DEVELOPMENT OF VULNERABILITY INDEX OF GROUND WATER BASED RURAL DRINKING WATER SUPPLY SYSTEM

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by

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February 2025

Dedicated to my father

LATE KANDARPA KR. GOSWAMI

and

my beloved family members

Indian Institute of Technology Guwahati
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STATEMENT

I do hereby declare that the content in the thesis entitled "**DEVELOPMENT OF VULNERABILITY INDEX OF GROUND WATER BASED RURAL DRINKING WATER SUPPLY SYSTEM**" is the result of investigation carried out by me at Department of Civil Engineering, Indian Institute of Technology Guwahati, Guwahati, India under the guidance of **Prof. Rajib Kumar Bhattacharjya**.

In keeping with the general practice of reporting scientific observations, due acknowledgements have been made wherever the work described is based on the findings of others investigators.

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CERTIFICATE

This is to certify that the work described in this thesis entitled "**DEVELOPMENT OF VULNERABILITY INDEX OF GROUND WATER BASED RURAL DRINKING WATER SUPPLY SYSTEM**" by **Mr. Jayanta Goswami (Roll No. 156104021)** for the award of **Doctoral of Philosophy** is an authentic record of the results obtained from the research work carried out under my supervision in the Department of Civil Engineering, Indian Institute of Technology Guwahati, Guwahati, Assam, India and this work has not been submitted elsewhere for a degree.

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ABSTRACT

Water is an integral component of all living organisms. Around 70% of the earth is covered with water but only 1% is usable for human consumption. Drinking water is the water which is safe to drink as to use for food preparation without risk of health problems. In urban areas in India, generally drinking water is supplied through surface and groundwater-based water supply schemes. But, for rural areas, it mainly comes from groundwater. Groundwater plays a crucial role in the country in increasing food and agricultural production, providing drinking water and facilitating industrial development. Due to rapid urbanization of developing country like India, the quantity as well as quality of ground water is affected due to excessive withdrawal of groundwater and waste disposal. According to WHO report, about 80% of the diseases in human beings are caused by lack of pure drinking water. So, it is the need of the hour to monitor quality of groundwater regularly to avoid ways and means to protect it. Moreover, the groundwater has been depleted in many parts of the country due to unplanned and over exploitation of groundwater. So, it is utmost important to have proper planning and management of this precise resource. Otherwise, a majority of the people of an area may face decline of agricultural productivity and deficiency of drinking water, which lead to wide spread socio-economic stresses. So, the primary factors responsible for vulnerability of groundwater-based drinking water supply systems are the water quality of the supplied water and ground water fluctuations. Moreover, vulnerability is also related to social factors such as age, literacy, economic status', asset value, and accessibility to drinking water sources. As such, the study considers the water quality, groundwater fluctuations along with the social factors to provide a composite social vulnerability index of groundwater-based drinking water supply systems. The district wise water quality data for the state of Assam, India has been collected from Assam Public Health Engineering Department, Government of Assam. The WQI values evaluated for all census districts using the 2011 census can be broadly categorized as either good or poor. The results show that out of 27 districts in Assam, 10 districts supply poor quality water, while 17 districts supply good quality water. The primary contaminants responsible for poor water quality are Iron and, in some areas, Magnese. The presence of arsenic and fluoride in certain districts necessitates advanced treatment methods such as reverse osmosis. The groundwater level data for the period of 2016-2022 are taken from the Groundwater monitoring wells of CGWB. Linear regression is applied using GRACE data and IMD rainfall as inputs, with groundwater level as the output, to establish a relationship that is then used to estimate groundwater levels. Time-series analysis from 2002 onward reveals a general trend of ground water depletion across all districts indicating a long-term increase in drinking water vulnerability. Socio-economic factors influencing drinking water vulnerability such as age, literacy, income, asset ownership, and water accessibility are calculated from the 2011 census of India data. Dibrugarh district has found the highest number of accessible water sources, while Dima Hasao has the lowest. Goalpara district has the highest proportion of children aged 0-6 years and the lowest literacy rate, making it highly vulnerable. Kamrup metropolitan district has the lowest proportion of young children and the highest literacy rate, reducing its vulnerability. On the other hand, Kamrup district scores highest in asset and economic factors, while Dhubri district has the lowest asset factor and Karbi Anglong has the lowest economic factor. The weight for the parameters is obtained as per the opinion survey conducted among the experts. The results of the composite vulnerability index calculations show that four districts have high vulnerability value, one district is in medium vulnerability range and the other districts are in a very low to low vulnerability level. The high value of vulnerability level in the districts are mainly due to high value of age factor and low value of asset factor, literacy factor, and economic factor.

Keywords:

Socio-economic factors, Composite Vulnerability Index, and Groundwater fluctuations

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LIST OF ABBREVIATIONS

IMD	Indian Meteorological Department
WQI	Water Quality Index
WHO	World Health Organization
UNDP	United Nations Development Program
GRACE	Gravity Recovery and Climate Experiment
GWS	Ground Water System
RO	Reverse Osmosis
APHED	Assam Public Health Engineering Department
CGWB	Central Ground Water Board
DCMG	Department of Community Medicine, Guwahati, Assam
LULC	Land Use Land Cover
BIS	Bureau of Indian Standards

Chapter – 1

INTRODUCTION

1.1 GENERAL

Water is one of the most fundamental resources for life on Earth, yet its true value is often realized only in its scarcity (Fuller, 1732). The sustainable development of human civilization has always been intricately linked to water in all its forms. Historically, surface water has been the primary source of consumption, but as it flows through various landscapes, it becomes susceptible to contamination. The consequences of consuming polluted water have been severe, leading to widespread health crises. Access to clean water is not merely a matter of convenience but a necessity for survival, as humans can only live for a few days without it. Beyond its role in sustaining life, adequate water intake is also crucial for preventing diseases, with studies suggesting that drinking sufficient amounts can reduce the risk of breast, colon, and bladder cancer (Freedrinkingwater.com). However, despite technological advancements, waterborne illnesses remain a leading cause of mortality, particularly in developing nations (Jones and Watkins, 1985). Alarmingly, approximately 1.1 billion people worldwide still lack access to safe drinking water, underscoring the urgency of addressing this crisis (UNDP, 2006).

Many countries rely heavily on groundwater as a resource. People began to use groundwater because of its unique nature and government and international initiatives. Moreover, insufficient availability of surface water makes people dependent on groundwater resources to fulfill their needs. Globally, it is the largest source of freshwater. A large percentage of people require potable water solely from groundwater (Bates, Kundzewicz, and Wu 2008). Since it passes through multiple soil layers, it is filtered and cleaned of many contaminants, making it the safest form of water. In light of population growth, scarcity of water, and unplanned water use, groundwater zones are becoming increasingly important as a source of fresh water. The scenario has further worsened in the agricultural sector due to rapid extension of agriculture since 1950s, and this has led to agriculture becoming the main user of freshwater (Bridget R Scanlon et al. 2007). Globally and in particular in north-west India, groundwater resources are being depleted at an alarming rate (Georgakakos and Graham 2008; Xu et al. 2012; Bhat et al. 2019; Avtar Singh Jasrotia et al. 2019; Haque et al. 2020; Sood et al. 2020; D. Kumar et al. 2021). A more dependent groundwater system can cause the water table to drop continuously due to a rapid consumption of groundwater relative to its natural replacement (Gleeson et al. 2010; Famiglietti 2014). Despite this, there is still uncertainty about the balance between natural water renewal and current rates of groundwater depletion (Gleeson et al. 2012). In other words, water demand, minimum daily consumption of water, planning for water resources, and groundwater depletion are all issues that are of concern around the world. To provide adequate amounts of water to all citizens both now and in the future, quantifying groundwater resources is a challenging task in densely populated regions of the globe.

Human health is directly influenced by groundwater quality. While the use of groundwater has protected many from waterborne diseases, its continuous and unregulated extraction in certain regions has led to severe issues such as arsenic poisoning and fluorosis. Additionally, rapid urbanization has exacerbated groundwater contamination through over-exploitation and improper waste disposal, further threatening both its availability and quality. In today's world, assessing groundwater quality is crucial for ensuring public health and environmental sustainability. Poor water quality increases the vulnerability of drinking water sources, making effective monitoring and management essential.

Water quality describes the physical, chemical, biologic, and aesthetic properties of water that are responsible for determining its purity, wholesomeness, potability, fitness for use, as well as its ability to maintain aquatic ecosystem health. Additionally, water quality refers to its chemical, physical, and biological properties, usually in terms of its suitability for a particular purpose. Depending on the intended use of water, water quality can be subjective (Joshi and Seth 2011). Water quality index estimate the exact quality of water based on the chemical analysis of water. Chemical analysis provides some numerical values that indicate the physical and chemical composition of water, but the water quality index gives a concept of its exact composition. As a result, the water quality index is one of the most effective tools to inform citizens and policy makers about water quality (D. F. Singh 1992; Mishra and Patel 2001; Naik and Purohit 2001).

A review of the literature indicates that the Water Quality Index (WQI) has been widely studied and reported by various researchers using different estimation methods. Among these, the Weighted Arithmetic Water Quality Index Method has been extensively applied due to its systematic approach in evaluating water quality. This method assigns weights to different water quality parameters based on their relative significance for drinking water purposes. However, conventional WQI calculations may not always provide a comprehensive representation of the actual water quality status. To address this limitation, this study proposes a modified approach for WQI assessment, incorporating the drinking water quality standards recommended by the Bureau of Indian Standards (BIS). In the proposed method, a threshold value is assigned when a parameter's concentration falls within the permissible limit. If a parameter exceeds this threshold, it indicates that its concentration surpasses the acceptable limit. To better reflect the severity of contamination, a linear weighting approach is applied beyond the permissible range, ensuring a more accurate assessment of water quality.

Initially, both the conventional and the newly proposed methods for Water Quality Index (WQI) assessment were applied to Kamrup district, Assam, India, as the study area. Water samples were collected from public water supply schemes across different blocks of the district and analyzed for twelve key parameters, including iron, alkalinity, turbidity, calcium, total dissolved solids, chloride, fluoride, total hardness, nitrate, pH, manganese, and magnesium. In the first phase, WQI values were calculated using the Weighted Arithmetic Water Quality Index Method, where parameter weights were assigned based on literature reviews. However, the computed WQI values did not accurately reflect the actual quality of the supplied water. To refine the weighting approach, an opinion survey was conducted among medical professionals from the Department of Community Medicine, Guwahati (DCMG), Assam, India. The doctors assigned risk-based ratings ranging from 1 to 10 for each parameter based on their impact on human health. Using these survey data, relative weights were recalculated, and WQI values were reassessed. Yet, even with these adjustments, the results did not fully align with the real field conditions. To address this gap, the newly proposed method was applied to evaluate block-wise WQI values, which provided a more accurate representation of the actual water quality in the region. Extending this approach, WQI values were further evaluated for all census districts based on the 2011 census. District-wise water quality data for 2019 and 2020 were obtained from the Assam Public Health Engineering Department, Government of Assam. The average parameter values for each district were considered in the final WQI calculations to ensure a comprehensive and reliable assessment of water quality across the region.

Building on the previous assessment, an online water survey was conducted to further evaluate the drinking water quality and supply status across Assam. The main objectives of this survey were to assess the availability and adequacy of drinking water sources throughout the region, as well as to evaluate the quality of supplied water and identify the presence of contaminants such as iron, fluoride, and arsenic. In addition, the survey aimed to gather public perceptions regarding water contamination and its potential health risks. It also sought to provide a detailed understanding of water quality variations in different census districts of Assam. By addressing these objectives, the survey complemented the earlier WQI evaluations and offered valuable insights into both the quantity and quality of drinking water, helping to identify areas that require intervention and improvement.

Socio-economic factors such as age, literacy, economic status, asset value, and water accessibility significantly influence the vulnerability of drinking water sources. These factors, available through census data, directly and indirectly affect the quality and availability of water. Childhood, in particular, is one of the most vulnerable stages of life, as children rely heavily on others for their basic needs and decision-making, making them particularly susceptible to water-related risks. Education plays a key role in shaping vulnerability, as it can directly impact risk perceptions, skills, and knowledge. Indirectly, education improves health, facilitates access to information, and fosters a sense of community. Studies have shown that individuals and communities with higher education levels are better prepared for and respond more effectively to disasters, experiencing fewer negative effects and recovering more quickly (Cutter, Boruff, and Shirley, 2012). Income also acts as a protective factor, as wealthier individuals are better able to absorb and recover from the impacts of disasters. A healthy asset base and greater economic status enhance resilience to the adverse effects of hazards. Additionally, when water sources are easily accessible, the vulnerability of drinking water is significantly reduced, ensuring better protection against water-related health risks.

A review of the literature reveals that no studies have been conducted thus far to develop a composite vulnerability index for drinking water that considers both water quality and socio-economic factors as indicators. To address this gap, a composite vulnerability index was calculated using the proposed formula, which incorporates the impact of various parameters on drinking water vulnerability. Initially, this index was applied to Kamrup district, Assam, India, to derive block-wise vulnerability index values. The block-wise Water Quality Index (WQI) values and relevant WQI factors were evaluated, while socio-economic factors were derived from the 2011 Census of India data. Using the proposed formula, the block-wise vulnerability index values were calculated, allowing the categorization of blocks into high, medium, low, and very low vulnerability levels with respect to drinking water.

In addition, groundwater storage changes, also referred to as groundwater fluctuations, play a crucial role in assessing vulnerability to groundwater-based drinking water sources. Negative fluctuations in groundwater levels can significantly increase vulnerability, while positive fluctuations may reduce it, thus further influencing the overall vulnerability index.

Quantifying groundwater storage changes requires dense networks of in-situ data and a solid understanding of subsurface hydrology (H. Chen et al., 2019). Groundwater monitoring through wells is a time-consuming, costly, and labor-intensive process. Monitoring wells are unevenly distributed, subsurface properties are complex, and groundwater recharge processes add further difficulty to the assessment. Due to the sparse density of groundwater observation wells, data on groundwater variability is limited on a large scale (Tapley et al., 2004a; Famiglietti and Rodell, 2013). However, continuous monitoring of the Earth's gravity field through the joint US-German GRACE satellite mission (Gravity Recovery and Climate Experiment) has helped track groundwater storage changes on a global scale. For example, GRACE was utilized in North-West India to monitor changes in the global hotspot depletion (V. M. Tiwari, Wahr, and Swenson, 2009a; B.R. Scanlon, Longuevergne, and Long, 2012).

The temporal fluctuations in groundwater were analyzed using GRACE data alongside IMD rainfall data. A linear model was proposed to examine the relationship between groundwater (GW) levels, GRACE values for the current time step, and rainfall data for the current month and the previous time step. Thiessen polygons were generated using QGIS software around the grid points of both datasets, representing the districts in Assam, India, based on the 2011 Census. The size of each district's area was used to assign weights to the grid points, and weighted averages were calculated for each district using both GRACE and IMD rainfall data.

Due to the limited availability of groundwater level data, K-means clustering was applied to group districts. A linear model was then used to explore the relationship between groundwater levels, GRACE values for the current month, and rainfall data for both the current and previous months. Since GRACE data for 2017 was unavailable and groundwater data before 2017 contained substantial missing values, model training began in 2018. Using 70% of the data for training and 30% for testing, the model was fitted for each cluster, with the accuracy assessed using the coefficient of determination (R^2). The equations derived from these linear models were then used to generate time series data for groundwater levels in each district starting from 2002. Trendlines were fitted to the groundwater time series for each district to analyze long-term trends, illustrating the direction and rate of change in groundwater levels over the study period. The slopes of these trendlines were used to compare groundwater trends across the state.

After incorporating groundwater fluctuations as an indicator in the vulnerability index calculation, the socio-economic factor values for all census districts of Assam were evaluated using the same procedure as in Kamrup district. With the district-wise WQI values, socio-economic factors, and groundwater fluctuations, the composite vulnerability index values were recalculated. As a result, districts were categorized as having high, medium, low, or very low vulnerability. This methodology can be applied to any other region to evaluate composite vulnerability.

1.2 OBJECTIVES OF THE THESIS

In recent years, there has been significant research on the potential for contamination in drinking water and groundwater-based drinking water systems, as well as studies on the vulnerability of groundwater and aquifers. Additionally, vulnerability studies focusing on water security systems and the socio-economic factors influencing vulnerability to natural hazards have been conducted globally. However, no study to date has integrated groundwater fluctuations, water quality, and socio-economic factors in calculating the vulnerability of groundwater-based drinking water systems.

In light of these gaps, the current study aims to achieve the following objectives:

- To propose an index for assessing the vulnerability of groundwater-based rural drinking water supply systems.
- To identify the key parameters to be used in the vulnerability index.
- To recommend measures for improving the index for more accurate and comprehensive vulnerability assessment.

1.3 RESEARCH QUESTIONS

The research questions for this study are as follows:

- What are the key indicators to be considered for evaluating vulnerability index values of groundwater-based drinking water systems?
- How do groundwater fluctuations (both positive and negative) impact the calculation of vulnerability index values?
- What is the effect of water quality on the vulnerability index values?
- How do socio-economic factors influence the vulnerability index values?
- What effective measures can be implemented to reduce the vulnerability level of groundwater-based drinking water systems?

1.4 ORGANIZATION OF THE THESIS

The thesis consists of eight chapters, including an introductory chapter. In **Chapter 2**, a review of relevant works from various researchers around the world is discussed in detail. In-situ groundwater observation wells and GRACE data are used to assess groundwater fluctuations, as well as the concept of vulnerability and the construction of a vulnerability index.

Chapter 3 discusses various methods for evaluating water quality index values. The weighted arithmetic water Quality Index method is used to evaluate WQI values in Kamrup district, Assam, India. A weightage obtained from the Opinion Survey conducted among the doctors is also used to evaluate the WQI values. Finally, the new proposed method reflects actual field conditions for evaluating the WQI values of samples.

Chapter 4 assesses the groundwater quality in each district of Assam, India, since the study area has been extended to cover all census districts in 2011. Each district-level laboratory in Assam provides groundwater quality data to the Assam Public Health Engineering Department, Government, for 2019-2020. In the following step, the new method is used to evaluate district WQI values.

Chapter 5 discusses the assessment of drinking water quality and supply in Assam through online water survey during the year 2020. Stress has been given both in quantity and quality of drinking water sources with a particular focus on the prevalence of contaminants such as iron, fluoride and arsenic. A total of 2470 responses were received from the households located throughout Assam.

Chapter 6 calculates the vulnerability index values for the blocks. Based on the new proposed method of evaluating WQI values as well as the socioeconomic factors values calculated based on the 2011 census of India. These values are for community development blocks in Kamrup district, Assam, India.

Chapter 7 discusses evaluation of temporal groundwater fluctuations in Assam using Grace data and ground- based observations. Composite vulnerability index values are evaluated using the WQI factor, groundwater fluctuation and the socio-economic factors.

Chapter 8 summary, conclusions and recommendations for future work.

LITERATURE REVIEW

2.1 GENERAL

The term vulnerability refers to both the risk of an incident occurring and the liability being assumed by society and the economy. It also refers to the ability to cope with the incident if it occurs. Vulnerability is a measure of how vulnerable a system is to hazards, according to Adger, 2006 and Proag, 2014. Since the late 1980s, it has been widely practiced to estimate social vulnerability indexes based on multiple variables. There are several pioneers who have contributed to the development and implementation of social vulnerability indexes, including (Blaikie and Brookfield 2015; Chambers 1989; Dahl 1991; Cutter 1996a; Blaikie et al. 2014a; 2014b; Mileti 1999; Morrow 1999; King and MacGregor 2000; Cutter 1996b). A vulnerability assessment is used in hydrogeology to evaluate whether an aquifer, water well, or water table is susceptible to contaminants that may negatively affect the quality of the water. In addition to raising public awareness about groundwater protection issues, vulnerability assessments work as powerful educational tools (Nowlan 2005).

Among the basic elements that sustain life and the natural environment, water is one of the most important. Water covers roughly 70% of this global village, but only 1% of it can be consumed by humans. Ideally, human-drinking water will be sterile and free of contaminants, but it will also contain essential minerals. Despite this, a clear and colorless sample of water without any taste or odor does not guarantee its purity and safety for drinking. As a result of the increase in population, modern civilization, and the fast-paced growth of industrial units, freshwater resources are degrading at a rapid rate. In many parts of the world, surface water is an important source of drinking water, yet groundwater is the most significant and safest. Despite being considered one of the most important and safe sources of drinking water in rural and urban areas, groundwater supplies only 0.9% of the total water resources on earth. Increasing water demand over the past few decades has increased groundwater depletion globally (Konikow 2011; Wada et al. 2010). A conflict in water quantity and quality has resulted from the increasing global demand for water (Global Water Partners, 2012). All report (Asoka et al. 2017; Bhanja et al. 2016; 2017) ground water depletion in some parts of India (J. Chen et al. 2016; V. M. Tiwari, Wahr, and Swenson 2009a; Panda and Wahr 2016). Drinking water supply is thus critically affected by groundwater depletion and fluctuations. Furthermore, the quality of water should be considered a top priority since it is important for human consumption at its most basic level. As water consumption per capita is an indicator of quality of life as well as economic and social status of the people, it relates closely to the health and happiness of the human race. The world's population can survive on fresh or good water quality provided they consume it with care. According to various researchers (Olayinka et al. 1999a; Foster et al. 2000; Chidambaram et al. 2008a), the quality of groundwater is dependent on the kinds of soils and rocks present on the pathway of groundwater saturation zone. Further, industrial, commercial, agricultural, and other anthropogenic activities together with natural conditions often deteriorate groundwater quality (Foster et al. 2003a; Nair et al. 2015a). In today's world, environmental protection agencies have become increasingly concerned with monitoring water quality. Per capita fresh water availability is decreasing at an alarming rate due to increasing demand from constant limited potable water resources. Groundwater-based drinking water has become more vulnerable as a result of both quantity and quality factors. Drinking water will be more vulnerable to contamination with higher groundwater fluctuations. As noted above, a high-water quality index value indicates poor water quality, thus indicating a higher vulnerability.

There are many social factors that affect the vulnerability of drinking water, including children up to the age of 6 (Six), literacy rate, economic condition, available water sources, and the type of assets. A census district level version of these variables is available. It is generally accepted that childhood is the most vulnerable time in a person's life. Behaviors that reduce vulnerability can be influenced by education. When it comes to economic conditions and asset values relating to vulnerability, income is regarded as a protective factor that aids victims in recovering from disasters and high asset values reduce vulnerability. Having access to water sources within and near premises reduces the level of vulnerability.

An overview of the literature related to groundwater-based drinking water vulnerability is presented in this chapter. According to the work, the literature review can be divided into three categories.

- Concept of vulnerability and construction of composite social vulnerability index.
- Water Quality Index (WQI) and Groundwater fluctuations.

2.2 CONCEPT OF VULNERABILITY AND CONSTRUCTION OF VULNERABILITY INDEX

Vulnerability has been used throughout many fields and disciplines as well as within disaster research. The term vulnerability has been defined several times over the past few decades. Although vulnerability has numerous applications in various fields, perhaps there is no precise definition. According to report (Cutter 1996a), there are 18 different definitions of vulnerability, ranging from the degree to which different classes of society are differentially exposed to natural disasters to the cost and benefits associated with living in disaster-prone areas. According to Lewis, 1999, vulnerability is the root cause of disasters (Gabor and Griffith 1979) and vulnerability is the context for risk (Lewis 1999). There are no adequate strategies to prepare, adapt, and mitigate natural hazards in developing countries. In the formulation of disaster risk reduction strategies, social vulnerability to natural hazards has become an important topic. It has been shown by both theoretical research and field-based case studies that social vulnerability is a multifaceted phenomenon involving a variety of social system dimensions, including social, economic, cultural, institutional, structural, etc. (Cutter and Finch 2008; Aubrecht et al. 2013; Birkmann et al. 2013).

A policy tool based on indices began to be used in 1920 (Edgeworth 1925a; Dimand 1998). Sullivan, 2002, states that indices are a measure of a quantity compared to a base period. Indicators are the inherent characteristics of a system that provide quantitative estimates of its condition. Generally, social vulnerability indexes are measured using two approaches. Inductive and deductive approaches are both used. Based on the relationships established by theories and conceptual frameworks, deductive approaches select indicators, whereas inductive approaches use statistical procedures to identify factors that have statistical significance based on a large number of variables and vulnerability. A household's vulnerability to natural hazards can be assessed or a district's vulnerability can be assessed depending on the data available. To create composite vulnerability indices, key vulnerability indicators should be selected with caution. Here are some well-known vulnerability indexes based on selection criteria and natural hazards.

The climate vulnerability index ranges from 0 to 1 (Sullivan 2002). There are six factors that contribute to the score: R-resources, A-access, C-capacity, U-usage, E-environment, G-geospatial, and w-relative weight.

$$\mathrm{CVI} = \frac{w_r R + w_a A + w_c C + w_u U + w_e E + w_g G}{w_r + w_a + w_c + w_u + w_e + w_g} \qquad 1$$

There are five major hazard types included in the Global Risk vulnerability index (UNEP, 2002): drought, floods, cyclones, volcanoes, and earthquakes. DRI (Disaster Risk Index) is derived from all available data and methods.

$$\mathrm{DRI} = \mathrm{Frequency} * \mathrm{Population} * \mathrm{Vulnerability} \qquad 2$$

Floods, earthquakes, cyclones, and droughts are the four hazards that constitute the Disaster Risk Index (UNDP, 2005).

$$\mathrm{In}\ (\mathrm{k}) = 0.78 \ln (\mathrm{Ph\ Exp}) - 0.45 \ln (\mathrm{GDP\ cap}) - 1.5 \ln (\mathrm{D}) - 5.22 \qquad 3$$

According to the following formula, K = Number of people who die in flooding, P Exp = Number of people who are exposed to flooding on average, and D = Density of the population. A measure of how vulnerable the shore is to changes due to sea level rise has been devised by Gornitz and Kanciruk (1999) by relating six variables in a measurable way.

$$\mathrm{CVI} = \left(\frac{abcdef}{6}\right)^{\frac{1}{2}} \qquad 4$$

in this equation, a = geomorphology, b = shoreline erosion, c = coastal slope, d = relative sea level, e = mean wave height, f = mean tide range

This study evaluates the composite social vulnerability index for groundwater-based rural drinking water supply by considering the socioeconomic factors as well as the quality of water and fluctuations in groundwater levels. Based on the above factors, no such studies have been found while reviewing the literature on composite social vulnerability indexes of rural drinking water supplies. The question of social vulnerability to environmental hazards has been explored by many authors and researchers around the world. In addition to drinking water contamination, groundwater aquifer vulnerabilities, etc. in different parts of the globe, some authors and researchers have worked on these issues as well.

According to (P. Das and Dey 2011a), flood-prone areas are socioeconomically viable. A village named Dud Patil (Part V) is located on the northern bank of Barak River in Cachar District of Assam, India. The socioeconomic situation of the area was determined by considering factors such as family size, gender ratio, the number of family members, the availability of drinking water, electricity, house types, and sanitation among others. According to the study, the most important factors contributing to flood vulnerability in rural areas are household income, access to pure drinking water, house types, latrine types, and the elderly population. In general, low vulnerability is correlated with high levels of infrastructure development, high literacy rates, and low agricultural gross domestic product (GDP) while the number of small-scale farmers, the dependence on rainfed agriculture, the extent of land degradation, and highly populated rural areas where agriculture is the main source of livelihood are associated with higher vulnerability (Gbetibouo and Ringler 2009).

When it comes to social vulnerability assessment, data constraint plays an important role and the results may differ depending on how many variables are included. In order to ensure precision and proper presentation of social vulnerability, a larger number of variables should be considered. Using district-level data, Gautam, 2017 examined the vulnerability of Nepal's social system to natural hazards. By using the census data available from all 75 districts, the study intends to quantify social vulnerability on a local scale. Data related to certain socioeconomic variables can only be obtained from the census in Nepal because the digital database is limited. Using only 13 variables in the study, the study is based on the 2011 Census. Summarizing the results, we find that the social vulnerability level of Western Mountain districts is very high to high. As a result, natural disasters are less likely to affect the eastern and central regions. Due to district-wide variations in social vulnerability to natural hazards, Nepal also needs decentralization in Preparedness, Response, and Recovery. According to Aksha et al., 2019, social vulnerability index methods were also adapted to Nepalese conditions in order to evaluate social vulnerability. As a reflection of the Nepali context, non-Nepali speaking/understanding populations were included.

Several studies have already examined the impacts of tropical cyclones from a technical and numerical perspective (Islam and Peterson 2008; Karim and Mimura 2008; Roy and Kovordányi 2012; Tasnim et al. 2015). In coastal Bangladesh, however, there is a lack of a comprehensive and comprehensive study on vulnerability factors and disaster mitigation measures. By identifying the vulnerability factors and examining disaster mitigation measures carried out by individuals, governments, and nongovernmental organizations in Bangladesh, (Hossain and Paul 2018a) examined the effectiveness of disaster mitigation measures. The authors conclude that disaster management and mitigation measures are crucial to ensuring the safety of coastal residents in Bangladesh. In Botswana, social vulnerability to natural hazards must be assessed before disaster risk reduction strategies can be developed. District social vulnerability index (DSVI) was developed using a total of 11 indicators, most of which are available in census districts. Study results suggest that social vulnerability is mainly determined by household size, disability, education, age, employment status, and level of poverty.

A variety of studies have been conducted regarding the vulnerability of drinking water by different authors and researchers. Drinking water comes primarily from groundwater. It is therefore of paramount importance to protect groundwater in industrialized countries. Scientists and resource managers have been searching for effective and efficient methods for protecting groundwater resources from contamination. As a result of activities near or at the land surface (NRC 1993), these areas are likely to be contaminated more frequently than others. In 1970, Taghavi et al., 2022 cited France as the first country to introduce the concept of groundwater vulnerability. As a result, other parties can develop management methods for protecting groundwater against surface pollutants based on recognition of sensitive areas where pollution may affect groundwater. In the meantime, groundwater vulnerability assessment has evolved into a variety of methods. According to Hoque et al., 2018, a complex three-dimensional groundwater vulnerability assessment system can be developed for assessing well vulnerability. An assessment of the groundwater vulnerability of the Rana groundwater basin was performed by Thakur et al., 2021. DRASTIC Parameters were rated and weighted according to new criteria in order to optimize the method. Water quality index values were used to validate DRASTIC and modified DRASTIC groundwater vulnerability results. There was a greater influence on groundwater vulnerability from groundwater level and net recharge. The poor management or untreated drinking water has caused many microbiological disease outbreaks around the world. To improve the safety of drinking water, a number of countries have developed strict and rigorous regulations. To rank drinking water systems (DWUS) based on their microbiological contamination vulnerability. Cool et al., 2010 proposed a multi-criteria analysis method. The province of Quebec, Canada, considered 28 groundwater-based drinking water systems for purposes of illustrating this approach. A number of studies have addressed the issue of drinking water contamination vulnerability, including Cool et al., 2010; Karamouz et al., 2017. The Design of Water Distribution Networks (DWDNs) is based on demand and water availability standards (Jia et al. 2019). Chemical and biological contaminants can affect these networks. (Ostfeld and Salomons 2004; Nwaiwu 2008). Distribution networks use chlorine primarily as a disinfectant. In an evaluation of DWDN response to biological and chemical contaminants in Tehran's eastern part, Karamouz et al., 2017 outlined a framework for evaluating the response of DWDN to biological and chemical contaminants. It is suggested that an index be developed to assess the vulnerability of the network based on its capability to satisfy demand with acceptable quality. In the proposed index, critical nodes are identified and performance in different scenarios can be compared, allowing for the identification of critical nodes. Also, residual chlorine plays an important role in contaminant decay and the assessment of DWDN's response. Cool et al., 2010 presented a methodology for assessing the risk of contamination for drinking water systems, particularly in rural agricultural areas. Groundwater and surface water quality may be degraded by changes in agricultural practices (Conboy and Goss 2000; X. Wang 2006). There are four barriers that need to be addressed: Source susceptibility to contamination, treatment efficiency, distribution system management, and overall quality management. 39 rural Quebec water systems were examined using the developed method. It is possible to use the model obtained for prioritizing water systems that need to be improved for planning purposes. Furthermore, Di Cristo et al., 2015 proposed a method of performing a vulnerability analysis in water distribution systems, using a criterion that estimates the amounts of trihalomethanes in the water and the amount of pathogenic risk for consumers. In terms of the types of exposures considered, the results show that the factor analysis identifies vulnerable nodes. The vulnerability of drinking water can be measured multidimensionally by Hughes, 2022. These methods are applied to cities within the Great Lakes region that have more than 50,000 residents, using composite indices. In this study, 105 cities in the region were evaluated for their drinking water vulnerability based on publicly available data. Violations of the Save Drinking Water Act are associated with these vulnerability index measures.

2.3 WATER QUALITY INDEX (WQI)

It is becoming increasingly important for countries to ensure that their drinking water is safe, given the concern that fresh water will become scarce in the future. As the most basic need for human consumption, water quality should be given priority. World's population can survive on fresh or good water quality provided they consume it wisely. In order to determine whether or not groundwater is suitable for human consumption, its quality must be evaluated. The individual chemical parameters of water are generally compared with the recommended allowable limits set by water engineering professionals. A concentration slightly above the allowable limit may also be acceptable in some areas with scarce water resources. Akoteyon et al., 2011 and Rao et al., 2010 both acknowledge that the use of individual quality parameters to describe water quality is not easily understood by the general public (Rao et al. 2010). By combining water quality data into a single value (Semiromi et al. 2011a), the water quality index (WQI) can be used to express data in a logical and simplified manner. A water's WQI value determines whether the water is good, poor, very poor, or unusable. Before human consumption, some treatments may be required if the water is of poor quality or very poor quality. Therefore, drinking water vulnerability is calculated using the Water Quality Index.

According to Horton, 1965, the WQI considers 10 different most commonly used parameters, for example, Dissolved Oxygen (DO), PH, Coliforms, Specific Conductance, alkalinity, and chloride. In European, Asian, and African countries, this WQI is widely accepted and used. As time went on, (Backman et al. 1998) developed a similar WQI to Horton's index. In order to summarize technical information on the status and trends in the Great Lakes ecosystem, Steinhart et al. came up with a novel environmental quality index (Aubrecht et al. 2013). The WQI was developed by Bhargava in India, and the scale goes from 0 to 100, with 0 being extremely polluted and 100 being unpolluted (D S Bhargava 1983). Since then, different scientists and experts have modified the WQI concept (Devendra Swaroop Bhargava 1983; Dwivedi, Tiwari, and Bhargava 1997). WQI would help clarify the combinatorial effect of each parameter on drinking water quality, according to reports by the "World Health Organization (WHO)" in 2004. In addition to Weight Arithmetic Water Quality Indexes (WAWQIs), National Sanitation Foundation Water Quality Indexes (WSFWQIs), Canadian Council of Ministers of Environment (CCMEWQIs), and Oregon Water Quality Indexes (OWQIs), many other water quality metrics have also been developed. Several organizations have developed them. Water quality indicators (WQI) are used to assess water quality over a specific location (Lumb, Halliwell, and Sharma 2002; Chaturvedi and Bassin 2010a). As compared with the relevant standards for each region, these indices use a variety of parameters to determine water quality. However, from reviewing the literature, it appears that the available indices have numerous limitations and variations based on the variables used and are not accepted throughout the world (Bordalo, Nilsumranchit, and Chalermwat 2001). Weighted Arithmetic Water Quality Index is currently being used by many scientists (Chauhan and Singh 2010; Chowdhury, Muntasir, and Hossain 2012; Rao et al. 2010; Balan, Shivakumar, and Kumar 2012).

Researchers from different parts of the world have studied the use of Water Quality Index to quantify water quality. According to(Ramakrishnaiah, Sadashivaiah, and Ranganna 2009a), 19 numbers of water quality parameters are considered in calculating the Groundwater Quality Index (WQI) for Tumkurtaluk, Karnataka state, India. In order to determine the overall quality of water for drinking, each parameter has been given a weight based on its relative importance. Among the samples, the WQI ranged from 89.21 to 660.56. Among the reasons for the high value of WQI are the high level of iron, nitrate, total dissolved solids, hardness, fluorides, bicarbonate, and manganese in the groundwater. Furthermore, the pre-monsoon nitrate value was 0.4 to 261 ppm and post-monsoon nitrate value ranged from 0.35 to 149 ppm. Over-application of fertilizer, improper manure management, and improper septic system operation and maintenance are all factors that contribute to the high nitrate concentrations found in the rural part of the study area. Their conclusion was that it is important to treat the groundwater before consuming it as well as to protect it from contamination risks. According to Patil & Patil, 2013, Amalner, Maharashtra, has also been identified as a town with poor groundwater quality. A total of 15 physio-chemical parameters were measured in water samples collected from 5 sampling points. A weighting system has also been applied here based on the relative importance each parameter has in the overall quality of drinking water. In three locations, groundwater samples indicate good quality and suitable for drinking, while in two other locations, there are indications of poor water quality based on higher WQIs. The quality of groundwater can be improved by treating and disposing of effluent properly, and draining domestic and agricultural wastes properly. Research on groundwater for Water Quality Index evaluation has also been undertaken by other researchers, such as (Krishan and Chopra 2015; Krishan, Singh, and Tashi 2015; B. D. Das and Choudhary 2021; Ghoderao, Meshram, and Meshram 2022). Other researchers are also working on groundwater. All variables were used and their weights were the same.

