, 67% - 90% of the variation in 11 parameters was explained by the four sources in accordance with the extraction of communalities **Error! Reference source not found.**. Considering RSSL, more than 73.40% of the variance is explained by the four components that have eigenvalues greater than 1. Approximately 85.45% of the water quality data in the dry season were explained by component 1 (alkalinity, bicarbonate and carbonate), component 2 (TDS, fluoride, total hardness, and magnesium), component 3 (sulfate, calcium and nitrate) and component 4 (manganese). The extracted communalities revealed that more than 66% of the variability in the 11 parameters was incorporated into the calculated factor loadings.

On the basis of the sanitary survey results and hydrochemical water type calculation with this analysis, naturally occurring sedimentary and igneous rocks and anthropogenic and agricultural activities are the most common sources of drinking water pollution in both seasons. In the above **Error! Reference source not found.**, alkalinity, bicarbonate and carbonate in component 1, fluoride in component 2, sulfate in component 3, and manganese in component 4 occurred in both seasons, which might indicate that these species came from similar sources that were not affected by the season of the year. However, the variable occurrence of TDS, calcium, magnesium and nitrate in each season may be due to their emergence from variable sources

3.4.4. Pollution source apportionment using PMF

In this study, 120 samples (60 samples from each season) of drinking water with 18 parameters, 197 samples of groundwater with 20 parameters and 70 samples with 19 parameters were prepared for the PMF model (**Table 30**). Accordingly, only samples were taken in the dry season, and groundwater samples were passed through a series of steps to predict the factor profile and source contributions of the subbasin since the PMF model was more accurate than source apportionment via PCA[354].

Table 30: Types, included parameters and number of samples

S/N	Sample Sites	# of Samples	# of Parameters	Parameters considered for PMF model	Note
1	Drinking Water Supply Schemes	60	24	11 (TDS, F^-,Mn,SO_4, Alkalinity, HCO_3, CO_3,Ca^{+2},TH, NO_3 and Mg^{+2})	These were primary data taken in wet and dry seasons (120 samples); however, samples of dry season were converging
2	Groundwater source (Boreholes)	197	20	15(TDS, Na^+, K^+, TH, Ca^{+2}, Mg^{+2}, Fe^+, F^-. Cl^-,NO_2,NO_3, HCO_3,SO_4, PO_4 and Alkalinity)	EC, pH, Mn, $CaCO_3$ and CO_3 were excluded from analysis as these were not satisfying the requirement of the model run.
3	Surface Water	70	19	Unmapped	10 River water sampling stations)
	Total	327			

3.4.5. Residual Analysis

There was no convergence of surface water from the river sampling stations or drinking water scheme samples from the wet season at the base run step. Initially, these were excluded from the residual analysis procedure. Eleven and twenty-four parameters from drinking water supply samples collected during the dry season, as well as 15 of the 20 parameters from groundwater samples, were included in the residual analysis process. The inclusion of species was carried out by residual analysis, which examined the coefficient of determination (R2), the observed/predicted scatter plot, and the species histogram to confirm the model's fit. The PMF technique states that the residual analysis indicates whether a normal curve exists for each species and whether it should be included in the following run.

3.4.6. Pollutant Source contribution

After passing through steps and triangulations in the process of PMF, four components were identified as sources of water pollution in this base run of groundwater samples: the determination of water pollution sources depends on sanitary survey (observational) results, hydrochemical water type calculation results and expert judgment. From natural sedimentary and igneous rocks and from external sources, anthropogenic and agricultural sources have been established. As a result, 14 contaminants from sedimentary rock, 12 from igneous rock, 12 from anthropogenic sources and 13 from agricultural sources originated. According to **Figure 15**, the sources of 38.7%, 28.4%, 21.4%, and 11.6% of the TDS were sedimentary rock, anthropogenic activity, igneous rock, and agriculture, respectively. Sodium contamination was caused by anthropogenic, igneous, and sedimentary rocks, which contributed 41.6%, 32.2%, and 22.9%, respectively. Agriculture was a minor source of sodium contamination. Sedimentary rock and anthropogenic rock contained approximately 71% and 24% of the potassium parameter, respectively. The potassium levels in the igneous rock and agricultural components were lower. Sedimentary rock and agricultural activities caused more than 70% and 20% of the total hardness of the water, respectively. The calcium and magnesium parameter sources were identical to the total hardness parameter source. Almost 81% and approximately 19% of iron contaminants originate from naturally occurring sedimentary and igneous rocks, respectively. Surprisingly, 42%, 41.4% and 15.8% of the fluoride originated from igneous, anthropogenic and agricultural activities, respectively. With a minimal proportion of agricultural sources, 45.3%, 27.8% and 23.4% of the chlorine parameters were derived from anthropogenic, igneous and sedimentary rocks, respectively. As expected, 85% of the nitrate originated from agricultural sources, whereas almost less than 10% originated from sedimentary or anthropogenic sources. In contrast, 58.5%, 28.5% and 12.9% of the nitrite contaminants emerged from agricultural, sedimentary and igneous rock sources, respectively. Approximately 45%, 22%, 19%, and 14% of the bicarbonate contaminants were associated with sedimentary, anthropogenic, igneous and agricultural sources, whereas 59.4% and 40.6% of the alkalinity was associated with igneous rock, and agricultural activities were responsible for contaminant sources. Most of the sulfate and phosphate were derived from anthropogenic sources. Since the requirements of base run error estimations such as BS, DISP and BS-DISP were satisfied, Fpeak rotation was not performed for the groundwater samples.

In terms of drinking water supply, the results of the base run and the Fpeak model run were compared since the BS-DISP error estimation of its swaps by factor findings was an invalid solution at the base run. Following the basic run evaluation. Fpeak with the PMF rotational tool has been applied to decrease the number of solutions. As a result, the rotating tool was used to obtain Fpeak data. The comparison revealed that the Fpeak model results deviated significantly from the base run model results. However, for eight parameters, there were unfavorable variances in the igneous rock sources.

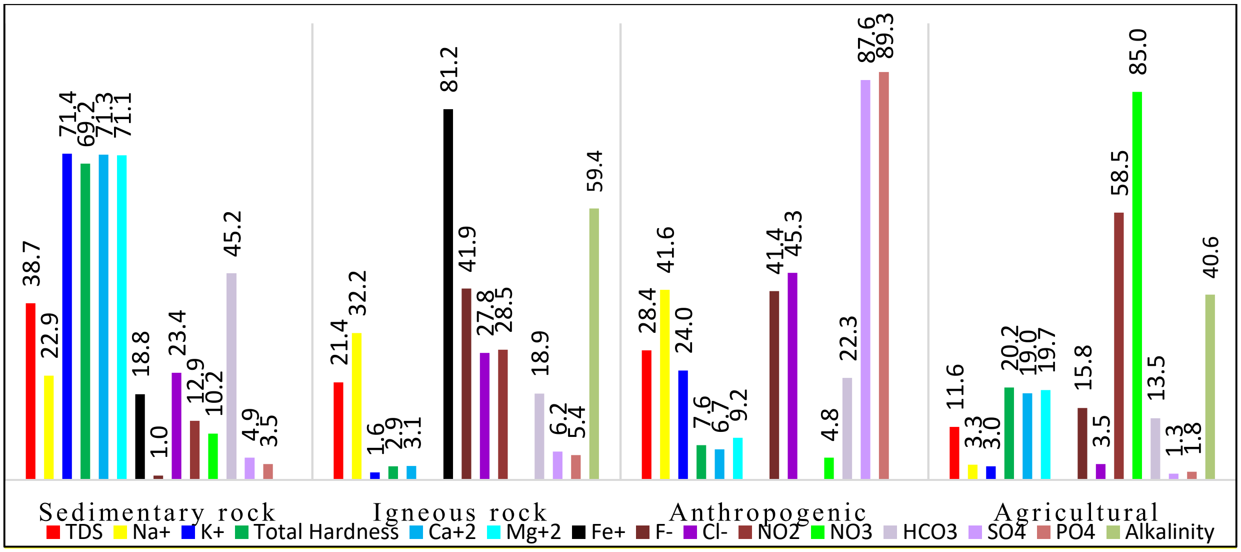


Figure 15: Factor profiles (% of species sum) from Base Run #3 (Convergent Run)

The Fpeak model results were similar to those of the base run; a greater proportion of sulfate originated from anthropogenic sources, nitrate originated from agricultural sources, and magnesium originated from sedimentary rock sources (**Figure 16**). In contrast with the base model, more than 63% of the manganese was in agriculture. Almost 30% - 47% of the alkalinity, bicarbonate, carbonate, calcium and total hardness were derived from agricultural sources. TDS (43.78%), fluoride (63.52%), alkalinity (39%), HCO_3 (39.16%) and CO_3 (39%) originated from igneous rock, and total hardness and magnesium originated from sedimentary rock sources. Approximately 34.68% of the TDS, 31.97% of the fluoride, 27.89% of the manganese, 25.77% of the alkalinity, 25.39% of the bicarbonate, 25.9% of the carbonate, 36.64% of the calcium, 45.29% of the total hardness and 80.39% of the magnesium originated from sedimentary rock.

In the Upper Awash subbasin, water pollution sources were classified as agricultural, anthropogenic rather than agricultural, sedimentary, and igneous rock. The following is a discussion of the source contributors to each species in a water quality sample.

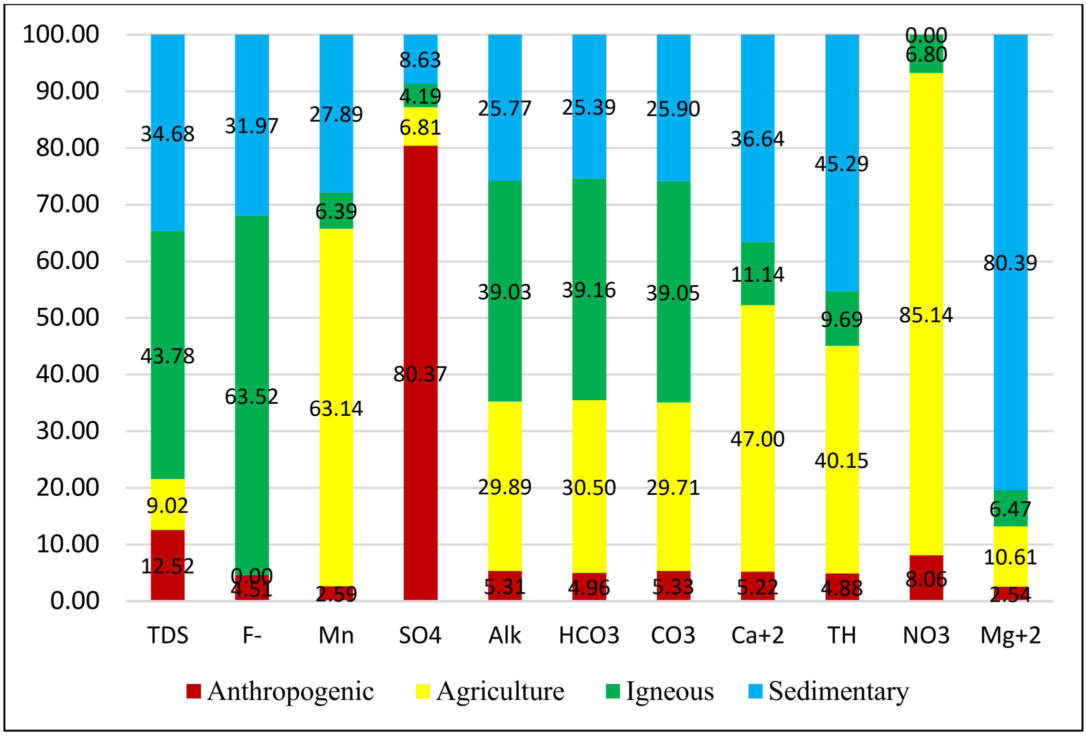


Figure 16: Factor profiles (% of species sum) from Fpeak Run #2, strength = -0.5 (Convergent Run)

3.4.6.1. Nitrate (Ammonia, Nitrite and Nitrate)

Nitrate pollutants were grouped into groundwater, surface water in the dry and wet seasons and drinking water samples in the dry and wet seasons as components 1st, 3rd, 3rd, 3rd, and 4^{th,} respectively, in the PCA, **Figure 15** & **Figure 16**. Accordingly, these components are assumed to be agricultural sources because of their correlations. The results of the PMF model revealed that 85% of the nitrate originated from agricultural sources, whereas almost less than 10% originated from sedimentary or anthropogenic sources. On the other hand, 58.5%, 28.5% and 12.9% of the nitrite pollutants in the groundwater emerged from agriculture. The literature from around the world has established that the source of nitrate pollution in groundwater is agricultural activities in the form of organic materials, fertilizers and animal wastes[353]. The nitrate concentration in groundwater has increased globally; for example, nitrate has increased in many European countries over the past 20 years[355]. In the upper Awash subbasin, nitrate concentrations are associated with untreated industrial waste, geogenic processes, urban sewage, and the application of fertilizers [269,356]. Furthermore, research suggests that nitrate is a prevalent contaminant in the study area as a result of the effects of climate change and growing populations, which contribute to the intensification of agricultural activities[357]. Drinking water supply schemes should be protected since shallow wells, which are the most common drinking water supply schemes, are more negatively impacted than deep wells are, as this may increase the exposure of nitrate risks in groundwater [358,359]. On the other hand, because it is closely related to nitrate, nitrite is a sign of bacterial contamination. In addition to nitrogenous waste from animals, nitrogen fixation, air deposition, and runoff from agricultural fields are sources of ammonia. On the other hand, nitrate is present and linked to microbial contamination[360].

3.4.6.2.Sulfate and Phosphate

Most of the sulfate (87.6%) and phosphate (89.3%) were derived from anthropogenic sources in the groundwater, with similar proportions in the drinking water samples Figure 15 and Figure 16. The source of sulfate is both anthropogenic and natural. It may be derived from gypsum, pyrite, and other sulfur-containing minerals in rocks and soils, as well as from some mining and industrial waste products[361]. Sulfate has been reported in the Upper Awash River Basin because wastewater effluents are released from industries located in and around Addis Ababa[362]. A high concentration of sulfate was reported in the treated effluent of industries that joined the river of the subbasin[363]. On the other hand, the high phosphate concentration may be due to the widespread use of phosphate-based detergents; agricultural activities, including pastures, urban wastewater and runoff; and industrial waste[356]. A study conducted in China indicated that the phosphate pollutants in groundwater, particularly in shallow aquifers and surface water, originate from the impact of urban land use[364], and in India, the phosphate levels in surface and groundwater are influenced by industrial and agricultural activities, population density, resident types, soil/rock types, and climate change[365]. Nevertheless, evidence suggests that there are more geological sources of phosphate in groundwater than fertilizer sources and that the release of phosphate from groundwater to streams, rivers, and lakes is enough to cause environmental pollution[366].

3.4.6.3.Sodium and potassium

The PMF model run for the groundwater samples in the subbasin revealed that anthropogenic, igneous, and sedimentary rocks contributed 41.6%, 32.2%, and 22.9% of the total sodium contamination, respectively, and approximately 71% and 24% of the potassium parameter was identified in sedimentary rock and anthropogenic rock, respectively. Agriculture, on the other hand, plays a smaller role as a source of sodium pollutants. According to review papers, potassium is common in many rocks that are largely soluble, increases pollutant levels in groundwater, and is also caused by wastewater discharge[367]. Potassium can be generated through agricultural sources such as potassium-rich fertilizers, anthropogenic sources such as waste products, naturally occurring minerals, and saltwater/saline water from geologic times. In contrast, the presence of potassium in water has been associated with total coliform bacteria[368]. Furthermore, sodium can be emitted by natural rock sources, and sodium contamination in water can be attributed to anthropogenic sources such as road salt and animal manure, which can serve as indicators of human impacts on shallow ground water[367]. In the Awash basin in the rift valley aquifer, sodium is the dominant pollutant because of its natural source contribution. As a matter of fact, dominance occurred on the farm of the sodium bicarbonate water type[269].

3.4.6.4.Calcium and Magnesium

The more or less calcium and magnesium present in the components were attributed to agricultural activities and anthropogenic and naturally occurring rock, particularly sedimentary rocks. These results revealed the sources of magnesium agricultural activities in the first and third components of the ground water samples in both seasons. The source of magnesium in drinking water is also from sedimentary rock and anthropogenic sources. Additionally, approximately 71% of the calcium and magnesium originated from naturally occurring sedimentary rocks and were more or less similar to the source of the total hardness parameter per the PMF model run for groundwater. In contrast, 79% and 14% of the magnesium originated from sedimentary rock and igneous rocks, respectively, and 49%, 33%, and 15.5% of the calcium from agricultural activities, sedimentary rock and igneous rock originated from dry season samples of drinking water. The PCA and PMF model results are supported by review articles. Calcium originates from rocks, particularly limestone, dolomite, and gypsum, and magnesium is associated with igneous and sedimentary rocks. In the study area, calcium and magnesium are predominant in the highland aquifer of the upper Awash subbasin[269]. In the Awash River Basin, the highlands have similar water chemistry contents and low TDS values, with a predominance of calcium–magnesium bicarbonate[369].

3.4.6.5. Alkalinity, Bicarbonate, Carbonate and Hardness.

In the case of groundwater, the PMF model revealed that sedimentary, anthropogenic, igneous, and agricultural sources accounted for approximately 45%, 22%, 19%, and 14% of the bicarbonate contaminants, respectively, whereas igneous rock and agricultural activities accounted for 59.4% and 40.6%, respectively, of the alkalinity.

In terms of total hardness, sedimentary rock and agriculture contributed 70% and 20%, respectively. In the case of drinking water samples, nearly 30% - 47% of the alkalinity, bicarbonate, carbonate, and total hardness were derived from agricultural sources, whereas alkalinity (39%), HCO3 (39.16%), and CO3 (39%) were derived from igneous rock, and 45%, 40%, 10%, and 5% of TH were derived from sedimentary, agricultural activities, igneous rocks, and anthropogenic effects, respectively. In the carbon system, water quality, alkalinity, bicarbonate, carbonate and water hardness are related to each other. Most hardness is caused by calcium and magnesium, which are also associated with carbonate minerals, which are the main sources of water alkalinity. In this study area, bicarbonate anions occurred predominantly in the highlands of the subbasin[269], and the calcium–magnesium bicarbonate type was associated with TDS[369].

