

Heavy rainfall leading to widespread flooding in eastern Mexico disproportionately impacts highly exposed Indigenous and socially vulnerable communities

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Main findings

- This region is highly prone to flooding, particularly due to its mountainous terrain where heavy rainfall quickly leads to overflowing rivers and landslides. It has experienced severe flood events in the past, notably during Hurricane Stan in 2005 and again in 2013, highlighting its vulnerability to extreme weather conditions.
- Remote villages and rural communities with a large proportion of Indigenous people were disproportionately impacted due to high exposure, chronic inequality and underinvestment in services and protection. These communities represent a diverse, Indigenous cultural heritage and yet were largely overshadowed by the impact in urban areas.
- At the national level, a forecast for heavy rainfall was issued by the National Meteorological Service (SMN) and the National Water Commission (CONAGUA), and communicated through government websites, bulletins, and civil-protection channels. However, when that weather forecast was translated into alerts at the local level, there was a mix of issues, including the timeliness of alerts, the translation into potential impacts, as well as people's understanding of the seriousness of the warnings and the action they should lead to. Improved translation of forecasts into potential impacts, risk education for the public, and enhanced communication protocols can ameliorate the system in the future. A comprehensive after-action review is necessary to identify specific gaps and areas for improvement.
- We evaluated the contributions of both climate change and ENSO to extreme 3-day rainfall events, and also to the June-October rainy season. The onset of La Niña in September has heightened the likelihood of heavy rainfall throughout the season and intensified short-term downpours, which in turn led to the severe impacts observed.
- For the seasonal analysis, the observed datasets show opposing trends: ERA5 indicates an increase with global warming, while CPC and MxHighResClimDB show a decrease. This discrepancy is largely due to discrepancies in reconstructed rainfall trends prior to the satellite era (1979). The observation-based datasets also display diverging trends in three-day rainfall extremes: two indicate a decrease associated with climate change, while the third shows an increase.
- The fact that satellite-based observations and reanalysis exhibit different signs on the trend highlights the need for a better observational ground network (with more and better-maintained meteorological stations). Literature assessing weather station data indicates that climate change does affect heavy rainfall in Mexico; however, the patterns are uneven across regions and time, and partly influenced by regional dynamics. In recent years, a drying

trend has been observed in the southern and central mountainous regions, while smaller, localized increases in rainfall have occurred in the north.

- Climate models exhibit a mixture of trends in both short-term extremes and seasonal rainfall. This is in line with previous research and IPCC assessments that also show no clear trends in heavy rainfall in both of the IPCC regions capturing Mexico. Current large-scale climate models struggle to capture localised changes.
- These findings do not suggest that climate change plays no role, but rather highlight that its impacts can vary significantly across regions. Our findings thus underscore the need for better observations and higher-resolution data to fully understand regional climate impacts. Knowing the baseline is critical to determine if there are changes in precipitation due to climate change and for preparing for those changes.
- Rapid urbanization has intensified the region's flood vulnerability by replacing natural drainage areas with impermeable surfaces, increasing runoff and overwhelming drainage systems. In Poza Rica, one of the areas most severely affected, unplanned urban growth driven by economic opportunities from the oil sector, have increased people's exposure to potential flooding. Additionally, the expansion of informal settlements in flood-prone areas has further heightened exposure to flood risks, amplifying the impacts of heavy rainfall events.
- Adaptation efforts should prioritise social and nature-based solutions that complement, rather than rely solely on, built infrastructure. Restoring ecosystems, strengthening community preparedness, and integrating risk into local planning can lead to more sustainable flood management, thereby reducing long-term vulnerability while enhancing resilience.

1 Introduction

From October 8th-10th, the Gulf Coast of Mexico experienced extremely heavy rainfall which led to widespread flooding and landslides, affecting the states of Veracruz, Puebla, Hidalgo, Querétaro and San Luis Potosí. By 22nd October, 78 deaths had been reported, with 23 people still missing ([El Universal, 2025](#)). A week later, 93 communities across the five states were still cut off ([La Jornada, 2025](#)).

About 50,000 homes were damaged, while thousands of homes, schools, hospitals, and businesses were heavily damaged or destroyed. Hundreds of thousands of residents were left without electricity, telecommunications, transportation, and other essential services ([Daily Flash, 2025](#); [JW, 2025](#); [AA Americas, 2025](#)). The city of Poza Rica was particularly affected, with floodwaters reaching over 3.5 meters in some areas.

1.1 Meteorological conditions

The heavy rain was driven by a combination of a low pressure system over the Pacific Ocean (Figure 1.1) an anticyclone of medium strength located over Texas and extending over the Gulf of Mexico along the coast of Tampico and Veracruz, and a tropical wave moving over the Caribbean (as reported by the National Meteorological Service (SMN) in Mexico and [NOAA](#)).

As Hurricane Priscilla intensified off the west coast of Mexico on October 4-5th, this second low pressure system deepened south of southern Mexico over a warm pool in the eastern Pacific (Figure 1.2; [NHC, 2025a](#)). The low pressure system began to draw moisture from both the eastern Pacific and the Gulf of Mexico, which also had significant positive surface temperature anomalies, from October 6th. At the same time the National Hurricane Centre (NHC) started monitoring a trough of low pressure moving over the Bay of Campeche, which was leading to a large area of disorganised showers and thunderstorms, and with very low probabilities (less than 10%) of formation of a tropical cyclone, and forecasted heavy rainfall on the coast of Gulf of Mexico by next couple of days ([NHC, 2025b](#)). By October 8th these systems resulted in heavy rainfall over eastern Mexico, which lasted until October 10th. On October 8th the SMN issued an alert for the occurrence of heavy to very extreme rainfall in Veracruz, southern Tamaulipas, Hidalgo and Puebla, with an estimated rainfall accumulation of 75 to 150 mm ([SMN on X](#)). On October 9th, the system over the Pacific was classified as tropical depression Raymond ([NHC, 2025c](#)), which intensified to tropical storm status on October 10th, before tracking into the cold pool left behind by the passage of Hurricane Priscilla ([NHC, 2025d](#)).

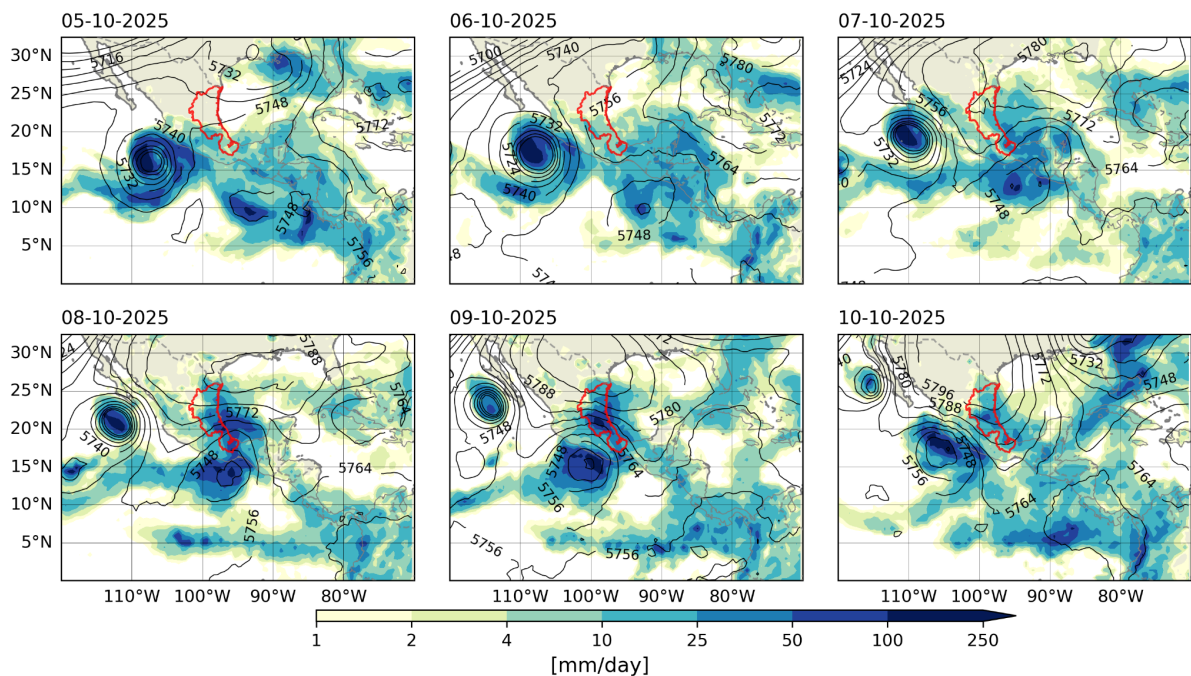


Figure 1.1: Daily rainfall and geopotential height (z500) between 5-10 October 2025. The study region is highlighted in red. Data ERA5.

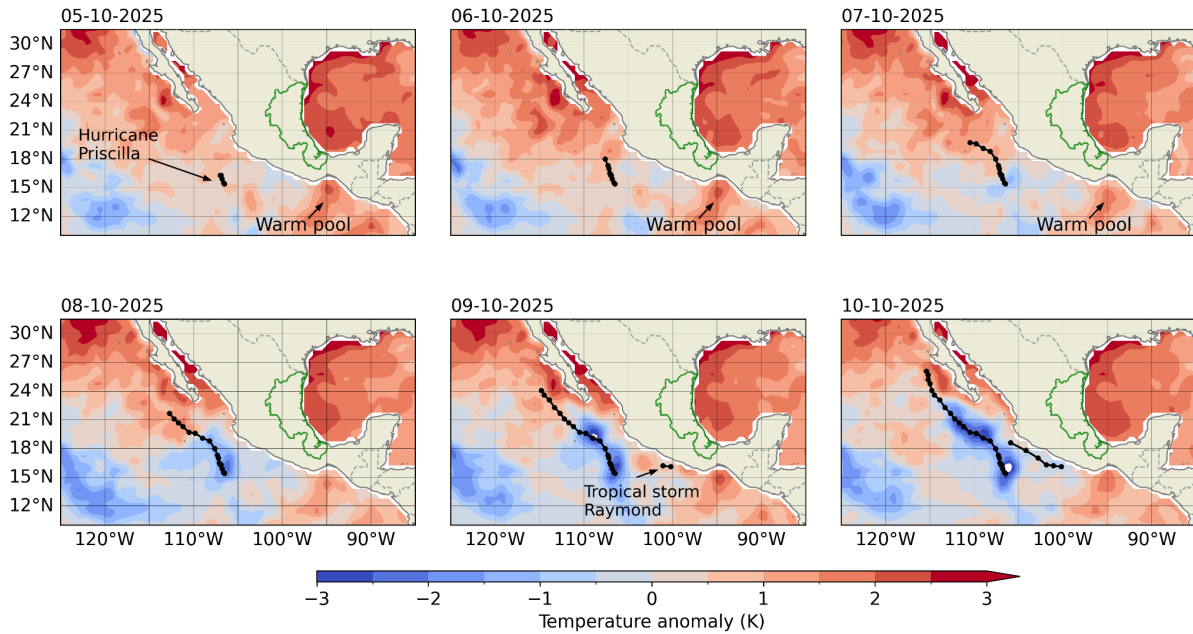


Figure 1.2: Daily sea surface temperature anomalies (with respect to October 1980-2010 climatology) between 5-10 October 2025 (Data: OI SST). Storm tracks for Hurricane Priscilla and Tropical Storm Raymond are shown in black (Data: [CIRA Realtime TC tracks](#)). The study region is shown in green.

The months before the floods had also been unusually wet, with above-average rainfall throughout the May-October rainy season. Over the region most affected by the event at the Eastern Coast of Mexico the season was unusually wet, following an almost equally wet 2024 season (see fig. 2). Mexico City, on the western edge of the affected region, also reported its highest ever annual rainfall ([Guardian, 2025](#)).

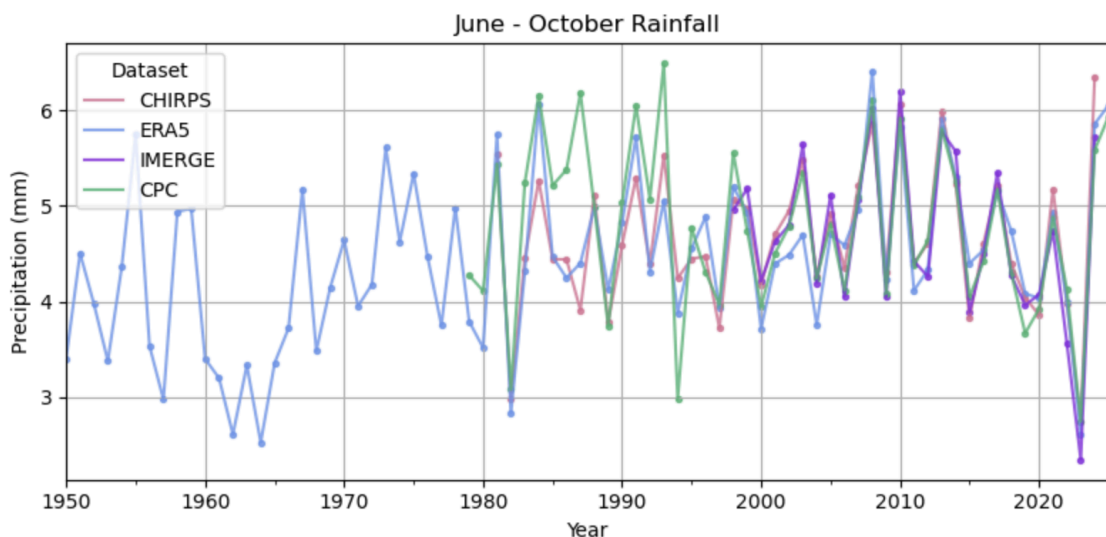


Figure 1.3: Total summer rainfall over Eastern Mexico in two datasets, ERA5 (blue), CHIRPS (orange), CPC (green) and IMERG (purple). IMERG and CHIRPS do not include the current year, 2025.

1.2 Seasonal and extreme rainfall in the Eastern Mexico

The eastern and southeastern portions of Mexico experience a bimodal precipitation pattern, which normally starts by the end of June, peaks in July, and has another peak in September; in August, precipitation decreases slightly, a phenomenon called midsummer drought or *canícula*.

The 2025 rainy season was wetter than normal almost all over the country, with most dams at 80 to 90% of capacity - all the more remarkable given that at the end of the 2024 rainy season, they were below 30% on average and by May, the dry season, some were under 15% which caused alarm, mostly in the central portion of the country. During most of the summer (rainy) season, a La Niña condition that prevailed for most of the summer favoured a more than averagely active hurricane season in the Pacific, with so far 19 named tropical systems and four major hurricanes, with almost half of those systems forming in the Western Hemisphere Warm Pool.

Using long-term monthly station-based records of precipitation and temperature, [Cuervo-Robayo et al. \(2020\)](#) examined the climate of Mexico, and found the changes in precipitation to be non-monotonic and regionally variable, throughout the twentieth century. From 1940 to 1970, the overall climate was characterised by decreasing temperatures and increasing precipitation, followed by a period of warming during 1970-2000, along with decreasing precipitation. Southern regions of Mexico, which have a tropical climate, showed consistent decreasing trends in precipitation in recent years, while the arid northern regions experienced increases. The authors noted that despite an overall increasing trend in precipitation throughout the century, the magnitude of this change generally declined post-1970, which may be partly influenced by the major drivers of natural variability in the region, namely, the El Niño Southern Oscillation, the Pacific Decadal Oscillation, and the Atlantic Multidecadal Oscillation. [Colorado-Ruiz & Cavazos \(2021\)](#) show that the intensity of heavy rainfall is projected to increase across different extreme rainfall indices in Eastern Mexico. They also analyse observations, especially in the northern part of the region where a significant trend in the number of days with higher than the 95th percentile of rainfall is identified; and also in the intensity of 5-day and 1-day rainfall extremes, with stronger trends in RX5day. CMIP5 models used in the analysis show a similar picture, but some individual models (eg. MPI & GFDL) do not show the observed wettening. In the latest IPCC assessment, AR6, no observed trends over Mexico were assessed due to a lack of data ([Seneviratne et al., 2021](#)). The model projections in the IPCC region Southern Central America, which includes the southern part of the region affected by the heavy rains, does not show a consistent increase or decrease across the region ([Gutierrez et al., 2021](#)). This is probably due to the fact that the IPCC region includes the Eastern coast of Mexico, as well as the Pacific coast, which have, according to [Colorado-Ruiz & Cavazos \(2021\)](#), strongly opposing trends. For the IPCC region Northern Central America (NCA) which includes the northern part of the region analysed here there is also no assessment of observed trends due to a lack of data, but projections in this region do show an increase in heavy rainfall ([Seneviratne et al., 2021](#)).

1.3 Event Definition

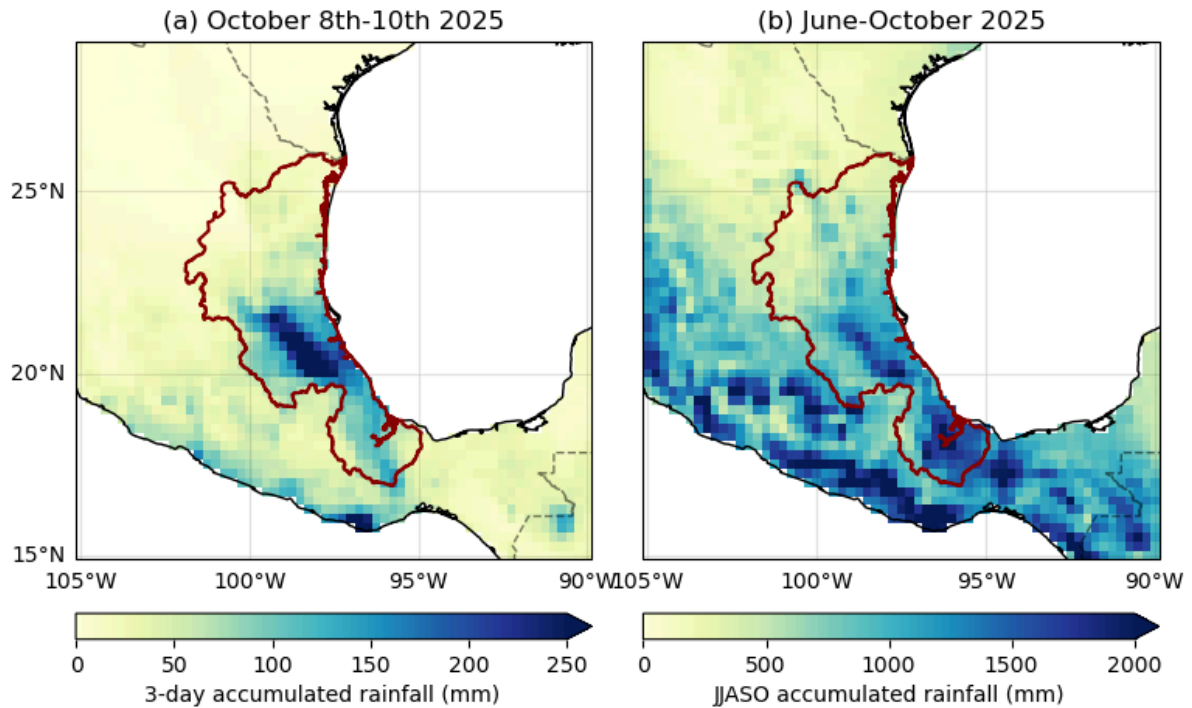


Figure 1.4: Maps of accumulated rainfall over eastern Mexico: (a) from October 8th-10th 2025 and (b) during the summer months of June-October 2025. The study region is outlined in dark red. Source: ERA5.

We use two different event definitions to examine trends in rainfall in eastern Mexico (shown outlined in red in Figure 1.4). To reflect the short-term rainfall that directly contributed to the flooding, we evaluate the wettest three-day period over the region each year: we denote the three-day maximum rainfall as RX3day. To reflect the wet conditions during the months preceding the floods, we also consider the total rainfall during the summer months (June-October inclusive): we denote the total annual summer rainfall as pr_JJASO (Figure 1.4b).

In sections 3-5 of this report, we study the influence of anthropogenic climate change by comparing the likelihood and intensity of similar RX3day and pr_JJASO extremes in 2025 with those in a 1.3°C cooler climate. We also extend this analysis into the future by assessing the influence of a further 1.3°C of global warming from present. This is in line with the latest Emissions Gap Report from the United Nations Environment Programme, which shows that the world is on track for at least 2.6°C temperature rise given currently implemented policies ([UNEP, 2024](#)).

To understand the contribution of the developing La Niña phase observed in 2025, we extend the statistical analysis to make a similar comparison between the September 2025 value of the detrended Niño3.4 index and a neutral state. The detrended Niño3.4 index is obtained by subtracting the mean tropical SST (20S-20N) from the mean SST over the Niño3.4 region (5S-5N, 170W-120W), to remove the linear trend associated with climate change. September conditions were chosen because the rainfall extremes analysed here most often occur between June and October. Consequently, the

September detrended Niño3.4 index provides a more relevant indicator of ENSO conditions influencing peak rainfall during this period. By September, developing El Niño or La Niña events are typically already apparent, whereas earlier months may not yet display a clear signal. Using the September Niño3.4 index therefore enables us to capture the developing phase of ENSO that can influence rainfall events occurring prior to the DJF peak.

