



Universidade de Brasília
Instituto de Geociências
Programa de Pós-graduação em Geologia

Tracking gold origin: A novel identification approach based on topology and machine learning applied to gold geochemical data

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Tese de Doutorado Nº 214

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Rastreamento da origem do ouro: Uma nova abordagem de identificação baseada em topologia e machine learning aplicada a dados geoquímicos de ouro

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RESUMO

A produção de ouro pode ser obtida por meio de três figuras principais: mineração artesanal, mineração industrial e mineração ilegal, que pode ser obtida de vários depósitos de minério. Normalmente, a mineração ilegal traz problemas ambientais, sociais e econômicos que podem variar de locais a nacionais. Portanto, torna-se imperativo garantir uma cadeia de produção responsável, desde o depósito até as mãos do consumidor.

Esta pesquisa demonstra o potencial transformador da integração de técnicas analíticas avançadas, modelagem geoquímica e aprendizado de máquina para desvendar as complexidades da gênese do depósito de ouro, aprimorar a rastreabilidade e apoiar aplicações forenses. As assinaturas geoquímicas derivadas de elementos residuais, incluindo Ag, Bi, Cu, Fe, Ni, Pb, Pd, Pt, Sb e Te, revelam percepções exclusivas sobre as condições físico-químicas da formação do ouro e permitem uma classificação robusta dos tipos de depósitos. Com o modelo otimizado de rede neural artificial (ANN), o OreGenes associa efetivamente as amostras de ouro ao seu depósito original. Ao mesmo tempo, as técnicas de aprendizagem múltipla, como a UMAP combinada com a distância de Hellinger, revelam relações geoquímicas em toda a cadeia de produção. Essas abordagens destacam o impacto dos processos industriais na assinatura química do ouro e fornecem ferramentas essenciais para o combate ao tráfico ilícito de ouro.

A metodologia foi validada por meio de estudos de caso, como o depósito Água Branca, em que o aprendizado de máquina apoiou sua reclassificação como um depósito orogênico. Embora a pesquisa ressalte a utilidade das ferramentas computacionais em geoquímica, ela enfatiza a importância de conjuntos de dados abrangentes, métodos geológicos tradicionais e aplicativos acessíveis para uma adoção mais ampla. Ao unir geoquímica, aprendizado de máquina e geologia forense, este trabalho avança na classificação de depósitos de ouro, aprimora o rastreamento de proveniência e fortalece os esforços em investigações forenses.

Palavras-chave: Ouro, Geoquímica, LA-ICP-MS, Machine learning, Manifold learning, Rastreabilidade, Cadeia de produção

ABSTRACT

Gold production may be achieved through three main figures: artisanal mining, industrial mining, and illegal mining, which could be obtained from various ore deposits. Usually, illegal mining comes with environmental, social, and economic problems that can scale from local to national. Therefore, ensuring a responsible production chain from the deposit to the consumer's hands becomes imperative.

This research demonstrates the transformative potential of integrating advanced analytical techniques, geochemical modeling, and machine learning to unravel the complexities of gold deposit genesis, enhance traceability, and support forensic applications. Geochemical signatures derived from trace elements, including Ag, Bi, Cu, Fe, Ni, Pb, Pd, Pt, Sb, and Te, reveal unique insights into the physicochemical conditions of gold formation and enable robust classification of deposit types. Optimized artificial neural network (ANN) model, OreGenes effectively associates gold samples with their original deposit. At the same time, manifold learning techniques such as UMAP combined with Hellinger distance unveil geochemical relationships across the production chain. These approaches highlight the impact of industrial processes on gold's chemical signature and provide critical tools for combating illicit gold trafficking.

The methodology was validated through case studies, the Água Branca deposit, where machine learning supported its reclassification as an orogenic deposit. While the research underscores the utility of computational tools in geochemistry, it emphasizes the importance of comprehensive datasets, traditional geological methods, and accessible applications for broader adoption. By bridging geochemistry, machine learning, and forensic geology, this work advances the

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Keywords: Gold, Geochemistry, LA-ICP-MS, Machine learning, Manifold learning, Traceability, Production chain

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Chapter 1

INTRODUÇÃO

1 INTRODUÇÃO

A geoquímica do ouro tem sido historicamente utilizada como uma ferramenta para a exploração mineral, auxiliando na descoberta de depósitos de minério. Além de sua forma física, que reflete seu histórico de transporte em uma bacia, a composição química do ouro é influenciada pelas condições físico-químicas de sua formação e pela estrutura geológica do depósito (McClenaghan, 2005; Chapman et al., 2009; McClenaghan e Cabri, 2011; Moles e Chapman, 2019). Desde a década de 1960, os avanços nas técnicas analíticas, especialmente o microanalisador de sonda de elétrons (EPMA), permitiram determinações altamente precisas da composição química do ouro natural de um amplo espectro de tipos de depósitos (Rinaldi e Llovet, 2015).

As características geoquímicas do ouro forneceram percepções significativas sobre sua formação. Por exemplo, Antweiler e Campbell (1977) demonstraram correlações entre as temperaturas de formação de determinados depósitos e as concentrações de elementos como Ag, Bi, Pb e Cu no ouro. Morrison et al. (1991) exploraram ainda mais as variações na finura do ouro em diferentes tipos de depósitos, enquanto Huston et al. (1992) investigaram as composições de elementos-traço e a finura em eletros de depósitos de sulfeto maciço hospedados em vulcões (VMS) na Austrália, relacionando essas variações à complexidade dos fluidos formadores de minério. Mais recentemente, Pochon et al. (2021) demonstraram o potencial de identificar ouro extraído ilicitamente da Guiana Francesa por meio da análise do teor de Ag, Cu e Hg, estabelecendo um meio de certificar sua origem. Além disso, Liu et al. (2021a) e Liu e Beaudoin

(2021a) utilizaram a geoquímica de elementos-traço de grãos de ouro em todo o mundo, combinada com algoritmos de aprendizado de máquina, para classificar tipos de depósitos com precisão de previsão que varia de 50% a 97%, dependendo do estilo do depósito.

Embora esses estudos tenham estabelecido com firmeza que o ouro carrega uma assinatura geoquímica distinta (Liu e Beaudoin, 2021a; Melo-Gomez, 2023; Verbel et al., 2023), relativamente poucas pesquisas abordaram como essa assinatura evolui ao longo da cadeia de produção. A complexidade dos processos de extração e refino de ouro muitas vezes torna o rastreamento de sua origem um desafio, sendo considerado por alguns uma tarefa impossível (Beck e Jodry, 2021).

1.1 MOTIVAÇÃO

A produção de ouro no Brasil aumentou de forma constante de 2009 a 2020, com um pico de 90 toneladas de ouro em 2019, o que o coloca na 11ª posição na lista de países por produção de ouro e a 3ª maior na América Latina. Portanto, essa atividade econômica desempenha um papel importante no PIB brasileiro. No entanto, a introdução de ouro ilegal na cadeia de suprimentos diminui os benefícios das atividades de mineração em uma região e aumenta os danos ambientais que a extração de ouro de locais não destinados a essa atividade pode causar. Portanto, o desenvolvimento de uma técnica mais geral para diferenciar a fonte do ouro, a despeito de sua origem ou dos processos pelos quais passou durante o processo de refinamento, seria uma ferramenta

imperativa para o desenvolvimento de países mineradores com áreas que apresentam a confluência de mineração ilegal, artesanal e industrial.

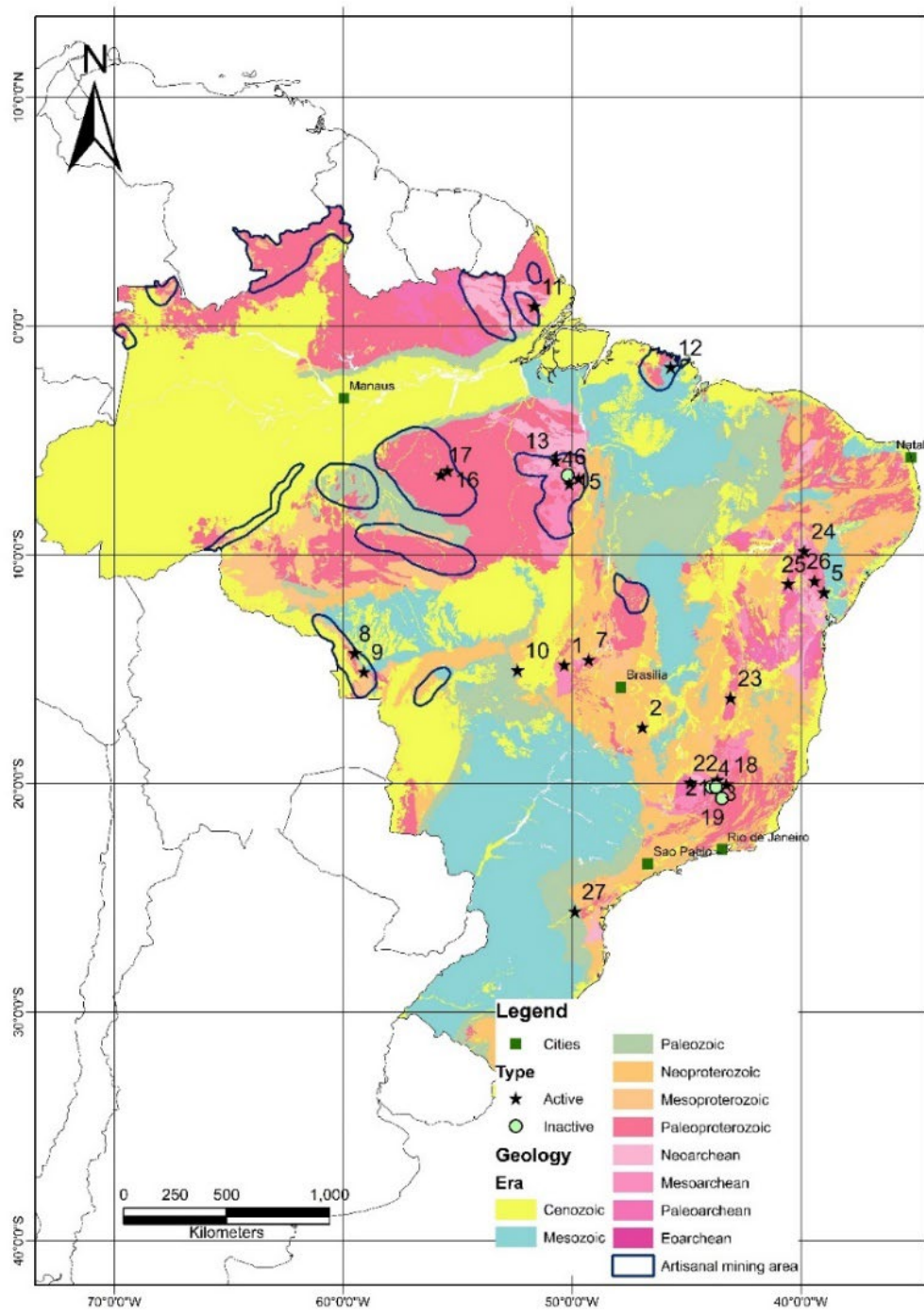


Fig. 1: Map of Brazil showing the artisanal areas and industrial mining projects over the geology. 1) Crixás; 2) Morro do Ouro; 3) Cuiabá; 4) Morro Velho; 5) Fazenda Brasileiro; 6) Igarapé Bahia; 7) Chapada; 8) São

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1.2 PREGUNTAS DE PESQUISA

- O ouro tem uma assinatura geoquímica natural?
- Se essa assinatura existir. Como ela muda quando o ouro é concentrado antropogenicamente em um Doré?

1.3 OBJETIVO GERAL

- Encontrar uma metodologia para determinar se a origem declarada do ouro corresponde à origem real

1.4 OBJETIVOS ESPECÍFICOS

- Determinar a assinatura geoquímica do ouro em diferentes depósitos de ouro.
- Determinar se há uma ligação entre os diferentes estágios da cadeia de suprimentos e as assinaturas geoquímicas do ouro.
- Determinar se os depósitos não vistos podem ser classificados com base nas assinaturas geoquímicas conhecidas dos depósitos conhecidos

1.5 ESTRUTURA DA TESE

Esta tese é apresentada como uma compilação de três artigos de pesquisa, cada um contribuindo para uma compreensão abrangente das características geoquímicas e mineralógicas do ouro e dos minerais associados em vários contextos. A pesquisa tem como objetivo explorar a evolução das assinaturas elementares de depósitos de minério para produtos de ouro refinados e avaliar o potencial dos modelos de aprendizado de máquina na discriminação mineral.

O primeiro artigo enfoca a assinatura geoquímica de grãos de ouro de diferentes depósitos de minério, fornecendo percepções sobre a variabilidade composicional e características distintas de grãos de ouro de diversos ambientes geológicos. Esse estudo fundamental estabelece uma estrutura geoquímica robusta para identificar fontes de ouro.

O segundo artigo apresenta um estudo de caso de um depósito de minério individual, investigando as mudanças na composição do ouro de seu estado natural para dorés de ouro refinados. Ao analisar a transformação das composições elementares durante o refino, esse trabalho lança luz sobre os processos metalúrgicos e seu impacto nas assinaturas geoquímicas.

O terceiro artigo integra os dados geoquímicos dos grãos de ouro do depósito de minério estudado no segundo artigo com os dados das análises LA-ICP-MS da pirita associada. Esse conjunto de dados combinado é avaliado usando modelos de aprendizado de máquina para discriminar o ouro de diferentes fontes e avaliar o potencial de análise preditiva em aplicações de exploração mineral.

Juntos, esses estudos fornecem uma narrativa coesa que abrange desde a variabilidade geoquímica natural do ouro até seus produtos refinados, demonstrando a utilidade de ferramentas computacionais avançadas na análise de conjuntos de dados mineralógicos complexos.

Por fim, esta introdução e as conclusões gerais são apresentadas em português e inglês em diferentes capítulos do documento, conforme exigido pela biblioteca da Universidade de Brasília.

Chapter 2

INTRODUCTION

2 INTRODUCTION

Gold geochemistry has historically been utilized as a tool for mineral exploration, aiding in the discovery of ore deposits. Beyond its physical shape, which reflects its transport history within a basin, the chemical composition of gold is influenced by the physicochemical conditions of its formation and the geological framework of the deposit (McClenaghan, 2005; Chapman et al., 2009; McClenaghan and Cabri, 2011; Moles and Chapman, 2019). Since the 1960s, advancements in analytical techniques, particularly the electron probe microanalyzer (EPMA), have enabled highly precise determinations of the chemical composition of natural gold from a broad spectrum of deposit types (Rinaldi and Llovet, 2015).

The geochemical characteristics of gold have provided significant insights into its formation. For instance, Antweiler and Campbell (1977) demonstrated correlations between the formation temperatures of certain deposits and the concentrations of elements such as Ag, Bi, Pb, and Cu in gold. Morrison et al. (1991) further explored variations in gold fineness across different deposit types, while Huston et al. (1992) investigated trace element compositions and fineness in electrum from volcanic-hosted massive sulfide (VMS) deposits in Australia, linking these variations to the complexity of ore-forming fluids. More recently, Pochon et al. (2021) demonstrated the potential to identify illicitly mined gold from French Guiana by analyzing Ag, Cu, and Hg content, establishing a means to certify its origin. Furthermore, Liu et al. (2021a) and Liu and Beaudoin (2021a) utilized trace element geochemistry from gold grains worldwide, combined with

machine learning algorithms, to classify deposit types with prediction accuracies ranging from 50% to 97%, depending on the deposit style.

While these studies have firmly established that gold carries a distinct geochemical signature (Liu and Beaudoin, 2021a; Melo-Gomez, 2023; Verbel et al., 2023), relatively little research has addressed how this signature evolves through the production chain. The complexity of gold extraction and refining processes often renders tracing its origin challenging, with some considering it an impossible task (Beck and Jodry, 2021).

2.1 Motivation

Brazil's gold production has increased steadily from 2009 to 2020, with a peak of 90 tons of gold in 2019, which puts it in the 11th position in the list of countries by gold production and the 3° largest in Latin America. Therefore, this economic activity plays an important role in the Brazilian GDP. However, introducing illegal gold in the supply chain diminishes the benefits of mining activities in a region and increases the environmental damage that the extraction of gold from places not intended for this activity may cause. Hence, the development of a more general technique to differentiate the source of gold despite its origin or the processes that it has gone through during the refinement process would be an imperative tool to the development of mining countries with areas featuring the confluence of illegal, artisanal and industrial mining.

2.2 Research questions

- Does gold have a natural geochemical signature?

- If this signature exists. How does it change when gold is anthropogenically concentrated into a Doré?

2.3 General objective

- Find a methodology to determine if the gold declared origin matches the real one

2.4 Specific objectives

- Determine the geochemical signature of gold in different gold deposits.
- Determine if there is a link between different stages of the supply chain and the geochemical signatures of gold.
- Determine if unseen deposits can be classified based on the known geochemical signatures of known deposits

2.5 Thesis structure

This thesis is presented as a compilation of three research papers, each contributing to a comprehensive understanding of the geochemical and mineralogical characteristics of gold and associated minerals across various contexts. The research aims to explore the evolution of elemental signatures from ore deposits to refined gold products and evaluate the potential of machine learning models in mineral discrimination.

The first paper focuses on the geochemical signature of gold grains from different ore deposits, providing insights into the compositional variability and distinguishing characteristics of gold grains from diverse geological settings. This

foundational study establishes a robust geochemical framework for identifying gold sources.

The second paper presents a case study of an individual ore deposit, investigating the compositional changes in gold from its natural state to refined gold dorés. By analyzing the transformation of elemental compositions during refining, this work sheds light on the metallurgical processes and their impact on geochemical signatures.

The third paper integrates the geochemical data of gold grains from the ore deposit studied in the second paper with data from LA-ICP-MS analyses of associated pyrite. This combined dataset is evaluated using machine learning models to discriminate gold from different sources and assess the potential for predictive analytics in mineral exploration applications.

Together, these studies provide a cohesive narrative that spans from the natural geochemical variability of gold to its refined products while demonstrating the utility of advanced computational tools in analyzing complex mineralogical datasets.

Finally, This introduction and the general conclusions are presented in Portuguese and English in different chapters of the document as required by the library of the Universidade de Brasília.

Chapter 3

OREGENES: AN OPTIMIZED NEURAL NETWORK TOOL FOR ORE DEPOSITS

CLASSIFICATION BASED ON GOLD GRAIN GEOCHEMISTRY

OREGENES: AN OPTIMIZED NEURAL NETWORK TOOL FOR ORE DEPOSITS CLASSIFICATION BASED ON GOLD GRAIN GEOCHEMISTRY

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Abstract

Assessment of gold grains and their characterization in abundance and morphology can be used as a discriminatory tool for mineral deposits. However, the processes that lead to the formation of an ore deposit are multiscale and nonlinear. As a result, the elemental compositions recorded in gold grains during mineralization seem mostly irregular and unpredictable. Here, we took advantage of the capabilities of neural networks, computational models composed of layers

of interconnected nodes. After training, it processed data through nonlinear transformations that approximate a complex natural function. It enabled the recognition of complex patterns and relationships in chemical variability observed in gold and relating it to the mineral system that formed the mineral, allowing for predictive modeling. This was achieved by using published trace element data in gold of four types of gold deposits (i.e., Orogenic, VMS, porphyry, and epithermal) from 47 different localities, obtained by laser ablation-inductively coupled plasma-mass spectrometry (LA- ICP-MS). The model was optimized by training five different architectures on the most influential elements, determined by principal component analysis (PCA). As a result, two hidden layers with ten neurons (series of nodes that process and transmit information) each were found to be the best architecture for using trace elements as predictors of the type of deposit that formed a natural gold grain. In order to encourage the use of the findings made in this paper, we introduce OreGenes, an app developed in Matlab2023b based on the best-obtained model. It allows any user who possesses compatible data the ability to import and process it to obtain a prediction with an average accuracy level of 88.9% confidence to assess the mineral deposit type that an unknown gold grain came from, which grants the user the ability to have a powerful tool for exploration or research.

Keywords: Ore deposits, Mineral exploration, Gold geochemistry, LA-ICP-MS, Artificial neural networks.

INTRODUCTION

Gold geochemistry has been used mainly as an exploration tool to trace ore deposits (McClenaghan 2005; Chapman et al. 2009; Moles and Chapman 2019), in addition to the external shape that the grain obtained during transport to the basin (McClenaghan 2005). The ability of gold to form alloys with many metals (e.g., Ag, Cu, Pb, Pt, Ga, In.) allows it to form continuous alloy series with a minimum distortion of the unit cell as with Ag due to the similarity between their atomic radii and sharing the same crystallographic structure, to form its structure leaving vacancies for other atoms that otherwise could not enter the structure (Boyle 1979). In addition to structural effects, there are kinetic effects, such as a fast crystal growth rate higher than its diffusion rate (Bryan 1974; Nielsen et al. 2013). All these variables are present during gold precipitation and affect the trace and minor elements content. Furthermore, these factors may determine whether they are held in the atomic structure or are evenly distributed as nano-inclusions. Thus, gold geochemistry may provide a reasonable estimate of the type and conditions of deposit formation (Keith et al. 2014; Frenzel et al. 2016; Miranda et al. 2022).

The quantification of the chemical composition of natural gold using high spatial resolution techniques dates back to the 1960s with the development of the electron probe micro analyzer (EPMA) with further advancements reaching trace element levels using laser ablation coupled to an inductively coupled plasma mass spectrometer (LA-ICP-MS) in the 1990s (Gray 1985; Rinaldi and Llovet 2015). These advances enable the geological interpretation of the role of

elemental composition in different deposit types and geological environments. One of the earliest observations involving major and minor elements in gold found a correlation with the physicochemical conditions of the corresponding ore deposit (Antweiler and Campbell 1977; Morrison et al. 1991; Huston et al. 1992). This served as a foundation for looking for a chemical signature in gold among different types of deposits from various terranes, aided by random forest analysis techniques, obtaining mixing results that vary from 50 to 97% accuracy depending on the type of deposit evaluated (Liu and Beaudoin 2021). However, compositional overlaps of different ore deposit types are frequently found, as is the case of porphyry and epithermal deposits in Au-Ag-Cu discrimination diagrams by Townley et al. (2003), among other examples (McClenaghan 2005; Chapman et al. 2009; McClenaghan and Cabri 2011; Moles and Chapman 2019). Thus, attempting to fully understand these complicated relationships between multiple trace elements and the mix of conditions involved in creating an ore deposit by the same traditional linear methods used so far in geoscience would produce somewhat equivocal results. Although methods applying artificial intelligence (AI) to data science have been developed since the late 1950s (Rosenblatt 1958), their application in geosciences and geochemistry is limited to the last 20 years (Farnham et al. 2002; Taylor et al. 2010; Ochoa et al. 2018; Gregory et al. 2019; Cone et al. 2020; Liu and Beaudoin 2021; Liu et al. 2021b; Nathwani et al. 2022; Lui et al. 2022; Freij et al. 2023). Using AI is still a relatively under-investigated field in geosciences, allowing us to innovate better to understand complex ore-forming processes.

Given the nature of geochemical data structure (positive, commutative, and constant total), we proposed to compare and contrast the classification accuracy of Artificial Neural Networks (ANNs) (improved through variations in their architecture) and Random Forest algorithms, which have been used archetypically in geosciences (Trott et al. 2022). This study represents a significant advance by introducing and evaluating the use of Neural Networks, an AI technique that offers the ability to model complex and nonlinear patterns in data. Analyzing the variance of each of the deposit's trace element contents in gold by applying Principal Component Analysis (PCA) allows us to quantify the elements influencing the variance of the deposits the most. Consequently, PCA evaluation using ANN will help us unveil the complex correlations of different trace elements. Finally, to provide geological context, the influence of each of the elements in the classification of the deposits is estimated and compared with their mobility in each type of deposit to better understand the underlying correlations of the model.

In this study, we have found that an architecture for a fully connected ANN consisting of two hidden layers with ten neurons each provides more accurate predictions. This is confirmed with validation and blind tests, which ensures that a general solution for the classification of ore deposits based on LA-ICP-MS elemental concentrations in natural gold has been reached based on ten elements (Pt, Pd, Te, Bi, Sb, Pb, Cu, Ni, Ag, and Fe) discriminated from the dataset by PCA.

MATERIALS AND METHODS

Data collection and considerations

Data collection from different studies must be done carefully since each study faces its own limitations: Different equipment, different operating conditions, procedures for data reduction, and different reference materials for calibration and quality control. This results in differences in accuracy, detection limits, and elements that can be analyzed. The compiled data consists of measurements made by quadrupole ICP-MS, allowing a dynamic mass sweep compared to high-resolution systems with higher standard deviations when the differences in the masses evaluated are over ~30% (Maher et al. 2003). The reference materials for calibration and quality control vary in the studies consulted, resulting in differences in detection limits across studies. However, the mean absolute difference between these is, on average, 0.07, making them comparable. All the studies performed the analyses in spot mode, allowing them to exclude micro-inclusions and possible contamination left during polishing from the time-resolved laser-ablation spectra. Under these criteria, the compiled data is considered parametric and suitable to enter the data processing pipeline after the pre-processing stage.

The production of polyatomic oxygen isobaric interferences during LA-ICP-MS is a common problem, particularly $109\text{Ag}+16\text{O}$ with 125Te , which could affect the amount of Te measured. However, Ag has a low oxide formation rate and is presented in a metallic matrix, which reduces the likelihood of oxide production

(Gilbert et al. 2017). For these reasons, this interference will not be considered in the presented model.

Mercury is an important element frequently associated with gold, as reported in most analyses (Supplementary Material 1). However, they were calibrated with the material reference MASS-1, and none of the quality control standards have not available certified values for Hg (Au-RM-2, NA-Au-31, and NA-Au.30) (Milidragovic et al. 2016; Liu and Beaudoin 2021). As a result, mercury values were not considered for the model development.

An additional model is available with the app package for users who may have oxide inclusions within the gold grains of interest that can increase the oxidation rate of Ag. This additional model was constructed under the same parameters as the one presented in this study.

Data

A total of 480 LA-ICP-MS for trace element analysis of 24 elements (Pt, Pd, Te, Se, Hg, In, Cd, Bi, Sb, Tl, Mo, Sn, As, Co, Pb, Cu, Cr, Ni, Ag, Zn, S, Mn, Ti, Fe) were carried out on by Liu and Beaudoin (2021), Liu et al. (2021a) and Melo-Gomez (2023) (Table S1) on gold grains, ranging from native to electrum gold (herein referred to as gold grains). The deposits analyzed correspond to geological settings hosted by rocks varying from magmatic (mafic to felsic) to sedimentary and ages ranging from Archean to Neogene (Fig. 2). All these significant variations allow us to consider compositional changes in gold during its precipitation process due to the physicochemical interaction between the

hydrothermal fluid and the country rock. Although limited to 4 deposit types, they represent 84% of the global production of primary gold or 60% of the total gold endowment (Lipson 2014).

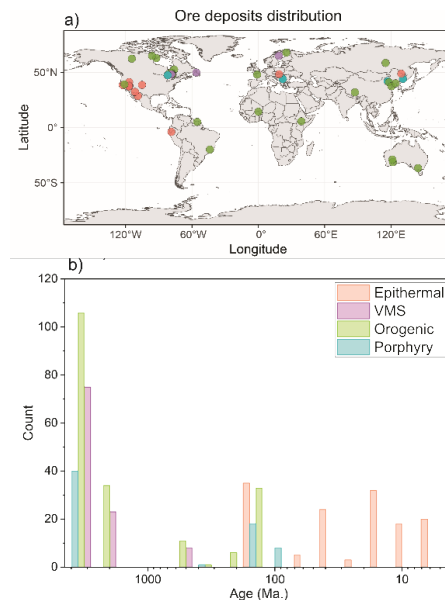


Fig. 2 Locations and ages of the evaluated deposits, data from (Liu et al. 2021a; Liu and Beaudoin 2021; Melo-Gomez 2023). a) Location of the ore deposits. b) Histogram of the age distribution of the samples.

Data pre-processing

The geochemical data was pre-processed prior to the statistical analysis following Templ et al. (2008): The three datasets were pre-processed for (1) geochemical feature selection; (2) substitution of censored (below the limit of detections) data; (3) screening missing values; (4) data transformation to a more symmetric distribution, preserving the modes and removing skewness; and (5) standardization. When analyzing trace elements, they will inevitably have values below the detection limit of the technique used, independent of the method applied. It is important to remember that elements below the detection limit for a particular ore deposit may be crucial for its identification as it may reflect

physicochemical processes; in contrast, others may be present. For this reason, the data pre-treatment was carried out considering the individual deposits to the complete database to avoid generating a bias during the pre-treatment. Elements with over 60% censored or missing values were excluded from the dataset. This procedure assures that if a component has an important role or occurs in a very low concentration (below the limit of detection), it will be adequately replaced, following the data structure of its respective type of deposit (Fig. 3).

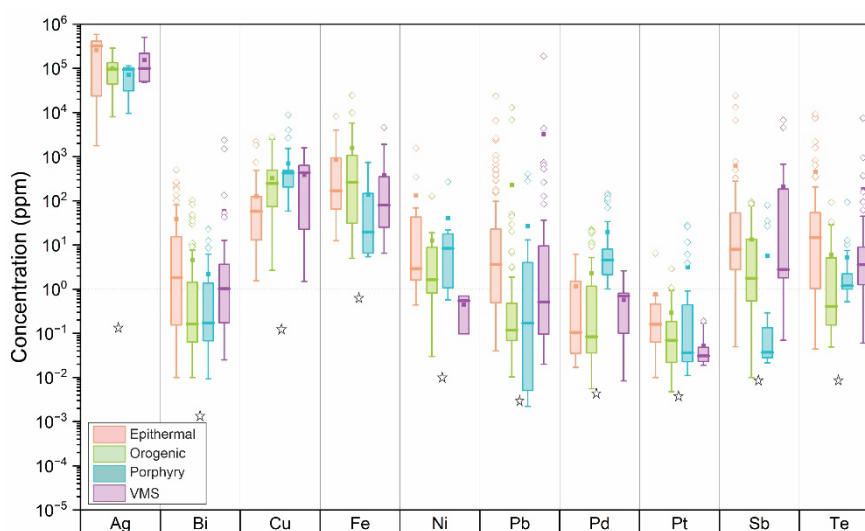


Fig. 3 Data structures are shown as multi-element box and whisker plots, separated by deposit type. The short line in the box represents the median value, whereas the filled square represents the mean value. Empty circles represent outliers, and a star represents the mean value of the detection limit for each element.

Left-censored concentrations were imputed based on the log-ratio expectation maximization algorithm “lrEM”, a function of the R package “zCompositions” (Palarea-Albaladejo et al. 2014; Palarea-Albaladejo and Martín-Fernández 2015). Subsequently, data was normalized to avoid biasing the model due to an overweight of high-concentration elements like Ag (Fig. 3). Z-scores were generated for the dataset as a standardization procedure, using the following

equation where z is the z-score (eq. 1), x is the concentration, μ is the population mean, and σ is the standard deviation of the population (Guilloux et al. 2011):

$$z = \frac{x - \mu}{\sigma} \quad (1)$$

Traditionally, in classical supervised machine learning examples, users only have access to the training set. Therefore, the normalization is usually estimated over this set, assuming that both training and test sets are part of the same distribution and share the same parameters. However, using individual Z-scores for the sets gives a better representation of the features compared to the original dataset (Chen et al. 2021). Although many combinations to calculate the Z-score can be performed, the Z_3 normalization was selected given its better performance (Apicella et al. 2023). This normalization calculates the μ and σ parameters for each set independently.

Data description

The dataset consists of 480 LA-ICP-MS analyses from 48 ore deposits, classified as epithermal (11), orogenic (27), porphyry (5), and VMS (4), distributed around the world (Fig. 2a), ranging in i) age, from the Archean to the Neogene (Fig. 2b) and ii) varying the host rock composition, capturing the physicochemical variance caused by the interaction between the hydrothermal fluid and the host rock. After replacing the data below the limit of detection (BDL), the general structure of the data is maintained (Fig. 2). In cases where most of the data is represented by BDL, these particular elements are treated like outliers, and the concentrations

are estimated by an expectation maximization algorithm. The complete raw dataset can be accessed in Supplementary Material1.

Principal components analysis (PCA)

This dimensionality reduction technique was introduced by Pearson (1901) is a multivariate analysis tool that reduces the dimensionality of the data, allowing for the observation of the variance of each dependent variable as a unique component, called principal components (PCs), which are combined to evaluate the general structure of the data in 2 or 3 dimensions. The generated PCs are ordered according to the variance that each represents from the maximum to the minimum variance in the data-oriented perpendicular to each other. Each component is influenced to some extent by the originally reported concentrations and is represented as Eigen vectors, maintaining their orientation during the linear transformation of the method and changing only its magnitude (Eigen values). This represents the influence of each element on the variance of the data. Thus, the purpose of using PCA on this dataset is to determine how elemental concentrations in gold from different ore deposits are related to the PCs and, therefore, identify if these concentrations may share similar controlling factors. The PCA sci-kit learn package was used on Python 3.9.13 to perform the PCA analysis.

Artificial neural networks

A neural network is a computational model made up of a certain number of nodes, called neurons, connected from an input layer corresponding to our

measurements to an output layer, a likelihood of correspondence to each class. Each connection between the neurons has i) a weight value (importance of the connection); ii) a bias, that represents how high the weighted sums need to be for a neuron to start being meaningfully active; and iii) an activation function, which will tell whether a neuron is active or inactive. The weights and biases are adjusted using back-propagation and gradient descent (Rumelhart et al. 1986), optimizing the values to reach a local minimum where the loss between the actual output vector and the desired output is as small as possible. This complex matrix multiplication approximates a nonlinear function in nature, which attempts to predict the membership of each new data entry based on the patterns learned from the data with which it has been trained (Rosenblatt 1958). All the ANNs architectures are activated depending on the Rectified-Linear-Unit (ReLU) activation function that was selected to avoid gradient dispersion (Ramachandran et al. 2018). The supervised algorithm architectures were completed with the NumPy package in Python 3.9.13.

The general processing pipeline used in this research is shown in (Fig. 4): First the data is separated into two batches, training (85%) and testing (15%) and normalizing each batch. The impact of every architecture is scrutinized on the proposed structures (i.e., single, double and triple hidden layers). Then, performances are evaluated on the testing set through the models $m1$, $m2$, $m3$, $m4$, and $m5$, fitted during the training stage and are compared to the accuracies of the models. The accuracy is measured in true positive discoveries (TPR), which refers to correctly predicted data located on the diagonal of the confusion

matrix, is measured as the number of correctly predicted data divided by the sum of the correctly predicted data (True positive (TP)) plus the erroneous predictions (False negative (FN)) for the evaluated deposit all times 100 (eq. 2). Finally, the bias towards each of the deposits is estimated with the false discovery rate (FDR) it is measured as the false predictions of the model (false positive (FP)) divided by the sum of FP plus TP times 100 (eq. 3). These calculations can be seen in (Table S2 to S6).

$$TPR = \left(\frac{TP}{TP + FN} \right) * 100 \quad (2)$$

$$FDR = \left(\frac{FP}{FP + TP} \right) * 100 \quad (3)$$

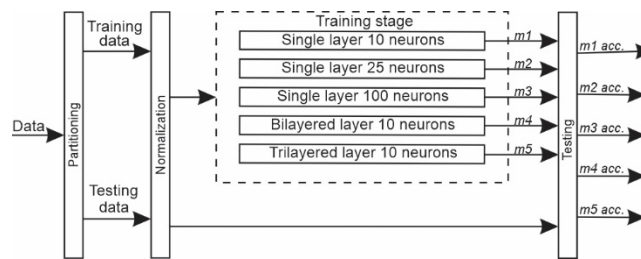


Fig. 4 Graphical representation of the processing pipeline used in this work. After partitioning and normalization, the training data is trained by five different proposed ANNs. Then, performances are evaluated on the testing set through the models m1, m2, m3, m4 and m5 and then compared.

RESULTS

Gold geochemistry

The most common way to represent the gold content in the Au-Ag alloy is by fineness, based on Eq. 4. Applying the results from the dataset, we can calculate the probability distribution of the data and approximate graphically its probability density function (Fig. 5 a and b). Based on the probability density function, which shows peaks where the data density is higher, one can observe bimodal

distributions (VMS, Epithermal) and multi-modal distributions (Orogenic and porphyry) either as fineness or Au and Ag probability density functions (Fig. 5a and b).

$$\frac{Au_{wt\%}}{Au_{wt\%} + Ag_{wt\%}} \times 1000 \quad (4)$$

Given the atomic similarities between Au and Ag, they can form a continuous alloy series, leading to a strong negative correlation (Fig. 5a). All deposits show an overlap at high-Au levels, although some differences can be noticed. Epithermal deposits represent the higher fineness values of gold with a value of 998, followed by the porphyry deposits, orogenic and VMS deposits. In terms of data dispersion, epithermal deposits exhibit the most significant variation from the highest to the lowest fineness (998 to 301), followed by VMS deposits (950 to 473), orogenic deposits (994 to 702), and porphyry-type deposits with fineness ranging between 990 and 879.

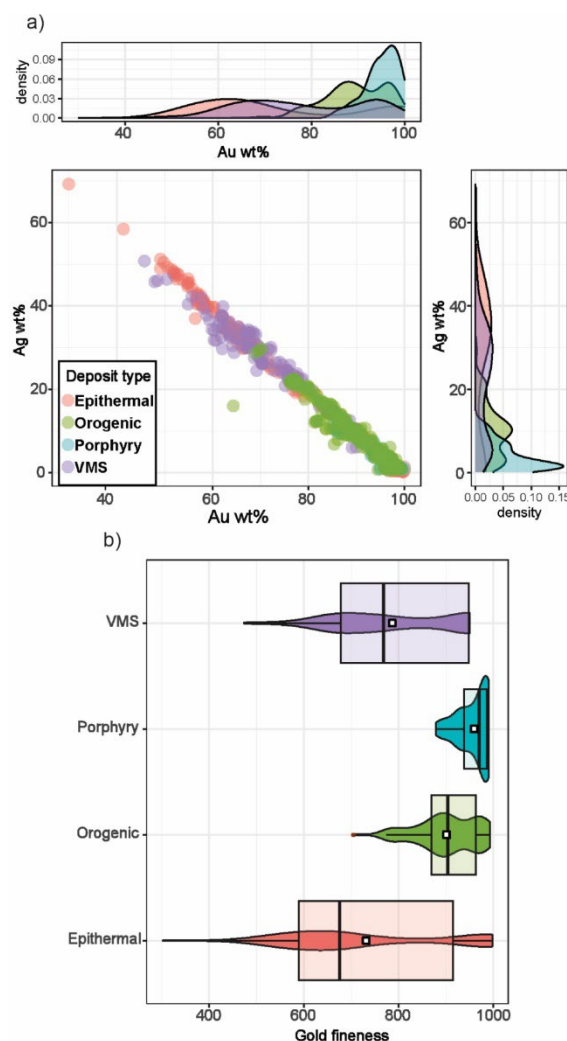


Fig. 5 Au – Ag content in gold grains subset by deposit type. a) Scatter plot of Au silver with the probability density function plot in the axis showing how concentrated is the data in certain ranges for each deposit. Each data point is described with an alpha value of 0.5, resulting in overlapping data that appears darker. b) Box and whisker plot showing the fineness range of each deposit with a black line in the box representing the median value and a white square representing the mean value it is plotted over a violin plot showing the complexity of the data distribution deviating from a normal one.

Frequently, the associations between gold-silver alloys and trace elements do not show clear correlations. However, calculated correlation factors on bivariate plots of Cu, Pb, Sb and Te against Ag show subtle correlations as gold fineness changes marked by correlation line determined by a Kendall interpolation (Fig. 5 and S1). At low Ag contents, the correlation with Cu presents a slight positive correlation up to 3.0 wt.% where the correlation becomes negative accompanied

by an increase in the Cu variance as fineness decreases. (Fig. 6a and S1). Lead and Ag maintain no significant correlation until the amount of Ag in the alloy reaches 10 wt.% then the correlation becomes positive with an increase in the Pb variance (Fig. 6b and S1). Similarly to the Pb-Ag correlation, there is no significant correlation between Sb and Ag at a high level of fineness. After Ag reaches 10 wt.%, the correlation becomes weakly positive, together with an increase in the Sb variance (Fig. 6c and S1). Finally, Te has a weakly positive correlation with Ag up to 15 wt.%. Beyond this point, the correlation becomes stronger and shifts to a negative correlation after Ag reaches 30 wt.%. The variance of Te increases following the increase in Ag content (Fig. 6d and S1). However, there are outliers, corresponding to epithermal deposits at high fineness levels, which were not considered for the correlation calculation (Fig. 6d and S1).

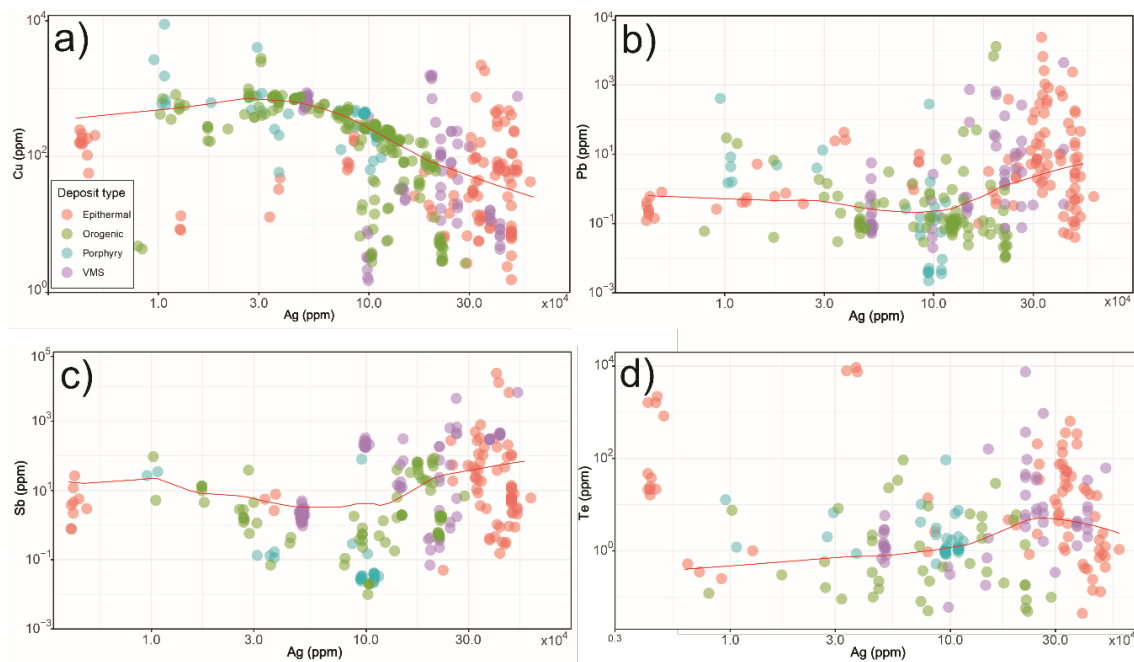


Fig. 6 Bivariate plots of trace elements in natural gold in parts per million (ppm), showing the general trends calculated of the elements in function of Ag variation in a logarithmic scale. Each data point is described with an alpha value of 0.5, resulting in overlapping data that appears darker. The calculated trends increase of the correlations are marked with a red line a) Ag versus Cu. showing a weak direct correlation up to Ag content of 3 wt.% and then becomes an inverse correlation. b) Ag versus Pb. Shows no correlation up to 10 wt.% where a direct correlation is marked along with increase in variance. c) Ag versus Sb, positive correlations are present in this pair of elements, at low Ag contents (0.3 - 1 wt.%) and higher than 10 wt.%, in between these values a negative correlation is observed. d) Ag versus Te, in general, a positive correlation between these elements can be observed, with outliers corresponding to epithermal deposits rich in Te. It should be noted that clusters observed of particular deposit types correspond to narrow values of Ag for specific deposits.

Principal component analysis (PCA)

This technique was performed for ten elements (Pt, Pd, Te, Bi, Sb, Pb, Cu, Ni, Ag, Fe) selected in the pre-processing of the dataset, 97.76% of the variability in the dataset by the principal components from 1 to 8 (20.9%, 19.49%, 12.38%, 10.54%, 9.9%, 9.63, 8.43%, 6.48%, respectively) where each of the percentages represents the variance represented by each of the principal components (Fig. 7). The variability can be divided into three segments; the first corresponds to high variability with (PC1 and PC2), around 20% variance. The second represents a medium variability from 12.38 to 6.48% with a mean decrease of the variance of 0.98% among the PCs 3 to 8. Finally, the last segment corresponds to low variances (PC9 and PC10), is considered background variability (noise) and does not add substantial variability to the dataset. Also, the variables not shown in (Fig. 7) were not plotted due to their low values.

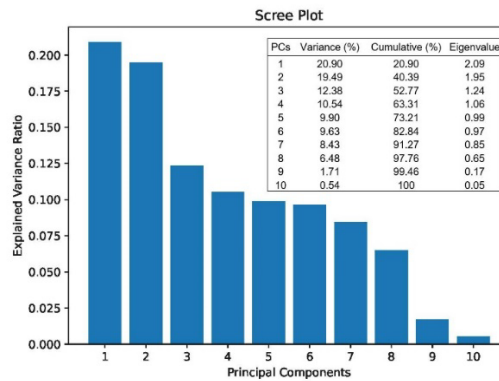


Fig. 7 Scree plot of the variance ratio of the ten PCs and corresponding values for variance and eigenvalues for each PCs. Presented in a table and as a cumulative histogram.

Four elements are the main contributors to the variance in the PC1-PC2 space, Pd, Pt, Pb and Bi (Fig. 7a). PC1 axis yields negative loadings for Pt, Pd and Cu while the rest contribute positively. Concurrently, the second PC is only affected negatively by Ag. The PC3-PC4 space shows positive loadings for Te, Fe, Pb and Cu for PC3 and Pb, Fe, Te, Pt for PC4. At the same time, Pt, Ag, Ni, and Sb correspond to negative loadings for PC3, and Ag, Ni, Sb, and Cu have a negative influence on PC4 (Fig. 7b). Three elements (Fe, Ni, and Te) have the most significant contribution to variance in the PC5-PC6 space. Iron, Ni, and Cu contribute with positive loadings to PC5, while Fe and Ag do it for PC6. Tellurium, Sb and Ag contribute negatively to the variance for PC5, while Sb, Te, Cu, and Ni have this effect on PC6 (Fig. 8c). Lastly, the space PC7-PC8 is characterized by a PC7 with positive loadings for Ag, Cu, Te, Fe Sb and Ni while just Pb and Bi contribute negatively to it. PC8 axis yields positive loadings for Pb, Ag, Cu, Te, and Fe and negative loadings for Bi, Ni, and Sb. A large percentage of the variance represented by the principal components increases steadily up to around 60%. Then it increases at a constant rate of about 7% for each new PC

until the last two PCs, where the variance showed by those PCs decreases to about 1% (Fig. 7). This is a reflection of the complexity of the data diverging from the Classical PCA where a single clear point of inflection can be found in the variance of the PCs.

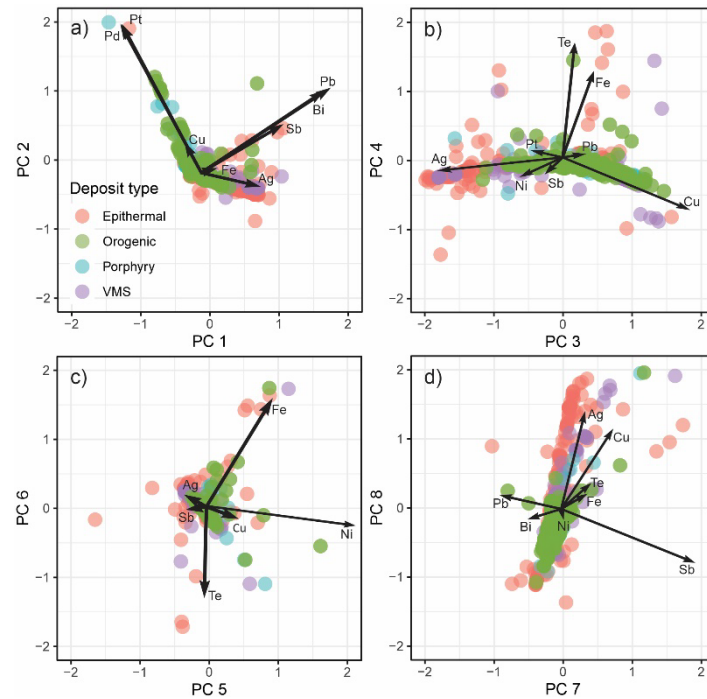


Fig. 8 PCA for gold trace elements dataset showing the distribution of the data and variables (elements) represented as vectors. Each data point is described with an alpha value of 0.5, resulting in overlapping data that appears darker. a) Biplot for PC1 vs. PC2; b) Biplot for PC3 vs. PC4; c) Biplot for PC5 vs. PC6; and d) Biplot for PC7 vs. PC8.

Artificial neural networks (ANN)

In this section, we present the results of a series of experiments with different combinations of architectures for the ANNs to find the best combination to classify gold-bearing deposits. Five different combinations are evaluated, ranging from a ten neurons single layer ANN to a triple hidden layered neural network (Fig. 4). The results can be seen in (Table 1) expressed as a function of the average F1 score of ten runs of each architecture. This evaluates the performance of

classification models by combining precision and true positive rate into a single value, providing a balanced measure of a model's accuracy (Powers 2011).

Table 1 F1 score of the proposed models and SMOTE correction in all the proposed architectures

Architecture	Number of neurons	Average F1 score	SMOTE Average F1 Score
Single layer	10	0.817± 0.056	0.777± 0.029
	25	0.918± 0.042	0.806 ± 0.017
	100	0.882± 0.045	0.835 ± 0.026
Bilayered	10	0.926± 0.054	0.800 ± 0.023
Trilayered	10	0.798± 0.034	0.817 ± 0.027

To ensure that the observations fit globally the data structure of each deposit and are well-represented, the data is partitioned randomly so that 85% of the dataset is used to train the model and 15% is applied to evaluate it. The reported scores are an average of 10 runs of such partitions. The chosen models shown in the following subsections correspond to the one closest to the F1 averages viewed in (Table 1) to avoid selecting an overfitted model.

Single-layer neural networks

Three different architectures with a single hidden layer were evaluated (10, 25, and 100 neurons). The first neural network has ten neurons and an F1 score of

0.817. This particular ANN performed well classifying epithermal, orogenic, and porphyry deposits, with an overall accuracy of 81.9% and a true positive rate (TPR) peak of 95.0% TPR in epithermal deposits. There is a bias in epithermal and orogenic-type deposits since, to some extent, part of the misclassified data falls mainly in these two categories. This can be seen in the false discovery rate (FDR), which is highest for epithermal followed by orogenic deposits (i.e., 24.0% and 16.7 respectively). Another critical feature of this model is that it has a high false negative rate (FNR) of 38.9% in VMS deposits, where almost 40% of the data is classified as VMS deposits, maybe due to the bias mentioned above. However, false predictions for this type of deposit are low, as reflected in a 4.2% FNR (Fig. 9a).

When the number of neurons is increased to 25, the overall performance of the ANN is increased to an F1 score of 0.918. This architecture reduces FNR for orogenic and VMS deposits by 8.3 and 22.2% respectively (Fig. 9b), with a bias now distributed between epithermal and porphyry type deposits, showing an FDR of 20.0 and 9.1%, respectively (Table S3). It is important to highlight that 100% TPR was obtained in two categories, porphyry and epithermal with the second lowest FDR obtained in all the models 20 and 9.1% respectively. In addition, orogenic deposits produced over 90% of TPR.

Finally, when the neural network structure reaches 100 neurons, it shows a general reduction of TPR compared with the previous structure (Fig. 9c) this is reflected in the F1 score of 0.882 (Table 1) while concentrating the bias towards

epithermal and orogenic deposits, with an FDR of 24% and 16% respectively (Table S4)

Trilayered neural network

This ANN consists of three hidden layers, each with 10 neurons. Contrary to expectations, increasing the number of layers does not increase the F1 score, reaching the lowest value among all the models evaluated in this study with an F1 score = 0.798. However, the model's performance is nearly equal to that of the lowest number of neurons in a single hidden layer (the closest F1 score) for the TPR of epithermal and porphyry deposits (Fig. 9c and e). The accuracy calculated when evaluating orogenic deposits drops to a TPR of 75.0%, a reduction of 11.3%. However, an increase in accuracy can be observed in VMS deposits, where the TPR increased by 6.6%. Even though this model's TPR is similar to the first model evaluated, the weakness of this model can be seen in the high percentages of FDR present in all the deposits (Table S6).

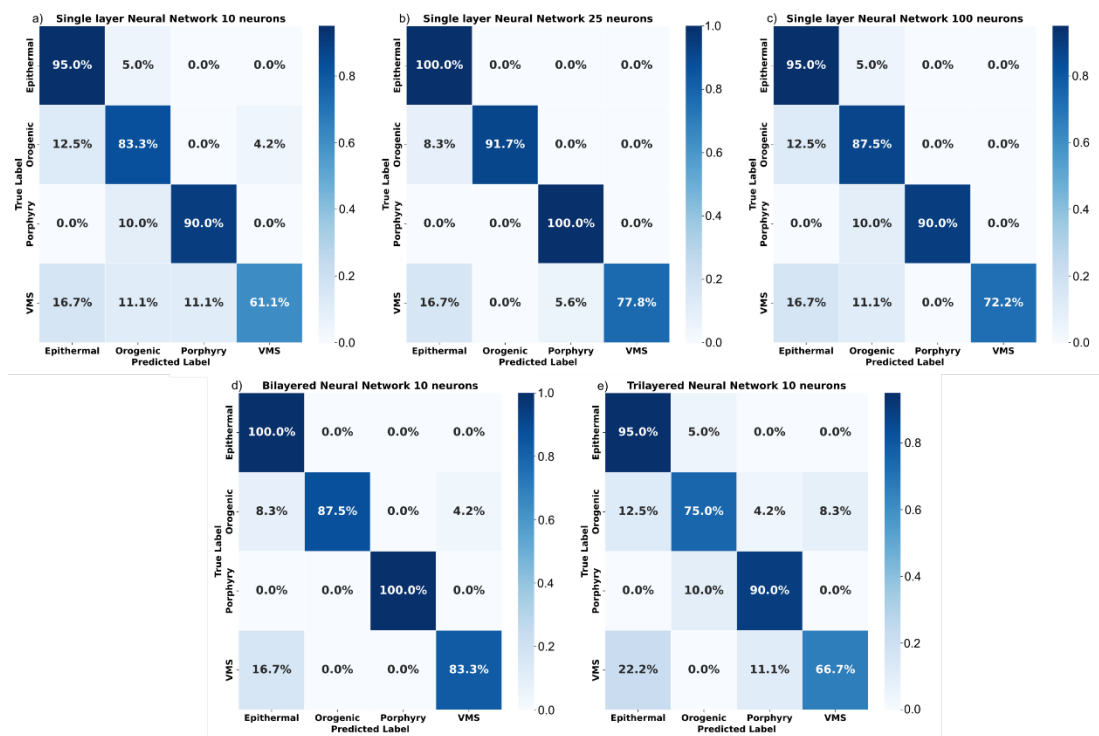


Fig. 9 Confusion matrix results of the single layer models. a) Confusion matrix for an artificial neural network with a single hidden layer and 10 neurons, b) Confusion matrix for an artificial neural network with a single hidden layer and 25 neurons, c) Confusion matrix for an artificial neural network with a single hidden layer and 100 neurons, d) Confusion matrix results of the bilayered neural network with 10 neurons each layer, e) Confusion matrix results of the trilayered neural network with 10 neurons each layer.

Bilayered neural network

This ANN consists of two hidden layers, each with 10 neurons. This structure gave the best results in terms of F1 score, 0.926 (Table 1), improving the epithermal classification, to be as good as the result obtained in the single hidden layer with 10 neurons, in terms of TPR and FDR (Table S5 and Fig. 9d). True predictions for orogenic deposits were equal to a wide single hidden layer with a clear improvement in the bias market by a 0% FDR. VMS deposits performance shows an improvement in TPR with a value of 83.3% (Fig. 9d). However, the bias increase of the model bias market by an FDR of 6.2% (Table S5) compared to the results of all single hidden layer models. Finally, the results for porphyry

deposits are comparable in accuracy to those obtained with 25 neurons, with a TDR of 100%. The additional advantage is that the model bias is eliminated, presenting zero false discoveries (Fig. 9d).

DISCUSSION

Oversampling

As in many other machine learning applications in real life, the dataset used in this study has unbalanced data, which leads to poor predictive accuracy in the minority class, as can be seen in the results presented by Liu and Beaudoin (2021). In these cases, it is standard procedure to match the sizes of the classes by oversampling; one of the most used is the Synthetic Minority Over-sampling Technique (SMOTE). This technique has proven to be very effective in many applications, sentence boundary detection, bioinformatics, photoreceptor enriched genes based on expression data (Liu et al. 2006; Batuwita and Palade 2009; Xiao et al. 2011; Johnson et al. 2012; Lui et al. 2022). However, as we increase the number of dimensions (variables), the effectiveness of this methodology seems to decrease or even result in poor performance compared to working with unbalanced data (Blagus and Lusa 2013). In this case study, oversampling by SMOTE resulted in a deterioration in the performances for every ANN architecture evaluated, compared with the uncorrected analysis (Table 1). Since these results do not represent an improvement in the classification, the full models are not presented in this paper.

Although there are more published gold geochemistry data, these were not included in the model as they would make it more unbalanced and risk biasing it and decreasing its accuracy. The apparent ineffectiveness of SMOTE on geochemical data does not make it advisable to add data that further unbalances the model.

Implications of data structure in ANN architectures

Mineral trace-element data have intrinsic mathematical properties that must be taken into account when analyzed: 1) probability distribution of the data, 2) general incompleteness, and 3) hierarchical data structure (Frenzel 2023). The first two properties are addressed in the pre-processing section according to generally accepted statistical treatment for compositional data and data BDL (Carranza 2011; Palarea-Albaladejo and Martín-Fernández 2015; Tolosana-Delgado et al. 2019; Frenzel 2023). However, the traditional treatment of data as a hierarchical structure was faced during the model optimization by stochastic gradient descent, starting from a random initialization hyperparameters are optimized by minimizing the cost function (the result of a prediction minus the desired result, squared) for random batches of the training samples. This results in optimized values for the hyperparameters that reach a minimum value for all the variance in the data studied. Hence, the influence of the hierarchical structure applied to trace elemental concentration to define a chemical signature generated by an ore deposit is inferred with a stochastic iterative approximation (Rumelhart et al. 1986).

The flexibility of the crystalline structure of gold to incorporate other elements is a determining factor in its ability to maintain a chemical signature associated with the particular physical and chemical conditions of the deposit responsible for its formation. The Au-Ag solid solution occurs smoothly due to their similar radii until the amount of silver exceeds 10 wt.% (Fig. 5 Fig. 6). After this limit, structural imperfections allow the incorporation of elements with different radii such as Pb or Sb (Fig. 6b and c). Meanwhile, elements like Te with a close affinity in ionic radii to Ag replace it directly in two possible ways: Ag^{2+} by Te^{4+} or Ag^{3+} by Te^{6+} , which are non-isovalent incorporations in the crystal lattice (Cook et al. 2015; Gao et al. 2023). Therefore, a direct relationship between these elements would be expected, as well as an increase in the variance result of the vacancies generated needed to compensate the charge valance (Fig. 6d).

Compositional data is represented with a vector $\vec{x}$ with a unique characteristic. It is commutative, unlike common issues in machine learning, such as facial or speech recognition, in which the spatial relationship between each of the data points results in critical patterns for the development of models for the identification and classification of this type of data (LeCun and Bengio 1995). This property allows us to use a more straightforward structure, a fully connected artificial neural network, as a robust base to explore performances on different architectures by changing the number of connections and layers.

