

Unplanned urbanisation fuels landslide disasters amid emerging rainfall trends

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Main findings

- In Juiz de Fora, February's exceptionally heavy rainfall saturated the soil, triggering widespread flooding and landslides. The severity of the disaster, however, was driven by the high exposure and social vulnerability. Risk assessments by Brazil's National Center for Monitoring and Early Warning of Natural Disasters (Cemaden) had previously identified around 130,000 residents living in high-risk zones, placing Juiz de Fora among the 10 cities in Brazil with the highest proportion of people living in such risky areas.
- Urbanization of the hills initially involved well-built housing supported by skilled labor. Historic growth along the Paraibuna River valley and northwest transport corridors, later reinforced by industrial districts and factories, drove residents to settle in lower-quality homes on steep slopes and valley bottoms. Rapid, largely unplanned expansion in these areas, often with poor drainage, low vegetation and weaker infrastructure, created high-risk zones for rainfall events, particularly in districts such as Benfica, Vila Esperanca, and Santa Cruz.
- Cemaden and INMET issued multiple warnings and alerts ahead of the heavy rainfall. While these alerts accurately indicated high landslide and flood risk, evidence suggests that some residents did not fully receive, understand, or know how to act on them. Factors include topographical constraints that limit siren effectiveness, long-term residence in hazard zones, and lack of accessible evacuation options. This highlights that warnings alone are insufficient, and must be complemented by clear guidance, risk education, and practical evacuation planning to strengthen community preparedness.
- Across the study region, gridded rainfall data show moderately high precipitation in February, with a return period of about 1 in 10 years. However, when compared with observations from the one available local weather station in the study region, the gridded products significantly underestimates the intensity of the event in Juiz de Fora, where the local return period is several 100 years.
- To estimate if human induced climate change influenced heavy rainfall over the region we first determine if there is a trend in observations in February precipitation, finding that observed trends in February total rainfall are highly variable, with the four datasets used showing for the two longest datasets no trends, while the two shorter ones show an increase between 25 and 60%.
- Climate models indicate no trends in February rainfall under current conditions in the small, highly variable study region, but project notable increases of about 7% with future warming. A pattern that aligns with findings from existing studies and IPCC assessments in the larger region that show a wettening trend emerging from 1.5C global warming onwards. Thus, an emerging trend is apparent, and might have contributed to the localised events even if it is not yet evident across the wider region.

- More intense rainfall, especially over the course of a month, saturates slopes, reduces soil stability, and increases the likelihood of slope failure. As a result, landslide hazard remains unlikely to diminish but might increase further.
- Given the large population already living in high-risk areas, risk reduction in Juiz de Fora requires viable, largely incremental adaptation measures. These can include targeted slope stabilization, improved drainage, reinforcing housing foundations, expanding early warning infrastructure, and community-level preparedness programs. Strengthening land use enforcement can gradually reduce exposure, while addressing the structural inequities that concentrate among low-income households.
- Brazil's past flood responses have quickly adapted existing social protection systems during climate hazards. By advancing payments, expanding coverage, and providing targeted emergency transfers, the government delivered timely support to affected populations. As climate change shortens intervals between disasters, public policy must go beyond planning, ensuring sustained investment in key sectors like health, with systems resilient to both climate impacts and disasters.

1 Introduction

At the end of February, more than 70 people ([ReliefWeb, 2026](#)) lost their lives after intense, localised rainfall triggered landslides across the Brazilian state of Minas Gerais. The city of Juiz de Fora was among the hardest hit, experiencing its wettest February on record, with over 750 mm of rainfall – three times the expected amount for that period and 65% more than the previous record of 456 mm of rainfall in 1988 ([INMET](#); Fig. 1.1). The first major rainfall event (229.9 mm) occurred between 22 and 24 February, causing severe landslides, followed by additional heavy rain on the 26th (138.2 mm). By the last day of the month, exceptionally high rainfall moved further north in Minas Gerais.

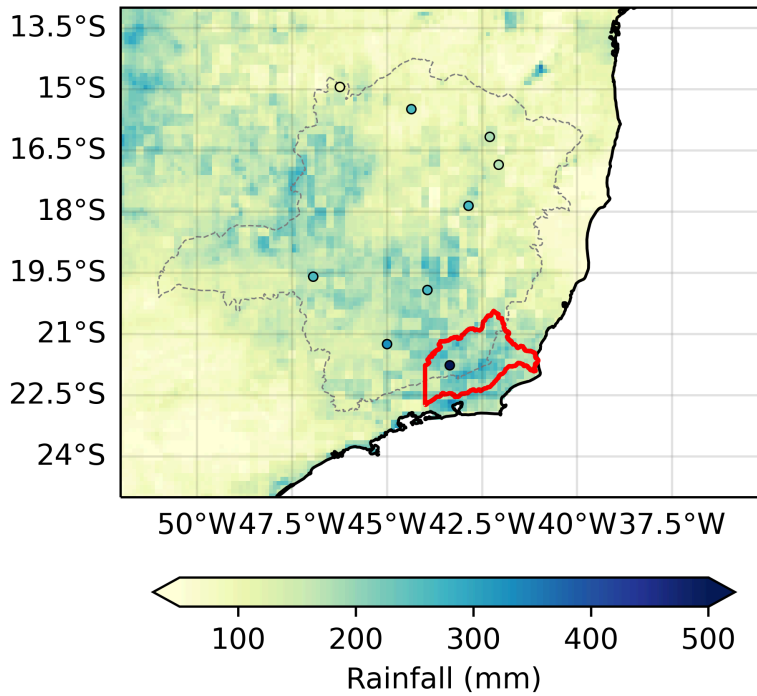


Figure 1.1: Accumulated rainfall over land, including the study region during 1st - 24th February 2026 in gridded reanalysis data and local weather stations. The study region is highlighted in red and the wider state of Minas Gerais is shown with the dashed line. Data: MSWEP and INMET.

The combination of various factors resulted in exceptionally high rainfall between 22 and 24 February. The passage of a frontal system along the southeastern coast of Brazil, together with a cutoff low over the adjacent ocean, amplified moisture transport, leading to the development of a supercell over the affected region ([INMET](#)).

The rainy season in eastern subtropical South America occurs during the austral summer (December–January–February, DJF) when South Atlantic convergence zone (SACZ) events develop as part of the South America Monsoon System ([Vera et al. 2006](#); [Marengo et al. 2012](#)). Equatorward propagation of cold fronts along eastern South America help establish the SACZ ([Nieto-Ferreira et al. 2011](#)), which is characterised by a band of strong precipitation oriented northwest to southeast, from the Amazon, over southeast Brazil towards the western South Atlantic ([Carvalho et al. 2004](#); [Carvalho et al. 2002](#)). The wettest season in southern Minas Gerais is therefore austral summer, with total precipitation typically ranging between 600 and 800 mm during December–February, of which about 350 mm typically falls in January alone ([Dalagnol et al., 2021](#)). The average annual rainfall is approximately 1600 mm ([Viola et al., 2010](#)).

The SACZ varies strongly on intraseasonal time scales, partially in response to varying with 30-60 day phases of the Madden–Julian Oscillation (MJO; [Madden and Julian 1994](#); [Liebmann et al. 2004](#); [Gonzalez and Vera 2014](#)). When convection is stronger near the date line (MJO phases 6 and 7), the SACZ tends to be enhanced. Conversely, convection mainly over the Indian Ocean (MJO phases 1 and 2) can trigger the wave train that leads to atmospheric blocking over eastern South America, preventing the establishment of the SACZ ([Rodrigues & Woollings 2017](#)). In addition, the Southern Annular Mode (SAM) can modulate the frequency, persistence, and position of the SACZ. A negative phase of the SAM is associated with a higher frequency of SACZ events, as westerly winds shift

towards the equator, altering circulation patterns that allow frontal systems to move further north, favouring a more northward position of the SACZ. In contrast, a positive phase of the SAM reduces SACZ activity in subtropical regions.

1.1 Impacts

The late-February 2026 floods and landslides in the Zona da Mata region of Minas Gerais, particularly affecting the municipalities of Juiz de Fora, Ubá, and Matias Barbosa, constitute a major disaster with significant human and socio-economic impacts. By 27 February, the event had displaced nearly 8,000 people from their homes and led to over 70 fatalities ([ECHO, 2026a](#)). Due to the scale of the impacts, state of public calamity or emergency were declared in the three municipalities, enabling the mobilization of state and federal assistance for search and rescue, temporary shelters, and the restoration of essential services.

Juiz de Fora experienced the most severe impacts, where intense rainfall triggered several landslides across the slopes surrounding the city. Most fatalities have been linked to these landslides, with early reports indicating at least 54 deaths and 14 missing persons associated mainly with slope failures ([Petley, 2026](#)). Around 65 residents were killed and 6,400 displaced in Juiz de Fora alone ([ECHO, 2026a](#); [ECHO, 2026b](#)). Flooding of the Paraibuna River also caused major disruption, inundating entire neighborhoods and critical roads, damaging infrastructure, flooding a hospital, and causing power outages affecting at least 1,000 people ([Sampaio, 2026](#)). In Ubá, severe flooding of the Ubá River (reaching 7.82m) inundated low-lying neighborhoods, causing at least seven fatalities and displacing about 700 people ([g1, 2026](#); [ECHO, 2026b](#)). Matias Barbosa also experienced notable impacts, with over 800 people displaced due to housing damage and ongoing landslide risk ([ECHO, 2026a](#)).

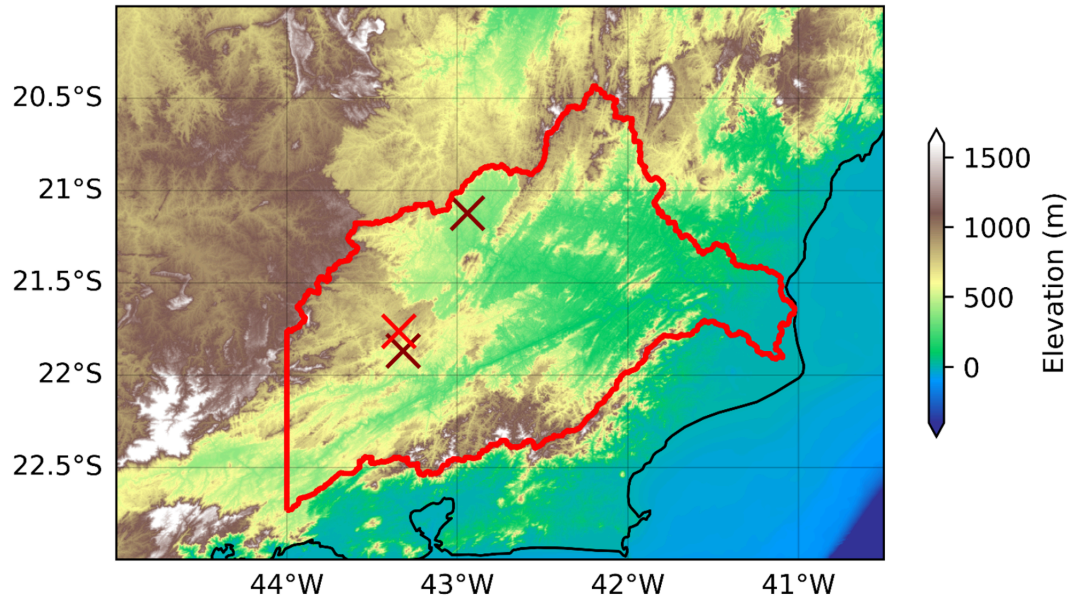


Figure 1.2: Elevation of the land area. The study region is outlined in red, while 3 sites with reported impacts are shown with red crosses: dark red for Ubá (northeast cross) and Mathias Barbosa (southwest cross), lighter red for Juiz de Fora.

1.2 Rainfall extremes in Southeastern Brazil

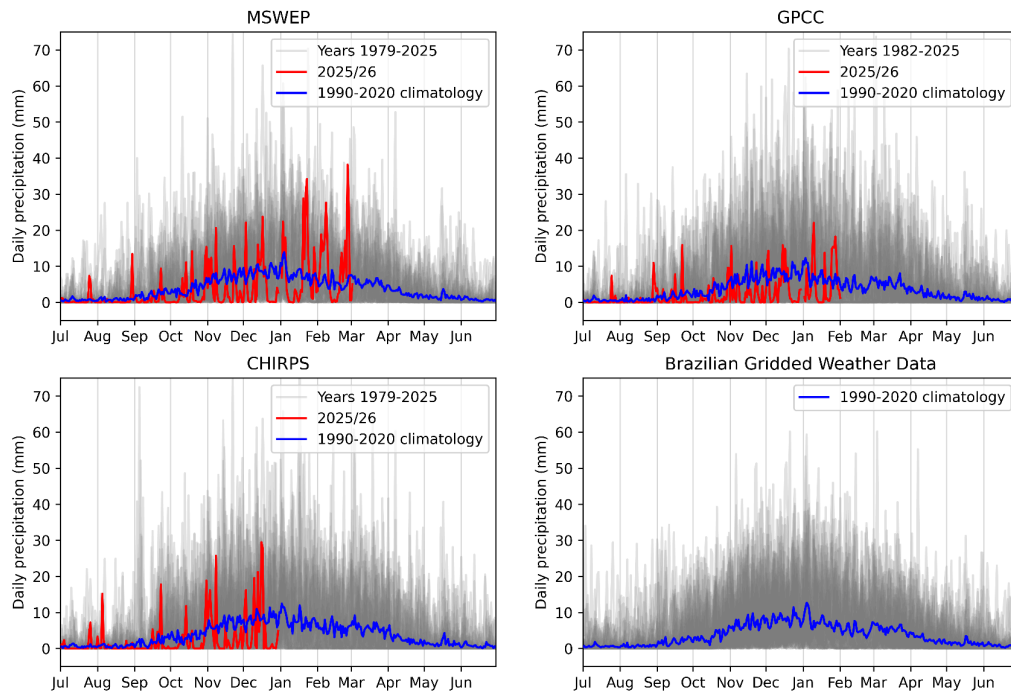


Figure 1.3: Daily precipitation over the study area for MSWEP (top left), GPCC (top right), CHIRPS (bottom left) and the Brazilian Gridded Weather Data (bottom right). On each panel gray corresponds to all available historical data, red is the data starting from July 2025 onwards and blue is the 1990-2020 climatology.

Human-induced increases in extreme rainfall—particularly short-duration, localized events—have been documented globally ([Fowler et al., 2021](#)). In contrast, attribution studies examining the influence of anthropogenic climate change in South America, and especially in southeastern Brazil, remain limited (e.g., [Otto et al., 2015](#); [de Abreu et al., 2019](#), [Dalagnol et al., 2021](#), [Clarke et al., 2024](#)). [Dalagnol et al., 2021](#) undertake an event attribution study of the January 2020, extreme rainfall event that struck southeastern Brazil, with its epicenter in Minas Gerais. An event that although heavy rainfall is common during the wet season, caused 56 fatalities, displaced more than 90,000 people, and resulted in at least BRL 1.3 billion (USD 240 million) in damages due to flooding and landslides. The study concluded that climate change made the event more than 70% more likely and contributed to approximately 41% of the total economic losses. They also found that despite its severe impacts, the event has an estimated return period of only four years, highlighting that events like these are relatively common. [Clarke et al., 2024](#), analysing the severe floods in Rio Grande do Sul, found comparable results, of an increase in the intensity and likelihood of the rainfall causing the floods.

This finding is in line with studies looking at the future. [Reboita et al., 2023](#) investigate changes in the South American monsoon with human-induced warming, looking at several GCMS and two scenarios found that the monsoon season is projected to shorten significantly towards the end of the century, with a later onset of the rainy season while the rainfall overall is increasing in intensity. Previous studies assessed by the latest IPCC report ([Seneviratne et al., 2021](#)) also found an increase in heavy precipitation over the region with future warming emerging from 1.5°C of warming, but did assign low confidence to observed and attributed trends.