2 Data and methods

2.1 Observational data

We first use observational and reanalysis data to estimate the return period of a similar event in the present day and to assess the historical trends with increasing GMST. The datasets used are as follows:

ERA5 - The European Centre for Medium-Range Weather Forecasts's 5th generation reanalysis product, ERA5, is a gridded dataset that combines historical observations into global estimates using advanced modelling and data assimilation systems ([Hersbach et al., 2020](#)). We use daily precipitation data from this product at a resolution of $0.25^{\circ} \times 0.25^{\circ}$. We use reanalysis data until the end of September, extended with analysis data for October to cover the period of the event. Data used in the main analysis was obtained from [KNMI's Climate Explorer](#) tool, coarsened to a resolution of $0.5^{\circ} \times 0.5^{\circ}$.

CPC - This is the gridded product from [NOAA](#) PSL, Boulder, Colorado, USA, known as the CPC Global Unified Daily Gridded data, available at $0.5^{\circ} \times 0.5^{\circ}$ resolution, for the period 1979-present. We use daily precipitation data.

CHIRPS - This rainfall product is developed by the UC Santa Barbara Climate Hazards Group and called "Climate Hazards Group InfraRed Precipitation with Station data" (CHIRPS; [Funk et al. 2015](#)). At the time of writing, daily data were available at 0.05° resolution, from 1981 until September 2025. The product incorporates satellite imagery with in-situ station data.

IMERG - This product uses NASA's Integrated Multi-satellitE Retrievals for GPM (IMERG) algorithm for combining information from the GPM satellite constellation to estimate precipitation over the majority of the Earth's surface ([Rozante et al. 2010](#)). IMERG fuses precipitation estimates collected during the TRMM satellite's operation (1998 - 2015) with recent precipitation estimates collected by the GPM mission (2014 - present). IMERG is available from 1998 to present in near real-time with estimates of Earth's precipitation updated every half-hour. Here daily precipitation data is used with a spatial resolution of 0.5×0.5 degrees.

MexHiResClimDB - This product- Mexico's High Resolution Climate Database (MexHiResClimDB; [Carrera-Hernández, 2025](#)) is created from quality-controlled daily station records obtained from Mexico's meteorological services. Station records are interpolated to a 20 arc-second (~ 560 m) grid using Kriging with External Drift on a local neighborhood (KEDl) using topography (from [ALOS AW3D30 DEM](#)) as an auxiliary variable. The resulting data are stored as high-resolution monthly rainfall rasters covering the 1951–2020 period across Mexico.

GISTEMP - As a measure of anthropogenic climate change we use the (low-pass filtered) global mean surface temperature (GMST), where GMST is taken from the National Aeronautics and Space Administration (NASA) Goddard Institute for Space Science (GISS) surface temperature analysis (GISTEMP, [Hansen et al., 2010](#) and [Lenssen et al. 2019](#)).

NOAA ERSST - The Extended Reconstructed Sea Surface Temperature (ERSST) dataset is a global monthly analysis of SST data derived from the International Comprehensive Ocean–Atmosphere Dataset (ICOADS). As a measure of the El Niño - Southern Oscillation cycle (ENSO) we compute the detrended Niño3.4 index from [NOAA’s ERSST v.5](#) sea surface temperatures, by subtracting the mean tropical SST (20S-20N) from the mean SST over the Nino3.4 region (5S-5N, 170W-120W). This index is therefore adjusted to remove the linear trend associated with climate change as proposed in [van Oldenborgh et al., 2021](#), but without rescaling each calendar month.

2.2 Model and experiment descriptions

We use two multi-model ensembles from climate modelling experiments using very different framings ([Philip et al., 2020](#)): Sea Surface temperature (SST) driven global circulation high resolution models and regional climate models.

1. We use ten runs from the **HighResMIP SST-forced model ensemble** ([Haarsma et al., 2016](#)), the simulations for which span from 1950 to 2050. The SST and sea ice forcings for the period 1950-2014 are obtained from the 0.25° x 0.25° Hadley Centre Global Sea Ice and Sea Surface Temperature dataset that have undergone area-weighted regridding to match the climate model resolution. For the ‘future’ time period (2015-2050), SST/sea-ice data are derived from RCP8.5 (CMIP5) projections, and combined with greenhouse gas forcings from SSP5-8.5 (CMIP6) simulations (see Section 3.3 of [Haarsma et al. \(2016\)](#) for further details).

2. We use 28 runs from the Coordinated Regional Climate Downscaling Experiment (**CORDEX**; [Giorgi and Gutowski, 2015](#); [Giorgi et al., 2021](#)). These simulations are produced by running regional climate models (RCMs) with boundary conditions taken from CMIP5 general circulation models (GCMs), using historical simulations up to 2005, and extended to the year 2100 using the RCP8.5 scenario. The selected models consist of 20 models at 0.44° resolution (CAM-44), produced by pairing eleven global models and five regional models; and eight models at 0.22° resolution (CAM-22), produced by pairing six global models and three regional models.

2.3 Statistical methods

Methods for observational and model analysis and for model evaluation and synthesis are used according to the World Weather Attribution Protocol, described in [Philip et al., \(2020\)](#), with supporting details found in [van Oldenborgh et al., \(2021\)](#), [Ciavarella et al., \(2021\)](#), [Otto et al., \(2024\)](#) and [here](#). The key steps, presented in sections 3-5, are: (3) trend estimation from observations; (4)

model validation; (5) multi-method multi-model attribution; and (6) synthesis of the attribution statement.

A nonstationary GEV distribution is used to model Rx3day, and a normal distribution to model pr-JJASO. In both cases, the distribution is assumed to scale exponentially with the covariates, with the dispersion (the ratio between the standard deviation and the mean) remaining constant over time. The parameters of the statistical model are estimated using maximum likelihood.

For each time series we calculate the return period and intensity of the event under study for the 2025 GMST and for 1.3°C cooler GMST: this allows us to compare the climate of now and of the preindustrial past (1850-1900, based on the [Global Warming Index](#)), by calculating the probability ratio (PR; the factor-change in the event's probability) and change in intensity of the event. We also make a similar comparison of the September 2025 detrended Niño3.4 index, to understand the expected contribution of the developing La Niña state to the rainfall observed in 2025.

2.3.1 Statistical modelling of the combined effect of GMST and ENSO

In order to examine the effect of the ENSO on rainy-season precipitation alongside that of increasing GMST, we extend the nonstationary model to accommodate an additional covariate. The variable of interest is assumed to follow a distribution in which the location and scale parameters vary with both GMST and ENSO, so that

$$\text{Rx3day} \sim \text{GEV}(\mu, \sigma \mid \mu_0, \sigma_0, \alpha, \beta, \xi, T, I) \quad \text{and} \quad \text{pr_JJASO} \sim N(\mu, \sigma \mid \mu_0, \sigma_0, \alpha, \beta, T, I),$$

where T is the smoothed GMST, I is the detrended Niño3.4 index, μ_0 and σ_0 are the mean and variance parameters of the nonstationary distribution, ξ is the shape parameter of the GEV distribution and α, β are the trends associated with a change of 1°C in GMST and ENSO, respectively. As a result, the location and scale of the distribution have a different value in each year, determined by both the GMST and Niño3.4 states. Maximum likelihood estimation is used to estimate the model parameters, with

$$\mu = \mu_0 \exp\left(\frac{\alpha T + \beta I}{\mu_0}\right) \quad \text{and} \quad \sigma = \sigma_0 \exp\left(\frac{\alpha T + \beta I}{\mu_0}\right).$$

This formulation reflects the Clausius Clapeyron relation, which implies that precipitation scales exponentially with temperature ([Trenberth et.al., 2003](#), [O’Gorman and Schneider 2009](#)), and so that precipitation will scale exponentially with the strength of the detrended Niño3.4 index. Under this model, the effects of GMST and the detrended Niño3.4 index are assumed to be independent of one another, so that the change in intensity due to GMST is unaffected by the change in intensity due to the ENSO phase. We note that this may not be the case in the real world, as the intensity and frequency of El Niño events may have been influenced by climate change ([Cai et al., 2021](#)); however, by using a detrended Niño3.4 index (see Section 2.1.2) we aim to minimise the correlation between the two factors, and so do not expect the qualitative findings of this study to be affected by this simplifying assumption.

2.3.2 Defining the ENSO state in climate models

The multi-method multi-model attribution step of the WWA protocol involves estimating, for each climate model, the effective return level of a 1-in- n -year event under the current climate state, and estimating the expected change in likelihood and intensity of such an event after a specified change in the covariates. Because the smoothed GMST is generally monotonically increasing, the standard WWA approach is simply to take the model's 2025 GMST as a covariate and to estimate the expected magnitude of an n -year event. However, the factual climate in this study is defined by the 2025 GMST and by the September value of the detrended Niño3.4 index. During the attribution step, the detrended Niño3.4 index derived from the climate model is standardised so that the subset from 1979-2025 has mean 0 and variance 1; the 'factual' climate is then defined as having the model's 2025 GMST and the 2025 observed value of the detrended Niño3.4 index, standardised in the same way. This removes any potential biases in the results due to differences between the amplitude of the modelled Niño3.4 index and that observed.

3 Observational analysis: return period and trend

3.1 Short-term extreme rainfall (Rx3day)

Three observed datasets - CPC, ERA5 and CHIRPS - were used to analyse the trends in the annual Rx3day event. All datasets exhibit high variability, suggesting the possibility of dynamic factors in driving extremes in the study region (Figure 3.1; Appendix Fig. A.1.1). Although all three datasets show good agreement in the year-to-year variability, they show discernible differences in the overall trends. The 76-year long ERA5 dataset shows an increasing tendency in rainfall during the first half and thereafter a decreasing trend, which is also captured by CPC, suggesting the possibility of the influence of multi-decadal dynamic phenomena being visible in the longer dataset. However, we can also not rule out changes in data quality, as we have not been able to compare the dataset with station data. Therefore additionally, we also consider ERA5 for the period starting from 1979 to match the shorter datasets, and we find a comparable decreasing trend consistent with CPC. CHIRPS, which covers a similar period (1981 onwards) shows an overall increasing tendency, despite it capturing the year-to-year variability well. Below we explore two complementary modelling approaches to assess potential drivers of changes in extreme rainfall in the region: first, fitting a nonstationary GEV distribution in which precipitation scales exponentially with GMST; and secondly, fitting a nonstationary GEV distribution in which precipitation scales exponentially with both GMST and the detrended Niño3.4 index (see Section 1.3).

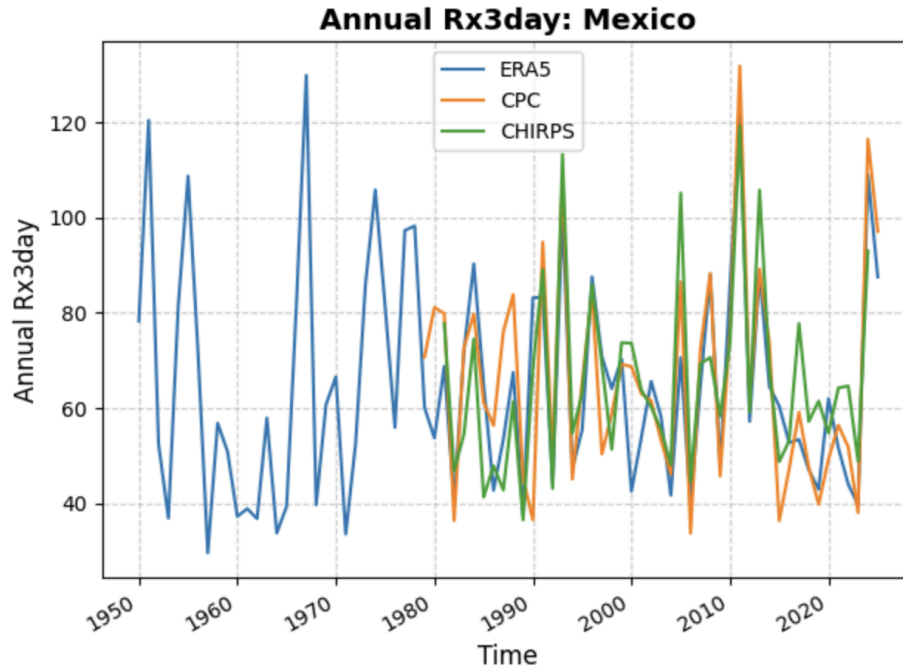


Figure 3.1: Annual Rx3day timeseries for ERA5, CPC and CHIRPS.

3.1.1. Influence of human-caused warming

The left-hand panels in Figure 3.2 show the annual Rx3day as a function of GMST alone. The three datasets exhibit contrasting trends (decreasing in CPC and increasing in CHIRPS, with very little change in ERA5) suggest that rainfall is not well represented in gridded data products in this region, highlighting the need for accurate station-based observations against which the data products can be validated. The right-hand panels in Figure 3.2 show the return period curves for the current (2025) climate and a 1.3°C cooler climate representing a pre-industrial world. Table 3.1 summarises the results of this analysis for the three datasets. In ERA5 the estimated return period of the event is 5 years (9 if including only data after 1979), and in CPC 21 years. Since we do not have a strong reason for trusting one of these datasets over the others, we use a rounded average return period of 10 years as the event definition for the attribution analysis in Section 6 and to estimate the probability ratio for the CHIRPS dataset, which did not contain the 2025 event at the time of doing the analysis. The estimated PRs from the individual datasets span changes in both directions, but with uncertainty ranges encompassing no change: CPC suggests that similarly extreme 3-day rainfall would have been three times more likely in a preindustrial climate, while CHIRPS suggests that such an event is now four times more likely than it would have been in a preindustrial climate, with very little change in ERA5 whether we consider the period from 1950-2025 or 1979-2025. This difference is also reflected in the intensity changes, with CPC registering a 22% decrease in the rainfall intensity between today's climate and the pre-industrial climate, while CHIRPS shows a 29% increase.

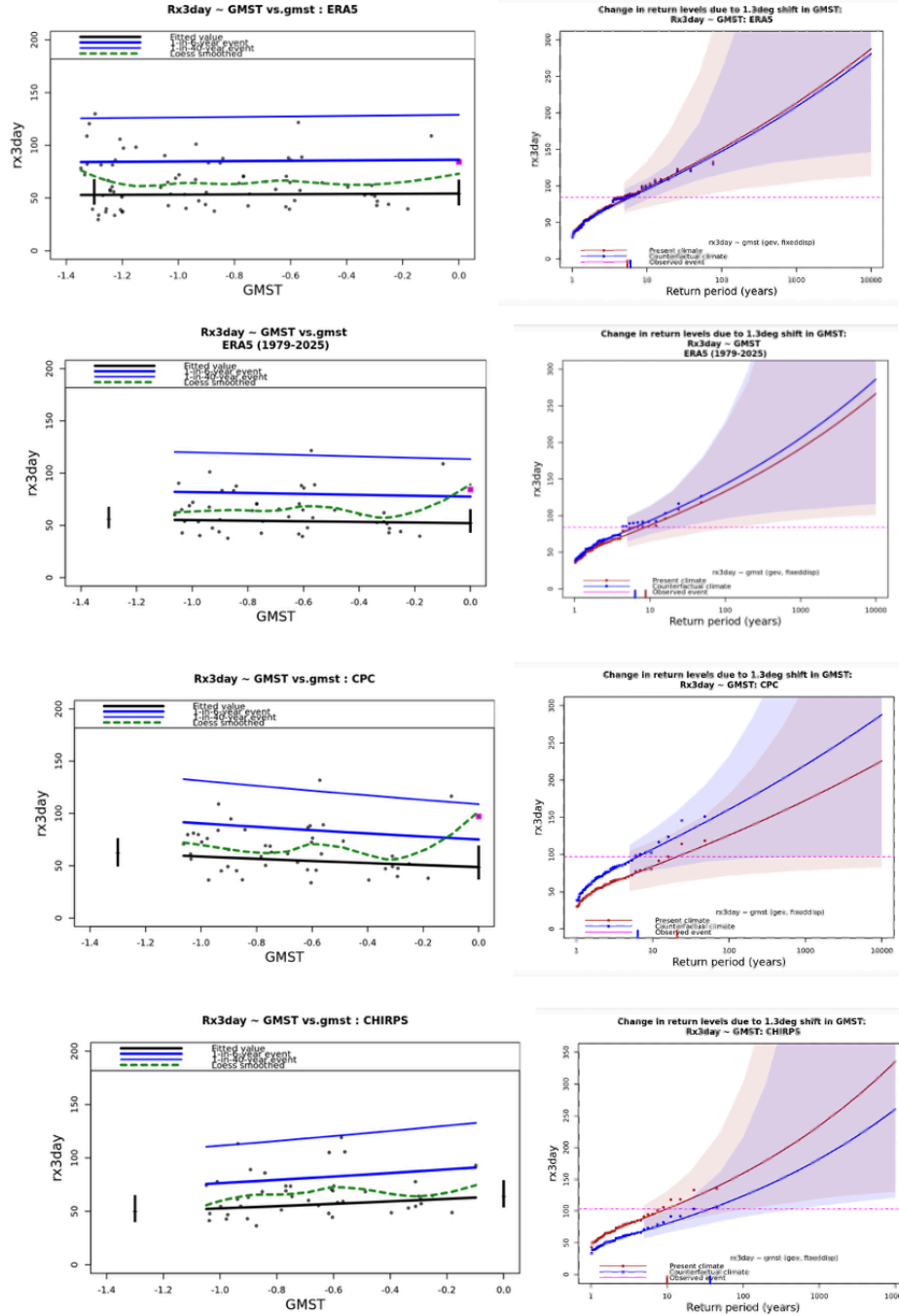


Figure 3.2: GEV fit with fixed dispersion parameter scaling proportional to GMST. **(Left)** observed annual Rx3day [mm/3day] as a function of the smoothed GMST. The thick black line denotes the time-varying location parameter. The vertical black lines show the 95% confidence interval for the location parameter, in the 2025 climate and the 1.3°C cooler counterfactual climate. The 2025 observation is highlighted with the magenta box. **(Right)** return time plots for the climate of 2025 (red) and a climate with GMST 1.3°C cooler (blue). The past observations are shown twice: once shifted up to the current climate and once shifted down to the climate of the pre-industrial era. The markers show the data and the lines show the expected return levels, with shading showing a bootstrapped 95% confidence interval. The magenta line shows the magnitude of the 2025 event analysed here. Results are shown for ERA5 (**top**), ERA5 (1979-2025) (**second row**), CPC (**third row**), and CHIRPS (**bottom**).

Table 3.1: Estimated return periods of annual Rx3day over the study region in each observational data product, along with the respective changes in probability ratio and magnitudes associated with 1.3°C of global warming. The AIC is the Akaike Information Criterion, a measure of goodness of fit that can be used to compare how well different models fit each dataset. Numbers in brackets are 95% confidence intervals obtained by bootstrapping. No confidence interval is given for the return period in CHIRPS because the data did not cover the event at the time of writing, so the return period was fixed at 10 years.

Dataset	Rx3day				
	Magnitude (mm)	Return period (years)	Probability Ratio	Change in magnitude (%)	AIC
ERA5	84.24	6 (3 to 39)	1.10 (0.12 to 3.51)	2.44 (-29.18 to 48.19)	688.46
ERA5 > 1979	84.24	9 (3 to 141)	0.73 (0.03 to 7.91)	-6.87 (-36.83 to 43.93)	411.22
CPC	97.1	21 (4 to inf)	0.31 (0 to 105.48)	-21.59 (-49.35 to 43.12)	424.25
CHIRPS	103.57	10	3.68 (0.31 to 42.67)	28.76 (-14.36 to 77.97)	380.95

3.1.2 Influence of modes of natural variability

To capture the observed variability associated with interannual climate dynamics, we extended the model by including ENSO, represented by the detrended September Niño3.4 index, as an additional covariate (see Section 2.3.3). Fitting a statistical model using both GMST and this ENSO index as covariates (Figure 3.3) gives a better fit to the data, according to the AIC, than GMST alone (see Table 3.1 and Table 3.2). In ERA5, the return period of the 2025 event in the current climate and the current La Niña state is estimated to be around 5 years (8 years when considering only data after 1979), and in CPC around 19 years. We therefore again use a return period of 10 years in the attribution step, and for estimating the event magnitude in the CHIRPS dataset.

In observational datasets (Table 3.2), the developing La Niña conditions in 2025 are consistently associated with increased rainfall, and increased likelihood of similarly extreme rainfall, compared to in a Neutral Niño3.4 state. The estimated probability ratios are between 1.4 and 2, and the estimated intensity changes between 6.6% and 16.%. These results are statistically significant across all the datasets, reflecting the fact that ENSO is an important driver of extreme rainfall in this region. The influence of GMST is unclear, with different datasets exhibiting different trends in Rx3day, all with relatively high uncertainty.

