Introduction of a Rock Typing Methodology in Crystalline Basement Reservoirs (Yemen)*

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Abstract

It is essential to investigate the petrographical composition of a reservoir, particularly with regard to the response of the relevant rock types to the borehole logs before petrophysical properties can be evaluated accurately. This applies in particular to basement reservoirs because their lithological content is very different from typical sedimentary reservoirs. The mineralogical composition of crystalline rocks in the Yemen Habban-Basement, containing metamorphic, volcanic as well as igneous rocks, is very variable and can be difficult to correlate between wells. Consequently, the reservoir delineation based on standard techniques was not successful, and a specific rock typing approach had to be invented.

Because the variety of different rock-building minerals was too large to be handled by a standard multi-mineral model, and also the responses of conventional logging measurements have not been calibrated to most of the minerals present in the basement, it was decided to run a rock-type model rather than a mineral model. This rock-type model has been based on a supervised neural-network which was trained on the petrographical analysis of cores, sidewall-cores and cuttings.

The lithological inventory has been grouped into five dominant rock-types which proved to be most representative for the reservoir. By using a neural-network model, these rock types could be identified successfully from the logging data in subsequent wells. Using this technique, key petrophysical parameters could be evaluated and associated to the basement lithology in a very cost effective way since only conventional logging data is required.

Introduction

Throughout the last five years OMV Yemen has successfully drilled several oil-bearing appraisal and development wells in the Block-S2 (Al-Uqlah) permit, located at the northern border of the Shabwah province in central Yemen. The Proterozoic crystalline fractured basement (referred to as Habban-Basement), which is structured as a series of horsts and grabens, is considered the primary target in this field development. The Block S2 (Al Uqlah) straddles the northern branch of the Sab'atayn Basin, which is a NW-SE- striking Late Jurassic intra-cratonic rift basin. It is part of an extensive system of basins which trend across southern Arabia and the Horn of Africa, from Sana'a in the northwest to the east coast of Somalia in the south.

The lithological composition of the crystalline basement consists mainly of various meta-volcanics (feldspar-gneisses, schists and amphibolites), which have been formed by regional metamorphism during at least two phases of deformation. Post-dating these events, the metamorphic roof has been intruded by a granitic pluton which later caused lamprophyres and acidic dykes to cut into the metamorphic rocks.

To attempt both lithological correlations between the wells and to derive continuous lithology logs in order to evaluate rock-type specific petrophysical parameter sets, extensive studies have been carried out to delineate the mineralogical and lithological composition of the basement rocks. The work presented here focuses on the identification of crystalline lithology from conventional borehole logs.

Methodology and workflow

In conventional sedimentary reservoirs the fundamental mineralogical composition is determined by multi-mineral solvers (probabilistic or deterministic) which are based on the known response of typical sedimentary minerals to geophysical borehole logs. Since the crystalline basement in Block-S2 is composed of abundant atypical minerals, which mostly have not been characterized by their responses to logging measurements, a conventional multi-mineral processing could not be applied successfully.

In addition to this, the limited number of available geophysical input equations did not allow us to model the mineralogical composition in respect to the vast number of different minerals that have been identified in thin sections and x-ray diffraction analysis. Therefore, it was deemed more practical to identify rock-types rather than to quantify the mineralogical composition of the Habban-Basement.

The initial stage of this study included logging data, cores and cuttings from six wells. The lithology analysis is based on a neural network that has been trained on the petrographic description of cuttings and cores. Five main litho types have been classified and identified from petrographic core and cutting analysis.

The neural-network lithology processing has been designed as a two-fold process. First, an unsupervised neural-network has been used to estimate the maximum number of rock-types that can be distinguished meaningfully from the available input logs. The second phase involved a supervised neural-network which was trained on specific intervals of logging data (two wells), representing known lithologies from core and cutting descriptions. The neural-network architecture consists of two hidden layers, including ten neurons each and was run with 200 iterations, which gave the most effective processing setup in the Habban-Basement case. To eliminate less reliable output, a probability threshold was introduced and sections showing less than 60% probability have been mapped as “undefined rock-type”. The calibrated neural-network model has been propagated to four offset wells in the field and its output has been successfully validated.

