Dissertation Based on Industrial Problems

"GROUND WATER QUALITY ASSESSMENT OF CHHOTA-UDAIPUR TALUKA USING ARTIFICIAL NEURAL NETWORK"

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CERTIFICATE

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It gives us an immense pleasure and deep satisfaction in presenting **Project on Industrial Problem** entitled "**Ground water quality assessment of Chhota-Udaipur taluka using Artificial Neural Network**"

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ABSTRACT

The present study has applied Artificial Neural Network (ANN) to predict the fitness of groundwater quality for drinking purpose of Chhota-Udaipur taluka, located in Chhota Udaipur district, Gujarat State. In view of this, ground water samples from 28 wells have been collected and analysed for the year 2010, 2011, 2012, 2013, 2014, 2017, 2018, 2019, 2020, 2021.The physicochemical parameters such as pH, Nitrate, Fluoride, Sulphate, Calcium, Magnesium, Hardness, Chloride, TDS, Alkalinity were considered for computing water quality index (WQI). The best results of modelling were obtained for network by two hidden layers with 10 and 9 neurons, employing ReLU activation function and trained using Stochastic Gradient Descent(SGD) over 447 iterations. Key performance metrics, including Mean Square Error(MSE) of 0.0244, Root Mean Square Error(RMSE) approximately 0.1562, and an impressive R-squared(R^2)score nearly 0.9999,signify the model's accuracy. The samples were classified in five categories excellent, good, poor, very poor and unfit for drinking. The results show how water quality in villages changed over time. While some villages improved and fell into the 'good' category, others still struggled, remaining in the 'very poor' or 'poor' categories. This highlights the need for ongoing efforts to manage water quality effectively.

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ABBREVIATIONS

WQI – Water Quality Index

BIS –Bureau of Indian Standards

APHA –American Public Health Association

TDS – Total Dissolved Solid

ANN –Artificial Neural Network

PCA –Principal component analysis

MLR –Multiple linear regression

TH –Total Hardness

IDW – Inverse Distance Weight

CHAPTER 1: INTRODUCTION AND BASIC PRELIMINARIES

1.1 Importance of water

In the evolution and sustainability of nation and in flourishment or deterioration of different cultures, water has its quite pivotal role.

Water is like the lifeblood for nations and societies. It's super important because it's the crucial resource that keeps everything alive. Unlike minerals, fuels, forests, and animals, water has a unique role that nothing else can replace. The survival of a country really depends on water.

Now, When we think about all the water on Earth, a large 97.3% is in the oceans, but it's salty and not suitable for us to use. What we can use is only a small part of it, just 2.7%, Which is fresh water. Within this small amount, 2.03% is frozen in polar ice and glaciers, and only 0.61% is hidden underground as groundwater. This groundwater is a big deal because it's the main Important source we use for drinking, farming, and industry all around the world.

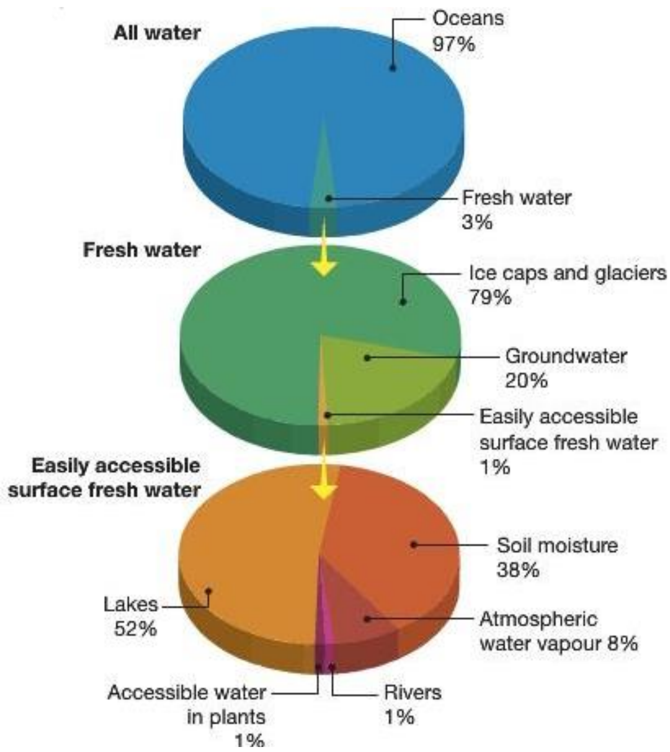


Figure 1 The global distribution of earths water resources

Fig. 1 visually articulates the pivotal role played by groundwater in the world's fresh water supply. Its significance escalates as the need for water intensifies, especially in regions grappling with inadequate surface water availability.

Defined as the subterranean water existing in the saturated zone of varying depth, groundwater resides within the cracks and pores of rocks and unconsolidated crystal layers, forming a substantial underground reservoir where precipitation finds sanctuary. Extraction is facilitated through Open wells and tube wells. Open wells serves as a traditional method, particularly in areas with a high groundwater table.

This study focuses on the quality assessment of groundwater in Chhota Udaipur Taluka, located in Chhota Udaipur district, Gujarat State, with a specific focus on its suitability for drinking purposes. This research endeavours to contribute meaningful insights to the ongoing discourse on sustainable water management.

1.2 Overview of groundwater

Groundwater, a crucial resource found beneath the Earth's surface, is facing escalating threats that challenge its sustainability. It acts as a vital reservoir, catering to diverse needs such as human consumption, agriculture, and industrial processes. Despite its significance, groundwater confronts complex challenges.

One primary concern is over-extraction of GW driven by the rising demand. With growing populations and expanding economic activities, there is increased pressure on groundwater. This excessive withdrawal not only depletes aquifers but also disrupts the natural balance of recharge and discharge processes.

Another significant issue is pollution, which worsens groundwater vulnerability. Contaminants from industrial discharges, agricultural runoff, and improper waste disposal seep into the subsurface, compromising water quality. The consequences go beyond immediate usability, impacting ecosystems and posing health risks to communities relying on groundwater.

Not enough rainwater is getting back into the ground, mainly because of Like cutting down trees, building cities, and changes in the weather. This makes the underground water supply even more stressed.

To fix this, we need a smart plan. We should use water wisely, stop polluting, and try to put more water back into the ground. Knowing that our underground water is in trouble means we need to act fast and make good plans to keep it around for our kids and grandkids.

1.3 Importance of water quality and resource management

Water quality and resource management are integral aspects of ensuring sustainable and accessible water supplies. Here are key points related to both:

Water quality:

- **Monitoring and Testing**: Regular testing of water sources is essential to assess parameters such as pH, dissolved oxygen, turbidity, and the presence of contaminants.
- **Standards and Regulations**: Governments and organizations establish water quality standards to safeguard public health. Compliance with these regulations helps maintain safe drinking water.
- **Treatment Processes**: Water treatment plants employ various processes like filtration, chlorination, and UV treatment to remove impurities and ensure water meets quality standards.
- **Source Protection**: Protecting water sources from pollution, deforestation, and industrial discharges is crucial for maintaining high water quality.

Resource management:

- **Sustainable Practices**: Implementing sustainable water use practices, including efficient irrigation methods and responsible industrial processes, helps manage water resources wisely.
- **Water Conservation**: Promoting water conservation measures at the individual, community, and industrial levels is essential for sustainable water management.

- **Integrated Planning**: Integrating water resource management into overall land-use planning ensures that water needs are considered alongside other development aspects.
- **Ecosystem Protection**: Maintaining healthy ecosystems, such as wetlands and forests, contributes to natural water filtration and regulation, benefiting overall water resource health.
- **Community Involvement**: Engaging local communities in water resource management decisions fosters a sense of ownership and encourages responsible water use.

Effective water quality and resource management involve a combination of scientific understanding, regulatory frameworks, technological interventions, and community participation to ensure a sustainable and equitable water future.

1.4 Ground water pollutants and types of pollutants

Water pollutants, including contaminants introduced through rainfall and interaction with soils in underground flows or surface bodies, warrant consideration. Non-point sources in urban areas encompass city streets and construction sites, while rural areas involve agriculture, logging, and mining. Runoff from these areas carries various pollutants, such as oil, grease, dirt, trash, and chemicals like metals, pesticides, and fertilizers. Groundwater characteristics typically include coolness, colourlessness, and low turbidity, except in the presence of iron or manganese salts. Hardness is common, with elevated levels of calcium and magnesium.

There are almost 40 parameters, depending on their level of presence (in different combination), people standardized empirically (over a period of time through various observations and outcomes) about their bifurcation relating to (1) Drinking water (2) Agricultural purpose (3) Industrial usage

For drinking purpose, valid chemical compositions which may be present and their permissible range (limit) in ground water:

Table 1 Drinking water standards and probable effects on human health

(BIS, IS 10500, 1991)

S. No.	**Parameters**	**Prescribed Limits**		**Probable effects**
		Desirable	**Permissible**	
1	COLOUR (HAZEN UNIT)	5	25	Aesthetically undesirable
2	ODOUR	Essentially free		Aesthetically undesirable
3	TASTE	Agreeable		Aesthetically undesirable
4	TURBIDITY (NTU)	5	10	Indicates pollution/contamination
5	pH	6.5	8.5	Affects taste, corrosivity & supply system.
6	HARDNESS, as CaCO3 mg/l	300	600	Causes scaling, excessive soap consumption, calcification of arteries.
7	IRON, as Fe mg/l	0.3	1	Causes staining of laundry and porcelain. In traces it is essential for nutrition.

8	CHLORIDE, as CI mg/l	250	1000	May be injurious to heart or kidney patients. Taste, indigestion, corrosion & palatability are affected
9	RESIDUAL CHLORINE only when Water is chlorinated	0.2	-	Excessive chlorination causes asthma, colitis & eczema
10	TOTAL DISSOLVED SOLIDS, mg/l	500	2000	May cause gastro-intestinal irritation corrosion and laxative effect to new users.
11	CALCIUM, as Ca, mg/	75	200	Excessive Cause incrustation, deficiency causes rickets, essential for nervous, muscular, cardiac functions and in coagulation of blood.
12	MAGNESIUM, as Mg, mg/l	30	100	Its salts are cathartics and diuretic. Excessive may cause laxative effect; deficiency causes structural and functional changes. It is activator of many enzyme systems.
13	COPPER, as Cu, mg/l	0.05	1.5	Beneficial in human metabolism, deficiency results in nutritional anaemia in infants. Large amounts may result in liver damage, causes central nervous system irritation & depression. Enhances corrosion of Al in water supply systems.

14	SULPHATE as SO4 mg/	200	400	Causes gastro-intestinal irritation, Along with Mo or Na can have a cathartic effect. Concentration more than 750 mg/ may have laxative effect.
15	NITRATE, as N, mg/l	45	100	Causes infant methaemoglobinaemia, at very high concentration causes gastric cancer and effects central nervous & cardiovascular system.
16	FLUORIDE as F, mg/	1	1.5	Reduces dental carries, very high concentration may cause crippling skeletal fluorosis,
17	CADMIUM, as Cd, mg/l	0.01	No relaxation	Acute toxicity may be associated with renal, arterial hypertension, itai-itai (bone disease). Cd salts cause cramps, nausea, vomiting & diarrhea.
18	LEAD , as Pb , mg / l	0.05	No relaxation	in mouth , severe Burning inflammation of gastro - intestinal tract with vomiting and diarrhea . Chronic toxicity produces nausea , severe abdominal pain , paralysis , mental confusion , visual disturbances , and anaemia etc.
19	ZINC , as Zn , mg / l	5	15	Essential & beneficial in human

				metabolism . Imparts astringent taste to water .
20	CHROMIUM , as Cr , mg / 1	0.05	No relaxation	Cr produces lung tumors , cutaneous and nasal mucous membrane ulcers and dermatitis .
21	ARSENIC , as As , mg / l	0.05	No relaxation	Causes skin damage , circulatory problems , increased risk of skin cancer .
22	ANTIMONY , as Sb , mg / l	0.006	No relaxation	Raises blood cholesterol , lowers blood sugar .
23	ALUMINIUM , as Al , mg / 1	0.03	0.2	Leads to neurological disorders .
24	BARIUM , as Ba , mg / l	2	No relaxation	Increases blood pressure .
25	BERYLLIUM , as Be , mg / l	nil	0.0002	Is carcinogenic
26	CYANIDE , as CN , mg / l	0.05	No relaxation	Causes problem . nerve damage , thyroid
27	MERCURY , as Hg , mg / l	0.001	No relaxation	Neurological and renal disturbances .Excess causes gonadotoxic and mutagenic effects and disturbs the cholesterol metabolism .
28	MANGANESE , as Mn , mg / l	0.1	0.3	Essential as a cofactor in enzyme systems and metabolism processes .Excessive causes change in appetite . and reduction in metabolism of iron to form haemoglobin .

				Imparts undesirable taste and stains plumbing fixtures and laundry .
29	SELENIUM , as Se , mg / l	0.01	No relaxation	Leads to hair , finger loss , and numbness in fingers or toes ,
30	BORON , as B , mg / l	1	5	Affects central nervous system , salts cramps , may cause nausea , convulsions , coma , etc.
31	ALKALINITY , as $CaCO_3$, mg / 1	200	600	Imparts unpleasant taste , deleterious to humans in presence of high pH , hardness and TDS .
32	PESTICIDES , ug / 1	nil	0.001	Imparts toxicity , accumulates in different organs of body , affects immune and nervous systems . Carcinogenic .
33	PHOSPHATE , as PO_4 , mg / l	No guideline		High concentration causes vomiting &diarrhoea stimulates secondary hyperthyroidism and bone loss .
34	SODIUM , as Na , mg / 1	No guideline		Harmful to persons suffering from cardiac , renal & circulatory diseases .
35	POTASSIUM , as K , mg / 1	No guideline		Essential nutrition element but excessive amounts is cathartic .

36	NICKEL , as Ni , mg / l	No guideline		Non - toxic element but may be carcinogenic in animals , can react with DNA resulting in DNA damage in animals .
37	PATHOGENS a) TOTAL COLIFORM No / dl b) FAECAL COLIFORM No / di	1	10	Causes water borne diseases like coliform jaundice ; Typhoid , Cholera etc. produces infections involving skin mucous membrane of eyes , ears and throat .
38	RADIOACTIVITY : -BETA PARTICLES -ALPHA PARTICLES -RADIUM	0-4 millirem / year 0-15 picocuries/ year 0-05 picocuries/ year		Increases risk of cancer .

In this chapter we saw importance of water and resource management. We also came across ground water pollutants and types of pollutants. For drinking purpose, valid chemical compositions which may be present and their permissible range (limit) in ground water were listed, along with its probable effect on human health.

CHAPTER2:PROBLEM DEFINITION AND OBJECTIVES

2.1 Problem definition

The main problem definition of our study is the assessment of groundwater quality of Chhota-Udaipur taluka located in Chhota Udaipur district, in the state of Gujarat, for drinking purpose with the help of machine learning method.

To achieve this, Artificial Neural Network (ANN) is employed as a tool for analysis. It is a computational model inspired by the human brain and it is utilized to analyse datasets and identify patterns in groundwater quality parameters.

In this study, the Water Quality Index (WQI) is predicted using Artificial Neural Networks (ANN). The WQI provides a single value to express the overall quality of water, incorporating multiple water quality parameters into a single metric. The ANN model is trained using various water quality parameters as inputs to predict the WQI.

Once the ANN model is trained and validated, the predicted WQI values is compared with those calculated using an traditional formula for WQI. This empirical formula incorporates weighted averages or other mathematical relationships between different water quality parameters to derive the WQI value.

By comparing the predicted WQI values from the ANN model with those from the Traditional formula, We can evaluate the accuracy and effectiveness of the ANN approach in predicting water quality compared to traditional methods. This comparison can provide insights into the reliability and potential advantages of using ANN for water quality assessment in Chhota Udaipur district.

2.2 Objectives

1. Identification of important parameters related to groundwater quality:

- To conduct an extensive review of literature and local data to identify key parameters influencing groundwater quality in the study area.
- To determine the most significant parameters affecting groundwater quality in Chhota Udaipur taluka.

2. Determination of Water Quality Index (WQI) by traditional method for the study area:

- To collect data on various water quality parameters including pH, TDS, sulphate, nitrate, magnesium, etc.
- To calculate the Water Quality Index (WQI) for the study area using conventional method.

3. Predicting WQI by Artificial Neural Network (ANN) model development:

- To develop an Artificial Neural Network (ANN) model using historical data on groundwater quality parameters and corresponding WQI values found by conventional method.
- To implement the ANN model in Python programming language, using libraries and tools for data pre-processing, model training, and evaluation.
- To train and validate the ANN model using appropriate techniques.

4. Comparison with traditional methods:

- To compare the WQI values predicted by the ANN model with those obtained using conventional method.
- To evaluate the performance of the ANN model in predicting WQI compared to traditional methods, highlighting the advantages of ANN modelling in terms of accuracy, efficiency, and scalability.

By focusing on the importance of ANN modelling and comparing its outcome with traditional method, this objective aims to showcase the benefits of using advanced modelling technique for groundwater quality assessment in Chhota Udaipur taluka

CHAPTER 3:LITERATURE REVIEW

3.1 Studies related to assessment and suitability of water

The literature review related to present study gives the information regarding the historical background of study, the present status of research in that field, and recent developments in the subject. It also provides a unique source of information about the groundwater contamination and its effect on human health in the rural, industrial and newly formed urban sectors, which has become path indicator for the studies and therefore forms the strong foundation of present study. In view of this, the present chapter includes the information on:

Below is denoting to review the study of previous investigators pertaining to assessment of groundwater quality.

3.2 Literature review

Studies related to water quality assessment and suitability for different purposes such as drinking irrigation, industrial etc. are enormous in literature. The methods to be adopted for determining the water quality are well established in the form of standard (APHA). The recent studies carried out in 21st century is reviewed here since the basis for these studies are in turn the works of earlier years and decades of the previous century.

Khudair, Basim Hussein, Mustafa Malik Jasim, and AwatifSoadedAlsaqqar, "Artificial neural network model for the prediction of groundwater quality." [10] (2018): The present article delves into the examination of groundwater quality, based on WQI, for drinking purposes in Baghdad City. Further, for carrying out the investigation, the data was collected from the Ministry of Water Resources of Baghdad, which represents water samples drawn from 114 wells in Al-Karkh and Al-Rusafa sides of Baghdad city. With the aim of further determining WQI, four water parameters such as (i) pH,(ii) Chloride (Cl),(iii) Sulphate (SO 4), and (iv) Total dissolved solids (TDS), were taken into consideration. According to the computed WQI, the distribution of the groundwater samples, with respect to their quality classes such as excellent, good, poor, very poor and unfit for human drinking purpose, was found to be 14.9%, 39.5%, 22.8%, 6.1%, and 16.7%, respectively. Additionally, to anticipate changes in groundwater WQI, IBM® SPSS® Statistics 19 software (SPSS) was used to develop an artificial neural network model (ANNM). With the application of this ANNM model, the results obtained illustrated high prediction efficiency, as the sum of squares error functions (for training and testing samples) and coefficient of determination (R 2), were found to be (0.038 and 0.005) and 0.973, respectively. However, the parameters pH and Cl influenced model prediction significantly, thereby becoming crucial factors in the anticipation carried out by using ANNM model.

Kulisz, M., and J. Kujawska,"Application of artificial neural network (ANN) for water quality index (WQI) prediction for the river Warta, Poland." [11] (2021): The aim of this paper is to present the potential of using neural network modelling for the prediction of the surface water quality index (WQI). An artificial neural network modelling has been performed using the physicochemical parameters (TDS, chloride, TH, nitrate, and manganese) as an input layer to the model, and the WQI as an output layer. The physicochemical parameters have been taken from five measuring stations of the river Warta in the years 2014-2018 via the Chief Inspectorate of Environmental Protection (GIOŚ). The best results of modelling were obtained for networks with 5 neurons in the hidden layer. A high correlation coefficient (general and within subsets) 0.9792, low level of MSE in each subset (training, test, validation), as well as RMSE at a level of 0.624507639 serve as a confirmation. Additionally, the maximum percentage of an error for WQI value did not exceed 4%, which confirms a high level of conformity of real data in comparison to those obtained during prediction. The aforementioned results clearly present that the ANN models are effective for the prediction of the value of the Surface water quality index and may be regarded as adequate for application in simulation by units monitoring condition of the environment.

Anjali. K. Ullas, Dipesh U. Srivastava, “Groundwater Quality Analysis Using GIS” [3] (2013): In this study, a spatial distribution of various water quality parameters like pH, TDS, Alkalinity, EC, Chloride, has been generated using GIS and the groundwater contaminations are identified.Seven samples were selected for this study. Water level analysis using GIS interpolation technique helps in the identification of groundwater sources have been studied using standard methods in laboratory. This study conclude that the overall quality of ground water was estimated using water quality index. The water quality index merged all the parameters in to a single value easily recognized by the common people. The ground water quality differed in different regions of the study area, but not a single sample was found to be unsuitable for drinking.

D. B. Pal, Dhruv H. Patel,“Assessment of Ground and Surface water quality along river Varuna, Varanasi, India” [7] (2015): In this study, the river Varuna is situated in the Indo-Gangetic plain and is a small tributary of river Ganga. The study area was monitored at seven sampling sites for 3 years (2010-2012), and eight physio-chemical parameters were considered for this study. The samples were collected during winter (2010-12) across a period of 3 months to monitor changes caused by anthropogenic as well as natural sources. The data obtained were analysed by multivariate statistical techniques to reveal the underlying implicit information regarding proposed interactions for the relevant area. The correlation coefficients calculated for various physiochemical parameters for ground and surface water established the correlations between them. Thus, this research presents the utility of multivariate statistical techniques for evaluation of the proposed interactions and effective future monitoring of potential sites. In observations, there is an interaction as hypothesized in our proposal which was exhibited by the statistical technique. Moreover, this analysis will help in future water control management program as it has outlined the parameters contributing to pollution for every site. This will make the future monitoring more economical and easier to comprehend. It is therefore needful, to develop a comprehensive river water quality monitoring program all over the world.

Abhishek kumar, “Groundwater quality assessment using the WQI and GIS mapping: Suitability for drinking and irrigation usage in the Sirdala block of Nawada district”[1] (2020): The research aimed to assess the suitability of groundwater for both drinking and irrigation purposes in the Sirdala block of Nawada district, Bihar, India. The study involved collecting and analyzing 65 groundwater samples to determine their quality for relevant parameters.

For evaluating the quality of groundwater for drinking purposes, several water quality parameters were considered, including pH, Total Dissolved Solids (TDS), Total Hardness (TH), Alkalinity (AS), and major ions such as calcium ($Ca2+$), magnesium ($Mg2+$) analyze for the drinking and irrigation suitability.

In terms of irrigation suitability, various irrigation indices were employed to assess groundwater quality. These indices included the soluble sodium percentage (Na%), sodium adsorption ratio (SAR), residual sodium bicarbonate (RSCB), permeability index (PI), magnesium hazards ratio (MHR), Kelly's Ratio (KR), Potential Salinity (PS), Mg2+ to Ca2+ ratio, and Na+ to Ca2+ ratio. These indices help determine the groundwater's compatibility with irrigation.

The findings showed that for drinking purposes, the calculated WQI ranged from 57.67 to

929.90. Unfortunately, a large majority (around 70.76%) of the samples were found to be unsuitable for drinking. On the other hand, for irrigation, the WQI varied from 87.88 to 434.67, with around 50% of the samples being suitable.

The study also used various plots and diagrams to visualize the chemical characteristics of groundwater. The Gibbs ratio plot and Piper diagram were utilized to gain insights into the hydrochemistry of the groundwater. The Gibbs ratio plot indicated that the balance between evaporation and precipitation significantly influenced the hydrochemistry. The Piper diagram, which considers major ion concentrations, suggested that the Na-HCO3 water type was the predominant hadrochemicalfacies in the groundwater samples.

Overall, this research highlighted the varying suitability of groundwater in the Sirdala block for both drinking and irrigation purposes, with significant proportions of samples being unsuitable for drinking but more suitable for irrigation. The hadrochemical analysis through plots and diagrams provided additional insights into the factors influencing groundwater quality.

AwachantAnkita R, “Ground Water Quality Assessment through WQIs”[5] (2017): The study focuses on addressing concerns arising from the extensive industrial growth and its potential impact on groundwater contamination due to waste discharge. Recognizing the need to assess groundwater quality, the research aims to utilize Water Quality Indices (WQIs) as a tool to simplify the representation of water quality by consolidating numerous parameters into a single value. This approach facilitates the interpretation of monitoring data and enhances the understanding of groundwater quality.The research specifically investigates the quality of bore well water in the Vishrambag area of Sangli. Water samples from 16 bore wells are collected and analyzed for 12 significant parameters, including pH, electrical conductivity, total dissolved solids, total alkalinity, and total hardness. These parameters are crucial indicators of water quality and play a pivotal role in assessing the suitability of water for various purposes.

To determine the potability of bore well water, the study employs the Indian Standard Drinking Water specification IS10500:2012 as a benchmark. This standard provides guidelines for safe drinking water quality. The analysis of both physicochemical and biological characteristics of the bore well water samples lead to the observation that the water is not suitable for direct consumption. It is evident that treatments, specifically aimed at hardness removal and disinfection, are imperative to improve the water's quality and safety for human use.

Alice Makonio,“Assessment of Groundwater Quality Using Water Quality Index from Selected Springs in Manga Subcounty, Nyamira County, Kenya” [2] (2022): The presented study focuses on assessing the quality of groundwater during the rainy season in November 2018 within the Manga region of Nyamira County, Kenya. The investigation centers on three springs: Kiangoso, Kerongo, and Tetema. The aim is to evaluate the water quality in these springs by employing a comprehensive set of parameters and subsequently calculating the Water Quality Index (WQI).

Water samples from the mentioned springs were collected and subjected to analysis based on fifteen parameters. These parameters include pH, turbidity, nitrate, phosphate, calcium, magnesium, chloride, sulphates, fluoride, iron, total phosphorous, total hardness, total alkalinity, total dissolved solids, and total coliform. Standard methods were utilized for the analysis, and the results were compared against the guidelines set by the World Health Organization (WHO) and the Kenya Bureau of Standards, with respect to both physiochemical and bacteriological parameters.

The Water Quality Index was calculated using the collected data. The WQI values were determined to be 21.32 for Kiangoso, 29.66 for Kerongo, and 25.64 for Tetema. These WQI values serve as indicators of the overall water quality status for each spring. Notably, Kiangoso exhibited an excellent quality status, while Kerongo and Tetema displayed good quality statuses according to the WQI classification.

The findings of the study are significant, indicating that the groundwater quality within the Manga region, as represented by the three springs, is generally favorable for various purposes. The calculated WQI values, all less than 30, suggest that the groundwater from these springs is suitable for consumption, irrigation, and industrial use. These outcomes hold importance for the future management of groundwater in the Manga region, providing valuable insights for decision-makers and stakeholders to make informed choices regarding the sustainable utilization and protection of groundwater resources.

Arjun Ram,"Groundwater quality assessment using water quality index (WQI) under GIS framework" [4] (2020): The literature survey revolves around the importance of groundwater as a primary drinking water source in the hard rock terrain of the Bundelkhand massif, particularly in District Mahoba, Uttar Pradesh, India. The study's objective is to assess the suitability of groundwater for human consumption in this region. To achieve this, a range of water quality parameters were analyzed, including pH, electrical conductivity, total dissolved solids, alkalinity, total hardness, various ions (calcium, magnesium, sodium, potassium, bicarbonate, sulfate, chloride, fluoride, nitrate), and trace metals (copper, manganese, silver, zinc, iron, nickel).

One of the key methodologies employed in the study is the Water Quality Index (WQI). This index is used to classify water quality into categories such as excellent, good, or poor. The application of WQI helps in providing a straightforward understanding of water quality, which can be beneficial for both local communities and policymakers. The calculated WQI values in the study area span a range from 4.75 to 115.93. The overall WQI assessment suggests that groundwater in the region is safe and suitable for consumption, with exceptions in specific areas like Charkhari and Jaitpur Blocks, which exhibit localized pockets of lower quality.

The Hill-Piper Trilinear diagram is used to visualize the hydrochemical composition of groundwater in the study area. It reveals that the groundwater primarily falls within the categories of Na+-Cl−, mixed Ca2+-Mg2+-Cl−, and Ca2+-HCO−3 water types. This variation is attributed to the mineral composition of the underlying granite-gneiss rock, rich in orthoclase feldspar and biotite minerals, which contribute to bicarbonate and chloride-rich groundwater through weathering processes.

The study also delves into the correlation matrix analysis, examining the relationships between different parameters and their influence on groundwater quality assessment. This approach aims to identify significant factors affecting groundwater quality.

SoumyaSingha,"Assessing Ground Water Quality using GIS" [15] (2015): The literature survey discusses a study focused on assessing the impact of mining activities on groundwater quality in the Korba coalfields region of Chhattisgarh, India. The study area covers approximately 530 square kilometers and is situated between latitudes 22°15′ and 22°30′N and longitudes 82°15′E and 82°15′E. The research aims to comprehensively understand the potential changes in groundwater quality resulting from mining activities in the region.

The methodology involves the collection of various types of data, including maps, toposheets, water quality data, well locations, mining lease areas, and village locations. These data are sourced from different government departments of Chhattisgarh. After data collection, a base map is prepared using ArcMap 9.3, a Geographic Information System (GIS) software. The collected water quality data is analyzed and utilized as an attribute database to generate thematic maps illustrating the distribution of various water quality parameters across the study area.

One of the significant components of the study involves the calculation of the Water Quality Index (WQI). The WQI is computed based on several water quality parameters, including pH, Turbidity, Total Hardness (TH), chloride, Total Dissolved Solids (TDS), calcium, nitrate, iron, and fluoride. The WQI is a comprehensive tool that condenses multiple water quality parameters into a single index, providing an easily understandable representation of overall water quality. A Water Quality Index map is developed to visualize the spatial distribution of water quality across the study area.

The study's findings are presented primarily through maps, which offer an effective means of conveying the complex information related to groundwater quality. These maps aid in providing a clear understanding of the existing water quality conditions in the Korba coalfields region. The analysis reveals that the groundwater in the study area requires field-specific treatment before being deemed suitable for various uses.

I Chenini "Evaluation of ground water quality using multiple linear regression and structural equation modeling"[9](2009): The literature survey discusses a methodology that combines multiple linear regression and structural equation modeling to characterize groundwater quality in watersheds using hydrochemical data. The primary focus of this research is to employ mathematical methods and modeling techniques to analyzehydrochemical data, understand the composition of groundwater samples from phreatic aquifers, and elucidate the sources of water mineralization. The study is conducted in the context of the Maknassy Basin, located in central Tunisia.

The methodology incorporates several analytical techniques to achieve its objectives. Principal Component Analysis (PCA) is utilized to identify the primary sources of variation among the hydrochemical parameters. The PCA reveals that variations in the dataset can be attributed to specific interactions, such as those involvingsulfuric acid and bicarbonate, sodium and chloride, and calcium and magnesium. These interactions are associated with water-rock interactions, contributing to the mineralization of the water.