Table 3.2: Estimated return periods of annual Rx3day over the study region in each observational data product, along with the respective changes in probability ratio and magnitudes associated with (a) 1.3°C of global warming and (b) the current developing La Niña state compared to a neutral ENSO state. The AIC is the Akaike Information Criterion, a measure of goodness of fit that can be used to compare how well different models fit each dataset. Numbers in brackets are 95% confidence intervals obtained by bootstrapping. No confidence interval is given for the return period in CHIRPS because the data did not cover the event at the time of writing, so the return period was fixed at 10 years.

	Return period (years)	(a) GMST		(b) ENSO		AIC
		Probability Ratio	Change in magnitude (%)	Probability Ratio	Change in magnitude (%)	
ERA5	5 (2 to 21)	0.82 (0.14 to 2.95)	-5.11 (-30.89 to 40.31)	1.51 (1.02 to 2.56)	10.28 (0.56 to 18.63)	684.76
ERA5 > 1979	8 (3 to 84)	0.46 (0.04 to 3.73)	-16.42 (-40.15 to 28.44)	1.53(1.06 to 2.63)	9.532(1.12 to 17.95)	408.55
CPC	19 (4 to 754)	0.16 (0.002 to 1.274)	-35.14 (-54.21 to 8.85)	2.05 (1.4 to 6.24)	16 (7.35 to 24.6)	414.28
CHIRPS	10	3.11 (0.23 to 26.20)	23.27 (-17.92 to 75.45)	1.39 (1.03 to 2.74)	6.55 (0.58 to 12.74)	379.6

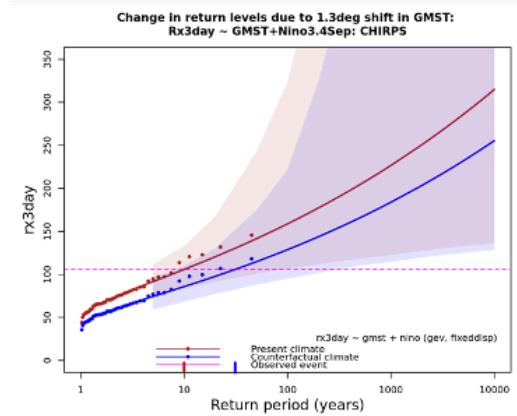
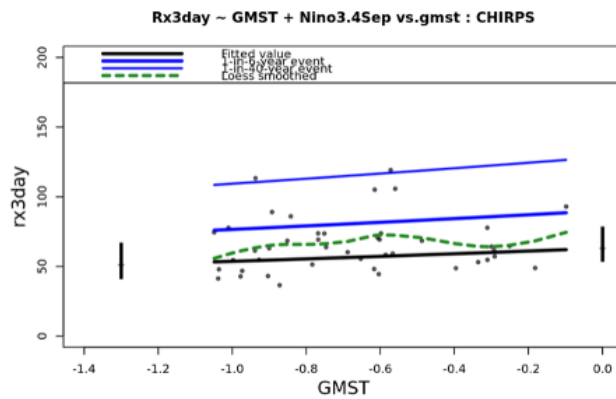
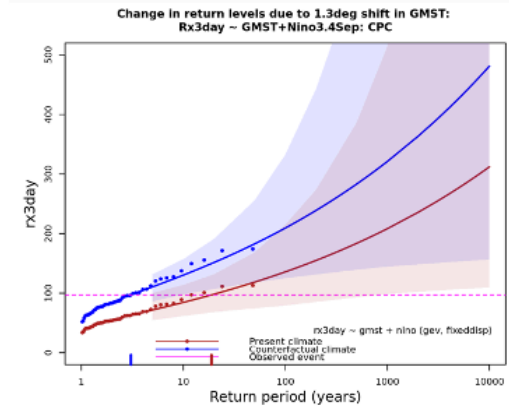
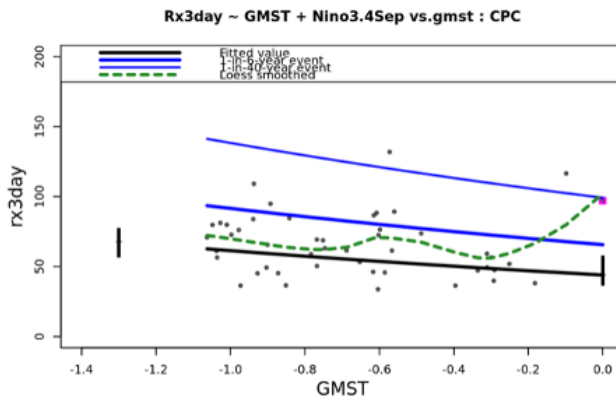
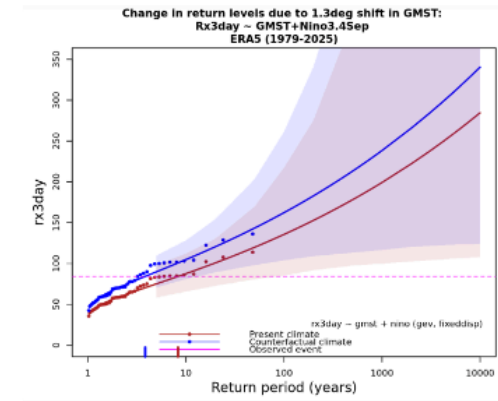
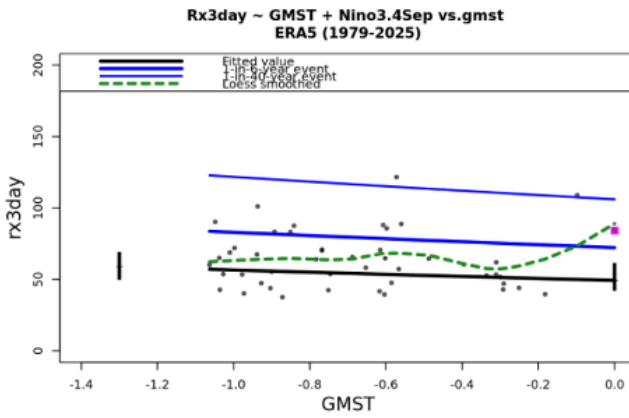
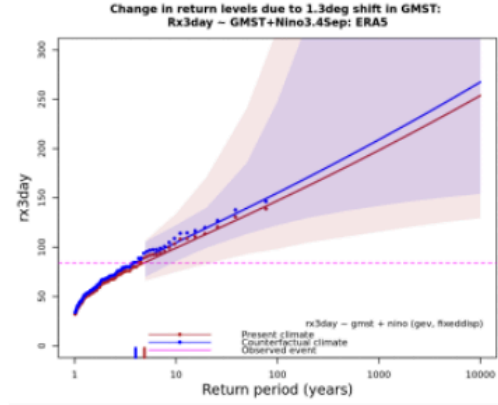
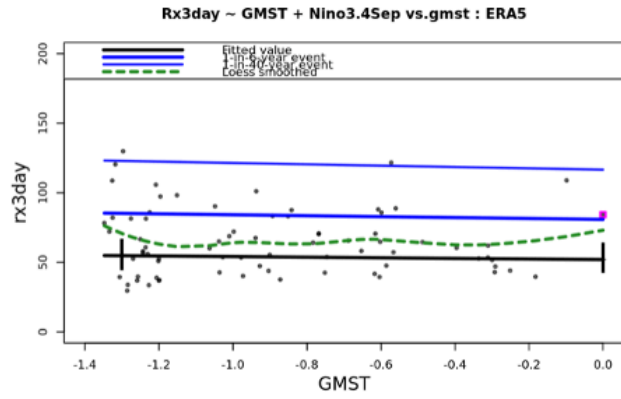


Figure 3.3: GEV fit with fixed dispersion parameter scaling proportional to GMST and ENSO. (Left) observed annual Rx3day [mm] as a function of the smoothed GMST. The thick black line denotes the time-varying location parameter. The vertical black lines show the 95% confidence interval for the

location parameter, in the 2025 climate and the 1.3°C cooler counterfactual climate. The 2025 observation is highlighted with the magenta box. **(Right)** return time plots for the climate of 2025 (red) and a climate with GMST 1.3°C cooler (blue). The past observations are shown twice: once shifted up to the current climate and once shifted down to the climate of the pre-industrial era. The markers show the data and the lines show the expected return levels, with shading showing a bootstrapped 95% confidence interval. The magenta line shows the magnitude of the 2025 event analysed here. Results are shown for ERA5 (**top**), ERA5 (1979-2025) (**second row**), CPC (**third row**), and CHIRPS (**bottom**).

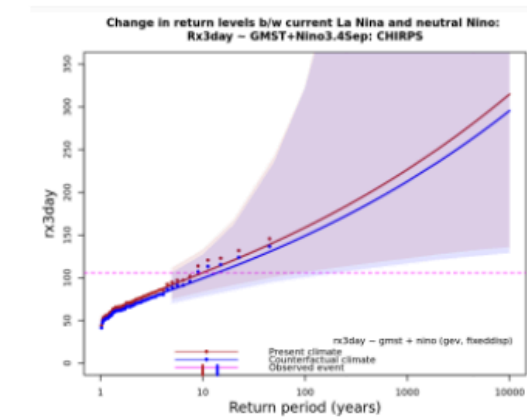
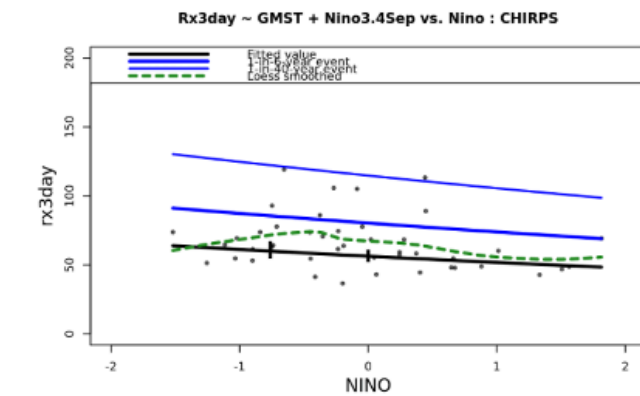
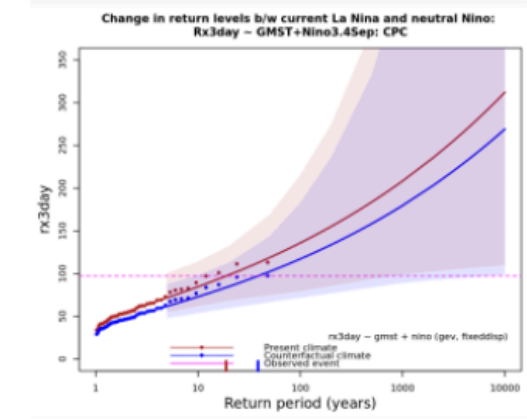
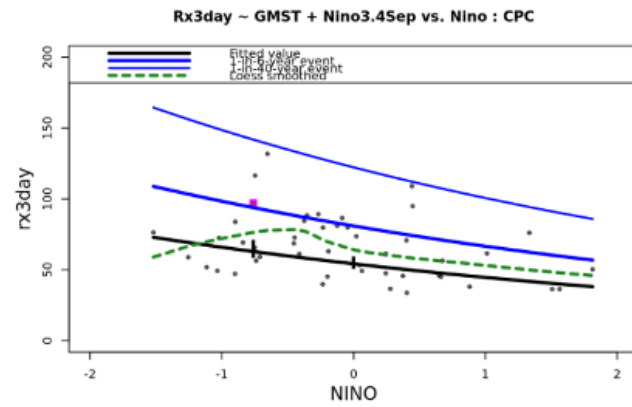
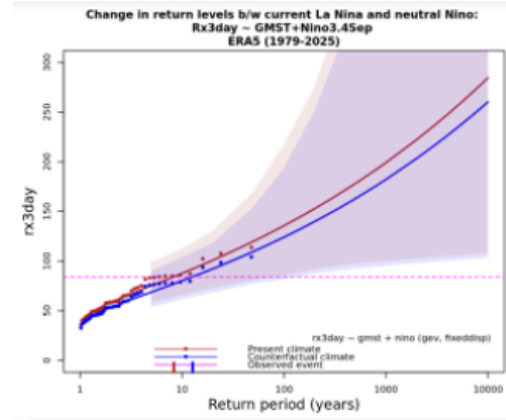
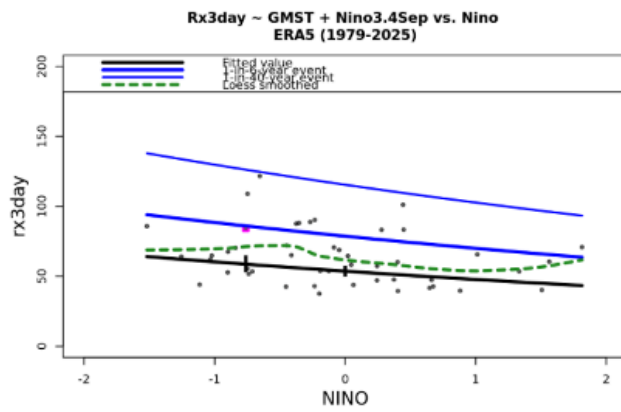
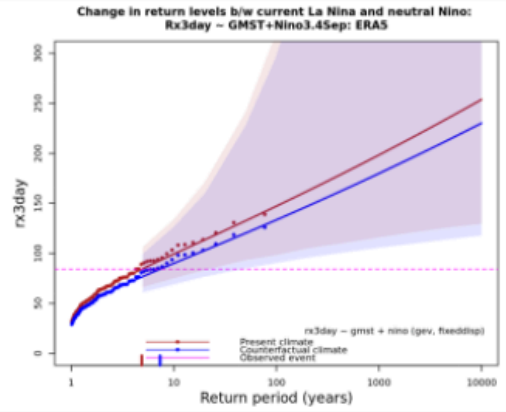
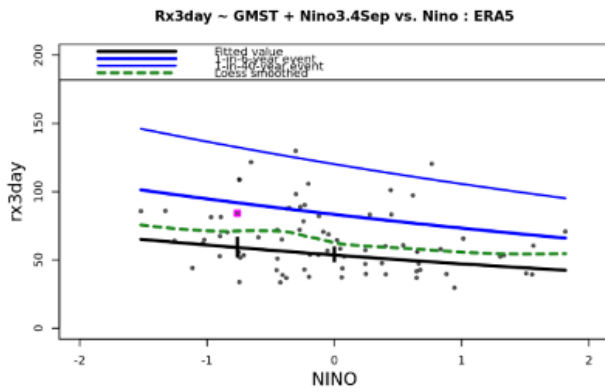


Figure 3.2: GEV fit with fixed dispersion parameter scaling proportional to GMST and ENSO. (Left) Observed annual Rx3day [mm/3day] as a function of detrended September Niño3.4 index. The thick

black line denotes the time-varying location parameter. The vertical black lines show the 95% confidence interval for the location parameter, in the September 2025 ENSO state and a neutral ENSO state. The 2025 observation is highlighted with the magenta box. **(Right)** Return time plots for the climate of 2025 (red) and a neutral ENSO state (blue). The markers show the data and the lines show the expected return levels, with shading showing a bootstrapped 95% confidence interval. The magenta line shows the magnitude of the 2025 event analysed here. Results are shown for ERA5 (**top**), ERA5 (1979-2025) (**second row**), CPC (**third row**), and CHIRPS (**bottom**).

3.2 Long-term seasonal rainfall (pr-JJASO)

Trends in June-October (JJASO) rainfall were analysed by fitting nonstationary normal distributions to the data. In Section 3.2.1, JJASO rainfall is assumed to scale with GMST, and in Section 3.2.2 with both GMST and September ENSO conditions. Four datasets were used for this analysis - CHIRPS, CPC, ERA5 and a very high-resolution monthly rainfall dataset, MexHighResClimDB (abbreviated here as MxHRC; see Section 2.1). Figure 3.5 shows the total seasonal rainfall, averaged over the study region, in each of these datasets. Since the beginning of the satellite era all datasets show relatively good agreement, although CPC tends to show more extreme JJASO rainfall in the 1980s and 1990s. Only two datasets cover the pre-satellite era, with the station-based MxHRC dataset consistently wetter than the ERA5 reanalysis, in which precipitation is a diagnostic variable.

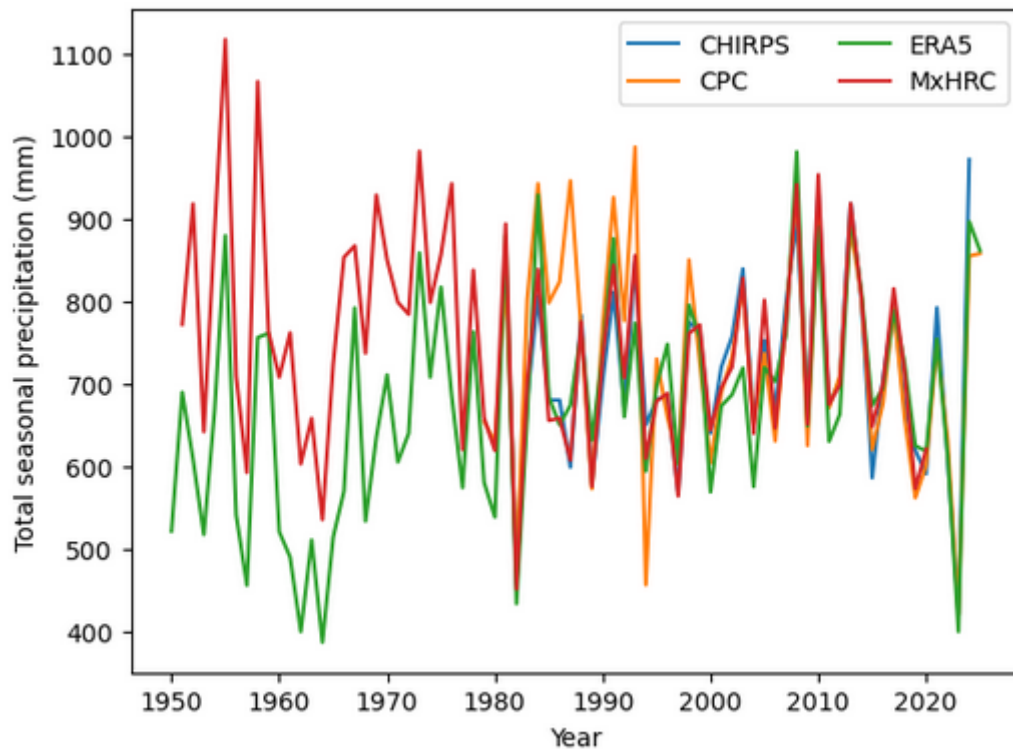


Figure 3.5: Annual time series of rainy-season (June-October, JJASO) total accumulated rainfall for ERA5, CPC and CHIRPS and IMERG.

3.2.1. Influence of human-caused warming

The left panels in Figure 3.6 show the response of seasonal (JJASO) rainfall in the region to GMST. The increasing trend in ERA5 vs. decreasing in CPC and MxHRC once again suggests that rainfall in this region is not well represented in these datasets. Given the high variability it is likely that there are other drivers influencing the temporal changes in addition to GMST, and more detailed investigation is needed to understand other contributing mechanisms.

The right panel in Figure 3.6 shows the return period curves for the current (2025) climate and a 1.3°C cooler climate representing a pre-industrial world. Table 3.3 summarises the results for this analysis for the four datasets. The estimated return period of the 2025 JJASO season is 4 years in ERA5 and 14 years in CPC; in the absence of station data for confirming the magnitude of the event, we use a rounded average return period of 10 years as the event definition for the attribution analysis in Section 6 and to estimate the probability ratio for the CHIRPS and MxHRC datasets, which did not contain the 2025 event at the time of doing the analysis.

The PR and intensity change estimated from the full ERA5 time series (1950-2025) show a statistically significant increase; however, the MxHRC dataset shows the opposite, with a statistically significant decrease in the likelihood and magnitude. Of the shorter time series, CPC shows very little change, while CHIRPS also has an increasing trend, albeit with high uncertainty. When considering only the period from 1979 onwards, the trends are more consistent, with ERA5, CHIRPS and MxHRC all indicating a weak wetting trend, with estimated increases of 5-7% in JJASO rainfall associated and approximately a doubling of the likelihood of similarly wet seasons in 2025 compared to what would be expected in a 1.3°C cooler climate (Table 3.3b).

