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Challenges in attributing the 2022 Australian rain bombs to climate change

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Abstract

In February and March 2022, the eastern coast of Australia recorded an unprecedented amount of precipitation with extended floods and damages to properties amounting at least to AUD 2.3 billions. In this paper we use both reanalysis and observations to perform a statistical and dynamical attribution of this precipitation event to climate change. We define 1948-1977 as the counterfactual period and 1990-2019 as the factual one. The statistical attribution is based on fitting the generalized extreme value distribution for 3-days averaged precipitation annual maxima for the two periods, while the dynamical attribution aims at looking at the recurrence properties of sea-level pressure and geopotential height patterns in both periods. We find that the dynamics of the event consists in an unprecedented combination of several factors: a tropical atmospheric river, the presence of the Coral low pressure system and a blocking anticyclone offshore Eastern Australia. Our main finding is that no clear attribution statements can be made, both because of the unprecedented nature of this

event, the lack of long high quality available data and the dependence of the results on the La Nina phase of El Nino Southern Oscillation.

Keywords: Climate Change, Extreme Precipitation, Attribution, Australia

1 Introduction

In the latest IPCC report (Masson-Delmotte et al, 2021), researchers confirm the role that human activity plays in the climate upheavals of recent decades. The scientists also confirm the role of anthropogenic greenhouse gases emissions in modifying frequency and intensity of extreme weather events that we experience today. The IPCC scientists warn in particular about the effects that climate change is having on the water cycle. Studies have shown that rising temperatures are leading to more intense rainfall, flooding but also to more severe droughts (Cook et al, 2018) in some regions of the world. The distribution, frequency and intensity of precipitations are changing significantly across the globe, especially in subtropical regions accustomed to monsoons (Douvillle et al, 2021). In the 21st century, coastal areas are already experiencing and will increasingly experience flooding due to heavy precipitations and sea level rise (Wilby and Keenan, 2012). Flooding from rising seas, which was only occasional a few decades ago, could occur every year by the end of the century (Hirabayashi et al, 2013).

Australian average land temperatures have risen by 1.44°C since 1910, according to the recent study by Grainger et al (2022). The oceans surrounding the continent have also warmed by an average of one degree over the same period, leading to more frequent marine heat waves. Half of the corals in Australia's Great Barrier Reef have died since 1995 because of this rise in water temperature in conjunction with increased acidification (Wolff et al, 2018; Holland et al, 2020). There is a wide consensus on the fact that sea levels will rise in future climates, affecting Australian coasts (Church et al, 2006; Woodruff et al, 2013; Church et al, 2017). As in other regions, this will likely increase the hazards linked to storm surges associated with tropical cyclones. Other authors have also pointed out that rainfall has decreased in southwestern Australia as well as in the fire-ravaged southeast, while increasing in the north, which has been hit by major floods and destructive cyclones in recent years (Dey et al, 2019; Abram et al, 2021).

If climate change projections for Australia are worrying, the country is already experiencing severe extreme weather events. Indeed, climate change has already taken its toll on Australia (Head et al, 2014; Abram et al, 2021; Canadell et al, 2021), which has been hit by fires, drought and intense cyclones. In 2019-2020 the country was already ravaged by wildfires of exceptional proportions after experiencing the hottest and driest year on record (Borchers Arriagada et al, 2020; Jetten et al, 2021). The fires destroyed an area almost the size of the United Kingdom, killed several people and killed

74 or displaced nearly three billion animals, costing the Australian economy about
75 7 billion AUD (Filkov et al, 2020). In the current 2022 year, both high and low
76 temperature records have been broken in Australia. On one hand, on the 13/01,
77 the coastal town of Onslow reached an unprecedented 50.7°C, the hottest tem-
78 perature ever recorded in Australia for sixty-two years (The Guardian, 2022).
79 On the other hand, on the 02/06, the temperature at the Thredbo Top weather
80 station reached -6.9°C and historic snowfalls for this time of year (The New
81 Daily, 2022). Future projections of climate-related disasters for the coastal
82 areas as well as the vast island-continent report an increasing risk of extreme
83 events capable of heavily damaging natural ecosystems and impact health and
84 agriculture (Hobday et al, 2018; Dey et al, 2019; Ukkola et al, 2020).

85 Here we will focus on the record-breaking extreme precipitation event which
86 occurred from the last week of February to mid-March 2022, in the eastern
87 coast of Australia. Heavy precipitations - 345mm of rain were recorded at
88 Brisbane on the 28th of February - met soils already close to saturation from
89 the recent rains in the end of 2021. This led to severe and enduring flooding
90 in March. This event caused 22 recorded casualties, rendered uninhabitable
91 25,000 homes and businesses, forced 200,000 people to evacuate and produced
92 massive power and transports outages for a total of ~2.32 billion AUD of
93 damage (Foreign Policy, 2022).

94 In order to explain this rain bomb event, we have identified two main
95 ingredients: i) an atmospheric river, formed north the continent around the
96 22nd of February, in the upper atmosphere – between eight and 10 kilometres
97 up – moved from the ocean to the south reaching the continent and produc-
98 ing a continuous flux of precipitation originating from the tropics, and ii) a
99 dipolar structure consisting of a low pressure system in the Coral Sea and a
100 blocking anticyclone further east. The combination of these elements allowed
101 to transport moist air from the tropics to the Coral Sea, and then condense
102 the moisture that has then fallen as rain thanks to the low pressure, while
103 winds were pushing rain over Queensland’s south east. Precipitation was fur-
104 ther enhanced by orographic effects. At an even larger scale, the phenomena
105 were embedded in a strong La Nina phase, which induces additional air mois-
106 ture in the south west Pacific and wind circulation patterns that could have
107 played a role in the intensity of the event.

