Geology differentiation: A new frontier in quantitative geophysical interpretation in mineral exploration

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Abstract

Geophysics aims to image subsurface geologic structure and identify different geologic units. While the former has dominated the interpretation of applied geophysical data, the latter has received much less attention. This appears to have persisted despite applications such as those in mineral exploration that inherently rely on the inference of geologic units from geophysical and geologic observations. In practice, such activities are routinely carried out in a qualitative manner. Thus, it is meaningful to examine this aspect and to develop a system of quantitative approaches to identify different geologic units. The development of geophysical inversions in the last three decades makes such interpretation tools possible. We refer to this newly emerging direction as *geology differentiation* and the resultant representation of geology model as a quasi-geology model. In this article, we will provide an overview of the historical background of geology differentiation and the current developments based on physical property inversions of geophysical data sets. We argue that integrating multiple physical property models to differentiate and characterize geologic units and work with the derived quasi-geology model may lead to a step change in maximizing the value of geophysical inversions.

Background

Beginning in the early 1990s, generalized inversions have transformed geophysical data interpretation in mineral exploration. The development moved interpretation from anomaly "bump hunting" in the data domain to 2D and 3D imaging in the model domain based on the inverted physical properties. Many successful examples have been presented in the literature. The decades of development of geophysical inversions have greatly expanded our ability to invert many different types of geophysical data and dramatically enhanced the capability of the algorithms in tackling ever increasing sizes of the data and model. New acquisition technology and newer data sets (e.g., distributed data acquisition with high-power transmitters in direct current resistivity and induced polarization [DC/IP], airborne gravity gradiometry, and z-axis tipper electromagnetics [ZTEM]) have greatly increased the depth of investigation of these data sets in the form of imaged physical property distribution at depth and the associated resolutions. Tremendous advances in inversion algorithms and software have occurred in the past two decades. Virtually all data types typically used in mineral exploration can now be inverted, and a comprehensive set of inversion tools are available.

Given the numerous successes of geophysical inversions and their routine use in the interpretation of exploration geophysical data, we might have expected a significant increase in the number of discoveries. However, such an outcome has not been borne out by statistics. Figure 1 shows a chart by Schodde (2017), which is well known in the mining community. One feature that has drawn much attention is the decreasing number of discoveries in the 2007–2012 period when the exploration expenditure was increasing. What is interesting but has not drawn attention is the following observation.

Around 1995 was when the widespread use of geophysical inversions started. One of the authors of this article is fortunate to be a part of that effort while working with the University of British Columbia Geophysical Inversion Facility (UBC-GIF), which contributed to many inversion algorithms and associated software. It could be stated that either the use of these inversion methods has not significantly increased the discovery rate or the increase has not been sufficient to offset other negative factors. Therefore, besides asking the common question of what the challenges for new discoveries are, one could also ask a different question from the point of view of geophysics. Why has quantitative interpretation based on geophysical inversions not made a clear difference in discovery rate? This question becomes even more important when considering the multitude of advances in geophysical instrumentation and field acquisition methods, which clearly have led to more and higher quality data necessary for geophysical inversions.

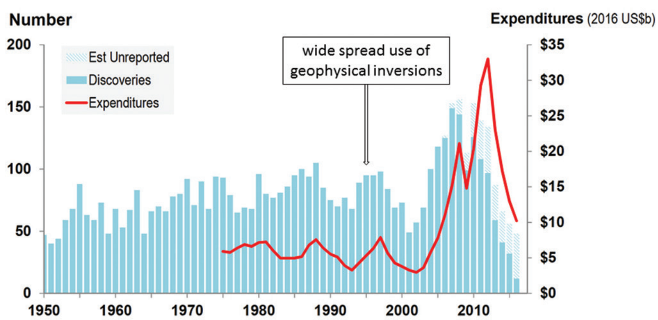

Figure 1. Number of discoveries in mineral exploration since 1950 presented by Schodde (2017). The year 1995 approximately marks when the widespread use of 2D and 3D geophysical inversions started. It appears that the introduction of geophysical inversions as a quantitative tool did not significantly change the discovery rate. (Modified from Schodde, 2017.)

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To understand why, it is worth asking another question. Have we tapped into the full potential of geophysical inversions? If one agrees that geophysical inversion has not fundamentally changed the discovery rate, the answer would be no. Such an answer then invites a logical question. What might be the next step change of data interpretation beyond geophysical inversions?

