https://doi.org/10.1016/j.jhydrol.2020.124768

Meta-heuristic algorithms in optimizing GALDIT framework: a comparative study for coastal aquifer vulnerability assessment

Mojgan Bordbar[a], Aminreza Neshat[a*], Saman Javadi[b], Biswajeet Pradhan[c,d]

[a] Department of GIS/RS, Faculty of Natural Resources and Environment, Science and Research Branch, Islamic Azad University, Iran

[b] Department of Irrigation and Drainage, Abouraihan Campus, University of Tehran, Iran

[c] Centre for Advanced Modelling and Geospatial Information Systems (CAMGIS), Faculty of Engineering and IT, University of Technology Sydney, New South Wales, Australia; Email. Biswajeet.Pradhan@uts.edu.au

[c] Department of Energy and Mineral Resources Engineering, Choongmu-gwan, Sejong University, 209, Neungdong-roGwangin-gu, Seoul 05006, Korea

Abstract

Creating a reliable groundwater vulnerability map is a key solution for protecting groundwater resources and further planning in coastal aquifers. The GALDIT framework is a well-known framework for assessing groundwater vulnerability in coastal zones. This framework was designed based on six hydrogeological parameters including groundwater occurrence, aquifer hydraulic conductivity, level of groundwater above sea level, distance from the shoreline, the impact of the existing status of seawater intrusion, and thickness of the aquifer. In this study, two meta-heuristic algorithms of Grey Wolf Optimizer (GWO) and Genetic Algorithm (GA) were proposed to optimize the weights of GALDIT framework. The GALDIT vulnerability index failed to provide an accurate assessment of vulnerability to seawater intrusion. Contrariwise, GALDIT-GWO and GALDIT-GA models provided results that are more reasonable. Both vulnerability maps depicted the close similarity of the vulnerability to seawater intrusion. The vulnerability maps demonstrated that the west and northwest parts of the study area suffer from seawater intrusion. Additionally, the correlation coefficient between the GALDIT index and TDS concentration was obtained as 0.47. The corresponding values of the GALDIT-GWO and GALDIT-GA frameworks were 0.63 and 0.61, respectively. Therefore, it can be concluded that the proposed optimization models are able to provide accurate results. Furthermore, these models reduce the subjectivity and increase the capability of GALDIT index.

Keywords: groundwater vulnerability; GALDIT framework; Genetic Algorithm; GIS; Grey Wolf Optimizer

Introduction

Groundwater resources are the most important water supply resources for the human and natural environment in coastal aquifers (Saidi et al., 2013). Human activities are increasing in these areas, especially during the summer, and these resources are subjected to seawater intrusion due to overexploitation and high water pumping. Therefore, identification of vulnerable areas can be done with the aim of land use planning, scientific supervision, and preventing groundwater contamination (Boudebala et al., 2016). Among various methods for assessing groundwater vulnerability, the rating methods are the most popular one. Numerous studies have used the rating frameworks to assess the groundwater vulnerability (Mogaji 2018; Bouderbala et al. 2016; Neshat and Pradhan 2015a; Neshat et al. 2014 a, b, c; Pacheco et al. 2015; Gorgij and Moghaddam 2016; Neshat and Pradhan 2017; Nadiri et al. 2017b; Arauzo 2017; Kazakis and Voudouris 2015; Majandang and Sarapirome 2013; Ribeiro et al. 2017; Pacheco and Fernandes 2013; Khosravi et al. 2018; Trabelsi et al. 2016; Jafari et al., 2016).

Vulnerability maps of GALDIT framework, which indicate the aquifer areas along the coastline, can be applied to accurately investigate the location of the contaminated areas (Luoma et al., 2017). The GALDIT framework developed by Chachadi (2005) is one of the most common methods to assess the vulnerability of coastal aquifers, and it is one of the most widely used methods among the rating index frameworks. In this framework, different parameters are classified according to different ranges, and estimates the potential of contamination of coastal aquifers considering six parameters of the hydrological system. The main downside of the GALDIT framework is the use of constant numerical values based on expert's ideas to determine the rating and weighting system of the parameters evaluated.

Several studies have been carried out to modify GALDIT framework considering the hydrological conditions of aquifers. In some studies, the alternate parameters, such as pumping rates, have been used to modify GALDIT model (Gorgij and Moghaddam, 2016). Others have applied the sensitivity analysis method for modifying the weights of GALDIT model (Gontara et al., 2016; Mahrez et al., 2018). Moreover, Kazakis et al. (2018) used fuzzy logic method to modify the GALDIT framework in northern Greece. The modified GALDIT index provided an accurate estimate of the level of vulnerability. Finally, they developed a guide map using GALDIT-F index in order to prevent and reduce the seawater intrusion.

In the past few years, artificial intelligence-based optimization methods have been widely used and their results are more accurate compared to traditional methods. Some of these widely used optimization algorithms include; Genetic algorithm (GA) (Holland, 1975), Particle Swarm Optimization (PSO) (Kennedy and Eberhat, 1995), Grey Wolf Optimizer (GWO) (Mirjalili et al., 2014), Ant Colony Optimization (ACO) (Dorigo, 1992), Artificial Bee Colony Optimization(ABC) (Karaboga, 2005), Harmony Search (HS) (Geem et al., 2001), Differential Evolution (DE) (Storn and Price, 1997), and Simulated Annealing (SA) (Kirkpatrick et al., 1983). A handful number of these algorithms have been applied in water resources studies (Nicklow et al., 2010; Gaur et al., 2013; Szemis et al., 2013; Mansouri et al., 2015).

The Gray Wolf Optimizer algorithm (GWO) is one of the new meta-heuristic algorithms, inspired by the social hierarchy and hunting behaviour. The advantages of this algorithm are its simplicity, flexibility, random searching, and avoiding local optimization (Yu and Lu, 2018). In the literature, the ability of GWO algorithm has been investigated in comparison with other meta-heuristic algorithms. For example, Yu and Lu (2018) used optimization algorithms to optimize the allocation of water resources in Songhua river basin. Their results revealed that GWO algorithm is superior to FA and PSO algorithms in water quantity optimization problems.

Genetic algorithm (GA) (Holland, 1975) is another commonly used meta-heuristic algorithm inspired by Darwinian biological evolution and natural selection. This algorithm can be easily implemented and optimized with discontinuous and continuous variables, and be able to solve the combined optimization problems. Meta-heuristic algorithms have been applied in the literature to obtain the optimal weights in order to reduce the subjectivity of the rating frameworks. For instance, Yang et al. (2017) used AHP methods and genetic algorithm to improve the DRASTIC framework in order to assess the vulnerability of Jianghan plain located in the central China. Their study concluded that the modified DRASTIC index improved the original DRASTIC framework and the correlation coefficient increased from 41.07 to 75.31% after modifying the model. In another study, Jafari and Nikoo (2016) examined the vulnerability of Shiraz plain (Iran) using the genetic algorithm and Wilcoxon statistical model in order to improve the DRASTIC index. The results showed that the hybrid Wilcoxon model and genetic algorithm with the highest correlation coefficient are the most suitable models to determine the vulnerability of the region with nitrate contaminant in the plain.

As it can be seen in the literature above, meta-heuristic algorithms have not applied to assess the vulnerability of coastal aquifers to seawater intrusion based on GALDIT framework. This paper aims to introduce new meta-heuristic methods such as Grey Wolf Optimizer (GWO) and Genetic Algorithm (GA) in order to obtain the optimal GALDIT's weights. In this regard, the same objective function of both optimization techniques was considered through maximizing the correlation between the GALDIT indices and TDS concentration with respect to the hydrogeological characteristics of the coastal aquifer. Firstly, six rating layers of GALDIT framework were combined through applying optimal weights of Grey Wolf Optimizer (GALDIT-GWO) and then, GALDIT rating layers were combined with optimal weights of Genetic Algorithm (GALDIT-GA). Furthermore, a comparison was made between the combined GALDIT-GA and GALDIT-GWO indices and the original GALDIT index in order to illustrate the effectiveness and the capability of the proposed frameworks to accurately identify the vulnerable areas.

