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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

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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 geothermal 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 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. Sadeghi 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 recovery 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 Kilic 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, Uyuz, 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 Malczewski 2008, 2010; Eldrandaly, 2013; Jelokhani-Niaraki and Malczewski, 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$F: I^n \rightarrow I$that has an associated set of order weights $V = [v_1, v_2,\ldots, v_n]$; $v_j\in [0,1]$ for $j = 1, 2, \ldots, n$ and$\sum_{j=1}^{n} v_j = 1$. Given a set of standardized attribute values $A_i = [a_{i1}, a_{i2},\ldots,a_{in}]$ 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:

$a \geq 0$

$$OWA_i(a_{i1}, a_{i2}, \ldots, a_{in}) = \sum_{j=1}^{n} v_j z_{ij} \tag{1}$$

where $z_{i1} \geq z_{i2} \geq \ldots \geq z_{in}$ is the sequence obtained by reordering the attribute values $a_{i1}, a_{i2},\ldots,a_{in}$. 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 $a_{i1}, a_{i2},\ldots,a_{in}$ 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_n assigned to the lowest attribute value. It should be noted that a particular value of a_{ij} is not associated with a particular weight v_j but rather the weight is assigned to a particular ordered position of a_{ij}. 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).