Rock typing in geothermal reservoirs: application of textural descriptors

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ABSTRACT

Geothermal energy is a key in the transition to 90% renewable electricity production by 2025, which is a target set by New Zealand government. 22% of the current national electricity generation comes from geothermal resources and it is expected to keep growing.

Geothermal systems can be represented at different space and time scales by reservoir models. A reservoir model provides useful information to make decisions and optimally manage these resources. For this purpose, robust models require coherent and realistic geoscientific and engineering input data, including physical properties of rocks. However, despite the fast development of tools to measure these properties, in many geothermal fields key petrophysical properties are not available at a scale appropriate to be used as input for reservoir modelling. This results in the need to explore alternative methods to determine such petrophysical properties.

This paper describes a rock typing method based on textural descriptors that are being adapted to volcanic rocks. It provides a classification method for rocks in geothermal fields based on their physical properties that govern the fluid flow. The geological implications of the rock typing system are discussed. Examples of potential applications of the method where the petrophysical data are limited are presented.

1. INTRODUCTION

New Zealand has committed to having 90% of its electricity generation from renewable sources in the next decade. In 2014, geothermal energy contributed to 22% in the national market and it is expected that will increase in the coming years (Ministry of Business Innovation & Employment (MBIE), 2015). In order to achieve this, ongoing research aims to enhance the understanding of geothermal systems and to pursue ways to reflect their complexity in the numerical reservoir models.

Reservoir models are key tools for decision makers to assess and manage the performance of geothermal reservoirs and ensure their sustainability over time. They represent the best knowledge of a geothermal system at any point in time by combining geoscientific and engineering data and information from all available sources. The key to a robust model is the reliability and coherence of its inputs, which is difficult to achieve if the appropriate data are not available.

In terms of petrophysical properties, computer simulators require numerical information about the hydraulic and thermal characteristics of the rocks to simulate the mass and energy transport processes observed (Pruess, Olderburg, and Moridis, 1999). These data, however, may not be available due to a lack of rock samples or laboratory tests, or the available data may be scarce, or not representative to be used at a reservoir scale. In these cases, important properties such as permeability, porosity and thermal conductivity, are assumed or fitted based on the best knowledge of the modeller.

In order to provide information about petrophysical properties for the numerical models, we are working on a rock typing method based on textural descriptors to be applied to volcanic and volcanogenic rocks in geothermal reservoirs. This approach will provide a way to assign values to the hydraulic properties of rocks in the numerical models when direct measurements or estimations of these properties are not available.

2. PETROPHYSICAL CHARACTERIZATION

For the purpose of reservoir simulation, rocks are better classified into units with similar physical properties (Archie, 1950; Corbett and Potter, 2004; Ebanks Jr, Scheihing, and Atkinson, 1992). In particular, petrophysical models aim to group rocks based on their ability to store and transport fluids and transfer heat. However these features are determined by the combination of the formational, diagenetical and tectonic processes that the rocks are subjected to (Sruoga and Rubinstein, 2007). This means that rocks belonging to the same lithotype, stratigraphic or depositional unit, for example, may display different petrophysical properties, therefore limiting the use of conventionally indexed rock units to non-altered rocks (Zou et al., 2013).

Various petrophysical classification methods are available for the characterization of reservoirs. They have been mainly developed for clastic or carbonate hydrocarbon reservoirs. Some of them, e.g., the Kozeny-Carmen equation and flow zone indicators (FZI), (Amaefule et al., 1992) require laboratory measurements of specific parameters and core analysis. This is a significant constraint in geothermal fields where core samples and measured properties are often not available. Other methods use relationships between porosity (φ) and permeability (k), but, because permeability does not have a simple correlation with porosity in complex reservoirs (Amaefule et al., 1993), simple correlations (e.g., Winland R_{35} in Pittman, 1992) have limited use for geothermal systems.

