EMBARGOED UNTIL 5pm EDT/10pm BST/11pm CEST JUNE 29

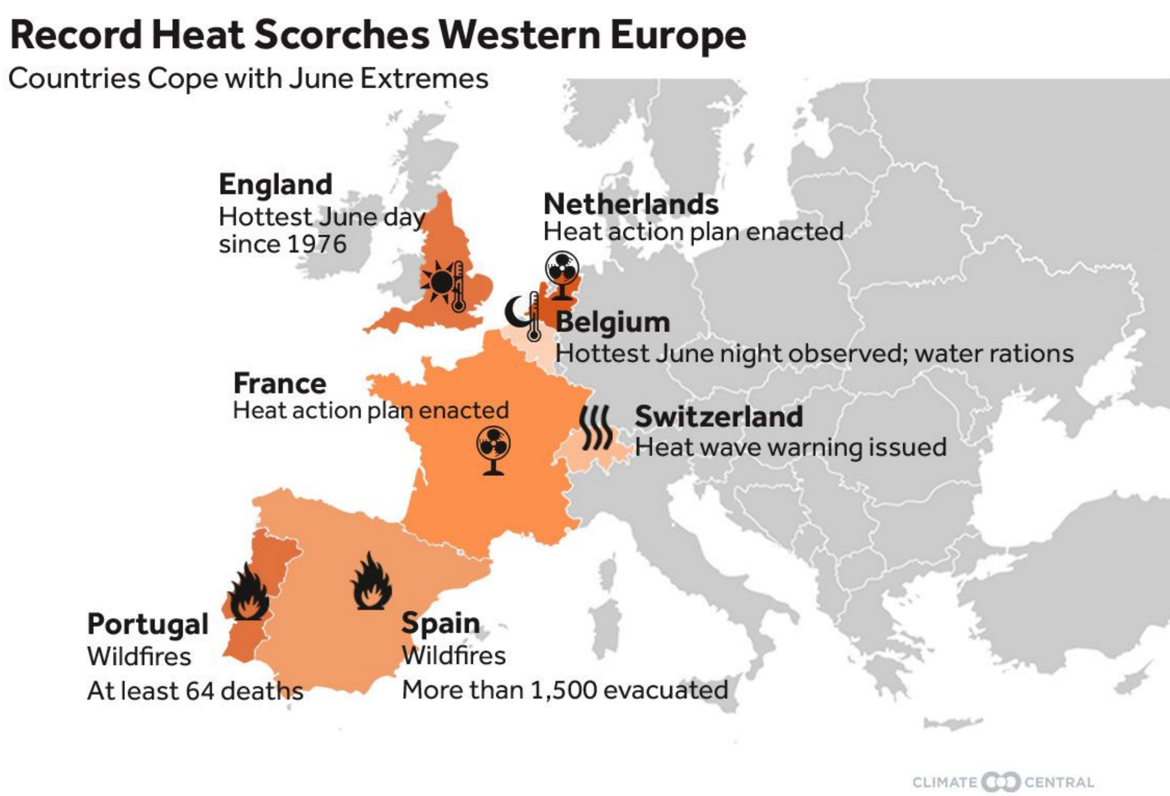
Extreme Heat:

Attribution of the Record June Temperatures in Europe and the UK

Friederike Otto (University of Oxford), Geert Jan van Oldenborgh (KNMI), Sarah Kew (KNMI), Sjoukje Philip (KNMI), Robert Vautard (LCSE-IPSL), Edward Hawkins (University of Reading), Andrew King (University of Melbourne), Sven Kotlarski (MeteoSwiss), Cornelia Schwierz (MeteoSwiss), Sarah Sparrow (University of Oxford), Davide Faranda (LCSE-IPSL), Jean-Michel Soubeyroux (Meteo France), Roop Singh (Red Cross Red Crescent Climate Centre) and Heidi Cullen (Climate Central)

KEY POINTS:

- **Record-breaking heat gripped most of Western Europe during June 2017, sending monthly mean temperatures about 3 degrees Celsius (4.8 degrees Fahrenheit) above normal (1981-2010).**
- **Scientists with World Weather Attribution (WWA) and partners in England, France and Switzerland conducted a multi-method analysis to assess whether and to what extent human-caused climate change played a role in the heat.**
- **These high temperatures are no longer rare in the current climate, occurring roughly every 10 to 30 years.**
- **The team found that climate change increased the frequency and intensity of such extreme events, which have at the very least doubled and in the south have increased by at least a factor 10. By the end of the century, these high temperatures will become the norm in Western Europe.**



INTRODUCTION

The month of June was marked by high temperatures across Western Europe with heat waves triggering national heat-health plans and wildfires requiring evacuations in Portugal and Spain. Heat waves can have significant impacts on human health and wellbeing including exacerbating existing medical conditions, particularly in the elderly and very young, and increasing energy demand, which can lead to disruptive power outages. In France, the night of June 21 will go down as the hottest June night ever recorded for most of the country as the average nighttime temperature reached 26.4 degrees Celsius (79.52 degrees Fahrenheit). The average monthly June temperature in France was the second warmest on record after June 2003 in the official "heat index" series. Level three of France's four-level heat wave plan, put in place after the devastating 2003 heat wave, was triggered for Paris as temperatures in the French capital topped 37 degrees Celsius (96.8 degrees Fahrenheit) during the week of June 19. In the Netherlands, June 2017 is likely to be the hottest June ever observed while in Switzerland, June 2017 is the second warmest since 1864 when observations began. In northern areas, the minimum nighttime temperatures reached record highs of 24-25 degrees Celsius (75.2-77 degrees Fahrenheit). A level 3 warning was activated from June 20-23. In Britain the UK Met Office reported that Wednesday, June 21 was the hottest June day in more than 40 years when temperatures reached 34.5 degrees Celsius at Heathrow.

A major forest fire in Spain forced more than 1,500 people from homes, campsites, and hotels, and encroached on a UNESCO World Heritage site housing endangered species. In Portugal, a deadly forest fire killed at least 64 people, injured 204, and displaced over 500 from their homes. Triggering the EU's Civil Protection Mechanism, France, Italy and Spain have provided firefighting planes to help get Portugal's "worst forest fire in more than a century" under control. The smoke of the wildfires in Portugal were catapulted high into the atmosphere and then transported several thousands of kilometers across Europe. Smoke from the fires could be seen all the way to the Swiss Alps from the station at Jungfraujoch (3580 m).

he World Weather Attribution team in partnership with experts from other European countries conducted an event attribution study to investigate whether and to what extent human-induced climate change played a role in the high June temperatures across different countries in Western Europe..

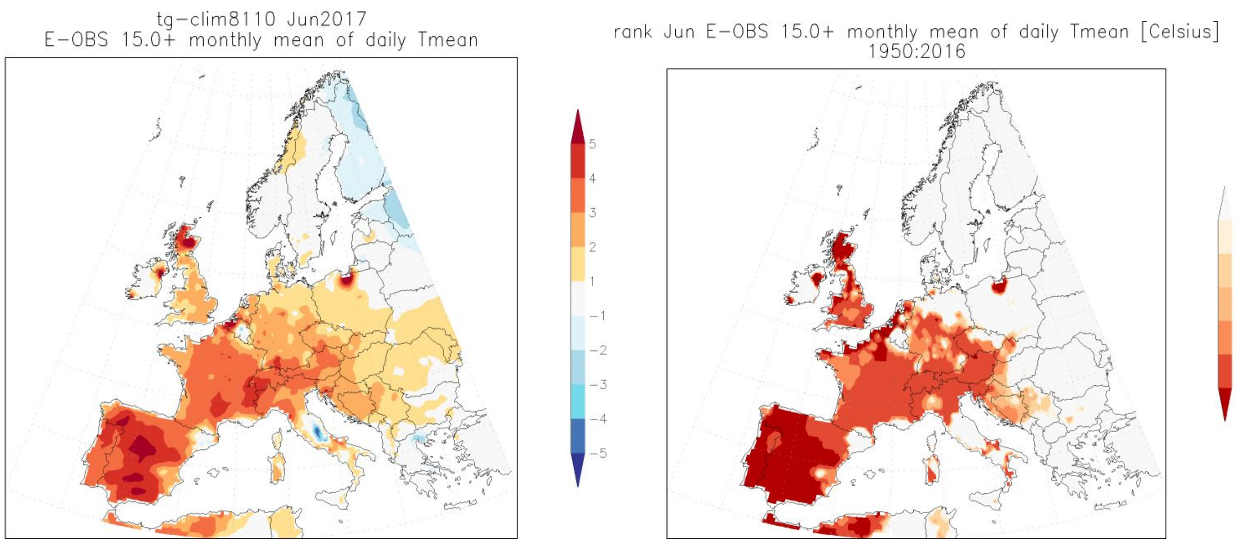


Figure 1. Left: first estimate of Tmean anomalies for June 2017 relative to 1981-2010, right: rank of the anomalies (dark red is highest value, bright red second highest, usually after 2003). Source: ERA-interim/ECMWF analysis/ECMWF forecast via KNMI Climate Explorer.

