

The non-green effects of *going green*: Local environmental and economic consequences of lithium extraction in Chile *

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Abstract

In this paper, we investigate the local environmental and economic effects of lithium extraction in the Atacama Salt Flat (ASF) in Chile. Utilizing granular administrative and remote sensing datasets, we assess the impacts of these operations on water availability, vegetation, economic activity (as proxied by nighttime light radiance), and population dynamics in the ASF. Our findings reveal significant declines in groundwater levels as well as notable reductions in vegetation, economic activity, and local populations due to exposure to the extraction of lithium. Particularly, we show that areas closer to the mining activities and with higher baseline vegetation experience the largest declines in vegetation. The main mechanism driving our results is the reduction in endemic forestry species and agricultural crops. We present evidence that the above led to reduced employment opportunities that possibly explain the population outflow from areas around the ASF and the subsequent drop in economic activity.

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Abstract

In this paper, we investigate the local environmental and economic effects of lithium extraction in the Atacama Salt Flat (ASF) in Chile. Utilizing granular administrative and remote sensing datasets, we assess the impacts of these operations on water availability, vegetation, economic activity (as proxied by nighttime light radiance), and population dynamics in the ASF. Our findings reveal significant declines in groundwater levels as well as notable reductions in vegetation, economic activity, and local populations due to exposure to the extraction of lithium. Particularly, we show that areas closer to the mining activities and with higher baseline vegetation experience the largest declines in vegetation. The main mechanism driving our results is the reduction in endemic forestry species and agricultural crops. We present evidence that the above led to reduced employment opportunities that possibly explain the population outflow from areas around the ASF and the subsequent drop in economic activity.

JEL Classification: D30, F22, J61, O15 *Keywords:* Environment, Chile, Lithium.

1 Introduction

The *Clean Energy Transition* and the reduction of greenhouse gas (GHG) emissions, as agreed within the United Nations Framework Convention on Climate Change (UNFCCC), are key objectives for governments around the world. Those efforts are concentrated on transforming both the production of secondary energy, through the introduction of renewables, and the final energy used directly by consumers. The *green* transition for final energy use is largely based on the introduction of sustainable transportation. According to the U.S. Environmental Protection Agency (EPA), transportation accounts for almost 15% of GHG emissions worldwide, calling for the introduction of electric vehicles (EVs) as a key component of the transition ([Environmental Protection Agency, 2023](#))

Over the past years, sales of EVs in the United States, Europe, and China have increased rapidly. More than 6 million EVs were registered in these economies in 2021, compared to less than 1 million in 2016 ([International Energy Agency, 2022b](#)). The projected market share of EVs is set to reach 96% by 2035 from 10% in 2020, a trend that is expected to continue beyond this date ([Boston Consulting Group, 2021](#)). Currently, half of all sales of cars in the world are “covered by zero-emission vehicle mandates”, while the U.S. and the E.U. are pushing for adoption of EVs through tax incentives and financial support in the *Inflation Reduction Act* and the *Green Deal Industry Plan*, respectively ([International Energy Agency, 2023](#)). However, as is true with most *green* technologies, EVs require energy storage and, therefore, their ramp-up is coupled with the production and use of batteries. Hence, this increased demand for EVs is driving up the demand for minerals used in battery storage, with lithium seeing the largest increase ([Department of Energy, 2017](#)). In particular, according to the International Energy Agency’s (IEA) Sustainable Development Scenario, demand for lithium is predicted to increase by almost 40 times by 2040 ([International Energy Agency, 2022a](#)).

While the need for adoption of *green* technologies and sustainable transportation is imminent, the impacts of sourcing the needed materials remain unclear. This is especially important as part of the extraction of those minerals takes place in developing countries, through processes that can have adverse effects for local populations. Specifically for lithium, despite the potential positive economic and technological benefits that come with its extraction, there are environmental and socioeconomic externalities that should be considered when evaluating the full supply-chain sustainability of its end uses; its extraction is a water-intensive process, impacting the availability of water in neighboring regions and the water cycle altogether ([Center for Strategic and International Studies, 2021](#)).

Lithium is mainly sourced in Australia, Chile, and China. However, Chile, together with Argentina and Bolivia, are part of what is known as the *Lithium Triangle*, a strategic area located in South America

that contains more than half of the world's lithium ore reserves (IDB, 2017). In this paper, we provide causal evidence of the local environmental and economic impacts of lithium extraction in this region. Our analysis focuses on Chile, the country with the largest reserves of *commercially viable* lithium worldwide (Center for Strategic and International Studies, 2021). More specifically, we study the environmental and economic impacts of lithium extraction around the area of the Atacama Salt Flat (ASF) in the north of Chile, where the bulk of extraction operations in the country take place.

To do so, we work with four main sources of data. First, we utilize a database on groundwater levels, measured both at the water wells surrounding the ASF as well as in the north of Chile overall. Second, we use data on the Normalized Difference Vegetation Index (NDVI) for the main localities¹ around the ASF, obtained through satellite images, at a $300\text{m} \times 300\text{m}$ resolution. Third, we use data on nighttime light radiance around the ASF, at a $500\text{m} \times 500\text{m}$ resolution. Lastly, we use a database proxying the density of human settlements within the same areas around the ASF, again through satellite images, at a $100\text{m} \times 100\text{m}$ resolution.

Our estimation of the effects of lithium extraction in the area around the ASF on groundwater levels relies on a comparison between water wells located in the ASF and water wells further away over time. On the other hand, the estimation of the effects on vegetation, human settlements, and nighttime light radiance relies on a measure of the exposure of each pixel to the extraction of lithium. We construct this measure as the ratio of the demand for EVs in Europe, the US, and China during the 2010-2020 period to the distance of each pixel from the water wells around the ASF. We consider both EV sales (time variation) and the distance measure (cross-sectional variation) to be plausibly exogenous to the environmental and economic outcomes we study. Specifically, to ensure the exogeneity of the cross-sectional variation in our strategy, we control for latitude, longitude, elevation, and locality fixed effects so that our estimates compare changes over time of our outcome variables for pixels that are very close to each other. Our measure of exposure is increasing in the amount of EVs sales and decreasing in the distance from the water wells. Therefore, the pixels closer to the wells and in years when EV sales are larger are more exposed to lithium extraction. Based on this, we compare changes over time for vegetation and nighttime light radiance over the period 2013-2020, and for human settlements over the period 2010-2020.

Four important results stem from our analysis. First, during the 2013-2019 period, there was a significant reduction of up to 15% in the groundwater levels around the ASF, compared to other water wells in the north of Chile, but further away from the flat. Second, an increase of 1 standard deviation

¹ Those are the localities reported in the census, as well as the National Reserves in the area. For more details on the identification and construction of the localities, please see Appendix A.2.

in our measure of exposure to lithium extraction reduced vegetation by 0.2%. This effect was more severe in those areas where the level of vegetation was higher at the beginning of our period of analysis and closer to the ASF. Third, a 1 standard deviation increase in our measure of exposure to lithium extraction reduced economic activity, as proxied by nighttime light radiance, by 2.6%. Last, but not least, a 1 standard deviation increase in our measure of exposure reduced human settlements by 1.5%.

To shed light on the mechanisms driving these results, we provide suggestive evidence of the drop in agricultural activity during the 2007-2021 time frame. Over that period, the total cultivated area in the region dropped significantly from almost 1,500 to 500 hectares. We argue that this reduction could explain the effect on vegetation found in our main results. In line with this, we demonstrate that agricultural employment was significantly reduced over the same period, potentially explaining the reduction in human settlements and economic activity.

Our results contribute to four main strands of the literature. First, we contribute to the literature on the local and regional socioeconomic impacts of natural resource extraction. Overall, the magnitude and direction of the impacts found in the literature are ambiguous ([van der Ploeg, 2011](#)). On the one hand, local communities can benefit from a boom in the extraction of natural resources in terms of employment and income; on the other hand, such activities can have adverse consequences for local populations. [Aragón and Rud \(2013\)](#) find a strong and positive impact on the income of communities within a 100-kilometer radius around the Yanacocha gold mine in Peru. They attribute these positive effects to the mine's demand for local inputs. On the other hand, in a related work analyzing the case of copper mining in Zambia, [Lippert \(2014\)](#) finds that increases in the production of copper mines have a positive impact on the living standards of the local communities even for households not directly employed by the new copper mines.

To the best of our knowledge, the most closely related work in the economic literature to our study is [Aragón and Rud \(2016\)](#), analyzing the effect of gold mining activity in Ghana on the productivity of the agricultural sector. The authors find that gold-mining activity reduces agricultural productivity and that the effect is concentrated within a 20-kilometer radius around the mines. Furthermore, using remote sensing data, the authors find suggestive evidence indicating that the gold-mining regions exhibit a significantly higher concentration of NO₂, which diminishes with distance from the sites. Hence, they point to pollution as the main driver of the drop in agricultural productivity (For a more comprehensive review of the economic literature, see, for instance, [Cust and Poelhekke, 2015](#); [Loayza and Rigolini, 2016](#); [Corral et al., 2018](#); [Pokorny et al., 2019](#); [Bazillier and Girard, 2020](#)). We show that negative environmental and economic consequences for communities around natural resource extrac-

tion sites can exist even if the pollution channel that Aragón and Rud (2016) indicate is not present. In the case of the ASF in Chile, management and depletion of water resources drive those effects, rather than pollution caused by the operations.

Second, we contribute to the literature on the socioeconomic impacts that changes in water availability have on local communities. Economic literature demonstrates an important impact of water availability on agricultural outcomes, although, surprisingly, the effects in terms of economic growth are ambiguous (See, for instance, Dell et al., 2012; Brown et al., 2013; Burke et al., 2015; Damania, 2020; Russ, 2020; Damania, 2020; Marbler, 2024). Related to this literature is the work of Burlig et al. (2021), who conclude that lower access to groundwater leads to a reduction in agricultural activity. However, most of these studies focus on changes in the availability of water through climate change, rainfall, or exogenous shocks such as electricity prices and their impact on the cost of groundwater extraction. Our contribution to this literature is twofold: (1) we provide evidence on how agricultural activity can be affected via anthropogenic shifts in underground water availability, and (2) we demonstrate that this depletion, which reduces agricultural activity in the area, in turn, affects migration decisions of the people in local communities.

Third, we contribute to the natural and environmental science literature by providing new causal estimates on the impact that lithium extraction in the ASF has on water availability and vegetation in the area. There is no clear consensus in this literature on the net impact that lithium extraction activities have on the region and overall (Flexer et al., 2018). Several studies have found that there is a significant reduction in water availability, vegetation, and soil moisture in the area, as well as higher temperature and evaporation rates (Liu et al., 2019; Marazuela et al., 2019, 2020; Liu and Agusdinata, 2020; Vera et al., 2023). All these consequences, which are correlated with the extraction of lithium in the area, according to the literature, affected the abundance of wildlife, particularly flamingos, which is a protected species in the region (Gutiérrez et al., 2022; Vera et al., 2023). However, other studies argue that the negative variations in the aforementioned environmental outcomes can be attributed to extreme weather phenomena in the region, and subsequently to climate change, but not to the lithium extraction operations per se (Munk et al., 2021; Moran et al., 2022).

Studies in the natural and environmental science literature, on both sides of the debate, run into identification issues; they rely purely on observational and correlational evidence, hence not being able to separately identify the impact of lithium extraction operations and distinguish it from the effect of other environmental phenomena in the area on the outcomes in question. In this paper, we provide, for the first time, causal evidence of the lithium extraction operations on vegetation and economic

activity. We do so by exploiting arguably exogenous variation in the exposure of each locality to lithium extraction, controlling for location differences across units of analysis in our sample. Hence, we are able to reach a clean identification of the estimated impact of lithium extraction on our outcome variables.

Finally, we contribute to the growing literature on the externalities of environmental regulations imposed within developed countries in developing ones. In their recent paper, [Tanaka et al. \(2022\)](#), focus on the “North-South displacement effects” of such environmental policies. They demonstrate how the tightening of air regulations in the United States impacts the relocation of polluting activities to Mexico and, in turn, negatively affects birth outcomes in this developing country (For additional papers on this literature, see, for example, [Copeland and Taylor, 2004](#); [Levinson, 2010](#); [Cherniwchan et al., 2017](#); [Cole et al., 2017](#)). We provide new evidence to this discussion by showing how the push for a regulatory framework fostering the adoption of EVs in the United States and Europe translates to local environmental and economic damages in a developing country like Chile. Furthermore, we show that the entirety of those damages is borne by rural and indigenous communities residing around the area where the extraction of lithium takes place.

The rest of the paper is organized as follows: Section 2 provides context about the lithium extraction process in the ASF and the potential mechanisms through which it can affect water availability and vegetation in this area. Section 3 describes the data we use for our analysis. Section 4 outlines the empirical strategy implemented in the paper to estimate the effect of lithium extraction on the outcomes of interest. Section 5 provides the main results of our estimates. Section 6 provides suggestive evidence of the mechanisms driving those results. Section 7 describes some robustness checks. Finally, Section 8 provides final remarks.

2 Context

In this section, we provide background on lithium extraction in South America, particularly in the *Lithium Triangle*, the region enclosed by Chile, Argentina, and Bolivia. We then continue to describe the context of extraction operations specifically in Chile and the different mechanisms through which they can lead to lower water availability in the area of the ASF. Finally, we discuss the specifics of the process of extracting lithium from brine deposits.

2.1 Extraction of lithium in South America

Hard-rock ores and continental brines are both utilized for lithium extraction, with the latter being the most prominent source.² The Altiplano-Puna high plateau in South America is one of the planet's most distinctive geological formations and is renowned for its unique brine-type deposits of lithium. Consequently, the global push for significant technology advancements in energy storage, in an effort to move towards the adoption of renewable energy and sustainable transportation, has driven the Andean *lithium rush*. While lithium's end uses vary from ceramics and glass to lubricating greases and air treatment, 87% of it is used for energy storage in batteries ([United States Geological Survey, 2024](#)).