As an alternative, other classification methods for clastic and carbonate reservoirs use textural features observed on hand samples (Archie, 1952; Lucia, 1995; Sneider et al, 1983; Watton et al., 2014).

2.1 Textural descriptors for rock typing

Classification methods based on textural features of clastic and carbonate reservoirs have shown that particle size, sorting, packing, consolidation and degree of cementation are features that determine the geometry, size, volume, and interconnectivity of the contemporary pore system; hence they indicate how the rocks are likely to behave under exploitation at present time.

This textural approach offers a descriptive system to define petrophysical rock types and extrapolate them to uncored sections where drill-cuttings are available. Recently, the authors have studied the applicability of textural descriptors using volcanic, volcaniclastic and effusive rocks of a geothermal field of New Zealand (e.g., Prieto et al., 2015; Prieto et al., 2014). They provided definitions, descriptive methods and classification of textural features in terms that are adaptable and applicable to geothermal systems. They also showed the correlations observed between these descriptors and the values of φ and k measured on core samples, and suggested that further work was required to incorporate other descriptors including nature, source and occurrence of the pore-filling materials. These studies have showed a route to identifying the textural features with a stronger correlation with φ and k in volcanogenic rocks.

Some well-known petrophysical classification methods based on rock texture use a combination of descriptors. Archie's (1952) carbonates classification includes surface appearance, particle size, and micro and visible porosity; Lucia's (1995) carbonate classification considers pore type, rock fabric and particle size, while Sneider et al.'s (1983) classification is based on visible porosity, microporosity, pore type and consolidation.

Following these models, the authors have explored combinations of descriptors that are relevant to rocks in geothermal fields based on their hydraulic properties (φ and k) (Prieto and Archer, 2015). Through the use of unsupervised artificial neural networks we observed an intrinsic clustering within the studied samples using a limited number of descriptors which consistently appear to be controlling the hydraulic behaviour of the rocks: surface appearance, rock fabric, groundmass content and pore volume. However, the implications of the observed clustering were still to be discussed and the rock typing classification to be applied.

3. METHODS

3.1 Samples

190 samples have been selected from drill-cores collected in five boreholes of the Tauhara Geothermal Field, the eastern area of the Wairakei-Tauhara Geothermal System, located at the south of the Taupo Volcanic Zone (TVZ) in New Zealand (Fig. 1).

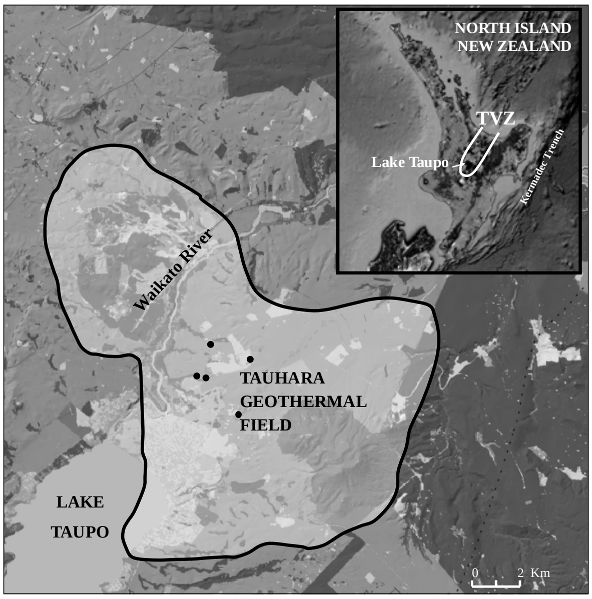

Figure 1: Location map of the studied wellbores in the Tauhara Geothermal Field (light grey shaded area) defined by the resistivity boundary at 500 mbgl (black outline, after Rosenberg et al., 2010) to the south of the Taupo Volcanic Zone, North Island of New Zealand.

The studied samples correspond to the Waiora Formation, Huka Falls Formation; Spa Andesite Formation and Racetrack Rhyolite Formation (Rosenberg et al., 2009), and include lava flows, pyroclastic and volcaniclastic rocks.

