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Groundwater Vulnerability and Sensitivity Optimization Using Geographical Information System for Kano Metropolis, North-Western Nigeria

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Abstract

This paper developed an optimization technique for groundwater vulnerability in Kano Metropolis, North-Western Nigeria. A combination of DRASTIC is taken from initial letters of seven parameters namely depth to water table (D), net recharge (R), aquifer media (A), soil media (S), topography (T), impact of vadose zone (V) and hydraulic conductivity (C), while GOD also represents groundwater confinement (G), overlaying strata (O), depth of water (D) and multi-criteria evaluation (MCE) techniques were used in the optimization method by integrating other important and sensitive parameters for groundwater pollution, principally the anthropogenic point source pollution parameters (dump site, petroleum stations, automobile shops and under storage tanks). Geographic Information System was used to perform the sensitivity analysis (SA) using the single parameter and map removal sensitivity methods. Result of sensitivity optimization revealed the depth to groundwater (D), net recharge (N), impact of vadose zone (V) from DRASTIC model, and groundwater conferment (G) from GOD model having significant impact on the groundwater vulnerability, respectively. A combination of these four parameters was used to generate DNVG groundwater vulnerability for the area. This suggests that an integration of other point source pollution parameters can enhance the influence of DRASTIC and GOD model parameters on groundwater vulnerability condition. The paper recommends for the application of the optimization method used in this study in another area with similar geological and anthropogenic point source of pollution with a view to validating or improving on it. In this study, several input data, such as anthropogenic point sources of contamination, are added to the existing DRASTIC and GOD model parameters as part of a sensitivity analysis aiming to optimise the performance of the resultant models.

Keywords

Groundwater Pollution, Sensitivity, Modelling, Optimization

1. Introduction

Reliance on groundwater for daily usage accounts for the one third of world population (Tukur et al., 2020). In many parts of the arid and semi-arid regions, reliance on groundwater has increased significantly mainly due to inadequate rainfall and surface water scarcity (Narany et al., 2018). Many people in developing countries particularly in Sub-Saharan regions generally rely on groundwater sources for potable water (Kura et al., 2016). However, in many regions around the world, the quality of groundwater is persistently threatened by pollutants that result from human activities such as waste from landfills dumpsites, septic tanks, seepages from underground storage tanks, and automobile shops etc (Umar et al., 2019). Groundwater occurs in most unconfined aquifers around Kano region of Northern Nigeria and is susceptible to anthropogenic contamination from surface sources such as industrial effluent, petrochemical seepage, and nitrate infiltration from agricultural land fields (Tahir et al., 2015; Javadi et al., 2011; Tukur et al., 2018a; Suleiman et al., 2020). The contamination of aquifers within arid zones could gradually evolve into a regional-scale environmental crisis because groundwater is often the sole water source for both domestic and non-domestic purposes, especially during the prolonged dry season (Ismaila et al., 2020; Shiru et al., 2020).

This GIS approach can be carried out through the systematic development of groundwater vulnerability models such as the DRASTIC (Aller et al., 1987) and GOD models (Foster, 1987). In most cases the geospatial data sets used in both DRASTIC and GOD models are evaluated for their significance using sensitivity analysis (SA). The process of evaluating sensitivity of a parameter is often applied as a means of identifying different variations of each parameter such as depth to groundwater, slope (topography), etc. and map removal represents the sensitivity associated with removing one or more parameter map. SA is also employed to avert the effect of the biased allocation of DRASTIC and weighting values assigned to each parameter (Napolitano & Fabbri, 1996; Gogu & Dassargues, 2000).

Hence, single parameter and map removal is now employed, when applying DRASTIC and GOD for this research. Although the DRASTIC and the GOD groundwater vulnerability models are widely used around the world (Tukur et al., 2018b; Hamza et al., 2015; Malik & Shukla, 2019; Hasan et al., 2019) for evaluating groundwater contamination, susceptibility can be attained by applying the principles of SA. In these types of assessment models are typically embedded in a (GIS) environment to facilitate the use of parameter model. According to Francos et al., (2003) models such as DRASTIC and GOD, SA permits the determination of accuracy levels by providing a platform for selecting the best parameter whose integration may lead to a significant improvement in accuracy levels (Narany et al., 2014; Abdullah et al., 2016). SA can serve as a guide in evaluating a model's strength, hence SA can serve as a useful phase in the validation of the numerical model and can be used as a check on the robustness on the final output against slight changes in the model parameters (Ticehurst et al., 2003; Mosbahi et al., 2015).

This process enhances the optimisation process by revealing optimum values within a given number of parameters in a GIS model. Although several sensitivity assessment methods exist, the map removal and single parameters (SA) design by (Babiker et al., 2005; Djémin et al., 2016) respectively remain invaluable for evaluating sensitivity for every parameter within these models (Evans & Myers, 1990); subsequently Rupert (2001) recommend the removal of one or more parameters for variations within the assessment. In this study, an attempt has been made to analyse the different variations within DRASTIC and GOD models by integrating point sources into the analysis.

The multi-criteria evaluation (MCE) techniques are part of a statistical method for generating weight of significance. In the spatial modelling of a given phenomenon, just as DRASTIC and GOD, are part of a decision-making process for assigning weights of significance to each parameter from DRASTIC and GOD model. Furthermore, applying MCE techniques is one of the methodological approaches that assist in the integration of new point-source data, (such as underground storage tanks from petrol station, dumpsite, and automobile garages etc.) into a more comprehensive assessment of groundwater vulnerability.

A pair-wise comparison method was to evaluate the validity of the parameters from DRASTIC, GOD model and anthropogenic point sources data. This makes it possible to determine the degree of consistency that has been used in developing the weight (Murthy & Mamo, 2009). In addition to the weight assigned to each DRASTIC and GOD parameter in this study, the parameter with the highest variation will be considered in determining the vulnerability index.

The fact that groundwater from Kano metropolis is vulnerable to pollution from various sources such as waste from landfills dumpsites, septic tanks, seepages from underground storage tanks, and automobile shops and considering the limitations of the 2 vulnerability models (DRASTIC and GOD), this study attempted to optimize groundwater vulnerability and sensitivity method by integrating other important vulnerability/sensitivity parameters with a view to improving the performance of the resultant models. In this study, several input data, such as anthropogenic point sources of contamination, are added to the existing DRASTIC and GOD model parameters as part of a sensitivity analysis aiming to optimise the performance of the resultant models.

