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Precipitation extremes in the Puna of Atacama Desert, Chile: How to manage current and future uncertainty?

Precipitación extrema en la Puna del Desierto de Atacama: ¿Cómo gestionar la incertidumbre actual y futura?

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Abstract

Chile is one of the Latin American countries most affected by Climate Change. There is a high level of uncertainty regarding the variability of precipitation and its projections in many regions of this country. This poses challenges for climate characterization and for defining strategies to reduce its risks. The study area is the Puna of Atacama Desert, Andean highlands located to the eastern side of the extreme arid lands, a region that concentrates the main copper and lithium mining at word scale, and where meteorological observations are scarce, with missing data and unreliable projections. Considering this data limitations, a daily precipitation database of 35 weather stations was constructed in order to evaluate some extreme precipitation indices that allow establishing changes between 1981-2017, in addition to spatial interpolations based on topography. It is concluded that most of the meteorological stations do not present significant trends of change, e.g. Extremely wet days (R99p), Wet days (RR) and Consecutive wet days (CWD). The index with the highest number of stations with a trend is CDD, which shows an increase in consecutive dry days. One of the main contributions of this research was to expand the number of observations and to generate maps of the spatial distribution of the indices of extremes. We are facing open questions regarding living with uncertainty, and meeting the challenges of maintaining records to increase the levels of certainty of climatic changes.

Keywords: Uncertainty; Extreme indices; Salar de San Pedro de Atacama; Precipitation trends.

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Resumen

Chile es uno de los países de América Latina más afectados por el cambio climático. Existe un elevado nivel de incertidumbre respecto a la variabilidad de las precipitaciones y sus proyecciones en muchas de sus regiones. Ello plantea desafíos para su caracterización climática y para definir estrategias para reducir los riesgos asociados. Se estudia la Puna del Desierto de Atacama, paisaje andino de altura que bordea las tierras áridas por el lado este, y que concentran las principales minas de cobre y litio a escala mundial, y donde existen escasas observaciones meteorológicas, con datos perdidos y proyecciones de poca fiabilidad. Es por ello que se construyó una base diaria de precipitación de 35 estaciones con el fin de evaluar algunos índices extremos que permitan establecer cambios entre 1981-2017, además de interpolaciones espaciales basadas en la topografía. Se concluye que la mayoría de las estaciones meteorológicas no presenta tendencias significativas de cambio, destacando días extremadamente húmedos (R99p), días húmedos (RR) y días húmedos consecutivos (CWD). El índice con mayor cantidad de estaciones con tendencia es CDD, que muestra un incremento de los días consecutivos secos. Uno de los principales aportes de esta investigación fue ampliar el número de observaciones y generar mapas de la distribución espacial de los índices de extremos. Nos quedan preguntas abiertas respecto a convivir con la incertidumbre, y alcanzar desafíos de mantener los registros para aumentar los niveles de certeza de los cambios climáticos.

Palabras clave: Incertidumbre; Índices de extremos; Salar de San Pedro de Atacama; Tendencias de precipitación.

1. Introduction

One of the main problems facing humanity on a global scale, and which constitutes a challenge for the different forms of social organization, is climate change (Hallegatte et al., 2016; Nordhaus, 2019). Palmer and Stevens (2019) research points out that while current climate models are useful for testing the basic tenets of our understanding of global climate change, they are inadequate to address the needs of society struggling to anticipate the impact of coming changes to weather and climate. This means challenges for water resources management (Greve et al., 2018), as well as for risk management associated with extreme events. Climate science through climate change studies has consolidated IPCC reports (e.g. AR6 in Zhongming et al., 2021) that point to evidence of global warming and its effects on temperature, precipitation and other meteorological parameters. All AR6 models have high reliability with respect to observed and projected changes in temperature, however, for precipitation, they have high uncertainty, particularly for subtropical and near arid and semi-arid regions. However, there are works in the opposite direction, i.e., indicating greater certainty in arid and hyper-arid zones (Yazdandoost et al., 2021). The latter is interesting, as it adds more complexity and also importance to climate-specific studies at regional and local scales.

Many climate scientists agree that despite significant advances over the past decade, model simulations possess biases and uncertainties, which are due to a variety of factors, including simple assumptions, limits in model parameterization, boundary conditions, among others (Kay et al., 2009; Curry & Webster, 2011; Liepert & Previdi, 2012; Khan et al., 2018; Yazdandoost et al., 2021)

For the mining sector climate change should be seen as a threat, but the literature in developing countries is scarce to non-existent. Australia and Canada are concerned about the problem being those belonging world (Odell et al., 2018). An example of considering climate change in economic activities is El Salvador (Odell et al., 2018), where it is made by state law a calling attention to the vulnerability of the water resources under climate change conditions, arguing that allowing mining implies a serious risk for the country, seriously aggravating its future by increasing vulnerability (Broad & Cavanagh, 2015; Spalding, 2013; Moran, 2005).

In Chile, the areas with the greatest uncertainty are in the northern regions (Babidge, 2019), made up of deserts and high-altitude tundra areas (Puna de Atacama), with summer precipitation (Sarricolea et al., 2017). IPCC models referring to precipitation in these areas show high uncertainty, i.e., there are no trends that indicate convergent projections of climate into the future. Therefore, it is necessary to know if in Chile there are any extreme indexes applied to local weather stations to detect with greater certainty changes in precipitation, and thus, plan the future of a mining region that is one of the most important in the world in copper and lithium production (Prieto, 2015; Liu & Agusdinata, 2020; Lui & Agusdinata, 2021), two commodities that require a lot of water in their extraction. In addition, the study area has indigenous populations that make their living from tourism, agriculture and livestock, and therefore require information and adaptation strategies (Romero & Opazo, 2019). To this must be added the large extractions of groundwater that the mining industry carries out in this region, since the amount of water stored in the aquifers is unknown, and the rate of overconsumption that they are supporting (Babidge, 2019). In addition to the impact that mining operations have on water quality, as they increase heavy metals in the water (Lizama-Allende et al., 2022).

