Improved Mine Water Quality Predictions Using Available International Hydrochemical Datasets

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Abstract

Mine waters exhibit variable compositions with a range of pH and dissolved solutes. Waters with pH less than six are referred to as acid mine drainage (AMD), and waters with pH greater than six are classified as saline drainage (SD) or neutral mine drainage (NMD) depending on the concentration of dissolved solutes. Plumlee *et al.*, (1999) developed a set of trace elements that when compared with pH, enabled definition of mine waters into twelve categories and later developed this into a geo-environmental model using mine sites from a limited geography within North America. This study uses a wider international sample-set of surface water drainage from mines to assess whether this model has global applicability.

Hydrochemical data from thirty-eight mines located on four continents were plotted onto the Plumlee model to assess the boundaries of each field. Early geology-based classification schemes (e.g. Cox and Singer, 1986) have evolved into mineral deposit models that classify deposits using geologic, geophysical and geochemical characteristics that consider the overall 'geodynamic' context of ore deposits (Gessner *et al.*, 2018).

The results of this study correlate well with the fields set out in the original Ficklin diagrams from the 1990s. This approach helps move towards more refined mine water quality predictions early on in a project development and allows easy revision of the model throughout the project life cycle. These models can be used as an improved predictive tool by researchers including consultants, mining professionals, regulators and other stakeholders.

Keywords: Ficklin Diagrams, Mine water, water quality prediction, international dataset

Introduction

Mine waters exhibit variable compositions with a range of pH and dissolved solutes, where waters with pH less than six are referred to as acid mine drainage (AMD), and waters with pH greater than six are classified as saline drainage (SD) or neutral mine drainage (NMD) depending on the concentration of dissolved solutes (Plumlee et al., 1994; Verburg et al., 2009, INAP, 2009). Increasing demand for metals and minerals to assist with the energy transition, and new methods and economic drivers for commodity recovery from former wastes and tailings make it more important than ever that mineral development is progressed responsibly. (e.g. World Economic Forum 2015, Arvanitidis et al., 2017). Planning and regulatory requirements across jurisdictions require a good understanding of the potential geochemical outcomes from the mining lifecycle, meaning predictive tools for geochemical evolution need to be accessible and robust for different situations.

Background

Ficklin diagrams showing sum of metal versus pH were originally developed to characterise surface water drainage from mineral deposits and classify waters into 1 of 12 fields (Fig. 1). Over the past three decades, these classifications have become widely used by an increasing range of consultants and academics working on geo-environmental studies, many of which are mining projects, but now also include other applications, including industrial processing and anthropogenic influences on environmental backgrounds.

Within the mining industry, Ficklin diagrams are used to characterise ground water and surface water types and are applied to baseline (pre-project) natural waters as well as modified water quality, throughout the entire mine life cycle, including closure and post-closure of a project. Static and kinetic laboratory test results are also plotted onto Ficklin diagrams to predict future mine waters and leachates from various facilities such as waste rock dumps (WRDs), pit lakes, and process plants. Collectively, these results are used to develop mine water and mine waste management plans, along with associated strategic risk assessments, mitigations where necessary, and stewardship of resources.

Geoenvironmental models and integration of mineralisation styles

Plumlee *et al.*, (1994) correlated water chemistry ranges into defined fields and related these to specific mineralization styles based on a limited geographic dataset, and these are displayed in grey fields presented in Fig. 1. Considering the wide application of Ficklin diagrams, which could be more widely used for resource and reserve definition of varying mineralisation styles, coupled with the need for robust prediction tools to derisk mining projects in the 21st century, this study