108 Preliminary results of the University of Melbourne reported by national
109 and international newspapers (see, e.g. The Guardian (2022)) showed that on
110 the 26th and 27th of February, the two days with heaviest rain, 16 times the
111 water held by Sydney harbour (500 bn liters) flowed in the atmospheric river
112 above Queensland. Indeed, during those days rainfall of over 400 millimetres
113 was recorded across the greater Brisbane area. This would add up on the 28th
114 February to a total of 676.8 millimetres of rainfall, the largest three, and seven,
115 day total ever recorded in Brisbane. Another record breaking amount of rain-
116 fall was recorded in Mount Glorious which received rainfall in excess of 1770
117 millimetres in the week until 28th of February. More than 30 locations across
118 the south-east recorded rainfall in excess of 1000 millimetres, resulting in the

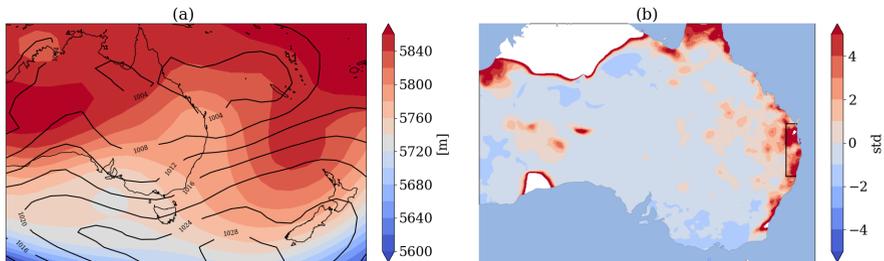
4 *Challenges in 2022 Australian rain bombs Attribution*

Fig. 1 Description of the rain bomb event. (a) Geopotential height at 500hPa (colors) and sea level pressure (contours) averaged over the 26th, 27th and 28th of February 2022. (b) Standardized anomaly of accumulated precipitations for the period 20th February - 20th March with respect to the 1990-2019 period. Regions in white correspond to standardized anomaly above 15 standard deviations.

119 floods being more intense than that of 1974. The unprecedented flooding that
 120 raised many rivers above record highs moved south, leaving towns underwa-
 121 ter. The area of Sydney was more affected on the 3rd and the 8th of March
 122 with the city's chief reservoir, spilling at a rate in excess of 70 gigalitres a day
 123 on March 3. Residents in parts of western Sydney were told to evacuate for
 124 the second year in a row as the city's Warragamba Dam overflowed. But the
 125 system stalled before it passed over Sydney.

126 Damage from floods is only partially estimated at this stage, but is expected
 127 to reach almost AUD 2.3 billion ([Foreign Policy, 2022](#)), an estimate that
 128 exceeds that of the Insurance Council of Australia, which also summed-up the
 129 cost of claims from the disaster to AUD 1.45 billion ([ClimateCouncilAustralia, 2022](#)).
 130 However, this is only a lower bound, as the estimates are still expected to
 131 grow.

132 Figure 1 (a) presents the synoptic situation averaged over the 26th, 27th
 133 and 28th of February over the region. We see the dipole structure with an
 134 upper level low pressure system centered above the Brisbane region and a high
 135 pressure system over the Coral sea. Figure 1 (b) presents the standardized
 136 anomaly of accumulated precipitations for a one month period (20/02-20/03)
 137 with respect to the 1990-2019 period. The standardized anomaly was computed
 138 by considering the series of accumulated precipitations for the 20/02-20/03
 139 period for each year over 1990-2019 and removing the mean and dividing by
 140 the standard deviation. The Eastern coast of Australia saw extremely strong
 141 precipitations, with many locations exceeding 5 standard deviation anomalies
 142 with respect to the climatology.

143 We study whether this event can be attributed to climate change using
 144 dynamical systems theory to target the concurrent atmospheric circulation
 145 patterns and search for pattern recurrences in the far (1948-1977) and recent
 146 past (1990-2019). Our working hypothesis is that the far past acts as a coun-
 147 terfactual world where the Earth climate was not influenced by anthropogenic
 148 forcing when compared to the recent past (the factual world). Additionally,

we assume that the 30-year period is long enough to average out the interannual variability of the atmospheric motions (as that caused, for example, by El-Niño - Southern Oscillation). Finally we verify that these events produce similar impacts on the targeted regions.

The paper is organized as follows: section 2 describes the data and methods used in this study. This is followed by the results (Section 3) providing both a statistical a dynamical attribution analysis. We conclude with a discussion and perspectives in Section 4.

2 Data and Methods

2.1 Data

In order to detect significant changes in the circulation associated with Australian Rain bombs, we use daily sea level pressure (*slp*), 500hPa geopotential height (*z500*) and 2m air temperature (*t2m*) data from the NCEP/NCAR reanalysis (Kalnay et al, 1996) over the period 01/01/1948 – 31/03/2022. The data have a horizontal resolution of $2.5^\circ \times 2.5^\circ$.

The precipitation data are taken from the high resolution daily rainfall gridded datasets of the Bureau of Meteorology of Australia. The data have a horizontal resolution of $0.05^\circ \times 0.05^\circ$. Daily precipitation data from the Alderley station, close to Brisbane, is also used solely. The gridded data set will be used for the dynamical attribution (section 3.2) and the station data for the statistical attribution (section 3.1). For the ENSO index, we used the Nino3.4 detrended index as in Van Oldenborgh et al (2021).

