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

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In this paper, we analyze the local environmental and economic impacts of lithium extraction in the Atacama Salt Flat (ASF) in Chile. We use satellite data to estimate the effects on vegetation at a resolution of $30m \times 30m$ as well as on the local human populations at a resolution of $100m \times 100m$ near the ASF. We compare changes over time in NDVI and human settlements and show how they are affected by exposure to lithium extraction. Our estimates suggest that an increase of 1 standard deviation in our measure of exposure to lithium extraction reduced vegetation in nearby areas by 0.09 standard deviations, and specifically in human settlements by 0.22 standard deviations. Also, human populations in the local villages were reduced by 0.04 standard deviations for 1 standard deviation closer to the ASF. Further, we show that the negative effect on NDVI was greater for those locations with higher levels of vegetation at baseline.

KEYWORDS
Environment, Chile, Lithium, Vegetation

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Los efectos no ecológicos de "volverse verde": Consecuencias medioambientales y económicas locales de la extracción de litio en Chile

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En este trabajo analizamos los impactos ambientales y económicos locales de la extracción de litio en el Salar de Atacama (SA) en Chile. Utilizamos datos satelitales para estimar los efectos sobre la vegetación a una resolución de $30m \times 30m$ así como sobre las poblaciones humanas locales a una resolución de 100×100 cerca del SA. Comparamos los cambios a lo largo del tiempo en el NDVI y los asentamientos humanos y mostramos cómo se ven afectados por la exposición a la extracción de litio. Nuestras estimaciones sugieren que un aumento de 1 desviación estándar en nuestra medida de exposición a la extracción de litio redujo la vegetación en las áreas cercanas en 0,09 desviaciones estándar, y específicamente en los asentamientos humanos en 0,22 desviaciones estándar. Asimismo, las poblaciones humanas de las aldeas locales se redujeron en 0,04 desviaciones estándar por 1 desviación estándar más cerca del SA. Además, mostramos que el efecto negativo sobre el NDVI fue mayor en aquellas localidades con mayores niveles de vegetación en el periodo inicial.

KEYWORDS

Medioambiente, Chile, Litio, Vegetación

1 | INTRODUCTION

Over the past years, sales of electric vehicles (EV) 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 (Boston Consulting Group, 2021).

This increase is driving up the demand for lithium, a key element in EV batteries (Department of Energy, 2017). Furthermore, the demand for minerals used in EVs, as well as battery storage, is projected to rise significantly in simulations of climate action scenarios, with lithium seeing the largest increase. According to the International Energy Agency's Sustainable Development Scenario (SDS), demand for lithium is predicted to increase by almost 40 times by 2040 (International Energy Agency, 2022a).

The largest producers of lithium worldwide are Australia, Chile, and China. However, Chile, Argentina, and Bolivia, known as "The Lithium Triangle", own more than half of the world's lithium ore reserves (IDB, 2017). Chile, in particular, has the largest reserves of "commercially viable" lithium in the area of the Atacama Salt Flat (ASF), which are owned by the Production Development Corporation (CORFO) and leased through public-private partnerships to several private companies, the two main ones being SQM and Albemarle (Center for Strategic and International Studies, 2021).

Despite the potential positive economic and technological impacts of the production of lithium, there are environmental concerns associated with lithium extraction that should be considered when evaluating the full supply-chain impact of a "green" technology. Lithium 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). Near the ASF, specifically, water availability, vegetation levels, and wildlife diet have been shown to be correlated with the extraction of lithium over time. (Washington Post, 2016; Liu et al., 2019; Marazuela et al., 2018; Dorador et al., 2018).

In this paper we provide causal evidence of the regional environmental and economic impacts of lithium extraction on several local Identified Vulnerable Areas (IVAs) around the ASF. Our estimates provide relevant evidence for policymakers to understand the potential negative effects that these activities can generate for the local populations in order to implement measures to ameliorate them.

We create a new database of the vegetation index (Normalized Difference Vegetation Index, NDVI) at a $30m \times 30m$ resolution in the main potentially vulnerable areas around the ASF obtained through satellite images. Based on this, we compare changes over time for the 2013-2020 period and between pixels with close proximity to each other. Thus, we analyze how the level of vegetation of each pixel is affected over time by our measure of exposure to the extraction of lithium. We show that an increase of 1 standard deviation in our measure reduced the vegetation by 0.09 standard deviations and specifically in human settlements by 0.22 standard deviations. We also show that the effect was significantly negative in those areas where the level of vegetation was higher at the beginning of our period of analysis.