1.3 Event Definition

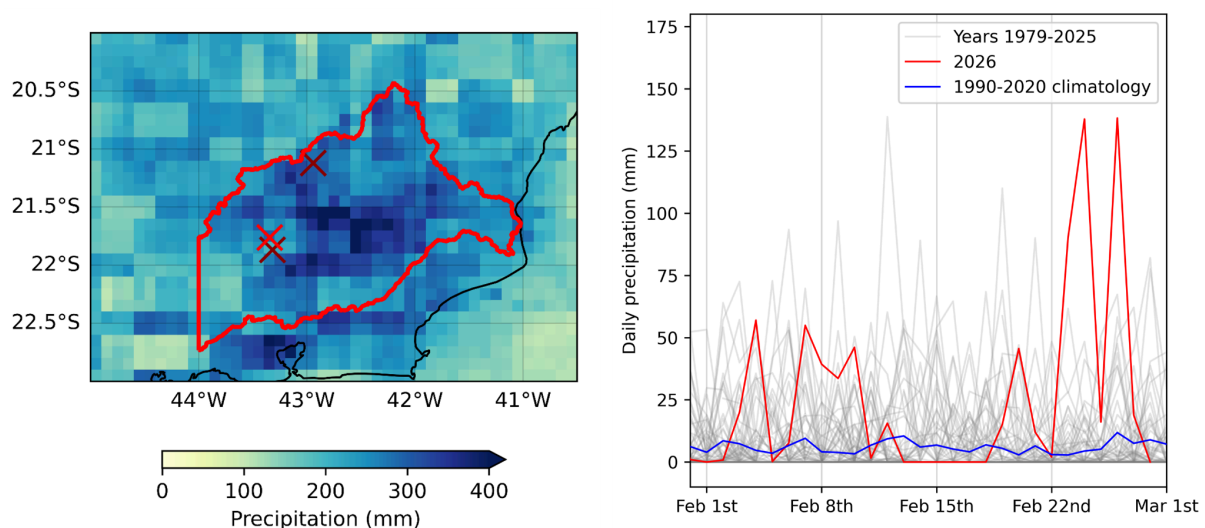


Figure 1.4: Left: Accumulated rainfall over the study region during February 2026. The study region is outlined in red, while 3 sites with reported impacts are shown with red crosses: dark red for Ubá (northeast cross) and Mathias Barbosa (southwest cross), lighter red for Juiz de Fora. Data: MSWEP. Right: Daily rainfall at Juiz de Fora weather station throughout February 2026 (red line), the average of the 1990-2020 climatology for February (blue), and all other February days in the record (grey).

The impacts of this event were driven by a series of devastating landslides, particularly in Juiz de Fora and other nearby locations including Ubá and Mathias Barbosa. All of these locations lie within the wider basin of Paraiba do Sul, a river in southeast Brazil that runs between mountainous terrain with narrow and steep complex valleys and the flatter coastal region (Fig 1.2). To capture the rainfall that drove the landslides, we therefore consider the lower end of this river basin in which the impacted regions are situated, cutting off everything west of 44 °W (Figs 1.2 & 1.4). Furthermore, while several short intense bursts of rainfall occurred in the region (see Figs 1.3 & 1.4), the reported impacts are the result of this sequence of events and the fact that this occurred later in the wet season when the ground was already saturated. We therefore consider the mean February rainfall over this study region, henceforth referred to as **PrcpFeb**. In order to test the sensitivity of this result, we also consider the wettest 30-day period each year (Jul-Jun) using observational datasets.

The event definitions are therefore as follows:

1. **PrcpFeb** - February average rainfall over the Paraiba do Sul hydrobasin east of 44 °W
2. **Rx30day** - wettest 30-day period considering the hydrological year that runs from July to June over the Paraiba do Sul hydrobasin east of 44 °W (observations only)

In this report, we study the influence of anthropogenic climate change by comparing the likelihood and intensity of similar extremes at present 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 2024 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](#)).

2 Observed trends

2.1 Trends in gridded data and station data

2.1.1 February rainfall

Time series of the mean February rainfall averaged across the study region are shown in Fig. 2.1 (upper panel). The gridded observational and reanalysis products are in broad agreement across the periods covered, though at the time of writing the event is only observed in MSWEP. The time series are characterised by high variability and no clear trend is evident visually. Furthermore, the observed event is not a historic record across this wider region in the MSWEP dataset. Fig. 2.1 also shows time series from Juiz de Fora itself (lower panel), both weather station data and the closest grid point to this location in MSWEP. The station data highlights that the February rainfall was unprecedented in this location, ultimately causing the landslides. While the MSWEP grid point does not capture the intensity of this event, it shows a reasonable degree of accuracy in both magnitude and variability of the February precipitation throughout the rest of the common historical period. We therefore do use this for trend analysis with the caveat that locally the calculated return periods are likely underestimates.

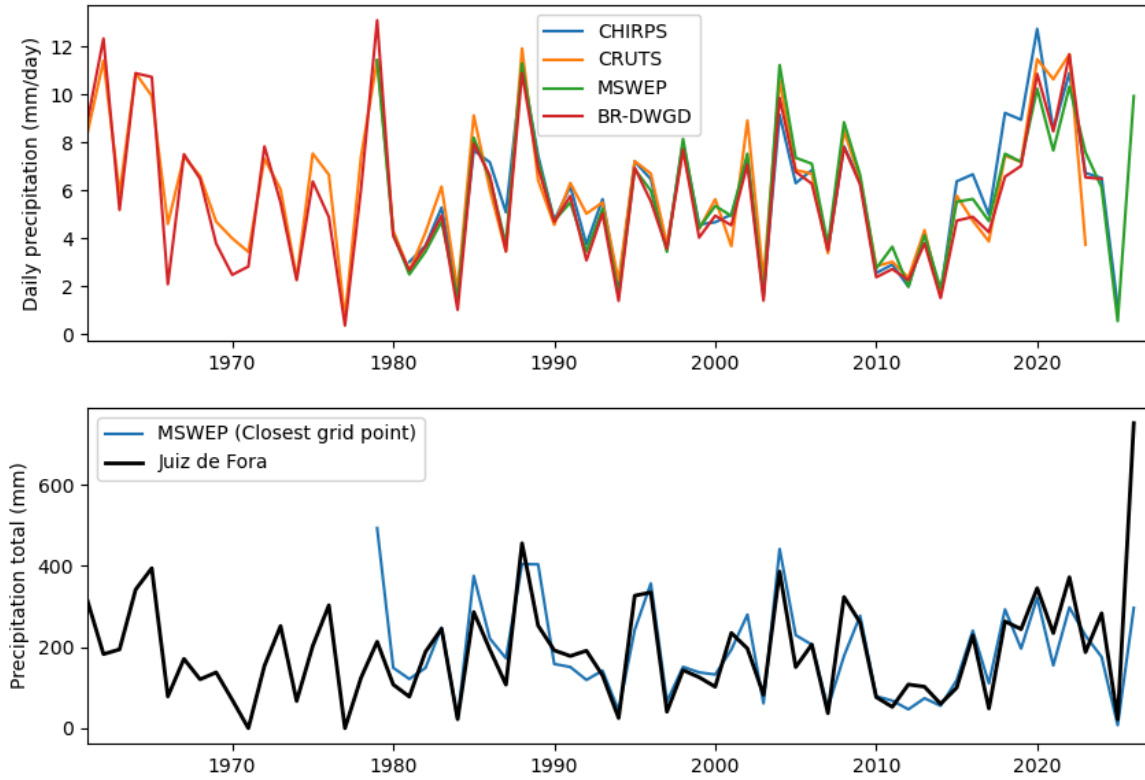


Figure 2.1: Time series of *PrcpFeb* over the wider study region (top panel) and in Juiz de Fora (bottom panel). Top: The four gridded observation-based datasets studied are shown from a common period of 1960 onwards. The 2026 event is only covered in MSWEP (green line). Bottom: Total precipitation in February from a weather station in Juiz de Fora (black) and the nearest grid point in MSWEP.

To test for the potential influence of anthropogenic forcing on February rainfall, we fit a nonstationary gaussian distribution that scales with global mean surface temperature and evaluate the relative likelihood and intensity of the 2026 event in the present climate, and the climate scaled to 1.3°C cooler (see section A1.3 for full methods). Additionally, the Southern Annular Mode (SAM) is known to sometimes play a part in precipitation in this region at certain times of the year (section 1). Therefore, we first investigate the effect of including this as an additional covariate in the statistical model (as in e.g. [Clarke et al., 2026](#)). SAM is represented by the zonal pressure difference between the latitudes of 40°S and 65°S. However, fitting a statistical model using both GMST and this SAM index as covariates does not improve the fit, according to the Akaike Information Criterion, relative to GMST alone. The influence of the current SAM state is therefore not considered throughout the rest of this study.

Table 2.1 and Figs. 2.2 and 2.3 show the modelled trends in each observation-based dataset with global warming and the change in likelihood and intensity of *PrcpFeb* due to 1.3°C warming. MSWEP was the only dataset that captured the full event and was therefore used to estimate the return period. The estimate of 7.6 (2.8-78) years is known to be an underestimate with respect to the intense totals observed in Juiz de Fora, however it provides a benchmark for the wider region that is not available via any other source, and still shows elevated totals across this region. We therefore use the

benchmark of 10 years for the event. We note that the choice of return period affects the estimated probability ratios but that the modelled changes in intensity are independent of this.

Dataset	Event magnitude (mm/day)	Return period (years)	Influence of GMST	
			Probability ratio	Change in magnitude (%)
MSWEP*	9.93 (10.4)	7.63 (2.76, 77.9) (10)	6.67 (0.085, 166000)	26.2 (-26.8, 140)
BR-DWGD	9.1	10	0.78 (0.048, 8.75)	-4.49 (-36.0, 41.3)
CHIRPS	11.6	10	430 (0.33, 10 ⁹)	63.2 (-10.2, 193)
CRUTS	9.8	10	1.08 (0.081, 3.92)	1.18 (-24.8, 25.8)

Table 2.1: Observed and expected event magnitude and the corresponding return period of PrcpFeb in the present climate in the study region in the four observation-based datasets, as well as the estimated change in probability ratio and magnitude for PrcpFeb in the study region due to GMST.

*The probability ratio shown is for the 10-year return period event.

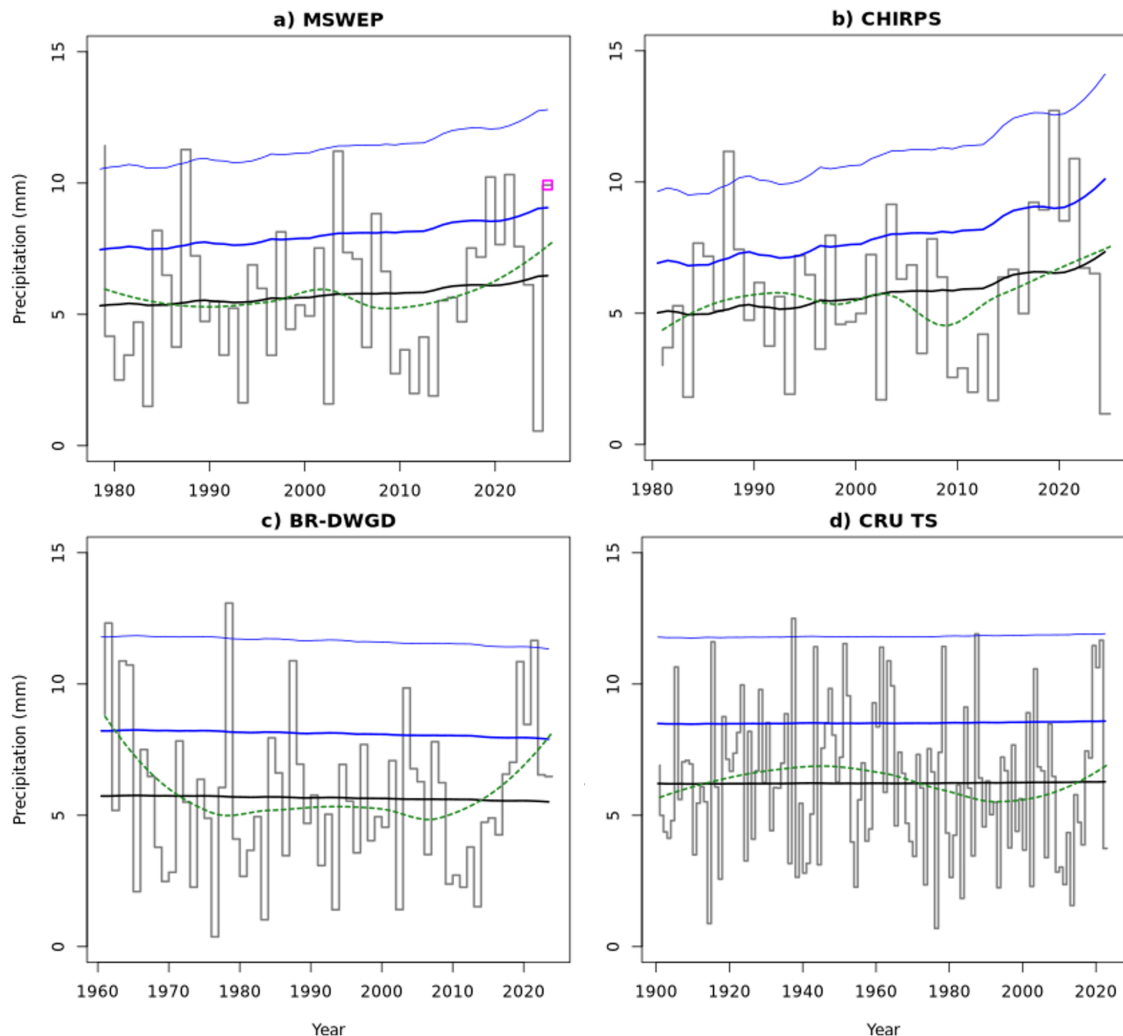


Figure 2.2: Time series of PrcpFeb in the study region in 4 different gridded observational and reanalysis datasets. The 2026 event is highlighted with a pink box in panel (a), and across all panels the fitted statistical model is shown via the expected value (black line), and 5- and 50-year return period values (bold and thinner blue lines, respectively). The green dashed line is a non-parametric Loess smoother.

The four datasets show different trends over time (Fig. 2.2). The loess smoother shows a consistent uptick in recent years across all datasets, likely due to a series of wet Februaries from 2018-2022. However, the shorter datasets - MSWEP and CHIRPS - show consistent increasing trends across the period from ~1979 to present, albeit with minor variability. On the contrary, the longer datasets BR-DWGD (back to 1960) and CRUTS (back to 1901) both show multi-decadal variations in the smoothed average, suggesting that the trend has not been consistent over the observed period and that the trend observed in the shorter datasets cannot be reliably extrapolated (though both datasets show increasing trends when restricted to the same baseline year of 1979 onwards - Table A1.1). This is also reflected in the model fits shown by the return curves in Fig. 2.3, with the wettest February events poorly represented by the Gaussian model in all datasets. We note however that the model provides a good fit up to the return period of interest. Both the multi-decadal variability and the challenge of capturing the distribution of February rainfall in the region results in both mixed trends and high uncertainties after fitting a statistical model that varies with GMST (Table 2.1).

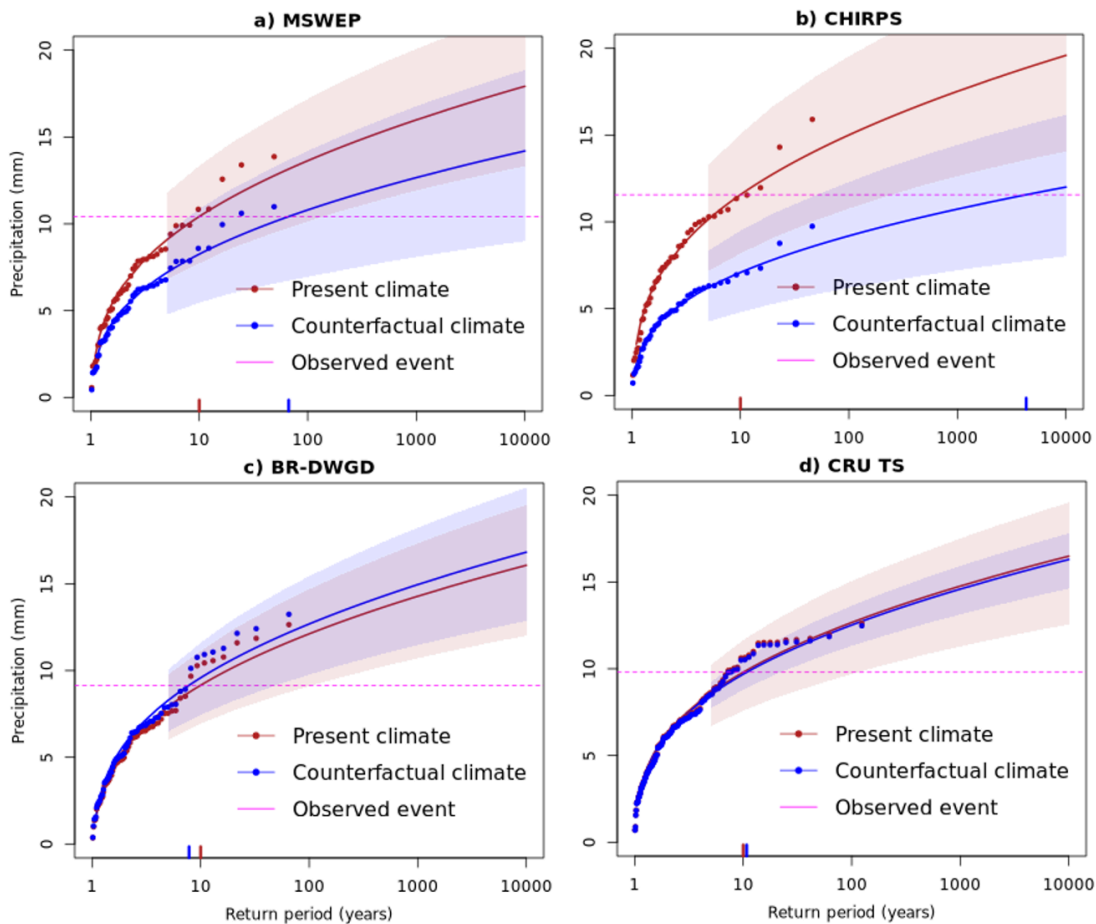


Figure 2.3: Expected return levels of PrcpFeb over the study region in the four observational and reanalysis datasets, in the 2026 climate (red lines) and in a 1.3°C cooler counterfactual climate (blue line). Shaded regions represent 95% confidence intervals obtained via bootstrapping. The pink line shows the magnitude of the expected 10 year event in the present climate. Red and blue ticks at the x axis indicate the estimated return level of the event in the 2026 climate and counterfactual climates, respectively.

