# Catastrophe Vulnerability and Risk Mapping in the Iron Quadrangle, Brazil – Preliminary Results in the Rio das Velhas Watershed

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## Abstract

The geochemistry of fluvial deposits is one of the most used proxies for contamination assessment in mined areas. A river sediment survey was carried out in Iron Quadrangle (IQ), Brazil, between 2013 and 2015. Subsequently, in the last four years, two dam failures happened, causing great environmental damage. Geostatistical modelling was used to model Potentially Toxic Elements' spatial patterns and the definition of hot/cold clusters for Arsenic contamination risk concerning catastrophic scenarios, such as dam failure. and so used as a tool for vulnerability and risk assessment. The preliminary results for Arsenic spatial distribution are introduced and discussed.

**Keywords:** Iron Quadrangle, Potentially Toxic Elements, Geostatistical Modelling

## Introduction

Fluvial sediments come from a myriad of sources, diffuse and punctual, whose relative contribution varies over time and space. Their geochemical composition is a response to the availability of materials, whether due to natural causes or human activities, such as mining. Mining industries produce enormous volumes of waste material, mainly tailings, which can be a relevant source of trace element contamination for the environment, especially in the river basins (Krıbek et al. 2014). Worldwide, billions of tonnes of tailings are contained in impoundments behind huge dams (Owen et al. 2020). Several characteristics of these structures make them more susceptible to failures.The enormous volume and characteristics of the material released in the environment with the collapse of the dam, especially in watersheds and river basins, affect the quality of sediments and water (Kossoff et al. 2014).

Mining is still among the most productive activities that support the Brazilian economy (12.5% of total exports and 36.6% of the trade balance – AMN 2019) and Minas Gerais State is responsible for the other 40% of the commercialized mineral production (AMN 2019). The Iron Quadrangle (IQ), southeast of Minas Gerais State, (fig. 1) is one of the most important mining producing provinces in Brazil and one of the World's most important mineral regions, covering an area of approximately 7,000 km$^2$. Mining activities are focus on iron and gold exploitations, whose wastes are stored in large tailings dams. The IQ yields the headwaters of two major Brazilian River basins: Doce and São Francisco. The last one, fed by Velhas (largest drainage basin in IQ) and Paraopeba rivers. Unfortunately, during the last six years, IQ experience two of the most dramatic accidents involving the dam's tailings failure. Fundão dam (Bento Rodrigues/Mariana), on 5 November 2015, released 4.3×10$^7$ m$^3$ of tailings in Doce River basin (Carmo et al. 2017) and Córrego do Feijão dam (Brumadinho), on 25 January 2019, released

$1.2\times10^7$ $m^3$ of tailings in Paraopeba River basin (Thompson et al. 2020).

A preliminary multivariate study was performed through Principal Component Analysis (PCA) (Shaw 2003) to understand the attributes of preferential association and the reduction of the space of analyses. The analysis begins with p random attributes X1, X2, …, Xp, where no assumption of multivariate normality is required. Considering the ACP outputs, Cr, Zn, Cd, Ni, Cu and Pb were kept for further spatial analysis as they can act accurate indicators for the pollution characterization.

In the herein survey the results for the As spatial distribution are introduced and discussed as As plays a key role in soil and sediments pollution (Gonzalez-Fernandez et al. 2018). Indeed, among the elements present in iron and gold tailings, Arsenic appears as one of the most dangerous to the environment, including human health (Fewtrell et al. 2005, Zhang et al., 2019). Although the interaction between arsenic and the various environmental compartments (sediment, soil, water) still needs to be better understood, there is no doubt that one of the main sources of arsenic contamination in river basins is mining activity (Deschamps & Matschullat, 2011). Several studies have identified anomalous concentrations of arsenic in IQ waters and sediments (Costa et al. 2015). In the case of sediments, there are reports of levels above 4700 $\mu g.g^{-1}$ (Borba et al. 2000), much higher than the average concentration in the Earth's crust (between 1.0 – 4.8 $\mu g.g^{-1}$, according to Taylor & McLennan, 1995 and Rudnick & Gao, 2003).

