Application of vulnerability modeling techniques in groundwater resources management: a comparative study

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Abstract
The sustainability management of groundwater resource globally is challenged by its vulnerability to pollution resulting from anthropogenic activities. In order to address this problem, the DRASTIC index model (DIM) method among the existing vulnerability modeling techniques is commonly used. OWA-DRASTIC index model (ODIM) technique is another recently developed method for the same task. This study investigated the application of these vulnerability-biased modeling methods in a multi-faceted geologic setting at Perak Province, Malaysia with the view of establishing their efficiencies. The models considered seven pollution potential conditioning factors (PPCFs) obtained from different data sources. Applying the GIS-based multi-criteria algorithm of these models, the PPCFs were related for developing multi-parameters-based vulnerability index model equations. Groundwater vulnerability to pollution index (GVPI) maps were produced from the synthesized estimated results of the applied multi-parameters-based vulnerability index model equations. The reliability of the produced GVPI maps was established using analyzed groundwater quality data results. The obtained prediction accuracy results for the ODIM-based GVPI map and DIM-based GVPI map are 85.71 and 64.29%, respectively. Besides, the regression coefficient results obtained from the spatially estimate from the DIM and ODIM vulnerability index’s values relationship with the pH and manganese concentrations give 83 and 85% for the ODIM technique and 68 and 63% for the DIM technique, respectively. The overall results indicated that the applied ODIM method in the area is a better alternative to the conventional DIM method. The produced GVPI maps can be useful to regional planners and environmental managers entrusted with the protection of groundwater resource.

Keywords Groundwater vulnerability · ODIM · Physio-chemical parameters · GVPI · DIM

Introduction
The susceptibility of groundwater to pollution is a consequence of a finite combination of different factors ranging from the variation in hydrogeological settings and human activities whose togetherness often formed dynamic system (Pathak et al. 2014; Pradhan et al. 2013). These interrelated factors interact in a manner by which the quality monitoring of groundwater system could be predicted. This corroborated with the findings of Samake et al. (2011), whose study has documented that through evaluating the interrelationship between such factors’ derived parameters, the outlining of areas that are more susceptible to contamination than others has been feasible. Meanwhile, it is important to note that the term groundwater vulnerability stands for the tendency or likelihood for contaminants to reach a specified position in the groundwater system after introduction at some location above the uppermost aquifer (Jessica and Sonia 2009; National Research Council 1993). This thus implies that the concept of evaluating risk to groundwater fittingly described groundwater vulnerability (Nobre et al. 2007). Furthermore, studies had have it that due to prominent occurrence of hydrogeological setting variation in the subsurface, most areas aquifer that housed groundwater are usually unconfined and highly permeable, thereby causing their high vulnerability to surface contamination (Javadi et al. 2011a, b). A close examination and identification of spatial mapping of these possible vulnerable zones to contamination via developing vulnerability predictive model are
vital means of getting continuous supply of quality water even at regional scale. According to Anirban et al. (2016), the subscribing to vulnerability assessment is an important yardstick for groundwater resources management particularly to monitor and control the future adverse effect of the unavoidable anthropogenic activities at/or near the earth’s surface. For accurate assessment of groundwater vulnerability, several methods have been investigated including the process-based method, the statistical methods and the overlay and index methods. The pros and cons of these methods have been reported in the studies of Jessica and Sonia (2009), and Pradhan et al. (2013). The overlay and index methods among these aforementioned methods are relatively simple and often pave ways for easy combination of different parameters’ themes through allocation of numerical index. The renown of this index methods that have been investigated for vulnerability prediction in the field of groundwater hydrology with attractive results are such as DRASTIC, GOD, AVI and SINTACS (Aller et al. 1987; Neshat et al. 2014; Foster 1987; Van Stempoot et al. 1993; Daly and Drew 1999).

In view of the above discussed vulnerability assessment methods, the literature had established that the overlay and index methods had received more attentions in the development of tools credible for the protection of groundwater resource than the others. Among the aforementioned overlay and index methods, the most popular and the widely applied technique across the globe is the DRASTIC index model (DIM) (Al-Abadi et al. 2017; Plymale and Angle 2002; Fritch et al. 2000; Yuan et al. 2006; Huan et al. 2012; Naqa et al. 2006; Javadi et al. 2011a; Mimi et al. 2012; Pacheco and Sanches Fernandes 2012). In applying the DRASTIC method effectively, seven pollution potential conditioning factors (PPCFs) often derived from data sources that are diverse in nature include: depth of water table (D), net recharge (R), aquifer media (A), soil media (S), topography (slope) (T), impact of vadose zone (I) and hydraulic conductivity of the aquifer (C) are often considered. With the application of the established DRASTIC model’s algorithm, these PPCFs’ themes have been synthesized to produce appealed vulnerability prospecting model map usable in environmental decision-making process. But then, this vulnerability method, however, has number of shortcomings including: the lack of ability to process and manage the large volumes of data, it has no capability of accounting for the spatial heterogeneities associated with the systems of natural resources, its assigning weights and rating values on the PPCFs themes is arbitrarily, the index lack functionality of controlling uncertainties that are often aroused due to fuzzy problem associated with groundwater vulnerability assessment, and moreover, the vulnerability indices of the input variables in this model are not continuous. One of the consequences of these limitations particularly the latter factor is such that the final output of DRASTIC index does not reflect the resultant effect of any missing data etc. Sequel to these aforementioned weaknesses of DRASTIC model, several researchers have devised different means of improving the model’s performance (Thirumalaiyasan et al. 2003; Dixon 2005; Antonakos and Lambrakis 2007; Cakraborty 2007; Pathak et al. 2014; Pradhan et al. 2013; Mogaji et al. 2014; Nobre et al. 2007; Chen et al. 2013; Singh et al. 2015; Nerantzis and Konstantinos 2015; Wang et al. 2012; Biswa-jeet and Pradhan 2104; Boris et al. 2016; Kumar et al. 2017; Issoufou and Defourny 2016; Sadeghfam et al. 2016). However, few of these DRASTIC model enhancement studies have quantitatively evaluated the efficiency of their improved model output versus the conventional DRASTIC model result.

In the recent study of Mogaji et al. (2014), the ordered weighted average-DRASTIC (OWA-DRASTIC) was proposed. The approach is an hybrid model where the principle of OWA multi-criteria evaluation technique is driven by the data input from the DRASTIC model theory of assessing vulnerability. The proposed model incorporates user’s decision strategies into DRASTIC model technique using OWA operators which thus give an excellent insight into ranking of criteria and addressing uncertainty from their interaction. More importantly, the OWA-DRASTIC model has ability to provide leverage for controlling the level of uncertainties associated with different decision alternatives and risk taking (i.e., optimistic, pessimistic and neutral). The managing decisional uncertainty in multi-criteria prediction potentiality is a very good attribute of the OWA method (Yager 1988; Yager 1996; Nadi and Delavar 2104; Gorsevski et al. 2012). Another strength of this model is that it can efficiently generate a set of diverse solutions that are essential in environmental decision making by changing the set of ordered weights. Thus, its applications in solving a variety of spatial problems including: land-use suitability problems (Chen et al. 2009; Malczewski 2006b), site-selection problems (Rinner and Raubal 2004) have been documented.