Since the beginning of the rush, more than ten years ago, the plateau area has become known as the *Lithium Triangle* (shown in the left-hand side of Figure 1). This informal term describes the region lying between Chile's ASF, Bolivia's Uyuni Salt Flat, and Argentina's Hombre Muerto Salt Flat, which constitute the most significant lithium reserves worldwide ([López Steinmetz and Salvi, 2021](#)). The two largest salt flats in Bolivia are the Uyuni and Coipasa, covering an area of about 10,000 km², with Uyuni being the largest salt flat in the world. However, according to [López Steinmetz and Salvi \(2021\)](#), as of 2021, both of the two salt flats in the Altiplano region in Bolivia were untapped. In Argentina, Hombre Muerto and Olaroz constitute the most important salt flats, and both are currently subject to lithium mining. Finally, in Chile, the most important is the ASF, which covers an area of 3,000 km², has the largest lithium extraction operations in the region, and will be the subject of our analysis.

According to [López Steinmetz and Salvi \(2021\)](#), the ASF contains the highest concentration of lithium among the salt flats in the *Lithium Triangle*. While the average concentration of lithium in the Altiplano Salt Flats in Bolivia is between 213 and 258 mg L⁻¹, and between 280 and 570 mg L⁻¹ in the Puna Salt Flats in Argentina, the average concentration in the ASF is about 1,400 mg L⁻¹. The particularly high levels of concentration of lithium in the ASF make it the most important lithium extraction operation with the richest lithium brine-type deposits in the world ([López Steinmetz and Salvi, 2021](#)). Consequently, Chile is one of the largest exporters of lithium worldwide.

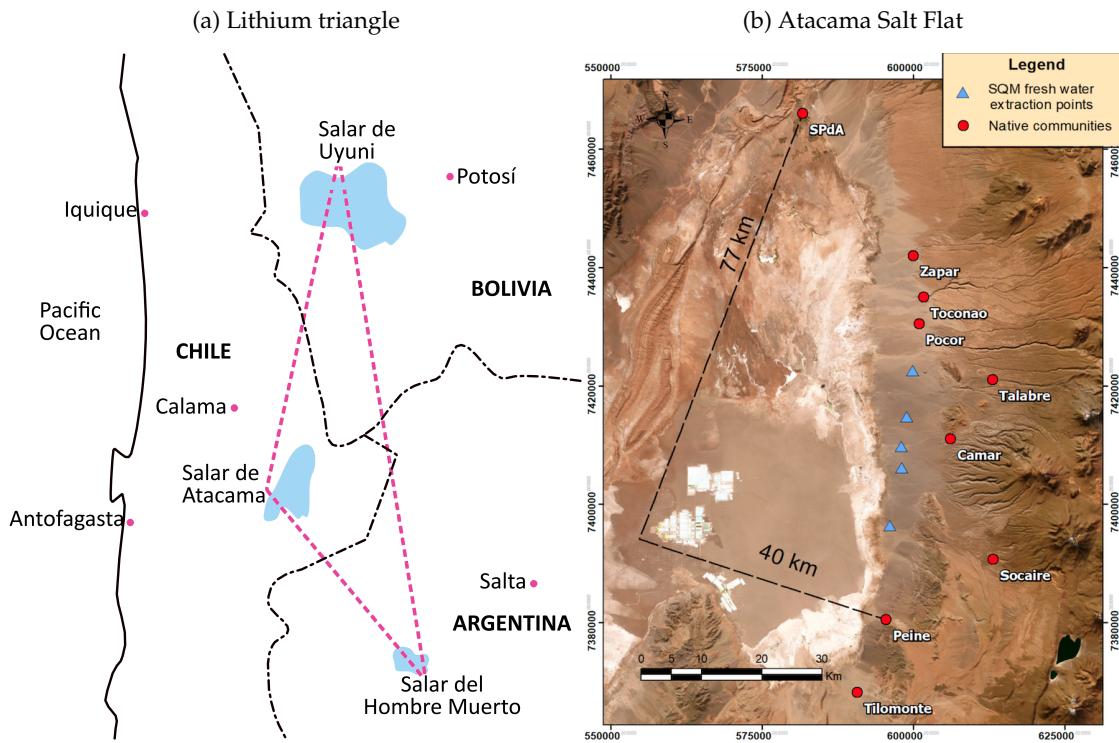
2.2 Extraction of lithium and water depletion mechanisms in the Atacama Salt Flat

The companies extracting lithium in the ASF in Chile have a lease agreement with the Production Development Corporation (CORFO) of the country. While there are several companies in the ASF exploiting lithium, such as Mineral La Escondida (MEL), Compañía Minera Zaldivar (CMZ), Sociedad

² Brine refers to a solution of water with a high concentration of salts.

Química y Minera (SQM), and Albermarle, the overall brine extraction is almost purely driven by the activities of SQM in the area (Moran et al., 2022). Hence, our data for water use and monitoring will come from SQM's reporting archives. The agreement between CORFO and SQM has been in place since 1993 and was recently revised in 2018. These agreements stipulate lease payment rates that are tied to the final sale prices, the obligation by SQM to contribute specified amounts to research and development activities, as well as reporting and environmental audit and control obligations for the company (U.S. Securities and Exchange Commission, 2018).

Figure 1: Main lithium extraction locations in South America



Notes. Figure 1(a) demonstrates what is known as the *Lithium Triangle*, while Figure 1(b) demonstrates the ASF area with the main localities under study. Source. Figure 1(a): De la Hoz et al. (2013). Figure 1(b): Own rendering.

Lithium extraction from brines involves two distinct processes that could contribute to water depletion. The first such process is the direct extraction of brine, which is done through the use of pumps. The extracted brine is placed in large evaporation ponds and as the water evaporates, several salts precipitate. After the useful ones are recovered, the remaining water is re-injected into the brine. The second process is the direct extraction of freshwater, mainly used for cleaning the equipment (Vera et al., 2023). While a clear consensus on which mechanism is the dominant one concerning water avail-

ability does not seem to exist, [Vera et al. \(2023\)](#) argue that brine extraction can lead to a reduction in brine volume, in turn causing freshwater to permeate the mixing zone and seize to be fresh ([Flexer et al., 2018](#); [Marazuela et al., 2020](#)). In our analysis, we remain agnostic about which mechanism is dominant. Rather, taking into account that in both cases a reduction in water levels would be observed at the points where freshwater is extracted, we use as reference the distance from SQM's freshwater wells, which, as can be seen in the right-hand side of Figure 1, are very close to the local communities. Furthermore, in Appendix A.3 we provide more insight on the impacts of water extraction through the use of a water balance calculation and a conceptual model, based on SQM's Environmental Impact Assessment report ([Sociedad Quimica y Minera de Chile, 2021](#)).

Over the last thirty years, as groundwater exploitation for mining purposes has expanded, Dirección General de Aguas (DGA), the country's top administrative body for water management, has been responsible for monitoring the use of water in the area. As a result of the DGA allocating rights for water use, multiple groundwater extraction wells were built over this period. SQM is granted the right to extract brine at a rate of no more than 1,600 liters per second, however, its pumping activity has been historically below this threshold. In 2020, through its corporate sustainability plan, the company announced that they aim to reduce pumping rates to 50% of the stipulated threshold within a decade ([Sociedad Quimica y Minera de Chile, 2021, 2022](#)). Additionally, as far as freshwater is concerned, SQM is authorized to extract at rates of up to 240 liters per second in its five freshwater wells. However, for the past 4 years overall extraction rate has been less than 50% of the stipulated limit ([Sociedad Quimica y Minera de Chile, 2024](#)).

In the area of the ASF, indigenous populations have been using surface water for domestic and agricultural purposes for decades ([Babidge, 2019](#)). However, the relationship between SQM and local communities over the past years has been turbulent. In 2019, the *Atacama Indigenous Council* (CPA) sued the company for excessive pumping, with the two sides settling the dispute a year later ([Reuters, 2020](#)). Since then, SQM has funded sewage water treatment plants for the community of Camar in the ASF. In section 3.4, we will analyze in greater depth the socioeconomic characteristics of the populations in the region.

2.3 The process of sourcing of lithium from brine deposits

Production of lithium carbonate (Li_2CO_3) from brines can be broken down into three key steps, namely mass reduction of brines in solar evaporation ponds, brine purification, and Li_2CO_3 precipitation. Brine is pumped from aquifers via wells located on the salt flat. It is subsequently transported to

solar evaporation ponds through pipelines to reduce its volume. After it reaches a certain lithium (Li) content, brine is delivered to a processing facility, where calcium (Ca), magnesium (Mg), and boron (B) impurities are removed from the Li-enriched brine solution. This is achieved through the use of quicklime to remove Mg, organic solvent extraction to remove B, and ion exchangers to remove Mg, Ca, and B. The methods and the sequence in which they are employed are determined by the particular brine composition at the site in question. Subsequently, Li_2CO_3 is precipitated by heating the pulp and adding soda ash. Technical grade Li_2CO_3 that has crystallized is then dissolved in cold water. Reheating the solution to 80 °C yields the precipitation of Li_2CO_3 , which constitutes what is known as “battery grade” product ([Garrett, D. E, 2004; Tran and Luong, 2015; Schenker et al., 2022](#))

Chile has long been a top producer of Li_2CO_3 , with output mainly coming from brine activities at the ASF. The extraction and evaporation of brine water take place on-site at the ASF, after which the lithium concentrates are transported for processing to two Li_2CO_3 processing plants and one lithium hydroxide monohydrate ($\text{LiOH}\bullet\text{H}_2\text{O}$) processing plant in Antofagasta, Chile ([Jaskula, B.W., 2018; Kelly et al., 2021](#)).

3 Data and Descriptive Statistics

In this section, we describe the data we utilize in our analysis and provide stylized facts and descriptive statistics about the supply and demand of lithium, as well as the socioeconomic and environmental characteristics of the region we analyze.

3.1 Data

We utilize seven sources of data in our analysis, namely groundwater levels, vegetation index, agricultural production, nighttime light radiance, human settlement estimates, elevation levels, and EV sales. The sources are as follows:

Groundwater levels: The first source of data concerns the levels of groundwater in the area of the ASF. These are obtained through public measurements of well levels available on the website of SQM, the predominant lithium extraction company in the ASF. As part of their hydrological monitoring, SQM reports values for 196 wells, which we have downloaded and used in our analysis. Additionally, we use data from monitoring wells in the north of Chile obtained through DGA. More specifically, we use measurements for a total of 109 monitoring wells between 2010 and 2019, within the regions of Antofagasta, Arica and Parinacota, and Tarapacá, which serve as a comparison group. In both cases,

we use the static water level, i.e. the distance from the top of the wells to the water table.

Vegetation Index: Measurements for vegetation are obtained through the API provided by the Earth Engine Data Catalog. More specifically, we obtain the Landsat 8 Collection 1 Tier 1 Annual NDVI Composite measure. We identify a radius of interest, split it into 300m×300m pixels, and recover the average NDVI values for each pixel and year between 2013 and 2020, within the localities around the ASF. The NDVI is a vegetation index that ranges from -1 to 1, where greener areas take values closer to 1.

Agricultural production: This data is available through the National Agricultural and Forestry Census carried out by the National Institute of Statistics of Chile (INE, by its acronym in Spanish) at the comuna level (which is equivalent to a county in the U.S.). More specifically, the available data shows the national planted area, production, and annual yields for vegetables, agricultural products, and forestry for the 2007 and 2021 years.

Nighttime light radiance: The data on nighttime lights are values of radiant flux from the API provided by the Earth Engine Data Catalog. We utilize the VIIRS Nighttime Day/Night Annual Band Composites through the joint NASA/NOAA Suomi NPP satellite at a 500mx500m resolution, using the average Day/Night Band (DNB) for each pixel in each year between 2013 and 2020. Nighttime light radiance has been widely used in the economic literature to proxy economic activity and development around the world (See, for instance, [Henderson et al., 2012](#); [Donaldson and Storeygard, 2016](#); [Ch et al., 2021](#)). Most of the studies in the field have found a strong correlation between nighttime luminosity and cross-sub-national level GDP and economic growth. It has also been shown very useful for proxying economic activity for low-population and rural areas in developing economies (See, for instance, [Michalopoulos and Papaioannou, 2013](#); [Chen and Nordhaus, 2015](#)). Regarding its validity, mainly for small areas and rural regions, [Pérez-Sindín et al. \(2021\)](#) show that nighttime luminosity for the case of Colombia, is a very good predictor of economic regional activity, even for locations with less than 5,000 people, and that this relationship is stronger for the case of the VIIRS data, which is the one used in this paper.

Human Settlements: To estimate the effects on local population settlements, we utilize the Global Human Settlement Layer (GHSL) dataset provided by the European Union through Copernicus. More specifically, we use the spatial raster product, a dataset that deduces the spatial distribution of human settlements based on satellite images from Sentinel-1 and 2. The population distribution is expressed as the number of people in each 100mx100m cell.

Elevation: For each centroid of each pixel in our analysis, we control for elevation, as we expect

pixels with higher elevation to be differentially affected. We download the 30-meter Shuttle Radar Topography Mission (SRTM) Digital Elevation Model (DEM) files through the NASA Earthdata platform.

EV sales: As part of our empirical strategy, we utilize the number of sales of EVs in the United States, Europe, and China. The data is obtained through the IEA and contains information on the annual sales of electric vehicles between 2010 and 2020. The sales data is provided by vehicle type for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs).

