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Assessment of extreme precipitation events under climate change scenarios in search of a resilient closure design

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Abstract

When planning the closure of a mining site multiple considerations must be addressed. Along with other factors it is essential to consider future climate conditions that will affect the study area. According to projections from global climate change models (GCM), future conditions are expected to be more extreme compared to the current ones. There are multiple factors that contribute to a significant level of uncertainty regarding the future, including the large number of GCMs, different scenarios related to trajectories of CO_2 *concentrations and the potential behaviour of humanity regarding future actions.*

The study examines the impact of climate change on extreme precipitation events in the long term and addresses its uncertainty. Future extreme precipitation is often used as input for the design of closure water management works, and for verification of the responses of numerous critical infrastructures at mining sites, with the aim of increasing infrastructure resilience at the time of mine closure. The applied approach allows decision-making to adapt to the different risk levels of each project while identifying future extreme precipitation events when planning for mine closure.

Results are presented for three mining operations, located in Brazil, Peru and Chile, where high uncertainty is observed for extreme precipitation projections. Consequently, for design/verification purposes it is recommended that the 75th or 85th percentile be considered for the most conservative shared socio-economic pathway (SSP) scenarios, according to the projections of the GCMs, the historical climate at the site and the risk level of each project.

Keywords: *climate change, extreme precipitation, uncertainty, resilient design*

1 Introduction

In the mine closure stage there are some critical infrastructures that will remain onsite because it is not feasible to remove them, including tailings dam, pits and waste dumps, which must be prepared for the future climate as their failure can be catastrophic for the environment or nearby communities.

Mining operations must face the challenges of climate change, assessing its effects and making decisions that allow the infrastructure to adapt to future conditions. To carry out a robust analysis on the effect of climate change, many sources of uncertainty must be considered before adopting an appropriate value for the design or verification of the remaining infrastructure of each mining operation. This includes various trajectories of CO_2 concentrations, depending on the potential future behaviour of humanity. This provides different possible scenarios for climate on the planet. Additionally, there are over 40 modelling centres globally, which results in several climate projections for each one and diverse methods for downscaling global projections to a local scale (data records). That could lead to different results.

A methodology is presented to estimate maximum precipitation under climate change applied to three mining operations located in Brazil, Peru and Chile. The uncertainty of climate change projections was addressed through percentiles and projections, and compared to the confidence interval of the probability

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distribution fitted to observed precipitation, allowing decision to be made based on the level of risk for each case study.

2 Study area

The three sites analysed in this study represent different climatic contexts and challenges for mining operations in South America. Operations in Brazil and Peru have high annual precipitation and wet climates, while the Chilean site has low annual precipitation and a semi-arid climate. Figure 1 shows the location of the mine sites in each country.

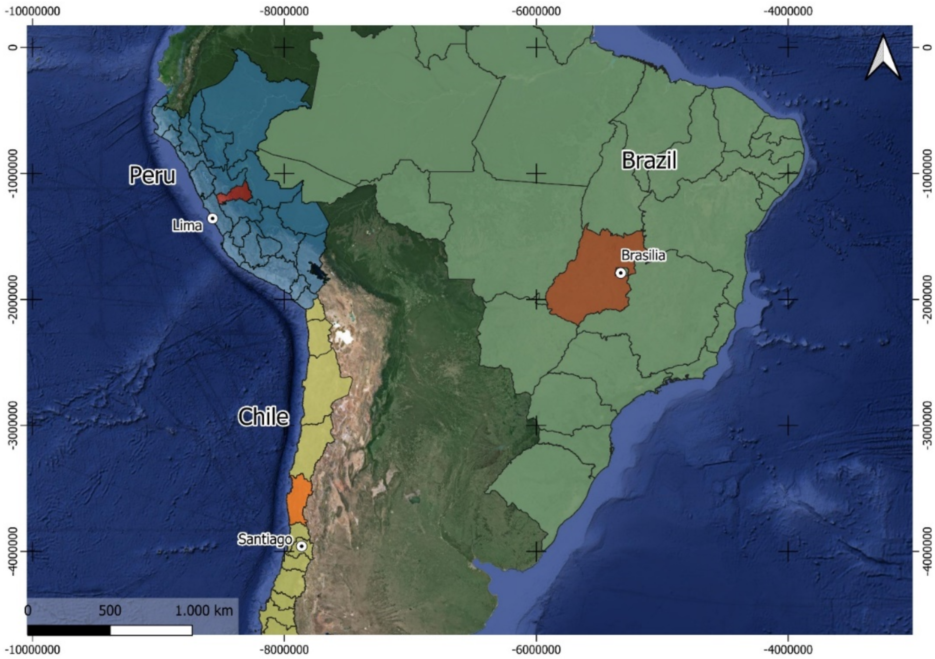

Figure 1 Location of the three mine sites — Brazil, Peru and Chile. UTM coordinates WGS84