Description of the study area

Gharesoo-Gorgan Rood aquifer is located between the east longitude 54˚00΄ to 56˚29΄and north latitude 36˚36΄ to 37˚47΄ in the Golestan province, Iran, which covers an area of approximately 4379 km^2 (Fig. 1). The study area has a dry and cold to semi-arid climate, as suggested by Emberger classification. The average annual precipitation is 300 mm and the annual temperature is 17 ^{0}c. The average monthly relative humidity ranges from 47 to 89 %. There are also 23485 wells in this region. Gharesoo-Gorgan Rood basin is located in the structural zone of Alborz Mountains. The most important lithological units in the study area include the Paleozonic, Gorgan green shists, a collection of Jurassic schists and limestone, and Cretaceous limestone. Loess liquorices are one of the widespread sediments of this region, which exist in the form of hills. In the study area, Neogene is composed of shale, Marl, sand, and conglomerate, which has the highest surface expansion. Approximately 62% of the water of this basin is supplied from groundwater resources.

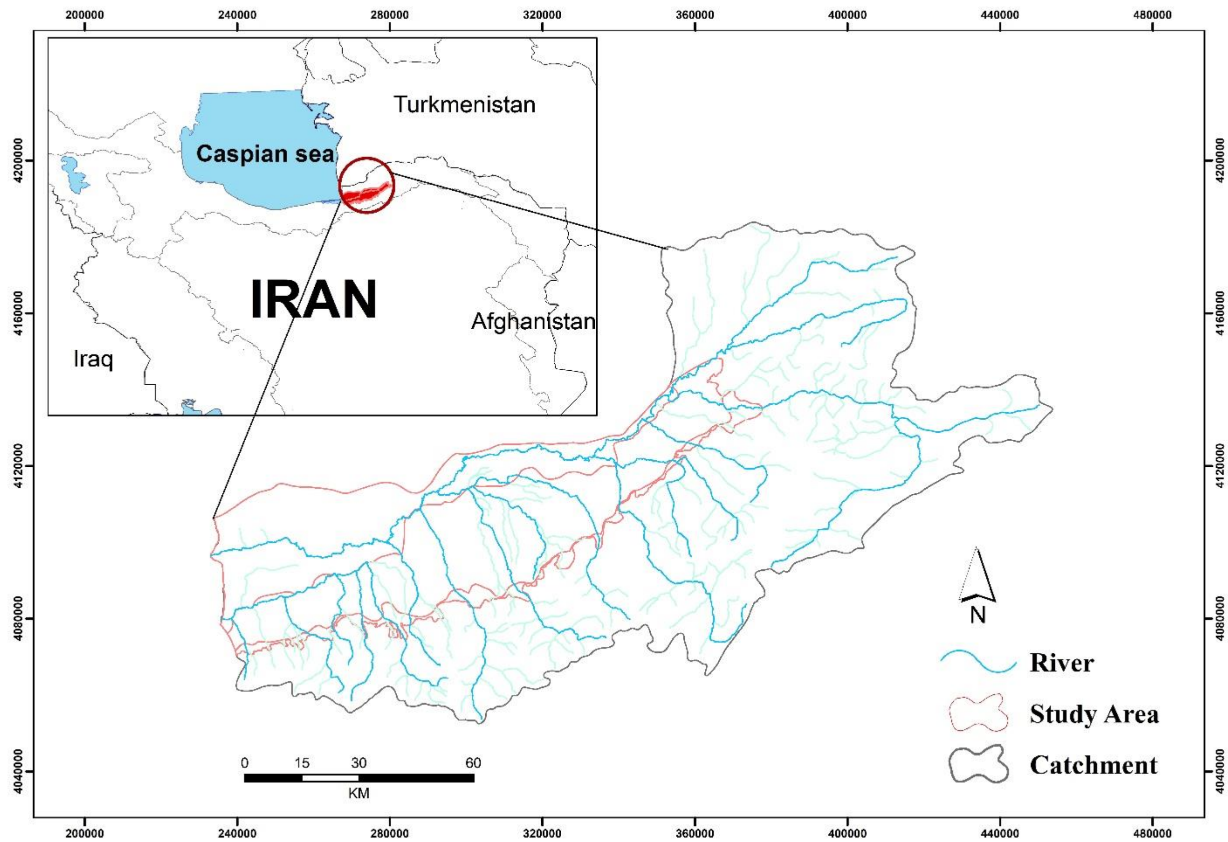

Fig 1- Location of the Gharesoo-Gorgan Rood coastal aquifer

Data and Methodology

The research methodology proposed in this study is summarized as follows: (i) gathering the row data of six parameters of GALDIT framework, (ii) preparing GALDIT layers, (iii) creating a groundwater vulnerability map for seawater intrusion, (iv) collecting TDS samples from quality wells, (v) optimizing the weights of the original GALDIT using two meta-heuristics techniques (GWO and GA), (vi) validating the frameworks and comparing the results, and (vii) determining the suitable framework for the study area. Figure 2 shows the data used and schematic structure of the applied models.

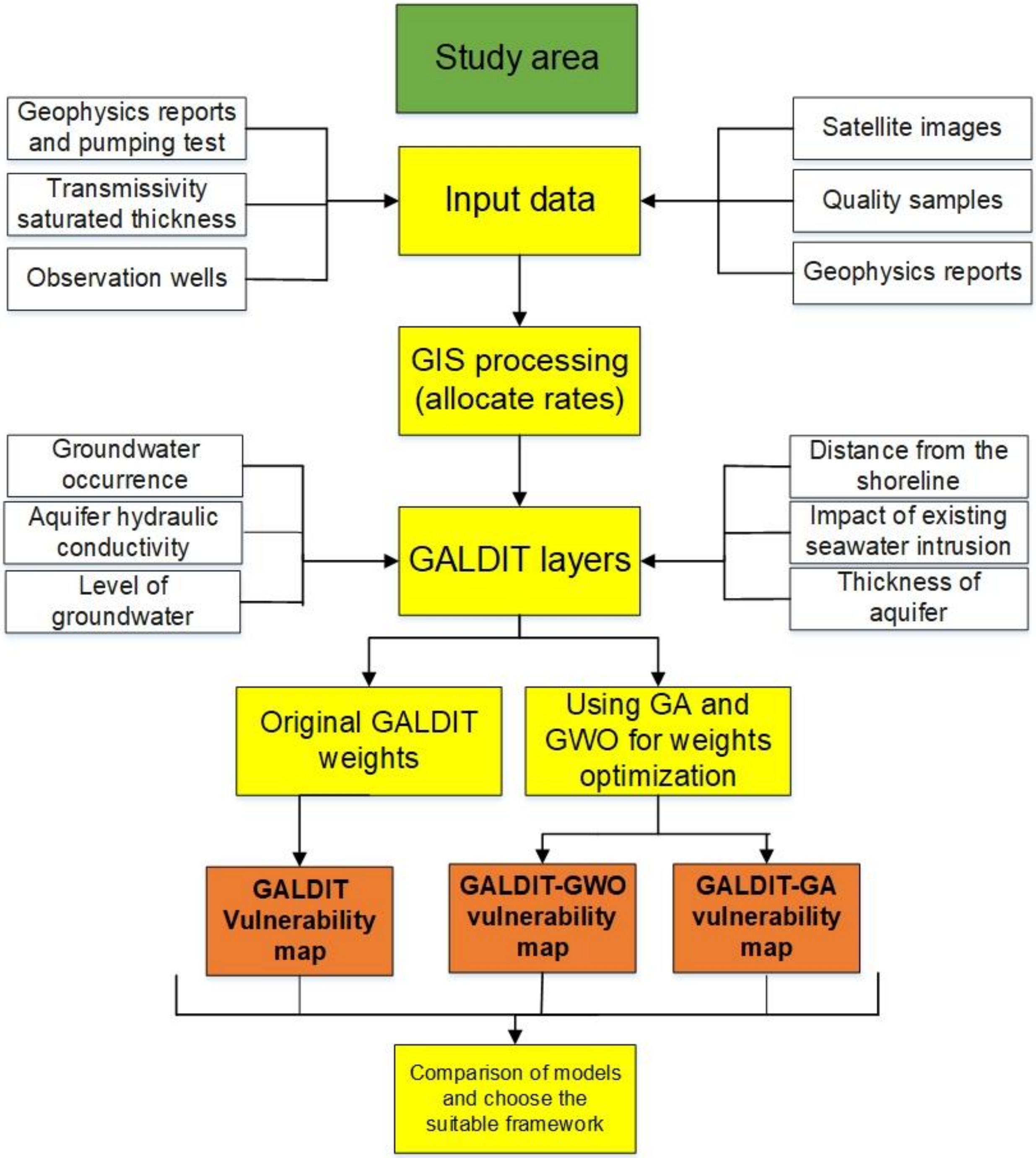

Fig 2- Flowchart of proposed methodology

GALDIT framework

The GALDIT framework introduced by Chachadi (2005) is widely used as a tool to assess the groundwater vulnerability in coastal aquifers. The GALDIT framework consists of six parameters including groundwater occurrence (G), aquifer hydraulic conductivity (A), level of groundwater above sea level (L), distance from the shoreline (D), impact of the existing status of seawater intrusion (I), and thickness of the aquifer (T). The GALDIT framework is composed of three sections including rating, range, and weights. The constant numerical rates of each parameter vary from 2.5 (the lowest potential of pollution) to 10 (the highest potential of pollution). In addition, the constant numerical weights of the parameters of GALDIT framework vary from 1 to 4 reflecting their relative importance in vulnerability (Chachadi, 2005) (Table 1).