The best estimates of the change in likelihood for a 10 year event range from a factor of 0.8-1.1 for the longer datasets, BR-DWGD and CRUTS, to increases of 7-430 in MSWEP and CHIRPS. This is matched by the change in intensity from -4 to +1% in the longer datasets to 25 to 60% in the shorter datasets. In essence, the shorter datasets suggest a strong emergent increase with recent warming in a region of high natural variability (associated with the SACZ), while the longer datasets show no change over the period of warming and would ascribe recent changes to multi-decadal variability. To further explore whether global warming has played a role to date and whether we will expect it to in future, the analysis is repeated with multiple ensembles of climate models and synthesised (section 3).

In addition, we studied data from a station based in Juiz de Fora, which began in 1961 and runs until present. At this station, the event was unprecedented (Fig. 2.1), and is estimated to have a return time of nearly 1000 years (Table 2.2). The local return periods of rainfall events within this region of complex topography are therefore likely much higher than the 1 in 10 years used for the regional average in this study. Repeating the analysis above using this time series, we find a very strong increasing trend with a likelihood increase of a factor of nearly 100 for the 10 year event, and 63% (-21 to 160%) in intensity. However, with the event itself removed, the expected magnitude of a 10 year return period event is comparable to the event magnitudes for the wider region, and the trend is substantially reduced, suggesting a small increase of a factor of 1.3 (0.07 to 19) in likelihood and 4.8% (-31 to +63%) in intensity.

Dataset	Event magnitude (mm/day)	Return period (years)	Influence of GMST	
			Probability ratio	Change in magnitude (%)
Juiz de Fora (with event)	26.9	778 (29.2, 10 ¹²)	754000 (2.92, 10 ¹¹)	63.4 (-21.4, 159)
	16.6	10	96.0 (0.03, 23500)	63.4 (-21.4, 159)
Juiz de Fora (without event)	11.7	10	1.29 (0.071, 19.3)	4.83 (-30.9, 62.8)

Table 2.2: Observed and expected event magnitude for a 1-in-10 year event and the corresponding return period of PrcpFeb in the present climate in Juiz de Fora based on rainfall records at a station, as well as the estimated change in probability ratio and magnitude for PrcpFeb in the study region due to GMST.

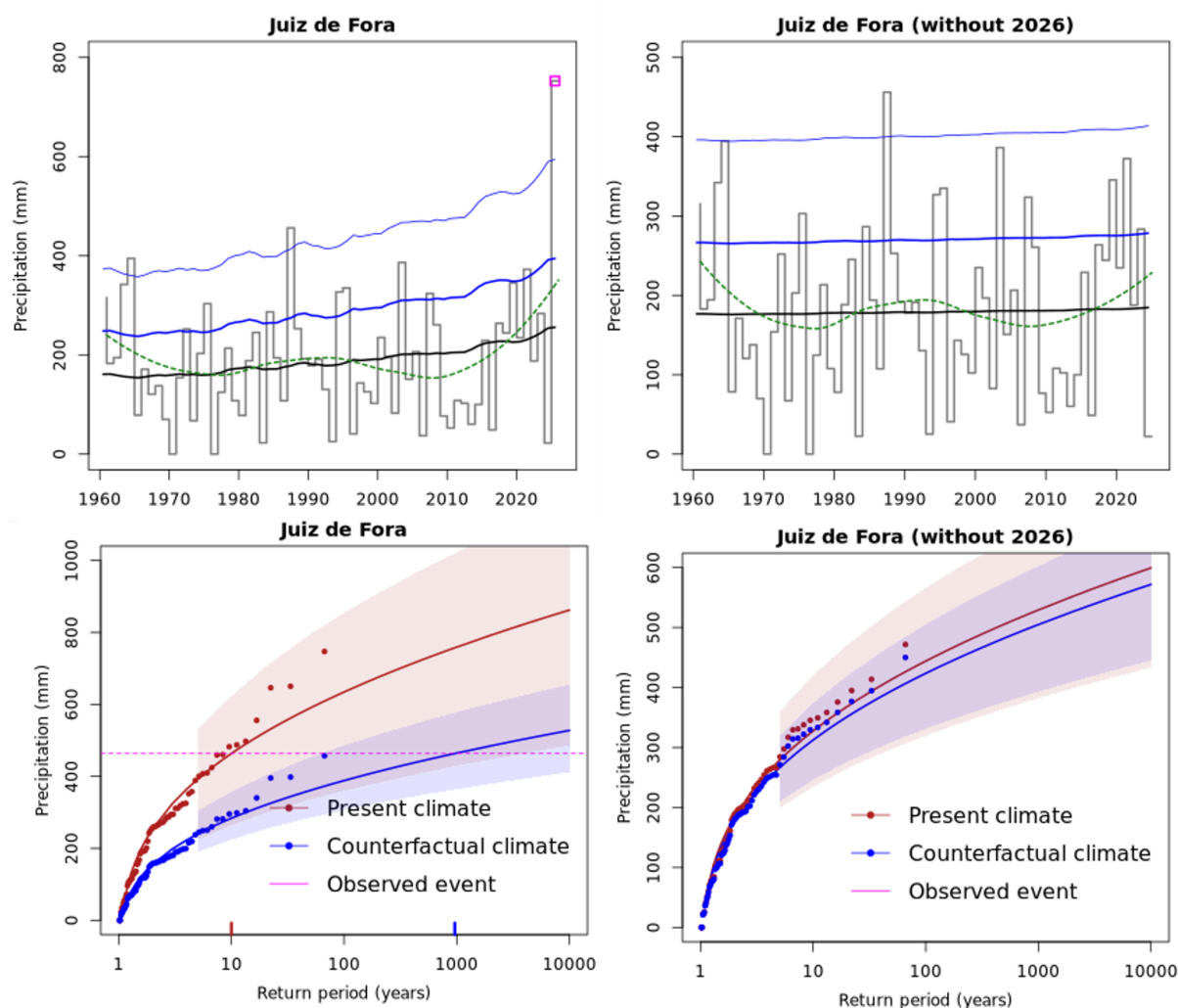


Figure 2.4: Top: Time series of PrcpFeb in Juiz de Fora based on weather station data. The 2026 event is highlighted with a pink box in the top left panel, the fitted statistical model is shown via the expected value (black line), and 5- and 50-year return period values (bold and thinner blue lines, respectively). The green dashed line is a non-parametric Loess smoother. Bottom: Expected return levels of PrcpFeb in Juiz de Fora, in the 2026 climate (red lines) and in a 1.3°C cooler counterfactual climate (blue line). Shaded regions represent 95% confidence intervals obtained via bootstrapping. In the bottom left panel the pink line shows the magnitude of the expected 10 year event in the present climate, and red and blue ticks at the x axis indicate the estimated return level of the event in the 2026 climate and counterfactual climates, respectively.

2.1.2 Rx30day

We also assess the time series of the wettest 30 day period from each year (July-June). In MSWEP, as is expected, the event is more common than the February rainfall with a return period of approximately 3 (1.6 to 6.8) years. Interestingly, the two shorter datasets that showed the strongest trends in February rainfall, MSWEP and CHIRPS, show decreasing trends in the wettest 30-day period, with the event likelihood decreasing to become approximately 0.4-0.5 times as compared to a 1.3°C cooler world, or equivalently about 15-22% less intense. However, this is not reflected in the

slightly longer BR-DWGD dataset, which is again consistent with no significant change. Similar to the previous analysis, we are unable to determine from observations alone whether there is an emerging trend due to warming or simply multi-decadal variability in the region. Furthermore, the discrepancy in the direction of trends from February alone to the wettest 30 days may also indicate a seasonal shift in rainfall patterns.

Dataset	Event magnitude (mm/day)	Return period (years)	Influence of GMST	
			Probability ratio	Change in magnitude (%)
MSWEP	10.7	3.01 (1.58, 6.75)	0.42 (0.16, 0.997)	-21.7 (-36.8, -0.084)
BR-DWGD	12.1	3	0.97 (0.32, 2.76)	-0.51 (-18.6, 21.3)
CHIRPS	11.3	3	0.52 (0.11, 2.29)	-14.9 (-36.6, 21.5)

Table 2.3: Observed or expected event magnitude and the corresponding return period of Rx30day in the present climate, as well as the estimated change in probability ratio and magnitude for PrcpFeb in the study region due to GMST. Statistically significant trends are also highlighted in **bold** font.

2.1.3 Seasonal shifts

Fig. 2.5 shows the change in monthly precipitation, using the statistical modelling approach used throughout this section, for each calendar month. Consistent drying signals are observed across the driest months of the year, from June-September. However, the wet season months in which this event occurred, from November to March, show mixed or no strong trends. February stands out in this period, with the two shorter datasets showing strong increases as shown in section 2.1.1, though November also bears similarity to February, with increases or no change across the datasets. Meanwhile, the wettest months of the year, January and December, do show a majority of weak drying trends. This is likely the reason for the discrepancy between the results for February and the Rx30day index.

This in turn may result from a discrepancy in the dominant influences upon the SACZ zone across the wet season. Among the key factors that feed and maintain the SACZ is the low-level convergence, from the interaction of humid air masses from the Amazon basin either with cold fronts or with surface low-pressure systems over Southeastern Brazil. The interaction with cold fronts (former) occurs more during the months of onset and decay, i.e., November and February, and with local low-pressure systems (latter) during the wettest months of December and January. However, persistent high-pressure centres (atmospheric blocking) are becoming more frequent during the wettest month (peak season), thereby inhibiting the formation of local low-pressure systems and SACZ events, which explains the slight decrease in rainfall during these months. As a result, SACZ events will occur only when cold fronts interact with humid air masses that feed instability and convection, and this is more likely to happen in November and February. After that, the South Atlantic Subtropical

High moves over Southeastern Brazil, marking the start of the dry season. Other factors may also be relevant to recent decreases in Rx30day, such as the reduction in moisture supply due to reduced evapotranspiration from the Amazon region. However, any attribution to more specific physical mechanisms would require further study.

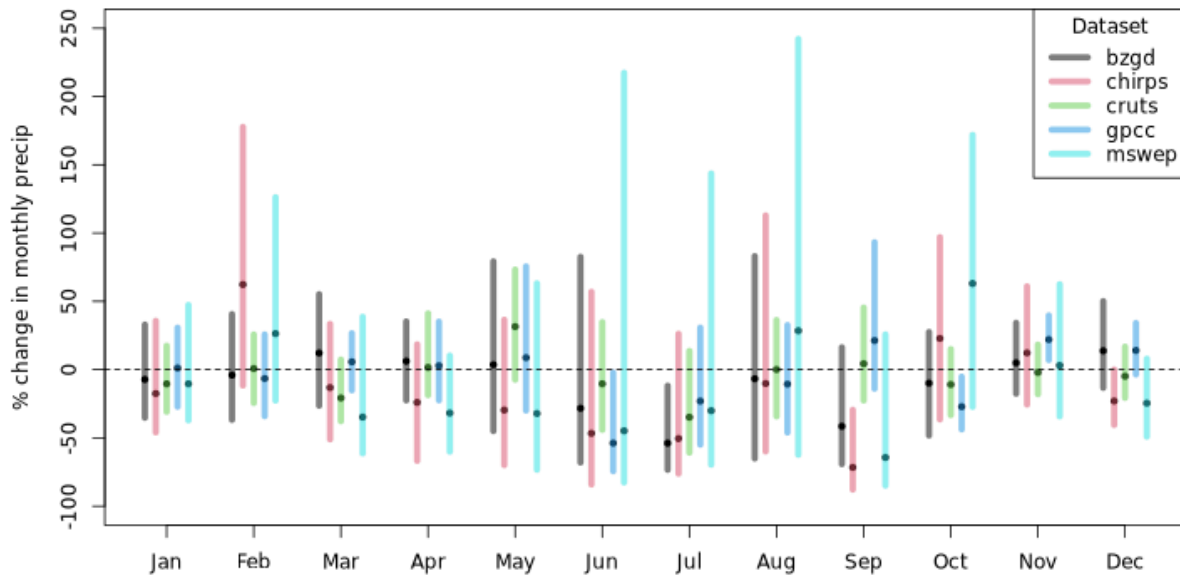


Figure 2.5: Change in monthly precipitation with a change in GMST of 1.3°C across each calendar month and 5 gridded observation-based datasets, including the four used in the trend analysis above and monthly GPCC. The 95% uncertainty range obtained through bootstrapping is shown as a coloured bar.

2.2 Circulation analogues

Atmospheric flow analogues can be used to assess changes in the intensity of dynamically similar events or changes in the frequency of occurrence of particular circulation patterns ([Vautard et al., 2023](#); [Jézéquel et al., 2018](#), [Thompson et al 2024](#)). Here we use ERA5 data to assess analogues identified from 500 hPa geopotential height (Z500) since 1979, to detect changes in the frequency of circulation patterns similar to those associated with the heavy rainfall event.

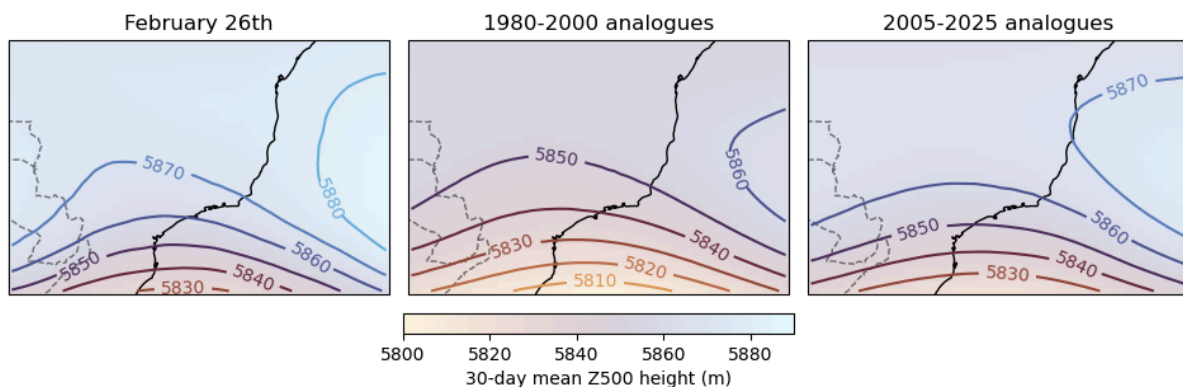


Figure 2.6: Composite plots of Z500 for 3 periods: the 30-day event leading up to 26th February 2026 (left), all analogues within the 1980-2000 past period (middle), and all analogues within the 2005-2025 present period (right).

To identify the most similar events, we compute the Euclidean distance between the Z500 anomaly field of the average 30-day fields leading up to 26th February 2025 and the 30-day average fields leading up to every other day (1980–2025) over the region bounded by 70° to 20°W, -40° to -0°N (Figs 2.6, A2.1&2.2). To avoid double-counting persistent events, the identified events (the last day of each 30-day period) must be separated by at least 35 days (Fig. A2.3 shows the resultant analogues by ranking and total precipitation). The region and circulation variable were determined by assessing the event itself, and earlier current understanding of the circulation drivers of similar events ([Holgate et al 2023](#)). To detect changes in the circulation pattern and intensity since 1980 we identify the closest 20 analogues across the two periods (May 1980 - May 2000 and May 2005 - May 2025) within the wet season of November-March. The average weather conditions associated with the two sets of analogues - called ‘composites’ - are then compared to assess differences between the two periods.