Figure 2 and Table 1 show the mean monthly precipitation in the three countries studied. In mine sites in Brazil and Peru, most of the precipitation occurs between October and March. In contrast, most of Chile's precipitation occurs between June and August. Also, there is a clear difference in the magnitudes of the precipitation: in Chile, the annual mean precipitation is 380 mm, while in Brazil and Peru it is 1,588 mm and 1,024 mm, respectively.

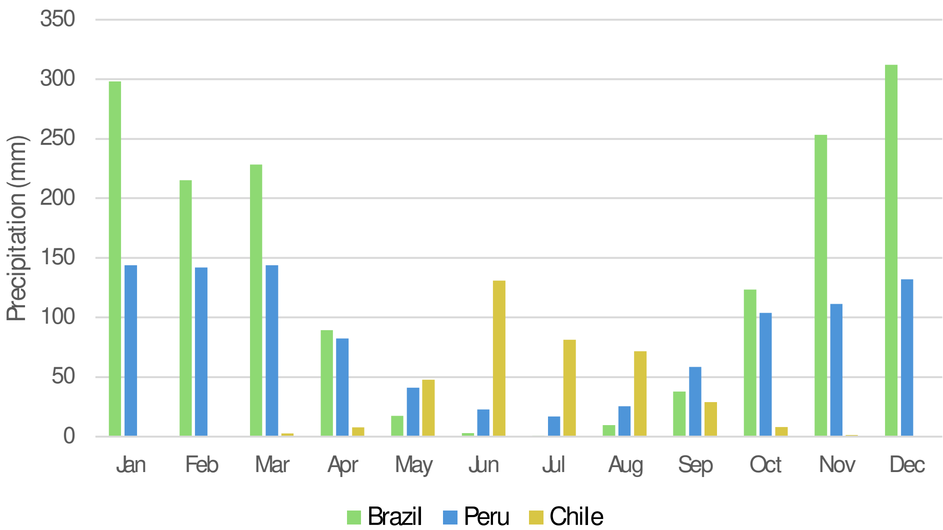

Figure 2 Monthly mean precipitation — Brazil, Peru and Chile sites

Table 1 Monthly mean precipitation (mm) and annual mean precipitation (mm) — Brazil, Peru and Chile

Site	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	Annual
Brazil	298	215	228	89	17	3	1	10	38	123	253	312	1,588
Peru	144	142	144	82	41	23	17	26	59	104	111	132	1,024
Chile	0	0	3	8	48	131	81	72	29	8	1	0	380

3 Methodology

To define the level of risk to be adopted according to the characteristics of each project, it is crucial to assess the uncertainty of the climate change projections. Section 3.1 presents the historical data and the climate change database used. Section 3.2 explains the adopted approach for the estimation of maximum precipitations for different return periods through frequency analysis. Section 3.3 describes the statistical downscaling process, which allows correcting of the GCM bias to obtain representative projections for a local scale. Finally, section 3.4 describes the methodology adopted to address the uncertainty of climate change projections.

3.1 Data

3.1.1 Historical records

Available historical records from local meteorological stations were used. In particular, the records of daily rainfall from the past 17 years at the Peruvian mine site, 20 years at the Chilean mine site and 30 years at the Brazilian mine site were used. Where records are not available or are incomplete, reanalysis products such as ERA5-Land might be used (after a validation/correction process) to complement meteorological records.

3.1.2 Climate change database

The NASA Earth Exchange Global Daily Downscaled Projections CMIP6 (NEX-GDDP-CMIP6) database was used. Developed by Thrasher et al. (2021), the database is composed of 34 GCMs with statistical bias correction and two climate change scenarios (shared socio-economic pathways [SSPs] 2–4.5 and 5–8.5) derived from the information of the CMIP6 (Coupled Model Intercomparison Project Phase 6) GCMs. This database provides daily precipitation information over the period 1950–2100 with a spatial resolution of 0.25° × 0.25° (~27.8 km). The nearest pixel data from global models was selected for each site.

