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

Leonardo Peñaloza-Pacheco[†] Vaios Triantafyllou [‡] Gonzalo Martínez [§]

August 27, 2024

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 economic opportunities that possibly explain the population outflow from areas around the ASF and the drop in economic activity.

[*]We appreciate the comments and suggestions of Ryan Bailey, Todd Gerarden, Agustin Olivo, Juan Pablo Rud, Nick Sanders, Sunoj Shajahan, Mike White, and participants in seminars and conferences at Development Bank of Latin America and the Caribbean - CAF, Cornell University, Universidad Católica Argentina, the International Economic Association World Congress, the Research Institute for Development, Growth and Economics (RIDGE) Forum Workshop on Environmental Economics, the Eastern Economic Association Annual Meetings, the Midwest Economic Association Annual Meetings, as well as the Royal Economic Society Annual Conference. We also appreciate the funding received by the Development Bank of Latin America and the Caribbean - CAF.

[†]Cornell University and Center for Distributive, Labor and Social Studies (CEDLAS), IIE-FCE, Universidad Nacional de La Plata. E-mail: leopacheco93@gmail.com.

[‡]Cornell University. E-mail: vaios.tria@gmail.com.

[§]Université de Liege. E-mail: gonmartinez95@gmail.com

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

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 economic opportunities that possibly explain the population outflow from areas around the ASF and the drop in economic activity.

JEL Classification: Q13, Q15, Q25, Q32, Q56

Keywords: Environment, Water, Vegetation, 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 localities[1] around the ASF, obtained through satellite images, at a 300m$\times$300m resolution. Third, we use data on nighttime light radiance around the ASF, at a 500m$\times$500m resolution. Lastly, we use a database proxying the density of human settlements within the same localities around the ASF, again through satellite images, at a 100m$\times$100m 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, nighttime light radiance, and human settlements 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 U.S., 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 EV 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 2010-2019 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 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

[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.3.

in our measure of exposure reduced human settlements by 1.5%. The results are robust to adjusting for spatial correlation.

To shed light on the mechanisms driving these results, we provide suggestive evidence of the drop in agricultural activity during the 2007-2021 timeframe. 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 economic activity and human settlements.

To ensure that the effect we are capturing is causal and in fact driven by the increase in the exposure to lithium extraction over the period in question, we carry out two placebo exercises. First, we repeat our main analysis for the most comparable salt flat to ASF, the Pintados Salt Flat (PSF). In the case of PSF, we see no statistically significant coefficients on groundwater levels, vegetation, economic activity, or human settlements after adjusting for spatial correlation. Second, we replace the numerator of our measure of exposure in our baseline specification for the ASF (which is the sales of EVs in Europe, U.S., and China over the period 2010-2020) with the imports of lithium by the main importing countries in the preceding 10-year period, i.e. 1999-2009. Once again, we see no statistically significant coefficients on vegetation, economic activity, or human settlements after adjusting for spatial correlation.

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 NO_2, 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 extraction 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 subsequent 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 groundwater 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 pixel to lithium extraction, controlling for 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 U.S. 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 outlines a simple analytical framework for the economic effects of lithium extraction. Section 4 describes the data we use for our analysis. Section 5 outlines the empirical strategy implemented in the paper to estimate the effect of lithium extraction on the outcomes of interest. Section 6 provides the main results of our estimates. Section 7 provides suggestive evidence of the mechanisms driving those results. Section 8 describes some robustness checks. Finally, Section 9 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 A.1 in the Appendix). 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).[3]

In Chile, the most important salt flat is the ASF. This salt flat covers an area of 3,000 km^2, 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*. Consequently, Chile is one of the largest exporters of lithium worldwide and lithium is the second most important commodity exported by the country, after copper, representing roughly 45% of Chilean exports. Hence, mining activity in the country represents about 3.4% of Chilean GDP and saw a real growth of 10.4% in 2022.

2.2 Lithium extraction 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 since 1993. While there are several companies in the ASF exploiting lithium, the overall brine extraction is almost purely driven by the activities of Sociedad Química y Minera (SQM) in the area (Moran et al., 2022). Hence, our data for water use and monitoring will come from SQM's reporting archives.

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, the lithium brine concentrates. After the useful salts are recovered, the remaining water is re-injected into the salt flat. The second

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

[3] The two largest salt flats in Bolivia are the Uyuni and Coipasa, covering an area of about 10,000 km^2, with Uyuni being the largest salt flat in the world. In Argentina, Hombre Muerto and Olaroz constitute the most important salt flats, and both are currently subject to lithium mining.

process is the direct extraction of freshwater, mainly used for cleaning the equipment (Vera et al., 2023). While a clear consensus on which water depletion mechanism is the dominant one 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 cease 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 A.1 in the Appendix, are very close to the local communities. Furthermore, in Appendix A.5 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 (SQM S.A., 2021a).

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. 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 2021, the company declared that in the period 2016-2019, "SQM reduced its water consumption in the Atacama basin by 25 percent." Furthermore, it announced that it aims to reduce pumping rates to 50% of the stipulated threshold within a decade (Sociedad Quimica y Minera de Chile, 2021, 2022). Both the realized reduction and the pledged goals for the future were despite increasing lithium extraction rates. However, the specific techniques for enhanced efficiency of water use are not outlined in the reports.[4]

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 and, in 2018, the Camar-2 well, the well closest to the community, stopped operations due to legal conflicts with the local indigenous communities. Later, it was dismantled with the pipe being removed in 2019 (SQM S.A., 2021b).[5] In section 4.4, we will analyze the socioeconomic characteristics of the populations in the region in greater detail.

[4] Detailed data on freshwater extraction from the wells is only available from 2019 onwards, hence we are not able to document those specific changes in water use patterns throughout the time period of study in this paper.

[5] This could have also contributed to the reduction in water use reported by the company.

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 to two Li_2CO_3 processing plants and one lithium hydroxide monohydrate ($LiOH \bullet H_2O$) processing plant in Antofagasta, Chile (Jaskula, B.W., 2018; Kelly et al., 2021).

3 Analytical Framework

In this section, we outline a simple analytical framework to rationalize the potential socioeconomic consequences of lithium extraction in the ASF. We interpret our analysis within a Roy-Borjas-type theoretical framework, in which the San Pedro de Atacama (SPdA) commune (surrounding the ASF) is one local economy and those regions farther away from the ASF constitute another economy (Roy, 1951; Borjas, 1987; Cattaneo and Peri, 2016). Under this setting, the mobility and migration decisions of individuals living in the ASF depend on their utility of staying vis-à-vis their utility of migrating elsewhere.

A particular feature of the communities living in the ASF is that they depend heavily on subsistence agriculture. Considering this, if they decide to stay in the ASF, their consumption is going to be constrained by their resources in the desert, namely, their land and labor endowments. For a given factor productivity, these endowments combined would allow them to produce goods for their consumption.[6] In this case, the

[6] Farmers may receive additional income from other jobs in the region created by the mining activity, however, these do not represent their main source of earnings. In particular, although SQM mining production might create potential employment opportunities for the communities in the ASF, according to information shared with us by SQM, only 2.2% of the population in the ASF is employed by the company. Hence it is expected that the potential income effect of lithium production through new employment opportunities is negligible.

total factor productivity can be thought of as a combination of the overall techniques used in farming, but also of the quality of the production inputs. By producing lithium in this region and reducing water availability, it is expected that the total factor productivity of the agricultural production process will decrease due to an increase in the dryness of the soil. This, in turn, will reduce the agricultural output and, therefore, the consumption from subsistence farming, negatively affecting their utility (Feng et al., 2012; Aragón and Rud, 2016).

On the other hand, by leaving the ASF and settling in a different region with a more dynamic labor market, the individuals' utility will depend on the consumption they can afford by selling their labor force for a given wage. Therefore, their decision to migrate will depend on the relative utilities from staying in the ASF or moving away, after adjusting for the monetary and non-monetary costs of migrating and adapting to those destination regions (Cattaneo and Peri, 2016).

Within this very simple framework, it is expected that the intensive utilization of water resources in the ASF due to the extraction of lithium might negatively affect vegetation and agricultural output around the flat. This would, in turn, reduce inhabitants' consumption and utility. Therefore, their expected benefit from staying in the ASF would be reduced relatively to their expected benefit of out-migration, increasing the probability of relocating elsewhere.

4 Data and Descriptive Statistics

4.1 Data

The sources of data used in the paper 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 commune 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 years 2007 and 2021.

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 we utilize 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 for the period 2010-2020. 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 and is available every 5 years.[7]

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 U.S., Europe, and China. The data is obtained through the IEA and contains information on the annual sales of EVs between 2010 and 2020. The sales data is provided by vehicle type for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs).

[7] To validate the utilization of GHSL as a proxy for population, we correlate the human settlements in 2020 to the population census in 2017, i.e. the two cross-sections that are closest to each other at the end of our period of interest. As shown in Figure A.3 of the Appendix, the two measures are indeed correlated.