To achieve this, a sensitivity assessment of the DRASTIC and GOD models was performed to identify the most effective weights, which were then implemented to improve the efficiency for the groundwater vulnerability assessment. This study is aimed at identifying the relative importance of each parameter, used in the development of both DRASTIC and GOD Model. Through comparing the DRASTIC and GOD sensitivity output obtained from both Single Parameter, and Map Removal (SA) Moreover, the MCE technique was employed to integrate different sources of contamination (anthropogenic sources).

2. Study Area

Kano Metropolis (Figure 1) is a capital city of Kano State and one of the largest cities in Nigeria. It is located between latitude 11˚55'23.93"N to 12˚3'53.10"N and

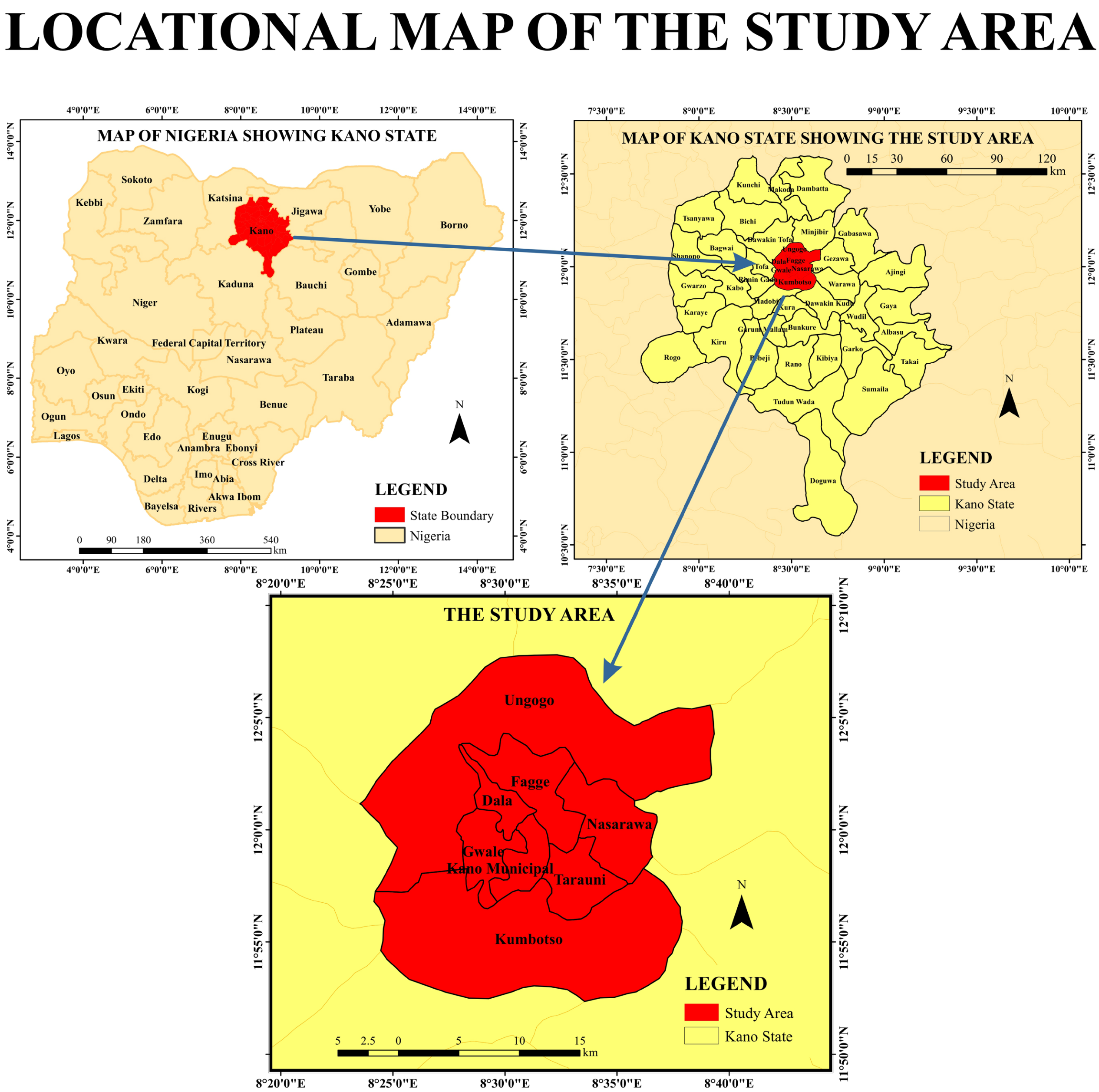

Figure 1. Map of the study area.

longitude 8˚27'42.26"E to 8˚36'41.62"E and is 1549 feet above sea level. The metropolis comprises eight out of forty-four Local Governments Councils in Kano State and the first largest commercial and industrial centre in Northern Nigerian and the second in the whole Nigeria. Kano has been experiencing higher population growth and rapid urbanization since independence in 1960 with over 12 million people. The climate of the area is tropical dry and wet type classified by Koppen as Aw. The wet season lasts from June to September with the remaining months of the year being dry. The dry season extends properly from mid-October of one calendar-year to mid-May of the next. The area is underlain by the Basement Complex rocks which consist mostly of igneous and metamorphic rocks with relatively shallow weathered mantle that permits very limited groundwater content (8).

3. Materials and Methods

3.1. Methods

The methodological pathway for implementing both SA using the single parameter and map removal sensitivity methods is illustrated on Figure 2. Based on this chart, seven parameters were used to evaluate sensitivity measures for the DRASTIC model while three parameters were employed for evaluating sensitivity measures for the GOD. The most sensitive parameters were further analyzed by applying statistical analysis to identifying the mean variation within the parameter and multi-criteria method was used to integrate different contaminate sources.

