Incorporating remote sensing techniques to the DRASTIC index to assess groundwater vulnerability at mining areas: application to Sonora river aquifer, northwestern Mexico

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ABSTRACT

Groundwater metal pollution is a major concern in mining areas. This study proposes a new addition to the DRASTIC method (DRASTIC+Lu) to assess groundwater vulnerability to metal pollution in mining areas by combining remote sensing (to locate metal pollution sources) and the DRASTIC index. The study was performed in a mining area in northwestern Mexico showing current and historical mining activities. The proposed methodology allowed locating known and unknown sources of metal pollution (mining tailings, active/inactive mines, and areas with exposed natural geochemical anomalies). Generally, the addition of the land use (Lu) parameter causes not only a decrease in vulnerability but also highlights very high vulnerable areas and identifies new ones in the vicinity of metal pollution sources. This result is relevant to focus stewardship efforts in very high vulnerable areas. Results allowed to identify the need to implement protection and restauration measures in the Sonora river channel and its vicinity. The proposed method could be implemented in other mining areas around the world –at a low cost– to locate unknown metal pollution sources and clearly identify very high vulnerable areas that play a key role in the protection of groundwater resources.

Key words: metal contamination; aquifer; pollution sources; imagery; vulnerability index.

RESUMEN

La contaminación de las aguas subterráneas con metales es una preocupación importante en los sitios mineros. En este trabajo proponemos una nueva adición al método DRASTIC (DRASTIC+Lu) para evaluar la vulnerabilidad de las aguas subterráneas a la contaminación con metales en sitios mineros, mediante la combinación de teledetección (para localizar fuentes de metales) y el índice DRASTIC. El estudio se llevó a cabo en una zona minera del noroeste de México que presenta minería actual e histórica. La metodología propuesta permitió localizar fuentes de contaminación conocidas y desconocidas (relaves mineros, minas activas/inactivas y áreas con anomalías geoquímicas naturales expuestas). De manera general, la adición del parámetro de uso de suelo (Lu) provocó una disminución de la vulnerabilidad. No obstante, ayudo a resaltar áreas de muy alta vulnerabilidad y a identificar nuevas en las cercanías de las fuentes de metales. Esto es relevante para enfocar los esfuerzos de gestión en las áreas de muy alta vulnerabilidad. Los resultados del estudio permitieron identificar que se requiere implementar medidas de protección y restauración en las inmediaciones del cauce del Río Sonora. El método propuesto podría implementarse en otros sitios mineros, a bajo costo, para localizar fuentes desconocidas de metales e identificar áreas muy vulnerables que jueguen un papel clave en la protección del agua subterránea.

Palabras clave: contaminación por metales; acuífero; fuentes de contaminación; detección remota; índice de vulnerabilidad.

INTRODUCTION

Groundwater is a valuable resource for human life and economic development. Its quantity and quality are of vital importance in arid and semi-arid areas, where climate conditions are characterized by low rainfall and high evapotranspiration, impacting surface water resources and aquifer recharge. The concept of groundwater vulnerability was first introduced by J. Margat in 1968, and today it is of utmost importance for the protection of groundwater resources. Assessing the vulnerability of an aquifer permits identifying areas that are more susceptible to being contaminated and allows performing effective protection measures and management plans for pollutants or wastes, which is relevant since aquifer remediation would be difficult and expensive (Aydi, 2018; Yin *et al.*, 2013). The intrinsic vulnerability defines the threat of an aquifer to a variety of pollutants, independently of their nature and related to the aquifer features (hydrological, geological, and hydrogeological) (Oke, 2020). Aquifers have different reactions to different pollutants because of their physicochemical characteristics. In those cases, it is more appropriate to talk about the specific vulnerability which defines the susceptibility to a specific contaminant or group of contaminants,

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considering their properties and interactions with the aquifer (Gogu and Dassargues, 2000; Voutchkova *et al.*, 2021).

Different methods have been developed to assess groundwater vulnerability, which can be classified into three types: simulation, statistical, and index methods. The index-based techniques have the advantage of not depending on data availability or similarities (Barbulescu, 2020). One of the most widely used index-based methods is DRASTIC (Aller, 1987), which considers seven parameters: depth to groundwater (D), net recharge potential (R), aquifer media (A), soil media (S), topography (T), impact of vadose zone (I), and hydraulic conductivity (C) of the aquifer. The DRASTIC index defines the aquifer intrinsic vulnerability; nevertheless, based on this model, contaminant-specific methods have been developed to assess groundwater vulnerability to nitrate (Jia *et al.*, 2019; Voutchkova *et al.*, 2021), pesticides (Al-Mallah and Al-Qurnawi, 2018; Thapa, 2018) and mining pollutants (Haque *et al.*, 2018; Tiwari *et al.*, 2016). Frequently, new and additional parameters have been used by other authors that include land use (Kozłowski and Sojka, 2019), lineament (Abdullah *et al.*, 2015), proximity to rivers, residential areas, and roads (Aydi, 2018), hydraulic parameters (Lappas, I and Matiatos, I, 2014), redox state of the aquifer (Voutchkova *et al.*, 2021), adsorption capacity of soils (Herlinger, and Viero, 2006), contamination index (Cd) and heavy metal pollution index (HPI) (Haque *et al.*, 2018).

Groundwater contamination related to the mining industry is an important global issue; acid mine drainage (AMD) is considered one of the main water pollutants in countries that have historic or current mining activities (Simate and Ndlovu, 2014). Mining areas are distinguished by the presence of waste dumps, mine tailings, water storage ponds, access roads, and heap leach pads. These features are detectable with remote sensing techniques (Werner *et al.*, 2019). Many efforts have been undertaken to detect mining wastes, their impacts, and site remediation by remote sensing (Balaniuk *et al.*, 2020; Buczyńska, 2020; LaJeunesse Connette *et al.*, 2016; Firozjaei *et al.*, 2021; Hao *et al.*, 2019; Khosravi *et al.*, 2021; McKenna *et al.*, 2020). Normalized difference vegetation index (NDVI) is mostly used in vegetation growth research (Wang *et al.*, 2021) and calculated as the level of greenness using imagery. NDVI is also a useful tool for distinguishing the boundaries of vegetated terrain from tailings impoundments, to which it primarily assigns negative pixel values (Firozjaei *et al.*, 2021; Schimmer, 2008; Zeng *et al.*, 2017).

In this context, the area of the Sonora river aquifer -located in northwestern Mexico- shows current and historical mining operations. Cananea, the major copper production center in Mexico, borders to the north. Also, small-scale mining and several abandoned mining wastes are widespread along the area. In 2014 the site was affected by the spill of 40,000 cubic meters (m^3) of toxic copper sulfate acid incoming from Cananea (COFEPRIS, 2014; Gutierrez-Ruiz, 2022). Important metal concentrations were already observed by several authors in the river network, soil, dust, vegetation, air and groundwater of the area (Archundia *et al.*, 2021; Calmus *et al.*, 2018; Del Rio-Salas *et al.*, 2019; Loredo-Portales *et al.*, 2020).

Therefore, this research study attempts to answer the following question: Can the DRASTIC index be modified to determine the aquifer vulnerability to metal contamination at mining sites? The hypothesis is that the addition of a land use (Lu) parameter, in which the metal contamination sources are identified, allows evaluating the aquifer vulnerability to metal pollution in mining sites. Thus, the aims of this study are to: (i) Propose a modified DRASTIC method to evaluate the aquifer vulnerability to metal pollution in mining sites; (ii) Identify possible sources of heavy metals (active and inactive mines, mining wastes, and mineralized areas) by remote sensing using a supervised classification procedure based on NDVI; (iii) Assess metal pollution vulnerability of the Sonora river aquifer located in a mining area; and (iv) Compare and validate the results obtained by the DRASTIC method and the proposed modified DRASTIC method.

