GEOSPATIAL AND PRINCIPAL COMPONENT ANALYSIS OF GROUNDWATER QUALITY IN EKOSODIN COMMUNITY.

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A PROJECT SUBMITTED IN PARTIAL FULFILMENT OF THE REQUIREMENTS FOR THE AWARD OF BACHELOR OF ENGINEERING (B.ENG) DEGREE.

IN

THE DEPARTMENT OF CIVIL ENGINEERING,

FACULTY OF ENGINEERING,

UNIVERSITY OF BENIN, BENIN CITY, NIGERIA

NOVEMBER, 2025

PLAGIARISM

This work **GEOSPATIAL AND PRINCIPAL COMPONENT ANALYSIS OF GROUNDWATER QUALITY IN EKOSODIN COMMUNITY** by OJO, Marvellous Simsi with matriculation number ENG2006199 of the Department of Civil Engineering, Faculty of Engineering, University of Benin City, Edo State, Nigeria, has PASSED the PLAGIARISM TEST.

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DEDICATION

This project is dedicated to God Almighty, who has provided me with the knowledge and wisdom I need to excel in every aspect of my academic journey and has graciously supported my life.

ACKNOWLEDGEMENT

I have the utmost gratitude to God Almighty for His constant direction and assistance during my research project and academic career. I would especially want to thank Engr. Dr. I. R Ilaboya , my project supervisor, whose careful proofreading, wise counsel, and professional direction greatly improved my work.

I also want to thank the staff of the Department of Civil Engineering for their significant efforts, as they have always shown a remarkable commitment to teaching and promoting excellence. Specifically, I thank the Head of Civil Engineering Department Engr. Prof. (Mrs.) N.I. Ihimekpen, My Project Coordinator; Engr. E. Oria-Usifo and all my lecturers; Engr. Prof. O. U. Orie, Engr. Prof. O.C. Izinyon, , Engr. Prof. H.A.P. Audu, Engr. Prof. J.O. Okovido, Engr. Prof. S.D. Iyeke, Engr. Prof R.I. Umasabor, Engr. Dr, R.O. Ogirigbo, Engr. Dr. (Mrs) N. Kayode-Ojo, Engr. Dr. P. N. Ogbiefun Engr. Dr. (Mrs.) L.O. Bobor, Engr. Dr. A. Agbonaye, Engr. Dr. (Mrs.) A. Rawlings, Engr. Dr. R. Ilaboya, Engr. Dr U. Ukeme, Engr. Dr. O. Oriakhi, Engr. Dr. B. Omosefe, Engr. C. Okolie, Engr. O. Osasu, Engr. N. Oghoyafedo, Engr. (Mrs.) E. Ambrose-Agabi, Engr. E. Musa, Engr. Dr. I. Iziengbe, Engr. U. Ogbonna, Engr. (Mrs.) G.E. Evbaru, Engr J.O. Odemerho and the laboratory staff.

I extend my heartfelt gratitude to my parents, Mr and Mrs. OJO, for their parayers, parental support and love that they have shown towards me , special gratitudes also goes to Alhaji Kamilu bello, Nuhu Omokide for their financial support throughout this journey. Finally, my appreciations goes to my ever loving family and friends in the likes of Mrs.Comfort Aiyedun, Felix Ozozoma Promise, Ojo Job, Edson, Akese and others for their support and love

ABSTRACT

This study assessed the quality of groundwater in Ekosodin community, Edo State, Nigeria, using geospatial techniques and Principal Component Analysis (PCA). The objectives were to analyze selected physicochemical parameters of groundwater, compare the results with World Health Organization (WHO) and Nigerian Industrial Standards (NIS), map the spatial distribution of groundwater quality, and identify the major factors influencing contamination. The study was necessitated by the increasing dependence on groundwater due to inadequate public water supply and the rising risk of contamination from anthropogenic activities.

Groundwater samples were collected from eight boreholes across the study area, and their geographic coordinates were recorded using a handheld GPS device. Laboratory analyses were conducted on selected physicochemical parameters including major ions and heavy metals using standard APHA procedures. Geospatial analysis was carried out using GIS (Inverse Distance Weighting) to map the spatial distribution of groundwater quality parameters. Principal Component Analysis (PCA) was applied to reduce data dimensionality and identify the dominant factors influencing groundwater quality.

The results revealed significant variation in groundwater quality across the study area. The Water Quality Index (WQI) ranged from 30.31 to 227.36, classifying samples into excellent, good, poor, and very poor categories. Samples 6 and 7 recorded excellent quality (30.54–41.84), while samples 2, 3, and 4 showed poor to very poor quality (136.47–227.36), indicating unsuitability for drinking without treatment. Principal Component Analysis (PCA) extracted four components accounting for 97.4% of the total variance, indicating that both geogenic processes and anthropogenic activities are the major factors influencing groundwater quality in the area. The study concluded that groundwater in Ekosodin is vulnerable to contamination and requires regular monitoring, improved waste management, and public awareness to ensure safe and sustainable use.

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CHAPTER ONE

INTRODUCTION

1.1 Background of Study

Groundwater is a vital natural resource and one of the most important sources of freshwater for human consumption, domestic use, irrigation, and industrial activities. Globally, it is estimated that groundwater accounts for nearly 30.1% of the world's freshwater resources and supports the livelihoods of billions of people, especially in regions with limited access to surface water (Famiglietti, 2020; Siebert et al., 2021). In Nigeria, groundwater is particularly important due to the irregularity and inadequacy of municipal water supplies in many urban and rural areas (Oluwasanya & Okoh, 2022).

Ekosodin community which is suitated near the University of Benin in Edo State, demonstrates this reliance on groundwater. The area is predominantly inhabited by students, academic and nonacademic staff, and the indigenous people of Ekosodin. Due to the absence of a centralized reliable water distribution network, residents primarily depend on hand-dug wells, underground concrete reservoirs and boreholes for their daily water requirements. These groundwater sources, while convenient and accessible, are increasingly vulnerable to pollution resulting from various human activities (Afolabi et al., 2020).

Rapid development and population growth in Ekosodin community have not been matched by adequate planning and infrastructure development. Improper waste disposal practices, including the indiscriminate dumping of solid waste and untreated wastewater, are not uncommon. Additionally, the widespread use of soak-away systems in close proximity to groundwater sources increases the risk of contamination, especially during the rainy season when leachates can infiltrate into the groundwater source(Nwankwo et al., 2024).

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Furthermore, agricultural practices which may sometimes involve the excessive application of fertilizers and pesticides may introduce phosphates, nitrates and other chemical residues into the groundwater (Akinbile et al., 2022; Ugbaja et al., 2023).

Traditional water quality assessments, which focus on measuring individual physical, chemical, and biological parameters, are often insufficient for identifying complex pollution sources or understanding spatial variability in contamination levels (Mustapha et al., 2021; Yidana et al., 2023). In such contexts, the integration of geospatial analysis and multivariate statistical techniques like Principal Component Analysis (PCA) becomes necessary. These method not only enhances the interpretation of water quality data but also reveal relationships between variables and geographical regions that may be missed by conventional methods (Zhang et al., 2022).

Geospatial techniques allow for the mapping and visualization of groundwater quality indicators across a geographic area, making it possible to identify pollution hotspots . On the other hand, by identifying main components, Principal Component Analysis decreases data complexity and highlights key trends. This can help distinguish between natural or geogenic and human sources of pollution and inform targeted intervention strategies (Khan et al., 2023).

Despite the increasing concern over water quality in Ekosodin, there is a lack of detailed, scientifically-grounded studies that combine both spatial and statistical techniques to evaluate groundwater quality comprehensively. This study, therefore, seeks to fill this gap by employing geospatial tools and Principal Component Analysis to assess the current state of groundwater in Ekosodin.

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This study is both timely and essential, playing a crucial role in safeguarding public health, promoting environmental sustainability, and guiding effective policy development. Thus contributing to the existing body of knowledge on groundwater quality assessment in peri-urban Nigerian communities and provide a scientific basis for water resource planning, pollution control, and community education in Ekosodin and similar environments.

1.2 Statement of the problem

Access to clean and safe drinking water is a critical component of public health. In many developing countries, including Nigeria, the majority of urban and peri-urban populations rely heavily on groundwater sources such as boreholes and hand-dug wells due to the inadequate coverage and reliability of municipal water distribution systems (Oluwasanya & Okoh, 2022). The Ekosodin community is one such area where residents depend almost entirely on groundwater for domestic, commercial, and small-scale agricultural use.

Over the past decade, Ekosodin has experienced rapid population growth driven largely by student migration. This expansion has occurred without corresponding improvements in sanitation, waste management, and urban infrastructure. As a result, the community faces increasing environmental and public health challenges. Solid waste is often dumped indiscriminately, septic tanks in some instances are sited too close to water sources, and there is little to no limited regulation of groundwater abstraction and protection (Efe & Ejaede, 2021; Nwankwo et al., 2024).

These conditions raise serious concerns about the quality of groundwater in Ekosodin, particularly the risk of contamination by pathogens and chemical substances. Despite these concerns, routine and comprehensive monitoring of groundwater quality is lacking. Most residents consume untreated water directly from wells and boreholes, unaware of its quality

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(Olanrewaju et al., 2021).Furthermore, there is a lack of spatially-explicit data that could guide targeted interventions. Without geospatial mapping, it is difficult to identify which parts of the community are more vulnerable to groundwater pollution. Similarly, without statistical tools like Principal Component Analysis (PCA), it is nearly impossible to distinguish between pollution arising from natural geologic sources and that caused by human activities such as waste disposal or agricultural runoff.

1.3 Aim and Objectives of the study

The study assessed the quality of groundwater in the Ekosodin community using geospatial techniques and principal component analysis (PCA).The objectives include:

1. Collection and analysis of groundwater samples from selected boreholes in different parts of Ekosodin community, focusing on key physical, chemical and biological water quality parameters.
2. Comparism of measured groundwater quality parameters with international drinking water standards.
3. Application of Geospatial Information System (GIS) techniques to map the spatial distribution of groundwater quality indicators and identify pollution hotspots within the study area.
4. Perform Principal Component Analysis (PCA) on the water quality data to reduce dimensionality and identify the key components contributing to groundwater contamination.

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1.4 Scope of Study

This study focuses on assessing the quality of groundwater in Ekosodin community, located in Ovia North- East LGA in Edo State, Nigeria. The research is limited in scope to the following dimensions:

1. The study area was confined to the Ekosodin community and its immediate surroundings. Sampling points were strategically selected to ensure spatial coverage across different parts of the community, including densely populated residential zones, areas close to waste disposal sites, and locations near agricultural activity.
2. Only groundwater sources from borehole was included in this study. Surface water bodies such as rivers or streams were excluded from this research. The focus was on sources used by residents for domestic and drinking purposes.
3. The water quality assessment included a selection of key physicochemical and biological parameters, which included pH,Total Dissolved Solids (TDS) ,Nitrate (NO_3^-) ,Chloride (Cl^-),Sulfate (SO_4^{2-}), Iron(Fe) ,Lead(Pb), Dissolved Oxygen, Potassium ,Turbidity.
4. The study applied descriptive statistical analysis to summarize water quality data, geospatial analysis using GIS software ArcGIS to map the spatial distribution of groundwater quality indicators and Principal Component Analysis (PCA) using Jamovi to reduce dataset complexity and identify major sources of contamination.

1.5 Justification of study

Groundwater remains the primary source of potable water for the majority of residents in Ekosodin community. The increasing dependence on groundwater has not been accompanied by adequate monitoring, regulation, or awareness regarding its quality. This

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presents serious concerns for public health, particularly in respect to the rapid urbanization and environmental degradation taking place in Ekosodin.

Several compelling reasons justify the need for this study:

1) By identifying the level and distribution of contaminants in groundwater, this study will provide critical data needed to protect the health of residents of Ekosodin.
2) This research fills a crucial knowledge gap by using Geospatial Information Systems (GIS) and Principal Component Analysis (PCA) to not only assess water quality, but also to spatially visualize pollution and identify its sources.
3) This research will offer actionable insights for policymakers and community leaders to develop effective strategies for improving water quality and safeguarding public health.
4) This study provides a foundation for community-level action and policy development to protect groundwater for current and future generations.
5) By sharing the results of this research with the local population, the study can help raise awareness about water safety and encourage behavioral changes—such as treating drinking water, improving waste disposal practices, and maintaining wells—that will reduce contamination risks.

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CHAPTER TWO

LITERATURE REVIEW

2.1. Introduction

Groundwater is one of the most vital natural resources on Earth, constituting a major source of freshwater supply for various uses including domestic consumption, agriculture, industry, and ecosystem support (Taylor et al., 2020). Globally, it is estimated that over two billion people rely on groundwater for their daily water needs, particularly in areas where surface water is scarce or unreliable (UNESCO, 2022). Despite its significance, groundwater resources are increasingly under threat from overexploitation, contamination, and climate-induced variability (Zhou et al., 2021; Gupta & Singh, 2023), making the need for thorough and up-to-date groundwater analysis more urgent than ever (Adeyemi et al., 2024). Groundwater quality, in particular, is influenced by a combination of natural factors such as geological formations and soil characteristics, as well as anthropogenic activities including agricultural runoff, industrial discharges, and improper waste disposal. Understanding these dynamics is essential for ensuring sustainable groundwater management and protecting public health.

This chapter presents a comprehensive review of existing literature relevant to groundwater analysis, with particular focus on quality assessment and analytical techniques. It begins by exploring the basic concepts of groundwater occurrence and hydrogeological systems, followed by a discussion of the key parameters used in assessing groundwater quality.

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2.2. Concept of Groundwater

Groundwater is the water that exists in the saturated zone beneath the Earth's surface, where all the pores and fractures in soil and rock are completely filled with water. This zone can vary in thickness and depth depending on the geology and hydrologic conditions of the area. Groundwater accumulates in aquifers—geological formations that can store, transmit, and yield water to wells and springs.

Common forms of groundwater include unconfined groundwater (water table aquifer), confined groundwater (artesian aquifer), perched groundwater, fossil groundwater (Paleowater) and juvenile or magmatic water.

2.2.1 importance of Groundwater

Groundwater is a vital resource essential for sustaining human life, supporting economic activities, and maintaining ecological stability. Its importance includes:

I. **Domestic Use:** Around the world, groundwater supplies close to half of the population with drinking water, making it a vital resource for billions (WWAP, 2022). In Nigeria, nearly 60% of people depend on groundwater as their main source of drinking water, with rural communities showing even greater reliance. Beyond consumption, it is also utilized for various household tasks such as cleaning and washing.

II. **Agriculture purpose:** Groundwater plays a crucial role in farming, by supporting both crop cultivation and animal husbandry, groundwater significantly contributes to food supply stability and helps sustain rural economies (FAO, 2022; Olanrewaju et al., 2023).

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III. **Industrial use:** Industries utilize groundwater for manufacturing, cooling, and cleaning.Its availability supports economic activities and contributes to employment and income generation.

IV. **Commercial use:** Hotels, restaurants, and offices widely use groundwater in form of boreholes for cleaning, cooking, and other routine operations. Many small businesses, including bakeries, laundries, and salons, depend on it to meet their daily water requirements (Nwachukwu et al., 2021).

V. **Ecosystem support:** Groundwater is vital for the stability and function of natural environments. It contributes to the recharge of surface water bodies such as wetlands, rivers, and lakes, which are home to a wide range of plant and animal life.

2.2.2. Characteristics of Groundwater

Groundwater can be majorly classified into the following categories.

I. **Physical Characteristics:** The physical properties of groundwater involve temperature, turbidity, resulting from fine suspended materials like clay; and taste and odor**,** normally absent but can indicate pollution when detected (Shrestha & Kazama, 2020; WHO, 2022).

II. **Chemical Characteristics:** These properties include it's pH level which shows the degree of acidity or alkalinity of the groundwater; Total Dissolved Solid (TDS) which indicates the total concentration of dissolved substances in the water. Hardness can also occur due to the presence of significant amount of either calcium or magnesium ion in the water.

III. **Biological Characteristics:** Biological characteristics of groundwater involve microbial contaminants like bacteria (e.g., E. coli), which suggest sewage pollution.

Viruses and protozoa are generally filtered out but can enter through compromised wells, while algae and fungi, though uncommon, may be present near recharge zones (Lutterodt et al., 2020; UNESCO, 2022).

2.2.3. Groundwater Occurrence

Groundwater is located beneath the Earth's surface, occupying spaces within fractures, pores, and cavities of rocks, sediments, and soils. Its availability is largely influenced by the region's geological makeup, rock characteristics, and prevailing climatic conditions (MacDonald et al., 2021). Following precipitation, a portion of the water seeps into the ground, travels through the unsaturated zone, and eventually collects in the saturated zone, where all available spaces are completely filled with water (Custodio, 2020; UNESCO, 2022).

2.2.4. Factor Affecting the Occurrence of Groundwater

i. **Climate**: Climatic conditions significantly affect how much water seeps into the ground to become groundwater. Regions experiencing frequent and intense rainfall usually allow more water to penetrate the soil and reach aquifers. In contrast, hot and dry environments with high levels of evaporation and transpiration tend to lose much of the available moisture to the atmosphere, limiting the amount that infiltrates into the subsurface layers (FAO, 2022; Olanrewaju et al., 2023).

ii. **Topography:** The shape and elevation of the land influence both the direction and extent of groundwater flow. Higher terrains, such as ridges and plateaus, usually serve as zones where groundwater recharge occurs, as water infiltrates more easily.

In contrast, lower-lying areas, like river valleys or basins, often become collection points where groundwater naturally emerges or accumulates.

iii. **Geology:** The underground composition of rocks and sediments determines how water behaves beneath the surface. Highly porous and permeable rocks, like sandstone or fractured limestone, allow water to pass through easily, forming productive aquifers. On the other hand, dense or fine-grained materials, such as clay or shale, restrict water flow and reduce storage potential.

iv. **Vegetation and Human Activity:** The type and density of vegetation directly influence water absorption into the soil. Thick plant cover can help water soak into the ground by slowing runoff and improving soil structure through root systems. Conversely, urban development, which introduces impermeable surfaces such as roads and rooftops, greatly limits natural infiltration. Agricultural practices also impact recharge and quality, particularly through irrigation methods, land clearing, and use of agrochemicals that may contaminate groundwater (WWAP, 2022; Lutterodt et al., 2020).

2.2.5 Groundwater Movement

Groundwater travels from zones of higher pressure or elevation (hydraulic head) toward zones of lower pressure, following what is known as the hydraulic gradient. This movement is usually gradual, commonly occurring at rates of just a few centimeters per day, and it adheres to the principles outlined in Darcy's Law (Zhou et al., 2021). Darcy law is expressed using Eq. (2.1)

$$Q = K.A.(dh/dl) \qquad (2.1)$$

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Where:

Q is the rate of groundwater flow (volume per time),

K is the hydraulic conductivity, indicating how easily water can pass through the material,

A represents the area through which water is flowing,

Dh/dl denotes the change in hydraulic head over a specific distance.

2.2.6. The Hydrologic Cycle and the Role of Groundwater

The hydrologic cycle, often referred to as the water cycle, describes the perpetual circulation of water between the Earth's surface and the atmosphere. This natural system comprises several interconnected processes—evaporation, condensation, precipitation, infiltration, runoff, and subsurface flow—which work collectively to maintain equilibrium among water bodies such as oceans, rivers, glaciers, soils, and the atmosphere (Zhang et al., 2021; Kumar & Singh, 2023).

Major Components of the Water Cycle

1. Evaporation: The sun's energy drives the conversion of surface water into vapor, primarily from large water bodies and moist soils.
2. Condensation: Rising water vapor cools and transitions into tiny liquid droplets, forming clouds.
3. Precipitation: When condensation intensifies, water falls to the ground in various forms such as rain, snow, or hail.

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4. Infiltration: A portion of the precipitation infiltrates the soil, continuing downward to recharge aquifers.
5. Surface Runoff: Water that doesn't infiltrate flows overland into nearby streams, rivers, or lakes.
6. Subsurface Flow: Water that infiltrates continues to move laterally or vertically underground, ultimately discharging to surface water or re-entering the atmosphere via plant transpiration or evaporation (Okechukwu et al., 2022).