Table 3.3: *Estimated return periods (RP) of annual pr-JJASO over the study region in each observational data product, along with the respective probability ratio (PR) and change in intensity (ΔI) associated with 1.3°C of global warming: (a) using all available data and (b) using only data from 1979 onwards for ERA5 and MxHRC. The AIC is the Akaike Information Criterion, a measure of goodness of fit that can be used to compare how well different models fit each dataset. Numbers in brackets are 95% confidence intervals obtained by bootstrapping. No confidence interval is given for the return period in CHIRPS or MxHRC because the data did not cover the event at the time of writing, so the return period was fixed at 10 years.*

		(a) Fitted to all years				(b) Fitted to 1979-			
	Mag. (mm)	RP	PR	ΔI (%)	AIC	RP	PR	ΔI (%)	AIC
ERA5	861	4 (2 to 12)	7 (1.32 to 68)	18.24(2.3 1 to 37.16)	957	6.8 (2.6 to 66)	2.3 (0.092 to 110)	6.7 (-16 to 33)	590
CPC	857	14 (4 to 383)	0.26 (0.005 to 2.42)	-12.5 (-32.6 to 8.34)	597	14 (4 to 383)	0.26 (0.005 to 2.42)	-12.45 (-32.6 to 8.34)	597
CHIRPS	883	10	2.04 (0.01 to 139)	4.97 (-21.9 to 35.4)	548	10	2.04 (0.01 to 139)	4.97 (-21.9 to 35.4)	548
MxHRC	811	10	0.2 (0.02 to 0.91)	-14.5 (-27.4 to -1.01)	879	10	2.8 (0.071 to 350)	6.7 (-13 to 37)	520

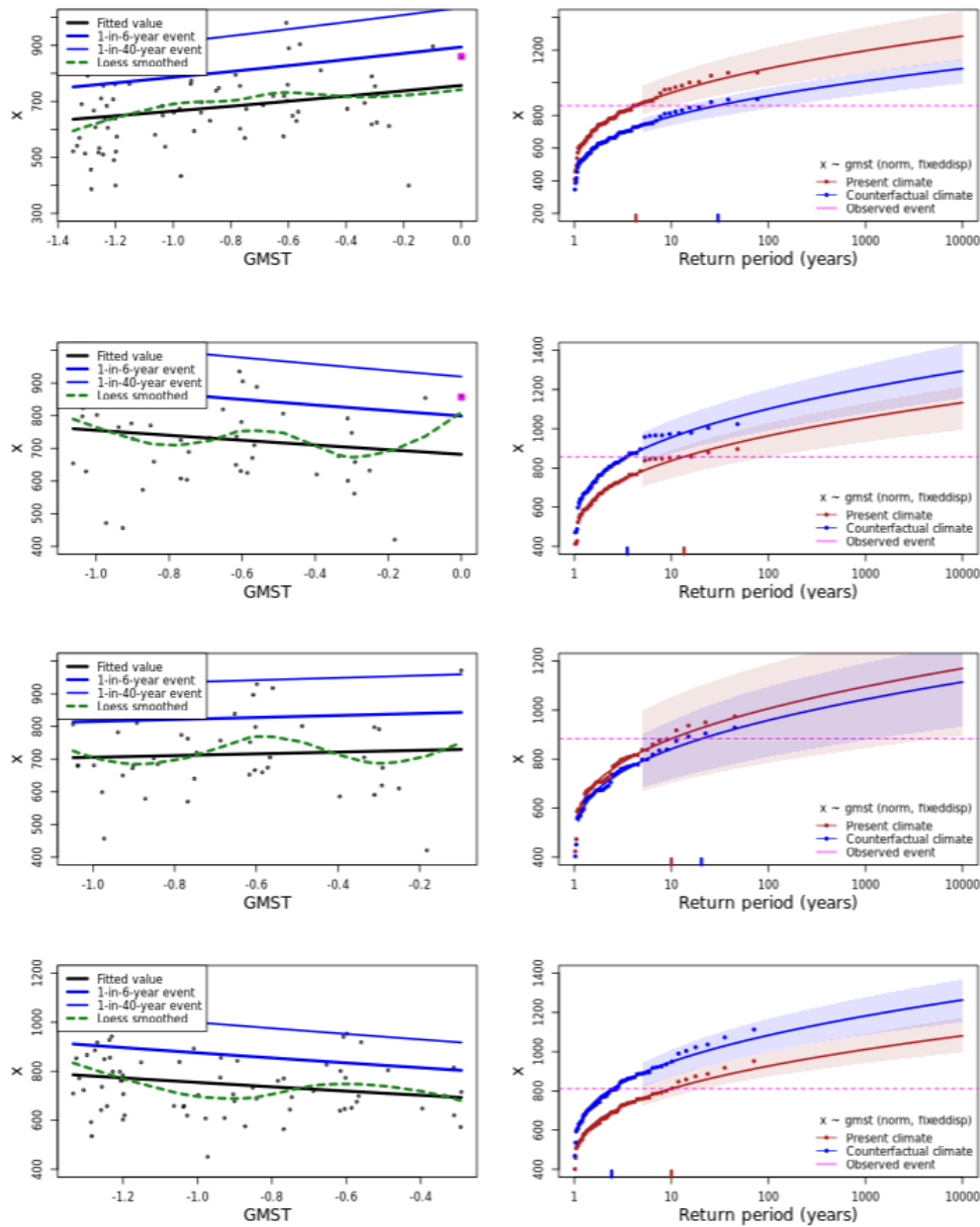


Figure 3.6: Gaussian fit with fixed dispersion parameter, scaling exponentially with GMST. **(Left)** observed annual JJASO [mm] as a function of the smoothed GMST. The thick black line denotes the time-varying location parameter. The vertical black lines show the 95% confidence interval for the location parameter, in the 2025 climate and the 1.3°C cooler counterfactual climate. The 2025 observation is highlighted with the magenta box. **(Right)** return time plots for the climate of 2025 (red) and a climate with GMST 1.3°C cooler (blue). The past observations are shown twice: once shifted up to the current climate and once shifted down to the climate of the pre-industrial era. The markers show the data and the lines show the expected return levels, with shading showing a bootstrapped 95% confidence interval. The magenta line shows the magnitude of the 2025 event analysed here. Results are shown for ERA5 (**top**), CPC (**second row**), CHIRPS (**third row**), and MxHRC (**bottom**).

3.2.2 Influence of modes of natural variability

The inclusion of ENSO in the non-stationary model alongside GMST again improves the fit by explaining some of the interannual variability in seasonal rainfall (Fig. A.1.2, and as seen from the lower AICs). The return period of the event in the current climate and the current La Niña state is estimated to be around 3 years in ERA5, and around 13 years in CPC: these numbers are very similar to the results obtained when using GMST along as a covariate. We therefore again use a return period of 10 years in the attribution step, and for estimating the expected event magnitude in the CHIRPS and MxHRC datasets.

In CHIRPS - where the confidence intervals are fairly symmetrical about zero, indicating that no strong trend associated with GMST was detected - the addition of the ENSO covariate changes the sign of the trend from weakly positive to weakly negative; in the other three datasets, the trends are largely unaffected by the inclusion of the extra covariate. While the observational data products disagree on the strength of the trend associated with global warming, they are more consistent on the contribution of ENSO, with estimated increases of 5-8% associated with the current emerging La Niña state compared to neutral ENSO conditions, and estimated PRs of 1.9 to 4.2 (Figure 3.6 and Table 3.4). Because of the importance of ENSO for seasonal rainfall in this region, we evaluate the contribution of both increased GMST and the emerging La Niña state in the attribution step in the next sections.

Table 3.4: Estimated return periods of annual *pr*-JJASO over the study region in each observational data product, along with the respective changes in probability ratio and magnitudes associated with (a) 1.3°C of global warming and (b) the current developing La Niña state compared to a neutral ENSO state. The AIC is the Akaike Information Criterion, a measure of goodness of fit that can be used to compare how well different models fit each dataset. Numbers in brackets are 95% confidence intervals obtained by bootstrapping. No confidence interval is given for the return period in CHIRPS or MxHRC because the data did not cover the event at the time of writing, so the return period was fixed at 10 years.

Dataset	Return period (95% C.I.)	(a) GMST		(b) ENSO		AIC
		Probability Ratio	Change in magnitude (%)	Probability Ratio	Change in magnitude (%)	
ERA5	3 (2 to 8)	4.14 (1.13 to 24.55)	15.23 (0.96 to 31.79)	1.9 (1.31 to 3.57)	7.87 (4.12 to 11.55)	946
CPC	13 (4 to 329)	0.16 (0.004 to 1.18)	-18.36 (-36.57 to 1.55)	2.22 (0.93 to 7.98)	5.3 (-0.59 to 10.73)	595
CHIRPS	10 (8 to 883)	0.57 (0.003 to 16.68)	-4.18 (-27.26 to 20.84)	4.2 (1.64 to 29.2)	8.41 (3 to 12.4)	539
MxHRC	10 (3 to 89)	0.18 (0.02 to 0.7)	-17.96 (-28.33 to -5.08)	3.25 (1.67 to 8.89)	7.41 (3.49 to 10.97)	867

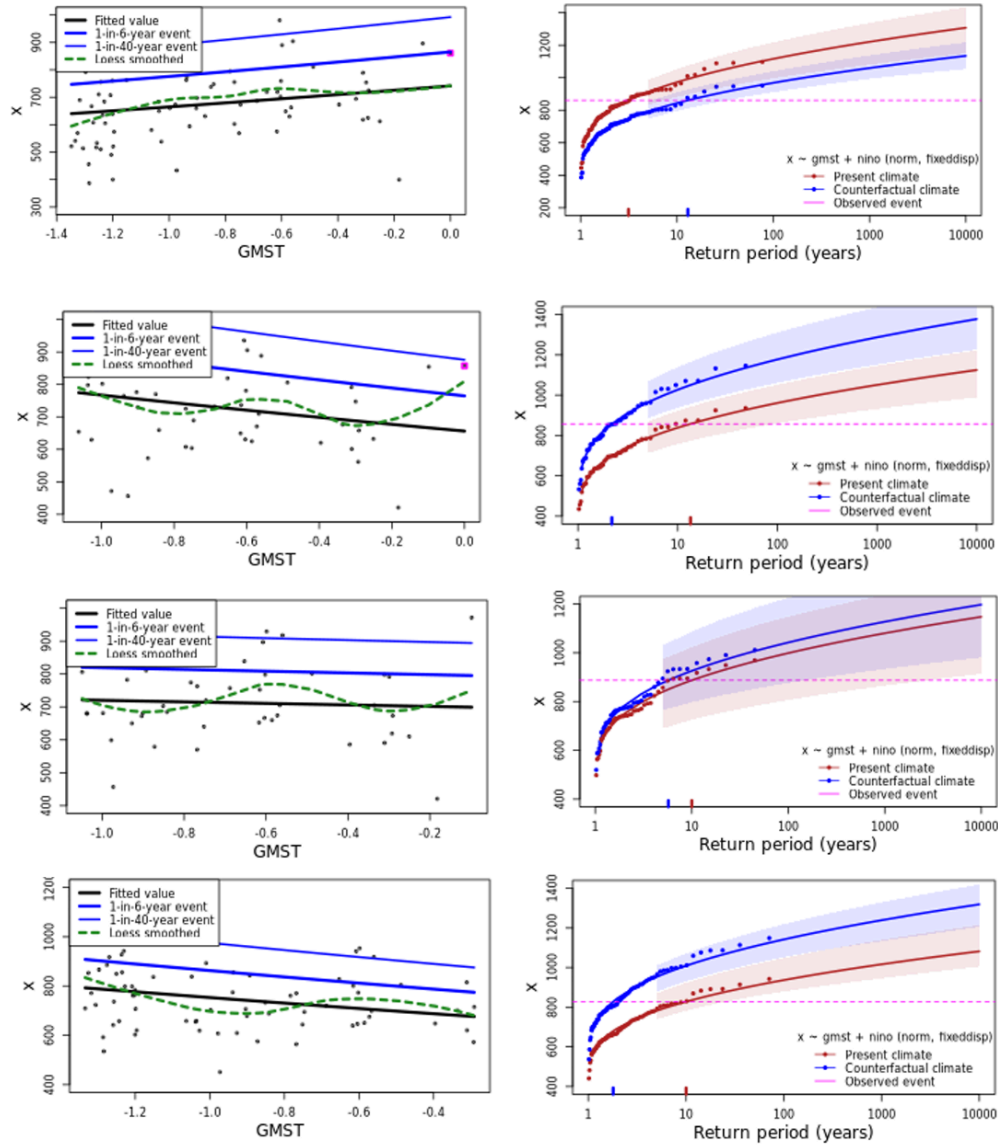


Figure 3.7: Gaussian fit with fixed dispersion parameter scaling proportional to GMST and ENSO. **(Left)** observed annual pr-JJASO [mm] as a function of the smoothed GMST. The thick black line denotes the time-varying location parameter. The vertical black lines show the 95% confidence interval for the location parameter, in the 2025 climate and the 1.3°C cooler counterfactual climate. The 2025 observation is highlighted with the magenta box. **(Right)** return time plots for the climate of 2025 (red) and a climate with GMST 1.3°C cooler (blue). The past observations are shown twice: once shifted up to the current climate and once shifted down to the climate of the pre-industrial era. The markers show the data and the lines show the expected return levels, with shading showing a bootstrapped 95% confidence interval. The magenta line shows the magnitude of the 2025 event analysed here. Results are shown for ERA5 (**top**), CPC (**upper middle**), CHIRPS (**lower middle**), and MxHRC (**bottom**).

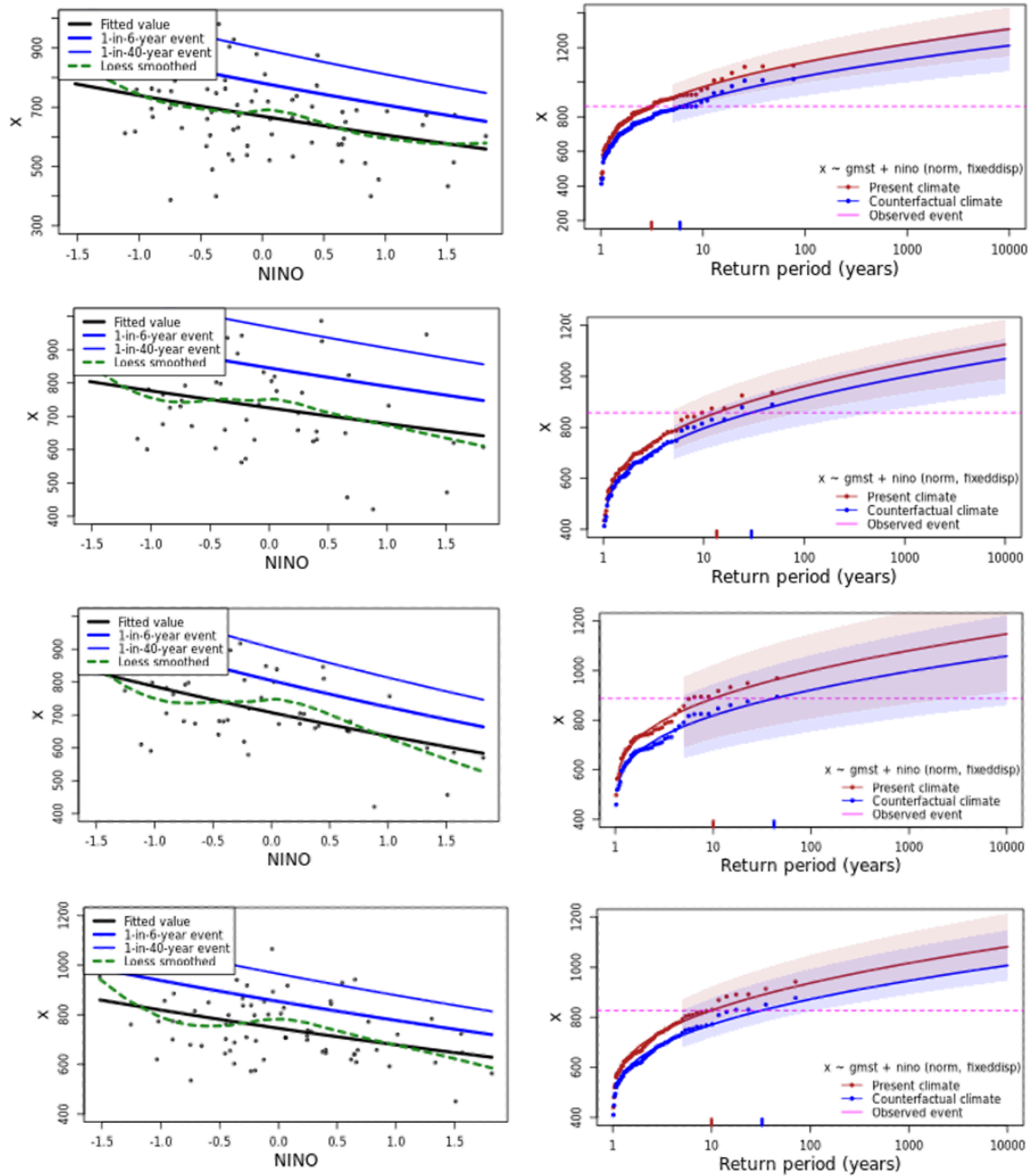


Figure 3.8: Gaussian fit with fixed dispersion parameter scaling proportional to GMST and ENSO. **(Left)** observed annual pr-JJASO [mm] as a function of the detrended September Niño3.4 index. The thick black line denotes the time-varying location parameter. The vertical black lines show the 95% confidence interval for the location parameter, in the September 2025 ENSO state and a neutral ENSO state. The 2025 observation is highlighted with the magenta box. **(Right)** return time plots for the climate of 2025 (red) and a neutral ENSO state (blue). The past observations are shown twice: once shifted up to the current climate and once shifted down to the climate of the pre-industrial era. The markers show the data and the lines show the expected return levels, with shading showing a bootstrapped 95% confidence interval. The magenta line shows the magnitude of the 2025 event analysed here. Results are shown for ERA5 (**top**), CPC (**upper middle**), CHIRPS (**lower middle**), and MxHRC (**bottom**).

4 Model evaluation

In the subsections below we show the results of the model evaluation. The climate models are evaluated against the observations for which daily observed precipitation was available (CHIRPS, CPC and ERA5) in their ability to capture:

1. Seasonal cycles over the study region: For this, we qualitatively compare the seasonal cycles based on model outputs against observations-based cycles. In this region, the three observational datasets show very similar seasonal cycles and their collective behaviour is used to evaluate the models. We discard the models that exhibit ill-defined peaks in their seasonal cycles. We also discard the model if the rainy season onset/termination varies significantly from the observations. Seasonal cycles exhibiting correctly timed peaks but with a mismatch in peak amplitudes are classed as 'reasonable', whereas seasonal cycles classed as 'good' are additionally required to have similar peak amplitudes to the observations.

2. Spatial patterns: Models that do not match the observations in terms of the large-scale precipitation patterns averaged over June to October are excluded. Models showing in the southern part of the domain higher seasonal rainfall totals near the coasts and lower totals inland with amplitudes similar to observed are evaluated as 'good'. If this spatial pattern is partly reproduced with reasonable amplitudes, it is evaluated as 'reasonable'. If the observed spatial pattern is not reproduced in a model or the amplitude is very weak, the model's spatial pattern is evaluated as 'bad'.

3. Parameters of the fitted statistical models, in which precipitation scales exponentially with both GMST and the detrended Niño3.4 index, for the two event definitions RX3day and pr_JJASO over the study region. We discard the model if the model and observation parameters ranges do not overlap.

The models are labelled as 'good', 'reasonable', or 'bad' based on their performances in terms of the three criteria discussed above. A model is given an overall rating of 'good' if it is rated 'good' for all three characteristics. If there is at least one 'reasonable', then its overall rating will be 'reasonable' and 'bad' if there is at least one 'bad'. For each framing or model setup we also use models that only just pass the evaluation tests if we only have five models or less for that framing that perform well.

4.1 Model validation for Rx3day

Results for models passing the evaluation test are shown in Table 4.1. An extended table also showing the Rx3day results of discarded models can be found in Appendix A.2.

Table 4.1: Evaluation results of the climate models considered for attribution analysis of Rx3day. For each model, the threshold for a 1-in-10-year event is shown, along with the best estimates of the

Dispersion and Shape parameters with their 95% confidence intervals. Furthermore evaluation of the seasonal cycle and spatial pattern are shown.