Using another method, the Canadian Council of Ministers of the Environment Water Quality Index (CCMEWQI), M.G. Mhgamage et al. (2015) assessed groundwater quality in the Kelani River basin. For a river basin to provide safe drinking water, continuous monitoring of water quality and proper management are required. In contrast, Chandra et al., 2017 calculated unit weights for the parameters based on the proportionality constant "K" for the parameters. Accordingly, 10 physiochemical parameters of the collected water samples were used to evaluate WQI values in Vijayawada, Andhra Pradesh. Study results show that pollutant levels are higher after monsoon than before monsoon in current study area during 2014. Coastal areas are concerned about the quality of drinking water due to contamination from sea water. In 2020, Prusty & Farooq, 2020 studied the suitability of drinking and irrigation water in Odisha, India's eastern coastal plain. Water quality was significantly influenced by seawater. Additionally, they found that the area's drinkable and irrigational water is mostly confined to a few patches. WQI is more accurate and accurate assessment results are achieved with entropy weight. Ding SF and Shizz, 2005) first introduced Shannon's notion of information entropy as a measure of stochasticity or information content. The information entropy method was employed to assign weights to each parameter in Pengyang County, Ningxia, Northwest China (2010). Nearly 90% of the region's groundwater is of excellent quality, and it still needs protection and long-term monitoring in case of future rapid industrial development.

Different water quality indices are utilized to assess surface water quality. Several Water Quality Indices (WQIs) were reviewed by Poonam et al., 2013 in their assessment of surface water quality. A universally accepted general Water Quality Index is difficult to come up with. Water Quality Indexes may be developed for specific regions and sources, however. The WQI criteria for appropriate drinking water sources were reviewed by Tyagi et al., 2013. As part of the study, a simplified "Water Quality Index" was also emphasized and called for, in order to be used on a much larger scale and represent a reliable indicator of water quality. Furthermore, the study provides information about the composition and mathematical form of important indices used in water quality vulnerability assessment.

It is imperative that the groundwater quality for the state of Assam, India is reviewed since the research work will be focused on Assam. The groundwater in some places of Assam is contaminated with iron, fluoride, and arsenic. According to Chakraborti et al., 2004, arsenic was first detected in groundwater in Assam in 2004. To measure the concentration of arsenic in water samples collected from 192 blocks of 22 Assam districts during the period 2004-2005, UNICEF supported a survey conducted by the Assam Public Health Engineering department. In 18 districts, 72 blocks had groundwater contaminated by arsenic, and 6.3% samples had arsenic levels above 0.05 ppm Nickson et al., 2007. Karbi Anglong district in Assam has also reported the first fluorosis case. Bagpani's groundwater levels have been found to have a fluoride concentration of 8.02mg/L, and Nopak-Killing's level has been found to have a fluoride concentration of 14.36mg/L. According to Chakraborti et al., 2000 and Dutta, 2013, conducted a comprehensive statistical analysis of the water quality parameters in small tea gardens of Sonitpur district (Assam), India, for the assessment of drinking water quality. Because of the poor quality of the drinking water sources in the tea garden community, they concluded that those water sources are not safe to use. The community is concerned about the adverse health effects resulting from continuous and uncontrolled use of different chemicals in the tea gardens of the region. In order to monitor fluoride concentrations in Dibrugarh district's tea gardens and brick industry areas, Jitumoni, 2011 collected groundwater samples from different sites. Fluoride concentrations and other physiochemical characteristics were also tested. It is permissible to have fluoride levels between 0.0222 and 0.789mg/L, which is quite below the maximum level of 1.5mg/L. Additionally, some useful studies were done by Borah et al., 2010 and Chakrabarty & Sarma, 2011, etc. Various parts of Assam have different levels of groundwater quality.

2.4 GROUNDWATER FLUCTUATIONS

Human settlement and agricultural economy rely heavily on groundwater as a valuable resource. Water that accumulates as groundwater has to pass through many soil layers in order to be considered safe among all forms of water. Fresh water makes up only 3% of the total available water on earth. The earth's fresh water supply consists of 3%, out of which 2.15 percent is found in glaciers and ice caps, and 0.05% is found in rivers and lakes. As for the rest, it occurs as groundwater. There are approximately 1.5 to 2.8 billion people in rural areas who rely on groundwater for drinking purposes (Moris, 2003). Various parts of the country have experienced excessive groundwater withdrawal due to both rapid population growth and industrialization, as well as increasing dependence on groundwater as a reliable source of water. Water management has been done traditionally on a self-sustaining basis by different communities in India. If enough information about the extension aquifer, its capacity and quality of water, and its vulnerabilities is available, it is possible to plan for its development. Due to the dynamic nature of groundwater systems, the groundwater system automatically adjusts to changes in climate, groundwater withdrawal, and land use. The groundwater storage fluctuates due to both natural and artificial factors. In the natural condition, rainfall recharges the ground, evapotranspiration discharges it, and subsurface inflows and outflows maintain the system. (Mohanty et al. 2010; Iqbal et al. 2017a) conclude that unplanned exploitation of groundwater has depleted groundwater in many parts of the country. A sustainable water management strategy has, however, replenished groundwater in parts of India (Bhanja et al. 2016; 2017). Planning and managing these precise resources are must. Agricultural production might decline and people may not have access to drinking water, which could lead to wide-spread socioeconomic stress (Rodell, Velicogna, and Famiglietti 2009a; 2009b). Almost all groundwater drafts are done by private companies without any control or regulation, making quantification difficult. As a result, rainwater recharges the ground by infiltrating into the soil. Several factors contribute to recharge, including rainfall intensity, frequency, quantity, soil and geology, groundwater depth, and also land use patterns. The cumulative effects of draft and recharge are reflected in this change in groundwater levels.

Due to its significant role in human life, monitoring groundwater fluctuations is of the utmost importance. Nowadays, groundwater monitoring is mandatory in many countries. (Kaika

2003). Groundwater monitoring has undergone many reforms since the beginning. The first methods of groundwater investigation used different types of instruments to measure level. Instruments such as steel tape, electronic measuring tape, pressure transducers, sounding devices, piezometers, digital water level recorders, exploratory well drilling and isotopes are used in geophysical exploration. As the oldest method of measuring water levels (Cunningham and Schalk 2011a; 2011b; Peralta, Mazure, and Dutram 1983), the conventional instrument steel tape is considered the most accurate. However, this method gives an accurate result when the water level is below 200 feet. (Garber and Koopman 1968; Cunningham and Schalk 2011a) report that steel tape stretches and expands when it is at a depth of more than 500 feet. In addition to speeding up the measurement process, pressure transducers and automated data loggers allow for the analysis of fluctuations over time (Cunningham and Schalk 2011a). Geophysical investigation techniques used for groundwater monitoring include electrical resistivity surveys, seismic investigations, gravity measurements, and magnetic investigations. The level of groundwater can also be measured using agricultural wells and domestic wells (Jelovčan and Šraj 2020; Bonacci and Roje-Bonacci 2018; Sattari et al. 2018). Observation well data are commonly used by hydrologists to measure groundwater variations (Kuss et al. 2012; F. Wang et al. 2022). Arid regions and hilly terrain make it difficult to install the observation well. Measurement of regional groundwater storage variations is challenging in arid regions due to the limited number of observation wells. A lack of monitoring data or inaccessibility prevents the use of satellite gravity observations (J. Chen et al. 2016). Hydrological studies based on satellite data were conducted for the first time in 1957. LANDSAT, MODIS, and similar satellite data have been used to assess the global hydrological system (Elbeih 2015; Nayak, Gupta, and Galkate 2015; Nouri et al. 2020). Instead of directly accessing groundwater resources, MODIS satellite data is used to improve groundwater modeling. Gravity Recovery and Climate Experiment launched two satellites in order to measure water column directly. As a result of GRACE's launch, regional research on water resources is now possible (J. Chen et al. 2016; Pokhrel et al. 2013; Yeh et al. 2006) describe a new technology that measures groundwater storage variations in real time. Groundwater storage monitoring is time-consuming and labor-intensive in ground stations because of lack of data. The GRACE satellite solves this problem. Groundwater storage change has been studied by researchers across many countries using GRACE satellite data (Muskett and Romanovsky 2009; Gleeson et al. 2010; Naik and Purohit 2001).

There are many GRACE – based studies of groundwater that showed substantial aquifer depletion for the large regions, for example, the North China, the northwest India, the Middle-East, the Murray Darling Basin of Australia and California's Central Valley aquifers of the USA (Rodell, Velicogna, and Famiglietti 2009a; D Chakraborti et al. 2000b; V. M. Tiwari, Wahr, and Swenson 2009b; Rodell, Velicogna, and Famiglietti 2009c; Karamouz, Zanjani, and Zahmatkesh 2017; Gleeson et al. 2010). Rodell et al., 2007 worked on Mississippi River basin in USA for estimating the change in groundwater storage using the GRACE data. Yigzaw et al., 2016 detect changes in groundwater, regionally averaged surface water and biomass variability was assumed to be negligible. In their study, Henry, 2011 used satellite data from the Gravity Recovery and Climate Experiment (GRACE) to estimate monthly groundwater storage changes and annual recharge across a region in southern Mali, Africa. Using the water table fluctuation method (Healy and Cook 2002), the study uses historical water-level records (1982-2002) to generate monthly groundwater-storage anomalies. A comparison was made between GRACE groundwater storage data and groundwater observations made from 1982 through 2002 at 16 wells within the study region to determine groundwater storage variability and net recharge. Developing regions that lack hydrological data might benefit from GRACE technology. An assessment of groundwater storage variability in India was conducted by (Bhanja et al. 2016). During this study, groundwater levels were measured at 3907 monitoring wells throughout 22 major rivers basins in India. Groundwater spatial variability has never been studied before due to the unreliable nature of well spacing. Groundwater wells in a network for groundwater management may be able to be positioned and prioritized using the results for interpreting large scale groundwater variations. According to the study, the CGWB's well network has relatively low uncertainty in its estimates of regional groundwater storage anomalies, because it has a high density of observations. In another study, Bhanja et al., 2017 analyzed groundwater storage changes in 22 major river basins across India using in-situ data gathered from 3420 observation sites from 2003-2014 in the article "Groundwater storage change detection from in-situ and GRACE-based estimates in major river basins across India.". Different hydrological and climatic conditions exist within the basins. Furthermore, there was a long-term decreasing trend in the Ganges and Brahmaputra basins during the period 2003-2014. According to the study, groundwater levels have decreased in the densely populated Ganges and Brahmaputra basins between 2003 and 2014 by 1.02 and 0.40 km3/year, respectively. While satellite and in-situ data indicate a rising trend in the Southern Indian basins.

In India, water security, drinking water supply, and food production are threatened by the unplanned and overexploited use of groundwater. Both in situ and satellite-based measurements were used by Bhanja et al., 2016 to estimate usable groundwater storage at the state level across the entire Indian subcontinent. The usable groundwater storage between 2005 and 2013 has been estimated by using in-situ monitoring data from 3907 wells across India. As indicated in the UGWS estimate, groundwater storage in north-east India is depleting rapidly (more than 75km3 per year). Despite the increased precipitation (i.e. Assam). In the Indus, Ganges and Brahmaputra basins, in the states of Punjab, Haryana, Uttar Pradesh, Bihar and West Bengal, satellite-based estimates (Gravity Recovery and Climate Experiment) suggest that GWS depletion zones have developed in unconsolidated sediments or lithotypes across the basins. Conversely, southern and central states of India, such as Andhra Pradesh, Maharashtra, Gujarat, Tamil Nadu and Chhattisgarh, are experiencing a replenishment of GWS. Additionally, during the study period, water-intensive cropping practices were applied in states with the highest groundwater depletion rates.

In terms of assessing groundwater reduction globally, GRACE might be the best option (Rodell et al. 2007b). It is necessary, however, to validate satellite data processing by comparing it with ground-based well data, especially when the study area is close or below GRACE's footprint. There have been a number of studies that have attempted to validate GRACE-measured changes in groundwater storage with groundwater well data in situ. As part of the assessment of the reliability of GRACE-based estimates of groundwater depletion, Yeh et al., 2006 compared ground-based estimates from well water levels with updated estimates using GRACE satellites. From October 2006 to March 2010, GRACE satellites showed a total depletion of 31.0+30km^3 of groundwater. For both April 2006 and September 2009, GRACE measured groundwater storage changes that agreed with well-data measurements (27km^3). GRACE's groundwater depletion measurements are generally consistent with ground-based estimates, increasing the confidence in its use. In addition, in-situ groundwater observation wells within 12 of India's largest river basins were used to validate a groundwater storage anomaly obtained from a combination of GRACE and land-surface model estimates. A total of more than 15000 groundwater observation wells distributed throughout the country were analyzed between 2005 and 2013. GWS anomalies between 2005 and 2013 were compared with GRACE-based GWS anomalies. According to GRACE, in climatologically and hydro geologically heterogeneous areas of India, GRACE estimates are relatively accurate when compared with ground-based estimates. The GRACE based groundwater storage anomalies have also been validated with GWS anomalies obtained from both in-situ and GRACE-based groundwater observation wells by other researchers such as Abou Zaki et al., 2019; Salam et al., 2020 and Sarkar et al., 2020, etc.

Groundwater fluctuations are affected by the Indian Summer Monsoon (ISM) and the Northeast monsoon. Around 80% of the annual precipitation over India comes from the ISM rainfall during June-September, which is part of the region's annual cycle of precipitation. During the month of October to December, the India Meteorological Department (IMD) refers to the northeast monsoon period (Ohar et al. 1983). By analyzing GRACE satellite data during the Indian summer monsoon (ISM) and North East monsoon (NEM) in 2019, Kumar et al., 2021 measured groundwater fluctuations over India. The groundwater storage depth over the country was found to increase by 20cm after the ISM season. An increase of 6.5 cm in groundwater storage was observed in Karnataka, Kerala, Tamil Nadu, and Andhra Pradesh after the NE monsoon period. In the northern and north-western parts of the country, the amount of recharged groundwater is very low. India is depleting its groundwater at a faster rate than it is replenishing it due to rapid population growth and industrialization. The precipitation situation is more alarming in North-West India, where there is low precipitation. In their study of Punjab and Haryana (2005-2015), A. K. Singh et al., 2021 utilized GRACE satellite data in order to monitor seasonal fluctuations in groundwater. According to their study, Punjab and Haryana lose 1.13 cm of groundwater per year on average and 0.92 cm per year respectively. There is a greater withdrawal of groundwater in these areas due to increased irrigation and evapotranspiration as they are densely populated and inundated. Accordingly, (F. Wang et al. 2022) used GRACE data to estimate long-scale groundwater drought conditions in China between 2003-2018, providing a new data source for investigating draughts. In the lower Transboundary Indus Basin, Ali et al., 2022 and Masood et al., 2022 estimated the spatiotemporal variations in groundwater storage using GRACE satellite data. According to Srivastava & Dikshit, 2022, GRACE data were used to study groundwater storage dynamics in the Indo-Gangetic plain and its temporal evolution.

Groundwater resources are being affected by human activities as a result of population growth and socioeconomic development (Liu, Liu, and Luo 2015). In order to access the water resources, information about the variation in groundwater storage must be available (Lin et al. 2020). In order to envision the composition of terrestrial water storage, it is essential to monitor groundwater fluctuations. According to (Masood et al. 2022), they discuss modern tools and methods for monitoring groundwater fluctuations, as well as advanced applications, along with traditional techniques. Monitoring groundwater fluctuations can be divided into three categories. Using classical instruments as well as electronic and physical investigation methods, the first method measures groundwater levels at points. Using satellite data is the second category. Nevertheless, GRACE satellite data can be integrated with other satellite products and computational tools. The most effective groundwater resource management techniques are GIS and hydro-climatic models. Groundwater numerical modelling is the third. Furthermore, they suggested that GRACE and numerical groundwater modelling be combined to access groundwater resources more effectively.

2.5 CONCLUSIONS

According to a comprehensive literature review, groundwater quality and groundwater fluctuations both affect the vulnerability of groundwater-based drinking water. Water quality indexes with a higher value imply poorer water quality and resulting in greater vulnerability. Nevertheless, groundwater fluctuations create a vulnerability for drinking water due to their negative value. For an evaluation of drinking water vulnerability, the following socio-economic factors are considered: 0-6-year-old children, literacy rates, economies, water accessibility, and asset values of households. NGO 2001; (Cutter et al. 2008) :251 cite children and the elderly as the most vulnerable groups in disaster events. Based on their study for measuring social vulnerability in Dintwa et al., 2019 found that highly vulnerable populations are comprised of those under 5 years and over 65 years of age. Skills, knowledge, and perception of risk are directly affected by education. Educating children about risk and reducing vulnerability is linked to increased risk awareness (Muttarak and Lutz 2014). Survivors of disasters rely on income to recover. As people are resilient to the effects of hazards when they have a healthy economic situation, they have a greater level of economic factor value and a higher asset value. As a result, the level of vulnerability is definitely reduced when access to water is available.

Based on the literature review, it is also evident that different researchers have conducted research on the vulnerabilities of drinking water, including the vulnerability of drinking water sources, the vulnerability of water distribution systems to contamination, vulnerability analyses in water distribution systems, and the response of drinking water distribution networks to biological and chemical contamination. In addition to considering social factors in vulnerability analysis to natural hazards, many researchers have also studied the threat assessment to natural hazards. In this study, water quality index, groundwater fluctuations, and socioeconomic factors are all considered in analyzing the vulnerability index of groundwater-based drinking water.

Chapter – 3

ASSESSMENT OF GROUNDWATER-BASED PUBLIC DRINKING WATER SUPPLY SYSTEM OF KAMRUP DISTRICT, ASSAM, INDIA USING A MODIFIED WATER QUALITY INDEX

3.1 INTRODUCTION

Water is one of the essential commodities and a precious national asset that has been exploited than any other natural resource. Around 70 percent of the earth is covered with water, but only one percent of them are usable for human consumption. The water for domestic and industrial purposes can be supplied from the available surface water sources as well as from the groundwater. Groundwater is the most vital resource for millions of people for both drinking and irrigation uses (Delgado et al. 2010a; Chandra, Asadi, and Raju 2017a; Ghalib 2017a; Mohammadi et al. 2017; Yousefi, Ghoochani, and Mahvi 2018a). At the same time, it is challenging to have a perennial surface source for the implementation of the water supply schemes. As such, the Govt. of Assam has implemented several groundwater-based water supply schemes for the rural areas of the state. The schemes are running at several parts of the state for supplying drinking water.

The quality of water must be considered in any assessment of water resources (Anon 1993). Although scientific measurement is used to define water quality, it is not easy to say about the quality of the water as good or bad. Therefore, the water quality is related to particular use only. Drinking water is the water that is safe to drink as well as to use for food preparation without risk of health problems. According to the WHO organization, about 80% of the diseases in human beings are caused due to the lack of pure drinking water (Ramakrishnaiah, Sadashivaiah, and Ranganna 2009b). The quality of groundwater depends on the nature of the soil and the rock masses present along the pathway of the groundwater saturation zone (Foster et al. 2008; Chidambaram et al. 2008b; Olayinka et al. 1999b; M. Das and Bhattacharjya 2020). However, as observed, the groundwater quality deteriorates due to residential, industrial, commercial, agricultural, and other anthropogenic activities together with natural conditions (Foster et al. 2003b; Nair et al. 2015b). The water quality of any specific area or specific source can be assessed by using physical, chemical, and biological parameters. The values are harmful to human health if they exceed the defined limit (Bureau of Indian Standards, Specification for drinking water. IS: 10500, New Delhi, India 2012; Guidelines for Drinking-water Quality, Fourth Edition, World Health Organization ISBN 978 92 4 154815 1 2012; Guide Manual: Water and Waste Water, Central Pollution Control Board, New Delhi 2013). The Water Quality Index (WQI) is an effective way to communicate information on the quality of water to the concerned citizen and policymakers. The use of individual quality parameters to describe water quality is not easily understandable to the common public. (Katyal 2011). Therefore, WQI can reduce the quality parameters into a single value that expresses the overall quality in a simplified and logical form (Semiromi et al. 2011b).

Horton, 1965 proposed a method for evaluation of WQI values ranking the categories of water as excellent, poor, very poor, and unsuitable for use. These categories are easily understandable for decision-makers and consumers. There are various methods to derive WQI values (Tyagi et al. 2013b). Usually, weighted WQI values are calculated in which the parameters have been assigned a weight according to their relative importance in the overall quality of water. Many studies have been carried out regarding the application of the weighted WQI approach in groundwater quality assessment (Ketata, Gueddari, and Bouhlila 2012; Alastal et al. 2016; Kawo and Karuppannan 2018; Sahu and Sikdar 2008; Rabeiy 2018). All these methods to derive WQI values are similar, the only difference being the number and type of parameters considered and their corresponding weights.

Many researchers have studied the quantification of water quality using the Water Quality Index (WQI). Assessment of WQI for the groundwater in Tumkur Taluk of Karnataka, India, was done by Ramakrishnaiah, Sadashivaiah and Ranganna, 2009a. After evaluation of the WQI values, they finally concluded that the groundwater of the area needs some degree of treatment before human consumption. Some researchers (Krishan et al. 2016; Patil and Patil 2013b; Chandra, Asadi, and Raju 2017a; Chaturvedi and Bassin 2010b; Yogendra and Puttaiah 2008) also done similar works in different areas. The only difference is the number and type of parameters used and their corresponding weight. Tyagi et al., 2013, in their work “Water Quality Assessment in Terms of Water quality Index” reviews some of the important water quality assessment, their mathematical structure, merits, and demerits of the methods. Besides, they highlight and draw attention towards the development of a new and globally accepted water quality index that represents a reliable picture of water quality. Poonam, Tanushree and Sukalyan, 2013 also reviewed the different water quality indices. They presented a list of selected studies carried out worldwide using water quality indices. Pei-Yue, Hui and Jian-Hua, 2010, on their work regarding groundwater quality assessment, entropy weight was calculated and assigned to different parameters for calculating WQI values.

The purpose of this study is to assess the suitability of the groundwater-based public drinking water supply system of Kamrup district, Assam, India base on computed WQI values. The WQI is initially calculated based on the weightage derived from the literature survey and also from DCMG Opinion Survey. However, the evaluation of the results shows that the resulted WQI values do not display the actual water quality of the supplied water. As such, a new method is proposed for calculating the WQI of the supplied water considering the permissible limit of the parameters in deriving the weightage of the parameters.

3.2 MATERIALS AND METHODS

Kamrup (Rural) district (**Figure 3.1**) lies between 25.46N and 26.49N latitude and between 90.48E and 91.50E longitude and has a total area of 3105 sq. km. The perennial tributaries like Puthimari, Digaru, Kulshi, Singra, etc., are passing through the district and join the river Brahmaputra. As per the 2011 census of Govt. of India, the total population of the district was 1,517,542 and population density is 490 per sq. km. The annual rainfall of the district ranges between 1500 mm to 2600mm. The major soil groups identified in the district are recent riverine alluvial soils, old riverine alluvial soils, old mountain valley alluvial soils, and laterite red soils. The economy of the district is based on industry and agriculture. The total cultivators in the district are 207262, out of which 150921 are small and marginal farmers. The literacy rate of the district is 70.95 %.**Figure 3.1** shows the district boundary along with the locations of the water supply projects considered in the study.

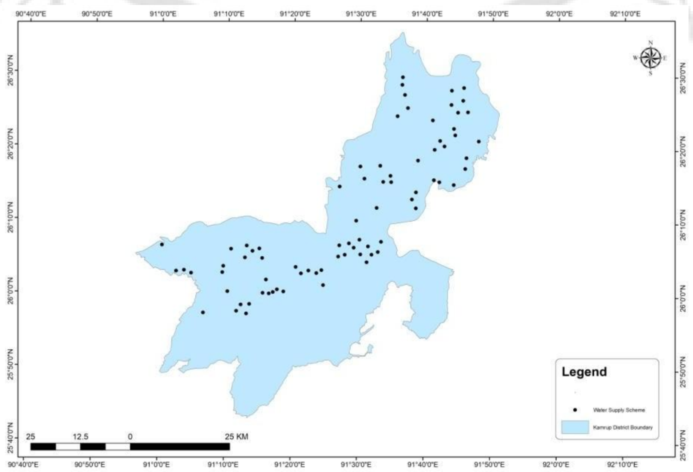


Figure 3.1 Kamrup district showing the rural water treatment plants

Water samples were collected from seventy-eight groundwater-based Public Water Supply schemes implemented by the Assam Public Health Engineering Department. The samples were collected in pre-cleaned plastic polyethylene bottles for physicochemical analysis during the year 2017. Before sampling, all the sampling containers were washed and rinsed thoroughly with the groundwater to be taken for analysis. For each water supply scheme, two numbers of water samples (raw water and treated water) are collected for testing. Raw water has been aerated, followed by rapid sand filtration, then disinfection at the storage level and distributed to beneficiaries.

All the one hundred and fifty-six numbers of water samples collected from different water supply schemes were tested in the district level laboratory of the Public Health Engineering Department. The samples were tested for twelve numbers of parameters generally done in regular testing of water samples observing the standard procedure followed by the department. The parameters are Iron, Alkalinity, Turbidity, Calcium Hardness, Total Dissolved Solids, Chloride, Fluoride, Total Hardness, Nitrate, pH, Manganese, and Magnesium. The chemical parameters of the raw water samples for different water supply schemes are plotted on the map prepared by GIS (Geographical Information System as shown in **Figure 3.2 and Figure 3.3**.

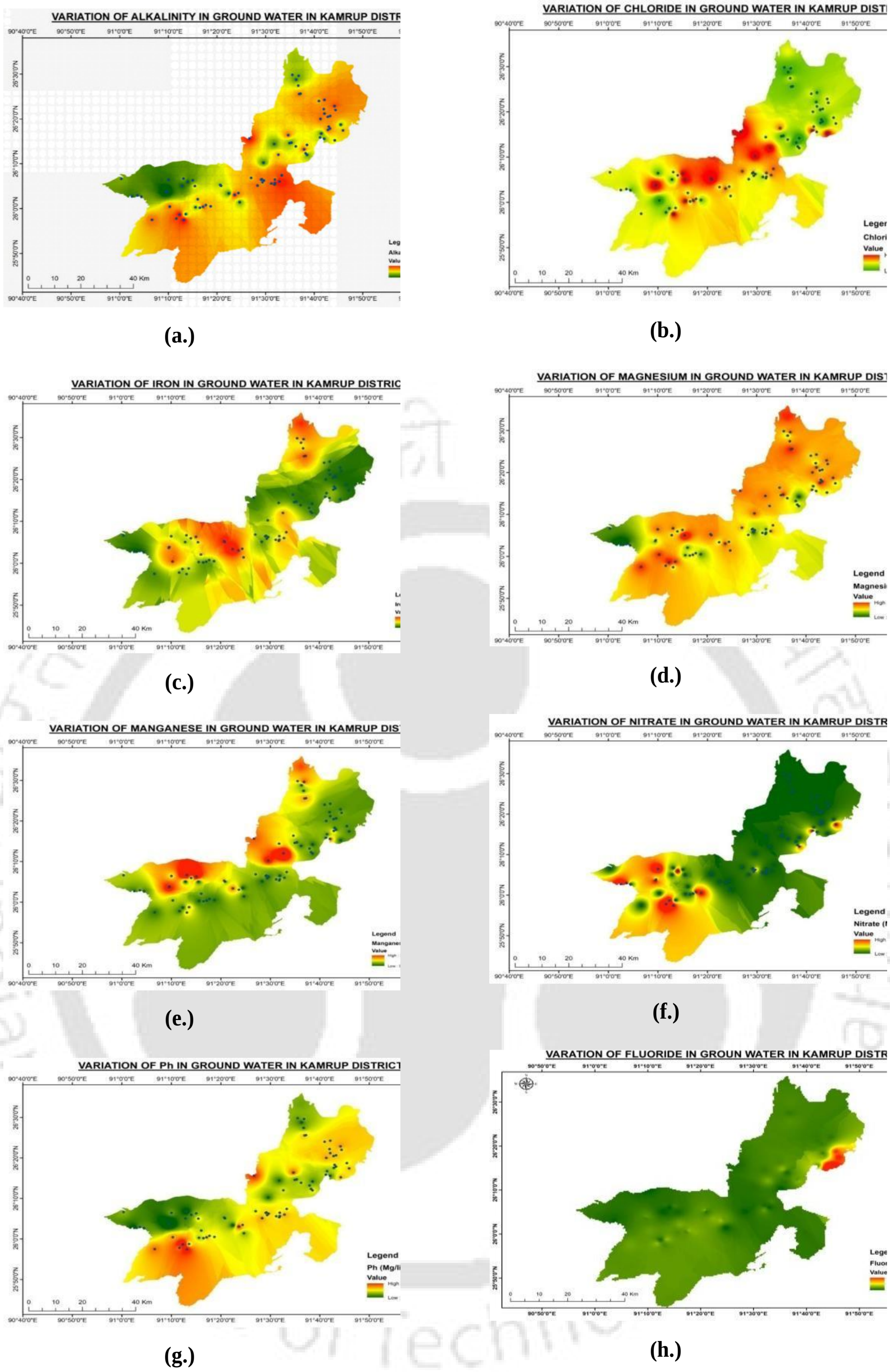


Figure 3.2 Map showing the distribution of various parameters in groundwater (a) Alkalinity, (b) Chloride, (c) Iron, (d) Magnesium, (e) Manganese, (f) Nitrate, (g) pH, (h) Fluoride

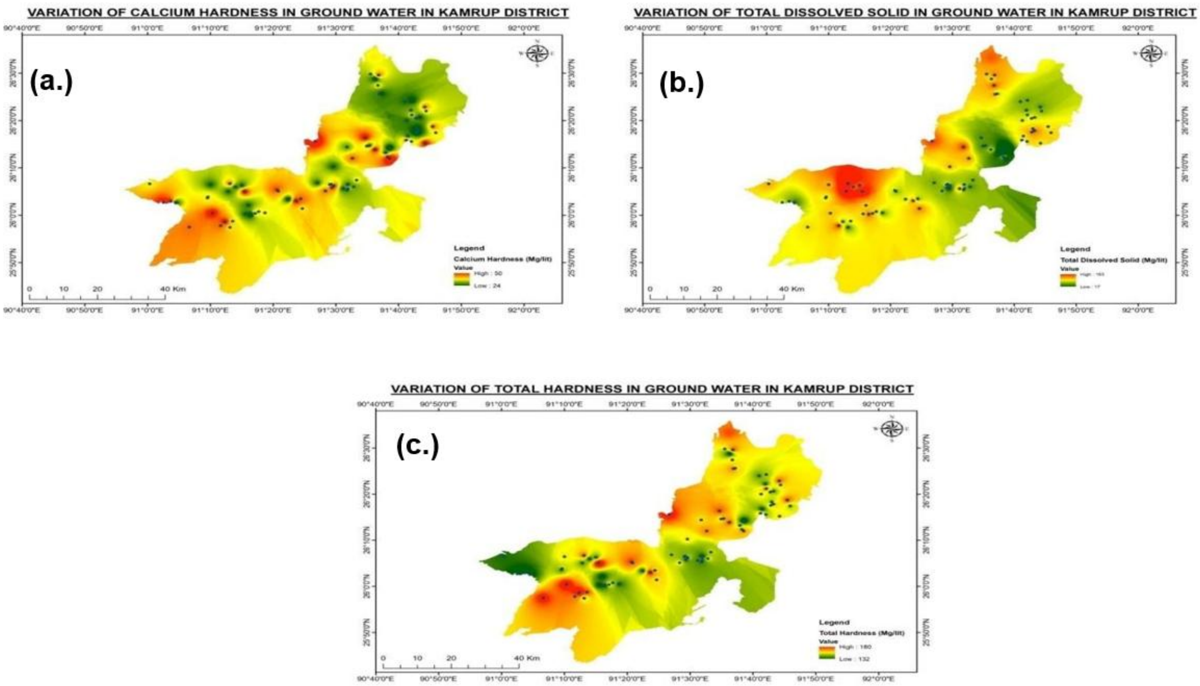


Figure 3.3 Map showing the distribution of various parameters in groundwater (a) Calcium hardness, (b)Total dissolved solid, (c) Total hardness

Figure 3.4 shows the box plot of the water quality parameters used in the study. It may be observed that the maximum concentration of Alkalinity is 128.0mg/L, and the minimum value is 68.0mg/L. In the case of Chloride, the maximum concentration is 16.0mg/L, and the minimum value of 6.0mg/L found in the Bhitarkhola public water supply scheme. The box plots of the other parameters like Iron, Magnesium, Manganese, Nitrate, pH, and Fluoride show that the maximum and minimum values of the parameters found in raw water as Iron ranges between 5.85mg/L to 0.11mg/L, Magnesium ranges between 35.0mg/L to 22.0mg/L, Manganese ranges from 3.48mg/L to 0.19mg/L, Nitrate ranges between 1mg/L to 0, pH value ranges between 8.33 to 6.30 and fluoride ranges from 6.5mg/L to 0. The box plot of hardness parameters like Calcium hardness, the maximum and minimum values found in raw water are 50mg/L and 24mg/L, respectively. In the case of total dissolved solids, it ranges between 165mg/L to 17mg/L, and for the case of total hardness, the maximum and minimum values are 180mg/L and 132mg/L, respectively.

The standards of drinking water quality recommended by the Bureau of Indian Standards (BIS) have been considered for computing water quality Index (WQI) values from the laboratory test data of the physicochemical parameters. The following steps are followed for the computation of WQI values. First, each of the twelve parameters has been assigned a weight (wi) according to their relative importance in water quality for drinking purposes. The weightage has been assigned based on the literature survey in the range of 1 to 5 (**Error! Reference source not found.**). The maximum weight of 5 has been assigned to the parameter Nitrate due to its more significance in water quality assessment. The high concentration of Nitrate can cause methemoglobinemia (Blue baby syndrome), which is excessively found in newborn infants. On the other hand, as it itself may not be harmful, Magnesium has assigned a weight of 1. The weight of the remaining parameters has been assigned according to their relative importance in the drinking water. The relative weight Wi is computed using Eq. 3.1.

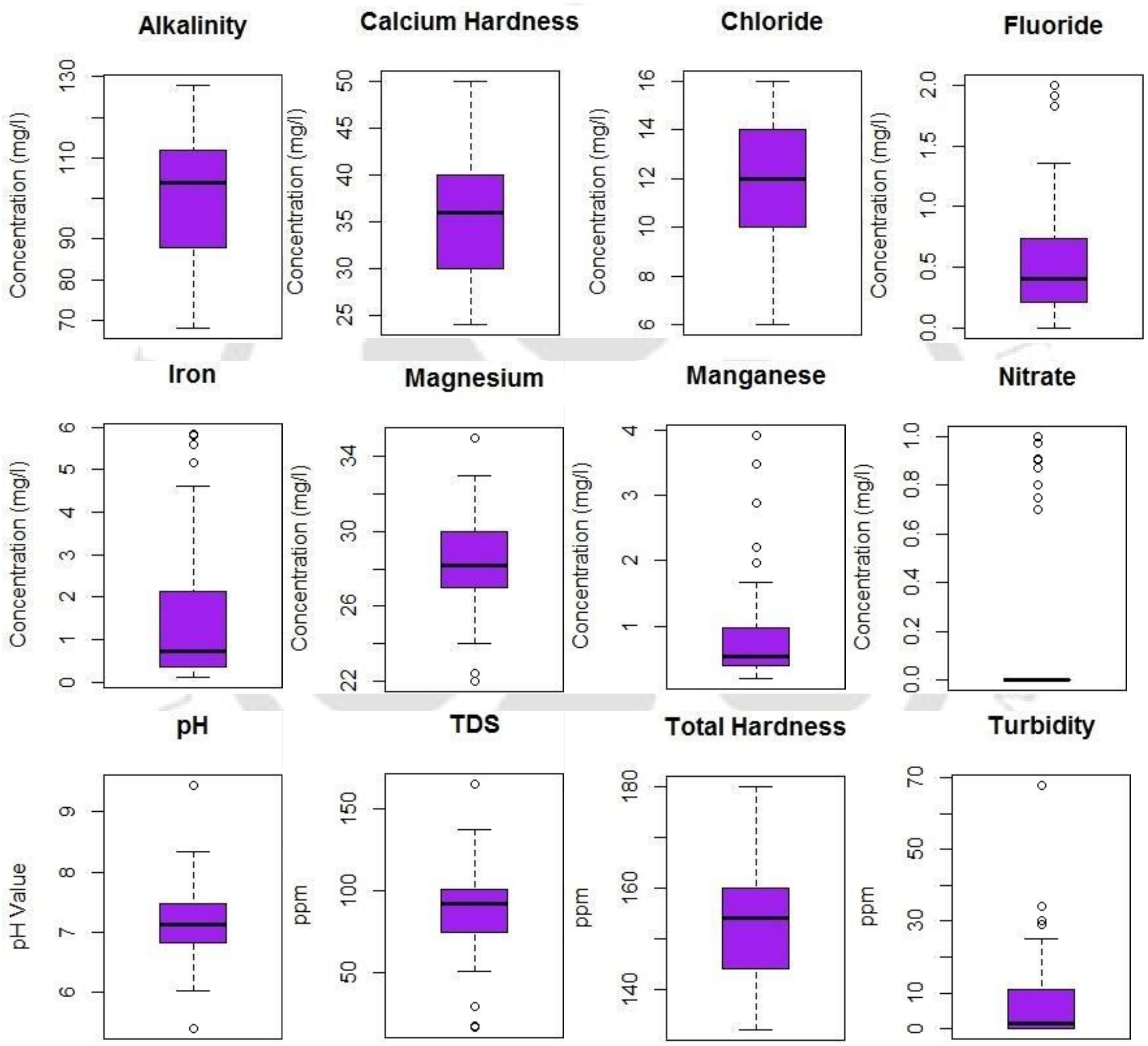


Figure 3.4 Box plot showing the values of different quality parameters of raw groundwater

$$W_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \qquad \textbf{3.1}$$

where, Wi is the relative weight, *wi* is the weight of each parameter, and n is the number of parameters.

