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Assessing Groundwater Quality and Pollution Risk Using an Integrated Water Quality Index (WQI) and Spatial Mapping Approach

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تقييم جودة المياه الجوفية ومخاطر التلوث باستخدام مؤشر متكامل لجودة المياه ومنهجية رسم الخرائط المكانية

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Abstract:
Groundwater is one of the most important sources of fresh water on Earth, and it supports drinking, farming, and industrial needs in many parts of the world. Despite its value, groundwater is facing growing pressure from human activity, weak waste handling, and natural rock interaction. This pressure leads to pollution that is often invisible until the water is tested. The present study brings together physicochemical data and the Water Quality Index (WQI) method to judge the drinking suitability of groundwater and to map pollution risk across space. Twelve common chemical parameters, namely pH, electrical conductivity, total dissolved solids, hardness, calcium, magnesium, sodium, potassium, bicarbonate, chloride, sulfate, and nitrate, were used to build the index, following the weighted arithmetic method. Data drawn from a well-documented Middle Eastern aquifer system, covering 246 groundwater wells, were used as a real-world case to show how the method performs in practice. Results show that just over half of the samples fall in the good category, while a smaller share falls in the excellent class, and the rest show fair to poor quality, mostly because of high chloride, nitrate, and total dissolved solids levels. Spatial mapping points to farming activity and wastewater leakage as the leading drivers of pollution in the more affected zones. The paper proposes a practical, low-cost framework that links the WQI score to direct management actions, such as well protection, monitoring priority, and land-use control. This approach gives planners a single number that is easy to read, yet still backed by solid chemistry. The findings support wider use of WQI mapping as a routine tool for groundwater protection in regions facing similar pressure from agriculture, growing cities, and limited rainfall.

Keywords: Groundwater Pollution; Water Quality Index; Spatial Mapping; Nitrate Contamination; Drinking Water; Aquifer Management; Physicochemical Parameters.

الملخص:
تُعدّ المياه الجوفية أحد أهم مصادر المياه العذبة على سطح الأرض، إذ تُسهم في تلبية احتياجات الشرب والزراعة والصناعة في العديد من مناطق العالم. ورغم قيمتها الحيوية، فإن المياه الجوفية تتعرض لضغوط متزايدة نتيجة الأنشطة البشرية، وضعف إدارة النفايات، والتفاعلات الطبيعية مع الصخور الجيولوجية. وتؤدي هذه الضغوط إلى تلوث غالبًا ما يكون غير مرئي ولا يُكتشف إلا بعد إجراء التحاليل المخبرية للمياه.
يهدف هذا البحث إلى دمج البيانات الفيزيائية والكيميائية مع منهجية دليل جودة المياه (WQI) لتقييم مدى صلاحية المياه الجوفية للاستخدام الشُربي، إضافة إلى تحديد التباين المكاني لمخاطر التلوث. وقد تم استخدام اثني عشر مؤشرًا كيميائيًا

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شائعًا، وهي: الرقم الهيدروجيني(pH) ، والتوصيلية الكهربائية، وإجمالي المواد الصلبة الذائبة، والعسر الكلي، والكالسيوم، والمغنيسيوم، والصوديوم، والبوتاسيوم، والبيكربونات، والكلوريد، والكبريتات، والنترات، وذلك لبناء مؤشر الجودة وفق طريقة المتوسط المرجح الحسابي.(Weighted Arithmetic Method)
وقد استُخدمت بيانات مستمدة من نظام مائي جوفي موثّق في منطقة من الشرق الأوسط، شملت 246 بئرًا جوفيًا، كدراسة حالة واقعية لإظهار أداء هذه المنهجية في التطبيق العملي. وأظهرت النتائج أن أكثر بقليل من نصف العينات يقع ضمن فئة "جيد"، بينما يقع جزء أصغر ضمن فئة "ممتاز"، في حين أظهرت بقية العينات جودة تتراوح بين "مقبول" و"ضعيف"، ويُعزى ذلك بشكل أساسي إلى ارتفاع مستويات الكلوريد والنترات وإجمالي المواد الصلبة الذائبة.
وأشارت الخرائط المكانية إلى أن النشاط الزراعي وتسرب مياه الصرف الصحي يُعدّان من أبرز مصادر التلوث في المناطق الأكثر تأثرًا. ويقترح البحث إطارًا عمليًا منخفض التكلفة يربط قيمة مؤشر جودة المياه (WQI) بإجراءات إدارية مباشرة، مثل حماية الآبار، وتحديد أولويات المراقبة، وتنظيم استخدامات الأراضي.
ويقدّم هذا النهج للمخططين رقمًا واحدًا سهل التفسير، مدعومًا بأساس كيميائي قوي. كما تدعم النتائج التوسع في استخدام خرائط WQI كأداة روتينية لحماية المياه الجوفية في المناطق التي تواجه ضغوطًا مشابهة نتيجة التوسع الزراعي، والنمو الحضري، ومحدودية معدلات الهطول المطري.