4.2 Descriptive Statistics

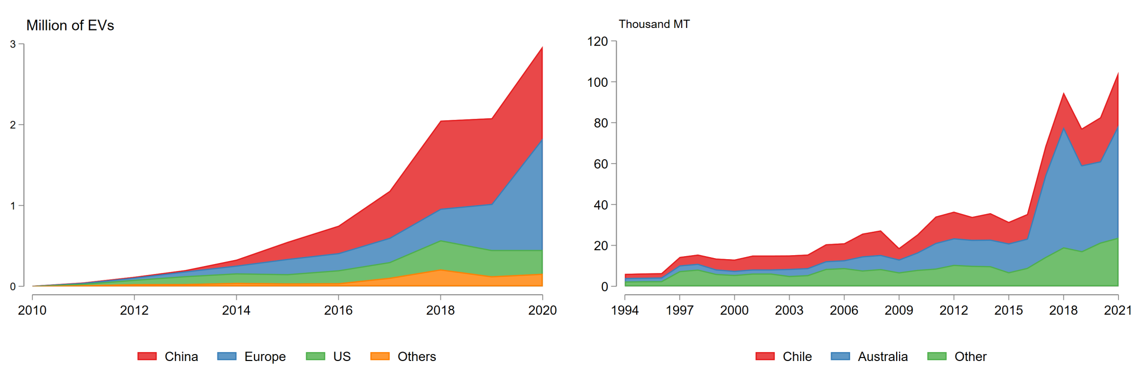
4.3 Lithium supply and demand

As can be seen in Panel (a) of Figure 1, 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 1 shows that Europe has gained a lot of momentum, representing 46% of the global demand as of 2020.

On the other hand, Panel (b) of Figure 1 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 2014. 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 1: Main lithium extraction locations in South America

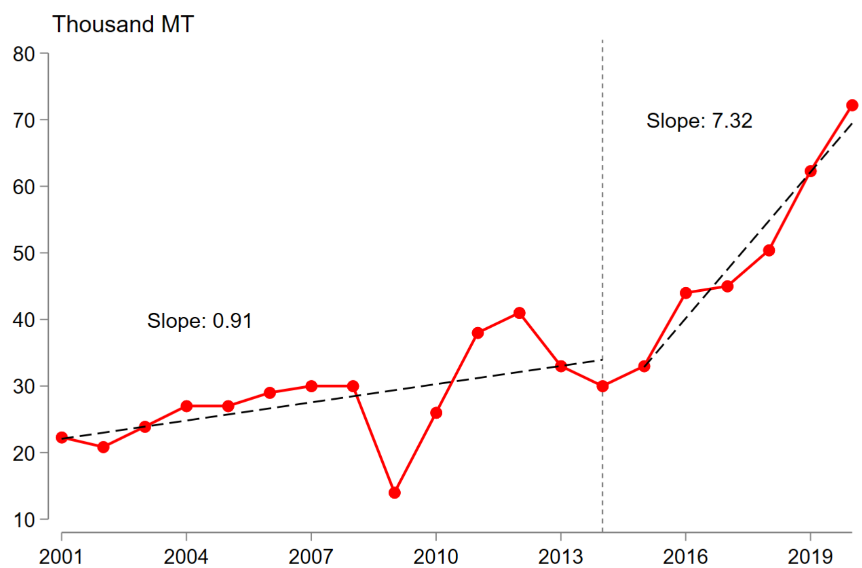
(a) EV Sales by Destination, 2010-2020 (b) Mine Production of Lithium by Origin, 1994-2021



Panel (a) 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. Panel (b) 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.

In Figure 2, we zoom into the production of lithium in Chile, particularly in the ASF, and the extraction carried out by SQM.[8] As can be seen, the aforementioned ramp-up in production coincides with increased lithium extraction activity in the ASF. Two distinct periods can be identified between 2001 and 2019. First, between 2001 and 2013, there seems to be a slight increase in the production of lithium in the ASF that was significantly reduced during the 2008 global crisis. During this first period, the production of lithium increased by about 48%, with an average annual increase of 3.6%. Secondly, during the 2014-2020 period, there was a significant increase in the production of lithium of about 140%, with an average annual increase of about 20%, according to the company's annual reports.

Figure 2: Production of Lithium in the ASF by SQM, 2001-2019



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.

We demonstrate this breaking point in Figure 2, with a linear fit in the production of lithium by SQM in the two aforementioned periods. As can be seen, the 2014-2020 period slope is about 8 times the slope for the 2001-2013 period, which indicates a more rapid increase after 2013. Given this trend in the production of lithium in the ASF, we would expect mining activities to have a more severe impact on surrounding localities during the 2014-2020 period. Hence, in the following sections, we will consider 2014 as the cutoff

[8] Although, due to data confidentiality, it is not possible to show explicitly the amount of lithium produced by SQM in the ASF that goes to the production of EV batteries, several indications suggest that the majority is, in fact, directly used for this purpose. First, according to SQM, about 75% of the total demand for lithium is driven by batteries, with demand for EV batteries amounting to roughly 54% of the total. Secondly, according to The Chilean Copper Commission (Cochilco), the production of EVs is recognized by the Chilean government as the main driver of lithium production. According to their estimates, while the demand for lithium specifically for EV batteries has increased during the 2016-2021 period by 375%, the demand for other end uses increased in the same period by only 52% (Sociedad Química y Minera de Chile S.A., 2020; Chilean Copper Commission, 2022).

year for our analysis.[9]

4.4 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 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.[10] As can be seen in Table A.1 of the Appendix, 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.[11]

In Panel B of Table A.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 industries is greater compared to Chile as a whole. This result is expected, given that the economic activity in the north of Chile, particularly in the area of SPdA, revolves around extracting natural resources and tourism. The share of people formally working

[9] To formally establish 2014 as our cutoff year, we ran a sequential test for multiple breaks at unknown breakpoints in the time series of production of lithium presented in Figure 2, following Ditzen et al. (2021). This test indicates a break point between 2014 and 2016 with a 95% of confidence. Hence, we consider 2014 (the lower bound of the interval) as the cutoff in our analysis.

[10] 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.

[11] 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)

in the primary sector in SPdA is not particularly high, especially compared to the region and country averages. This can be explained by agricultural activity in the SPdA primarily being subsistence farming and not commercial in nature.

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

The first characteristic that we observe in Table A.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.

On top of that, despite extensive efforts of the government to provide access to water for rural communities through the *Agua Potable Rural* (APR) program, a clean water infrastructure program that scaled up in Antofagasta after 2010, 35% of the population of SPdA did not have access to any formal source of clean water as of 2017 (Ruffino et al., 2022; Nicolas-Artero et al., 2022).

In Table A.3 of the Appendix 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.[12] We calculate the mean, standard deviation, minimum, and maximum values of each variable for all the 300m$\times$300m pixels of each locality. Given that the nature of potential impacts is local, we only utilize the localities that are enclosed within a distance of a 50 km radius of the location of the freshwater extraction wells and only present descriptive statistics for those.

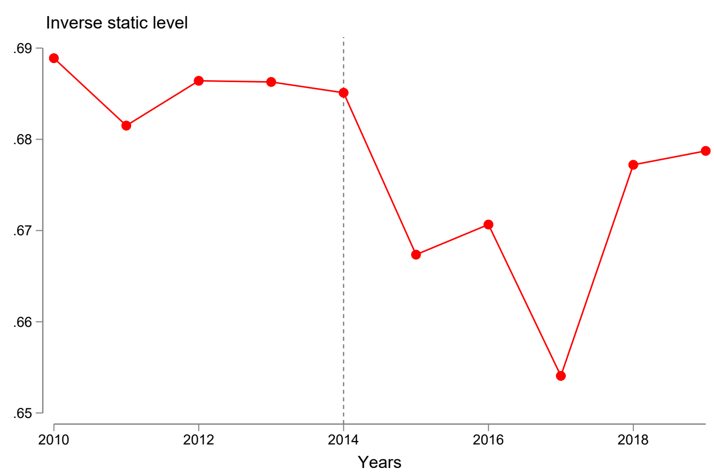
As can be seen, these localities are characterized by low levels of vegetation measured by NDVI, with Camar being the locality with the lowest average NDVI (0.044). In Panel B we can see the same statistics for the distance of each locality to the wells. As can be seen, there is a significant dispersion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

[12] 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.3.

In Table A.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 SPdA with 0.312 people per cell. Lastly, Toconao, SPdA, and Peine, on average, show the highest values of nighttime light radiance.

Next, we analyze the average level of freshwater measured by SQM in the ASF from 196 measurement stations that they report around the mining area in seven monitoring systems. Figure 3 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 (our defined cutoff) 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, as mentioned in Section 2.2 can be attributed to the reduction in freshwater extraction after SQM stopped Camar-2 well operations due to legal conflicts with the local communities.