Table 3.1 BIS value, weight, and relative weight of different parameters

Parameter	BIS value	Weight (w_i)	Relative Weight (W_i)
Iron	0.3mg/L	3	0.0857
Alkalinity	200-600mg/L	2	0.0571
Turbidity	1-5 NTU	3	0.0857
Calcium	75-200mg/L	2	0.0571
Total Dissolved solid	500-2000mg/L	4	0.1143
Chloride	250-1000mg/L	3	0.0857
Fluoride	1–1.5mg/L	4	0.1143
Total Hardness	200–600mg/L	2	0.0571
Nitrate	45mg/L	5	0.1429
pH	6.5–8.5	4	0.1143
Manganese	0.1-0.3mg/L	2	0.0571
Magnesium	30-100mg/L	1	0.0286
		$\sum w_i = 35$	$\sum W_i = 1$

In addition to assigning weight to the different physicochemical parameters from the literature survey and by considering the significance of the parameters in the overall water quality, an opinion survey conducted by the author among the doctors in the Department of Community Medicine, Guwahati (DCMG), Assam, India for giving weightage to the different parameters. They have valued the different parameters ranging from 1 to 10 in terms of risk to human health. From the survey data, the relative weight of different parameters has been calculated. **Table 3.2** shows the relative weight calculated based on the literature survey and the DCMG opinion survey.

To bring the water quality parameters on the same scale, the parameters have been normalized using Eq. 3.2. The result is multiplied by 100 to make it a whole number.

$$q_i = 100 \times \max\left[\left(\left|\frac{C_i - S_i}{C_{imax} - S_i}\right|\right), 0\right] \quad \textbf{3.2}$$

where C_i is the concentration of ith parameters (mg/L), SI is the Indian drinking water standard of the ith parameter (mg/L), and C_{imax} is the permissible concentration of the ith parameters (mg/L), N is the number of parameters. The WQI values of different water supply schemes are calculated by using Eq. 3.3.

$$\mathrm{WQI} = \sum_{i=1}^{n} W_i q_i \qquad \mathbf{3.3}$$

After the calculation of the WQI values of different water supply schemes, the values are grouped (**Table 3.3**) according to the status of the water quality (Chatterjee, Chatterjee, and Raziuddin 2007).

Table 3.2 Comparative statement of relative weights

Parameter	Relative Weight	
	DCMG Survey	Literature Survey
Iron	0.078	0.0857
Alkalinity	0.079	0.0571
Turbidity	0.101	0.0857
Calcium	0.075	0.0571
Total Dissolved solid	0.097	0.1143
Chloride	0.075	0.0857
Fluoride	0.102	0.1143
Total Hardness	0.086	0.0571
Nitrate	0.094	0.1429
pH	0.0897	0.1143
Manganese	0.063	0.0571
Magnesium	0.062	0.0286

Table 3.3 Water quality classification based on WQI value

Water quality Index Level	Water quality Status	Number of Schemes	
		DCMG opinion Survey	Literature Survey
0-25	Excellent water Quality	0	0
26-50	Good water quality	0	0
51-75	Poor water quality	15	33
76-100	Very poor water quality	63	45
More than 100	Unsuitable for drinking	0	0

The evaluation of the results shows that the computed WQI values are in the range of poor-quality water to very poor-quality water. According to opinion survey conducted by the author among the doctors in the Department of Community Medicine, Guwahati (DCMG) 15 numbers of schemes fall in the category of supplying poor-quality water and 63 numbers with very poor-quality water. But according to literature survey, 33 numbers of schemes fall in the category of supplying poor-quality water and 45 numbers with very poor-quality water. However, it has been observed that all the parameters except Iron, Fluoride, and Manganese are within the permissible limit. In some of the projects, Iron and Manganese concentration are slightly higher than the permissible value. In the case of fluoride, its value exceeds the limit only in five numbers of projects. This shows that the WQI calculated using the weight as discussed above is not reflecting the actual water quality of the supplied water. As such, to have a more realistic picture, a new method for evaluating WQI values is proposed considering the maximum permissible value of the parameters. In the proposed method, we have assigned a weight of 0.30, if the concentration of the parameter within the permissible limit. A linear relation is then used to assign the weightage beyond the permissible limit. **Figure 3.5** shows the variation of weightage for the parameters considered in the study.

The water quality indices of different supply schemes are evaluated using Eq. 3.4, and the result is multiplied by 100 to convert the WQI values to the whole number

$$\mathrm{WQI} = \frac{1}{\mathrm{N}} 100 \sum \max \left[\left| \frac{0.30\mathrm{C_i}}{\mathrm{S_{imax}}} \right|, 0.30 \right] \qquad \mathbf{3.4}$$

where C_i is the concentration of i^{th} parameters (mg/L), S_{imax} is the maximum value as per the Indian drinking water standard for the i^{th} parameters (mg/L), N is the number of parameters.

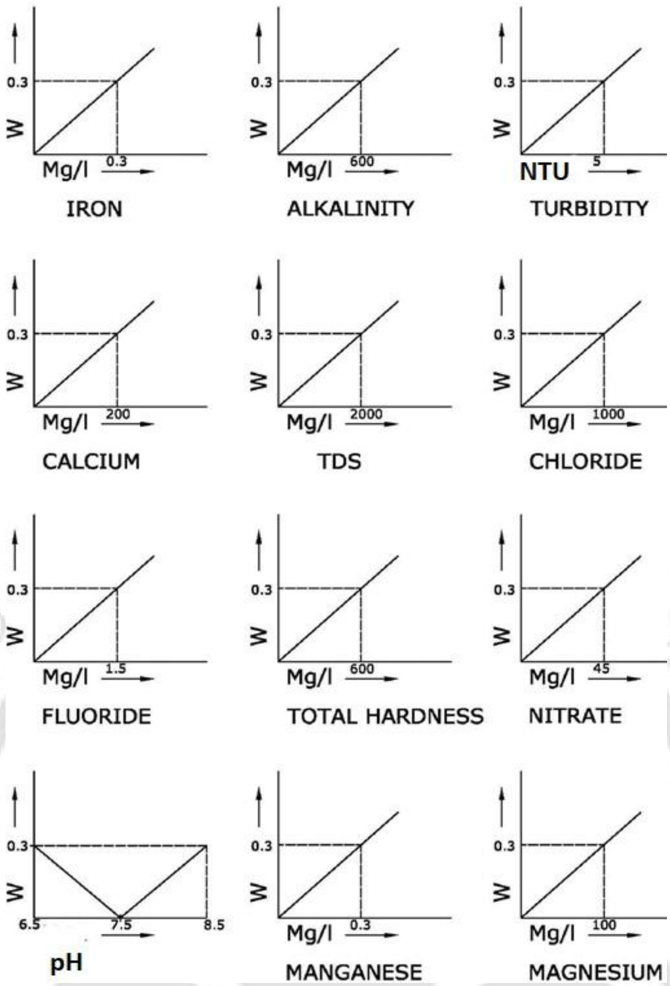


Figure 3.5 The variation of weightage of different parameters as per the proposed method

After calculating the WQI values of the water supply projects, they are grouped (**Table 3.4**) according to the status of water quality proposed for the new method. When the WQI is 0.3, it indicates that all the water quality parameters are with the permissible limits. If it is more than 0.3, it suggests that the concentration is more than the allowable limits for one or more parameters.

Table 3.4 Water quality classification based on WQI value as per the proposed method

Water Quality Index (%)	Water quality Status	Number of Schemes
<=30	Good Water Quality	47
31-60	Poor Water Quality	31
61-90	Very Poor Water Quality	0
More than 90	Unsuitable for Drinking	0

3.3 RESULTS AND DISCUSSIONS

The WQI values for treated water are evaluated by considering 12 (Twelve) nos of Physicochemical parameters for seventy-eight locations of water supply schemes. The assessed WQI values using the weightage obtained from the DCMG opinion Survey ranges from 69 to 96. The index calculated by using the literature survey is ranging from 66 to 89. It gives some general ideas regarding possible problems with water for a particular reason (Anurag, Ashutosh, and Aviral 2010). The WQI values of different water supply projects using both the weightage are shown in **Figure 3.6**. Again, it is observed that in DCMG opinion Survey, some parameters have been assigned more weightage in comparison to their relative importance in the overall quality of water. The WQI values calculated by considering both the weightage shows higher values, and the water quality falls in the range of poor water quality to very poor water quality. But the concentration of the parameters except Iron, Fluoride, and Manganese are within the permissible limit in all the water supply projects. Iron in groundwater occurs naturally. As the water moves through the underground rock formations, some of the Iron dissolves and accumulates in aquifers which serve as a source for groundwater. It is not hazardous to health, but it is considered a secondary or aesthetic contaminant. While considering raw water, 82.05% of the schemes are found to be contaminated beyond the permissible limit. Iron concentration in raw water is found maximum to the tune of 5.85mg/L in the Aggumi water supply scheme in the Chaygaon development block. But in the case of supplied water, 35.89% of the schemes are found contaminated with Iron beyond the permissible limit. A maximum of 1.60mg/L of Iron concentrations in supplied water is found in the Sapathuri water supply scheme in the Rampur development block. But in most of the Iron contaminated schemes supplying water, it just crosses the permissible value of 0.30mg/L but within 1.0mg/L. Although in some of the water supply projects, the Turbidity value for raw water is found beyond the permissible limit, it comes to the desirable after treatment. The value of the chemical parameters like Alkalinity, Calcium Hardness, Total Dissolved Solids, Chloride, Total Hardness, Nitrate, pH, and Magnesium are found within the permissible limit both in raw and treated water. Out of seventy-eight water supply schemes considered under the study, fluoride is found beyond the permissible value only in five nos. of schemes under the Bezera development block. It is known from the department that in all the Fluoride contaminated schemes, water has been extracted from rock boring type of deep tube well. This has been done due to the unavailability of a water-bearing sandy layer, i.e., the confined aquifer in that area. In all other seventy- three locations of schemes, water has been extracted from a confined aquifer. Fluoride is beneficial for human health for the prevention of dental cavities. If the concentration of fluoride exceeds the permissible value, it can cause dental fluorosis, and a much higher concentration result in skeletal fluorosis (Shah et al., 2008). Moreover, Nitrate, the other most harmful chemical parameter, has been found within the permissible limit in all the projects and even up to a maximum value of 1mg/L. The high concentration of Nitrate in drinking water is toxic and causes blue baby diseases in children and gastric carcinomas (Gilli, Corrao, and Favilli 1984; Alam, Rais, and Aslam 2012a; 2012b). In some of the schemes, Manganese concentration is found beyond the permissible limit both for raw and treated water. But this concentration is not so high. So, the above information regarding poor to very poor-quality of water is not reflecting the true water quality of the supplied water and will give some negative impact regarding supplied water. Therefore, a new method for evaluating WQI value is being proposed.

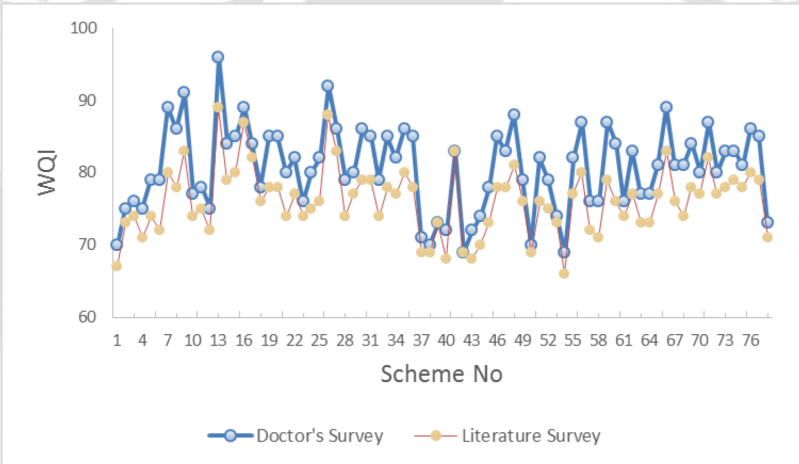


Figure 3.6 Water Quality Index values calculated using Doctor's and literature survey

In the proposed method, a weight of 0.30 is being considered if the concentration of the parameters is within the permissible limit. The WQI values evaluated by observing this method fall in the range of good water quality to poor water quality. The water quality indices of different water supply schemes as per the newly proposed method are plotted on the map prepared using GIS (**Figure 3.7**). According to the proposed method, out of seventy-eight locations of water supply projects considered in the study, forty-seven numbers were found supplying good quality water and thirty-one numbers with poor-quality water. This poor-quality of water is mainly due to high values of Iron, Manganese, and specially Fluoride in Schemes Sl no 14 to 18 (**Figure 3.6**). Only in Sl. No. 19 to 24 (**Figure 3.6**), all the projects are supplying good quality water, whereas, in Sl no 14 to 18 (**Figure 3.6**), all the projects are supplying poor-quality water. This poor- quality water can easily be used for drinking purposes by applying the normal filtration process at the domestic level. But, the poor-quality water with more Fluoride concentration, especially in Sl no 14 to 18 (**Figure 3.6**), RO filtration process, is required before human consumption.

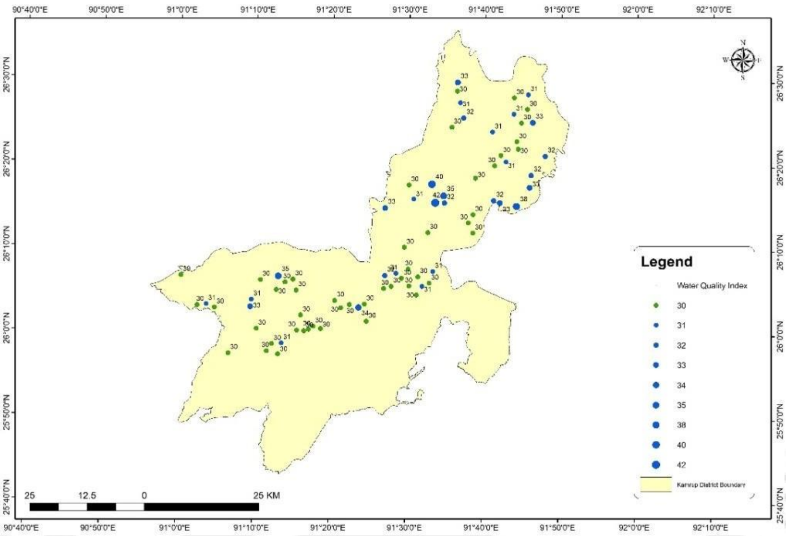


Figure 3.7 Map showing WQI values using the proposed method

Statistical analysis is carried out to study the correlation between the water quality parameters and WQI calculated using the proposed method. **Figure 3.8** shows the scatter plot and correlation matrix of physicochemical parameters and WQI. It can be observed that there is a significant positive correlation among Chloride, Calcium hardness, Manganese, Alkalinity, and pH value. A high positive association has been observed between Manganese and Total hardness with a coefficient of correlation value of 0.81. The other positive correlations are Chloride and Calcium hardness with a coefficient of correlation value of 0.35, Chloride, and Manganese with a coefficient of correlation value of 0.32, etc. On the other hand, Alkalinity is negatively correlated with TDS with a coefficient of correlation value of -0.38. The correlation between the WQI and the water quality parameters shows that the WQI has a significant positive relationship with Manganese, Chloride, Fluoride, Calcium hardness, TDS, pH, etc. Among all these water quality parameters, the WQI has a very high correlation with Manganese with a coefficient of correlation value of 0.86, followed by 0.4 with Chloride and 0.34 with fluoride.

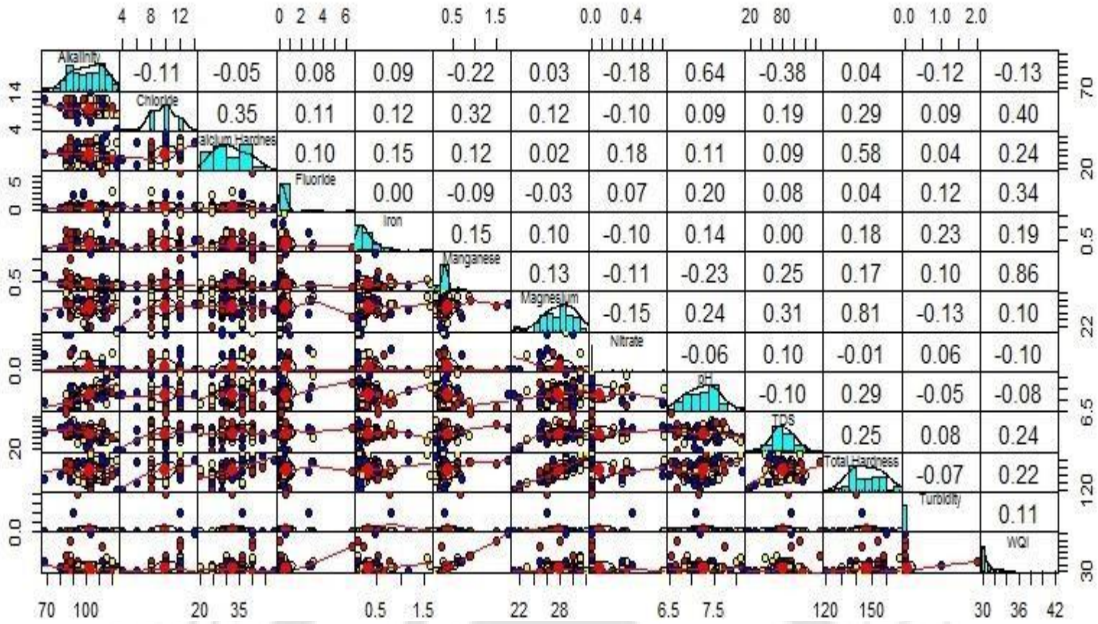


Figure 3.8 Scatter plot and correlation matrix of physicochemical parameters and WQI

3.4 CONCLUSIONS

From the field test results, it has been observed that almost all the parameters of the public water supply distribution system are within the permissible limit. In some of the water supply projects, only Iron, Manganese, and Fluoride have been found beyond the permissible limit. The study shows that the assignment of weight is very crucial in deriving a convincing water quality index of drinking water supply schemes. It shows that the weight calculated by using the literature survey and DCMG opinion Survey provides wrong information about the water quality of the supplied water. The new method proposed in this study provides a logical value that reflects the true water quality. The WQI evaluated with the proposed method falls in the category of good water quality and poor water quality. This poor-quality water can easily be used for drinking purposes applying the normal filtration process at the domestic level, as Iron and Manganese are not shown harmful to human health. But, the poor-quality water with more Fluoride concentration, especially in Bezera Development Block, RO filtration, may be applied before human consumption. As fluoride has been detected in the rock-boring type of deep tub well, it is advisable to stop the rock-boring type of deep tube well for the implementation of a water supply scheme. At the same time, we should go for perennial surface sources for the implementation of the water supply projects in the areas where groundwater has been found contaminated with fluoride. The method has been applied at the Kamrup district of Assam, India. However, it can be used for any other location in the world.

Evaluation of Groundwater Quality and Its Suitability for Public Drinking Water Supply in Assam, India: An Assessment Using Modified Water Quality Index

4.1 INTRODUCTION

Water is one of the most vital natural resources, yet it has been extensively exploited by mankind for domestic, agricultural, and industrial purposes. Groundwater and surface water are the primary sources of fresh water, with groundwater being preferred in many regions due to its unexposed nature and ease of development. In India, the widespread availability and relatively lower development costs of groundwater have led to its unhindered use. However, rapid population growth, urbanization, industrialization, and unsustainable agricultural practices have significantly increased the demand for fresh water over the past few decades. Concurrently, these anthropogenic activities have adversely impacted both the availability and quality of groundwater.

The indiscriminate use of fertilizers, unsanitary conditions, and improper waste disposal have introduced pollutants into groundwater systems, posing a significant threat to public health. In addition, natural processes such as weathering, rock dissolution, soil leaching, and biological activities further influence groundwater quality (Khatri and Tyagi 2015; Subba Rao et al. 2020; Adimalla and Wu 2019; Hamed et al. 2018). These factors, combined with the interaction of groundwater with contaminated surface water, necessitate robust monitoring and management programs to ensure the safety of water resources.

The Government of Assam has implemented groundwater-based water supply schemes due to their relatively lower initial costs and maintenance expenditures. However, challenges persist in ensuring the suitability of groundwater for public drinking purposes, particularly in the face of increasing contamination risks. Groundwater quality assessment, therefore, plays a critical role in determining its usability for various purposes, including public water supply. Chemical analysis provides insights into the physical and chemical composition of groundwater, while water quality indices (WQIs) simplify and summarize complex datasets into a single value, offering a comprehensive understanding of the overall water quality (Semiromi et al. 2011;

Das, Panigrahi, and Panda 2012; Ansari and Hemke 2013; Bhadja and Vaghela 2013; Srinivas, Purushotham, and Krishna 2013; Srivastava and Dikshit 2022).

Since the introduction of the Water Quality Index (WQI) concept in 1965 (Horton 1965), several WQIs have been developed globally, including the Weighted Arithmetic Water Quality Index (WAWQI), the National Sanitation Foundation Water Quality Index (NSFWQI), the Canadian Council of Ministers of the Environment Water Quality Index (CCMEWQI), and the Oregon Water Quality Index (OWQI). These indices provide valuable insights into water quality across different regions but also exhibit variations and limitations depending on the specific parameters used and the regional context (Bordalo et al. 2001). Despite significant advancements, there remains a need for a standardized global index that can effectively evaluate water quality across time and space.

In the context of Assam, Das and Bhattacharjya (2020) introduced a regression-based analysis to assess the impact of fluoride-rich river water on adjacent groundwater aquifers, with a specific case study in the Bharalu River Basin of Guwahati. This study highlighted the influence of river water quality on groundwater aquifers, emphasizing the need for a comprehensive assessment of groundwater quality in regions influenced by surface water interactions. Their work aligns with other studies that focus on groundwater vulnerability, such as the assessment of groundwater-based public drinking water systems in Kamrup district using social and water quality parameters (Goswami and Bhattacharjya 2020a, 2020b).

Similarly, broader studies on social vulnerability and flood impacts, such as those by Isia et al. (2023a, 2023b) and Kumar and Bhattacharjya (2020a, 2020b), emphasize the interconnectedness of natural and anthropogenic factors in influencing water resource sustainability. These findings reinforce the necessity of an integrated approach to groundwater quality assessment.

Building on prior studies, this research aims to comprehensively assess groundwater quality across Assam using water quality index values, focusing on its suitability for public drinking water supply. The study involves the collection and analysis of groundwater samples from various districts of Assam, evaluating physical, chemical, and biological parameters to calculate WQI values. Additionally, this study incorporates the impact of both natural and anthropogenic factors, such as agricultural runoff, industrial discharge, and surface water interactions, on groundwater quality.

The research also introduces a spatial analysis of groundwater quality trends across Assam, offering insights into regional variations and potential contamination hotspots. By integrating these findings with social vulnerability parameters, as explored in related studies, the research aims to provide a holistic framework for groundwater management. The results are intended to assist policymakers in developing sustainable strategies to ensure safe and reliable drinking water access for the population of Assam.

4.2 MATERIALS AND METHODOLOGY

4.2.1 Study Area

The study was conducted in Assam, a state in North-eastern India, located between 24ºN to 28ºN latitude and 90ºE to 96ºE longitude, with a total area of 78,438 km² (**Figure 4.1**). As per the 2011 Census data, Assam has a population of 31,169,272 and a population density of 398 persons per km². The Brahmaputra and Barak river systems, along with their numerous tributaries, serve as the primary water sources for the region. The state has a literacy rate of 72.19%, and agriculture forms the backbone of the economy, with 69% of the population engaged in it.

4.2.2 Data Collection

Water quality data for the years 2019 and 2020 were collected from the Assam Public Health Engineering Department (APHE), Government of Assam, India. The dataset includes information from different water sources such as shallow tube wells, open wells, springs, and deep tube wells. Water used by the population includes raw water directly sourced from shallow tube wells and open wells, as well as treated water supplied through public water supply schemes, where deep tube well water undergoes rapid sand filtration.

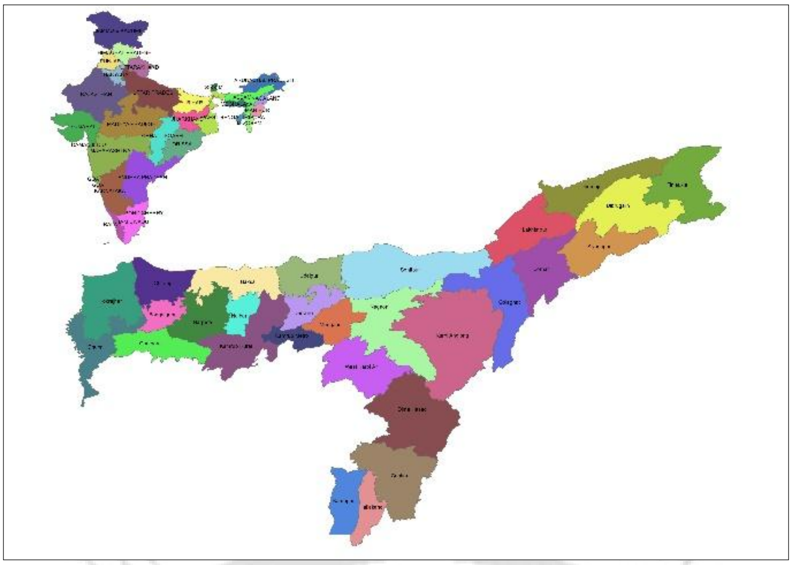


Figure 4.1 The study area

4.2.3 Chemical Parameters and GIS Mapping

The chemical parameters analysed include alkalinity, chloride, iron, magnesium, manganese, nitrate, pH, arsenic, fluoride, calcium, hardness, total dissolved solids (TDS), and total hardness. The district-wise average values of these parameters for raw water were spatially represented using Geographic Information System (GIS) maps (**Figure 4.2**). These maps provide an overview of the distribution of water quality parameters across Assam, aiding in visualizing potential areas of concern.

4.2.4 Water Quality Index (WQI) Calculation

The suitability of water, both raw and treated, for household use was assessed using the Water Quality Index (WQI) methodology proposed by Bhattacharjya and Goswami (2021). This method utilizes the standards for drinking water quality recommended by the Bureau of Indian Standards (BIS), as shown in **Table 4.1**.

The WQI was calculated using the following equation:

$$WQI = \frac{1}{N} 100 \sum max \left[\left| \frac{0.30C_i}{S_{imax}} \right|, 0.30 \right] \quad \textbf{(}4.1)$$

Where, C_i is the concentration of the ith parameter (mg/L), $\mathrm{S_{imax}}$ is the maximum permissible value as per BIS for the ith parameter (mg/L), and N is the total number of parameters.

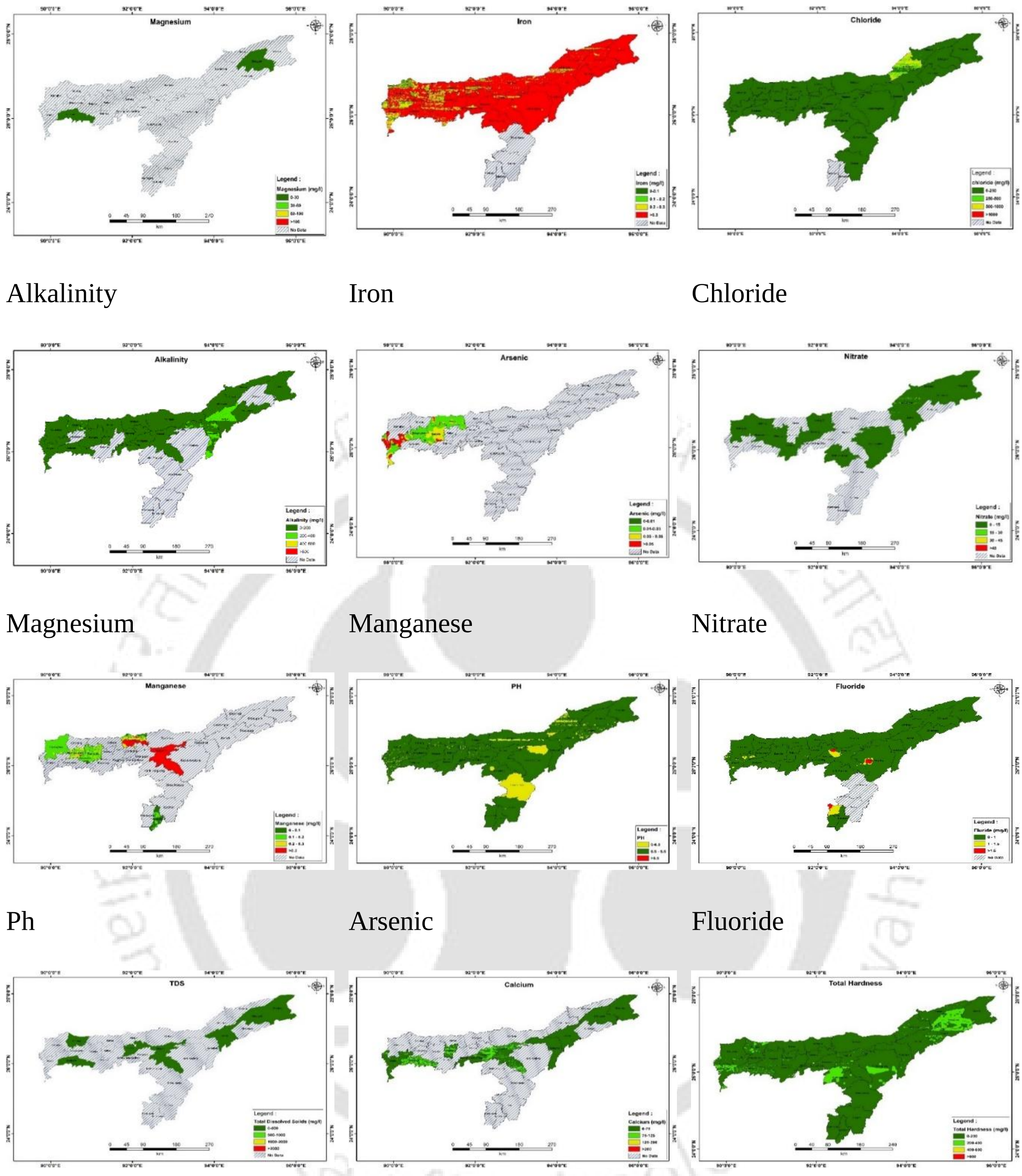


Figure 4.2 Map showing the distribution of various parameters in groundwater

If the concentration of a parameter is below the permissible limit, its contribution to the WQI is 0.30. A value above 0.30 indicates that one or more parameters exceed the permissible limit, with a linear relationship applied for weightage beyond the limit.

Table 4.1 BIS value of different parameters

Sl. No.	Parameter	BIS value
1	Iron	0.3mg/L
2	Alkalinity	200 - 600mg/L
3	Turbidity	1 - 5NTU
4	Calcium	75 - 200mg/L
5	Total Dissolved solid	500 - 2000mg/L
6	Chloride	250 - 1000mg/L
7	Fluoride	1 – 1.5mg/L
8	Total Hardness	200 – 600mg/L
9	Nitrate	45mg/L
10	Ph	6.5 – 8.5
11	Manganese	0.1 - 0.3mg/L
12	Magnesium	30 - 100mg/L
13	Arsenic	0.01-0.05mg/L

Table 4.2 Water quality index values for different districts of Assam

District	WQI (Treated)
Barpeta	30
Baska	30
Bongaigaon	30
Cachar	30
Chirang	30

Darrang	33
Dhemaji	31
Dhubri	31
Dibrugarh	30
Dima Hasao	31
Goalpara	30
Golaghat	32
Hailakandi	30
Jorhat	31
Kamrup	30
Kamrup Metropolitan	30
Karbi Anglong	30
Karimganj	30
Kokrajhar	30
Lakhimpur	30
Morigaon	37
Nagaon	31
Nalbari	33
Sivasagar	31
Sonitpur	30
Tinsukia	30
Udalguri	30

The district-wise average values of chemical parameters were considered while calculating the WQI values. The results for treated water across 27 districts of Assam are presented in **Table 4.2**. These districts correspond to the administrative divisions outlined in the 2011 Census, as more districts were created later. Based on the WQI values, the districts were categorized into different water quality statuses as per Error! Reference source not found.

Table 4.3 Water quality classification based on WQI value

Water quality Index Level	Water quality Status
0-30	Good water quality
31-60	Poor water quality
61-90	Very poor water quality
More than 90	Unsuitable for drinking

4.3 RESULTS AND DISCUSSIONS

The Water Quality Index (WQI) analysis highlights significant spatial variability in treated water quality across Assam, with WQI values ranging from 30 to 37, as depicted in **Figure 4.3**. This variability underscores the profound influence of specific water quality parameters on the WQI. Among the 27 districts, 10 fall under the "poor" water quality category, with Morigaon district recording the highest WQI value of 37.

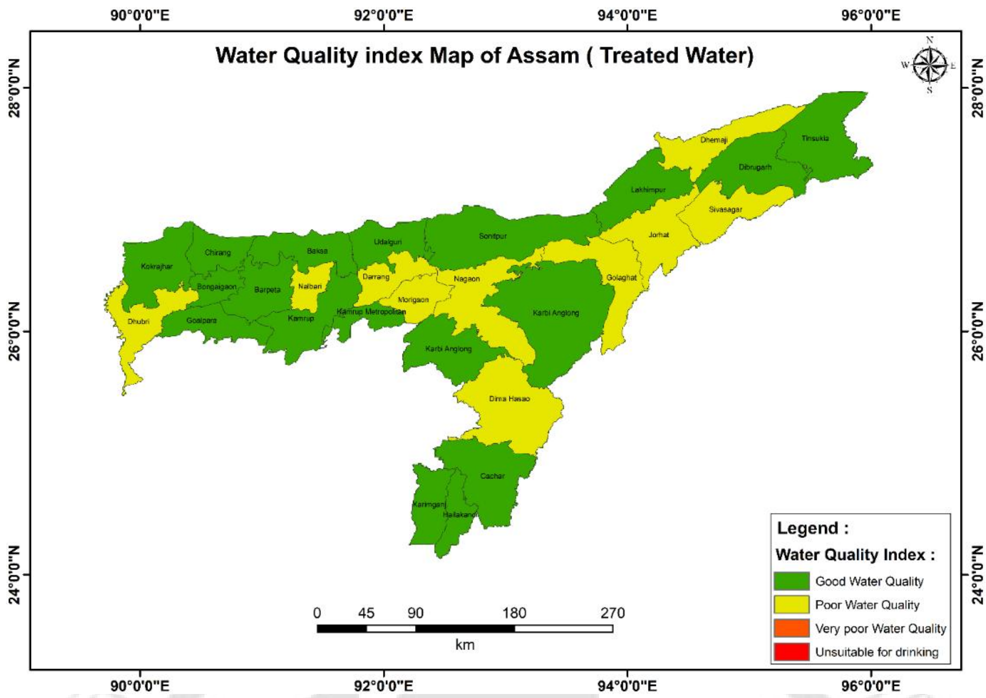


Figure 4.3 Water Quality Index map of Assam for Treated water

High concentrations of iron, manganese, arsenic, and fluoride emerge as critical factors contributing to poor WQI values. Elevated levels of these contaminants, particularly in Morigaon and other districts with poor water quality, reveal the limitations of conventional treatment methods like rapid sand filtration, which are effective for iron and manganese but inadequate for arsenic and fluoride. This necessitates the adoption of advanced treatment technologies, especially in areas severely affected by these toxins.

Chloride concentrations, ranging from 500 to 1000 mg/L in some districts, significantly impact the WQI, as shown in **Figure 4.3**, with values exceeding the desirable limit of 250 mg/L. These elevated levels, likely due to anthropogenic influences such as poor drainage and inadequate environmental maintenance, not only deteriorate water quality but also pose health risks, including hypertension and kidney issues. Similarly, nitrate concentrations, while generally within safe limits, reach concerning levels in Lakhimpur district due to agricultural runoff and improper waste management practices.

Alkalinity levels, mostly within acceptable limits, exhibit localized deviations, notably in districts like Jorhat and Golaghat, where values approach 400 mg/L. While not directly harmful, these variations can alter the buffering capacity of water, influencing its interaction with other contaminants. Additionally, pH levels, critical for water chemistry, remain within the acceptable range of 6.5–8.5 across most districts, but localized acidity is observed in areas like Dima Hasao, potentially mobilizing metals such as iron and manganese and exacerbating contamination issues.

The presence of arsenic, particularly in districts such as Dhubri, Baska, and Barpeta, poses a severe challenge to water quality, with concentrations exceeding the permissible limit of 0.05 mg/L. Chronic exposure to arsenic-contaminated water has significant health implications, including cancer and other systemic effects. Fluoride contamination, as observed in districts like Karbi Anglong and Dhubri, further impacts the WQI, with concentrations in some locations far exceeding permissible limits. These high fluoride levels contribute to widespread health issues like dental and skeletal fluorosis.

Although parameters such as magnesium, calcium, and total dissolved solids (TDS) generally remain within acceptable ranges, localized anomalies, including elevated hardness in districts like Dhubri and Chirang, underscore the complexity of water quality management. These findings, illustrated in **Figure 4.3**, demonstrate that the WQI is highly sensitive to specific contaminants, particularly those with severe health implications. Addressing these disparities requires targeted interventions, enhanced treatment infrastructure, and sustained monitoring efforts, with a focus on mitigating both natural geochemical influences and anthropogenic activities.

4.4 CONCLUSIONS

The evaluation of water quality data and Water Quality Index (WQI) values for Assam reveals that both raw and treated water (processed through rapid sand filtration) are generally suitable for use. However, certain water sources exhibit elevated levels of chemical parameters, such as iron, manganese, fluoride, and arsenic, exceeding permissible limits. While iron and manganese can be effectively removed through conventional filtration processes, which render the water safe for human consumption, addressing fluoride and arsenic contamination requires advanced treatment methods.