We observe that the dominant interpretation approach used for gravity, magnetic, DC/IP, and electromagnetic data through inversions is based on the inverted physical properties. These physical property models tend to be used in a qualitative interpretation manner similar to that of bump hunting — where the changes in the physical properties contribute to the structural geology interpretation. Thus, these interpretation methods essentially use the corresponding physical properties as proxies of geology. Although geophysicists are familiar with such models and interpretations while communicating with geologists, one extra step is needed by geologists to transform these interpretations into rock types and ore-hosting models to obtain useful insights that can guide future decision making and exploration activities. Current inversion algorithms are effective in imaging these proxies but may not be sufficiently effective in imaging geology as defined by lithologies, alteration zones, or different mineralization zones. However, geophysics is meant to image and characterize geology; focusing on the proxies alone is insufficient. Therefore, it is high time to move the focus back to geology.

In fact, such approaches have been used extensively in other disciplines. For example, in medical diagnostics, a magnetic resonance image (MRI) of a human brain is routinely segmented and classified into different categories such as white matter, gray matter, and spinal fluids, which provides more useful information to doctors for diagnosis than the raw MRI images. In hyperspectral imaging of minerals, multiple airborne images from different spectral bands are fused into one map that identifies the existence of various minerals and their spatial distribution. With the availability of advanced geophysical inversion algorithms, we are now in the position to do the same with multiple physical properties recovered from geophysical data sets to image geology.

Geology differentiation

We formally term this approach of mapping different geologic units using multiple physical property models obtained from geophysical inversions as "geology differentiation." It consists of two parts: differentiation and characterization. The former seeks to ascertain if multiple anomalous regions in inverted physical property models belong to the same type or different geologic units, whereas the latter identifies what geologic unit or type a given model region corresponds to, such as different lithology, alteration types, or mineralization zones. The ultimate goal is to produce a representation of geology from inverted physical properties.

There has been a long line of such research in exploration geophysics, dating back to Garland (1951) and Kanasewich and Agarwal (1970), in the data domain using gravity and magnetic data. Dransfield et al. (1994) map pseudolithology using airborne gravity gradiometry and magnetic data.

With widespread use of 3D inversion algorithms, researchers have investigated geology differentiation in the model domain based on physical properties recovered from inverting geophysical data sets. For example, Williams et al. (2004) use invert density and magnetic susceptibility values to approximate the relative abundance of hematite and magnetite as a predictor of two types of alteration in the Olympic Cu-Au province, South Australia, and produce a 3D prospectivity map that correlates well with known major deposits. The study covers an area of 150 km on a side. Kowalczyk et al. (2010) use regional-scale gravity and magnetic inversions to produce a 3D pseudolithology map for the entire Quesnel terrane in British Columbia. This regional study spans approximately 1000 km along the terrane and produces 19 different lithology classes.

These seminal works have focused on regional-scale studies and emphasized geology differentiation. The results have clearly demonstrated the value of integrating multiple geophysical inversions and the potential for deriving value-added and more specific geologic information by combining different physical property models.

Can we use such an approach on deposit scales? Can specific lithology or geologic units be identified? Our recent work has demonstrated that both are feasible. The work by UBC-GIF has also shown that sufficient information exists in physical property models on the deposit scale (Devriese et al., 2017; Fournier et al., 2017; Kang et al., 2017) such that different zones associated with a diamondiferous kimberlite can be differentiated.

We present three case studies in the following as illustrations. The first two assume separate inversions of different geophysical data sets, and the third is based on a formal joint inversion. In each case, we combine physical property models obtained through geophysical inversion and different levels of prior geologic information to obtain a quasi-geology model, which can be interpreted in much the same way as a traditional geology model constructed from direct observables such as outcrops and drill hole information.

Case 1: Lithology characterization in iron ore exploration. For cases in which specific geologic units present in the subsurface are known and we simply seek to identify where they occur, we can utilize prior knowledge in conjunction with geophysical models to map physical properties to the lithology(s) of interest. In this example from iron ore exploration in the Quadrilátero Ferrífero in Brazil, airborne gravity gradient and magnetic data are used to characterize the spatial distribution of known types of iron formation and other lithologic units based on limited prior information (Martinez and Li, 2015). The deposit in question resides in the Minas Series, which is an iron-bearing formation composed of Precambrian metasedimentary rocks. Within the Minas Series, the Cauê Itabirite (banded-iron formation) hosts most of the economic iron mineralization. The prior knowledge is in the form of a geologic cross section created from borehole information, and that is used to link recovered physical property values in the inverted geophysical models to likely lithologies. The objective is to identify the spatial distribution of hematite and different types of itabirite.