3.2 Descriptive Statistics

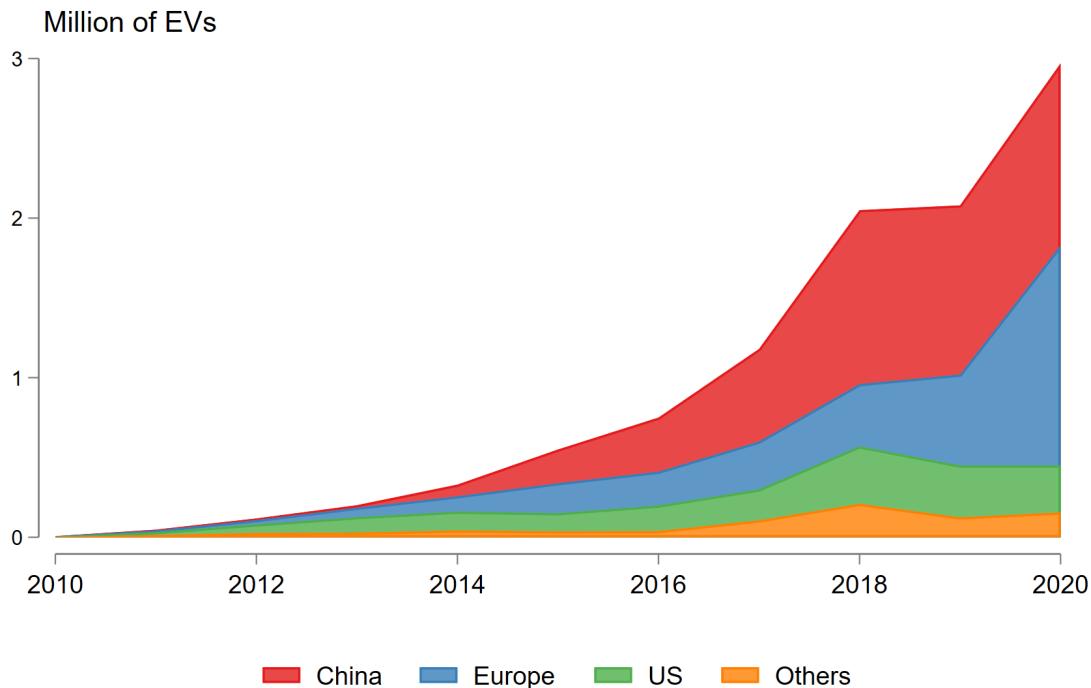
In this section, we provide statistics on the evolution of supply and demand for lithium around the world and in Chile, as well as on the sociodemographic characteristics of the populations residing around the ASF. Finally, we provide statistics on the evolution of underground water levels and vegetation levels in the area during the period under study to motivate the main empirical strategy and results presented in or analysis.

3.3 Lithium supply and demand

As can be seen in Figure 2, there has been a significant increase in the demand for EVs worldwide since 2010. Over the previous decade, EV sales skyrocketed from 7.5 thousand in 2010 to 3 Million in 2020. The demand for EVs is driven by three regions, namely China, Europe, and the U.S. By 2020, these three regions represented about 95% of total EV sales globally. While China has historically been the main EV market, Figure 2 shows that Europe has gained a lot of momentum, representing 46% of the global demand as of 2020.

On the other hand, Figure 3 shows the mine production of lithium in Thousand Metric Tons (MT) between 1994 and 2021 by producer country. Two main takeaways emerge from this figure. First, the mine production of lithium worldwide has increased significantly, particularly after 2016. Second, most of the production of lithium has been concentrated in Chile and Australia. In recent years Australia seems to have become the leader, representing about 48% of the worldwide production, with Chile in second place contributing to 26% of production as of 2021.

Figure 2: EV Sales by Destination, 2010-2020

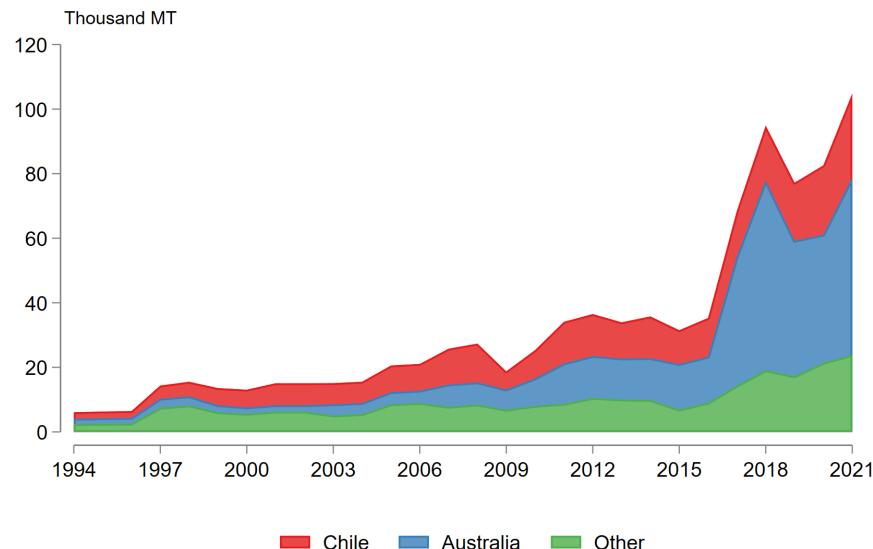


Notes. Overall EV sales in Million cars for the U.S., Europe, China, and the rest of the world. Source: Own elaboration based on data from the IEA.

Finally, a key observation from Figures 2 and 3 is that the production of lithium, and its increase in recent years, seem to be strongly correlated with the demand for electric vehicles and lithium batteries in Europe, the U.S. and China. This fact will be crucial in the design and implementation of our empirical strategy and, therefore, in our identification.

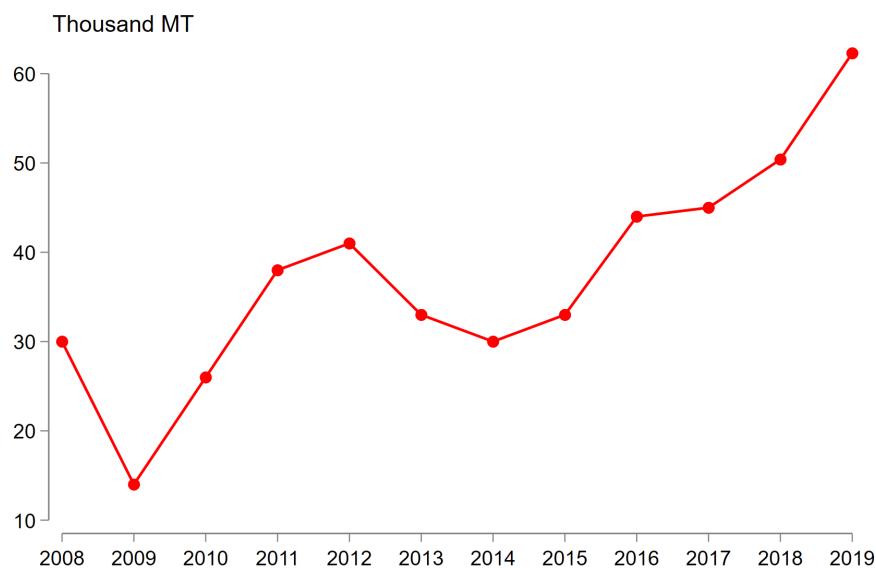
In Figure 4, we zoom into the production of lithium in Chile, particularly in the ASF, and the extraction carried out by SQM. As can be seen, the aforementioned ramp-up in production coincides with an increase in the lithium extraction activity in the ASF. There seems to be a significant increase in the amount of lithium produced in the ASF by SQM from 30,000 MT in 2013 to 60,000 MT in 2019, according to the company's annual reports.

Figure 3: Mine Production of Lithium by Origin, 1994-2021



Notes. Mine production of lithium over time in thousand MT of contained lithium per year for Chile, Australia, and the rest of the world. Source. Own elaboration based on data from the Mineral Commodity Summaries from the US Department of the Interior and the US Geological Survey.

Figure 4: Production of Lithium in the ASF by SQM, 2008-2019



Notes. Production of lithium over time in Thousand Metric Tons by SQM in the area of the ASF. Source. Own elaboration based on data from the SQM's annual reports.

3.4 Socioeconomic characteristics of the Atacama Salt Flat

The ASF and the region where the lithium extraction operations take place is located in the municipality of San Pedro de Atacama (SPdA), in the north of the country (in the region of Antofagasta). This region, and particularly the SPdA municipality, is characterized by arid desert conditions. Hence, vegetation is scarce and population density is low compared to other regions of the country.

In this subsection, we characterize the population residing in the SPdA municipality, using the 2002 and 2017 Chilean national censuses.³ As can be seen in Table 1, while in 2002 roughly 5 thousand people resided in SPdA, 15 years later that number more than doubled. These people, who are exposed to the lithium extraction activity in the region, have a similar age distribution to the population in the Antofagasta region and in Chile overall. However, the population in SPdA is particularly overrepresented by male individuals, relative to the whole country, and this is true for both years. In terms of educational attainment, the distribution in both years is similar to that of Chile as a whole.

Furthermore, the population of SPdA is particularly represented by indigenous individuals, relative to both the region of Antofagasta and Chile overall. Our estimates indicate that, while in 2002 about 61% of the population in SPdA self-identified as indigenous, this proportion was only 5% for the entire country. This is especially important since indigenous people have a special legal status in the country, whereby public authorities ought to protect them and ensure their development.⁴

In Panel B of Table 1 we show the economic characteristics of the population in SPdA, the region of Antofagasta, and the rest of Chile, as well as statistics on the labor market participation for each of the three groups. As can be seen, in terms of labor force participation and employment overall, individuals in SPdA seem to do better compared to people in the region and the rest of Chile, which might partially be explained by the overrepresentation of male individuals in the municipality. Additionally, the participation of individuals working in mining, hotels, and restaurant sectors is greater compared to Chile as a whole. This result is expected, given that the economic activity in the north of Chile, particularly the area of SPdA, revolves around extracting natural resources and tourism.

Next, we analyze the dwelling conditions under which individuals in the SPdA municipality live. In Table 2 we show descriptive statistics of each of the variables, using individual observations. We use

³ The 2002 census is the only reliable Chilean census before the 2017 one. While in 2012 a census was carried out, the results are not considered reliable due to the disruptions caused by an earthquake that took place in the same year.

⁴ According to the Chilean Law 19.253 sanctioned in 1993 “*It is the duty of society in general and of the State in particular, through its institutions, to respect, protect and promote the development of indigenous peoples, their cultures, families and communities, adopting appropriate measures for such purposes, and to protect indigenous lands, ensure their adequate exploitation, their ecological balance and promote their expansion.*” ([Biblioteca del Congreso Nacional de Chile, 2024](#))

individual rather than dwelling units, as observations in SPdA are more likely to have a greater number of people per dwelling. Hence, we aim to avoid underestimating the magnitude of the descriptive statistics for the region.

Table 1: Population characteristics, 2002 - 2017

	SPdA		Antofagasta		Chile	
	2002	2017	2002	2017	2002	2017
Panel A: Demographic characteristics						
Head of household	0.27 (0.44)	0.27 (0.45)	0.25 (0.43)	0.29 (0.45)	0.27 (0.45)	0.32 (0.47)
Age	31.75 (20.24)	34.38 (18.75)	29.96 (19.73)	33.39 (20.35)	31.60 (20.81)	35.83 (21.97)
Male	0.59 (0.49)	0.56 (0.50)	0.52 (0.50)	0.52 (0.50)	0.49 (0.50)	0.49 (0.50)
Secondary Education	0.82 (0.38)	0.63 (0.48)	0.79 (0.41)	0.66 (0.47)	0.82 (0.38)	0.68 (0.47)
Post-secondary Education	0.18 (0.38)	0.27 (0.45)	0.20 (0.40)	0.24 (0.43)	0.16 (0.37)	0.23 (0.42)
Indigenous	0.61 (0.49)	0.50 (0.50)	0.05 (0.21)	0.14 (0.34)	0.05 (0.21)	0.12 (0.33)
Observations	4,969	10,996	493,984	607,534	15,116,435	17,574,003
Panel B: Labor Force characteristics						
Labor force	0.59 (0.49)	0.79 (0.41)	0.55 (0.50)	0.65 (0.48)	0.52 (0.50)	0.61 (0.49)
Employed	0.58 (0.49)	0.76 (0.43)	0.54 (0.50)	0.60 (0.49)	0.51 (0.50)	0.56 (0.50)
Unemployed	0.01 (0.11)	0.03 (0.18)	0.02 (0.12)	0.08 (0.27)	0.02 (0.14)	0.07 (0.26)
Primary sector	0.05 (0.22)	0.03 (0.16)	0.02 (0.14)	0.01 (0.10)	0.11 (0.31)	0.06 (0.24)
Mining	0.12 (0.32)	0.11 (0.31)	0.12 (0.32)	0.12 (0.33)	0.01 (0.12)	0.02 (0.13)
Manufacturing	0.03 (0.18)	0.03 (0.18)	0.08 (0.27)	0.05 (0.22)	0.12 (0.33)	0.06 (0.24)
Commerce	0.10 (0.30)	0.07 (0.25)	0.18 (0.38)	0.13 (0.34)	0.19 (0.39)	0.16 (0.36)
Hotels and Restaurants	0.15 (0.35)	0.17 (0.38)	0.03 (0.18)	0.05 (0.21)	0.03 (0.17)	0.04 (0.20)
Other economic activity	0.55 (0.50)	0.59 (0.49)	0.57 (0.50)	0.64 (0.48)	0.53 (0.50)	0.66 (0.47)
Observations	3,961	9,197	361,138	479,672	11,226,309	14,050,253

Notes. The table shows the demographic and labor force characterization of the population around SPdA, relative to the Antofagasta region and Chile as a whole. Source. Own elaboration based on data from the Chilean censuses.