Given the reduced number of meteorological stations in the Norte Grande (Amigo & Ramírez, 1998), efforts are required to maintain data continuity, as well as to perform adequate interpolations of the extreme indices, in order to know the spatial distribution of these indicators, and thus, to have a more territorial vision of extreme conditions in the region.

Studying precipitation in the Atacama Desert is a challenge, since according to the latest IPCC report (Zhongming et al., 2021) this region is classified as having high uncertainty for trends and projections. This is due to the fact that the variability of precipitation expressed in standard deviations exceeds the central tendency values (annual means), a fact that is reflected in most of the meteorological stations. In this regard, Schulz et al. (2012) pointed out that changes in precipitation in the coastal desert have gone unnoticed, and few studies have examined some aspects of its evolution in recent decades (Houston, 2006). However, in the Andean highlands the causes of such uncertainty seem to be more related to changes in atmospheric circulation and Amazonian deforestation (Ruiz-Vásquez et al., 2020, Sulca et al., 2022). Beside this, based on reconstructed meteorological series, the area experienced trends in the daily precipitation concentration (Meseguer-Ruiz et al., 2019). It has also been evidenced that certain weather regimes configurations favor positive precipitation anomalies (Meseguer-Ruiz et al., 2020). Moreover, the occurrence of the most torrential precipitation in the area are related to moist transport in the mid and upper troposphere from the Amazon basin (Meseguer-Ruiz et al., 2020; Segura et al., 2022).

All these uncertainties generate gaps in knowledge about the extreme behavior of the climate in the Altiplano, and the need to quantify in a more robust way, the magnitude of extreme indices and the recent and projected IPCC trends. In other words, this work expects, through rainfall data filling methodologies, local scale evidence of regional projections of climate change. Despite the uncertainty, the study of precipitation trends provides potential indicators for modeling future climate change patterns and thus offers an important contribution to the scientific debate. This is pointed out by Souvignet et al. (2012) and Sarricolea et al. (2017), highlighting the importance of the study of local climates in this regard. But not only that, because they can lead to actions that seek precautionary principles with respect to water resources, in order to achieve more sustainable forms among the various actors and agents that pressure and coexist in these territories.

Thus, the novelty of this work lies in generating a daily resolution pluviometric database, generating indices of extremes occurrences and mapping this information based on a simple and replicable geostatistical method. This information is essential for making strategic proposals for resource use, as well as proposing improvements to the system for monitoring environmental variables continuously and minimizing gaps, in addition to mapping using methods that give importance to local climatology.

The objectives of this research are 1) to generate a daily database and calculate a number of precipitation extreme indices; 2) to evaluate the trends of the extreme indices; 3) to interpolate the calculated indices based on a geostatistical approach based on altitude; and 4) to discuss the results, in particular, the high uncertainty existing in most of the extreme indices.