Core plugs (40 mm x 20-30 mm) were drilled from the drill-cores, washed with water, oven-dried for 48 hours at 40ºC, and then cooled down to room temperature. Details of sample collection are described in Nehler (2012). End trims of 1 to 1.5 cm long were cut off from the plugs and polished. Subsequently, end trims were broken apart to get freshly broken and dried samples available. A selected part of them was oven-dried again for 24 hours, vacuum saturated with a blue colored resin, and left to permeate for 24 hours. The dyed surfaces were polished to better identify the 2D pore geometry. High resolution digital photomicrographs of the samples were taken with reflected light before and after impregnation for image analysis.

3.2 Petrophysical tests

Petrophysical properties measured in the collected samples of the Tauhara Geothermal Field include density, porosity, matrix permeability, thermal conductivity and specific heat capacity (ρ, φ, k, h). The analyses, methods and results are reported in detail by Mielke el al. (2015). In this study, only hydraulic properties are used.

Drilled core plugs were used to calculate effective gas permeability by using steady-state air flow in a Hassler-cell columnar permeameter that uses the steady-state air flow method. Plug end trims were used to measure raw density in a helium-driven pycnometer, AccuPyc II 1340 (Micromeritics, 2014b); and gross volume in a density analyser, Geopyc 1360 (Micromeritics, 2014a), that applies a displacement technique to a quasi-fluid. Subsequently, bulk density and air effective porosity (%) were calculated.

3.3 Textural descriptions

Prieto and Archer (2015); Prieto et al.(2015); Prieto et al. (2014); Prieto (2014) have provided detailed definitions and classification of the studied textural descriptors. Each descriptor was analyzed and classified on every sample using classes and numbers from Table 1.

Drill-cores, plugs and end trims were broken systematically to record the sample degree of consolidation (Sneider et al., 1983). The dried, freshly broken chips were examined under a binocular microscope with reflected light at 20x magnification to determine classes of rock surface appearance (Archie, 1952), rock fabric (Lucia, 1995), sorting (Folk and Ward, 1957), groundmass content, micropores (Archie, 1952) and macropores volume (Sneider, 2010a), particle and pore size (Wentworth-Udden-Krumbein scale), pore type (Lucia, 1995), and pore-filling material, origin and occurrence (Prieto et al, in preparation).

Comparison charts (Beard and Weyl, 1973; Folk, 1951) were used as aids to visually identify classes for particle and pore size, sorting, and percentage of groundmass content and visible pore volume.

Additionally, image analyses on digital photomicrographs of pre- and post-impregnated end trims were performed using JMicroVision (Roduit, 2014) to corroborate the percentage of groundmass content, particle size and sorting.

Table 1: Classification of textural descriptors, modified from Prieto and Archer (2015).

	Textural parameter	Class	Description	Class	Description
	Rock surface appearance (SA)	1 2 3	Granular Chalky Compact		
	Rock fabric (RF)	1 2 3 4 5	PDom/ PSup + open IPS PDom / PSup + open IPS part. filled GmDom / PSup + IPS filled GmDom / GmSup with >10% PC GmDom / GmSup with <10% PC		
	Particle size (mm) (PS)	1 2 3 4	>2 1 – 2 0.5 - 1 0.25–0.5	5 6 7 8	0.12 – 0.25 0.06 – 0.12 0.02 – 0.06 <0.02
	Sorting (SO)	1 2 3 4 5	Equigranular Moderately equigranular Inequigranular Very inequigranular Bimodal		
	Groundmass content (%) (GMC)	1 2 3	0 – 30 >30 – 60 >60		
	Consolidation (CO)	1 2 3 4 5 6	Unconsolidated Slightly consolidated Moderately consolidated Moderately-well consolidated Well consolidated Very well consolidated		
Visible porosity	Pore volume (%) (PV)	1 2 3 4	>30 30-20 20-10 <10		
Visible porosity	Pore size (mm) (PORS)	1 2 3 4	PORS-A non-visible PORS-B <0.125 PORS-C 0.125-2 PORS-D>2		
Visible porosity	Pore types (PT)	1 2 3	Separated vugs Touching vugs Interparticle		
Pore-filling material	Material (PFM)	1 2 3 4	Clay Silica Glass Groundmass (unidentified)		
Pore-filling material	Source (PFS)	1 2 3	Detrital Diagenetic Metamorphic		
Pore-filling material	Occurrence (PFO)	1 2	Matrix Cement		

