Evaluation of Groundwater Vulnerability to Pollution using Drastic-Based Fuzzy Logic System's Strategy for Selected Sites in Bwari Area Council, Federal Capital Territory, Nigeria

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Abstract
The vulnerability of groundwater to pollution has drawn enormous attention because of increasing threats to groundwater resources in the face of rising demand for water due to increasing population, need for irrigation and use and disposal of chemicals on the land. In view of this, recognition of groundwater vulnerability to pollution will help in the protection of groundwater resources and management of its quality conflicts. Thus, the study attempted to look at the vulnerability of groundwater to pollution of selected sites in Bwari Area Council of the Federal Capital Territory, Nigeria, by employing DRASTIC-based fuzzy logic systems protocol. To achieve this, Fuzzy Pattern Recognition model at Two and Ten-levels were adopted. The results obtained indicate that the ten-level fuzzy pattern recognition model gave the best output with the third hydrogeological setting (i.e. Gyeidna) in the study area with the least index value of 5.329 and a ranking of 1 being the most difficult to be polluted; the fifth and the thirteenth settings (i.e. Kaura and Dawaki) show a low tendency of being polluted with index values of 5.417 and 5.493, respectively. The others show a higher tendency of being polluted with the fourth setting (i.e. Dutsen Alhaji) found to be the easiest to be polluted having the highest index value of 5.855 and the thirteenth in ranking. Based on the findings of this study, it could be concluded that by taking fuzziness into consideration, the fuzzy logic approach reflects effectively the fuzzy nature of groundwater vulnerability to pollution. However, though the results obtained established the effectiveness of the approach as applied using DRASTIC as a base platform, it suffices to note that generalisation of the result should be treated with cautious optimism considering seasonality and data implications. Thus, it is recommended that a hybrid Fuzzy Neural Network should be considered because of its relative composite strength in allowing for robust learning of the feature characteristics of the input-output regime.
Keywords: Groundwater, vulnerability, pollution, DRASTIC, Fuzzy logic

Introduction

Groundwater is a valued renewable resource that is vital for life and economic development. It is a main source of replaceable water on earth (Gupta, 2014). It is essential in meeting water supply demands due to climate change and scanty surface water sources (Morris *et al.*, 2003). There is an increasing global dependence on groundwater as a key source of supply for domestic and industrial purposes. As a nation, Nigeria continues to witness this shift of attention from surface water sources to underground water both in urban and rural areas. Nevertheless, as a result of growing population, other human activities, topographic and relief changes, land use and cover pattern, this essential resource has encountered many transformations that has led to its deterioration as it is being over exploited and stressed as a result of growing demand and less availability of same on the surface.

Pollution of groundwater takes place when contaminants released on the surface of the land find their ways down to the aquifer (Heath, 2004). The contaminants result mostly from inappropriate dumping of waste on the land. Main sources are industrial and household chemicals, garbage landfills, industrial lagoons and waste water from mines, oil field, brine pit, underground oil storage tanks and pipeline that are leaking, sewage sludge and septic tanks. The pollution of groundwater by contaminants from the land surface is possible since precipitation or surface water that penetrates down constitute the major source of all groundwater (Winter *et al*., 1998). This water carries along with it contaminants in the process, though it is not every contaminant that may eventually get to the aquifer to pollute it. The contamination of the aquifer in this way is to a huge extent influenced by certain factors that has to do with natural protection for the aquifer against contamination; the level of fortification provided for an aquifer against contamination is described by the concept of vulnerability.