2.2 Methods

Extreme Value Theory (EVT) has been introduced in the study of atmospheric flows a decade ago (Freitas et al, 2008) and has gained a considerable amount of attention in both the applied mathematics and the climate science communities (Lucarini et al, 2012, 2016; Faranda et al, 2019). It can be used to compute recurrence times statistics for meteorological observables, but also gives access to important information on the stability and the predictability of a particular climatic state. We can apply this framework to the study how weather extremes are influenced by anthropogenic-driven climate change conditioned to the occurrence of a specific atmospheric circulation pattern (Faranda et al, 2020). Indeed weather extremes are associated with synoptic objects, i.e. a cyclone, an anticyclone, or a couple of these structures. During this identification, we select a region (a longitude/latitude box) that fits the synoptic objects that we want to examine. Once fixed the day of interest ζ , we scan all the 3-days rolling averaged sea-level pressure (*slp*) and 500hPa geopotential (*z500*) maps of the selected region in two periods: 1948-1977 (counterfactual world) and 1990-2019 (factual world). For both periods, we select the best 35 analogues as the *slp* and *z500* maps minimizing the pointwise euclidean distance with the target day ζ . We verified that the results are not sensitive to the

190 choice of the number of analogues provided that we extract between 25 and 50
 191 analog maps. 30 years long factual and counterfactual periods ensure a large
 192 enough statistical sample of slp and $z500$ maps to be able to select sufficiently
 193 authentic analogues. Furthermore, it is short enough to satisfy the assumption
 194 of climate stationarity, with respect to anthropogenic climate change, while
 195 still long enough for the interannual and interdecadal natural variability of the
 196 atmospheric circulation to be averaged over.

197 Once obtained the two sets of analogues for the factual and counterfactual
 198 periods, we average them out to search for significant differences Δslp and
 199 $\Delta z500$. To determine significant changes, we apply a two-tails Welch's t-test
 200 (Welch, 1947) with different variance at each grid point. We mark as signifi-
 201 cant only grid point changes for which the p -value of the test is below 0.05.
 202 Conditioning to the dates determined for slp or $z500$ maps, we also study the
 203 associated 2 meters temperatures $t2m$ and total precipitation maps tp . The
 204 Welch's t-test procedure is repeated on these ensembles to identify significant
 205 changes.

206 Using the dynamical systems framework described above, we then intro-
 207 duce a few metrics to determine the recurrence properties of the map in the
 208 counterfactual and factual worlds. These metrics are computed twice, once
 209 with the set of analogues obtained in each period. The formulas for comput-
 210 ing these metrics are given in appendix A. For more information, please refer
 211 to Faranda et al (2022).

- 212 • **Analog Quality Q :** We can study the typicality of ζ by comparing the
 213 euclidean distance of ζ from its analogues with the distances of the analogues
 214 from their own analogues. If the value of Q belongs to the same distribution
 215 of the values of Q analogues, then the typicality of the event is ensured and
 216 attribution of ζ can be performed. If instead the Q for the chosen day is
 217 larger than that of the analog days, then this is an unprecedented slp or $z500$
 218 configuration and the results for attribution must be taken more carefully.
 219 A difference in Q between the counterfactual and factual periods indicate a
 220 change in typicality of the event due to climate change.
- 221 • **Predictability Index D :** Also called instantaneous dimension. For an atmo-
 222 spheric state ζ , $D(\zeta)$ measures the density of similar configurations. We can
 223 compute $D(\zeta)$ in both the periods to detect a climate-change induced shift
 224 in predictability. Indeed, D is a proxy for the number of degrees of freedom
 225 of the map, meaning that the higher the dimension the more unpredictable
 226 the next slp or $z500$ maps will be. If the dimension D of the chosen day is
 227 higher or lower than that of the analogues, then the day will be less or more
 228 predictable than its closest dynamical situations.
- 229 • **Persistence Index Θ :** Another information derived from the dynamical sys-
 230 tems theory is the persistence of a given configuration. The persistence
 231 counts for how many days we are likely to observe a map that will resemble
 232 ζ . Once again we will compute Θ for the two different periods and using the
 233 analogs as well to detect shifts from the factual to the counterfactual worlds.

- Seasonality of Analogs: We can also simply count the number of analogs in each month to detect whether a given circulation shifts towards earlier or later months. This can have strong thermodynamic implications.

We also provide results of the attribution conditional not on the past and present climate, but on the El-Niño - Southern Oscillation (ENSO) mode. ENSO is known to be a major factor in the variability of tropical and subtropical regions around the Pacific and likely played a role in the February 2022 event for which the mode was strongly negative. Therefore, we decided to run the attribution analysis conditional on the Nino3.4 index being above the 75% percentile (ENSO+) and below the 25% percentile (ENSO-) for the period 1948-2019. Analogues are then computed in those two pools of data using either 3-days rolling averaged *slp* or *z500* maps.

3 Results

3.1 Statistical attribution

In order to assess the possible changes in the probability of occurrence for the event due to climate change, we use the rapid statistical attribution method described in Section 2. We fit the 3-days averaged precipitation yearly maxima to a Generalized Extreme Value (GEV) law for the factual and counterfactual periods for three stations, namely the Alderley station (Brisbane) at the epicentre of the 26th-28th February event, the Sydney Botanic garden station and the Cairns Aero station . We repeat the same analysis over the region 152°-154°W, 25.5°-31°S centered on Brisbane where the event was the most extreme (see, e.g. Figure 1b) .

Figure 2 shows the resulting GEV fits for Brisbane (a), Brisbane region (b), Sydney (c) and Cairns (d). In both the factual and counterfactual worlds the event of April 2022 in Brisbane was exceptional, with return periods estimated of more than a thousand years. The event was also a 100-year precipitation event in the Brisbane region in both periods. The 26th-28th February event was less extreme in Sydney and Cairns, with return periods of less than a decade in both stations for the factual and counterfactual periods. In Alderley station return levels are slightly higher in the counterfactual period. We can explain this by the occurrence of an extreme precipitation events in January 1974, that also produced floods in Brisbane. However, the 95% confidence intervals are too wide to conclude to any detectable effect of climate change with this method.

