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Mapping vulnerability of multiple aquifers using multiple models and fuzzy logic to objectively derive model structures

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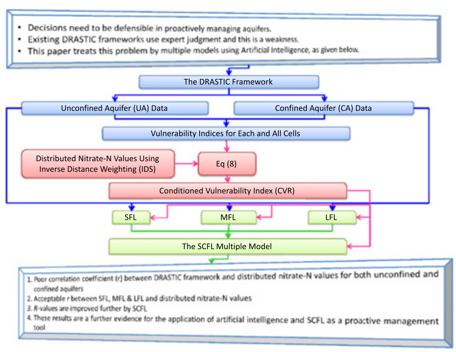
HIGHLIGHTS

- DRASTIC vulnerability indices (VI) are improved to protect multiple aquifers system.
- Inherent expert judgment is higher in VI values with unconfined/confined aquifers.
- Correlations between basic VI and measured nitrate-N values are poor.
- Acceptable correlation between SFL/MFL/LFL results and distributed nitrate-N values
- Multiple models of SCFL give more defensible results to serve as proactive tools.

GRAPHICAL ABSTRACT



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ABSTRACT

Driven by contamination risks, mapping Vulnerability Indices (VI) of multiple aquifers (both unconfined and confined) is investigated by integrating the basic DRASTIC framework with multiple models overarched by Artificial Neural Networks (ANN). The DRASTIC framework is a proactive tool to assess VI values using the data from the hydrosphere, lithosphere and anthroposphere. However, a research case arises for the application of multiple models on the ground of poor determination coefficients between the VI values and non-point anthropogenic contaminants. The paper formulates SCFL models, which are derived from the multiple model philosophy of Supervised Committee (SC) machines and Fuzzy Logic (FL) and hence SCFL as their integration. The Fuzzy Logic-based (FL) models include: Sugeno Fuzzy Logic (SFL), Mamdani Fuzzy Logic (MFL), Larsen Fuzzy Logic (LFL) models. The basic DRASTIC framework uses prescribed rating and weighting values based on expert judgment but the four FL-based models (SFL, MFL, LFL and SCFL) derive their values as per internal strategy within these models. The paper reports that FL and multiple models improve considerably on the correlation between the modeled vulnerability indices and observed nitrate-N values and as such it provides evidence that the SCFL multiple models can be an alternative to the basic framework even for multiple aquifers. The study area with multiple aquifers is in Varzeqan plain, East Azerbaijan, northwest Iran.

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1. Introduction

Tools are required for defensible decisions on proactive management of complex aquifer systems, in which anthropogenic contaminant risks directly affect the environment and human health. Complex aquifers are the subject of this paper, which cover physical varieties of groundwater aquifer types sometimes found in a single study area. The assessment of the DRASTIC Vulnerability Indices (VI) of complex aquifers require appropriate care, as discussed in the paper. Aquifer types depend on their source (alluvial, glacial drifts or rock fissures) but more so, on the hydraulics of groundwater level in the form of unconfined and confined aquifers. Multiple aquifers configured by a number of unconfined and confined aquifers in one basin are already known to the vulnerability index assessment problems using the DRASTIC framework as given by Aller et al. (1987). This paper investigates a data-driven model for the DRASTIC framework, in which vulnerability indices of multiple aquifers are identified through Artificial Intelligence (AI) techniques.

The DRASTIC framework comprises generally the seven hydrogeological parameters covering the hydrosphere and lithosphere: Depth to water table (D), net Recharge (R), Aquifer media (A), Soil media (S), Topography or slope (T), Impact of the vadose zone (I), and hydraulic Conductivity (C). However, the local variations are accounted for by assigning rates to each parameter and the relative importance of each of these parameters is accounted for by assigning weights. Recently, the framework has been successfully applied to unconfined aquifers (Babiker et al., 2005; Huan et al., 2012; Ouedraogo et al., 2016; Shrestha et al., 2016; Sadeghfam et al., 2016; Baghapour et al., 2016; Jafari and Nikoo, 2016). The procedure of groundwater vulnerability assessment in multiple aquifers is the same for both unconfined and confined aquifers except for Depth (D), Aquifer (A) and Impact (I). This framework is a top-down prescriptive approach but despite its popularity, the DRASTIC framework is susceptible to: (i) the need for expert judgment on assigning weights and rates for each parameter, which expose the output vulnerability maps to uncertainties; and (ii) methodological problems in assessing vulnerability of two adjacent unconfined and confined aquifers in the same study area. The framework is also consensual and as such there are no right or wrong VI values and they cannot be measured.