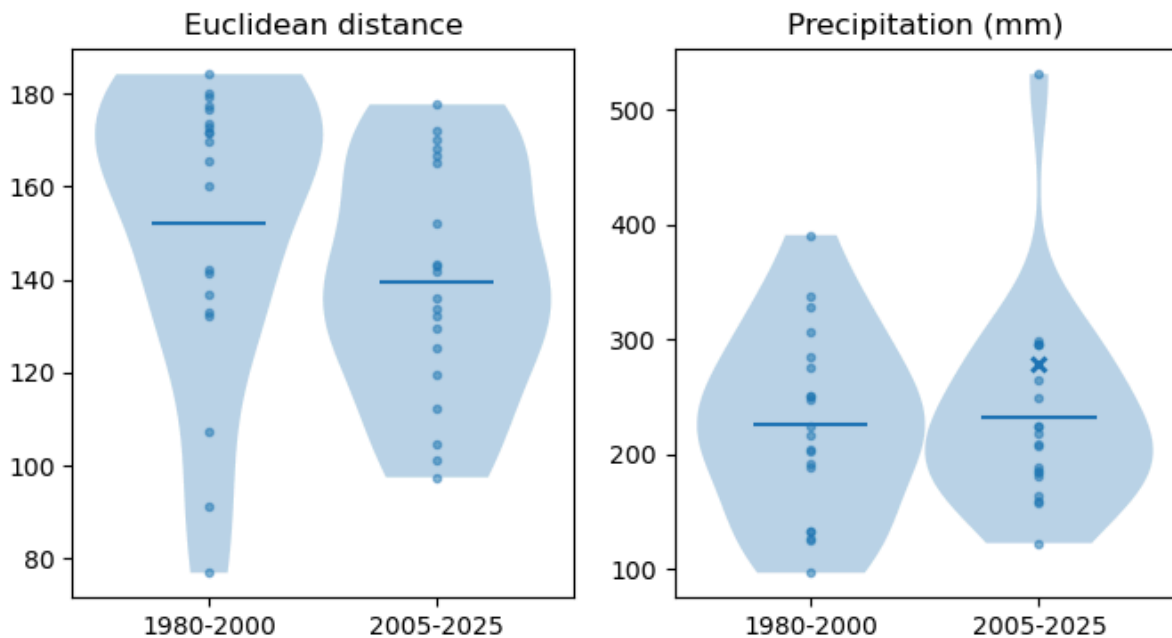


Figure 2.7: Left: Euclidean distances for analogues within each period. Right: Precipitation over the study region corresponding with each analogue date (representing the preceding 30-day period), with the X showing the 2026 event. In both panels, the horizontal line shows the median value.

The analogues in both periods correspond with a range of precipitation values, suggesting that the metric used here to identify analogues does not isolate events that consistently lead to rainy conditions in the study region (Fig. 2.7). However, several events in both periods do exceed the value of the 2026 event, suggesting the presence of extreme events in the sets. Computing the mean precipitation from analogues in each period, we find that events in the past had 225.6 mm and the present period had 232.9 mm. This gives an increase of approximately 7.3 mm, corresponding to an increase of 3.2%. This change is broadly in line with the trend-based analysis, which indicates weak evidence of a possible increase in intensity that requires further investigation.

3 Attribution of trends

3.1 Evaluation of climate models

In the subsections below, we show the results of the model evaluation for each location. The climate models are evaluated against the observations in their ability to capture:

1. Seasonal cycles: For this, we qualitatively compare the seasonal cycles of precipitation based on model outputs against observations-based cycles. We discard any 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.
2. Spatial patterns: Models that do not match the observations in terms of the large-scale precipitation patterns during the month of February are excluded.
3. Parameters of the fitted statistical models. We discard the model if the model and observation parameters ranges do not overlap.

In this study, we evaluated CORDEX and HighResMIP models (see appendix A1.2 for descriptions) on the three criteria listed above. The models are labelled as ‘good’, ‘reasonable’, or ‘bad’ based on their performances in terms of the four criteria discussed above. A model is given an overall rating of ‘good’ if it is rated ‘good’ for all four characteristics. If there is at least one ‘reasonable’, then its overall rating will be ‘reasonable’ and ‘bad’ if there is at least one ‘bad’. We aim to use only ‘good’ models where possible, but for each framing or model setup we also include ‘reasonable’ models if we would otherwise retain five or fewer models for that framing. For HighResMIP models, we only used models with spatial resolution of 50kms or below due to the small scale of the event. For all 5 models evaluated, all passed validation. For CORDEX, 9 out of 17 models evaluated passed the test. Only one model (CanESM2 RCA4) was ‘good’, with the rest being reasonable. Tables of the model evaluation results can be found in Appendix A3. Tables of the model evaluation results can be found in Appendix A4.

3.2 Synthesis of results

For the event definitions described above we evaluate the influence of anthropogenic climate change on the event by calculating the probability ratio as well as the change in intensity using observations and climate models. Models which do not pass the evaluation described above 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. Tables of the results of this model fitting can be found in Appendix A4.

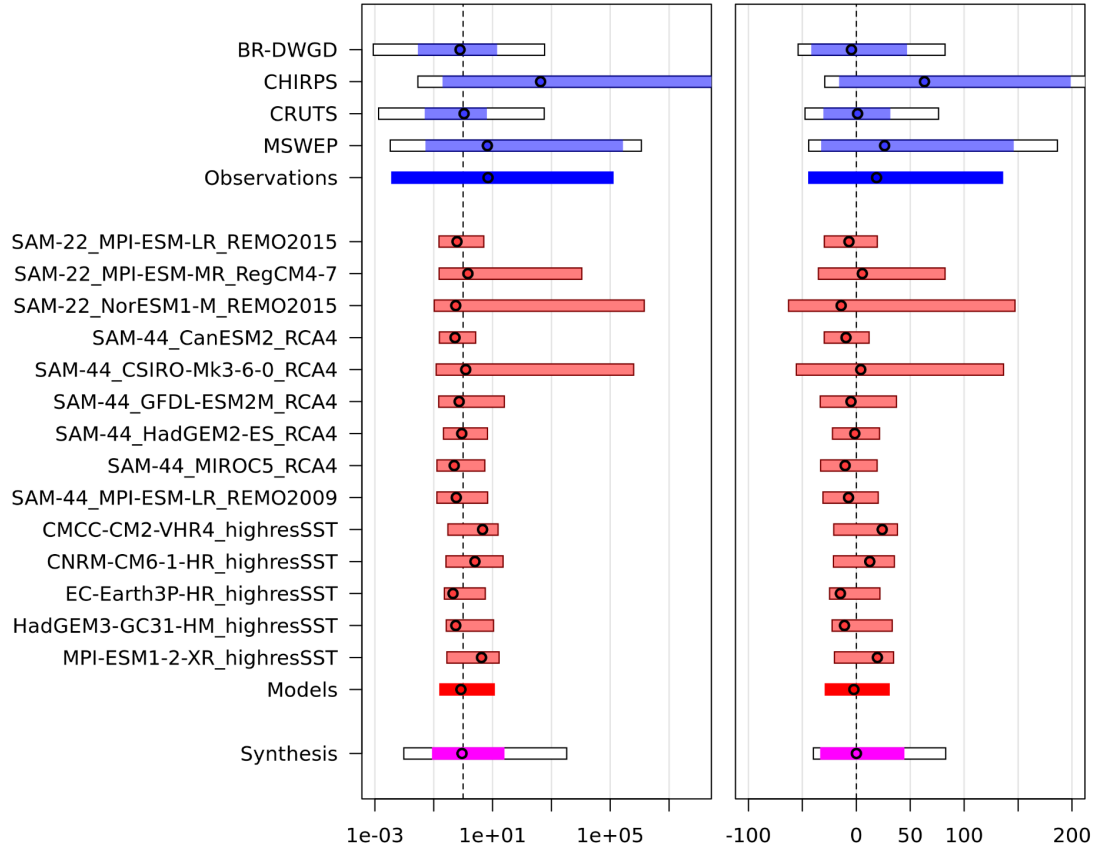


Figure 3.1: Synthesised changes in (left) likelihood and (right) changes in intensity of *PrcpFeb* in the study region when comparing the 2026 climate and a 1.3°C cooler climate representing the preindustrial past. Observation-based datasets are shown in blue, climate models are shown in red, and the synthesis is shown in magenta.

Figures 3.1 & 3.2 show the changes in probability and intensity for the observations (blue) and models (red). Before combining them into a synthesised assessment, first, a representation error is added (in quadrature) to the observations, to account for the difference between observations-based datasets that cannot be explained by natural variability. This is shown in these figures as white boxes around the light blue bars. The dark blue bar shows the average over the observation-based products. Next, a term to account for intermodel spread is added (in quadrature) to the natural variability of the models. This is shown in the figures as white boxes around the light red bars. The dark red bar shows the model average, consisting of a weighted mean using the (uncorrelated) uncertainties due to natural variability plus the term representing intermodel spread (i.e., the inverse square of the white bars).

Observation-based products and models are combined into a single result in two ways. Firstly, we neglect common model uncertainties beyond the intermodel spread that is depicted by the model average, and compute the weighted average of models (dark red bar) and observations (dark blue bar): this is indicated by the magenta bar. As, due to common model uncertainties, model uncertainty can be larger than the intermodel spread, secondly, we also show the more conservative estimate of an unweighted, direct average of observations (dark blue bar) and models (dark red bar) contributing 50% each, indicated by the white box around the magenta bar in the synthesis figures.

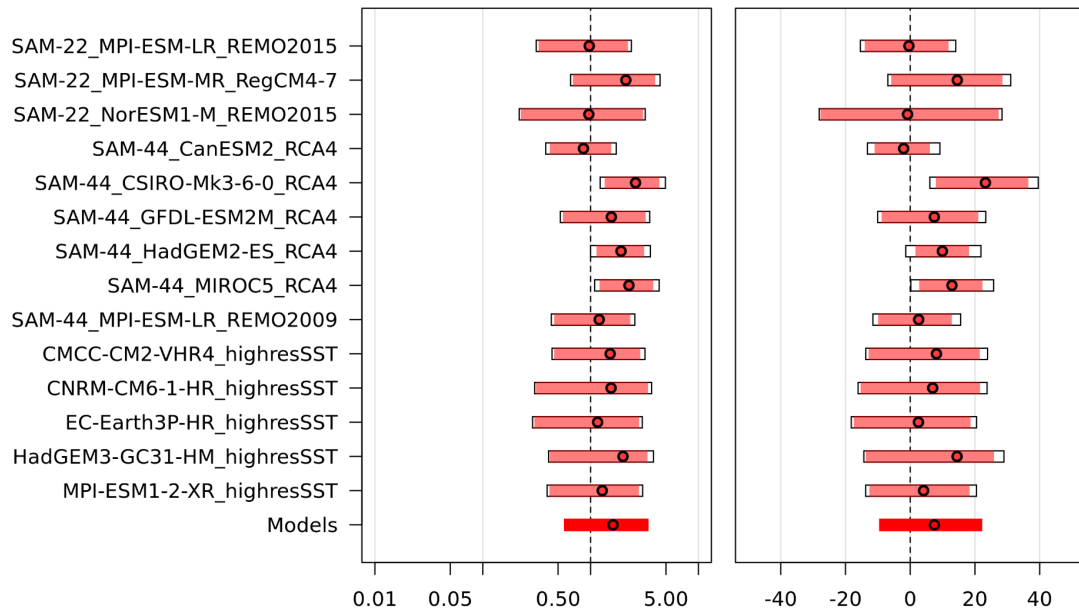


Figure 3.2: Synthesised changes in (left) likelihood and (right) changes in intensity of *PrcpFeb* in the study region when comparing (top row) the 2026 climate and a 1.3°C warmer climate representing the end of the century under current policies.

The synthesis of observations suggests an increasing likelihood and intensity of February precipitation as in 2026, but this has a substantial uncertainty, with a range of 0.006 to 80000 for the change in likelihood and -39% to +130% for the change in intensity (Table 3.1). This uncertainty arises due to the qualitative differences in the modelled trends between datasets, with datasets beginning around 1980 giving strong increasing trends and those from 1960 or earlier showing no trend due to a pronounced multi-decadal variability. An additional factor in combining multiple datasets is that while the longer-term datasets enable us to capture longer-term patterns of variability, the shorter datasets are based on data acquired during the satellite era, thus enhancing their reliability. This underlines the need for additional lines of evidence. Both circulation analogues and analysis of the Juiz de Fora weather station are consistent with a small increase in analogous wet season and February rainfall, respectively. Analysis of Rx30day also shows mixed trends but with decreases in the same shorter datasets that show increases for February, indicating a possible seasonal shift. In conclusion, if there is a trend in February precipitation associated with global warming, it has only recently begun to emerge.

The synthesis of evidence from climate models is consistent with no change in February precipitation at present, with a change in likelihood of a factor of 0.8 (0.3 to 7.3) and a change in intensity of -2% (-24% to +25%). This results in an overall synthesis of no change, with a change in likelihood of a factor of 0.9 (0.1 to 16) and a change in intensity of 0% (-28% to +39%). However, in a world with an additional 1.3°C of warming from present, climate models show a majority increasing trend, with 9 of 14 models showing an increasing trend and 5 consistent with no change. This results in an overall synthesis of increasing rainfall, with a change in likelihood of a factor of 1.6 (0.7 to 3) and a change in intensity of 7% (-8% to +20%).

Data	GMST		
		Probability ratio (95% CI)	Intensity change (%) (95% CI)
Observations	Past-Present	7.01 (0.006, 80000)	18.8 (-38.7, 130)
Models		0.84 (0.25, 7.32)	-2.23 (-23.5, 25.2)
Synthesis		0.92 (0.14, 15.6)	0.10 (-27.7, 38.8)
Models only	Present-Future	1.61 (0.65, 3.02)	7.45 (-7.67, 20.3)

Table 3.1: Summary of results for February rainfall, presented in Figs 3.1 & 3.2: changes due to GMST include past-present changes and present-future changes, for a world 1.3 cooler and warmer than present, respectively.

3.3 Conclusions from hazard attribution

Within the study region, a section of the lower Paraíba do Sul basin, landslides are driven by local-scale heavy rainfall. The heavy rainfall observed in the recent February event was not captured by the gridded reanalysis product (MSWEP) used in the location of Juiz de Fora, where a large number of the impacts were recorded. This hampers our ability to accurately assess the return period of the local-scale event. However, MSWEP did prove reasonably accurate at representing past February rainfall, suggesting that it is appropriate for use in studying trends (see Fig.2.1). Our analysis also focuses on the wider hydrobasin for this reason, as gridded products are likely more accurate over larger spatial scales. This also helps to assess hazards across this wider region.

Observational products starting at ~1980 onwards show an increasing trend in February rainfall, though longer datasets show a pronounced multi-decadal variability. It is therefore difficult to disentangle how much (if any) of recent trends are driven by variability or are emerging with warming, and to quantify changes associated with warming. Meanwhile, the observed trends in Rx30day similarly show mixed trends, with the shorter datasets suggesting a recent decrease but the same multi-decadal variability evident in the longer dataset. This is likely driven by changes in the wettest months of the year (primarily December and January), as e.g. discussed in [Reboita et al., \(2023\)](#) who find a significant shift towards a later onset of the rainy season with global warming.

On February rainfall, models show mixed trends at present, aligning with the high uncertainty in observations. However, with an additional 1.3C of global warming from present day, the same models show a systematic shift towards increasing rainfall. While 5 out of 14 models show best estimates close to 0, suggesting no change, the remaining majority suggest a rising likelihood and intensity of extreme February precipitation. This results in a synthesis suggesting a rise in the likelihood of a factor of 1.6 (0.7 to 3) and a change in intensity of 7% (-8% to +20%). This aligns with expectations

from the literature discussed in section 1.2, including the latest [IPCC assessments](#) and suggests that trends in extreme February precipitation will emerge with additional warming, if they have not already.

4 Vulnerability and exposure

Understanding disaster risk requires attention not only to hazards, but also to vulnerability, exposure, and coping capacity, which jointly determine how hazards translate into disasters. In risk frameworks such as those used by the IPCC ([Rod. Aall & Selseng, 2025](#)), disasters occur when hazardous events interact with exposed populations that have limited capacity to anticipate, cope with, and recover from impacts. Vulnerability refers to the social, economic, and physical conditions that increase susceptibility to harm; exposure describes the presence of people, systems, and assets in hazard-prone areas; and coping capacity reflects the ability of individuals, households, communities, and institutions to manage and reduce impacts. Together, these factors explain why similar hazards can produce very different impacts across locations.

