Public Health and Metal Mining Pollution: A GIS Study in the Republic of Armenia

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Abstract

This research filled a critical gap in the literature by measuring the effect of toxic contaminants from metal mining activities on public health in Armenia. Soil polluted by toxic chemicals in mining areas is a widespread and significant problem in Armenia and many developing countries. In the absence of control or restoration measures, humans and animals may be exposed and have unfettered access to a contaminated site. A localized disturbance to the ground can cause increased dispersion and exposure of broader populations to the contaminants through wind or water pathways.

This study implemented proximity analysis and downstream trace analysis with GIS technology to spatially quantify the effect of the concentration and spread of those pollutants on health. A unique geospatial database was created based on contamination data from Pure Earth and health data from Demographic Health Surveys. The presence and concentration of heavy metals such as arsenic, cadmium, chromium, lead, and mercury, and proximity to nearby communities, were used to measure the impact of contamination. Incidence of miscarriages, stillbirths, anemia, and low birth weight were used as measures of public health burdens, contrasted for populations living proximal and distal to metal mines.

Higher levels of contaminants and living in proximity to metal mines were positively associated with poorer health outcomes. Incidences of fetal mortality and anemia in areas within 10 km of a contaminated site were associated with elevated levels of arsenic and chromium. Arsenic, chromium, and lead were also negatively associated

with birth weight, suggesting potential health risks to mothers due to proximity to a metal mine.

The results of individual chemicals were mixed, with mercury having no significant association with any of the health outcomes and lead only being statistically associated with lower birth weight. On the other hand, the hazard index of five chemicals (arsenic, cadmium, chromium, lead, and mercury) was positively associated with the incidence of fetal mortality and anemia and was negatively associated with birth weight, indicating poorer health for people living within 10 km of contaminated sites.

In addition, living within 50 km of any metal mine was associated with elevated incidence of miscarriages and stillbirths. The magnitude of this association was substantial: there was a 20% higher incidence of miscarriages and stillbirths in areas within 50 km from any metal mine.

This study highlighted how contamination created from underregulated mining practices can affect the public health of populations living in nearby areas. These findings may be relevant not only for Armenia but other countries with similar economies and geography.

Dedication

I dedicate this work to the Armenian people who, despite having endured the first genocide of the twentieth century and continue to face centuries of oppression, aggression, and ethnic cleansing, continue to survive, hope and build on the last remaining slice of their homeland. My travels throughout the Republics of Armenia and Artsakh over the last two decades have left me inspired by their love, hope, determination, ingenuity, and bravery. May this research serve as a very small contribution to the building of a sustainable future for generations to come. I wish them health, peace, security, stability, and prosperity.

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Table of Contents

List of Tables

List of Figures

Definition of Terms

ADHS	Armenia Demographic and Health Surveys
AMD	Acid mine drainage
As	Arsenic
ATSDR	Agency for Toxic Substances and Disease Registry
AUA	American University of Armenia
Cd	Cadmium
CDC	Center for Disease Control
Cr	Chromium
Cr(VI)	Hexavalent Chromium
DHS	Demographic and Health Surveys
DiD	Difference in Difference
EA	Enumeration Areas
FALCON	Fingerprint Analysis of Leachate Contaminants
GDP	Gross Domestic Product
GIS	Geographic Information System
GPS	Global Positioning System
Hb	Hemoglobin
Hg	Mercury
HQ	Hazard Quotient
HI	Hazard Index
ICF	Inner City Fund
IDW	Inverse Distance Weighting
IRB	Institutional Review Board
IRIS	Integrated Risk Information System
ISO	International Standardization Organization
ISS	Initial Site Screening
MAC	Maximum Allowable Concentrations

MCL	Maximum Contaminant Level
MCLG	Maximum Contaminant Level Goal
OLS	Ordinary Least Squares
Pb	Lead
PRG	Preliminary Remediation Goals
RA	Republic of Armenia
RAIS	Risk Assessment Information System
RfC	Reference Concentration
RfD	Reference Dose
RL	Recommended Limits
RSL	Regional Screening Levels
THM	Toxic Heavy Metals
THQ	Target Hazard Quotient
TSIP	Toxic Sites Identification Program
UNEP	United Nations Environment Programme
UNIDO	United Nations Industrial Development Organization
USAID	United States Agency for International Development
USEPA	United States Environmental Protection Agency
VIF	Variance Inflation Factor
WHO	World Health Organization
XRF	X-ray Fluorescence

Chapter I

Introduction

Lack of experimental evidence of the impact of mining activities on health has created significant issues for the current government of the Republic of Armenia (RA), which has found itself at the crossroads of having to accept new gold mining activity against the recent backdrop of active environmental opposition and physical blockades by the citizens and diaspora of Armenia (Kubiak, 2018). For instance, in 2016, Lydian International Limited, a U.K.-based leading international gold mining company, announced the development of its heap leach gold mining operations at Amulsar Mountain in Vayots Dzor. In the last several years, there have been extensive environmental and politico-economic debates around gold mining expansion in Vayots Dzor, a remote province of Armenia (Grigoryan, 2019). This discussion's deep-rooted prevailing concerns are around the adverse effects of mining on the environment and, consequently, public health.

In 2018, a political revolution occurred in Armenia, where a progressive government replaced the previous corrupt administration. Transparency International (2017) rated the previous Armenian government at risk for collusion with mining companies without representing community members' interests. They were also rated at high risk in four of seven corruption metrics, such as the risk of no verification of the accuracy or truthfulness of environmental impact assessment reports; risk of mining reforms being written to favor private interests before the public interest; risk that criteria for awarding licenses will not be publicly knowable; and risk that applicants for licenses will be controlled by undeclared beneficial owners. The new government has been scoring higher than the previous government (up from 35 in 2018 to 49 in 2020), although there hasn't been an updated report from Transparency International since 2017.

Shortly after the 2018 revolution, environmental groups, media, and much of the populace voiced opposition to the proposed mining activities, citing fear of harmful impacts on neighboring communities and distant areas that could be impacted by mining-related contamination permeating rivers and lakes. These sentiments, according to protestors, existed before the revolution but were not voiced out of fear of reprisals from the previous government (CEE Bankwatch Network, 2021).

Most recently, Prime Minister of the Republic of Armenia Nikol Pashinyan agreed to allow the continuation of the Amulsar mining operations, citing the massive beneficial economic impact of these activities, but noted that he "would never agree to the operation of the mine to the detriment of the health of the residents in the neighboring villages or irreversible damage to the environment and the country" (News.am, 2020). Those opposing these activities argue that there was a lack of a third-party independent impact assessment and that the study, conducted by Lydian International and adopted by the RA government, was unreliable and biased (Sargsyan, 2019).

According to the head of the RA National Academy of Sciences' Center for Ecological-Noosphere Studies, Dr. Armen Saghatelyan, lack of monitoring and standards in the Armenian mining sector has been a prevalent issue in recent decades (Hetq.am, 2011). Mine operators often fail to manage dangerous contaminants within acceptable levels, which may pass from the ground to agricultural produce and then to humans

(Ghazaryan, Movsesyan, Ghazaryan, Gevorgyan, & Grigoryan, 2014; Kurkjian, Dunlap, & Flegal, 2002).

Adverse environmental and net socioeconomic impacts of mining in Armenia have been measured by relatively few studies (World Bank, 2016). The highly contested discussions of the externalities of mining make evident that a comprehensive analysis measuring the impact of soil contaminants on health is lacking for Armenia and other neighboring countries in the Caucasus region. Scholars have used a Geographic Information System (GIS) approach to measure the environmental impacts of contaminants in other parts of the world. It provides the advantage of controlling for various spatial confounding causes to measure the effects of mining on contamination (Werner, Bebbington, & Gregory, 2019).

Research Significance and Objectives

This research filled a critical gap in the literature by measuring the association between mining contaminants and human health. It implemented GIS technology to spatially quantify the effect of the concentration and spread of those pollutants on the health of residents in Armenia. GIS analysis is the most appropriate methodology to deal with the unique challenges associated with mining operations (Lechner, Owen, Ang, & Kemp, 2019). Deep-rooted distrust and emerging concerns around the adverse effects of mining on the environment and consequently public health highlight the importance of exploring this issue. Heavy metals, such as arsenic, cadmium, chromium, lead, and mercury, are considered as contributors to health burdens (Tchounwou, Yedjou, Patlolla, & Sutton, 2012). Understanding the effect from each may be necessary to inform future policy decisions and recommendations. Findings from this study offer citizens and policymakers in Armenia insight into whether the recent concerns around mining are justified and may help shape the way Armenian mines are operated in the future.

A few broad objectives of my study were to:

- Conduct hot spot analysis in GIS to identify the risk that different mining contaminants pose to public health as a function of geospatial covariates.
- Advise future investigations of mining-related health and environmental data collection and analyses.
- Provide citizens and policymakers with the information on mining-related health issues so that they may better appreciate the tradeoff between negative health impacts and economic benefits of mining operations.
- Produce findings that can inform decision-makers in other countries with similar economies or geography.

Background

Mining produces significant environmental and socioeconomic impacts and is one of the few industries that can change entire landscapes (Mudd, 2010). Contamination resulting from mining activities has been documented to pose various health and environmental hazards (USEPA, 2017). Humans can be harmed by hazardous pollutants at a contaminated site via exposure to soil, air, surface, and groundwater. In addition, contaminated soils can leach toxic chemicals into nearby areas (USEPA, 2017), migrate to waterways, or be further distributed through windborne dust, affecting local ecosystems and human health (Northey, Mudd, Werner, Haque, & Yellishetty, 2019).

Environmental Impacts of Mining Contamination

In developing countries, soil pollution by toxic chemicals in mining areas is a widespread and significant problem. The magnitude of risk posed by certain minerals depends on the concentration, chemical form, particle size, the soil or water pH, and the extent of exposure to the element (Kelepertsis, Argyraki, & Alexakis, 2006). In the absence of control or restoration measures, a localized disturbance to the ground can cause increased dispersion and exposure of broader populations to the contaminants through wind (Zota et al., 2011) or water pathways (Razo, Carrizales, Castro, Díaz-Barriga, & Monroy, 2004).

Metal-laden drainage from mines can have detrimental effects on aquatic resources, contaminate drinking water, and contribute to the corrosion of infrastructure such as bridges (USGS, 2020). Acid mine drainage (AMD) is one of the most severe environmental hazards from the mining industry since it is known to generate high levels of arsenic and other heavy metal pollution (Razo et al., 2004).

AMD may occur in groundwater associated with deep mines, which is generally not a problem when a mine is active, and water tables are kept artificially low by pumping. However, when mines are closed and abandoned, the pumps get turned off, and the rebound of the water table can lead to contaminated groundwater being discharged and cause disastrous environmental events (Johnson & Hallberg, 2005). Varying elevation of source locations combined with drainage to streams and rivers enables contaminants in soils around the mines to spread into groundwater sources far away from the mines.

The mining of metals generates considerable amounts of waste materials, that vary depending on their physical and chemical composition, the type of mining, and the way the mineral is processed. Millions of tons of ore are processed every year by the mining industry, greater than 95% of which is disposed of in the form of waste rocks and mine tailings (Falagán, Grail, & Johnson, 2017). The latter is finely ground rock particles generated during the processing of ore materials and the separation of target metal minerals. Mine tailings, in general, are voluminous and contain toxic elements that may be released and introduced into the biogeosphere (Jain, Cui, & Domen, 2016). Furthermore, uncovered mine tailings allow contamination to spread by the prevailing winds, which can result in inhalation exposures of toxic metals by persons who live near the source locations and impact them in various ways as it migrates indoors (Zota et al., 2011).

Additionally, mining operations often liberate dust and aerosols if effective management and prevention measures are not implemented (Csavina et al., 2012). Considerable quantities of dust containing heavy metals and radioactive materials are often released into the atmosphere during mining and other related operational processes. These activities then pose a significant threat to persons living around mines and communities that are farther from such areas since fine particles have a longer atmospheric half-life and can migrate across vast distances (Ni et al., 2018).

Some heavy metals such as iron, cobalt, copper, manganese, zinc, and molybdenum are crucial for metabolic activity at low concentrations and are considered essential elements or micronutrients (Peralta-Videa, Lopez, Narayan, Saupe, & Gardea-

Torresdey, 2009). However, exposure to elevated levels of heavy metals can result in adverse health effects (Ali, Khan, & Sajad, 2013).

While high concentrations of all heavy metals present toxic effects, certain heavy metals such as arsenic (As), cadmium (Cd), lead (Pb), mercury (Hg), and hexavalent chromium (Cr(VI)) are non-threshold toxins and rank among the priority heavy metals due to their high toxicity (UNEP & AMAP, 2013). These metals have been referred to as toxic heavy metals (THMs) (Brathwaite & Rabone, 1985; Clemens & Ma, 2016).

THMs are considered to be the highest threat substances by various international bodies such as the Agency for Toxic Substances and Disease Registry (ATSDR), United Nations Environment Programme (UNEP), United States Environmental Protection Agency (US EPA), and the World Health Organization (WHO). As, Pb, Hg, Cd, and Cr(VI) are ranked 1st, 2nd, 3rd, 7th, and 17th, respectively, in the priority list of hazardous substances. These pose the most significant potential threat to human health due to their known or suspected toxicity, the potential for human exposure, and frequency of occurrence at superfund sites (ATSDR, 2019). All five chemicals have been categorized as the most hazardous pollutants at mining and ore processing sites by Pure Earth (2016).

The location of mining contamination in relation to residential communities is a critical factor in the resulting impact on the surrounding environment and public health therein. Various environmental impacts have been explained by distance, elevation, and slope of mining locations (Aznar, Richer-Laflèche, Bégin, & Marion, 2007; Groscheová, Novák, Havel, & Černý, 1998). For example, communities at lower elevations than the mines may experience higher concentrations of chemical contamination due to the erosion of soils from the mountain slopes and its deposition in the valleys (Jonathan et al., 2009).

Toxic metals may spread through water and air and end up in nearby farming regions, affecting the food supply and exposing a more substantial number of people through food distribution. Direct contact with contaminated soils not only can lead to hazardous dermal exposures but also through incidental ingestion of soils (e.g., hand-to-mouth), with young children at the highest risk (Ozkaynak, Xue, Zartarian, Glen, & Smith, 2011; Wang et al., 2021). Mining-associated contamination has been found in nearby agricultural, suburban, and roadside soil (Cao, Luan, Wang, & Zhang, 2009). Heavy metals are non-degradable and can persist in the environment (Wu et al., 2010). They can be toxic to microbes, plants, and animals, making environmental contamination by heavy metals one of the most significant issues of the present era (Rahman & Singh, 2019).

There has been considerable development of environmental protection legislation in the last century, and many developed countries have adopted clean-up, remediation, and rehabilitation standards and procedures (Carvalho, 2017). These remediation actions started in the United States with the Superfund project in 1980 and have been implemented mainly in North America and Western Europe (USEPA, 2015). Developing countries have yet to make similar strides in adopting and enforcing independent oversight and accountability (Carvalho, 2017).

Geology and Metallogeny in Armenia

The Republic of Armenia is located in the South Caucasus mountains in Eurasia, bordering the Republics of Azerbaijan, Turkey, Georgia, and the Islamic Republic of Iran. The complex topography of modern Armenia was formed 25 million years ago in a geographic upheaval that raised the earth's crust to form the Armenian Plateau. The terrain is rugged, with the Lesser Caucasus range running from Armenia's border with Iran north along the Armenian-Azerbaijani border into Northern Armenia and the Georgian border. The present-day Republic of Armenia consists of an area that is approximately 29,800 km^2, over half of which is at an elevation of greater than 2000 m (Curtis, 1995).

Armenia is situated on the convergence of the Africa-Arabian continental plate and the Eurasian plate. Volcanism, most recently around twelve thousand years ago, and the associated deep underground geological processes have resulted in diverse geology and mineral deposits. Armenia's mining sector is a crucial contributor to its economy, where ore concentrates, and metals account for over half of Armenia's exports in recent years.

Armenia has 30 active metal mines, including 14 gold and gold-polymetallic, seven copper-molybdenum, four copper, two polymetallic, two iron ore mines, and one aluminum mine (Appendix 1, Table 9). Armenia's most abundant extracted minerals include gold and copper and their associated byproducts silver and molybdenum, respectively. Other extracted minerals include lead, zinc, silver, antimony, and aluminum.

Copper and copper-molybdenum deposits are most concentrated in Alaverdi, Akhtala, and Shamlugh mines in Lori Province in the North, Kapan, and Kajaran, Agarak, and the Zangezur mountains within Syunik Province in the south. Gold is found most prominently in the Sotk and Amulsar deposits east and south of the southern shores of Lake Sevan in Gegharkunik Province (Curtis, 1995; World Bank, 2016).

Mining Contamination in Armenia

Although many developed countries have reduced toxic emissions from mining in the last century, low- and middle-income countries, such as Armenia, are still struggling to reduce and better manage the residual heavy metals (Pacyna et al., 2007). Armenia's complex topography and the distribution of mines across the country have exacerbated the potential health risks posed by mining operations. Only a handful of studies measured the mining impact on the environment in the Republic of Armenia (Akopyan, Petrosyan, Grigoryan, & Melkomian, 2014, 2018; Petrosyan et al., 2004) and other parts of the Caucasus region (Burdzieva, Zaalishvili, Beriev, Kanukov, & Maysuradze, 2016; Caruso et al., 2012).

Armenia has centuries of mining and smelting history. Environmental contamination due to extensive historic and present mining activities has been a source of concern about potential health risks. Its mining operations and regulations are based on the RA Law on Environmental Impact Assessment and Expert Examination (2014) and the RA Mining Code (2012). Still, there is a general lack of important pieces of secondary legislation or guidelines to aid the law's implementation, including proper procedures or methodologies for assessing the impact on human health or biodiversity. If properly implemented, environmental laws and regulations could potentially address most of the problems related to underregulated mining practices. However, there often are problems with legal ambiguity, laws not being streamlined or properly implemented (World Bank, 2016).

According to the most recent report by World Bank (2016, p. 103) assessing the status of Armenia's mining sector, "none of the existing metal mining operations in Armenia can be seen to be environmentally sustainable." They cite substantial environmental damage from existing mines and processing activities and excessive risks for existing tailings impoundment infrastructure due to inappropriate construction designs and engineering (e.g., upstream rise designs). And with the overall lack of adequate plans and funds, the mined-out areas are often left without rehabilitation and reclamation.

Pollution from these problem sites, in most cases, is not contained and is thereby able to spread. There are many examples of ineffective exclusion of persons and animals from contaminated sites in the Republic of Armenia. Most often, these controls are non-existent. For example, investigative journalists reported that approximately 250 milk cows belonging to locals in the village of Lernadzor graze on the tailing dam site. Grasses sampled at the site contained elevated levels of toxic elements. Milk from the cows grazed on this site similarly contained excessive levels of lead, arsenic, and mercury. Locals have also used the tailing dam site to grow food crops such as dill, beans, and potatoes, all of which were sampled and exhibited high levels of copper and molybdenum. Local authorities were aware that such practices are forbidden and that those practices are taking place without enforcement (Nazaryan, 2008).