Figure 3: Reduction in water levels of Atacama Salt Flat wells, 2010-2019



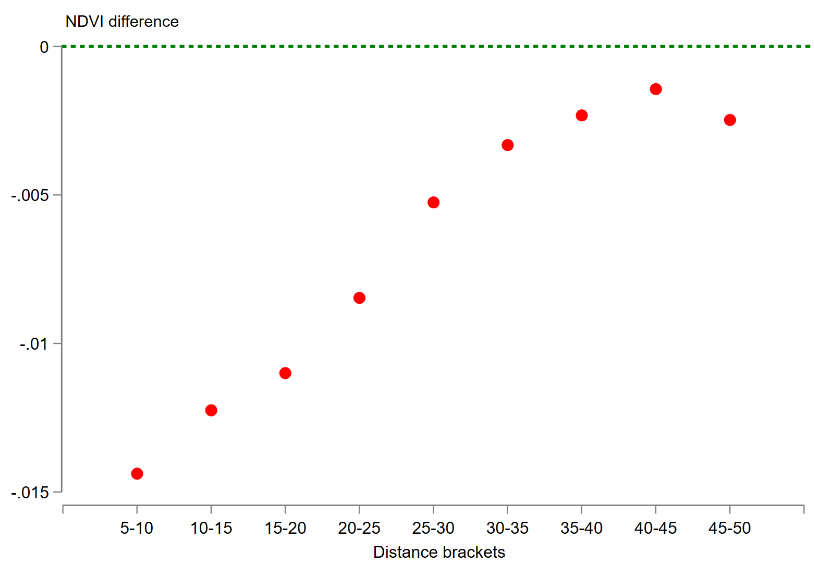
Notes: This figure shows the average inverse of the static levels of the wells in the ASF. The static level is calculated as the difference between the ground surface and the water level table for each well in meters. We present the three-year moving average of the static levels to account for noise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

Apart from the environmental impact of lithium extraction in the ASF in terms of vegetation, we also estimate the subsequent economic impacts. We would like 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 freshwater in the area. However, given the lack of granular data for the potentially affected areas, we consider NDVI as a proxy variable for the impact on agriculture. In Section 7, we present suggestive evidence of the types of crops that were reduced over the period in question to support our main results.[13]

A first overview of the relationship between lithium extraction and NDVI in the area surrounding the ASF is presented in Figure 4. In this figure, we show a non-parametric estimate of the relationship between changes in NDVI between 2013 and 2020 for each 300m×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 NDVI level would be more negative.

As can be seen in Figure 4, there seems to be a significant decrease of up to 0.015 NDVI units for those areas located in a radius of 5 to 40 kilometers from the flat. 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 4 shown here.

Figure 4: Non-parametric relationship between distance to ASF and NDVI change, 2013-2020



Notes: This 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.

[13] In Figure A.2 of the Appendix we show the relationship between the average NDVI and the total cultivated area for agriculture (in logs) in each municipality of Chile. As can be seen, NDVI and total cultivated area for agricultural purposes seem to be positively and strongly correlated across municipalities in Chile in general, but also in the North of the country, which provides validity of the utilization of NDVI as a proxy measure of agricultural activity.

5 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 2014 as the cutoff, as it is the year in which lithium production activity carried out by SQM in the ASF started to significantly increase (see Figure 2). 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.[14] We define our variable of interest I_{ijt} as follows:

[14] 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.

$$I_{ijt} = \frac{V_t}{min\{D_{ij1}, ..., D_{ij5}\}} \tag{3}$$

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 outcome variables over time with exposure to lithium extraction for pixels within the same locality, with similar latitude and longitude, and with similar elevation. This ensures that we are not capturing other trends in our coefficient of interest, such as the attractiveness of remoteness dropping during our period of study.

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 at 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 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.

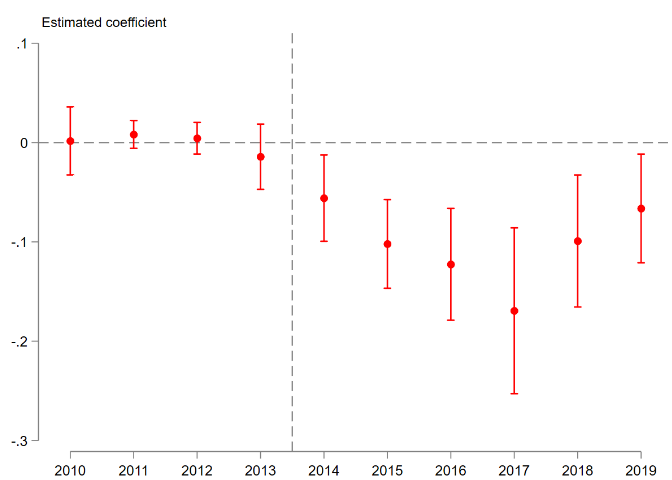
6 Main impacts of lithium extraction

6.1 The impact on groundwater levels

First, we present the results concerning the effect of lithium extraction on groundwater levels in the ASF area.[15] The estimates are shown in Figure 5. 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).[16]

As can be seen, before the ramping up in lithium production in 2014, 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 negative impact of about 15% relative to the 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, possibly due to the reduction in water extraction reported during the 2016-2019 period. 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 5: 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. The 90% confidence intervals are also plotted. Standard errors are clustered on the well level. Source: SQM measurement well reporting and DGA.

[15] All results in this sub-section refer to freshwater levels.

[16] For more details on the construction of the dependent variable, see the footnote of Figure 5.

6.2 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 the NDVI of each pixel of the identified localities in the region, where higher values of the dependent variable indicate healthier vegetation. Table 1 shows our main results.

In the different columns of Table 1 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.

Table 1: Effect of Lithium extraction on NDVI

	(1)	(2)	(3)	(4)
Exposure to extraction	-0.002***	-0.002***	-0.002***	-0.002***
	(0.000)	(0.000)	(0.000)	(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 × Year FE	No	Yes	Yes	Yes
Lat & Lon × Year FE	No	No	Yes	Yes
Elevation × Year FE	No	No	No	Yes

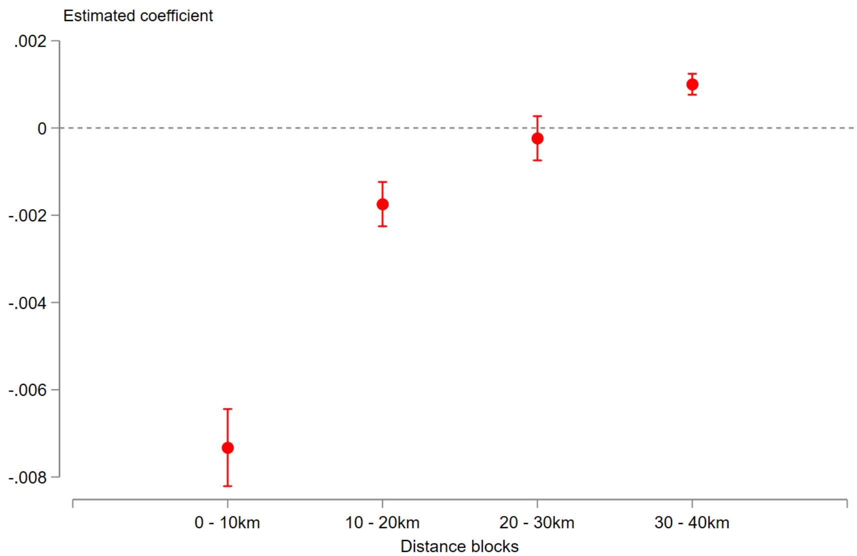
Notes: This table reports coefficients of a regression based on Equation 2, where the dependent variable is NDVI in logs. Pixel FE corresponds to a dummy variable for each pixel in our sample. Location FE corresponds to a dummy for each locality in our sample. Coordinate FE correspond to the latitude 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.

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, albeit with pollution, not water management and utilization, as the main driver.

To put our measure of the degree of exposure to lithium extraction 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 10 km 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 12 km away from the wells to a pixel located 5 km away.

Additionally, instead of considering a continuous measure of exposure to the extraction activity, we 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.

Figure 6: 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. The 90% confidence intervals are also plotted. Standard errors are clustered on a pixel level. Source: Own elaboration based on data from Landsat 8 Collection 1 Tier 1.

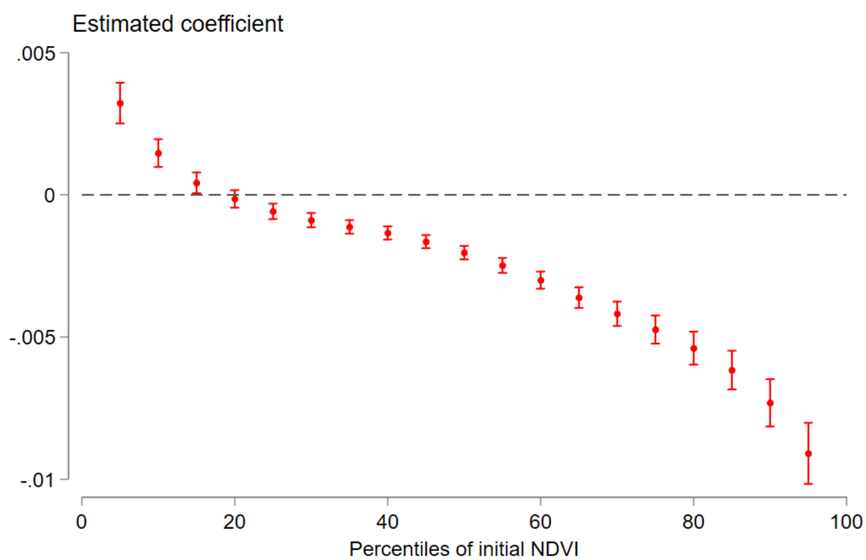
Hence, we analyze how this exposure to the demand for lithium worldwide affects different pixel blocks based on the distance to the freshwater extraction wells around the ASF. In doing so, we consider the furthest distance block, namely those pixels between 40 km and 50 km away, as our baseline group. We run a regression of 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 6 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 40-50 km distance block. The size of this impact is four times higher than that for the next distance block, i.e. the 10-20 km group.

These results are consistent with the nature of the variation considered in this paper, where we expect that the impact on vegetation is larger for the pixels located closer to the freshwater extraction wells. They are also consistent with the descriptive evidence presented above in Figure 4 where we show that the negative difference in vegetation between 2013 and 2019 was larger for the pixels between 5 km and 40 km 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 7.

Figure 7: 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 show in Figure A.2 of the Appendix, 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.

