



Contribution of anthropogenic climate change to April-May 2017 heavy precipitation over the Uruguay River basin

Article

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1 **Contribution of anthropogenic climate change to April-May 2017 heavy precipitation over**
2 **the Uruguay River basin**

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24 **Capsule**

25 Anthropogenic climate change has increased the risk of the April-May 2017 extreme rainfall in
26 the Uruguay River basin, which has caused extensive flood and major socio-economic impacts, by
27 at least twofold with a most-likely increase of about five.

28

29 **1. Introduction**

30 The Uruguay River is a transboundary river of great economic importance in South America. Its
31 headwaters lie in southern Brazil, the middle reach forms part of the Brazil-Argentina border, the
32 lower reach forms the Argentina-Uruguay border, and it then empties into the La Plata River with
33 a catchment area of $3.65 \times 10^5 \text{ km}^2$. The river basin has a temperate climate with annual mean
34 precipitation of 1,750 mm with little seasonality. During the late twentieth century, the Uruguay
35 basin had a positive trend in precipitation (Barros et al. 2008) and streamflow (Pasquini and
36 Depetris 2007). Based on hydrological modeling, Saurral et al. (2008) attributed the 1960-2000
37 streamflow trend mainly to the increase in precipitation rather than land cover change. The upper
38 Uruguay River catchment has relatively high relief, low soil storage capacity, and land use is
39 mostly pasture and cropland. Therefore, the catchment has a fast hydrologic response in which
40 flood occurrence is more dependent on meteorology than on initial conditions of soil moisture and
41 flow (Tucci et al. 2003). A cascade of hydroelectric dams is used for flood control operations.
42 However, when more persistent and intensive rainfall systems develop over the upper catchment,
43 the high soil moisture, fast rainfall-runoff response and limited storage capacity of reservoirs
44 overwhelm the flood control operations and result in downstream flooding. Flood related impacts
45 have also increased, resulting in a growing concern regarding the need to identify the causes of
46 increased flood frequency and establish effective mitigation efforts.

47

48 Explaining the increase in flood frequency requires assessing the role of climate change in shifting
49 the likelihood of extreme rainfall events over the catchment and building more detailed
50 understanding of ongoing changes in the linkage between rainfall and hydrological mechanisms
51 that cause flooding in this flow regulated catchment. To address the former, we analyzed the
52 influence of anthropogenic climate change on the likelihood of the heavy rainfall that occurred in
53 April-May 2017, which led to widespread overbank flooding along the Uruguay River that peaked
54 in June causing significant impacts such as direct economic loss in Brazil of 102 million U.S.
55 dollars (FAMURS 2017) and displacement of more than 3,500 people in Uruguay (BBC 2017).

56

57 **2. Data and methods**

58 The Climate Prediction Center Global Unified Precipitation data (CPC; Chen et al. 2008) with a
59 spatial resolution of $0.5^\circ \times 0.5^\circ$ was used to characterize the precipitation over the Uruguay River
60 catchment for the period 1979-2017 (Figure 1). We applied the Met Office Hadley Centre
61 atmosphere-only general circulation model HadGEM3-A (Ciavarella et al. 2018) at N216
62 resolution (approximately 60 km in the mid-latitudes) to assess the influence from anthropogenic
63 forcings. For 1980-2013 two ensembles of 15 members were used. The first ensemble (“Actual”)
64 is driven by both natural (variability in the solar irradiance in the top of the atmosphere and
65 volcanic activity) and anthropogenic forcings (greenhouse gases (GHG), zonal-mean ozone
66 concentrations, aerosol emissions and land use changes), with sea surface temperatures (SSTs) and
67 sea ice coverage from HadISST (Rayner et al. 2003). The second ensemble (“Natural”) is driven
68 only by natural atmospheric forcings, and has the estimated impact of anthropogenic forcings
69 removed from SST and sea ice patterns using the attribution method described in Pall et al. (2011)

70 and Christidis et al. (2013). In order to estimate the change in likelihood of the 2017 heavy
71 precipitation, we analyze the extensions of these ensembles (denoted “ActualExt” and
72 “NaturalExt”) that were available from March to August 2017 with 525 ensemble members each.