To our knowledge, this is the first attempt to evaluate groundwater vulnerability to metal pollution by adding a land-use (Lu) parameter in which possible metal sources are considered to provide greater certainty to vulnerability assessment in mining areas.

MATERIALS AND METHODS

Study site and context

The Sonora river aquifer is located in northwestern Mexico in the state of Sonora (Figure 1), covering an area of about 12615 km^2. The area accounts for a population of 23261 inhabitants (CIAD, 2013), the major usage of groundwater is for agriculture, followed by industrial and domestic use. The lateral limits of this unconfined aquifer correspond to intrusive igneous rocks of the granitic type and extrusive rocks of the rhyolitic and andesitic types. In some areas, such as the Ures and San Felipe de Jesús valleys, the Báucarit formation emerges (CONAGUA, 2015). The lithology of the study site and cross sections, as well as the hydrogeological units can be found in the Supplementary material (SI) (Figures SI.1, SI.2 and SI.3). The main lithologies that dominate the Sonora river Aquifer (based on the morphology, porosity and permeability) are, high permeability alluviums, conglomerates with medium permeability, granite and limestone fractured rocks with low permeability, low permeability volcanic rocks (Báucarit Formation (Basalts)) and consolidated material (quartzites and schists) with low to zero permeability constituting the aquifer basement. Due to the morphology, porosity and permeability of its lithology, the Sonora river aquifer consist of three independent hydrogeological units (Aconchi, Ures and Topahue, see Figure SI.3 in the Supplementary material) which are superficially interconnected by the Sonora riverbed (Fajardo Calzada, 2016).

The aquifer receives considerable amounts of water related to the summer rainfall that occurs during July and August; this water input corresponds to approximately 43.26 $hm^3 \cdot year^{-1}$. The underground flow follows substantially the same directions as the surface runoff from Northwest to Nouthwest for the Aconnchi and Ures hydrogeological units and from North to South for the Topahue hydrogeological unit. Due to water extraction for human and industrial uses and natural processes, such as evaporation, evapotranspiration, or underground flow (towards other basins or the sea), an output of approximately 57.12 hm^3 $year^{-1}$of water is estimated, which indicates a negative change in storage of 13.86 $hm^3 \cdot year^{-1}$ (CONAGUA, 2015). Main mineralized zones within the area are, from north to south: Buenavista del Cobre (Cu–Mo) in Cananea; El Gachi (Pb–Zn) east of Arizpe; Santa Elena (Au) east of Banámichi; San Felipe de Jesús (Cu, Pb, Zn and Au), El Jaralito (W), and Washington (Cu, W, and Mo) to the west and east of Baviácora, respectively (Archundia *et al.*, 2021). The area has three active mines, Buenavista del Cobre, El Jaralito, and Santa Elena and 15 known abandoned mines (Guzmán *et al.*, 2019).

Evaluation of the intrinsic aquifer vulnerability

The DRASTIC method (Aller, 1987) has already been used to assess groundwater vulnerability to pollution in mining areas (Bukowski *et al.*, 2006; Haque *et al.*, 2018; Tiwari *et al.*, 2016). The method produces index numbers derived from the rating (r) and weights (w) assigned to each parameter (r and w are found in Table SI.1 in the supplementary material), where the higher the DRASTIC index, the greater the groundwater pollution potential is, and calculated as follows:

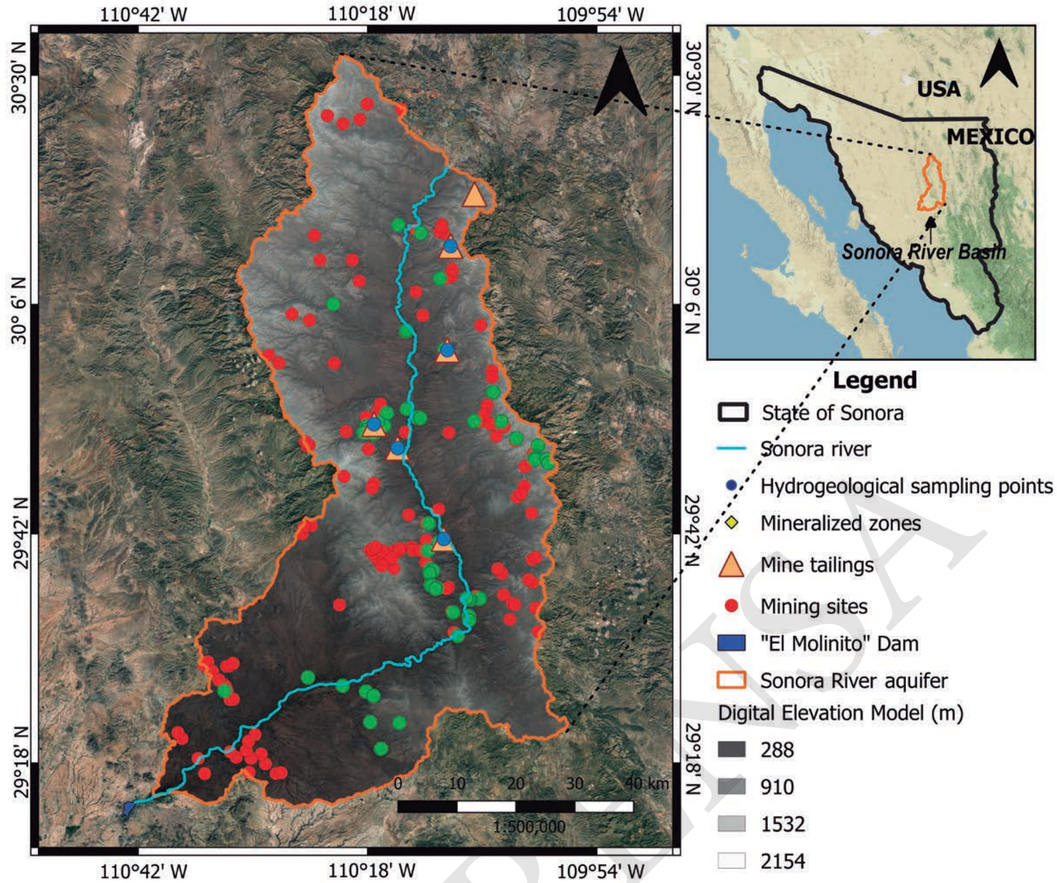

Figure 1. Study area corresponding to the Sonora river aquifer in the northwestern state of Sonora, Mexico. The figure contains the municipalities, known mineralizes zones, mine tailings, mining sites and hydrogeological sampling points used to validate the results.

$$D = D_rD_w + R_rR_w + A_rA_w + S_rS_w + T_rT_w + I_rI_w + C_rC_w$$

The DRASTIC index varies from 23 to 230.

The maps corresponding to the seven parameters were constructed with available hydrogeological data (described below) in the QGIS Development Team (2019). QGIS Geographic Information System. Open Source Geospatial Foundation Project. http://qgis.osgeo.org".

The depth to groundwater was estimated from 2014 piezometric data from 169 wells, which were obtained from the Comisión Nacional del Agua (CONAGUA) supply wells located along the Sonora river (Figure SI.4). For the areas where no data were available, they were interpolated using the Inverse distance weighted interpolation based on existing values.

The studied area has desert climate where the mean precipitation (400.6 mm/year) is significantly less than the mean potential evaporation (2400 mm/year) (CONAGUA, 2015); thus, the recharge was estimated using the formula:

$$RN = P\text{-}Er \text{ (mm/year)}$$

Where RN is the net recharge (mm); P is the mean annual precipitation (mm); and Er is the real annual evapotranspiration (mm). The Er was estimated using the Turc method (Gudulas *et al.*, 2013) which calculates the actual annual evapotranspiration (E) using the following equation:

$$E = \frac{P}{\sqrt{0.90 + \frac{P^2}{L^2}}}$$

where E: actual annual evapotranspiration, mm; P: annual rainfall, mm, T: mean annual temperature; ˚C and L: thermal indicator, defined by the equation:

$$L = 300 + 25T + 0.05 * T^3$$

Daily precipitation and temperature data were obtained from CONAGUA climatological stations at Arizpe (1961-2011), Banámichi(1961-2011), Ures (1921-2011), Mazocahui (1976-2011), Huépac (1979-2011), Sinoquipe (1982-2011), Topahue (1981-2011), and Aconchi (1998-2011) (Table SI.2). Averaged data for calculations are in Table SI.2. Calculated RN data were then interpolated to the whole study area using the Inverse distance weighting (IDW) method.

