Geothermal prospectivity mapping using GIS-based Ordered Weighted Averaging approach: A case study in Japan’s Akita and Iwate provinces

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ABSTRACT

The exploration of geothermal regions is the first step for the use of these resources. This paper attempts to incorporate the concept of risk into the GIS-based analysis for generating geothermal prospectivity maps via Ordered Weighted Averaging (OWA) approach. The use of OWA-based approach provides a model that generates geothermal prospectivity maps with different pessimistic or optimistic strategies. The results indicate that the values of wells percentages in high favorite areas for the most pessimistic and optimistic strategies are 85% and 100%, respectively. Regarding the prediction rate, the results show that the rate for the most pessimistic and optimistic strategies are 18.55 and 1.18, respectively.

1. Introduction

Geothermal, solar, wind and biomass are known as renewable energy resources. These resources have been portrayed as resources by small CO₂ emissions during exploitation and energy generation (Kiavarz Moghaddam et al., 2013; Kiavarz Moghaddam et al., 2014; Howari, 2015; Noorollahi et al., 2015). Geothermal energy is immense heat energy within the earth, whose surface manifestation are volcanoes, fumaroles, geysers, streaming grounds and hot springs (Kiavarz Moghaddam et al., 2014). According to a report by Bertani (2016) about the use of geothermal resources for power generation, the installed capacity (MWe) and produced electricity (GWh) from 1950 to 2015 are 12,635 and 73,549, respectively.

The exploration of subsurface in search of active geothermal regions is the first step for the use of these resources. The information gained via exploration is the basis for an evaluation of geothermal energy-producing potential and the subsequent building of geothermal engineering plans and construction cost estimates. Kiavarz Moghaddam et al. (2014) argue that the aim of exploration is finding areas with the best possible location for siting wells for energy production with the minimum risk of drilling a dry well. Developing an appropriate geothermal favorability map could present potential areas for geothermal resources by classifying and prioritizing the zones of potential geothermal resources (Noorollahi et al., 2007; Kiavarz Moghaddam et al., 2014; Procesi et al., 2015). Noorollahi et al. (2015) argue that active geothermal areas have various natural manifestations at the ground surface. They discuss that hot springs, fumaroles, mud pots, and hydrothermal alteration, particularly in areas of high thermal activity, are natural indicators of geothermal activity, providing an evident sign of the transport of heat and mass through the Earth’s crust. Integration of the data relevant to these indicators using decision making models can generate appropriate geothermal prospectivity maps for further exploration.

GIS-based Multi Criteria Decision Analysis (MCDA) techniques provide appropriate analytical tools for geothermal prospectivity mapping (e.g., Noorollahi et al., 2007; Carranza et al., 2008; Noorollahi et al., 2008; Kiavarz Moghaddam et al., 2014; Sadeghi and Khalajmasoumi, 2015). These tools involve the use of geographical data, weights, and an MCDA aggregation function that combines spatial data and weights of criteria to evaluate locations (Jelokhani-Niaraki and Malczewski, 2015a, 2015b; Malczewski and Rinner, 2015). The main rationale behind integrating GIS and MCDA is that these two distinct areas of research can complement each other in different stages of geothermal exploration. While GIS is commonly recognized as a powerful and integrated tool with unique capabilities for storing, manipulating, analyzing and visualizing geothermal criterion maps, MCDA provides a rich collection of procedures and algorithms for evaluating the geothermal potential of regions (Kiavarz Moghaddam et al., 2014; Yalcin and Kilic Gul, 2017).

This study adopts a GIS-based Ordered Weighted Averaging (OWA) decision analysis approach to evaluate all of the locations and generate geothermal prospectivity maps for Japan’s Akita and Iwate provinces. Using this approach, one can control the level of mapping risk and develop low- or high-risk geothermal maps. The paper proceeds with an overview of previous studies employing GIS-based MCDA techniques for geothermal prospectivity mapping in Section 2. Section 3 is focused
on the detailed description of the methodology. Experimental issues including study area and results are discussed in Section 4. Finally, a conclusion is given in Section 5.