RETURN PERIODS & TRENDS IN OBSERVATIONS

First we analyze the observed June temperature record in several Western European countries to assess whether or not there is a trend toward increasing temperature. We also compute the return periods of average monthly June temperature as observed in 2017 to assess how rare this heat event is. For two countries, Portugal and Spain, we additionally analyze the average maximum June temperatures as in these two countries not only minimum and mean temperatures but also the maxima were exceptional. The data are taken as the average of the 0.5º CRU TS 4.00 analysis 1901-2015 over all grid points within the boundaries of Portugal (without the Azores and Madeira), Spain (without the Canary Islands), France (without overseas territories but including Corsica) and Belgium. This was extended to June 25 using E-OBS v15.0 to Dec 2016, the monthly updates to May 2017 and the daily updates for 1–26 June 2017, with a bias correction to CRU TS computed from the overlap period 1950–2015. The data for June 27–30 were taken from the ECMWF analysis (27) and forecasts (28–30) with a bias correction to the daily E-OBS analysis starting 1979 using ERA-interim.

For Switzerland we used the Swissmean 1.0 series (1854–now) based on homogenized station data. The Netherlands were represented by the Central Netherlands Temperature v1.1 (1906–now). As this does not include the coastal areas, we restricted the model analyses to the box 51.5–52.5 ºN, 4.5–6.5 ºE. The same holds for England, where we used the Central England Temperature and the box 51–54 ºN, 0–3 ºW to represent the temperature series in models. As the variability of the CET is much larger before 1900 (King et al, 2015) we start our analyses in that year. All these series were extended to June 2017 using E-OBS for June 1–26 and ECMWF forecasts for June 27–30 as discussed above (for the CNT these are for the underlying stations rather than a box).

Based on these series we expect the mean temperature of June 2017 to be the highest one in the series in Portugal, Spain, France and the Central Netherlands. Note the Météo France "heat index" series based on 30 non-public stations gives a second place, after 2003. In Switzerland it is expected to be the second-highest since observations began in 1864, after 2003. Based on the CRU TS data, in Belgium it will be about the fifth warmest. The Central England June temperature will likely end up as the fourth highest June value since 1900.

We analyzed the observational data by fitting all June temperature observations to a distribution that shifts proportional to the smoothed global mean temperature. This method assumes that global warming is the main factor affecting local temperatures on the 100-yr time scale. This assumption is correct almost everywhere over land, which is dominated by the day-to-day variations of the weather. Natural variability with time scales of more than a century has a very small amplitude over land (Suckling 2016). It also assumes that climate change is linear, i.e., that all temperatures go up the same amount. This is not the case in areas where soil moisture depletion is important (Seneviratne 2010) and this assumption is checked in regional climate scenarios provided by the CORDEX initiative. For the distribution we take a Normal distribution, which fits the monthly mean data well. This reduces the fit to a simple linear regression. All fits exclude the year being studied, June 2017. The fits are shown in Figure 2 as a function of the global mean temperature with the linear fit, and as a function of the return period for the climates of 1901 (blue) and 2017 (red).

The probability in the climate of 1901 requires an extrapolation of several orders of magnitude in probability in the southern countries. This extrapolation depends very strongly on the distribution that is assumed, the uncertainty of this assumption is not included in the margins quoted. The model results below with more data points show that the tail of the distribution is likely thinner than a Normal distribution, which implies that the fits here may well underestimate the Risk Ratio, i.e. the change in the likelihood of the event occurring due to climate change.

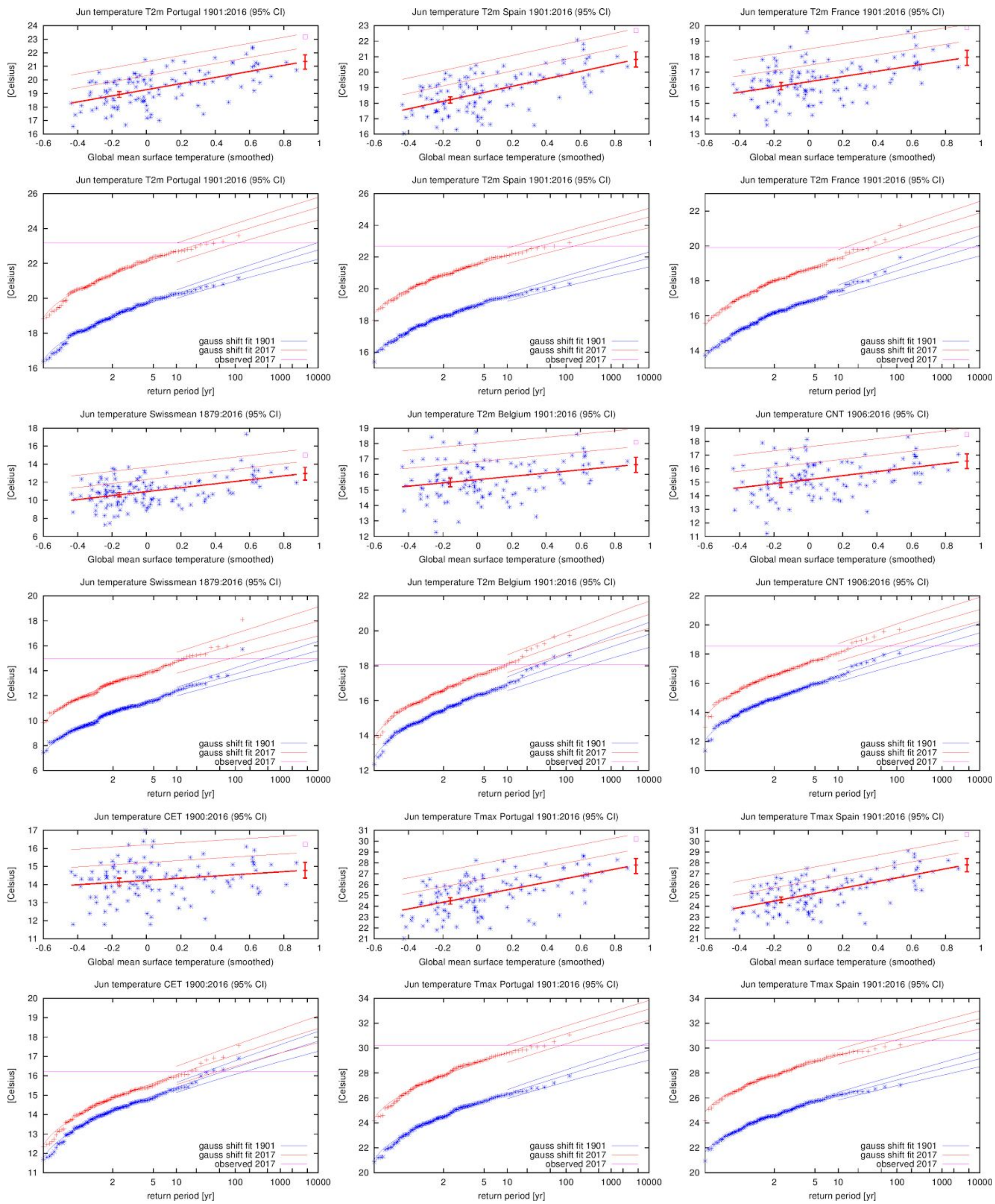


Figure 2. Fits to the June temperature time series as described in the text of Tmean of Portugal, Spain, France, Switzerland, Belgium, the Central Netherlands and Central England; Tmax in Portugal and Spain. The red lines indicate the current climate, the blue ones the climate of around 1901. The purple symbol and lines indicate June 2017 (not included in the fits).

The results for the observed temperature in 2017 and return periods (including 95% Confidence Intervals, CI) of this value in the current climate are shown in Tables 1 and 2. The return periods are not very high, around 10 years (10% chance per year) in the northern countries and Switzerland to around 20 years (5% chance per year) in France, Spain and Portugal. This means that we can expect another hot June like this before too long. The maximum temperature averaged over Spain was more exceptional, around 80 years, almost certainly more than 30 years (less than 3% chance every year).

Table 1. Observed/forecast value and return period of June 2017

Country (rank) Tmean	**Observed/forecast Tmean, anomaly**	**Return period in current climate**	**95% CI on return period**
Portugal (1)	23.2 ºC 2.9 ºC	25 yr (4 %/yr)	10 ... 110 yr
Spain (1)	22.7 ºC 3.0 ºC	35 yr (3 %/yr)	13 ... 150 yr
France (1/2*)	19.9 ºC 2.9 ºC	30 yr (3 %/yr)	12 ... 140 yr
Switzerland (2)	15.2 ºC 3.2 ºC	20 yr (5%/yr)	7 ... 130 yr
Belgium (~5)	18.1 ºC 2.0 ºC	9 yr (11 %/yr)	2.5 ... 45 yr
Central Netherlands (1)	18.5 ºC 2.8 ºC	20 yr (5 %/yr)	8 ... 70 yr
Central England (~4)	16.4 ºC 1.9 ºC	15yr (7 %/yr)	7 ... 50 yr
Tmax			
Portugal (1)	30.2 ºC 4.2 ºC	20 yr (5 %/yr)	10 ... 80 yr
Spain (1)	30.6 ºC 4.3 ºC	80 yr (1 %/yr)	30 ... 500 yr

* The CRU TS 4.00 / E-OBS v15.0+ / ECMWF series gives the highest value, the Météo France "heat index" series based on 30 non-public stations the second-highest.

The fit also allows us to compare the probability in the climate around 1901 (i.e., with a global mean temperature as observed around 1901) with the climate of today. We emphasise again that this extrapolation is very uncertain in the southern countries and may well lead to an underestimation of the Risk Ratio.

Table 2: Risk Ratios estimated from observed trends.

