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LETTER

Anthropogenic influence on the drivers of the Western Cape drought 2015–2017

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Abstract

In the period 2015–2017, the Western Cape region has suffered from three consecutive years of below average rainfall—leading to a prolonged drought and acute water shortages, most prominently in the city of Cape Town. After testing that the precipitation deficit is the primary driver behind the reduced surface water availability, we undertake a multi-method attribution analysis for the meteorological drought, defined in terms of a deficit in the 3 years running mean precipitation averaged over the Western Cape area. The exact estimate of the return time of the event is sensitive to the number of stations whose data is incorporated in the analysis but the rarity of the event is unquestionable, with a return time of more than a hundred years. Synthesising the results from five different large model ensembles as well as observed data gives a significant increase by a factor of three (95% confidence interval 1.5–6) of such a drought to occur because of anthropogenic climate change. All the model results further suggest that this trend will continue with future global warming. These results are in line with physical understanding of the effect of climate change at these latitudes and highlights that measures to improve Cape Town's resilience to future droughts are an adaptation priority.

1. Introduction

The Western Cape province in South Africa experienced overall below average rainfall over the period 2015–2017. This led to the worst drought since 1904 and an unprecedented water shortage (Botai *et al* 2017, Wolski 2018). Furthermore, this extreme climate event has taken place while observed and modeled long-term aridity in most of Southern Africa is increasing (Shongwe *et al* 2009, Feng and Fu 2013, Huang *et al* 2017, Lehner *et al* 2017), consistent with expectation from the large-scale dynamic and thermodynamic response of the hydrologic cycle to warming (Held and Soden 2006, Cook *et al* 2015). Besides this general trend towards more arid conditions, southern South Africa is also among the few regions where precipitation variability on daily to interannual time scales is expected to decrease with warming (Pendergrass *et al* 2017) a decrease that has been in fact already detected in a broader defined South African region (Gergis and Henley 2017).

The capital city of the region, Cape Town, which is the house of the South African Parliament, was particularly affected by the recent rainfall deficit and the associated water crisis, with the anomaly heavily impacting the area directly surrounding the six large reservoirs that provide fresh water to the city of Cape Town. In this local region, the three years anomaly is an extremely rare event with a return period exceeding 300 years, while over the greater Western Cape the extremeness of the rainfall deficit has an occurrence probability of one event in approximately 150 years. However, as is usually the case (Angelil *et al* 2014) the result is very sensitive to the number of stations and length of station data included (see below) as well as the spatial event definition. The meteorological analysis of the event indicates that below average total rainfall in the region was caused by a strong rainfall anomaly in the shoulder seasons (March–May and August–October), while the core of the rainy winter season (June and July) was characterised by near normal rainfall (Wolski *et al* 2018).

The most prominent impact of the drought manifested through low runoff from source catchments to water supply reservoirs that rely on the annual rainy-season replenishment. This led to insufficient water storage to satisfy the water demand of ~3.7 million residents of Cape Town and irrigated agriculture in the Western Cape from the end of 2017 and throughout the dry season into 2018. The diminished runoff and thus the hydrological drought as well as the reservoir storage was likely also affected by higher than normal, but not unprecedented, temperatures, lower relative humidity and therefore increased evaporation.

The water crisis associated with the drought was very extreme at the beginning of 2018 to the point that the city of Cape Town was expected to run out of water in March 2018 (reservoir replenishment from the 2018 rainy season was not expected to happen before June). As the city was preparing for 'day zero'—the day on which all pipes would run dry and residents would have to get water from communal taps—extreme restrictions on water usage were implemented starting from August 2017 in an attempt to save water and to push out 'day zero' further into the future. The water conservation efforts implemented by citizens helped to significantly cut down consumption. One of these restrictions was however to completely cease irrigation (in February 2018). Thus, while 'day zero' could be avoided (City of Cape Town Day Zero Dashboard http://coct.co/water-dashboard/), losses are very large in the agricultural sector (e.g. Phakathi, B., 5 February 2018, 'Farmers lose R14bn as Cape drought bites'. Business Day, RSA).

Even though the worst case scenario has been averted, at least for the time being, the question of building resilience for future climatic extremes and longer term planning remains. In short, the question to be asked is whether and to what extent the prolonged drought situation is indeed still a very rare event or, if in a changing climate, a drought like this has become more common, and will continue to occur with increased frequency. The question is thus whether anthropogenic climate change had a role in the lack of rainfall itself, but also whether increasing temperatures have exacerbated the impacts of the below average precipitation. Or, in other words, should the Western Cape region and with that, the city of Cape Town be investing heavily in drought resilience, e.g. in infrastructure projects to increase its water storage capacity and diversify its sources of water (e.g. desalination plants) or are we over-focusing on drought which remains a very rare event taking away adaptation resources from more relevant and different risks (e.g. flooding)?