Vulnerability of groundwater or aquifer to pollution is a description of the ease or difficulty with which contaminant at the land surface get to a production aquifer or is a measure of the extent of insulation that natural or man-made factors provide to keep contaminants away from the aquifer (Morris *et al*., 2003). Therefore, the more vulnerable an aquifer is, the easier it is to be polluted and vice-versa. The recognition of vulnerable areas would aid in the management of local groundwater resource against overexploitation and additional deterioration as well as necessary actions to be taken for the improvement of groundwater quantity and quality. The evaluation of Groundwater vulnerability is carried out with the understanding that the features of the aquifer differs from one location to another and also that certain land areas have higher tendencies of deterioration in terms of quantity and quality compared to others (Gogu and Dassargues, 2000). Therefore, it demarcates areas which are prone to contamination, and assist scientists to carryout remediation (if aquifer is already contaminated), protect (where the aquifer is highly vulnerable). It also helps policy makers in the management of the resource using an approach that is sustainable so as to assure availability of this all important resource continuously, therefore resulting in sustainability which has now become the main goal of all the economies globally. There are two kinds of aquifer vulnerability; the first is *intrinsic vulnerability; this is* due to aquifer geology like thickness of the layer of clay, thickness of lateritic layer and overlaying media with the second being *specific vulnerability*. This targets specific pollutants or some sources that are incorporated along with the integrated susceptibility (Vrba and Zoporozec, 1999).

The available methods for assessing aquifer vulnerability to pollution are grouped into three main classes; viz; Process-based models, Statistical methods, and Overlay and index methods (National Research Council, 1993). The process-based approach includes the use of models ranging from simple to complex 3-D models. Analytical solution of advection dispersion equation like Attenuation factor introduced by Rao *et al*. (1985) and Behaviour Assessment Models which are employed in the assessment of aquifer susceptibility. The process-based approaches are more complex and unambiguous which require large data that are often not accessible.

The statistical approaches generally are centred on the theory of probability and need widely covered field data; response variables like contaminant probability, occurrence and concentration are derived by this approach. In the application of this technique, the existence or non-existence of a pollutant (specific vulnerability) in area under consideration can be predicted. Principal Component Analysis (PCA), Logistic regression, Multivariate Analysis and several other methods also have been utilised for vulnerability of aquifer evaluation; for instance, Rao *et al*. (1985) and Dixon (2005). In combination with other techniques, the result could be used in decision making, planning and management. Despite this though, intensively monitored data are usually required by this technique; hence the recourse to the use of variables in explaining the vulnerability. The third methods which are also the most commonly used, are the Overlay and Index methods which were developed due to limitations observed in the process-based models and absence of monitoring data for statistical methods (Dixon, 2005). The adoption of this approach to watershed and regional scale was accelerated by the advent of Geographic Information System (GIS). The Overlay and Index methods are built on relating maps of a number of physiographic features by allocating a score or an index to each of the attributes (National Research Council, 1993). Quantitative or qualitative indices are obtained which aggregates the main factors assumed to control the processes of transportation of pollutants (Connell and Van den Daele, 2003). Hence, the Overlay and Index-based models of the vulnerability of aquifer primarily incorporate attributes and ratings of essential factors like pollutant characteristics, rate of recharge, and depth to water table, land use and management practices, soil / aquifer properties, and transportation of contaminants from the surface of the ground to the aquifer (Harnerlinck and Arneson, 1998). Initial samples of these evaluation methods are ***DRASTIC model, GOD index, ISIS method and EPIK*** (Aller *et al*., 1985; Foster, 1987; Civita and De Regibus, 1995; Doerfliger *et al*., 1999). Several systems based on indices have overtime been developed, in some cases broadening the range of parameters comprised in the evaluation of susceptibility (Secunda *et al*., 1998).