The research further explores the formulation of an equation that characterizes the sampled groundwater. This equation serves to describe the hydrochemical relationships within the groundwater. To comprehensively analyze the entire system of variables, such as sodium, magnesium, sulfate, bicarbonate, chloride, and calcium, as well as their relationship with total dissolved solids, the study employs Structural Equation Modeling (SEM). This modeling approach, facilitated by Amos software, enables a simultaneous investigation of interactions between different groundwater components and their correlations with total dissolved solids.

The integrated results of this methodology offer a comprehensive approach to characterizing groundwater quality through the utilization of statistical analyses and modeling techniques. The specific context of the Maknassy Basin in Tunisia is used to exemplify how these methods can elucidate the origin and composition of groundwater chemistry. By employing a combination of mathematical tools, PCA, regression, and SEM, the study provides insights into the complex interplay of hydrochemical factors influencing groundwater quality. This research contributes to the understanding of groundwater systems and offers a methodological framework that can be adapted to other watersheds and regions, thereby aiding in groundwater quality assessment and management strategies.

Batabyal A. K,"Correlation and Multiple Linear Regression Analysis of Groundwater Quality Data of Bardhaman District, West Bengal, India" [6] (2014): The literature survey discusses a study that explores the hydrogeochemistry of groundwater in a shallow aquifer system, along with correlation-regression analysis to understand the relationships between different water quality parameters. The study area primarily encompasses a rural region where the local population heavily relies on groundwater for various purposes. The research involves the collection and analysis of representative groundwater samples during both pre-monsoon and post-monsoon periods.

The hydrogeochemical composition of the groundwater is evaluated through a comprehensive physico-chemical analysis of 28 samples. The dominant major ions are ranked as follows: HCO3 > Ca > Na > Mg > Cl > SO4 during pre-monsoon, and HCO3 > Ca > Mg > Na > Cl > SO4 during post-monsoon. Notably, iron concentrations were elevated at several sites, particularly after the monsoon period. Despite this, the groundwater is generally found to be suitable for drinking and domestic use. The presence of high iron levels is attributed to ferruginous sand, lateritic gravel, and laterite near the surface, with water-rock interaction contributing to the iron content.

The research involves the identification of correlation coefficients among various water parameters, particularly in relation to total dissolved solids (TDS). Similar trends in the correlations between parameters are observed during both pre- and post-monsoon periods. Strong to good correlations are identified between parameters such 18 as electrical conductivity (EC), TDS, hardness, alkalinity, Ca^{2+}, Mg^{2+}, HCO_3^-, Na^+, and SO_4^{2-}.

The study employs Multiple Linear Regression (MLR) analysis to establish a predictive equation for TDS based on correlated water parameters, including Ca^{2+}, Mg^{2+}, and Na^+. This equation serves to quantify and predict TDS values. A comparison between the observed and predicted TDS values validates the accuracy of the MLR equation. The utilization of such predictive equations has the potential to aid in assessing groundwater quality in various areas.

CHAPTER 4: STUDY AREA AND DATA COLLECTION

4.1 General profile of the Chhota Udaipur taluka

Nestled in the Eastern part of Gujarat's Chhota Udaipur district, Chhota Udaipur Taluka is bordered by Madhya Pradesh. Covering an area of 74926 square kilometres, it sits at 22.09 latitude and 74.05 longitude, with an elevation of 92 meters above sea level. The taluka is home to 144 villages, housing a total population of 241377 people.

The rivers Orsang and Hiren are passing through the taluka which are tributaries of Narmada River. These rivers contribute to the ground water present at shallow depth and acts as natural boundary for underlying aquifer system. Generally, a hot and dry atmosphere is found for the study region. It goes as high as 45 degrees centigrade in summer and as low as 8 degrees in winter season. Average annual rainfall is 750 mm in the region during the monsoon season. Chhota Udaipur Taluka consists of 27,687 hector area of forest and 5324 hector of barren land [13].

The Chhota Udaipur taluka region is known for its rich agriculture with fine crops of cotton, horticulture and vegetables due to fertile alluvial soils and perennial availability of water but 95% ground water sources used as irrigation for cultivated area [8].

The net geographical area of Chhota Udaipur Taluka watershed is about 3988.60 ha out of which 29% is forest area. Most of the villages in this area are surrounded by hilly and rocky mountains.

About 51% of land is under agriculture which is completely rain- fed; mainly a Khari crop is taken. About 14% of the total land is classified under wasteland of which 41% is cultivable and rest is not fit for agriculture. (Detailed project report (dpr) iwmp- 8 (selva), 2010-2011)

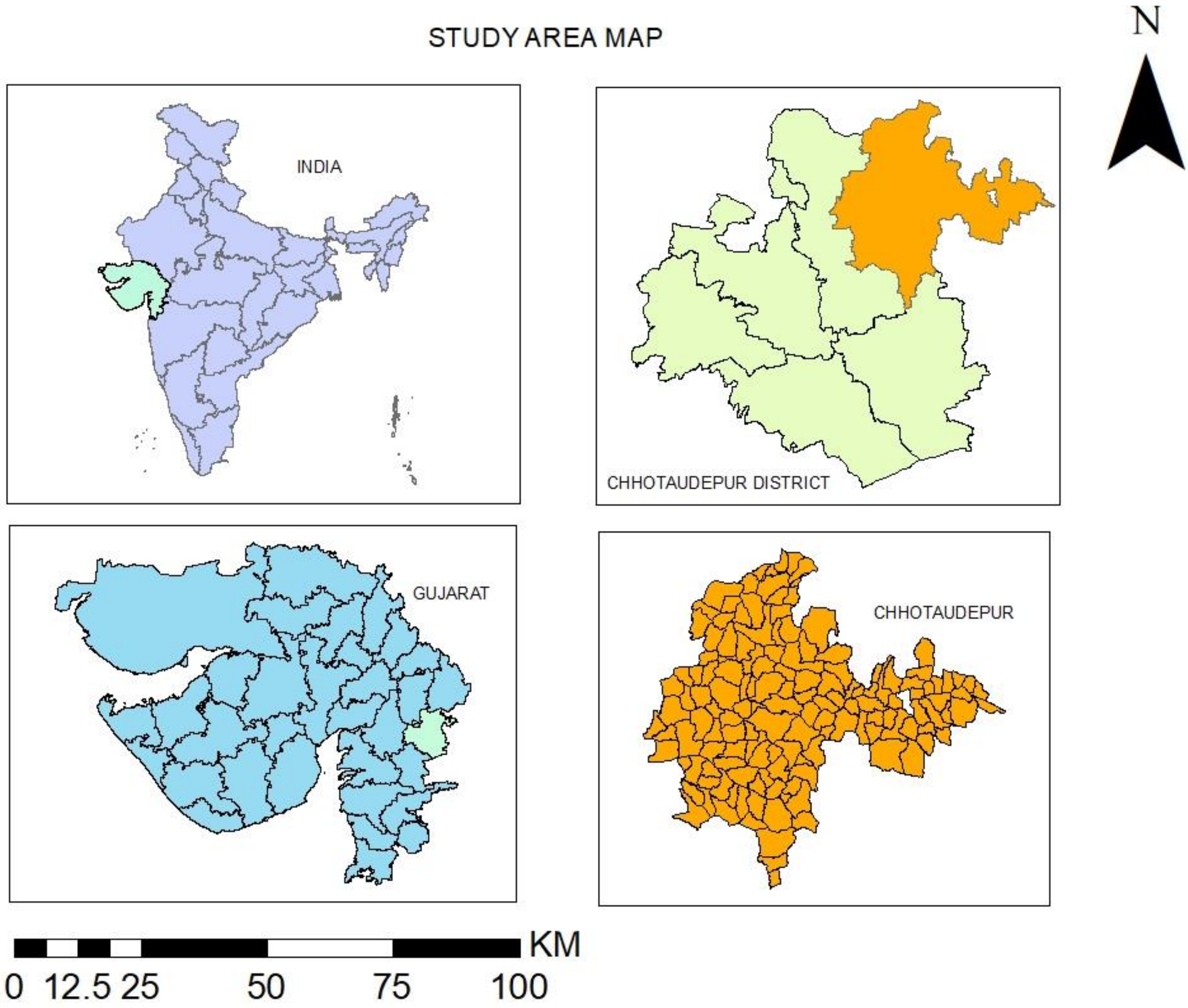


Figure 2location map of study area

4.2 Data collection

The objective of this study is to develop a predictive model using Artificial Neural Networks (ANNs) to estimate the Water Quality Index (WQI) based on ten water quality parameters, including pH, Nitrate, Fluoride, Sulphate, Calcium, Magnesium, Hardness, Chloride, TDS, Alkalinity. The WQI serves as a comprehensive indicator of overall water quality, and the prediction model aims to provide accurate assessments for monitoring and management purposes.

The dataset used in this study is obtained from website of National Rural Drinking Water Programme [12], comprising measurements of ten water quality parameters. Prior to model training, the dataset undergoes pre-processing steps including data cleaning, standardizing, handling of missing values to ensure the quality and consistency of the data.

The samples were collected from 28 wells located in the villages of Chhota Udaipur taluka namely Ambala, Zoz, Vasedi, Surkheda ,Simal, Faliya, Pelsanda, Olimba ,Raysingpura, Motisadhli, Ode, Mithibor, Gunata , Ferkuva, Dumali , Mandava , Kikavada , Jamli Jamla , Chilarvant, Chichod , Chisadia , Devaliya , Bodgam , Bhordali, Bhilpur, Antroli .

The data were collected for total 10 years, 2010, 2011 ,2012, 2013, 2014, 2017, 2018, 2019, 2020, and 2021.

Fig 3 shows the location of wells from where the samples were collected.

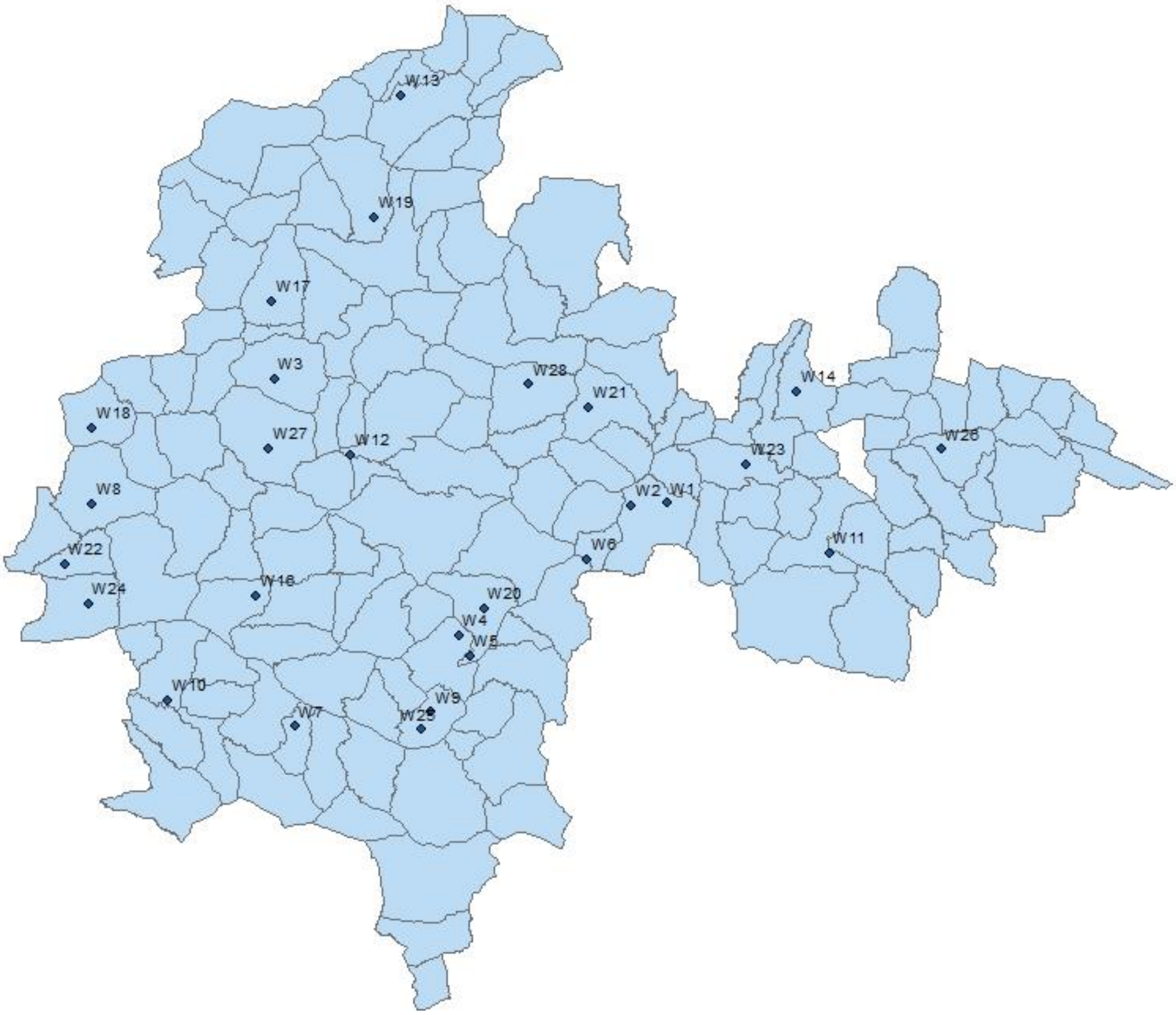


Figure 3Well locations

Table 2 latitude and longitude of well location

WELL NO	VILLAGE	LAT	LONG
W1	AMBALA	22.386922	74.10075
W2		22.385769	74.087402
W3	ZOZ	22.433669	73.952701
W4	VASEDI	22.337067	74.022382
W5		22.329576	74.026424
W6	SURKHEDA	22.365766	74.070609
W7	SIMAL FALIYA	22.302909	73.96045
W8	PELSANDA	22.386495	73.88408
W9	OLIMBA	22.308247	74.011786
W10	RAYSINGPURA	22.312933	73.912461
W11	MOTISADHLI	22.367997	74.162189
W12	ODE	22.405038	73.981517
W13	MITHIBOR	22.540067	74.000692
W14	GUNATA	22.428901	74.149719
W15	FERKUVA	22.160561	73.827247
W16	DUMALI	22.35211	73.945749
W17	MANDAVA	22.462775	73.95177
W18	KIKAVADA	22.415085	73.883926
W19	JAMLI	22.494041	73.990545
W20	JAMLA	22.347468	74.031755
W21	CHILARVANT	22.422751	74.071425
W22	CHICHOD	22.363935	73.873629
W23	CHISADIA	22.40153	74.130798
W24	DEVALIYA	22.349215	73.882547
W25	BODGAM	22.301826	74.007992
W26	BHORDALI	22.407092	74.204254
W27	BHILPUR	22.407285	73.950535
W28	ANTROLI	22.431369	74.048949

Table 3 Water quality parameters for the year-2010

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.89	18.55	0.84	16.67	52.7	42.1	304.2	97.11	646.5	312.6
W2		7.89	18.55	0.84	16.67	52.7	42.1	304.2	97.11	646.5	312.6
W3	ZOZ	7.888	18.55	1.26	15	35	47	284	64	508	264
W4	VASEDI	8	27.52	0.84	24	70	29	296	64	516	348
W5		8.02	18.55	0.5	12	35	54	312	72	432	316
W6	SURKHEDA	7.85	18.55	0.97	15	51	67	408	124	864	424
W7	SIMAL FALIYA	8.12	2.75	0.84	16.67	26	9	104	24	202	156
W8	PELSANDA	7.89	18.55	0.84	16.67	52.7	42.1	304.2	97.11	646.5	312.6
W9	OLIMBA	7.86	18.99	0.84	24	50	61	380	200	900	408
W10	RAYSINGPURA	7.96	18.55	0.16	27	58	72	444	260	1080	348
W11	MOTISADHLI	7.89	18.55	0.84	16.67	52.7	42.1	304.2	97.11	646.5	312.6
W12	ODE	7.5	18.55	0.75	30	136	29	460	97.11	1190	368
W13	MITHIBOR	7.98	2.11	0.52	6	29	23	168	112	280	236
W14	GUNATA	7.89	18.55	0.84	16.67	52.7	42.1	304.2	97.11	646.5	312.6
W15	FERKUVA	7.89	18.55	0.84	16.67	52.7	42.1	304.2	97.11	646.5	312.6
W16	DUMALI	7.32	18.55	1.34	21	74	38	344	97.11	632	384
W17	MANDAVA	7.92	32.7	1.21	21	46	51	260	68	648	360
W18	KIKAVADA	8.32	20.04	1.2	18	51	42	304	48	708	308
W19	JAMLI	8.12	18.55	0.47	18	50	32	260	96	596	268
W20	JAMLA	7.68	18.55	0.54	15	50	56	360	84	592	256
W21	CHILARVANT	7.26	18.55	0.39	15	88	27	332	64	512	276
W22	CHICHOD	7.89	18.55	0.84	16.67	52.7	42.1	304.2	97.11	646.5	312.6
W23	CHISADIA	8.23	29.53	1.34	3	29	31	200	40	442	340
W24	DEVALIYA	8.04	18.55	0.81	30	67	64	436	248	1092	264
W25	BODGAM	7.79	14.77	0.84	3	26	23	160	40	644	332
W26	BHORDALI	7.89	18.55	0.84	16.67	52.7	42.1	304.2	97.11	646.5	312.6
W27	BHILPUR	7.98	18.55	1.09	15	46	42	292	100	620	388
W28	ANTROLI	7.78	18.55	0.97	6	37	45	280	40	472	208

Table 4 Water quality parameters for the year-2011

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.23	10.55	0.9	15	59	48	348	144	828	572
W2		7.96	23	0.92	24	57	48	344	68	656	284
W3	ZOZ	7.95	23	0.73	21	61	61	408	160	698	264
W4	VASEDI	7.86	23	0.9	18.9	45.77	47.27	301.81	124.84	677.9	308.86
W5		7.86	23	0.9	18.9	45.77	47.27	301.81	124.84	677.9	308.86
W6	SURKHEDA	7.98	23	0.66	0.66	45	45	300	48	614	284
W7	SIMAL FALIYA	8.07	17.4	0.9	8	30	24	176	44	320	264
W8	PELSANDA	7.86	23	0.9	18.9	45.77	47.27	301.81	124.84	677.9	308.86
W9	OLIMBA	7.95	44.8	1.3	10	27	30	192	336	1292	480
W10	RAYSINGPURA	8.14	22	1.18	8	24	29	176	196	522	35
W11	MOTISADHLI	8.15	23	0.87	11	50	50	332	88	674	272
W12	ODE	7.99	16.9	0.9	18	61	60	400	124.84	726	252
W13	MITHIBOR	7.17	26.3	0.9	33	35	38	248	124.84	580	340
W14	GUNATA	8.14	39.5	0.9	7	46	97	312	80	492	320
W15	FERKUVA	7.8	23	0.86	33	67	72	468	124.84	948	472
W16	DUMALI	7.86	23	0.9	18.9	45.77	47.27	301.81	124.84	677.9	308.86
W17	MANDAVA	7.32	23	1.05	29	54	55	364	112	740	308
W18	KIKAVADA	7.71	19.2	0.9	7	46	37	268	84	582	364
W19	JAMLI	7.86	23	0.9	18.9	45.77	47.27	301.81	124.84	677.9	308.86
W20	JAMLA	8.04	23	0.89	51	46	44	300	108	778	328
W21	CHILARVANT	7.88	23	0.61	28	46	47	312	172	648	208
W22	CHICHOD	7.86	23	0.9	18.9	45.77	47.27	301.81	124.84	677.9	308.86
W23	CHISADIA	7.87	23	1.12	22	42	33	244	60	468	156
W24	DEVALIYA	7.34	23	0.75	27	53	60	380	268	1076	372
W25	BODGAM	8.05	13.5	1.42	7	19	29	168	80	484	372
W26	BHORDALI	8.02	28.4	0.69	11	61	60	400	104	678	348
W27	BHILPUR	7.74	23	0.53	29	48	49	324	156	756	276
W28	ANTROLI	8.49	14.47	0.82	16	30	24	176	64	354	224

Table 5 Water quality parameters for the year-2012

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.89	30.65	1.25	33	28	84.76	192	32	468	248
W2		7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W3	ZOZ	7.24	26.7	0.41	11	62	59	400	104	714	208
W4	VASEDI	8.1	26.7	0.7	18	65	66.6	436	176	928	132
W5		8.06	26.7	0.99	18	43	45	296	112	682	80
W6	SURKHEDA	8.12	26.7	0.66	33	51	48	328	112	704	296
W7	SIMAL FALIYA	7.63	26.7	0.23	14	66	62	424	96	738	336
W8	PELSANDA	7.98	19.35	0.69	34	45	37	268	109.71	562	160
W9	OLIMBA	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W10	RAYSINGPURA	7.31	44.9	0.69	22	51	49	336	64	634	400
W11	MOTISADHLI	8.01	26.7	0.59	17	67	53	388	112	694	132
W12	ODE	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W13	MITHIBOR	7.79	23.81	0.59	14	50	47	320	109.71	532	328
W14	GUNATA	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W15	FERKUVA	8.28	26.7	0.6	14	66	66	424	109.71	688	336
W16	DUMALI	8	26.7	0.56	29	93	88	600	109.71	1426	232
W17	MANDAVA	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W18	KIKAVADA	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W19	JAMLI	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W20	JAMLA	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W21	CHILARVANT	7.95	26.7	1.01	11	59	58	392	256	988	68
W22	CHICHOD	8.04	12.09	0.6	29	45	46	304	272	894	188
W23	CHISADIA	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W24	DEVALIYA	7.91	26.7	0.69	19.89	51.78	84.76	346.89	109.71	688.44	212.89
W25	BODGAM	8.13	44.82	0.58	29	42	21	188	56	558	324
W26	BHORDALI	7.99	26.7	0.69	14	29	23	168	24	324	96
W27	BHILPUR	7.98	26.7	0.88	16	51	53	348	80	594	136
W28	ANTROLI	7.91	11.26	0.69	2	19	20	432	40	264	132

Table 6 Water quality parameters for the year-2013

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.93	23.5	0.59	31	60	58	392	120	708	280
W2		7.86	23.5	0.9	42.81	69.4	63.63	436	138.12	835.18	372.72
W3	ZOZ	7.86	23.5	0.9	42.81	69.4	63.63	436	138.12	835.18	372.72
W4	VASEDI	8.03	23.5	0.97	58	96	86	600	216	1120	416
W5		7.86	23.5	0.98	58	86	84	576	176	1038	344
W6	SURKHEDA	7.86	23.5	0.84	42	64	61	416	80	680	360
W7	SIMAL FALIYA	7.86	23.5	0.9	42.81	69.4	63.63	436	138.12	835.18	372.72
W8	PELSANDA	7.6	23.5	0.82	13	36	37	248	138.12	486	216
W9	OLIMBA	7.8	44.9	0.47	69	118	75	520	312	1376	384
W10	RAYSINGPURA	8.12	23.5	0.58	14	41	40	272	104	586	312
W11	MOTISADHLI	7.68	5.63	1.22	23	43	41	280	84	610	400
W12	ODE	7.68	23.5	0.99	49	76	78	480	138.12	920	496
W13	MITHIBOR	7.86	23.5	0.9	42.81	69.4	63.63	436	138.12	835.18	372.72
W14	GUNATA	7.74	23.39	0.9	23	36	35	240	138.12	428	208
W15	FERKUVA	7.99	21.76	0.75	58	94	87	600	138.12	1020	504
W16	DUMALI	8	44.9	0.48	62	96	86	600	138.12	1740	560
W17	MANDAVA	7.86	23.5	0.9	42.81	69.4	63.63	436	138.12	835.18	372.72
W18	KIKAVADA	7.82	23.5	1.02	54	80	74	512	136	886	408
W19	JAMLI	7.72	39.45	1.22	45	72	68	464	72	682	400
W20	JAMLA	7.9	23.5	1.41	44	65	62	424	64	660	344
W21	CHILARVANT	7.72	23.5	1.12	48	70	63	440	104	798	416
W22	CHICHOD	7.84	29.56	0.54	20	32	30	208	112	620	368
W23	CHISADIA	7.86	0.81	0.9	17	24	25	168	16	338	264
W24	DEVALIYA	8	1.09	0.88	52	80	72	504	160	898	336
W25	BODGAM	7.9	23.5	0.69	48	78	73	504	376	958	376
W26	BHORDALI	7.86	23.5	0.9	42.81	69.4	63.63	436	138.12	835.18	372.72
W27	BHILPUR	8.03	23.5	0.78	58	96	86	600	128	968	448
W28	ANTROLI	7.8	23.5	1.49	56	84	79	544	88	854	360

Table 7 Water quality parameters for the year-2014

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.26	9.8	0.92	22	43	41	280	60	434	240
W2		7.74	17.87	1.16	46	75	72	488	76	784	320
W3	ZOZ	7.38	17.87	0.23	48	94	87	600	120	1018	272
W4	VASEDI	7.61	15.78	0.92	30	59	56	384	112	642	384
W5		7.68	17.87	1.05	58	94	87	600	164	1051	368
W6	SURKHEDA	7.68	17.87	0.74	58	94	87	600	152	1024	344
W7	SIMAL FALIYA	7.86	26.08	0.49	24	36	36	240	220	848	424
W8	PELSANDA	7.46	22.72	0.92	20	41	40	272	98.09	426	248
W9	OLIMBA	7.3	15.45	1.49	18	33	33	224	40	458	296
W10	RAYSINGPURA	7.38	44.3	0.92	58	94	87	600	72	872	448
W11	MOTISADHLI	7.39	3.24	0.73	20	35	34	232	36	432	312
W12	ODE	7.94	44.3	0.68	42	65	62	424	98.09	664	408
W13	MITHIBOR	7.42	18.44	1.24	21	36	36	248	98.09	394	264
W14	GUNATA	7.36	27.98	0.92	26	49	47	328	92	478	288
W15	FERKUVA	7.46	1.05	0.92	34	62	58	400	98.09	834	392
W16	DUMALI	7.1	31.53	1.21	58	94	86	600	98.09	1372	448
W17	MANDAVA	7.57	17.87	0.61	48	94	87	600	156	1058	296
W18	KIKAVADA	7.07	28.44	0.72	44	68	66	448	112	786	288
W19	JAMLI	7.8	11.71	0.45	34	52	51	344	88	564	272
W20	JAMLA	7.38	17.65	1.07	40	80	74	512	88	822	288
W21	CHILARVANT	7.76	4.9	1.21	20	32	32	216	64	466	304
W22	CHICHOD	7.68	26.37	0.82	22	43	41	280	120	646	376
W23	CHISADIA	7.68	17.87	1.35	34	65	62	424	80	710	368
W24	DEVALIYA	7.68	13.22	0.91	10	17	20	120	112	650	416
W25	BODGAM	7.49	1.45	1.49	40	80	74	512	84	822	328
W26	BHORDALI	7.39	18.03	1.24	14	25	26	176	28	282	128
W27	BHILPUR	7.96	8.67	0.73	26	44	44	296	60	462	296
W28	ANTROLI	7.66	2.16	0.74	58	94	87	600	120	964	368

Table 8 Water quality parameters for the year-2017

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.59	12.13	0.83	30.74	38	34	240	68	638	452
W2		7.34	28.57	0.41	35.86	102	36	488	64	798	360
W3	ZOZ	7.45	28.57	0.83	37.96	87.32	43.54	381.45	159.76	794.64	300.73
W4	VASEDI	7.32	44.28	0.83	25.61	86	23	312	112	698	420
W5		7.56	28.57	1.49	40.98	96	84	592	156	1082	396
W6	SURKHEDA	7.56	44.3	0.78	25.61	105	25	368	180	832	44
W7	SIMAL FALIYA	7.46	44.26	0.96	30.74	38	71	392	120	716	420
W8	PELSANDA	7.36	35.28	1.49	46.11	99	75	560	56	768	328
W9	OLIMBA	7.38	44.26	1.19	56.35	134	98	512	108	1068	348
W10	RAYSINGPURA	7.32	8.37	1.19	20.49	41	23	200	28	414	312
W11	MOTISADHLI	7.26	15.37	0.83	15.37	44	12	160	28	248	144
W12	ODE	7.45	28.57	0.83	37.96	87.32	43.54	381.45	159.76	794.64	300.73
W13	MITHIBOR	7.51	14.04	1.08	30.74	38	21	184	159.76	422	288
W14	GUNATA	7.45	28.57	0.83	37.96	87.32	43.54	381.45	159.76	794.64	300.73
W15	FERKUVA	7.46	28.57	0.21	46.11	86	30	344	159.76	684	296
W16	DUMALI	7.33	25.94	1.3	35.86	35	48	288	159.76	598	376
W17	MANDAVA	7.41	11.5	0.38	35.86	105	38	424	159.76	708	428
W18	KIKAVADA	7.37	29.26	0.86	20.49	41	15	168	159.76	302	148
W19	JAMLI	7.33	3.86	0.44	71.72	83	42	384	716	1614	104
W20	JAMLA	7.45	28.57	0.83	37.96	87.32	43.54	381.45	159.76	794.64	300.73
W21	CHILARVANT	7.58	44.3	0.78	46.11	188	29	592	128	974	332
W22	CHICHOD	7.54	20.08	0.48	46.11	125	64	568	360	1372	360
W23	CHISADIA	7.45	28.57	0.83	37.96	87.32	43.54	381.45	159.76	794.64	300.73
W24	DEVALIYA	7.57	28.57	0.66	56.35	147	88	464	272	1396	340
W25	BODGAM	7.52	28.57	0.14	40.98	89	25	328	76	618	256
W26	BHORDALI	7.54	44.3	0.54	40.98	89	54	448	120	848	232
W27	BHILPUR	7.62	44.26	1.49	35.86	112	23	376	124	684	232
W28	ANTROLI	7.45	28.57	0.83	37.96	87.32	43.54	381.45	159.76	794.64	300.73

Table 9 Water quality parameters for the year-2018

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.38	8.7	0.77	25.61	38	52	312	28	518	412
W2		7.34	21.53	0.51	30.74	70	69	464	44	694	336
W3	ZOZ	7.46	21.53	0.37	25.61	49	39	288	88	574	236
W4	VASEDI	7.36	39.17	0.77	20.49	44	36	264	52	452	284
W5		7.46	21.53	1.23	30.74	115	32	424	104	724	316
W6	SURKHEDA	7.42	21.53	0.65	35.56	137	17	416	108	728	300
W7	SIMAL FALIYA	7.44	21.53	0.68	40.98	96	74	552	156	978	312
W8	PELSANDA	7.28	35.66	0.77	25.61	54	27	248	48	444	280
W9	OLIMBA	7.28	22.07	1.05	20.49	35	53	312	136	522	376
W10	RAYSINGPURA	7.62	10.22	0.8	46.11	150	100	560	244	1274	236
W11	MOTISADHLI	7.34	21.53	0.87	40.98	86	71	512	188	958	160
W12	ODE	7.54	21.53	0.69	35.86	89	54	448	131.33	808	312
W13	MITHIBOR	7.31	13.01	1.98	20.49	41	29	224	44	426	296
W14	GUNATA	7.52	25.85	0.77	30.74	70	52	392	131.33	776	208
W15	FERKUVA	7.54	8.11	0.31	15.37	51	21	216	131.33	584	400
W16	DUMALI	7.42	44.3	0.77	15.37	99	55	480	131.33	668	452
W17	MANDAVA	7.34	21.53	0.87	30.74	108	21	360	96	658	240
W18	KIKAVADA	7.46	6.96	0.69	20.49	48	28	240	32	346	212
W19	JAMLI	7.48	2.22	0.48	40.98	84	51	424	128	816	264
W20	JAMLA	7.54	44.3	1.31	35.86	172	69	372	396	1454	372
W21	CHILARVANT	7.52	44.26	0.47	56.35	179	78	292	192	1224	388
W22	CHICHOD	7.46	19.88	0.58	40.98	137	98	382.63	316	1346	376
W23	CHISADIA	7.46	1.86	0.56	46.11	128	65	592	232	1038	160
W24	DEVALIYA	7.38	21.53	0.54	99.9	136	46	531	264	1216	322
W25	BODGAM	7.58	20.41	0.84	20.49	70	40	344	60	572	300
W26	BHORDALI	7.32	33.63	0.99	20.49	38	25	200	40	344	144
W27	BHILPUR	7.58	6.97	0.71	30.74	96	49	448	84	734	272
W28	ANTROLI	7.47	21.53	0.49	35.86	86	48	416	72	692	296

