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GIS-Based Modeling Approach for Analysis of Groundwater Quality in the Dry Zone of Sri Lanka

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ABSTRACT

Groundwater is a vital resource in Sri Lanka's dry zone, where limited rainfall and surface water make communities heavily dependent on groundwater for daily needs. This study assesses groundwater quality in the region using a GIS-based modeling approach that integrates the Analytic Hierarchy Process (AHP) and Multi-Criteria Decision Analysis (MCDA). Six key groundwater quality parameters, pH, Electrical Conductivity (EC), Total Dissolved Solids (TDS), Alkalinity, Hardness, and Fluoride, were used to develop thematic layers via the Inverse Distance Weighted (IDW) interpolation method in ArcGIS 10.4. These layers were classified based on World Health Organization (WHO) drinking water standards. Using MCDA, proportional weights were assigned to each parameter and corresponding feature class. The results reveal that groundwater quality is suboptimal in parts of the study area: 16.75% of areas fall under moderate quality, while 4.37% are categorized as unsuitable water quality. These statistical methods were employed to enhance understanding of the interrelationships among water quality parameters. Multivariate statistical techniques, Principal Component Analysis (PCA), K-means Cluster Analysis, and Correlation Matrix analysis were employed to support the analysis further. A notable negative correlation was found between EC and TDS with pH ($r = -0.14$), while alkalinity and hardness exhibited a strong positive correlation ($r = 0.98$). These findings underscore the effectiveness of geospatial methods over traditional techniques in assessing spatial variations in water quality. The results provide valuable insights for planners and policymakers to improve water resource management in Sri Lanka's dry zone.

1 Introduction

Groundwater is stored in aquifers, which are permeable geological formations of rock, sand, and gravel capable of holding substantial amounts of water. It infiltrates the ground primarily through rainfall and snowmelt, influenced by various physical factors (UN, 2022). Groundwater supplies about half, or 25%, of the water volume for domestic use, including drinking water, for the vast majority of the global rural population that is not supplied with water through public or private supply systems (UN, 2022). The expansion in population and economic activity necessitates the acquisition of more

water resources in locations with such extreme weather conditions (Abdelkareem and Abdalla, 2022; Abdelkareem et al., 2012; Zhu and Abdelkareem, 2021). Nowadays, researchers commonly utilize geospatial technologies in environmental planning and natural resource management due to their ability to identify, analyze, and prioritize complex factors for informed decision-making (Akbar et al., 2022; Jayasinghe and Withanage, 2020; Naz et al., 2023; Nuwanka and Withanage, 2024; Withanage et al., 2023). In groundwater quality studies, Geospatial methods are particularly valuable for mapping spatial variations, identifying contamination hotspots, and integrating diverse datasets such as hydrology, geology, and land use. Geographic Information Systems (GIS) techniques were employed to create integrated maps of groundwater contamination and health risks, and to thoroughly assess the spatial relationships (Karnena and Saritha, 2019; Kavurmacı and Karakuş, 2020). This integration supports Multi-Criteria Decision Making (MCDM) and prioritization, especially when combined with models like the Analytic Hierarchy Process (AHP) and Multi-Criteria Decision Analysis (MCDA). Specifically, the interpolation techniques

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in the geospatial environment were employed to illustrate spatial variations in groundwater quality across different sampling points (Mitas and Mitasova, 1999). The Inverse Distance Weighted (IDW) method can handle non-normally distributed parameters, and can be used to infer water quality for the entire study area (Chen and Liu, 2012). Hence, various researchers have assessed groundwater geochemistry using methods like multivariate statistical analysis to evaluate physicochemical properties, followed by Hierarchical Cluster Analysis (HCA) and Principal Component Analysis (PCA) to group samples (Boateng et al., 2016; Bodrud-Doza et al., 2016; Gulgundi and Shetty, 2016; Rajput and Goyal, 2017). Additionally, correlation matrix analysis is used to examine the relationships and strengths between different water quality parameters (Bodrud-Doza et al., 2016; Krishna Kumar et al., 2015). Moreover, Wimalseena and Withanage (2021) investigated the spatial variation of drinking well water quality in the Buttala area, Sri Lanka, using parameters such as pH, turbidity, electrical conductivity (EC), fluoride, and nitrate. Their findings revealed that 11.2% of the wells in the study area contained water classified as highly suitable for consumption. Thus, De Silva (2013) studied drinking water quality in five districts in Sri Lanka (Jaffna, Vavuniya, Anuradhapura, Kurunegala, and Hambantota) and found that heavy metals like cadmium and arsenic were linked to kidney disease development. These studies underscore the growing concern over groundwater safety in various climatic regions of the country, emphasizing the need for spatially integrated assessments like the one undertaken in this research. On the other hand, in a global context, in India, Singha et al. (2015) conducted a study to assess the quality of groundwater using GIS in the state of Chhattisgarh, India, based on 77 villages, and water quality parameters such as pH value, chloride calcium, and nitrate hardness etc. Hence, a mathematical method called the GIS-based Water Quality Index (WQI) converts a significant quantity of data on water quality into a single, comparable result (Abbasi and Abbasi, 2012; Sánchez et al., 2007). WQI is an effective method for assessing the quality of groundwater (Bodrud-Doza et al., 2016). The WQI is derived by choosing significant water quality parameters, weighing them based on their influence on health, measuring the parameters' concentrations, and combining them using a rating system (Liu et al., 2024). For this study area, groundwater, a WQI was calculated based on six physicochemical indicators: pH, EC, Total Dissolved Solids (TDS), Alkalinity, Hardness, and Fluoride. When combined with GIS-based thematic mapping, AHP, and statistical tools like PCA, Cluster, and Correlation Matrix analysis, this integrated approach enhances the reliability and interpretability of groundwater quality patterns. In Sri Lanka's dry zone, groundwater plays a critical role in sustaining rural communities due to limited and erratic surface water availability. Agricultural practices, especially in rural areas, are often intensified to meet food demands, leading to potential environmental concerns. The majority of people in this study area rely on well water for their daily needs. Due to widespread Chena cultivation, excessive use of agrochemicals may leach into the groundwater, leading to a decline in water quality. Such a detailed spatial

analysis of groundwater quality has not been previously conducted in this region. This research addresses that critical gap by combining GIS with AHP and MCDA techniques, methods globally recognized for their effectiveness in environmental assessment, yet underutilized in this region. Understanding the quality of well water used for domestic purposes is crucial. Therefore, this study aims to contribute to advancing GIS technology and its strategic applications in groundwater quality assessment. The primary objective is to develop a consistent geospatial database of groundwater quality levels for the selected study area in the Mihinthale Divisional Secretariat Division (DSD). Specifically, the study intends to: (i) identify the spatial distribution of key groundwater quality parameters within the selected Grama Niladhari Divisions (GNDs) of the MDS, and (ii) apply statistical methods such as cluster analysis, PCA, and correlation analysis to interpret the data and recommend actions to ensure the sustainability of groundwater resources.

2 Materials and Methods

2.1 Study Area

The study area, covering 55.16 km² within the 211.06 km² MDS of 25 GNDs, lies between 8° 16' - 8° 23' N and 80° 30' - 80° 35' E (Fig. 1), with a population of 35,898 (MDS, 2022). The area has a predominantly dry climate, especially in February, March, June, July, August, and September, with rainfall mainly occurring during the Northeast Monsoon, and agriculture is the primary livelihood. Farming is carried out in the Yala-Maha seasons, and in addition to paddy cultivation, other crops such as maize, cowpea, green gram, and banana are cultivated.