Fluoride contamination, identified in six districts, poses challenges for drinking and cooking purposes. However, reverse osmosis (RO) filtration technology can effectively treat fluoride-contaminated water, making it safe for household use. Additionally, utilizing perennial surface water sources as alternative water supplies in fluoride-affected areas is recommended to ensure access to safe water.

Arsenic contamination, detected in three districts, requires specialized treatment technologies for its removal. Approaches such as absorption (using activated alumina), co-precipitation (involving oxidation, coagulation, and filtration), or ion exchange can be employed to mitigate arsenic contamination. Implementing community water treatment systems connected to large-diameter tube wells or hand pump tube wells can provide safe drinking water in arsenic-affected areas. Alternatively, surface water, arsenic-safe dug wells, or rainwater harvesting systems with appropriate treatment can serve as viable water sources, ensuring the removal of microbial and chemical contaminants.

Overall, the findings underscore the need for adopting advanced treatment technologies, enhancing water infrastructure, and exploring alternative water sources to address localized contamination challenges and ensure sustainable access to safe water across Assam.

Assessment of Drinking Water Quality and Supply in Assam: A Survey on Access and Contaminants

5.1 INTRODUCTION

Water is fundamental to life, ecosystems, and economic development, playing a critical role in agriculture, industry, and domestic consumption. Its availability and quality are essential for sustaining human health and well-being. However, factors such as population growth, industrialization, and urbanization have contributed to a decline in both the quantity and quality of water resources globally (Briscoe and Malik 2006; Famiglietti and Rodell 2013; Rodell, Velicogna, and Famiglietti 2009a). Groundwater, which serves as a vital source of drinking water, irrigation, and industrial processes, is increasingly threatened by overexploitation and contamination (Cheema, Immerzeel, and Bastiaanssen 2014; Lin, Biswas, and Bennett 2020a; 2020b).

In India, groundwater quality is deteriorating due to various anthropogenic activities, including the indiscriminate disposal of industrial effluents, mining activities, and agricultural practices (Chopra and Krishan 2014; Raju et al. 2015a; 2015b). Factors such as rainfall quality, geological structures, and aquifer mineralogy also influence groundwater chemistry, often exacerbating contamination risks (Mirzabeygi et al. 2017; Yousefi, Ghoochani, and Mahvi 2018b; 2018c). The impact of contaminants such as arsenic, fluoride, and heavy metals on public health is particularly concerning, as these elements, even in trace amounts, can accumulate over time and cause chronic health issues (Debels et al. 2005b; Sood et al. 2020).

Assam, a state in Northeast India, faces significant challenges concerning drinking water quality. The region's groundwater is often characterized by high iron content, as observed in several studies (Aowal 1981; Borah, Bhuyan, and Sarma 2010). Additionally, fluoride contamination has been reported in districts such as Nagaon, Karbi Anglong, and Kamrup, with documented cases of fluorosis affecting local populations (Sival et al. 1997; Chakraborti et al. 2000b; Sattari et al. 2018). The Upper Brahmaputra Plain has also been identified as a hotspot for arsenic contamination, with reports dating back to 2004 highlighting its prevalence in groundwater sources (Chakraborti et al. 2004). These findings emphasize the urgent need for comprehensive groundwater quality assessments in the state.

Water quality assessments involve evaluating physical, chemical, and biological parameters to determine suitability for consumption and other uses (Bartram and Ballance 1996). Various studies have emphasized the need to monitor and manage groundwater quality to ensure its safety for human consumption (Rodell, Velicogna, and Famiglietti 2009b; 2009c). The United Nations recognizes safe drinking water as a basic human right, underscoring the importance of addressing water quality challenges, particularly in developing regions where access to clean water remains inadequate (Debels et al. 2005b).

This study aims to systematically assess the drinking water quality in Assam by analyzing key physical, chemical, and biological parameters of groundwater. It seeks to identify contamination hotspots, evaluate compliance with permissible limits set by standards such as BIS and WHO, and provide actionable insights for sustainable water resource management and public health policymaking in the region.

5.2 MATERIAL AND METHODS

To evaluate the drinking water status in Assam, India, for the year 2020, an online survey was conducted using Google Forms. The survey aimed to collect comprehensive data on both the quantity and quality of drinking water across the state. A total of 2470 responses were received from households located throughout Assam, providing a robust dataset for analysis.

5.3 SURVEY FORM DESIGN

The survey was structured to gather information on:

5.3.1 Water Quantity:

- **Source of Water**: Participants were asked to identify the type of water source they relied on, including tap water, tube wells, deep tube wells, open wells, and other sources.
- **Availability**: Feedback was collected on whether households had sufficient water throughout the year or faced shortages.
- **Fluctuations in Groundwater Levels**: Respondents were asked about observed changes in the groundwater table over the past 5–10 years.

Water Survey/পানীৰ জৰীপ

নমস্কাৰ। আই আই টি গুৱাহাটীত চলি থকা এটা গৱেষণাৰ বাবে মই খোৱা পানী সম্পৰ্কীয় এই জৰীপতো কৰিব ওলাইছোঁ। এই জৰীপৰ প্ৰধান উদ্দেশ্য হ'ল খোৱা পানীৰ তথ্য সংগ্ৰহ কৰা আৰু ইয়াৰ বৈজ্ঞানিক বিশ্লেষণৰ দ্বাৰা অসমৰ খোৱা পানীৰ এটা স্থায়ী সমাধানৰ ব্যৱস্থা কৰা। এই জৰীপত কাৰো ব্যক্তিগত তথ্য সংগ্ৰহ কৰা হোৱা নাই। ফৰ্ম খন পূৰণ কৰিবলৈ আপোনাৰ ২-3 মিনিট সময় লাগিব।

জয়ন্ত গোস্বামী, এ. ই. ই., জন স্বাস্থ্যকাৰী বিভাগ, অসম
গবেষক ছাত্ৰ, আই আই টি গুৱাহাটী

Greetings! As a part of the research work carried out at the Department of Civil Engineering, IIT Guwahati, I am conducting a survey to know the perception of people about the drinking water. It will take hardly 2 to 3 minutes to fill the form. Your feedback will be a great help to have a better solution to the drinking water problem of the state. It may be noted that we are not collecting any personal information.

Jayanta Goswami (AEE) (PHE)
Research Scholar, Department of Civil Engineering, IITG

Source of water/পানীৰ উৎস *

- Tap water (Govt. supply)/টেপৰ পানী
- Tube well/টিউবওয়েল
- Deep tube well/গভীৰ টিউবওয়েল
- Open Well/কুৱা
- Pond/পুখুৰী
- River/নদী
- Stream (Hilly areas)/জুৰি
- Other/অনন্য

Availability of water/পানীৰ সহজলভ্যতা *

- Sufficient and no change in last 5-10 years/যথেষ্ট আৰু কোনো সলনি হোৱা নাই যোৱা ৫-10 বছৰত
- Not Sufficient and no change in last 5-10 years/যথেষ্ট নহয় আৰু কোনো সলনি হোৱা নাই যোৱা ৫-10 বছৰত
- Sufficient but reducing in last 5-10 years/যথেষ্ট কিন্তু লাহে লাহে কমি আহিছে যোৱা ৫-10 বছৰত
- Not Sufficient and reducing in last 5-10 years/যথেষ্ট নহয় লাহে লাহে কমি আহিছে যোৱা ৫-10 বছৰত
- Other/অনন্য

Colour of water /পানীৰ ৰং *

- No colour/ৰং নাই
- Reddish/ৰঙচুৱা
- Brownish/বাদমী
- Blackish/অলপ কলা
- Other/অনন্য

Turbidity of water/পানীৰ অস্বচ্ছতা *

- Clear/পৰিষ্কাৰ
- Slightly dirty/অলপ লেতেৰা
- Dirty/লেতেৰা
- Very Dirty/বহুত লেতেৰা

Odor of water/ পানীৰ গোন্ধ *

- Pleasant/ভাল লগা/কোনো গোন্ধ নাই
- Bad odor/বেয়া গোন্ধ

Do you suspect/know that the water contains iron?/আপুনি ভাবে/জানে নেকি যে পানীত আয়ৰণ আছে? *

- Yes/হয়
- No/নহয়

Do you suspect/know that the water contains Fluoride?/আপুনি ভাবে/জানে নেকি যে পানীত ফ্লুৰাইড আছে? *

- Yes/হয়
- No/নহয়

Do you suspect/know that the water contains Arsenic?/আপুনি ভাবে/জানে নেকি যে পানীত আৰ্চেনিক আছে? *

- Yes/হয়
- No/নহয়

Filter medium used/ফিল্টাৰৰ ব্যৱহাৰ *

- No filter used/ফিল্টাৰৰ ব্যৱহাৰ নকৰো
- Traditional sand filter/ঘৰুৱা বালিৰ ফিল্টাৰ
- Candle filter/কেণ্ডেল ফিল্টাৰ
- UV filter (Aquaguard, Kent, etc)/উভি ফিল্টাৰ (অকুৱাগাৰ্ড, কেন্ট, আদি)
- RO filter/আৰো ফিল্টাৰ
- Prefiltration (sand filter, pressure filter, etc.)+Candle filter/প্ৰিফিল্টাৰ (বালিৰ ফিল্টাৰ, ..)+কেণ্ডেল ফিল্টাৰ
- Prefiltration (sand filter, pressure filter, etc.)+UV filter/প্ৰিফিল্টাৰ (বালিৰ ফিল্টাৰ, ..)+উভি ফিল্টাৰ (অকুৱাগাৰ্ড, কেন্ট, আদি)
- Prefiltration (sand filter, pressure filter, etc.)+RO filter/প্ৰিফিল্টাৰ (বালিৰ ফিল্টাৰ, ..)+আৰো ফিল্টাৰ
- Other/অনন্য

Figure 5.1: The survey form

5.3.2 Water Quality:

- **Physical Parameters**: Data on colour, turbidity, and odour of drinking water were collected to assess physical quality.
- **Chemical Parameters**: The study focused on the presence of iron, fluoride, and arsenic in drinking water. While iron does not significantly impact human health, excessive levels of fluoride and arsenic are hazardous. Respondents provided feedback on the presence and levels of these chemicals in their water.

5.3.3 Water Purification Practices:

- Information was collected on whether households used water filters or other purification methods to improve water quality.

The survey form is shown in **Figure 5.1**.

5.4 DATA ANALYSIS

The survey data were analysed to assess both the quantity and quality of drinking water in Assam:

- **Water Quantity Analysis**: The proportion of households relying on various water sources was determined, along with the percentage of households experiencing water scarcity. Trends in groundwater level fluctuations over the last decade were also evaluated.
- **Water Quality Analysis**: The physical and chemical characteristics of drinking water were analysed. The focus was on comparing groundwater quality across the state with respect to iron, fluoride, and arsenic levels, particularly in relation to the permissible limits established by the Bureau of Indian Standards (BIS) and the World Health Organization (WHO).
- **Regional Variations**: Regional differences in water quality and quantity were examined to identify potential hotspots for water quality issues.

Significance

By synthesizing the responses, the study aimed to provide an updated status of drinking water in Assam, highlighting areas with significant water quality and availability concerns. The findings offer critical insights for policymakers and stakeholders to prioritize interventions for safe and sustainable drinking water in the region.

5.5 RESULTS AND DISCUSSIONS

Drinking Water Sources and Availability in Assam

The evaluation of Assam's drinking water supply, based on an online survey, reveals a significant dependence on various water sources. In 2020, 26.6% of households used treated tap water, with urban households typically receiving it from municipal authorities, while rural areas rely on water supply schemes implemented by the Assam Public Health Engineering Department (APHED), which provide treated water via house connections or street taps. For 46.3% of households, tube wells serve as the primary source of drinking water, offering a safe and convenient alternative where tap water is unavailable. In some urban areas, deep tube wells, utilized by 13.4% of households, are the only viable option due to limited access to tap water and challenges such as water-bearing sandy layers. A smaller percentage of households depend on open wells or other less common water sources.

Despite the challenges, significant progress has been made in improving water availability in Assam. As of March 2023, the director of the Jal Jeevan Mission (JJM) in Assam reported that the state is on track to achieve over 95% tap water coverage by the end of the financial year 2024, a remarkable achievement. This marks a substantial improvement compared to 2019, when only 1.11 lakh rural households had access to tap water connections. While the majority of households (58.4%) have experienced stable water levels over the past 5–10 years, localized groundwater shortages are evident in 15.3% of households. Additionally, trend analysis using GRACE data from 2002–2022 highlighted a gradual decline in groundwater levels across the state, underscoring the need for continued focus on sustainable water resource management.

Survey data, illustrated in **Figure 5.2**, provide insights into household perceptions, water sources, and the quality of drinking water. The figures emphasize key trends such as dependence on tube wells, the widespread use of untreated water, and public concerns over contaminants like iron, fluoride, and arsenic, which significantly affect water quality in several districts of Assam.

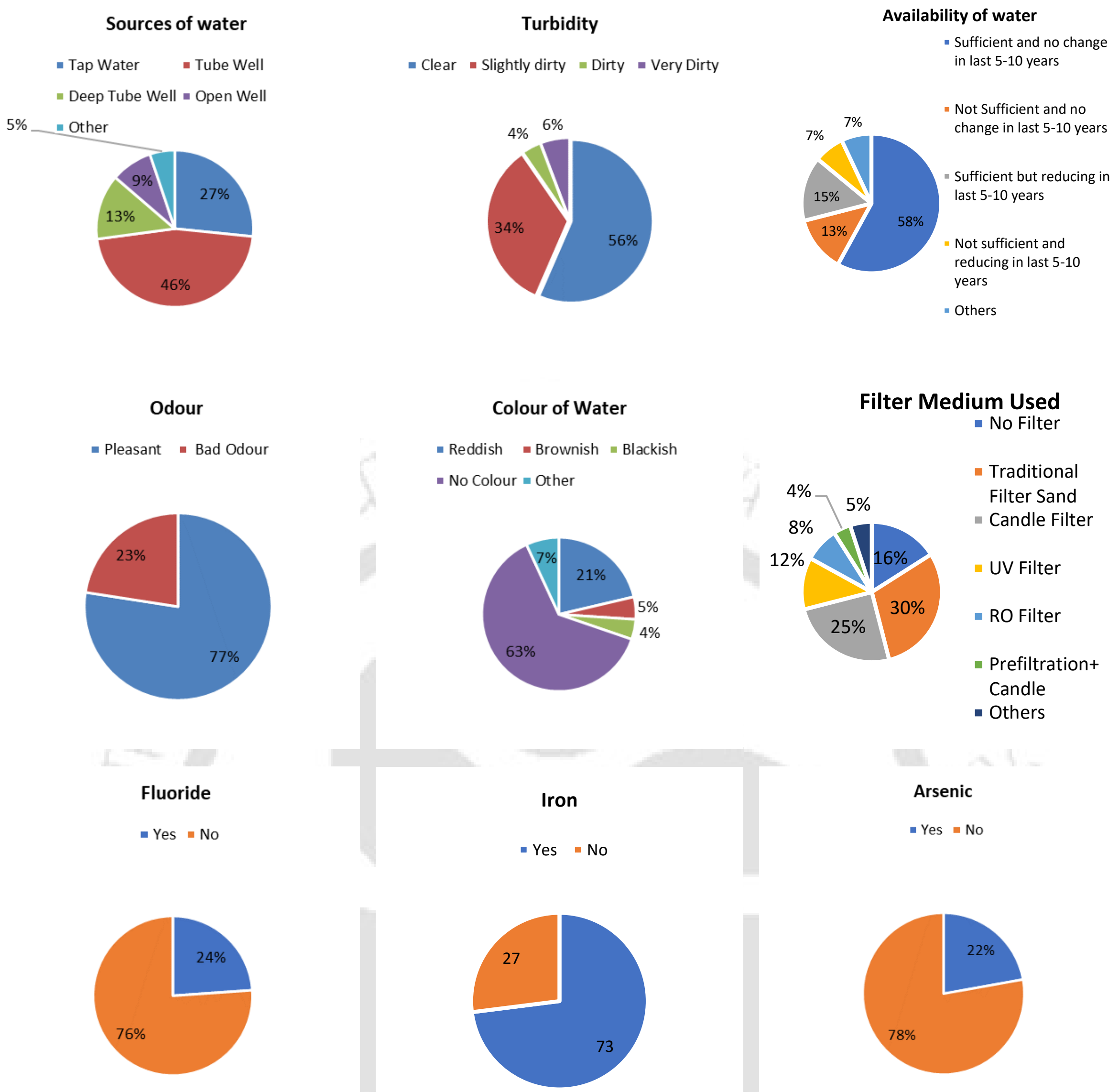


Figure 5.2 Pie diagram showing Types of water sources, Availability of water, Color of water, Turbidity of water, Odor of water, Filters used by households, Iron in water, Fluoride in water, Arsenic in water.

Physical Characteristics of Drinking Water

1. **Color**:

   Drinking water should ideally be colourless. However, 62.8% of surveyed households reported non-colourless water, with hues ranging from reddish and brownish to blackish. High iron content is likely the primary cause, as iron contamination is prevalent in Assam's groundwater.

2. **Turbidity**:

   Turbidity, or water clarity, is an aesthetic issue rather than a health concern. Survey findings revealed that 56.51% of households accessed clean water (<1 NTU), while 33.9% used slightly turbid water, and 9.6% reported high turbidity. Turbidity often results from improper treatment processes, surface runoff during the rainy season, or leaks in distribution pipelines.

3. **Odour**:

   22.6% of households reported unpleasant-smelling drinking water, often caused by microbial activity and decaying organic matter.

Chemical Contamination in Drinking Water

1. **Iron**:

   Iron is naturally present in groundwater as rainwater interacts with geologic formations. Despite its aesthetic nature, iron contamination exceeds the BIS permissible limit of 0.3 mg/L in many regions, causing metallic taste, staining, and greasy texture. Rapid sand filtration has been employed in several districts to reduce iron levels.

2. **Fluoride**:

   Fluoride, derived from natural and anthropogenic sources, is essential for human health in small amounts but becomes harmful at high concentrations. BIS guidelines recommend a fluoride concentration of 1.0 mg/L (desirable) and 1.5 mg/L (permissible). In Assam, fluoride contamination was detected in districts like Dhubri, Morigaon, Nagaon, Karbi Anglong, Karimganj, and Kamrup. Notable concentrations in some specific parts of the state include:

   - 8.05 mg/L in Howraghat (Karbi Anglong)
   - 6.5 mg/L in Bezera (Kamrup)
   - 2.05 mg/L in Binnakandi, Kathiatoli, and Jugijan (Nagaon)

   Chronic exposure to high fluoride levels causes severe health issues such as dental and skeletal fluorosis, gastrointestinal problems, and long-term debilitation.

3. **Arsenic**:

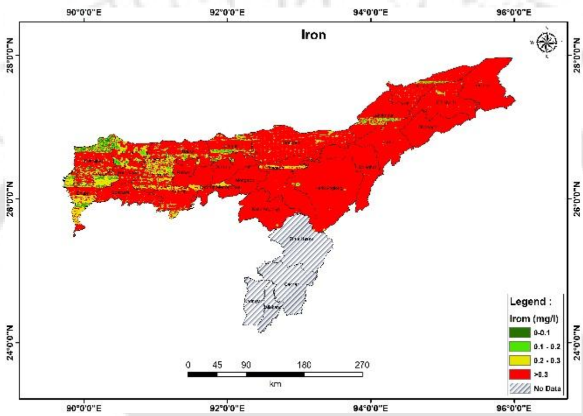
   Arsenic contamination, exceeding the BIS permissible limit of 0.05 mg/L, was reported in Dhubri, Baska, and Barpeta districts. Significant findings in some parts of the state include:

   - 1.0 mg/L in Fekamari and Jamadarhati (Dhubri)

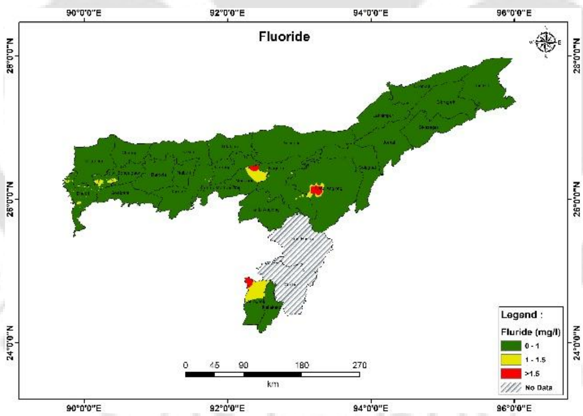
- 0.371 mg/L in Barpeta
Prolonged arsenic exposure poses severe health risks, including cancer and neurological damage.

GIS Mapping of Water Quality Parameters

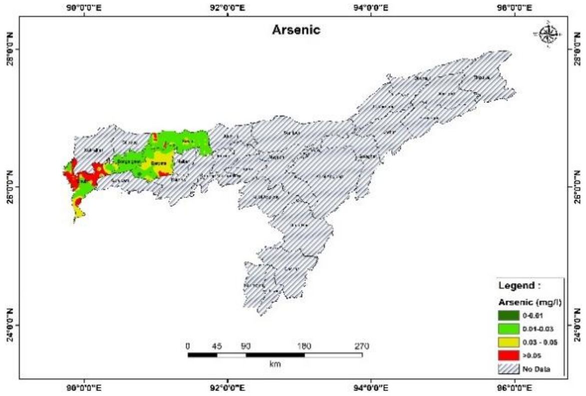
To visualize contamination patterns, GIS maps were developed to illustrate the spatial distribution of iron, fluoride, and arsenic across Assam (**Figure 5.3**). These maps identify contamination hotspots, aiding targeted intervention strategies.



a. Iron concentration



b. Fluoride concentration



c. Arsenic concentration

Figure 5.3 (a) Iron concentration map of Assam, **(b)** Fluoride concentration map of Assam, and **(c)** Arsenic concentration map of Assam

Discussion

The findings emphasize the critical challenges in Assam's drinking water sector, including dependency on untreated water sources, uneven availability, and significant contamination with iron, fluoride, and arsenic. While government programs like Jal Jeevan Mission aim to enhance water access, addressing chemical contamination is equally crucial. Comprehensive strategies, including robust monitoring, advanced treatment technologies, and community education, are imperative to ensure safe and sustainable drinking water access for Assam's population.

5.6 CONCLUSIONS

The assessment of drinking water in Assam highlights significant challenges in terms of both access and quality. While a small percentage of households currently have access to piped water connections, the Jal Jeevan Mission is actively working to ensure universal access to safe drinking water. Groundwater serves as the primary source of drinking water in the region, yet it is plagued by high levels of contamination from iron, fluoride, and arsenic in some parts of the state.

Iron contamination, though primarily an aesthetic concern, can be addressed effectively through conventional filtration methods. However, fluoride and arsenic contamination present more serious health risks, particularly in regions where their concentrations exceed permissible limits. Mitigation strategies such as reverse osmosis (RO) for fluoride removal, and activated alumina adsorption, oxidation, coagulation, and filtration for arsenic removal, are essential for ensuring safe drinking water. Additionally, technologies like ion exchange systems and community-based treatment plants can provide localized solutions.

To further safeguard public health, alternative sources such as perennial surface water, arsenic-safe dug wells, and rainwater harvesting systems must be developed and treated appropriately to meet drinking water standards. These measures, combined with targeted interventions in fluoride- and arsenic-endemic areas, will be instrumental in achieving long-term water security for Assam.

The ongoing efforts under the Jal Jeevan Mission, complemented by sustainable groundwater management and innovative treatment solutions, have the potential to transform the water supply landscape in Assam, ensuring safe and reliable access to clean drinking water for all.

Chapter – 6

VULNERABILITY ASSESSMENT OF GROUNDWATER-BASED PUBLIC DRINKING WATER SUPPLY SYSTEM OF KAMRUP DISTRICT, ASSAM, INDIA CONSIDERING SOCIAL PARAMETERS

6.1 INTRODUCTION

Water is a key natural resource and is considered as a valuable asset of a nation. In general, rivers, lakes, rainwater, groundwater, etc., are primary water sources. In urban areas of India, drinking water is generally provided through surface and groundwater-based water supply schemes. But rural India gets drinking water from groundwater. So, groundwater is considered as the prime source of water both for drinking and irrigation use (Delgado et al. 2010b; Chandra, Asadi, and Raju 2017b; Ghalib 2017b; Karim and Mimura 2008; Yousefi, Ghoochani, and Mahvi 2018b). Drinking water is water in which salts, minerals, sediments, ions and foreign objects are within the permissible value. On the other hand, the absolute absence of these salts and minerals is undesirable. It is one of WHO's primary goals and the collective goals of its member states that "everyone has the right to a safe supply of drinking water, regardless of their social or economic status" (WHO, 2004). Drinking water plays a crucial role in human life. Rural people in India generally get their drinking water from spot sources (government/private) or from piped water supply schemes provided by the government or other agencies. The surface water-related water supply scheme's initial cost and maintenance expenditure are considerably higher than the groundwater-based water supply scheme. In addition, implementing water supply schemes requires a perennial surface source. As such, the Assam Government has implemented several groundwater-based water supply schemes for the state's rural areas. This study focuses on assessing the vulnerability of water supply in rural areas of the state.

The concept of vulnerability is used in the different disciplines. Vulnerability studies are made in the field of disaster management, environmental studies, sociology, health, development, economics, geography, anthropology, global change, etc. (Cutter 1996a; Alwang, Siegel, and Jorgensen 2001). During the last few years, researchers on water resources and services have conducted several studies related to flood, drought and scarcity of water. Some studies were also conducted on the role of water in prosperity, poverty and health. Presently, it becomes an important topic of discussion regarding vulnerability to their use of water in relation to flood and drought, change in climate and poverty (Handmer, Dovers, and Downing 1999; Adger 1999; Soussan and Arriëns 2004). Soussan explained how the concept of vulnerability can be used in understanding the relationship between poverty and water (Soussan 2003; Soussan et al. 2006). Many authors and researchers have studies vulnerability on water security. Dustin Evan Garrick and Jim Hall (Garrick and Hall 2014) on their work on “Water security and society: Risks, Metrics, and Pathway” examined water security indicators and indices to identify thresholds for water – related risks across multiple dimensions of water security and examine how these vary across different scales and socio-economic context. (Dosu and Hanrahan 2021; Cutter et al. 2008) also made vulnerability studies on water security. Adger (Adger 1999) explained vulnerability at two level, i.e., individual and collective vulnerability. While the individual vulnerability is at a household level, the collective vulnerability is at a community level or at a regional and national levels. The various factors of individual or household level vulnerability are socio-economic status, age, sex, race, and, ethnicity (Blaikie et al. 2014c; Peacock, Gladwin, and Morrow 2012; Hewitt 2014; Cutter 1996a; Cutter, Boruff, and Shirley 2012b; 2012a; Cutter, Mitchell, and Scott 2012; Thomas et al. 2009). According to the United Nations (1979), flood vulnerability refers to the amount of loss caused by flooding of a given magnitude to any element or set of elements. The scale ranges from 0 (no damage) to 1 (total damage). Quantifying vulnerability is essential for decision makers, therefore parameters and indicators (indices) should be formulated to provide information about specific areas and to weigh the risk of various hazards societies may encounter, like floods. In this study, water quality index factor, and the socio-economic factors like age factor, literate factor, economic factor, water accessibility factor and asset factors are identified as the indicators for drinking water vulnerability. High water quality index factor value implies poor water quality which signifies more vulnerability. The most vulnerable groups to disasters are children and the elderly (Cutter and Finch 2008). There is a lack of involvement of children in disaster-scenario exercises, perhaps because paternal responsibility for children is assumed (Martin, Bush, and Lynch 2006). Healthy economic condition i.e., more economic factor value as well as the asset factor value makes people resilience to withstand the effect of hazards. Accessible water sources definitely reduce the vulnerability level. Education makes people more informative, hence less vulnerable to any disaster. Education has a direct influence on risk perception, skills and knowledge. Overall, it is effective at reducing poverty, improving health, and improving access to information and resources. Education is believed to make an individual, household, or society more resilient in the event of disasters. In this way, high risk awareness is associated with education, which in turn helps to reduce vulnerability behaviors (Muttarak and Lutz 2014). The vulnerability of social groups to drinking water is therefore impacted by these factors.

Many researchers have carried out several studies regarding the evaluation of social vulnerability related to different hazards. Measurement of district level social vulnerability in Botswana due to natural hazard was carried out by (Dintwa, Letamo, and Navaneetham 2019b). In their work, eleven variables were considered for developing the district social vulnerability index. The study results show that social vulnerability mainly depends on household size and status, age, education level, employment status, disability, social security, and poverty. (D. Gautam 2017b), in his work "Assessment of social vulnerability to natural hazards in Nepal," investigated district level social vulnerability related to natural hazards in Nepal. Census data of all the 75 districts of Nepal were considered to quantify the social vulnerability. A total of 13 variables were selected for his study. (Ge, Dou, and Dai 2017; Hossain and Paul 2018b; P. Das and Dey 2011b), also worked on measuring social vulnerability related to different hazards. Assessment of the groundwater vulnerability of the Rana groundwater basin, Odisha, India was done by (Thakur et al. 2021b). In their study, they are in the opinion that groundwater level and net recharge are having a greater influence on groundwater vulnerability. In addition, (Hughes 2022) developed a multidimensional approach to measuring drinking water vulnerability. (Di Cristo et al. 2015; Karamouz, Zanjani, and Zahmatkesh 2017) found that these vulnerability index measures are related to performance outcomes, including violations of the safe drinking water act. They also investigated the vulnerability of water distribution systems to biological and chemical contaminants in drinking water distribution networks. But to date, no studies have been conducted regarding the evaluation of social vulnerability related to rural drinking water supply considering water quality and socio-economic factors.

Groundwater quality has been studied in different parts of the world. They have attempted to determine whether groundwater is suitable for drinking and other uses by using water quality parameters and evaluating WQI values. As part of their study (Prusty and Farooq 2020), the authors evaluated whether coastal water on the eastern coast of Odisha, India, was suitable for drinking and irrigation. Physico-chemical analysis revealed that the number of patches of drinkable water and irrigational water in the area that could be utilized to supply the coastal population with drinking water is a small percentage based on a few physico-chemical parameters. (B. D. Das and Choudhary 2021) assessed the quality of groundwater in Biratnagar Metropolitan, Nepal. The WQI values of the area were evaluated using eleven physico-chemical parameters. In light of the study's results, it appears that groundwater in the area requires some sort of treatment before consumption. The same test was conducted by (Sarkar et al. 2020; P. K. Gautam et al. 2017; Haque et al. 2020) in the Jabalpur district of Madhya Pradesh, India, to determine if groundwater could be used for drinking purposes. Groundwater quality was estimated by analyzing eleven parameters. According to the findings of the study, pre-consumption treatment is necessary. Specifically, this study examines the socio-economic and WQI values of the groundwater-based drinking water supply system in Kamrup district to assess its social vulnerability.

6.2 MATERIALS AND METHODS

Historically, vulnerability indices had been used as a policy tool since 1920 (Fisher 1922; Edgeworth 1925b). Numbers based on indicators are used to assess quantities over time (Sullivan 2002). An asset or asset group's vulnerability is evaluated in order to determine the likelihood of loss, damage, or destruction. Economic strengthening interventions can be monitored and evaluated, designed and targeted with it (Taghavi et al. 2022). Social vulnerability can be measured inductively or deductively, respectively. According to (Cutter 1996b; Wu, Yarnal, and Fisher 2002; Zahran et al. 2008), a deductive approach based on scientific knowledge is used. The inductive approach is a data-based approach that depends on the relation between vulnerability and its statistical outcomes (S. R. Singh, Eghdami, and Singh 2014; T. T. Nguyen and Rujikiatkamjorn 2016). In the present study, a deductive approach is used to determine the social vulnerability index (SVI) at a block level by taking into consideration various factors, such as water quality, age, literacy, economics, water access, and assets (T. T. X. Nguyen et al. 2016).

Among the most important factors contributing to the vulnerability of drinking water is the Water Quality Index (WQI). Hydro geochemical processes play a prominent role in groundwater movement between recharge and discharge areas. Consequently, the chemical reaction between soil masses and rock present in a pathway determines the quality of water (Olayinka et al. 1999a; Foster et al. 2003a; Chidambaram et al. 2008a). In addition to natural conditions, poorly disposed industrial effluents, domestic sewage, agricultural activities, and other man-made activities deteriorate the groundwater quality (Foster et al. 2003a; Nair et al.

2015a). Any specific area or source of water can be evaluated using physical, chemical, and biological parameters. The parameters are harmful to human health if they exceed the defined limit (Bureau of Indian Standards, Specification for drinking water IS: 10500, New Delhi, India 2012; World Health Organization Guidelines for Drinking-water Quality, Fourth Edition, ISBN 978 92 4 154815 1 2012; Central Pollution Control Board, Water and Waste Water Guide Manual, 2013). In the district level laboratory of the Assam Public Health Engineering Department, 78 water samples collected from different locations of the district were tested for WQI values according to the standard procedure. In general, water samples are tested for 12 parameters. A number of parameters are taken into account, including Iron, Alkalinity, Turbidity, Calcium hardness, Total Dissolved Solids, Chloride, Fluoride, Total hardness, Nitrates, Ph, Manganese, and Magnesium. The WQI can be calculated using a variety of methods (Tyagi et al., 2013b). In different parts of the world, water quality has been quantified using a water quality index. (Ramakrishnaiah, Sadashivaiah, and Ranganna 2009a; Patil and Patil 2013a; Srinivas, Purushotham, and Murali Krishna 2013; Chandra, Asadi, and Raju 2017b) also provided valuable insight into water quality.

6.2.1 STUDY AREA

Kamrup is a district in the state of Assam in India with 13 (thirteen) numbers of community development blocks. It lies between 25.46°N and 26.49°N latitude and between 90.48°E and 91.50°E longitude and has a total area of 3105sq.km (**Figure 6.1 (a)**). Some perennial tributaries like Puthimari, Digaru, Kulshi, Singra, etc. are passing through the district and join the river Brahmaputra. As per the 2011 census of Govt. of India, the district's total population is 15, 17,542, and population density is 490 per sq.km. The annual rainfall of the district ranges between 1500 to 2600mm. The major soil groups identified in the district are recent riverine alluvial soils, old riverine alluvial soils, old mountain valley alluvial soils, and lateralized red soils. The economy of the district is based on agriculture and small industries. The total number of cultivators in the district is 207262, out of which 150921 are small and marginal farmers. The literacy rate of the district is 70.95%. The public health engineering department has implemented several groundwater-based water supply projects to provide drinking water to rural people. This study considers seventy-eight numbers of groundwater-based drinking water supply schemes of the district. **Figure 6.1 (b)** shows the district along with the locations of the public water supply schemes. Most of the people of the district are very much dependent on the water supplied by the projects. As such, it is necessary to have a study to evaluate the vulnerability of supplied drinking water. By knowing the vulnerability index values, the policymakers can take a decision for improvement and adjustment of policies and programs regarding drinking water supply projects.

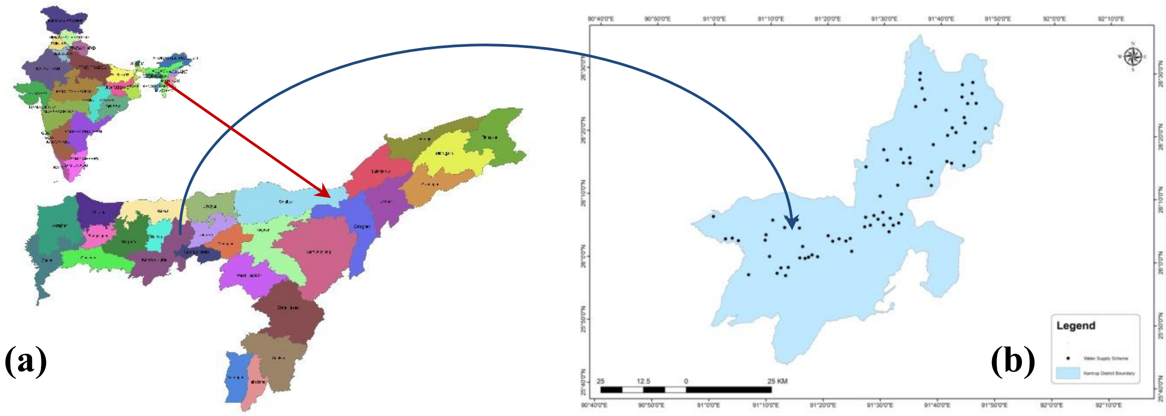


Figure 6.1 (a) Location map of Kamrup District, (b) Kamrup District showing the rural water treatment plants

6.3 CALCULATION OF WATER QUALITY INDEX

In this study, the method proposed by (Goswami and Bhattacharjya 2021) has been used to calculate the WQI values. As per the proposed method, if the concentrations of the parameters are less than the maximum permissible value, the WQI will be 0.30. If the WQI is more than 0.30, this means that one or more parameters have a concentration more than the permissible limit. A linear relation has been used to assign the weightage beyond the permissible limit. The water quality index values are calculated using Eq. 4.1. After calculation of WQI values of the water supply projects, they are grouped according to the status of water quality as per **Table 3.4**. For block wise WQI value, it is assumed that if more than 50% of schemes in a block have a WQI value of 30%, the block is considered to have a WQI value of 30%. If it is equal to or less than 50%, the maximum WQI value of the schemes in that block is taken into consideration. The Water Quality Index factor is calculated by dividing the WQI value of each block by the maximum WQI value for all the schemes. **Table A1** shows the WQI values of different water supply schemes and subsequent Water Quality Index factors.