The following eight borehole logs have been selected for input to the supervised neural-network as they showed sufficiently high sensitivity to the five main rock types:

RHOB	(bulk density)	**NPHI**	(neutron porosity, borehole corrected)
GR	(total gamma ray)	**PEF**	(photoelectric factor)
URAN	(uranium content)	**THOR**	(thorium content)
PR	(poisson ratio)	**POTA**	(potassium content)

Crystalline Rock-Types and Their Response to Borehole Logs

As mentioned in the introduction the Habban-Basement consists of a metamorphic series which was intruded by a granitic pluton. Five dominant rock types have been defined and grouped by the neural-network approach:

- **felsites** (mainly acidic meta-volcanics with gneiss and schist texture)
- **basic meta-volcanics** and dykes (lamprophyres, amphibolites as well as cemented cataclasites)
- **hydrothermal altered meta-volcanics** (mafic and felsic rocks)
- **granite** (low potassium)
- **granite** (high potassium)

To display and extract significant relationships between rock-types and log responses, and to control the output of the neural-network, cross-plots have been used. The most sensitive logs for rock matrix variations for all crystalline rocks within the Habban-Basement are the RHOB bulk density log and the GR log (Figure 1), in particular the potassium content of the gamma spectra log (Figure 2). With regard to rock type and the mineralogical composition, the amount of K-bearing minerals controls the GR and potassium (POTA) logs to different degree.

Potassium shows the highest correlation to the mineral group K-feldspars (orthoclase), muscovite (here sericite) and biotite, since these minerals contain a considerable amount of potassium in their crystal lattice. Consequently, a change in the potassium content is indicative of both granite rock types due to the variation in content of potassium minerals.

The potassium content in certain gneiss and schists (felsic meta-volcanics) also shows a range of potassium levels. However, these acidic meta-volcanics cannot be distinguished from each other based on the input logs. The low-K meta-volcanics most likely represent hornblende (amphibole) gneiss, while the high-K meta-volcanics represent muscovite and sericite-gneiss.

The same observation can be made at the rock class as basic meta-volcanics are most likely caused by the variations of biotite content.

Low potassium content is assumed to be indicative of increased chlorite content in the Habban-Basement.

Correlation analysis has also revealed strong correlations between rock density and mineralogy. Since heavy minerals, such as amphibole, pyroxene and biotite, are the main components in the mafic meta-volcanics and dykes, bulk density can be used to map these rock types. Generally, the bulk densities of granites and acidic meta-volcanics are comparably low and read about 2.60–2.70g/cc, whereas RHOB ranges between 2.75–3.30g/cc in the mafic rocks (maximum reached in amphibolites). However, cataclasites also show increased bulk densities due to the content of pyrite, ankerite (Fe-carbonate) and dolomite cements.

The classical RHOB-NPHI cross-plot (Figure 2) displays how altered rocks are differentiated by their density from acidic rocks (granites and felsic meta-volcanics) and mafic rocks. A clear trend towards higher grain densities is observed from acidic mineral paragenesis to basic mineralogy. The NPHI to RHOB spacing is the critical discrimination of altered rocks to mafic rocks in the neural network. Altered rocks tend to have a higher content of sheet silicates, such as mica (e.g., chlorite).

This trend is also followed by the poisson ratio PR. Those rocks showing high bulk densities can be differentiated by their dynamic elastic properties from other rock classes. Generally the stiffness of mafic meta-volcanics, such as amphibolite and lamprophyres, is higher than most of the acidic meta-volcanics. Nevertheless, the correlation of poisson ratio to rock types is not as strong as the one of bulk density. Only a weak trend can be observed.