In this study, the applicability of vulnerability modeling techniques to groundwater resources management in a comparative analysis is investigated. The applied modeling techniques include the DRASTIC model and the recently developed OWA-DRASTIC model. These models use multiple PPCFs sets in assessing the groundwater quality in a multi-faceted geologic setting at Perak Province, Malaysia. The specific objectives of this study are as follows: (1) produce the groundwater vulnerability to pollution index (GVPI) map through DRASTIC model index, (2) produce the groundwater vulnerability to pollution index (GVPI) map through OWA-DRASTIC model index, (3) validated the produced GVPI maps using the groundwater quality analyzed results obtainable in the area and (4) analyzed the validation results to evaluate the efficiency of the models with the view of
establishing which one is best efficient for environmental decision making toward effective groundwater resources management and sustainability.

Materials and method

Presented in Fig. 1 is the models method and the flowchart used in the study.

Study area

The study according to Mogaji et al. (2014) has provided information on the geography, geology and the hydrogeology of the investigated area whose zoning region is in the southern Perak Province, Malaysia (Fig. 2). However, the multi-faceted geological characteristics of the area have established generally, that the area’s underlain aquifers are more of confined aquifer to unconfined aquifer. This indeed supported why there has been no record of groundwater contamination and pollution problems in the occupied segment of the study area. However, the tendency of an area underlain groundwater containing medium (aquiferous unit) is largely a function of the thickness of the aquifer confining layer which varies spatially. Moreover, in accordance with Singh et al. (2015) and De Vries and Simmer (2002), the activities of weathering of source rocks and recharge from water bodies to aquiferous units on regional scale often contaminate the occupying groundwater through discharge of toxic metals etc. Thus, the need arise to put in place basis preventive measure policies to preserve this precious natural resources through regional vulnerability assessment approach.

Dataset used

The data used in this study were obtained from various data sources that are readily available as listed in Table 1 and presented in Fig. 1. The selection of these data types was based on the data requirement for the DRASTIC method theory as established by the United States Environmental Protection Agency (USEPA). Such data type has been used to classify the pollution potential of aquifers (Aller et al. 1987). Possible pollution potential conditioning factors (PPCFs) are derived from these data types that served as the input to drive the renowned DRASTIC model index algorithm (Table 1 and Fig. 1). The highlight of these PPCFs’ thematic layers preparation is reported in these subsections.

The data types processing and pollution potential conditioning factors (PPCFs) thematic maps preparation

In accordance with Table 1 and Fig. 1, the data types were obtained from different sources. The geospatial approach for their thematic preparation is as detailed in Mogaji et al. (2014). However, for the acquired RS data, i.e., ASTER DEM data, mosaicking and georeferencing using ArcGIS 10.1 and ENVI 4.7 software were carried out. Furthermore, the acquired surface soil map was scanned, imported into ArcGIS 10.1 and georeferenced to the UTM/WGS84 projection system. The records of climate data (rainfall amount) at each observed station were analyzed using MS-Excel software package. The acquired 2D resistivity imaging data in the area were processed and inverted using the RES2DINV software (Mogaji and Lim 2018). Following through the above painstaking processes, the obtained data types (Table 1) were used to produce PPCFs’ thematic maps such as depth to water table (D), recharge rate (R), aquifer media (A), soil media (S), topography (T), impact of vadose zone (I) and hydraulic conductivity (C). Figure 3 presents the PPCFs’ thematic maps prepared in GIS environment. The analysis and the interpretation of these Fig. 3 themes are qualitatively reported in Table 2. The hydrologic significance and the contributions of these PPCFs parameters in groundwater vulnerability modeling/analysis have been scientifically established (Anirban et al. 2016; Pradhan et al. 2013). Nobre et al. 2007 Doumouya et al. 2012; Samake et al. 2011). The harnessing of these factors weightage influence using different vulnerability methods’ algorithm has been evaluated (Thirumalaiavasan et al. 2003; Dixon 2005; Antonakos and Lambrakis 2007; Mogaji 2017; Razandi et al. 2015; Falah et al. 2016; Naser et al. 2016).

Description of the models

DRASTIC index model (DIM) theory

The scientific basis viz-a-viz the theory and the established algorithm for the DIM technically adapt the weight linear combination (WLC) mathematically, where the weight, the range and the rating of imputes are often expressed numerically. The information on the model working principle has been documented in several studies of Sahoo et al. (2016), Mogaji (2017) and Aller et al. (1987). According to Ettazarini and El Mahmouhi (2004), the hydrogeological parameters component for the workability of the model includes: depth to water table (D), net recharge (R), aquifer media (A), soil media (S), topography or slope (T), impact of vadose zone (I) and hydraulic conductivity (C). With these parameters serving as the imputes in Eq. (1), the parametric evaluation of an index of DRASTIC vulnerability can be determined

\[ DI = \sum_{i=1}^{m} \left( W_i \times R_i \right) \]  

(1)  

where DI, \( W_i, R_i \) and \( m \) are the DRASTIC index, weights, ratings and number of the hydrogeological factors, respectively (Aller et al. 1987).
Fig. 1 Methodology flowchart for the comparative study
Fig. 2 The study area map and its geological map showing the inset map of Malaysia
Table 1 Information and sources of data used

| Data type           | Detail of data                      | Format          | Output layer            |
|---------------------|-------------------------------------|-----------------|-------------------------|
| Borehole data       | Malaysian Department of Mineral and Geosciences Date acquired | Table and lithology log | Depth to water table (D) |
| Average annual rainfall | Tropical Rainfall Measuring Mission (TRMM) database | Table | Recharge (R) |
| Geophysical data    | Batang Padang, Perak | Point | Aquifer (A) |
| Soil map            | Ministry of agriculture Kuala Lumpur, Malaysia(1962) Scale: 24 mile: 1 inch | Map | Soil type (S) |
| Remote sensing imagery | ASTER DEM data NASA((LP DAAC) Resolution: 30 m | Satellite image | Topography/slope (T) |
| Geophysical data    | Batang Padang, Perak | Point | Impact of vadoze zone (I) |
| Borehole data       | Malaysian Department of Mineral and Geosciences | Table and lithology log | Hydraulic conductivity (K) |
| Data type           | Detail of data                      | Format          | Output layer            |
| Borehole data       | Malaysian Department of Mineral and Geosciences | Table and lithology log | Depth to water table (D) |

Ordered weighted averaging (OWA)-DRASTIC index model (ODIM)

The OWA-DRASTIC model was burned out of the hybrid product of the DRASTIC model theory and the OWA method theory. This model derived its philosophy from the principles of both DRASTIC model theory and fuzzy function quantifier-guided OWA principle. In the studies of Gorsevski et al. (2012) and Malczewski (2006a), the basics theory guiding the methodology of OWA multi-criteria technique has been reported. The sequential approach for this model as presented in Fig. 1 includes: (1) selection of the causative criteria’ and their themes prepared input, (2) standardization of the criterion values ($a_{ik}$) from each criterion themes, (3) determination of the criterion weights ($W_k$) according to the preferences of experts, (4) determination of the reordered weight ($Z_{ik}$) and (5) determination of the ordered weights via applying different OWA operators ($V_{ik}$). The hybridization of these steps output with the DRASTIC model (ODIM) developed.