الكلمات المفتاحية: تلوث المياه الجوفية؛ مؤشر جودة المياه؛ النمذجة المكانية؛ تلوث النترات؛ مياه الشرب؛ إدارة الخزانات الجوفية؛ المعايير الفيزيائية والكيميائية.

1. Introduction

Fresh water below the ground surface makes up almost all the liquid fresh water that exists on our planet. This hidden resource supplies drinking water to a large part of the rural world and supports roughly a quarter of all water used for crops worldwide (United Nations World Water Development Report, 2022). Because it sits out of sight, many people forget how easily it can be harmed. Once pollution enters an aquifer, cleaning it is slow, costly, and sometimes impossible within a human lifetime. For this reason, regular checking of groundwater chemistry is not a luxury; it is a basic need for any region that depends on wells for daily life.

Groundwater pollution comes from many directions. Farmers spread fertiliser and manure on fields, and the leftover nitrogen seeps down through the soil. Towns and factories release wastewater that is not always treated well before it reaches the land or rivers near recharge zones. Septic tanks leak slowly over years. Even natural rock dissolution can raise salt and mineral levels beyond safe limits, especially in dry and semi-dry regions where water moves slowly through the ground (Hyarat, Al Kuisi, & Saffarini, 2022).

A single chemical reading, taken alone, rarely tells the full story of water quality. A well may show normal nitrate but high salt, or normal salt but troubling bacteria counts. To solve this problem, water scientists built the Water Quality Index, often called WQI. This index takes several chemical readings, gives each one a weight based on how much it matters for drinking safety, and folds them into one number. A low WQI number means good water; a high number signals trouble (Tiwari & Mishra, 1985). Because the WQI turns a pile of numbers into a single score, it speaks clearly to planners, engineers, and ordinary citizens who may not read chemistry tables.

This paper sets out three things. First, it explains the chemical and human-driven problem behind groundwater pollution in arid and semi-arid regions, where wells supply most of the daily water needs. Second, it places this problem within the broader domain of water resource management and public health protection, the field that this study belongs to. Third, it offers a working solution: an integrated WQI and spatial mapping method that turns raw chemistry into a usable decision tool for local water managers. The paper draws on a documented Middle Eastern case, the Amman-Zarqa Basin in Jordan, as a real and detailed example of how the method performs when applied to a genuine and fairly large groundwater dataset of 246 wells (Hyarat et al., 2022).

2. Literature Review

Many researchers around the world have used the WQI to judge drinking water safety, and the method has proven flexible enough to fit very different settings. In Jordan, a detailed study of the Amman-Zarqa Basin gathered chemistry data from 246 wells over two years and found that just over half the wells held good water, while about a third showed only fair quality, mainly due to high chloride and nitrate readings tied to farming and city waste (Hyarat et al., 2022 ;Zhmool et al., 2026a). A separate look at the Greater Amman area used 26 drinking water samples and found WQI scores between 29 and 62, again landing in the excellent to good range, though quality had slipped slightly over a five-year period because of rapid population growth (El-Naqa & Al Raei, 2021; Zhmool et al., 2026b)

Outside Jordan, similar work has appeared across South Asia and East Asia. A study in southern India tested 246 samples and reported WQI values stretching from 33 up to 442, showing that some wells were unfit for drinking due to heavy mineral loading (specifications reported in regional groundwater datasets, as summarised by Hyarat et al., 2022). Nitrate pollution in particular has drawn wide attention because it harms infants and can raise cancer risk over long exposure. Research in southern India linked nitrate readings as high as 415 mg/L to clear health risk for both children and adults, far above the safe limit of 50 mg/L set by global health guidance (World Health Organization, 2017; Lamma et al., 2015).