Here, we investigate these questions primarily from a meteorological perspective by looking at the impact of climate change on the rainfall deficit. We provide the first step in analyzing the causes of a complex phenomenon but acknowledge that they do not stop at large scale rainfall but also include complex interactions of catchment size, land management, local precipitation, wind and temperature. Nonetheless, the lack of rainfall in the larger region of the Western Cape is a key driver of the drought and one for which a qualified quantification of the role of anthropogenic climate change is possible, as it is the spatial scale where a number of large ensembles of climate model simulations are available, which allow for a multi-model event attribution study. Using multiple independent models is key to enable an assessment of confidence in the attribution results.

The analysis uses the recommended multi-method approach (NAS 2016) and follows the standard structure of event attribution analyses (e.g. Otto 2017, Philip *et al* 2018) by defining an event in section 2, describing data and models used in section 3, assessing trends in section 4 and attributing the event in section 5. Section 6 synthesis the results which are put in the context of vulnerability and exposure in section 7. The paper ends with a brief conclusion.

2. Event definition

Drought is a complex phenomenon (e.g. Mishra and Singh 2010, Hao *et al* 2018) and notoriously difficult to attribute to anthropogenic climate change (e.g. Otto *et al* 2015, Martins *et al* 2018, Uhe *et al* 2017, Philip *et al* 2018). The regional extent of the drought is not always consistent when looking from the point of view of the impacts and meteorological drivers. In the case of the Western Cape drought, 30%–50% below average rainfall in a relatively large region from 35 to 31°S and from 18 to 21°E persisted for three years (2015–2017) (figure 1(a)). In a much smaller region around the reservoirs securing the water availability in the metropolitan area of Cape Town the negative rainfall anomaly was particularly large and led to a severe water crisis in the city. While crucial for Cape Town, the local drought around the reservoirs immediately surrounding the city is of a spatial extent that requires high-resolution climate and hydrological models to disentangle in detail the drivers of the water crisis at the urban scale. However, these reservoirs are

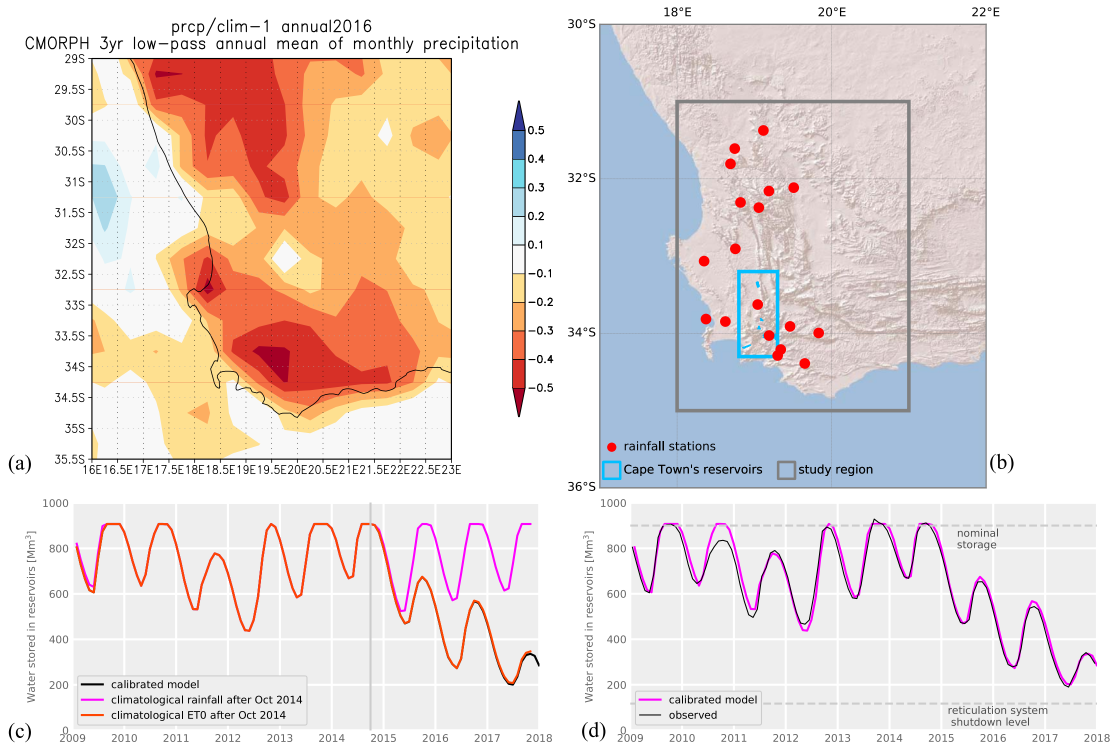

Figure 1. (a) Anomalies of the 2015–2017 precipitation in this region relative to 1998–2014 (b) the study region (grey square) and the location of the reservoirs (blue square). (c) Simulations of reservoir storage with a simple hydrological model accounting for catchment rainfall, evapotranspiration, soil moisture, reservoir evapotranspiration and water use, (d) model simulations with climatological (2000–2014) rainfall and potential evapotranspiration in the post October 2014 period, with other variables unchanged.

part of a larger system of water management in a wide Western Cape region which is well described by the rectangular box over which our analyses are focused (figure 1(b)).

