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Assessment of groundwater vulnerability mapping methods for sustainable water resource management: An overview

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Abstract: Groundwater is a vital resource for domestic, agricultural, and industrial activities, as well as for ecosystem services. Despite this, the resource is under significant threat, due to increasing contamination from anthropogenic activities. Therefore, to ensure its reliability for present and future use, effective management of groundwater is important not only in terms of quantity (i.e. abstraction) but also quality. This can be achieved by identifying areas that are more vulnerable to contamination and by implementing protective measures. To identify the risk and delineate areas that are more exposed to pollution, various groundwater vulnerability assessment techniques have been developed across the globe. This paper presents an overview of some of the commonly used groundwater vulnerability assessment models in terms of their unique features and their application. Special emphasis is placed on statistical methods and overlay-index techniques. The assessment of the literature shows that statistical methods are limited in application to the assessment of groundwater vulnerability to pollution because they rely heavily on the availability of sufficient and quality data. However, in areas where extensive monitoring data are available, these methods estimate groundwater vulnerability more realistically in quantitative terms. Many works of research indicate that index-overlay methods are used extensively and frequently in groundwater vulnerability assessments. Due to the qualitative nature of these models, however, they are still subject to modification. This study offers an overview of a selection of relevant groundwater vulnerability assessment techniques under a specific set of hydro-climatic and hydrogeological conditions.

Keywords: aquifer vulnerability, groundwater, intrinsic vulnerability, specific vulnerability, vulnerability assessment methods

INTRODUCTION

Groundwater (GW) is becoming a vital resource for domestic consumption, agricultural and industrial activities, and ecosystem services [Chen *et al.* 2018; Howard 2014]. Its utilisation for these services has been increasing significantly in the last couple of decades and is also expected to increase in the future, owing to the rapid population growth, urbanisation, industrialisation, and the high susceptibility of surface water resources to anthropogenic activities [Khatri, Tyagi 2014; Piga *et al.* 2017] (Fig. 1), and to climate change [Field *et al.* 2014]. Traditionally, GW has been considered more resilient to pollution compared with surface water sources and is rarely influenced to any great extent by drought and climate change [Howard 2014]. However, contaminants from unregulated industries, urbanisation, and agricultural activities are threatening GW availability and sustainability [Devic *et al.* 2014; Jiang *et al.* 2009].

GW contamination is a hidden surface-subsurface process, which is not directly visible from the surface. It can be noticed only once a spring or a well becomes contaminated, or the contaminant is released into surface waters [Jang *et al.* 2017]. Thus, it may take several years to notice GW contamination. Once GW is polluted, it is expensive to clean it and it takes a long time to restore it to its original condition. Also, data constraints, variation in geographical locations, and physical inaccessibility impede the monitoring of all waters and make remedial actions costly and impractical in many areas [Babiker *et al.* 2005; Shrestha *et al.* 2017; Wang, Yang 2008; Yang, Wang 2010]. Therefore, the proverb ‘prevention is better than cure’ applies to the proper management of GW resources [Butler *et al.* 2010]

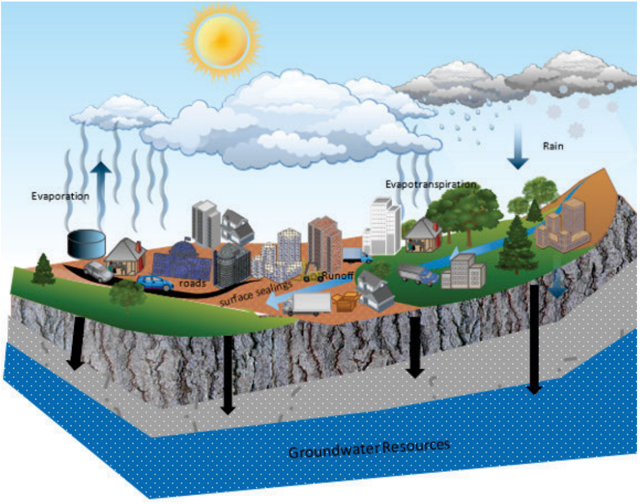

Fig. 1. Conceptual groundwater pollution model drawn using concept draw demo; source: own elaboration

because prevention is less expensive and easier than remedial measures.

One of the ways of protecting GW against pollution is assessing its vulnerability to contamination. Various types of Groundwater Vulnerability (GWV) assessment methods are available to protect GW against pollution. These methods are commonly classified into statistical methods, quantitative approaches, and subjective methods [Machiwal *et al.* 2018; NRC 1993; Wang, Yang 2008; Worrall, Besien 2005]. Not all these GWV assessment methods are universally used for vulnerability assessment in all hydrogeological conditions. Their application to GWV assessment varies from one method to another, depending on the availability of sufficient quantitative and qualitative data, and their spatial distribution; purpose and scale of mapping; costs associated with the formulation of the model, and the specific hydrogeological settings of the aquifer being studied [Aydi 2018; Ribeiro *et al.* 2017]. Besides, some of the GWV methods, such as DRASTIC (Depth to water (D), Net Recharge (R), Aquifer media (A), Soil media (S), Topography (T), Impact of the vadose zone (I), and the hydraulic conductivity (C)), are still subject to adjustments by way of using statistical methods to fit the peculiar features of the study area, and to obtain better vulnerability assessment results. On the other hand, the vulnerability of GW to pollution due to anthropogenic activities, such as industrialisation, urbanisation, and agriculture, is also becoming a growing concern across the world. Thus, it is essential to review the existing methods and recent developments made in the area of GWV assessment techniques. The purpose of the current study is to present an overview of different methods used for the assessment of GWV to pollution and the recent progress made in these methods.