Country **Tmean**	**Risk Ratio (p_1/p_0)**	**95% CI on RR**	**∆T, change in magnitude**	**95% CI on ∆T**
Portugal	2000	300 ... 30000	2.4 ºC	1.8 ... 3.0 ºC
Spain	9000	1000 ... 300000	2.6 ºC	2.0 ... 3.2 ºC
France	200	30 ... 2000	1.8 ºC	1.2 ... 2.4 ºC
Switzerland	150	30 ... 900	2.4 ºC	1.5 ... 3.1 ºC
Belgium	8	2.4 ... 40	1.1 ºC	0.5 ... 1.8 ºC
Central Netherlands	30	6 ... 250	1.6 ºC	0.9 ... 2.3 ºC
Central England	4	1.3 ... 13	0.7 ºC	0.1 ... 1.2 ºC
Tmax				
Portugal	1400	150 ... 20000	3.3 ºC	2.4 ... 4.1 ºC
Spain	25000	1500 ... 1000000	3.2 ºC	2.5 ... 3.9 ºC

Furthermore, the Risk Ratio estimates have large uncertainties due to the relatively small number of data points (for most countries 116). However, they are always (much) larger than one, showing that the probability of observing a temperature as high as in 2017 or higher has increased, in many regions strongly, over the past century.

ATTRIBUTION - MODEL RESULTS

The next step in our analysis is to assess whether and to what extent external drivers, in particular anthropogenic climate change, caused this positive June temperature trend in the observational data. Answering this question requires the use of climate models, in which the relative impact of various external "forcings" such as changes in solar insolation, volcanoes, and greenhouse gas concentrations can be quantified. We need to use climate models because the observational record can assess correlation (is there a trend?) but not causation (what caused the trend?).

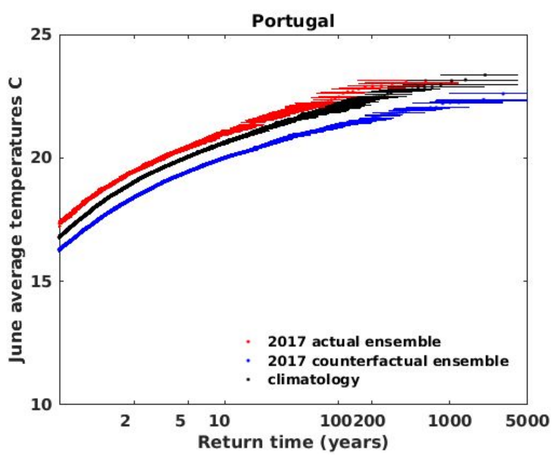
For this analysis we looked at five different climate models and modelling initiatives respectively (weather@home, HadGEM3-A, EC-Earth 2.3, CMIP5 and CORDEX). CMIP5, the "5th Coupled Model Intercomparison Project" (Taylor et al. 2012), is a collection of coordinated experiments from climate models run at centers across the world and is used in the IPCC Fifth Assessment Report. The EC-Earth 2.3 model, which also forms part of the CMIP5 ensemble, was run 16 times at KNMI. The CORDEX ensemble of Regional Climate Model (RCM) runs downscales CMIP5 runs from 1950-2100 to much higher resolutions over Europe (11km). 11 bias-adjusted ensemble members of the European CORDEX branch EURO-CORDEX (www.euro-cordex.net) are used in this analysis. Two further ensembles of atmosphere-only models are used: the UK Met Office HadGEM3-A model at N219 (60km) and the very large ensemble of Oxford's weather@home runs of HadRM3P simulations at (50km). These models are all run with and without (the "counterfactual") human-caused emissions of greenhouse gases and aerosols, allowing us to isolate and quantify the influence of human-induced climate change on the likelihood of June warm spells within the climate models.

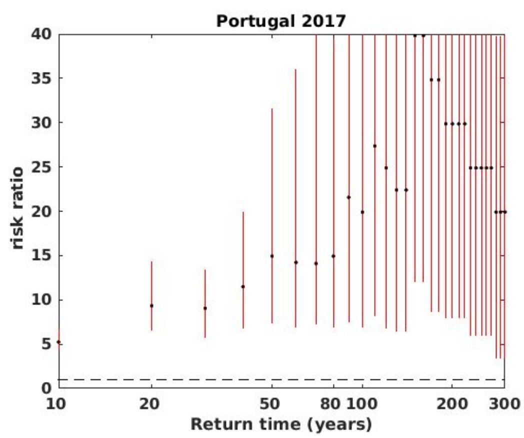
weather@home

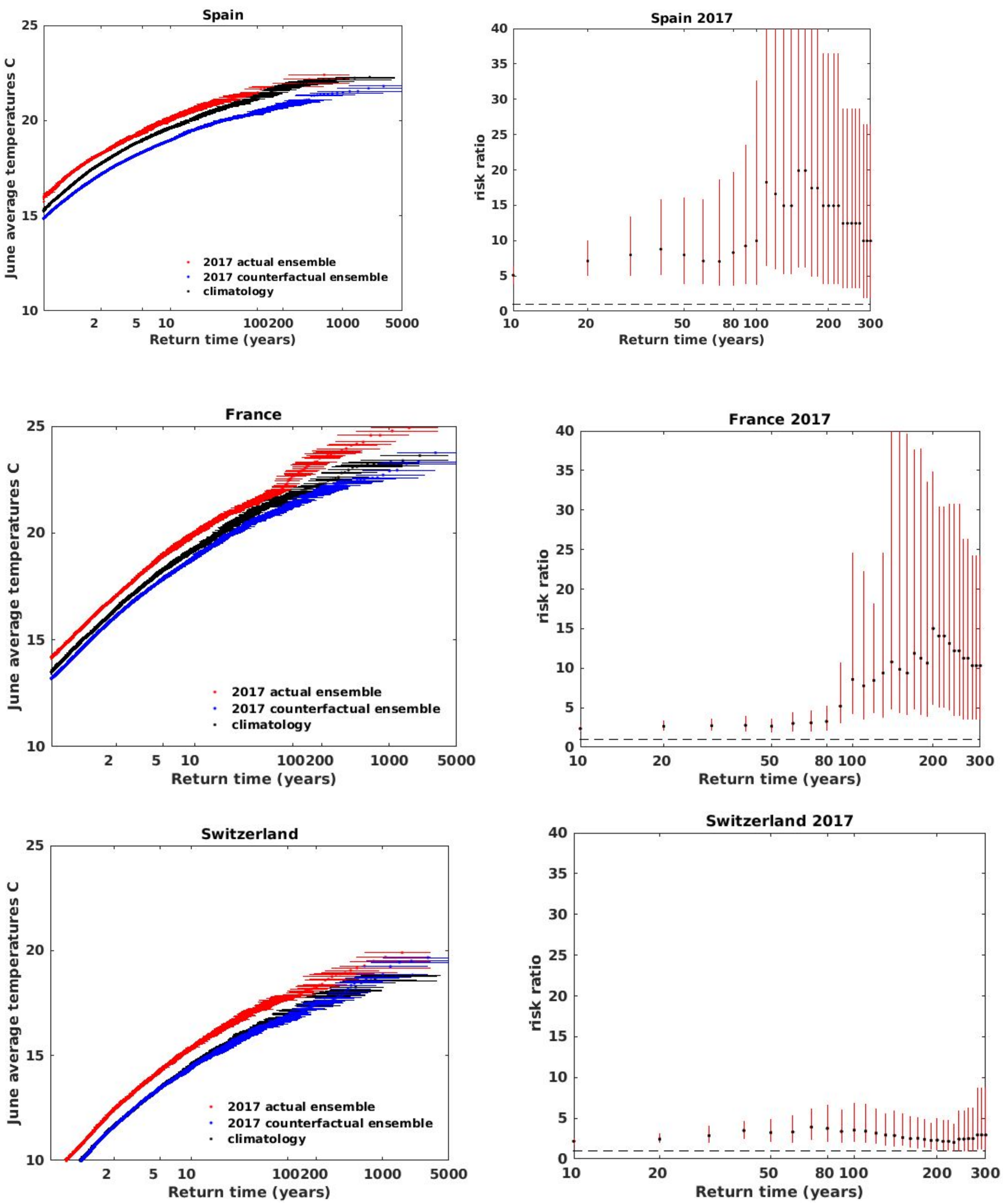
Using the distributed computing framework known as weather@home (Massey et al. 2015), we simulate two different large ensembles of June 2017 using the Met Office Hadley Centre regional climate model HadRM3P at 50km resolution over Europe embedded in the atmosphere-only global circulation model HadAM3P. The first set of ensembles represents possible June weather under current climate conditions. This ensemble is called the "all forcings" scenario and includes human-caused climate change. The second set of ensembles represents possible June weather in a world as it might have been without anthropogenic climate drivers. This ensemble is called the "natural" or "counterfactual" scenario.

As weather@home is an atmosphere-only modelling framework, observed sea surface temperatures (SSTs) are necessary to drive the model. SSTs for the "natural" simulations are obtained by subtracting various estimates of the difference between pre-industrial and present-day conditions from CMIP5 (Schaller et al., 2014). As observed SSTs are not yet available at the time of writing, the model is forced using seasonal forecast SSTs from the Met Office forecasting system GloSEA5 (Haustein et al., 2016). While biased warm in most countries, the distribution of average June temperatures compares well with observed distributions of June temperatures in the analyzed countries apart from the southernmost, Spain and Portugal, where the bias is cold. While the distribution and variability in the model climatology compare well with observations, the difference in June temperatures between the all forcings and counterfactual simulations is only about 1 ºC suggesting the counterfactual simulations underestimate the trend from human-induced warming. Results from weather@home simulations thus are likely a very conservative estimate of the risk ratio. Return periods of June temperatures in the two ensembles as well as the climatology are shown in Figure 3 as well as the risk ratios and their change with return period. Table 3 shows the risk ratios for the observed June 2017 events.