Whereas fencing off an area may prevent animals from accessing a site, they are only good for as long as they're in place and maintained. In a 2009 report from the town of Alaverdi, the so-called Arsenic Graveyard was described as entirely neglected and accessible to all. When the reporter inquired with the local Armenian Copper Programme's Director of Production, Nikolai Feofanov, why there was no fence around the graveyard and no hazard communication signage, he stated that in the past, the area was fenced off, but the fence had been stolen. As a result, livestock would openly graze, couples would bring a bottle of wine and stare at the stars, and looters, believing there was gold mixed with the arsenic waste, would loot sacks of the material spreading it around the region and beyond (Paremuzyan, 2009).

Sometimes the contaminated media has been intentionally removed from the storage site and moved to an area where humans, animals, and crops will be directly exposed to it, such as in the case with fill. In these cases, effective physical barriers such as an asphalt cap are challenging to implement and require routine inspection and maintenance. However, in the case of Armanis basic school, overburden from the nearby gold mine was intentionally brought on site to level the schoolyard. As a result, the schoolyard became contaminated with lead, arsenic, and chromium. After protests from the local community, the waste rock was partially covered with a thin layer of soil. The school children continue to participate in physical education activities in the schoolyard (Pure Earth, 2019).

Examples such as the Armanis basic school demonstrate that decisions are made in which mining contamination is intentionally brought to locations where humans, particularly children, are being exposed at a higher rate than they would be otherwise. And to make matters worse, an effective engineering control such as an asphalt or concrete cap over the contaminated material rather than a thin, inconsistent layer of dirt on a school playground has not been implemented.

The examples of spread to nearby communities are numerous: wastewater from the tailing dumps of the Syunik, Agarak Copper and Molybdenum Combine have damaged the nearby orchards. A 165-hectare tailing dump located in the Ararat Valley, rich in cyanide and numerous heavy metals, is in the immediate vicinity of a 79-hectare fishpond. The 330-hectare Artsvanik tailing dump in Syunik was constructed only 500 m from the village of Atchanan. (Yenoqyan, 2019).

Storage of contaminants in such proximity while lacking proper containment allows for various pathways of contamination, such as direct human interaction with soil and water, inhalation of air, or animals grazing on the site and drinking from contaminated water. The effect of which may be felt much farther from the village where these animals or their byproducts may end up being food for others (Figure 1).

Figure 1. Cow drinking water near Artsvanik tailing pond.

Artsvanik tailing pond belongs to the Zangezur Copper-Molybdenum mine in Kajaran. Image is from the "Investigative Photojournalism for Human Rights and Clear Environment" project, made possible through the assistance of the Open Society Foundations- Armenia. The project was implemented by Socioscope Non-governmental Organization (American University of Armenia, 2013). Photo by Nazik Armenakyan, 4plus.org.

Tailing ponds in very close proximity to villages and towns are found all over the country. Such an example is the Nahatak tailing dump located in close proximity to the Mets Ayrum village (Figure 2). A town resident said, "There are cattle grazing here, children playing, there have been times when people's cattle have fallen into the dump and died." (Yenoqyan, 2019).

Figure 2. Nahatak tailing dump in Lori (Yenoqyan, 2019).

In March of 2015, the villagers of Shnogh and Teghut in northeastern Armenia alerted journalists that the outer structure of the tailing dam of a nearby copper mine was damaged and leaking heavy metals and eroded soil into the Shnogh River (EcoLur, 2015). This river then flows to contaminate a larger water body, the Debed River, a 178-km-long transboundary river (Figure 3).

Figure 3. Polluted Shnogh River meets Debed River (EcoLur, 2015).

An independent assessment of the sustainability of the Teghut tailing dump found that its design is inadequate both in environmental and physical stability terms. This is a significant concern for the villagers who live just a few hundred meters away, directly below the tailing dam in Teghut and Shnogh (Figure 4). The report noted that the tailings pond was engineered with the upstream rise method, which is inadequate for seismically active areas such as Teghut, located in an 8-magnitude seismic zone (EcoLur, 2016).

The upstream method is often used because of its low cost. However, it is not only most susceptible to seismic instability but also excessive post-earthquake deformations (Harper, McLeod, & Davies, 1992). The Aramis and Shnogh River cases demonstrate that a national system is nonexistent to ensure adequate engineering controls are implemented, monitored, and maintained.

Figure 4. Teghut tailing dump in relation to the Teghut village (EcoLur, 2016).

The government of Armenia has been prone to corruption and illicit financial transactions in the mining industry. For example, the 32-hectare Geghanush Tailing Dump in the Syunik Region was approved after an expert assessment was submitted, which was based solely on data from the mining company itself. The tailing dump for this mine was constructed immediately adjacent to a nearby village (Figure 5).

In Syunik, the Zangezur Copper and Molybdenum Combine performed 5 million tons of illegal soil management and mining in 2017, according to inspections of the Artsvanik tailing dump, for which no criminal case had been filed. The RA has a fee of

30 Armenian Drams (about $0.06 US Dollars) per 1 ton of hazardous waste, less than they charge for domestic waste.

Figure 5. Geghanush tailing pond, built on a river gorge in Syunik (Yenoqyan, 2019).

In the case of Teghut mine, independent assessments issued in 2001 found that there would be "considerable technical and financial challenges to depositing 500 million tons of tailings and 600 million tons of various waste in a safe and environmentally acceptable manner" (Ecolur, 2019b). Nevertheless, the mine operator concealed and ignored these warnings and, after 30 million tons had been deposited, discontinued operations due to tailing dam sustainability. Maintaining the status-quo of contaminating soils, water, and air will subsequently pose the potential to affect people in all parts of the country.

Despite this dismal situation, there are a handful of case studies but few country-level studies considering the impact of mining in Armenia without environmental stewardship. In 2013-2014 researchers at the American University of Armenia's (AUA) Turpanjian School of Public Health conducted a thorough soil analysis in 11 communities affected by mining and smelting industries in the Republic of Armenia (Akopyan et al., 2014). Their work was carried out in collaboration with Pure Earth, previously known as the Blacksmith Institute. They found that most arsenic, cadmium, and chromium samples collected from residential areas exceeded the Maximum Allowable Concentration (MAC) levels.

Pure Earth has subsequently collected data from many other mining sites, none of which have been used for country-level analysis of health impacts. While this initial data collection did not consider the impact on public health, it is the only comprehensive source for mining contamination in Armenia.

Some of the case studies found that pollution from mines farther from residential areas was less likely to reach inhabited areas (Akopyan et al., 2018). Environmental hazards of mining in mountainous terrain are significantly higher than similar flat terrain, which implies that additional measures are needed to ensure environmental safety in mountainous regions (Burdzieva, Alborov, Tedeeva, Makiev, & Glazov, 2018).

Public Health Impacts of Mining Contamination

Heavy metal pollutants in soils usually enter the human body and pose health risks through various direct and indirect pathways. For example, people can be directly exposed to toxic chemicals from an impacted site by inhaling or ingesting dust or vapor, getting the substance on their skin, or drinking groundwater or surface water that flows through or under the contaminated area.

In addition, people can be indirectly exposed through food grown on the land contaminated through dust or vapor or irrigated with water contaminated with the pollutants which have migrated from the site (Z. Wang, Chai, Yang, Wang, & Wang, 2010). The adverse effects of heavy metals on human health have been studied extensively.

These effects manifest themselves as various acute and chronic ailments, such as gastrointestinal, lung, and kidney problems. An extensive list of associated ailments is provided in Table 1, adapted from Rahman & Singh (2019). Studies found low birth weight and other birth issues associated with arsenic (Huyck et al., 2007), lead (Ahern, Mullett, MacKay, & Hamilton, 2011; McMichael, Vimpani, Robertson, Baghurst, & Clark, 1986; Nishioka et al., 2014), chromium (Xia et al., 2016), cadmium (Johnston, Valentiner, Maxson, Miranda, & Fry, 2014; Loiacono et al., 1992) and various air and water pollutants (Ahern, Mullett, et al., 2011). Low birth weight has been found to have a substantial impact on the health of children (McGovern, 2019). Similarly, stillbirths and miscarriages have been found to be impacted by mining pollutants (Ahern, Hendryx, et al., 2011).

The Integrated Risk Information System (IRIS) of the U.S. Environmental Protection Agency's National Center for Environmental Assessment identifies and characterizes the health hazards of chemicals found in the environment (USEPA, 2022a). IRIS health hazard assessment summaries are categorized into non-carcinogenic effects and carcinogenicity assessments for lifetime exposure.

Table 1. Effects of THMs on humans (adapted from Rahman & Singh (2019)).

Properties		**Arsenic**	**Cadmium**	**Chromium***	**Mercury**	**Lead**
Effect at cellular level		Carcinogenic and neurotoxic	Carcinogenic	Carcinogenic and mutagenic	Neurotoxic	Neurotoxic
Ailments in human	Acute	Gastrointestinal symptoms of cholera, diffuse skin rash, acute psychosis, heart muscle disease, cardiomyopathy, and acute encephalopathy	Bronchitis, chemical pneumonitis, pulmonary edema, and gastrointestinal symptoms	Tubular necrosis and renal failure	Induce severe pneumonitis and acute necrotizing bronchitis for Hg(0), gastrointestinal tract and kidney effect for Hg(II), and central nervous system for organic Hg	Hemolytic anemia, hypertension, cardiovascular disease, Fanconi's syndrome
		Saha et al. (1999); Ratnaike (2003)	WHO (2010a)	ATSDR (2015)	Garnier et al. (1981); Berlin, Zalups, & Fowler (2007); Bernhoft (2011)	Navas-Acien, Guallar, Silbergeld, & Rothenberg, (2007); Rastogi (2008); Gidlow (2015)
	Chronic	Arsenicosis, abnormality of Mee's lines, night blindness, cirrhotic portal hypertension, hepatic angiosarcoma, diabetes mellitus, cortical necrosis, and peripheral neuropathy	Tubular cell necrosis, renal failure characterized by proteinuria, anemia, impaired lung function, osteoporosis, and bone fractures	Skin sensitization, transient renal effects	Mercurial tremor, erethism, immune dysfunction, nonspecific symptoms of weight loss and gastrointestinal disturbance for Hg(0) and central nervous system for organic Hg	Encephalopathy, hemolytic anemia, hypertension, and cardiovascular disease
		Ng, Wang, & Shraim (2003); Hashim et al. (2013); Saha et al. (1999); Bundschuh et al. (2012)	Orlowski & Piotrowski (2003); Friberg, Elinder, Kjellstrom, & Nordberg (1985); HPA (2010); WHO (2010a)	ATSDR (2015)	Friberg & Vostal (1972); Berlin et al. (2007); Bernhoft (2011)	Navas-Acient et al. (2007); Rastogi (2008); Flora et al. (2011); Gidlow (2015)

**Toxicological properties of Cr are referred for Cr(VI).*

The Chronic Oral Exposure Reference Dose (RfD) for inorganic arsenic is 3E-4 mg/kg-day. Critical effects include hyperpigmentation, keratosis, and possible vascular complications. It is worth noting that EPA scientists did not reach a clear consensus on the oral RfD for inorganic arsenic. While more than 40,000 people were included in the assessment, given that the doses were not well characterized and that there was the presence of other contaminants and other factors, the EPA IRIS assessment was assigned a medium level of confidence in the Oral RfD for inorganic arsenic.

The Carcinogenicity Assessment for Lifetime Exposure to inorganic arsenic classified it as a human carcinogen. EPA estimated carcinogenic risk from inhalation exposure is 4.3×10^{-3} per $\mu g/m^3$. Increased lung cancer mortality due to inhalation exposure to inorganic arsenic has been found in human studies. Liver, kidney, lung, and bladder cancers resulted in increased mortality. In addition, consumption of drinking water that was high in inorganic arsenic was correlated with an increased incidence of skin cancer (USEPA, 2022b).

Cadmium’s Chronic Health Hazard Assessments for Non-carcinogenic Effects produced an RfD of 5E-4 mg/kg/day for water and 1E-3mg/kg/day for food with a critical effect of significant proteinuria. It is classified as a probable human carcinogen based on sufficient evidence of carcinogenicity in rats and mice by inhalation and injection. Oral administration of cadmium acetate, sulfate, and chloride in rats showed no evidence of carcinogenicity. Workers exposed to cadmium dust or fumes exhibit an association with prostate cancer that is statistically significant and positive. Carcinogenicity due to ingestion of cadmium has not been established due to inadequate study on this pathway (USEPA, 2022c).

Hexavalent chromium's Chronic Health Hazard Assessments for Non-carcinogenic Effects produced an RfD of 3E-3 mg/kg-day. A 1965 study in China found that subjects given 20mg/L chromium (VI) were observed to have gastrointestinal effects such as mouth sores, vomiting, indigestion, stomach pain, diarrhea, higher rates per capita of lung and stomach cancer, and elevated white blood cell counts compared to controls (Zhang & Li, 1987).

EPA classifies hexavalent chromium as a known human carcinogen via inhalation as the route of exposure at a unit risk level of 1.2×10^{-2} per $\mu g/m^3$. However, due to inadequate data to support or refute human carcinogenicity, the oral route is not classifiable as such. Studies of occupational exposure of workers in the chrome pigment sector have demonstrated an association between hexavalent chromium exposure and lung cancer (USEPA, 2022c) (Davies, 1984; Frentzel-Beyme, 1983; Hayes, Sheffet, & Spirtas, 1989; Langård & Vigander, 1983).

EPA's Chronic Health Hazard Assessments for Non-carcinogenic Effects of Lead exposure via the oral route noted health effects including but not limited to impairment of hearing acuity, hemoglobin synthesis and male reproduction, neurotoxicity, hypertension, and developmental delays. The effects of lead exposure in children are both more significant and higher risk due to hand-to-mouth behavior. EPA does not provide an RfD for inorganic lead.

The Carcinogenicity Assessment for Lifetime Exposure finds that lead is a probable human carcinogen based on sufficient evidence in animal studies. The same assessment finds that there is inadequate data to support a determination of human carcinogenicity. All of the available studies on lead exposure and carcinogenicity lacked quantitative exposure information and controls for smoking and exposure to other metals such as arsenic, cadmium, and zinc (USEPA, 2022d).

In 1991, EPA established the Lead and Copper Rule to reduce exposure to lead in drinking water (USEPA, 1991). The Rule established a Maximum Contaminant Level Goal (MCLG) of zero for lead because there is no level of exposure to lead that is without risk. High-profile public health crises like Flint, Michigan (Zartarian, Xue, Tornero-Velez, & Brown, 2017), Newark, New Jersey, and others have prompted EPA to revise the Rule, effective December 16, 2021, to protect U.S. communities better and to remove lead from the nation's drinking water ultimately. EPA-recommended action levels for lead concentrations are at 0.15 per $\mu g/m^3$ in ambient air, 15 $\mu g/l$ in drinking water and 15ppb, 400-1200 ppm for soil in play and not play areas (ATSDR, 2015) and the recommended level by the Center for Disease Control (CDC) for lead in human blood is 5 $\mu g/dl$ (USEPA, 2022f).

The Chronic Oral Exposure Reference Concentration (RfC) for inhalation of elemental Mercury is 3E-4 mg/cu.m and is analogous to the oral RfD. Critical effects include hand tremors, increases in memory disturbance, and there is slight subjective and objective evidence of autonomic dysfunction. Elemental mercury is not classifiable as to human carcinogenicity based on inadequate human and animal data. Findings in epidemiological studies were confounded by concurrent exposures to other chemicals and failed to show a correlation between elemental mercury vapor exposure and carcinogenicity (USEPA, 2022e).

Public Health Impacts of Mining Contamination in Armenia

The effects of these chemicals due to mining operations and geospatial characteristics unique to the country have not been studied in Armenia. Only one generalized study attempted to analyze mining effects on health, using proximity to, and not presence or contaminant concentration at, Armenian mines (Yepremyan, 2018). The source for health data used in the study was the 2015/2016 Armenian Demographic and Health Survey (ADHS). Yepremyan (2018) found that the closer a population lived to mines, the more likely they were to have miscarriages, stillbirths, and lower birth weights. This study, however, seemingly arbitrarily selected six mines (Akhtala, Alaverdi, Teghut, Kajaran, Sotk, and Drmbon) to test for associated health effects.

Risks from mining activities have been found to be greatest as a function of proximity, disproportionately affecting communities nearest to mines (Sonter, Moran, Barrett, & Soares-Filho, 2014). Academics and international organizations have employed GIS to assess environmental and socio-economic risks associated with mining (Werner et al., 2019). Findings from these studies have assisted in adjudicating on mining-related conflicts, particularly in countries with low public trust in mining companies (Moffat & Zhang, 2014).

A GIS analysis is the leading method for assessing differences in public health due to the geographic complexities of exposure to mining contamination (Werner et al., 2019). By controlling for geospatial characteristics, researchers have conducted multivariate regression analysis, and difference-in-differences (DiD) tests to find links between health and distance from mining locations (Goltz & Barnwal, 2019; Yepremyan, 2018). Most exposure and health concerns in epidemiologic studies lack specificity of exposure impact and center around chemical concentrations and environmental and occupational exposures complicated by a variety of risks (Fedak, Bernal, Capshaw, & Gross, 2015).

Research Questions, Hypotheses, and Specific Aims

This research explored if soil contamination from mining sites in the Republic of Armenia impacted the public health of nearby communities, taking into account the type of contaminant, proximity, and other spatial characteristics. Thus, the main research question of this study was: Are people living near mine sites more likely to have poorer health than those that live farther away?

This question was explored by testing the following hypotheses:

- H1: Lower negative health impact is a function of a greater distance between mining operations and residential communities. Where,
    - health impacts were measured using low birth weight and incidences of miscarriages, stillbirths, and anemia, and
    - individual and aggregate levels of arsenic, cadmium, chromium, lead, and mercury were used to estimate soil contamination.
- H2: Health indicators in downstream communities are associated with contaminated run-off, despite being farther from mining operations.
- H3: Elevation of mines in relation to communities increases the impact of contaminants on health.

Specific Aims

To address the questions and hypotheses mentioned above, the following specific aims were identified:

1. Create a contamination database by downloading individual testing site contaminant data from Pure Earth (2019), coding, and merging them into one dataset.
2. Map the concentrations of contaminants (using latitude/longitude) as a function of the distance from mining locations and in relation to other spatial factors, such as elevation and water runoff using ArcGIS.
3. Create a database of health impacts by cluster by downloading the GPS shapefile from DHS Survey data.
4. Use ArcGIS to generate distance, downstream runoff, and elevation data.
5. Convert spatial data developed through ArcGIS analyses into a Stata file to conduct statistical analysis.
6. Conduct multivariate Ordinary Least Squares (OLS) analysis to measure if public health differed in areas near mines with a high level of contamination.
7. Conduct a difference-in-differences test by creating a pseudo-panel that compared the potentially exposed households living close to the mine with potentially not exposed households living farther from mines.

Chapter II

Methods

A unique, geospatial, and micro-level database of birth records and mine contamination in Armenia was created to assess the impact of mining pollution on public health. The presence, concentration, and proximity of heavy metals such as arsenic, cadmium, chromium, lead, and mercury were used to measure the impact of contamination. Incidences of miscarriages, stillbirths, anemia, and low birth weight measured the health of neighboring communities (definitions of the variables are provided in Table 8).