The gravity gradient and magnetic data are separately inverted to obtain 3D density and susceptibility models. The iron ore formation is readily differentiated from the dolomitic and quartz-rich country rock by a distinctly high-density contrast that produces well-defined anomalies in airborne gravity gradiometry data. The high-grade hematite iron ores are associated with low and moderate susceptibilities, making magnetic data useful in distinguishing between iron formation lithologies. The susceptibility of the iron ore in this area is generally low for hard compact hematite, slightly higher for that of soft porous hematite, and higher still for that of economic itabirite.

By matching the geologic cross section (Figure 2a) with the spatially coincident density (Figure 2b) and susceptibility cross section (Figure 2c), the physical property ranges associated with each lithology are identified and subsequently applied to the full 3D physical property value ranges in a crossplot (Figure 3a). From the crossplot, ranges of the physical properties associated with specific lithologies can be mapped across the physical property space based on which 3D lithology model in spatial domain is obtained. A depth slice through the 3D lithology model is shown in Figure 3b where the spatial distribution of iron formation can be identified by the potential lithology type (hematite, friable itabirite, and compact itabirite).

Case 2: Mapping mineralized zones at an IOCG deposit. In many scenarios, such as greenfield exploration, we may not have sufficient prior knowledge to carry out the end-member analysis as in the preceding example. Different approaches are then required. We use the exploration for iron-oxide-copper-gold (IOCG) deposits in Carajás, Brazil, as an example to illustrate the characterization of different mineralized zones in the absence of prior information on the relationship between recovered physical properties and geologic units.

The Cristalino copper-gold deposit is an IOCG deposit located in northern Brazil and hosted by a splay of a deep crustal fault. The splay fault acted as a conduit for hydrothermal fluids. The copper and gold ore was formed by hydrothermal alteration of a volcano-sedimentary sequence consisting of mafic and felsic volcanic rocks interlayered with iron formation (which contains magnetite) and intruded by a younger gabbro dike. The main ore mineral is chalcopyrite.

Melo et al. (2017) develop and apply to Cristalino a geology differentiation by combining inverted physical property models, sparse geologic data, and textbook physical property values for different minerals. The first step of the method is constructing a conceptual crossplot (Figure 4a) with different groupings of physical property values (e.g., electrical conductivity and magnetic susceptibility) corresponding to distinct geologic units. This crossplot integrates information from drilling, published reference values for minerals of interest