MATERIALS AND METHODS

GENERAL INFORMATION

Statistical methods, the physical process-based methods (quantitative approaches), and subjective methods or the overlay – index (GIS-based qualitative) methods are the commonly used GWV assessment methods (Fig. 2). The first two approaches (statistical technique and qualitative methods) focus on evaluating intrinsic vulnerability, while process-based models are aimed at assessing specific vulnerability [Machiwal *et al.* 2018]. More emphasis is placed on statistical methods and overlay-index techniques. 127 accredited references published between 1987 and 2020 indexed in Scopus, Norwegian list, SiELO SA, and WoS were searched from various databases using the names of the methods and keywords, and used for synthesising the present paper.

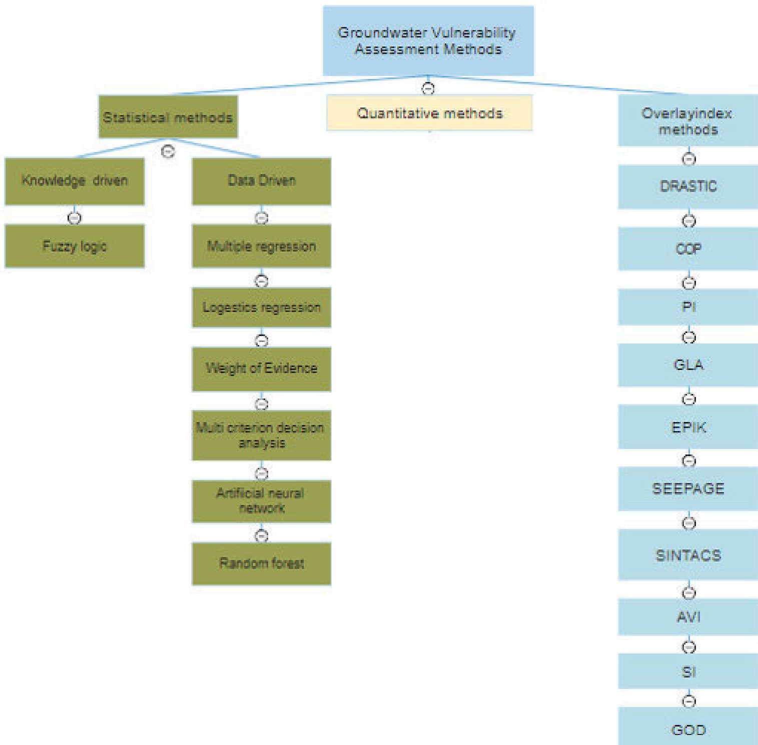

Fig. 2. Types of commonly applied groundwater vulnerability mapping methods, source: own elaboration

STATISTICAL METHODS

Statistical techniques range from basic descriptive statistics of the concentration of particular pollutants to more advanced regression analysis, which includes the effects of many predictor parameters [Focazio *et al.* 2002]. They have been used to define the concentration of contaminants or probabilistic contamination using the relationship between spatial variables or simulated results, such as aquifer properties, and observed data in the aquifer from monitoring and measured data [Babiker *et al.* 2005; Focazio *et al.* 2002; NRC 1993]. Statistical methods have been applied to calibrate or verify other methods such as DRASTIC [Javadi *et al.* 2011] or have been applied to prove or disprove a relationship between observed pollutants, or different environmental factors [Masetti *et al.* 2009]. They are mainly applied in locations with non-point sources of pollution, such as detection of nitrate sources over the agricultural area, and produce spatially distributed probabilities of exceedance, instead of categorised low, medium, and high ranking [Liggett, Talwar *et al.* 2009]. The commonly used statistical approaches applied in GWV assessment are presented in the subsequent subsections. Their advantage and disadvantages were summarised in Table 1.

