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Multi-Sensor Data Fusion and GIS-DRASTIC Integration for Groundwater Vulnerability Assessment with Rainfall Consideration

Wu Jiazhe, Dai Xinrui, Su YanCheng, Zheng Xiangtian, Bushra Gaffar, Rabiya Nasir, Ahsan Jamil, Zeeshan Zafar, Muhammad Sohail Meer, M. Abdullah-Al-Wadud, Rahila Naseer, Hesham El-Askary

***Abstract*— In many areas of the world, particularly in arid and semi-arid regions, groundwater is the primary source of fresh water, and it supplies around one-third of the world's fresh water. Agriculture is the primary economic sector on the coast in the southern district (Nowshera). More food productivity is required due to the expanding population and diminishing agricultural lands, which increases the use of chemical pesticides and fertilizers in farming. The current study was conducted in northwestern parts of Pakistan to evaluate the impacts of the frequent use of pesticides and fertilizers in agricultural fields. Nine hydrogeological Parameters were considered, and the GIS-based DRASTIC index was used to generate the final groundwater vulnerability map. The index map (ranging from 220 to 1980) was further classified into five classes based on index vulnerability: very low (220 - 345), low (346 - 670), moderate (671 - 730), high (731 - 1239), and very high 1240 - 1980). Nitrate and TDS, the two reliable and recognized scientific water quality measurements, have been used to validate the model. By regulating and controlling anthropogenic and agricultural pollution, the danger of contamination can be decreased. This research will aid in understanding the possible dangers and risks related to the usage of pesticides in agriculture and other industries. Furthermore, it will help identify the specific pesticides causing the contamination, assess the extent and severity of the contamination, and develop strategies to protect public health and the environment.**

***Index Terms*— Multispectral data; Groundwater contamination; Vulnerability; Rainfall; Agricultural management**

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Jiazhe Wu, Xinrui Dai, Xiangtian Zheng, Yancheng Su are with the School of Computer Engineering, Nanjing Institute of Technology, Nanjing 211167, China, and also with the School of Geography and Marine Science, Nanjing University, Nanjing 210023, China (e-mail: 2112657297@qq.com; 1765834449@qq.com; zxt@njit.edu.cn; 1756729480@qq.com).

Bushra Gaffar is with the Department of Environmental Science, Faculty of Sciences, International Islamic University, Islamabad (e-mail: bushra.ghaffar@iiu.edu.pk).

Rabiya Nasir is with the Department of Environmental Science, The University of Lahore, Pakistan (e-mail: rabiya_nasir@live.com).

Ahsan Jamil is with the Department of Plant and Environmental Sciences, New Mexico State University, 3170S Espina Str, Las Cruces, NM 88003, USA (e-mail: ahsan@nmsu.edu).

Zeeshan Zafar, State Key Laboratory of Water Resources Engineering and Management, Wuhan University, Wuhan 430072, China (e-mail: zams706@whu.edu.cn).

Muhammad Sohail Meer, is with the Centre for Remote Sensing and Geoinformatics, Sathyabama Institute of Science and Technology, Chennai 600119, Tamil Nadu, India (e-mail: mohdsuhailrs@gmail.com).

M. Abdullah-Al-Wadud is with the Department of Software Engineering, College of Computer and Information Sciences, King Saud University, Riyadh 11543, Saudi Arabia (e-mail: mwadud@ksu.edu.sa).

Rahila Naseer is with the Department of Economics, Applied Statistics and International Business, College of Business, New Mexico State University, Las Cruces, NM 88003-8001, USA (e-mail: rn2020@nmsu.edu).

Hesham El-Askary is with the Earth Systems Science and Data Solutions Lab, Chapman University, Orange, CA 92866, USA, the Schmid College of Science and Technology, Chapman University, Orange, CA 92866, USA, and the Department of Environmental Sciences, Faculty of Science, Alexandria University, Alexandria 21522, Egypt (e-mail: elaskary@chapman.edu).

I. INTRODUCTION

WATER scarcity and pollution have become major global issues in recent decades. There are billions of people without access to water or who experience water scarcity worldwide; maintaining the quality of the groundwater is crucial for ensuring water availability for drinking water [1], [2]. When no other water supply is available, groundwater is the sole substantial source of life support for cultivable and non-cultivable lands [3], [4]. Groundwater is the primary source of drinking water for more than two billion people [5]. However, in recent years, the quantity and quality of groundwater sources have been declining globally as a result of the world's population growth, agricultural demands, and high manufacturing standards [6]. Contaminated drinking water has caused significant health concerns in recent years due to increased contamination in groundwater [7], [8]. Statistics show that drinking water contamination is responsible for 40% of all deaths and 30% of all diseases [9]. Once the aquifers are contaminated, restoring them is difficult or even impossible. Due to this, planners and engineers must identify essential terrain to protect clean groundwater by considering the vulnerability [10], [11]. Worldwide, around 260 million hectares of land is used for agriculture. More than half of the world's crops are produced by Pakistan, China, the United States, and India [12]. Two-thirds of all freshwaters, mainly from groundwater, is used to irrigate and harvest about 60% of the world's agricultural lands. According to statistics, groundwater extraction for agricultural purposes is expected to reach between 750 and 800 billion cubic meters annually [13]. Furthermore, due to a growing population and elevated living standards, the percentage rises by 1-3% annually worldwide [12].

In Pakistan, 90% of the population depends on groundwater to meet domestic needs. Population growth has increased water demand, severely stressing groundwater resources and worsening groundwater vulnerability. Once the subsurface aquifer has been contaminated, cleaning the water that has been polluted is a complex and expensive process [14]. According to community health surveys in Pakistan, water pollution is the primary cause of 50% of illnesses and

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40% of deaths [15]. A total of 7000 random water samples were collected from Pakistan, and the results revealed that, on average, fecal and total coliforms were present in approximately 58% and 71% of the samples, respectively [16], [17]. In 2015, 62% of the groundwater in Pakistan's various regions, including Chichawatni, Vehari, and Rahimyar Khan, was unsuitable for human consumption. Recently, Ali et al. [18] evaluated the impacts of multiple pesticides in drinking water sources from the Peshawar basin, Pakistan, and found that the study area's selected water sources were all contaminated by various pesticides sprayed in the region. Approximately 66% of all water use comprises mechanical pumps and piping systems [19].

In other cases, the method of purification could be more commercially feasible. To protect the groundwater from further contamination, it is crucial to identify the polluted areas of the aquifers and take the necessary precautionary measures [20], [21]. This is why there are significant problems with groundwater availability and quality [22]. The susceptibility evaluation indicates the groundwater quality's contamination or pollution vulnerability level. To raise awareness of groundwater vulnerability, France was the first to establish the concept in late 1960 [23]. The evaluation can categorize the zones based on the degree of contamination and generate calculated findings to protect groundwater in the specified areas in the target areas. Various techniques have been developed to examine and assess the susceptibility of aquifer formations. Numerous strategies were developed, including statistical, process-based, and overlay index procedures [24]. The DRASTIC method is the most thorough method under the overlay and index procedure [22].

Groundwater monitoring is costly and labor-intensive, and it is difficult to accurately depict pollution on a larger scale [25]. Therefore, researchers have created a variety of approaches that are less expensive, more straightforward to use, and do not need a lot of data or complicated calculations [26]. Anantha Rao et al. [10], developed a DRASTIC, the most well-known, and commonly applied empirical rank/score-based index approach for vulnerability evaluation for the US Environmental Protection Agency [27]. This approach is based on nine hydrogeological factors, including hydraulic conductivity (C), topography (T), influence of the vadose zone (I), aquifer medium (A), net recharge (R), depth to water table (D), elevation (E) and drainage density (D). However, despite its widespread use, the DRASTIC technique has several drawbacks, and it has been criticized for its subjectivity and ambiguity in assessing the ratings and weights of its criteria [28], [29].

Numerous researchers [30], [31] have begun improving the approach to fix this issue to increase its efficacy and precision for a particular aquifer [32]. Some examples of these enhancements include the optimization of the ratings and weights of the severe parameters through the use of the Fuzzy Analytic Hierarchy Process (FAHP)[33], the Analytic Hierarchy Process (AHP), multiple linear regression, the sensitivity analysis, and the Analytic Network Process (ANP) [34], [35]. Other researchers have proposed incorporating extra factors, such as land use and irrigation type [36], [37], [38]. The primary objective of this study is to assess the vulnerability of groundwater contamination resulting from the regular application of pesticides and fertilizers in agricultural areas in the central regions of the KPK province in Pakistan. An integrated GIS-DRASTIC model incorporated nine essential hydrogeological parameters to generate the DRASTIC index, a necessary component for creating a groundwater vulnerability map.