The availability of a global gold geochemistry dataset (Liu et al. 2021a; Liu and Beaudoin 2021) allows us to apply different AI techniques, like artificial neural

networks, as in this study. It is optimized by different architectures, improving the accuracy compared with previous models on the same data (Liu and Beaudoin 2021). Even though the size of the dataset is still small compared to most available used on other machine learning applications, the results obtained show that neural networks are a powerful tool for analyzing the relationships between compositional data. This not only drives the application of these models in mineral deposit exploration but also the enrichment of the dataset by generating new data when evaluating a new deposit.

Elemental variation and model selection

Trace elemental composition of gold from different ore deposit types results from the physicochemical conditions under which the individual gold grains were formed (Morrison et al. 1991). Each mineralization style has unique features in its formation process (e.g., country rock, temperature, pH, complexing agents, salinity, etc.). This promotes compositional variance between distinct deposit types and overlaps in the database, which can be challenging to interpret. Consequently, the variance of the data generated by each of the elements measured will have a particular influence on the predictive model, so it can be inferred that the correlations between them are not causal.

Chloride and bisulfide complexes are the main ligands responsible for gold transportation in hydrothermal systems, and their efficiency depends on the physicochemical conditions of the system (i.e., pH, fO_2 temperature, pressure, country rock composition (Mei et al., 2013; Seward et al., 2014). All these

variables play a role in the final composition of gold (Chapman et al. 2009). Thus, even mineral deposits classified in the same category (i.e., orogenic) do not necessarily share the same genetic conditions and may comprise a distinct gold geochemical signature. For example, La Lucette and Cuiabá orogenic deposits are hosted by black shales and mafic volcanic rocks, respectively, which could result in a variation in the gold's chemical signature despite the same geological process (Ribeiro-Rodrigues et al. 2007; Pochon et al. 2016). Therefore, having the gold composition of ore deposits with different features allows the model to select the general combination of elemental concentrations that are signatures of each analyzed deposit. Nevertheless, secondary processes have been pointed out as crucial to forming high-grade ore zones in Au deposits: Solid state transport as nanoparticles and Au-polymetallic melts rich in low melting point chalcophiles (Hastie et al. 2020). If Au is remobilized as nanoparticles or solid-state ductile flow, it should retain the original or mixed signatures. In contrast, if it is remobilized as polymetallic melt in low melting point chalcophiles, the trace elements in gold would equilibrate to the new physicochemical conditions.

Machine learning methods are often considered to be obscure or convoluted, (Ribeiro et al. 2016; Samek et al. 2021). This study evaluates the influence of each selected element for classification on the model, assuming them independent variables, a partial dependence plot (PDP) was designed, applying a score from 0 to 1, according to the concentration of the normalized elements (Fig.S2 to S11). Probabilities are then compared to the element's behaviour in the hydrothermal system to understand the model's decision making.

Orogenic deposits

Orogenic deposits are formed within or proximal to deep crustal fault zones, with a complex structural history and involve fluids from metamorphic processes (Goldfarb et al. 2005). These deposits are found predominantly in three distinctive geotectonic settings: late Archean greenstone, Paleoproterozoic hosted by sedimentary and volcanic rocks at the margins of greenstone terrains, and Ediacaran-Phanerozoic related to collisional continental margins (Goldfarb et al. 2001). The hydrothermal fluids responsible for these deposits display a strong dominance of CO₂ and low salinity (1 – 3 wt.% NaCl equiv.) with a pH range from neutral to mildly alkaline; under these conditions, the ligand responsible for gold transport is HS⁻.

During metamorphic process under greenschist and amphibolite facies conditions, it is possible to facilitate the liberation of metals such as Au, Ag, As, Bi, Cd, Mo, Hg, Sb, Te and W (Pitcairn et al. 2006; Groves et al. 2020). These elements are commonly used as a geochemical proxy for orogenic gold deposits in soil or whole rock geochemical analysis (Groves et al. 2020). However, Contrary to common reasoning, these essential elements (Bi, Sb and Te, evaluated in this model) do not play an important role in the identification of orogenic deposits by the model (Fig.S3, S10 and S11) since the partition coefficient of these elements is higher than other minerals that precipitate in the deposit leaving less contents in the fluid to be assimilated by gold when it precipitates. Despite having an important role as a proxy in the system, the

concentration of these elements in gold grains is better related to VMS or epithermal deposits.

Silver has two significant peaks at low concentrations (Fig.S2), resulting in a high fineness (Fig.S3). This can be the result of devolatilization processes over metasedimentary rocks, where diagenetic pyrite is transformed to pyrrhotite during the metamorphic event, generating reduced S to transport gold, and buffered by the CO₂ content to maintain the fluid conditions where Au is most efficiently transported by near neutral pH fluids (Large et al. 2011; Tomkins 2013). While Pb in orogenic deposits is related to the fluid interaction with felsic rocks (Ridley and Diamond 2000; Liu et al. 2021a), this interaction with the surrounding rocks influences the presence or absence of this element so that in some cases, there may be high scores for low concentrations and low scores at high concentrations (Fig.S7), following the probability density function for the distribution of the element across the evaluated deposits (Fig. 5b).

The high variability of the models, choosing an orogenic deposit over other genetic models, can be noted prominently in the simpler models (Fig. 9a and b) where the false discovery rates are higher, and therefore, it can be inferred that their bias is high. As the models become more complex, they can reduce the false discovery rate across all deposits and consequently reduce the effect of sample bias through the correct model architecture design. However, there are methodologies to minimize the bias with existing data (Elith et al., 2010; Barber et al., 2022). This is not recommended for this dataset due to the low number of

samples in general, and it would be recommended to increase the number of samples from other deposit types to build a more robust model.

Porphyry deposits

Porphyry deposits are magmatic-hydrothermal systems, formed because of the concentrated release of metal-bearing saline fluid from cooling crustal hydrous magma (Sillitoe 2010; Weis et al. 2012; Sun et al. 2015). At the time of separation of this fluid, it has an approximately neutral pH. As the fluid rises, it reaches the solvus and separates into a hypersaline phase and an acidic gaseous phase (Hedenquist 1995; Heinrich et al. 2004; Kouzmanov and Pokrovski 2012). Based on the economically predominant metal precipitated they can be grouped into 5 categories: Au, Cu, Mo, W and Sn, contributing to the global production of ~60% of copper, ~95% of molybdenum and ~15% of gold (Seedorff et al. 2005; Lipson 2014; Heidari et al. 2024). Gold-rich porphyry deposits, the deposits of interest for this paper (Herein, Porphyry deposits), range from Cu as its dominant metal and Au being a byproduct to Au only end members, seem to be favored by K-rich calc-alkaline magmatic systems, which seem to increase the precipitation factor of Au by 5 in comparison to Cu precipitation (Sillitoe 2017; Chiaradia 2020).

Porphyry deposits should present the highest uncertainty for our model due to the low scores obtained in PDP (Fig.S2 to S11). However, the results obtained show that even though individually, the selected elements are not strongly discriminant, when evaluated as a set, their combination results in high accuracy predictions (Fig. 9). However, we can highlight the influence of Pt, as in

epithermal deposits it also contributes as an important factor in the decision making of the model although, in a smaller proportion, its underlying cause may be similar to that shown by epithermal deposits with the difference that when separating the phases, only the brine would contain part of the platinum extracted from the silica melt (Simon and Pettke 2009).

Copper also contributes to the decision making process to determine if the origin of the gold grain is a porphyry type deposit, although it seems the Cu contents are not highly important to determine if the deposit belongs to the porphyry style (Fig.S4). However, not definitive because the deposits where gold is an integral part of the ore present genetic differences with the porphyries rich in Cu and poor in Au, the latter are associated with typical calc-alkaline magmatism where deposit size is directly related to crustal thickness and time of formation (Chiaradia and Caricchi 2017). In contrast, Au-rich porphyry-type deposits are associated with K-rich calc-alkaline magmas where the crucial factor for their formation is the efficiency of gold precipitation (Chiaradia 2020). This factor can be reached by a decrease in pressure that allows for an effective precipitation of Au along with Cu (Murakami et al. 2010). It also decreases the fluid's oxygen fugacity, making it more likely to precipitate Au and not Cu. Hence, the Cu content in precipitated Au under these conditions is expected to be low (Fig.S4).

Epithermal deposits

The term epithermal was coined a little over 100 years ago, assigning this term to mineral deposits of Au, Ag and base metals that are formed in upper crustal

hydrothermal processes process (~1.5 km), temperatures of mineral formation between 150° to 300°C, and are related to the emplacement of an igneous body (Lindgren 1922). Over the years, these have been divided into subcategories based on the sulphidation state of the sulphide mineral assemblages, a mineralogical feature that reflects the physicochemical conditions of the fluid from which it formed (Hedenquist et al. 2000). Low sulfidation deposits are characterized by pyrite-pyrrhotite-arsenopyrite and high Fe sphalerite from basic to neutral fluids with low salinity (<5 wt.% NaCl equiv.). On the other side of the spectrum are high sulphidation epithermal deposits, characterized by the association of pyrite-enargite-luzonite-covellite in an acid environment and low salinity. A transition phase is described as an intermediate sulphidation state, often associated with the development of a high sulphidation deposit, characterized by the assemblage of pyrite-tetrahedrite/tennantite-chalcopyrite and low Fe sphalerite. This middle member is also richer in Ag contents (Hedenquist et al. 2000; Sillitoe and Hedenquist 2005).

The available amount of data on high sulfidation deposits (n= 24 from La India) is not enough to establish different styles of epithermal deposits. However, its inclusion allows for the broadening of the spectrum of that class by improving generalization through the increase in variability. More data on the whole spectrum of epithermal deposits is needed to accurately establish a gold geochemical signature for epithermal types and subtypes. The presented model can confidently distinguish the geochemical features in gold grains of an

epithermal deposit, but additional geological information would be required to determine the specific subtype.

Silver content in epithermal has the greatest variation among the evaluated data, overlapping with other deposits at intermediate concentrations of Ag (Fig. 5). As a result, epithermal deposits strongly influence the model when Ag contents are too low or too high, <10 wt.% & >30 wt.%, respectively (Fig.S2). The presented range of Ag in this deposit is related to the temperature range. Cooler fluids allow for Ag saturation, resulting in a low fineness of gold, whereas acidic and hot fluids would result in a higher fineness (Morrison et al. 1991). However, these deposits record the whole range of Ag concentration due to the evolution of the fluid through the hydrothermal system (Chapman et al. 2000; Sillitoe and Hedenquist 2005; Heinrich and Candela 2014). Therefore, Ag alone is not a good indicator of whether or not the analyzed gold grain belongs to an epithermal deposit.

Bismuth and Sb have similar thermodynamic properties and prefer to be transported as neutral complexes type $(OH)_3$ (Tooth et al. 2013). Therefore, these elements have similar tendencies in the decision-making process (Fig.S3 and S10). However, Bi also can be transported as a chloride complex (Etschmann et al. 2016), which makes the orders of magnitude of the concentrations found for both elements very different despite having a similar chemistry. Epithermal deposits are a source of base metals, such as Pb, although their importance is overshadowed by their great importance as sources of precious metals (Lindgren

1933; Hedenquist et al. 2000). Lead is transported mainly as a chloride complex, precipitating from solution when temperature, salinity, or pressure decrease (Corbett and Leach 1998). Its content is recorded in the composition of trace elements in gold grains, allowing the model to predict that they are epithermal deposits when they contain Pb contents higher than 0.6 wt.% (Fig. S7). Platinum contributes considerably to define a deposit as epithermal (Fig.S9). This element can originate from magmatic fluids from intrusions of intermediate composition associated with this type of deposit, transported in an early phase of either steam or brine with a low abundance of sulfides, promoting an increase in the transport of this element from a silicate melt (Simon and Pettke 2009).

Volcanogenic Massive Sulfide (VMS) deposits

VMS deposits are strata-bound metal sulfide accumulations (Cu, Zn, Pb), sometimes containing significant amounts of Au, formed at or near the seafloor and are genetically associated with a volcanic setting (Hannington et al. 1997; Franklin et al. 2005). Gold can be leached from the volcanic pile by low-temperature sea water as an $\text{Au}(\text{HS})_2^-$ Complex or from the magmatic-hydrothermal fluid as a chlorine complex while other metals (Zn, Pb, Cu) are mainly transported as chlorine complexes (Large 1992; Gammons and Williams-Jones 1995). Lastly, the hydrothermal fluid rises from secondary permeability (synvolcanic faults, thermal contraction fractures) that allows a focused discharge at the sea floor, getting the fluid in contact with low-temperature seawater, so it loses the ability to carry metals through cooling and dilution, forming and depositing sulfides and precious metals (Lydon 1988; Humphris et al. 1995).

The Ag contents in VMS deposits produce two peaks with higher importance for the model (15 and 25 wt. %) (Fig.S2). In addition to precipitation by thermal shock, temperature differences between the hydrothermal fluid and seawater play an important role. Gold will be produced with lower Ag contents if the fluid presents chloride complexes and high temperatures (250° - 350°C). On the other hand, if the temperatures are more moderate (<250°C) the amount of Ag that precipitates associated with Au increases (Huston et al. 1992; Large 1992; Gammons and Williams-Jones 1995). Other important elements for the model are Bi, Pb, Sb and Te. They are transported as bisulfide complexes in solution from the fluid-rock interface and become more likely to be incorporated into the gold structure as the temperature decreases and oxygen fugacity in the hydrothermal fluid increases due to contact with seawater, destabilizing the sulfide complexes (Large 1992; Gammons and Williams-Jones 1995). These elements present similar trends for the model in terms of prediction score to those presented by epithermal deposits but vary in the transport by OH complexes that seem to be less important in this type of deposits (Tooth et al. 2013).

Predictions on blind data

The presented model is based on the postulate that a 'geochemical signature' is recorded in the composition of gold grains left by the geological process that formed the ore deposit. However, many Au-bearing systems result from gold being enriched and modified through one or multiple metamorphic processes, mobilizing Au along with other elements and possibly obliterating the original signature in gold (Hastie et al. 2020; Fabricio-Silva et al. 2021). To check the

model on this scenario, the model is evaluated on geochemical data from deposits that have been considered mesothermal orogenic (Hollinger, McIntyre, and Aunor) located in the Abitibi greenstone belt, near Timmins, Ontario (Velasquez 2014). They are mineralized quartz-carbonate veins hosted by metamorphosed volcano-sedimentary sequences (pillowed lavas, tuffaceous basalts, felsic flows) aligned with east-west crustal structures, related to a shortening event (Robert 2001). Their close association with the Pearl Lake porphyry intrusions along with factors such as potassic alteration, zonation in the alterations present, and the presence of base metals suggest that there was a previous magmatic-hydrothermal deposit that was remobilized by fluids of an orogenic nature (Mathieu 2021).

These LA-ICP-MS analyses were used as blind data (assuming that the target class are orogenic deposits) to evaluate the best model efficiency on data unseen by the model. Using those geochemical analyses in bi-layered with ten neurons, each considering the ten elements previously selected based on PCA, we obtained 89.1% correct predictions (Fig. 9). These predictions were made with the app OreGenes, weights and biases can be found in the application metadata (Supplementary Application 1).

The Hollinger deposit was incorrectly classified as an epithermal deposit in 15.8% of the cases (i.e., 3 out of 19 samples). This results from a complex combination of factors that led the model to predict that they were from an epithermal deposit. However, it is in concordance with the expected results (Fig. 9d) showing no

predictions of porphyry deposits and not misclassifying any data as VMS, given its low bias toward this type of deposit (Fig. 10). On the other hand, the McIntyre deposit was correctly classified 100% of the time as an orogenic deposit. Although the improvement is high compared to the Hollinger deposit, in this case, the difference might be attributed to the low quantity of data evaluated in this deposit. Finally, the Aunor deposit is misclassified 7.4% of the time for epithermal and porphyry deposits. In this case, the total error is close to the expected total error in coherence with the model's accuracy.

These results expand upon those obtained by Liu and Beaudoin (2021), improving the classification accuracy by 11.32% on the blind data, while misclassifications of VMS type deposits were not present in our model, and those in the epithermal type are only slightly higher. It should be noted that our model does present misclassifications as porphyry deposits, but it only represents 3.1% of the cases. These results and their simple implementation make this an effective technique for identifying gold-bearing deposit types if they were formed under one of the evaluated deposit types.

The results on blind data show little evidence of a pre-existing geochemical signature of deposit contributing to the present mineralization (about 10% of the samples) which could be attributed to the model error rather than an inherited signature. The geochemical signature in gold grains seems to stabilize under the new physicochemical conditions obliterating the previous one and favoring the Au-polymetallic melts model for the deposit gold enrichment.

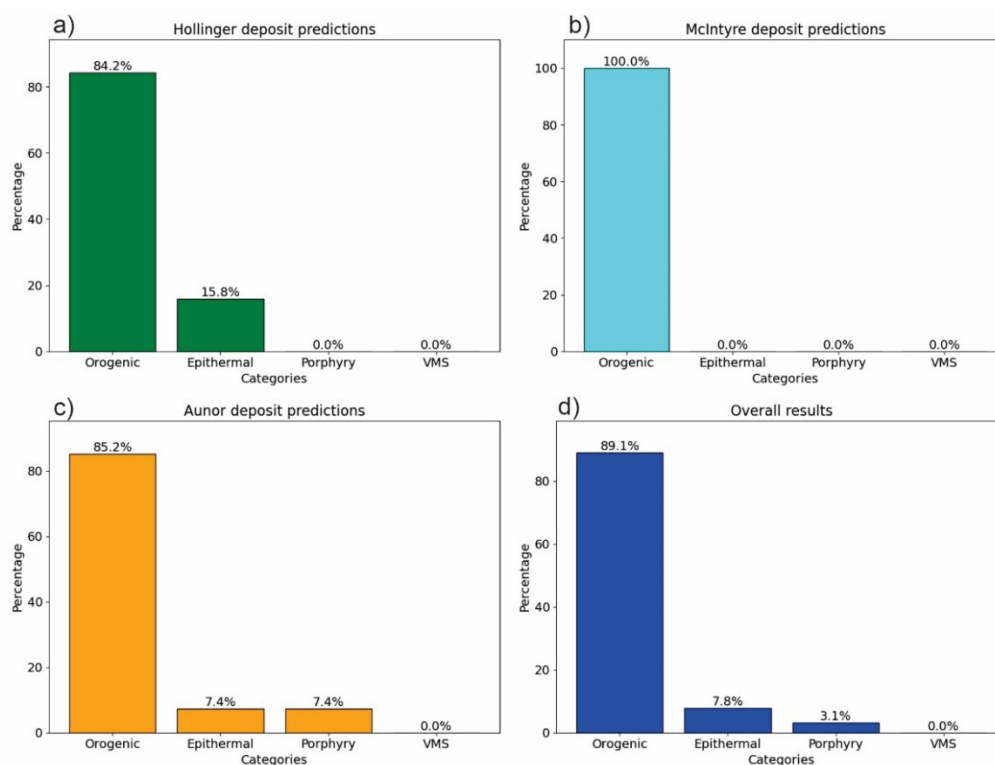


Fig. 10 Histogram of the predictions based on bilayered neural network model on 64 gold analyses of orogenic deposits from Velasquez (2014). They are separated between Hollinger, McIntyre and Aunor deposits, showing the high likelihood that all deposits correspond to an orogenic deposit. a) Histogram of predictions for Hollinger deposit. b) Histogram of predictions for McIntyre deposit. c) Histogram of predictions for Aunor deposit. d) Histogram of predictions for all three deposits in the district.

Self-implementation

OreGenes is an app developed by the authors based on the two hidden layers model described in this paper. It can be found in (Supplementary Application 1) for any user interested in interpreting gold trace element analysis measured by LA-ICP-MS and suspects that they belong to one of the evaluated deposits. The app is constructed as a simple way for users to interact with a machine learning algorithm. First, the users upload the data, it should be pre-treated and include only the elements the model evaluates (one example is provided in the installation package). The model is then imported to the app, allowing future models that might include more deposits or with different architectures to be run with this

same app. Finally, using the predict button, a table with the predicted deposit will be generated, each one corresponding to an individual analysis. Additionally, if the user wishes to see the results as a graphical output, a button to create a histogram will become available after completing the prediction. The Statistics and Machine Learning Toolbox will need to be installed on the user system to run all the functions in the app properly.

CONCLUSIONS

In this study, we examined the effect of different ANN architectures over published databases of natural gold composition measured by LA-ICP-MS, based on selecting the most influential elements to the deposits evaluated. The model that had the best performance against unobserved data (separated before the training) was tested with blind data from published gold grain geochemistry from 3 deposits, to ensure that the model was not biased and could be used reliably in other datasets.

The presence of trace elements that do not share radii similar to those of Au or Ag (that cannot enter as a solid solution) may be present as impurities in high fineness gold when the Ag content is greater than 10.0 wt.% in the gold, and the structure will present sufficient dislocations for other elements with different radii to be part of the gold structure. These elements incorporated into the mineral are evaluated by principal component analysis (PCA) to highlight their influence on the variance, allowing us to have clarity on the elements that have more influence on the variability of the data: Ag, Bi, Cu, Fe, Ni, Pb, Pd, Pt, Sb and Te which will

provide us with the most information to determine the ‘chemical signature’ of each of the evaluated deposit types, reflected in the high level of variance observed in the first eight principal components.

The results of the systematic iterations of different architectures of fully connected neural networks impact the classification performance, especially when identifying porphyry deposits that had few samples. An architecture of two hidden layers with ten neurons can unveil the nonlinear patterns present and accurately associate the chemical signature of each evaluated deposit, minimizing the bias inherent in the dataset. This allows us to accurately capture the variance presented in the evaluated ore deposits and interpret the trace element concentrations in natural gold to one of the deposits analyzed.

The final decision on the probability that a gold grain belongs to one of the evaluated deposit types results from a nonlinear probabilistic combination of the concentrations of the determined elements. However, when analyzing from a simplistic point of view, assuming that each of the elements behaves independently in a PDP allows us to look at important factors that may be related to the particular conditions of each deposit type that perhaps are counterintuitive. For instance, Cu concentrations commonly associated with porphyry deposits are not found in significant concentrations as a trace element in gold grains as they are primarily precipitated in other minerals as well as Bi, Sb and Te in gold grains from orogenic deposits. Although the results suggest that there is a geochemical signature in the structure of gold associated with the conditions under which it

formed, they also show that they are complicated nonlinear correlations that need to be further investigated in addition to the effect that subsequent processes have on it.

The presented model is limited to 4 types of mineral deposits, which makes it impossible to correctly identify other sources of gold. In addition, remobilization of primordial sources in metamorphic processes obliterates the original chemical fingerprint by stabilizing gold's trace elements to equilibrium with the new conditions. Future research on gold geochemistry of gold grains from other mineral systems and the changes that gold's trace elements go through in different conditions of metamorphism could expand the capabilities of the model.

Finally, the best model architecture is packed and provided as an app developed in Matlab R2023a app designer. Using the weights and biases obtained in our experiments, the app allows users to explore the model with their data. taking into account the limitations of this model only evaluating 4 types of ore deposits and overprinting signatures that required additional geological information to be addressed.

Chapter 4

Unveiling gold sources from

statistical manifolds constructed

from LA-ICP-MS analyses along the

production chain

**UNVEILING GOLD SOURCES FROM STATISTICAL MANIFOLDS
CONSTRUCTED FROM LA-ICP-MS ANALYSES ALONG THE PRODUCTION
CHAIN**

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Abstract

Gold is a precious metal that has been treasured throughout human history, and it has gained increasing importance in the development of electrical and technological industries in the last 50 years due to its high electrical conductivity. However, its extraction by non-regulated parties involves a series of problems, from environmental and human rights to economic issues that extend from local communities affected by mining to national concerns. Governmental initiatives

have been made to fight illegal mining and mitigate its effects. However, intricate systems are in place to pass off illegal gold as legal, and proving to a judiciary system that gold has been mixed from different sources is challenging. A recently developed nonlinear dimensionality-reduction technique called Uniform Manifold Approximation and Projection (UMAP) has been introduced for analyzing various types of high-dimensional data. Here, we apply it to gold compositional data expressed as probability vectors comparing similarities based on Hellinger distance. This demonstrates that even though gold geochemistry changes during the beneficiation process, a geochemical signature is retained between the natural samples and the manufactured products, allowing the identification of gold that has been produced in other locations as well as smuggled within the mine.

Keywords: Gold; Forensic geology; LA-ICP-MS; Trace-element geochemistry; Lead isotope ratios; Statistical manifolds; UMAP.

INTRODUCTION

Gold has played a central role in global finance, culture, and history for millennia. However, its integration into society presents significant environmental, economic, and ethical challenges that governmental regulations have tackled (Wagner, 2016). However, the rising demand for gold, driven by escalating prices, has led to an increase in mining from unregulated sources in remote regions, particularly in Latin America, where it accounts for approximately 28% of total production. This expansion hinders the capacity of governments to effectively

regulate such activities (Wagner, 2016). While police operations seizing gold from unregulated sources are effective if all the material comes from an unregulated area, distinguishing unregulated gold once it enters the legal production chain remains a complex and ongoing challenge.

Gold production in Brazil could be simplified as coming from 3 primary sources (Fig. 11): (1) big to medium-scale mining, local refinement of the ore, and exporting the commodity for high-purity refinement and commercialization; (2) Small-scale artisanal mining (locally known as garimpo) is recognized by the government, and limited to selling the commodity to local authorized trading houses (DTVMs). (3) Unregulated mining that introduces gold in the legal path at several vital points, such as part of the local refinement products, into a local authorized trading house, or to make artisanal jewelry. Finally, (4) Gold products can be recycled from different stages in the production chain, reentering as new products. The strategic points where unregulated gold meets the regular pathway are crucial to differentiate between those incompatible sources. There have been several attempts to identify the origin of metals (processed and unprocessed) with geochemistry (Melcher et al., 2008; Dixon, 2014; Roberts et al., 2016; Dixon and Merkle, 2021). These authors relate samples from a likely origin with processed ones, finding that reference materials for the origins are needed to compare with the suspected samples controlled in different stages of the production chain to track compositional changes caused by the beneficiation process (Dixon and Merkle, 2021).

Gold produced from primary sources comes from a handful of ore deposits (Lipson, 2014). Its geochemistry can differentiate these deposits, an approach often used in whole-rock and soil geochemistry as exploration methods by the mining industry. However, analyzing the gold grains as a tool to differentiate ore deposits allows us to use these signatures as a starting point to evaluate the influence of anthropogenic intervention on natural gold (Liu et al., 2021b; Liu and Beaudoin, 2021b). Traditionally, studies on the origin of ancient metals use lead isotope ratios to compare with likely nearby deposits and determine the origin of the sample (Milot et al., 2021; Berger et al., 2022; Vaxevanopoulos et al., 2022; Ma et al., 2022). Hence, having the lead isotope ratios and trace element concentrations from the raw materials to the final product would allow for quantifying and tracing the evolution of the material through the production chain.

In this study, we report lead isotopic ratios from gold bars samples with a declared origin of 'Água Branca deposit' located in southeastern of the State of Pará, Brazil, with gold bars obtained in the declared mine and gold grains of the ore. They show congruent lead isotope ratios among the three sample types (Fig. 2). However, in a detailed evaluation of the trace element concentrations as vectors of probabilities laying on a statistical manifold (the geometry of the manifold is reconstructed from the discrete data), we unveil the similarities of the samples in a high dimensional space, demonstrating that samples produced in the mine retain a geochemical signature in this high dimensional space compared to natural gold grain compositions (Samples AuNat). In contrast, seized samples by

the police do not share this signature, revealing that the declared origin had been fake.

This approach not only enhances our ability to verify the provenance of gold, thereby contributing to the mitigation of the environmental and social problems associated with unregulated mining, but it also offers a powerful tool for more accurately determining the origins of man-made metals throughout history. Applying this methodology could give us a deeper insight into our past and valuable data to construct a more sustainable and equitable future.

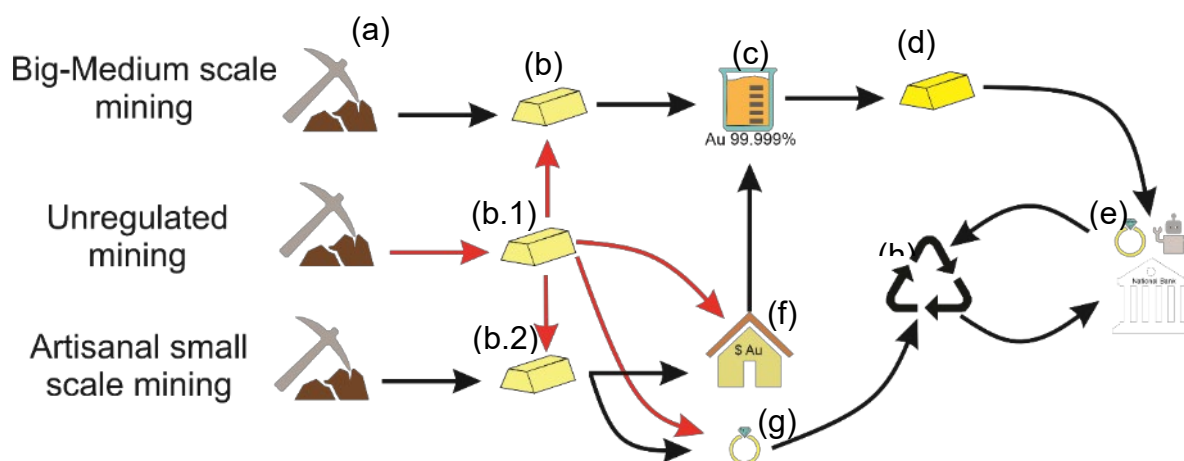


Fig. 11 Schematic workflow of gold's production chain in Brazil, marking gold's regulated and unregulated pathways as black and red arrows, respectively. 1) path of gold from big scale mining: (a) ore extraction, (b) local refinement, (c) high purity refinement out of the country, (d) high purity gold bar production, (e) final applications, and (h) recycling; 2.1) path of gold from artisanal small scale mining: (a) ore extraction, (b.2) local refinement, (f) sell to an authorized trading house (DTVM), (c) high purity refinement out of the country, (d) high purity gold bar production, (e) final applications, and (h) recycling; 2.2) path of gold from artisanal small scale mining: (a) ore extraction, (b.2) local refinement, (g) local production of jewelry and other applications, (h) recycling; 3) path of gold from unregulated sources: (a) ore extraction, (b.1) local refinement. After local refinement, it can be mixed in the legal production chain in points (b) and (b.2), (f) it can be sold to an authorized trading house (DTVM) with a fake origin, or (g) it can be used for local production of jewelry and other applications.

RESULTS

The samples for this study were collected by the Brazilian Federal Police in Sao Paulo before they were exported for further refinement under the suspicion of

containing smuggled gold. Approximately 80 Kg of gold, separated in two batches with the exact declared origin, were intended for exportation. This amount was greater than the declared production (c.a. 35 Kg/year)(De Oliveira Barros et al., 2021). Based on the geochemical variations of major elements obtained by X-ray fluorescence from the 77 seized gold bars were sub-sampled. This resulted in 23 samples from the first seizure (GRU-1) and 8 samples from the second seizure (GRU-2). To determine the veracity of the declared origin, a police operation was carried out at the mine, obtaining 2.5 kg of concentrated ore before any refinement process from which 230 gold grains were handpicked (AuNat) and 4 gold bars (D1, D2, D3, D4) allegedly produced in the mine. These samples were analyzed by LA-ICP-MS/MS for 33 elements, including all Pb stable Isotopes (^{204}Pb , ^{206}Pb , ^{207}Pb , ^{208}Pb) (see methodology).

Lead isotope ratios and elemental concentrations in gold

Lead isotopic ratios are reported in Table S1, comprising samples of natural gold grains and processed gold. Fig. 12 shows an overlap between AuNat grains and most of the analyses of the gold bars. Suggesting that they may share the same origin. Beyond a visual inspection of the data, following the “AMALIA algorithm(Rodríguez et al., 2023)” procedure comparing Pb isotope ratios and their analytical errors results in contradictory findings (Table S2). All the gold samples from the deposit match the isotopic signature of the natural gold grains. However, although most of the samples seized before export do not match those obtained at the deposit, 32% do (Table S1 and S2), an amount of gold that

exceeds the calculated production by the time of the operation(De Oliveira Barros et al., 2021).

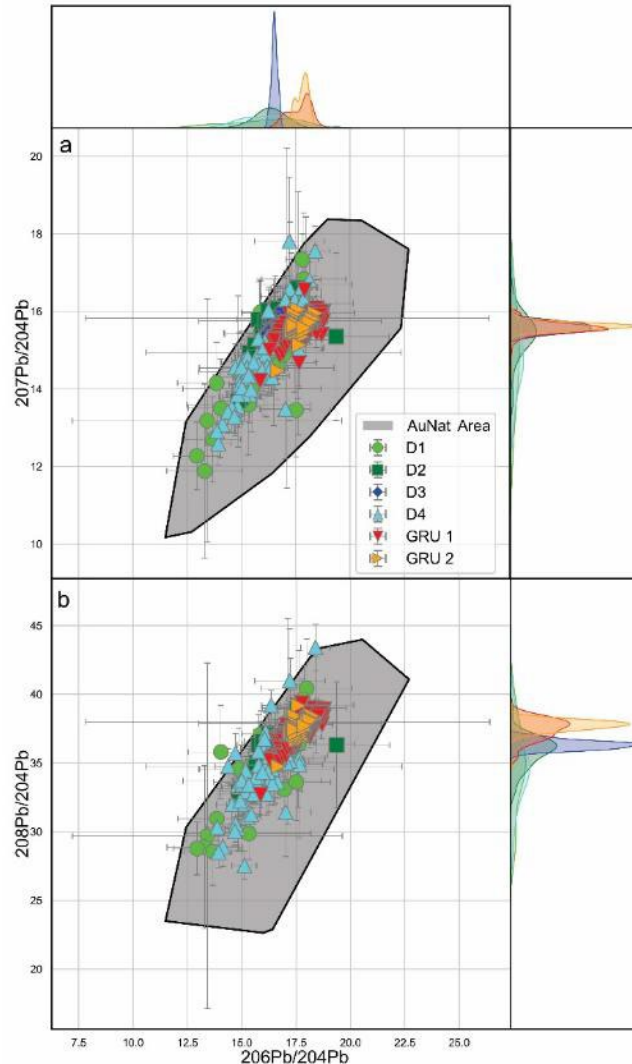


Fig. 12 Lead isotope ratios of the gold bars recovered by the Brazilian Federal Police compared with natural gold composition. The density of the data is represented on the sides of the scatterplots following the same colors as individual samples. Error bars represent two standard deviations. A) $^{206}\text{Pb}/^{204}\text{Pb}$ vs. $^{207}\text{Pb}/^{204}\text{Pb}$. B) $^{206}\text{Pb}/^{204}\text{Pb}$ vs. $^{208}\text{Pb}/^{204}\text{Pb}$.

All elemental concentrations are reported in Table S3. The beneficiation process via amalgamation recovers about 50% of the gold in the ore(De Oliveira Barros et al., 2021), resulting in variable elemental concentrations and gold fineness in the resulting products. Noticeable differences can be seen in samples retrieved

from the mine (e.g. Fig. 13a, b, d, e, i). This makes using traditional geochemical representations as evidence in a court of law challenging. In general, AuNat grains have a wide range in fineness (c.a. 413 to 769) with a median value of 581. This coincides with the fineness range of samples D1, D3, and D4 and disagrees with the values measured in samples D2, GRU 1, and GRU 2 (Fig. 13a). They are enriched in Al, As, Fe, Ge, Mo, Ti, V, Th, and U while maintaining comparable concentrations of Co and Ni compared to all the processed gold bars (Fig. 13 and TableS3). In contrast, samples from the ore (AuNat) are depleted in Bi, Cu, and Pb. It should be noted that sample D3 shows atypical concentrations of Cu and Zn compared to the rest of the samples analyzed (Fig. 13d and i). Finally, the remaining elements in AuNat and samples from the mine are within a similar range. In contrast, samples seized in São Paulo have noticeably higher concentrations in comparison (Bi, Pb, Pt, Sb, Sn).

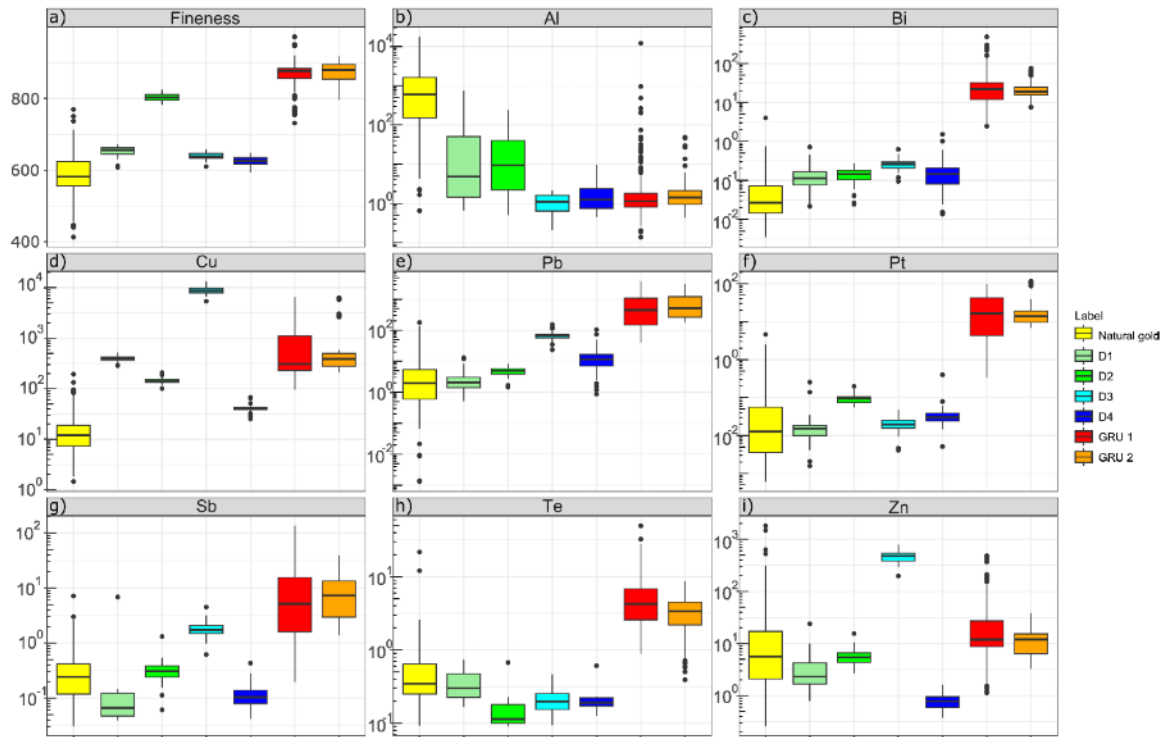


Fig. 13 Boxplot comparing gold fineness and elemental concentrations from the data obtained by LA-ICP-MS/MS analyses. Data are plotted in parts per thousand for fineness and in parts per million (ppm) on a vertical $\log_{10}$ scale for the concentrations. Boxplots are divided into sample types. Yellow color represents data from AuNat ($n = 204$), Samples D1, D2, D3, and D4 from the mine in colors; pale-green ($n = 39$), green ($n = 38$), cyan ($n = 53$) and blue ($n = 79$) respectively. Lastly, samples with reported origin from the Água Branca Deposit seized in the two operations were divided into samples GRU1 and GRU2 in red ($n = 442$) and orange ($n = 152$). In each boxplot, the box marks the 25th – 75th percentile with a black horizontal line representing the median value, whiskers the 5th -95th percentile, and outliers beyond the whiskers range are represented in black fill circles.

Low-dimensional embedding of gold trace elements

Due to the mathematical properties of mineral compositions (reported as fractions of a whole in ppm or wt. %) always being positive with a constant sum of all its components, a log-ratio space is used to work with the data. In this study, we evaluate the geochemical data as vectors of probabilities, regularizing them through a standardization type L_2 (Shi et al., 2024). Each sample is a point in an N-dimensional state space where each axis is represented by a vector component (elemental composition), forming a swarm in the state space. A dimensionality reduction method is applied to visualize the high dimensional

similarity between gold samples based on their 'chemical signatures', uniform manifold approximation and projection (UMAP)(McInnes et al., 2020). These dimensional reduction techniques were evaluated using Hellinger distance (D_H) as a metric, a type of f-divergence that measures the differences between two probability distributions(Wu and Karunamuni, 2012).

If our vectors of probabilities lay on a statistical manifold M , a Riemannian metric can be defined on M as a function of the Hellinger distance(Carter et al., 2009) approximating the manifold's geometry as a cover of discrete points. The shortest distance between two points (i.e., Geodesic) will be the sum of segments in a connected graph formed as a Čech complex. Hence, the similarity between the average composition of unprocessed gold and each data analysis of processed products will be marked by the magnitude of the geodesic distance on the manifold. These distances are summarized in Fig. S1 as a kernel density plot comparing the samples' geodesic from the average composition of AuNat. The spurious gold samples (GRU 1 and GRU 2) have longer geodesic distances compared to the distances of natural gold, with a slight overlap with the most dissimilar samples of natural gold (Fig. S1). Three of the samples retrieved in the mine fully overlap with the distances of AuNat samples (i.e. D1, D2, D4), suggesting a high similarity between these samples. Sample D3 has an unexpected geodesic distance to the average composition of gold, making it dissimilar to the samples retrieved before exportation.

The ability of UMAP to preserve the global structure information while maintaining the local structure (group similar samples in clusters while maintaining significant information between clusters). The results show that the samples are grouped into three main clusters. First, a cluster from the samples retrieved before exportation, some samples from the group GRU 1 are dispersed in the embedding, not matching with other clusters. Then, one cluster with AuNat samples and three recovered at the deposit shared similar chemical signatures oriented in different directions to the AuNat cluster due to variations in the elemental concentrations produced in the beneficiation process. Lastly, sample D3 is isolated in its cluster, not matching with other compositions.

Previous geochemical studies demonstrate that there is a relationship between gold's geochemistry and the conditions of formation under which it was precipitated (Velasquez, 2014; Liu and Beaudoin, 2021b; Melo-Gomez, 2023; Verbel et al., 2024). This effect can be observed in the low-dimensional projections as a single cluster from the sample AuNat with a notable elongation reflecting compositional changes (Fig. 14a) these changes are often attributed to changes in the fluid's physicochemical conditions (e.g., boiling, cooling, or a second pulse). Still, they come from a single source that maintains the data in the same cluster.

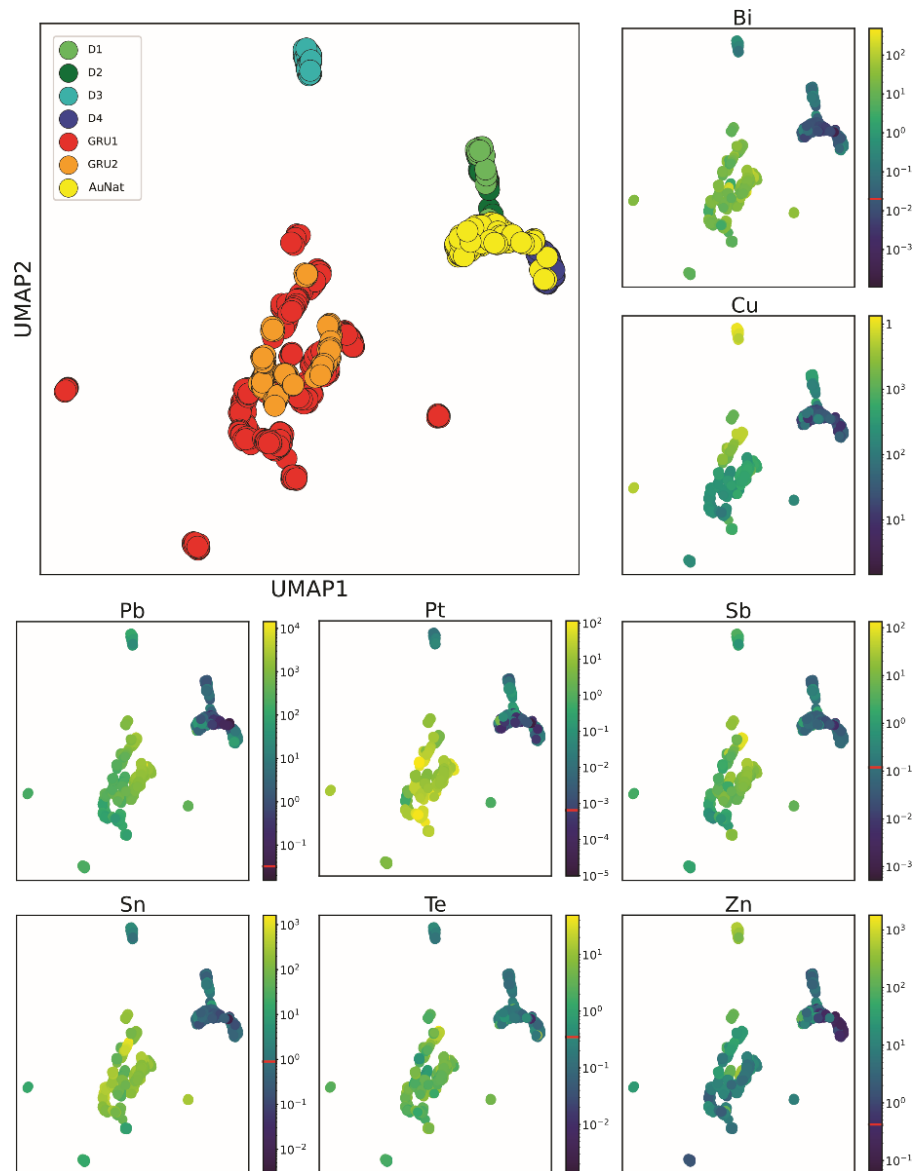


Fig. 14 UMAP projection of gold geochemistry, each dot represents a laser ablation analysis colored by the concentration found in the element. The average limit of detection of each element is marked as a red line in the color bar. a, UMAP visualization of the data set colored by sample type. b-i, UMAP projection of the dataset colored by the elemental concentration determined via LA-ICP-MS/MS according to the color bar next to each plot (a red line in the color bar indicates the average limit of detection).

DISCUSSION

Forensic geology's main goals are to narrow a sample's probable origin and sample match (Dawson and Hillier, 2010). This study shows that Pb isotope ratios have the ability to sustain themselves through the processes of gold beneficiation.

However, they seem to be highly related to the ore deposit type. This characteristic could help to differentiate between gold samples from different metallogenetic provinces but not in a local scale. In contrast, manifold learning techniques with the proper metric distance on geochemical data unveil similarities between gold grains (AuNat) and samples refined from it in a high-dimensional space. These similarities are observed as closer geodesic distances in the high dimensional space, projected in 2D embedding as clusters via UMAP (Fig S1, S2, and Fig. 14). Samples with different origins are projected as divergent clusters, further from AuNat's signature. Although the samples of the two batches obtained in two separate police operations claim to come from the studied deposit, all the low-dimensional projections suggest that they share the same origin but do not match the declared one (Fig. 14). Sample D3 shows similar fineness values compared with AuNat, D1, and D4 but is highly enriched in Cu, Sb, Pb, and Zn (Fig. 13 & Fig. 14). These elements are common in copper wires(Meng et al., 2023); a mixture of them with gold during melting to increase non-gold mass could explain the sample isolation in the low-dimensional projection. Another option could be smuggling gold into the mine from another gold deposit rich in those elements. To be certain about the sample's origin, a more comprehensive number of samples and LA-ICP-MS data is needed to understand it fully.

Mineral inclusions in gold have been studied as proxies for the origin of gold (i.e., from placer gold to ore deposits, from manmade artifacts to natural gold(Chapman et al., 2022; Standish et al., 2022)) Omitting high-temperature and

chemical processes involved in the industrial production of gold would homogenize or even obliterate those signals, shifting the original chemical signatures but maintaining a close relation that allows for traceability. This study only shows one case of study; however, gold geochemistry has been used successfully to relate trace elements in gold's structure with the original ore deposit(Liu et al., 2021b; Verbel et al., 2024; Román et al., 2024), making the shown procedure shown a valuable tool for tracing gold sources on a local scale. Based on its ease of use and the results of our analyses, we anticipate that UMAP used with Hellinger distance will be a valuable tool in geochemistry, not only for forensic geology but also for tracking the evolution of geochemical systems.

METHODS

LA-ICP-MS/MS

All lead isotopic and trace element analyses in gold samples were performed using an Agilent 8900 triple quadrupole ICP-MS in MS/MS mode with NH₃ addition to the reaction cell. It was coupled to a laser ablation system, Applied Spectra Resolution S155 SE, at the United States Geological Survey, LTRACE laboratory in Denver, Colorado. The samples were ablated for 40 seconds in spot mode with 38 and 50 µm spot sizes, energy density of ca. 3.5 J/cm², and the beam operating at 10 Hz frequency. Trace element contents of ²⁷Al, ⁴⁹Ti, ⁵¹V, ⁵³Cr, ⁵⁵Mn, ⁵⁷Fe, ⁵⁹Co, ⁶⁰Ni, ⁶³Cu, ⁶⁶Zn, ⁷⁴Ge, ⁷⁵As, ⁹⁵Mo, ¹⁰³Rh, ¹⁰⁵Pd, ¹⁰⁷Ag, ¹¹⁸Sn, ¹²¹Sb, ¹²⁵Te, ¹⁸²W, ¹⁸⁵Re, ¹⁸⁹Os, ¹⁹³Ir, ¹⁹⁵Pt, ¹⁹⁷Au, ²⁰⁴Pb, ²⁰⁵Tl, ²⁰⁶Pb, ²⁰⁷Pb, ²⁰⁸Pb, ²⁰⁹Bi, ²³²Th, ²³⁸U. The masses of Ge, Ag, W, Au, and U were corrected for the reaction with NH₃ At the back quadrupole. The operating parameters of laser

ablation and mass spectrometric measurements are reported in (Supplementary Material 1). The quantifications were made using secondary standard corrections and matrix and element-specific correction factors; first, a good counting statistic for all the masses is obtained from the reference materials at a larger spot size to measure (80 μm). Later, the secondary standards are measured at the same spot size as the unknown, and the matrix correction factor is applied to the primary calibration. Lastly, the unknown samples are measured at the proper size. The reference materials GSD-1g, MASS-1, and MASS-3 were used to quantify trace elements, and NIST-612 to quantify Pb ratios. The standards NIST-481, NIST-482, BHVO-2g, and GSE-1g were used for quality control by a bracketing procedure. To ensure that the LA-ICP-MS analysis reflects the chemistry of gold samples, inclusions are excluded from integrating the depth profile. However, nano-inclusions or mineral nanoparticles within the mineral that affect the Au-Ag ratio (i.e., deviate from the linear correlation between Au-Ag) are excluded from the analysis.

Data preprocessing

Mineral inclusions were monitored and excluded from the presented data (Table S3) via the LA-ICP-MS depth profile and the Au/Ag ratio. Left-censored concentrations were imputed based on the log-ratio expectation maximization algorithm “lrEM”, a function of the R package “zCompositions” as a standard procedure for treating geochemical data (Carranza, 2011; Palarea-Albaladejo et al., 2014; Palarea-Albaladejo and Martín-Fernández, 2015). However, it should be noted that thanks to the method's high resolution and the measurements made

with Hellinger distance as the correct distance measure for geochemical data, we are able to replace the data below the limit of detection as zero, resulting in fully comparable results with standard procedures established (Fig. S2).

Uniform manifold approximation and projection (UMAP)

UMAP is a nonlinear dimensional reduction algorithm (McInnes et al., 2020). It computes the nearest neighbor graph of the high-dimensional data based on the Hellinger distance (Čech complex), capturing the topological information of the samples in the high-dimensional space. The high dimensional topology of the manifold is projected into a 2-dimensional Euclidean space, minimizing the error between the representation via cross-entropy. This approach maintains the relative interrelationship between data points.

Chapter 5

Deciphering the Genesis of the Água Branca Deposit, Tapajós, Brazil: A Machine Learning Approach to Classify Gold Deposits

DECIPHERING THE GENESIS OF THE ÁGUA BRANCA DEPOSIT, TAPAJÓS, BRAZIL: A MACHINE LEARNING APPROACH TO CLASSIFY GOLD DEPOSITS

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Abstract

Recent advancements in machine learning allow addressing the archetypical limitations of traditional geochemical analyses by leveraging high-dimensional elemental data for predictive modeling. Trace elemental concentrations can be used to predict the type of deposit with which the mineral assessed is associated. Although many papers have shown the effectiveness of machine learning-based models for ore deposit type prediction, not much research has been done applying these results to problematic deposits or exploration campaigns.

In this paper, we will use as an example the Água Branca deposit, a Paleoproterozoic gold deposit (proven Au reserves of 35.8 t @1.97 g/t) interpreted as genetically related to its host intrusion in a porphyry-type environment that evolves into an epithermal-type environment. However, by analyzing the trace element composition of pyrite grains in the mineralization by LA-ICP-MS and published data of the trace element composition of gold grains from the deposit by the same methodology, we obtained that both machine

learning models (Random Forest and Artificial Neural Networks, respectively for each mineral) show that the assessed minerals have a trace elemental composition coherent with an orogenic deposit. These results are complemented by a dimensional reduction technique (Parametric UMAP) to have an insight view of the models' decision-making and a comparison with the available conditions of formation: aqueous-carbonic fluid inclusion with low salinity and temperatures of homogenization between 200 and 420°C, formed at depths of ca. 8.5Km for the mineralization and the crystallization of the host monzogranite (2.45 and 2.5 kbar, respectively). Conditions coherent with orogenic deposits. Implementing machine-learning tools complemented with geological information is proven to be a powerful combination for understanding metallogenetic processes, and it should be implemented as a complementary tool in exploration projects.

Keywords: Machine learning models, Geochemistry, Gold, Pyrite, UMAP

INTRODUCTION

The ability to accurately predict the type of mineral deposit during the early stages of an exploration campaign significantly enhances project efficiency. Early identification allows geological predictive models to focus exploration strategies on the appropriate deposit type, reducing time and costs (Gregory et al., 2019). Traditionally, mineral deposit differentiation relies on binary or ternary plots of elemental concentrations or ratios (Loftus-Hills and Solomon, 1967; Dupuis and Beaudoin, 2011; Zhang et al., 2016; Breiter et al., 2020). While this method is simple and effective for comparing two deposit types, it often struggles with

overlaps when analyzing more complex systems involving multiple deposit types, leading to interpretive challenges (Gregory et al., 2019).

In recent years, machine learning models have gained prominence for predicting deposit types by leveraging high-dimensional elemental datasets from various minerals. These models have demonstrated their ability to reduce interpretive ambiguity and enhance predictive accuracy (e.g., Gregory et al., 2019; Liu and Beaudoin, 2021; Verbel et al., 2023; Li et al., 2024; Wang et al., 2024a; Wang et al., 2024b).

The Água Branca deposit, a gold deposit hosted in granitoids within a Precambrian terrain, exemplifies this complexity (De Souza, 2009; Croscop et al., 2024). This deposit is genetically linked to the intrusions that hosted it, based on similarities in formation pressures and crystallization conditions (De Souza, 2009). Its mineralization and alteration are interpreted as Paleoproterozoic in origin, transitioning from a porphyry environment to epithermal conditions due to the uplift of the hydrothermal system (Croscop et al., 2024).

This study explores the application of two machine-learning models—Random Forest and artificial neural networks—to two key minerals: pyrite (the most common sulfide) and gold (the mineral of economic interest). The objective is to evaluate the models' predictions considering geological information such as petrography, fluid inclusions, and geobarometry. To further interpret the models' decisions, dimensionality reduction techniques based on distance metrics provide a visual framework for understanding the results (McInnes et al., 2018).

GEOLOGICAL SETTING

The “Água Branca” gold deposit is located in the central part of Tapajós gold province, associated with the Parauari intrusive Suite (ca. 1883 – 1801 Ma) (Fig. 15b). The province is formed by the Tapajós-Parima Orogen, a magmatic arc accreted to the Amazonian craton between 2.04 -1.88 Ga (Fig. 15a). This orogen comprises two events; first, the Mundurucus orogeny (2040-1957 Ma) started as island arc magmatism around 2040 Ma, forming the Cuiú-Cuiú Complex. This phase included turbiditic sediments accumulated in the back-arc basin (Jacareacanga Group) and forming an Andean-type continental arc. After a hiatus of ca., 50 Ma began the Tropas Orogeny (1906-1886 Ma), characterized by island arc magmatism and the formation of a late continental arc (Parauari Suite)—rocks hosting the Água Branca deposit from this collisional event (Santos et al., 2004).

The mineralization comprises 3 main orebodies limited and controlled by NE-SW faults (Fig. 15c) with a deep supergene enrichment zone of ca. 30 m, which is also responsible for the rock weathering, making it challenging to identify the contact between the granitic facies on the surface. Two open pits have extracted this enriched supergene alteration, and ca. 3000 m of drill cores have been made to determine the project's availability, resulting in the calculated reserves of over 35 metric tons of Au (Appendix A). The host rocks (Diorites and Monzo-Granites from the Paraguarí intrusive suite) are cross-cut by quartz veins or stockwork with variable degrees of alteration.

MATERIAL AND METHODS

Over 3000 m of drill cores have been sampled by the mining company, and from those, 12 sections of ca. 50 cm were selected for further analysis, representing the different alterations and mineralization presented in the deposit from the two bodies with the higher concentration of gold (Fig. 15c). 12 thin polished sections were made. Additionally, data from LA-ICP-MS on 194 gold grains from the deposit is used in this paper. This data and descriptions of the samples can be found in (Verbel et al. *In Review b*).

EPMA

We analyzed pyrite grains using a five wavelength-dispersive spectrometer JEOL JXA-8230 SuperProbe electron probe microanalyzer (EPMA) at the University of Brasília (Brazil). Operating conditions were: fully focused beam, 40 degrees take-off angle and beam energy of 15 keV. The beam current was 40nA. Elements were acquired using the following analyzing crystals: LIF for Co K α ; LIFH for Fe K α , Zn K α and Ni K α ; TAP for As L α and Se L α ; and PETJ for S K α , Bi M β , Sb L α , Hg M α , Cu K α , Pb M α , Te L α , Ag L α , Au M α . Counting time (peak) was 20 s for Fe K α , Co K α , Cu K α , Zn K α , Au M α , Hg M α , and Bi M β ; 30 s for S K α , Ag L α , Sb L α , Ni K α , and Te L α ; 40 s for Pb M α ; and 50 s for As L α and Se L α . This calibration focuses on detecting the Au present in pyrite as Au⁰ as inclusions or micro-inclusions (Román et al., 2019).

LA-ICP-MS

Trace element analyses in pyrite were performed using a quadrupole ICP-MS (Thermo Fisher Scientific iCAP Q) coupled to an excimer laser ablation system at the University of Sao Paulo. The samples were analyzed for 70 seconds; 30 seconds for pre-ablation measuring the background and 40 seconds for ablation in spot mode with 50 μm spot size with an energy density of ca. 5.13 J/cm², and the beam operating at 15 Hz frequency. Trace element contents of ²⁹Si, ⁴⁵Sc, ⁴⁹Ti, ⁵¹V, ⁵³Cr, ⁵⁵Mn, ⁵⁷Fe, ⁵⁹Co, ⁶⁰Ni, ⁶³Cu, ⁶⁶Zn, ⁷¹Ga, ⁷⁵As, ⁷⁷Se, ⁸⁵Rb, ⁸⁸Sr, ⁸⁹Y, ⁹¹Zr, ⁹³Nb, ⁹⁵Mo, ¹⁰⁷Ag, ¹¹¹Cd, ¹¹⁵In, ¹¹⁸Sn, ¹²¹Sb, ¹²⁵Te, ¹³³Cs, ¹³⁹La, ¹⁴⁰Ce, ¹⁴¹Pr, ¹⁴⁵Nd, ¹⁴⁷Sm, ¹⁵¹Eu, ¹⁵⁹Tb, ¹⁶³Dy, ¹⁶⁵Ho, ¹⁶⁶Er, ¹⁶⁹Tm, ¹⁷³Yb, ¹⁷⁵Lu, ¹⁷⁸Hf, ¹⁸¹Ta, ¹⁹⁵Pt, ¹⁹⁷Au, ²⁰²Hg, ²⁰⁵Tl, ²⁰⁶Pb, ²⁰⁷Pb, ²⁰⁸Pb, ²⁰⁹Bi, ²³²Th, ²³⁸U. The data integration and reduction were carried out using LADR with total Fe as the internal standard, and UQAM FeS₄ was used as a primary calibration standard. Additionally, GSE-1G reference material was used as a secondary standard for quality control. Exposed inclusions were avoided, and inclusions beneath the surface, which were shown as irregular signal profiles, were resolved by excluding these profile sections from the integration. Considering that the minimum particle size detected in LA-ICP-MS profiles at a swipe time of 1.1 seconds is ca. 1 μm , small nano-inclusions of mineral may affect the overall signal.