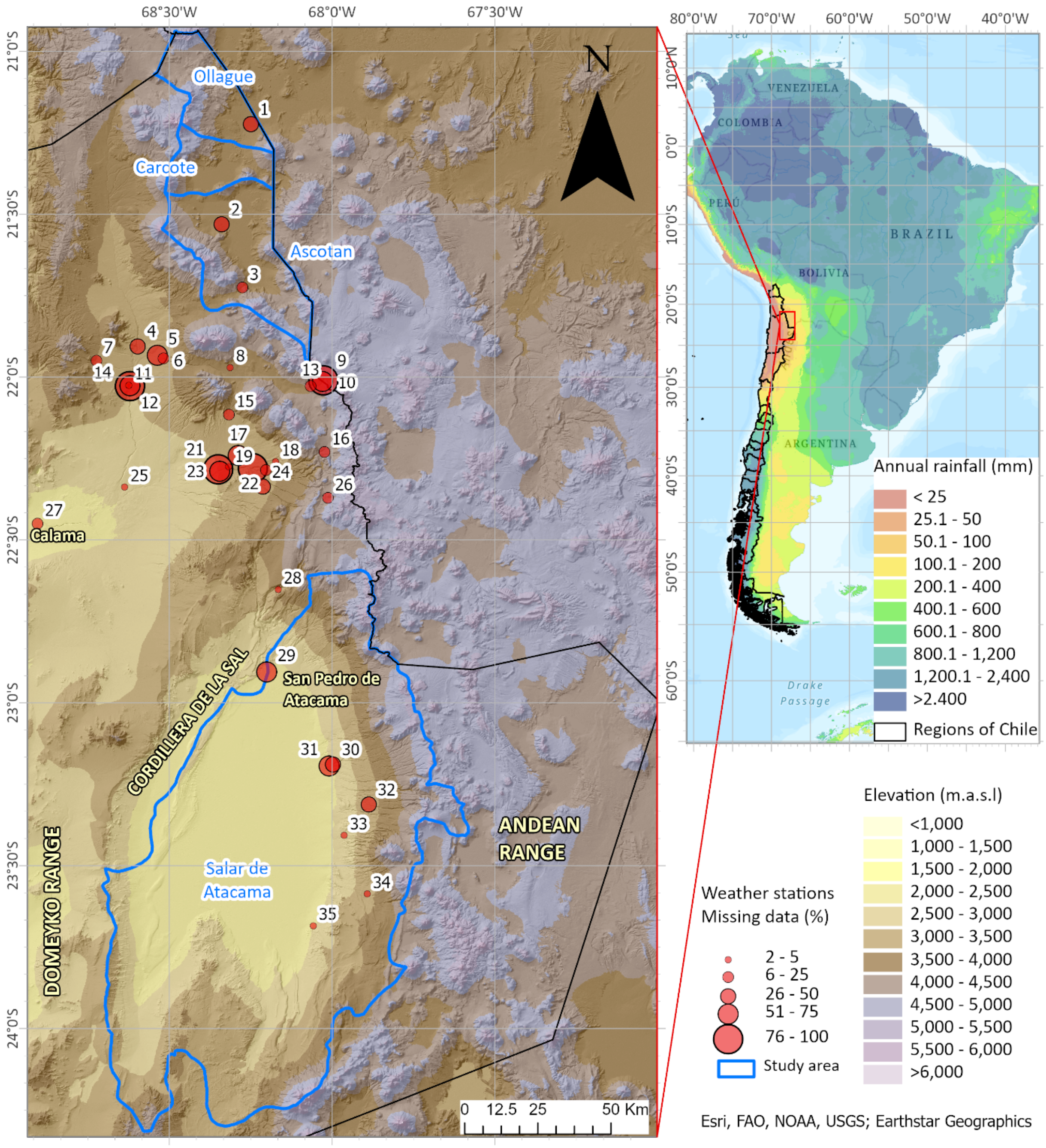
2. Methodology

2.1. Study area

The Puna de Atacama is located in the Central Andes, between ~18 °S and ~27 °S latitudes. According to Latorre et al. (2005), it is composed by the Precordillera (2,200- 3,500 m a.sl.) and the semi-arid plateaus above 3,500 m a.s.l. (Jaksic et al., 1997).

This study is limited to the Puna de Atacama of the Antofagasta Region (Figure 1), specifically, the upper basins of the Loa River (including Ollague, Carcote and Ascotán saltflats) and the Salar de Atacama, under high altitude tundra summer rainfall climates (Etw) and semi-arid high altitude climates (BSk).

Figure 1. Study area and station network



Topographic map of northern Chile and the high Andean salt flats (left) and mean annual precipitation of the South American region (right)

Source: Fick & Hijmans (2017). Own elaboration

2.2. Data sources and methods

Rainfall data from 35 meteorological stations (1981-2017), belonging to both the National Water General Direction (DGA for its Spanish acronym) and Meteorological Direction of Chile (DMC for its Spanish acronym; http://www.meteochile.cl), are used for this study (Table 1). The daily data were obtained from the repository of the Center for Climate and Resilience Research (CR2) of the University of Chile. All the data were quality-controlled daily scaled, with the deletion of suspicious values, outliers and suspicious dry/humid days according to Serrano-Notivoli et al. (2017). After this step, precipitation data were estimated for all the missing days at every station. Both processes were afforded with the reddPrec R package (Serrano-Notivoli et al., 2017). The method used is very efficient in filling gap in very short series with other complete series or with few gaps, since it constructs independent daily equations for each case, which for daily precipitation data is critic. Almost all the instrumental time series are affected by a percentage of missing data. In the case of this region, the Rio Salado and Sifon Ayquina stations have more than 95% of no data. However, and thinking about the gridded products, it is better to have some measured data than only interpolated data, since they allow us to know from information measured in a short period of time what the precipitation is really like. However, we understand that they should be viewed with great care, since, like the gridded products, they are data derived from the method of filling in missing data. A way out of this difficulty is to exclude periods with missing values from data analysis, or to ignore the problem if their amount is not very large. Such approaches, however, may disregard valuable information and can induce biases in many climate investigations (Simolo et al., 2010).

Table 1. weather stations used, by location (latitude, longitude and altitude) and percentage of missing data from the original daily series 1981-2017

ID	Name	Latitude	Longitude	Altitude (m a.sl.)	Missing data (%)
1	Ollague	-21.22	-68.25	3,700	37.3
2	Cebollar	-21.53	-68.34	3,730	42.7
3	Ascotan	-21.73	-68.28	3,970	14.0
4	Quinchamale	-21.91	-68.60	3,080	41.1
5	San Pedro De Conchi	-21.93	-68.54	3,217	66.5
6	Parshall 2	-21.94	-68.52	3,318	10.1
7	Conchi Viejo	-21.95	-68.72	3,491	14.3
8	Ojos San Pedro	-21.97	-68.31	3,800	4.0
9	Rio Siloli	-22.01	-68.03	4,000	89.4
10	Silala	-22.01	-68.03	4,305	55.9
11	Conchi Embalse	-22.03	-68.62	3,010	4.8
12	Conchi Muro Embalse	-22.03	-68.62	3,000	71.8
13	Inacaliri	-22.03	-68.07	4,040	5.1
14	Rio Loa/Embalse Conchi	-22.03	-68.62	2,950	86.4
15	Cupo	-22.11	-68.32	3,370	5.5
16	Linzor	-22.23	-68.02	4,100	12.5
17	Turi	-22.24	-68.29	3,070	66.9
18	Toconce	-22.26	-68.17	3,310	2.8
19	Ayquina	-22.28	-68.32	3,031	3.0
20	Rio Salado / Curti	-22.28	-68.24	3,080	96.4
21	Sifon Ayquina	-22.28	-68.35	3,000	99.5
22	Salado Embalse	-22.29	-68.20	3,200	5.2
23	Rio Salado / Sifon Ayquina	-22.29	-68.34	2,980	58.2
24	Caspana	-22.34	-68.21	3,260	27.0
25	Chiu-Chiu	-22.34	-68.64	2,524	3.3
26	El Tatio	-22.37	-68.01	4,370	7.4
27	Calama	-22.45	-68.90	2,300	6.9
28	Rio Grande	-22.65	-68.17	3,250	2.2
29	San Pedro De Atacama	-22.91	-68.20	2,450	63.0
30	Toconao Experimental	-23.19	-68.00	2,500	27.3
31	Toconao Reten	-23.19	-68.01	2,460	72.3
32	Talabre	-23.31	-67.89	3,300	42.2
33	Camar	-23.41	-67.96	2,700	1.5
34	Socaire	-23.59	-67.89	3,251	4.6
35	Peine	-23.68	-68.06	2,460	2.8

Own elaboration

This study area has salt flats, cultivation and human setlement area called "Ayllus", which can be seen in Figures 2a y 2b, and are also under pressure from lithium mining activities.