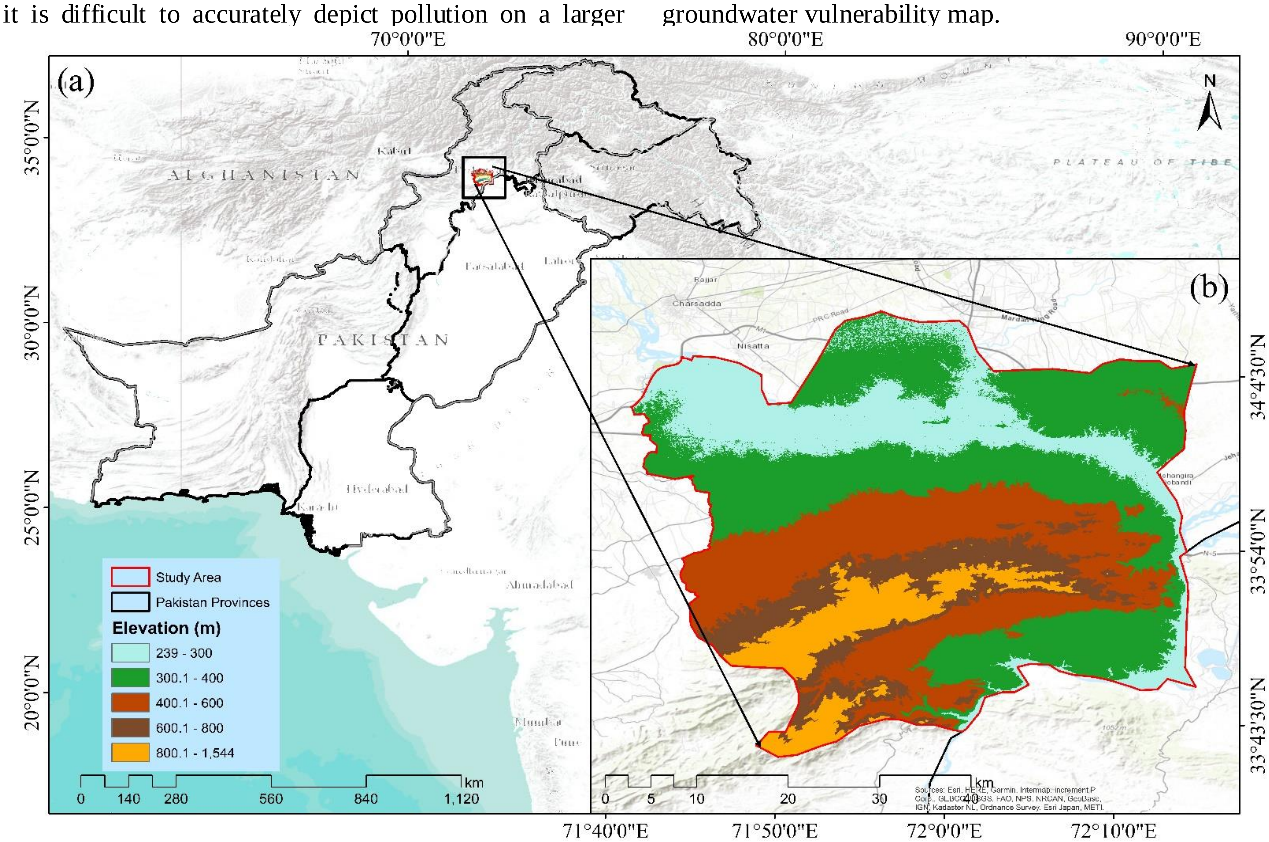

Figure 1: (a) Geographical location of Pakistan (b) study region map of District Nowshera.

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II. MATERIAL AND METHODS

A. Study area

The Nowshera District, located in the Khyber Pakhtunkhwa province of Pakistan, is approximately centered at latitude 34.0151° N and longitude 71.9747° E with an area of 1,748 km^2 and elevation 1544 meters above sea level. These coordinates provide a general reference for the district, which spans a larger area with varying geographical boundaries [39], [40]. The region's geology is complex, comprising sedimentary formations, alluvial deposits, and active fault lines, which collectively influence the distribution and accessibility of groundwater resources [41]. Nowshera's susceptibility to recurrent flooding underscores the importance of understanding its subsurface hydrology for disaster risk reduction and informed urban planning [42]. The district's climate, classified as "Cwa" under the Köppen climate classification system, is characterized by humid subtropical conditions with dry winters and hot summers [43]. Weather fluctuations are substantial, with summer temperatures reaching up to 40 °C and winter temperatures occasionally nearing freezing levels. The region's soils are generally deep and well-drained, though their fertility varies according to local topographical and drainage conditions [44]. Topographical variation plays a crucial role in shaping the district's hydrological and agricultural dynamics. Fertile plains formed by natural drainage systems are suitable for cultivation, while steeper terrains are prone to erosion and landslides [45], [46].

B. Data Collection

The data for the DRASTIC model was collected from primary and secondary sources. Water samples were collected from the field to validate the results. The groundwater depth data and water detecting diver were also collected during the field. Global precipitation measurement (GPM) rainfall data generated the net recharge map. The impact of vadose zone data was gathered from the public health engineering department (Table I). The soil map of the study area was collected from the Soil Survey of KPK, and the geological map was collected from the Geological Survey of Pakistan. ALOS PALSOR Digital elevation model with 12.5-meter resolution was downloaded from Earth data open access hub (https://scihub.copernicus.eu/dhus/#/home).

TABLE I
THE PRIMARY DATA SOURCES UTILIZED IN THIS STUDY.

S. No	Datasets	Source
1	Water Quality data (Nitrate and TDS	Sample collection from the field (60 samples from open wells)
2	Depth to Groundwater	Depth data collected from the field (30 locations)
3	Net Recharge	Rainfall data downloaded from GPM (Global Precipitation Measurement)
4	Vadose zone	Public Health Engineering Department Nowshera Division
5	Soil media	Soil Survey of Khyber Pakhtunkhwa
6	Aquifer Media	Geological Survey of Pakistan
7	Topography	ALOS PALSAR with 12.5 meters spatial resolution was downloaded from Earth data open access hub.
8	Hydraulic conductivity	Hydraulic conductivity data were collected from the public health engineering department of the Nowshera Division

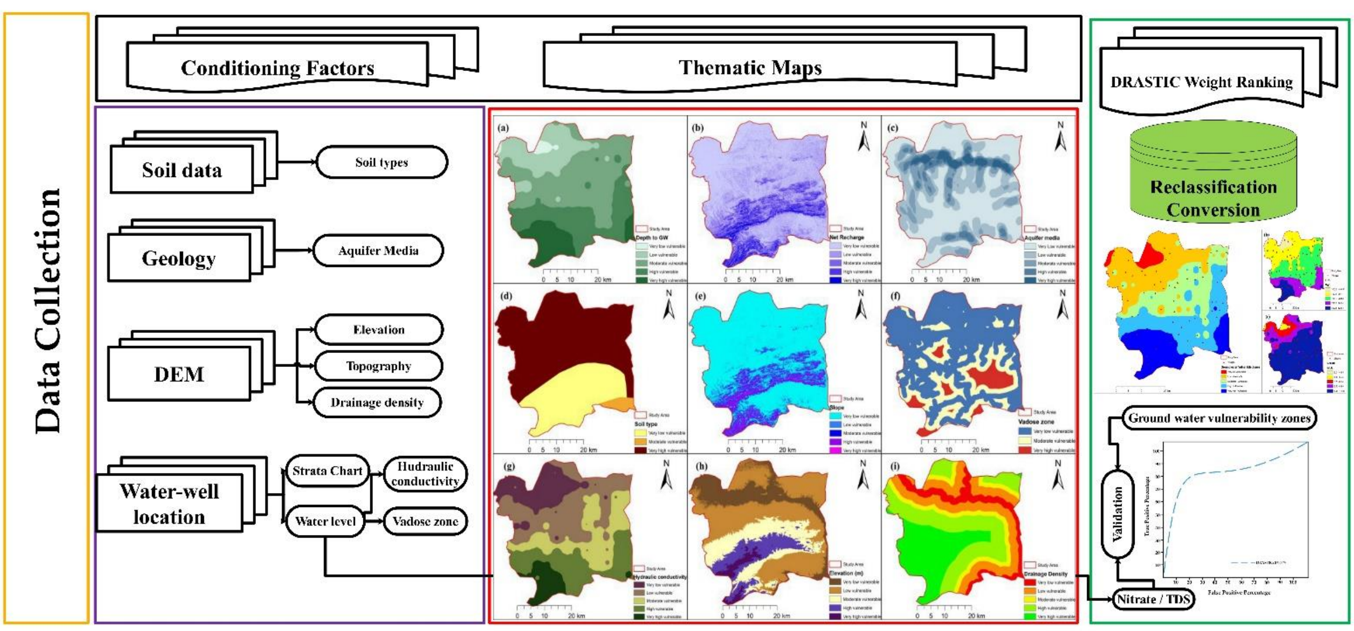

Figure 2: The present study employs a methodology flow chart to outline the sequential steps and procedures undertaken in the research process. The flow chart serves as a visual representation of the research methodology.

C. Method

The DRASTIC technique also considers the environmental factors affecting groundwater contamination risk. Each factor is divided into ranges, and each range is given a rating based on how it affects the aquifer's vulnerability. According to Eq. 1, the final DRASTIC vulnerability index (DVI) was calculated by multiplying the rating (i.e., 1-10) by the weights (from 1 to 5).

$$\mathrm{DVI} = \mathrm{DrDw} + \mathrm{RrRw} + \mathrm{ArAw} + \mathrm{SrSw} + \mathrm{TrTw} + \mathrm{IrIw} + \mathrm{CrCw} \quad (1)$$

where the letters w stand for weight and r represents the rates for each of the nine geo-environmental parameters: D, R, A, S, T, I, and C. This approach is simple to use, and it considers each parameter's rate and weight. The rates (1–10) are random and are determined by the expertise of professionals. One of the most critical limitations of this approach is that the weights assigned to each parameter are subjective [45]. The researchers made enhancements or adjustments to a significant extent by modifying the weights of the initial model, taking into account the specific attributes of the study region and the correlation coefficient between a particular contaminant, such as nitrate, and nine hydrogeological layers [47], [48], [49], as well as the parameters and the rates [50]. Figure 2 shows the methodology flow chart.