2. Literature review

The field of GIS-MCDA has strongly been adopted within the geo-thermal community. The use of GIS-MCDA techniques allows geothermal analysts and decision makers to think about the spatial relationships in a more sophisticated and meaningful manner than is otherwise possible. Geothermal resource researchers have made remarkable efforts in using GIS or GIS-MCDA methods as a means of evaluating geothermal potential locations (e.g., Carranza et al., 2008; Abedi and Norouzi, 2012; Yousefi et al., 2012; Kiavarz Moghaddam et al., 2014; Trumpy et al., 2015). Coolbaugh et al. (2003) used logistic regression model as a favorability mapping model for undiscovered geothermal resources and high temperature geothermal resources. They found that a predictive map of geothermal potential based only on areas of high extensional strain rates and high heat flux appropriately predict the location of most known geothermal systems in Nevada. Noorollahi et al. (2007) used a GIS-based decision making tool to target potential regional-scale geothermal resources in the Akita and Iwate prefectures of northern Japan. The objective of their study was to determine the relationships between geothermal wells and geological, geochemical, and thermal map layers within the GIS and to use these relationships to identify promising areas for geothermal exploration. The results found in this study show that 97% of currently productive geothermal wells in Akita and Iwate prefectures are located within the first priority zone selected by the tool.

Carranza et al. (2008) demonstrated the application of data-driven evidential belief functions in GIS-based predictive mapping of regional-scale geothermal potential in West Java. The resulting maps led to delineation of high potential zones occupying 25% of West Java, which is a substantial reduction of the search area for further exploration of geothermal resources. They argue that the methods for spatial data analysis and integration not only provides the ability to delineate zones where geothermal resources may be present on a regional-scale, but also the opportunity to improve our understanding of why geothermal resources are not present everywhere. Yousefi et al. (2010) presented a geothermal exploration and resource identification method that is based on building a map of potential geothermal resource areas by combining geological, geochemical and geophysical datasets to develop Iran’s geothermal map. The map highlighted 18 promising geothermal areas. In a study by Kiavarz Moghaddam et al. (2014), fry analysis and weights of evidence were employed to study the spatial distribution and spatial association between known occurrences of geothermal resources and publicly available geoscience data sets at a regional-scale. They employed Boolean index overlay, Boolean index overlay with OR operation, Multi-class index overlay and Fuzzy logic prediction models to develop geothermal favorability map for two province of Japan. Sadegh and Khalajmasoumi (2015) utilized the binary index overlay and fuzzy logic methods for integrating the available data (volcanic and intrusive rocks, volcanoes, hot springs and faults) for geothermal exploration in NW of Iran. The results showed that a good correspondence can be seen between the methods used. Noorollahi et al. (2015) developed a GIS toolbox in ArcGIS environment as a decision-making tool to locate potential geothermal areas. The tool employed the Boolean “OR” and “AND” models for creating a geothermal map in Akita and Iwate prefectures in northern Japan. Trumpy et al. (2015) presented a data integration tool to identify potentially undiscovered geothermal resources in the island of Sicily, Italy. The factors facilitating the discovery of exploitable geothermal energy including both geological and economic aspects were defined, and were combined using an Index Overly method to generate favourability maps for exploring geothermal systems. Ito et al. (2016) proposed a new geostatistical method to integrate a variety of geological data sets to produce maps of geothermal resource prospectivity for the State of Hawaii. They employed the basic principles of Bayesian statistics to estimate the joint probability of geothermal regions.

Yalcin and Kilee Gul (2017) identified geothermal potential areas using a GIS-Analytic Hierarchy Process (AHP) approach in Afyonkarahisar within the boundaries of Akarcay Basin. The results of their study were compared with the existing hot springs locations in the Gazligol, Omer, Gecek, Kizik, Uuyez, Heybeli geothermal fields. They found that all of the existing hot springs are in the extremely high classes of geothermal favourability map.

Mostly, the previous GIS-MCDA studies for geothermal exploration used Boolean overlay (And and OR operations) and the index overlay (weighted linear combination or WLC) methods, the two fundamental, most often used classes of the decision analysis approach in GIS-MCDA. This paper uses an OWA-based decision analysis approach to incorporate the concept of risk into the GIS-based analysis for generating geothermal prospectivity maps. Moreover, the two types of combination rules can be generalized within the framework of OWA (Eastman, 1997; Jiang and Eastman, 2000; et al., 2008; Boroushaki and Malezewski 2008, 2010; Eldrandaly, 2013; Jelokhani-Niaari and Malezewski, 2015a, 2015b; Malczewski and Rinner, 2015).