The aquifer media and impact of the vadose zone thematic maps were constructed based on existing geological maps from the Comisión Estatal del Agua (CEA, 2005); data were reclassified according to the types of lithology recommended by Aller, (1987).

The soil media map was constructed based on the World Soil Information (2017) database; data were reclassified according to the soil types recommended by Aller, (1987). The topography data (slope %) were generated from the Continuum of Mexican Elevations of the Mexican National Institute of Statistic and Geography (INEGI, 2013) by using the GDAL/ORG "Slope" tool (QGIS Development Team (2019)). Slope (%) data were reclassified according to the classification recommended by Aller, (1987).

Hydraulic conductivity data were obtained from the Global Hydrogeology Maps (GLHYMPS) of permeability and porosity (Gleeson *et al.*, 2014) applying the formula:

$$K = \frac{k\rho g}{\mu}$$

Where K (m/s) is the hydraulic conductivity that depends on fluid viscosity and density; k (m^2) is permeability; ρ (kg·m^3) is fluid density (water = 999.97 kg·m^3); g (m·s^2) is the acceleration due to gravity (9.8 m·s^2); and μ (kg m·s^{-1}) is fluid viscosity (water = 0.001); K data were reclassified according to the classification recommended by Aller, (1987).

Evaluation of the aquifer vulnerability to metal pollution in mining areas: DRASTIC + Lu

A modification to the DRASTIC method was performed by adding a land-use parameter (Lu) including the location of possible metal sources (known mining areas, mining wastes, and mineralized areas) detected using remote sensing methods. The detection of the possible metal sources was performed following the supervised classification method based on the NDVI values of known mining areas, mining wastes, and mineralized areas of the study site.

Detecting possible sources of metallic contamination by remote sensing

Remote sensing was used to locate potential metal sources related to mining activity (mining tailings, active/inactive mines) or areas with exposed natural geochemical anomalies using freely-available satellite images obtained from SENTINEL 2 at a resolution of 10 m, which were processed with the Open Source Software Quantum GIS (QGIS Development Team, 2019). Two May 22, 2019 images covering the study area were used, which showed 0.1 % cloudiness, in a Universal Transverse Mercator (UTM) / WGS84 projection of 100 km × 100 km. The bands 2, 3, 4, and 8 with a spatial resolution of 10 m were selected and processed using QGIS and the Semi-Automatic Classification Plugin (SCP) to carry out the atmospheric correction using the dark pixel subtraction method (DOS1). Selected bands were combined to produce a mosaic dataset using the Mosaic Raster Layer de SAGA (System for Automated Geoscientific Analyses) by the Nearest Neighbor method. Spectral characteristics of tailings and other background features (water bodies, vegetation, and bare soil) were studied by the 5-point photo-interpretation (selected manually) of each class located within the study area.

NDVI was used to distinguish the vegetated terrain boundaries from tailings impoundments, mining sites, and areas with exposed natural geochemical anomalies characterized by negative pixel values (Zeng *et al.*, 2017), focused on negative values close to 0 corresponding to areas with bare or rocky soil (Saravanan *et al.*, 2019) and calculated as follows:

$$\mathrm{NDVI} = \frac{NIR - Red}{NIR + Red}$$

To increase the method precision, the optimal NDVI threshold was defined based on the minimum and maximum NDVI values shown by five training fields (areas of known identity) including mining wastes and active/inactive mines of the study site (Table 1).

The polygons generated as described above were subsequently verified and validated manually to ensure the selection of polygons corresponding to the class "possible sources of metal contamination" counting for mining tailings, active/inactive mines, and areas with exposed natural geochemical anomalies. Areas of at least 400 m^2 or four pixels were considered. Detection was validated by comparing the identified polygons visually with known pollution sources consigned in Table 1 (see also Figure 1 mineralized zones, mine tailings and mining sites).

Table 1. Training fields.

Training field	Description	Coordinates UTM (X, Y)
San Felipe de Jesús	Mine tailings	572710.25, 3302388.74
Santa Elena Mine	Active mine, mine tailings	580748.16, 3321310.64
Santa Rosa	Mine tailings	568697.7, 3306965.56
El Carmen	Mine tailings	581333.92, 3341470.91
El Realito	Processing plant	580574.86, 3284836.18

DRASTIC + Lu

The DRASTIC method was modified by introducing a Land Use (Lu) parameter (100 m^2 resolution) in which the potential metal sources (identified using remote sensing) were integrated as one class type. The original Lu data were obtained from the Mexican National Institute of Statistic and Geography (INEGI, 2016). Ratings were defined based on the potential to lead to metal contamination of each class. Assigned ratings and the Lu parameter weight are shown in Table 2. Since large amounts of agrochemicals containing metals could have been applied in agricultural activities, ratings of 6 and 7 were given to this depending on irrigation type since water infiltration promotes contaminant mobility to the aquifer. A rating of 1 was assigned to classes not representing a metal source. Ratings of 5, 6 and 7 represent anthropic areas possibly contributing to metal pollution. Finally, a rating of 10 was assigned to the mining/mineralized areas due to their higher metal pollution potential.

The DRASTIC + Lu index was calculated as follows:

$$D_{Lu} = D_r D_w + R_r R_w + A_r A_w + S_r S_w + T_r T_w + I_r I_w + C_r C_w + Lu_r Lu_w$$

To compare both methods, the results obtained in the original and modified DRASTIC method were normalized to a scale from 0 to 100. The index was divided into five categories: very low (<20), low (20–40), medium (40–60), high (60–80), and very high (80–100) vulnerabilities.

Validation

Map removal sensitivity analysis of the DRASTIC + Lu

To investigate the effects of adding the Lu parameter on the vulnerability map, the map removal sensitivity analysis was performed – showing the sensitivity of the vulnerability map by removing one or more parameters from the analysis – and computed in the following manner (Babiker *et al.*, 2005):

$$S = \left(\left| \frac{V}{N} - \frac{V'}{n} \right| \Big/ V \right) * 100$$

where S is the sensitivity measure expressed in terms of variation index, V and V' are the unperturbed (DRASTIC) and the perturbed (DRASTIC + Lu) vulnerability indices respectively, and N and n are the number of data layers used to compute V and V'.

Correlation between groundwater metal concentrations and calculated indexes

The groundwater metal concentrations from governmental surveys (public data) carried out by the National Water Commission (CONAGUA) were used to correlate the metal concentrations in groundwater to the vulnerability indexes obtained (DRASTIC and modified method). Data are freely available at http://www.fideicomisoriosonora.gob.mx/fideicomiso.html and correspond to Al, Cu, Zn, Mn y Fe average concentrations (measurements between August and September 2014 in mg·L^{-1}) from 28 wells located following the Sonora river (see hydrogeological sampling points in Figure 1). The Spearman correlation was used to calculate the non-normality of data.

Table 2. Ratings and description of considered land use (Lu) classes and weight of the Lu parameter in mining areas of the northwestern state of Sonora, Mexico.