Table 1. Advantages and disadvatges of selected statistical GWVA models

Model	Advantages	Disadvantages	References
MLR	– concentrations are easily compared with water quality standards or guidelines – simple and straightforward when initial measured data are available	– requires measured data, which sometimes is difficult to find in many places	Boy-Roura *et al.* [2013], Machiwal *et al.* [2018]
LR	– uses observed data to calculate adequate weights; – disregards statistically insignificant parameters, – enables the choice of significant parameters, and consequently removes subjectivity from the analysis	– sensitive to initial data, like MLR, mainly when the size of measured data is small	Focazio *et al.* [2002], Machiwal *et al.* [2018]
RF	– non-parametric nature and high predictive accuracy; – results of the prediction are unaffected by outliers and redundant data – can effectively handle small samples – can effectively manage missing data and determine variable importance	– harder to interpret when compared with single regression – cannot extrapolate outside the training range – the theoretical properties of RF are not entirely understood	Tyralis *et al.* [2019]
ANN	– does not require prior knowledge of the model, and is adaptive (i.e., learning from inputs parameters); – non-linear modelling tools and do not require an exact formulation of the physical relationship of the problem – does not need an understanding of the natural processes - suitable for sensitivity and uncertainty analysis	– its "black box" nature; – immense complexity of network structure, and require colossal processing time for large neural networks (NN) and the neural network (NN) that requires training to operate	Sahoo *et al.* [2006], Pavlis *et al.* [2010], Yesilnacar *et al.* [2007]
MCDA	– possibility to include views of many decision-makers, takes uncertainty into account, and incorporates preferences – uses individual scores to sufficiently characterise complex situations	– interdependence between criteria and alternatives – subject to inconsistencies in judgment and ranking criteria – rank reversal phenomenon and absence of threshold values	Velasquez, Hester [2013], Costa *et al.* [2019]
FL	– can process incomplete data and provide estimated answers for problems that are hard to solve by other techniques – communicates knowledge more effectively than other methods because it uses reasoning similar to human reasoning – tolerant to imprecise data and well adapted to coping with uncertainties when there is limited information available	– its inability to generalise or to learn from available data and interpretation of results requires experts or familiarity – involves complicated steps and calculation in the process	Dixon [2005], Iqbal *et al.* [2014b]
WoE	– it transforms an independent variable to establish a monotonic relationship to the dependent variable – many (sparsely populated) discrete values can be grouped into categories	– loss of data (variety) due to binning to a few classifications – it is a "univariate" measure, so it doesn't consider connection between independent factors – it is easy to manipulate (overfit) the effect of variables	Strickland [2017]

Source: own elaboration.

- **Multiple linear regression**

Multiple Linear Regression (MLR) method is an extension of linear regression that uses multiple explanatory variables [Knoll *et al.* 2019]. It determines the relationship between a dependent parameter and many independent parameters and is used for evaluating the susceptibility of GW to pollution in many places. It is applied, for instance, for the purposes of detecting pesticide contamination [Steichen *et al.* 1988], detection of triazine concentration [Chen, Druliner 1988], and detection of atrazine in shallow GW [Stackelberg *et al.* 2012].

- **Logistic regression**

The Logistic Regression (LR) is a multivariate statistical approach developed to predict the probability of a dependent variable from a single parameter or various independent continuous parameters [Pavlis *et al.* 2010]. Studies in which LR is applied include the assessment of GWV to nitrate [Greene *et al.* 2005; Gurdak Qi 2012; Jang, Chen 2015; Mair, El-Kadi 2013; Sorichetta *et al.* 2013; Tesoriero, Voss 1997], and aquifer vulnerability to contamination with heavy metals [Twarakavi, Kaluarachchi 2005].

- **Random forest**

Random Forest (RF), developed initially by Breiman [2001], is an ensemble learning method used for classification and regression [Fawagreh *et al.* 2014]. It is usually described in biological and graphical terms by using a tree structure to predict new data from training data [Chen *et al.* 2012]. The application of the RF method in GWV assessment is recent [Tyralis *et al.* 2019]. However, it has been successfully employed in various studies, carried out, for example, in Spain [Rodriguez-Galiano *et al.* 2014] and the USA [Canion *et al.* 2019; Messier *et al.* 2019; Tesoriero *et al.* 2017; Wheeler *et al.* 2015].

- **Artificial Neural Networks**

Artificial Neural Networks (ANN) is a statistical method designed to imitate the characteristics of the human biological neural networks to provide a number of their unique features, including the ability to determine data patterns, to learn, and to adapt [Li *et al.* 2016; Pavlis *et al.* 2010]. It is a data-driven model and contains an input layer, middle (hidden layer), and output layers with node activation functions [Li *et al.* 2016]. The ANN has been used in aquifer vulnerability assessment in various studies, including prediction of the incidence of pesticide contaminants in shallow GW wells [Sahoo *et al.* 2005; 2006], and nitrate concentrations in shallow groundwater [Yesilnacar *et al.* 2007]. In recent years, there has been an increase in the use of ANN in combination with other GWV assessment models such as DRASTIC [Baghapour *et al.* 2016; Barzegar *et al.* 2018; Nadiri *et al.* 2018].

- **Weights of Evidence**

Weights of Evidence (WoE) is a data-driven statistical technique that uses contaminants' occurrence as a modelling training site to produce maps from categorical input data or weighted continuous layers based on prior knowledge [Sorichetta *et al.* 2011]. It is based on the ideas of prior probability (probability of the phenomena occurring before) and posterior probability (after consideration of any predictor evidence) [Uhan *et al.* 2010]. WoE uses a log-linear form which enables the addition of weights from the evidential themes [Pavlis *et al.* 2010]. The model combines the weights of the predictor variables from the input data to express a probability that a unit cell will contain a training point [Arthur *et al.* 2007]. The WoE method has been applied for the GVW assessment in several places (such as in Italy, USA) to evaluate the vulnerability of shallow aquifers to nitrate contaminant sources [Masetti *et al.* 2007; Sorichetta *et al.* 2011; 2013; Stevenazzi *et al.* 2017]. It was also applied to evaluate the reliability of other methods, such as DRASTIC in combination with an analytical element method [Khosravi *et al.* 2018]. Furthermore, a Bayesian WoE technique was employed to create a state-wide aquifer vulnerability map of Florida [Arthur *et al.* 2007].