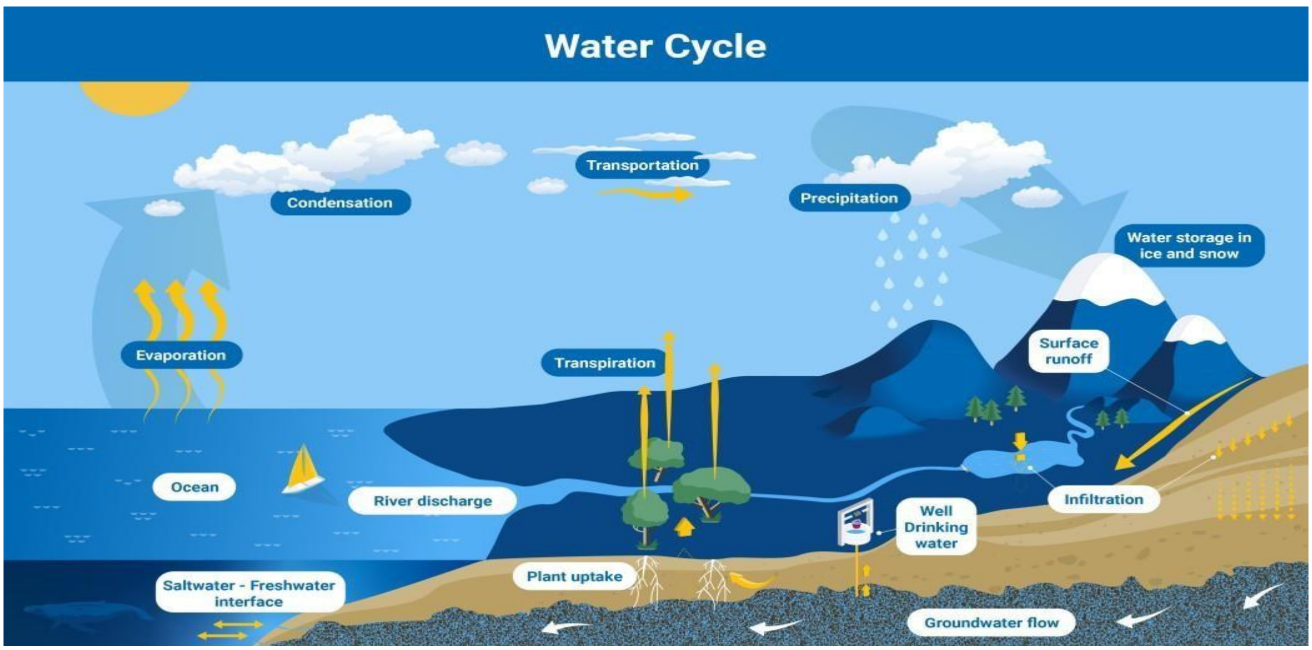

Fig 2.1 Hydrologic (water) cycle (IAEA, 2023)

Groundwater's Contribution to the Hydrologic Cycle

Groundwater serves as a critical storage and flow component within the hydrologic system. Depending on subsurface conditions, groundwater may be stored for short durations or for centuries, thereby regulating the availability of water over time (Adeyemi et al., 2021).

Key roles of groundwater include:

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1) Sustaining Base flow: During dry spells, groundwater maintains stream and river flow by discharging slowly into surface systems, a phenomenon vital for the health of aquatic ecosystems (Gupta & Ahmed, 2020).
2) Water Resource Supply: Groundwater is a primary source for domestic, industrial, and agricultural uses, especially in areas with limited surface water access (Ibrahim & Musa, 2023).
3) Ecosystem Support: Many wetlands, springs, and riparian habitats depend on consistent groundwater discharge, which contributes to ecological balance and species diversity (Nwachukwu et al., 2022).
4) Flood and Drought Mitigation: By storing excess rainfall and releasing it slowly, groundwater helps buffer hydrological extremes, reducing the impact of floods and sustaining water during drought periods (Tella & Olorunfemi, 2024).

2.2.7.Aquifer

An aquifer is a geologic formation, or a group of formations, which contains water and permits significant amount of water to move through it under ordinary field conditions. Aquifers are generally extensive and may be overlain or underlain by a confining bed. A confining bed may be an aquiclude, aquifuge or aquitard.

2.2.8.Types of Aquifer

Aquifer can be basically classified into;

i. **Unconfined Aquifer:** An unconfined aquifer, also known as a water table aquifer, is the most common type and occurs when the water table is open to the atmosphere through permeable material. It has no overlying confining layer (aquitard), allowing direct recharge from precipitation and surface water infiltration.

ii. **Confined Aquifer:** A confined aquifer is bounded above and/or below by impermeable or semi-permeable layers known as aquitards or aquicludes. Water in a confined aquifer is under pressure, often resulting in artesian conditions where water rises above the top of the aquifer when tapped by a well.

iii. **Leaky Aquifer:** A semi-confined aquifer is partially bounded by layers of lower permeability that allow some vertical leakage of water. These aquifers are intermediate between confined and unconfined systems.

iv. **Perched Aquifer:** A perched aquifer forms when a localized impermeable layer (e.g., clay or shale) lies above the main water table and prevents the downward movement of infiltrating water, resulting in a small, perched zone of saturation.

v. **Artesian Aquifer:** This is a special case of a confined aquifer where water is under enough pressure that, when tapped by a well, it flows upward without the need for pumping.

2.2.9. Challenges of Groundwater Management in Developing Area

Groundwater management in developing regions faces numerous obstacles that compromise both the quality and sustainability of this critical resource. These challenges include:

1. Rapid population growth increases groundwater use and causes depletion of aquifers.
2. Improper waste disposal pollutes groundwater and reduces water quality.
3. Many regions lack proper monitoring systems for groundwater levels and quality.
4. Weak governance allows uncontrolled groundwater extraction and poor management.
5. Low public awareness leads to unsustainable groundwater use and contamination.
6. Climate change reduces groundwater recharge and increases water scarcity.

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7. Limited technology and funding hinder effective groundwater management.

2.3.1 Factors Influencing Groundwater Quality

The quality of groundwater is affected by both natural and human activities (anthropogenic).

2.3.2. Natural Factors

Natural Factors are environmental or geological elements that influence groundwater quality and availability without human intervention. These factors originate from the Earth's natural phenomenon. They include:

i. Geological Formations
ii. Climate and Rainfall
iii. Soil Composition.
iv. Topography
v. Naturally Occurring Contaminants such as fluoride, iron, and arsenic can enter groundwater naturally from geological formations, presenting health concerns even in areas with minimal human activity (WHO, 2021; Hussain et al., 2023).

2.3.3. Anthropogenic Factors

Athropogenic factors are human-induced activities or influences that affect the quality and quantity of groundwater. These factor are:

i. Agricultural Practices
ii. Industrial Waste Disposal
iii. Improper Waste Management
iv. Sewage and Septic Systems
v. Urbanization

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vi. Over extraction

2.3.4 Parameters Measured In Groundwater Analysis

When determining the quality of groundwater, some parameters are required in order to classify it's quality, suitability for several activities. Some of these parameters include: Turbidity, Color, Taste, Odor, pH,Total Dissolved Solid (TDS), Electrical Conductivity, Chemical Oxygen Demand (COD), Biological Oxygen Demand (BOD), Fluoride, Iron, Major Ions (e.g. Calcium, Magnesium etc.), Total Coliform Bacteria .

2.3.5. Common Groundwater Contaminants

Groundwater quality can be compromised by various contaminants:

i. **Nitrates:** Often originating from agricultural fertilizers, septic systems, and animal waste, high nitrate levels in drinking water can lead to health issues such as methemoglobinemia in infants (WHO, 2017).

ii. **Heavy Metals:** Elements like lead, cadmium and chromium can enter groundwater through natural mineral deposits or industrial activities.

iii. **Microbial Pathogens:** Bacteria, viruses, and protozoa from sewage leaks or animal waste can contaminate groundwater, leading to diseases like cholerae and typhoid.

2.3.6.Sources of Groundwater Contaminants

i. Agricultural activities contribute significantly to groundwater pollution through the excessive use of fertilizers and pesticides, which leach into the soil and contaminate aquifers with nitrates, chemicals, and pathogens from animal waste (Kumarl., 2020).

ii. Poor sanitation infrastructure, including unsealed pit latrines and malfunctioning septic systems, contributes to groundwater contamination by allowing effluent rich

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in nutrients, pathogens, and organic substances to percolate into the shallow water table (Howard et al., 2003; Adeyemi et al., 2014).

iii. Industrial discharges, when improperly managed, can introduce toxic substances like heavy metals, solvents, and hydrocarbons into the soil, which eventually reach groundwater sources (Nickson et al., 2005).

iv. Natural geological sources may release elements such as fluoride, arsenic, or iron into groundwater through rock weathering and mineral dissolution, depending on the local geology (Nickson et al., 2005; Edmunds & Smedley, 2013).

2.3.7. Impact of Contaminated Groundwater

Contaminated groundwater presents significant risks to human health, ecological balance, and socio-economic development.

i. **Health-Related Concerns:** Groundwater pollution may introduce hazardous substances such as nitrates, pathogens, heavy metals, and organic toxins. Diseases such as cholera, typhoid, and diarrhea can occur. Cancer risks originating from chronic exposure to substances such as arsenic and benzene (WHO, 2017; Edmunds & Smedley, 2013).

ii. **Agricultural Consequences:** Using polluted groundwater for farming may negatively affect both crop production and soil health.This can impact fertility and structure (Oke et al., 2022).

iii. **Environmental Impact:** Ecosystems that depend on clean groundwater—such as wetlands and streams—may be disrupted by pollution. Contaminated groundwater can lead to reduction in the diversity of species in aquatic systems due to the

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presence of toxic pollutants. Nutrient loading which lead to algae blooms and in turn reduces the oxygen levels on water surfaces (Hassan et al., 2023).

2.4 Geospatial Technology in Groundwater Studies

Geospatial technology refers to a group of tools, techniques and technology used to gather, analyze, interpret and visualize spatial or geographic data. At its core, it's all about location and the relationships between different points on the Earth's surface. This technology enables us to create maps, analyze patterns, and make informed decisions based on the geographic context of the data (Brooke, 2024).

Through spatial interpolation techniques such as Inverse Distance Weighting (IDW) and kriging, GIS facilitates the generation of groundwater quality maps, highlighting the spatial variability of parameters such as pH, total dissolved solids (TDS), nitrate, fluoride, and heavy metals. This enables the classification of groundwater suitability for domestic, agricultural, and industrial use (Kumar et al., 2020; Oke et al., 2022).

2.4.1 Components of Geospatial Technology

The key components of geospatial technology are listed below:

i. **Global Positioning System:** is a computer-based system for capturing, analysing,interpreting, checking, and displaying data related to positions on the Earth's surface. In groundwater studies, GIS is extensively used to integrate diverse spatial datasets such as topography, soil characteristics, land use/land cover (LULC), rainfall, geology, and borehole data. This integration allows researchers to visualize patterns, perform spatial analyses, and make informed decisions regarding aquifer behavior and water resource management (Agarwal & Garg, 2020).

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ii. **Geographic Information System:** GIS is a computer-based system for capturing, storing, checking, and displaying data related to positions on the Earth's surface. In groundwater studies, GIS is extensively used to integrate diverse spatial datasets such as topography, soil characteristics, land use/land cover (LULC), rainfall, geology, and borehole data. This integration allows researchers to visualize patterns, perform spatial analyses, and make informed decisions regarding aquifer behavior and water resource management (Agarwal & Garg, 2020).

iii. **Remote Sensing:** This involves collecting data about the Earth's surface without direct physical contact. Remote sensing, on the other hand, involves the acquisition of information about an object or phenomenon without making physical contact, typically through satellites or aerial sensors. In the context of groundwater, remote sensing enables the monitoring of large and inaccessible areas, providing valuable information on surface conditions such as vegetation cover, land use changes, surface temperature, and moisture content. These indicators are indirectly linked to subsurface water dynamics, helping scientists estimate potential recharge areas and monitor seasonal changes (Hassan et al., 2023).

2.4.2. Role of Geospatial Technology in Hydrology and Water Management

Geospatial technology has played a very key role in the hydrological sector be in the following ways;

1) GIS helps identify pollution sources, estimate contamination levels, and track pollutant spread using spatial data such as land use and industrial discharge (Kumar et al., 2021; Al-Ansari et al., 2023).

2) GIS monitors rainfall, soil moisture, and reservoir levels to forecast droughts and improve water conservation and irrigation efficiency (Yuan et al., 2020; Chen et al., 2022).
3) GIS and remote sensing map flood-prone areas, simulate flood events, and create inundation maps for early warning and risk management (Teng et al., 2017; Muthusamy et al., 2024).
4) Remote sensing and satellite imagery monitor surface water bodies to support ecosystem protection and water resource management.
5) GIS maps watersheds and basins to assess water supply, flood potential, and sustainable land and water use (Rahmati et al., 2021; Adnan et al., 2023).
6) GIS and remote sensing identify groundwater potential zones by analyzing geological, climatic, and surface indicators (Jha et al., 2020; Sahoo et al., 2022; Adeyemi et al., 2024).

2.5. Statistical and Multivariate Techniques in Groundwater Quality Analysis

Assessing and managing groundwater quality typically involves handling extensive datasets comprising numerous variables, including physicochemical properties, major and trace ions, and various contaminants. Given the complexity and interdependence of these parameters, conventional statistical tools often fall short in revealing intricate relationships, underlying patterns, or concealed sources of pollution. To overcome these limitations, researchers employ multivariate statistical techniques, which provide a more holistic and nuanced understanding of the data (Kumar et al., 2020; Rezaei et al., 2023). These advanced methods are particularly effective in simplifying high-dimensional data, identifying correlations among variables, grouping sampling locations with similar water quality characteristics, and distinguishing between natural geogenic influences and anthropogenic (human-induced) pollution sources (Ghimire & Regmi, 2022; Alidadi et al., 2024). By uncovering hidden structures and dominant factors within groundwater datasets, multivariate analysis supports more informed decision-making for water resource monitoring, protection, and sustainable management.

2.5.1. Principal Component Analysis

Principal Component Analysis (PCA) is an advanced statistical technique used to simplify complex datasets by reducing the number of variables while maintaining most of the original information (Sharma et al., 2021) . It is especially useful when the dataset includes numerous variables that are highly correlated, such as chemical constituents and physical parameters in groundwater analysis. The main goal of PCA is to convert the original set of correlated variables into a new set of uncorrelated variables known as principal components (Gouda et al., 2023; Mishra et al., 2024).

2.5.2. Purpose of Principal Component Analysis in Groundwater Studies

Principal Component Analysis (PCA) is a vital analytical method used in evaluating and interpreting groundwater quality, especially when dealing with datasets that involve numerous interrelated variables. Its main function is to streamline the analytical process by reducing data complexity while uncovering important patterns and connections that are not easily identified through basic statistical techniques. The major purposes of PCA in groundwater studies include:

1. PCA helps condense complex groundwater datasets by transforming numerous correlated parameters—such as major ions, trace metals, and physicochemical

variables—into fewer independent components. This dimensionality reduction enhances interpretability while retaining most of the original data variance (Shrestha & Kazama, 2020; Li et al., 2023).

2. It enables the identification of major hydro geochemical processes affecting groundwater quality by evaluating variable loadings on each principal component. This makes it possible to distinguish natural geogenic processes, such as mineral dissolution or ion exchange, from anthropogenic activities like fertilizer use and industrial discharge (Rahman et al., 2021; Adeyemi et al., 2024).
3. PCA supports pollution source identification by grouping related variables that exhibit similar behavior, allowing the separation of human-induced contamination from natural sources. For instance, a principal component with high nitrate and phosphate loadings may signal agricultural runoff, while elevated sodium and chloride may indicate saltwater intrusion or wastewater influence (Kaur et al., 2022; Zhang et al., 2020).
4. It assists in uncovering spatial and temporal trends in groundwater chemistry by showing patterns across sampling locations and identifying seasonal or long-term shifts in water quality (Aghazadeh & Mogaddam, 2020; Mwangi et al., 2023).
5. PCA enhances the clarity of groundwater data by eliminating components with low explanatory power, thus reducing background noise and emphasizing the strongest variable relationships (Hossen et al., 2021; Ibrahim & Musa, 2022).
6. This technique is valuable for informed groundwater resource management, as it provides insights for prioritizing monitoring sites, designing effective pollution control measures, and developing predictive models that reflect the key factors influencing water quality (Chen et al., 2023; Olanrewaju et al., 2025).

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2.5.3 Application of Principal Component Analysis in Groundwater Studies

1. **Understanding Key Geochemical Mechanisms**

PCA is instrumental in identifying the natural geochemical processes that shape groundwater composition. These include silicate and carbonate weathering, ion exchange reactions, redox processes, and mineral dissolution. By examining how various chemical parameters contribute to the principal components, researchers gain insights into the dominant geochemical interactions occurring within an aquifer (Rahman et al., 2021; Aghazadeh & Mogaddam, 2020).

2. **Pollution Source Apportionment**

Through grouping variables with correlated patterns, PCA distinguishes between different contamination sources in groundwater.

3. **Detection of Spatial and Seasonal Variability**

PCA is used to analyze groundwater quality changes across different geographic regions and time periods. It helps researchers track how land use or climatic changes influence water chemistry, observe seasonal shifts and long-term trends, group similar water types or locations for targeted analysis (Mwangi et al., 2023; Chen et al., 2023).

4. **Guiding Groundwater Resource Management**

The outcomes from PCA serve as a foundation for planning and implementing groundwater protection measures. It assists in locating areas that need remediation or stricter controls, establishing monitoring priorities, informing policies and strategic decisions for sustainable water resource use (Olanrewaju et al., 2025; Adeyemi et al., 2024)

5. **Improving Efficiency of Monitoring Programs**

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PCA highlights the most impactful parameters in a dataset, allowing environmental professionals to eliminate redundant or low-importance variables. This not only reduces the cost of monitoring but also enhances data reliability and interpretation (Hossen et al., 2021)a

6. Advanced Multivariate Data Analysis

By simplifying the complexity of multi-parameter datasets, PCA reveals latent patterns and trends. It is frequently integrated with other multivariate tools such as cluster or discriminant analysis to better classify groundwater samples and water types (Li et al., 2023).

7. Groundwater Prediction and Risk Evaluation

PCA provides a statistical basis for building models that forecast groundwater quality under various environmental or anthropogenic pressures. It also contributes to assessing aquifer vulnerability and identifying areas at greater risk of contamination (Shrestha & Kazama, 2020).

2.6. Review Of Previous Related Studies

In a study conducted by **Tahir et al (2022)** on Principal Component Analysis (PCA)–Geographic Information System (GIS) Modeling for Groundwater and Associated Health Risks in Abbottabad, Pakistan. The authors employed Principal Component Analysis (PCA) and integrated Geographic Information System (GIS)-based statistical model to estimate the spatial distribution of exceedance levels of groundwater quality parameters and related health risks for two union councils (Mirpur and Jhangi) located in Abbottabad, Pakistan. A field survey was conducted, and samples were collected from 41 sites to analyze the groundwater quality parameters. The data collection includes the data for 15 water quality parameters. The Global Positioning System (GPS) Essentials application was used to obtain the geographical coordinates of sampling locations in the study area. After sampling, the

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laboratory analyses were performed to evaluate groundwater quality parameters. PCA was applied to the results, and the exceedance values were calculated by subtracting them from the World Health Organization (WHO) standard parameter values. The nine groundwater quality parameters such as Arsenic (As), Lead (Pb), Mercury (Hg), Cadmium (Cd), Iron (Fe), Dissolved Oxygen (DO), Electrical Conductivity (EC), Total Dissolved Solids (TDS), and Colony Forming Unit (CFU) exceeded the WHO threshold. The highly exceeded parameters, i.e., As, Pb, Hg, Cd, and CFU, were selected for GIS-based modeling. The Inverse Distance Weighting (IDW) technique was used to model the exceedance values. The PCA produced five Principal Components (PCs) with a cumulative variance of 76%. PC-1 might be the indicator of health risks related to CFU, Hg, and Cd. PC-2 could be the sign of natural pollution. PC-3 might be the indicator of health risks due to As. PC-4 and PC-5 might be indicators of natural processes. GIS modeling revealed that As, Pb, Cd, CFU, and Hg exceeded levels 3, 4, and 5 in both union councils. The study concluded that there could be greater risk for exposure to diseases such as cholera, typhoid, dysentery, hepatitis, giardiasis, cryptosporidiosis, and guinea worm infection.