The first characteristic that we observe in Table 2 is that individuals in SPdA are more likely to live under precarious and vulnerable conditions compared to the rest of Chileans. As can be seen, while the proportion of individuals living in dwellings with precarious walls, ceilings, and floors in SPdA is about 20%, 6%, and 2% in 2017, these figures are only 3%, 1%, and 0%, respectively, for the whole country. Moreover, in terms of water access, in 2017 only 57% of individuals in SPdA had access to a public network of potable water, compared to 86% in the entire country. This is evidence that access to potable water, either for consumption or for any other activity that the community carries out in the municipality, seems to be a crucial consideration when analyzing any potential impact of the mining activity in the region.

Table 2: Dwelling characteristics, 2002 - 2017

	SPdA		Antofagasta		Chile	
	2002	2017	2002	2017	2002	2017
Number of rooms	3.13 (2.54)	2.40 (1.31)	4.82 (2.14)	3.01 (1.26)	4.80 (1.81)	2.75 (1.07)
Precarious walls	0.32 (0.47)	0.20 (0.40)	0.04 (0.20)	0.02 (0.15)	0.05 (0.23)	0.03 (0.16)
Precarious ceiling	0.01 (0.10)	0.06 (0.24)	0.00 (0.06)	0.01 (0.11)	0.00 (0.05)	0.01 (0.08)
Floor material: earth	0.02 (0.12)	0.02 (0.15)	0.01 (0.08)	0.01 (0.09)	0.00 (0.07)	0.00 (0.05)
Water from public network	0.69 (0.46)	0.57 (0.50)	0.94 (0.24)	0.85 (0.35)	0.90 (0.30)	0.86 (0.34)
Water from wells	0.01 (0.09)	0.01 (0.09)	0.00 (0.04)	0.00 (0.04)	0.05 (0.23)	0.04 (0.18)
Water from river/creek/stream	0.06 (0.23)	0.03 (0.16)	0.01 (0.08)	0.00 (0.06)	0.03 (0.16)	0.01 (0.12)
Water from other sources	0.24 (0.43)	0.40 (0.49)	0.05 (0.23)	0.14 (0.35)	0.02 (0.14)	0.09 (0.28)
Observations	4,969	12,108	493,984	638,464	15,116,435	18,552,095

Notes. The table shows dwelling characterization of the population around SPdA, relative to the Antofagasta region and Chile as a whole. Source. Own elaboration based on data from the Chilean censuses.

In Table 3 we show descriptive statistics in terms of the NDVI for each locality in SPdA and the distance to SQM's freshwater extraction wells in the ASF.⁵ We calculate the mean, standard deviation, minimum, and maximum values of each variable for all the 300m×300m pixels of each locality. Given that the nature of potential impacts is local, we only utilize the localities that are enclosed within a

⁵ We define 20 localities in the SPdA municipality: 9 of them are human settlements and 11 are Natural Reserves. For a more detailed description of the locality definition, please see Appendix A.2.

distance of a 50 km radius of the location of the freshwater extraction wells and only present descriptive statistics for those.

As can be seen, these locations are characterized by low levels of vegetation measured by the NDVI, with Camar being the location with the lowest average NDVI (0.044). In Panel B we can see the same statistics for the distance of each locality to the ASF. As can be seen, there is a significant dispersion and variability in terms of the distance of each locality from the extraction points. For instance, the closest pixel to the SQM freshwater extraction wells located in the ASF is located at 2.46 kilometers in Quelana, whereas the location with the average largest distance is the Salar de Pujsa with an average distance of 47.05 km.

Table 3: Vegetation and Distances to the Atacama Salt Flat

	NDVI		Distances	
	Mean	SD	Mean	SD
Valle de la Luna	0.081	0.041	45.955	2.127
Tabmillo	0.097	0.042	26.609	4.628
Tebenquiche	0.095	0.085	30.303	1.301
Soncor	0.066	0.067	12.072	2.629
Quelana	0.071	0.027	5.794	1.600
Science preserve	0.075	0.035	41.749	4.945
Miscanti and Miñiques	0.050	0.095	40.400	4.950
Laguna Lejia	0.059	0.099	37.099	2.498
Salar de Pujsa	0.070	0.028	47.052	1.872
San Pedro de Atacama	0.109	0.077	43.698	3.612
Toconao	0.093	0.044	12.758	0.794
Camar	0.044	0.023	7.747	1.037
Socaire	0.108	0.028	18.649	4.117
Peine	0.075	0.043	15.548	0.789
Zapar	0.096	0.032	20.291	0.707
Pocor	0.068	0.005	7.947	0.341
Talabre	0.076	0.025	13.085	1.570
Tilomonte	0.074	0.019	28.528	0.719

Notes. This table shows the average and standard deviation of the NDVI and distances to freshwater extraction wells for each locality. NDVI data was obtained from Landsat 8 Collection 1 Tier 1 Annual NDVI Composite measure. Source. Own elaboration based on data from LANDSAT and our estimates.

In Table 4 we show additional descriptive statistics in terms of the population for each of the nine localities that are villages (as opposed to Natural Reserves). As can be seen, on average, the densest is Toconao with 0.563 people per cell, followed by San Pedro de Atacama with 0.312 people per cell. Lastly, Toconao, San Pedro de Atacama, and Peine, on average, show the highest values of nighttime light radiance.

Table 4: Human Settlements (2010) and Nighttime Light Radiance (2013) within localities

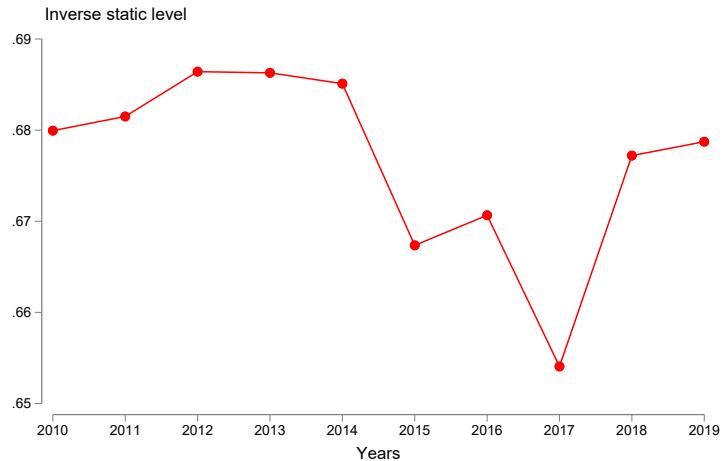
	Human settlements		Nighttime Light Density	
	Mean	SD	Mean	SD
San Pedro de Atacama	0.312	1.856	0.478	1.577
Toconao	0.563	2.415	1.567	2.735
Camar	0.041	0.297	0.046	0.005
Socaire	0.010	0.245	0.065	0.114
Peine	0.220	1.105	0.464	0.786
Zapar	0.022	0.186	0.057	0.005
Pocor	0.022	0.126	0.055	0.006
Talabre	0.038	0.391	0.072	0.054
Tilomonte	0.011	0.154	0.054	0.006

Notes. This table shows the average and standard deviation of people per cell and value of nighttime light radiance in each of the 9 localities that are villages. Source. Own elaboration based on data from Global Human Settlement Layer, VIIRS Nighttime Day/Night Annual Band Composites, and our estimates.

Next, we analyze the average level of fresh water measured by SQM in the ASF from 196 measurement stations that they report around the mining area in seven monitoring systems. Figure 5 shows the inverse of the static level of the wells in the ASF for the 2010-2019 period. Hence, the smaller the value of each point, the greater the static level of the well, and the lower the water table. As can be seen, in general, before 2014 the static level was relatively constant. After that, there was a reduction in the water level of the wells that intensified in the following periods until 2017. This could be a consequence of the utilization of water for the mining process. This trend was reversed after 2017, which could be explained by more efficient and environmentally friendly use of water resources in the area. It is expected that, if this reduction in the levels of water near the ASF had an ecological impact in terms of vegetation, the areas closer to the ASF would have been affected the most.

Apart from the environmental impact of lithium extraction in the ASF in terms of vegetation, we would also like to estimate the subsequent economic impacts. We want to do this by analyzing how the levels of crops relate to agriculture and how agricultural activity in general, was affected by the intensive use of fresh water in the area. However, given the lack of granular data for the potentially affected areas, we consider the NDVI as a proxy variable for the impact on agriculture. In Section 6, we present suggestive evidence of the types of crops that were reduced over the period in question to support our main results.

Figure 5: Reduction in water levels of Atacama Salt Flat wells, 2010-2019



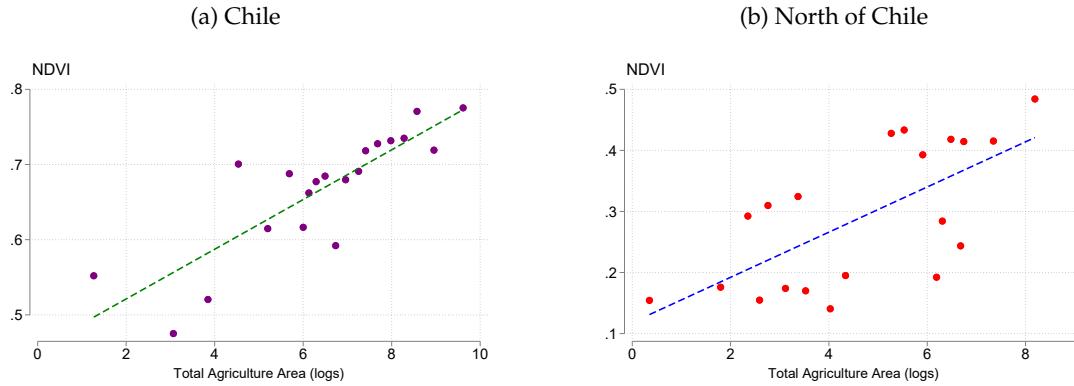
Notes. The figure shows the average inverse of the static levels of the wells in the Atacama Salt Flat. The static level is calculated as the difference between the ground surface and the water level table for each well in meters. We present the three-year moving average of the static levels to reduce the noise of the variable. Source. Own elaboration based on data from SQM.

In Figure 6 we show the relationship between the average NDVI and the total cultivated area for agriculture (in logs) in each municipality of Chile. Panel (a) shows the relationship for the whole country, whereas Panel (b) restricts the sample to municipalities located in the North Region of Chile. As can be seen, NDVI and total cultivated area for agriculture purposes seem to be positively and strongly correlated across municipalities in Chile in general, but also in the North of the country. This positive correlation provides evidence of the validity of the utilization of NDVI as a proxy measure of agricultural activity in the areas close to the ASF.

A first overview of the relationship between lithium extraction and NDVI in the area surrounding the ASF is presented in Figure 7. In this figure, we show a non-parametric estimate of the relationship between changes in the NDVI between 2013 and 2020 for each $300m \times 300m$ pixel and the distance to the ASF. It is expected that those areas located closer to the ASF are the ones in which the change in the NDVI level should be more negative.

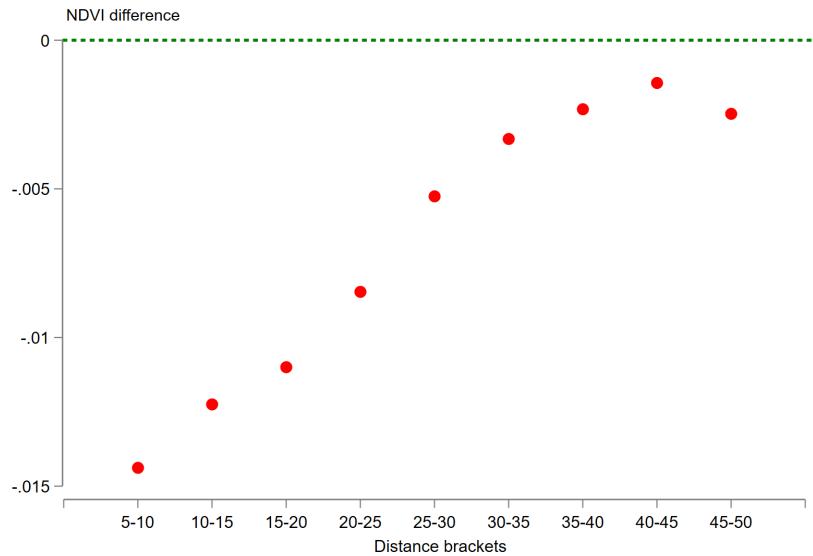
As can be seen in Figure 7, there seems to be a significant decrease in the NDVI for those areas located in a radius of 5 to 40 kilometers to the ASF of up to 0.015 NDVI units. In the next section, we will show our preferred empirical specification in which we will include control variables that will allow us to compare the effect between different pixels with close proximity over time. However, as we will show, results remain robust and consistent with Figure 7 shown here.

Figure 6: Relationship between NDVI (2010) and Total Cultivated Area (2007)



Notes. Figure (a) shows the binscatter between the average NDVI in 2010 in each one of the 287 municipalities for which there is information available in the Agricultural Census in 2007 and the total agricultural cultivated area (in logs). Figure (b) shows the same information but restricts the sample to municipalities in the North of Chile (Antofagasta Region, Arica y Parinacota Region, Atacama Region, Tarapacá Region, and Coquimbo Region). Source. Own elaboration based on data from the 2007 Agricultural Census and Landsat 8 Collection 1 Tier 1 Annual NDVI Composite measure.