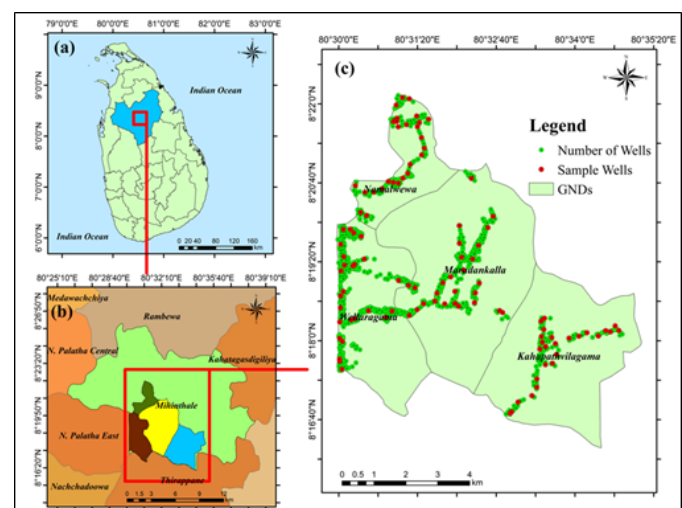


Fig. 1: Geographical location of the study area: (a) Location of Sri Lanka in the Indian Ocean; (b) Location of the Mihinthale DSD and GNDs; (c) Total number of wells and sample wells.

Table 1: Variability of the Water Quality Parameters of the study area.

Name of the GND / Sample No	X Coordinate	Y coordinate	Water Source	Groundwater Quality Parameters					
				pH	EC (μS/cm)	TDS (mg/L)	Alkalinity (mg/L)	Hardness (mg/L)	Fluoride (mg/L)
Wellaragama									
well378	8.330344°	80.504251°	DW	7.10	1020	653	356	372	0.83
well320	8.294241°	80.500304°	DW	7.01	916	586	296	288	1.25
well201	8.305891°	80.503501°	DW	7.46	522	334	188	172	1.10
well88	8.321048°	80.504054°	DP	6.66	360	180			
well74	8.322971°	80.507216°	DW	7.14	710	350			
well179	8.309282°	80.500512°	DW	7.1	1310	650			
well09	8.331300°	80.501304°	DW	6.61	1270	630			
well48	8.323732°	80.501200°	DW	7.13	550	270			
well68	8.321471°	80.504483°	DW	6.69	950	470			
well279	8.308340°	80.515061°	DW	7.09	1170	580			
well120	8.315615°	80.519738°	DW	7.06	600	290			
well192	8.305301°	80.500323°	DW	7.27	990	490			
well124	8.319626°	80.500681°	DW	7.2	840	420			
well163	8.312551°	80.500557°	DW	7.51	620	300			
well357	8.329353°	80.506411°	DW	7.39	870	430			
well222	8.308419°	80.508425°	DW	7.31	820	400			
well336	8.292002°	80.500902°	DP	6.6	800	400			
well28	8.327125°	80.500591°	DW	7.43	330	160			
well152	8.313878°	80.501307°	DW	6.94	670	330			
well345	8.331362°	80.503275°	DW	6.69	890	440			
well203	8.306203°	80.504541°	DW	7.43	540	260			
well318	8.294865°	80.500270°	DP	6.9	1310	650			
well288	8.300665°	80.500274°	DP	7.62	1250	620			
Maradankalla									
well390	8.307109°	80.519899°	DW	7.90	553	354	164	172	1.21
well503	8.322973°	80.537784°	DP	7.01	1929	1235	560	512	0.96
well554	8.335025°	80.543574°	DW	7.42	1379	883	424	396	1.51
well563	8.345692°	80.537457°	DW	7.23	1465	938	404	400	0.72
well607	8.307944°	80.546260°	DW	7.49	489	313	172	164	0.48
well571	8.310497°	80.532851°	DP	7.43	965	618	348	324	1.67
well479	8.313891°	80.532814°	DP	6.34	1060	520			
well606	8.308489°	80.545413°	DW	7.58	840	410			
well418	8.313383°	80.527756°	DW	7.3	1610	800			
well406	8.310454°	80.523934°	DW	7.8	1060	520			
well588	8.310719°	80.538335°	DW	7.05	1510	750			
well400	8.308770°	80.522132°	DW	7.16	910	450			
well544	8.331835°	80.542126°	DW	7.74	1030	510			
well489	8.319891°	80.535254°	DW	7	1380	690			
well615	8.314907°	80.521565°	DW	7.29	880	430			
well594	8.313499°	80.538572°	DW	7.28	1620	800			
well497	8.323484°	80.534689°	DP	6.74	1660	830			

well602	8.316224°	80.539665°	DW	7.23	2770	1380			
well412	8.311141°	80.527157°	DW	7.7	1660	830			
well575	8.309698°	80.533878°	DP	7.01	1490	740			
well429	8.316324°	80.529439°	DW	7.27	1440	720			
well456	8.327415°	80.534089°	DW	7.34	1910	950			
well435	8.317989°	80.531628°	DW	7.54	1360	670			
well464	8.332393°	80.534036°	DW	7.45	1050	520			
well512	8.326860°	80.539488°	DP	7.02	1240	620			
well469	8.310369°	80.529940°	DW	6.8	1280	630			
Namalwewa									
well760	8.335264°	80.507897°	DW	7.46	780	499	256	264	0.90
well772	8.341776°	80.507474°	DP	7.23	824	527	288	272	0.79
well806	8.344579°	80.515397°	DW	6.97	742	475	240	232	0.80
well846	8.354182°	80.524184°	DW	7.65	918	588	312	296	1.88
well860	8.361473°	80.522780°	DW	7.47	795	509	256	268	0.70
well915	8.366344°	80.516238°	DP	7.16	1155	739	324	356	1.11
well812	8.344362°	80.516896°	DW	6.54	610	300			
well888	8.361744°	80.516377°	DW	7.26	1500	750			
well832	8.349632°	80.520198°	DW	6.73	430	210			
well886	8.362631°	80.516524°	DP	6.96	1370	680			
well907	8.368111°	80.519939°	DP	6.73	920	460			
well780	8.341831°	80.509847°	DW	6.57	900	450			
well855	8.360224°	80.522233°	DW	6.38	290	140			
well872	8.363244°	80.522020°	DW	7.19	1290	640			
well788	8.342793°	80.512286°	DP	7.06	620	300			
well909	8.368491°	80.518039°	DW	6.92	580	280			
well829	8.347113°	80.519482°	DW	7.13	970	480			
well880	8.360852°	80.519141°	DP	7.28	1100	550			
well895	8.361725°	80.515401°	DP	6.8	2570	1280			
well794	8.344821°	80.514010°	DW	6.68	520	260			
well863	8.362362°	80.525371°	DP	6.64	1020	510			
well767	8.343662°	80.504713°	DP	7.04	1210	600			
well752	8.336134°	80.506238°	DW	7.05	700	350			
well838	8.352305°	80.523428°	DW	6.27	1220	600			
well852	8.357195°	80.523395°	DW	7.22	1330	660			
well890	8.360221°	80.516809°	DW	6.61	540	260			
well819	8.345762°	80.518146°	DP	6.69	700	340			
Kahapathvilagama									
well630	8.279592°	80.548410°	DW	7.12	760	486	212	196	1.50
well645	8.286888°	80.555900°	DW	7.65	582	372	188	172	0.58
well675	8.297623°	80.556765°	DW	7.91	1219	780	340	328	1.63
well705	8.306325°	80.558086°	DP	7.81	1123	719	336	344	1.87
well727	8.302259°	80.570077°	DW	7.57	1060	678	312	300	0.81
well743	8.304180°	80.578049°	DW	7.63	1345	861	396	372	1.43
well638	8.282721°	80.550614°	DW	7.01	1170	580			
well666	8.296151°	80.561476°	DW	6.97	1130	560			
well717	8.300734°	80.565018°	DW	7.69	1340	660			

well669	8.299216°	80.561162°	DW	7.02	1130	560
well693	8.301178°	80.557205°	DP	6.63	870	430
well736	8.302842°	80.575360°	DW	6.95	2550	1270
well688	8.299582°	80.557489°	DP	6.91	1110	550
well672	8.298349°	80.558441°	DW	7.28	1210	600
well709	8.300940°	80.560119°	DW	7.01	2550	1270
well660	8.293275°	80.558343°	DW	7.08	1370	680
well702	8.305500°	80.557075°	DW	7.48	1050	520
well642	8.284540°	80.554512°	DW	7.1	1030	510
well730	8.301335°	80.573277°	DW	6.84	760	370
well739	8.302527°	80.576718°	DP	7.37	1550	770
well657	8.291662°	8.291662°	DW	7.23	1070	530
well663	8.293643°	80.560345°	DW	7.22	1700	840
well631	8.279989°	80.548796°	DP	7.06	610	300
well696	8.303167°	80.557867°	DW	7.18	630	310
well650	8.289223°	80.555928°	DW	7.12	1400	690
well745	8.302879°	80.579062°	DW	6.94	700	340
well722	8.301283°	80.567816°	DW	8.04	750	370