By looking at the PR-NPHI cross-plot (Figure 3) a broad range in poisson ratio can be observed for the felsic meta-volcanics compared to relatively narrow poisson ratio bandwidth in all other basement rock-types. The poisson ratio in the acidic meta-volcanics is likely to be a function of schistosity and fracture density. A significant correlation between neutron porosity NPHI and rock composition has also been revealed. NPHI increases with increasing quantities of amphiboles and micas (muscovite and biotite). Rocks with high mica and amphibole content, such as amphibolite and biotite gneiss, plot in a different area of a NPHI/POTA cross-plot compared to granites and acidic meta-volcanics. The high neutron porosity values of some rock-types and the observed correlation to mineralogy can be explained by the physics of the neutron log measurement.

It is evident that the recorded high neutron porosities are a result of rock matrix effects. Apart from the NPHI response to minor clay volumes in altered basement, OH-bearing minerals can contribute significantly to the total hydrogen content in crystalline rocks measured by the neutron logs. One can observe a positive correlation of neutron log response with the volume of amphibole and mica-bearing rocks since these minerals have incorporated OH-groups in their lattice. On the contrary, quartz and feldspars are free of hydrogen. Since the overall effective porosity in the basement rocks is less than 3% on average, the response of the neutron log to fluids is negligible. Furthermore, the presence of certain rare-earth and trace elements with particularly large capture cross-sections (e.g., boron, lithium and cadmium) can have a significant effect on the neutron log readings.

Uranium along with potassium (as discussed above) shows strong correlations to both granite rock-types (Figure 4). This correlation makes it possible to distinguish high potassium (>2%), low uranium (<15ppm) granite from low-potassium, high-uranium granite (Figure 5). Most likely the uranium-bearing mineral is zircon.

Thorium content (associated with monazite) is relatively high whenever the potassium volume is increased and vice versa. Although this trend is not that strong, thorium can be used as discriminator for the granite rock-types in addition to the potassium and uranium content. No correlation of thorium to the other rock-types has been observed.

Uranium and thorium are also quoted in the literature as inclusions in biotite, pyroxene and amphiboles. Nevertheless, the thorium content is generally lower in the basic meta-volcanics than in the acidic ones.

No correlation to rock-types has been observed at the resistivity log and the sonic p-wave slowness. Both logs seem to be essentially insensitive to the mineralogical composition of the basement rocks. However, this behavior of resistivity and sonic log in basement environment is important for the evaluation of total porosity, as will be shown in a successive publication.

Conclusions and Discussion

Considering the limited number of borehole logs together with the manifoldness of the crystalline lithology in the Habban-Basement, as observed in cores and cuttings, a fully quantified and detailed lithology breakdown could not be achieved. However, by designing a neural-network-driven identification process of main basement rock-types the prevailing lithologies could effectively be quantified from standard borehole logs without acquiring expensive geochemical logs or coring extensively. The most powerful discrimination between different rock-types in the Habban-Basement is given by a combination of conventional bulk density, neutron porosity and potassium logs.

An attempt to correlate lithologies between wells based on the result of this study could not be achieved, apart from the successful correlation of the granitic intrusion. The Habban-Basement is intersected by vertical to sub-vertical faults showing substantial throw in the order of hundreds of meters, making any correlation effort impossible, even between closely spaced wells (one kilometer apart). Nevertheless, due to the availability of continuous lithology logs, together with the approach described in this work, it was possible to understand the impact of lithology on petrophysical parameters, such as porosity, porosity-types and fracturing. This was an essential step towards populating the basement earth-model with rock-type specific reservoir parameter sets.