To achieve the objectives of applying sensitivity analysis, the methodological framework obtained in Figure 2, represents the DRASTIC and GOD model parameters. Information about the model was used via geographic information system (GIS) software to create an interactive geospatial data base. These parameters

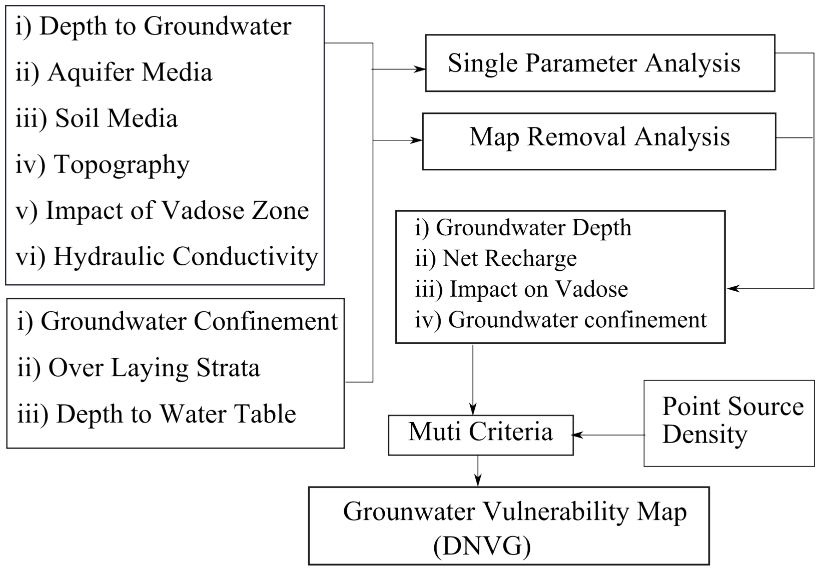

Figure 2. Methodology flow chart.

are created by using interpolation technique. However, aquifer media, impact of vadose zone, groundwater confinement, overlaying strata soil media, depth of water, net recharge and topography maps were all geo-referenced and digitised from data files and two different sensitivity analysis apply namely single parameter and map removal analysis was applied to check the different variations of the model parameters. Multiple criteria analysis is an approach used to consider the integration of point sources within DRASTIC and GOD parameters and understands groundwater vulnerability assessment.

3.2. Drastic Model

Different techniques of assessing groundwater vulnerability exist, however, (Kumar et al., 2015) classified these techniques into 3 major types, namely statistical techniques, process-based simulation technique and index-based technique (Tukur et al., 2018b; Gaya et al., 2019; Tukur et al., 2020). Parametric models such as Drastic (1987), Sintacs (1994), Seepage (1996), Epik (1999), Hazard Pathway Target (2002), non-parametric models like Indicator Kriging (2002), and hybrid models such as ISIS (2007) are the 3 major categories of index-based models. Among all other index-based vulnerability models, DRASTIC is the most widely used model. The DRASTIC model was published by Aller et al., (1987) and is a knowledge-driven model which incorporates seven parameters for defining the vulnerability of groundwater across zones characterized by the following physical parameters: depth to groundwater (D), net-recharge (R), aquifer media (A), soil media (S), topography (T), impact of vadose zone (I), and hydraulic conductivity (C) depending on the state and nature of each parameter (**Table 1**) A rating ranging from 1 - 10 reflecting lesser pollution potential to higher pollution potential, respectively. A weighting from 1 - 5 will then be assigned to the rated parameters pending on the significances of individual parameter in protecting groundwater from surface contamination.

Table 1. DRASTIC Rating and weighting values for hydrogeological parrameter.

DRASTIC parameters	Range	Rating	Weight
Depth to water table (m)			5
	1 - 2	9	
	2 - 4	8	
Net recharge (mm)			4
	35 - 45	7	
	45 - 55	8	
	55 - 60	9	
	>60	10	
Aquifer media (Ø)			3
	Sandstone and shale stone	4	
	Sand and clay	5	
	Sand and coral	8	

Continued

Soil Media (mm)			2
	Fine sand	9	
	Gravely sandy loam	7	
	Clayey sandy gravel	5	
	Loamy clay	3	
Topography (slope%)			1
	<2	10	
	2 - 6	9	
	6 - 2	5	
	12 - 18	3	
	>18	1	
Impact of Vadose zone			5
	Sandstone and shale stone	4	
	Sand, gravel, and clay	5	
	Sand and shell	8	
Hydraulic conductivity (m/day)			3
	10	1	
	20	2	
	30	3	
	40	4	

3.3. Abbreviations and Acronyms

A combination of DRASTIC is taken from initial letters of seven parameters namely depth to water table (D), net recharge (R), aquifer media (A), soil media (S), topography (T), impact of vadose zone (V) and hydraulic conductivity (C), while GOD also represents Groundwater confinement (G), overlaying strata (O), depth of water (D) and multi-criteria evaluation (MCE) techniques. Sensitivity Analysis (SA), where W refers to the weight of each parameter, Pr and Pw are the rating value and parameter, V represents the total vulnerability index of the sensitivity index.

3.4. GOD Model

The GOD is a vulnerability assessment method developed in Great Britain. The model was proposed by Foster (1987) and consists of three parameters for evaluating groundwater vulnerability: groundwater confinement (G), overlaying strata (O) and depth to groundwater (D) were designed to map groundwater vulnerability over a particular region. The lowest level for aquifer pollution vulnerability is attributed to values < 0.1 (negligible), while the highest level is ascribed to values > 0.7 (extreme). Scores are assigned to each of the three categories and then multiple to yield a final score. For the GOD index can be divided into five categories: negligible (0 - 0.1), low (0.1 - 0.3), moderate (0.3 - 0.5) high (0.5 - 0.7) and extremely high (0.7 - 1). The higher number shows the greater relative pollution potential risk to another one. GOD were rated from 0 to 1 on **Table 2** only using rating values.

3.5. Sensitivity Analysis (SA)

The SA of the DRASTIC and GOD parameters was carried out to evaluate the relative importance of individual parameters in identifying an area's susceptibility to groundwater contamination. Two sensitivity tests were performed for DRASTIC and GOD vulnerability models and has been characterized using all the parameters obtainable in the models (Evans & Myers, 1990). This is believed to limit the impact of errors and uncertainness in the individual parameters on the final output (Babiker et al., 2005). However, (Barber, 1994) have claimed the incorporation of the most significant into the standardized results obtained from the models. The SA analysis compares the effective weight of the parameters with their theoretical weights as illustrated in **Table 1**. The real vulnerability indices were obtained by contribution of all seven from DRASTIC and three parameters considered for the assessment from GOD. The computed vulnerability and employed fewer layers were considered as the turbulent vulnerability. In this method, each of the employed parameter was eliminated and a new vulnerability index was obtained at each time for the remaining layers overlapping each

Table 2. GOD rating values for hydrogeological parameter.