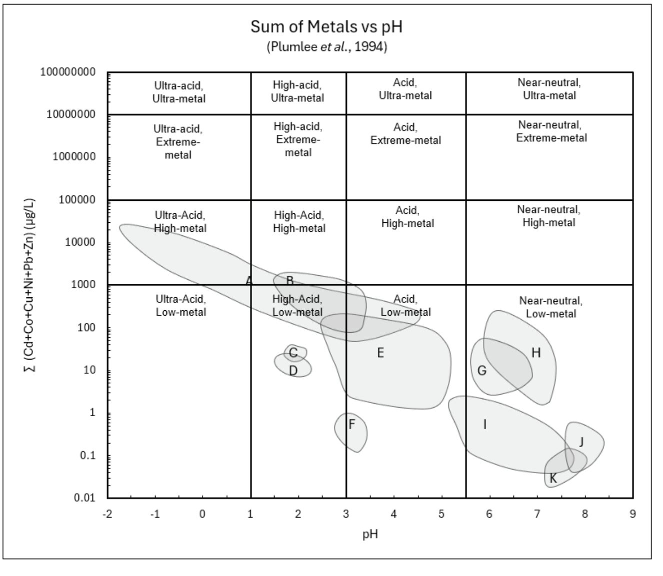

***Figure 1** Plumlee et al (1994) mineralisation fields for: A Pyrite rich massive sulfides; B sulfide rich ores (with pyrite, enargite, bromite etc) in wallrock highly altered to silica, alunite, kaolinite and clays; C high-sulfide, low-base metal hot spring ores in acid-altered wallrock; D high-sulfide low-base metal, porphyry Mo ores in igneous wallrock; E pyrite- and base metal- rich polymetallic veins and disseminations in wallrock with low acid-buffering capacity; F pyrite-rich, base metal-poor veins and disseminations in wallrock with low acid-buffering capacity; G Pyrite- and base metal-rich, polymetallic veins that are carbonate-rich or occur in wallrock altered to contain carbonate; H Pyrite- and base metal-rich, polymetallic replacements and veins in carbonate-rich sediments; I polymetallic veins with moderate to low pyrite and base metal content that's all carbonate rich or occur in carbonate rich wallrock; J pyrite-poor, polymetallic replacements in carbonate-rich sediments; K pyrite-poor, Au-Te veins and breccias with carbonate gangue*

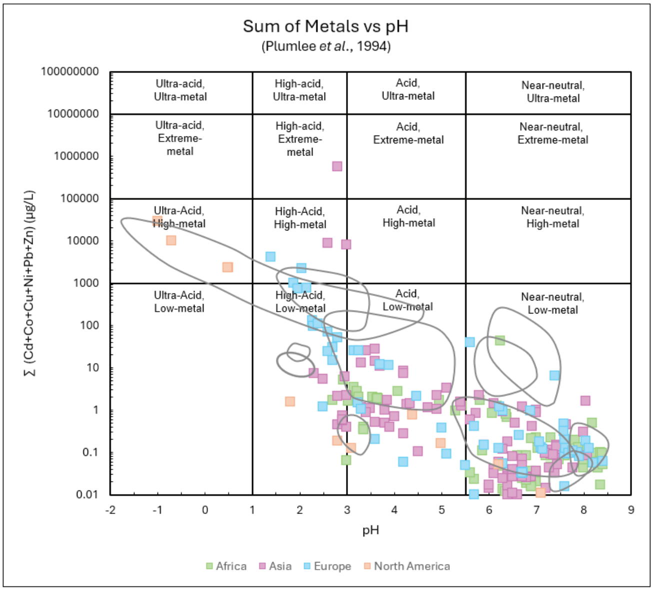

Figure 2 Global dataset displaying continent from which it originates compared to the fields in Plumlee et al (1999)

aims to further define these fields using a wider and more varied dataset collected from a range of published international projects.

A desktop investigation was performed using Google scholar and various other resources to access publicly available river water, groundwater and mine water data associated with mining activities, distributed across different continents. Additionally, unpublished data and internal Wardell-Armstrong International mine water data was used with permission from our client-base. This international dataset comprises 287 samples across four continents, including 89 from Africa, 97 from Asia, 62 from Europe and 39 from North America (Fig. 2), and reflecting 12 commodities (Au, Co, Cu, Fe, Mn, Pb, S, U, Zn, coal, dolomite and fluorite) (Fig. 3).

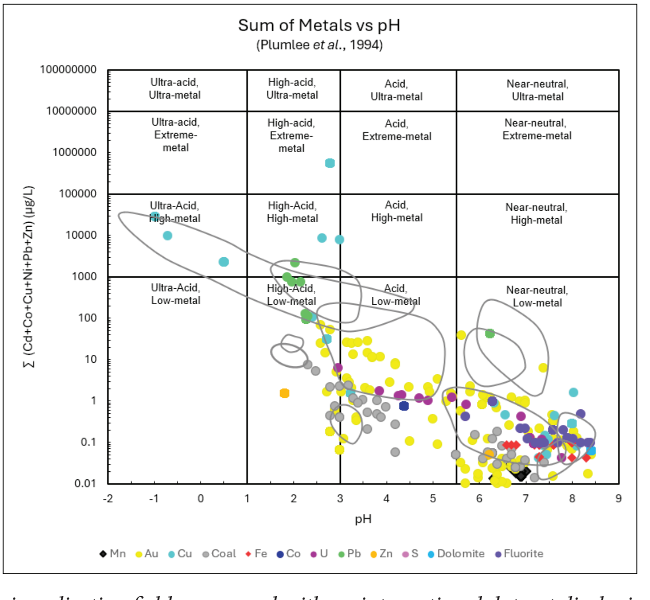

Figure 3 Plumlee mineralisation fields compared with an international dataset displaying main commodity extracted at each project