Figure 7: Non-parametric relationship between distance to ASF and NDVI change, 2013-2020

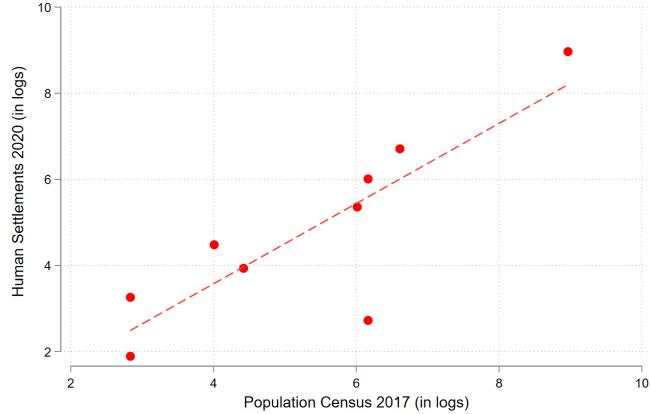


Notes. The figure shows the scatterplot smoothed relationship between the NDVI measure change over the 2013-2020 period in each 300m × 300m pixel surrounding the ASF and the corresponding distance to it. Source. Own elaboration based on data from Landsat 8 Collection 1 Tier 1.

Additionally, we validate that the Global Human Settlement Layer constitutes a good proxy of

actual population within the villages surrounding the ASF. To do that, we correlate the human settlements in 2020 to the population census in 2017, i.e. the two cross-sections that are close to each other at the end of our period of interest. As shown in Figure 8, the two measures are indeed correlated.

Figure 8: Relationship between human settlements estimation and population in the ASF



Notes. This Figure shows the binscatter between the total estimate of people within each of the 9 localities that are populated in 2020 and the total number of people reported in each of these localities in the 2017 census (in logs). Source. Own elaboration based on data from the Global Human Settlement Layer and the 2017 Chilean census.

4 Empirical strategy

The empirical strategy can be divided into two parts. First, we study the impact of the exposure to lithium extraction on the water levels in the region surrounding the ASF. To do so, we estimate a difference-in-differences specification. We compare the evolution of the water levels for measurement wells around the SQM mine in the ASF to the evolution of those installed by the DGA in the northern region of the country over time. We use 2013 as the cutoff, as it is the year in which the lithium production activity carried out by SQM in the ASF started to significantly increase. More specifically, we estimate the following equation:

$$y_{it} = \alpha + \sum_{t=2010}^{2019} \beta_t W_i D_t + \sigma_i + \rho_t + \varepsilon_{it} \quad (1)$$

Here, y_{it} is an index of the static level (2010 = 100) in each well i and year t . We use an index as opposed to the raw static level values to avoid problems with the differences in the measurement units across wells in our sample. W_i is a dummy variable that takes a value equal to 1 if the measurement

well i is located in the ASF region and 0 otherwise; D_t is a vector of time dummies for the years between 2010 and 2019; finally, σ_i and ρ_t are well and year fixed-effects. Our coefficients of interest are β_t which indicate the annual differences in groundwater levels between wells in the ASF and wells in locations far away from the lithium extraction activities. Finally, ε_{it} captures the measurement errors of our specification, which are clustered at the well level.

To allow for more flexibility in our difference-in-differences specification, we follow [Miller \(2023\)](#) and do not impose that a specific year has to be equal to 0, i.e. what is commonly known as the baseline period. Instead, we impose that the average of all coefficients β_t between 2010-2013 has to be equal to 0, allowing us to obtain less noisy estimates.

In the second part, we estimate the impact of exposure to lithium extraction on NDVI, nighttime light radiance, and human settlements. To do this, we estimate the following equation:

$$y_{ijt} = \alpha + \beta I_{ijt} + \Gamma[X_{ij} \times \rho_t] + [\delta_j \times \rho_t] + \phi_{ij} + \varepsilon_{ijt} \quad (2)$$

Here, y_{ijt} is the average annual NDVI (in logs) for each 300m \times 300m pixel i located in each locality j , the average annual nighttime light radiance (in logs) in each 500m \times 500m pixel, or the average annual number of people in each five year period (in logs) in each 100m \times 100m pixel.⁶ We define our variable of interest I_{ijt} as follows:

$$I_{ijt} = \frac{V_t}{\min\{D_{ij1}, \dots, D_{ij5}\}} \quad (3)$$

Where we have that D_{ijk} indicates the distance between each pixel i in locality j and each freshwater extraction well k in the ASF, where $k \in [1, 5]$. Hence, the denominator of I_{ijt} captures the minimum distance between each pixel and the extraction of water near the ASF. V_t is the total sales of electric vehicles in the U.S., Europe, and China, which is arguably exogenous and does not affect directly the level of vegetation in the ASF through channels other than lithium extraction. Additionally, as we showed above, it is strongly correlated with the amount of lithium production in the area. Therefore, the variable I_{ijt} captures the exposure of each pixel i to the lithium extraction and demand.

Finally, $[\delta_j \times \rho_t]$ are locality fixed-effects interacted with year fixed-effects, ϕ_{ij} are pixel fixed-effects and $[X_{ij} \times \rho_t]$ is a vector of controls in which we interact the latitude, longitude, and elevation of each pixel i with time fixed-effects. Therefore, in our identification strategy, we compare changes in our

⁶ Due to data availability limitations, we do not have annual data for human settlements. Instead, we have data in 5-year periods, hence we utilize the average number of people per cell in each of the three available years, i.e. 2010, 2015, and 2020.

outcome variables over time with exposure to lithium extraction for pixels within the same locality, with similar latitude and longitude, and with similar elevation.

Our coefficient of interest is β , which shows the effect of our measure of exposure to lithium extraction on the outcome variable. Our error terms are clustered on the pixel level. Considering that the outcomes might be spatially and serially correlated, we also show our main results, adjusting the p-values taking into account this potential spatial and serial correlation following the [Conley \(1999\)](#) and [Hsiang \(2010\)](#) approaches. In our main specifications, we consider a serial correlation with a full-period length and a spatial correlation that follows a Bartlett kernel with a distance cutoff of 500 meters, vanishing as we move farther away from each pixel i . In our robustness checks, we show the sensitivity of our results to the distance cutoff for the spatial correlation.

The identification assumptions in this empirical strategy are two: on the one hand, we argue that the time-varying component of our independent variable of interest V_t is exogenous because it is driven by external factors. In short, the variation in the production of lithium in Chile is demand-driven by the consumption of EVs in Europe, the U.S., and China, which is, in turn, exogenous to our outcome variables in the ASF region. On the other hand, we control for locality, elevation, and coordinates interacted with year fixed-effects. Hence, we compare changes over time in the outcomes explained by the exposure to the extraction of lithium for pixels that are very close to each other and with very similar elevation characteristics. Therefore, any differences in changes over time of our outcome variable cannot be explained by other unobserved confounders such as climate differences or extreme weather phenomena.

5 Main impacts of lithium extraction

5.1 The impact on groundwater levels

Our first results are related to the effect of lithium extraction on groundwater levels in the ASF area. The estimates are shown in Figure 9. Each point represents the difference in the static level index between treatment and control for each year relative to their average difference over the baseline period (2010-2013).⁷

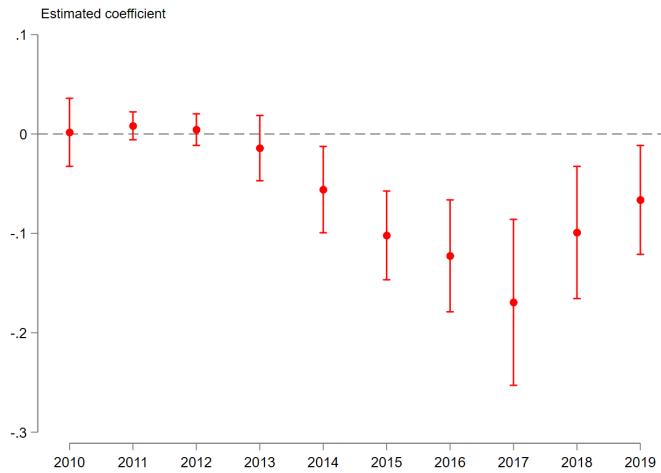
As can be seen, before the ramping up in lithium production (roughly in 2013), there was no statistically significant difference between the water levels of the two groups of wells. However, since then, the groundwater levels close to the ASF have been significantly reduced, reaching a maximum

⁷ For more details on the construction of the dependent variable, see the footnote of Figure 9.

negative impact of about 15% relative to baseline in 2017. Our estimates are in line with the descriptive evidence presented above, according to which, the levels of groundwater in the ASF dropped at a very high rate during the 2014-2017 period, recovering after 2017.

These results confirm the first step in the causal chain that we hypothesize in this paper, namely, that lithium extraction has a direct effect on water availability, which in turn affects vegetation and socioeconomic outcomes for the communities around the ASF.

Figure 9: Estimated effect of extraction of lithium on groundwater levels



Notes. This figure reports coefficients of a difference-in-differences regression based on Equation 1, where the dependent variable is an index (2010=100) of the static level of each well. The static level is defined as the distance between the ground surface and the water level for each well in meters. We calculate the 3-year moving average of the dependent variable to account for noise in the time series. Given that a higher value of the dependent variable implies a more adverse effect, we multiplied it by -1 to provide a more intuitive interpretation of the coefficient. The regression controls for well and year fixed effects. Standard errors are clustered on the well level. Source. SQM measurement well reporting and DGA.

5.2 The impact on vegetation

The next step in this analysis is looking at the effect of lithium extraction on vegetation. We do so by studying the impact on NDVI of each pixel of the identified localities in the region, where higher values of the dependent variable indicate healthier vegetation. Table 5 shows our main results.

In the different columns of Table 5 we sequentially include different combinations of control variables that allow us to confirm the causal interpretation of our coefficient. Our estimates indicate that a 1 standard deviation increase in the exposure to our measure of lithium extraction negatively affects vegetation (NDVI), by 0.2%. These results are robust and consistent even when taking into account the latitude and longitude of the different pixels in our sample. This remains true when controlling for shocks that affect pixels differentially over time based on their elevation.

Although the effects presented here are not directly comparable to those in existing economic literature, our estimates are in line with those of [Aragón and Rud \(2016\)](#) on the impact of mining activity on agricultural output in Ghana. The authors also find a negative effect, however pollution, not water management and utilization, is the main driver.

To put the degree of exposure to our measure in context, an increase in our independent variable can be achieved either by increasing the EV sales or by considering pixels closer to the freshwater extraction wells. For instance, a 1 standard deviation increase in our independent variable, for a fixed distance of 10km from the wells, implies an increase of EV sales by 700,000 units. Alternatively, the same increase, when fixing the number of EVs to 1 million, can be achieved by moving from a pixel 12km away from the wells to a pixel located at a distance of 5km away.

Table 5: Effect of Lithium extraction on NDVI

	(1)	(2)	(3)	(4)
Exposure to extraction	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)	-0.002*** (0.000)
Adjusted P-value	[0.000]	[0.000]	[0.000]	[0.000]
2013 NDVI Mean	0.076	0.076	0.076	0.076
Observations	199,096	199,096	199,096	199,096
Pixel FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Location FE \times Year FE	No	Yes	Yes	Yes
Coordinates \times Year FE	No	No	Yes	Yes
Elevation \times Year FE	No	No	No	Yes

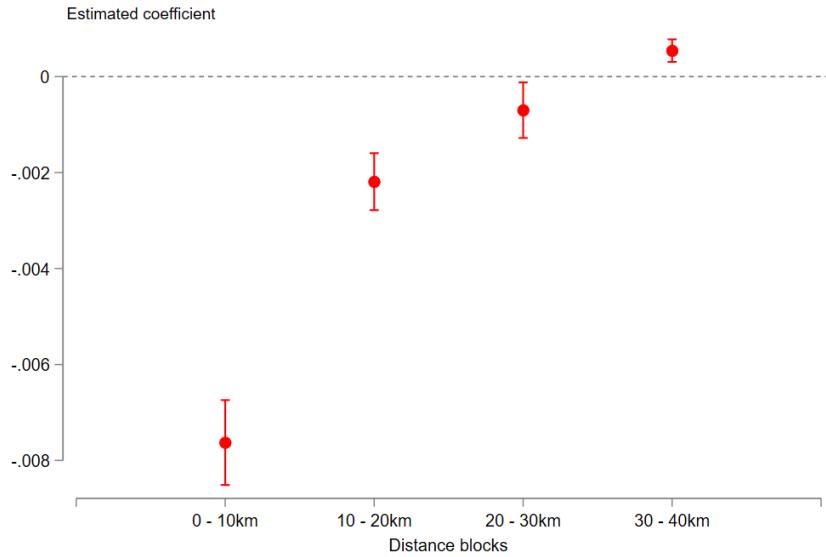
Notes. This table reports coefficients of a regression based on Equation 2, where the dependent variable is NDVI in logs. Pixel FE corresponds to a dummy variable for each pixel in our sample. Location FE corresponds to a dummy for each locality in our sample. Coordinate FE correspond to the latitude and longitude of each pixel in our sample, while Elevation FE to the elevation of each pixel from the sea level. Errors are clustered on a pixel level. Also, we report p-values considering a serial correlation with an 8-period length and a spatial correlation that follows a Bartlett kernel with a distance cutoff of 500 meters. Source. Own elaboration based on data from Landsat 8 Collection 1 Tier 1.