In order to identify the respective roles of precipitation and evapotranspiration as a function of temperature we analyse a simple hydrological model representing the water stored in the reservoirs supporting Cape Town's fresh water supply (supplementary material is available online at stacks.iop.org/ERL/13/124010/mmedia for details). Figure 1(c) shows observations of water stored in the reservoirs and the hydrological model simulations when using observed rainfall and station-based Penman–Monteith potential evapotranspiration (ET0: Allen *et al* 2005) to drive the model. The effects of the drought can be clearly seen in the last three years of the timeseries. To identify the importance of rainfall compared to temperature we repeat the simulation but once using climatological rainfall with observed ET0 and once using climatological ET0 with observed rainfall (figure 1(d)). While the 2015–2017 anomalies in ET0 translate into a minimal, almost imperceptible impact on water resources, the 2015–2017 rainfall anomalies have a very strong impact on the reservoir storage. The results of this simulation are conditional on the sensitivity of the hydrological model to ET0 and rainfall, respectively but give a strong indication that it was primarily the lack of rainfall driving the drought.

We therefore focus on the regional scale drought of the Western Cape in the area (land points in 31°–35°S, 18°–21°E) covering a broadly defined southern part of the Western Cape's winter rainfall region (Philippon *et al* 2012) and encompassing the headwaters catchments of Berg and Breede Rivers, within which Cape Town supply reservoirs are located, as well as the region of intensely irrigated agriculture surrounding the metropolitan area of Cape Town. In this region rainfall is predominantly frontal, brought in by a series of cyclones forming within the temperate westerlies; it exhibits an interannual variability that has been associated with SST and sea ice anomalies in the central South Atlantic and Southern Ocean (Reason *et al* 2002), and with the position of the Westerly Jet and state of circumpolar pressure anomalies described by the southern annular mode (SAM, Reason and Jagadheesha 2005, Dieppois *et al* 2016). While some of the potential drivers exhibit significant trends (SAM, Arblaster and Meehl 2006) the connection with Western Cape precipitation is not necessarily causal, and explain only a fraction of the observed variability. The relationship of the region's rainfall with ENSO is also very weak (Philippon *et al* 2012).

The focus on the broader region rather than on the relatively small area of water supply reservoirs and their catchments is dictated mostly by the need for compatibility in scale with attribution models/methods that are currently available. The main analysis is based on three years rainfall average and focuses on whether and to what extent anthropogenic climate change played a role in the lack of rainfall. In addition, potential evapotranspiration as a measure of drought can be useful, as it affects irrigated agriculture by determining the climate-driven demand for water, counterpart to the natural supply from precipitation (e.g. Hartmann 1994). However, due to the fact that the event is extremely rare in the ET0 reanalysis data and model simulations differ greatly over this variable, we do not assess the attributable signal in ET0.

3. Data and methods

While acknowledging that different climate models have different strengths and weaknesses, we employ the standard multi-method approach to event attribution to analyse whether and to what extent anthropogenic climate change altered the likelihood of the 2015–2017 Western Cape drought. The multi-method approach enables an assessment of the confidence in the resulting attribution statement. By using coupled models as well as atmosphere-only models this also allows to see whether atmosphere-only models are biased towards a particular attribution result as found by Fischer *et al* (2018) in the case of temperature extremes. The description of the models used and their evaluation can be found in the SI. In addition to two coupled climate models (EC-Earth) and two atmosphere-land models (HadGEM3-A, HadAM3P), we use station data, and the gridded observational data series CRU-TS 4.01 updated to 2017 with the GPCC monitoring analysis,

To evaluate the models' ability to reproduce the observed rainfall distribution we fit a Gaussian or Generalized Pareto Distribution (GPD) to the observational data (see below) as well as to the model data (see SI). We compare the model fit parameters with the fit parameters obtained from observational data (figure S2). We only use the model if the fit parameters of the model are within the 95% confidence interval (CI) of those from observations. For this event we use the dispersion parameter σ/μ (the standard deviation over the mean) as the evaluation criteria.

3.1. Observational data

There are >200 South African Weather Service meteorological stations providing daily rainfall data in the region which we use as basis of an analysis of observational data. A gap-screening was used to remove months with fewer than 20 data days and years with fewer than 11 data months. Only 18 stations have more than 90% of data years in the 1930–2017 period and cover the 2015–2017 period.