The DRASTIC method (an acronym that stands for hydrogeological factors (parameter) considered by the model: *Depth to groundwater, Net recharge, Aquifer media, Soil media, Topography, Impact of Vadose zone media and Hydraulic Conductivity of the aquifer*) is the most commonly adopted of the Overlay and Index approaches due to its characteristic simplicity and usefulness. However, allocating ratings to parameters that are related and in a certain range, makes it possible for DRASTIC to overlook difference of parameters that fall into a given range and hence poorly reflect the effect of parameter variation. In other words, in describing vulnerability, there exist a range of situations from *most difficult to be polluted to the easiest to be polluted* so that inherent in vulnerability of groundwater is a fuzzy nature; therefore, the fuzzy set theory will be appropriate for assessing it (Rezai *et al*., 2012). Fuzzy logic and fuzzy set theory have widely been adopted in decision making for modelling ambiguity and uncertainty (Pathak *et al*., 2008). The fundamental idea in fuzzy logic is that, not only are statements “true” or “false” but there is degree of truth or falseness for each input. Numerous techniques have been adopted to apply fuzzy set theory to problems associated with water resources. These include fuzzy pattern recognition and optimisation methods (Chen, 1998; Zhou *et al*., 1999; Mao *et al*., 2006), and fuzzy inference systems (Afshar *et al*., 2007; Uricchio *et al*., 2004). Zhou *et al*. (1999) employed a fuzzy pattern recognition model; precisely, a two-level optimisation model. Shouyu and Guangtao (2003) further developed a generalised form of the above optimisation model for the evaluation of groundwater vulnerability by considering only Standard Value matrix of five samples.

Against the backdrop of the issues highlighted, the central thrust of the paper is to demonstrate the capability of fuzzy pattern recognition model in assessing groundwater vulnerability; purely by establishing the need for reliable results and interpretability concerns in the management of groundwater resources

Materials and Methods

Study Location

The study area (Bwari Area Council) is situated between latitudes 9° 25' 23" N and 9° 01' 8" N and longitudes 7° 011' 53" E and 7° 45' E. The total spatial area is approximately 40 km^2 and located in the North Eastern part of the Federal capital territory (FCT), Abuja (See Fig. 1**)**. It receives, on an average, 1000-1600mm of rainfall annually with the peak between August and September. The area enjoys tropical continental with a climatic condition that is neither too hot (35ºC) nor too cold (22ºC) all year round (Federal Capital Development Authority, 1979).

Hydrogeology of the Study Area

The rocks underlying the FCT basically consist of sedimentary rocks and basement complex. About 48% of the area is covered by the basement rocks made up mainly of metamorphic and igneous rocks and the land in certain places, is covered by hills and terrains that are dissected (Mabogunje, 1977). It is underlain by granitoids and migmatite-gneiss complex (Rahaman, 1989). The rocks are mostly made up of gneiss, schists and older granite. About 52 % of the total area of the FCT is underlain by sedimentary rocks which largely constitute the undulating plains. The current remnants of the quarternary period's erosional processes are formed by these plain (Mabogunje, 1977). Okechukwu (1974) opined that the geology is predominantly metamorphic and igneous rocks of high grades from the Precambrian age. These rocks are made up of migmatites, gneiss and granites and outcrops of schist belt can be seen along the eastern margin of the area (Rahaman, 1989; Okechukwu, 1974). The belt extends southwards and reaches maximum development to the south-eastern part of the area which has rugged topography and high relief. FCT falls belongs to Hydrological Area II (i.e. Niger Central) with geology made up of 80% basement and 20% sediments (NIHSA, 2014). The hydrological situation reveals that the Nupe sandstone and the alluvial deposits along River Niger form good aquifer, though high variations are observed in the yield of boreholes in the area due to changes in hydrogeological characteristics; fracturing occurs in the meta-sediments and borehole yield are very good in the fractured zones with younger granites in the North-eastern and north central parts (NIHSA, 2014).

Data Selection and Model Development.

In this study, hydrogeological data based on DRASTIC parameters were utilised to assess the groundwater vulnerability to pollution of the area using Fuzzy pattern recognition model at two and ten-levels. Particularly, DRASTIC parameters values for 13 hydroge1ological settings of the study area were used. For the parameters A, S and I which cannot be evaluated numerically, their ratings were used. Table 1 gives the hydrogeological parameter values for the study area as reported in Njemanze (2016).