Work from northern Iraq examined nitrate behaviour across wet and dry seasons in urban wells near Erbil and found that about a quarter of samples broke the safe drinking limit, with farming and untreated waste named as the chief causes (hydrogeochemical evolution and nitrate-enriched groundwater study, Erbil and Bnaslawa, 2024). A separate paper from Kazakhstan reported that more than half the population relies on groundwater that often falls short of safety standards, and the study used a hazard-based scoring system to show that infants and small children face the highest risk from nitrate-laden drinking water (health risk assessment of nitrate, Almaty, Kazakhstan, 2024).

Several authors have paired the WQI with spatial tools, most often Geographic Information Systems, to convert point-based well readings into continuous pollution maps. This pairing lets planners see at a glance where water is safest and where it needs urgent attention, rather than reading through long tables of numbers (Hyarat et al., 2022; Lamma & Swamy, 2015). Multivariate statistics, including factor analysis and cluster analysis, have also been used alongside WQI to trace (Outhman & Lamma, 2020)

pollution back to its likely source, whether that source is rock weathering, farm runoff, or city sewage (Hyarat et al., 2022; Lamma, 2021).

Taken together, the literature shows two clear patterns. First, nitrate and chloride are the parameters most often responsible for poor WQI scores across many different countries and climates, pointing to farming and waste management as shared global problems. Second, while many studies stop at description and mapping, fewer studies go the extra step of linking WQI results directly to a structured management response. This gap is the starting point for the present paper, which builds a practical bridge between the index score and real-world action.

3. Materials and Methods

3.1 Study Area and Data Source

To ground this paper in real chemistry rather than only theory, the study draws on a fully published and openly available dataset from the Amman-Zarqa Basin in Jordan, a semi-arid region that depends heavily on groundwater for drinking, farming, and industry (Hyarat et al., 2022). This basin covers about 866 square kilometres and is home to more than 6.5 million people spread across Amman, Zarqa, and Ruseifa. Industrial growth since the early 1980s, combined with farming and city waste, has placed real strain on the main aquifer, known as the Amman-Wadi As Sir aquifer (B2/A7). This setting offers a strong real-world test of the WQI method because it combines natural rock chemistry with clear signs of human-driven pollution.

Samples were drawn from 246 wells across two years, with each well checked twice yearly to capture seasonal change. Twelve physicochemical parameters were measured for every well:

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pH, electrical conductivity (EC), total dissolved solids (TDS), total hardness (TH), calcium, magnesium, sodium, potassium, bicarbonate, chloride, sulfate, and nitrate (Hyarat et al., 2022; Mohammad et al., 2015). These twelve parameters were chosen because each one has a known and well-studied link to either taste, health risk, or industrial usability of drinking water.

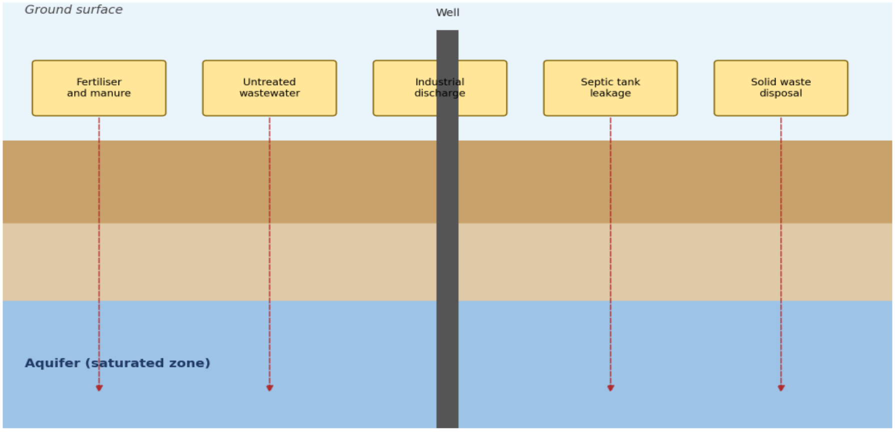

Figure 1 Conceptual diagram of common pollution pathways reaching a groundwater aquifer, including fertiliser runoff, untreated wastewater, industrial discharge, septic leakage, and solid waste.