The composite rainfall (mean of all station series) shows a non-significant positive linear trend (2.4 mm/decade ($p = 0.34$) in 1930–2017, and 5.4 mm/decade ($p = 0.06$) in 1930–2014). Based on a stationary Gaussian fit to the three years running mean (excluding the event), the 2015–2017 event return interval is 150 with a 95% CI of 56–540 years.

In order to be able to compare models with observations we use the gridded observed data CRU TS 4.01 at 0.5° horizontal resolution (Harris *et al* 2014). This dataset does not include 2017, which was taken from the GPCC monitoring analysis (Schneider *et al* 2015). The CRU TS dataset has approximately constant station density from 1901–2016, whereas GPCC has many fewer stations before 1950 and after 1998.

The mean in this dataset shows that most rain falls in the south-western part of the index region where the winter westerlies meet the mountains (figure S1). The northern part is much drier. The trends over 1901–2017 (regression on the global mean temperature, GMST) reflect this difference, with drying trends in the south and wetting trends in the north. The latter are much smaller in absolute changes, but similar as a fraction of the mean precipitation (not shown). The CRU data for this region is based on a limited number of stations (about 50 contribute) and therefore cannot reflect the complexities of the orographically-driven rainfall in this region, which means that individual places can have different trends from the area average. This explains the difference between the trend in the CRU analysis with the the trend in the station composite.

A Gaussian distribution whose parameters scale with a 4 years smoothed global mean surface temperature time series (Hansen *et al* 2010) is fitted to the area-averaged precipitation (figure 2) and shows a downward trend with GMST that is however not significant when excluding the event itself from the data ($p \approx 0.12$ two-sided). The low number of independent data points (38) in the fit causes the trend to be poorly constrained: it can be between -12% and $+3\%$ since 1901 with the best fit -7%.

The current return period of the 2015–2017 3 years annual mean precipitation is approximately 150 years for the observed value of 0.72 mm d^{-1}. We use the (rounded) 100 years return time event of three years running mean precipitation in the selected Western Cape region (land area of 31°–35°S, 18°–21° E) as event definition, noting that the changes in probability depend only weakly on the return time chosen. We furthermore use the fit-parameters from a Gaussian distribution to evaluate the models. We allow for a multiplicative bias correction but ensure that the dispersion parameter σ/μ is compatible with the 95% uncertainty range of 9%–12% from the CRU data fit.

4. Attribution to anthropogenic factors

Using the methods and models described above and in the SI we calculate the ratios for a change of the 1 in 100 years event as defined above with respect to a world that might have been without climate change as

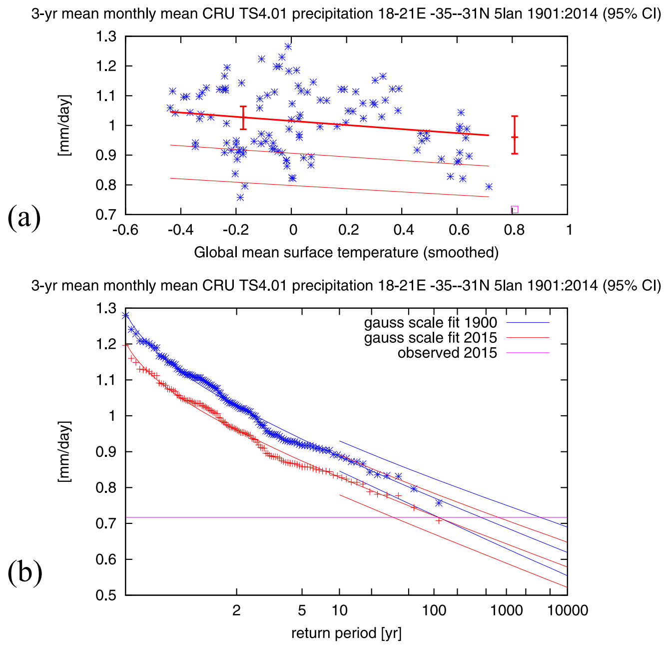

Figure 2 CRU TS 4.01 data averaged over the land points in 31°–35°S, 18°–21°E and over three years (as a running mean) fitted to a Gaussian distribution that scales with smoothed global mean temperature. (a) Individual data points (asterisks) and mean μ, μ-σ and μ-2σ (lines) as a function of t global mean temperature (GISTEMP, four years running mean). The last point (2015–2017, purple) was not included in the fit (the value for 2017 was taken from the GPCC monitoring analysis). (b) Return period of the 2015–2017 event in the current climate (red) and the climate of around 1900 (blue) as inferred by the corresponding values of global mean temperature. The purple line depicts the 2015–2017 event.

well as how the likelihood of such an event could change in a world 2 °C warmer than preindustrial, 1 °C warmer than today. While the term probability ratio would be more accurate we use the established term risk ratio (RR) to determine the ratio between the likelihood of the event occurring in today's climate compared to the occurrence likelihood in the historical climate (RR) and in a 2 °C warmer world (RR2.0). We also estimate how the intensity of a 1 in 100 years event today has changed compared to a 1 in 100 years event in the past. Table S1 gives an overview of the results which are summarised in figure 4 below. There are differences in the framing in these different models, discussed in section 6, as well as differences in the scenarios used. Because the latter have less influence on the overarching result than the former we use the scenarios for which more simulations are available.