In a study conducted by **Syeda et al (2022)** on Geospatial assessment of water quality using principal components analysis (PCA) and water quality index (WQI) in Basho Valley, Gilgit Baltistan (Northern Areas of Pakistan). A total of 23 water samples were collected and then analyzed to elucidate the current status of physico-chemical, metals, and microbial parameters. Principal component analysis (PCA) was applied. The study concludes that water quality is satisfactory in terms of physico-chemical characteristics; however, analysis of metals shows that the concentrations of copper (Cu) (0.40 ± 0.16 mg/L), lead (Pb)

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(0.24 ± 0.10 mg/L), zinc (Zn) (6.77 ± 27.1 mg/L), manganese (Mn) (0.19 ± 0.05), and molybdenum (Mo) (0.07 ± 0.02 mg/L) are exceeding the maximum permissible limit as set in the WHO guidelines for drinking water. Similarly, the results of the microbial analysis indicate that the water samples are heavily contaminated with fecal pollution (TCC, TFC, and TFS > 3 MPN/100 mL). On the basis of PCA, WQI, and IDW, the main sources of pollution are most likely to be concluded as the anthropogenic activities including incoming pollution load from upstream channels. A few underlying sources by natural process of weathering and erosion may also cause release of metals in surface and groundwater. This study recommends ensuring public health with regular monitoring and assessment of water resources in the valley.

Sabyasachi et al (2022), conducted a study on Groundwater quality assessment using geospatial and statistical approaches over Faridabad and Gurgaon districts of National Capital Region, India. The authors applied geospatial and statistical approach to this study. The groundwater quality parameters viz.,pH, electrical conductivity (EC), carbonate (CO_3^{2-}), bicarbonate (HCO_3^-), chloride (Cl^-), sulphate (SO_4^{2-}), nitrate (NO_3^-), fluoride (F^-), calcium (Ca^{2+}), magnesium (Mg^{2+}), sodium (Na^+), potassium (K^+), silica (SiO_2), and total hardness (TH) are obtained from 28 sites over the study area. The result of the WQI analysis revealed that 10 out of the 28 sites are unsuitable for drinking purposes. The results of PCA revealed the first principal component (PC1) to explain more than 95% of the total variance, thereby significantly reducing the dimensionality. The deteriorated water quality may be mainly attributed to anthropogenic activities, i.e., reckless industrial growth, population explosion, and rapid urbanization. This study emphasizes the need for regular water quality monitoring, and the information reported will certainly help for water resources planning and management, especially over the industrial regions of NCR, India.

Shahjad et al (2024) conducted a study on Groundwater quality assessment using water quality index and principal component analysis in the Achnera block, Agra district, Uttar Pradesh, Northern India. 50 groundwater samples were collected and analyzed for major ions along with some important trace element. The results confirm that, majority of the collected groundwater samples were alkaline in nature. The variation of concentration of anions in collected groundwater samples were varied in the sequence as, $HCO_3^- > Cl^- > SO_4^{2-} > F^-$ while in contrast the sequence of cations in the groundwater as $Na > Ca > Mg > K$. The results showed water quality index mostly ranged between 105 and 185, hence, the study area fell in the category of unsuitable for drinking purpose category. The PCA showed pH, Na^+, Ca^{2+}, HCO_3^- and fluoride with strong loading, which pointed out geogenic source of fluoride contamination. The outcomes of the present study will be helpful for the regulatory boards and policymaker for defining the actual impact and remediation goal.

Silva et al (2021) conducted a study on the Assessment of groundwater quality in a Brazilian semiarid basin using an integration of GIS, water quality index and multivariate statistical techniques. Probability curves were used to identify the critical variables and a regional Water Quality Index (WQIR) to assess groundwater quality. 22 samples from wells in the Araipe sedimentary basin were analyzed for their groundwater quality. The result for the variables phosphorus, Nitrate-N, thermotolerant coliforms, pH, and turbidity exceeded the regulatory limits, mainly in areas affected by anthropogenic sources with an insufficient

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sewage network. Nitrate-N and turbidity had a marked seasonal behavior. The WQIR showed that the aquifer's waters can be classified mainly as Regular (18.2%) or Good (82.8%). The spatial behavior maps of the hydro geochemical variables and the WQIR allow us to prioritize those areas requiring mitigation and monitoring actions. This study contributes to the assessment of water quality by policy makers and stakeholders, enabling the planning and management of groundwater resources.

Akshay et al (2021), assessed groundwater quality using geospatial technique based water quality index (WQI) approach in a coal mining region of India. This investigation was performed to understand this problem by calculating a water quality index (WQI) with a geographic information system (GIS) to assess groundwater quality in the coal mining region of the Ramgarh and Hazaribagh districts, Jharkhand, India. Groundwater samples were obtained during the pre-monsoon (n = 45) and post-monsoon (n = 31) seasons from multiple sampling sites in the study area. The samples were examined for 10 physicochemical and 5heavy metal parameters such as arsenic (As), copper (Cu), iron (Fe), manganese (Mn), and lead (Pb). Except Fe and Mn remaining elements were below the detection level (BDL). Results of the study revealed that the maximum portion of the study area is under a poor to unsuitable zone (77.65%) for drinking purposes during pre-monsoon, whereas the same area found suitable for drinking usage in the post-monsoon season.

Gilbert et al (2022), investigated on Integrated groundwater quality analysis using Water Quality Index, GIS and multivariate technique: a case study of Guwahati City.The analysis was carried out using hydrogeochemical characterization, Water Quality Index (WQI), geographic information system, and principal component analysis (PCA). The water samples were tested for physicochemical parameters (such as pH, turbidity, total hardness, total dissolved solids, alkalinity), major anions (F^-, Cl^-, NO_3^-, SO_4^-, HCO_3^-), and cations (Na^+, K^+, Ca^{2+}, Mg^{2+}, Fe^+). The results indicate the abundance of cations and anions in the following orders: Na^+ (43.05%) > Ca^{2+} (26.37%) > Mg^{2+} (17.19%) > K^+ (12.31%) > Fe^+ (1.08%) and HCO_3^- (78.47%) > Cl^- (11%) > SO_4^- (8.74%) > NO_3^- (1.45%) > F^- (0.34%), respectively. The computed WQI in the study area ranges from 19 to 108, which indicates that 25 sites had "excellent" categories of water quality for drinking. PCA indicated that the groundwater variation in Guwahati city is explained by primary factors such as ion exchange and mineral dissolution due to rock weathering and secondary factors such as anthropogenic activities. These findings suggested that monitoring wells are required to be installed in and around the study area to keep track of the water's quality before it deteriorates.

Baisakhi et al (2021) conducted a research on Geospatial Assessment of Groundwater Quality for Drinking through Water Quality Index and Human Health Risk Index in an Upland Area of Chota Nagpur Plateau of West Bengal, India.Drinking water suitability is analyzed by a composite Water Quality Index based on standard limit of each parameter for drinking purpose set by Bureau of Indian Standard. 52 groundwater samples were collected during pre-monsoon and post-monsoon seasons to estimate hydro-chemical characteristics and its suitability to human health. The results showed that the overall Water Quality Index ranges from 59.40 to 171.43. 'Sabari' (171.43) and 'Purana Panchakot' (168.21) village indicates highest Water Quality Index value during pre- and post-monsoon seasons, respectively. GIS analysis shows most of the area falls under 'good' to 'moderate' water

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quality zone. This study identified the hot spots of groundwater contamination where remedial measures as suggested in this work can be undertaken.

Sevda (2023) conducted a research on Estimation of groundwater quality using an integration of water quality index, artificial intelligence methods and GIS: Case study, Central Mediterranean Region of Turkey. In this study, the suitability of groundwater for irrigation was determined by using sodium adsorption ratio (SAR), residual sodium carbonate (RSC), Kelly index (KI), percentage of sodium (Na%), magnesium ratio (MR), potential salinity (PS) and permeability index (PI). The groundwater samples were collected and analyzed from 37 different sampling stations for this purpose. Spatial distribution maps were generated for measured and ANN model-estimated irrigation water quality indices using the IDW interpolation method. Spatial distributions of groundwater quality indices revealed that MR was higher than the allowable limits in most of the study areas and the other quality criteria were within the permissible limits. It has been determined that the interpolation maps obtained as a result of artificial intelligence methods have appropriate sensitivity when compared with the observed maps.

In a study conducted by **Ritesh et al (2022)** on Groundwater quality characterization for safe drinking water supply in sheikhpura district of Bihar, India. The study was carried out using integrated interpolation, geographical information systems, and regression analysis which were used to analyze groundwater quality parameters, such as fluoride, iron, total dissolved solids, turbidity, and pH. A total of 206 dug wells and bore wells were analyzed for in-situ observations in the Sheikhpura district of Bihar, India.The analysis indicated that the periphery south of Chewara and Ariari blocks, i.e., about 9.16% of district area, is

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affected by fluoride content (1.55–2.32 mg/l) which is highly unsuitable for consumption, as recommended by the WHO and BIS standards. However, the remaining area (90.84%) is within the permissible limit of fluoride content (0.37–1.54 mg/l). In most areas, iron content is beyond WHO permissible limits (>0.1 mg/l), except 3.1% area in the eastern region with 0.06–0.12 mg/l iron, although iron concentrations in groundwater are under the acceptable limit (<0.3 mg/l) as per BIS standard across the district. However, pH and total dissolved solids were within permissible limits. Each of the modeled geospatial maps was validated using a set of 17 in-situ observations. The best-fit model between observed and predicted variables such as fluoride, iron, total dissolved solids, and pH produced a coefficient of determination (R2) of 0.96, 0.905, 0.91, and 0.906, respectively. The findings of this study provide insights and understanding on groundwater pollution regimes and minimize uncertain causes because of the high spatial distribution of geogenic fluoride and iron occurrence, and will also be helpful to policymakers for better planning, investments, and management to supply potable water in the area.

Biplab et al (2021) conducted a study on the Evaluation of groundwater quality in West Tripura, Northeast India, through combined application of water quality index and multivariate statistical techniques. Water Quality Index (WQI) and Multivariate statistical tool, PCA, cluster Analysis methods were employed during this study. 38 groundwater sample were analyzed for this research. The result identified iron (Fe) followed by turbidity and dissolved oxygen (DO) as the most influencing parameters for non-portability of groundwater samples. Fe contamination in 34 samples exceeded WHO standard limit (0.3–1 mg/L) and the maximum value was recorded as 15.23 mg/L. Outcomes of PCA followed by

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a scree plot diagram extracted three major factors with a total variance of 84.5% clarifying the explanations behind water quality deterioration. Based on data ranges of all parameters, the spatial distribution map has been procured following the methods for identification and management. CA investigated three major groups using Ward's method of either sampling locations or analyzed parameters and showing through dendrogram plots. The study suggested that physicochemical parameters should be monitored periodically to preserve water resources and provide emphasis on management practices to maintain water quality.

Elemile et al (2021) conducted a research on Principal component analysis of groundwater sources pollution in Omu-Aran Community, Nigeria. Ninety-six groundwater samples were collected from eight locations both during dry and wet seasons. The study adopted the use of principal component analysis (PCA), water quality index (WQI) and independent sample to analyze water pollution sources, fully assess water quality and examine temporal variations in the sampling stations respectively. This study accessed the water quality under varying temporal conditions. The mean values for measured parameters all fall within the Nigerian Standard Drinking Water Quality guideline values with the exception of pH, nitrite, dissolved oxygen and T. coliform. This pollution was attributed to sewage pollution arising from anthropogenic sources. Water quality decreased during rainy season as compared to the dry season with significant differences ($P < 0.05$) between these periods except for pH, total hardness and fluoride. WQI ranged from 28.17 to 108.15 which lies on the "good" to "unsuitable for drinking" spectrum. The study recommends that regular assessment and proper monitoring to evaluate the quality of these sources should be done in order to ensure they meet standards before use.

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Ishola (2024) conducted a study on the evaluations of groundwater quality using principal component analysis and associated multivariate techniques: a case history in ewekoro communities, south-west Nigeria. Water samples were collected from 25 boreholes at various sampling stations across the study area. Standard analytical water quality methods using Inductively Coupled Mass Spectrometry (ICP-MS)/Optical Emission Spectrometry (ICP-OES) and Pour Plate Techniques were respectively employed in the laboratory for the samples' geochemical and bacteriological analyses. The raw data were processed and analyzed using Principal Component Analysis and other multivariate techniques. The study revealed that boreholes in Ewekoro were polluted and posed potential risk to biomedical safety and overall human health. Intervention measures are therefore necessary to safeguard the inhabitants from water-related diseases and their consequences.

EoagaEoaga & Idowu (2022) conducted a research on multivariate analysis of physico-chemical parameters of groundwater from selected communities in Yewa North local government area of Ogun State, Southwestern Nigeria. A total of 104 samples were drawn from 52 wells each in dry and wet seasons. The samples were analyzed using standard methods for the examination of water and waste waters. The parameters analyzed are pH, temperature, electrical conductivity (EC), total dissolved solids, total hardness, calcium hardness, magnesium hardness, PO4 3-, NO3-, HCO3-, Cl-and SO4 2-. The result of the study shows that most of the parameters analyzed fall within the WHO permissible limits for drinking water, while therefore groundwater from hand-dug wells in the study area may be suitable for both domestic and agricultural purposes.

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Usman et al (2022) conducted a study on Innovative Approach for Groundwater Quality Assessment with the Integration of Various Water Quality Indexes with GIS and Multivariate Statistical Analysis—a Case of Ujjain City, India. For the study, 54 groundwater samples consisting of eight physicochemical parameters were evaluated to assess water quality using four indexing methods: Numerow's pollution index (NPI), Weighted Arithmetic Water Quality Index (WA WQI), Groundwater Quality Index (GWQI), and the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI). A Geographic Information System (GIS) was employed to outline the spatial distribution maps of eight physicochemical parameters and WQI maps using the Inverse Distance Weighted (IDW) technique. Multivariate statistical analysis such as correlation analysis, principal component analysis (PCA), and cluster analysis (CA) were used for the evaluation of large and complicated groundwater quality data sets in the study. The results of the WQI indicate that 43% (NPI), 96% (WAWQI), 74% (GWQI), and 94% (CCME WQI) of groundwater samples had poor to unsuitable drinking water quality. The study recommended to monitor the physicochemical parameters on a regular basis in order to safeguard groundwater resources and to prioritize management strategies in order to maintain the drinking quality of water.

After critically reviewing the related literatures, my study differs in the following regard; the study focuses on Ekosodin, a peri-urban area in southern Nigeria with unique socio-envirommnental conditions, potentially affected by student population, waste discharge, and increasing urbanization while most reviewed studies are from Pakistan, India, Brazil, and other parts of Nigeria, with different climatic, geological, and anthropogenic influences.

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This study include recent or unique combinations of multivariate analysis (e.g., PCA, cluster analysis) along with geospatial techniques to pinpoint contaminant zones and pollution sources, some reviewed studies use PCA alone (Elemile et al., 2021), while others use different WQIs or Artificial Neural Networks (ANN) (Sevda, 2023).

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CHAPTER THREE

METHODOLOGY

3.1. Description of Study Area

Ekosodin is a community located within Ovia North-East Local Government Area of Edo State, in the southern region of Nigeria. It is situated adjacent to the University of Benin, Ugbowo Campus. Geographically, Ekosodin lies approximately between latitudes 6°24’29”N and longitudes 5°37’18”E (Google Earth, 2023) covering an area of about 5 square kilometers. It is one of the key communities within the Ovia North-East LGA and is bounded by Ugbowo to the east, Ekiadolor to the west, and the University of Benin to the south. Other nearby communities include Oluku, Iguovbiobo, and Isihor. The majority of the population in Ekosodin belongs to the Edo ethnic group, although the influx of people from other parts of Nigeria, particularly students and traders, has created a multicultural environment. The population of ekosodin was estimated to be around 7,000 people, according to the 2006 national census, but the population was estimated to be around 45,000 in 2022 using geometric growth method.

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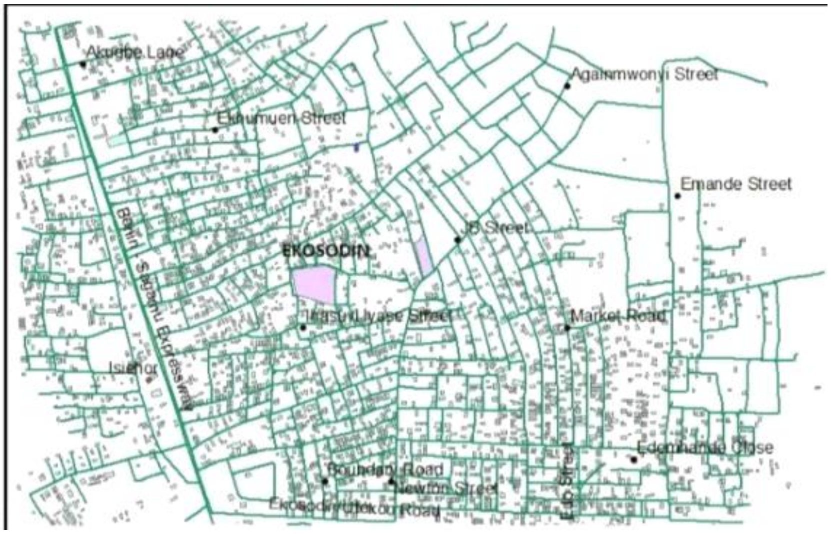

Fig 3.1 : Map of ekosodin

3.2 Materials and Method

The materials and methods that were employed in the study are discussed below:

3.2.1 Water Sampling

Groundwater samples were collected from eight different boreholes at random locations in ekosodin community. The coordinates of each borehole location was recorded using a handheld GPS unit. Pretreated plastic cans of 0.75 liters each was used for the collection of the groundwater Samples. The plastic cans were sealed, labeled, and transported to a Laboratory in Benin City for analysis.

3.3 Laboratory Analysis

This study utilized a range of physical and chemical analytical techniques, leveraging state of-the-art equipment in a well-equipped Quality Analytical Laboratory. The equipment that were employed during this study includes various laboratory glassware such as beakers, measuring cylinders, micropipettes, volumetric flasks, burettes, funnels, test tubes, and

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Erlenmeyer flasks, as well as thermometers, stopwatches, ovens, electronic mills, refrigerators, filter papers, and stirrers. Flameless Atomic Absorption Spectrometry (FAAS) was also employed to measure metal concentrations, while a potentiometric digital pH meter and conductivity meter was used for pH and conductivity measurements, respectively. Groundwater samples were analyzed for 22 parameters with all analytical procedures being meticulously documented.

3.3.1 Parameters

The samples were analyzed for twenty two physiochemical parameters, namely: pH, Temperature, Electrical Conductivity (EC) ,Total Dissolved Solids (TDS) ,Dissolved Oxygen (DO) ,Turbidity ,Calcium (Ca^{2+}) ,Magnesium (Mg^{2+}), Potassium (K^+) ,Sodium (Na^+) ,Chloride (Cl^-) ,Nitrite (NO_2^-) ,Nitrate (NO_3^-) ,Sulfate (SO_4^{2-}) ,Iron (Fe), Zinc (Zn) ,Copper (Cu) ,Lead (Pb) ,Total Suspended Solids (TSS) ,Nickel (Ni).

All laboratory analyses were conducted in accordance with the techniques described by the American Public Health (APHA), and the methods to be adopted for analyzing the groundwater quality parameters were indicated.

3.3.2 Procedure for the analysis of in- situ parameters (pH, EC, TDS, DO and Temperature) of the groundwater.

Field measurements were carried out for parameters such as pH, electrical conductivity (EC), total dissolved solids (TDS), temperature, and dissolved oxygen (DO), as these indicators are highly sensitive to changes during storage and transportation (APHA, 2017; Adimalla, 2020). A handheld multiparameter device was used to measure the pH, EC, TDS, and temperature, while a dissolved oxygen meter was used for DO evaluation.

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To measure the pH, the multiparameter probe was inserted approximately 4 cm below the surface of the water sample. The sample was gently stirred, and the pH mode was activated. The meter was allowed to stabilize before readings were recorded. Measurements for EC, TDS, and temperature were also taken similarly by switching to the respective functions on the device. Each parameter was measured three times to ensure reliability, and the mean value of the measurements was recorded. (Li et al., 2021).