Table 10 Water quality parameters for the year-2019

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.56	87.09	0.5	27.28	96	44	424	40	638	328
W2		7.51	24.1	0.94	121.42	73.42	46.15	344.83	162	817.33	303.54
W3	ZOZ	7.52	24.1	0.35	30.74	73	44	368	112	752	204
W4	VASEDI	7.54	44.28	1.14	25.61	83	46	400	160	748	303.54
W5		7.7	24.1	1.49	28.64	169	46.15	344.83	224	1622	364
W6	SURKHEDA	7.48	24.1	0.64	21.82	64	49	368	72	608	280
W7	SIMAL FALIYA	7.32	24.1	1.13	40.98	96	71	536	224	1128	160
W8	PELSANDA	7.55	24.1	5.01	25.61	60	21	344.83	136	618	344
W9	OLIMBA	7.41	26.95	0.94	20.49	48	19	200	228	506	372
W10	RAYSINGPURA	7.32	42.070	0.3	30.74	70	52	392	72	612	392
W11	MOTISADHLI	7.51	24.1	0.54	1.34	30.01	96	84	188	1140	360
W12	ODE	7.38	35.39	1.4	30.74	83	75	520	162	886	384
W13	MITHIBOR	7.52	18.61	0.94	15.37	51	13	184	162	306	196
W14	GUNATA	7.7	23.34	0.94	15.37	51	25	232	162	356	216
W15	FERKUVA	7.76	3.18	0.58	42.28	76	63	456	162	876	412
W16	DUMALI	7.59	24.1	0.6	46.11	64	36	312	162	1412	440
W17	MANDAVA	7.54	11.84	1.11	28.64	76	65	464	184	908	404
W18	KIKAVADA	7.58	24.1	0.83	31.37	48	38	280	64	542	256
W19	JAMLI	7.62	24.1	0.6	20.49	64	36	312	100	614	180
W20	JAMLA	7.41	3.23	0.92	25.91	73	56	416	72	664	348
W21	CHILARVANT	7.21	24.1	0.96	25.61	57	42	320	84	586	300
W22	CHICHOD	7.48	27.24	0.94	25.61	60	33	288	100	518	152
W23	CHISADIA	7.48	19.76	0.7	35.46	172	69	488	384	1606	388
W24	DEVALIYA	7.36	24.1	0.54	40.98	73.42	60	344.83	496	1736	412
W25	BODGAM	7.66	24.1	0.24	20.49	67	27	280	60	512	296
W26	BHORDALI	7.48	10.29	0.85	24.55	44	38	272	40	462	160
W27	BHILPUR	7.56	24.1	0.66	20.49	67	44	352	72	604	244
W28	ANTROLI	7.54	2.07	0.64	40.38	67	38	328	452	1108	300

Table 11 Water quality parameters for the year-2020

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.62	24.03	0.47	35.86	96	82	584	184	1022	404
W2		7.46	10.88	0.76	25.55	28	22	164	56	356	204
W3	ZOZ	7.18	24.03	0.28	49.1	60	52	368	80	658	240
W4	VASEDI	7.28	28.31	0.76	28.64	48	40	288	116	596	324
W5		7.44	24.03	1.47	77.47	67	99	584	168	1112	316
W6	SURKHEDA	7.37	24.03	1.49	24.55	112	74	592	324	1268	32
W7	SIMAL FALIYA	7.58	24.03	0.88	27.28	28	23	108	88	698	496
W8	PELSANDA	7.47	24.03	0.76	34.04	63.8	50.92	332.36	154.1	757.6	285.28
W9	OLIMBA	7.81	24.03	1.49	30.01	51	44	312	154.1	812	408
W10	RAYSINGPURA	7.17	24.03	0.82	43.64	188	73	488	332	1582	316
W11	MOTISADHLI	7.16	4.39	1.16	0.54	81.83	115	69	160	1188	464
W12	ODE	7.61	44.18	0.72	24.55	44	17	184	154.1	388	240
W13	MITHIBOR	7.48	22.28	0.82	21.82	28	23	168	154.1	306	188
W14	GUNATA	7.73	16.39	0.76	34.1	57	15	208	154.1	372	228
W15	FERKUVA	7.32	24.03	0.36	21.82	48	38	280	154.1	492	184
W16	DUMALI	7.51	44.25	0.92	31.37	70	75	424	154.1	732	488
W17	MANDAVA	7.46	24.03	0.31	38.19	51	44	312	84	598	268
W18	KIKAVADA	7.58	24.03	0.83	31.37	48	38	280	64	542	256
W19	JAMLI	7.12	24.03	0.45	47.74	60	52	368	140	796	244
W20	JAMLA	7.47	24.03	0.76	34.04	63.8	50.92	332.36	154.1	757.6	285.28
W21	CHILARVANT	7.48	24.03	0.32	27.28	54	25	240	24	406	204
W22	CHICHOD	7.47	24.03	0.76	34.04	63.8	50.92	332.36	154.1	757.6	285.28
W23	CHISADIA	7.15	24.03	0.51	38.19	54	46	328	76	602	220
W24	DEVALIYA	7.31	24.03	0.61	39.55	83	73	512	184	974	304
W25	BODGAM	7.58	24.03	0.21	38.19	60	54	376	132	788	264
W26	BHORDALI	7.56	41.12	1.16	35.46	60	50	360	76	632	320
W27	BHILPUR	7.62	24.03	1.11	38.19	54	46	328	188	848	344
W28	ANTROLI	7.58	4.52	0.37	42.28	64	53	384	452	1172	176

Table 12Water quality parameters for the year-2021

WELL NO	VILLAGE	PH	NITRATE	FLOURIDE	SULPHATE	CALCIUM	MAGNESIUM	HARDNESS	CLORIDE	TDS	ALKALINITY
W1	AMBALA	7.42	19.13	0.58	24.55	57	50	352	116	664	328
W2		7.5	13.78	0.78	38.19	35	30	216	52	604	428
W3	ZOZ	7.61	19.13	0.51	33.36	67	38	328	88	614	228
W4	VASEDI	7.32	19.13	1.39	25.91	60	49	336	60	582	320
W5		7.51	19.13	0.79	24.55	70	50	384	124	754	320
W6	SURKHEDA	7.51	5.33	1.21	32.73	86	77	536	256	760.4	260
W7	SIMAL FALIYA	7.62	6.55	0.78	19.09	35	27	200	40	332	216
W8	PELSANDA	7.48	19.13	0.78	33.36	66.18	48.37	335.88	138.77	760.4	304.31
W9	OLIMBA	7.48	19.13	1.48	39.55	64	53	384	96	872	404
W10	RAYSINGPURA	7.16	13.290	0.8	23.19	57	44	328	100	642	200
W11	MOTISADHLI	7.41	19.13	0.63	0.86	35.46	92	81	136	998	316
W12	ODE	7.12	19.13	0.89	40.92	64	55	392	138.77	718	388
W13	MITHIBOR	7.46	22.88	0.91	23.19	48	28	240	69	392	260
W14	GUNATA	7.54	28.86	0.78	21.82	35	25	192	138.77	326	160
W15	FERKUVA	7.58	19.13	0.47	36.82	73	62	448	138.77	802	444
W16	DUMALI	7.36	43.96	0.56	150	94	48.37	44	138.77	936	140
W17	MANDAVA	7.68	19.13	0.76	38.19	131	48.37	335.88	452	1662	360
W18	KIKAVADA	7.44	19.13	0.66	33.36	86	44	400	152	774	292
W19	JAMLI	7.22	19.13	0.38	34.1	83	73	512	140	902	316
W20	JAMLA	7.62	1.72	0.78	19.09	38	21	184	124	742	496
W21	CHILARVANT	7.62	9.82	0.92	32.73	102	78	584	228	1118	460
W22	CHICHOD	7.77	18.36	1.04	33.36	75	59	440	252	1236	548
W23	CHISADIA	7.37	5.28	0.78	19.09	25	21	192	32	296	152
W24	DEVALIYA	7.48	19.13	0.78	33.36	66.18	48.37	335.88	138.77	760.4	304.31
W25	BODGAM	7.37	19.13	0.25	30.01	35	29	304	64	554	212
W26	BHORDALI	7.68	44.08	1.4	30.01	67	55	400	120	706	280
W27	BHILPUR	7.58	19.13	0.28	34	131	42	504	232	1018	160
W28	ANTROLI	7.56	29	0.42	28.64	67	59	416	120	766	224

CHAPTER 5:METHODOLOGY

5.1 Introduction

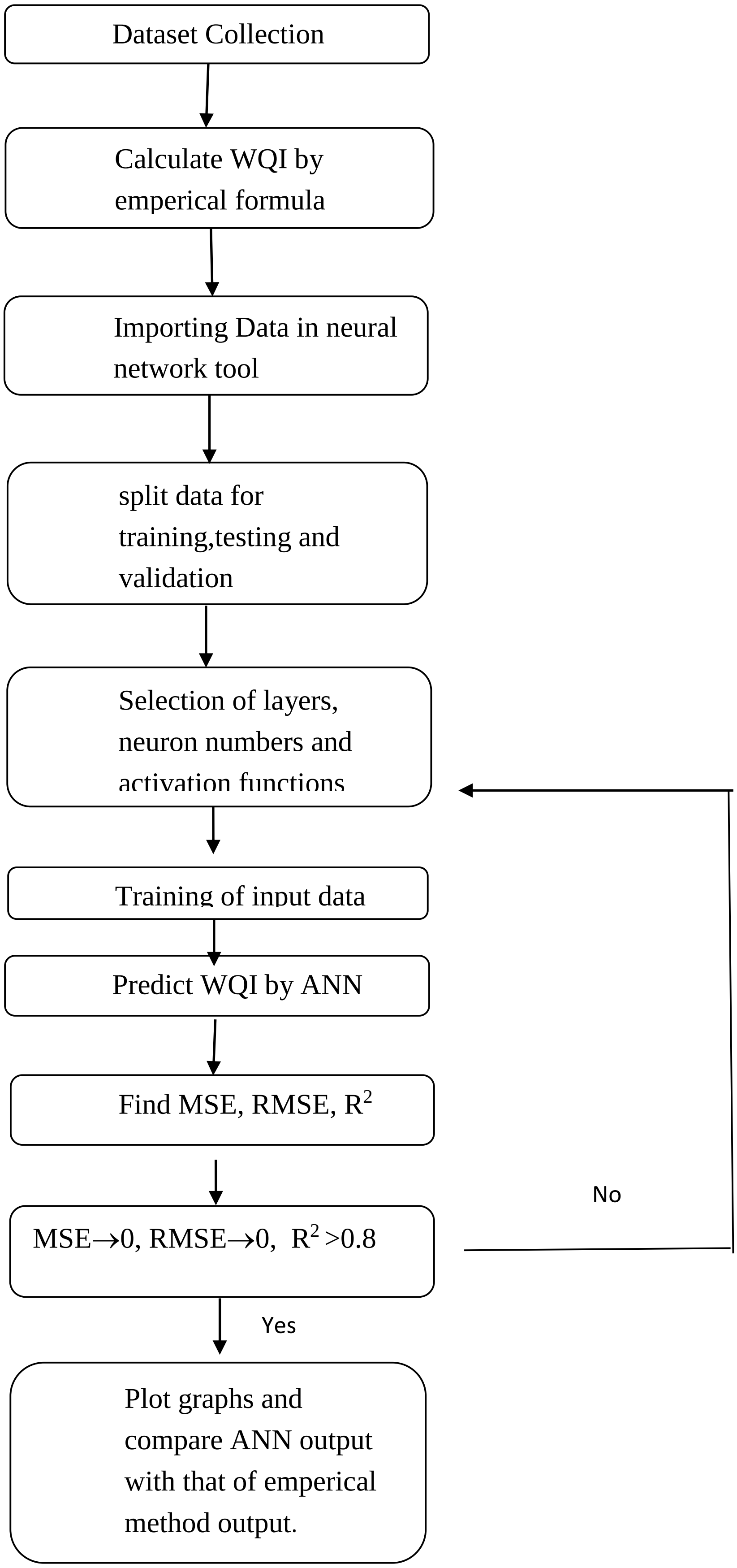
The present study has been carried out to assess the groundwater quality in Chhota Udaipur taluka, Chhota Udaipur district.The study in general, has been undertaken in three steps

1. Collection of data of various parameters and physico-chemical analysis
2. Determination of Water Quality Index with the help of traditional method(weighted arithmetic index method.)
3. Predicting WQI by ANN model
4. Create Map Using ARC-GIS (Geographical Information System) & IDW Tool.

This chapter deals with the methodology involves in performing the above tasks.

Section 5.2 deals with assessment of water quality using Weighted Arithmetic Index method (WQI). **Section 5.3** deals with Artificial Neural Network(ANN).

Figure 4Flow chart of methodology



5.2 Water quality index (WQI) calculation using traditional method

The water quality indices are generally indicating the pollution level of water. It is one of evaluation technique of water quality. An index number is formed by mathematically combining all water quality parameters and provides a general and readily understood description of water. In this way, the index can be used to assess water quality relative to its desirable state (as defined by water quality objectives) and to provide insight into the degree to which water quality is affected by human activity.

Water Quality Index (WQI) is one of the most effective tools to communicate information on overall quality status of water to the concerned user community and policy makers. Thus, it becomes an important parameter for the assessment and management of groundwater.

The Following steps are considered for the calculation of WQI

Weightage factor:

For water quality index calculation, first the weightage of each parameter is calculated. The weightage for various water quality parameters is assigned to be inversely proportional to the recommended standards for the corresponding parameters.

Therefore;$Wi \propto \frac{1}{Si}$

$$Wi = \frac{K}{Si}$$

Water quality rating:

Rating is calculated based on the following equation. And Va and Vi are actual and ideal values of water quality parameters present in the water sample. For all parameters ideal value is zero except for pH.

$$qi = \left[\left\{\frac{Va - Vi}{Si - Vi}\right\} \times 100\right]$$

Water quality index calculation

Essentially, WQI is a compilation of several parameters that can be used to determine the overall quality of water. The parameters involved in the WQI are pH,Nitrate,Fluoride,Sulphate,Calcium,Magnesium,Hardness,Chloride,TDS,Alkalinity.The numerical value of quality rating is then multiplied by a weightage factor that is relative to the significance of the test to water quality. The sum of the resulting values is added together to arrive at an overall water quality index.

$$WQI = \Sigma\,(qi \times Wi)$$

Where, qi (water quality rating)

$$qi = \left[\left\{\frac{Va - Vi}{Si - Vi}\right\} \times 100\right]$$

Va = actual value present in the water sample. Vi = ideal value (0 for all parameters except pH) $Wi = \frac{K}{Si}$

Where, Wi (unit weight)

K(constant) $= \frac{1}{\left(\frac{1}{S1}+\frac{1}{S2}+\cdots+\frac{1}{Sn}\right)}$,*Sn*=standard value

Table 13Assigned weightage factor of water quality parameters

Parameters	Standard Value	Assigned Weightage Factor(Wi)
pH	8.5	0.13458
Nitrate(mg/l)	45	0.02542
Fluoride(mg/l)	1.5	0.7626
Sulphate(mg/l)	150	0.00763
Calcium(mg/l)	75	0.01525
Magnesium(mg/l)	30	0.03813
Hardness(mg/l)	300	0.00381
Chloride(mg/l)	250	0.00458
TDS(mg/l)	500	0.00229
Alkalinity(mg/l)	200	0.00572

Table 14Water Quality Index &Corresponding Water Quality

Water Quality Index (WQI)	Quality of Water
0-24	EXCELLENT
25-49	GOOD
50-74	POOR
75-100	VERY POOR
>100	UNFIT FOR DRINKING

5.3 Water quality using Artificial Neural Network (ANN)

Introduction to artificial neural networks (ANNs)

Neural networks (also known as **Artificial Neural Networks** or neural **nets**, abbreviated **ANN** or **NN**) are computational models inspired by the structure and function of biological neural networks found in the brain. They consist of interconnected nodes arranged in layers.

ANNs excel at learning complex patterns and relationships from data, making them powerful tools in machine learning and artificial intelligence.

ANNs are widely used for tasks such as classification, regression, clustering, and pattern recognition due to their ability to handle non-linear relationships and high-dimensional data.

Neural network architecture

Neural networks consist of layers: input layer, hidden layers, and output layer. Each layer contains neurons that process data through weighted connections.

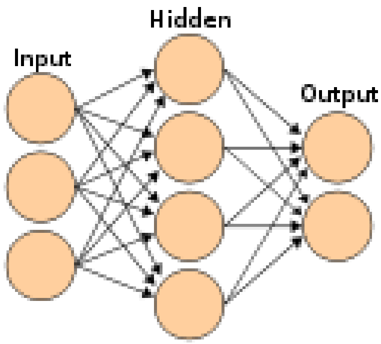


Figure 5Network

The flow of data through the network involves forward propagation, where inputs are passed through the layers to produce predictions, and backward propagation, where errors are propagated back to update the weights during training.

The output $a_j^{(l)}$ of a neuron in a hidden layer l is computed as:

$a_j^{(l)} = \sigma(\sum_i w_{ij}^{(l)} . a_i^{(l-1)} + b_j^{(l)})$

where $w_{ij}^{(l)}$ is the weight connecting neuron i in layer l-1 to neuron j in layer l , $a_i^{(l-1)}$is the output of neuron i in layer l-1, $b_j^{(l)}$is the bias term for neuron j in layer l , and σ is the activation function.

Activation functions

Activation functions determine the output of neurons and introduce non-linearity to the network.

Sigmoid: $\sigma(x) = \frac{1}{1+e^{-x}}$

Tanh: tanh(x)= $\frac{e^x - e^{-x}}{e^x + e^{-x}}$

ReLU (Rectified Linear Unit): $ReLU(x) = max(0, x)$

Softmax: Softmax(xi) = $\frac{e^{x_i}}{\sum_{j=1}^{N} e^{x_j}}$

ReLU (Rectified Linear Unit)

ReLU, short for Rectified Linear Unit, is a widely used activation function in neural networks. It's defined as:

$$ReLU(x) = \max(0, x)$$

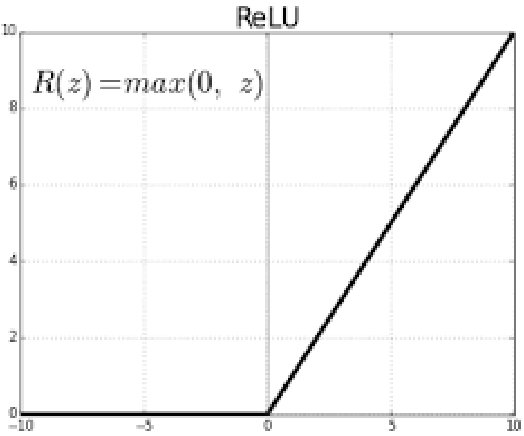


Figure 6Graph of ReLU

In simpler terms, ReLU returns 0 if the input is negative, and it returns the input itself if it's positive. This activation function introduces non-linearity to the network, allowing it to learn complex patterns and relationships in the data. It's popular because it's computationally efficient and has been shown to work well in many different types of neural network architectures.

5.3.5Training methods

Learning is the adaptation of the network to better handle a task by considering sample observations. Learning involves adjusting the weights (and optional thresholds) of the network to improve the accuracy of the result. This is done by minimizing the observed errors. Learning is complete when examining additional observations does not usefully reduce the error rate. Even after learning, the error rate typically does not reach 0. If after learning, the error rate is too high, the network typically must be redesigned. Practically this is done by defining a cost function that is evaluated periodically during learning. As long as its output continues to decline, learning continues. The cost is frequently defined as a statistic whose value can only be approximated. The outputs are actually numbers, so when the error is low, the difference between the output and the correct answer is small. Learning attempts to reduce the total of the differences across the observations.

Backpropagation adjusts the weights of connections between neurons to minimize the error between predicted and actual outputs.

Stochastic Gradient Descent (SGD) is an optimization algorithm commonly used to train machine learning models, including neural networks. Unlike traditional gradient descent, which calculates the gradient of the loss function with respect to all training examples, SGD computes the gradient for each training example individually or in small batches.

The weight update rule for gradient descent is:

$$w_{ij}^{l} = w_{ij}^{l} - \alpha \frac{\partial J}{\partial w_{ij}^{l}}$$

where J is the loss function, α is the learning rate, and $\frac{\partial J}{\partial w_{ij}^{l}}$ is the partial derivative of the loss function with respect to the weightw_{ij}^{l} .

5.3.6 Model evaluation and validation

Model performance is evaluated using various metrics, such as accuracy, R2, Mean square error (MSE), Root Mean Square Error (RMSE).

Mean Square Error (MSE): It is the average of the squared differences between the predicted values and the actual values. It measures the average of the squares of the errors or deviations, which gives a relative measure of the model's goodness of fit.

Root Mean Square Error (RMSE): It is the square root of the MSE. RMSE gives a more interpretable measure of the average magnitude of the errors. It is in the same unit as the target variable, making it easier to understand and interpret.

Cross-validation techniques, such as k-fold cross-validation, estimate the generalization performance of the model on unseen data and prevent overfitting.

K-fold Cross Validation is a technique used to assess the performance of a machine learning model. In K-fold cross-validation, the dataset is divided into K subsets or folds. The model is trained K times, each time using K-1 folds for training and the remaining fold for validation. This process is repeated K times, with each of the K folds used exactly once as the validation data. The performance measure reported is usually the average performance across all K folds.

5.3.7 Software and tools

The implementation and training of neural networks for regression tasks in this study are primarily facilitated by scikit-learn's MLPRegressor module, a part of the scikit-learn library in Python.

Scikit-learn provides comprehensive support for various machine learning algorithms.

MLPRegressor is a flexible implementation of multi-layer perceptron (MLP) neural networks for regression tasks. It allows for the creation of neural network architectures with customizable parameters such as the number of hidden layers, neurons per layer, activation functions, and regularization techniques.

The experiments in this study are conducted using Google Colab, a cloud-based Jupyter notebook environment provided by Google. Google Colab offers free access to computing resources.

Additionally, the experiments are conducted on a system with 2.00 GB of RAM and 32 bit operating system, providing sufficient computational resources for model training and evaluation.

CHAPTER 6: APPLICATION OF ANN IN WATER QUALITY ANALYSIS

6.1 Introduction

Artificial neural network (ANN) is chosen as the modelling approach for this prediction task due to their ability to capture complex non-linear relationships among input features and their proven effectiveness in various prediction tasks. ANNs offer flexibility in modelling diverse datasets and are well-suited for handling the multidimensional nature of water quality data.

The training procedure involves the iterative process of forward propagation and backpropagation to update the network weights. The backpropagation algorithm, coupled with gradient descent optimization, is employed to minimize the loss function and improve prediction accuracy.

In our study the input parameters will be pH, Nitrate, Fluoride, Sulphate, Calcium, Magnesium, Hardness, Chloride, TDS, Alkalinity. The initial weights will be taken randomly and will be updated during learning. The output of our ANN model will be the value of Water Quality Index (WQI)

The neural network model is implemented using Python programming language with the aid of libraries/frameworks such as scikit-learn. The implementation follows best practices and adheres to established standards to ensure reproducibility and transparency of the results.

Experiments are conducted using a systematic approach, with careful consideration of hyperparameter tuning and model validation. Hyper parameter such as number of epochs are optimized through random search to identify the optimal configuration

The desired output which is considered in our model will be the WQI calculated by empirical formula, which was calculated in Microsoft excel 2016. The table 15 gives the WQI by empirical formula.

Table 15 WQI calculated by empirical formula

WELL NO	WQI(2010)	WQI(2011)	WQI(2012)	WQI(2013)	WQI(2014)	WQI(2017)	WQI(2018)	WQI(2019)	WQI(2020)	WQI(2021)
W1	60.00	58.51	86.00	50.26	57.21	55.44	52.4227	44.89	46.07	43.88
W2	60.00	65.74	58.24	66.77	79.57	34.47	42.4934	63.68	47.93	51.51
W3	81.30	57.92	34.94	66.77	31.55	57.35	31.7022	32.65	26.89	40.35
W4	60.19	63.61	58.52	75.92	63.69	54.49	51.6136	74.98	50.73	83.92
W5	44.88	63.61	69.16	74.10	76.35	97.89	76.4027	95.47	96.84	55.70
W6	69.97	51.85	54.21	63.03	60.49	53.93	45.0753	47.52	94.25	80.34
W7	55.38	61.25	30.16	66.77	41.84	67.63	53.6278	74.93	56.97	50.93
W8	60.00	63.61	52.01	55.31	59.63	94.86	49.7403	266.98	54.02	54.60
W9	62.81	84.38	58.24	48.85	85.69	84.21	66.6526	58.45	93.38	91.09
W10	30.79	76.60	49.75	48.55	68.52	69.09	65.2228	30.72	60.75	51.19
W11	60.00	64.94	50.14	76.58	47.38	48.68	61.3695	48.21	79.19	50.92
W12	52.63	66.34	58.24	72.17	57.11	57.35	52.0679	90.42	49.13	58.10
W13	40.11	56.26	47.28	66.77	74.70	65.42	110.2098	57.50	52.03	57.69
W14	60.00	73.20	58.24	60.36	60.31	57.35	55.1498	61.05	50.72	51.24
W15	60.00	65.49	55.31	64.43	61.96	24.10	26.7737	48.71	29.84	42.19
W16	80.49	63.61	54.45	52.52	80.18	79.52	56.9480	45.87	67.51	44.14
W17	80.92	67.68	58.24	66.77	52.73	33.17	55.1397	74.40	29.66	57.87
W18	82.13	60.69	58.24	74.32	50.79	52.61	45.3671	56.18	56.18	48.07
W19	41.71	63.61	58.24	83.23	40.06	35.77	39.1352	44.78	35.17	35.74
W20	44.43	64.54	58.24	92.45	72.05	57.35	89.3243	61.33	54.02	51.07
W21	30.07	48.86	71.62	76.71	74.91	57.49	47.2929	60.37	27.47	68.03
W22	60.00	63.61	49.26	43.03	57.42	44.33	52.9432	60.40	54.02	73.17
W23	86.88	72.29	58.24	58.42	87.18	57.35	45.9110	56.63	37.23	47.42
W24	63.47	53.85	58.24	67.12	57.90	57.44	43.8346	44.69	48.62	54.60
W25	55.62	88.13	47.35	58.43	93.58	20.16	57.3405	25.93	27.35	23.02
W26	60.00	56.76	49.73	66.77	72.21	45.52	60.0533	55.04	75.88	90.12
W27	73.55	44.07	64.14	66.12	54.38	90.88	51.8670	48.55	72.62	30.68
W28	65.10	60.76	47.94	98.56	59.40	57.35	40.2002	46.51	34.88	38.76

6.2 Python code

```
# Importing necessary libraries

import matplotlib.pyplot as plt

import pandas as pd

import numpy as np

from sklearn.neural_network import MLPRegressor

from sklearn.model_selection import train_test_split, cross_val_score

from sklearn.metrics import mean_squared_error, r2_score

from sklearn.preprocessing import StandardScaler


# Loading the dataset

data = pd.read_excel('MERGEDdATA.xlsx')


# Separating features and target variable

X = data[['PH', 'NITRATE ', 'FLUORIDE', 'SULPHATE', 'CALCIUM', 'MAGNESIUM',
'HARDNESS', 'CHLORIDE', 'TDS', 'ALKALINITY']]

y = data["WQI"]


# Scaling the features

scaler = StandardScaler()

X = scaler.fit_transform(X)


# Splitting the dataset into training and testing sets
```

```
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)


# Creating MLP Regressor model
mlp_regressor = MLPRegressor(hidden_layer_sizes=(10,9), activation='relu', solver='sgd',
max_iter=1000, random_state=42)


# Training the model
mlp_regressor.fit(X_train, y_train)


# Printing model information and evaluation metrics
print("Activation Function:", mlp_regressor.activation)
print("Hidden Layers:", mlp_regressor.n_layers_ - 2)
print("Neurons in Each Hidden Layer:", mlp_regressor.hidden_layer_sizes)
print("Solver:", mlp_regressor.solver)
print("Iterations:", mlp_regressor.n_iter_)
print("Training Set Size:", len(X_train))
print("Test Set Size:", len(X_test))


# Predicting values and calculating evaluation metrics
predicted_values = mlp_regressor.predict(X)
mse = mean_squared_error(y, predicted_values)
rmse = mean_squared_error(y, predicted_values, squared=False)
r2 = r2_score(y, predicted_values)
print('\nMean Squared Error(MSE):', mse)
print('\nRoot Mean Squared Error(RMSE):', rmse)
```

```
print('\nR-squared (R^2):', r2)


# Cross-validation
cv_scores = cross_val_score(mlp_regressor, X_train, y_train, cv=5)
print("\nCross-validation Scores:", cv_scores)
print("Mean Cross-validation Score:", cv_scores.mean())


# Printing weights of the model
print("\nWeights:")
for i, weights in enumerate(mlp_regressor.coefs_):
    print("\nLayer", i+1, "Weights:")
    for j, neuron_weights in enumerate(weights):
        weights_array = np.array(neuron_weights)
        print("\nNeuron", j+1, "Weights:")
        print(weights_array)


# Displaying true and predicted values for the entire dataset
pd.set_option('display.max_rows', None)
pd.set_option('display.max_columns', None)
true_predicted_df = pd.DataFrame({'True': y.round(1), 'Predicted':
predicted_values.round(1)})
print("\nTrue and Predicted Values for the Entire Dataset:")
print(true_predicted_df)


# Visualizing true vs predicted values for each year
```

```
years = [2010, 2011, 2012, 2013, 2014, 2017, 2018, 2019, 2020, 2021]
for year in years:
    plt.figure()
    plt.title(f'True vs Predicted Values ({year})')
    plt.xlabel('True Values')
    plt.ylabel('Predicted Values')
    start_idx = (years.index(year)) * 28
    end_idx = start_idx + 28
    plt.scatter(y[start_idx:end_idx], predicted_values[start_idx:end_idx], label=f'Year
{year}')
    plt.plot(y[start_idx:end_idx], y[start_idx:end_idx], color='red', linestyle='--')
    plt.legend()
    plt.show()

# Visualizing true vs predicted values for the training set
plt.figure()
plt.title('True vs Predicted Values (Training Set)')
plt.xlabel('True Values')
plt.ylabel('Predicted Values')
plt.scatter(y_train, mlp_regressor.predict(X_train), label='Training Set')
plt.plot(y_train, y_train, color='red', linestyle='--')
plt.legend()
plt.show()

# Visualizing true vs predicted values for the testing set
```

```
plt.figure()

plt.title('True vs Predicted Values (Testing Set)')

plt.xlabel('True Values')

plt.ylabel('Predicted Values')

plt.scatter(y_test, mlp_regressor.predict(X_test), label='Testing Set')

plt.plot(y_test, y_test, color='red', linestyle='--')

plt.legend()

plt.show()


# Visualizing epoch vs error

plt.figure()

plt.title('Epoch vs Error')

plt.xlabel('Epoch')

plt.ylabel('Error')

plt.plot(range(1, mlp_regressor.n_iter_ + 1), mlp_regressor.loss_curve_, linestyle='-')

plt.show()


# Splitting the training set into training and validation sets

X_train, X_val, y_train, y_val = train_test_split(X_train, y_train, test_size=0.2,
random_state=42)


# Visualizing true vs predicted values for the validation set

plt.figure()

plt.title('True vs Predicted Values (Validation Set)')

plt.xlabel('True Values')
```

```
plt.ylabel('Predicted Values')

predicted_val = mlp_regressor.predict(X_val)

plt.scatter(y_val, predicted_val, label='Validation Set')

plt.plot(y_val, y_val, color='red', linestyle='--')

plt.legend()

plt.show()
```