Alternatively, instead of considering a continuous measure of exposure to the extraction activity, we also employ a discrete measure that depends on distance blocks between the freshwater extraction wells and the pixels in our sample. To do so, we proceed as follows: First, we split the pixels in our sample into five bins of 10 km each. Second, we interact the distance dummies with total sales of EVs (V_t in our main specification), which is expressed in standard deviations. Hence, we analyze how this exposure to the demand for lithium worldwide affects different pixel blocks based on the distance to

the freshwater extraction wells around the ASF. In doing so, we consider the furthest distance block, namely those pixels between 40 km and 50 km away, as our baseline group. We run a regression of the NDVI over time on these interacted dummy variables, including the same controls presented in our main specification (locality-year fixed effects, coordinate-year fixed effects, and elevation-year fixed effects).

Figure 10 shows the main results of this exercise. The plotted coefficients should be interpreted as the differential effect of the exposure of each distance block to the extraction activity, relative to the effect on the baseline group. As can be seen, the closer the pixels are to the freshwater extraction wells, the more negative the impact on vegetation over the 2013-2019 period. For the closest distance block, we find a reduction in vegetation of about 0.8% relative to the 40-50km distance block. The size of this impact is four times higher than that for the next distance block, i.e. the 10-20km group.

Figure 10: Estimated effect of exposure to extraction activity by distance blocks

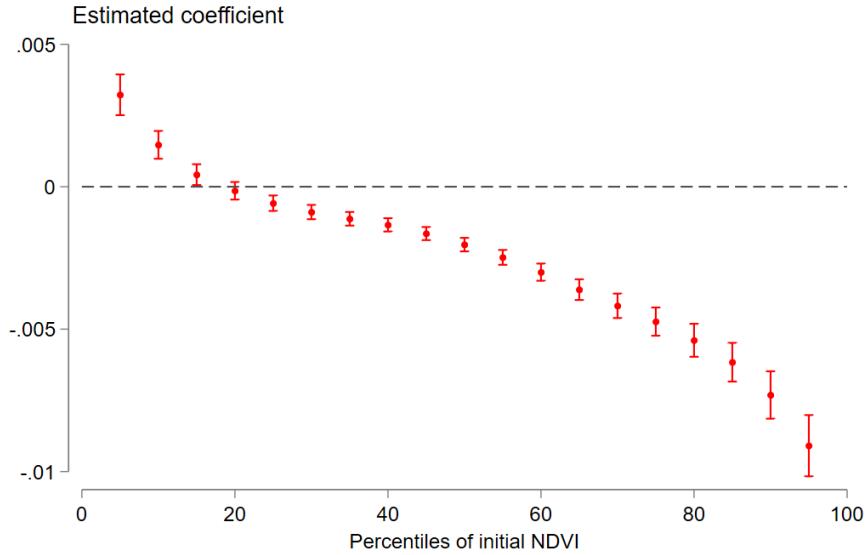


Notes. This figure reports coefficients of a regression of NDVI (in logs) on distance block dummies, interacted with EV sales in standard deviations. The omitted baseline group is the 40-50km block. The regression controls for locality-year, coordinate-year, and elevation-year fixed effects. Standard errors are clustered on a pixel level. Source. Own elaboration based on data from Landsat 8 Collection 1 Tier 1.

These results are consistent with the nature of the variation considered in this paper, where we expect that the impact on vegetation will be larger for the pixels located closer to the freshwater extraction wells. They are also consistent with the descriptive evidence presented above in Figure 7 where we show that the negative difference in vegetation between 2013 and 2019 was larger for the pixels between 5km and 40km away from the center of the flat.

Additionally, we analyze whether or not the impact of the exposure to extraction activity on vegetation varies according to the level of vegetation of the pixels in our sample in 2013. To do so, we take advantage of the panel structure of our data and interact our independent variable of interest with the NDVI of each pixel i in 2013. We show those results on heterogeneous effects in Figure 11.

Figure 11: Estimated effect of exposure to extraction activity by baseline level of NDVI



Notes. Each point corresponds to the estimated effect according to the 2013 distribution of NDVI (in logs) across all pixels in our area of analysis. We run a version of equation 2 in which we interact the independent variable of interest with the NDVI in 2013 for each pixel (in logs). The regression controls for locality-year, coordinate-year, and elevation-year fixed effects. Standard errors are clustered on a pixel level. The 90% confidence intervals are also plotted. Source. Own elaboration based on data from Landsat 8 Collection 1 Tier 1.

Our estimates demonstrate that the negative impact of lithium extraction on vegetation was mainly concentrated in those pixels that were greener at the beginning of our analysis period (2013). For instance, according to our results, the impact on the pixels located in the 80th percentile of the 2013 NDVI distribution was more than double compared to that on the pixels in the median of the same distribution.

As we showed in Figure 6, NDVI serves as a good proxy of agricultural activity in the region. Hence, the larger effect in the greener areas at baseline is consistent with our hypothesis that the areas that were more dependent on agriculture were more severely affected.

5.3 The socioeconomic impacts

Motivated by our previous findings that the areas strongly dependent on agriculture were affected the most, we turn to the effect on economic activity as proxied by nighttime light radiance data and the stock of population in the ASF region. To perform our analysis, we implement the same specification outlined before in equation 2. However, for the socioeconomic impacts presented in this subsection, we restrict our sample only to the 9 out of 20 localities in our sample that were human settlements (i.e. not National Reserves).

In Table 6, we show the estimated impact on economic activity proxied by nighttime light radiance. Two main features of our estimates are worth mentioning. First, independently of the specification that we consider, the estimated impact of the exposure to lithium extraction on economic activity is negative and statistically significant. Second, controlling for locality-time fixed effects seems to be relevant in our case, as it significantly increases the magnitude of our estimated effect. This is expected given that, in this case, we compare pixels within the same localities that are close to each other and, therefore, do not have important differences in their economic performance.

In our preferred specification in column (4) of Table 6, we find a reduction of 2.6% in the economic activity of the ASF communities for a 1 standard deviation increase in our measure of exposure over the period in question. These results are in line with part of the economic literature. For instance, in the case of Ghana, [Aragón and Rud \(2016\)](#) find that exposure to mining activity increased poverty rates within a 20km radius around the gold mines. In our case, we find a negative impact on economic activity, which, similar to the poverty rate, is a proxy for well-being.

Finally, it is important to consider that our estimates capture the net impact on economic activity in the region. It is expected that mining companies in this area of Chile also create a demand shock and positive economic and social spillovers for the communities in the ASF. For instance, according to information provided to us by SQM, the company has been involved in educational, economic, and social initiatives that could have potentially positively impacted the living standards of the communities in the region. Therefore, as [Aragón and Rud \(2016\)](#) emphasize for the case of gold mining in Ghana, our estimates show that those efforts have not been able to compensate for the negative impacts on the surrounding localities caused by the extraction activities.

Table 6: Effect of Lithium extraction on Nighttime Light Radiance

	(1)	(2)	(3)	(4)
Exposure to extraction	-0.010*** (0.002)	-0.004*** (0.002)	-0.018*** (0.006)	-0.026*** (0.006)
Adjusted P-value	[0.000]	[0.008]	[0.003]	[0.000]
2010 Dep. Var. Mean	0.299	0.299	0.299	0.299
Observations	17,104	17,104	17,104	17,104
Pixel FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Location FE \times Year FE	No	Yes	Yes	Yes
Coordinates \times Year FE	No	No	Yes	Yes
Elevation \times Year FE	No	No	No	Yes

Notes. This table reports coefficients of a regression based on Equation 2, where the dependent variable is nighttime light radiance. Pixel FE corresponds to a dummy variable for each pixel in our sample. Location FE corresponds to a dummy for each IVA in our sample. Coordinates FE corresponds to the latitude and longitude of each pixel in our sample, while elevation FE to the elevation from sea level of each pixel. Errors are clustered on a pixel level. Also, we report p-values considering a serial correlation with an 8-period length and a spatial correlation that follows a Bartlett kernel with a distance cutoff of 500 meters. Source. Own elaboration based on data from VIIRS Nighttime Day/Night Annual Band Composites.

The next step in our analysis relates to the impact of exposure to lithium extraction on human settlements and the local populations in the ASF. As shown above, the reduction in water availability and vegetation caused by this exposure led to a negative impact on the living conditions of people in the region, as measured by the drop in economic activity. Given this result, it is expected that such a negative impact on the economic conditions of surrounding localities could have affected the population dynamics in the region, possibly translating into a flight of people out of these areas. Hence, we turn to the effect of exposure to lithium extraction on the stock of the local population.

The results of our specification with regards to human settlements are shown in Table 7. In our preferred specification in column (4), there seems to be a negative effect of 1.5% on the stock of people in local villages for a 1 standard deviation increase in our measure of exposure to lithium extraction. This effect aligns with the impact on the economic activity in the region under study, while the coefficient is smaller compared to the estimates using the nighttime light radiance as an outcome variable. This is expected given the, potentially, lower sensitivity of mobility decisions.

Additionally, this estimated effect is consistent with census data related to the migration of people from SPdA to the rest of the country. According to the censuses of 2002 and 2017, the number of people who 5 years ago resided in SPdA and at the point of the survey live in a city outside of the

Antofagasta Region (the region SPdA belongs to) increased from 197 in 2002, to 840 in 2017. If we express these numbers relative to the population of SPdA in each census, the corresponding figures are 3.9% and 7.6%, for 2002 and 2017 respectively. These values indicate a significant change in the outflow of people from SPdA to the rest of the country, which is in line with the impacts outlined in this paper.

Table 7: Effect of Lithium extraction on human settlements

	(1)	(2)	(3)	(4)
Exposure to extraction	-0.004*** (0.000)	-0.002*** (0.000)	-0.022*** (0.001)	-0.015*** (0.001)
Adjusted P-value	[0.000]	[0.000]	[0.000]	[0.000]
2010 Dep. Var. Mean	0.162	0.162	0.162	0.162
Observations	125,892	125,892	125,892	125,892
Pixel FE	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No
Location FE \times Year FE	No	Yes	Yes	Yes
Coordinates \times Year FE	No	No	Yes	Yes
Elevation \times Year FE	No	No	No	Yes

Notes. This table reports coefficients of a regression based on Equation ??, where the dependent variable is the change in human settlements (in logs) between 2020 and 2010. Location FE corresponds to a dummy for each IVA in our sample. Coordinates controls correspond to the latitude and longitude of each pixel in our sample, while elevation controls to the elevation from sea level of each pixel. Also, we report p-values considering spatial correlation that follows a Bartlett kernel with a distance cutoff of 500 meters. Source. Own elaboration based on data from Global Human Settlement Layer and own estimates.

This last piece of evidence goes in line with the hypothesis that exposure to lithium extraction not only had an environmental impact in terms of water availability and vegetation, but also impacted the quality of life for communities around the ASF through a reduction in agricultural yields (as proxied by the NDVI). This, in turn, led some of the inhabitants to seek alternative income sources out of those communities.

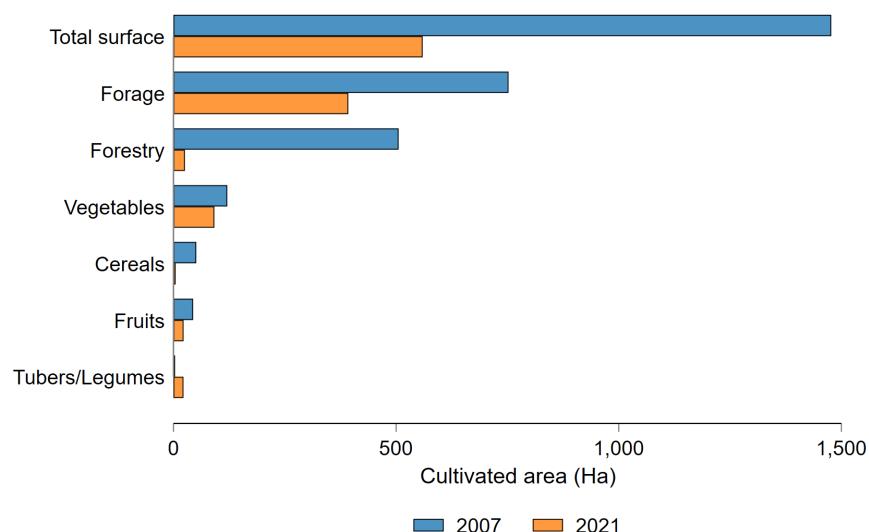
6 Mechanisms: Evolution of local agricultural activity

In this section, we present descriptive and suggestive evidence derived from the Chilean Agricultural censuses from the years 2007 and 2021. The objective is to shed light on potential mechanisms contributing to the adverse effects of lithium extraction activity on vegetation and human settlements within the region. Considering the limited granularity of available information regarding agricultural

activity in the ASF, it is not feasible to generate comparable results to those presented in the preceding section. Nevertheless, we can provide evidence of the trends in agricultural performance of individuals residing in the SPdA municipality overall (which groups the local communities analyzed above).

The primary hypothesis posited in this paper asserts that the water-intensive nature of lithium extraction in the ASF may have led to a decline in groundwater levels in the area. This, in turn, could have had adverse effects on vegetation, both on the endemic flora of the region and on vegetation closely associated with agricultural activities. As can be seen in Figure 12, based on data from the Agricultural Census, the predominant vegetation in the region in 2007 (before the ramp-up of the lithium extraction) consisted mainly of forage plants and endemic species (labeled as Forestry in the figure), with a limited presence of vegetables, cereals, fruits, and legumes.

Figure 12: Evolution of activity in the Agricultural sector - SPdA, 2007-2021



Source. Own elaboration based on the 2007 and 2021 Agricultural Censuses of Chile.

Analyzing the changes in cultivated surface for various crops between 2007 and 2021 (the period in which lithium extraction activities intensified in the region), Figure 12 illustrates a significant and noteworthy reduction in the cultivated area. As can be seen, it diminished substantially from approximately 1,500 hectares in 2007 to just over 500 hectares in 2021. A closer examination of the primary contributors to this reduction reveals that forage and forestry played pivotal roles. The cultivated area for forage, for instance, witnessed a nearly 50% decline from 2007 to 2021. Remarkably, the forestry and endemic crops in the region experienced a drastic decline, virtually disappearing over the period.

between the two censuses.