*Note: DP – Domestic Plumbing; DW – Domestic Wells

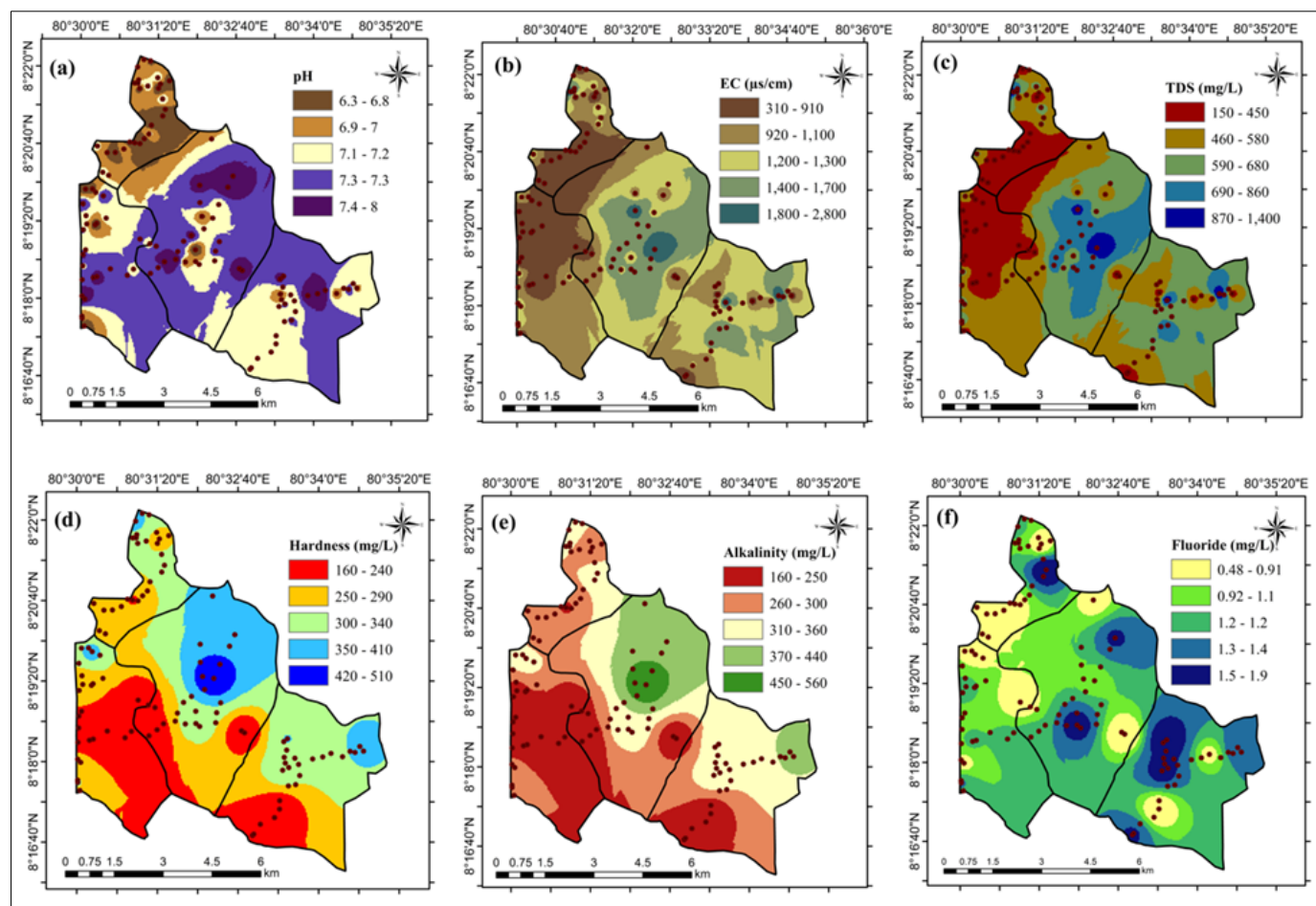


Fig. 2: Geospatial variation of groundwater quality parameters, (a) pH, (b) EC, (c) TDS, (d) Hardness, (e) Alkalinity, (f) Fluoride.

Typically, water springs are located at depths ranging from approximately 8.5 to 10.7 m (from the field survey conducted in 2022, and MDS, Report 2022). The study area contains several major tanks, which have a high water storage capacity. Four soil types are identified in the study area as: Reddish Brown Earth and Low Humic Gley, Reddish Brown Earth with a high amount of gravel, Red-Yellow Podzolic, and Alluvial Soil (D-Irrigation, 1988; Mapa, 2020). The composition and location of geological rocks are also related to the change in the chemical composition of groundwater. The main rock types that can be identified in the study area are: Charnockitic Gneiss, Granitic Gneiss (GSMB, 1992). Granitic Gneiss rock type is observed in the northern part of the Kahapatvilagama area. As mentioned in the 'Introduction' section, six water quality parameters were analyzed, and their spatial distribution is illustrated in Fig. 2. Per Table 1, the pH levels of domestic well water range from 6.3 to 8.5, generally aligning with the Sri Lanka Standards Institute (SLSI) guidelines of 6.5-8.5. EC values range from 310 to 2800 $\mu\text{S}/\text{cm}$, indicating both low and very high salinity levels. TDS ranges between 150–1400 mg/l, exceeding the recommended SLSI limit of 500 mg/l in several areas. Alkalinity ranges from 160 to 560 mg/l, above the ideal limit of 200 mg/l. Water hardness varies from 160 to 510 mg/l, indicating moderately suitable to high levels, exceeding the 250 mg/l threshold in some locations. Fluoride levels range from 0.48 to 1.9 mg/l, with several wells surpassing the recommended 1.0 mg/l, suggesting potential health concerns due to long-term exposure. Given these physical environmental and socio-economic conditions, it is crucial to understand the spatial distribution and quality of groundwater in the study area to ensure sustainable water use.

2.2 Nature of Data

Based on previous literature, the existing situation, issues, and potential for managing and improving groundwater quality in Sri Lanka were examined and addressed in this study. In this research, spatial data related to the quality parameters of drinking water were collected from well samples across four GNDs. Based on the Global Positioning System (GPS) coordinates and the corresponding water sample results, spatial maps were created to illustrate water quality distribution in the study area. In the initial stage of the study, a total of 815 domestic wells were identified across the study area through field observation before sample collection (Fig. 1(c) and Table 1). In the second stage, a random sampling method was employed to ensure adequate spatial coverage across the selected GNDs. A total of 107 wells were sampled across the four GNDs. Water samples were collected as follows: 27 each from Kahapathvilagama, Namalwewa, and Wellaragama GNDs, and 26 samples from Maradankalla GND. The GPS coordinates of the sampled wells were recorded using the 'CT Droid' mobile application in Sri Lanka. All these processes are shown in the flow chart below (Fig. 3).