Model / Observations	Seasonal cycle	Spatial pattern	Dispersion	Shape parameter	Conclusion
CHIRPS			0.227 (0.151 ... 0.273)	0.11 (-0.11 ... 0.53)	
CPC			0.252 (0.183 ... 0.304)	0.16 (-0.19 ... 0.43)	
ERA5			0.316 (0.260 ... 0.356)	0.036 (-0.19 ... 0.45)	
CORDEX					
CAM-22_GFDL-ESM2M_r1i1p1_CRCM5	reasonable	good	0.253 (0.192 ... 0.299)	-0.24 (-0.64 ... -0.0063)	reasonable
CAM-22_GFDL-ESM2M_r1i1p1_RegCM4-7	reasonable	reasonable	0.325 (0.238 ... 0.377)	-0.036 (-0.33 ... 0.53)	reasonable
CAM-22_HadGEM2-ES_r1i1p1_REMO2015	good	good	0.379 (0.288 ... 0.435)	-0.024 (-0.37 ... 0.33)	reasonable
CAM-22_MPI-ESM-MR_r1i1p1_RegCM4-7	reasonable	reasonable	0.244 (0.186 ... 0.295)	-0.12 (-0.52 ... 0.20)	reasonable
CAM-44_CanESM2_r1i1p1_RCA4	reasonable	reasonable	0.213 (0.155 ... 0.249)	0.13 (-0.17 ... 0.41)	reasonable
CAM-44_CSIRO-Mk3-6-0_r1i1p1_RCA4	good	reasonable	0.324 (0.243 ... 0.375)	0.023 (-0.45 ... 0.45)	reasonable
CAM-44_HadGEM2-ES_r1i1p1_REMO2015	good	good	0.379 (0.288 ... 0.435)	-0.024 (-0.37 ... 0.33)	reasonable
CAM-44_MPI-ESM-LR_r1i1p1_RCA4	reasonable	reasonable	0.305 (0.222 ... 0.345)	-0.054 (-0.44 ... 0.55)	reasonable
CAM-44_MPI-ESM-MR_r1i1p1_RegCM4-3	reasonable	reasonable	0.230 (0.137 ... 0.289)	0.018 (-0.27 ... 0.45)	reasonable
CAM-44_MPI-ESM-MR_r1i1p1_RegCM4-7	reasonable	reasonable	0.244 (0.186 ... 0.295)	-0.12 (-0.52 ... 0.20)	reasonable
HighResMIP					
CMCC-CM2-HR4_r1i1p1f1	reasonable	good	0.344 (0.186 ... 0.420)	0.30 (0.094 ... 1.0)	reasonable
CMCC-CM2-VHR4_r1i1p1f1	good	good	0.388 (0.293 ... 0.451)	-0.0030 (-0.39 ... 0.26)	reasonable
EC-Earth3P_r1i1p1f1	good	good	0.173 (0.116 ... 0.210)	0.16 (-0.099 ... 0.52)	good

4.2 Model validation for pr_JJASO

Results for models passing the evaluation test are shown in Table 4.2. An extended table also showing the pr_JJASO results of discarded models can be found in Appendix A.2.

Table 4.2: Evaluation results of the climate models considered for attribution analysis of pr_JJASO. For each model, the threshold for a 1-in-10-year event is shown, along with the best estimates of the Dispersion parameters are shown, along with a 95% confidence intervals. Furthermore evaluation of the seasonal cycle and spatial pattern are shown.

Model / Observations	Seasonal cycle	Spatial pattern	Dispersion	Conclusion
CHIRPS			0.142 (0.108 ... 0.163)	
CPC			0.171 (0.132 ... 0.198)	
ERA5			0.172 (0.140 ... 0.198)	
mxhighresclimdb			0.150 (0.124 ... 0.170)	
CORDEX				
CAM-22_GFDL-ESM2M_r1i1p1_CRCM5	reasonable	good	0.189 (0.137 ... 0.222)	reasonable

CAM-22_GFDL-ESM2M_r1i1p1_RegCM4-7	reasonable	reasonable	0.222 (0.170 ... 0.250)	reasonable
CAM-22_HadGEM2-ES_r1i1p1_REMO2015	good	good	0.252 (0.189 ... 0.286)	reasonable
CAM-22_MPI-ESM-MR_r1i1p1_RegCM4-7	reasonable	reasonable	0.202 (0.154 ... 0.227)	reasonable
CAM-44_CanESM2_r1i1p1_RCA4	reasonable	reasonable	0.173 (0.133 ... 0.197)	reasonable
CAM-44_CNRM-CM5_r1i1p1_CRCM5	good	good	0.159 (0.114 ... 0.183)	good
CAM-44_CSIRO-Mk3-6-0_r1i1p1_RCA4	good	reasonable	0.196 (0.153 ... 0.222)	reasonable
CAM-44_HadGEM2-ES_r1i1p1_REMO2015	good	good	0.252 (0.189 ... 0.286)	reasonable
CAM-44_MPI-ESM-LR_r1i1p1_RCA4	reasonable	reasonable	0.172 (0.128 ... 0.199)	reasonable
CAM-44_MPI-ESM-MR_r1i1p1_RegCM4-3	reasonable	reasonable	0.155 (0.118 ... 0.175)	reasonable
CAM-44_MPI-ESM-MR_r1i1p1_RegCM4-7	reasonable	reasonable	0.202 (0.154 ... 0.227)	reasonable
HighResMIP				
CMCC-CM2-HR4_r1i1p1f1	reasonable	good	0.182 (0.137 ... 0.215)	reasonable
CMCC-CM2-VHR4_r1i1p1f1	good	good	0.226 (0.175 ... 0.265)	reasonable
EC-Earth3P_r1i1p1f1	good	good	0.176 (0.133 ... 0.204)	good

5 Hazard synthesis

For both Rx3day and pr-JJASO, we evaluate the influence of both anthropogenic climate change and the emerging La Niña conditions by calculating the associated probability ratio and change in intensity for similarly extreme events using observation-based products and climate models. Models which do not pass the evaluation described in Section 4 are excluded from the analysis. The aim is to synthesise results from models that pass the evaluation along with the observations-based products, to give an overarching attribution statement. Full tables of attribution results for the observational data products and those climate models that passed the evaluation in Section 4 are given in Appendix A.4. For full details of how the results are synthesised, see [Otto et al. \(2024\)](#).

5.1 Short-term extreme rainfall (Rx3day)

Figure 5.1 shows the synthesised changes in intensity for a 1-in-10-year Rx3day event associated with (a) 1.3°C of warming from the preindustrial period to 2025, and (b) the emerging La Niña state observed in September 2025 (the equivalent figures for probability ratios, which show a very similar pattern, are given in Appendix A.3.1). As discussed in Section 3.1.2, the individual observational data products (lighter blue bars) exhibit quite different trends in response to global warming, with the combined result (dark blue bar) being a decrease of around 9%, but with a 95% confidence interval (-56%, +95%) encompassing a wider spread of increases than decreases. The climate models that passed evaluation tend to show a weakly increasing trend in Rx3day, although uncertainty is again high, with the models estimating an increase of about 5% (95% interval: -9.9%, +27%). The overall synthesised result, taking into account both observations and climate models, is an estimated 4.5% increase in Rx3day associated with global warming (95% interval: -16%, +34%).

The observational datasets all show a consistent influence from the current emerging La Niña state (panel b), with an estimated 11% more precipitation (95% interval: -0.97%, +23%) than in a neutral Nino 3.4 state. However, most of the climate models fail to capture this relationship, suggesting that they may fail to represent processes critical to accurate simulation of extreme rainfall in eastern Mexico. A similar pattern is seen in the probability ratios (Table 5.1 and Figure A.3.1), with similarly extreme 3-day rainfall around 30% more likely in the current La Niña state (95% interval: 30% less likely, 2.8 times as likely). Under a further 1.3°C of warming, representing the end of the century under current policies, the models consistently simulate a slightly stronger increase in Rx3day of 7.8% (95% interval: -4.1, 20; Table 5.1 and Figure A.3.2), suggesting that there may be an emerging trend.

Because of the lack of agreement between the climate models and observational data products, we are unable to confidently identify any strong trends in extreme 3-day rainfall in this area to date, although we conclude from the observational products that the current emerging La Niña conditions increased the amount of rain that fell by around 11% compared to what would be expected in a neutral ENSO state, and note that climate models consistently project a small increase in the intensity of Rx3day. The lack of agreement between the different observational data products highlights the need for a robust, well-maintained network of weather stations in this region, along with improved models, to

support more reliable estimates of historic and future trends.

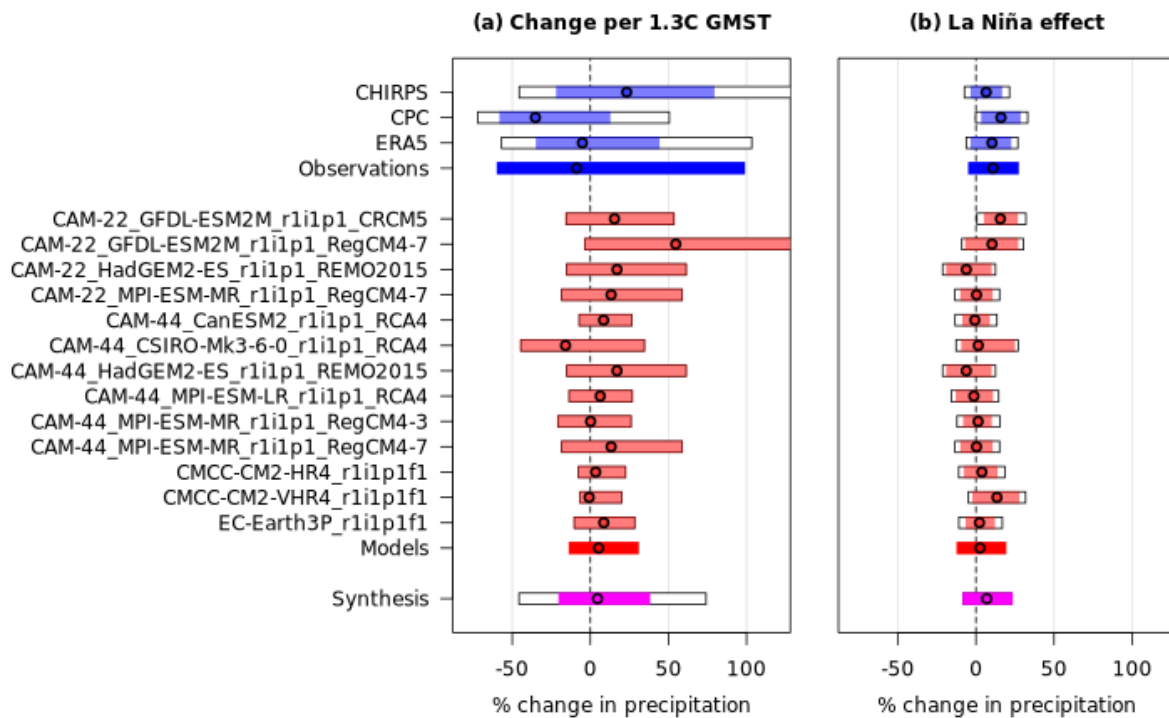


Figure 5.1: Synthesis of relative change in intensity of Rx3day in eastern Mexico when comparing (a) the 2025 climate and a 1.3°C cooler climate representing the preindustrial past and (b) the 2025 La Niña state compared to a neutral ENSO3.4 state in September.

Data	(a) GMST			(b) September Nino3.4	
		Probability ratio (95% CI)	Intensity change (%) (95% CI)	Probability ratio (95% CI)	Intensity change (%) (95% CI)
Observations	Past- Present	0.75 (0.013, 24)	-8.8 (-56, 95)	1.6 (0.95, 3.9)	11 (-0.97, 23)
Models		1.1 (0.69, 3.7)	5.3 (-9.9, 27)	1.1 (0.64, 2.2)	2.6 (-8.4, 15)
Synthesis		1.1 (0.41, 4.4)	4.5 (-16, 34)	1.3 (0.76, 2.8)	6.9 (-4.6, 20)
Models only	Present - Future	1.5 (0.78, 2.9)	7.8 (-4.1, 20)	-	-

Table 5.1: Summary of synthesised changes in Rx3day, presented in Figures 6.1, and A.3.1 and A.3.2 (to 2 significant figures).

5.2 Long-term seasonal rainfall (pr-JJASO)

Figure 5.2 shows the synthesised changes in intensity for 1-in-10-year pr-JJASO associated with (a) 1.3°C of warming from the preindustrial period to 2025, and (b) the emerging La Niña state observed in September 2025 (the equivalent figures for probability ratios are given in Appendix A.3.3, again showing a very similar pattern). As discussed in Section 3.2.2, the individual observational data products (lighter blue bars) exhibit quite different long-term trends in response to global warming, largely due to differences in the representation of the period prior to 1979. Overall the observations indicate a reduction of 7%, with a wide confidence interval centred on zero (-36%, 34%), indicating no clear trend overall. Most climate models that passed evaluation tend to show either no trend or a weakly decreasing trend in JJASO rainfall, although uncertainty is again high, with the models estimating a reduction of about 4% (95% interval: -19%, +12%). The overall synthesised result, taking into account both observations and climate models, is an estimated 4.5% decrease in JJASO rainfall associated with global warming (95% interval: -23%, +17%).

The observational datasets all show a consistent influence from the current emerging La Niña state (panel b), with an estimated 7% more precipitation (95% interval: +1.8%, +12%) than in a neutral Nino 3.4 state. However, all but two of the climate models fail to capture this relationship, suggesting that they may also fail to represent processes critical to accurate simulation of seasonal rainfall in eastern Mexico. A similar pattern is seen in the probability ratios (Table 5.2 and Figure A.3.3), with similarly extreme seasonal rainfall almost three times more likely in the current La Niña state (95% interval: 10% more likely, 11 times as likely) in observational datasets, but .

Under a further 1.3°C of warming, representing the end of the century under current policies, the models simulate a wide spread of changes in JJASO precipitation, with best estimates ranging between -11% and +14% (Figure A.3.4). This results in an overall estimate of close to zero change (Table 5.2), although this is indicative of uncertainty about whether any change exists rather than a confident estimate of no change.

Because of the lack of agreement between the individual climate models and observational data products, we are again unable to confidently identify any strong trends in JJASO seasonal rainfall in this area to date, although we conclude that the current emerging La Niña conditions increased the amount of rain that fell by around 7% compared to what would be expected in a neutral ENSO state. The lack of agreement between the different observational data products again highlights the need for a robust, well-maintained network of weather stations in this region, along with improved models, to support more reliable estimates of historic and future trends.

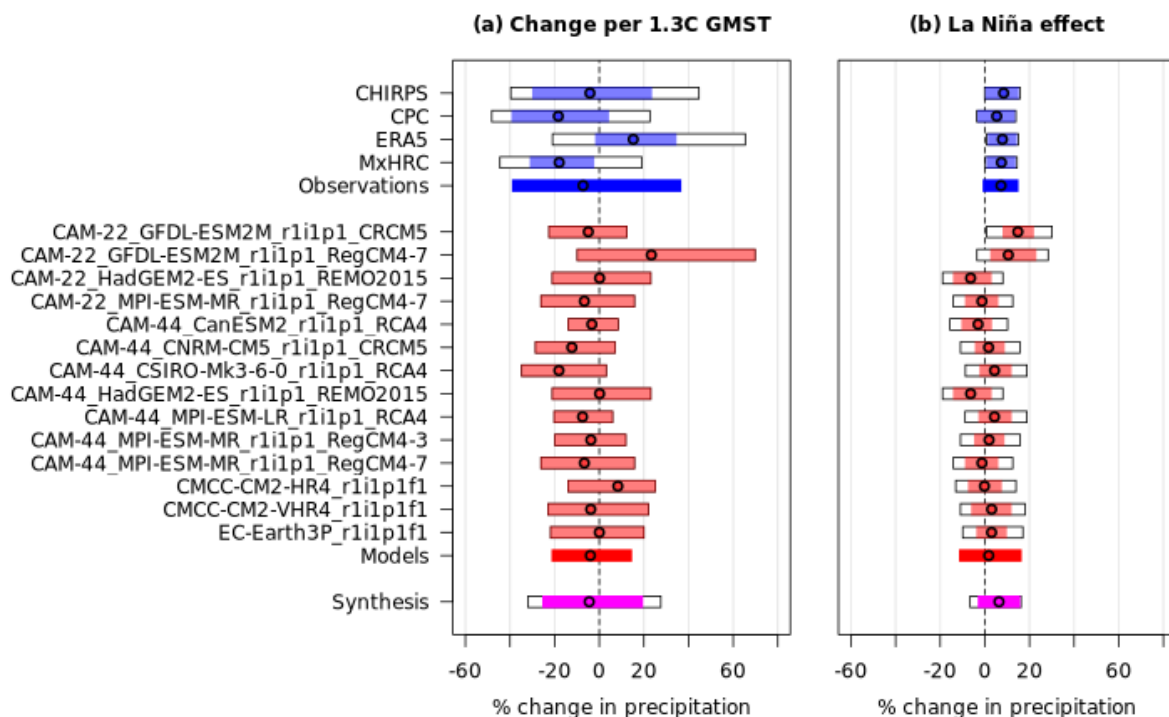


Figure 5.2: Synthesis of relative change in intensity of pr-JJASO in eastern Mexico when comparing (a) the 2025 climate and a 1.3°C cooler climate representing the preindustrial past and (b) the 2025 La Niña state compared to a neutral ENSO3.4 state in September.

Data	(a) GMST			(b) September Nino3.4	
		Probability ratio (95% CI)	Intensity change (%) (95% CI)	Probability ratio (95% CI)	Intensity change (%) (95% CI)
Observations	Past- Present	0.51 (0.0073, 19)	-7.3 (-36, 34)	2.8 (1.1, 11)	7.2 (1.8, 12)
Models		0.53 (0.19, 4)	-4 (-19, 12)	1.2 (0.33, 4.9)	1.7 (-8.8, 14)
Synthesis		0.53 (0.085, 5.3)	-4.5 (-23, 17)	1.9 (0.61, 7.8)	6.3 (-0.34, 13)
Models only	Present - Future	1.1 (0.25, 3.3)	0.21 (-12, 12)	-	-

Table 5.2: Summary of synthesised changes in pr-JJASO, presented in Figures 6.2, and A.3.3 and A.3.4 (to 2 significant figures). Statistically significant trends are highlighted in bold.

6 Vulnerability and exposure

In just four days of heavy rain between October 6-9, Mexico's central and Gulf states accumulated an amount comparable to half the region's average annual rainfall ([García, 2025](#)). Torrential rains triggered flooding and landslides, causing rivers to overflow, bridges to collapse, and streets to be washed away. Thousands of people in 191 communities were left isolated, and around 100,000 houses destroyed or seriously damaged ([OCHA, 2025](#)), leading to a major humanitarian crisis ([ERCC, 2025](#)). Authorities reported 111 affected municipalities across five states with 83 deaths, 37 in Veracruz, 22 in Hidalgo, 23 in Puebla, 1 in Queretaro, and 16 missing people ([Gobierno de Mexico, 2025](#)). There are about 80,000 affected or displaced people in Puebla alone, and tens of thousands more across Veracruz and Hidalgo ([Serve Source, 2025](#)).

The torrential rains came toward the end of a heavy rainy season, leaving river basins already swollen and hillsides weakened, susceptible for landslides ([Al Jazeera, 2025](#)). The impact multiplied as the rainfall coincided with urban sprawl on flood plains and unstable slopes, insufficient or blocked drainage, saturated soils from previous events and uneven local disaster risk management ([Proceso, 2025](#)).

According to the Third Biennial Update Report (BUR3) submitted by Mexico to the UNFCCC, 68% of the country's population and 71% of its GDP are exposed to climate impacts ([World Bank, 2024](#)). Furthermore, the World Risk Index ranks the country *very high*, with a score of 38.9, placing it among the top countries in terms of natural disaster risk. This is due to a combination of high exposure to natural events and significant social vulnerability ([Bündnis Entwicklung, 2025](#)).

The flood footprint extended along the Gulf Coast plain in Veracruz and inland toward central Mexico, leaving a corridor of substantial impacts stretching from low-lying river valleys in Veracruz into mountainous terrain in Hidalgo and northern Puebla. While urban centres bore the brunt of economic and infrastructural loss, rural and mountain communities endured isolation, fatalities, displacement and livelihood destruction.

The National Water Agency issued alerts on 9 October, flagging the risk of river overflow, with a particular focus on the Cazonces River. The Veracruz state authorities asked residents of Poza Rica to go to shelters about seven hours after the agency issued its alert. The Veracruz Civil Protection agency suspended classes in several municipalities, established three Regional Command Posts, and set up seven temporary shelters. However, the population was not asked to go to the shelters until much later in the night. Alerts asked the population to be attentive to communications from local authorities. It was not until late at night that the municipal authority issued a warning for neighbourhoods close to the risk zone to move to temporary shelters ([Carabaña, 2025](#)). Yet, many people did not deem the severity of the alert to be of great urgency and did not evacuate, or were left with a significantly reduced time window to respond (Mexican Red Cross, 2025).

In Veracruz, the primary problem was large river overflows (Cazonces, Pantepec, Moctezuma, Tuxpan, and Nautla river basins); in Hidalgo and Puebla, the impacts combined many small stream flash floods and landslides in steep terrain ([N+, 2025](#)). The runoff rushing down the mountain with debris, branches and stones, caused the most damage ([Arrucha, 2025](#); [Mexico News Daily, 2025](#)). Of the 212 municipalities that make up the state of Veracruz, 37 were affected ([Zamudio, 2025](#)). Two of the most

affected cities are Poza Rica (Veracruz), a coastal city with an economy based on the oil sector, and Huauchinango, Puebla, which lies between two rivers.