Class	Description	Rating
Possible source of metals	Mining areas, mining wastes and mineralized areas	10
Rainfed agriculture	Annual and semi-permanent agriculture	6
Irrigated Agriculture	Annual irrigation and semi-permanent irrigation agriculture	7
Urban	Urban	5
Water body	Water body	1
Pastureland	Cultivated Grassland, Induced Grassland, Natural Grassland	1
Forest	Oak and Prosopis scrub	1
Scrub	Microphyllous desert scrub, thorn, subtropical scrub and Prosopis scrub	1
Secondary vegetation	Shrubby Secondary Vegetation of oak Forest, Shrubby Secondary Vegetation of Sarcocaule Scrub, Shrubby Secondary Vegetation of Subtropical Prosopis and Shrubby Secondary Vegetation of Xerophilous Prosopis	1

RESULTS

Assessment of the intrinsic aquifer vulnerability with DRASTIC

Resulting maps for the seven DRASTIC parameters are shown in Figures 2 and 3.

Groundwater Depth (D)

According to the input data, the parameter varies between 0 and 23 m. The ratings assigned according to the DRASTIC method (Aller, 1987) ranged between 3 and 10. Input data were obtained from existing supply wells which are located following the Sonora river from north to south of the studied aquifer, adequately representing the longitudinal variability. However, some imprecision could be attributed to lateral spatial variation depth variability due to the longitudinal positioning of existing wells. Nevertheless, groundwater depth is largely accepted to range in the area from 1 to 30 m (CONAGUA, 2015), following the basement topography underlying alluvial and fluvial deposits. Ground water depth is also influenced by the narrowing of the Sonora river that rises the water level, causing it to emerge increasing in the direction of the Sonora river (Archundia *et al.*, 2021; CONAGUA, 2015).

Recharge (R)

This parameter was calculated based on precipitation input data from eight climatological stations dating from 1925 - 2012 and IDW interpolation (see Figure SI.4 for the location of climatological stations). Some imprecision in cross-sectional recharge variability could be expected regarding the lateral spatial variability of the data since climatological stations were located longitudinally at the study site, where the municipalities of the area are located. Recharge values from 0 to 51 mm were obtained in the central part of the southern portion; values from 51 to 102 mm were obtained on the margins of the southern portion, and values from 102 to 178 mm were found in the upper and more extensive part. The ratings assigned according to the DRASTIC method (Aller, 1987) were from 1 to 9.

Aquifer media (A)

The lithology of the study area is mainly of igneous and metamorphic rocks, which are poorly permeable and non-porous unless fractured (rating 3). Sequences of sedimentary rocks, such as sandstones and shales, appear sporadically within the study area (rating 6). In some areas located near San Felipe de Jesús and Arizpe conglomerates and basalt occur; a high rating was assigned (7 and 8, respectively) since they show interconnected pores and fractures. The alluvium (rating 10) is mainly located in the Sonora streambed and its tributaries.

Soil (S)

According to the World Soil Information (2017), four soil texture types occur in the study area: clay-loam (27–40 % clay and silt, 64–34 % sand); clay (55–100 % clay, 40–100 % silt and 40–65 % sand); sandy-clay-loam (20–35 % clay and silt, 60–90 % sand) and sandy-clay (35–55 % clay and silt, 63–83 % sand) (based on the United States Department of Agriculture classification). Clay-loam (46.5 %) soils are present in higher proportions and its presence decrease to the south (rating 5). Clay soils are the second type of soil with the greatest presence (39.3 %) and its presence increase to the south (rating 3). Sandy-clay-loam soils (9.7 %) are found in the highest altitudinal areas (>1500 m Figure 1 and Figure 2) and are present in the north and middle sections of the study site where igneous and metamorphic rocks are located (rating 6). Sandy-clay soils are found in the lower proportions (4.5 %) and especially in the middle and southern portions of the study area (rating 4). It is important to note that the World Soil Information combines existing regional and national updates of soil information worldwide, so it may lack precision at a local scale. Soil texture is an important parameter when speaking of aquifer vulnerability, it will be desirable to have more precise information at the local level.

Topography (T)

Most of the study area has slope values greater than 18%, in the Sonora riverbed and in the southeastern plain, very low and null slope values occur. Rating varies from 1 to 10 (Figure 3).

Impact of vadose zone (I.)

The impact of vadose zone map in Figure 2 show that igneous and metamorphic rocks with reduced permeability are located in the eastern and western parts of the study area (rating 4). Sedimentary and permeable rocks occur from north to south following the Sonora river channel (rating 6). Basaltic rocks, which could show significant porosity and permeability, are in spots at the north and center (rating 7). Finally, the alluvium, highly permeable, is found from north to south associated with the Sonora river channel (rating 8) (Figure 3).

Hydraulic Conductivity (C)

Most of the studied area showed values from 0 to 28.55 cm·day^{-1}. Some spots which coincide with the presence of carbonate rocks (see limestones in Figure SI.1) show values greater than 81 cm·day^{-1}, corresponding to an average conductivity in free aquifers. The area with the lowest hydraulic conductivity (rating 1) corresponds to the igneous body known as the Aconchi batholith (Figure 3).

The DRASTIC vulnerability index was computed overlaying the seven hydro-geological parameter maps discussed above: values range from 64 to 171 (Figure 4). Groundwater vulnerability of the Sonora river aquifer fluctuates from low, at some places in the center and the south, to high. The results of this study show that 32.89 % of the study area has low, 63.68 % moderate, and 3.43 % high vulnerabilities. The distribution of the Sonora river aquifer intrinsic vulnerability is mainly conditioned by lithology and the impact of the vadose zone. The yellow