Figure 3 shows the same analysis but conditioned to the phases of El Niño Southern oscillation. In particular, we condition using Nino 3.4 index, sampling ENSO+ phases and ENSO- phase, defined respectively as the first and last quartile of the index. Results show a stronger effect of the la Niña phase (ENSO-) on precipitation rates at both Brisbane stations (3a). The 2022 26th to 28th February event is very rare during ENSO+ phases with a return period of over 400 years. Instead, it has a return period of 120 years in ENSO- phases.

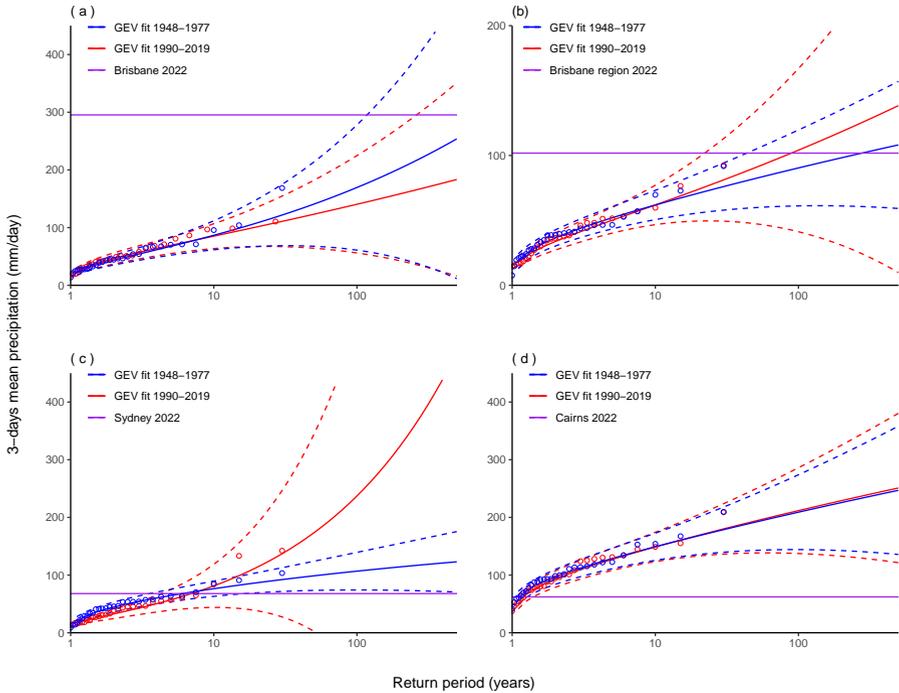


Fig. 2 Fit of the annual maximum of 3-days averaged precipitation running means at Brisbane (Alderley station) (a), the Brisbane region (152° - 154° W, 25.5° - 31° S) (b), Sydney (Sydney Botanic gardens station) (c) and Cairns (Cairns Aero station) (d) to a GEV in the factual and counterfactual periods. Gumbel plot of the GEV fit over 1948-1977 (blue lines with 95% confidence intervals), and 1992-2021 (red lines) using the maximum likelihood estimation. The purple line shows the value of intensity of the observed event at the station or area of interest in 2022.

276 This is in agreement with the influence of the strong la Niña phase currently
 277 ongoing on the intensity of the 2022 event suggested in 1. This effect is less clear
 278 if we consider the Brisbane region (3b): in this case the confidence intervals
 279 are so wide that it is difficult to draw any conclusion. The same procedure
 280 applied to Sydney (3c) and Cairns (3d) station data does not allow to draw
 281 any conclusion because of the wide confidence intervals, wich prevent to obtain
 282 statistical significant differences, at least at the 95% level chosen in this study.

283 3.2 Dynamical attribution

284 To identify the dynamical and thermodynamic factors which may have played
 285 a role in the intensity of the event, we ran the dynamical attribution framework
 286 presented previously.

287 Figures 4 and 5 present the results using respectively *slp* and *z500* analogues.
 288 These figures display the *slp/z500* (a-d), *t2m* (e-h) and *prate* (i-l)
 289 maps and, from left to right, the maps of the event (a,e,i), the composites of