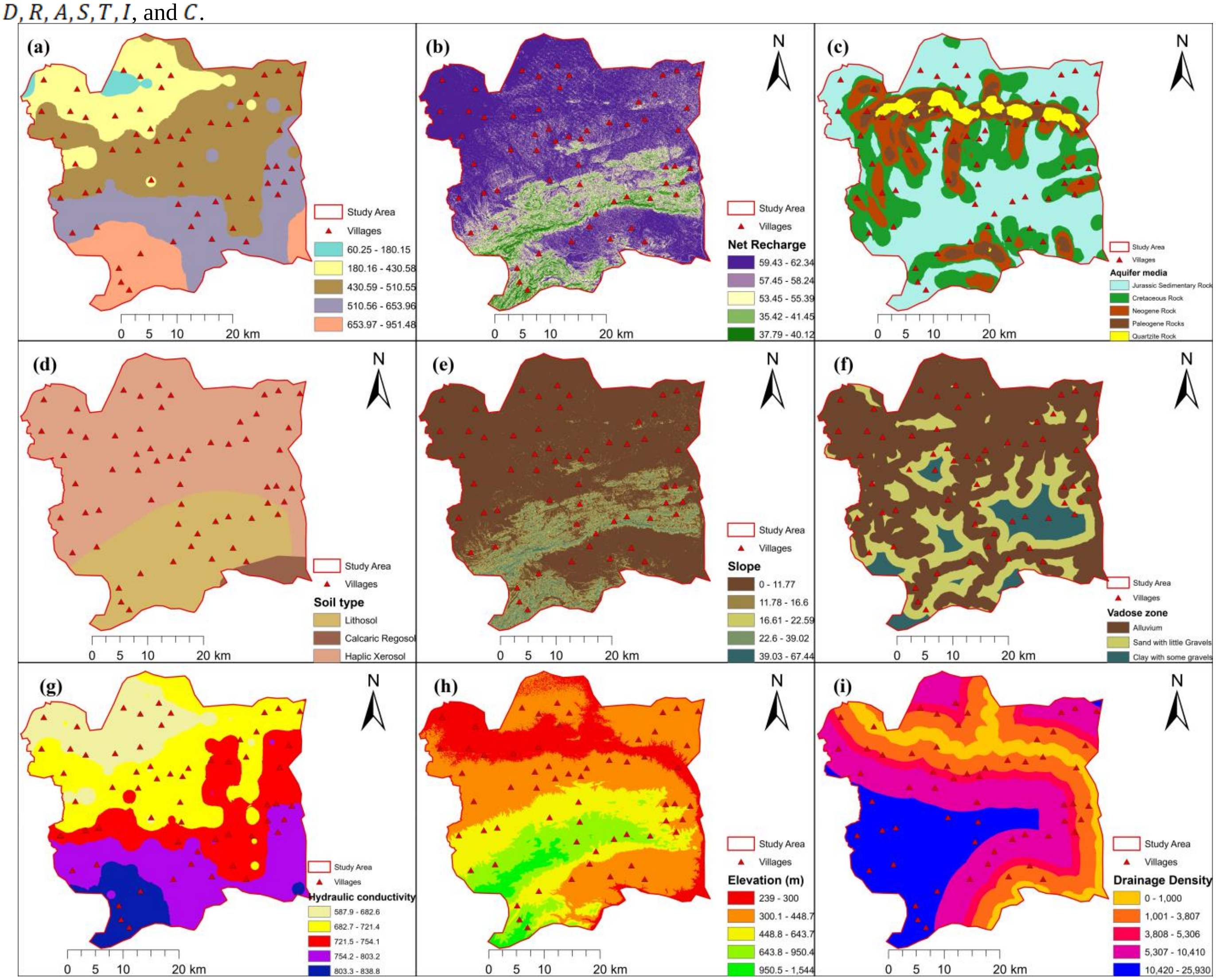

Figure 3: Maps of the conditioning factors (a) depth to groundwater, (b) net recharge, (c) aquifer media, (d) soil types, (e) topography, (f) vadose zone, (g) hydraulic conductivity, (h) elevation and (i) drainage density.

D. Preparation of DRASTIC factors

1) Depth to groundwater

The groundwater depth determines a possible pollutant's travel time to the water table. The depth-to-water table data were collected from 40 bore wells in the study area using an electric diver and GPS for locational coordinates. The depth-to-water table data were imported into the GIS environment for further processing. The inverse distance weighted (IDW) tool generated the surface inside the spatial analyst extension. The IDW data for depth to groundwater were classified into five classes: 60.25 – 180.15 feet, 180.16 – 430.58 feet, 430.59 – 510.55 feet, 510.56 - 653.96 feet, and 653.96 – 951.48 feet. Figure 3a Shows the depth of the groundwater map of the study area.

2) Net Recharge

Water infiltration into the soil and groundwater table occurs from precipitation and other artificial sources. *Net recharge* is the term used to describe the quantity of water percolating per square foot of soil. According to Shirazi et al. [6], this recharge is influenced by several variables, including slope, permeability, rainfall, land cover, and water seeping. High recharge correlates with higher contamination susceptibility and vice versa. Precipitation data from GPM was downloaded from 2006 to 2024. The GPM (raster) data were further processed in GIS. The study area receives 40.12 – 59.43mm average annual rainfall. The data were further classified into five classes: 59.43 – 62.34, 57.45- 58.24, 53.45 – 55.39, 35.42 – 41.25, and 37.79 – 40.12 mm. Figure 3b Shows the net recharge map of the study area.

3) Aquifer media

This factor considers the physical properties of the saturated zone's media, such as porosity, grain size, and permeability, which control the pollutant absorption processes [50], [51]. This data was collected from the Geological Survey of Pakistan and tabulated and processed in GIS. Five main types of lithologies are found: Jurassic sedimentary rock, Cretaceous rock, Neogene rock, Paleogene rocks and Quartzite. Figure 3c shows the aquifer media map.

4) Soil types

This parameter considers the biologically active soil texture on the earth's surface [52]. The soil type controls the amount of recharge that may saturate groundwater [53], [54]. The soil map was collected from the Soil Survey of Khyber Pakhtunkhwa. It was Georeferenced and Digitized. Three types of Soil were found in the study area: Lithosol, Calcaric Regosol and Haplic Xerosol. Figure 3d shows the soil map of the study area.

5) Topography

This parameter describes the ground slope of the research area and affects how much water can permeate the soil. Digital elevation model ALOS PALSAR with 12.5 meters spatial resolution was downloaded from Earth data open access hub. The area was extracted using an extraction by-mask tool surface tools inside the spatial analyst extension generated slope in degrees [40], [41]. The slope was categorized into five classes: 0 – 11.77, 11.78 – 16.60, 16.61 – 22.59, 22.60 – 39.02, and 39.03 – 67.44 degrees. Figure 3e shows the topography map of the study area.

6) Vadose Zone

This parameter makes a reference to material from the unsaturated zone. The water flow in the unsaturated zone impacts the transport of contaminants to the aquifer. The Impact of Vadose zone data was collected from the Public Health Engineering Department of KPK. The department provided the strata chart of the constructed bore wells in the study area. According to these charts, Alluvium, Sand with little Gravel, and Clay with some gravel were found in the study area[55]. Figure 3f shows the impact of the Vadose zone map.

7) Hydraulic conductivity

Hydraulic conductivity describes how easily water (and dissolved pollutants) travel throughout the groundwater/aquifer system. This data was also collected from the Public Health Engineering Department in Khyber Pakhtunkhwa. The Hydraulic conductivity values range from 587.9 – 682.6, 682.7 – 721.4, 721.5 – 754.1, 754.2 – 803.2, and 803.3 – 838.8 in the study area. The data was divided into five classes. Figure 3g shows the hydraulic conductivity map.

8) Elevation

The Nowshera District's elevation is critical in influencing groundwater distribution and accessibility [56]. With elevations ranging from approximately 239 meters to 300 meters above sea level in the plains, the district benefits from the Kabul River and associated alluvial formations that enhance groundwater recharge in lower-lying areas. However, steep gradients and rocky substrates reduce infiltration capacity in the elevated and rugged terrains, limiting groundwater potential [42]. These elevation-induced variations emphasize the need for detailed hydrological studies to identify and manage groundwater resources effectively across diverse topographical zones. Figure 3h shows the elevation map.

9) Drainage density

Drainage density, defined as the total length of streams and rivers per unit area, is a crucial indicator of groundwater potential in a region. A low drainage density typically signifies a high infiltration rate and greater potential for groundwater recharge, as surface water has more time to percolate into the subsurface. Conversely, areas with high drainage density often exhibit reduced infiltration due to surface runoff dominance, indicating limited groundwater recharge potential [57]. In regions like Nowshera District, where topographical and geological variations influence hydrology, understanding drainage density is vital for identifying groundwater potential zones and managing water resources sustainably. Figure 3i shows the drainage density map of the study region.

E. Validation of Model Results

Model results were validated with water samples collected from the open wells evenly distributed throughout the study area. For this purpose, 40 water samples from the study area were analyzed for TDS and nitrate in the geochemistry laboratory at the National Centre of Excellence in Geology, University of Peshawar, Pakistan. The concentration of TDS and nitrate was cross-checked with a resultant vulnerability map.

III. RESULTS

A. Results of DRASTIC factors

1) Depth to water level

The term "depth to water table" refers to the distance between the ground's surface and the water table. Pollutants and contaminants travel this distance before dissolving in the groundwater, according to Aller et al. [51], the probability of groundwater pollution decreases with increasing depth. The water table in the study area varies from 70.10 to 797.93 feet. The data was collected using an electric water diver. The data was classified into five classes ranging from 60.25 -180.15, 180.16 - 430.58, 430.59 – 510.55, 510.56 - 653.96, and 653.97 – 951.48 feet having the theoretical ranking 9, 8, 7, 5, 3, respectively and DRASTIC weight of 44, 42, 36, 18 and 12, respectively (Table II). The data was collected from Akora Khattak, Amangarh, Pirpai, Cherat, Jalozai, Risalpur, Khawarai, Kaka Sahib, Pabbi, Azakhel, Manki Sharif, and Shaidu and 20 samples of data along with well depth were collected from each major village. Figure 4a shows the reclassified weighted map of depth to groundwater.

2) Net recharge

The DRASTIC ranks for each precipitation class are 9,5,4,3 and 1, respectively. The weight assigned to net recharge was five, and the total DRASTIC weights for each precipitation class were 43, 39, 37, 33, and 25 respectively (Table II). The weights were assigned according to the vulnerability to contamination. Figure 4b shows the reclassified net recharge map of the study area.

3) Aquifer media

The underlying rock formations significantly influence the permeability rate and subsequent breakdown of the pollutants into the groundwater. Additional activities like filtration, cation exchange, and sorption occur when the water penetrates inside. Therefore, aquifer media is a crucial factor in influencing groundwater quality. The formation's permeability and thickness consequently influence the passage of the pollutants. Reduced danger of contamination and a higher rate of pollutant dilution are exhibited by thicker formations and lower permeability, respectively [58]. Weights and ranks were assigned according to the vulnerability to pollution of different rock types. The total weight assigned to aquifer media was 3, the DRASTIC ranks were 7, 5, 4, 3 and 2, and the DRASTIC weights were 29, 25, 18, 15, and 9, respectively (Table II). Figure 3c shows the reclassified aquifer media map.

TABLE II
DRASTIC RATES, RANKS, AND TOTAL WEIGHT OF THE FACTORS

Factors	Class Range	DRASTIC Index Rate	DRASTIC Index Weight	Total DRASTIC Weight (Rating × Weight)
Depth to water level (in feet)	60.25 -180.15	9	05	44
	180.16 - 430.58	8		42
	430.59 – 510.55	7		36
	510.56 - 653.96	5		18
	653.97 – 951.48	3		12
Net recharge (in/ year)	59.43 – 62.34	9	07	43
	57.45- 58.24	5		39
	53.45 – 55.39	4		37
	35.42 – 41.25	3		33
	37.79 – 40.12	1		25
Aquifer media	Jurassic sedimentary rock	7	03	29
	Cretaceous rock	5		25
	Neogene rock	4		18
	Paleogene rocks	3		15
	Quartzite	2		09
Soil types	Lithosol	7	05	25
	Calcaric Regosol	6		23
	Haplic Xerosol	3		19
Topography (Slope in %)	0 – 11.77	9	06	25
	11.78 – 16.60	7		19
	16.61 – 22.59	4		18
	22.60 – 39.02	2		11
	39.03 – 67.44	1		08
Vadose zone	Alluvium	6	07	35
	Sand with little Gravels	5		24
	Clay with some gravel	4		11
Hydraulic conductivity	587.9 – 682.6	9	04	32
	682.7 – 721.4	8		22
	721.5 – 754.1	7		18
	754.2 – 803.2	5		11
	803.3 – 838.8	4		08
Elevation	239 – 300	8	06	49
	300.1 – 448.7	7		45
	448.9 – 643.7	5		39
	643.8 – 950.4	4		28
	950.5 – 1544	1		18
Drainage Density	0 – 1000	9	05	69
	1001 – 3807	8		65
	3808 – 5306	7		58
	5307 – 10410	6		41
	10420 – 25930	4		39

4) Soil types

The soil media is the uppermost layer of the vadose zone with biological life. The soil media actively contributes to the movement of pollutants through the formations and controls the area's recharge. Because of its efficient adsorption and attenuation, soil media is essential in removing contaminants. The soil media facilitates increased cationic exchange and the removal of heavy metals since it is chemically active and rich in organic matter. The soil dramatically influences the presence of pollutants and how they move vertically into the vadose zone. The ranks for Lithosol were 7, Calcaric Regosol were 6 and 3 for Haplic Xerosol, while weights for these soil classes were 25, 23 and 19, respectively (Table II). The weights and ranks were assigned according to the porosity and vulnerability to pollution. Figure 4d shows the soil media map of the study area.