- **Multi-Criteria Decision Analysis**

The Multi-Criteria Decision Analysis (MCDA) is a process that integrates and transforms the judgment of a decision-maker and geographical data into useful and appropriate information for environmental decision-making [Costa *et al.* 2019]. It provides decision options, i.e. from the most preferred to the least preferred option, by using many techniques, such as Analytic Hierarchy Process (AHP), and Fuzzy Set Theory approach [Velasquez, Hester 2013]. MCDA techniques have been widely used for assessing GWV and are useful in reducing the subjectivity of over-lay index methods such as DRASTIC [Costa *et al.* 2019]. It was used to evaluate the potential pollution of groundwater from anthropogenic activities in Brazil [Costa *et al.* 2019], and Southern Tunisia [Aydi 2018].

- **Fuzzy logic**

Fuzzy logic (FL) is a knowledge-based technique that utilises parameters of the linguistic type to generate a decision-support system that imitates the features of human experts [Pavlis *et al.* 2010]. The fuzzy logic analysis comprises of three stages: fuzzification, fuzzy derivation and defuzzification which are outlined in detail by Muhammetoglu and Yardimci [2006]. Fuzzy logic methods have been widely applied in many GWV assessment studies and also for the adjustment of subjectivity in overlay-index methods. Examples of studies applying the fuzzy model include: Iqbal *et al.* [2014a; 2014b], Jafari and Nikoo [2019], Muhammetoglu and Yardimci [2006], Nadiri *et al.* [2017], Rezaei *et al.* [2013].

INDEX-OVERLAY METHODS

Index-overlay methods, commonly referred to as parametric or subjective methods, are the most commonly applied GWV assessment methods [Kumar *et al.* 2015]. They are applied on many different spatial scales that range from a catchment level (local) to global scales in the form of vulnerability maps [Jang *et al.* 2017; Wachniew *et al.* 2016]. In the index-overlay methods, vulnerability parameters are rated commonly as a layer within a GIS environment and combined on the basis of subjective ratings of the importance of these physical parameters [Wachniew *et al.* 2016]. The commonly applied index-overlay methods are briefly presented in the subsequent subsections. The advantages and disadvantages of these methods, as well as the spatial extent, climate, and hydrogeological condition of the GWVA models, were summarised in Tables 2 and 3.

- **GOD**

The GOD, developed in Great Britain, is an acronym of three factors from which the name of the model has originated. It stands for Groundwater occurrence, Overall aquifer class, and Depth of groundwater table [Foster 1987]. The final vulnerability

Table 2. Advantages and disadvatges of selected Overlay index GWVA models

GWVA	Advantages	Disadvantages	References
GOD	– uses fewer parameters than other models – appropriate for data scarce areas and simple to use in large areas – applicable to all types of aquifers except for the karst aquifers	– using limited parameters may tend to ignore the necessary process taking place in hydrogeological environments – ignores heterogeneities in the used parameters, and overrates parameter D	KUMAR *et al.* [2015], OKE [2017]
SI	– best suited for areas of vertical agricultural pollution caused by nitrate and pesticide contaminants	– subjectivity in rating and weighing	RIBEIRO [2000]
AVI	– require only few data and fewer resources and therefore easily applicable – doesn't consider relative ratings and weights, – suitable for land use management – suitable for masking sites for land usage excerption	– since it uses a limited number of parameters, it tends to ignore the main processes that take place in the soil and bedrock – aquifer water quality and aquifers are not separately considered in the model	PAVLIS *et al.* [2010], KUMAR *et al.* [2015]
SINTACS	– more suitable for areas where extensive land-use activities are taking place, such as coal fields and oil-rich areas – more appropriate for the Mediterranean and alluvial context, simple and low cost	– subjective in rating and weighting of parameters like DRASTIC – neglects other critical hydrological parameters	KUMAR *et al.* [2015], JAUNAT *et al.* [2019]
SEEPAGE	– considers the soil parameter most comprehensively – best suited to areas where intensive agricultural activities with excessive use of pesticides and fertiliser are taking place, affecting soil, thereby polluting the GW	– assigning a larger range for the ratings and weights	KUMAR *et al.* [2015]
EPIK	– suited for karst (carbonate) aquifers – less subjective because it has a more selective choice of parameters and lower relative ratings	– only applicable to karstic aquifers – does not consider necessary parameters such as recharge and thickness – requires more detailed geomorphology of the karst which is expensive and time-consuming, as it requires detailed geophysical and hydraulic investigation	KUMAR *et al.* [2015]
GLA	– can be used for resource protection and land use planning for all types of aquifers	– it only considers the unsaturated zone and excludes attenuation processes in the saturated zone – it does not sufficiently take into account the unique properties of karstic aquifers	
PI	– more suitable for the assessment of the intrinsic vulnerability of karst aquifers – considers all types of hydrogeological settings	– does not consider physical attenuation process	MACHIWAL *et al.* [2018]
COP	– variables required for the COP-method are relatively simple to obtain, and straight forward	– due to many calculation processes involved, the map compilation is tedious and needs the GIS software for processing	ABDULLAHI [2009], KUMAR *et al.* [2015]
DRASTIC	– broadly accepted model – simple to use, low application cost – requires limited input data and shorter computation time because it does not require complex numerical analysis or simulation process that requires many parameters – produces a product that is easily interpretable and incorporated into the decision-making process	– selection of hydrological parameters is redundant, for instance, the factors A and C – more subjectivity in rating and weighting that may lead to human error and uncertainty – difficult to represent leaky and stacked aquifers and doesn't consider recharge and discharge areas	AN and LU [2018], KHOSRAVI *et al.* [2018], WU *et al.* [2018], KUMAR *et al.* [2015]