73
74 The Actual and Natural ensemble members are multidecadal simulations, from 1960 to 2013,
75 designed primarily for model validation, while the ActualExt and NaturalExt are shorter
76 simulations with a higher number of ensemble members used for attribution assessments. The
77 “Ext” simulations are continuations of the 1959-2013 runs, with the ensemble members increased
78 by producing batches of members branching from the end of a single multi-decadal simulation,
79 therefore sharing the initial conditions of the small size ensemble but different in the realisation of
80 the stochastic physics (Ciavarella et al. 2018).

81
82 To establish how representative the precipitation in the climate model is for our study region we
83 applied a non-parametric two sample Kolmogorov–Smirnov (KS) test to verify if the CPC
84 precipitation and the “Actual” model simulations from 1979 to 2013 were from the same
85 distribution (Wilks 2006). Gamma distributions were fitted to ActualExt and NaturalExt to
86 estimate the risk ratio (RR). To test sensitivity to the fitted distribution we also fitted a Generalized
87 extreme value (GEV) distribution to both distributions. Risk ratio is a metric recommended for use
88 in attribution (National Academy of Sciences, Engineering and Medicine 2016) to indicate the
89 change in probability of an event with climate change, and is simply the ratio of the actual
90 probability to the natural. Uncertainties within the simulations were computed using a bootstrap
91 resampling method (Efron and Tibshirani 1993).

92

93 **3. Results and discussion**

94 The region is characterized by monthly precipitation distributed equally throughout the year, and
95 is susceptible to floods year round. However, April-May 2017 precipitation was the largest April-
96 May anomaly and the eighth highest anomaly for a two month consecutive period since 1979
97 (Figure 1b). It resulted from a succession of intense events from synoptic scale to mesoscale in the
98 region (CPTEC 2017a,b). A major component was the interaction of midlatitude meteorological
99 systems with the low-level jet to the east of the Andes that supplied additional moisture from
100 tropical regions, enhancing the associated convection. April events enhanced the streamflow in the
101 basin (Figure 1c) and also led to increased soil moisture and reservoir levels. In May, more heavy
102 rainfall over the hydrological wet conditions resulted in flooding that peaked in the beginning of
103 June with a return period of 40 years, causing great economical impacts.

104

105 Unlike most of the large anomalies in Figure 1b, April-May 2017 coincided with a neutral phase
106 of El Niño. However, the austral summer of 2017 was characterized by an unusual fast warming
107 of the far eastern Pacific, denominated by a coastal El Niño (Garreaud 2018). Generally, positive
108 precipitation anomalies in southern Brazil are expected during El Niños (Grimm et al. 1998, 2000)
109 which can cause significant floods (Pasquini and Depetris 2007). Due to the low streamflow in the
110 end of March (Figure 1c), the low soil moisture storage and fast response of the basin, no
111 preconditioning of soil moisture from earlier months would have had a significant impact on the
112 flood. However, we cannot reject the hypothesis that this El Niño increase the frequency of the
113 low-level jet (Silva et al., 2009) which is a key component in producing precipitation in the region.

114

115 To avoid a selection effect we consider 1986 April-May precipitation as a threshold for record
116 breaking events. Although this was a moderate El Niño year, the 1986 flood occurred in April of
117 that year and had similar meteorological conditions to 2017, with heavy precipitation events in the
118 headwater of the basin during a two month period, resulting in the second highest April-May
119 anomaly on record for the CPC dataset with 517 mm and a positive anomaly of 73 %.

120

121 At the 5% significance level, the KS test indicated that we cannot reject the hypothesis that both
122 datasets, CPC observations and “Actual” historical simulations (1980-2013), were drawn from the
123 same distribution (p-value = 0.9). This suggests that the Actual simulations were able to correctly
124 reproduce the statistics of April-May historical precipitation over the catchment area of the
125 Uruguay River (see also online supplemental material). When the same test was used to check
126 whether “Actual” and “Natural” simulations were different, the result indicated that they were not
127 drawn from the same distribution (p-value = 0.005), suggesting a difference between the
128 simulations over the catchment area.