Mining Contamination

Mining contamination data were obtained from the Toxic Sites Identification Program (TSIP), the largest global database of sites contaminated with toxic chemicals. TSIP is a Pure Earth program funded by United States Agency for International Development (USAID), European Commission, UNIDO, The World Bank, and others. TSIP trains and supports low- and middle-income countries to assess contaminated sites and sample environmental data using the Initial Site Screening (ISS) protocol. This is a rapid assessment tool based on US EPA protocols, developed with the input and advice of experts from the US EPA, Johns Hopkins School of Public Health, and others.

An ISS is completed on-site over a period of 2-3 days by professionally trained investigators and is designed to collect information related to human health risks. ISS is used to measure the health impact of a contaminant on a population as a function of its toxicity and the received dose. The dose is a function of the concentration of the toxic compound, migration routes, duration of exposure, and the pathway into the body.

Key factors in measuring the level of contaminant hazard on public health include the presence of chemicals as well as their concentration. The critical indicator of the hazard posed by a site is if the concentration exceeds its maximum “safe” recommended levels set by international standards. Once the chemical is identified as hazardous to human health, experts need to identify possible migration routes, i.e., the spread of the contaminant from a source to a community. Substances can spread through various channels, such as airborne emission of dust or vapors, wind, storm runoff, or groundwater, eventually reaching agriculture, plants and animals, and the food chain.

Pollutants can enter the body through various direct and indirect pathways, such as ingestion (swallowing, often in food or water), inhalation (as dust or vapor), or direct dermal (skin) contact. In essence, people can be directly exposed to toxic chemicals from an impact site by inhaling or ingesting dust, getting the substance on their skin, or drinking groundwater or surface water that flows through or under the site. But they can also be indirectly exposed through food grown on the land contaminated through dust or vapor or irrigated with water contaminated with the chemicals migrated from the site. This model of Pollution-Migration-Pathway-People is central to the TSIP’s basis for understanding and assessing risks at a particular site.

Pure Earth partnered with experts from the American University of Armenia and trained site investigators to conduct the assessments in Armenia (Akopyan et al., 2014). The fieldwork locations were selected based on the rapid risk screening results of toxic waste sites in Armenia from 2012-2014. The initial sample included 11 sites in the most affected communities in the Lori and Syunik regions. Since then, data from more sites have been collected across the country. While the TSIP's primary goal is improving public health, it stops short of demonstrating the health consequences of a particular site. They aim to determine if a credible health risk is attached to a site and if this risk deserves further investigation.

Pure Earth contamination data is not freely available. I requested access to soil sampling and contamination data from Pure Earth in May 2020 by submitting a proposal about my project. Login credentials were provided to the TSIP database, where data are published (Pure Earth, 2019). Data on over 5000 toxic sites in 50 countries can be viewed and sorted in the database. An easy-to-use graphical user interface organizes the data, beginning with a map that can then be zoomed in and out, and various contaminated sites can be selected from the map (Figure 6).

The source includes the following contamination types for Armenia: lead, mercury, pesticides, arsenic, cadmium, chromium, and other. Once a site is selected, data are organized under a site page that includes the following sections: Screening Risk Assessment, Physical Description, Release Risk, Site Stakeholders, and Linked Report Images.

The TSIP database listed data for 51 sites available for Armenia under the industry category Mining and Ore Processing. Some sites were missing entirely or had missing data which had been assessed in the 2012-2014 period, the results of which were published in a report by the AUA research team (Akopyan et al., 2014). Although the report did not include information on levels of mercury, I was able to obtain part of the missing data for the available metals from Varduhi Petrosyan, the Dean of AUA Turpanjian School of Public Health, who was the second author of the report.

Of the remaining sites, some were incorrectly categorized as being mining-related (e.g., waste sites of facilities, such as factories), and yet others had incomplete or missing information (e.g., the site is available on the database, but the levels of contamination are missing, or the page states “Needs More Info”).

Figure 6 shows the TSIP interface for Armenia and an inset of individual contaminant collection sites. Spatial data for each location were individually downloaded for this research, merged into an excel file, and quantified to enable statistical analysis. After cleaning, correcting the available data, and acquiring the missing data, my final dataset included 4,459 samples from the 2012-2014 and 2018-2019 assessments of 44 sites near 18 currently operating metal mines in Armenia.

Data for concentrations of heavy metals arsenic, cadmium, chromium, lead, and mercury in soil were obtained, along with a detailed description of the site (in most cases). The number of soil samples was determined based on the population size at risk in the communities affected by potential sources of pollution, such as mining and ore processing factories, smelters, and tailing ponds.

Some soil samples were collected at the mines and tailing ponds. Others were collected from affected communities, yards, gardens, schools, and kindergarten playgrounds in addition to background samples at the surface, 10 cm (~4”), and 20 cm (~8”) depth, and were quantified using a portable X-ray fluorescence (XRF) spectrometer. The final Pure Earth dataset included geolocation of the mines, and other relevant information, such as the name of the investigators, year of sampling, sample types, pathways, and a description of each site recorded by the investigator.

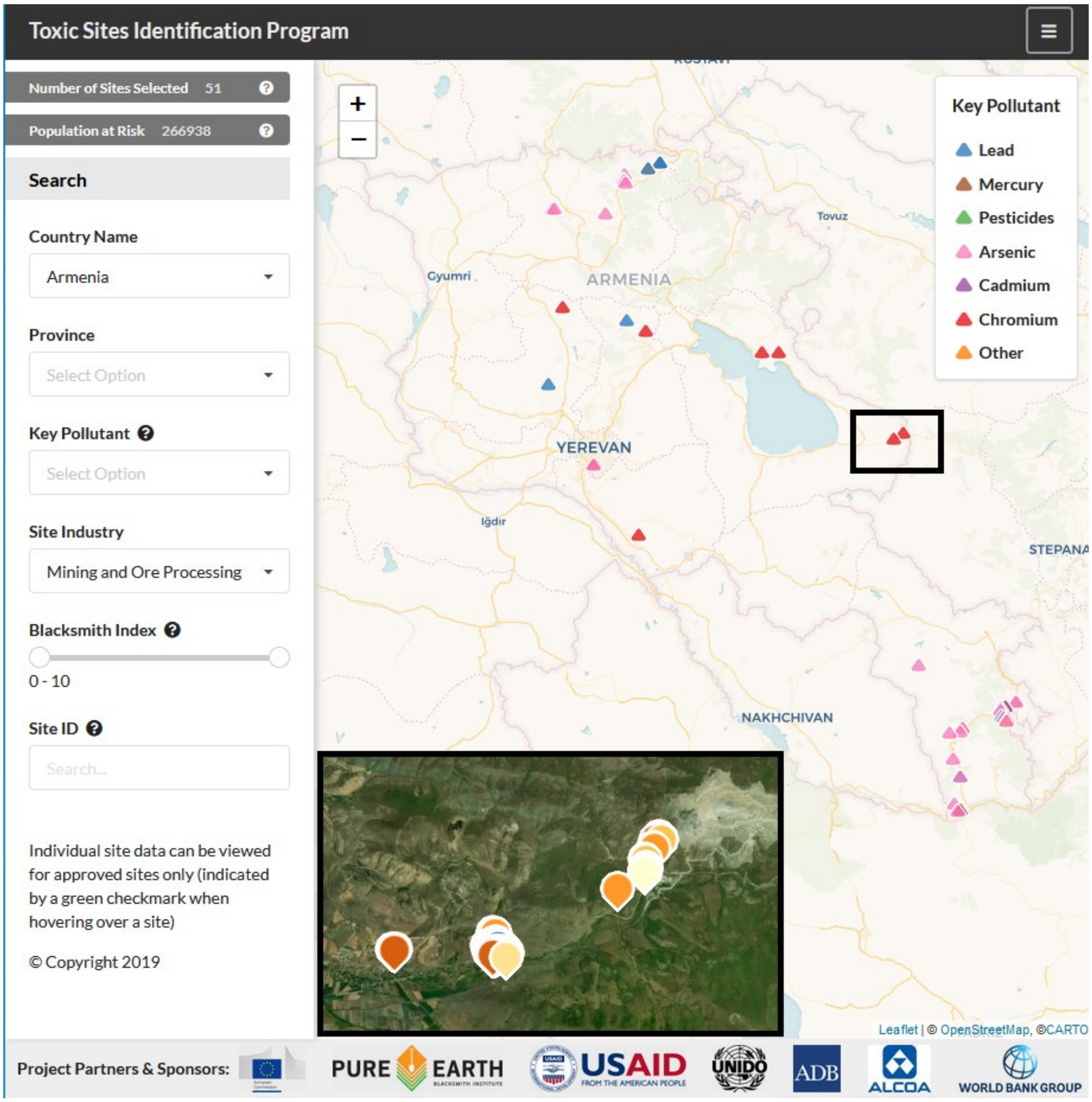

Figure 6. Screenshot of Pure Earth database of Armenia (Pure Earth, 2019).

Recommended Levels

As heavy metals naturally occur in soil, it is necessary to determine if the concentrations recorded exceeded levels associated with health risks. Investigators compared the contaminant concentrations with Maximum Recommended Levels (Pure Earth, 2021), which are based on various international standards (primarily European and Canadian). As these standards change over time and vary from country to country, I built a list of screening levels based on current US EPA recommendations.

Pure Earth data categorizes different pathways by which a person is most likely to be exposed (e.g., ingestion, inhalation) and various types of media samples, such as residential, industrial, and agricultural soil. However, there are no known sources where one can obtain US standards for all of these pathways and media types. US EPA developed a screening level calculation tool to assist risk assessors with Superfund sites in developing or refining safe contaminant screening levels. The regional screening levels (RSLs) are risk-based and are calculated using the latest toxicity values, default exposure assumptions, and physical and chemical properties. EPA provides an RSL calculator where default parameters can be changed to reflect site-specific risks (USEPA, 2022g).

US EPA's RSLs could be used for industrial and residential soil but not for agricultural. In addition, EPA identifies possible problems (section 3.3 (USEPA, 2022g)) using RSLs, such as applying inappropriate target risks or changing a cancer target risk without considering its effect on non-cancer, and not performing additional screening for pathways not included in these screening levels (e.g., farmer scenario for agricultural soil limits). US EPA recommends using the PRGs (Preliminary Remediation Goals) early in the assessment process as an identification tool of possible remedial goals (USEPA, 2022g).

An EPA-provided PRG calculator (USEPA, 2021) is used by risk assessors and others involved in decision-making at hazardous waste sites to determine whether levels of contamination found at the site may warrant further investigation or site cleanup, or whether no further investigation or action may be required (USEPA, 2022h). PRGs are not cleanup goals or cleanup standards, which made them more appropriate for my study. Recommended levels derived using the EPA's PRG calculator can be found in Appendix 1, Table 10**.**

Using information on the type of soil and pathway of exposure, I had to create a novel dataset that included recommended limits for the three soil types studied. To do this, I calculated non-carcinogenic PRG thresholds to derive a variable for recommended limits (RL) of soil, using a PRG calculator provided by EPA. RL in agricultural soil was derived by combining the residential and farmer scenarios in the PRG calculator provided by EPA (USEPA, 2021). Non-cancer risk from the contaminants was calculated based on a target hazard quotient (THQ) = 0.1, a relevant unit when multiple chemicals are present at sites (section 5.15, RSL User's Guide (USEPA, 2022g)).

Hazard Calculation

Per EPA recommendation (section 5.15.2, RSL User's Guide (USEPA, 2022g)), hazard quotients can be computed by dividing each maximum site-specific concentration by its respective non-cancer RL:

$$HQ = \frac{C_i}{RL_i}, \tag{1}$$

where HQ, C, and RL are hazard quotient, concentration, and recommended limits for an individual toxin, *i*. As multiple samples were available per site, the maximum concentration of each contaminant at each site was selected to represent the level of that chemical's contamination at that site. With an HQ of greater than 1, there is an increased potential for adverse effects.

As large number of substances are typically present in contaminated sites, combining the HQs is often appropriate to understand the potential health risks associated with aggregate exposures to multiple pollutants. To estimate the cumulative non-cancer hazard for each exposure pathway, the hazard quotients for individual chemicals at each site are summed to create a non-carcinogenic hazard index (HI):

$$HI_i = \sum HQ_i = HQ_{As} + HQ_{Cr} + HQ_{Cd} + HQ_{Pb} + HQ_{Hg}, \tag{2}$$

where HI is hazard index, and HQ is hazard quotient for each chemical, *i*. Subscripts *As*, C*r*, *Cd*, *Pb,* and *Hg* stand for arsenic, cadmium, chromium, lead, and mercury. As with the hazard quotient, an aggregate exposure value below an HI of 1.0 means adverse non-cancer effects are unlikely and, therefore, can be considered to have negligible hazard risk. An HI greater than 1 suggests further evaluation as potential may exist for adverse effects. The EPA cautions that higher values of hazard index do not necessarily suggest a likelihood of adverse effects, and it is not an entirely accurate indicator of risk.

The Pure Earth database contained data on relatively few water samples. To avoid hasty generalizations based on small samples, water samples were excluded from this analysis. Only one of the measured water samples had contaminant concentrations over the RL, three samples of arsenic in fishing water. The table with descriptive statistics for water contamination is provided in Appendix 1 (Table 12).

Mine Locations

Armenia has 30 active metal mines and is rich in iron, copper, molybdenum, lead, zinc, gold, silver, antimony, aluminum, and other metals and minerals (Appendix 1, Table 9). As Pure Earth only collected data near 18 mines, I needed to identify the locations of all metal mines in the country. To find if nearby mining activities were correlated with health problems, I needed to separate potentially exposed communities living near mines, not just the ones that Pure Earth has data for, but all metal mines, to ensure that the potentially not exposed communities are not affected by nearby mine operations.

A single source that provides the list of the metal mines with their geolocations does not exist. Several incomplete sources offered locations of the mines at some level of accuracy, but no single source existed with complete and accurate information. A database had to be built to enable this research. As a first step, I collected the names of active mines and approximate locations using a map of Armenia's metal mines from the website of the RA Ministry of Energy Infrastructures and Natural Resources (Ministry of Energy, 2010).

Vector data, a coordinate-based GIS format, of some of the mines in Armenia were accessed from the website of the Acopian Center for the Environment at the American University of Armenia (AUA, 2021). Google Earth was used with the approximate locations from the Ministry's map and the AUA vector map, and other secondary sources to identify the exact coordinates of the mines. In some cases, online pictures were used to geolocate the mine when multiple mines were close to one another. A source produced by EcoLur, a Non-governmental Organization, consisting of independent journalists (EcoLur, n.d.), was beneficial in this effort since most of their reporting on the mines also included detailed photos of the areas.

Documents published by the Extractive Industries Transparency Initiative program, a global standard to promote open and accountable management of natural resources, provided data relating to mining activities in Armenia. Through this initiative, subsoil use contracts for extracting mineral resources in Armenia are published on the website of the Ministry of Energy and Infrastructures and Natural Resources of the Republic of Armenia (Ministry of Energy, 2021). These contracts between the government and mine companies were used to obtain spatial coordinates for the end points of the area allocated for exploitation.

Coordinates obtained from the documents were imported to ArcGIS, a software by Esri, a mapping and analytics software for spatial analysis. A centroid GPS (Global

Positioning System) location was generated to represent the location of the mine. Google Maps was used to precisely pinpoint the mine locations, as some of the contracts included large areas that had not been exploited but were transferred to the mine companies. Ultimately, I was able to build a novel database of all active metal mines in Armenia, including their geolocations and the types of ores processed. The constructed data is provided in the Appendix, Table 9, and the map of the mines is presented in Figure 7.

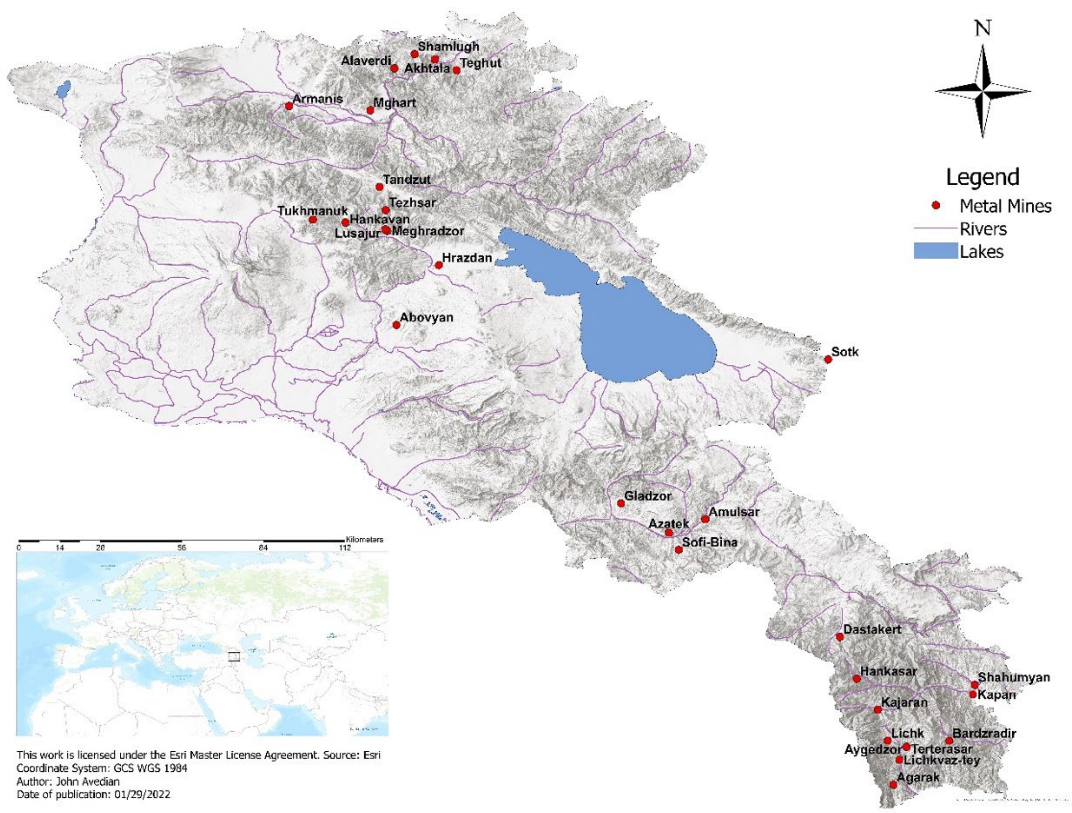

Figure 7. Map of metal mines in Armenia.

Health Indicators

Disaggregate health-related datasets with associated spatial information are scarce. Self-assessed health data are frequently employed in social science research. However, one of their main shortcomings is that they offer little information and too much variation on the actual state of health of the respondent (Au & Johnston, 2014). In addition, data from the 2009-2019 Caucasus Barometer (CRRC, 2019), which assessed the overall satisfaction of individuals working in mining, with their work conditions and income relative to the satisfaction of workers in other industries, indicated that the Republic of Armenia's mining sector workers didn't perceive themselves to be less healthy than workers in other sectors.

When asked to rate their health from one to five, with one being very poor, and five being very good, mining sector workers rated their health at an average of 3.3 compared to the average rating of 3.0 for workers from other sectors; this difference was statistically significant at a 99% confidence level (CRRC, 2019). One reason for this may be that only about 0.5% of the sampled persons were working in the mining and quarrying sectors and that they were significantly younger than workers in other sectors ($p<0.01$).