The GALDIT vulnerability index (GVI) is calculated from the following equation:

$$GVI = (G \times 1) + (A \times 3) + (L \times 4) + (D \times 4) + (I \times 1) + (T \times 2) \qquad (1)$$

where, G, A, L, D, I and T are the rates of six parameters of GALDIT framework.

Table1- GALDIT rates and weights values (Chachadi 2005)

Abbreviation	Parameter	Description	Range	Rating
G	Groundwater occurrence	The seawater intrusion to coastal areas depends on the type of the aquifer.	Confined aquifer Unconfined aquifer Leaky confined aquifer Bounded aquifer	10 7.5 5 2.5
A	Aquifer hydraulic conductivity	Hydraulic conductivity shows the ability to transfer water to the aquifer.	>40 40-10 10-5 <5	10 7.5 5 2.5
L	Level of groundwater	This parameter shows the groundwater level considering the mean height of sea level in many areas.	<1.0 1.0-1.5 1.5-2 >2.0	10 7.5 5 2.5
D	Distance from the shoreline	The extent of seawater to a coastal aquifer is related to the distance from the shoreline.	<500 500-750 750-1000 >1000	10 7.5 5 2.5
I	Impact of existing seawater intrusion	The ratio of Cl/HCO_3 determines the expansion of seawater to coastal aquifer	>2 1.5-2.0 1-1.5 <1	10 7.5 5 2.5
T	Thickness of aquifer	This parameter shows the thickness of the saturation region of the aquifer	>10 7.5-10 5-7.5 <5	10 7.5 5 2.5

Grey Wolf Optimizer (GWO)

Grey Wolf Optimizer (GWO) is a new meta-heuristic algorithm introduced by Mirjalili et al. (2014), which is inspired by the social hierarchy and hunting behaviour of grey wolves. There are four sorts of grey wolves, including alpha (α), beta (β), delta (δ) and omega (ω) (Fig. 3).

The first level of the hierarchy is called alpha (α) which is the pack's leader. The alpha wolves are responsible for decision-making and other wolves must obey their commands. They are the best managers in the pack. The second level of the hierarchy is called beta (β). Beta wolves help alpha in making decisions. The beta wolves are able to command other wolves in the pack, but they also must follow alpha. The third level of the hierarchy is called delta (δ). Delta wolves help alpha (α) and beta (β) wolves, and do their commands, but they are superior to the omega (ω). The last level and the least ranking wolf of the hierarchy is called omega (ω) which follows the alpha, beta and delta's commands. Furthermore, omega can be a babysitter in the pack and helps in preying

The steps of the GWO algorithm are as follows: social hierarchy, encircling the preys, hunting, attacking the prey (exploitation), and searching the prey (exploration) (Mirjalili et al., 2104) (Fig. 4).

1-Social hierarchy

To mathematically design the grey wolf model, the fittest value is considered as alpha (α). The beta (β) and delta (δ) wolves are the second and third best solutions, respectively. The rest of the wolves (ω) in the pack are named omega wolves. In GWO algorithms, (α), (β) and (δ) are leaders in the hunting mechanism, and the ω wolves follow them for the purpose of finding the optimum solution.

2- Encircling the preys

The wolves encircle their prey. The following equations present the mathematical model of the encircling mechanism:

$$\vec{D} = \left|\vec{C}\,.\vec{X}_p(t) - \vec{X}(t)\right| \tag{2}$$

$$\vec{X}(t+1) = \vec{X}_p(t) - \vec{A}.\vec{D} \tag{3}$$

where, t is the current iteration, $\vec{X}_p$ is the prey position, and $\vec{X}$ is the grey wolf position.

$\vec{A}$ and $\vec{C}$ are coefficient vectors calculated by using the following equations:

$$\vec{A} = 2\vec{a}.\vec{r_1} - \vec{a} \tag{4}$$

$$\vec{C} = 2.\vec{r}_2 \tag{5}$$

where, r_1 and r_2 are random vectors in the range of [0,1], and $\vec{a}$ was linearly reduced from 2 to 0 during iterations.

3- Hunting

The alpha wolves guide the hunting mechanism, and beta and delta wolves help them. The three best solutions (α, β and δ) are saved, and other solutions (ω) update their positions based on the best solutions. The mathematical expressions are given as follows:

$$\vec{D}_x = \left|\vec{C}_1.\vec{X}_\alpha - \vec{X}\right|, \left|\vec{C}_2.\vec{X}_\beta - \vec{X}\right|, \left|\vec{C}_3.\vec{X}_\delta - \vec{X}\right| \tag{6}$$

$$\vec{X}_1 = \vec{X}_\alpha - \vec{A}_1.\left(\vec{D}_\alpha\right), \vec{X}_2 = \vec{X}_\beta - \vec{A}_2.\left(\vec{D}_\beta\right), \vec{X}_3 = \vec{X}_\delta - \vec{A}_3.\left(\vec{D}_\delta\right) \tag{7}$$

$$X(t+1) = \frac{\vec{X}_1+\vec{X}_2+\vec{X}_3}{3} \quad (8)$$

4-Attaking the prey (Exploitation)

The process is ended by attacking the prey. To mathematically model, the process indicated by decreasing the rate of $\vec{a}$ and $\vec{a}$ is reduced from 2 to 0 during iterations. $\vec{A}$ is a random rate in the range of [-2a,2a]. When $|A| < 1$, the wolves attack the prey.

5-Searching the prey (Exploration)

Grey wolves diverge from each other to search for the prey. To mathematically model the divergence, $\vec{A}$ is used with random values between 1 and -1. When $|A| > 1$, wolves separate from the prey to search for better prey. The component $\vec{C}$ varies from 0 to 2, which estimates the random weights for prey.

The GWO algorithm used in this study is programmed using MATLAB environment. The GWO algorithm codes can be found in Mirjalili et al., (2014).