6.3 Output of the code

Activation Function: relu

Hidden Layers: 2

Neurons in Each Hidden Layer: (10, 9)

Solver: sgd

Iterations: 447

Training Set Size: 224

Test Set Size: 56

Mean Squared Error(MSE): 0.024385258615032143

Root Mean Squared Error(RMSE): 0.15615780036563062

R-squared (R^2): 0.9999398128469238

Cross-validation Scores: [0.99790375 0.99925043 0.99978495 0.9995922 0.99907539]

Mean Cross-validation Score: 0.9991213435477915

Weights:

Layer 1 Weights:

Neuron 1 Weights:

[0.14403997 0.34738691 -0.08731944 -0.10904549 -0.11821392 -0.24959959

 -0.5135795   0.23707341 0.15633247 0.17952824]

Neuron 2 Weights:

[-0.63574695 0.16331058 0.05152209 -0.5803151   0.04157175 -0.39899021

  0.1761594   0.00903932 0.15376034 -0.02484392]

Neuron 3 Weights:

[0.86890744 0.24531228 -0.08492719 1.92764367 0.42743945 0.52946518

  0.03728119 2.28930524 0.64477246 -0.63373686]

Neuron 4 Weights:

[-0.30516946 -0.14018654 -0.29611702 0.23369287 0.10405051 0.07284436

 -0.07395083 0.02591893 0.02091365 -0.08360447]

Neuron 5 Weights:

[-0.8927964 -0.0074687 -0.43736901 -0.14118542 0.08897286 -0.09137421
  0.01890278 0.05474788 0.01754277 -0.11788934]

Neuron 6 Weights:

[0.87885275 0.27866887 0.31702354 0.42059118 0.15715599 0.26396928
 -0.0598418   0.20584476 -0.56843686 -0.28298433]

Neuron 7 Weights:

[-0.03032356 -0.36020372 0.2585815 -0.01629596 -0.29054259 -0.13320152
 -0.2199993   0.20549904 -0.47390694 0.54597731]

Neuron 8 Weights:

[-0.17977855 0.20605992 -0.31373033 -0.32660458 0.23263399 -0.04389919
  0.15472934 -0.10975686 -0.11536881 -0.35725698]

Neuron 9 Weights:

[0.11112084 0.16049313 -0.12121509 -1.2168856 -0.16109272 -0.50867136
  0.27790998 0.00563904 0.42518584 0.08967924]

Neuron 10 Weights:

[-0.51695198 0.01549142 0.09697383 0.15062506 0.3724642 -0.01564246
  0.16265532 -0.07089792 -0.3987343 -0.51019128]

Layer 2 Weights:

Neuron 1 Weights:

[-0.2633211 -0.27061326 0.51276329 -0.09894547 0.01807181 0.36253029
  0.31350632 -0.36181504 0.49656715]

Neuron 2 Weights:

[-0.05538624 0.58134963 0.67868464 0.34572278 -0.45771181 -0.25045236
 -0.17082105 0.10984293 0.53083995]

Neuron 3 Weights:

[-0.58212301 0.17665921 0.09567127 0.07892814 -0.43953573 -0.135542
  0.40281399 -0.37665223 0.16186759]

Neuron 4 Weights:

[-0.03943507 -0.06403178 0.78413776 -0.17169072 -0.51108564 -0.25902124
 -0.21890817 -0.28600669 -0.51458576]

Neuron 5 Weights:

[-0.13434645 0.18408219 -0.30174229 0.60925209 0.1007613 -0.18800491
 -0.40656096 -0.0811886   0.90708028]

Neuron 6 Weights:

[-0.44117002 0.16273557 0.59624299 -0.13355152 0.00764073 -0.13763797
  0.12832379 0.11486658 0.1341058]

Neuron 7 Weights:

[-0.54405259 0.57438086 -0.22014703 -0.07130809 -0.63403971 0.2042293
  0.19310298 -0.55183246 0.25686607]

Neuron 8 Weights:

[-0.47260644 0.73348744 0.02063146 1.96824879 -0.23746707 0.95201978
 -0.45293911 -0.38346434 -0.52094512]

Neuron 9 Weights:

[0.29829654 0.40593167 -0.27867635 -0.03472303 0.24210249 0.15686056
  0.02698606 -0.31230637 -0.43877335]

Neuron 10 Weights:

[0.38591682 0.39482201 0.0911252 -0.55104873 -0.19637735 0.31112795
  0.42845691 0.39196722 0.29118707]

Layer 3 Weights:

Neuron 1 Weights:

[-0.36019585]

Neuron 2 Weights:

[0.83894062]

Neuron 3 Weights:

[0.84159795]

Neuron 4 Weights:

[3.68547898]

Neuron 5 Weights:

[-0.09707244]

Neuron 6 Weights:

[0.18403271]

Neuron 7 Weights:

[-0.37528741]

Neuron 8 Weights:

[-0.09898555]

Neuron 9 Weights:

[0.55665128]

Traditional method based output (for WQI) and ANN based output (for WQI) for Entire Dataset:

	Traditional method based output	ANN based output
0	60.0	60.0
1	60.0	60.0
2	81.3	81.2
3	60.2	60.3
4	44.9	44.9
5	70.0	70.0
6	55.4	55.4
7	60.0	60.0
8	62.8	62.7
9	30.8	31.0
10	60.0	60.0
11	52.6	52.9
12	40.1	40.1
13	60.0	60.0
14	60.0	60.0
15	80.5	80.6
16	80.9	80.9
17	82.1	82.2
18	41.7	41.8
19	44.4	44.4
20	30.1	30.3
21	60.0	60.0

22	86.9	86.8
23	63.5	63.5
24	55.6	55.6
49	63.6	63.6
50	72.3	72.3
51	53.9	53.8
52	88.1	88.1
53	56.8	56.8
54	44.1	44.1
55	60.8	60.7
56	86.0	85.9
57	58.2	58.3
58	34.9	35.0
59	58.5	58.6
60	69.2	69.2
61	54.2	54.2
62	30.2	30.2
63	52.0	51.9
64	58.2	58.3
65	49.8	49.9
66	50.1	50.1
67	58.2	58.3
68	47.3	47.3
69	58.2	58.3

70	55.3	55.3
71	54.5	54.6
72	58.2	58.3
73	58.2	58.3
74	58.2	58.3
75	58.2	58.3
76	71.6	71.8
77	49.3	49.5
78	58.2	58.3
79	58.2	58.3
80	47.4	47.2
81	49.7	49.6
82	64.1	64.0
83	47.9	47.7
84	50.3	50.2
85	66.8	66.8
86	66.8	66.8
87	75.9	76.0
88	74.1	74.2
89	63.0	63.1
90	66.8	66.8
91	55.3	55.2
92	48.9	48.7
93	48.5	48.6

94	76.6	76.6
95	72.2	72.2
96	66.8	66.8
97	60.4	60.3
98	64.4	64.5
99	52.5	52.4
100	66.8	66.8
101	74.3	74.4
102	83.2	83.3
103	92.5	92.5
104	76.7	76.7
105	43.0	43.0
106	58.4	58.4
107	67.1	67.1
108	58.4	58.4
109	66.8	66.8
110	66.1	66.3
111	98.6	98.6
112	57.2	57.2
113	79.6	79.6
114	31.6	31.3
115	63.7	63.7
116	76.4	76.4
117	60.5	60.6

118	41.8	42.0
119	59.6	59.6
120	85.7	85.7
121	68.5	68.6
122	47.4	47.4
123	57.1	57.1
124	74.7	74.7
125	60.3	60.3
126	62.0	62.0
127	80.2	80.3
128	52.7	52.6
129	50.8	50.8
130	40.1	39.9
131	72.1	72.1
132	74.9	74.9
133	57.4	57.4
134	87.2	87.2
135	57.9	57.8
136	93.6	93.6
137	72.2	72.2
138	54.4	54.3
139	59.4	59.5
140	55.4	55.5
141	34.5	34.8

142	57.4	57.4
143	54.5	54.5
144	97.9	97.9
145	53.9	53.9
146	67.6	67.8
147	94.9	95.0
148	84.2	84.2
149	69.1	69.2
150	48.7	48.7
151	57.4	57.4
152	65.4	65.4
153	57.4	57.4
154	24.1	23.8
155	79.5	79.5
156	33.2	33.3
157	52.6	52.6
158	35.8	35.7
159	57.4	57.4
160	57.5	57.2
161	44.3	44.2
162	57.4	57.4
163	57.4	57.4
164	20.2	21.6
165	45.5	45.3

166	90.9	91.0
167	57.4	57.4
168	52.4	52.6
169	42.5	42.5
170	31.7	31.6
171	51.6	51.6
172	76.4	76.6
173	45.1	45.1
174	53.6	53.7
175	49.7	49.8
176	66.7	66.7
177	65.2	65.2
178	61.4	61.3
179	52.1	52.1
180	110.2	110.3
181	55.1	55.1
182	26.8	26.8
183	56.9	57.0
184	55.1	55.2
185	45.4	45.3
186	39.1	39.1
187	89.3	89.3
188	47.3	47.6
189	52.9	53.1

190	45.9	45.9
191	43.8	44.1
192	57.3	57.4
193	60.1	60.1
194	51.9	51.8
195	40.2	40.0
196	44.9	44.1
197	63.7	63.7
198	32.7	32.6
199	75.0	75.0
200	95.5	95.7
201	47.5	47.4
202	74.9	74.9
203	267.0	267.1
204	58.5	58.4
205	30.7	30.7
206	48.2	49.4
207	90.4	90.4
208	57.5	57.6
209	61.1	61.1
210	48.7	48.8
211	45.9	45.9
212	74.4	74.4
213	56.2	56.2

214	44.8	44.8
215	61.3	61.4
216	60.4	60.4
217	60.4	60.3
218	56.6	56.5
219	44.7	45.2
220	25.9	25.7
221	55.0	55.0
222	48.6	48.5
223	46.5	46.5
224	46.1	46.1
225	47.9	48.0
226	26.9	27.1
227	50.7	50.7
228	96.8	96.7
229	94.3	94.2
230	57.0	56.9
231	54.0	54.0
232	93.4	93.3
233	60.8	60.7
234	79.2	79.1
235	49.1	49.1
236	52.0	52.0
237	50.7	50.8

238	29.8	29.7
239	67.5	67.5
240	29.7	29.4
241	56.2	56.2
242	35.2	35.1
243	54.0	54.0
244	27.5	27.2
245	54.0	54.0
246	37.2	37.1
247	48.6	48.6
248	27.4	27.2
249	75.9	75.9
250	72.6	72.6
251	34.9	35.0
252	43.9	43.9
253	51.5	51.6
254	40.4	40.2
255	83.9	83.9
256	55.7	55.7
257	80.3	80.3
258	50.9	50.9
259	54.6	54.6
260	91.1	91.1
261	51.2	51.3

262	50.9	51.5
263	58.1	58.1
264	57.7	57.7
265	51.2	51.2
266	42.2	42.2
267	44.1	44.1
268	57.9	57.8
269	48.1	48.1
270	35.7	35.6
271	51.1	51.1
272	68.0	68.1
273	73.2	73.2
274	47.4	47.4
275	54.6	54.6
276	23.0	23.0
277	90.1	90.1
278	30.7	30.5
279	38.8	38.6

6.4 Output analysis

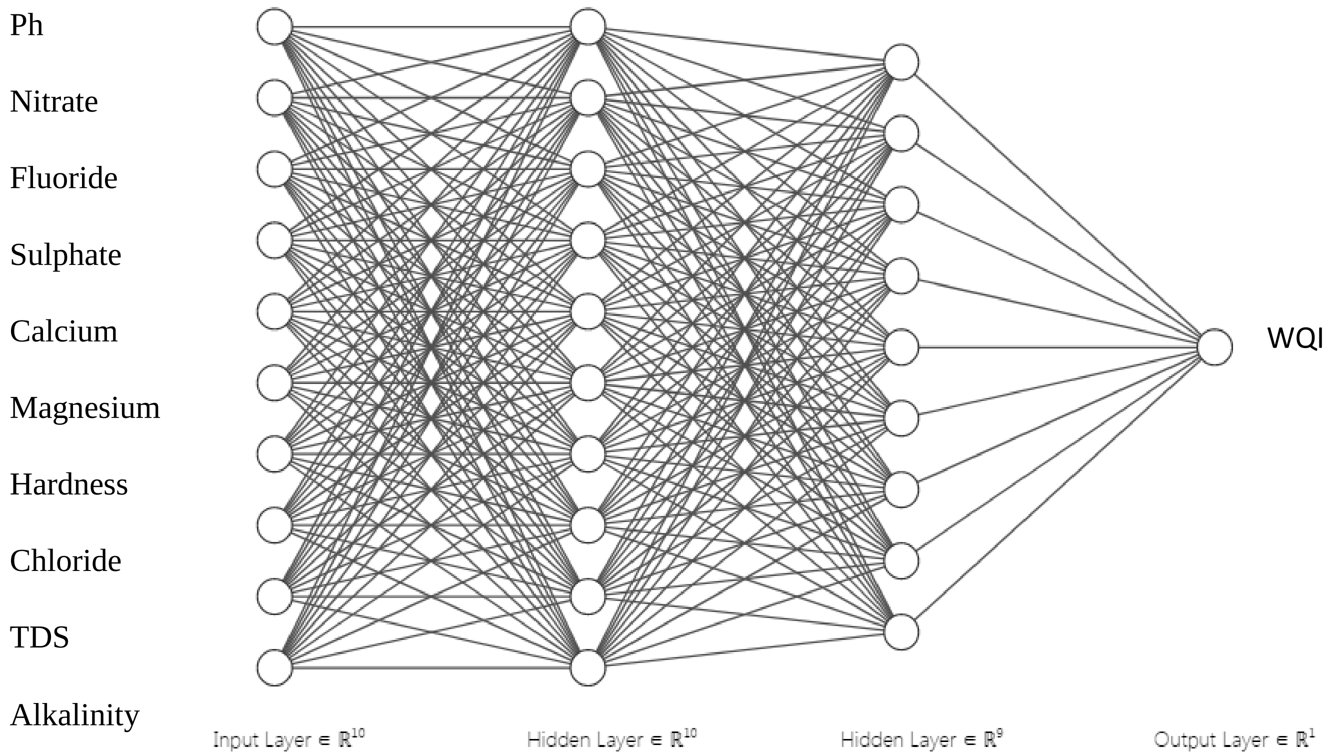


Figure 7 ANN Model Architecture

The configuration of the neural network model includes essential parameters such as the activation function, hidden layers, neurons in each hidden layer, solver type, and the number of iterations. These parameters define the architecture and optimization approach of the model, contributing to its learning process and predictive capabilities. In this case, the ReLU activation function is utilized, along with two hidden layers consisting of 10 and 9 neurons respectively, trained using Stochastic Gradient Descent (SGD) over 447 iterations.

Key performance metrics include a Mean Squared Error (MSE) of 0.0244, Root Mean Squared Error (RMSE) of approximately 0.1562, and an impressive R-squared (R^2) score of approximately 0.9999. Cross-validation scores, averaging at 0.9991, demonstrate the model's consistency and reliability across validation sets.

Weights learned by the model reveal the importance assigned to each input feature.True and predicted values for the entire dataset showcase the model's performance.

Python Libraries Used:

matplotlib.pyplot: A plotting library used to create visualizations such as scatter plots, line plots, etc.

pandas: A data manipulation and analysis library used to handle datasets, perform operations on dataframes, and more.

numpy: A library used for numerical operations in Python, particularly for arrays and matrices.

sklearn.neural_network. MLPRegressor: This class implements a multi-layer perceptron regressor that trains using backpropagation. It's part of scikit-learn, a machine learning library in Python.

sklearn.model_selection: This module provides functions to split datasets into train and test sets, and for cross-validation.

sklearn.metrics: This module provides functions to evaluate the performance of machine learning models, such as mean squared error, R-squared score, etc.

sklearn.preprocessing.StandardScaler: This class standardizes features by removing the mean and scaling to unit variance. It's often used to pre-process data before feeding it into machine learning models.

The scatter plots in the code is showcased in chapter 7.

CHAPTER 7: ANALYSIS AND CONCLUSION

7.1 General

Section 7.2deal with results and discussions relating to the analysis of physico-chemical parameters of the year 2010, 2011, 2012, 2013,2014, 2017,2018,2019,2020 and 2021.

Section 7.3 deals with WQI found by Artificial Neural Network (ANN) for the year 2010, 2011, 2012, 2013,2014, 2017,2018,2019,2020 and 2021.

Section 7.4 deals with the conclusion

7.2 Analysis of physico chemical parameters

Table 16Yearly variation of water quality parameters for the year 2010, 2011 & 2012

	2010		2011		2012	
Parameter	**Minimum**	**Maximum**	**Minimum**	**Maximum**	**Minimum**	**Maximum**
pH	7.26	8.32	7.17	8.49	7.24	8.28
Nitrate(mg/l)	2.11	32.7	10.55	44.8	11.26	44.9
Fluoride(mg/l)	0.16	1.34	0.53	1.42	0.23	1.25
Sulphate(mg/l)	3	30	0.66	51	2	34
Calcium(mg/l)	26	136	19	67	19	93
Magnesium(mg/l)	9	72	24	97	20	666
Hardness(mg/l)	104	460	168	468	168	600
Chloride(mg/l)	24	260	44	336	24	272
TDS(mg/l)	202	1190	320	1292	264	1426
Alkalinity(mg/l)	156	424	35	572	68	400

Table 17Yearly variation of water quality parameters for the year 2013, 2014 & 2017

	2013		2014		2017	
Parameter	**Minimum**	**Maximum**	**Minimum**	**Maximum**	**Minimum**	**Maximum**
pH	7.6	8.12	7.07	7.96	7.26	7.62
Nitrate(mg/l)	0.81	44.9	1.05	44.3	3.86	44.3
Fluoride(mg/l)	0.47	1.49	0.23	1.49	0.14	1.49
Sulphate(mg/l)	13	69	10	58	15.37	71.72
Calcium(mg/l)	24	118	17	94	35	188
Magnesium(mg/l)	25	87	20	87	12	98
Hardness(mg/l)	168	600	120	600	160	592
Chloride(mg/l)	16	376	28	220	28	716
TDS(mg/l)	338	1740	282	1372	248	1614
Alkalinity(mg/l)	208	560	128	448	44	452

Table 18Yearly variation of water quality parameters for the year 2018, 2019, 2020 &2021

	2018		2019		2020		2021	
Parameter	**Minimum**	**Maximum**	**Minimum**	**Maximum**	**Minimum**	**Maximum**	**Minimum**	**Maximum**
pH	7.28	7.62	7.21	7.76	7.12	7.81	7.12	7.77
Nitrate(mg/l)	1.86	44.3	2.07	87.09	4.39	44.25	1.72	44.08
Fluoride(mg/l)	0.31	1.98	0.24	5.01	0.21	1.49	0.25	1.48
Sulphate(mg/l)	15.37	99.9	1.34	2561	0.54	77.47	0.86	150
Calcium(mg/l)	35	179	30.01	172	28	188	25	131
Magnesium(mg/l)	17	100	13	96	15	115	21	92
Hardness(mg/l)	200	592	84	536	69	592	44	584
Chloride(mg/l)	28	396	40	496	24	452	32	452
TDS(mg/l)	344	1454	306	1736	306	1582	296	1662
Alkalinity(mg/l)	144	452	152	440	32	496	140	548