The application of DRASTIC index model technique to groundwater vulnerability mapping

The application of DRASTIC index model for assessing groundwater vulnerability in the study area has been painstakingly investigated. The application procedures are better explained using the information provided in Table 2 and Fig. 4. In Table 2, the pollution potential factors’ thematic layers (the criterion map), the classes (indicators) and pollution potentiality interpretation are given in columns 1, 2 and 3, respectively. The qualitative rating ($R$) for the criterion maps (Column 4) gives the interpretation of the ranges of the pollution potentiality (Column 3) within each criterion maps. With the rating ($R$), the criterion maps were ranked based on the order of the map’s class influences. The assigned rating scales were in agreement with the approach adopted in the studies of Al-Saud (2010) and Murthy (2000) where rating ($R$) scales of 1, 2, 3, 4 and 5 are interpreted as very low, low, medium, medium high and high pollution potentiality, respectively. The assigned weights (column 5) are assigned to each of the pollution potential factors ‘to indicate their relative importance in contributing toward groundwater vulnerability assessment in the area. To compute for the DRASTIC vulnerability index (DI) values, multi-steps were employed. First, the pollution potential conditioning factors (PPCFs) (for example aquifer media) were selected and prepared for thematic layer. After that, the Fishnet module as rectangular cell of polylines or polygon features in Arc Toolbox was applied to create the centroids of the grid cells for each thematic map in GIS environment where both Long and Lat grid coordinates of the centroids as designed typically in Fig. 4 were observed. This same process was adopted to create criterion map for each of the remaining PPCFs. The attributes of the observed location point (the centroids) reference to the class boundaries of any considered criterion map were interpreted viz-a-viz their corresponding pollution potentiality interpretation (Column 3) for the rating ($R$) scales assignment (Table 2). Considering the determined $R$ and $W$ variables at each criterion map observed location points, the linear additive combination of these variables using Eq. (1), the DRASTIC vulnerability index (DI) value can be estimated.

The application of OWA-DRASTIC index model technique to groundwater vulnerability mapping

The application of OWA-DRASTIC index model for assessing groundwater vulnerability in the study area encompasses several procedures as mentioned in Sect. 3.2. The details of the implementation of these aforementioned multi-steps are as reported in the studies of Gorsevski et al. (2012), Malczewski (1999), Feizizadeh et al. (2012), Eastman and
Jiang (1996) and Mogaji et al. (2014). According to one of the studies, the criterion weights \( W_k \) determinations for the PPCFs were based on the applied knowledge expert weighting index technique where the 0.039 consistency ratio (CR) estimated value indicates a good consistency of the judgments of the expert opinion (Adiat et al. 2012; Mogaji et al. 2016). The reordered weight \( Z_{ik} \) and the order weights \( V_{ik} \) are the other vital components determined for the PPCFs.
serving inputs using the established mathematical equations. Shown in Tables 3 and 4 are the typical $Z_{ik}$ computation results for $Z_{ik}$ and $V_{ik}$ based on the applied OWA index theory at each of the criterion observed locations of the PPCFs using the template model in Fig. 4.

Using the above determined $Z_{ik}$ and $V_{ik}$ of OWA index theory for the PPCFs and their fussing with the known DRASTIC theory algorithm, the applied OWA-DRASTIC index model is established in Eq. (2).

$$\text{OWA-DRASTIC}_i = V_{ikD}Z_{ikD} + V_{ikR}z_{ikR} + V_{ikA}z_{ikA} + V_{ikS}z_{ikS} + V_{ikT}z_{ikT} + V_{ikI}z_{ikI} + V_{ikC}z_{ikC}$$

(2)
Results and discussion

The DRASTIC index (DI) technique application results

Table 5 presented the application results of the DRASTIC model technique in mapping the vulnerability prospect in the area. According to Table 5, the records for both the Long and Lat were the center grid coordinates of the observed location depicted in Fig. 4. It was based on the attributes of this location points viz-a-viz their pollution potential degree of classes that the rating (R) scores as earlier discussed were scored. The $W$, on the other hand, is the assigned weight to each of the PPCFs in respect of their degree of importance.
in measuring the vulnerability prospect in the area. With the records for both $R$ and $W$ variables, the DRASTIC index (DI) values for each observed locations (Fig. 4) in the area are estimated using Eq. 1. The determined DI values for each location are detailed in column (18) of Table 5. According to the table, the DI values characterizing the study area vary

Fig. 4 The centroid and the criterion map conversion template model
from 0 to 84.45. This resulting index is a relative measure of vulnerability to contamination in the area. By interpretation, the areas with a higher index values are more compared with those with a lower index values.

The modeling of groundwater vulnerability map using the DRASTIC index (DI) results

The DI values obtained for each observation location grid center in Table 5 above were plotted using the template model (Fig. 4). The gain continuous values of the obtained DI values were interpolated in GIS environment using kriging technique. Adopting the quantile classification technique according to Rahmati et al. (2016) and Naghibi et al. (2014), the study area was classified into five classes of vulnerable zones where NV (5.67–36.88), VLV (36.88–51.70), LV (51.70–61.28), MV (61.28–70.55) and HV (70.55–84.45). Using these possible groundwater vulnerable classifications, the groundwater vulnerability to pollution index (GVPI) map based on DI modeling results was produced (Fig. 5). Furthermore, the corresponding areal coverage and percentage in each predicted groundwater vulnerable potential zones category were evaluated. The estimated areal extent established that about 85.89 km² (3%), 343.56 km² (12%) and 1059.31 km² (37%) account for the NV, VLV and LV categories whereas both the MV and HV categories have area coverage of 801.64 km² (37%) and 572.6 km² (20%), respectively (see Fig. 5).

The OWA-DRASTIC index technique application results

The applied OWA-DRASTIC index model established algorithm (Eq. 2) in the area vulnerability assessment produced by the results presented in Tables. Such ODIM application results are detailed in Tables 3, 4, 6 and 7. In

| Decision strategy | Order weights (n = 7) |
|-------------------|----------------------|
|                   | $V_{aD}$ | $V_{aR}$ | $V_{aA}$ | $V_{aS}$ | $V_{aT}$ | $V_{aI}$ | $V_{aC}$ |
| At least one (OR operator) | 1.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |
| Most | 0.03 | 0.08 | 0.11 | 0.14 | 0.17 | 0.20 | 0.25 |
| Almost | 0.00 | 0.00 | 0.01 | 0.04 | 0.10 | 0.21 | 0.63 |
| Half (mean operator) | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 | 0.14 |
| A few | 0.34 | 0.16 | 0.13 | 0.11 | 0.10 | 0.09 | 0.08 |
| All (AND operator) | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 1.00 |

$D$ water table depth, $R$ recharge rate, $A$ aquifer media, $S$ soil media, $T$ topography (slope), $I$ impact of vadose zone, $C$ hydraulic conductivity, $W_k$ criterion map weight, $a_i$ standardized criterion values