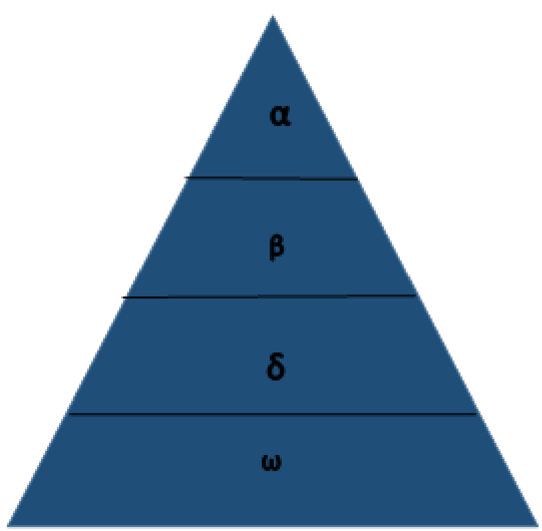

Fig 3. Hierarchy of grey wolves

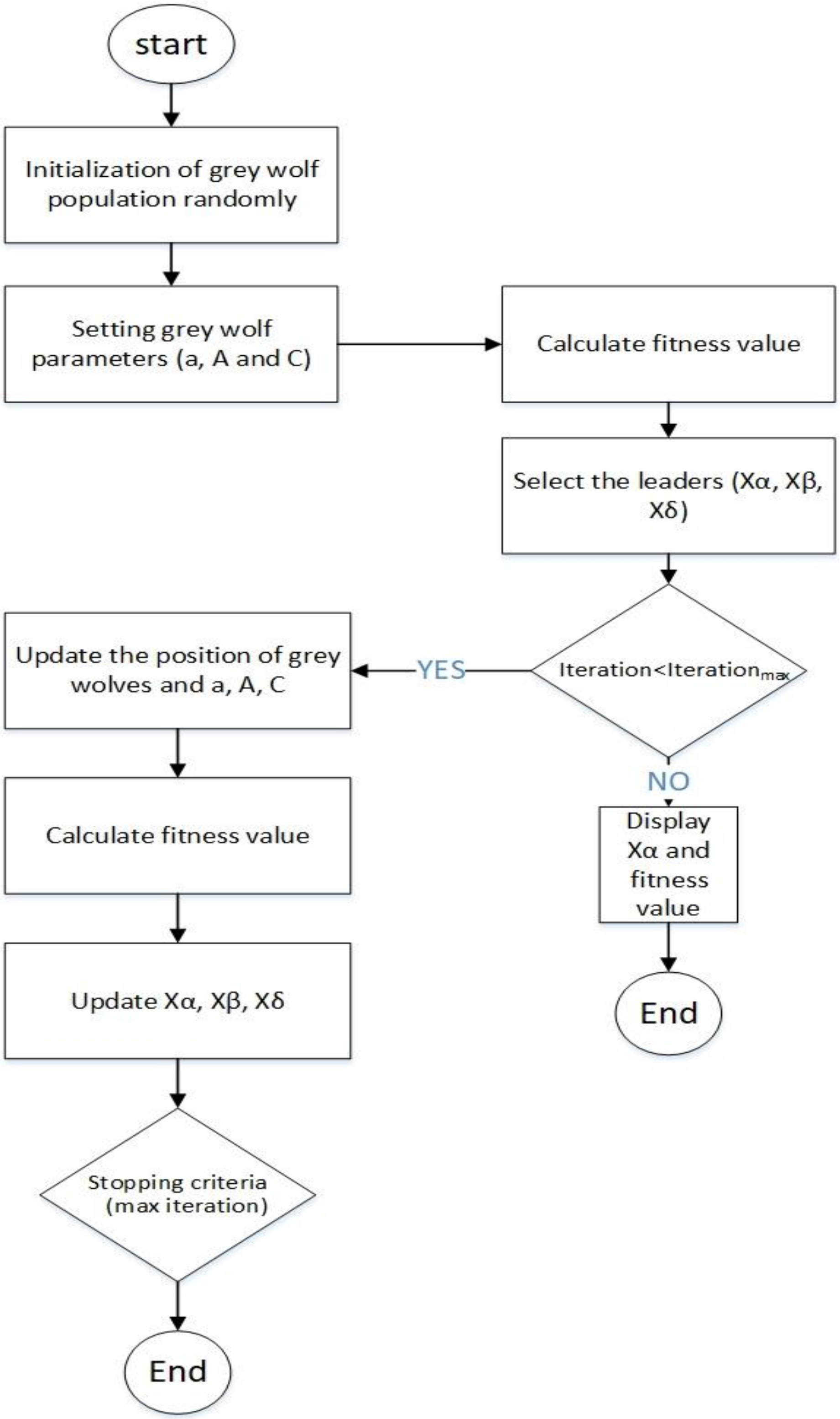

Fig 4- GWO flowchart

Genetic algorithm (GA)

Genetic algorithm (GA) is one of the evolutionary algorithms, inspired by biological evolution in nature called Darwin's theory. This algorithm was first introduced by Holland in 1975 (Holland, 1975). It is one of the earliest and most practical evolutionary algorithms, which is used in different fields to optimize the complex problems (Chen et al., 2017). In genetic algorithm, the number of generation is denoted as NG and the size of the population of chromosomes is denoted as Pop. The GA starts with a population of random chromosomes as the solutions to the problem. From the initial population, the fittest threads which are measured by objective functions are selected to transmit the genetic data to the next generation. A set of solutions from the selective members of the previous population are used by selection, crossover and mutation operators. This process continues until it reaches the predetermined scale (Fig. 5) (Ketabchi and Ataie-Ashtiani, 2015).

The three selection, crossover, and mutation operators are summarized in the following (Chen et al., 2017).

Selection operator: At this stage, the best chromosome from the population, which is the best solution for the problem, is identified by calculating the fitness function of each chromosome. Chromosomes are used as parents to reproduce offspring which is the new child chromosome, and the next generation is generated in this way.

Crossover operator: This operator produces the offspring, which is the new child chromosome, from two chromosomes of the parent and these chromosomes have better fitness compared to their parents. Indeed, crossover operator is used to determining the structure and ratio of offspring chromosomes to parents' chromosomes.

Mutation operator: This operator searches for new areas in the space available. The results lead to local optimization, which are not as acceptable as the best solution. For this reason, some genes are changed in random chromosomes.

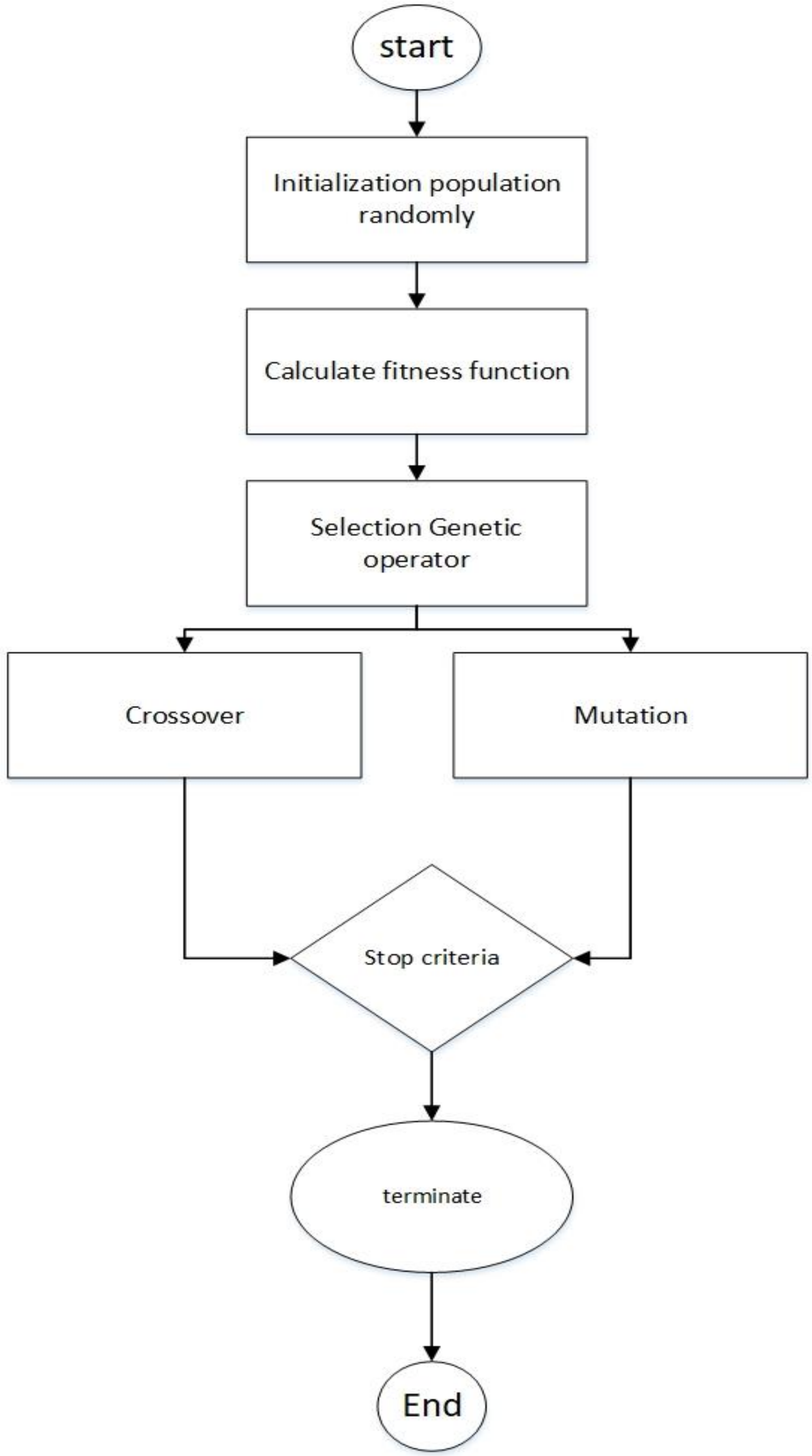

Fig 5- GA flowchart

Objective function for optimization models

The Spearman correlation coefficient is a nonparametric statistical test developed by Spearman (1904) to measure the power of the relationship between two variables. Spearman correlation coefficient can evaluate an optional linear uniform function, which describes the relationship between two variables without any hypothesis about the frequency distribution of variables. This correlation coefficient is applied for variables measured by ordinal scale (Hauke, 2011). In this study, the purpose of optimization is to find the optimal weights for six parameters of GALDIT framework. The vulnerability level of coastal aquifers is evaluated by determining the weights of the parameters of this framework. For this purpose, the objective function (equation 9) was defined as the maximum correlation between two variables of vulnerability index (GI) and TDS contaminant concentration considering all hydrological features, and the optimal weights were obtained for all six parameters of this framework.

$$Maximize\ F = Correlation\ (GI, TDS)$$

$$F = 1 - \frac{6\sum_{j=1}^{N} d_i^2}{n(n^2-1)} \qquad (9)$$

$$d_i = R_{GI_i} - R_{TDS_i}$$

Subject to : $1 < W_j < 4$, $\forall j = 1 , 2 , 3 ,\dots , 6$

where, F is the objective function, n is the sample size, d_i is the rate difference, and R_{GI_i} and R_{TDS_i} are the rates of vulnerability index and TDS contaminant concentration, respectively.