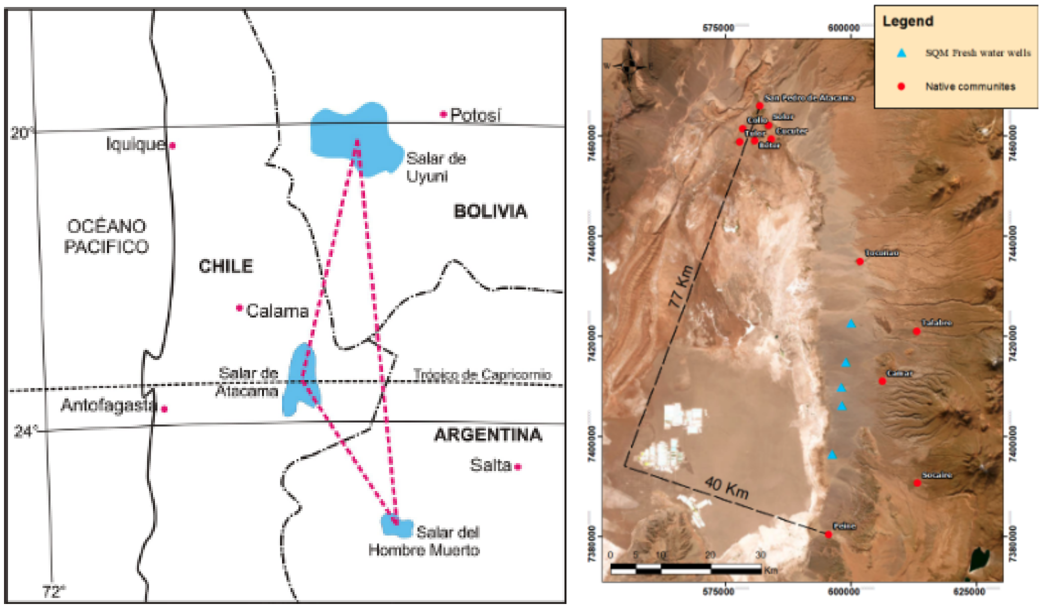
Furthermore, we use satellite images at a $100\text{m} \times 100\text{m}$ resolution to estimate the population in the villages around the ASF and the effect of the exposure to lithium extraction on population changes during our period of analysis. We find that a 1 standard deviation increase in the proximity to the center of the ASF, reduced the population of the villages around the ASF by 0.04 standard deviations. These results can be interpreted as a consequence of the negative effect on vegetation that the extraction of lithium seems to have caused in the region.

The rest of the paper is organized as follows: in Section 2 we provide some context about the lithium extraction process in the Atacama Salt Flat and the potential mechanisms through which it can affect water availability and vegetation in this area. In section 3 we describe the data we use for our analysis. Section 4 describes the empirical strategy implemented in the paper to estimate the effect of lithium extraction on vegetation and human populations. In Section 5 we provide the main results of our estimates. Finally, Section 6 concludes.

2 | CONTEXT

2.1 | Extraction of lithium in South America

Today, hard-rock ores and continental brines are used to extract lithium, with the latter being the most prominent source. 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 environmental requirements for significant technology advancements to replace fossil fuels have driven the Andean lithium rush. Since the beginning of the rush, more than ten years ago, the plateau area has become known as "The Lithium Triangle" (Figure 1).



(a) Lithium triangle

(b) Atacama Salt Flat

FIGURE 1 Main lithium extraction locations in South America. *Notes:* Figure 1(a) demonstrates what is known as the “Lithium Triangle”, while Figure 1(b) demonstrates the Atacama Salt Flat area with lithium mining activities and the distances to local native communities. *Source:* Figure 1(a): de la Hoz et al. (2013). Figure 1(b): own rendering.

This informal name describes the region lying between Chile’s Atacama Salt Flat (ASF), Bolivia’s Uyuni Salt Flat, and Argentina’s Hombre Muerto Salt Flat, which constitute the most significant lithium extraction locations worldwide (López Steinmetz and Salvi, 2021). In this paper, we focus on Chile’s ASF given that it is the most important in terms of lithium extraction, as we will show later.

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

Chile has long been a top producer of Li_2CO_3, with output mainly coming from brine activities at the ASF. The extraction and evaporation of brine water take place on-site at the ASF, after which the lithium concentrates are transported for processing to two Li_2CO_3 processing plants and one lithium hydroxide monohydrate ($LiOH \bullet H_2O$) processing plant in Antofagasta, Chile (Jaskula, B.W., 2018; Kelly et al., 2021).

2.3 | Environmental impacts of lithium extraction in Chile

The environmental science literature, to which we contribute in this paper, analyzes the effects of lithium extraction on local communities by examining the correlation between lithium extraction and several environmental outcome variables, or qualitative data. For instance, Liu et al. (2019) show that in the ASF region, there was a significant vegetation decline, increases in daytime temperature, decreases in the soil moisture, and an increase in draughtiness, all of which seem to be correlated with the production of lithium. Additionally, many stakeholders interested in understanding the environmental effects of the switch to green energy along the lithium-ion battery supply chain have recently focused on the extraction of lithium brines and related freshwater use in arid regions, such as the ASF (Gajardo and Redón, 2019; Gutiérrez et al., 2022; Sonter et al., 2020)

A comprehensive scientific understanding of the hydrological and geochemical systems of a salt flat is necessary to study and model the impacts of freshwater extraction (Moran et al., 2022). However, some authors have used techniques such as remote sensing analysis to discuss the negative effects of freshwater extraction from mining companies on the activities of native people living nearby mining areas, like agriculture (Garcés and Alvarez, 2020; Giglio, 2021). Figure 1 displays a map indicating the location of native communities near the SQM project and the freshwater wells used by the company to extract industrial water.

In the area of the ASF, indigenous populations have been using surface water for domestic and agricultural purposes for decades (Babidge, 2019). Over the last thirty years, as groundwater exploitation for mining purposes has expanded, Dirección General de Aguas (DGA), the country's top administrative body 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.