Acknowledgements

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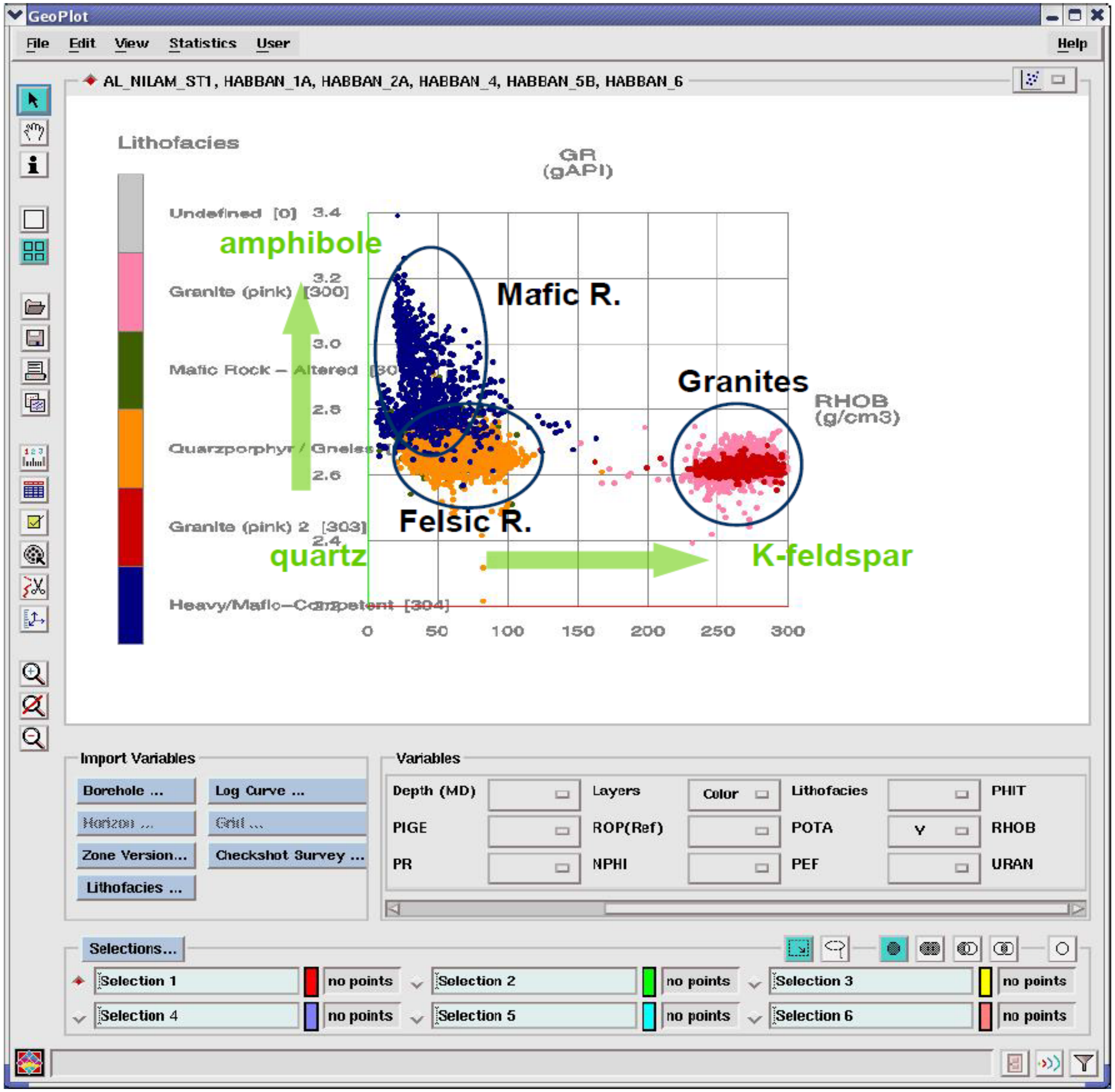

Figure 1. GR-RHOB cross-plot with rock types. Diagram including the mineralogical end-members which control the relationship between gamma-ray and density in Habban-Basement lithology.