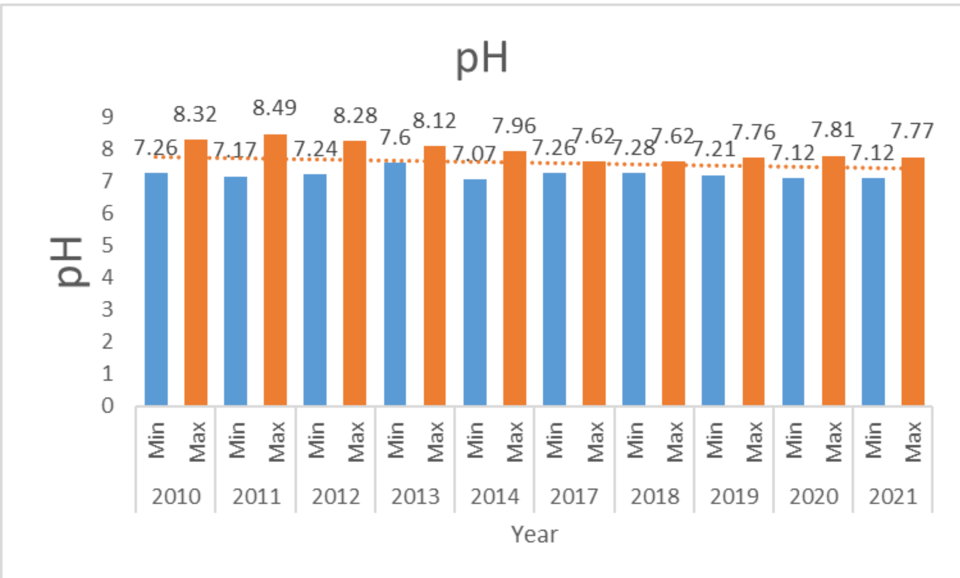


Figure 8Yearly variation in pH for the year 2010-2021

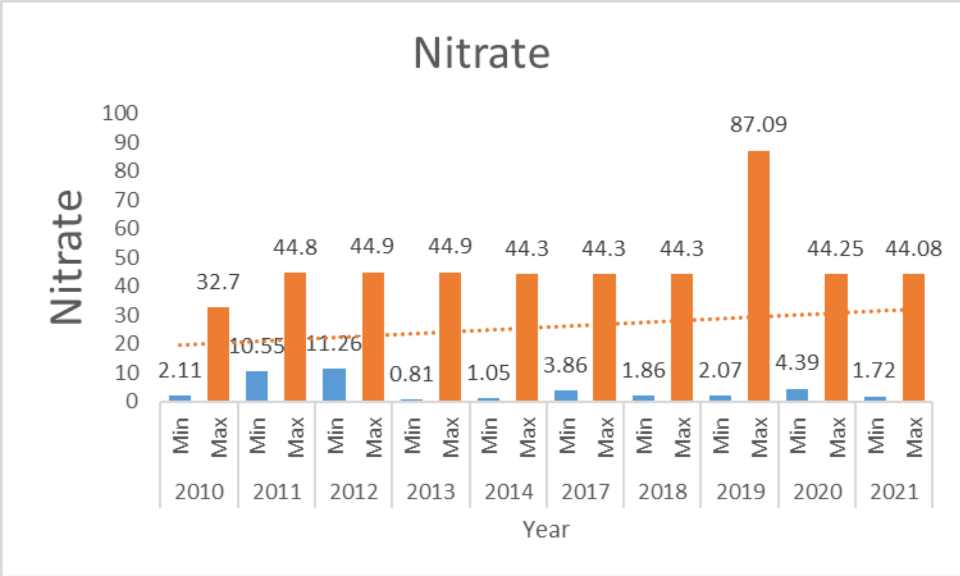


Figure 9Yearly variation in Nitrate for the year 2010-2021

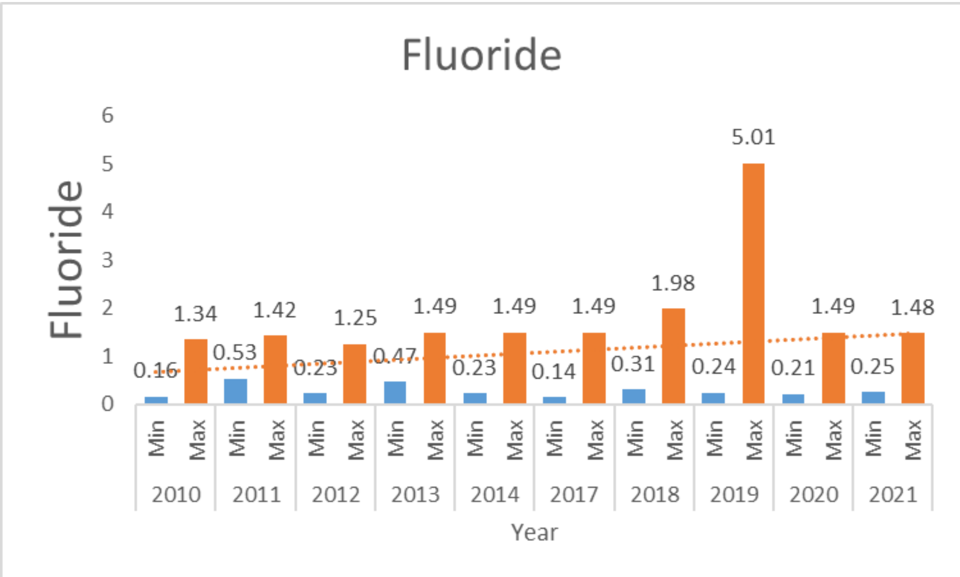


Figure 10Yearly variation in Fluoride for the year 2010-2021

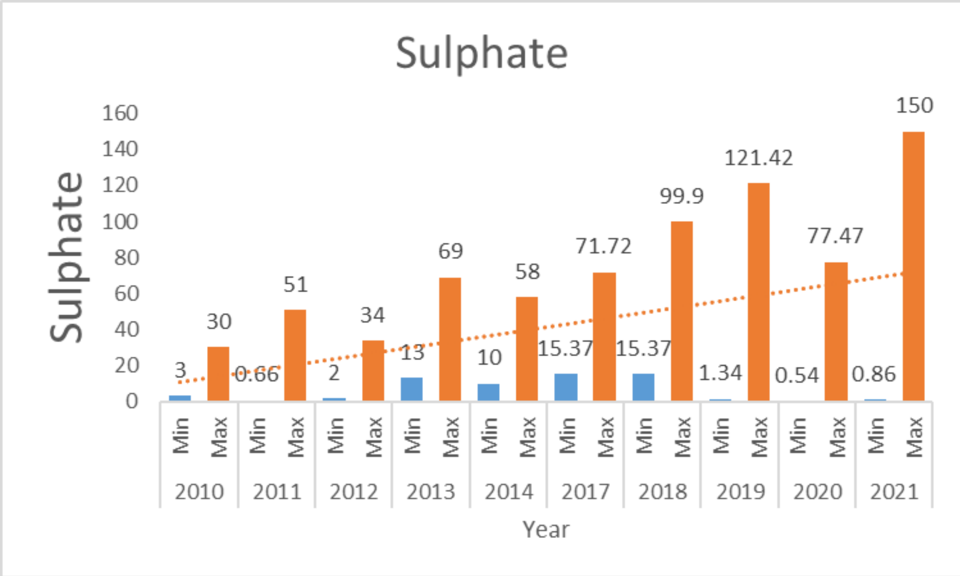


Figure 11Yearly variation in Sulphate for the year 2010-2021

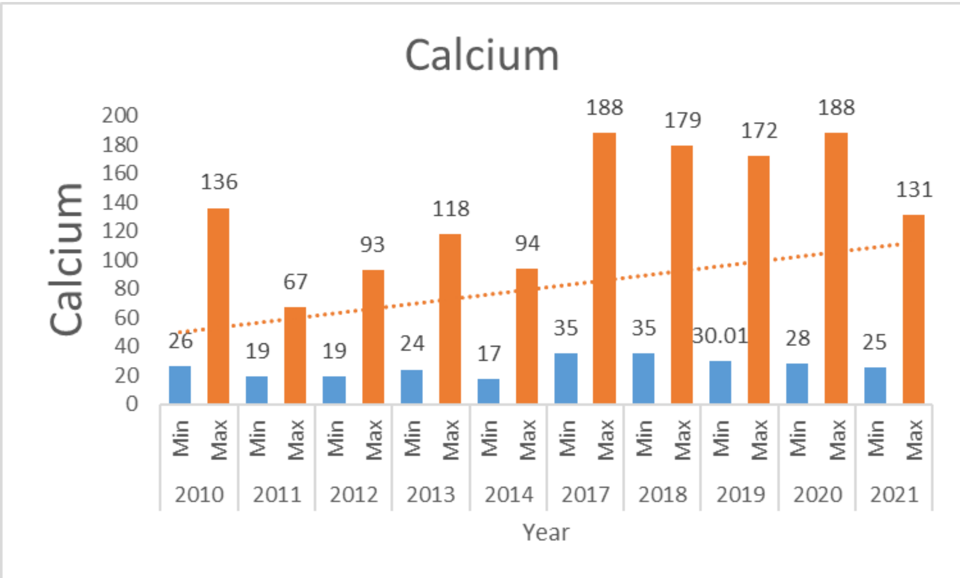


Figure 12Yearly variation in Calcium for the year 2010-2021

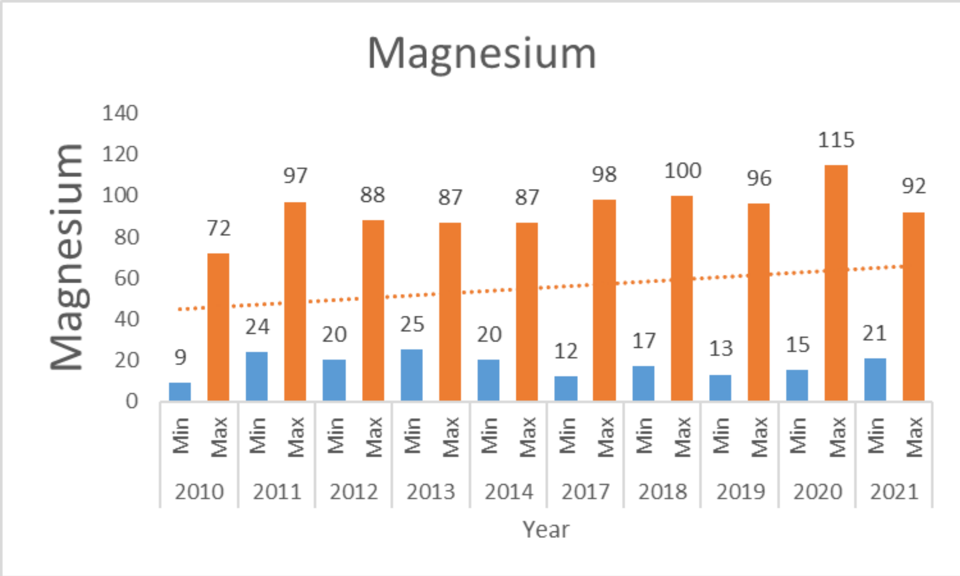


Figure 13Yearly variation in Magnesium for the year 2010-2021

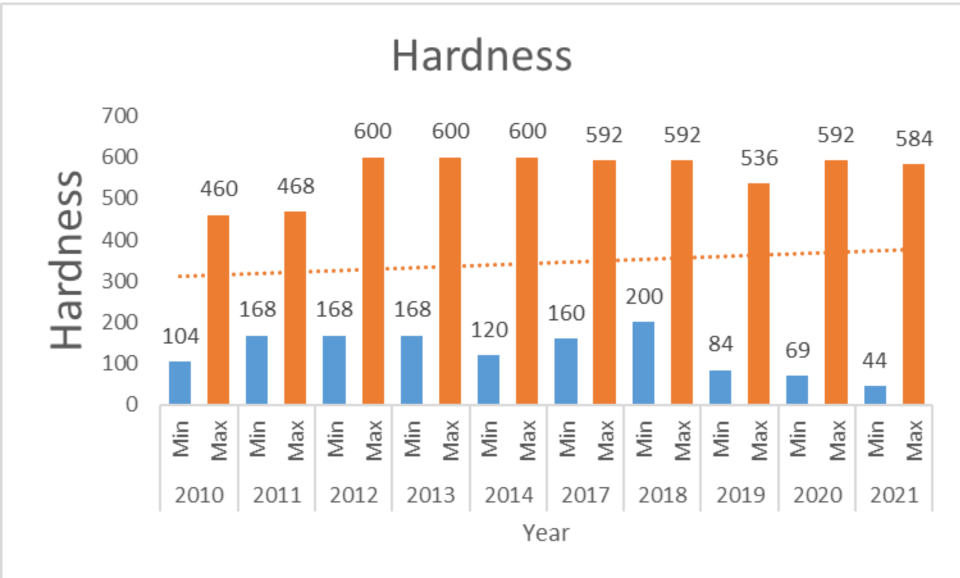


Figure 14Yearly variation in Hardness for the year 2010-2021

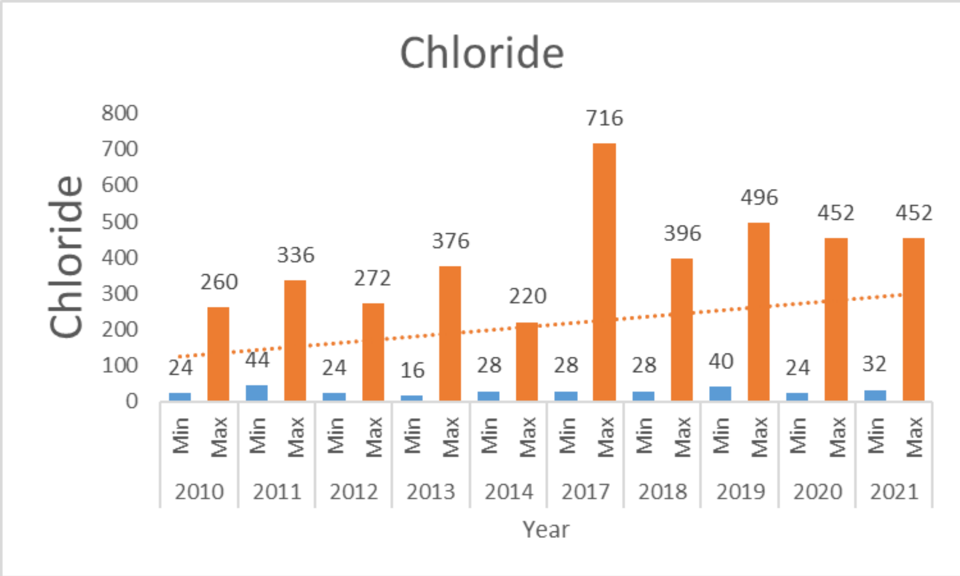


Figure 15Yearly variation in Chloride for the year 2010-2021

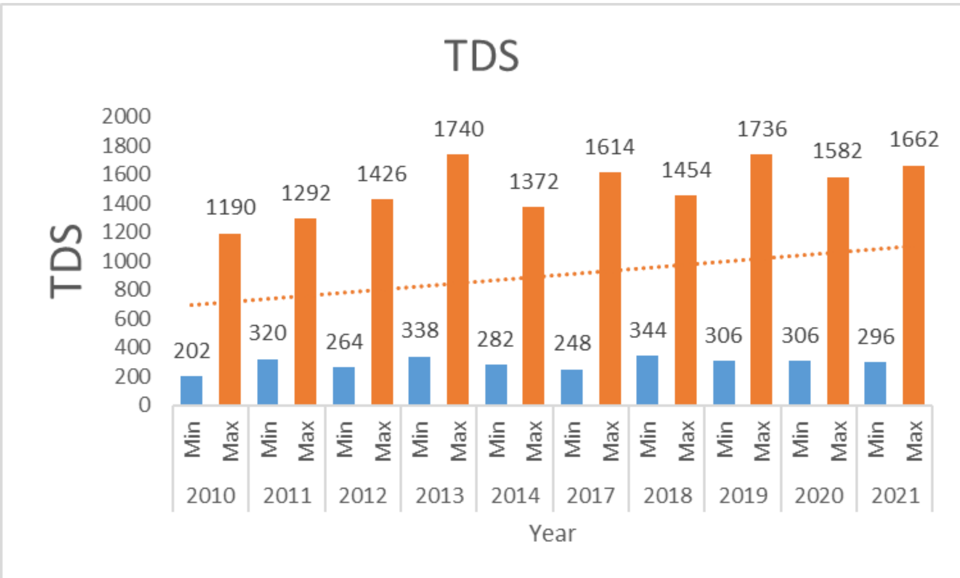


Figure 16Yearly variation in TDS for the year 2010-2021

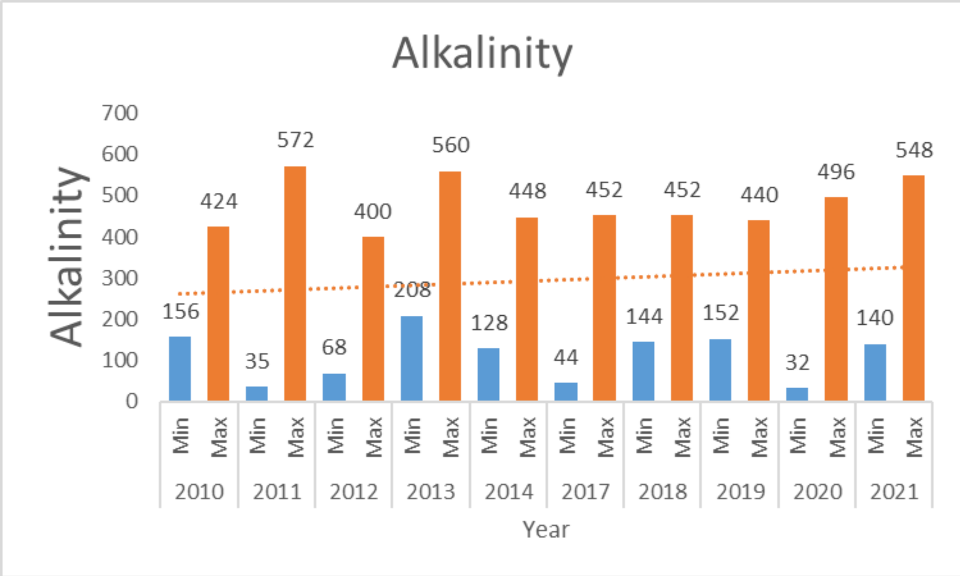


Figure 17Yearly variation in Alkalinity for the year 2010-2021

Result:

The obtained results are explained here by the following parameters.

pH

- There is a considerable change in the pH value.
- pH values varies from 7.07 to 8.49 for the last ten years.

Total Alkalinity

- The Total alkalinity varies from 32 mg/l to 572 mg/l for the last ten years.

Total Dissolved Solids (TDS) and Total Hardness (TH)

- The TDS stands for the mixture of inorganic minerals (mainly calcium, magnesium, sodium and potassium salts of sulphates, chlorides, and bicarbonates) and little amount of organic components. The TDS value is obtained from 202 mg/l to 1740 mg/l.
- The TH in groundwater is mostly owing to the occurrence of calcium and magnesium salts. The TH obtained from 44 mg/l to 600 mg/l.

Calcium (Ca^{2+}) and Magnesium (Mg^{2+})

- Hardness Ca2+ and mg2+ ions are important minerals and helpful to the health of humans in several aspects. Insufficient intake of these ions is capable of imparting adverse health effects. The more intake of calcium can impede the quality of groundwater by causing kidney or bladder stone development, disturbance in urinary section in human beings, encrustation.
- High intake of Mg2+ concentration may cause purgative impact while its deficiency impacts structural and utilitarian changes and is not suitable for the domestic point of view. The Ca2+ concentration obtained from 17 mg/l to 188 mg/l respectively. The Mg2+ concentration obtained from 9 mg/l to 115 mg/l.

Fluoride (F^-) and Chloride (Cl^-)

- Fluoride is essential to human beings at low levels and it helps to avoid the tooth rot in children.
- The excessive intake of high fluoride contained water with a long period can bring about health problems like softening of bones, mottling of teeth, dental fluorosis and different neurologic harms. Chloride is a necessary electrolyte mineral which keeps the quantity of a cell fluid inside and around in a balancing way. It also keeps up appropriate blood volume and pressure of a cell. The Fluoride (F-) ion is obtained from 0.14 mg/l to 5.01 mg/l. The chloride (Cl-) ion is obtained from 16 mg/l to 716 mg/l.

Sulphate ($SO4^{2-}$) and Nitrate ($NO3^{1-}$)

- A few soils and rocks generally contain sulphate minerals. Normally groundwater travels through soils and rocks a part of the sulphate- containing minerals are dissolved.
- Sulphate gives a severe or therapeutic taste to water if it exceeds a concentration of 250 mg/l.The amount of Nitrate in groundwater is a perfect indicator of anthropogenic contamination particularly it demonstrates contributions of fertilizer used in the agricultural fields. The sulphate ($SO4^{2-}$) ion is obtained from 0.54 mg/l to 150 mg/l. The nitrate ($NO3^{-1}$) ion is obtained from 0.81 mg/l to 87.09 mg/l.

Table 19 Range of parameters

Parameter	Min. Vaue	Max. Value	Range (Desirable Permissible)
PH	7.07	8.32	6.5 – 8.5
NO3	0.81	87.09	45 - 100
Flouride	14	5.01	1 – 1.5
SO4	0.66	99.9	200 - 400
Calcium	17	188	75 - 200
Magnesium	09	666	30 -100
Hardness	44	600	300 - 600
Chloride	16	716	250 - 1000
TDS	202	1740	500 - 2000
Alkalinity	32	572	200 - 600

It is Observed that except PH all other parameter are having variation in there values which is either greater or lesser Than Prescript limit of desirable or permissibles Value

Fluoride & Magnesium have Variation having Minimum Values Much Lesser than desirable limit and Maximum Value excessively larger than permissible limit value.

All other parameter wise NO3, SO4, Ca, Hardness, Chloride, TDS, Alkalinity having much lesser minimun Value than desirable Limit attributes the degradation of overall Groundwater Quality.

This Values of different parameter lesser than desirable or more than permissible can be Potential for Crippling skeletal fluorosis.

Alkalinity imparts unpleasant taste, deleterious to humans in presence of high PH hardness and TDS.

7.3 WQI by Artificial Neural Network

Table 20Water Quality Index for the year 2010

WELL NO	VILLAGE	WQI	QUALITY OF WATER
W1	Ambala	60	Poor
W2		60	Poor
W3	Zoz	81.2	Very poor
W4	Vasedi	60.3	Poor
W5		44.9	Good
W6	Surkheda	70	Poor
W7	Simal faliya	55.4	Poor
W8	Pelsanda	60	Poor
W9	Olimba	62.7	Poor
W10	Raysingpura	31	Good
W11	Motisadhli	60	Poor
W12	Ode	52.9	Poor
W13	Mithibor	40.1	Good
W14	Gunata	60	Poor
W15	Ferkuva	60	Poor
W16	Dumali	80.6	Very poor
W17	Mandava	80.9	Very poor
W18	Kikavada	82.2	Very poor
W19	Jamli	41.8	Good
W20	Jamla	44.4	Good
W21	Chilarvant	30.3	Good
W22	Chichod	60	Poor
W23	Chisadia	86.8	Very poor
W24	Devaliya	63.5	Poor
W25	Bodgam	55.6	Poor
W26	Bhordali	60	Poor
W27	Bhilpur	73.5	Poor
W28	Antroli	65.2	Poor

Table 21Water Quality Index for the year 2011

WELL NO	VILLAGE	WQI	QUALITY OF WATER
W1	Ambala	58.5	Poor
W2		65.7	Poor
W3	Zoz	57.9	Poor
W4	Vasedi	63.6	Poor
W5		63.6	Poor
W6	Surkheda	52	Poor
W7	Simal faliya	61.2	Poor
W8	Pelsanda	63.6	Poor
W9	Olimba	84.4	Very poor
W10	Raysingpura	76.7	Very poor
W11	Motisadhli	65	Poor
W12	Ode	66.3	Poor
W13	Mithibor	56.3	Poor
W14	Gunata	73.3	Poor
W15	Ferkuva	65.5	Poor
W16	Dumali	63.6	Poor
W17	Mandava	67.6	Poor
W18	Kikavada	60.7	Poor
W19	Jamli	63.6	Poor
W20	Jamla	64.6	Poor
W21	Chilarvant	48.8	Good
W22	Chichod	63.6	Poor
W23	Chisadia	72.3	Poor
W24	Devaliya	53.8	Poor
W25	Bodgam	88.1	Very poor
W26	Bhordali	56.8	Poor
W27	Bhilpur	44.1	Good
W28	Antroli	60.7	Poor

Table 22Water Quality Index for the year 2012

WELL NO	VILLAGE	WQI	QUALITY OF WATER
W1	Ambala	85.9	Very poor
W2		58.3	Poor
W3	Zoz	35	Good
W4	Vasedi	58.6	Poor
W5		69.2	Poor
W6	Surkheda	54.2	Poor
W7	Simal faliya	30.2	Good
W8	Pelsanda	51.9	Poor
W9	Olimba	58.3	Poor
W10	Raysingpura	49.9	Poor
W11	Motisadhli	50.1	Poor
W12	Ode	58.3	Poor
W13	Mithibor	47.3	Good
W14	Gunata	58.3	Poor
W15	Ferkuva	55.3	Poor
W16	Dumali	54.6	Poor
W17	Mandava	58.3	Poor
W18	Kikavada	58.3	Poor
W19	Jamli	58.3	Poor
W20	Jamla	58.3	Poor
W21	Chilarvant	71.8	Poor
W22	Chichod	49.5	Poor
W23	Chisadia	58.3	Poor
W24	Devaliya	58.3	Poor
W25	Bodgam	47.2	Good
W26	Bhordali	49.6	Poor
W27	Bhilpur	64	Poor
W28	Antroli	47.7	Good

Table 23Water Quality Index for the year 2013

WELL NO	VILLAGE	WQI	QUALITY OF WATER
W1	Ambala	50.2	Poor
W2		66.8	Poor
W3	Zoz	66.8	Poor
W4	Vasedi	76	Very poor
W5		74.2	Very poor
W6	Surkheda	63.1	Poor
W7	Simal faliya	66.8	Poor
W8	Pelsanda	55.2	Poor
W9	Olimba	48.7	Good
W10	Raysingpura	48.6	Good
W11	Motisadhli	76.6	Very poor
W12	Ode	72.2	Poor
W13	Mithibor	66.8	Poor
W14	Gunata	60.3	Poor
W15	Ferkuva	64.5	Poor
W16	Dumali	52.4	Poor
W17	Mandava	66.8	Poor
W18	Kikavada	74.4	Very poor
W19	Jamli	83.3	Very poor
W20	Jamla	92.5	Very poor
W21	Chilarvant	76.7	Very poor
W22	Chichod	43	Good
W23	Chisadia	58.4	Poor
W24	Devaliya	67.1	Poor
W25	Bodgam	58.4	Poor
W26	Bhordali	66.8	Poor
W27	Bhilpur	66.3	Poor
W28	Antroli	98.6	Very poor

Table 24Water Quality Index for the year 2014

WELL NO	VILLAGE	WQI	QUAITY OF WATER
W1	Ambala	57.2	Poor
W2		79.6	Very poor
W3	Zoz	31.3	Good
W4	Vasedi	63.7	Poor
W5		76.4	Very poor
W6	Surkheda	60.6	Poor
W7	Simal faliya	42	Good
W8	Pelsanda	59.6	Poor
W9	Olimba	85.7	Very poor
W10	Raysingpura	68.6	Poor
W11	Motisadhli	47.4	Good
W12	Ode	57.1	Poor
W13	Mithibor	74.7	Very poor
W14	Gunata	60.3	Poor
W15	Ferkuva	62	Poor
W16	Dumali	80.3	Very poor
W17	Mandava	52.6	Poor
W18	Kikavada	50.8	Poor
W19	Jamli	39.9	Good
W20	Jamla	72.1	Poor
W21	Chilarvant	74.9	Very poor
W22	Chichod	57.4	Poor
W23	Chisadia	87.2	Very poor
W24	Devaliya	57.8	Poor
W25	Bodgam	93.6	Very poor
W26	Bhordali	72.2	Poor
W27	Bhilpur	54.3	Poor
W28	Antroli	59.5	Poor

Table 25Water Quality Index for the year 2017

WELL NO	VILLAGE	WQI	QUALITY OF WATER
W1	Ambala	55.5	Poor
W2		34.8	Good
W3	Zoz	57.4	Poor
W4	Vasedi	54.5	Poor
W5		97.9	Very poor
W6	Surkheda	53.9	Poor
W7	Simal faliya	67.8	Poor
W8	Pelsanda	95	Very poor
W9	Olimba	84.2	Very poor
W10	Raysingpura	69.2	Poor
W11	Motisadhli	48.7	Good
W12	Ode	57.4	Poor
W13	Mithibor	65.4	Poor
W14	Gunata	57.4	Poor
W15	Ferkuva	23.8	Excellent
W16	Dumali	79.5	Very poor
W17	Mandava	33.3	Good
W18	Kikavada	52.6	Poor
W19	Jamli	35.7	Good
W20	Jamla	57.4	Poor
W21	Chilarvant	57.2	Poor
W22	Chichod	44.2	Good
W23	Chisadia	57.4	Poor
W24	Devaliya	57.4	Poor
W25	Bodgam	21.6	Excellent
W26	Bhordali	45.3	Good
W27	Bhilpur	91	Very poor
W28	Antroli	57.4	Poor

Table 26Water Quality Index for the year 2018

WELL NO	VILLAGE	WQI	QUALITY OF WATER
W1	Ambala	52.6	Poor
W2		42.5	Good
W3	Zoz	31.6	Good
W4	Vasedi	51.6	Poor
W5		76.6	Very poor
W6	Surkheda	45.1	Good
W7	Simal faliya	53.7	Poor
W8	Pelsanda	49.8	Poor
W9	Olimba	66.7	Poor
W10	Raysingpura	65.2	Poor
W11	Motisadhli	61.3	Poor
W12	Ode	52.1	Poor
W13	Mithibor	110.3	Unfit for drinking
W14	Gunata	55.1	Poor
W15	Ferkuva	26.8	Good
W16	Dumali	57	Poor
W17	Mandava	55.2	Poor
W18	Kikavada	45.3	Good
W19	Jamli	39.1	Good
W20	Jamla	89.3	Very poor
W21	Chilarvant	47.6	Good
W22	Chichod	53.1	Poor
W23	Chisadia	45.9	Good
W24	Devaliya	44.1	Good
W25	Bodgam	57.4	Poor
W26	Bhordali	60.1	Poor
W27	Bhilpur	51.8	Poor
W28	Antroli	40	Good

Table 27Water Quality Index for the year 2019

WELL NO	VILLAGE	WQI	QUALITY OF WATER
W1	Ambala	44.1	Good
W2		63.7	Poor
W3	Zoz	32.6	Good
W4	Vasedi	75	Very poor
W5		95.7	Very poor
W6	Surkheda	47.4	Good
W7	Simal faliya	74.9	Very poor
W8	Pelsanda	267.1	Unfit for drinking
W9	Olimba	58.4	Poor
W10	Raysingpura	30.7	Good
W11	Motisadhli	49.4	Poor
W12	Ode	90.4	Very poor
W13	Mithibor	57.6	Poor
W14	Gunata	61.1	Poor
W15	Ferkuva	48.8	Good
W16	Dumali	45.9	Good
W17	Mandava	74.4	Very poor
W18	Kikavada	56.2	Poor
W19	Jamli	44.8	Good
W20	Jamla	61.4	Poor
W21	Chilarvant	60.4	Poor
W22	Chichod	60.3	Poor
W23	Chisadia	56.5	Poor
W24	Devaliya	45.2	Good
W25	Bodgam	25.7	Good
W26	Bhordali	55	Poor
W27	Bhilpur	48.5	Good
W28	Antroli	46.5	Good

Table 28Water Quality Index for the year 2020

WELL NO	VILLAGE	WQI	QUALITY OF WATER
W1	Ambala	46.1	Good
W2		48	Good
W3	Zoz	27.1	Good
W4	Vasedi	50.7	Poor
W5		96.7	Very poor
W6	Surkheda	94.2	Very poor
W7	Simal faliya	56.9	Poor
W8	Pelsanda	54	Poor
W9	Olimba	93.3	Very poor
W10	Raysingpura	60.7	Poor
W11	Motisadhli	79.1	Very poor
W12	Ode	49.1	Poor
W13	Mithibor	52	Poor
W14	Gunata	50.8	Poor
W15	Ferkuva	29.7	Good
W16	Dumali	67.5	Poor
W17	Mandava	29.4	Good
W18	Kikavada	56.2	Poor
W19	Jamli	35.1	Good
W20	Jamla	54	Poor
W21	Chilarvant	27.2	Good
W22	Chichod	54	Poor
W23	Chisadia	37.1	Good
W24	Devaliya	48.6	Good
W25	Bodgam	27.2	Good
W26	Bhordali	75.9	Very poor
W27	Bhilpur	72.6	Poor
W28	Antroli	35	Good

Table 29Water Quality Index for the year 2021

WELL NO	VILLAGE	WQI	QUAITY OF WATER
W1	Ambala	43.9	Good
W2		51.6	Poor
W3	Zoz	40.2	Good
W4	Vasedi	83.9	Very poor
W5		55.7	Poor
W6	Surkheda	80.3	Very poor
W7	Simal faliya	50.9	Poor
W8	Pelsanda	54.6	Poor
W9	Olimba	91.1	Very poor
W10	Raysingpura	51.3	Poor
W11	Motisadhli	51.5	Poor
W12	Ode	58.1	Poor
W13	Mithibor	57.7	Poor
W14	Gunata	51.2	Poor
W15	Ferkuva	42.2	Good
W16	Dumali	44.1	Good
W17	Mandava	57.8	Poor
W18	Kikavada	48.1	Good
W19	Jamli	35.6	Good
W20	Jamla	51.1	Poor
W21	Chilarvant	68.1	Poor
W22	Chichod	73.2	Poor
W23	Chisadia	47.4	Good
W24	Devaliya	54.6	Poor
W25	Bodgam	23	Excellent
W26	Bhordali	90.1	Very poor
W27	Bhilpur	30.5	Good
W28	Antroli	38.6	Good