4.1. HadGEM3-A

A fit of the regional average 3 years mean precipitation to a Gaussian distribution for the years 1960–2016 gives a RR of 2.1 (1.1...3.8) relative to 1900. We do not use the extrapolation to a 2 °C warmer world indicated in figure 3(a).

4.2. Weather@home

In the weather@home (figure 3(b)) the intensity of 100 years event is 0.452 mm d^{-1} (95% CI: 0.449, 0.454) in the natural ensemble, 0.442 mm d^{-1} (95% CI: 0.438, 0.445) in the all forcing ensemble, and 0.412 mm d^{-1} (95% CI: 0.410, 0.414) in the 2 °C future ensemble. As the present day simulations are centred around the year 2000 we scale the resulting RRs by the increase in GMST since then. A 1 in 100 years event in the actual scenario would have been a 1 in 263.2 years event (95% CI: 176.4, 416.0) under the counterfactual scenario, while such event will be a 1 in 26.5 years event (95% CI: 21.6, 33.3) under the 2 °C future scenario. Hence, for an event with return period of 100 years the RR between the actual and natural ensembles (RR) is 2.63 (95% CI: 1.76, 4.16) while the RR between the 2 °C future and actual ensembles (RR2.0) is 3.77 (95% CI: 3, 4.62).

4.3. EC-Earth

A fit of a Gaussian distribution that scales with the modelled global mean temperature (figure 3(c)) gives a RR of 3.98 (2.7...7.78) for 2015 relative to 1900, or equivalently a change in relative precipitation of −4.9% (−7.4% to −3.7%). In 1900 this still was a 1 in about 400 years event

For the projections, 2050 represents a 2°C warmer world relative to late 19th century in EC-Earth, by then the probability has increased by an additional factor of about three.

4.4. CESM

A Gaussian does not describe the low tail of the distribution well, so we use a Generalised Pareto Distribution (GPD) fitted to the highest 20%. As a covariate, the model global ensemble mean surface air