According to the National Centre for Disaster Prevention (CENAPRED), Poza Rica is at *very high* risk of flooding and has a high degree of vulnerability ([Ayuntamiento de Poza Rica, 2018](#)). The Poza Rica – Tuxpan region consists of 48 municipalities, although the impact locations span further out of this area, it is notable that only in this region 15 of the 48 municipalities in the Poza Rica–Tuxpan area have a medium HDI (31.25%), and 10 have a low HDI (20.83%) ([ORFIS, 2018](#)), generally coinciding with the most affected areas. In 2023, Poza Rica had a population of 222,611, with 49.8% of the population living in poverty and 22.3% lacking access to basic services in their homes. According to 2020 data, the municipality had 2,368 houses with bare earth floors (4.3%), 16,952 houses without access to water, 3,156 without drainage (5.7%), 539 with unstable walls, and 4,357 with overcrowding ([Gobierno de México, 2024](#)). These factors increase the population's susceptibility to impacts from the floods.

In Poza Rica, the overflow of the Cazones River directly impacted an estimated 40% of the total population, as the submerged area followed a low-lying corridor of the city's most densely populated neighbourhoods. At the peak of the flooding event, approximately 17% of the municipality's total area was inundated (about 10.9km² out of 64km²). This figure increases to 30-35% if only the urban area is considered, which was the most affected ([Cardillo, 2025](#)).

A rapid census identified almost 3,000 indigenous peoples affected, from the Nahuatl, Otomí, Totonaco, Teneek, Pame, Tepehua, and Afro-Mexican communities ([Villaseñor, 2025](#)). Within the Papantla, Poza Rica, Álamo corridor, Papantla is the indigenous cultural centre of the Totonac people and lies in the region that saw severe river flooding and urban inundation. Many rural settlements in this coastal to inland corridor have Totonac or mixed indigenous populations. The National Indigenous Congress (CNI) and the Zapatista Army of National Liberation (EZLN) called for "urgent solidarity with the indigenous peoples of the northern highlands of Veracruz" affected by the rains ([Henríquez, 2025](#)).

The Huasteca region is home to the Huastec communities in many small indigenous towns across Hidalgo, Puebla and San Luis Potosí. The 400 people village of Chapula (Hidalgo), where residents had built their houses along the riverbank, has been declared uninhabitable. Authorities have stated the village will no longer be inhabited due to the conditions of the area, and that the same will likely happen to other localities that were affected ([Montoya, 2025](#)). The indigenous population in this village accounts for 3.43% of the total population, according to data from 2020 ([Pueblos America, 2020](#)). Similarly, the impoverished town of San Bartolo was cut off for four days. It lies in the Otomí indigenous region, with houses made of wood and tin roofs, nestled in the mountains ([AFP, 2025](#)). Cell phone coverage and alert penetration are weaker in these remote indigenous areas; even when warnings exist they may not reach, be trusted, or be actioned by these populations.

In the Sierra Norte and Sierra de Puebla (Huauchinango area) and northern Puebla foothills, the dependence on local agriculture and daily wages from these communities reduces their coping capacity, increasing an already persistent food insecurity ([Aguirre et al., 2025](#)). This exposes the need for recovery efforts to avoid reinforcing risk or perpetuating the structural conditions that have repeatedly left these populations vulnerable to disaster.

Beyond the incalculable cultural loss, the economic loss remains complex to calculate. Most of the damaged dwellings and small and medium-sized businesses do not have access to insurance. In addition to the loss of property, people lost cars, furniture, and personal belongings. Moreover, there are still businesses, clinics and pharmacies that remain closed (Mexican Red Cross, 2025).

According to a G20 Climate Risk Atlas, the river basins on the Gulf coast may experience more frequent and intense flooding, leading to annual economic losses of USD\$6.5–\$9.8 billion by mid-century (CMCC, 2021). Similarly, the likelihood of increased intense rainfall and flooding, leading to greater risks of landslides and mudslides, disproportionately affects low-income populations residing on marginal land.

Response

The Government of Mexico is working on four main axes of action to address the emergency. The first one included immediate emergency response. It activated emergency protocols in the 111 most affected municipalities and deployed 5,400 staff members from the Ministry of Defense, the Navy, and other response teams (España, 2025). Meanwhile, six thousand people received assistance in 149 temporary shelters across the most affected states (OCHA, 2025).

The second axis involves support to affected families. The federal government will provide direct aid to victims, including up to \$1,150 Mexican pesos per family and \$2,900 for local businesses. For agricultural recovery, resources could reach \$5,800, and \$29,000 (\$1,572 USD) will be allocated for the reconstruction of health clinics (Rocha, 2025).

The third consists of reconstructing infrastructure and housing. Families whose homes are located in high-risk areas or riverbeds will be relocated by the Ministry of Agrarian, Territorial, and Urban Development (SEDATU) to safe areas (Rojas, 2025). While relocation can reduce exposure by moving families out of high-risk areas, it also poses significant social and cultural challenges, particularly when it involves the loss of ancestral lands, community ties or livelihoods. The success of such measures will depend on whether new settlements provide comparable or improved living conditions, access to services, and opportunities for a sustained recovery.

The fourth pillar focuses on strengthening the forecasting, early warning, and risk management system. It contemplates the strengthening of the Scientific Committee for forecasting and risk, as well as the updating of risk atlases at the state and municipal levels. Finally, the implementation of the National Digital Alert System developed by the Agency for Digital Transformation and Telecommunications (ATDT) (Crónica Veracruz, 2025).

Past events

In recent years, Mexico has faced a growing number of disasters due to extreme hydrometeorological phenomena such as tropical cyclones, hurricanes, floods, droughts, changes in rainfall patterns, heat waves, among others, which have caused human losses and high economic and social costs. In 2020, the impact of these types of events was estimated at 26.678 billion pesos (\$1.24 billion USD). Rainfall and flooding accounted for 79.5% representing the highest cost (equivalent to \$986 million USD) (SEMARNAT, 2025).

The region has experienced similar events on other occasions. Despite being a riverine area, the risk of living next to the river has been minimised. People did not believe that something this serious would happen, from the presidency and governors to the general population. According to a local perception survey conducted by Civil Protection in Poza Rica, which was distributed in neighbourhoods most vulnerable to disruptive natural hazards, the population is divided in terms of risk perception, with varying fears among the population. The greatest fear is the potential overflow of the Cazonces River, followed by the dangers of the oil industry, and flooding in third place. Similarly, it was found that most people know where to go and who to turn to in an emergency ([Ayuntamiento de Poza Rica, 2018](#)). Yet, this event revealed a gap between awareness and preparedness, or what appears to be a disconnect between the perceived and actual severity of risk, underscoring the need for stronger risk communication and public engagement before disasters strike.

The Risk Atlas for the municipality of Álamo Temapache, published in 2011, recognises that the town is located in the Tuxpan River basin, posing a risk to 25 communities with more than 5,000 homes damaged in previous events ([Sandoval, 2025](#)).

In 2004, a study analysed the vulnerability of human settlements to flooding in the vicinity of the Tecolutla River, Veracruz. The area has been historically affected by floods, with a major event in October 1999 causing \$2.7 million pesos in losses. It found that the combination of potential flooding hazards and the high vulnerability of specific communities placed around 30% of the municipality's population at risk ([Garnica and Alcántara, 2004](#)). Following the 1999 flood, researchers also found substantial mental health impacts in survivors of the flood ([Norris et al., 2005a](#)) and reduced social embeddedness, in particular for women and people with lower educational attainment, worsening as time progressed following a 2-year study ([Norris et al., 2005b](#)).

The Mexican Red Cross highlighted in a report based on the lessons learned from the 2020 floods in Tabasco, that grey infrastructure can only mitigate flood risk within the limits of the design's capacity (when properly maintained). As climate change generates more intense rainfall, we can expect increasingly severe floods that exceed the design thresholds of protective infrastructure ([Mexican Red Cross, 2020](#)).

Cascading long-term impacts

The floods triggered cascading impacts, including an eight-kilometre oil spill in the Pantepec River that could ripple through the Gulf economy ([Associated Press, 2025](#)). The Pantepec River crosses northern Veracruz and supplies water for a number of communities, including the city of Tuxpan. Residents in Poza Rica reported that floodwaters left a black, oily residue, believed to have originated from nearby oil and gas installations, coating trees and rooftops ([Marentes, 2025](#)).

The Mexican oil company (Pemex) reported that it had safely completed repairs to the Naranjos–Poza Rica pipeline, which had been affected by heavy rainfall ([Guevara, 2025](#)). The mayor of this town commented he was working with local and state officials to keep the spill from reaching municipal water systems and private businesses, fishermen and others had helped to install containment barriers. An NGO activist with Foundation Chalchi, said it was too early to determine the spill's environmental impact but that recovery of the ecosystem could take years ([Associated Press, 2025](#)). These

consecutive and overlapping disasters strain the limits of existing response capacities, underscoring the need for a more dynamic and anticipatory approach to risk management.

Health

Dozens of health centres were damaged, including one in Álamo, Veracruz, where floodwaters reached two meters, destroying all equipment, forcing medical staff to work outdoors ([Marentes, 2025](#)). In the state of Hidalgo, at least 59 hospitals and clinics were damaged due to the flooding and subsequent landslides ([CBS, 2025](#)), limiting health care in the region. According to reports from local residents, hydrocarbon waste has already reached the Tuxpan River, causing concern among communities that depend on this water source ([Guevara, 2025](#)).

Studies have already reported an increased spread of dengue in Veracruz linked to rising temperatures and post-rainfall conditions ([Hurtado-Díaz et al., 2007](#); [Carreto et al., 2022](#)). As part of response efforts, health teams fumigated affected areas to prevent outbreaks of dengue ([Marentes, 2025](#)). The recent floods risk worsening this trend, making it critical that health interventions, such as fumigation and disease surveillance reach all affected communities to prevent new outbreaks.

Urban planning and land-use changes

Human-induced changes in land use can alter water infiltration, increase surface runoff, and lead to sediment buildup in lakes, rivers, and dams, thereby intensifying the impacts of heavy rainfall and increasing the risk of flooding. In the southern Gulf Coast region, agricultural land has expanded by approximately 60% between 1970 and 2010 ([Zúñiga & Magaña, 2018](#)). Even after this main period of agricultural expansion, Veracruz was one of the Mexican regions with the biggest increase in pasture land between 2003-2014 ([Bonilla-Moheno & Aide, 2020](#)). In addition, Veracruz - the region bearing the brunt of the flooding - has lost 30–80% of its wetlands, significantly weakening natural hydrologic regulation systems ([Zúñiga et al., 2020](#)).

In Poza Rica, land use transitioned from a process of accelerated agricultural change, with a strong presence of original vegetation, to an industrial context that disregarded many environmental considerations, favouring industrial exploitation and uncontrolled urban expansion as a by-product ([Ayuntamiento de Poza Rica, 2018](#)). The 2019 Municipal Urban Development Plan recognised that Poza Rica has been severely affected in recent decades by the overflowing of the Czones River, and warned of the vulnerability of the urban subsoil due to the network of hydrocarbon pipelines that cross the area ([Sandoval, 2025](#)).

The state of Puebla showed a decrease of 21% in natural vegetation due to increased agricultural activity between 1980 and 2016 ([Rodriguez et al., 2022](#)). These patterns of deforestation and drainage of wetlands to create agricultural spaces lead to a reduced infiltration capacity of the soil, potentially adding to the magnitude of the observed floods ([Zúñiga & Magaña, 2018](#)).

Mexico's urban population grew by 100% between 1980 and 2010 and by 2019, 80% of all Mexicans lived in urban areas ([Urbanet, 2019](#)). The consequential uncontrolled rapid urban development in large Mexican cities and the surrounding areas has led to a deterioration of landscape and an increased settlements near rivers, as seen in cities such as Veracruz ([Bonasia & Lucatello, 2019](#); [Zúñiga et al., 2020](#)). As observed during the intense rainfalls in October 2025, urban growth in hydrological basins, for example close to rivers, increases the risk of being affected by overflow. Furthermore, the negative

effects of heavy rainfalls are exacerbated when natural vegetation has been replaced with impervious materials or land types that increase water runoff. Coastal urbanization along the Southern Gulf Coast has shown to negatively impact ecosystems and natural flood defenses, mainly around tourist areas or economically important cities ([Salgado et al., 2022](#)). Additionally, deficient drainage systems in urban areas further intensify negative effects of intense precipitation ([Zúñiga et al., 2020](#)).

The Mexican government currently oversees 232 Natural Protected Areas (NAPs) of which 53 lie in the affected eastern coastal area ([dataMares, n.d.](#)). The protection and conservation of essential ecosystems and flora in Mexico, especially the flood prone coastal regions could decrease the risk of flooding by serving as natural barriers and through soil retention. Reforestation in order to avoid unnecessary runoff could improve the population's security during intense rainfall events ([Zúñiga et al., 2020](#)).

The Mexican floods revealed a dual landscape of vulnerabilities. On the one hand, there is a high density of economic losses due to concentrated assets with fragile infrastructure in urban areas, as well as inadequate housing built on floodplains. On the other hand, the constant social exclusion of rural areas, characterized by weak communication and limited warning coverage, reflects a lower coping capacity. Furthermore, both contexts require significant investments in flood protection infrastructure and systems.

Areas in steep terrain or rural mountains (Sierra Norte de Puebla, northern Veracruz highlands, rural Hidalgo, and parts of San Luis Potosí) were more susceptible to landslides and debris flows, which left homes, farms, and roads buried ([Montoya, 2025](#)). Flash floods from several small tributaries lead to widespread crop destruction, livestock loss, and soil degradation. Riverbank erosion destroyed rural bridges, cutting communities off for days.

Water retention walls

The retaining wall project on the Cazonas River in Poza Rica was initially planned in three stages between 2009 and 2014. However, the final phase, intended to cover 4.3 kilometers along the right bank was never completed ([San Jose and Carabaña, 2025](#)). This wall had been recognised as a 'high priority' for over a decade to prevent river overflow, with approximately 145.2 million pesos projected for its construction and a drainage expansion project. The need for it was affirmed in the Poza Rica development plan from 2018-2021, and the 2023 municipal Risk Atlas warned about the need to complete the work along with the clearing of streams and other sanitation works ([García, 2025](#)). Construction stalled at 10%, leaving the containment wall largely incomplete at the time of the floods, despite the municipality reportedly spending about 14 million MXN on this effort ([García Orozco, 2025](#)). This situation has led to allegations of fund mismanagement from local reports and municipal admissions ([Cruz, 2025](#)).

Due to a lack of scenario studies and water quantification, it is uncertain whether the infrastructure would have retained the water to make a difference. The absence of a publicly available engineering dossier with the planning threshold, dimensions of the containment level, or hydrological design standard (return period) makes it hard to determine whether a completed wall could have prevented this specific flood. The President has announced renewed plans and a technical study to assess the construction of a proper containment wall, which she claimed “is a pending project in the area” ([Sánchez, 2025](#)). However, integrated flood risk management requires that such physical

infrastructure be complemented by social and nature-based solutions, combining structural protection with community engagement, ecosystem restoration, and sustainable land-use planning to ensure long-term resilience.

Flood risk management

In terms of flood prevention, CONAGUA has played a primary role in infrastructure building, technically supported by National Centre for Disaster Prevention (CENAPRED) and National Ministry of Environment and Natural Resources (SEMARNAT), coordinated politically by Civil Protection, and implemented locally by state and municipal protection agencies with support from the urban development national ministry and infrastructure ministries ([Flores et al., 2019](#)). While land use and urban policies are under the jurisdiction of local municipal authorities, river beds and their surrounding areas are the responsibility of CONAGUA. This fragmented landscape of federal competence overlaps with those of the states and municipalities, which has in some cases meant that regulations are not enforced ([OECD, 2013](#)). In this context, this translates into a divided management of the basin into different administrative levels and states' jurisdictions.

Financing mechanisms are under scrutiny after the termination in 2021 of two trusts, raising concerns about the long-term funding of prevention and mitigation works. The Natural Disaster Fund (FONDEN) was a fund used to finance prevention and recovery operations in the wake of a disaster. In addition, the FOPREDEN was used to finance prevention activities and was one of the fundamental instruments for promoting risk reduction. Projects included strengthening early warning systems, small-scale infrastructure work, and raising disaster risk awareness. However, its functions and resources are now administered through other mechanisms, mainly by the Ministry of Finance and Public Credit and the National Civil Protection Coordination, through annual programmes and budgets for risk management and emergency response ([Hernández, 2021](#)). The centralisation of disaster prevention and mitigation funds raises the question of whether it is meant to safeguard continuity for long-term flood prevention projects, and if so, how can it ensure flexible and locally responsive financing?

According to an OECD review, Mexico's National Civil Protection System has made significant progress over time ([OECD, 2013](#)). While policies and frameworks for disaster risk reduction exist, their implementation is uneven. Key reforms include bolstering financial and technical support for municipal risk atlases, developing a National Atlas on Climate Change Impacts and Vulnerability, and engaging the private sector more actively in risk assessment. Improving early warning integration and enhancing coordination between federal, state, and municipal actors are essential to make flood prevention and response more effective and locally responsive.

In 2024, a flood protection project began in the municipality of Misantla, Veracruz, to safeguard communities. The measures include dredging the Bobos and Chapachapa rivers and constructing embankments along the Bobos River. The project is 74.3% complete, although it was delayed by two years ([Quartucci, 2024](#)).

Early Warning Systems

Across Veracruz, Puebla, and Hidalgo, flood early warning systems operate through a multi-level coordination structure linking federal, state, and municipal actors, although with varying degrees of

capacity and effectiveness. At the federal level, the National Water Commission (CONAGUA) and National Meteorological Service (SMN) generate hydrometeorological forecasts and river monitoring data, which feed into the National Civil Protection Coordination (CNPC) for dissemination of national alerts. Each state's Civil Protection agency then acts as the operational hub, translating national warnings into state-specific advisories, updating risk maps, and coordinating municipal preparedness actions such as shelter activation and evacuation planning. Municipal Civil Protection Units are responsible for implementing these alerts on the ground, mobilising community brigades, and ensuring local populations are informed and evacuated when needed.

The National Met Services and the National Water Commission (CONAGUA) issue forecast alerts through government websites, bulletins, and civil-protection channels. It is then up to the States and local civil protection agencies to issue additional alerts locally and translate them into action. In this case, national forecasts flagged heavy rains across central/eastern Mexico in early October, but inconsistencies surfaced across municipalities in how, when and whether alerts were issued. This highlights a potential gap in the system between meteorological forecasting and actionable local warnings.

Issues with the current state of the Early Warning System include that warnings are not specific enough or communicated effectively, and the exact timing and severity are hard to translate into effective local evacuation orders ([Agaci, 2025](#)). A researcher at the Atmosphere and Climate Change Institute at Mexico's National Autonomous University Mexico evaluates that although Mexico has risk maps, and civil defence officials who are in charge of alerting people, "beyond alerting, the people have to also understand what is being said", so not only do civil defence officials require training, but people need to be educated too ([AP, 2025](#)).

There are gaps in monitoring infrastructure, and providing earlier, location-specific alerts, real-time monitoring is needed (including river-level sensors, additional weather radars, and stream gauges) ([AP, 2025](#)). Additionally, Mexico lacks the necessary instrumentation to measure river levels in real-time, which hinders the provision of detailed local and frequent hydrological forecasts ([Verza, 2025](#)).

As part of a pledge to the World Meteorological Organisation, Mexico committed to creating a universal, individually accessible early warning system by 2020 ([Aristegui, 2025](#)). In 2025, it launched a new national mass-alert system to send emergency messages directly to mobile phones nationwide, complementing existing sirens, radio, and TV alerts. The system can target alerts by location and covers multiple hazards, including floods, hurricanes, and earthquakes, using cell broadcast technology. It was publicly tested on 19 April and 19 September 2025, achieving near-national coverage ([Carter, 2025](#)).

Despite the infrastructure for a national mobile mass alert now being in place, the operational trigger thresholds and institutional protocols (when to send, what message text, who activates, how to localise it) still seem to be lacking for it to be universal, personalised and effective. While the system represents a major advance in early-warning capacity, it appears to have been operationally focused on seismic drills and not yet fully integrated into real-time flood-alert protocols, leaving gaps in the final link between forecasts and actionable public warnings. Furthermore, strengthening early warning

must go hand in hand with building public awareness and fostering a collective memory of risk, so that future threats are neither underestimated nor ignored.

Data availability

All time series used in the attribution analysis are available via the Climate Explorer.

References

All references are given as hyperlinks in the text.