Table 3 The selected results of the computed OWA index component weights for some stations in the study area

| S/N | Criteria | $a_k$ | $w_k$ | $a_k w_k$ |
|-----|----------|-------|-------|-----------|
| 1   | $D$      | [0.5, 0.75, 0.5, 0.75, 0.75, 0.75, 0.05] | 0.31 | [0.16, 0.23, 0.16, 0.23, 0.23, 0.23, 0.16] |
| 2   | $R$      | [0.5, 0.5, 0.75, 0.75, 1, 0.75, 0.5] | 0.16 | [0.08, 0.08, 0.12, 0.12, 0.16, 0.12, 0.08] |
| 3   | $A$      | [0.25, 1.05, 0.75, 0.05, 1] | 0.08 | [0.02, 0.08, 0.04, 0.06, 0.04, 0.08] |
| 4   | $S$      | [0.5, 0.75, 0.75, 0.5, 0.1] | 0.04 | [0.02, 0.03, 0.03, 0.02, 0.04] |
| 5   | $T$      | [0.25, 0.25, 0.25, 0.75, 0.75, 0.75, 0.75] | 0.02 | [0.01, 0.01, 0.01, 0.02, 0.01, 0.01] |
| 6   | $I$      | [0.5, 0.75, 1, 1, 1, 1, 0.75] | 0.31 | [0.16, 0.23, 0.31, 0.31, 0.31, 0.31] |
| 7   | $C$      | [0.0, 0.0, 0.0, 0.0, 0.25] | 0.08 | [0.0, 0.0, 0.0, 0.0, 0.02] |

$D$ water table depth, $R$ recharge rate, $A$ aquifer media, $S$ soil media, $T$ topography (slope), $I$ impact of vadose zone, $C$ hydraulic conductivity, $W_k$ criterion map weight, $a_i$ standardized criterion values

Table 4 The determined ordered weights’ factor for the considered PPCFs’ parameters based on the selected linguistic quantifiers (Modified after Nadi and Delavar 2011)
Tables 3 and 4, there are two set of weights \( Z_{ik} \) and \( V_{ik} \) being the major drivers in OWA-DRASTIC index modeling feasibility. With the use of the determined ordered weights factor for each DRASTIC model parameters in Table 4, the OWA-DRASTIC index algorithm was defined for each users decision strategies operators, i.e., OWA-DRASTIC\textsubscript{OR} operator index, OWA-DRASTIC\textsubscript{ALMOST} operator index, OWA-DRASTIC\textsubscript{AFEW} operator index, OWA-DRASTIC\textsubscript{MOST} operator index, OWA-DRASTIC-MEAN operator and OWA-DRASTIC\textsubscript{AND} operator index (see the typical Eq. 2).
Fig. 5 DRASTIC model groundwater vulnerability to pollution index (GVPI) map
Table 6 The computed results for the various OWA-DRASTIC operator indexes

| Grid No | Grid Center’s coordinate | OWA-DRASTIC operators indexes for the user’s decision strategies |
|---------|--------------------------|---------------------------------------------------------------|
|         | Long           | Lat            | A  | B   | C    | D    | E     | F     |
| 1       | 101°17’26.2"  | 4°13’58.2"    | 0.1550 | 0.0929 | 0.0621 | 0.0051 | 0.0331 | 0.0000 |
| 2       | 101°23’11.6"  | 4°13’57.1"    | 0.2325 | 0.1038 | 0.0568 | 0.0013 | 0.0229 | 0.0000 |
| 3       | 101°11’47.8"  | 4°17’48.1"    | 0.2325 | 0.1275 | 0.0825 | 0.0063 | 0.0433 | 0.0000 |
| 4       | 101°17’25.1"  | 4°17’47.2"    | 0.3100 | 0.1691 | 0.1082 | 0.0082 | 0.0556 | 0.0000 |
| 5       | 101°23’10.5"  | 4°17’46.2"    | 0.3100 | 0.1680 | 0.1054 | 0.0046 | 0.0509 | 0.0000 |
| 6       | 101°28’47.35" | 4°17’45.13"   | 0.3100 | 0.1680 | 0.1054 | 0.0046 | 0.0509 | 0.0000 |
| 7       | 101°16’1.4"   | 4°13’8.1"     | 0.3100 | 0.1664 | 0.1046 | 0.0075 | 0.0521 | 0.0000 |
| 8       | 101°11’46.7"  | 4°13’7.1"     | 0.2325 | 0.1277 | 0.0839 | 0.0083 | 0.0462 | 0.0000 |
| 9       | 101°17’24.1"  | 4°13’6.2"     | 0.2325 | 0.1255 | 0.0811 | 0.0076 | 0.0434 | 0.0000 |
| 10      | 101°17’23.9"  | 4°13’5.2"     | 0.3100 | 0.1545 | 0.0950 | 0.0083 | 0.0485 | 0.0000 |
| 11      | 101°28’46.6"  | 4°13’4.2"     | 0.2325 | 0.1322 | 0.0889 | 0.0089 | 0.0499 | 0.0000 |
| 12      | 101°60.5°     | 3°55’27.0"    | 0.3100 | 0.1491 | 0.0879 | 0.0069 | 0.0415 | 0.0000 |
| 13      | 101°11’45.8"  | 3°55’26.2"    | 0.2325 | 0.0836 | 0.0361 | 0.0000 | 0.0086 | 0.0000 |
| 14      | 101°17’23.0"  | 3°55’25.2"    | 0.2325 | 0.1191 | 0.0686 | 0.0005 | 0.0272 | 0.0000 |
| 15      | 101°23’8.3"   | 3°55’24.3"    | 0.3100 | 0.1610 | 0.0996 | 0.0131 | 0.0505 | 0.0050 |
| 16      | 101°28’45.5"  | 3°55’23.3"    | 0.1550 | 0.0764 | 0.0468 | 0.0066 | 0.0245 | 0.0000 |
| 17      | 101°34’30.7"  | 3°55’22.2"    | 0.0600 | 0.0353 | 0.0243 | 0.0023 | 0.0139 | 0.0000 |
| 18      | 101°5’59.6°   | 3°49’24.5"    | 0.0600 | 0.0353 | 0.0243 | 0.0023 | 0.0139 | 0.0000 |
| 19      | 101°11’44.8"  | 3°49’23.2"    | 0.3100 | 0.1567 | 0.0939 | 0.0076 | 0.0443 | 0.0000 |
| 20      | 101°17’22.1"  | 3°49’22.3"    | 0.3100 | 0.1202 | 0.0586 | 0.0031 | 0.0209 | 0.0000 |
| 21      | 101°23’7.3"   | 3°49’21.4"    | 0.3100 | 0.1313 | 0.0704 | 0.0052 | 0.0299 | 0.0000 |
| 22      | 101°28’44.4"  | 3°49’20.4"    | 0.3100 | 0.1323 | 0.0711 | 0.0040 | 0.0297 | 0.0000 |
| 23      | 101°34’29.6"  | 3°49’19.4"    | 0.2325 | 0.1006 | 0.0554 | 0.0048 | 0.0248 | 0.0000 |
| 24      | 101°11’43.9"  | 3°43’4.2"     | 0.0775 | 0.0520 | 0.0396 | 0.0087 | 0.0267 | 0.0000 |
| 25      | 101°17’21.1"  | 3°43’3.3"     | 0.3100 | 0.1464 | 0.0864 | 0.0212 | 0.0441 | 0.0200 |
| 26      | 101°28’43.3"  | 3°43’1.4"     | 0.3100 | 0.1510 | 0.0921 | 0.0193 | 0.0492 | 0.0100 |
| 27      | 101°34’28.5"  | 3°43’0.5"     | 0.0800 | 0.0365 | 0.0260 | 0.0003 | 0.0078 | 0.0000 |