129

130 The fitted probability distribution functions (Figure 2a) indicates different shapes for ActualExt
131 and NaturalExt, with a high narrower PDF in the NaturalExt world in comparison to the ActualExt
132 world. On the other hand, ActualExt shows increased probabilities in the right tail of the
133 distribution, indicating greater chance of extreme events due to anthropogenic forcings, such as
134 the 1986 and the 2017 thresholds. ActualExt also shows a 61 year return time (Figure 2b) for the
135 1986 threshold while NaturalExt indicates a return period of 285 years according to the fitted
136 gamma distributions. Furthermore, for the 61 year return time, NaturalExt has 11 % lower

137 precipitation than ActualExt.

138

139 We assessed the risk ratio using the fitted gamma distributions for ActualExt and NaturalExt. The
140 value obtained was about 4.6, suggesting that the chance of occurrence of an 1986-like event is
141 about five times greater in ActualExt than in the NaturalExt. Uncertainty in the RR was estimated
142 using bootstrapping. For each model ensemble one thousand samples, with replacement, were
143 produced and gamma distributions fitted. They were used to calculate the probability of exceeding
144 the threshold, for both the ActualExt and NaturalExt simulations. In this case, the RR distribution
145 had a median of 5.2 with 5 and 95 % percentiles of 2.6 and 10.4, respectively. Using a GEV fit
146 and identical methodology we find that the RR distribution was highly skewed with a median of
147 4.7 with 5 and 95 % percentiles of 2.0 and 17.7 respectively.

148

149 The historical record of CPC alone (Figure 1b) didn't seem to foresee the anomalous event of
150 2017, with 13 years since 2000 experiencing close to or below average anomalies in April-May.
151 However, the increase in probability of enhanced precipitation events in ActualExt is consistent
152 with the findings of Soares and Marengo (2008). They investigated the South-American low-level
153 jet in a warming climate due to anthropogenic influence and found an increase in the meridional
154 moisture transport from the Amazonian region to the south part of Brazil, where the Uruguay River
155 basin is located, mainly because of an increased temperature gradient between the tropical and
156 subtropical South America.

157

158 **4. Conclusions**

159 This paper examined the April-May 2017 extreme rainfall in a historical context, and analyzed the

160 influence of anthropogenic climate change on the likelihood of such an event that led to severe
161 flooding of the Uruguay River. We found that anthropogenic climate change has increased the risk
162 of the April-May 2017 extreme rainfall in this catchment by at least twofold with a median increase
163 of about five. However, when considering event attribution it is necessary to consider
164 methodological limitations. The removal of the anthropogenic effect in the SST and SIC is a major
165 source of uncertainty, as well as land use changes. Also, there is a need for a more thorough
166 evaluation of the circulation patterns in the model simulations for that particular region that is
167 beyond the scope of this paper.

168
169 Our study made reference to the 2017 flooding of the Uruguay River as the main impact caused
170 by extreme rainfall over a two-month period. The length of the period was defined based on the
171 prerequisite of high levels in the reservoirs for the occurrence of high impact floods. The flood
172 wave travel time from the upper to mid catchment toward the end of the period after heavy rainfall
173 over antecedent high soil moisture and high reservoir levels was of the order of 5-6 days. Hence
174 an analysis based on precipitation outputs on a daily to weekly scale would also be important to
175 track individual heavy rainfall events more specifically. Future research to understand the linkage
176 between rainfall and hydrological mechanisms that cause flooding in this flow regulated catchment
177 is necessary to fully explain the increase in flood frequency.