Results

The layers of the parameters of GALDIT framework were prepared in Raster format in ArcGIS software environment (Fig. 6).

Groundwater occurrence

Aquifers are classified into four types of the unconfined aquifer, confined aquifer, leaky confined aquifer, and bounded aquifer. The aquifer type map showed that the study area is covered by two types of the unconfined aquifer and confined aquifer. The unconfined aquifer covers the southern lands of the plan, which is rated as 7.5 based on Chachadi's table (2005). In the northern and western parts of the region, the aquifer is a kind of confined aquifers, which is rated as 10. The majority of the study area is composed of the unconfined aquifer.

Aquifer hydraulic conductivity (A)

This parameter is obtained by dividing the transmissivity coefficient (T) into the aquifer thickness (B) ($k = \frac{T}{B}$). The high hydraulic conductivity increases salinity. An aquifer creates a large cone from the declining level during the pumping process (Chandio and Lee, 2012; Jakovovic et al., 2016; Motevalli et al., 2018). The hydraulic conductivity map was divided into four ranges of >40, 10-40, 5-10, and <5 m/day. This map shows that the highest level of conductivity belongs to the class 10-40 m/day.

Level of groundwater (L)

The height of the groundwater level above the sea level is one of the most important parameters for assessing vulnerability to seawater intrusion. The values of groundwater level less than sea level are of great importance, because it causes the possibility of more vulnerability to seawater intrusion (Najib et al., 2012). The parameter of the height of groundwater levels for the study area varies from -31.3 to 95.1 m. The lowest height of the groundwater level is in the west of the study area near the sea.

Distance from the shoreline (D)

The map of distance from the shoreline is obtained using buffer tool in ArcGIS environment. The map of this parameter was classified into four classes of low vulnerability to high vulnerability. The area near the shoreline (distance less than 500 m) has the highest vulnerability to seawater intrusion and it is rated as 10. Therefore, the more is the distance from the shoreline (distance more than 1000 m), the less is the vulnerability of the region to seawater intrusion.

Impact of existing status of seawater intrusion (I)

The groundwater is always under pressure and this pressure changes the natural balance between the fresh groundwater and salt water (Trabelsi et al., 2016). The data related to the concentrations of chloride and carbonate was obtained from different wells. To prepare the intrusive seawater map, the ratio of Cl/HCO_3 was used to determine the expansion of seawater to the coastal aquifer. The lowest level of Cl/HCO_3 was observed in the southern and eastern areas of the aquifer, which was ranked as less (2.5).

Thickness of the aquifer (T)

This parameter is considered as the resonant parameter in the level of seawater intrusion in coastal areas (Mahrez et al., 2018). Therefore, this parameter is determined from the difference between the groundwater level and the end of the aquifer. The thickness of the aquifer map showed that the western parts of the study aquifer have the lowest thickness, while the highest thickness was observed in the east and south parts of the aquifer. The map of this parameter was classified into four vulnerability classes of 2.5, 5, 7.5, and 10.

GALDIT framework

The GALDIT vulnerability index was calculated using equation (1) (Table 1). The GALDIT vulnerability index was classified into four classes of very-high, high, moderate, and low vulnerability. The final vulnerability map showed very-high vulnerability in the west, north, and southwest parts of the region, while the east and south areas are placed in the class of low vulnerability (Fig. 7a). The results of vulnerability distribution showed that the very-high and high vulnerability classes cover 24% and 30% of the study area, respectively. A small part of the region (14%) is placed in low vulnerability class, while most of the region (32%) is placed in the class of moderate vulnerability (Fig. 8). The Spearman correlation coefficient between the GALDIT vulnerability index and TDS concentration was obtained as 0.47. The original GALDIT needs to be optimized due to its weak correlation coefficient in order to obtain a more reliable vulnerability map of the study area. In this study, two meta-heuristics algorithms were used to optimize the weights of the original GALDIT framework.

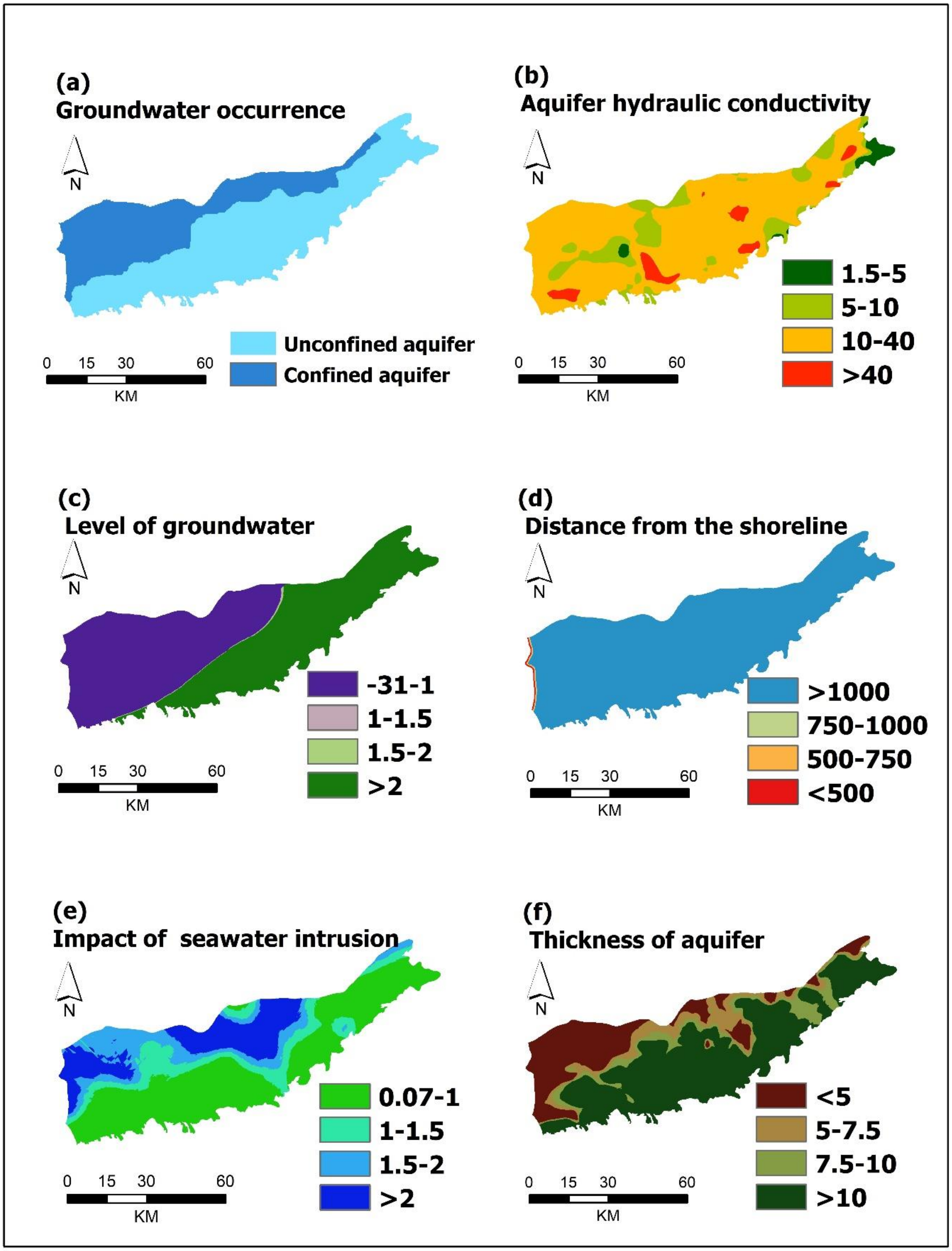

Fig 6. Six layers of GALDIT parameters

Grey Wolf Optimizer (GWO)

In this study, the Grey Wolf Optimizer algorithm was used to optimize the weights of the parameters of GALDIT framework. The objective function (equation 9) was defined with maximizing the least distinction between GALDIT vulnerability index and TDS concentration. Before starting Grey Wolf Optimizer algorithm, it is necessary to determine the parameters, such as the number of population and iterations, and these parameters are characterized based on the type of problem. The stop criterion in Grey Wolf algorithm is the maximum number of iterations. Table 2 shows the parameters used in this study to optimize the weights of GALDIT model.