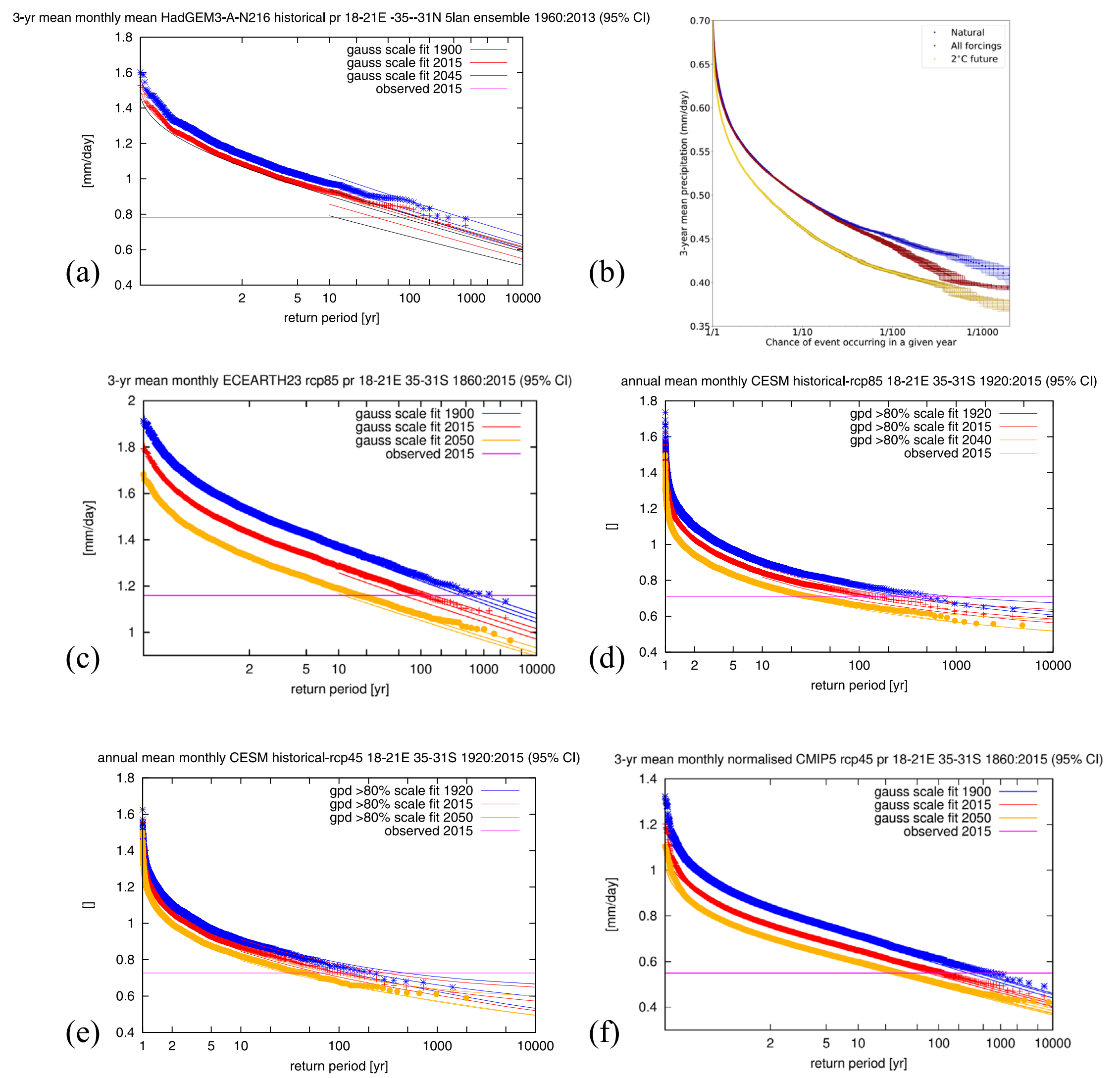

Figure 3. (a) Return time plot of three years mean precipitation in HadGEM3A in natural ensemble (blue), all forcings ensemble (red) and extrapolated for 2045 (yellow); (b) as in (a) for weather@home with the 2 °C future ensemble (yellow); (c) as in (a) for the EC-Earth model; (d) return times in the CESM Large Ensemble driven by the historical/RCP8.5 scenario in 1920–1922 (blue), 2015–2017 (red) and 2040–2042 (orange (corresponding to a 2 °C world; (e)) as in (d)) for the Medium Ensemble driven by historical/RCP4.5, in which a 2 °C global mean temperature is represented by the year 2050; (f) as in (a) for the 42 models of the CMIP5 ensemble historical/RCP4.5, each normalised to a common mean. The data up to 2017 were fitted to a Gaussian distribution/Generalized Pareto on the case of CESM (lines). The event is defined by the current return time of 100 years.

temperature is used. The Large Ensemble using RCP8.5 gives a RR of 3.3 (1.7–10) for three years low precipitation events with a return time of 100 years relative to 1920. Using the temperature difference between 1900–1920 of 0.26 °C this corresponds to a RR relative to 1900 of 4.6 (2.4–13). This corresponds to a change in precipitation for these extremes of −8.8% (−3.7% to −13%). Note that the reference period of 1900 is derived from the single ensemble member that is available for the period starting in 1850, as a 20 years average value around the 1900 date. The global mean temperature reaches 1 °C above 2015 in 2040, so we take that year as the nearest equivalent to a 2 °C climate. The RR from 2015–2040 is found to be 3.0 (2.7–4.3) in this large ensemble (note that the additional years of data decrease the width of the uncertainty bounds).

The same model with a medium-sized ensemble of historical/RCP4.5 scenarios gives a RR of 2.7 (1.0–5.2) over the period from 1900–2017, corresponding to a change of three years mean precipitation extremes of −5.8% (−9.6% to +2.4%), using only data up to 2017 in the fit. The change from now to 2050, the time when the RCP4.5 scenario pushes the global mean temperature to 1 °C over the 2015 one, is a factor 1.9 (1.4–2.9) using data up to 2050.

4.5. CMIP5

When normalising each climate model multiplicatively to the same mean we obtain a smooth CDF that is described well by a Gaussian up to return times of about 100 years (figure 3(f)). This fit gives a RR of 3.5 with a 95% range of 2.7–4.1. This corresponds to a decrease in three years mean precipitation of 6.6% (6.5%–8.6%) up to 2015–2017.

5. Synthesis

In the period 2015–2017, the Western Cape region has suffered from three consecutive years of below average rainfall with particularly poor rains in March to May and August to October—leading to drought conditions and water shortages. Given the dominance of the precipitation deficit over evaporative losses in driving the reduced surface water availability, we adopt a perspective of meteorological drought and define the event for the main analysis as the three years running mean precipitation deficit, for rainfall averaged over the area 31°−35°S, 18°–21°E. A multi-method attribution was performed, based on observational precipitation analyses (station data and CRU TS gridded data based on stations), and multiple climate models' simulations of precipitation (EC-EARTH, weather@-home, CESM, HadGEM3-A) to examine the rarity and changes in probability of such a prolonged rainfall deficit. For comparison and to assess other important factors we also investigated the potential evapotranspiration over the same timeframe and spatial area in ERA-interim reanalysis data. We do not compare this result with model analyses as none of the models for which we calculated ET0 reproduce the distribution of ET0 calculated from the observations in a way that would meet the minimum criteria of a similar σ/μ dispersion coefficient.