Among different AI techniques, this paper uses two different AI techniques: Fuzzy Logic (FL) to treat subjectivity in DRASTIC indices and Artificial Neural Networks (ANN) but this is for a specific purpose, as discussed later. Application of FL techniques to the DRASTIC framework is categorized in Table 1 with a focus on the treatment of the ratings and weightings as required by the basic framework. This paper builds on them and identifies the values of the ratings and weightings for the parameters using Supervised Committee Machine with Artificial Intelligence (SCMAI) both in unconfined and confined aquifers except for the D, A and I parameters, as discussed in due course. The Committee Machine with Artificial Intelligence (CMAI) models may be implemented as a linear (CMAI) or nonlinear (SCMAI) method which is introduced by Nadiri et al. (2013).

If DRASTIC vulnerability indices are to serve as defensible tools, the following gaps need to be treated: (i) hydrogeology parameters are inherently uncertain and imprecise; (ii) unconfined and confined aquifers use prescriptive values based on expert judgment to estimate groundwater vulnerability. This research attempts to fill these gaps by applying FL to input and output data to cater for their inherent uncertainty and imprecision and by employing (i) three FL models of Sugeno Fuzzy Logic (SFL), Mamdani Fuzzy Logic (MFL), Larsen Fuzzy Logic (LFL) models, which normally provide similar acceptable accuracy but with different strengths and weaknesses; and (ii) a nonlinear version of the Supervised Committee Fuzzy Logic (SCFL) is applied by to exploit the synergy inherent in these FL models.

The use of ANN in this study is confined to identifying and seeking synergies in the constituent FL models by receiving the outputs from the three individual FL models as its input and derives new predictions as its final output and conditioning of these outputs using the measured nitrate-N values. Each individual FL model has its own way of handling uncertain parameters in the DRASTIC framework.

The program of research currently undertaken by the authors provides evidence for the proof-of-concept to the application of AI through Supervised Committee techniques to DRASTIC-based vulnerability indices. Proof-of-concept is Technological Readiness Level 4 (akin to the NASA classification, see: https://www.nasa.gov/sites/default/files/trl.png) but insufficient to ensure the delivery of working tools. This

Table 1
Past applications of FL and ANN types of AI to DRASTIC framework.

ID	Model references	AHP	FAHP	FLT	Individual AI modeling				SCMAI	SCFL	Aquifer type		
					ANN	SFL	MFL	LFL	ANN, NF, FL MFL, by ANN	SFL,MFL, LFL by ANN	Unconfined aquifer	Confined aquifer	Multiple aquifer
1	Sener and Davraz (2015)	✔									✔		
2	Şener and Şener (2015)		✔								✔		
3	Dixon (2005)			✔							✔		
4	Mohammadi et al. (2009)			✔							✔		
5	Rezaei et al. (2013)					✔					✔		
6	Fijani et al. (2013)				✔	✔	✔		✔		✔		
7	Nadiri et al. (2017a)				✔				✔		✔		
8	Present study					✔	✔	✔		✔	✔	✔	✔

Category 1: AHP modifies weights of DRASTIC parameters by a scheme in terms of relative importance of the DRASTIC parameters - e.g. (reference in row 1); none of the data is fuzzified. FAHP as in AHP but the DRASTIC data layers are fuzzified.(reference in row 2).
Category 2: FLT use GIS software to process input data and fuzzify overlays of DRASTIC layers; output data are defuzzifies vulnerability indices and modeled through unsupervised FL modeling, e.g. reference in row 3 and 4.
Note 1: These models have no optimization & rule definitions but assign weights as per Aller et al. (1987).
Note 2: These applications were prescribed rules and if involved rule definitions by data clustering to improve output results, they probably used manual processing susceptible to expert opinions, subjectivity and uncertainty.
Category 3: FL models applied to the DRASTIC framework, e.g. (reference in row 5) using SFL and (reference in row 6) using NF.
Category 4: SCMAI models implemented by combining multiple AI models, where the model combination may be linear, e.g. (reference in row 6), or nonlinear, e.g. (reference in row 7); SCFL model uses multiple FL models in multiple aquifers (reference in row 8).
Note: The term 'Machine' is another word for artificial; 'Committee' refers to drawing information from multiple models; and 'Supervised' refers to using supervised learning techniques in AI modeling.
Abbreviations: AHP: Analytic Hierarchy Process, ANN: Artificial Neural Network, FAHP: Fuzzy Analytic Hierarchy Process, NF: Neuro-Fuzzy, LFL: Larsen Fuzzy Logic, MFL: Mamdani Fuzzy Logic, SFL: Sugeno Fuzzy Logic, SCMAI: Supervised Committee Machine with Artificial Intelligence, SCFL: Supervised Committee with Fuzzy Logic.