Two-level fuzzy pattern Recognition Model

For a given aquifer, certain sections can be demarcated in accordance to the hydrogeological conditions and then considered as the fuzzy sets. In this method, the aquifer susceptibility was obtained as the degree of membership of the section. If the degree of membership is 1, it is an indication that the section is *most vulnerable to pollution* while membership degree of 0 indicates *least vulnerability to pollution* for the section. Letting the number of samples (hydrogeological settings) to be designated as n and parameters (factors) as m, then the samples' *parameter matrix* is formulated as in equation (1)

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{n1} & x_{n2} & \cdots & x_{nm} \end{bmatrix} \qquad (1)$$

where x_{ij} represents parameter j value corresponding to sample i.

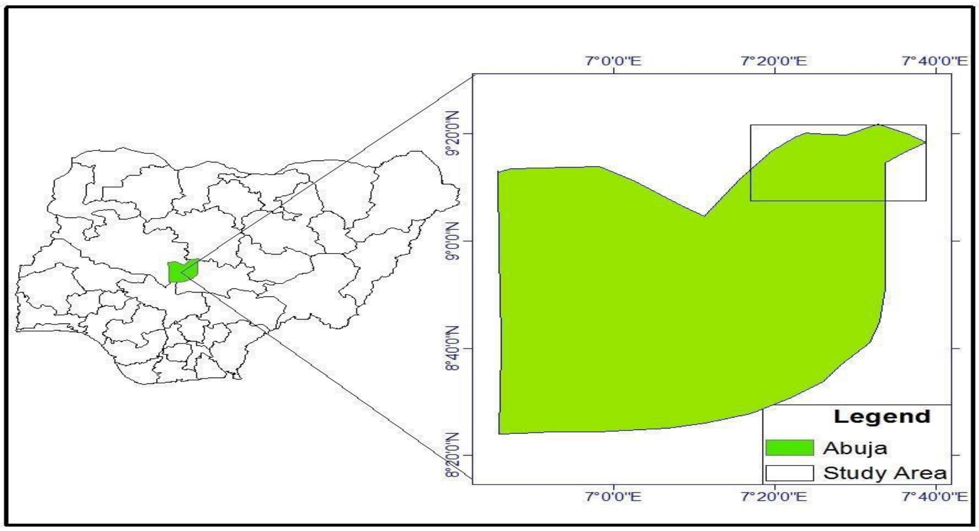

Fig.1: Map of the Study area (Njemanze, 2016)

Table 1: Hydrogeological parameter values in the study area

Locations (Hydrogeological Settings)	D(m)	R(mm)	A	S	T	I	C(m/day)
Bazango West (1)	6.50	132.0	4	6	1.5	6	0.003
Gaba(2)	6.40	132.0	4	6	0.07	6	0.003
Gyeidna(3)	11.13	132.0	4	6	0.0064	6	0.003
Dutsen Alhaji(4)	1.20	132.0	4	6	5.09	6	0.003
Kaura (5)	8.40	132.0	4	6	24.27	6	0.003
Shere (6)	6.30	132.0	4	6	4.65	6	0.003
Runji (7)	8.40	132.0	4	5	0.0016	6	0.014
Baragoni (8)	7.40	132.0	4	6	0.024	6	0.003
Peyi (9)	4.50	132.0	4	6	5.29	6	0.003
Snape (10)	7.30	132.0	4	6	2.37	6	0.003
Gbazango (11)	6.00	132.0	4	6	1.475	6	0.003
Kubwa II (12)	6.00	132.0	4	6	0.0203	6	0.003
Dawaki (13)	8.00	132.0	4	6	7.317	6	0.003

The relative membership degree of groundwater vulnerability for parameter j in sample i (rij), therefore computed as defined in equations (2) and (3)

$$r_{i,j} = \begin{cases} \frac{x_{i,j}-x_{minj}}{x_{maxj}-x_{minj}} \end{cases} \qquad (2)$$

and

$$r_{i,j} = \begin{cases} 1 - \frac{x_{i,j}-x_{minj}}{x_{maxj}-x_{minj}} \end{cases} \qquad (3)$$