For DO analysis, the oxygen probe was lowered to about 10 cm depth into the water sample. This procedure was done carefully to prevent trapping air bubbles, which could compromise the accuracy of the readings (Jameel et al., 2020). Prior to the commencement of each parameter measurement, the equipment was calibrated in line with the manufacturer's specifications.

3.3.3 Procedures for the analysis of heavy metals

An atomic absorption spectrometer (AAS) was used to quantify metal ions such as calcium, magnesium, potassium, sodium, iron, zinc, copper, lead, and nickel. For each element, a specific hollow cathode lamp—made from the target metal—emits light at a characteristic wavelength. This radiation passes through an acetylene-air flame into which the sample was introduced. Within the flame, the sample is atomized as water evaporates and metal compounds dissociate into free atoms. These atoms absorb the lamp's radiation and become excited to higher energy states. The absorbed light was filtered through a monochromator and detected by a photomultiplier tube, which converts it into an electrical signal. The metal concentrations are then displayed digitally.

Table 3.1 shows the wavelength and lamp current of some metals and cation

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Table 3.1 Heavy metal and their corresponding wavelength and lamp current

Elements	Wavelength (nm)	Lamp current (mA)
Calcium	422.7	10
Magnesium	285.2	4
Potassium	766.5	8
Sodium	589.0	8
Iron	248.3	15
Zinc	213.9	10
Copper	324.8	5
Lead	217.0	10
Nickel	232.0	15

3.3.4 Procedures for the analysis of nitrate using a spectrophotometer

Reagents

1. 2.5% brucine: 2.5g of brucine sulphate was dissolved in 100ml of glacial acetic acid.

2. Concentrated H_2SO_4 (SG=1.84 and 97-99% pure)

3. Standard NO3, 1000PPM stock: 0.1613g of KNO3 was dissolved in water and 0.5ml of chloroform was added as a preservative and made to 100ml.

4.Working NO_3 Standard (10PPM) Solution: 10ml of the stock was pipetted into 100ml flask and made to mark. From this solution; 0.1, 2, 3, 4 and 5ml was taken each into 50ml flask to

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have 0.0, 0.2, 0.4, 0.6, 0.8 and 1.0ppm was made to mark after adding the color developing reagents.

Procedure

A 50 mL portion of the water sample (filtrate) was transferred into a 50 mL volumetric flask. To this, 1 mL of the brucine reagent and 5 mL of concentrated H_2SO_4 was added quickly. The mixture was thoroughly shaken and kept to stand for 10 minutes to allow color development. The same procedure was applied to the prepared standards. After the reaction period, all solutions were diluted to the 50 mL mark. Absorbance readings were recorded at 470 nm using a spectrophotometer.

3.3.5 Procedure for the analysis of Sulphate using a Spectrophotometer

Reagents

1. Gelatine

2.Barium chloride

3.Gelatine – $BaCl_2$ Reagent

4. Standard SO_4^{2-} stock solution (100ppm). 0.15444g of anhydrous K_2SO_4 was dissolved in water and made to 1 liter.

5. Working SO_4^{2-} standard (10ppm): 10ml of the stock was pipetted into 100ml flask and made to mark. From this solution, 0, 2.5, 5.0, 7.5, 10.0 and 12.5ml each was also pipetted into 50ml flask to obtain 0.5, 5.0, 10.0, 15.0, 20.0 and 25.0ppm when made to mark after adding reagents. (Note: 0 is the extractant for SO_4^{2-}).

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Procedure

10ml of the filtrate was pipetted into a 50ml flask. Water was added to bring the volume of the solution to about 20ml. 1ml of the gelatin ($BaCl_2$) reagent was also added. The resulting mixture was allowed to stand for 30 minutes, then made to mark with water and mixed very well. The standards was treated similarly. Sulphate was then read at 420nm using a spectrophotometer. Sulphate concentration was calculated using Eq. (3.1) .

$$SO4 = \frac{Instrument\ Reading\ \times Slope\ Reading \times\ volume}{Aliquot\ Taken} \tag{3.1}$$

3.3.6 Procedure for the analysis of Chloride using Silver Nitrate Titration

Reagents

1. Potassium chromate indicator (5%): 5.0g of K_2CrO_4 was dissolved in 100ml of water
2. Standard $AgNO_3$ 0.05M: 8.4936g of this salt was dissolved in water and diluted to 1 Litre.
3. Standard chloride stock and working solutions.

Procedure

5ml of filtrate was pipetted into a 250ml conical flask. 1ml of K_2CrO_4 was added. Titration was done with standard 0.05M $AgNO_3$ until a slight red precipitate occurred. The blank, 9ml of the K_2CrO_4 indicator and 10ml of 20ppm Cl^- were treated. Chloride concentration was then calculated using Eq. (3.2) .

Calculation

$$CL = \frac{Molarity \times\ Titre \times\ Molarity\ Weight\ \times\ 1000}{Aliquot\ Taken} \tag{3.2}$$

3.3.7 Procedure for the analysis of Suspended Solids in Water by Calorimetry

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Procedure

15cm Whatman Filter Paper was dried at 50°C. The weight of the filter paper was recorded as (X_1g). 100ml of water sample was filtered through the weighed paper, then oven dried at 50°C. The filter paper was weighed with its content and recorded as (X_2g). Suspended solids is calculated using Eq. (3.3)

Calculation

$$Suspended\ Solids(mg/L) = (X_2 - X_1) \tag{3.3}$$

3.3.8 Procedure for the analysis of Turbidity using Spectrophotometer

To determine the turbidity of the water samples using a turbidimeter, calibrate the instrument with a set of standard Formazin solutions, typically at 0, 20, 100, and 400 NTU. Pour each standard into a clean, dry cuvette, ensuring it's free of smudges and bubbles, then insert it into the device for calibration. Next, gently mix the water sample to evenly distribute suspended particles without introducing air bubbles. Transfer the sample into a cleaned cuvette up to the indicated level, wipe it with a soft, lint-free cloth, and place it in the turbidimeter. Follow the instructions to take a reading, which displayed the turbidity value in NTU. For accuracy, take multiple readings and average the results, cleaning the cuvette thoroughly between each sample to avoid contamination.

3.4 Water Quality Index Modelling

Water quality index was calculated for each of the sample of water collected from the various boreholes for assessing the variation of the overall quality of the water sample at each specific borehole location. The water quality index modeling was done by considering about twenty two (22) important physico-chemical parameters. The selected physico-chemical parameters included; pH, Hardness, Electrical Conductivity (EC), Total Dissolved

Solids (TDS), Dissolved Oxygen (DO), Turbidity, Calcium (Ca^{2+}), Magnesium (Mg^{2+}), Potassium (K^{+}), Sodium (Na^{+}), Chloride (Cl^{-}), Nitrite (NO_2^{-}), Nitrate (NO_3^{-}), Sulfate (SO_4^{2-}), Iron (Fe), Zinc (Zn), Copper (Cu), Lead (Pb), Total Suspended Solids (TSS), Nickel (Ni). The basic steps that were involved in the modeling of water quality index are as follows:

3.4.1 Parameter Weightage Determination

For water quality index calculation, the weightage of each of the parameters identified was calculated. Parameters which have higher permissible limits are less harmful because they cannot significantly change the quality of the water sample even when they are present in high concentration. Weightage of tested parameters have an inverse relationship with its permissible limits. Therefore

$$Wn = \frac{K}{Sn} \tag{3.4}$$

Where;

$$K = \frac{1}{\Sigma\left(\frac{1}{Sn}\right)} \tag{3.5}$$

Wn = Unit weight of the different parameters tested

Sn = Standard values of selected parameters (WHO Standard Permissible Limit)

3.4.2 Quality Rating or Sub Index of Selected Parameters

The Quality Rating for the selected test parameter was computed using Eq. (3.6)

$$Qn = \frac{100(Vn - Vio)}{(Sn - Vio)} \tag{3.6}$$

Where:

$Qn =$ Quality rating

`

Vn = Laboratory test result for each parameter tested

Sn = Standard permissible value of each parameter tested

Vio= ideal value of selected parameters tested.

When Qn = 0, it implies that the measured concentration of that parameter is equal to the ideal or permissible standard, and it poses no risk to the water quality. The ideal value for all parameters is zero except pH which is 7.0 and dissolved Oxygen that is 14.6mg/L.

3.4.3Water Quality Index Calculation

Water Quality Index (WQI) is a series of test done on a water sample to determine its overall quality. The following steps will be employed in computing the overall water quality index calculation.

a) The weightage unit (Wn) for all parameters tested was summed up to obtain $\sum Wn$.

b) The quality rating for all parameters tested was summed up to obtain $\sum Qn$.

c) Then $(Wn \times Qn)$ was calculated for each parameter tested and thereafter summed up to obtain $\sum (Wn \times Qn)$.

d) Finally, Water Quality Index (WQI) was computed for each borehole location using Eq. (3.7) .

$$WQI = \frac{\sum (Wn \times Qn)}{\sum Wn} \quad (3.7)$$

Table 3.2 was used to interprete the WQI calculation results.

Table 3.2 Table showing the Interpretation of Water Quality Index (WQI) result

WQI Level	Water Quality Status	Grading

<50	Excellent Water Quality	A
51- 100	Good Water Quality	B
101 - 200	Poor Water Quality	C
201- 300	Very Poor Water Quality	D
>300	Not Suitable For Drinking	E

3.5. Principal Component Analysis

Principal component analysis, or PCA, is a dimensionality reduction method that is often used to reduce the dimensionality of large data sets, by transforming a large set of variables into a smaller ones (Principal Components) that still contains most of the information in the large set. For this study, Jamovi will be utilized for carrying out the analysis. The steps that will be used are listed below:

1. Data Standardization

Before applying PCA to the parameters, the dataset was screened for completeness and consistency. Since the variables were measured in different units, Z-score normalization was used to standardize them.

The standardized value was computed using Eq. (3.8)

$$Z = \frac{x - \bar{x}}{\sigma} \tag{3.8}$$

Where:

X = observed mean

$\bar{x}$ = mean

`

σ = Standard deviation

2. Correlation Matrix Computation

After standardization, a Pearson correlation matrix was generated to examine relationships among variables and to serve as input for the PCA. A positive covariance suggests that two parameters increase or decrease together, while a negative covariance implies inverse relationships while a zero covariance suggest no linear relationship.

The Pearson correlation coefficient was calculated using Eq. (3.9)

$$r_{xy} = \frac{\sum (x - \bar{x})(y - \bar{y})}{\sqrt{\sum (x - \bar{x})^2 \sum (y - \bar{y})^2}} \tag{3.9}$$

Where:

r_{xy} = correlation coefficient between variables X and Y

3. Eigen Decomposition and Principal Components Identification

Principal components were extracted using the eigenvalue decomposition of the correlation matrix. Eigenvalues and eigenvectors are extracted from the covariance matrix. Eigenvalues tell you how much variance (information) each principal component (PC) explains while the eigenvectors indicate the direction of each PC in the original variable space. Eigenvalue was computed using Eq. (3.10) .

$$|R - \lambda I| \tag{3.10}$$

Where:

R = correlation matrix

λ = eigenvalues

I = identity matrix

Each principal component is calculated using Eq. (3.11) .

`

$$PC_i = a_{i1}X_1 + a_{i2}X_2 + \ldots + a_{in}X_n \tag{3.11}$$

Where:

PC_i = i-th principal component

a_{i1}, a_{i2} = eigenvector loadings

n = number of variables

X_1, X_2, X_3 = Standardized variables

4. Variance explained

The eigenvalues obtained from the decomposition of the correlation matrix were used to determine the amount of variance explained by each principal component.

The percentage variance explained by each component was computed using Eq.(3.12)

$$\text{Variance explained (\%)} = \frac{\lambda_i}{\sum \lambda} \times 100 \tag{3.12}$$

Where:

λ_i = Eigenvalue of each principal component

$\sum \lambda$ = Total variance of the dataset

5. Component retention criteria

The number of components retained was based on:

a) **Kaiser Criterion**: Eigenvalues that are greater or equal to one are retained (i.e $\lambda \geq 1$)

b) **Scree plot** : The components retained were before the point where the curve starts to flatten(elbow).

6. **Rotation of Components**

`

To improve interpretability, varimax rotation was applied. This maximizes the variance of squared loading, producing a simpler structure where variables load strongly on one component. It also reduces the case of cross loading.

3.6 Groundwater Analysis Using Geostatistical Analyst

Geospatial interpolation of groundwater quality parameters was performed using Geographic Information System (GIS) techniques. The Inverse Distance Weighting (IDW) method was employed to interpolate the values of groundwater quality parameters, such as pH, TDS, and heavy metals, across the study area. The interpolation was based on the measured values at the sampling locations, and the resulting maps provided a visual representation of the spatial distribution of groundwater quality.

Procedure for Geospatial Analysis

Water samples was collected from eight different boreholes located within Ekosodin community. These locations were strategically selected to reflect varying distances and directions from one another allowing for better assessment of spatial contamination trends. The coordinates of each sampling point was recorded using a handheld GPS device and entered into a geospatial database for mapping and analysis in GIS. Table 3.3 shows the different sample locations and their coordinate.

Table 3.3: Sample location and coordinates

`

Sample ID	Sample location	Latitude	Lomgitude
1	Eguaveon Street	6.411958	5.619216
2	Fair View Hostel	6.410192	5.616390
3	Boundary Road	6.407658	5.616882
4	Town hall Road	6.410559	5.623441
5	Ekosodin Primary School road	6.415618	5.623818
6	Imafidon Street	6.407852	5.620824
7	JB Street	6.408610	5.627628
8	Newton Road	6.416205	5.620175

a) The GPS coordinates of water sampling points was imported into ArcGIS as point data layers. Attributes such as sampling ID, water quality paramerter values were also added.

b) The analysis environment was set, including the study area extent, cell size, and projection.

c) The IDW tool was used to interpolate the values of groundwater quality parameters, specifying the power parameter, search radius, and output raster.

d) The IDW tool created an output raster, representing the interpolated values of groundwater quality parameters across the study area.

e) The output raster was visualized and analyzed to identify spatial patterns and trends in groundwater quality parameters.

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f) A map was created to display the interpolated values, including legends, labels, and other cartographic elements.

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CHAPTER FOUR

RESULTS AND DISCUSSION

4.1 Introduction

This chapter contains the results obtained after carrying out the geospatial analysis of groundwater around Ekosodin community. During this project the concentration level and the spatial distribution were analyzed using ArcGIS, integrating field measurements and coordinating data obtained from eight sampling points in Ekosodin.

4.2. Data for water quality index computation

The lab results for the selected parameters is recorded in Table 4.1 .

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Table 4.1: Parameters for water quality index computation.

Parameters	Sample 1	Sample 2	Sample 3	Sample 4	Sample 5	Sample 6	Sample 7	Sample 8
pH	6.1	5.4	5.4	4.8	4.7	4.7	6.1	5.2
Nitrate	0.584	0.630	0.683	0.650	0.505	0.550	0.615	0.518
E.C	142	190	231	207	48	80	188	60
Turbidity	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
DO	1.2	1.0	0.7	0.8	1.8	1.5	1.0	0.8
TDS	72	95	116	104	25	40	95	31
Sodium	0.48	0.66	0.80	0.74	0.33	0.41	0.50	0.38
Lead	0.002	0.011	0.00	0.005	0.004	0.0021	0.0015	0.0058
Sulphate	0.550	0.582	0.660	0.614	0.414	0.474	0.561	0.440
Zinc	0.160	0.144	0.120	0.121	0.272	0.172	0.151	0.181
Copper	0.080	0.062	0.051	0.058	0.140	0.087	0.071	0.114
Chloride	60.1	77.4	84.3	80.6	50.4	54.3	61.3	51.7
Iron	0.251	0.218	0.202	0.207	0.333	0.266	0.240	0.274
HCO3	9.45	10.89	12.97	12.87	6.44	7.47	9.96	7.07
TSS	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
Nitrite	0.009	0.011	0.021	0.017	0.005	0.007	0.010	0.006
Cadmium	0.001	0.009	0.006	0.007	0.0021	0.0015	0.0011	0.0017
Nickel	0.007	0.004	0.002	0.00	0.011	0.007	0.005	0.009
Magnesium	1.36	1.51	1.87	1.64	0.83	0.94	1.43	0.88
Phosphate	0.013	0.018	0.030	0.021	0.007	0.010	0.015	0.009
Alkalinity	40.6	48.7	60.1	56.3	30.6	38.8	44.4	38.5
Calcium	1.51	1.87	2.11	2.07	1.21	1.44	1.63	1.38

4.3 Water Quality Index Computation

Water quality index modeling was done by considering about twenty two (22) important physicochemical parameters. The reference table for interpreting the water quality index values is presented in Table 4.2 .

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Table 4.2: Standard Table for Water Quality Index Interpretation (Prasad et al., 2019)

Class	**WQI value**	**Water Quality Status**
A	< 50	Excellent
B	50 - 100	Good
C	100- 200	Poor
D	200 -300	Very Poor
E	>300	Water unsuitable for drinking

The result of the computed water quality index (WQI) for water samples collected from the different boreholes are presented in Tables below;

Table 4.3: Water quality index calculation results for sample 1 .

S/No	Parameters	(Vi)	(Sn)	1/Sn	K	(Wn=K/Sn)	Lab Results (Vn)	(qn)	[(Wn*qn)]
1	pH	7	8.5	0.11765	0.00203	0.0002388	6.1	-93.33	-0.01433
2	Nitrate	0	50	0.02000		0.0000406	0.584	8.02	0.00005
3	E.C	0	1000	0.00100		0.0000020	142	173.60	0.00003
4	Turbidity	0	5	0.20000		0.0004060	0	10.00	0.00000
5	DO	14.6	5	0.20000		0.0004060	1.2	122.92	0.05667
6	TDS	0	500	0.00200		0.0000041	72	173.60	0.00006
7	Sodium	0	200	0.00500		0.0000102	0.48	4.25	0.00000
8	Lead	0	0.01	100.00000		0.2030000	0.002	160.00	4.06000
9	Sulphate	0	100	0.01000		0.0000203	0.55	2.73	0.00001
10	Zinc	0	3	0.33333		0.0006767	0.16	5.27	0.00361
11	Copper	0	2	0.50000		0.0010150	0.08	3.80	0.00406
12	Chloride	0	250	0.00400		0.0000081	60.1	132.16	0.00020
13	Iron	0	1	1.00000		0.0020300	0.251	21.70	0.05095
14	HCO_3	0	250	0.00400		0.0000081	9.45	32.08	0.00003
15	TSS	0	5	0.20000		0.0004060	0	24.00	0.00000
16	Nitrite	0	0.2	5.00000		0.0101500	0.009	360.00	0.04568
17	Cadmium	0	0.003	333.33333		0.6766667	0.001	300.00	22.55556
18	Nickel	0	0.02	50.00000		0.1015000	0.007	185.00	3.55250
19	Magnesium	0	150	0.00667		0.0000135	1.36	9.80	0.00001
20	Phosphate	0	0.5	2.00000		0.0040600	0.013	20.40	0.01056
21	Alkalinity	0	600	0.00167		0.0000034	40.6	19.37	0.00002
22	Calcium	0	200	0.00500		0.0000102	1.51	11.15	0.00001
				∑ = 492.9437		∑ = 1.00068			∑ = 30.32567
WQI = [∑(Wn*qn)]/[(∑Wn)] = 30.31									

The water quality index value for sample one was computed as 30.31% which falls within the Excellent category of classification of water quality, indicating that the groundwater at this location is suitable for drinking and domestic use. Most physicochemical parameters were within the permissible limits of the WHO stsandards. The pH was slightly acidic.

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Heavy metals such as iron, lead, copper and nickel were also within safe limits. Overall, the excellent WQI rating signifies that the sample originates from a n unpolluted aquifer.