The CMIP6 Global Climate Models correspond to the new version of climate change models used as base for the AR6 report (Intergovernmental Panel on Climate Change [IPCC] 2021), which defines future scenarios as the result of combining radiative forcing trajectories and their effect on climate change with alternative socio-economic development pathways (O'Neill et al. 2014).

SSPs are thus defined as reference trajectories that describe plausible alternative trends in the evolution of society and ecosystems over a century, which are combined with different radiative forcing.

A general description of the level of adaptation and mitigation challenges associated with the different narratives used in SSP climate change scenarios (CMIP6), according to Riahi et al. (2017), follows:

- SSP 1, or Sustainability — Taking the Green Road — low challenges in adaptation and mitigation, related to a gradual and general shift to a more sustainable development
- SSP 2, or Middle of the Road — medium challenges for adaptation and mitigation, related to a path in which socio-economic and technological trends do not deviate markedly from historical patterns
- SSP 3, or Regional Rivalry — A Rocky Road — high challenges in adaptation and mitigation, associated with regional conflicts pushing countries to focus more and more on national issues

- SSP 4, or Inequality — A Road Divided — adaptation presents the greatest challenges due to highly unequal investments in human capital combined with growing disparities in economic opportunity and political power, leading to increased inequalities and stratification
- SSP 5, or Fossil-fuelled Development — Taking the Highway — mitigation presents the greatest challenges as the drive for economic and social development is combined with the exploitation of abundant fossil fuel resources and the adoption of resource- and energy-intensive lifestyles.

The narratives are combined with different radiative forcings (W/m²), allowing different levels of risk to be explored in the future. The main SSP scenarios (used by models to simulate future climates) are briefly described below, while Figure 3 shows the total CO_2 emissions' trajectories for each SSP scenario.

- SSP 1–1.9 scenario — seeks to limit warming to below 1.5°C by 2100, relative to pre-industrial levels
- SSP 1–2.6 scenario — seeks to limit warming to below 2.0°C by 2100, relative to pre-industrial levels
- SSP 2–4.5 scenario — represents the middle part of the range of future forcing trajectories, i.e. business-as-usual
- SSP 3–7.0 — scenario that represents the medium-high level of the range of future radiative forcing trajectories
- SSP 5–8.5 scenario — represents the upper end of the range of future radiative forcing trajectories, i.e. a worst-case scenario.

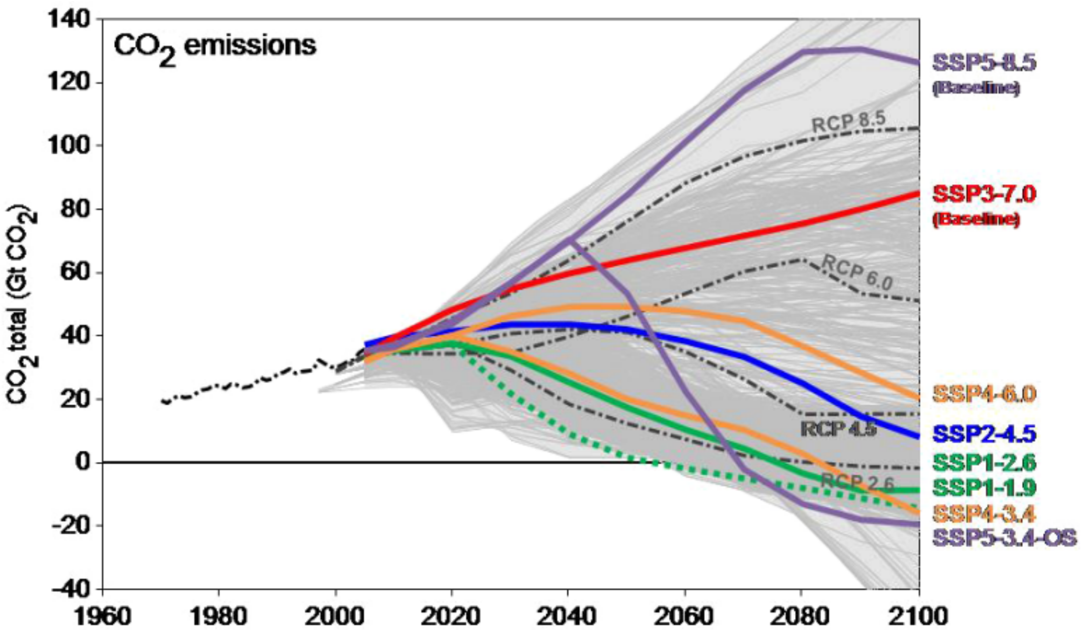

Figure 3 Total CO_2 emissions from the shared socio-economic pathway scenarios (O'Neill et al. 2016)