Social vulnerability index: As discussed earlier, social factors also impact the vulnerability of drinking water. Social factors such as age factor, literate factor, economic factor, water accessibility factor, and asset factor have been identified as the social factors towards the vulnerability of drinking water.

Age factor: Disaster events place children and elders at the greatest risk (Cutter and Finch 2008). In disaster-scenario exercises, children are rarely incorporated because parents assume responsibility for them (Martin, Bush, and Lynch 2006). A child's vulnerability is greater when he or she is 0 to 6 years old compared to an elderly individual. By dividing the total population of the block by the total population of the age group 0 to 6 years, the age factor is determined. Vulnerability is directly affected by age.

Literate factor: The benefit of education is that it makes people more knowledgeable, which decreases their vulnerability to disasters. Knowledge, skills, and perception of risk are directly influenced by education. Finally, it improves health, promotes access to information, and reduces poverty. Disaster recovery is thought to be easier for educated individuals, households, and societies. This results in a high level of risk awareness that reduces vulnerability through the use of education (Muttarak and Lutz 2014). Using the literate factor, each block's population is divided by the total number of literate residents. Inversely, it affects vulnerability. The vulnerability will decrease as the literacy factor increases.

Economic factor: The income level of disaster victims is generally considered a protective factor, since they are able to absorb and recover from disaster impacts more quickly (Cutter et al. 2008). The economic condition also has an effect on the vulnerability of drinking water. The economic factor is considered as the ratio of the total yearly income of all workers or laborers and the total household of the block. The workers are main workers, marginal workers, agricultural laborers, household industry workers, and other workers. It is assumed that the main workers work for nine months, marginal workers work for six months, marginal workers (3-6 months) work for 4.5 months, and marginal workers (0-3 months) work for 1.5 months. A survey was conducted amongst the cultivators and agricultural laborers in different villages of the blocks to calculate the monthly income of the cultivators and daily wages paid to agricultural laborers (**Table A2**). The average monthly income of cultivators is Rs. 4621.00 (Rupees Four Thousand Six Hundred and Twenty-One) only, and daily wages paid to labor are Rs. 350.00 (Rupees Three Hundred and Fifty) only. Again, it is assumed that the monthly income of household industry workers is Rs. 15000 (Rupees Fifteen Thousand) and other workers is Rs. 30000 (Rupees Thirty Thousand) only. From all the above consideration, the yearly income of the block and subsequent economic factor is evaluated. A healthy economic condition will definitely reduce the vulnerability level.

Water accessibility factor: Water sources within and nearby premises are considered accessible. Water accessibility factor is considered as the ratio of total water accessible household to total household of the sub-districts. With more accessible sources, i.e., the high-water accessible factor, the vulnerability will be less.

Asset Factor: Households with radio/transistor, television, mobile phone, scooter/motorcycle/moped, and car/jeep/van are considered assets. For converting the two and four-wheelers to the same scale, it is assumed that the cost of a two-wheeler is around 1/8th the cost of four-wheelers. The asset values of each sub-districts are evaluated considering the households having these assets and total households. The asset factor is the summation of all the asset values. The high asset factor value will minimize the vulnerability level.

6.4 CALCULATION OF SOCIAL FACTORS

The social factors like age factor, literate factor, economic factor, water accessibility factor, and asset factor are calculated using the Census of India 2011 data. As a result, this study was able to analyze all the variables needed in census data. Kamrup district's demography is shown in **Figure 6.2.**

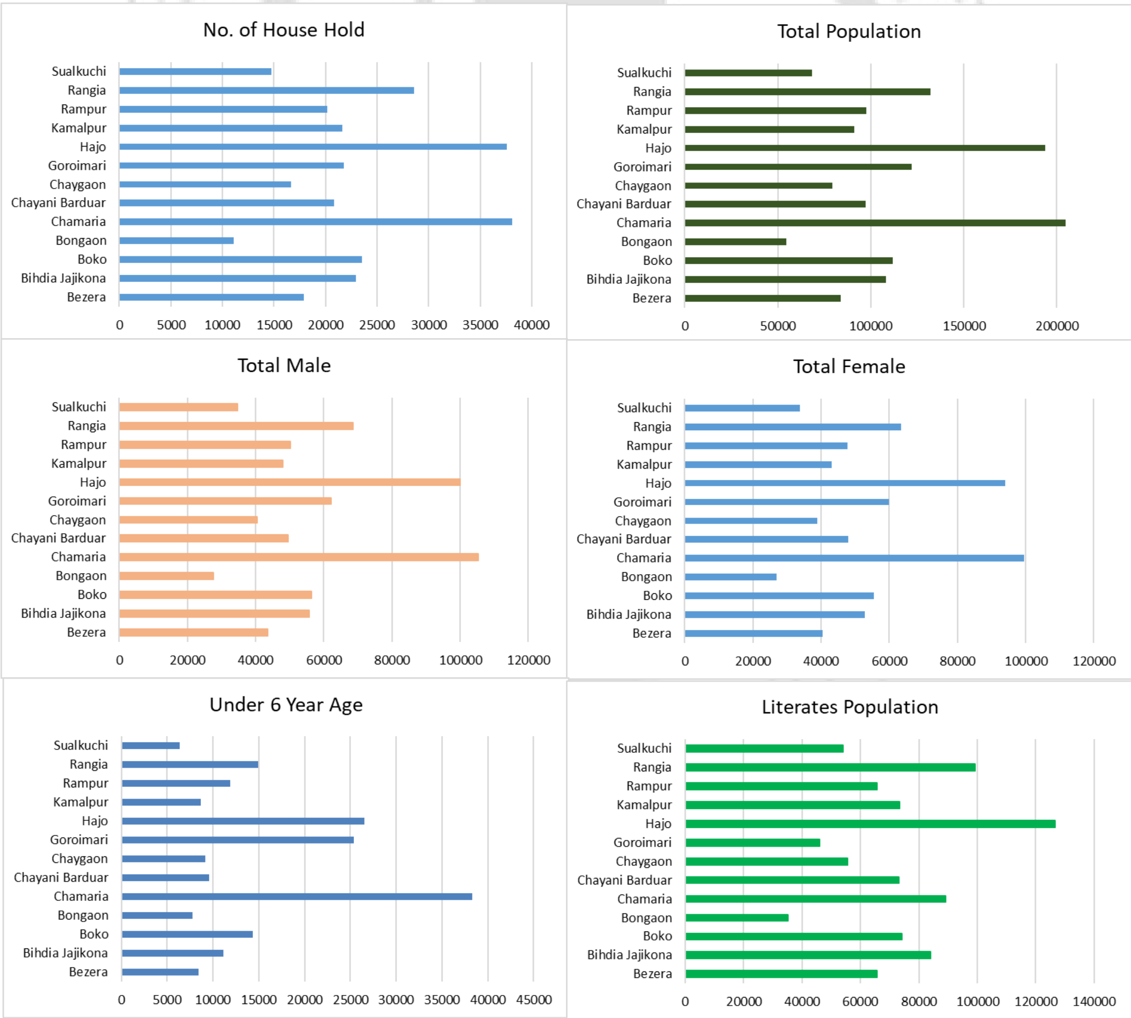


Figure 6.2 Demography of Kamrup district

Table 6.1 Age factor, literate factor, and economic factor for different blocks of Kamrup district

Factor	Block												
	Bezera	Bihdia Jajikona	Boko	Bongaon	Chamaria	Chayani Barduar	Chaygaon	Goroimari	Hajo	Kamalpur	Rampur	Rangia	Sualkuchi
Age Factor	0.1	0.1	0.13	0.14	0.19	0.1	0.12	0.21	0.14	0.1	0.12	0.11	0.09
Literate Factor	0.78	0.78	0.66	0.64	0.44	0.75	0.7	0.38	0.65	0.81	0.67	0.75	0.79
Economic Factor	0.92	0.7	0.62	0.68	0.61	0.82	0.76	0.55	0.81	0.65	0.91	0.61	1.00

The age factor and literate factor for different blocks are calculated using the demographic data. From the census data, considering the numbers of main workers, marginal workers, cultivators, agricultural labor, household industry workers, other workers, and their daily/ monthly earnings, block wise yearly earnings are calculated. Accordingly, economic factors are evaluated. Table 6.1 shows the block wise age factor, literate factor, and economic factor for different blocks of the Kamrup district.

In the Census, household data on water sources and assets are available sub-district-wise. There are 13 numbers of community development blocks and 11 numbers of sub-districts in the Kamrup district.

Table 6.2 Water accessibility factor of different blocks of Kamrup district

<table>
<tr><th>Sl. No</th><th>Name of Sub- District</th><th>Name of the Block</th><th>Area of Sub-District(Sq. Km)</th><th>Area of Block (Sq. Km)</th><th>Conservation Weightage Factor</th><th>Accessibility to Water Source</th><th>Converted Accessibility to Water Source</th></tr>
<tr><td>1</td><td>Boko</td><td>Boko</td><td>511.14</td><td>511.14</td><td>1.00</td><td>0.81</td><td>0.81</td></tr>
<tr><td>2</td><td>Chamaria</td><td rowspan="2">Chamaria</td><td>108.54</td><td rowspan="2">241.19</td><td rowspan="2">2.22</td><td>0.81</td><td rowspan="2">0.80</td></tr>
<tr><td>3</td><td>Nagarbera</td><td>132.65</td><td>0.80</td></tr>
<tr><td>4</td><td rowspan="2">Chaygaon</td><td>Chaygaon</td><td rowspan="2">486.89</td><td>185.49</td><td>0.38</td><td rowspan="2">0.84</td><td>0.32</td></tr>
<tr><td>5</td><td>Bongaon</td><td>301.40</td><td>0.62</td><td>0.52</td></tr>
<tr><td>6</td><td>Goraimari</td><td>Goraimari</td><td>181.43</td><td>181.43</td><td>1.00</td><td>0.76</td><td>0.76</td></tr>
<tr><td>7</td><td>Goreswar</td><td>Bihdia Jajikona</td><td>89.99</td><td>89.99</td><td>1.00</td><td>0.87</td><td>0.87</td></tr>
<tr><td>8</td><td rowspan="2">Hajo</td><td>Hajo</td><td rowspan="2">357.94</td><td>134.70</td><td>0.38</td><td rowspan="2">0.87</td><td>0.33</td></tr>
<tr><td>9</td><td>Sualkuchi</td><td>223.24</td><td>0.62</td><td>0.54</td></tr>
<tr><td>10</td><td rowspan="2">Kamalpur</td><td>Kamalpur</td><td rowspan="2">485.64</td><td>147.95</td><td>0.30</td><td>0.88</td><td>0.27</td></tr>
<tr><td>11</td><td rowspan="2">Bezera</td><td>337.69</td><td>0.70</td><td rowspan="2">0.80</td><td rowspan="2">0.71</td></tr>
<tr><td>12</td><td>North Guwahati</td><td>87.87</td><td>87.87</td><td>1.00</td></tr>
</table>

13	Palasbari	Chayani Barduar	356.22	203.12	0.57	0.88	0.50
14		Rampur		153.10	0.43		0.38
15	Rangia	Rangia	227.39	227.39	1.00	0.90	0.90

Figure 6.3 shows the superimposed map of blocks and sub-districts of the Kamrup district. From the superimposed map and considering the areas of blocks and sub-districts, the conversion factor for water accessibility and asset factor is calculated.

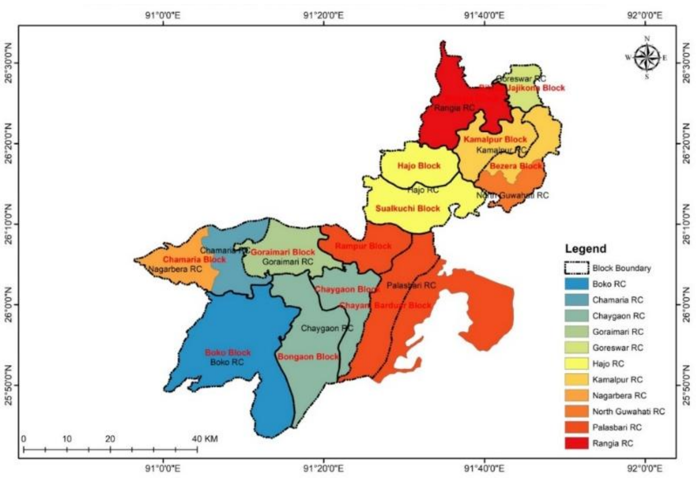


Figure 6.3 Superimposed map of block and sub-district of Kamrup district

Table 6.2 and Table 6.3 show the water accessibility factor and asset factor of different blocks, respectively.

Table 6.3 Asset factor for different blocks of Kamrup district

Sl. No	Name of Sub-District	Name of the Block	Area of Sub-District (Sq. Km)	Area of Block (Sq. Km)	Conservation Weightage Factor	Asset Factor	Converted Asset Factor
1	Boko	Boko	511.14	511.14	1.00	0.75	0.75
2	Chamaria	Chamaria	108.54	241.19	2.22	0.46	0.48
3	Nagarbera		132.65			0.49	
4	Chaygaon	Chaygaon	486.89	185.49	0.38	0.76	0.29
5		Bongaon		301.40	0.62		0.47
6	Goraimari	Goraimari	181.43	181.43	1.00	0.42	0.42
7	Goreswar	Bihdia Jajikona	89.99	89.99	1.00	0.78	0.78
8	Hajo	Hajo	357.94	134.70	0.38	0.96	0.36
9		Sualkuchi		223.24	0.62		0.60
10	Kamalpur	Kamalpur	485.64	147.95	0.30	1.04	0.32
11		Bezera		337.69	0.70		1.02

12	North Guwahati		87.87	87.87	1.00	1.31	
13	Palasbari	Chayani Barduar	356.22	203.12	0.57	0.95	0.54
14		Rampur		153.10	0.43		0.41
15	Rangia	Rangia	227.39	227.39	1.00	1.04	1.04

6.4.1 CALCULATION OF COMPOSITE SOCIAL VULNERABILITY INDEX (SVI)

For assigning weight to different parameters, an opinion survey is being conducted by the author among the experts. They have valued the different parameters ranging from 0 to 10 in terms of importance of the parameters regarding vulnerability of drinking water. Accordingly, the relative weight of the parameters is calculated. **Table A3** shows the relative weight of the parameters as per opinion survey. Moreover, as discussed earlier, the different indicators have a direct or inverse relation to vulnerability. **Table 6.4**. shows the information of indicators for social vulnerability.

Table 6.4 Information of indicators for social vulnerability

Sl.No.	Indicator	Description	Impact to SVI
1	Water Quality Index	Good water quality reduces the vulnerability level	Direct
2	Age factor	Childhood is considered as the most vulnerable period of life	Direct
3	Literate factor	Education helps in vulnerability reduction behavior	Inverse
4	Economic factor	Income is considered as the protective factor for the victims to recover from disaster impacts	Inverse
5	Water accessibility factor	Accessible water sources reduce the vulnerability level	Inverse
6	Asset factor	High asset value reduces the vulnerability level	Inverse

Using the fractions with indicators such as water quality parameters, i.e., water quality index factors and subsequent social factors, as part of numerator or denominator, depending on their effect on vulnerability, the composite social vulnerability index (SVI) is calculated using the proposed **Eq. 6.1**

$$SVI = \frac{W_q A_g}{L_t E_c A_w A_{ss}} \qquad 6.1$$

where Wq is the weighted Water Quality Index Factor, Ag is the weighted Age Factor, Lt is the weighted Literate Factor, Ec is the weighted Economic Factor, Aw is the weighted Accessibility to Water Source, Ass is the weighted Asset Factor.

For comparison between the SVI values of different blocks, the values are normalized. The normalized value is obtained as SVI value of a block divided by the maximum SVI value within all the blocks. The maximum normalized SVI is 1 which represents highly vulnerable to drinking water. By seeing the maximum and minimum vulnerability index values and its affecting parameters, the blocks are classified as very low, low, medium, and highly vulnerable. **Table 6.5** shows the range of vulnerability index values and vulnerability levels.

Table 6.5 Range of vulnerability index values & vulnerability level

Sl. No.	Range of vulnerability index values	Vulnerability level
1	0.00 - 0.25	Very Low
2	0.26 - 0.50	Low
3	0.51 – 0.75	Medium
4	0.76-1.00	High

6.5 RESULTS AND DISCUSSIONS

This study examined water quality parameters and social factors to determine the composite social vulnerability index of Kamrup district's rural drinking water supply. The water quality of supplied water as evaluated using the Water Quality Index value is mainly good. Only in five numbers blocks, the supplied water has been found of poor-quality. The WQI values of different blocks are plotted on a GIS and shown in **Figure 6.4**.

In all of the water supply projects, the laboratory test data found the concentration of all parameters except Iron, Fluoride, and Manganese was within the permissible limit. All twelve parameters are listed in **Table A4**. The Bezera Development Block has only five water supply projects with fluoride in the water. Rocks contain a large amount of fluoride. Several minerals, including fluorite, cryolite, apatite, hornblende, mica, among others, leach fluoride into groundwater. For healthy dental growth, 1mg of calcium per day is essential. Fluoride overdose, however, can cripple a person for the rest of their lives (Chand, 1998). Today, fluoride contaminated groundwater is one of the most significant environmental issues across the globe due to its toxic effects. Many states in India are plagued by fluoride problems in their groundwater (Muralidharan, Nair, & Sathyanarayana, 2002). Fluorosis was reported in the Karbi Anglong and Nagaon districts of Assam, India due to severe fluoride contamination in groundwater (Chakraborti et al., 2000b). In groundwater, manganese is often present along with iron. The trace element manganese is essential for organisms. Although manganese poisoning is not toxic to humans in the short term, it causes progressive degeneration of the central nervous system over time. In groundwater, iron is naturally present. Human nutrition relies on it. Laundry and plumbing fixtures are stained by water with a high concentration of iron. Fatigue, vomiting, headaches, and weight loss are some of the symptoms associated with water containing higher concentrations of iron. Through a normal filtration process, poor-quality water can be readily used, except for those contaminated with fluoride. Water contaminated with fluoride can, however, be filtered through RO to be used for drinking.

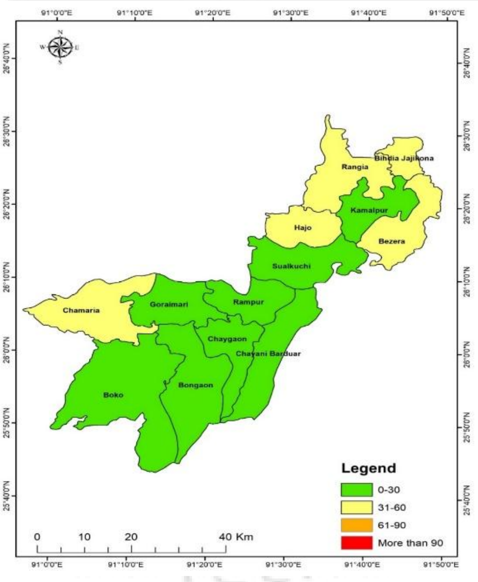


Figure 6.4 WQI values of different blocks

Social factors like age factor, literate factor, economic factor, accessibility to the water source, and asset factor affect the vulnerability of drinking water. Age factor, i.e., children up to 6 years of age are considered more vulnerable to drinking water. From the Census of India 2011 data, the highest value of age factor is found in Goroimari Community Development Block to the tune of 0.21, and 0.19 in Chamaria Community Development Block. The minimum age factor of 0.09 is found in Suwalkuchi Community Development Block. Regarding literacy, as evaluated as a literate factor, both Goroimari and Chamaria Community Block are found to have a low literate factor. On the other hand, Kamalpur Community Development Block is found to have the maximum value of the literate factor. More the value of the literate factor, there will be less vulnerability to drinking water. The economic factor evaluated from the Census 2011 data is 0.55 for Goroimari Community Development Block, which is the minimum amongst all the blocks. This factor value is 0.61 for Chamaria Community Development Block. Most of the people of these areas are agricultural labourers, and most people are illiterate and economically backward. So, the high value of age factor and low value of economic factor has made both the blocks more vulnerable to drinking water. Accordingly, both the blocks fall in the category of medium vulnerability level. It is also suggested that low education has a negative impact on social vulnerability (Dintwa, Letamo and Navaneetham, 2019) on their study of measuring social vulnerability in Botswana. According to their study, high percentages of under-5-year-olds and high percentages of people older than 65 years also contribute greatly to social vulnerability to natural hazards in Botswana. Therefore, drinking water supplies are more vulnerable to contamination. While considering the accessibility to a water source, the people of four blocks, namely Chaygaon, Hajo, Kamalpur, and Rampur have less access to drinking water sources. But in Rangia Community Development Block, the accessibility to a water source is found maximum, hence less vulnerable. The asset factor as evaluated is found minimum in four blocks, namely Boko, Chaygaon, Hajo, and Rangia. But Suwalkuchi Community Development Block has the highest asset factor value of 1.04. Less asset factor value implies more vulnerability to drinking water. The low value of water accessibility factor and asset factor has made Chaygaon block in medium vulnerability level in respect of drinking water. Hajo block is found highly vulnerable. This is mainly due to poor water quality and low value of accessible water source and asset value. **Table 6.6** shows the social vulnerability index values of different blocks of the Kamrup district.

From the vulnerability index values, as calculated, the blocks are categorized as very low, low, medium, and highly vulnerable to drinking water. The block wise Vulnerability Index Values according to the above classification are plotted on a GIS map. **Figure 6.5** shows the Vulnerability Index Values of different blocks.

Accordingly, six blocks fall within a very low vulnerable level and three blocks within a low vulnerable level. On the other hand, three blocks namely, Chamaria, Goroimari and Chaygaon fall within medium vulnerable level and Hajo Community Development Block falls within the highly vulnerable level. This high vulnerability is mainly due to poor water quality and low value of accessible water source and asset factor.

Table 6.6 Social vulnerability index of different blocks of Kamrup district

Sl. No.	Name of Block	Weighted Water Quality Index Factor	Weighted Age Factor	Weighted LIT Factor	Weighted Economic Factor	Weighted Accessibility to Water Source	Weighted Asset Factor	Vulnerability Index	Vulnerability Index (Normalized)
1	Bezera	0.20	0.01	0.13	0.18	0.17	0.11	5.72	0.09
2	Bihdia Jajikona	0.17	0.01	0.13	0.14	0.21	0.07	8.42	0.14
3	Boko	0.16	0.02	0.11	0.12	0.20	0.04	26.02	0.43
4	Bongaon	0.16	0.02	0.11	0.14	0.13	0.07	20.17	0.33
5	Chamaria	0.17	0.02	0.07	0.12	0.19	0.06	40.43	0.66
6	Chayani Barduar	0.16	0.01	0.12	0.16	0.13	0.11	6.78	0.11
7	Chaygaon	0.16	0.01	0.12	0.15	0.07	0.05	37.26	0.61
8	Goroimari	0.16	0.03	0.06	0.11	0.18	0.09	38.00	0.62
9	Hajo	0.22	0.02	0.11	0.16	0.08	0.05	61.17	1.00
10	Kamalpur	0.16	0.01	0.13	0.13	0.07	0.14	11.89	0.19
11	Rampur	0.16	0.01	0.11	0.18	0.08	0.08	17.01	0.28
12	Rangia	0.17	0.01	0.12	0.12	0.22	0.05	13.86	0.23
13	Suwalkuchi	0.16	0.01	0.13	0.20	0.13	0.15	3.50	0.06

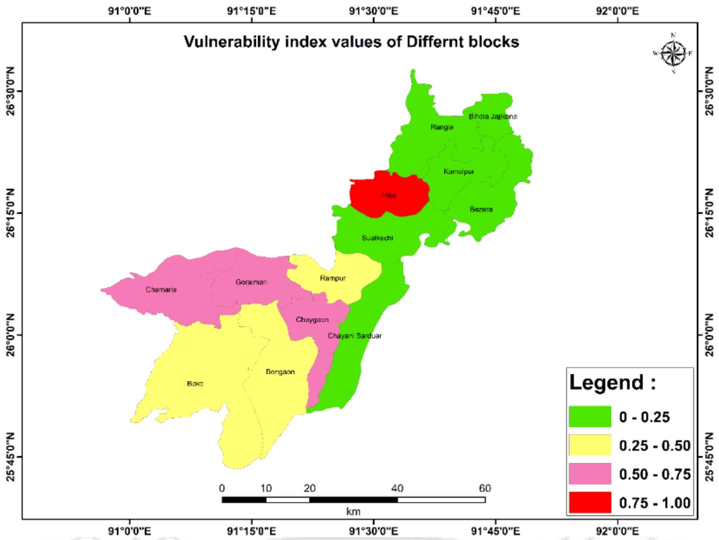


Figure 6.5 Vulnerability index values of different blocks

6.6 CONCLUSIONS

Almost all public water supply distribution systems of the Kamrup are found suitable from the evaluation of the field test results of water samples and subsequent water quality index calculation. In some of the water supply projects, only Iron, Manganese, and Fluoride have been found beyond the permissible limit. The parameters have made the quality of water poor. The water with excess Iron and Manganese, which are not so harmful to human health, can be used for drinking through a normal filtration process. On the other hand, fluoride is found beyond the permissible limit only in five numbers of water supply projects located in the Bezera Development Block. This fluoride-contaminated water can be used for other household purposes except cooking and drinking. However, this contaminated water can be used for cooking and drinking after the filtration using the RO system. Again, it is learned that water has been extracted from a rock-boring type of deep tube in all the fluoride-contaminated projects. It has been done due to the unavailability of the undergroundwater-bearing sandy layer in those particular locations. So, it is adviceable to evaluate the water quality of the rock-boring type of deep tube well before supplying the water to the community. Regarding vulnerability, Hajo block is found highly vulnerable. This is mainly due to poor water quality and low value of accessible water source and asset value. As there is no any record of groundwater contamination with fluoride in Hajo development block, the poor water quality in some of the sources is mainly due to presence of iron and manganese in the water. So, the normal filtration process will definitely improve the water quality. Regarding accessible water source, the number of water sources are minimum in comparison to number of families. But, under the programme of Jal Jeevan Mission, announced by government of India, it is targeted to connect every household with water tap connection. This will definitely reduce the vulnerability level in regards to accessible water source. Though physically, both Goroimari and Chamaria blocks fall in the category of medium vulnerability level, the economic factor and asset factor value are minimum and children in the age group of 0-6 years i.e. age factor value is maximum amongst all the blocks of the district. Due to poor literacy, they have less knowledge about proper family planning and at the same time they are not aware about the possible effects of hazards. Implementation of proper education and employment generation policy will definitely educate the people and upgrade their economic status to withstand the possible effects of hazards.

Chapter – 7

Evaluation of Composite Social Vulnerability considering Temporal Groundwater Fluctuations in Assam Using GRACE Data and Ground-Based Observations

7.1 INTRODUCTION

Precipitation is the primary source of freshwater on Earth, encompassing various forms such as rain, snow, hail, and dew. However, rain constitutes the most significant contributor to freshwater resources, with groundwater being an essential component formed by the infiltration of rainwater into the soil. Groundwater accounts for approximately 30% of the world's total freshwater (Earth's Freshwater, 2019) and plays a vital role in meeting domestic, agricultural, and industrial water needs. In India, over 85% of rural domestic water, 50% of urban water, and more than 50% of irrigation requirements are sourced from groundwater (Abou Zaki et al., 2019). Its widespread availability and reliability have made groundwater a key resource, particularly in rural areas, where it plays a crucial role in poverty alleviation and water security.

Despite its significance, groundwater resources are under increasing pressure due to over-exploitation driven by growing agricultural demand, climate change, and rapid urbanization. This has resulted in noticeable depletion of groundwater in several regions (Marchant and Bloomfield, 2018; Han et al., 2019; Li et al., 2019). This issue is particularly concerning in regions where the rate of groundwater recharge is insufficient to meet extraction demands, leading to unsustainable use (Kumar et al., 2006). In India, where groundwater plays a significant role in both domestic and agricultural water supply, depletion is a critical concern, particularly in rapidly urbanizing and industrializing areas Khan et al., 2014; Iqbal et al., 2017b). Studies have indicated a decline in groundwater levels across various states, and Assam is no exception (Chinnasamy et al., 2015).

The groundwater system is dynamic, influenced by anthropogenic activities such as pumping, surface water recharge, and climatic factors like rainfall and evapotranspiration. Assam, located in northeastern India, experiences both summer and winter monsoons, which bring substantial rainfall from the southwest and northeast monsoons. Long-term analyses of rainfall in the region indicate slight variations in the total rainfall distribution, with no significant long-term trends (Singh, Eghdami, and Singh, 2014; Jain, Kumar, and Saharia, 2013; Das, Panigrahi, and Panda, 2012).

The Gravity Recovery and Climate Experiment (GRACE) mission, launched by NASA in 2002, provides a novel approach to monitoring changes in the Earth's gravity field, which is sensitive to variations in water storage, including groundwater. GRACE has been extensively used globally to track groundwater variations and assess trends in groundwater depletion (Rodell et al., 2007c; Famiglietti, 2014). By measuring minute changes in Earth's gravity, GRACE can detect shifts in terrestrial water storage across large spatial scales. Although the GRACE data does not directly measure groundwater, it offers crucial information on changes in water mass, which can be correlated with other datasets, such as precipitation, to estimate fluctuations in groundwater levels (Ahmed and Abdelmohsen, 2018). Thus, GRACE data plays a significant role in understanding regional groundwater dynamics.

In Assam, groundwater levels are monitored by the Central Groundwater Board through 414 observation wells. Data is collected during key periods of the year, including pre-monsoon (January, March/April/May), monsoon (August), and post-monsoon (November), to assess the impact of seasonal variations, recharge, and groundwater withdrawals. Groundwater levels are measured in meters below ground level (mbgl), providing a standardized metric for temporal and spatial comparisons. Groundwater fluctuations from 2016 to 2022 offer valuable insights into the temporal variations in groundwater levels across the state.

The objective of this study is to evaluate the temporal fluctuations of groundwater in Assam using GRACE data in conjunction with ground-based observations. By analyzing the spatial and temporal variations in groundwater levels from 2016 to 2022, this study aims to offer a comprehensive understanding of groundwater dynamics in the state. Furthermore, it will examine the role of climatic factors such as rainfall on groundwater fluctuations, contributing to more informed and sustainable water management strategies in Assam.

7.2 MATERIALS AND METHODOLOGY

This study aimed to evaluate the temporal fluctuations of groundwater in Assam using GRACE data and IMD rainfall data. The challenge of spatial resolution discrepancies between the datasets was addressed by utilizing QGIS software to create Thiessen polygons around the grid points of both datasets. GRACE data had a resolution of 1° x 1°, while IMD rainfall data had a finer resolution of 0.25° x 0.25°. Each Thiessen polygon represented a district within the study area, and the grid points were weighted based on the area size within each district. Weighted averages were then calculated for each district using both the GRACE and IMD rainfall data (**Figure 7.1**).

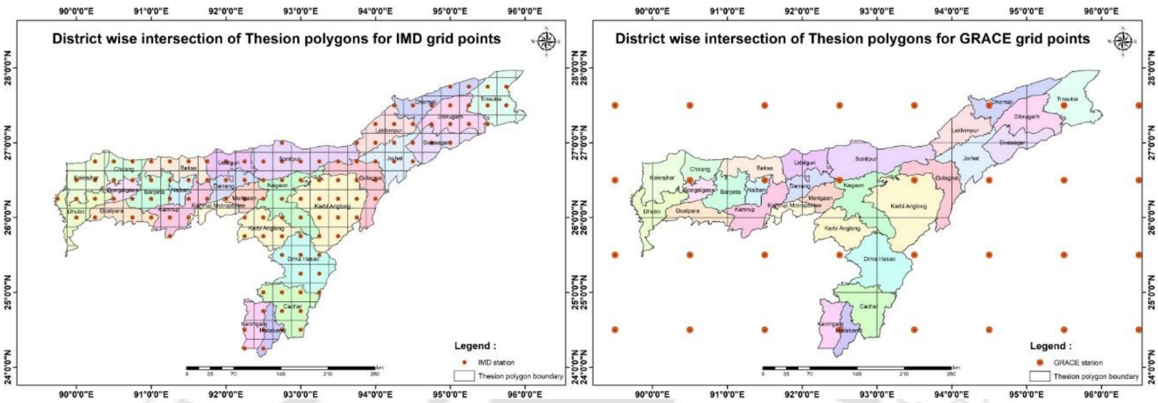


Figure 7.1 District wise intersection of Theisen polygons for IMD and GRACE grid points

Due to the limited availability of groundwater level data for Assam's 27 districts—only quarterly observations from 2016 to 2022 (January, March/April/May, August, and November)—a K-means clustering approach was employed to augment the dataset. K-means clustering, a widely-used unsupervised machine learning technique, was selected for its ability to partition data into distinct groups based on shared characteristics. This algorithm operates iteratively, starting with randomly initialized centroids, and refines them to minimize the sum of squared distances between data points and their nearest centroid. The core principle of this method is to ensure that the within-cluster variance is minimized while maintaining distinctiveness between clusters.

In this study, clustering was performed using key parameters derived from the groundwater level data, including the average, maximum, minimum, and standard deviation of groundwater levels for each district. These parameters were chosen because they effectively captured both the central tendencies and variability of groundwater levels, which are critical for understanding hydrogeological patterns. The iterative process adjusted the centroids based on these parameters, ensuring the optimal grouping of districts with similar groundwater behaviours.

The selection of the number of clusters (k) is a pivotal step in the K-means process, as it determines the granularity of the clustering results. Different values of K were tested to identify the optimal number of clusters, with each configuration evaluated based on its ability to capture meaningful patterns in the data. After careful analysis, K was set to 9, as this configuration not only provided distinct and interpretable groupings but also yielded better results when applied in subsequent linear models, as discussed later in this study. The resulting 9 clusters, as presented in **Table 7.1**, revealed distinct hydrogeological patterns across the state, addressing the data scarcity and enabling more localized modelling.

Table 7.1 Clustering the Districts of Assam

Cluster No.	Districts
1	Dhemaji, Udalguri, Sonitpur
2	Cachar, Hailakandi, Kamrup Metropolitan
3	Chirang, Tinsukia
4	Golaghat, Karbi Anglong, Kokrajhar
5	Jorhat, Karimganj, Lakhimpur
6	Baska, Nalbari, Dima Hasao
7	Barpeta, Sivasagar, Kamrup, Golaghat, Morigaon, Dibrugarh
8	Bongaigaon, Nagaon, Darrang
9	Dhurbi

After clustering the districts, a linear model was employed to examine the relationship between groundwater (GW) levels, GRACE values for the current time step, and rainfall data from the current month and the previous time step.

The functional form of the model is expressed as:

$$\mathrm{GW_t} = (C_1\mathrm{Grace_t} + C_2\mathrm{Rainfall_{t-1}} + C_3\mathrm{Rainfall_t}) + Y \qquad \textbf{(7.1)}$$

Here, $C_1, C_2,$ and C_3 are the coefficients, and Y is the intercept. The coefficients and intercepts obtained from the linear regression are provided in **Table 7.2**.

Given the unavailability of GRACE data for 2017 and the substantial missing values in the groundwater dataset before 2017, the model training began from 2018 onwards. The dataset was split into 70% for training and 30% for testing, allowing for model development and evaluation. This partitioning enabled the model to be tailored to each district cluster, ensuring the parameters reflected the localized hydrogeological conditions. The performance of the model was evaluated using the testing set, assessing its generalizability and predictive accuracy.

While the process was successfully applied to eight of the nine district clusters, the 9th cluster, which included only one district (Dhubri), had very limited data. As a result, a robust linear model with a reliable R^2 value could not be trained for this cluster. Therefore, all steps were performed for the remaining eight clusters shown in **Table 7.3**.

This process was applied to each of the eight district clusters, ensuring that the resultant linear models captured the unique environmental dynamics of each group. The iterative nature of this process accounted for the heterogeneity in groundwater behavior across Assam's diverse districts, improving the model's predictive capability.

Table 7.2 Coefficients and intercepts obtained from the linear regression model

Cluster No.	C1	C2	C3	Y
1	-2.764894	-0.000756	-0.001986	2.678734
2	-6.393546	0.000506	0.002360	1.423051
3	-0.029437	-0.005793	0.002033	3.776152
4	2.698644	-0.009986	0.000784	5.598596
5	-5.605760	0.001223	0.000599	0.885680
6	-6.265907	0.000726	-0.000297	2.228489
7	-5.700373	-0.000590	0.003008	2.270326
8	-3.667550	-0.001715	-0.000909	3.223019

Table 7.3 Performance of Linear Regression model for each cluster

Cluster No.	Districts	R^2 – training	R^2 – testing
1	Dhemaji	0.57	0.58
	Udalguri		
	Sonitpur		
2	Cachar	0.709	0.526
	Hailakandi		

	Kamrup Metropolitan		
3	Chirang	0.551	0.751
	Tinsukia		
4	Golaghat	0.604	0.587
	Karbi Anglong		
	Kokrajhar		
5	Jorhat	0.525	0.628
	Karimganj		
	Lakhimpur		
6	Baska	0.5658	0.781
	Nalbari		
	Dima Hasao		
7	Barpeta	0.561	0.68
	Sivasagar		
	Kamrup		
	Golaghat		
	Morigaon		
	Dibrugarh		
8	Bongaigaon	0.642	0.56
	Nagaon		
	Darrang		

In the subsequent step, the equations derived from the linear models were used to generate time series (TS) data for groundwater levels in each district, starting from the year 2002. This aligns with the availability of GRACE data from 2002 onwards, while IMD rainfall data extends beyond this period. The resulting time series data encapsulated the modeled relationships between groundwater levels, GRACE values, and historical rainfall patterns. To analyze long-term trends, a trend line was fitted to each district's time series, visually and quantitatively representing the evolving groundwater dynamics over time.