Utilizing measurements from those wells, along with satellite imagery, we go one step further and causally estimate the impact of lithium extraction on vegetation and human settlements. We do so by exploiting differentials in the exposure of Identified Vulnerable Areas (IVAs), and the corresponding populations, to our proxy of extraction, i.e. to the ratio of electric car sales worldwide to the distance from the center of the salt flat.

According to data shared with us by SQM, there are roughly 11,000 indigenous people who live in settlements nearby the salt flat, as shown in Figure 1. Out of these people, 77% are classified as rural populations, while 19% are migrants. Indigenous people from these communities constitute 17% of the workforce in the ASF. Several years ago, legal action was taken from the indigenous community of Camar against SQM for excessive use of water in the region, which was later settled by the two sides. Both anecdotal evidence and correlations presented in the relevant literature point to adverse environmental impacts of the extraction of lithium in the ASF, affecting the indigenous populations. In this paper, we causally estimate the magnitude and spatial distribution of those impacts.

3 | DATA AND DESCRIPTIVE STATISTICS

3.1 | Data

We utilize five main sources of data in our analysis, namely groundwater levels, vegetation index, agricultural production and livestock, human settlement estimates, and EV sales. The sources are as follows:

Groundwater levels: The first source of data concerns the levels of groundwater in the area of the ASF. These were 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.

Vegetation Index: Measurements for vegetation were obtained through the API provided by Landsat 8 through the Earth Engine Data Catalog. More specifically, we obtained the Landsat 8 Collection 1 Tier 1 Annual NDVI Composite measure. We identified a radius of interest, split it into $30m \times 30m$ pixels, and recovered the average NDVI values for each pixel and year between 2013 and 2020 within the IVAs. The NDVI is a vegetation index that ranges from -1 to 1, where greener areas take values closer to 1.

Agricultural production and livestock: This data is available through the Chilean Office of Agrarian Studies and Policy (ODEPA) at the region level. More specifically, the available data shows the national planted area, production, and annual yields for vegetables and agricultural products from the 1990s until 2021.

Human Settlements: In order to estimate the effects on local population settlements, we utilized the Global Human Settlement Layer (GHSL) dataset provided by the European Union through Copernicus. More specifically, we used 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 $100m \times 100m$ cell.

Electric vehicle sales: As part of our empirical strategy we utilized the number of sales of electric vehicles in the United States, Europe, and China. The data was obtained through the International Energy Agency and contains information on the annual sales of electric vehicles between 2010 and 2021. The sales data is provided by vehicle type for Battery Electric Vehicles (BEVs) and Plug-in Hybrid Electric Vehicles (PHEVs).

3.2 | Descriptive Statistics

Recently, the mine production of lithium worldwide has increased significantly. As can be seen in Figure 2 most of the production of lithium has been concentrated in Chile and Australia. However, since 2016 the production has increased particularly in Australia. This rise in the production of lithium coincides with the exponential increase in the total sales of electric vehicles worldwide.

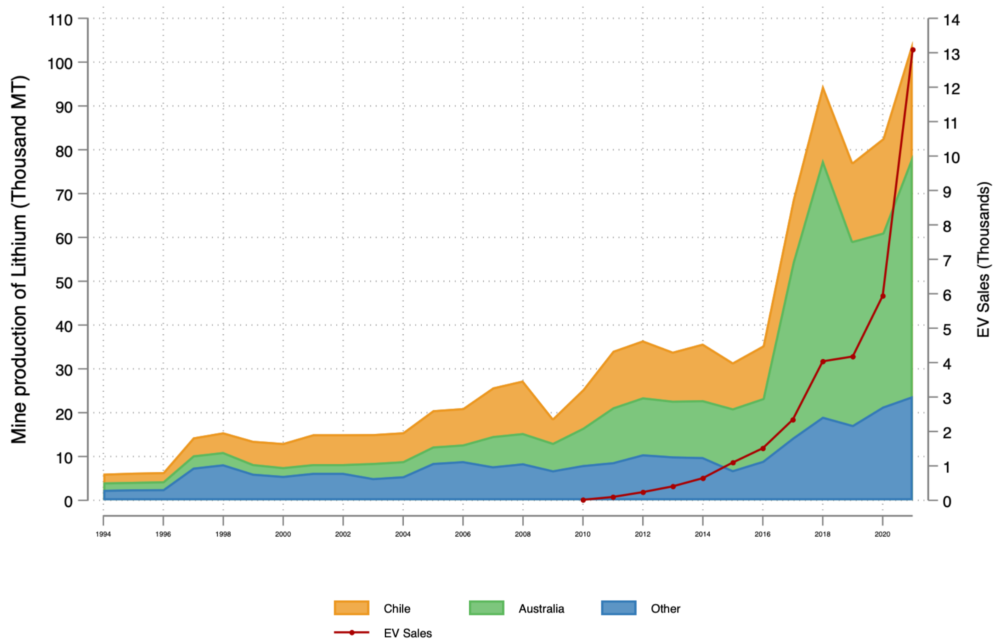


FIGURE 2 Notes. Mine production of lithium over time in thousand MT of contained lithium per year for Chile, Australia, and the rest of the world and overall electric vehicle sales in thousand units for the U.S., Europe, and China. Source: own elaboration based on data from the International Energy Agency and the Mineral Commodity Summaries from the US Department of the Interior and the US Geological Survey.