where x_{maxj} and x_{minj} equals the maximum and respective minimum parameter j values for the whole samples. Equation (2) was used for DRASTIC parameters***: Net recharge (R), Aquifer media (A), Soil media (S), Impact of Vadose zone media (I) and Hydraulic Conductivity of the aquifer(C***) for which the vulnerability of groundwater increases with increasing parameters values while Equation (3) was used for factors: ***Depth to water (D) and Topography (T)*** where vulnerability of groundwater decreases with increasing value of the parameter. Equations (2) and (3) were employed for the different situations based on the fact that they allow for normalisation and reduction of the range to an allowable limit and hence regularises values of the feature elements,

$$u_{i,} = \left\{ \left[1 + \frac{\sum_{j=1}^{7} [w_j(r_{i,j}-1)]^2}{\sum_{j=1}^{7} (w_j * r_{i,j})^2} \right] \right\}^{-1} \qquad (4)$$

where w_j stands for the normalised weighing factor of the parameter j (See Table 1)
For each sample from the study area, u_i was derived as the ***groundwater vulnerability*** of the section using the data in Table1. The resulting membership degrees of the samples were ranked.

Functional concept of the Ten-level Fuzzy Pattern Recognition Model

The assessment of vulnerability of groundwater to pollution is seen as the process of identifying the level to which a sample, when compared with the standard values belong to according to the seven factor values of the sample (Shuoyu and Guangtao, 2003). This approach is unlike the Two-level approach used in the preceding section. In applying the Ten-level Fuzzy Pattern Recognition approach, groundwater vulnerability was recognised by the standard value of ten-levels with respect to the seven DRASTIC parameters (Factors). Tables 2 and 3 show the Standard Value matrix of the factors and Standard Value of ten-levels for the seven parameters, respectively (Federal Capital Development Authority, 1979).

Table 2: Standard Value Matrix of Factor

30.5	26.7	22.9	15.2	12.1	9.1	6.8	4.6	1.5	0.0
0.0	51.0	71.4	91.8	117.2	147.0	178.0	216.0	235.0	254.0
10.0	9.0	8.0	7.0	6.0	5.0	4.0	3.0	2.0	1.0
10.0	9.0	8.0	7.0	6.0	5.0	4.0	3.0	2.0	1.0
18.0	17.0	15.0	13.0	11.0	9.0	7.0	4.0	2.0	0.0
10.0	9.0	8.0	7.0	6.0	5.0	4.0	3.0	2.0	1.0
0.0	4.1	12.2	20.3	28.5	34.6	40.7	61.1	71.5	81.5

The seven factors were organised into two types in line with the behaviour of the level, h: (i) Those whose level decreases with increase in standard value $y_{i,h}$; i.e., factors D, A, S, T and I; (ii) those whose level h increases with increase in standard value $y_{i,h}$ i.e. factors R and C (See Table 3). With respect to the notion "*most difficult to be polluted*", a degree of membership of 0 and 1 were assigned to tenth and first levels Standard Values respectively. The membership degree of the other levels is between 0 and 1. The membership degree $S_{i,h}$ of $y_{i,h}$ with respect to the "***Most difficult to be pollluted***" was calculated using the formula below

$$s_{i,h=} \begin{cases} 0,\ if\ (y_{i,h} - y_{i,10})/(y_{i,1} - y_{i,10}) \\ 1,\ if\ y_{i,h} = y_{i,10} \\ y_{i,h} = y_{i,1},\ if\ y_{i,1} > y_{i,h}\ Or\ y_{i,1} < y_{i,h} < y_{i,10} \end{cases} \quad (5)$$

where the first and tenth levels standard values are $y_{i,1}$ and $y_{i,10}$, respectively where the standard value of level h with regard to factor i is represented by $y_{i,h}$; By employing the above equation, the factors matrix of Standard Values was transformed into the degree of membership matrix of standard values.