7.3 RESULTS AND DISCUSSIONS

The performance of the linear models for each cluster of districts was assessed using the coefficient of determination $(R^2)$to evaluate how well the models predicted groundwater levels. The training phase utilized 70% of the data, while the remaining 30% was reserved for validation. Scatter plots representing observed groundwater levels and data predicted from the trained models for all eight clusters have been added in **Figure 7.2**. These plots provide a visual comparison of the observed and predicted values. As shown in **Table 7.3**, the R^2 values for both the training and validation phases were satisfactory, exceeding 0.50. These results confirm that the developed models effectively captured the relationships between groundwater levels, GRACE data, and IMD rainfall data.

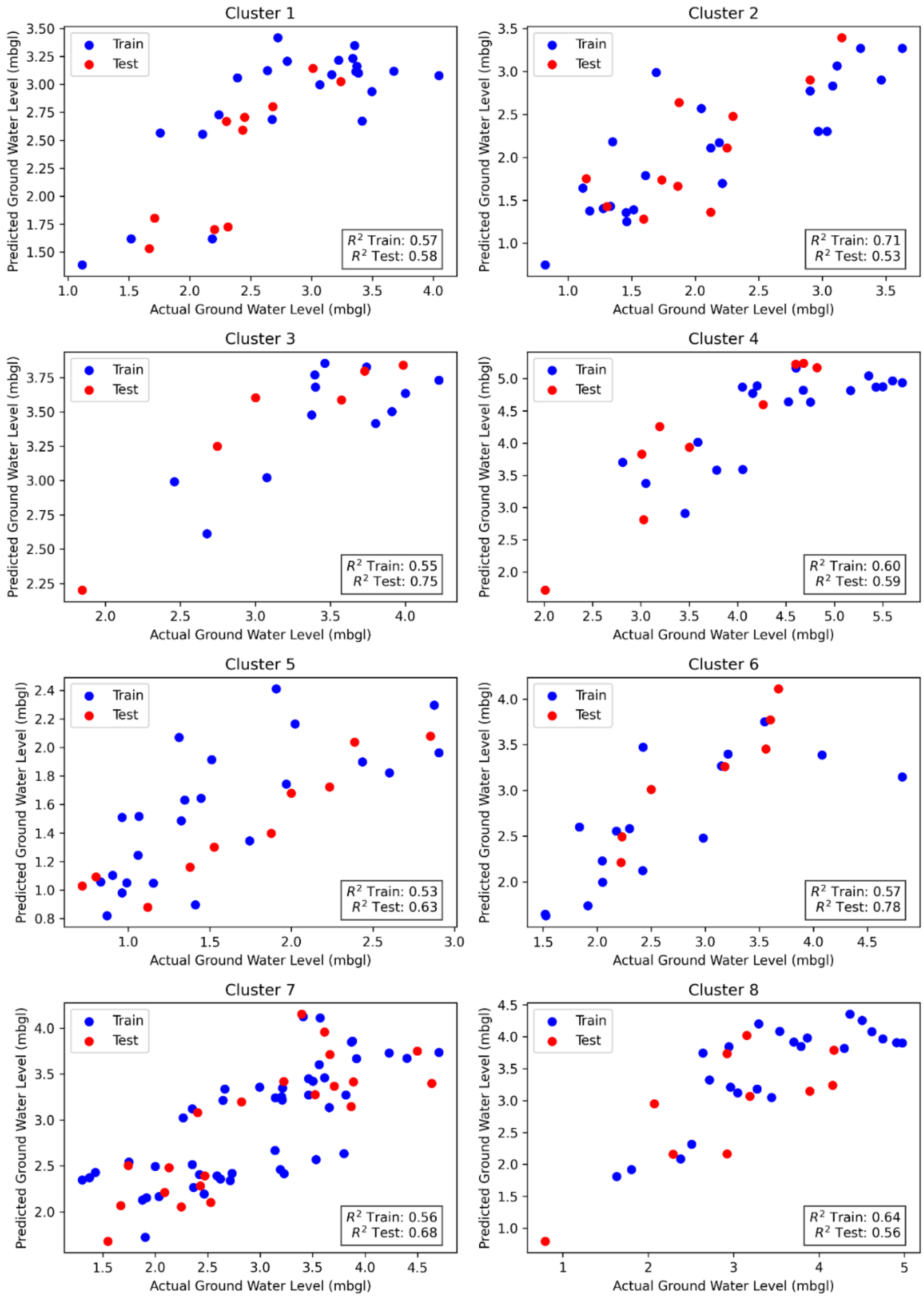


Figure 7.2 Scatter plots of observed and predicted groundwater levels

Using these validated models, groundwater levels were predicted for each district in Assam for the months of January, March, August, and November during the period 2002–2022. The temporal fluctuations in groundwater levels, expressed in meters below ground level (mbgl), are presented **Figure 7.3**. This time series plot reveals seasonal and inter-annual variability across districts, highlighting the dynamic nature of groundwater resources influenced by rainfall patterns and anthropogenic activities.

A trend line was fitted to the groundwater time series for each district to analyze long-term trends, illustrating the direction and rate of change in groundwater levels over the study period. The slopes of these trend lines served as a basis for comparing groundwater trends across the state. For the Dhubri district (Cluster 9), due to insufficient data, a linear model could not be trained. Instead, the average slope values of its neighboring districts, Bongaigaon and Goalpara, were used to approximate the trend for the Dhubri district. These findings, summarized in **Table 7.4**, reveal significant spatial variability in groundwater trends across the state.

Table 7.4 Slope for each district

Sl. No.	District	Slope	Normalized Slope
1	Baksa	0.0054	1
2	Barpeta	0.0046	0.852
3	Bongaigaon	0.0039	0.722
4	Cachar	0.0021	0.389
5	Chirang	0.0005	0.093
6	Darrang	0.0035	0.648
7	Dhemaji	0.0028	0.519
8	Dhubri	0.0042	0.777
9	Dibrugarh	0.0032	0.593
10	Dima Hasao	0.0031	0.574
11	Goalpara	0.0045	0.833
12	Golaghat	0.0002	0.037
13	Hailakandi	0.0024	0.444
14	Jorhat	0.0026	0.481
15	Kamrup	0.0039	0.722
16	Kamrup Metropolitan	0.0045	0.833
17	Karbi Anglong	0.0004	0.074
18	Karimganj	0.0022	0.407
19	Kokrajhar	0.002	0.370
20	Lakhimpur	0.0037	0.685
21	Morigaon	0.0041	0.759
22	Nogaon	0.0029	0.537

23	Nalbari	0.0053	0.981
24	Sivasagar	0.003	0.556
25	Sonitpur	0.0022	0.407
26	Tinsukia	0.0007	0.130
27	Udalguri	0.0023	0.630

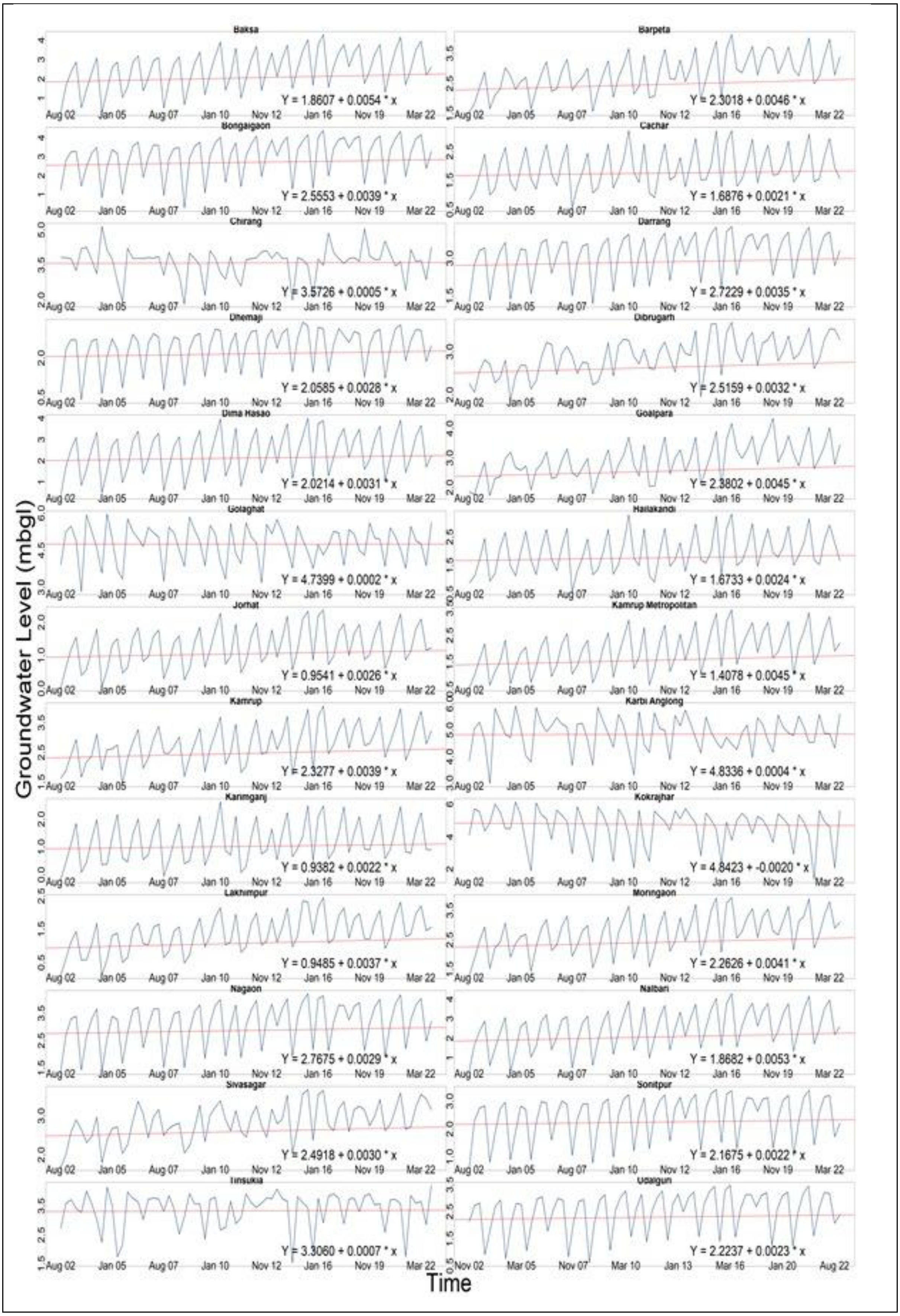


Figure 7.3 Time Series of Groundwater fluctuation for different districts

The results from **Table 7.4** indicate that all districts experienced declining groundwater levels, reflecting a general trend of depletion across the region. However, the rate of decline varied among districts, with some showing steeper negative slopes, signaling more rapid groundwater depletion, while others exhibited milder slopes, indicating a slower rate of depletion. This variation highlights the differing dynamics of groundwater extraction and recharge across districts, emphasizing the need for targeted water management interventions. Districts with steeper slopes particularly warrant urgent attention, as they are at higher risk of significant groundwater depletion.

The methodology used in this study integrates GRACE satellite data with IMD rainfall and ground-based measurements, demonstrating its utility in regions where groundwater data is sparse. By leveraging this approach, as illustrated in **Table 7.3** and **Table 7.4**, it becomes possible to generate district-specific insights into groundwater dynamics, enabling policymakers to design localized, sustainable groundwater management strategies. This study highlights the importance of adopting advanced geospatial and statistical methods to address challenges in water resource management, especially in regions with complex hydrogeological characteristics.

7.4 EVALUATION OF COMPOSITE SOCIAL VULNERABILITY INDEX

From the water quality data of different districts, taking the average value of the parameters, the WQI values were evaluated as enlisted in **Chapter – 4**. The district wise WQI factors are calculated by dividing the WQI value for each district with the maximum WQI value among all the districts of Assam. **Table 7.5** shows the WQI factor for the districts of Assam.

Table 7.5 Water quality index Factor for different districts of Assam

District	WQI (Treated)	WQI Factor
Barpeta	30	0.811
Baska	30	0.811
Bongaigaon	30	0.811
Cachar	30	0.811
Chirang	30	0.811
Darrang	33	0.892
Dhemaji	31	0.838

Dhubri	31	0.838
Dibrugarh	30	0.811
Dima Hasao	31	0.838
Goalpara	30	0.811
Golaghat	32	0.865
Hailakandi	30	0.811
Jorhat	31	0.838
Kamrup	30	0.811
Kamrup Metropolitan	30	0.811
Karbi Anglong	30	0.811
Karimganj	30	0.811
Kokrajhar	30	0.811
Lakhimpur	30	0.811
Morigaon	37	1.000
Nagaon	31	0.838
Nalbari	33	0.892
Sivasagar	31	0.838
Sonitpur	30	0.811
Tinsukia	30	0.811
Udalguri	30	0.811

The district wise social factors like age factor, literate factor, economic factor, water accessibility factor and asset factor were calculated using the Census of India 2011 data. These factors were calculated using the same procedure as illustrated in **Chapter-6**. **Table 7.6** shows the social factors for different districts of Assam.

Table 7.6 Social factors for different districts of Assam

District	Accessibility to Water Source	Asset Factor	Age Factor	LIT Factor	Economic Factor
Barpeta	0.79	0.460	0.144	0.610	0.591
Baska	0.87	0.390	0.157	0.538	0.911
Bongaigaon	0.88	0.450	0.106	0.735	0.350
Cachar	0.68	0.420	0.173	0.661	0.443

Chirang	0.78	0.370	0.115	0.703	0.452
Darrang	0.82	0.400	0.112	0.701	0.305
Dhemaji	0.84	0.470	0.136	0.708	0.353
Dhubri	0.85	0.250	0.172	0.504	0.507
Dibrugarh	0.93	0.600	0.122	0.683	0.742
Dima Hasao	0.54	0.460	0.157	0.611	0.297
Goalpara	0.81	0.440	0.198	0.457	0.365
Golaghat	0.75	0.510	0.139	0.616	0.543
Hailakandi	0.63	0.300	0.162	0.645	0.272
Jorhat	0.80	0.580	0.132	0.682	0.617
Kamrup	0.88	1.000	0.107	0.758	1.000
Kamrup Metropolitan	0.85	0.580	0.097	0.788	0.683
Karbi Anglong	0.69	0.490	0.177	0.522	0.234
Karimganj	0.67	0.300	0.156	0.715	0.390
Kokrajhar	0.81	0.330	0.157	0.522	0.434
Lakhimpur	0.82	0.470	0.125	0.740	0.460
Morigaon	0.88	0.410	0.166	0.567	0.289
Nagaon	0.85	0.420	0.145	0.595	0.660
Nalbari	0.89	0.600	0.109	0.741	0.834
Sivasagar	0.85	0.590	0.126	0.696	0.584
Sonitpur	0.81	0.430	0.160	0.529	0.580
Tinsukia	0.92	0.520	0.140	0.652	0.404
Udalguri	0.78	0.480	0.100	0.661	0.517

Groundwater fluctuations have a direct or inverse effect on vulnerability. If there is positive fluctuation, it reduces the vulnerability level and vice-versa. As per the opinion survey conducted amongst the experts, weightage has been given to different vulnerability parameters which have been enlisted in **Chapter – 6**. Considering the importance of groundwater fluctuations on vulnerability of drinking water, the weight for fluctuation is taken as the same as that for accessibility to water sources. Now, from the water quality index factor; groundwater fluctuation and social factors, the composite social vulnerability index values are evaluated using the equation 7.2.

$$SVI = \frac{W_q A_g W_f}{L_t E_c A_w A_{ss}} \text{ if } w_f \text{ is negative}$$

$$SVI = \frac{W_q A_g}{L_t E_c A_w A_{ss} W_f} \text{ if } w_f \text{ is positive} \quad \textbf{(7.2)}$$

where w_q is the weighted water quality index factor, w_f is the weighted fluctuation, A_g is the weighted age factor, L_t is the weighted literate factor, E_c is the weighted economic factor, Aw is the weighted accessibility to water source, Ass is the weighted asset factor. The values of all these calculated factors are enlisted in **Table 7.7**.

Now, the districts are classified as very low, low, medium and highly vulnerable according to the range of vulnerability index values and vulnerability level as proposed in **Chapter-6**. The district wise vulnerability index values according to the proposed classification are plotted on a GIS map as shown in **Figure 7.4**.

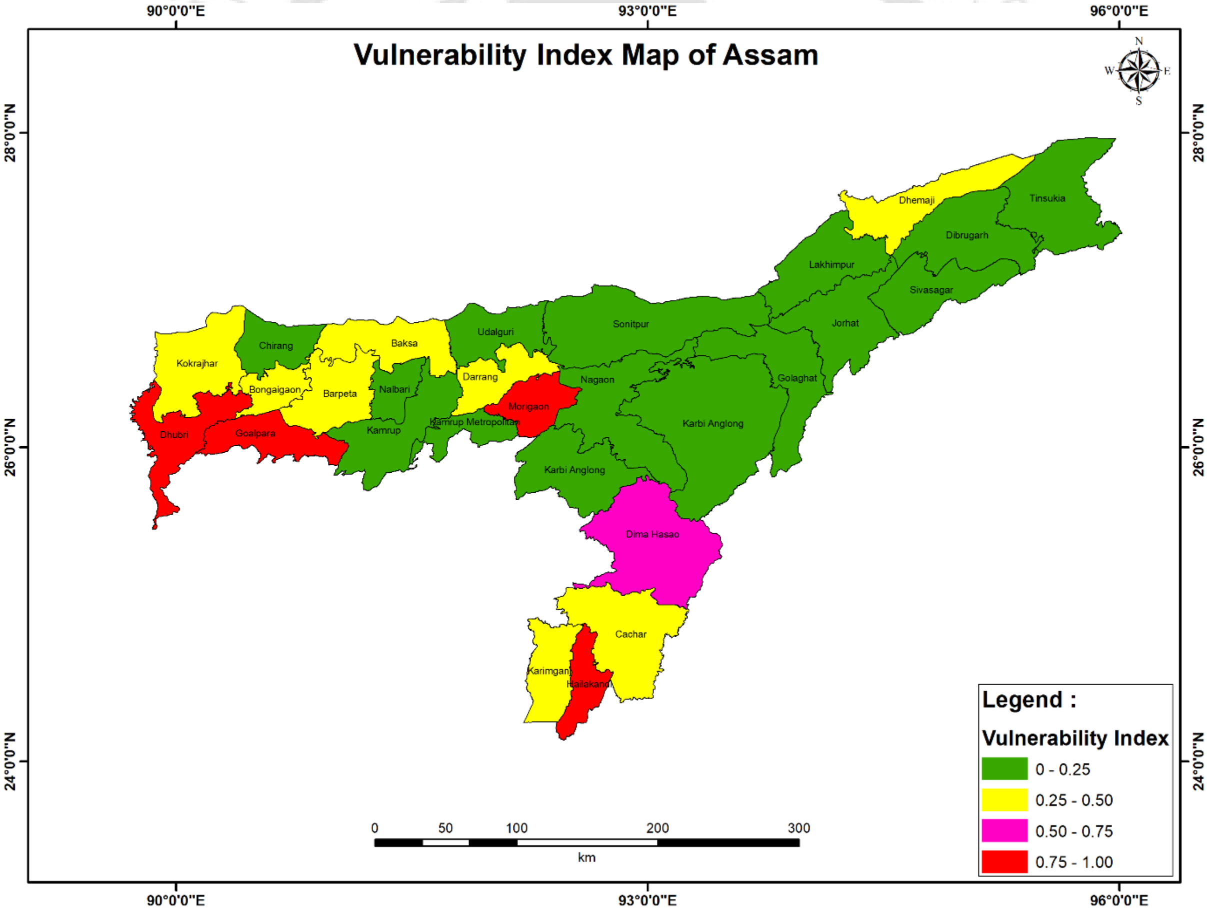


Figure 7.4 Vulnerability map of Assam

7.5 CONCLUSIONS

This study provides a comprehensive analysis of groundwater dynamics in Assam by integrating GRACE satellite data, IMD rainfall data, and ground-based measurements. By developing cluster-specific linear models, this research has effectively addressed the challenge of limited groundwater data availability, enabling the estimation of groundwater levels for the period 2002–2022. The satisfactory R^2 values achieved during the training and validation phases affirm the robustness of the models in capturing the relationships between groundwater levels, GRACE data, and rainfall.

The temporal analysis of groundwater levels revealed significant variability across districts, reflecting the interplay of seasonal, climatic, and anthropogenic factors. Long-term trends derived from these time series highlighted areas experiencing notable groundwater depletion, emphasizing the need for targeted water management strategies in such regions. Conversely, districts with stable groundwater levels provide insights into sustainable practices or favourable recharge conditions that can serve as benchmarks for other regions.

This research underscores the utility of GRACE satellite data in groundwater studies, particularly in data-scarce regions like Assam. By combining advanced geospatial techniques and statistical modelling, this study offers a replicable framework for monitoring and managing groundwater resources. The findings provide critical inputs for policymakers and water resource managers to design localized, sustainable groundwater management practices. Future work could focus on incorporating additional variables such as land use changes, population growth, and irrigation patterns to further refine the models and enhance the understanding of groundwater dynamics in Assam.

While considering the composite vulnerability index, four districts, namely Hailakandi, Moringaon, Goalpara, and Dhurbi are found to be most vulnerable. Dima Hasao district is in the medium vulnerability level, and the other districts are in the very low to low vulnerability level.With the improvement of social factors, the vulnerability level may be reduced. Moreover, implementation of sustainable groundwater management strategies such as managed aquifer recharge, rainwater harvesting etc. will enhance the groundwater recharge leading to a rise in groundwater levels of already vulnerable aquifers.

Table 7.7 Vulnerability Index Values of different districts of Assam

Sl. No.	District	WQI Factor	Weighted WQI Factor	Ground Water Fluctuation	Weighted Ground Water Fluctuation	Accessibility to water Source	Weighted Accessibility to water Source	Asset Factor	Weighted Asset Factor	Age Factor	Weighted Age Factor	Literate Factor	Weighted Literate Factor	Economic Factor	Weighted Economic Factor	Vulnerability Index	Normalized Vulnerability Index
1	Baksa	0.811	0.178	1	0.241	0.87	0.21	0.39	0.055	0.157	0.02	0.538	0.089	0.911	0.182	4.59	0.34
2	Barpeta	0.811	0.178	0.852	0.205	0.79	0.19	0.46	0.065	0.144	0.018	0.61	0.1	0.591	0.118	4.51	0.34
3	Bongaigaon	0.811	0.178	0.722	0.174	0.88	0.212	0.45	0.064	0.106	0.013	0.735	0.121	0.35	0.07	3.50	0.26
4	Cachar	0.811	0.178	0.389	0.094	0.68	0.164	0.42	0.06	0.173	0.022	0.661	0.109	0.443	0.088	3.90	0.29
5	Chirang	0.811	0.178	0.093	0.022	0.78	0.188	0.37	0.053	0.115	0.014	0.703	0.116	0.452	0.09	0.53	0.04
6	Darrang	0.892	0.196	0.648	0.156	0.82	0.198	0.4	0.057	0.112	0.014	0.701	0.115	0.305	0.061	5.41	0.41
7	Dhemaji	0.838	0.184	0.519	0.125	0.84	0.202	0.47	0.067	0.136	0.017	0.708	0.117	0.353	0.07	3.53	0.27
8	Dhubri	0.838	0.184	0.777	0.187	0.85	0.205	0.25	0.036	0.172	0.021	0.504	0.083	0.507	0.101	11.68	0.88
9	Dibrugarh	0.811	0.178	0.593	0.143	0.93	0.224	0.6	0.085	0.122	0.015	0.683	0.112	0.742	0.148	1.21	0.09
10	Dima Hasao	0.838	0.184	0.574	0.138	0.54	0.13	0.46	0.065	0.157	0.02	0.611	0.101	0.297	0.059	10.09	0.75
11	Goalpara	0.811	0.178	0.833	0.201	0.81	0.195	0.44	0.063	0.198	0.025	0.457	0.075	0.365	0.073	13.30	1.00
12	Golaghat	0.865	0.19	0.037	0.009	0.75	0.181	0.51	0.072	0.139	0.017	0.616	0.101	0.543	0.108	0.20	0.02
13	Hailakandi	0.811	0.178	0.444	0.107	0.63	0.152	0.3	0.043	0.162	0.02	0.645	0.106	0.272	0.054	10.18	0.77

14	Jorhat	0.838	0.184	0.481	0.116	0.8	0.193	0.58	0.082	0.132	0.016	0.682	0.112	0.617	0.123	1.57	0.12
15	Kamrup	0.811	0.178	0.722	0.174	0.88	0.212	1	0.142	0.107	0.013	0.758	0.125	1	0.2	0.53	0.04
16	Kamrup Metropolitan	0.811	0.178	0.833	0.201	0.85	0.205	0.58	0.082	0.097	0.012	0.788	0.13	0.683	0.136	1.44	0.11
17	Karbi Anglong	0.811	0.178	0.074	0.018	0.69	0.166	0.49	0.07	0.177	0.022	0.522	0.086	0.234	0.047	1.50	0.11
18	Karimganj	0.811	0.178	0.407	0.098	0.67	0.161	0.3	0.043	0.156	0.019	0.715	0.118	0.39	0.078	5.20	0.39
19	Kokrajhar	0.811	0.178	0.37	0.089	0.81	0.195	0.33	0.047	0.157	0.02	0.522	0.086	0.434	0.087	4.62	0.35
20	Lakhimpur	0.811	0.178	0.685	0.165	0.82	0.198	0.47	0.067	0.125	0.016	0.74	0.122	0.46	0.092	3.16	0.24
21	Morigaon	1	0.22	0.759	0.183	0.88	0.212	0.41	0.058	0.166	0.021	0.567	0.093	0.289	0.058	12.75	0.96
22	Nagaon	0.838	0.184	0.537	0.129	0.85	0.205	0.42	0.06	0.145	0.018	0.595	0.098	0.66	0.132	2.69	0.20
23	Nalbari	0.892	0.196	0.981	0.237	0.89	0.214	0.6	0.085	0.109	0.014	0.741	0.122	0.834	0.166	1.77	0.13
24	Sivasagar	0.838	0.184	0.556	0.134	0.85	0.205	0.59	0.084	0.126	0.016	0.696	0.115	0.584	0.117	1.70	0.13
25	Sonitpur	0.811	0.178	0.407	0.098	0.81	0.195	0.43	0.061	0.16	0.02	0.529	0.087	0.58	0.116	2.91	0.22
26	Tinsukia	0.811	0.178	0.13	0.031	0.92	0.222	0.52	0.074	0.14	0.017	0.652	0.107	0.404	0.081	0.66	0.05
27	Udalguri	0.811	0.178	0.63	0.152	0.78	0.188	0.48	0.068	0.1	0.012	0.661	0.109	0.517	0.103	2.26	0.17

Chapter – 8

SUMMARY AND CONCLUSIONS

8.1 GENERAL

The study provides a comprehensive assessment of the vulnerability of groundwater-based drinking water systems by integrating water quality, groundwater fluctuations, and socio-economic factors. The key findings indicate that water quality plays a significant role in determining vulnerability levels. The Water Quality Index (WQI) values, evaluated using district-wise data from the Assam Public Health Engineering Department, reveal that out of 27 districts, 10 districts supply poor-quality water, primarily due to iron contamination, and in some cases, arsenic and fluoride. While iron contamination can be mitigated through simple filtration, arsenic and fluoride require advanced filtration techniques like reverse osmosis.

Water quality has been identified as one of the most critical factors affecting drinking water vulnerability. The district-wise water quality parameters, obtained from the Assam Public Health Engineering Department, have been used to calculate WQI values. Additionally, social factors such as age, literacy, asset ownership, water accessibility, and economic status play a crucial role in determining vulnerability. These factors were assessed using Census of India 2011 data.

Groundwater fluctuations also influence drinking water vulnerability, with positive fluctuations reducing vulnerability levels and negative fluctuations exacerbating them. Groundwater level data, collected from the Central Groundwater Board (CGWB), includes in-situ measurements taken during January, March/April/May, August, and November from 2016 to 2022. These observations were supplemented with GRACE satellite data, and a trend analysis was conducted using a linear regression model that incorporates GRACE data and rainfall data from the India Meteorological Department (IMD) to estimate groundwater levels from 2002 to 2022.

By integrating WQI values, groundwater fluctuations, and social factors, the study has developed a district-wise composite social vulnerability index. This index provides a comprehensive framework for assessing groundwater-based drinking water vulnerability and can be instrumental in guiding policy decisions and water management strategies to ensure safe and sustainable drinking water access across Assam.

8.2 CONCLUSIONS

The following conclusions have been made.

8.2.1 Water Quality Index (WQI) Values and Their Effect on Vulnerability

The evaluation of water quality through the Water Quality Index (WQI) has been widely studied, with various estimation techniques employed by researchers. Among these, the Weighted Arithmetic Water Quality Index Method is commonly used due to its structured approach in assigning weights to different water quality parameters based on their significance for drinking water. However, conventional WQI calculations often do not fully capture the actual conditions of water quality. To overcome this limitation, this study introduces a modified WQI assessment approach that aligns with the drinking water quality standards set by the Bureau of Indian Standards (BIS). This method assigns a threshold value when a parameter is within permissible limits and applies a linear weighting approach beyond the acceptable range, providing a more precise evaluation of contamination severity.

The study initially applied both the conventional and newly proposed WQI methods to Kamrup district, Assam, India. Water samples were collected from public water supply schemes across different blocks and analyzed for twelve key parameters, including iron, alkalinity, turbidity, calcium, total dissolved solids, chloride, fluoride, total hardness, nitrate, pH, manganese, and magnesium. The traditional Weighted Arithmetic Water Quality Index Method was first used; however, the computed WQI values did not fully reflect the actual quality of the supplied water. To refine the weighting approach, an opinion survey was conducted among medical professionals from the Department of Community Medicine, Guwahati (DCMG), Assam, India. Based on health risk ratings provided by the experts, parameter weights were reassessed, yet the results still did not completely align with field observations. The newly proposed WQI method was then applied, leading to a more accurate block-wise assessment of water quality.

Building on this methodology, WQI values were further evaluated for all census districts using the 2011 census. District-wise water quality data for 2019 and 2020 were obtained from the Assam Public Health Engineering Department, Government of Assam. The district-wise average values of key water quality parameters were incorporated into the WQI calculations, following the approach proposed by Goswami and Bhattacharjya (2021). The findings indicate that the supplied water quality in Assam can be broadly categorized as either good or poor.

The results show that out of 27 districts in Assam, 10 districts supply poor-quality water, while 17 districts supply good-quality water. The primary contaminants responsible for poor water quality are iron and, in some areas, manganese. While water with high iron and manganese levels can be treated using standard filtration techniques, the presence of arsenic and fluoride in certain districts necessitates advanced treatment methods such as reverse osmosis.

This study highlights the significance of improving WQI assessment techniques to accurately identify regions with vulnerable drinking water conditions. By adopting a more refined WQI calculation method, policymakers and water management authorities can develop targeted interventions to improve water quality and ensure safe drinking water for all communities.

8.2.2 Groundwater Fluctuations and Their Effects on Vulnerability

Groundwater fluctuations significantly impact the vulnerability of drinking water, with positive fluctuations reducing vulnerability and negative fluctuations increasing it. To assess these variations, groundwater level data from 2016 to 2022 were obtained from monitoring wells of the Central Groundwater Board (CGWB) and analyzed using GRACE satellite data. The areal average depth to groundwater level was computed for the months of January, March, August, and November, and district clustering was performed using the K-Means clustering algorithm based on groundwater level statistics.

The study highlights that GRACE satellite data can be effectively used to estimate groundwater fluctuations, providing a reliable alternative to traditional monitoring methods. The advantage of using GRACE data lies in its ability to capture large-scale groundwater variations across regions, even in areas where in-situ monitoring wells are sparse or unavailable. By integrating GRACE data with rainfall records, a linear model was developed for each district cluster to estimate groundwater level variations. These estimations allow for a more comprehensive understanding of groundwater trends over time.

Time-series analysis from 2002 onward reveals a general trend of groundwater depletion across all districts, indicating a long-term increase in drinking water vulnerability. The study emphasizes the importance of incorporating satellite-based assessments like GRACE to enhance groundwater monitoring, enabling policymakers to make informed decisions for sustainable water resource management.

8.2.3 Social Factors and Their Effect on Vulnerability

Several socio-economic indicators were identified as key factors influencing drinking water vulnerability, including age, literacy, income, asset ownership, and water accessibility. Among these:

- The age factor is critical, as children aged 0-6 years are the most vulnerable to any disaster, increasing drinking water vulnerability.
- Literacy plays an essential role in risk perception, knowledge dissemination, and access to resources, reducing vulnerability.
- Economic and asset factors act as protective elements, allowing financially stable populations to recover more quickly from water crises.
- Accessibility to water sources lowers vulnerability, with Census of India (2011) data being used for district-wise evaluation of these factors.

8.2.4 Evaluation of Composite Social Vulnerability

By integrating WQI values, groundwater fluctuations, and socio-economic factors, a Composite Vulnerability Index was developed to categorize districts into different vulnerability levels. The findings are as follows:

- Most vulnerable districts: Hailakandi, Morigaon, Goalpara, and Dhubri.
- Medium vulnerability district: Dima Hasao.
- Low to very low vulnerability districts: The remaining districts.
- The study further reveals that:
- The overall water quality in Assam ranges from good to poor, with significant iron contamination detected in almost all districts. Arsenic and fluoride contamination is also present in some areas.
- Groundwater levels are consistently declining across all districts, exacerbating drinking water vulnerability.
- Dibrugarh district has the highest number of accessible water sources, while Dima Hasao has the lowest.
- Goalpara district has the highest proportion of children aged 0-6 years and the lowest literacy rate, making it highly vulnerable.
- Kamrup Metropolitan district has the lowest proportion of young children and the highest literacy rate, reducing its vulnerability.

- Kamrup district scores highest in asset and economic factors, while Dhubri has the lowest asset factor and Karbi Anglong has the lowest economic factor.

8.3 RECOMMENDATIONS FOR FUTURE WORK

This study provides a comprehensive assessment of the vulnerability of groundwater-based drinking water by integrating water quality, groundwater fluctuations, and socio-economic factors. However, there are several areas where future research and improvements can be made to enhance the accuracy and applicability of the findings. The following recommendations are proposed:

- **Incorporation of Additional Water Quality Parameters:** The present study evaluates WQI values using thirteen water quality parameters, including iron, alkalinity, turbidity, calcium, total dissolved solids, chloride, fluoride, total hardness, nitrate, pH, manganese, magnesium, and arsenic. However, additional parameters such as biological contaminants, heavy metals, and emerging pollutants may be considered to provide a more comprehensive assessment of water quality.
- **Enhanced Groundwater Level Prediction Models:** The study employs a linear regression model using GRACE data and rainfall data (IMD) as inputs to predict groundwater fluctuations. Future studies may improve the accuracy of groundwater level predictions by incorporating additional influencing factors such as temperature, evapotranspiration, and soil moisture content.
- **Incorporation of Land Use Land Cover (LULC) Changes:** Groundwater availability is significantly affected by land use and land cover (LULC) changes, including deforestation, urbanization, and agricultural expansion. Future studies should integrate LULC dynamics into groundwater fluctuation models to better understand the impact of anthropogenic activities on groundwater resources.
- **Expansion of Vulnerability Assessment Criteria:** This study evaluates drinking water vulnerability based on water quality, groundwater fluctuations, and social factors. However, additional factors such as climate variability, infrastructure conditions, and institutional governance may also influence vulnerability. Future studies should consider these aspects to develop a more holistic vulnerability assessment framework.

By incorporating these recommendations, future research can enhance the accuracy and applicability of vulnerability assessments, leading to more effective water resource management strategies and sustainable drinking water solution.

This study establishes a methodology for assessing the vulnerability of groundwater-based drinking water supply systems, integrating water quality, groundwater fluctuations, and socio-economic parameters. The findings highlight key regions requiring urgent interventions, particularly in terms of improving water treatment infrastructure, ensuring sustainable groundwater management, and addressing socio-economic disparities.

The methodology applied in this study can be extended to other regions for evaluating groundwater-based drinking water vulnerability. Future research should focus on incorporating real-time monitoring systems, advanced filtration technologies, and policy interventions to enhance water security and reduce vulnerability in highly affected.

Table A1. WQI values and WQI factor for different water supply schemes of Kamrup district.