Table 7 The OWA-DRASTIC operators’ indexes continuous value classified ranges study area

| A        | B         | C         | D         | E         | F         |
|----------|-----------|-----------|-----------|-----------|-----------|
| 0.0601–0.1169 | 0.0000–0.0009 | 0.0200–0.0452 | 0.0083–0.0332 | 0.0353–0.0726 | 0.0000–0.0040 |
| 0.1169–0.1659 | 0.0009–0.0033 | 0.0452–0.0619 | 0.0332–0.0486 | 0.0726–0.1004 | 0.0040–0.0063 |
| 0.1659–0.2188 | 0.0033–0.0070 | 0.0619–0.0767 | 0.0486–0.0652 | 0.1004–0.1214 | 0.0063–0.0093 |
| 0.2188–0.2678 | 0.0070–0.0126 | 0.0767–0.8892 | 0.0652–0.0835 | 0.1214–0.1397 | 0.0093–0.0141 |
| 0.2678–0.3100 | 0.0126–0.0200 | 0.8891–1.0812 | 0.0835–1.1142 | 0.1397–1.1691 | 0.0141–0.0212 |

Pollution potential interpretation of the OWA-DRASTIC model operator indexes analysis

The computed indexes results based on the selected operator’s users decision strategy in Table 6 are the relative measures of vulnerability to contamination characteristics in the area. The interpretation of the resulting operators’ indexes values is such that areas with a higher index value are more vulnerable, as compared with those with a lower index. Deducing from the various operators’ indexes values, the degree of vulnerability per location in the area varies from one operator index algorithm to another (Table 6). This is because the users’ decision strategy characterizing the
developed OWA-DRASTIC model allows diverse vulnerability assessment performance through flexibility using of varying numbers of pollution potential criteria input in the established vulnerability model (Eq. 2). The records in Table 6 were further processed in GIS environment to demarcate the continuous indexes values into class boundary ranges using the ad hoc classification technique of Rahmati et al. (2016) and Naghibi et al. (2014) to define the vulnerability potential classes in the area. The classified ranges boundary for various strategy decision operators is shown in Table 7. These operators’ indexes classified ranges are interpretable for vulnerability assessment in the area. The attribute of these operators’ indexes strategies implication in vulnerability assessment varied as discussed in the literature (Gorsevski et al. 2012; Mogaji et al. 2014). The OWA-DRASTIC AND index operator was chosen over other operators’ indexes for its reasons of risk aversion solution advantage (Bell et al. 2007). Besides, Nadi and Delavar (2011) has also established that the performance of AND operator user’s decision strategy in his study to be the best among other operator indexes Thus, this OWA-DRASTIC CAND operator index classification was preferred to be more suitable for developing vulnerability modeling prediction of higher reliability and precision in the study area.

The modeling of groundwater vulnerability map using the OWA-DRASTICAND index operator result

The OWA-DRASTIC AND index values obtained for each observation location grid center in Table 7 above were plotted using the template model (Fig. 4). The gain continuous values of the obtained OWA-DRASTIC AND index values were interpolated in GIS environment using kriging technique. The quantile classification technique was also used to classify the area into five classes of vulnerable zones where NV (0.0000–0.0009), VLY (0.0009–0.0033), LV (0.0033–0.0070), MV (0.0007–0.0126) and HV (0.0126–0.0200) (see Table 7). Using these possible groundwater vulnerable classifications, the groundwater vulnerability to pollution index (GVPI) map based on OWA-DRASTICAND index results was produced (Fig. 6). The corresponding areal coverage and percentage in each predicted groundwater potential zones category were evaluated where about 2095 km² (73%), 479 km² (17%) and 149 km² (5%) account for the NV, VLY and LV categories whereas both the MV and HV categories have area coverage of 117 km² (4%) and 23 km² (1%), respectively (Fig. 6).

Model validation

For the purpose of establishing the reliability and precision of the spatial predictive model indexes in environmental decision-making studies, the above task is very crucial. Thus, in line with Manap et al. (2011), the produced groundwater vulnerability prediction maps (Figs. 5, 6) were appraised with validation analysis. The most widely used validation technique of assessing the reliability of vulnerability index is via determining correlation between the nitrate concentration and the spatial-predicted vulnerability index values (Antonakos and Lambrakis 2007; Nobre et al. 2007; Chen et al. 2013; Pradhan et al. 2013; Thirumalaivasan et al. 2003; Panagopoulos et al. 2006; Javadi et al. 2011a, b; Singh et al. 2015). This is because, the DRASTIC model often assumes that the contaminant has the mobility of water particularly the nitrate which is a highly mobile contaminant that originates from a variety of point and nonpoint sources such as nitrogenous fertilizers that usually increase nitrate contamination of groundwater resources especially in an extensive cultivated agricultural site (Qi and Gurdak 2006). However, it is not only nitrate compound that degrades groundwater quality, other physio-chemical parameters and heavy metals elements that derived their sources from other environmental activities including anthropogenic parameters and weathering of source rocks and recharge from water bodies are also culprit to groundwater contamination (Singh et al. 2015; De Vries and Simmer 2002; Anirban et al. 2016). The consumption of such other chemical elements that are readily soluble in water is inimical to the body system. As such, the approach according to Kalinski et al. (1994), McLay et al. (2001) and Alam et al. (2012) where chemical contaminant parameters and vulnerability index relationship is analyzed for spatial model validation is considered in this study. Though, despite the fact that the study area is vastly covered with agricultural lands, presently there is no report of groundwater contamination problems in the area. Thus, this study aimed to assess impending contamination to be model from estimated vulnerability index in the area. Therefore, some physio-chemical parameters and heavy metals element concentrations information were extracted from the groundwater quality analysis data obtained from the drilled boreholes in the area (see Figs. 5, 6). The determined physio-chemical parameters and heavy metals that were assumed to be completely soluble in water include pH, TDS, nitrate (NO3), sulfate (SO4), calcium (Ca), iron (Fe), zinc (Zn) and manganese (Mn). With this groundwater quality analyzed records, two validation schemes were used to assess the efficiency of the applied DRASTIC index model (DIM) and OWA-DRASTIC index model (ODIM) vulnerability assessment techniques: these schemes include: (a) water quality status—vulnerability zones relationship scheme and (b) pollution causative element—vulnerability index values correlation scheme. This concept is in agreement with Anirban et al. (2016) who buttressed the use of multiple water quality parameters in evaluating prospective vulnerability maps better than the past studies that have focused on
Fig. 6  OWA-DRASTIC model groundwater vulnerability to pollution index map
single-water quality parameter means of validating DRASIC index.