3.4 Rock typing

Each analyzed sample was identified by combining the descriptors numbers as exemplified by Sneider's 2010 (Fig. 2). The combination of descriptors relevant to these samples was studied by using Self-Organizing Maps (SOMs), useful in the observation of intrinsic patterns within the dataset.

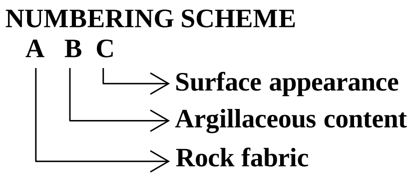

Figure 2: Example of sample number classification scheme after Sneider (2010).

The SOMs were built using the Neural Network Toolbox 8.1 (MatLab R2013b®). Normalized descriptors numbers (between 0 and 1) were used as inputs. To train the networks, the batch SOM weight learning function was used for an arbitrary number of neurons (e.g., 9, 12, 16), arranged in a 2-dimensional hexagonal topology. The Euclidean distance was used to calculate the distance between neurons, and the negative Euclidean distance was used to calculate the difference between weights and input vectors. In the learning phase, the neighborhood size was set to decay linearly from 3 to 1 over 1000 steps and the learning rate was set to 0.9, while in tuning phase they were set to 1 and 0.02 respectively. See Prieto and Archer (2015) for details on SOMs definition, set up and use. The graphical output of the networks (hit plots, weight distances plots and weight planes) allows establishing relationships and trends between the input parameters and grouping input data in classes if existing.

4. RESULTS

To take into account the wide variety of materials occluding the pore space, the nature (composition), source (origin) and occurrence (manifestation) of the pore-filling materials have been incorporated in the analysis. Cross-plots of effective porosity and air permeability show the correlation between classes of these descriptors and these two hydraulic properties. No correlation is observed between the composition or origin of the pore-filling materials and these two properties (Fig. 3a and 3b). In contrast, it is observed that cemented rocks display lower values of φ and k compared to those ones formed by a matrix (Fig. 3c).

The correlations between individual descriptors and k/φ showed stronger effects of some features over others, namely rock fabric, groundmass content, consolidation, pore volume, pore size, pore type and occurrence of pore-filling material (Fig. 4). These features were used to initialize the SOMs which help determining the relevant descriptors for a rock typing system.

Fig. 5 shows the graphical output of a neural network for the numbering scheme RT1: RF, GMC, CO, PV, PORS, PT, PFO. The distribution of Best Matching Units in the hits plot (Fig. 5a) suggests three clusters around the highest concentration of samples. However, the connections between neurons do not create valleys separating these clusters (Fig. 5b); therefore, there is no clear subdivision of the samples. The weight plots show a positive correlation between consolidation and pore size, and smaller weights or relevance for rock fabric and pore volume.

Figure 6 shows the graphical output of RT2: GMC, CO, PORS, PT, PFO; and RT3: GMC, CO, PT, PFO where four clusters are identified. The clusters are evident with the high number of samples concentrated within few neurons and with low distances (light colors) between close neurons. Additionally, the separation distance between the clusters is big (darker connections) making it easier to distinguish them. Better differentiation is observed for the clustering type RT3.