GOD parameters	Range	Rating	weight	Total weight (rating × weight)
Groundwater confinement				
	Overflowing	0		0
	confined	0.2		0.2
	Semi-confined	0.6		0.6
	unconfined	1.0		1.0
Overlaying strata	Residual soil	0.4		0.4
	Limon alluvial, loess, shale, fine lime stones	0.5		0.5
	Aeolian sand, siltiest, Tuf, igneous rock	0.6		0.6
	Sand and gravel, sandstone tufa	0.7		0.7
	Gravel	0.8		0.8
Depth to water table (m)				
	5 - 10	0.8		0.8
	10 - 20	0.7		0.7
	20 - 50	0.6		0.6

other. By this procedure, the effect of the eliminated layer in the model was identified.

3.5.1. Single Parameter Sensitivity Analysis

The single parameter measure introduced by (Napolitano & Fabbri, 1996) was applied in this study to determine and assess the impact of the seven parameters of the DRASTIC and GOD model on the resulting vulnerability index. This analysis of sensitivity evaluates the degree of influence for every parameter for the resulting groundwater vulnerability. Statistically, the single parameter SA can be expressed using Equation (1.1): (Napolitano & Fabbri, 1996)

$$W = \left(P_r \times P_w / V\right) \times 100 \tag{1.1}$$

where W refers to the "effective" weight of each parameter, P_r and P_w are the rating value and weight of each parameter, V represents the total vulnerability index of the sensitivity index.

3.5.2. Map Removal Sensitivity Analysis

The Map removal sensitivity, as defined by Lodwick et al. (1990), evaluates the sensitivity analysis technique require removing each model parameter individually and computing variations index of every parameter within the DRASTIC and GOD parameters. These maps represent variations in the spatial distribution of different vulnerability classes of the variation index, in Equation (1.2) (Lodwick et al. 1990),

$$S = \left(/V / N - V' / n \,|\, /V \times 100i \right) \tag{1.2}$$

where S represents the sensitivity index, V and V' represents the total vulnerability output that incorporates every parameter within a define model, and N and n are the number of data layers used to compute V and V'. The actual vulnerability index obtained using all seven parameters was considered as a parameter vulnerability index obtained using all seven parameters was considered as an vulnerability while the vulnerability computed using a lower number of data layers was considered.

3.6. Model Optimization

3.6.1. Spatial Integration of Most Sensitive Parameters

Evidence from map removal and single parameter sensitivity assessment suggest some parameters are more effective for vulnerability assessment than others. i.e. (higher variations index/values). The integration of these higher variations of the model parameters is more likely to improve the prediction accuracy of the model. In this study, most sensitive parameters extracted from the GOD and DRASTIC models were further integrated using the multi-criteria analytical approach. In many regions around the world, the quality of groundwater is persistently threatened by pollutants that result from human activities such as waste from landfills dumpsites, septic tanks, seepages from underground storage tanks, and automobile shops etc (Umar et al., 2019; Edogbo et al., 2020).

Groundwater occurs in most unconfined aquifers around Kano region of Northern Nigeria and is susceptible to anthropogenic contamination from surface sources such as industrial effluent, petrochemical seepage, and nitrate infiltration from agricultural land fields (Javadi et al., 2011). The contamination of aquifers within arid zones could gradually evolve into a regional-scale environmental crisis because groundwater is often the sole water source for both domestic and non-domestic purposes, especially during the prolonged dry season (Ismaila et al., 2020; Shiru et al., 2020).

To effectively monitor groundwater quality, there is a greater need to identify and map spatial zones that are susceptible to groundwater contamination. Hence, continuous evaluation using Geographical Information Systems (GIS) can be invaluable in mitigating unwanted scenario attributed to groundwater contamination. This GIS approach can be carried out through the systematic development of groundwater vulnerability models such as the DRASTIC (Aller et al., 1987) and GOD models (Foster, 1987). In most cases the geospatial data sets used in both DRASTIC and GOD models are evaluated for their significance using sensitivity analysis (SA).

The process of evaluating sensitivity of a parameter is often applied as a means of identifying different variations of each parameter such as depth to groundwater, slope (topography), etc. and Map removal represents the sensitivity associated with removing one or more parameter map. SA is also employed to avert the effect of the biased allocation of DRASTIC and weighting values assign to each parameter (Napolitano & Fabbri, 1996; Gogu & Dassargues, 2000). Hence, single parameter and map removal is now employed, when applying DRASTIC and GOD for this research.

Although the DRASTIC and the GOD groundwater vulnerability models are widely used around the world (Rajput et al., 2020; Malik & Shukla, 2019; Hasan et al., 2019) for evaluating groundwater contamination, susceptibility can be attained by applying the principles of SA. In this study, several input data, such as anthropogenic Point sources of contamination, are added to the existing DRASTIC and GOD model parameters as part of a sensitivity analysis aiming to optimize the performance of the resultant models. In these types of assessment models are typically embedded in a (GIS) environment to facilitate the use of parameter model. Francos et al. (2003) models such as DRASTIC and GOD, SA permit the determination of accuracy levels by providing a platform for selecting the best parameter whose integration may lead to a significant improvement in accuracy levels.

SA can serve as a guide in evaluating a model's strength, hence SA can serve as a useful phase in the validation of the numerical model and can be used as a check on the robustness on the final output against slight changes in the model parameters (Ticehurst et al., 2003; Mosbahi et al., 2015). This process enhances the optimization process by revealing optimum values within a given number of parameters in a GIS model. Although several sensitivity assessment methods exist, the map removal and single parameters (SA) design by (Babiker et al., 2005;

Djémin et al., 2016) respectively remain invaluable for evaluating sensitivity for every parameter within these models (Evans & Myers, 1990); subsequently Rupert (2001) recommend the removal of one or more parameters for variations within the assessment.

In this study, an attempt has been made to analyze the different variations within DRASTIC and GOD models by integrating point sources into the analysis. The multi-criteria evaluation (MCE) techniques are part of a statistical method, for generating weight of significance. In the spatial modeling of a given phenomenon, just as DRASTIC and GOD, are part of a decision-making process for assigning weights of significance to each parameter from DRASTIC and GOD model. Furthermore, applying MCE techniques is one of the methodological approaches that assist in the integration of new point-source data, (such as underground storage tanks from petrol station, dumpsite, and automobile garages etc.) into a more comprehensive assessment of groundwater vulnerability.