It is to be expected that the changes in probability in the atmosphere-only simulations do not exactly compare with observations and coupled model simulations. While observations and coupled models include changes due to natural variability and, in case of the observations other forcings, the atmosphere-only simulations of an individual year allow the change in probability due to anthropogenic forcings alone to be quantified. Everything else, including SST patterns, is kept the same. However, compared to the trend from human-induced warming, these other influences are small (at least over Europe) and thus cannot explain the discrepancies to trends in observations.






Spain
Spain 2017
France
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Switzerland
Switzerland 2017
June average temperatures C
risk ratio
Return time (years)
2017 actual ensemble
2017 counterfactual ensemble
climatology

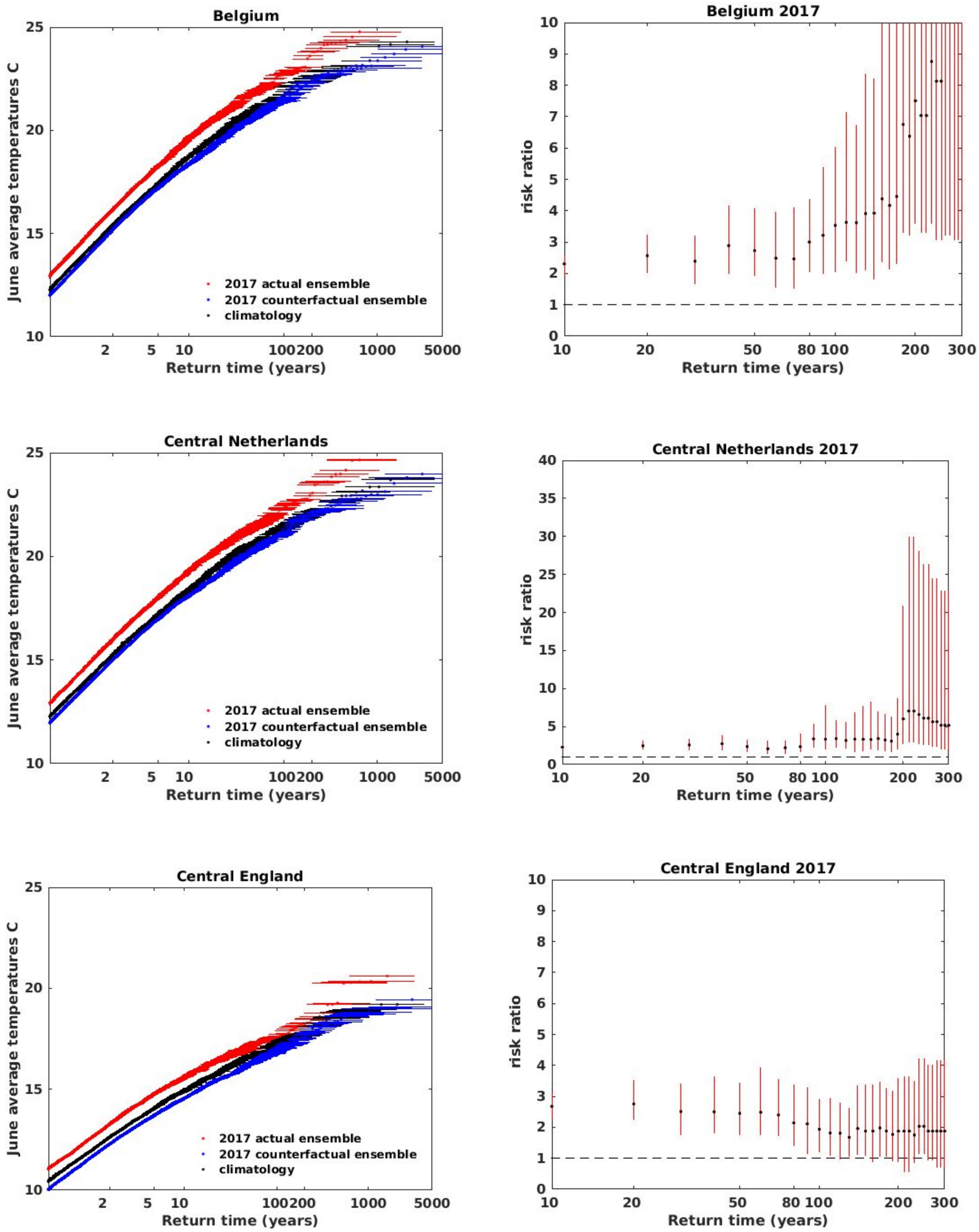


Figure 3. Left-hand side: Return periods of June mean temperatures for the seven analyzed countries in three different weather@home ensembles: the "all-forcings" for 2017 (red), the "counterfactual" simulations for June 2017 (blue) and the climatology of average June

temperatures from 1986-2015 (black). Right-hand side: risk ratios between the "all-forcings" and "counterfactual" simulations depending on the return time.

Table 3. Risk ratios from weather@home for the observed 2017 events in the seven analyzed countries. Changes in magnitude for all countries are approx. 1°C.

Tmean	**Risk Ratio**	**95% CI**
Portugal	8.5	5.6...12.8
Spain	8.7	5...17.2
France	2.7	2.1...3.6
Switzerland	2.3	1.9...2.9
Belgium	2.2	1.8...2.5
Central Netherlands	2.5	2...3.2
Central England	2.8	2.3...3.3
Tmax		
Portugal	3.8	2.9...4.9
Spain	5.1	2.8...13.2

CMIP5

For the CMIP5 analysis, we first checked which of the 15 models (Taylor et al. 2012; Table 4) with the required simulations for the analysis have a temperature anomaly distribution that is compatible with the observed distribution (following the method of Lewis and Karoly 2013; King et al. 2015). Temperature anomalies were extracted from the observational data (1961-1990 baseline) and compared with historical model simulations using the same baseline. The number of models used in each regional analysis is shown in Table 5. This evaluation process was done over seven regions for June mean temperature (Tmean) and over two regions (Spain and Portugal) for June average maximum temperature (Tmax).

The change in the likelihood of hot June temperatures (above the the observed June 2017 temperature anomalies) was computed between a natural model ensemble, based on historicalNat simulations, and an all-forcings current-world ensemble, based on RCP8.5 for 2006-2026. The Risk Ratio for hot June temperatures in the current world relative to the natural world was calculated using all available model simulations (shown as the best estimate in Table 5) and on 10000 bootstrapped sub-ensembles so the sampling uncertainty could be quantified. The resulting 95% confidence intervals in the Risk Ratios are also shown in Table 5.

Changes in intensity of extreme heat events were estimated by finding the location of June 2017 in the statistical distribution from the current-world ensemble and finding the corresponding point in the natural-world ensemble. The best estimate of this change is shown in Table 5.

Table 4: CMIP5 model simulations used in this analysis.

Model	**Historical**	**Historical Nat**	**RCP2.6**	**RCP4.5**	**RCP6.0**	**RCP8.5**
ACCESS1-3	1,2,3	1		1		1
bcc-csm1-1	1,2,3	1	1	1	1	1
CanESM2	1,2,3,4,5	1,2,3,4,5	1,2,3,4,5	1,2,3,4,5		1,2,3,4,5
CCSM4	1,2,3,4,5,6	1,2,4,6	1,2,4,6	1,2,4,6	1,2,4,6	1,2,4,6
CESM1-CAM5	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3	1,2,3
CNRM-CM5	1,2,3,4,5,6,7,8,9,10	1,2,4	1	1		1,2,4
CSIRO-Mk3-6-0	1,2,3,4,5,6,7,8,9,10	1,2,3,4,5	1,2,3,4,5	1,2,3,4,5	1,2,3,4,5	1,2,3,4,5
GFDL-CM3	1,2,3,4,5	1	1	1	1	1
GISS-E2-H	1,2,3,4,5	1,2	1	1,2	1	1,2

HadGEM2-ES	1,2,3,4,5	1,2,3,4	1,2,3,4	1,2,3,4		1,2,3,4
IPSL-CM5A-LR	1,2,3,4,5,6	1,2,3	1,2,3	1,2,3	1	1,2,3
IPSL-CM5A-MR	1,2,3	1	1	1	1	1
MIROC-ESM	1,2,3	1	1	1	1	1
MRI-CGCM3	1,2,3	1	1	1	1	1
NorESM1-M	1,2,3	1	1	1	1	1

Table 5: Risk Ratios (best estimate and 95% confidence intervals) for hot June temperatures in model simulations representing the current world compared with a counterfactual natural world.

	Number of models	Best estimate Risk Ratio	95% CI	Best estimate Change in Magnitude (degrees C)
Belgium	6	3	1.2 ... 5.3	1.03
CET	9	5.7	3.6 ... 9.5	1.35
France	13	6.3	2.8 ... 20	1.32
Netherlands	14	5.5	2.7 ... 11.3	1.18
Portugal T	13	15.6	5 ... 78	1.56
Portugal TX	14	8.6	2.9 ... 70	1.78
Spain T	11	50	10 ... Inf	1.59
Spain TX	7	30	5 ... Inf	1.96
Switzerland	13	8	3.75 ... 50	1.65

The likelihood of high June temperatures similar to those we have seen in 2017 is estimated for two future scenarios. Model ensembles representing global warming of 1.5-degrees C and 2-degrees C above a pre-industrial baseline were extracted from the model projections (following King et al. (2017)). These ensembles were used to examine the likelihood of high June temperatures at the policy-relevant Paris global warming targets (Figure 4).