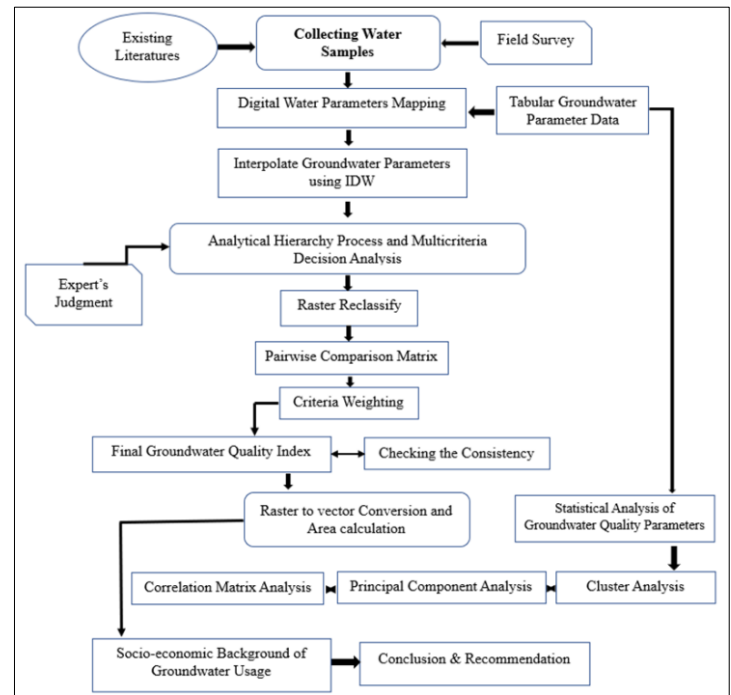


Fig. 3: Methodological flow chart.

2.3 Methods and GIS Approach

The quality of groundwater in four selected GNDs of MDS was analyzed by testing the domestic well water quality. The majority of these wells are situated along roadsides and in proximity to agricultural lands within the selected GNDs. Water sample collection was carried out in two stages. While 25 water samples were collected in the first stage, 82 were collected in the second stage. Six water quality parameters were analyzed from the 25 water samples collected during the first stage. The parameters selected for this study pH, EC, TDS, Alkalinity, Hardness, and Fluoride are commonly utilized in both regional and global groundwater quality assessments. Their selection is further supported by previous studies conducted in similar environmental contexts (Akbar et al., 2022; Chandrajith et al., 2011; Jayasumana et al., 2015; Naz et al., 2023; Saqib et al., 2023; Tiwari et al., 2017; Wimalasena and Withanage, 2021). In the second phase, three key parameters, pH, EC, and TDS, were analyzed from the remaining 82 water samples to assess groundwater quality. Experts who have an understanding of the quality conditions of drinking water were identified, and quality information was obtained from them. Accordingly, interviews were conducted with Grama Niladhari officers, Divisional Secretariat officials, engineers from the Water Supply and Drainage Board, geologists, and residents. Additionally, the household members from the 107 locations where water samples were collected participated in the survey. Water quality maps were analyzed based on the data obtained from the questionnaire survey. Additionally, MCDA models were employed to assign weights to the generated rating maps corresponding to the concentration levels of each groundwater quality parameter (Jenifer et al., 2021).

2.4 GIS and Inverse Distance Weighted (IDW)

After collecting 107 water samples across four GNDs, thematic maps were created to visualize the spatial distribution of groundwater quality parameters. The IDW method was used to interpolate point data on the concentration of groundwater quality parameters in the ArcGIS environment. This assumes that a value at any location is predicted by the values measured at the site sampled. Calculations were thus carried out using the weighted values of known points to estimate concentrations across the broader study area. It can depict how the water quality has changed in various ways, both clearly and accurately. The AHP method has been used to recreate the maps by placing comparative weights on the parameters.

2.5 Analytic Hierarchy Process (AHP)

The AHP method is a mathematical method developed by Saaty (1980). These values are then prioritized using Saaty's 9-point fundamental scale of relative importance as shown in Table 2.

Table 2: The AHP scales for paired comparisons (Source: Saaty, 1980).

Numerical Scale	Description
1	Equally important
3	Moderately important
5	Strongly important
7	Very strongly important
9	Extremely important
2,4,6,8	The importance lies between the two degrees

The AHP is a structured method used to organize and analyze complex decision-making. It involves pairwise comparisons to determine the relative importance of various criteria. Expert judgment plays a central role in assigning weights, enabling a systematic evaluation of each parameter based on its significance to the objective. The experts must define the values for each pair of criteria in the pair-wise comparison approach that have the greatest bearing on groundwater quality. A structured questionnaire for each expert is used to weigh these criteria. In this study, initial maps were generated for each individual parameter, followed by the creation of composite maps based on the comparative weights assigned by the experts to the various parameters. Seven experts participated in the AHP weighting process, each completing a semi-structured questionnaire designed to gather informed judgments. The panel included university lecturers, laboratory engineers from the Water Supply and Drainage Board, civil engineers, and GIS specialists. Experts were selected based on their relevant academic backgrounds and professional experience in groundwater

quality assessment and spatial analysis. Further, under the Spatial analysis tools, the Raster calculator and Weighted Overlay tool technology have been used in Raster analysis of the ArcGIS environment in generating these maps. The following are the comparative weights given based on experts' experience and knowledge about these parameters (Table 3).

Table 3: Main Criteria Weight Matrix.

Variables	pH	EC	TDS	Hardness	Alkalinity	Fluoride
pH	1	5	3	5	3	$\frac{1}{3}$
EC	$\frac{1}{5}$	1	$\frac{1}{5}$	$\frac{1}{3}$	1	$\frac{1}{7}$
TDS	$\frac{1}{3}$	5	1	3	3	$\frac{1}{5}$
Hardness	$\frac{1}{5}$	3	$\frac{1}{3}$	1	1	$\frac{1}{5}$
Alkalinity	$\frac{1}{3}$	1	$\frac{1}{3}$	1	1	$\frac{1}{5}$
Fluoride	3	7	5	5	5	1

The importance of each criterion was comparatively assessed using the AHP method, drawing on expert experience. The significance of the criteria is reflected in the weights assigned to the various parameters, which provide a structured basis for prioritizing groundwater quality factors. Using ArcGIS software 10.8, the Weighted Linear Combination (WLC) approach was applied to all of the parameter maps to construct the groundwater quality map. Six layers that were added to the GIS were used to create groundwater quality areas, which were then used to generate the groundwater quality index (GWQI). The WLC procedure is outlined in equation (1) (Malczewski, 1999; Sarkar and Majumder, 2021; Sener et al., 2005).

$$GWQI = \sum_{w=1}^m \sum_{i=1}^n W_j \times X_i \quad (1)$$

Here, GWQI is the groundwater potential index, W is the normalized weight of the j -th thematic layer, X_i refers to the weight of the i class of the parameters, m represents the number of parameters, and n denotes the total number of classes.

The validity of the AHP matrix is assessed using the Consistency Ratio (CR). Once the weights are derived, the CR calculated as shown in equation (2) is used to verify the consistency of the judgments. A CR value below 0.1 indicates acceptable consistency, confirming that the

matrix is reliable for use in spatial analysis (Saaty, 1980; Saaty, 2002).

$$CI = \frac{\lambda_{max} - n}{n - 1} \quad (2)$$

where λ_{max} is the largest eigenvalue of the matrix, and n is the size of the comparison matrix AHP in the analysis. After calculating CI , it is possible to obtain the CR, consistency ratio, using equation (3)

$$CR = \frac{CI}{RI} \quad (3)$$

where CI is the consistency index, and RI is the random inconsistency index value, which is dependent on the number of factors used in the pairwise matrix. In this study, the pairwise comparison matrix was developed using six groundwater quality parameters. The calculated CR is 0.062, which is below the acceptable threshold of 0.1. This indicates that the pairwise comparison matrix is consistent and suitable for use in the AHP-based spatial analysis.