Machine learning techniques and visualization

Several tools have been developed to discriminate ore deposits based on trace elemental concentrations in minerals, mainly pyrite, which have been used due to its ubiquitousness in several deposits. In addition, for gold deposits, gold itself has also been used as a proxy to identify the deposit type that formed the grains analyzed based on the trace elements held on its structure. The models used to evaluate the Água Branca deposit were:

Random forest

We employed random forest models trained on elemental compositions obtained through LA-ICP-MS analyses to classify the deposit type using pyrite geochemistry. Two models were evaluated: one based on methodologies described in Gregory et al., (2019). Feature selection was performed to identify the most discriminative elements, ensuring robust classification. Both models were implemented in a supervised learning framework, where the random forest classifier was optimized using grid search to determine the best hyperparameters, including the number of trees and the depth of the model. Model performance was evaluated using cross-validation and an independent test set, with metrics such as accuracy, precision, recall, and F1-score assessed to determine effectiveness. This comparative analysis allowed us to identify the most suitable random forest implementation for accurately discriminating ore deposit types based on pyrite trace elemental signatures.

OreGenes (Artificial Neural Network)

OreGenes is a MATLAB-based application designed to classify the origin of natural gold grains based on trace element compositions. The app leverages a neural network model trained on data from 47 localities representing four deposit types: orogenic, volcanogenic massive sulfide (VMS), porphyry, and epithermal systems. The model architecture comprises two hidden layers with ten neurons each, achieving an average prediction accuracy of 88.9%. Ten elements (Pt, Pd, Te, Bi, Sb, Pb, Cu, Ni, Ag, and Fe) from published LA-ICP-MS analyses of gold grains from the Água Branca deposit (Verbel et al., *in Review*) were used to evaluate the likelihood of them to coincide with one of the 4 deposits of the model.

Parametric UMAP

Parametric UMAP is a Uniform Manifold Approximation and Projection (UMAP) variant that integrates neural networks to learn a parametric mapping from high-dimensional data to a lower-dimensional space. This approach creates a stable embedding that can generalize to new data. Initially, the elemental data is preprocessed, including normalization. The parametric UMAP model is trained using a supervised approach, incorporating class labels to guide the embedding process and optimize class separability. The resulting embeddings were then used as input features for a classification model, such as a random forest or support vector machine, to predict the type of ore deposit. The model's performance is evaluated using cross-validation and independent test data to

ensure robustness and reliability, particularly for distinguishing samples from different deposit types. This methodology combines the interpretability of UMAP with the predictive power of machine learning classifiers, enabling efficient and accurate classification of complex geochemical datasets.

RESULTS

Mineralization and alteration

The Água Branca gold deposit consists of three main ore bodies with proven reserves of 35.8t at an Au grade of 1.97 g/t (Geoconsult, unpub. report, 2019). The ore body is restricted to quartz veins that vary from ca. 0.5 cm to sub-metric size, holding the gold as free gold in fractures of the quartz² vein and pyrite³ and as inclusions of pyrite³ along with inclusions of galena (Fig. 16c, d, e and f). The rocks surrounding the quartz veins have a pervasive sericitic

alteration that obliterates the original texture of the rock and previous alterations (Fig. 16e), leaving behind quartz¹ and partially altered alkaline feldspar. Unaltered rocks can be recognized in the drill core samples and vary from monzogranitic to granodioritic composition with medium-sized subhedral to anhedral crystals of quartz¹, alkaline feldspar, and plagioclase, the latter with a slight saussuritization alteration. Alkaline feldspar is often presented with a perthitic texture. The hosting rocks contain magnetite, sphene, apatite, and zircon as accessory minerals. Previous alteration processes of the rocks can be found at some superficial levels when supergene processes do not obliterate them, and it is marked by propylitic alteration in irregular veins and pervasive in the host

rock (Fig. 16 b and c). Additionally, relics of this alteration can be seen embedded in the late quartz₂ veins (Fig. 16c), suggesting that it pre-dates the main mineralization event.

The main sulfide minerals in the analyzed samples are pyrite and galea, with minor contents of sphalerite and chalcopyrite. These minerals are predominant in the quartz₂ veins and the surrounding sericitic halos. However, a previous generation of pyrite (Py₂) can be found to be associated with the cross-cut propylitic alteration, and distal pyrite (Py₃) found in veinlets of carbonate and chlorite with weakly altered rocks.

One gold event can be recognized within the Água Branca granite (composition varying from monzogranitic to granodioritic), hosted in the quartz₂ veins. It can be found in quartz₂, pyrite₃, and galena fractures, interstitial spaces between quartz₂ grains, and inclusions in sulfides. E-W local inverse faults limit and control the orebodies of the deposit (Fig. 16c) are aligned with the fault orientation, concentrating the richest orebodies near the conjunction of faults. A subordinated orebody can be found associated with the lithological change of faces between monzogranite and granodiorite; however, it seems to be linked in-depth to the main orebody (Appendix A). Pyrite from the mineralization is divided into 3 types depending on the mineral association they are presented with. Pyrite₁ (Py₁) has a fine grain size and euhedral to subhedral shapes. scarce and appears in veinlets with carbonate and chlorite within weakly altered host rocks. Pyrite₂ (Py₂) is also presented in veinlets with carbonate and chlorite, but it is associated

with rocks with a high grade of propylitic alteration. Finally, pyrite³ (Py₃) in quartz² veins in paragenesis with galena, ± sphalerite, the crystals formed vary from coarse to fine grain size with euhedral forms; they tend to have a high number of mineral inclusions, they include quartz, galena, sphalerite, chalcopyrite, and gold. The inclusions were identified under the microscope and in the LA-ICP-MS depth profile.

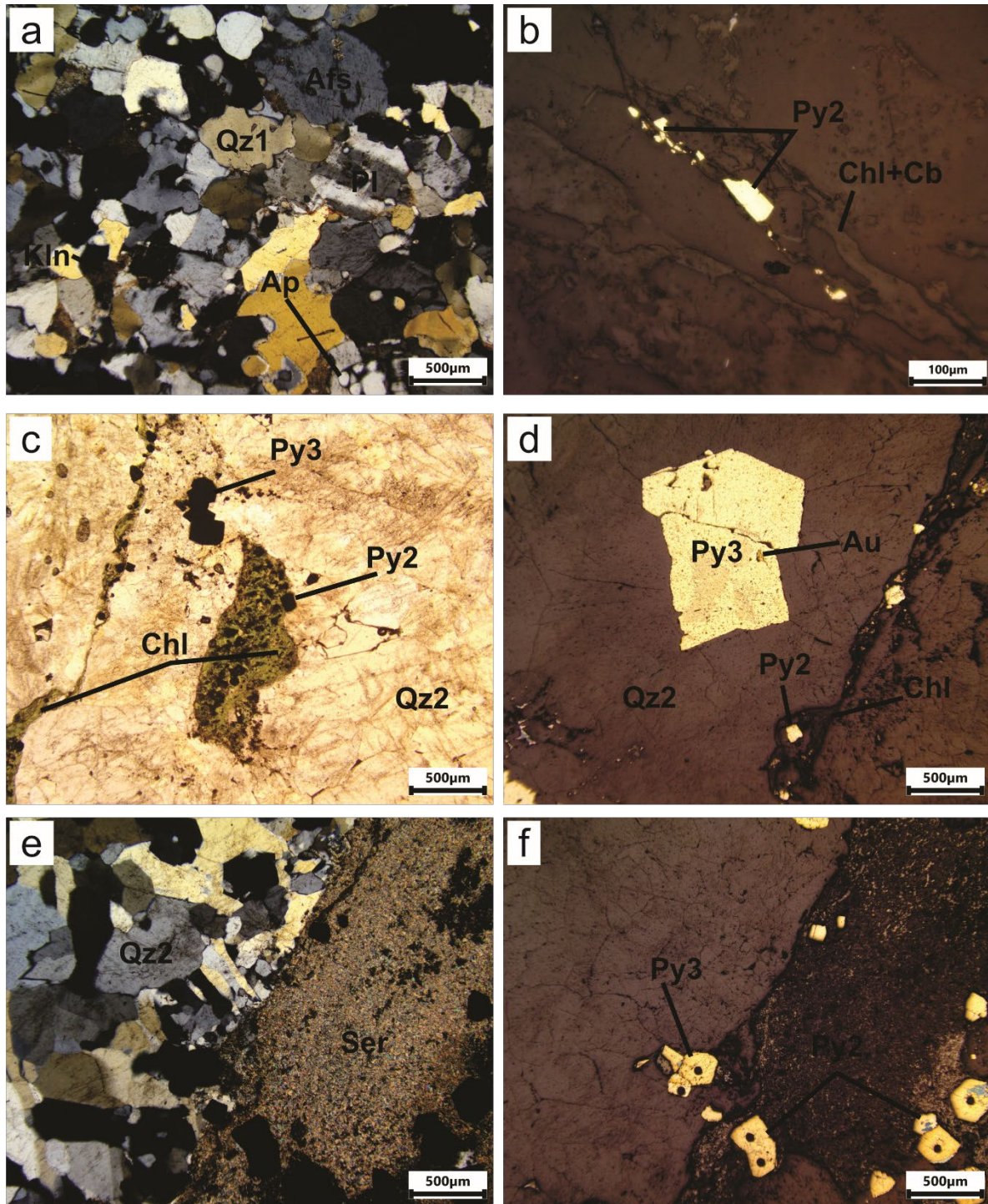


Fig. 16. Microphotograph showing the host rock, alterations, and mineral relationships at the Água Branca deposit in transmitted and reflected light. A) Transmitted double polarized microphotograph of relatively fresh host rock classified as a monzogranite showing alkaline felspar (Afs) with little perthitic exsolution and some crystals altered to kaolinite (Kln), quartz 1 (Qz1) appears yellowish due to the thickness of the thin polished section and plagioclase does not have alteration, apatite (AP) is a common accessory mineral. Biotite and hornblende are sparse in the rock but not in the microphotograph. B) Reflected light microphotograph of veinlets with pyrite2 (Py2) chlorite (Chl) and carbonate (Cb) in host rock with pervasive propylitic alteration.

C) Transmitted single polarized light microphotograph showing a fragment of rock with pervasive alteration to chlorite (Chl) and pyrite2 (Py2) embedded in a quartz2 (Qz2) vein accompanied with pyrite3 (Py3). D) Reflected light microphotograph of quartz2 (Qz2) vein with pyrite3 (Py3) grains containing a gold (Au) inclusion. A border of chlorite and pyrite2 (Py2) can be observed. E) Transmitted double polarized light microphotograph showing a quartz2 (Qz2) vein with a sericitic (Ser) halo. F) Reflected light microphotograph showing pyrite2 (Py3) in the quartz vein and pyrite2 (Py2) in the sericitic alteration halo.

Chemical composition of pyrite

All the analyses of EPMA and LA-ICP-MS performed are reported in (Appendix B). Whereas the statistical parameters of the dataset are presented as boxplots (Fig. 17). Noticeable inclusions that appear on the LA-ICP-MS depth profiling were excluded from the integration. However, nano-inclusions that may be presented as a spiky signal are not resolvable. Concentrations measured using EPMA are higher than those determined by LA-ICP-MS due to the latter technique's lower detection limit. Additionally, EPMA data can be affected by micro to nano-inclusions, explaining the discrepancy between both analyses. Arsenic is the only element where the results from both techniques are concordant, while the rest seem to be affected by nano-to-micro inclusions. Pyrite from the Água Branca deposit is enriched in minor and trace elements, where As, Pb, Cu, Zn, Ni, and Co reach maximum concentrations >1 wt.%. It should be noted that these concentrations possess a high variability, expanding several orders of magnitude (Fig. 17). Gold concentrations reach a maximum of 63.7 ppm with a median concentration of 0.92 ppm (measured by LA-ICP-MS).

In general, pyrite from the Água Branca deposit is characterized by a high concentration of As, detected in all the analyses, with a median of 0.081 wt.%. Cobalt and Pb were also detected in all the LA-ICP-MS analyses, with a 3.3 and 32.19 ppm median, respectively. Antimony, Cu, Ag, Au, Zn, and Ni were detected

in almost all the analyses (91.8 to 98.4% of the time); their concentrations vary between three to four orders of magnitude with median values of 1.71, 8.66, 2.5, 1.0, 1.78, and 3.19 ppm, respectively. EPMA did not detect Bi nor Hg, but they were found in 68% and 51% of the LA-ICP-MS analyses (Appendix B), showing median values of ca. 0.05 and 0.79 ppm, respectively.

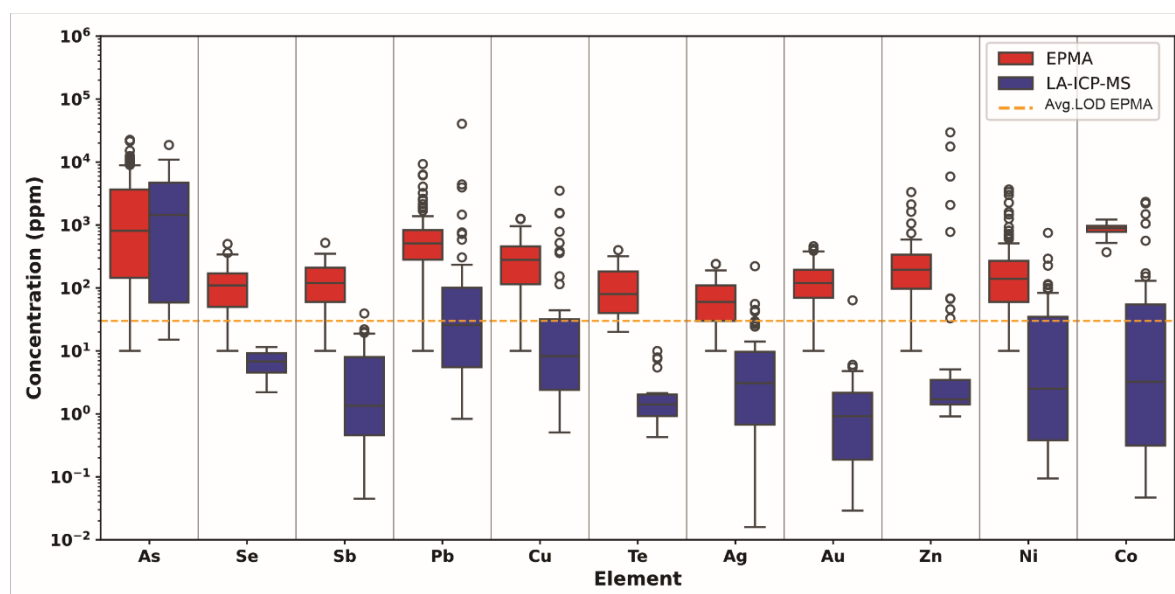


Fig. 17. Concentration plot for minor and trace elements in pyrite from Água Branca deposit. EPMA and LA-ICP-MS (inclusion-free). Data are plotted in parts per million (ppm) on a vertical logarithmic scale. The black line in the box represents the median value. Empty circles represent outliers and the dashed orange line represents the average value of the limits of detection of the EPMA analyses.

Elemental scatterplots

Elemental concentration scatter plots for As-Au, Ag-Au, Pb-Ag, Pb-Sb, Sb-Bi, and Ni-Cu are shown in Fig. 18, considering inclusion-free data (LA-ICP-MS) and included inclusions data (EPMA). Arsenic shows a weak positive relation with Au for inclusion-free data. In contrast, the data contemplating inclusions show no relationship (Fig. 18a). The data is well separated into two groups by the line of Au solubility in pyrite proposed by Deditius et al. (2014) rather than the typical

limit proposed by Reich et al., (2005). Gold and Ag do not show correlations between the variables, but it should be noted that LA-ICP-MS data spans widely from ca. 0.01 to 100 Au/Ag. In contrast, EPMA data is concentrated between 0.1 to 10 Au/Ag (Fig. 18b). Positive trends were found for Ag-Pb (Fig. 18c) and Sb-Pb (Fig. 18d), showing similar behavior. Both correlations are approximately centered at a ratio of 0.1 with an excursion to a lower ratio at higher Pb content. Bi-Sb (Fig. 18e) is the only scatter plot to show a noticeable difference between distal pyrite, associated with propylitic veinlets in relatively fresh rock (Py1), and pyrite from the ore quartz2 veins (Py3), marked by the higher Bi/Sb ratio of about 10. Finally, Cu shows a scatter pattern when plotted against As (Fig. 18f).

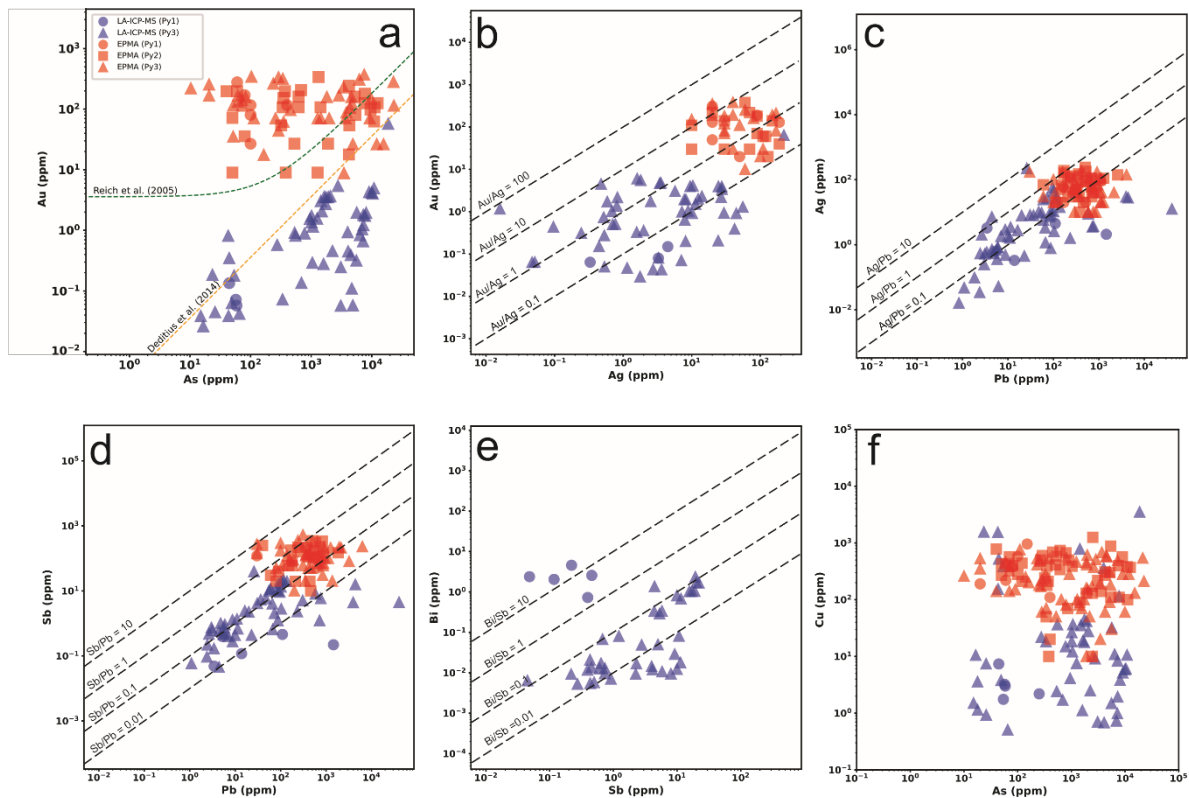


Fig. 18. Elemental concentration scatter plots in pyrites from the Água Branca deposit (LA-ICP-MS inclusion free, $n = 61$ & EPMA including micro-inclusions $n = 227$). (a) Au vs. As; (b) Au vs. Ag; (c) Ag vs. Pb; (d) Sb vs. Pb; (e) Bi vs. Sb; (f) Cu vs. Ni. In (a) the green dashed line represents the solubility limit of Au as a function of the concentration of As at a temperature of 150°C (Reich et al., 2005) while the orange dashed

line represents this solubility under the orogenic deposit conditions (Deditius et al., 2014). In (b), (c), (d) and (e) the black dashed lines represent different elements ratios as references.

Random forest on pyrite geochemistry

Elemental concentrations of Co, Ni, Cu, Zn, As, Mo, Ag, Sb, Te, Tl, and Pb in pyrite (excluding inclusions identified in the LA-ICP-MS depth profile) were used in the model developed by Gregory et al. (2019). The random forest model's predictions for the pyrite samples from the Água Branca deposit, suggest that the composition of the analyzed pyrites corresponds to an orogenic gold deposit, with 43.3% of the analyses classified as corresponding to this deposit type by the majoring of the voting (Fig. 19). However, 25% of the pyrite was predicted to belong to hydrothermal breccias. Interestingly, 18.3% of the pyrites were classified as volcanic-hosted massive sulfide deposits (VHMS) deposits, and 13.3% of the predictions correspond to porphyry deposits. It should be noted that these results represent the totality of the data analyzed. Still, as suggested by the methodology, results with less than 40% of the model's votes should be discarded, which results in 67.2% of the analyses available for interpretation, as detailed in Appendix C. However, the proportionality has few modifications, reducing the analyses classified as orogenic deposits by 1.8%. These do not affect the presented results that suggest the deposit corresponds to an orogenic deposit.

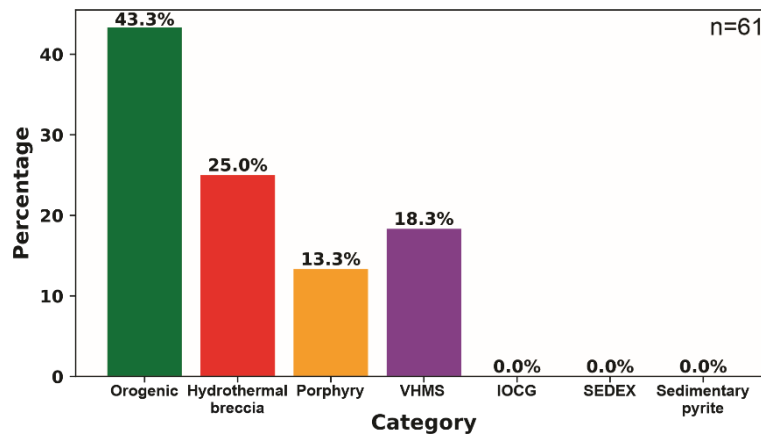


Fig. 19 Full results of the Random Forests classifier model developed by Gregory et al. (2019) using LA-ICP-MS data of pyrites from the Água Branca gold deposit.

OreGenes on gold geochemistry (Artificial Neural Networks)

Using published geochemistry data obtained by LA-ICP-MS of natural gold grains from the Água Branca deposit (Verbel et al. *In Review a*). The dataset contains 194 analyses of gold grains. They are evaluated using an ANN called OreGenes, available for MatLab with the elemental concentrations for Ag, Bi, Cu, Fe, Ni, Pb, Pd, Pt, Sb, and Te. The model compares the concentrations as an activation input layer, resulting in the analysis being predicted as one of the 4 ore deposits evaluated by this model (i.e., Orogenic, epithermal, VMS, and porphyry). As a result, the model predicts that 98.5% of the gold grains evaluated have a chemical signature corresponding to an orogenic deposit, while just 1.5% is classified as an epithermal deposit (Fig. 20).

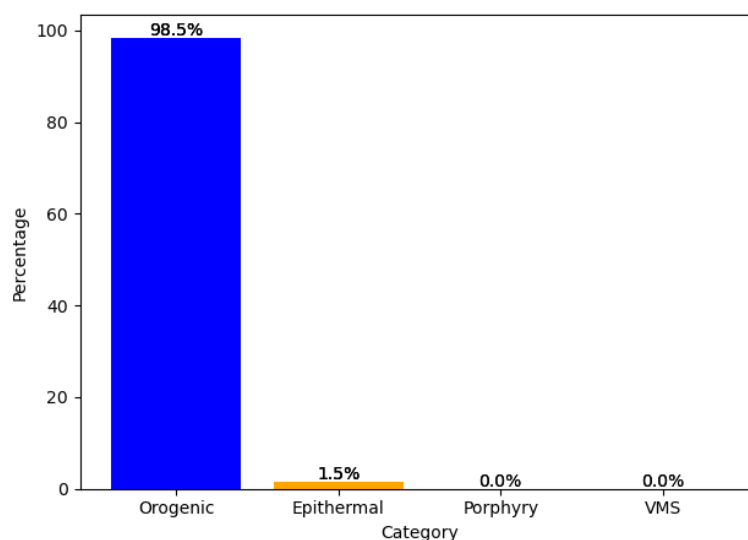


Fig. 20 Results of the deposit classification using the Artificial Neural Network OreGenes developed by Verbel et al. In review of 194 natural gold analyses by LA-ICP-MS from Verbel et al. In review.

DISCUSSION

The comparative evaluation of two predictive models offers valuable insights into the effectiveness of geochemical data in classifying ore deposit types. The first model, employing Random Forest on pyrite geochemistry (Gregory et al., 2019), demonstrates moderate classification performance across six deposit types (IOCG, SEDEX, VHMS, porphyry, hydrothermal breccia, and orogenic) alongside sedimentary pyrites as non-mineralized examples. The model's predictions reveal a predominance of the orogenic deposit type (43.3%), followed by hydrothermal breccia (25%), porphyry (13.3%), and VHMS (18.3%). These results suggest that while pyrite geochemistry provides proper differentiation, the overlap in geochemical signatures across deposit types limits the model's predictive precision.

In contrast, the second model leverages LA-ICP-MS-derived geochemistry from natural gold grains to classify four deposit types (i.e., orogenic, porphyry, VMS,

and epithermal). This model exhibits a strikingly high classification accuracy, with 98.5% of the analyses attributed to orogenic deposits and a marginal 1.5% to epithermal deposits. This stark disparity may reflect the higher geochemical fidelity of gold grains in preserving depositional environment signals compared to pyrite, or it may result from differences in the complexity of the classification problem (e.g., fewer deposit types, less geochemical overlap).

The discrepancies between the models underscore the importance of selecting appropriate geochemical proxies for deposit classification. Pyrite geochemistry provides broader contextual information but may suffer from compositional overlap due to its formation conditions. Additionally, the long swipe time (1.1 seconds) in the measurements results in difficulty in identifying the more minor mineral inclusions that may also play a key role in the low accuracy of determining the mineral deposit that formed the analyzed pyrite grains. In contrast, the gold grain model likely benefits from gold's robustness as a tracer of its source environment. Future work should explore integrating these datasets or refining the features used in the models to enhance classification accuracy while addressing each dataset's inherent challenges.

Usually, machine learning models are seen as black boxes where the proper data is put in, and it will give you a prediction. However, recent efforts have been made to improve the understanding of machine learning decision-making by using visual aids that help the user to make a conscious decision on the model selection (Wang et al., 2024b). We will delve into the data by comparing the mineral

chemistry of pyrite and gold using a parametrized dimensional reduction technique, Uniform Manifold Approximation and Projection (UMAP)(McInnes et al., 2018; McInnes et al., 2020)By parametrizing the training data, we can add new unseen data and compare its relationship to the generated manifold structures.

Parametric UMAP

Pyrite is a ubiquitous mineral in several ore deposits and sedimentary (non-mineralized) environments that has been widely studied with the ability to preserve its concentration of trace elements up to mid-greenschist metamorphic conditions (Large et al., 2009; Gregory et al., 2019). This results in databases of considerable size. In addition to the publicly available data used in the random forest predictive model, data from two other studies was added (Li et al., 2024; Wang et al., 2024b and references within them). The number of analyses increased to 7012 among 10 categories (Duplicity was considered and eliminated between the databases). Fig. 21a shows the UMAP projection of the combined dataset clustering analysis with similar chemical composition based on the Hellinger distance. At the center of the projected manifold, sedimentary unmineralized pyrites are found next to pyrites from SEDEX deposits with slight overlapping. The ore deposits are concentrated on the sides of the manifold, and each of the two distinct groups form seems to have a convergence point at its respective side of the manifold where the composition among them is similar, evolving and differentiating as we move towards the center of the manifold. The first group comprises Ni-Cu/PGE, Porphyry, IOCG, IOA, and VMS deposits.

Transitioning in compositions can be seen in related deposits IOCG to IOA and porphyry to skarn, but most of the samples from skarn deposits belong to the other cluster. The second cluster is composed of orogenic, carlin, and skarn deposits. This cluster follows a similar trend to the first one, where some porphyry samples seem to transition to skarn deposits (in terms of similarity based on Hellinger distance). It should be noticed that even though orogenic deposits are concentrated in the second cluster, several analyses are sparse throughout the manifold, overlapping with most of the generated clusters. This could result from high-grade metamorphic processes, coupled dissolution-reprecipitation process, or low melting chalcophile elements effect that modify the elemental composition of the pyrite, creating the dispersion and overlapping seen in the UMAP projection. Figure 7b shows how the elemental composition of pyrite obtained from the Água Branca deposit relates to the 7012 analyses evaluated. Most of the samples are associated with the second cluster described, following a similar trend as the orogenic samples from the training dataset. Still, some of the data overlaps with other deposit types. This effect can be seen in the random forest results (Fig. 5). Since the two datasets have different amounts of training examples and categories, they cannot be directly comparable. However, this example illustrates the problems faced when pyrite geochemistry is used as a classification tool.

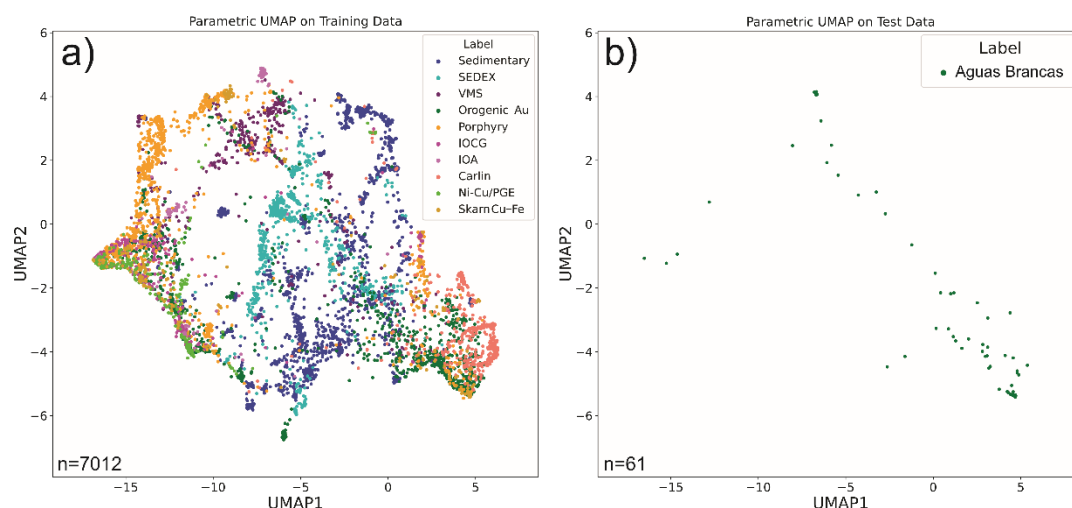


Fig. 21 Parametric UMAP on pyrite geochemistry A) 2-dimensional Euclidean space embedding of 7012 pyrite analyses (Li et al., 2024; Wang et al., 2024b) with 10 categories from mineralized and unmineralized environments. B) UMAP parametric projection of the analyzed pyrites from the Águas Branca deposit.

Gold has recently been used as a mineral indicator for gold deposits or deposits where it is present as a secondary ore (Liu et al., 2021b; Liu and Beaudoin, 2021b; Chapman et al., 2021; Melo-Gomez, 2023) by taking advantage of its resistance to weathering in superficial environments and the ability to hold trace elements on its structure with elemental concentrations that fluctuate depending on the physicochemical conditions under which it was formed (Boyle, 1979; Liu and Beaudoin, 2021b; Verbel et al., 2024). Two approaches have been developed to predict the type of ore deposit that forms a gold grain: a random forest approach (Liu and Beaudoin, 2021b) and artificial neural networks (Verbel et al., 2023; Verbel et al., 2024). This paper evaluates the latter (Fig. 6) since it performs better with category predictions with a high imbalance in the assessed categories (i.e., a low quantity of porphyry deposits in the training dataset). Independently of the machine learning method, the parametric UMAP is performed based on the similarity Hellinger distance in the high-dimensional

space; ergo, the resulting low-dimensional representation (Fig. 8) is applicable for both models since they use the same training data.

The resulting embedding (Fig. 8) shows a clear differentiation among the evaluated ore deposits. Interestingly, most of the samples from orogenic deposits seem to be embedded in a one-dimensional manifold (the data falls into an approximately continuous structure where the changes in elemental concentrations follow a single direction in the high-dimensional space (Bobok et al., 2024)). This characteristic is worth comparing with the different parameters that affect orogenic deposits (e.g., Age, host rock, fluid composition, etc.) to better understand this behavior. The limited sample size makes it challenging to evaluate whether the rest of the clusters are also one-dimensional manifolds with gaps in the composition (e.g., porphyry deposits) or, in fact, form two distinct clusters.

Some samples appear to be wrongly associated with other deposit types: epithermal samples with orogenic, orogenic samples with VMS, and porphyry samples with orogenic. Additionally, some samples are embedded as separate clusters in all four deposits. These effects could be caused by variations in the composition of gold grain during their formation, resulting in some overlapping or minor analytical errors.

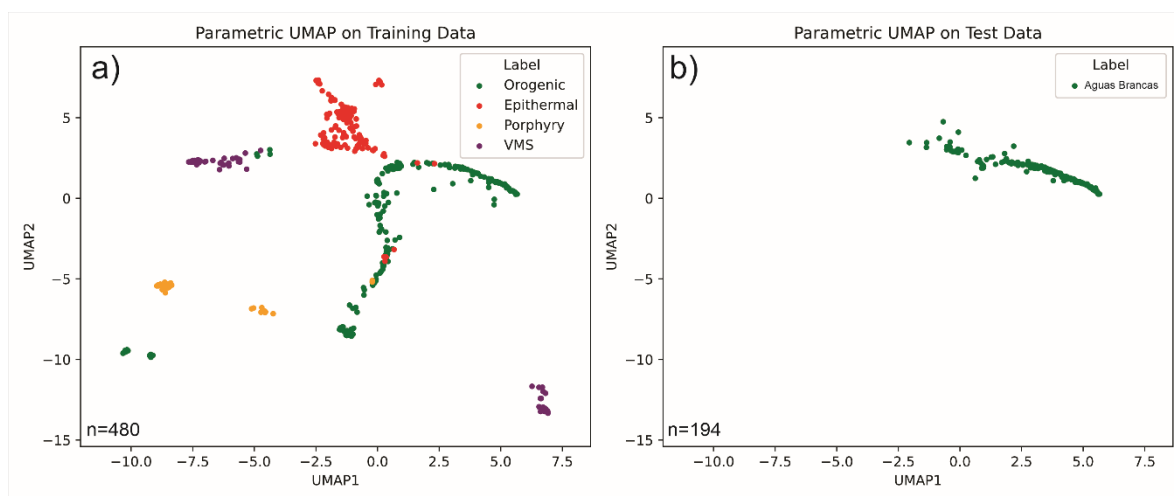


Fig. 22 Parametric UMAP on gold geochemistry. A) 2-dimensional Euclidean space embedding of 480 analyses of gold grains (Liu et al., 2021b; Liu and Beaudoin, 2021b; Melo-Gomez, 2023) with 4 categories of gold deposits. UMAP parametric projection of 194 compositional analyses of gold grains from the Água Branca deposit (Verbel et al. In Review).

Physicochemical conditions of formation of the deposit

Even though both evaluated models predict that the Água Branca deposit belongs to an orogenic gold deposit, it is imperative to consider the geological information of the deposit to assess the decisions made by the models.

The Água Branca Gold deposit has scarce local geological information limited to unpublished reports and a thesis (De Souza, 2009; Geoconsult unpublish, 2019). De Souza, 2009 classifies the de Água Branca deposit as an oxidized intrusion-related deposit based on the geometry of the quartz2 veins observed in drill holes cataloged as sheeted veins. However, fluid inclusions are described as aqueous-carbonic with low salinity (i.e., 0.4 to 7.9 wt.% NaCl eq.) with a total homogenization temperature of primary fluid inclusions between 200 and 420°C calculating a total composition of the fluid X_{H_2O} between 79.8 and 92.5%, X_{CO_2}

between 5.8 and 17.3% and XNaCl between 1.7 and 2.9 (all values are molar fractions). Additionally, the calculated depth of crystallization of the deposit based on the hornblende geobarometer coincides with the calculated pressure for deposit formation, 2.5 and 2.45 Kbar, respectively (ca. 8.5 km) (De Souza, 2009). This argument supports the idea that the monzogranite hosting the deposit is the causative intrusion of the ore deposit, generating an oxidized intrusion-related gold deposit. However, models of rhyolitic melts ascending from depths of about 17 Km (4.5 Kbars) show that CO₂ can exsolve from the magma without affecting the concentration of H₂O until it rises to shallow depths (ca. 1-4 km) under this lower pressure H₂O can be exsolved from the melt with the remaining CO₂ (Lowenstern, 2001). At these shallower depths, the resulting fluids can form aqueous-carbonic magmatic-hydrothermal like the ones forming an orogenic mineral deposit (Goldfarb and Pitcairn, 2023). Consequently, it is unlikely that the fluids responsible for forming the Água Branca deposit have formed because of fluids exsolved from the silicate melt that generates the host rocks.

No regional orogenic events have been recorded after the deposit's host rocks formation 1876.8 ± 15 Ma. during the Tropas Orogeny in the Parauari Arc (Santos et al., 2004). However, the alignment of the ore along fault structures suggests an epigenetic influence on deposit formation, as these structures help to focus a late orogenic fluid that will form the Água Branca deposit. More studies are needed to confirm this postulate. An example that may serve as an analog to the proposed mineralization process is the Archean Sigma-Lamaque gold deposit,

which features late-orogenic vein mineralization controlled by structural features (Cowan, 2020; Cowan and Hobbs, 2024).

CONCLUSIONS

This study highlights the comparative strengths and limitations of using geochemical datasets derived from pyrite and gold grains to classify ore deposit types. Pyrite geochemistry, analyzed using Random Forest models, offers broad insights into deposit classification but faces challenges such as geochemical overlaps and compositional variability. These challenges, including the inability to detect minor inclusions, contribute to the model's moderate performance across diverse deposit types. Despite these limitations, incorporating extensive published datasets (i.e., 7012 analyses) and advanced dimensionality reduction techniques like parametric UMAP successfully reveals clustering patterns that correlate with geological processes, enhancing our understanding of pyrite's geochemical variability.

Conversely, gold grain geochemistry, processed through an Artificial neural networks model, demonstrates superior classification accuracy. Gold grains' high fidelity in preserving geochemical signals provides a robust basis for distinguishing between ore-forming environments. The corresponding UMAP projections further underscore the clarity with which gold geochemistry differentiates deposit types, with a notable one-dimensional embedding for orogenic deposits. However, the misclassification of some gold samples highlights the influence of formation conditions and analytical uncertainties, emphasizing the need for refined model training and data quality.

The Água Branca deposit case study highlights the importance of integrating machine learning predictions with geological data. Both models classify the deposit as orogenic, and geological evidence supports this classification, suggesting a late-orogenic epigenetic fluid origin influenced by structural controls. This finding reinforces the necessity of contextual geological assessment to

complement geochemical analyses, ensuring robust and accurate deposit characterization.

Future directions should focus on integrating pyrite and gold geochemical datasets into unified predictive frameworks, leveraging their complementary strengths. Enhancements in feature selection, dimensionality reduction techniques, and model interpretability are essential to address the inherent challenges of geochemical overlap and compositional variability. Additionally, expanding publicly available datasets and incorporating advanced visualization tools can facilitate better decision-making and understanding of machine learning predictions, supporting more accurate and reliable classification of ore deposit types.

Chapter 6

GENERAL CONCLUSIONS

GENERAL CONCLUSIONS

This research highlights the transformative potential of advanced analytical techniques, geochemical modeling, and machine learning in understanding the genesis of gold deposits, tracing gold provenance, and supporting forensic investigations. Collectively, the findings from these studies underscore the value of combining geochemical data with innovative computational tools to address challenges in deposit characterization, traceability, and classification.

1. Geochemical Signatures and Deposit Classification:

The geochemical composition of natural gold grains reflects the unique physicochemical conditions and geological settings of their formation. Trace elements such as Ag, Bi, Cu, Fe, Ni, Pb, Pd, Pt, Sb, and Te emerge as key contributors to the variability in gold chemistry, providing a "chemical signature" indicative of specific deposit types. Machine learning models, particularly artificial neural networks (ANNs), have proven effective in identifying nonlinear patterns within these signatures. The optimized model architecture, comprising two hidden layers with ten neurons, successfully associated gold samples with their respective deposit types, demonstrating its reliability across unobserved and blind datasets. However, these models remain limited by the dataset's scope, emphasizing the need for further research into other mineral systems and the effects of metamorphism on gold's trace element composition.

2. Traceability and Evolution of Geochemical Signatures:

The traceability of gold through its production chain is a critical challenge in forensic geology. While Pb isotope ratios remain relatively stable during gold beneficiation, they are primarily effective at differentiating metallogenetic provinces rather than local scales. In contrast, manifold learning techniques such as UMAP, combined with Hellinger distance metrics, effectively capture geochemical similarities and divergences between natural gold and refined samples. These methods revealed that samples claiming a specific origin might instead share a common, undeclared source. The study also highlights the influence of industrial processes, such as the addition of Cu, Sb, Pb, and Zn, in modifying gold's chemical signature, while maintaining sufficient traceability for forensic applications.

3. Forensic Applications and Local Traceability:

The integration of geochemical data with machine learning and dimensionality reduction techniques provides a robust framework for forensic geology. The demonstrated methodology enables the identification of gold's provenance at a local scale, offering valuable tools for combating illicit gold trafficking. However, its effectiveness depends on the availability of comprehensive datasets and complementary evidence, such as petrographic and geobarometric analyses, to address uncertainties and strengthen conclusions.

4. Applications to Ore Deposit Genesis:

Machine learning methods applied to mineralogical data, such as pyrite and gold compositions, offer significant insights into deposit genesis. In the case of the Água Branca deposit, these techniques confirmed its classification as an orogenic deposit, challenging previous interpretations. This example illustrates the potential of machine learning as a supplementary tool for deposit classification, provided it is used alongside traditional geological methods, including petrography and mineral inclusion studies.

5. Future Directions:

While this research demonstrates the power of integrating geochemical analyses with computational tools, it also underscores the need for further advancements. Expanding datasets to include more deposit types, understanding the effects of metamorphic processes, and refining models for better accuracy are crucial steps forward. Additionally, developing accessible tools, such as the Matlab-based app for ANN modeling, ensures that researchers and practitioners can widely adopt these methods.

By bridging the gap between geochemical research, computational techniques, and practical applications, this work lays a foundation for more precise gold deposit classification, improved traceability of gold through the production chain, and enhanced forensic and geological investigation tools.

Chapter 7

CONCLUSÕES GERAIS

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Esta pesquisa destaca o potencial transformador de técnicas analíticas avançadas, modelagem geoquímica e aprendizado de máquina para compreender a gênese dos depósitos de ouro, rastrear a proveniência do ouro e apoiar investigações forenses. Coletivamente, as descobertas desses estudos ressaltam o valor da combinação de dados geoquímicos com ferramentas computacionais inovadoras para enfrentar os desafios na caracterização, rastreabilidade e classificação de depósitos.

1. Assinaturas geoquímicas e classificação de depósitos:

A composição geoquímica dos grãos de ouro naturais reflete as condições físico-químicas exclusivas e as configurações geológicas de sua formação. Os oligoelementos, como Ag, Bi, Cu, Fe, Ni, Pb, Pd, Pt, Sb e Te, surgem como os principais contribuintes para a variabilidade da química do ouro, fornecendo uma “assinatura química” indicativa de tipos específicos de depósitos. Os modelos de aprendizado de máquina, especialmente as redes neurais artificiais (RNAs), têm se mostrado eficazes na identificação de padrões não lineares nessas assinaturas. A arquitetura otimizada do modelo, composta por duas camadas ocultas com dez neurônios, associou com sucesso amostras de ouro aos seus respectivos tipos de depósitos, demonstrando sua confiabilidade em conjuntos de dados cegos e não observados. No entanto, esses modelos permanecem limitados pelo escopo do conjunto de dados, enfatizando a necessidade de mais pesquisas sobre outros sistemas minerais e os efeitos do metamorfismo na composição do elemento traço do ouro.

2. Rastreabilidade e evolução das assinaturas geoquímicas:

A rastreabilidade do ouro ao longo de sua cadeia de produção é um desafio fundamental na geologia forense. Embora as proporções de isótopos de Pb permaneçam relativamente estáveis durante o beneficiamento do ouro, elas são eficazes principalmente para diferenciar províncias metalogenéticas em vez de

escalas locais. Em contrapartida, as técnicas de aprendizagem múltipla, como a UMAP, combinadas com a métrica de distância Hellinger, capturam com eficácia as semelhanças e divergências geoquímicas entre o ouro natural e as amostras refinadas. Esses métodos revelaram que as amostras que alegam uma origem específica podem, em vez disso, compartilhar uma fonte comum não declarada. O estudo também destaca a influência dos processos industriais, como a adição de Cu, Sb, Pb e Zn, na modificação da assinatura química do ouro, mantendo a rastreabilidade suficiente para aplicações forenses.

3. Aplicativos forenses e rastreabilidade local:

A integração de dados geoquímicos com técnicas de aprendizado de máquina e redução de dimensionalidade fornece uma estrutura robusta para a geologia forense. A metodologia demonstrada permite a identificação da procedência do ouro em escala local, oferecendo ferramentas valiosas para o combate ao tráfico ilícito de ouro. No entanto, sua eficácia depende da disponibilidade de conjuntos de dados abrangentes e de evidências complementares, como análises petrográficas e geobarométricas, para lidar com as incertezas e fortalecer as conclusões.

4. Aplicações à gênese de depósitos de minério:

Os métodos de aprendizado de máquina aplicados a dados mineralógicos, como composições de pirita e ouro, oferecem percepções significativas sobre a gênese do depósito. No caso do depósito de Água Branca, essas técnicas confirmaram sua classificação como um depósito orogênico, desafiando interpretações anteriores. Esse exemplo ilustra o potencial do aprendizado de máquina como uma ferramenta complementar para a classificação de depósitos, desde que seja usado juntamente com métodos geológicos tradicionais, incluindo petrografia e estudos de inclusão mineral.

5. Orientações futuras:

Embora esta pesquisa demonstre o poder da integração de análises geoquímicas com ferramentas computacionais, ela também ressalta a necessidade de mais avanços. A expansão dos conjuntos de dados para incluir mais tipos de depósitos, a compreensão dos efeitos dos processos metamórficos e o refinamento dos modelos para melhorar a precisão são passos cruciais. Além disso, o desenvolvimento de ferramentas acessíveis, como o aplicativo baseado em Matlab para modelagem ANN, garante que pesquisadores e profissionais possam adotar amplamente esses métodos.

Ao preencher a lacuna entre a pesquisa geoquímica, as técnicas computacionais e as aplicações práticas, este trabalho estabelece uma base para uma classificação mais precisa dos depósitos de ouro, melhor rastreabilidade do ouro ao longo da cadeia de produção e ferramentas aprimoradas de investigação forense e geológica.

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APPENDIXES

Table S1 Trace element concentrations in gold determined by LA-ICP-MS from Liu et al. (2021); Liu and Beaudoin (2021) and Melo-Gómez (2023). Units in ppm.

Deposit type	Deposit name	Pt	Pd	Te	Se	Hg	In	Cd	Bi	Sb	Tl	Mo	Sn	As	Co	Pb	Cu	Cr	Ni	Ag	Zn	S	Mn	Ti	Fe	Reference
Epithermal	Original Bullfrog	<BDL	0.021	<BDL	<BDL	5.81	<BDL	<BDL	0.03	0.153	<BDL	<BDL	<BDL	<BDL	0.03	0.055	66.2	<BDL	<BDL	419184	0.6	87	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	0.4	<BDL	4.07	0.008	<BDL	0.054	0.88	<BDL	<BDL	<BDL	<BDL	<BDL	0.16	74.2	<BDL	<BDL	419184	<BDL	87.5	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	0.13	<BDL	12.6	<BDL	0.03	0.171	2.2	0.0097	<BDL	<BDL	<BDL	<BDL	0.24	110	<BDL	<BDL	480255	<BDL	94.3	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	<BDL	<BDL	10.9	<BDL	<BDL	0.155	0.32	<BDL	<BDL	<BDL	<BDL	<BDL	0.32	60.4	<BDL	<BDL	447193	<BDL	96.1	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	0.24	0.6	6.78	<BDL	0.138	0.76	47.4	0.084	1.55	<BDL	93	<BDL	79	331	<BDL	<BDL	442342	1.13	93.1	<BDL	<BDL	65	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	0.14	<BDL	5.56	<BDL	0.029	0.059	0.281	0.004	<BDL	<BDL	<BDL	<BDL	0.049	61.2	<BDL	<BDL	442342	<BDL	97.4	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	16.5	1.23	6.4	<BDL	<BDL	0.069	0.322	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	78	<BDL	<BDL	430589	<BDL	79	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	0.017	0.044	<BDL	17.8	<BDL	0.018	0.058	0.46	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	53.1	<BDL	<BDL	397516	<BDL	102.7	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	0.42	<BDL	18	<BDL	0.43	4.3	180	0.51	0.68	<BDL	2.8	<BDL	6.5	330	<BDL	<BDL	407122	0.9	77	<BDL	<BDL	33	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	<BDL	<BDL	10.1	<BDL	0.28	1.59	38	0.047	0.67	<BDL	76	<BDL	10.3	280	<BDL	<BDL	407122	<BDL	58	<BDL	<BDL	25	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	<BDL	<BDL	10	<BDL	<BDL	0.2	1.04	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	84	<BDL	<BDL	407189	<BDL	84	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	<BDL	<BDL	4.8	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.033	<BDL	69.9	<BDL	<BDL	407189	<BDL	79	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	<BDL	<BDL	5.7	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	63.4	<BDL	<BDL	412249	<BDL	92	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	<BDL	0.6	4.5	<BDL	0.11	0.053	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	71.1	<BDL	<BDL	412249	<BDL	69	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	<BDL	<BDL	6.2	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	75	<BDL	<BDL	412249	<BDL	65	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	1.99	20	2.2	46.6	<BDL	4.3	134	13200	10.8	25	<BDL	137	0.155	480	492	<BDL	1.66	413893	141	116	51	<BDL	770	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	6.2	15.7	<BDL	42.6	<BDL	11.5	205	6700	11.3	117	<BDL	378	<BDL	2370	473	<BDL	10.3	462276	452	570	72	43	24	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	<BDL	<BDL	<BDL	8.2	<BDL	<BDL	0.056	0.93	<BDL	<BDL	<BDL	<BDL	<BDL	0.115	48	<BDL	<BDL	462276	<BDL	63	<BDL	<BDL	24.4	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	1.03	23.2	2.9	43.1	<BDL	15.1	506	24200	37.2	145	0.28	504	0.3	670	437	<BDL	1.62	404133	177	116	77	2	89	Liu et al. (2021)
Epithermal	Original Bullfrog	<BDL	6	0.51	<BDL	55.3	<BDL	2.3	10.1	333	0.51	9.3	<BDL	7.2	0.25	10.1	456	<BDL	5.5	399274	299	319	<BDL	<BDL	62	Liu et al. (2021)
Epithermal	Palisades	<BDL	<BDL	2.4	3.7	255	<BDL	<BDL	<BDL	0.88	0.028	<BDL	<BDL	<BDL	<BDL	0.53	63.3	<BDL	<BDL	493205	<BDL	299	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Palisades	<BDL	<BDL	1.07	<BDL	47.3	<BDL	<BDL	<BDL	6.06	0.021	<BDL	<BDL	<BDL	0.11	0.6	42.7	<BDL	<BDL	584239	<BDL	151	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Palisades	<BDL	<BDL	0.84	13.9	192	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	8.4	230	<BDL	<BDL	489836	3.6	82	<BDL	<BDL	125	Liu et al. (2021)
Epithermal	Palisades	<BDL	<BDL	<BDL	16.8	209	1.02	423	<BDL	8.2	0.6	<BDL	5.8	<BDL	2.78	4.9	240	<BDL	<BDL	487633	218000	1730	54	<BDL	419	Liu et al. (2021)
Epithermal	Palisades	<BDL	<BDL	<BDL	<BDL	148	<BDL	<BDL	<BDL	2.35	<BDL	<BDL	<BDL	<BDL	<BDL	157	63.9	<BDL	<BDL	477361	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Palisades	<BDL	<BDL	1.23	3.5	7.46	<BDL	<BDL	<BDL	3.2	0.009	<BDL	<BDL	<BDL	<BDL	2.28	76	<BDL	<BDL	504656	<BDL	101	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Palisades	<BDL	<BDL	0.44	4.2	14.4	<BDL	<BDL	<BDL	2.08	<BDL	0.23	<BDL	<BDL	0.015	46	63.6	<BDL	<BDL	504656	<BDL	96.8	<BDL	0.31	<BDL	Liu et al. (2021)
Epithermal	Palisades	<BDL	<BDL	0.75	1.59	8.3	<BDL	<BDL	<BDL	2.78	<BDL	<BDL	<BDL	<BDL	<BDL	0.155	59.4	<BDL	<BDL	504656	<BDL	89	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Little Florence	<BDL	<BDL	830	23.1	150.7	<BDL	<BDL	250	3	<BDL	<BDL	<BDL	1.46	<BDL	0.81	205.4	<BDL	<BDL	4998	<BDL	123	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Little Florence	<BDL	<BDL	1630	1.85	108.9	<BDL	<BDL	81	0.76	<BDL	<BDL	<BDL	<BDL	<BDL	0.32	163.9	<BDL	<BDL	4236	<BDL	81.2	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Little Florence	<BDL	<BDL	21.7	<BDL	234	<BDL	<BDL	20.5	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.12	0.143	185	<BDL	<BDL	4604	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Little Florence	0.18	0.1	16.2	<BDL	152	<BDL	<BDL	37.8	2.2	<BDL	<BDL	<BDL	<BDL	<BDL	0.218	217	<BDL	<BDL	4327	<BDL	44	<BDL	2	<BDL	Liu et al. (2021)
Epithermal	Little Florence	0.11	<BDL	21.3	5.7	151.6	<BDL	<BDL	181	11.9	0.029	<BDL	<BDL	<BDL	<BDL	0.179	151.5	<BDL	<BDL	4327	<BDL	413	<BDL	2.1	<BDL	Liu et al. (2021)
Epithermal	Little Florence	<BDL	<BDL	24.5	<BDL	248	<BDL	0.14	32.9	4.6	<BDL	<BDL	<BDL	<BDL	6.2	0.23	0.25	189	<BDL	<BDL	4332	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Little Florence	<BDL	<BDL	47	6.7	225	<BDL	<BDL	38.3	0.8	<BDL	<BDL	<BDL	<BDL	<BDL	0.122	159.4	<BDL	1.61	4226	<BDL	98	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Little Florence	<BDL	<BDL	21.3	<BDL	204	0.3	0.35	99.9	3.8	0.06	<BDL	0.86	<BDL	0.52	0.41	248	350	<BDL	4232	<BDL	144	<BDL	1.5	<BDL	Liu et al. (2021)
Epithermal	Little Florence	<BDL	<BDL	37.8	<BDL	196	<BDL	0.14	265	26.5	<BDL	<BDL	1.07	<BDL	<BDL	0.6	161	40	<BDL	4386	<BDL	600	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Little Florence	<BDL	<BDL	1600	163	371	<BDL	<BDL	7.1	5.7	<BDL	<BDL	6.6	<BDL	<BDL	<BDL	105	<BDL	<BDL	4594	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Little Florence	0.73	<BDL	2200	74	252	<BDL	<BDL	<BDL	<BDL	0.31	<BDL	<BDL	<BDL	<BDL	<BDL	57	<BDL	<BDL	4662	<BDL	<BDL	<BDL	13	<BDL	Liu et al. (2021)
Epithermal	Cripple Creek	<BDL	<BDL	7900	307	14.8	0.094	0.1	2.07	5.6	8.7	0.21	5.3	23.3	0.34	24.3	12.9	11.8	<BDL	33744	22.3	650	56	6900	1499	Liu et al. (2021)
Epithermal	Cripple Creek	<BDL	0.45	7500	430	<BDL	0.38	<BDL	3.2	7.8	19	1.6	15.4	54	3.6	26	48	12	1.9	37819	270	1700	430	3100	235	Liu et al. (2021)
Epithermal	Cripple Creek	<BDL	<BDL	9300	520	280	0.8	<BDL	1.08	2.62	11.3	<BDL	6.9	51	1.2	43	33	14.9	1.5	37272	180	840	160	1180	179	Liu et al. (2021)
Epithermal	Ken Snyder	<BDL	<BDL	342	4.4	20.5	<BDL	<BDL	<BDL	0.417	0.0085	<BDL	<BDL	<BDL	<BDL	<BDL	8.72	<BDL	<BDL	375587	<BDL	92	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Ken Snyder	<BDL	<BDL	204	2.8	12	<BDL	<BDL	<BDL	0.374	<BDL	<BDL	<BDL	<BDL	0.029	<BDL	9.12	<BDL	<BDL	375587	<BDL	96	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Ken Snyder	<BDL	<BDL	<BDL	160	2140	<BDL	<BDL	4.3	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	12.8	2.69	<BDL	<BDL	292679	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Ken Snyder	<BDL	<BDL	<BDL	28	610	0.22	<BDL	0.77	<BDL	<BDL	0.21	<BDL	<BDL	<BDL	5.2	6.8	<BDL	<BDL	292679	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Ken Snyder	<BDL	<BDL	<BDL	16	58	<BDL	<BDL	0.104	3	<BDL	<BDL	<BDL	<BDL	<BDL	1.27	13.1	<BDL	<BDL	362280	<BDL	371	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	Ken Snyder	0.19	<BDL	<BDL	<BDL	108	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	11	<BDL	<BDL	384807	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)