5) Topography

Topography accurately depicts where contaminants accumulate, infiltrate, and contaminate underground water. In regions with more excellent slopes, infiltration is slower, and there is less chance that pollutants will seep downward. The slope (in degree) was categorized into five classes and DRASTIC Index Rates were assigned accordingly: 0 – 11.77 (DIR 25), 11.78 – 16.60 (DIR19), 16.61 – 22.59 (DIR18),

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22.60 – 39.02 (DIR11), and 39.03 – 67.44 (DIR 8) (Table II). Figure 4e shows the topography map of the study area.

6) Impact of vadose zone

Jalayer et al. [59] state that the vadose zone is the under-saturated area above the water table. The vadose zone significantly influences the amount of contaminated water that percolates down. Therefore, by serving as a conduit, the vadose zone media controls the number of contaminants that travel to the water table and their absorption. Different bio-chemical degradation processes like filtration and straining take place in this zone. Alluvium, Sand with little gravel, and clay with some gravels were found in the study area. The DIR were assigned to these classes: Alluvium (6), Sand with little Gravel (5), and Clay with some gravel (4). The weightage for each class was set at 35, 24, and 11, respectively (Table II). The weights and DIR were assigned according to their vulnerability to pollution and contamination. Figure 4f shows the impact of the vadose zone reclassified map.

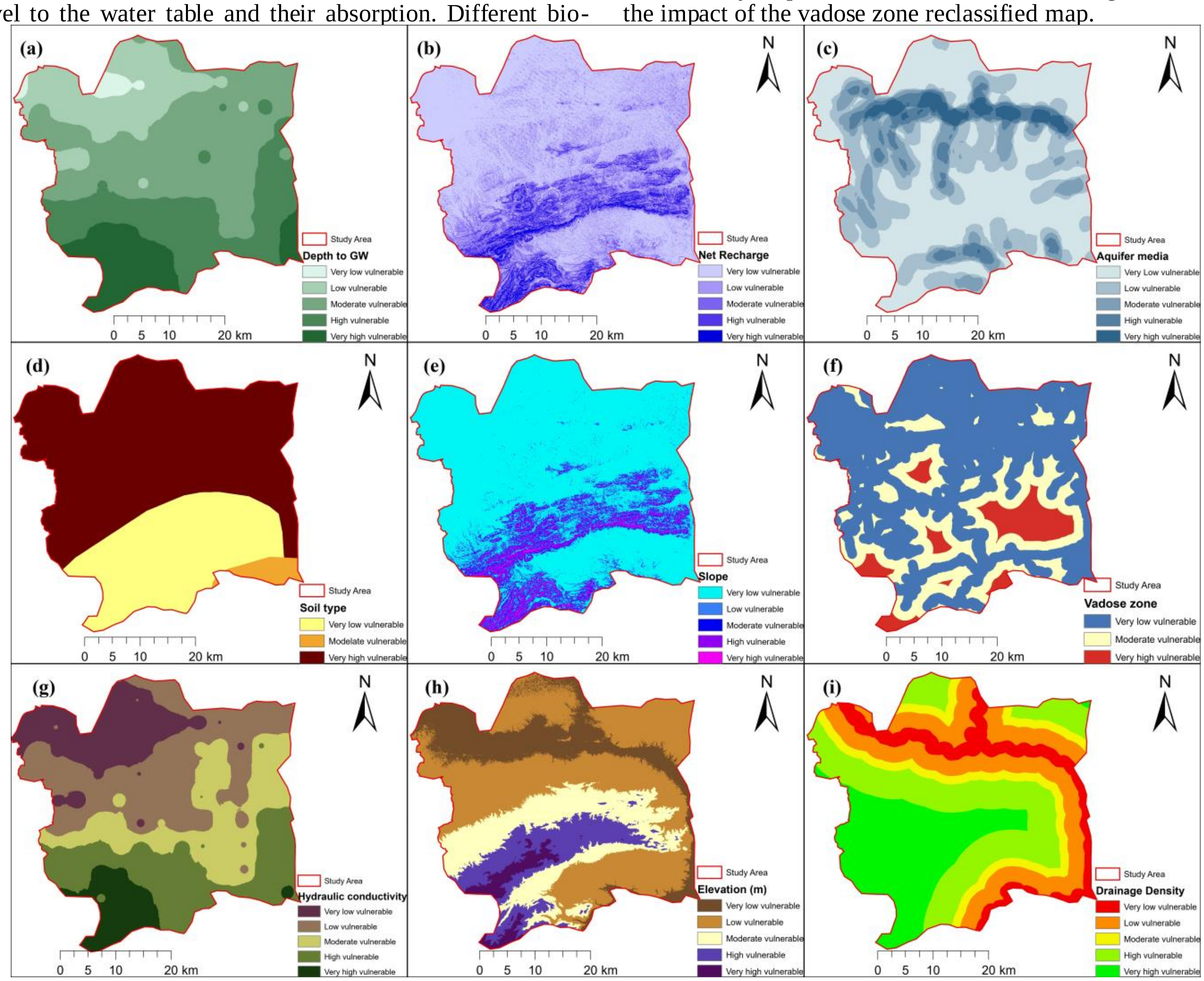

Figure 4: Results of the conditional factors were utilized in this study (a) depth to groundwater, (b) net recharge, (c) aquifer media, (d) soil types, (e) topography, (f) vadose zone, (g) hydraulic conductivity, (h) elevation and (i) drainage density.

7) Hydraulic conductivity

Hydraulic conductivity is a crucial factor that affects how quickly groundwater moves into the saturation zone and, in turn, how quickly pollutant-rich water is transmitted into the aquifer. The risk of contamination increases with higher hydraulic conductivity. The Hydraulic conductivity values range from 587.9 to 838.8 in the study area. The data was divided into five classes, and accordingly, DIR were assigned: 587.9 – 682.6 (DIR 9), 682.7 – 721.4 (DIR 8), 721.5 – 754.1 (DIR 7), 754.2 – 803.2 (DIR 5) and 803.3 – 838.8 (DIR 4). The weights for each class were set at 3, 9, 15, 24, and 27 (Table II). Figure 4g shows the hydraulic conductivity map of the study area.

8) Elevation

The elevation-based analysis of groundwater vulnerability in the Nowshera District reveals a significant relationship between elevation ranges and groundwater susceptibility. The lowest elevation range, 239–300 meters, exhibits the highest groundwater vulnerability with a score of 8 and a notable frequency of 49. This indicates increased susceptibility due to flat terrain, higher infiltration, and proximity to river plains. The elevation range is 300.1–448.7 meters followed by a vulnerability score of 7 and a frequency of 45, suggesting moderate susceptibility. As the elevation increases to 448.9–643.7 meters, the vulnerability score drops to 5 with a frequency of 39, reflecting reduced infiltration potential due to slope and terrain variability. In higher elevations, such as 643.8–950.4 meters, the vulnerability decreases further with a score of 4 and a frequency of 28, attributed to steeper gradients and reduced groundwater recharge capacity. The highest elevation range, 950.5–1544 meters, has the lowest vulnerability score of 1 and a frequency of 18, indicating minimal groundwater susceptibility due to limited recharge

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and increased runoff. This pattern demonstrates that groundwater vulnerability in Nowshera District is primarily concentrated in lower elevations where topography favors groundwater recharge. In comparison, higher elevations exhibit decreased vulnerability due to their geomorphological characteristics.

9) Drainage density

The drainage density in the Nowshera District is a critical factor influencing groundwater vulnerability. The model classifies drainage density into five ranges, revealing a trend where higher drainage densities correlate with increased groundwater recharge potential and vulnerability to contamination. The lowest drainage density range, 0–1000, is associated with the highest score (9) and accounts for 69 units, indicating areas with minimal surface drainage, likely to have greater infiltration potential. The 1001–3807 range scores 8 with 65 units, representing moderate drainage density areas where surface runoff is more prominent. In the 3808–5306 range, the score drops to 7 with 58 units, while the 5307–10410 range has a score of 6 and 41 units, suggesting areas with higher surface drainage and reduced infiltration potential. The highest drainage density range, 10420–25930, scores 4 and has 39 units, signifying regions with extensive surface drainage networks that limit recharge and increase runoff.

B. DRASTIC groundwater vulnerability zones

Based on an overlay map of the DRASTIC map index, Figure 5 shows the study area's groundwater vulnerability. The range of the index values was 220 to 1980. The index map was further classified into five classes based on index vulnerability: very low (220 - 345), low (346 - 670), moderate (671 - 730), high (731 - 1239), and very high 1240 - 1980). This study reveals that out of the total area of 1748 km^2 in the study area, very low area is 54.68 km^2 (3.13%), low area is 244.18 km^2 (13.97%), moderate area is 478.33 km^2 (27.37%), high area is 409.65 km^2 (23.44%), and very high vulnerable zone's area is 561.02 km^2 (32.10 %) (Table III). The data was collected from Akora Khattak, Amangarh, Pirpai, Cherat, Jalozai, Risalpur, Khawarai, Kaka Sahib, Pabbi, Azakhel, Manki Sharif, and Shaidu and 20 samples of data along with well depth were collected from each major village. Due to the lack of an adequate sewage infrastructure in the area, domestic wastewater discharge from residential areas, schools, Govt offices, and agriculture activities increases the risk of groundwater pollution.