The hardness of water is caused by calcium and magnesium ions from sedimentary rocks, seepage and runoff from soils[370]. According to research conducted in the study region, hardness in industrial discharges is greater than that in chemical manufacturing enterprises, which require wastewater softening before discharge to water bodies[371]. Alkalinity is positively related to electrical conductivity and its elevated concentration because mostly carbonates and bicarbonates are present in the studied area. These products are also derived from industrial wastes, sewage, and sedimentary rocks such as limestone, dolomite, and magnesites[356]. The alkalinity in the Awash River Basin ranges from 104 to 980 mg/l CaCO3. Carbonate buffering serves as a good source of water alkalinity in sedimentary rock, such as limestone. The high alkalinity in this area's wells is due to bicarbonate and carbonate weathering from calcite mineral weathering[350]. Pollution caused by agrochemicals, fertilizers, and hardness because of urbanization and agricultural intensification has been noted. During the rainy season, the total hardness increases somewhat, whereas the total dissolved solids, chloride, and sulfate contents decrease[318]. In upper Awash, the increase in total hardness is most likely due to the presence of noncarbonate and carbonate chemicals. It increases the alkalinity and pH of the surrounding environment[371]. The presence of correlations between contaminants such as alkalinity, bicarbonate, total hardness, and carbonate was supported by articles using similar approaches, indicating that these contaminants are derived from the same source[316]. Furthermore, a study conducted in southern Ethiopia revealed that silicate and carbonate weathering processes were bicarbonate sources[372]. Research has demonstrated that, outside of the study region, total hardness pollution of urban groundwater is induced by water–rock interactions and anthropogenic activities. [373].

3.4.6.6.Total Dissolved Solids (TDS)

In addition to the PCA, the PMF run findings revealed that groundwater, sedimentary rock, anthropogenic activity, igneous rock, and agriculture were the sources of 38.7%, 28.4%, 21.4%, and 11.6% of the TDS, respectively, and that drinking water, igneous rock, sedimentary rock, anthropogenic activity, and agriculture were the sources of 43.73%, 34.68%, 12.52%, and 9.02% of the TDS, respectively. TDS is composed of three types of parameters: main constituents (Na, Ca, Mg, Cl, HCO3, SO4, etc.), minor constituents (K, Fe, CO3, NO3, F), and trace elements. TDS values will be high if there are high concentrations of cations and anions in the water[374]. In groundwater and surface water, TDS is associated with the magnesium, potassium and sodium concentrations[375]. The TDS concentrations in the Awash River Basin vary due to water–rock interactions, with the highland portion of the basin having a lower concentration (57). The TDS is raised from the topmost basin to the rift, with the exception of some axial fractures and recharge from highland rainfall. Furthermore, significant TDS concentrations have been reported in the Akaki River basin area around Addis Ababa as a result of anthropogenic activities[376].

3.4.6.7.Iron, Manganese and Chromium

Manganese was derived from agricultural, sedimentary rock, igneous, and anthropogenic sources (63.14%, 27.77%, 6.39%, and 2.6%, respectively) in the PMF model. The naturally occurring igneous and sedimentary rock types provided 81.2% and 18.8% of the iron, respectively. Iron is the second most prevalent metallic element in crustal rocks, and it can be found in both igneous and sedimentary rocks. Mafic rocks are igneous rocks with high magnesium and iron concentrations. The sedimentary rocks include hematite, magnetite, limonite, and siderite. However, accurate identification of the iron origin is difficult because of iron ore weathering. Iron and other heavy metals were found in Awash River water, with considerable concentration differences among sampling locations and a rising temporal trend[377]. Furthermore, greater levels of heavy metals such as chromium, iron, and manganese have been detected in surface water samples from the awash basin[378]. Nigeria/Around the Worldwide, the source of iron in groundwater is thought to be iron minerals from rocks and soils, as well as from land use activities[379], and in India, it may be due to the dissolution of rocks, smelting processes and the seepage of domestic sewage effluents[380].

Manganese is also found in many igneous rocks and some sedimentary rocks, such as dolomites and limestone. Manganese in groundwater is caused by the dissolution of manganese-containing minerals as well as human activities such as mining, industrial discharge, and landfill leaching. Manganese pollution is caused mostly by industrial waste and sewage discharge in the Modjo River, which is part of the upper Awash subbasin [381]. In China, the source of iron and manganese in groundwater is the clay layer and soil aquifer for surface water contamination[382]. Reports have revealed that chromium (Cr) and manganese (Mn) are abundant in Lake Koka and its inflows. Chromium occurs most frequently in igneous rocks and anthropogenic sources[383].

3.4.6.8. Chloride and Fluoride

The PMF run revealed 45.3%, 27.8% and 23.4% fluoride from anthropogenic, igneous and sedimentary rocks and 41.9%, 41.4% and 15.8% chloride from igneous, anthropogenic and agricultural sources, respectively. Naturally, chloride is an abundant element in the Earth's crust and mainly originates from the mineral halite in sedimentary rocks. This is also due to sewage, industrial effluent, and seawater. In the rift direction of the Awash River, chloride is the dominant anion[69]. Research in China. Sewage effluents and fertilizers may be the primary sources of chloride in groundwater systems[384]. Fluoride is mostly obtained from thermal and fluoride-rich deep well fluids in the Akaki basin of this study region[385]. The fluoride levels in northwestern Addis Ababa city have increased due to human activity and the urban environment[386]. Fluorite, fluorapatite, biotite, amphibole, micas, topaz, cryolite, muscovite, and fluorspar are the principal geogenic sources of fluoride in groundwater. Furthermore, phosphate rock, which is also a component of phosphate fertilizers, is the primary source of fluoride[387].

3.4.7. Water pollutant Source profile

In **Figure 17**, anthropogenic sources of water contaminants were responsible for 44.23% of TDS, 30.15% of bicarbonate, 11.2% of sodium, and 15% of other contaminants, such as total hardness, sulfate, chloride, magnesium, and calcium, in groundwater PMF analysis. Agriculture was responsible for 35% of the alkalinity, 21.03% of the bicarbonate, 15.08% of the total hardness, 20.81% of the TDS, 3.5% of the calcium, and 1.9% of the nitrate, with extremely small levels of sodium, magnesium, and chloride. Sedimentary rock, on the other hand, was responsible for 31.53% of the TDS, 32% of the bicarbonate, 23.48% of the total hardness, 6% of the calcium, 3.2% of the sodium, 1.78% of the magnesium, and 0.86% of the chloride. Furthermore, igneous rock was responsible for 38.15% of the alkalinity, 28.5% of the TDS, 21.83% of the bicarbonate, 7.39% of the sodium, 1.67% of the chloride, and 1.6% of the overall hardness

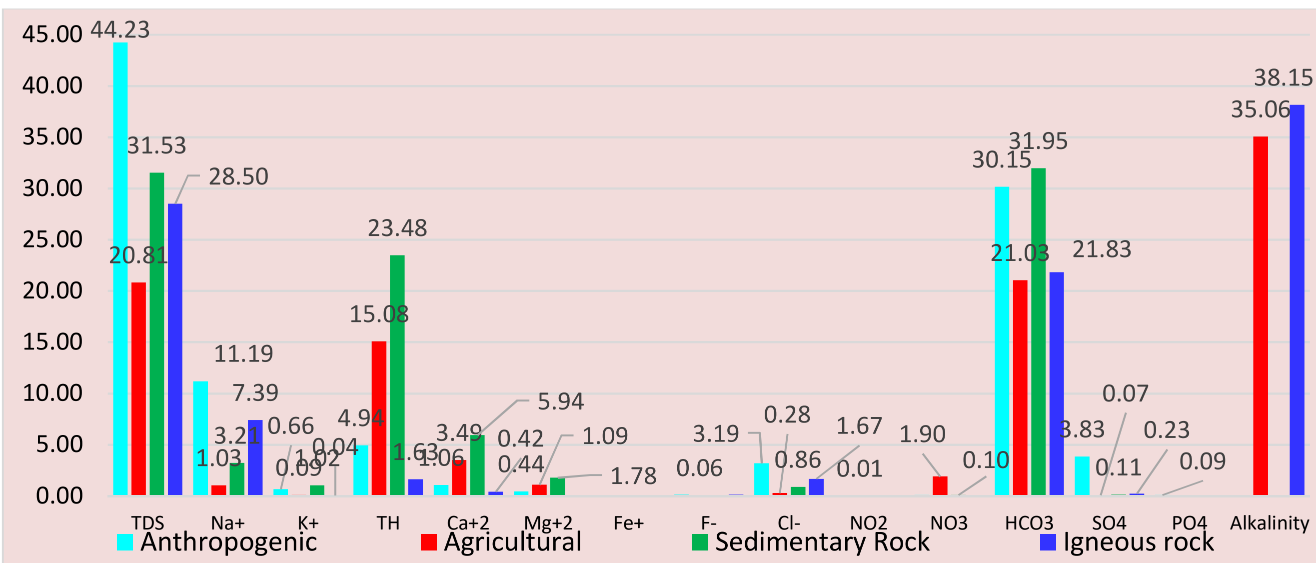


Figure 17: Factor Profiles (Percentage of factor total) from Base Run #3 (Convergent Run) and kind of sources and distribution of sources in each parameter.

Bicarbonate, sodium, potassium, total hardness, sulfate, chloride, and phosphate pollution in groundwater are caused by sedimentary rocks, igneous rocks, and anthropogenic and agricultural sources. On the other hand, the majority of nitrate pollution is caused by agricultural sources, whereas iron is caused by igneous rocks.

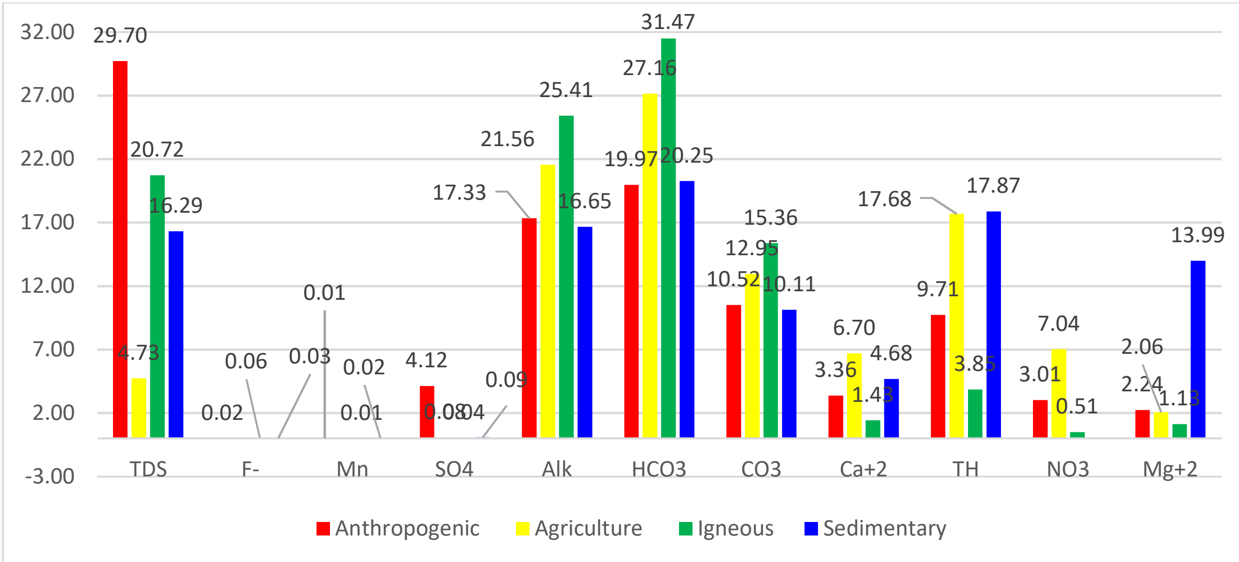
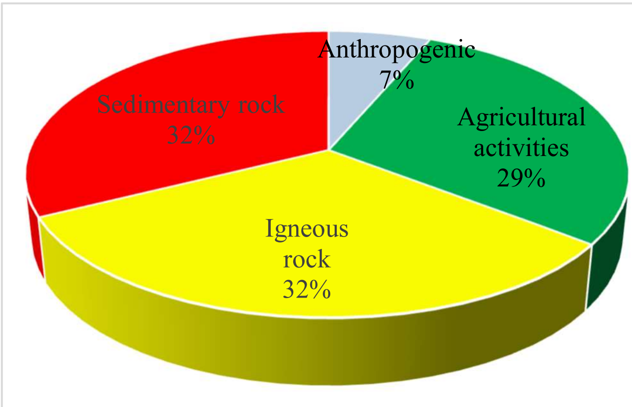


Figure 18: Factor Profiles (% of factor total) from Fpeak Run #2, Strength = -0.5 (Convergent Run)

PMF model analysis, the base run revealed that anthropogenic activities, agricultural activities and naturally occurring igneous rock and sedimentary rock interactions contributed pollutants to the drinking water supply. However, the Fpeak run results were presented, as it is the best result compared with the base run because of the intervention of the rotational tool for the goodness of fit of the model. The results of the Fpeak run revealed that anthropogenic sources contributed 29.7% of the TDS, 19.97% of the bicarbonate, 17.33% of the alkalinity, 10.52% of the carbonate, 9.7% of the total hardness and less than 5% of the sulfate, magnesium, nitrate and calcium in the drinking water supply. This model revealed the presence of similarities among species and unexaggerated proportions of contaminants in anthropogenic sources of water contaminants. According to the comparison of the base model and Fpeak model, fewer differences are observed in the agricultural source. This source contributed 27.16% of the bicarbonate, 21.56% of the alkalinity, 17.68% of the total hardness, 12.95% of the carbonate, 7.04% of the nitrate, 6.7% of the calcium and 4.7% of the TDS pollutants in the drinking water in the study area. The Fpeak run tracked species, particularly naturally occurring igneous and sedimentary rocks. For example, igneous rock contributed 31.47% of the bicarbonate, 25.41% of the alkalinity, 20.72% of the TDS, 15.36% of the carbonate, 3.85% of the total hardness and lower proportions of calcium, magnesium and fluoride. Sedimentary rock was responsible for

20.25% of the bicarbonate, 17.87% of the total hardness, 16.65% of the alkalinity, 16.29% of the TDS, 13.99% of the magnesium and 9.28% of the alkalinity pollutants.



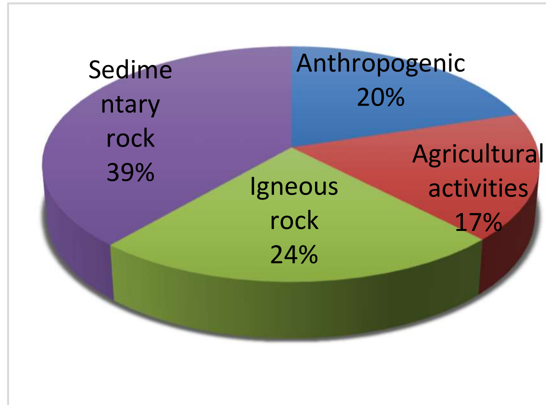


Figure 19: Factor profiles (concentration of Species) of drinking water (Fpeak Run #2, Strength = -0.5) at left side and groundwater (Base Run #14) at right side

According to the concentration of species in each pollutant source for the drinking water supply, 64% of the pollutants were derived from geogenic sources, such as sedimentary (32%) and igneous (32%) rocks, whereas 29% and 7% of the sources were agricultural activities and anthropogenic, respectively. Additionally, 63% of the pollutant sources were geogenic, whereas 20% and 17% of the pollutants originated from anthropogenic and agricultural activities, respectively. In general, the distribution of species in each source profile, such as agricultural, anthropogenic, sedimentary and igneous sources, is described below

3.4.7.1.Anthropogenic source of pollutants

In the case of groundwater PMF analysis, anthropogenic rather than agricultural sources of water pollutants were responsible for 44.23% of the TDS, 30.15% of the bicarbonate, 11.2% of the sodium and 15% of the other pollutants, such as total hardness, sulfate, chloride, magnesium and calcium. In the case of drinking water, anthropogenic pollutants composed of 29.7% TDS; 19.97% bicarbonate; 17.33% alkalinity; 10.52% carbonate; 9.7% total hardness; and less than 5% other pollutants, such as sulfate, calcium, nitrate and magnesium.

The evidence indicates that anthropogenic sources of contamination for both groundwater and surface water originated in the upper Awash subbasin, which includes few and great Akaki tributaries, particularly rivers near or adjacent to Addis Ababa[388]. Around the bottom of the subbasin, the anthropogenic activities in the Modjo River Basin, such as urban sewage, are sources of contaminants[269]. Analyses of pollution profiles along the Little Akaki River revealed that anthropogenic sources were mostly organic matter, nutrients, dissolved salts, and trace metals[341]. In studies of the Jinjiang River (China), anthropogenic sources such as papermaking and textiles, metal manufacturing, chemical and metal production, metal refining and iron ore mining were identified as the main sources of pollution[389]. According to reports, urban wastewater, including sewage (fecal) and toxic chemical dumping from industrial effluents, is a major source of water pollution. Furthermore, anthropogenic activities are considered sources of waterborne diseases, accounting for approximately 80% of all diseases and 33% of all deaths[339].

3.4.7.2. Agriculture source of water pollutants

In groundwater, agricultural activities were responsible for 35% of the alkalinity; 21.03% of the bicarbonate; 15.08% of the total hardness; 20.81% of the TDS; 3.5% of the calcium; 1.9% of the nitrate; and very low proportions of sodium, magnesium and chloride pollutants. For the drinking water supply, 27.16% bicarbonate, 21.56% alkalinity, 17.68% total hardness, 12.95% carbonate, 7.04% nitrate, 6.70% calcium and 4.73% TDS were agricultural pollutants. Agricultural nonpoint source pollutants such as nitrogen, phosphorus and trace metals originate from commercial fertilizer, animal manure, fuels and solvents from agricultural machinery, pesticides and organic wastes from crop cultivation, fruits and vegetables[390].

The results of this study are supported by research conducted in the Modjo River Basin. In addition to other pollutants, agricultural activities, including fertilizers and urban agriculture, are factors that govern the groundwater chemistry of the study area[269]. Evidence from around the world indicates that, somewhere in China, basins with large livestock populations are responsible for 5–10 times greater nutrient discharges than crops or forestry discharges are, and water quality issues related to diseases caused by animal grazing are also justified. These all resulted from agricultural nonpoint source pollution, which is a major source in the majority of basins[391]. Notably, agricultural activities had a significant effect on water quality under low-flow conditions; however, under high-flow conditions, the source of pollution shifted from agriculture to urban land use. As a result, agricultural nonpoint source pollution prevention measures should be designed for subbasins to apply source protection.

3.4.7.3.Natural source of pollutants

Owing to rock–water interactions, groundwater and surface water may be polluted, particularly when groundwater flows through the aquifer, and water-contaminated minerals in the rock can be dissolved by water–rock interactions, leading to elevated concentrations of contaminants. In this study, the sources of water quality parameters were identified as natural sources, such as sedimentary and igneous rock sources. The sedimentary rock was responsible for 32% of the bicarbonate, 31.53% of the TDS, 23.48% of the total hardness and less than 6% of the other species in the groundwater. It is also responsible for 20.25% of the bicarbonates, 17.87% of the total hardness, 16.29% of the TDS, 16.65% of the alkalinity, 13.99% of the magnesium, 10.11% of the bicarbonate and other species with lower proportions in drinking water. Additionally, igneous rock accounted for 38.15% of the alkalinity, 28.50% of the TDS, 21.83% of the bicarbonate, 7.39% of the sodium and other species with lower amounts in the groundwater samples. Approximately 31.47% bicarbonate, 25.41% alkalinity, 20.72% TDS, 15.36% carbonate and other species were present in lower proportions in the drinking water samples. In the study area along the Modjo River Basin, reports have shown that in addition to anthropogenic factors, rock–water interactions and cation exchange are responsible for the features of geochemical water types in groundwater [269]. A review of articles revealed that the source of groundwater contaminants originated from the aquifer because of dissolution of natural mineral deposits. For example, TDS in water may be elevated in ground water as a result of both natural and human activities[392]. The existence of different types of minerals, such as granite and alkaline volcanic rocks of geogenic origin, affects groundwater quality in different ways. For example, this is due to the interaction of waters with highly altered volcanic and pyroclastic rocks [393]. Generally, groundwater pollution is invisible because it is mostly colorless and odorless, has difficulty recovering in terms of quality, has undetected acute and chronic health impacts, challenges intervention in terms of cost and technology, subsurface location and long residence, and self-purification requires many years[392]. Therefore, groundwater pollution prevention methods such as groundwater quality monitoring, practice zoning, the design and development of policies and strategies to apply laws and regulations, integrated education and research and the application of appropriate waste disposal management systems are needed.