Results

The international dataset is graphically displayed in Fig. 2, showing the geographical distribution and comparing this with Plumlee's (1994) original mineralisation fields. There is generally a good correlation between the international dataset and Plumlee's fields. There are also some key differences, across the continents, notably North American mines report the lowest recorded pH values while Asian mines record the highest concentrations of dissolved metals.

There are several mine waters which plot outside, but near, to Plumlee's fields. More work needs to be done to collect robust internationally relevant data that can be scrutinised against mineralisation types. This information is often not available in public domain published hydrochemistry studies.

Like the geographically based dataset, the general fit of the international commodity dataset shows good correlation with Plumlee's mineralisation fields. In the section below we present a series of graphs showing different "major commodities" and compare these against Plumlee's mineralisation fields.

Zinc deposits typically exhibit a lower sum of metal concentrations in comparison to the lead and copper deposits. There is some overlap between copper and zinc deposits where copper deposits show more variability with pH, ranging from ultra-acid to near-neutral pH and the sum of metals extending from low-metal to extreme-metal concentrations (Fig. 4).

Fig. 5 shows gold mineralisation extends from high-acid, low-metal to near-neutral, low-metal pH and the sum of metal concentration is positioned within the low metal range. Gold and copper exhibit similar trends (Fig. 4). Uranium deposits (Fig. 6) are defined as near-neutral, low-metal to high-acid, low-metal compositions. These data form a narrow band that superimposes the Au and Cu deposits. A single Co deposit is characterised by an acid, low-metal composition, and partially overlaps with the U deposit field (Fig. 9).

Iron and manganese ore deposits (Fig. 7) all plot within the near-neutral, low metal range, with the pH for iron ore deposits extending to more alkaline pH (up to 8.5), whereas manganese ores exhibit constrained pH between 6 and 7.5. These fields are like those observed for fluorite and dolomite, which also plot within the near-neutral, low-metal field (Fig. 9).

Coal fields range from near-neutral, low-metal to high-acid low-metal, and typically exhibit lower sum of metals compared to Au, U and Cu deposits (Fig. 8), but have a similar trend to zinc deposits (Fig. 4).The similar Plumlee fields observed for Cu (C,D,F,G,H), Au (A,E,F,H,I,J,K) and Pb (A,B,H) are all high-sulfide / pyrite-rich base-metal poor to rich fields.

Uranium deposits (E,I) partially superimposes the pyrite (low-medium) with low to high acid buffering capacity which occur associated with carbonates. Mn (I,K,H), Fe (I,J,K), dolomite (I,J,K) and fluorite (I,J,K)