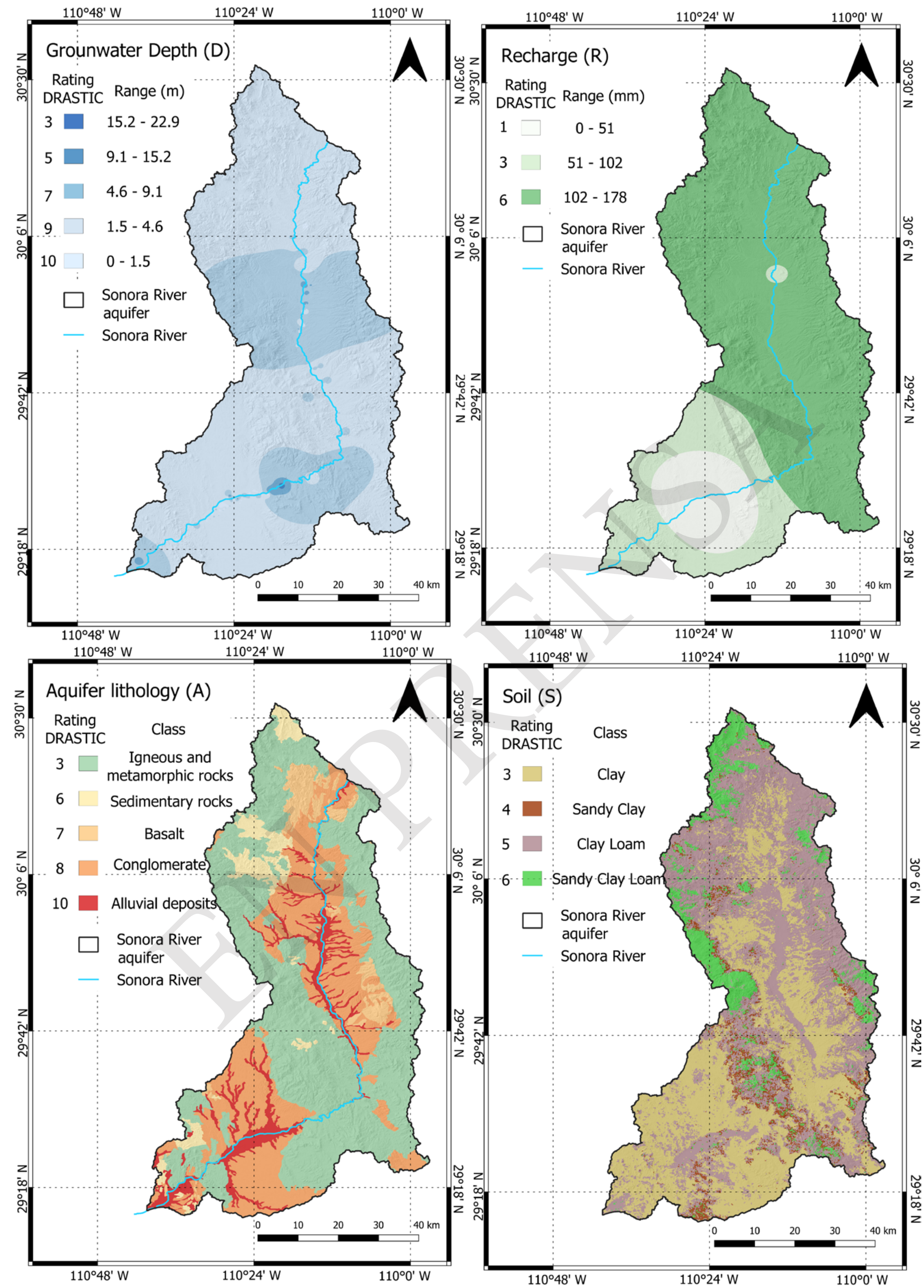

Figure 2. DRASTIC parameters map of: groundwater depth, recharge, aquifer lithology and soil in the Sonora river aquifer area in Sonora, Mexico.

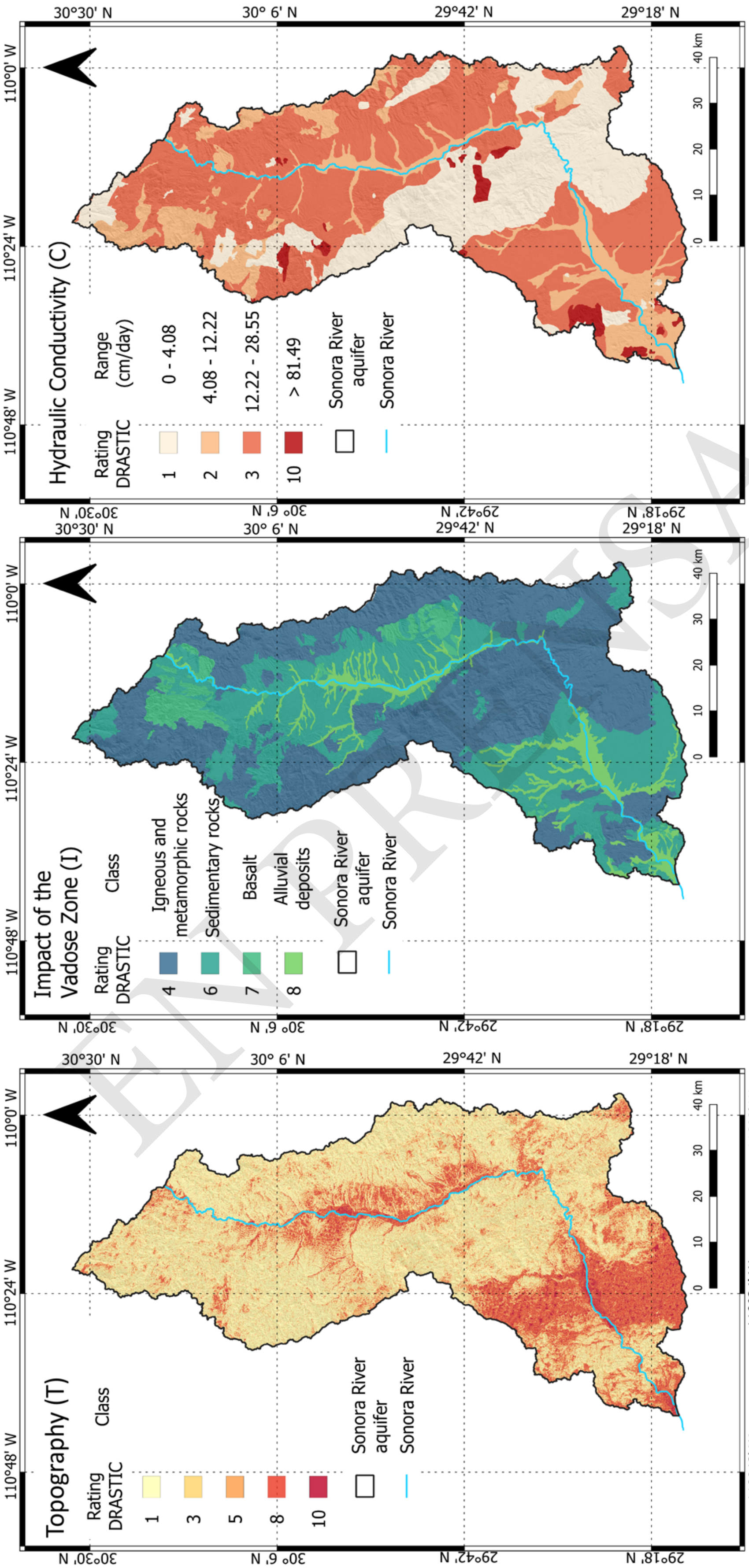

Figure 3. DRASTIC parameters map of: groundwater topography, impact of vadose zone and hydraulic conductivity.

and green colors correspond to areas with igneous rocks, which were classified as low permeable rocks. In the center of the study area, the orange color corresponds to the conglomerate rocks and the red color represents the channel of the Sonora river where alluvium is found. In the southeast zone, high vulnerability areas match with alluvial deposits and a low slope. These observations are of great importance since most of the drinking water supply wells are located near the channel of the Sonora river of high vulnerability.

Evaluation of the Sonora river aquifer vulnerability to metal pollution (DRASTIC + Lu index)

The DRASTIC method was modified by introducing an extra parameter considering the Land Use (Lu) in which the potential metal sources, identified by remote sensing, were incorporated.

Detection of possible sources of metallic contamination by remote sensing

The averaged spectral characteristics (surface reflectance) of tailings, water bodies, vegetation, and bare soil at the study site are shown in Figure SI.5.

Spatial variation of NDVI is shown in Figure SI.6, green coloration indicates the presence of vegetation and a reddish one indicates absence of vegetation. The NDVI value threshold defined based on training fields was from -0.2504 to 0.1946**.** The NDVI allowed finding areas with scarce vegetation and null vegetation including the training fields (see Table 1). Based on the defined NDVI threshold and after the manual filtration, 60 areas representing the possible metal pollution sources were located (Figure 5 and Table SI.3).

DRASTIC + Lu index

The identified possible sources of metal pollution were integrated into the Land use layer of the Mexican National Institute of Statistics and Geography (INEGI, 2016), (Figure 6). Most of the study area can be observed with secondary vegetation where most of the anthropic areas, including agriculture, are located following the Sonora river channel. The mining/mineralized areas are also mostly located in the vicinity of the Sonora river channel or longitudinally.