A pair-wise comparison method was to evaluate the validity of the parameters from DRASTIC, GOD model and anthropogenic point sources data. This makes it possible to determine the degree of consistency that has been used in developing the weight (Murthy & Mamo, 2009). In addition to the weight assigned to each DRASTIC and GOD parameter in this study, the parameter with the highest variation will be considered in determining the vulnerability index.

3.6.2. Integration of Point Sources Data

The inflexible attributes of the DRASTIC and GOD models often impose limitations on improving their sensitivity measures and adapting them to suit a specific geological environment. However, a slight modification of the DRASTIC and GOD models can be undertaken by integrating more representative parameters having a significant sensitivity attribute. Different point sources related to factors on groundwater contamination through the groundwater pollution generated by anthropogenic activities (Ribeiro et al., 2017) such as Dumpsites, automobile shops, under storage tanks within petrol station and Depots, it could negatively impact groundwater through infiltration of contaminates from the Dumpsites and used oil been spill on the surface within automobile shops, under storage tanks and Depot sites (where petroleum product are been stored). Data will be integrated with the most parameters are likely to improve the accuracy of the predicated vulnerability map in identification of groundwater vulnerable zones.

3.6.3. Multi-Criteria Evaluation (MCE)

Muti-criteria evaluation (MCE) is a method introduced to determine weights for each parameter (Saaty, 1980). This is one of the most accepted forms of scaling the weights factors whose entries indicate the strength with which one factor dominates over the other in relation to the relative criterion. The relative importance of individual class within the thematic maps is compared to each other and anthropogenic point sources by pair wise comparison matric. As such matrices are constructed, where each criterion is compared with other criteria relative to its importance's. On a score of 1 represents equal importance's between the factors and a score of 9 indicates the extreme importance of one factor compared to the other one (Saaty & Vargas, 2001; Yalcin & Gul, 2017). In this study, the MCE generates weight for each parameter based on pairwise comparison of both DRASTIC and GOD parameters. The most important parameter obtained the higher weight. Scores are assigned to each option according to a pairwise comparison of the options based on the criterion. Scores that are higher represents a better performance of the options; ratio scales from both individual parameters and different point sources of contamination affecting groundwater aquifers, can be developed within MCE, DRASTIC and GOD were obtained by replacing the original weights with the implementation of the MCE for generating weight of significance consists of five steps: in (Harker & Vargas, 1987), considering criteria to be compared in this case DRASTIC, GOD Parameters and point-sources data (Anthropogenic sources such as Dumpsites automobile shops, under storage tanks and Depots). The software package supporting MCE is called Expert choice and was used to make these calculations and improve the consistency.

This table represents the entries indicate the strength, which one factor have relative to one another in terms of model parameters and anthropogenic sources. Matric are constructed for every criterion (model parameters) will be constructed using matrices. Each criterion compared with other criteria relative to its importance's on Saaty's scale from 1 to 9 as illustrated in **Table 3**. A score of 1 represents equal importance between the two factors and a core of 9 indicates the extreme importance's of factors of one factor compared to the other one. The following 5 steps will be used.

Step 1:

The first step is the hierarchy which is structured on different levels: from the overall objective that need to be achieved to the different levels of the structure which consist of criteria, and sub criteria on which subsequent levels depend to the lowest alternatives. for this assessment DRASTIC and GOD parameters will be determine based on lower number of parameters after performing (SA) and points sources (anthropogenic sources) i.e.: actual observations to conduct this investigation will be compared in a square matrix.

Step 2:

At the second step, the relative importance of every criterion (criterion is the word used instead of parameter in Multi-criteria evaluation) within each level is defined using a pair-wise comparison matrix (PWCM). The comparison between two criterions is often made using weight to define the relative importance of each criterion. The numbers measure the impact on the results obtained, between two criteria of DRASTIC, GOD model parameters and point sources. The weight of each criterion is then calculated using a comparative matrix A Equation (1.3) (Saaty, 1980).

Table 3. Scale of preferences between the model parameters.

Scale	Degree of preferences	Description	Agronomy used for this Analysis	Explanation
1	Equally	Two activities contribute to the objective.	H	Equal importance's
3	Moderately	Experiences and judgments slightly to moderately favour one activity over another.	M	Moderately
5	Strong	Experience and judgments strongly favour one activity over another.	MH	Moderate high
7	Very strongly	An Activity is strongly or essentially favour one activity over another.	HH	High
9	Extremely	The evidence of favouring one activity over another is of the highest degree possible of an affirmation.	VH	Very High
2, 4, 6, 8	Intermediate values	Illustrates compromises between the preferences in weights 1, 3, 5, 7, and 9.	MH	Moderate high

And validated using a consistency check.

$$A_w^{\mathrm{T}} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \cdots & a_{nn} \end{bmatrix} \tag{1.3}$$

where $a_{11}, a_{22}, \cdots, a_n$ represent DRASTIC, GOD and point sources (anthropogenic sources) such as dumpsites, petrol station etc. The diagonal elements in the matrix A_w^{T} are self-compared of the alternatives as produced. The matrix A is reciprocal and should be consistent, furthermore the numbers of judgments needed for a particular matrix of order A, (A − 1/2) because it is reciprocal, and the diagonal elements are equal to unity.

Step 3:

In step 3: A developed a priority vector to weight elements within the matrix. This process is followed by normalized eigenvector (Eigen value is each of a set of values of a parameter for which a differential equation has a non-zero solution under given conditions) of the matrix. The normalization of the geometric mean method is used to determine the importance degrees of criteria. Let w_i represents the important degree for the i^{th} 2 criteria, then, A Equation (1.4) (Saaty, 1980).

$$w_i = \frac{\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}}{\sum_{i=1}^{n}\left(\prod_{j=1}^{n} a_{ij}\right)^{1/n}} \tag{1.4}$$

Step 4:

At this stage, the consistency of the important degree of criteria is tested to ensure a reasonable and acceptable PWCM. Let C represent n-dimensional column vector that describes the sum of the weight for the important criteria, then, as set of evaluation criteria C_j refers to the determination of decision matrix for the alternatives, $A \cdot w_{n\times 1}^{\mathrm{T}}$, $i = 1, 2, \cdots, n$), a qualitative assessment.
$W = (W_1, W_2, W_3)$ referred to as criteria weights representing the reactive importance of the evaluation criteria with respect to the overall objectives of the problem Equation (1.5) (Saaty, 1980).