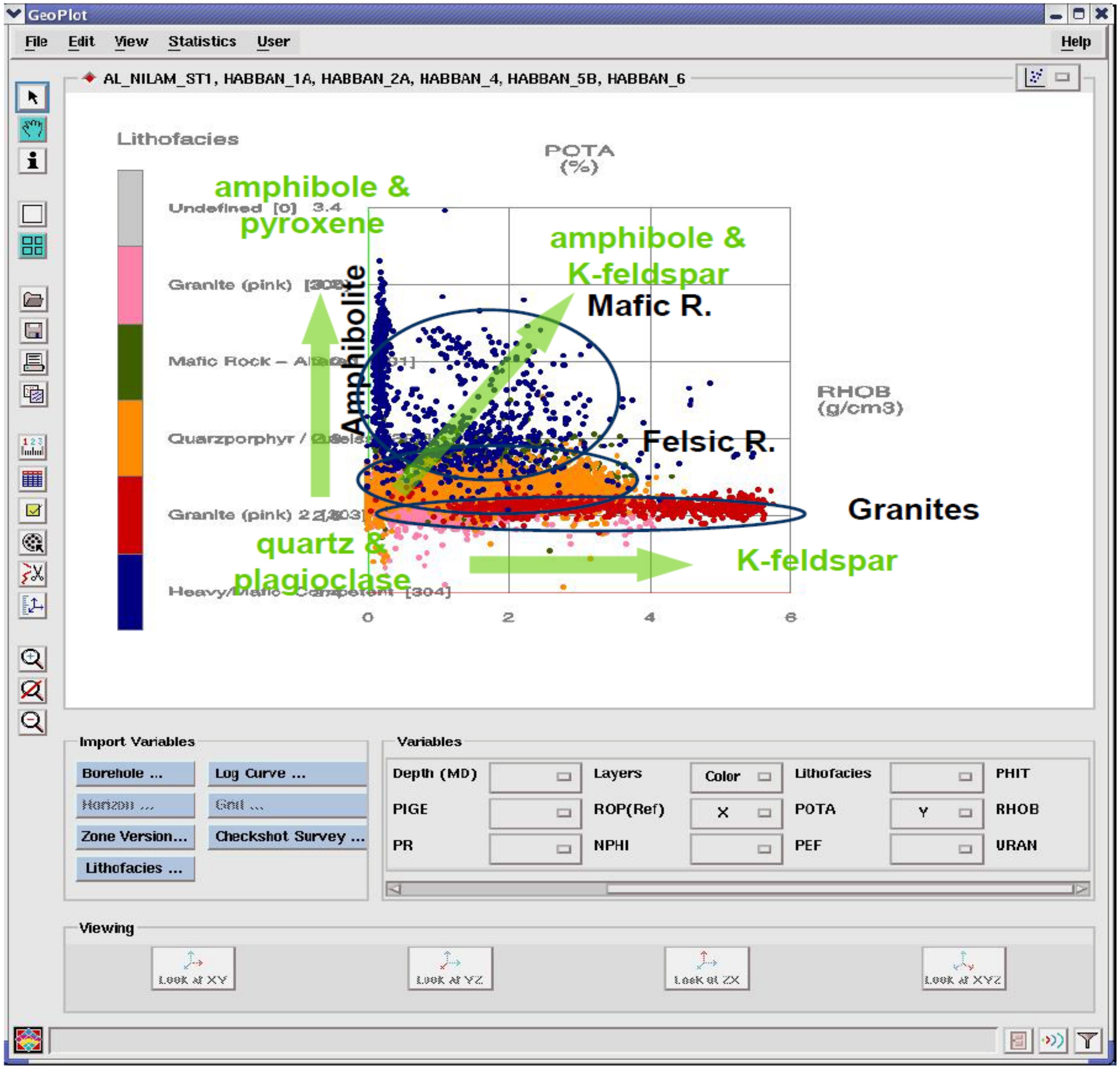

Figure 2. POTA-RHOB cross-plot with rock types. Diagram including the mineralogical end-members which control relationship between potassium and density in Habban-Basement lithology.