Explanation: GWVA = Groundwater Vulnerability Assessment.
Source: own elaboration.

Table 3. Spatial extent, climate and hydrogeological condition of the Groundwater Vulnerability Assessment (GWVA) models

Model	Spatial scale	Climate	Hydrogeology formations	References
GOD	regional	semi-arid	all formations	FOSTER [1987]
SI	medium to regional	semi-arid	all formations	RIBEIRO [2000]
AVI	regional	semi-arid areas	all formations	STEMPVOORT *et al.* [1993]

cont. Tab. 3

Model	Spatial scale	Climate	Hydrogeology formations	References
SINTACS	local and regional	Mediterranean climate	all formations	Civita [1994]
SEEPAGE	local aquifers	all climates	non-karst formations	Moore and John [1990]
EPIK	regional	all climates	karst	Doerfliger *et al.* [1999]
PI	local and regional	all climates	karstic	Goldscheider [2002]
COP	local and regional	all climates	karst	Vias *et al.* [2002]
DRASTIC	local and regional	all climates	all formations	Aller *et al.* [1987]

Source: own elaboration.

index is the multiplication result of the three equally weighted parameters, as indicated in the equation (1):

$$GOD_{index} = G_r\, O_r\, D_r \tag{1}$$

where: G_r = rating designated for groundwater occurrence factor, O_r = rating designated for overlying lithology factor, D_r = assigned rate for depth to the water table variable.

The variables can be rated on a scale of 0 to 1.0. Higher index values indicate higher vulnerability of an aquifer to pollution, while the lowest values indicate low potential risk to pollution. The GOD technique has been used successfully in many assessments, such as assessing the vulnerability of alluvial aquifer to pollution with GIS platform [Ghazavi, Ebrahimi 2015], in determining GWV to pollution [Oroji 2018], and in combination with longitudinal conductance and Geoelectric parameter methods [Oni *et al.* 2019]. The GOD model provided considerably fairer results than the two approaches [Oni *et al.* 2019]. This method, in combination with the DRASTIC, was applied to evaluate aquifer vulnerability in Zimbabwe [Misi *et al.* 2018]; Algeria [Boufekane, Saighi 2018]; Nepal [Shrestha *et al.* 2017], and several other studies.

- **Susceptibility Index**

The Susceptibility Index (SI) method was initially developed in Portugal and used to assess aquifer vulnerability in medium to large scales (e.g., 1:50,000–1:200,000) [Ribeiro 2000]. It is mainly applied to evaluate the susceptibility of the aquifer to vertical agricultural pollution caused, firstly, by nitrate sources and, secondly, by pesticide contaminants. This model considers five variables, four of them (T: topography; A: aquifer media; R: effective recharge; D: depth to the water table) are the same parameters that are used in the original DRASTIC but have different ratings, and the 5th parameter is the land use (LU) intended to consider anthropological influence. The ratings of the first four parameters are assigned by multiplying the original DRASTIC ratings by 10, and the land use rating is assigned on the basis of Ribeiro [2000]. The rated and weighted parameters are summed up to obtain the aquifer vulnerability by using the Equation (2):

$$SI = 0.186D_r + 0.212R_r + 0.259A_r + 0.121T_r + 0.222LU_r \tag{2}$$

where: r stands for the ratings for the parameters, and the values 0.186, 0.212, 0.259, 0.121 and 0.222 are the weights of depth to the water table (D), net recharge (R), aquifer media (A), topography (T), and land use (U), respectively, and the weights add up to 1.

SI method has been successfully used in GWV assessments in different places as a separate model, for example in Ecuador [Ribeiro *et al.* 2017], Morocco [El Himer *et al.* 2013] or in combination with other models such as original and modified DRASTIC and GOD models in Nepal [Shrestha *et al.* 2017], India [Brindha and Elango 2015], Tunisia [Aydi *et al.* 2012; Anane *et al.* 2013], Portugal [Stigter *et al.* 2005], and the USA [van Beynen *et al.* 2012].