Were

$$A_w^{\mathrm{T}} = \begin{bmatrix} a & a_{12} & \cdots & a_{1n} \\ a_{21} & 1 & \cdots & a_{2n} \\ a_n & a_{n2} & \cdots & a \end{bmatrix} \cdot [w_1, w_2, \cdots, w_3]^{\mathrm{T}} = \begin{bmatrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{bmatrix} \tag{1.5}$$

The consistency value for the cluster criteria can be represented by vector $CV = |CV|_{n\times 1}$ with a typical element CV_i defined in Equation (1.6) (Saaty, 1980).

$$CV_i = \frac{C_i}{w_i}, i = 1, 2, \cdots, n \tag{1.6}$$

To minimise inconsistency in a multi scale scenario, the maximum eigen value is often used to evaluate the effectiveness of the measurements. The maximum eigenvector max can be calculated using Equation (1.7) (Saaty, 1980).

$$\lambda_{\max} = \frac{\sum_i^n cv_i}{N}, i = 1, 2, \cdots, n \tag{1.7}$$

By employing the maximum eigenvalue, the consistency index can be calculated using Equation (1.8) (Saaty, 1980).

$$C_i = \frac{\lambda_{\max} - n}{n - 1} \tag{1.8}$$

A computed C_i value of 0 suggests complete consistency for the pair-wise matrix. However, the closer a value is to the maximum eigenvalue, the more consistent the evaluation is. Based on consistency index, a consistency ratio can be calculated using the formula on Equation (1.9) (Saaty, 1980).

$$RI = 1.98 \frac{n - 2}{n} \tag{1.9}$$

where RI represents an average random index with values obtained by different orders of the pair-wise comparison matrix. If CR is below 0.1, the evaluation of important criteria for different requirements by a pair-wise matrix is considered reasonable (Saaty, 1980).

Step 5:

The final stage Determine the relative overall importance degree of criteria. The relative overall importance of criteria is based on the overall importance degrees of criteria.

4. Results and Discussion

4.1. Sensitivity Analysis

4.1.1. Single Parameter Sensitivity Analysis

1) Statistics of Single Parameter for DRASTIC Model Parameters

The results of the single parameter sensitivity analysis SA are shown on Table 4 and illustrate the contribution of every parameter within the DRASTIC model and identify those parameters with significant influence on groundwater vulnerability assessment. The analysis is based on 564 grid points covering the 600 km^2 of the study area evaluated in each of the grid square. It is evident that the impact of vadose zone data with a mean value of 27.07% appear to be the most influential parameters for ground water vulnerability mapping using the DRASTIC approach; like the high values of this parameter obtained by (Oke, 2020) of 31.6%. This was followed by net recharge zone and depth to groundwater with a mean weighting of 25.98% and 22.92%, respectively. From the literature (Rahman, 2008) reported a similar effective weight value of 25.3% of net recharge. The least influential parameters were the hydraulic conductivity, topography and soil data having a mean weight of 2.38%, 2.97% and 7.24%, respectively. Lastly, aquifer media from DRASTIC parameters with (7.94%). Similarly (Thapa et al., 2018) revealed 7.14% for aquifer media while applying sensitivity analysis in Birbhum district, India. According to (Das & Pal, 2019) integrating the parameters with high variations will invariably lead to a significant performance of the groundwater vulnerability assessment; thus, of net recharge, impact of vadose zone and depth to groundwater parameters reveal higher variations from the assessment. Here the main objectives of finding the higher variations have been achieved in Table 4 which forms part of the objectives. Furthermore, Parameters Colum represent DRASTIC parameters with real assigned weight values based on the range of susceptibility to contamination range from 1 - 5 (Aller et al., 1987). e.g., depth to water, which was based on the how deep the water level was to contamination between the range of 1 - 5. Theoretical weight is for sensitivity

Table 4. Statistics of single parameter for DRASTIC model parameters.

Parameter	Real Weight	Theoretical weight %	Effective weight %		Mean	SD
			Maximum	minimum		
Depth	5	12.74	36.29.	8.47	22.92	4.02
Net recharge	4	17.39	34.04.	17.65	25.98	2.12
Aquifer media	3	13.04	13.19	6.16	7.94	1.25
Soil	2	8.70	10.1	4.14	7.27	1.42
Topography	1	4.30	4.35	0.74	2.97	0.4
Vadose	5	21.74	42.11	13.99	27.07	4.4
Conductivity	3	13.04	3.33	1.92	2.38	0.18

analysis to compare the subjectivity in assigning weight to six parameters. Lastly the effective weight is function of the actual values of the six parameters obtained within this study.

2) Statistics of Single Parameter for GOD Model Parameters

The sensitivity of each of the three GOD model parameters was evaluated: Groundwater conferment, overlaying strata, and depth to groundwater and the results shown in Table 5. The SA was carried out according to the description in Equation (1.1). Thus, DRASTIC have wider coverage of researchers compare to GOD index model.

4.1.2. Map Removal Sensitivity Analysis

1) Statistics of Map Removal Sensitivity Analysis for DRASTIC Model Parameters

Table 6 illustrates the summary of map removal of one or more parameters form the DRASTIC model parameters. The sensitivity decreases as more layers are extracted from DRASTIC model. Statistically, the removal of (D) RASTIC parameter reveals a mean variation of 23.80%. However, the removal of (R) DASTIC led to a decrease in the mean variation index down to 11.46% after the removal of aquifer media. Note that the results reported by (Rahman, 2008) showed a similar value of 11.3% for the (A) DRSTIC model. A further decrease in the mean variations index was observed upon the removal of (S) DRATIC (8.14%). (Bazimenyera & Zhonghua, 2008) reveal a similar value of 8.9%. More significant values were observed upon the removal of (T) DRASIC (27.90%) and (I) DRASTC (26.86%), and DRASTI with (3.26%). Furthermore, through map removal sensitivity analysis it is clear, considerable variation in the vulnerability assessment is expected if few parameters have been integrated.

2) Statistics of Map Removal Sensitivity Analysis for GOD Model Parameters

Table 7: illustrates the contribution of all parameters within the GOD model and identifies those with higher variation index within the parameter. From the computed mean values, it is evident that the groundwater conferment, with a mean value of (29.18%) appears to be the most influential parameters for using the GOD approach, while (45) recorded a variation increase with (34.28%) and (51.92%) was reported by (Şener, 2021). This was followed by the overlaying strata and depth of water table, with a mean variation (23.03%) and (23.51%) respectively, on the other hand similarly result was obtained from (Akinlalu et al., 2021) of (23.3%), respectively.