Name of Block	Name of Pipe Water Supply Scheme (PWSS)	Latitude	Longitude	WQI	WQI (Block Wise)	WQI Factor
Hajo	Domdoma PWSS	26.2429160	91.5822970	32	42	1.00
	Manahkuchi PWSS	26.2727870	91.5776920	30		
	Nawpara PWSS	26.1999380	91.5439070	42		
	Khalihamari PWSS	26.2606473	91.4448999	40		
	Bamundi PWSS	26.1704310	91.4928900	35		
	Balasuba PWSS	26.2401550	91.5296600	31		
Sualkuchi	Pacharia Dolar Pathar PWSS	26.2362103	91.6421826	30	30	0.71
	Dakhin Pakorkona PWSS	26.2449780	91.5890990	30		

	3 No. singimari PWSS	26.2198836	91.6322720	30		
	Sarmajuli PWSS	26.1998330	91.6425220	30		
	Dolibari PWSS	26.2056510	91.6375190	30		
	Alikash PWSS	26.2311310	91.6038720	33		
Bezera	Balaibil	26.2593670	91.7010230	33	38	0.90
	Islampur PWSS	26.2785332	91.6912339	32		
	Bhetamukh PWSS	26.2641409	91.6872659	32		
	Chandra PWSS	26.2534510	91.7373560	38		
	Barnizara PWSS	26.2903760	91.7655660	33		
	Bamunigaon PWSS	26.3115460	91.7577920	32		
Bongaon	Lampara PWSS	26.0031094	91.2752452	30	30	0.71
	Paneri Rabha Para PWSS	26.0344953	91.2677367	30		
	Lamgaon PWSS	26.0125480	91.2954879	30		

	Deliapara PWSS	26.0044364	91.2600130	30		
	Nijbagoi PWSS	26.0080564	91.3117439	30		
	Birpara PWSS	26.0064702	91.2854386	30		
Rampur	Satrapara PWSS	26.1090824	91.4874102	30	30	0.71
	Sapathuri PWSS	26.1140313	91.4508278	32		
	Nahira Kaibarta Para PWSS	26.1072304	91.4845828	31		
	Dahali PWSS	26.1041791	91.4943836	30		
	Rampur PWSS	26.0855244	91.4722264	30		
	Bhauria Para PWSS	26.0976577	91.4894373	30		
Chayani Barduar	Koch Para PWSS	26.0890050	91.5304517	30	30	0.71
	Parlly PWSS	26.1231983	91.5555510	31		
	Sar Para PWSS	26.0935667	91.5199683	30		
	Borkuchi PWSS	26.0999933	91.5477960	30		

	Kokjhar PWSS	26.1076900	91.5321500	30		
	New Colony PWSS	26.0937433	91.5320317	31		
Chaygaon	Pachim Dhuli PWSS	26.0234667	91.4115817	30	30	0.71
	Dhoomgora PWSS	26.0846000	91.3479267	30		
	Doloipara PWSS	26.0561850	91.3741183	30		
	Aggumi PWSS	26.0876666	91.3449700	30		
	Balashidi No 1 PWSS	26.0507737	91.3942163	34		
	Nowapara PWSS	26.0575233	91.4067810	30		
Goroimari	Achalpara	26.1111892	91.2185812	35	30	0.71
	Pukhuripar No-1 PWSS	26.0834658	91.2576021	30		
	Choudhuripam PWSS	26.1073075	91.1669750	30		
	Majortop PWSS	26.1048841	91.2504499	30		
	Dakhinkanhara PWSS	26.0840230	91.2143331	30		

	Tukrapara PWSS	26.0991225	91.2333152	30		
Boko	Boko PWSS	25.9788492	91.2264618	31	30	0.71
	Mugakhol PWSS	25.9772007	91.2052467	30		
	Tarapara PWSS	25.9571027	91.2192460	30		
	Jobepara PWSS	25.9629520	91.1940798	30		
	Sekhadari PWSS	25.9580750	91.1108441	30		
	Jalukbari PWSS	26.0068935	91.1714089	30		
Chamaria	Chamaria Satra PWSS	26.0642757	91.1603100	31	33	0.79
	Habilagaon PWSS	26.0485480	91.0610652	31		
	Dokuchi PWSS	26.1105595	91.0055540	30		
	Dolagaon PWSS	26.0451219	91.0420931	30		
	Mandira Pathar PWSS	26.0443448	91.0742722	30		
	Chamaria PWSS	26.0607845	91.1588652	33		

Rangia	Tarani PWSS	26.5553746	91.6035675	31	33	0.79
	Kajigaon PWSS	26.4268857	91.6201266	32		
	Sahan Bongaon PWSS	26.4254526	91.6153870	30		
	Balagaon PWSS	26.4933666	91.6137861	33		
	Pubsitara PWSS	26.4569494	91.6121670	31		
	Kararagarbhitar PWSS	26.4795528	91.6051776	30		
Kamalpur	Bhitarkhola PWSS	26.2974375	91.7214163	30	30	0.71
	Dorakahara PWSS	26.2922566	91.7141834	31		
	Madanpur PWSS	26.3046980	91.7165822	30		
	Kokeria PWSS	26.3330333	91.6884812	30		
	Niz-Modartola PWSS	26.3408858	91.7130491	31		
	Jalimura PWSS	26.3530913	91.7018506	30		
Bihdia Jajikona	Kalmani No-1PWSS	26.3996408	91.6832241	31	33	0.79

	Jajikona PWSS	26.4040055	91.7019204	30		
	Radhakuchi PWSS	26.3663605	91.7399425	33		
	Dagaon PWSS	26.3696729	91.6995416	30		
	Nagaon PWSS	26.3439511	91.7218377	31		
	Baregaon PWSS	26.3807784	91.7364608	30		

Table A2. Economic survey for cultivator and agricultural labors

CULTIVATORS	AREA OF LAND CULTIVATED IN BIGHA	PERSONS INVOLVED IN CULTIVATION	ANNUAL INCOME FROM CULTIVATION (RS.)	WAGES PAID TO LABOURS (RS.)	MONTHLY INCOME (RS.)
1	20	1	52,000.00	350.00	4333.00
2	22	1	60,000.00	350.00	5000.00
3	20	2	52,000.00	350.00	4333.00
4	21	1	56,000.00	350.00	4667.00

5	20	1	52,000.00	350.00	4333.00
6	22	1	48,700.00	350.00	4058.00
7	20	2	52,000.00	350.00	4333.00
8	22	2	58,300.00	350.00	4858.00
9	20	1	52,000.00	350.00	4333.00
10	22	1	58,300.00	350.00	4858.00
11	20	2	52,000.00	350.00	4333.00
12	20	1	52,000.00	350.00	4333.00
13	21	1	54,000.00	350.00	4500.00
14	21	1	52,000.00	350.00	4333.00
15	20	2	52,000.00	350.00	4333.00
16	20	1	52,000.00	350.00	4333.00
17	22	1	57,000.00	350.00	4750.00
18	20	1	52,000.00	350.00	4333.00

19	22	2	57,000.00	350.00	4750.00
20	16	1	50,000.00	350.00	4167.00
21	16	3	45,000.00	350.00	3750.00
22	9	1	45,000.00	350.00	3750.00
23	12	1	70,000.00	350.00	5833.00
24	5	1	45,000.00	350.00	3750.00
25	10	2	80,000.00	350.00	6667.00
26	8	4	60,000.00	350.00	5000.00
27	8	2	50,000.00	350.00	4167.00
28	8	2	60,000.00	350.00	5000.00
29	7.5	1	50,000.00	350.00	4167.00
30	15	2	75,000.00	350.00	6250.00
31	15	1	70,000.00	350.00	5833.00
32	10	1	50,000.00	350.00	4167.00

33	20	1	70,000.00	350.00	5833.00
34	10	2	45,000.00	350.00	3750.00
35	10	2	60,000.00	350.00	5000.00
36	12	2	50,000.00	350.00	4167.00
Average monthly income					4621.00
Daily wages paid to labors					350.00

Table A3. Average weight of the parameters as per opinion survey

VULNERABILITY RANK (0-10)												
EXPERT	WATER QUALITY INDEX	WEIGHTED WATER QUALITY INDEX	AGE FACTOR	WEIGHTED AGE FACTOR	LITERATE FACTOR	WEIGHTED LITERATE FACTOR	ECONOMIC FACTOR	WEIGHTED ECONOMIC FACTOR	WATER ACCESSIBILITY FACTOR	WEIGHTED WATER ACCESSIBILITY FACTOR	ASSET FACTOR	WEIGHTEDASSET FACTOR
1	8	0.25	5	0.156	6	0.188	4	0.167	4	0.143	5	0.156
2	7	0.189	5	0.135	7	0.189	6	0.200	6	0.194	6	0.162
3	10	0.270	3	0.081	6	0.162	6	0.222	8	0.276	4	0.108
4	10	0.256	4	0.103	7	0.179	6	0.207	8	0.258	4	0.103
5	10	0.250	5	0.125	7	0.175	6	0.200	8	0.250	4	0.100
6	9	0.176	10	0.196	8	0.157	7	0.167	8	0.186	9	0.176
7	10	0.270	4	0.108	6	0.162	5	0.185	8	0.276	4	0.108
8	10	0.270	4	0.108	6	0.162	5	0.185	8	0.276	4	0.108
9	10	0.256	5	0.128	7	0.179	6	0.207	8	0.258	3	0.077

10	8	0.205	4	0.103	6	0.154	7	0.226	8	0.258	6	0.154
11	9	0.225	3	0.075	7	0.175	7	0.226	8	0.250	6	0.150
12	10	0.250	5	0.125	6	0.150	5	0.167	8	0.250	6	0.150
13	9	0.214	5	0.119	7	0.167	6	0.182	9	0.273	6	0.143
14	9	0.209	6	0.140	7	0.163	6	0.176	9	0.265	6	0.140
15	9	0.214	5	0.119	7	0.167	6	0.182	9	0.273	6	0.143
16	8	0.181	6	0.136	9	0.205	7	0.194	8	0.222	6	0.136
17	9	0.209	6	0.140	8	0.186	7	0.206	7	0.194	6	0.140
18	9	0.183	6	0.122	8	0.163	9	0.225	10	0.256	7	0.143
19	9	0.219	5	0.122	7	0.171	6	0.188	8	0.242	6	0.146
20	10	0.263	5	0.132	6	0.158	5	0.179	7	0.226	5	0.132
21	10	0.277	3	0.083	6	0.167	5	0.192	8	0.286	4	0.111
22	9	0.219	5	0.122	7	0.171	6	0.188	8	0.242	6	0.146
23	7	0.189	5	0.135	7	0.189	6	0.200	6	0.194	6	0.162
24	7	0.189	5	0.135	7	0.189	6	0.200	6	0.194	6	0.162
25	7	0.189	7	0.189	6	0.162	6	0.200	6	0.194	5	0.135
26	10	0.213	6	0.128	10	0.213	8	0.216	7	0.175	6	0.128
27	8	0.228	4	0.114	3	0.086	5	0.185	9	0.346	6	0.171
28	8	0.228	4	0.114	3	0.086	5	0.185	9	0.346	6	0.171

29	8	0.200	5	0.125	7	0.175	6	0.188	8	0.250	6	0.150
30	9	0.195	6	0.130	8	0.174	6	0.162	9	0.243	8	0.174
31	10	0.217	5	0.109	8	0.174	6	0.167	9	0.243	8	0.174
32	9	0.236	6	0.158	6	0.158	5	0.172	7	0.226	5	0.132
33	8	0.200	4	0.100	6	0.150	7	0.219	8	0.250	7	0.175
34	8	0.190	8	0.190	6	0.143	7	0.206	6	0.167	7	0.167
35	7	0.184	5	0.132	6	0.158	7	0.226	7	0.226	6	0.158
36	8	0.205	4	0.103	6	0.154	7	0.226	8	0.258	6	0.154
37	9	0.204	6	0.136	6	0.136	8	0.229	8	0.222	7	0.159
38	10	0.200	8	0.160	8	0.160	8	0.200	8	0.190	8	0.160
39	9	0.214	4	0.095	7	0.167	7	0.212	9	0.273	6	0.143
40	9	0.219	5	0.122	7	0.171	6	0.188	8	0.242	6	0.146
41	8	0.205	4	0.103	7	0.179	6	0.194	8	0.258	6	0.154
42	9	0.230	4	0.103	6	0.154	7	0.233	8	0.258	5	0.128
43	9	0.230	4	0.103	6	0.154	7	0.233	8	0.258	5	0.128
44	9	0.225	5	0.125	7	0.175	7	0.226	7	0.212	5	0.125
45	9	0.236	4	0.105	6	0.158	7	0.241	8	0.267	4	0.105
Average Weightage		**0.219**		**0.1243**		**0.1647**		**0.1995**		**0.2410**		**0.1421**

Table A4. BIS values of different parameter

Sl. No.	Parameter	BIS value
1	Iron	0.3mg/L
2	Alkalinity	200 – 600mg/L
3	Turbidity	1 - 5 NTU
4	Calcium	75 – 200mg/L
5	Total Dissolved solid	500 – 2000mg/L
6	Chloride	250 – 1000mg/L
7	Fluoride	1 – 1.5mg/L
8	Total Hardness	200 – 600mg/L
9	Nitrate	45mg/L
10	pH	6.5 – 8.5
11	Manganese	0.1 - 0.3mg/L

12	Magnesium	30 – 100mg/L

REFERENCES

Abou Zaki, Nizar, Ali Torabi Haghighi, Pekka M. Rossi, Mohammad J. Tourian, and Bjørn Kløve. 2019. 'Monitoring Groundwater Storage Depletion Using Gravity Recovery and Climate Experiment (GRACE) Data in Bakhtegan Catchment, Iran'. *Water* 11 (7): 1456.

Adger, W Neil. 1999. 'Social Vulnerability to Climate Change and Extremes in Coastal Vietnam'. *World Development* 27 (2): 249–69.

———. 2006. 'Vulnerability'. *Global Environmental Change* 16 (3): 268–81.

Adimalla, Narsimha, and Jianhua Wu. 2019. 'Groundwater Quality and Associated Health Risks in a Semi-Arid Region of South India: Implication to Sustainable Groundwater Management'. *Human and Ecological Risk Assessment: An International Journal* 25 (1–2): 191–216. https://doi.org/10.1080/10807039.2018.1546550.

Ahmed, Mohamed, and Karem Abdelmohsen. 2018. 'Quantifying Modern Recharge and Depletion Rates of the Nubian Aquifer in Egypt'. *Surveys in Geophysics* 39: 729–51.

Akoteyon, I S, A O Omotayo, O Soladoye, and H O Olaoye. 2011. 'Determination of Water Quality Index and Suitability of Urban River for Municipal Water Supply in Lagos-Nigeria'. *European Journal of Scientific Research* 54 (2): 263–71.

Aksha, Sanam K, Luke Juran, Lynn M Resler, and Yang Zhang. 2019. 'An Analysis of Social Vulnerability to Natural Hazards in Nepal Using a Modified Social Vulnerability Index'. *International Journal of Disaster Risk Science* 10: 103–16.

Alam, Masood, Sumbul Rais, and Mohd Aslam. 2012a. 'Hydrochemical Investigation and Quality Assessment of Ground Water in Rural Areas of Delhi, India'. *Environmental Earth Sciences* 66: 97–110.

———. 2012b. 'Hydrochemical Investigation and Quality Assessment of Ground Water in Rural Areas of Delhi, India'. *Environmental Earth Sciences* 66: 97–110.

Alastal, Khalil M, Jawad S Alagha, Azzam A Abuhabib, and Rachid Ababou. 2016. 'Groundwater Quality Assessment Using Water Quality Index (WQI) Approach: Gaza Coastal Aquifer Case Study'. *Journal of Engineering Research and Technology* 2 (1).

Ali, Shoaib, Qiumei Wang, Dong Liu, Qiang Fu, Md Mafuzur Rahaman, Muhammad Abrar Faiz, and Muhammad Jehanzeb Masud Cheema. 2022. 'Estimation of Spatio-Temporal Groundwater Storage Variations in the Lower Transboundary Indus Basin Using GRACE Satellite'. *Journal of Hydrology* 605: 127315.

Alwang, Jeffrey, Paul B Siegel, and Steen L Jorgensen. 2001. 'Vulnerability: A View from Different Disciplines'. Citeseer.

Ansari, K, and N Hemke. 2013. 'Water Quality Index for Assessment of Water Samples of Different Zones in Chandrapur City'. *Ground Water* 3 (3).

Anurag, Tewari, Dubey Ashutosh, and Trivedi Aviral. 2010. 'A Study on Physico-Chemical Characteristics of Ground Water Quality.' *Journal of Chemical and Pharmaceutical Research* 2 (2): 510–18.

Asoka, Akarsh, Tom Gleeson, Yoshihide Wada, and Vimal Mishra. 2017. 'Relative Contribution of Monsoon Precipitation and Pumping to Changes in Groundwater Storage in India'. *Nature Geoscience* 10 (2): 109–17.

Aubrecht, Christoph, Klaus Steinnocher, Mario Köstl, Johann Züger, and Wolfgang Loibl. 2013. 'Long-Term Spatio-Temporal Social Vulnerability Variation Considering Health-Related Climate Change Parameters Particularly Affecting Elderly'. *Natural Hazards* 68: 1371–84.

Backman, B, D Bodiš, P Lahermo, S Rapant, and T Tarvainen. 1998. 'Application of a Groundwater Contamination Index in Finland and Slovakia'. *Environmental Geology* 36: 55–64.

Balan, Inanda, M Shivakumar, and P Madan Kumar. 2012. 'An Assessment of Groundwater Quality Using Water Quality Index in Chennai, Tamil Nadu, India'. *Chronicles of Young Scientists* 3 (2): 146.

Bartram, Jamie, and Richard Ballance. 1996. *Water Quality Monitoring: A Practical Guide to the Design and Implementation of Freshwater Quality Studies and Monitoring Programmes*. CRC Press.

Bates, Bryson, Zbigniew Kundzewicz, and Shaohong Wu. 2008. *Climate Change and Water*. Intergovernmental Panel on Climate Change Secretariat.

Bhadja, Poonam, and Ashokkumar Vaghela. 2013. ‘Assessment of Physico-Chemical Parameters and Water Quality Index of Reservoir Water’. *International Journal of Plant, Animal and Environmental Sciences* 3 (3): 89–95.

Bhanja, Soumendra N, Abhijit Mukherjee, Matthew Rodell, Yoshihide Wada, Siddhartha Chattopadhyay, Isabella Velicogna, Kishore Pangaluru, and James S Famiglietti. 2017. ‘Groundwater Rejuvenation in Parts of India Influenced by Water-Policy Change Implementation’. *Scientific Reports* 7 (1): 7453.

Bhanja, Soumendra N, Abhijit Mukherjee, Dipankar Saha, Isabella Velicogna, and James S Famiglietti. 2016. ‘Validation of GRACE Based Groundwater Storage Anomaly Using In-Situ Groundwater Level Measurements in India’. *Journal of Hydrology* 543: 729–38.

Bhargava, D S. 1983. ‘A Light-Penetration Model for the Rivers Ganga and Yamuna’. *Int J Dev Technol (England)* 1 (3): 199–205.

Bhargava, Devendra Swaroop. 1983. ‘Use of Water Quality Index for River Classification and Zoning of Ganga River’. *Environmental Pollution Series B, Chemical and Physical* 6 (1): 51–67.

Bhat, M Sultan, Akhtar Alam, Bashir Ahmad, Bahadur S Kotlia, Hakim Farooq, Ajay K Taloor, and Shabir Ahmad. 2019. ‘Flood Frequency Analysis of River Jhelum in Kashmir Basin’. *Quaternary International* 507: 288–94.

Bhattacharya, Munna, and Saswata Goswami. 2020. ‘Microalgae–A Green Multi-Product Biorefinery for Future Industrial Prospects’. *Biocatalysis and Agricultural Biotechnology* 25: 101580.

Birkmann, Joern, Omar D Cardona, Martha L Carreño, Alex H Barbat, Mark Pelling, Simon Schneiderbauer, Stefan Kienberger, Margreth Keiler, David Alexander, and Peter Zeil. 2013. ‘Framing Vulnerability, Risk and Societal Responses: The MOVE Framework’. *Natural Hazards* 67: 193–211.

Blaikie, Piers, and Harold Brookfield. 2015. *Land Degradation and Society*. Routledge.

Blaikie, Piers, Terry Cannon, Ian Davis, and Ben Wisner. 2014a. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. Routledge.

———. 2014b. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. Routledge.

———. 2014c. *At Risk: Natural Hazards, People's Vulnerability and Disasters*. Routledge.

Bonacci, Ognjen, and Tanja Roje-Bonacci. 2018. 'Analysis of Groundwater Levels and Lake Vrana Water Levels on the Cres Island'. *Hrvatske Vode* 26 (103): 39–47.

Borah, Kamala Kanta, Bhabajit Bhuyan, and Hari Prasad Sarma. 2010. 'Lead, Arsenic, Fluoride, and Iron Contamination of Drinking Water in the Tea Garden Belt of Darrang District, Assam, India'. *Environmental Monitoring and Assessment* 169: 347–52.

Bordalo, A A, W Nilsumranchit, and K Chalermwat. 2001. 'Water Quality and Uses of the Bangpakong River (Eastern Thailand)'. *Water Research* 35 (15): 3635–42.

Brindha, K, K V Neena Vaman, K Srinivasan, M Sathis Babu, and L Elango. 2014. 'Identification of Surface Water-Groundwater Interaction by Hydrogeochemical Indicators and Assessing Its Suitability for Drinking and Irrigational Purposes in Chennai, Southern India'. *Applied Water Science* 4 (2): 159–74. https://doi.org/10.1007/s13201-013-0138-6.

Briscoe, John, and Ravinder P S Malik. 2006. *India's Water Economy: Bracing for a Turbulent Future*. New Delhi: Oxford University Press.

Chakrabarty, Sutapa, and Hari Prasad Sarma. 2011. 'Fluoride, Iron and Nitrate Contaminated Drinking Water in Kamrup District, Assam, India'. *Archives of Applied Science Research* 3 (4): 186–92.

Chakraborti, D, C R Chanda, G Samanta, U K Chowdhury, S C Mukherjee, A B Pal, B Sharma, K J Mahanta, H A Ahmed, and B Sing. 2000a. 'Fluorosis in Assam, India.' *Current Science* 78 (12): 1421–23.

———. 2000b. 'Fluorosis in Assam, India.' *Current Science* 78 (12): 1421–23.

Chakraborti, Dipankar, Sad Ahamed, Mohammad Mahmudur Rahman, Mrinal Kumar Sengupta, Dilip Lodh, Bhaskar Das, Mohammad Amir Hossain, Subhash Chandra Mukherjee, Shymapada Pati, and Niloy Kanti Das. 2004. 'Risk of Arsenic Contamination in Groundwater: Response from Chakraborti et Al'. *Environmental Health Perspectives* 112 (1): A20–A20.

Chambers, Robert. 1989. 'Editorial Introduction: Vulnerability, Coping and Policy'.

Chand, Dinesh. 1998. 'Rajiv Gandhi National Drinking Water Mission, Ministry of Rural Areas and Employment, CGO Complex Lodhi Road, New Delhi, Fluoride and Human Health Cause for Concern Indian J. of Env'. *Prot* 19 (2): 81–89.

Chandra, D Satish, S S Asadi, and M V S Raju. 2017a. ‘Estimation of Water Quality Index by Weighted Arithmetic Water Quality Index Method: A Model Study’. *International Journal of Civil Engineering and Technology* 8 (4): 1215–22.

———. 2017b. ‘Estimation of Water Quality Index by Weighted Arithmetic Water Quality Index Method: A Model Study’. *International Journal of Civil Engineering and Technology* 8 (4): 1215–22.

Chatterjee, Pinaki Ranjan, Chinmoy Chatterjee, and M Raziuddin. 2007. ‘Impact of Human Activity on Water Quality of a Lentic Water Body in Asansol’. *Nature, Environment and Pollution Technology* 6 (1): 59–62.

Chaturvedi, M K, and J K Bassin. 2010a. ‘Assessing the Water Quality Index of Water Treatment Plant and Bore Wells, in Delhi, India’. *Environmental Monitoring and Assessment* 163: 449–53.

———. 2010b. ‘Assessing the Water Quality Index of Water Treatment Plant and Bore Wells, in Delhi, India’. *Environmental Monitoring and Assessment* 163: 449–53.

Chauhan, Avnish, and Suman Singh. 2010. ‘Evaluation of Ganga Water for Drinking Purpose by Water Quality Index at Rishikesh, Uttarakhand, India’. *Report and Opinion* 2 (9): 53–61.

Cheema, M J M, W W Immerzeel, and W G M Bastiaanssen. 2014. ‘Spatial Quantification of Groundwater Abstraction in the Irrigated Indus Basin’. *Groundwater* 52 (1): 25–36.

Chen, Hao, Wanchang Zhang, Ning Nie, and Yuedong Guo. 2019. ‘Long-Term Groundwater Storage Variations Estimated in the Songhua River Basin by Using GRACE Products, Land Surface Models, and in-Situ Observations’. *Science of the Total Environment* 649: 372–87.

Chen, Jianli, James S Famigliett, Bridget R Scanlon, and Matthew Rodell. 2016. ‘Groundwater Storage Changes: Present Status from GRACE Observations’. *Remote Sensing and Water Resources*, 207–27.

Chidambaram, S, A L Ramanathan, M V Prasanna, P Anandhan, K Srinivasamoorthy, and S Vasudevan. 2008a. ‘Identification of Hydrogeochemically Active Regimes in Groundwaters of Erode District, Tamilnadu–A Statistical Approach’. *Asian Journal of Water, Environment and Pollution* 5 (3): 93–102.

———. 2008b. ‘Identification of Hydrogeochemically Active Regimes in Groundwaters of Erode District, Tamilnadu–A Statistical Approach’. *Asian Journal of Water, Environment and Pollution* 5 (3): 93–102.

Chinnasamy, Pennan, Luna Bharati, Utsav Bhattarai, Ambika Khadka, Vaskar Dahal, and Shahriar Wahid. 2015. ‘Impact of Planned Water Resource Development on Current and Future Water Demand in the Koshi River Basin, Nepal’. *Water International* 40 (7): 1004–20.

Chopra, Rajinder Pal Singh, and Gopal Krishan. 2014. ‘Analysis of Aquifer Characteristics and Groundwater Quality in Southwest Punjab, India’. *Journal of Earth Science and Engineering* 4 (10): 597–604.

Chowdhury, Rumman Mowla, SARDAR YAFEE Muntasir, and M MONOWAR Hossain. 2012. ‘Water Quality Index of Water Bodies along Faridpur-Barisal Road in Bangladesh’. *Glob Eng Tech Rev* 2 (3): 1–8.

Conboy, M J, and M J Goss. 2000. ‘Natural Protection of Groundwater against Bacteria of Fecal Origin’. *Journal of Contaminant Hydrology* 43 (1): 1–24.

Cool, Geneviève, Manuel J Rodriguez, Christian Bouchard, Patrick Levallois, and Florent Joerin. 2010. ‘Evaluation of the Vulnerability to Contamination of Drinking Water Systems for Rural Regions in Québec, Canada’. *Journal of Environmental Planning and Management* 53 (5): 615–38.

Cristo, C Di, A Leopardi, C Quintiliani, and G De Marinis. 2015. ‘Drinking Water Vulnerability Assessment after Disinfection through Chlorine’. *Procedia Engineering* 119: 389–97.

Cunningham, William L, and Charles W Schalk. 2011a. ‘Groundwater Technical Procedures of the US Geological Survey’. *US Geological Survey Techniques and Methods*, 1-A1.

———. 2011b. ‘Groundwater Technical Procedures of the US Geological Survey’. *US Geological Survey Techniques and Methods*, 1-A1.

Cutter, Susan L. 1996a. ‘Vulnerability to Environmental Hazards’. *Progress in Human Geography* 20 (4): 529–39.

———. 1996b. ‘Vulnerability to Environmental Hazards’. *Progress in Human Geography* 20 (4): 529–39.

Cutter, Susan L, Lindsey Barnes, Melissa Berry, Christopher Burton, Elijah Evans, Eric Tate, and Jennifer Webb. 2008. 'A Place-Based Model for Understanding Community Resilience to Natural Disasters'. *Global Environmental Change* 18 (4): 598–606.

Cutter, Susan L, Bryan J Boruff, and W Lynn Shirley. 2012a. 'Social Vulnerability to Environmental Hazards'. In *Hazards Vulnerability and Environmental Justice*, 143–60. Routledge.

Cutter, Susan L, BryanJ Boruff, and W Lynn Shirley. 2012b. 'Social Vulnerability to Environmental Hazards'. *Hazards Vulnerability and Environmental Justice*, 115.

Cutter, Susan L, and Christina Finch. 2008. 'Temporal and Spatial Changes in Social Vulnerability to Natural Hazards'. *Proceedings of the National Academy of Sciences* 105 (7): 2301–6.

Cutter, Susan L, Jerry T Mitchell, and Michael S Scott. 2012. 'Revealing the Vulnerability of People and Places: A Case Study of Georgetown County, South Carolina'. In *Hazards Vulnerability and Environmental Justice*, 111–42. Routledge.

Dahl, A L. 1991. 'UNEP Regional Seas Directories and Bibliographies No. 35'. *UNEP, Nairobi*.

Das, Bishnu Dev, and Sunil Kumar Choudhary. 2021. 'Application of Water Quality Index (WQI) for Groundwater Quality Assessment of Biratnagar, Nepal'. *Our Nature* 19 (1): 54–61.

Das, Kausik Kumar, Tanuja Panigrahi, and R B Panda. 2012. 'Evaluation of Water Quality Index (WQI) of Drinking Water of Balasore District, Odisha, India'. *Discovery Life* 1 (3): 48–52.

Das, M, and R K Bhattacharjya. 2020. 'A Regression-Based Analysis to Assess the Impact of Fluoride Reach River Water on the Groundwater Aquifer Adjacent to the River: A Case Study in Bharalu River Basin of Guwahati, India'. *Pollution* 6 (3): 637–50.

Das, Pulak, and N B Dey. 2011a. 'Socio-Economic Vulnerability in a Flood Affected Village of Barak Valley, Assam, India'. *Asia Pacific Journal of Social Sciences* 3 (2): 110–23.

———. 2011b. 'Socio-Economic Vulnerability in a Flood Affected Village of Barak Valley, Assam, India'. *Asia Pacific Journal of Social Sciences* 3 (2): 110–23.

Debels, Patrick, Ricardo Figueroa, Roberto Urrutia, Ricardo Barra, and Xavier Niell. 2005a. 'Evaluation of Water Quality in the Chillán River (Central Chile) Using Physicochemical Parameters and a Modified Water Quality Index'. *Environmental Monitoring and Assessment* 110 (1): 301–22. https://doi.org/10.1007/s10661-005-8064-1.

———. 2005b. 'Evaluation of Water Quality in the Chillán River (Central Chile) Using Physicochemical Parameters and a Modified Water Quality Index'. *Environmental Monitoring and Assessment* 110: 301–22.

Delgado, C, Julia Pacheco, A Cabrera, Eduardo Batllori, Roger Orellana, and FJAWM Bautista. 2010a. 'Quality of Groundwater for Irrigation in Tropical Karst Environment: The Case of Yucatan, Mexico'. *Agricultural Water Management* 97 (10): 1423–33.

———. 2010b. 'Quality of Groundwater for Irrigation in Tropical Karst Environment: The Case of Yucatan, Mexico'. *Agricultural Water Management* 97 (10): 1423–33.

Dimand, Robert W. 1998. 'Irving Fisher and The Making of Index Numbers1'. *The Economic Mind in America: Essays in the History of American Economics*, 128.

Dintwa, Kakanyo F, Gobopamang Letamo, and Kannan Navaneetham. 2019a. 'Measuring Social Vulnerability to Natural Hazards at the District Level in Botswana'. *Jàmbá: Journal of Disaster Risk Studies* 11 (1): 1–11.

———. 2019b. 'Measuring Social Vulnerability to Natural Hazards at the District Level in Botswana'. *Jàmbá: Journal of Disaster Risk Studies* 11 (1): 1–11.

Dosu, Benjamin, and Maura Hanrahan. 2021. 'Barriers to Drinking Water Security in Rural Ghana: The Vulnerability of People with Disabilities'. *Water Alternatives* 14 (2): 453–68.

Dunnette, D A. 1979. 'A Geographically Variable Water Quality Index Used in Oregon'. *Journal (Water Pollution Control Federation)*, 53–61.

Dutta, Joydev. 2013. 'Fluoride, Arsenic and Other Heavy Metals Contamination of Drinking Water in the Tea Garden Belt of Sonitpur District, Assam, India'. *Int J ChemTech Res* 5 (5): 2614–22.

Dwivedi, S, I C Tiwari, and D S Bhargava. 1997. 'Water Quality of the River Ganga at Varanasi'. *Journal-Institution Of Engineers India Part En Environmental Engineering Division*, 1–4.

Edgeworth, Francis Y. 1925a. 'The Plurality of Index-Numbers'. *The Economic Journal* 35 (139): 379–88.

———. 1925b. 'The Plurality of Index-Numbers'. *The Economic Journal* 35 (139): 379–88.

Elbeih, Salwa Farouk. 2015. 'An Overview of Integrated Remote Sensing and GIS for Groundwater Mapping in Egypt'. *Ain Shams Engineering Journal* 6 (1): 1–15.

Famiglietti, James S. 2014. 'The Global Groundwater Crisis'. *Nature Climate Change* 4 (11): 945–48.

Famiglietti, James S, and Matthew Rodell. 2013. 'Water in the Balance'. *Science* 340 (6138): 1300–1301.

Fernández, Nelson, Alberto Ramírez, and Fredy Solano. 2004. 'Physico-Chemical Water Quality Indices-a Comparative Review'. *Bistua: Revista de La Facultad de Ciencias Básicas* 2 (1): 19–30.

Fisher, Irving. 1922. *The Making of Index Numbers: A Study of Their Varieties, Tests, and Reliability*. Boston: Houghton Mifflin Company, 1923 [c1922].

Foster, Stephen, John Chilton, Marcus Moencg, Franklin Cardy, and Manuel Schiffler. 2000. *Groundwater in Rural Development: Facing the Challenges of Supply and Resource Sustainability*. The World Bank.

Foster, Stephen, John Chilton, Marcus Moench, Franklin Cardy, and Manuel Schiffler. 2008. 'Groundwater in Rural Development: Facing the Challenges of Supply and Resource Sustainability'.

Foster, Stephen, Ricardo Hirata, Daniel Gomes, Monica D'Elia, and Marta Paris. 2003a. 'Groundwater Quality Protection: A Guide for Water Utilities, Municipal Authorities, and Environment Agencies: Proteccion de La Calidad Del Agua Subterranea: Guia Para Empresas de Agua, Autoridades Municipales y Agencias Ambientales'.

———. 2003b. 'Groundwater Quality Protection: A Guide for Water Utilities, Municipal Authorities, and Environment Agencies: Proteccion de La Calidad Del Agua Subterranea: Guia Para Empresas de Agua, Autoridades Municipales y Agencias Ambientales'.

Fuller, Thomas. 1732. *Gnomologia: Adagies and Proverbs; Wise Sentences and Witty Sayings, Ancient and Modern, Foreign and British*. Vol. 1. B. Barker.

Gabor, Thomas, and Terri K Griffith. 1979. 'The Assessment of Community Vulnerability to Acute Hazardous Materials Incidents'.

Gandhi, Rajiv. 1993. 'National Drinking Water Mission'. *Ministry of Rural Development, New Delhi, India*.

Garber, M S, and F C Koopman. 1968. 'Methods of Measuring Water Levels in Deep Wells'. US Govt. Print. Off.,.

Garrick, Dustin, and Jim W Hall. 2014. 'Water Security and Society: Risks, Metrics, and Pathways'. *Annual Review of Environment and Resources* 39: 611–39.

Gautam, Dipendra. 2017a. 'Assessment of Social Vulnerability to Natural Hazards in Nepal'. *Natural Hazards and Earth System Sciences* 17 (12): 2313–20.

———. 2017b. 'Assessment of Social Vulnerability to Natural Hazards in Nepal'. *Natural Hazards and Earth System Sciences* 17 (12): 2313–20.

Gautam, Param K, Saksham Arora, Suresh Kannaujiya, Anjali Singh, Ajanta Goswami, and Prashant K Champati. 2017. 'A Comparative Appraisal of Ground Water Resources Using GRACE-GPS Data in Highly Urbanised Regions of Uttar Pradesh, India'. *Sustainable Water Resources Management* 3: 441–49.

Gbetibouo, Glwadys Aymone, and Claudia Ringler. 2009. *Mapping South African Farming Sector Vulnerability to Climate Change and Variability: A Subnational Assessment*. Citeseer.

Ge, Yi, Wen Dou, and Jianping Dai. 2017. 'A New Approach to Identify Social Vulnerability to Climate Change in the Yangtze River Delta'. *Sustainability* 9 (12): 2236.

Georgakakos, Konstantine P, and Nicholas E Graham. 2008. 'Potential Benefits of Seasonal Inflow Prediction Uncertainty for Reservoir Release Decisions'. *Journal of Applied Meteorology and Climatology* 47 (5): 1297–1321.

Ghalib, Hussein B. 2017a. 'Groundwater Chemistry Evaluation for Drinking and Irrigation Utilities in East Wasit Province, Central Iraq'. *Applied Water Science* 7: 3447–67.

———. 2017b. 'Groundwater Chemistry Evaluation for Drinking and Irrigation Utilities in East Wasit Province, Central Iraq'. *Applied Water Science* 7: 3447–67.

Ghoderao, Sudesh Bhaskar, Sarita Gajbhiye Meshram, and Chandrashekhar Meshram. 2022. 'Development and Evaluation of a Water Quality Index for Groundwater Quality

Assessment in Parts of Jabalpur District, Madhya Pradesh, India'. *Water Supply* 22 (6): 6002–12.

Gilli, Giorgio, G Corrao, and S Favilli. 1984. 'Concentrations of Nitrates in Drinking Water and Incidence of Gastric Carcinomas: First Descriptive Study of the Piemonte Region, Italy'. *Science of the Total Environment* 34 (1–2): 35–48.

Gleeson, Tom, Jonathan VanderSteen, Marios A Sophocleous, Makoto Taniguchi, William M Alley, Diana M Allen, and Yangxiao Zhou. 2010. 'Groundwater Sustainability Strategies'. *Nature Geoscience* 3 (6): 378–79.

Gleeson, Tom, Yoshihide Wada, Marc F P Bierkens, and Ludovicus P H Van Beek. 2012. 'Water Balance of Global Aquifers Revealed by Groundwater Footprint'. *Nature* 488 (7410): 197–200.

Goswami, Jayanta, and Rajib Kumar Bhattacharjya. 2021. 'Assessment of Groundwater Based Public Drinking Water Supply System of Kamrup District, Assam, India Using a Modified Water Quality Index'. *Pollution* 7 (3): 495–509.