Another issue with self-assessed health measures is that working respondents may tend to self-assess as generally with poorer health than those who do not work (World Bank, 2014). Lastly, the use of the general population as a reference has been found to cause serious underestimation of the risk of cancer in working populations because of the healthy worker effect (Knight et al., 2015).

Due to these shortcomings with self-assessed health surveys, researchers have used various health indicators provided by the Demographic and Health Survey (DHS). DHS conducts nationally representative surveys on a range of demographic and health-related issues worldwide. To carry out the Armenia Demographic Health Survey, they partnered with Armenia's Ministries of Health and National Statistical Service to conduct four surveys in Armenia every five years since 2000. The DHS geographic data collected during the last two surveys in 2010 and 2015-16 (ADHS, 2017), were used to perform this study.

The two surveys were based on a population estimate close to 3.3 million in 2010 and around 3 million in 2015. Armenia's population has shrunk following large-scale migrations due to the ethnic cleansing of Armenians in Nagorno Karabakh and the unresolved conflict, post-Soviet turmoil, economic collapse, and long-lasting corrupt governments (Abramian, 2020; ADHS, 2012).

Sampling designs of the two surveys were based on the 2001 and 2011 National Population Censuses (Armenia Population and Housing Census). Armenia comprises 11 administrative regions (marzer), including Yerevan, its capital city. Yerevan accounts for more than one-third of all respondents. Close to two-thirds of the population lives in urban areas (National Statistical Service - NSS/Armenia, Ministry of Health - MOH/Armenia, & ICF, 2017). Each region, in turn, is subdivided into districts, which are divided into census enumeration areas (EA).

A subset of these EAs was selected from this master sample and was stratified separately by urban and rural areas. Samples were selected from the EAs based on a stratified two-stage cluster design, consisting of around 300 clusters that were selected systematically with probability proportional to size, with households selected from the clusters.

All women aged 15-49 who were either permanent residents of the households or visitors present in the home on the night before the survey were eligible to be interviewed. Interviews were completed with 5,922 women in 2010 and 6,116 women in 2015, yielding a response rate of 98% in both years. As the location of residents is an important factor for studying the impact of local contamination on health, all the visitors were excluded from this analysis. This dropped 31 respondents from the 2010 survey and 25 respondents from the 2015 survey.

Table 2 shows descriptive statistics of the 2010 and 2015 ADHS samples. There were 67% urban clusters selected for the 2010 cohort and 58% for the 2015 cohort. Pregnancy rates tend to be higher in rural areas than urban areas, which was true for both years. Less than 0.1% of respondents reported having no education in the 2010 and 2015-2016 cohorts.

Primary and Secondary education, as the highest level achieved, were 6 and 37% in 2010, respectively, and 7 and 42%, respectively, in 2015-2016. Lastly, respondents who reported finishing higher education were 56% in 2010 and 51% in 2015-2016. In both years, the highest pregnancy rates were reported with women whose highest education was Secondary.

Respondents' wealth was determined using five categories beginning with lowest, second, middle, fourth, and finally highest. As these are quantiles, the number was distributed evenly by wealth. In the 2010 and 2015-2016 surveys, a higher percentage of women below the middle wealth index were pregnant than women above the index.

The characteristics for women living within 10 km of mines from women living more than 10 km from a mine were similar (Table 2). The results showed that women living within 10 km from a mine had a slightly higher age and percentage of pregnancies on average than women living more than 10 km from a mine, but these differences are substantially insignificant.

Table 2. Characteristics of the ADHS respondents.

	2010 ADHS				2015-2016 ADHS			
	N	%	Age	Pregnant %	N	%	Age	Pregnant %
Residence								
Urban	3,950	67	31.5	63	3,529	58	31.8	66
Rural	1,941	33	31.2	67	2,562	42	31.2	69
Education								
No education	4	0.1	27.3	0	5	0.1	33.2	60
Primary	358	6.1	26.1	48	405	6.6	27.9	55
Secondary	2,202	37	32.2	72	2,572	42	31.8	72
Higher	3,327	56	31.4	61	3,109	51	31.8	65
Wealth								
Lowest	1,062	18	31.2	65	1,135	19	31.1	69
Second	1,304	22	31.5	66	1,348	22	31.5	67
Middle	1,318	22	31.6	65	1,318	22	31.6	68
Fourth	1,274	22	31.3	64	1,288	21	31.7	66
Highest	933	16	31.3	60	1,002	16	31.6	67
≤ 10 km	1,298	22	31.7	66	1,204	20	31.6	69
> 10 km	4,593	78	31.3	64	4,887	80	31.5	67
Total women	5,891	100	31.4	64	6,091	100	31.5	67

Note: 2010 and 2015 ADHS individual-level statistics.

Institutional Review Board

The DHS Program maintains strict standards for protecting the privacy of survey respondents. Their survey procedures and questionnaires have been reviewed and approved by the Institutional Review Board (IRB) of Inner City Fund (ICF), the organization that, in collaboration with USAID, implements the DHS surveys. Additionally, country-specific DHS survey protocols are reviewed by the ICF IRB and typically by an IRB in the host country. ICF IRB ensures that the study complies with the U.S. Department of Health and Human Services regulations for protecting human subjects (45 CFR 46), while the host country IRB ensures that the survey complies with the laws and norms of that nation.

Merging the DHS survey dataset of health indicators with the pollution data does not alter the respondents' anonymity or make them more identifiable. Communication with Harvard IRB detailing the study and use of these datasets yielded an informal confirmation that this research does not meet the criteria of needing formal submission for a review by the Harvard IRB. This study was not considered human subject research based on Harvard's Committee on the Use of Human Subjects guidelines.

Displaced Geolocations

To ensure that respondent confidentiality is maintained, DHS randomly displaces the GPS latitude and longitude positions for all surveys. Urban clusters contain a minimum of zero and a maximum of two km of error, and rural clusters have a minimum of zero and a maximum of five km of positional error. One percent of the rural clusters are further displaced a minimum of zero and a maximum of 10 km. The displacement is restricted so that the locations stay within the country and the DHS survey region. In surveys released since 2009, the removal is limited to the country's second administrative level, where possible.

This displacement introduces random error, which can substantively affect the results of analyses that look at small geographic areas. However, the error is not too problematic for this analysis since the dispersion is unlikely to introduce a significant error given the size of communities to be analyzed and their distances from mining sites.

Incidence of Fetal Mortality

DHS collects data on indicators that have been found to be associated with mining contamination, such as low birth weight (McGovern, 2019), incidence of stillbirths and miscarriages (Ahern, Hendryx, et al., 2011), and incidence of anemia (Rahman & Singh, 2019). Based on ADHS questions, three variables were constructed as health measures for this study: incidence of fetal mortality, incidence of anemia, and birth weight. To find if mining-related contamination was associated with poorer health, the DHS variables were used to contrast the health of residents living in potentially exposed areas with the health of respondents living away from contaminated sites.

One issue with demographic survey questions on infant mortality, for example, is underreporting of deceased children by survey respondents, for reasons such as survey timing relative to the time of deaths (Joyce, Kaestner, & Korenman, 2002) or unintended pregnancies (Smith-Greenaway & Sennott, 2016). There may also be underreporting of recent events due either to forgetfulness or conscious avoidance of recalling the tragedy of losing a child. Despite this and other shortcomings discussed in this section, the DHS estimates of key demographic and health indicators on a spatial and disaggregate level made it the best available data source for this study.

The incidence of fetal mortality was computed by adding the number of stillbirths and miscarriages (named s209a and s209b in the DHS database, respectively). The questions asked for the number of stillbirths the respondent had, including an early fetal death (5-6 months pregnancy) or a late fetal death (7 or more months pregnancy), and the number of miscarriages, including due to an ectopic pregnancy. Individual women's data is aggregated at the cluster level to compute the mortality rate of unborn and stillborn children. The incidence rate of fetal mortality was calculated by dividing the number of women who miscarried or had a stillbirth at some point in the past by the total number of women who have been pregnant in their lives for each cluster.

Another proxy used in the literature to measure the fetal mortality rate is derived by dividing the total number of miscarriages and stillbirths by the total number of pregnancies per cluster. This variable was not an ideal measure for this study, as it may not show women's overall health per cluster if the numbers of miscarriages, stillbirths, or pregnancies are highly skewed. For example, out of 20 survey participants, 10 women may have miscarried, but due to a high number of pregnancies (over 10 for some), the overall mortality rate may be much lower and not show that 50% of the women in that cluster had a miscarriage or a stillbirth at some point in their lives. However, this measure of the rate of fetal mortality, based on the number of pregnancies and not the number of pregnant women, was used in the sentitivity analysis as an alternate proxy.

Anemia

The second variable used to measure the respondent's health was incidence of anemia. WHO classified Armenia as having "mild public health problems" related to anemia (WHO, 2008). Thirteen percent of tested women in ADHS surveys suffer from some degree of anemia, a quarter of which with severe anemia and 1% with moderate anemia. Due to the well-studied lead-anemia connection (discussed in the background section), anemia was used as an additional health measure, albeit only for the 2015-16 data, as the 2010 survey did not incorporate anthropometry and anemia testing in its questionnaires.

All women ages 15-49 in households interviewed in the survey were offered an anemia test and asked if they would permit drawing their blood. Ninety-three percent of eligible women participated in the hemoglobin measurement. Medically trained personnel on each interviewing team performed the testing procedures on eligible and consenting respondents. The protocol for anemia testing was reviewed and approved by the National Center for AIDS Prevention of the Ministry of Health of Armenia and the IRB of ICF.

Anemia is classified differently based on the reported pregnancy status of the respondent. For non-pregnant women, anemia is classified as severe, moderate, or mild based on blood Hgb concentrations below 7 g/dL, from 7-9.9 g/dL, and 10-11.9 g/dL, respectively, or as a binary classification indicating anemia with blood Hgb below 12 g/dL. Pregnant women are classified as anemic with blood Hgb below 11 g/dL (WHO, 2011).

The effective hemoglobin count is lowered as altitude increases since less oxygen is available in higher elevations. An adjustment is made to the hemoglobin levels with the following formula (Croft, Marshall, & Allen, 2018):

$$adjust = -0.032 * alt + 0.022 * alt^2$$
$$adjHb = Hb - adjust \ if \ adjust > 0, \quad (3)$$

where *adjust* is the amount of the adjustment calculated based on altitude (alt), which is 1,000 ft (converted from m by dividing by 1,000 and multiplying by 3.3), *adjHb* is the adjusted hemoglobin level, and Hb is the measured hemoglobin level in grams per deciliter. No adjustment is made for altitudes below 1,000 m.

In addition, Hgb is adjusted for pregnancy and smoking status of surveyed women using the formulas recommended by CDC (1998), as both affect hemoglobin concentrations (WHO & CDC, 2004). Adjustments of -0.3, -0.5, -0.7 were made to the hemoglobin levels of smokers of 10-19, 20-39, and 40 or more cigarettes per day, respectively. If the quantity was unknown or they smoked non-cigarettes, the adjustment made was -0.3 (Croft et al., 2018). A smoker of fewer than 10 cigarettes per day had no adjustment made to their Hb (g/dl) concentration.

The number of women who reported smoking was less than 1% in the ADHS samples, and therefore the adjustment for smoking was minimal. Incidence of anemia is obtained by dividing the number of women with anemia over the number who agreed to participate in hemoglobin collection in each cluster. Descriptive statistics of incidences of fetal mortality and anemia are provided in Table 7.

Birth Weight

Birth weight or size at birth is an important indicator of children's susceptibility to illnesses and their chances of survival. Birth weight data were obtained for 99% of all births in the five years before the survey. A total of 1448 and 1662 births were recorded in the 2010 and 2015-16 surveys, respectively. The variable for birth weight (named m19 in the DHS database) was measured in grams.

In Armenia, health cards for children are maintained at the local healthcare facilities. The recorded weights were based on the child's health card (when available) and the mother's recollection for all births in the five years before the survey. For children whose health cards were available, information on the cards was used instead of information obtained from the mother. Only a quarter of the birth weights in the 2010 and 2015-16 ADHS surveys were collected from healthcare facilities. This can introduce bias in the measure as studies assessing birthweight within DHS datasets found that mothers who could report a birthweight were more likely to have delivered in a facility and be of higher socioeconomic status on average (Chang et al., 2018).

In addition, to uncertainty added from recording birth weight based on the mother's recollection, information regarding the gestational age was not collected. This introduces yet another source of bias and potential problems with the validity of the DHS measure of birth weight.

Of the recorded weights, less than 6% weighed less than 2.5 kg (irrespective of gestational age), a WHO-recommended standard of low birth weight (WHO, 2019). A standardized measure of birth weight or birth weight z-scores (Schisterman, Whitcomb, Mumford, & Platt, 2009) has been recognized as the best method for analyzing anthropometric data because of its advantages compared to the other methods (WHO, 1997). The formula for calculating the Z-score is:

$$\text{Z-score} = \frac{(observed\ value - median\ value\ of\ the\ reference\ population)}{standard\ deviation\ value\ of\ reference\ population} \quad (4)$$

Due to limitations with the measurement of this variable, results regarding low birth weight are provided in Appendix 1, Table 11.

Confounding Measures

Health may be associated with the respondent's income, as wealthier women may have better access to health care, possibly better food, and resources to be treated when they need it. Although DHS has robust data on maternal and child health, including anthropometrics, similar to other demographic surveys, it doesn’t collect information on the respondent’s income. Due to inconsistencies with self-reporting of income such as forgetfulness, concealment, change in employment, multiple jobs, pay frequency, and other issues, DHS uses information on various wealth indicators (ADHS, 2017).

DHS computed the wealth index as a proxy for income (Rutstein & Johnson, 2004). Respondents were ranked according to the total score of the household in which they reside. To measure the household socio-economic status, DHS calculated the wealth index based on whether the household is in an urban-rural location, the dwelling characteristics, and household services. The variable was constructed by dividing the calculated household wealth score into quintiles—five groups, each with the same number of individuals, with higher values correlating with more measured wealth.

Wealth is often found to be highly correlated with education. Both the wealth index and education were included in the analysis as control variables. DHS has two measures for education: the number of years of education and the highest educational attainment, with the following categories: no education, some primary, completed primary, some secondary, completed secondary, secondary special, and higher.

Because of the non-proportional allocation of the sample to regions, urban and rural areas, and differences in response rates, analysis of ADHS data required weighting the data to ensure the representation of the survey results at the national level and the domain levels. Because the survey was based on a two-stage stratified cluster sampling design, weights were based on probabilities calculated separately for each sampling stage and each cluster. The design weights were adjusted for non-response to obtain sampling weights for households and for respondents. Regressions with household data aggregated for each DHS cluster were weighted with cluster sample weights provided by DHS.

Geographic Information System

Publicly available non-spatial DHS data were in Stata format, and GPS data were in GIS shapefiles. The GPS data were restricted and were obtained with special approval from DHS by submitting a summary of research purpose. GIS coordinates were provided by clusters and not households. The individual survey data were downloaded separately from the GPS data and merged using the DHS cluster IDs before being imported into ArcGIS.

The use of distance as a proxy for exposure is a simplification commonly used in environmental exposure studies. The use of proximity to measure exposure assumes that there is a distance-decay function of the impact of the potential contamination. This is a great simplification of the true function of exposure, that in addition to proximity is dependent on types of metals, media (soil, water, air, water), pathways, and local circumstances (e.g., weather, topography) (Zandbergen & Chakraborty, 2006). Despite these limitations, proximity is often adopted as a proxy for exposure in ecological studies and is also adopted for this study.

To measure the spread of contaminants and differences in public health, the contamination data from Pure Earth and health data from DHS were spatially matched using the site and cluster latitude and longitude information. Using ArcGIS software, several distance variables were constructed. Armenia is a rugged, mountainous country, and simple distance measures are insufficient to capture the true impact of mining contamination. Such measures don't consider important factors such as the topography or whether communities are positioned downstream from mines and their tailings, providing pathways of pollution spread via water run-off.

Inverse distance weighting (IDW) is one of the most frequently used spatial interpolation methods in mining pollution analysis due to its fast implementation, ease of use, and straightforward interpretation (Huang et al., 2015; Iñigo, Andrades, Alonso-Martirena, Marín, & Jiménez-Ballesta, 2011; Lee, Li, Shi, Cheung, & Thornton, 2006; C. Zhang, 2006). IDW, derived from Shepard's (1968) method of spatial interpolation, gives spatially close points more weight than distant points based on the inverse of distance to a power, which agrees with logical intuition. For example, in some of Armenia's provinces, there are contaminated sites and mines located very close to one another. Selecting the nearest site to a cluster could result in overestimating its impact because it ignores the cumulative effects of all nearby mines (because only one of them is selected as nearest).

Calculating a weighted impact of the mines that are within a chosen radius, e.g., weighting the contamination by distance for all mines within 10 km, could be useful. For several reasons, however, IDW was not an appropriate measure for this study. Its disadvantages are that it is not the most desired measure for peaks or mountainous areas (Guo et al., 2021). Also, the accuracy of the interpolation result can decrease for unevenly distributed samples (Ding, Wang, & Zhuang, 2018). Therefore, several distance measures were calculated using various spatial analyses in ArcGIS to identify areas that are close to the contaminated sites and could be potentially exposed.

Proximity and downstream trace analyses were conducted using GIS network analysis technology to measure the distance between contaminated sites and clusters and potential contamination spread. The first measure of distance to the nearest mine was constructed through GIS proximity analysis using the Near tool in ArcGIS. The Near tool calculates the distance from each point in one feature class (the contamination sites) to the nearest point feature in another feature class (the DHS clusters). This tool includes an option to perform calculations using planar distance or geodesic distance.

Planar distance is a straight-line Euclidean distance calculated in a 2D Cartesian coordinate system. Geodesic distance is calculated in a 3D spherical space as the distance across the curved surface of the world. Geodesic distance is recommended for the Spatial Analyst distance tools to calculate distance and direction accurately in any direction between any locations (Banerjee, 2005), and therefore was selected for finding the nearest mines.

Previous literature on mining's impact on health (Aragón & Rud, 2013; Goltz & Barnwal, 2019; Kotsadam & Tolonen, 2016) indicated that the influence of mine exposures and thus effects should be concentrated to communities within 5-20 km from the mine. As DHS household coordinates are displaced by 1-5 km, and up to 10 km in 1% of the cases, when ignored, this offset of locations can inflate the bias of the statistical model estimators for analyses that use distance to closest resources as a covariate. If the study area is at a larger spatial scale (> 10 km), DHS recommends generating distance covariates at this scale or larger (Perez-Haydrich, Warren, Burgert, & Emch, 2013).

Benshaul-Tolonen (2019) uses a 10 km baseline for identifying areas of likely exposure, while Kotsadam and Tolonen (2016) find the strongest exposure effects within 10 km from the mine's center point. For this reason, the baseline minimum distance was set at 10 km, i.e., potentially exposed clusters were identified as those that fall within 10 km from a Pure Earth contaminated site. Due to the impact of weather and water runoff, contamination can migrate many miles away via downstream rivers and pathways. Therefore, a cluster should be identified as exposed not only if it is within 10 km from a contaminated site as the crow flies but also if it is within 10 km from a potentially contaminated downstream.