Upon analyzing the crops predominantly affected by the decrease in cultivated areas close to the ASF, Table 8 reveals that the decline in forage and forestry crops can be attributed primarily to the diminished presence of Alfalfa and Tamarugo, both species with particular features that make them resilient to the adverse climate of the ASF.

Table 8: Variation in cultivated area by main crops - SPdA, 2007-2021

	2007	2021	Difference
Forage	752.43	392.58	-359.85
Alfalfa	749.94	392.08	-357.86
Forestry	505.53	25.50	-480.03
Tamarugo	505.53	11.80	-493.73
Vegetables	120.68	91.81	-28.87
Corn	82.91	69.33	-13.58
Cereals	51.09	4.67	-46.42
Corn	25.98	3.15	-22.83
Fruits	43.99	22.59	-21.40
Pear	14.89	12.82	-2.07
Tubers/Legume	3.55	22.35	18.80
Potato	3.55	16.55	13.00

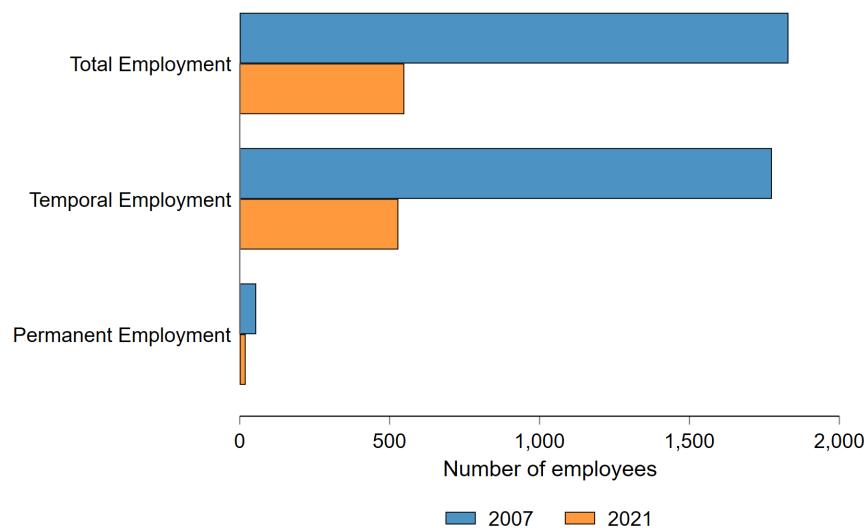
Source. Own elaboration based on the 2007 and 2021 Agricultural Censuses of Chile.

On the one hand, Alfalfa, a distinctive crop thriving in the region, exhibits remarkable adaptation to the aridity of the desert locale due to its long taproots and its crucial role for the maintenance of livestock of the local producers (Ovalle et al., 2015; Sepúlveda Rivera et al., 2015). Tamarugo, on the other hand, is a particularly threatened species, undergoing a significant reduction over the same period. A distinctive feature of the Tamarugo tree is its endemic nature (Chávez et al., 2013). It has developed unique characteristics to adapt to the arid conditions of the Atacama desert. More specifically, Tamarugo has a “dual root system”, with both deep roots that reach the phreatic levels to access underground water, as well as a “dense superficial root mat”. This way, it can transfer water from the groundwater to the mat system, store it there, and optimize its consumption (Mooney et al., 1980;

Sudzuki, 1985). Hence, the abundance of groundwater in the region has historically been documented to affect the Tamarugo population (Chávez et al., 2016; Decuyper et al., 2016).

Per our approach, the observed decline in vegetation can be attributed to the water-intensive mining activities which, in turn, lead to a reduction in groundwater levels. This happens as those activities may impact the ability of vegetation to access sufficient water beneath the ground, consequently affecting their reproduction and diminishing green areas within the region.

Figure 13: Evolution employment in the Agricultural sector - SPdA, 2007-2021



Source. Own elaboration based on the 2007 and 2021 Agricultural Censuses of Chile.

Finally, as demonstrated earlier, lithium extraction appears to have adversely affected human settlements in the region. This impact could be attributed to the challenging conditions arising from reduced water availability in the area. This is not only due to the reduction in potable water for consumption, but also due to (a) the reduction of water available for irrigation and (b) the direct influence that the reduction of groundwater might have had on vegetation. Figure 13 provides supporting evidence in this direction. It illustrates a notable decline in agricultural employment in SPdA during the 2007-2021 period, primarily driven by a decrease in temporary employment from almost 2,000 to nearly 500 employees. This decline aligns with the reduction in vegetation, the increasingly unfavorable conditions for vegetation growth, the negative impact on economic activity, and the consequent effects on the population dynamics in localities close to the ASF, as highlighted in the main results of the paper.

Our findings indicate that lithium extraction activity reduces water availability in the vicinity of the ASF. This adversely impacts both the vegetation and the local population in the region. This section offers suggestive evidence supporting our earlier causal findings. Specifically, during the 2007-2021 period, a timeframe characterized by a boom in lithium extraction and an increase in water utilization by mining companies, the ASF community experienced a significant decline in agricultural activity and crop-cultivated areas. Descriptive evidence reveals a substantial reduction in the agricultural workforce during the period in question, aligning with the results on the reduction of human settlements and nighttime light radiance in the region.

7 Robustness Checks

In the Appendix, we test the robustness of the results of our main specifications. First, in Figure A.1 of Appendix A.1 we test the robustness of our difference-in-differences water levels specification to alternative definitions of the control group. More specifically, instead of comparing the wells around the ASF to all measurement wells of DGA in the North of Chile, we restrict the control to (a) the North of Chile without Arica and Parinacota, (b) the North without Antofagasta, and (c) the North without Tarapacá. The results remain quite robust regardless of the specification.

Furthermore, in Figure A.2 of Appendix A.1 we test the robustness of the results on NDVI, nighttime light radiance, and human settlements for different values of the distance cutoff in the Bartlett kernel of spatial correlation adjustment. We show the t-statistic of the lithium extraction exposure coefficient of our preferred specification for each of the main outcomes (i.e. the specification in which we control for locality-, coordinate-, and elevation-time fixed effects). More specifically, we vary the distance cutoff from 500 to 1,200 meters at increments of 100 meters and present the t-statistic. All our results remain virtually the same in this robustness check.

8 Final Remarks

The energy transition is a predominant goal for governments around the world and lithium is an important component of that transition. It has also developed into a key raw material for the Chilean economy and the creation of a future roadmap for its exploitation is at the forefront of public discussion in the country and the region. However, the environmental and socioeconomic consequences of lithium extraction on local areas and populations are not yet clear and there is no consensus on that matter within the scientific community.

In this paper, we aim to contribute to this debate by providing causal evidence of the environmental and socioeconomic impact of lithium extraction in areas around the ASF. Several important takeaways emerge from our analysis. First, we find that the exposure to lithium extraction activity had a negative impact on water availability and vegetation in the surrounding areas. This, in turn, translated into a worsening of the living conditions of the population in that region, affecting economic activity and reducing the number of people living there.

Notwithstanding the evidence we provide in this paper, it should be stressed that a life-cycle cost-benefit analysis would also be important to complement our results. First, lithium extraction has positive economic impacts for the economies that exploit this raw material. For the case of Chile, lithium is a major export commodity and an important source of revenue. According to information from the Central Bank of Chile, exports of lithium carbonate represented about 0.8% of total exports on average during the 2013-2021 period, while in 2022 this share grew to about 8%. This makes lithium the second most important commodity exported by the country right after copper, which represents about 45% of Chilean exports. On the other hand, lithium extraction leads the mining activity in the country, representing about 3.4% of Chilean GDP and experiencing a real growth of 10.4% in 2022. Given this, it represents a key source of economic resources for the country, which could be invested in social public policies, education, and health that might contribute to the development of the Chilean population in the future. Second, lithium also plays a key role in the energy transition, a process that is necessary for tackling climate change globally. It is important to understand the scope and magnitude of the negative impacts in order to carry out a complete analysis of the supply-chain of lithium.

Both aspects, i.e. the benefits that lithium extraction might represent and the potential environmental and economic costs for the populations surrounding the ASF must be taken into account when implementing optimal public and social policies. When approaching this matter, it is also key to consider two additional components. First, most of the people living in the ASF belong to indigenous communities that have a special and particular status under the law in the country and around the world. Therefore, when weighing the potential negative effects for these communities, it is worth considering that they must receive particular attention. Secondly, it is important to take into account the environmental value of the ASF as an ecosystem, and how any negative implications in terms of vegetation, wildlife abundance, and water availability that lithium extraction activities might entail, could be amplified.

Our analysis sheds light on a crucial matter for Chile, however, the implications are also relevant for the other countries located in the *Lithium Triangle*, namely Bolivia and Argentina. It is important that

policymakers take into account the potential negative environmental and economic effects that might come with lithium extraction, in order to address them and compensate the affected communities moving forward.

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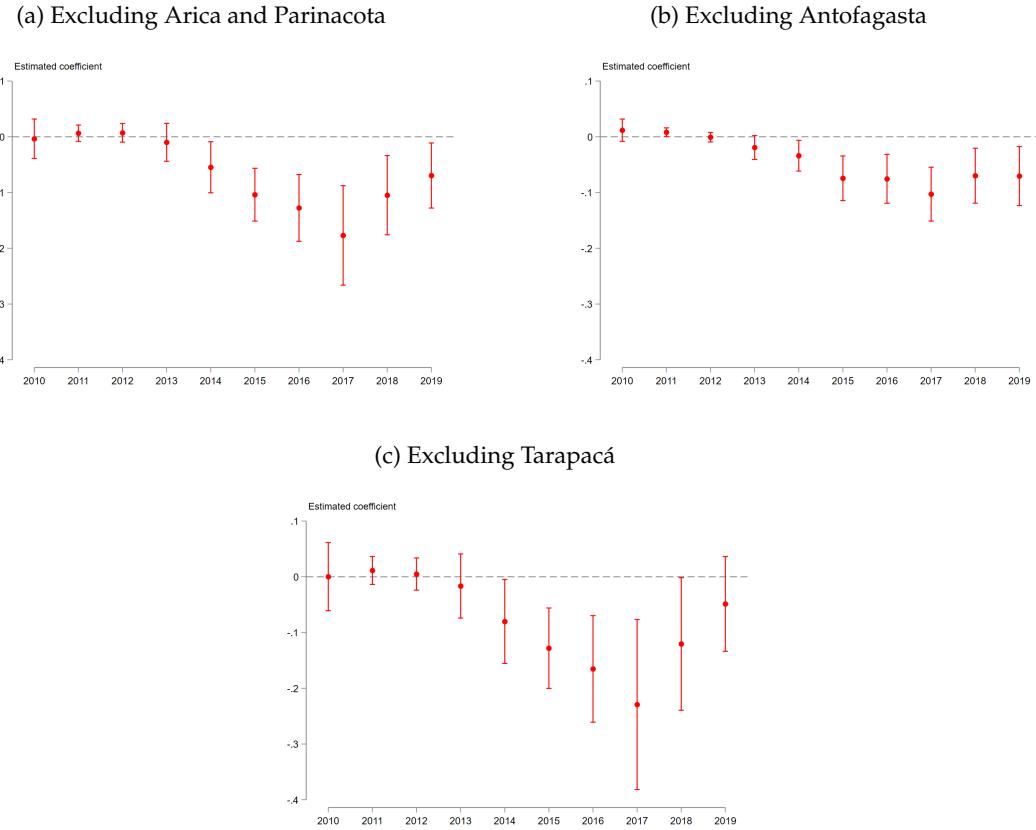
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A Appendix

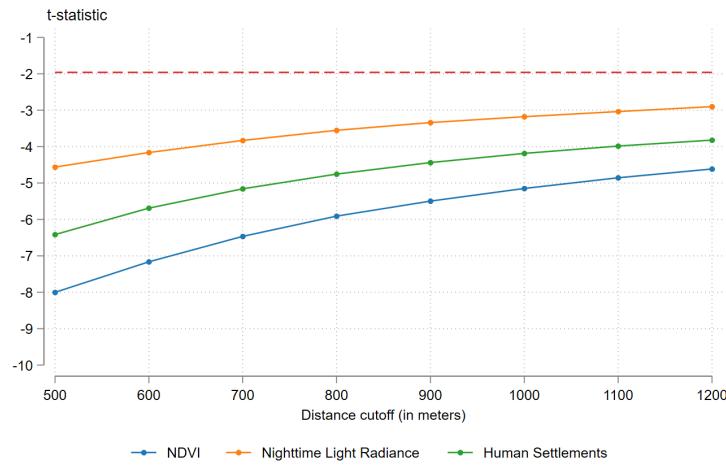
A.1 Robustness checks

Figure A.1: Robustness of the effect of the exposure to the extraction of lithium on wells levels for different control groups



Notes. This figure reports coefficients of a difference-in-differences regression based on Equation 1, where the dependent variable is an index (2010=100) of the static level of each well. The static level is defined as the distance between the ground surface and the water level for each well in meters. We calculate the 3-year moving average of the dependent variable to account for noise in the time series. Given that a higher value of the dependent variable implies a more adverse effect, we multiplied it by -1 to provide a more intuitive interpretation of the coefficient. The regression controls for well and year fixed effects. Each panel introduces a different definition of the control group, by excluding a region. Standard errors are clustered on the well level. Source. SQM measurement well reporting and DGA.