Table 5. Statistics of single parameter for GOD model parameters.

Parameters	Variation Index %			
N/O	MIN	MAX	MEAN	STD
G	10.10	36.93	29.18	4.76
O	17.02	70	23.03	4.5
D	18.77	70.00	23.51	3.95

Table 6. Statistics of map removal sensitivity analysis for DRASTIC model parameters.

Parameter Removed	Parameters used	Variation's index (%)			
		Max	Min	Mean	Std
D	RASTIC	36.71	7.96	23.80	3.95
R	DASTIC	36.84	16.92	26.86	2.50
A	DRSTIC	16.66	6.71	11.46	1.59
S	DRATIC	13.13	1.80	8.14	1.77
T	DRASIC	7.36	3.29	3.85	1.53
I	DRASTC	40.20	14.17	27.90	4.56
C	DRASTI	6.31	0.00	3.26	1.18

Table 7. Statistics of map removal sensitivity analysis for GOD parameters.

Parameter Removed	Parameters Used	MIN	Max	Mean %	STD
G	OD	4.00	64.17	53.47	8.35
O	GD	7.83	63.00	47.32	4.55
D	GO	5.01	63.15	47.80	4.75

This is based on the map removal SA from the GOD parameter. The sensitivity strength from each of the GOD parameters was estimated as illustrated above in Table 7. Groundwater conferment (G) was the first parameter that was removed with a higher mean value of (53.47%). Likewise, a variation of (50.2%) by (Boulabeiz et al., 2019). The mean value decreases as overlaying strata (O) and depth to groundwater (D) was removed from the analysis with slight differences of 47.32% and 47.80% respectively with similarly result obtained of (45%) from (Akinlalu et al., 2021) while (Guastaldi et al., 2014) recorded higher variation of (84.5%) Groundwater conferment was sensitive for the analysis compared to overlaying strata and depth to water table. Integration of points sources of Contamination. Multi-criteria evaluation (MCE) technique is used for incorporating multiple parameters for quantifying groundwater vulnerability at site specific guideline (Kaliraj et al., 2015). The structure is based on analysing multiple vulnerability parameters with different point sources for finding decisions related to groundwater vulnerability based on the assigned weights of decision criteria (Saaty, 2014).

4.2. Model Optimization

4.2.1. Developed Criteria for Pair Wise Comparison

Pair wise comparisons have been established based on the first set in Table 8. The application of pair wise are developed into three level structure among the criteria of the parameters for vulnerability assessment and various sources of contamination affecting groundwater aquifers such as petrol station, automobile shops, depots and dumpsites are among the element in the hierarchy for this study. Groundwater conferment from GOD model parameters, depth of water,

Table 8. Fundamental of rating for eight preferences.

	C_1	C_2	C_3	C_4	C_5	C_6	C7
(A_1)	(VH, H, H)	(H, VH, VH)	(MH, MH, MH)	(MH, MH, M)	(M, MH, M)	(M, M, M,)	(MH, MH, H)
(A_2)	(VH, VH, VH)	(MH, H, MH)	(M, ML, ML)	(H, HV, VH,)	(M, MH, M,)	(MH, H, M)	(MH, MH, MH)
(A_3)	(MH, MH, H)	(M, M, MH)	(MH, H, MH)	(M, MH, M)	(ML, VL, VL)	(H, H, H)	(H, H, VH)
(A_4)	(MH, MH, H)	(M, MH, H)	(MH, MH, H)	(MH, MH, H)	(VL, L, VL)	(VH, VH, VH)	(M, M, M, MH)
(A_5)	(H, H, VH)	(MH, MH, MH)	(MH, M, M,)	(MH, MH, M)	(ML, M, ML)	(VH, VH, VH)	(H, H, VH)
(A_6)	(VH, VH, VH)	(H, H, HV)	(MH, MH, MH)	(H, MH, MH)	(H, MH, MH)	(L, ML, L),	(M, M, ML)
(A_7)	(VH, VH, H)	(MH, MH, MH)	(MH, MH, H)	(H, MH, H)	(MH, MH, H)	(MH, MH, MH)	(H, H, VH),
(A_8)	(VH, VH, VH)	(MH, MH, H)	(H, H, VH)	(MH, MH, MH)	(H, MH, H)	(M, M, M)	(VH, H, H)

net recharged, impact of vadose zone are the parameters from DRASTIC with the highest variations for the study. Multi criteria use groundwater vulnerability parameters and point sources to evaluate the importance of parameters and the ratings alternatives with respect to various attributes in this research, selecting the suitable parameters for groundwater vulnerability assessment, to illustrate the idea of Pair wise compares.

We deliberately transform the existing values for the SA and point sources to different values of seven-levels. Linguistic variables; very high (VH), high (H), middle high (MH), middle (M), middle low (ML), low (L), very low (VL), where (VL) = 0, L = 1, ML = 3, M = 5, MH = 7, H = 9 and VH = 10. Assume that eight parameters (A_1), depth to groundwater, (A_2) net recharge, (A_3), Aquifer media, (A_4) soil media (A_5) topography, impact of vadose zone (A_6) hydraulic conductivity, (A_7), and Groundwater conferment (A_8) are evaluated for groundwater vulnerability models are evaluated by three main studied: D_1, D_2 and D_3, against the six criteria of different sources of petrol station (C_1), automobile shop (C_2), dumpsites (C_3) industrial effluent (C_4) septic tanks, (C_5) pit latrines, (C_6). The importance weights of the criteria are determined by these three decisions. The total of each comparison is based on subjective accuracy, consistency ration (Cr) is required to ensure the selection of each criterion accurately so that lax, random consistency ration was calculated for all pairwise comparisons matrixes. Thus, for all matrixes the consistency ration is less than 0.06 and the logically substantiated decision for constructing the pairwise comparison of the criteria has been made.

4.2.2. Multi-Criteria Evaluation

Table 9 list the different technical parameters needed for the determination of groundwater vulnerability assessment within the study area. The selection of the most suitable parameter with the highest weight values is a multi-criteria decision-making process, which will be achieved at the end of the analysis.

These are the three different criteria to be determined within the decision-making process in Table 10 experiences are utilized to estimate the relative factors through pair-wise comparisons. Each respondent compares the relative

Table 9. Technical parameters for the vulnerability assessment.