3.2 Selection and Weighting of Parameters

The WQI method calls for two steps before any maths can begin. First, every parameter receives a weight that reflects how strongly it affects drinking safety. Second, that weight is turned into a relative weight so that all weights together add up to one. Parameters tied closely to health and taste, such as TDS, sodium, chloride, nitrate, bicarbonate, and total hardness, receive the highest weight of five. Parameters such as pH, calcium, magnesium, and sulfate receive a middle weight between two and five. Potassium receives the lowest weight of two because it plays a smaller role in everyday drinking safety (Tiwari et al., 2014, as cited in Hyarat et al., 2022). Table 1 lists each parameter together with its weight, relative weight, and the permissible drinking limit used for comparison.

Table 1 Weight, relative weight, and permissible drinking limits for the twelve parameters used in the WQI calculation.

Parameter	Weight (wi)	Relative weight (Wi)	WHO limit (mg/L)	National limit (mg/L)
pH	4	0.111	8.5	6.5-8.5
TDS	4	0.044	1,000	1,000
Calcium (Ca2+)	4	0.111	100	200
Magnesium (Mg2+)	2	0.044	50	150
Sodium (Na+)	4	0.111	200	200
Potassium (K+)	2	0.044	20	10
Chloride (Cl-)	4	0.111	250	500
Nitrate (NO3-)	4	0.111	50	50
Sulfate (SO4 2-)	3	0.088	250	500
Bicarbonate (HCO3-)	4	0.111	200	250
Total hardness (TH)	4	0.111	500	500

3.3 Calculation of the Water Quality Index

Once the weights are fixed, the WQI is built through three connected formulas. First, the relative weight (Wi) of each parameter equals its weight (wi) divided by the sum of all weights. Second, the quality rating (qi) for each parameter equals the measured concentration

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(Ci) divided by the permissible standard (Si), then multiplied by one hundred. Third, the sub-index (SIi) equals the relative weight multiplied by the quality rating. Adding all twelve sub-indices together gives the final WQI score for that well (Hyarat et al., 2022; Lamma, 2023). Figure 2 sets out this six-step process in visual form so that readers unfamiliar with the formulas can follow the logic at a glance.

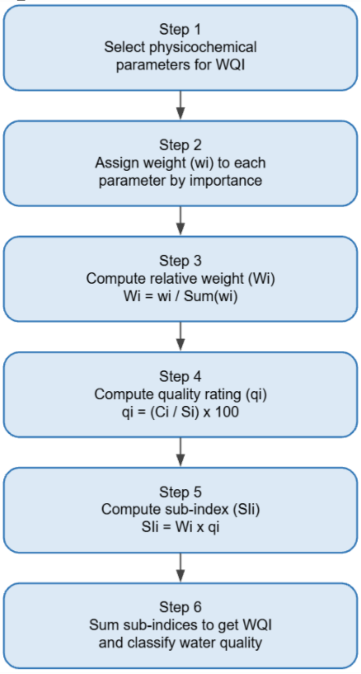

Figure 2 Stepwise procedure for computing the Water Quality Index (WQI), from parameter selection through to final classification.

Once every well receives a single WQI score, the score is sorted into one of five bands: excellent, good, fair, poor, or very poor. A score below 50 marks excellent water, a score between 51 and 100 marks good water, a score between 101 and 175 marks fair water, a score between 176 and 300 marks poor water, and any score above 300 marks water that is unfit for drinking without treatment (Hyarat et al., 2022).