Table 3: Standard Values of 10 Levels for Seven Factors

Factors	Levels									
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
D (m)	30.5	26.7	22.9	15.2	12.1	9.1	6.8	4.6	1.5	0.0
R (mm)	0.0	51.0	71.4	91.8	117.2	147.6	178.0	216.0	235.0	254.0
A	10.0	9.0	8.0	7.0	6.0	5.0	4.0	3.0	2.0	1.0
S	10.0	9.0	8.0	7.0	6.0	5.0	4.0	3.0	2.0	1.0
T (%)	18.0	17.0	15.0	13.0	11.0	9.0	7.0	4.0	2.0	0.0
I	10.0	9.0	8.0	7.0	6.0	5.0	4.0	3.0	2.0	1.0
C (md^{-1})	0.0	4.1	12.2	20.3	28.5	34.6	40.7	61.1	71.5	81.5

In addition, Tables 4-6 below show the range, Standard Values, and corresponding levels for the parameters as contained in DRASTIC; precisely, by way of definition or characterisation of those parameters that cannot be determined numerically.

Table 4: Standard values and levels for aquifer media A

Range	Level	Standard Value
Massive Shale	1	10
Metamorphic/Igneous rock	2	9
Moderately weathered metamorphic/Igneous rock	3	8
Weathered metamorphic/Igneous rock	4	7
Glacial till	5	6
Massive Sandstone, Massive Limestone	6	5
Bedded Sandstone, Limestone and Shale Sequences	7	4
Sand and Gravel	8	3
Basalt	9	2
Karst Limestone	10	1

Table 5: Standard values and levels for soil media (S)

Range	level	Standard Value
Non-shrinking and Non-aggregated clay	1	10
Muck	2	9
Clay loam	3	8
Silty loam	4	7
Loam	5	6
Sandy loam	6	5
Shrinking and/or aggregated clay	7	4
Peat	8	3
Sand	9	2
Gravel	10	1

Table 6: Standard value and levels for impact of the Vadose zone media (I)

Range	level	Standard Value
Confining layer	1	10
Shale	2	9
Silt/Clay	3	8
Metamorphic/Igneous	4	7
Limestone/sandstone	5	6
Bedded limestone, sandstone, shale	6	5
Sand and gravel with significant silt	7	4
Sand and gravel	8	3
Basalt	9	2
Karst limestone	10	1

Application of the Ten- level Fuzzy Pattern Recognition Model

Supposing the following Factor Value matrix is formed by the Factor Values of samples,

$$X = \left(x_{i,j}\right)_{7xn} \tag{6}$$

where x_{ij} stand for sample j value with respect to factor i: the number of samples to be assessed is represented by n. For the first set of factors (parameters), the calculation of the degree of membership can be done by using equation (7).

$$r_{i,j} = \begin{cases} 0 & x_{ij} \leq y_{i,10} \\ \left(x_{i,j} - y_{i,10}\right)/\left(y_{i,1} - y_{i,10}\right) & y_{i,1} > x_{ij} > y_{i,10} \\ 1 & x_{ij} \geq y_{i,1} \end{cases} \tag{7}$$

But for the second type,

$$r_{i,j} = \begin{cases} 0 & x_{ij} \geq y_{i,10} \\ \left(x_{i,j} - y_{i,10}\right)/\left(y_{i,1} - y_{i,10}\right) & y_{i,1} > x_{ij} > y_{i,10} \\ 1 & x_{ij} \leq y_{i,1} \end{cases} \tag{8}$$

where r_{ij} stand for the degree of membership of sample j with respect to the factor i and notion **"Most difficult to be polluted".** This was achieved by applying equations (9-11); to this end, equation. (9) was converted into a degree of membership of factors. It therefore follows that the formula for computing the degree of membership of sample j pertaining to level h is as given by equation (9).