Epithelial	Ken Snyder	<BDL	<BDL	3.9	21000	900	<BDL	<BDL	8.7	3.62	0.095	13	0.52	<BDL	0.3	42	13.8	<BDL	<BDL	340402	<BDL	225	<BDL	1.13	147	Liu et al. (2021)	
Epithelial	Bell	<BDL	<BDL	<BDL	520	1310	0.111	0.75	3.06	208	0.39	4.1	1.32	9.6	<BDL	48.2	25.7	<BDL	<BDL	456403	<BDL	650	<BDL	2.6	75	Liu et al. (2021)	
Epithelial	Bell	0.063	<BDL	5.5	<BDL	2300	<BDL	<BDL	<BDL	93.5	<BDL	<BDL	1.68	<BDL	0.19	0.72	2.4	<BDL	<BDL	453622	1.9	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Bell	<BDL	<BDL	<BDL	13.8	6200	<BDL	<BDL	0.094	109	<BDL	<BDL	0.68	<BDL	<BDL	2.02	1.54	<BDL	<BDL	474546	<BDL	314	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	1.04	104	52400	<BDL	0.021	3.7	5.87	0.04	0.066	<BDL	<BDL	<BDL	2.9	9.5	<BDL	<BDL	474546	0.82	357	<BDL	<BDL	23.7	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	1.4	16	<BDL	<BDL	0.088	6.16	0.0075	0.22	<BDL	<BDL	<BDL	0.48	7.5	<BDL	<BDL	474546	<BDL	108.7	<BDL	<BDL	12.5	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	34.1	35000	0.01	0.02	5	12.1	0.055	0.111	<BDL	<BDL	<BDL	0.07	2.84	7.23	<BDL	<BDL	474546	<BDL	287	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	<BDL	98.1	1.2	<BDL	<BDL	4.56	<BDL	<BDL	<BDL	<BDL	0.27	0.112	7.77	<BDL	<BDL	474546	0.64	113.1	<BDL	11.1	170	Liu et al. (2021)	
Epithelial	Golden Arrow	0.01	0.025	1.72	112	63600	<BDL	0.032	3.91	12.3	0.149	0.054	<BDL	0.97	0.1	1.03	8.2	<BDL	<BDL	474546	1.23	658	<BDL	<BDL	27.1	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	0.71	1.15	<BDL	<BDL	<BDL	<BDL	5.5	<BDL	<BDL	<BDL	<BDL	<BDL	0.04	6.16	<BDL	<BDL	474546	<BDL	125	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	<BDL	3.1	<BDL	0.073	<BDL	4.92	<BDL	<BDL	<BDL	<BDL	<BDL	0.087	6.69	<BDL	<BDL	474546	<BDL	106	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Golden Arrow	0.054	<BDL	<BDL	<BDL	161.7	<BDL	<BDL	<BDL	6.25	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	3.47	<BDL	<BDL	474546	<BDL	106	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	<BDL	78.7	<BDL	<BDL	<BDL	4.35	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	6.61	<BDL	<BDL	474546	<BDL	84	<BDL	<BDL	94	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	2.09	150.4	<BDL	0.063	0.46	5.9	0.017	1.46	<BDL	51	<BDL	0.48	7.75	8	<BDL	474546	13.2	153.1	<BDL	<BDL	226	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	2.6	445	<BDL	0.15	0.403	6.61	0.049	3.23	<BDL	199	0.093	21.7	18.8	<BDL	0.44	474546	21.5	193	<BDL	2.6	177	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	6	664	<BDL	0.19	0.57	9.9	0.11	6.6	<BDL	260	1.69	17.5	113	<BDL	0.65	474546	32.2	317	35	18.1	74	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	49	<BDL	<BDL	5	15.4	100	0.36	29	4	920	1.1	180	410	100	3.7	474546	290	5300	220	28	28	Liu et al. (2021)	
Epithelial	Golden Arrow	<BDL	<BDL	<BDL	5.2	90	<BDL	0.3	2.2	13.9	0.016	11	<BDL	460	<BDL	7.4	39	<BDL	<BDL	474546	58	390	<BDL	3.4	23	Liu et al. (2021)	
Epithelial	Fruta Del Norte	0.16	<BDL	57.8	22.2	4090	<BDL	0.59	0.76	274	1.07	190	<BDL	50	0.18	23800	26.3	<BDL	<BDL	328548	<BDL	1960	<BDL	<BDL	92	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	361	8.3	4280	<BDL	0.14	<BDL	115	0.57	13.8	<BDL	<BDL	0.36	6600	11.2	<BDL	<BDL	333305	<BDL	1000	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	51	<BDL	14700	<BDL	<BDL	<BDL	64	0.2	15.8	<BDL	<BDL	<BDL	153	11.6	<BDL	<BDL	338577	<BDL	<BDL	2200	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	0.07	<BDL	27.3	<BDL	3340	<BDL	<BDL	<BDL	38.3	0.22	<BDL	<BDL	<BDL	0.33	1.66	5.7	<BDL	<BDL	332199	<BDL	940	37.2	<BDL	73	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	40	<BDL	13400	<BDL	<BDL	0.156	20.2	<BDL	2.04	<BDL	<BDL	0.46	520	5.7	<BDL	<BDL	332199	<BDL	<BDL	<BDL	1.9	168	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	0.11	12.8	10.3	8310	<BDL	<BDL	0.049	53.2	0.131	<BDL	<BDL	154	<BDL	98	25	<BDL	<BDL	298093	<BDL	970	<BDL	1.7	555	Liu et al. (2021)	
Epithelial	Fruta Del Norte	0.46	<BDL	54	25.2	6730	<BDL	3.6	<BDL	329	1.07	23.2	<BDL	<BDL	2260	1.26	2600	162	<BDL	<BDL	337862	810	4710	107	<BDL	3225	Liu et al. (2021)
Epithelial	Fruta Del Norte	<BDL	<BDL	24.1	3.8	14100	1.8	420	<BDL	790	18.6	4	1.97	1630	2.6	1060	2230	<BDL	<BDL	340978	84000	1910	28.6	<BDL	1553	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	4.7	<BDL	9570	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.7	3.2	59.9	<BDL	<BDL	183314	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	2.3	<BDL	7810	0.11	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	2.36	60	<BDL	<BDL	248010	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	6.5	<BDL	6190	0.11	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	2.05	91	<BDL	<BDL	312490	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	75	<BDL	17650	<BDL	<BDL	<BDL	54.8	0.14	<BDL	<BDL	<BDL	1.8	9.5	19.9	<BDL	<BDL	252940	<BDL	320	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	135	<BDL	13110	0.061	<BDL	<BDL	24.6	0.193	<BDL	<BDL	300	21	18.1	43	<BDL	<BDL	322690	<BDL	260	<BDL	8	3500	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	197	<BDL	18660	<BDL	<BDL	<BDL	40	0.48	<BDL	<BDL	550	22	32	97	<BDL	<BDL	321990	<BDL	<BDL	69	7.9	8200	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	207	<BDL	7580	0.11	<BDL	<BDL	279	<BDL	<BDL	<BDL	<BDL	<BDL	2	56	<BDL	<BDL	248010	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	75	<BDL	21930	<BDL	<BDL	<BDL	49	0.76	<BDL	<BDL	<BDL	3.1	7.1	29	<BDL	<BDL	312490	<BDL	<BDL	85	38	940	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	35	<BDL	23600	0.19	<BDL	<BDL	18.8	<BDL	<BDL	<BDL	<BDL	<BDL	4.1	26.8	<BDL	<BDL	252940	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	19	<BDL	11390	0.26	<BDL	<BDL	22.4	<BDL	<BDL	<BDL	<BDL	<BDL	4.05	748	<BDL	<BDL	322690	8.7	<BDL	<BDL	<BDL	320	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	2.4	77	<BDL	10930	1.45	19.7	<BDL	498	2.38	<BDL	<BDL	700	4.5	288	96	<BDL	<BDL	321990	4940	350	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithelial	Fruta Del Norte	<BDL	<BDL	2	<BDL	19200	<BDL	<BDL	<BDL	18.6	<BDL	<BDL	<BDL	<BDL	<BDL	2.74	12.8	<BDL	<BDL	343131	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithelial	Fruta Del Norte	<BDL	<BDL	<BDL	516	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	70	<BDL	<BDL	80204	<BDL	<BDL	<BDL	36	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	13.9	<BDL	967	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	83	<BDL	<BDL	78962	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	<BDL	<BDL	10290	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	10.1	168	<BDL	<BDL	85347	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	<BDL	<BDL	10610	0.32	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	6.1	201	<BDL	<BDL	84975	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	2.6	<BDL	13910	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	5.9	170	<BDL	<BDL	84973	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	1.01	<BDL	12960	0.066	<BDL	<BDL	8.5	<BDL	<BDL	<BDL	<BDL	<BDL	0.78	44.8	<BDL	<BDL	331983	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	1.19	<BDL	11540	0.037	<BDL	<BDL	11	<BDL	<BDL	<BDL	<BDL	<BDL	1.47	13.8	<BDL	<BDL	326816	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	<BDL	<BDL	2379	0.1	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.94	79.7	<BDL	<BDL	80204	<BDL	<BDL	<BDL	8.2	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	0.95	<BDL	1124	0.09	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.31	63.6	<BDL	<BDL	78962	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	640	9.7	12580	<BDL	<BDL	<BDL	105	0.58	42	<BDL	<BDL	<BDL	360	82	<BDL	<BDL	349528	14.9	2350	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithelial	Fruta Del Norte	<BDL	<BDL	<BDL	<BDL	9950	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	343793	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithelial	Fruta Del Norte	<BDL	<BDL	<BDL	<BDL	10360	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	10.1	<BDL	<BDL	<BDL	348600	&lt						

Epithermal	Fruta Del Norte	<BDL	<BDL	<BDL	<BDL	15270	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	4.9	<BDL	<BDL	<BDL	350840	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Fruta Del Norte	<BDL	<BDL	<BDL	<BDL	16320	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	293	<BDL	<BDL	<BDL	347770	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Fruta Del Norte	<BDL	<BDL	41	<BDL	9790	<BDL	<BDL	0.46	182	4.6	74	<BDL	4000	63	840	1830	<BDL	354450	15.5	6500	<BDL	<BDL	355	Liu et al. (2021)	
Epithermal	Rozália	<BDL	0.07	<BDL	<BDL	1063.32	<BDL	10.31	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	7.16	6.83	<BDL	<BDL	228208	2165.32	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Rozália	<BDL	0.03	0.84	<BDL	642.42	<BDL	1.2	0.01	0.05	<BDL	<BDL	<BDL	<BDL	388.36	6.35	<BDL	<BDL	228209	292.68	425.18	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Rozália	<BDL	<BDL	<BDL	<BDL	1285.84	0.01	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.33	14.57	<BDL	<BDL	241019	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Rozália	<BDL	<BDL	3.61	<BDL	370.56	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.37	16.36	<BDL	<BDL	198744	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Rozália	<BDL	0.08	<BDL	<BDL	1007.57	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.1	26.28	<BDL	<BDL	164149	30.17	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Rozália	<BDL	0.04	<BDL	<BDL	878.4	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.82	19.31	<BDL	<BDL	192235	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Rozália	<BDL	0.2	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.51	13.09	<BDL	<BDL	198902	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	Gaosongshan	<BDL	<BDL	10	<BDL	281	<BDL	<BDL	<BDL	<BDL	1.79	<BDL	1850	<BDL	63	162	191	<BDL	349	304893	26.1	18820	760	1990	<BDL	Liu et al. (2021)
Epithermal	Gaosongshan	<BDL	<BDL	4.4	<BDL	307	<BDL	<BDL	<BDL	<BDL	0.14	2.3	222	<BDL	17.4	20.3	32	<BDL	69	310126	<BDL	1980	<BDL	189	<BDL	Liu et al. (2021)
Epithermal	Gaosongshan	<BDL	<BDL	<BDL	<BDL	174	0.25	<BDL	<BDL	<BDL	0.106	<BDL	214	<BDL	18.4	7.33	31.7	24.8	41	312677	6	2820	123	247	<BDL	Liu et al. (2021)
Epithermal	Gaosongshan	<BDL	<BDL	<BDL	<BDL	124	0.15	<BDL	<BDL	<BDL	0.092	<BDL	212	<BDL	8.9	7.27	29.5	26	45	312677	4.2	2590	93	226	<BDL	Liu et al. (2021)
Epithermal	Gaosongshan	<BDL	<BDL	5.9	<BDL	229	0.119	<BDL	<BDL	<BDL	0.048	31.5	135	<BDL	30.3	5.56	137	204	1570	308476	7.4	1240	170	120	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	0.52	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	8	<BDL	<BDL	<BDL	<BDL	6417	<BDL	<BDL	<BDL	<BDL	1500	Liu et al. (2021)	
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	6417	<BDL	<BDL	<BDL	<BDL	4000	Liu et al. (2021)	
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	15	<BDL	<BDL	<BDL	<BDL	14467	<BDL	1200	<BDL	<BDL	3500	Liu et al. (2021)	
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1	<BDL	0.56	8.2	<BDL	12772	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.37	<BDL	<BDL	<BDL	23791	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	4	<BDL	<BDL	13.4	<BDL	<BDL	12789	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	79	<BDL	<BDL	<BDL	<BDL	2673	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	4.8	<BDL	<BDL	400	<BDL	<BDL	<BDL	<BDL	<BDL	8264	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	8	<BDL	<BDL	<BDL	<BDL	<BDL	8264	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	12640	<BDL	<BDL	<BDL	<BDL	1700	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	14303	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	30	<BDL	5.2	<BDL	<BDL	14303	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	34	<BDL	0.75	<BDL	<BDL	19590	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	0.35	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	15	<BDL	<BDL	<BDL	<BDL	<BDL	7256	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	6.5	<BDL	0.25	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	3.5	<BDL	0.26	<BDL	<BDL	<BDL	9138	<BDL	<BDL	<BDL	16	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.41	<BDL	<BDL	<BDL	12116	<BDL	<BDL	<BDL	<BDL	1100	Liu et al. (2021)	
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.49	<BDL	<BDL	23	<BDL	<BDL	<BDL	<BDL	<BDL	3189	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	29	<BDL	<BDL	<BDL	<BDL	<BDL	1768	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	190	<BDL	<BDL	<BDL	<BDL	<BDL	7162	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	8	1.7	<BDL	<BDL	<BDL	<BDL	11307	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.3	0.6	<BDL	<BDL	<BDL	17372	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	2	<BDL	<BDL	<BDL	<BDL	<BDL	12909	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	1	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	14	3.8	<BDL	<BDL	<BDL	<BDL	12659	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
Epithermal	La India	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.42	8.6	<BDL	<BDL	12659	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	Queмонт	<BDL	0.85	<BDL	<BDL	209	<BDL	0.2	<BDL	2.69	<BDL	<BDL	<BDL	<BDL	0.047	<BDL	740.6	<BDL	<BDL	49752	<BDL	64	<BDL	0.3	<BDL	Liu et al. (2021)
VMS	Queмонт	<BDL	0.7	2.9	<BDL	249	0.221	0.44	0.97	1.67	<BDL	<BDL	<BDL	<BDL	<BDL	0.088	662.1	<BDL	<BDL	50092	<BDL	78	340	0.31	4600	Liu et al. (2021)
VMS	Queмонт	<BDL	0.91	<BDL	<BDL	222	0.064	0.188	0.23	1.18	<BDL	<BDL	<BDL	<BDL	0.085	<BDL	570	<BDL	<BDL	50391	<BDL	89	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Queмонт	0.024	0.83	<BDL	<BDL	242	0.056	0.3	<BDL	2.79	<BDL	<BDL	<BDL	<BDL	0.104	<BDL	731	<BDL	<BDL	50160	<BDL	66.6	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Queмонт	<BDL	0.71	1.34	<BDL	251	0.065	0.23	<BDL	1.6	<BDL	<BDL	<BDL	<BDL	0.084	619.6	<BDL	<BDL	49779	<BDL	86	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Queмонт	<BDL	0.35	<BDL	<BDL	266	<BDL	0.271	0.411	1.58	<BDL	<BDL	<BDL	<BDL	0.041	0.096	586	<BDL	<BDL	49412	<BDL	67	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Queмонт	<BDL	0.82	<BDL	<BDL	245	0.062	0.279	<BDL	2.2	<BDL	<BDL	<BDL	<BDL	<BDL	722.2	<BDL	<BDL	49834	<BDL	44	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Queмонт	<BDL	0.88	<BDL	<BDL	321	<BDL	0.213	0.51	2.06	<BDL	<BDL	<BDL	<BDL	0.073	0.66	649	<BDL	<BDL	50234	<BDL	80	<BDL	0.5	<BDL	Liu et al. (2021)
VMS	Queмонт	<BDL	0.78	<BDL	<BDL	315	0.058	0.37	<BDL	2.55	0.019	<BDL	<BDL	<BDL	<BDL	760	<BDL	<BDL	50843	<BDL	67	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Queмонт	0.023	0.68	1.21	<BDL	362	0.082	0.28	0.403	2.01	<BDL	<BDL	<BDL	<BDL	0.083	<BDL	600	<BDL	<BDL	50696	<BDL	87	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Queмонт	<BDL	0.74	<BDL	<BDL	362	0.067	0.185	0.141	1.67	<BDL	<BDL	<BDL	<BDL	0.088	<BDL	615.7	<BDL	<BDL	50588	<BDL	89	<BDL	<BDL	<BDL	Liu et al. (2021)

VMS	Quemont	<BDL	0.94	<BDL	<BDL	364	0.073	0.263	<BDL	1.33	0.014	<BDL	<BDL	<BDL	0.037	<BDL	608.5	<BDL	<BDL	49664	<BDL	95	<BDL	0.36	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.87	0.69	<BDL	390	<BDL	0.31	<BDL	2.41	<BDL	<BDL	<BDL	<BDL	0.017	<BDL	720.3	<BDL	<BDL	48759	<BDL	90.7	<BDL	0.3	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.78	1.49	<BDL	493	<BDL	0.38	0.15	1.59	<BDL	<BDL	<BDL	<BDL	<BDL	0.345	605	<BDL	<BDL	49789	<BDL	85	<BDL	0.3	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.84	<BDL	<BDL	496	0.087	0.33	<BDL	1.72	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	579.1	<BDL	<BDL	50858	<BDL	44.8	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.69	<BDL	<BDL	496	0.072	0.24	0.161	1.56	0.013	<BDL	<BDL	<BDL	0.082	<BDL	588.9	<BDL	<BDL	50065	<BDL	45	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.88	<BDL	<BDL	482	<BDL	0.35	<BDL	1.98	0.019	<BDL	<BDL	<BDL	0.021	<BDL	616.6	<BDL	<BDL	50832	<BDL	94	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.73	<BDL	<BDL	502	<BDL	0.214	<BDL	2.85	0.0092	<BDL	<BDL	<BDL	<BDL	<BDL	779	<BDL	<BDL	50786	<BDL	96	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.82	<BDL	<BDL	535	<BDL	0.255	0.05	4.18	0.018	<BDL	<BDL	<BDL	<BDL	<BDL	633.9	<BDL	<BDL	49983	<BDL	97	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.8	<BDL	<BDL	535	<BDL	0.196	<BDL	0.95	<BDL	<BDL	<BDL	<BDL	<BDL	0.062	576	<BDL	<BDL	50505	<BDL	86.9	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.65	<BDL	<BDL	555	<BDL	0.3	<BDL	2.58	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	692	<BDL	<BDL	50228	<BDL	87.8	<BDL	0.42	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.77	<BDL	<BDL	573	<BDL	0.25	<BDL	2.26	0.0071	<BDL	<BDL	<BDL	<BDL	<BDL	629	<BDL	<BDL	50543	<BDL	99	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.85	5.8	16.9	521	<BDL	0.29	7.56	1.56	<BDL	<BDL	<BDL	1.74	0.114	5.63	539	<BDL	<BDL	50362	3.43	367	1000	2	670	Liu et al. (2021)
VMS	Quemont	<BDL	0.8	2.39	2.8	751	<BDL	0.192	0.91	1.17	<BDL	<BDL	<BDL	<BDL	<BDL	0.56	542.7	<BDL	<BDL	49696	1.05	272	<BDL	0.95	350	Liu et al. (2021)
VMS	Quemont	<BDL	2.6	2.8	137	502	2.01	0.44	2.03	4.99	<BDL	<BDL	0.49	<BDL	<BDL	1.98	593	<BDL	<BDL	50212	50	1194	<BDL	0.8	97	Liu et al. (2021)
VMS	Quemont	<BDL	0.75	<BDL	<BDL	715	<BDL	0.2	<BDL	2.64	<BDL	<BDL	<BDL	<BDL	0.1	<BDL	621	<BDL	<BDL	50608	<BDL	60	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	0.021	0.64	1.1	<BDL	707	0.059	0.174	1.609	2.81	0.027	<BDL	<BDL	<BDL	0.054	0.071	545	<BDL	<BDL	50192	<BDL	67	<BDL	0.54	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.76	1.15	<BDL	675	<BDL	0.185	<BDL	2.89	0.0098	<BDL	0.19	<BDL	0.099	<BDL	678	<BDL	<BDL	50889	<BDL	82.7	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	0.024	0.71	<BDL	<BDL	664	<BDL	0.27	<BDL	2.8	<BDL	<BDL	<BDL	<BDL	0.046	<BDL	676	<BDL	<BDL	50889	<BDL	66	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.83	<BDL	<BDL	697	<BDL	0.141	<BDL	2.18	0.0078	<BDL	<BDL	<BDL	<BDL	0.058	600	<BDL	<BDL	50097	<BDL	72	<BDL	<BDL	25.2	Liu et al. (2021)
VMS	Quemont	<BDL	0.71	<BDL	2.3	674	<BDL	0.26	3.56	2.07	0.029	<BDL	<BDL	<BDL	<BDL	0.205	867	<BDL	<BDL	50681	3.1	71	<BDL	<BDL	101	Liu et al. (2021)
VMS	Quemont	0.031	0.022	<BDL	<BDL	719	<BDL	0.239	0.108	1.93	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	526	<BDL	<BDL	49510	<BDL	51.1	<BDL	<BDL	16.8	Liu et al. (2021)
VMS	Quemont	0.019	0.052	<BDL	<BDL	708	<BDL	0.31	0.907	2.33	<BDL	<BDL	<BDL	<BDL	0.028	<BDL	484	<BDL	<BDL	48726	<BDL	74	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.66	<BDL	<BDL	753	<BDL	0.3	<BDL	2.29	0.0062	<BDL	<BDL	<BDL	<BDL	<BDL	636	<BDL	<BDL	50856	<BDL	101	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.59	<BDL	<BDL	740	<BDL	0.36	0.186	1.26	0.0069	<BDL	<BDL	<BDL	<BDL	0.07	566	<BDL	<BDL	50832	<BDL	42	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	0.051	0.9	<BDL	<BDL	766	0.045	0.39	<BDL	2.61	<BDL	<BDL	<BDL	<BDL	<BDL	0.097	784	<BDL	<BDL	50679	<BDL	45.5	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	0.019	0.67	<BDL	<BDL	753	<BDL	0.29	<BDL	2.42	0.0057	<BDL	<BDL	<BDL	<BDL	<BDL	682	<BDL	<BDL	49835	<BDL	101	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	0.031	0.77	<BDL	<BDL	750	0.064	0.237	<BDL	1.99	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	628	<BDL	<BDL	50748	<BDL	116.9	<BDL	<BDL	16.7	Liu et al. (2021)
VMS	Quemont	0.021	0.82	<BDL	<BDL	768	0.045	0.32	<BDL	2.22	<BDL	<BDL	<BDL	<BDL	0.015	0.052	655	<BDL	<BDL	50610	<BDL	58	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.74	<BDL	<BDL	772	<BDL	0.28	0.092	3.14	<BDL	<BDL	<BDL	<BDL	0.056	0.083	816	<BDL	<BDL	51594	<BDL	50	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.67	<BDL	<BDL	801	<BDL	0.32	0.59	1.59	0.0074	<BDL	<BDL	<BDL	0.05	0.095	634	<BDL	<BDL	50221	<BDL	56	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	0.048	0.62	1.26	2.2	740	<BDL	0.21	0.134	2.18	<BDL	<BDL	<BDL	<BDL	0.101	0.154	705	<BDL	<BDL	49848	<BDL	52	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.77	0.56	<BDL	823	<BDL	0.235	<BDL	2.8	0.018	<BDL	<BDL	<BDL	<BDL	<BDL	691	<BDL	<BDL	50285	<BDL	93	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.82	<BDL	<BDL	864	<BDL	0.33	<BDL	1.81	<BDL	<BDL	<BDL	<BDL	0.039	<BDL	700	<BDL	<BDL	50451	<BDL	132	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.79	<BDL	<BDL	910	<BDL	0.268	<BDL	1.92	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	624	<BDL	<BDL	51792	<BDL	99	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.65	<BDL	<BDL	872	<BDL	0.25	<BDL	2.54	<BDL	<BDL	<BDL	<BDL	0.074	<BDL	640	<BDL	<BDL	50212	<BDL	59	<BDL	0.5	<BDL	Liu et al. (2021)
VMS	Quemont	<BDL	0.48	0.8	<BDL	928	0.052	0.25	<BDL	2.27	<BDL	<BDL	<BDL	<BDL	0.086	<BDL	619	<BDL	<BDL	51082	<BDL	67.2	<BDL	0.86	<BDL	Liu et al. (2021)
VMS	Boliden	0.032	<BDL	0.18	2.4	543	<BDL	0.076	0.32	17.8	<BDL	<BDL	<BDL	<BDL	<BDL	0.27	33.7	<BDL	<BDL	144581	<BDL	77.3	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	1.88	22.2	1480	<BDL	0.057	52.7	71.5	0.0146	<BDL	<BDL	8.6	0.083	85	24	<BDL	<BDL	148604	<BDL	69.8	<BDL	<BDL	25.4	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	0.7	3	919	<BDL	0.056	3.8	12.3	<BDL	<BDL	<BDL	<BDL	0.055	0.31	31.5	<BDL	<BDL	146755	<BDL	80.9	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	<BDL	7	988	<BDL	<BDL	0.23	14.4	<BDL	<BDL	<BDL	430	0.68	0.56	33.5	<BDL	<BDL	139578	<BDL	82	<BDL	<BDL	45	Liu et al. (2021)
VMS	Boliden	0.023	<BDL	<BDL	3.1	693	<BDL	0.088	0.063	13.1	<BDL	<BDL	<BDL	2.8	<BDL	0.31	33	<BDL	<BDL	143732	<BDL	89.8	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	<BDL	2.7	630	0.025	0.037	0.065	11.46	<BDL	<BDL	<BDL	2.04	<BDL	0.2	35.6	<BDL	<BDL	143732	<BDL	103.6	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	<BDL	2.9	583	<BDL	0.053	1.9	55	<BDL	<BDL	<BDL	4.9	0.049	0.58	33	<BDL	<BDL	143732	1.16	94.8	<BDL	0.51	350	Liu et al. (2021)
VMS	Boliden	<BDL	0.046	62	1920	61400	0.105	4.94	2380	6780	7.7	<BDL	18	3.88	<BDL	189000	770	<BDL	<BDL	507921	<BDL	551	46	1.29	1900	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	1.6	1.59	38900	1.1	0.091	12.8	432	0.146	<BDL	0.98	2.61	<BDL	3.07	46	<BDL	<BDL	264332	<BDL	92.7	<BDL	16.9	230	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	<BDL	<BDL	39900	<BDL	0.031	1.11	452.3	<BDL	<BDL	0.54	2.35	<BDL	0.31	10.5	<BDL	<BDL	262459	<BDL	75.2	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	8.9	3.3	26900	0.105	0.76	134	4570	0.043	0.021	1.08	4.58	0.084	12	237	<BDL	<BDL	262459	10.5	182.2	<BDL	<BDL	590	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	160	160	227	<BDL	0.046	1500	310	0.058	<BDL	<BDL	41	0.097	740	22.7	<BDL	<BDL	148604	0.82	219	11.6	<BDL	630	Liu et al. (2021)
VMS	Boliden	<BDL	<BDL	34	<BDL	12560	0.7	0.16	43	640	<BDL	<BDL	3.9	<BDL	<BDL	8.3	80	<BDL	<BDL	245146	12	490	<BDL	<BDL	80	Liu et al. (2021)
VMS	Boliden	<BDL	0.06	0.06	<BDL	<BDL	<BDL	<BDL	0.14	275.41	<BDL	<BDL	0.23	<BDL	<BDL	<BDL	8.04									

VMS	Boliden	<BDL	0.05	<BDL	<BDL	<BDL	<BDL	<BDL	0.09	331.51	<BDL	<BDL	1.75	<BDL	<BDL	0.02	7.27	<BDL	<BDL	99067	<BDL	195.59	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	Boliden	<BDL	0.06	0.31	<BDL	<BDL	0.03	<BDL	1.03	247.11	0.03	<BDL	0.31	<BDL	<BDL	2.65	384.78	<BDL	<BDL	99533	<BDL	1989.13	<BDL	1.31	375.15	Liu et al. (2021)	
VMS	Boliden	<BDL	0.07	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	255.21	<BDL	<BDL	0.17	<BDL	<BDL	<BDL	3.29	<BDL	<BDL	100084	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	Boliden	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.78	181.17	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.07	2.17	<BDL	<BDL	98180	<BDL	429.83	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Boliden	0.19	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.39	173.07	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.5	<BDL	<BDL	99388	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	Boliden	<BDL	0.06	<BDL	<BDL	<BDL	<BDL	<BDL	0.08	183.36	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.04	1.66	<BDL	<BDL	98650	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Boliden	0.17	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.04	213.49	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	3.63	<BDL	<BDL	103212	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	Boliden	<BDL	0.05	0.45	<BDL	<BDL	<BDL	<BDL	2.07	214	0.1	<BDL	0.21	<BDL	<BDL	<BDL	0.47	3.33	<BDL	<BDL	97353	<BDL	<BDL	<BDL	6.22	23.45	Liu et al. (2021)
VMS	Boliden	<BDL	0.02	<BDL	<BDL	<BDL	<BDL	<BDL	0.56	178.49	<BDL	<BDL	0.13	<BDL	<BDL	<BDL	0.15	3.17	<BDL	<BDL	99074	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)
VMS	Ming	0.04	0.11	<BDL	3.43	<BDL	0.03	0.86	5.9	0.07	<BDL	<BDL	<BDL	1.72	<BDL	649.62	1500.61	<BDL	<BDL	198225	1.96	1208	<BDL	<BDL	42.07	Liu et al. (2021)	
VMS	Ming	<BDL	0.12	<BDL	<BDL	<BDL	0.15	0.48	4.21	0.43	0.49	<BDL	14.29	6.3	<BDL	31.83	1397.38	<BDL	<BDL	198362	11.24	1150.75	<BDL	<BDL	35.11	Liu et al. (2021)	
VMS	Ming	<BDL	0.09	<BDL	<BDL	<BDL	0.02	0.59	5.21	0.19	<BDL	0.05	0.09	2.15	<BDL	526.4	1596.61	<BDL	<BDL	199458	<BDL	830.68	<BDL	<BDL	47.73	Liu et al. (2021)	
VMS	Ming	0.14	0.11	<BDL	5.27	<BDL	0.06	<BDL	4.3	0.39	<BDL	<BDL	<BDL	<BDL	<BDL	36.52	1563.58	<BDL	<BDL	194785	<BDL	1426.92	<BDL	<BDL	105.28	Liu et al. (2021)	
VMS	Ming	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	3.51	<BDL	<BDL	0.05	<BDL	<BDL	<BDL	17.1	712.66	<BDL	<BDL	199258	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	Ming	<BDL	<BDL	95	<BDL	2858	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.03	<BDL	61.5	<BDL	<BDL	222708	<BDL	79.9	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	Ming	<BDL	<BDL	<BDL	<BDL	5500	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.4	<BDL	320	<BDL	<BDL	207429	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	Ming	<BDL	0.019	0.34	<BDL	466	<BDL	0.013	0.025	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.34	140	1.91	0.098	298896	0.5	83	<BDL	<BDL	15	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	6.4	<BDL	109.3	<BDL	0.042	0.238	671	<BDL	<BDL	<BDL	<BDL	<BDL	0.076	154	<BDL	<BDL	264090	<BDL	68	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	0.0084	950	2.2	96.9	<BDL	0.13	6.5	5.9	0.27	0.036	0.17	9.7	<BDL	264	20.1	<BDL	<BDL	264090	4.5	198	<BDL	20	85	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	40	<BDL	87.3	<BDL	<BDL	0.216	0.82	0.04	<BDL	<BDL	<BDL	<BDL	10.8	236.3	<BDL	<BDL	246106	<BDL	104	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	6.5	<BDL	96.5	<BDL	<BDL	0.65	1.2	<BDL	<BDL	<BDL	1.45	0.024	3.79	233.3	<BDL	<BDL	246106	1.12	83.9	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	8	<BDL	116.8	<BDL	<BDL	<BDL	54.9	<BDL	<BDL	<BDL	<BDL	<BDL	81.9	<BDL	<BDL	246106	<BDL	124.1	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	0.0089	39	<BDL	71.8	<BDL	0.029	0.069	0.418	<BDL	<BDL	<BDL	<BDL	0.014	1.48	98.2	<BDL	<BDL	219239	<BDL	74.6	<BDL	<BDL	6.7	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	16.1	<BDL	75.7	<BDL	0.031	0.136	0.226	<BDL	<BDL	<BDL	<BDL	<BDL	2.55	105.9	<BDL	<BDL	219239	<BDL	91.7	<BDL	0.31	7	Liu et al. (2021)	
VMS	LaRonde	<BDL	0.009	7500	1.61	86.1	<BDL	0.41	2.76	23.8	3.62	<BDL	<BDL	2.01	0.076	128	117.9	<BDL	0.55	219239	8.1	92	5.9	4.9	650	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	45	<BDL	85.9	<BDL	<BDL	<BDL	0.36	0.089	<BDL	<BDL	<BDL	<BDL	1.28	106.7	<BDL	<BDL	219239	<BDL	62.3	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	370	<BDL	83.4	<BDL	<BDL	1.63	0.45	0.46	<BDL	<BDL	<BDL	<BDL	3.5	106.5	<BDL	<BDL	219239	<BDL	79.4	<BDL	0.6	35	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	4.9	<BDL	94.4	<BDL	<BDL	0.097	74.5	<BDL	<BDL	<BDL	<BDL	<BDL	0.072	11.46	<BDL	<BDL	219239	<BDL	65.4	<BDL	<BDL	6.5	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	6	<BDL	87.7	<BDL	0.059	0.067	18.21	<BDL	<BDL	<BDL	<BDL	0.02	0.073	17.16	<BDL	<BDL	219239	<BDL	65.8	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	9	<BDL	151.3	<BDL	<BDL	1.35	412	<BDL	<BDL	0.329	<BDL	<BDL	<BDL	7.04	<BDL	<BDL	419617	<BDL	95.3	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	4.2	<BDL	143.1	<BDL	0.151	1.96	387.6	<BDL	<BDL	0.31	<BDL	0.045	<BDL	8.6	<BDL	<BDL	419617	<BDL	86	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	2	<BDL	162	<BDL	<BDL	1.72	409	<BDL	<BDL	0.309	<BDL	<BDL	<BDL	8.48	<BDL	<BDL	419617	<BDL	82.2	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	<BDL	<BDL	165.7	<BDL	<BDL	2.98	456	<BDL	<BDL	0.289	<BDL	0.044	<BDL	4.83	<BDL	<BDL	419617	<BDL	80.8	<BDL	0.48	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	2.9	<BDL	165.1	<BDL	<BDL	2.24	464	<BDL	<BDL	0.274	0.92	0.016	14	4.32	<BDL	<BDL	419617	<BDL	98.4	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	7.3	<BDL	156.2	<BDL	<BDL	3.48	414	<BDL	<BDL	0.26	<BDL	<BDL	0.36	10.3	<BDL	<BDL	419617	<BDL	118.2	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	34	98	159.9	<BDL	0.141	8.1	415	0.32	<BDL	0.41	<BDL	<BDL	4400	6.7	3.6	<BDL	419617	<BDL	118	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	4.4	<BDL	167.4	<BDL	<BDL	3.83	289.1	0.0047	<BDL	0.244	<BDL	<BDL	<BDL	14.08	<BDL	<BDL	376108	<BDL	95.3	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	3.3	<BDL	177	<BDL	<BDL	12	296	0.0067	<BDL	0.136	<BDL	<BDL	<BDL	16.24	<BDL	<BDL	376108	<BDL	87.9	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	3.6	<BDL	164.1	<BDL	0.16	3.93	290.2	<BDL	<BDL	0.158	<BDL	<BDL	<BDL	15.95	<BDL	<BDL	376108	<BDL	77.3	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	4.1	<BDL	163.1	<BDL	<BDL	3.73	315	<BDL	<BDL	0.21	<BDL	<BDL	<BDL	12.11	<BDL	<BDL	376108	<BDL	79	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	1.3	<BDL	157.2	<BDL	0.053	2.63	304	<BDL	<BDL	0.138	<BDL	0.0071	<BDL	11.34	<BDL	<BDL	376108	<BDL	67.2	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	3.3	<BDL	190	<BDL	0.063	<BDL	184	0.11	<BDL	<BDL	<BDL	<BDL	0.36	26.81	<BDL	<BDL	219239	<BDL	88.8	<BDL	2.2	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	4.1	<BDL	244	<BDL	<BDL	0.348	1.75	0.9	<BDL	<BDL	<BDL	<BDL	24	17.7	<BDL	<BDL	264090	<BDL	76	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	<BDL	<BDL	<BDL	<BDL	197	<BDL	<BDL	0.072	2.66	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	35.2	<BDL	<BDL	219239	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
VMS	LaRonde	0.037	0.053	<BDL	<BDL	307	<BDL	0.3	<BDL	186	<BDL	<BDL	<BDL	<BDL	<BDL	1.53	182.3	<BDL	<BDL	219239	<BDL	38	<BDL	<BDL	<BDL	Liu et al. (2021)	
Porphyry	Jinchang	0.153	7.85	3.13	<BDL	195	<BDL	<BDL	<BDL	<BDL	0.056	<BDL	<BDL	<BDL	<BDL	0.155	484	<BDL	<BDL	86147	<BDL	184	<BDL	1.8	<BDL	Liu et al. (2021)	
Porphyry	Jinchang	0.178	9.42	2.22	<BDL	201	<BDL	<BDL	0.133	<BDL	<BDL	<BDL	<BDL	<BDL	0.03	0.045	447	<BDL	<BDL	86147	<BDL	171	<BDL	<BDL	19.8	Liu et al. (2021)	
Porphyry	Jinchang	<BDL	3.82	10.2	<BDL	385	0.038	<BDL	0.296	<BDL	<BDL	<BDL	<BDL	<BDL	98	0.267	127	<BDL	270	73665	88	206	376	28.3	157	Liu et al. (2021)	
Porphyry	Jinchang	0.19	15.6	<BDL	<BDL	834	<BDL	<BDL	0.73	<BDL	<BDL	<BDL	<BDL	<BDL	7.9	6.1	0.125	250	<BDL	<BDL	101467	0.96	184	<BDL	<BDL	101	Liu et al. (20

	Porphyry	Jinchang	0.196	3.98	0.52	<BDL	105.9	<BDL	0.05	<BDL	0.29	<BDL	0.075	<BDL	<BDL	8	0.076	271	<BDL	22	86147	7.2	237	37	5.3	111	Liu et al. (2021)		
	Porphyry	Jinchang	11.65	98.7	<BDL	<BDL	12.4	<BDL	<BDL	<BDL	0.134	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	468	<BDL	<BDL	31067	<BDL	78	<BDL	<BDL	<BDL	Liu et al. (2021)		
	Porphyry	Jinchang	0.83	12.35	<BDL	<BDL	90.6	<BDL	<BDL	0.172	0.132	<BDL	<BDL	<BDL	<BDL	<BDL	0.139	<BDL	253	<BDL	35624	<BDL	48.5	<BDL	<BDL	11.4	Liu et al. (2021)		
	Porphyry	Jinchang	28.4	145.8	<BDL	<BDL	27.2	<BDL	0.163	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.25	<BDL	853	<BDL	0.57	30990	<BDL	104	<BDL	<BDL	17.9	Liu et al. (2021)	
	Porphyry	Jinchang	26	134.3	<BDL	<BDL	31	<BDL	0.081	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.32	<BDL	786	<BDL	0.99	29284	<BDL	104	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Jinchang	6.22	70	<BDL	<BDL	40.6	<BDL	0.077	<BDL	<BDL	<BDL	<BDL	0.125	<BDL	<BDL	<BDL	<BDL	427	<BDL	<BDL	41439	<BDL	73.9	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Jinchang	3.92	34	<BDL	<BDL	102.7	<BDL	<BDL	0.183	0.114	<BDL	<BDL	<BDL	<BDL	<BDL	0.044	<BDL	206	<BDL	<BDL	37379	<BDL	44.8	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Jinchang	0.444	3.67	0.87	<BDL	37	<BDL	<BDL	0.0467	0.169	<BDL	<BDL	<BDL	<BDL	<BDL	0.046	<BDL	58.6	<BDL	<BDL	37379	<BDL	28.4	<BDL	0.17	<BDL	Liu et al. (2021)	
	Porphyry	Jinchang	26.1	114.2	<BDL	<BDL	3.74	<BDL	0.081	<BDL	<BDL	0.0067	<BDL	<BDL	<BDL	<BDL	0.69	<BDL	638	<BDL	1.15	37379	<BDL	70	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Jinchang	0.042	1.89	93	10	454	8.8	8.7	8.6	80	0.09	37	392	28.2	6.8	280	450	304	13.7	95254	70	415	4400	87000	617	Liu et al. (2021)		
	Porphyry	Jinchang	<BDL	2.14	6.4	0.87	387	<BDL	0.081	0.173	<BDL	<BDL	0.11	<BDL	<BDL	4	0.171	86	<BDL	8.4	105215	3.2	330	12	13.7	740	Liu et al. (2021)		
	Porphyry	Jinchang	<BDL	<BDL	<BDL	<BDL	114	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	477	<BDL	<BDL	73221	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Jinchang	<BDL	<BDL	4.2	<BDL	83	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	432	<BDL	<BDL	73221	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Bor	<BDL	<BDL	6.7	14	147	0.31	<BDL	6.2	<BDL	<BDL	13.1	49	<BDL	<BDL	13.1	4050	<BDL	<BDL	29441	<BDL	1010	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Bor	<BDL	8.1	2	<BDL	<BDL	<BDL	<BDL	8.7	<BDL	<BDL	15.3	41	<BDL	1.4	4	486	<BDL	<BDL	27620	3.9	1390	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Bor	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	18	<BDL	687	<BDL	<BDL	10797	<BDL	2400	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Bor	<BDL	<BDL	<BDL	<BDL	<BDL	0.73	<BDL	1.24	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	4.9	623	<BDL	<BDL	17785	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Bor	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	4.6	35	<BDL	<BDL	4.1	285	270	<BDL	4.4	8900	<BDL	<BDL	10691	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Bor	<BDL	<BDL	1.2	<BDL	<BDL	<BDL	<BDL	22.9	<BDL	<BDL	<BDL	48	<BDL	<BDL	8.3	1537	<BDL	<BDL	10691	<BDL	1750	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Bor	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.48	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.6	580	<BDL	<BDL	10841	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Bor	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.51	605	<BDL	<BDL	10380	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Billihe	<BDL	<BDL	12.8	<BDL	665	0.8	<BDL	3.9	27	<BDL	<BDL	<BDL	270	<BDL	410	2673	<BDL	<BDL	9529	73	1470	<BDL	<BDL	<BDL	<BDL	Liu et al. (2021)	
	Porphyry	Côté Gold	0.02	4.45	0.95	<BDL	120.61	<BDL	0.18	1.49	0.03	0.00	<BDL	<BDL	0.08	<BDL	0.01	437.66	1.23	<BDL	94955.15	<BDL	1311.15	1.62	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.01	4.78	1.86	<BDL	136.34	0.00	0.23	0.12	0.03	0.00	0.13	<BDL	0.10	0.08	1.62	435.04	2.67	<BDL	96288.77	0.83	1076.26	2.34	<BDL	14.99	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.04	4.81	1.02	<BDL	104.74	0.00	0.22	0.10	0.03	<BDL	<BDL	<BDL	<BDL	<BDL	0.00	422.79	1.78	<BDL	94522.33	<BDL	1199.95	1.70	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.03	4.90	1.01	<BDL	107.03	<BDL	0.29	0.15	0.03	0.00	<BDL	<BDL	<BDL	<BDL	0.00	422.02	1.53	<BDL	94784.93	<BDL	1087.02	1.71	<BDL	6.09	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.04	4.89	0.98	<BDL	106.15	<BDL	0.30	0.21	0.03	0.00	<BDL	<BDL	<BDL	<BDL	0.00	424.73	1.56	<BDL	93997.70	<BDL	1224.03	1.62	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.02	4.40	0.88	<BDL	104.77	<BDL	0.22	0.09	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	429.38	1.76	<BDL	95608.97	<BDL	1110.63	2.27	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.02	5.17	0.83	<BDL	106.82	0.00	0.19	0.09	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	431.36	1.84	<BDL	95557.78	<BDL	989.33	2.67	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.01	4.59	1.22	<BDL	116.79	<BDL	0.23	0.77	<BDL	0.00	<BDL	<BDL	<BDL	<BDL	<BDL	459.55	1.86	<BDL	96143.52	<BDL	1075.10	1.87	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.02	5.16	1.09	<BDL	103.66	<BDL	0.24	0.07	0.03	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	432.19	1.96	<BDL	94947.78	<BDL	1022.60	1.84	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Côté Gold	0.04	4.40	0.88	<BDL	98.80	<BDL	0.22	0.08	0.02	<BDL	0.13	<BDL	<BDL	<BDL	0.00	428.67	2.07	<BDL	94688.05	<BDL	1103.78	2.07	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.02	1.38	1.04	<BDL	170.69	<BDL	0.23	0.01	0.02	0.01	0.17	<BDL	<BDL	<BDL	<BDL	205.59	2.15	<BDL	10076.80	<BDL	971.83	1.84	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.03	2.14	1.06	<BDL	162.38	<BDL	0.17	0.04	0.04	<BDL	0.16	<BDL	<BDL	<BDL	0.00	202.94	<BDL	<BDL	10968.70	<BDL	907.82	1.61	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.01	1.12	7.52	<BDL	168.48	<BDL	<BDL	12.61	0.04	0.00	<BDL	<BDL	<BDL	<BDL	0.06	198.33	1.93	<BDL	108667.00	<BDL	1056.19	2.84	<BDL	147.79	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.03	1.27	0.93	<BDL	176.85	<BDL	0.22	0.03	0.02	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	207.05	2.10	<BDL	108832.60	<BDL	1107.71	1.92	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.03	1.01	1.09	<BDL	177.73	<BDL	0.23	0.01	0.03	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	192.29	5521.00	<BDL	108409.90	<BDL	994.37	1.82	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.02	1.04	2.02	<BDL	182.30	0.00	0.16	0.06	<BDL	<BDL	0.11	<BDL	<BDL	<BDL	<BDL	166.70	2.02	<BDL	108590.20	<BDL	1023.01	1.72	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.04	1.05	1.62	<BDL	217.75	0.01	0.23	1.00	0.03	0.00	<BDL	<BDL	<BDL	<BDL	0.42	97.19	1.77	<BDL	114355.80	<BDL	901.34	1.72	<BDL	5.40	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.01	1.95	1.12	<BDL	167.02	<BDL	0.17	0.06	0.03	0.00	<BDL	<BDL	<BDL	<BDL	0.01	202.23	1.91	<BDL	109859.90	<BDL	1059.77	<BDL	<BDL	6.55	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.02	2.23	1.17	<BDL	158.58	0.00	0.21	0.02	0.04	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	208.78	1.97	<BDL	10835.30	<BDL	1080.15	1.32	<BDL	<BDL	Melo-Gómez (2023)		
	Porphyry	Gosselin	0.03	2.03	1.25	<BDL	163.58	0.01	0.20	0.02	0.04	0.00	0.19	<BDL	<BDL	<BDL	0.00	223.11	1.51	<BDL	10897.80	<BDL	809.22	1.82	<BDL	5.91	Melo-Gómez (2023)		
	Orogenic	Lucien Béliveau	<BDL	9.85	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	301.09	<BDL	<BDL	106306	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)		
	Orogenic	Lucien Béliveau	0.1	11.02	<BDL	<BDL	<BDL	0.01	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	299.85	<BDL	<BDL	107888	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
	Orogenic	Lucien Béliveau	<BDL	11.64	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	292.83	<BDL	<BDL	106633	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
	Orogenic	Lucien Béliveau	0.12	11.77	<BDL	<BDL	144	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	286.63	<BDL	<BDL	107894	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
	Orogenic	Lucien Béliveau	<BDL	10.83	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	265.55	<BDL	<BDL	108029	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
	Orogenic	Lucien Béliveau	<BDL	10.76	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL</																

Orogenic	Lucien Béliveau	<BDL	18.75	<BDL	<BDL	1857.92	<BDL	<BDL	<BDL	<BDL	0.04	<BDL	<BDL	<BDL	<BDL	<BDL	445.44	<BDL	<BDL	72456	<BDL	703.94	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lucien Béliveau	<BDL	23.12	0.08	<BDL	2125.41	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	396.36	<BDL	<BDL	73458	<BDL	425.39	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lucien Béliveau	<BDL	21.81	<BDL	<BDL	2022.7	0.01	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	465.17	<BDL	<BDL	71485	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lucien Béliveau	<BDL	20.55	1.28	<BDL	2457.32	<BDL	<BDL	1.55	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.36	365.08	<BDL	<BDL	72487	<BDL	647.46	<BDL	0.51	<BDL	Liu and Beaudoin (2021)
Orogenic	Kittilä	0.02	0.04	<BDL	<BDL	41915	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	22.92	<BDL	<BDL	106461	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Kittilä	<BDL	0.05	<BDL	<BDL	41718	0.01	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	14.27	<BDL	<BDL	106477	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Kittilä	<BDL	0.06	<BDL	<BDL	37955	<BDL	<BDL	<BDL	<BDL	<BDL	0.03	<BDL	4.38	<BDL	<BDL	8.52	<BDL	<BDL	104591	<BDL	507.57	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Kittilä	<BDL	<BDL	<BDL	<BDL	45415	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	206.55	<BDL	<BDL	5.68	<BDL	<BDL	121278	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Kittilä	<BDL	0.1	<BDL	<BDL	46605	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	6.61	<BDL	<BDL	5.85	<BDL	<BDL	123224	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Kittilä	<BDL	<BDL	6.27	<BDL	46048	0.01	<BDL	0.19	0.32	<BDL	<BDL	<BDL	3.56	1.37	0.96	16.99	<BDL	2.57	122647	<BDL	<BDL	130.71	<BDL	76.71	Liu and Beaudoin (2021)	
Orogenic	Kittilä	<BDL	0.06	<BDL	<BDL	46948	0.01	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	17.65	<BDL	<BDL	124188	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	0.12	<BDL	<BDL	801.68	<BDL	<BDL	0.65	1.81	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	294.08	<BDL	<BDL	87677	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	<BDL	9.35	<BDL	999.34	<BDL	<BDL	10.32	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.44	257.75	<BDL	79352	<BDL	<BDL	<BDL	<BDL	443.23	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	<BDL	<BDL	<BDL	475.67	<BDL	<BDL	0.16	<BDL	<BDL	<BDL	<BDL	1.67	<BDL	<BDL	254.24	<BDL	<BDL	96765	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	<BDL	<BDL	<BDL	460.82	<BDL	<BDL	0.19	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	260.56	<BDL	<BDL	94479	<BDL	1508.89	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	<BDL	<BDL	<BDL	447.77	<BDL	<BDL	0.11	0.23	<BDL	<BDL	<BDL	<BDL	<BDL	0.15	261.78	<BDL	1.41	96136	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	<BDL	<BDL	<BDL	468.37	0.01	<BDL	0.15	0.35	<BDL	<BDL	<BDL	<BDL	<BDL	0.16	251.23	<BDL	<BDL	96136	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	0.1	<BDL	<BDL	393.92	<BDL	<BDL	0.42	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.78	260.79	<BDL	<BDL	95904	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	<BDL	<BDL	<BDL	455.43	<BDL	<BDL	0.3	0.55	<BDL	<BDL	<BDL	<BDL	<BDL	0.68	271.05	<BDL	<BDL	95904	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	0.08	<BDL	<BDL	422.03	<BDL	<BDL	0.63	0.83	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	265.08	<BDL	<BDL	95904	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	<BDL	<BDL	<BDL	1460	<BDL	5.06	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	306.1	<BDL	<BDL	95904	<BDL	<BDL	<BDL	<BDL	304.28	Liu and Beaudoin (2021)	
Orogenic	Giant Yellowknife	<BDL	0.04	<BDL	<BDL	586.68	<BDL	<BDL	0.06	0.54	<BDL	<BDL	<BDL	<BDL	<BDL	0.12	271.25	<BDL	<BDL	95904	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Tarmoola	<BDL	<BDL	<BDL	<BDL	655.67	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	179.4	<BDL	<BDL	154352	<BDL	<BDL	<BDL	<BDL	4144.25	Liu and Beaudoin (2021)	
Orogenic	Tarmoola	<BDL	<BDL	<BDL	<BDL	310.13	<BDL	<BDL	<BDL	1.33	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	124.08	<BDL	<BDL	120004	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Tarmoola	<BDL	<BDL	<BDL	<BDL	379.75	<BDL	<BDL	0.05	0.18	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	167.7	<BDL	<BDL	135581	<BDL	2997.5	<BDL	<BDL	375.72	Liu and Beaudoin (2021)	
Orogenic	Tarmoola	<BDL	<BDL	<BDL	<BDL	224.4	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	113.44	<BDL	<BDL	130353	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Tarmoola	<BDL	0.17	<BDL	<BDL	255.94	<BDL	<BDL	<BDL	<BDL	<BDL	0.09	<BDL	<BDL	<BDL	<BDL	144.18	<BDL	<BDL	127646	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	La Lucette	<BDL	<BDL	<BDL	<BDL	22644	<BDL	0.04	<BDL	0.02	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	3.41	<BDL	<BDL	103144	<BDL	56.58	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	La Lucette	<BDL	0.01	<BDL	<BDL	15135	<BDL	0.05	<BDL	0.02	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	3.83	<BDL	<BDL	103144	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	La Lucette	<BDL	<BDL	<BDL	<BDL	15135	<BDL	0.04	<BDL	0.02	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	2.83	<BDL	<BDL	103261	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	La Lucette	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.03	0.03	0.01	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	3.58	<BDL	<BDL	101819	<BDL	53.1	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	La Lucette	<BDL	<BDL	0.12	<BDL	4947	<BDL	<BDL	2.99	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.06	4.81	<BDL	<BDL	8001	<BDL	<BDL	202.47	<BDL	24547.65	Liu and Beaudoin (2021)	
Orogenic	La Lucette	<BDL	0.01	<BDL	<BDL	21529	<BDL	0.05	<BDL	<BDL	<BDL	0.01	<BDL	<BDL	<BDL	<BDL	4.37	<BDL	0.03	8377	<BDL	67.44	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Empire	<BDL	0.13	<BDL	<BDL	3796	<BDL	0.43	<BDL	21.49	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	156.75	<BDL	<BDL	181562	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Empire	<BDL	<BDL	<BDL	<BDL	3695	<BDL	<BDL	<BDL	19.9	<BDL	<BDL	<BDL	<BDL	<BDL	1.29	100.24	<BDL	<BDL	187564	38.92	<BDL	<BDL	<BDL	1174.22	Liu and Beaudoin (2021)	
Orogenic	Empire	<BDL	<BDL	<BDL	<BDL	2727	<BDL	<BDL	2.14	28.38	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	161.8	<BDL	<BDL	175874	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Empire	<BDL	<BDL	28.97	<BDL	2500	<BDL	<BDL	<BDL	33.15	<BDL	<BDL	<BDL	<BDL	<BDL	50.35	86.37	<BDL	<BDL	160350	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Empire	<BDL	<BDL	4.61	<BDL	3796	<BDL	3.91	2.39	18.98	<BDL	<BDL	<BDL	<BDL	<BDL	6805.56	65.17	<BDL	<BDL	193278	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Sigma	<BDL	0.03	0.22	<BDL	1391.23	<BDL	0.7	0.03	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.08	297.03	<BDL	<BDL	80372	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Sigma	0.04	0.03	<BDL	<BDL	1467.99	<BDL	0.6	0.12	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	314.08	<BDL	<BDL	80372	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Sigma	<BDL	0.06	<BDL	<BDL	1899.86	<BDL	0.73	<BDL	<BDL	<BDL	0.04	<BDL	<BDL	<BDL	<BDL	444.05	<BDL	<BDL	77076	<BDL	773.97	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Sigma	<BDL	0.08	<BDL	<BDL	1488.5	<BDL	0.67	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	258.53	<BDL	<BDL	77662	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Sigma	<BDL	0.03	<BDL	<BDL	2244.42	<BDL	0.47	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	418.82	<BDL	<BDL	77141	<BDL	635.97	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Sigma	<BDL	<BDL	<BDL	<BDL	2423.71	<BDL	0.52	0.01	<BDL	<BDL	<BDL	<BDL	<BDL	0.08	<BDL	360.97	<BDL	<BDL	77158	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Fosterville	<BDL	<BDL	<BDL	<BDL	23296.19	0.01	<BDL	<BDL	4.54	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	167.98	<BDL	<BDL	17607	<BDL	374.08	<BDL	3.69	<BDL	Liu and Beaudoin (2021)	
Orogenic	Fosterville	<BDL	<BDL	0.3	<BDL	29165.15	<BDL	<BDL	<BDL	13.29	<BDL	<BDL	<BDL	<BDL	<BDL	6.66	171.62	<BDL	<BDL	17158	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Fosterville	<BDL	0.03	<BDL	<BDL	33331.73	<BDL	<BDL	<BDL	9.85	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	274.37	<BDL	<BDL	17158	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Fosterville	<BDL	0.02	<BDL	<BDL	39674.99	<BDL	<BDL	<BDL	13.57	<BDL	<BDL	<BDL	<BDL	<BDL	0.04	257.53	<BDL	<BDL	17158	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic</																											