Table 2- GWO features

Parameters	**Values**
Maximum number of Search Agents (SA)	50
Number of iterations	100
Lower bounds	1
Upper bounds	4

Genetic Algorithm (GA)

The genetic algorithm used in this study was applied to find the optimal weights of the parameters of GALDIT framework. The decision variables of the problem are six weights of GALDIT framework. The objective function of the optimization model was defined with maximizing the least distinction between the vulnerability index (GI) and TDS concentration (Spearman correlation coefficient), and the optimal weights were calculated for each parameter of the GALDIT framework. The optimization codes of the genetic algorithm were written in MATLAB environment. The algorithm was performed with a population size of 50 chromosomes. Table 3 presents the features of the genetic algorithm used in this study.

Table 3- Genetic Algorithm features

Number of chromosomes in the population	**50**
Number of generation	100
selection	Roulette wheel
Crossover	Arithmetic crossover
Crossover probability	0.8
Mutation probability	0.01

Weights optimization and new frameworks

GALDIT-GWO framework

GALDIT-GWO framework was obtained from combining the rates of the original GALDIT and optimal weights of GWO algorithm given by the equation (10). The optimal weights for parameters of the type of aquifer, hydraulic conductivity of aquifer, the height of groundwater level above the sea level, distance from the shoreline, the impact of seawater intrusion, and thickness of the aquifer were obtained as 3.40, 1, 3.73, 1.47, 1.54, and 1, respectively (Table 4). The GALDIT-GWO vulnerability map was classified into four groups ranged from low vulnerability to very-high vulnerability, and showed that the northwest and west areas of Gharesoo-Gorgan Rood aquifer are placed in the class of very-high vulnerability, while the south and east areas of the aquifer are placed in the class of low vulnerability (Fig. 7b). The diagram of vulnerability distribution showed that 33% and 21% of the study area are placed in the classes of very high and high vulnerability, while 7% and 39% of the study area has a moderate and low vulnerability, respectively (Fig. 8).

The GALDIT-GWO is calculated as follows:

$$GALDIT - GWO = G_r \times G_{GWO} + A_r \times A_{GWO} + L_r \times L_{GWO} + D_r \times D_{GWO} + I_r \times I_{GWO} + T_r \times T_{GWO} \quad (10)$$

where, GWO is the optimal weights and r is the rates of the original GALDIT.

GALDIT-GA framework

The hybrid GALDIT-GA framework is obtained from the rates of the original GALDIT and the optimal weights of GA by using the equation (11). The optimal weights for parameters of G, A, L, D, I, and T were obtained as 3.80, 2.81, 3.27, 2.18, 1.77, and 1.1, respectively. The GALDIT-GA map was classified into four vulnerability classes of low, moderate, high, and very-high. The higher vulnerability index shows the higher potential of contamination in those areas. This map showed that the northwest and west areas of the aquifer have very-high vulnerability to seawater intrusion, while the south and east areas of aquifer are placed in the class of low vulnerability (Fig. 7c). The diagram of vulnerability distribution showed that 32% and 23% of the study area are placed in the classes of very high and high vulnerability, respectively, while 14% and 31% of it have moderate and low vulnerability (Fig. 8). The GALDIT-GA is calculated as follows:

$$GALDIT - GA = G_r \times G_{GA} + A_r \times A_{GA} + L_r \times L_{GA} + D_r \times D_{GA} + I_r \times I_{GA} + T_r \times T_{GA}$$

where, GA is optimal weights, and *r* is the rates of the original GALDIT.

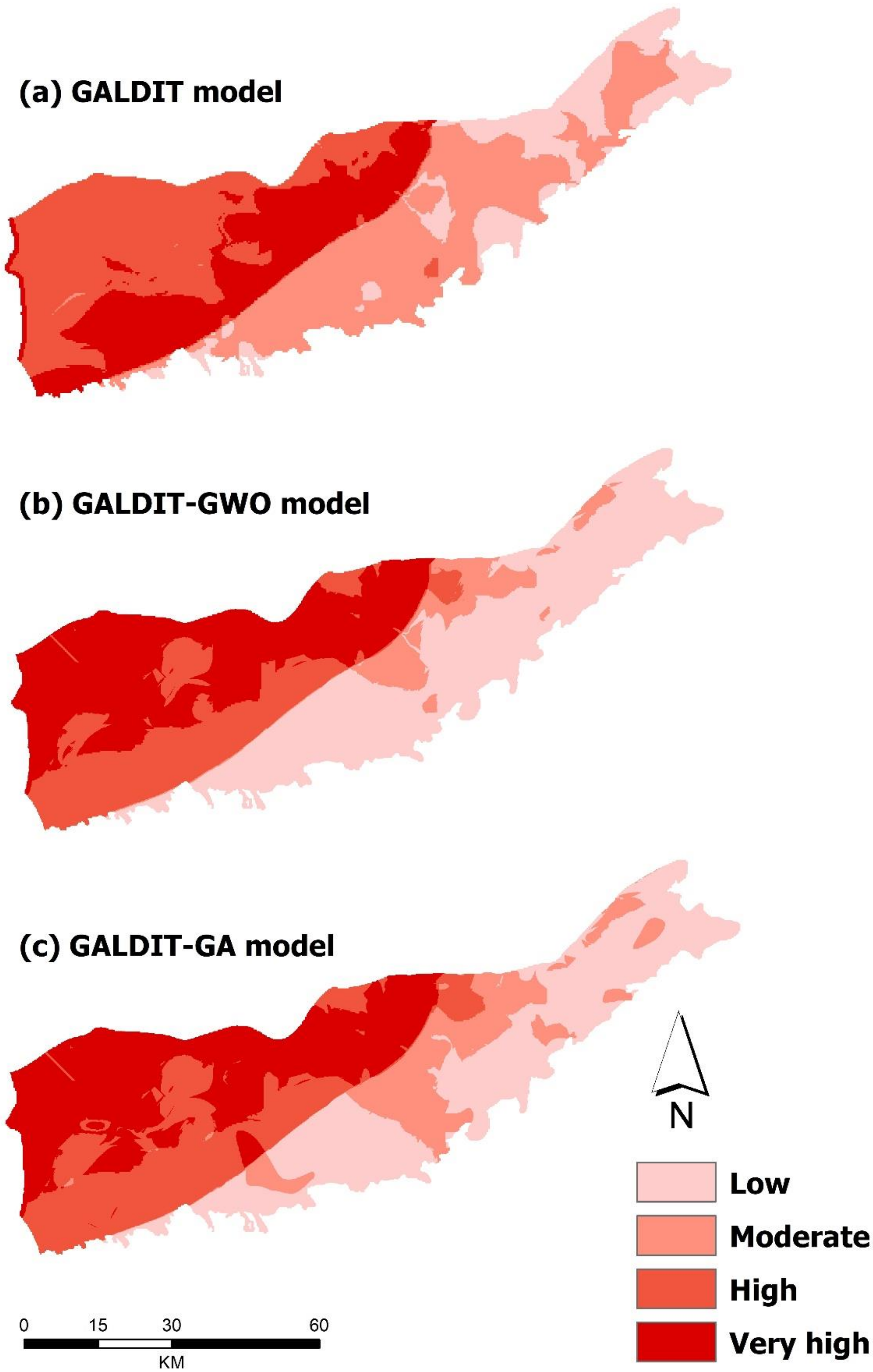
(a) GALDIT model
(b) GALDIT-GWO model
(c) GALDIT-GA model
N
Low
Moderate
High
Very high
0
15
30
60
KM

Figure 7.Vulnerability maps using different frameworks: (a) GALDIT, (b) GALDIT-GWO, (c) GALDIT-GA

Table4- Original GALDIT weights and optimization weights

Parameters	**GALDIT framework**	**GALDIT-GWO**	**GALDIT-GA**
G	1	3.40	3.80
A	3	1	2.81
L	4	3.73	3.27
D	4	1.47	2.18
I	1	1.54	1.77
T	2	1	1.1

Validation methods

Aquifer vulnerability methods need to be validated. Validation reduces subjectivity and increases the reliability of the models (Allouche et al., 2016). Although vulnerability assessments have been reported in many areas in the world, few studies have reported the validation of the methods used (Luoma et al., 2017). Therefore, the methods applied in this study were validated using correlation coefficient between vulnerability indices and TDS contaminant concentration. TDS concentration is used as the contaminant index to validate the models applied. TDS samples were collected in October 2018. The highest level of TDS concentration is in the shallow areas of the aquifer in the northwest and west parts of the aquifer along the shoreline. The higher values of TDS indicate the seawater intrusion. The lowest value of TDS was observed in the eastern parts of the study area. The results showed that the level of the correlation coefficient between GALDIT vulnerability index and TDS parameter is equal to 0.47, while the results from the proposed model showed that the performance of these models has enhanced compared to the original GALDIT, and the level of these coefficients for GALDIT-GWO and GALDIT-GA frameworks were obtained as 0.63 and 0.61, respectively.