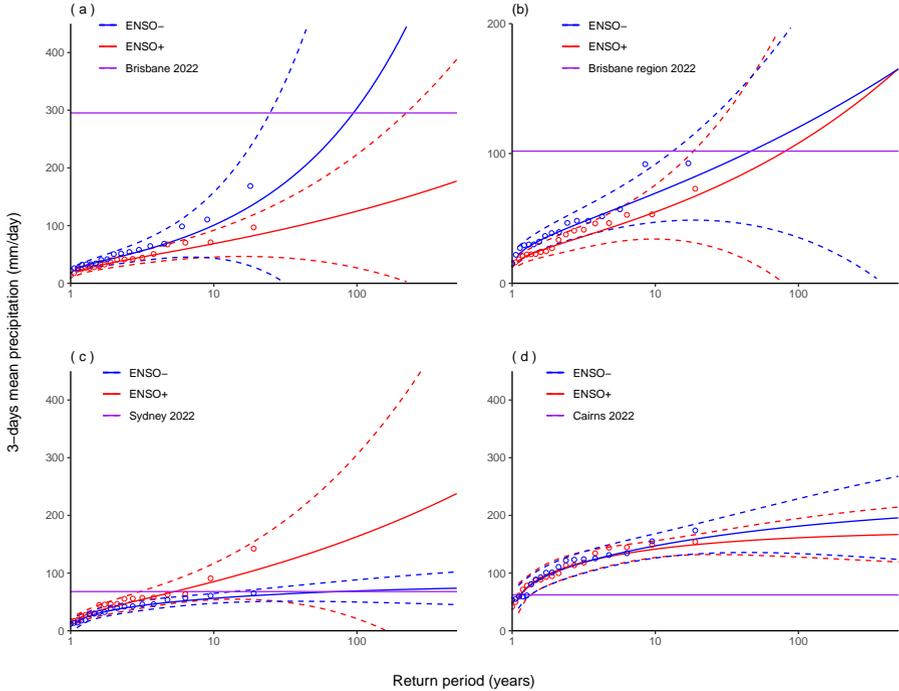


Fig. 3 Fit of the annual maximum of 3-days averaged precipitation running means at Alderley station (a) and over the Brisbane region (152°-154°W, 25.5°-31°S) (b) to a GEV, depending on El Niño 3.4 detrended index. Gumbel plot of the GEV fit over years in the 1st quartile (red lines) and 4th quartile (blue lines) of NINO3.4 index average over JFM from 1948 to 2021, with 95% confidence intervals. The purple line shows the value of intensity of the observed event at Alderley station in 2022.

290 counterfactual (b,f,j) and factual (c,g,k) analogs and the difference between
 291 the factual and counterfactual analogs (d,h,l) where hashed-filled areas show
 292 significant differences. Distributions of additional metrics comparing the
 293 counterfactual and factual periods, namely analogs quality, predictability,
 294 persistence and distribution by season are shown in panels m–p, respectively.

295 For the *slp* analogues, we firstly notice that the analogues quality (Q) is not
 296 good and therefore results must be interpreted carefully (panel (m)). In the
 297 factual period, there is a signal of intensified high-pressures over New Zealand,
 298 which may be related to the stronger advection of moist air from the Coral
 299 sea. When we look at the precipitation difference map (Fig. 4 (l)), there are
 300 indeed stronger precipitations on the Eastern coast of Australia in the factual
 301 period but only few regions are significantly different than the counterfactual
 302 period and do not fully correspond to the regions where the precipitations
 303 are maximum during the February 2022 event. There is moreover no strong
 304 temperature signal as depicted in panel (h) using 2m air temperature which
 305 does not display significant differences between the factual and counterfactual
 306 periods on the Eastern coast and in the Coral sea. However, panel (o) and (p)

show that the predictability is lower and the persistence is higher in the factual period. The event is particularly persistent compared to its analogues in the factual period which may explain the intensity of the event.

This results are confirmed when using the $z500$ analogues (Fig. 5), which are better as shown in panel (m). The factual period displays stronger high $z500$ over the northern region but also almost no significant temperature signal (panel (h)). The low predictability D (panel (n)) but high persistence Θ (panel (p)) of the event is also noticed using $z500$ analogues. When it comes to precipitations, even though they are stronger during the factual period (panel (l)), this difference is not significant.

These results are coherent with the statistical attribution in so far as the temperature signal associated with climate change is weak. There is however a noticeable dynamical signal in the two periods as represented in the slp and $z500$ analogues difference maps. One may indeed notice that ENSO, which is the major driver of variability in the region, was in a strong and persistent La Nina phase during the event, which is not fully represented using analogues (see figure 6). We therefore decided to run the same dynamical attribution analysis using the Nino3.4 index to define ENSO- phases and factual ENSO+ phases.

The results of this analysis are presented in figures 7 and 8 using respectively slp and $z500$ analogues. On the dynamical side, there is a significant stronger upper level low during ENSO- phases (Fig. 8 panel (d)) analogues. Using both analogues, the temperature signal is much stronger during ENSO+ phases, which may explain the absence of signal when doing the analysis during past and present periods: the natural variability is stronger than the climate change signal on this region. When it comes to precipitations, there is a strong positive signal on the Eastern coast and Brisbane regions during La Nina phases using slp analogues but the quality of analogues is low and these results are not significant using $z500$ analogues.

4 Conclusions

In this paper we have performed a statistical and dynamical attribution of the Australian rain bomb event of February 2022. We have used both reanalyses and historical records of daily precipitations in the past (1948-1977, counterfactual) and present (1990-2019, factual) periods. From a statistical point of view, this extreme precipitation event was unprecedented in the Brisbane region and very intense with respects to previous historical records in the broader Eastern coast of Australia. The statistical attribution suggests that this event has a low probability to happen both in the past and present climate (less than one in a century). There is no clear signal of a climate change influence (high uncertainty) which translates in a low evidence for the attribution of this event to climate change.

The dynamical attribution, performed using the method of analogues circulation patterns proposed in Faranda et al (2022) to those observed during the