Arsenic is defined as a 'Regionalized Variable (Matheron 1971) and consequently additive by construction, since the mean value within given observed support is equal to the arithmetic average of sample values, regardless of the statistical distribution of the values. Geostatistical modelling (Goovaerts 1997, Journel and Huijbregts 1978) was used, throughout conventional variography followed by Sequential Gaussian Simulation algorithm (SGS) and local G clustering, to model Arsenic concentration's spatial patterns and the definition of hot/cold spots for contamination risk. The Standard Deviation map, obtained from the performed one hundred simulations (SGS), allowed the visualization of the correspondent spatial uncertainty and, therefore, acting

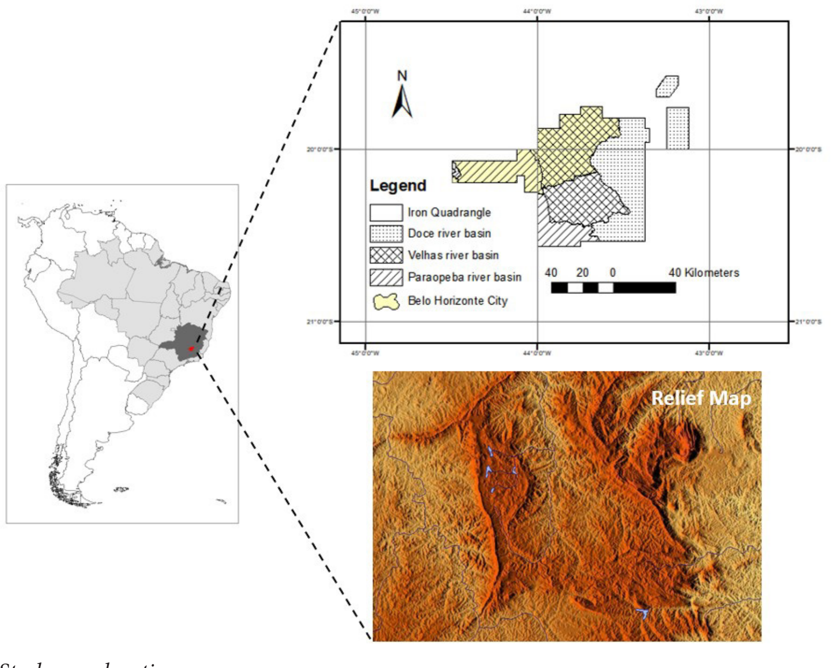


***Figure 1** Study area location.*

as a measurement of the obtained clusters robustness and providing a faster and more intuitive way to verify whether the problematic zones detected previously are true of concern, focusing on the visualization and delineation of potential zones for future monitoring and remediation.

## Methods

Five hundred and forty-one (541) stream sediments were sampled throughout the entire IQ (7,000 km$^2$), providing a sampling density of one sample per 13 km$^2$. The concentrations of the key PTEs: As; Cd; Co; Cr; Cu; Ni; Pb and Zn and associated metals (Fe, Mn) were obtained through aqua regia digestion followed by ICP-AES (Spectro Ciros CCD) analysis.

A three-stepgeostatistical modelling methodology was used for the construction of the Arsenic spatial distribution maps and the definition of spatial hot-spots, as follows:

1. Selected attributes went through structural analysis and experimental variograms were computed. The variogram is a vector function used to compute the spatial variation structure of regionalized variables (Matheron 1971; Journel and Huijbregts 1978);
2. Sequential Gaussian Simulation (SGS) was used as a stochastic simulation algorithm. SGS starts by defining the univariate distribution of values, performing a normal score transform of the original values to a standard normal distribution. Normal scores at grid node locations were simulated sequentially with simple kriging (SK) using the normal score data and a zero mean (Goovaerts 1997). Once all normal scores had been simulated, they were back-transformed to original grade values (Albuquerque et al., 2017). For the computation, the Space-Stat Software V. 4.0.18, Biomedwere, was used. The outcome of a simulation is a twisted version of an estimation process, which reproduces the statistics of the known data, making a realistic look of the exemplar, but providing a low prediction behaviour. If multiple sequences of simulation is designed, it is possible to obtain more reliable probabilistic maps;
3. Finally, Local G clustering allowed measurement of the degree of association that results from the concentration of weighted points (or region represented by a weighted point) and all other weighted points included within a radius of distance from the original (Getis and Ord 1992).