The climate change scenarios considered in this analysis correspond to SSP 2–4.5 and 5–8.5, which are considered representative of business-as-usual and worst-case conditions (in terms of CO_2 emissions). The choice of the SSP 2–4.5 is supported by considering that if all current greenhouse gas reduction commitments were fulfilled, a path very similar to that described by this scenario would be followed, as explained by the United Nations (2021) and shown in Figure 4.

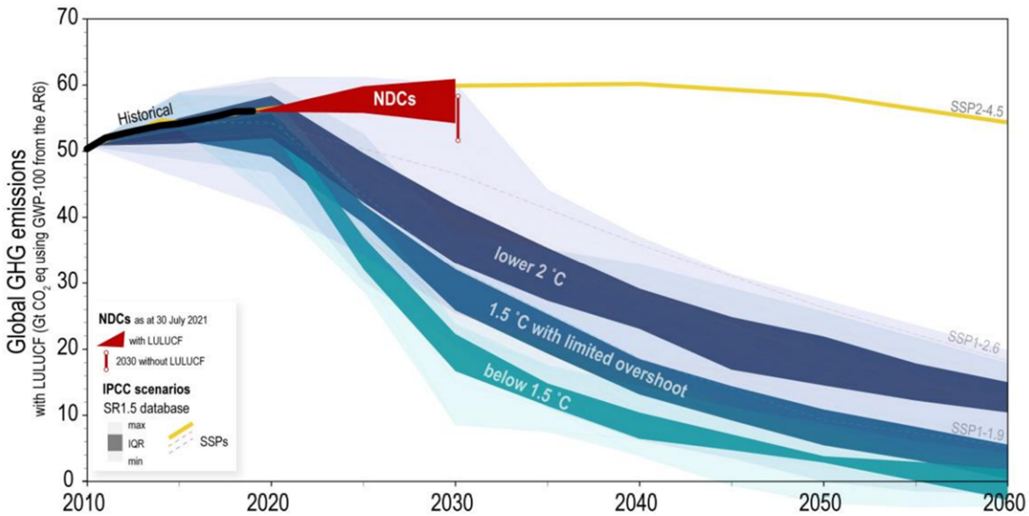

Figure 4 Comparison of global emissions under scenarios assessed in the Intergovernmental Panel on Climate Change Special Report on Global Warming of 1.5°C, with total global emissions according to nationally determined contributions (United Nations 2021)

3.2 24-, 48- and 72-hour maximum precipitation and frequency analysis

3.2.1 Historical

The maximum precipitation for one, two and three days of the historical records were obtained. Daily values were multiplied by correction factors to transform them into 24-, 48- and 72-hour maximum precipitation. The transformation factors recommended by World Meteorological Organization (2009) were used.

With the historical maximum precipitation series for 24, 48 and 72 hours, a frequency analysis was applied to fit five probability distributions for each duration: normal, Gumbel, Pearson 3, gamma and log-normal. The parameter estimation was carried out through the maximum likelihood method and the goodness of fit was evaluated through the Anderson-Darling test, where results indicated whether the distribution was rejected (R) or not rejected (NR). The selection of each distribution (within NR distributions) was also based on the visual adjustment of high-return periods, the correlation coefficient and the confidence interval of each series. Based on these criteria, the best distribution was chosen for each duration for the historical period. Return periods from two to 10,000 years were estimated as this range covers the return periods usually considered for the design/verification in the hydrological assessment of critical infrastructure, depending on their size or relevance.

3.2.2 Projections

For the climate change models, the maximum precipitation for one, two and three days was extracted and corrected through a statistical downscaling method (Section 2.3), using as a base the historical 24-, 48- and 72-hour series to make a GCM series representative of local conditions. With the bias corrected for the 24-, 48- and 72-hour maximum precipitation GCM series, the frequency analysis was carried out using the same approach applied to the historical series: fitting five probability distributions for the 2031–2060 and 2071–2100 periods and estimating the return periods from two to 10,000 years for two climate change scenarios.