7.4 True vs Predicted graphs

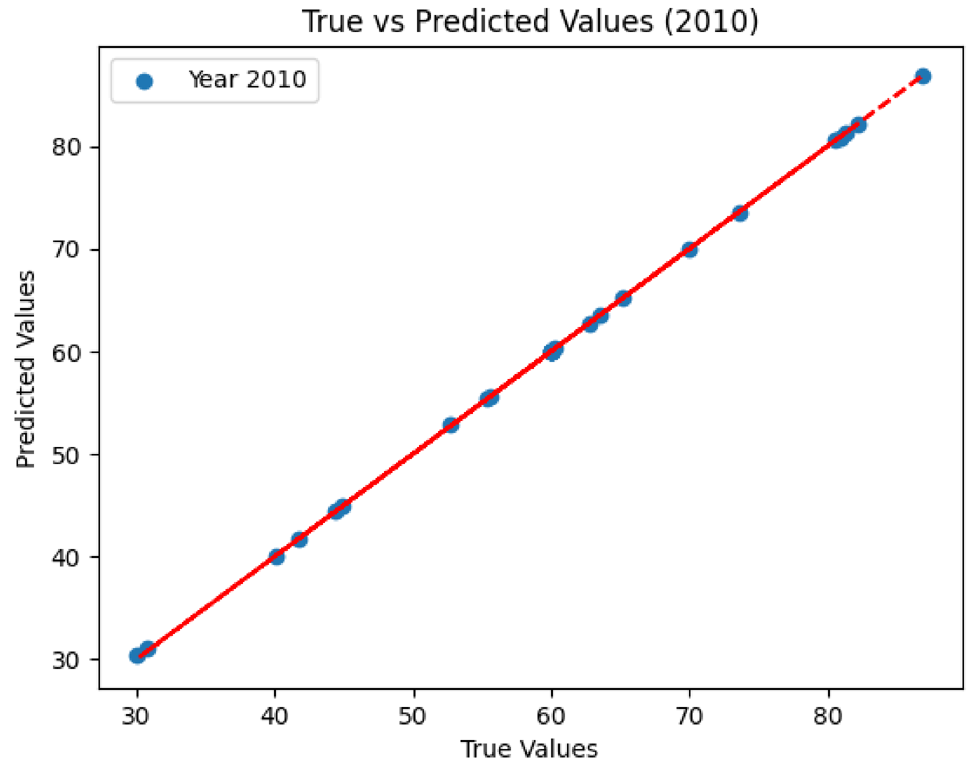


Figure 18True vs Predicted for the year 2010

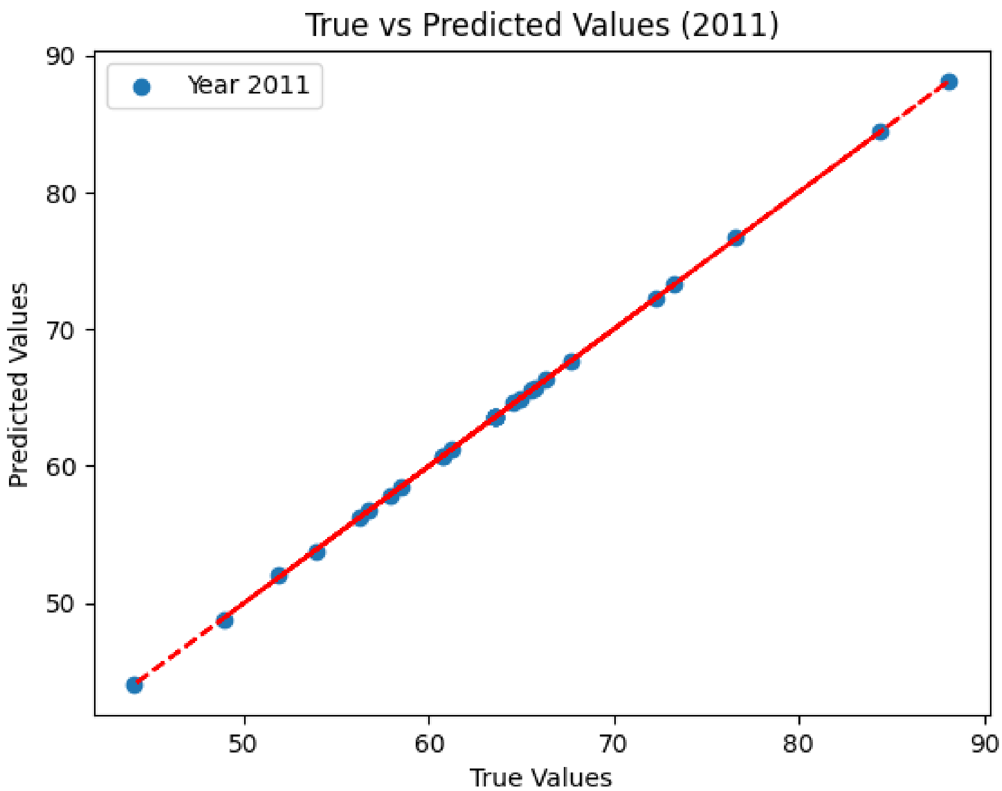


Figure 19True vs Predicted for the year 2011

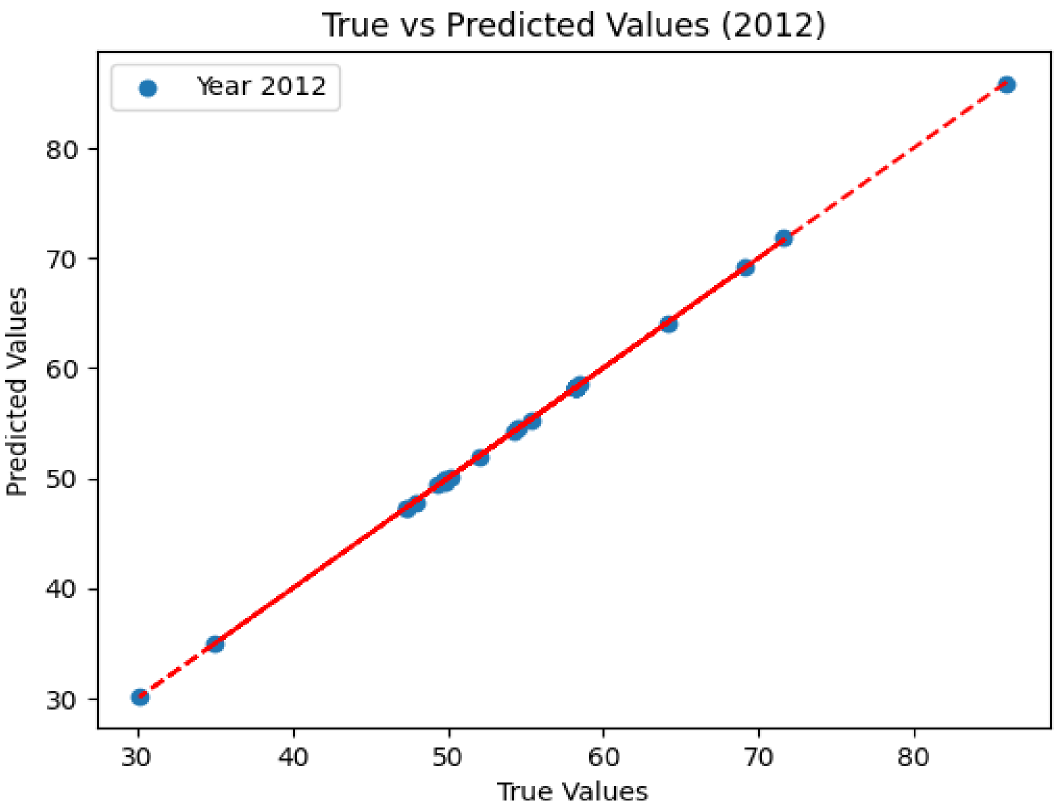


Figure 20True vs Predicted for the year 2012

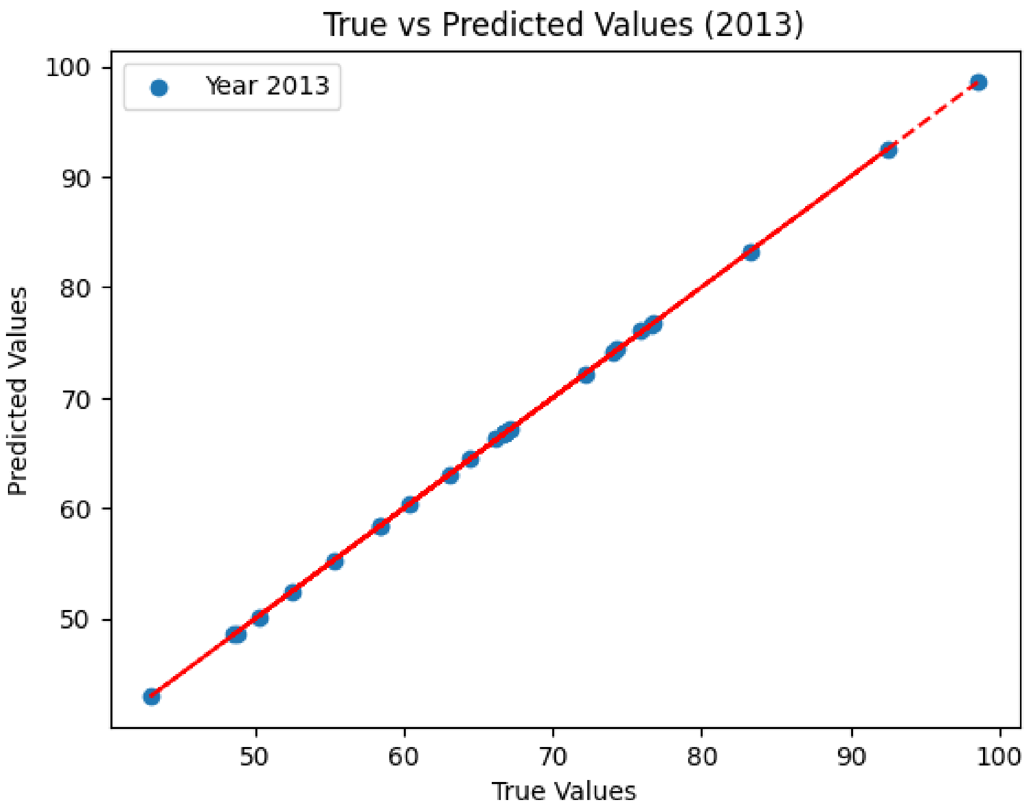


Figure 21True vs Predicted for the year 2013

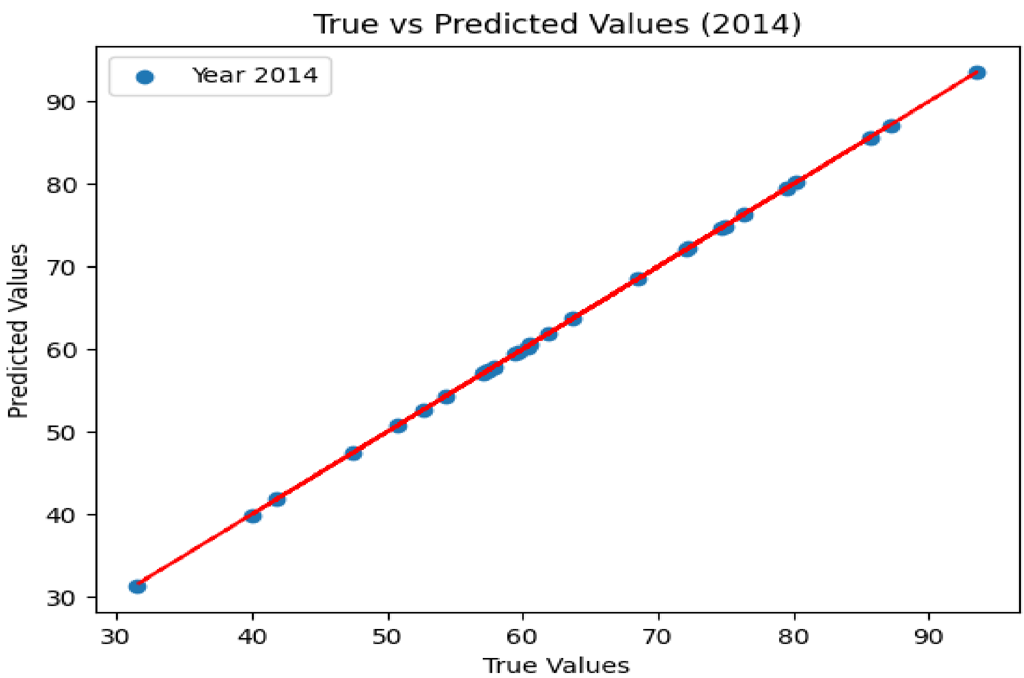


Figure 22True vs Predicted for the year 2014

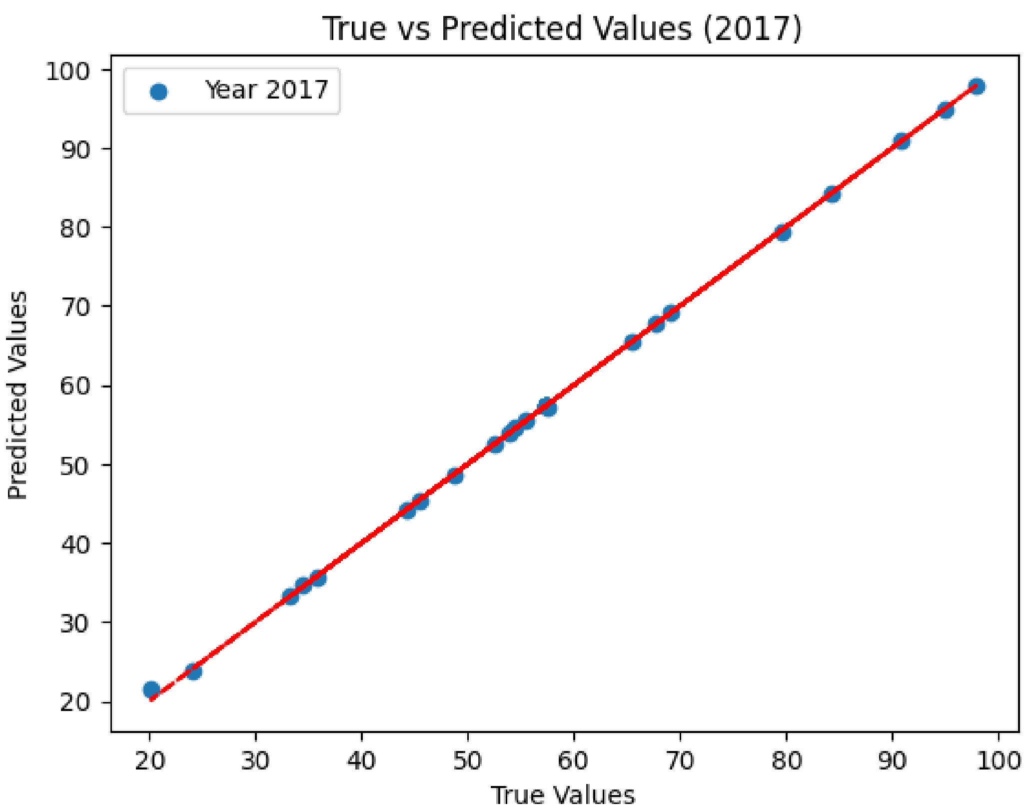


Figure 23True vs Predicted for the year 2017

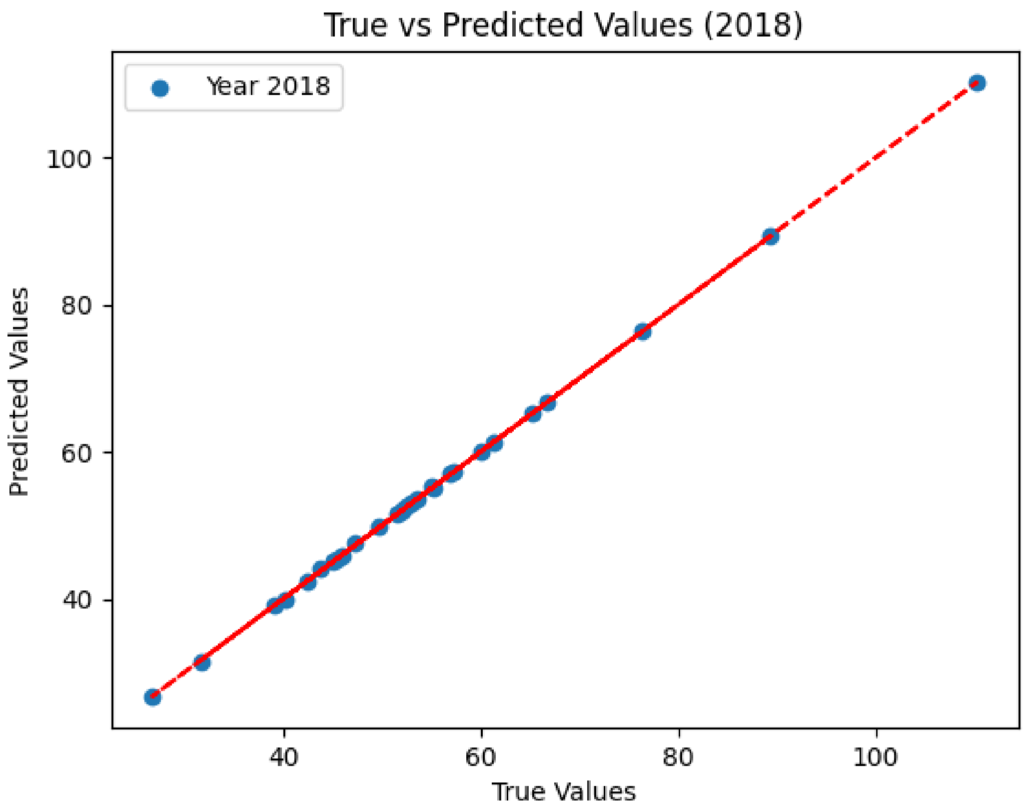


Figure 24True vs Predicted for the year 2018

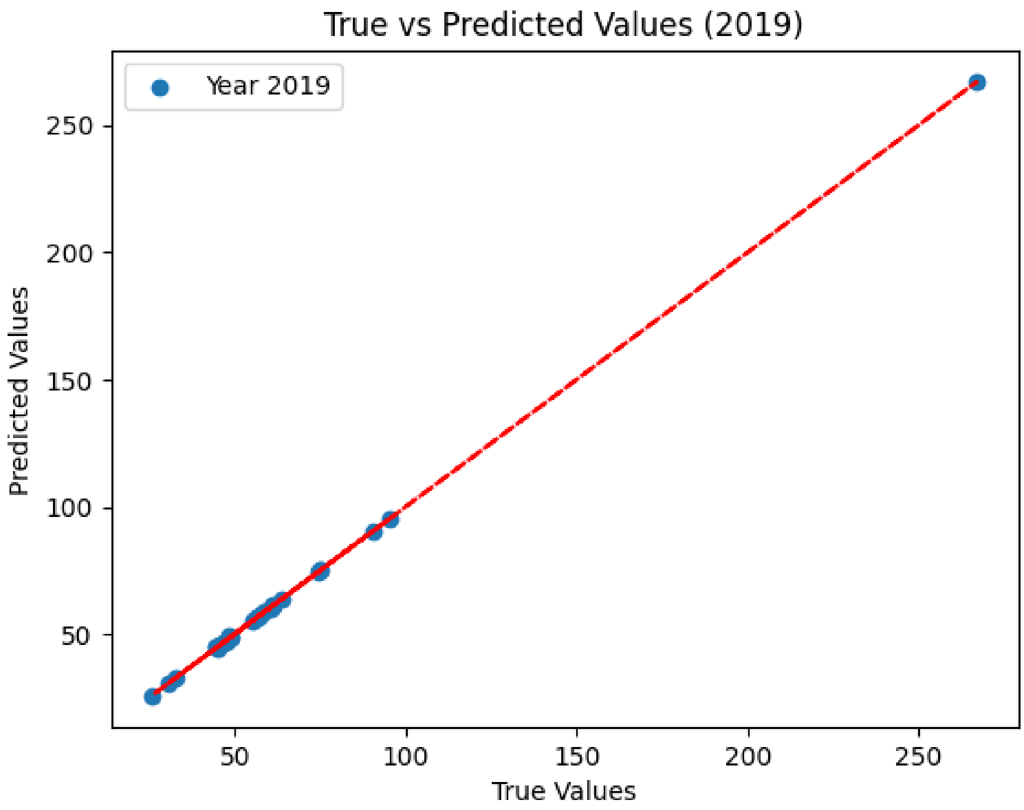


Figure 25True vs Predicted for the year 2019

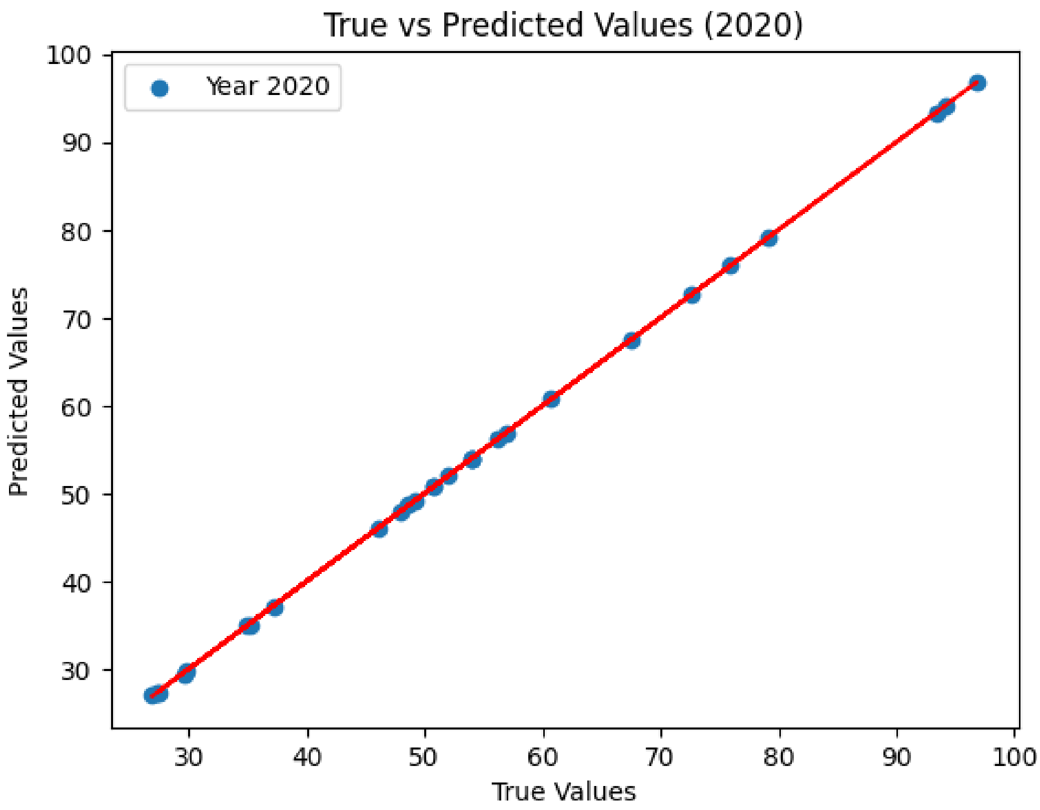


Figure 26True vs Predicted for the year 2020

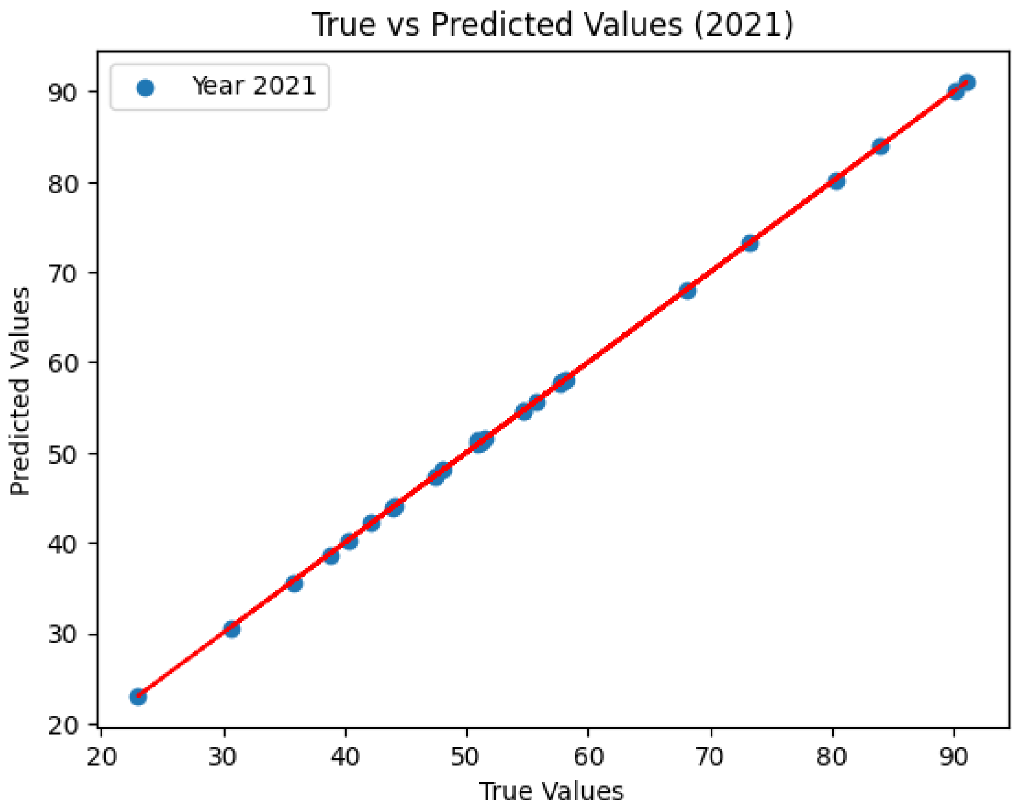


Figure 27True vs Predicted for the year 2021

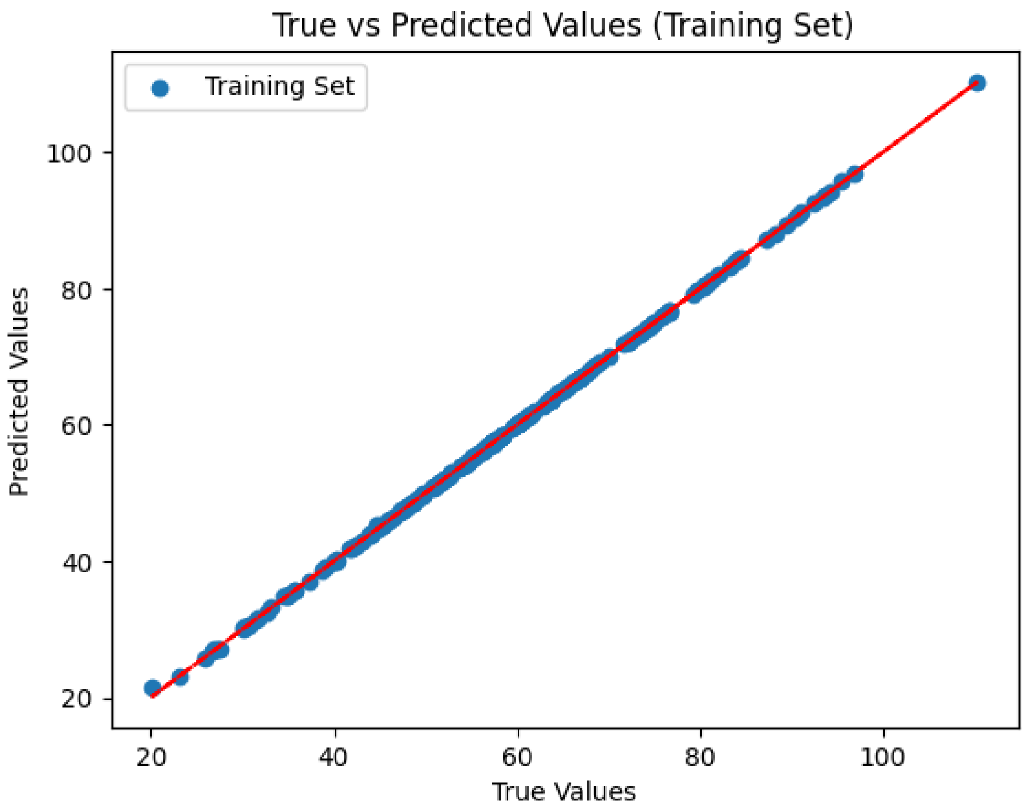


Figure 28True vs Predicted for the training set

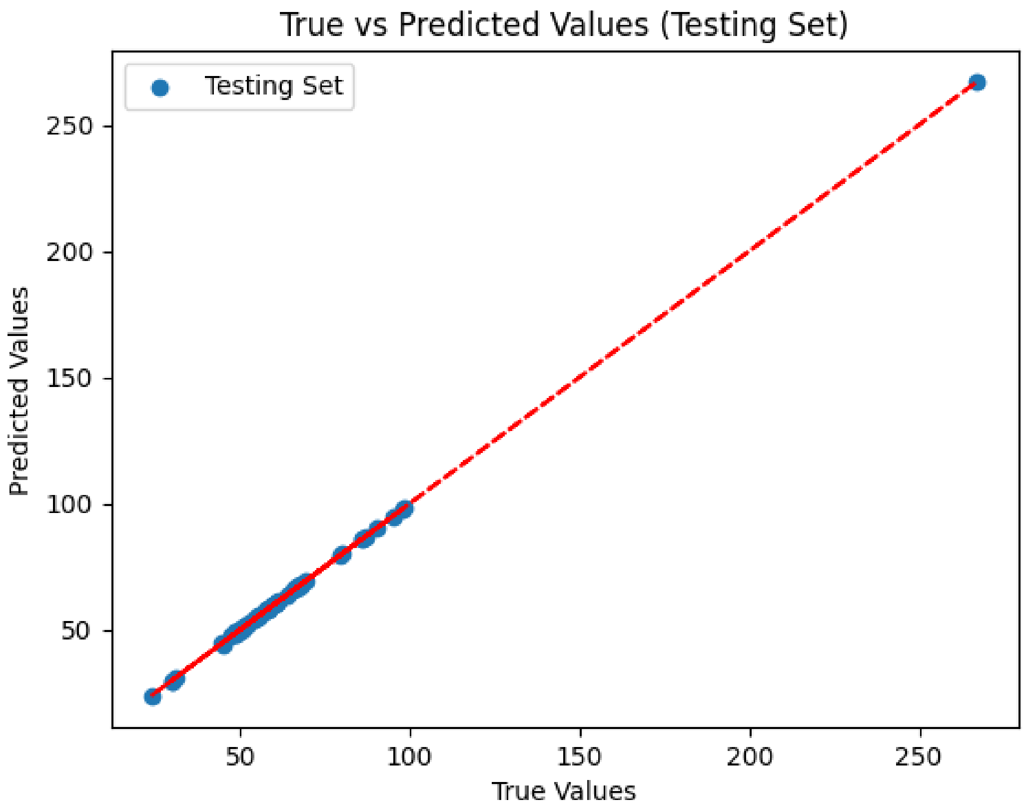


Figure 29True vs Predicted for the testing set

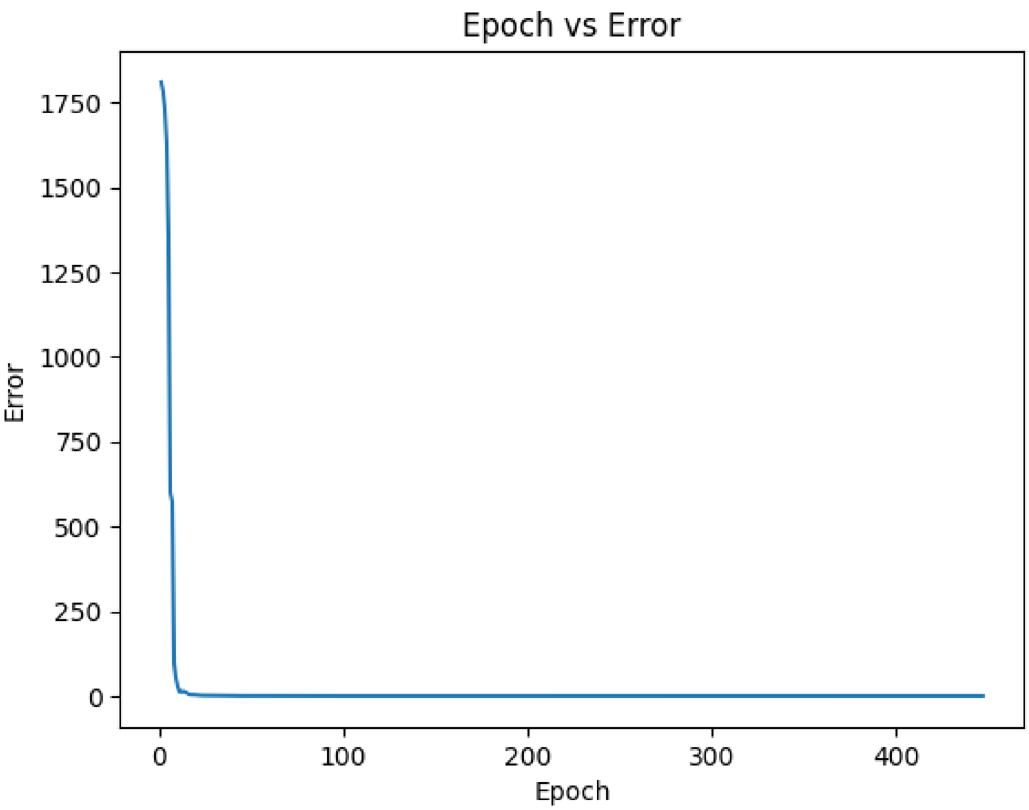


Figure 30Epoch vs Error

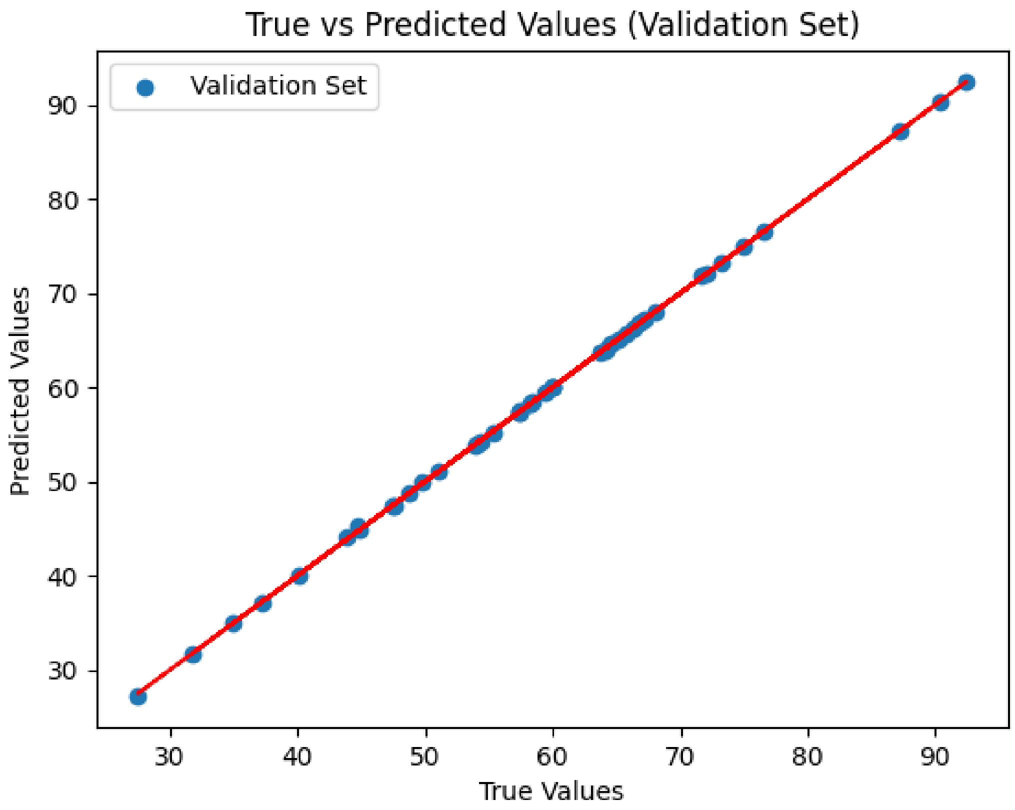


Figure 31True vs Predicted for the validation set

7.5 Percentage representation of WQI classification

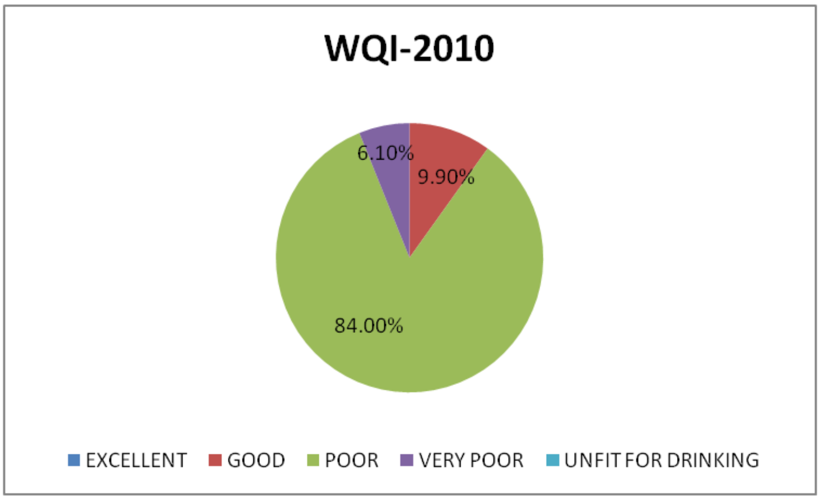


Figure 32 Percentage representation of WQI classification for 2010

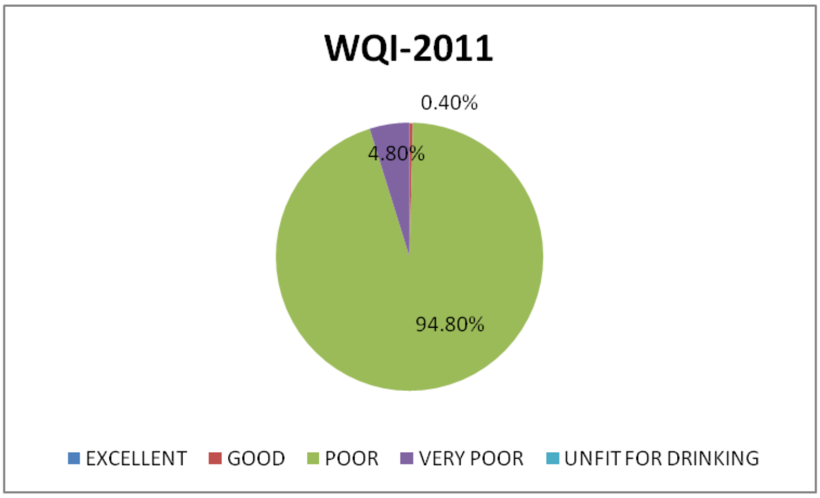


Figure 33 Percentage representation of WQI classification for 2011

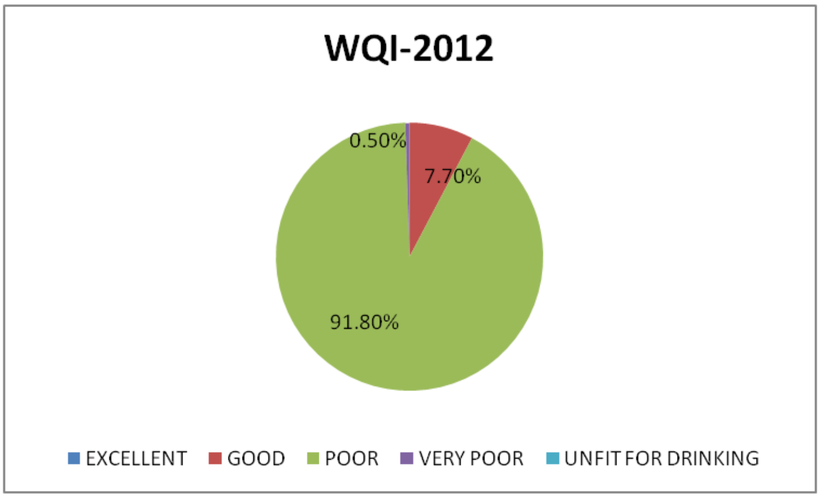


Figure 34 Percentage representation of WQI classification for 2012

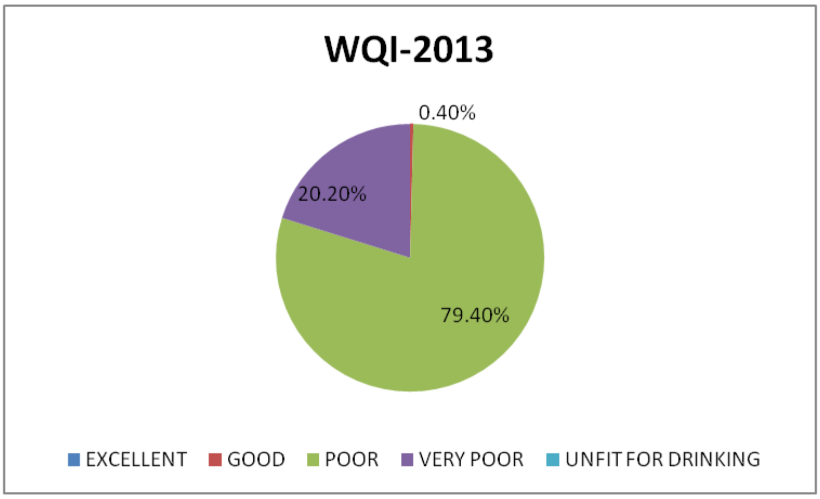


Figure 35 Percentage representation of WQI classification for 2013

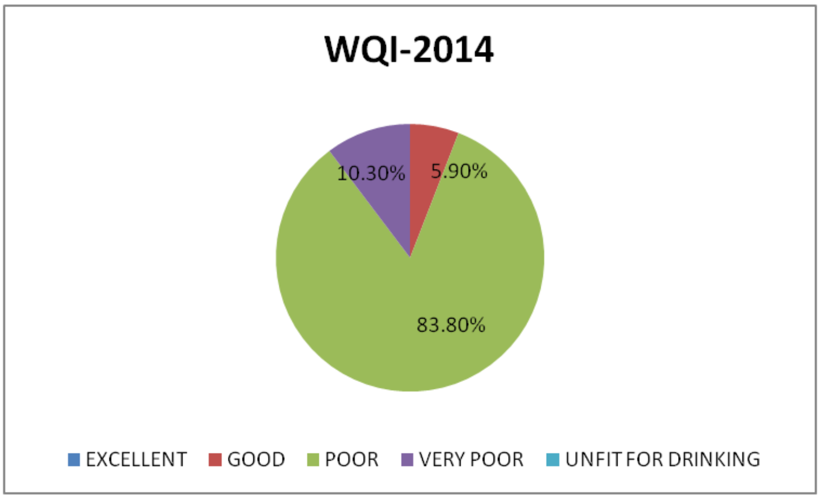


Figure 36 Percentage representation of WQI classification for 2014

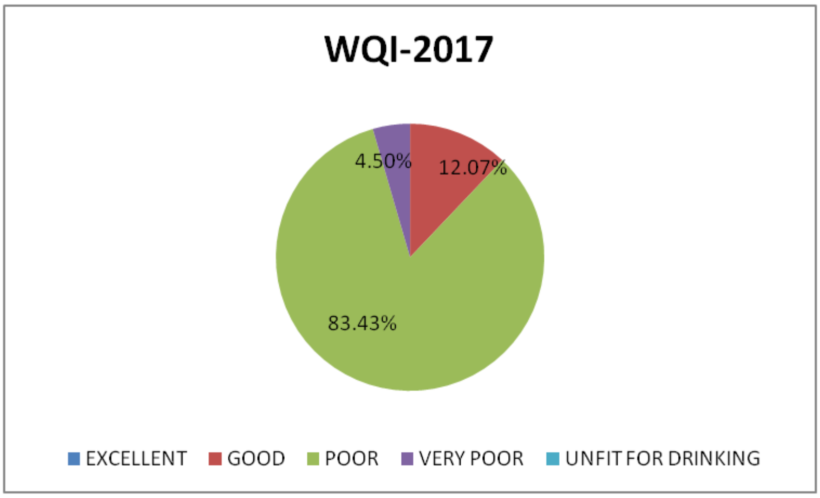


Figure 37 Percentage representation of WQI classification for 2017

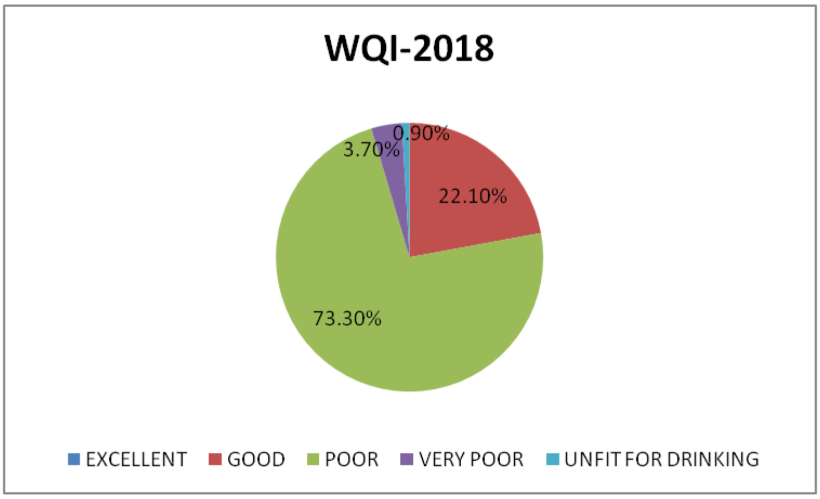


Figure 38 Percentage representation of WQI classification for 2018

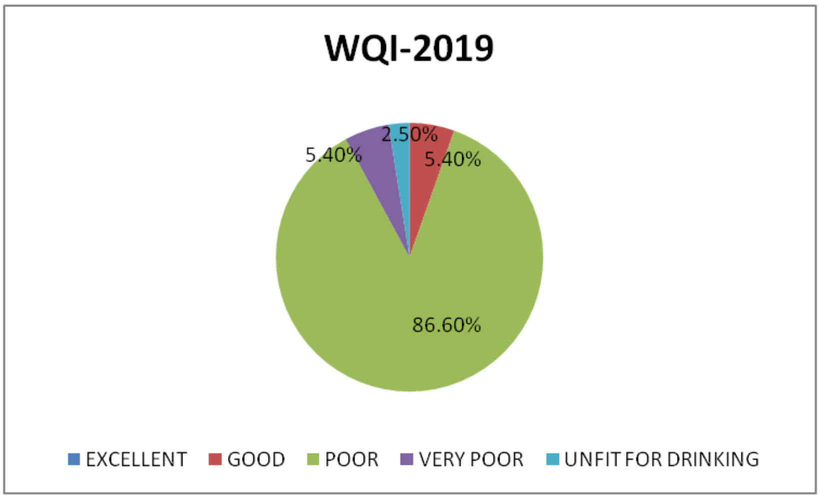


Figure 39 Percentage representation of WQI classification for 2019

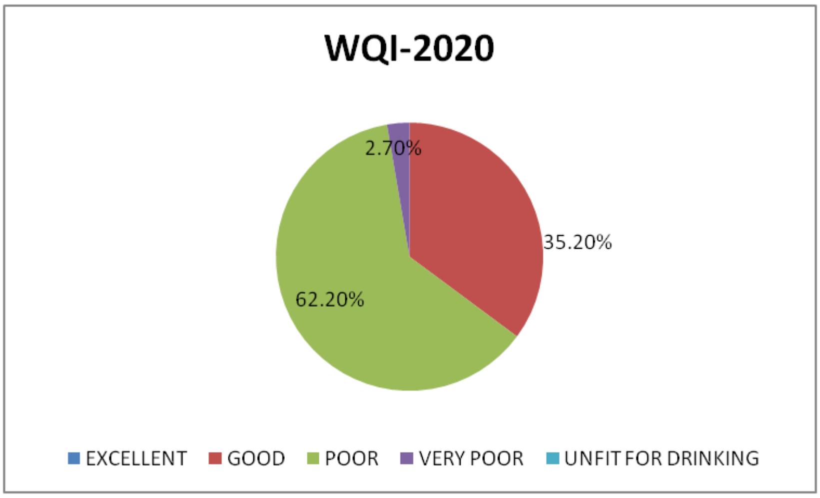


Figure 40 Percentage representation of WQI classification for 2020

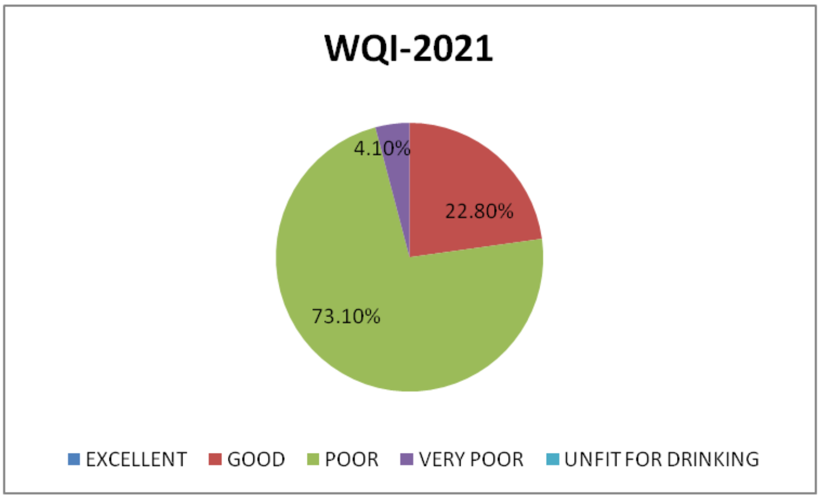


Figure 41 Percentage representation of WQI classification for 2021

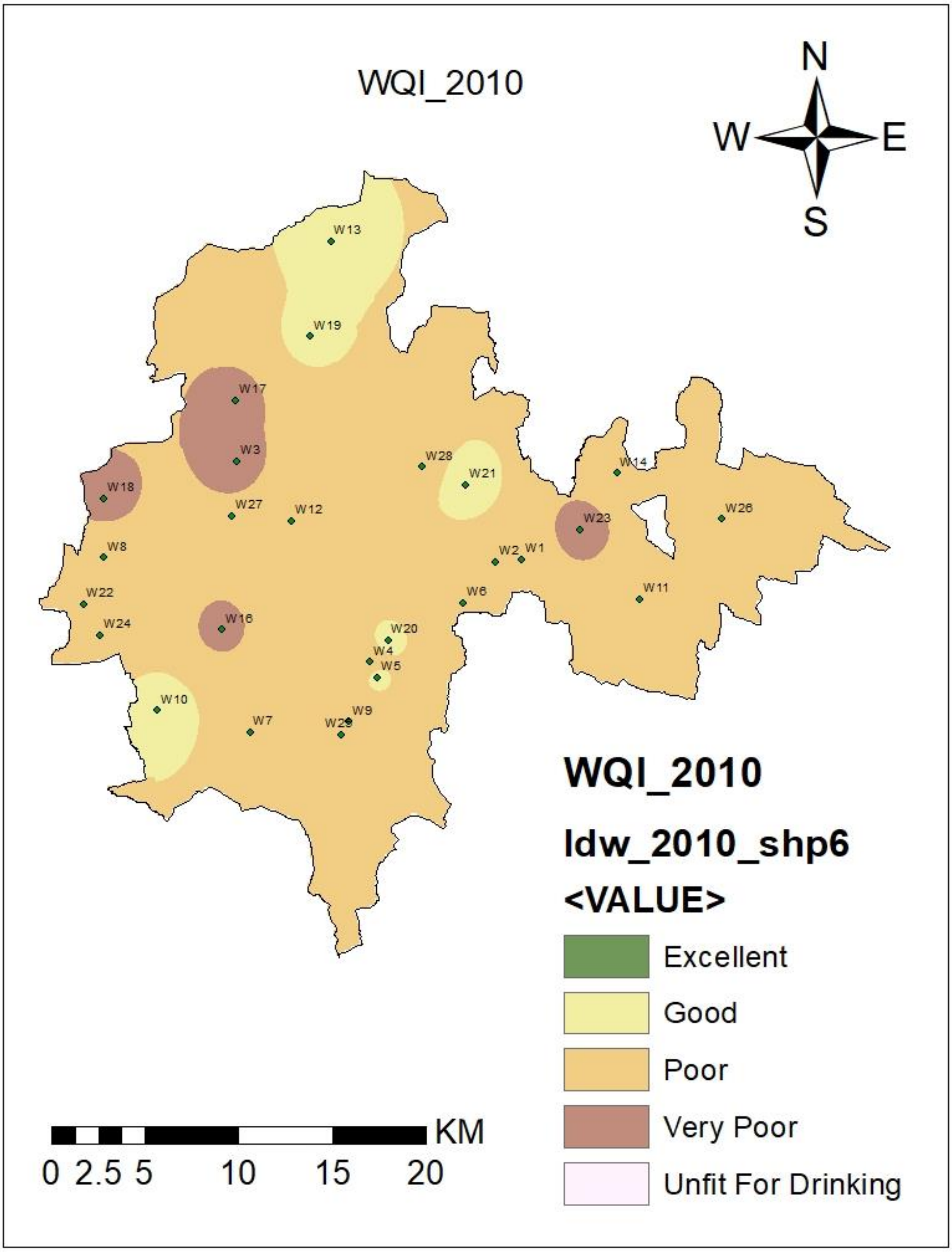


Figure 42Thematic map of WQI - 2010

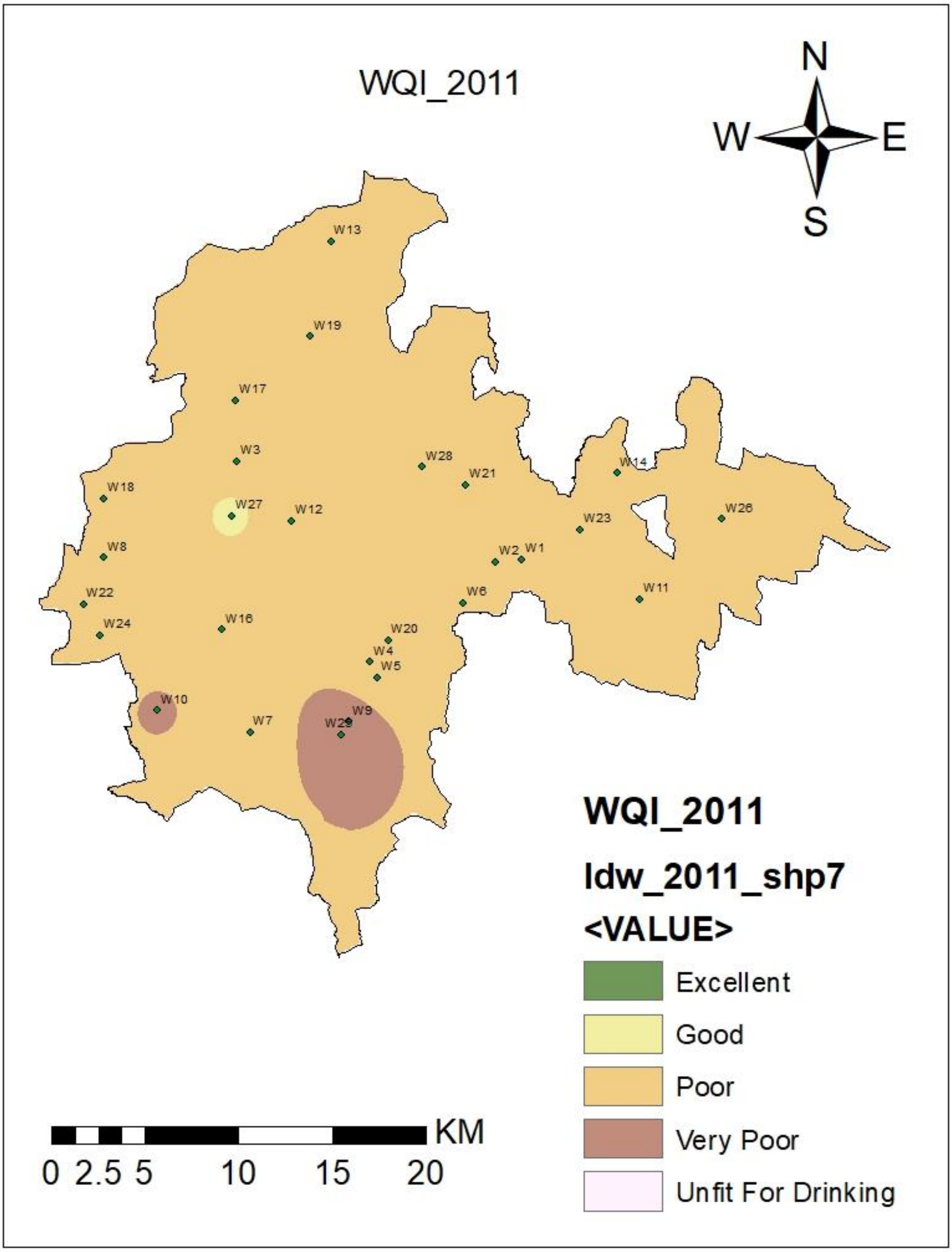


Figure 43Thematic map of WQI - 2011

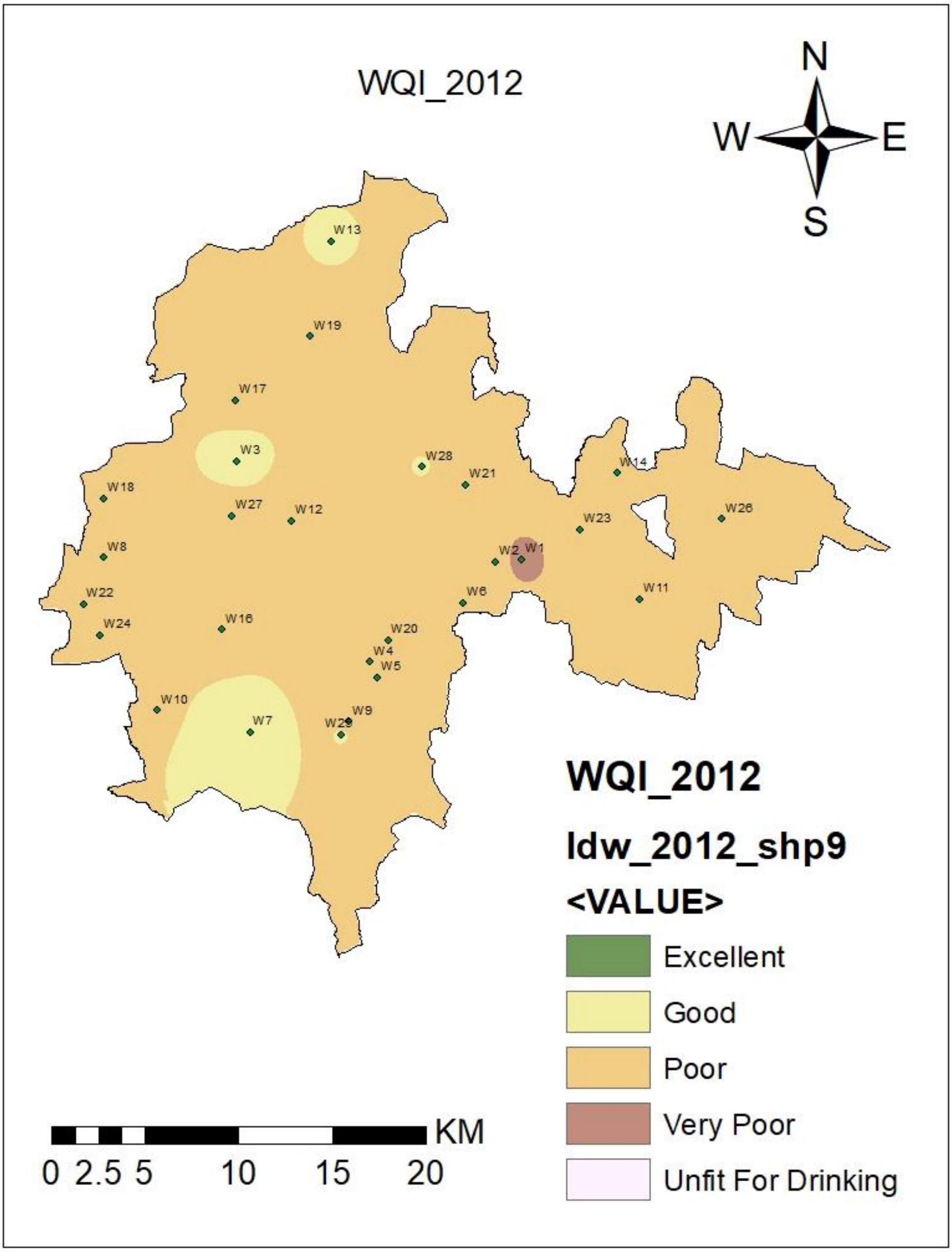


Figure 44Thematic map of WQI - 2012

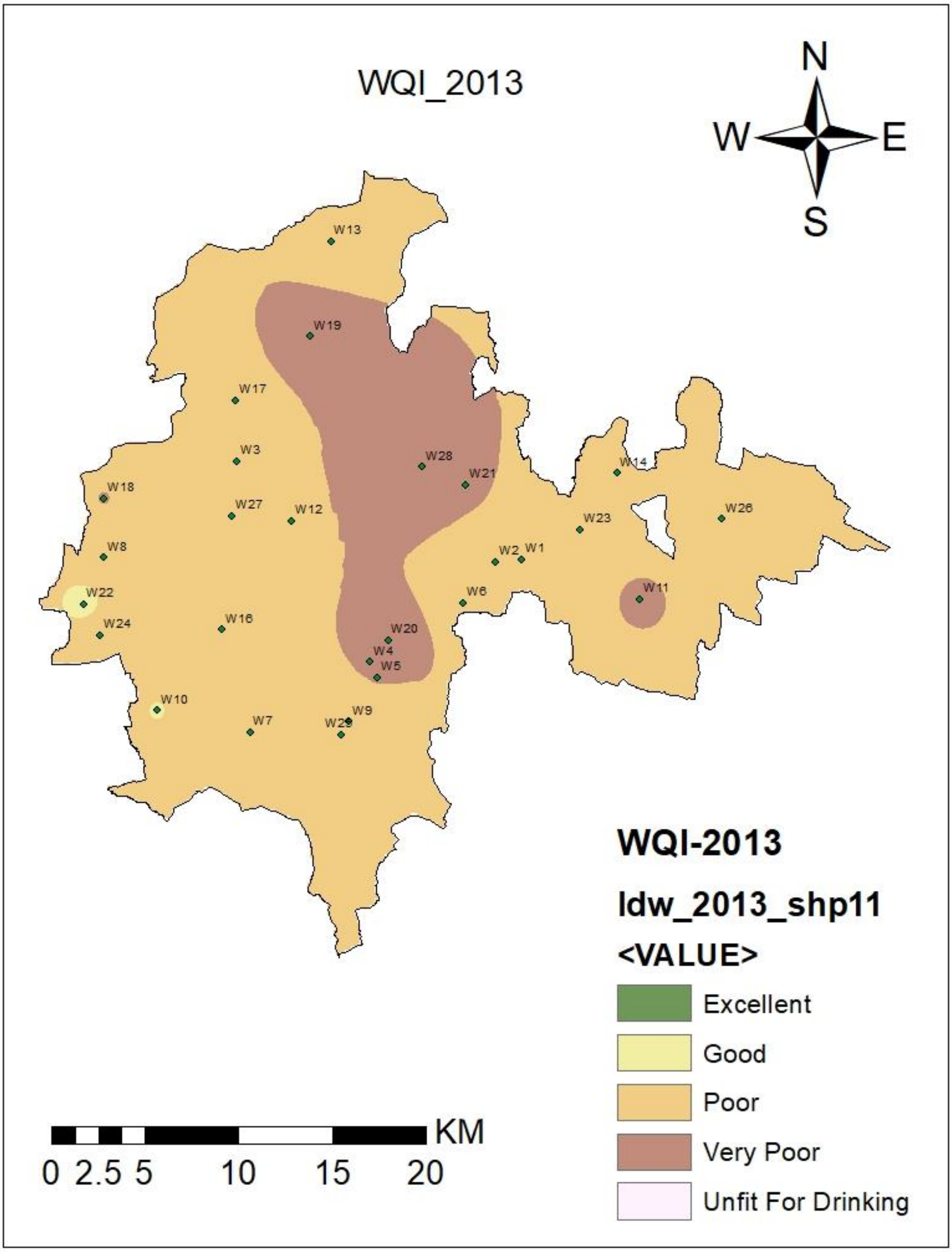


Figure 45Thematic map of WQI - 2013

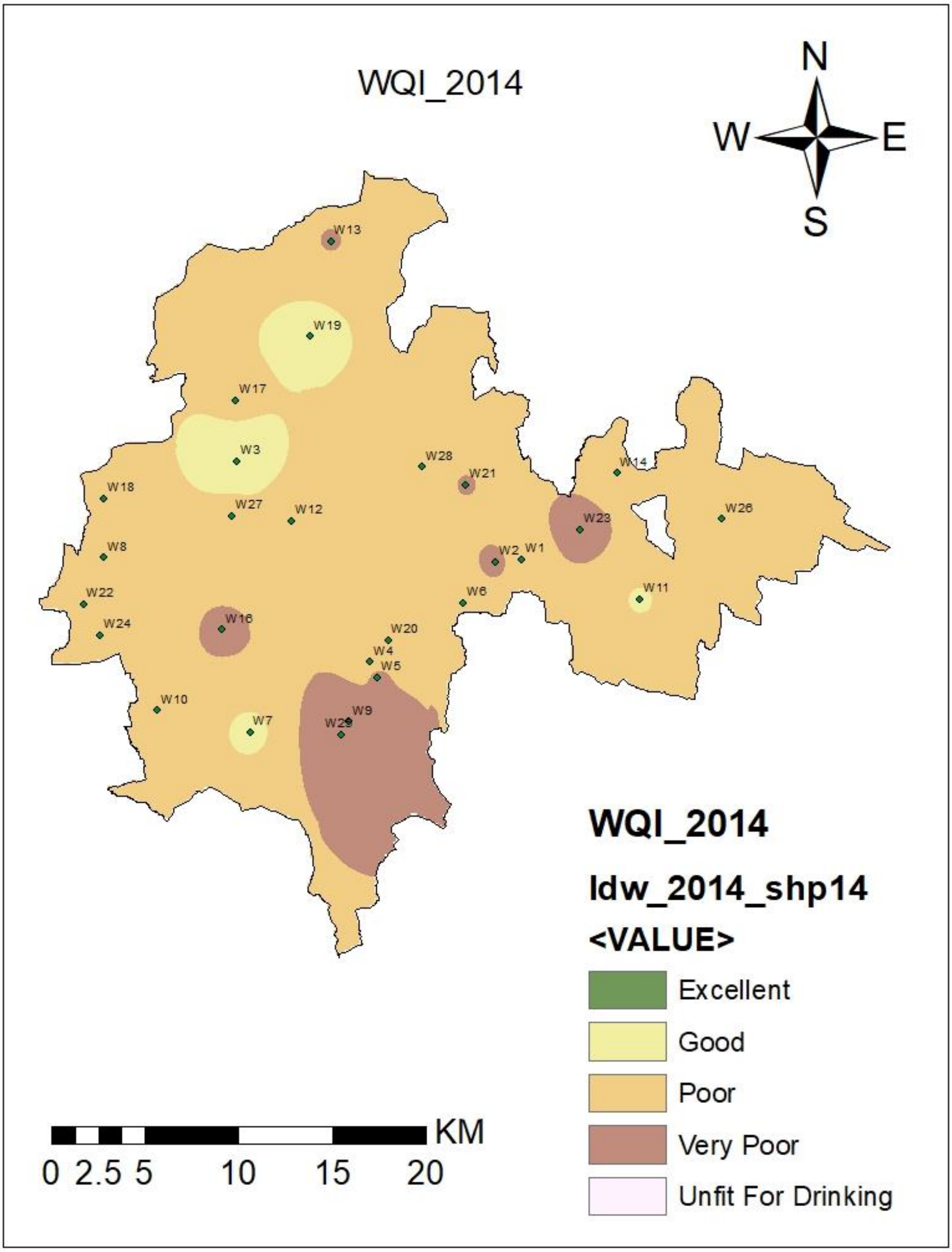


Figure 46Thematic map of WQI - 2014

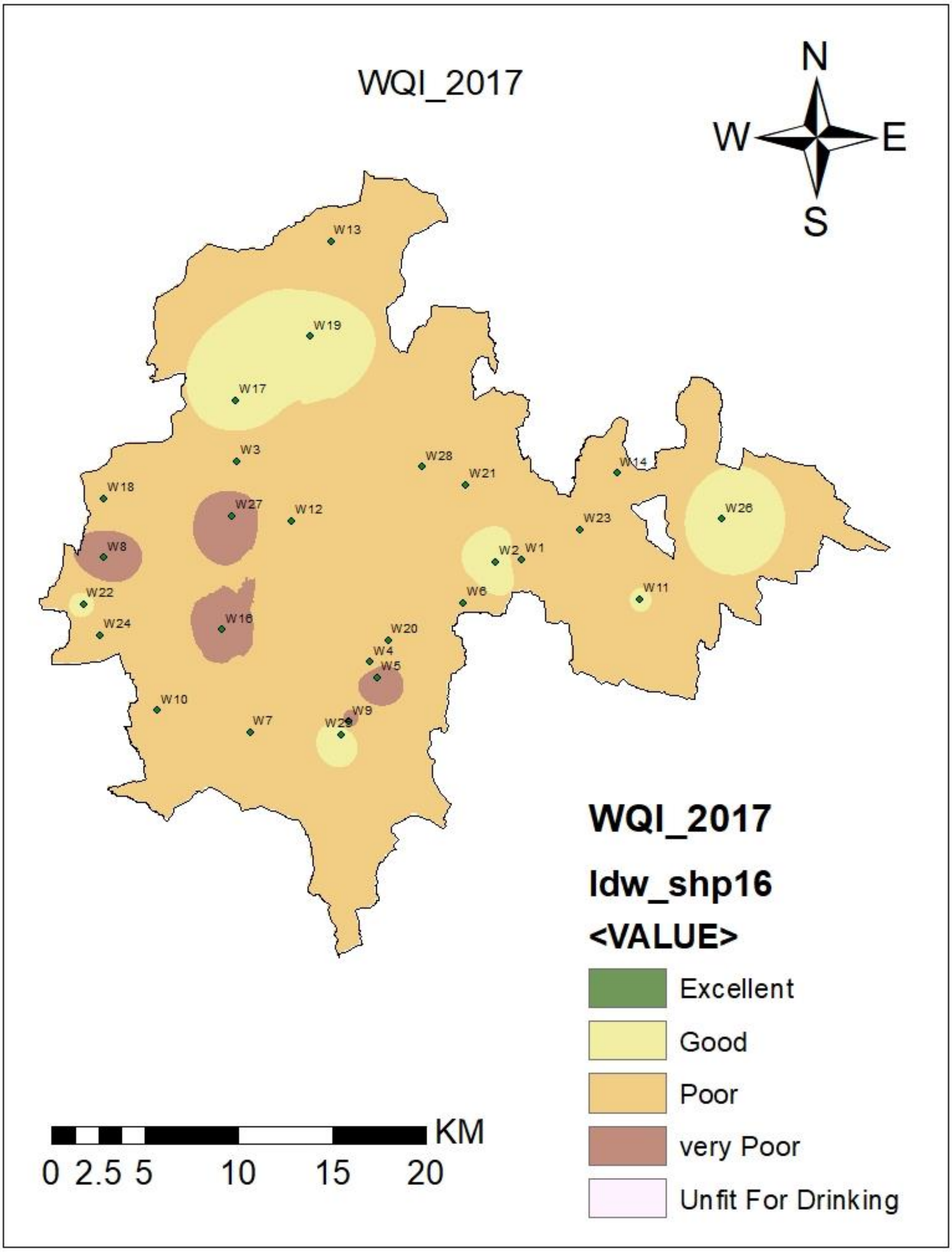


Figure 47Thematic map of WQI - 2017

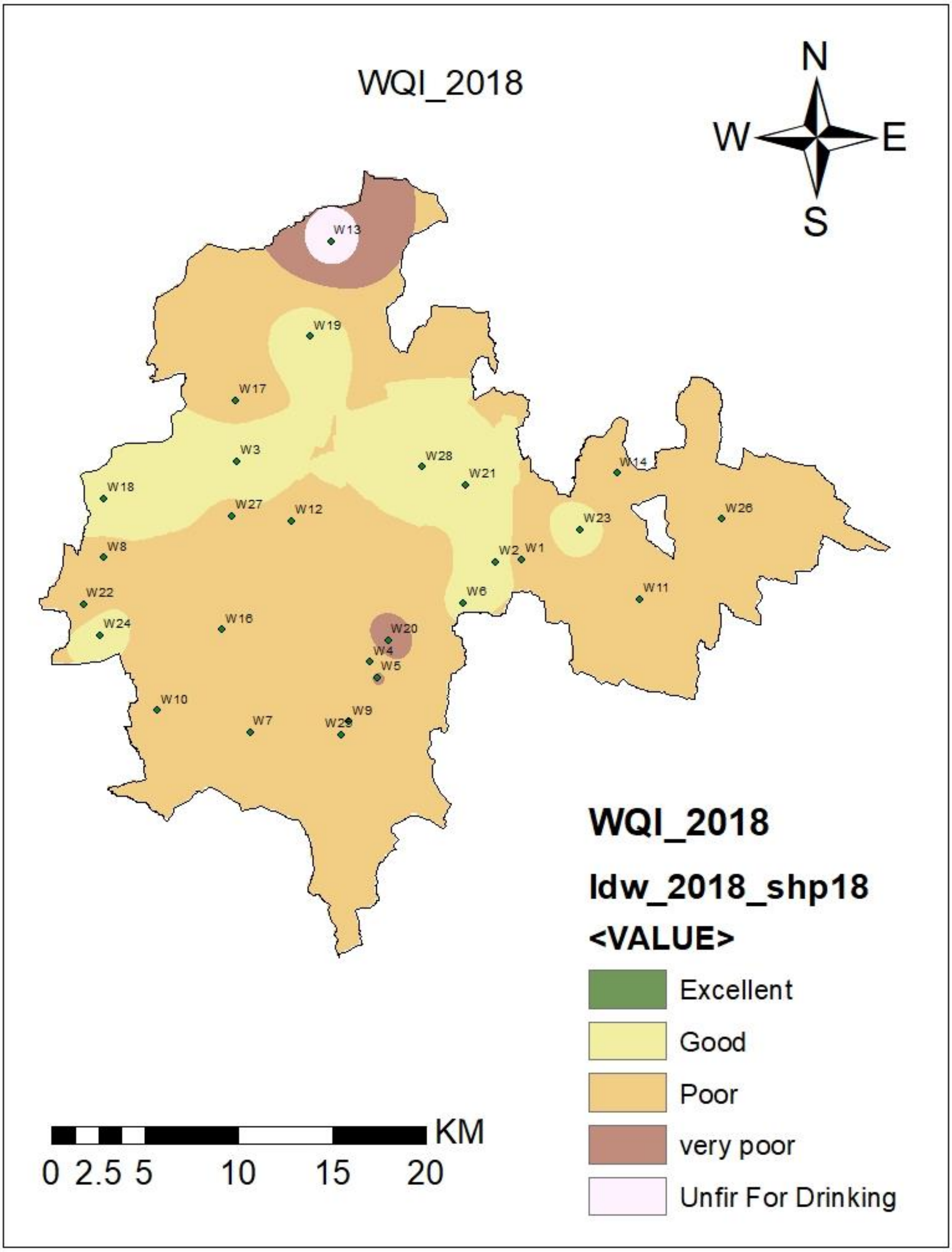


Figure 48Thematic map of WQI - 2018

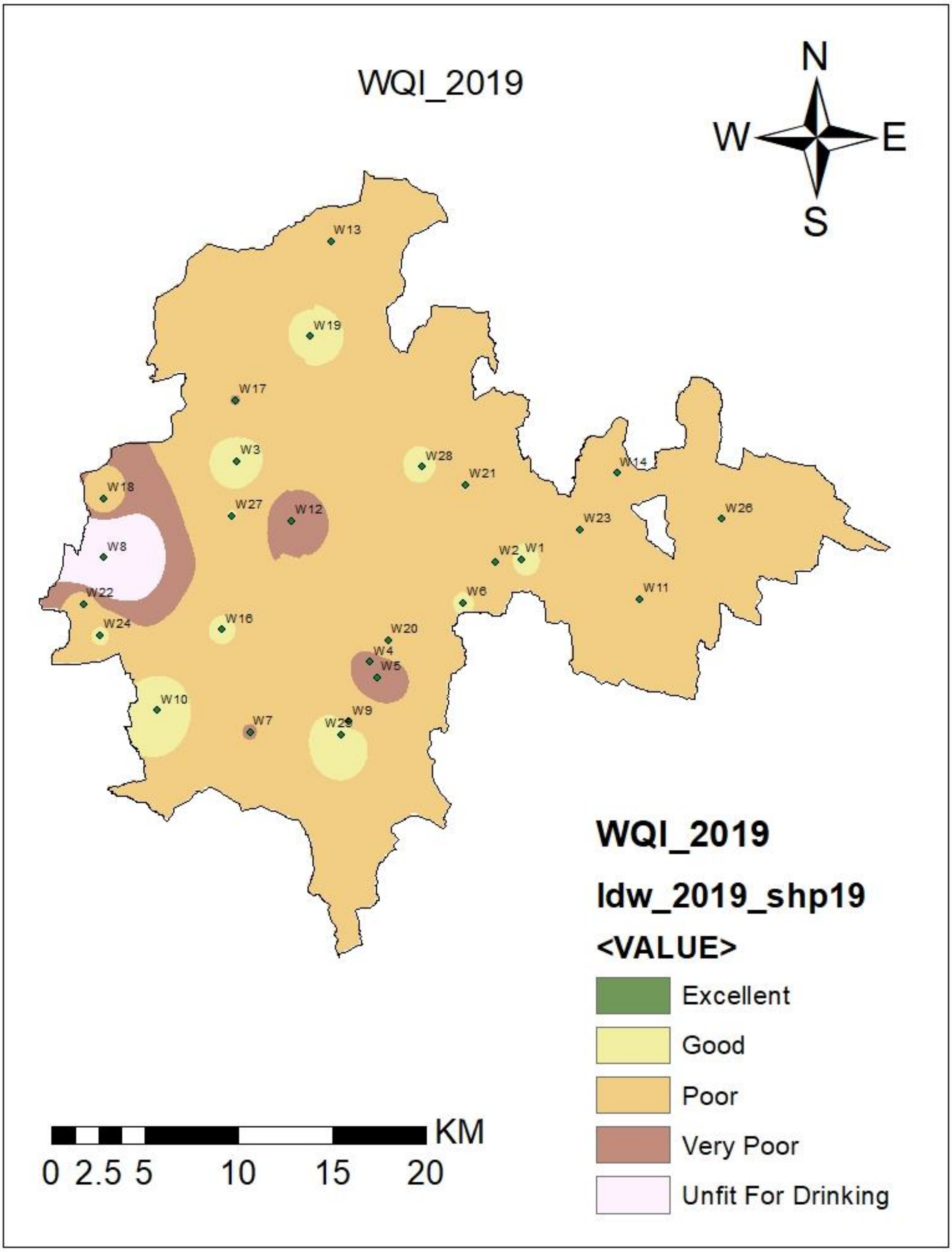


Figure 49Thematic map of WQI - 2019

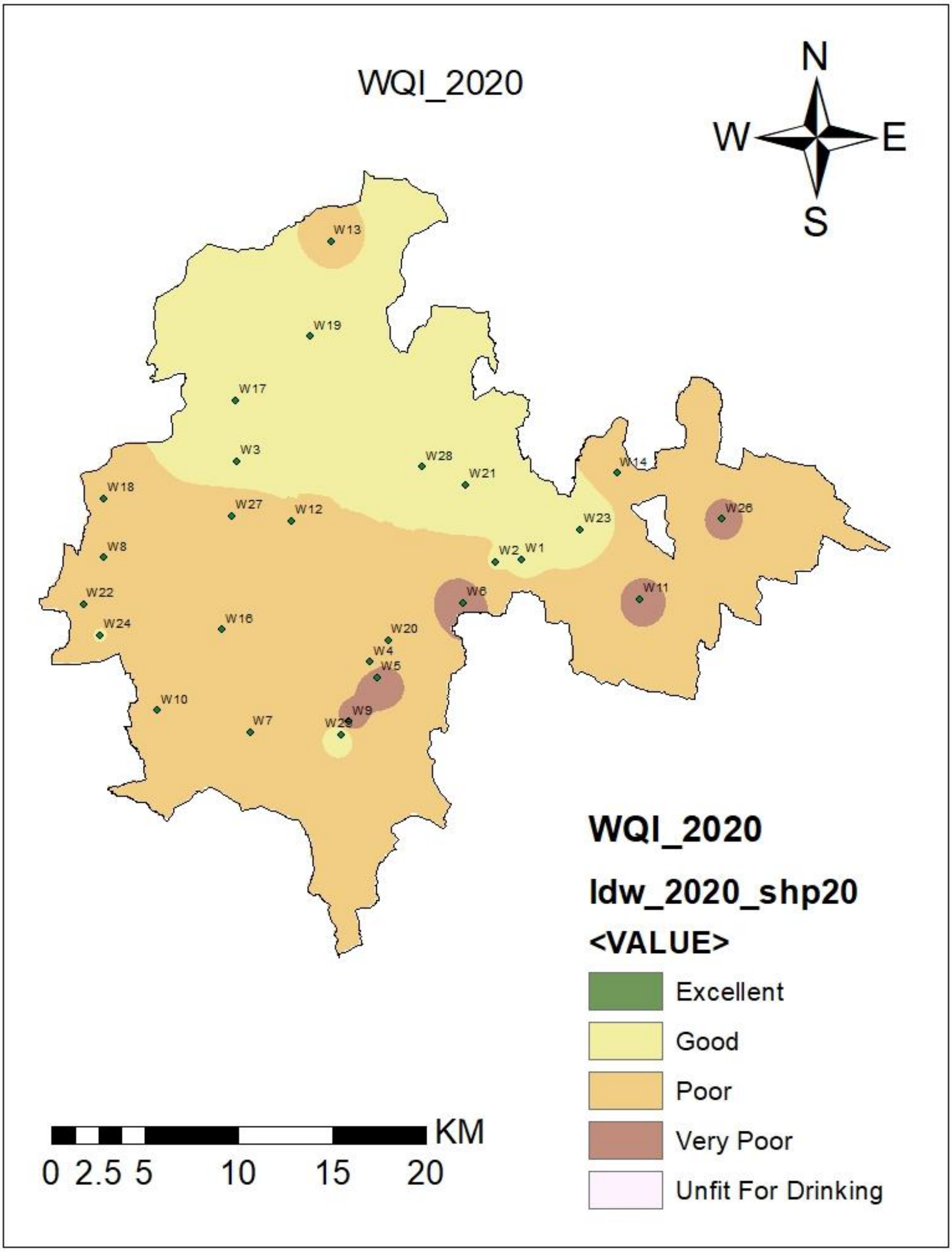


Figure 50Thematic map of WQI - 2020

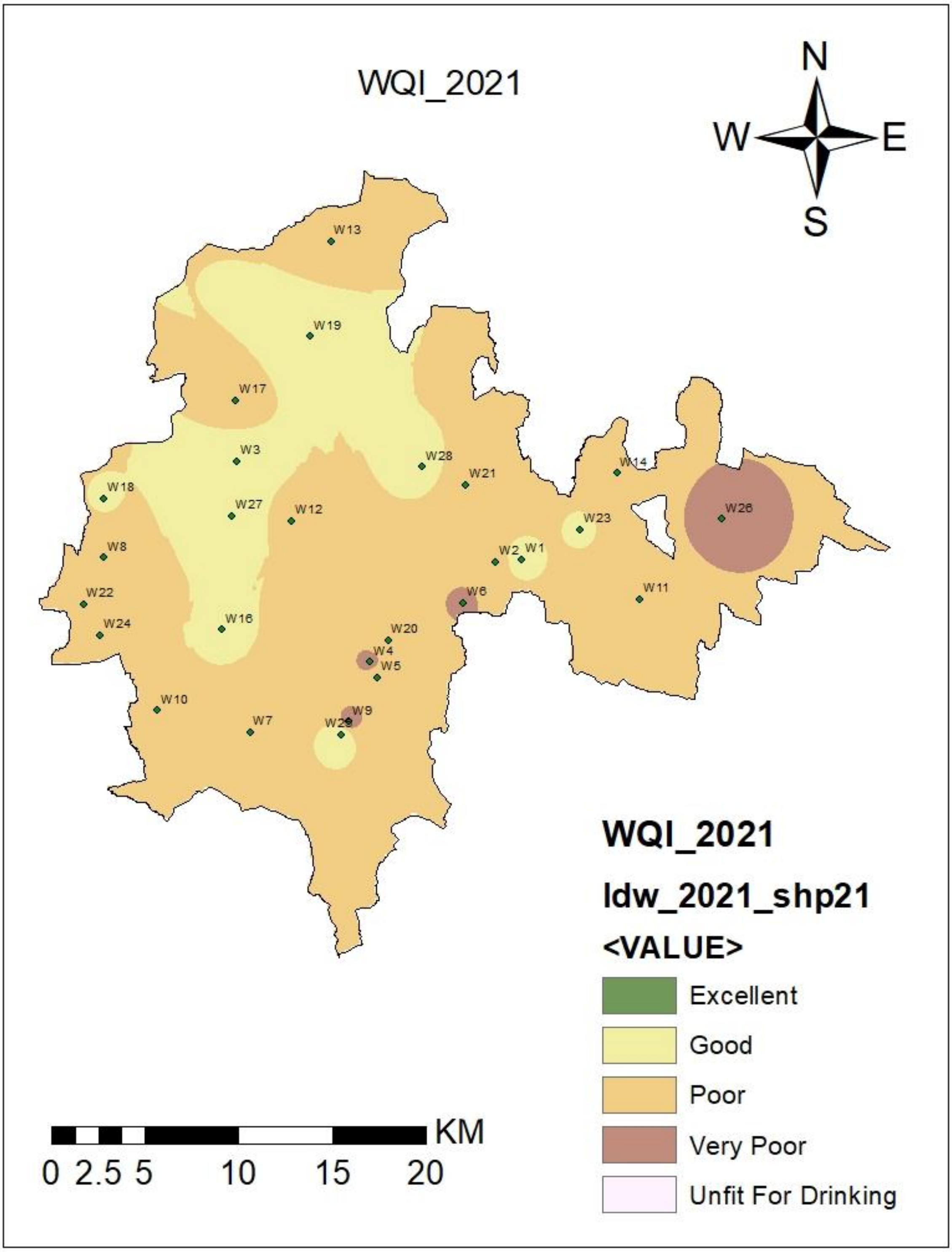


Figure 51Thematic map of WQI – 2021

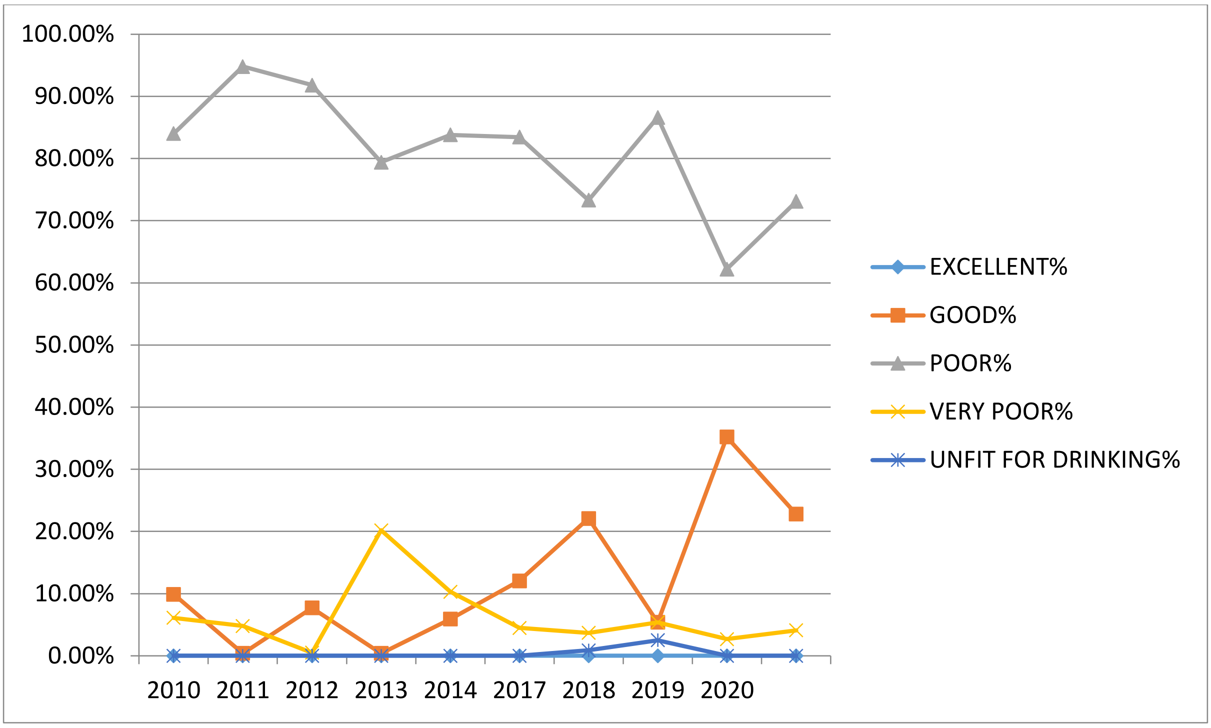


Figure 52 graph of year vs percentage

Table 30 percentages of classification

YEAR	EXCELLENT%	GOOD%	POOR%	VERY POOR%	UNFIT FOR DRINKING%
2010	0.00%	9.90%	84.00%	6.10%	0.00%
2011	0.00%	0.40%	94.80%	4.80%	0.00%
2012	0.00%	7.70%	91.80%	0.50%	0.00%
2013	0.00%	0.40%	79.40%	20.20%	0.00%
2014	0.00%	5.90%	83.80%	10.30%	0.00%
2017	0.01%	12.07%	83.43%	4.50%	0.00%
2018	0.00%	22.10%	73.30%	3.70%	0.90%
2019	0.00%	5.40%	86.60%	5.40%	2.50%
2020	0.00%	35.20%	62.20%	2.70%	0.00%
2021	0.00%	22.80%	73.10%	4.10%	0.00%

7.6 Conclusion

7.6.1 Overall Observation on Year Wise WQ Variation

1. In 2010, the Water Quality Index (WQI) data indicated that 9.90% of area fell into the good category ,while 84% were classified as poor and 6.10% as very poor.(Table 20)
2. The following year, 2011, saw a decrease in the percentage of area with good water quality to 0.40%, with 94.8% falling into the poor category and a staggering 4.80% categorized as very poor. (Table 21)
3. However, there was a slight improvement in 2012, with 7.70% of area classified as good, 91.8% as poor, and 0.50% as very poor.(Table 22)
4. Subsequently, in 2013, while the percentage of area with good water quality remained relatively low at 0.40%, the proportion categorized as very poor increased to 20.20%, with 79.4% falling under the poor category.(Table 23)
5. The year 2014 witnessed a similar trend, with 5.90% of area categorized as good, 83.8% as poor, and 10.30% as very poor.(Table 24)
6. Notably, 2017 marked a turning point, as 0.01% of area achieved excellent water quality, while 12.07% fell into the good category, signalling progress. However, challenges persisted, with 83.43% categorized as poor and 4.50% as very poor. (Table 25)