Orogenic	Beaufor	0.05	3.99	<BDL	<BDL	154	<BDL	<BDL	0.88	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	729.7	<BDL	<BDL	34816	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)		
Orogenic	Beaufor	<BDL	3.66	<BDL	<BDL	<BDL	<BDL	<BDL	0.05	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	36560	<BDL	686.98	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)		
Orogenic	Beaufor	<BDL	3.43	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	35746	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)		
Orogenic	Beaufor	<BDL	3.44	<BDL	<BDL	<BDL	0.01	<BDL	<BDL	0.07	<BDL	<BDL	<BDL	<BDL	<BDL	0.2	758.66	<BDL	<BDL	35879	<BDL	631.99	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Beaufor	0.11	2.96	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.03	765.8	<BDL	<BDL	34752	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Beaufor	<BDL	3.55	<BDL	<BDL	<BDL	<BDL	<BDL	0.8	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.62	738.81	<BDL	<BDL	34756	<BDL	718.36	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Lapa	<BDL	<BDL	<BDL	<BDL	1083	<BDL	0.3	0.16	2.86	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	419.15	<BDL	<BDL	25661	<BDL	607.5	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lapa	<BDL	<BDL	<BDL	<BDL	1227	<BDL	<BDL	0.07	4.52	<BDL	<BDL	<BDL	<BDL	<BDL	0.58	542.2	<BDL	0.91	29950	<BDL	<BDL	<BDL	<BDL	32.34	Liu and Beaudoin (2021)	
Orogenic	Lapa	<BDL	<BDL	0.16	<BDL	1068	<BDL	<BDL	0.03	1.44	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	754.74	<BDL	<BDL	27112	<BDL	696.02	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Lapa	<BDL	<BDL	<BDL	<BDL	1073	<BDL	0.8	0.14	2.81	<BDL	0.06	0.06	<BDL	<BDL	<BDL	993.02	<BDL	<BDL	26800	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lapa	<BDL	0.04	<BDL	<BDL	1073	<BDL	0.22	0.09	1.65	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	856.06	<BDL	<BDL	26843	<BDL	<BDL	<BDL	<BDL	14.11	Liu and Beaudoin (2021)	
Orogenic	Lapa	<BDL	<BDL	0.58	<BDL	1075	0.03	<BDL	0.07	1.66	<BDL	<BDL	0.06	<BDL	<BDL	<BDL	765.74	<BDL	<BDL	26823	<BDL	838.04	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Lapa	<BDL	0.06	<BDL	<BDL	1085	<BDL	0.35	0.07	1.21	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	736.58	<BDL	<BDL	26867	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lapa	<BDL	<BDL	<BDL	<BDL	1242	<BDL	0.53	0.09	38.64	<BDL	0.25	0.14	4.33	<BDL	1.87	785.12	4.13	8.95	28313	<BDL	457.81	3.03	<BDL	422.7	Liu and Beaudoin (2021)	
Orogenic	Rosebel	<BDL	0.25	33.66	<BDL	19137.4	0.03	<BDL	42.07	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.4	438.51	<BDL	<BDL	57650	<BDL	<BDL	4.31	<BDL	323.9	Liu and Beaudoin (2021)	
Orogenic	Rosebel	<BDL	0.56	<BDL	<BDL	25586.46	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	510.16	<BDL	<BDL	58538	<BDL	615.06	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Rosebel	<BDL	0.5	<BDL	<BDL	22899.18	0.01	<BDL	0.35	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	526.55	<BDL	<BDL	57881	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Rosebel	<BDL	0.48	<BDL	<BDL	26083.99	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	593.07	<BDL	<BDL	61525	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Rosebel	<BDL	0.36	23.04	<BDL	28439.77	<BDL	<BDL	29.58	<BDL	<BDL	<BDL	0.46	<BDL	0.2	0.37	504.73	<BDL	1.79	52480	<BDL	<BDL	7.74	2.13	681.79	Liu and Beaudoin (2021)	
Orogenic	Rosebel	<BDL	<BDL	92.31	<BDL	5572.53	<BDL	<BDL	102.29	<BDL	<BDL	<BDL	381.38	34.14	3.41	3.11	591.97	<BDL	8.98	61025	<BDL	<BDL	293.18	<BDL	9872.67	Liu and Beaudoin (2021)	
Orogenic	Lac Herbin	0.06	0.09	<BDL	<BDL	1041.49	0.01	<BDL	0.16	<BDL	<BDL	<BDL	<BDL	<BDL	0.08	<BDL	796.85	<BDL	<BDL	38750	<BDL	<BDL	<BDL	<BDL	73.59	Liu and Beaudoin (2021)	
Orogenic	Lac Herbin	<BDL	0.09	<BDL	<BDL	970.01	0.01	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	713.88	<BDL	<BDL	37029	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lac Herbin	<BDL	<BDL	<BDL	<BDL	1168.33	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	637.52	<BDL	<BDL	37318	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lac Herbin	<BDL	<BDL	<BDL	<BDL	984.23	<BDL	1.08	0.58	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	608.4	<BDL	<BDL	37318	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lac Herbin	0.25	<BDL	<BDL	<BDL	801.23	<BDL	<BDL	7.62	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	524.5	<BDL	<BDL	37038	<BDL	<BDL	<BDL	<BDL	112.12	Liu and Beaudoin (2021)	
Orogenic	Orfée	1.08	<BDL	<BDL	<BDL	2318.83	0.01	7.23	2.17	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	255.12	<BDL	<BDL	21398	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Orfée	<BDL	0.47	8.27	<BDL	2221.28	<BDL	<BDL	48.54	1.14	<BDL	<BDL	<BDL	<BDL	<BDL	1.44	405.14	<BDL	<BDL	30982	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Orfée	<BDL	0.08	7.56	<BDL	639.85	0.06	<BDL	83.49	94.86	<BDL	<BDL	<BDL	667.35	<BDL	29.65	419.8	<BDL	<BDL	10202	<BDL	7034.56	65.45	72.52	1009.75	Liu and Beaudoin (2021)	
Orogenic	Orfée	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	11.08	5.2	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	709.71	<BDL	<BDL	10473	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Goldex	<BDL	3.97	<BDL	<BDL	643.4	<BDL	<BDL	<BDL	<BDL	<BDL	0.55	<BDL	<BDL	<BDL	<BDL	564.59	<BDL	<BDL	13345	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Goldex	<BDL	4.35	<BDL	<BDL	715.77	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	601.59	<BDL	<BDL	12579	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Goldex	<BDL	1.47	<BDL	<BDL	<BDL	<BDL	<BDL	35.37	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	20.38	353.95	<BDL	<BDL	11485	<BDL	<BDL	<BDL	<BDL	1301.56	Liu and Beaudoin (2021)	
Orogenic	Goldex	<BDL	3.29	<BDL	<BDL	463.03	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	523.56	<BDL	<BDL	12537	<BDL	<BDL	7.15	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Goldex	<BDL	5.21	<BDL	<BDL	527.06	<BDL	<BDL	1.73	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	494.81	<BDL	<BDL	12548	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Goldex	<BDL	9.34	<BDL	<BDL	<BDL	<BDL	<BDL	2.14	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	816.77	<BDL	<BDL	12085	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Wulong	<BDL	<BDL	<BDL	<BDL	1271.52	<BDL	<BDL	9.25	<BDL	<BDL	<BDL	<BDL	<BDL	0.14	0.42	6.73	<BDL	<BDL	90549	<BDL	<BDL	<BDL	<BDL	29.65	Liu and Beaudoin (2021)	
Orogenic	Wulong	<BDL	0.11	<BDL	<BDL	854.39	<BDL	<BDL	0.23	0.39	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	19.6	<BDL	<BDL	92987	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Wulong	0.64	<BDL	<BDL	<BDL	975.68	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	16.32	<BDL	<BDL	92489	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	St Ives Goldfield	0.08	<BDL	0.09	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	422.85	<BDL	<BDL	32089	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	St Ives Goldfield	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	473.8	<BDL	<BDL	34941	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	St Ives Goldfield	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	2787.29	<BDL	<BDL	30752	<BDL	2453.27	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	St Ives Goldfield	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.93	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	2481.34	<BDL	<BDL	30701	<BDL	<BDL	<BDL	<BDL	1365.39	Liu and Beaudoin (2021)	
Orogenic	Lega Dembi	<BDL	0.23	<BDL	<BDL	<BDL	0.01	<BDL	<BDL	50.72	<BDL	<BDL	<BDL	<BDL	<BDL	0.07	12.69	<BDL	<BDL	205485	<BDL	481.48	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lega Dembi	<BDL	1.15	<BDL	<BDL	178	0.01	0.32	<BDL	61.31	<BDL	<BDL	<BDL	<BDL	<BDL	0.12	39.11	<BDL	<BDL	172491	<BDL	631.94	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lega Dembi	<BDL	1.22	<BDL	1.87	178	<BDL	0.33	<BDL	66.76	<BDL	0.02	<BDL	<BDL	<BDL	<BDL	44.66	<BDL	<BDL	172489	<BDL	781.24	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lega Dembi	<BDL	1.17	0.2	<BDL	<BDL	<BDL	0.61	<BDL	64.92	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	41	<BDL	<BDL	174952	<BDL	664.84	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lega Dembi	<BDL	1.07	<BDL	<BDL	288	<BDL	<BDL	<BDL	52.88	<BDL	<BDL	<BDL	<BDL	<BDL	0.06	35.96	<BDL	<BDL	173478	<BDL	580.55	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Lega Dembi	<BDL	1.22	<BDL	<BDL	<BDL	<BDL	0.26	<BDL	40.35	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	24.66	<BDL	<BDL	174895	<BDL	505.06	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Essakane	0.08	0.09																								

Orogenic	Essakane	0.12	0.16	0.05	1.96	3715.8	<BDL	<BDL	<BDL	0.07	<BDL	<BDL	<BDL	<BDL	<BDL	491.29	<BDL	<BDL	79184	<BDL	494.62	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)		
Orogenic	Essakane	<BDL	0.13	<BDL	<BDL	3716.91	0.01	<BDL	0.03	<BDL	<BDL	0.01	<BDL	<BDL	<BDL	493.31	<BDL	<BDL	79561	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)		
Orogenic	Sukhooi Log	0.25	0.72	<BDL	<BDL	1402.79	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	176.83	<BDL	<BDL	140742	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)		
Orogenic	Cuiabá	<BDL	<BDL	<BDL	<BDL	131	<BDL	<BDL	<BDL	86.98	<BDL	<BDL	<BDL	1079.68	<BDL	<BDL	61.35	<BDL	<BDL	207869	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Cuiabá	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	63.14	0.12	<BDL	<BDL	150.44	<BDL	<BDL	72.19	<BDL	<BDL	202791	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Cuiabá	0.94	0.12	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	77.61	<BDL	<BDL	<BDL	<BDL	<BDL	76.74	<BDL	<BDL	202849	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)		
Orogenic	Cuiabá	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	16.44	<BDL	<BDL	<BDL	566.74	<BDL	<BDL	69.95	<BDL	<BDL	205411	<BDL	4647.19	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Meliadine	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.37	<BDL	<BDL	<BDL	<BDL	208.66	<BDL	<BDL	426.14	11.95	<BDL	71113	<BDL	<BDL	<BDL	<BDL	1840.36	Liu and Beaudoin (2021)	
Orogenic	Meliadine	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	1.68	0.06	<BDL	<BDL	<BDL	<BDL	25.5	<BDL	<BDL	410.38	<BDL	<BDL	70029	<BDL	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	0.033	<BDL	<BDL	991	<BDL	<BDL	0.065	<BDL	<BDL	<BDL	<BDL	<BDL	0.099	687.5	9.1	<BDL	44327	<BDL	80	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	0.046	<BDL	<BDL	976	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	701.4	<BDL	<BDL	44327	<BDL	56	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	0.018	<BDL	<BDL	950	<BDL	<BDL	0.046	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	713	<BDL	<BDL	44327	<BDL	64.3	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	<BDL	0.15	<BDL	1041	<BDL	0.035	0.103	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	748.3	<BDL	<BDL	47304	<BDL	85.5	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	0.031	0.22	<BDL	1041	<BDL	<BDL	0.135	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	759.2	<BDL	<BDL	47304	<BDL	80.9	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	<BDL	<BDL	<BDL	1020	<BDL	<BDL	0.149	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.071	759	<BDL	<BDL	47304	<BDL	79.4	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	0.033	<BDL	<BDL	1032	<BDL	<BDL	0.15	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.051	721.9	<BDL	<BDL	44556	<BDL	83	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	0.016	<BDL	<BDL	<BDL	1083	<BDL	0.032	0.198	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.081	721.9	<BDL	<BDL	44556	<BDL	53.5	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	<BDL	0.1	<BDL	1323	<BDL	<BDL	0.166	0.44	<BDL	<BDL	<BDL	<BDL	0.022	0.14	724.7	<BDL	<BDL	44556	<BDL	79.6	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	0.029	<BDL	<BDL	1240	<BDL	<BDL	0.23	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.111	717.6	<BDL	<BDL	44556	<BDL	88.8	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	0.017	0.051	0.34	<BDL	1284	<BDL	<BDL	0.169	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.095	704	<BDL	<BDL	44132	<BDL	68.4	<BDL	<BDL	9	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	0.07	<BDL	<BDL	1271	<BDL	<BDL	0.202	0.3	0.0064	<BDL	<BDL	<BDL	<BDL	0.078	701.4	<BDL	<BDL	44132	<BDL	85.4	<BDL	<BDL	9.1	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	<BDL	1.63	<BDL	1219	<BDL	<BDL	1.8	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.123	696.4	<BDL	<BDL	44132	<BDL	71	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Veine	<BDL	<BDL	2.2	<BDL	1348	<BDL	<BDL	2	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.3	687	<BDL	<BDL	44132	<BDL	84.3	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Wedding	<BDL	<BDL	<BDL	<BDL	4560	<BDL	<BDL	0.062	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.107	72.8	<BDL	<BDL	186499	<BDL	113	<BDL	31	<BDL	Liu and Beaudoin (2021)	
Orogenic	Wedding	<BDL	<BDL	<BDL	<BDL	3910	<BDL	<BDL	0.136	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.03	92.2	<BDL	<BDL	186499	<BDL	128	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Wedding	<BDL	<BDL	<BDL	<BDL	4160	<BDL	<BDL	0.078	<BDL	0.0144	<BDL	<BDL	<BDL	<BDL	0.049	79.7	<BDL	<BDL	186499	<BDL	135	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Wedding	<BDL	<BDL	<BDL	<BDL	3940	<BDL	<BDL	0.047	<BDL	0.0039	<BDL	<BDL	<BDL	0.056	<BDL	86.6	<BDL	<BDL	186499	<BDL	97	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Wogogoosh	<BDL	0.016	<BDL	<BDL	586	<BDL	<BDL	<BDL	0.57	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	376.4	<BDL	<BDL	28564	<BDL	57.6	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Wogogoosh	0.049	0.045	<BDL	<BDL	629	<BDL	0.046	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	382.9	11.1	<BDL	28564	<BDL	74	<BDL	<BDL	13.4	Liu and Beaudoin (2021)	
Orogenic	Dome	<BDL	<BDL	<BDL	<BDL	868	<BDL	<BDL	2.55	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	45.1	<BDL	<BDL	104574	<BDL	111	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Dome	<BDL	<BDL	<BDL	<BDL	996	<BDL	<BDL	0.183	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	41.9	<BDL	<BDL	106948	<BDL	87	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.042	<BDL	<BDL	12.44	<BDL	0.019	0.0164	1.763	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	4.49	<BDL	<BDL	224907	<BDL	39.7	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.039	<BDL	<BDL	11.98	<BDL	<BDL	0.023	1.759	0.0034	<BDL	<BDL	<BDL	<BDL	<BDL	4.86	<BDL	<BDL	223410	<BDL	38.6	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.042	<BDL	<BDL	12.58	<BDL	0.027	1.51	1.355	0.0012	<BDL	<BDL	<BDL	<BDL	0.0083	0.0114	2.88	<BDL	<BDL	221368	<BDL	51.6	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Amaruq	<BDL	0.037	<BDL	<BDL	11.66	<BDL	0.017	0.06	1.627	0.002	<BDL	<BDL	<BDL	<BDL	0.023	2.94	<BDL	<BDL	221368	<BDL	34.6	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.036	0.086	<BDL	11.84	<BDL	0.017	0.0287	1.782	<BDL	<BDL	<BDL	<BDL	0.0071	0.0115	3.73	<BDL	<BDL	221071	<BDL	34.2	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.036	0.057	<BDL	11.19	<BDL	<BDL	0.0392	1.897	<BDL	<BDL	<BDL	<BDL	<BDL	0.0103	4.93	<BDL	<BDL	219487	<BDL	30.5	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.032	<BDL	<BDL	12.04	<BDL	0.018	0.065	1.65	<BDL	<BDL	<BDL	<BDL	<BDL	0.046	3.21	10.6	<BDL	224479	0.51	33.4	<BDL	0.37	7.6	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.024	0.049	<BDL	14.69	<BDL	<BDL	0.0256	1.83	<BDL	<BDL	<BDL	<BDL	0.0091	0.0226	2.9	<BDL	<BDL	224479	<BDL	24.5	<BDL	<BDL	5	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.017	0.025	0.618	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	6.3	<BDL	<BDL	216368	<BDL	22.4	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	<BDL	<BDL	<BDL	14.41	<BDL	<BDL	0.264	0.543	0.0116	<BDL	<BDL	<BDL	<BDL	0.54	0.234	5.84	<BDL	129	215856	<BDL	38.1	<BDL	0.15	95	Liu and Beaudoin (2021)
Orogenic	Amaruq	<BDL	<BDL	<BDL	<BDL	9.58	<BDL	0.011	0.026	0.594	<BDL	<BDL	<BDL	<BDL	<BDL	0.021	5.21	<BDL	<BDL	215820	<BDL	31.9	3	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.01	<BDL	<BDL	9.49	<BDL	0.02	<BDL	0.541	<BDL	<BDL	<BDL	<BDL	0.004	<BDL	5.8	<BDL	<BDL	218633	<BDL	23.9	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.013	0.177	<BDL	9.71	<BDL	<BDL	<BDL	0.504	<BDL	<BDL	<BDL	<BDL	<BDL	5.49	<BDL	<BDL	218404	<BDL	22.5	<BDL	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	<BDL	0.184	<BDL	9.83	<BDL	<BDL	0.117	0.485	<BDL	<BDL	<BDL	<BDL	<BDL	0.042	4.98	<BDL	<BDL	218404	<BDL	28	14	<BDL	37	Liu and Beaudoin (2021)	
Orogenic	Amaruq	0.0048	0.0058	1.36	<BDL	15.8	<BDL	0.019	0.447	0.461	0.0033	<BDL	0.182	<BDL	<BDL	0.92	6.65	100	0.152	218404	3.2	27.5	330	3.6	1140	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.0056	0.099	<BDL	16.1	<BDL	<BDL	<BDL	6.88	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	2.69	<BDL	<BDL	286684	<BDL	18.4	<BDL	0.069	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.074	<BDL	<BDL	89.9	<BDL	0.251	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.029	143.5	<BDL	0.38	89535	<BDL	75.9	<BDL	0.23	76	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.064	0.45	<BDL	109.5	<BDL	0.34	0.066	&																	

	Amaruq	<BDL	0.084	<BDL	<BDL	24.7	<BDL	0.546	<BDL	1.87	<BDL	<BDL	<BDL	<BDL	<BDL	0.044	84.3	<BDL	<BDL	146515	<BDL	39.8	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.046	<BDL	<BDL	25	<BDL	0.629	<BDL	1.97	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	82.4	<BDL	<BDL	146515	<BDL	52.3	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	0.0064	0.112	0.35	<BDL	82	<BDL	0.243	0.0144	1.97	<BDL	0.012	0.089	<BDL	<BDL	0.077	42.7	<BDL	<BDL	146515	<BDL	96	<BDL	0.2	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	<BDL	1.85	<BDL	7.6	<BDL	0.81	0.041	39.6	<BDL	<BDL	0.28	<BDL	<BDL	0.48	170.3	<BDL	<BDL	139025	<BDL	49	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.177	5.6	<BDL	41.2	0.066	0.56	3.84	1.64	0.021	0.28	0.66	36	2	45	164	18	19	139025	58	126	2080	44	5800	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.13	3.2	<BDL	<BDL	<BDL	0.8	0.71	6.35	<BDL	<BDL	<BDL	<BDL	<BDL	3.2	179.8	<BDL	<BDL	139025	<BDL	71.2	850	<BDL	700	Liu and Beaudoin (2021)	
Orogenic	Amaruq	<BDL	0.51	<BDL	<BDL	30.4	<BDL	0.136	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.109	32.5	<BDL	<BDL	139025	<BDL	48	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	0.02	<BDL	<BDL	<BDL	1290	0.051	0.023	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.066	226.7	<BDL	<BDL	121555	<BDL	37	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1270	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.067	241	<BDL	<BDL	124896	<BDL	67	<BDL	0.66	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	0.034	<BDL	<BDL	1283	<BDL	0.056	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.037	0.128	225.5	<BDL	<BDL	122117	<BDL	87	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1500	0.057	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.097	241.4	<BDL	<BDL	125613	<BDL	102	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	0.018	<BDL	<BDL	1164	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.101	216.2	<BDL	<BDL	125455	<BDL	99	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1420	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.085	247.1	<BDL	<BDL	119695	<BDL	123	<BDL	0.4	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1400	<BDL	0.025	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.084	214.3	<BDL	<BDL	124308	<BDL	103	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	<BDL	0.53	2.1	1002	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.056	201	<BDL	<BDL	122534	<BDL	100.2	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1600	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.051	0.097	246.2	<BDL	<BDL	121925	<BDL	55	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1410	<BDL	0.027	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.09	164.4	<BDL	<BDL	128920	<BDL	62	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1630	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.038	0.112	248.8	<BDL	<BDL	122659	<BDL	122	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1840	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.034	0.143	200.5	<BDL	<BDL	127576	<BDL	99.1	<BDL	<BDL	19.5	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1590	<BDL	<BDL	<BDL	<BDL	0.027	<BDL	<BDL	<BDL	<BDL	<BDL	0.075	219.4	<BDL	<BDL	120517	<BDL	87	<BDL	0.74	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	0.024	0.038	<BDL	<BDL	1820	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.046	232.1	<BDL	<BDL	122923	<BDL	73	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1800	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.139	221.3	<BDL	<BDL	118465	<BDL	51	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	0.024	<BDL	<BDL	1970	<BDL	0.081	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.128	208.5	<BDL	<BDL	125297	<BDL	44	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	0.021	<BDL	<BDL	2220	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.075	0.119	187.3	<BDL	<BDL	121541	<BDL	85	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	0.024	<BDL	<BDL	5290	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.23	127.2	<BDL	<BDL	127431	<BDL	70	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)	
Orogenic	Shangxu	2.9	0.009	6	20	4500	0.06	<BDL	4.6	10.1	0.014	0.53	1.5	15	8.9	13000	74	240	1.5	199202	<BDL	1000	100	<BDL	118	Liu and Beaudoin (2021)	
Orogenic	Shangxu	<BDL	0.06	<BDL	<BDL	4380	0.063	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.14	218.7	<BDL	<BDL	109912	<BDL	60	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	4850	<BDL	0.064	<BDL	<BDL	0.0087	<BDL	<BDL	<BDL	<BDL	<BDL	0.55	192.5	<BDL	<BDL	112098	<BDL	90	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	<BDL	<BDL	<BDL	1582	<BDL	0.031	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.04	0.122	219.8	<BDL	<BDL	127646	<BDL	70	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	0.037	<BDL	<BDL	1110	<BDL	<BDL	<BDL	0.49	0.015	<BDL	<BDL	<BDL	9.2	0.21	7.2	135	<BDL	0.82	114810	6.7	95.1	<BDL	<BDL	940	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	0.025	<BDL	<BDL	2850	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	<BDL	0.069	206.2	<BDL	<BDL	113072	<BDL	77.4	<BDL	<BDL	<BDL	Liu and Beaudoin (2021)
Orogenic	Shangxu	<BDL	0.024	<BDL	<BDL	6860	<BDL	<BDL	<BDL	<BDL	0.0093	<BDL	<BDL	<BDL	<BDL	<BDL	0.136	113.3	<BDL	<BDL	135396	<BDL	64	<BDL	<BDL	30.1	Liu and Beaudoin (2021)
	Min	0.005	0.006	0.044	0.600	3.100	0.001	0.011	0.009	0.010	0.001	0.010	0.060	0.084	0.004	0.002	1.500	1.232	0.030	1768.000	0.500	18.400	1.322	0.069	5		
	Average	1.40	4.58	221.54	363.55	4186.77	0.29	5.20	26.71	252.63	1.34	14.03	61.42	212.44	8.23	929.30	330.83	168.31	63.64	155607.67	5044.40	497.33	248.91	1317.84	876.11		
	Max	28.40	145.8	9300	21000	68266.73	8.8	423	2380	24200	37.2	190	1850	4000	590	189000	8900	5521	1570	584239	218000	18820	4400	87000	24547.65		

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- Liu H, Beaudoin G, Makvandi S, et al (2021a) Multivariate statistical analysis of trace element compositions of native gold from orogenic gold deposits: Implication for mineral exploration. *Ore Geology Reviews* 131:104061. <https://doi.org/10.1016/j.oregeorev.2021.104061>
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Table S2. Lead isotopic ratios. The uncertainty level is given in 1 standard deviation propagated within-run

Group	Sample number	206Pb/204Pb	206Pb/204Pb 2 σ%	207Pb/204Pb	207Pb/204Pb 2σ%	207Pb/206Pb	207Pb/206Pb 2σ%	208Pb/204Pb	208Pb/204Pb 2σ%	208Pb/206Pb	208Pb/206Pb 2σ%
D1	2285-1	13.42	12.40	13.18	6.26	0.982	0.092	29.69	25.16	2.212	0.204
		17.62	5.16	15.95	6.27	0.905	0.133	36.38	13.63	2.065	0.220
		14.04	3.00	13.50	2.54	0.961	0.049	35.80	6.82	2.549	0.271
		15.84	3.25	15.41	2.83	0.973	0.051	34.62	6.79	2.186	0.119
		17.59	3.54	15.26	3.00	0.868	0.058	35.05	6.57	1.993	0.142
		17.87	3.87	16.83	3.43	0.942	0.061	39.00	6.19	2.183	0.105
		14.85	3.65	14.45	3.90	0.974	0.054	34.54	6.00	2.326	0.121
		16.48	11.75	14.94	3.78	0.907	0.058	34.73	5.70	2.108	0.124
		16.24	2.76	14.93	2.01	0.920	0.040	34.27	5.69	2.110	0.125
		17.51	3.16	13.45	2.40	0.768	0.032	33.62	5.61	1.920	0.108
		16.15	6.19	14.54	2.54	0.901	0.036	34.54	4.66	2.139	0.079
		17.30	2.52	15.90	1.99	0.919	0.038	37.52	4.49	2.169	0.091
		13.85	3.60	14.15	2.10	1.021	0.070	30.94	4.42	2.233	0.198
		16.67	2.01	14.61	1.75	0.877	0.045	35.20	4.18	2.112	0.095
		12.94	2.14	12.27	1.73	0.948	0.043	28.77	3.83	2.223	0.094
		15.66	2.01	14.37	1.66	0.918	0.045	34.20	3.72	2.185	0.116
		15.88	1.76	15.98	1.61	1.006	0.047	37.10	3.36	2.337	0.111
		15.47	6.35	14.00	2.20	0.905	0.056	33.70	3.29	2.178	0.133
		17.80	1.50	17.34	1.31	0.975	0.033	39.61	2.98	2.225	0.065
		16.94	1.67	14.88	1.10	0.879	0.054	33.06	2.87	1.951	0.119
D2	2285-3	17.10	18.60	15.82	8.77	0.925	0.078	38.00	15.03	2.222	0.228
		13.30	3.48	11.88	4.49	0.893	0.061	28.87	11.84	2.171	0.134
		19.36	4.86	15.35	4.31	0.793	0.075	36.30	9.17	1.875	0.165
		17.98	4.21	16.69	3.50	0.928	0.058	40.43	7.20	2.249	0.137
		16.36	2.79	15.10	2.57	0.923	0.061	36.01	6.06	2.201	0.167
		17.44	2.71	15.08	2.35	0.865	0.076	37.74	5.81	2.165	0.135
		17.29	2.76	16.39	2.25	0.948	0.042	37.50	5.53	2.169	0.108
		16.94	2.35	15.84	2.08	0.935	0.048	36.53	5.03	2.156	0.128
		13.68	2.59	12.70	2.21	0.929	0.068	28.55	4.92	2.087	0.145
		15.78	1.96	15.79	1.94	1.001	0.061	36.31	4.43	2.302	0.117
		16.77	1.99	15.73	1.86	0.938	0.043	36.79	4.30	2.194	0.099
		14.90	1.86	13.81	1.59	0.927	0.040	32.74	3.91	2.196	0.114
		16.52	1.99	15.69	1.97	0.949	0.043	36.82	3.81	2.228	0.083
		15.33	5.69	13.59	2.60	0.887	0.037	29.86	3.75	1.948	0.091
		17.34	1.98	15.46	1.56	0.892	0.044	36.47	3.63	2.104	0.123
		17.54	1.79	16.61	1.69	0.947	0.044	38.95	3.55	2.221	0.106
		17.04	1.63	16.15	1.53	0.948	0.034	36.59	3.42	2.148	0.078
		17.15	1.56	15.92	1.44	0.928	0.032	36.34	3.26	2.119	0.079
		14.99	1.76	13.77	1.38	0.918	0.042	33.16	3.19	2.212	0.093
		16.98	1.57	15.32	1.60	0.903	0.052	35.35	3.19	2.082	0.092
		15.37	1.40	14.87	1.15	0.967	0.035	34.75	2.92	2.260	0.096
		14.84	1.72	13.69	1.37	0.923	0.035	32.91	2.89	2.218	0.069
		15.95	1.66	15.45	1.56	0.969	0.034	36.57	2.87	2.293	0.080
		16.23	1.22	16.03	1.20	0.987	0.031	37.16	2.75	2.290	0.065
		15.73	1.40	14.63	1.16	0.930	0.037	34.36	2.69	2.184	0.081
		16.96	1.37	15.40	1.14	0.908	0.033	36.31	2.58	2.141	0.064
		16.57	1.19	15.60	1.12	0.941	0.027	35.87	2.54	2.164	0.062
		17.08	1.11	15.79	1.02	0.924	0.023	36.71	2.35	2.149	0.052
		16.44	1.20	15.37	1.00	0.935	0.023	36.22	2.25	2.204	0.051
		15.95	1.18	14.47	1.06	0.907	0.033	34.67	2.23	2.173	0.081
		16.86	1.11	15.54	0.95	0.922	0.025	36.11	2.23	2.142	0.057
		15.39	1.07	14.94	0.98	0.971	0.033	34.02	2.20	2.210	0.058
		16.09	1.05	15.72	0.98	0.977	0.024	35.24	2.17	2.190	0.051
		16.57	0.97	16.02	0.93	0.967	0.022	37.06	2.13	2.237	0.053
		15.68	0.94	15.02	0.90	0.958	0.024	35.04	2.05	2.235	0.053
		16.65	1.05	16.07	0.90	0.965	0.024	36.90	2.03	2.216	0.053
		16.55	0.86	15.61	0.81	0.943	0.021	35.87	1.83	2.168	0.046
		16.14	0.78	15.33	0.74	0.950	0.018	36.26	1.71	2.246	0.042
		16.30	0.79	15.26	0.74	0.936	0.022	35.50	1.68	2.178	0.042
		16.52	0.84	15.50	0.76	0.938	0.018	36.01	1.67	2.180	0.039
		17.28	0.89	15.52	0.70	0.898	0.021	36.18	1.59	2.093	0.046
		16.15	0.73	15.26	0.68	0.945	0.020	35.58	1.54	2.204	0.042
		15.63	0.77	15.14	0.69	0.968	0.015	34.74	1.41	2.222	0.037
		16.39	0.63	15.39	0.59	0.939	0.016	35.96	1.34	2.193	0.032
		15.98	0.65	15.21	0.56	0.952	0.014	34.68	1.25	2.170	0.031
		15.57	0.62	14.82	0.55	0.952	0.014	34.31	1.17	2.203	0.030
		15.98	0.54	15.23	0.51	0.953	0.013	35.18	1.16	2.202	0.029
		16.29	0.48	15.61	0.45	0.958	0.011	35.95	1.02	2.207	0.025
		16.50	0.56	15.49	0.66	0.939	0.013	36.54	1.43	2.214	0.036
		16.45	0.53	15.49	0.52	0.942	0.020	36.16	1.16	2.198	0.037
		16.47	0.45	15.50	0.44	0.941	0.011	36.22	1.04	2.199	0.027
		16.35	0.45	15.62	0.44	0.955	0.012	36.52	1.03	2.233	0.025
		16.58	0.45	15.71	0.44	0.947	0.012	36.43	1.01	2.196	0.029
		16.41	0.41	15.42	0.42	0.940	0.012	35.97	0.99	2.192	0.031
		16.77	0.40	15.84	0.38	0.944	0.010	36.56	0.85	2.180	0.032
		16.70	0.38	15.75	0.33	0.943	0.010	36.73	0.84	2.199	0.029
		16.55	0.36	15.66	0.35	0.946	0.010	36.42	0.84	2.200	0.025
		16.48	0.37	15.58	0.36	0.946	0.010	36.36	0.83	2.207	0.021
		16.75	0.37	15.78	0.35	0.942	0.010	36.92	0.82	2.204	0.025
		16.69	0.37	15.64	0.36	0.937	0.009	36.94	0.82	2.213	0.021
		16.43	0.34	15.56	0.34	0.947	0.010	36.37	0.79	2.214	0.024
		16.27	0.38	15.33	0.36	0.943	0.010	35.85	0.79	2.204	0.019
		16.54	0.34	15.49	0.34	0.937	0.010	36.49	0.79	2.206	0.022

D3	2285-5	16.61	0.35	15.77	0.35	0.949	0.009	36.97	0.78	2.225	0.022
		16.46	0.40	15.69	0.36	0.953	0.010	36.33	0.77	2.208	0.022
		16.63	0.32	15.71	0.33	0.945	0.008	36.66	0.76	2.204	0.023
		16.67	0.32	15.76	0.32	0.946	0.009	36.87	0.76	2.212	0.020
		16.51	0.34	15.66	0.32	0.948	0.010	36.42	0.75	2.206	0.021
		16.56	0.33	15.76	0.31	0.952	0.008	36.55	0.73	2.207	0.020
		16.72	0.33	15.77	0.32	0.944	0.009	36.77	0.72	2.200	0.018
		16.44	0.35	15.49	0.32	0.942	0.008	36.05	0.71	2.193	0.017
		16.65	0.30	15.70	0.30	0.943	0.008	36.45	0.70	2.189	0.019
		16.55	0.42	15.65	0.33	0.946	0.011	36.63	0.69	2.213	0.026
		16.76	0.31	15.92	0.32	0.950	0.008	37.05	0.68	2.211	0.018
		16.29	0.32	15.34	0.30	0.941	0.008	35.86	0.67	2.201	0.016
		16.34	0.29	15.37	0.29	0.941	0.008	35.95	0.64	2.201	0.017
		16.25	0.26	15.42	0.27	0.949	0.010	35.87	0.64	2.207	0.023
		16.46	0.26	15.51	0.27	0.943	0.007	36.07	0.63	2.192	0.019
		16.65	0.29	15.69	0.29	0.942	0.008	36.56	0.63	2.195	0.015
		16.51	0.25	15.61	0.26	0.945	0.007	36.51	0.60	2.211	0.017
		16.54	0.24	15.63	0.26	0.945	0.007	36.37	0.60	2.199	0.018
		16.54	0.25	15.49	0.26	0.937	0.007	36.03	0.60	2.179	0.018
		16.40	0.23	15.50	0.25	0.945	0.007	35.95	0.58	2.192	0.017
		16.51	0.22	15.50	0.24	0.939	0.007	36.06	0.57	2.184	0.017
		16.44	0.24	15.52	0.25	0.944	0.008	36.20	0.56	2.202	0.020
		16.65	0.22	15.65	0.24	0.940	0.007	36.38	0.56	2.186	0.017
		16.59	0.22	15.62	0.23	0.942	0.007	36.37	0.55	2.192	0.019
		16.51	0.22	15.47	0.23	0.937	0.007	36.02	0.55	2.181	0.018
		16.52	0.22	15.61	0.24	0.945	0.007	36.18	0.55	2.190	0.017
		16.19	0.21	15.36	0.23	0.948	0.007	35.60	0.54	2.198	0.017
		16.51	0.22	15.55	0.23	0.942	0.007	36.25	0.54	2.196	0.018
		16.70	0.21	15.74	0.23	0.943	0.007	36.53	0.54	2.188	0.017
		16.40	0.21	15.43	0.23	0.941	0.007	35.87	0.53	2.187	0.017
		16.57	0.21	15.66	0.23	0.945	0.007	36.36	0.53	2.194	0.017
		16.56	0.21	15.61	0.23	0.943	0.007	36.25	0.53	2.189	0.017
		16.47	0.20	15.54	0.22	0.943	0.007	36.14	0.52	2.194	0.017
		16.55	0.20	15.63	0.22	0.945	0.007	36.20	0.52	2.188	0.017
		16.52	0.19	15.52	0.22	0.940	0.007	36.20	0.51	2.192	0.017
		16.42	0.19	15.50	0.22	0.944	0.007	35.94	0.51	2.189	0.017
		16.33	0.19	15.43	0.21	0.945	0.007	35.87	0.50	2.197	0.017
		16.51	0.18	15.54	0.21	0.941	0.007	36.13	0.49	2.188	0.017
D4	2285-7	17.23	8.40	15.75	5.11	0.914	0.051	37.86	9.48	2.198	0.123
		17.21	3.22	17.81	3.31	1.035	0.072	40.99	7.56	2.381	0.156
		18.40	3.49	16.20	3.01	0.880	0.061	39.22	7.04	2.132	0.134
		16.56	4.75	15.45	2.95	0.933	0.055	35.54	6.97	2.146	0.120
		17.02	2.32	13.48	2.57	0.792	0.106	31.42	6.46	1.845	0.304
		14.99	2.58	14.32	2.31	0.955	0.063	33.60	5.38	2.242	0.137
		16.03	2.32	14.34	2.06	0.895	0.051	34.84	4.95	2.174	0.120
		17.22	1.74	16.58	1.53	0.963	0.055	35.16	4.87	2.042	0.126
		17.63	2.38	16.23	2.18	0.921	0.047	35.32	4.72	2.004	0.141
		16.89	2.77	15.65	1.92	0.927	0.033	35.33	4.37	2.093	0.068
		14.90	1.65	14.69	1.52	0.986	0.050	33.28	4.14	2.234	0.104
		17.65	2.16	15.02	1.91	0.851	0.024	34.89	3.88	1.977	0.073
		16.32	1.89	15.06	1.64	0.923	0.036	33.89	3.84	2.077	0.087
		15.65	1.17	14.54	0.94	0.929	0.031	33.74	3.40	2.156	0.064
		18.39	1.34	17.56	1.27	0.955	0.049	43.41	3.38	2.360	0.118
		15.37	1.71	13.86	1.46	0.902	0.047	32.71	3.37	2.129	0.102
		14.82	1.22	13.55	1.35	0.914	0.050	30.26	3.26	2.042	0.138
		17.03	1.47	16.30	1.50	0.957	0.031	37.66	3.26	2.212	0.068
		15.11	1.61	13.85	1.38	0.917	0.033	31.98	3.13	2.117	0.072
		16.14	1.75	14.80	1.40	0.917	0.045	32.77	3.09	2.031	0.113
		15.51	1.75	14.49	1.52	0.934	0.034	33.62	3.07	2.168	0.082
		17.76	1.50	16.61	1.31	0.935	0.025	37.82	3.03	2.129	0.055
		16.80	1.44	15.34	1.31	0.913	0.045	36.37	3.02	2.165	0.082
		14.55	1.44	13.51	1.26	0.928	0.033	31.98	2.90	2.198	0.084
		16.10	1.39	15.17	1.27	0.942	0.032	36.23	2.86	2.250	0.074
		14.13	1.48	13.09	1.29	0.927	0.052	28.90	2.85	2.045	0.135
		14.71	1.17	14.56	1.20	0.990	0.029	35.72	2.85	2.429	0.087
		16.66	1.51	15.37	1.28	0.923	0.029	37.52	2.77	2.252	0.102
		15.74	1.81	14.88	1.30	0.946	0.037	33.99	2.73	2.160	0.116
		15.28	1.16	14.82	1.04	0.970	0.050	31.07	2.61	2.033	0.118
		14.72	1.26	13.33	1.08	0.906	0.041	30.55	2.60	2.076	0.087
		14.37	1.17	13.41	1.09	0.933	0.031	34.76	2.57	2.418	0.098
		16.40	1.45	14.53	1.31	0.886	0.028	34.33	2.54	2.094	0.070
		16.05	1.19	14.39	1.11	0.897	0.030	34.98	2.48	2.179	0.067
		17.45	0.98	16.30	0.96	0.934	0.033	38.72	2.46	2.219	0.093
		15.26	0.99	14.55	0.96	0.954	0.037	34.06	2.43	2.232	0.063
		16.24	1.26	16.02	1.08	0.987	0.036	35.88	2.42	2.210	0.083
		17.05	1.05	15.48	0.93	0.908	0.030	35.01	2.38	2.053	0.073
		16.64	1.46	15.52	1.25	0.933	0.034	33.63	2.38	2.021	0.070
		17.89	1.10	16.37	0.91	0.915	0.022	38.50	2.36	2.152	0.062
		17.15	1.22	15.52	1.07	0.905	0.025	37.92	2.31	2.210	0.055
		13.93	1.19	12.59	1.09	0.903	0.044	28.52	2.28	2.046	0.099
		16.10	1.08	14.89	1.09	0.925	0.022	37.26	2.26	2.313	0.099
		16.47	0.93	15.14	0.93	0.919	0.022	35.47	2.22	2.154	0.057
		18.13	1.06	16.81	0.94	0.927	0.021	38.96	2.18	2.149	0.058
		15.42	1.82	14.42	1.14	0.935	0.038	33.86	2.18	2.196	0.130
		16.20	1.32	15.36	0.84	0.948	0.046	34.35	2.15	2.121	0.117
		16.35	0.85	14.55	0.71	0.890	0.026	39.20	2.14	2.397	0.097
		15.77	0.86	14.63	0.89	0.928	0.033	35.87	2.13	2.275	0.091

		15.12	1.13	14.74	1.09	0.975	0.037	27.54	2.08	1.822	0.061
		16.41	1.01	14.30	0.88	0.871	0.033	34.56	2.08	2.106	0.084
		15.18	0.97	14.29	0.90	0.941	0.029	34.45	2.06	2.269	0.069
		16.19	0.91	14.58	1.00	0.901	0.032	35.48	2.06	2.192	0.068
		14.68	0.87	13.28	0.84	0.905	0.023	30.03	2.04	2.046	0.069
		16.26	1.02	15.19	0.86	0.934	0.027	35.45	2.04	2.180	0.077
		13.87	1.04	12.91	1.01	0.931	0.033	30.31	2.03	2.186	0.077
		17.24	0.87	15.66	0.83	0.909	0.020	37.54	1.98	2.178	0.049
		17.08	0.96	15.41	0.77	0.902	0.023	35.67	1.98	2.088	0.051
		15.56	0.77	14.68	0.82	0.943	0.025	32.75	1.97	2.105	0.073
		15.63	1.04	14.34	0.85	0.918	0.021	33.94	1.97	2.171	0.054
		15.12	1.07	14.29	0.92	0.945	0.024	32.94	1.95	2.179	0.060
		14.81	0.86	13.85	0.87	0.935	0.034	33.38	1.91	2.254	0.085
		16.41	0.94	15.29	0.96	0.932	0.022	33.49	1.91	2.040	0.057
		14.93	0.98	14.11	0.79	0.945	0.034	32.23	1.91	2.158	0.070
		16.61	0.92	15.62	0.79	0.940	0.027	35.63	1.84	2.145	0.065
		15.44	0.76	13.99	0.65	0.906	0.021	31.26	1.84	2.024	0.067
		17.86	0.77	16.31	0.72	0.913	0.021	38.70	1.82	2.166	0.061
		15.78	0.97	15.30	0.77	0.969	0.035	34.84	1.82	2.207	0.087
		15.00	0.82	14.56	0.75	0.970	0.033	33.73	1.78	2.248	0.065
		15.02	0.85	14.03	0.79	0.934	0.037	33.44	1.71	2.226	0.082
		16.76	0.78	15.58	0.73	0.930	0.019	35.40	1.65	2.113	0.059
		15.33	0.78	14.35	0.74	0.936	0.028	33.41	1.57	2.179	0.051
		15.95	0.79	14.49	0.76	0.908	0.022	34.34	1.55	2.153	0.051
		16.04	0.70	15.08	0.62	0.940	0.028	36.76	1.41	2.292	0.075
		16.54	0.60	15.06	0.53	0.911	0.015	35.32	1.40	2.135	0.036
		16.70	0.74	15.24	0.60	0.913	0.021	35.66	1.31	2.136	0.058
		16.69	0.62	15.14	0.54	0.907	0.016	35.23	1.27	2.111	0.039
	4640-1	17.90	0.25	15.41	0.19	0.861	0.006	37.26	0.60	2.082	0.015
		18.08	0.24	15.56	0.17	0.861	0.006	37.75	0.57	2.089	0.015
		17.96	0.22	15.42	0.16	0.858	0.007	37.20	0.57	2.072	0.016
		18.09	0.23	15.57	0.17	0.860	0.006	37.64	0.57	2.081	0.015
		17.98	0.23	15.46	0.17	0.859	0.006	37.46	0.56	2.083	0.015
		18.11	0.22	15.57	0.16	0.860	0.006	37.71	0.55	2.082	0.015
		17.91	0.22	15.35	0.15	0.857	0.006	37.22	0.55	2.078	0.015
		18.09	0.21	15.52	0.15	0.858	0.006	37.20	0.55	2.057	0.015
		18.15	0.22	15.56	0.15	0.858	0.006	37.06	0.54	2.042	0.016
		18.10	0.21	15.54	0.15	0.858	0.006	37.65	0.53	2.080	0.015
	4640-2	18.13	1.05	15.57	0.83	0.859	0.025	36.89	1.61	2.035	0.056
		16.74	0.29	15.53	0.35	0.927	0.012	35.91	0.91	2.145	0.037
		18.19	0.30	15.49	0.22	0.852	0.009	37.91	0.66	2.084	0.024
		17.97	0.26	15.34	0.19	0.853	0.006	37.33	0.61	2.077	0.016
		16.66	0.27	15.44	0.27	0.927	0.007	36.42	0.59	2.186	0.017
		18.17	0.24	15.51	0.18	0.854	0.006	37.75	0.58	2.077	0.015
		18.10	0.25	15.39	0.18	0.851	0.006	37.31	0.58	2.062	0.015
		16.72	0.27	15.38	0.24	0.920	0.007	36.54	0.58	2.186	0.020
		18.07	0.24	15.49	0.17	0.857	0.006	37.48	0.58	2.074	0.015
		16.63	0.27	15.54	0.26	0.934	0.008	36.46	0.57	2.192	0.018
		16.68	0.28	15.39	0.26	0.923	0.008	36.21	0.57	2.171	0.021
		18.01	0.24	15.41	0.17	0.855	0.006	37.20	0.56	2.065	0.015
		18.11	0.23	15.47	0.16	0.854	0.006	37.65	0.56	2.079	0.015
		18.06	0.23	15.42	0.16	0.854	0.006	37.62	0.56	2.083	0.015
		18.03	0.23	15.40	0.16	0.854	0.006	37.48	0.56	2.078	0.015
		18.14	0.22	15.53	0.15	0.856	0.006	37.93	0.55	2.091	0.015
		18.19	0.23	15.52	0.16	0.854	0.006	37.76	0.55	2.076	0.015
		18.12	0.22	15.51	0.16	0.856	0.006	37.58	0.55	2.074	0.015
		18.12	0.22	15.47	0.15	0.854	0.006	37.66	0.54	2.079	0.015
		17.57	0.26	15.62	0.24	0.889	0.008	37.69	0.54	2.145	0.018
		18.12	0.22	15.49	0.15	0.855	0.006	37.69	0.54	2.080	0.015
		17.94	0.22	15.46	0.16	0.862	0.006	37.35	0.54	2.082	0.015
		18.19	0.22	15.52	0.15	0.853	0.006	37.87	0.54	2.081	0.015
		18.11	0.22	15.54	0.15	0.858	0.006	37.53	0.54	2.072	0.015
	4640-3	16.71	0.25	15.52	0.24	0.929	0.007	36.56	0.53	2.189	0.016
		17.57	0.25	15.59	0.23	0.888	0.006	37.50	0.52	2.134	0.015
		17.58	0.25	15.59	0.23	0.887	0.006	37.56	0.52	2.136	0.016
		16.70	0.24	15.48	0.23	0.927	0.007	36.22	0.52	2.169	0.016
		17.55	0.25	15.47	0.23	0.882	0.006	37.39	0.51	2.131	0.016
		17.77	0.37	15.74	0.28	0.886	0.012	39.34	0.77	2.215	0.035
		17.70	0.24	15.55	0.18	0.878	0.007	38.23	0.66	2.159	0.019
		17.70	0.21	15.51	0.14	0.877	0.006	38.34	0.56	2.167	0.015
		17.64	0.21	15.48	0.15	0.878	0.006	38.33	0.55	2.172	0.016
		17.61	0.21	15.47	0.15	0.879	0.006	38.38	0.55	2.179	0.016
		17.65	0.21	15.47	0.14	0.877	0.006	38.31	0.54	2.171	0.015
		17.72	0.21	15.52	0.14	0.876	0.006	38.35	0.54	2.165	0.015
		17.68	0.21	15.49	0.14	0.876	0.006	38.16	0.54	2.159	0.015
		17.65	0.21	15.47	0.15	0.876	0.006	38.53	0.54	2.183	0.016
		17.63	0.21	15.46	0.14	0.877	0.006	38.29	0.54	2.171	0.015
		18.16	0.37	15.73	0.34	0.866	0.013	38.21	0.92	2.104	0.038
		17.92	0.36	15.58	0.33	0.869	0.007	37.56	0.73	2.096	0.016
		17.98	0.34	15.55	0.31	0.865	0.011	37.89	0.70	2.108	0.028
		18.21	0.32	15.85	0.28	0.870	0.007	38.35	0.65	2.107	0.017
		16.76	0.20	15.49	0.15	0.925	0.006	36.06	0.56	2.152	0.019
		17.98	0.27	15.59	0.24	0.867	0.006	37.92	0.56	2.108	0.015
		17.02	0.27	15.71	0.23	0.923	0.007	35.72	0.56	2.099	0.019
		18.07	0.27	15.67	0.24	0.867	0.007	38.05	0.55	2.106	0.016
		17.97	0.27	15.59	0.24	0.868	0.006	37.84	0.55	2.106	0.015
		18.00	0.27	15.60	0.24	0.867	0.006	37.84	0.55	2.102	0.015

4640-7	17.93	0.26	15.54	0.23	0.867	0.006	37.62	0.55	2.099	0.015
	16.80	0.21	15.53	0.16	0.924	0.008	35.67	0.52	2.123	0.018
	16.53	0.19	15.29	0.15	0.925	0.006	35.52	0.52	2.149	0.016
	16.84	0.20	15.58	0.15	0.925	0.007	35.78	0.51	2.125	0.017
	16.80	0.21	15.50	0.15	0.923	0.007	35.50	0.51	2.113	0.017
	16.83	0.21	15.52	0.15	0.922	0.007	35.50	0.51	2.110	0.017
	16.66	0.20	15.37	0.14	0.923	0.007	35.39	0.50	2.125	0.016
	16.47	0.20	15.24	0.15	0.925	0.007	35.32	0.50	2.145	0.016
	16.73	0.20	15.48	0.15	0.925	0.007	35.44	0.50	2.118	0.016
	16.79	0.20	15.50	0.15	0.923	0.007	35.59	0.50	2.120	0.016
	16.72	0.20	15.45	0.15	0.924	0.007	35.53	0.50	2.125	0.016
	16.54	0.19	15.31	0.15	0.925	0.006	35.26	0.50	2.132	0.015
	16.54	0.19	15.34	0.14	0.927	0.006	35.37	0.49	2.138	0.015
	16.53	0.19	15.30	0.14	0.925	0.006	35.33	0.49	2.137	0.015
	16.45	0.19	15.19	0.15	0.924	0.006	35.22	0.49	2.141	0.015
	16.52	0.19	15.26	0.14	0.924	0.006	35.21	0.49	2.132	0.015
	16.31	0.19	15.00	0.14	0.920	0.006	35.19	0.49	2.158	0.015
4640-8	16.76	0.29	14.86	0.24	0.887	0.011	35.12	0.68	2.096	0.024
	16.90	0.27	14.92	0.23	0.883	0.007	35.47	0.65	2.098	0.022
	17.07	0.21	15.16	0.17	0.888	0.008	36.23	0.62	2.122	0.021
	17.20	0.23	15.28	0.20	0.889	0.008	36.29	0.61	2.110	0.021
	17.10	0.24	15.20	0.18	0.889	0.007	36.08	0.60	2.110	0.016
	17.39	0.21	15.47	0.15	0.890	0.007	36.30	0.51	2.088	0.014
	17.27	0.21	15.45	0.15	0.894	0.007	36.47	0.51	2.112	0.015
	17.20	0.20	15.31	0.15	0.890	0.006	36.41	0.50	2.118	0.014
	17.08	0.21	15.16	0.14	0.887	0.007	36.03	0.50	2.109	0.014
	17.03	0.20	15.05	0.15	0.884	0.006	35.51	0.50	2.085	0.013
	17.27	0.21	15.36	0.15	0.889	0.007	36.02	0.50	2.085	0.015
	17.14	0.21	15.23	0.15	0.889	0.007	36.05	0.49	2.104	0.014
	17.10	0.20	15.26	0.14	0.892	0.006	36.09	0.49	2.110	0.014
	17.20	0.20	15.29	0.14	0.889	0.006	36.21	0.49	2.105	0.013
4640-9	17.50	0.31	15.47	0.24	0.884	0.008	36.53	0.66	2.087	0.024
	17.40	0.22	15.34	0.17	0.882	0.007	36.27	0.59	2.085	0.019
	17.40	0.21	15.35	0.15	0.882	0.007	36.30	0.55	2.087	0.016
	17.52	0.22	15.38	0.16	0.877	0.007	36.18	0.54	2.064	0.019
	17.45	0.21	15.39	0.15	0.882	0.006	36.56	0.53	2.096	0.014
	17.53	0.21	15.51	0.15	0.885	0.007	36.59	0.52	2.088	0.015
	17.46	0.21	15.36	0.15	0.880	0.006	36.20	0.52	2.074	0.015
	17.47	0.21	15.40	0.15	0.882	0.006	36.66	0.51	2.099	0.014
	17.56	0.21	15.59	0.14	0.888	0.006	37.46	0.51	2.133	0.013
	17.48	0.20	15.45	0.14	0.884	0.006	36.67	0.51	2.098	0.013
	17.53	0.21	15.51	0.15	0.885	0.006	37.14	0.50	2.119	0.014
	17.52	0.21	15.49	0.14	0.884	0.006	36.94	0.50	2.109	0.014
	17.47	0.20	15.42	0.14	0.882	0.006	36.34	0.50	2.080	0.013
	17.45	0.20	15.47	0.14	0.886	0.006	36.83	0.49	2.110	0.013
	17.55	0.21	15.51	0.14	0.884	0.006	36.93	0.49	2.105	0.013
	17.48	0.20	15.39	0.14	0.880	0.006	36.47	0.49	2.087	0.013
4640-15	18.23	0.48	15.98	0.42	0.876	0.010	38.92	1.00	2.135	0.024
	17.37	0.48	15.13	0.42	0.871	0.010	37.00	1.00	2.129	0.025
	18.45	0.45	16.08	0.40	0.871	0.009	38.99	0.93	2.113	0.019
	17.92	0.44	15.53	0.37	0.867	0.009	38.00	0.85	2.121	0.019
	18.16	0.41	15.72	0.36	0.866	0.010	38.28	0.84	2.108	0.021
	18.13	0.41	15.73	0.37	0.868	0.009	38.38	0.84	2.117	0.024
	18.07	0.41	15.70	0.35	0.869	0.008	38.26	0.83	2.117	0.021
	18.18	0.41	15.81	0.36	0.870	0.009	38.49	0.83	2.118	0.018
	18.15	0.40	15.71	0.31	0.866	0.008	38.13	0.82	2.101	0.022
	17.90	0.39	15.57	0.35	0.870	0.008	37.90	0.81	2.117	0.021
	18.28	0.37	15.84	0.34	0.867	0.008	38.71	0.80	2.118	0.019
	18.16	0.38	15.90	0.33	0.875	0.008	38.65	0.79	2.128	0.019
	18.16	0.39	15.93	0.34	0.877	0.007	38.70	0.79	2.131	0.017
	18.30	0.38	16.00	0.34	0.874	0.008	38.72	0.78	2.116	0.019
	18.19	0.37	15.90	0.34	0.874	0.007	38.78	0.77	2.133	0.019
	18.37	0.39	15.99	0.31	0.871	0.008	38.89	0.76	2.118	0.018
	18.30	0.36	15.97	0.32	0.873	0.008	38.89	0.76	2.125	0.018
	18.24	0.37	15.86	0.32	0.870	0.008	38.51	0.76	2.111	0.019
	18.12	0.38	15.74	0.32	0.869	0.008	38.46	0.75	2.123	0.020
	17.97	0.39	15.76	0.31	0.877	0.008	38.37	0.75	2.135	0.018
	18.26	0.36	15.83	0.32	0.867	0.007	38.62	0.75	2.115	0.019
	18.03	0.36	15.67	0.32	0.869	0.008	38.05	0.74	2.111	0.018
	18.13	0.35	15.72	0.32	0.867	0.008	38.28	0.73	2.112	0.020
	18.13	0.36	15.80	0.31	0.871	0.007	38.40	0.73	2.118	0.017
	18.31	0.37	15.95	0.31	0.871	0.007	39.00	0.73	2.130	0.016
	18.02	0.35	15.67	0.31	0.869	0.007	38.18	0.72	2.118	0.020
	18.04	0.35	15.64	0.31	0.867	0.007	38.16	0.72	2.115	0.017
	18.01	0.35	15.69	0.31	0.871	0.008	38.07	0.71	2.114	0.018
	17.98	0.33	15.63	0.29	0.869	0.007	38.27	0.69	2.128	0.018
	18.07	0.34	15.70	0.29	0.869	0.007	38.32	0.68	2.121	0.019
	18.13	0.32	15.75	0.28	0.869	0.007	38.27	0.68	2.111	0.019
	18.10	0.33	15.67	0.29	0.866	0.007	38.16	0.68	2.109	0.018
	18.06	0.33	15.73	0.29	0.871	0.007	38.34	0.67	2.123	0.018
	18.10	0.33	15.77	0.29	0.872	0.007	38.46	0.65	2.125	0.017
	18.16	0.32	15.90	0.27	0.876	0.006	38.65	0.65	2.129	0.016
	18.23	0.31	15.73	0.27	0.863	0.007	38.51	0.63	2.113	0.016
	17.95	0.31	15.56	0.26	0.867	0.007	37.98	0.64	2.116	0.018
	18.00	0.26	15.63	0.25	0.868	0.007	37.49	0.62	2.083	0.020
	18.10	0.28	15.72	0.25	0.869	0.007	38.16	0.60	2.108	0.018
	18.03	0.28	15.78	0.26	0.875	0.007	37.79	0.58	2.096	0.017