Table 4.4: Water quality index calculation results for sample 2

S/N	Parameters	(Vi)	(Sn)	1/Sn	K	(Wn=K/Sn)	Vn= Test Result	(qn)	[(Wn*qn)]
1	pH	7	8.5	0.11765	0.00203	0.0002388	5.4	-93.33	-0.02547
2	Nitrate	0	50	0.02000		0.0000406	0.63	8.02	0.00005
3	E.C	0	1000	0.00100		0.0000020	190	173.60	0.00004
4	Turbidity	0	5	0.20000		0.0004060	0	10.00	0.00000
5	DO	14.6	5	0.20000		0.0004060	1	122.92	0.05752
6	TDS	0	500	0.00200		0.0000041	95	173.60	0.00008
7	Sodium	0	200	0.00500		0.0000102	0.66	4.25	0.00000
8	Lead	0	0.01	100.00000		0.2030000	0.011	160.00	22.33000
9	Sulphate	0	100	0.01000		0.0000203	0.582	2.73	0.00001
10	Zinc	0	3	0.33333		0.0006767	0.144	5.27	0.00325
11	Copper	0	2	0.50000		0.0010150	0.062	3.80	0.00315
12	Chloride	0	250	0.00400		0.0000081	77.4	132.16	0.00025
13	Iron	0	1	1.00000		0.0020300	0.218	21.70	0.04425
14	HCO_3	0	250	0.00400		0.0000081	10.89	32.08	0.00004
15	TSS	0	5	0.20000		0.0004060	0	24.00	0.00000
16	Nitrite	0	0.2	5.00000		0.0101500	0.011	360.00	0.05583
17	Cadmium	0	0.003	333.33333		0.6766667	0.009	300.00	203.00000
18	Nickel	0	0.02	50.00000		0.1015000	0.004	185.00	2.03000
19	Magnesium	0	150	0.00667		0.0000135	1.51	9.80	0.00001
20	Phosphate	0	0.5	2.00000		0.0040600	0.018	20.40	0.01462
21	Alkalinity	0	600	0.00167		0.0000034	48.7	19.37	0.00003
22	Calcium	0	200	0.00500		0.0000102	1.87	11.15	0.00001
				$\sum$ = 492.9437		$\sum$ = 1.00068			$\sum$ =227.51365
WQI = [$\sum$(Wn*qn)]/[($\sum$Wn)] = 227.36									

The WQI value of 227.36% indicates very poor water quality, suggesting that the water is unsuitable for drinking without treatment. The high index was as a result of high concentration of lead and cadmium, which exceeded the WHO limits. The water is acidic as a result of low pH, which can increase metal solubility. This signifies significant anthropogenic influence, likely from waste disposal or corrosion of plumbing materials.

Table 4.5: Water quality index calculation results for sample 3

S/No	Parameters	(Vi)	(Sn)	1/Sn	K	(Wn=K/Sn)	Vn= Test Result	(qn)	[(Wn*qn)]
1	pH	7	8.5	0.11765	0.00203	0.0002388	5.84	-93.33	-0.02547
2	Nitrate	0	50	0.02000		0.0000406	0.683	8.02	0.00006
3	E.C	0	1000	0.00100		0.0000020	231	173.60	0.00005
4	Turbidity	0	5	0.20000		0.0004060	0	10.00	0.00000
5	DO	14.6	5	0.20000		0.0004060	0.7	122.92	0.05879
6	TDS	0	500	0.00200		0.0000041	116	173.60	0.00009
7	Sodium	0	200	0.00500		0.0000102	0.8	4.25	0.00000
8	Lead	0	0.01	100.00000		0.2030000	0	160.00	0.00000
9	Sulphate	0	100	0.01000		0.0000203	0.66	2.73	0.00001
10	Zinc	0	3	0.33333		0.0006767	0.12	5.27	0.00271
11	Copper	0	2	0.50000		0.0010150	0.051	3.80	0.00259
12	Chloride	0	250	0.00400		0.0000081	84.3	132.16	0.00027
13	Iron	0	1	1.00000		0.0020300	0.202	21.70	0.04101
14	HCO_3	0	250	0.00400		0.0000081	12.97	32.08	0.00004
15	TSS	0	5	0.20000		0.0004060	0	24.00	0.00000
16	Nitrite	0	0.2	5.00000		0.0101500	0.021	360.00	0.10658
17	Cadmium	0	0.003	333.33333		0.6766667	0.006	300.00	135.33333
18	Nickel	0	0.02	50.00000		0.1015000	0.004	0.002	1.01500
19	Magnesium	0	150	0.00667		0.0000135	1.51	1.87	0.00002
20	Phosphate	0	0.5	2.00000		0.0040600	0.018	0.03	0.02436
21	Alkalinity	0	600	0.00167		0.0000034	60.1	19.37	0.00003
22	Calcium	0	200	0.00500		0.0000102	2.11	11.15	0.00001
				∑ = 492.9437		∑ = 1.00068			∑ = 136.55947
WQI = [∑(Wn*qn)]/[(∑Wn)] =136.47									

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The WQI of 136.47% falls under the poor category indicating that the water is unsuitable for direct consumption without treatment. The low pH and moderate TDS suggest mild acidity and mineralization. The major contributors to the poor quality were cadmium and iron, which can be toxic if consumed overtime.

Table 4.6:Water quality index calculation results for sample 4

S/No	Parameters	(Vi)	(Sn)	1/Sn	K	(Wn=K/Sn)	Vn= Test Result	(qn)	[(Wn*qn)]
1	pH	7	8.5	0.11765	0.00203	0.0002388	4.8	-93.33	-0.03662
2	Nitrate	0	50	0.02000		0.0000406	0.650	8.02	0.00004
3	E.C	0	1000	0.00100		0.0000020	207	173.60	0.00001
4	Turbidity	0	5	0.20000		0.0004060	0.0	10.00	0.00000
5	DO	14.6	5	0.20000		0.0004060	0.8	122.92	0.05413
6	TDS	0	500	0.00200		0.0000041	104	173.60	0.00002
7	Sodium	0	200	0.00500		0.0000102	0.74	4.25	0.00000
8	Lead	0	0.01	100.00000		0.2030000	0.005	160.00	8.12000
9	Sulphate	0	100	0.01000		0.0000203	0.614	2.73	0.00001
10	Zinc	0	3	0.33333		0.0006767	0.121	5.27	0.00614
11	Copper	0	2	0.50000		0.0010150	0.058	3.80	0.00711
12	Chloride	0	250	0.00400		0.0000081	80.6	132.16	0.00016
13	Iron	0	1	1.00000		0.0020300	0.207	21.70	0.06760
14	HCO_3	0	250	0.00400		0.0000081	12.87	32.08	0.00002
15	TSS	0	5	0.20000		0.0004060	0.0	24.00	0.00000
16	Nitrite	0	0.2	5.00000		0.0101500	0.017	360.00	0.02538
17	Cadmium	0	0.003	333.33333		0.6766667	0.007	300.00	47.36667
18	Nickel	0	0.02	50.00000		0.1015000	0.00	0.002	5.58250
19	Magnesium	0	150	0.00667		0.0000135	1.64	1.87	0.00001
20	Phosphate	0	0.5	2.00000		0.0040600	0.021	0.03	0.00568
21	Alkalinity	0	600	0.00167		0.0000034	56.3	19.37	0.00002
22	Calcium	0	200	0.00500		0.0000102	2.07	11.15	0.00001
				∑ = 492.9437		∑ = 1.00068			∑ = 168.213
WQI = [∑(Wn*qn)]/[(∑Wn)] =168.10									

With a WQI of 168.10%, this sample also shows poor quality. The acidic pH (4.8) and moderate EC indicate possible chemical alteration of the aquifer. The lead (0.005 mg/L) and

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cadmium contents exceeded safe limits, while elevated iron suggests leaching from pipes or geogenic sources. Though nitrate and TDS are within limits, the cumulative effect of metal contaminants significantly deteriorates overall quality.

Table 4.7: Water quality index calculation results for sample 5

S/No	Parameters	(Vi)	(Sn)	1/Sn	K	(Wn=K/Sn)	Vn= Test Result	(qn)	[(Wn*qn)]
1	pH	7	8.5	0.11765	0.00203	0.0002388	4.7	-93.33	-0.03662
2	Nitrate	0	50	0.02000		0.0000406	0.505	8.02	0.00004
3	E.C	0	1000	0.00100		0.0000020	48	173.60	0.00001
4	Turbidity	0	5	0.20000		0.0004060	0	10.00	0.00000
5	DO	14.6	5	0.20000		0.0004060	1.8	122.92	0.05413
6	TDS	0	500	0.00200		0.0000041	25	173.60	0.00002
7	Sodium	0	200	0.00500		0.0000102	0.33	4.25	0.00000
8	Lead	0	0.01	100.00000		0.2030000	0.004	160.00	8.12000
9	Sulphate	0	100	0.01000		0.0000203	0.414	2.73	0.00001
10	Zinc	0	3	0.33333		0.0006767	0.272	5.27	0.00614
11	Copper	0	2	0.50000		0.0010150	0.14	3.80	0.00711
12	Chloride	0	250	0.00400		0.0000081	50.4	132.16	0.00016
13	Iron	0	1	1.00000		0.0020300	0.333	21.70	0.06760
14	HCO_3	0	250	0.00400		0.0000081	6.44	32.08	0.00002
15	TSS	0	5	0.20000		0.0004060	0	24.00	0.00000
16	Nitrite	0	0.2	5.00000		0.0101500	0.005	360.00	0.02538
17	Cadmium	0	0.003	333.33333		0.6766667	0.0021	300.00	47.36667
18	Nickel	0	0.02	50.00000		0.1015000	0.011	0.002	5.58250
19	Magnesium	0	150	0.00667		0.0000135	0.83	1.87	0.00001
20	Phosphate	0	0.5	2.00000		0.0040600	0.007	0.03	0.00568
21	Alkalinity	0	600	0.00167		0.0000034	30.6	19.37	0.00002
22	Calcium	0	200	0.00500		0.0000102	1.21	11.15	0.00001
				$\sum$ = 492.9437		$\sum$ = 1.00068			$\sum$ = 61.1988
WQI = [$\sum$(Wn*qn)]/[($\sum$Wn)] =61.16									

`

The WQI value of 61.16 classifies this sample as "Good", meaning it is acceptable for drinking after minor treatment. The pH (4.7) indicates acidity, possibly from soil CO_2 or organic decay. Lead (0.004 mg/L) and cadmium (0.0021 mg/L) were slightly elevated, while other parameters such as nitrate (0.505 mg/L) and chloride (50.4 mg/L) remained low. The water is relatively safe but could be affected by mild metal intrusion or acidic infiltration.

Table 4.8: Water quality index calculation results for sample 6

S/No	Parameters	(Vi)	(Sn)	1/Sn	K	(Wn=K/Sn)	Vn= Test Result	(qn)	[(Wn*qn)]
1	pH	7	8.5	0.11765	0.00203	0.0002388	4.7	-93.33	-0.03662
2	Nitrate	0	50	0.02000		0.0000406	0.55	8.02	0.00004
3	E.C	0	1000	0.00100		0.0000020	80	173.60	0.00002
4	Turbidity	0	5	0.20000		0.0004060	0	10.00	0.00000
5	DO	14.6	5	0.20000		0.0004060	1.5	122.92	0.05540
6	TDS	0	500	0.00200		0.0000041	40	173.60	0.00003
7	Sodium	0	200	0.00500		0.0000102	0.41	4.25	0.00000
8	Lead	0	0.01	100.00000		0.2030000	0.0021	160.00	4.26300
9	Sulphate	0	100	0.01000		0.0000203	0.474	2.73	0.00001
10	Zinc	0	3	0.33333		0.0006767	0.172	5.27	0.00388
11	Copper	0	2	0.50000		0.0010150	0.087	3.80	0.00442
12	Chloride	0	250	0.00400		0.0000081	54.3	132.16	0.00018
13	Iron	0	1	1.00000		0.0020300	0.266	21.70	0.05400
14	HCO_3	0	250	0.00400		0.0000081	7.47	32.08	0.00002
15	TSS	0	5	0.20000		0.0004060	0	24.00	0.00000
16	Nitrite	0	0.2	5.00000		0.0101500	0.007	360.00	0.03553
17	Cadmium	0	0.003	333.33333		0.6766667	0.0015	300.00	33.83333
18	Nickel	0	0.02	50.00000		0.1015000	0.007	0.002	3.55250
19	Magnesium	0	150	0.00667		0.0000135	0.94	1.87	0.00001
20	Phosphate	0	0.5	2.00000		0.0040600	0.1	0.03	0.08120
21	Alkalinity	0	600	0.00167		0.0000034	38.8	19.37	0.00002
22	Calcium	0	200	0.00500		0.0000102	1.44	11.15	0.00001
				∑ = 492.9437		∑ = 1.00068			∑ = 41.84698
WQI = [∑(Wn*qn)]/[(∑Wn)] =41.84									

`

This sample's WQI of 41.84 falls under the "Excellent" category, indicating safe and clean groundwater. The pH (4.7) was low, but other parameters such as TDS (40 mg/L), EC (80 µS/cm), and nitrate (0.55 mg/L) were within safe limits. Trace metals like lead (0.0021 mg/L) and cadmium (0.0015 mg/L) were minimal, suggesting natural filtration and low anthropogenic interference. The water is suitable for consumption and domestic uses.

Table 4.9: Water quality index calculation results for sample 7

	Parameters	**(Vi)**	**(Sn)**	**1/Sn**	**K**	**(Wn=K/Sn)**	**Vn= Test Result**	**(qn)**	**[(Wn*qn)]**
1	pH	7	8.5	0.11765	0.00203	0.0002388	6.1	-93.33	-0.03662
2	Nitrate	0	50	0.02000		0.0000406	0.615	8.02	0.00004
3	E.C	0	1000	0.00100		0.0000020	188	173.60	0.00002
4	Turbidity	0	5	0.20000		0.0004060	0	10.00	0.00000
5	DO	14.6	5	0.20000		0.0004060	1	122.92	0.05540
6	TDS	0	500	0.00200		0.0000041	95	173.60	0.00003
7	Sodium	0	200	0.00500		0.0000102	0.5	4.25	0.00000
8	Lead	0	0.01	100.00000		0.2030000	0.0015	160.00	4.26300
9	Sulphate	0	100	0.01000		0.0000203	0.561	2.73	0.00001
10	Zinc	0	3	0.33333		0.0006767	0.151	5.27	0.00388
11	Copper	0	2	0.50000		0.0010150	0.071	3.80	0.00442
12	Chloride	0	250	0.00400		0.0000081	61.3	132.16	0.00018
13	Iron	0	1	1.00000		0.0020300	0.24	21.70	0.05400
14	HCO_3	0	250	0.00400		0.0000081	9.96	32.08	0.00002
15	TSS	0	5	0.20000		0.0004060	0	24.00	0.00000
16	Nitrite	0	0.2	5.00000		0.0101500	0.01	360.00	0.03553
17	Cadmium	0	0.003	333.33333		0.6766667	0.0011	300.00	33.83333
18	Nickel	0	0.02	50.00000		0.1015000	0.005	0.002	3.55250
19	Magnesium	0	150	0.00667		0.0000135	1.43	1.87	0.00001
20	Phosphate	0	0.5	2.00000		0.0040600	0.015	0.03	0.08120
21	Alkalinity	0	600	0.00167		0.0000034	44.4	19.37	0.00002
22	Calcium	0	200	0.00500		0.0000102	1.63	11.15	0.00001
				∑ = 492.9437		∑ = 1.00068			∑ = 30.55591
WQI = [∑(Wn*qn)]/[(∑Wn)] =30.54									

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With a WQI of 30.54, this sample is also rated “Excellent”. The pH (6.1) and TDS (95 mg/L) values suggest a near-neutral, low-salinity water type. Concentrations of major ions and metals were minimal—lead (0.0015 mg/L) and cadmium (0.0011 mg/L) were well below limits. This indicates good natural recharge and protection from surface contamination, making the water safe for all domestic purposes.

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Table 4.10: Water quality index calculation result for sample 8

S/No	Parameters	(Vi)	(Sn)	1/Sn	K	(Wn=K/Sn)	Vn= Test Result	(qn)	[(Wn*qn)]
1	pH	7	8.5	0.11765	0.00203	0.0002388	5.2	-93.33	-0.02866
2	Nitrate	0	50	0.02000		0.0000406	0.518	8.02	0.00004
3	E.C	0	1000	0.00100		0.0000020	60	173.60	0.00001
4	Turbidity	0	5	0.20000		0.0004060	0	10.00	0.00000
5	DO	14.6	5	0.20000		0.0004060	1.6	122.92	0.05498
6	TDS	0	500	0.00200		0.0000041	31	173.60	0.00003
7	Sodium	0	200	0.00500		0.0000102	0.38	4.25	0.00000
8	Lead	0	0.01	100.00000		0.2030000	0.0058	160.00	11.77400
9	Sulphate	0	100	0.01000		0.0000203	0.44	2.73	0.00001
10	Zinc	0	3	0.33333		0.0006767	0.181	5.27	0.00408
11	Copper	0	2	0.50000		0.0010150	0.114	3.80	0.00579
12	Chloride	0	250	0.00400		0.0000081	51.7	132.16	0.00017
13	Iron	0	1	1.00000		0.0020300	0.274	21.70	0.05562
14	HCO_3	0	250	0.00400		0.0000081	7.07	32.08	0.00002
15	TSS	0	5	0.20000		0.0004060	0	24.00	0.00000
16	Nitrite	0	0.2	5.00000		0.0101500	0.006	360.00	0.03045
17	Cadmium	0	0.003	333.33333		0.6766667	0.0017	300.00	38.34444
18	Nickel	0	0.02	50.00000		0.1015000	0.009	0.002	4.56750
19	Magnesium	0	150	0.00667		0.0000135	0.88	1.87	0.00001
20	Phosphate	0	0.5	2.00000		0.0040600	0.009	0.03	0.00731
21	Alkalinity	0	600	0.00167		0.0000034	38.5	19.37	0.00002
22	Calcium	0	200	0.00500		0.0000102	1.38	11.15	0.00001
				∑ = 492.9437		∑ = 1.00068			∑ = 54.81583
WQI = [∑(Wn*qn)]/[(∑Wn)] =54.78									

The WQI value of 54.78 indicates "Good" water quality, suitable for domestic use after slight purification. The pH (5.2) shows mild acidity, while TDS (31 mg/L) and EC (60 µS/cm) were low, denoting low dissolved mineral content. Slightly elevated lead (0.0058 mg/L) and iron (0.274 mg/L) suggest minor contamination, likely from plumbing or geogenic processes. Overall, the water remains largely safe with minimal health risk.

The summary of the calculated WQI values for all the sampled locations is presented in Table 4.11.

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Table 4.11: Summary results of water quality index computation.

Location	Computed WQI(%)	Remark
Sample 2	227.36	Very Poor
Sample 3	136.47	Poor
Sample 4	168.10	Poor
Sample 5	61.16	Good
Sample 6	41.84	Excellent
Sample 7	30.54	Excellent
Sample 8	54.78	Good

The Water Quality Index (WQI) results for the eight groundwater samples show distinct variations in quality across the study area, reflecting differing degrees of contamination and aquifer protection. Samples 1, 6, and 7, with WQI values of 30.31%, 41.84%, and 30.54%, respectively, fall within the Excellent category, indicating clean and safe water suitable for domestic use, likely due to low concentrations of dissolved solids and metals. Samples 5 and 8, classified as Good with WQI values of 61.16% and 54.78%, suggest slightly elevated contamination levels, possibly from agricultural runoff or domestic activities. In contrast, Samples 2 and 3 and 4 with WQI values of 227.36% and 136.47%, 168.10% are rated Very Poor and Poor, implying that the water from these locations is unfit for drinking without proper treatment, likely due to high levels of total dissolved solids, electrical conductivity, and heavy metals such as lead and cadmium.

4.4. Geospatial analysis of the water quality parameters.

To study the spatial distribution of the water quality parameters around the study location, Geospatial analysis was performed using the Inverse Distance Weighting method.

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4.4.1. Generation of water quality parameters distribution map

The spatial distribution maps of the analyzed water quality parameters were generated using the Inverse Distance Weighting (IDW) interpolation techniqu within the GIS environment. These map visually depict how each parameter varies across the study area, highlighting potential contamination zones.

The spatial distribution maps of the analyzed water quality parameters are presented in Figure 4.1 to Figure 4.10 .