3. Methodology

Fig. 1 demonstrates the analysis steps for generating geothermal prospectivity maps. Developing and normalizing criteria maps is the first stage in the proposed framework. The second step involves one or more decision makers to specify their criteria preferences (i.e. weights) and ORness values for computing order weights. The value of ORness indicates the degree of risk in decision making process (Malczewski and Rinner, 2015). In the third step, the GIS-based OWA model was used to integrate the criteria maps and decision makers’ preferences into an overall assessment of each location for developing a variety of geothermal prospectivity maps. Finally, the validity and accuracy of the resulting prospectivity maps were evaluated according to two different measures.

3.1. The OWA operator

The concept of OWA operator was proposed by Yager (1988) to provide a parameterized family of aggregation methods. For a given set of $n$ attributes (criteria), an OWA operator can be defined as a function $F$ such that $F: I^n \rightarrow I^m$ has an associated set of order weights $V = \{v_1, v_2, \ldots, v_m\}, \forall v \in [0,1]$ for $j = 1, 2, \ldots, n$ and $\sum_{j=1}^{n} v_j = 1$. Given a set of standardized attribute values $A_i = \{a_{i_1}, a_{i_2}, \ldots, a_{i_m}\}$ for $i = 1, 2, \ldots, m$, where $a_{ij} \in [0,1]$ is the $j$-th attribute associated with the $i$-th location, the OWA operator is defined as follows:

$$a \geq 0$$

$$\text{OWA} (a_{i_1}, a_{i_2}, \ldots, a_{i_m}) = \sum_{j=1}^{n} v_j z_j$$

where $z_1 \geq z_2 \geq \ldots \geq z_m$ is the sequence obtained by reordering the attribute values $a_{i_1}, a_{i_2}, \ldots, a_{i_m}$. The reordering process is central to the OWA operator. It involves associating a weight, $v_j$ with a particular ordered position of the attribute values $a_{i_1}, a_{i_2}, \ldots, a_{i_m}$ for the $i$-th location. The first order weight, $v_1$, is assigned to the highest attribute value for the $i$-th location, $v_2$ is associated with the second highest value for the same location, and so on with $v_m$ assigned to the lowest attribute value. It should be noted that a particular value of $a_j$ is not associated with a particular weight $v_j$ but rather the weight is assigned to a particular ordered position of $a_j$. The generality of OWA is related to its capability to implement a wide range of map combination operators by selecting appropriate order weights (Malczewski and Rinner, 2015).
3.2. Attribute value standardization

As mentioned earlier, the OWA-based GIS-MCDA requires that the attribute/criteria values be commensurate. To do so, a standardization of the attribute values is required. Many approaches can be used to make the attribute values commensurate. Here, we adopt a standardization procedure that uses the minimum and maximum values of an attribute as scaling points. Depending on whether the attribute is to be maximized (i.e., the larger the raw value, the better the performance) or minimized (i.e., the lower the value, the better the performance), Eqs. (2) and (3) can respectively be used to convert the raw attribute values into standardized values (comparable units).

\[
a_{ij} = \frac{S_{ij} - S_{j}^{\text{min}}}{S_{j}^{\text{max}} - S_{j}^{\text{min}}}
\]

(2)

\[
a_{ij} = \frac{S_{j}^{\text{max}} - S_{ij}}{S_{j}^{\text{max}} - S_{j}^{\text{min}}}
\]

(3)

where \(S_{ij}\) is the raw value for the \(i\)-th location and the \(j\)-th attribute, \(S_{j}^{\text{min}}\) represents the minimum value for the \(j\)-th attribute, \(S_{j}^{\text{max}}\) is the maximum value for the \(j\)-th attribute, \(a_{ij}\) is the standardized value for the \(i\)-th location and the \(j\)-th attribute. The standardized attribute values range from 0 to 1.