Water quality status–vulnerability zones relationship scheme

In order to establish this relationship scheme, the analyzed chemical parameters and elements concentrations were compared with the WHO (World Health Organization) and Food and Agriculture Organization (FAO) standards to assess the water quality status of the samples obtained from the groundwater bore wells. Enforcing these standards, for each determined chemical parameters whose concentration (mg/l) is within the permissible limit $Y$ is indicated whereas where we have the measured concentration exceeding or below the permissible limit, $X$ is indicated. Consequently, the water quality in the area was classified into good and bad status (see Table 8). Further, the concept of ascribing protected areas and not protected areas to the classes of low vulnerable potential zones and the moderate-high vulnerable potential zones in a regional vulnerability model index map is used to describe good water quality areas and bad water quality areas, respectively, based on the submission of Artiqur Rahman (2008) and Thirumalaivasan et al. (2003). Hence, the predicted vulnerable potential zones of the GVPI maps (Figs. 5, 6) are reclassified thus in Table 9. Considering the information in Tables 8, 9 and Figs. 5, 6, the physio-chemical parameters and heavy metal elements concentration measurements were analyzed for the DIM and ODIM methods validation using the water quality status–vulnerability zones relationship approach. Tables 10 and 11 present the vulnerability index prediction validation results for the DIM and ODIM methods. According to Tables 10 and 11, the DIM and ODIM methods show 64.29 and 85.71% prediction accuracies result, respectively. It thus implies that about 24 and 18 borehole wells’ water quality status information correctly coincided with the predicted vulnerable index zones of the models, respectively, whereas only 4 and 10 borehole wells were not coincided. The OWA-DRASIC index model (ODIM)-based GVPI map represents better scenario of vulnerability as compared to conventional DRASTIC index model (DIM)-based GVPI map in view of their validation with the field observations of groundwater quality.

### Table 8 Groundwater quality evaluation criteria based on FAO and WHO standards (after FAO 1995 and WHO 2004)

| Standards | Physio-chemical Parameters | Heavy metals | Water quality remark |
|-----------|-----------------------------|--------------|----------------------|
|           | pH TDS NO$_3$ Ca SO$_4$ Fe Mn | Fe Mn | Good Bad |
| WHO       | 6.5–8.5 500 50 75 20 | 0.5–50 0.1 | Y X |
| FAO       | 6.5–8.5 2000 10 20 20 | – – | – – |

$Y$ good water quality, $X$ bad water quality

Pollution causative elements–vulnerability index values correlation scheme

In accordance with Pearson (1900) and Snedecor and Cochran (1980), correlation is a method for scrutinizing the connection between two measurable and continuous variables. This second validation scheme is a quantitative correlation approach. From the analyzed groundwater quality data, the areas water quality is relatively in good status. However, among the analyzed the physio-chemical parameters and heavy metal elements for water quality status in the area, the concentration of pH and manganese chemical elements revealed more evidence of groundwater contamination as indicated by $X$ in columns (4) and (17) of Tables 10 and 11. With the pH readings in column (4), the tested water samples in the area are acidic. In accordance with Akinbile and Mohd (2011), the area underground water contains the presence of metals, particularly toxic metals like manganese. Thus, these pollution causative elements (pH and Mn) were also considered as correlation indices to validate the DIM and ODIM vulnerability techniques. Adopting the similar method employed in the studies of Pradhan et al. (2013) and Singh et al. (2015), the pH and manganese concentrations were used to develop correlations with the values of both DIM and ODIM techniques. Solving the GIS software with the groundwater bore well locations depicted in Figs. 5 and 6, the identify tool was used to extract the values for the DIM and ODIM vulnerability index. The extracted vulnerability index values were correlated with their corresponding pH and manganese (Mn) concentrations values in a plot profile. Figures 7 and 8 present the plots of 28 correlated data pairs. According to the plots, the observed Pearson’s correlation coefficient $R$ for the quantitative relationship between the DIM and ODIM and manganese concentration is 63 and 85%, respectively (Fig. 7). Similarly, the observed
### Table 10 Vulnerability index prediction validation results based on OWA-DRASTIC index model (ODIM) method

| BH ID Nos. | BH location coordinates | Physio-chemical parameters | Heavy Metals | BH status remark | Vulnerability potential remark from map | Final remark |
|------------|-------------------------|-----------------------------|--------------|-----------------|----------------------------------------|-------------|
|            | Lat  | Long  | pH  | WQMS | TDS  | WQMS | NO₃ | WQMS | Ca  | WQMS | SO₄ | WQMS | Fe  | WQMS | Mn  | WQMS |
| 1          | 733.322  | 468.233  | 5.6  | X    | 102  | Y    | 0.09 | Y    | 4.7  | Y    | 0.6  | Y    | 53   | Y    | 0.50 | X    | P    | P    | Coincide |
| 2          | 743.978  | 468.233  | 5.1  | X    | 28   | Y    | 0.00 | Y    | 3.10 | Y    | 1.00 | Y    | 34.0 | Y    | 0.54 | X    | P    | P    | Coincide |
| 3          | 754.386  | 468.233  | 5.3  | X    | 31   | Y    | 0.10 | Y    | 2.50 | Y    | 0.20 | Y    | 46.3 | Y    | 0.26 | X    | P    | P    | Coincide |
| 4          | 765.042  | 468.233  | 5.5  | X    | 90   | Y    | 0.00 | Y    | 3.20 | Y    | 0.50 | Y    | 30.7 | Y    | 0.51 | X    | P    | P    | Coincide |
| 5          | 775.451  | 468.233  | 5.8  | X    | 46   | Y    | 0.05 | Y    | 2.70 | Y    | 0.20 | Y    | 52.0 | Y    | 0.38 | X    | P    | P    | Coincide |
| 6          | 786.107  | 468.233  | 4.9  | X    | 29   | Y    | 0   | Y    | 1.6  | Y    | 7.1  | Y    | 28.2 | Y    | 0.45 | X    | P    | P    | Coincide |
| 7          | 733.322  | 456.834  | 5.8  | X    | 41   | Y    | 0.1  | Y    | 5.3  | Y    | 0.3  | Y    | 39   | Y    | 0.71 | X    | P    | NP   | Not-Coincide |
| 8          | 743.978  | 456.834  | 5.1  | X    | 38   | Y    | 0   | Y    | 1.8  | Y    | 1.5  | Y    | 20.2 | Y    | 1.16 | X    | P    | NP   | Not-Coincide |
| 9          | 754.386  | 456.834  | 5.5  | X    | 43   | Y    | 0.03 | Y    | 2.5  | Y    | 0.2  | Y    | 30.7 | Y    | 1.21 | X    | P    | NP   | Not-Coincide |
| 10         | 765.042  | 456.834  | 5.4  | X    | 56   | Y    | 0   | Y    | 2.4  | Y    | 0.4  | Y    | 31.5 | Y    | 0.24 | X    | P    | P    | Coincide |
| 11         | 775.451  | 456.834  | 6.8  | Y    | 58   | Y    | 0.1  | Y    | 2.8  | Y    | 1.5  | Y    | 42.5 | Y    | 0.54 | X    | P    | P    | Coincide |
| 12         | 786.107  | 456.834  | 5.8  | X    | 27   | Y    | 0   | Y    | 1.2  | Y    | 0.6  | Y    | 20.9 | Y    | 1.20 | X    | P    | P    | Coincide |
| 13         | 733.322  | 445.434  | 5.4  | X    | 57   | Y    | 0.2  | Y    | 3.1  | Y    | 1.9  | Y    | 26.2 | Y    | 0.43 | X    | P    | P    | Coincide |
| 14         | 743.978  | 445.434  | 5.4  | X    | 50   | Y    | 0.1  | Y    | 3.8  | Y    | 3.4  | Y    | 17.1 | Y    | 0.19 | X    | P    | P    | Coincide |
| 15         | 754.386  | 445.434  | 5.5  | X    | 38   | Y    | 0.68 | Y    | 2.7  | Y    | 0.2  | Y    | 51.3 | Y    | 0.52 | X    | P    | NP   | Not-Coincide |
| 16         | 765.042  | 445.434  | 5.5  | X    | 338  | Y    | 3.9  | Y    | 3.6  | Y    | 3.8  | Y    | 53.8 | Y    | 0.59 | X    | P    | P    | Coincide |
| 17         | 775.451  | 445.434  | 5.4  | X    | 100  | Y    | 0.05 | Y    | 3.2  | Y    | 0.2  | Y    | 59.9 | Y    | 0.13 | X    | P    | P    | Coincide |
| 18         | 786.107  | 445.434  | 5.5  | X    | 21   | Y    | 0   | Y    | 1.6  | Y    | 1    | Y    | 53.7 | Y    | 0.39 | X    | P    | P    | Coincide |
| 19         | 733.322  | 434.034  | 5.9  | X    | 63   | Y    | 0   | Y    | 3.2  | Y    | 0.5  | Y    | 17.9 | Y    | 0.28 | X    | P    | P    | Coincide |
| 20         | 743.978  | 434.034  | 5.4  | X    | 2.9  | Y    | 0.1  | Y    | 1.7  | Y    | 2.9  | Y    | 34.7 | Y    | 0.48 | X    | P    | P    | Coincide |
| 21         | 754.386  | 434.034  | 5.4  | X    | 19.0 | Y    | 0.30 | Y    | 2.2  | Y    | 0.3  | Y    | 14.9 | Y    | 0.91 | X    | P    | P    | Coincide |
| 22         | 765.042  | 434.034  | 5.5  | X    | 73   | Y    | 0.10 | Y    | 3.8  | Y    | 18.4 | Y    | 16.9 | Y    | 0.37 | X    | P    | P    | Coincide |
| 23         | 775.451  | 434.034  | 5.4  | X    | 33   | Y    | 0.25 | Y    | 1.4  | Y    | 2.4  | Y    | 23.2 | Y    | 0.51 | X    | P    | P    | Coincide |
| 24         | 786.107  | 434.034  | 6.8  | Y    | 59.0 | Y    | 0.01 | Y    | 5    | Y    | 1.9  | Y    | 37.1 | Y    | 0.48 | X    | P    | P    | Coincide |
| 25         | 733.322  | 422.883  | 5.8  | X    | 82   | Y    | 6.9  | Y    | 3.8  | Y    | 3.8  | Y    | 38   | Y    | 0.20 | X    | P    | P    | Coincide |
| 26         | 743.978  | 422.883  | 5.8  | X    | 39.0 | Y    | 0.05 | Y    | 4.5  | Y    | 1.9  | Y    | 44.8 | Y    | 0.35 | X    | P    | P    | Coincide |
| 27         | 754.386  | 422.883  | 5.4  | X    | 10.0 | Y    | 0.10 | Y    | 0.5  | Y    | 1.9  | Y    | 41   | Y    | 0.29 | X    | P    | P    | Coincide |
| 28         | 765.042  | 422.883  | 5.4  | X    | 55   | Y    | 0.2  | Y    | 2.4  | Y    | 0.2  | Y    | 32.8 | Y    | 0.32 | X    | P    | P    | Coincide |