3.4 Spatial Mapping Procedure

After every well receives a WQI score, the scores are placed onto a map using their well coordinates. A method called ordinary kriging is then used to estimate WQI values at points between wells, producing a smooth, continuous surface rather than scattered dots (Hyarat et al., 2022). This step turns a table of numbers into a picture that shows, at a glance, which parts of the study area carry the highest pollution risk. Spatial mapping software such as ArcGIS is commonly used for this task, and the same kriging approach has been applied in many other groundwater studies across different countries and aquifer types (Jiang, Guo, Jia, Cao, & Hu, 2015).

4. Results

4.1 Physicochemical Characteristics

Table 2 sets out the statistical summary of all twelve parameters measured across the 246 sampled wells. Electrical conductivity ranged from 358 to 6,580 microsiemens per centimetre, with an average close to 1,647, and about 40 percent of wells broke the safe limit of 1,500 (Hyarat et al., 2022; Lamma, 2024). Total dissolved solids followed a similar pattern, ranging from 229 to 4,211 milligrams per litre, with roughly 40 percent of wells above the 1,000 milligram limit. Nitrate showed the widest public health concern: values ranged from near zero up to 237 milligrams per litre, with 46 percent of wells exceeding the 50 milligram safety limit set by both national and global health guidance (World Health Organization, 2017).

Table 2 Statistical summary of the twelve physicochemical parameters measured across 246 groundwater wells. Source: Data reported in Hyarat, Al Kuisi, and Saffarini (2022), Water Practice & Technology, an open-access article distributed under the Creative Commons Attribution Licence (CC BY 4.0)

Parameter	Minimum	Maximum	Mean	Std. dev.	% over limit
EC (µS/cm)	358	6,580	1,647	1,132.6	40%
TDS (mg/L)	229.1	4,211.2	1,054.2	724.9	40%
pH	6.5	8.5	7.39	0.31	0%
Calcium (mg/L)	15.16	372.0	138.63	62.86	14%
Magnesium (mg/L)	2.64	310.0	60.86	49.03	3.5%
Sodium (mg/L)	2.78	661.7	181.25	152.46	6%
Potassium (mg/L)	0.00	46.8	7.68	6.81	2%
Bicarbonate (mg/L)	65.05	1,146.8	376.40	149.03	86%
Chloride (mg/L)	26.98	1,493.1	374.92	315.15	29%
Sulfate (mg/L)	2.90	711.5	119.32	133.74	2%
Nitrate (mg/L)	0.06	237.4	45.59	39.56	46%
Total hardness (mg/L)	60.0	1,677.6	529.71	304.54	-

Figure 3 places the mean value of each parameter next to its safe drinking limit, making it easy to see at a glance which parameters sit closest to, or beyond, the boundary of safety.

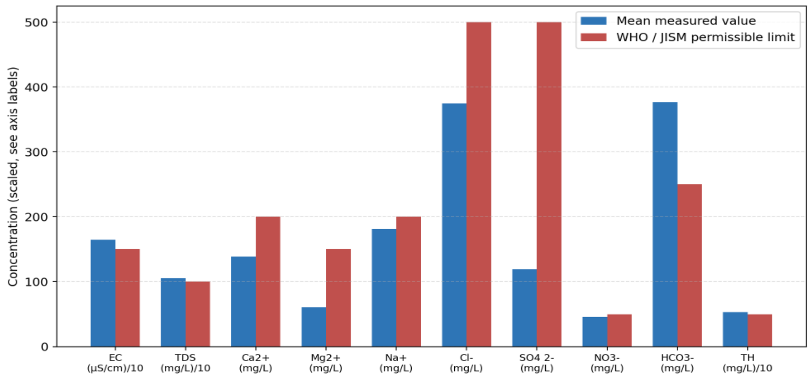

Figure 3 Mean measured concentrations of major physicochemical parameters compared with WHO and national permissible limits.

Figure 4 shows the spread of six major ions through box plots, which reveal not just the average value but also how widely the readings vary from well to well. Wide boxes and long whiskers point to uneven pollution pressure across the study area, rather than a uniform background level.