2.6 Spatial Analysis Procedure

Numbered data layers related to each parameter were created based on water monitoring stations, GPS location, and measured parameters data in the study area, and interrelationship data layers were generated between the monitoring stations using the IDW method. The layers were reclassified according to the judgment of experts in the field, and the data strata were overlapped (Table 4). Accordingly, these water quality maps were converted to vector format, and the area for each quality level was calculated. The weights assigned to the feature classes of each thematic layer are presented in Table 5.

Table 4: Water quality score for attribute values for each sub-criterion.

Unsuitable Water Quality	Very Poor Water Quality	Poor Water Quality	Moderately Water Quality	Good Water Quality
0	1	3	5	7

Table 5: Weight Assessment for Groundwater Quality Parameters

Unit	Sub Criteria	Attribute Value	Water quality score
A	pH value	6.27 – 6.81	1
		6.82 – 7	7
		7.01 – 7.15	7
		7.16 – 7.34	7
		7.35 – 8.04	3

B	Electrical Conductivity (µs/ cm)	312 – 906	5
		907 – 1160	1
		1170 – 1360	1
		1370 – 1710	0
		1720 – 2760	0
C	Total Dissolved Solids (mg/l)	151 – 453	5
		454 – 578	7
		579 – 683	7
		684 – 861	3
		862 – 1370	1
D	Alkalinity (mg/l)	164 – 246	7
		247 – 296	5
		297 – 357	1
		358 – 437	3
		438 – 560	0
E	Hardness (mg/l)	164 – 236	5
		237 – 286	7
		287 – 341	5
		342 – 411	3
		412 – 512	1
F	Fluoride (mg/l)	0.48 – 0.90	5
		0.91 – 1.07	1
		1.08 – 1.23	1
		1.24 – 1.45	0
		1.46 – 1.88	0

2.7 Developing a GIS Model

The GIS Model Builder methodology is a technology that can be used to build a visual document of the actions in research. This is a method developed by Environmental Systems Research Institute (ESRI) in the United States. This is automatically created in an obvious way in GIS. Using the output of one process as the input of another, a diagrammatic model is made in this GIS Model Builder that links a sequence of operations together (Fig. 4). The entire process comprised of water sample collection, laboratory analysis, expert-based weighting of criteria, and the generation of corresponding spatial maps within the framework of this research.

3 Results

Groundwater quality analysis in the Dry Zone of Sri Lanka is crucial for several reasons, particularly because of the region's dependence on groundwater for drinking, agriculture, and other essential uses. The Dry Zone, which covers much of the country's northern, eastern, and southeastern parts, faces unique challenges related to

water availability and quality. Understanding spatial variations and parameter-specific trends in water quality is, therefore, essential to support sustainable resource management and protect public health.

3.1 Groundwater Quality Classified Maps

Columns 5 – 10 of Table 1 illustrates the variability of key groundwater quality parameters across the four GNDs, providing a comparative overview of how each parameter differs spatially within the study area. Based on that, maps that represent the distribution of water quality related to each parameter have been created (Fig. 5)

3.1.1 pH

One crucial factor in determining whether drinking water is naturally acidic or alkaline is its pH level. pH readings can change as a result of interactions between various minerals and organic materials (Tiwari et al., 2017). In the study area, pH values of groundwater ranged from 6.27 to 8.04, falling within the broader acceptable range for drinking water (6.5–8.5) as recommended by the Sri Lanka Standards Institute. Deviations from this range can indicate contamination from industrial or agricultural activities.

The distribution area of Good Water Quality from the 107 sampling points of the pH value study area is 37.18 km² of the total area. The distribution area of Poor Water Quality in the pH value is shown in green color and comprises of 14.37 km². The region with the lowest pH values, classified as Very Poor Water Quality, covers 3.60 km² of the total land area. These lower pH values (around 6.27) may enhance the mobility of heavy metals in the groundwater.

3.1.2 Electrical Conductivity (EC)

In groundwater quality analysis, EC is a key parameter as it reflects the concentration of dissolved ions in the water. In the Mihinthale area, high EC values could suggest the presence of saline intrusion or excessive use of fertilizers in agriculture, both of which can degrade groundwater quality. High EC values indicate high salinity, which can be detrimental to both human health and agriculture. The study area results show that EC ranged from 312 mg/L to 2760 mg/L. The extent of Unsuitable Water Quality, based on the EC values within the study region, spans 8.16 km², representing zones with low usability. Regions classified as Moderately Water Quality and Very Poor Water Quality cover 7.75 km² and 39.25 km², respectively, of the total study site. In groundwater quality analysis, EC is a key parameter as it reflects the concentration of dissolved ions in the water.

3.1.3 Total Dissolved Solids (TDS)

One of the key indicators of groundwater quality for household and drinking purposes is TDS, as it reflects the concentration of dissolved substances that may affect health and usability. The amount of total inorganic and organic dissolved materials in an aqueous solution is measured by TDS (Vaiphei et al., 2020). According to WHO standards, the TDS level in drinking water should not exceed 1000 mg/L (WHO, 2007). The findings indicate a

TDS range of 151–1370 mg/L/. According to the Water Quality Association (WQA, 2017), drinking low-TDS water has no long-term negative health impacts. The spatial analysis reveals that 1.17 km² of the study area falls under the Very Poor Water Quality category based on TDS, with an additional 4.78 km² marked as Poor. Conversely, 6.85 km² is classified as Moderate Water Quality, while 42.35 km² is considered Good. These findings highlight the spatial variability of groundwater quality in the region and emphasize the need for targeted water management strategies in areas with elevated TDS concentrations.

3.1.4 Alkalinity

High alkalinity in groundwater can indicate the presence of carbonate rocks or soil leaching, which is common in areas like Mihinthale. While it is generally not harmful, it can affect the taste of water and interact with other water treatment processes. Alkalinity controls the pH value of water in the area (Vaiphei et al., 2020). According to drinking water standards, alkalinity levels up to 200 mg/L are considered acceptable; beyond this, water may develop a bitter taste (Bozorg-Haddad et al., 2021). In the study area, alkalinity values ranged from 164 to 560 mg/L, indicating considerable spatial variation. The spatial analysis revealed that 9.3 km² of the area falls under the Good Water Quality category, while 31.25 km² is classified as Moderate. Poor and Very Poor Water Quality areas cover 5.4 km² and 8 km², respectively. Additionally, 1.21 km² is marked as Unsuitable for drinking due to excessive alkalinity. These findings underscore the need for monitoring and localized water treatment in areas where alkalinity exceeds recommended thresholds, thereby ensuring safe and palatable groundwater for domestic use.

3.1.5 Hardness

The allowable limits of Total Hardness (TH), another significant groundwater quality criterion, are contingent upon the specific uses of the water, including industrial, agricultural, and residential. The effects of water hardness on various communities can vary depending on the surrounding conditions (Tiwari et al., 2017). TH measures the concentration of calcium and magnesium ions in water (Vaiphei et al., 2020). Water with high hardness levels may be unsuitable for drinking due to potential health and taste concerns. In the study area, hardness values ranged from 164 to 341 mg/L. The distribution of Moderately Water Quality, based on hardness values, covers 38.32 km² within the study region. An additional 5.24 km² is identified as Poor Water Quality, while the most critical zone—classified as Very Poor Water Quality—occupies 0.77 km² of the total area. According to Kozisek (2005), hardness concentrations exceeding permissible limits have been linked to a heightened risk of kidney disorders, urinary tract issues, gallstone formation, and arthropathies within the population. In the present study, the zone classified as Good Water Quality spans approximately 10.83 km² of the total region. In regions like Mihinthale, which rely heavily on groundwater, hardness is important in water treatment and usability.