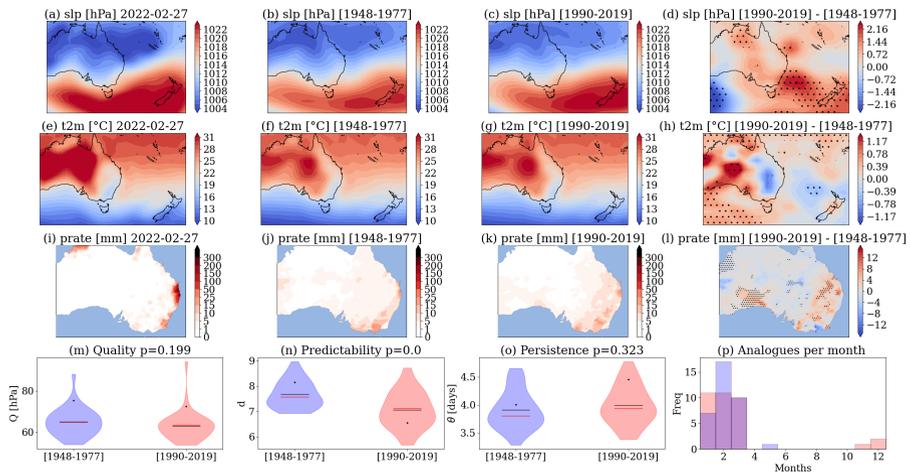


Fig. 4 Dynamical attribution using *slp* analogues for the Australian rain bomb on 27-02-2022. 3-days rolling mean sea-level pressure *slp* (a), 2-meter temperatures *t2m* (e) and total precipitation *prate* (i) centered on the 27-02-2022. Average of the 35 sea-level pressure analogs found for the counterfactual [1948-1977] (b) and factual [1990-2019] (c) periods and corresponding 2-meter temperatures (f,g) and daily precipitation rate (j,k). Δslp (d), $\Delta t2m$ (h) and $\Delta prate$ (i) between factual and counterfactual periods: hashed-filled areas show significant differences. Violin plots for counterfactual (blue) and factual (red) periods for the Analogs Quality Q (m) the Predictability index D (n), the Persistence index θ (o) and the distribution of analogs in each month (p). Values for the selected day are marked by a black dot. Black (resp. red) lines represent the empirical mean (resp. median) of the distribution.

350 events suggest the exceptional characteristics of the event which appears to be
 351 unprecedented in both the factual and counterfactual distributions of weather
 352 patterns: it has arisen as the combination of ingredients: the tropical moisture
 353 was deflected to the subtropics, collected and lifted by a low pressure system
 354 which stationed over Eastern Australia blocked by an high pressure offshore
 355 the Coral sea. This combination created an atmospheric river capable of transporting
 356 several gigaliters of water towards the Queensland and the South West
 357 of the continent. Finally, La Niña phase of the El-Niño-Southern-Oscillation
 358 likely played a significant role in the intensity of the event.

359 The main limitation of this study is that we do not use climate models:
 360 the rationale for doing so comes from the evidence that both large, regional
 361 and local phenomena contributed to this event. In order to perform an attribution
 362 study based on models, we would need a large ensemble of convection
 363 permitting models resolving at least the region shown in Fig. 1, with specific
 364 runs capable to evaluate also the contribution of la Nina to the event. Even
 365 with such models, the detailed physics of the precipitation could still depend
 366 on the microphysics introduced in the model as shown by Ban et al (2021).
 367 A further limitation of this study is the use of factual and counterfactual periods
 368 consisting of only 30 years. While we could in principle consider the whole
 369 period twice, as in the protocol described by Philip et al (2020), we cannot

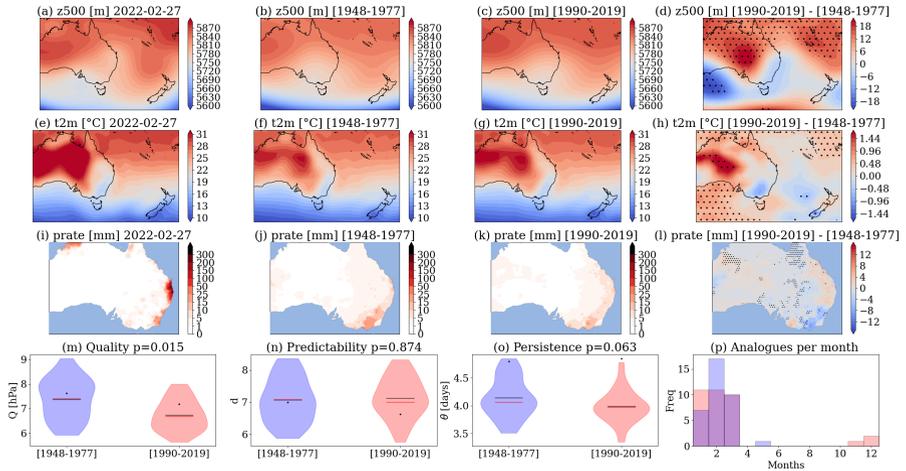
12 *Challenges in 2022 Australian rain bombs Attribution*

Fig. 5 Dynamical attribution using $z500$ analogues for the Australian rain bomb on 27-02-2022. 3-days rolling mean 500hPa geopotential height $z500$ (a), 2-meter temperatures $t2m$ (e) and total precipitation $prate$ (i) centered on the 27-02-2022. Average of the 35 500hPa geopotential height analogs found for the counterfactual [1948-1977] (b) and factual [1990-2019] (c) periods and corresponding 2-meter temperatures (f,g) and daily precipitation rate (j,k). $\Delta z500$ (d), $\Delta t2m$ (h) and $\Delta prate$ (i) between factual and counterfactual periods: hashed-filled areas show significant differences. Violin plots for counterfactual (blue) and factual (red) periods for the Analogs Quality Q (m) the Predictability index D (n), the Persistence index θ (o) and the distribution of analogs in each month (p). Values for the selected day are marked by a black dot. Black (resp. red) lines represent the empirical mean (resp. median) of the distribution.

370 here use the implicit assumption of stationarity of the variability of the rain-
 371 fall extremes that is underlying the protocol. While this is a limitation on the
 372 available data, it is a fair way to account for the variability of extremes, allow-
 373 ing for a larger uncertainty and a conservative estimates on the role of climate
 374 change to triggering this event.