3.3. Order weights

The OWA operator in Eq. (1) exclusively focuses on the order weights. It ignores the fact that most of the GIS-based decision-making problems require a set of different weights to be assigned to criteria. To overcome this problem, Yager (1997) proposed an attribute weight modification approach for generating the order weights based on inclusion of the attribute weights into the OWA operator as follows:

\[
v_{ij} = \left(\frac{\sum_{i=1}^{n-1} \mu_{i}}{\sum_{i=1}^{n} \mu_{i}}\right)^{\alpha} \left(\frac{\sum_{i=1}^{n-1} \mu_{i}}{\sum_{i=1}^{n} \mu_{i}}\right)^{\beta}
\]

(4)
where $w_j$ is the reordered $j$-th attribute weight, $w_j$, according to the reordered attribute value $z_j$. The attribute weight $w_j$ is assigned to $j$-th attribute for all locations to indicate the relative importance of the attribute according to the decision maker's preferences. This weight reflects the values and interests of a decision participant with respect to the decision attribute, representing a priority that can be assigned to each attribute. All locations for the $j$-th attribute are assigned the same weight of $w_j$. The order weights, $v_j$, are associated with the attribute values on a location-by-location basis. They are assigned to the $i$-th location's attribute values in decreasing order without consideration of which attribute they are associated. In the GIS-based multicriteria evaluation procedures, the attribute weights typically have the following property: $\sum_{j=1}^{n} w_j = 1$. Accordingly, $\sum_{j=1}^{n} u_j = 1$ and Eq. (4) can be written as follows:

$$v_j = \left(\sum_{j=1}^{n} u_j\right)^\alpha - \left(\sum_{j=1}^{n-1} u_j\right)^\alpha$$

(5)

Given the sets of attribute weights, $w_j$, and the order weights, $v_j$, the OWA operator can be defined as:

$$\text{OWA}_i = \sum_{j=1}^{n} \left(\left(\sum_{j=1}^{n} u_j\right)^\alpha - \left(\sum_{j=1}^{n-1} u_j\right)^\alpha\right) z_{ij}$$

(6)

The value of $\alpha$ is related to ORness (or degree of risk) according to Equation (7) (Yager, 1996). The measure of ORness ranges from 0 to 1. It controls the degree to which an OWA operator is similar to the logical OR in terms of its combination behaviour (Malczewski, 2006).

$$\text{ORness} = \frac{1}{\alpha + 1}, \quad a \geq 0$$

(7)

The degree of ORness indicates the position of the OWA on a continuum between the AND or OR combination rules. Thus, with different ORness values (or $\alpha$ parameter) one can generate different sets of the OWA weights and, in turn, a variety of GIS-based map combination strategies ranging from a minimum-type (logical AND) combination through all intermediate types (including the conventional WLC) to a maximum-type (logical OR) combination (see Yager, 1988; Jiang and Eastman, 2000; Malczewski et al., 2003) (see Fig. 2). The AND and OR operators represent the extreme cases of OWA. The ORness value of 0 ($\alpha = \infty$) represents the strategy corresponding to the MIN operator. The order weights associated with the MIN operator are: $v_n = 1$, and $v_j = 0$ for all other weights, which results in $\text{OWA}_{\text{MIN}}(a_{ij}) = a_{ij}$. For ORness = 1 ($\alpha = 0$) represents the strategy corresponding to the MAX operator. The following weights are associated with the MAX operator: $v_1 = 1$, and $v_j = 0$ for all other weights, and consequently $\text{OWA}_{\text{MAX}}(a_{ij}) = a_{ij}$. If ORness = 0.5 ($\alpha = 1$), then the strategy corresponds to the conventional WLC in which the order weights equal to the original attribute weights. In the extreme cases of OR and AND (ORness = 0 and 1), there is no trade-off between evaluation criteria.

By choosing a particular value of ORness, one can control the level of risk for the decision problem. The ORness parameter guides the decision makers along the continuum ranging from the pessimistic to optimistic decision strategies. The decision makers can specify their own preferred ORness value to put emphasis on the higher (better) values or the lower (worse) values in a set of the attributes associated with the $i$-th location. Both theoretical and empirical evidence show that decision makers with optimistic (or risk-taking) attitudes tend to be more concerned with the good properties (better values) of locations, while pessimistic (or risk-averse) decision-makers tend to concentrate more on the bad properties (worse values) of locations (Bodily, 1985; Mellers and Chang, 1994).