- **AVI (Aquifer Vulnerability Index)**

The AVI, is a Canadian model developed to estimate aquifer vulnerability to pollution by considering the two physical variables: a) the thickness (d) of each sedimentary layer above the uppermost saturated aquifer surface; and b) the hydraulic conductivity (K) of each of these sedimentary layers [Busico *et al.* 2017; Stempvoort *et al.* 1993]. Based on the variables K and d, the ratio named as hydraulic resistance (c) of the vadose to vertical flow can be computed for n layers by applying the following Equation (3) [Stempvoort *et al.* 1993]:

$$c = \sum_{i=1}^{n} \frac{d_i}{K_i} \tag{3}$$

where: d_i and K_i stand for the thickness and hydraulic conductivity of the n^{th} deposit layer, respectively.

It should be noted that c does not represent the travel time of contaminant flow; instead, it indicates the time where water is traveling downward through the poriferous media over the aquifer surface by a phenomenon called advection, that involves temperature change [Kumar *et al.* 2015].

The AVI method does not use ratings and weights to estimate the vulnerability index; instead, the calculated c, termed as hydraulic resistance, qualitatively relates to the AVI index. The AVI method has been applied for assessing GW in Brazil [Santos, Pereira 2011], Northeast of Portugal [Fraga *et al.* 2013] as a separate model, and also alongside with modified SINTACS in Italy [Busico *et al.* 2017]; modified SINTACS and GALDIT models in southern Finland [Luoma *et al.* 2016].

- **SINTACS**

The SINTACS method, developed in Italy [Civita 1994] is a version of the DRASTIC model adapted to the Italian conditions, characterised by highly diverse and mostly karstic hydrogeology. In the SINTACS method, the GWV is estimated by using seven parameters as in the case of the DRASTIC method; however, having Italian words for each parameter [Civita 1994]. These parameters are (S – soggiacenza i.e. depth to water table, N – non saturo, i.e. unsaturated zone, T – tipologia della copertura, i.e. soil type, A – acquifero, i.e. aquifer hydrogeological features, C – conducibilità, i.e. aquifer hydraulic conductivity, S – superficie topografica, i.e. roughness of land surface) [Civita 1994]. It differs from the DRASTIC model in the way these parameters are relatively rated and weighed. The rates and weights are allocated more comprehensively to consider all the environmental situations associated with the seven variables utilised in the model [KUMAR *et al.* 2015], and they also vary depending on the hydrogeological conditions of the area. Thus, ratings and weighting of parameters are more flexible in SINTACS than the DRASTIC model [PAVLIS *et al.* 2010]. The SINTACS vulnerability index (SI_v) is computed by multiplying the sum of the rating of each of the seven parameters with the associated weight using Equation (4):

$$SI_v = \sum_{i=1}^{7}\sum_{j=1}^{n}(P_i\, W_j) \tag{4}$$

where: P_i is assigned rating for the i^{th} parameter, W_j is assigned weight of the j^{th} weight classification.

The higher the SI_v value, the higher the vulnerability. The SINTACS model provides six weight classes, namely, seepage/drainage (by streams), karst (aquifers), fissured (aquifers), nitrate contaminants, severe impact, and normal impact [CIVITA, DE MAIO 2004; WACHNIEW *et al.* 2016]. The SINTACS model was applied to determine the vulnerability of the aquifer to pollution [AL-AMOUSH *et al.* 2010].

- **SEEPAGE**

The SEEPAGE model originated in the U.S.A., and is an abbreviation of System for Early Evaluation of Pollution potential of Agricultural Groundwater Environments [MOORE, JOHN 1990]. In the SEEPAGE model, more details of soil properties are considered than in the DRASTIC method [KUMAR *et al.* 2015]. However, the rating and weighting values of parameters in SEEPAGE model are relatively higher than in the DRASTIC model. For instance, each parameter is given a rating, and weight ranges from 1–50, based on its relative significance, with the most critical parameter influencing the water quality assigned 50 and the least important assigned 1. The weights and ratings of each parameter are then multiplied and added to estimate the SEEPAGE vulnerability Index (S_{index}) according to the linear Equation (5).

$$S_{index} = R_1 A_P + R_2 A_M + R_3 V_I \ + \ R_4 S_D + R_5 S_T \ + R_6 D_w \tag{5}$$

where: A_p is assigned weight for attenuation potential parameter; A_M is assigned weight for aquifer material; V_I is assigned weight for the impact of the vadose zone; S_D denotes the weight assigned to soil depth; S_T is the weight assigned to soil topography; D_w is assigned weight for the depth of water table; R_i (i = 1–6) is relative rating designated to various parameters.

The formula for the attenuation potential is given below:

$$A_P = \sum_{i=1}^{n}(\text{soil parameters}_i\ R_i) \tag{6}$$

The higher SEEPAGE vulnerability index implies a relatively greater vulnerability of the groundwater to pollution. According to the literature review, this model is applied in a few research studies. The SEEPAGE model has been applied to estimate the vulnerability of GW from diffuse agricultural sources in Kumluca Plain, Turkey [MUHAMMETO LU *et al.* 2002] and nitrate contamination on a regional scale using GIS [NAVULUR, ENGEL 1998].