Likelihood of hot Junes like 2017

LOCATION	VARIABLE	NATURAL	CURRENT	1.5°C	2°C
		Chance of similar event per year			
Belgium	T	6% (3-11%)	16% (10-23%)	19% (15-23%)	33% (27-40%)
Central England	T	6% (4-7%)	28% (21-35%)	31% (25-39%)	39% (33-46%)
France	T	4% (2-5%)	15% (11-20%)	22% (18-28%)	33% (28-39%)
Netherlands	T	5% (4-7%)	23% (18-28%)	28% (23-33%)	37% (31-43%)
Portugal	T	3% (2-4%)	18% (13-22%)	24% (20-28%)	34% (29-39%)
	TX	3% (2-4%)	14% (11-18%)	20% (16-23%)	29% (25-34%)
Spain	T	2% (1-2%)	14% (10-19%)	24% (20-29%)	34% (28-40%)
	TX	1% (1-2%)	10% (6-14%)	18% (13-22%)	26% (21-31%)
Switzerland	T	4% (2-6%)	17% (12-21%)	25% (20-31%)	37% (31-44%)

Figure 4: Estimates of the likelihood of high June temperatures in each European region under each of the four scenarios for mean temperatures (T) and maximum temperatures (TX). Best estimates are shown with 90% confidence intervals in parentheses.

EC-Earth 2.3

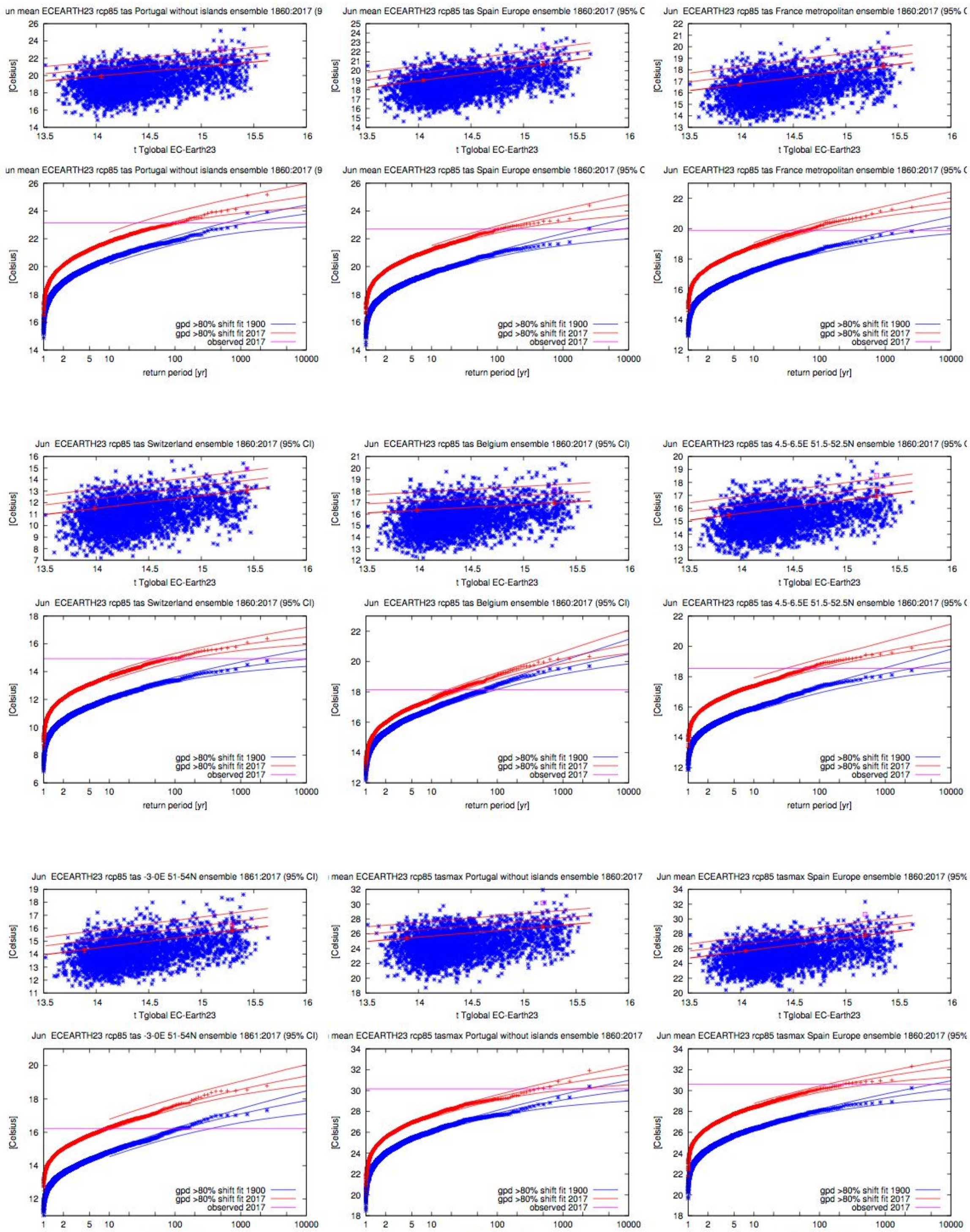
EC-Earth 2.3 is a coupled atmosphere-ocean general circulation model ensemble with 16 members (Hazeleger et al. 2010), each producing a transient climate simulation from 1860 to 2100. The model resolution is T159 which translates to around 150 km in the European domain. The underlying scenarios are the historical CMIP5 protocols until the year 2005 and the RCP8.5 scenario (Taylor et al. 2012) from 2006 onwards. Up to about 2030, the historical and RCP8.5 temperature evolution is very similar. As for the observations, we fit all modelled June temperatures to a distribution that shifts proportionally to the modelled global mean temperature (smoothed per ensemble member). We use all years up to 2017 to investigate the event in the recent and past climate, and the entire ensemble up to 2100 to investigate the event in the future climate.

For the EC-Earth analysis we checked for each region separately that the model has a temperature distribution that is compatible with the observed one, after a bias correction in the June mean temperature. We do this by fitting the data to a Normal distribution and comparing the scale parameter, allowing for a bias in the mean. For the bias correction we compare the modelled mean June temperatures between 1900-2016 with the mean June temperature of CRU TS data, and add the difference to the model. After that the model data is fitted to a General Pareto Distribution (GPD), because this fits the highest temperatures better than a Normal distribution. The fits are shown in Figure 5 as a function of the model global mean temperature, and as a function of the return period for the climates of 1900 and 2017. The Risk Ratios between 2017 and 1900 are shown in Table 6. Upper bounds are not always well-defined because the return periods in the climate of 1900 are very high.

By the year 2100, under the assumption of the RCP8.5 scenario, for all regions the June 2017 temperatures will be normal, occurring almost every year.

Table 6. Risk Ratios calculated from EC-Earth model data, calculated with a GPD distribution.

Tmean	**RR**	**95% CI**	**∆T**	**95% CI**
Portugal	16	8 ... 2000	1.2	1.1 ... 2.3
Spain	70	20 ... ∞	1.7	1.5 ... 2.1
France	50	20 ... 900	1.6	1.4 ... 1.9
Switzerland	140	17 ... ∞	1.6	1.2 ... 2.0
Belgium	3	2 ... 5	0.6	0.4 ... 1.0
Central Netherlands	35	12 ... 400	1.5	1.3 ... 2.2
Central England	14	9 ... 76	1.466	1.271 ... 2.205
Tmax				
Portugal	40	9 ... ∞	1.536	1.223 ... 1.803
Spain	170	27 ... ∞	2.074	1.884 ... 2.555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[Celsius]
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gpd >80% shift fit 2017
observed 2017

Figure 5. GPD Fits to the June temperature EC-Earth series as described in the text, for Tmean of Portugal, Spain, France, Switzerland, Belgium, the Central Netherlands and Central England; Tmax in Portugal and Spain. The red lines indicate the current climate, the blue ones the climate of 1900. The purple symbol and lines indicate the magnitude of the observed event of June 2017.

HadGEM3-A

The 15 HadGEM3-A coupled historical runs 1960–2015 (Christidis et al, 2013) (N216, about 60km) are evaluated for the separate regions. The model turns out to have a too high variability. Therefore we reject this model for this analysis and do not use this model for calculations on the Risk Ratio.

CORDEX

A subsample from the EURO-CORDEX ensemble (Jacob et al., 2014) was used in order to calculate the change in odds of an exceedance of the observed mean temperature in the different countries. Ten 11-km GCM-RCM model combinations were considered, made available through the Copernicus Climate Change Service project CLIM4ENERGY (http://clim4energy.climate.copernicus.eu). Simulations were bias adjusted using the Watch Forcing Data Era Interim (WFDEI, Weedon et al., 2014) and applying the so-called CDFt method (Vrac et al., 2016). By construction, daily temperatures were corrected and verifications were made against station data (Vautard et al., 2017, in preparation).