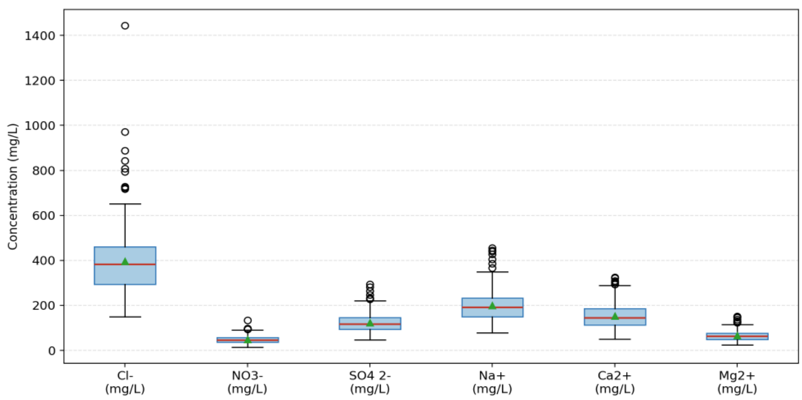

Figure 4 Box plots showing the spread of chloride, nitrate, sulfate, sodium, calcium, and magnesium concentrations across sampled wells.

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4.2 Correlation Among Parameters

A strong link appears between electrical conductivity and several major ions, especially chloride. This pattern matches what is expected chemically, since dissolved salts are the main driver of electrical conductivity in water. The original study reported a correlation strength reaching as high as 0.95 between EC and the major cations and anions, pointing to a shared origin behind salinity build-up across the basin (Hyarat et al., 2022). Figure 5 illustrates this relationship between EC and chloride.

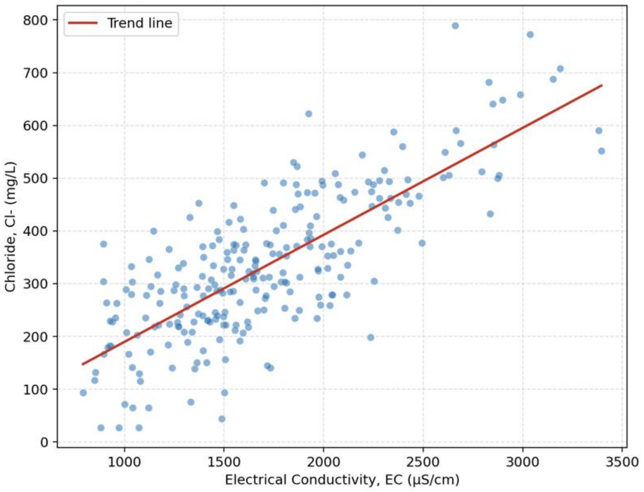

Figure 5 Relationship between electrical conductivity and chloride concentration across sampled wells, showing a strong positive trend.

4.3 Water Quality Index Results

The calculated WQI values across the 246 wells ranged from 31 to 335, with an average score of about 95, placing the basin, on average, at the boundary between good and fair water quality (Hyarat et al., 2022). Table 3 sets out the five WQI categories together with the share of wells falling into each one.

Table 3. WQI classification categories and the share of sampled wells falling into each category.

Category	WQI range	Interpretation	Share of wells
Excellent	0-50	Safe for drinking without concern	12%
Good	51-100	Safe for drinking, minor mineral load	53%
Fair	101-175	Usable but needs monitoring	31%
Poor	176-300	Treatment recommended before use	4%
Very poor	301-335	Not fit for drinking without treatment	0%*

Figure 6 turns these shares into a simple pie chart, giving a fast visual read of how groundwater quality is spread across the basin.

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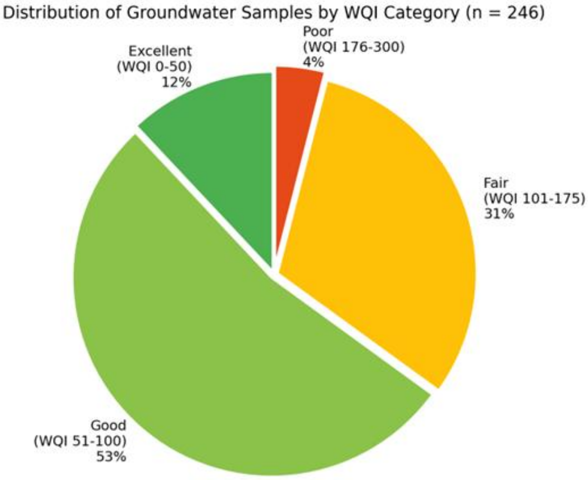

Figure 6 Distribution of the 246 groundwater samples across the four observed WQI categories.