3.3 Statistical downscaling

Climate change models have inherent biases because they were developed to reproduce global climatic conditions; showing a poor historical performance compared to, for example, meteorological stations, which collect information at the local level.

The poor representation of local climatic conditions is related to GCMs' low spatial resolution, in addition to parameterising and simplifying physical processes for each cell. These biases are evident when comparing simulated historical periods and historical data/records. GCM biases can be corrected using different statistical correction techniques in addition to long-term local records.

Model biases for daily maximum precipitation (one, two and three days) were corrected for the SSP 2–4.5 and 5–8.5 scenarios using the quantile delta mapping (QDM) method for all climate change models. The QDM method corrects climate change model values by fitting a probability distribution (gamma, in this case) to historical and simulated data, then comparing the quantiles of both fitted distributions. The multiplicative approach of the QDM method makes it suitable for correcting precipitation series relative to other scaling methods such as quantile mapping, power transformation or linear scaling. In addition, the method does not assume stationarity and uses moving time windows for bias correction, thus preserving the projected variation between the future and historical periods. The QDM method is described in detail by Cannon et al. (2015).

3.4 Assessing the uncertainty of climate change projections

Percentiles are used to assess the uncertainty of climate change projections. As mentioned above, this uncertainty is related to different climate change scenarios (SSP 2–4.5 and 5–8.5), with more than 30 GCMs for each scenario and, in most cases, two future periods analysed.

A percentile is a statistical measure that divides a series of data ordered from smallest to largest into 100 equal parts. Thus, for example, the amount associated with the 25th percentile means that 25% of the GCM projections are under this value.

All available GCM projections are evaluated, with no particular one being selected, to incorporate and reflect the level of uncertainty inherent in this type of study and to allow the choosing of a percentile according to the risk level adopted for the project. The percentiles evaluated depend on each project, but the most commonly used are the 15th, 25th, 50th, 75th and 85th.

In some cases the percentiles are not enough to evaluate the uncertainty of the projections, and estimating the confidence interval of the probability distribution fitted to observed data results in a useful indicator of the possible variation range of precipitation in the area.

4 Results

This paper presents the results of applying the methodology to three mining operations. For practical purposes only the 24-hour maximum precipitations are analysed.

For each operation the projections of different percentiles (15th, 25th, 50th, 75th and 85th) for the period 2071–2100 under two scenarios (SSP 2–4.5 and 5–8.5) are compared with the historical estimates and their confidence intervals.

4.1 Brazil mining operation: 24-hour maximum precipitation

Figure 5 and Table 2 show the 15th, 25th, 50th, 75th and 85th percentiles for the 24-hour maximum precipitation projections for 2071–2100 with SSP 2–4.5 and 5–8.5 scenarios. Moreover, historical estimates are shown for comparison (green line) along with their corresponding 95% upper confidence interval (black line). The percentages shown in the figures correspond to the variation for the 50th and 75th percentiles, using as a reference a 100-year return period, and comparing future projections against the historical estimation.

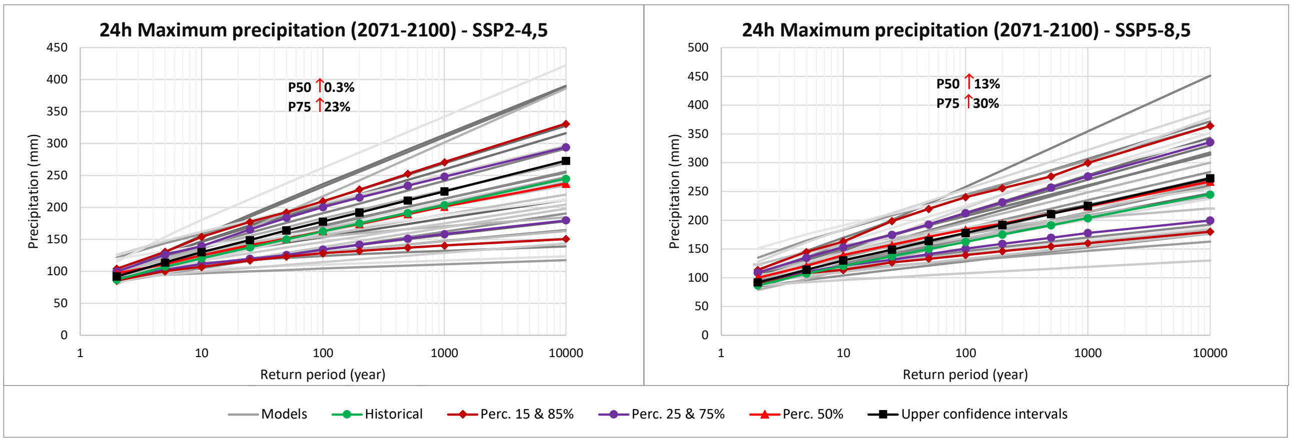

Figure 5 Climate change projections for the 24-hour maximum precipitation from 2071–2100 with scenarios SSP 2–4.5 and 5–8.5 — Brazilian site