TABLE 1 Summary Statistics: NDVI and distances to ASF

	Mean (1)	Std. Dev. (2)	Min. (3)	Max. (4)
Panel A. Normalized difference Vegetation Index				
Valle de la Luna	0.077	0.035	-0.024	0.693
Tabmillo	0.099	0.053	-0.018	0.602
Tebenquiche	0.084	0.166	-0.913	0.531
Soncor	0.065	0.086	-0.867	0.426
Quelana	0.072	0.033	-0.356	0.470
Miscanti and Miñiques	0.048	0.105	-0.721	0.224
Laguna Lejia	0.054	0.127	-0.724	0.155
San Pedro de Atacama	0.102	0.088	-0.650	0.809
Toconao	0.100	0.099	-0.023	0.708
Camar	0.045	0.045	0.008	0.627
Socaire	0.108	0.038	-0.057	0.706
Peine	0.075	0.063	-0.029	0.690
Zapar	0.094	0.059	0.039	0.684
Pocor	0.069	0.014	0.053	0.238
Talabre	0.073	0.047	0.006	0.737
Tilomonte	0.078	0.048	0.017	0.609
Panel B. Distances to the Atacama Salt Flat				
Valle de la Luna	61.11	2.43	56.96	66.27
Tabmillo	49.10	4.61	39.80	58.29
Tebenquiche	40.12	0.98	38.42	41.88
Soncor	24.07	3.56	15.96	31.85
Quelana	17.45	2.00	13.20	22.54
Miscanti and Miñiques	59.57	4.98	47.48	71.62
Laguna Lejia	58.35	2.54	53.91	62.83
San Pedro de Atacama	65.39	5.29	55.84	75.33
Toconao	42.72	0.87	40.59	44.82
Camar	30.89	1.01	28.84	32.93
Socaire	38.67	4.16	30.33	46.95
Peine	27.44	1.00	25.05	29.81
Zapar	48.42	0.74	46.63	50.19
Pocor	38.12	0.41	37.14	39.08
Talabre	41.25	1.42	38.24	44.25
Tilomonte	36.03	0.77	34.21	37.86

Notes: NDVI data was obtained from Landsat 8 Collection 1 Tier 1 Annual NDVI Composite measure. We show the descriptive statistics of the NDVI and distance from the ASF for each Identified Vulnerable Area (IVA) *Source:* Own elaboration based on data from LANDSAT and our estimates.

As we aim to estimate the effects of the ramp-up of this extraction on areas around the ASF, we are going to focus on the local IVAs around it. There are twenty IVAs that are located near the ASF. Eleven out of the twenty IVAs are part of the National Reserve Los Flamencos (Valle de la Luna y Sierra de Orbate, Reserva Natural Puritama, Tambillo, Tebenquiche, Soncor, Quelana, Reserva Científica de Chajnantor, Miscanti and Miñiques, Laguna Lejia, Salar de Pujsa, and Salares de Tara and Aguas Calientes), while the other nine are human settlements (San Pedro de Atacama, Toconao, Camar, Socaire, Peine, Zapar, Pocor, Talabre, and Tilomonte), where mainly indigenous communities reside.

In Table 1 we show some descriptive statistics in terms of the NDVI for each IVA and the distance to the ASF. We calculate the mean, standard deviation, minimum, and maximum values of each variable for all the $30\mathrm{m} \times 30\mathrm{m}$ pixels of each IVA. Given that the nature of potential impacts is local, we are only utilizing the IVAs that are enclosed within an 80 km radius from the center of the ASF and only present descriptive statistics for those.

As can be seen, the IVAs are locations characterized by low levels of vegetation measured by the NDVI, with Camar being the IVA with the lowest average NDVI (0.045). Some of these NDVI values are negative indicating the presence of some water bodies in the area. In Panel B we can see the same statistics for the distance of each IVA to the Atacama Flat. As can be seen, there is a significant dispersion and variability in terms of the distance for each IVA. For instance, the closest pixel to the Atacama Flat is located at 13.2 kilometers in the Quelana IVA, whereas the furthest pixel is in San Pedro de Atacama at more than 75 kilometers from the flat.

TABLE 2 Summary Statistics: Human Settlements

Human Settlements	Mean (1)	Std. Dev. (2)	Min. (3)	Max. (4)
San Pedro de Atacama	0.234	1.599	0.000	68.872
Toconao	0.563	2.415	0.000	20.817
Camar	0.041	0.297	0.000	4.005
Socaire	0.010	0.245	0.000	15.844
Peine	0.220	1.105	0.000	12.132
Zapar	0.022	0.186	0.000	3.685
Pocor	0.022	0.126	0.000	1.385
Talabre	0.038	0.391	0.000	10.958
Tilomonte	0.011	0.154	0.000	3.859

Notes: Human settlement data were obtained from the Global Human Settlement Layer. We show the average of the human populations, meaning the estimated number of people per $100\mathrm{m} \times 100\mathrm{m}$ pixel, for each Identified Vulnerable Area (IVA). *Source:* Own elaboration based on data from the Global Human Settlement Layer and our estimates.