Return periods were estimated by pooling the 10 models together and using data in 30-year periods, 1971-2000 for past periods and 2001-2030 for the “current period”. Through this pooling we obtain an ensemble of 300 simulations of the month June from which return periods of the events with the observed magnitude were calculated for each respective ensemble and sampling uncertainty was estimated using the same bootstrapping procedure as for weather@home simulations keeping the full time series in the random drawings.

For this ensemble we also used two future periods in order to understand how the likelihood of extreme June temperatures would evolve under the RCP8.5 concentration scenario.

In this ensemble, the high temperatures observed in Western Europe in 2017 would have been rare events with return periods close to a hundred years at the end of the 20th century (see Figure 6). In the current climate, the likelihood of events like the observed to occur generally increased by varying factors from 2 to 6 depending on the country corresponding to a 1-to-10 to 1-to-20 year event today (see Table 7). This factor, the Risk Ratio, would apply again comparing today’s climate with future periods (2021-2050 and 2041-2070), with a likelihood increase by typically a factor 2 for the near future and 4 for the middle of the century relative to the current climate. Therefore in the absence of climate policies, one would expect such events to occur about once in 3 years in several countries.

It is interesting to remark that in many of the countries, there is a relative divergence of the return period curves with the increase in risk being higher for rare events. This may be due to soil-atmosphere interactions inducing positive feedback between drought and heatwaves (Seneviratne 2010).

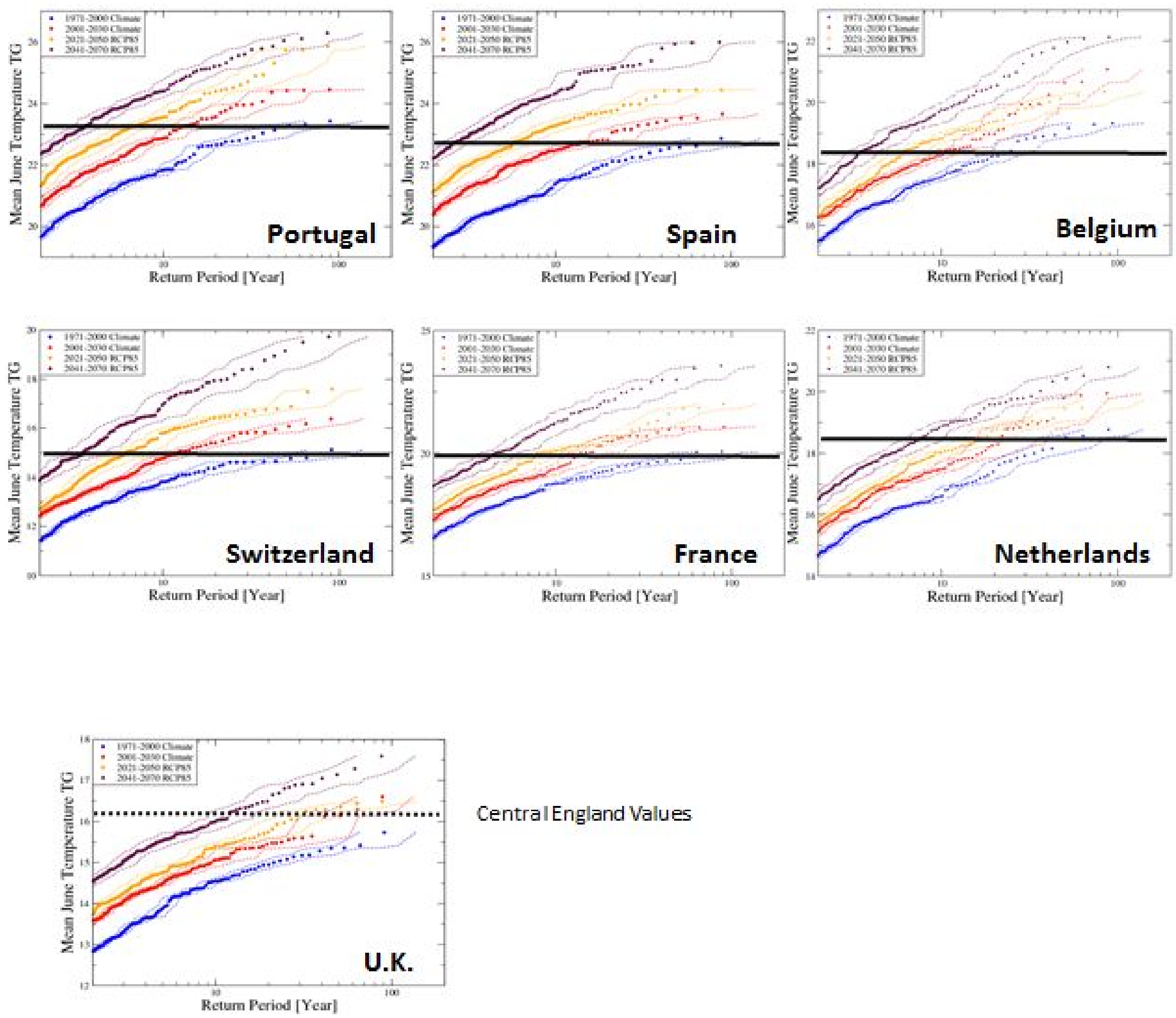


Figure 6. *Return periods of June mean temperatures for the seven analyzed countries in four different CORDEX ensemble simulations: 1971-2000 (blue), 2001-2030 (red), 2021-2050 (yellow) and 2041-2070 (purple).*

Table 7. Risk Ratios for the EURO-CORDEX experiment

Country	Risk Ratio	Conf. Interval 5-95%
Portugal (1)	3.6	2.3 ... 7.6
Spain (1)	5.0	2.7 ... 21.5
France (1)	3.7	2.3 ... 8.9
Switzerland (2)	6.3	3.9 ... 13.6
Belgium (4)	2.2	1.7 ... 3.3
Central Netherlands (1)	3.5 (NL)	1.7 ... 8.0

The same bias-adjusted EURO-CORDEX ensembles for RCPs 4.5 and 8.5 have been employed to provide a European-scale picture on the future (end of 21st Century) likelihood of mean June temperatures to exceed the maximum mean June temperature of a historical reference period (1981-2010). By definition, the latter has an empirical probability to occur once in 30 years in 1981-2010. Results reveal that already for the moderate RCP4.5 emission scenario probabilities are larger than 10% (i.e., at least once in 10 years) over the entire European continent (Figure 7, left panel). Regions along the Mediterranean coast and in Northern Europe can show probabilities exceeding 40%. Even higher values are obtained for RCP8.5 (Figure 7, right panel). Over large parts of the continent, the probability for mean June temperatures to exceed the reference period's maximum is larger than 50% and can reach values of more than 80% in Southern Europe. Mean June temperatures that are exceptional in a today's climate would appear regularly by the end of the century with potentially drastic impacts on human health.