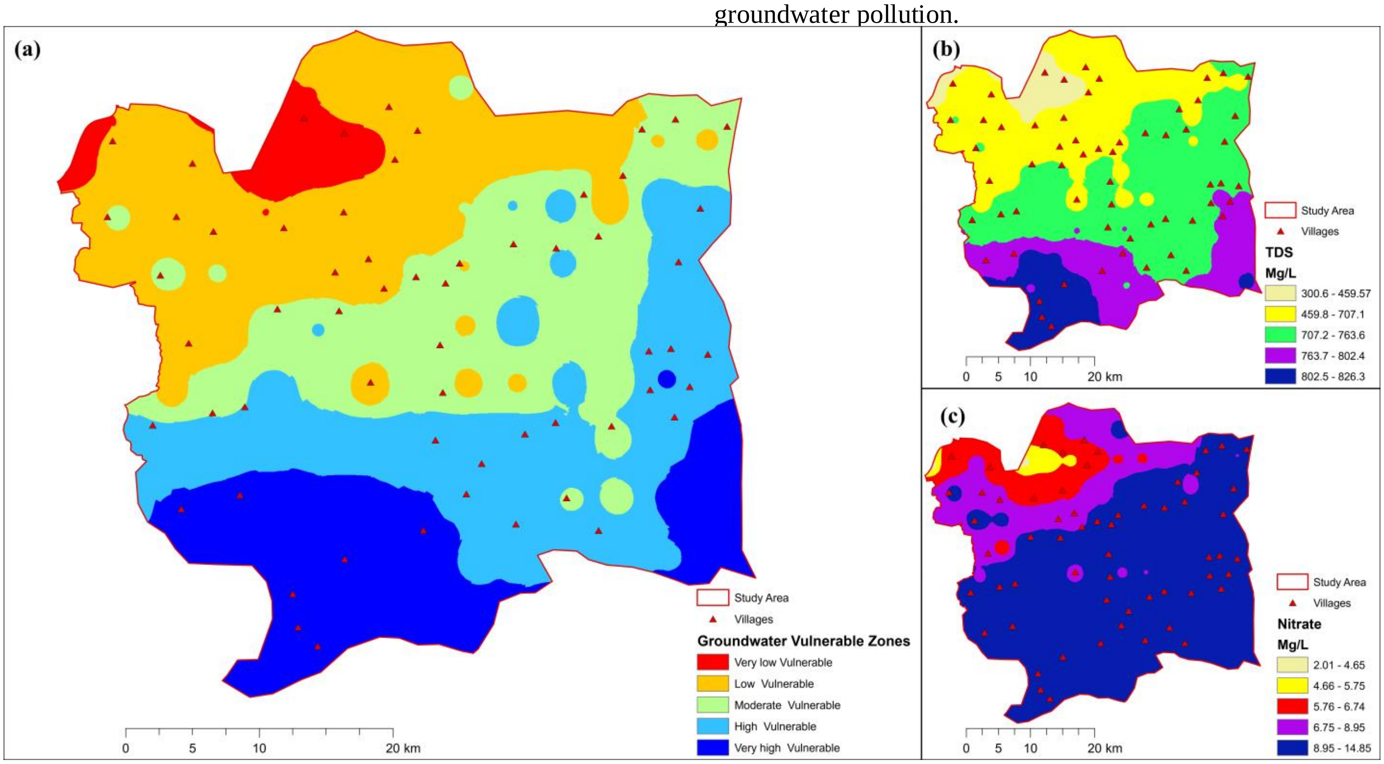

Figure 5: (a) Groundwater vulnerability zone (b) TDS concentration (c) Nitrate concentration

TABLE III
GROUNDWATER VULNERABLE ZONE AREA IN THE STUDY REGION

S. No	DRASTIC Index	Vulnerable zone	Area (km^2)	Area (%)
1	220 - 345	Very low vulnerable	54.68	3.13
2	346 - 670	Low vulnerable	244.18	13.97
3	671 - 730	Moderate vulnerable	478.33	27.37
4	731 -1239	High vulnerable	409.65	23.44
5	1240 - 1980	Very high vulnerable	561.02	32.10

C. Validation

Nitrate and TDS parameters have been utilized to validate the DRASTIC model results, which were used to create the final groundwater vulnerability map. Samples were collected and analyzed in a laboratory for Nitrate and total dissolved solid (TDS) values. In the study area, the nitrate and TDS concentrations ranged from 2.01 to 14.85 mg/l and 300.6 to 826.3 mg/l, respectively (Figure 6). The geographic distribution of the parameters in the north area shows that Akora Khattak, Amangarh, Pirpai, Cherat, Jalozai, Risalpur exhibit low nitrate concentrations between 2.01 and 4.68 mg/L, and similarly show low TDS concentrations between 300.6 and 459.57 mg/L. These areas have a low level of groundwater vulnerability. The southwest part of the region (district Nowshera), specifically the Akora Khattak, Amangarh, Pirpai, Cherat, Jalozai, Risalpur regions, have incredibly high levels of groundwater vulnerability, as well as high concentrations of nitrate, ranging between 8.95 to 14.85 mg/L and high TDS concentrations ranged between 802.5 and 826.3 mg/L. The contaminants from agriculture combine with the recharge water and contaminate the groundwater. TDS and nitrate concentrations are also high in areas where the DRASTIC index is similarly high.

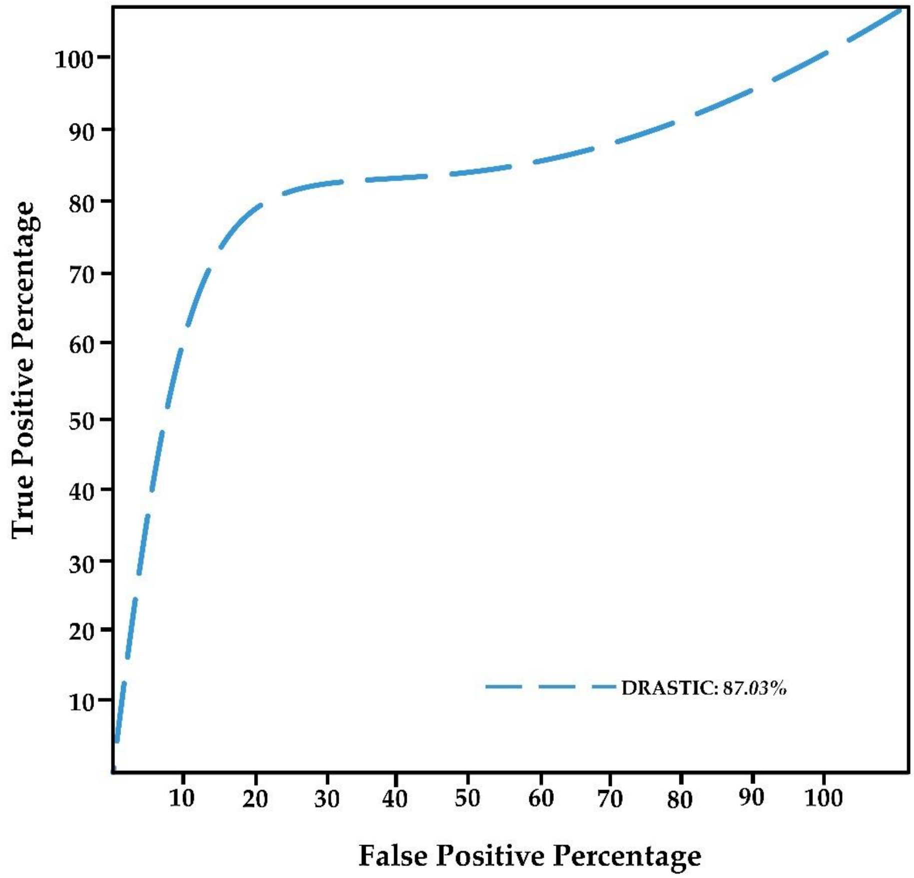

Figure 6: Validation of the DRASTIC model using AUC_ROC

IV. Discussion

It is essential to determine how vulnerable groundwater aquifers are to pollution if they are to continue functioning [60]. The US Environmental Protection Agency introduced the DRASTIC model, which is mainly employed to assess groundwater's vulnerability to pollution [22]. Datasets were created using the sources listed in Table I, according to Aller et al. [51], the water table's depth is the most critical factor in groundwater vulnerability. Additionally, the water table in the study area varies from 60.25 to 180.15 feet. The data was collected using an electric water diver. The data was classified into five classes: 60.25 -180.15, 180.16 - 430.58, 430.59 – 510.55, 510.56 - 653.96 and 653.97 – 951.48 feet as classified by different researchers and planners [61], [62]. Higher water table readings indicate more frequent water pumping occurs in the area.

Groundwater contamination is also significantly impacted by net recharge (R) [63]. The study area receives 59.43 – 40.12 mm Average annual rainfall. The data was further classified into five classes: 59.43 – 62.34, 57.45- 58.24, 53.45 – 55.39, 35.42 – 41.25, and 37.79 – 40.12 mm annual rainfall. Aquifer media control the path that contaminants take and how long they travel. The parameter, which also contains sand, is given a high weight. Aquifer media in the study area includes Jurassic sedimentary rock, Cretaceous rock, Neogene rock, Paleogene rocks, and Quartzite. The exact weights were assigned in the study [64] . According to Aslam et al. [65] the weights and ratings given to soil media were based on previous studies. Figure 3d depicts two different soil media, including clay loam and loam soil, for the research region. The soil with the most permeability was assigned the highest rating value, and the soil with the lowest permeability was given a lower rating.

The slopes in the study area were categorized into five classes (degrees): 0 – 11.77, 11.78 – 16.60, 16.61 – 22.59, 22.60 – 39.02, and 39.03 – 67.44, according to the ratings and weights assigned by Maqsoom et al. [66], these values were assigned since water drainage is higher on steeper slopes, and pollutants are less likely to be present there. The vadose zone is responsible for water movement in the subsurface. Results showed that alluvium, sand, and clay with gravel are the primary elements in the vadose zone. According to Figure 3g, alluvium receives a rating of 6, sand gets a rating of 5, and clay with gravel gets a rating of 4. Hydraulic conductivity, the nine parameter of the DRASTIC model, can influence the rate of pollution transmission [60]. An aquifer can carry water [67]. The Hydraulic conductivity values range from 587.9 to 838.8 in the study area. The data was divided into five classes: 587.9 – 682.6, 682.7 – 721.4, 721.5 – 754.1, 754.2 – 803.2, and 803.3 – 838.8.