In Table 2 we show additional descriptive statistics in terms of the population for each of the nine IVAs that are human settlements, or villages. As can be seen, on average, the most dense is Toconao with 0.563 people per cell, while the one with the highest number of people per cell is San Pedro de Atacama with almost 69 people per $100\mathrm{m} \times 100\mathrm{m}$ cell. Lastly, Socaire is the one with the lowest number of people per cell on average.

We then analyzed the average level of fresh water measured by SQM in the ASF from 196 measurement stations that they report around the mining area in 7 monitoring systems. Figure 3 shows the average deviation for each year relative to the historic average level of water in the wells from 2010 to 2020. Lighter lines show the value for each one of the seven monitoring systems, whereas the dark purple dotted line plots the average of all the systems. As can be seen, in general, since 2014 there seems to be a negative difference in the level of the wells relative to the historical average, which could be a consequence of the utilization of fresh water for the mining process. These negative values, however, went positive in approximately 2019, which could be explained by more efficient and environmentally friendly use of the water resources in the area. It is expected that, if this reduction in the levels of fresh water in the areas near the ASF had an ecological impact in terms of vegetation, then those areas closer to the ASF should be the ones that were affected the most.

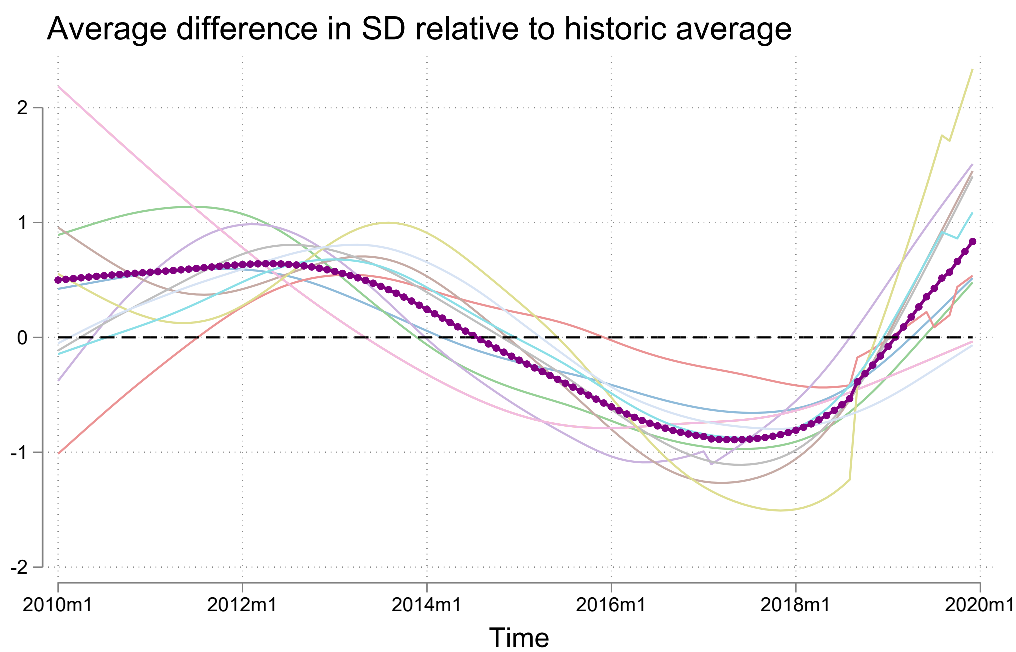
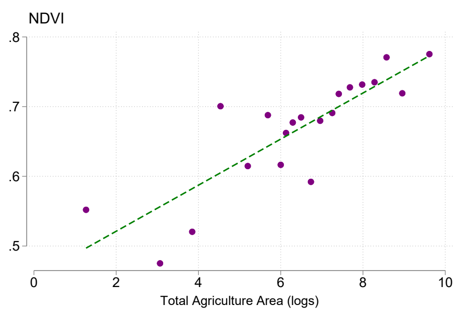


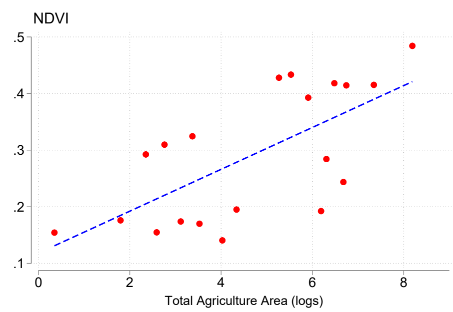
FIGURE 3 Well levels in the Atacama Salt Flat, 2010-2020. *Notes:* For each well, we calculated the trend using a Hodrick-Prescott filter with a smoothing parameter of 14,400 and calculated the difference of each value relative to the historical average in the 2013-2020 period for each well relative to the standard deviation of the same period. Each light line shows the value in standard deviations for each one of the seven SQM monitoring systems and the connected purple line shows the average over time of the seven systems. *Source:* Own elaboration based on data from SQM.

Ideally, apart from the environmental impact of lithium extraction in the ASF in terms of vegetation, we would also like to estimate the corresponding 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 fresh water in the area. However, given the lack of granular data for the potentially affected areas, we consider the NDVI as a proxy variable for the impact on agriculture.