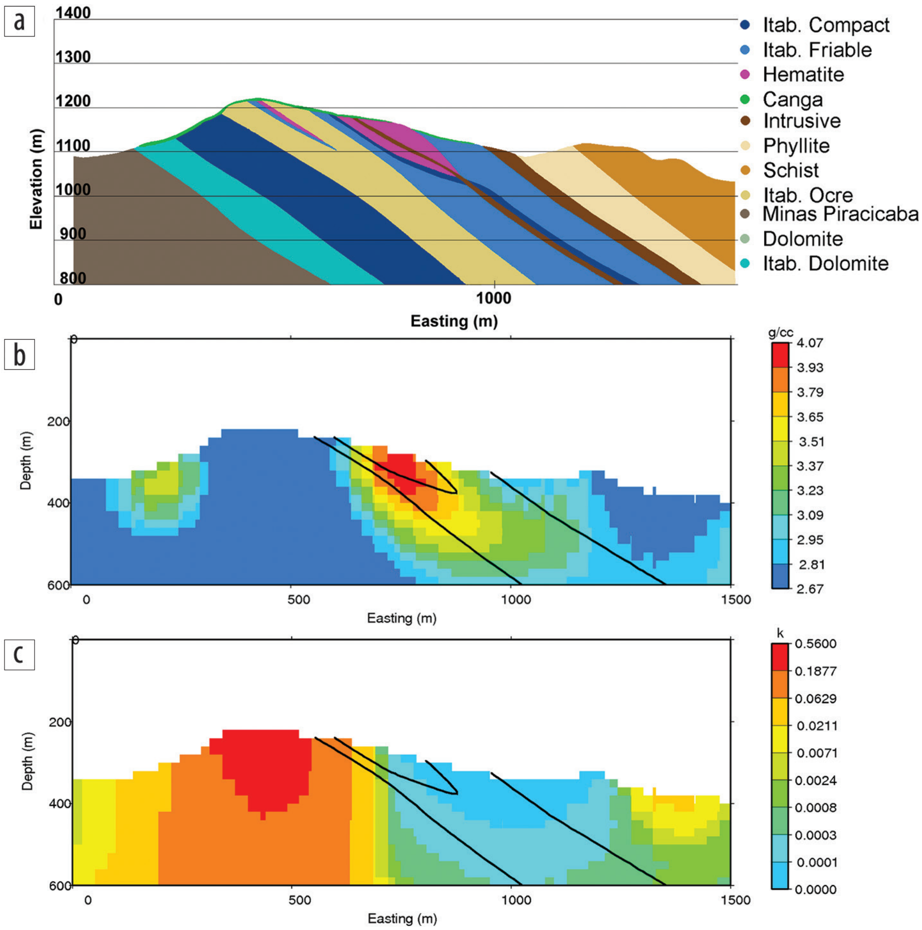

Figure 2. (a) Geologic cross section constructed based on drill hole data. (b) Corresponding cross section through the density model obtained from 3D inversion of gravity gradient data. (c) Corresponding cross section through the susceptibility model obtained from 3D inversion of residual magnetic data.

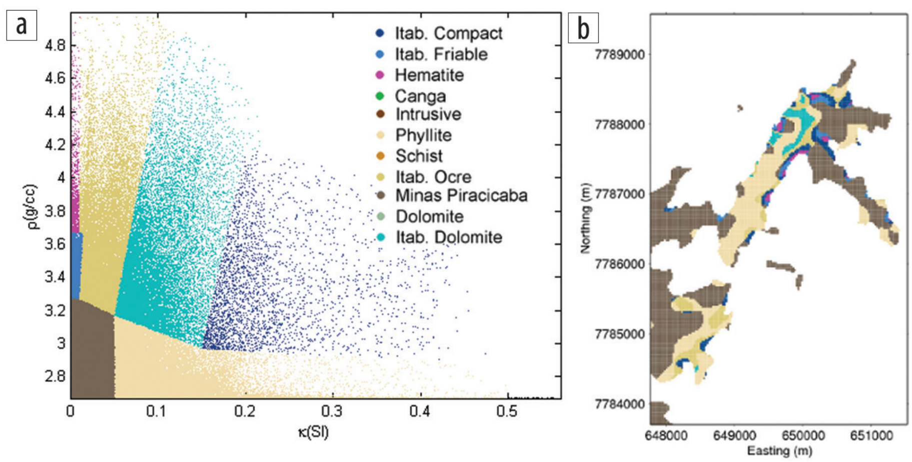

Figure 3. (a) Crossplot of the density and susceptibility values estimated from inversions of gravity gradient and magnetic data color coded by the assigned lithologic units. (b) Depth slice through the 3D lithologic model at an elevation of 1150 m showing the distribution of assigned lithologic units by linking known geology cross section to geophysical models.

(i.e., chalcopyrite and magnetite), sparse geologic information, and a geologist's understanding of the exploration target. The grouping patterns established in the first step then apply to the crossplot of physical property values estimated from separate inversion of magnetic and DC data (Figure 4b). The classification result in Figure 4b, when summarized in spatial domain as shown in Figure 5b, is highly similar to the geologic section in Figure 5a despite the fact that no direct information from the section was used. Subsequent work has also extended the differentiation method to 3D and multiple physical property models and achieved similar results. The differentiation result from this study is also interesting in two aspects. First, the differentiation has clearly worked in a problem covering a spatial extent of 1 km and the differentiated zones are on the order of 200 m. Secondly, the characterized units are primarily of different mineral assemblages rather than lithology.