While the GIS-DRASTIC integrated technique represents a valuable approach for groundwater vulnerability assessment under semi-arid to arid conditions, it is crucial to acknowledge certain limitations inherent in its application. Firstly, the technique heavily relies on available data, and the accuracy of the vulnerability map is contingent upon the quality and spatial resolution of input parameters such as lithology, soil, and land use. In regions with limited data availability or inconsistent datasets, the accuracy of vulnerability assessments may be compromised. Additionally, the model assumes steady-state conditions and does not account for potential temporal variations in land use, climate, or groundwater recharge, which may impact the reliability of long-term predictions [64]. The GIS-DRASTIC method also simplifies the complex hydrogeological processes by using predetermined weightings for each parameter, potentially oversimplifying the variability in the vulnerability landscape. Furthermore, the technique may not fully capture the dynamic interplay of anthropogenic activities and their evolving impact on groundwater quality over time. Recognizing these limitations requires practitioners and policymakers to interpret results judiciously and supplement GIS-DRASTIC outcomes with site-specific investigations for a more comprehensive groundwater vulnerability assessment.

This study utilizes a DRASTIC risk map to assist planners and engineers in identifying areas with a high risk of contamination. The groundwater Vulnerable Zones map was divided into categories: low vulnerable zone, medium vulnerable zone, high vulnerable zone, and very high vulnerable zone of groundwater contamination. The outcome of this study will help achieve the United Nations' sustainable development goals (SDGs) related to the good health and well-being of people, food security, and the provision of clean water. Specifically, our approach provides a quantitative measure for the indicator 6.1.1 Proportion of population using safely managed drinking water services. The approach adopted in this study can be further improved by adding parameters of land use. Also, hospital data for various diseases in the study area related to pesticide contamination water will greatly impact policymakers to plan accordingly.

V. Conclusion

The prevention of groundwater pollution depends on functional groundwater planning and management because groundwater is an essential and precious resource for many human activities. The groundwater vulnerability zones in the Nowshera District are classified into five categories based on their susceptibility. The very low vulnerable zone covers an area of 54.68 km², representing only 3.13% of the total area, indicating minimal groundwater contamination risk. The low vulnerable zone occupies 244.18 km² (13.97%), reflecting relatively low susceptibility to contamination. The moderate vulnerable zone, which accounts for 478.33 km² or 27.37%, represents a significant portion of the district where groundwater contamination potential is moderate. The high vulnerable zone covers 409.65 km², constituting 23.44%, signifying regions with a considerable risk of groundwater contamination. Finally, the very high vulnerable zone, with the largest area of 561.02 km² (32.10%), highlights regions most susceptible to groundwater contamination. This classification emphasizes that a substantial portion of the district lies within high and very high vulnerable zones, underscoring the need for sustainable groundwater management and targeted mitigation strategies.

A study on groundwater susceptibility can benefit management and policymaking authorities by establishing regulations that prevent bodily waste from mixing with groundwater. These policies will help maintain a healthy environment as the local population grows.

The study provides valuable insights into groundwater vulnerability by conducting a comprehensive assessment of the impacts of frequent pesticide and fertilizer use in agricultural fields of District Nowshera. Utilizing nine hydrogeological parameters and the GIS-based DRASTIC index represents a methodological advancement in evaluating the potential risks associated with agricultural practices. The generated groundwater vulnerability map, classified into four categories, is crucial for policymakers, land managers, and farmers to identify at-risk areas and implement targeted mitigation measures. The validation of the model using scientifically recognized water quality measurements, namely Nitrate and TDS, enhances the reliability of the findings. The research contributes to our understanding of the region's specific contaminants and offers a blueprint for proactive measures to regulate and control anthropogenic and agricultural pollution. This approach not only aids in reducing the danger of contamination but also holds the potential to identify specific pesticides causing pollution, assess the extent of contamination, and prioritize remedial actions. Several future actions and measures are crucial to safeguard the aquifer in the most vulnerable areas of District Nowshera, Pakistan. Firstly, implementing sustainable agricultural practices, including precise pesticide and fertilizer application, can mitigate groundwater contamination. Promoting awareness programs among farmers and the community about responsible water usage and pollution prevention is essential. Establishing monitoring wells and regularly assessing groundwater quality will enable early detection of contamination. Implementing stringent regulations on land use and development in vulnerable zones, coupled with effective enforcement, is imperative. Collaborative efforts between local authorities, communities, and environmental agencies will be essential for successful aquifer protection and ensuring a sustainable water supply for the future.

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VI. REFERENCES

[1] W. Wei, J. Gong, J. Deng, and W. Xu, "Effects of Air Vent Size and Location Design on Air Supply Efficiency in Flood Discharge Tunnel Operations," *J. Hydraul. Eng.*, vol. 149, no. 12, pp. 1–12, Dec. 2023, doi: 10.1061/JHEND8.HYENG-13305.

[2] W. Wei, W. Xu, J. Deng, and Y. Guo, "Self-aeration development and fully cross-sectional air diffusion in high-speed open channel flows," *J. Hydraul. Res.*, vol. 60, no. 3, pp. 445–459, May 2022, doi: 10.1080/00221686.2021.2004250.

[3] H. Rajput, R. Goyal, and U. Brighu, "Modification and optimization of DRASTIC model for groundwater vulnerability and contamination risk assessment for Bhiwadi region of Rajasthan, India," *Environ. Earth Sci.*, vol. 79, no. 6, 2020, doi: 10.1007/S12665-020-8874-Z.

[4] C. Ouyang, Z. Wang, H. An, X. Liu, and D. Wang, "An example of a hazard and risk assessment for debris flows—A case study of Niwan Gully, Wudu, China," *Eng. Geol.*, vol. 263, 2019, doi: 10.1016/j.enggeo.2019.105351.

[5] Y. Zhu, H. Dai, and S. Yuan, "The competition between heterotrophic denitrification and DNRA pathways in hyporheic zone and its impact on the fate of nitrate," *J. Hydrol.*, vol. 626, p. 130175, 2023, doi: https://doi.org/10.1016/j.jhydrol.2023.130175.

[6] S. M. Shirazi, H. M. Imran, S. A.-J. of Risk Research, and undefined 2012, "GIS-based DRASTIC method for groundwater vulnerability assessment: a review," *Taylor Fr. Shirazi, HM Imran, S AkibJournal Risk Res. 2012•Taylor Fr.*, vol. 15, no. 8, pp. 991–1011, 2012, doi: 10.1080/13669877.2012.686053.

[7] C. Edmonds, "Improved groundwater vulnerability mapping for the karstic chalk aquifer of south east England," *Eng. Geol.*, vol. 99, no. 3–4, pp. 95–108, 2008, doi: 10.1016/j.enggeo.2007.11.019.

[8] B. Aslam, S. Ismail, and I. Ali, "A GIS - based DRASTIC model for assessing aquifer susceptibility of Safdarabad Tehsil , Sheikhupura District , Punjab Province , Pakistan," *Model. Earth Syst. Environ.*, no. 0123456789, 2020, doi: 10.1007/s40808-020-00735-8.

[9] B. Cosgrove and F. Rijsberman, "World water vision," *J. Hydraul. Res. Rech. Hydraul.*, vol. 38, no. 4 SUPPL., p. 57, 2000, doi: 10.4324/9781315071763.

[10] D. A. Rao, P. K. Naik, S. K. Jain, K. V. Kumar, and E. N. D. Rao, "Assessment of vulnerability zones for ground water pollution using GIS-DRASTIC-EC model: A field-based approach," *J. Earth Syst. Sci.*, vol. 127, no. 4, 2018, doi: 10.1007/S12040-018-0944-1.

[11] G. ya Wang *et al.*, "Land rebound after banning deep groundwater extraction in Changzhou, China," *Eng. Geol.*, vol. 229, pp. 13–20, 2017, doi: 10.1016/j.enggeo.2017.09.006.

[12] M. T. Bhatti, A. A. Anwar, and M. Aslam, "Groundwater monitoring and management: Status and options in Pakistan," *Comput. Electron. Agric.*, vol. 135, pp. 143–153, 2017, doi: 10.1016/j.compag.2016.12.016.

[13] A. Shakoor *et al.*, "Delineation of regional groundwater vulnerability using DRASTIC model for agricultural application in Pakistan," *Arab. J. Geosci.*, vol. 13, no. 4, 2020, doi: 10.1007/s12517-020-5161-y.

[14] Y. Tian *et al.*, "Improving CMIP6 Atmospheric River Precipitation Estimation by Cycle-Consistent Generative Adversarial Networks," *J. Geophys. Res. Atmos.*, vol. 129, no. 14, p. e2023JD040698, Jul. 2024, doi: https://doi.org/10.1029/2023JD040698.

[15] M. K. Daud *et al.*, "Drinking Water Quality Status and Contamination in Pakistan," *BioMed Research International*, vol. 2017. 2017. doi: 10.1155/2017/7908183.

[16] H. Xu, Y. Zhao, D. Zhao, Y. Duan, and X. Xu, "Improvement of disastrous extreme precipitation forecasting in North China by Pangu-weather AI-driven regional WRF model," *Environ. Res. Lett.*, vol. 19, no. 5, 2024, doi: 10.1088/1748-9326/ad41f0.

[17] S. H. I. A. Shah *et al.*, "Classification of aquifer vulnerability by using the drastic index and geo-electrical techniques," *Water (Switzerland)*, vol. 13, no. 16, 2021, doi: 10.3390/w13162144.

[18] U. Ali *et al.*, "A data-driven approach for multi-scale GIS-based building energy modeling for analysis, planning and support decision making," *Appl. Energy*, vol. 279, no. August, p. 115834, 2020, doi: 10.1016/j.apenergy.2020.115834.

[19] Y. Tian, Y. Zhao, S.-W. Son, J.-J. Luo, S.-G. Oh, and Y. Wang, "A Deep-Learning Ensemble Method to Detect Atmospheric Rivers and Its Application to Projected Changes in Precipitation Regime," *J. Geophys. Res. Atmos.*, vol. 128, no. 12, p. e2022JD037041, Jun. 2023, doi: https://doi.org/10.1029/2022JD037041.

[20] L. Sun *et al.*, "CRNet: Channel-Enhanced Remodeling-Based Network for Salient Object Detection in Optical Remote Sensing Images," *IEEE Trans. Geosci. Remote Sens.*, vol. 61, pp. 1–14, 2023, doi: 10.1109/TGRS.2023.3305021.

[21] G. Zhou, W. Liu, Q. Zhu, Y. Lu, and Y. Liu, "ECA-MobileNetV3(Large)+SegNet Model for Binary Sugarcane Classification of Remotely Sensed Images," *IEEE Trans. Geosci. Remote Sens.*, vol. 60, pp. 1–15, 2022, doi: 10.1109/TGRS.2022.3215802.