The DRASTIC+Lu index varied from 69 to 201 (Figure 7). The study area shows from low to very high vulnerability values, according to the vulnerability scale proposed by Aller (1987). The elevated areas located between Mazocahui and Ures (south of the study area) display low vulnerability values (64-106), representing 14.11 % of the study area. Moderate vulnerability values from 106 to 146, correspond to igneous rocks with elevated slopes, representing 75.78 % of the area. Areas of high vulnerability (147–188) are located following the Sonora

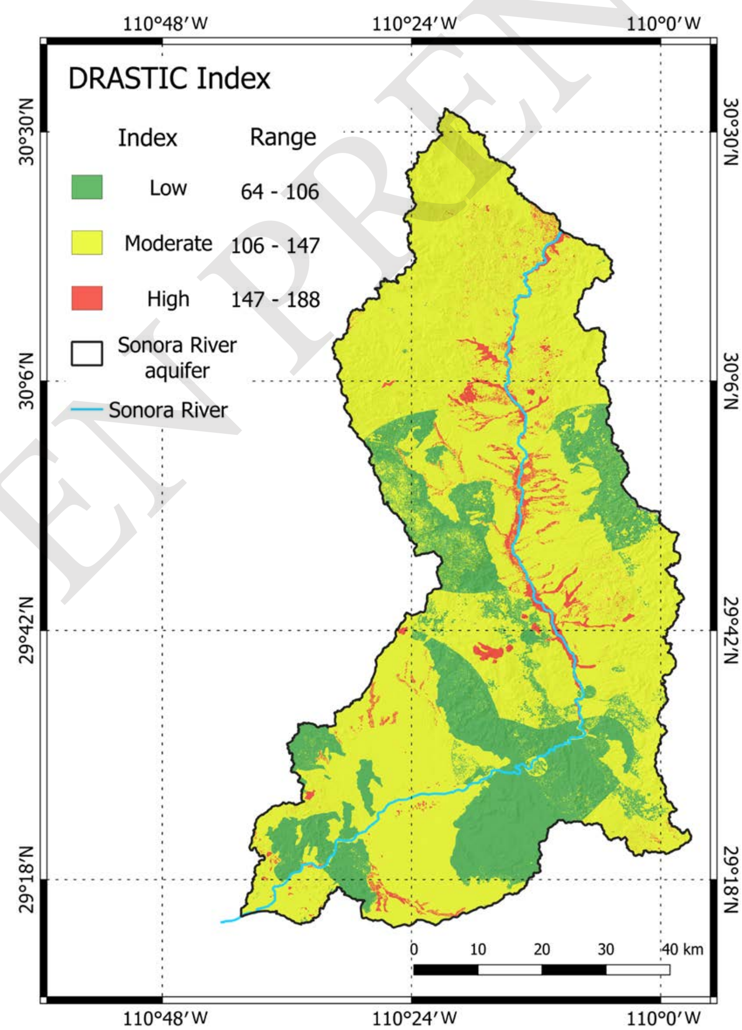

Figure 4. DRASTIC index vulnerability map.

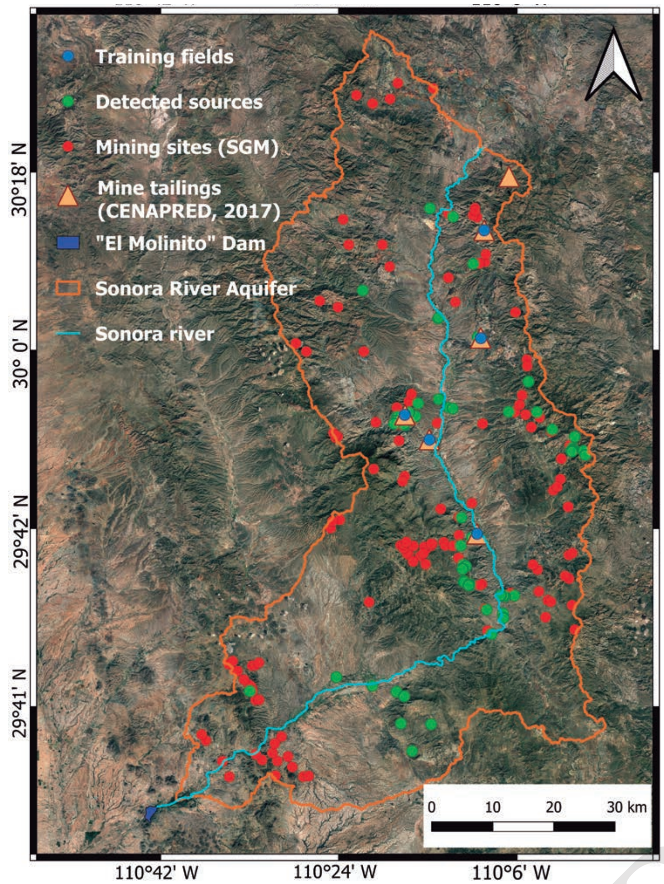

Figure 5. Detected metal pollution sources. The figure also shows the known mining sites (Servicio Geologico Mexicano SGM) and mining tailings (CENAPRED, 2017) in Sonora, Mexico.

river and correspond to conglomerate rocks, representing 9.49 % of the zone. Areas with very high vulnerability (188–230) correspond to the Sonora riverbed, representing 0.62 %.

DISCUSSION

Detection of possible sources of metallic contamination by remote sensing

Observed reflectance values (Figure SI.5) are consistent with values reported by other authors (Mukherjee *et al.,* 2021; Capolupo *et al.*, 2020; Ammirati *et al.* 2022). When comparing spectral signatures, the different behaviors of background features were observed, which validate the use of remote sensing for the identification of possible metal contamination sources as mine tailings. The group "Water body" and "Vegetation" show typical behaviors. The reflectance value of a water body decreases as the wavelength increases, due to low reflection in the near-infrared. Vegetation shows a peak in the infrared spectrum. Both the Mine Tailings and Bare Soil groups show high reflectance values in the studied bands. However, the first one tends to have a reflectance peak in the red band and higher reflectance values.

The NDVI values observed by Firozjaei *et al.*, (2021) for mining environments are consistent with those in this study. Defined NDVI threshold by Schimmer (2008) for active tailing impoundments was from -0.39 to -0.35, which was more restrictive than the one in this study. Zeng *et al.*, (2017) determined the optimal NDVI value for surface coal mining areas at 0.13. Firozjaei *et al.* (2021) concluded that mining activities can significantly alter the surface biophysical characteristics including NDVI values, thus validating their use to identify mining areas.

The tailings of the Santa Elena mine and the Santa Elena mine itself were detected 4.5 km east from the Banámichi municipality, which together form the largest detected pollution source were approximately 779297 m^2. The mining tailings of San Felipe de Jesús have 33022 m^2 and are located 670 m southeast of the municipality of San Felipe de Jesús in front of an agricultural area affected by metal pollution (Loredo-Portales *et al.*, 2020). Natural mineralized areas were located northwest of Banámichi. Other identified areas correspond to excavation areas located close to the mines or the mines themselves. Generally, identified areas are distributed parallel to the Sonora river and in the highest elevation zones. The results in this study only estimate the extent of exposed natural mineralization areas because they could be masked by alluvial deposits, vegetation, or landslides. The number of newly identified mining areas is notable southeast of Ures when they were compared with the existing information from the Mexican Geological Survey (Servicio Geológico Mexicano, SGM). All mining wastes identified by the Mexican National Center for Disaster Prevention (CENAPRED, 2017), as well as all considered training fields were identified through the proposed methodology (Figure 5). Balaniuk *et al.* (2020) and LaJeunesse Connette *et al.* (2016) also achieved the identification of mining sites using free imagery and free software.

Compared with the entire study site, the extension of the mining/mineralized areas are imperceptible, for example, the tailings and abandoned mine near San Felipe de Jesús (Figure 6), and the Santa Elena Mine and their tails However, despite their extension, they represent a potential risk with concerning local effects.

Comparison between calculated indexes

Normalized vulnerability maps (on a scale from 1 to 100) obtained by the DRASTIC and DRASTIC+Lu methods are shown in Figure 8. In both maps, the areas of lower vulnerability can be seen corresponding to igneous rocks and areas with pronounced slopes. The greatest vulnerability values indicating very high vulnerability (dark red color) correspond to conglomerate rocks, the presence of agricultural areas, and low slopes. The mining and mineralized areas are almost imperceptible on the map scale, but they have increased vulnerability at a local level. Comparing both maps, a general decrease in vulnerability can be observed in the DRASTIC + Lu map. The area of very high vulnerability (80–100) decreased by 15%; the extent of high vulnerability (60–80) decreased by 81.3 %; the zone of medium vulnerability increased slightly (8.4 %); the area of low vulnerability increased in 94 %, and the area of very low vulnerability increased by 154.9 %. Even though a general decrease in vulnerability (decrease of 81 % in the high vulnerability class) was observed, the addition of the Lu parameter helped to highlight new areas of very high vulnerability class located in the Sonora river channel (*e.g.* highly vulnerable area located at 29°20' N, 110°24' W in Figure 8) and locate small sites showing strong negative local effects of metal pollution sources (increase of vulnerability imperceptible at the study site scale see Figure SI.7). This result is important since those kinds of areas play a key role on groundwater resource protection, so its identification helps to focus efforts for the prevention of groundwater pollution by metals.