Figure A.2: Robustness of the effect of extraction of lithium on NDVI, nighttime light radiance, and human settlements



Notes. This figure presents the t-statistics of our preferred specifications (in which we control for locality-time, coordinates-time, and elevation-time fixed effects) when altering the distance cutoff of the Bartlett kernel from 500 meters to 1.2 kilometers, for NDVI, nighttime light radiance, and human settlements. Source. Own elaboration based on data from Landsat 8 Collection 1 Tier, Global Human Settlement Layer, and VIIRS Nighttime Day/Night Annual Band Composites

A.2 Identification and construction of localities

In our analysis, we restrict our sample to 20 localities around the ASF. This section serves to explain the method followed to identify those localities and to define their area. We begin by obtaining the coordinates of the ASF and defining a radius of 50km around it. Next, we query the online tool of the Chilean census for all populated areas around the ASF and within the ASF. The populated areas returned are all within the commune of SPdA. The specific localities returned are San Pedro de Atacama, Camar, Talabre, Toconao, Peine, and Socaire. While Pocor and Zapar fit under the locality of Toconao, we split this into three localities of Pocor, Zapar, and Toconao separately, given that they are far away from each other. Additionally, we realize the Tilomonte is referenced in other literature as an additional locality around the ASF, hence we include it in our analysis.

After completing this process, we end up with 9 populated areas around the ASF. Consequently, we query them on OpenStreetMap and we draw rectangles that encompass all the visible settlements and vegetation around the said areas. We use those rectangles as the specified areas of analysis. It is worth noting that we do not consider Campamento Andino, which is a community dedicated to employees of mining companies.

Next, we identify the Natural Reserves around the ASF. Again through OpenStreetMap, we are able to view the defined borders of the Natural Reserves and we draw rectangles that enclose those borders in order to simplify the process of data collection. We end up with 11 Natural Reserves, namely Valle de la Luna, Tambillo, Tebenquiche, Soncor, Quelana, Science preserve, Miscanti and Miñiques, Laguna Lejia, and Salar de Pujsa. All resulting rectangles, used as shapefiles, are part of the Online Appendix.

A.3 Technical appendix

This section serves to provide a top-level overview of water balance calculations. To comprehensively examine the impact of water extraction in a specific area or region, it is essential to explore the details of its water balance and the hydrogeological system it encloses. In this context, we focus on the ASF basin, through the use of a conceptual model, to elucidate the underlying processes operating within the broader earth-atmosphere system. This conceptual framework can also be encapsulated mathematically, through what is typically referred to as the water balance equation. The water balance equation provides a simple mathematical depiction of the hydrogeological phenomena at play over a defined time frame, encompassing the fundamental principles of mass and energy balance ([Davie, 2019](#)). The fundamental equation can be expressed as follows:

$$\text{Recharge}(R) - \text{Discharge}(D) = \text{Change in storage}(\Delta S) + \epsilon \quad (\text{A.1})$$

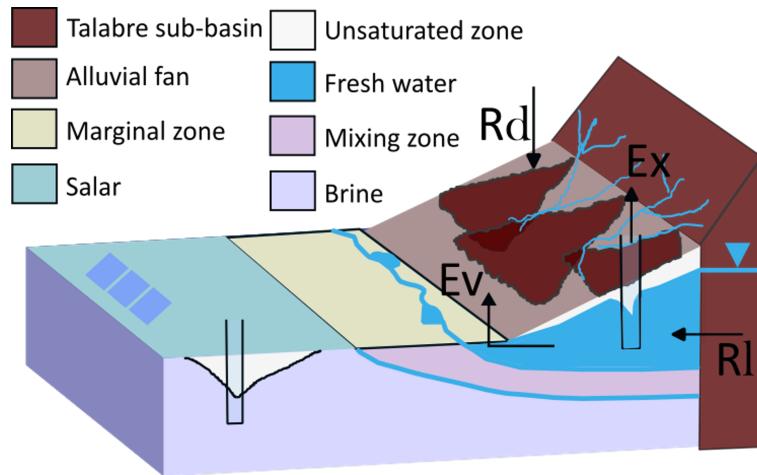
Now, further breaking down the recharge and discharge components, we can re-write equation [A.1](#) as follows:

$$Rd + RO + RI - EVS - EVL - EVT - EXT = \Delta S + \epsilon \quad (\text{A.2})$$

where Rd is the direct recharge from precipitation, RO is the runoff, RI is the lateral recharge, EVS is the evaporation from the aquifer, EVL is the evaporation from the free water surface (such as ponds and lakes), EVT is the evapotranspiration, EXT is the extraction, ΔS is the change in storage, and ϵ is the error term. This water balance equation determines whether there has been a change in water storage (groundwater) over a specific measurement period and identifies potential factors contributing to this change. Figure [A.3](#) shows a conceptual model of the eastern border of ASF, depicting the various terms entering Equation [A.2](#).

To complement our empirical results on the impact of water extraction on water levels, we utilize the Environmental Impact Assessment report submitted by SQM in 2021. To calculate the water balance within ASF basin, “balance areas” were defined using specific criteria, including altitude, geographical location, and the type of fluid under analysis ([SQM S.A., 2021](#)). The last criterion holds particular importance as it divides the ASF basin into two distinct systems: the brine system and the water system.

Figure A.3: Conceptual model of ASF eastern border



Notes. Conceptual visualization of Equation A.2 for the eastern border of the ASF. Source. Adapted from [Floyd \(2021\)](#).

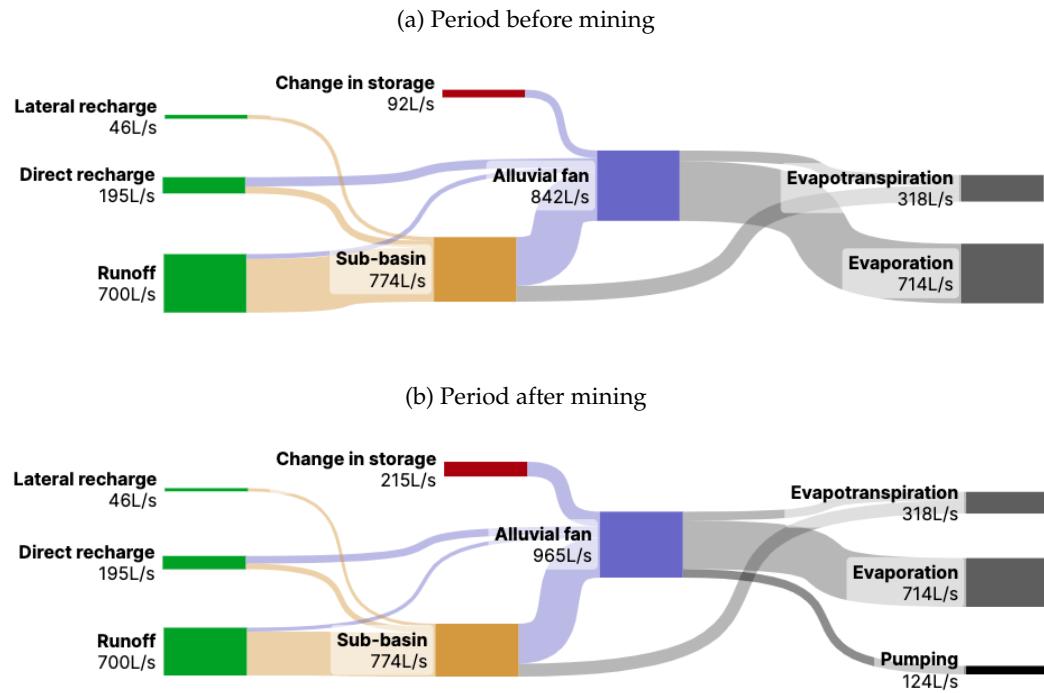
The sub-basin and alluvial fan areas within the ASF basin constitute the water system, as seen in Figure A.3. The marginal zone is a blend of brine and water, while the nucleus primarily contains brine. The balancing calculation, visualized in Figure A.4 incorporates data gathered from the Talabre and Socaire Sub-basins, as well as within the alluvial fan. Consequently, it enables the estimation of Recharge and Discharge along the East border of the ASF, from which SQM extracts water.

The water balance was calculated for a pre-operational scenario (1986-1994), considering the period before extraction began, and an operational scenario (1994-2019), representing the period of brine and industrial water extraction by SQM. It is important to highlight that pre-operational data is scarce ([SQM S.A., 2021](#)). Figure A.4 visualizes the water balance for the periods before and after mining, respectively, in the eastern sector for the Talabre and Socaire sub-basin areas and the alluvial fan. For the sub-basin, we see a positive balance with high Runoff as Recharge (R) and relatively slow EVT as Discharge (D). Consequently, a positive water balance is obtained, which will flow downstream as a Recharge of the alluvial fan area. There is neither evaporation nor pumping in the sub-basins in the pre-operational period (Figure A.4(a)). In the operational period (Figure A.4(b)) we see that there is extraction (D) of water by SQM through pumping wells. Consequently, there is a notable increase in Discharges. The water balance calculations reveal a larger change in water storage (ΔS), signifying a reduction in the volume of water stored within the system over the specified timeframe.⁸ It should be noted that, even in the absence of any human-induced water extraction during the pre-operational

⁸ It is worth noting that none of the (R) or (D) components, other than extraction, seem to change between the two periods as presented in the report.

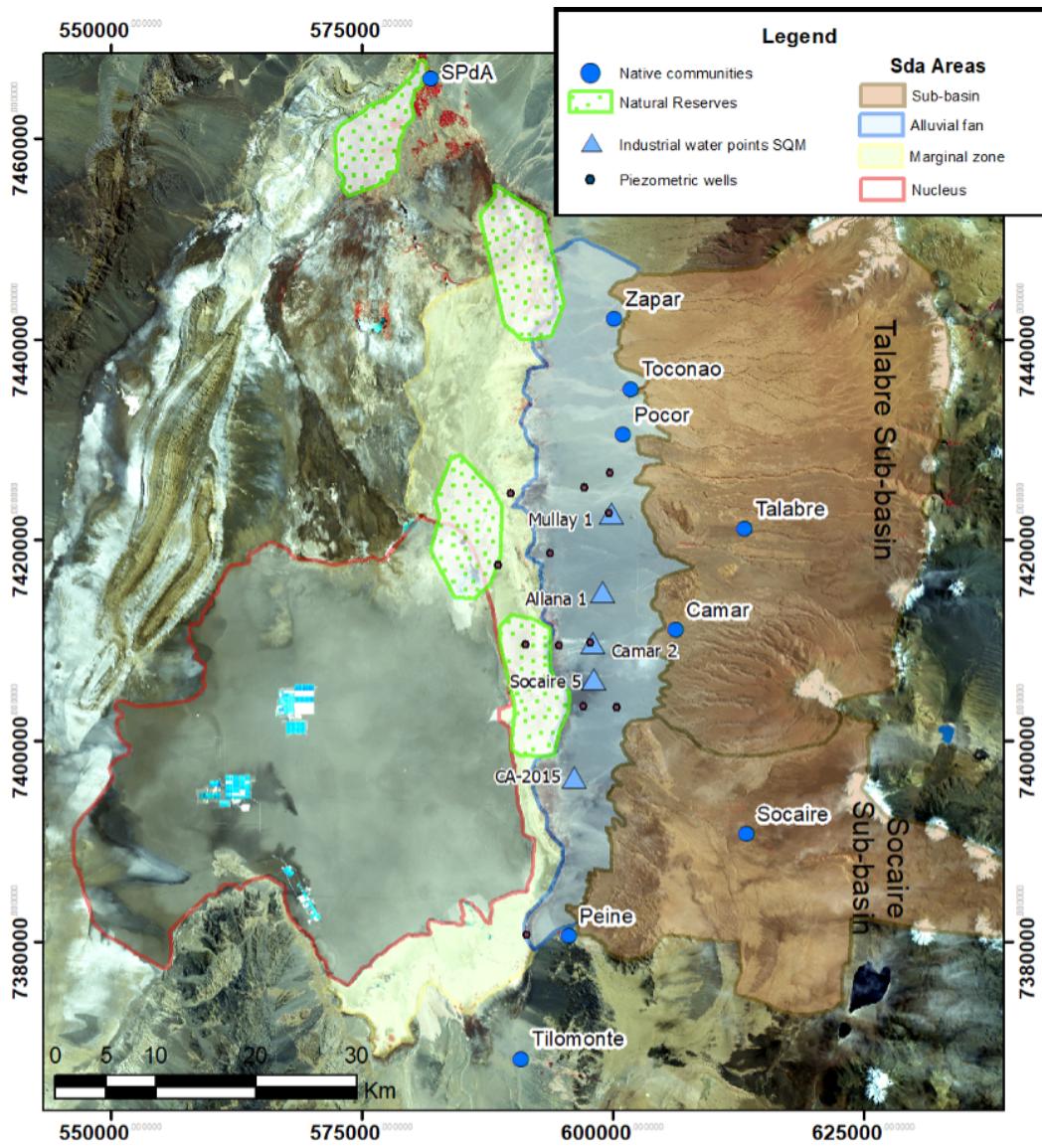
period, change in water storage (ΔS) was negative, as seen in Figure A.4(a), indicating a natural draw-down of the aquifers that was subsequently exacerbated by anthropogenic water pumping.

Figure A.4: Pre and post-operational water balance



Notes. This figure depicts the defined water balance areas of the ASF, including the sub-basin, alluvial fan, marginal zone, and nucleus. Also, it shows the locations of the communities analyzed in this paper, some of the natural reserves, as well as the industrial water points used by SQM. Source. Adapted from ([SQM S.A., 2021](#)).

Figure A.5: Sattelite image of ASF with defined water balance areas



Notes. Conceptual visualization of Equation A.2 for the eastern border of the ASF. Source. Adapted from [Vesilind \(2003\)](#).