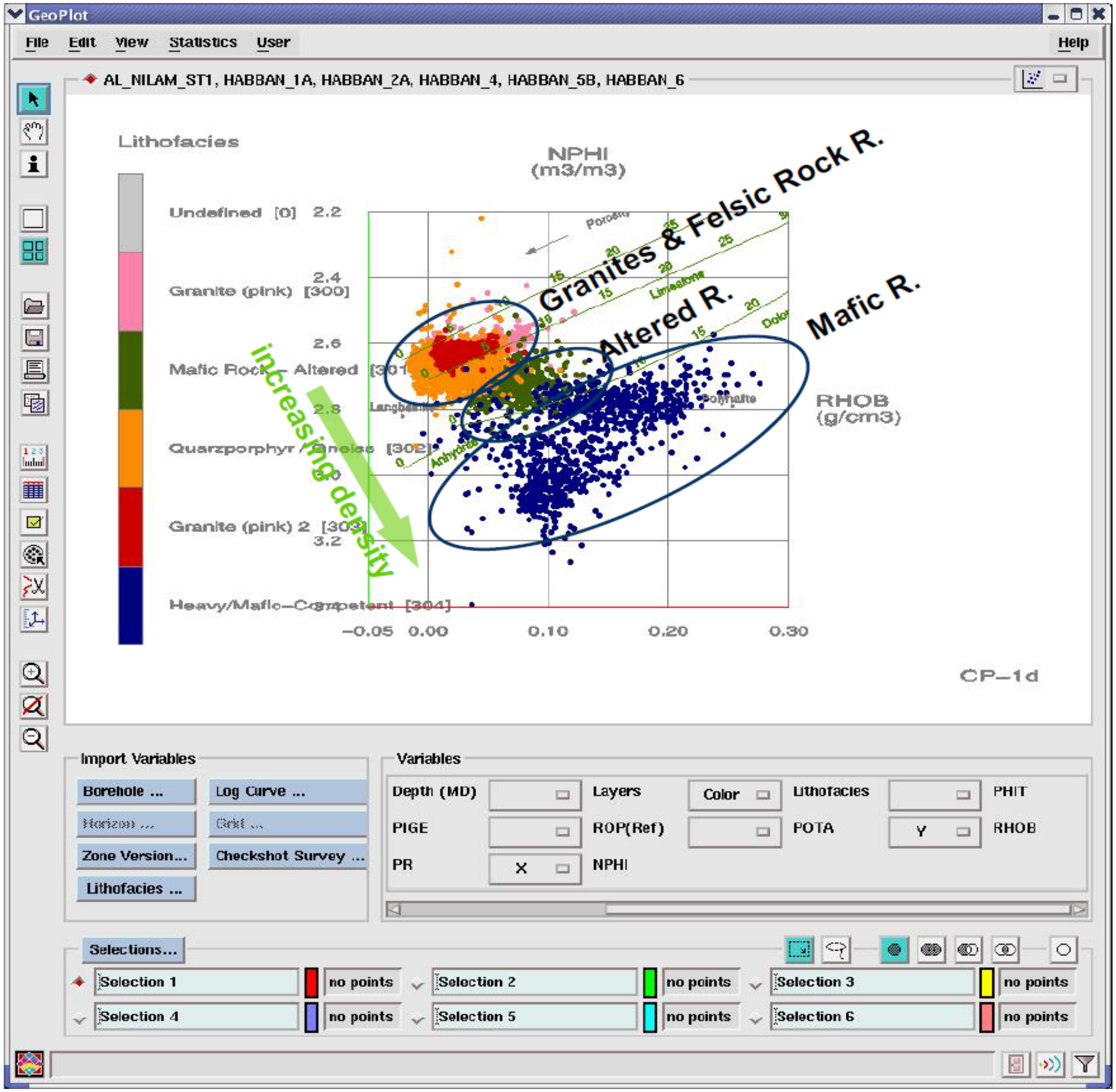

Figure 3. RHOB-NPHI cross-plot with rock types. Diagram with ovely (sediments) showing differentiation of mafic altered rocks and acidic igneous rocks.