Validation of the proposed DRASTIC + Lu method

In this case the map removal sensitivity analysis was preferred because it tests the sensitivity of operations between map layers

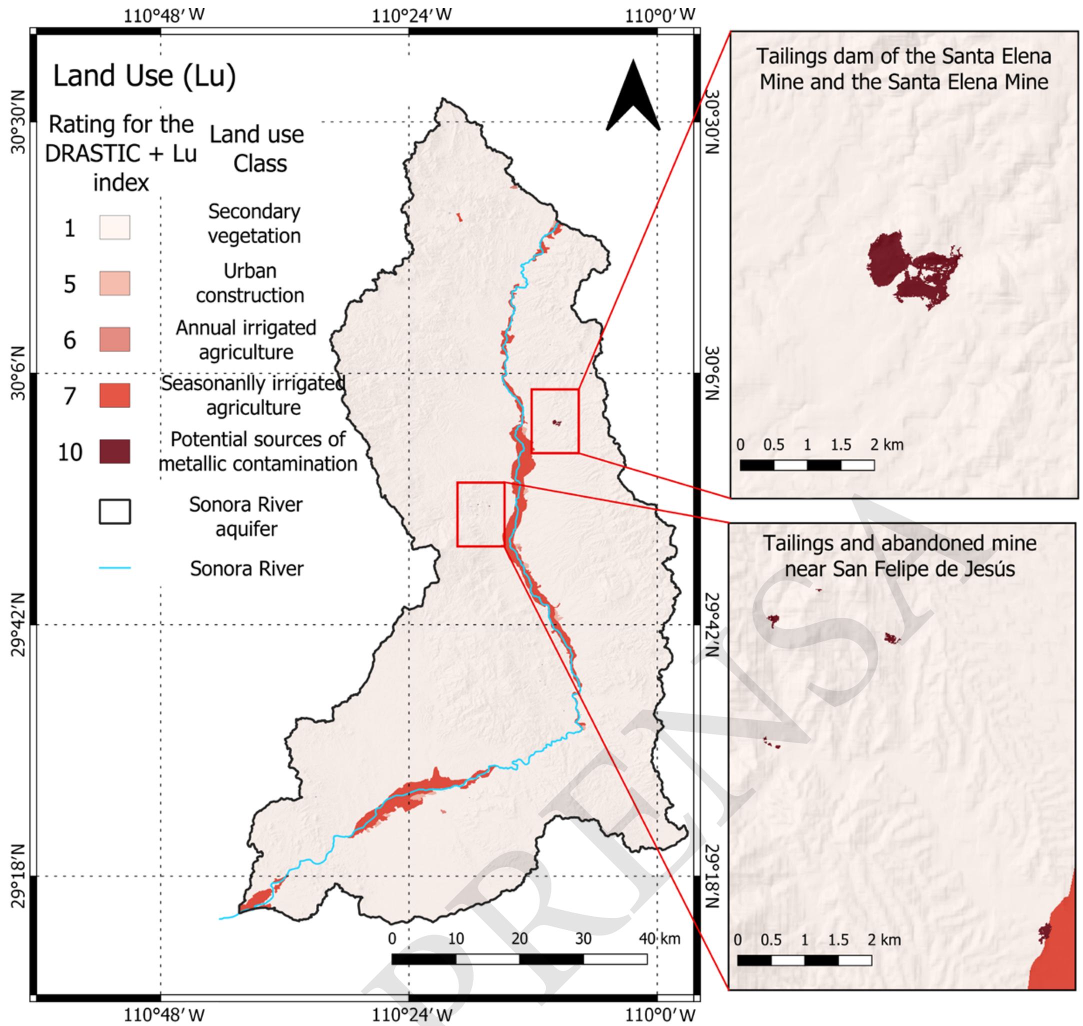

Figure 6. Land use map including SIG localized sources of metals (On the right above: the tailings dam of the Santa Elena Mine and the Santa Elena mine. On the right below: tailings and abandoned mine near San Felipe de Jesús).

(Thapa, 2018), which helps to evaluate its influence on the vulnerability assessment. Table 3 shows statistical calculation of the results. The DRASTIC + Lu vulnerability index computed for the study area is least sensitive to the Aquifer media (average value 0.82) and highly sensitive to the groundwater depth (average value 3.75). Regarding the effect of GIS-identified sources of metal pollution included on the Lu parameter, the influence of the Lu cover is high in the study area showing the third highest value. Aydi (2018) and Kozłowski and Sojka (2019) also observed high sensitivity to the land use parameter, which validates the performed modification to the DRASTIC method and demonstrates the importance of considering a land use parameter including sources of metal contaminants when groundwater vulnerability is assessed in a mining context.

The observed groundwater metal concentrations from governmental surveys (public data) did not show a significant correlation (p = > 0.1 for all tested metals) with the vulnerability zones identified using DRASTIC and DRASTIC + Lu methods. Tiwari *et al.*, (2016) observed a good match between Fe concentrations and DRASTIC index values in a coal mining of India. This observation could suggest that in this study site observed metal concentrations were of geogenic origin rather than superficial. Nevertheless, the lack of a significant correlation could also be associated with the fact that metal concentrations were determined after the mining spill at the Buenavista del Cobre mine. Thus, the observed metal concentrations may be related to the horizontal transport process within the aquifer. Furthermore, metals can show high reactivity with some vadose zone and aquifer components not considered in this study, which affect the correlation between considered metal concentrations and computed vulnerability values. Evidence of the stabilizing power of the soils of the study area has been demonstrated. Rivera-Uria *et al.* (2018) observed that soil carbonate content has an impact on acid solution neutralization causing metal immobilization. Recently, Archundia *et al.* (2021) detected no metal groundwater pollution in the study area, possibly indicating that no entry of metal pollutants from the surface is actually occurring. Based on these findings, the results produced in this study can be used for the design of protective measures and land use plans that effectively prevent groundwater pollution in very high-vulnerable class detected areas.

To better understand metal (and other) pollutant fate and dynamics in the study area, studies on groundwater flow prediction should be performed, as well as, superficial soil, and subsurface (vadose zone) properties and reactivity against metals. In that sense and to improve vulnerability assessment, soil types and properties should be characterized, as well as groundwater depth at a local scale.