178

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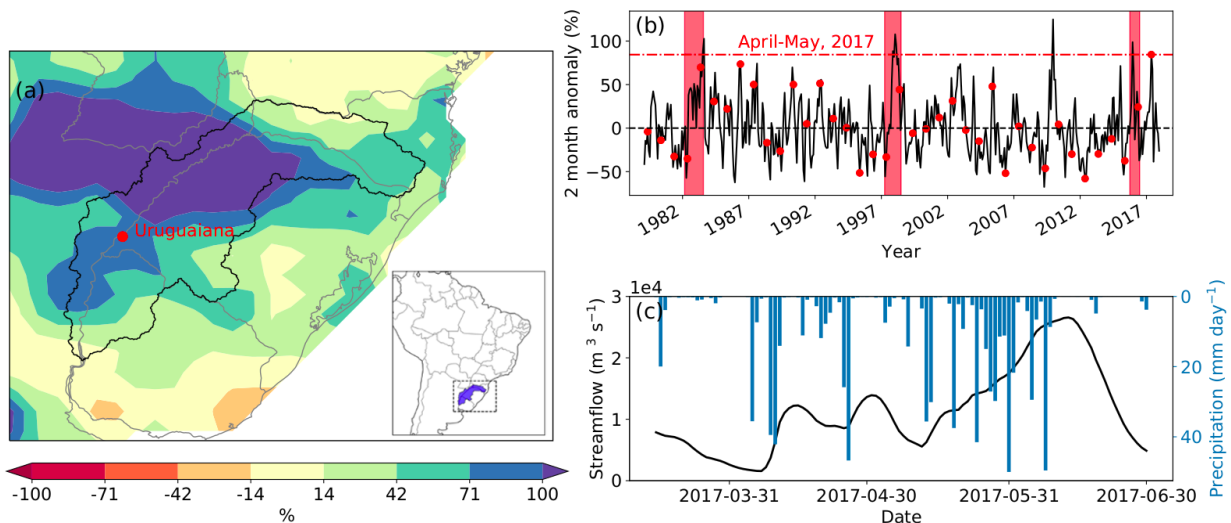
269 **Figure Caption List**

270 Figure 1 (a) 2017 April and May anomalous precipitation in the Uruguay basin as percentage
271 difference from a 1979-2013 climatology, based on the Climate Prediction Center (CPC) Global
272 Unified Precipitation data. The grey borders indicates the geographic boundaries for coastlines,
273 countries and Brazilian states, while black line indicates the boundaries of the Uruguay river basin;
274 (b) Two month precipitation anomaly related to the period of 1979-2017 as percentage difference

275 from the 1979-2013 climatology, based on the Uruguay catchment average calculated using the
 276 CPC data (black line). Red bars in b highlight very strong El Niño events, where the Oceanic Niño
 277 Index (ONI) were greater than 2 °C for more than 3 consecutive months, red dots indicate April-
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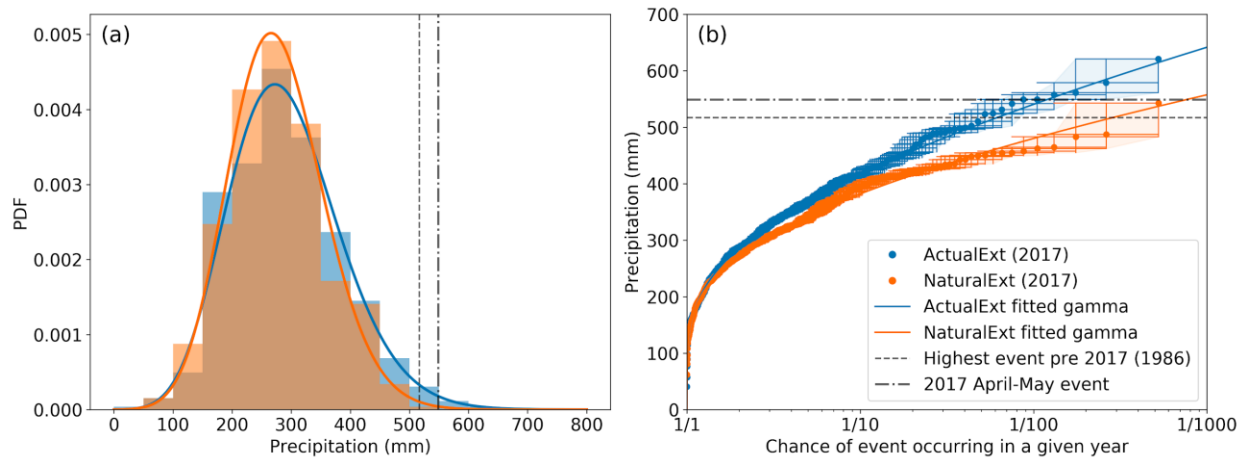
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 282 Figure 2 (a) Probability distribution function for fitted gamma distributions of ActualExt and
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 284 (b) Return time for the ActualExt and NaturalExt experiments. Each marker represents an
 285 ensemble member and the blue and orange lines are the fitted gamma return period for the
 286 ActualExt and NaturalExt, respectively. The errors bars indicate the 95% confidence interval using
 287 bootstrap resampling. Black dashed line indicating the 517 mm threshold based on the 1986 event
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289
 290 **Figures:**



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