Hamed, Younes, Rihab Hadji, Belgacem Redhaounia, Karim Zighmi, Fathi Bâali, and Attiya El Gayar. 2018. 'Climate Impact on Surface and Groundwater in North Africa: A Global Synthesis of Findings and Recommendations'. *Euro-Mediterranean Journal for Environmental Integration* 3 (1): 25. https://doi.org/10.1007/s41207-018-0067-8.

Han, Zhiming, Shengzhi Huang, Qiang Huang, Guoyong Leng, Hao Wang, Qingjun Bai, Jing Zhao, Lan Ma, Lu Wang, and Meng Du. 2019. 'Propagation Dynamics from Meteorological to Groundwater Drought and Their Possible Influence Factors'. *Journal of Hydrology* 578: 124102.

Handmer, John W, Steven Dovers, and Thomas E Downing. 1999. 'Societal Vulnerability to Climate Change and Variability'. *Mitigation and Adaptation Strategies for Global Change* 4: 267–81.

Haque, SkMafizul, Suresh Kannaujiya, Ajay Kumar Taloor, Dipika Keshri, Rakesh Kumar Bhunia, Prashant Kumar Champati Ray, and Prakash Chauhan. 2020. 'Identification of Groundwater Resource Zone in the Active Tectonic Region of Himalaya through Earth Observatory Techniques'. *Groundwater for Sustainable Development* 10: 100337.

Healy, Richard W, and Peter G Cook. 2002. 'Using Groundwater Levels to Estimate Recharge'. *Hydrogeology Journal* 10: 91–109.

Henry, Chris M. 2011. 'An Integrated Approach to Estimating Groundwater Recharge and Storage Variability in Southern Mali, Africa'.

Hewitt, Kenneth. 2014. *Regions of Risk: A Geographical Introduction to Disasters*. Routledge.

Hoque, Muhammad Al-Amin, Stuart Phinn, Chris Roelfsema, and Iraphne Childs. 2018. 'Modelling Tropical Cyclone Risks for Present and Future Climate Change Scenarios Using Geospatial Techniques'. *International Journal of Digital Earth* 11 (3): 246–63.

Horton, Robert K. 1965a. 'An Index Number System for Rating Water Quality'. *J Water Pollut Control Fed* 37 (3): 300–306.

———. 1965b. 'An Index Number System for Rating Water Quality'. *J Water Pollut Control Fed* 37 (3): 300–306.

Hossain, Md Nazir, and Shitangsu Kumar Paul. 2018a. 'Vulnerability Factors and Effectiveness of Disaster Mitigation Measures in the Bangladesh Coast'. *Earth Systems and Environment* 2 (1): 55–65.

———. 2018b. 'Vulnerability Factors and Effectiveness of Disaster Mitigation Measures in the Bangladesh Coast'. *Earth Systems and Environment* 2 (1): 55–65.

Hughes, Sara. 2022. 'A Multidimensional Approach to Evaluating the Vulnerability of Drinking Water Systems'. *Journal of Environmental Policy & Planning* 24 (2): 210–26.

Iqbal, Naveed, Faisal Hossain, Hyongki Lee, and Gulraiz Akhter. 2017a. 'Integrated Groundwater Resource Management in Indus Basin Using Satellite Gravimetry and Physical Modeling Tools'. *Environmental Monitoring and Assessment* 189: 1–16.

———. 2017b. 'Integrated Groundwater Resource Management in Indus Basin Using Satellite Gravimetry and Physical Modeling Tools'. *Environmental Monitoring and Assessment* 189: 1–16.

Islam, Tanveerul, and Richard E Peterson. 2008. 'Tropical Cyclone Wind Characteristics for the Bangladesh Coast Using Monte Carlo Simulation'. *Journal of Applied Sciences* 8 (9): 1249–55.

Jain, Sharad Kumar, Vijay Kumar, and M Saharia. 2013. 'Analysis of Rainfall and Temperature Trends in Northeast India'. *International Journal of Climatology* 33 (4): 968–78.

Jasrotia, A S, and A Kumar. 2014. ‘Estimation of Replenishable Groundwater Resources and Their Status of Utilization in Jammu Himalaya, J&K, India’. *Eur Water* 48: 17–27.

Jasrotia, Avtar Singh, Rajesh Kumar, Ajay Kumar Taloor, and Arun Kumar Saraf. 2019. ‘Artificial Recharge to Groundwater Using Geospatial and Groundwater Modelling Techniques in North Western Himalaya, India’. *Arabian Journal of Geosciences* 12: 1–23.

Jelovčan, Mateja, and Mojca Šraj. 2020. ‘Analysis of Groundwater Levels in Piezometers in the Vipava Valley’. *Acta Hydrotechnica* 33 (58): 61–78.

Jia, Ling Yan, Yong Gui Chen, Wei Min Ye, and Yu Jun Cui. 2019. ‘Effects of a Simulated Gap on Anisotropic Swelling Pressure of Compacted GMZ Bentonite’. *Engineering Geology* 248 (January): 155–63. https://doi.org/10.1016/j.enggeo.2018.11.018.

Jitumoni, Borah. 2011. ‘A Comparative Study of Groundwater with Special Reference to Fluoride Concentration in Some Parts of the Dibrugarh District, Assam, India.’ *Advances in Applied Science Research* 2 (5): 318–22.

Jones, F, and J Watkins. 1985. ‘The Water Cycle as a Source of Pathogens’. *Journal of Applied Microbiology* 59 (s14): 27S-36S.

Joshi, Anita, and Gita Seth. 2011. ‘Hydrochemical Profile for Assessing the Groundwater Quality of Sambhar Lake City and Its Adjoining Area’. *Environmental Monitoring and Assessment* 174: 547–54.

Kaika, Maria. 2003. ‘The Water Framework Directive: A New Directive for a Changing Social, Political and Economic European Framework’. *European Planning Studies* 11 (3): 299–316.

Karamouz, M, S Zanjani, and Z Zahmatkesh. 2017. ‘Vulnerability Assessment of Drinking Water Distribution Networks to Chemical and Biological Contaminations: Case Study’. *Journal of Water Resources Planning and Management* 143 (6): 06017003.

Karim, Mohammed Fazlul, and Nobuo Mimura. 2008. ‘Impacts of Climate Change and Sea-Level Rise on Cyclonic Storm Surge Floods in Bangladesh’. *Global Environmental Change* 18 (3): 490–500.

Katyal, Deeksha. 2011. ‘Water Quality Indices Used for Surface Water Vulnerability Assessment’. *International Journal of Environmental Sciences* 2 (1).

Kawo, Nafyad Serre, and Shankar Karuppannan. 2018. ‘Groundwater Quality Assessment Using Water Quality Index and GIS Technique in Modjo River Basin, Central Ethiopia’. *Journal of African Earth Sciences* 147: 300–311.

Ketata, Mouna, Moncef Gueddari, and Rachida Bouhlila. 2012. ‘Use of Geographical Information System and Water Quality Index to Assess Groundwater Quality in El Khairat Deep Aquifer (Enfidha, Central East Tunisia)’. *Arabian Journal of Geosciences* 5: 1379–90.

Khan, Armugha, Himanshu Govil, Ajay Kumar Taloor, and Gaurav Kumar. 2020. ‘Identification of Artificial Groundwater Recharge Sites in Parts of Yamuna River Basin India Based on Remote Sensing and Geographical Information System’. *Groundwater for Sustainable Development* 11: 100415.

Khan, Mahfuzur R, Clifford I Voss, Winston Yu, and Holly A Michael. 2014. ‘Water Resources Management in the Ganges Basin’.

Khatri, Nitasha, and Sanjiv Tyagi. 2015. ‘Influences of Natural and Anthropogenic Factors on Surface and Groundwater Quality in Rural and Urban Areas’. *Frontiers in Life Science* 8 (1): 23–39. https://doi.org/10.1080/21553769.2014.933716.

King, David, and Colin MacGregor. 2000. ‘Using Social Indicators to Measure Community Vulnerability to Natural Hazards’. *Australian Journal of Emergency Management, The* 15 (3): 52–57.

Konikow, Leonard F. 2011. ‘Contribution of Global Groundwater Depletion since 1900 to Sea-level Rise’. *Geophysical Research Letters* 38 (17).

Krishan, Gopal, and R P S Chopra. 2015. ‘Assessment of Water Logging in South-Western (SW) Parts of Punjab, India–a Case Study from Muktsar District’. *NDCWWC Journal (A Half Yearly Journal of New Delhi Centre of WWC)* 4 (1): 7–10.

Krishan, Gopal, R P Singh, and K S Tashi. 2015. ‘Water Level Fluctuation as the Sum of Environmental and Anthropogenic Activities in Southeast, Punjab (India)’. *Journal of Environmental & Analytical Toxicology* 5 (5): 1.

Krishan, Gopal, Surjeet Singh, C P Kumar, Suman Gurjar, and N C Ghosh. 2016. ‘Assessment of Water Quality Index (WQI) of Groundwater in Rajkot District, Gujarat, India’. *Journal of Earth Science and Climatic Change* 7: 341.

Krishna Kumar, S, R Bharani, N S Magesh, Prince S Godson, and N Chandrasekar. 2014. 'Hydrogeochemistry and Groundwater Quality Appraisal of Part of South Chennai Coastal Aquifers, Tamil Nadu, India Using WQI and Fuzzy Logic Method'. *Applied Water Science* 4: 341–50.

Kulshreshtha, Surendra N. 1998. 'A Global Outlook for Water Resources to the Year 2025'. *Water Resources Management* 12 (3): 167–84. https://doi.org/10.1023/A:1007957229865.

Kumar, Dhirendra, Anoop Kumar Singh, Ajay Kumar Taloor, and Dhruv Sen Singh. 2021. 'Recessional Pattern of Thelu and Swetvarn Glaciers between 1968 and 2019, Bhagirathi Basin, Garhwal Himalaya, India'. *Quaternary International* 575: 227–35.

Kumar, Sujay V, Christa D Peters-Lidard, Yudong Tian, Paul R Houser, James Geiger, S Olden, L Lighty, Joseph L Eastman, B Doty, and P Dirmeyer. 2006. 'Land Information System: An Interoperable Framework for High Resolution Land Surface Modeling'. *Environmental Modelling & Software* 21 (10): 1402–15.

Kuss, Amber, William T Brandt, Joshua Randall, Bridget Floyd, Abdelwahab Bourai, Michelle Newcomer, Cindy Schmidt, and J W Skiles. 2012. 'Comparison of Changes in Groundwater Storage Using GRACE Data and a Hydrological Model in California's Central Valley'. In *ASPRS Ann. Conf., Sacramento, CA.*

Lewis, James. 1999. 'Development in Disaster-Prone Places'. *(No Title).*

Li, Bailing, Matthew Rodell, Sujay Kumar, Hiroko Kato Beaudoing, Augusto Getirana, Benjamin F Zaitchik, Luis Gustavo de Goncalves, Camila Cossetin, Soumendra Bhanja, and Abhijit Mukherjee. 2019. 'Global GRACE Data Assimilation for Groundwater and Drought Monitoring: Advances and Challenges'. *Water Resources Research* 55 (9): 7564–86.

Lin, Mi, Asim Biswas, and Elena M Bennett. 2020a. 'Socio-Ecological Determinants on Spatio-Temporal Changes of Groundwater in the Yellow River Basin, China'. *Science of the Total Environment* 731: 138725.

———. 2020b. 'Socio-Ecological Determinants on Spatio-Temporal Changes of Groundwater in the Yellow River Basin, China'. *Science of the Total Environment* 731: 138725.

Liu, Dong, Wenting Liu, and Tianqi Luo. 2015. 'The Effect Degree Analysis of Human Activities on Regional Groundwater Level Based on Variable Fuzzy Optimization

Model'. *International Journal of Agricultural and Environmental Information Systems (IJAEIS)* 6 (3): 63–76.

Lumb, A, D Halliwell, and T Sharma. 2002. 'Canadian Water Quality Index to Monitor the Changes in Water Quality in the Mackenzie River–Great Bear'. In *Proceedings of the 29th Annual Aquatic Toxicity Workshop,(Oct. 21–23), Whistler, BC, Canada*.

Marchant, B P, and J P Bloomfield. 2018. 'Spatio-Temporal Modelling of the Status of Groundwater Droughts'. *Journal of Hydrology* 564: 397–413.

Martin, Shelly D, Anneke C Bush, and Julia A Lynch. 2006. 'A National Survey of Terrorism Preparedness Training among Pediatric, Family Practice, and Emergency Medicine Programs'. *Pediatrics* 118 (3): e620–26.

Masood, Amjad, Muhammad Atiq Ur Rahman Tariq, Muhammad Zia Ur Rahman Hashmi, Muhammad Waseem, Muhammad Kaleem Sarwar, Wasif Ali, Rashid Farooq, Mansour Almazroui, and Anne W M Ng. 2022. 'An Overview of Groundwater Monitoring through Point-to Satellite-Based Techniques'. *Water* 14 (4): 565.

McCarthy, Mark I. 2004. 'Progress in Defining the Molecular Basis of Type 2 Diabetes Mellitus through Susceptibility-Gene Identification'. *Human Molecular Genetics* 13 (suppl_1): R33–41.

Mileti, Dennis. 1999. *Disasters by Design: A Reassessment of Natural Hazards in the United States*. Joseph Henry Press.

Mirzabeygi, Majid, Nader Yousefi, Abbas Abbasnia, Hadi Youzi, Mahdi Alikhani, and Amir Hossein Mahvi. 2017. 'Evaluation of Groundwater Quality and Assessment of Scaling Potential and Corrosiveness of Water Supply Networks, Iran'. *Journal of Water Supply: Research and Technology—AQUA* 66 (6): 416–25.

Mishra, P C, and R K Patel. 2001. 'Study of the Pollution Load in the Drinking Water of Rairangpur, a Small Tribal Dominated Town of North Orissa'. *Indian J Environ Ecoplan* 5 (2): 293–98.

Mohammadi, Ali Akbar, Mahmood Yousefi, Mehdi Yaseri, Mohsen Jalilzadeh, and Amir Hossein Mahvi. 2017. 'Skeletal Fluorosis in Relation to Drinking Water in Rural Areas of West Azerbaijan, Iran'. *Scientific Reports* 7 (1): 17300.

Mohanty, Sheelabhadra, Madan K Jha, Ashwani Kumar, and K P Sudheer. 2010. 'Artificial Neural Network Modeling for Groundwater Level Forecasting in a River Island of Eastern India'. *Water Resources Management* 24: 1845–65.

Moore, Scott, and Joshua B Fisher. 2012. 'Challenges and Opportunities in GRACE-Based Groundwater Storage Assessment and Management: An Example from Yemen'. *Water Resources Management* 26: 1425–53.

Morrow, Betty Hearn. 1999. 'Identifying and Mapping Community Vulnerability'. *Disasters* 23 (1): 1–18.

Muralidharan, D, Anitha P Nair, and U Sathyanarayana. 2002. 'Fluoride in Shallow Aquifers in Rajgarh Tehsil of Churu District, Rajasthan–an Arid Environment'. *Current Science* 83 (6): 699–702.

Muskett, Reginald R, and Vladimir E Romanovsky. 2009. 'Groundwater Storage Changes in Arctic Permafrost Watersheds from GRACE and in Situ Measurements'. *Environmental Research Letters* 4 (4): 045009.

Muttarak, Raya, and Wolfgang Lutz. 2014. 'Is Education a Key to Reducing Vulnerability to Natural Disasters and Hence Unavoidable Climate Change?' *Ecology and Society* 19 (1).

Naik, Shrikanta, and K M Purohit. 2001. 'Studies on Water Quality of River Brahmani in Sundargarh District, Orissa'. *Indian J Environ Ecoplan* 5 (2): 397–402.

Nair, Indu S, S P Rajaveni, M Schneider, and L Elango. 2015a. 'Geochemical and Isotopic Signatures for the Identification of Seawater Intrusion in an Alluvial Aquifer'. *Journal of Earth System Science* 124: 1281–91.

———. 2015b. 'Geochemical and Isotopic Signatures for the Identification of Seawater Intrusion in an Alluvial Aquifer'. *Journal of Earth System Science* 124: 1281–91.

Nayak, T R, S K Gupta, and R Galkate. 2015. 'GIS Based Mapping of Groundwater Fluctuations in Bina Basin'. *Aquatic Procedia* 4: 1469–76.

Nguyen, Thang T X, Jarbas Bonetti, Kerrylee Rogers, and Colin D Woodroffe. 2016. 'Indicator-Based Assessment of Climate-Change Impacts on Coasts: A Review of Concepts, Methodological Approaches and Vulnerability Indices'. *Ocean & Coastal Management* 123: 18–43.

Nguyen, Thanh T, and Cholachat Rujikiatkamjorn. 2016. *Natural Prefabricated Vertical Drains-Structure and Geohydraulic Properties Acid Sulphate Soil Remediation View Project Internal Stability of Granular Filters under Cyclic Loading View Project*. https://www.researchgate.net/publication/327468450.

Nickson, R, C Sengupta, P Mitra, S N Dave, A K Banerjee, A Bhattacharya, S Basu, N Kakoti, N S Moorthy, and M Wasuja. 2007. 'Current Knowledge on the Distribution of Arsenic in Groundwater in Five States of India'. *Journal of Environmental Science and Health, Part A* 42 (12): 1707–18.

Nouri, Hamideh, Pamela Nagler, Sattar Chavoshi Borujeni, Armando Barreto Munez, Sina Alaghmand, Behnaz Noori, Alejandro Galindo, and Kamel Didan. 2020. 'Effect of Spatial Resolution of Satellite Images on Estimating the Greenness and Evapotranspiration of Urban Green Spaces'. *Hydrological Processes* 34 (15): 3183–99.

Nowlan, L. 2005. 'Buried Treasure: Groundwater Permitting and Pricing in Canada. Walter and Duncan Gordon Foundation'.

Nwaiwu, Blessing Ifeyinwa Minz. 2008. *Safety and Security of Drinking Water Supply Systems: Approaches and Instruments for Implementation*. na.

Olayinka, A I, A F Abimbola, R A Isibor, and A R Rafiu. 1999a. 'A Geoelectrical-Hydrogeochemical Investigation of Shallow Groundwater Occurrence in Ibadan, Southwestern Nigeria'. *Environmental Geology* 37: 31–39.

———. 1999b. 'A Geoelectrical-Hydrogeochemical Investigation of Shallow Groundwater Occurrence in Ibadan, Southwestern Nigeria'. *Environmental Geology* 37: 31–39.

Opie, Simon, Richard G Taylor, Chris M Brierley, Mohammad Shamsudduha, and Mark O Cuthbert. 2020. 'Climate–Groundwater Dynamics Inferred from GRACE and the Role of Hydraulic Memory'. *Earth System Dynamics* 11 (3): 775–91.

Ostfeld, Avi, and Elad Salomons. 2004. 'Optimal Layout of Early Warning Detection Stations for Water Distribution Systems Security'. *Journal of Water Resources Planning and Management* 130 (5): 377–85.

Panda, Dileep K, and John Wahr. 2016. 'Spatiotemporal Evolution of Water Storage Changes in I Ndia from the Updated GRACE-derived Gravity Records'. *Water Resources Research* 52 (1): 135–49.

Patil, V T, and P R Patil. 2013a. 'Groundwater Quality Status Using Water Quality Index in Amalner Town, Maharashtra'. *Journal of Chemical and Pharmaceutical Research* 5 (5): 67–71.

———. 2013b. 'Groundwater Quality Status Using Water Quality Index in Amalner Town, Maharashtra'. *Journal of Chemical and Pharmaceutical Research* 5 (5): 67–71.

Peacock, Walter Gillis, Hugh Gladwin, and Betty Hearn Morrow. 2012. *Hurricane Andrew: Ethnicity, Gender and the Sociology of Disasters*. Routledge.

Pei-Yue, Li, Qian Hui, and W U Jian-Hua. 2010. 'Groundwater Quality Assessment Based on Improved Water Quality Index in Pengyang County, Ningxia, Northwest China'. *E-Journal of Chemistry* 7 (S1): S209–16.

Peralta, Richard C, Vince Mazure, and Paul Dutram. 1983. 'Monitoring of Groundwater Levels for Real-Time Conjunctive Water Management'.

Pokhrel, Yadu N, Ying Fan, Gonzalo Miguez-Macho, Pat J-F Yeh, and Shin-Chan Han. 2013. 'The Role of Groundwater in the Amazon Water Cycle: 3. Influence on Terrestrial Water Storage Computations and Comparison with GRACE'. *Journal of Geophysical Research: Atmospheres* 118 (8): 3233–44.

Poonam, Tirkey, Bhattacharya Tanushree, and Chakraborty Sukalyan. 2013a. 'Water Quality Indices-Important Tools for Water Quality Assessment: A Review'. *International Journal of Advances in Chemistry* 1 (1): 15–28.

———. 2013b. 'Water Quality Indices-Important Tools for Water Quality Assessment: A Review'. *International Journal of Advances in Chemistry* 1 (1): 15–28.

Proag, Virendra. 2014. 'The Concept of Vulnerability and Resilience'. *Procedia Economics and Finance* 18: 369–76.

Prusty, Pintu, and Syed Hilal Farooq. 2020. 'Application of Water Quality Index and Multivariate Statistical Analysis for Assessing Coastal Water Quality'. *Environmental Processes* 7: 805–25.

Rabeiy, Ragab ElSayed. 2018. 'Assessment and Modeling of Groundwater Quality Using WQI and GIS in Upper Egypt Area'. *Environmental Science and Pollution Research* 25 (31): 30808–17. https://doi.org/10.1007/s11356-017-8617-1.

Rahman, Mohammad Mahmudur, Uttam Kumar Chowdhury, Subhash Chandra Mukherjee, Badal Kumar Mondal, Kunal Paul, Dilip Lodh, Bhajan Kumar Biswas, Chitta Ranjan Chanda, Gautam Kumar Basu, and Kshitish Chandra Saha. 2001. 'Chronic Arsenic Toxicity in Bangladesh and West Bengal, India—a Review and Commentary'. *Journal of Toxicology: Clinical Toxicology* 39 (7): 683–700.

Raju, N Janardhana, Anurag Chaudhary, Sadaf Nazneen, Shubhra Singh, and Ankur Goyal. 2015a. 'Hydro-Geochemical Investigation and Quality Assessment of Groundwater for Drinking and Agricultural Use in Jawaharlal Nehru University (JNU), New Delhi, India'. *Management of Natural Resources in a Changing Environment*, 3–27.

———. 2015b. 'Hydro-Geochemical Investigation and Quality Assessment of Groundwater for Drinking and Agricultural Use in Jawaharlal Nehru University (JNU), New Delhi, India'. *Management of Natural Resources in a Changing Environment*, 3–27.

Ramakrishnaiah, C R, C Sadashivaiah, and G Ranganna. 2009a. 'Assessment of Water Quality Index for the Groundwater in Tumkur Taluk, Karnataka State, India'. *E-Journal of Chemistry* 6 (2): 523–30.

———. 2009b. 'Assessment of Water Quality Index for the Groundwater in Tumkur Taluk, Karnataka State, India'. *E-Journal of Chemistry* 6 (2): 523–30.

Rao, Chandaluri Subba, B Sreenivasa Rao, AVLNSH Hariharan, and N Manjula Bharathi. 2010. 'Determination of Water Quality Index of Some Areas in Guntur District Andhra Pradesh.'

Rodell, Matthew, Jianli Chen, Hiroko Kato, James S Famiglietti, Joe Nigro, and Clark R Wilson. 2007a. 'Estimating Groundwater Storage Changes in the Mississippi River Basin (USA) Using GRACE'. *Hydrogeology Journal* 15: 159–66.

———. 2007b. 'Estimating Groundwater Storage Changes in the Mississippi River Basin (USA) Using GRACE'. *Hydrogeology Journal* 15: 159–66.

———. 2007c. 'Estimating Groundwater Storage Changes in the Mississippi River Basin (USA) Using GRACE'. *Hydrogeology Journal* 15: 159–66.

Rodell, Matthew, Jay S Famiglietti, David N Wiese, J T Reager, Hiroko K Beaudoing, Felix W Landerer, and M-H Lo. 2018. 'Emerging Trends in Global Freshwater Availability'. *Nature* 557 (7707): 651–59.

Rodell, Matthew, Isabella Velicogna, and James S Famiglietti. 2009a. 'Satellite-Based Estimates of Groundwater Depletion in India'. *Nature* 460 (7258): 999–1002.

———. 2009b. 'Satellite-Based Estimates of Groundwater Depletion in India'. *Nature* 460 (7258): 999–1002.

———. 2009c. 'Satellite-Based Estimates of Groundwater Depletion in India'. *Nature* 460 (7258): 999–1002.

Roy, Chandan, and Rita Kovordányi. 2012. 'Tropical Cyclone Track Forecasting Techniques―A Review'. *Atmospheric Research* 104: 40–69.

Sahu, Paulami, and P K Sikdar. 2008. 'Hydrochemical Framework of the Aquifer in and around East Kolkata Wetlands, West Bengal, India'. *Environmental Geology* 55 (4): 823–35. https://doi.org/10.1007/s00254-007-1034-x.

Salam, Muhammad, Muhammad Jehanzeb Masud Cheema, Wanchang Zhang, Saddam Hussain, Azeem Khan, Muhammad Bilal, Arfan Arshad, Sikandar Ali, and Muhammad Awais Zaman. 2020. 'Groundwater Storage Change Estimation Using Grace Satellite Data in Indus Basin'. *Big Data in Water Resources Engineering (BDWRE)* 1: 13–18.

Sarath Prasanth, S V, N S Magesh, K V Jitheshlal, N Chandrasekar, and KJAWS Gangadhar. 2012. 'Evaluation of Groundwater Quality and Its Suitability for Drinking and Agricultural Use in the Coastal Stretch of Alappuzha District, Kerala, India'. *Applied Water Science* 2: 165–75.

Sarkar, Tandrila, Suresh Kannaujiya, Ajay Kumar Taloor, Prashant Kumar Champati Ray, and Prakash Chauhan. 2020. 'Integrated Study of GRACE Data Derived Interannual Groundwater Storage Variability over Water Stressed Indian Regions'. *Groundwater for Sustainable Development* 10: 100376.

Sattari, Mohammad Taghi, Rasoul Mirabbasi, Reza Shamsi Sushab, and John Abraham. 2018. 'Prediction of Groundwater Level in Ardebil Plain Using Support Vector Regression and M5 Tree Model'. *Groundwater* 56 (4): 636–46.

Scanlon, B R, L Longuevergne, and D Long. 2012. 'Ground Referencing GRACE Satellite Estimates of Groundwater'.

Scanlon, Bridget R, Ian Jolly, Marios Sophocleous, and Lu Zhang. 2007. ‘Global Impacts of Conversions from Natural to Agricultural Ecosystems on Water Resources: Quantity versus Quality’. *Water Resources Research* 43 (3).

Scanlon, Bridget R, Zizhan Zhang, Himanshu Save, Alexander Y Sun, Hannes Müller Schmied, Ludovicus P H Van Beek, David N Wiese, Yoshihide Wada, Di Long, and Robert C Reedy. 2018. ‘Global Models Underestimate Large Decadal Declining and Rising Water Storage Trends Relative to GRACE Satellite Data’. *Proceedings of the National Academy of Sciences* 115 (6): E1080–89.

Semiromi, F Babaei, A H Hassani, Ali Torabian, A R Karbassi, and F Hosseinzadeh Lotfi. 2011a. ‘Water Quality Index Development Using Fuzzy Logic: A Case Study of the Karoon River of Iran’. *African Journal of Biotechnology* 10 (50): 10125–33.

———. 2011b. ‘Water Quality Index Development Using Fuzzy Logic: A Case Study of the Karoon River of Iran’. *African Journal of Biotechnology* 10 (50): 10125–33.

Singh, Anil Kumar, Jayant Nath Tripathi, Ajay Kumar Taloor, Bahadur Singh Kotlia, Kamalesh Kumar Singh, and Shiv Dass Attri. 2021. ‘Seasonal Ground Water Fluctuation Monitoring Using GRACE Satellite Technology over Punjab and Haryana during 2005–2015’. In *Water, Cryosphere, and Climate Change in the Himalayas: A Geospatial Approach*, 175–86. Springer.

Singh, D F. 1992. ‘Studies on the Water Quality Index of Some Major Rivers of Pune, Maharashtra’. In *Proc Acad Environ Biol*, 1:61–66.

Singh, Sapam Ranabir, Mohammad Reza Eghdami, and Sarbjeet Singh. 2014. ‘The Concept of Social Vulnerability: A Review from Disasters Perspectives’. *International Journal of Interdisciplinary and Multidisciplinary Studies* 1 (6): 71–82.

Sival, F. P., A. P. Grootjans, P. J. Stuyfzand, and T. De La Verschoore Houssaye. 1997. ‘Variation in Groundwater Composition and Decalcification Depth in a Dune Slack: Effects on Basiphilous Vegetation’. *Journal of Coastal Conservation* 3 (1): 79–86. https://doi.org/10.1007/BF02908182.

Sood, Vishakha, Sartajvir Singh, Ajay Kumar Taloor, Shivendu Prashar, and Ravneet Kaur. 2020. ‘Monitoring and Mapping of Snow Cover Variability Using Topographically Derived NDSI Model over North Indian Himalayas during the Period 2008–19’. *Applied Computing and Geosciences* 8: 100040.

Soussan, John. 2003. ‘Water and Poverty: Fighting Poverty through Water Management’.

Soussan, John, and Wouter Lincklaen Arriëns. 2004. *Poverty and Water Security: Understanding How Water Affects the Poor*.

Soussan, John, Stacey Noel, Joakim Harlin, and Susanne Schmidt. 2006. ‘Linking Poverty Reduction and Water Management’. *United Nations Development Programme Stockholm Environment Institute Poverty-Environment Partnership*, 194–210.

Srinivas, J, A V Purushotham, and KVSG Murali Krishna. 2013. ‘Determination of Water Quality Index in Industrial Areas of Kakinada, Andhra Pradesh, India’. *International Research Journal of Environment Sciences* 2 (5): 37–45.

Srivastava, Saurabh, and Onkar Dikshit. 2022. ‘Analysis of Groundwater Storage (GWS) Dynamics and Its Temporal Evolution for The Indo-Gangetic Plain Using GRACE Data’. *Remote Sensing Applications: Society and Environment* 25: 100685.

Subba Rao, N, B Sunitha, N Adimalla, and M Chaudhary. 2020. ‘Quality Criteria for Groundwater Use from a Rural Part of Wanaparthy District, Telangana State, India, through Ionic Spatial Distribution (ISD), Entropy Water Quality Index (EWQI) and Principal Component Analysis (PCA)’. *Environmental Geochemistry and Health* 42 (2): 579–99. https://doi.org/10.1007/s10653-019-00393-5.

Sullivan, Caroline. 2002. ‘Calculating a Water Poverty Index’. *World Development* 30 (7): 1195–1210.

Taghavi, Nasrin, Robert K Niven, David J Paull, and Matthias Kramer. 2022. ‘Groundwater Vulnerability Assessment: A Review Including New Statistical and Hybrid Methods’. *Science of the Total Environment* 822: 153486.

Tapley, Byron D, Srinivas Bettadpur, John C Ries, Paul F Thompson, and Michael M Watkins. 2004a. ‘GRACE Measurements of Mass Variability in the Earth System’. *Science* 305 (5683): 503–5.

———. 2004b. ‘GRACE Measurements of Mass Variability in the Earth System’. *Science* 305 (5683): 503–5.

———. 2004c. ‘GRACE Measurements of Mass Variability in the Earth System’. *Science* 305 (5683): 503–5.

Tasnim, Khandker Masuma, Tomoya Shibayama, Miguel Esteban, Hiroshi Takagi, Koichiro Ohira, and Ryota Nakamura. 2015. ‘Field Observation and Numerical Simulation of Past and Future Storm Surges in the Bay of Bengal: Case Study of Cyclone Nargis’. *Natural Hazards* 75: 1619–47.

Thakur, Ipsita, Suraj Jena, Rabindra Kumar Panda, Manaswini Behera, and Susanta Kishore Pattanaik. 2021a. ‘Groundwater Vulnerability Assessment from a Drinking Water Perspective: Case Study in a Tropical Groundwater Basin in Eastern India’. *Journal of Hazardous, Toxic, and Radioactive Waste* 25 (3): 05021004.

———. 2021b. ‘Groundwater Vulnerability Assessment from a Drinking Water Perspective: Case Study in a Tropical Groundwater Basin in Eastern India’. *Journal of Hazardous, Toxic, and Radioactive Waste* 25 (3): 05021004.

Thomas, Deborah S K, Brenda D Phillips, Alice Fothergill, and Lynn Blinn-Pike. 2009. *Social Vulnerability to Disasters*. CRC press.

Tiwari, Shivam, Abhijit Gogoi, and K. Anki Reddy. 2019. ‘What Governs the Nature of Fouling in Forward Osmosis (FO) and Reverse Osmosis (RO)? A Molecular Dynamics Study’. *Physical Chemistry Chemical Physics* 21 (43): 24165–76. https://doi.org/10.1039/c9cp04393d.

Tiwari, Virendra M, John Wahr, and S Swenson. 2009a. ‘Dwindling Groundwater Resources in Northern India, from Satellite Gravity Observations’. *Geophysical Research Letters* 36 (18).

———. 2009b. ‘Dwindling Groundwater Resources in Northern India, from Satellite Gravity Observations’. *Geophysical Research Letters* 36 (18).

Tyagi, Shweta, Bhavtosh Sharma, Prashant Singh, and Rajendra Dobhal. 2013a. ‘Water Quality Assessment in Terms of Water Quality Index’. *American Journal of Water Resources* 1 (3): 34–38.

———. 2013b. ‘Water Quality Assessment in Terms of Water Quality Index’. *American Journal of Water Resources* 1 (3): 34–38.

Wada, Yoshihide, Ludovicus P H Van Beek, Cheryl M Van Kempen, Josef W T M Reckman, Slavek Vasak, and Marc F P Bierkens. 2010. ‘Global Depletion of Groundwater Resources’. *Geophysical Research Letters* 37 (20).

Wang, Fei, Hexin Lai, Yanbin Li, Kai Feng, Zezhong Zhang, Qingqing Tian, Xiaomeng Zhu, and Haibo Yang. 2022. 'Identifying the Status of Groundwater Drought from a GRACE Mascon Model Perspective across China during 2003–2018'. *Agricultural Water Management* 260: 107251.

Wang, Xiaoyan. 2006. 'Management of Agricultural Nonpoint Source Pollution in China: Current Status and Challenges'. *Water Science and Technology* 53 (2): 1–9.

World Water Assessment Programme (United Nations). (2006). *Water: A shared responsibility* (No. 2). UN-HABITAT.

Wu, Shuang-Ye, Brent Yarnal, and Ann Fisher. 2002. 'Vulnerability of Coastal Communities to Sea-Level Rise: A Case Study of Cape May County, New Jersey, USA'. *Climate Research* 22 (3): 255–70.

Xu, Xu, Guanhua Huang, Hongbin Zhan, Zhongyi Qu, and Quanzhong Huang. 2012. 'Integration of SWAP and MODFLOW-2000 for Modeling Groundwater Dynamics in Shallow Water Table Areas'. *Journal of Hydrology* 412: 170–81.

Yeh, Pat J-F, Sean C Swenson, James S Famiglietti, and Matthew Rodell. 2006. 'Remote Sensing of Groundwater Storage Changes in Illinois Using the Gravity Recovery and Climate Experiment (GRACE)'. *Water Resources Research* 42 (12).

Yigzaw, Zemenu Geremew, Olivier Cuisinier, Luc Massat, and Farimah Masrouri. 2016. 'Role of Different Suction Components on Swelling Behavior of Compacted Bentonites'. *Applied Clay Science* 120 (February): 81–90. https://doi.org/10.1016/j.clay.2015.11.022.

Yin, Wenjie, Litang Hu, and Jiu Jimmy Jiao. 2017. 'Evaluation of Groundwater Storage Variations in Northern China Using GRACE Data'. *Geofluids* 2017.

Yogendra, Kambalagere, and E T Puttaiah. 2008. 'Determination of Water Quality Index and Suitability of an Urban Waterbody in Shimoga Town, Karnataka'. In *Proceedings of Taal2007: The 12th World Lake Conference*, 342:346.

Yousefi, Mahmood, Mahboobeh Ghoochani, and Amir Hossein Mahvi. 2018a. 'Health Risk Assessment to Fluoride in Drinking Water of Rural Residents Living in the Poldasht City, Northwest of Iran'. *Ecotoxicology and Environmental Safety* 148: 426–30.

———. 2018b. ‘Health Risk Assessment to Fluoride in Drinking Water of Rural Residents Living in the Poldasht City, Northwest of Iran’. *Ecotoxicology and Environmental Safety* 148: 426–30.

———. 2018c. ‘Health Risk Assessment to Fluoride in Drinking Water of Rural Residents Living in the Poldasht City, Northwest of Iran’. *Ecotoxicology and Environmental Safety* 148: 426–30.

Zahran, Sammy, Samuel D Brody, Walter Gillis Peacock, Arnold Vedlitz, and Himanshu Grover. 2008. ‘Social Vulnerability and the Natural and Built Environment: A Model of Flood Casualties in Texas’. *Disasters* 32 (4): 537–60.

PUBLICATIONS

1. Goswami, J., Bhattacharjya, R.K. Vulnerability Assessment of Groundwater-Based Public Drinking Water Supply System of Kamrup District, Assam, India Considering Social Parameters. *J. Inst. Eng. India Ser. A* **104**, 483–499 (2023). DOI: https://doi.org/10.1007/s40030-023-00724-x
2. Goswami, J. and Bhattacharjya, R. K. (2021). Assessment of Groundwater Based Public Drinking Water Supply System of Kamrup District, Assam, India using a Modified Water Quality Index. *Pollution*, *7*(3), 495-509. DOI: https://doi.org/10.22059/poll.2021.309035.883