The floods and landslides in Minas Gerais in late February 2026 illustrate this interaction. In Juiz de Fora, February precipitation exceeded 716 mm (Cemaden's rain gauge 313670216A), creating saturated soils and triggering flooding and widespread landslides. However, the scale of impacts was shaped by exposure and vulnerability. Risk assessments by Brazil's National center for Monitoring and Early Warning of Natural Disasters (Cemaden) estimated that approximately one-fourth of Juiz de Fora's residents (about 129,000 people) lived in areas susceptible to landslides and flooding, based on the 2010 Census and hazard mapping produced in 2012. However, a later assessment conducted by the Geological Survey of Brazil (SGB/CPRM) in 2017 - using its own risk-area mapping - estimated a smaller exposed population of roughly 59,000 residents in mapped risk areas ([CPRM, 2021](#)). This estimate ranked the city 9th nationally in terms of the share of residents living in high-risk areas ([Tavares, 2026](#)). More broadly, about one-third of municipalities in Minas Gerais (283) have elevated susceptibility to rainfall-related disaster, suggesting structural exposure across the state ([Levorato, 2026](#)).

Historical records from Cemaden and the municipal Civil Defense indicate a relatively low recurrence of landslides in Juiz de Fora until 2019, with annual occurrences typically remaining in the single digits ([Nogueira & Rodrigues, 2026](#)). However, from 2020 onwards, this pattern has changed, with a clear increase in recorded events to between 10-80 events annually, with the exception of 2025 hitting pre-2019 levels. The drivers of this apparent increase have not been investigated. Because Cemaden compiles its database from multiple reporting sources, part of this increase may reflect improved reporting rather than only higher occurrence. However, the number of Cemaden rainfall alerts has also risen since 2020, suggesting more frequent and/or intense rainfall events. Strikingly, by 27 February 2026, around 1,200 rain-related incidents have already been registered in the municipality. These records refer to incidents attended by the Civil Defense during the extreme rainfall period and may include a range of rain-related impacts, rather than solely slope failures. For comparison, Cemaden's database, tracking reported landslide impacts since 2016, shows a previous annual peak in 2023.

This analysis examines disaster risk through several interconnected dimensions, including sociodemographic and health conditions, and economic and livelihood contexts. It also considers spatial planning, settlement patterns, and land use land cover change, alongside key elements of flood and landslide risk management, including governance and policy frameworks, early warning early action, emergency response, and the role of insurance and social protection in supporting recovery and resilience going forward.

4.1 Sociodemographics

The population residing on steep slopes and deforested hillsides with reduced native vegetation is highly exposed to landslides. In contrast, people living in proximity to rivers and low-lying areas, especially in river valleys, are highly exposed to floods across the cities of Juiz de Fora, Ubá and Matias Barbosa in the state of Minas Gerais in Brazil ([BBC, 2026](#) ; [Petley, 2026](#)).

It is estimated that approximately 129,000 people live in the areas at risk of flooding and landslides in Juiz de Fora ([BBC, 2026](#)). Additionally, among approximately 16,000 dwellings and 52,000 residents in the high- and very-high-risk landslide zones in Juiz de Fora, nearly all (99.78%) are exposed ([CPRM, 2021](#)). Self-built houses with no foundation, made of low-resistance materials such as discarded wood and paperboard, amplify residents' vulnerability to landslides in settlements on near-vertical slopes ([Galvao, 2007](#)).

Older adults, children and residents with limited mobility face greater difficulty evacuating quickly from landslide-threatened slopes, and so, they are highly vulnerable to landslides in Juiz de Fora ([CPRM, 2021](#); [Santos et al., 2026](#)). In Ubá, residents and small businesses in the central district and low-lying neighbourhoods along the Ribeirão Ubá are particularly vulnerable to flooding, especially since half of the area is highly urbanised and falls within high or very-high flood-risk zones ([Paiva, 2024](#)). The workers in the furniture industry are also vulnerable in Ubá ([Neves, 2026](#)). The city of Matias Barbosa is the last city in the Rio Paraibuna basin before its confluence. As a result, residents of low-lying central neighbourhoods along the Rio Paraibuna, as well as families living in densely populated, unregulated housing along Córrego Monte Alegre and Córrego São Fidélis, are highly exposed to flood risks ([Silva, 2016](#) ; [Oliveira, 2026](#)).

The dwellers in low-income neighbourhoods are among the most vulnerable population groups due to floods, landslides, and mudslides, as they often inhabit the most hazardous areas, increasing their exposure to these hazards in the state of Minas Gerais ([Bloomberg, 2026](#)). In Minas Gerais state, one-fourth (25%) of the population lives in poverty or extreme poverty ([acaps, 2022](#)). Furthermore, ethnic minorities, such as Black and Brown (Pardo) communities, can also be considered a vulnerable population, as most of them are settled or relocated in areas that are more susceptible to hazards like landslides and floods ([IIASA, 2021](#)).

Juiz de Fora is one of the cities in the state of Minas Gerais that has experienced high positive migration balances and net-migration rates from 1980 to 2010 ([Carvalho, 2015](#)). Additionally, between 2003-21, Ubá's urban population has grown significantly ([Cruz, 2023](#)). Long-term in-migration has led poorer households to settle in high-risk areas such as slopes and floodplains, posing additional pressure on urban services and local governance ([Dias & Silva, 2016](#); [Cruz, 2023](#); [CPRM, 2021](#); [IIASA, 2021](#)). However, there is little to no evidence in favour of long-term migration or permanent displacement following disasters in these regions. Floods and landslides have caused short-term displacement. For instance, 3500 people have been reported displaced in Juiz de Fora due to recent flooding and landslides ([CTB, 2026](#) ; [IOM, 2026](#)). Additionally, heavy rainfall, followed by flooding, has displaced 160 people and left 35 homeless in Matias Barbosa ([Angelica, 2026](#)).

4.1.1 Health

Following the severe impacts of the 2024 Rio Grande do Sul floods, the ongoing floods have strained already recovering health-care systems and amplified a wide range of health consequences extending beyond immediate injuries and fatalities. As climate change contributes to shortening the time between disasters, researchers stress that effective public policies must go beyond planning and include sustained state investment in key sectors like health, with health systems adapted to climate change and resilient to disasters ([Escuri, 2024](#)).

The health system in Juiz de Fora, serving as a regional hub in Minas Gerais, is facing severe strain from the ongoing floods and has mounted a multi-level response involving local, state, and federal resources. According to key facilities such as Hospital de Pronto Socorro, Dr. Mozart Teixeira remained operational amid flooding, handling trauma cases despite 11 primary care units temporarily closing ([Ministry of Health, 2026](#)). A

multi-country study on the long-term health impact of flooding found that flood events have led to an increase in hospitalisation for various diseases, including cardiovascular disease, respiratory disease, infectious disease, and others. Conducted across 747 communities in eight countries, including the Amazon and the southern region of Brazil, between 2010 and 2019, the research highlights the prolonged and wide-ranging health consequences of flooding ([UNDRR, 2025](#)). Evidence indicates that floods have caused severe transportation disruptions, making hospital access difficult and delaying emergency response, leading to increased mortality as healthcare systems struggle to cope with the indirect impacts of flooding ([Yang et al., 2025](#); [Wassmer et al., 2025](#)).

Vulnerable populations living in poor socio-economic and sanitary conditions, with limited access to healthcare, face the greatest health risks during floods in Brazil. Contaminated floodwaters increase exposure to water-borne and vector-borne diseases, while damaged infrastructure delays medical treatment ([Teles et al., 2023](#); [España et al., 2024](#)). Children, the elderly, persons with disabilities, and people with pre-existing health conditions are particularly susceptible to water-borne and infectious diseases following floods, due to weaker immune systems and greater exposure to unsafe water and sanitation conditions ([Aggarwal et al., 2025](#); [Aziz et al., 2025](#); [Pham and Nguyen, 2025](#)). Standing water left after flooding creates ideal breeding grounds for mosquitoes, contributing to the spread of diseases such as dengue, a persistent public health challenge in Brazil ([Varzim et al., 2024](#); [Pereira, 2025](#)). Beyond physical illness, research also indicates a spike in mental health conditions like anxiety, post-traumatic stress disorder (PTSD), and depression as an aftermath of the 2024 floods. With limited access to sustained public mental health services, the findings emphasize the urgent need to strengthen psychosocial support networks, including family, community, and informal care systems ([Feter et al., 2026](#)).

During the 2024 floods, authorities implemented key public health measures, including the allocation of 1.2 million vaccine doses to prevent flood-related diseases such as hepatitis, rabies, and measles. Nevertheless, several people were exposed to water contamination, leading to a rise in waterborne illnesses. More than 7,800 cases of leptospirosis were reported in the following weeks, causing symptoms like fever, muscle ache, nausea and vomiting, alongside hepatitis A linked to a potential mixing of flood waters with sewage ([Pasqualotto et al., 2025](#); [BBC, 2024](#)). In the following weeks, 10 outbreaks of diarrhoeal diseases and 1,370 cases of venomous animal injuries were reported, further compounding the challenges faced by an already disrupted and overstretched healthcare system in providing timely diagnosis and treatment ([Pasqualotto et al., 2025](#)). While the full scale of health impact from the current floods will only become clear once water levels recede, the overall strain on the healthcare system and the extent of associated health risks remain uncertain.

4.2 Economic context, capacity and livelihoods

Recurrent floods in Brazil have significantly impacted people's livelihoods and local economies, causing immediate disruptions and prolonged recovery periods. The repeated flood events continuing into this year are placing additional strain on the already fragile and recovering economic conditions, thereby deepening financial instability for affected communities. The displacement of communities, destruction of homes and infrastructure, damaged roads and agricultural land have severely disrupted daily life and economic activity in heavily affected areas like Minas Gerais and other regions of the south. As per findings from the first European Climate Risk Assessment, climate risks are triggering cascading economic challenges as the pace of adaptation is not keeping up with scale and speed of disruptions ([European Environment Agency, 2025](#)). The total economic damages due to the 2024 floods in Brazil, were estimated at approximately US\$15 billion (adjusted for inflation), with less than US\$ 1 billion covered by insurance ([Murray News, 2024](#)).

Regions like Cerrado Mineiro in the state of Minas Gerais host large, highly mechanized coffee plantations and account for approximately 45–55% of Brazil's annual coffee production ([Solidaridad Network 2024](#)). However, coffee production in Brazil has been facing a serious climate-driven crisis with severe drought, hailstorm, and recurring floods, damaging extensive areas of arabica plantations and reducing output by an estimated 15-20%,

thereby driving prices higher up. Experts also highlight that recovery may be slow due to the increasing frequency of extreme weather events, including ongoing flooding in key production regions ([Matteo Borea, 2025](#)). According to official estimates, the 2024 floods in Rio Grande do Sul struck more than 206,000 rural properties, destroying crops, killing livestock, damaging storage and farm infrastructure, and disrupting vital production systems for smallholder farmers and cooperatives. These losses have hit both livelihoods and local food supplies, exacerbating economic and social vulnerability in one of Brazil's key agricultural regions. These impacts could mirror the effects in Minas Gerais, adding severe strain to the agriculture sector.

The current flooding in the Ubá region of Minas Gerais, one of Brazil's main furniture industry hubs, has resulted in more than seven reported deaths and widespread damage ([BBC, 2026](#)). The Intermunicipal Union of Furniture Industries of Ubá (Intersind) estimated total minimum losses of R\$16 million (approximately US\$ 3 million) for the furniture manufacturing hub, and the projection is to exceed R\$35 million (approximately US\$ 6.7 million) in Ubá due to the ongoing heavy rain in the region. Furthermore, around 55% of industries shut down completely, while 42% did so temporarily ([Neves, 2026](#)).

Juiz de Fora is the third most important industrial center in the state with important steel mills, automotive factories (Mercedes-Benz) and several textile factories situated in the area, making it an important trade center ([Tasca et al., 2013](#)). With at least 64 fatalities and more than 440 people stranded homeless, the floods have not only disrupted lives but also interrupted industrial operations, transport networks, and supply chains (*ibid*). The resulting shutdowns, infrastructure damage, and displacement of workers are likely to intensify economic stress, affecting production output, wages, small businesses dependent on industrial activity, and broader regional trade flows.

4.3 Land use land cover changes and exposure

Rapid and often unregulated urban expansion onto the steep slopes and floodplains has prevented natural drainage with impervious surfaces, amplifying the adverse impacts on people, basic services, and infrastructure. Rural-urban migration flows, followed by urban-urban migration from smaller to major cities, has pushed many incoming residents toward the outskirts of Brazilian cities that are exposed to higher risk ([Guedes et al., 2023](#)). Like in many urban areas, Juiz de Fora's affected neighborhoods include a mix of regular apartments, houses, and favelas, with the city hosting around 37 such settlements according to the Census on Brazilian favelas. Many of these, particularly in the Zona da Mata region, are located on hillsides prone to landslides and have been designated as zones for disaster monitoring. A 2021 assessment by the Geological Survey of Brazil (CPRM) identified 304 locations in Juiz de Fora classified as high or very high landslide risk, encompassing approximately 16,400 households, highlighting the scale of exposure associated with hillside occupation ([Lana, 2021](#)). A neighborhood-level study of the Três Moinhos settlement in eastern Juiz de Fora illustrates this dynamic: aerial photographic analysis traced the occupation of a hillside area where slopes exceed 30% across virtually the entire surface (the threshold that both federal and municipal law define as unsuitable for construction) showing that by 2000, already 97% of what would become the settlement's built footprint had been occupied, driven by the absence of affordable alternatives rather than any formal planning process ([Dias & Silva, 2016](#)).

According to Professor Cássia Ferreira from the Federal University of Juiz de Fora ([UFJF](#)), "The urbanization of the hills initially occurred with high levels of technical employment and good housing. But urban expansion led to housing of lower quality and poorer infrastructure by people who had less ability to hire an engineer to assist with structural issues" ([BBC Brazil, 2026](#)). A study examining underlying risk factors of the multi-hazard event that hit the North Coast of São Paulo, Brazil, in 2023 found that 46 % fewer buildings would have been damaged if the same event had happened around 2 decades earlier when the urban sprawl was not as much pronounced ([Moroz and Thieken, 2024](#)).

The city's historical expansion from the Paraibuna River valley has replaced natural vegetation with buildings, roads, and other impervious surfaces, reducing water infiltration and increasing surface runoff during heavy rainfall. Urban development in Juiz de Fora has been shaped by a long process of corridor expansion that began in the 19th century along the Paraibuna River valley and transport routes such as the Estrada União e Indústria, which supported coffee and mineral trade. Later industrialization, including the establishment of Industrial Districts I and II, and the Mercedes-Benz plant in 1996, reinforced growth toward the Benfica area roughly 10 km from the city centre. Today, this northwest area hosts roughly 75,000 residents across multiple districts, but expansion has often occurred with limited planning and infrastructure. Mapping of Juiz de Fora shows that the highest landslide risk areas are located on steep slopes with weak, fractured rock and easily eroded soils ([Rocha et al., 2010](#)). Even where population density is low, these areas remain highly vulnerable and rapid urban growth, especially industrial-driven expansion, has pushed low-income households onto these deforested, poorly serviced slopes.

Deforestation and the removal of riparian vegetation have weakened the land's ability to retain water and stabilize slopes. Combined with Juiz de Fora's steep topography and fractured geology, these landscape changes can saturate soils and increase landslide risk during intense rainfall ([Rocha et al., 2003](#)). In several neighborhoods in the northwest zone, including Benfica, Vila Esperança, and Santa Cruz, irregular slope cutting, water discharge, and waste management further destabilize hillsides, contributing to landslide risk. Prior research in Juiz de Fora had already identified empirical rainfall–landslide probability relationships from historical Civil Defense records, with landslide occurrence probabilities increasing to 82% when daily rainfall exceeded 50 mm, to 100% for daily totals above 100 mm in the observed sample, to 74% for 10-day accumulated rainfall ≥ 150 mm, and to 67% for 15-day accumulated rainfall ≥ 200 mm. These results indicate that the February 2026 disaster, while exceptional in magnitude, was broadly consistent with previously documented rainfall conditions associated with landslide occurrence in the municipality ([Fonseca et al., 2017](#)).