The overall results are in good agreement with respect to the sign and significance of the change in probability towards an increased risk of such an event with anthropogenic forcing. The only exception is the analysis of the station data, which however is very sensitive to the choices of which stations to include in the assessment due to the large differences in trends over the study area (figure 2(b)). Return periods for the event in the station data very between about 100 and 300 years depending on whether only long term stations are included or not. The gridded data provide a return time of about a 150 years but with a very large uncertainty due to the large variability of precipitation. Irrespective of these uncertainties, it clearly was a rare event. Given the uncertainty around the return time and the fact that results are more robust for less extreme events we use the 1 in 100 years event in the present day climate for the low end of three years average precipitation as the definition of the event.

Using CRU TS as the observed data set for the analysis, the best guess is an increase in risk of 3.5 but the result is not significant ($p = 0.12$). The small number of stations contributing to the CRU data estimate, combining both weak and strong drought signals because of the complex topography of the region is one reason for the uncertainty in the observational analysis. Further, the length of the station data is likely also important: the analysed region has a quasi 40 years component (Dieppois *et al* 2016) that underlies the previous severe droughts recorded in 1930s and 1970s, and the records' length is bound to reflect this multidecadal variability in rainfall.

Combining the observational analysis as well as the models and using a simple average to synthesise the results, the likelihood of an event like the observed 2015–2017 drought has increased by a factor of 3.3 (1.4–6.4). Unlike for other drought analyses in other parts of Africa, this is a very clear result with anthropogenic climate change having significantly increased the likelihood of such a drought to occur.

Although there are differences in precipitation trends between the models, the CI obtained from observations encompasses the CIs of all model results. In the weather@home model, as well as HadGEM3A and CMIP5 the probability ratio is defined as the change in probability between the present day and preindustrial conditions. In EC-Earth and CESM we use the 16 or 40 (respectively) ensemble members over the historical period (1900–2016) and perform the same analysis as in the observations. The assumption is that the climate around 1900 is similar to the preindustrial climate due to the cooling effect of a few large volcanic eruptions compensating the small greenhouse warming up to that time (Hawkins *et al* 2017). Despite these differences in framing the results are consistent..

In addition to the attribution analysis we also assess how the likelihood of the same event occurring is changing in the future under an additional degree of global warming, leading to a 2 °C warming relative to pre-industrial. Of course, for the scenarios of the future we do not have any observations. Furthermore, the framing of the analysis differs more widely between the different models. We thus do not attempt to synthesise the results but present them individually in figure 4(b). In all available models the probability ratio increases further by a factor comparable to the ratio of increase resulting from the degree of warming up to today, suggesting that drought risk in this area scales linearly with warming, at least for warming up to 2 °C.

6. Vulnerability and exposure

Exposure is the presence of people, their livelihoods, infrastructure, and economic and social assets in places that could be affected by extreme events, such as rainfall or drought, while vulnerability denotes the propensity or predisposition for those people or assets to be affected (Cardona *et al* 2012). In this section we summarise the vulnerability and exposure factors that have also contributed to the impacts throughout the Western Cape, including strict water usage limits in the City of Cape Town, and agricultural drought in the surrounding areas.