4.4 Spatial Pattern of Pollution Risk

When WQI scores are placed on a map and smoothed using kriging, a clear pattern appears. The southern part of the basin generally holds better water, while the northern part carries higher pollution risk (Hyarat et al., 2022). This pattern lines up closely with land use, since the northern zone faces heavier irrigation pumping and sits closer to wastewater treatment discharge points. Figure 7 presents a schematic version of this spatial pattern to illustrate how WQI mapping reveals risk zones that a simple table cannot show.

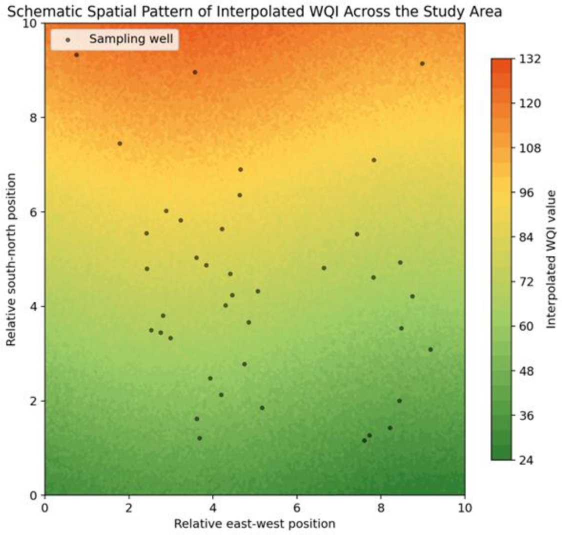

Figure 7 Schematic spatial pattern of interpolated WQI values, showing better water quality toward the south and higher pollution risk toward the north of the study area.

5. Discussion

5.1 Linking Chemistry to Human Activity

The results point clearly toward human activity as a major driver of groundwater pollution in this basin, sitting alongside natural rock dissolution. Nitrate, the parameter most often blamed for poor drinking water quality worldwide, shows a strong tie to farming practice. Fertiliser, animal manure, and treated or partly treated wastewater used for irrigation all add nitrogen to the soil, and this nitrogen slowly washes down into the aquifer (Hyarat et al., 2022). This pattern matches findings from many other regions facing similar farming pressure, including northern Iraq, where nitrate readings were also tied closely to agricultural land use near urban

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wells (hydrogeochemical evolution and nitrate-enriched groundwater study, Erbil and Bnaslawa, 2024), and southern India, where nitrate concentration climbed as high as 415 milligrams per litre in heavily farmed districts (exposure and health risk assessment study, Coimbatore and Tirupur, 2021).

The strong correlation between electrical conductivity and chloride supports a second story: salt build-up driven by both natural mineral dissolution and human overuse of the aquifer.Heavy pumping for irrigation pulls water from deeper, saltier layers over time, raising the overall salt content near the surface (Hyarat et al., 2022). This kind of slow salt creep is common in dry and semi-dry regions where rainfall cannot easily refill the aquifer at the same pace water is removed.

5.2 Why a Single Index Matters

One strength of the WQI approach lies in its simplicity for non-specialist readers. A city planner or local official does not need to understand twelve separate chemical readings to grasp the message behind a single WQI number. A score of 95, for instance, sits right at the line between good and fair water, signalling a need for closer watch rather than panic. This kind of clear signal supports faster, better-informed decisions than a raw data table ever could (Tiwari & Mishra, 1985).

At the same time, the WQI carries a known limitation: the choice of weight for each parameter can shift the final score, sometimes by a meaningful margin (Mukate, Wagh, Panaskar, Jacobs, & Sawant, 2019, as cited in Hyarat et al., 2022). A parameter given too much weight may hide the true risk from a parameter given too little weight. For this reason, any WQI study should state its weighting choices clearly, as this paper has done in Table 1, so that other researchers and planners can judge the index fairly and compare it against other studies using the same standard.