In Figure 4 we show the relationship between the average NDVI and the total cultivated area for agriculture (in logs) in each municipality of Chile. Panel (a) shows the relationship for the whole country, whereas Panel (b) restricts the sample to municipalities located in the North Region of Chile. As can be seen, NDVI and total cultivated area for agriculture purposes seem to be positively and strongly correlated across municipalities in Chile in general, but also in the North of the country. This positive correlation provides evidence of the validity of the utilization of NDVI as a proxy measure for agricultural activity in the areas close to the ASF.



(a) Chile



(b) North of Chile

FIGURE 4 Relationship between NDVI (2010) and Total Cultivated Area (2007). *Notes:* Figure (a) shows the binscatter between the average NDVI in 2010 in each one of the 287 municipalities for which there is information available in the Agricultural Census in 2007 and the total agricultural cultivated area (in logs). Figure (b) shows the same information but restricts the sample to municipalities in the North of Chile (Antofagasta Region, Arica y Parinacota Region, Atacama Region, Tarapacá Region, and Coquimbo Region). *Source:* Own elaboration based on data from the 2007 Agricultural Census and Landsat 8 Collection 1 Tier 1 Annual NDVI Composite measure.

A first overview of the impact of lithium extraction in the ASF on the NDVI in the area surrounding the Lithium mine is presented in Figure 5. In this figure, we show a non-parametric estimate of the relationship between changes in the NDVI between 2013 and 2020 for each $30m \times 30m$ pixel and the distance to the ASF. It is expected that those areas located closer to the ASF are the ones in which the change in the NDVI level should be more negative. This is because those are the areas that could be more affected by the scarcity of fresh water due to its utilization for the process of lithium extraction.

As can be seen in Figure 5, there seems to be a significant decrease in the NDVI for those areas located in a radius of 15 to 30 kilometers to the ASF and this effect seems to be a reduction of up to 0.7 standard deviations. In the next section, we will show our preferred empirical specification in which we will include controls for the latitude and longitude of each pixel which will, in turn, 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 5 shown here.

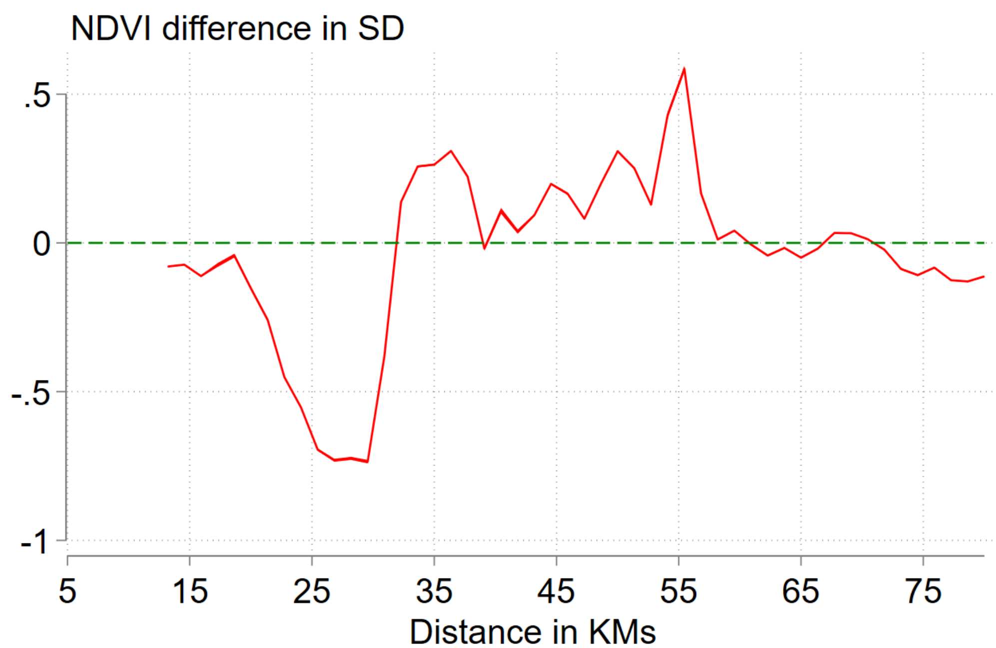


FIGURE 5 Non-parametric relationship between distance to the Atacama Salt Flat and NDVI change, 2013-2019. *Notes:* The red line shows the Kernel-weighted local polynomial smoothed relationship between the NDVI measure change over the 2013-2020 period in each $60m \times 60m$ pixel surrounding the ASF and the corresponding distance to it. The lighter area corresponds to the 95% confidence interval. The NDVI is measured in standard deviations. *Source:* Own elaboration based on data from Landsat 8 Collection 1 Tier 1.

4 | EMPIRICAL STRATEGY

The empirical strategy can be divided into two parts. In the first part, we will estimate the impact of exposure to lithium extraction on NDVI. To do this, we will estimate the following:

$$NDVI_{it} = \alpha + \beta \left(\frac{V_t}{D_i} \right) + \Gamma[C_i \times \rho_t] + \rho_t + \phi_i + \varepsilon_{it} \tag{1}$$

where $NDVI_{it}$ is the average annual NDVI for each $30m \times 30m$ pixel i, D_i is the distance between each pixel and the ASF, and V_t is the total sales of EVs in the U.S., Europe, and China. $[C_i \times \rho_t]$ is a vector of controls in which we interact the latitude and longitude of each pixel i with time fixed-effects. Our coefficient of interest is β, which will show the effect of our measure of exposure to lithium extraction on NDVI. ρ_t are year fixed-effects and ϕ_i pixel fixed-effects. Standard errors are clustered at the pixel level.