6.3 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 2, 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, and coordinate-time fixed effects seems to be relevant in our case, as it significantly increases the magnitude of our estimated effect (the same pattern is present when analyzing the impact on population, see Table 3). This is expected given that we compare pixels within the same localities that are close to each other and, therefore, we ensure there are no other omitted variables across localities in the sample.

In our preferred specification in column (4) of Table 2, 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 2: Effect of Lithium extraction on Nighttime Light Radiance

	(1)	(2)	(3)	(4)
Exposure to extraction	-0.010***	-0.004***	-0.018***	-0.026***
	(0.002)	(0.002)	(0.006)	(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
Lat & Lon $\times$ 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 3. 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 were living 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 3: Effect of Lithium extraction on human settlements

	(1)	(2)	(3)	(4)
Exposure to extraction	-0.004***	-0.002***	-0.022***	-0.015***
	(0.000)	(0.000)	(0.001)	(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
Lat & Lon $\times$ 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 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 NDVI). This, in turn, led some of the inhabitants to seek alternative income sources out of those communities.

7 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 Panel (a) of Figure 8, based on data from the Agricultural Census, the predominant vegetation in the region in 2007 (before the ramp-up of 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.

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 8 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 A.5 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.

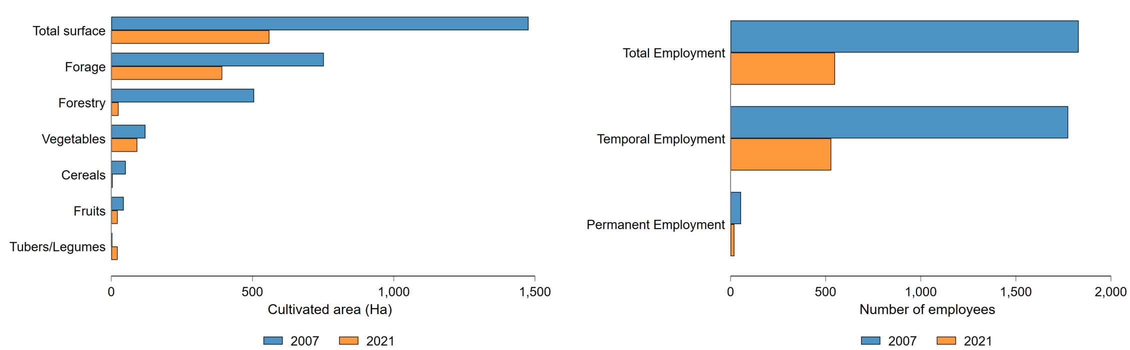
On the one hand, Alfalfa, a distinctive crop thriving in the region, exhibits remarkable adaptation to the aridity of the desert locale due to its long taproots and its crucial role for the maintenance of livestock of the local producers (Ovalle et al., 2015; Sepúlveda Rivera et al., 2015). Tamarugo, 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 8: Evolution of activity in the Agricultural sector - SPdA, 2007-2021

(a) Cultivated Surface

(b) Agricultural Employment



Notes. 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. Panel (b) of Figure 8 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.

8 Robustness Checks

In the Appendix, we test the robustness of the results of our main specifications. First, in Figure A.4 of Appendix A.2 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.5 of Appendix A.2 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-, latitude-, longitude-, 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.

Furthermore, one potential threat to our identification strategy is that the timeseries of EV sales in Europe, the U.S., and China, is monotonically changing, as are other economic and environmental variables. Hence, in order to alleviate concerns that our effects might not be directly driven by the increase in EV sales particularly, we carry out two placebo exercises in Appendix A.4. First, in Appendix A.4.1, we repeat the above analysis for groundwater levels, vegetation, economic activity, and human settlements for PSF, the most comparable salt flat to ASF based on (a) flat size, (b) geographic characteristics, and (c) non-mining related population size. In the case of PSF, we see no statistically significant coefficients for groundwater levels, vegetation, or economic activity as shown on Figure A.6 and Table A.7. A negative coefficient on human settlements that is less than one-third the size of the effect found for ASF becomes non-statistically significant when we control for spatial correlation.

Second, in section A.4.2, we repeat our baseline specification with a shift different from the EV sales over the period 2010-2020. More specifically, we replace the numerator of our measure of exposure in our baseline specification for the ASF with the imports of lithium carbonate and lithium hydroxide by the main importing countries in the preceding 10-year period, i.e. 1999-2009. We see no statistically significant coefficients for vegetation or economic activity, while a positive negligible coefficient on human settlements becomes non-statistically significant after adjusting for spatial correlation, as shown in Table A.8.

9 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 represents 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. Therefore, 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 policy-makers 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.

References

Aragón, F. M. and Rud, J. P. (2013). Natural Resources and Local Communities: Evidence from a Peruvian Gold Mine. *American Economic Journal: Economic Policy*, 5(2):1–25.

Aragón, F. M. and Rud, J. P. (2016). Polluting Industries and Agricultural Productivity: Evidence from Mining in Ghana. *The Economic Journal*, 126(597):1980–2011.

Babidge, S. (2019). Sustaining Ignorance: The Uncertainties of Groundwater and its Extraction in the Salar de Atacama, Northern Chile. *Journal of the Royal Anthropological Institute*, 25(1):83–102.

Bazillier, R. and Girard, V. (2020). The Gold Digger and the Machine. Evidence on the Distributive Effect of the Artisanal and Industrial Gold Rushes in Burkina Faso. *Journal of Development Economics*, 143:102411.

Biblioteca del Congreso Nacional de Chile (2024). Ley chile.

Borjas, G. (1987). Self-selection and the earnings of immigrants. *American Economic Review*, 77:531–553.

Boston Consulting Group (2021). Why Electric Cars Can't Come Fast Enough. https://www.bcg.com/publications/2021/why-evs-need-to-accelerate-their-market-penetration, Last accessed on 2022-10-30.

Brown, C., Meeks, R., Ghile, Y., and Hunu, K. (2013). Is Water Security Necessary? An Empirical Analysis of the Effects of Climate Hazards on National-Level Economic Growth. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 371(2002):20120416.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global Non-Linear Effect of Temperature on Economic Production. *Nature*, 527(7577):235–239.

Burlig, F., Preonas, L., and Woerman, M. (2021). Energy, Groundwater, and Crop Choice. NBER Working Paper 28706, National Bureau of Economic Research. Available at SSRN: https://ssrn.com/abstract=3832203.

Cattaneo, C. and Peri, G. (2016). The migration response to increasing temperatures. *Journal of development economics*, 122:127–146.

Center for Strategic and International Studies (2021). South America's Lithium Triangle: Opportunities for the Biden Administration. https://www.csis.org/analysis/south-americas-lithium-triangle-opportunities-biden-administration, Last accessed on 2022-10-30.

Ch, R., Martin, D. A., and Vargas, J. F. (2021). Measuring the size and growth of cities using nighttime light. *Journal of Urban Economics*, 125:103254.

Chávez, R., Clevers, J., Decuyper, M., de Bruin, S., and Herold, M. (2016). 50 years of water extraction in the pampa del tamarugal basin: Can prosopis tamarugo trees survive in the hyper-arid atacama desert (northern chile)? *Journal of Arid Environments*, 124:292–303.

Chávez, R. O., Clevers, J. G., Herold, M., Acevedo, E., and Ortiz, M. (2013). Assessing water stress of desert tamarugo trees using in situ data and very high spatial resolution remote sensing. *Remote Sensing*, 5(10):5064–5088.

Chen, X. and Nordhaus, W. (2015). A test of the new viirs lights data set: Population and economic output in africa. *Remote Sensing*, 7(4):4937–4947.

Cherniwchan, J., Copeland, B. R., and Taylor, M. S. (2017). Trade and the Environment: New Methods, Measurements, and Results. *Annual Review of Economics*, 9:59–85.

Chilean Copper Commission (2022). Lithium production and consumption towards 2030. Technical report, Chilean Copper Commission. Accessed: 2024-08-23.

Cole, M. A., Elliott, R. J., and Zhang, L. (2017). Foreign Direct Investment and the Environment. *Annual Review of Environment and Resources*, 42:465–487.

Conley, T. G. (1999). Gmm Estimation with Cross Sectional Dependence. *Journal of econometrics*, 92(1):1–45.

Copeland, B. R. and Taylor, M. S. (2004). Trade, Growth, and the Environment. *Journal of Economic literature*, 42(1):7–71.

Corral, L. R., Schling, M., and Montiel, C. (2018). The Economic and Ecological Impact of Natural Resource Extraction: The Case of the Camisea Gas Project in Peru. Technical report, IDB Working Paper Series.

Cust, J. and Poelhekke, S. (2015). The Local Economic Impacts of Natural Resource Extraction. *Annu. Rev. Resour. Econ.*, 7(1):251–268.

Damania, R. (2020). The Economics of Water Scarcity and Variability. *Oxford Review of Economic Policy*, 36(1):24–44.

Davie, T. (2019). *Fundamentals of Hydrology*. Routledge.

De la Hoz, G. M., Martinez, V. R., and Vedia, J. L. (2013). El Litio: Desde los Salares de la Puna a Nuestros Celulares. *Instituto de Bio y Geociencias del NOA*, 25.

Decuyper, M., Chávez, R. O., Copini, P., and Sass-Klaassen, U. (2016). A multi-scale approach to assess the effect of groundwater extraction on prosopis tamarugo in the atacama desert. *Journal of Arid Environments*, 131:25–34.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Department of Energy (2017). How Does Lithium-Ion Battery Work. https://www.energy.gov/eere/articles/how-does-lithium-ion-battery-work, Last accessed on 2022-10-30.