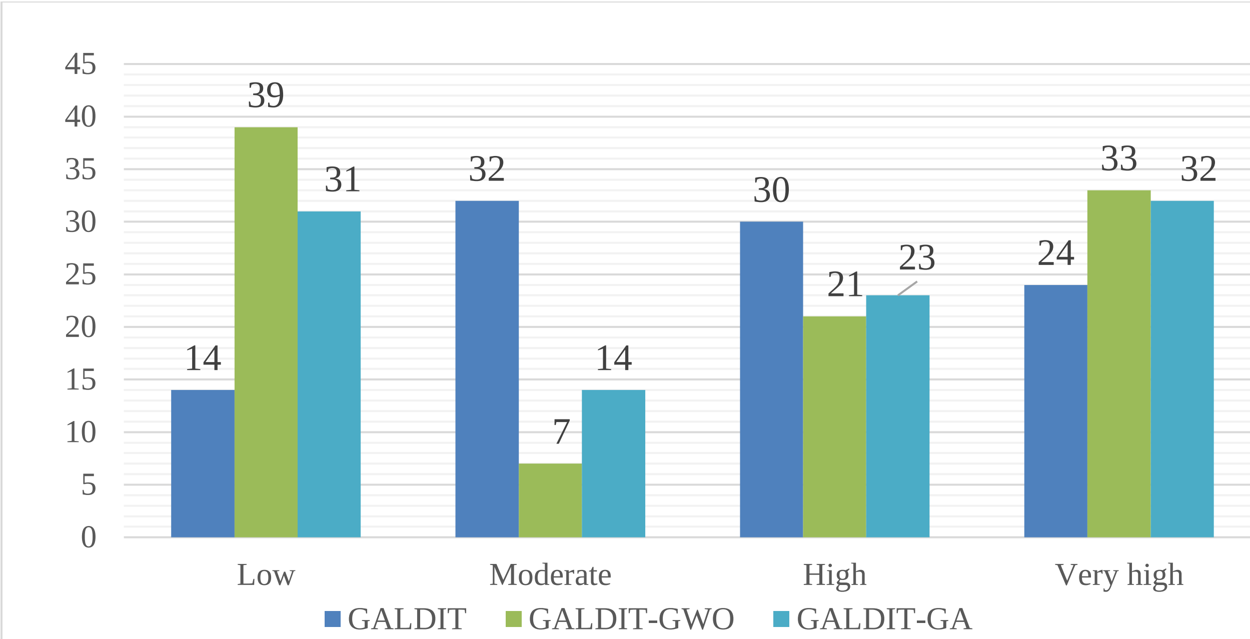

Figure 8. Percentage of vulnerability for each framework

Discussion

In this study, GALDIT framework was used to identify the areas vulnerable to seawater intrusion in coastal aquifer. According to the results from this model, the vulnerable areas were not accurately identified due to the effect of subjectivity in the weighting and rating systems of the evaluated parameters. Mahrez et al. (2018) concluded that the subjectivity of the rating frameworks has a strong effect on the final vulnerability map. In addition, different weights were used for each parameter to calculate the vulnerability index considering the study area (Saidi et al., 2011; Gontara et al., 2016).

The spatial distribution of groundwater quality index (TDS concentration) is also considered as the main contaminant of seawater intrusion in coastal areas (Luoma et al., 2017; Trabelsi et al., 2016). In this regard, the hydrological features of the coastal aquifer and the effects of total dissolved solids (TDS) were used in the study area. Indeed, it is necessary to optimize the weight of each parameter to prepare the vulnerability map in order to prevent seawater intrusion in each region. There is no study conducted on the capability of meta-heuristic algorithms to optimize the weights of GALDIT, although the application of these algorithms in optimizing the rating index of DRASTIC has been extensively investigated. Jafari and Nikoo (2016) stated that the optimal weights for the DRASTIC framework were obtained using genetic algorithm technique. They also stressed that the optimized weights are the main solution to create a proper vulnerability map. The genetic algorithm solves the problem in an expanded space and its decisions are random, so that all possible solutions are considered. On the other hand, Yu and Lu (2018) showed that the GWO algorithm having features such as high convergence speed, optimization accuracy, ability to strong global optimization, and good convergence stability is superior to other algorithms.

According to the results of this study, it was found out that almost similar weights were obtained from both GA and GWO algorithm. These weights are different from those of the original GALDIT, which indicate the good performance of this algorithm in the optimization process. In both models, the highest weights were obtained for groundwater occurrence (G) and level of groundwater (L). Two vulnerability maps were obtained using the above-mentioned algorithms and then they were classified into four classes of vulnerability. The high and very classes of vulnerability covered the west and northwest parts of the aquifer along the shoreline. Moreover, the optimization algorithms can be applied in further studies within different hydrological conditions due to their optimal weights. It should be noted that the optimization algorithm is needed to create a comprehensive vulnerability map in coastal aquifers in order to determine vulnerable regions.

Conclusions

In this paper, the GALDIT framework was applied in Gharesoo-Gorgan Rood coastal aquifer to identify vulnerable areas to seawater intrusion. The results from the original GALDIT framework did not accurately show the vulnerability, which was also, confirmed by the poor correlation with TDS values. The GALDIT framework was optimized using Genetic Algorithm (GA) and Grey Wolf Optimizer (GWO) methods. Then, the optimal weights were multiplied by the rated layers according to GALDIT framework, and the vulnerability maps of GALDIT-GWO and GADIT-GA were obtained. The GA and GWO algorithms showed almost similar results. Both methods depicted the vulnerable areas in the northwest and west parts of the study area along the shoreline, exposed to seawater intrusion. In addition, the correlation coefficient between vulnerability indices of GALDIT-GWO, GALDIT-GA, and TDS parameter were obtained as 0.63 and 0.61, which indicate the strong correlation between these two frameworks. Using the optimization algorithms in each region increases the accuracy of the index and reduces the subjectivity considering the conditions of the aquifer. Applying these algorithms, a proper understanding was acquired on the vulnerability of coastal aquifer to seawater intrusion. Moreover, the result of this paper provides a practical reference for hydrologists and decision makers to protect the groundwater resources in coastal aquifers.

References

Babiker, I. S., Mohamed, M. A., Hiyama, T., & Kato, K. (2005). A GIS-based DRASTIC model for assessing aquifer vulnerability in Kakamigahara Heights, Gifu Prefecture, central Japan. *Science of the Total Environment*, *345*(1-3), 127-140.

Bouderbala, A., Remini, B., Hamoudi, S., Pulido-Bosch, A., 2016. Assessment of groundwater vulnerability and quality in coastal aquifers: a case study (Tipaza, North Algeria). Arab. J. Geosci. 9, 181. https://doi.org/10.1007/s12517-015-21516.

Chachadi, A. G. & Lobo Ferreira, J. P. C. (2001) Sea water intrusion vulnerability mapping of aquifers using the GALDIT method. Proc. Workshop on modeling in hydrogeology. Anna University, CHENNAI, pp. 143-156

Chachadi, A.G., 2005. Seawater intrusion mapping using modified GALDIT indicator model-case study in Goa. Jalvigyan Sameeksha. 20, 29-45.

Chandio, A. S., & Lee, T. S. (2012). Managing saline water intrusion in the lower Indus Basin aquifer. *Water resources management*, *26*(6), 1555-1576.