Appendix

A.1 Trend plots for all observational datasets

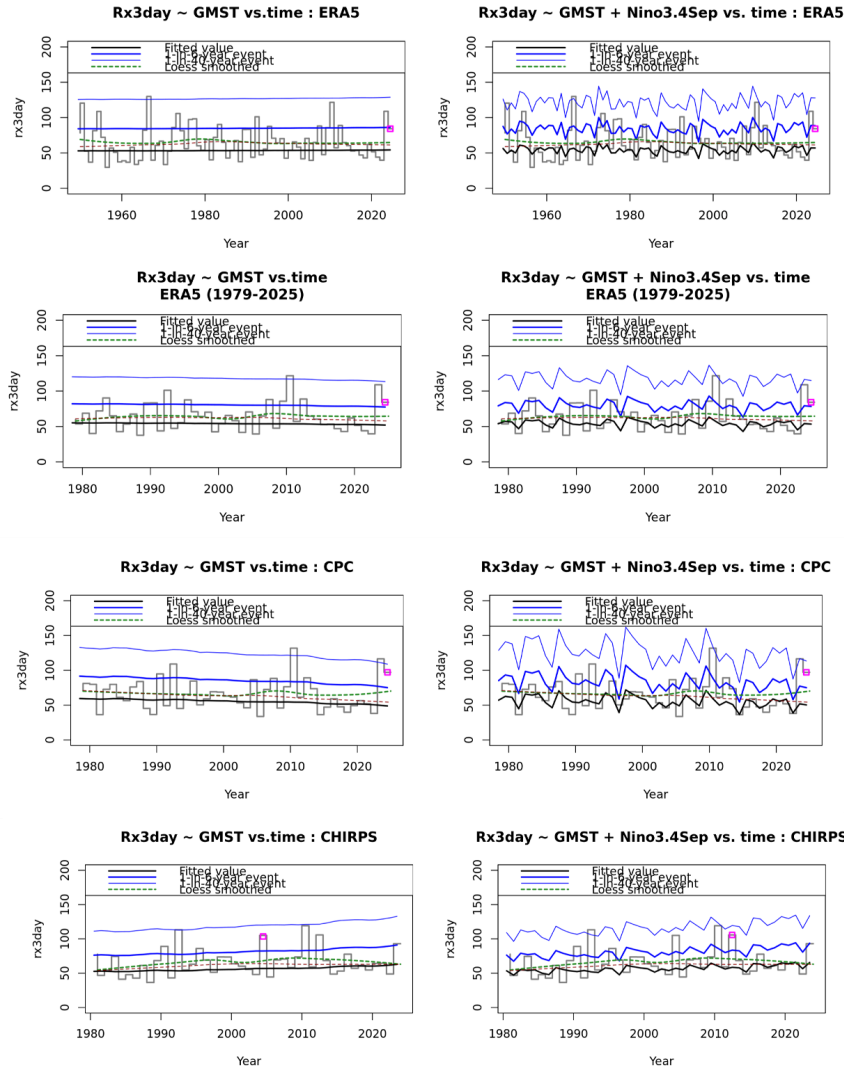


Figure A.1.1: Annual 3-day accumulated rainfall over the study region in three observational datasets (ERA5, ERA5 (1979-2025), CPC, CHIRPS). **Left:** The solid black line shows the fitted trend associated with increasing GMST, while the blue lines indicate the expected magnitude of 1-in-6-year and 1-in-40-year events under the same statistical model. The dotted red line shows a nonparametric Loess smoother fitted to the observations. The 2025 event is marked with a pink dot; note that in CHIRPS, the 2025 maximum does not include the most extreme precipitation in October. **Right:** The solid black line shows the fitted trend associated with increasing GMST and Niño3.4, with blue lines again indicating the expected magnitude of 1-in-6-year and 1-in-40-year events. The dotted red line shows a nonparametric Loess smoother fitted to the observations, and the 2025 event is shown as a pink dot.

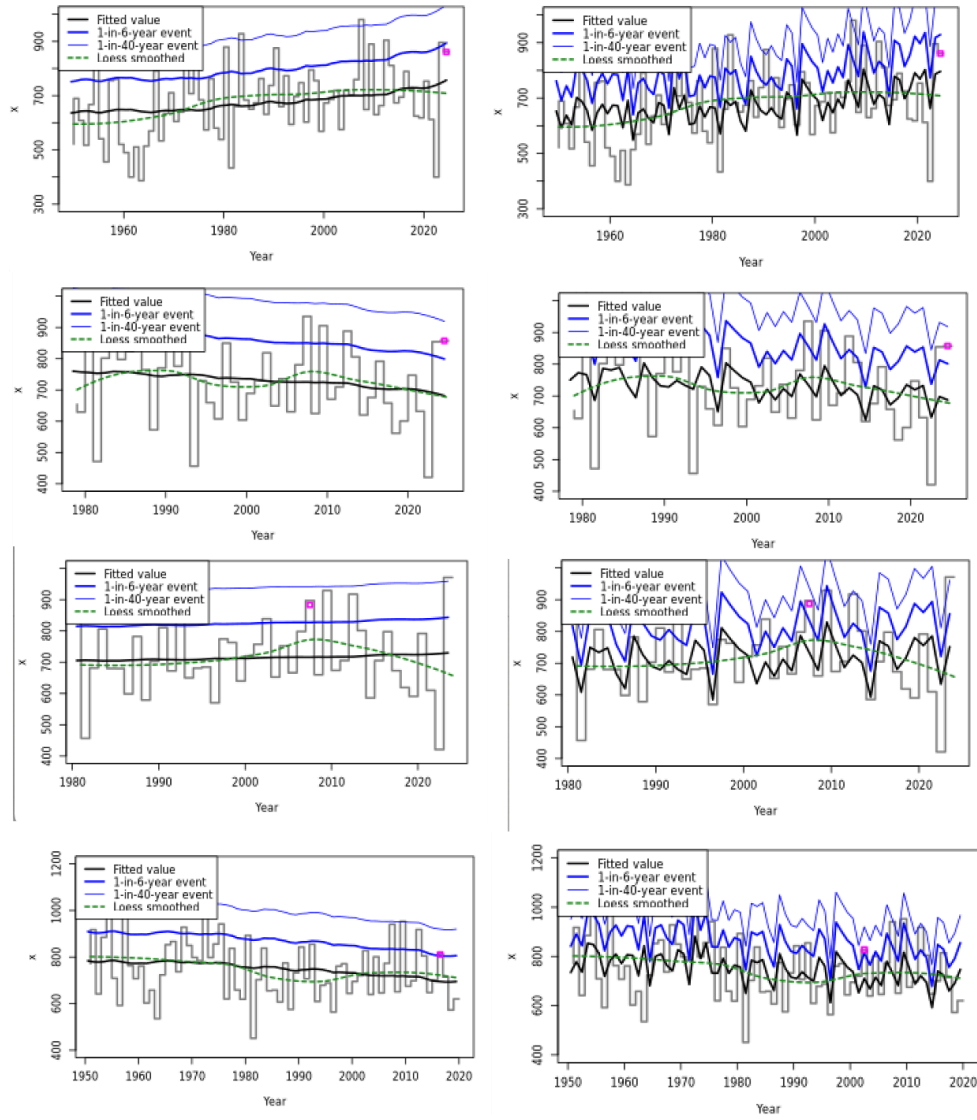


Figure A.1.2: Seasonal (JJASO) accumulated rainfall over the study region in four observational datasets (ERA5, CPC, CHIRPS and mexHighResclimDB). **Left:** The solid black line shows the fitted trend associated with increasing GMST, while the blue lines indicate the expected magnitude of 1-in-6-year and 1-in-40-year events under the same statistical model. The dotted red line shows a nonparametric Loess smoother fitted to the observations. The 2025 event is marked with a pink dot; note that in CHIRPS, the 2025 maximum does not include the most extreme precipitation in October. **Right:** The solid black line shows the fitted trend associated with increasing GMST and Niño3.4, with blue lines again indicating the expected magnitude of 1-in-6-year and 1-in-40-year events. The dotted red line shows a nonparametric Loess smoother fitted to the observations, and the 2025 event is shown as a pink dot.

A.2 Model evaluation tables

Table A2.1: Evaluation results of the climate models considered for attribution analysis of Rx3day. For each model, the threshold for a 1-in-10-year event is shown, along with the best estimates of the Dispersion and Shape parameters, with their 95% confidence intervals. Furthermore evaluation of the seasonal cycle and spatial pattern are shown.

Model / Observations	Seasonal cycle	Spatial pattern	Dispersion	Shape parameter	Conclusion
CHIRPS			0.227 (0.151 ... 0.273)	0.11 (-0.11 ... 0.53)	
CPC			0.252 (0.183 ... 0.304)	0.16 (-0.19 ... 0.43)	
ERA5			0.316 (0.260 ... 0.356)	0.036 (-0.19 ... 0.45)	
CORDEX					
CAM-22_CanESM2_r1i1p1_CRCM5	bad	reasonable	0.187 (0.100 ... 0.226)	0.030 (-0.36 ... 1.1)	bad
CAM-22_GFDL-ESM2M_r1i1p1_CRCM5	reasonable	good	0.253 (0.192 ... 0.299)	-0.24 (-0.64 ... -0.0063)	reasonable
CAM-22_GFDL-ESM2M_r1i1p1_RegCM4-7	reasonable	reasonable	0.325 (0.238 ... 0.377)	-0.036 (-0.33 ... 0.53)	reasonable
CAM-22_HadGEM2-ES_r1i1p1_RegCM4-7	bad	reasonable	0.257 (0.180 ... 0.306)	-0.16 (-0.69 ... 0.26)	bad
CAM-22_HadGEM2-ES_r1i1p1_REMO2015	good	good	0.379 (0.288 ... 0.435)	-0.024 (-0.37 ... 0.33)	reasonable
CAM-22_MPI-ESM-LR_r1i1p1_REMO2015	bad	reasonable	0.305 (0.234 ... 0.351)	-0.058 (-0.59 ... 0.13)	bad
CAM-22_MPI-ESM-MR_r1i1p1_RegCM4-7	reasonable	reasonable	0.244 (0.186 ... 0.295)	-0.12 (-0.52 ... 0.20)	reasonable
CAM-22_NorESM1-M_r1i1p1_REMO2015	bad	bad	0.232 (0.152 ... 0.274)	0.18 (-0.26 ... 0.69)	bad
CAM-44_CanESM2_r1i1p1_CRCM5	bad	reasonable	0.233 (0.130 ... 0.270)	-0.067 (-0.41 ... 0.78)	bad
CAM-44_CanESM2_r1i1p1_RCA4	reasonable	reasonable	0.213 (0.155 ... 0.249)	0.13 (-0.17 ... 0.41)	reasonable
CAM-44_CNRM-CM5_r1i1p1_CRCM5	good	good	NA (NA ... NA)	NA (NA ... NA)	bad
CAM-44_CNRM-CM5_r1i1p1_RCA4	good	bad	0.306 (0.237 ... 0.361)	-0.13 (-0.70 ... 0.19)	bad
CAM-44_CSIRO-Mk3-6-0_r1i1p1_RCA4	good	reasonable	0.324 (0.243 ... 0.375)	0.023 (-0.45 ... 0.45)	reasonable
CAM-44_EC-EARTH_r12i1p1_RCA4	bad	reasonable	NA (NA ... NA)	NA (NA ... NA)	bad
CAM-44_GFDL-ESM2M_r1i1p1_RCA4	bad	reasonable	0.294 (0.210 ... 0.342)	-0.043 (-0.32 ... 0.36)	bad
CAM-44_HadGEM2-ES_r1i1p1_RCA4	NA	NA	0.239 (0.169 ... 0.280)	0.0051 (-0.25 ... 0.33)	bad
CAM-44_HadGEM2-ES_r1i1p1_RCA4-	reasonable	reasonable	NA (NA ... NA)	NA (NA ... NA)	bad
CAM-44_HadGEM2-ES_r1i1p1_RegCM4-3	NA	NA	0.260 (0.175 ... 0.316)	0.14 (-0.32 ... 0.69)	bad
CAM-44_HadGEM2-ES_r1i1p1_RegCM4-3-	good	reasonable	NA (NA ... NA)	NA (NA ... NA)	bad
CAM-44_HadGEM2-ES_r1i1p1_RegCM4-7	bad	reasonable	0.257 (0.180 ... 0.306)	-0.16 (-0.69 ... 0.26)	bad
CAM-44_HadGEM2-ES_r1i1p1_REMO2015	good	good	0.379 (0.288 ... 0.435)	-0.024 (-0.37 ... 0.33)	reasonable
CAM-44_HadGEM2-ES_r2i1p1_RegCM4-3	reasonable	reasonable	NA (NA ... NA)	NA (NA ... NA)	bad
CAM-44_IPSL-CM5A-MR_r1i1p1_RCA4	reasonable	bad	0.209 (0.133 ... 0.242)	0.16 (-0.13 ... 0.71)	bad
CAM-44_MIROC5_r1i1p1_RCA4	bad	reasonable	0.174 (0.130 ... 0.209)	-0.054 (-0.28 ... 0.17)	bad
CAM-44_MPI-ESM-LR_r1i1p1_RCA4	reasonable	reasonable	0.305 (0.222 ... 0.345)	-0.054 (-0.44 ... 0.55)	reasonable
CAM-44_MPI-ESM-LR_r1i1p1_REMO2015	bad	reasonable	0.305 (0.234 ... 0.351)	-0.058 (-0.59 ... 0.13)	bad
CAM-44_MPI-ESM-MR_r1i1p1_RegCM4-3	reasonable	reasonable	0.230 (0.137 ... 0.289)	0.018 (-0.27 ... 0.45)	reasonable
CAM-44_MPI-ESM-MR_r1i1p1_RegCM4-7	reasonable	reasonable	0.244 (0.186 ... 0.295)	-0.12 (-0.52 ... 0.20)	reasonable
CAM-44_NorESM1-M_r1i1p1_RCA4	bad	bad	0.210 (0.149 ... 0.247)	-0.039 (-0.43 ... 0.24)	bad
CAM-44_NorESM1-M_r1i1p1_REMO2015	bad	bad	0.232 (0.152 ... 0.274)	0.18 (-0.26 ... 0.69)	bad

HighResMIP					
CMCC-CM2-HR4_r1i1p1f1	reasonable	good	0.344 (0.186 ... 0.420)	0.30 (0.094 ... 1.0)	reasonable
CMCC-CM2-VHR4_r1i1p1f1	good	good	0.388 (0.293 ... 0.451)	-0.0030 (-0.39 ... 0.26)	reasonable
CNRM-CM6-1_r1i1p1f2	bad	reasonable	0.202 (0.144 ... 0.249)	0.29 (-0.056 ... 0.62)	bad
CNRM-CM6-1-HR_r1i1p1f2	bad	reasonable	0.244 (0.128 ... 0.303)	0.42 (-0.0024 ... 1.7)	bad
EC-Earth3P_r1i1p1f1	good	good	0.173 (0.116 ... 0.210)	0.16 (-0.099 ... 0.52)	good
HadGEM3-GC31-HM_r1i1p1f1	bad	reasonable	NA (NA ... NA)	NA (NA ... NA)	bad
HadGEM3-GC31-LM_r1i14p1f1	reasonable	bad	0.351 (0.256 ... 0.409)	0.22 (-0.29 ... 0.93)	bad
HadGEM3-GC31-MM_r1i1p1f1	bad	reasonable	0.325 (0.218 ... 0.393)	-0.023 (-0.22 ... 0.23)	bad
MPI-ESM1-2-HR_r1i1p1f1	bad	bad	0.217 (0.163 ... 0.254)	0.053 (-0.15 ... 0.34)	bad
MPI-ESM1-2-XR_r1i1p1f1	bad	bad	0.236 (0.174 ... 0.275)	-0.075 (-0.36 ... 0.28)	bad

Table A.2.2: Evaluation results of the climate models considered for attribution analysis of *pr_JJASO*. For each model, the threshold for a 1-in-10-year event is shown, along with the best estimates of the Dispersion parameters are shown, along with a 95% confidence intervals. Furthermore evaluation of the seasonal cycle and spatial pattern are shown.

Model / Observations	Seasonal cycle	Spatial pattern	Dispersion	Conclusion
CHIRPS			0.142 (0.108 ... 0.163)	
CPC			0.171 (0.132 ... 0.198)	
ERA5			0.172 (0.140 ... 0.198)	
mxhighresclimdb			0.150 (0.124 ... 0.170)	
CORDEX				
CAM-22_CanESM2_r1i1p1_CRCM5	bad	reasonable	0.136 (0.106 ... 0.153)	bad
CAM-22_GFDL-ESM2M_r1i1p1_CRCM5	reasonable	good	0.189 (0.137 ... 0.222)	reasonable
CAM-22_GFDL-ESM2M_r1i1p1_RegCM4-7	reasonable	reasonable	0.222 (0.170 ... 0.250)	reasonable
CAM-22_HadGEM2-ES_r1i1p1_RegCM4-7	bad	reasonable	0.209 (0.173 ... 0.231)	bad
CAM-22_HadGEM2-ES_r1i1p1_REMO2015	good	good	0.252 (0.189 ... 0.286)	reasonable
CAM-22_MPI-ESM-LR_r1i1p1_REMO2015	bad	reasonable	0.195 (0.160 ... 0.225)	bad
CAM-22_MPI-ESM-MR_r1i1p1_RegCM4-7	reasonable	reasonable	0.202 (0.154 ... 0.227)	reasonable
CAM-22_NorESM1-M_r1i1p1_REMO2015	bad	bad	0.182 (0.141 ... 0.208)	bad
CAM-44_CanESM2_r1i1p1_CRCM5	bad	reasonable	0.176 (0.128 ... 0.212)	bad
CAM-44_CanESM2_r1i1p1_RCA4	reasonable	reasonable	0.173 (0.133 ... 0.197)	reasonable
CAM-44_CNRM-CM5_r1i1p1_CRCM5	good	good	0.159 (0.114 ... 0.183)	good
CAM-44_CNRM-CM5_r1i1p1_RCA4	good	bad	0.161 (0.124 ... 0.185)	bad
CAM-44_CSIRO-Mk3-6-0_r1i1p1_RCA4	good	reasonable	0.196 (0.153 ... 0.222)	reasonable
CAM-44_EC-EARTH_r12i1p1_RCA4	bad	reasonable	NA (NA ... NA)	bad
CAM-44_GFDL-ESM2M_r1i1p1_RCA4	bad	reasonable	0.212 (0.169 ... 0.241)	bad
CAM-44_HadGEM2-ES_r1i1p1_RCA4	NA	NA	0.172 (0.123 ... 0.214)	bad
CAM-44_HadGEM2-ES_r1i1p1_RCA4-	reasonable	reasonable	NA (NA ... NA)	bad
CAM-44_HadGEM2-ES_r1i1p1_RegCM4-3	NA	NA	0.166 (0.129 ... 0.193)	bad
CAM-44_HadGEM2-ES_r1i1p1_RegCM4-3-	good	reasonable	NA (NA ... NA)	bad

CAM-44_HadGEM2-ES_r1i1p1_RegCM4-7	bad	reasonable	0.209 (0.173 ... 0.231)	bad
CAM-44_HadGEM2-ES_r1i1p1_REMO2015	good	good	0.252 (0.189 ... 0.286)	reasonable
CAM-44_HadGEM2-ES_r2i1p1_RegCM4-3	reasonable	reasonable	NA (NA ... NA)	bad
CAM-44_IPSL-CM5A-MR_r1i1p1_RCA4	reasonable	bad	0.157 (0.117 ... 0.184)	bad
CAM-44_MIROC5_r1i1p1_RCA4	bad	reasonable	0.162 (0.118 ... 0.194)	bad
CAM-44_MPI-ESM-LR_r1i1p1_RCA4	reasonable	reasonable	0.172 (0.128 ... 0.199)	reasonable
CAM-44_MPI-ESM-LR_r1i1p1_REMO2015	bad	reasonable	0.195 (0.160 ... 0.225)	bad
CAM-44_MPI-ESM-MR_r1i1p1_RegCM4-3	reasonable	reasonable	0.155 (0.118 ... 0.175)	reasonable
CAM-44_MPI-ESM-MR_r1i1p1_RegCM4-7	reasonable	reasonable	0.202 (0.154 ... 0.227)	reasonable
CAM-44_NorESM1-M_r1i1p1_RCA4	bad	bad	0.169 (0.129 ... 0.200)	bad
CAM-44_NorESM1-M_r1i1p1_REMO2015	bad	bad	0.182 (0.141 ... 0.208)	bad
HighResMIP				
CMCC-CM2-HR4_r1i1p1f1	reasonable	good	0.182 (0.137 ... 0.215)	reasonable
CMCC-CM2-VHR4_r1i1p1f1	good	good	0.226 (0.175 ... 0.265)	reasonable
CNRM-CM6-1_r1i1p1f2	bad	reasonable	0.192 (0.150 ... 0.217)	bad
CNRM-CM6-1-HR_r1i1p1f2	bad	reasonable	0.226 (0.165 ... 0.268)	bad
EC-Earth3P_r1i1p1f1	good	good	0.176 (0.133 ... 0.204)	good
HadGEM3-GC31-HM_r1i1p1f1	bad	reasonable	NA (NA ... NA)	bad
HadGEM3-GC31-LM_r1i14p1f1	reasonable	bad	0.337 (0.263 ... 0.385)	bad
HadGEM3-GC31-MM_r1i1p1f1	bad	reasonable	0.220 (0.168 ... 0.260)	bad
MPI-ESM1-2-HR_r1i1p1f1	bad	bad	0.214 (0.171 ... 0.247)	bad
MPI-ESM1-2-XR_r1i1p1f1	bad	bad	0.206 (0.163 ... 0.236)	bad

A.3 Additional synthesis plots

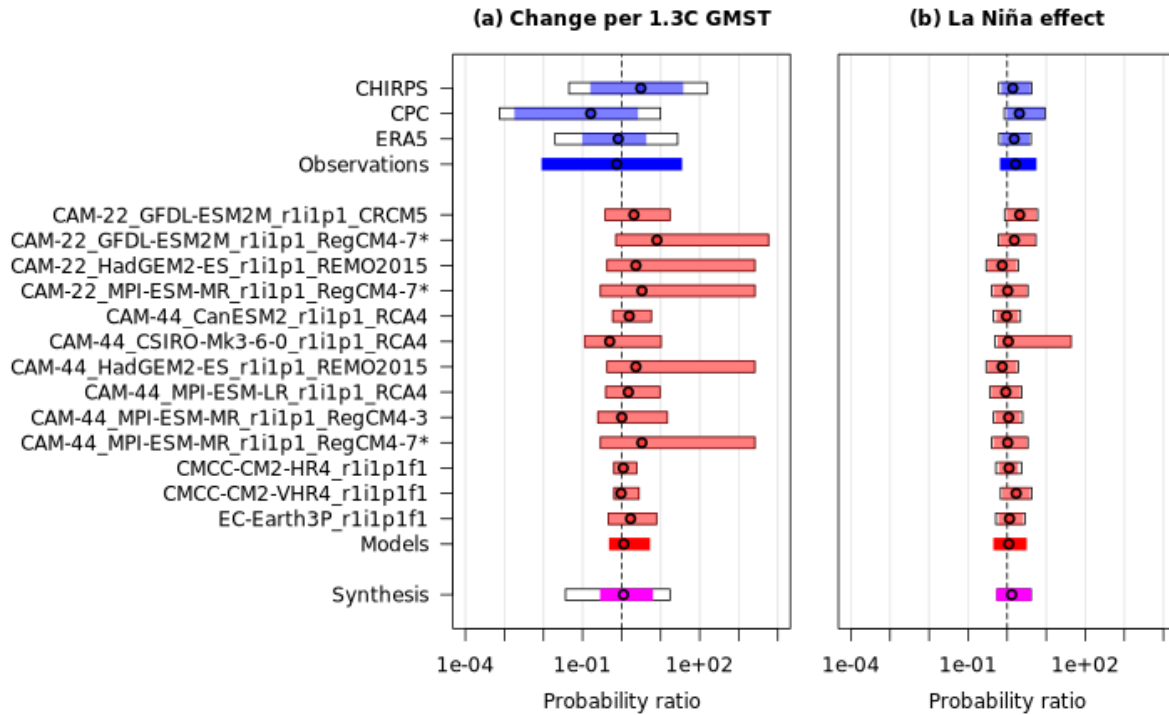


Figure A.3.1: Synthesis of probability ratio of what was, in 2025, one-in-10-year Rx3day in eastern Mexico when comparing (a) the 2025 climate and a 1.3°C cooler climate representing the preindustrial past and (b) the 2025 La Niña state compared to a neutral ENSO3.4 state in September.