Ditzen, J., Karavias, Y., and Westerlund, J. (2021). Testing and estimating structural breaks in time series and panel data in stata. *arXiv preprint arXiv:2110.14550*.

Donaldson, D. and Storeygard, A. (2016). The view from above: Applications of satellite data in economics. *Journal of Economic Perspectives*, 30(4):171–198.

Environmental Protection Agency (2023). Global greenhouse gas emissions data. https://www.epa.gov/ghgemissions/global-greenhouse-gas-emissions-data, Last accessed on 2024-29-01.

Feng, S., Oppenheimer, M., and Schlenker, W. (2012). Climate change, crop yields, and internal migration in the united states. Technical report, National Bureau of Economic Research.

Flexer, V., Baspineiro, C. F., and Galli, C. I. (2018). Lithium Recovery from Brines: A Vital Raw Material for Green Energies with a Potential Environmental Impact in its Mining and Processing. *Science of the Total Environment*, 639:1188–1204.

Floyd, M. J. (2021). The path to groundwater sustainability for lithium mining: The salar de atacama, chile.

Garrett, D. E (2004). Handbook of Lithium and Natural Calcium Chloride.

Gutiérrez, J. S., Moore, J. N., Donnelly, J. P., Dorador, C., Navedo, J. G., and Senner, N. R. (2022). Climate Change and Lithium Mining Influence Flamingo Abundance in the Lithium Triangle. *Proceedings of the Royal Society B*, 289(1970):20212388.

Henderson, J. V., Storeygard, A., and Weil, D. N. (2012). Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028.

Hsiang, S. M. (2010). Temperatures and Cyclones Strongly Associated with Economic Production in the Caribbean and Central America. *Proceedings of the National Academy of sciences*, 107(35):15367–15372.

IDB (2017). Lithium: White Gold for a Region's Development. https://www.iadb.org/en/improvinglives/lithium-white-gold-regions-development#:~:text=The%20white%20gold%20for%20developement,to%20the%20U.S.%20Geological%20Survey, Last accessed on 2022-10-30.

International Energy Agency (2022a). The Role of Critical Minerals in Clean Energy Transitions. https://www.iea.org/reports/the-role-of-critical-minerals-in-clean-energy-transitions/, Last accessed on 2023-05-13.

International Energy Agency (2022b). Trends in Electric Light-Duty Vehicles. https://www.iea.org/reports/global-ev-outlook-2022/trends-in-electric-light-duty-vehicles, Last accessed on 2022-10-30.

International Energy Agency (2023). Gloval ev outlook 2023 policy developments. https://www.iea.org/reports/global-ev-outlook-2023/policy-developments, Last accessed on 2024-29-01.

Jaskula, B.W. (2018). U.S. Geological Survey 2016 Minerals Yearbook. U.S. Geological Survey, Lithium.

Kelly, C. J., Wang, M., Dai, Q., and Winjobi, O. (2021). Energy, Greenhouse Gas, and Water Life Cycle Analysis of Lithium Carbonate and Lithium Hydroxide Monohydrate from Brine and Ore Resources and their Use in Lithium Ion Battery Cathodes and Lithium Ion Batteries. *Resources, Conservation and Recycling*, 174:105762.

Levinson, A. (2010). Offshoring Pollution: Is the United States Increasingly Importing Polluting Goods? *Review of Environmental Economics and Policy*, 4(1):63–83.

Lippert, A. (2014). Spill-overs of a Resource Boom: Evidence from Zambian Copper Mines.

Liu, W. and Agusdinata, D. B. (2020). Interdependencies of Lithium Mining and Communities Sustainability in Salar de Atacama, Chile. *Journal of Cleaner Production*, 260:120838.

Liu, W., Agusdinata, D. B., and Myint, S. W. (2019). Spatiotemporal Patterns of Lithium Mining and Environmental Degradation in the Atacama Salt Flat, Chile. *International Journal of Applied Earth Observation and Geoinformation*, 80:145–156.

Loayza, N. and Rigolini, J. (2016). The Local Impact of Mining on Poverty and Inequality: Evidence from the Commodity Boom in Peru. *World development*, 84:219–234.

López Steinmetz, R. L. and Salvi, S. (2021). Brine Grades in Andean Salars: When Basin Size Matters. A Review of the Lithium Triangle. *Earth-Science Reviews*, 217:103615.

Marazuela, M., Vázquez-Suñé, E., Ayora, C., and Garcia-Gil, A. (2020). Towards More Sustainable Brine Extraction in Salt Flats: Learning from the Salar de Atacama. *Science of the Total Environment*, 703:135605.

Marazuela, M., Vázquez-Suñé, E., Ayora, C., García-Gil, A., and Palma, T. (2019). The Effect of Brine Pumping on the Natural Hydrodynamics of the Salar de Atacama: The Damping Capacity of Salt Flats. *Science of the Total Environment*, 654:1118–1131.

Marbler, A. (2024). Water Scarcity and Local Economic Activity: Spatial Spillovers and the Role of Irrigation. *Journal of Environmental Economics and Management*, page 102931.

Michalopoulos, S. and Papaioannou, E. (2013). Pre-colonial ethnic institutions and contemporary african development. *Econometrica*, 81(1):113–152.

Miller, D. L. (2023). An introductory guide to event study models. *Journal of Economic Perspectives*, 37(2):203–230.

Mooney, H., Gulmon, S., Rundel, P., and Ehleringer, J. (1980). Further observations on the water relations of prosopis tamarugo of the northern atacama desert. *Oecologia*, 44:177–180.

Moran, J. B., Boutt, F. D., McKnight, V. S., Jenckes, J., Munk, L. A., Corkran, D., and Kirshen, A. (2022). Relic Groundwater and Prolonged Drought Confound Interpretations of Water Sustainability and Lithium Extraction in Arid Lands. *Earth's Future*, 10(7).

Munk, L. A.and Boutt, F. D., Moran, B. J., McKnight, S. V., and Jenckes, J. (2021). Hydrogeologic and Geochemical Distinctions in Freshwater-Brine Systems of an Andean Salar. *Geochemistry, Geophysics, Geosystems*, 22(3).

Nicolas-Artero, C., Blanco, G., Bopp, C., and Carrasco, N. (2022). Modes of access to water for domestic use in rural chile: a typological proposal. *Water Policy*, 24(7):1179–1194. Crossmark: Check for Updates. Article history.

Ovalle, C., Espinoza, S., Barahona, V., Gerding, M., Humphries, A., and del Pozo, A. (2015). Lucerne and other perennial legumes provide new options for rain fed livestock production in the mediterranean-climate region of chile. *Ciencia e investigación agraria*, 42(3):453–460.

Pérez-Sindín, X. S., Chen, T.-H. K., and Prishchepov, A. V. (2021). Are night-time lights a good proxy of economic activity in rural areas in middle and low-income countries? examining the empirical evidence from colombia. *Remote Sensing Applications: Society and Environment*, 24:100647.

Pokorny, B., von Lübke, C., Dayamba, S. D., and Dickow, H. (2019). All the Gold for Nothing? Impacts of Mining on Rural Livelihoods in Northern Burkina Faso. *World Development*, 119:23–39.

Reuters (2020). The Atacama Indigenous Council (CPA) Accuses SQM of Over-Extracting Brine from the Salt Flat. https://www.reuters.com/article/idUSKCN25A2PA. Accessed: yyyy-mm-dd.

Risacher, F., Alonso, H., and Salazar, C. (2003). The origin of brines and salts in chilean salars: a hydrochemical review. *Earth-Science Reviews*, 63(3-4):249–293.

Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford economic papers*, 3(2):135–146.

Ruffino, B., Campo, G., Crutchik, D., Reyes, A., and Zanetti, M. (2022). Drinking water supply in the region of antofagasta (chile): A challenge between past, present and future. *International Journal of Environmental Research and Public Health*, 19(21):14406.

Russ, J. (2020). Water Runoff and Economic Activity: The Impact of Water Supply Shocks on Growth. *Journal of Environmental Economics and Management*, 101:102322.

Schenker, V., Oberschelp, C., and Pfister, S. (2022). Regionalized Life Cycle Assessment of Present and Future Lithium Production for Li-ion Batteries. *Resources, Conservation and Recycling*, 187:106611.

Sepúlveda Rivera, I., Molina Otárola, R., Delgado-Serrano, M. d. M., and Guerrero Ginel, J. E. (2015). Aguas, riego y cultivos: cambios y permanencias en los ayllus de san pedro de atacama. *Estudios atacameños*, (51):185–206.

Sociedad Quimica y Minera de Chile (2021). Sustainable Lithium. https://www.sqmlithium.com/wp-content/uploads/2021/05/SQM-Sustainable-Lithium-English-20210504.pdf. Accessed: January 25th, 2024.

Sociedad Quimica y Minera de Chile (2022). Sqm Shares its Views on Salar Futuro. https://ir.sqm.com/English/news/news-details/2022/SQM-Shares-Its-Views-on-Futuro-Salar/default.aspx. Accessed: yyyy-mm-dd.

Sociedad Quimica y Minera de Chile (2024). Agua industrial. Accessed: 2024-02-18.

Sociedad Química y Minera de Chile S.A. (2020). Annual report 2020. Technical report, Sociedad Química y Minera de Chile S.A. Accessed: 2024-08-23.

SQM S.A. (2021a). Estudio de impacto ambiental sqm s.a. proyecto plan de reducción de extracciones en el salar de atacama. anexo 5-1: Modelo hidrogeológico conceptual del salar de atacama.