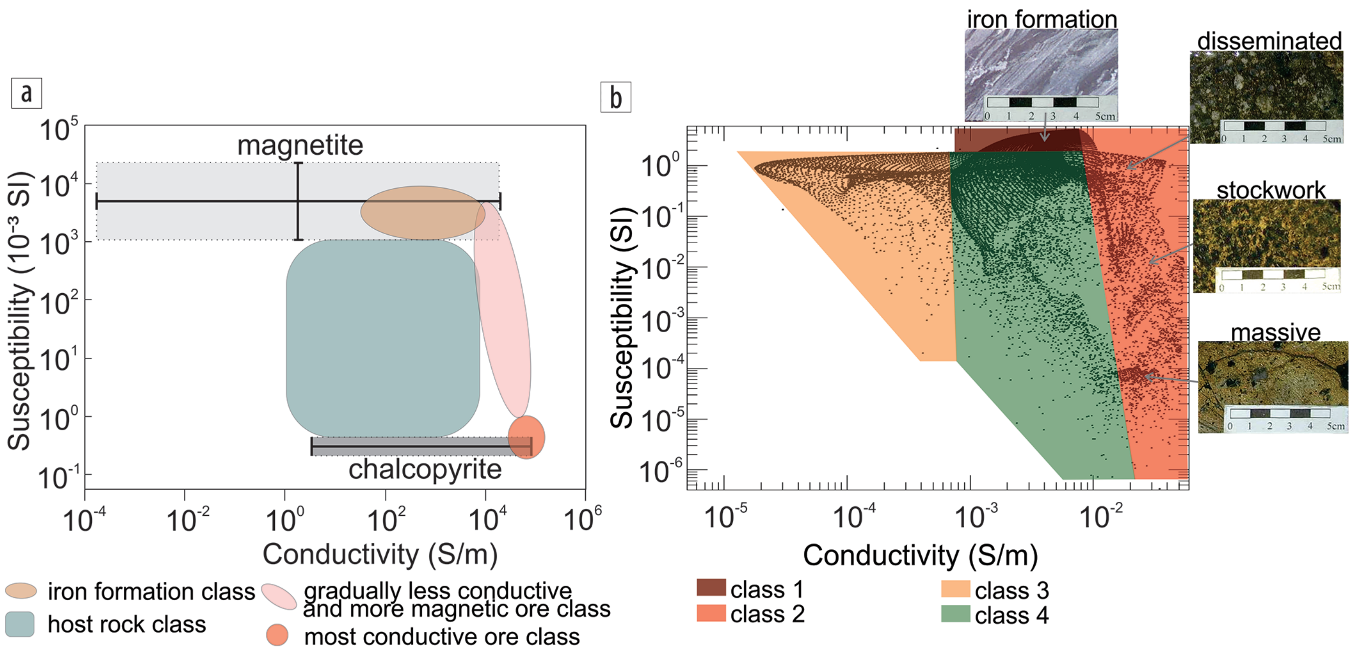

Figure 4. (a) Conceptual scatterplot of the electrical conductivity and magnetic susceptibility values for magnetite and chalcopyrite (based on Telford et al., 1990) showing the expected grouping patterns of the ore unit and the iron formation as well as the relative positioning of different units. (b) Differentiation and characterization results on top of the scatterplot of estimated susceptibility and conductivity values from the 2D inversions. Each black point corresponds to one pair of susceptibility and conductivity values at one model cell overlain by the classification (indicated by the polygons of different colors) based on the conceptual grouping patterns established in (a) and natural groupings in the inverted physical property values. Class 1 is associated with the iron formation, class 2 with copper ore, class 3 with host rock I, and class 4 with host rock II.