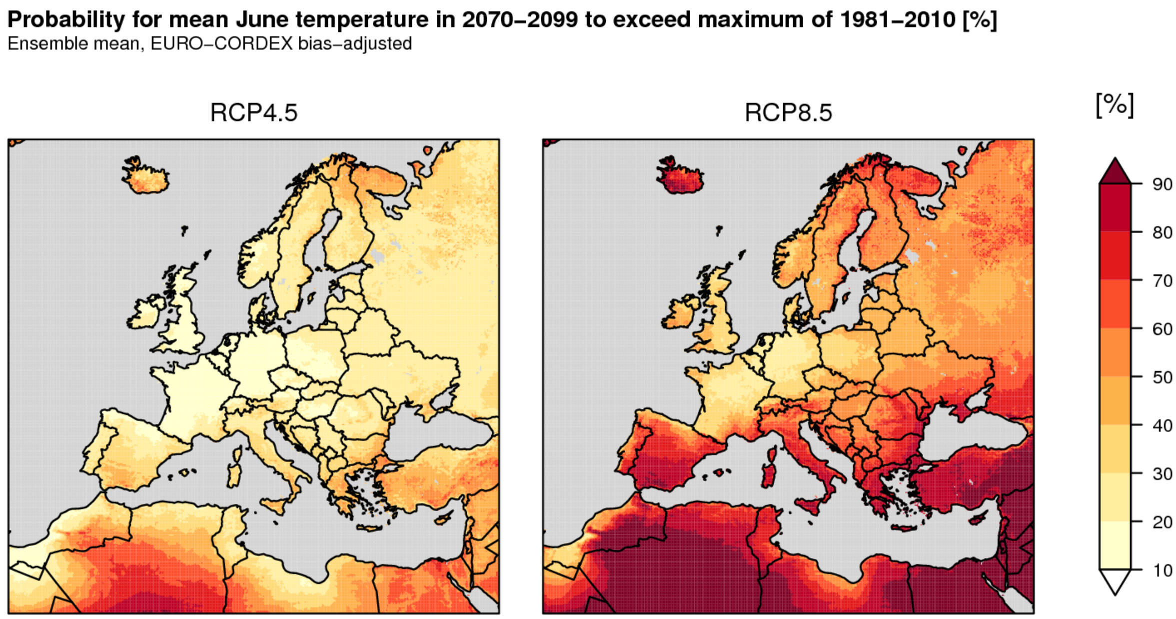
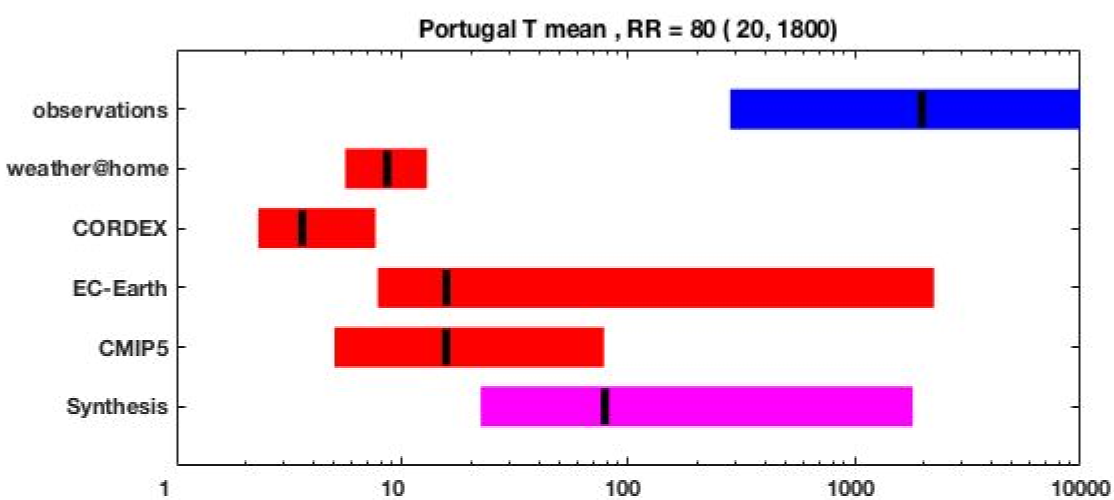
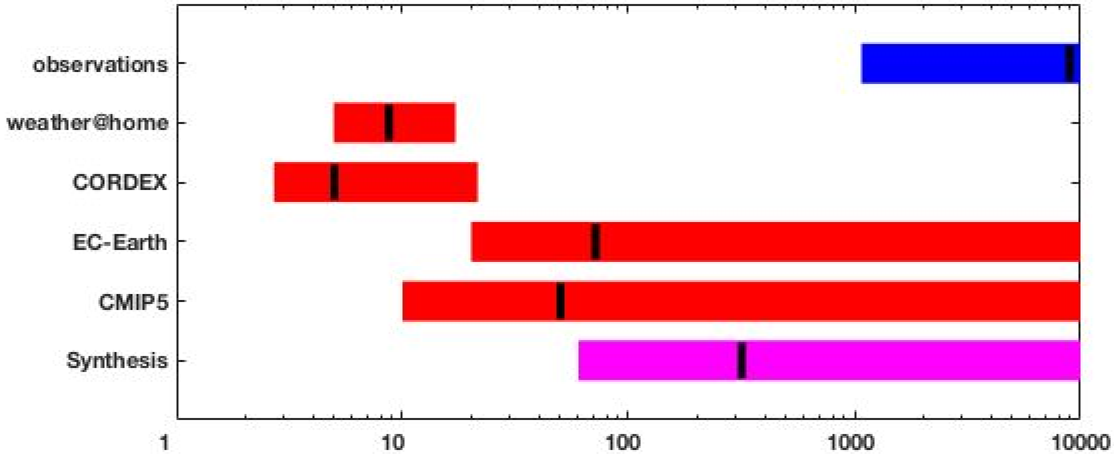


Figure 7: Probability for mean June temperature in the period 2070-2099 to exceed the maximum mean June temperature of a reference period's climate (here 1981-2010). Left panel: RCP4.5, right panel: RCP8.5. Shown are ensemble mean probabilities as provided by bias-adjusted EURO-CORDEX regional climate scenarios.

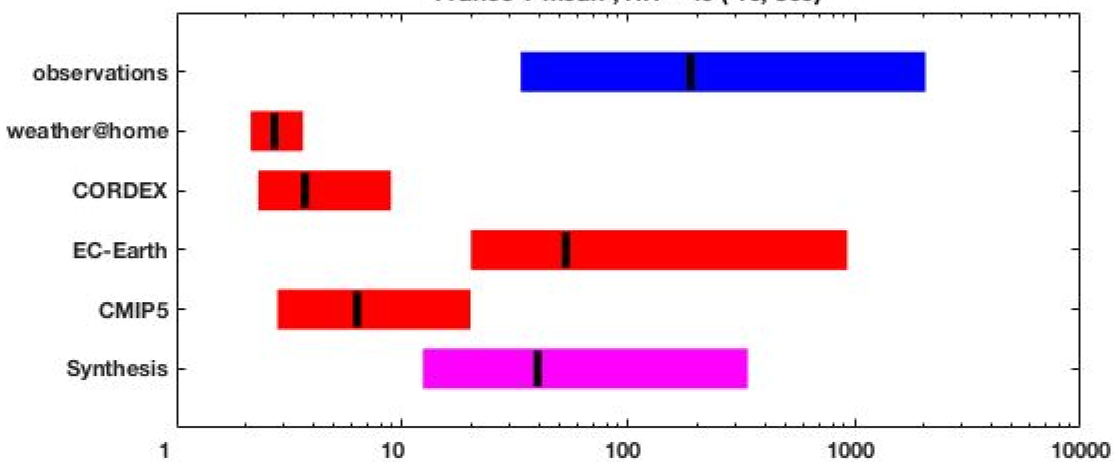
SYNTHESIS



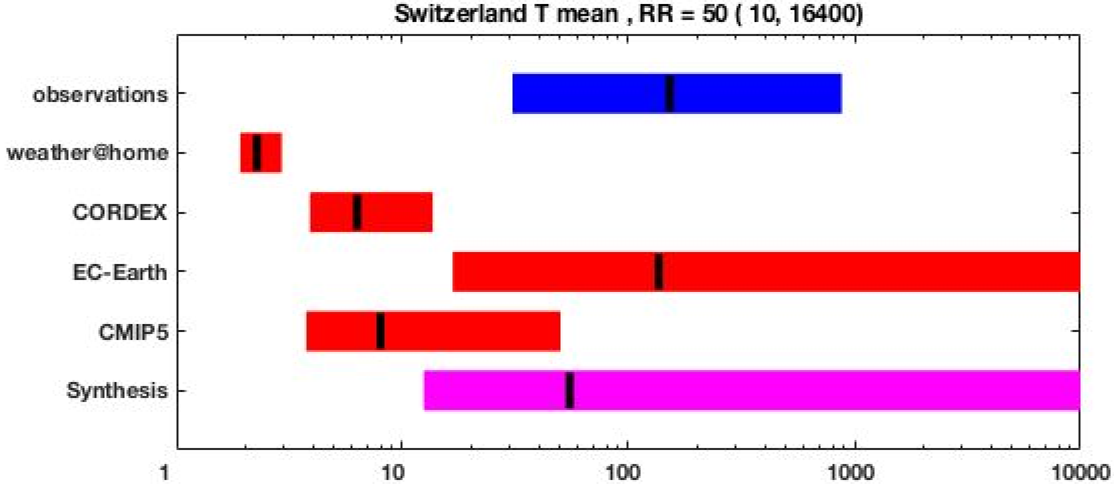
Spain T mean , RR = 320 (60, Inf)



France T mean , RR = 40 (10, 300)



Switzerland T mean , RR = 50 (10, 16400)