$$u_{h,j} = \left(d_{hj}^2 \sum_{k=1}^{10} d_{kj}^{-2}\right)^{-1} d_{hj} \neq 0 \qquad (9)$$

where $d_{h,j}$ is given by equation (10)

$$d_{h,j} = \left\{\sum_{i=1}^{7} \left[w_i\left(r_{i,j} - s_{i,h}\right)\right]^p\right\}^{\frac{1}{p}} \qquad (10)$$

and is defined as the distance of sample j to level h, p represents a distance parameter and the value of p is equal to 1 and 2 for Hamming and Euclidean distances, respectively. Euclidean distance was adopted for this study since it allows for normalisation. Whenever $d_{hj} = 0$, i.e. $r_{ij} = s_{ih}$, it simply means that sample j fully belongs to level h, so $u_{hj} = 1$. It suffices to note that the assessment level of the samples is obtained as rank feature value by applying equation (11)

$$H_j = (1,2,\ldots,10).u_j^* = \sum_{h=1}^{10} u_{hj}^*.h \qquad (11)$$

Here, H_j is the rank feature value and is taken as a sample's index; $u_{h,j}^*$ represent the degree of membership of individual samples pertaining to each level and u_j^* is its column vector. The rank feature value describes the assessment of a sample when compared with the Standard Values; i.e., the higher the rank feature value, the ***easier it is for the sample to be polluted*** (Shuoyu and Guangtao, 2003).

Results and Discussion

Table 7 shows the resulting relative membership degree (vulnerability) values for the 13 hydrogeological settings using the two-level fuzzy pattern recognition model. The membership degree to vulnerability value ranges from 0.06 to 0.34 with the third hydrogeological setting having a value of 0.06 being the **most difficult to be polluted** and the fourth setting with a value of 0.34 being the **easiest to be polluted**. Similarly, the result presented in Table 8 shows that the 3rd hydrogeological setting with an index value of 5.329 and with a rank of 1 is the most difficult to be polluted, with other two settings i.e. the 5th and the 13th depicting a low tendency of being polluted having the values 5.417 and 5.493 and ranking of 2 and 3, respectively. The other settings show a higher tendency of being polluted with the 4th setting being the easiest to be polluted having a value of 5.855, and the 13th in ranking. Fig. 2 brings to the fore the characteristics of the Two-level fuzzy pattern recognition and the Ten-level fuzzy pattern recognition models, in this regard, comparatively. In this case, vulnerability is comparatively low for 4 settings i.e., the 3rd, 5th, 10th, and 13th settings and high for the 4th and 9th hydrogeological settings. Also, like the, the Two-level fuzzy pattern recognition model has the same values in 7 hydrogeological settings i.e. the 1st, 2nd and 6th; 8th and 10th; 11th and 12th settings. While for the Ten-level fuzzy pattern recognition model, the 13 settings have different vulnerability values, this outcome could be as a result of the fact that the Two-level pattern recognition model does not utilise the totality of available information set for evaluation whereas the contrast is the case for the Ten-level fuzzy pattern recognition approach; the physical implication of this development is that evaluation is coarse in the former due to hard or crisp recognition strategy and much finer in the later. Thus for the Ten-level pattern recognition, since it allows for fuzzy membership, the DRASTIC degree of vulnerability is a matter of membership degree with a flexible degree of freedom. The performance of the model is similar to that obtained by Shuoyu and Guangtao (2003) who applied it to five hydrogeological settings from the Dalian peninsula in the north east of China. They obtained a vulnerability value of 4.085 for the most difficult to be polluted hydrogeological setting and 5.744 for the ***easiest to be polluted*** setting.

Table 7: Membership degree (Vulnerability) of samples and their ranking

Samples (Hydrogeological Settings)	Membership Degree	Ranking Order
1	0.140	5
2	0.140	5
3	0.060	1
4	0.340	9
5	0.080	2
6	0.140	5
7	0.150	6
8	0.110	4
9	0.210	8
10	0.110	4
11	0.161	7
12	0.161	7
13	0.090	3

Table 8: Groundwater Vulnerability of Samples and their Rankings

Sample (Hydrogeological Settings)	Index	Rank
	5.607	8
1	5.612	9
2	**5.329**	**1**
3	**5.855**	**13**
4	5.417	2
5	5.595	7
6	5.525	4
7	5.593	6
8	5.694	12
9	5.550	5
10	5.624	10
11	5.629	11
12	5.493	3