SQM S.A. (2021b). Sqm sustainability report 2021. Technical report, SQM S.A. Accessed: 2024-07-06.

Sudzuki, F. (1985). Environmental moisture utilization by prosopis tamarugo phil. In Habit, M., editor, *The Current State of Knowledge on Prosopis Tamarugo*. F.A.O, Rome.

Tanaka, S., Teshima, K., and Verhoogen, E. (2022). North-South Displacement Effects of Environmental Regulation: The Case of Battery Recycling. *American Economic Review: Insights*, 4(3):271–288.

Tran, T. and Luong, T. V. (2015). *Lithium Process Chemistry*, chapter 3, pages 81–124. Elsevier.

United States Geological Survey (2024). Lithium. Technical report, United States Geological Survey. Accessed: January 25th, 2024.

van der Ploeg, F. (2011). Natural Resources: Curse or Blessing? *Journal of Economic Literature*, 49(2):366–420.

Vera, M. L., Torres, W. R., Galli, C. I., Chagnes, A., and Flexer, V. (2023). Environmental Impact of Direct Lithium Extraction from Brines. *Nature Reviews Earth & Environment*, 4(3):149–165.

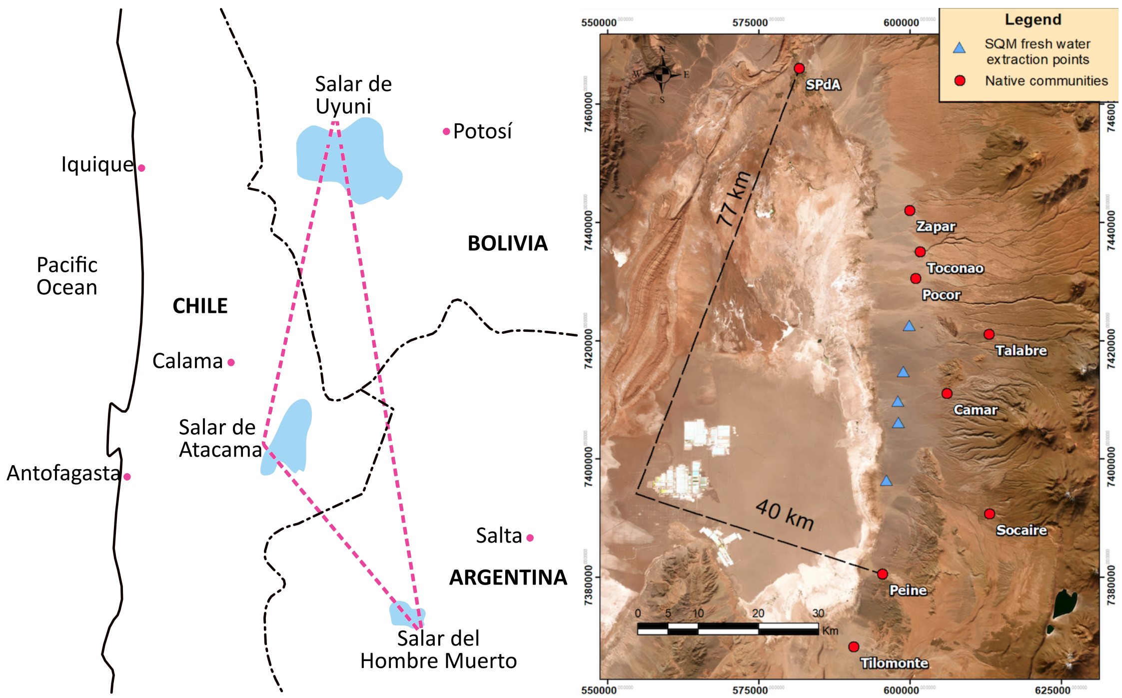
Vesilind, P. J. (2003). The driest place on earth. *National Geographic*, 204(2):30–49.

A Online Appendix

A.1 Tables and Figures

Figure A.1: Main lithium extraction locations in South America

(a) Lithium triangle (b) Atacama Salt Flat



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

Table A.1: Population characteristics, 2002 - 2017

	SPdA		Antofagasta		Chile	
	2002	2017	2002	2017	2002	2017
Panel A: Demographic characteristics						
Head of household	0.27	0.27	0.25	0.29	0.27	0.32
	(0.44)	(0.45)	(0.43)	(0.45)	(0.45)	(0.47)
Age	31.75	34.38	29.96	33.39	31.60	35.83
	(20.24)	(18.75)	(19.73)	(20.35)	(20.81)	(21.97)
Male	0.59	0.56	0.52	0.52	0.49	0.49
	(0.49)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Secondary Education	0.82	0.63	0.79	0.66	0.82	0.68
	(0.38)	(0.48)	(0.41)	(0.47)	(0.38)	(0.47)
Post-secondary Education	0.18	0.27	0.20	0.24	0.16	0.23
	(0.38)	(0.45)	(0.40)	(0.43)	(0.37)	(0.42)
Indigenous	0.61	0.50	0.05	0.14	0.05	0.12
	(0.49)	(0.50)	(0.21)	(0.34)	(0.21)	(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	0.79	0.55	0.65	0.52	0.61
	(0.49)	(0.41)	(0.50)	(0.48)	(0.50)	(0.49)
Employed	0.58	0.76	0.54	0.60	0.51	0.56
	(0.49)	(0.43)	(0.50)	(0.49)	(0.50)	(0.50)
Unemployed	0.01	0.03	0.02	0.08	0.02	0.07
	(0.11)	(0.18)	(0.12)	(0.27)	(0.14)	(0.26)
Primary sector	0.05	0.03	0.02	0.01	0.11	0.06
	(0.22)	(0.16)	(0.14)	(0.10)	(0.31)	(0.24)
Mining	0.12	0.11	0.12	0.12	0.01	0.02
	(0.32)	(0.31)	(0.32)	(0.33)	(0.12)	(0.13)
Manufacturing	0.03	0.03	0.08	0.05	0.12	0.06
	(0.18)	(0.18)	(0.27)	(0.22)	(0.33)	(0.24)
Commerce	0.10	0.07	0.18	0.13	0.19	0.16
	(0.30)	(0.25)	(0.38)	(0.34)	(0.39)	(0.36)
Hotels and Restaurants	0.15	0.17	0.03	0.05	0.03	0.04
	(0.35)	(0.38)	(0.18)	(0.21)	(0.17)	(0.20)
Other economic activity	0.55	0.59	0.57	0.64	0.53	0.66
	(0.50)	(0.49)	(0.50)	(0.48)	(0.50)	(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.

Table A.2: Dwelling characteristics, 2002 - 2017

	SPdA		Antofagasta		Chile	
	2002	2017	2002	2017	2002	2017
Number of rooms	3.13	2.40	4.82	3.01	4.80	2.75
	(2.54)	(1.31)	(2.14)	(1.26)	(1.81)	(1.07)
Precarious walls	0.32	0.20	0.04	0.02	0.05	0.03
	(0.47)	(0.40)	(0.20)	(0.15)	(0.23)	(0.16)
Precarious Ceeling	0.01	0.06	0.00	0.01	0.00	0.01
	(0.10)	(0.24)	(0.06)	(0.11)	(0.05)	(0.08)
Floor material: earth	0.02	0.02	0.01	0.01	0.00	0.00
	(0.12)	(0.15)	(0.08)	(0.09)	(0.07)	(0.05)
Water from public network	0.69	0.57	0.94	0.85	0.90	0.86
	(0.46)	(0.50)	(0.24)	(0.35)	(0.30)	(0.34)
Water from trucks	0.00	0.04	0.00	0.02	0.00	0.01
	(0.00)	(0.19)	(0.00)	(0.13)	(0.00)	(0.11)
Water from wells	0.01	0.01	0.00	0.00	0.05	0.04
	(0.09)	(0.09)	(0.04)	(0.04)	(0.23)	(0.18)
Water from river/creek/stream	0.06	0.03	0.01	0.00	0.03	0.01
	(0.23)	(0.16)	(0.08)	(0.06)	(0.16)	(0.12)
No access	0.24	0.35	0.05	0.11	0.02	0.07
	(0.43)	(0.48)	(0.23)	(0.32)	(0.14)	(0.25)
Observations	4,969	12,108	493,984	638,464	15116435	18552095

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.

Table A.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.

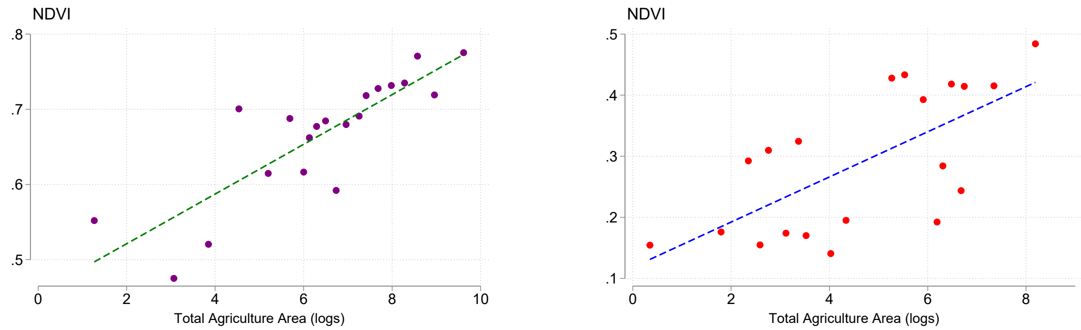
Table A.4: Human Settlements (2010) and Nighttime Light Radiance (2013) within localities

	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.