- **EPIK**

EPIK is an acronym of the four parameters that the model considers: epikarst (E), a protective cover (P), infiltration conditions (I), and karstic network (K). It was developed in Switzerland to estimate intrinsic aquifer vulnerability, specifically for karst (carbonate) aquifers [DOERFLIGER *et al.* 1999]. The particularities of karst aquifers are that they are composed of carbonate rocks (usually dolomite and limestone) and characterised by highly soluble rocks which allow for the fast and turbulent flow of water [KUMAR *et al.* 2015]. The EPIK vulnerability index is computed using Equation (7):

$$Vulnerability_{index} = 3E_r + P_r + 3I_r + 2K_r \tag{7}$$

where: E_r, P_r, I_r and K_r are relative rating assigned for the Epikarst variable, the protection cover variable, the infiltration parameter, and the karst mesh parameter, respectively. The values 3, 1, 3, and 2 are their respective weight coefficients. The vulnerability index values can be between 9 and 34.

In contrast to other models, higher vulnerability index values correspond to lower vulnerability and vice versa, as the index is converse of the protection factor [VIAS *et al.* 2004]. EPIK has been applied in some studies and also compared with the other methods such as AVI, GOD, and DRASTIC [VIAS *et al.* 2004].

- **GLA (The German method)**

The GLA (Geologisches LAndsamt) method was developed by the State Geological Surveys of Germany. It considers the protective effectiveness of the layers (soil cover, sediment or rocks) overlying groundwater [HÖLTING *et al.* 1995]. The GLA method is based on a point count system similar to the generic DRASTIC method [MACHIWAL *et al.* 2018]. The equation (8) calculates the final vulnerability index:

$$S = \left(B + \sum\nolimits_{i=1}^{m} M_i G_i\right) W + Q + HP \tag{8}$$

where: S is the protective function, B the effective field capacity of the topsoil, M_i the thickness of each subsoil layer, G_i the protective effectiveness of each subsoil layer (grain size distribution), W is the percolation rate, Q are bonus points for perched aquifers (500), and HP bonus points for hydraulic (artesian) conditions (1500) [PAVLIS *et al.* 2010]. The advantage of the GLA-Method is that it can be used for resource protection and land use planning for all types of aquifers. However, it only considers the unsaturated zone and excludes attenuation processes in the saturated zone in the vulnerability concept. Furthermore, it does not sufficiently take into account the unique properties of karstic aquifers.

- **PI**

The PI is a modified form of the GLA model developed to consider the preferential infiltration paths, which are typical of karst aquifer [GOLDSCHEIDER *et al.* 2000; GOLDSCHEIDER 2002]. It integrates the Protective cover (P) and the Infiltration (I) conditions of the area and focuses on the assessment of the intrinsic vulnerability of karst aquifers; however, it can also be applicable to all other types of aquifers. In the PI-Method both factors, the protective cover and the infiltration, are separately mapped as individual maps and then multiplied to form the final groundwater vulnerability index (denoted π). The P factor is computed on the basis of a slightly modified version of the

German (GLA) method [HÖLTING *et al.* 1995] and categorised into five levels (from $P = 1$ for a very low degree of protection to $P = 5$ for very thick and protective overlaying layers).

$$P = (B + \sum_{i=1}^{m} M_i G_i) + \sum_{j=1}^{n} B_j M_j)\ W + Q + HP \tag{9}$$

where: B stands for the effective field capacity; M_i and M_j stand for the thickness of each stratum in subsoil and bedrock; G_i denotes the protective effectiveness of the subsoil stratum; W denotes the recharge (infiltration rate); HP stands for bonus points for hydraulic pressure conditions (1500). The protective effectiveness of bedrock B_j is measured by multiplying the value corresponding to the type of lithology (L) with the value of the level of fracturing (F) [PAVLIS *et al.* 2010].

The I factor describes the infiltration conditions and ranges from 1.0 for diffuse infiltration in the flat area to 0.0 when a swallow hole completely bypasses the protective cover. The final protection factor p is the product of P and I and is subdivided into five classes from 1 with the highest to 5, indicating the lowest vulnerability to contamination sources [GOLDSCHEIDER 2002]. The PI-Method has been successfully used in groundwater vulnerability assessment, particularly in several sites of Europe [GHANEM *et al.* 2017; GOLDSCHEIDER 2005; POLEMIO *et al.* 2009].

- **COP-Method (European Approach for Karst Aquifers)**

COP was developed in Spain with the framework of the COST 620 program as a standard method for groundwater vulnerability mapping in karst aquifers [VIAS *et al.* 2002]. It considers the following factors: concentration of flow (C), overlying layers (O) and precipitation (P).

The COP-vulnerability Index is estimated by Equation (10):

$$COP\ Vulnerability_{index} = C_{score} O_{score} P_{score} \tag{10}$$

The COP-Method is like the PI-Method with the exception that the COP-Method incorporates the variable precipitation. The COP method has been applied for groundwater vulnerability mapping in karstic aquifers of Spain [VÍAS *et al.* 2006]; Greece [NANOU, ZAGANA 2018], and Iran [BAGHERZADEH *et al.* 2018].