Groundwater vulnerability models	Parameters
DRASTIC Models	Depth of table
	Net recharge
	Aquifer media
	Soil media
	Topography
	Impact of vadose zone
	Hydraulic conductivity
GOD Models	Groundwater confinement
	Overlaying strata
	Depth of water
Point sources (Anthropogenic activities)	Dumpsites
	Petrol station
	Auto mobile shops
	Depot
	Industrial effluent
	Septic tanks
	Pit latrines

Table 10. Three alternative objective from the vulnerability objective decision maker.

Decision Makers	C_1	C_2	C_3	C_4	C_5	C_6
D_1	VH	H	H	H	MH	ML
D_2	VH	H	VH	H	H	ML
D_3	VH	VH	H	MH	MH	MH

importance for each pair of the items illustrated above using deception of VH = very high, H = high, MH = medium high, ML = medium low.

4.2.3. Normalization and Consistency Analysis

The Normalization process was implemented by dividing the statistical values within each column on the sum for that column, in Table 11, Row 1, column 2 was normalized by dividing it statistical entry on the sum of column 2. A sum of each row reveals the relative importance (weight) of each criterion. A computed Ci value of 0 suggests complete consistency for the pair-wise matrix. However, the closer a value is to the maximum, the more consistent the evaluation is. Based on consistency index describe above. The normalized value was weighted with respect to the criteria and rated with respect to the alternatives within the column (Tesfamariam & Sadiq, 2006). Where CM, is consistency measure for each alternative, RI, the Radom.

Table 11. Pair wise comparison of criteria from the goal and weights.

	C_2	C_3	C_4	C_5	C_6
C_1	1.00	0.56	1.56	2.00	2.56
C_2	2.00	1.00	1.56	2.56	3.56
C_3	0.66	0.66	1.00	2.56	3.56
C_4	1.00	0.4	0.4	1.00	1.56
C_5	0.4	0.28	0.00	0.66	1.00
C_6	0.5	2.50	0.3	0.1	0.00

Table 12. Alternatives based on impact value normalization matrix.

Normalised Matrix									
	DNVG (modified parameters)	**Petrol station**	**Dump**	**Automobile shop**	**US Tank**	**Total**	**Average**	**Cont. measure**	**Wt**
DNVG (modified parameters)	0.218978	0.175292	0.320122	0.230769	0.208333	1.153495	0.384498	3.485158	**38.45**
Pet Sta	0.437956	0.350584	0.320122	0.288462	0.291667	1.688791	0.337758	6.018389	**33.776**
Dump	0.145985	0.233723	0.213415	0.288462	0.291667	1.173251	0.23465	5.49833	**23.465**
Mobile	0.109489	0.140234	0.085366	0.115385	0.125	0.575473	0.115095	5.725759	**11.509**
Us tank	0.087591	0.100167	0.060976	0.076923	0.083333	0.40899	0.081798	5.81765	**8.1798**
							CI	0.077264	
							RI	1.12	
							CR	0.068986	

Selecting the most suitable parameter for vulnerability assessment, in Table 12 with different sources of contamination is a multi-criterion decision making problem. SA was performed to find out the statistical variations within the model parameters. The benefits that affect the performances of each attribute have been examined critically to make logically decision for the assessment. It was reveal from the analysis, model parameters are the most important factor with (0.06) consistency value among different parameters and potential sources of contamination.

4.2.4. Variations Indices for Vulnerability Assessment within Kano Metropolis

Table 13: illustrates and compares variations of the vulnerability index values of both DRASTIC, GOD models and different sources of contaminate. The parameters with the highest sensitivities were integrated to predict most sensitive parameters for groundwater vulnerability assessment. Sensitive assessment was carried out using single parameter and map removal sensitivity methods. Groundwater vulnerability within Kano metropolis is more sensitive to the depth of water, net recharge, and impact of the vadose zone. From the GOD parameters,

Table 13. Variations indices for vulnerability assessment within Kano Metropolis.

Model	Type of Analysis	Parameters Chosen	High Variation index %	Parameter	Class	General Weighting	Class Weight
Drastic	Parameter output	Depth of water	22.92	DNVG	Very Low		38
		Net recharge	25.98		Low		
		Impact of vadose zone	27.02		High		
GOD		Groundwater conferment	29.18		Very High		
					Ex. High		
Non-point sources		Dumpsites		Pollution classes	Very Low		8.17
		Automobile shops			Low		11.50
		Under storage tank			Moderate		23.46
		Petrol station			High		33.77
						CR = 0.06	

sensitivity appears to be favoured by Groundwater conferment and depth to water table. From the sensitivity analysis, in Table 9 the relative importance of each parameter used for both DRASTIC and GOD parameters were observed using the statistical value of the parameters to have positive or negative impacts on the vulnerability value as described in (Sinha et al., 2016). Based on the single parameter and map removal assessment, impact of vadose, depth to groundwater and net recharge had a more significant impact on the DRASTIC model. In the GOD model a more significant value was attained when the Groundwater conferment was used for sensitivity assessment. By all these implications, a more sensitivity vulnerability can be attained by integrating these parameters with high significant values. Thus, it was essential to develop a new model based on the integration of parameters with the highest mean variations from the analysis. The resultant output model accounts for effects of pollution sources on groundwater neglected by the DRASTIC and GOD models.

5. Conclusion

The groundwater vulnerability assessment is found to be realistic and suitable across different regions of the world, principally in urban areas where the resources are vulnerable to pollution from different anthropogenic sources. The influence of different anthropogenic activities affecting groundwater is not accounted within groundwater vulnerability models. This paper improved the groundwater vulnerability assessment by integrating point source pollution parameters (dump site, petroleum stations, automobile shops and under storage tanks) into original DRASTIC and GOD models through sensitivity analysis and multi criteria evaluation methods.

The study revealed that depth to groundwater, net recharge and impact of vadose zone induces an elevated risk of contamination, whereas hydraulic conductivity and topography induces a minimal risk of contamination. Sensitivity analyses help to validate and evaluate the consistency of analytical results. The single parameters analysis and map removal sensitivity analysis reveals the contribution effect of every parameter in groundwater vulnerability assessment. Based on SA analysis, the depth to groundwater and net recharge displayed an effective contribution of 8.47% and 17.65%, respectively. However, a relative assessment of this contribution effect using the map removal analysis suggests sensitivity values are more likely to drop by 23.3% and 26.86%, respectively. The paper recommends for the application of the optimization method used in this study in another area with similar geological and anthropogenic point source of pollution with a view to validating or improving on it.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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