Figure 2. Photographs of the study area

2a Photography taken from a drone of Ayllu "Pucará Quitor", San Pedro de Atacama, May 2022. 22°53'22.7"S 68°12'54.6"W. 2b Photography of Ascotán Saltflats, May 2022. 21°28'54.4"S 68°23'43.8"W

Photograph by the authors

A total of six indices of extremes were calculated. They come from the Expert Team on Climate Change Detection and Indices (ETCCDI) (Karl et al., 1999; Peterson et al., 2001), and correspond to Wet days (RR), Extremely wet days (R99p), Maximum 5-day precipitation (RX5day), Single day intensity index (SDII) and Maximum number of consecutive dry and consecutive wet days (CDD and CWD). These indices are used here with slight modifications, in particular with regard to the threshold of 1mm (RR and SDII), often used as a cut-off value to define rain events (Table 2). To analyze the trends, the Mann-Kendall test (Mann, 1945; Kendall, 1975) was applied, which allows the detection of statistically significant trends. The Mann-Kendall test is a nonparametric test that evaluates the monotonic behavior of a data series and is very suitable for the study of precipitation since it does not require normality or linearity. In this article, significant trends are those that reach the first confidence level, 95% ($p< 0.05$). The test has been widely used in the analysis of hydro-meteorological time series. The MK statistic is obtained as follows:

$$S = \sum_{i=1}^{n-1} \sum_{j=i+1}^{n} sgn(x_j - x_i)$$

$$(x_j - x_i) = z$$

$$sgn(z) = \begin{cases} 1 \; if \; (z) \geq 0 \\ 0 \; if \; (z) = 0 \\ -1 \; if \; (z) \leq 0 \end{cases}$$

where n is the dimension of the series and x_j and x_i are the annual values, respectively, in the years j and i, with j [i. For n [10, given that x_i is an independent and randomly ordered series, the statistic S follows a normal distribution whose mean is equal to 0, and the variance is provided by:

$$Var(S) = \left[n(n-1)(2n+5) \sum_{i=1}^{n} t_i i(i-1)(21+5) \right] / 18$$

where t_i represents a margin of error of i. The standardized statistical test Z_{MK} follows a standard normal distribution, and is represented by:

$$Z_{MK} = \begin{cases} \dfrac{S-1}{\sqrt{Var(S)}} \; if \; S > 0 \\ 0 \; if \; S = 0 \\ \dfrac{S+1}{\sqrt{Var(S)}} \; if \; S < 0 \end{cases}$$

Using a two-tailed test, if Z_{MK} is greater than $Z_{(\alpha/2)}$, with a significance level α, then it is possible to reject the null hypothesis and the trend can be considered significant. At the 5% significance level, the null hypothesis of no trend is rejected if |Z| > 1.96.

To estimate the magnitude of the slope we use the nonparametric Sen slope estimator (Sen, 1968). This approach involves computing the slopes for all temporally ordered pairs of data points and then calculating the median of these slopes as an estimate of the overall slope. Since Sen's slope is not greatly affected by single data errors or outliers and missing values are also allowed, it is more rigorous than the commonly used regression slopes and thus provides a realistic measure of the trends in the time series. Sen's method can be used in cases where the trend can be assumed to be linear. This means that f(t) is equal to

$$f(t) = Qt + B$$

where f(t) is a continuous monotonic increasing or decreasing function of time, Q is the slope and B is a constant. To obtain the slope estimate Q in Eq. (6) we first calculate the slopes of all data value pairs

$$Q_i = \frac{x_j - x_k}{j - k}$$

in which j > k. A positive value of Q_i indicates an increasing trend whereas a negative value indicates a decreasing trend. If there are n values x_j in the time series we get as many as N=n(n-l)/2 slope estimates Q_i. The Sen's estimator of slope is the median of these N values of Q_i. The N values of Q_i are ranked from the smallest to the largest and the Sen's estimator is

$$Q = \begin{cases} Q_{[(N+1)/2]}\ if\ N\ is\ odd \\ \dfrac{Q_{\left[\frac{N}{2}\right]} + Q_{\left[\frac{(N+2)}{2}\right]}}{2}\ if\ N\ is\ even \end{cases}$$

The Q sign denotes data trend reflection, while its value indicates the steepness of the trend. To determine whether the median slope is statistically different from zero, one should obtain the confidence interval of Q at specific probability. The confidence interval about the time slope can be computed as follows:

$$C_\alpha = Z_{1-\alpha/2}\sqrt{Var(S)}$$

where Var(S) is same defined as the variance in Mann-Kendall test and $Z_{1-\alpha/2}$ is obtained from the standard normal distribution table. In this study, we calculated the confidence interval at α=0.05.

Then M_1=(N-C_a)/2 and M_2=(N+C)/2 are computed. The lower and upper limits of the confidence interval, Q_{min} and Q_{max}, are the M_1^th largest and the (M_2 + 1) the largest of the N ordered slope estimates Q_i. The slope Q is statistically different from zero if the two limits (Q_{min} and Q_{max}) have the same sign. To obtain an estimate of B, the n values of differences x_i - Q_{ti} are calculated. Their median of these values gives an estimate of B. Estimates for the constant B of lines of the 95% confidence interval are calculated by a similar procedure.