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, US, and China which is exogenous to the vegetation levels in Chile. On the other hand, our identification assumption relies on the fact that we are controlling for coordinates interacted with year fixed-effects. Hence, we are comparing changes over time in NDVI explained by the exposure to the extraction of lithium for pixels that are very close to each other.

Then, we analyze how the effect was different splitting up the estimated impact for locations in human settlements and locations that are part of the National Reserve Los Flamencos. If the effect was mainly driven by a reduction in the NDVI due to the negative impact of the scarcity of water on agricultural activity, we would expect to see that the negative effect is mainly concentrated in human settlements where agriculture plays a crucial role. In order to analyze this we estimate the following:

$$NDVI_{it} = \alpha + \beta \left(\frac{V_t}{D_i}\right) + \delta \left(\frac{V_t}{D_i}\right) \times H_i + \Gamma[C_i \times \rho_t] + \rho_t + \phi_i + \varepsilon_{it} \tag{2}$$

where we define H_i as a dummy variable that takes a value of 1 if pixel i is in an IVA that is classified as a human settlement, namely any of the villages around ASF, and 0 otherwise. In this case, β will indicate the average effect on the locations in any of the IVAs belonging to the National Reserve los Flamencos, and $\beta + \delta$ will indicate the effect for the human settlements around the flat.

The second part of our empirical strategy concerns the estimation of the impact of lithium extraction in the ASF on human settlements and is driven by the lack of time-series data for human settlements throughout the period we are looking at. We estimate the following regression:

$$\triangle HS_i = \alpha + \beta D_i + \gamma C_i + \varepsilon_i \tag{3}$$

Where $\triangle HS_i$ is the change in the population between 2010 and 2020 for each $100m \times 100m$ pixel in the region; D_i is the distance between each pixel and the ASF multiplied by -1. C_i are latitude and longitude controls, ρ_i are pixel fixed-effects and, finally, ε_i is the error term. Our coefficient of interest is β, which will show the average effect of lithium extraction on human settlements.

Our identification strategy relies on the assumption that when comparing changes in the human settlements of $100m \times 100m$ pixels very close to each other over time, any change could only be attributed to the proximity to the ASF and, therefore, to the extraction of lithium in this area. It is worth noting that, although there could exist a negative relationship between the human settlements and the distance from each point to ASF, our identification strategy is exploiting changes over time of the human settlements in the different pixels in close proximity, which we should expect to change at a relatively similar rate.

All the independent and dependent variables of interest in all our specifications are expressed in standard deviations.

5 | RESULTS

Our main results are shown in Table 3. In the first column, we consider the coefficient for the model in which we regress the NDVI for each location on the exposure to lithium extraction, including pixel and year fixed-effects. In the second column, we further interact location fixed effects, namely longitude and latitude, with time dummies. Our estimates indicate that those pixels that are exposed to 1 more standard deviation of our measure of lithium extraction were affected negatively by a reduction in the vegetation measured by the NDVI of between 0.05 and 0.09 standard deviations.

Further, we consider how different the effect on NDVI between pixels in villages and pixels in one of the IVAs that belong to the National Reserve Los Flamencos is. In column 3 we can observe that most of the reduction in the NDVI was explained by human settlements. This goes in line with a reduction in the total cultivated area with agricultural crops hypothesized above. We estimate that those locations that are exposed to 1 more standard deviation of our measure of lithium extraction were negatively affected by a reduction in the NDVI by approximately 0.22 standard deviations, the sum of the two coefficients.

TABLE 3 Effect of Lithium extraction on NDVI

	(1)	(2)	(3)
Exposure to extraction	-0.049***	-0.094***	-0.077***
	(0.000)	(0.000)	(0.000)
Exposure to extraction x Village dummy			-0.150***
			(0.002)
Pixel FE	✓	✓	✓
Year FE	✓	✓	✓
Coordinates x Year FE		✓	✓
Observations	16,665,368	16,665,368	16,665,368

Notes: *** p<0.01, ** p<0.05, * p<0.1. Pixel FE corresponds to a dummy variable for each pixel in our sample. Coordinates FE corresponds to the latitude and longitude of each pixel in our sample. The Village Dummy variable takes a value equal to 1 if the observation corresponds to any of the nine human settlements, namely San Pedro de Atacama, Toconao, Camar, Socaire, Peine, Zapar, Pocor, Talabre, or Tilomonte. *Source:* Own elaboration based on data from Landsat 8 Collection 1 Tier 1 and own estimates.

In Figure 6 we show the estimated effect by considering the initial level (in 2013) of NDVI for each pixel in our sample, showing that the effect seems to be particularly higher the greater the NDVI index in 2013. Hence, those areas that were more strongly affected were those in which the level of vegetation was significantly higher at baseline.