3.4.7.4.Error Estimation

In this process, three error estimation methods were analyzed to estimate the uncertainties of the PMF model results. Bootstrap (BS) analysis revealed that the number of factors in both cases was appropriate for every 100 runs, as the mapping of the boot factor with base factors was greater than 80%, which is the threshold level for verifying the appropriateness of the factors (Table 31). The proportions of boot and base factors ranged from 85% - 99% for the drinking water samples collected during the dry season and 83% - 97% for the groundwater samples. However, in both samples, the BS data did not capture the source variability. For example, in the case of drinking water schemes, agricultural sources are mapped to anthropogenic, igneous and sedimentary sources 6, 15, and 10 times, respectively, instead of 100% mapping with a boot factor.

Table 31: Results of bootstrap (BS) error estimation and Fpeak bootstrap factors to base factors

S/N	Boot Factors	Base Factor				
		Anthropogenic	Agriculture	Igneous	Sedimentary	Unmapped
a	Drinking water samples in dry season					
1	Boot anthropogenic	89	6	5	0	0
2	Boot agriculture	0	99	1	0	0
3	Boot igneous	0	15	84	0	1
4	Boot sedimentary	0	10	5	85	0
b	Fpeak bootstrap factors to base factors (Drinking water samples in dry season)					
1	Anthropogenic	100	0	0	0	0
2	Agriculture	0	100	0	0	0
3	Igneous	0	1	99	0	0
4	Sedimentary	0	0	0	100	0
c	Groundwater					
1	Boot sedimentary	5	5	7	83	0
2	Boot igneous	4	0	94	1	1
3	Boot anthropogenic	97	0	1	2	0
4	Boot agriculture	5	87	0	5	3

Base Model Displacement (DIS) and BS-DISP: As the base model displacement (DISP) is used to identify rotational ambiguity in the PMF solution, the swap counts are zero in both cases, which shows that the solutions for the models are stable **Table 32**. However, factor swaps were observed in the BS-DISP error estimation.

Table 32: Results of DIS and BS-DISP error estimates of the PMF model

S/N	Diagnostics	Characteristics of error estimation	Groundwater Samples				Drinking Water Schemes			
1	Base Run (#3)	Converged	Yes				Yes			
		Q(Robust)	9210.27				772.737			
		Q(True)	9500.56				824.278			
2	DISP Diagnostics	Error Code:	0				0			
		Largest Decrease in Q	-0.085				0			
		%dQ	-0.0009				0			
		Swaps by Factor	0	0	0	0	0	0	0	0
3	BS-DISP Diagnostics	# of Cases Accepted	88				68			
		% of Cases Accepted	88%				68%			
		Largest Decrease in Q	-177.44				-31.94			
		%dQ	-1.92				-4.33			
		# of Decreases in Q	12				7			
		# of Swaps in Best Fit	0				8			
		# of Swaps in DISP	0				17			
		Swaps by Factor	0	0	0	0	9	6	2	3

3.5. PUBLIC HEALTH RISKS

3.5.1. Descriptive statistics

3.5.1.1. Physicochemical Water Quality Parameters

The dry season results in the Bereh district revealed that the mean values of three parameters, alkalinity, Cr(VI), and nitrate, and the maximum values of pH, EC, Mn, and calcium did not meet the compulsory Ethiopian standard. (CES-58) or the WHO's drinking water standard. Wet season tests from this district revealed iron, alkalinity, Cr(VI), and magnesium levels that exceeded drinking water regulations (Table 33). The maximum EC, Mn, calcium, nitrate, and magnesium readings did not meet the aforementioned criteria, whereas the mean values of EC, Mn, Cr, and Mg in the dry season and EC, alkalinity, and Cr(VI) in the wet season in the Sebeta-Hawas district (low water pollution risk areas) satisfied the CES-58 (WHO standard). The temperature was 19.71 in Bereh District during the dry season and 24.98 in Sebeta-Hawas district during the dry season in both seasons and districts (**Table 34**). The maximum values for six parameters in the dry season and eight parameters in the wet season were much lower than the drinking water standards. The mean values of pH, TDS, fluoride, nitrite, sulfate, and arsenic were within the CES-58 standard for all situations. EC, alkalinity, magnesium, Cr(VI), Mn, iron, and nitrate did not always comply with the standards.

Table 33: Water quality status of Bereh District in the dry and wet seasons

S/N	Water quality Parameters	Bereh district – dry season				Bereh district -Wet season				CES-58
		Mean	Std.D	Min	Max	Mean	Std.D	Min	Max	
1	Tem (C°)	19.71	3.78	18.00	25.20	21.67	1.77	18.50	25.60	
2	PH	7.52	0.39	6.55	8.60	7.41	0.32	6.88	8.30	6.5-8.5
3	TDS(mg/l)	176.48	103.08	66.04	575.0	191.12	91.88	88.30	535.00	1000
4	EC(*S/m)*	385.11	346.30	11.55	1810.0	333.95	138.29	105.30	654.00	
5	F^- (mg/l)	0.30	0.18	0.08	0.80	0.48	0.23	0.10	0.96	1.5
6	NO_2(mg/l)	0.03	0.05	0.01	0.26	0.03	0.06	0.01	0.26	3
7	Fe (mg/l)	0.05	0.04	0.01	0.15	0.57	1.50	0.01	8.00	0.3
8	Mn (mg/l)	0.42	0.21	0.01	1.16	0.10	0.23	0.01	1.16	0.5
9	SO_4 (mg/l)	5.96	7.52	0.00	24.0	4.00	6.09	0.30	25.00	250
10	Alk(mg/l)	243.13	64.83	130.00	400.0	303.34	84.46	145.00	450.00	200
11	HCO_3(mg/l)	300.72	74.48	160.00	490.0	370.19	104.24	175.00	550.00	
12	$CaCO_3$(mg/l)	146.66	38.70	80.00	240.0	182.05	50.65	85.00	270.00	
13	Cr(VI) (mg/l)	0.05	0.03	0.00	0.10	0.07	0.02	0.05	0.10	0.05
14	Ca(mg/l)	53.53	28.51	2.00	160.0	59.07	28.77	6.00	160.00	75
15	NH_3(mg/l)	0.03	0.03	0.00	0.17	0.02	0.01	0.01	0.06	1.5
16	TH(mg/l)	126.24	49.38	5.00	235.0	151.64	59.70	10.00	270.00	300
17	As(µ/l)	0.87	1.57	0.00	6.00	0.30	1.055	0.00	5.00	0.01
18	NO_3(mg/l)	65.28	53.03	1.00	300.0	6.86	16.88	0.59	80.00	50
19	Mg(mg/l)	13.81	8.10	0.49	38.88	90.12	45.16	4.00	178.00	50

The results of this study revealed that the temperature does not meet the 15 degrees Celsius required value of the Canadian and British drinking water supply standards, even though temperature is not mentioned in the CES-58. Management techniques and alternative measures that have been well explored are needed to prevent the effects of elevated temperature in drinking water since temperature affects the physical, chemical, and biological characteristics of water quality[394]. These findings point to dangers and risks that may have particular negative health implications. The seasonal variations in the parameters are substantial. In the dry season, the EC and total hardness decreased from the upper to the lower portions of the Awash River Basin[318]. Ca_{2+} and Mg^{2+} are predominant in the highland aquifer in the upper Awash subbasin of the region, whereas HCO_3 is the predominant anion[269]. These different kinds of groundwater support the local EC, alkalinity, and magnesium parameter associations.

Drinking water contains chromium from both anthropogenic and natural sources. As there were no industrial activities in the sampling areas, contamination was from a natural source or other anthropogenic sources, as it is widely scattered across the Earth's crust. The evidence from a comprehensive review indicates that in Ethiopia, the maximum value is closest to the study's mean value, with the mean content of chromium in drinking water ranging from 0.0089 mg/l to 0.054 mg/l[395].

Table 34: Water quality status of Sebeta-Hawas district

S/N		**Sebeta-Hawas –Dry season**				**Sebeta-Hawas –Wet Season**				**CES-58**
		Mean	Std.D	Min	Max	Mean	Std.D	Min	Max	
1	Tem (C°)	24.98	4.04		36.6	23.90	1.65	20.00	26.90	
2	PH	6.76	0.28	6.5	7.12	6.89	0.29	6.27	7.27	6.5-8.5
3	TDS(mg/l)	298.61	195.09	1000	883.0	303.80	179.96	55.60	915.00	1000
4	EC(*S/m)*	594.53	358.69		1495.0	616.75	369.50	6.32	1834.00	
5	F^- (mg/l)	0.67	0.32	1.5	1.41	0.74	0.40	0.01	1.43	1.5
6	NO_2(mg/l)	0.01	0.01	3	0.05	0.52	1.79	0.01	8.00	3
7	Fe (mg/l)	0.06	0.15	0.3	0.84	0.23	0.27	0.00	0.90	0.3
8	Mn (mg/l)	0.57	0.60	0.5	2.50	0.36	1.15	0.01	6.00	0.5
9	SO_4 (mg/l)	19.45	45.94	250	180.0	15.03	24.09	0.50	100.00	250
10	Alk(mg/l)	313.27	166.43	200	700.0	460.52	308.27	75.00	1125.00	200
11	HCO_3(mg/l)	383.33	204.91		870.0	565.50	381.98	95.00	1375.00	
12	$CaCO_3$(mg/l)	179.33	90.65		400.0	247.42	175.60	45.00	687.50	
13	Cr(VI) (mg/l)	0.05	0.09	0.05	0.50	0.07	0.08	0.02	0.120	0.05
14	Ca(mg/l)	60.67	32.01	75	190.0	66.53	31.39	16.00	129.00	75
15	NH_3(mg/l)	0.27	0.22	1.5	0.67	0.39	117.75	0.02	0.67	1.5
16	TH(mg/l)	211.53	98.52	300	470.0	207.73	85.65	55.00	350.00	300
17	As(µ/l)	0.034	0.182	0.01	1.00	0.00	0.000	0.00	0.001	0.01
18	NO_3(mg/l)	15.98	30.34	50	128.5	11.81	18.10	0.09	73.48	50
19	Mg(mg/l)	148.93	70.65	50	280.0	21.64	42.60	0.01	225.00	50

Chromium was also detected in Akaki River water, which is used for irrigated vegetables [306]. The conversion of Cr(III) to Cr(VI) is supported by the presence of minerals such as Mn and alkalinity. Even though it was increased to 0.120 mg/l, which is the maximum value of this study, the concentration of total chromium in drinking water is often less than 0.02 mg/l, according to a WHO report[396]. Compared with the WHO drinking water quality criteria, the surface water in the basin contained increased concentrations of Mn and Fe. The upper Awash River subbasin is hydraulically connected to the Awash River[376]. It has been proposed that the reduction in water quality along the Awash River can be utilized to explain these poor water quality indicators[306]. Additionally, the geochemistry of the basin, the growth of metropolitan centers, and the increasing use of fertilizers have an impact on the drinking water quality of the study area [269]. In contrast, research carried out in the basin revealed that groundwater quality indices, including pH, EC, TDS, Ca, Mg, HCO_3, SO_4, and F-, were within the WHO guidelines[397]..

3.5.1.2.Microbial Water Quality Parameter

Compared with the dry season, the rainy season had a greater mean dose of *E. coli* per 100 mL. In contrast to those from the Bereh District, samples from the Sebeta-Hawas District had more *E. coli*. To prevent waterborne disease, the Sebeta-Hawas District's 28.15 mean dosage of *E. coli* (27.57–28.74, 95% CI) required more attention than did the Bereh district's 23.44 mean dose (22.85–24.03, 95% CI). However, the mean dose of *E. coli* in the rainy season was greater than that in the dry season (Table 35).

Table 35: Mean doses of *TC* and *E. coli*/100 mL and daily mean doses of *TC* and *E. coli*/2000 mL and Monte Carlo simulation results of the mean dose of *E.* coli

S/N	Descriptive	Sample Mean (CFU/100 mL)		Daily Mean (CFU/2000 mL)		E.coli Mean (CFU/ 2000 mL)	Std. D	95% CI for Mean	
		TC	*E.coli*	*TC*	*E.coli*			Lowe Bound (LB)	Upper Bound (UB)
1	*E.coli* dose in dry season	46	14	929	287	23.17	25.83	22.66	23.67
2	*E.coli* dose in wet season	88	18	1753	355	27.94	42.51	27.11	28.78
4	*E.coli* average dose (Bereh District)	56	15	1124	293	23.44	30.28	22.85	24.03
5	*E.coli* average dose (Sebeta Hawas District)	78	17	1558	349	28.15	29.80	27.57	28.74
3	*E.coli* seasonal average dose					25.25	30.20	24.66	25.84

3.5.2. Public Health Risk analysis and Risk characterization

3.5.2.1. Non-cancer risk Analysis

The hazard quotient (HQ) of NO_3 is greater than unity in the dry season for all three categories, according to a risk study of 60 samples from the Bereh district (30 samples in the dry season and 30 samples in the wet season) (Table 36). This suggests that NO_3 is a potential risk for the area's population. During the wet season, only the chemical chromium poses a concern to women and children.

Table 36: Hazard quotient of drinking water quality parameters (Bereh District)

No	Group	WQP	Dry Season				Wet Season			
			Mean	Std. D	Lower bound	Upper bound	Mean	Std. D	Lower bound	Upper bound
1	Men	F	2.0E-01	1.2E+00	1.8E-01	2.3E-01	3.1E-01	7.7E-01	3.0E-01	3.3E-01
		No2	1.3E-02	1.3E-01	1.0E-02	1.5E-02	1.2E-02	8.4E-02	1.1E-02	1.4E-02
		Fe	2.9E-03	1.4E-02	2.7E-03	3.2E-03	3.3E-02	2.0E-01	2.9E-02	3.7E-02
		Cr	6.7E-01	2.2E+00	6.2E-01	7.1E-01	9.3E-01	2.7E+00	8.8E-01	9.8E-01
		As	3.4E-01	1.1E+00	1.2E+00	1.6E+00	2.4E-01	1.37+00	4.2E-01	5.2E-01
		NO3	1.6E+00	7.8E+00	1.5E+00	1.8E+00	1.8E-01	2.2E+00	1.4E-01	2.3E-01
2	Women	F	2.3E-01	1.2E+00	2.0E-01	2.5E-01	3.6E-01	1.7E+00	3.3E-01	4.0E-01
		NO2	1.4E-02	4.7E-02	1.3E-02	1.5E-02	1.6E-02	1.9E-01	1.2E-02	1.9E-02
		Fe	3.3E-03	1.9E-02	2.9E-03	3.6E-03	3.6E-02	1.9E-01	3.3E-02	4.0E-02
		Cr	7.5E-01	3.0E+00	6.9E-01	8.1E-01	1.1E+00	7.2E+00	9.3E-01	1.2E+00
		As	3.8E-01	9.0E+00	1.1E+00	1.5E+00	2.6E-01	1.1E+00	4.7E-01	7.0E-01
		NO3	1.8E+00	7.7E+00	1.7E+00	2.0E+00	1.8E-01	5.7E-01	1.7E-01	1.9E-01
3	Children	F	3.0E-01	1.8E-01	3.0E-01	3.1E-01	4.9E-01	2.4E-01	4.9E-01	4.9E-01
		No2	5.9E-02	9.8E-02	5.7E-02	6.1E-02	1.8E-02	3.7E-02	1.8E-02	1.9E-02
		Fe	4.3E-03	3.5E-03	4.3E-03	4.4E-03	4.9E-02	1.3E-01	4.6E-02	5.1E-02
		Cr	1.0E+00	6.0E-01	9.9E-01	1.0E+00	1.4E+00	4.1E-01	1.4E+00	1.4E+00
		As	5.3E-01	5.7E-01	1.9E+00	2.0E+00	3.6E-01	1.1E+00	6.8E-01	7.6E-01
		NO3	2.5E+00	2.0E+00	2.4E+00	2.5E+00	2.6E-01	6.5E-01	2.5E-01	2.7E-01

There are no season-specific noncancer hazards associated with the other characteristics. Table 10 shows that only the fluoride parameter (HQ=3.2E+00) in the dry season and chromium (1.4E+00) in the rainy season were identified as potential noncancer risk factors for the children in the Sebeta-Hawas district. According to the seasonal average HQ data, NO_3 and chromium may pose noncancer dangers to children, whereas NO_3 may do so for women during the dry season. Only chromium poses a noncancer risk to children during the rainy season. Therefore, NO_3 is a noncancer risk for children in both seasons and mothers and children in the dry season compared with chromium (**Table 37**).