4640-17	18.00	0.27	15.53	0.24	0.863	0.007	37.89	0.56	2.105	0.017
	18.09	0.27	15.65	0.25	0.866	0.007	38.01	0.56	2.102	0.017
	18.14	0.28	15.64	0.24	0.862	0.007	38.11	0.56	2.100	0.017
	18.00	0.28	15.58	0.25	0.865	0.007	38.01	0.55	2.112	0.017
	18.20	0.26	15.69	0.24	0.862	0.007	37.50	0.55	2.061	0.016
	18.08	0.26	15.70	0.24	0.869	0.007	38.18	0.55	2.112	0.018
	18.04	0.27	15.58	0.24	0.863	0.006	37.95	0.54	2.104	0.015
	17.95	0.27	15.50	0.24	0.864	0.006	37.81	0.54	2.107	0.015
	18.21	0.26	15.77	0.24	0.866	0.007	37.80	0.54	2.075	0.016
	18.03	0.26	15.58	0.23	0.864	0.007	37.96	0.53	2.105	0.017
	18.06	0.26	15.62	0.23	0.865	0.007	37.96	0.53	2.101	0.016
	18.05	0.26	15.64	0.23	0.867	0.006	37.99	0.53	2.105	0.016
	18.03	0.27	15.59	0.23	0.865	0.006	37.89	0.52	2.102	0.015
	18.12	0.26	15.75	0.23	0.869	0.007	37.94	0.52	2.094	0.017
4640-22	17.93	0.35	15.58	0.28	0.869	0.006	37.76	0.67	2.105	0.016
	17.96	0.32	15.68	0.29	0.873	0.007	37.94	0.66	2.113	0.017
	17.75	0.31	15.44	0.28	0.869	0.007	37.38	0.64	2.105	0.016
	17.95	0.31	15.70	0.28	0.875	0.007	37.92	0.64	2.113	0.016
	17.79	0.33	15.48	0.28	0.870	0.006	37.53	0.64	2.109	0.016
	17.74	0.30	15.51	0.27	0.874	0.006	37.46	0.63	2.111	0.015
	17.88	0.30	15.51	0.27	0.868	0.007	37.66	0.62	2.107	0.016
	17.91	0.30	15.59	0.27	0.871	0.007	37.89	0.62	2.116	0.017
	17.77	0.30	15.50	0.27	0.872	0.006	37.63	0.62	2.117	0.015
	17.80	0.30	15.57	0.27	0.875	0.006	37.76	0.61	2.121	0.015
	17.80	0.30	15.47	0.26	0.869	0.006	37.67	0.61	2.116	0.015
	17.76	0.30	15.49	0.27	0.872	0.006	37.50	0.61	2.111	0.015
	17.93	0.32	15.61	0.27	0.870	0.006	37.93	0.61	2.115	0.015
	17.97	0.30	15.61	0.26	0.868	0.006	37.81	0.61	2.104	0.016
	17.98	0.30	15.64	0.26	0.870	0.006	37.82	0.61	2.104	0.015
	17.75	0.30	15.45	0.26	0.871	0.007	37.40	0.60	2.107	0.016
	17.77	0.29	15.56	0.26	0.876	0.007	37.63	0.60	2.117	0.016
	17.90	0.29	15.56	0.26	0.870	0.006	37.79	0.60	2.112	0.015
	17.94	0.29	15.70	0.26	0.875	0.007	38.02	0.60	2.120	0.016
	17.95	0.29	15.61	0.26	0.870	0.006	37.93	0.60	2.113	0.017
	17.97	0.29	15.68	0.26	0.873	0.006	37.96	0.60	2.112	0.015
	17.91	0.28	15.66	0.25	0.874	0.007	37.82	0.57	2.111	0.016
	18.00	0.27	15.63	0.24	0.868	0.006	37.81	0.55	2.100	0.015
4640-24	17.54	0.29	15.47	0.25	0.882	0.009	36.55	0.74	2.084	0.034
	17.56	0.38	15.60	0.32	0.888	0.008	37.48	0.71	2.135	0.021
	17.17	0.29	15.31	0.29	0.892	0.007	36.11	0.69	2.103	0.019
	17.33	0.26	15.42	0.27	0.890	0.008	36.54	0.65	2.109	0.024
	17.36	0.24	15.59	0.23	0.898	0.007	37.29	0.62	2.147	0.024
	17.47	0.25	15.55	0.24	0.890	0.007	36.59	0.60	2.095	0.019
	17.36	0.26	15.54	0.25	0.895	0.007	37.29	0.58	2.148	0.020
	17.38	0.26	15.50	0.24	0.892	0.007	37.17	0.58	2.138	0.018
	17.47	0.26	15.56	0.25	0.890	0.007	37.26	0.57	2.133	0.018
	17.40	0.26	15.58	0.25	0.895	0.008	37.20	0.56	2.137	0.018
	17.38	0.25	15.57	0.24	0.896	0.007	37.11	0.56	2.135	0.019
	17.34	0.26	15.48	0.27	0.893	0.008	37.23	0.56	2.148	0.020
	17.29	0.26	15.51	0.24	0.897	0.008	37.22	0.56	2.153	0.019
	17.34	0.27	15.53	0.25	0.896	0.008	37.34	0.55	2.153	0.019
	17.41	0.25	15.54	0.23	0.893	0.007	37.24	0.55	2.139	0.017
	17.41	0.27	15.57	0.24	0.894	0.008	37.43	0.55	2.150	0.020
	17.44	0.24	15.60	0.24	0.895	0.006	37.07	0.55	2.125	0.018
	17.30	0.25	15.38	0.23	0.889	0.007	36.74	0.55	2.123	0.017
	17.23	0.26	15.45	0.23	0.897	0.008	36.47	0.54	2.117	0.018
	17.41	0.26	15.57	0.24	0.894	0.008	36.92	0.54	2.120	0.019
	17.51	0.25	15.60	0.23	0.891	0.007	37.37	0.54	2.135	0.018
	17.40	0.24	15.53	0.22	0.892	0.007	36.77	0.54	2.113	0.017
	17.36	0.25	15.52	0.23	0.894	0.008	36.91	0.54	2.125	0.018
	17.50	0.25	15.55	0.24	0.889	0.007	37.03	0.54	2.116	0.019
	17.32	0.25	15.41	0.23	0.890	0.007	36.46	0.53	2.105	0.017
	17.28	0.25	15.46	0.23	0.894	0.007	36.76	0.53	2.127	0.017
	17.33	0.25	15.45	0.23	0.891	0.007	36.56	0.53	2.109	0.017
	17.40	0.25	15.62	0.23	0.898	0.007	36.91	0.52	2.121	0.017
	17.32	0.26	15.40	0.23	0.889	0.007	36.96	0.52	2.134	0.018
	17.22	0.24	15.37	0.22	0.893	0.007	36.60	0.52	2.126	0.016
	17.42	0.25	15.60	0.23	0.895	0.007	36.89	0.52	2.118	0.017
	17.33	0.25	15.49	0.23	0.894	0.007	37.15	0.52	2.144	0.016
	17.32	0.25	15.53	0.23	0.896	0.007	36.98	0.52	2.135	0.017
	17.42	0.25	15.54	0.23	0.892	0.007	36.40	0.52	2.090	0.017
	17.34	0.24	15.51	0.23	0.894	0.007	36.77	0.52	2.120	0.017
	17.36	0.25	15.57	0.23	0.897	0.008	36.92	0.51	2.127	0.018
	17.35	0.25	15.47	0.23	0.892	0.008	37.03	0.51	2.134	0.018
	17.41	0.25	15.56	0.23	0.894	0.007	37.52	0.51	2.155	0.017
	17.27	0.24	15.44	0.22	0.894	0.007	36.49	0.51	2.113	0.016
	17.46	0.24	15.66	0.22	0.897	0.007	36.88	0.50	2.112	0.016
	17.38	0.24	15.50	0.23	0.892	0.006	36.55	0.50	2.104	0.016
	18.06	0.61	15.61	0.52	0.865	0.013	37.43	1.23	2.073	0.031
	17.89	0.50	15.60	0.44	0.872	0.013	37.80	1.03	2.113	0.037
	17.88	0.44	15.60	0.39	0.872	0.010	37.59	1.03	2.103	0.027
	17.63	0.43	15.20	0.38	0.863	0.010	36.61	0.88	2.077	0.025
	18.11	0.41	15.65	0.39	0.864	0.010	37.73	0.84	2.084	0.023
	18.39	0.40	15.96	0.35	0.868	0.011	38.73	0.83	2.106	0.026
	17.97	0.39	15.55	0.34	0.865	0.009	37.84	0.82	2.106	0.021
	18.07	0.38	15.77	0.34	0.873	0.009	38.41	0.80	2.126	0.021
	18.09	0.36	15.77	0.34	0.872	0.007	37.91	0.78	2.096	0.020

4640-25	18.04	0.38	15.59	0.33	0.864	0.009	37.59	0.78	2.083	0.022
	17.90	0.37	15.65	0.33	0.875	0.008	37.72	0.76	2.107	0.018
	18.14	0.39	15.73	0.33	0.867	0.008	38.04	0.75	2.097	0.023
	18.19	0.34	15.80	0.32	0.869	0.007	38.21	0.74	2.100	0.018
	18.36	0.37	15.96	0.31	0.869	0.008	38.67	0.73	2.106	0.017
	18.22	0.35	15.80	0.31	0.867	0.007	38.15	0.71	2.094	0.016
	18.10	0.35	15.64	0.31	0.864	0.007	37.83	0.71	2.090	0.017
	18.01	0.34	15.62	0.30	0.867	0.007	38.01	0.70	2.110	0.018
	18.07	0.34	15.72	0.30	0.870	0.006	38.12	0.70	2.109	0.016
	18.03	0.35	15.59	0.30	0.865	0.006	37.81	0.69	2.097	0.017
	18.24	0.34	15.96	0.30	0.875	0.007	38.44	0.69	2.108	0.018
	17.99	0.33	15.60	0.29	0.867	0.007	37.62	0.68	2.091	0.015
	17.96	0.32	15.54	0.29	0.865	0.007	37.65	0.68	2.096	0.018
	18.38	0.33	15.91	0.29	0.866	0.006	38.53	0.67	2.096	0.015
	17.98	0.33	15.66	0.29	0.871	0.007	37.96	0.67	2.111	0.017
	18.19	0.32	15.84	0.29	0.871	0.006	38.37	0.67	2.110	0.015
	18.06	0.33	15.74	0.29	0.871	0.007	38.00	0.67	2.104	0.016
	17.99	0.32	15.62	0.29	0.868	0.007	37.81	0.66	2.102	0.017
	17.97	0.32	15.60	0.28	0.868	0.007	37.98	0.66	2.114	0.016
	18.04	0.32	15.67	0.28	0.869	0.007	38.06	0.66	2.110	0.016
	17.98	0.33	15.63	0.28	0.870	0.007	37.83	0.66	2.104	0.017
	18.03	0.32	15.66	0.28	0.869	0.006	37.91	0.65	2.102	0.016
	18.03	0.32	15.79	0.28	0.876	0.006	37.99	0.65	2.107	0.015
	18.03	0.32	15.67	0.28	0.869	0.006	37.87	0.65	2.100	0.015
	18.02	0.33	15.72	0.28	0.872	0.007	38.10	0.65	2.114	0.015
	17.91	0.32	15.64	0.29	0.873	0.007	37.79	0.65	2.110	0.015
	17.81	0.32	15.54	0.28	0.873	0.006	37.56	0.65	2.109	0.016
	18.04	0.32	15.71	0.28	0.871	0.007	37.84	0.65	2.098	0.016
	17.87	0.33	15.55	0.28	0.870	0.007	37.58	0.64	2.103	0.017
	18.04	0.32	15.65	0.28	0.867	0.007	37.80	0.64	2.095	0.019
	18.15	0.31	15.75	0.28	0.868	0.006	38.12	0.64	2.100	0.015
	18.00	0.30	15.68	0.27	0.871	0.006	37.99	0.62	2.111	0.016
	18.01	0.30	15.64	0.26	0.868	0.007	37.70	0.60	2.093	0.017
4640-26	18.40	0.33	15.68	0.28	0.852	0.009	38.46	0.66	2.090	0.022
	18.32	0.26	15.77	0.27	0.861	0.009	38.49	0.61	2.101	0.023
	18.37	0.26	15.70	0.23	0.854	0.006	38.45	0.56	2.093	0.016
	18.30	0.26	15.68	0.23	0.857	0.006	38.32	0.55	2.095	0.015
	18.33	0.27	15.65	0.24	0.854	0.006	38.23	0.54	2.086	0.016
	18.16	0.27	15.47	0.23	0.852	0.006	37.82	0.54	2.083	0.015
	18.26	0.27	15.62	0.24	0.856	0.007	38.22	0.54	2.094	0.017
	18.28	0.27	15.62	0.23	0.855	0.006	38.19	0.54	2.090	0.016
	18.26	0.27	15.65	0.23	0.857	0.006	38.22	0.53	2.093	0.015
	18.37	0.27	15.76	0.23	0.858	0.006	38.46	0.53	2.094	0.015
	18.27	0.26	15.66	0.23	0.857	0.006	38.24	0.53	2.093	0.015
	18.38	0.27	15.72	0.24	0.856	0.006	38.38	0.53	2.089	0.015
	18.28	0.26	15.64	0.23	0.856	0.006	38.22	0.53	2.091	0.016
	18.30	0.26	15.61	0.23	0.853	0.006	38.34	0.53	2.095	0.015
	18.32	0.26	15.67	0.23	0.855	0.006	38.32	0.53	2.091	0.015
	18.21	0.26	15.54	0.23	0.854	0.007	38.04	0.53	2.089	0.016
	18.29	0.26	15.62	0.23	0.854	0.006	38.17	0.53	2.086	0.015
	18.26	0.26	15.63	0.23	0.856	0.006	38.11	0.53	2.087	0.016
	18.36	0.26	15.69	0.23	0.855	0.006	38.51	0.53	2.097	0.015
	18.23	0.26	15.63	0.23	0.857	0.006	38.15	0.53	2.092	0.015
	18.31	0.26	15.69	0.23	0.857	0.006	38.21	0.53	2.087	0.015
	18.22	0.26	15.59	0.23	0.856	0.006	38.01	0.53	2.086	0.015
	18.24	0.26	15.59	0.23	0.855	0.006	38.12	0.52	2.089	0.015
	18.28	0.26	15.61	0.23	0.854	0.007	38.14	0.52	2.086	0.016
	18.27	0.26	15.68	0.23	0.858	0.006	38.22	0.52	2.092	0.015
	18.31	0.26	15.67	0.23	0.856	0.006	38.24	0.52	2.089	0.016
	18.25	0.26	15.59	0.23	0.854	0.006	38.07	0.52	2.086	0.015
	18.31	0.26	15.57	0.23	0.850	0.006	38.21	0.52	2.086	0.015
	18.29	0.26	15.62	0.23	0.854	0.006	38.21	0.52	2.089	0.016
	18.31	0.26	15.68	0.23	0.856	0.006	38.20	0.52	2.086	0.015
	18.33	0.26	15.65	0.23	0.854	0.006	38.35	0.51	2.092	0.015
	18.21	0.26	15.54	0.22	0.854	0.006	38.00	0.51	2.087	0.015
4640-27	18.02	0.40	15.73	0.34	0.873	0.009	37.54	0.79	2.083	0.020
	17.80	0.43	15.54	0.36	0.873	0.008	37.26	0.79	2.093	0.018
	17.74	0.37	15.60	0.33	0.880	0.008	37.16	0.76	2.095	0.022
	17.95	0.38	15.68	0.31	0.874	0.007	37.68	0.75	2.100	0.018
	17.95	0.41	15.77	0.32	0.879	0.007	37.61	0.74	2.096	0.019
	17.78	0.36	15.63	0.32	0.879	0.007	37.36	0.74	2.101	0.015
	17.74	0.36	15.55	0.31	0.877	0.007	37.21	0.71	2.098	0.016
	17.93	0.35	15.61	0.30	0.871	0.007	37.46	0.70	2.090	0.017
	17.96	0.35	15.81	0.31	0.880	0.007	37.72	0.70	2.100	0.016
	17.93	0.34	15.70	0.31	0.876	0.007	37.55	0.69	2.094	0.015
	17.89	0.34	15.76	0.31	0.881	0.007	37.50	0.69	2.095	0.017
	17.68	0.33	15.61	0.30	0.883	0.008	37.45	0.69	2.118	0.016
	17.68	0.34	15.45	0.31	0.874	0.007	37.21	0.68	2.104	0.016
	17.85	0.34	15.61	0.29	0.874	0.008	37.34	0.68	2.092	0.017
	17.77	0.33	15.52	0.29	0.873	0.007	37.06	0.67	2.086	0.016
	17.78	0.33	15.63	0.29	0.879	0.007	37.40	0.67	2.103	0.015
	17.76	0.33	15.57	0.29	0.876	0.007	37.12	0.67	2.090	0.017
	17.77	0.33	15.53	0.29	0.874	0.006	37.16	0.67	2.092	0.017
	17.70	0.34	15.52	0.29	0.877	0.007	37.09	0.66	2.096	0.016
	17.75	0.32	15.51	0.28	0.874	0.008	37.10	0.65	2.091	0.020
	17.80	0.31	15.56	0.28	0.874	0.007	37.21	0.63	2.091	0.018
	17.82	0.34	15.48	0.30	0.869	0.009	37.58	0.77	2.108	0.024

4640-28	18.00	0.31	15.64	0.28	0.869	0.009	37.93	0.64	2.107	0.021
	17.96	0.28	15.62	0.25	0.870	0.007	37.88	0.59	2.109	0.020
	17.95	0.29	15.64	0.25	0.871	0.006	37.89	0.58	2.111	0.016
	18.01	0.29	15.63	0.26	0.868	0.006	37.88	0.57	2.104	0.015
	18.01	0.28	15.65	0.25	0.869	0.007	37.90	0.57	2.104	0.016
	18.01	0.27	15.63	0.24	0.868	0.006	37.89	0.56	2.104	0.015
	18.00	0.28	15.69	0.25	0.872	0.006	37.99	0.56	2.111	0.015
	18.11	0.27	15.75	0.25	0.869	0.006	38.28	0.56	2.113	0.015
	17.94	0.28	15.61	0.24	0.870	0.006	37.78	0.56	2.106	0.015
	17.83	0.27	15.55	0.24	0.872	0.006	37.64	0.55	2.111	0.015
	17.88	0.27	15.54	0.25	0.869	0.006	37.53	0.55	2.099	0.015
	17.90	0.27	15.54	0.24	0.868	0.006	37.59	0.55	2.100	0.015
	17.92	0.27	15.60	0.24	0.871	0.006	37.80	0.55	2.110	0.015
	17.93	0.27	15.61	0.24	0.870	0.006	37.83	0.55	2.109	0.015
	17.98	0.27	15.63	0.24	0.869	0.006	37.84	0.55	2.105	0.015
	17.82	0.27	15.52	0.24	0.871	0.006	37.69	0.55	2.115	0.015
	17.85	0.27	15.50	0.24	0.868	0.006	37.53	0.55	2.103	0.015
	18.00	0.27	15.68	0.24	0.871	0.006	38.05	0.54	2.114	0.015
	17.95	0.27	15.58	0.24	0.868	0.006	37.80	0.54	2.105	0.015
	17.98	0.27	15.64	0.24	0.870	0.006	37.91	0.54	2.109	0.015
4640-30	17.01	0.26	15.59	0.26	0.916	0.008	36.69	0.60	2.157	0.019
	16.92	0.25	15.52	0.25	0.918	0.008	36.39	0.58	2.151	0.019
	16.80	0.24	15.42	0.23	0.918	0.007	36.59	0.55	2.178	0.017
	16.89	0.24	15.57	0.24	0.922	0.008	36.65	0.55	2.170	0.022
	16.84	0.25	15.50	0.24	0.920	0.007	36.86	0.55	2.189	0.016
	16.89	0.24	15.48	0.23	0.917	0.007	36.79	0.54	2.179	0.017
	16.85	0.24	15.46	0.23	0.918	0.007	36.42	0.53	2.162	0.017
	16.89	0.25	15.50	0.23	0.918	0.008	36.90	0.52	2.185	0.018
	16.84	0.24	15.50	0.23	0.921	0.007	36.81	0.52	2.186	0.016
	16.91	0.24	15.52	0.24	0.918	0.007	36.53	0.52	2.160	0.018
	16.86	0.24	15.50	0.23	0.919	0.007	36.79	0.51	2.182	0.017
	16.91	0.23	15.53	0.22	0.919	0.007	36.62	0.50	2.166	0.016
4640-31	18.72	0.45	15.95	0.38	0.852	0.008	38.61	0.89	2.062	0.018
	18.76	0.40	15.74	0.34	0.839	0.010	38.38	0.81	2.046	0.025
	18.57	0.36	15.72	0.31	0.847	0.008	38.17	0.73	2.056	0.017
	18.68	0.35	15.95	0.30	0.854	0.007	38.60	0.71	2.067	0.015
	18.47	0.35	15.70	0.31	0.850	0.008	38.17	0.70	2.067	0.018
	18.77	0.35	15.98	0.30	0.851	0.007	38.89	0.70	2.071	0.017
	18.64	0.34	16.00	0.29	0.858	0.007	38.70	0.66	2.076	0.016
	18.69	0.33	15.95	0.28	0.853	0.006	38.64	0.66	2.068	0.015
	18.70	0.35	15.84	0.28	0.847	0.007	38.47	0.65	2.057	0.016
	18.63	0.31	15.90	0.27	0.853	0.006	38.57	0.63	2.070	0.015
	18.45	0.31	15.75	0.27	0.854	0.006	38.15	0.61	2.068	0.015
	18.50	0.31	15.77	0.27	0.853	0.006	38.19	0.61	2.065	0.015
	18.51	0.29	15.79	0.26	0.853	0.006	38.39	0.59	2.074	0.015
4640-33	17.52	0.30	15.62	0.27	0.892	0.006	37.59	0.62	2.145	0.016
	17.27	0.30	15.38	0.27	0.890	0.006	36.89	0.61	2.136	0.015
	17.51	0.29	15.66	0.27	0.894	0.006	37.51	0.61	2.142	0.015
	17.41	0.29	15.57	0.27	0.894	0.006	37.26	0.60	2.140	0.015
	17.42	0.30	15.55	0.27	0.892	0.006	37.37	0.60	2.145	0.015
4640-36	17.90	1.52	16.55	1.22	0.925	0.018	38.58	3.26	2.155	0.050
	15.86	0.58	14.21	0.91	0.896	0.031	32.68	1.96	2.060	0.063
	17.20	0.44	15.94	0.59	0.927	0.017	37.53	1.22	2.182	0.033
	17.04	0.29	15.58	0.27	0.914	0.010	37.75	0.97	2.215	0.055
	17.03	0.29	15.62	0.28	0.917	0.009	37.29	0.72	2.189	0.024
	16.81	0.28	15.26	0.28	0.908	0.007	36.08	0.67	2.146	0.019
	17.13	0.40	15.73	0.33	0.918	0.009	37.37	0.66	2.181	0.025
	16.85	0.26	15.48	0.25	0.918	0.009	35.91	0.64	2.131	0.024
	16.84	0.34	15.49	0.27	0.920	0.011	35.96	0.63	2.136	0.028
	16.96	0.26	15.49	0.27	0.913	0.008	36.74	0.62	2.166	0.022
	17.00	0.26	15.48	0.25	0.911	0.008	37.09	0.61	2.182	0.020
	16.92	0.25	15.45	0.25	0.913	0.008	36.84	0.61	2.177	0.022
	16.93	0.25	15.54	0.24	0.918	0.007	36.79	0.59	2.173	0.019
	16.85	0.25	15.50	0.25	0.920	0.008	36.98	0.58	2.194	0.020
	17.03	0.25	15.54	0.24	0.913	0.008	37.05	0.57	2.176	0.020
	16.99	0.25	15.62	0.24	0.920	0.008	37.31	0.57	2.197	0.019
	16.92	0.27	15.53	0.25	0.918	0.009	36.82	0.57	2.177	0.021
	16.98	0.26	15.50	0.26	0.913	0.009	36.47	0.56	2.148	0.024
	16.95	0.25	15.54	0.25	0.917	0.008	36.85	0.55	2.175	0.020
	16.96	0.26	15.57	0.25	0.918	0.008	37.11	0.55	2.187	0.020
	17.07	0.26	15.69	0.24	0.919	0.008	37.30	0.54	2.185	0.020
	17.01	0.25	15.59	0.24	0.916	0.008	37.14	0.53	2.183	0.020
	16.92	0.24	15.57	0.23	0.920	0.007	36.88	0.53	2.179	0.016
	17.02	0.25	15.51	0.24	0.911	0.008	36.79	0.53	2.161	0.021
	16.95	0.25	15.51	0.23	0.915	0.008	36.60	0.53	2.160	0.019
	16.90	0.25	15.48	0.24	0.916	0.008	36.67	0.52	2.170	0.020
	16.94	0.25	15.51	0.23	0.916	0.007	36.94	0.52	2.181	0.018
	17.08	0.24	15.64	0.22	0.916	0.007	36.80	0.51	2.155	0.016
	16.93	0.24	15.55	0.22	0.919	0.007	36.91	0.51	2.181	0.017
	16.96	0.23	15.57	0.22	0.918	0.007	36.77	0.50	2.168	0.016
	16.97	0.24	15.53	0.23	0.915	0.007	36.84	0.50	2.171	0.017
	16.98	0.24	15.53	0.23	0.915	0.007	36.63	0.50	2.158	0.016
	16.95	0.23	15.55	0.22	0.917	0.007	36.70	0.49	2.165	0.016
	16.98	0.24	15.52	0.22	0.914	0.007	36.68	0.49	2.160	0.016
	17.50	0.34	15.45	0.32	0.883	0.008	36.93	0.75	2.110	0.024
	17.86	0.32	15.62	0.28	0.874	0.008	37.60	0.68	2.105	0.021
	17.78	0.31	15.62	0.27	0.878	0.006	37.47	0.63	2.107	0.016

	4640-39	17.89	0.31	15.63	0.27	0.874	0.007	37.57	0.62	2.100	0.015
		17.81	0.31	15.51	0.27	0.871	0.007	37.50	0.62	2.105	0.015
		17.83	0.30	15.52	0.27	0.871	0.006	37.49	0.61	2.103	0.015
		17.77	0.32	15.51	0.27	0.873	0.007	37.19	0.61	2.092	0.017
		17.73	0.30	15.51	0.27	0.875	0.007	37.20	0.61	2.098	0.016
		17.87	0.29	15.70	0.26	0.879	0.006	37.73	0.60	2.111	0.015
		17.65	0.29	15.45	0.26	0.875	0.006	37.17	0.60	2.106	0.015
		18.01	0.30	15.68	0.26	0.871	0.007	37.78	0.60	2.097	0.017
		17.80	0.29	15.63	0.26	0.878	0.007	37.44	0.59	2.104	0.015
		17.77	0.29	15.51	0.26	0.873	0.006	37.15	0.58	2.091	0.016
	4640-40	17.11	0.26	15.45	0.25	0.903	0.008	36.83	0.63	2.152	0.022
		17.11	0.27	15.53	0.26	0.908	0.007	37.17	0.62	2.173	0.018
		17.13	0.25	15.50	0.25	0.905	0.007	36.96	0.62	2.158	0.019
		17.07	0.29	15.49	0.27	0.907	0.007	36.89	0.61	2.161	0.017
		17.07	0.25	15.55	0.27	0.911	0.008	36.66	0.60	2.148	0.019
		16.92	0.28	15.41	0.26	0.910	0.008	36.74	0.60	2.171	0.018
		17.22	0.27	15.68	0.25	0.911	0.008	37.40	0.59	2.171	0.019
		17.13	0.29	15.56	0.25	0.909	0.007	36.97	0.58	2.159	0.020
		17.14	0.27	15.51	0.25	0.905	0.007	36.93	0.57	2.155	0.016
		17.16	0.27	15.55	0.25	0.906	0.007	37.11	0.57	2.163	0.018
		17.06	0.28	15.45	0.25	0.905	0.007	36.90	0.56	2.163	0.017
		17.16	0.26	15.57	0.25	0.908	0.007	36.99	0.56	2.156	0.016
		16.90	0.26	15.36	0.25	0.909	0.008	36.65	0.55	2.168	0.018
		17.14	0.26	15.54	0.24	0.907	0.007	37.06	0.55	2.162	0.016
		17.08	0.26	15.50	0.24	0.908	0.007	36.83	0.55	2.157	0.017
		17.11	0.25	15.48	0.23	0.905	0.007	36.97	0.54	2.161	0.018
		17.14	0.25	15.55	0.24	0.908	0.007	37.08	0.54	2.164	0.016
		17.14	0.26	15.58	0.24	0.909	0.007	37.11	0.53	2.165	0.016
		17.08	0.25	15.46	0.23	0.905	0.007	36.88	0.52	2.159	0.016
	4644-2	17.13	0.24	15.53	0.23	0.907	0.007	36.95	0.51	2.157	0.016
		17.13	0.24	15.56	0.23	0.908	0.007	37.02	0.50	2.160	0.016
		18.30	0.33	15.84	0.29	0.866	0.008	38.36	0.67	2.097	0.020
		18.04	0.31	15.62	0.28	0.866	0.007	38.12	0.64	2.113	0.018
		18.07	0.31	15.57	0.26	0.862	0.007	37.94	0.64	2.100	0.016
		18.24	0.31	15.78	0.28	0.865	0.007	38.34	0.64	2.101	0.016
		17.96	0.31	15.55	0.27	0.866	0.007	37.88	0.63	2.108	0.017
		18.15	0.31	15.71	0.27	0.866	0.006	38.11	0.62	2.100	0.016
		18.13	0.29	15.68	0.25	0.865	0.007	38.14	0.61	2.104	0.019
		18.00	0.30	15.55	0.27	0.864	0.008	37.62	0.61	2.090	0.019
		18.07	0.30	15.64	0.26	0.866	0.007	38.07	0.60	2.107	0.017
		17.96	0.29	15.53	0.26	0.865	0.006	37.90	0.60	2.110	0.015
		18.18	0.29	15.72	0.26	0.865	0.006	38.15	0.59	2.098	0.015
		18.14	0.28	15.65	0.26	0.863	0.006	38.17	0.59	2.104	0.016
		18.01	0.29	15.52	0.25	0.862	0.006	37.68	0.58	2.092	0.015
		18.03	0.29	15.55	0.26	0.862	0.006	37.91	0.58	2.102	0.015
		18.07	0.29	15.65	0.26	0.866	0.007	37.96	0.58	2.101	0.016
		18.09	0.28	15.61	0.24	0.863	0.006	38.06	0.57	2.104	0.016
		18.08	0.29	15.63	0.25	0.864	0.006	38.04	0.57	2.104	0.015
		18.26	0.28	15.76	0.25	0.863	0.007	38.39	0.57	2.102	0.016
		18.15	0.28	15.77	0.25	0.869	0.007	38.46	0.57	2.118	0.016
		18.11	0.28	15.67	0.25	0.865	0.006	38.02	0.56	2.099	0.015
		18.21	0.27	15.67	0.24	0.860	0.006	38.34	0.56	2.105	0.015
		18.02	0.27	15.60	0.24	0.866	0.007	37.99	0.55	2.108	0.016
	4644-5	18.07	0.30	15.66	0.27	0.866	0.007	38.10	0.63	2.108	0.018
		18.12	0.31	15.70	0.27	0.867	0.006	38.07	0.62	2.101	0.015
		18.09	0.32	15.74	0.27	0.870	0.007	38.11	0.61	2.106	0.016
		17.94	0.30	15.54	0.26	0.866	0.007	37.71	0.60	2.102	0.016
		18.03	0.31	15.64	0.27	0.868	0.006	37.98	0.60	2.106	0.015
		18.21	0.30	15.78	0.26	0.866	0.006	38.44	0.60	2.111	0.015
		18.09	0.31	15.71	0.26	0.868	0.006	38.18	0.60	2.111	0.015
		18.27	0.29	15.80	0.26	0.865	0.006	38.13	0.60	2.086	0.015
		18.13	0.29	15.68	0.26	0.865	0.006	38.20	0.60	2.107	0.015
		17.97	0.30	15.59	0.27	0.868	0.006	37.67	0.60	2.097	0.015
		18.03	0.29	15.62	0.26	0.866	0.006	37.94	0.60	2.105	0.015
		18.11	0.30	15.71	0.26	0.868	0.007	38.13	0.60	2.105	0.016
		18.03	0.29	15.67	0.26	0.869	0.006	38.02	0.60	2.109	0.015
		17.92	0.30	15.55	0.26	0.868	0.006	37.67	0.60	2.103	0.016
		17.99	0.30	15.57	0.27	0.866	0.006	37.87	0.59	2.106	0.015
		17.96	0.30	15.63	0.26	0.870	0.006	37.89	0.59	2.110	0.015
		17.86	0.29	15.48	0.26	0.867	0.006	37.47	0.58	2.099	0.015
	4644-10	18.00	0.30	15.62	0.26	0.868	0.006	37.86	0.58	2.103	0.015
		18.14	0.28	15.72	0.25	0.866	0.006	38.11	0.58	2.100	0.015
		17.88	0.29	15.58	0.25	0.871	0.006	37.71	0.57	2.110	0.015
		17.98	0.29	15.62	0.27	0.869	0.008	37.97	0.65	2.112	0.019
		17.99	0.26	15.69	0.24	0.872	0.007	37.99	0.58	2.112	0.018
		17.89	0.27	15.65	0.24	0.875	0.007	37.82	0.56	2.114	0.017
		17.93	0.26	15.59	0.24	0.870	0.006	37.74	0.55	2.105	0.016
		17.91	0.27	15.60	0.23	0.871	0.006	37.71	0.55	2.106	0.015
		17.91	0.27	15.61	0.24	0.872	0.006	37.76	0.54	2.108	0.015
		17.83	0.27	15.55	0.24	0.872	0.006	37.70	0.54	2.115	0.016
		17.91	0.27	15.65	0.24	0.874	0.007	37.90	0.54	2.116	0.016
		18.05	0.26	15.74	0.24	0.872	0.007	38.23	0.53	2.118	0.017
		18.13	0.26	15.79	0.24	0.871	0.007	38.21	0.53	2.107	0.016
		18.00	0.26	15.69	0.23	0.872	0.006	37.98	0.53	2.110	0.015
		17.98	0.26	15.69	0.23	0.873	0.006	38.06	0.53	2.117	0.015
		18.02	0.27	15.67	0.23	0.870	0.006	38.10	0.53	2.114	0.015
		17.94	0.26	15.63	0.23	0.871	0.006	37.88	0.53	2.112	0.015

	18.01	0.26	15.65	0.23	0.869	0.006	38.01	0.52	2.111	0.015
	17.94	0.26	15.60	0.23	0.870	0.006	37.81	0.52	2.108	0.015
	17.98	0.26	15.66	0.23	0.871	0.006	37.98	0.52	2.112	0.015
	17.96	0.26	15.67	0.23	0.873	0.006	38.00	0.52	2.116	0.015
	17.88	0.26	15.57	0.23	0.871	0.006	37.64	0.51	2.105	0.015
4644-11	18.40	0.54	15.95	0.43	0.866	0.007	38.28	0.92	2.080	0.018
	17.79	0.47	15.57	0.42	0.875	0.010	37.61	0.88	2.114	0.025
	17.75	0.30	15.48	0.26	0.872	0.007	37.36	0.60	2.106	0.015
	17.79	0.29	15.48	0.26	0.870	0.006	37.37	0.60	2.100	0.015
	17.88	0.29	15.61	0.26	0.873	0.007	37.92	0.59	2.121	0.018
	17.84	0.29	15.65	0.26	0.878	0.006	37.66	0.59	2.111	0.015
	17.85	0.28	15.55	0.25	0.871	0.006	37.65	0.58	2.109	0.015
	18.00	0.28	15.76	0.26	0.875	0.006	38.06	0.58	2.114	0.015
	17.91	0.28	15.64	0.25	0.873	0.006	37.67	0.58	2.103	0.015
	17.89	0.28	15.51	0.25	0.867	0.007	37.35	0.57	2.088	0.016
	17.83	0.28	15.53	0.25	0.871	0.006	37.60	0.56	2.109	0.015
	17.94	0.28	15.64	0.25	0.872	0.006	37.76	0.56	2.105	0.015
	17.70	0.28	15.48	0.25	0.874	0.006	37.24	0.56	2.104	0.015
4644-13	17.86	0.29	15.64	0.26	0.876	0.006	37.95	0.60	2.125	0.016
	17.98	0.29	15.72	0.26	0.874	0.006	38.10	0.59	2.119	0.016
	18.06	0.29	15.81	0.26	0.875	0.006	38.27	0.59	2.119	0.016
	17.89	0.29	15.60	0.25	0.872	0.006	37.78	0.58	2.112	0.015
	17.94	0.28	15.68	0.25	0.874	0.006	38.04	0.58	2.120	0.015
	17.84	0.29	15.59	0.25	0.874	0.006	37.78	0.58	2.118	0.015
	17.79	0.28	15.55	0.25	0.874	0.006	37.74	0.58	2.121	0.015
	18.00	0.28	15.68	0.25	0.871	0.006	38.00	0.57	2.112	0.015
	17.77	0.28	15.59	0.25	0.877	0.006	37.81	0.57	2.128	0.015
	17.77	0.28	15.53	0.25	0.874	0.006	37.75	0.57	2.124	0.015
	17.84	0.28	15.56	0.25	0.872	0.006	37.79	0.57	2.119	0.015
	17.86	0.28	15.66	0.25	0.876	0.006	37.96	0.57	2.125	0.015
	17.83	0.28	15.60	0.25	0.875	0.006	37.82	0.57	2.121	0.015
	17.72	0.28	15.53	0.25	0.876	0.006	37.70	0.57	2.127	0.015
	17.93	0.28	15.66	0.25	0.873	0.006	38.04	0.57	2.122	0.015
	17.83	0.28	15.54	0.25	0.871	0.006	37.73	0.56	2.116	0.015
	17.88	0.28	15.65	0.25	0.876	0.006	37.98	0.56	2.125	0.015
4644-20	17.60	0.31	16.05	0.39	0.912	0.025	39.17	1.17	2.226	0.065
	17.77	0.29	15.35	0.39	0.864	0.018	36.75	0.96	2.068	0.045
	17.51	0.32	15.45	0.32	0.882	0.007	36.68	0.82	2.096	0.022
	17.61	0.29	15.44	0.30	0.877	0.008	37.18	0.80	2.112	0.024
	17.70	0.29	15.58	0.28	0.880	0.007	37.16	0.69	2.100	0.020
	17.73	0.26	15.60	0.27	0.880	0.007	37.55	0.66	2.118	0.024
	17.55	0.30	15.46	0.28	0.881	0.007	37.27	0.65	2.123	0.018
	17.80	0.27	15.65	0.25	0.880	0.009	38.01	0.63	2.136	0.021
	17.85	0.26	15.74	0.25	0.882	0.007	37.79	0.62	2.117	0.019
	17.69	0.26	15.59	0.26	0.881	0.007	37.15	0.60	2.100	0.021
	17.70	0.25	15.46	0.24	0.873	0.007	37.09	0.59	2.096	0.019
	17.77	0.26	15.63	0.24	0.880	0.007	37.81	0.58	2.128	0.018
	17.73	0.27	15.54	0.27	0.877	0.008	37.44	0.58	2.112	0.021
	17.71	0.27	15.59	0.26	0.880	0.007	37.65	0.58	2.125	0.020
	17.66	0.26	15.55	0.23	0.881	0.007	37.69	0.54	2.134	0.017
4644-23	16.68	0.55	14.47	0.42	0.867	0.019	34.74	1.11	2.082	0.053
	17.43	0.25	15.92	0.36	0.913	0.015	38.42	0.89	2.204	0.039
	17.45	0.31	15.45	0.33	0.885	0.010	36.92	0.78	2.115	0.032
	17.31	0.30	15.47	0.27	0.894	0.011	37.23	0.75	2.151	0.033
	17.43	0.30	15.57	0.27	0.893	0.010	37.46	0.63	2.150	0.024
	17.45	0.28	15.74	0.26	0.902	0.009	37.75	0.62	2.163	0.021
	17.45	0.26	15.65	0.25	0.897	0.008	37.46	0.60	2.147	0.019
	17.46	0.25	15.65	0.24	0.896	0.007	37.61	0.60	2.154	0.018
	17.37	0.25	15.60	0.25	0.898	0.007	37.41	0.59	2.154	0.019
	17.50	0.27	15.68	0.25	0.896	0.008	37.51	0.59	2.144	0.018
	17.41	0.28	15.58	0.25	0.895	0.007	37.39	0.59	2.147	0.017
	17.45	0.26	15.57	0.24	0.892	0.008	37.36	0.58	2.140	0.018
	17.50	0.26	15.72	0.24	0.898	0.008	37.56	0.57	2.146	0.020
	17.50	0.25	15.79	0.26	0.902	0.007	37.66	0.57	2.152	0.017
	17.48	0.28	15.73	0.25	0.900	0.008	37.83	0.57	2.164	0.020
	17.23	0.27	15.45	0.25	0.897	0.009	37.08	0.57	2.152	0.021
	17.39	0.26	15.52	0.24	0.892	0.007	37.21	0.56	2.139	0.017
	17.28	0.26	15.48	0.24	0.896	0.008	37.56	0.56	2.174	0.020
	17.26	0.25	15.46	0.23	0.896	0.007	37.20	0.55	2.156	0.020
	17.40	0.25	15.60	0.23	0.897	0.007	37.56	0.55	2.159	0.018
	17.35	0.26	15.61	0.24	0.900	0.007	37.60	0.54	2.168	0.018
	17.51	0.26	15.67	0.24	0.895	0.008	37.62	0.54	2.148	0.019
	17.34	0.25	15.49	0.23	0.893	0.008	37.13	0.54	2.141	0.018
	17.32	0.26	15.50	0.23	0.895	0.007	37.34	0.54	2.156	0.018
	17.32	0.26	15.57	0.24	0.899	0.008	37.39	0.53	2.158	0.018
	17.52	0.25	15.69	0.23	0.896	0.007	37.58	0.53	2.145	0.016
	17.42	0.26	15.63	0.24	0.898	0.007	37.52	0.53	2.154	0.016
	17.37	0.25	15.52	0.23	0.893	0.007	37.05	0.53	2.133	0.018
	17.39	0.25	15.57	0.23	0.895	0.007	37.42	0.52	2.152	0.017
	17.43	0.25	15.55	0.23	0.892	0.007	37.25	0.52	2.137	0.016
	17.41	0.25	15.64	0.23	0.898	0.007	37.44	0.52	2.151	0.017
	17.46	0.25	15.61	0.23	0.894	0.007	37.44	0.52	2.144	0.018
	17.45	0.25	15.59	0.23	0.894	0.007	37.38	0.52	2.142	0.017
	17.45	0.25	15.63	0.23	0.896	0.007	37.37	0.51	2.142	0.017
	17.46	0.25	15.62	0.23	0.895	0.007	37.15	0.51	2.128	0.017
	17.43	0.24	15.61	0.23	0.895	0.006	37.40	0.51	2.145	0.016
	17.67	0.25	15.13	0.30	0.856	0.014	36.94	0.80	2.091	0.039

		4644-24	17.67	0.26	15.60	0.25	0.883	0.008	37.75	0.59	2.137	0.019
			17.69	0.27	15.66	0.25	0.885	0.007	37.84	0.56	2.139	0.018
			17.73	0.25	15.63	0.23	0.882	0.007	37.56	0.55	2.118	0.016
			17.61	0.27	15.55	0.24	0.883	0.008	37.51	0.55	2.129	0.019
			17.73	0.25	15.68	0.23	0.885	0.006	37.89	0.54	2.137	0.015
			17.75	0.26	15.67	0.23	0.883	0.007	37.80	0.54	2.129	0.016
			17.80	0.25	15.67	0.23	0.880	0.006	37.55	0.52	2.110	0.015
			17.61	0.25	15.52	0.23	0.881	0.007	37.37	0.51	2.121	0.016
			17.75	0.25	15.68	0.23	0.884	0.006	37.72	0.51	2.126	0.016
			17.67	1.51	14.46	1.06	0.818	0.028	34.56	2.54	1.955	0.066
AuNat	Natural Au		18.85	11.99	16.62	11.93	0.882	0.122	38.54	23.76	2.045	0.271
			18.15	18.22	16.35	11.08	0.901	0.178	42.71	18.61	2.353	0.334
			17.36	6.40	16.98	5.47	0.978	0.078	40.36	13.46	2.324	0.172
			22.34	6.04	15.57	4.67	0.697	0.099	40.32	12.29	1.804	0.161
			17.27	7.31	16.37	5.29	0.948	0.150	37.94	12.13	2.197	0.284
			16.12	5.64	15.98	4.79	0.992	0.160	37.45	11.75	2.323	0.281
			18.37	4.96	16.29	5.77	0.887	0.156	41.17	11.47	2.241	0.335
			22.69	9.72	17.61	4.56	0.776	0.094	41.09	11.09	1.811	0.281
			21.10	6.46	16.30	3.88	0.772	0.087	39.81	10.56	1.887	0.197
			16.83	5.43	14.54	4.16	0.864	0.107	35.92	10.23	2.134	0.360
			19.53	6.80	15.83	4.70	0.810	0.081	38.75	10.08	1.984	0.256
			17.89	8.93	17.76	5.07	0.993	0.186	36.07	10.01	2.016	0.210
			18.98	8.58	16.54	4.43	0.872	0.124	37.34	9.65	1.967	0.178
			16.35	5.85	14.63	4.71	0.895	0.145	29.33	9.40	1.794	0.315
			17.06	4.17	16.02	3.82	0.939	0.102	36.79	8.67	2.157	0.268
			19.74	4.31	17.16	3.55	0.869	0.100	41.73	8.57	2.114	0.238
			18.97	4.91	18.38	6.95	0.969	0.265	33.00	8.39	1.740	0.231
			14.37	6.00	14.81	4.07	1.031	0.150	29.55	8.08	2.056	0.232
			18.01	4.98	16.48	3.32	0.915	0.088	38.64	7.70	2.145	0.205
			15.32	2.81	12.13	2.37	0.792	0.088	28.07	7.22	1.833	0.260
			11.49	3.81	10.17	2.88	0.885	0.334	23.49	7.16	2.044	0.515
			16.54	7.70	15.36	3.99	0.929	0.087	35.39	6.92	2.140	0.205
			16.21	7.34	14.59	2.81	0.900	0.084	33.45	6.90	2.064	0.165
			15.58	3.49	12.43	3.04	0.798	0.056	29.92	6.85	1.920	0.114
			18.17	3.02	12.79	2.16	0.704	0.068	33.33	6.46	1.834	0.171
			15.91	3.37	13.68	3.06	0.860	0.094	32.13	6.29	2.019	0.181
			20.55	3.16	18.34	2.63	0.893	0.110	43.98	6.15	2.141	0.244
			17.15	2.69	15.50	2.06	0.904	0.081	36.03	6.15	2.101	0.215
			13.41	3.00	13.26	3.00	0.989	0.094	25.83	5.83	1.927	0.298
			15.26	2.89	11.38	2.15	0.746	0.071	29.73	5.81	1.948	0.141
			12.44	2.94	13.15	2.91	1.057	0.114	30.32	5.74	2.437	0.252
			19.13	2.28	16.43	1.88	0.859	0.051	39.75	5.56	2.078	0.084
			16.10	2.86	13.36	2.38	0.830	0.059	31.49	5.56	1.956	0.150
			16.28	2.48	14.30	2.27	0.878	0.058	34.57	5.41	2.124	0.119
			16.43	2.33	11.83	1.53	0.720	0.039	29.55	5.36	1.799	0.103
			15.69	2.66	15.19	1.91	0.968	0.061	37.27	5.16	2.375	0.226
			15.88	2.70	13.87	2.19	0.873	0.041	34.97	5.13	2.202	0.115
			18.95	2.82	15.96	2.25	0.842	0.047	36.10	5.04	1.904	0.118
			16.29	2.24	15.73	2.17	0.966	0.050	35.64	4.86	2.188	0.123
			20.38	2.08	16.13	1.92	0.791	0.036	38.08	4.72	1.869	0.136
			16.17	2.37	13.82	2.22	0.855	0.047	34.76	4.71	2.150	0.161
			15.67	3.76	12.82	2.28	0.818	0.067	30.11	4.66	1.921	0.126
			18.13	2.63	14.04	1.94	0.774	0.049	35.46	4.65	1.955	0.135
			13.40	1.68	13.05	1.89	0.974	0.031	30.73	4.57	2.293	0.096
			14.17	1.89	12.95	1.82	0.914	0.065	30.07	4.39	2.123	0.149
			15.06	2.32	14.11	1.84	0.937	0.080	32.85	4.28	2.182	0.179
			18.14	1.74	16.12	2.64	0.889	0.072	37.69	4.25	2.077	0.128
			21.35	2.59	16.20	1.44	0.759	0.032	40.05	4.24	1.876	0.087
			16.46	1.97	15.50	1.85	0.942	0.044	35.57	4.21	2.162	0.107
			12.70	2.22	10.31	1.62	0.812	0.068	29.40	4.07	2.315	0.214
			12.06	2.03	11.50	1.72	0.954	0.060	25.49	4.02	2.114	0.142
			17.98	2.13	14.32	1.49	0.796	0.050	33.89	3.99	1.885	0.103
			20.11	1.70	15.80	1.51	0.786	0.048	38.79	3.93	1.929	0.120
			16.42	2.45	12.87	2.15	0.784	0.108	22.89	3.91	1.394	0.181
			19.07	2.07	15.35	1.31	0.805	0.039	38.89	3.90	2.039	0.092
			15.05	2.20	11.39	1.73	0.756	0.058	26.22	3.86	1.742	0.122
			14.27	1.95	13.05	1.71	0.914	0.090	29.38	3.83	2.058	0.151
			17.40	2.61	15.36	1.62	0.883	0.038	37.17	3.80	2.136	0.064
			16.05	1.48	14.12	1.24	0.880	0.034	32.90	3.76	2.050	0.122
			15.95	1.71	15.22	1.57	0.954	0.047	37.24	3.69	2.335	0.168
			16.36	2.19	13.01	1.69	0.795	0.079	31.97	3.65	1.954	0.092
			15.59	1.58	14.23	1.43	0.913	0.038	33.44	3.33	2.145	0.104
			19.87	1.90	16.55	1.51	0.833	0.035	38.65	3.29	1.945	0.080
			16.74	1.66	14.76	1.54	0.882	0.058	32.77	3.24	1.957	0.101
			16.64	1.82	15.31	1.66	0.920	0.039	29.96	3.21	1.800	0.171
			14.98	2.26	12.72	1.45	0.849	0.041	28.25	3.18	1.886	0.078
			13.28	1.39	12.98	1.28	0.978	0.052	31.88	3.12	2.402	0.140
			19.87	2.00	15.47	1.36	0.779	0.039	37.74	2.99	1.900	0.108
			16.09	1.51	15.92	1.37	0.989	0.049	36.51	2.89	2.268	0.102
			18.71	1.61	14.72	0.89	0.787	0.040	36.67	2.75	1.961	0.109
			16.90	1.28	15.77	1.09	0.933	0.043	36.80	2.55	2.177	0.100
			16.58	1.34	13.67	1.01	0.824	0.039	31.42	2.36	1.895	0.091
			15.68	1.23	14.32	1.10	0.913	0.039	34.03	2.33	2.170	0.091
			16.77	1.09	15.39	0.87	0.917	0.023	35.76	2.26	2.132	0.064
			15.99	0.72	15.35	0.77	0.960	0.020	22.63	2.23	1.415	0.125
			18.48	1.33	14.22	0.91	0.769	0.031	36.08	2.17	1.953	0.061
			14.13	1.03	13.88	0.86	0.982	0.039	31.20	2.10	2.207	0.085

		14.49	0.91	14.07	0.93	0.971	0.026	31.69	2.01	2.187	0.070
		13.42	1.09	13.63	1.01	1.016	0.040	31.61	2.01	2.356	0.102
		13.92	0.81	13.67	0.83	0.982	0.022	31.76	1.97	2.282	0.067
		14.02	1.09	13.62	0.82	0.971	0.056	30.39	1.95	2.167	0.136
		15.07	1.07	14.14	0.99	0.938	0.056	29.39	1.92	1.950	0.077
		15.90	0.86	15.48	1.02	0.973	0.042	34.95	1.73	2.198	0.087
		14.18	1.31	12.75	1.05	0.899	0.051	31.41	1.69	2.214	0.124
		19.23	0.88	14.60	0.63	0.759	0.020	36.58	1.49	1.902	0.051
		15.84	0.71	15.01	0.68	0.947	0.026	33.98	1.47	2.145	0.069
		19.58	0.70	15.14	0.56	0.774	0.016	38.46	1.17	1.965	0.043
		15.91	0.43	15.41	0.46	0.969	0.017	36.07	1.04	2.267	0.071
		16.25	0.43	15.62	0.30	0.961	0.019	36.57	0.92	2.251	0.038
		15.82	0.46	15.44	0.41	0.976	0.015	35.12	0.86	2.220	0.044
		16.09	0.24	15.76	0.26	0.980	0.012	36.17	0.71	2.248	0.038
		16.21	0.18	15.32	0.19	0.945	0.008	35.13	0.49	2.167	0.032

Table S3. Results on the AMALIA algorithm comparing the differences between average lead isotope ratios of natural gold grains and processed gold bars

		Difference 206Pb/204Pb			Difference 207Pb/204Pb			Difference 208Pb/204Pb			Overall result on the 204 triplet		
		Dif. AuNat-Samp.	Avg. Uncer.	Dif.<= Unc.	Dif. AuNat-Samp.	Avg. Uncer.	Dif.<= Unc.	Dif. AuNat-Samp.	Avg. Uncer.	Dif.<= Unc.	Triplet match		Sample (>40%)
D1	2285-1	3.30	7.75	MATCH	1.51	4.32	MATCH	4.56	15.24	MATCH	MATCH	MATCH	
		0.90	4.13	MATCH	1.26	4.32	MATCH	2.14	9.47	MATCH	MATCH		
		2.68	3.04	MATCH	1.19	2.46	MATCH	1.55	6.07	MATCH	MATCH		
		0.88	3.17	MATCH	0.72	2.61	MATCH	0.37	6.05	MATCH	MATCH		
		0.87	3.32	MATCH	0.58	2.69	MATCH	0.80	5.94	MATCH	MATCH		
		1.15	3.48	MATCH	2.14	2.91	MATCH	4.76	5.75	MATCH	MATCH		
		1.87	3.37	MATCH	0.24	3.14	MATCH	0.29	5.66	MATCH	MATCH		
		0.24	7.42	MATCH	0.25	3.08	MATCH	0.49	5.51	MATCH	MATCH		
		0.48	2.92	MATCH	0.24	2.20	MATCH	0.02	5.50	MATCH	MATCH		
		0.79	3.13	MATCH	1.24	2.39	MATCH	0.63	5.46	MATCH	MATCH		
		0.57	4.64	MATCH	0.15	2.46	MATCH	0.29	4.99	MATCH	MATCH		
		0.58	2.81	MATCH	1.21	2.19	MATCH	3.28	4.90	MATCH	MATCH		
		2.87	3.34	MATCH	0.54	2.24	MATCH	3.31	4.87	MATCH	MATCH		
		0.05	2.55	MATCH	0.07	2.07	MATCH	0.96	4.75	MATCH	MATCH		
		3.78	2.62	-	2.42	2.06	-	5.48	4.57	-	-		
		1.06	2.55	MATCH	0.31	2.02	MATCH	0.04	4.52	MATCH	MATCH		
		0.85	2.42	MATCH	1.29	1.99	MATCH	2.86	4.34	MATCH	MATCH		
		1.25	4.72	MATCH	0.69	2.29	MATCH	0.54	4.30	MATCH	MATCH		
		1.08	2.29	MATCH	2.66	1.85	-	5.36	4.15	-	-		
		0.22	2.38	MATCH	0.19	1.74	MATCH	1.19	4.10	MATCH	MATCH		
D2	2285-3	0.38	10.85	MATCH	1.13	5.57	MATCH	3.75	10.17	MATCH	MATCH	MATCH	
		3.42	3.29	-	2.81	3.43	MATCH	5.37	8.58	MATCH	-		
		2.64	3.98	MATCH	0.66	3.34	MATCH	2.05	7.25	MATCH	MATCH		
		1.26	3.65	MATCH	2.00	2.94	MATCH	6.19	6.26	MATCH	MATCH		
		0.36	2.94	MATCH	0.41	2.47	MATCH	1.77	5.69	MATCH	MATCH		
		0.71	2.90	MATCH	0.39	2.36	MATCH	3.50	5.56	MATCH	MATCH		
		0.57	2.93	MATCH	1.70	2.32	MATCH	3.26	5.43	MATCH	MATCH		
		0.22	2.72	MATCH	1.15	2.23	MATCH	2.28	5.17	MATCH	MATCH		
		3.04	2.84	-	1.99	2.29	MATCH	5.69	5.12	-	-		
		0.94	2.53	MATCH	1.10	2.16	MATCH	2.07	4.87	MATCH	MATCH		
		0.05	2.54	MATCH	1.05	2.12	MATCH	2.55	4.81	MATCH	MATCH		
		1.82	2.48	MATCH	0.88	1.99	MATCH	1.51	4.61	MATCH	MATCH		
		0.20	2.54	MATCH	1.00	2.18	MATCH	2.57	4.56	MATCH	MATCH		
		1.39	4.39	MATCH	1.10	2.49	MATCH	4.38	4.53	MATCH	MATCH		
		0.62	2.54	MATCH	0.77	1.97	MATCH	2.22	4.47	MATCH	MATCH		
		0.82	2.44	MATCH	1.92	2.04	MATCH	4.70	4.43	-	-		
		0.32	2.36	MATCH	1.46	1.95	MATCH	2.35	4.37	MATCH	MATCH		
		0.43	2.33	MATCH	1.23	1.91	MATCH	2.10	4.29	MATCH	MATCH		
		1.73	2.43	MATCH	0.92	1.88	MATCH	1.09	4.25	MATCH	MATCH		
		0.26	2.33	MATCH	0.63	1.99	MATCH	1.10	4.25	MATCH	MATCH		
		1.35	2.25	MATCH	0.18	1.77	MATCH	0.50	4.12	MATCH	MATCH		
		1.88	2.40	MATCH	0.99	1.88	MATCH	1.33	4.11	MATCH	MATCH		
		0.77	2.37	MATCH	0.76	1.97	MATCH	2.32	4.09	MATCH	MATCH		
		0.49	2.15	MATCH	1.34	1.79	MATCH	2.92	4.03	MATCH	MATCH		
		0.99	2.24	MATCH	0.06	1.77	MATCH	0.11	4.00	MATCH	MATCH		
		0.24	2.23	MATCH	0.71	1.76	MATCH	2.07	3.95	MATCH	MATCH		
		0.15	2.14	MATCH	0.91	1.75	MATCH	1.62	3.93	MATCH	MATCH		
		0.36	2.10	MATCH	1.10	1.70	MATCH	2.46	3.83	MATCH	MATCH		
		0.28	2.15	MATCH	0.68	1.69	MATCH	1.98	3.78	MATCH	MATCH		
		0.77	2.13	MATCH	0.22	1.72	MATCH	0.43	3.78	MATCH	MATCH		
		0.14	2.10	MATCH	0.85	1.66	MATCH	1.86	3.77	MATCH	MATCH		
		1.33	2.08	MATCH	0.26	1.68	MATCH	0.22	3.76	MATCH	MATCH		
		0.63	2.07	MATCH	1.03	1.68	MATCH	1.00	3.74	MATCH	MATCH		
		0.15	2.03	MATCH	1.33	1.66	MATCH	2.82	3.72	MATCH	MATCH		
		1.04	2.01	MATCH	0.33	1.64	MATCH	0.80	3.68	MATCH	MATCH		
		0.07	2.07	MATCH	1.38	1.64	MATCH	2.66	3.68	MATCH	MATCH		
		0.17	1.98	MATCH	0.92	1.60	MATCH	1.62	3.58	MATCH	MATCH		
		0.58	1.94	MATCH	0.65	1.56	MATCH	2.01	3.52	MATCH	MATCH		
		0.42	1.94	MATCH	0.57	1.56	MATCH	1.25	3.50	MATCH	MATCH		
		0.20	1.96	MATCH	0.81	1.57	MATCH	1.76	3.49	MATCH	MATCH		
		0.56	1.99	MATCH	0.83	1.54	MATCH	1.93	3.45	MATCH	MATCH		
		0.57	1.91	MATCH	0.57	1.53	MATCH	1.34	3.43	MATCH	MATCH		
		1.09	1.93	MATCH	0.45	1.53	MATCH	0.50	3.37	MATCH	MATCH		
		0.33	1.86	MATCH	0.70	1.48	MATCH	1.72	3.33	MATCH	MATCH		
		0.74	1.87	MATCH	0.52	1.47	MATCH	0.44	3.28	MATCH	MATCH		
		1.15	1.86	MATCH	0.13	1.46	MATCH	0.07	3.24	MATCH	MATCH		
		0.74	1.82	MATCH	0.54	1.45	MATCH	0.94	3.24	MATCH	MATCH		
		0.43	1.79	MATCH	0.92	1.42	MATCH	1.71	3.17	MATCH	MATCH		
D3	2285-5	0.22	1.83	MATCH	0.81	1.52	MATCH	2.29	3.37	MATCH	MATCH	MATCH	
		0.27	1.81	MATCH	0.80	1.45	MATCH	1.92	3.24	MATCH	MATCH		
		0.25	1.77	MATCH	0.82	1.41	MATCH	1.98	3.18	MATCH	MATCH		
		0.37	1.77	MATCH	0.93	1.41	MATCH	2.28	3.17	MATCH	MATCH		
		0.14	1.77	MATCH	1.02	1.41	MATCH	2.18	3.16	MATCH	MATCH		
		0.31	1.75	MATCH	0.73	1.40	MATCH	1.72	3.15	MATCH	MATCH		
		0.05	1.75	MATCH	1.15	1.38	MATCH	2.31	3.08	MATCH	MATCH		
		0.02	1.73	MATCH	1.06	1.35	MATCH	2.49	3.08	MATCH	MATCH		
		0.17	1.73	MATCH	0.97	1.37	MATCH	2.18	3.08	MATCH	MATCH		
		0.25	1.73	MATCH	0.90	1.37	MATCH	2.11	3.07	MATCH	MATCH		
		0.03	1.73	MATCH	1.09	1.37	MATCH	2.67	3.07	MATCH	MATCH		
		0.03	1.73	MATCH	0.95	1.37	MATCH	2.69	3.07	MATCH	MATCH		
		0.29	1.71	MATCH	0.87	1.36	MATCH	2.13	3.05	MATCH	MATCH		
		0.45	1.74	MATCH	0.64	1.37	MATCH	1.61	3.05	MATCH	MATCH		
		0.18	1.72	MATCH	0.81	1.36	MATCH	2.25	3.05	MATCH	MATCH		
		0.11	1.72	MATCH	1.08	1.36	MATCH	2.73	3.05	MATCH	MATCH		
		0.26	1.75	MATCH	1.00	1.37	MATCH	2.08	3.04	MATCH	MATCH		
		0.09	1.71	MATCH	1.02	1.35	MATCH	2.42	3.04	MATCH	MATCH		
		0.05	1.71	MATCH	1.07	1.35	MATCH	2.63	3.04	MATCH	MATCH		
		0.21	1.72	MATCH	0.97	1.35	MATCH	2.18	3.04	MATCH	MATCH		
		0.16	1.71	MATCH	1.07	1.35	MATCH	2.30	3.02	MATCH	MATCH		
		0.00	1.71	MATCH	1.08	1.35	MATCH	2.53	3.02	MATCH	MATCH		
		0.28	1.72	MATCH	0.80	1.35	MATCH	1.81	3.02	MATCH	MATCH		
		0.07	1.69	MATCH	1.01	1.34	MATCH	2.21	3.01	MATCH	MATCH		
		0.17	1.75	MATCH	0.97	1.36	MATCH	2.39	3.01	MATCH	MATCH		
		0.04	1.70	MATCH	1.23	1.35	MATCH	2.81	3.00	MATCH	MATCH		
		0.43	1.70	MATCH	0.65	1.34	MATCH	1.61	3.00	MATCH	MATCH		
		0.39	1.69	MATCH	0.68	1.33	MATCH	1.70	2.98	MATCH	MATCH		
		0.47	1.67	MATCH	0.73	1.33	MATCH	1.62	2.98	MATCH	MATCH		
		0.26	1.67	MATCH	0.82	1.32	MATCH	1.83	2.97	MATCH	MATCH		
		0.07	1.69	MATCH	1.00	1.33	MATCH	2.31	2.97	MATCH	MATCH		
		0.21	1.67	MATCH	0.92	1.32	MATCH	2.26	2.96	MATCH	MATCH		
		0.18	1.66	MATCH	0.94	1.32	MATCH	2.13	2.96	MATCH	MATCH		