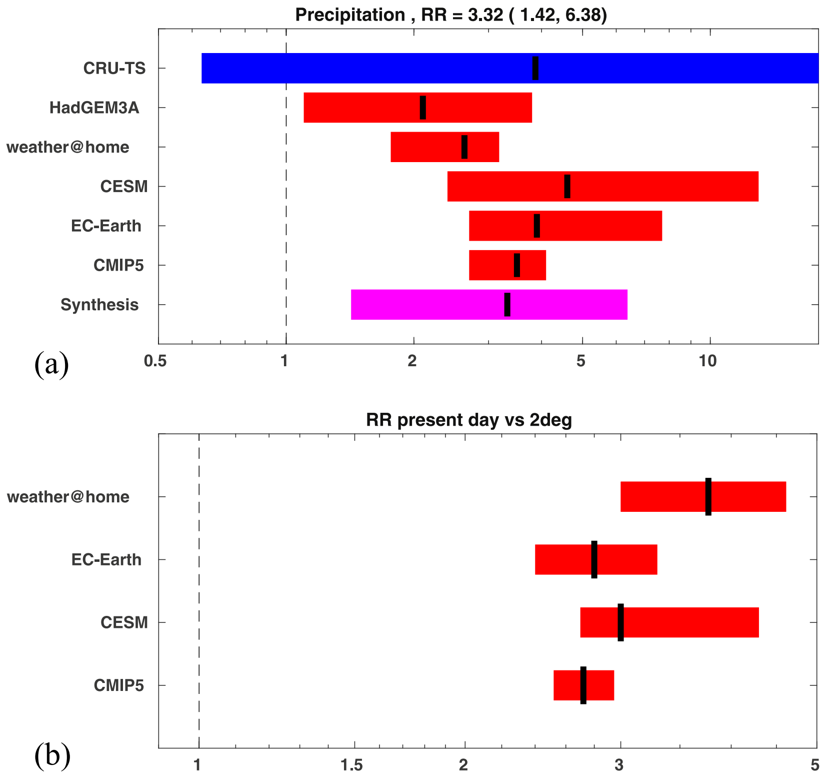

Figure 4. (a) provides an overview of the multi-method results for changes in return periods depicted as probability (risk) ratios with 95% uncertainty intervals; (b) provides an overview of the multi-method results for changes in return periods depicted as probability (risk) ratios with 95% uncertainty intervals in a world with GMST warmer by 2 °C.

The Western Cape Water Supply System consists of 14 dams and pipelines managed by the City of Cape Town and the National Department of Water and Sanitation. The system's capacity is provided by six dams, the largest of which are located outside of the city limits and supply water to both the city of Cape Town (64%) and surrounding farmland (32%) (Water Services and the Cape Town Water Cycle, March 2018, https://resource.capetown.gov.za/documentcentre/Documents/Graphics%20and%20educational%20material/Water%20Services%20and%20Urban%20Water%20Cycle.pdf.) The system is almost entirely dependent on rainfall, making it highly vulnerable to climate variability and change. Although the system was designed to provide sufficient water storage to mitigate droughts with a return interval of 1 in 50 years (Water Outlook 2018, https://greencape.co.za/assets/;Uploads/Water-Outlook-2018-Rev-22-updated-23-March-2019.pdf.), this paper shows that the return time of extreme droughts has changed due to climate change, leaving the population and economy protected by this system more vulnerable to drought risks than previously anticipated. The system's reliability made it so that few people had back-up water tanks in case the system failed, a contrast to other large cities that have faced similar water crisis such as Sao Paulo (Campos and de Carvalho Stutdart 2008).

Droughts in South Africa affect both the local and national economy, by adding pressure to the nation's agro-economic system, including increased unemployment, negative impacts on upstream economic activities and production loss over several years (Baudoin *et al* 2017). While the agricultural sector only makes up 4% of total Western Cape GDP, it is a key formal and informal employer in the Western Cape and provides inputs for other industry such as the agri-processing. South Africa's 'Provincial Economic Review and Outlook 2017' listed the water crisis as both a physical and financial risk to companies in the Western Cape with water tariffs reducing competitiveness, adding risk to operations, and impacting businesses reputation for reliability and quality (e.g. https://westerncape.gov.za/assets/departments/treasury/Documents/Research-and-Report/2017/2017_pero_printers_proof_21_september_2017_f.pdf).

While Cape Town's population continues to grow, the City has been internationally recognised for its water conservation demand management practices which have stabilised water demand growth to around 2% per annum. However, this has not been sufficient to avoid the impacts of the current drought due, in part, to changing risks and has a disproportionate negative impact on poorer households (Mahlanza *et al* 2016). In addition to increasing water efficiency, and implementing water restrictions and tariffs to manage demand, the City explored options for augmenting the water supply. Planned desalination plants are focused on providing water for strategically important infrastructure such as hospitals and the commercial city centre, in order to reduce their vulnerability to future droughts. These augmentation activities are intended to supplement the existing water supply starting in 2019, and were catalyzed be concern for the potentially serious consequences if rainfall was again poor during the 2018 rainy season.

7. Conclusion

While the event today is a very rare event, climate change has significantly increased, more than doubled, the likelihood of a prolonged drought to occur. All the model results available to us suggest that this trend will continue with a similar rate into the future.

The hydrological analysis revealed a dominant role for rainfall in this drought compared to evapotranspiration, prompting us to focus on precipitation as the key variable through which to understand the impact of anthropogenic climate change on the Western Cape drought today. This is consistent with other modeling results suggesting that the future increase in drought risk over South Africa is predominantly precipitation-driven.

However, a brief analysis of evapotranspiration in reanalysis data (see SI) revealed a strong upward trend in recent years, consistent with the regional warming trend. This suggests that more research is needed to better understand the role of temperature in a drought like this.

While Cape Town has narrowly avoided the taps running dry in this instance, this has been at the cost of water to irrigate the farms in the Western Cape. The increasing risk of drought, coupled with high reliance on rain-fed dams that supply water to a growing city and agricultural sector, provides a strong basis for reassessing the current water supply and management to adapt to changing risks. This may include considerations for diversifying the current water supply through desalination and groundwater extraction along with ecosystem-based adaptation approaches that ensure replenishment of groundwater supplies, for example.

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