Table 2 100-, 1,000- and 10,000-year return period projections for SSP 2–4.5 and 5–8.5 scenarios with 24-hour maximum precipitation (mm) — Brazilian site

Return period (years)	Historical	75th percentile		85th percentile		95% confidence interval (upper)
		SSP 2–4.5	SSP 5–8.5	SSP 2–4.5	SSP 5–8.5	
100	163	200	210	212	240	178
1,000	204	248	271	276	300	225
10,000	245	294	331	336	364	273

Regarding the results of the SSP 2–4.5 scenario, there is a high dispersion in the projections where the 50th (red line, left graph Figure 5) is very close to the historical results (green line, left graph Figure 5), which implies that almost a half of the GCMs project an increase for 24-hour maximum precipitation. In contrast, in the SSP 5–8.5 scenario, although there is also a high dispersion in the projections, the 50th percentile is above the historical results, which means that more that the half of the models project an increase for the 24-hour maximum precipitation at the site.

4.2 Peru mining operation: 24-hour maximum precipitation

Figure 6 and Table 3 show the 15th, 25th, 50th, 75th and 85th percentiles for the 24-hour maximum precipitation projections for 2070–2100 and for the SSP 2–4.5 and 5–8.5 scenarios. Moreover, historical estimates are shown for comparison (green line) along with their corresponding 95% upper confidence interval (black line). The percentages shown in the figures correspond to the variation for 50th and 75th percentiles, using as a reference a 100-year return period, and comparing future projections against the historical estimation.

In this case a consistent 24-hour maximum precipitation increase of the 50th percentile projection for both scenarios is observed, with the SSP 5–8.5 scenario showing a higher projection than the 2–4.5 scenario.

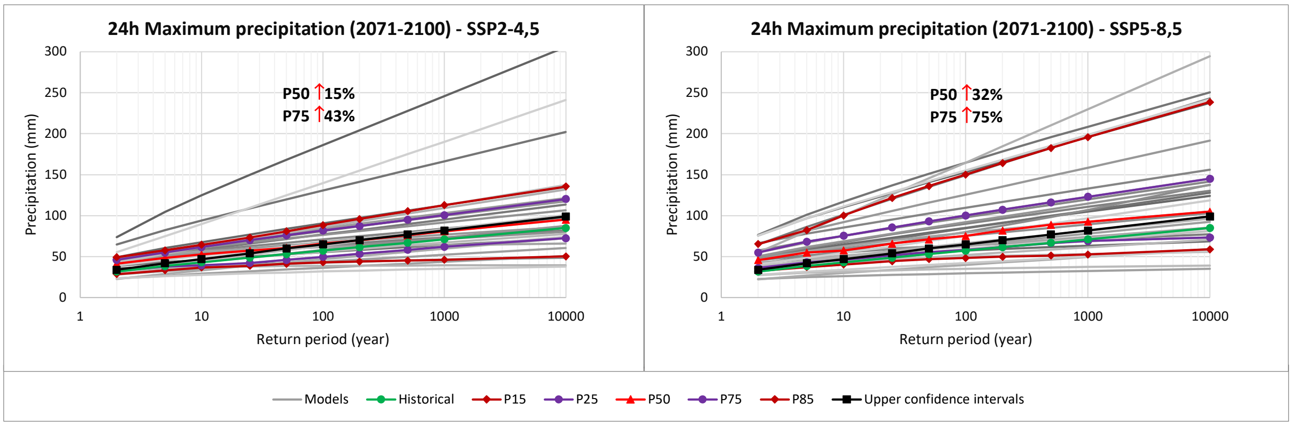

Figure 6 **Climate change projections for the 24-hour maximum precipitation from 2071–2100 with scenarios SSP 2–4.5 and 5–8.5 — Peruvian site**