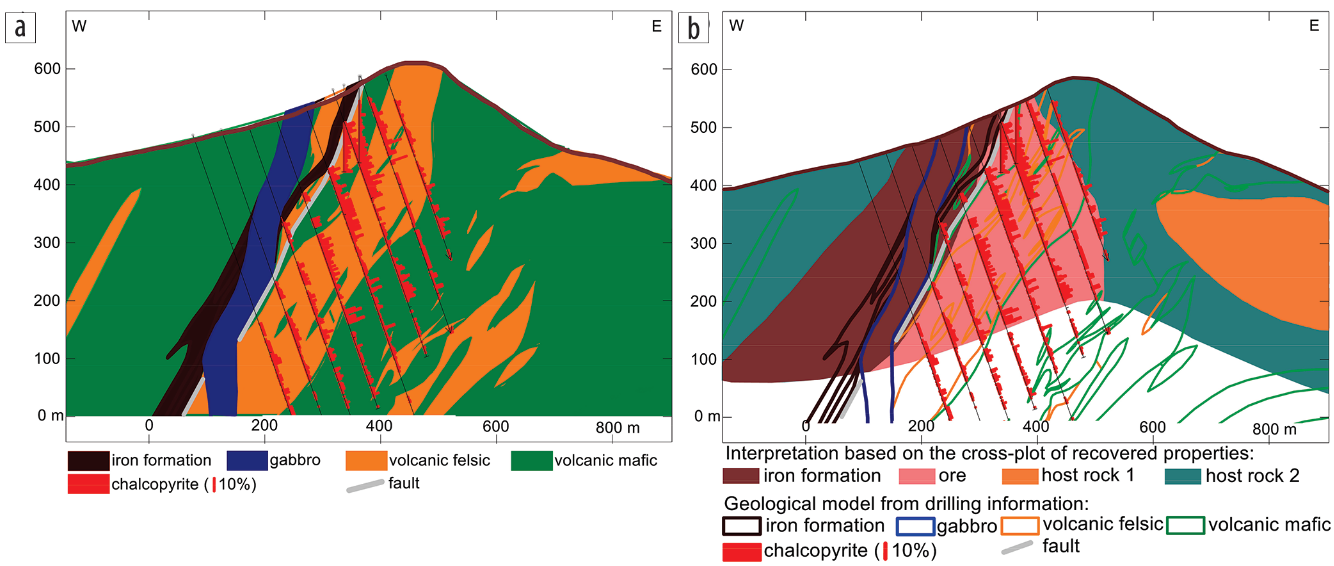

Figure 5. (a) Geologic cross section through the Cristalino copper deposit superimposed with the drill hole traces and chalcopyrite concentrations of the hydrothermal zone hosted by the volcanic and sedimentary rocks (modified from Vale, 2004). (b) Geology characterization overlain by the geologic section in (a) showing the high spatial correspondence between the identified ore class and the high concentration of chalcopyrite from petrophysical measurements.

Case 3: Ore body mapping through joint inversions at Heath Steele Stratmat. With the advancement of joint inversion in exploration applications, the quality of inverted physical property models is expected to improve significantly, rendering improved geology differentiation results attainable. In the cases where prior petrophysical data are available, multiple geophysical and petrophysical data can be constructively integrated at the inversion stage, leading to improved physical property models that are better suited for geology differentiation. We present such an example.

The Stratmat Main Zone, located south of the Bathurst Mining Camp in northeast New Brunswick, Canada, hosts a volcanic massive sulfide (VMS) deposit. The diamond drill holes reveal four major lithologic units in this area: massive sulfides, volcanic (crystal, felsic, and lapilli) tuffs, metasedimentary rocks, and mafic intrusions (diabase dikes and gabbros). Their density and magnetic susceptibility variations give rise to distinct gravity and magnetic signatures. From the separately inverted density and susceptibility models, one can readily identify the location of the VMS deposit. However, those separately inverted models do not provide much useful information on the distribution of the various lithological units. A better understanding of the VMS system may be developed if the distribution of the different lithological units can be better imaged. Sun and Li (2015) apply the joint clustering inversion method (Sun and Li, 2017), combine the gravity and magnetic data with the petrophysical data, and develop a 3D pseudolithology model that shows the spatial distribution of the different lithological units. This 3D pseudolithology model may provide geologists with new insights into how the VMS system was formed and how different chemical and alteration processes led to the formations of the copper-lead-zinc deposit. This knowledge will be helpful in guiding future exploration activities for similar targets.

Beginning with limited and overly simplified petrophysical data, Sun and Li (2015) iteratively develop new hypotheses about the petrophysical relationships (i.e., grouping patterns) between density and susceptibility values for different lithological units and test them through the earlier mentioned joint clustering inversion. The final hypothesis arrived at is that the density and susceptibility values, when crossplotted against each other, contain three circular and two elliptical clusters, with each cluster corresponding to one unique lithological unit. The jointly inverted physical property values in Figure 6 exhibit well-defined clustering features at approximately the expected locations. Each cluster represents a group of similar or correlated density and susceptibility values and, therefore, can be interpreted as one unique lithological unit. We note that, for the previous two approaches, grouping patterns for each geologic unit are established based on either an available geologic cross section (case 1) or published textbook reference values (case 2), whereas in this case, joint inversion directly outputs grouping patterns for each unit.