- **DRASTIC Model**

DRASTIC is a standardised model developed in the USA by ALLER *et al.* [1987] for evaluating the pollution potential of a specific area, using known hydrogeological properties. It has three essential features: hydrogeological parameters, rating system, and parameter weights. The seven hydrogeological parameters are those that form the name DRASTIC: Depth to water (D), Net Recharge (R), Aquifer media (A), Soil media (S), Topography (T), Impact of the vadose zone (I), and hydraulic conductivity (C) [ALLER *et al.* 1987; RIBEIRO *et al.* 2017]. Each of these hydrogeological variables is assigned a rating on a 1 to 10 scale based on a range of values, in which one denotes the least vulnerable, while ten stands for the most vulnerable areas. The hydrogeological parameters are further assigned relative weights from 1 to 5, where the most significant parameters are assigned a weight of 5 while the least significant is assigned the weight of 1 [KIHUMBA *et al.* 2017]. The ratings and weights of each parameter are then multiplied and added to provide the vulnerability index values by applying the following linear equation [ALLER *et al.* 1987]:

$$DR_i = D_w D_r + R_w R_r + A_r A_w + S_r S_w + T_r T_w + I_w I_r + C_w C_r \tag{11}$$

where: DR_i = DRASTIC vulnerability index, D, R, A, S, T, I, and C are seven parameters of the model; w = assigned weight of DRASTIC parameter; r = assigned rate for the respective DRASTIC parameter. GIS is used to produce the final vulnerability map by combining each of the thematic maps of DRASTIC parameters.

DRASTIC is one of the most widely applied methods of GWV mapping used in many areas of the world [BARBULESCU 2020]. To improve the accuracy of the DRASTIC model and better represent the local conditions that consider anthropogenic impacts, several researchers have modified the model. This was mainly achieved by means of: 1) Introduction of additional parameters to original DRASTIC such as Land use/cover DRASTICLU [JESIYA, GOPINATH 2019; KOZŁOWSKI, SOJKA 2019; MUSEKIWA, MAJOLA 2013; SAHOO *et al.* 2016b; HUANG *et al.* 2017]; contamination index (Cd) and heavy metal pollution index (HPI) DRASTIC-CdHPI [HAQUE *et al.* 2018], Pesticides, DRASTIC-Pesticide [CHANDOUL *et al.* 2014; GÜLER *et al.* 2013; SAHA, ALAM 2014], characteristics of fractured bedrock aquifers (DRASTIC-Fm) [DENNY *et al.* 2006], land use (L) and groundwater exploitation (E) DRASTIC-LE [LIANG *et al.* 2019], and other agricultural contaminants [SAHOO *et al.* 2016b]; 2) Exclusion/substitution of less influential parameters with more significant parameters AHP-DRASTLE model [WU *et al.* 2018], DRAV [ZHOU *et al.* 2009]; and 3) Modification of the rating and weighing of the original DRASTIC parameters by using statistical methods (Entropy information method (E-DRASTIC), Fuzzy pattern recognition method (F-DRASTIC), and (Single parameter sensitivity analysis (SA-DRASTIC)) based on local measurement data [SAHOO *et al.* 2016a]. In recent studies, there is an a growing tendency to use statistical methods (Fuzzy logic, Weight of Evidence [KHOSRAVI *et al.* 2018], Artificial Neural Network [SAHOO *et al.* 2016a]) in combination with the modified DRASTIC model to account for errors and uncertainties. Fuzzy rule-based models provide comparable results with fewer input data, as well as improved vulnerability prediction when DRASTIC factors are used [DIXON 2005]. Incorporation of fuzzy rules and neural network (NN) with DRASTIC variables improved vulnerability prediction for pesticides [OKE 2015].

CONCLUSIONS

This study has attempted to provide an overview of commonly applied statistical and overlay-index methods used for assessing GWV to pollution. Each of these methods has its own advantages and limitations. Major advantages of the statistical techniques are: the most appropriate explanatory variables may be objectively selected; they account for uncertainty, try to minimise the error, and use parameters coefficient instead of weight. They can also be easily updated (except for the artificial neural networks) when new information is readily available and testable against new groundwater observations. Validation procedures may be performed easily if new and updated groundwater observations are available. They can be very useful since they reduce the data requirements of the overlay index and process-based methods. However, they require extensive and quality monitoring (initial) data and some level of contamination in the area to be considered. This means that if the required data is limited, the vulnerability results will face substantial uncertainties. Moreover, extensive groundwater quality data collection may be costly, and time-consuming and therefore make statistical methods expensive for GWV assessment.

In contrast to statistical models, overlay-index techniques are used extensively in groundwater vulnerability assessments and applied more frequently in research literature. Overlay-index techniques are easy to apply, require less data which can be available easily such as land use/ cover, topography, hydrogeology, soil type, and depth to the water table, and describe GWV in an easy to understand manner. They are also capable of assessing GWV spatially over large areas. However, index-overlay methods have drawbacks, due to the subjectivity in assigning the factor weighting and assignment of numerical values arbitrarily designated based on the researcher's expertise leading to inherit bias. Although various efforts are being made in different places to reduce the subjectivity problems of overlay-index methods, there are still concerns about obtaining accurate model results.

Since all the models have their own limitations and strengths, care must be taken when selecting the method for the assessment of groundwater vulnerability to contamination. Also, improving groundwater vulnerability assessment models to fit into specific places is necessary to help sustainable management of the groundwater.

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