Table 37: Hazard quotient of drinking water quality parameters (Sebeta-Hawas district)

No	Group	WQP	Dry Season				Wet Season			
			Mean	Std. D	LB	UB	Mean	Std. D	LB	UB
1	Men	F	4.5E-01	1.8E+00	4.2E-01	4.9E-01	4.9E-01	1.5E+00	4.6E-01	5.2E-01
		NO_2	1.7E-04	1.3E-03	1.5E-04	2.0E-04	9.0E-05	8.0E-04	7.4E-05	1.1E-04
		Fe	3.5E-03	2.5E-02	3.0E-03	4.0E-03	1.3E-02	5.5E-02	1.2E-02	1.4E-02
		Cr	7.0E-01	5.3E+00	6.0E-01	8.1E-01	8.9E-01	2.2E+00	8.5E-01	9.3E-01
		As	9.24E-03	2.2E-03	1.5E-01	1.8E-01	1.4E-03	4.3E-03	1.3E-03	1.4E-03
		NO_3	4.2E-01	4.1E+00	3.4E-01	5.0E-01	3.0E-01	1.3E+00	2.7E-01	3.2E-01
2	Women	F	4.9E-01	1.5E+00	4.6E-01	5.2E-01	5.5E-01	1.7E+00	5.2E-01	5.8E-01
		NO_2	2.1E-01	1.4E+00	1.8E-01	2.4E-01	1.9E-01	3.7E+00	1.2E-01	2.6E-01
		Fe	1.3E-02	5.5E-02	1.2E-02	1.4E-02	1.6E-02	1.9E-01	1.2E-02	1.9E-02
		Cr	8.9E-01	.2E+00	8.5E-01	9.3E-01	1.0E+00	6.2E+00	9.3E-01	1.2E+00
		As	1.36E-03	4.3E-03	1.3E-03	1.4E-03	1.4E-03	2.4E-03	1.4E-03	1.6E-03
		NO_3	3.0E-01	1.3E+00	2.7E-01	3.2E-01	3.3E-01	8.2E-01	3.2E-01	3.5E-01
3	Children	F	3.2E+00	1.5E+00	3.1E+00	3.2E+00	7.5E-01	4.1E-01	7.5E-01	7.6E-01
		NO_2	6.2E-03	6.1E-03	6.0E-03	6.3E-03	3.1E-01	1.1E+00	2.9E-01	3.3E-01
		Fe	5.1E-03	1.3E-02	4.9E-03	5.4E-03	1.9E-02	2.3E-02	1.9E-02	2.0E-02
		Cr	2.2E-01	3.9E-01	2.1E-01	2.2E-01	1.4E+00	1.6E+00	1.4E+00	1.4E+00
		As	1.42E-02	4.0E-03	2.5E-03	2.6E-03	2.0E-03	2.0E-03	2.0E-03	2.0E-03
		NO_3	5.9E-01	1.2E+00	5.7E-01	6.1E-01	4.6E-01	6.9E-01	4.5E-01	4.7E-01

Table 38: Seasonal hazard quotients of drinking water quality parameters

S/N	Categories	Parameters	**Dry Season**				**Wet Season**			
			Mean	Std.D	LB	UB	Mean	Std.D	LB	UB
1	Men	F	3.3E-01	1.1E+00	3.1E-01	3.6E-01	4.1E-01	1.4E+00	3.8E-01	4.4E-01
		NO_2	5.8E-06	2.5E-04	8.3E-07	1.1E-05	9.0E-02	1.7E+00	5.7E-02	1.2E-01
		Fe	7.6E-07	6.0E-05	-4.2E-07	1.9E-06	2.0E-02	2.5E-01	1.5E-02	2.5E-02
		Cr	7.2E-01	4.9E+00	6.3E-01	8.2E-01	9.4E-01	3.1E+00	8.8E-01	1.0E+00
		As	2.6E-05	8.0E-05	2.8E-04	3.0E-04	1.8E-02	2.0E-01	2.9E-01	3.8E-01
		NO_3	6.3E-04	2.1E-02	2.1E-04	1.0E-03	2.5E-01	1.3E+00	2.2E-01	2.7E-01
2	Women	F	3.6E-01	1.2E+00	3.4E-01	3.9E-01	4.6E-01	2.3E+00	4.1E-01	5.0E-01
		NO_2	9.6E-03	5.9E-02	8.4E-03	1.1E-02	1.1E-01	2.3E+00	6.2E-02	1.5E-01
		Fe	1.3E-05	8.3E-05	1.1E-05	1.5E-05	2.4E-02	8.8E-02	2.2E-02	2.6E-02
		Cr	7.8E-01	6.4E+00	6.5E-01	9.1E-01	1.0E+00	1.9E+00	9.8E-01	1.1E+00
		As	7.2E-02	3.5E-01	6.3E-01	1.2E+00	2.0E-02	2.0E-01	2.9E-01	3.8E-01
		NO_3	1.3E+00	1.7E+01	9.3E-01	1.6E+00	2.5E-01	8.6E-01	2.4E-01	2.7E-01
3	Children	F	5.0E-01	3.4E-01	4.9E-01	5.1E-01	6.1E-01	3.6E-01	6.1E-01	6.2E-01
		NO_2	1.2E-02	2.4E-02	1.2E-02	1.3E-02	1.7E-01	7.8E-01	1.5E-01	1.8E-01
		Fe	5.1E-03	9.6E-03	4.9E-03	5.3E-03	3.5E-02	9.5E-02	3.3E-02	3.7E-02
		Cr	1.0E+00	1.2E+00	9.9E-01	1.0E+00	1.4E+00	1.2E+00	1.4E+00	1.4E+00
		As	9.6E-02	5.3E-02	1.1E+00	1.2E+00	3.2E-02	1.0E-01	4.4E-01	5.0E-01
		NO_3	1.6E+00	1.9E+00	1.5E+00	1.6E+00	3.6E-01	6.7E-01	3.5E-01	3.8E-01

Figure 200's hazard index (HI) values for the six water quality parameters, such as F, NO2, Fe, Cr(VI), NO3 and As demonstrated that, with the exception of the seasonal average for the male group, the HI for noncancer hazards was greater than one (HI>1). This value exceeds the permissible limit of the HI for the total noncancer risk.

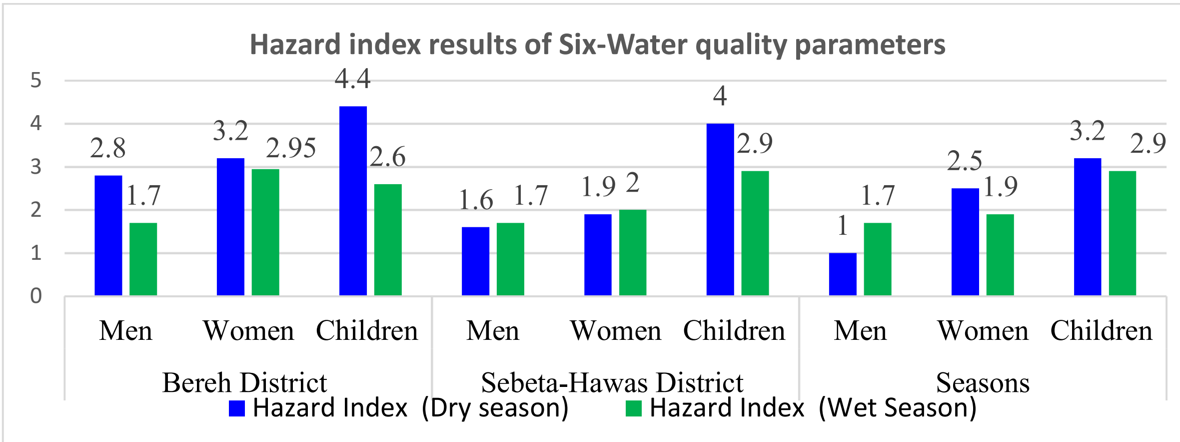


Figure 20: Hazard index results for the six water quality parameters

Generally, the noncancer risks of NO3, chromium, and fluoride were identified in this study, and the discussion points are presented as follows:

a) Nitrate

The HQ of men was 1.6E+00, while that of women was 1.8E+00. On average, 1.6E+00 for children during the dry season, 2.5E+00 for children, and 1.3E+00 for women. Among the public health concerns associated with short-term exposure, methemoglobinemia is the most common health concern in babies. In addition, researchers have reported that there is a risk of childhood central nervous system, stomach, brain and colon cancers; glioma; and birth defects [398,399]. Nitrate speeds up the production of chloropicrin, which is a disinfection byproduct responsible for mutagenesis in bacterial experiments; however, some of the hazards of nitrate as a cause of cancer remain controversial[400]. Watershed-based publications have shown that children have greater noncancer risks as a result of drinking nitrate-contaminated groundwater[401], which is similar to the findings of this investigation. Children, babies, and teenagers are therefore more vulnerable to risk because they fall within vulnerable age categories in the population. Even though there is minimal difference in risk between the dry and rainy seasons, there is evidence that nitrate contamination of drinking water occurs in both seasons for a variety of reasons. Because washout accelerates the accumulation of pollutants from ground surfaces and pulls them down to groundwater sources, nitrate concentrations are relatively high during the wet season. The nitrate concentration of groundwater increases throughout the dry season and decreases in the rainy season due to the diluting effects of significant precipitation [243,402].

According to studies conducted in the Awash basin in general and the upper Awash subbasin in particular, increased concentrations of nitrate are linked to untreated industrial waste, geogenic processes, urban sewage, and fertilizers[269]. Its concentration is expected to increase due to the effects of climate change, poor waste disposal, fertilizer application and population growth[357]. It is evident that nitrate noncancer hazards are a global concern, extending to the targeted subbasin. Despite the presence of nitrate hazards in the subbasin, records from Legedadi and Gefersa Dams, significant water sources supplying Addis Ababa, revealed compliance with the WHO's acceptable guideline values for nitrate, nitrite, and ammonia levels[403]. Internationally, reports from Indonesia indicate risks associated with nitrate in drinking water, particularly for sensitive populations, with potential implications for infant methemoglobinemia and birth defects[404]. In Jordan, infants are more susceptible to nitrate exposure in drinking water than are children and adults[405]. The specific case of Kazerun, Iran, highlights the HQ for nitrate among children, with the HI for all three contaminants surpassing 1 in 56% of cases, indicating a serious risk[406]. Furthermore, a health risk assessment of nitrate in bottled water in Iran revealed HQ values exceeding unity in 10% of samples for both infants and children, indicating potential adverse noncarcinogenic health effects upon consumption [407]. These collective findings underscore the nuanced challenges associated with nitrate contamination, emphasizing the need for targeted interventions and ongoing monitoring to mitigate health risks in diverse geographical contexts.

b) Fluoride

Fluoride is harmful to human health when its concentration exceeds 1.5 mg/L[387]. Fluoride has been linked to specific noncancer hazards that have been reported worldwide. In this study, compared with adults, children in the Sebeta-Hawas district during the dry season were at noncancer risk from fluoride (HQ=3.2E+00). The noncarcinogenic risks for children in the study area to southern China ranged from 0.75--8.44, 0.34--3.84 for women, and 0.27--3.01 for men[408]. These findings were also supported by articles from around the world[409]. Comparable risks are observed on the east and west coasts of Bangladesh and India, where children exhibit higher mean HQ ingestion values for fluoride, emphasizing the significant noncarcinogenic risk for children[410]. Türkiye's lentic ecosystem similarly identifies fluoride as a major health risk, particularly linked to daily water intake[411]. Kazerun, Iran, presents potential adverse health effects from fluoride intake, with HQs exceeding 1 across various age groups[407]. These findings collectively underscore the consistent health risks associated with fluoride exposure, emphasizing the need for targeted interventions. Fluorosis is caused by groundwater contaminated with fluoride, which harms 200 million people in 25 different countries[412]. In eleven sub-Saharan African nations, dental fluorosis is common[387]. Skeletal fluorosis is prevalent in the Rift Valley of Ethiopia at 21.4% [413], and dental fluorosis is estimated to be as prevalent as 28% because of its high concentration in the Rift Valley [414]. Fluoride is mostly obtained from thermal and fluoride-rich deep well fluids in this study area in the Akaki catchment. In addition, fluoride levels in northwestern Addis Ababa city increased due to human activity and the urban environment [386]. This explains why there was a greater concentration of fluoride than in samples taken from the city's eastern region. The fluoride concentrations in the Sebeta-Hawas District range from 0.32 mg/l to 1.41 mg/l, with a mean of 0.67 mg/l (Table 38). The main geogenic sources of fluoride in groundwater are fluorite, fluorapatite, biotite, amphibole, micas, topaz, cryolite, muscovite, fluorspar and phosphate rock[387]. The presence of sodium bicarbonate-type water may create an influx of fluoride and a deficiency of calcium[412]. These findings are particularly applicable to the Ethiopian Rift Valley, where the increased fluoride levels can be attributed to volcanic activity and geothermal temperatures within the rift system. As highlighted in the referenced article, the primary contributors to elevated fluoride levels in both groundwater and surface water in this study area are the utilization of phosphate fertilizers, improper disposal of sewage sludge, and the application of pesticides for agricultural purposes. This underscores the localized sources of fluoride contamination, emphasizing the importance of understanding and addressing specific contributors to effectively manage and mitigate fluoride-related concerns in the Ethiopian Rift Valley[409].

Chromium (Cr(VI))

Chromium is a potential noncancer risk in both districts and the seasonal average for women and children in both districts during the rainy season as well as for children during both seasons, according to Table 36,

There are no season-specific noncancer hazards associated with the other characteristics. Table 10 shows that only the fluoride parameter (HQ=3.2E+00) in the dry season and chromium (1.4E+00) in the rainy season were identified as potential noncancer risk factors for the children in the Sebeta-Hawas district. According to the seasonal average HQ data, NO3 and chromium may pose noncancer dangers to children, whereas NO3 may do so for women during the dry season. Only chromium poses a noncancer risk to children during the rainy season. Therefore, NO3 is a noncancer risk for children in both seasons and mothers and children in the dry season compared with chromium Table 37 and Table 38. The Bereh HQ (1.1E+00) for women and the HQ (1.4E+00) for children, as well as the Sebeta-Hawas HQ (1.4E+00) for children and the Seasonal HQ (1.4E+00) for children.

3.5.2.2. Cancer Risk Analysis

a) Arsenic (As)

Table 39 reported that the cancer risk of arsenic has a significant effect on children in both seasons, and for all groups (men, women, and children) in the Bereh district in each season, the risk level is greater than 1 in 10,000 people, which is unacceptable to the WHO standard. While the HQ value of arsenic was less than unity (HQ<1), which is an acceptable noncancer risk level, the cancer risk of arsenic in the Sebeta-Hawas district during the dry season was within the permissible range (below 1 in 10,000 people). According to studies conducted in this subbasin, soils that were irrigated with water from the Akai River presented relatively high concentrations of arsenic[415]. Arsenic levels increase throughout the dry season and are higher than the WHO threshold[279]. Arsenic was also more mobile in Lake Koka at the subbasin outlet during the dry season than it was during the wet season [383]. The highest level of arsenic was found in the fish liver at this location, which may be related to water retrieved from the subbasin[416]. Consistent with reviewed publications, 220 million people could be exposed to high levels of arsenic through their groundwater[417]. Both long-term and short-term arsenic exposure increase the likelihood of mutagenesis, carcinogenesis, neoplasms, hyperkeratosis, abnormalities and disorders, whereas acute toxicity affects the intestinal, circulatory, and central nervous systems and can lead to death[169]. Evidence has shown that anthropogenic and natural activities are sources of arsenic for water supply contamination[279].

Table 39: Cancer risk of arsenic contaminants in the drinking water supply

S/N	Category	Groups	Mean	Std.D	LB	UB
1	Dry Season	Men	2.35E-08	7.18E-08	2.21E-08	2.49E-08
		Women	3.22E-05	1.57E-04	2.92E-05	3.53E-05
		Children	1.29E-04	7.17E-05	1.28E-04	1.30E-04
2	Wet Season	Men	8.16E-06	8.51E-05	6.49E-06	9.83E-06
		Women	9.58E-06	7.96E-05	8.02E-06	1.11E-05
		Children	4.29E-05	1.37E-04	4.02E-05	4.56E-05
3	Bereh district in the dry season	Men	3.04E-04	1.00E-03	2.84E-04	3.23E-04
		Women	1.71E-04	4.06E-04	1.63E-04	1.79E-04
		Children	7.10E-04	7.65E-04	6.95E-04	7.25E-04
4	Bereh district in Wet Season	Men	1.10E-04	6.15E-04	9.75E-05	1.22E-04
		Women	1.16E-04	5.03E-04	1.06E-04	1.26E-04
		Children	4.90E-04	1.50E-03	4.60E-04	5.19E-04
5	Sebeta-Hawas in dry season	Men	4.16E-06	9.82E-06	3.97E-06	4.35E-06
		Women	6.11E-07	1.92E-06	5.73E-07	6.49E-07
		Children	1.92E-05	5.45E-06	1.91E-05	1.93E-05
6	Sebeta- Hawas in Wet Season	Men	6.11E-07	1.92E-06	5.73E-07	6.49E-07
		Women	6.45E-07	1.10E-06	6.23E-07	6.67E-07
		Children	2.74E-06	2.75E-06	2.69E-06	2.79E-06

b) Chromium (Cr(VI))

Among the chromium species, Cr (VI) is a substance that causes cancer and significantly increases the burden of cancer worldwide. Cr (IV) had a higher cancer risk than the WHO-acceptable risk level for both the seasonal average and all the sampling sites. From 1 in 1000 to 9.78 in 10,000, it was possible. The evidence suggests that the calculated cancer risk of Cr(VI) values was 2.8E–03 for adults and 6.3E–03 for children in a work done in the Awash River Basin, despite the lack of comparable suitable studies in the region[378]. The risk of Cr(IV) is a burden worldwide [418]. It is responsible for and suspected to be the cause of DNA damage, stomach malignancies, skin tumors, and lung cancer and impacts the immunological, gastrointestinal, liver, and kidney systems and cancer mortality [419]. The average amount of total chromium in drinking water is less than 0.02 mg/l; however, the cited research [420] reported amounts as high as 0.120 mg/l. The effluent from the factory in the upper Awash River subbasin included a large amount of Cr(VI) as well[371]. Chromium has also been detected in Akaki River water, which is used for irrigated vegetables [306]. Cr (IV) pollution in water is caused by both anthropogenic and natural processes. The three main factors that affect the presence of Cr(IV) in groundwater are a well's hydrologic characteristics, geochemical evolution, and geological setting[421], and four different types of sources, including arid alluvial basins, chromite ores, saline brines in evaporite basins, and serpentinite ultramafic terrains, contribute to the presence of Cr(IV) in groundwater[422]. Consequently, agricultural fertilizers, local geological formations, and nonpoint sources from solid and wastewater sources in urban, semiurban, and rural locations are some examples of the sources suggested in this study, although the sampling sites were not near an industrially impacted area. Among anthropogenic sources, phosphate fertilizer is one of the suspected sources in the study area, as it is the main source of pollutants from chemical fertilizers[423]. Chromium has been recognized as a public health-important water quality parameter in the study area, and further research is needed to identify the source of chromium contamination in drinking water.