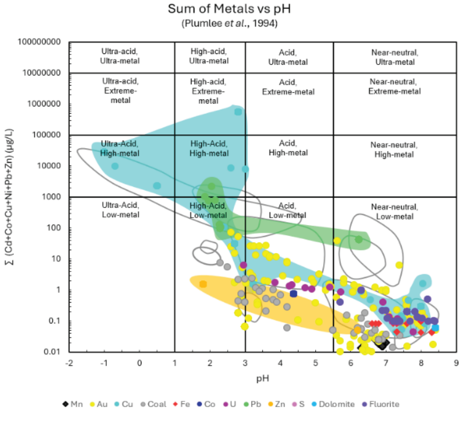

Figure 4 Zn, Pb and Cu deposits

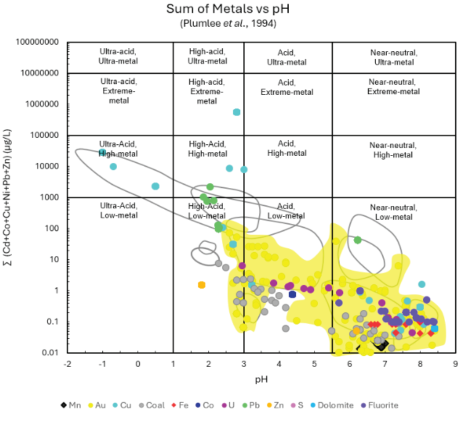

Figure 5 Au deposits

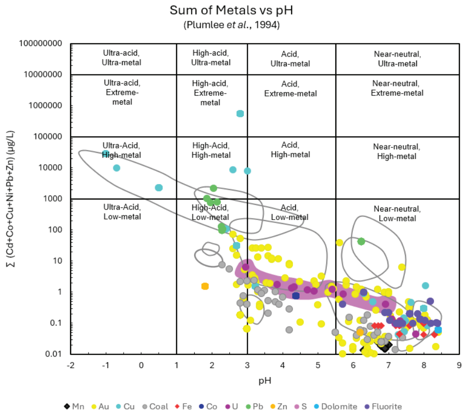

Figure 6 U deposits

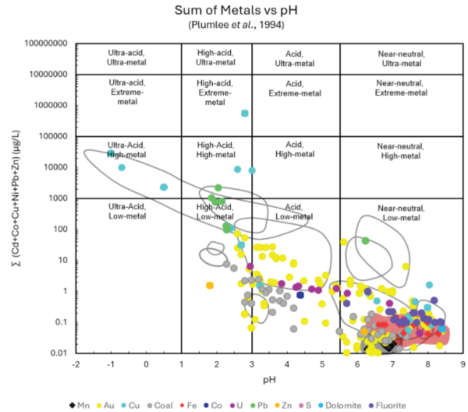

Figure 7 Iron ore and manganese deposits

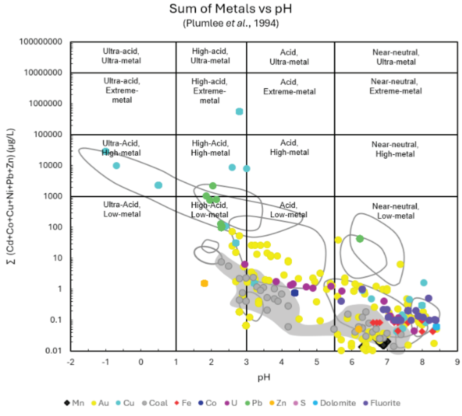

Figure 8 Coal fields

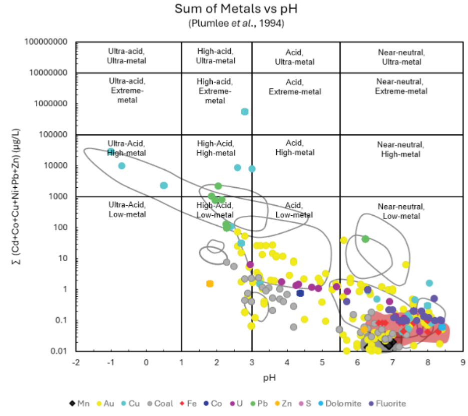

Figure 9 Co, fluorite and dolomite deposits

all partially superimpose the pyrite poor with high buffering capacity, possibly associated with carbonates. Coal (D,E,F,I,K) exhibits trends that range from pyrite poor to pyrite rich, with poor to high buffering capacity. The trends observed generally fit well with the mineralisation styles as noted by Plumlee *et al.* (1994). The analysis shows a clear basis for distinction between ore types and their hydrogeochemical signature. Further work would be needed to confirm the statistical strength of the classifications, for instance using analysis of variance (ANOVA).

Conclusions

By including hydrochemical characterisation of surface waters and groundwaters, which are routinely monitored at advanced exploration and PFS stages of projects today, this approach moves toward more refined predictions of water quality early in project development. This allows mitigatory steps to be implemented sooner for higher-risk projects and later for lower-risk projects as well as allocation of appropriate risk and budget to be spent in accordance with mine project development. Surface and groundwater hydrochemistry data collected at the PFS stage can be used to generate environmental baselines that are deposit-specific and help develop environmental quality standards that are robust for closure, and free-from legislative criteria which sometimes are not available, except as international best practices. Since these data are usually collected, it represents an opportunity to gain additional insights into geochemical characterisation.

While this model is only as good as the diversity of mineral deposits and commodities used to define each trajectory, these models can be used as an improved predictive tool by researchers including consultants, mining professionals, regulators and other stakeholders. This dataset is comparatively small and does not cover all the mineralisation styles listed in Cox and Singer (1986), as it represents clients that Wardell Armstrong International have represented, together with published data in the public domain, mostly from academic papers. To improve the predictive ability of this approach, it is recommended that an improved global mine water database is generated and made available for public use.

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