		0.18	1.67	MATCH		0.80	1.32	MATCH		1.79	2.96	MATCH	MATCH	
		0.32	1.66	MATCH		0.81	1.31	MATCH		1.70	2.95	MATCH	MATCH	
		0.21	1.66	MATCH		0.81	1.31	MATCH		1.81	2.94	MATCH	MATCH	
		0.28	1.67	MATCH		0.83	1.31	MATCH		1.96	2.94	MATCH	MATCH	
		0.07	1.66	MATCH		0.96	1.31	MATCH		2.14	2.94	MATCH	MATCH	
		0.13	1.66	MATCH		0.93	1.31	MATCH		2.12	2.93	MATCH	MATCH	
		0.21	1.65	MATCH		0.78	1.31	MATCH		1.77	2.93	MATCH	MATCH	
		0.20	1.65	MATCH		0.92	1.31	MATCH		1.94	2.93	MATCH	MATCH	
		0.53	1.65	MATCH		0.67	1.31	MATCH		1.35	2.93	MATCH	MATCH	
		0.21	1.66	MATCH		0.86	1.31	MATCH		2.00	2.93	MATCH	MATCH	
		0.02	1.65	MATCH		1.05	1.31	MATCH		2.29	2.93	MATCH	MATCH	
		0.32	1.65	MATCH		0.74	1.30	MATCH		1.63	2.92	MATCH	MATCH	
		0.15	1.65	MATCH		0.97	1.30	MATCH		2.11	2.92	MATCH	MATCH	
		0.16	1.65	MATCH		0.92	1.30	MATCH		2.01	2.92	MATCH	MATCH	
		0.25	1.65	MATCH		0.85	1.30	MATCH		1.89	2.92	MATCH	MATCH	
		0.18	1.65	MATCH		0.94	1.30	MATCH		1.96	2.92	MATCH	MATCH	
		0.21	1.64	MATCH		0.83	1.30	MATCH		1.96	2.91	MATCH	MATCH	
		0.30	1.64	MATCH		0.81	1.30	MATCH		1.70	2.91	MATCH	MATCH	
		0.39	1.64	MATCH		0.74	1.30	MATCH		1.62	2.91	MATCH	MATCH	
		0.21	1.64	MATCH		0.85	1.29	MATCH		1.89	2.90	MATCH	MATCH	
D4	2285-7	0.50	5.75	MATCH		1.06	3.74	MATCH		3.62	7.40	MATCH	MATCH	MATCH
		0.49	3.16	MATCH		3.12	2.85	-		6.75	6.44	-	-	
		1.68	3.29	MATCH		1.51	2.70	MATCH		4.98	6.18	MATCH	MATCH	
		0.16	3.92	MATCH		0.76	2.67	MATCH		1.30	6.14	MATCH	MATCH	
		0.30	2.71	MATCH		1.20	2.47	MATCH		2.83	5.89	MATCH	MATCH	
		1.73	2.84	MATCH		0.37	2.35	MATCH		0.64	5.35	MATCH	MATCH	
		0.69	2.71	MATCH		0.35	2.22	MATCH		0.60	5.13	MATCH	MATCH	
		0.50	2.42	MATCH		1.89	1.95	MATCH		0.91	5.09	MATCH	MATCH	
		0.91	2.73	MATCH		1.54	2.28	MATCH		1.08	5.02	MATCH	MATCH	
		0.17	2.93	MATCH		0.96	2.15	MATCH		1.09	4.84	MATCH	MATCH	
		1.82	2.37	MATCH		0.00	1.95	MATCH		0.96	4.73	MATCH	MATCH	
		0.93	2.63	MATCH		0.33	2.14	MATCH		0.65	4.60	MATCH	MATCH	
		0.40	2.49	MATCH		0.37	2.01	MATCH		0.35	4.58	MATCH	MATCH	
		1.07	2.13	MATCH		0.15	1.66	MATCH		0.50	4.36	MATCH	MATCH	
		1.67	2.21	MATCH		2.87	1.83	-		9.17	4.35	-	-	
		1.35	2.40	MATCH		0.82	1.92	MATCH		1.53	4.34	MATCH	MATCH	
		1.90	2.16	MATCH		1.13	1.86	MATCH		3.98	4.29	MATCH	MATCH	
		0.31	2.28	MATCH		1.61	1.94	MATCH		3.42	4.29	MATCH	MATCH	
		1.61	2.35	MATCH		0.84	1.88	MATCH		2.27	4.22	MATCH	MATCH	
		0.58	2.42	MATCH		0.11	1.89	MATCH		1.47	4.20	MATCH	MATCH	
		1.21	2.42	MATCH		0.20	1.95	MATCH		0.62	4.19	MATCH	MATCH	
		1.04	2.30	MATCH		1.92	1.85	-		3.57	4.17	MATCH	-	
		0.08	2.26	MATCH		0.65	1.85	MATCH		2.12	4.17	MATCH	MATCH	
		2.17	2.27	MATCH		1.18	1.82	MATCH		2.27	4.11	MATCH	MATCH	
		0.62	2.24	MATCH		0.48	1.83	MATCH		1.98	4.09	MATCH	MATCH	
		2.59	2.29	-		1.59	1.84	MATCH		5.35	4.08	-	-	
		2.02	2.13	MATCH		0.13	1.79	MATCH		1.47	4.08	MATCH	MATCH	
		0.07	2.30	MATCH		0.68	1.83	MATCH		3.27	4.05	MATCH	MATCH	
		0.98	2.45	MATCH		0.19	1.84	MATCH		0.25	4.02	MATCH	MATCH	
		1.44	2.12	MATCH		0.13	1.71	MATCH		3.18	3.96	MATCH	MATCH	
		2.01	2.17	MATCH		1.36	1.73	MATCH		3.69	3.96	MATCH	MATCH	
		2.35	2.13	-		1.28	1.74	MATCH		0.51	3.94	MATCH	-	
		0.33	2.27	MATCH		0.16	1.85	MATCH		0.09	3.93	MATCH	MATCH	
		0.67	2.14	MATCH		0.30	1.75	MATCH		0.74	3.90	MATCH	MATCH	
		0.73	2.03	MATCH		1.61	1.67	MATCH		4.48	3.89	-	-	
		1.46	2.04	MATCH		0.14	1.67	MATCH		0.18	3.87	MATCH	MATCH	
		0.48	2.17	MATCH		1.33	1.73	MATCH		1.64	3.87	MATCH	MATCH	
		0.33	2.07	MATCH		0.79	1.65	MATCH		0.76	3.85	MATCH	MATCH	
		0.08	2.28	MATCH		0.83	1.82	MATCH		0.61	3.85	MATCH	MATCH	
		1.17	2.10	MATCH		1.68	1.65	-		4.26	3.84	-	-	
		0.43	2.15	MATCH		0.83	1.72	MATCH		3.67	3.81	MATCH	MATCH	
		2.79	2.14	-		2.10	1.74	-		5.73	3.80	-	-	
		0.62	2.09	MATCH		0.20	1.73	MATCH		3.01	3.79	MATCH	MATCH	
		0.25	2.01	MATCH		0.45	1.66	MATCH		1.22	3.77	MATCH	MATCH	
		1.41	2.08	MATCH		2.12	1.66	-		4.72	3.75	-	-	
		1.30	2.46	MATCH		0.27	1.76	MATCH		0.39	3.75	MATCH	MATCH	
		0.52	2.20	MATCH		0.67	1.61	MATCH		0.11	3.74	MATCH	MATCH	
		0.37	1.97	MATCH		0.14	1.55	MATCH		4.96	3.73	-	-	
		0.95	1.98	MATCH		0.06	1.64	MATCH		1.62	3.72	MATCH	MATCH	
		1.61	2.11	MATCH		0.05	1.73	MATCH		6.71	3.70	-	-	
		0.31	2.05	MATCH		0.39	1.63	MATCH		0.32	3.70	MATCH	MATCH	
		1.54	2.03	MATCH		0.40	1.64	MATCH		0.20	3.69	MATCH	MATCH	
		0.53	2.00	MATCH		0.11	1.69	MATCH		1.24	3.69	MATCH	MATCH	
		2.04	1.98	-		1.41	1.61	MATCH		4.21	3.68	-	-	
		0.46	2.05	MATCH		0.50	1.62	MATCH		1.21	3.68	MATCH	MATCH	
		2.85	2.07	-		1.78	1.70	-		3.94	3.67	-	-	
		0.52	1.98	MATCH		0.97	1.61	MATCH		3.30	3.65	MATCH	MATCH	
		0.36	2.02	MATCH		0.72	1.57	MATCH		1.42	3.65	MATCH	MATCH	
		1.16	1.93	MATCH		0.01	1.60	MATCH		1.49	3.64	MATCH	MATCH	
		1.09	2.06	MATCH		0.34	1.61	MATCH		0.30	3.64	MATCH	MATCH	
		1.60	2.08	MATCH		0.40	1.65	MATCH		1.31	3.63	MATCH	MATCH	
		1.91	1.98	MATCH		0.84	1.63	MATCH		0.86	3.61	MATCH	MATCH	
		0.31	2.01	MATCH		0.60	1.67	MATCH		0.76	3.61	MATCH	MATCH	
		1.79	2.04	MATCH		0.58	1.59	MATCH		2.02	3.61	MATCH	MATCH	
		0.11	2.01	MATCH		0.93	1.58	MATCH		1.39	3.58	MATCH	MATCH	
		1.28	1.93	MATCH		0.70	1.52	MATCH		2.98	3.58	MATCH	MATCH	
		1.14	1.93	MATCH		1.62	1.55	-		4.45	3.57	-	-	
		0.94	2.03	MATCH		0.61	1.58	MATCH		0.59	3.57	MATCH	MATCH	
		1.72	1.96	MATCH		0.13	1.57	MATCH		0.51	3.55	MATCH	MATCH	
		1.70	1.97	MATCH		0.66	1.59	MATCH		0.81	3.51	MATCH	MATCH	
		0.04	1.94	MATCH		0.89	1.55	MATCH		1.16	3.48	MATCH	MATCH	
		1.39	1.93	MATCH		0.34	1.56	MATCH		0.84	3.44	MATCH	MATCH	
		0.77	1.94	MATCH		0.20	1.57	MATCH		0.09	3.43	MATCH	MATCH	
		0.68	1.90	MATCH		0.39	1.50	MATCH		2.51	3.36	MATCH	MATCH	
		0.18	1.84	MATCH		0.37	1.45	MATCH		1.07	3.36	MATCH	MATCH	
		0.02	1.92	MATCH		0.55	1.49	MATCH		1.41	3.31	MATCH	MATCH	
		0.03	1.86	MATCH		0.45	1.46	MATCH		0.98	3.29	MATCH	MATCH	
4640-1		1.18	1.67	MATCH		0.72	1.28	MATCH		3.02	2.96	-	-	-
		1.35	1.66	MATCH		0.87	1.28	MATCH		3.51	2.94	-	-	
		1.24	1.66	MATCH		0.73	1.27	MATCH		2.96	2.94	-	-	
		1.37	1.66	MATCH		0.88	1.27	MATCH		3.40	2.94	-	-	
		1.26	1.66	MATCH		0.77	1.27	MATCH		3.22	2.94	-	-	
		1.39	1.66	MATCH		0.88	1.27	MATCH		3.47	2.93	-	-	
		1.19	1.66	MATCH		0.67	1.27	MATCH		2.98	2.93	-	-	
		1.37	1.65	MATCH		0.83	1.26	MATCH		2.95	2.93	-	-	

		1.43	1.65	MATCH		0.87	1.27	MATCH		2.82	2.93	MATCH		MATCH			
		1.38	1.65	MATCH		0.85	1.26	MATCH		3.41	2.92	-	-				
4640-2		1.41	2.07	MATCH		0.88	1.61	MATCH		2.65	3.46	MATCH		MATCH			
		0.02	1.69	MATCH		0.84	1.36	MATCH		1.67	3.11	MATCH		MATCH			
		1.47	1.69	MATCH		0.80	1.30	MATCH		3.66	2.99	-		-			
		1.25	1.67	MATCH		0.65	1.29	MATCH		3.08	2.96	-		-			
		0.06	1.68	MATCH		0.75	1.32	MATCH		2.18	2.95	MATCH		MATCH			
		1.45	1.67	MATCH		0.82	1.28	MATCH		3.51	2.95	-		-			
		1.38	1.67	MATCH		0.70	1.28	MATCH		3.06	2.95	-		-			
		0.00	1.68	MATCH		0.69	1.31	MATCH		2.29	2.95	MATCH		MATCH			
		1.35	1.67	MATCH		0.80	1.28	MATCH		3.24	2.95	-		-			
		0.09	1.68	MATCH		0.85	1.32	MATCH		2.21	2.94	MATCH		MATCH			
		0.04	1.68	MATCH		0.70	1.32	MATCH		1.96	2.94	MATCH		MATCH			
		1.29	1.67	MATCH		0.72	1.28	MATCH		2.95	2.94	-		-			
		1.39	1.66	MATCH		0.78	1.27	MATCH		3.40	2.94	-		-			
		1.34	1.66	MATCH		0.73	1.27	MATCH		3.38	2.94	-		-			
		1.31	1.66	MATCH		0.71	1.27	MATCH		3.23	2.94	-		-			
		1.42	1.66	MATCH		0.84	1.27	MATCH		3.68	2.94	-		-			
		1.47	1.66	MATCH		0.84	1.27	MATCH		3.51	2.93	-		-			
		1.40	1.65	MATCH		0.82	1.27	MATCH		3.34	2.93	-		-			
		1.40	1.66	MATCH		0.78	1.27	MATCH		3.41	2.93	-		-			
		0.85	1.68	MATCH		0.93	1.31	MATCH		3.44	2.93	-		-			
		1.40	1.66	MATCH		0.80	1.27	MATCH		3.45	2.93	-		-			
		1.22	1.66	MATCH		0.77	1.27	MATCH		3.11	2.93	-		-			
		1.47	1.66	MATCH		0.83	1.27	MATCH		3.62	2.93	-		-			
		1.39	1.66	MATCH		0.85	1.27	MATCH		3.29	2.93	-		-			
		0.01	1.67	MATCH		0.83	1.31	MATCH		2.32	2.92	MATCH		MATCH			
		0.85	1.67	MATCH		0.90	1.31	MATCH		3.25	2.92	-		-			
		0.86	1.67	MATCH		0.90	1.31	MATCH		3.32	2.92	-		-			
		0.02	1.67	MATCH		0.79	1.30	MATCH		1.98	2.92	MATCH		MATCH			
		0.83	1.67	MATCH		0.78	1.30	MATCH		3.14	2.91	-		-			
4640-3		1.05	1.73	MATCH		1.05	1.33	MATCH		5.10	3.04	-		-			
		0.98	1.67	MATCH		0.86	1.28	MATCH		3.98	2.99	-		-			
		0.98	1.65	MATCH		0.83	1.26	MATCH		4.10	2.94	-		-			
		0.92	1.65	MATCH		0.79	1.26	MATCH		4.08	2.93	-		-			
		0.89	1.65	MATCH		0.79	1.26	MATCH		4.13	2.93	-		-			
		0.93	1.65	MATCH		0.78	1.26	MATCH		4.06	2.93	-		-			
		1.00	1.65	MATCH		0.83	1.26	MATCH		4.11	2.93	-		-			
		0.96	1.65	MATCH		0.80	1.26	MATCH		3.91	2.93	-		-			
4640-7		0.93	1.65	MATCH		0.78	1.26	MATCH		4.28	2.93	-		-	MATCH		
		0.91	1.65	MATCH		0.77	1.26	MATCH		4.04	2.93	-		-			
		1.44	1.73	MATCH		1.04	1.36	MATCH		3.96	3.12	-		-			
		1.20	1.73	MATCH		0.89	1.36	MATCH		3.31	3.03	-		-			
		1.26	1.72	MATCH		0.86	1.35	MATCH		3.65	3.01	-		-			
		1.48	1.70	MATCH		1.16	1.33	MATCH		4.11	2.98	-		-			
		0.04	1.65	MATCH		0.80	1.27	MATCH		1.82	2.94	MATCH		MATCH			
		1.26	1.68	MATCH		0.90	1.31	MATCH		3.68	2.94	-		-			
		0.30	1.68	MATCH		1.02	1.30	MATCH		1.48	2.94	MATCH		MATCH			
		1.35	1.68	MATCH		0.98	1.31	MATCH		3.81	2.94	-		-			
		1.25	1.68	MATCH		0.90	1.31	MATCH		3.60	2.93	-		-			
		1.28	1.68	MATCH		0.91	1.31	MATCH		3.59	2.93	-		-			
		1.21	1.68	MATCH		0.85	1.31	MATCH		3.38	2.93	-		-			
		0.08	1.65	MATCH		0.84	1.27	MATCH		1.43	2.92	MATCH		MATCH			
		0.19	1.64	MATCH		0.61	1.26	MATCH		1.28	2.92	MATCH		MATCH			
		0.12	1.65	MATCH		0.89	1.27	MATCH		1.54	2.92	MATCH		MATCH			
	4640-8		0.08	1.65	MATCH		0.81	1.27	MATCH		1.26	2.91	MATCH			MATCH	MATCH
			0.11	1.65	MATCH		0.83	1.27	MATCH		1.26	2.91	MATCH			MATCH	
		0.06	1.64	MATCH		0.68	1.26	MATCH		1.15	2.91	MATCH		MATCH			
		0.25	1.64	MATCH		0.55	1.26	MATCH		1.08	2.91	MATCH		MATCH			
		0.01	1.65	MATCH		0.79	1.26	MATCH		1.19	2.91	MATCH		MATCH			
		0.07	1.64	MATCH		0.81	1.26	MATCH		1.35	2.91	MATCH		MATCH			
		0.00	1.64	MATCH		0.76	1.26	MATCH		1.28	2.91	MATCH		MATCH			
		0.18	1.64	MATCH		0.62	1.27	MATCH		1.02	2.91	MATCH		MATCH			
		0.18	1.64	MATCH		0.65	1.26	MATCH		1.13	2.90	MATCH		MATCH			
		0.19	1.64	MATCH		0.61	1.26	MATCH		1.08	2.90	MATCH		MATCH			
		0.27	1.64	MATCH		0.50	1.26	MATCH		0.97	2.90	MATCH		MATCH			
		0.21	1.64	MATCH		0.57	1.26	MATCH		0.97	2.90	MATCH		MATCH			
		0.41	1.64	MATCH		0.31	1.26	MATCH		0.95	2.90	MATCH		MATCH			
4640-9			0.04	1.69	MATCH		0.17	1.31	MATCH		0.88	3.00	MATCH		MATCH	MATCH	
		0.18	1.68	MATCH		0.23	1.30	MATCH		1.22	2.98	MATCH		MATCH			
		0.35	1.65	MATCH		0.47	1.27	MATCH		1.98	2.97	MATCH		MATCH			
		0.48	1.66	MATCH		0.59	1.29	MATCH		2.05	2.96	MATCH		MATCH			
		0.38	1.66	MATCH		0.51	1.28	MATCH		1.84	2.96	MATCH		MATCH			
		0.66	1.65	MATCH		0.78	1.27	MATCH		2.05	2.91	MATCH		MATCH			
		0.55	1.65	MATCH		0.76	1.27	MATCH		2.22	2.91	MATCH		MATCH			
		0.47	1.65	MATCH		0.62	1.27	MATCH		2.17	2.91	MATCH		MATCH			
		0.36	1.65	MATCH		0.47	1.26	MATCH		1.79	2.91	MATCH		MATCH			
		0.31	1.65	MATCH		0.36	1.27	MATCH		1.27	2.91	MATCH		MATCH			
		0.55	1.65	MATCH		0.67	1.26	MATCH		1.77	2.91	MATCH		MATCH			
		0.42	1.65	MATCH		0.54	1.26	MATCH		1.81	2.90	MATCH		MATCH			
		0.38	1.65	MATCH		0.57	1.26	MATCH		1.85	2.90	MATCH		MATCH	MATCH		
		0.48	1.65	MATCH		0.61	1.26	MATCH		1.97	2.90	MATCH		MATCH			
		0.78	1.70	MATCH		0.79	1.31	MATCH		2.28	2.99	MATCH		MATCH			
		0.68	1.66	MATCH		0.65	1.28	MATCH		2.03	2.95	MATCH		MATCH			
		0.68	1.65	MATCH		0.66	1.27	MATCH		2.05	2.93	MATCH		MATCH			
		0.80	1.65	MATCH		0.69	1.27	MATCH		1.93	2.93	MATCH		MATCH			
		0.72	1.65	MATCH		0.70	1.27	MATCH		2.31	2.92	MATCH		MATCH			
		0.81	1.65	MATCH		0.82	1.27	MATCH		2.34	2.92	MATCH		MATCH			
		0.74	1.65	MATCH		0.67	1.26	MATCH		1.96	2.92	MATCH		MATCH			
		0.74	1.65	MATCH		0.71	1.26	MATCH		2.41	2.92	MATCH		MATCH			
		0.84	1.65	MATCH		0.90	1.26	MATCH		3.22	2.91	-		-			
		0.76	1.65	MATCH		0.76	1.26	MATCH		2.42	2.91	MATCH		MATCH			
		0.80	1.65	MATCH		0.82	1.26	MATCH		2.89	2.91	MATCH		MATCH			
		0.79	1.65	MATCH		0.80	1.26	MATCH		2.69	2.91	MATCH		MATCH			
		0.75	1.65	MATCH		0.73	1.26	MATCH		2.10	2.91	MATCH		MATCH			
		0.73	1.65	MATCH		0.78	1.26	MATCH		2.58	2.91	MATCH		MATCH			
		0.82	1.65	MATCH		0.82	1.26	MATCH		2.69	2.91	MATCH		MATCH			
		0.76	1.65	MATCH		0.70	1.26	MATCH		2.23	2.90	MATCH		MATCH			
		1.51	1.79	MATCH		1.29	1.40	MATCH		4.68	3.16	-		-			
		0.65	1.79	MATCH		0.44	1.40	MATCH		2.75	3.16	MATCH		MATCH			
		1.73	1.77	MATCH		1.39	1.39	MATCH		4.75	3.12	-		-			
		1.20	1.77	MATCH		0.85	1.38	MATCH		3.76	3.08	-		-			
		1.44	1.75	MATCH		1.04	1.37	MATCH		4.03	3.08	-		-			
		1.41	1.75	MATCH		1.04	1.37	MATCH		4.14	3.08	-		-			
		1.35	1.75	MATCH		1.02	1.37	MATCH		4.02	3.07	-		-			

	4640-15	1.45	1.75	MATCH		1.12	1.37	MATCH		4.25	3.07	-		-	
		1.42	1.75	MATCH		1.02	1.34	MATCH		3.88	3.07	-		-	
		1.18	1.74	MATCH		0.88	1.36	MATCH		3.66	3.06	-		-	
		1.56	1.73	MATCH		1.15	1.36	MATCH		4.47	3.06	-		-	
		1.44	1.74	MATCH		1.21	1.36	MATCH		4.41	3.05	-		-	
		1.44	1.74	MATCH		1.24	1.36	MATCH		4.45	3.05	-		-	
		1.58	1.74	MATCH		1.31	1.36	MATCH		4.48	3.05	-		-	
		1.47	1.73	MATCH		1.21	1.36	MATCH		4.54	3.04	-		-	
		1.65	1.74	MATCH		1.30	1.35	MATCH		4.65	3.04	-		-	
		1.58	1.73	MATCH		1.28	1.35	MATCH		4.64	3.04	-		-	
		1.52	1.73	MATCH		1.17	1.35	MATCH		4.27	3.04	-		-	
		1.40	1.73	MATCH		1.05	1.35	MATCH		4.22	3.04	-		-	
		1.25	1.74	MATCH		1.07	1.35	MATCH		4.12	3.03	-		-	
		1.54	1.73	MATCH		1.14	1.35	MATCH		4.38	3.03	-		-	
		1.31	1.73	MATCH		0.98	1.35	MATCH		3.80	3.03	-		-	
		1.41	1.72	MATCH		1.03	1.35	MATCH		4.04	3.03	-		-	
		1.41	1.72	MATCH		1.11	1.35	MATCH		4.16	3.02	-		-	
		1.59	1.73	MATCH		1.26	1.35	MATCH		4.75	3.02	-		-	
		1.30	1.72	MATCH		0.98	1.34	MATCH		3.94	3.02	-		-	
		1.32	1.72	MATCH		0.95	1.34	MATCH		3.91	3.02	-		-	
		1.29	1.72	MATCH		1.00	1.34	MATCH		3.83	3.02	-		-	
		1.26	1.71	MATCH		0.94	1.34	MATCH		4.03	3.00	-		-	
		1.35	1.71	MATCH		1.01	1.34	MATCH		4.08	3.00	-		-	
		1.41	1.70	MATCH		1.06	1.33	MATCH		4.02	3.00	-		-	
		1.38	1.71	MATCH		0.98	1.34	MATCH		3.92	3.00	-		-	
		1.34	1.71	MATCH		1.04	1.33	MATCH		4.10	2.99	-		-	
		1.38	1.71	MATCH		1.08	1.33	MATCH		4.22	2.98	-		-	
		1.44	1.70	MATCH		1.21	1.33	MATCH		4.40	2.98	-		-	
		1.51	1.70	MATCH		1.04	1.32	MATCH		4.26	2.97	-		-	
	4640-17	1.23	1.70	MATCH		0.87	1.32	MATCH		3.73	2.98	-		-	
		1.28	1.68	MATCH		0.94	1.32	MATCH		3.25	2.97	-		-	
		1.38	1.69	MATCH		1.03	1.32	MATCH		3.91	2.96	-		-	
		1.31	1.68	MATCH		1.09	1.32	MATCH		3.54	2.95	-		-	
		1.28	1.68	MATCH		0.84	1.31	MATCH		3.65	2.94	-		-	
		1.37	1.68	MATCH		0.97	1.32	MATCH		3.77	2.94	-		-	
		1.42	1.69	MATCH		0.95	1.31	MATCH		3.86	2.94	-		-	
		1.28	1.69	MATCH		0.89	1.31	MATCH		3.77	2.94	-		-	
		1.47	1.68	MATCH		1.00	1.31	MATCH		3.25	2.93	-		-	
		1.36	1.68	MATCH		1.01	1.31	MATCH		3.93	2.93	-		-	
		1.32	1.68	MATCH		0.89	1.31	MATCH		3.71	2.93	-		-	
		1.23	1.68	MATCH		0.81	1.31	MATCH		3.56	2.93	-		-	
		1.49	1.68	MATCH		1.08	1.31	MATCH		3.56	2.93	-		-	
		1.31	1.68	MATCH		0.89	1.31	MATCH		3.72	2.92	-		-	
		1.34	1.67	MATCH		0.93	1.31	MATCH		3.72	2.92	-		-	
		1.33	1.68	MATCH		0.95	1.31	MATCH		3.75	2.92	-		-	
		1.31	1.68	MATCH		0.90	1.31	MATCH		3.64	2.92	-		-	
		1.40	1.68	MATCH		1.07	1.31	MATCH		3.69	2.92	-		-	
	4640-22	1.21	1.72	MATCH		0.89	1.33	MATCH		3.51	3.00	-		-	
		1.24	1.71	MATCH		0.99	1.33	MATCH		3.70	2.99	-		-	
		1.03	1.70	MATCH		0.75	1.33	MATCH		3.14	2.98	-		-	
		1.23	1.70	MATCH		1.01	1.33	MATCH		3.68	2.98	-		-	
		1.07	1.71	MATCH		0.79	1.33	MATCH		3.29	2.98	-		-	
		1.02	1.70	MATCH		0.83	1.33	MATCH		3.22	2.97	-		-	
		1.15	1.70	MATCH		0.82	1.33	MATCH		3.42	2.97	-		-	
		1.19	1.70	MATCH		0.90	1.32	MATCH		3.65	2.97	-		-	
		1.05	1.70	MATCH		0.81	1.32	MATCH		3.38	2.97	-		-	
		1.08	1.69	MATCH		0.88	1.32	MATCH		3.51	2.97	-		-	
		1.08	1.70	MATCH		0.78	1.32	MATCH		3.43	2.96	-		-	
		1.04	1.69	MATCH		0.80	1.32	MATCH		3.25	2.96	-		-	
		1.21	1.71	MATCH		0.92	1.32	MATCH		3.69	2.96	-		-	
		1.25	1.69	MATCH		0.92	1.32	MATCH		3.56	2.96	-		-	
		1.26	1.69	MATCH		0.95	1.32	MATCH		3.58	2.96	-		-	
		1.03	1.69	MATCH		0.76	1.32	MATCH		3.16	2.96	-		-	
		1.05	1.69	MATCH		0.88	1.32	MATCH		3.39	2.96	-		-	
		1.18	1.69	MATCH		0.88	1.32	MATCH		3.55	2.96	-		-	
		1.22	1.69	MATCH		1.01	1.32	MATCH		3.77	2.96	-		-	
		1.23	1.69	MATCH		0.92	1.32	MATCH		3.69	2.96	-		-	
		1.25	1.69	MATCH		0.99	1.32	MATCH		3.71	2.96	-		-	
		1.19	1.69	MATCH		0.97	1.32	MATCH		3.58	2.95	-		-	
		1.28	1.68	MATCH		0.94	1.31	MATCH		3.56	2.93	-		-	
	4640-24	0.82	1.69	MATCH		0.78	1.32	MATCH		2.31	3.03	MATCH		MATCH	
		0.84	1.73	MATCH		0.91	1.35	MATCH		3.23	3.01	-		-	
		0.45	1.69	MATCH		0.63	1.33	MATCH		1.86	3.01	MATCH		MATCH	
		0.61	1.68	MATCH		0.74	1.33	MATCH		2.29	2.98	MATCH		MATCH	
		0.64	1.67	MATCH		0.90	1.30	MATCH		3.04	2.97	-		-	
		0.75	1.67	MATCH		0.86	1.31	MATCH		2.35	2.96	MATCH		MATCH	
		0.64	1.67	MATCH		0.85	1.32	MATCH		3.04	2.95	-		-	
		0.66	1.67	MATCH		0.81	1.31	MATCH		2.93	2.95	MATCH		MATCH	
		0.75	1.68	MATCH		0.87	1.31	MATCH		3.01	2.95	-		-	
		0.68	1.67	MATCH		0.89	1.31	MATCH		2.96	2.94	-		-	
		0.66	1.67	MATCH		0.89	1.31	MATCH		2.86	2.94	MATCH		MATCH	
		0.62	1.68	MATCH		0.79	1.32	MATCH		2.99	2.94	-		-	
		0.57	1.67	MATCH		0.82	1.31	MATCH		2.97	2.94	-		-	
		0.62	1.68	MATCH		0.85	1.31	MATCH		3.10	2.94	-		-	
		0.69	1.67	MATCH		0.85	1.31	MATCH		3.00	2.93	-		-	
		0.69	1.68	MATCH		0.88	1.31	MATCH		3.19	2.93	-		-	
		0.72	1.67	MATCH		0.91	1.31	MATCH		2.82	2.93	MATCH		MATCH	
		0.58	1.67	MATCH		0.69	1.31	MATCH		2.49	2.93	MATCH		MATCH	
		0.51	1.68	MATCH		0.76	1.31	MATCH		2.23	2.93	MATCH		MATCH	
		0.69	1.68	MATCH		0.88	1.31	MATCH		2.68	2.93	MATCH		MATCH	
		0.79	1.67	MATCH		0.91	1.31	MATCH		3.13	2.93	-		-	
		0.68	1.67	MATCH		0.84	1.30	MATCH		2.52	2.93	MATCH		MATCH	
		0.64	1.67	MATCH		0.83	1.31	MATCH		2.66	2.93	MATCH		MATCH	
		0.78	1.67	MATCH		0.86	1.31	MATCH		2.79	2.93	MATCH		MATCH	
		0.60	1.67	MATCH		0.72	1.31	MATCH		2.22	2.93	MATCH		MATCH	
0.56		1.67	MATCH	0.77		1.30	MATCH	2.52		2.93	MATCH	MATCH			
0.61		1.67	MATCH	0.76		1.30	MATCH	2.32		2.92	MATCH	MATCH			
0.68		1.67	MATCH	0.93		1.31	MATCH	2.67		2.92	MATCH	MATCH			
0.60		1.68	MATCH	0.71		1.31	MATCH	2.72		2.92	MATCH	MATCH			
0.50		1.67	MATCH	0.68		1.30	MATCH	2.35		2.92	MATCH	MATCH			
0.70		1.67	MATCH	0.91		1.30	MATCH	2.65		2.92	MATCH	MATCH			
0.61		1.67	MATCH	0.80		1.31	MATCH	2.91		2.92	MATCH	MATCH			
0.60		1.67	MATCH	0.84		1.30	MATCH	2.74		2.92	MATCH	MATCH			
0.70	1.67	MATCH	0.85	1.30	MATCH	2.16	2.92	MATCH	MATCH						
0.62	1.67	MATCH	0.82	1.30	MATCH	2.53	2.92	MATCH	MATCH						

GRU1		0.64	1.67	MATCH		0.88	1.31	MATCH		2.67	2.92	MATCH		MATCH	
		0.63	1.67	MATCH		0.79	1.31	MATCH		2.79	2.92	MATCH		MATCH	
		0.69	1.67	MATCH		0.87	1.30	MATCH		3.28	2.91	-		-	
		0.54	1.67	MATCH		0.75	1.30	MATCH		2.24	2.91	MATCH		MATCH	
		0.74	1.67	MATCH		0.97	1.30	MATCH		2.63	2.91	MATCH		MATCH	
		0.65	1.67	MATCH		0.81	1.30	MATCH		2.31	2.91	MATCH		MATCH	
	4640-25	1.34	1.85	MATCH		0.92	1.45	MATCH		3.19	3.27	MATCH		MATCH	
		1.16	1.80	MATCH		0.91	1.41	MATCH		3.55	3.18	-		-	
		1.16	1.76	MATCH		0.91	1.38	MATCH		3.35	3.17	-		-	
		0.91	1.76	MATCH		0.52	1.38	MATCH		2.36	3.10	MATCH		MATCH	
		1.39	1.75	MATCH		0.96	1.39	MATCH		3.49	3.08	-		-	
		1.67	1.75	MATCH		1.27	1.37	MATCH		4.49	3.07	-		-	
		1.25	1.74	MATCH		0.86	1.36	MATCH		3.60	3.07	-		-	
		1.35	1.74	MATCH		1.09	1.36	MATCH		4.17	3.06	-		-	
		1.37	1.72	MATCH		1.08	1.36	MATCH		3.66	3.05	-		-	
		1.32	1.74	MATCH		0.90	1.36	MATCH		3.35	3.05	-		-	
		1.18	1.73	MATCH		0.96	1.35	MATCH		3.47	3.04	-		-	
		1.42	1.74	MATCH		1.04	1.36	MATCH		3.80	3.03	-		-	
		1.47	1.72	MATCH		1.11	1.35	MATCH		3.96	3.03	-		-	
		1.64	1.73	MATCH		1.27	1.35	MATCH		4.42	3.02	-		-	
		1.50	1.72	MATCH		1.11	1.34	MATCH		3.91	3.01	-		-	
		1.38	1.72	MATCH		0.95	1.34	MATCH		3.59	3.01	-		-	
		1.29	1.72	MATCH		0.93	1.34	MATCH		3.77	3.01	-		-	
		1.35	1.72	MATCH		1.03	1.34	MATCH		3.88	3.01	-		-	
		1.31	1.72	MATCH		0.90	1.34	MATCH		3.57	3.00	-		-	
		1.52	1.71	MATCH		1.27	1.34	MATCH		4.20	3.00	-		-	
		1.27	1.71	MATCH		0.91	1.34	MATCH		3.38	3.00	-		-	
		1.24	1.71	MATCH		0.85	1.33	MATCH		3.41	3.00	-		-	
		1.66	1.71	MATCH		1.22	1.34	MATCH		4.28	2.99	-		-	
		1.26	1.71	MATCH		0.97	1.33	MATCH		3.71	2.99	-		-	
		1.47	1.71	MATCH		1.15	1.33	MATCH		4.13	2.99	-		-	
		1.34	1.71	MATCH		1.05	1.33	MATCH		3.76	2.99	-		-	
		1.27	1.71	MATCH		0.93	1.33	MATCH		3.57	2.99	-		-	
		1.25	1.71	MATCH		0.91	1.33	MATCH		3.74	2.99	-		-	
		1.32	1.71	MATCH		0.99	1.33	MATCH		3.81	2.99	-		-	
		1.26	1.71	MATCH		0.94	1.33	MATCH		3.58	2.99	-		-	
		1.31	1.71	MATCH		0.97	1.33	MATCH		3.66	2.99	-		-	
		1.31	1.70	MATCH		1.10	1.33	MATCH		3.74	2.98	-		-	
		1.31	1.70	MATCH		0.98	1.33	MATCH		3.62	2.98	-		-	
		1.30	1.71	MATCH		1.03	1.33	MATCH		3.86	2.98	-		-	
		1.19	1.70	MATCH		0.95	1.34	MATCH		3.55	2.98	-		-	
		1.09	1.70	MATCH		0.85	1.33	MATCH		3.32	2.98	-		-	
		1.32	1.70	MATCH		1.02	1.33	MATCH		3.60	2.98	-		-	
		1.15	1.71	MATCH		0.86	1.33	MATCH		3.34	2.98	-		-	
		1.32	1.70	MATCH		0.96	1.33	MATCH		3.56	2.98	-		-	
		1.43	1.70	MATCH		1.06	1.33	MATCH		3.88	2.98	-		-	
		1.28	1.70	MATCH		0.99	1.33	MATCH		3.75	2.97	-		-	
		1.29	1.70	MATCH		0.95	1.32	MATCH		3.45	2.96	-		-	
	4640-26	1.68	1.71	MATCH		0.99	1.33	MATCH		4.21	2.99	-		-	
		1.60	1.68	MATCH		1.08	1.33	MATCH		4.24	2.97	-		-	
		1.65	1.68	MATCH		1.01	1.31	MATCH		4.21	2.94	-		-	
		1.58	1.67	MATCH		0.99	1.31	MATCH		4.08	2.93	-		-	
		1.61	1.68	MATCH		0.96	1.31	MATCH		3.98	2.93	-		-	
		1.44	1.68	MATCH		0.78	1.31	MATCH		3.58	2.93	-		-	
		1.54	1.68	MATCH		0.93	1.31	MATCH		3.98	2.93	-		-	
		1.56	1.68	MATCH		0.93	1.31	MATCH		3.95	2.93	-		-	
		1.54	1.68	MATCH		0.96	1.31	MATCH		3.98	2.93	-		-	
		1.65	1.68	MATCH		1.08	1.31	MATCH		4.22	2.93	-		-	
		1.55	1.68	MATCH		0.97	1.31	MATCH		4.00	2.93	-		-	
		1.66	1.68	MATCH		1.03	1.31	MATCH		4.14	2.92	-		-	
		1.56	1.68	MATCH		0.95	1.31	MATCH		3.98	2.92	-		-	
		1.58	1.68	MATCH		0.92	1.31	MATCH		4.09	2.92	-		-	
		1.60	1.68	MATCH		0.98	1.31	MATCH		4.08	2.92	-		-	
		1.49	1.68	MATCH		0.85	1.31	MATCH		3.80	2.92	-		-	
		1.57	1.68	MATCH		0.93	1.31	MATCH		3.92	2.92	-		-	
		1.54	1.68	MATCH		0.94	1.31	MATCH		3.86	2.92	-		-	
		1.64	1.68	MATCH		1.00	1.31	MATCH		4.27	2.92	-		-	
		1.51	1.68	MATCH		0.94	1.31	MATCH		3.91	2.92	-		-	
		1.59	1.68	MATCH		1.00	1.31	MATCH		3.97	2.92	-		-	
		1.50	1.68	MATCH		0.91	1.30	MATCH		3.76	2.92	-		-	
		1.52	1.68	MATCH		0.90	1.31	MATCH		3.87	2.92	-		-	
		1.56	1.68	MATCH		0.92	1.31	MATCH		3.89	2.92	-		-	
		1.55	1.68	MATCH		0.99	1.31	MATCH		3.98	2.92	-		-	
		1.59	1.68	MATCH		0.98	1.31	MATCH		3.99	2.92	-		-	
		1.53	1.68	MATCH		0.90	1.30	MATCH		3.83	2.92	-		-	
		1.59	1.68	MATCH		0.88	1.30	MATCH		3.97	2.92	-		-	
		1.57	1.68	MATCH		0.94	1.30	MATCH		3.97	2.92	-		-	
		1.59	1.68	MATCH		0.99	1.30	MATCH		3.96	2.92	-		-	
		1.61	1.67	MATCH		0.96	1.30	MATCH		4.10	2.92	-		-	
		1.49	1.67	MATCH		0.85	1.30	MATCH		3.76	2.91	-		-	
	4640-27	1.30	1.75	MATCH		1.04	1.36	MATCH		3.30	3.05	-		-	
		1.08	1.76	MATCH		0.85	1.37	MATCH		3.02	3.05	MATCH		MATCH	
		1.02	1.73	MATCH		0.91	1.36	MATCH		2.91	3.04	MATCH		MATCH	
		1.23	1.73	MATCH		0.99	1.35	MATCH		3.43	3.04	-		-	
		1.22	1.75	MATCH		1.08	1.35	MATCH		3.37	3.03	-		-	
		1.06	1.73	MATCH		0.94	1.35	MATCH		3.11	3.03	-		-	
		1.02	1.72	MATCH		0.86	1.35	MATCH		2.97	3.01	MATCH		MATCH	
		1.21	1.72	MATCH		0.92	1.34	MATCH		3.22	3.01	-		-	
		1.24	1.72	MATCH		1.12	1.35	MATCH		3.48	3.01	-		-	
		1.21	1.72	MATCH		1.01	1.34	MATCH		3.30	3.00	-		-	
		1.17	1.72	MATCH		1.07	1.34	MATCH		3.25	3.00	-		-	
		0.96	1.71	MATCH		0.92	1.34	MATCH		3.21	3.00	-		-	
		0.96	1.71	MATCH		0.76	1.34	MATCH		2.96	3.00	MATCH		MATCH	
		1.13	1.72	MATCH		0.92	1.34	MATCH		3.09	3.00	-		-	
		1.05	1.71	MATCH		0.83	1.34	MATCH		2.82	3.00	MATCH		MATCH	
		1.06	1.71	MATCH		0.94	1.34	MATCH		3.15	2.99	-		-	
		1.04	1.71	MATCH		0.88	1.34	MATCH		2.88	2.99	MATCH		MATCH	
		1.05	1.71	MATCH		0.84	1.34	MATCH		2.92	2.99	MATCH		MATCH	
		0.98	1.72	MATCH		0.83	1.33	MATCH		2.84	2.99	MATCH		MATCH	
		1.02	1.71	MATCH		0.82	1.33	MATCH		2.86	2.99	MATCH		MATCH	
		1.08	1.70	MATCH		0.87	1.33	MATCH		2.96	2.98	MATCH		MATCH	
		1.10	1.72	MATCH		0.79	1.34	MATCH		3.33	3.04	-		-	
	1.28	1.70	MATCH		0.95	1.33	MATCH		3.69	2.98	-		-		
	1.24	1.69	MATCH		0.94	1.32	MATCH		3.64	2.96	-		-		
	1.23	1.69	MATCH		0.95	1.32	MATCH		3.65	2.95	-		-		

4640-28	1.28	1.69	MATCH	0.94	1.32	MATCH	3.64	2.95	-	-	-
	1.29	1.69	MATCH	0.96	1.32	MATCH	3.65	2.94	-	-	
	1.29	1.68	MATCH	0.94	1.31	MATCH	3.64	2.94	-	-	
	1.28	1.68	MATCH	1.00	1.31	MATCH	3.75	2.94	-	-	
	1.39	1.68	MATCH	1.06	1.31	MATCH	4.03	2.94	-	-	
	1.22	1.68	MATCH	0.92	1.31	MATCH	3.53	2.94	-	-	
	1.11	1.68	MATCH	0.86	1.31	MATCH	3.39	2.94	-	-	
	1.16	1.68	MATCH	0.85	1.31	MATCH	3.29	2.94	-	-	
	1.18	1.68	MATCH	0.85	1.31	MATCH	3.35	2.94	-	-	
	1.19	1.68	MATCH	0.91	1.31	MATCH	3.55	2.94	-	-	
4640-30	1.21	1.68	MATCH	0.92	1.31	MATCH	3.58	2.93	-	-	MATCH
	1.26	1.68	MATCH	0.94	1.31	MATCH	3.59	2.93	-	-	
	1.10	1.68	MATCH	0.83	1.31	MATCH	3.45	2.93	-	-	
	1.13	1.68	MATCH	0.81	1.31	MATCH	3.29	2.93	-	-	
	1.28	1.68	MATCH	0.99	1.31	MATCH	3.81	2.93	-	-	
	1.23	1.68	MATCH	0.89	1.31	MATCH	3.55	2.93	-	-	
	1.25	1.68	MATCH	0.95	1.31	MATCH	3.67	2.93	-	-	
	0.29	1.67	MATCH	0.90	1.32	MATCH	2.45	2.96	MATCH	MATCH	
	0.20	1.67	MATCH	0.84	1.31	MATCH	2.15	2.95	MATCH	MATCH	
	0.08	1.67	MATCH	0.73	1.31	MATCH	2.35	2.93	MATCH	MATCH	
4640-31	0.17	1.67	MATCH	0.88	1.31	MATCH	2.40	2.93	MATCH	MATCH	-
	0.12	1.67	MATCH	0.81	1.31	MATCH	2.62	2.93	MATCH	MATCH	
	0.17	1.67	MATCH	0.79	1.31	MATCH	2.55	2.93	MATCH	MATCH	
	0.13	1.67	MATCH	0.78	1.31	MATCH	2.17	2.92	MATCH	MATCH	
	0.16	1.67	MATCH	0.81	1.31	MATCH	2.65	2.92	MATCH	MATCH	
	0.12	1.67	MATCH	0.81	1.31	MATCH	2.56	2.92	MATCH	MATCH	
	0.19	1.66	MATCH	0.83	1.31	MATCH	2.28	2.92	MATCH	MATCH	
	0.14	1.67	MATCH	0.81	1.31	MATCH	2.54	2.91	MATCH	MATCH	
	0.19	1.66	MATCH	0.84	1.30	MATCH	2.38	2.91	MATCH	MATCH	
	2.00	1.77	-	1.26	1.38	MATCH	4.36	3.10	-	-	
4640-33	2.04	1.75	-	1.06	1.36	MATCH	4.14	3.06	-	-	-
	1.85	1.73	-	1.03	1.35	MATCH	3.93	3.02	-	-	
	1.96	1.72	-	1.27	1.34	MATCH	4.35	3.01	-	-	
	1.75	1.72	-	1.01	1.34	MATCH	3.92	3.01	-	-	
	2.05	1.72	-	1.29	1.34	MATCH	4.64	3.01	-	-	
	1.92	1.71	-	1.31	1.34	MATCH	4.46	2.99	-	-	
	1.96	1.71	-	1.26	1.33	MATCH	4.40	2.99	-	-	
	1.98	1.72	-	1.15	1.33	MATCH	4.23	2.99	-	-	
	1.91	1.70	-	1.21	1.33	MATCH	4.33	2.97	-	-	
	1.73	1.70	-	1.06	1.32	MATCH	3.90	2.96	-	-	
4640-36	1.78	1.70	-	1.08	1.32	MATCH	3.95	2.96	-	-	MATCH
	1.79	1.69	-	1.10	1.32	MATCH	4.14	2.95	-	-	
	0.80	1.70	MATCH	0.94	1.33	MATCH	3.35	2.97	-	-	
	0.55	1.70	MATCH	0.69	1.32	MATCH	2.65	2.96	MATCH	MATCH	
	0.79	1.69	MATCH	0.97	1.32	MATCH	3.27	2.96	-	-	
	0.69	1.69	MATCH	0.88	1.32	MATCH	3.02	2.96	-	-	
	0.70	1.70	MATCH	0.86	1.33	MATCH	3.13	2.96	-	-	
	1.18	2.31	MATCH	1.86	1.80	-	4.34	4.29	-	-	
	0.86	1.83	MATCH	0.48	1.65	MATCH	1.57	3.64	MATCH	MATCH	
	0.48	1.76	MATCH	1.25	1.48	MATCH	3.29	3.27	-	-	
4640-39	0.32	1.69	MATCH	0.89	1.32	MATCH	3.51	3.14	-	-	-
	0.31	1.69	MATCH	0.93	1.33	MATCH	3.05	3.02	-	-	
	0.09	1.69	MATCH	0.57	1.33	MATCH	1.84	3.00	MATCH	MATCH	
	0.41	1.75	MATCH	1.04	1.35	MATCH	3.12	2.99	-	-	
	0.13	1.67	MATCH	0.79	1.32	MATCH	1.66	2.98	MATCH	MATCH	
	0.12	1.72	MATCH	0.80	1.33	MATCH	1.72	2.97	MATCH	MATCH	
	0.24	1.68	MATCH	0.80	1.32	MATCH	2.49	2.97	MATCH	MATCH	
	0.28	1.67	MATCH	0.79	1.31	MATCH	2.85	2.96	MATCH	MATCH	
	0.20	1.67	MATCH	0.76	1.32	MATCH	2.60	2.96	MATCH	MATCH	
	0.21	1.67	MATCH	0.85	1.31	MATCH	2.55	2.95	MATCH	MATCH	
4640-40	0.13	1.67	MATCH	0.81	1.32	MATCH	2.73	2.95	MATCH	MATCH	MATCH
	0.31	1.67	MATCH	0.85	1.31	MATCH	2.80	2.94	MATCH	MATCH	
	0.27	1.67	MATCH	0.93	1.31	MATCH	3.07	2.94	-	-	
	0.20	1.68	MATCH	0.84	1.32	MATCH	2.58	2.94	MATCH	MATCH	
	0.26	1.68	MATCH	0.81	1.32	MATCH	2.22	2.94	MATCH	MATCH	
	0.23	1.67	MATCH	0.85	1.31	MATCH	2.61	2.94	MATCH	MATCH	
	0.24	1.68	MATCH	0.88	1.31	MATCH	2.87	2.93	MATCH	MATCH	
	0.35	1.67	MATCH	1.00	1.31	MATCH	3.06	2.93	-	-	
	0.29	1.67	MATCH	0.90	1.31	MATCH	2.89	2.93	MATCH	MATCH	
	0.20	1.66	MATCH	0.88	1.30	MATCH	2.64	2.92	MATCH	MATCH	
4640-40	0.30	1.67	MATCH	0.82	1.31	MATCH	2.54	2.92	MATCH	MATCH	-
	0.22	1.67	MATCH	0.82	1.31	MATCH	2.35	2.92	MATCH	MATCH	
	0.18	1.67	MATCH	0.79	1.31	MATCH	2.42	2.92	MATCH	MATCH	
	0.22	1.67	MATCH	0.82	1.31	MATCH	2.70	2.92	MATCH	MATCH	
	0.36	1.66	MATCH	0.95	1.30	MATCH	2.55	2.91	MATCH	MATCH	
	0.21	1.66	MATCH	0.86	1.30	MATCH	2.67	2.91	MATCH	MATCH	
	0.24	1.66	MATCH	0.88	1.30	MATCH	2.52	2.91	MATCH	MATCH	
	0.25	1.67	MATCH	0.84	1.30	MATCH	2.59	2.91	MATCH	MATCH	
	0.25	1.66	MATCH	0.84	1.30	MATCH	2.39	2.91	MATCH	MATCH	
	0.23	1.66	MATCH	0.86	1.30	MATCH	2.46	2.91	MATCH	MATCH	
4640-39	0.26	1.66	MATCH	0.83	1.30	MATCH	2.44	2.90	MATCH	MATCH	MATCH
	0.78	1.72	MATCH	0.76	1.35	MATCH	2.68	3.03	MATCH	MATCH	
	1.14	1.70	MATCH	0.93	1.33	MATCH	3.36	3.00	-	-	
	1.06	1.70	MATCH	0.93	1.33	MATCH	3.23	2.97	-	-	
	1.17	1.70	MATCH	0.94	1.33	MATCH	3.32	2.97	-	-	
	1.09	1.70	MATCH	0.82	1.32	MATCH	3.25	2.97	-	-	
	1.10	1.70	MATCH	0.83	1.32	MATCH	3.24	2.96	-	-	
	1.05	1.70	MATCH	0.82	1.32	MATCH	2.94	2.96	MATCH	MATCH	
	1.01	1.70	MATCH	0.82	1.32	MATCH	2.95	2.96	MATCH	MATCH	
	1.15	1.69	MATCH	1.01	1.32	MATCH	3.48	2.96	-	-	
4640-40	0.93	1.69	MATCH	0.76	1.32	MATCH	2.92	2.96	MATCH	MATCH	-
	1.29	1.69	MATCH	0.99	1.32	MATCH	3.53	2.96	-	-	
	1.08	1.69	MATCH	0.94	1.32	MATCH	3.20	2.95	-	-	
	1.05	1.69	MATCH	0.82	1.32	MATCH	2.91	2.95	MATCH	MATCH	
	0.39	1.68	MATCH	0.76	1.32	MATCH	2.59	2.97	MATCH	MATCH	
	0.39	1.68	MATCH	0.84	1.32	MATCH	2.93	2.97	MATCH	MATCH	
	0.41	1.67	MATCH	0.81	1.31	MATCH	2.71	2.97	MATCH	MATCH	
	0.35	1.69	MATCH	0.80	1.33	MATCH	2.64	2.97	MATCH	MATCH	
	0.35	1.67	MATCH	0.86	1.32	MATCH	2.41	2.96	MATCH	MATCH	
	0.20	1.69	MATCH	0.72	1.32	MATCH	2.50	2.96	MATCH	MATCH	
4640-40	0.50	1.68	MATCH	0.99	1.32	MATCH	3.15	2.95	-	-	MATCH
	0.40	1.69	MATCH	0.87	1.32	MATCH	2.72	2.95	MATCH	MATCH	
	0.42	1.68	MATCH	0.82	1.32	MATCH	2.69	2.94	MATCH	MATCH	
	0.44	1.68	MATCH	0.87	1.32	MATCH	2.87	2.94	MATCH	MATCH	
	0.34	1.68	MATCH	0.76	1.31	MATCH	2.65	2.94	MATCH	MATCH	

		0.44	1.68	MATCH		0.88	1.31	MATCH		2.74	2.94	MATCH	MATCH	
		0.18	1.68	MATCH		0.67	1.31	MATCH		2.41	2.94	MATCH	MATCH	
		0.42	1.68	MATCH		0.86	1.31	MATCH		2.82	2.94	MATCH	MATCH	
		0.36	1.67	MATCH		0.81	1.31	MATCH		2.59	2.93	MATCH	MATCH	
		0.39	1.67	MATCH		0.79	1.31	MATCH		2.73	2.93	MATCH	MATCH	
		0.41	1.67	MATCH		0.86	1.31	MATCH		2.83	2.93	MATCH	MATCH	
		0.42	1.68	MATCH		0.89	1.31	MATCH		2.87	2.92	MATCH	MATCH	
		0.36	1.67	MATCH		0.77	1.31	MATCH		2.63	2.92	MATCH	MATCH	
		0.41	1.67	MATCH		0.84	1.30	MATCH		2.70	2.91	MATCH	MATCH	
		0.41	1.67	MATCH		0.87	1.30	MATCH		2.77	2.91	MATCH	MATCH	
GRU2	4644-2	1.58	1.71	MATCH		1.15	1.34	MATCH		4.12	2.99	-	-	
		1.32	1.70	MATCH		0.93	1.33	MATCH		3.88	2.98	-	-	
		1.35	1.70	MATCH		0.88	1.32	MATCH		3.70	2.98	-	-	
		1.52	1.70	MATCH		1.09	1.33	MATCH		4.09	2.98	-	-	
		1.24	1.70	MATCH		0.86	1.33	MATCH		3.63	2.98	-	-	
		1.42	1.70	MATCH		1.02	1.33	MATCH		3.87	2.97	-	-	
		1.41	1.69	MATCH		0.99	1.32	MATCH		3.90	2.97	-	-	
		1.28	1.70	MATCH		0.86	1.32	MATCH		3.37	2.97	-	-	
		1.35	1.69	MATCH		0.95	1.32	MATCH		3.83	2.96	-	-	
		1.24	1.69	MATCH		0.84	1.32	MATCH		3.65	2.96	-	-	
		1.46	1.69	MATCH		1.03	1.32	MATCH		3.90	2.96	-	-	
		1.42	1.69	MATCH		0.96	1.32	MATCH		3.93	2.95	-	-	-
		1.29	1.69	MATCH		0.83	1.32	MATCH		3.44	2.95	-	-	
		1.31	1.69	MATCH		0.86	1.32	MATCH		3.66	2.95	-	-	
		1.35	1.69	MATCH		0.96	1.32	MATCH		3.71	2.95	-	-	
		1.37	1.69	MATCH		0.92	1.31	MATCH		3.81	2.95	-	-	
		1.36	1.69	MATCH		0.94	1.32	MATCH		3.79	2.94	-	-	
		1.54	1.69	MATCH		1.07	1.32	MATCH		4.14	2.94	-	-	
		1.43	1.69	MATCH		1.08	1.31	MATCH		4.21	2.94	-	-	
		1.39	1.68	MATCH		0.98	1.31	MATCH		3.78	2.94	-	-	
		1.49	1.68	MATCH		0.98	1.31	MATCH		4.10	2.94	-	-	
		1.30	1.68	MATCH		0.91	1.31	MATCH		3.74	2.93	-	-	
	4644-5	1.35	1.70	MATCH		0.97	1.33	MATCH		3.85	2.97	-	-	
		1.40	1.70	MATCH		1.01	1.33	MATCH		3.82	2.97	-	-	
		1.37	1.70	MATCH		1.06	1.32	MATCH		3.86	2.96	-	-	
		1.22	1.69	MATCH		0.85	1.32	MATCH		3.46	2.96	-	-	
		1.31	1.70	MATCH		0.95	1.33	MATCH		3.73	2.96	-	-	
		1.49	1.69	MATCH		1.09	1.32	MATCH		4.20	2.96	-	-	
		1.36	1.70	MATCH		1.02	1.32	MATCH		3.93	2.96	-	-	
		1.55	1.69	MATCH		1.11	1.32	MATCH		3.88	2.96	-	-	
		1.41	1.69	MATCH		0.99	1.32	MATCH		3.96	2.96	-	-	
		1.24	1.70	MATCH		0.90	1.32	MATCH		3.42	2.96	-	-	
		1.31	1.69	MATCH		0.93	1.32	MATCH		3.70	2.96	-	-	
		1.39	1.70	MATCH		1.02	1.32	MATCH		3.88	2.96	-	-	
		1.31	1.69	MATCH		0.98	1.32	MATCH		3.78	2.96	-	-	
		1.20	1.69	MATCH		0.86	1.32	MATCH		3.43	2.96	-	-	
		1.27	1.70	MATCH		0.88	1.32	MATCH		3.63	2.95	-	-	
		1.24	1.69	MATCH		0.94	1.32	MATCH		3.65	2.95	-	-	
		1.13	1.69	MATCH		0.79	1.32	MATCH		3.23	2.95	-	-	
		1.28	1.69	MATCH		0.93	1.32	MATCH		3.61	2.95	-	-	
		1.42	1.69	MATCH		1.03	1.32	MATCH		3.86	2.95	-	-	
		1.16	1.69	MATCH		0.89	1.32	MATCH		3.47	2.95	-	-	
	4644-10	1.26	1.69	MATCH		0.94	1.32	MATCH		3.73	2.98	-	-	
		1.27	1.68	MATCH		1.00	1.31	MATCH		3.75	2.95	-	-	
		1.17	1.68	MATCH		0.97	1.31	MATCH		3.57	2.94	-	-	
		1.21	1.68	MATCH		0.90	1.31	MATCH		3.50	2.94	-	-	
		1.19	1.68	MATCH		0.91	1.31	MATCH		3.47	2.93	-	-	
		1.19	1.68	MATCH		0.92	1.31	MATCH		3.51	2.93	-	-	
		1.11	1.68	MATCH		0.86	1.31	MATCH		3.46	2.93	-	-	
		1.19	1.68	MATCH		0.96	1.31	MATCH		3.65	2.93	-	-	
		1.33	1.68	MATCH		1.05	1.31	MATCH		3.98	2.93	-	-	
		1.41	1.68	MATCH		1.10	1.31	MATCH		3.96	2.93	-	-	-
		1.28	1.68	MATCH		1.00	1.31	MATCH		3.74	2.92	-	-	
		1.26	1.68	MATCH		1.00	1.31	MATCH		3.82	2.92	-	-	
		1.30	1.68	MATCH		0.98	1.31	MATCH		3.86	2.92	-	-	
		1.22	1.68	MATCH		0.94	1.31	MATCH		3.64	2.92	-	-	
		1.29	1.68	MATCH		0.96	1.31	MATCH		3.76	2.92	-	-	
		1.22	1.67	MATCH		0.91	1.31	MATCH		3.57	2.92	-	-	
		1.26	1.67	MATCH		0.97	1.31	MATCH		3.74	2.92	-	-	
		1.24	1.67	MATCH		0.98	1.31	MATCH		3.75	2.92	-	-	
		1.16	1.67	MATCH		0.88	1.30	MATCH		3.40	2.92	-	-	
	4644-11	1.68	1.82	MATCH		1.26	1.41	MATCH		4.03	3.12	-	-	
		1.07	1.78	MATCH		0.88	1.40	MATCH		3.36	3.10	-	-	
		1.03	1.70	MATCH		0.79	1.32	MATCH		3.12	2.96	-	-	
		1.07	1.69	MATCH		0.79	1.32	MATCH		3.13	2.96	-	-	
		1.16	1.69	MATCH		0.92	1.32	MATCH		3.68	2.95	-	-	
		1.12	1.69	MATCH		0.97	1.32	MATCH		3.41	2.95	-	-	
		1.13	1.69	MATCH		0.86	1.32	MATCH		3.40	2.95	-	-	
		1.28	1.69	MATCH		1.07	1.32	MATCH		3.81	2.95	-	-	
		1.19	1.69	MATCH		0.95	1.32	MATCH		3.43	2.95	-	-	
		1.17	1.69	MATCH		0.82	1.32	MATCH		3.11	2.94	-	-	
	4644-13	1.11	1.68	MATCH		0.84	1.31	MATCH		3.35	2.94	-	-	
		1.22	1.68	MATCH		0.95	1.31	MATCH		3.52	2.94	-	-	
		0.98	1.68	MATCH		0.79	1.31	MATCH		3.00	2.94	-	-	
		1.14	1.69	MATCH		0.95	1.32	MATCH		3.71	2.96	-	-	
		1.26	1.69	MATCH		1.03	1.32	MATCH		3.85	2.95	-	-	
		1.34	1.69	MATCH		1.12	1.32	MATCH		4.03	2.95	-	-	
		1.17	1.69	MATCH		0.92	1.32	MATCH		3.54	2.95	-	-	
		1.22	1.69	MATCH		0.99	1.32	MATCH		3.80	2.95	-	-	
		1.12	1.69	MATCH		0.90	1.32	MATCH		3.54	2.95	-	-	
		1.07	1.69	MATCH		0.86	1.32	MATCH		3.49	2.95	-	-	
		1.27	1.69	MATCH		0.99	1.32	MATCH		3.76	2.95	-	-	
		1.05	1.69	MATCH		0.90	1.32	MATCH		3.57	2.95	-	-	-
		1.05	1.69	MATCH		0.84	1.32	MATCH		3.51	2.95	-	-	
		1.12	1.69	MATCH		0.87	1.31	MATCH		3.54	2.94	-	-	
		1.14	1.68	MATCH		0.97	1.32	MATCH		3.71	2.94	-	-	
		1.11	1.68	MATCH		0.91	1.31	MATCH		3.57	2.94	-	-	
		1.00	1.68	MATCH		0.84	1.31	MATCH		3.45	2.94	-	-	
		1.21	1.68	MATCH		0.97	1.31	MATCH		3.80	2.94	-	-	
		1.11	1.69	MATCH		0.85	1.31	MATCH		3.48	2.94	-	-	
		1.16	1.69	MATCH		0.96	1.31	MATCH		3.74	2.94	-	-	
		0.87	1.70	MATCH		1.36	1.39	MATCH		4.92	3.24	-	-	
		1.05	1.69	MATCH		0.66	1.39	MATCH		2.50	3.14	MATCH	MATCH	
		0.78	1.71	MATCH		0.76	1.35	MATCH		2.44	3.07	MATCH	MATCH	
		0.88	1.69	MATCH		0.75	1.34	MATCH		2.94	3.06	MATCH	MATCH	