Lithology differentiation is accomplished by assigning a unique integer categorical number (i.e., 1, 2, 3, 4) to each cluster in Figure 6 and then visualizing in 3D spatial domain in the form of a 3D pseudolithology model as shown in Figure 7. The 3D pseudolithology map displays the spatial distribution of each lithological unit and contains useful information for geologists to better understand the geologic and mineralogical processes that resulted in the formation of VMS deposits.

Summary

From these examples and the earlier mentioned works by other authors, a clear pattern is emerging. The general approach of geology differentiation using multiple physical property models has shown promising results on a wide range of scales from 1 km covering a deposit to 1000 km covering an entire mining terrane. The geologic units mapped through the differentiation approach include identified lithology types, zones of mineralization, and different types of alteration.

A surprisingly encouraging observation is that separately inverted models, when examined jointly, contain sufficient information for this approach to produce meaningful results in many cases. This bodes well for the practical applications of

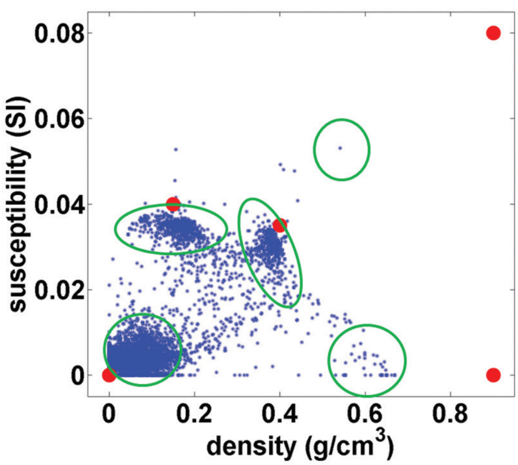

Figure 6. The crossplot of the jointly inverted density and susceptibility values in blue and the hypothesized average physical property values for each lithological unit in red. The green circles and ellipses represent the identified clusters (or equivalent lithological units) among the inverted density and susceptibility values.

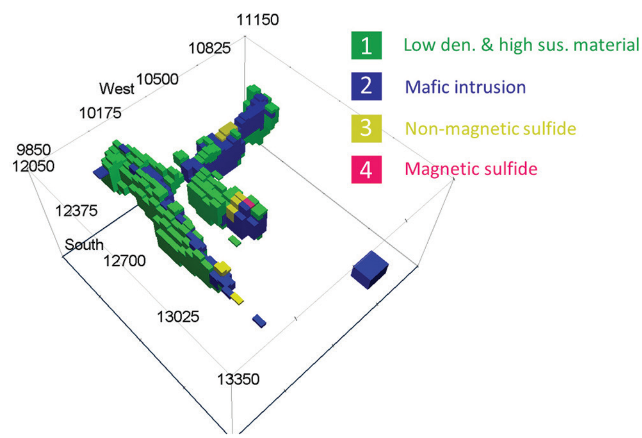

Figure 7. The 3D pseudolithology model derived from the joint inversion of gravity and magnetic data. Each color, assigned an integer categorical number, represents one unique lithological unit. The background corresponding to sediments and felsic rocks is removed. The identified magnetic sulfide marked in red agrees well with drill hole information.