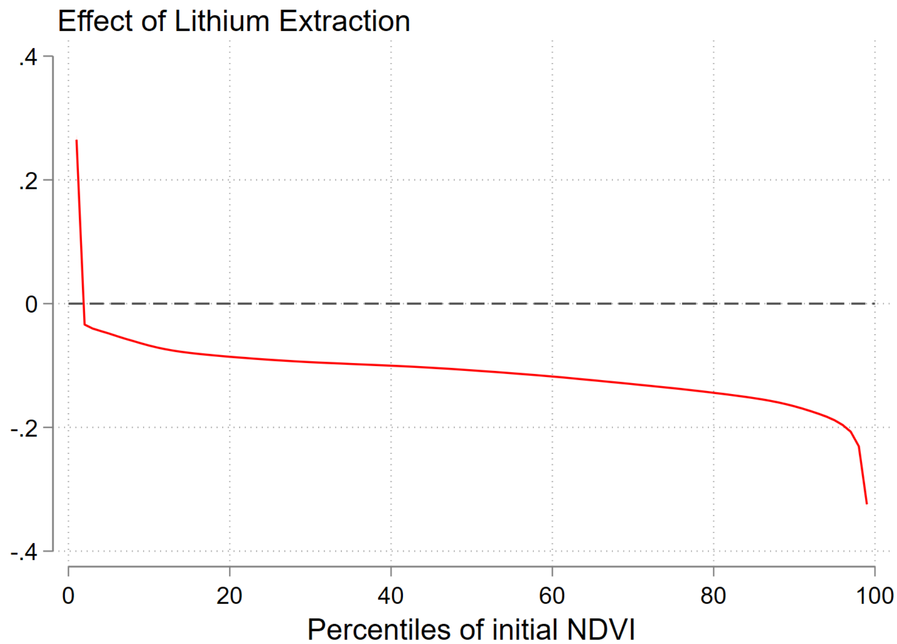


FIGURE 6 Estimated effect of exposure to lithium extraction by baseline level of NDVI. *Notes:* Each point corresponds to the estimated effect according to the 2013 distribution of NDVI across all pixels in our area of analysis. The red light area indicates the 95% confidence interval. *Source:* Own elaboration based on data from Landsat 8 Collection 1 Tier 1 and own estimates.

Additionally, the results of our specification with regards to human settlements are shown in Table 4. In the first column, we do not include any controls in our regression and only consider the coefficient for the model in which we regress the change in the population for each location on the distance to the ASF. In the second column, we estimate our preferred specification including also location fixed effects to compare changes in pixels very close to each other over time.

TABLE 4 Effect of Lithium extraction on human settlements

	(1)	(2)
Distance (Kms)	-0.011***	-0.037***
	(0.003)	(0.010)
Coordinates Control		✓
Observations	3,144	3,144

Notes: *** p<0.01, ** p<0.05, * p<0.1.Location FE corresponds to a dummy variable for the latitude and longitude of each pixel in our sample. *Source:* Own elaboration based on data from Global Human Settlement Layer and own estimates.

Hence, in our preferred specification, there seems to be a negative effect of 0.04 standard deviations on human populations in local villages for 1 standard deviation closer to the ASF.

To put this into perspective, 1 standard deviation of distance from the center of the ASF translates to approximately 10 kilometers. Equivalently, 1 standard deviation of human settlements, or number of people per pixel, in 2010 is equal to 4 people. Hence, the effect represents a reduction of 0.15 people per pixel. Now, if we consider that, on average, each IVA has 350 pixels, this represents an approximate reduction of 50 people per IVA for every 10 kilometers closer to the ASF, or 6.5% of the average population of an IVA in 2010.

6 | CONCLUDING REMARKS

Lithium has 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. However, the environmental and economic 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. It is important that relevant policymakers obtain visibility on the magnitude and extent of those consequences in order to address them moving forward.

In this paper, we aimed to contribute to this debate by providing causal evidence of the impact of lithium extraction on vegetation in areas around the ASF. To do this we built on relevant environmental literature that has only provided correlational evidence between the extraction and several environmental variables. This literature guided us in identifying the relevant vulnerable areas, as well as those environmental variables that the extraction could have potentially affected. Additionally, we moved one step further by attempting, for the first time, to evaluate how population changes might have responded to this activity.

Several important takeaways emerged from our analysis. First, in terms of NDVI, the negative effect seems to be statistically significant for all values in the initial distribution of vegetation index in locations around the ASF. Also, the effect seems to be particularly higher the greater the NDVI index in 2013. Secondly, in terms of human populations, our preferred specification yields a statistically significant negative result.

Overall, in this study we provide causal evidence that the extraction reduces vegetation around the ASF and show that the vegetation index that is reduced is strongly correlated with agriculture historically in Chile. Furthermore, we causally show that populations were reduced in those same areas, positing a causal chain that reduced agriculture might have caused human flight out of the IVAs.

Our analysis sheds light on a crucial matter for Chile, however, the implications are also relevant for the other two countries located in the lithium triangle of South America, namely Bolivia and Argentina. It is important that policymakers take into account the potential negative environmental and economic impacts that might come with lithium extraction in order to address them and compensate the affected communities.

Notwithstanding the evidence we provide in this paper in terms of the environmental and economic consequences of lithium extraction, it should be stressed that a life-cycle cost-benefit analysis would also be important to complement our results. Lithium extraction has positive economic impacts for the economies that exploit this raw material, as well as for decarbonizing the economy altogether, and it is important to understand the scope and magnitude of the negative impacts in order to carry out a holistic analysis of the supply-chain of lithium.

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