The indexed samples given by the SOM for RT3 were then plotted in a φ-k cross-plot (Fig. 7) to show their distribution. It can be observed that four clusters are distributed in different regions of the plot, three of them with a parallel distribution mainly varying the k/φ ratio between them, and a fourth more limited to low values of both porosity and permeability.

5. DISCUSSION

The rocks found in geothermal fields are highly subjected to diagenetic processes; therefore it is important to determine to what extent diagenetic processes modify the petrophysical properties of the rocks. This study shows that knowing the occurrence of the pore-filling material is more relevant than its composition or its origin in terms of texture, and so this descriptor is to be included in our analysis.

SOMs are useful in the detection of unknown patterns and clusters within datasets for petrophysical analysis. Although every network generates a different result in each training session, we find that they provide a consistent output in terms of clusters within our set of data. Nevertheless, the statistical difference between the clustering types and other topologies will be further investigated and reported in future work. Using SOMs is an alternative to the subjective criteria of the analyser regarding which descriptors are to be used in a petrophysical classification.

By reducing the descriptors to be considered, we aim to simplify the analysis to be carried out in order to give a first estimate of porosity and permeability for reservoir characterization when there are not laboratory tests available. With a combination of four parameters we are able to see a distribution of samples within the φ and k map that will allow us determining a mathematical representation to be used for prediction purposes. This is subject of current work.

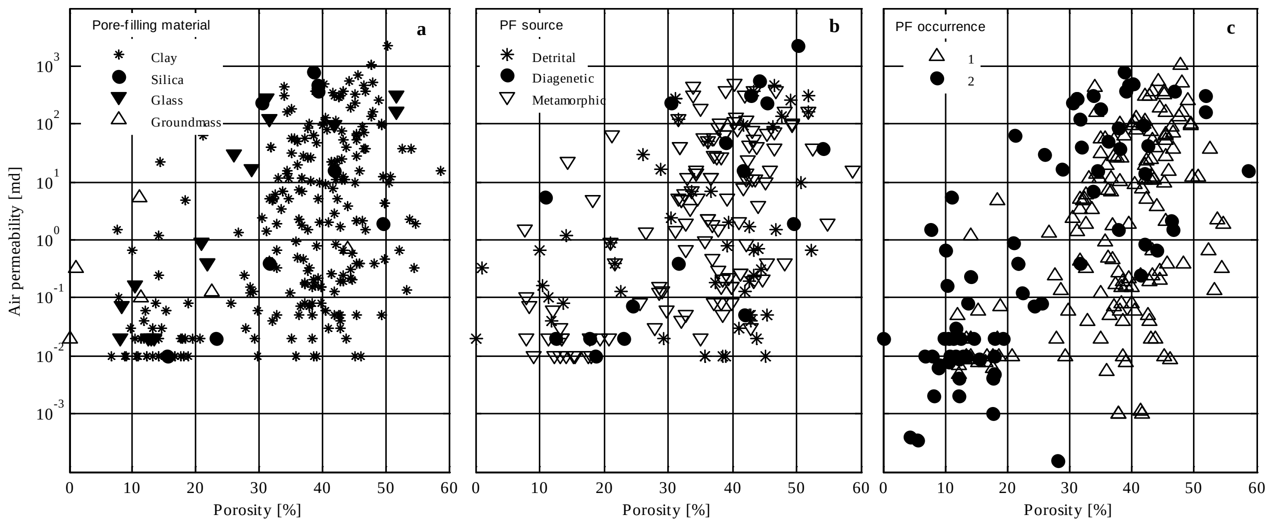

Figure 3: Effective porosity vs. air permeability cross plots comparing classes of textural descriptors (a) pore filling material-PFM; (b) pore-filling origin-PFS; (c) pore-filling occurrence-PFO.