Similarly other cities, namely Ubá and Matias Barbosa have been affected by the floods mainly due to the high number of people living in highly exposed areas. Rio Ubá reportedly overflowed to historic levels (7.82m) causing massive flooding, landslides, major transport disruptions in Ubá city ([BBC Brazil, 2026](#)). The Paraibuna river, which overflowed, submerged large parts of the city of Matias Barbosa causing landslides and disrupting highways like BR-040 and BR-267 ([Correi de Minas, 2026](#)). Flooded roads isolated hospitals, delaying ambulances, staff arrivals, and supply deliveries like medications and food ([Ministry of Health](#)).

In Juiz de Fora, the hardest-hit city, downtown stores endured repeated damage from initial storms and follow-up rains, with extensive stock losses, water-damaged interiors, and urgent cleanups that idled sales for over a week. Public transport shutdowns isolated suppliers and customers, amplifying losses for retail and services representing much of the city's commerce ([CVT News, 2026](#)).

In response to 2024 Rio Grande do Sul floods, several Brazilian cities have implemented innovative flood resilience measures, often blending nature-based solutions with urban planning, drawing lessons from past disasters ([UNDRR, 2025](#)). Partnering with TU Delft, the Municipality of Porto Alegre installed temporary water level sensors (divers) at 10 locations along the Jacuí River Delta, Guaíba River, and Patos Lagoon to improve real-time monitoring during wet seasons ([NEA, 2024](#)).

These examples illustrate that the exposure and vulnerabilities of urban areas to hazards are hugely defined by how and where the cities are built and to what extent the risk information and nature based solutions are integrated into the urban planning policy and practice.

4.4 Flood and landslide risk management

4.4.1 Governance, policies, and plans

Flood and landslide risk governance in Brazil is structured across federal, state, and municipal levels. At the federal level, disaster risk management is coordinated through the Sistema Nacional de Proteção e Defesa Civil (SINPDEC), led by the Ministry of Integration and Regional Development via its Secretaria Nacional de Proteção e Defesa Civil (SEDEC), with technical support from Centro Nacional de Monitoramento e alertas de Desastres Naturais (CEMADEN, for monitoring and early warnings and studies supporting decision-making in disaster risk management), Brazilian Geological Survey (CPRM/SGB, for geo-hydrological risk mapping), Agência Nacional de Águas e Saneamento Básico (ANA, for hydrological monitoring and flood forecasting), and Instituto Nacional de Meteorologia (INMET, for meteorological forecasts and meteorological warnings) ([Government of Brazil, 2016](#); [GFDRR, 2021](#)).

Municipal governments hold legal responsibility for local disaster risk management through municipal civil defense units, operating under their mayors within SINPDEC and the Minas Gerais state system ([Government of Brazil, 2016](#)). In practice, municipalities play a critical role in land use planning, enforcement of building regulations, local risk mapping, and emergency response. Effective risk reduction requires integrated spatial planning that prevents occupation of high-risk slopes and flood-prone areas, combined with watershed management, risk education, and community preparedness. In Juiz de Fora, however, studies suggest challenges in fully aligning regulatory frameworks with settlement patterns. Although Municipal Law 6.908/1986 prohibits construction on slopes of 30% or greater without specific authorization, 56% of the landslide risk points mapped by Civil Defense in the city (124 of 222) are located on slopes at or above this threshold. These areas are predominantly occupied by low-income households, reflecting broader constraints to housing availability and urban development pressures ([Fonseca et al., 2017](#); [Dias & Silva, 2016](#)).

Policy frameworks include the National Climate Change Policy (Law 12.187/2009), which mandates climate change adaptation and vulnerability reduction, while the National Civil Protection and Defense Policy (Law 12.608/2012) provides the core disaster risk management framework covering risk mapping, monitoring, emergency declarations, and recovery ([Sales & de Queiroz, 2025](#); [Presidência da República, 2012](#)). More recently, the National Policy for Integrated Disaster Risk Management, approved by the Senate in 2024 and pending full enactment as of 2026, signals a shift from reactive disaster response toward more anticipatory risk management ([Agência Senado, 2024](#)). Despite these legal frameworks, implementation capacity varies across municipalities. Survey data from the 2020 IBGE MUNIC study indicate that only about 43% of Brazilian municipalities have adopted at least one formal disaster risk management policy instrument, such as flood risk mapping or local warning systems ([Alves et al., 2025](#)).

Several structural mitigation projects have been proposed or approved in high-risk municipalities. For example, slope stabilization works in Juiz de Fora have received funding through the federal Growth Acceleration Program (PAC), along with earlier investments ([Tavares, 2026](#)). A case in point is the Três Moinhos settlement, formally recognized since 2000 in Juiz de Fora's Municipal Development Plan as an area requiring intervention, where the only significant structural investment delivered over more than a decade was a single PAC-funded retaining wall completed in 2014 - described by researchers as providing safety to only a small portion of the area while leaving the broader settlement's risk conditions unchanged ([Dias & Silva, 2016](#)). However, the pace of implementation can depend on administrative procedures and coordination between levels of government. Research on disaster risk management policies in Brazil suggests that the effectiveness of local measures often depends not only on their adoption, but also on governance quality, institutional capacity, and the availability of financial resources to sustain preventive investments ([Alves et al., 2025](#)).

More broadly, the availability of financial resources for disaster prevention has fluctuated in recent years. Budget allocations for rainfall-related risk reduction programs in Minas Gerais have declined significantly between 2023-2025 ([Salgado, 2026](#)), while federal spending constraints and competing priorities have also hindered preventive investments. This reflects a widespread governance challenge identified by Alves et al.

(2025), namely that political and financial incentives may sometimes prioritize post-disaster relief spending over long-term prevention investment.

4.4.2 Early warning and early action

Cemaden issued early warning No. 0949/2026 for landslide-related disaster risk in Juiz de Fora, Minas Gerais, on 19 February 2026 at 22:13, with a Moderate risk level, based on the cumulative rainfall observed during the first weeks of February (more than 200 mm), the intense rainfall occurring at the time of issuance, the forecast for continued precipitation, as well as the high susceptibility to mass movements and the large population living in areas exposed to geo-hazards. The alert remained in effect until 23 February, during which isolated intense rainfall persisted and was sufficient to trigger localized landslides on 20, 21, and 22 February. On 23 February at 18:57, as rainfall intensified according to rain gauge and satellite observations, the early warning 09:49 was updated to high risk, with accumulations reaching 46 mm in 1 hour and 201 mm in 72 hours. Given the forecast of continued rainfall, the alert then indicated a high probability of multiple rainfall-induced landslides, as well as scattered failures on natural slopes, with high impact potential.

It is also important to note that Cemaden's daily geo-hydrological disaster risk forecast bulletins ([Cemaden, 2026](#)), issued during the early morning hours and valid for the same day, had already indicated Moderate disaster risk related to landslides for the Intermediate Geographic Region of Juiz de Fora on 20, 21, and 22 February. For 23 and 24 February, the forecast risk level was High, consistent with the observational evidence available at the time and aligned with the municipal alerts that were issued or remained in effect during the event.

There is a value chain for disseminating and enriching warnings from the meteorological office to the citizens. In general, INMET meteorological warnings are intended to indicate conditions favorable to the occurrence of adverse atmospheric phenomena and, precisely because of this meteorological scope, they do not by themselves constitute an integrated disaster risk analysis; rather, they support broader preparedness actions and provide input for subsequent risk-assessment stages. Next, Cemaden's geo-hydrological risk forecast bulletins translate meteorological forecasting into the potential occurrence of processes such as flash floods, floods, and mass movements, by combining rainfall forecasts with current hydrological and geological risk conditions over broader regional domains. As the event evolves and additional evidence, especially observational data, becomes available, Cemaden disaster risk alerts support decision-making at the municipal scale. Finally, Civil Defense public alerts are intended to communicate imminent risk to the population and to guide self-protection measures.

The municipality of Juiz de Fora operates an early warning system that includes sending text messages to the residents ([Agência Brasil, 2026](#)). A resident from Juiz de Fora reported that they had not received official warnings about the landslides and noted that sirens could have helped alert citizens about the risks they were facing, however sirens are not considered effective by the municipality because of the topography of the terrain ([Agência Brasil, 2026](#)). Possible reasons for the lack of preventive action following the warning by the government is that some residents who have lived in the area for a long period might underestimate the risk and others might not have any other place to evacuate to ([Agência Brasil, 2026](#)). Juiz de Fora was in 4th place of cities that had received the most warnings in 2025 across Brazil, with the most common warnings being related to flooding and landslides of inhabited slopes. These warnings are sent directly to Defesa Civil to support local decision-making, however local authorities are unable to process all warnings adequately, leading to a lack of preventive actions ([BBC, 2026](#)).

Marengo et al. (2025) investigated the role of Cemaden following the 2024 flooding in the state of Rio Grande do Sul, southern Brazil. Findings from that study show that although early warning signals were raised, it was often not clear how to follow-up on these signals as only 23% of the affected municipalities had early warning protocols in place. Further, the authors note there was too much fragmentation of information and they recommended a better integration of information. Also, it was advised to move from hazard-based, to

impact-based warning flood warning systems and develop vulnerability-specific warning systems (e.g., for individuals that are not able to easily evacuate by themselves). A final reported recommendation was to improve the disaster risk perception, to increase the willingness of individuals to take early action. Considering the recency of that publication, it provides relevant background to the 2026 Minas Gerais flooding event.

4.4.3 Emergency response

Response efforts involved coordinated action across federal, state, municipal, and civil society actors. The federal government mobilized emergency funding (R\$2.9M, R\$1.2M and R\$1.2M for Juiz de Fora, Matias Barbosa, and Ubá, respectively) and inter-ministerial coordination, releasing financial resources for rescue operations, humanitarian assistance, and early recovery in affected municipalities, while rapidly recognizing states of calamity to unlock additional support ([Secretaria de Comunicacao Social, 2026](#)). In total, R\$16.1M was allocated by late February for assistance and recovery in affected areas.

At the state level, the government of Minas Gerais strengthened operational response by activating its emergency coordination structures and deploying additional firefighters, search-and-rescue teams, and specialized equipment to the most affected municipalities, while issuing evacuation orders for high-risk zones including Juiz de Fora ([Ferreira, 2026](#)).

Municipal governments prioritized immediate relief measures, including evacuations, establishment of temporary shelters, distribution of essential items, and road and urban clearance to restore access to critical services ([MPMG, 2026](#); [Parreiras, 2026](#)). Local civil defense teams also conducted rapid risk inspections and stabilization works in vulnerable areas. Humanitarian organizations, volunteers, and international agencies complemented these efforts by supporting shelter management, providing relief items and meals, and assisting affected populations.

4.4.4 Insurance and social protection

Brazil has been actively adapting its social protection system to provide support to affected populations during shocks, demonstrating how existing social protection programmes can be scaled effectively in the face of extreme weather events. The 2024 floods in the state of Rio Grande do Sul that affected more than 2 million people led the government to implement some measures to support vulnerable groups in recovery. For instance, the payment of upcoming instalments of major social benefits were advanced by a month, including the Bolsa Familia for low income families, the tax financed pension Beneficio de Prestação Continuada and the Government's annual salary bonus Abono Salarial for low wage workers in affected municipalities ([ILO, 2024](#)). The Government also expanded social protection coverage by enrolling more than 21,000 additional families into the national social assistance programme Bolsa Família after they lost income due to the floods (ibid). Further operational adaptations to social protection system components included enabling alternative payment access for beneficiaries who had lost identification documents, deploying mobile payment units in flooded areas, and extending deadlines for updating registry information to ensure continued access to benefits (ibid).

In addition to these, given the massive infrastructure loss in the country, one-off reconstruction payment of around USD 1,000 was given to approximately 240,000 families in affected areas. Income continuity for affected individuals was ensured by letting workers withdraw up to USD 1,200 from mandatory severance accounts and extending unemployment benefits by two additional payments during the period of emergency. Other complimentary policy actions included temporarily suspending mortgage payments of social housing loans like Minha Casa and Minha Vida along with introducing targeted income tax rebates (ibid). Furthermore, the provision of shock-responsive social protection assistance for the 2024 flood response included the introduction of new initiatives such as the emergency Programa Volta Por Cima at the state level, backed by climate disaster exposure data to target affected populations. Drawing on Brazil's Single Registry (Cadastro Único), the government delivered a one-off payment of approximately US\$450 to households left homeless by the floods, highlighting how existing social protection data enabled a rapid and targeted response in affected

areas ([Tebalsi, 2025](#); [McCord and Ridout, 2025](#)). Along similar lines, private donations were channelled to more than 37,000 families using the national registry who were not eligible for state support as their family income was above the cut-off. National companies were also incentivised to keep jobs active for 100,000 workers for a 4-month period during the reconstruction process, thereby indicating targeted labour market interventions to recover from the impacts of the shock (ibid).

Although detailed information on all social protection measures to combat the impacts of the ongoing floods remain limited, the National Social Assistance Task Force (FORSUAS) under the Ministry of Development and Social Assistance, Family and Fight Against Hunger, has been mobilised to support for the February 2026 flood-affected areas. In coordination with the International Organization for Migration (IOM), volunteers are providing technical assistance to shelters hosting displaced families. Additionally, civil society initiatives have complemented national and state-level efforts, with crowdfunding platforms like Vakinha raising funds to provide clean drinking water, food and hygiene supplies to affected communities ([IOM, 2026](#)). The federal government has also allocated USD 660,000 for reconstruction efforts and humanitarian assistance ([Aljazeera, 2026](#)). As demonstrated during the 2024 floods, social protection programmes can be effective when informed by climate risk forecasts to deliver shock-responsive benefits, including the potential for extension and scale-up under various climate-risk scenarios to support affected populations that might otherwise fall outside regular programme coverage. Similar efforts will be required in this instance, building on Brazil's robust social protection systems and its established experience in delivering comprehensive support to affected populations.

5 Conclusions

In conclusion, the risk of landslides is very high in all three components of risk: hazard, exposure, and vulnerability. In order to reduce this risk, all three areas need to be addressed.

More intense and prolonged rainfall saturates soils, reduces slope stability, and raises the likelihood of slope failure. As precipitation intensity increases with further warming, landslide hazards will also increase. Addressing this requires both local risk reduction measures and global climate mitigation efforts, including rapidly reducing and ultimately stopping the burning of fossil fuels.

Exposure remains very high in landslide-prone areas, where settlements and infrastructure are located on or below unstable slopes. Reducing risk will therefore require improved land-use planning, slope stabilization, monitoring systems, and careful management of development in high-risk terrain.

Vulnerability must also be reduced through stronger and more adaptive social and institutional systems. Brazil's past flood responses demonstrate how existing social protection mechanisms can be quickly adapted to support affected populations, through advanced payments, expanded coverage, and targeted emergency transfers. As climate change shortens the time between disasters, sustained investment in resilient public services, particularly health systems, will be essential to protect communities.

Data availability

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

Acknowledgements

We'd like to acknowledge Dr Gareth Marshall for rapidly providing both preliminary and updated data for the Southern Annular Mode analysis. We'd also like to acknowledge the assistance of Dr Lincoln Alves in providing up to date weather station data for this analysis.

This work used a number of services for data provision and computing resources:

- JASMIN, the UK's collaborative data analysis environment (<https://www.jasmin.ac.uk>)
- Imperial College Research Computing Service, DOI: 10.14469/hpc/2232
- The KNMI Climate explorer web tool (<https://climexp.knmi.nl/start.cgi>).

References

All references are given as hyperlinks in the text.

Appendices

A1 Data and methods

A1.1 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:

- **CRU TS** - The Climatic Research Unit gridded Time Series version 4 (CRU TS v4) multivariate dataset is available for all land regions except Antarctica, at 0.5° spatial resolution and from 1901-present, updated annually ([Harris et al., 2020](#)). It is constructed using monthly climate observations, interpolated from networks of weather stations using angular distance weighting. In this study we use precipitation data from this dataset.
- **MSWEP** - The Multi-Source Weighted-Ensemble Precipitation v2.8 dataset (updated from [Beck et al., 2019](#)) is fully global, available at 3-hourly intervals and at 0.1° spatial resolution, available from 1979 to ~3 hours from real-time. This product combines gauge-, satellite-, and reanalysis-based data, including ERA5.
- **CHIRPS** - The rainfall product developed by the UC Santa Barbara Climate Hazards Group called “Climate Hazards Group InfraRed Precipitation with Station data” (CHIRPS; [Funk et al. 2015](#)). Daily data are available at 0.05° resolution, from 1981-31 Jan 2026. The product incorporates satellite imagery with in-situ station data.
- **GPPC** - This is the Full Data Monthly Product Version 2022 of monthly global land-surface precipitation totals from rain-gauges built on GTS and historical data. It is provided at a regular latitude/longitude grid with a spatial resolution of 1.0 x 1.0 degree and covers the time period from January 1891 to December 2020 ([Schneider et al., 2022](#)).
- **BR-DWGD** - Brazilian Daily Weather Gridded Data (BR-DWGD) is available for the entire land surface of Brazil at spatial resolution of 0.1° x 0.1°, from 1961/01/01-2024/03/20 ([Xavier et al., 2022](#)).
- **Juiz de Fora weather station** - We use daily accumulated rainfall from 1960-01-01 to 2026-02-28. Station details: latitude -21.77 °N, longitude -43.36 °E, INMET station code A518, GHCN-D code BR002143012.