[22] A. Singh, S. K. Srivastav, S. Kumar, and G. J. Chakrapani, "A modified-DRASTIC model (DRASTICA) for assessment of groundwater vulnerability to pollution in an urbanized environment in Lucknow, India," *Environ. Earth Sci.*, vol. 74, no. 7, pp. 5475–5490, 2015, doi: 10.1007/S12665-015-4558-5.

[23] H. Xu, Q. Li, and J. Chen, "Highlight Removal from A Single Grayscale Image Using Attentive GAN," *Appl. Artif. Intell.*, vol. 36, no. 1, p. 1988441, Dec. 2022, doi: 10.1080/08839514.2021.1988441.

[24] K. Zhang *et al.*, "Xin'anjiang Nested Experimental Watershed (XAJ-NEW) for Understanding Multiscale Water Cycle: Scientific Objectives and Experimental Design," *Engineering*, vol. 18, pp. 207–217, 2022, doi: https://doi.org/10.1016/j.eng.2021.08.026.

[25] G. Zhou, J. Li, Z. Tian, J. Xu, and Y. Bai, "The Extended Stumpf Model for Water Depth Retrieval From Satellite Multispectral Images," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 17, pp. 6779–6790, 2024, doi: 10.1109/JSTARS.2024.3368761.

[26] Z. Liu *et al.*, "Increasing irrigation-triggered landslide activity caused by intensive farming in deserts on three continents," *Int. J. Appl. Earth Obs. Geoinf.*, vol. 134, p. 104242, Nov. 2024, doi: 10.1016/j.jag.2024.104242.

[27] A. Boufekane, S. Yahiaoui, H. Meddi, M. Meddi, and G. Busico, "Modified DRASTIC index model for groundwater vulnerability mapping using geostatistic methods and GIS in the Mitidja plain area (Algeria)," *Taylor Fr. Boufekane, S Yahiaoui, H Meddi, M Meddi, G BusicoEnvironmental Forensics, 2022•Taylor Fr.*, vol. 23, no. 5–6, pp. 539–556, 2022, doi: 10.1080/15275922.2021.1913674.

[28] G. Zhou *et al.*, "Adaptive Adjustment for Laser Energy and PMT Gain Through Self-Feedback of Echo Data in Bathymetric LiDAR," *IEEE Trans. Geosci. Remote Sens.*, vol. 62, pp. 1–22, 2024, doi: 10.1109/TGRS.2024.3403895.

[29] D. Goyal, A. K. Haritash, and S. K. Singh, "A comprehensive review of groundwater vulnerability assessment using index-based, modelling and coupling methods," *Journal of Environmental Management*, vol. 296. 2021. doi: 10.1016/j.jenvman.2021.113161.

[30] C. Xiong *et al.*, "Using satellite imagery to estimate CO2 partial pressure and exchange with the atmosphere in the Songhua River," *J. Hydrol.*, vol. 634, p. 131074, 2024, doi: https://doi.org/10.1016/j.jhydrol.2024.131074.

[31] A. Fannakh and A. Farsang, "DRASTIC, GOD, and SI approaches for assessing groundwater vulnerability to pollution: a review," *Environ. Sci. Eur.*, vol. 34, no. 1, 2022, doi: 10.1186/S12302-022-00646-8.

[32] L. Chen *et al.*, "Dataset of stable isotopes of precipitation in the Eurasian continent," *Earth Syst. Sci. Data*, vol. 16, no. 3, pp. 1543–1557, Mar. 2024, doi: 10.5194/essd-16-1543-2024.

[33] L. Chen *et al.*, "Influence of mountain orientation on precipitation isotopes in the westerly belt of Eurasia," *Glob. Planet. Change*, vol. 240, p. 104543, 2024, doi: https://doi.org/10.1016/j.gloplacha.2024.104543.

[34] E. Sener and A. Davraz, "Assessment of groundwater vulnerability based on a modified DRASTIC model, GIS and an analytic hierarchy process (AHP) method: The case of Egirdir Lake basin (Isparta, Turkey)," *Hydrogeol. J.*, vol. 21, no. 3, pp. 701–714, 2013, doi: 10.1007/s10040-012-0947-y.

[35] S. K. Garewal, A. D. Vasudeo, V. S. Landge, and A. D. Ghare, "A GIS-based Modified DRASTIC (ANP) method for assessment of groundwater vulnerability: a case study of Nagpur city, India," *iwaponline.comSK Garewal, AD Vasudeo, VS Landge, AD GhareWater Qual. Res. Journal, 2015•iwaponline.com*, 2017, doi: 10.2166/wqrj.2017.046.

[36] M. A. Sresto, S. Siddika, M. N. Haque, and M. Saroar, "Groundwater vulnerability assessment in Khulna district of Bangladesh by integrating fuzzy algorithm and DRASTIC (DRASTIC-L) model," *Model. Earth Syst. Environ.*, vol. 8, no. 3, pp. 3143–3157, 2022, doi: 10.1007/S40808-021-01270-W.

[37] K. Brindha, L. E.-J. of Hydrology, and undefined 2015, "Cross comparison of five popular groundwater pollution vulnerability index approaches," *Elsevier*, 2015, doi: 10.1016/j.jhydrol.2015.03.003.

[38] M. Sarkar and S. C. Pal, "Application of DRASTIC and Modified DRASTIC Models for Modeling Groundwater Vulnerability of Malda District in West Bengal," *J. Indian Soc. Remote Sens.*, vol. 49, no. 5, pp. 1201–1219, 2021, doi: 10.1007/S12524-020-01176-7.

[39] C. Zhan, Z. Dai, S. Yin, K. C. Carroll, and M. R. Soltanian, "Conceptualizing future groundwater models through a ternary framework of multisource data, human expertise, and machine intelligence," *Water Res.*, vol. 257, p. 121679, 2024, doi: https://doi.org/10.1016/j.watres.2024.121679.

[40] D. Xianglin *et al.,* "Advanced machine vision techniques for groundwater level prediction modeling geospatial and statistical research," *Adv. Sp. Res.*, no. xxxx, Nov. 2024, doi: 10.1016/j.asr.2024.11.018.

[41] S. M. Farooqi *et al.*, "Integrating Geo-AI with RS & GIS for comprehensive assessments of urban land cover transformations and integrated responses," *Environ. Earth Sci.*, vol. 84, no. 1, p. 3, Jan. 2025, doi: 10.1007/s12665-024-12005-2.

[42] L. Feng *et al.*, "Seasonal Dynamics in Land Surface Temperature in Response to Land Use Land Cover Changes Using Google Earth Engine," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 17, pp. 17983–17997, 2024, doi: 10.1109/JSTARS.2024.3466191.

[43] H. Mustafa *et al.*, "Integrating multisource data and machine learning for supraglacial lake detection: Implications for environmental management and sustainable development goals in high mountainous regions," *J. Environ. Manage.*, vol. 370, no. September, p. 122490, Nov. 2024, doi: 10.1016/j.jenvman.2024.122490.

[44] M. Farhan, T. Wu, M. Amin, A. Tariq, R. Guluzade, and H. Alzahrani, "Monitoring and prediction of the LULC change dynamics using time series remote sensing data with Google Earth Engine," *Phys. Chem. Earth, Parts A/B/C*, vol. 136, p. 103689, Dec. 2024, doi: 10.1016/j.pce.2024.103689.

[45] B. Tu, X. Yang, B. He, Y. Chen, J. Li, and A. Plaza, "Anomaly Detection in Hyperspectral Images Using Adaptive Graph Frequency Location," *IEEE Trans. Neural Networks Learn. Syst.*, pp. 1–15, 2024, doi: 10.1109/TNNLS.2024.3449573.

[46] M. Farhan *et al.*, "Predicting Land Use Land Cover Dynamics and Land Surface Temperature Changes Using CA-Markov-Chain Models in Islamabad, Pakistan (1992–2042)," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 17, pp. 16255–16271, 2024, doi: 10.1109/JSTARS.2024.3441241.

[47] J. Kang, L. Zhao, R. Li, H. Mo, Y. L.-G. International, and undefined 2017, "Groundwater vulnerability assessment based on modified DRASTIC model: a case study in Changli County, China," *Taylor Fr. Kang, L Zhao, R Li, H Mo, Y LiGeocarto Int. 2017•Taylor Fr.*, vol. 32, no. 7, pp. 749–758, 2017, doi: 10.1080/10106049.2016.1167969.

[48] A. Neshat, B. Pradhan, S. Pirasteh, and H. Z. M. Shafri, "Estimating groundwater vulnerability to pollution using a modified DRASTIC model in the Kerman agricultural area, Iran," *Environ. Earth Sci.*, vol. 71, no. 7, pp. 3119–3131, 2014, doi: 10.1007/S12665-013-2690-7.

[49] M. Sadat-Noori and K. Ebrahimi, "Groundwater vulnerability assessment in agricultural areas using a modified DRASTIC model," *Environ. Monit. Assess.*, vol. 188, no. 1, pp. 1–18, 2016, doi: 10.1007/S10661-015-4915-6.

[50] X. Wu and Y. Zhao, "A Novel Heat Pulse Method in Determining 'Effective' Thermal Properties in Frozen Soil," *Water Resour. Res.*, vol. 60, no. 12, p. e2024WR037537, Dec. 2024, doi: https://doi.org/10.1029/2024WR037537.

[51] L. Aller and J. Thornhill, *DRASTIC: a standardized system for evaluating ground water pollution potential using hydrogeologic settings*. 1987.

[52] M. Sahoo, S. Sahoo, A. Dhar, and B. Pradhan, "Effectiveness evaluation of objective and subjective weighting methods for aquifer vulnerability assessment in urban context," *J. Hydrol.*, vol. 541, pp. 1303–1315, 2016, doi: 10.1016/j.jhydrol.2016.08.035.

[53] S. Lee, "Evaluation of waste disposal site using the DRASTIC system in Southern Korea," *Environ. Geol.*, vol. 44, no. 6, pp. 654–664, 2003, doi: 10.1007/S00254-003-0803-4.

[54] L. Jin, L. Li, F. Xu, and J. Zhang, "The synthesis and application of L-cysteine graphene quantum dots for quantitative analysis of nitrite content in water," *Phys. Scr.*, vol. 99, no. 6, p. 65124, 2024, doi: 10.1088/1402-4896/ad4c24.

[55] M. E. Huq *et al.*, "Changes monitoring in Hongjiannao Lake from 1987 to 2023 using Google Earth Engine and analysis of climatic and anthropogenic forces," *Phys. Chem. Earth, Parts A/B/C*, vol. 136, no. September, p. 103756, Dec. 2024, doi: 10.1016/j.pce.2024.103756.