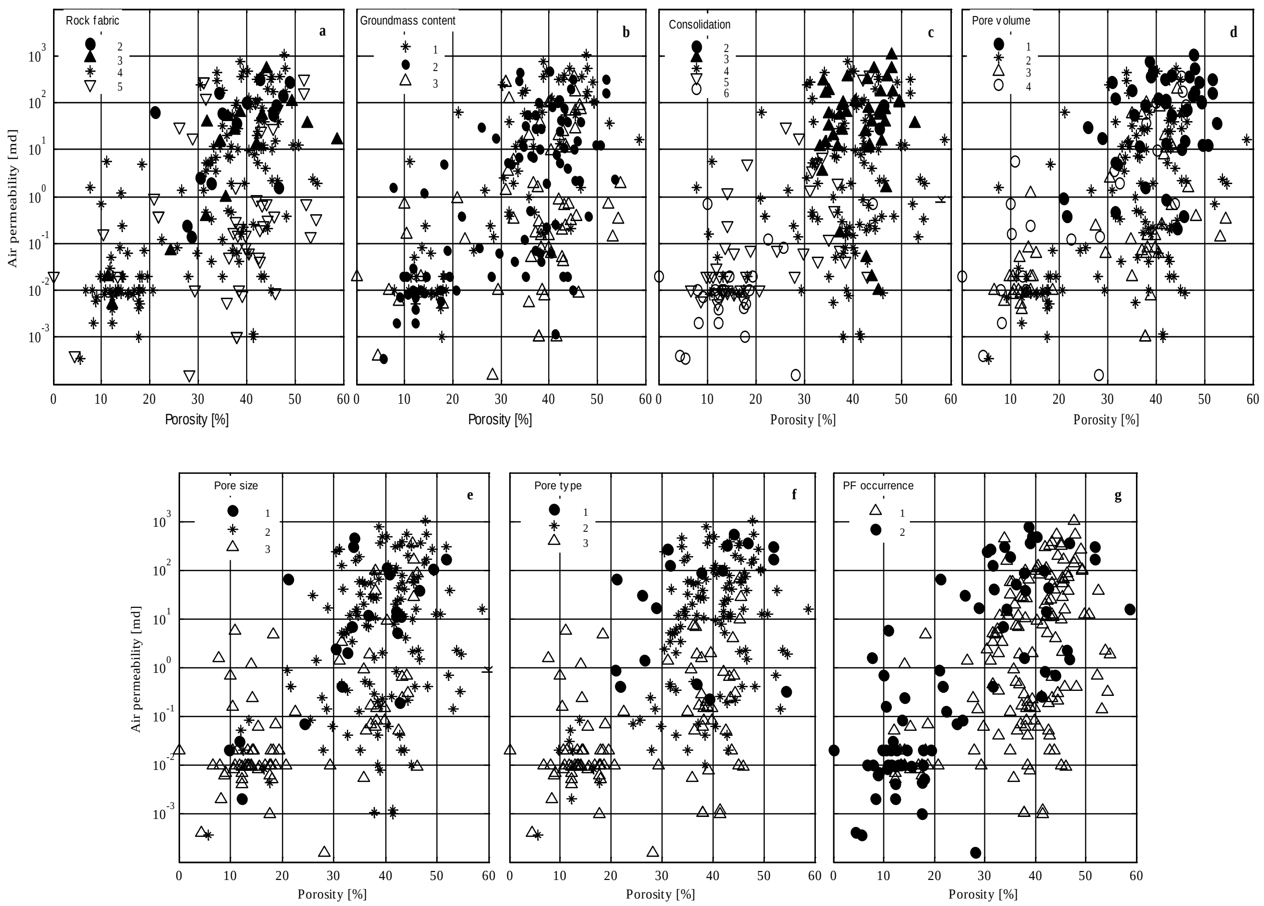

Figure 4: Effective porosity vs. air permeability cross plots comparing classes of selected textural descriptors (a) rock fabric; (b) groundmass content; (c) consolidation; (d) pore volume; (e) pore size; (f) pore type; (g) pore-filling material occurrence.