7. Subsequent years saw improvements, with 2018 recording a significant increase in area classified as good (22.10%) and 2019 has 5.40% in good category. **In 2020 and 2021, the percentage of area with good water quality remained relatively high at 35.2% and 22.8%, respectively.**(Table 26)
8. Out of total 10 years analysed for 8 years the study area seems to have water quality characterized in three categories viz good, poor and very poor except for year 2020. For all other remaining years majority of the study area is having ground water quality in a poor condition.
9. Very poor ground water quality is observed in varying proportion for different years being maximum percentage of area in year 2013. From 2018 onwards good quality area seems to have consistently increase except for year 2019.

10. **Maximum percentage of good quality water is found in 2020.** The central part of study area seems to have poor quality of ground water consistently for most of the year taken for study, exceptionally for year 2013 and 2019 the central part is found to have ground water quality very poor**. Water quality unfit for drinking is found in some part of north region in 2018 and west region in 2019.**
11. Overall, there has been a notable improvement in water quality over the years, particularly evident in the **increasing percentages of villages falling into the good category from 2018 onwards except 2019**.However, challenges persist, as indicated by the fluctuating percentages of villages categorized as **very poor, with peaks observed in 2013, 2014, and 2021**. **In 2019 high Nitrate(87.09 mg/l) and fluoride (5.01 mg/l) levels were detected leading to increased poor quality water. The very poor quality of water in 2013 is due to high TDS(1740 mg/l) and Hardness level(600 mg/l). In 2021 increased sulphate level(150 mg/l) was found**. **2014 also had high Hardness concentration of 600 mg/l.**The consistent presence of villages falling under the poor category underscores the need for sustained efforts in water quality management. Despite progress, there is still work to be done to ensure universal access to clean and safe drinking water for all communities.

7.6.2 Specific Conclusion

There Observed Wide Range of Variability in Concentration of Individual Where Quality Parameter Values During Study Period Of One Decade. WQI helps in getting idea of overall Water quality Variation in study area as it represents Composite or integrated effect of all Parameters.

It is observed That there is Overall improvement of quality in last 3 Years 2018, 2020 and 2021.

No Villages like Ambala, Zoz, & Ferkuva indicates Imorovement from Bodgam Shows Continuous improvement from overall poor quality during 2010-2018 then good to excellent.

Villages like Vasedi, Mithibor Shows degradasion of water quality from poor to very poor or overall poor during fars decade.

The Variation in Values may be change to influence of factors like Rainfall, Pumping Waste Disposal which is Varying time to time Crusing Variation in individual parameter Values.

1. The efforts of local and central government body of GWRDC(Ground Water Resources Development Corporation) and CGWB(Central Ground Water Board) are observed, as the **increasing trend of 'Good water' and decreasing trend of 'Poor water' is clearly observed in last few years, specifically from 2019 to 2021.** The reason are introduction of Artificial recharge structures like recharge shafts and Defunct Tube well installed in study area. However Overly Nitrate Concentration is With in Permissible Limit.

2. The higher concentrations of Nitrate in groundwater, in observed Orsang River especially, Sukhi, Bharaj. The main causes of Nitrate contribution in ground water is from sewage, waste disposal, nitrate fertilizer and decaying of organic matter in this study area.

3. High Fluoride in groundwater of Chhota Udaipur Taluka is from geogenic sources by weathering of metasediments in Hard rock terrain. The concentration of fluoride in shallow aquifer reaches 5.01 mg/l (Pelsanda, Chhota Udaipur Taluka).

4. Higher fluoride concentration is observed in isolated pockets of study area. Ground water in such areas should be used after blending with surface water. In areas where ground water has higher concentration of Nitrate is observed, necessary sanitation measures should be adopted.

5. The eastern portion of the Chhota Udaipur taluka is hilly terrain with several ridges, plateaus and isolated relict hills have elevation in range of 150 to 481 m amsl. The slope of study region from North-East to South-West, is responsible virtually by having the poor and very poor zones at south-west zone. This phenomenon has been verified by observing the year wise spatial distribution maps of WQI. (2010-2021)