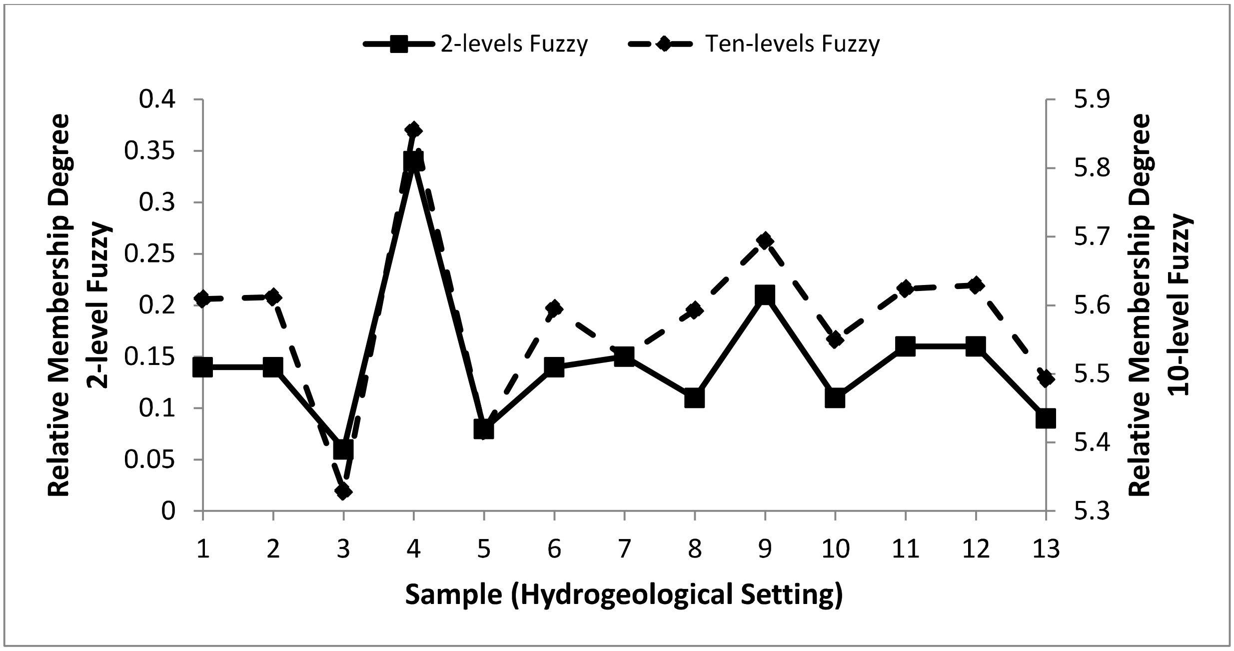

Fig. 2: Comparison of relative membership degree of samples for the two - level and ten - level Fuzzy pattern recognition method

Conclusion

This study employed fuzzy pattern recognition approaches at two and ten levels in determining the vulnerability of groundwater to pollution. By taking the fuzziness into consideration, the results from the fuzzy methods especially the ten-level fuzzy pattern recognition model reflect effectively the fuzzy nature of the groundwater vulnerability and the influence of the hydrogeological parameters The result reflect the capacity of the Ten-level fuzzy pattern recognition model to take into account the fuzziness inherent in vulnerability continuously and effectively. This is obvious in the ranking order where no two sites are found to be of the same rank but differences are shown no matter how little; this portrays the continuous transitional nature of vulnerability. The result of this approach indicated that among the 13 evaluation samples, the third (**Gyeidna**) with a rank of 1 is the **most difficult to be polluted** with an evaluation value of 5.329 which in normal language represent "Difficult to be polluted", while the fourth setting (**Dutsen Alhaji**) with a rank of 13 is the **easi**1**est to be pollu**1**ted**, with the highest evaluation value of 5.855. The findings here have relevance for both environmental and water resources research; especially contaminant fate transport, considering well hydraulics, siting and drilling of wells.

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