Table 40: Cancer risk of chromium contaminants in the drinking water supply

No	Categories		Mean	Std.D	LB	UB
1	Dry Season	Men	1.08E-03	7.33E-03	9.39E-04	1.23E-03
		Women	1.17E-03	9.66E-03	9.81E-04	1.36E-03
		Child	4.55E-03	5.47E-03	4.44E-03	4.66E-03
2	Wet Season	Men	1.40E-03	4.68E-03	1.31E-03	1.50E-03
		Women	1.53E-03	2.91E-03	1.47E-03	1.59E-03
		Child	6.39E-03	5.44E-03	6.28E-03	6.50E-03
3	Bereh Woreda in the dry season	Men	1.00E-03	3.32E-03	9.35E-04	1.07E-03
		Women	1.12E-03	4.57E-03	1.03E-03	1.21E-03
		Child	4.52E-03	2.71E-03	4.47E-03	4.58E-03
4	Bereh District in Wet Season	Men	1.39E-03	3.99E-03	1.31E-03	1.47E-03
		Women	1.61E-03	1.08E-02	1.40E-03	1.83E-03
		Child	6.39E-03	1.83E-03	6.35E-03	6.42E-03
5	Sebeta-Hawas District in dry season	Men	1.05E-03	7.94E-03	8.99E-04	1.21E-03
		Women	1.33E-03	3.26E-03	1.27E-03	1.40E-03
		Child	9.78E-04	1.75E-03	9.44E-04	1.01E-03
6	Sebeta- Hawas in Wet Season	Men	1.33E-03	3.26E-03	1.27E-03	1.40E-03
		Women	1.57E-03	9.28E-03	1.39E-03	1.76E-03
		Child	6.27E-03	7.35E-03	6.12E-03	6.41E-03

3.5.2.3.Microbial Risks Analysis

The risk of diarrheal diseases caused by *E.* coli, one of the pathogens that causes the majority of cases of diarrhea, especially in developing countries, has been the focus of the prediction of the risk of waterborne diseases in the upper Awash subriver basin. Five categories of *E. coli*, including enterotoxigenic, enteropathogenic, Shiga toxin-producing, enteroinvasive, and enteroaggregative strains, are pathogenic strains of *E. coli* among the total *E. coli* microorganisms [198]. In this study, harmful strains of *E. coli* were estimated to make up 8% of the *E. coli* strains found in 60 water supply systems during the wet and dry seasons[303]. As a result, Table 41's infection risk shows that all daily infection risks during the dry and wet seasons, on a seasonal average, and in both districts are higher than the tolerable risk of the 1 in 10,000,000 WHO threshold. The seasonal average, Bereh district average, wet season risk of infection, and annual risk of infection were 6, 2, 9, and 8 in 10,000, respectively, exceeding the WHO's acceptable annual risk of infection criterion of 1 in 10,000. The Sebeta-Hawas District, however, had a 1 in 1,000 annual risk of infection, which was higher than both this norm and another viewpoint of the samples[424]. Given that *E. coli* is a significant public health risk in low-income settings, the amount of these daily and yearly infection risks indicates that appropriate interventions must be taken to protect residents of the subbasin. Studies in Ethiopia have identified various enteropathogenic *E. coli* serotypes in infants and children with acute gastrointestinal symptoms, highlighting the prevalence of waterborne pathogens in the region[202]. In the southern Wondogenet District, 25% of the water samples had fecal coliform bacteria, exceeding the 14% reported in the 2016 national survey[36]. *E. coli* serves as a prevalent etiological factor for diarrheal illnesses and a straightforward biological hazard indicator in water quality monitoring[204,205]. Regions such as Karnataka, India, and San Cristóbal de Las Casas, Chiapas, Mexico, show exposure and infection risk inequalities on the basis of water sources[425]. Southern Sindh and recreational water use pose health risks, highlighted by a beta-Poisson model[241]. Additionally, the biological hazard presented a risk of diarrheal disease caused by *E. coli* spp. *E. coli* is among the most prevalent etiological factors for diarrheal illnesses. It is a straightforward test to determine the biological hazard of water quality during monitoring and surveillance and serves as an indicator organism for risk-based management.

Table 41: *E. coli* daily and annual risks of infection

S/N	Descriptive	Mean	Std. Deviation	95% CI for Mean	
				Lowe Limit	Upper Limit
A	**Daily infection risk**				
1	Dry season daily risk	2.31E-06	2.58E-06	2.26E-06	2.36E-06
3	Wet season daily risk	2.79E-06	4.25E-06	2.71E-06	2.87E-06
5	Seasonal average daily risk	2.52E-06	3.02E-06	2.46E-06	2.58E-06
7	Bereh District daily risk	2.34E-06	3.02E-06	2.28E-06	2.40E-06
9	Sebet-Hawas District daily risk	2.81E-06	2.98E-06	2.75E-06	2.87E-06
B	**Annual infection risk**				
2	Dry season annual risk	6.36E-04	7.09E-04	6.22E-04	6.50E-04
4	Wet season annual risk	2.51E-04	3.82E-04	2.44E-04	2.59E-04
6	Season average annual risk	9.20E-04	1.10E-03	8.98E-04	9.41E-04
8	Bereh District annual risk	8.54E-04	1.10E-03	8.32E-04	8.75E-04
10	Sebeta-Hawas District annual risk	1.03E-03	1.09E-03	1.00E-03	1.05E-03

CHAPTER 5: GENERAL DISCUSSION, CONCLUSION, RECOMMENDATIONS AND FUTURE WORKS

5.1. GENERAL DISCUSSION

The study of water quality dynamics and public health risks in the upper Awash River subbasin addresses several key issues. This approach involves interlinked issues, including comprehensive mapping of surface and groundwater sources and estimation of exposed populations, delineation of protection zones, analysis of water quality dynamics, identification and characterization of pollution sources, and quantification of public health risks associated with drinking water consumption.

By using methods such as the groundwater pollution risk index (GWPRI), surface water pollution risk index (SWPRI), integrated water source pollution risk (WSPR), and water pollution indexing, this study explains the complexities of environmental risk and estimates the exposed population within a subbasin. The prediction of potential water pollution risks and calculation of the Nemerow pollution index were performed to assess the pollution status of surface water on the basis of samples from ten monitoring sites. This innovative approach not only delineates risk levels on the basis of the complex interaction of contributing factors to water pollution but also identifies the population exposed to these risks. This highlights the urgent need for interventions and strategic planning to safeguard water resources and protect public health in the Upper Awash Subriver Basin. Accordingly, approximately 32.96%, 53.56%, and 13.5% of the surface water is at low, moderate, and high risk, respectively, while the surface water has lower pollution levels, with 72.64% at low risk and 27.36% at more than moderate risk, including 4.82% at high and 3.7% at very high risk. The combined analysis of water source pollution risk indicates that 68.1% of water sources are exposed to low pollution risk, 27.5% are at moderate risk, and 4.4% are categorized as high-risk areas. Moreover, approximately 5.64%, 3.88%, and 2.30% of the population is exposed to high groundwater, surface water, and combined water source pollution risks, respectively. These findings highlight the potential health implications for populations residing in higher-risk areas, emphasizing the critical need for continuous water quality monitoring and management strategies, including establishing protection zones for drinking water sources (section 4.2.). In conclusion, the detailed analysis presented in this study provides valuable insights into the distribution, severity, and drivers of groundwater and surface water pollution risks, informing targeted interventions, policy decisions, and resource allocation efforts aimed at safeguarding water resources and protecting public health within the study area and in a similar context. It is important, as the Awash River basin is not only the most important but also the most polluted river basin in Ethiopia[426]. It has even worsened around impacted areas due to industrial areas, settlements and flower farming[24]. The subbasin accommodates millions of people, featuring numerous industrial zones, varied settlement patterns, emerging towns, high population growth, rapid urbanization, flourishing farms, loss of vegetation, soil erosion, and other significant factors[19,426]. Therefore, the findings are valuable contributions to site-specific environmental impact assessments for new developments, aiding in the prioritization of pollution control measures on the basis of identified risk levels and improving the availability of evidence and institutional setup at the grassroots level[25,427].

This study not only mapped water pollution risks and estimated the exposed population in the subbasin but also identified vulnerable water supply schemes and delineated protection zones on the basis of the WASH inventory results and the DRASTIC model. The results revealed that a significant proportion (39.23%) of the water supply schemes were located in high-vulnerability areas, and 12.32% of the schemes were located in very high-vulnerability areas. Only 8% of the schemes were located in low-vulnerability areas. These findings emphasize the urgent need for protective measures for vulnerable water supply systems.

Moreover, this study introduces a novel approach by integrating National WASH inventory results with groundwater vulnerability assessments and protection zone experiences. This method goes beyond traditional sanitary surveys, transforming WASH inventory data into actionable insights. One effective strategy for limiting water resource pollution involves dividing areas around water sources into three protection zones via a ring buffer tool in ArcGIS. This study designates inner (50 m), immediate (500 m), and outer (entire water catchment) protection zones for water supply schemes[105,107]. This protection is equally crucial for wellheads, sanitary seals around well casings, and surface water intakes[294]. As a result, this study calls for authorities to implement water source protection, as demonstrated in this study through the use of GIS technology and integrated watershed management practices that encompass regulatory controls and conservation strategies. This approach is also recommended for replication in similar contexts and at the national level for the translation of the national WASH inventory into the WASH program. Further research is needed to better understand pollutant travel times, assimilation capacities, and land-use priorities to refine protection zone delineation.

The water supply greatly contributes to the health and well-being of human beings and the ecosystem and socioeconomic development of nations. However, water quality deterioration is becoming a critical concern at the global level in large and developing countries in particular[32]. It leads to high morbidity and mortality rates of waterborne diseases[34]. As a result, in addition to mapping water pollution risks, estimating the exposed population for vulnerable water supply sources, and establishing protection zones, a comprehensive assessment of water quality dynamics was conducted. By understanding temporal and spatial variations in water quality, stakeholders can effectively address pollution sources and enhance ecosystem health, ultimately leading to better water resource management and sustainable practices.

Understanding these dynamics is crucial, as they directly influence water quality and, in turn, public health outcomes. By employing various data analysis techniques, including the application of ANNs to predict the WQI, this study provides insights into the temporal and spatial characteristics of water quality parameters. This study parameterized the subbasin’s water quality via advanced modeling techniques to analyze its temporal and spatial distributions. Given the subbasin's pivotal role as the country's socioeconomic and political hub, as well as its function as a primary water catchment area serving urban populations, addressing water quality challenges is critically important for both environmental sustainability and public health protection.

This approach revealed significant variations in water quality across different locations and times, highlighting the need for targeted management strategies. However, gaps remain in long-term monitoring systems and the integration of real-time data, which are essential for refining predictive models such as ANNs and ensuring accurate WQI predictions. To close these gaps, further investments in monitoring infrastructure and data collection are recommended, alongside continued research to improve the precision of water quality predictions over time and across diverse areas. For example, only 26% of water supply samples met acceptable microbial risk standards, indicating a significant prevalence of microbial contamination that poses health risks.

On the other hand, 75.8% of the water supply schemes were rated as good, 13.3% as excellent, and 9.2% as poor. The surface water quality exhibited greater variability, with 10% classified as excellent, 43% as good, 30% as poor, and 17% as very poor. Significant differences in the mean WQI values of the groundwater sources were observed due to spatial variability within the study area. Surface water parameters such as total hardness, total dissolved solids, pH, fluoride, magnesium, chloride, and bicarbonate also exhibited notable variability between the dry and wet seasons. Furthermore, 85% of the variability in drinking water quality was explained by five key parameters, with 94% accuracy, whereas four surface water quality parameters predicted the WQI with 95.1% accuracy.

These findings highlight the critical need for water source protection, particularly given the broader range of water quality conditions in surface water than in groundwater sources. The results emphasize the importance of conducting vulnerability assessments and delineating protection zones to safeguard water sources from deteriorating quality. Without protective measures, the risk of unacceptable water quality affecting users remains high, which could lead to adverse public health outcomes. This study calls for urgent interventions to mitigate contamination and enhance the resilience of water supply schemes. In summary, the findings emphasize the presence of critical challenges related to microbial contamination and noncompliance with water quality standards in drinking water supplies, along with significant variability in surface water quality. These findings call for actions such as water quality surveillance, source protection, household water treatment, and strengthened water quality monitoring efforts to ensure safe and sustainable water resources for the population in the study area. Water pollution risks, water quality dynamics in terms of temporal and spatial parameters, and public health risks due to poor water quality were quantified in the aforementioned chapters.

However, the sources of pollution are not explained, so this study also highlighted the assessment of sources of water pollution by employing Aquachem 2014.2, the PMF model and PCA models. These methods are important for identifying dominant pollutants and their sources to generate evidence for water source protection[226,228]. This is a critical measure to design and develop policies and strategies for the establishment of institutional setups, identify stakeholders and their roles and address the need for capacity building[428]. Accordingly, as explained in section 4.4., water quality deterioration is aggravated by population growth, industrialization, urbanization, agricultural activities, deforestation, and other contributing factors, which are strongly manifested in the subbasin. Thus, the identification of major pollutants and their sources is crucial in this study to address this problem through source protection, including decreasing vulnerability, avoiding potential hazardous pollutants in the subbasin system and instituting interventions. The source protection approach is considered a more feasible and cost-effective technique. Source identification was performed through a comprehensive dataset of 197 boreholes, 70 surface water samples and 60 water supply samples.

Consequently, the sanitary assessment results revealed that animal grazing, agriculture, and other human activities significantly contribute to water pollution risk, accounting for 66.7%, 61.7%, and 40%, respectively. With respect to water chemistry, the analysis identified the dominant water types as Na-HCO_3 (sodium bicarbonate) for 65% and Ca-HCO_3 (calcium bicarbonate) for 32.5% of the water types. This characterization offers insights into the water treatment technology applied by considering the chemical composition of groundwater and is vital for assessing its suitability for various uses. Pollutant source analysis also indicated that 64% of pollutants originate from geogenic (naturally occurring) sources due to groundwater's natural contamination, whereas anthropogenic (human-induced) and agricultural sources contribute 29% and 7%, respectively, to drinking water supply schemes. Similar patterns were observed in groundwater, with 63% of the pollutants attributed to geogenic sources and 20% and 17% from anthropogenic and agricultural activities, respectively.

Water pollution in the upper Awash subbasin has been aggravated by rapid population growth, urbanization, industrialization, agricultural expansion, and deforestation[19,20,22,23]. Key pollution sources include industries, mining, agricultural practices, and mixed geogenic-anthropogenic factors [274]. These issues are compounded by poor wastewater management, insufficient source protection, and a lack of institutional coordination. Inadequate enforcement and grassroots institutional setups also contribute to the degradation of water resources. To address these challenges, generating scientific evidence on pollution sources is essential. Implementing integrated watershed management, risk management approaches, and policy development will help mitigate public health risks and protect water quality in the region.

In summary, these results call attention to the complex interactions of natural and human-induced factors influencing water quality in the study area. Effective management strategies should prioritize mitigating pollution sources from agriculture, human activities, and naturally occurring contaminants to safeguard water resources and ensure safe drinking water supplies for the local population.

Despite the importance of water source protection, several gaps persist, particularly in risk management and long-term ecological monitoring. Vulnerability assessments and contamination identification often lack comprehensive data, especially in less developed countries. Even in developed nations, gaps in protection can lead to outbreaks of waterborne diseases[429]. This study highlights insufficient adherence to regulatory standards and a limited understanding of anthropogenic impacts on water quality. Moreover, risk assessments are hindered by inadequate environmental impact evaluations and a lack of effective, localized solutions[155]. To close these gaps, integrated approaches such as watershed management and enhanced data-driven risk assessments are needed to mitigate public health risks. These include quantifying public health risks, assessing the vulnerability of drinking water schemes, delineating protection zones for these water supply schemes, mapping water pollution risks against the population exposed to these risks, identifying pollution sources to implement preventive measures, and characterizing temporal and spatial water quality distributions to understand the basin's water quality aspects. These investigations have been conducted adequately to inform sector authorities, stakeholders and the scientific community.

In this study, hazard identification, exposure assessment, dose–response analysis, and risk characterization, including hazard quotient (HQ), cancer risk (CR), hazard index (HI), and probability of infection, were applied to quantify the risk to public health through hazard identification to understand the extent of the problem and provide evidence for advocacy and risk reduction management strategies. As a result, nitrate levels, indicated by the hazard quotient (HQ), exceeded unity (HQ > 1) across all groups during the dry season, suggesting potential health impacts related to nitrate contamination in drinking water. Chromium was identified as a health risk, particularly a noncancer risk, with hazard quotient (HQ) values exceeding 1 (HQ > 1) for women (1.1E+00) and children (1.4E+00) during the wet season in high water pollution risk (WPR) areas such as Bereh woreda and for children (1.4E+00) specifically during the wet season in low WPR areas such as Sebeta-Hawas woreda. Despite the sampling areas being distant from industrial pollution sources, the chromium source is assumed to be agricultural fertilizer, as it is a constituent of industrial fertilizers. Fluoride levels (HQ > 1) for children

(3.2E+00) during the dry season in low WPR areas are associated with aquifer geology and anthropogenic activities.

On the other hand, the arsenic-related cancer risk exceeded 1 in 10,000 persons for children during the dry season across all groups and for women and children during the wet season in high WPR areas. The cancer risk associated with chromium ranges from 1 in 1000 people, which exceeds safe limits. Furthermore, the hazard index (HI) was consistently above unity (HI>1) in most cases, indicating that the cumulative health risks associated with multiple pollutants in water sources were above the acceptable level. These findings highlight the potential long-term health consequences of arsenic and chromium exposure through contaminated drinking water sources. Additionally, the study revealed elevated risks of *E. coli* infection, with daily and annual risks exceeding acceptable levels. This finding indicates a significant risk of infection from *E. coli* bacteria in the studied context. Such findings typically prompt the need for intervention measures to mitigate risks and ensure the safety of water sources and other relevant aspects that impact public health. These results highlight the urgent need for effective water quality management to mitigate health risks. Key actions include comprehensive monitoring, household water treatment, and targeted remediation, especially in highly contaminated areas and seasons. Linking watershed management with health promotion is essential to protect public health and reduce waterborne diseases in the upper Awash River subbasin.

In conclusion, this study successfully achieves its objectives by developing a comprehensive map of surface and groundwater sources, highlighting pollution risks across the subbasin. Protection zones were delineated on the basis of vulnerability assessments and pollution risk factors, offering a robust framework for water source protection. Using advanced modeling techniques, the temporal and spatial distributions of water quality can be effectively parameterized. The study also identified and characterized key pollution sources impacting water quality. Finally, it quantified public health risks linked to drinking water consumption, establishing clear connections between water quality parameters and associated health risks.

5.2. CONCLUSION

The conclusions of this study are the key findings in relation to the objective of determining the temporal and spatial patterns of water pollution and associated public health risks in the Upper Awash Sub-River Basin. Through comprehensive analysis, this study successfully addressed each of the specific objectives, providing significant insights into water quality dynamics and public health risks within the subbasin, with the potential for replication in similar basins. Innovative assessment tools and management strategies were developed to address the identified gaps, offering practical recommendations for improving both water quality and public health outcomes in the study area. The detailed conclusions are presented as follows:

The assessment of surface water and groundwater pollution risks, along with the computation of the water pollution index (WPI), reveals alarming findings that highlight the severity of water pollution in the studied areas. Moreover, the estimation of the proportion of the population exposed to different pollution risk levels contributes significantly to understanding and addressing these risks, offering essential information for implementing source protection measures. The study findings indicate that over 13.5% of groundwater, 8.52% of surface water, and 4.4% of both water sources in the subbasin are challenged with high pollution risks, with approximately 17.47% of the population residing in moderately risked areas. Additionally, 5.64%, 3.88%, and 2.30% of the population faces high risks specifically related to groundwater pollution (GWPR), surface water pollution (SWPR), and overall water pollution (WSPR), respectively. Moreover, the WPI values computed for the dry season surpassed 1 for all ten monitoring sites, indicating a state of pollution in the surface water. The WSP strategy involves a comprehensive risk assessment and offers a promising approach for mitigating contamination risk. However, its implementation faces significant challenges, including inadequate source protection measures and a lack of legal restrictions. This research assessed the vulnerability of water supply systems and delineated source protection zones. Accordingly, 14.4% of the water supply scheme sources had a water safety plan, 20.7% had water safety practices, and 6% had a reported incidence of waterborne diseases. More than 39.23% of these schemes were located in highly vulnerable areas, 12.32% were in highly vulnerable areas, and only 8% were in less vulnerable areas. Furthermore, coordination, capacity-building efforts and the development of guidelines were strengths at the national level; however, a lack of institutionalization, catchment protection, legal frameworks and climate information were the major challenges of water source protection.