When predicting the risk of contamination (e.g. months ahead), it is mandatory to stress the relevance of the chances for the future estimated values exceeding maximum admissible values. The delineation of zones of high and low risk requires the interpolation of risk values to the nodes of a regular grid making possible proper risk assessments, and a prediction model working as guidance to a more sustainable environmental management. The three watersheds (Doce, Velhas, and Paraopeba) were processed separately (fig. 2) guarantying that only the samples inside each geographic envelop were

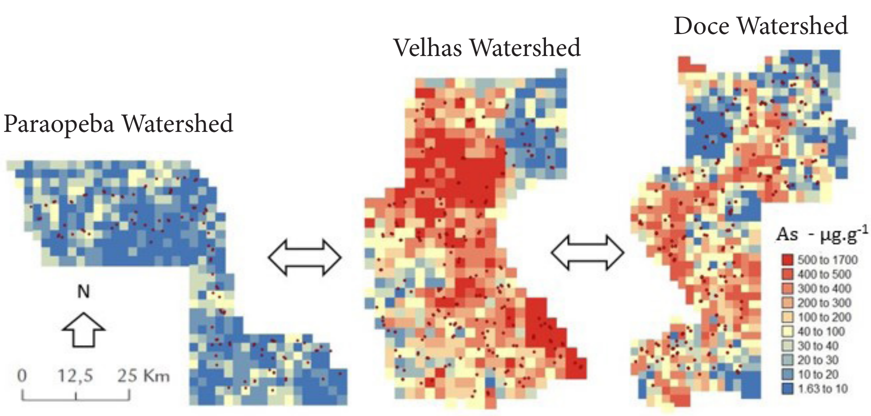


*Figure 2 Arsenic Spatial Distribution – SGS mean image.*

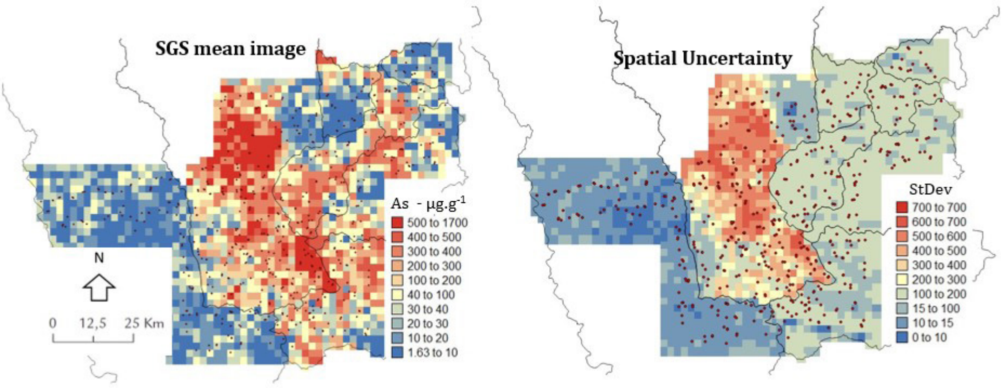


***Figure 3*** *Arsenic Spatial Distribution – SGS mean image and spatial uncertainty (standard deviation).*

used for the correspondent spatial modelling. Finally, all the representations were projected together for visualization purposes (fig. 3 and fig. 4). Observing the three surveyed units, Velhas, Doce, and Paraopeba watersheds, it is possible to acknowledge, for As spatial distribution, the low risk in the Paraopeba and the high risk observed mostly in the central area of the Velhas basin.

It is also worth notice the high spatial uncertainty associated with the Velhas' basin data, mainly due to the presence of several severe outliers within the studied area (fig. 3). Seventeen percent of As concentration values are higher than the mean (32.33 $\mu g.g^{-1}$) and 6,7% higher or equal to 100 $\mu g.g^{1}$.

Finally, when observing the G-clusters it is possible to identify high rings (hot spots for As pollution) and low rings (cold spots for As pollution) pointing out to the Velhas and Doce watersheds as the ones in need of close monitoring.

Still, a source of countless debates, the anthropogenic contribution to high concentrations of arsenic in fluvial sediments is not well defined. Even so, establish the natural abundance of an element is essential to support any type of environmental analysis. Concerning sediments, global or regional standards can be used. Arsenic average concentrations calculated for QF (18.17 $\mu g.g^{1}$), Velhas river basin (32.33 $\mu g.g^{-1}$) and Doce river basin (14.23 $\mu g.g^{-1}$) are considerably higher than the highest value