Table 2. List of precipitation extreme indices, definitions and units, adapted from the ETCCDI

Index	Index name	Definition	Units
RR	Wet days	Number of days with precipitation (P) > 0 mm	days
R99p	Extremely wet days	Number of days with P ≥ 99th percentile of precipitation (P99) in the 1981-2017 period.	days
RX5day	Max 5-day precipitation	Maximum 5-day accumulated P in one year	mm
SDII	Single day intensity index	$SDII_j$ = SUM(Rain > 0)/Rmm_j where Rmm_j represents the number of wet days in a period j	mm/day
CDD and CWD	Maximum number of consecutive dry and consecutive wet days	Let Rrij be the daily precipitation amount on day I in period j. Count the largest number of consecutive days where rRij < 1mm (CDD) and rRij > 1 mm (CWD)	days

Source: http://etccdi.pacificclimate.org/list_27_indices.shtml. Own elaboration

Finally, the calculated extreme indices were interpolated. One of the most suitable methods corresponds to Empirical Bayesian Kriging (EBK) regression prediction, which is a geostatistical interpolation solution that combines kriging with regression analysis for more accurate predictions. This was tested by Antal et al. (2021) using many alternatives to interpolate precipitation, with EBK regression being the most accurate of all the methods used. Other work has tested EBKs, for example, in Spain to interpolate bioclimatic trends in drought (Ferreiro-Lera et al., 2022), in the United States for teleconnection and temperature patterns (González-Pérez et al., 2022), or on trends in precipitation and dry days in India (Pathak & Dodamani, 2020).

3. Results

The high level of precipitation weather stations with missing values is not encouraging. The missing data show as median 14.3%, in an Inter quartile range (IQR) varying from 4.8% to 63% (Table 3). After the data filling process, we have obtained the six indices of extremes for the period 1981-2017. Consecutive dry days dominate this territory, with an IQR between 220.8-271.5. Consecutive wet days (CWD) are rather modest (1.08-5.14), although in 5-day windows (RX5) they can accumulate up to 105.32 mm (Rio Siloli), although the median of these events for the 35 stations reaches about 26 mm. The number of wet days per year (RR) fluctuates between 2.4 and 21.4, the three with the highest index being Rio Siloli, El Tatio and Silala. The intensity of the events (SDII) varies between 2.18 and 12.6, which in an arid environment can generate a lot of erosion and a sudden increase in surface flows. Finally, the R99p reaches median figures of 3.9 days, with a maximum value of 39.86 in Rio Siloli.

Table 3. Indexes of extremes applied to the study area. Bold marks those indexes that mark significant trends (pvalue≤0.05)

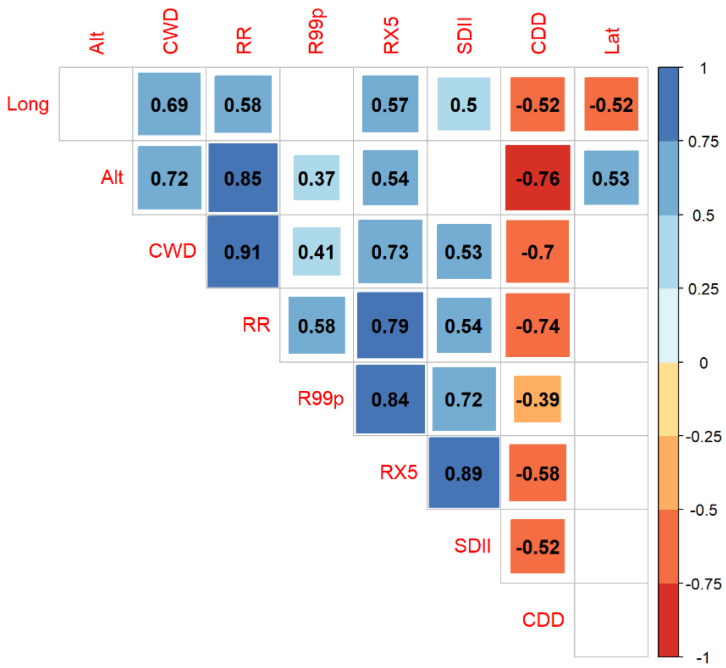
ID	Missing data (%)	CDD	CWD	RR	RX5	SDII	R99p
1	37.3	**219.06**	2.92	12.11	27.71	5.74	3.90
2	42.7	**220.83**	2.97	11.49	30.98	6.35	3.59
3	14.0	**207.83**	3.14	12.51	25.18	5.07	4.90
4	41.1	259.91	1.92	6.35	14.17	**4.07**	1.57
5	66.5	246.56	2.08	7.24	16.67	4.51	5.71
6	10.1	253.89	2.11	6.78	16.34	4.11	2.69
7	14.3	223.81	2.08	7.51	20.80	5.17	3.49
8	4.0	**227.94**	**3.75**	**10.86**	**25.96**	5.00	1.86
9	89.4	**183.92**	4.33	21.41	**105.32**	**10.76**	39.86
10	55.9	**195.28**	4.92	**19.43**	**46.04**	**5.91**	5.87
11	4.8	269.09	1.86	5.81	10.89	3.89	2.96
12	71.8	**276.24**	**1.61**	4.95	14.31	4.78	6.30
13	5.1	**196.89**	5.31	18.32	45.34	6.02	5.42
14	86.4	285.81	1.42	5.43	17.25	5.90	1.59
15	5.5	244.14	3.94	11.00	36.04	5.73	4.12
16	12.5	**190.97**	5.75	20.62	58.02	6.79	12.73
17	66.9	245.22	3.31	9.35	26.14	4.63	1.66
18	2.8	**216.64**	5.14	13.41	44.86	6.42	9.64
19	3.0	**264.37**	3.00	7.73	23.25	**4.94**	5.01
20	96.4	245.14	3.81	10.51	79.74	12.61	16.81
21	99.5	284.34	2.86	6.89	19.87	4.58	5.03
22	5.2	223.17	4.17	13.43	37.48	5.15	5.63
23	58.2	300.06	2.72	7.43	24.43	5.40	3.19
24	27.0	249.11	4.06	9.78	39.07	7.04	4.69
25	3.3	379.07	1.08	2.51	5.53	2.95	0.00
26	7.4	**207.49**	5.89	20.32	48.87	5.98	5.14
27	6.9	504.61	0.83	2.46	4.13	2.18	0.74
28	2.2	**239.83**	3.97	11.38	36.10	7.23	10.76
29	63.0	339.35	2.31	6.08	17.82	4.52	4.07
30	27.3	271.50	2.89	7.62	23.31	5.23	2.81