The strategy associated with the ORness = 0 (the Boolean AND operator) is referred to as the pessimistic strategy (extremely pessimistic) (see Fig. 2); it is the decision situation in which only the lowest attribute value of each location is considered in the evaluation process. If the lowest attribute value meets a desired minimum value, then all of the other attribute scores also meet (and exceed) that minimum value. This implies that the AND operator is a very conservative or risk averse operation, where an location is considered suitable only if all criteria have been met (Eastman, 2006). Conversely, the extreme optimistic strategy can be found at the opposite end of the risk continuum (ORness = 1, the Boolean OR operator). This strategy assigns an order weight of 1 to the highest value at each location. Under this strategy, the decision maker is characterized by optimistic attitudes represented by the best possible outcome, that is, only the highest possible value is selected at each location. While the Boolean AND require all attributes to be met for an to be called suitable, the Boolean OR requires that at least one attribute (i.e., the highest attribute value) be met (Eastman, 2006). Such a decision strategy is too risky because, for any suitable location, all except the one attribute could be unacceptable.

Fig. 3 shows an example of the OWA operator for ORness = 0.25. For a set of standardized attribute values at the $i$th location, $a_{ij} = [0.4, 0.9, 0.5]$, the procedure involves the following steps: (i) specifying the attribute weights according, $w_j = [0.2, 0.3, 0.5]$; (ii) ranking the attribute values, and so $z_{ij} = [0.9, 0.5, 0.4]$; (iii) re-ordering the attribute weights according to $z_{ij}$; the attribute weights, $uj = [0.3, 0.5, 0.2]$; (iv) calculating the order weights, $v_j = [0.027, 0.485, 0.488]$; and (v) calculating OWA score for the location $i$; $\text{OWA}_i = 0.462$. Similarly, for the ORness values of 0, 0.5, and 1 this value is calculated and presented in the figure.

4. Experimental issues

4.1. Study area

Japan includes many geothermal regions. Most of them have been...
formed in Quaternary volcanic and Tertiary volcanic zones, where 0.2 percentage of Japan’s total energy generation is supplied by twenty geothermal power plants located in 17 different areas. Most of Japan’s high temperature geothermal resources occur in two regions. The first region goes from north to south in eastern Japan (from Hokkaido, via the eastern half of Honshu Island, to the Izu Islands), and the second one runs from Kyushu Island to the Southwestern Islands (Sugino and Akeno, 2010; Tamanyu et al., 2000).

In these zones, it is assumed that the heat is generated by Quaternary andesitic or dacitic volcanism and plutonism. Moreover, a large number of hot springs and fumaroles fields are located in Quaternary volcanic zones, which indicate a sign of magma within young volcanoes as heat resources of geothermal (Kiavarz Moghaddam et al., 2014). Consequently, these regions have a higher potential for geothermal exploration. Tamanyu et al. (2000) suggest that the high temperature resource areas are selected according to the temperature of existing hot springs within or around Quaternary volcanoes.

The main objective of this study is to develop geothermal prospectivity maps for Akita and Iwate provinces within Tohoku volcanic arc, in northern Japan using the OWA-based GIS (see Fig. 4). Akita and Iwate’s geothermal fields are associated with the convergent plate margins that include volcanic arc and intrusive complexes which can be viewed as evidences for geothermal formation. Magma that are stored at shallow depths are considered as hydromagmatic resources (Erðlac and Gross, 2008).

4.2. Criteria and weights

The geothermal literature was consulted to identify the evaluation criteria relevant for developing geothermal prospectivity maps. Based on the literature review, a set of seven distinct criteria for assessing the geothermal occurrence potential has been identified (see Table 1). The set of criteria include: six cost (minimization) criteria and one benefit (maximization) criteria. The smaller the values of cost criteria for a location, the more likely it is that the geothermal resource exist in that location. In contrary, the greater the values of benefit criterion (i.e., heat degree) show a greater probability of being geothermal resource. The more information about the following criteria dataset can be available from the online database provided by Geological Survey of Japan (see https://www.gsj.jp/Map/EN/geology6.html). Kiavarz Moghaddam et al. (2014) presented how to create the criteria maps in more details.

Kiavarz Moghaddam et al. (2013) used weights of evidence (WofE) and evidential belief function (EBFs) methods as spatial association methods to compute and compare the criteria weights with known geothermal occurrences evidences. They calculated a set of weights for the geothermal prospectivity mapping based on geothermal wells. These weights have been used in the present study (see Table 1).