[56] S. Mahdi, M. Nejad, D. Abbasi-moghadam, A. Sharifi, and A. Tariq, "Capsular attention Conv-LSTM network (CACN): A deep learning structure for crop yield estimation based on multispectral imagery," *Eur. J. Agron.*, vol. 161, no. September, p. 127369, 2024, doi: 10.1016/j.eja.2024.127369.

[57] L. Wang *et al.*, "Research on high precision localization of space target with multi-sensor association," *Opt. Lasers Eng.*, vol. 184, p. 108553, 2025, doi: https://doi.org/10.1016/j.optlaseng.2024.108553.

[58] A. E. Edet, B. J. Merkel, and O. E. Offiong, "Contamination risk assessment of fresh groundwater using the distribution and chemical speciation of some potentially toxic elements in Calabar (southern Nigeria)," *Environ. Geol.*, vol. 45, no. 7, pp. 1025–1035, 2004, doi: 10.1007/S00254-004-0963-X.

[59] S. Jalayer, A. Sharifi, D. Abbasi-Moghadam, A. Tariq, and S. Qin, "Modeling and Predicting Land Use Land Cover Spatiotemporal Changes: A Case Study in Chalus Watershed, Iran," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 15, pp. 5496–5513, 2022, doi: 10.1109/JSTARS.2022.3189528.

[60] A. Maqsoom *et al.*, "A gis-based groundwater contamination assessment using modified drastic geospatial technique," *Water (Switzerland)*, vol. 13, no. 20, 2021, doi: 10.3390/w13202868.

[61] A. Neshat, B. Pradhan, and S. Javadi, "Risk assessment of groundwater pollution using Monte Carlo approach in an agricultural region: An example from Kerman Plain, Iran," *Comput. Environ. Urban Syst.*, vol. 50, pp. 66–73, 2015, doi: 10.1016/j.compenvurbsys.2014.11.004.

[62] I. Khosravi, A. Safari, S. H.-I. J. of, and undefined 2018, "MSMD: maximum separability and minimum dependency feature selection for cropland classification from optical and radar data," *Taylor Fr. Khosravi, A Safari, S HomayouniInternational J. Remote Sensing, 2018•Taylor Fr.*, vol. 39, no. 8, pp. 2159–2176, 2018, doi: 10.1080/01431161.2018.1425564.

[63] A. Kumar, A. P. K.-G. International, and undefined 2020, "Groundwater vulnerability and contamination risk assessment using GIS-based modified DRASTIC-LU model in hard rock aquifer system in India," *Taylor Fr. Kumar, A Pramod KrishnaGeocarto Int. 2020•Taylor Fr.*, vol. 35, no. 11, pp. 1149–1178, 2019, doi: 10.1080/10106049.2018.1557259.

[64] A. Widaa, M. Elamin, A. B. Saeed, N. A. Aballa, N. Abd, and E. Elsheikh, "Impact Of Groundwater Quality On Soil Properties And Crop Production Under Khartoum State Condition," *Int. J. Technol. Enhanc. Emerg. Eng. Res.*, vol. 3, no. 11, p. 4, 2015.

[65] B. Aslam, A. Zafar, and U. Khalil, "Comparison of multiple conventional and unconventional machine learning models for landslide susceptibility mapping of Northern part of Pakistan," *Environ. Dev. Sustain.*, 2022, doi: 10.1007/s10668-022-02314-6.

[66] A. Maqsoom *et al.*, "A GIS-based DRASTIC Model and an Adjusted DRASTIC Model (DRASTICA) for Groundwater Susceptibility Assessment along the China–Pakistan Economic Corridor (CPEC) Route," *ISPRS Int. J. Geo-Information*, vol. 9, no. 5, 2020, doi: 10.3390/ijgi9050332.

[67] A. Tariq, "Quantitative comparison of geostatistical analysis of interpolation techniques and semiveriogram spatial dependency parameters for soil atrazine contamination attribute," in *Geoinformatics for Geosciences*, N. Stathopoulos, A. Tsatsaris, and K. B. T.-G. for G. Kalogeropoulos, Eds., Elsevier, 2023, pp. 261–279. doi: 10.1016/B978-0-323-98983-1.00016-8.

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Wu Jiazhe is currently a senior student at Nanjing Engineering Institute and the University of Oulu, majoring in Software Engineering. His research interests focus on data science, with particular emphasis on computer vision and big data analytics. Wu Jiazhe has contributed to the field through the invention of a patented method and device for optimal peak-shaving measurement in power systems, which has been recognized for its potential to enhance the efficiency of power system operations. Wu Jiazhe is keen to continue exploring advancements in data science and its applications in solving real-world problems.

Dai Xinrui is currently a junior student majoring in Software Engineering. His academic interests lie in the fields of Geographic Information Systems, Data Science. Dai Xinrui is eager to further explore cutting-edge innovations in GIS and data-driven technologies, aspiring to address complex challenges through creative and effective solutions.

Su Yan Cheng is a senior student at Nanjing Institute of Technology, majoring in Software Engineering within the School of Computer Engineering and Technology. His research interests are keenly focused on Geographic Information Systems (GIS). Su YanCheng is committed to pushing the boundaries of GIS applications, with the goal of contributing to sustainable urban development and environmental conservation.

Zheng Xiangtian was born in Qiqihar, Heilongjiang, China in 1991. He received Ph.D. degree in Computer Application Technology from China University of Mining Technology (CUMTB), Beijing, China, in 2019. He was a post-doctor in Department of surveying and mapping, Hohai University. Since 2021, he has been a lecturer in Nanjing Institute of Technology (NJIT) and has been supported by YKJ202118 for research. His research interest is mainly in the area of Geo-Information fusion.

Bushra Ghaffar received her Ph.D. degree in Environmental Sciences from the International Islamic University, Islamabad, in 2022. She is currently a Lecturer in the Department of Environmental Science at the same university and the author of 18 journal research articles. Her research interests focus on groundwater contamination, particularly arsenic and fluoride, using predictive modeling and geospatial intelligence to support water safety and resource management, disaster risk assessment and mitigation, climate change, and ecosystem sustainability. Her work addresses key environmental challenges and advances knowledge in predictive modeling. Her research interests lie in the application of machine learning and geospatial technologies to solve environmental issues and enhance environmental sustainability.

Rabiya Nasir obtained her PhD degree from The University of the Punjab in Environmental Sciences in 2022. Currently she is working as an Assistant Professor in the University of Lahore, Pakistan. Her areas of specialization include: GHG emissions calculation, Energy Modeling, Sustainability Sciences, Carbon market analysis and Climate change. In the said areas she participated in many international and national conference. She published 20 peer reviewed international papers.

Ahsan Jamil is a Ph.D. candidate in Water Science & Management at New Mexico State University, USA. He holds an M.S. in Remote Sensing & GIS from PMAS-AAUR, Pakistan in 2018. His academic foundation includes a B.S degree in Geophysics from Bahria University, Islamabad, where he developed strong technical expertise in geophysical sciences.
Ahsan's research interests lie in developing machine learning algorithms for geophysical electrical resistivity inversion and hydrogeological characterization. He focuses on integrating geospatial data science, remote sensing, and computational methods to tackle challenges in subsurface characterization and environmental modeling.

Zeeshan Zafar earned his doctoral degree in Physical Geography from Northwest University, Xi'an, China in 2022. Currently serving as a postdoctoral researcher at Wuhan University, China. His academic pursuits have yielded numerous publications in esteemed journals, exploring topics such as land use mapping, urbanization, climate change and ecosystem services. His work has garnered significant attention, with over 300 citations to his credit. He is a multifaceted researcher with expertise in remote sensing, geographic information systems (GIS), machine learning, and environmental science.

Mohammad Suhail Meer completed his Ph.D. in Geoinformatics in 2022 from Sathyabama Institute of Science and Technology, Chennai, India. Dr. Meer has received several accolades, including the Best Paper Awards at national and international conferences, such as the "Water Resources Management in Hilly Regions Under Changing Climate" conference in 2022 and the "International Conference on Applied Sciences and Engineering" in Mongolia in 2021. His expertise encompasses satellite image processing, machine learning, making him a sought-after expert in geospatial technologies. His vision is to advance Geoinformatics research to address critical environmental and societal challenges, fostering sustainable development and resilience in the face of climate change.

M. Abdullah-Al-Wadud is working as an associate professor in the Department of Software Engineering at King Saud University, Saudi Arabia. He received his B.S. degree in computer science and M.S. in computer science and engineering from the University of Dhaka, Bangladesh, in 2003 and 2004, respectively. In 2009, he completed his PhD in Computer Engineering from Kyung Hee University, South Korea. Afterward, he served as a faculty member of the Department of Industrial and Management Engineering at Hankuk University of Foreign Studies, South Korea, from 2009 to 2014. He also served as a lecturer at Daffodil International University, Bangladesh, and East West University, Bangladesh. His research interests include artificial intelligence, optimization, computer vision, cloud computing, recommender systems, software engineering, sensor and ad hoc networks.

Rahila Naseer is a PhD student in Applied Statistics at New Mexico State University (NMSU), where she also earned her Master of Science in Applied Statistics in 2021. Her research expertise spans statistical modeling, data visualization, and advanced data analysis techniques. Her professional skills include proficiency in SAS, R, and SPSS, alongside a strong background in teaching statistics and quantitative analysis at universities in Pakistan and the United States. Rahila is committed to advancing the use of statistical tools for meaningful societal impact.

Hesham Mohamed El-Askary (Member, IEEE) received a B.S. degree in physics with a focus on geophysics from Alexandria University, Alexandria, Egypt, in 1994, and two M.S. degrees in Earth systems science and computational science and informatics and a Ph.D. degree with a focus on environmental physics from George Mason University, Fairfax, VA, USA, in 2003 and 2004, respectively. Since 2008, he has been with the Schmid College of Science and Technology, Chapman University, Orange, CA, USA, where he is a professor of earth systems science and remote sensing. He serves as the Program Director for the Computational and Data Sciences Graduate Program at Chapman University. He also holds a Full Professor Position with the Faculty of Science, Alexandria University (on leave). His research interests include modeling and observations of Earth systems' processes with a focus on natural disasters. He has published over 100 peer-reviewed articles, book chapters, full conference proceedings, and other conference papers. He is a Peer Reviewer for several international journals such as Atmospheric Chemistry and Physics, Remote Sensing, IEEE Transactions on Geosciences and Remote Sensing, and others. His work has been funded by NASA, United States Department of Agriculture (USDA), NSF, and the European Union (EU).