3.1.6 Fluoride

If fluoride is consumed in low amounts (0.5 to 1.5 mg/L), it is beneficial to human health (Tiwari et al., 2017). Fluoride is a naturally occurring mineral in groundwater, and its concentration can vary depending on geological conditions. Human health is at risk when fluoride concentrations in drinking water are above the recommended threshold (> 1.5 mg/L) (Hussain et al., 2010). In the study area, concentrations range from 0.48 to 1.88 mg/L. This element commonly enters groundwater through the natural dissolution of fluoride-bearing minerals and geological formations (Saqib et al., 2023). In Sri Lanka's Dry Zone,

including the Mihinthale region, elevated fluoride levels are common due to the area's geological characteristics. According to groundwater quality standards, the area classified as having Unsuitable Water Quality based on fluoride levels covers 7.89 km², while the Very Poor Water Quality zone extends over 42.31 km². It was observed that in all GN divisions except Wellaragama, fluoride levels range from 1.46 to 1.88 mg/L, exceeding the recommended limit of 1.0 mg/L. Meanwhile, the area with Moderately Acceptable Water Quality based on fluoride spans 4.95 km². Monitoring fluoride levels is crucial for managing the health risks associated with long-term exposure.

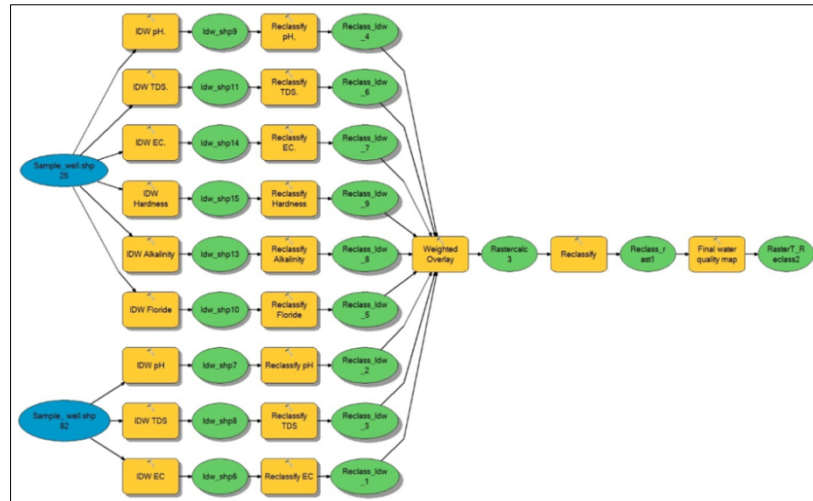


Fig. 4: ArcGIS model for groundwater quality analysis.

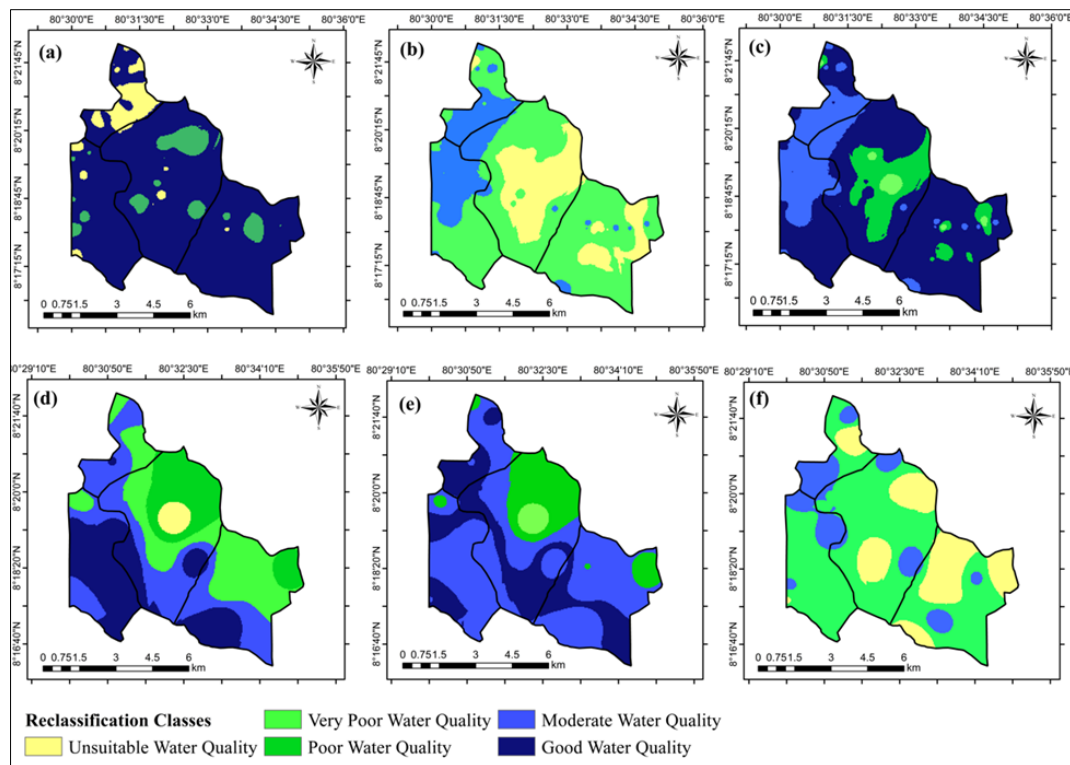


Fig. 5: Reclassification maps for (a) pH, (b) EC, and (c) TDS, (d) Alkalinity, (e) Hardness, and (f) Fluoride.

3.1.7 Ground Water Quality Index

The distribution of groundwater quality selected for these studies can be identified under four main categories: Moderate Water Quality, Poor Water Quality, Unsuitable Water Quality, and Very Poor Water Quality (Fig. 6).

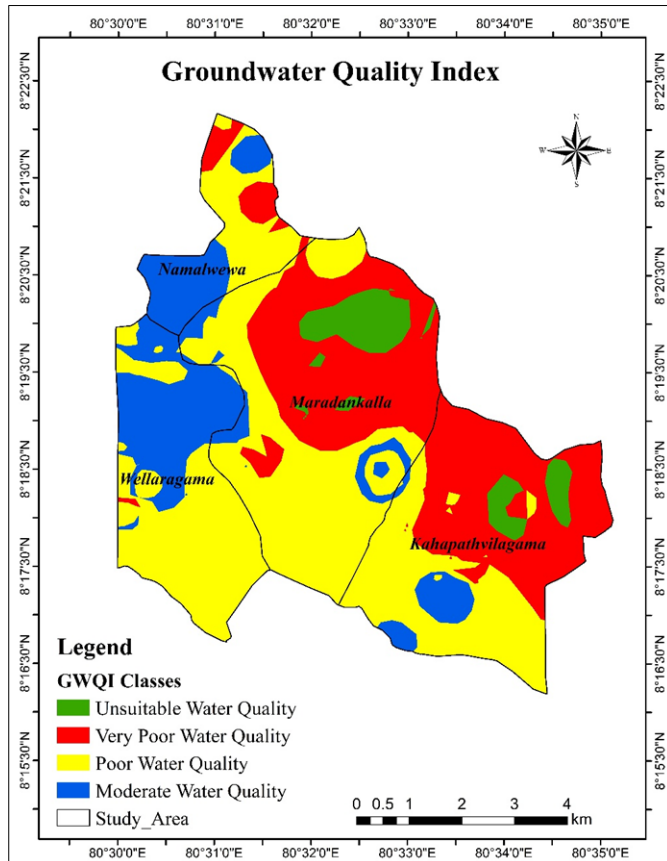


Fig. 6: Groundwater Quality Index of the study area.