To address the problem of water quality deterioration, water source protection from pollutants is a pioneering strategy to minimize the effects and impacts of the problem. The first step is the identification of the source of water pollution, which is accomplished through the use of sanitary surveys, hydrochemical water type calculations, principal component analysis (PCA) and a positive matrix factorization model. Accordingly, animal entry (grazing), agricultural activities and settlement and human activities were found to be potential causes of pollution for 66.7%, 61.7% and 40% of the water supply schemes, respectively. In addition, the most dominant water types were Na-HCO3 (65%) and Ca-HCO3 (32.5%), whereas Na-CO3 (35%), Na-HCO3 (13.3%), Ca-CO3 (11.7%) and other water types were detected in the surface water. In addition, considering the concentration of species in each pollutant source for the drinking water supply, 64% of the pollutants originated from geogenic sources, such as sedimentary (32%) and igneous (32%) rocks, whereas 29% and 7% of the sources were agricultural activities and anthropogenic, respectively. Additionally, 63% of the pollutant sources were geogenic, whereas 20% and 17% of the pollutants originated from anthropogenic and agricultural activities, respectively. Additionally, only 26% (31) of the samples presented acceptable levels of microbial risk, whereas 74% (89) of the water supply schemes presented unacceptable levels of microorganisms according to the WHO drinking water standard. Compared with the dry season, the rainy season had a greater mean dose of *E. coli* per 100 mL (18>14 CFU/100 mL), and the Sebeta-Hawas District had more *E. coli* (17>15 CFU/100 ml) than did the Bereh District. Furthermore, the results of the WQI computation demonstrated that drinking water quality was categorized as excellent, good, or bad in 13.3% (16), 75.8% (91), or 9.2% (11) of the water supply schemes, respectively. The surface water quality indices were also excellent, good, poor, and very low at 10% (3), 43% (13), 30% (9), and 17% (5), respectively. Additionally, ten water quality parameters predicted the drinking WQI with accuracies of 94% and 5.6% relative error, and four parameters predicted the surface WQI with 95.1% accuracy and 9.8% relative error via the ANN model.

Considering the local settings and other indications, five water quality parameters, nitrite, nitrate, chromium, iron, and arsenic, were analyzed for chemical parameters, and *E. coli* was analyzed for microbial risk. Accordingly, nitrate, chromium, and fluoride have potential effects on noncancer risks, and chromium and arsenic have effects on carcinogenic risks. For men (1.6E+00), women (1.8E+00), and children (2.5E+00) in Bereh District, as well as for women (1.3E+00) and children (1.6E+00) for the seasonal average during the dry season, the HQ values of nitrate were greater than unity (HQ>1). For women (1.1E+00) and children (1.4E+00) in the Bereh District and for children (1.4E+00) in the Sebeta-Hawas District during the wet season, and for children in both seasons for seasonal average risk, the HQ values of chromium were greater than unity (HQ>1). Children in the Sebeta-Hawas District had fluoride HQ values (3.2E+00) that were greater than unity (HQ>1) during the dry season. Chromium and arsenic present cancer risks that are higher than permissible risk levels. Moreover, except for the seasonal average for men, the hazard index (HI) of the six water quality parameters was greater than unity (HI>1), which exceeded the total noncancer risk level. Arsenic may have a substantial impact on women (3.22E-05) and children (1.29E-04) during the dry season, children (4.29E-05) during the wet season, Bereh District, and all other groups during the dry season. Both the seasonal average provided by the WHO and the permitted risk level for all sample sites are exceeded by the cancer risk associated with chromium. Although it is less than 1 in 10,000, the cancer risk associated with Sebeta-Hawas during the dry season is tolerable. It varies from 1 in 1000 to 9.78 in 10,000. All the daily and annual risks of infection due to *E. coli* were higher than the tolerable risks. In conclusion, the following recommendations are proposed to enhance water quality management and mitigate public health risks in the Upper Awash Sub-River Basin, ensuring long-term sustainability and improved outcomes for similar basins and contexts.

5.3. RECOMMENDATIONS

The following recommendations can be used to guide strategic actions, policy interventions, and future research areas to safeguard water sources, protect public health, and promote sustainable water management practices in the Upper Awash Sub-River Basin, with potential for replication in similar basins. These recommendations are described as follows:

1) Action for robust policy measures, improved regulatory frameworks, and community awareness initiatives are a must to do to address the identified sources of pollution and safeguard the quality of both surface water and groundwater for the well-being of the communities and the ecosystems. This involves incorporating public health considerations

into Integrated Water Supply Management (IWSM), revising regulations, strategically allocating resources, prioritizing interventions, delineating water protection zones, and providing inputs for environmental impact assessments related to new investments. Additionally, public and ecosystem health issues in IWSM, including source control, treatment technologies, and regulatory measures for sustainable and resilient water management practices, should be considered by the responsible sectors such as natural resource, socio-economic, social and governance sectors.

2) To address unacceptable findings and promote public health, several key actions are necessary. First, there is a need for the implementation of water source protection measures, as demonstrated in this study, which integrate vulnerability assessment with NWI-2 as WASH national program monitoring and evaluation system and integrated watershed management, including water conservation strategies, WSP, and regulatory control. Additionally, efforts should be made to institutionalize WSP practices and establish a robust legal framework to support source protection initiatives. By implementing these measures, ministry of water and energy at national level, water bureau at regional level and water office at woreda level can ensure the long-term sustainability of water supply systems and safeguard public health, and a plan for future research should focus on the pollutant duration of travel, assimilation capacity, and land use priorities to delineate specific protection zones more accurately.

3) Numerous sectors, including the Ministry of Water and Energy, Regional Water Bureaus, Woreda Administrations, the Ministry of Environment, Forest and Climate Change, the Ministry of Urban Development and Infrastructure, Land Administration and Survey Agencies, the Ministry of Agriculture, the Ministry of Health, and the Ministry of Education, alongside other relevant ministries and bureaus within the subbasin, should engage in collaborative efforts to ensure comprehensive water source protection and sustainable practices. These joint actions should encompass strengthening acceptable waste disposal management systems to effectively minimize water source pollution, construct water supply schemes within low vulnerable areas and implementing zoning regulations to safeguard existing water sources. Furthermore, coordinated strategies are needed to control

unsustainable agricultural practices, specifically the use of fertilizers and animal grazing. Finally, these sectors must collaborate to enhance the development of evidence-based policies and to actively raise awareness about water resource management among all relevant stakeholders, including government bodies at various levels, local communities, and civil society organizations.

4) Promptly detecting water quality status and assessing ongoing interventions will mitigate risks and ensure the sustainable management of water resources. Consequently, it is imperative to implement water treatment technologies in terms of both the water source and point of use and the application of sanitation measures complemented by establishing buffer zones around drinking water sources and fostering an environment conducive to integrated watershed management in urban and rural areas. Moreover, it is essential to continually assess interventions and prioritize research efforts to identify primary sources of water pollution and areas within the subbasin most vulnerable to contamination.

5) Parallel to implementation of strong risk management for the quantified carcinogenic, noncancer and infectious risks of drinking water, immediate public awareness campaigns, enhancement of treatment processes at the source and point of use levels, remediation of contaminated sources supported by continuous monitoring, revision of health programs, and community engagement initiatives are recommended to be executed by Ministry of health, water and energy, bureaus, woreda offices and other relevant stakeholders. Furthermore, those responsible organizations should develop proper policies, enforce regulatory measures, integrate watershed management and establish long-term sustainable water treatment technologies for urban, semiurban, and rural settlements in the upper awash subbasin on the basis of the identified and quantified risk levels.

5.4. FUTURE WORKS

Future works are proposed to extend the findings of this dissertation and address the identified challenges related to water quality and public health risks in the Upper Awash Sub-River Basin.

1. The DRASTIC model's reliance on seven factors may overlook complex hydrogeological interactions that determine groundwater vulnerability. This approach may inadequately address site-specific conditions, such as the nature and intensity of contaminant sources. The model also treats confined aquifers similarly to unconfined aquifers and represents a single point in time without considering future land use or climate changes. Further research should explore pollutant travel times, assimilation capacities, and land use priorities to delineate specific protection zones. Replicating these approaches in similar basins will provide broader insights and guide sustainable water management practices on a larger scale.
2. This study's public health risk assessment was limited to water ingestion, but other sources of toxic element exposure, such as dermal contact, inhalation, and the ingestion of polluted soils, were not included and should be investigated. Additionally, this research predicted infection risks on the basis of *E. coli*, but the probability of infection from other waterborne disease agents in the subbasin should also be studied.
3. The use of WASH inventory data is constrained by the inherent limitations of secondary data sources. These limitations emphasize the need for careful interpretation and complementation with additional approaches to ensure a comprehensive assessment of water supply scheme vulnerability and protection zone delineation.

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CHAPTER 6: ANNEXES

1. WATER QUALITY PARAMETER, PERMISSIBLE LIMIT, WEIGHT & RELATIVE WEIGHT FOR WQI COMPUTE

S/N	Parameters	si (permissible Limit)	Weight (wi)	Relative Weight (Wi)
1	TDS (mg/L)	1,000.00	4	0.08
2	pH	7.50	4	0.08
3	Na(mg/L)	200.00	2	0.04
4	K(mg/L)	1.50	2	0.04
5	Total Hardness (mg/L)	300.00	2	0.04
6	Ca(mg/L)	75.00	2	0.04
7	Mg(mg/L)	50.00	2	0.04
8	Fe (mg/L)	0.30	4	0.08
9	Mn(mg/L)	0.50	4	0.08
10	F(mg/L)	1.50	5	0.10
11	Cr(mg/L)	250.00	5	0.06
12	NO_2(mg/L)	3.00	5	0.10
13	NO_3(mg/L)	50.00	5	0.10
14	HCO_3 (mg/L)	488.00	3	0.06
15	SO_4(mg/L)	250.00	4	0.08
		Total	53	1.00

2. **DRINKING WATER QUALITY INFORMATION**

2.1. Descriptive statistics of drinking water quality parameters

S/N	Water Quality Parameters	Mean	95% CI for Mean		Std. D	Min	Max
			Lower Bound	Upper Bound			
1	Total Dissolved Solids(TDS)mg/l	240.80	211.79	269.81	160.50	11.55	915.00
2	pH	7.28	6.99	7.57	1.60	6.05	23.90
3	Sodium(Na) mg/l	55.96	51.31	60.61	25.74	0.07	129.54
4	Potassium(K) mg/l	6.61	5.78	7.44	4.60	0.42	26.26
5	Total Hardness(TH)mg/l	174.29	159.21	189.37	83.42	5.00	470.00
6	Calcium (Ca) mg/l	59.95	54.49	65.41	30.19	2.00	190.00
7	Magnesium(Mg) mg/l	68.62	55.55	81.69	72.30	0.01	280.00
8	Iron(Fe) mg/l	0.23	0.09	0.37	0.79	0.00	8.00
9	Manganese(Mn) mg/l	0.36	0.24	0.48	0.68	0.01	6.00
10	Fluoride(F) mg/l	0.55	0.49	0.61	0.34	0.01	1.43
11	Chloride(Cl) mg/l	0.06	0.05	0.07	0.06	0.00	0.50
12	Nitrite(NO2) mg/l	0.15	-0.02	0.31	0.91	0.01	8.00
13	Nitrate(NO3) mg/l	24.98	17.72	32.25	40.19	0.08	300.00
14	Bicarbonate(HCO3) mg/l	404.94	360.86	449.01	243.82	75.00	1375.00
15	Sulfate(SO4) mg/l	11.11	6.26	15.96	26.82	0.00	180.00
16	Carbonate(CO3) mg/l	188.87	169.18	208.55	108.88	35.00	687.50
17	Ammonia(NH3) mg/l	9.83	-1.11	20.78	60.54	0.00	648.00
18	Alkalinity(Alk) mg/l	330.06	294.31	365.81	197.78	60.00	1125.00
19	Arsenic(As) µg/l	0.30	0.12	0.48	1.00	0.00	6.00

20	Electrical Conductivity (EC)S/m	485.29	424.38	546.20	336.98	6.32	1834.00

2.2. Drinking water quality parameters normality tests results

S/N	Water Quality Parameters	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
1	Total Dissolved Solids (TDS)	0.174	120	0.000	0.809	120	0.000
2	pH	0.306	120	0.000	0.270	120	0.000
3	Sodium(Na)	0.038	120	.200*	0.993	120	0.830
4	Potassium(K)	0.145	120	0.000	0.858	120	0.000
5	Total Hardness(TH)	0.115	120	0.001	0.958	120	0.001
6	Calcium (Ca)	0.162	120	0.000	0.881	120	0.000
7	Magnesium(Mg)	0.196	120	0.000	0.842	120	0.000
8	Iron(Fe)	0.386	120	0.000	0.250	120	0.000
9	Manganese(Mn)	0.301	120	0.000	0.480	120	0.000
10	Fluoride(F)	0.118	120	0.000	0.943	120	0.000
11	Chloride(Cl)	0.240	120	0.000	0.463	120	0.000
12	Nitrite(NO2)	0.446	120	0.000	0.135	120	0.000
13	Nitrate(NO3)	0.268	120	0.000	0.634	120	0.000
14	Bicarbonate(HCO3)	0.192	120	0.000	0.788	120	0.000
15	Sulfate(SO4)	0.339	120	0.000	0.420	120	0.000
16	Carbonate(CO3)	0.193	120	0.000	0.793	120	0.000
17	Ammonia(NH3)	0.435	120	0.000	0.142	120	0.000
18	Alkalinity(Alk)	0.202	120	0.000	0.796	120	0.000
19	Arsenic(As)	0.485	120	0.000	0.341	120	0.000
20	Electrical Conductivity(EC)	0.171	120	0.000	0.818	120	0.000
21	Water Quality Index (WQI)	0.149	120	0.000	0.767	120	0.000
	*. This is a lower bound of the true significance.						
	a. Lilliefors Significance Correction						

2.3. Drinking water quality parameters Homogeneity of Variances test results

S/N		Levene Statistic	df1	df2	Sig.
1	Total Dissolved Solids(TDS)	10.881	1	118	0.001
2	Sodium(Na)	10.697	1	118	0.001
3	Potassium(K)	13.756	1	118	0.000
4	Total Hardness(TH)	12.344	1	118	0.001
5	Calcium (Ca)	1.009	1	118	0.317
6	Magnesium(Mg)	19.525	1	118	0.000
7	Iron(Fe)	4.451	1	118	0.037
8	Manganese(Mn)	7.078	1	118	0.009
9	Fluoride(F)	18.751	1	118	0.000
10	Chloride(Cl)	3.747	1	118	0.055

11	Nitrite(NO2)	7.611	1	118	0.007
12	Nitrate(NO3)	16.330	1	118	0.000
13	Bicarbonate(HCO3)	36.367	1	118	0.000
14	Sulfate(SO4)	20.487	1	118	0.000
15	Carbonate(CO3)	25.638	1	118	0.000
16	Ammonia(NH3)	8.375	1	118	0.005
17	Alkalinity(Alk)	34.531	1	118	0.000
18	Arsenic(As)	42.594	1	118	0.000
19	Electrical Conductivity (EC)	5.506	1	118	0.021
20	Water Quality Index (WQI)	2.342	1	118	0.129

2.4. Non-parametric test of One-Way ANOVA of drinking water quality

S/N	Rejected Null Hypothesis: distribution of the parameter is the same across categories of sample sites (Bereh and Sebeta-Hawas districts)		S/N	Rejected Null Hypothesis: distribution of the parameter is the same across dry and wet seasons	
	Parameters	Sig		Parameters	Sig
1	TDS	0.000	1	Na	0.008
2	PH	0.000	2	Fe	0.000
3	Na	0.000	3	Mn	0.000
4	K	0.000	4	F	0.039
5	TH	0.000	5	Cr	0.000
6	F	0.000	6	NO_3	0.000
7	Cr	0.000	7	HCO_3	0.003
8	NO2	0.000	8	CO_3	0.011
9	NO3	0.042	9	NH_3	0.017
10	HCO3	0.046	10	Akl.	0.003
11	SO4	0.03	11	As.	0.024
12	Akl	0.036			
13	As	0.000			
14	EC	0.000			

3. SURFACE WATER QUALITY

3.1. Surface water quality parameters descriptive statics

S/N	Descriptive	Mean	95% Confidence Interval for Mean		Std. Deviation	Minimum	Maximum
			Lower Bound	Upper Bound			
1	Total Dissolved Solids(TDS)	318.7118	246.1292	391.2944	194.37983	59.87	852.80
2	PH	7.2807	7.0900	7.4714	0.51073	6.63	8.21
3	Sodium(Na)	77.5168	60.7147	94.3188	44.99664	5.51	175.53
4	Potassium(K)	15.6235	12.3886	18.8584	8.66326	1.24	36.56
5	Total Hardness (TH)	145.8333	121.7629	169.9037	64.46174	25.00	285.00
6	Calcium(Ca)	37.0333	28.2814	45.7853	23.43808	11.00	129.00

7	Magnesium(Mg)	21.0557	11.7814	30.3299	24.83699	0.49	140.00
8	Iron(Fe)	0.2093	0.1269	0.2917	0.22064	0.02	1.26
9	Manganese(Mn)	0.3983	0.2850	0.5115	0.30334	0.00	1.26
10	Fluoride(F)	4.8980	0.9105	8.8855	10.67865	0.29	59.00
11	Chloride(Cl)	64.2343	46.6708	81.7979	47.03612	0.03	155.00
12	Nitrite(NO2)	0.2524	-0.0637	0.5684	0.84638	0.00	4.00
13	Nitrate(NO3)	20.5696	6.8953	34.2439	36.62051	1.26	208.42
14	Bicarbonate(HCO3)	282.5000	214.5846	350.4154	181.88074	65.00	850.00
15	Sulfate(SO4)	10.1200	4.8562	15.3838	14.09677	0.00	67.00
16	Water Quality Index(WQI)	125.1616	90.3073	160.0160	93.34168	29.06	510.61