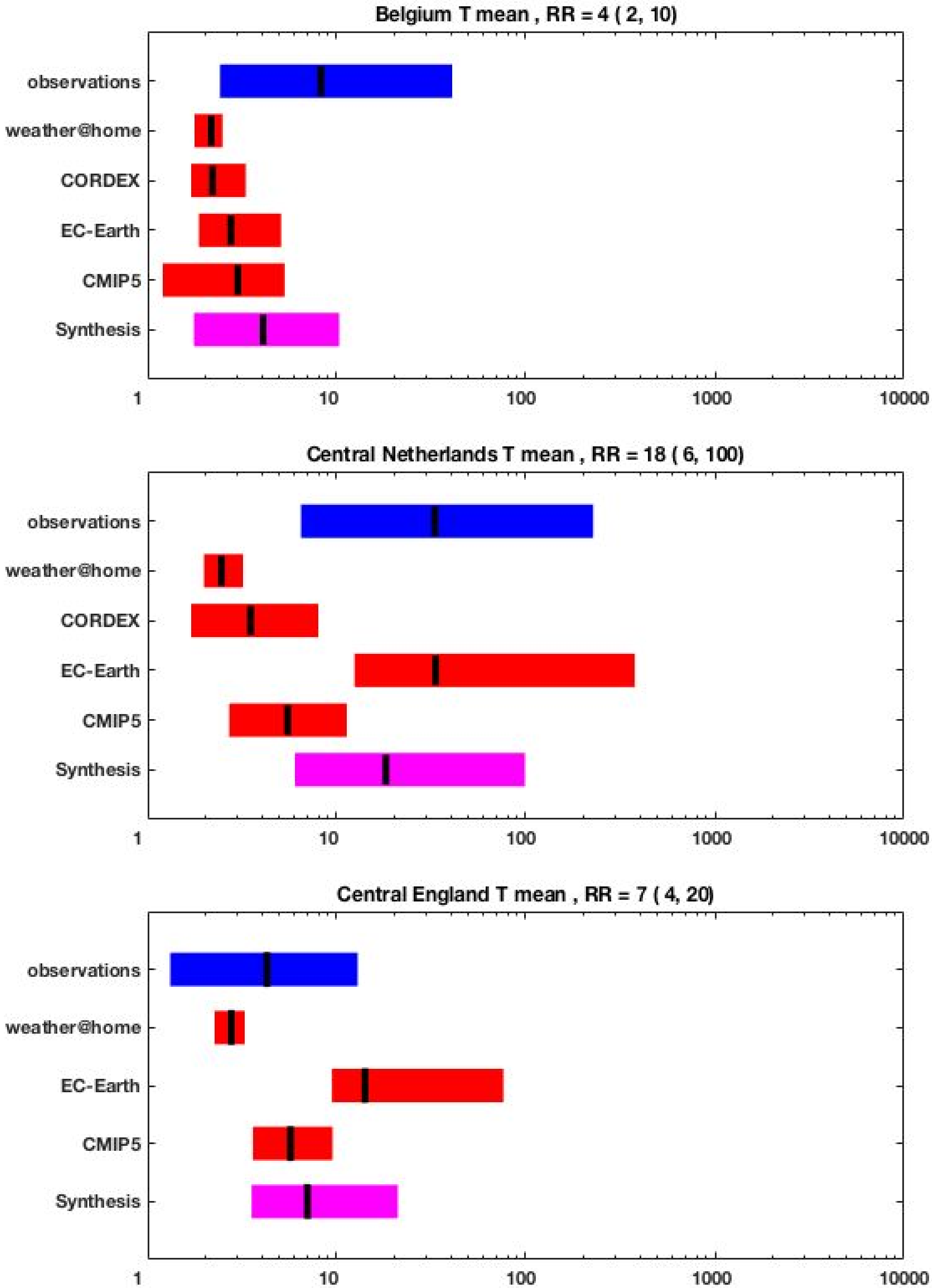


Figure 8 shows the estimates of the change in risk for the different methodologies with model results in red and observations in blue. The synthesis result in magenta does not include the CORDEX and weather@home results. In weather@home the warming trend is not compatible *with the observed trend whereas the simulations in CORDEX are very different in terms of the actual time period simulated that a quantitative comparison is not meaningful.*

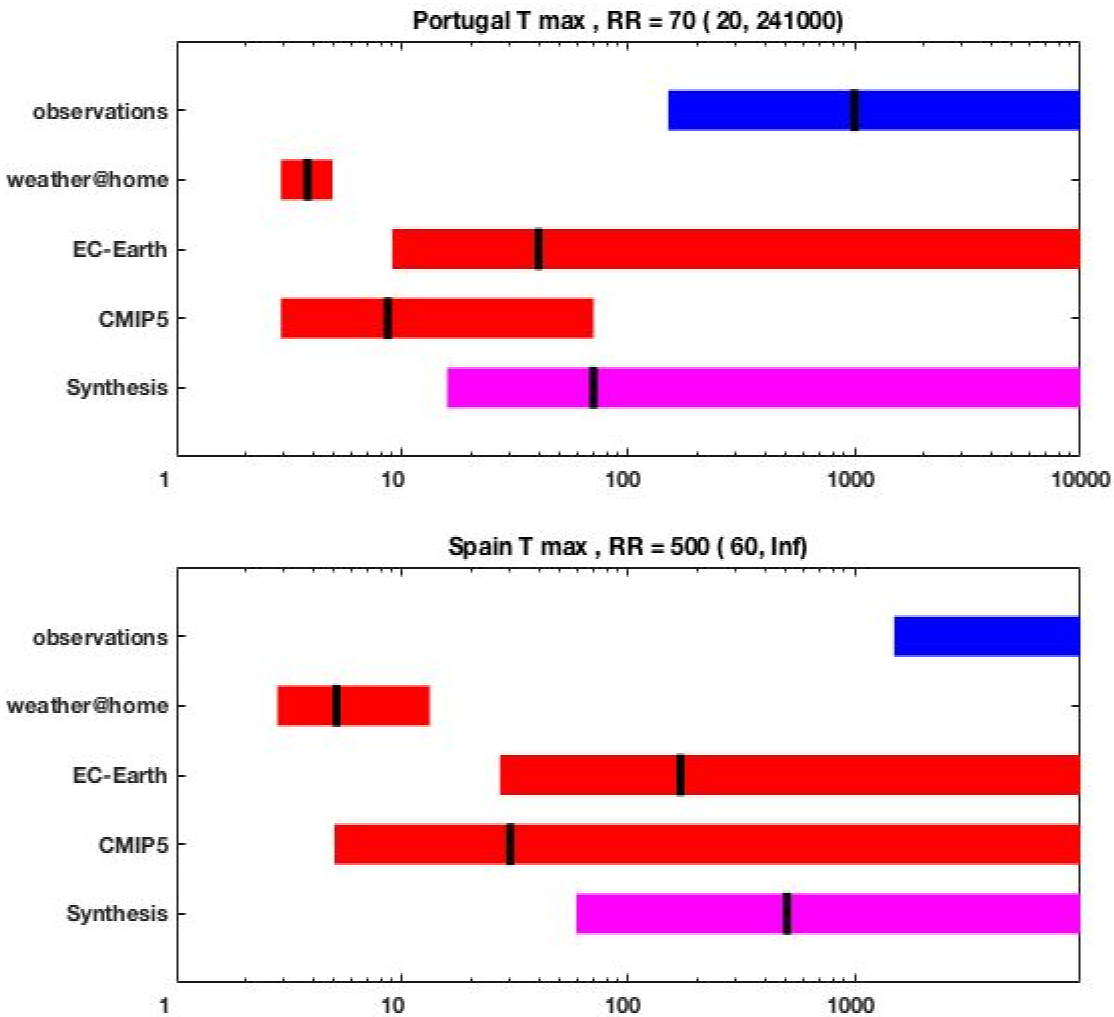


Figure 9 same as Figure 8 but for the average maximum temperatures in Spain and Portugal.

Figures 8 and 9 summarize all the results on the change in probability from the observed trend (blue) and the model ensembles (red). We computed a unweighted average of all results, but excluding the two model results where the trends are incompatible with the observations (CORDEX and weather@home) this is shown in magenta. In all seven countries the likelihood of hot Junes has increased significantly. In all countries the observed changes in the likelihood of the event, average June temperatures as high as 2017, are much larger than in the model simulations with the regional models in weather@home and CORDEX showing the lowest increase in risk. As June temperatures were more extreme in Portugal and Spain it is not surprising that increases in Risk Ratios are higher for these countries. In Gaussian distributed variables or GPD distributions with negative shape parameter the dependency on the exact threshold is strongest further in the tail of the distribution.

Still, the difference between the Risk Ratios derived from observations and most models is sizeable. As we verified that the variability is similar (we rejected a model with too high variability) and as we corrected for biases in the mean, this is mainly due to differing estimates of the effect of anthropogenic emissions on summer temperatures in Europe. This difference is especially large in Tmax in Portugal and Spain. The discrepancy was found for CMIP3 models in southern Europe (van Oldenborgh et al, 2009) and also present for 3-day extremes in the summer of 2015 (Sippel et al, 2016). The cause for the differing trends is unknown. A first possibility is inhomogeneous observations, although the time series for Switzerland and the Netherlands are based on homogenised series. Part of the discrepancy could be due to random weather fluctuations, even though the high value for 2017 that is not included in the trend estimate is evidence against that. There could be decadal or longer time scale variability, but the autocorrelations of the residuals are compatible with white noise after subtracting the trend as a factor times the smoothed global mean temperature (in Belgium there is a step downward around 1950, whilst the CNT and CET show relatively cool weather in the 1970s and 1980s connected to air pollution). Finally, there may be model deficiencies in this area that cause a trend underestimation. However, for the whole SREX MED (Mediterranean) region, observed trends agree well with CMIP5. Maybe all these explanations contribute somewhat.

In any case, despite the spread, we can conclude that the probability of a June temperature as high as observed in 2017 or higher has increased by a factor more than ten due to global warming in Portugal and Spain, and at least doubled in the other analyzed countries.

CONCLUSION

The model results indicate that past historical increases in greenhouse gases have raised the odds of a warm June in Belgium, France, the Netherlands, Portugal, Spain, Switzerland and the CET region of UK considerably (see Table 8). The observed trend is compatible with the effects of human-induced emissions of greenhouse gases. Since past and projected future greenhouse gas increases will continue to raise the temperatures, the frequency of summer months like June 2017 should be expected to increase over the coming decades and what is still an unusually hot June today would be a normal June later this century.

Table 8. Synthesis estimates of Risk Ratio from pre-industrial to today for average June temperatures, as shown in Figure 8 and 9.

	Change in odds from pre-industrial to today
Belgium	4 (2...10)

France	40 (10...300)
The Netherlands (CNT region)	18 (6...100)
Portugal (Tmean)	80 (20...1800)
Portugal (Tmax)	70 (20...241000)
Spain (Tmean)	320 (60...∞)
Spain (Tmax)	500 (60...∞)
Switzerland	50 (10...16400)
United Kingdom (CET region)	7 (4...20)

As the intensity and frequency of extreme heat events increases, many countries in Europe have made efforts to reduce vulnerability to extreme heat. For example, following the deadly 2003 heatwave, France implemented a national heat wave plan that included health monitoring activities, public cooling centres, home visiting plans for elderly people living alone and other actions that reduced mortality in subsequent heat waves (Murray et al. 2012). While we won't know the mortality and morbidity impacts of the current heat wave until pubic health records are made available, it's likely that many impacts were avoided as a result of the heatwave plan (Fouillet et al., 2008). At the same time, efforts to optimize the performance of heatwave watch and warning plans will be key to managing the vulnerability of populations as the frequency of extreme heatwave events increases.