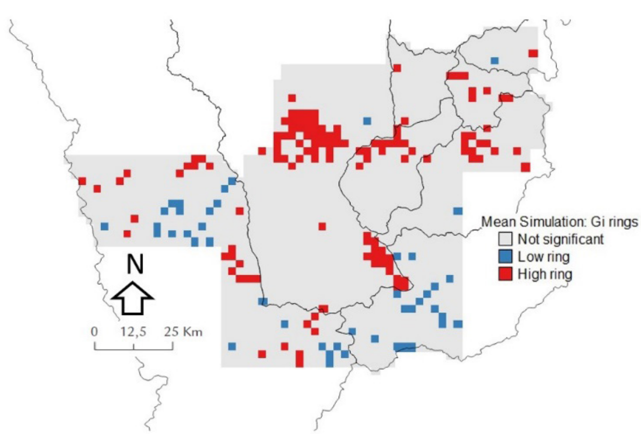


***Figure 4*** *Arsenic Spatial G-Clusters.*

set for the Earth's crust (4.8 μg.g$^{-1}$ – Rudnick & Gao 2003). Only in the Paraopeba river watershed As mean concentration is lower (4.01 μg.g$^{-1}$). Besides that, Costa et al. (2015) defined the natural background of As concentration in IQ as 6.1 μg.g$^{-1}$ and values >12.8 μg.g$^{-1}$ as anomalies. Regardless of the limits considered, Velhas and Doce river basins can be considered areas with anomalous values of As concentrations.

Several studies pointed out that in IQ, arsenic concentrations in water and sediments are related to gold deposits, present in minerals such as arsenopyrite and arseniferous pyrites (Borba et al. 2000). Gold can be found in veins of quartz and carbonates from the Nova Lima Group (base of the Rio das Velhas Supergroup) and base of the Minas Supergroup (Deschamps and Matschullat, 2011). Moreover, gold mine waste (tailings) containing arsenic have been released to the environment or store in tailing dams for the last three centuries (Matschullat et al. 2000, Borba et al. 2000). Although iron ores usually have As concentrations <1 μg.g$^{-1}$, sorbed, or coprecipitated in iron (oxy)(hydr) oxides, their tailings can be enriched in As. Indeed, it is possible to identify significant-high rings in the northern and southeast areas of the Velhas River watershed, all famous locations for primary gold deposits and gold mines. Considering the Au/As ratio presented by Costa (2007) for gold ore exploitations in IQ, almost 2,000,000 tons of As are potentially scattered in the basin or stored in waste piles and tailings dams, including abandoned mines, which represents a major concern in catastrophic scenarios identified in this research. Besides that, in Velhas river basin there are, actually, 16 iron tailing dams, five of then with a high risk of failure. It should be noted that in the high ring identified in the north of figure 3, currently, 450,000 inhabitants live, in addition to hosting the main source of water supply for the city of Belo Horizonte, the state capital, with 2,500,000 inhabitants. Three of the five dams with a risk of failure are localized in or upstream this area, and part of the people living downstream from these structures have already been removed.

## Conclusions

The stochastic modelling of the arsenic concentrations in the fluvial sediments in the IQ allowed to identify the Velhas River watershed as the most vulnerable area to catastrophic risk given the high concentrations of Arsenic in this basin, with an average of 32.33 μg.g$^{-1}$, about 16 times above the upper crustal average, showing that there is a significant amount of this element scattered throughout the watershed.

In this basin there are 18 gold mines, six in operation and 12 paralyzed, (Pinto and Silva, 2014), which extracted approximately 692 tons of gold over the last 40 years (Goldfarb and Groves 2015, Codemge 2017), considering the Au/As ratio presented by Costa (2007), it is estimated that 1,868,400 tons of As, are potentially scattered in the basin or stored in tailings piles, including abandoned mines and waste pile, which represents a major concern in catastrophic scenarios, which are identified in this research.

Although recent dam breaks have occurred in the Doce river basin and the Paraopeba River Basin, the average As concentrations in these areas, when compared with Velhas river basin, are much lower, 4.01 μg.g$^{-1}$ (8 times below) in the Paraopeba river and 14.23 μg.g$^{-1}$ (2.3 times below) in the Doce River, which points to its higher risk in the event of the failure of one or more tailings dams, as in the other two basins.

Thus, it was observed that in the Rio das Velhas Basin there is a greater catastrophe vulnerability, which confirms the need to apply geostatistical modeling as a tool to identify these areas and spatial patterns of PTEs, supporting government agencies in the prevention of environmental damage and the execution of more accurate monitoring.

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