31	72.3	255.47	2.81	8.70	37.24	7.73	2.74
32	42.2	250.81	3.83	10.38	**45.07**	7.34	2.27
33	1.5	268.14	2.86	6.65	22.85	**5.11**	1.42
34	4.6	**263.09**	3.11	8.14	26.79	5.55	2.27
35	2.8	287.06	1.83	4.84	15.64	4.49	2.35
Median	14.3	249.1	3.0	8.7	26.0	5.2	3.9
P25	4.8	220.8	2.1	6.6	17.3	4.6	2.3
P75	63	271.5	4.0	12.1	39.1	6.3	5.6

Own elaboration

When performing the analysis of the correlations between the indices and the location of the stations (latitude, longitude and altitude) it is possible to point out that altitude and longitude correlate significantly (p-value≤0.05) with all variables except R99p and SDII for each case (Figure 3). The strongest Pearson correlations of the location variables and indices are 0.85 (altitude vs RR) followed by -0.76 (altitude vs CDD) and 0.72 (altitude vs CDW). Among the six extreme indices we can see that they are positively related to each other, except for consecutive dry days (CDD) which has negative correlations with all variables. It is important to note that all correlations shown in Figure 4 are statistically significant (p value ≤ 0.05).

Figure 3. Correlations between the six extreme indices, latitude, longitude and altitude