4.3. Results and discussion

Given the standardized criteria values, the ORness value, and the criteria weights, one can utilize the OWA-based decision analysis approach to develop a set of geothermal prospectivity maps. Each potential map is associated with a given value of ORness (see Fig. 5). The geothermal prospectivity maps have been constructed under the assumption that the weights of the criteria remain fixed through the scenarios, and only the value of ORness changes. These maps represent the occurrence of geothermal resources along the continuum from pessimistic (or risk-averse to optimistic (or risk-taking) strategies based on the number between 0 (no probability of being geothermal resource) and 1 (the highest probability of being geothermal resource). By increasing the ORness degree, greater and greater order weights are assigned to the higher attribute values at a given location at the expense of assigning smaller weights to the smaller attribute values at that location. This implies that, as the ORness degree increases, a more optimistic and high-risk decision strategy is being taken in the geothermal mapping process.

In order to examine how the potential areas, change as a function of ORness value, the overall OWA scores in the geothermal potential maps were categorized in five classes. As shown in Fig. 6, the geothermal potential areas with higher values (i.e., class 0.8–1) increase as ORness value increases, while potential areas with lower values (e.g., class 0–0.2) decreases. The strategy associated with the ORness = 0 is referred to as the pessimistic strategy (extremely pessimistic) (see Fig. 2); in this decision situation only the lowest attribute value of each location (i.e., pixel) is considered in the evaluation process. If the lowest value meets a desired minimum value, it means that all of the other attribute values (i.e., the higher values) are accepted as well. This situation is a very conservative (or risk averse), in which a location is considered to
be a potential location for geothermal resource only if all criteria have been met. Such an attitude places more constraints on the locations, thus allowing for determining a lower number of potential geothermal locations, and in turn, a smaller area will be considered for further exploration. Conversely, the extreme optimistic strategy lies at the opposite end of the risk continuum (ORness = 1). This strategy assigns an order weight of 1 to the highest value at each location. Under this strategy, the decision maker holds optimistic attitudes represented by the best possible outcome, that is, only the highest attribute value controls the OWA score at each location.

Kiavarz Moghaddam et al. (2014) argue that the performance of prediction models for geothermal prospectivity mapping can be evaluated against the known resource sought occurrences in the study area. They suggest two measures for evaluating the geothermal prospectivity maps: (i) the percentage of known geothermal wells that fall within the predicted potential areas and (ii) the ratio of areas of known geothermal wells to whole potential area in a class. The accuracy of the geothermal prospectivity maps was calculated based on the two measures. A total of 152 known geothermal occurrences were used for evaluation of results. The percentage of geothermal wells in the five classes and the prediction rate of the geothermal maps are shown in Fig. 7 and Fig. 8.

The results indicate that the percentage of geothermal wells for the most important class with values from 0.8 to 1 and ORness = 0 is 85%. This means that only 85 percent of the geothermal wells are correctly predicted as potential locations in this class. It is evident from figure

Table 1
The criteria for assessing geothermal potential.