3.2. Surface water quality parameter Normality Test Results

S/N	Water Quality Parameters	Kolmogorov-Smirnov			Shapiro-Wilk		
		Statistic	df	Sig.	Statistic	df	Sig.
1	Water Quality Index(WQI)	0.158	30	0.053	0.913	30	0.018
2	log10WQI	0.114	25	.200*	0.939	25	0.140
3	Total Dissolved Solids(TDS)	0.184	30	0.011	0.921	30	0.028
4	log10TDS	0.147	25	0.169	0.948	25	0.221
5	PH	0.193	30	0.006	0.898	30	0.008
6	log10ph	0.188	25	0.023	0.911	25	0.032
7	Sodium(Na)	0.120	30	.200*	0.969	30	0.515
8	Potassium(K)	0.111	30	.200*	0.962	30	0.349
9	Total Hardness (TH)	0.144	30	0.113	0.967	30	0.465
10	Calcium(Ca)	0.218	30	0.001	0.755	30	0.000
11	log10cal	0.112	25	.200*	0.977	25	0.810
12	Magnesium(Mg)	0.253	30	0.000	0.566	30	0.000
13	log10mg	0.188	25	0.023	0.881	25	0.007
15	Iron(Fe)	0.317	30	0.000	0.559	30	0.000
14	log10Fe	0.174	25	0.049	0.941	25	0.158
16	Manganese(Mn)	0.134	30	0.180	0.927	30	0.042
17	log10mn	0.246	25	0.000	0.748	25	0.000
18	Fluoride(F)	0.333	30	0.000	0.400	30	0.000
19	log10F	0.192	25	0.018	0.933	25	0.101
20	Chloride(Cl)	0.131	30	0.198	0.917	30	0.023
21	log10Cl	0.243	25	0.001	0.657	25	0.000
22	Nitrite(NO2)	0.472	30	0.000	0.313	30	0.000
23	log10No2	0.276	25	0.000	0.811	25	0.000
24	Nitrate(NO3)	0.345	30	0.000	0.377	30	0.000
25	log10No3	0.150	25	0.150	0.894	25	0.014
26	Bicarbonate(HCO3)	0.141	30	0.133	0.888	30	0.004
27	log10HCO3	0.132	25	.200*	0.968	25	0.592
28	Sulfate(SO4)	0.286	30	0.000	0.639	30	0.000
29	log10So4	0.106	25	.200*	0.970	25	0.654

3.3. Detail Surface water quality parameter results of ANOVA

ANOVA

Water Quality Parameters		Sum of Squares	df	Mean Square	F	Sig.
Total Hardness (TH)	Between Groups	41946.667	2	20973.333	7.208	0.003
	Within Groups	78557.500	27	2909.537		
	Total	120504.167	29			
Chloride(Cl)	Between Groups	30840.349	2	15420.174	12.496	0.000
	Within Groups	33319.165	27	1234.043		
	Total	64159.514	29			
Sodium(Na)	Between Groups	442.717	2	221.359	0.103	0.903
	Within Groups	58273.517	27	2158.278		
	Total	58716.235	29			
Potassium(K)	Between Groups	222.968	2	111.484	1.541	0.232
	Within Groups	1953.540	27	72.353		
	Total	2176.508	29			
Iron(Fe)	Between Groups	0.043	2	0.022	0.427	0.657
	Within Groups	1.368	27	0.051		
	Total	1.412	29			
Fluoride(F)	Between Groups	252.103	2	126.052	1.114	0.343
	Within Groups	3054.872	27	113.143		
	Total	3306.975	29			
Calcium(Ca)	Between Groups	952.267	2	476.133	0.858	0.435
	Within Groups	14978.700	27	554.767		
	Total	15930.967	29			
log10TDS	Between Groups	0.826	2	0.413	6.703	0.004
	Within Groups	1.664	27	0.062		
	Total	2.490	29			
log10ph	Between Groups	0.017	2	0.008	24.311	0.000
	Within Groups	0.009	27	0.000		
	Total	0.026	29			
log10cal	Between Groups	0.091	2	0.045	0.932	0.406
	Within Groups	1.315	27	0.049		
	Total	1.406	29			
log10mg	Between Groups	1.584	2	0.792	4.903	0.015
	Within Groups	4.362	27	0.162		
	Total	5.946	29			
log10Fe	Between Groups	0.082	2	0.041	0.300	0.744
	Within Groups	3.683	27	0.136		
	Total	3.765	29			
log10mn	Between Groups	0.154	2	0.077	0.249	0.782
	Within Groups	7.721	25	0.309		
	Total	7.874	27			
log10F	Between Groups	1.604	2	0.802	3.162	0.058
	Within Groups	6.848	27	0.254		
	Total	8.452	29			
log10Cl	Between Groups	3.536	2	1.768	4.494	0.021

Water Quality Parameters		Sum of Squares	df	Mean Square	F	Sig.
	Within Groups	10.624	27	0.393		
	Total	14.160	29			
log10No2	Between Groups	0.069	2	0.034	0.068	0.935
	Within Groups	13.157	26	0.506		
	Total	13.225	28			
log10No3	Between Groups	0.468	2	0.234	1.658	0.209
	Within Groups	3.806	27	0.141		
	Total	4.274	29			
log10HCO3	Between Groups	0.760	2	0.380	6.824	0.004
	Within Groups	1.503	27	0.056		
	Total	2.263	29			
log10So4	Between Groups	0.466	2	0.233	1.011	0.378
	Within Groups	5.764	25	0.231		
	Total	6.231	27			
log10WQI	Between Groups	0.114	2	0.057	0.951	0.399
	Within Groups	1.620	27	0.060		
	Total	1.734	29			

3.4. Post Hoc Tests (Surface water quality) Multiple Comparisons Tukey HSD

	Dependent Variable			Mean Difference	Std. Error	Sig.	95% Confidence Interval	
							Lower Bound	Upper Bound
1	Total Hardness (TH)	JJAS	ONDJ	-88.00000	24.12276	0.003	-147.8104	-28.1896
			FMAM	-66.00000	24.12276	0.028	-125.8104	-6.1896
		ONDJ	JJAS	88.00000	24.12276	0.003	28.1896	147.8104
			FMAM	22.00000	24.12276	0.638	-37.8104	81.8104
2	Total Dissolved Solids (TDS)	JJAS	ONDJ	-.36971	0.11102	0.007	-0.6450	-0.0944
			FMAM	-.33125	0.11102	0.016	-0.6065	-0.0560
		ONDJ	JJAS	.36971	0.11102	0.007	0.0944	0.6450
			FMAM	0.03846	0.11102	0.936	-0.2368	0.3137
3	PH	JJAS	ONDJ	-0.01718	0.00830	0.115	-0.0378	0.0034
			FMAM	-.05648	0.00830	0.000	-0.0771	-0.0359
		ONDJ	JJAS	0.01718	0.00830	0.115	-0.0034	0.0378
			FMAM	-.03929*	0.00830	0.000	-0.0599	-0.0187
4	Magnesium (Mg)	JJAS	ONDJ	-.51968	0.17975	0.020	-0.9654	-0.0740
			FMAM	-.44706	0.17975	0.049	-0.8927	-0.0014
		ONDJ	JJAS	.51968	0.17975	0.020	0.0740	0.9654
			FMAM	0.07262	0.17975	0.914	-0.3731	0.5183
5	Chloride(Cl)	JJAS	ONDJ	-0.45904	0.28053	0.248	-1.1546	0.2365
			FMAM	-.83977	0.28053	0.016	-1.5353	-0.1442
		ONDJ	JJAS	0.45904	0.28053	0.248	-0.2365	1.1546
			FMAM	-0.38073	0.28053	0.377	-1.0763	0.3148
6	Bicarbonate (HCO3)	JJAS	ONDJ	-.35692	0.10552	0.006	-0.6185	-0.0953
			FMAM	-.31422	0.10552	0.016	-0.5758	-0.0526
		ONDJ	JJAS	.35692	0.10552	0.006	0.0953	0.6185
			FMAM	0.04270	0.10552	0.914	-0.2189	0.3043

3.5. Post Hoc Tests (Surface water quality) Multiple Comparisons

Dependent Variable	Independent Variables		Mean Difference	Std. Error	Sig.	95% CI	
						Lower Bound	Upper Bound
log10TDS	JJAS	ONDJ	-0.370	0.111	0.007	-0.645	-0.094
		FMAM	-0.331	0.111	0.016	-0.607	-0.056
	ONDJ	JJAS	0.370	0.111	0.007	0.094	0.645
		FMAM	0.038	0.111	0.936	-0.237	0.314
Total Hardness (TH)	JJAS	ONDJ	-88.000	24.123	0.003	-147.810	-28.190
		FMAM	-66.000	24.123	0.028	-125.810	-6.190
	ONDJ	JJAS	88.000	24.123	0.003	28.190	147.810
		FMAM	22.000	24.123	0.638	-37.810	81.810
log10F	JJAS	ONDJ	-0.365	0.225	0.254	-0.924	0.193
		FMAM	-0.558	0.225	0.050	-1.116	0.001
	ONDJ	JJAS	0.365	0.225	0.254	-0.193	0.924
		FMAM	-0.192	0.225	0.674	-0.751	0.366
Chloride(Cl)	JJAS	ONDJ	-12.497	15.710	0.709	-51.449	26.455
		FMAM	-73.397	15.710	0.000	-112.349	-34.445
	ONDJ	JJAS	12.497	15.710	0.709	-26.455	51.449
		FMAM	-60.900	15.710	0.002	-99.852	-21.948
log10HCO3	JJAS	ONDJ	-0.357	0.106	0.006	-0.619	-0.095
		FMAM	-0.314	0.106	0.016	-0.576	-0.053
	ONDJ	JJAS	0.357	0.106	0.006	0.095	0.619
		FMAM	0.043	0.106	0.914	-0.219	0.304
log10WQI	JJAS	ONDJ	-0.064	0.110	0.831	-0.335	0.208
		FMAM	-0.151	0.110	0.368	-0.422	0.121
	ONDJ	JJAS	0.064	0.110	0.831	-0.208	0.335
		FMAM	-0.087	0.110	0.711	-0.358	0.185
Sodium(Na)	JJAS	ONDJ	7.034	20.776	0.939	-44.480	58.547
		FMAM	8.930	20.776	0.904	-42.583	60.443
	ONDJ	JJAS	-7.034	20.776	0.939	-58.547	44.480
		FMAM	1.897	20.776	0.995	-49.617	53.410
Potassium(K)	JJAS	ONDJ	0.429	3.804	0.993	-9.003	9.861
		FMAM	-5.557	3.804	0.325	-14.989	3.875
	ONDJ	JJAS	-0.429	3.804	0.993	-9.861	9.003
		FMAM	-5.986	3.804	0.274	-15.418	3.446
Calcium(Ca)	JJAS	ONDJ	-6.800	10.533	0.796	-32.917	19.317
		FMAM	7.000	10.533	0.786	-19.117	33.117
	ONDJ	JJAS	6.800	10.533	0.796	-19.317	32.917
		FMAM	13.800	10.533	0.402	-12.317	39.917
Iron(Fe)	JJAS	ONDJ	0.043	0.101	0.905	-0.207	0.293
		FMAM	-0.050	0.101	0.874	-0.300	0.200
	ONDJ	JJAS	-0.043	0.101	0.905	-0.293	0.207
		FMAM	-0.093	0.101	0.630	-0.343	0.157
Manganese(Mn)	JJAS	ONDJ	0.023	0.139	0.984	-0.320	0.367
		FMAM	-0.093	0.139	0.782	-0.437	0.251
	ONDJ	JJAS	-0.023	0.139	0.984	-0.367	0.320
		FMAM	-0.116	0.139	0.682	-0.460	0.227
log10No3	JJAS	ONDJ	-0.236	0.168	0.353	-0.652	0.180

		FMAM	-0.287	0.168	0.221	-0.703	0.130
	ONDJ	JJAS	0.236	0.168	0.353	-0.180	0.652
		FMAM	-0.051	0.168	0.951	-0.467	0.366
log10So4	JJAS	ONDJ	0.127	0.215	0.826	-0.408	0.662
		FMAM	0.323	0.228	0.346	-0.244	0.891
	ONDJ	JJAS	-0.127	0.215	0.826	-0.662	0.408
		FMAM	0.196	0.228	0.669	-0.371	0.764

4. VULNERABILITY ASSESSMENT SUPPLEMENTARY MATERIALS

4.1. Land use characteristics and runoff coefficient

Land use characteristics refer to the composition and distribution of different types of land cover within a given area. The runoff coefficient quantifies the proportion of rainfall that becomes surface runoff and is influenced by land use types such as impervious surfaces or vegetation cover. Understanding land use characteristics helps determine the recharge ratio, which is crucial for assessing hydrological processes and managing water resources effectively. The proportion of the recharge ratio is described in the following table.

S/N	Land use characteristics	Recharge Ratio
1	Built area	0.20
2	Forest	0.73
3	Open field/lawn	0.75
4	Agricultural field fields with clay	0.60
5	Agricultural field fields with Sand	0.70

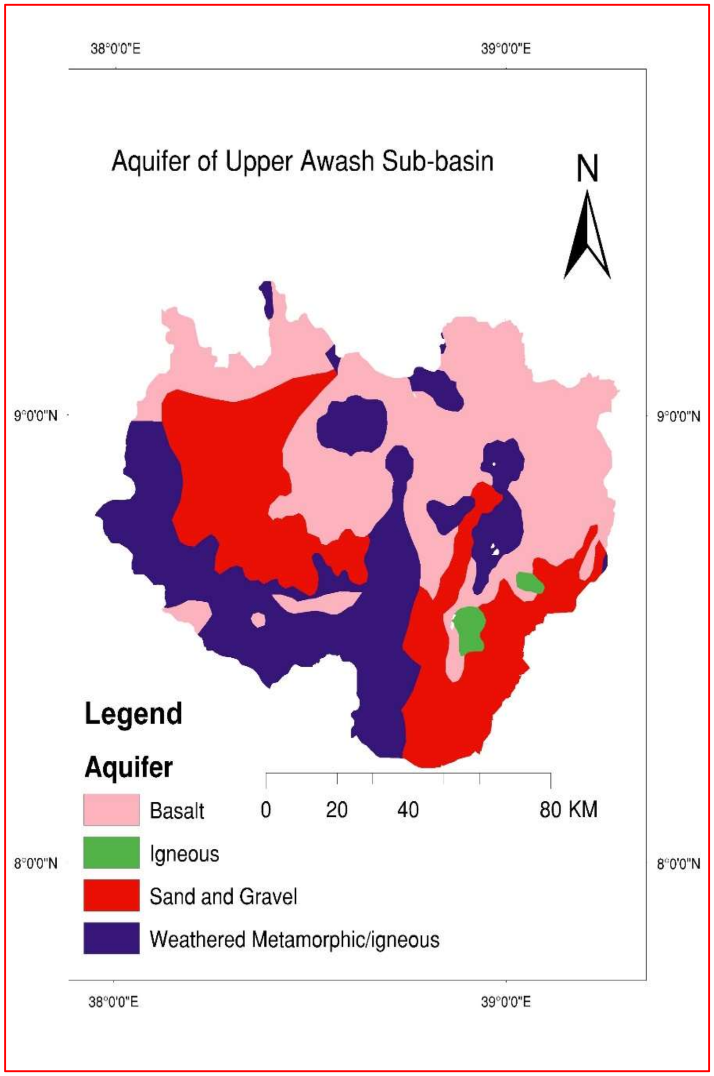
4.2. DRASTIC and land use index ratings and weight values for each parameter.

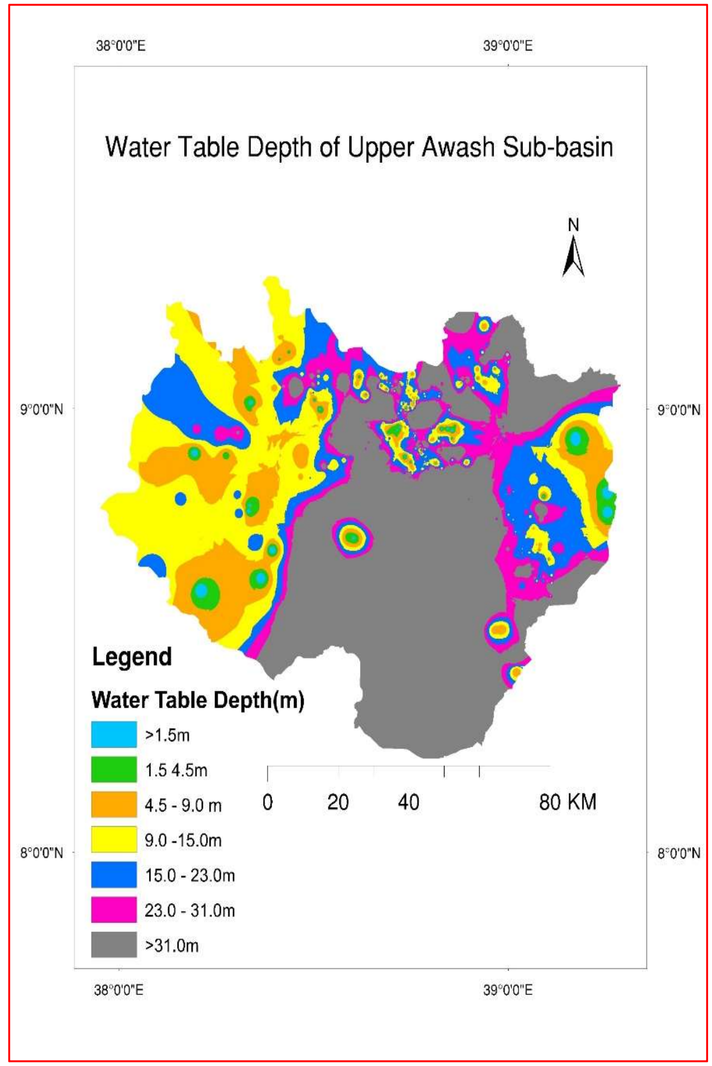
DRASTIC is a widely used method for assessing groundwater vulnerability that assigns rating and weight values to parameters such as depth to the water table, recharge, aquifer media, soil media, topography, impact of the vadose zone, and hydraulic conductivity. These values are based on the parameter's influence on the groundwater contamination potential. Similarly, land use index ratings assign values to different land uses based on their potential to contribute to groundwater pollution, with higher ratings indicating higher pollution potential. Both methods help prioritize areas for groundwater protection and management strategies.