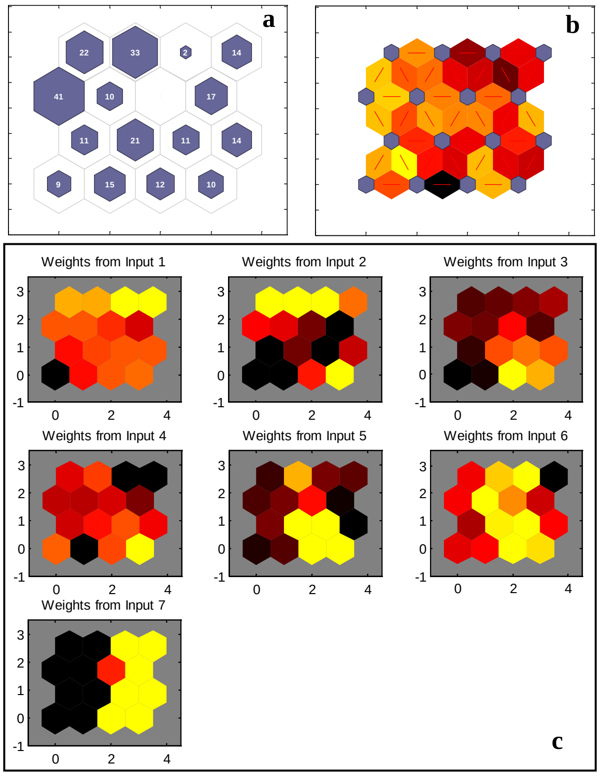

Figure 5: Graphical representations of a SOM for the numbering scheme RT1. (a) hit plot; (b) weight distances plot; (c) weight planes plot featuring descriptors: RF, GMC, CO, PV, PORS, PT, PFMO.

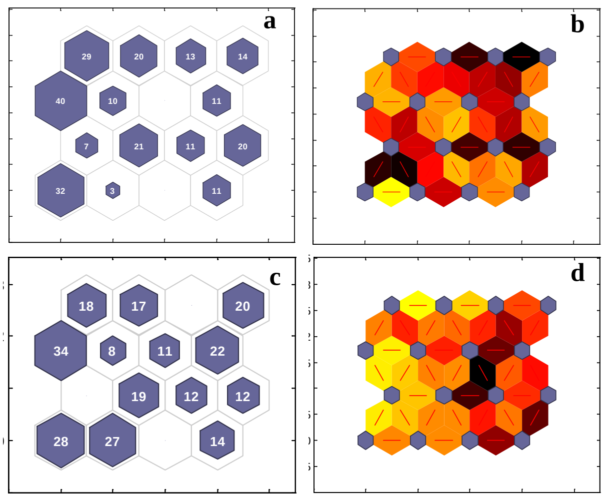

Figure 6: Hit and weight distances plots of SOMs for the numbering schemes RT2 (a-b) and RT3 (c-d).

In terms of geological significance, it can be observed that rocks that display different textural features may correspond to the same petrophysical class. This is because in all rocks there are one or two dominant features that condition their hydraulic behaviour. For example, rocks corresponding to class 2 of RT3 have <60% groundmass content, are mainly moderately to well consolidated, have touching vugs as a pore type and are not cemented. In contrast, class 3 rocks may have any groundmass content, are mainly well to very well consolidated, do not have visible porosity and are cemented. This rock typing method simplifies the values of porosity and permeability to be assigned to entire sections of wellbores, across geological formations, as shown in Fig. 8. This is a potential application to enhance the upscaling of petrophysical data from cores to reservoir scale.