<table>
<thead>
<tr>
<th>#</th>
<th>Criteria</th>
<th>Description</th>
<th>Criterion type</th>
<th>Weight</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Distance to volcano crater</td>
<td>Volcanoes, craters, and calderas are the most common surface manifestations occurring over the subduction zones showing magma activity near the surface. The vicinity of these geological features is more probable than the other areas for geothermal resource exploration (Watts, 1987; Gupta and Roy, 2007; Glassley and Ghassemi, 2010; Kiavarz Moghaddam et al., 2013; Kiavarz Moghaddam et al., 2014).</td>
<td>Minimize</td>
<td>0.1228</td>
</tr>
<tr>
<td>2</td>
<td>Distance to volcanic rock</td>
<td>It is assumed that, the vicinity of volcanic rocks are high potential areas for exploration because they act as cap rocks for geothermal sources and shows volcanic activity near these areas (Wibowo, 2006; Gupta and Roy, 2007; Kiavarz Moghaddam et al., 2013; Kiavarz Moghaddam et al., 2014).</td>
<td>Minimize</td>
<td>0.0526</td>
</tr>
<tr>
<td>3</td>
<td>Distance to fault</td>
<td>Geothermal activity is spatially correlated with faults/fractures that are being stressed by fault planes acting as plumbing systems (Blewitt et al., 2002; Noorollahi et al., 2007; Kiavarz Moghaddam et al., 2013; Kiavarz Moghaddam et al., 2014).</td>
<td>Minimize</td>
<td>0.1754</td>
</tr>
<tr>
<td>4</td>
<td>Distance to hotspring</td>
<td>Hotsprings are extraordinary and easily recognizable manifestations of hydrothermal geothermal resources in ocean and continental subduction environments (Glassley and Ghassemi, 2010; Kiavarz Moghaddam et al., 2013; Kiavarz Moghaddam et al., 2014).</td>
<td>Minimize</td>
<td>0.1754</td>
</tr>
<tr>
<td>5</td>
<td>Distance to alteration zone</td>
<td>The primary minerals in rocks of geothermal resource fields react with raised hot fluid to form hydrothermal alteration zones (secondary minerals) which are the evidence of prospective areas for geothermal resources and give important information about temperature and permeability (Brown, 1978; Bogie and Lawless, 2000; Noorollahi et al., 2007; Kiavarz Moghaddam et al., 2014).</td>
<td>Minimize</td>
<td>0.1579</td>
</tr>
<tr>
<td>6</td>
<td>Distance to fumarole</td>
<td>Fumaroles are extraordinary and simply recognizable manifestations of hydrothermal geothermal resources in ocean and continental subduction environments (Carranza et al., 2008; Glassley and Ghassemi, 2010; Kiavarz Moghaddam et al., 2014).</td>
<td>Minimize</td>
<td>0.1579</td>
</tr>
<tr>
<td>7</td>
<td>Heat degree</td>
<td>High heat conditions are a good indicator for hydrothermal geothermal exploration (Barbier, 2002; Kiavarz Moghaddam et al., 2014).</td>
<td>Maximize</td>
<td>0.1580</td>
</tr>
</tbody>
</table>
that only geothermal wells within regions A and D are appropriately predicted according to extremely pessimistic scenario (see Fig. 5e). This situation is a very conservative (or risk averse), in which a location is considered to be a potential location for geothermal resource only if all criteria have been met. Such an attitude places more constraints on the locations, thus allowing for determining a lower number of potential geothermal locations. When the ORness value increases from 0.5 to 1, nearly all of the geothermal wells are predicted as potential locations. This shows a more optimistic attitude. Such a decision strategy is risky because for any potential geothermal location all except one attribute could be unacceptable. It places less restrictions on the locations, thus allowing for determining a higher number of potential geothermal locations. While an increase in the ORness value shows a higher percentage of geothermal wells for the classes with higher values (e.g., 0.8–1), it presents a lower percentage of geothermal wells for the classes with lower values (e.g., 0–0.2).

Fig. 5. Geothermal prospectivity maps for the selected values of ORness: (a) Extremely Optimistic (ORness = 1), (b) Optimistic (ORness = 0.83), (c) Neutral (ORness = 0.5), (d) Pessimistic (ORness = 0.16) and (e) Extremely Pessimistic (ORness = 0).
Fig. 6. The percentage of predicted geothermal prospectivity areas.

Fig. 7. The percentage of known geothermal wells for each of the ORness values and classes.
Fig. 8 shows that the prediction rate decreases as a result of increase in the ORness value. This implies that, as a more optimistic and high-risk decision strategy is being taken, the prediction rate decreases. While the highest prediction rate (18.55) for the important class 0.8-1 belongs to the very pessimistic strategy (ORness = 0), the lowest rate (1.18) is for the very optimistic strategy (ORness = 1). Therefore, an appropriate predication rate (i.e., the higher value of predication rate) is the one that predicts a higher percentage of known geothermal resources in less amount of area. This means that it is risky to drill in areas with ORness = 1 and the risk of not finding a geothermal resource is least for ORness = 0.