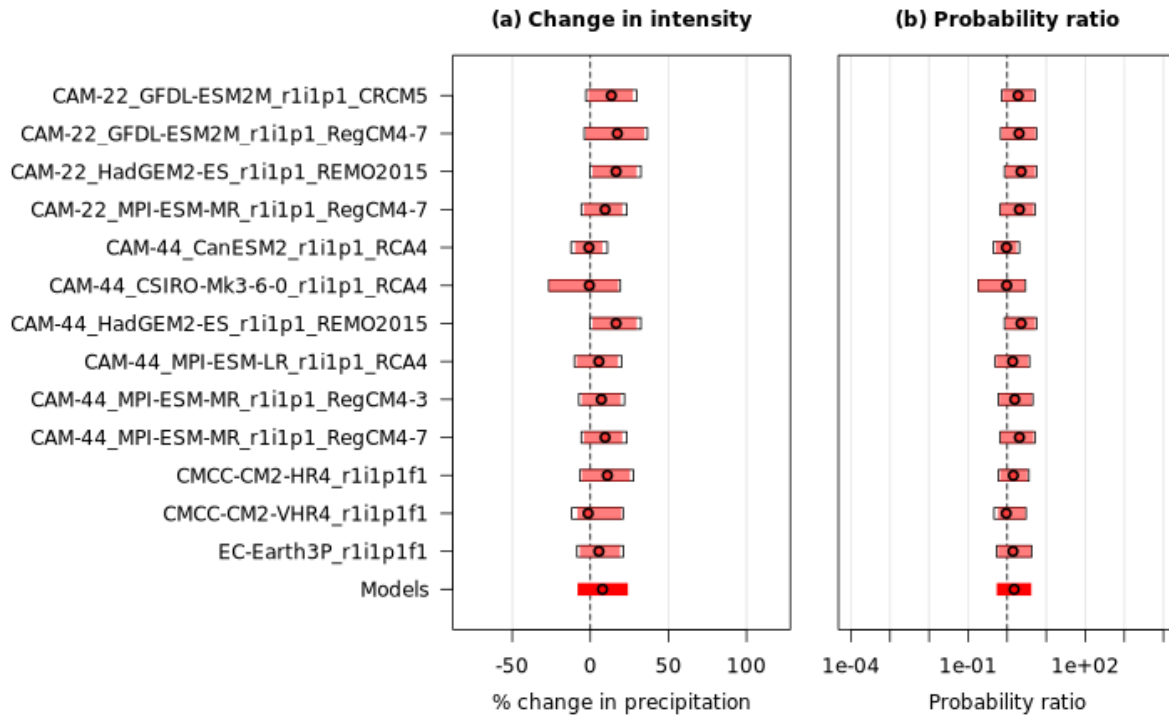


Figure A.3.2: Synthesis of projected changes in (a) intensity and (b) likelihood of what was, in 2025, one-in-10-year Rx3day in eastern Mexico, comparing the 2025 climate with a 1.3°C warmer climate

representing the end of the century under current policies.

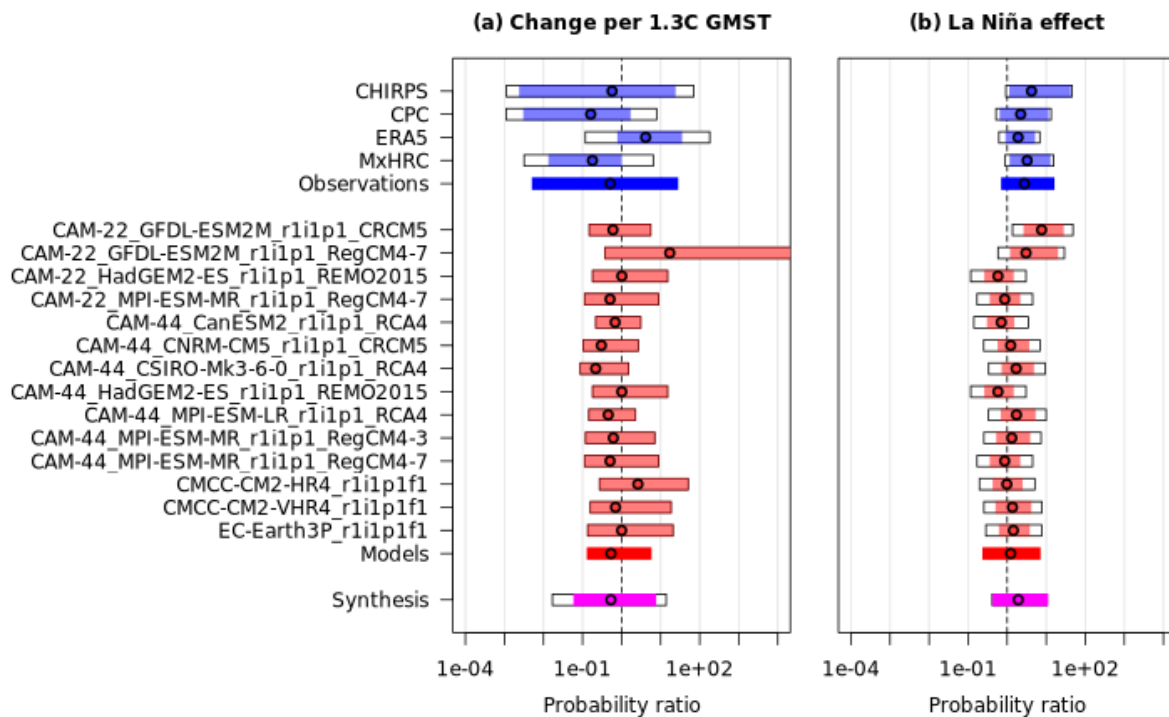


Figure A.3.3: Synthesis of probability ratio of what was, in 2025, one-in-10-year pr-JJASO in eastern Mexico when comparing (a) the 2025 climate and a 1.3°C cooler climate representing the preindustrial past and (b) the 2025 La Niña state compared to a neutral ENSO3.4 state in September.

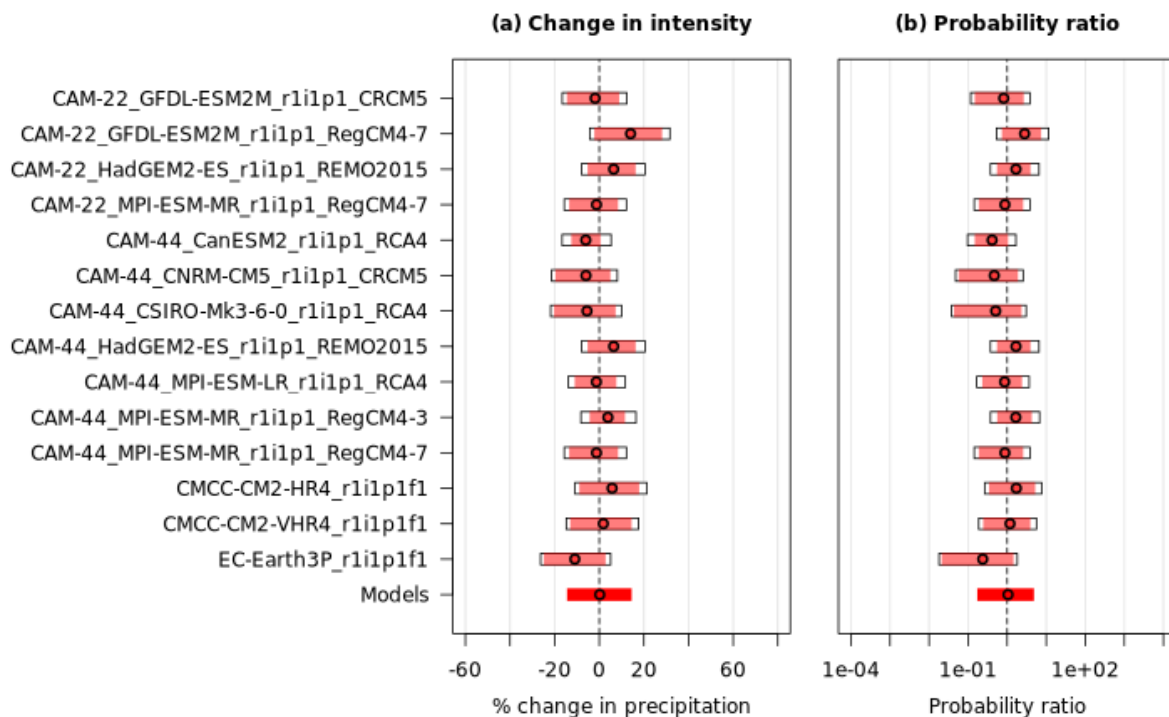


Figure A.3.4: Synthesis of projected changes in (a) intensity and (b) likelihood of what was, in 2025, one-in-10-year pr-JJASO in eastern Mexico, comparing the 2025 climate with a 1.3°C warmer climate representing the end of the century under current policies.

A.4 Tables of attribution results

This section shows probability ratios (PRs) and relative changes in intensity (ΔI) for all observational datasets and those models that passed model evaluation.

Table A.4.1: Changes in intensity and probability ratios for what was in 2025 a 1-in-10-year Rx3day event over the study region, for observational datasets and for each model that passed evaluation: ‘past warming’: from the 1.3°C cooler preindustrial climate to the present; ‘future warming’: from the present to 2.6°C above preindustrial (1.3°C warmer than the present); ‘ENSO’: associated with 2025 La Niña state vs a neutral ENSO state. All results are presented to 2 significant figures.

	% change in intensity			Probability ratio		
Dataset Obs / models	Past warming	Future warming	ENSO	Past warming	Future warming	ENSO
CHIRPS	23 (-18, 75)	NA	6.6 (0.58, 13)	3.1 (0.23, 26)	NA	1.4 (1, 2.7)
CPC	-35 (-54, 8.8)	NA	16 (7.4, 25)	0.16 (0.0026, 1.8)	NA	2.1 (1.4, 6.2)
ERA5	-5.1 (-31, 40)	NA	10 (0.56, 19)	0.82 (0.14, 3)	NA	1.5 (1, 2.6)
CAM-22_GFDL-ESM2M CRCM5	15 (-12, 50)	13 (2.8, 23)	16 (9.1, 23)	2.1 (0.53, 12)	1.9 (1.1, 3.3)	2.1 (1.4, 3.9)
CAM-22_GFDL-ESM2M RegCM4-7	55 (0.14, 140)	17 (1.1, 31)	10 (-2.9, 23)	8 (1, Inf)	2 (1, 3.7)	1.5 (0.93, 3.6)
CAM-22_HadGEM2-ES REMO2015	17 (-11, 58)	16 (5.4, 26)	-6.2 (-15, 6)	2.3 (0.59, 1800)	2.3 (1.3, 3.6)	0.75 (0.46, 1.2)
CAM-22_MPI-ESM-MR RegCM4-7	13 (-15, 55)	9.4 (-0.1, 16)	0.37 (-6, 6.7)	3.3 (0.4, Inf)	2.1 (0.99, 3.3)	1 (0.64, 2.2)
CAM-44_CanESM2 RCA4	8.5 (-3.5, 23)	-0.92 (-5.7, 3.7)	-0.72 (-4.7, 4.8)	1.6 (0.83, 4.1)	0.96 (0.74, 1.2)	0.96 (0.77, 1.3)
CAM-44_CSIRO-Mk3-6-0 RCA4	-16 (-41, 31)	-0.66 (-22, 14)	1.5 (-5.4, 21)	0.5 (0.16, 7.3)	0.97 (0.26, 1.9)	1.1 (0.82, 30)
CAM-44_HadGEM2-ES REMO2015	17 (-11, 58)	16 (5.4, 26)	-6.2 (-15, 6)	2.3 (0.59, 1800)	2.3 (1.3, 3.6)	0.75 (0.46, 1.2)
CAM-44_MPI-ESM-LR RCA4	6.3 (-10, 23)	5.5 (-4.8, 14)	-1.3 (-8.9, 6.9)	1.5 (0.55, 6.9)	1.4 (0.76, 2.4)	0.92 (0.57, 1.5)
CAM-44_MPI-ESM-MR RegCM4-3	0.19 (-17, 22)	7 (-1.5, 15)	1.4 (-4.2, 6.2)	1 (0.35, 11)	1.6 (0.92, 2.9)	1.1 (0.72, 1.5)
CAM-44_MPI-ESM-MR RegCM4-7	13 (-15, 55)	9.4 (-0.1, 16)	0.37 (-6, 6.7)	3.3 (0.4, Inf)	2.1 (0.99, 3.3)	1 (0.64, 2.2)
CMCC-CM2-HR4_r1i1p1f1	3.4 (-4, 19)	11 (-1.5, 21)	3.8 (-3.8, 9.8)	1.1 (0.89, 1.7)	1.4 (0.96, 2.3)	1.1 (0.89, 1.3)
CMCC-CM2-VHR4_r1i1p1f1	-0.76 (-3, 16)	-1.4 (-4.3, 16)	13 (1.7, 24)	0.97 (0.9, 2)	0.95 (0.84, 2)	1.7 (1.1, 2.7)
EC-Earth3P_r1i1p1f1	8.6 (-6.7, 25)	5.5 (-2.7, 15)	2.2 (-2.6, 8.2)	1.7 (0.64, 5.6)	1.4 (0.84, 2.8)	1.1 (0.86, 1.8)

Table A.4.2: Changes in intensity and probability ratios for what was in 2025 1-in-10-year pr-JJASO over the study region, for observational datasets and for each model that passed evaluation: ‘past warming’: from the 1.3°C cooler preindustrial climate to the present; ‘future warming’: from the present to 2.6°C above preindustrial (1.3°C warmer than the present); ‘ENSO’: associated with 2025 La Niña state vs a neutral ENSO state. All results are presented to 2 significant figures.

	% change in intensity			Probability ratio		
Dataset Obs / models	Past warming	Future warming	ENSO	Past warming	Future warming	ENSO
CHIRPS	-4.2 (-27, 21)	NA	8.4 (3, 12)	0.57 (0.0034, 17)	NA	4.2 (1.6, 29)
CPC	-18 (-37, 1.6)	NA	5.3 (-0.59, 11)	0.16 (0.0044, 1.2)	NA	2.2 (0.93, 8)
ERA5	15 (0.96, 32)	NA	7.9 (4.1, 12)	4.1 (1.1, 25)	NA	1.9 (1.3, 3.6)
MxHRC	-18 (-28, -5.1)	NA	7.4 (3.5, 11)	0.18 (0.019, 0.7)	NA	3.3 (1.7, 8.9)
CAM-22_GFDL-ESM2M CRCM5	-4.9 (-20, 9.8)	-1.9 (-12, 6.1)	15 (11, 19)	0.6 (0.21, 4)	0.82 (0.21, 1.8)	7.6 (3.8, 19)
CAM-22_GFDL-ESM2M RegCM4-7	23 (-7.4, 67)	14 (0.61, 25)	11 (5.2, 20)	17 (0.52, 1500000)	2.8 (1.1, 5.1)	3 (1.7, 14)
CAM-22_HadGEM2-ES REMO2015	0.15 (-19, 21)	6.4 (-2.4, 14)	-6.4 (-11, 0.23)	1 (0.25, 11)	1.7 (0.79, 2.7)	0.58 (0.38, 1)
CAM-22_MPI-ESM-MR RegCM4-7	-6.7 (-24, 13)	-1.3 (-11, 5.6)	-1.3 (-6.1, 3.2)	0.51 (0.16, 6.3)	0.87 (0.27, 1.8)	0.86 (0.52, 1.5)
CAM-44_CanESM2 RCA4	-3.3 (-11, 5.9)	-6.1 (-9.7, -2.2)	-3 (-7.7, 0.39)	0.68 (0.31, 2.2)	0.41 (0.21, 0.73)	0.71 (0.44, 1)
CAM-44_CNRM-CM5 CRCM5	-12 (-26, 4.6)	-6 (-17, 2.2)	1.7 (-1.7, 6.1)	0.3 (0.15, 1.9)	0.47 (0.083, 1.3)	1.2 (0.82, 2.5)
CAM-44_CSIRO-Mk3-6- 0 RCA4	-18 (-32, 0.64)	-5.5 (-17, 4.5)	4.3 (0.34, 9.2)	0.22 (0.12, 1.1)	0.51 (0.063, 1.6)	1.7 (1, 3.4)
CAM-44_HadGEM2-ES REMO2015	0.15 (-19, 21)	6.4 (-2.4, 14)	-6.4 (-11, 0.23)	1 (0.25, 11)	1.7 (0.79, 2.7)	0.58 (0.38, 1)
CAM-44_MPI-ESM-LR RCA4	-7.5 (-18, 3.5)	-1.3 (-8.2, 4.8)	4.3 (-0.064, 9.2)	0.45 (0.2, 1.6)	0.86 (0.33, 1.7)	1.7 (0.99, 3.7)
CAM-44_MPI-ESM-MR RegCM4-3	-3.8 (-17, 9.4)	3.9 (-1.5, 8.7)	1.9 (-2, 6)	0.61 (0.17, 5.1)	1.7 (0.8, 2.9)	1.3 (0.76, 2.7)
CAM-44_MPI-ESM-MR RegCM4-7	-6.7 (-24, 13)	-1.3 (-11, 5.6)	-1.3 (-6.1, 3.2)	0.51 (0.16, 6.3)	0.87 (0.27, 1.8)	0.86 (0.52, 1.5)
CMCC-CM2-HR4_r1i1p1 f1	8.3 (-11, 23)	5.8 (-6.1, 15)	-0.2 (-4.7, 4.8)	2.6 (0.38, 36)	1.7 (0.5, 3.6)	0.98 (0.62, 1.7)
CMCC-CM2-VHR4_r1i1 p1f1	-3.8 (-20, 20)	1.8 (-10, 12)	3 (-3.3, 9.1)	0.7 (0.22, 13)	1.2 (0.35, 2.7)	1.4 (0.73, 2.9)
EC-Earth3P_r1i1p1f1	0.032 (-19, 17)	-11 (-22, 0.035)	3 (-1, 7)	1 (0.19, 15)	0.24 (0.03, 1)	1.4 (0.89, 2.6)