375 To frame our results in a more general framework, we observe that they
 376 are in line with what the IPCC report AR6, WG1, Chapter 11.4, states about
 377 rainfall over the region, namely that “Available evidence has not shown an
 378 increase or a decrease in heavy precipitation over Australasia as a whole
 379 (medium confidence), but heavy precipitation tends to increase over North-
 380 ern Australia (particularly the north-west) and decrease over the eastern and
 381 southern regions.” (Seneviratne et al, 2021) . We however observe that the
 382 compounding dynamical elements driving this event are also observed in a
 383 series of unprecedented extreme weather events occurred in the last few years,
 384 including the 2021 Canada heat dome, the Antarctica atmospheric rivers, the
 385 2022 Indian, Chines, Western European and North American heatwaves. Such
 386 series of record breaking events raise the question of the emergence of new phe-
 387 nomena linked to global warming, a field to explore statistically, e.g. by using
 388 the concept of time of emergence introduced in Hawkins and Sutton (2012)

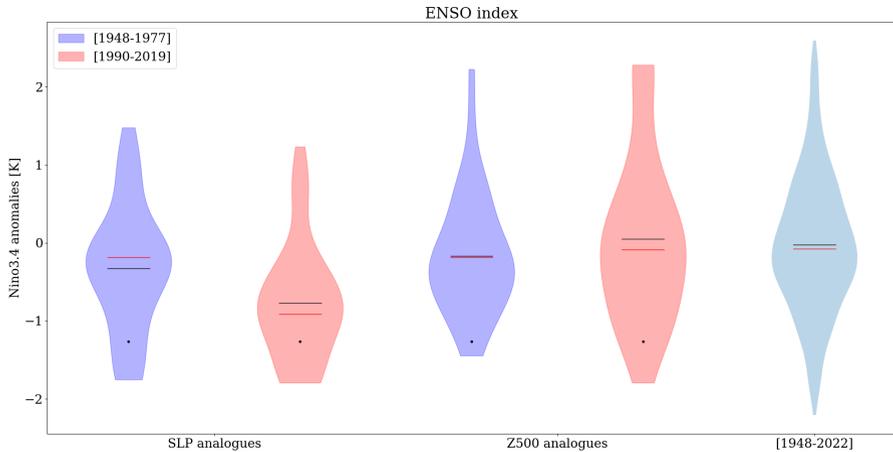


Fig. 6 Distribution of ENSO index between factual and counterfactual periods for the two types of analogues. Blue (resp. red) violin plots represent the distribution of the ENSO index for the analogues in the counterfactual (resp. factual) period. The red (resp. black) line depicts the median (resp. mean) of the distribution. The black dot corresponds to the value of the ENSO index during the February 2022 event. The last violin plot depicts the distribution of the ENSO index for all dates between 1948 and 2019.

389 and dynamically, e.g. by looking the possible presence of tipping elements in
 390 the climate system (Lenton et al, 2008).

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- 407 • Consent for publication: Not applicable.
- 408 • Availability of data and materials: NCEP data are available on the
 409 NOAA website at <https://psl.noaa.gov/data/gridded/data.ncep.reanalysis>.

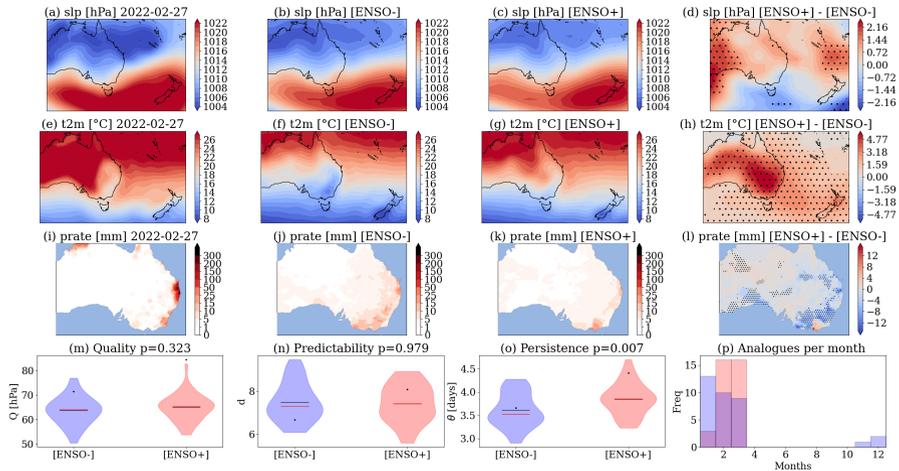


Fig. 7 Dynamical attribution using *slp* analogues for the Australian rain bomb on 27-02-2022 relative to the ENSO index. 3-days rolling mean 500hPa geopotential height $z500$ (a), 2-meter temperatures $t2m$ (e) and total precipitation $prate$ (i) centered on the 27-02-2022. Average of the 35 sea-level pressure analogs found for the counterfactual [ENSO-] (b) and factual [ENSO+] (c) periods and corresponding 2-meter temperatures (f,g) and daily precipitation rate (j,k). $\Delta z500$ (d), $\Delta t2m$ (h) and $\Delta prate$ (i) between factual and counterfactual periods: hashed-filled areas show significant differences. Violin plots for counterfactual (blue) and factual (red) periods for the Analogs Quality Q (m) the Predictability index D (n), the Persistence index θ (o) and the distribution of analogs in each month (p). Values for the selected day are marked by a black dot. Black (resp. red) lines represent the empirical mean (resp. median) of the distribution.

410 [html](#). Rainfall data over Australia are available at the National Computa-
 411 tional Infrastructure (NCI) THREDDS server at [https://dapds00.nci.org.](https://dapds00.nci.org.au/thredds/catalog/zv2/agcd/v1/precip/total/r005/01day/catalog.html)
 412 [au/thredds/catalog/zv2/agcd/v1/precip/total/r005/01day/catalog.html](https://dapds00.nci.org.au/thredds/catalog/zv2/agcd/v1/precip/total/r005/01day/catalog.html).

- 413 • Code availability: The main results of this work were obtained using Python.
 414 The scripts are available upon request.
- 415 • Authors' contributions: CC, NM and RN performed the analysis. DF
 416 designed the analyses. All authors participated to the manuscript prepara-
 417 tion and writing.