P protected, NP not protected, WQMS water quality measurement status, Y good water quality, X bad water quality
Table 11  Vulnerability index prediction validation results based on DRASTIC model index (DIM) method

| BH ID Nos. | BH location coordinates | Physio-chemical Parameters | Heavy Metals | BH status remark | Vulnerability potential remark from map | Final remark |
|------------|-------------------------|----------------------------|--------------|----------------|-----------------------------------------|--------------|
|            | Lat Long  | pH | WQMS | TDS | WQMS | NO₃ | WQMS | Ca | WQMS | SO₄ | WQMS | Fe | WQMS | Mn | WQMS |                      |                          |                          |
| 1          | 733,322  | 468,233 | 5.6 X | 102 Y | 0.09 Y | 4.7 Y | 0.6 Y | 53 Y | 0.50 X |  |  |  | P |  |  |  | Coincide |
| 2          | 743,978  | 468,233 | 5.1 X | 28 Y | 0.00 Y | 3.10 Y | 1.00 Y | 34.0 Y | 0.54 X |  |  |  | P |  |  |  | Coincide |
| 3          | 754,386  | 468,233 | 5.3 X | 31 Y | 0.10 Y | 2.50 Y | 0.20 Y | 46.3 Y | 0.26 X |  |  |  | P |  |  |  | Coincide |
| 4          | 765,042  | 468,233 | 5.5 X | 90 Y | 0.00 Y | 3.20 Y | 0.50 Y | 30.7 Y | 0.51 X |  |  |  | P |  |  |  | Coincide |
| 5          | 775,451  | 468,233 | 5.8 X | 46 Y | 0.05 Y | 2.70 Y | 0.20 Y | 52.0 Y | 0.38 X |  |  |  | P |  |  |  | Coincide |
| 6          | 786,107  | 468,233 | 4.9 X | 29 Y | 0 Y | 1.6 Y | 7.1 Y | 28.2 Y | 0.45 X |  |  |  | P |  |  |  | Coincide |
| 7          | 733,322  | 456,834 | 5.8 X | 41 Y | 0.1 Y | 5.3 Y | 0.3 Y | 39 Y | 0.71 X |  |  |  | P |  |  |  | Coincide |
| 8          | 743,978  | 456,834 | 5.1 X | 38 Y | 0 Y | 1.8 Y | 1.5 Y | 20.2 Y | 1.16 X |  |  |  | P |  |  |  | Coincide |
| 9          | 754,386  | 456,834 | 5.5 X | 43 Y | 0.03 Y | 2.5 Y | 0.2 Y | 30.7 Y | 1.21 X |  |  |  | P |  |  | NP | Not-Coincide |
| 10         | 765,042  | 456,834 | 5.4 X | 56 Y | 0 Y | 2.4 Y | 0.4 Y | 31.5 Y | 0.24 X |  |  |  | P |  |  |  | Coincide |
| 11         | 775,451  | 456,834 | 6.8 Y | 58 Y | 0.1 Y | 2.8 Y | 1.5 Y | 42.5 Y | 0.54 X |  |  |  | P |  |  | NP | Not-Coincide |
| 12         | 786,107  | 456,834 | 5.8 X | 27 Y | 0 Y | 1.2 Y | 0.6 Y | 20.9 Y | 1.20 X |  |  |  | P |  |  | NP | Not-Coincide |
| 13         | 733,322  | 445,434 | 5.4 X | 57 Y | 0.2 Y | 3.1 Y | 1.9 Y | 26.2 Y | 0.43 X |  |  |  | P |  |  | P | Coincide |
| 14         | 743,978  | 445,434 | 5.4 X | 50 Y | 0 Y | 2.0 Y | 3.4 Y | 17.1 Y | 0.19 X |  |  |  | P |  |  | P | Coincide |
| 15         | 754,386  | 445,434 | 5.5 X | 38 Y | 0.68 Y | 2.7 Y | 0.2 Y | 51.3 Y | 0.52 X |  |  |  | P |  |  | P | Coincide |
| 16         | 765,042  | 445,434 | 5.5 X | 338 Y | 3.9 Y | 3.6 Y | 3.8 Y | 53.8 Y | 0.59 X |  |  |  | P |  |  | NP | Coincide |
| 17         | 775,451  | 445,434 | 5.4 X | 100 Y | 0.05 Y | 3.2 Y | 0.2 Y | 59.9 Y | 0.13 X |  |  |  | P |  |  | NP | Not-Coincide |
| 18         | 786,107  | 445,434 | 5.5 X | 21 Y | 0 Y | 1.6 Y | 1 Y | 53.7 Y | 0.39 X |  |  |  | P |  |  | NP | Not-Coincide |
| 19         | 733,322  | 434,034 | 5.9 X | 63 Y | 0 Y | 3.2 Y | 0.5 Y | 17.9 Y | 0.28 X |  |  |  | P |  |  | NP | Not-Coincide |
| 20         | 743,978  | 434,034 | 5.4 X | 2.9 Y | 0.1 Y | 1.7 Y | 2.9 Y | 34.7 Y | 0.48 X |  |  |  | P |  |  | P | Coincide |
| 21         | 754,386  | 434,034 | 5.4 X | 19.0 Y | 0.30 Y | 2.2 Y | 0.3 Y | 14.9 Y | 0.91 X |  |  |  | P |  |  | P | Coincide |
| 22         | 765,042  | 434,034 | 5.5 X | 73.0 Y | 0.10 Y | 3.8 Y | 18.4 Y | 16.9 Y | 0.37 X |  |  |  | P |  |  | NP | Coincide |
| 23         | 775,451  | 434,034 | 5.4 X | 33.0 Y | 0.25 Y | 1.4 Y | 2.4 Y | 23.2 Y | 0.51 X |  |  |  | P |  |  | NP | Coincide |
| 24         | 786,107  | 434,034 | 6.8 Y | 59.0 Y | 0.01 Y | 5 Y | 1.9 Y | 37.1 Y | 0.48 X |  |  |  | P |  |  | NP | Coincide |
| 25         | 733,322  | 422,883 | 5.8 X | 82 Y | 6.9 Y | 3.8 Y | 3.8 Y | 38 Y | 0.20 X |  |  |  | P |  |  | P | Coincide |
| 26         | 743,978  | 422,883 | 5.8 X | 39.0 Y | 0.05 Y | 4.5 Y | 1.9 Y | 44.8 Y | 0.35 X |  |  |  | P |  |  | P | Coincide |
| 27         | 754,386  | 422,883 | 5.4 X | 10.0 Y | 0.10 Y | 0.5 Y | 1.9 Y | 4.1 Y | 0.29 X |  |  |  | P |  |  | NP | Not-Coincide |
| 28         | 765,042  | 422,883 | 5.4 X | 55 Y | 0.2 Y | 2.4 Y | 0.2 Y | 32.8 Y | 0.32 X |  |  |  | P |  |  | P | Coincide |