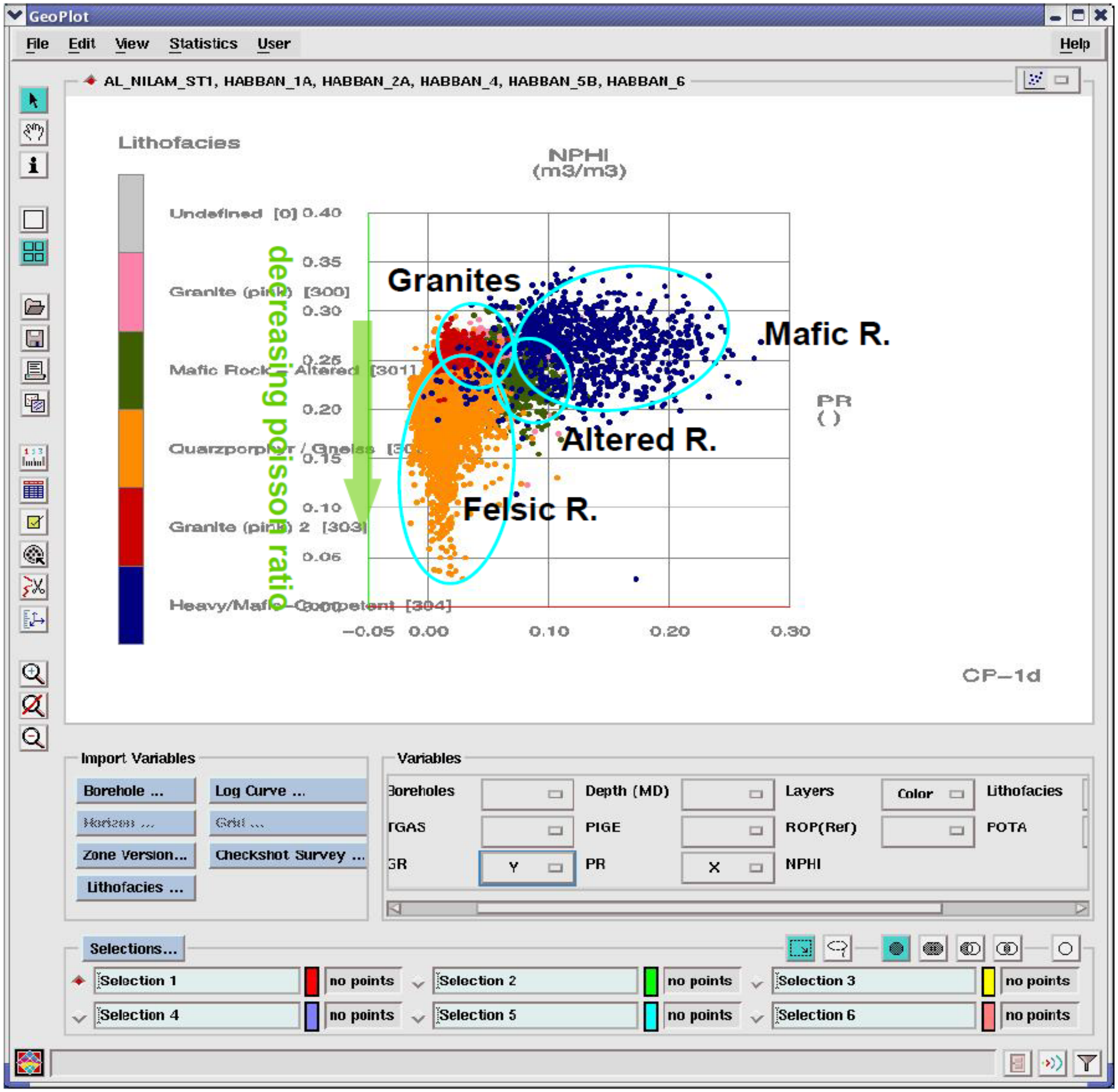

Figure 4. PR-NPHI cross-plot with rock types. Diagram showing broad range of PR in felsic rocks compared to granites, altered,and mafic rocks.