Based on the AHP analysis, fluoride was identified as the most critical parameter, and was assigned a weight of 0.4426 (44.27%), highlighting its significant impact on groundwater suitability in the region, especially given the health implications linked to high fluoride concentrations. The next most influential factor was pH, with a weight of 0.2434 (24.34%), as it affects both water chemistry and the solubility of other contaminants. TDS followed, with a weight of 0.1425 (14.25%), indicating its role in reflecting overall water salinity and usability. Hardness and alkalinity were given weights of 0.0688 (6.88%) and 0.0608 (6.09%), respectively, due to their influence on water taste, scaling, and potential interactions with infrastructure. EC, while still relevant, received the lowest weight of 0.0416 (4.17%), likely due to its overlapping information with TDS and its broader interpretative nature. Moreover, no areas with Good Water Quality were identified, highlighting a critical concern for local water usability. Moderate Water Quality covers approximately 8.91 km², primarily concentrated from the center of the Wellaragama area, extending through Namalwewa to the North and Kahapathvilagama to the South. Poor Water Quality, which poses potential health

risks over long-term exposure, spans 24.30 km², forming one of the most extensive zones. Very Poor Water Quality, the second most widespread class covers 19.53 km², distributed from the center of Maradankalla GND northward and across parts of the Kahapathvilagama area to the North and East. Unsuitable Water Quality, indicating highly contaminated and undrinkable conditions, is found in 2.42 km², notably concentrated in central Maradankalla and parts of eastern Kahapathvilagama. Further, the region has been affected by Chronic Kidney Disease of unknown etiology (CKDu), a significant public health issue in Sri Lanka. The dry zone's limited water resources make it essential to manage groundwater sustainably. Over-extraction or contamination of groundwater can lead to long-term depletion and degradation of this critical resource. Climate change is expected to alter rainfall patterns, potentially exacerbating the dry conditions in the region. Understanding the spatial distribution of groundwater quality is essential to planning access to safe water and mitigating health risks in affected communities.

4 Discussion

4.1 Statistical Distribution of Water Quality Parameters

To gain a deeper understanding of the groundwater quality dynamics in the MDS, various statistical methods were applied as they help identify key relationships between parameters, reduce dimensionality, and classify water samples based on similarity. This integrated statistical approach not only supports a more robust interpretation of complex water quality datasets but also enhances the decision-making process for sustainable groundwater management.

4.1.1 Correlation Matrix Analysis

In this work, the multivariate statistical method of Pearson's correlation coefficient (r) was used to determine the association between observed groundwater quality measures for drinking purposes (Fig. 7). The value range of a Pearson correlation coefficient is -1 to 1 , indicating that there is no association between the two variables is the r -value being close to zero (Mudgal et al., 2009). The groundwater samples' inter-parameter correlation matrix is provided, with the red colour indicating a positive correlation and the blue colour indicating a negative correlation for each water quality metric. With r values of -0.16 and -0.17 , respectively, the pH value exhibits a substantial negative connection with hardness and Alkalinity. On the other hand, EC and TDS show a strong positive correlation with hardness and Alkalinity ($r = 0.97$ and $r = 0.98$). The r -values of 0.97 and 0.98 indicate a nearly linear relationship, meaning that as alkalinity and hardness increase, TDS and EC increase proportionally. The strong correlations suggest that in our groundwater samples, the variations in EC and TDS are predominantly driven by alkalinity and hardness levels. This also implies that monitoring EC or TDS could give a fairly accurate estimate of the water's alkalinity and hardness, and vice

versa. All parameters A show a weak positive correlation (r-value of 0.28) with fluoride. This means that while there is a slight tendency for fluoride levels to increase as other parameters (like EC, TDS, alkalinity, and hardness) increase, this relationship is not strong or consistent. The weak positive correlation between fluoride and other groundwater parameters indicates that while there is some relationship, it is neither strong nor direct.

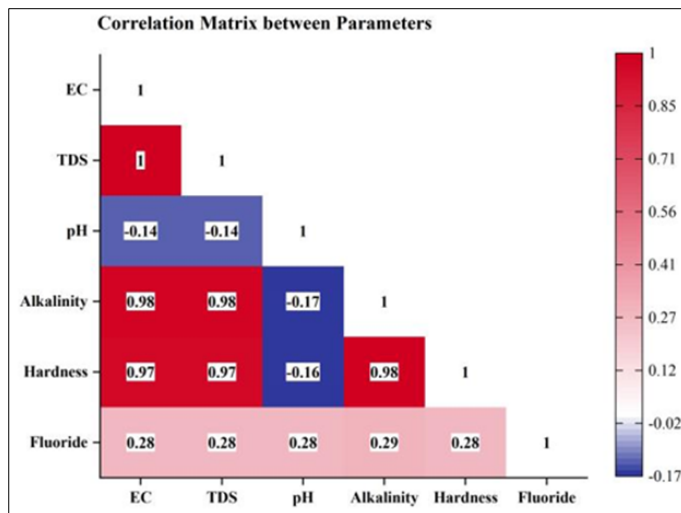


Fig. 7: Correlation matrix of the groundwater quality parameters.

4.1.2 Principal Component Analysis (PCA)

It has been noted that PCA is an effective pattern identification method that aims to elucidate the variance of the inter-correlated variables within a dataset (Ravikumar and Somashekar, 2017). In the current work, OriginPro was used to perform PCA on the groundwater quality dataset. By lowering the number of variables that must be taken into account, PCA increases research process efficiency by enabling faster and more focused analysis. Table 6 shows the PCA findings for the water quality metrics, along with the eigenvalues, variability %, and cumulative percentage by each principal component (PC).

Table 6: Summary of Principal Components Analysis (PCA).

Parameters	Eigenvalue	Percentages of Variance (%)	Cumulative (%)	Coefficient of PC 1	Coefficient of PC 2
EC	4.057	67.62	67.62	0.491	-0.020
TDS	1.270	21.18	88.80	0.491	-0.020
pH	0.605	0.09	98.90	-0.0813	0.748
Alkalinity	0.051	0.86	99.76	0.491	-0.033
Hardness	0.014	0.24	100	0.488	-0.035
Fluoride	0	0.00	100	0.173	0.661

Figure Fig. 8 shows how each groundwater quality metric varies with PC factors 1 (67.62%) and 2 (21.18%). These two components together explain 88.8% of the total variance in our groundwater quality data.

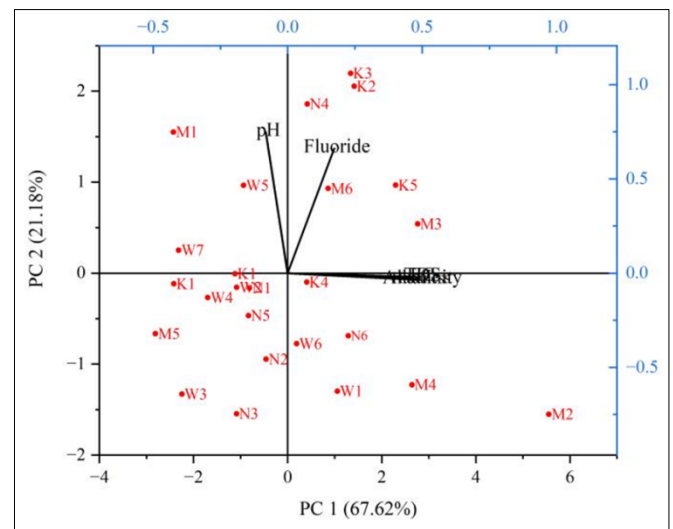


Fig. 8: Bi-plot of the water quality parameters.