418 A Predictability and Persistence Indices

419 The attractor of a dynamical system is a geometric object defined in the space
 420 hosting all the possible states of the system (phase-space). Each point ζ on the
 421 attractor can be characterized by two dynamical indicators: the local dimension
 422 D , which indicates the number of degrees of freedom active locally around
 423 ζ , and the persistence Θ , a measure of the mean residence time of the system
 424 around ζ (Faranda et al, 2017). To determine D , we exploit recent results from
 425 the application of extreme value theory to Poincaré recurrences in dynamical
 426 systems. This approach considers long trajectories of a system — in our

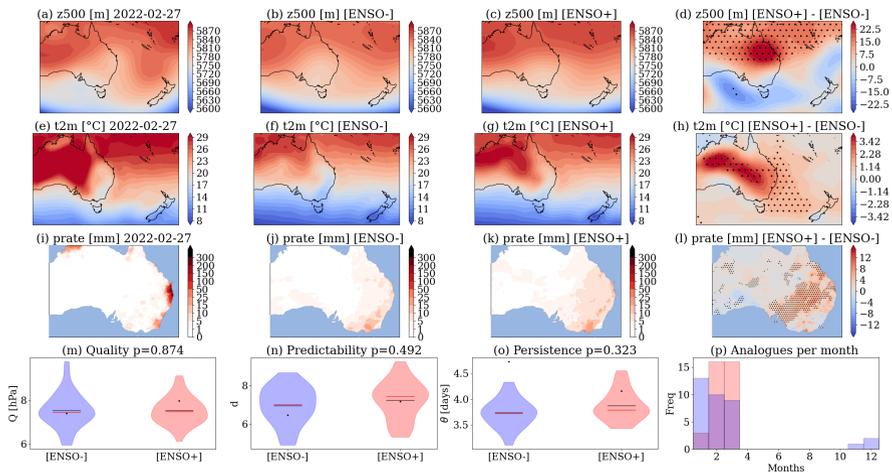


Fig. 8 Dynamical attribution using $z500$ analogues for the Australian rain bomb on 27-02-2022 relative to the ENSO index. 3-days rolling mean 500hPa geopotential height $z500$ (a), 2-meter temperatures $t2m$ (e) and total precipitation $prate$ (i) centered on the 27-02-2022. Average of the 35 500hPa geopotential-height analogs found for the counterfactual [ENSO-] (b) and factual [ENSO+] (c) periods and corresponding 2-meter temperatures (f,g) and daily precipitation rate (j,k). $\Delta z500$ (d), $\Delta t2m$ (h) and $\Delta prate$ (i) between factual and counterfactual periods: hashed-filled areas show significant differences. Violin plots for counterfactual (blue) and factual (red) periods for the Analogs Quality Q (m) the Predictability index D (n), the Persistence index θ (o) and the distribution of analogs in each month (p). Values for the selected day are marked by a black dot. Black (resp. red) lines represent the empirical mean (resp. median) of the distribution.

427 case successions of daily SLP latitude–longitude maps — corresponding to a
 428 sequence of states on the attractor. For a given point ζ in phase space (e.g., a
 429 given SLP map), we compute the probability that the system returns within
 430 a ball of radius ϵ centered on the point ζ . The Freitas et al (2010) theorem,
 431 modified by Lucarini et al (2012), states that logarithmic returns:

$$g(x(t)) = -\log(\text{dist}(x(t), \zeta)) \quad (1)$$

432 yield a probability distribution such that:

$$\text{Pr}(z > s(q)) \simeq \exp \left[-\vartheta(\zeta) \left(\frac{z - \mu(\zeta)}{\sigma(\zeta)} \right) \right] \quad (2)$$

433 where $z = g(x(t))$ and s is a high threshold associated to a quantile q
 434 of the series $g(x(t))$. Requiring that the orbit falls within a ball of radius
 435 ϵ around the point ζ is equivalent to asking that the series $g(x(t))$ is over
 436 the threshold s ; therefore, the ball radius ϵ is simply $e^{-s(q)}$. The resulting
 437 distribution is the exponential member of the Generalized Pareto Distribution
 438 family. The parameters μ and σ , namely the location and the scale parameter
 439 of the distribution, depend on the point ζ in phase space. $\mu(\zeta)$ corresponds
 440 to the threshold $s(q)$ while the local dimension $D(\zeta)$ can be obtained via the

441 relation $\sigma = 1/D(\zeta)$. This is the metric of predictability introduced in Sect.
442 [2.2](#).

443 When $x(t)$ contains all the variables of the system, the estimation of D
444 based on extreme value theory has a number of advantages over traditional
445 methods (e.g. the box counting algorithm ([Liebovitch and Toth, 1989](#); [Sarkar](#)
446 [and Chaudhuri, 1994](#))). First, it does not require to estimate the volume of
447 different sets in scale-space: the selection of $s(q)$ based on the quantile provides
448 a selection of different scales s which depends on the recurrence rate around
449 the point ζ . Moreover, it does not require the a priori selection of the maximum
450 embedding dimension as the observable g is always a univariate time-series.

451 The persistence of the state ζ is measured via the extremal index $0 <$
452 $\vartheta(\zeta) < 1$, an adimensional parameter, from which we extract $\Theta(\zeta) = \Delta t/\vartheta(\zeta)$.
453 Here, Δt is the timestep of the dataset being analysed. $\Theta(\zeta)$ is therefore the
454 average residence time of trajectories around ζ , namely the metric of persis-
455 tence introduced in Sect. [2.2](#), and it has unit of a time (in this study days).
456 If ζ is a fixed point of the attractor, then $\Theta(\zeta) = \infty$. For a trajectory that
457 leaves the neighborhood of ζ at the next time iteration, $\Theta = 1$. To estimate
458 ϑ , we adopt the Süveges estimator ([Süveges, 2007](#)). For further details on the
459 the extremal index, see [Moloney et al \(2019\)](#).

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