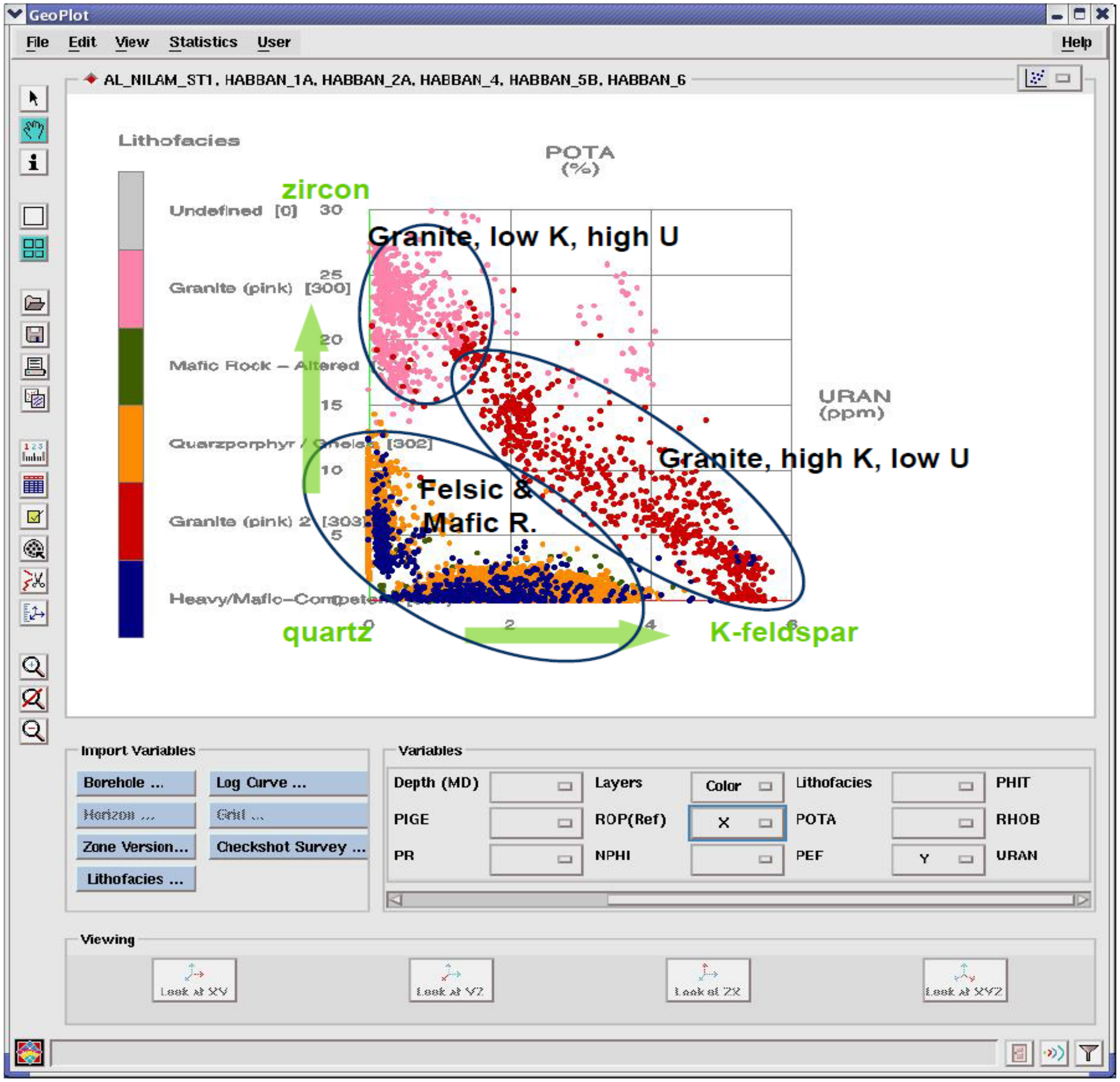

Figure 5. POTA-URAN cross-plot with rock types. Diagram including the mineralogical end-members which control the relationship between potassium and uranium in Habban-Basement lithology.