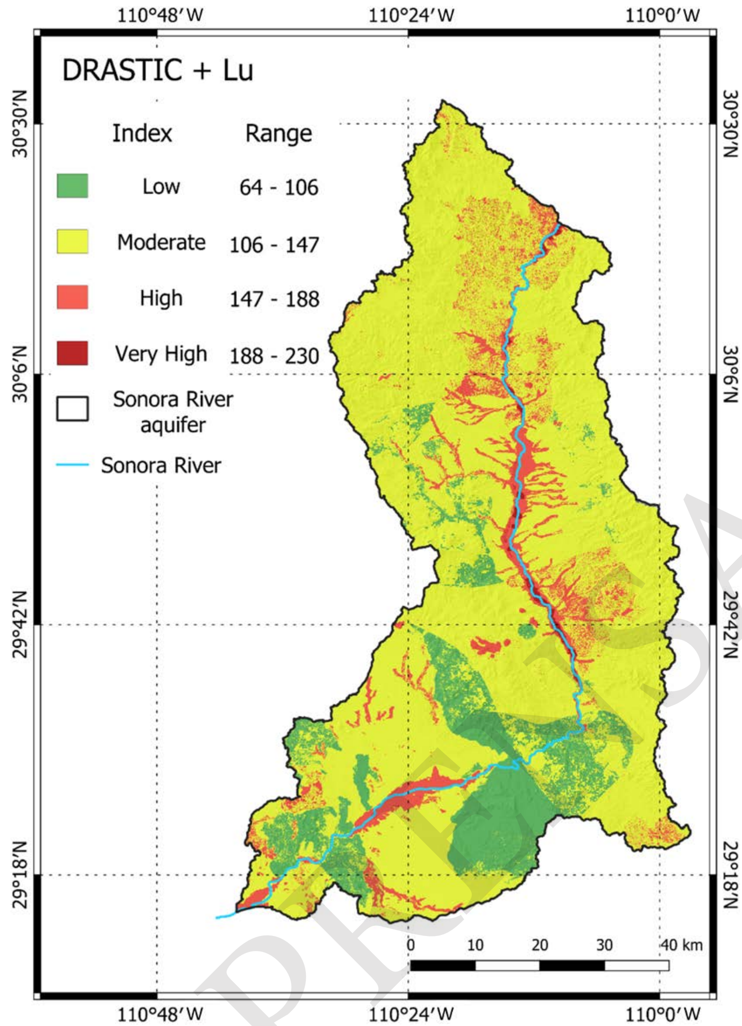

Figure 7. DRASTIC+Lu index map.

CONCLUSION

The proposed remote sensing methodology allowed to locate possible sources of metal contamination, corresponding to mining tailings, open-pit wastes, areas with exposed natural mineralization and those with current mining activity. Within the identified sources, only three of them correspond to exposed natural mineralization areas, possibly indicating that the method might not be sensitive enough. The use of higher resolution satellite images may improve the precision to locate them but would significantly increase the costs of the method. Effort in characterizing water depth and soil type information at the local scale is needed. Nevertheless, it is not feasible at the short and medium terms due to the extension of the studied area and difficulty in assessing soil type at the local scale in large areas.

With the application of the modified DRASTIC index and, in comparison with the results obtained with the traditional DRASTIC index, a decrease in vulnerability was observed, mainly in conglomerate rocks and higher elevation areas located parallel to the Sonora river channel. Nevertheless, very high vulnerable areas (located in the Sonora river channel) and small sites with strong negative local effects of metal pollution sources were highlighted. It is relevant to focus stewardship efforts on those areas to better protect the studied aquifer and related populations. Since the developed method allowed a clear identification of very high vulnerable areas in this study, it could be applied to other mining sites at a low cost to generate useful information for the design of policies and plans to prevent groundwater pollution by metals.

The Sonora river channel shows the highest vulnerability in both calculated vulnerability indices (DRASTIC and DRASTIC+Lu), which deserves attention, as most of the water supply wells for the population of the area are in the vicinity of the Sonora river channel. In that sense, the mining operations occurring in the vicinity of the Sonora river

Table 3. DRASTIC + Lu map removal sensitivity analysis.

Removed factor	Min Index value	Max Index value	Mean index value	Std. Deviation
D	0	5.27	3.75	0.7
R	0	2.71	1.08	0.47
A	0	2.27	0.82	0.34
S	0.02	3.2	1.48	0.61
T	0	3.25	1.73	0.46
I	0.02	3.7	1.45	0.71
C	0.13	3.02	1.28	0.37
L	0.1	4.46	1.51	0.3

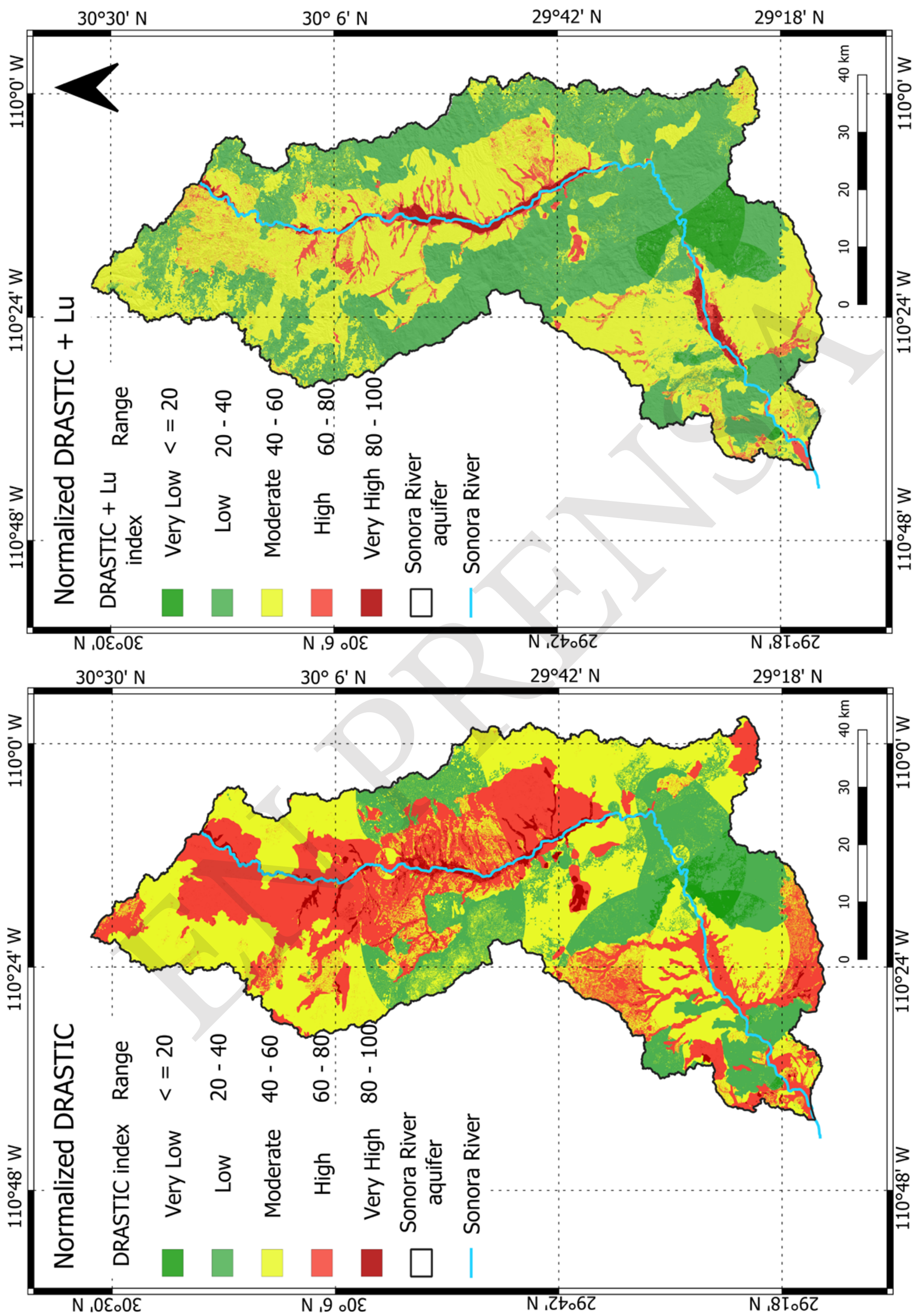

Figure 8. Comparison between the DRASTIC and the DRASTIC +Lu normalized maps.

channel, which show very high vulnerability, needs to be controlled and protection measures must be clearly established, as well as the required actions for the remediation of mining tailings and open-pit wastes in that area.

The results previously mentioned support the hypothesis of this study that the addition of a land use (Lu) parameter, in which the metal contamination sources are identified, allows evaluating the aquifer vulnerability to metal pollution in mining sites.

SUPPLEMENTARY MATERIAL

The Figures and Tables of the supplementary material can be downloaded at the preview page of this paper in the web page of this journal <www.rmcg.unam.mx>.

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