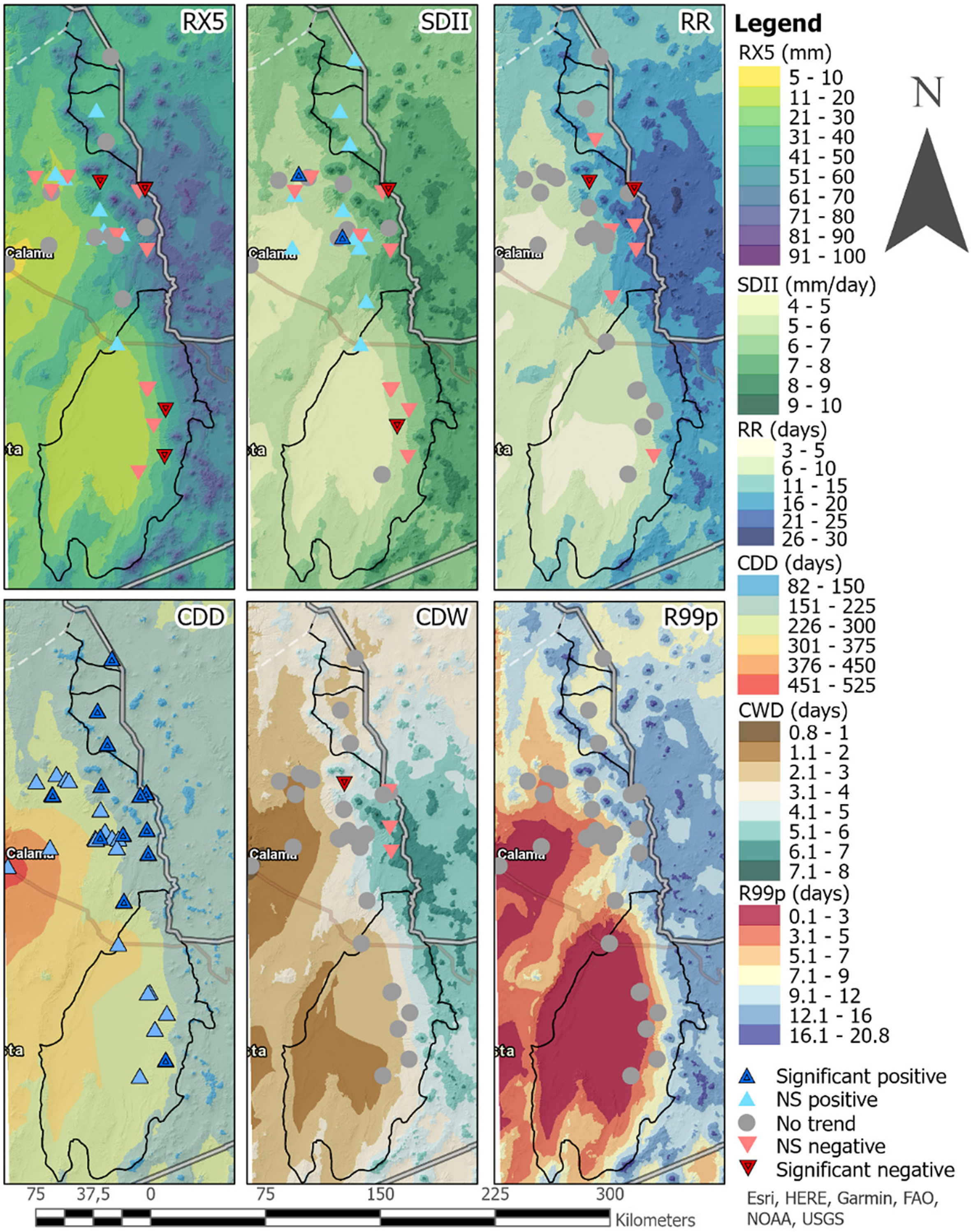


Own elaboration

Now, when analyzing the results in the maps of Figure 4, interpolated using altitude as a variable, we can point out that we find values that are higher or lower than the punctual data of the stations, since it is an extensive territory with a very complex topography, which even exceeds 4,500 meters above sea level. This generates higher values in all indices with altitude, except in the case of consecutive dry days (CDD), a matter noted in the correlation test (Figure 3). Therefore, the Empirical Bayesian Kriging (EBK) regression prediction models are geographically consistent.

The changes observed in the period 1981-2017 are significant for a larger set of weather stations in the index of consecutive dry days, and with a trend of increase with time. This is consistent with the reduction of rainfall amounts in 5 consecutive days (RX5) and wet days (RR). This is not the case for the SDII index, which has significant increasing and decreasing trends. In the case of R99p, there is no trend in the analyzed stations.

Figure 4. Spatial distribution and trends of extreme indices in the study area



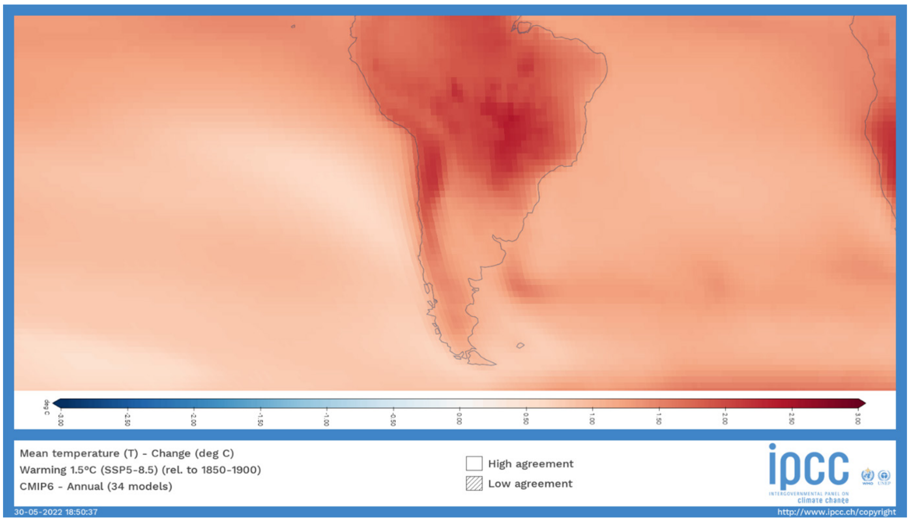
Own elaboration

4. Discussion

It is very concerning that uncertainty dominates the climate information (and the water availability in a territory where important mining (copper and lithium) at word scale is located, competing for resources with indigenous communities and nature conservation sites. However, demands for water have different levels of resource pressure. On the one hand, mining requires a lot of water for its productive processes today, while the communities seek to maintain their livelihoods and ecological landscapes for present and future generations. This implies the application of precautionary principles (Ploberger, 2020), because although the models coincide in warming with a high agreement (Figure 5) regarding the most reliable extreme index from the trends calculated from in situ meteorological stations (CDD), the AR6 models reach a low level of agreement in this planetary region (Figure 6). This is very interesting, because in Chile there are real efforts to improve climate services, interest in generating gridded products and incorporating automatic stations to the network of meteorological observatories and surface and groundwater observatories. Moreover, there are even plans to desalinate water and bring this resource to the altiplano.

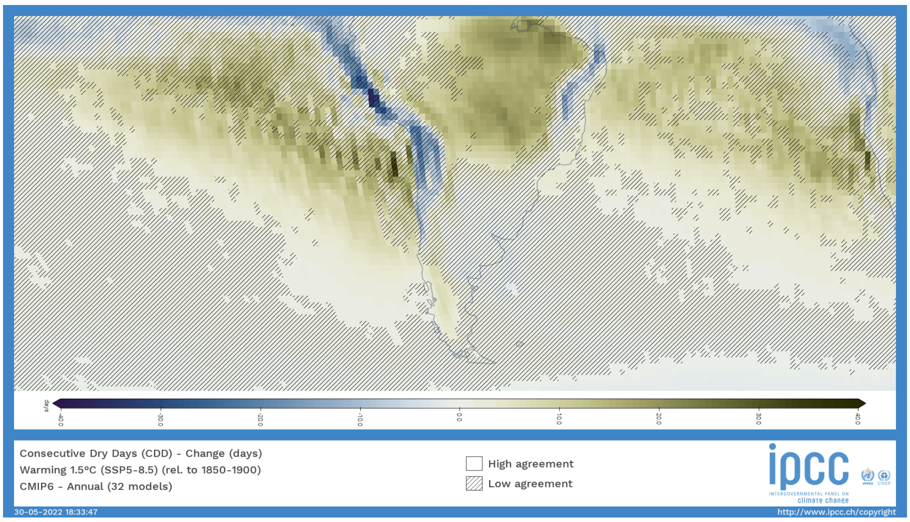
This implies a better maintenance of national precipitation and temperature records, precisely to avoid high percentages of missing data (Meseguer-Ruiz et al., 2019) or series of very few years, and with this, to build trends that generate more reliable future scenarios. This is a challenge that should be a priority for national and international organizations. Chile is currently strengthening its regional governance with greater automation and a climate change law approved in 2021, which will make it possible to guarantee improvements to the weather and climate observation system.