Kiavarz Moghaddam et al. (2014) adopted Boolean overlay operations, Multi-class index overlay and Fuzzy logic prediction models for generating geothermal prospectivity maps in the same study area. The result of their study indicates that the fuzzy logic model has a higher prediction performance than the others and can predict the geothermal occurrences in a less prospectivity area. They argue that fuzzy procedures take into account the inherent uncertainty and imprecision in criteria values and the decision maker preferences. The results of this study shows that the percentage of known geothermal wells and prediction rates for high favorite classes are 82 percent and 25, respectively. The comparison between their findings and the results of this paper shows that geothermal prospectivity maps generated by OWA with ORness = 0 have a higher percentage of wells and lower prediction rate compared to Kiavarz Moghaddam et al. (2014). However, the benefits of using an OWA-based approach is that it can generate a variety of optimistic and pessimistic prospectivity maps.

The property of either risk-taking or risk-aversion could be appropriate depending on the need to explore a larger number of potential locations with lower level of accuracy (the higher percentage of wells and lower prediction rate) or find lower number of potential locations with higher level of accuracy (the lower percentage of wells and higher prediction rate). In other words, the choice between these two geothermal exploration strategies involves a tradeoff between increased number of potential sites and the accuracy. Typically, risk-taking strategies (higher ORness values) would allow one to find a larger number of geothermal sites with lower level of accuracy which means it may lead to searching much wider areas without any discoveries, whereas a risk aversion strategy (lower ORness values) would allow one to find sites with higher level of accuracy but with fewer failed exploration efforts. Identifying the most suitable ORness value (decision strategy) for exploring geothermal resources is influenced by several factors, such as the purpose of study and scale of study area. For example, the exploration of the subsurface in search of active geothermal resources with the goal of building a geothermal power plant may involve different phases of research, such as geology, geochemistry, and geophysics. As the cost of a geochemical survey is relatively low compared to other methods, such as geophysical surveys, researchers in the geochemistry phase might take more optimistic and high-risk decision strategy (a higher value of ORness) to generate geothermal prospectivity maps. In this phase, geochemical researchers could explore a higher number of locations being identified as potentially suitable geothermal locations. For geophysical surveys that involve measuring the physical properties of the ground and require more expensive and accurate processes, researchers may take low-risk decision strategies (a lower value of ORness) to develop geothermal prospectivity maps.

As another example, the scale of study area is an important factor that affects the choice of an appropriate ORness or decision strategy for exploring geothermal regions. If the study area under consideration is large (a large area of analysis) the researchers may be conservative and interested in a more risk-averse strategy. In such a context, researchers might be very concerned with identifying appropriate locations at which even the lowest attribute value (worst properties) would be acceptable for considering the location as potential geothermal spot. This is due to the fact that exploring geothermal resources in a large area typically requires more financial resource, time, and human labor than a small area. In this context, researchers might be interested in an extremely risk-averse strategy for examining the geothermal regions (an extremely pessimistic attitude). Based on the extreme risk aversion strategy, a location that is not suitable when considering one geothermal criterion value, while it is an excellent location with respect to all other criteria values, is not considered as a potential geothermal region. Alternatively, if the study involves a small area of analysis, researchers might take a lower risk-aversion attitude, resulting in a higher number of locations being identified as potentially suitable geothermal locations.

5. Conclusion

This paper presents an application of OWA-based method to develop geothermal prospectivity maps along the continuum ranging from the pessimistic to optimistic strategies. By specifying a value of ORness, decision-maker is able to control the level of risk and generate either a low or high-risk geothermal prospectivity map. The property of either risk-taking or risk-aversion could be suitable depending on the need to find a larger number of potential locations with lower level of accuracy (the higher percentage of wells and lower prediction rate) or find lower number of potential locations with higher level of accuracy (the lower percentage of wells and higher prediction rate). Since the value of ORness affects the number of locations (areas) being identified as
potential geothermal regions, an appropriate ORness could be determined as a function of geothermal development fund, time, and etc. For example, if the more fund and time are devoted to geothermal project, the bigger area could be explored, and then the higher value of ORness should be considered. In the case of limitations in cost, search time, and human resources, a more pessimistic strategy for generating geothermal prospectivity maps can be used. Malczewski and Rinner (2015) suggest that Fuzzy MCDM approaches provide us with a meaningful representation of uncertainties in GIS-based procedures. Consequently, the capabilities of risk modeling and uncertainties in OWA-based approach and fuzzy logic, respectively, could be combined to generate more accurate geothermal prospectivity maps.

References