AuNat	4644-20	0.98	1.69	MATCH	0.89	1.33	MATCH	2.91	3.00	MATCH	MATCH	MATCH
		1.01	1.67	MATCH	0.91	1.32	MATCH	3.31	2.99	-	-	
		0.83	1.69	MATCH	0.77	1.33	MATCH	3.02	2.98	-	-	
		1.08	1.68	MATCH	0.96	1.32	MATCH	3.76	2.97	-	-	
		1.13	1.68	MATCH	1.05	1.32	MATCH	3.55	2.97	-	-	
		0.97	1.68	MATCH	0.90	1.32	MATCH	2.90	2.96	MATCH	MATCH	
		0.98	1.67	MATCH	0.77	1.31	MATCH	2.85	2.95	MATCH	MATCH	
		1.05	1.67	MATCH	0.95	1.31	MATCH	3.57	2.95	-	-	
		1.01	1.68	MATCH	0.85	1.33	MATCH	3.20	2.95	-	-	
		0.99	1.68	MATCH	0.90	1.32	MATCH	3.40	2.95	-	-	
		0.94	1.67	MATCH	0.86	1.31	MATCH	3.44	2.93	-	-	
	4644-23	0.04	1.82	MATCH	0.22	1.40	MATCH	0.49	3.21	MATCH	MATCH	-
		0.71	1.67	MATCH	1.23	1.37	MATCH	4.17	3.10	-	-	
		0.73	1.70	MATCH	0.76	1.36	MATCH	2.67	3.05	MATCH	MATCH	
		0.59	1.70	MATCH	0.78	1.32	MATCH	2.98	3.03	MATCH	MATCH	
		0.71	1.70	MATCH	0.88	1.33	MATCH	3.22	2.98	-	-	
		0.73	1.69	MATCH	1.06	1.32	MATCH	3.51	2.97	-	-	
		0.73	1.68	MATCH	0.96	1.32	MATCH	3.21	2.96	-	-	
		0.74	1.67	MATCH	0.96	1.31	MATCH	3.36	2.96	-	-	
		0.65	1.67	MATCH	0.91	1.32	MATCH	3.17	2.95	-	-	
		0.78	1.68	MATCH	0.99	1.32	MATCH	3.27	2.95	-	-	
		0.69	1.68	MATCH	0.90	1.32	MATCH	3.14	2.95	-	-	
		0.73	1.67	MATCH	0.88	1.31	MATCH	3.11	2.95	-	-	
		0.78	1.67	MATCH	1.03	1.31	MATCH	3.31	2.95	-	-	
		0.78	1.67	MATCH	1.10	1.32	MATCH	3.42	2.94	-	-	
		0.76	1.68	MATCH	1.04	1.32	MATCH	3.58	2.94	-	-	
		0.51	1.68	MATCH	0.76	1.32	MATCH	2.83	2.94	MATCH	MATCH	
		0.67	1.68	MATCH	0.83	1.31	MATCH	2.96	2.94	-	-	
		0.55	1.68	MATCH	0.79	1.31	MATCH	3.31	2.94	-	-	
		0.54	1.67	MATCH	0.77	1.31	MATCH	2.96	2.94	-	-	
		0.68	1.67	MATCH	0.91	1.30	MATCH	3.31	2.93	-	-	
		0.63	1.67	MATCH	0.93	1.31	MATCH	3.36	2.93	-	-	
		0.79	1.68	MATCH	0.98	1.31	MATCH	3.38	2.93	-	-	
		0.62	1.67	MATCH	0.80	1.31	MATCH	2.89	2.93	MATCH	MATCH	
		0.60	1.67	MATCH	0.81	1.31	MATCH	3.10	2.93	-	-	
		0.60	1.67	MATCH	0.88	1.31	MATCH	3.15	2.93	-	-	
		0.80	1.67	MATCH	1.00	1.31	MATCH	3.34	2.92	-	-	
		0.70	1.67	MATCH	0.95	1.31	MATCH	3.27	2.92	-	-	
		0.65	1.67	MATCH	0.83	1.31	MATCH	2.80	2.92	MATCH	MATCH	
		0.67	1.67	MATCH	0.88	1.30	MATCH	3.18	2.92	-	-	
		0.71	1.67	MATCH	0.86	1.31	MATCH	3.01	2.92	-	-	
		0.69	1.67	MATCH	0.95	1.30	MATCH	3.20	2.92	-	-	
		0.74	1.67	MATCH	0.93	1.31	MATCH	3.20	2.92	-	-	
		0.73	1.67	MATCH	0.90	1.31	MATCH	3.13	2.92	-	-	
		0.73	1.67	MATCH	0.94	1.30	MATCH	3.12	2.91	-	-	
		0.74	1.67	MATCH	0.93	1.30	MATCH	2.90	2.91	MATCH	MATCH	
		0.71	1.67	MATCH	0.92	1.30	MATCH	3.16	2.91	-	-	
	4644-24	0.95	1.67	MATCH	0.44	1.34	MATCH	2.70	3.06	MATCH	MATCH	-
		0.95	1.68	MATCH	0.91	1.32	MATCH	3.51	2.95	-	-	
		0.97	1.68	MATCH	0.97	1.31	MATCH	3.60	2.94	-	-	
		1.01	1.67	MATCH	0.94	1.31	MATCH	3.31	2.94	-	-	
		0.89	1.68	MATCH	0.86	1.31	MATCH	3.26	2.93	-	-	
		1.01	1.67	MATCH	0.99	1.31	MATCH	3.65	2.93	-	-	
		1.03	1.67	MATCH	0.98	1.31	MATCH	3.55	2.93	-	-	
		1.08	1.67	MATCH	0.98	1.30	MATCH	3.31	2.92	-	-	
		0.89	1.67	MATCH	0.83	1.30	MATCH	3.12	2.91	-	-	
		1.03	1.67	MATCH	0.99	1.30	MATCH	3.48	2.91	-	-	
	Natural Au	0.95	2.30	MATCH	0.23	1.72	MATCH	0.32	3.93	MATCH	MATCH	MATCH
		2.13	7.54	MATCH	1.93	7.16	MATCH	4.30	14.54	MATCH	MATCH	
		1.43	10.66	MATCH	1.66	6.73	MATCH	8.46	11.96	MATCH	MATCH	
		0.64	4.74	MATCH	2.29	3.92	MATCH	6.11	9.39	MATCH	MATCH	
		5.62	4.56	-	0.88	3.52	MATCH	6.08	8.80	MATCH	-	
		0.55	5.20	MATCH	1.68	3.84	MATCH	3.69	8.73	MATCH	MATCH	
		0.60	4.37	MATCH	1.30	3.59	MATCH	3.20	8.53	MATCH	MATCH	
		1.65	4.03	MATCH	1.60	4.08	MATCH	6.93	8.39	MATCH	MATCH	
		5.97	6.41	MATCH	2.92	3.47	MATCH	6.85	8.20	MATCH	MATCH	
		4.38	4.78	MATCH	1.61	3.13	MATCH	5.57	7.94	MATCH	MATCH	
		0.11	4.26	MATCH	0.15	3.27	MATCH	1.67	7.77	MATCH	MATCH	
		2.81	4.95	MATCH	1.14	3.54	MATCH	4.51	7.70	MATCH	MATCH	
		1.17	6.01	MATCH	3.07	3.72	MATCH	1.82	7.66	MATCH	MATCH	
		2.26	5.84	MATCH	1.85	3.40	MATCH	3.09	7.48	MATCH	MATCH	
		0.37	4.47	MATCH	0.06	3.55	MATCH	4.91	7.36	MATCH	MATCH	
		0.34	3.63	MATCH	1.33	3.10	MATCH	2.55	6.99	MATCH	MATCH	
		3.02	3.70	MATCH	2.47	2.96	MATCH	7.49	6.94	-	-	
		2.25	4.00	MATCH	3.69	4.67	MATCH	1.24	6.85	MATCH	MATCH	
		2.35	4.54	MATCH	0.12	3.23	MATCH	4.70	6.70	MATCH	MATCH	
		1.29	4.04	MATCH	1.79	2.85	MATCH	4.40	6.51	MATCH	MATCH	
		1.40	2.95	MATCH	2.56	2.37	-	6.18	6.27	MATCH	-	
		5.23	3.45	-	4.51	2.63	-	10.75	6.24	-	-	
		0.18	5.40	MATCH	0.67	3.19	MATCH	1.14	6.12	MATCH	MATCH	
		0.51	5.22	MATCH	0.10	2.60	MATCH	0.80	6.11	MATCH	MATCH	
		1.14	3.29	MATCH	2.26	2.71	MATCH	4.32	6.08	MATCH	MATCH	
		1.45	3.06	MATCH	1.89	2.27	MATCH	0.92	5.89	MATCH	MATCH	
		0.81	3.23	MATCH	1.01	2.72	MATCH	2.12	5.81	MATCH	MATCH	
		3.83	3.13	-	3.65	2.51	-	9.74	5.74	-	-	
		0.43	2.89	MATCH	0.81	2.22	MATCH	1.79	5.73	MATCH	MATCH	
		3.31	3.05	-	1.43	2.69	MATCH	8.41	5.58	-	-	
		1.46	2.99	MATCH	3.31	2.27	-	4.51	5.57	MATCH	-	
		4.28	3.02	-	1.54	2.65	MATCH	3.92	5.53	MATCH	-	
		2.41	2.69	MATCH	1.74	2.13	MATCH	5.50	5.44	-	-	
		0.62	2.98	MATCH	1.33	2.38	MATCH	2.75	5.44	MATCH	MATCH	
		0.44	2.79	MATCH	0.39	2.32	MATCH	0.33	5.36	MATCH	MATCH	
		0.29	2.71	MATCH	2.86	1.96	-	4.69	5.34	MATCH	-	
		1.03	2.88	MATCH	0.50	2.14	MATCH	3.02	5.24	MATCH	MATCH	
		0.84	2.90	MATCH	0.82	2.29	MATCH	0.73	5.22	MATCH	MATCH	
		2.23	2.96	MATCH	1.27	2.31	MATCH	1.85	5.18	MATCH	MATCH	
		0.43	2.67	MATCH	1.04	2.27	MATCH	1.39	5.09	MATCH	MATCH	
		3.66	2.59	-	1.44	2.15	MATCH	3.84	5.02	MATCH	-	
		0.55	2.73	MATCH	0.87	2.30	MATCH	0.51	5.01	MATCH	MATCH	
		1.05	3.42	MATCH	1.87	2.33	MATCH	4.14	4.99	MATCH	MATCH	
		1.41	2.86	MATCH	0.65	2.16	MATCH	1.21	4.98	MATCH	MATCH	
		3.32	2.39	-	1.64	2.13	MATCH	3.52	4.94	MATCH	-	
		2.55	2.49	-	1.73	2.10	MATCH	4.18	4.86	MATCH	-	
		1.67	2.71	MATCH	0.58	2.11	MATCH	1.39	4.80	MATCH	MATCH	
		1.42	2.42	MATCH	1.43	2.51	MATCH	3.44	4.79	MATCH	MATCH	

		4.62	2.84	-		1.51	1.91	MATCH		5.80	4.78	-	-	
		0.26	2.53	MATCH		0.82	2.11	MATCH		1.33	4.76	MATCH	MATCH	
		4.02	2.66	-		4.38	2.00	-		4.84	4.70	-	-	
		4.66	2.56	-		3.19	2.05	-		8.75	4.67	-	-	
		1.26	2.61	MATCH		0.37	1.94	MATCH		0.35	4.66	MATCH	MATCH	
		3.39	2.39	-		1.11	1.95	MATCH		4.55	4.62	MATCH	-	
		0.30	2.77	MATCH		1.82	2.27	MATCH		11.35	4.61	-	-	
		2.35	2.58	MATCH		0.66	1.85	MATCH		4.64	4.61	-	-	
		1.67	2.64	MATCH		3.30	2.05	-		8.02	4.59	-	-	
		2.45	2.52	MATCH		1.64	2.05	MATCH		4.87	4.57	-	-	
		0.68	2.85	MATCH		0.68	2.00	MATCH		2.93	4.56	MATCH	MATCH	
		0.67	2.29	MATCH		0.57	1.81	MATCH		1.35	4.54	MATCH	MATCH	
		0.77	2.40	MATCH		0.53	1.98	MATCH		3.00	4.50	MATCH	MATCH	
		0.36	2.64	MATCH		1.68	2.03	MATCH		2.27	4.48	MATCH	MATCH	
		1.13	2.33	MATCH		0.46	1.91	MATCH		0.81	4.32	MATCH	MATCH	
		3.15	2.49	-		1.86	1.94	MATCH		4.40	4.30	-	-	
		0.02	2.38	MATCH		0.07	1.96	MATCH		1.48	4.28	MATCH	MATCH	
		0.08	2.46	MATCH		0.63	2.02	MATCH		4.29	4.26	-	-	
		1.74	2.68	MATCH		1.97	1.92	-		5.99	4.25	-	-	
		3.45	2.24	-		1.71	1.83	MATCH		2.36	4.22	MATCH	-	
		3.14	2.54	-		0.78	1.87	MATCH		3.50	4.16	MATCH	-	
		0.63	2.30	MATCH		1.23	1.87	MATCH		2.27	4.10	MATCH	MATCH	
		1.98	2.35	MATCH		0.04	1.63	MATCH		2.43	4.03	MATCH	MATCH	
		0.18	2.18	MATCH		1.08	1.73	MATCH		2.56	3.93	MATCH	MATCH	
		0.14	2.21	MATCH		1.02	1.70	MATCH		2.82	3.84	MATCH	MATCH	
		1.04	2.16	MATCH		0.37	1.74	MATCH		0.21	3.82	MATCH	MATCH	
		0.05	2.09	MATCH		0.70	1.63	MATCH		1.51	3.79	MATCH	MATCH	
		0.73	1.90	MATCH		0.66	1.58	MATCH		11.62	3.78	-	-	
		1.76	2.21	MATCH		0.47	1.64	MATCH		1.84	3.74	MATCH	MATCH	
		2.59	2.06	-		0.81	1.62	MATCH		3.05	3.71	MATCH	-	
		2.23	2.00	-		0.62	1.66	MATCH		2.56	3.66	MATCH	-	
		3.30	2.09	-		1.06	1.70	MATCH		2.64	3.66	MATCH	-	
		2.80	1.95	-		1.02	1.61	MATCH		2.49	3.64	MATCH	-	
		2.70	2.09	-		1.07	1.60	MATCH		3.86	3.63	-	-	
		1.65	2.08	MATCH		0.55	1.69	MATCH		4.85	3.62	-	-	
		0.82	1.97	MATCH		0.79	1.70	MATCH		0.70	3.52	MATCH	MATCH	
		2.54	2.20	-		1.94	1.72	-		2.83	3.51	MATCH	-	
		2.51	1.99	-		0.09	1.51	MATCH		2.33	3.40	MATCH	-	
		0.88	1.90	MATCH		0.32	1.53	MATCH		0.26	3.39	MATCH	MATCH	
		2.85	1.90	-		0.46	1.47	MATCH		4.21	3.24	-	-	
		0.81	1.76	MATCH		0.73	1.42	MATCH		1.82	3.18	MATCH	MATCH	
		0.47	1.76	MATCH		0.93	1.34	MATCH		2.33	3.12	MATCH	MATCH	
		0.90	1.77	MATCH		0.75	1.40	MATCH		0.87	3.09	MATCH	MATCH	
		0.63	1.67	MATCH		1.07	1.32	MATCH		1.92	3.01	MATCH	MATCH	
		0.51	1.64	MATCH		0.63	1.29	MATCH		0.88	2.90	MATCH	MATCH	

[illegible]

	0.6150	<0.00	<0.00	<0.00	0.2823	34.2930	0.1789	2.0774	191.8077	8.2921	<0.00	<0.00	<0.00	0.0081	167.2335	115.9687983	77.9802	1.4643	2.3477	<0.00	0.0012	<0.00	<0.00	0.0086	44.8641	881.278.1706	141.9068	0.0219	131.0149	142.9197	138.9399	37.3736	<0.00	<0.00				
	0.8214	<0.00	<0.00	<0.00	0.2835	36.8275	0.0801	2.7978	198.8203	8.6788	<0.00	<0.00	<0.00	0.0090	172.6225	115.9686883	78.5299	1.4637	2.4673	<0.00	<0.00	<0.00	<0.00	<0.00	0.0016	41.6432	882.876.4046	143.9934	0.0220	132.5233	143.4205	140.7957	37.9533	<0.00	<0.00			
	-1.4001	<0.00	<0.00	<0.00	0.2164	30.8030	0.3808	2.9880	208.3366	10.1038	<0.00	<0.00	<0.00	0.0185	0.0083	647.9207	115.9686730	78.1542	1.5470	2.9994	<0.00	<0.00	<0.00	0.0020	38.8162	882.886.0045	143.8377	0.0218	145.1537	157.1777	135.8499	41.8903	<0.00	<0.00				
	1.4601	<0.00	<0.00	<0.00	0.2830	36.8275	0.0801	2.7978	198.8203	8.6788	<0.00	<0.00	<0.00	0.0090	172.6225	115.9686883	78.5299	1.4637	2.4673	<0.00	<0.00	<0.00	<0.00	<0.00	0.0016	41.6432	882.876.4046	143.9934	0.0220	132.5233	143.4205	140.7957	37.9533	<0.00	<0.00			
	0.7981	<0.00	<0.00	<0.00	0.2360	35.0376	0.3310	2.0261	188.4276	8.1336	<0.00	<0.00	<0.00	<0.00	<0.00	0.0099	80.9769	115.9681486	75.6545	1.3455	2.3065	<0.00	<0.00	<0.00	<0.00	46.864	883.075.6065	131.7580	0.0319	121.6235	131.1384	127.8449	37.0964	<0.00	<0.00			
	1.4011	<0.00	0.0010	0.0022	0.2931	33.8009	0.2584	2.5136	186.9325	8.5846	<0.00	<0.00	<0.00	<0.00	<0.00	0.0094	76.8672	115.9680447	75.5753	1.0414	1.3777	<0.00	<0.00	<0.00	<0.00	43.8486	883.076.3469	116.0281	0.0161	106.9592	114.9362	112.9092	39.1581	<0.00	<0.00			
	2.0875	<0.00	<0.00	<0.00	0.5536	61.750	0.8270	2.2129	173.0083	6.5522	<0.00	<0.00	<0.00	0.0148	0.0059	769.932	115.9681386	79.2210	1.7471	1.1584	<0.00	<0.00	<0.00	<0.00	<0.00	0.0115	43.8022	883.122.3232	79.8800	0.0178	141.573	79.9294	77.6622	39.7487	<0.00	<0.00		
	0.6271	<0.00	0.0075	0.0020	0.2187	36.7472	0.3478	2.0268	204.0138	10.0232	<0.00	<0.00	<0.00	<0.00	<0.00	0.0092	66.5518	115.9681117	81.5384	1.5459	1.3497	<0.00	<0.00	<0.00	<0.00	0.0181	41.1056	883.136.4601	148.4997	0.0141	136.7778	148.037	144.9877	38.4631	<0.00	<0.00		
	1.5672	<0.00	<0.00	<0.00	0.2974	37.0521	0.3545	2.4853	191.9778	13.1514	<0.00	<0.00	<0.00	<0.00	<0.00	0.0130	74.05125	115.9680461	79.4234	1.3704	1.7427	<0.00	<0.00	<0.00	<0.00	0.0109	44.1489	883.154.8409	127.0041	0.0227	117.6756	126.748	123.8600	39.7040	<0.00	<0.00		
	0.4048	<0.00	<0.00	<0.00	0.1642	22.968	0.4433	0.5138	2.3171	202.9688	10.1684	<0.00	<0.00	0.0471	0.0108	760.282	114.867.520	68.1282	1.1246	2.640	<0.00	<0.00	<0.00	<0.00	<0.00	<0.00	47.359	883.894.9106	112.6451	0.0225	104.9718	138.6835	105.6489	37.0781	<0.00	<0.00		
	484.8484	<0.00	<0.00	<0.00	0.4481	44.453	0.5111	1.4451	72.7770	45.811	<0.00	<0.00	<0.00	0.1188	0.040	873.0756	115.9687651	98.3239	3.7500	0.910	<0.00	<0.00	<0.00	<0.00	<0.00	0.0563	51.2483	87.521.3745	72.4735	0.013	69.7157	73.0391	726.510	22.908	<0.00	0.0096		
	0.4042	<0.00	<0.00	<0.00	0.1384	20.8269	0.1734	1.5464	267.2928	13.1045	<0.00	<0.00	<0.00	<0.00	<0.00	0.0180	768.7897	115.968777	125.642.8317	330.2022	7.6757	11.4471	0.0319	<0.00	0.0661	42.7809	87.1885.3622	962.7208	0.0251	906.5680	962.8200	933.0150	20.885	<0.00	<0.00			
	1.0651	<0.00	<0.00	<0.00	0.8354	21.9431	0.1266	1.1886	252.1515	13.2801	<0.00	<0.00	<0.00	<0.00	<0.00	0.0412	843.316	124.585.9339	294.8048	6.9396	9.8455	<0.00	<0.00	<0.00	0.0331	0.028	51.7251	87.2997.4899	889.6140	0.0207	84.83378	889.3377	889.9770	29.2334	<0.00	<0.00		
	1.4034	<0.00	<0.00	<0.00	0.1482	16.7945	0.1225	1.9865	238.3030	13.2386	<0.00	<0.00	<0.00	<0.00	<0.00	0.0150	793.0145	124.511.3148	328.9350	7.9583	7.971	<0.00	<0.00	<0.00	<0.00	0.0088	54.7636	87.581.1904	1.007.731	0.0221	64.1497	1.002.6475	901.012	23.7026	<0.00	<0.00		
	1.5122	0.0652	0.0072	<0.00	0.1275	18.0611	0.1263	1.4483	238.9314	13.1703	<0.00	<0.00	<0.00	<0.00	<0.00	0.0187	862.2398	124.168.3834	238.4153	5.2561	7.8577	0.0585	<0.00	<0.00	<0.00	0.0371	52.6631	87.694.1628	690.8800	0.0181	64.9693	689.317	676.056	22.1131	<0.00	0.0011		
	2.2803	0.0379	0.0127	<0.00	0.0955	19.3207	0.1327	1.3911	239.6977	12.1627	<0.00	<0.00	<0.00	0.0966	0.0248	914.003	123.858.9498	274.2020	4.6967	11.2091	<0.00	<0.00	<0.00	<0.00	<0.00	0.0088	54.702	87.699.2174	880.1529	0.0158	828.3204	879.7611	873.4800	21.1194	<0.00	0.0021		
	1.1561	<0.00	<0.00	<0.00	0.1132	19.9328	0.1158	1.2993	238.5750	12.9388	<0.00	<0.00	<0.00	0.0138	0.0238	908.4950	123.261.8025	249.8784	5.4064	8.7394	<0.00	<0.00	<0.00	<0.00	<0.00	0.0082	50.7078	87.697.2012	851.8572	0.0203	795.7456	872.0769	855.8215	22.7408	<0.00	<0.00		
	0.8372	<0.00	<0.00	<0.00	0.1349	21.9956	0.1500	1.7322	236.1322	10.7193	<0.00	<0.00	<0.00	<0.00	<0.00	0.0248	868.7983	124.080.6328	249.4824	5.3778	7.7732	<0.00	<0.00	<0.00	<0.00	<0.00	0.0084	54.477	87.738.1951	721.7446	0.0168	669.1226	706.9872	702.4023	28.3878	<0.00	<0.00	
	1.4107	<0.00	<0.00	<0.00	0.0850	17.9264	0.1029	1.2452	220.0855	10.4320	<0.00	<0.00	<0.00	0.0458	0.0256	959.870	124.152.6729	232.6770	4.1546	4.8077	<0.00	<0.00	<0.00	<0.00	<0.00	<0.00	0.0089	58.6136	87.8324.4526	525.147	0.0149	49.27805	523.6149	516.8675	25.0231	<0.00	0.0022	
	1.5231	<0.00	<0.00	<0.00	0.1082	16.7945	0.1225	1.9865	238.3030	13.2386	<0.00	<0.00	<0.00	<0.00	<0.00	0.0150	793.0145	124.511.3148	328.9350	7.9583	7.971	<0.00	<0.00	<0.00	<0.00	<0.00	0.0088	54.7636	87.581.1904	1.007.731	0.0221	64.1497	1.002.6475	901.012	23.7026	<0.00	<0.00	
	0.6495	<0.00	<0.00	<0.00	0.1430	20.1883	0.1539	1.2881	235.0899	11.9670	<0.00	<0.00	<0.00	<0.00	<0.00	0.0247	906.4211	123.555.5079	249.6400	5.7157	7.7108	<0.00	<0.00	<0.00	<0.00	<0.00	0.0052	50.500	87.7449.7227	704.3306	0.0167	664.2104	706.9660	698.8481	22.5023	<0.00	<0.00	
	1.4555	4.3376	<0.00	<0.00	0.2023	24.1499	0.1933	1.6158	255.7275	12.8254	<0.00	<0.00	<0.00	<0.00	<0.00	0.0210	805.5830	122.960.1523	298.327	6.6861	10.6424	<0.00	<0.00	<0.00	<0.00	<0.00	0.0200	49.0324	87.694.6913	869.5288	0.0269	815.5900	864.0081	851.4182	25.9963	<0.00	<0.00	
	1.5993	<0.00	<0.00	<0.00	0.1082	16.7945	0.1225	1.9865	238.3030	13.2386	<0.00	<0.00	<0.00	<0.00	<0.00	0.0150	793.0145	124.511.3148	328.9350	7.9583	7.971	<0.00	<0.00	<0.00	<0.00	<0.00	0.0088	54.7636	87.581.1904	1.007.731	0.0221	64.1497	1.002.6475	901.012	23.7026	<0.00	<0.00	
	0.5201	<0.00	<0.00	<0.00	0.2092	17.9901	0.1403	1.2462	238.3319	11.9355	<0.00	<0.00	<0.00	<0.00	<0.00	0.0180	845.665	123.587.5688	255.9193	6.1133	11.9688	<0.00	<0.00	<0.00	<0.00	<0.00	<0.00	0.0143	50.975	87.740.2020	853.980	0.0239	766.3487	843.7380	860.7939	27.9100	<0.00	<0.00
	1.3865	<0.00	<0.00	<0.00	0.2255	21.5713	0.1214	1.4956	237.2413	12.1403	<0.00	<0.00	<0.00	<0.00	<0.00	0.0187	916.078	123.001.8232	257.4272	6.0001	7.6972	<0.00	<0.00	<0.00	<0.00	<0.00	0.0258	53.3138	87.743.7441	689.072	0.0177	643.5767	684.613	675.2656	20.3466	<0.00	<0.00	
	0.4244	<0.00	<0.00	<0.00	0.1132	17.0031	0.1448	1.2625	246.1005	12.1245	<0.00	<0.00	<0.00	0.0214	0.0187	872.5326	122.717.4993	268.8719	5.8058	8.5259	<0.00	<0.00	<0.00	<0.00	<0.00	<0.00	0.0270	52.7209	87.743.7441	733.689	0.0225	726.4508	733.728	743.347	24.8035	<0.00	<0.00	
	0.8382	<0.00	<0.00	<0.00	0.1099	16.4794	0.1209	1.1773	241.427	10.9527	<0.00	<0.00	<0.00	0.0259	0.0147	945.072	122.861.8025	249.8784	5.4064	8.7394	<0.00	<0.00	<0.00	<0.00	<0.00	<0.00	0.0046	54.5022	87.743.7441	689.072	0.0177	643.5767	684.613	675.2656	20.3466	<0.00	<0.00	
	0.9753	<0.00	<0.00	<0.00	0.1541	18.9186	0.1538	1.7739	235.1541	11.6347	<0.00	<0.00	<0.00	0.0341	0.0194	871.7752	122.650.7592	248.8719	5.4990	8.8579	<0.00	<0.00	<0.00	<0.00	<0.00	<0.00	0.0031	52.6289	87.743.7441	689.072	0.0177	643.5767	684.613	675.2656	20.3466	<0.00	<0.00	
	1.9522	<0.00	<0.00	<0.00	0.1540	20.0035	0.1542	2.1794	242.4095	12.1247	<0.00	<0.00	<0.00	0.0326	0.0162	836.304	122																					

[illegible]

Minimum	0.13841	0.18487	0.00131	0.10450	0.03164	2.17363	0.02365	0.13810	1.45147	0.26014	0.01190	0.31266	0.00227	0.00021	0.00611	27922.45590	0.20704	0.03082	0.09121	0.00813	0.00027	0.01538	0.00243	0.00061	412689.78952	0.05105	0.00081	0.02749	0.01713	0.01526	0.00350	0.00440	0.00026
Maximum	22648.89	2521.93	121.79	292.12	14036.42	43971.03	97.77	1084.31	13344.69	1812.18	12.30	209.08	7.51	0.59	2731.82	586297.21	1619.15	134.37	49.46	7.04	0.59	9.98	3.76	115.48	970818.91	4288.25	1.49	3570.13	4127.00	3845.09	482.50	501.10	411.56
Average LOD	1.24	0.06	0.02	0.08	0.24	7.82	0.14	0.27	0.21	0.42	0.15	3.24	0.02	0.0007	0.02	2.62	0.89	0.12	0.35	0.00150	0.00484	0.00090	0.00056	0.66	0.13	0.0066	0.04	0.039	0.032	0.02	0.00482	0.00069	

Table S5: EMPA Analyses of pyrite from the Água Branca deposit. Concentrations in weight percentage (wt. %), n = 227. <LOD = value below the limit of detection

Sample	Rock	Pyrite	As	Se	S	Bi	Sb	Hg	Pb	Cu	Te	Fe	Ag	Au	Zn	Ni	Co	Total
G09	One	Py3	<LOD	0.022	53.335	<LOD	0.012	<LOD	0.083	<LOD	<LOD	44.797	<LOD	0.012	0.333	0.006	0.088	99.688
G09	One	Py3	0.001	<LOD	53.344	<LOD	<LOD	<LOD	0.033	<LOD	<LOD	45.325	0.006	0.025	0.106	<LOD	0.104	99.571
G09	One	Py3	0.516	0.05	52.963	<LOD	<LOD	<LOD	0.031	<LOD	<LOD	46.164	0.011	<LOD	<LOD	0.014	0.062	99.831
G09	One	Py3	<LOD	0.018	54.204	<LOD	<LOD	<LOD	0.058	0.03	<LOD	45.483	0.001	<LOD	0.182	<LOD	0.098	100.062
G09	One	Py3	0.002	0.019	54.394	<LOD	0.013	<LOD	0.089	0.035	<LOD	45.118	0.007	<LOD	0.038	<LOD	0.063	99.646
G09	One	Py3	0.007	0.007	52.922	<LOD	<LOD	<LOD	0.024	0.032	<LOD	46.491	<LOD	<LOD	0.052	<LOD	0.102	99.637
G09	One	Py3	<LOD	<LOD	52.881	<LOD	<LOD	<LOD	<LOD	0.031	0.004	46.596	0.002	<LOD	0.074	<LOD	0.078	99.696
G09	One	Py3	<LOD	0.007	53.991	<LOD	<LOD	<LOD	0.029	<LOD	<LOD	46.549	0.017	0.021	0.094	0.041	0.095	99.801
G09	One	Py3	0.08	<LOD	53.283	<LOD	<LOD	<LOD	<LOD	0.008	<LOD	46.481	<LOD	<LOD	0.009	<LOD	0.086	99.947
G09	One	Py3	0.007	<LOD	53.248	<LOD	<LOD	<LOD	0.02	0.038	<LOD	46.21	<LOD	0.013	<LOD	<LOD	0.104	99.84
G09	One	Py3	0.027	0.001	53.966	<LOD	0.023	<LOD	0.046	0.037	<LOD	46.072	<LOD	<LOD	0.028	<LOD	0.092	99.898
G09	One	Py3	0.011	0.028	53.031	<LOD	<LOD	<LOD	0.078	<LOD	<LOD	46.046	0.003	0.008	0.213	<LOD	0.069	99.483
G09	One	Py3	0.994	0.004	52.615	<LOD	<LOD	<LOD	0.078	0.006	<LOD	45.988	0.005	<LOD	0.053	0.027	0.093	99.861
G09	One	Py3	0.517	0.011	53.366	<LOD	<LOD	<LOD	0.033	<LOD	<LOD	46.556	0.012	<LOD	0.022	<LOD	0.102	100.344
G09	One	Py3	0.448	<LOD	53.117	<LOD	<LOD	<LOD	0.035	<LOD	<LOD	46.367	0.004	<LOD	0.014	<LOD	0.083	100.006
G09	One	Py3	0.358	0.006	52.617	<LOD	<LOD	<LOD	0.077	<LOD	<LOD	46.334	<LOD	0.008	0.024	<LOD	0.097	99.521
G09	One	Py3	0.009	0.002	53.365	<LOD	<LOD	<LOD	0.032	<LOD	<LOD	46.599	<LOD	0.006	<LOD	0.007	0.093	99.747
G09	One	Py3	0.193	<LOD	53.002	<LOD	0.005	<LOD	0.046	0.041	<LOD	46.709	<LOD	<LOD	0.04	<LOD	0.089	100.125
G09	One	Py3	0.331	<LOD	53.371	<LOD	<LOD	<LOD	<LOD	<LOD	<LOD	46.516	<LOD	0.026	0.02	<LOD	0.088	100.392
G09	One	Py3	0.191	0.002	53.363	<LOD	0.012	<LOD	0.037	0.016	<LOD	46.147	<LOD	<LOD	<LOD	<LOD	0.11	100.269
G09	One	Py3	2.252	<LOD	51.634	<LOD	0.052	<LOD	0.031	0.021	<LOD	45.811	<LOD	0.013	0.001	0.001	0.075	99.891
G09	One	Py3	0.57	0.003	51.993	<LOD	<LOD	<LOD	0.113	<LOD	<LOD	46.605	<LOD	<LOD	<LOD	<LOD	0.099	99.443
G09	One	Py3	0.039	0.004	52.584	<LOD	<LOD	<LOD	0.083	0.053	0.003	46.707	<LOD	<LOD	0.008	<LOD	0.091	99.565
G09	One	Py3	0.201	0.003	53.349	<LOD	<LOD	<LOD	0.008	<LOD	<LOD	46.699	<LOD	<LOD	<LOD	<LOD	0.072	100.109
G09	One	Py3	<LOD	0.011	53.379	<LOD	<LOD	<LOD	<LOD	<LOD	<LOD	46.591	<LOD	0.003	0.04	<LOD	0.092	100.116
G09	One	Py3	0.028	0.001	53.536	<LOD	0.011	<LOD	<LOD	0.006	<LOD	46.568	<LOD	0.005	<LOD	<LOD	0.069	100.224
G09	One	Py3	0.216	<LOD	53.348	<LOD	<LOD	<LOD	0.084	<LOD	<LOD	46.685	<LOD	<LOD	<LOD	0.07	100.261	
G09	One	Py3	<LOD	<LOD	53.479	<LOD	<LOD	<LOD	0.035	<LOD	0.004	46.321	<LOD	<LOD	<LOD	0.043	0.037	99.919
G09	One	Py3	<LOD	0.01	53.319	<LOD	0.002	<LOD	0.137	0.004	<LOD	46.223	<LOD	<LOD	0.001	0.023	0.063	99.762
G09	One	Py3	0.07	<LOD	53.333	<LOD	<LOD	<LOD	0.09	<LOD	<LOD	46.513	<LOD	<LOD	0.004	<LOD	0.112	100.248
G09	One	Py3	0.033	<LOD	53.015	<LOD	0.008	<LOD	<LOD	0.028	<LOD	46.748	<LOD	0.036	<LOD	<LOD	0.072	99.904
G09	One	Py3	<LOD	0.024	53.133	<LOD	<LOD	<LOD	0.246	0.036	<LOD	46.599	<LOD	<LOD	0.012	0.014	0.094	99.758
G09	One	Py3	0.981	0.012	51.991	<LOD	<LOD	<LOD	0.029	0.054	<LOD	44.683	<LOD	0.016	0.002	<LOD	0.077	99.809
G09	One	Py3	0.002	<LOD	53.495	<LOD	0.005	<LOD	0.008	0.053	<LOD	46.519	<LOD	0.029	0.003	<LOD	0.079	100.193
G09	One	Py3	0.006	0.012	53.536	<LOD	0.008	<LOD	0.088	<LOD	<LOD	46.595	0.001	0.015	0.012	<LOD	0.077	100.346
G09	One	Py3	0.009	0.002	53.343	<LOD	0.011	<LOD	0.031	<LOD	<LOD	45.624	0.004	<LOD	0.007	0.014	0.078	99.018
G09	One	Py3	0.034	<LOD	53.336	<LOD	0.015	<LOD	<LOD	0.007	<LOD	45.716	0.003	0.007	<LOD	<LOD	0.07	99.188
G09	One	Py3	<LOD	0.015	53.077	<LOD	0.014	<LOD	<LOD	0.001	<LOD	45.957	<LOD	<LOD	0.016	<LOD	0.091	99.171
G09	One	Py3	0.195	0.017	52.961	<LOD	<LOD	<LOD	0.031	<LOD	<LOD	45.966	0.003	<LOD	<LOD	<LOD	0.096	100.078
G09	One	Py3	<LOD	0.001	53.472	<LOD	0.011	<LOD	0.042	<LOD	<LOD	45.712	<LOD	0.013	<LOD	0.013	0.088	99.352
G09	One	Py3	0.092	<LOD	53.301	<LOD	<LOD	<LOD	0.058	0.028	0.01	45.604	0.001	<LOD	0.008	<LOD	0.076	99.178
G09	One	Py3	0.516	0.002	52.474	<LOD	<LOD	<LOD	0.011	<LOD	<LOD	46.034	0.004	<LOD	0.019	<LOD	0.076	99.157
G09	One	Py3	<LOD	0.015	51.7	<LOD	<LOD	<LOD	<LOD	0.047	0.004	47.536	<LOD	<LOD	0.022	<LOD	0.084	99.408
G09	One	Py3	0.044	0.017	52.901	<LOD	<LOD	<LOD	<LOD	<LOD	<LOD	47.367	0.005	0.011	<LOD	<LOD	0.067	100.442
G09	One	Py3	0.006	0.002	53.159	<LOD	<LOD	<LOD	0.031	0.046	<LOD	47.096	0.016	0.019	0.02	0.016	0.097	100.855
G09	One	Py3	<LOD	<LOD	53.049	<LOD	0.009	<LOD	0.019	0.033	<LOD	46.841	0.006	0.001	<LOD	<LOD	0.087	100.045
G09	One	Py3	0.023	<LOD	53.061	<LOD	<LOD	<LOD	0.053	0.024	46.059	0.005	<LOD	<LOD	<LOD	<LOD	0.062	99.317
G09	One	Py3	0.02	<LOD	53.337	<LOD	<LOD	<LOD	0.089	<LOD	<LOD	45.908	0.006	<LOD	<LOD	<LOD	0.057	99.401
G09	One	Py3	0.004	0.006	53.322	<LOD	<LOD	<LOD	0.029	0.014	<LOD	46.118	0.001	<LOD	<LOD	<LOD	0.066	99.456
G09	One	Py3	<LOD	0.011	53.203	<LOD	0.035	<LOD	0.024	0.035	0.032	46.054	<LOD	0.008	<LOD	0.002	0.09	99.494
G09	One	Py3	0.296	0.006	54.189	<LOD	0.027	<LOD	0.003	0.051	<LOD	45.675	0.017	<LOD	<LOD	<LOD	0.102	100.596
G09	One	Py3	0.87	0.004	52.961	<LOD	<LOD	<LOD	0.008	<LOD	<LOD	45.783	<LOD	<LOD	<LOD	<LOD	0.092	99.261
G09	One	Py3	0.33	0.018	54.74	<LOD	0.009	<LOD	<LOD	<LOD	<LOD	45.799	0.001	<LOD	<LOD	<LOD	0.075	100.972
G09	One	Py3	0.242	<LOD	53.951	<LOD	0.007	<LOD	0.007	0.017	0.024	45.752	<LOD	<LOD	<LOD	<LOD	0.1	100.136
G09	One	Py3	0.728	0.01	53.437	<LOD	0.001	<LOD	<LOD	<LOD	<LOD	47.335	<LOD	0.042	<LOD	<LOD	0.171	100.711
G09	One	Py3	0.899	<LOD	52.862	<LOD	<LOD	<LOD	0.062	0.028	<LOD	45.527	<LOD	0.008	<LOD	<LOD	0.071	99.457
G09	One	Py3	0.007	0.02	53.751	<LOD	0.031	<LOD	<LOD	0.014	<LOD	45.366	0.008	0.016	0.01	<LOD	0.091	99.314
G09	One	Py3	0.424	<LOD	53.763	<LOD	<LOD	<LOD	0.022	0.006	0.005	45.796	0.003	0.012	0.041	<LOD	0.102	100.148
G09	One	Py3	0.279	<LOD	53.274	<LOD	<LOD	<LOD	0.075	<LOD	<LOD	45.641	0.004	0.019	<LOD	<LOD	0.107	99.399
G09	One	Py3	0.173	<LOD	53.548	<LOD	0.01	<LOD	0.094	0.01	0.027	45.73	0.007	<LOD	<LOD	0.006	0.093	99.698
G09	One	Py3	0.448	0.012	52.451	<LOD	<LOD	<LOD	0.009	<LOD	<LOD	45.574	0.003	0.016	0.005	<LOD	0.09	99.763
G09	One	Py3	1.035	0.011	52.316	<LOD	<LOD	<LOD	0.062	<LOD	<LOD	46.303	0.012	<LOD	<LOD	<LOD	0.076	99.815
G09	One	Py3	0.025	0.006	53.62	<LOD	0.021	<LOD	0.091	0.018	<LOD	46.45	0.017	0.008	<LOD	<LOD	0.07	100.326
G09	One	Py3	0.12	0.033	53.534	<LOD	<LOD	<LOD	0.031	<LOD	<LOD	46.006	0.007	<LOD	<LOD	<LOD	0.063	99.801
G09	One	Py3	<LOD	<LOD	52.788	<LOD	0.008	<LOD	0.322	0.001	<LOD	46.608	<LOD	<LOD	0.024	0.003	0.075	99.829
G09	One	Py3	0.012	0.008	53.507	<LOD	<LOD	<LOD	0.04	<LOD	<LOD	47.008	<LOD	<LOD	0.036	<LOD	0.113	100.724
G09	One	Py3	0.005	<LOD	53.41	<LOD	0.005	<LOD	<LOD	<LOD	<LOD	46.146	<LOD	0.004	0.011	<LOD	0.097	99.806
G09	One	Py3	0.008	<LOD	53.367	<LOD	0.013	<LOD	0.036</									

TableS6: LA-ICP-MS analyses of pyrite from the Águia Branca deposit. Excluding mineral inclusions identified in the depth profile. Concentrations in parts per million (ppm), n = 61, <LOD = value below the limit of detection

[illegible]

	29S1	45Sc	49Ti	51V	52Cr	55Mn	58Co	60Ni	63Cu	66Zn	71Ga	75As	77Se	85Rb	88Sr	89Y	91Zr	93Nb	95Mo	107Ag	111Cd	115In	118Sn	121Sb	125Te	133Cs	138La	140Ce	141Pr	145Nd	147Sm	151Eu	157Dy	159Tb	163Dy	165Ho	166Er	169Tm	173Yb	175Lu	178Hf	181Ta	195Pt	197Au	202Hg	205Tl	206Pb	207Pb	208Pb	209Bi	232Th	238U			
Min	39.35	0.3	23.53	0.1	1.4	0.78	0.06	0.11	0.55	0.85	0.04	16.71	2.38	0.13	0.01	0.02	0.1	0	0	0.06	0.15	0.01	0.06	0.04	0.92	0.02	0.01	0	0	0.06	0.15	0.01	0.05	0.01	0.02	0.01	0.01	0.03	0.1	0.01	0.01	0.05	0.01	0.4	0.01	0.68	0.76	0.66	0.01	0	0	0			
Max	8186.63	2.65	47.42	24.91	5.34	153	2279.99	760.5	3723.13	29829.99	3.45	18621.98	11.48	29.34	11.92	20.41	23.69	0.45	0.92	231.21	298.77	3.43	35.53	39.72	9.94	0.78	32.57	57.19	10.09	33.55	11.62	2.35	7.24	0.81	3.55	0.96	2.45	0.18	1.26	0.13	0.85	0.01	0.05	64.05	2.74	0.31	40614.84	43595.58	41466.52	4.55	0.42	0.21			
Mean	2015.775	0.41	28.7	0.2	2.14	1.92	3.3	3.19	8.66	1.78	0.42	14915.7	6.82	5.955	0.09	0.04	1.17	0.02	0.25	2.5	0.64	0.015	0.105	1.71	1.405	0.16	0.02	0.015	0.01	0.11	5.885	0.01	0.05	0.01	0.04	0.01	0.02	0.01	0.05	0.01	0.03	0.01	0.05	1.00	0.79	0.045	30.35	31.66	32.19	0.05	0	0			
Median	266.35	0.23	1.77	0.12	2.24	0.88	0.05	0.11	0.33	0.48	0.04	4.93	4.37	0.13	0.02	0.03	0.14	0.01	0.09	0.05	0.55	0.02	0.01	0.01	0.09	0.05	0.02	0.01	0.01	0.01	0.08	0.05	0.01	0.04	0.01	0.03	0.01	0.02	0.01	0.04	0.04	0.01	0.02	0.01	0.06	0.02	0.51	0.01	0.08	0.06	0.04	0.01	0.00	0.00	0.00

Sample	Analysis	Pyrite type	Model Decission	Random Forest (IOCG)	Random Forest (Orogenic Au)	Random Forest (Porphyry)	Random Forest (SEDEX)	Random Forest (Sedimentary)	Random Forest (VHMS)	Random Forest (hydrothermal breccia)		Votes >40%	1st place	2nd place
				% of votes for each deposit type										
GG11	GG-11-3_Py_A2_P1	Py1	Porphyry	7%	25%	57%	0%	1%	4%	7%		+	Porphyry	Orogenic
GG11	GG-11-3_Py_A2_P2	Py1	Porphyry	4%	26%	57%	0%	1%	7%	5%		+	Porphyry	Orogenic
GG11	GG-11-3_Py_A2_P3	Py1	hydrothermal breccia	10%	10%	25%	2%	2%	5%	47%		+	HB	Porphyry
GG11	GG-11-3_Py_A2_P4	Py1	hydrothermal breccia	8%	9%	22%	2%	3%	17%	40%		+	HB	Porphyry
GG11	GG-11-3_Py_A1_P1	Py1	Porphyry	8%	14%	44%	3%	4%	5%	20%		+	Porphyry	HB
GG9	GG9-1_Py_A5_P1	Py2	Orogenic Au	2%	35%	9%	1%	13%	11%	28%		-	-	-
GG9	GG9-1_Py_A5_P2	Py2	hydrothermal breccia	4%	34%	9%	0%	5%	9%	39%		-	-	-
GG9	GG9-1_Py_A5_P3	Py2	Orogenic Au	5%	39%	13%	0%	4%	10%	29%		-	-	-
GG9	GG9-1_Py_A5_P4	Py2	Orogenic Au	5%	48%	11%	0%	3%	9%	24%		+	Orogenic	HB
GG9	GG9-1_Py_A5_P5	Py2	Orogenic Au	5%	43%	10%	0%	4%	10%	28%		+	Orogenic	HB
GG9	GG9-1_Py_A5_P6	Py2	hydrothermal breccia	5%	31%	6%	0%	7%	13%	39%		-	-	-
GG9	GG9-1_Py_A5_P7	Py3	hydrothermal breccia	4%	34%	6%	0%	6%	12%	38%		-	-	-
GG9	GG9-1_Py_A5_P8	Py3	Orogenic Au	2%	34%	6%	1%	7%	15%	34%		-	-	-
GG9	GG9-1_Py_A3_P1	Py3	Orogenic Au	4%	49%	19%	1%	2%	8%	17%		+	Orogenic	Porphyry
GG9	GG9-1_Py_A3_P2	Py3	Orogenic Au	3%	49%	26%	2%	2%	8%	9%		+	Orogenic	Porphyry
GG9	GG9-1_Py_A2_P1	Py3	Orogenic Au	5%	50%	15%	0%	1%	16%	13%		+	Orogenic	VHMS
GG9	GG9-1_Py_A2_P2	Py3	VHMS	0%	35%	1%	0%	0%	51%	12%		+	VHMS	Orogenic
GG9	GG9-1_Py_A2_P3	Py3	hydrothermal breccia	2%	23%	7%	2%	11%	22%	32%		-	-	-
GG9	GG9-1_Py_A2_P4	Py3	hydrothermal breccia	3%	29%	7%	0%	2%	19%	41%		+	HB	Orogenic
GG9	GG9-1_Py_A2_P5	Py3	hydrothermal breccia	2%	27%	6%	0%	2%	23%	40%		+	HB	Orogenic
GG9	GG9-1_Py_A2_P6	Py3	Orogenic Au	4%	47%	28%	1%	1%	12%	7%		+	Orogenic	Porphyry
GG9	GG9-1_Py_A2_P7	Py3	Orogenic Au	3%	36%	9%	1%	5%	12%	34%		-	-	-
GG9	GG9-1_Py_A2_P8	Py3	Orogenic Au	5%	47%	25%	0%	2%	12%	8%		+	Orogenic	Porphyry
GG9	GG9-1_Py_A1_P1	Py3	VHMS	1%	3%	2%	0%	0%	78%	15%		+	VHMS	HB
GG9	GG9-1_Py_A1_P2	Py3	VHMS	3%	19%	8%	0%	1%	39%	31%		-	-	-
GG9	GG9-1_Py_A1_P3	Py3	Orogenic Au	3%	32%	11%	0%	0%	32%	23%		-	-	-
GG9	GG9-1_Py_A1_P4	Py3	VHMS	1%	4%	1%	0%	1%	80%	13%		+	VHMS	Orogenic
GG9	GG9-1_Py_A1_P5	Py3	hydrothermal breccia	3%	9%	7%	3%	2%	25%	50%		+	HB	VHMS
GG9	GG9-1_Py_A1_P6	Py3	VHMS	1%	3%	1%	1%	0%	77%	17%		+	VHMS	HB
GG9	GG9-1_Py_A1_P7	Py3	hydrothermal breccia	3%	19%	3%	0%	1%	32%	43%		+	HB	VHMS
GG9	GG9-1_Py_A7_P1	Py3	hydrothermal breccia	6%	10%	17%	10%	7%	18%	33%		-	-	-
GG9	GG9-1_Py_A7_P2	Py3	Porphyry	14%	26%	41%	0%	1%	7%	11%		+	Porphyry	Orogenic
GG9	GG9-1_Py_A7_P3	Py3	Orogenic Au	7%	36%	20%	0%	1%	20%	17%		+	Orogenic	Porphyry
GG9	GG9-1_Py_A7_P4	Py3	Porphyry	5%	26%	60%	0%	0%	5%	4%		+	Porphyry	Orogenic
GG9	GG9-1_Py_A7_P5	Py3	hydrothermal breccia	2%	19%	3%	0%	1%	35%	40%		+	HB	VHMS
GG9	GG9-1_Py_A7_P6	Py3	hydrothermal breccia	2%	20%	2%	0%	1%	29%	46%		+	HB	VHMS
GG9	GG9-1_Py_A7_P7	Py3	Orogenic Au	7%	30%	7%	1%	2%	26%	27%		-	-	-
GG9	GG9-1_Py_A7_P8	Py3	hydrothermal breccia	11%	12%	28%	1%	2%	15%	30%		-	-	-
GG9	GG9-1_Py_A7_P9	Py3	VHMS	2%	23%	9%	2%	4%	36%	24%		-	-	-
GG9	GG9-1_Py_A7_P10	Py3	Orogenic Au	7%	36%	20%	0%	1%	20%	17%		-	-	-
GG9	GG9-1_Py_A7_P11	Py3	Porphyry	4%	16%	37%	0%	0%	26%	17%		-	-	-
GG9	GG9-1_Py_A7_P12	Py3	Orogenic Au	5%	37%	13%	0%	1%	22%	21%		-	-	-
GG9	GG9-1_Py_A7_P13	Py3	VHMS	1%	6%	1%	0%	0%	63%	29%		+	VHMS	HB
GG9	GG9-1_Py_A6_P1	Py3	Porphyry	6%	21%	56%	1%	1%	9%	7%		+	Porphyry	Orogenic
GG9	GG9-1_Py_A6_P2	Py3	Orogenic Au	3%	45%	7%	1%	0%	27%	17%		+	Orogenic	VHMS
GG9	GG9-1_Py_A6_P4	Py3	Orogenic Au	3%	47%	6%	1%	0%	27%	16%		+	Orogenic	VHMS
GG9	GG9-1_Py_A6_P3	Py3	Orogenic Au	6%	41%	15%	0%	1%	18%	18%		+	Orogenic	HB
GG9	GG9-1_Py_A6_P5	Py3	Porphyry	9%	12%	21%	10%	14%	16%	19%		-	-	-
GG9	GG9-1_Py_A6_P6	Py3	Orogenic Au	3%	54%	11%	0%	0%	18%	13%		+	Orogenic	VHMS
GG9	GG9-1_Py_A6_P7	Py3	hydrothermal breccia	4%	12%	7%	1%	2%	30%	44%		+	HB	VHMS
GG9	GG9-1_Py_A6_P8	Py3	Orogenic Au	2%	44%	7%	0%	0%	26%	20%		+	Orogenic	VHMS
GG9	GG9-1_Py_A6_P9	Py3	Orogenic Au	4%	49%	5%	0%	1%	23%	18%		+	Orogenic	VHMS
GG9	GG9-1_Py_A6_P10	Py3	VHMS	0%	4%	3%	0%	2%	79%	12%		+	VHMS	HB
GG9	GG9-1_Py_A6_P11	Py3	VHMS	0%	11%	5%	1%	2%	70%	11%		+	VHMS	Orogenic
GG9	GG9-1_Py_A6_P12	Py3	VHMS	2%	11%	2%	1%	1%	45%	39%		+	VHMS	HB
GG9	GG9-1_Py_A6_P13	Py3	VHMS	1%	25%	3%	0%	0%	51%	20%		+	VHMS	Orogenic
GG9	GG9-1_Py_A6_P14	Py3	Orogenic Au	4%	41%	12%	0%	0%	25%	18%		+	Orogenic	VHMS
GG9	GG9-1_Py_A6_P15	Py3	Orogenic Au	6%	25%	23%	2%	4%	20%	21%		-	-	-
GG9	GG9-1_Py_A6_P16	Py3	Orogenic Au	3%	50%	26%	1%	1%	12%	7%		+	Orogenic	Porphyry
GG9	GG9-1_Py_A6_P17	Py3	Orogenic Au	6%	42%	24%	0%	0%	15%	12%		+	Orogenic	Porphyry
GG9	GG9-1_Py_A6_P18	Py3	Orogenic Au	4%	49%	5%	0%	1%	23%	18%		+	Orogenic	VHMS
													(%) 1st place	(%) 2nd place
												Orogenic	42.86	26.19
												Porphyry	14.29	21.43
												HB	21.43	21.43
												VHMS	21.43	30.95