7.6.3 Conclusion On Model

1. Current progress in the management of water resources has expanded the demands for modelling techniques that can provide safe, effective and exact nonlinear dynamics of groundwater quality representation.
2. Restricted water quality information and the significant expense of water quality checking frequently cause major issues for process based modelling strategies.
3. In this project work, **Python software** was used to predict the groundwater quality parameters and groundwater quality criterion using ANN. Data were collected from different locations of Chhota Udaipur taluka for training the neural network. By giving the parameters like pH, Nitrate, Fluoride, Sulphate, Calcium, Magnesium, Hardness, Chloride, TDS, Alkalinity as input, the predicted values show a very close resemblance to the reference value and **high R^2value were also obtained**.
4. The model exhibited impressive statistical performance, including a Mean Squared Error (MSE) of 0.0244, Root Mean Squared Error (RMSE) of approximately 0.1562, and an R-squared (R^2) score of approximately 0.9999. Additionally, cross-validation scores, averaging at 0.9991, demonstrated the model's consistency and reliability across validation sets.
5. Thus, the model is exhibiting high prediction efficiency. Using the Artificial Neural Network modelling, we were able to classify (7.3) whether the quality of water was excellent, good, poor, very poor and unfit for drinking and also to predict WQI with very high accuracy.
6. Findings of an observation from ANN model is correlated with other analysis for realistic and effective characterization of area with reference to groundwater quality of that area.
7. In essence, even though Artificial Neural Networks (ANN) have their limits, they're still really helpful for accurately predicting groundwater quality. This shows how valuable they are in helping us manage water resources effectively.

7.7 (a) General comparison between traditional methods and ANN method:

Traditional Methods:

Traditionally popularly known approaches for the purpose are Water quality index method (i.e. Empirical formula based approach), Indicator kriging method, Bayesian belief networks, Chemical indices and GIS mapping etc. But are having following limitations in general.

Limitations: Linear assumption, complexity handling, subjective classification, lack of adaptability, sensitivity to noise, limited spatial resolution, impact of outliers, data distribution assumptions, incomprehensive assessment, data quality concerns, and inefficiency with large datasets.

Artificial Neural Networks (ANNs):

Above described limitations of traditional approaches can be addressed reasonably using **ANN** based approach, **having following advantages, despite its limitations**.

Limitations: **i)** It requires high quality of data for training. If the data set is limited or contains errors, then it can lead to inaccurate WQI calculations.

ii) If the data is not heterogeneous, ANN model performs well on the training data set, but fails to generalize the unseen data. This can result in inaccurate WQI assessments.

iii) Imbalanced datasets, where certain water quality categories are under-represented, can pose challenges for ANNs in learning the minority classes effectively. This can impact the accuracy of WQI calculations.

Advantages: It can handle, non-linearity in modeling, can be useful in pattern recognition, superior in data complexity handling, prediction accuracy can be increased, moreover features like adaptability, robustness to noise, efficient interpolation, spatial consideration, outlier handling, flexibility in data distribution, comprehensive assessment, adaptive to changes, and efficiency with large datasets make it useful tool in modern scientific investigations.

(b) Validation of the ANN approach based on the traditional method(for WQI):

1) The output as displayed on page numbers 58 to 69, clearly suggests that using

   ANN (after sufficient training of model) we get the accuracy of individual output for WQI with difference of maximum

   |(WQI by traditional method) - (WQI by ANN approach)| = 0.3.

2) The model exhibited impressive statistical performance, including

   a Mean Squared Error (MSE) of 0.0244,

   Root Mean Squared Error (RMSE) of approximately 0.1562, and

   R-squared (R^2) score of approximately 0.9999.

   Additionally, cross-validation scores, averaging at 0.9991, demonstrated the model's consistency and reliability across validation sets.

These points clearly indicates that ANN works successfully and can replace the traditional approach easily and effectively in all future calculations for required purposes, in particular it is reliable to use ANN for future prediction index also.

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