Table 3 **100-, 1,000- and 10,000-year return period projections for SSP 2–4.5 and 5–8.5 scenarios with 24-hour maximum precipitation (mm) — Peruvian site**

Return period (years)	Historical	75th percentile		85th percentile		95% confidence interval (upper)
		SSP 2–4.5	SSP 5–8.5	SSP 2–4.5	SSP 5–8.5	
100	57	82	100	88	150	65
1,000	71	101	123	113	196	82
10,000	85	120	145	136	238	99

4.3 Chile mining operation: 24-hour maximum precipitation

Figure 7 and Table 4 show the 15th, 25th, 50th, 75th and 85th percentiles for the 24-hour maximum precipitation projections for 2071–2100 and for the SSP 2–4.5 and 5–8.5 scenarios. Moreover, historical estimates are shown for comparison (green line) along with their corresponding 95% upper confidence interval (black line). The percentages shown in the figures correspond to variation for the 50th and 75th percentiles, using as a reference a 100-year return period, and comparing future projections against the historical estimation.

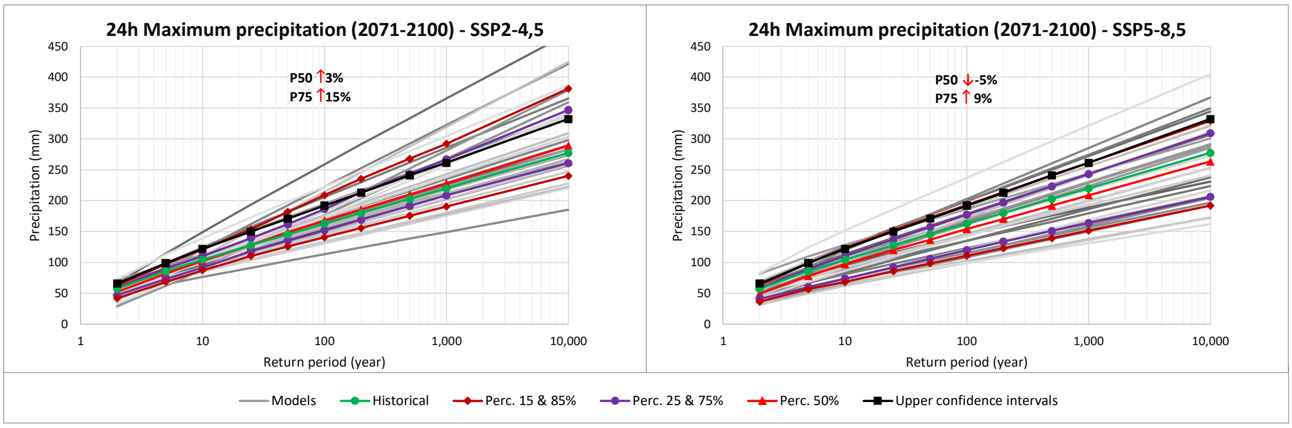

Figure 7 **Climate change projections for the 24-hour maximum precipitation for 2071–2100 with scenarios SSP 2–4.5 and 5–8.5 — Chilean site**

Table 4 100-, 1,000- and 10,000-year return period projections for SSP 2–4.5 and 5–8.5 scenarios with 24-hour maximum precipitation — Chilean site

Return period (years)	Historical	75th percentile		85th percentile		95% Confidence interval (upper)
		SSP 2–4.5	SSP 5–8.5	SSP 2–4.5	SSP 5–8.5	
100	163	187	177	209	193	192
1,000	220	267	243	292	261	261
10,000	277	347	309	381	329	332

In this case the 50th percentile projections show almost no variation with respect to the historical results. Also, the percentiles of the moderate scenario SSP 2–4.5 present higher projections than the pessimistic CO_2 emission scenario (SSP 5–8.5), showing the importance of evaluating more than one climate change scenario. This means that a scenario with higher CO_2 concentrations does not necessarily lead to an increase or decrease in precipitation because there are many other factors involved. Therefore, it is crucial to consider a variety of potential climate futures to better understand the risks and uncertainties associated with climate change.

4.4 Adoption of a future design precipitation value

To assess critical mining infrastructure for closure it is necessary to define a projection of maximum precipitation.

As there are no clear criteria for choosing one GCM, SSP scenario or percentile over another, each case must be assessed individually. As critical infrastructure it should be evaluated under the two worst feasible scenarios (SSP 2–4.5 and 5–8.5) and the 75th and 85th percentiles as the latter indicate the results of a group of models with the highest projections for the total of models evaluated.