Figure 5. CMIP6–- Mean temperature (T) Change deg C–- Warming 1.5°C SSP5-8.5 (rel. to 1850-1900)–- Annual (34 models)



Source: https://interactive-atlas.ipcc.ch/permalink/tcjSxN6I. Own elaboration

Figure 6. CMIP6–- Consecutive Dry Days (CDD) Change days–- Warming 1.5°C SSP5-8.5 (rel. to 1850-1900)–- Annual (32 models)



Source: https://interactive-atlas.ipcc.ch/permalink/fPX6nwYR. Own elaboration

We believe that care must be taken with respect to interpolations. They should be valid within the altitudinal range of the stations (2,300 to 4,370 m a.sl.). Above or below those altitudes it is necessary to have more stations to avoid limitations in the over or under estimated interpolations of extreme indices. The interpolated area ranges from 2,224 to 6,203, i.e. about 1,833 m a.sl. above the highest station. In addition, it is necessary to avoid reconstructing precipitation series with a lot of missing data, so the data from at least Rio Salado and Sifon Ayquina must be analyzed very carefully to give representativeness to their trends.

It is very relevant to make efforts to intercompare different products gridded at different scales with observational data. Although Schumacher et al. (2020) made progress in this direction, it is necessary to persist in this direction in order to achieve more conclusive evidence, minimizing uncertainties. The use of satellite data and reanalysis, such as new on-site weather stations, are key to improving gridded products and obtaining more reliable results.

If the water resource is being depleted by lower rainfall and higher temperatures (Sarricolea et al., 2017) it is to be expected from all water users a better management. However, in the case of groundwater, in San Pedro de Atacama there has been a growing demand, and as a consequence, a deepening of extraction wells (Lui & Agusdinata, 2021), an issue that could also be happening in the Alto Loa (Ollague, Carcote and Ascotán). Guaranteeing water for future generations is very necessary given climate change projections and the vision and strategy of these territories where rainfall variability is so high and difficult to quantify.

Environmental legislation in Chile is not strict enough to guarantee the protection of resources for future generations (Orihuela, 2021; Bolívar et al., 2022). Neither are the water monitoring systems (Muñoz et al., 2020), since there are not enough stations, there are long periods with missing values and, in addition, they are questionable by mining companies and communities that do not recognize their quality and thus evidence of impacts. Therefore, the uncertainty inherent to climate change adds to the lack of knowledge of the real impacts of the pressure on water resources. If this is not improved, there are few options to begin to reverse the lack of water and excessive exploitation of resources (Fuders & Pastén, 2020). In other areas of Latin America, there have been recent processes that have re-founded Constitutions, where the main search and objectives are the common good and a balanced relationship between society and nature. In the case of Chile, the capitalist and extractives system is not conducive to a development that guarantees resources with social equity and economic growth. Rather, it is a system that is predatory of territorial resources.

5. Conclusions

We must understand as soon as possible the limited local capacity of global models to deliver useful information in small regions, and work to gradually improve models with observational data will not be on the road to anticipating surprises, quantifying risks, and addressing the challenge that climate change poses to science. We must increase our role, something that begins with critical self-reflection, for climate science runs the risk of not communicating and thus not realizing its relevance to societies struggling to respond to global warming.

IPCC projections are assemblages that only suggest probabilities of the direction or trajectory of change (Curry & Webster, 2011), but in general do not consider local behaviors such as those recorded by weather stations located in sites of complex topography. In any case, and due to the predominance of temporal and spatial variability of climates in this section of Chile, it is advisable to adopt precautionary measures and manage the environments and territories in terms of increasing their levels of resilience and adaptive capacity.

The incorporation of local stations to the analysis of extremes is essential in areas of high uncertainty, as has been demonstrated in this work, consecutive dry days (CDD) are increasing significantly, something that is not highlighted by the IPCC. Therefore, it is necessary to insist on having better data and greater spatial and temporal coverage to carry out studies that are useful for society.

In the future, it would be relevant to separate the trends by seasons of the year, as this would allow us to better regionalize the sources of precipitation in the region, for example, from easterly winds or frontal systems from the southeastern South Pacific.

In order to reduce uncertainty and to commensurate water in the Andean systems, it is essential to strengthen environmental legislation and control and to carry out measurements that are accepted by all those involved. This will allow more robust analysis of hydroclimatic extremes for all users and stakeholders involved in development.

The results demonstrate that it is possible through robust methodologies to backfill series in order to construct indices of extremes in a planetary region dominated by missing precipitation data.

The calculated indices allow a better understanding of climate variability as we focus on wet and dry days (RR, R99p, CDD, CDW and RX5day), in addition to an intensity index (SDII). The R99p did not show any trend in the analyzed period, but the other indices have shown interesting trends, especially the case of consecutive dry days (CDD), which are increasing significantly and in a generalized way in the study area.

It is highly advisable to improve and strengthen climate services and take advantage of the climate change law to provide territories with better information on the current state of resources and future scenarios. In this sense, the analysis at the scale of hydrographic basins is fundamental.

The maps produced give an idea of the topoclimates within the watersheds analyzed. In the case of the index trends, it is concluded that most of the stations do not show significant trends, but despite this, the mapping of the extreme indexes provides valuable information for managing these territories.

Mining territories, as well as indigenous territories, require information to improve responsible decision making with resources and to enable them to mitigate, adapt and transform themselves in the global and local scenarios that are expected due to climate change and a just socio-ecological transition. Therefore, research must continue with the best available information and orienting efforts to reduce the levels of uncertainty.

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