5.3 Proposed Management Framework

The central contribution of this paper is not the WQI calculation itself, since that method is well established, but rather the structured link drawn between the WQI score and direct management action. Figure 8 sets out this proposed framework. Field data and chemistry results feed into the WQI engine, which produces both a classification and a spatial map. This output then feeds into a decision-support stage aimed at water managers, who can act through three parallel paths: closer monitoring in poor-quality zones, tighter control over fertiliser and land use, and stronger wastewater treatment paired with better well protection.

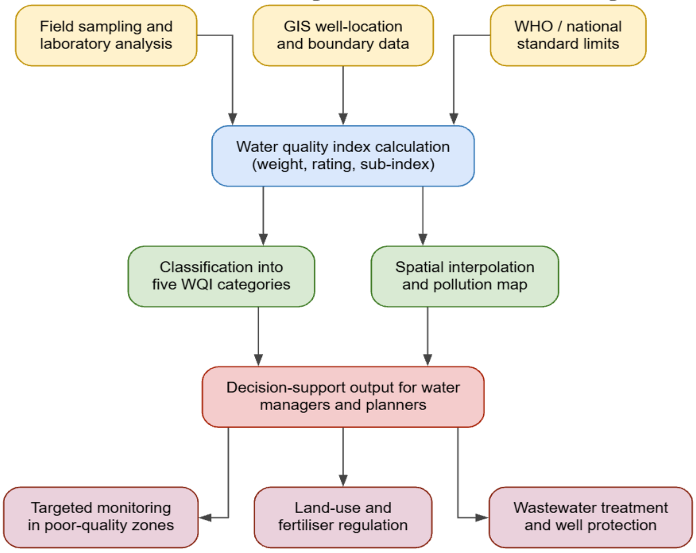

Figure 8 Proposed integrated framework linking WQI calculation and spatial mapping to practical groundwater management actions.

This framework matters because many earlier WQI studies stop at description. They report which wells are good and which are poor, then close the discussion. Planners are left to guess what comes next. By contrast, this framework draws a direct line from index score to a named set of actions, making the WQI output something a water authority can act on immediately rather than simply file away as a report finding. The framework is also low-cost, since it relies on routine chemical testing already required by most national drinking water programmes, combined with basic mapping software, rather than expensive new equipment or advanced laboratory methods.

5.4 Limitations of the Study

This study relies on a single, well-documented dataset rather than fresh field sampling, and the spatial pattern shown in Figure 7 is presented in schematic form to illustrate the general trend rather than to reproduce the precise published map. Readers seeking the exact kriged surface for the Amman-Zarqa Basin should consult the original source directly (Hyarat et al., 2022). The WQI method also treats all twelve parameters as independent, when in truth several of them move together due to shared chemical origin, as shown by the strong EC-chloride link. Future work could explore weighting methods that account for this overlap, alongside health-risk models that estimate actual exposure rather than relying on a single index score.

6. Conclusion

This study set out to judge groundwater quality and map pollution risk using the Water Quality Index method, grounded in a real and detailed dataset of 246 wells from a semi-arid Middle Eastern basin. The findings show that just over half the wells hold good drinking water, while nitrate, chloride, and bicarbonate stand out as the parameters most often breaking safe limits, pointing to farming and wastewater leakage as the main drivers of pollution. Spatial mapping reveals that pollution risk is not spread evenly; it builds up in specific zones tied to heavy irrigation pumping and closeness to waste discharge points.

Beyond reporting these results, this paper offers a structured framework that ties the WQI score directly to management action, closing a gap left open by many earlier studies that stop at description alone. This framework gives water authorities a clear, low-cost path from chemistry data to field decisions such as monitoring priority, land-use control, and well protection. Because the method relies on standard chemical tests and widely available mapping tools, it can be adopted by water agencies in other arid and semi-arid regions facing similar pressure from farming, population growth, and limited rainfall.

Future research should test this framework against fresh field data from other basins, explore weighting methods that better handle overlapping parameters, and pair WQI scores with direct health-risk estimates for vulnerable groups such as infants and pregnant women. Doing so would strengthen the bridge between laboratory chemistry and the daily decisions made by the people responsible for protecting groundwater for the next generation.

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