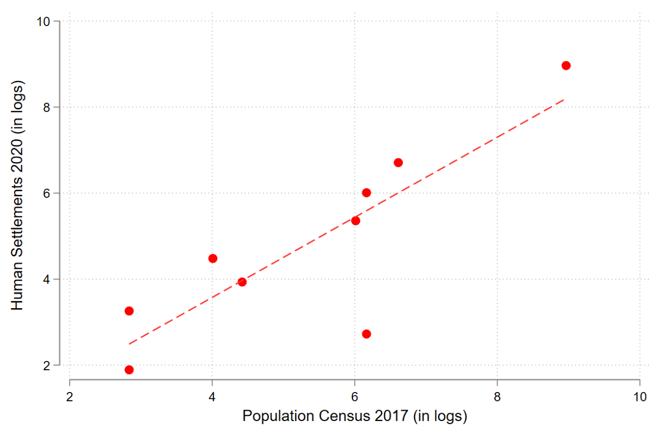
Figure A.2: Relationship between NDVI (2010) and Total Cultivated Area (2007)

(a) Chile (b) North of Chile



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 A.3: 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.

Table A.5: Variation in cultivated area by main crops - SPdA, 2007-2021

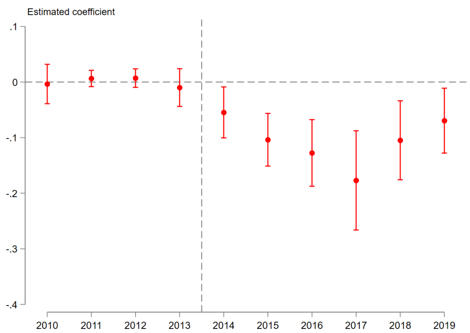
	2007	**2021**	**Difference**
Forage	752.43	392.58	-359.85
Alfalfa	749.94	392.08	-357.86
Forestry	505.53	25.50	-480.03
Tamarugo	505.53	11.80	-493.73
Vegetables	120.68	91.81	-28.87
Corn	82.91	69.33	-13.58
Cereals	51.09	4.67	-46.42
Corn	25.98	3.15	-22.83
Fruits	43.99	22.59	-21.40
Pear	14.89	12.82	-2.07
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.

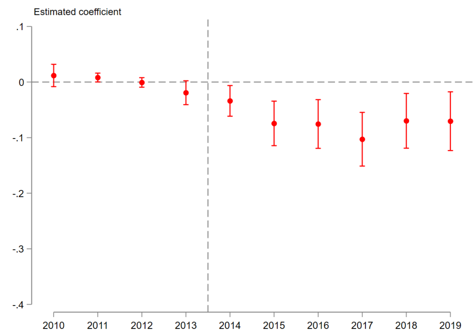
A.2 Robustness checks

Figure A.4: Robustness of the effect of the exposure to the extraction of lithium on wells levels for different control groups

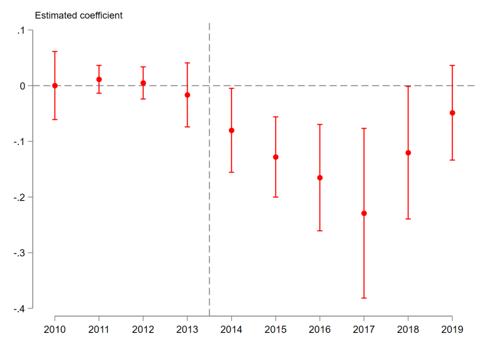
(a) Excluding Arica and Parinacota



(b) Excluding Antofagasta

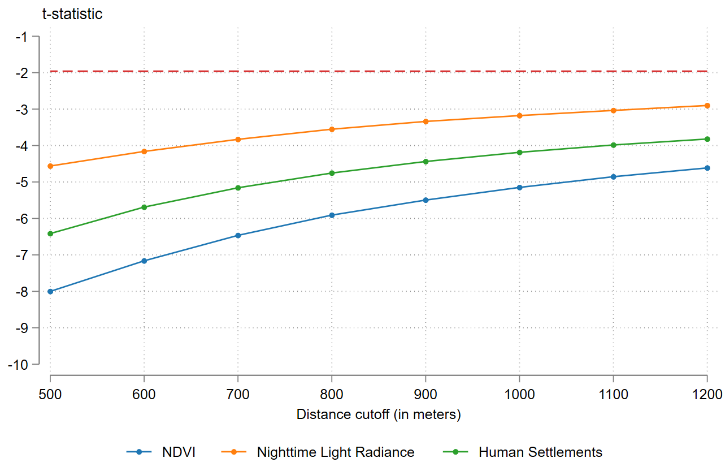


(c) Excluding Tarapacá



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.5: 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 form 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.3 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.4 Placebo tests

A.4.1 Repeating estimates for a similar salt flat

In this section, we repeat our main specification for a salt flat similar to the ASF, where there is no such activity of lithium extraction. To do so, we draw from the comprehensive list of basins in Northern Chile put together by Risacher et al. (2003). After sorting by the size of the salt flat area, we are left with the top 10 flats, as presented in Table A.6.

Table A.6: List of other salt flats by size and surrounding population

	Flat size (km^2)	Basin size (km^2)	Urban pop.	Rural pop.	Region
Pintados	377	17,150	13190	8507	Tarapaca
Pedernales	335	3,620	853	6032	Atacama
Punta Negra	250	4,263	0	5525	Antofagasta
Ascotan	243	1,757	0	386	Antofagasta
La Isla	152	858	0	1132	Atacama
Maricunga	145	3045	0	360	Atacama
Surire	144	574	0	582	Arica y Parinacota
Aguas Calientes 2	134	1,168	0	2129	Antofagasta
Carcote	108	561	0	4759	Antofagasta
Pajonales	104	1,984	0	310	Antofagasta

Notes: The table shows the Characteristics of the top 10 salt flats in Chile, sorted by descending salt flat size, along with the corresponding basin size, and populations surrounding them within a 50 km radius. Source: Own elaboration based on data from Risacher et al. (2003) as well as from the National Institute of Statistics 2017 Census report.

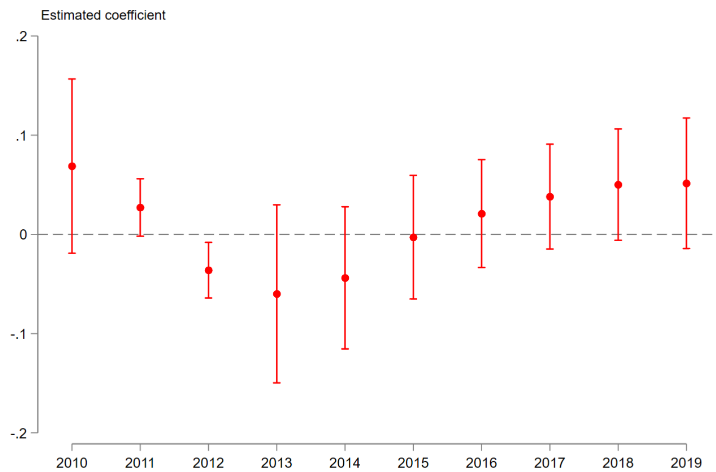
For reference, the area of the ASF is 3000 km^2, while its basin area is 18,100 km^2. The second largest salt flat is the Pintados Salt Flat (PSF), which is located in Tarapaca, has an alluvial fan, and similar weather conditions to ASF. Additionally, and most importantly for its relevance in the placebo exercise, this is the salt flat with a number of people comparable to that of ASF, which had over ten thousand inhabitants as of 2017. The salt flats that are next in the order and with populations in the range of several thousand people (Salar de Pedernales, Salar de Punta Negra) are surrounded predominantly by mining settlements and, therefore are not suitable for the placebo exercise. There is still mining activity mainly for iodine and nitrates around PSF, however, there is no evidence of extensive water use in this case.

Therefore, we utilize PSF as our salt flat of choice for the placebo exercise, and in a similar manner as for ASF we construct localities around it, using the center of the flat as our reference point. Due to the stark difference in size between the two salt flats, we began by restricting the radius 10-fold (proportional to the flat size ratio between ASF and PSF), however, this left us with no populations around the center of the flat. Hence, we expanded the radius to 25km around the flat to ensure sufficient surrounding populations are included in our analysis.

Doing so, we are left with three localities, namely La Tirana, Pozo Almonte, and Sara, which are all populated villages. Lastly, we omit Pampa del Tamarugal, the only natural reserve within the specified radius from our vegetation estimates because, over the past years, there have been consistent reforestation efforts with artificially planted Tamarugo trees.

Figure A.6 presents the placebo estiamtates of lithium extraction on groundwater levels, comparing wells in the Tarapaca region, where PSF is located, to wells in Arica and Parinacota.

Figure A.6: Estimated placebo effect of extraction of lithium on groundwater levels for PSF



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. The 90% confidence intervals are also plotted. Standard errors are clustered on the well level. Source: SQM measurement well reporting and DGA.

Figure A.7 presents the placebo estimates of lithium extraction on vegetation, nighttime light radiance, and human settlements, as in our baseline specification.