Studies have found contaminated water and soil hundreds of km downstream from the source of mining contamination. The downstream spread of the contaminants diffuses from the riverbanks to nearby areas through different channels, e.g., rain or heavy rain-induced floods, or human usage of the water for various reasons. The dispersion pattern for metals transported downstream is complicated due to many factors, a few examples of which are the presence of multiple point-sources in the catchment, a river's hydraulic capacity to transport sediments, or the amount of rainfall (Bradley & Cox, 1986).

One of the chemicals studied by this research, mercury, has been found to impact regions more than 125 km downstream from the source (Ullrich, Ilyushchenko, Uskov, & Tanton, 2007). The dispersion pattern of lead extended over 20 km from another mine (Mann & Lintern, 1983), while other heavy metals were found 14-22 km downstream of mining activities (Besser et al., 2009).

Recent research incorporating environmental (e)DNA metabarcoding to assess the impacts of metal contaminants on sediment and water downstream of metal mines found that concentrations of lead in water and sediment fell below recommended guideline concentrations at 10 and 20 km downstream, respectively. Metals such as copper and Zinc fell below their guideline values after 40-60 km downstream. (Kavehei, Hose, Chariton, & Gore, 2021).

Downstream flows needed to be identified from each Pure Earth site to measure potentially exposed areas. For each cluster, an access point was identified on the riverbank that was the closest to its latitude and longitude. The distance from this access point to the contaminated site was the downstream distance. This simplified model assumed every resident's impact, in addition to their proximity to a contaminated site, was from their closest access point on the downstream. This distance can then be used to identify buffer zones.

Studies conducting risk assessments for contaminated groundwaters along river banks found high arsenic levels within various distances from the riverbank, in the 5-20 km range (Erban, Gorelick, Zebker, & Fendorf, 2013; Rabbani, Mahar, Siddique, &

Fatmi, 2017). There is conflicting literature on the impact of proximity to the potentially contaminated riverbank, with studies finding no effect and even a health-improving effect on birth outcomes for households within 20 km of a mine (Romero & Saavedra, 2016).

A distance measure from riverbank to cluster was constructed to ensure that only clusters that were near the riverbanks were included and the clusters that are hundreds of km away from their nearest river were excluded from the potentially exposed areas. With this simplified measure, an assumption was made that only clusters near the rivers were potentially exposed and doesn't measure how contaminated waters can pollute near and far through local and transported water usage for food, irrigation, or washing and bathing.

To create exposure buffer zones, ArcGIS was used to locate the contaminated sites and clusters, identify downstream rivers flowing from the contaminated sites, locate the nearest access points for each cluster and measure the distances. To measure the distance of the river, a downstream trace was first created in ArcGIS using its spatial network model. This tool was used to construct a line graph composed of links representing linear channels of flow (the downstream river) and nodes representing their connections (the contaminated sites and clusters).

After creating the downstream trace, the network analyst tool in ArcGIS Pro was used to create a "Closest facility analysis layer." The facilities feature class stores the network locations (sites and clusters) used as the starting or ending points. This tool allows measuring the distance of the river from the contaminated sites. Based on the above-mentioned extensive literature of the far-reaching downstream contamination by heavy metals, a conservative 10 km threshold was chosen for the downstream distance between the contaminated sites and each cluster's nearest access point on its closest downstream.

The length of the downstream trace alone is not sufficient to identify exposure zones. For example, an access point 10 km downstream may still be hundreds of km away from the cluster, even if it has been identified as the cluster's closest point on the downstream. More specifically, a cluster that is 50 km from the nearest river is unlikely to be exposed as much as a cluster within 1 km from a contaminated river. Using the Near tool in ArcGIS, the distance from each cluster to its nearest downstream access point was calculated. The distance between a cluster and its nearest access point and the distance from this access point to the nearest contaminated site were then summed to construct the total downstream distance from cluster to mine. An illustration of the distance measures is provided in Figure 8.

The above-mentioned distance measures were used to identify exposure buffers, where a cluster may be potentially exposed if:

1. its straight distance to the contaminated site was less than 10 km, or
2. its downstream distance was less than 10 km from the contaminated site to its nearest access point, and
3. its distance was less than 10 km from the access point.

Based on other study findings, 10 km was very conservative and, if too small, would show reduced impact differences between areas that were potentially exposed and areas that were not. In addition to the distance measures, ArcGIS Pro was used to identify cluster and mine elevations to control for elevation-based spread of the contaminants. Hot spot analysis was conducted to identify regions with the poorest health outcomes.

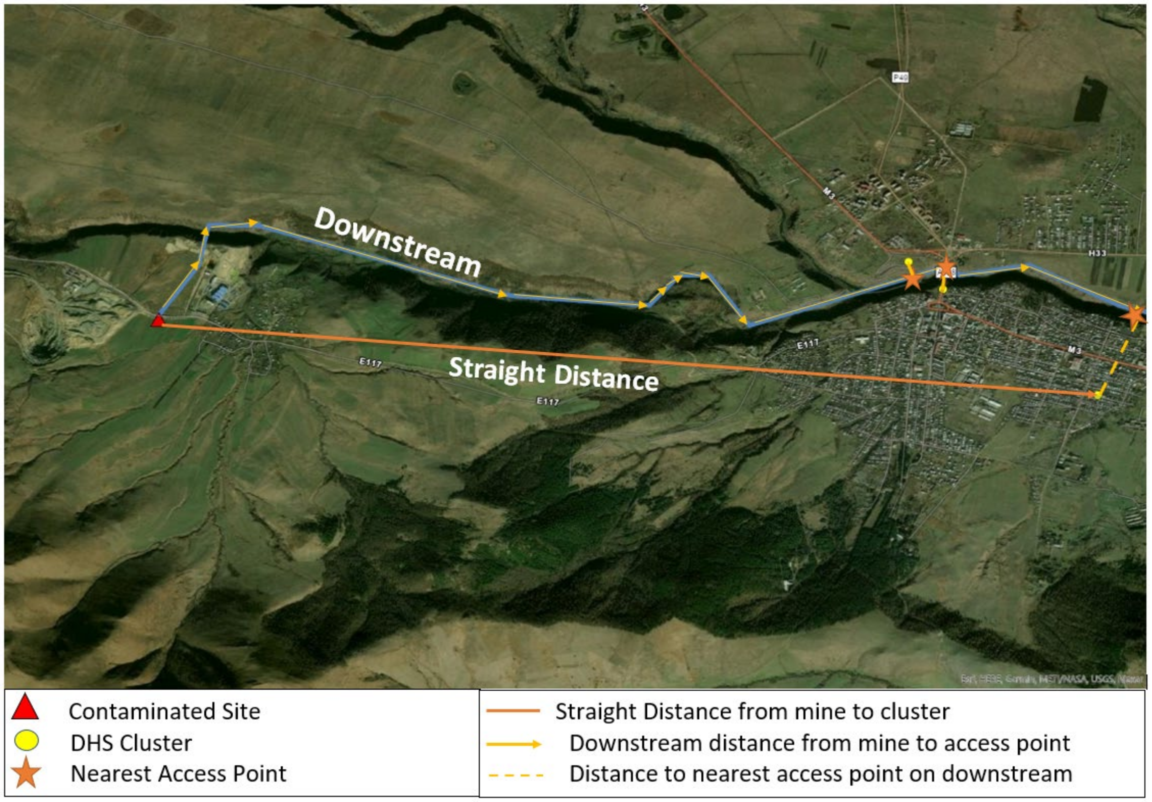

Figure 8. Illustration of the distance measures through downstream.

Figure shows the blue downstream trace, which starts at the Pure Earth mines (red triangles) and passes by DHS clusters (green dots).

After various spatial analyses in ArcGIS, the datasets were exported, and the analyses were performed independently from the GIS software.

Statistical Analysis

The empirical analysis aimed to explore the importance of mining-related pollution on public health by comparing health outcomes for households that may be potentially exposed due to nearby mining-related contamination with households that live outside the exposure areas. Several models were conducted to test the impact of mining-related heavy metal contamination on health, with geographic, demographic, and socio-economic variables as explanatory and control variables.

Exposure status was based on proximity to a mining-related contaminated site. Baselines and thresholds used in the literature studying mining impact on health were adopted in this research for studying the differences in health outcomes near contaminated sites. As the strongest exposure effects have been found within 10 km from a mine's center point (Benshaul-Tolonen, 2019; Kotsadam & Tolonen, 2016), the cutoff for identifying clusters of potential exposure in this study was within 10 km from a contaminated site.

Dietler et al (2021) and Benshaul-Tolonen (2019) restricted their samples to clusters within 100 km from mines. This limit was set to identify similar comparison groups for the clusters located closer to mines. Clusters further away may be differently affected by external factors, which may be influencing public health, such as access to water or sanitation infrastructures in the clusters closer to the highly impacted areas (Dietler et al., 2021). Clusters that were more than 100 km away from mines or contaminated sites were excluded from this study.

The identification strategy was a difference-in-differences procedure that used proximity to identify potentially exposed clusters. The outcome variables for health, the cluster-level incidences of fetal mortality and anemia, and birth weight z-scores were regressed on the level of nearby contamination. Contamination was measured with chemicals' Hazard Quotient (HQ) values and Hazard Index (HI) within 10 km from a cluster.

To ensure that the control groups were not possibly affected by mining activities of other metal mines in Armenia, for which Pure Earth did not have data, a binary variable was created to indicate if there was a metal mine within 50 km (regardless of the availability of contaminant data from Pure Earth). For similar reasons, an indicator variable, measuring if a cluster is within 50 km of a potentially contaminated riverbank, was added to the model.

Multivariate Ordinary Least Squares (OLS) regressions controlled for other covariates, which included an indicator for whether the cluster was in an urban or rural setting, age, wealth, and years of education, and an indicator if the mine was at a higher elevation than the cluster. To control for health care access, a binary variable, whether the respondent thought the distance to the nearest healthcare facility was problematic or not, was also included.

The regressions were estimated using sample weights and heteroscedasticity robust standard errors clustered by contamination sites. The errors were clustered taking into account the possible spatial correlation between contaminated sites. All regressions included year and region fixed time effects, controlling for the cluster's region, years of DHS surveys, and Pure Earth data collections.

The main specification was the following:

$$Health_c = \beta_0 + \beta_1 HQ_{cp} + \beta_2 Anymine_{cm} + \beta_3 Anyriver_{cm} + \beta_4 X_{cm} + \varepsilon_{cm} \tag{5}$$

where $Health_c$ was the outcome variable for health, measured by cluster-level incidences of fetal mortality, anemia, or birth weight z-scores. HQ_{cp} represented an individual hazard quotient for arsenic, cadmium, chromium, and mercury that was present at the nearest contaminated site within 10 km of a cluster.

Subscript c indicates a DHS cluster, p represents a Pure Earth contaminated site, and m represents a metal mine. $Anymine_{cm}$ is an indicator equal to 1 if there is a metal mine within 50 km from a cluster (regardless of the availability of contaminant data from Pure Earth). And Anyriver_{cm} is an indicator equal to 1 if there is a potentially contaminated downstream within 50 km from a cluster. X_{cm} represents respondent- or cluster-level controls. Other distance cutoff levels, such as households within 5, 15, and 20 km, were analyzed in a series of sensitivity analyses and presented in Appendix 2.

Before running the regression analyses, the independent variables were tested for multicollinearity using Tolerance Value and Variance Inflation Factor (VIF). If the Tolerance Value was less than 0.1 or the value of VIF was 10 or above, then multicollinearity may be problematic (Belsley, Kuh, & Welsch, 2005). The VIF ranged from 1.03 to 2.52; as all of them were below 10, multicollinearity was excluded. Outlier diagnostics using Cook's D was used to test whether the results were driven by specific observations (Belsley et al., 2005). Based on the Cook's D statistic, no outliers were identified.

Tobit analysis, a model devised by Tobin (1958), also referred to as the censored regression model, is designed to estimate linear relationships with censored dependent variables (Boulton & Williford, 2018). The basic intuition behind the application of the Tobit model to the mortality rate, for example, was guided by the fact that a sizeable number of sample clusters (close to one-fifth) were reported to have 'zero' fetal mortality.

These 'zero' values pose a problem of non-observability of the miscarriages and stillbirths.

A limitation of using OLS when the variable is censored is that OLS may provide biased and inconsistent estimates of the parameters, as the sample may not be representative of the population (McDonald & Moffitt, 1980). Depending on the variance of the conditional distribution, Tobit has been shown to perform either at least as poorly as the OLS model or better in Monte-Carlo simulations (Austin, Escobar, & Kopec, 2000).

Spatial Analysis

Spatial clusters of incidences of fetal mortality and anemia were identified using the ArcGIS Pro 2.9.1 software. The spatial analysis was conducted at the cluster level. DHS sample clusters did not necessarily overlap with administrative boundaries due to random spatial displacement. Using these point data, Global Moran's I spatial autocorrelation tool was used to identify the threshold distance for the analysis. This distance band was then used to perform Getis-Ord Gi* hot spot analyses (Ord & Getis, 2010) to measure global and local clustering of incidences of miscarriages, stillbirths, and anemia. Getis-Ord Gi* is an appropriate analytical method for detecting hot spots for the health outcomes because the point dataset is based on latitude and longitude coordinates at the center of DHS clusters of sample households.

To prevent the exclusion of local factors by imposing sharp boundaries, zone of indifference was used for the distance a hot spot boundary covers. Using this method, the neighboring sample households within the specified critical distance boundary of a target

DHS sample-household cluster were selected in the analyses for identifying hot or cold spots in the dataset. Once the specified critical distance boundary is reached, the level of impact of the neighboring clusters is reduced.

The Getis-Ord Gi* analysis compared the local mean incidences of fetal mortality and anemia (the mean of the incidences for each cluster of DHS sample households and its nearest neighboring cluster of DHS sample households) to the global mean rate (the mean of the incidences for all clusters of DHS sample households). It produces a z-score and a p-value for each cluster of DHS sample households, based on deviation of local means from the global means. A z-score that was positive and statistically significant indicated a hot spot of high rates, meaning that the chances are very low that the spatial clustering results from random processes. Similarly, a DHS cluster with negative and statistically significant z-score indicates local clustering of especially low rates or a cold spot (Getis & Ord, 1992). A 95% statistical significance level, corresponding to z scores >1.96 and <-1.96, was adopted as cut-off points for significant hot spots and cold spots, respectively.

Chapter III

Results

Pure Earth data provided a dire picture of highly contaminated soil around metal mines. All the Pure Earth contamination sites had at least one chemical with an HQ greater than 1, which was expected as the Pure Earth team had identified the most affected mine sites based on rapid risk screening results of toxic waste sites in Armenia. Table 3 presents the total number of samples and the percentage of samples with HQs greater than 1 per site. In 66% of the Pure Earth contamination sites, more than half of the samples were above their recommended levels.

Table 3. The number of Pure Earth samples and percentage of samples with HQ > 1 per site.

Site ID	Number of Samples	Percent of Samples with HQ > 1
AM-1112	40	100
AM-4118	5	100
AM-4200	10	100
AM-7851	116	100
AM-1123	248	98
AM-7762	232	97
AM-7642	162	95
AM-1113	248	95
AM-2221	40	90
AM-7639	125	86
AM-7736	142	77
AM-2222	72	76
AM-2223	40	75
AM-3270	12	75
AM-2225	220	71
AM-8266	186	67
AM-3636	3	67

Site ID	Number of Samples	Percent of Samples with HQ > 1
AM-7737	112	66
AM-7540	45	64
AM-4117	21	62
AM-1111	30	60
AM-7764	172	59
AM-3306	18	56
AM-4115	9	56
AM-4131	9	56
AM-7446	173	53
AM-3273	12	50
AM-3376	6	50
AM-4114	6	50
AM-7837	246	44
AM-7763	388	43
AM-3276	12	42
AM-8268	120	42
AM-3388	5	40
AM-8269	62	37
AM-7745	179	37
AM-3391	9	33
AM-7740	242	31
AM-7818	261	28
AM-3244	12	25
AM-4116	24	25
AM-7746	273	23
AM-2224	10	20
AM-7743	102	16

Note. Samples from 44 contamination sites, collected by Pure Earth between 2013 and 2019

Pure Earth data were collected with information on soil or water type. Most of the data consisted of soil samples, with a handful of water samples. There were samples from agricultural, residential, and industrial soil and water used for drinking, irrigation, and fishing. Table 4 provides summary statistics of metal concentrations by soil type. It also includes information on the number of samples and recommended limits for each metal.

There were only 1-2 samples of each contaminant sampled in industrial soil in the Pure Earth dataset, with no measures of elemental or inorganic mercury. Contaminant metal concentrations in agricultural soil were higher than their recommended levels for all the chemicals, with inorganic mercury being the exception. It is worth noting that we need to be careful interpreting these results, as this can be explained by the relatively low recommended thresholds for contaminant levels in agricultural soil compared to industrial and even residential due to higher human risk to pathways of exposure. Adults engaged in outdoor agricultural and other commercial activities can be exposed to contaminants in soil not only through direct contact but also incidental ingestion pathways.

As shown in Table 4, residential soil samples were the most plentiful of all the samples studied. Contaminant metal concentrations for arsenic, chromium, and lead had a significant number of samples with HQ levels greater than 1. None of the few samples of cadmium and inorganic mercury exceeded their RLs. And elemental mercury was not sampled in residential soil.

To measure the impact of contamination at nearby mines, a 10 km threshold was used to identify clusters that were potentially exposed to contamination due to their proximity to a contaminated site. Table 5 presents a statistical summary of the chemical HQs at sites nearest to potentially exposed clusters. In addition to the 10 km baseline cut-off distance to identify potentially exposed households, for descriptive purposes, the table presents statistics by varying levels of distance thresholds from 5-20 km at 5 km radii intervals.

Table 4. Summary statistics for metal concentrations (mg/kg) in soil.

Metals	N	Mean	Min	25pct	Median	75pct	Max	SD	RL	% HQ>1
Panel A: Agricultural soil										
Arsenic	58	16	0.5	5	12	19	71	15	0.01	100
Cadmium	23	153	0.31	0.59	100	180	667	193	0.07	100
Chromium	60	4191	46	231	363	587	54670	11901	0.13	100
Lead	43	67	7	9	14	18	2045	310	2	100
Mercury (elemental)	23	215	11	27	91	351	1063	277	0.001	100
Mercury (inorganic)	8	0.16	0.003	0.02	0.03	0.31	0.57	0.25	0.003	88
Panel B: Industrial soil										
Arsenic	1	75	-	-	-	-	-	-	48	100
Cadmium	1	0.7	-	-	-	-	-	-	98	0
Chromium	2	51	23	23	51	78	78	39	50	50
Lead	2	521	163	163	521	878	878	506	385	50
Mercury (elemental)	-	-	-	-	-	-	-	-	-	
Mercury (inorganic)	-	-	-	-	-	-	-	-	-	
Panel C: Residential soil										
Arsenic	1,822	297	0	16	44	117	80951	2852	34	56
Cadmium	11	8	0.43	0.64	0.88	4.98	65	19	68	0
Chromium	571	270	0	95	120	177	4229	571	35	100
Lead	1,813	692	0	30	77	217	113966	5101	82	48
Mercury (elemental)	-	-	-	-	-	-	-	-	-	
Mercury (inorganic)	10	0.15	0	0	0.01	0.02	1.34	0.42	25	0

Notes. Descriptive statistics for chemical concentrations (mg/kg) measured by Pure Earth in agricultural, industrial, and residential soil near metal mines in Armenia from 2014 to 2019. Chemical cells marked with (-) symbols had no samples collected. The hazard quotient (HQ) is contamination divided by its recommended limit (RL), with target hazard quotient (THQ) equal to 0.1.