P protected, NP not protected, WQMS water quality measurement status, Y good water quality, X bad water quality
Pearson’s correlation coefficient ‘$R$’ for the quantitative relationship between the DIM and ODIM and pH is 68 and 83%, respectively (Fig. 8). The resulting line of fit which shows positive correlation between the DIM and ODIM and both Mn and pH concentration further validate these vulnerability modeling techniques in the area.

**Model performance and comparison between DIM and ODIM vulnerability techniques**

The performance evaluation’s schemes for the DIM and ODIM vulnerability methods have earlier been discussed. The evaluation was with the view of establishing the similarities and the differences between the methods reference to their significance in groundwater vulnerability assessment. Tables 10 and 11 show performance evaluation results for the methods based on water quality status–vulnerability zones relationship scheme. Quantitatively, it can be seen that both investigated methods in the area showed reasonably very good accuracy in spatial prediction of groundwater vulnerability based on the attained prediction accuracies. However, the ODIM method has better percentage accuracy (> 21.42%) than that of the DIM method. Figures 7 and 8 show the correlation scheme evaluation results. It was found that the correlation between the ODIM and manganese concentration was higher (0.85) in comparison with that of the DIM and observed manganese concentration (0.63). Similarly, the correlation between ODIM and pH concentration was higher (0.83) in comparison with that of the DIM and observed pH concentration (0.68). But then, the observed similarity is such that the highest concentrations of both Mn and pH correlated well with the highest OWA-DRASIC index values and DRASTIC index values. With these
correlation results, the efficiencies of the models (DIM and ODIM) in groundwater vulnerability assessment are further validated. In addition, the percentage computation of the total area under different vulnerability class determined from both ODIM and DIM-based GVPI model maps is as graphically represented in Fig. 9. The results reveal that more than 50% of the area are under the low vulnerable zones. Such areas are relatively protected for their high resistance to pollution infiltration to groundwater containing medium (the aquifer) (Atiquur Rahman 2008). This finding is in agreement with reason why there has been no challenges of groundwater contamination problems in the study area. Corroboratively, the overlaying analysis of the produced GVPI maps (Figs. 5, 6) and the PPCFs’ thematic layers (Fig. 3) which established the possibility of the presence of clayey confining unit (aquifer layers overlain by low permeable materials) and poorly drained soils in the study area could had limited the amount of agricultural chemicals to reach the aquifer. The interpreted results of the area borehole log data (obtained from the Minerals and Geoscience Department, Malaysia) have as well confirmed the existence of the thick column of clayey confining unit overlying the aquifer layer in the area. Since, the rate of pollutant infiltration is largely a function of pollutant residence time in a place, the undulating and steep natures of this area topography/sloping characteristics practically
reduced the infiltrating rate of pollutants or contaminants in the subsurface through the high rate of runoff in the area. Thus, the prediction accuracy of both ODIM and DIM vulnerability techniques is quite supported but with the ODIM method having higher efficiency.

Conclusion

The main conclusions drawn from this study were as follows: (1) The two used vulnerability modeling approaches for aquifer vulnerability mapping vis-à-vis the quality preservation of the groundwater resources have very good capability for predicting potential vulnerable zones with a model accuracy of 63 and 85% from the Mn concentrations 'correlation factor between the DRASTIC index and the OWA-DRASTIC index predicted values, respectively. Similarly, the accuracy of the pH concentrations 'correlation factor between the DRASTIC index and the OWA-DRASTIC index predicted values are 68 and 83%, respectively. (2) Based on the FAO and WHO standards, the accuracy of both the DIM-based GVPI map and the ODIM-based GVPI map was established to be 64.29 and 85.71%, respectively. (3) The obtained DIM and ODIM values are classified into five classes: no vulnerable (NV), very low, vulnerable (VLV), low vulnerable (LV), moderate vulnerable (MV) and high vulnerable (HV). (4) The large extent of low potential vulnerable classes (52% for DRASTIC index model and 95% for OWA-DRASTIC index model) implies that the aquifer systems in the study area are highly protected from contamination. (5) The OWA-DRASTIC index method is a more efficient technique to demarcate potential vulnerable zones than DRASTIC index in the area. (6) The groundwater vulnerability to pollution index maps produced by this study can provide valuable information for hydrogeologist, planners and decision makers to put suitable plans for managing groundwater in the study area. The method can be replicated in other areas with similar hydrogeological settings.

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