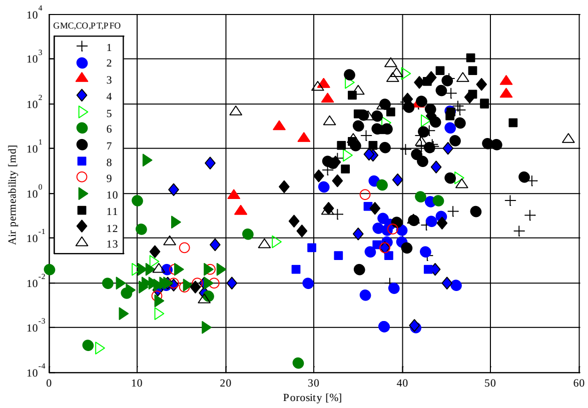

Figure 7: Effective porosity and air permeability cross- plot with indexed samples for RT3.

Another application includes the prediction of petrophysical values. Once there are sample rocks available with known properties, it is possible to use them as analogues and assign these properties to the uncored or untested sections, regardless of the lithology, geological formation or location. Few sections of the wellbores in Fig. 8 are represented by the same numbering scheme and, therefore, the same rock type could be assigned even without measured values available.

6. CONCLUSIONS

This work complements previous studies evaluating textural descriptors to be used in petrophysical characterization of geothermal reservoirs. It has been observed that rock fabric, groundmass content, consolidation, pore volume, pore size, pore type and occurrence of pore-filling material are descriptors that display a stronger correlation with porosity and permeability. We have used groundmass content, consolidation, pore type and occurrence of pore-filling material as features to generate rock types.

In terms of geological significance, there are one or two features that affect in a stronger way the hydraulic properties of a rock. Rocks may display different textural features and still belong to the same rock type. Therefore, the same rock types can be found across also wellbores and formations regardless of the geological formations or lithologies.

SOMs are useful tools to study clustering and classification patterns of samples where they are not obvious to the human eye. The graphical output available to visualize the results aids in recognizing

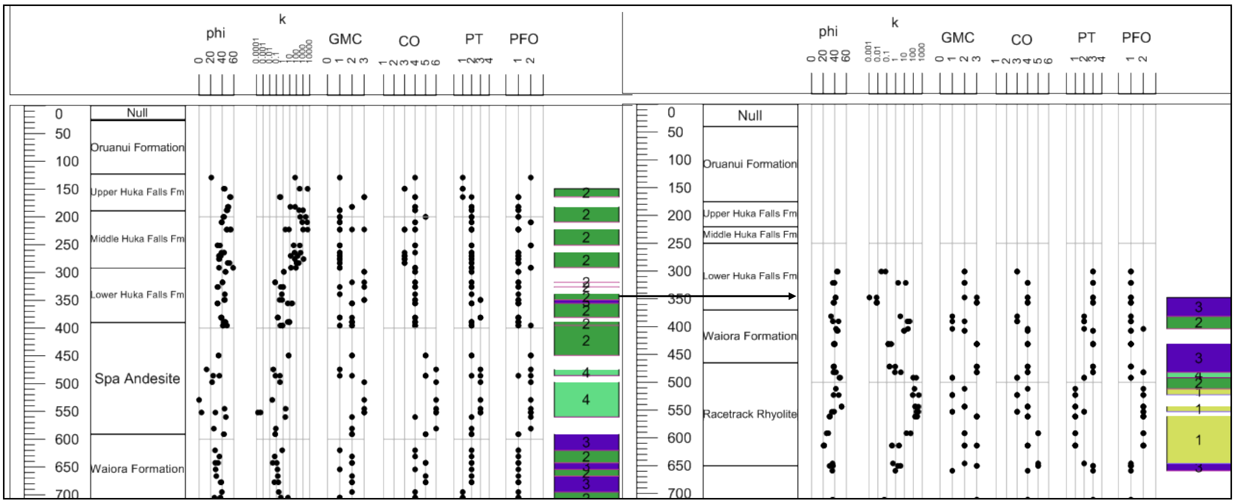

Figure 8: Well sections displaying measured porosity and permeability and descriptors logged at depth.

trends and correlations. This makes the SOMs useful for petrophysical analysis application.

Further work is needed to study the effect of textural descriptors in thermal properties, so they can be included in the petrophysical characterization of geothermal reservoir rocks.

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