This is a significant amount, meaning that most of the variation in our data is captured by these two components. This small negative loading (-0.0831) suggests that pH has a relatively minor influence on PC1. Since PC1 explains 67.62% of the total variance, and pH is negatively correlated, this strong positive loading (0.748) indicates that pH has a significant influence on PC2, which explains 21.18% of the variance. This means that differences in pH levels are a major factor in the secondary patterns of variation within the groundwater quality. This positive loading (0.173) suggests that fluoride has a moderate influence on PC1. While not as strong as other potential factors, it still contributes to the primary variation in the groundwater quality. A loading of 0.491 suggests that EC is a significant contributor to the variance captured by PC1. EC is closely related to the ionic content of the water, which is influenced by dissolved salts and minerals. The same loading value as EC indicates that TDS is equally influential in PC1. Further, this identical loading value to EC and TDS shows that Alkalinity is also a significant factor in PC1. A loading of 0.173 suggests that Hardness is a moderately contributing factor to PC1, but it's not as influential as EC, TDS, or Alkalinity. EC, TDS, and Alkalinity are the most influential parameters in PC1, all with identical loadings (0.491). This indicates that the primary variation in groundwater quality is strongly driven by the overall ionic content and buffering capacity of the water.

4.1.3 Cluster Analysis (K-means)

K-means clustering allows for a grouping of groundwater samples into clusters based on their similarity across the six water quality parameters (such as pH, EC, TDS). This means that samples within the same cluster have similar water quality characteristics, while samples in different

clusters are distinct from each other (Fig. 9). The distances between the final cluster centers in a k-means clustering analysis provide important insights into how distinct each cluster is from the others. This moderate distance (972.16) suggests that Cluster 1 and Cluster 2 are somewhat distinct but still have similarities. The water quality in the samples belonging to Cluster 1 and Cluster 2 likely shares some common characteristics, but with noticeable differences. This large distance (1556.37) indicates that Cluster 1 and Cluster 3 are very distinct from each other. The groundwater quality parameters in these clusters are quite different. This smaller distance (584.64) suggests that Cluster 2 and Cluster 3 are relatively similar, with some differences in groundwater quality parameters. The large distance between Cluster 1 and Cluster 3 suggests these two clusters represent the most divergent groundwater conditions. With a moderate distance, Cluster 1 and Cluster 2 represent groundwater that is different, but not as drastically as Cluster 1 and Cluster 3.

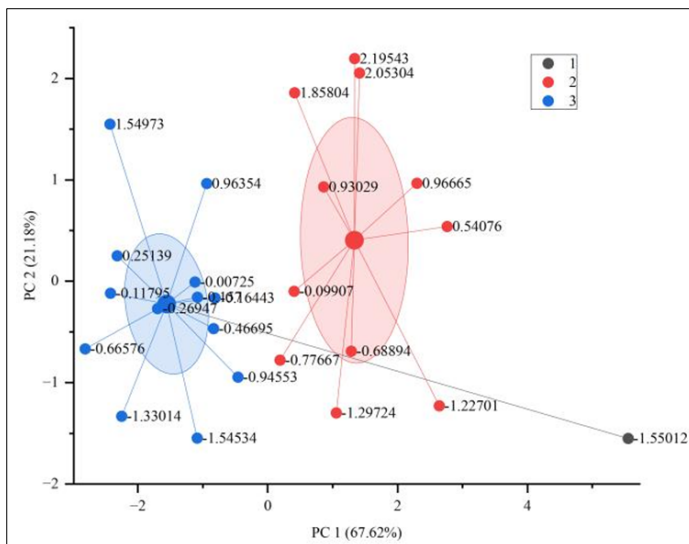


Fig. 9: K-means Cluster Analysis for Water Quality Parameters.

4.1.4 Socio-Economic Implications of Groundwater Quality

Understanding the socio-economic context of groundwater usage, it is essential to interpret the practical implications of water quality findings. The survey conducted among 107 households revealed that the majority of residents rely on groundwater as their primary drinking source, with many families accessing water from wells located within 10–30 m of agricultural land. This is significant considering that several groundwater samples showed elevated levels of fluoride and salinity, parameters that can be influenced by agrochemical leaching and poor well maintenance. Fig. 10, which shows the distribution of water source usage (e.g., domestic wells, tap water, purified water, and groundwater pipe wells), illustrates that a significant portion of the population depends on purified water (58 households), with fewer relying on direct groundwater sources. Households also reported concerns about visible impurities and rainwater mixing into wells, especially during the

monsoon. The lack of adequate protective measures around wells and proximity to farmland further supports the relationship between poor land-use practices and degraded water quality. By combining hydrochemical findings with socio-economic data, this study provides a more comprehensive understanding of the public health and livelihood risks in the Mihinthale DSD, strengthening the case for improved water management strategies and community education programs.

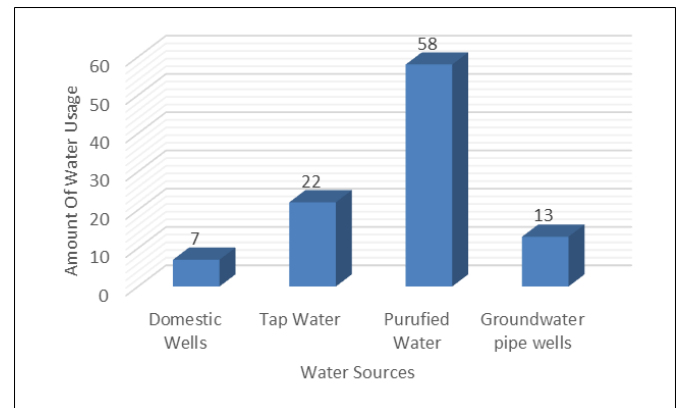


Fig. 10: Use of different water sources for drinking (Source: Field Survey, 2022).

5 Conclusion and Recommendation

In this study, IDW interpolation effectively identified and mapped the distribution of domestic drinking well water quality levels with both ease and accuracy. Three different statistical methods, namely correlation analysis, PCA, and k-means cluster analysis, were employed for the statistical analysis of groundwater quality in the study area. Regarding the final map generated by integrating all parameters, it was determined that the quality of drinking well water in the study area is below acceptable levels. Considering the quality of groundwater in these GNDs, the water in the Wellaragama area is less contaminated than that in the Kahapatvilagama and Maradankalla areas. However, in the Wellaragama area, 11 kidney patients were reported in 2022, while 8 kidney patients were reported in the Kahapatvilagama area. Thus, it is evident that in the Wellaragama area, where there is a significant prevalence of unsuitable and very poor water quality, the number of kidney patients is more concerning than in the Kahapatvilagama GND. One key finding from this study was the need to expand the existing purified water distribution points in the area. Several issues related to the current distribution points were identified across the four regions. The Kahapatvilagama temple has operated a water treatment project as a community-based initiative for about four years. Additionally, there are only three private treated water stations distributing water in the Wellaragama GND, one of which is a community water project managed by a private institution. Furthermore, there is a single community water project implemented by the Sri Lankan Navy near Maradankalla School in the Maradankalla area. In Namalwewa, only two points

distribute purified private water, which has been operational for about five years. To address these issues, it is recommended that future water distribution infrastructure be developed through community water projects, either state-sponsored or private, based on population density and mapped groundwater quality. These projects should include solar-powered treatment units for energy efficiency and cost-effectiveness in rural areas. Moreover, awareness programs should be expanded through local health officers, village committees, and school-based education to increase understanding of the health impacts of poor water quality. Given the dual monsoon rainfall pattern, rainwater harvesting should be implemented as a supplementary water source. This could involve rooftop rainwater collection systems, supported by government subsidies or microfinance for low-income households. Moreover, Future research should focus on long-term groundwater monitoring, including seasonal changes and emerging contaminants such as pesticides, which were not part of this study. And also, integrating advanced modeling techniques, such as machine learning combined with GIS and AHP, may improve the prediction and classification of groundwater quality risk zones. Finally, research into the policy frameworks and governance mechanisms involved in rural water supply can help ensure better planning, implementation.

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Author Contributions

Conceptualization, methodology, analysis, writing - original draft preparation, P.G.A.S. and writing - review and editing, P.H. and W.M.D.C. All authors have read and agreed to the published version of the manuscript.

Conflict of Interest

The authors declare no conflict of interest.

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