Three criteria were applied to decide future design precipitation values:

1. selection of the most conservative SSP scenario in terms of climate projections as SSP 5–8.5 did not always result in the highest precipitation
2. choice of a percentile (between 75th and 85th) that results in higher or at least similar precipitation levels to the historical 95% confidence interval
3. evaluation of a ratio between the future 100-year return period and historical 1,000-year return period and the ratio between the future 1,000-year return period and historical 10,000-year return period to confirm that the selected percentile is conservative enough but not extremely conservative.

Climate change projections were compared against the 95% confidence interval of the historical results to understand if the 75th and 85th percentiles of GCM's projections were conservative enough. As shown in Figures 5 and 6 (Brazil and Peru), the confidence interval of the historical series is far below the 75th percentile of the climate change projections and therefore this percentile is conservative enough. Figure 7 (Chile) shows the confidence interval is higher than the 75th percentile and close to the 85th, therefore the latter is more appropriate in this case.

Table 5 presents the percentage variation between the 100-year return period for the series of the 75th and 85th percentiles of both SSP scenarios with respect to the 1,000-year return period of the historical results.

Table 5 Variations between the 100-year return period of the 75th and 85th percentiles series with respect to the 1,000-year return period of the historical results

Site	75th percentile		85th percentile	
	SSP 2–4.5	SSP 5–8.5	SSP 2–4.5	SSP 5–8.5
Brazil	–2%	3%	4%	18%
Peru	15%	41%	24%	111%
Chile	–15%	–20%	–5%	–12%

In Table 5, Brazil's 75th percentile shows a smaller difference of about 3% between the 100-year return period of the series of the 75th percentiles with respect to the 1,000-year return period of the historical results. The 85th percentile indicates a higher increase for the same period, suggesting that the 75th percentile may be conservative enough. In Peru the differences are larger and the 85th percentile exhibits a significant increase of up to 111% for the 100-year return period compared to the historical value for the 1,000-year return period, which supports the conservativeness of the 75th percentile. In Chile the situation is different, as both percentiles show a decrease for the 100-year return period relative to the historical value for the 1,000-year return period, but the differences are smaller at the 85th percentile. Therefore, in this case, the more conservative option would be the one with the lower decrease.

Table 6 shows the percentage variation between the 1,000-year return period of the series of the 75th and 85th percentiles of both SSP scenarios, and the 10,000-year return period of the historical results. The behaviour is consistent with Table 5, which reinforces the previous percentile selection.

Table 6 Variation between the 1,000-year return period of the 75th and 85th percentiles series with respect to the 10,000-year return period of the historical results

Site	75th percentile		85th percentile	
	SSP 2–4.5	SSP 5–8.5	SSP 2–4.5	SSP 5–8.5
Brazil	1%	11%	13%	22%
Peru	19%	45%	33%	131%
Chile	–4%	–12%	5%	–6%

Therefore, based on the above analysis, the 75th percentile of the SSP 5–8.5 scenario was chosen for the sites in Brazil and Peru, as this represented the most conservative scenario for both locations. On the other hand, for the site in Chile, the 85th percentile of the SSP 2-4.5 scenario was the most conservative option and thus selected.

5 Conclusion

The methodology used provides an adequate approach to evaluate the uncertainty of climate change projections where it is relevant to consider the most recent versions of GCMs and evaluate more than one SSP scenario. Also, the future period must be chosen to represent the closure stage of the operation and to evaluate the remaining infrastructure. Usually the 2071–2100 period is considered, which is the latest GCM period with available information.

The results shows that the 75th percentile for the most conservative SSP scenario (in terms of climate projections between SSP 2–4.5 and 5–8.5) seems to be conservative enough for most cases to adopt for closure design/verification purposes. However, for some cases, a higher percentile (e.g. the 85th) could be more appropriate, depending on the potential impact and the failure risk level of the infrastructure. The comparison of the percentiles and the confidence intervals of the historical data was a useful tool for decision-making.

The proposed methodology provides a simple approach to assess the uncertainty of the climate change projections, estimating the maximum precipitation under climate change associated with a risk level that allows the design and verification of closure infrastructure resilient to future climate conditions. The methodology can be applied to different types of infrastructure and climate variables as long as the GCM data are available and reliable. The methodology can also be updated and improved as new versions of the GCMs and SSPs scenarios are released.

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