To characterise the large-scale drivers affecting these extremes indices, we use the following datasets as covariates:

- 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](#)). To remove the effect of the El Niño - Southern Oscillation on global mean temperatures, we use a four-year running mean of the GMST, centred on the third year.
- As a measure of the Southern Annular Mode (SAM) we use the station-based index of zonal pressure difference between the latitudes of 40°S and 65°S, based on normalised monthly sea level pressure from six stations at each of these two latitudes ([Marshall, 2003](#); data access via <https://legacy.bas.ac.uk/met/gjma/sam.html>). We detrend the SAM by regressing against the

smoothed GMST time series and subtracting the fitted trend, to ensure that the two time series are not confounded. The whole contribution from global warming is therefore associated with the GMST covariate, even when mediated via changes in the SAM.

A1.1.1 Trends from 1979

Dataset	Event magnitude (mm/day)	Return period (years)	Influence of GMST	
			Probability ratio	Change in magnitude (%)
MSWEP*	9.93 (10.4)	7.63 (2.76, 77.9) (10)	6.67 (0.085, 166000)	26.2 (-26.8, 140)
BR-DWGD (1979 onwards)	9.34	10	5.26 (0.03, 10 ⁹)	24.0 (-39.3, 184)
CHIRPS	11.6	10	430 (0.33, 10 ⁹)	63.2 (-10.2, 193)
CRUTS (1979 onwards)	10.5	10	9.61 (0.003, 10 ⁹)	30.5 (-48.9, 187)

Table A1.1: The same as Table 2.1 but with all datasets restricted to 1979 onwards. Observed and expected event magnitude and the corresponding return period of PrcpFeb in the present climate in the study region in the four observation-based datasets, as well as the estimated change in probability ratio and magnitude for PrcpFeb in the study region due to GMST. *The probability ratio shown is for the 10-year return period event.

A1.2 Model and experiment descriptions

We use 2 ensembles of climate models from climate modelling experiments using very different framings ([Philip et al., 2020](#)): Sea Surface Temperature (SST) driven global circulation high resolution models, coupled global circulation models and regional climate models.

1. Coordinated Regional Climate Downscaling Experiment CORDEX-CORE (11 models with at 0.44° resolution (SAM-44) and 6 models at 0.22° resolution (SAM-22)) multi-model ensemble ([Giorgi and Gutowski, 2015](#); [Giorgi et al., 2021](#)), comprising 14 simulations resulting from pairings of Global Climate Models (GCMs) and Regional Climate Models (RCMs)). These simulations are composed of historical simulations up to 2005, and extended to the year 2100 using the RCP8.5 scenario.

2. 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) data, and combined with

greenhouse gas forcings from SSP5-8.5 (CMIP6) simulations (see Section 3.3 of Haarsma et al. 2016 for further details). We only used models from this ensemble with a horizontal resolution of 50 km or lower to reflect the small spatial scale of the domain used and the extreme rainfall.

A1.3 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 3-6, are: (3) trend estimation from observations; (4) model validation; (5) multi-method multi-model attribution; and (6) synthesis of the attribution statement.

In this report we analyse time series of February mean precipitation in the hydrobasin around Juiz de Fora. A nonstationary normal distribution is used to model this index. 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. This formulation reflects the Clausius Clapeyron relation, which implies that precipitation scales exponentially with temperature ([Trenberth et.al., 2003](#), [O’Gorman and Schneider 2009](#)).

For each time series we calculate the return period and intensity of the event under study for the 2026 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.

The variable of interest, X , is assumed to follow a normal distribution in which the location and scale parameters vary with both GMST:

$$X \sim NORM(\mu, \sigma \mid \mu_0, \sigma_0, \alpha, T),$$

where X denotes the variable of interest, rainy-season precipitation; T is the smoothed GMST; μ_0 , σ_0 and ξ are the location, scale and shape parameters of the nonstationary distribution; and α is the trend due to GMST. As a result, the location and scale of the distribution have a different value in each year, determined by the GMST. Maximum likelihood estimation is used to estimate the model parameters, with

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

A2 Analogues

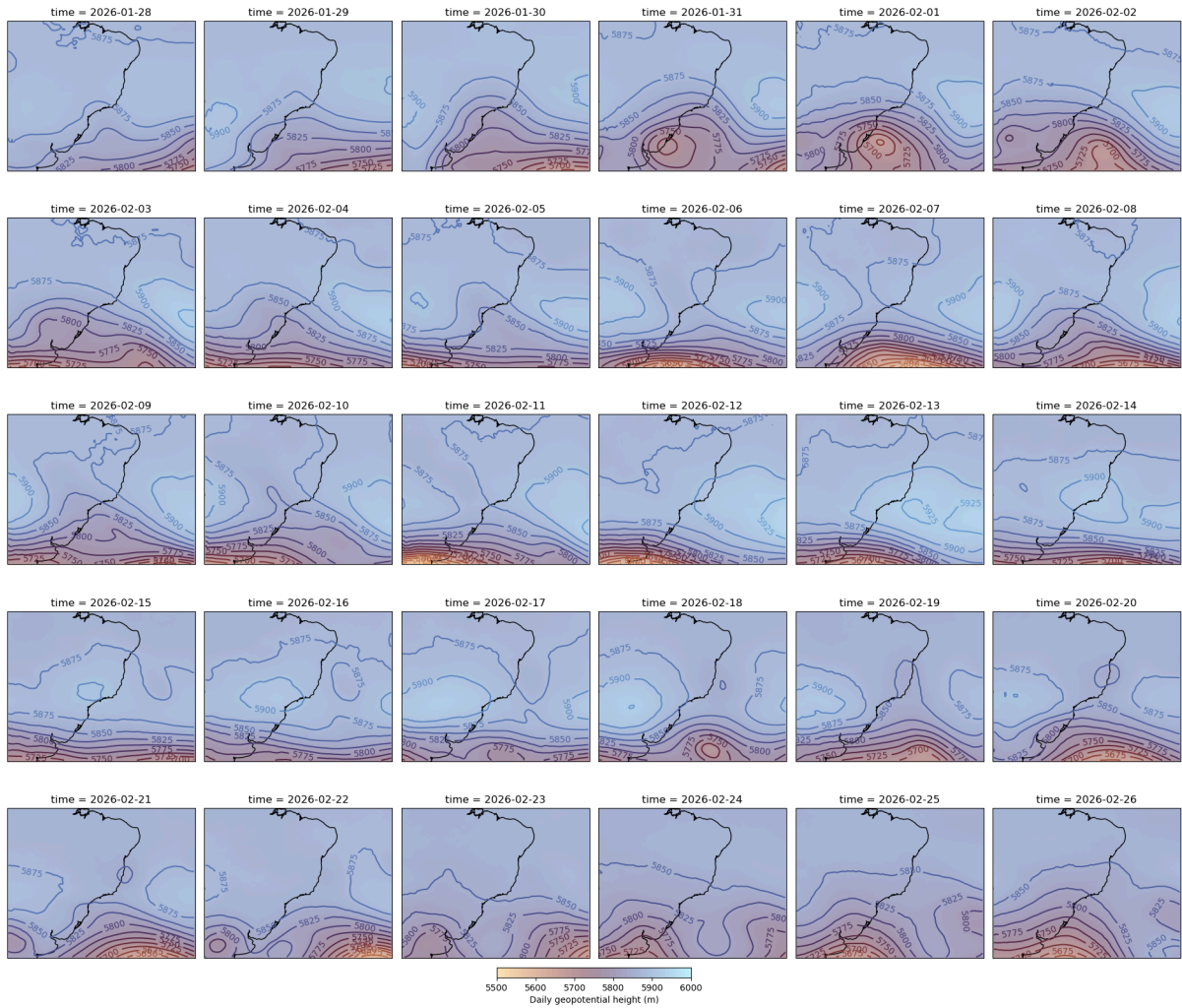


Figure A2.1: Daily field of Z500 over a region around southeastern Brazil and the western Atlantic ocean, during the 30 days leading up to 26th February 2026.

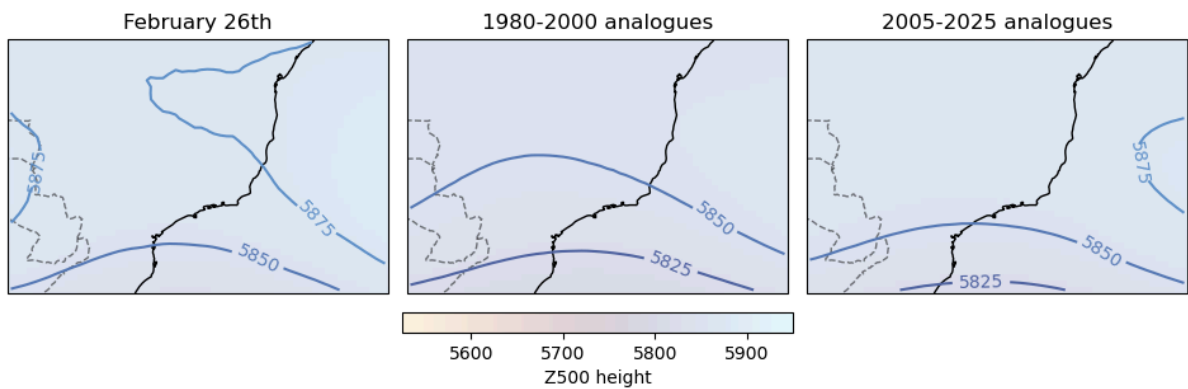


Figure A2.2: Composite plots of Z500 for 3 periods: the 30-day event leading up to 26th February 2026 (left), all analogues within the 1980-2000 past period (middle), and all analogues within the 2005-2025 present period (right). This figure is the same as Fig. 2.6 but with the same colourbar as the daily fields above for direct comparison.

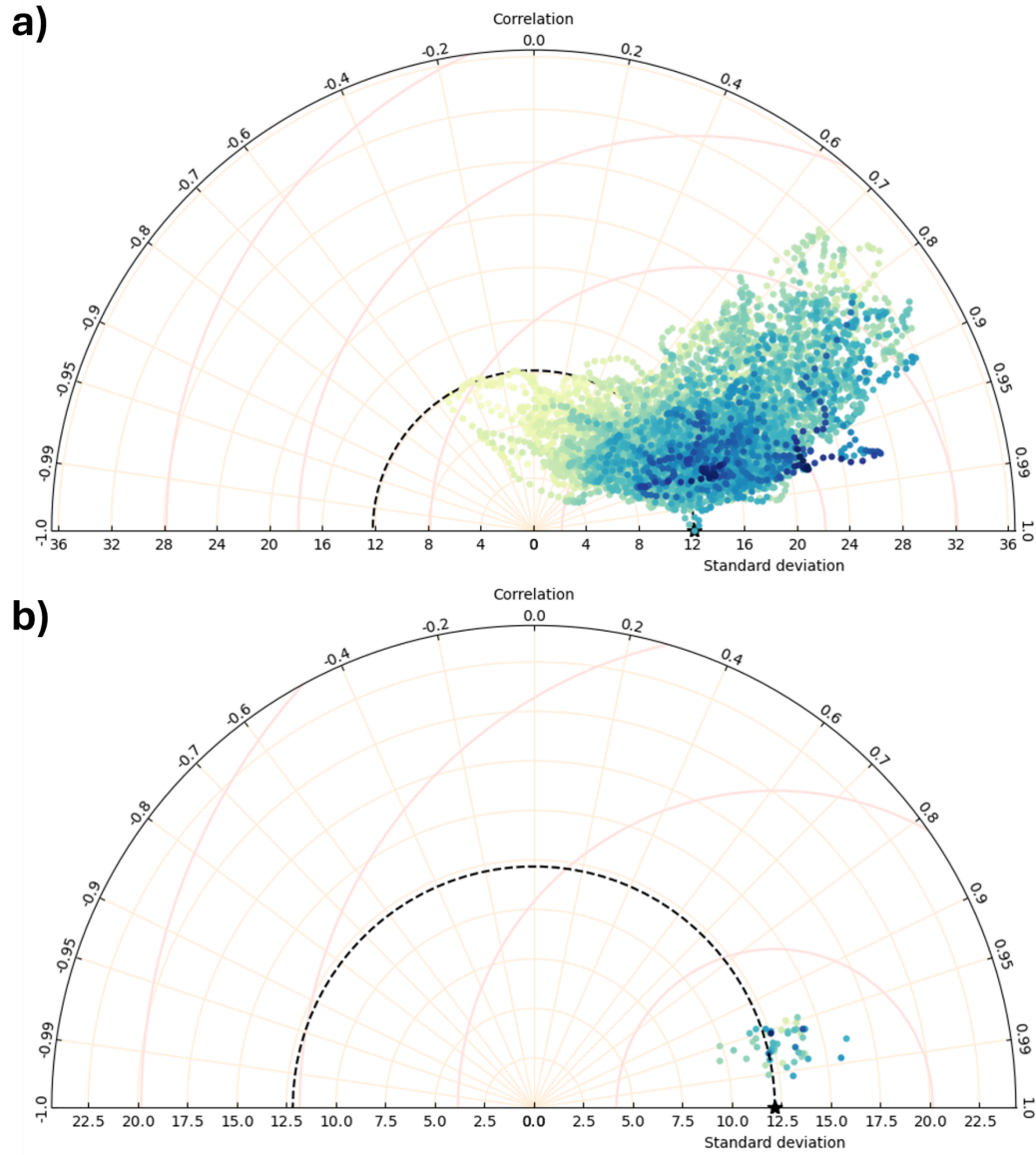


Figure A2.3: Taylor diagrams illustrating the ranking of analogues across different metrics including Euclidean distance and spatial correlation. The colour of each point represents the total precipitation of the previous 30 days, with darker blue meaning higher precipitation. a) All days after calculating the rolling 30-day mean of Z500 field. b) Selected analogues after ranking by Euclidean distance and requiring a minimum separation of 35 days between analogues.

A3 Model evaluation

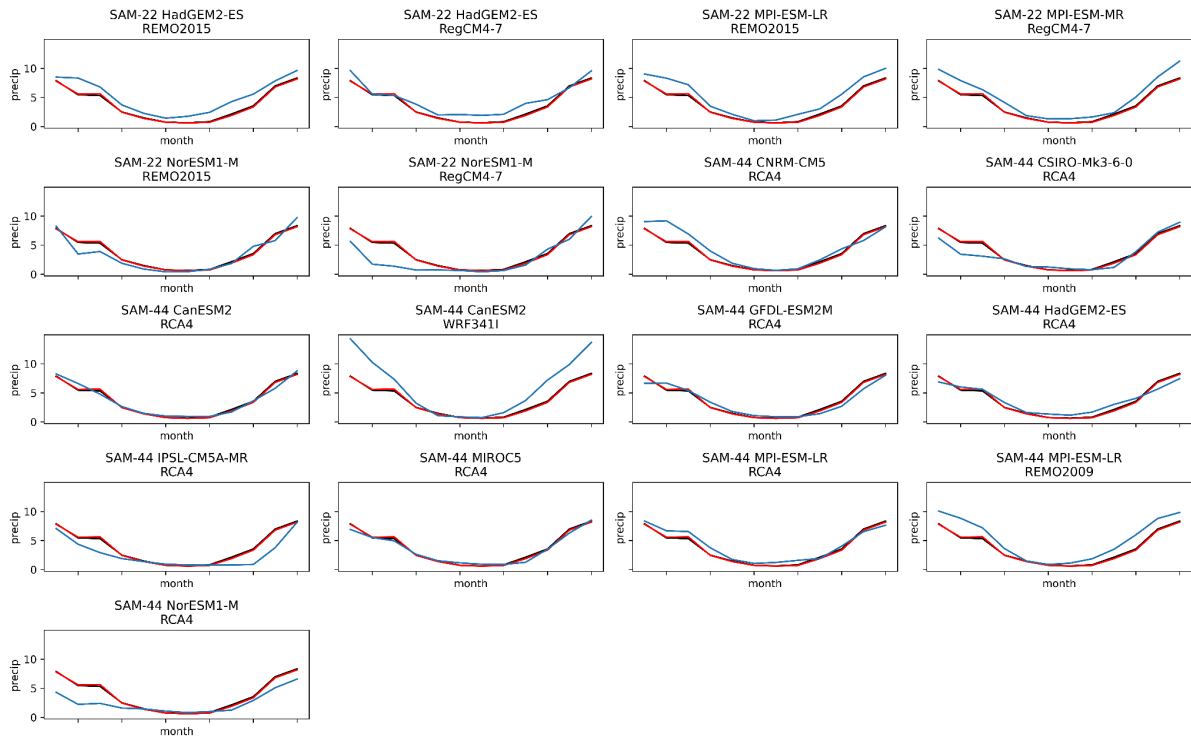


Figure A3.1: Seasonal cycles of monthly rainfall in observations (MSWEP and CHIRPS, black and red) and CORDEX-SAM models (blue), for climatological period 1991-2020.