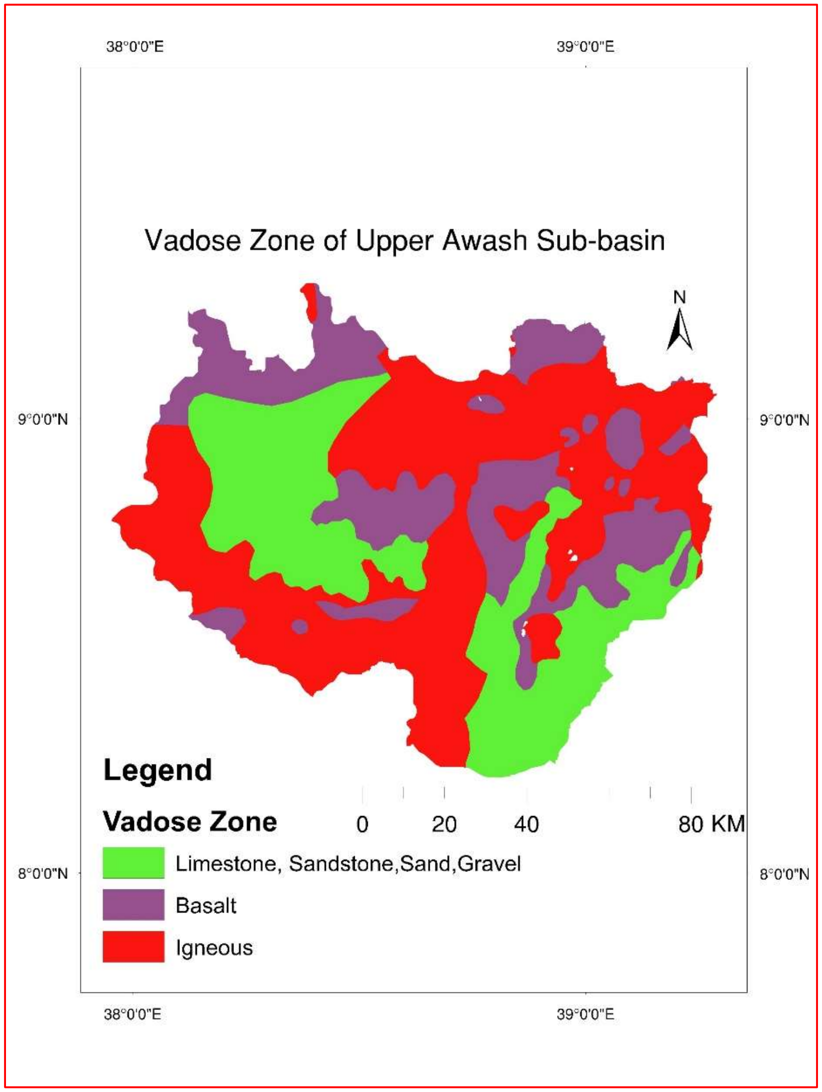
Rating	D(m), W= 5	R (mm/y), W= 4	A, W=3	S, W=2	T(%), W=1	I, W=5	C, (GPD/ft2) W= 3
10	0.0 -1.5		Karst Limestone	Thin or absent, gravel	0-2	Karst Limestone	>2000
09	1.5 - 4.5	>250	Basalt	Sandstone & volcanic	2-6	Basalt	
08		180-250	Sand and Gravel	Peat		Sand and Gravel	1000-2000
07	4.5 - 9		Massive Sandstone & limestone	Shrinking/aggregate clay/alluvium		Gravel, sand	

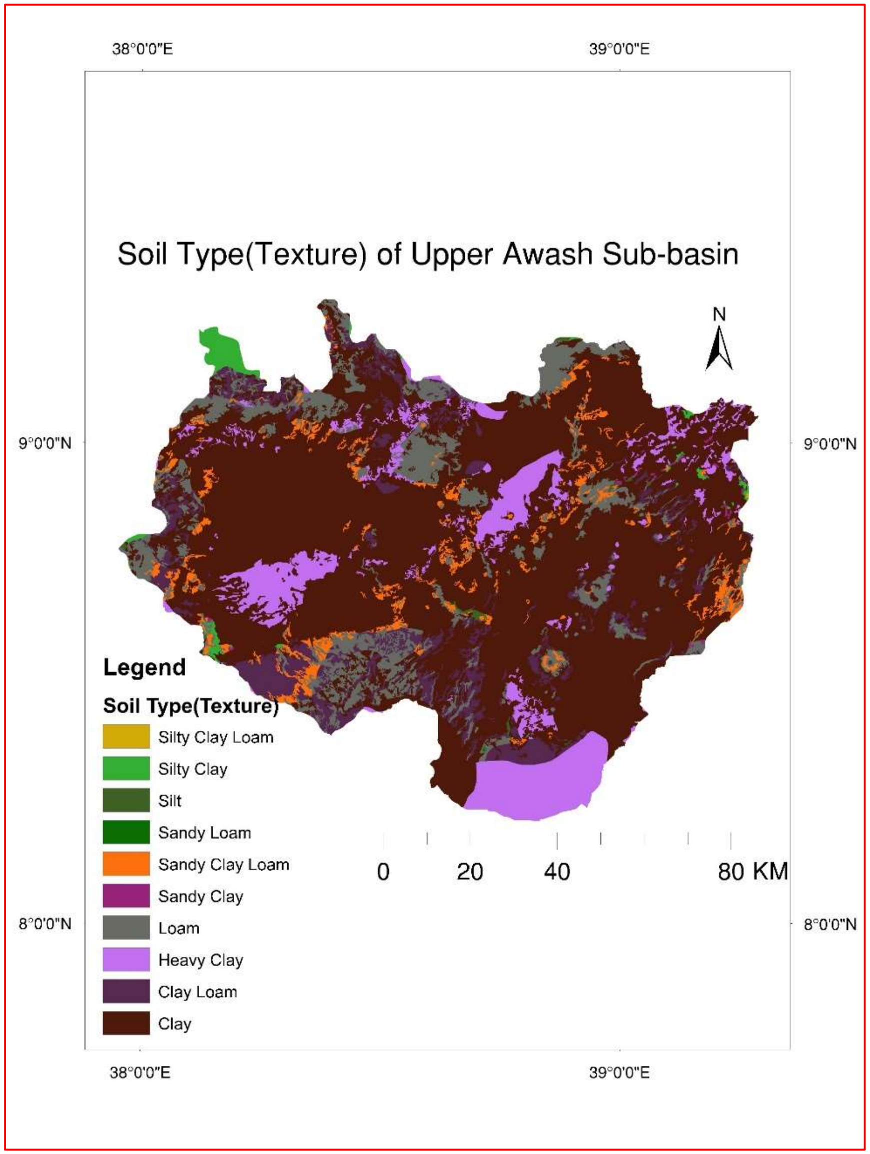
Rating	D(m), W= 5	R (mm/y), W= 4	A, W=3	S, W=2	T(%), W=1	I, W=5	C, (GPD/ft2) W= 3
06		100-180	Bedded sandstone & lime stone	Sandy loam, schist, sand, karst volcanic		Limestone, Sandstone, Sand and Gravel with significance Silt & clay	700-1000
05	9 -15		Glacial	loam	6-12		
04			Weathered Metamorphic/igneous	Silt loam		Metamorphic/ igneous	300-700
03	15 - 23	50-100	Metamorphic/ Igneous	Clay loam	12-18	Shale	
02	23 - 31		Massive Shale				100-300
01	>31	0.0-50		Nonshrink & Nonaggregated clay	>18	Silt/Clay	1-100

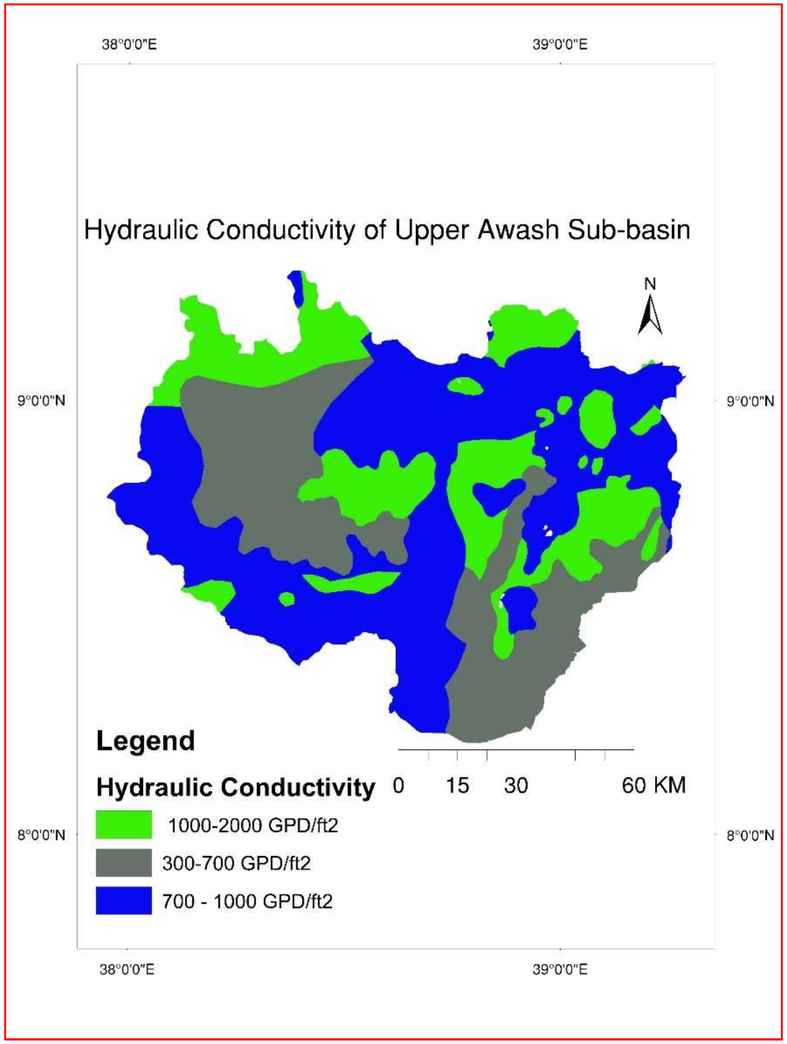
4.3. Analyzed parameters of the DRASTIC model

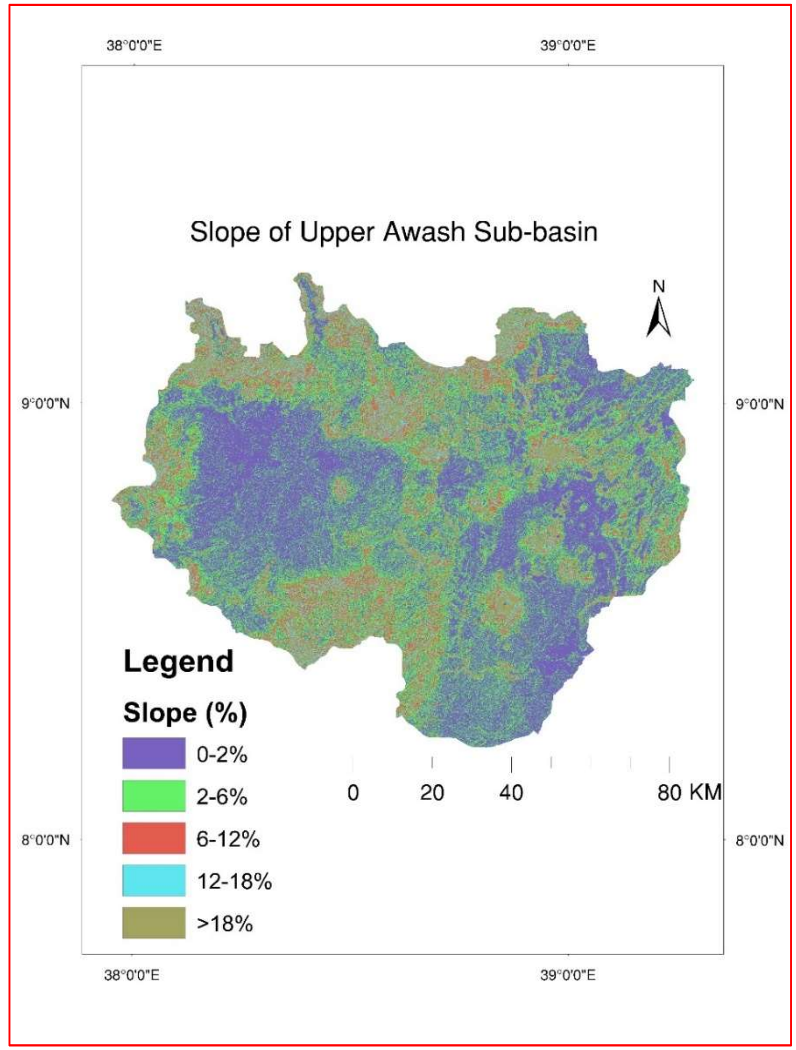


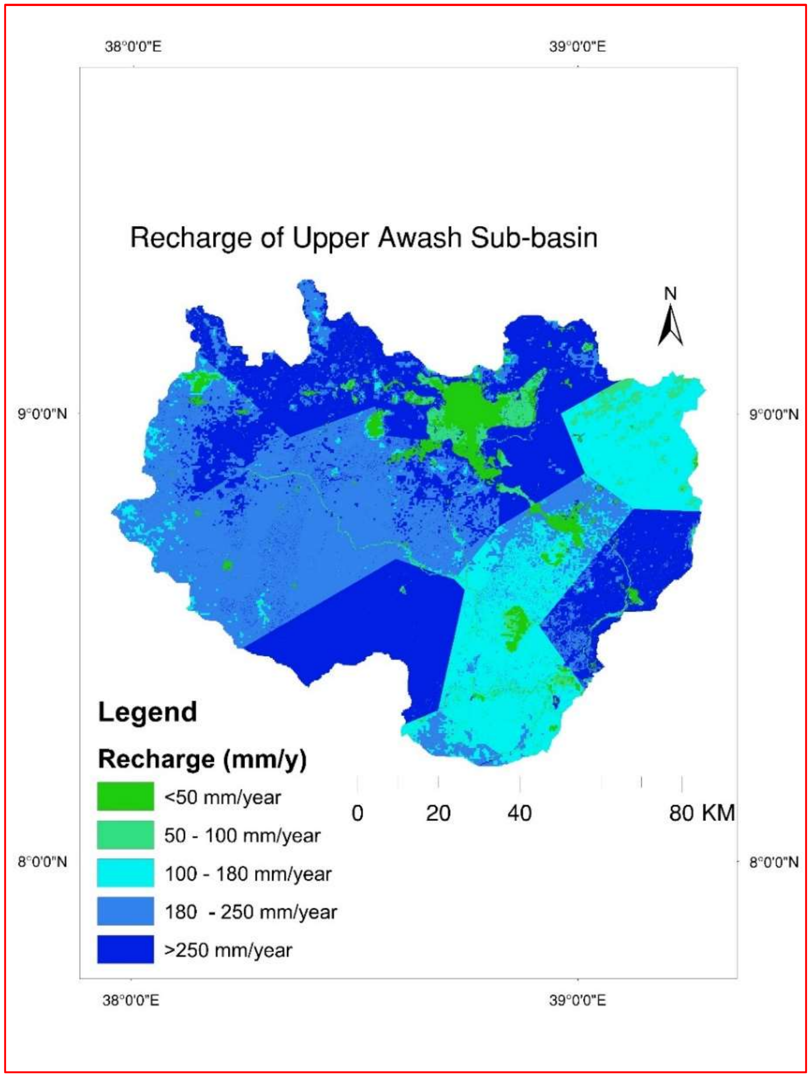



38°0'0"E
39°0'0"E
9°0'0"N
8°0'0"N
Vadose Zone of Upper Awash Sub-basin
N
0
20
40
80 KM
Legend
Vadose Zone
Limestone, Sandstone,Sand,Gravel
Basalt
Igneous


38°0'0"E
39°0'0"E
9°0'0"N
8°0'0"N
Soil Type(Texture) of Upper Awash Sub-basin
N
Legend
Soil Type(Texture)
Silty Clay Loam
Silty Clay
Silt
Sandy Loam
Sandy Clay Loam
Sandy Clay
Loam
Heavy Clay
Clay Loam
Clay
0
20
40
80 KM


38°0'0"E
39°0'0"E
Hydraulic Conductivity of Upper Awash Sub-basin
N
9°0'0"N
9°0'0"N
Legend
Hydraulic Conductivity
0 15 30 60 KM
1000-2000 GPD/ft2
300-700 GPD/ft2
700 - 1000 GPD/ft2
8°0'0"N
8°0'0"N
38°0'0"E
39°0'0"E


38°0'0"E
39°0'0"E
Slope of Upper Awash Sub-basin
N
9°0'0"N
9°0'0"N
Legend
Slope (%)
0-2%
2-6%
6-12%
12-18%
>18%
0 20 40 80 KM
8°0'0"N
8°0'0"N
38°0'0"E
39°0'0"E


38°0'0"E
39°0'0"E
Recharge of Upper Awash Sub-basin
N
9°0'0"N
9°0'0"N
Legend
Recharge (mm/y)
<50 mm/year
50 - 100 mm/year
100 - 180 mm/year
180 - 250 mm/year
>250 mm/year
0 20 40 80 KM
8°0'0"N
8°0'0"N
38°0'0"E
39°0'0"E

5. UNSTRUCTURED QUESTIONNAIRE

Unstructured Questions for Technical Expert Discussion (FGD) for Vulnerability Assessment and Protection Zone Delineation for Water Supply Schemes in the Upper Awash Subbasin, Ethiopia, Sub-Saharan Africa

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I. Introduction:

Welcome to the Focus Group Discussion (FGD) on water safety planning and source protection. This discussion aims to gather insights and perspectives from participants regarding ongoing activities, challenges, and future directions in implementing water safety planning and source protection measures. Your valuable input will help in enhancing understanding and guiding effective strategies for ensuring safe and sustainable water supply systems.

Consent to Start FGD: Before we proceeded with the discussion, I would like to seek your consent to participate in this FGD. Your participation is voluntary, and you are free to withdraw at any time without providing a reason. Please note that the information shared during this discussion will be used for research purposes only and will be kept confidential. By continuing with the FGD, you are indicating your consent to participate. If you have any questions or concerns, feel free to raise them now. Otherwise, let us begin the discussion.

II. General Information

- Sector: ______________________
- Date_____________________________
- Names of Participants:

S/N	Name	Responsibility	Remark
1			
2			
3			
4			
5			

III. Questions

1. Does the Ministry of Water and Energy (MOWE) have a National Water Supply and Sanitation Program Technical Working Group (N-WSP-TWG)? If so, please identify the members. a) Water supply system design, operation, and maintenance. b) Health and environmental health, including regulation of standards. c) Environment and meteorology, focusing on vulnerability and adaptation assessments related to climate change. d) Hydrology and climatology. e) Agriculture and natural resource/watershed management. f) Other (please specify).
2. Is GIS technology utilized at the national level for source protection in the implementation of water safety plans (WSPs), source protection, and delineation of vulnerable areas?
3. What are the main activities currently ongoing to implement the Community-Managed Rural Water Supply Program (CR-WSP)?
   a) Capacity building
   b) Development of documents such as guidelines, standard operating procedures (SOPs), and training materials
   c) Conducting risk and vulnerability assessments
   d) Regular supportive supervision, providing feedback on reports, and conducting review meetings with regional Technical Working Groups (TWG) on WSP monitoring
   e) Identifying issues for research and providing technical guidance; f) Mobilizing resources and coordinating the scale-up of WSP implementation nationwide
   f) Facilitating the dissemination of monitoring results to national stakeholders
4. What were the major activities conducted for water safety planning (WSP), source protection, zoning, and buffering at the national level?
5. What are the major challenges faced in implementing WSP and source protection initiatives at the national level?

Acknowledgments:

We would like to extend our sincere appreciation to all the participants who took the time to join us for this Focus Group Discussion (FGD) on water safety planning and source protection. Your valuable insights and contributions are crucial in shaping our understanding of the challenges and opportunities in this field.

Thank you for your participation and active engagement throughout the discussion. Your input will greatly inform and guide our efforts toward ensuring safe and sustainable water supply systems.

Promise to Disseminate Findings:

We want to assure all participants that the insights and outcomes from this Focus Group discussion will be diligently documented and analyzed. Furthermore, we are committed to widely disseminating the findings to all stakeholders involved in water safety planning and source protection initiatives. Our goal is to ensure that the valuable insights shared during this discussion contribute to informed decision-making processes and facilitate the implementation of effective strategies to enhance water quality and safety.

Thank you once again for your invaluable contributions, and we look forward to sharing the outcomes with you and the broader community.