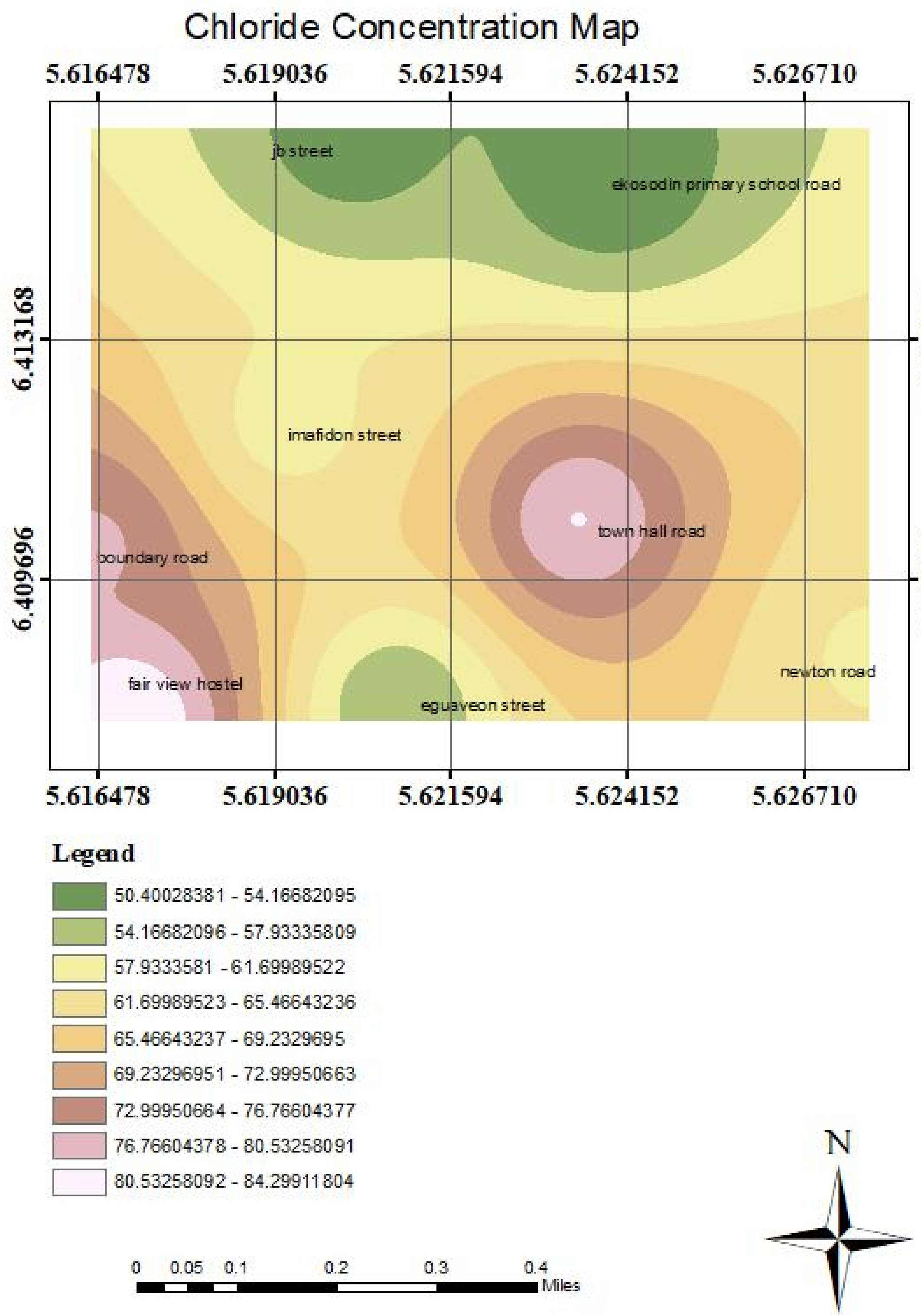

Figure 4.1: Final prediction map for chloride distribution.

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Figure 4.1 presents the spatial variation of chloride concentration in Ekosodin groundwater. High chloride zones are observed around areas such as Town hall road, JB street and environs surrounding fair view hostel possibly influenced by domestic waste infiltration,sewage leakage while moderate and low chlorine concentrations appeared along Boundary Road , newton road, around Ekosodin primary school road and Eguaveon street suggesting minimal contamination and better groundwater quality. Generally, chloride values were below the WHO permissible limit of 250 mg/L, indicating that the groundwater is safe from salinity issues, though regular monitoring and improved waste management are recommended.

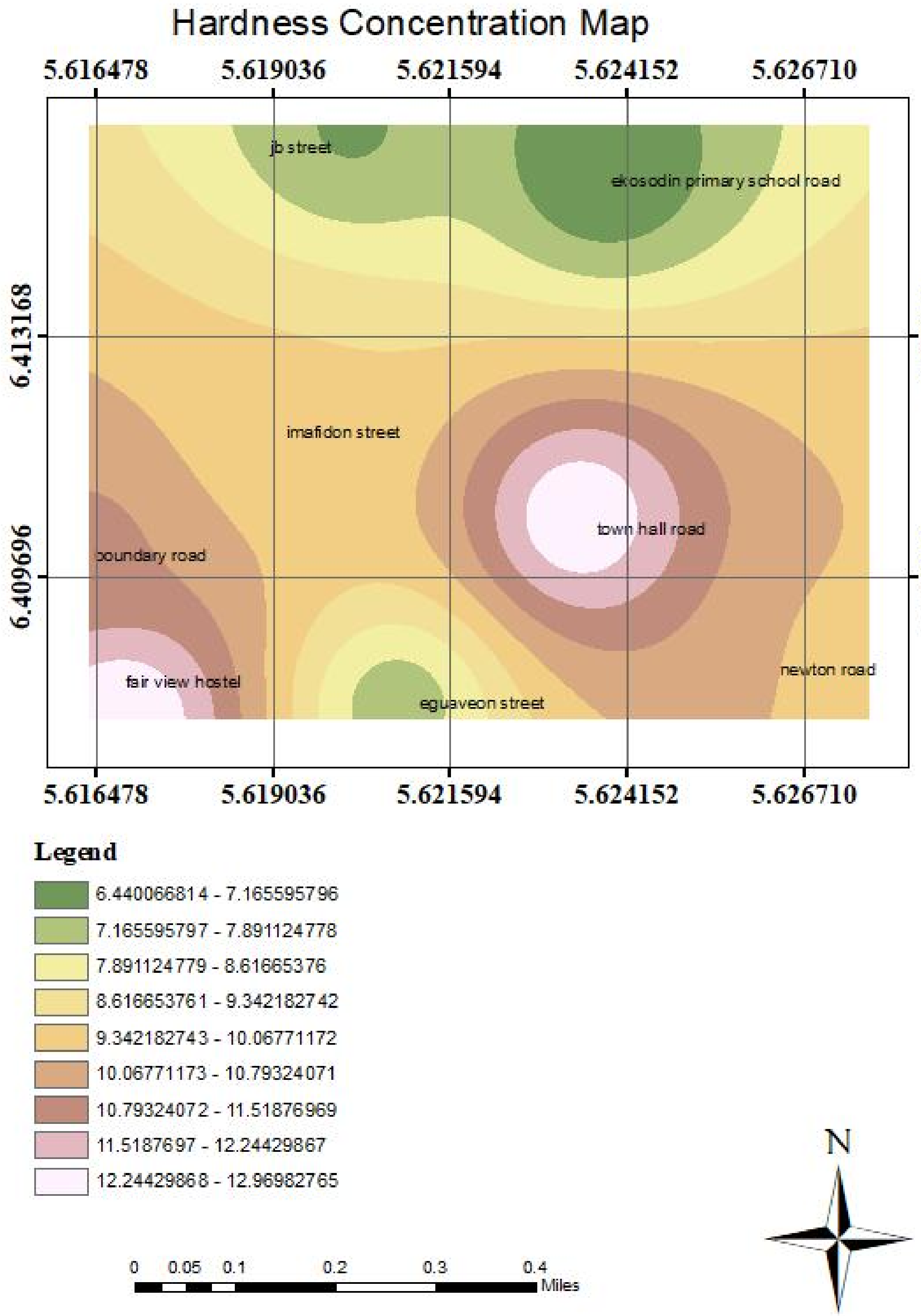

Figure 4.2: Final prediction map for hardness distribution.

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Figure 4.2 shows the spatial variation of groundwater hardness across Ekosodin. The highest hardness values occurred around Town hall road, Boundary road and Fair view hostel likely due to the dissolution of calcium and magnesium minerals or leaching from cemented soils. Lower hardness levels were observed in JB street, ekosodin primary school road, Imafidon street and Newton street indicatingless mineralized water and active recharge. All measured values were below the WHO permissible limit of 500 mg/L, signifying soft to moderately hard water. This suggests that the groundwater poses minimal scaling risk and remains suitable for domestic use, though periodic assessment is encouraged.

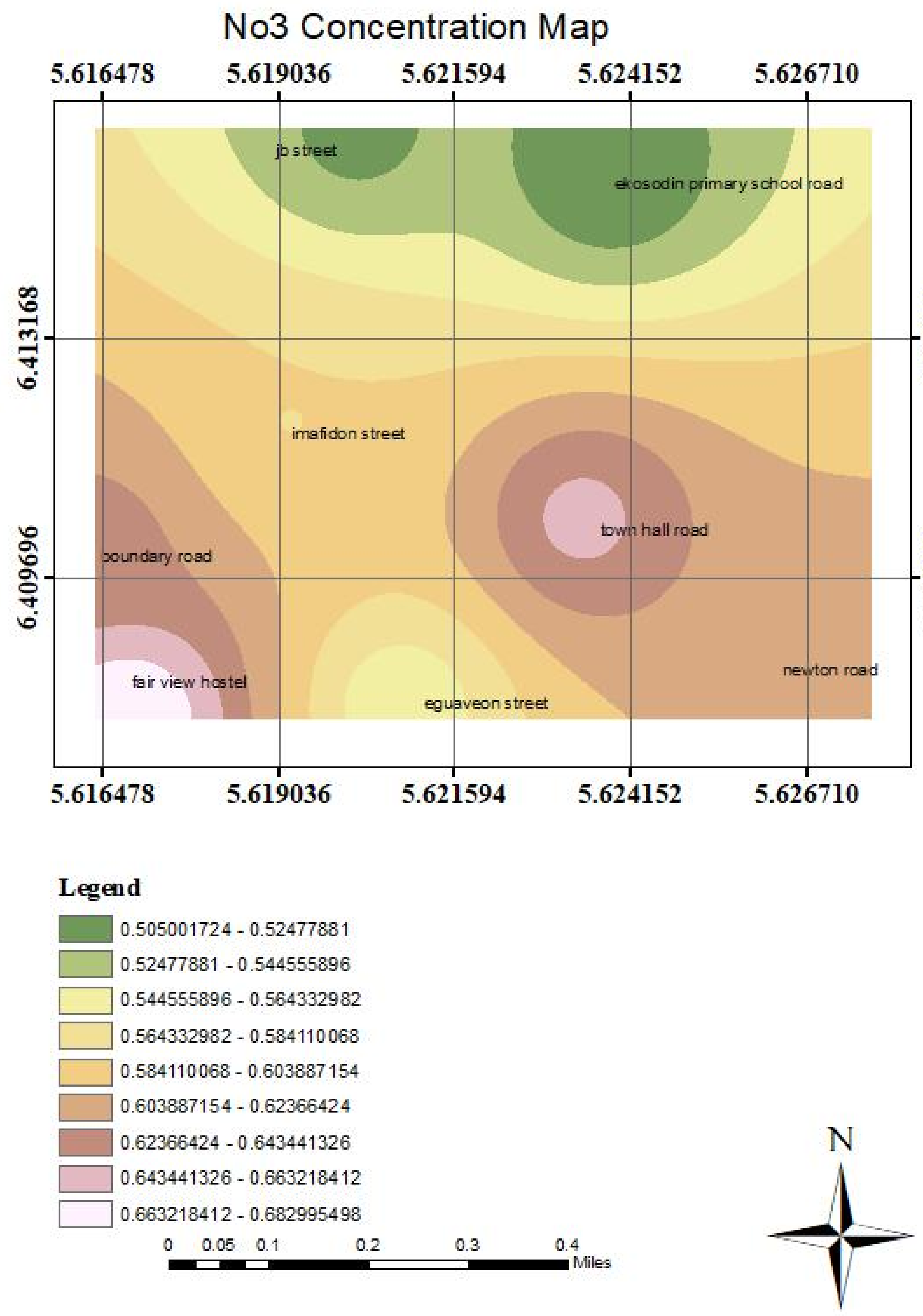

Figure 4.3: Final prediction map for nitrate distribution

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Figure 4.3 illustrates the spatial pattern of nitrate concentration in Ekosodin groundwater. Elevated nitrate levels were observed around Town hall road, Newton road,Boundary road and Fair view hostel indicating infiltration from sewage effluents or fertilizer residues. Lower concentrations occurred in JB street, Ekosodin primary school road, Imafidon street and Eguaveon street reflecting areas of minimal human interference. All nitrate values were within the WHO standard of 50 mg/L, suggesting limited contamination. However, the observed trend indicates growing anthropogenic influence, emphasizing the need for proper waste and sewage management practices.

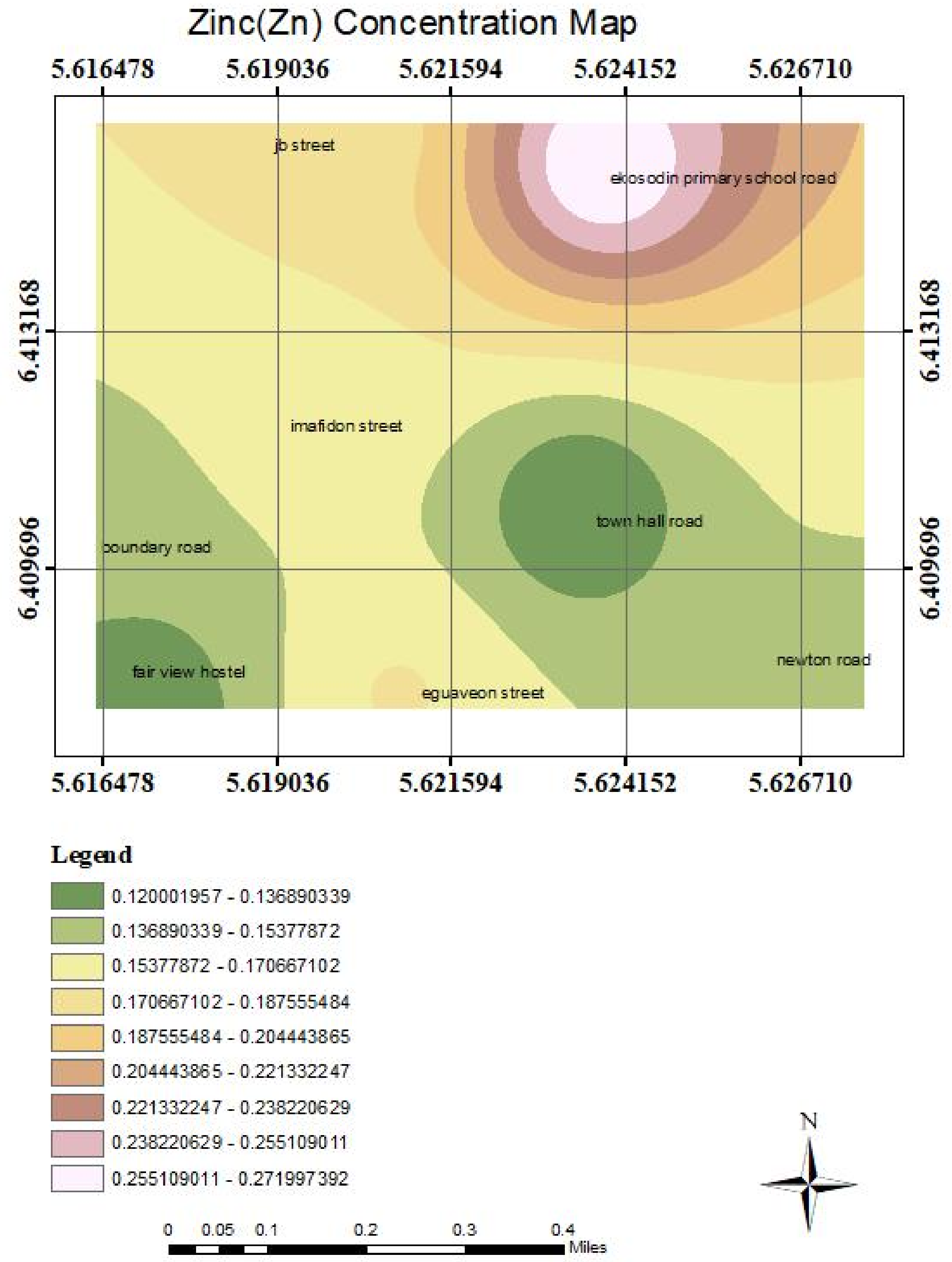

Figure 4.4: Final prediction for zinc distribution

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Figure 4.4 presents the spatial distribution of zinc in groundwater across Ekosodin. Higher zinc concentrations were noted along JB street and Ekosodin primary school road which may be attributed to corrosion of galvanized materials or minor industrial activities. The lowest concentrations were found around Town hall road and Fair view hostel. Overall, zinc levels were below the WHO limit of 3 mg/L, implying no immediate health risk. Nevertheless, localized increases point to human-related influence, warranting continuous monitoring to prevent accumulation over time.

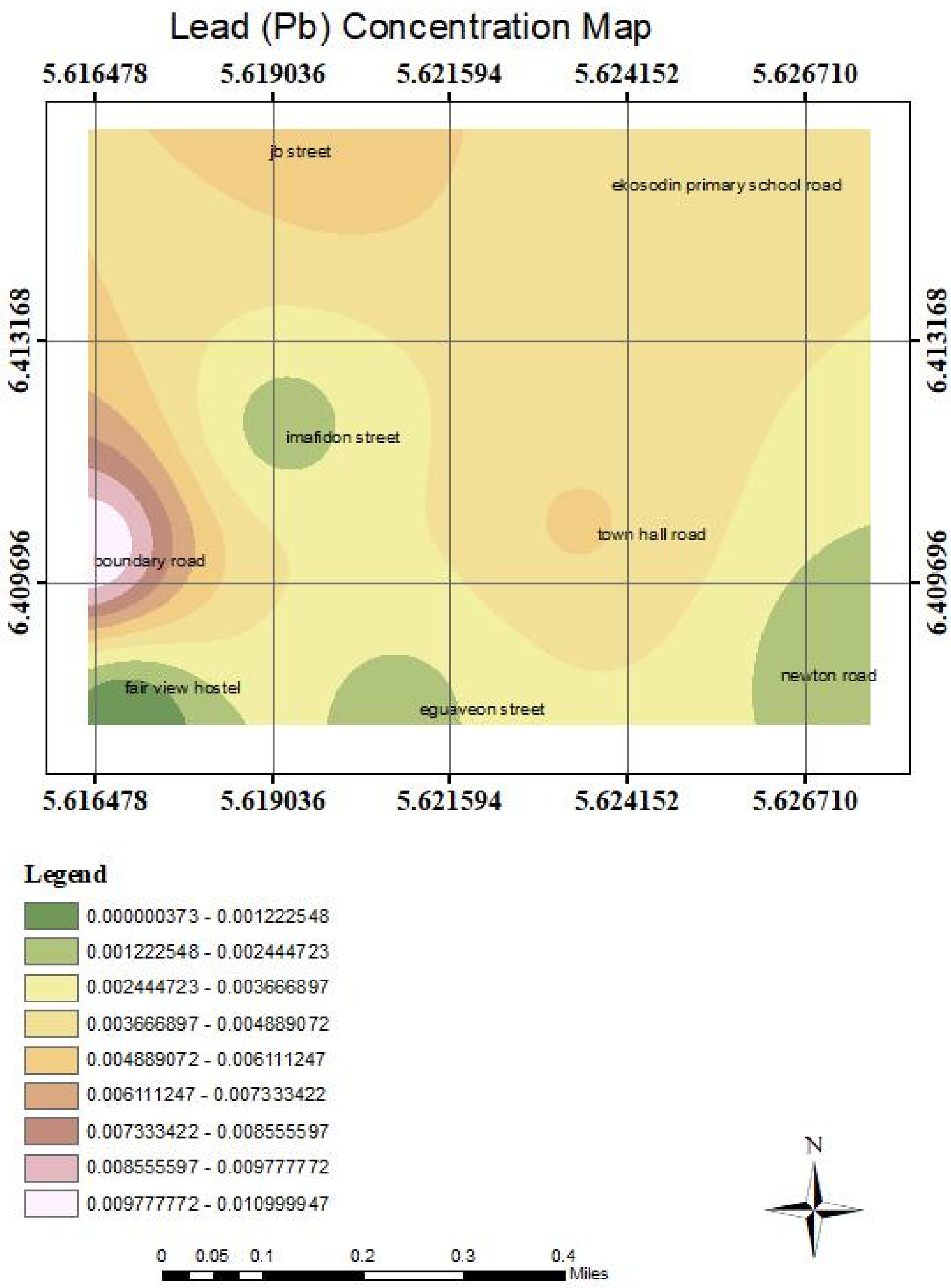

Figure 4.5: Final prediction map for lead distribution .