Contaminated sites nearest to the potentially exposed clusters had lower elevations on average than the mean elevation of all the sites in the dataset (1857 m) (Table 5). This is likely due to the study design having been based on a distance measure, as the mines with higher elevation would have been too distant to be included in the chosen distance threshold.

Table 5. Descriptive statistics of contaminated sites nearest to potentially exposed clusters.

	Potential Exposure			
	≤ 5 km	**≤ 10 km**	**≤ 15 km**	**≤ 20 km**
N of Clust	94	96	121	153
Statistics for Nearest Contaminated Sites				
Elevation	1,623	1,621	1,651	1,685
Arsenic H	892 (94)	941 (96)	967 (121)	1239 (153)
Cadmium	8 (13)	8 (13)	8 (13)	8 (14)
Chromium	1,353 (35)	11,353 (35)	18,991 (56)	36,681 (70)
Lead HQ	412 (51)	412 (51)	386 (54)	383 (62)
Mercury H	26 (39)	26 (39)	26 (60)	33 (73)

Notes. This table presents average As, Cd, Cr, Pb, and Hg Hazard Quotients (HQ) at sites nearest to potentially exposed clusters within 5-20 km thresholds, in 5 km intervals. It includes number of potentially exposed clusters within each threshold as well as the number of clusters whose nearest contaminated site had data for each chemical inside parentheses next to each chemical HQ. Elevation is in meters and describes the nearest contaminated site to a cluster.

Within all the thresholds, there were fewer potentially exposed clusters than potentially not exposed clusters, meaning the areas that DHS surveyed generally tended to be farther away from the mines. Naturally, the larger the radius from the contamination, the more clusters were identified as potentially exposed, with 63% more clusters identified in the potentially exposed group within 20 km compared to 5 km.

Hazard quotients provided in Table 5 represent the ratio of contaminant concentration level over its associated recommended level. Within 10 km, the average lead hazard quotient was higher than the average lead HQ at contaminated sites that were farther than 10 km from the clusters. However, it was still 48% less than the average lead HQ in the dataset ($\bar{y} = 730$). Similar to the lead quotient, at 10 km, chromium HQ was 86% less than its overall average ($\bar{y} = 79{,}991$). As only 14 clusters were near contaminated sites that had cadmium data, cadmium was not used or discussed individually in the regression models.

Arsenic, chromium, and mercury HQs were higher when the distance threshold was 20 km compared to the lesser thresholds. It is important to note that this doesn't mean that there was less contamination near mines than there was farther from mines. It only means that the households that DHS chose to survey tended to be closer to Pure Earth sites with lower contamination. The hazard quotient for arsenic was lower than the sample's average arsenic HQ ($\bar{y} = 918$) at the thresholds below 20 km. Indeed, at a 5 km threshold, all the HQs at contaminated sites nearest to clusters were less than their overall contamination levels in the dataset.

These results don't imply that there were no populations living near sites with higher contamination, as it only means that there was no DHS data for those areas. The finding that the DHS clusters were farther away from the most contaminated sites with arsenic, lead, and mercury limits studying the full potential impact to populations living near the more contaminated sites.

Table 6 shows descriptive statistics of cluster-level health indicators. The 2010 and 2015-16 ADHS clusters were combined and identified as potentially exposed if they were within 10 km from a contaminated site. Similar to the Pure Earth site statistics, for descriptive purposes, panels (A) – (D) present summary statistics of the DHS variables. If the nearest contaminated site was within 5, 10, 15, or 20 km from a cluster, the cluster was identified as potentially exposed. It was considered potentially not exposed if it was outside the set thresholds.

The percentage of the urban-dwelling makeup of each group within each panel was lower for the potentially exposed clusters, which was expected as mines and contaminated sites tended to be near rural areas more than urban areas. The incidence of fetal mortality in the potentially exposed clusters decreased with distance, from 25% at 5 km to 22% at 20 km. In contrast, the incidence of fetal mortality in clusters not expected to be exposed stayed consistent at 23% and even increased with distance. A higher incidence of fetal mortality within 10 km from a contaminated site indicates that an association between contamination and health in nearby communities is possible.

Incidence of anemia was, on average, much higher in the potentially exposed clusters, with an average of 20% higher incidence than in clusters that were not likely to be exposed. However, there was no significant change from one distance threshold to the other for clusters in any of the groups. The differences in incidence of severe anemia (Hgb < 7 g/dL) were even more stark. The incidence rate of severe anemia in the exposed groups was almost double the incidence rate in the groups that were likely not exposed (difference significant at 5% level). There was also a clear trend with distance, with the incidence of severe anemia being larger in clusters closer to the mine (Table 10).

Table 6. Descriptive statistics of health indicators by exposed/not exposed clusters.

	(1)	(2)	(3)	(4)	(5)
Potential Exposure	Urban	Fetal Mortality		Anemia	
	Percent	Incidence	N	Incidence	N
Panel A: 5 km Exposure					
≤ 5 km	61.70%	24,837	94	15,704	57
>5 km	67.40%	23,054	527	13,454	256
Panel B: 10 km Exposure					
≤ 10 km	60.40%	24,334	96	15,797	58
>10 km	67.60%	23,120	525	13,427	255
Panel C: 15 km Exposure					
≤ 15 km	65.30%	23,415	121	15,616	68
>15 km	66.80%	23,251	500	13,425	245
Panel D: 20 km Exposure					
≤ 20 km	62.10%	21,706	153	15,921	88
>20 km	67.90%	23,652	468	13,163	225

Notes. Cluster-level health indicators from the 2010 and 2015-2016 ADHS surveys. Panels A-D present summary statistics for incidences of fetal mortality and anemia by different potential exposure thresholds. Incidence rates are per 100,000 women. Sample size is provided for each measure.

Table 7 shows the regression results for health outcomes, using a 10 km distance cut-off from a contaminated site. The panels present models for the two health outcome measures, the incidence of fetal mortality and incidence of anemia. In columns (1) – (5), each health outcome measure was regressed on arsenic, chromium, lead, and mercury hazard quotients and their cumulative hazard index at sites within 10 km from a cluster.

To ensure that the population identified as potentially not exposed was not affected by any of the other metal mines not included in the Pure Earth database, two indicators were included in the models to control for clusters that were within 50 km from any metal mine or 50 km from a potentially contaminated downstream. Regression models were conducted with heteroscedasticity robust standard errors, clustered at the contaminated site level, and included controls for education, wealth, whether the cluster was in an urban area, time, and regional fixed effects.

As the HQ and HI measures were based on ratios and were computed based on multiple calculations, interpretation of their impact using the size of the coefficients is not very useful. Since statistical significance rather than the magnitude of association is the accepted benchmark for judging the strength of an observed association and potential causality (Fedak et al., 2015), I will discuss the direction and significance of these coefficients.

Incidence of fetal mortality was positively associated with arsenic and chromium HQs and was not associated with lead and mercury levels within 10 km from a contaminated site, holding all else constant. In addition, the incidence of miscarriages and stillbirths was statistically significantly associated with being within 50 km from a metal mine in models with HI, arsenic, and lead HQs.

Living within 50 km from a metal mine was associated with 4,887 to 7,260 more miscarriages and stillbirths on average per 100,000 women who have been pregnant before, in the models with arsenic and lead HQs and the HI. In practical terms, the

Table 7. Effect of mine contamination and river proximity exposure on health.

Panel A: Incidence of Fetal Mortality

	(1)	(2)	(3)	(4)	(5)
Arsenic HQ	2.167***				
	-0.484				
Chromium HQ		0.036**			
		-0.014			
Lead HQ			-2.966		
			-2.418		
Mercury HQ				-11.485	
				-20.085	
Hazard Index					0.015*
					-0.008
<50 km mine	4915**	2,148	7260***	4,488	4887**
	-2,049	-1,339	-571	-2,515	-2,066
<50 km river	1,044	4627***	1,427	3398*	1,363
	-2,084	-968	-1,845	-1,277	-1,974
N	621	201	384	440	621

Panel B: Incidence of Anemia

	(1)	(2)	(3)	(4)	(5)
Arsenic HQ	1.951**				
	-0.91				
Chromium HQ		0.033***			
		-0.006			
Lead HQ			-0.62		
			-2.966		
Mercury HQ				103.583*	
				-37.229	
Hazard Index					0.053***
					-0.016
<50 km mine	5,218	4,932	2,809	7,772	5,043
	-6,181	-13,122	-6,102	-8,844	-6,132
<50 km river	2,508	-1,277	1,239	-105	2,805
	-2,417	-6,753	-1,858	-2,687	-2,326
N	313	101	194	221	313

*Notes: ***p<0.01, **p<0.05, *p<0.1. Linear probability models. Panels A and B present models with incidences of fetal mortality and anemia as dependent variables. Columns (1) – (5) include contaminant hazard quotients and hazard index at sites within 10 km from a cluster. Heteroscedasticity robust standard errors, clustered at the site level, are in parentheses. All regressions controlled for age, age square, wealth, urban, education, and an indicator if the nearest mine was at higher elevation than the cluster. All regressions include year and region fixed effects.*

association of health outcomes with being within 50 km of a mine was also substantially significant compared with the sample means.

With the average incidence of fetal mortality at 24,885 per 100,000, these results indicated a 20-29% increase in the incidence of fetal mortality for women who lived within 50 km from any metal mine.

Living within 50 km from a potentially contaminated river was positively associated with the incidence of miscarriages and stillbirths in two of the models, including chromium and mercury HQ, with a 14-19% increase in the incidence of fetal mortality. The binary variable indicating if the contaminated site was at a higher elevation than the cluster was insignificant. This could be due to the distance measures capturing the impact of elevation based on their design. Incidence of fetal mortality was positively associated with the hazard index within 10 km from a contaminated site. There was an average 20% increase in the incidence of miscarriages and stillbirths for women living within 50 km from any metal mine in the HI models, even when we used different thresholds for the distance between clusters and contaminated sites (Table 13, Appendix 2).

Results of the sensitivity analysis using a proxy of fetal mortality are presented in Panel A of Table 15. While the incidence of fetal mortality was calculated based on the total number of women who were ever pregnant per cluster, the fetal mortality rate was calculated based on the total number of pregnancies per cluster. The results of the HQs were very similar, but the likelihood of mortality was found to be statistically significantly associated with a cluster being within 50 km from the access point of a potentially contaminated river in three out of five models. Being within 50 km from a mine was only significant in the model with lead HQ.

Incidence of anemia was associated with HI, arsenic, chromium, and mercury HQs for clusters within 10 km from a contaminated site. Unlike the patterns found in panel A for incidence of fetal mortality, living within 50 km of a metal mine or potentially contaminated downstream had no impact on the incidence of anemia in any of the models. Even though the incidence of anemia seemed not to be associated with living within 50 km of a mine or a potentially contaminated downstream, the hazard index consistently and significantly remained associated with a higher incidence of anemia for clusters within 5-20 km from a contaminated site (Table 13).

Tobit models were conducted as part of the robustness checks of the OLS model results. As discussed in the methods section, Tobit has been recommended as a preferred model to OLS in similar survey-based health studies (Shera & Dar, 2014). The results, presented in Table 14, show the hazard index variable was statistically associated with incidences of fetal mortality and anemia, with magnitudes similar or larger than the OLS coefficients.

The results of the birth weight z-scores are presented in Table 15. Lower birth weight z-scores were associated with arsenic and lead HQs and the HI. Overall, there seemed to be a consistent impact across the different thresholds for the hazard index, signifying an increasing association for incidence of fetal mortality and anemia and a negative association with the birth weight z-score. Lower birth weight was associated with HI in all the models with varying distances from the cluster. Living within 50 km of a mine was positively associated with the birth weight z-scores, which was inconsistent with the other health variables. These inconsistencies could be due to validity issues with the birth weight measure and, therefore, will not be discussed further.

Spatial Analysis Results

Results from the hot spot analysis showed a significant burden of incidence of fetal mortality in the northern half of the country (Figure 9). Incidence of fetal mortality seemed to be higher in the largest cities in the country, Yerevan, Gyumri, and Vanadzor. This spatial statistic matched the average mortality rate by urban status in the country, with clusters in urban areas experiencing 15% more miscarriages and stillbirths on average than rural clusters.

In the south, there were clusters in very close proximity to the Agarak and Kapan mines. The 330-hectare Artsvanik tailing dump, built 500 m from the nearest village, and discussed in the introduction section, is near the Kapan mine. A number of negative environmental, health, and economic impacts on nearby communities have been attributed to activities at the Agarak mine (EcoLur, 2019a).

Several clusters with a high incidence of fetal mortality were near the Tandzut mine, which is only 6 km from the country’s third-largest city, Vanadzor. Five years ago, researchers from the Armenian Environmental Front civil initiative collected and tested soil and water samples around the mine and uncovered the spread of dangerous amounts of heavy metals due to acid drainage from the mine (Armecofront, 2017).

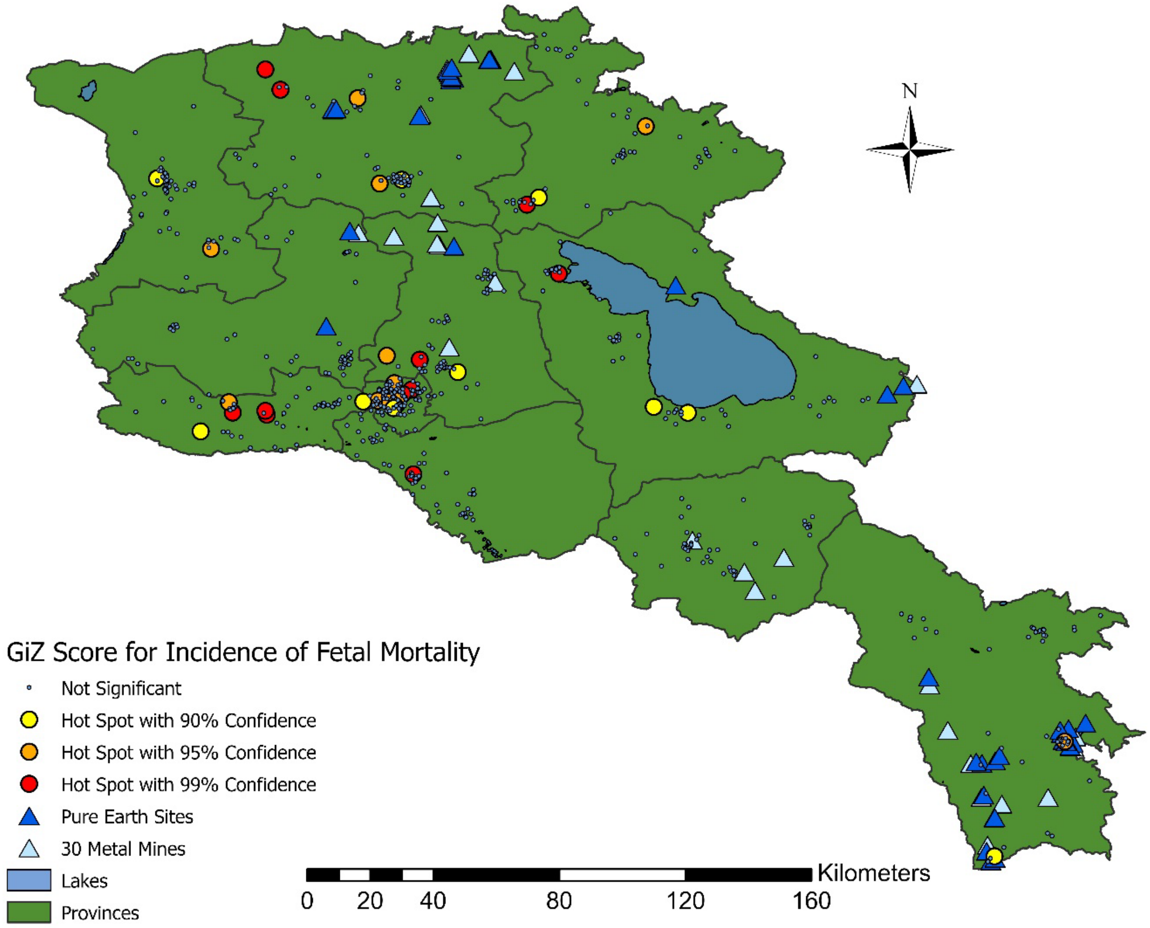

Figure 9. Hot spots of incidence of fetal mortality.

Each dot represents a cluster of DHS sample households, and the boundaries shown are provinces. Light and dark blue triangles represent all the metal mines and Pure Earth contaminated sites. Yellow, orange, and red dots represent hot spots of high mortality rate at 90, 95, and 99% significance levels.

Figure 10 presents an interesting picture of the incidence of anemia. Hot spot analysis identified the highest incidences of anemia along the largest lake in Armenia, lake Sevan. A study of the lake in 2016 found high levels of vanadium in the lake due to heavy metal pollution induced by nearby gold mining (Gevorgyan, Mamyan, Hambaryan, Khudaverdyan, & Vaseashta, 2016). This chemical has been found to cause anemia, among other health effects (Amuah, Fei-Baffoe, & Kazapoe, 2021), and could potentially explain this spatial behavior. Although vanadium was not one of the chemicals collected by Pure Earth, this finding is important for identifying potentially harmful health impacts of mining that have been unmeasured.

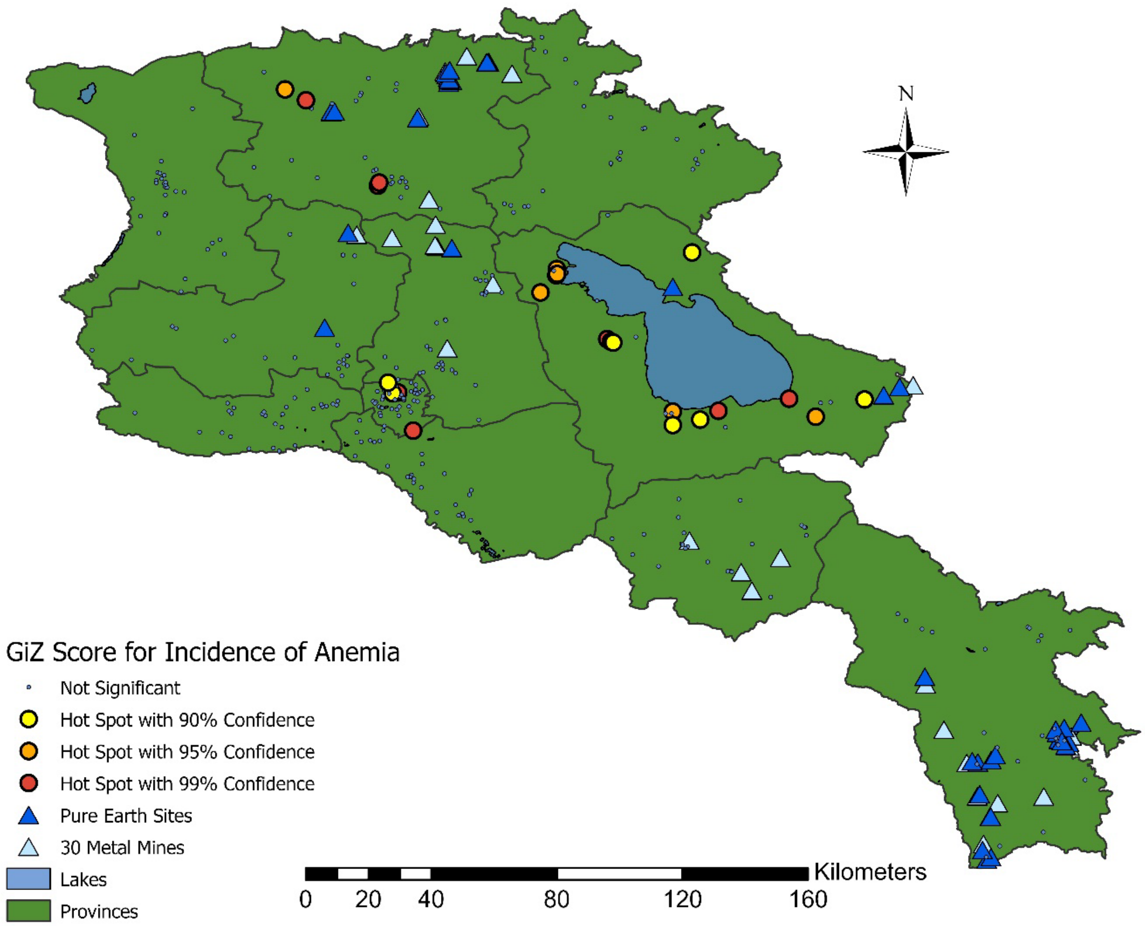

Figure 10. Hot spots of incidence of anemia.