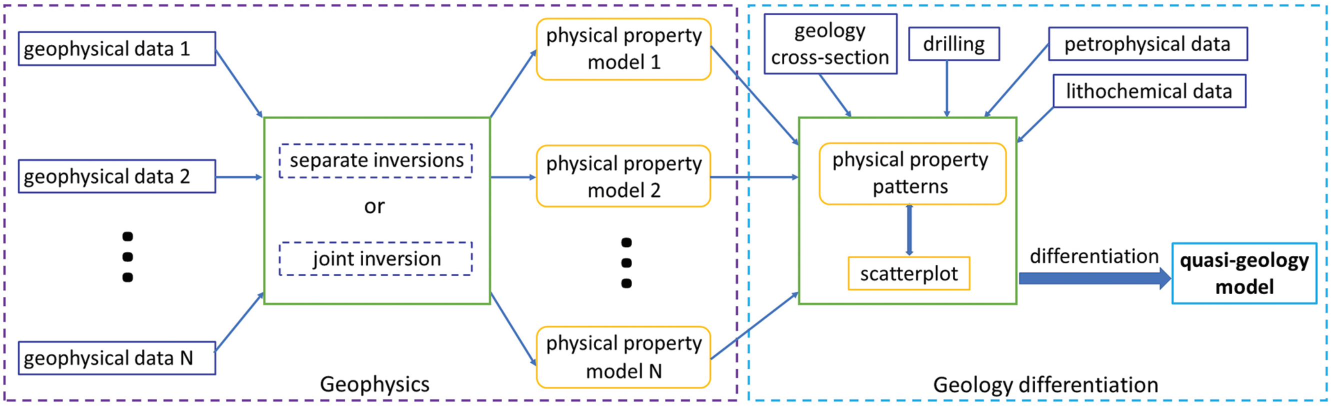

Figure 8. A general flowchart for geology differentiation.

geology differentiation since it can be readily applied in active exploration projects using the variety of inversion tools that are already available. Furthermore, we point out that because of the better defined grouping features directly resulting from joint inversion and the consequent ease of performing geology differentiation, joint inversion holds great promise for further advancing and automating geology differentiation. Considering the fact that joint inversion methods, algorithms, and software are still to be developed and tested, we remark that geology differentiation still has much time to be further improved by including joint inversion in the workflow.

We summarize the general workflow for geology differentiation in Figure 8. The workflow starts with multiple types of geophysical data followed by geophysical inversion (either separate inversions or a single joint inversion) and reconstructs a set of physical property models. These estimated physical property values are then summarized in a scatterplot. A critical component of geology differentiation is to establish the expected grouping patterns of physical property values for all the geologic units by combining information from existing geologic cross sections, drilling data, physical property values from laboratory measurements, and literature. The established grouping patterns then apply directly to the scatterplot obtained from geophysical inversions. The identified groups (or clusters) in the scatterplot represent the geology differentiation results that can be further visualized in 3D spatial domain for subsequent knowledge discovery and insight development. We reiterate that, in this workflow, geophysical inversion only serves as a tool to convert geophysical data to physical property models, and the end product of the workflow is a 3D quasi-geology model.

Conclusions

Data image-based interpretation was dominated by "anomaly bump hunting" or a similar qualitative approach in the early state of exploration geophysics. Inversions have increased the quantitative level significantly and changed the paradigm from the data domain to model domain of physical properties, but a significant portion of the interpretation appears to have remained in the mode of bump hunting by focusing on anomalous physical property zones. Combining multiple physical property models, however, may enable us to differentiate between lithologic units, alteration types, and mineralization zones, or even identify them. We believe that such an integrated interpretation is the next step change in quantitative interpretation of geophysical data.

We have the requisite inversion tools, and inversion of different geophysical data sets is also a routine part of data interpretation. Thus, we have the essential components to perform geology differentiation on a routine basis. To accomplish this objective, we also need supplemental information from petrophysical database, geochemical, and lithochemical data to establish reasonable grouping patterns among the inverted physical property values so they can be mapped into different geology units.

Furthermore, what is required is a mindset that may be described by the following adage: "No one cares about geophysics unless it can solve geology problems." Thus, the focus should be on geology and not necessarily on geophysics by itself. Adopting this mindset logically requires geophysicists in research and practice to think and act as geoscientists with some understanding of the geologic and mineral systems in which we explore, of mineralogy, and of geochemistry. Consequently, we cannot focus primarily on geophysical methods in a semivacuum setting.

Returning to the question of why the advances and widespread use of geophysical inversions have not apparently contributed significantly to discoveries, we surmise that the reason is the use of these algorithms has been confined as geophysical tools instead of ultimate geologic tools. To advance to the next stage, it has long been recognized that we must produce geologic models. Specifically, these geologic models include 3D maps of alterations types, lithologies, or zones of different mineral assemblages. When we geophysicists can predict and map geology in such manners, we may be able to affect another game change in the landscape of mineral exploration and increase the discovery rate in the coming decades. Thus, geology differentiation is a new frontier.

The change will be in the way geophysical technology is used, but more importantly, the change should be in our mindset. As a profession, geophysicists also need to think and act in this way in order to stay competitive and highly relevant. That is, we must adopt a geoscientists' mindset. Otherwise, our profession may risk becoming relegated to the equivalent of imaging technologists and geophysicists becoming the ultimate technicians. Therefore, geophysicists must go beyond geophysics. TLE

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