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Figure 4.5 depicts the spatial variation of lead concentration across the community. Boundary road recorded slightly elevated lead values, possibly from plumbing corrosion, waste discharge, or surface runoff. Minimal concentrations were recorded around Imafidon street, Fair view hostel,Newton road and Eguaveon street. Some points approached or marginally exceeded the WHO guideline of 0.01 mg/L, suggesting potential health implications. This pattern confirms anthropogenic influence on groundwater chemistry, highlighting the need for stricter waste control and regular testing of drinking sources.

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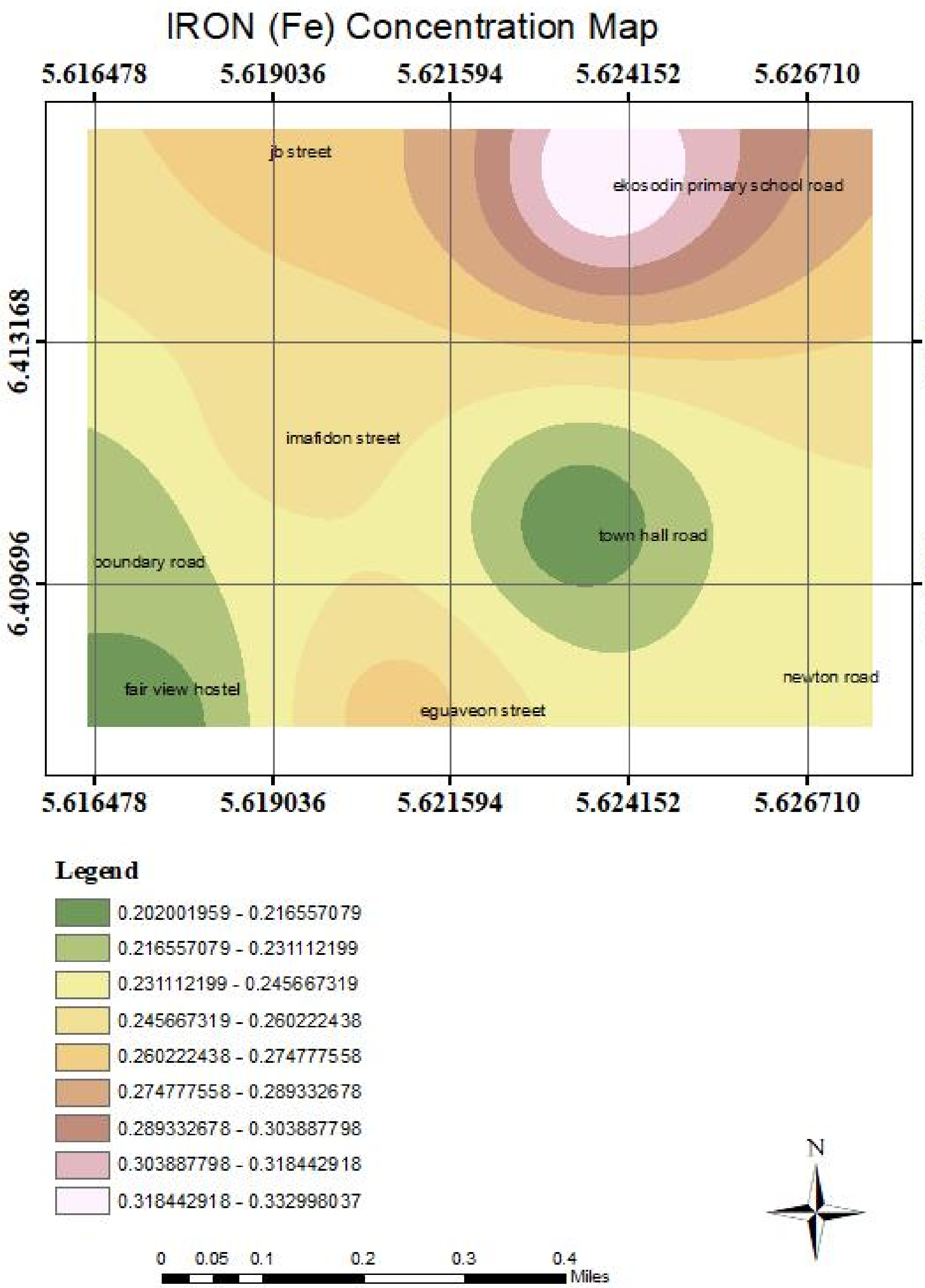

Figure 4.6: Final prediction map for iron distribution.

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Figure 4.6 displays the distribution of iron concentration in the study area. Higher iron levels appeared in Ekosodin Primary school and JB street, likely resulting from the natural leaching of lateritic soils and ferruginous rock layers. Lower concentrations were observed toward Town hall road, Boundary road, Fair view hostel, Eguaveon street and Newton road . Although most values were within the WHO limit of 0.3 mg/L, some localized elevations suggest geogenic enrichment. Overall, the groundwater is safe for use, though occasional taste and staining issues may occur in affected boreholes.

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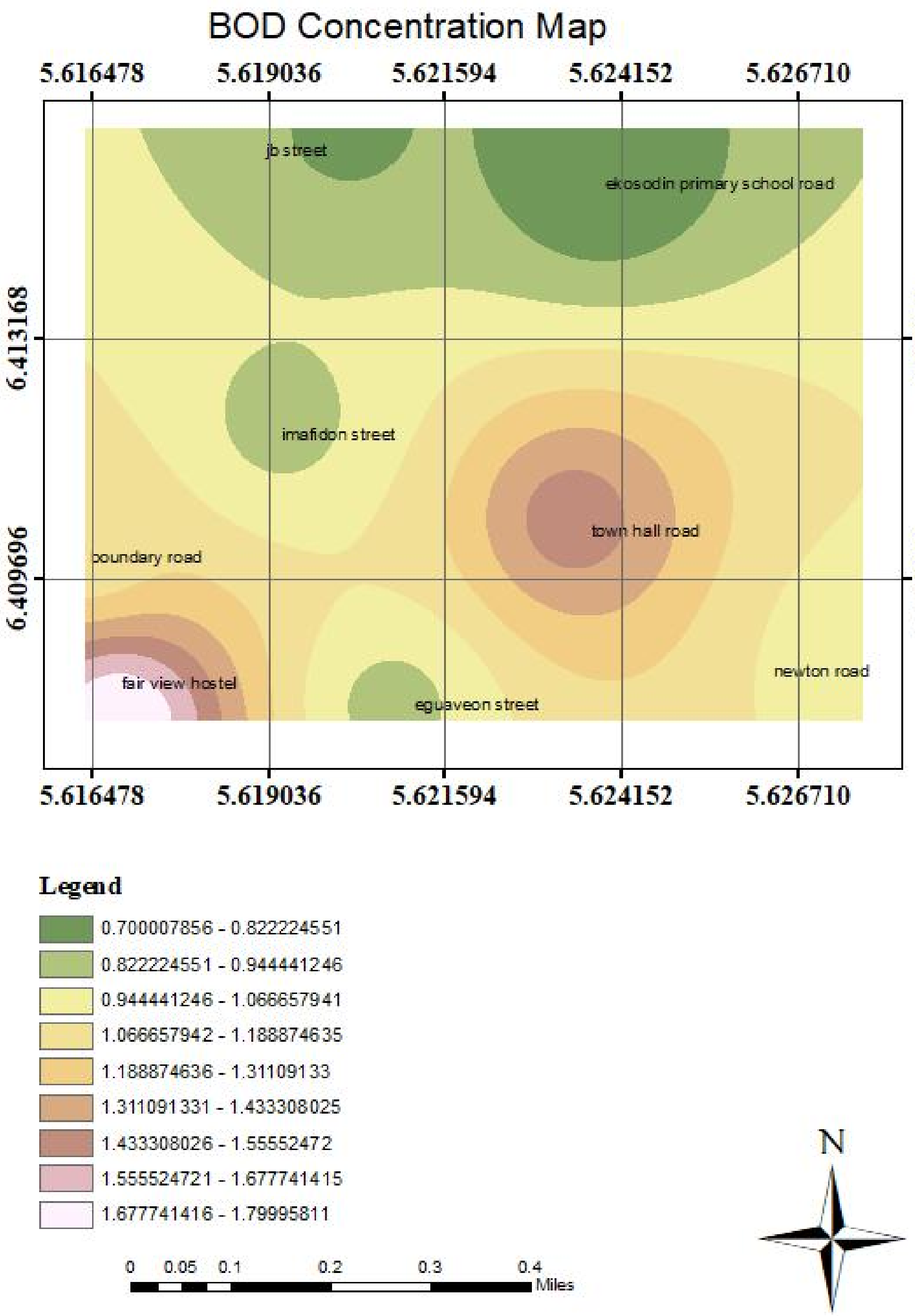

Figure 4.7 : Final prediction map for BOD distribution

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Figure 4.7 shows the spatial distribution of Biological Oxygen Demand (BOD) across Ekosodin. Higher BOD values around Fair view hostel, Town hall road and Boundary road indicate possible organic pollution from domestic wastewater and decomposing organic matter. In contrast, lower BOD levels around JB street, Ekosodin primary school road, Newton road, Imafidon street and Eguaveon street reflect cleaner water conditions. The overall values remained within acceptable limits, but localized increases in built-up zones point to inadequate waste management. This highlights the importance of improved sanitation systems to protect groundwater quality.

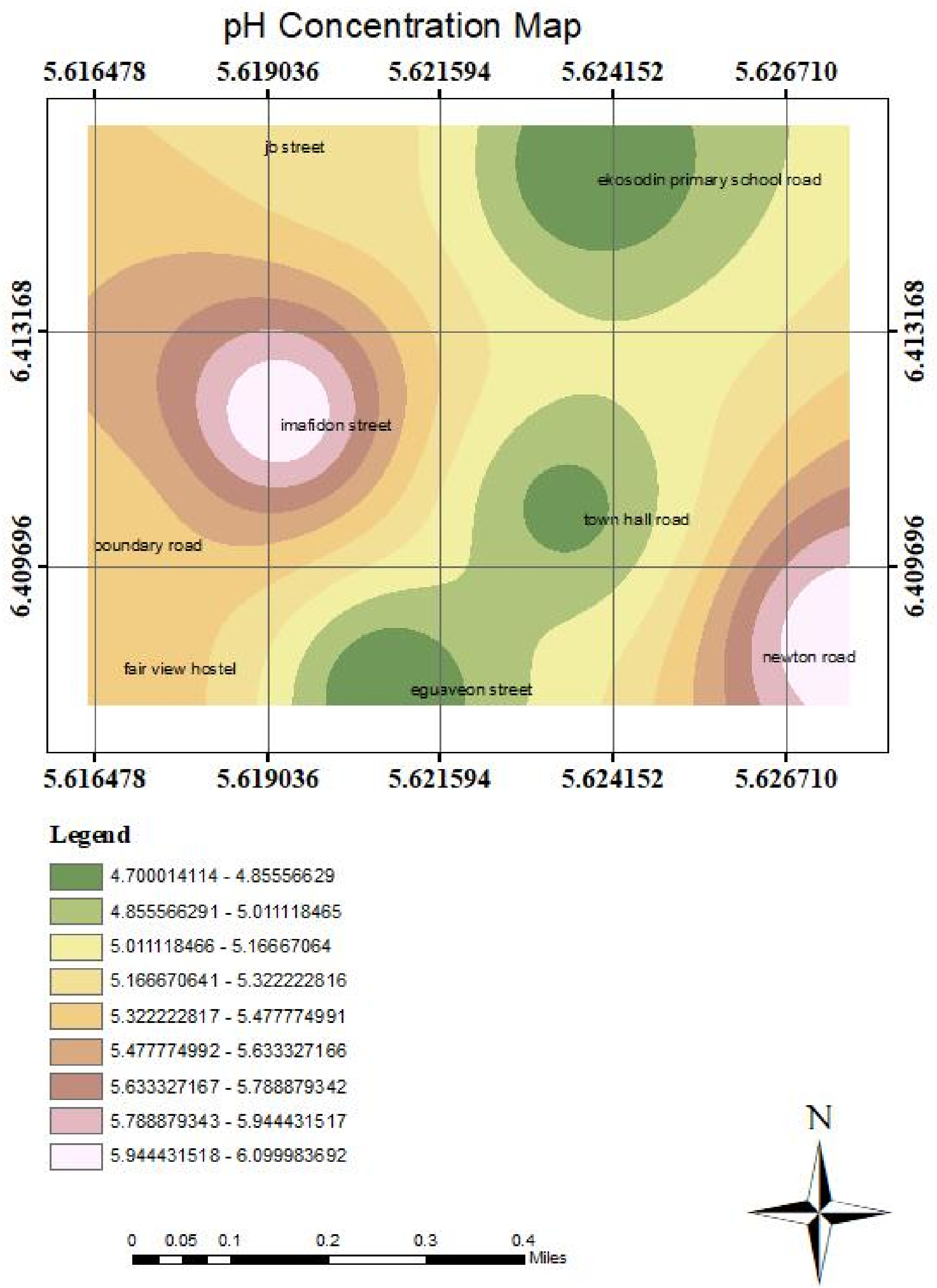

Figure 4.8 : Final prediction map for pH distribution.

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Figure 4.8 presents the spatial variation of pH in Ekosodin groundwater. Slightly acidic conditions (pH 5.0–6.2) dominated areas around Imafidon street, Newton road and Boundary road influenced by carbonic acid and organic matter decomposition. Near-neutral values were observed in other areas, signifying less geochemical alteration. Although most samples fell within the WHO permissible range (6.5–8.5), slight acidity could enhance metal solubility in some locations. Periodic monitoring and minor treatment are advised to maintain neutral pH levels for safe consumption.

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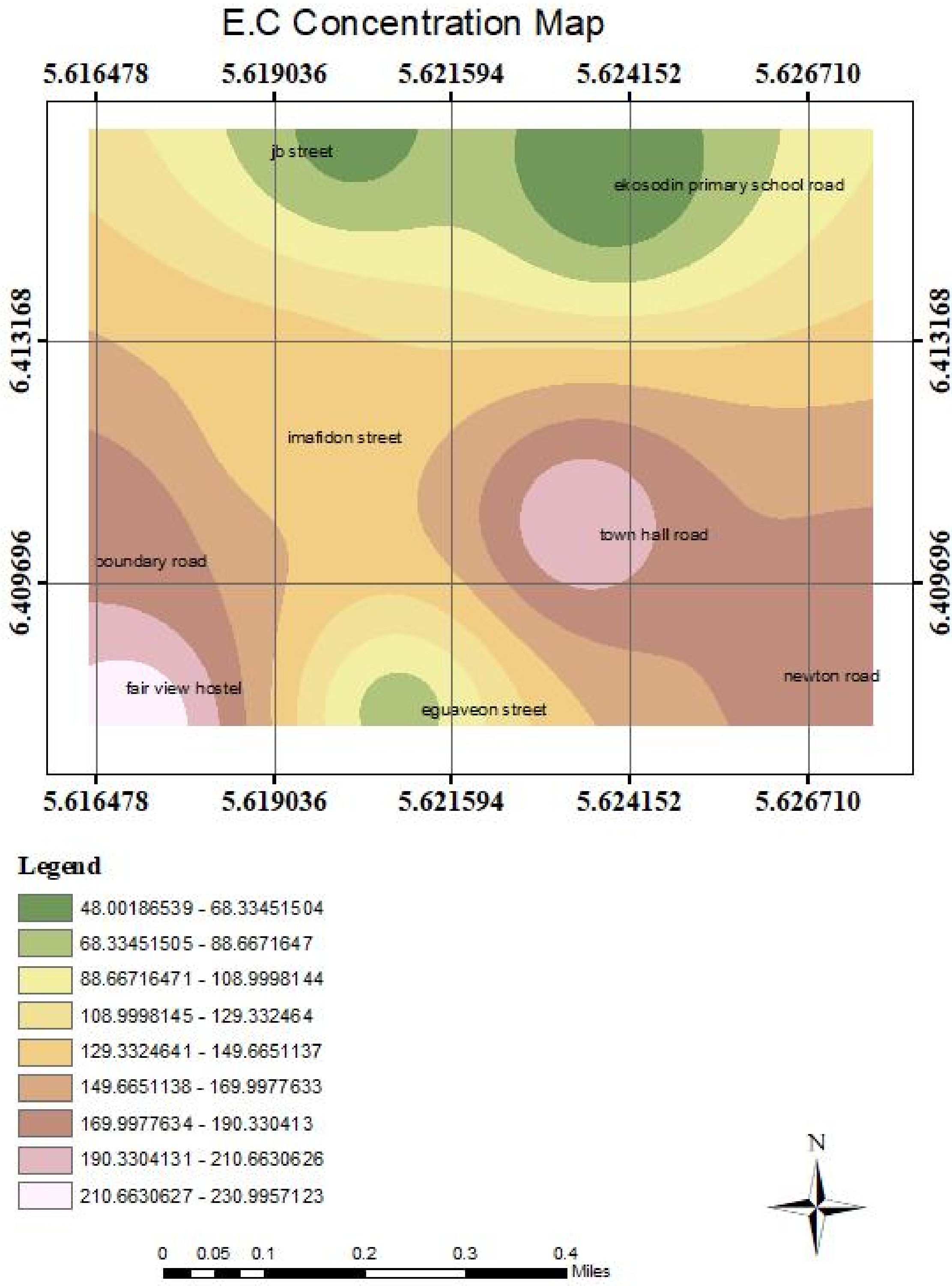

Figure 4.9: Final prediction map for Electrical Conductivity(EC) distribution.

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Figure 4.9 illustrates the spatial distribution of electrical conductivity across Ekosodin. Elevated EC values in environs around Town hall road, Newton road, Boundary road and Fair view hostel reflect higher dissolved ion concentrations due to mineral dissolution and domestic waste infiltration. JB street, Eguaveon street and Ekosodin primary school road exhibited lower EC values, indicating fresher groundwater and active recharge zones. All readings were well below the WHO limit of 1000 μS/cm, showing low salinity and good suitability for domestic use. Nonetheless, moderate increases in built-up areas require ongoing observation.