Each dot represents a cluster of DHS sample households, and the boundaries shown are provinces. Light and dark blue triangles represent all the metal mines and Pure Earth contaminated sites. Yellow, orange, and red dots represent hot spots of high mortality rates at 90, 95, and 99% significance levels.

Around the Armanis gold mine, all three health outcomes had clusters of high incidences. This mine was discussed in the introduction as an example of heavy metal contamination spread in a schoolyard when overburden from the mine was brought in for use in leveling the yard.

The incidence of low birth weight was clustered around larger cities, which matched with the statistics from the sample, with a 45% higher incidence of low birth weight in urban areas than in rural areas. Many of the clusters around metal mines were identified as hot spots for incidence of low birth weight (Figure 11).

Chapter IV

Discussion

This research set out to explore the extent to which mining-related soil contamination in the Republic of Armenia has any impact on the public health of nearby communities by examining how health outcomes are associated with the type of the contaminant, level of contamination, elevation, proximity to mines and downstream water sources. More specifically, the research focused on answering whether people living near mine sites were more likely to have poorer health outcomes than those who lived farther away.

The results indicated that there were heavy metal concentrations above recommended levels at each contaminated site, posing health risks to populations living in proximity. The hazard index of five chemicals (arsenic, cadmium, chromium, lead, and mercury) was positively associated with the incidence of fetal mortality and anemia and was negatively associated with birth weight z-scores. In addition, the study found that women who lived within 50 km of any metal mine were at a higher risk of having miscarriages and stillbirths.

Summary statistics of health outcomes showed the incidence of fetal mortality decreased the farther the mine was from a cluster, descending from 25% at 5 km to 22% at 20 km. Birth weight was also lower the farther away the clusters were from the mines, although the difference from one distance threshold to another wasn't substantially significant. Also, the difference in birth weights between the potentially exposed and not exposed groups was very small.

Incidence of anemia was, on average, much higher for the potentially exposed clusters than the potentially not exposed clusters. However, the levels of anemia didn't seem to change significantly from one distance threshold to the other. The incidence of anemia in the potentially exposed clusters was 17-21% higher than that in the clusters not potentially exposed. The differences in these statistics suggest that poorer health was generally observed the closer a person lived to a mine.

The regression analyses showed that incidences of fetal mortality and anemia within 10 km of a contaminated site were associated with elevated levels of arsenic and chromium. In addition, arsenic, chromium, and lead were negatively associated with birth weight z-scores, suggesting potential health risks to mothers due to living near a metal mine. The results of individual chemicals were mixed, with mercury having no significant association with any of the health outcomes and lead only being statistically associated with lower birth weight. The cumulative impact of all of the metals was statistically significant, indicating poorer health for people living within 10 km of contaminated sites.

In addition, living within 50 km of any metal mine was associated with an increase in the incidence of miscarriages and stillbirths. The association was substantially significant: with a 20% increase in the incidence of miscarriages and stillbirths for women living within 50 km from any metal mine in the HI models, even when different thresholds were used for the distance between clusters and contaminated sites.

These results supported my hypothesis that negative health impacts, measured as the incidence of miscarriages, stillbirths, and anemia, and lower birth weight, were expected for residential communities as a function of distance and toxic contamination due to mining operations. This work builds on the research by Yepremyan (2018) and Akopyan et al. (2014) by including data on metal contamination and anemia, a larger study area, as well as measuring the impact of proximity at varying distance thresholds to all metal mines in the country.

In addition, the findings of this study build on the existing evidence that impacts from mining activities are generally geographic in nature, where mining disproportionately impacts the communities nearest to them found by Sonter et al. (2014). The adverse impacts of these toxic metal contaminants are coherent and biologically plausible. The findings are also consistent with existing literature regarding the etiology and mechanism of disease (Fedak et al., 2015).

The results of the downstream analysis were not as strong as that of the distance from the nearest metal mines. Unlike distance from a near mine, living within 50 km from a possibly contaminated downstream was generally found not to be statistically associated with adverse health outcomes. Downstream distance was only associated with the incidence of fetal mortality in two of the models. This finding partially confirmed intensifying impacts of downstream runoff, consistent with previous studies of mining consequences on health (Wang et al., 2010; Werner et al., 2019). Living within 50 km from a potentially contaminated downstream was associated with a 14-19% increase in the incidence of fetal mortality, but there was no association with the incidence of anemia.

Existing research, such as that of Werner et al. (2019), has recommended more studies on the topic to enable a better understanding of how mining activities impact the health of nearby populations and the environment. More studies at an intermediate basis rather than the extremes of a per-mine or global basis are needed in part because they can provide concrete recommendations for the management of health in nearby communities and wastes at individual mine sites (Werner et al., 2019). Findings from this study on public health impacts of metal mining in the Republic of Armenia based on a novel GIS database contribute to the scholarly body of work on the topic.

Mining-related contamination impacts can be multifold, e.g., resettlement and loss of property value, adverse effects on livelihoods and public health, migration, and others (World Bank, 2014). The value of real estate can be negatively impacted for community members in towns and villages impacted by nearby pollution due to living in proximity to mining operations or contaminated sites. This could result in mining companies suffering from declining investment in mining due to the stigma of being associated with an industry that negatively impacts public health (World Bank, 2014). Politicians and regulators may be dissuaded from permitting mining operations to protect their reputations or electability in future political contests.

Metal mining is a critically important industry, vital to the Armenian economy and the creation and growth of new jobs. In recent years about 12% of the Republic of Armenia's Gross Domestic Product (GDP) growth rate has been attributable to the mining sector (World Bank, 2016). In considering the mining sector's significant contribution to the economy, the case has been made that it should continue to operate in the long term in a way that does not impact public health or the safety and value of local real estate.

The costs to human health and environmental sustainability of maintaining the status quo of mining in Armenia are likely to be many factors more significant than the costs of implementing existing, sound controls and standards. To ensure sustainable practices in the development of the mining industry that incorporates long-term economic growth and shared prosperity, the mining processes and strategic planning in Armenia need to account for the integration of all social and environmental aspects and actors. Despite the cost and lack of data availability, actual economic costs of social, ecological, and health impacts need to be defined and assigned. Based on these calculations and indicators, adopted policies can benefit the population, the government, and the mining industry.

Research Limitations

Aside from limitations regarding the datasets used in this analysis, and discussed in the methods section, several others should be considered. First, it was out of this project's scope to calculate the costs associated with implementing any of the policy recommendations born from the study results. Its findings shall be useful to future studies or policymakers in understanding the potential health impacts of mining-related contamination.

This study was ecological in nature; it explored statistical differences in health indicators between people living near or far from the mines and did not implicitly establish temporality within the study design. Environmental exposures from mining activity often involve low levels of exposure over extended time frames, with low incidence, localized outcomes occurring after long latency periods (Fedak et al., 2015). These factors make it difficult and potentially unfeasible to design a study with firmly established temporality due to time, cost, and other factors. The use of biomarkers, which are considered today's state-of-the-art analytical testing methods at low detection limits

(Plumb, 2004), can help us understand the temporality of toxicity and disease progression.

The measures of health outcomes are observational in nature; therefore, the study lacked the power of validity that can be derived through experimental manipulation (Fedak et al., 2015). Longitudinal birth cohorts have been considered the gold standard for evidence in the origins of diseases (Golding, 2009). Environmental exposures during pregnancy have been found to have major consequences on the health and development of the offspring. Follow-up of parents and their children from pregnancy to adulthood provides information to clearly delineate temporal relationships between exposures and outcomes (Walsh et al., 2020). Experimentation for studies including adverse outcomes with a long latency period may be the cornerstone of such analyses, albeit costly and time-consuming. Consistent with other ecological studies, this study drew evidence from existing toxicological findings to predict potential human health outcomes.

In the absence of control or restoration measures, a localized disturbance to the ground can cause increased dispersion and exposure of broader populations to the contaminants through wind or water pathways (Razo et al., 2004). It is established that contaminated soils can be distributed well beyond the location where they are initially deposited, migrating by not only water but also windborne dust (Northey et al., 2019; Sonter et al., 2014). Due to data limitations, this study did not include wind pathways in its scope. In addition, the magnitude of hazards caused by certain minerals depends not only on the concentration and pathways but also their chemical form, particle size, the soil or water pH, and the extent of exposure to the element (Kelepertsis et al., 2006). Controlling for these was out of the scope of this study.

Underreporting deceased children by survey respondents, for reasons such as the timing of the survey relative to the time of deaths or for unintended pregnancies, has been one of the most studied issues with demographic surveys. Underreporting may also be due to forgetfulness or conscious avoidance of recalling the tragedy of losing a child. There is no reason to believe that this phenomenon would differ for the potentially exposed clusters from the clusters not believed to be potentially exposed. Also, using multiple health measures helped to reduce possible bias caused by issues of underreporting deaths. In addition, as the study only explored the incidence of fetal mortality, it remains possible and untested that more children survived their first birthday but faced poorer long-term health.

Results regarding low birth weight were not used in the main body of the text and were provided in the appendix due to limitations with the measurement of the variable. Lack of information on gestational age and 75% of the data being based on the mother's recollection introduced uncertainty around the internal validity of the DHS measure of low birth. This made the findings from this research limited in its ability to study the impact of contamination on birth weight.

One other limitation of the study was not being able to control for direct exposure to contaminants for those who not only lived near a mine but also worked in one. It is possible that the DHS samples could have included workers of mining and quarrying sectors. In Armenia, fewer women than men are employed in technical fields such as manufacturing, construction, or mining sectors. According to a labor market survey of employed persons by types of economic activity conducted by the Statistical Committee of the Government of Armenia in 2021, close to 90% of sampled persons employed in the mining and quarrying sector are men (Armstat, 2021). Although a small sample of men was included in the DHS surveys, excluding them from the analysis provided some level of control for the impact of potential exposure from working at metal mines, as it reduced the probability that a DHS respondent worked in the mining industry.

The selection of clusters could have been impacted by the DHS displacement of geographical coordinates of the clusters with a random error of 5 km in rural areas and 2 km in urban areas. This introduced a measurement error that may have impacted the estimates. Some clusters may have been misclassified into an incorrect exposure or non-exposure zone due to the random displacement of GPS coordinates. The resulting measurement error was most likely random, as there was no indication to believe that this could have affected the potentially exposed clusters any differently than the potentially not exposed clusters.

There were also some limitations with the Pure Earth data. Due to the small sample size, the impact of cadmium was not tested directly but only as part of the hazard index. This was unfortunate because many cadmium samples were quite elevated above their RL. Due to this study design being based on distance, not all contaminated sites were included in the potentially exposed sample. The nearest contaminated site was selected for analysis, which means that data from contaminated sites not included in the exposed group were not studied. In addition, due to the limited number of water samples, a complete hydrological analysis of the data was not possible. If more data becomes available in the future, it will be possible to explore a more comprehensive analysis.

Another limitation is that data from Pure Earth were not randomly selected. Instead, the 44 sites were chosen because Pure Earth researchers classified them as the most likely to be affected by mining activities. For this reason, the findings can't be generalized to all the metal mines in Armenia, as it is possible that the health of people living near other mines was not associated with contamination at the same level or at all. An indicator variable for communities within 50 km from mines was added to the regressions to minimize this limitation. It showed a statistically and substantially increased health impact for clusters within 50 km from any metal mines.

The use of proximity as a proxy for actual exposure conditions is an assumption commonly used in traditional environmental exposure analysis. Using the distance to measure distance is based on a general assumption that there is a distance-decay function of the impact of the potential contamination. This, of course, is a great simplification of reality, as distance-decay functions often vary greatly depending on types of media (soil, water, air), metals, and local circumstances (e.g., weather, topography) (Zandbergen & Chakraborty, 2006). In the absence of such data, distance is often adopted as a proxy for exposure, i.e., exposure is some function of distance. Although the distance to a pollution source was used to provide an estimate of potential exposure in this study, the actual extent and magnitude of exposure were not known and may not have been a simple function of distance.

In addition to possible limitations with using proximity as an exposure proxy, there is also a limitation with the assumption of what constitutes a control or potentially not exposed cluster. Examples of varying types of spreads of contamination make it difficult to define true control groups. One such example was Alaverdi's Arsenic Graveyard which, according to Ecolur investigative journalists, has had some of their contaminant waste stolen in bags by persons who believed the waste to contain gold

(Paremuzyan, 2009). It is unknown how far this contamination was spread across the country. Once it was understood that gold was not contained in the waste, it is unlikely that these individuals would waste their time to return the waste to its original location.

Another example was the tailings from the Sotk gold mine being moved by train to a dump in the Ararat valley, making it what Ecolur journalists called “the most contaminated site in the entire country” (EcoLur, 2019b). This differed from the Arsenic Graveyard case in that it was intentionally brought there with the knowledge and coordination of the mine leadership. These intentional and unintentional spreads of contaminants presented some degree of probability that clusters identified as potentially not exposed may have been impacted by such outside factors and not represented “true” control groups. While this was a limitation of measurement, when present, it only meant that the impacts from contamination were even stronger than the findings suggested.

Despite the abovementioned possible limitations in studying mining-related health outcomes, there are several promising avenues for future research.

Recommendations

Fingerprinting tools through DNA-based technologies predominantly used in forensic science have shown significant advantages in the identification and quantification of contamination sources in environmental studies (Tang et al., 2021). An example of one such tool is EPA developed Fingerprint Analysis of Leachate Contaminants (FALCON). The tool allows combining data for several contaminants and the development of a distinctive fingerprint or multi-parameter chemical signature of the sample. The fingerprints are then used to identify the source of a contaminant, differentiate the contaminant plume from background conditions at the source, and to monitor the contaminants' spread into the environment. These tools can be applied to a wide range of contaminant concentrations (Plumb, 2004). Data collected through this technology would significantly improve the available data and allow linking the source to the exposure of contamination. And in conjunction with longitudinal birth cohort data, it will be possible to identify temporal relationships between exposures and outcomes more reliably (Walsh et al., 2020).

The objective of this research was to identify and quantify potential risks to populations living in proximity to metal mines. I am hopeful the results from this study will lead to interventions to reduce the risks and impacts of mining activity. Interventions can be focused on any or all the components creating a toxic contamination problem, such as: elimination of the toxic substances; control of migration routes (such as installation of pollution control equipment or covering waste piles); elimination of pathways (such as covering or paving contaminated areas or providing clean drinking water sources); or reducing public access in contaminated areas (such as by fencing off disposal sites or providing on-site security services).

Based on findings of negative health outcomes and mining risks, the author's hope and intention would be for this research to serve as a call to action to address the public health effects of mining by adopting global best practices (UNDP, 2019) in the mining sector and implementing appropriate standards for pollution controls.

Future research and advancement in our understanding of the true relationships of health outcomes due to mining activities will be possible with more complete coverage of contamination data. Collecting more samples from different types of soil and water, information on water sources, better health data, as well as including other metal mines will allow to overcome some of the limitations discussed for this research. Measuring windborne dust distribution of contaminated soil will be useful to evaluate and study the public health impacts of communities downwind from contamination sites. Atmospheric dispersion of mine waste particles can potentially migrate to communities close to active and abandoned mining areas and can be an important route of human exposure to toxic chemicals (Zota et al., 2009).

. My recommendation to mine regulators and policymakers in RA is to follow acceptable implementation standards, monitor and maintain physical barriers, hazard communication, site exclusion, and security to prevent trespassing by livestock and humans, and theft of waste material and infrastructure such as hazard signage and fencing (International Organization for Standardization, 2021). Implementation of an effective system to ensure that contamination managed in place is isolated from exposure to the health and safety of biota and release to the environment. Where engineering controls such as a structural containment system or physical cap is used, the system should also ensure that that infrastructure is professionally designed and constructed to international and mining industry standards, is periodically inspected and maintained/repaired when problems are found for as long as the waste creates a hazard to humans, animals, and the environment.

Closure plan and financial instrument: implementation of a management system by all mining permit applicants and permit holders that addresses an effective mine closure and reclamation plan, including addressing socio-economic impacts, provision of a financial instrument, and plan in the event of mine closure or abandonment and a post-closure management plan. The framework for such a management system was recently released by the International Standardization Organization (ISO) in the form of ISO 21795-1:2021 (International Organization for Standardization, 2021).

National-level adoption of such standards would help ensure that the cost of managing contamination for the impacted generations to come would be covered regardless of the willingness or ability of a mining permit holder to fund said management at the time of closure or abandonment, rather than rely on the seemingly failed honor system.

This study only explored the possibility of negative health risks that might result from or be correlated to mining activity. It did not calculate the costs associated with implementing any of the relevant policy recommendations. Policies discussed above or strengthening environmental governance and institutions and creating mechanisms for the contribution of mining to local development may be costly but worthwhile. Future research associated costs would greatly complement this research. Being the first to conduct a generalized spatial analysis of mining contamination and health in Armenia, this study's findings of potential health impacts of mining-related contamination should be useful for future studies, government, businesses, and population of the Republic of Armenia.

Conclusions

Metals play an essential role in modern life, driving technological advances and even helping the world address global issues such as climate change. Mining these metals is important for national and local economies helping increase GDP and decrease unemployment, which is especially important in developing countries such as Armenia. Mining requires a great deal of investment, from exploration to extraction, transportation, processing, marketing, and export. It also requires a great deal of responsibility to the communities and ecosystems that are impacted by mining activities. Governments and the mining industry should ensure that the consequences of mining, including the costs of containment and remediation of contaminants, are included in the calculation of net benefits and that robust mechanisms are in place to manage mining externalities.

This research sheds much-needed light on contamination due to metal mine activities in the Republic of Armenia and its association with public health in nearby communities. Health outcomes, such as incidences of miscarriages, stillbirths, and anemia, and lower birth weight, were found to be associated with levels of contamination and proximity to mines and potentially contaminated downstream.