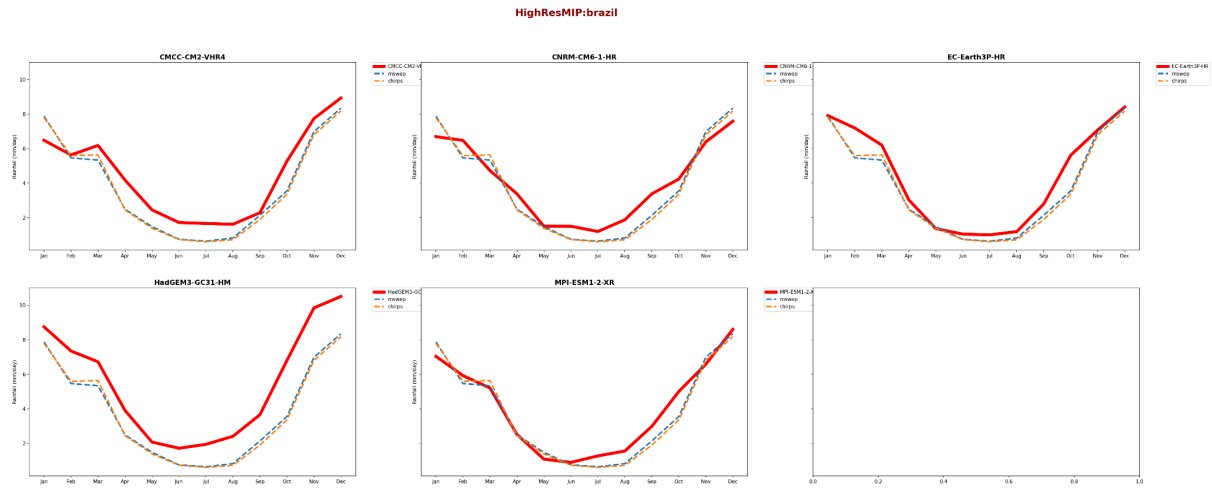


Figure A3.2: Seasonal cycles of monthly rainfall in observations (MSWEP and CHIRPS, blue and orange) and CORDEX-SAM models (red), for climatological period 1991-2020.

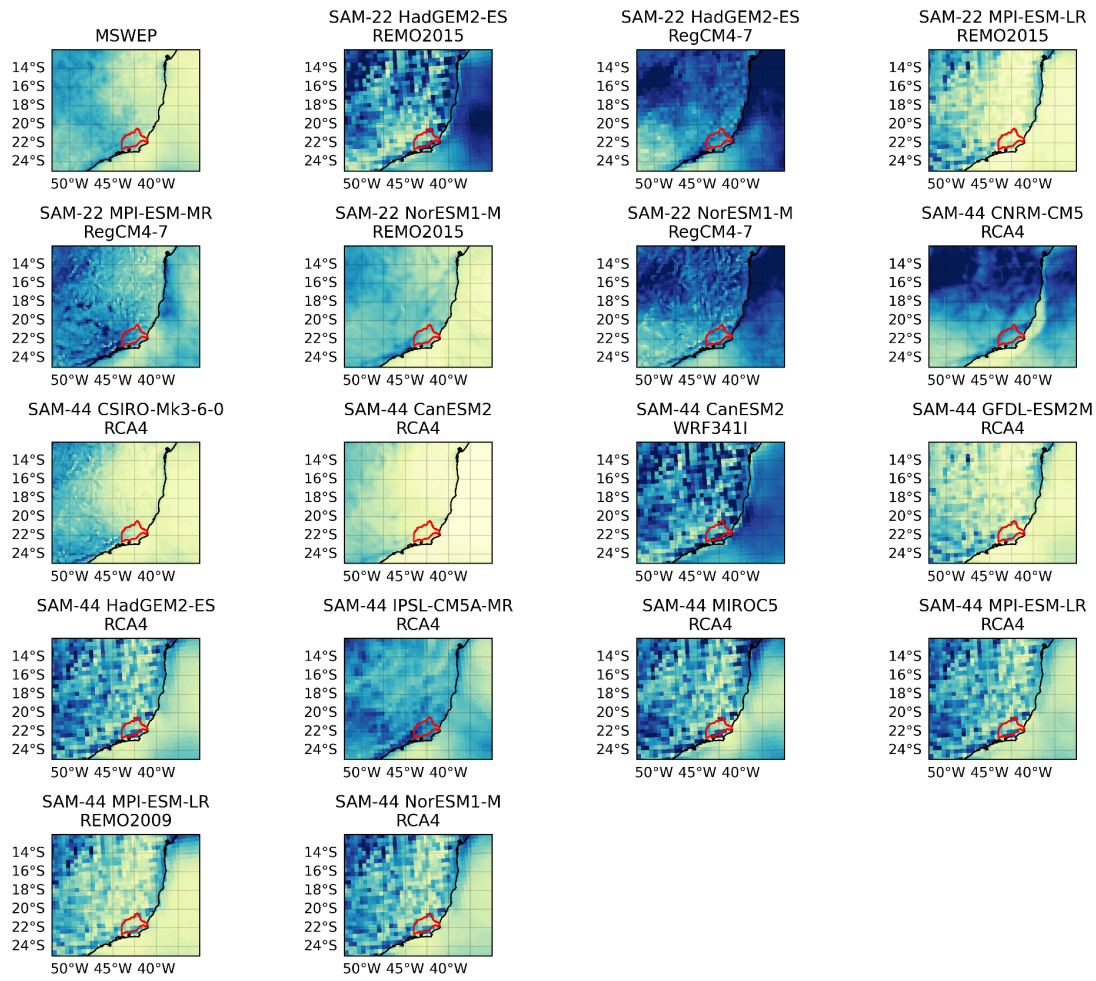


Figure A3.3: Spatial patterns of rainfall during February in observations (MSWEP) and CORDEX-SAM models, for climatological period 1991-2020.

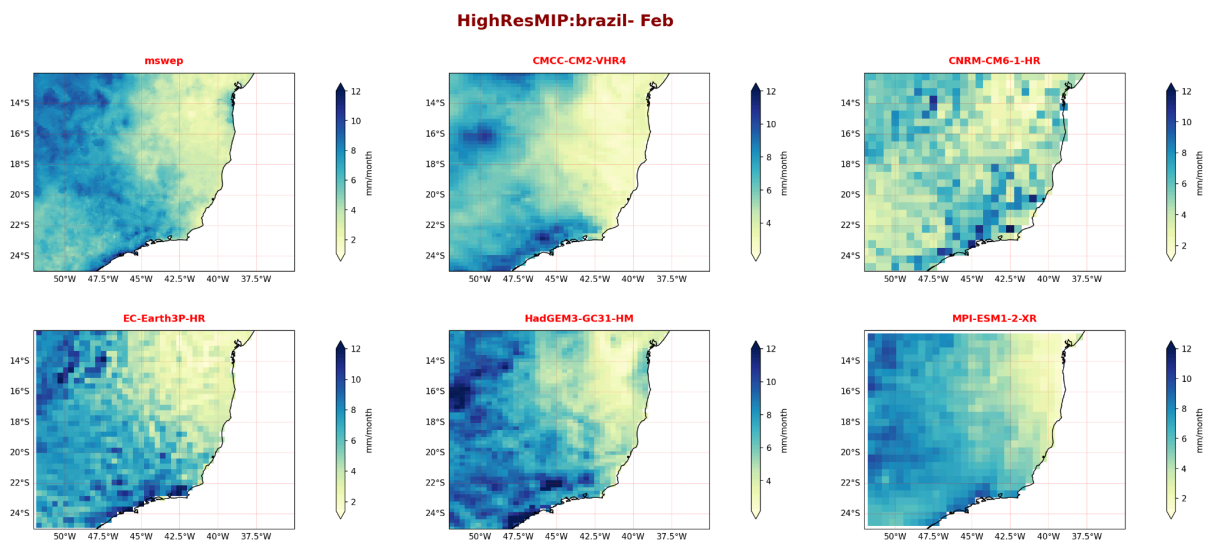


Figure A3.4: Spatial patterns of rainfall during February in observations (MSWEP) and HighResMIP models, for climatological period 1991-2020.

Model / Observations	Seasonal cycle	Spatial pattern	Dispersion	Conclusion
BR-DWGD			0.514 (0.427 ... 0.596)	
CHIRPS			0.449 (0.347 ... 0.537)	
CRUTS			0.437 (0.383 ... 0.483)	
MSWEP			0.475 (0.372 ... 0.558)	
HighResMIP				
CMCC-CM2-VHR4_highresSST (1)	good	good	0.542 (0.415 ... 0.647)	good
CNRM-CM6-1-HR_highresSST (1)	good	reasonable	0.437 (0.324 ... 0.545)	reasonable
EC-Earth3P-HR_highresSST (1)	reasonable	good	0.400 (0.302 ... 0.498)	reasonable
HadGEM3-GC31-HM_highresSST (1)	good	good	0.529 (0.394 ... 0.628)	reasonable
MPI-ESM1-2-XR_highresSST (1)	good	good	0.425 (0.314 ... 0.511)	good
CORDEX				
SAM-22_HadGEM2-ES_RegCM4-7 (1)	good	bad	0.925 (0.668 ... 1.07)	bad
SAM-22_HadGEM2-ES_REMO2015 (1)	good	bad	0.383 (0.291 ... 0.443)	bad
SAM-22_MPI-ESM-LR_REMO2015 (1)	reasonable	good	0.350 (0.255 ... 0.426)	reasonable
SAM-22_MPI-ESM-MR_RegCM4-7 (1)	reasonable	reasonable	0.424 (0.346 ... 0.474)	reasonable
SAM-22_NorESM1-M_RegCM4-7 (1)	bad	bad	1.15 (0.915 ... 1.43)	bad
SAM-22_NorESM1-M_REMO2015 (1)	reasonable	reasonable	0.676 (0.534 ... 0.801)	reasonable
SAM-44_CanESM2_RCA4 (1)	good	good	0.347 (0.279 ... 0.413)	good
SAM-44_CanESM2_WRF341I (1)	bad	bad	0.400 (0.324 ... 0.453)	bad
SAM-44_CNRM-CM5_RCA4 (1)	reasonable	bad	0.259 (0.197 ... 0.298)	bad
SAM-44_CSIRO-Mk3-6-0_RCA4 (1)	reasonable	good	0.654 (0.529 ... 0.754)	reasonable
SAM-44_GFDL-ESM2M_RCA4 (1)	good	reasonable	0.397 (0.315 ... 0.464)	reasonable
SAM-44_HadGEM2-ES_RCA4 (1)	good	reasonable	0.311 (0.238 ... 0.374)	reasonable
SAM-44_IPSL-CM5A-MR_RCA4 (1)	bad	bad	0.572 (0.446 ... 0.674)	bad
SAM-44_MIROC5_RCA4 (1)	good	reasonable	0.325 (0.253 ... 0.389)	reasonable
SAM-44_MPI-ESM-LR_RCA4 (1)	good	reasonable	0.303 (0.250 ... 0.344)	bad
SAM-44_MPI-ESM-LR_REMO2009 (1)	reasonable	good	0.323 (0.251 ... 0.376)	reasonable
SAM-44_NorESM1-M_RCA4 (1)	bad	reasonable	0.772 (0.601 ... 0.899)	bad

Table A3.1: Evaluation results of the climate models considered for attribution analysis of PrcpFeb. For each model, the best estimates of the Dispersion parameter are shown, along with 95% confidence intervals. Furthermore evaluation of the seasonal cycle and spatial pattern are shown.

A4 Estimated trends in climate models

This section shows Probability Ratios and change in intensity ΔI for models that passed model evaluation and also includes the values calculated from the fits with observations.

Model / Observations	Threshold for return period 10 yr (mm)	Change up to present (1.3 C above preindustrial)		Change in future (1.3 C above present)	
		Probability ratio PR [-]	Change in intensity ΔI [%]	Probability ratio PR [-]	Change in intensity ΔI [%]
BR-DWGD	9.1	0.78 (0.047 ... 8.8)	-4.5 (-36 ... 41)		
CHIRPS	11.6	4.3e+2 (0.33 ... 3.1e+9)	63 (-10 ... 1.9e+2)		
CRUTS	9.8	1.1 (0.081 ... 3.9)	1.2 (-25 ... 26)		
MSWEP	10.4	6.7 (0.085 ... 1.7e+5)	26 (-27 ... 140)		
CMCC-CM2-VHR4_highresSST (1)	10	4.6 (0.48 ... 9.8)	24 (-16 ... 33)	1.5 (0.53 ... 2.5)	8.1 (-11 ... 20)
CNRM-CM6-1-HR_highresSST (1)	10	2.5 (0.41 ... 15)	13 (-16 ... 30)	1.5 (0.36 ... 3.0)	7.0 (-13 ... 20)
EC-Earth3P-HR_highresSST (1)	9.9	0.45 (0.36 ... 3.6)	-15 (-20 ... 17)	1.2 (0.34 ... 2.5)	2.5 (-15 ... 17)
HadGEM3-GC31-HM_highresSST	11	0.56 (0.42 ... 7.0)	-11 (-17 ... 28)	2.0 (0.48 ... 2.9)	14 (-12 ... 24)
MPI-ESM1-2-XR_highresSST	10	4.2 (0.44 ... 11)	20 (-15 ... 29)	1.3 (0.47 ... 2.5)	4.1 (-11 ... 16)
SAM-22_MPI-ESM-LR_REMO2015 (1)	12	0.62 (0.24 ... 3.2)	-6.8 (-24 ... 14)	0.97 (0.38 ... 1.9)	-0.40 (-12 ... 9.9)
SAM-22_MPI-ESM-MR_RegCM4-7 (1)	12	1.5 (0.24 ... 7.0e+3)	5.6 (-30 ... 77)	2.1 (0.78 ... 3.5)	15 (-3.9 ... 27)
SAM-22_NorESM1-M_REMO2015 (1)	7.0	0.56 (0.16 ... 9.2e+5)	-14 (-58 ... 1.4e+2)	0.96 (0.26 ... 2.7)	-0.83 (-26 ... 25)
SAM-44_CanESM2_RCA4 (1)	9.4	0.53 (0.24 ... 1.7)	-9.5 (-24 ... 6.6)	0.86 (0.48 ... 1.4)	-2.0 (-9.1 ... 4.1)
SAM-44_CSIRO-Mk3-6-0_RCA4 (1)	6.4	1.2 (0.19 ... 4.0e+5)	4.2 (-50 ... 1.3e+2)	2.6 (1.5 ... 3.8)	23 (9.9 ... 35)
SAM-44_GFDL-ESM2M_RCA4 (1)	10	0.73 (0.23 ... 16)	-4.9 (-28 ... 32)	1.6 (0.63 ... 2.8)	7.4 (-6.9 ... 19)
SAM-44_HadGEM2-ES_RCA4 (1)	8.4	0.90 (0.33 ... 4.3)	-1.4 (-17 ... 16)	1.9 (1.3 ... 2.7)	9.9 (3.6 ... 16)
SAM-44_MIROC5_RCA4 (1)	7.9	0.50 (0.20 ... 3.5)	-10 (-28 ... 14)	2.3 (1.4 ... 3.3)	13 (4.7 ... 20)
SAM-44_MPI-ESM-LR_REMO2009 (1)	12	0.58 (0.20 ... 4.4)	-7.2 (-26 ... 15)	1.2 (0.52 ... 2.0)	2.6 (-8.0 ... 11)

Table A4.1: Event magnitude, probability ratio and change in intensity for 10-year return period for *PrcpFeb* for observational datasets and each model that passed the evaluation tests. (a) from pre-industrial climate to the present and (b) from the present to 2.6°C above pre-industrial climate.