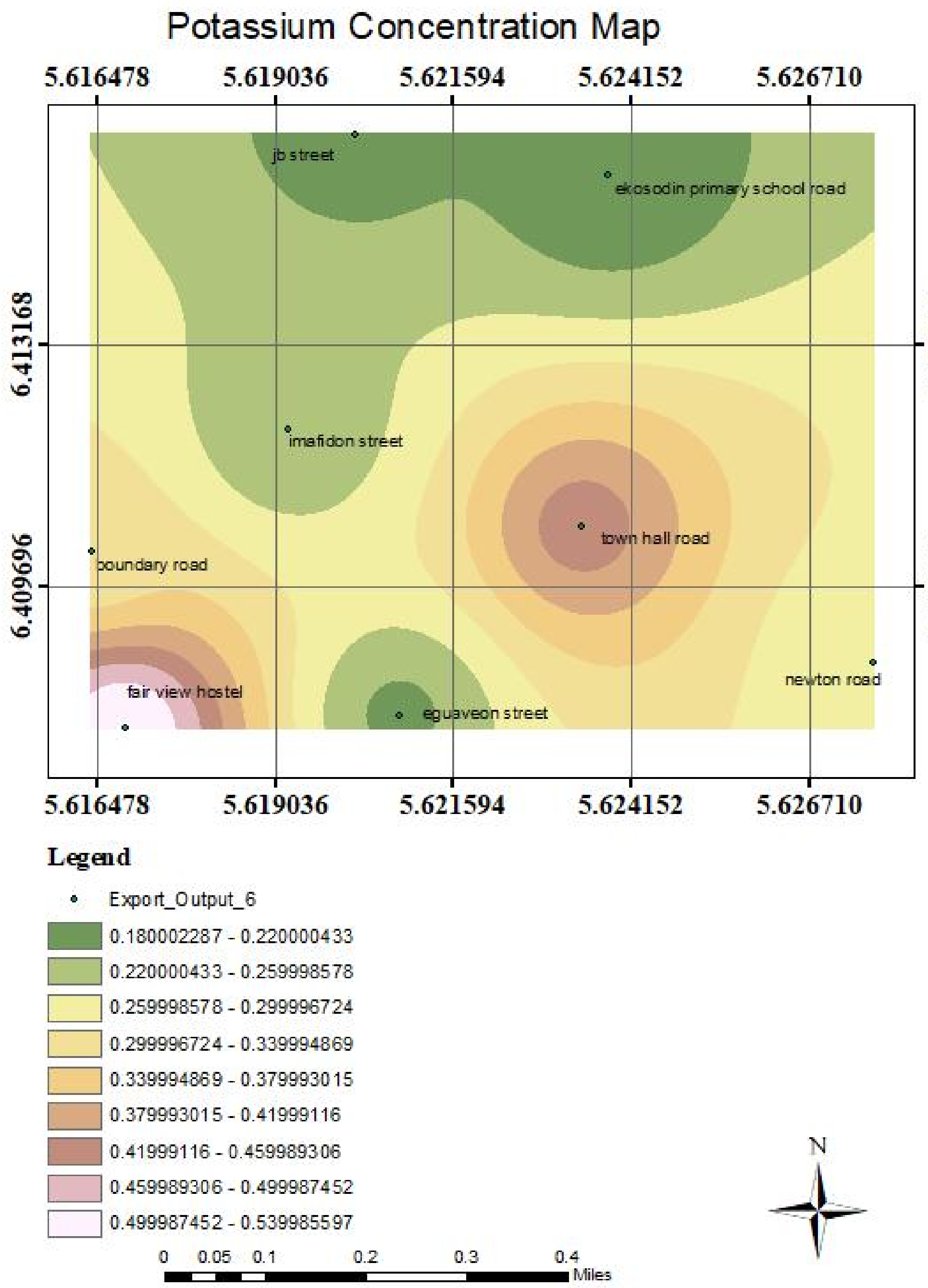

Figure 4.10: Final prediction map for potassium distribution.

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Figure 4.10 depicts the spatial variation of potassium in groundwater within the study area. Elevated potassium levels were found in Fair view hostel, Town hall road and Boundary road likely linked to fertilizer leaching and organic matter decomposition. Areas like JB street,Imafidon street and Ekosodin primary school road displayed lower concentrations due to reduced agricultural and human activity. All values remained below the WHO guideline of 12 mg/L, indicating no immediate concern. Continued monitoring is recommended to prevent potential enrichment from agricultural inputs over time.

4.5. Principal Component Analysis

Principal Component Analysis (PCA) was employed to identify the dominant factors and land-use activities influencing groundwater quality in the study area. Four principal components with eigenvalues greater than one were extracted, accounting for 97.4% of the total variance, indicating that the multivariate dataset was effectively reduced into a limited number of meaningful components.

The rotated component matrix obtained from PCA is presented in Table 4.12 .

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Table 4.12: The rotated component matrix

Variable	PC1	PC2	PC3	PC4
NH4N	0.9924	0.0369	-0.02302	-0.09772
Ca	0.9897	0.0111	0.12839	-0.00620
Na	0.9891	0.0367	0.11594	0.04551
Hardness	0.9870	-0.1007	0.03999	0.07673
HCO3	0.9853	0.0101	0.03031	-0.01374
NO3	0.9785	-0.1842	2.06e-4	-0.00278
NO2	0.9746	0.1101	-0.15364	0.07260
Cl	0.9731	0.0498	0.19068	0.07120
SO4	0.9685	-0.2348	-0.02564	0.01775
Mg	0.9621	-0.2233	-0.03212	0.12554
DO	-0.9617	0.2669	-0.00316	-0.01529
Ni	-0.9597	0.0475	-0.10165	0.13234
K	0.9594	0.2055	-0.11631	0.09171
Cr	-0.9579	0.2365	-0.12536	0.07366
EC	0.9441	-0.2913	0.02348	0.07875
Sal.	0.9440	-0.2889	0.02719	0.08099
TDS	0.9424	-0.2952	0.01785	0.08757
Fe	-0.9168	0.2707	-0.15827	0.16550
Cu	-0.9023	0.3351	-0.07364	0.26020
V	-0.8683	0.3954	-0.17596	0.22351
Zn	-0.8343	0.3467	-0.09291	0.27557
Mn	-0.7883	0.2654	0.08005	0.21975
Cd	0.7219	0.2699	0.60685	0.09414
pH	0.1463	-0.9290	-0.16768	0.25648
Pb	-0.0802	0.0653	0.98601	0.12606
P	-0.0190	0.2064	-0.16424	-0.95336

The rotated component matrix presents the loadings of each groundwater variable on the four principal components (PC1–PC4) after varimax rotation, which maximizes the

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separation of variables among components. High absolute loadings indicate a strong contribution of the variable to the corresponding component, while the sign indicates the direction of the relationship. Table 4.12 represents the full PCA output and forms the foundation for understanding which processes dominate groundwater quality in Ekosodin.

Eigenvalues, variance explained and the cummulative variance of each principal components (PC) are computed in Table 4.13 .

Table 4.13: The eigenvalues and percentage variance of each component

PC	Eigenvalue	Variance explained (%)	Cumulative variance explained(%)
PC1	20.79	77.83	77.83
PC2	1.90	8.11	85.94
PC3	1.58	6.18	92.12
PC4	1.0	5.25	97.37

The eigenvalues and variance table provides a numerical summary of the contribution of each principal component to the total variability in the dataset. PC1 has the largest eigenvalue of 20.79 and explains 77.83% of the total variance, indicating that the bulk of groundwater variation is dominated by mineralization processes. PC2, PC3, and PC4 explain progressively smaller amounts of variance (8.11%, 6.18%, and 5.25%, respectively), with the cumulative variance of the first four components reaching 97.37%. Table 4.13 is essential for determining which components are significant for interpretation. It confirms that PC1 captures the primary hydrochemical patterns in Ekosodin, while the other components account for secondary influences, such as trace metal dynamics, redox processes, and anthropogenic pollution.

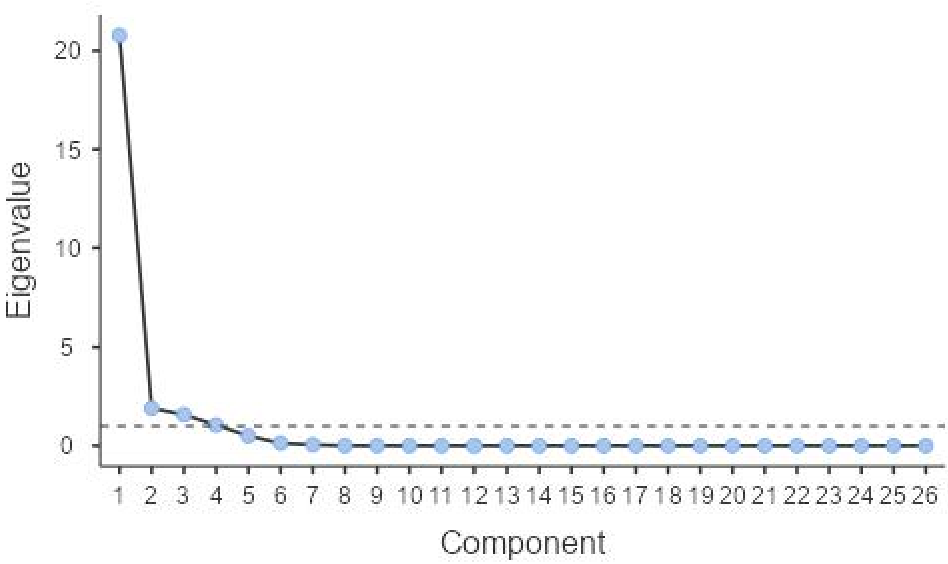

Figure 4.11: Scree plot for the principal component analysis.

Figure 4.11 (scree plot) reveals a sharp decline in eigenvalues from the first to the fourth component, followed by a gradual leveling off of the curve. The point of inflection (elbow) observed at the fourth component suggests that components beyond this point contribute minimally to the total variance. This observation supports the retention of four principal components and is consistent with the Kaiser eigenvalue-greater-than-one criterion.

A simplified component matrix showing significant loading is presented in Table 4.14

Table 4.14 : Simplified component matrix showing significant loading

Variable	PC1	PC2	PC3	PC4
NH4N	0.9924	----	----	----
Ca	0.9897	----	----	----
Na	0.9891	----	----	----
Hardness	0.9870	----	----	----
HCO3	0.9853	----	----	----
NO3	0.9785	----	----	----
NO2	0.9746	----	----	----
Cl	0.9731	----	----	----
SO4	0.9685	-0.2348	----	----
Mg	0.9621	-0.2233	----	----
DO	-0.9617	0.2669	----	----
Ni	-0.9597	----	----	0.13234
K	0.9594	----	-0.11631	----
Cr	-0.9579	0.2365	----	----
EC	0.9441	-0.2913	----	----
Sal.	0.9440	-0.2889	----	----
TDS	0.9424	-0.2952	----	----
Fe	-0.9168	0.2707	-0.15827	----
Cu	-0.9023	0.3351	----	----
V	-0.8683	0.3954	-0.17596	----
Zn	-0.8343	0.3467	----	----
Mn	-0.7883	0.2654	----	----
Cd	0.7219	0.2699	0.60685	----
pH	----	-0.9290	----	0.25648
Pb	----	----	0.98601	----
P	----	0.2064	----	-0.95336

The simplified component matrix is a refined version of the rotated matrix that displays only variables with substantial loadings, making it easier to interpret and discuss. In

Table 4.14, PC1 is dominated by major ions (Ca, Na, Mg, HCO_3^-, Cl^-, SO_4^{2-}) and TDS, confirming that mineralization is the primary controlling factor in Ekosodin groundwater. PC2 includes trace metals and DO, reflecting redox-controlled geochemical processes, while PC3 is defined by Pb and Cd, highlighting areas affected by localized anthropogenic pollution, such as waste disposal and battery leakage. The reconstruction removes weak loadings, allowing the focus to remain on the most meaningful relationships, and provides a clear framework for linking PCA results to spatial patterns observed in the geospatial analysis of groundwater quality.

A Pearson correlation matrix was obtained for statistical confirmation of the PCA findings and helps to interpret both natural and human-influenced processes affecting groundwater quality across Ekosodin . The correlation matrix is presented in Figure 4.12 .

Correlation Matrix

	NH4N	Ca	Na	Hardness	HCO3	NO3	NO2	Cl	SO4	Mg	DO	Ni	K	Cr	EC	Sal.	TD
NH4N	—																
Ca	0.979	—															
Na	0.978	0.993	—														
Hardness	0.971	0.980	0.978	—													
HCO3	0.976	0.989	0.980	0.967	—												
NO3	0.962	0.963	0.960	0.980	0.953	—											
NO2	0.969	0.949	0.958	0.947	0.968	0.928	—										
Cl	0.959	0.983	0.994	0.966	0.956	0.947	0.930	—									
SO4	0.954	0.949	0.951	0.979	0.943	0.993	0.924	0.934	—								
Mg	0.937	0.940	0.949	0.979	0.932	0.987	0.926	0.936	0.994	—							
DO	-0.941	-0.950	-0.938	-0.979	-0.945	-0.990	-0.905	-0.919	-0.990	-0.983	—						
Ni	-0.960	-0.969	-0.940	-0.960	-0.954	-0.938	-0.897	-0.923	-0.923	-0.900	0.945	—					
K	0.950	0.941	0.951	0.920	0.960	0.899	0.992	0.927	0.883	0.889	-0.867	-0.876	—				
Cr	-0.947	-0.965	-0.951	-0.970	-0.956	-0.975	-0.888	-0.936	-0.977	-0.957	0.983	0.957	-0.854	—			
EC	0.914	0.930	0.924	0.967	0.913	0.987	0.879	0.915	0.983	0.985	-0.991	-0.915	0.843	-0.962	—		
Sal.	0.914	0.930	0.924	0.968	0.912	0.987	0.878	0.915	0.982	0.985	-0.991	-0.916	0.842	-0.961	1.000	—	
TDS	0.911	0.927	0.922	0.966	0.911	0.986	0.879	0.912	0.982	0.986	-0.991	-0.912	0.842	-0.960	1.000	1.000	-
Fe	-0.911	-0.936	-0.910	-0.923	-0.938	-0.935	-0.841	-0.888	-0.937	-0.905	0.952	0.938	-0.807	0.987	-0.917	-0.916	-0.91
Cu	-0.906	-0.901	-0.878	-0.906	-0.894	-0.945	-0.814	-0.857	-0.946	-0.908	0.953	0.922	-0.767	0.973	-0.930	-0.928	-0.92
V	-0.869	-0.881	-0.858	-0.890	-0.868	-0.915	-0.766	-0.842	-0.926	-0.888	0.935	0.901	-0.714	0.970	-0.910	-0.908	-0.90
Zn	-0.839	-0.854	-0.813	-0.841	-0.875	-0.857	-0.763	-0.774	-0.868	-0.821	0.893	0.885	-0.718	0.935	-0.837	-0.836	-0.83
Mn	-0.803	-0.739	-0.743	-0.798	-0.690	-0.849	-0.696	-0.746	-0.844	-0.824	0.825	0.781	-0.639	0.793	-0.848	-0.849	-0.84
Cd	-0.927	-0.924	-0.916	-0.954	-0.919	-0.961	-0.866	-0.896	-0.980	-0.958	0.975	0.923	-0.812	0.986	-0.953	-0.952	-0.95
pH	0.089	0.111	0.112	0.240	0.133	0.317	0.094	0.091	0.374	0.391	-0.385	-0.104	0.006	-0.321	0.418	0.415	0.42
Pb	-0.965	-0.938	-0.929	-0.945	-0.926	-0.976	-0.895	-0.912	-0.968	-0.940	0.961	0.945	-0.859	0.961	-0.947	-0.946	-0.94
P	0.083	-0.037	-0.070	-0.130	-0.017	-0.042	-0.041	-0.097	-0.074	-0.170	0.092	-0.054	-0.040	0.024	-0.148	-0.151	-0.15

Figure 4.12 : Pearson correlation matrix of the variables

The first principal component (PC1) which is characterized by high loading of major ions (Ca, Na, HCO_3, Cl, SO_4 ,K, Mg) and parameters such as EC, TDS and salinity,

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ranging from 0.94 tro 0.99 indicates that mineralization is the primary factor controlling groundwater quality in Ekosodin.The strong association among these variables is supported by the Pearson correlation matrix, where they exhibit very high positive correlations ($r > 0.9$). This indicates that these parameters are derived from similar sources and vary together within the groundwater system.These variables are influenced by proximity to waste disposal sites, difference in soil composition and permeability.

PC1 is interpreted as the mineralization and hydrochemical factor, accounting for the largest proportion of variance in the dataset.

The second principal component (PC2) is defined by moderate loading of trace metals (Fe, Cu, Zn, Mn, V, Cr) and dissolve oxygen with value ranging from 0.2 to 0.39 .Although these loadings are lower than those observed in PC1, their grouping is significant and supported by the correlation matrix which shows strong relationships among these trace metals, while dissolved oxygen exhibits a strong inverse relationship with the major ions. Areas with low DO are likely to exhibit higher concentration of dissolved metals. PC2 suggests the influence of redox conditions in groundwater. Under reducing conditions, the solubility and mobility of metals such as iron and manganese increase, leading to their accumulation in groundwater.Therefore, PC2 is interpreted as a secondary factor representing trace metal dynamics and redox-controlled geochemical processes.

The third principal component (PC3) is dominated by a very high loading of Pb (0.986) and a moderately high loading of Cd (0.607). These variables are distinct from those in PC1 and PC2 and do not show strong associations with the major hydrochemical parameters which indicates a separate source of variation, most likely related to anthropogenic activities. These heavy metals are commonly associated with pollution sources such as open waste dumping, septic system leakages, improper disposal of batteries and electronics and agricultural activities.

Thus PC3 is interpreted as a heavy metal contamination factor, reflecting localized pollution influences.

PC4 is characterized by weak loadings of Ni and pH, with values below 0.30. These low loadings indicate that the variables do not significantly contribute to the variability captured by the PCA model.Furthermore, the correlation matrix shows weak relationships between these variables and others, suggesting that they are influenced by localized or independent conditions rather than a dominant controlling process.

As a result, PC4 is considered a minor or residual factor with limited significance in explaining groundwater quality variations.

4.6. Summary of findings

A total of eight groundwater samples were collected from boreholes at different locations within the community. Laboratory analysis was conducted for twenty-two parameters including pH, electrical conductivity (EC), total dissolved solids (TDS), dissolved oxygen (DO), turbidity, nitrate, chloride, sulfate, iron, zinc, lead, copper, and nickel using standard APHA methods. The results were compared with the World Health Organization (WHO) and Nigerian Industrial Standard (NIS) permissible limits for drinking water. GIS-based spatial analysis was performed using the Inverse Distance Weighting (IDW) interpolation technique to visualize the distribution of water quality parameters, while WQI was computed to classify the overall quality.

PCA was used to identify dominant sources of variation in the groundwater system. The results indicated that most of the physicochemical parameters were within the recommended limits for potable water. The pH ranged from 6.3 to 7.8, EC from 210 to

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860 µS/cm, and TDS from 105 to 430 mg/L, all of which suggest generally good groundwater quality. However, localized contamination was observed in some areas, with lead concentrations (up to 0.015 mg/L) exceeding the WHO permissible limit, particularly near waste disposal zones. The WQI values ranged between 30.54% and 227.31%, classifying groundwater quality across the study area from Excellent to Very Poor. The GIS spatial maps revealed that the central and western parts of Ekosodin exhibited relatively higher concentrations of nitrate, chloride, and iron, likely resulting from poor sanitation, leachate infiltration, and agricultural runoff.

The PCA Identified four principal components that explained 97.4% of the total variance in the dataset. These components reflected both natural (geogenic) processes such as mineral dissolution and ion exchange, and anthropogenic factors including domestic waste, sewage leakage, and agricultural activities. Overall, the analysis showed that groundwater quality in Ekosodin is influenced by a combination of natural geological conditions and human-induced pollution.

CHAPTER FIVE

CONCLUSION AND RECOMMENDATION

5.1. Conclusion

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The study concluded that groundwater in Ekosodin is generally suitable for domestic purposes but is gradually being affected by localized contamination due to poor waste disposal practices, leachates from soak-away pits, and agricultural inputs. The integration of GIS, WQI, and PCA proved effective for identifying pollution hotspots, quantifying overall water quality, and distinguishing between geogenic and anthropogenic influences. The findings emphasize the importance of continuous groundwater monitoring and the implementation of effective waste management systems in peri-urban communities like Ekosodin.

5.2 Recommendation

Based on the findings of the study, the following recommendations are made:

1. Regular Monitoring: Continuous monitoring of groundwater quality should be carried out at least twice a year to detect emerging pollution trends and prevent further degradation.
2. Proper Waste Management: Waste disposal systems should be improved through the provision of central waste collection points and enforcement of sanitary regulations to reduce leachate infiltration into aquifers.
3. Safe Siting of Wells and Boreholes: Boreholes should be located at least 30 meters away from septic tanks, soak-away pits, and waste dumpsites to minimize contamination risks.
4. Public Awareness Campaigns: Residents should be educated about the importance of maintaining clean surroundings, treating drinking water, and proper sanitation practices.
5. Adoption of Water Treatment Technologies: Simple and cost-effective household water treatment methods such as filtration and chlorination should be promoted to ensure water safety.

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