This research lays the foundation for future research and, most importantly, serves as the first step toward reformative action in Armenia's mining sector. The Armenian authorities can implement more robust security and public education campaigns, as well as regulations for the mining industry that address potential threats to the health of exposed communities and ecosystems. The mining sector may take the lead in addressing issues of contamination management in a way that sets an example for other industries in the country, such as quarrying, smelting, and industrial chemical production. The public will have new knowledge at their fingertips about the hazards they are potentially exposed to under the status quo and be in a better position to make informed decisions about daily life, such as where their livestock graze, where their children play, and where they choose to live. Most importantly, policymakers, industry leaders, and community members must re-engage in a partnership to further study this issue and solve the challenges they're facing together related to mining contamination with a more equitable balance of power across these groups.

It is apparent that without changes in mining regulation, stakeholder engagement, and management of mining contamination in Armenia, the industry risks exhausting resources while leaving behind a legacy of poor management that resulted in contamination and ill health effects to nearby communities. Leaders from Armenia's mining sector have a unique role in the collaboration between their industry, governmental regulators, and the public. They are positioned to model exemplary protection of the environment and community stakeholders while also positively impacting the local economy and engaging in commerce. Doing so offers the opportunity to make metal mining in Armenia sustainable for generations to come.

Appendix 1

Additional Descriptive Statistics

Table 8 includes names and definitions of all the variables used in regression analyses.

Table 8. Variable definitions.

Variable name	Definition
ADHS variables	
Incidence of fetal mortality	Number of miscarriages and stillbirths divided by number of women who have been pregnant before
Fetal mortality rate	Number of miscarriages and stillbirths divided by number of pregnancies
Incidence of anemia	Number of women classified as anemic divided by number of women who agreed to be tested for hemoglobin levels
Low birth weight z score	Standardized measure of birth weight
Region	Armenia's provinces
Year	Years of ADHS surveys, 2010 and 2015/2016
Education	Indicator equal to 1 if average number of years of education of the cluster is 12 or above, and 0 otherwise
Wealth	Indicator equal to 1 if average wealth index of the cluster is middle or above, and 0 otherwise
Age	Average age per cluster
Urban	Indicator equal to 1 if cluster is in urban area, 0 otherwise
Pure Earth variables	
Contaminated Site	Pure Earth sampling locations
Contamination	Highest value of contamination per metal per site
Pure Earth years	Years representing Pure Earth sampling, ranging from 2013 to 2019
Metal mine	All active and inactive metal mines in Armenia listed by the Republic of Armenia
Constructed variables	
Anymine	Indicator equal to 1 if there is a metal mine within 50 km from a cluster
Anyriver	Indicator equal to 1 if there is a possibly contaminated downstream within 50 km from a cluster
Recommended level	Maximum recommended levels of metal concentration
Hazard quotient	Ratio of metal's contamination over its recommended limit
Hazard index	Summation of all the hazard quotients per site
Downstream	Downstream trace originated from each contaminated site using ArcGIS
Elevation	Indicator equal to 1 if the Pure Earth contaminated site is at a higher elevation than the DHS cluster

Table 9 lists all the metal mines in Armenia, including their latitude and longitude, province, type of metal extracted, and operating status.

Table 9. Metal mines in Armenia.

Name	Lat	Long	Province	Metals	Operating Status
Shamlugh	41.1653	44.7199	Lori	Copper	Operating
Akhtala	41.1571	44.7842	Lori	Copper	Not Operating
Alaverdi	41.1239	44.6454	Lori	Copper	Operating
Teghut	41.1056	44.8371	Lori	Copper, Molybdenum	Operating
Tandzut	40.7888	44.5288	Lori	Gold oxide	Not Operating
Armanis	41.0073	44.3088	Lori	Gold, Copper, Zinc, Lead	Operating
Mghart	40.9944	44.5709	Lori	Gold	Operating
Tezhsar	40.6864	44.6183	Kotayk	Nepheline syenite	Not Operating
Hankavan	40.6442	44.4814	Kotayk	Copper, Molybdenum	Operating
Meghradz	40.6368	44.6419	Kotayk	Gold	Operating
Lusajur	40.6445	44.621	Kotayk	Gold	Not Operating
Tukhmanu	40.6552	44.3829	Aragatsotn	Gold, Silver	Operating
Hrazdan	40.5329	44.7811	Kotayk	Iron	Operating
Abovyan	39.7017	45.5241	Kotayk	Iron	Operating
Sotk	40.2357	45.971	Gegharkunik	Gold	Operating
Gladzor	39.0169	46.1947	Vayots Dzor	Copper, Lead, Zinc	Operating
Azatek	39.705	45.4844	Vayots Dzor	Gold, polymetallic	Operating
Sofi-Bina	39.7017	45.5241	Vayots Dzor	Gold	Operating
Amulsar	39.7488	45.7133	Vayots Dzor	Gold	Operating
Dastakert	39.352	46.0314	Syunik	Copper, Molybdenum	Operating
Hankasar	39.2289	46.1503	Syunik	Copper, Molybdenum	Operating
Kapan	39.2326	46.3968	Syunik	Copper, Molybdenum	Operating
Shahumya	39.224	46.4261	Syunik	Gold, Copper, Zinc, Lead, Silver	Operating
Kajaran	39.1451	46.138	Syunik	Copper, Molybdenum	Operating
Lichk	39.0497	46.1683	Syunik	Copper	Not Operating
Lichkvaz-	39.0169	46.1947	Syunik	Gold, Copper, Silver	Not Operating
Bardzradi	39.0664	46.3603	Syunik	Gold	Not Operating
Terterasar	39.0301	46.2267	Syunik	Gold	Operating
Aygedzor	38.9992	46.2051	Syunik	Gold, Copper, Molybdenum	Not Operating
Agarak	38.9199	46.1857	Syunik	Copper, Molybdenum	Operating

Table 10 provides recommended limits of contaminants in different types of soil and water. Using a PRG calculator provided by EPA, based on information on the type of soil and pathway of the sites and metals, non-carcinogenic PRG limits were computed for deriving chemical recommended limits (RL). Non-cancer risk from the contaminants was calculated based on target hazard quotient (THQ) = 0.1, which is recommended when multiple chemicals are present at sites (section 5.15, RSL User's Guide (USEPA, 2022g)).

Table 10. Recommended Limits (RL) for chemicals in soil and water.

		Arsenic	Cadmium	Chromium	Lead	Mercury
Water	Drinking (µg/l or ppb)	10	5	100	15	2
	Irrigation (µg/l or ppb)	100	10	100	100	1.4
	Fishing (µg/l or ppb)	0.02				
Soil	Residential (mg/kg or ppm)	34	68	35.14	82	25-inorganic 1-elemental
	Agriculture (mg/kg or ppm)	0.01	0.08	0.13	2	0.003-inorganic 0.001-elemental
	Industry (mg/kg or ppm)	48	98	49.71	385	35-inorganic 3.66-elemental

Agricultural soil level was computed by adding residential PRGs with farm PRGs obtained with the PRG calculator, provided by EPA at https://rais.ornl.gov/cgi-bin/prg/PRG_search, with adults and children aged 34 and 6, respectively. Chromium total was not provided for soil. It was derived by dividing Cr(VI) by 7, based on information from (USEPA, 2004) and (USEPA, 2022g). EPA calculates mercury elemental SL without including RfD; RAIS (Risk Assessment Information System) PRG includes CalEPA-based RfD value. All the soil values for elemental mercury have been calculated to include the RfD value for consistency.

Table 11 presents summary statistics of birth weight and severe anemia for clusters that were potentially exposed and not exposed based on the distance threshold.

Table 11. Additional descriptive statistics of health indicators by exposed/not exposed clusters.

Potential Exposure	Birth Weight		Severe Anemia	
	Mean	N	Incidence	N
Panel A: 5 km Exposure				
≤ 5 km	3,183	88	6,976	57
>5 km	3,200	518	3,607	256
Panel B: 10 km Exposure				
≤ 10 km	3,178	90	6,825	58
>10 km	3,201	516	3,622	255
Panel C: 15 km Exposure				
≤ 15 km	3,176	115	6,574	68
>15 km	3,201	491	3,621	245
Panel D: 20 km Exposure				
≤ 20 km	3,173	146	6,072	88
>20 km	3,204	460	3,550	225

Notes. Cluster-level health indicators from the 2010 and 2015-2016 ADHS surveys. Panels (A) – (D) present summary statistics by different potential exposure thresholds. Sample size is provided for each measure.

Table 12 presents descriptive statistics of chemical concentrations (μg/l) in Pure Earth water samples. Drinking water RLs were based on maximum contaminant levels (MCL) under National Primary Drinking Water Regulations. MCLs are the highest level of a contaminant allowed in drinking water pursuant to the US Safe Drinking Water Act. Recommended limits for irrigation and fishing water are based on National Recommended Water Quality Criteria pursuant to US Clean Water Act. Fishing water RL was only provided for metals in Pure Earth data.

Table 12. Summary statistics for metal concentrations (µg/l) in water.

Metals	N	Mean	Min	25pct	Median	75pct	Max	Std. Dev.	RL	% above RL
Panel A: Drinking water										
Arsenic	4	0.82	0.2	0.2	0.49	1.44	2.11	0.9	10	0
Cadmium	-	-	-	-	-	-	-	-	-	
Chromium	2	7.19	3.56	3.56	7.19	10.82	10.82	5.13	100	0
Lead	-	-	-	-	-	-	-	-	-	
Mercury	2	0.11	0.09	0.09	0.11	0.12	0.12	0.02	2	0
Panel B: Irrigation water										
Arsenic	11	4.1	0.55	1.58	1.7	6.74	13.38	4.09	100	0
Cadmium	1	0.07	-	-	-	-	-	-	10	0
Chromium	5	11.15	2.14	3.8	6.84	20.91	22.04	9.59	100	0
Lead	6	0.67	0.01	0.08	0.34	0.73	2.52	0.94	100	0
Mercury	9	0.13	0.1	0.11	0.13	0.15	0.15	0.02	1.4	0
Panel C: Fishing water										
Arsenic	3	0.63	0.4	0.4	0.5	1	1	0.32	0.02	100
Cadmium	-	-	-	-	-	-	-	-	-	
Chromium	-	-	-	-	-	-	-	-	-	
Lead	-	-	-	-	-	-	-	-	-	
Mercury	-	-	-	-	-	-	-	-	-	

Notes. Descriptive statistics for chemical concentrations (µg/l) measured by Pure Earth in drinking, irrigation, and fishing water near metal mines in Armenia from 2014 to 2019.

Appendix 2

Sensitivity Analysis

Table 13. Sensitivity analysis of the effect of hazard index on health outcomes within 5-20 km from the cluster.

Panel A: Incidence of Fetal Mortality

	Hazard Index at different distances from clusters			
N=621	< 5 km	< 10 km	< 15 km	< 20 km
HI	0.020*	0.021*	0.022*	0.025**
	-0.011	-0.01	-0.011	-0.009
< 50 km mine	4891**	4896**	4985**	5298***
	-2054	-2051	-1985	-1835
< 50 km river	2,037	2,258	2,399	3,371
	-2589	-2436	-2479	-1960

Panel B: Incidence of Anemia

N=313	< 5 km	< 10 km	< 15 km	< 20 km
HI	0.049**	0.048**	0.048**	0.049***
	-0.018	-0.018	-0.018	-0.016
< 50 km mine	5097	5113	5035	4849
	-6106	-6108	-6195	-6295
< 50 km river	1966	1784	1937	1584
	-2473	-2492	-2319	-2629

*Notes: ***p<0.01, **p<0.05, *p<0.1. Linear probability models. Panels A and B present models with incidences of fetal mortality and anemia as dependent variables. Columns (1) – (4) include hazard indexes at sites within 5 – 20 km from a cluster. Sample sizes for Panels A and B are 621 and 313, respectively. Heteroscedasticity robust standard errors clustered at site level. Fixed year and region effects were included. All models controlled for age, age square, wealth, education, urban, and an indicator if the nearest mine was at a*

Table 13 presents models with Hazard Index values at different distance thresholds between clusters and contaminated sites. The varying distances fall within 5-

20 km from the nearest contaminated site. Incidences of fetal mortality and anemia are the dependent variables in Panel A and panel B, respectively.

Tobit models were conducted as part of the robustness checks of the OLS model results. Table 14 includes the same variables from Table 13 but is based on the Tobit model.

Table 14. Sensitivity analysis of health outcomes and hazard index in Tobit models.

Panel A: Incidence of Fetal Mortality

	Hazard Index at different distances from clusters			
N=621	< 5 km	< 10 km	< 15 km	< 20 km
HI	0.024**	0.026**	0.027**	0.030***
	-0.011	-0.011	-0.011	-0.01
< 50 km mine	4,503	4,510	4,623	5007*
	-2,896	-2,892	-2,840	-2,680
< 50 km river	2,105	2,390	2,481	3731*
	-2,889	-2,705	-2,708	-2,170

Panel B: Incidence of Anemia

N=313	< 5 km	< 10 km	< 15 km	< 20 km
HI	0.050**	0.049**	0.049**	0.048***
	-0.02	-0.02	-0.02	-0.017
< 50 km mine	5,901	5,917	5,840	5,605
	-6,443	-6,444	-6,553	-6,681
< 50 km river	2,437	2,187	2,255	1,662
	-2,682	-2,697	-2,463	-2,736

*Notes: ***p<0.01, **p<0.05, *p<0.1. Tobit models. Panels A and B present models with incidences of fetal mortality and anemia as dependent variables. Columns (1) – (4) include hazard indexes at sites within 5 – 20 km from a cluster. Sample sizes for Panels A and B are 621 and 313, respectively. Heteroscedasticity robust standard errors clustered at site level. Fixed year and region effects were included. All models controlled for age, age square, wealth, education, urban, and an indicator if the nearest mine was at a higher elevation than the cluster.*

Table 15. Sensitivity analysis of the effect of mine contamination and river proximity exposure on fetal mortality rate and birth weight z scores.

Panel A: Fetal Mortality Rate

	-1	-2	-3	-4	-5
Arsenic HQ	0.980***				
	-0.249				
Chromium HQ		0.011**			
		-0.005			
Lead HQ			-0.717		
			-0.987		
Mercury HQ				-5.768	
				-7.564	
Hazard Index					0.005
					-0.003
<50 km mine	1,341	-284	2348***	1,192	1,329
	-806	-497	-157	-978	-812
<50 km river	194	1769***	337*	1178*	340
	-852	-230	-902	-481	-804
N	621	201	384	440	621

Panel B: Birth weight z scores

	-1	-2	-3	-4	-5
Arsenic HQ	-0.000**				
	0				
Chromium HQ		0			
		0			
Lead HQ			-0.000**		
			0		
Mercury HQ				0.001	
				-0.001	
Hazard Index					-0.000**
					0
<50 km mine	0.083*	0.198*	0.08	0.099*	0.083*
	-0.043	-0.095	-0.081	-0.033	-0.042
<50 km river	-0.036	-0.115	0.122	-0.104**	-0.044
	-0.06	-0.104	-0.162	-0.032	-0.059
N	605	196	376	429	605

*Notes: ***p<0.01, **p<0.05, *p<0.1. Linear probability models. Panels A and B present models with fetal mortality rate and birth weight z scores as dependent variables. Columns (1) – (5) include contaminant hazard quotients and hazard index at sites within 10 km from a cluster. Heteroscedasticity robust standard errors clustered at site level. Fixed year and region effects were included. All regressions controlled for age, age square, wealth, urban, education, and an indicator if the nearest mine was at a higher elevation than the cluster.*

Appendix 3

Hot Spot Analysis for Birth Weight

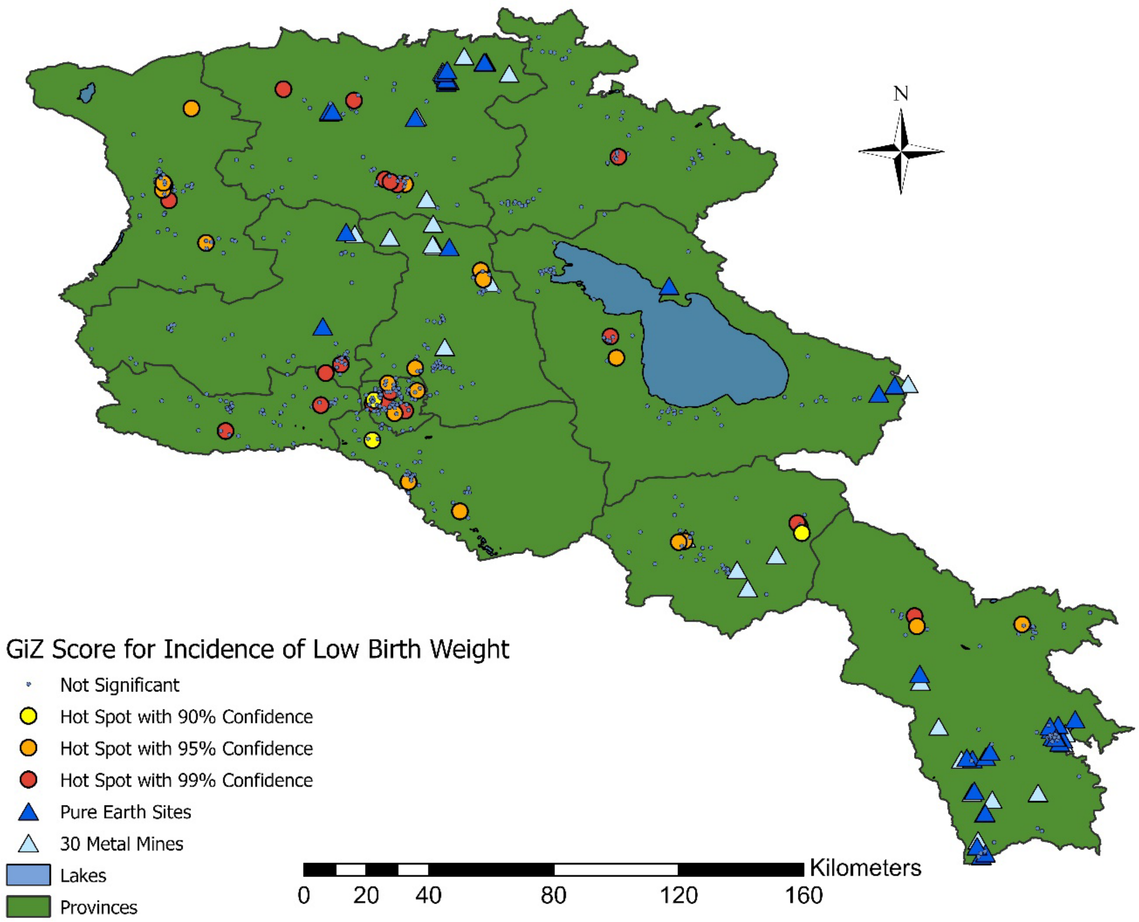

Figure 11. Hot spots of incidence of low birth weight.

Each dot represents a cluster of DHS sample households, and the boundaries shown are provinces. Light and dark blue triangles represent all the metal mines and Pure Earth contaminated sites. Yellow, orange, and red dots represent hot spots of high mortality rates at 90, 95, and 99% significance levels.

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