Table A.7: Estimated placebo effect of extraction of lithium on vegetation, economic activity and human settlements for PSF

	Vegetation (NDVI)	Nighttime Light Radiance	Human Settlements
Exposure to extraction	-0.000	0.000	-0.004**
	(0.001)	(0.008)	(0.002)
Adjusted P-value 500 m	[0.972]	[0.965]	[0.578]
Adjusted P-value 800 m	[0.976]	[0.972]	[0.681]
Adjusted P-value 1200 m	[0.979]	[0.977]	[0.739]
Observations	26,785	11,744	86,562
Pixel FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Location FE × Year FE	Yes	Yes	Yes
Lat & Lon × Year FE	Yes	Yes	Yes
Elevation × Year FE	Yes	Yes	Yes

Notes: This table reports coefficients of a regression based on Equation 2, 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.

A.4.2 Repeating baseline specification with a different shift

Table A.8: Placebo estimates replacing EVs by Imports of Lithium, 1999-2009

	Vegetation (NDVI)	Nighttime Light Radiance	Human Settlements
Exposure to extraction	0.000 (0.000)	-0.008 (0.007)	0.004*** (0.001)
Adjusted P-value 500 m	[0.475]	[0.433]	[0.309]
Adjusted P-value 800 m	[0.606]	[0.571]	[0.451]
Adjusted P-value 1200 m	[0.690]	[0.653]	[0.550]
Observations	199,096	17,104	125,892
Pixel FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Location FE × Year FE	Yes	Yes	Yes
Lat & Lon × Year FE	Yes	Yes	Yes
Elevation × Year FE	Yes	Yes	Yes

Notes: This table reports coefficients of a regression based on Equation 2, 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.

A.5 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:

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

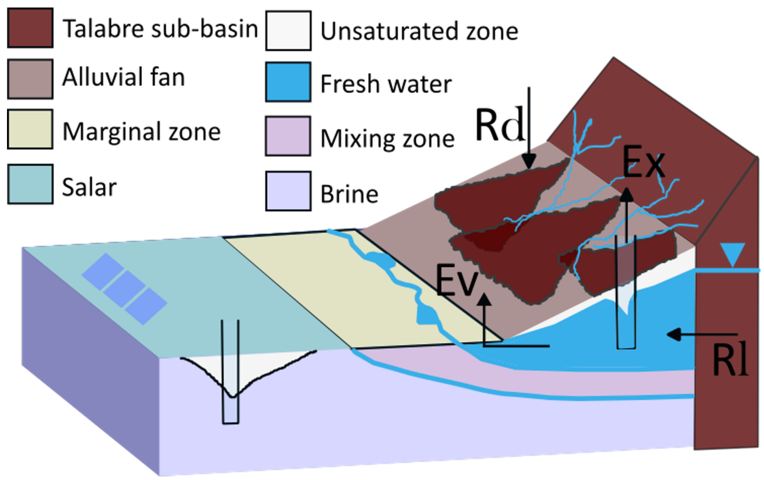
Now, further breaking down the recharge and discharge components, we can re-write equation A.1 as follows:

$$Rd + RO + Rl - EVS - EVL - EVT - EXT = \Delta S + \epsilon \tag{A.2}$$

where Rd is the direct recharge from precipitation, RO is the runoff, Rl 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.7 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., 2021a). 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.7: 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.7. The marginal zone is a blend of brine and water, while the nucleus primarily contains brine. The balancing calculation, visualized in Figure A.8 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.

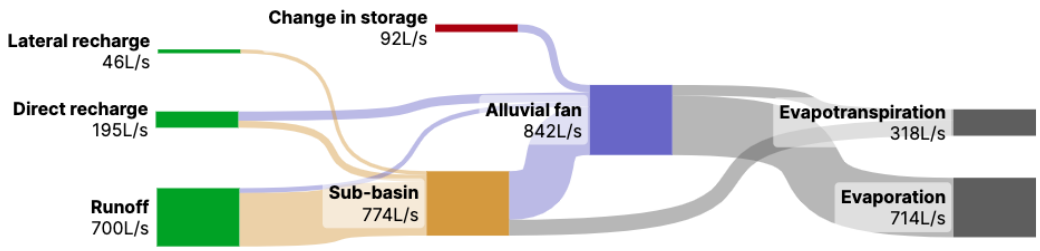
The water balance was calculated for a pre-operational scenario (1986-1994), considering the period before extraction began, and an operational scenario (1994-2019), representing the period of brine and industrial water extraction by SQM. It is important to highlight that pre-operational data is scarce (SQM S.A., 2021a). Figure A.8 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.8(a)). In the operational period (Figure A.8(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.[17] It should be noted that, even in the absence of any human-induced water extraction during the pre-operational period, change in water storage (ΔS) was negative, as seen in Figure A.8(a), indicating a natural drawdown of the aquifers that was subsequently exacerbated by anthropogenic

[17] 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.

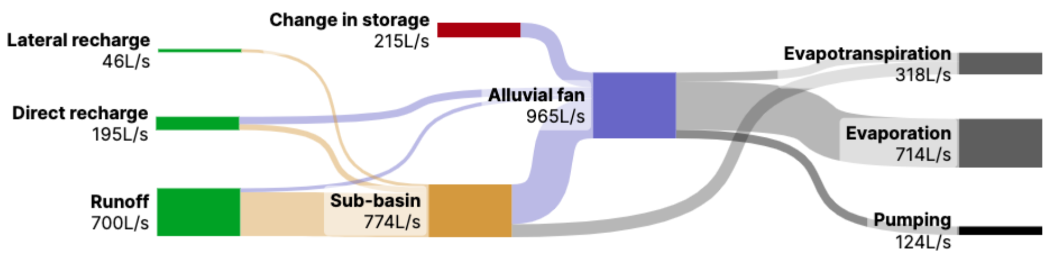
water pumping.

Figure A.8: Pre and post-operational water balance

(a) Period before mining

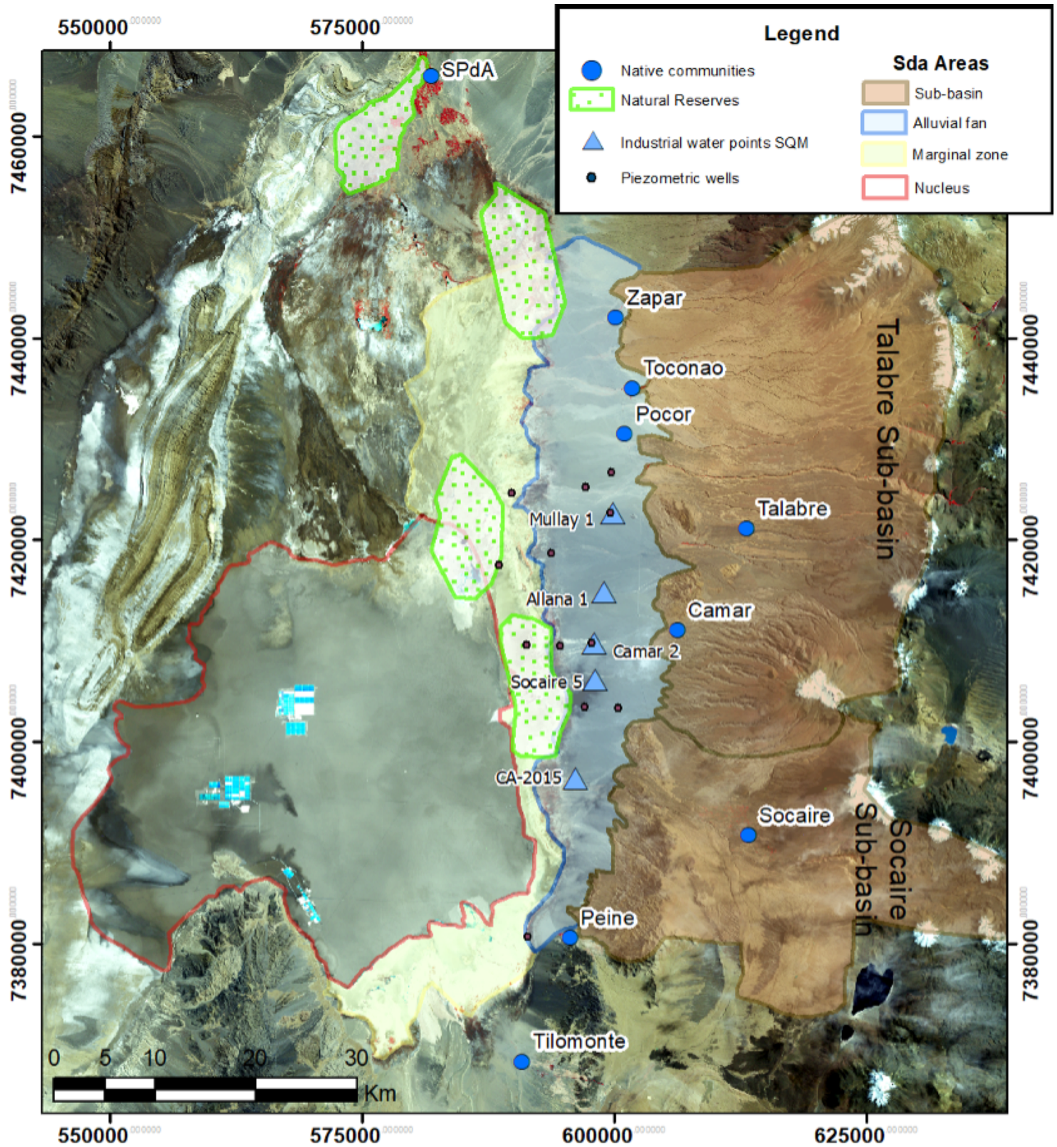


(b) Period after mining



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., 2021a).

Figure A.9: 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).