Chen, W., Panahi, M., & Pourghasemi, H. R. (2017). Performance evaluation of GIS-based new ensemble data mining techniques of adaptive neuro-fuzzy inference system (ANFIS) with genetic algorithm (GA), differential evolution (DE), and particle swarm optimization (PSO) for landslide spatial modelling. *Catena*, *157*, 310-324.

Dorigo, M. (1992). Optimization, learning and natural algorithms. *PhD Thesis, Politecnico di Milano*.

Gaur, S., Ch, S., Graillot, D., Chahar, B. R., & Kumar, D. N. (2013). Application of artificial neural networks and particle swarm optimization for the management of groundwater resources. *Water resources management*, *27*(3), 927-941.

Geem, Z. W., Kim, J. H., & Loganathan, G. V. (2001). A new heuristic optimization algorithm: harmony search. *simulation*, *76*(2), 60-68.

Gontara, M., Allouche, N., Jmal, I., Bouri, S., 2016. Sensitivity analysis for the GALDIT method based on the assessment of vulnerability to pollution in the northern Sfax coastal aquifer, Tunisia. Environ. Earth Sci. 75, 669. https://doi.org/10.1007/s12665-016- 5459-y.

Gorgij, A.D., Moghaddam, A.A., 2016. Vulnerability Assessment of saltwater intrusion using simplified GAPDIT method: a case study of Azarshahr Plain Aquifer, East Azerbaijan, Iran. Arab. J. Geosci. 9(2), 106. http://dx.doi.org/ 10.1007/s12517-015-2200-1.

Hauke, J., & Kossowski, T. (2011). Comparison of values of Pearson's and Spearman's correlation coefficients on the same sets of data. *Quaestiones geographicae*, *30*(2), 87-93.

Holland, J. (1975). Adaptation in natural and artificial systems: an introductory analysis with application to biology. *Control and artificial intelligence*.

Jafari, F., Javadi, S., Golmohammadi, G., Mohammadi, K., Khodadadi, A., & Mohammadzadeh, M. (2016). Groundwater risk mapping prediction using mathematical modeling and the Monte Carlo technique. Environmental Earth Sciences, 75(6), 491.

Jafari, S. M., & Nikoo, M. R. (2016). Groundwater risk assessment based on optimization framework using DRASTIC method. *Arabian Journal of Geosciences*, *9*(20), 742.

Jakovovic, D., Werner, A. D., de Louw, P. G., Post, V. E., & Morgan, L. K. (2016). Saltwater upconing zone of influence. *Advances in water resources*, *94*, 75-86.

Karaboga, D. (2005). *An idea based on honey bee swarm for numerical optimization* (Vol. 200). Technical report-tr06, Erciyes university, engineering faculty, computer engineering department.

Kazakis, N., Spiliotis, M., Voudouris, K., Pliakas, F.K., Papadopoulos, B., 2018. A fuzzy multicriteria categorization of the GALDIT method to assess seawater intrusion vulnerability of coastal aquifers. Sci. Total Environ. 621, 524-534. https://doi.org/10.1016/j.

Kennedy, J., Eberhart, R.C., 1995. Particle swarm optimization. Proc. IEEE int'l conf. on neural networks. 1942-1948. IEEE service center, Piscataway, NJ.

Ketabchi, H., & Ataie-Ashtiani, B. (2015). Evolutionary algorithms for the optimal management of coastal groundwater: a comparative study toward future challenges. *Journal of Hydrology*, *520*, 193-213.

Kirkpatrick, S., Gelatt, C. D., & Vecchi, M. P. (1983). Optimization by simulated annealing. *science*, *220*(4598), 671-680.

Luoma, S., Okkonen, J., Korkka-Niemi, K., 2017. Comparison of the AVI, modified SINTACS and GALDIT vulnerability methods under future climate-change scenarios for a shallow low-lying coastal aquifer in southern Finland. Hydrogeol. J. 25, 203–222. DOI 10.1007/s10040-016-1471-2.

Mahrez, B., Klebingat, S., Houha, B., & Houria, B. (2018). GIS-based GALDIT method for vulnerability assessment to seawater intrusion of the Quaternary coastal Collo aquifer (NE-Algeria). *Arabian Journal of Geosciences*, *11*(4), 71.

Mirjalili, S., Mirjalili, S. M., & Lewis, A. (2014). Grey wolf optimizer. *Advances in engineering software*, *69*, 46-61.

Mogaji, K. A. (2018). Application of vulnerability modeling techniques in groundwater resources management: a comparative study. *Applied Water Science*, *8*(5), 127.

Motevalli, A., Moradi, H. R., & Javadi, S. (2018). A Comprehensive evaluation of groundwater vulnerability to saltwater up-coning and sea water intrusion in a coastal aquifer (case study: Ghaemshahr-juybar aquifer). *Journal of Hydrology*, *557*, 753-773.

Najib, S., Grozavu, A., Mehdi, K., Breaban, I. G., Guessir, H., & Boutayeb, K. (2012). Application of the method GALDIT for the cartography of groundwaters vulnerability: aquifer of Chaouia coast (Morocco). *Analele stiintifice ale Universitatii" Alexandru Ioan Cuza" din Iasi-seria Geografie*, *58*(2), 77-88.

Neshat A, Pradhan B, Dadras M. 2014c. Groundwater vulnerability assessment using an improved DRASTIC method in GIS. Resour Conserv Recycl. 86:74–86.

Neshat A, Pradhan B, Pirasteh S, Shafri HZM. 2014a. Estimating groundwater vulnerability to pollution using a modified DRASTIC model in the Kerman agricultural area, Iran. Environ Earth Sci. 71(7):3119–3131.

Neshat A, Pradhan B, Shafri HZM. 2014b. An integrated GIS based statistical model to compute groundwater vulnerability index for decision maker in agricultural area. J Indian Soc Remote Sens. 42(4):777-788.

Neshat A, Pradhan B. 2015. An integrated DRASTIC model using frequency ratio and two new hybrid methods for groundwater vulnerability assessment. Nat Hazards. 76(1):543-563.

Neshat A, Pradhan B. 2017. Evaluation of groundwater vulnerability to pollution using DRASTIC framework and GIS. Arab J Geosci. 10(22):501.

Nicklow, J., Reed, P., Savic, D., Dessalegne, T., Harrell, L., Chan-Hilton, A., ... & Zechman, E. (2009). State of the art for genetic algorithms and beyond in water resources planning and management. *Journal of Water Resources Planning and Management*, *136*(4), 412-432.

Saidi, S., Bouri, S., Dhia, H. B., & Anselme, B. (2011). Assessment of groundwater risk using intrinsic vulnerability and hazard mapping: application to Souassi aquifer, Tunisian Sahel. *Agricultural Water Management*, *98*(10), 1671-1682.

Saidi, S., Bouri, S., Dhia, H.B., 2013. Groundwater management based on GIS techniques, chemical indicators and vulnerability to seawater intrusion modelling: application to the Mahdia–Ksour Essaf aquifer, Tunisia. Environ. Earth Sci. 70(4), 1551-1568. https://doi.org/ 10.1007/s12665-013-2241-2.

Spearman C.E, 1904b. General intelligence, objectively determined and measured. *American Journal of Psychology* 15: 201–293.

Storn, R., & Price, K. (1997). Differential evolution–a simple and efficient heuristic for global optimization over continuous spaces. *Journal of global optimization*, *11*(4), 341-359.

Szemis, J. M., Dandy, G. C., & Maier, H. R. (2013). A multiobjective ant colony optimization approach for scheduling environmental flow management alternatives with application to the River Murray, Australia. *Water Resources Research*, *49*(10), 6393-6411.

Trabelsi, N., Triki, I., Hentati, I., & Zairi, M. (2016). Aquifer vulnerability and seawater intrusion risk using GALDIT, GQI SWI and GIS: case of a coastal aquifer in Tunisia. *Environmental Earth Sciences*, *75*(8), 669.

Yang, J., Tang, Z., Jiao, T., & Muhammad, A. M. (2017). Combining AHP and genetic algorithms approaches to modify DRASTIC model to assess groundwater vulnerability: a case study from Jianghan Plain, China. *Environmental Earth Sciences*, *76*(12), 426.

Yu, S., & Lu, H. (2018). An integrated model of water resources optimization allocation based on projection pursuit model–Grey wolf optimization method in a transboundary river basin. *Journal of Hydrology*, *559*, 156-165.