METHODOLOGY

I. UNIVERSITY OF MELBOURNE:
European record 2014 temperatures in CMIP5

Contacts: David Karoly - dkaroly@unimelb.edu.au; Andrew King - andrew.king@unimelb.edu.au; Sophie Lewis - sophie.lewis@anu.edu.au

THE UNIVERSITY OF MELBOURNE

This is a brief summary of the methods we used to calculate whether anthropogenic activity has changed the risk of hot European years like 2014.

This analysis was conducted for both calendar years and December-November 12-month periods.

Firstly, 51 historical simulations from 16 different CMIP5 models were regridded onto a common 1.5° by 1.5° regular grid over the European region (12W-45E, 30N-75N). The HadCRU-TS-3.22 dataset was regridded to the same resolution. For both the observations and all model simulations, European-average annual timeseries were calculated as anomalies from the 1961-1990 climatological period.

A Kolmogorov-Smirnov (KS) test was then employed to determine whether the model simulations adequately represented the variability seen in the observational record over the common 1901-2005 period. To account for the high lag correlations in the observed timeseries (~ 0.6 at a 1-year lag) the degrees of freedom used to determine the significance of the KS-statistic were reduced accordingly. Models were deemed to have passed this test if:

1. At least three historical simulations were available for analysis, and
2. No more than one of the three (or more) historical simulations was significantly different ($p < 0.05$) from the observational timeseries.

This resulted in the selection of simulations from nine climate models to be investigated further (see Table).

Table: Models passing KS-test.
Model simulations in **bold** were available for FAR analysis.

MODEL	SIMULATION
ACCESS1-3	**r1i1p1**,r2i1p1,r3i1p1
CanESM2	**r1i1p1,r2i1p1,r3i1p1,r5i1p1**
CESM1-CAM5	**r1i1p1,r2i1p1,r3i1p1**
CNRM-CM5	**r1i1p1,r2i1p1**,r3i1p1,r5i1p1
FGOALS-g2	**r1i1p1**,r2i1p1,r3i1p1,r5i1p1
GISS-E2-H	**r1i1p1**,r3i1p1,r5i1p1
GISS-E2-R	**r1i1p1,r2i1p1**,r3i1p1,r5i1p1
IPSL-CM5A-MR	**r1i1p1**,r2i1p1,r3i1p1
NorESM1-M	**r1i1p1**,r2i1p1,r3i1p1

To use the HistoricalNat simulations in our FAR analysis we adjusted the temperature anomalies (from the base period of 1961-90) by accounting for the warming prior to that period. This was done by adding anomalies for each model to the HistoricalNat simulations calculated as:

$$\Delta T = \{MEAN(Hist_{1901-1930}) - MEAN(Hist_{1961-1990})\} - \{MEAN(HistNat_{1901-1930}) - MEAN(HistNat_{1961-1990})\}$$

This resulted in a shift of the HistoricalNat PDFs for each model towards cooler temperatures by between 0.02°C and 0.46°C depending on the magnitude of warming seen in each model.

Using the 16 RCP8.5 (2006-2020) and HistoricalNat (1900-2005) runs from these models (see Table, in bold), an estimate of the Fractional Attributable Risk (FAR) was calculated. Ten thousand estimates of the FAR were calculated by bootstrap resampling 50% (i.e. 8) of the 16 pairs of RCP8.5 and HistoricalNat simulations. Using these 10000 FAR estimates a median FAR and tenth percentile FAR were calculated.

CLIMATE CENTRAL Environmental Change Institute eci UNIVERSITY OF OXFORD THE UNIVERSITY OF MELBOURNE KNMI

2. OXFORD:
EUROPEAN RECORD 2014 TEMPERATURES USING WEATHER@HOME

**Contacts: Myles Allen - myles.allen@ouce.ox.ac.uk; Fredi Otto - friederike.otto@ouce.ox.ac.uk;
Karsten Haustein - karsten.haustein@ouce.ox.ac.uk**

Environmental *Change* Institute

We are using large ensembles of the Met Office regional climate model HadRM3P over Europe embedded in the atmosphere-only global circulation model HadAM3P to simulate possible European temperatures in 2014 (01-12-2013 to 30-11-2014) under two different climate scenarios: i) the observed climate of 2014 (Figure 1) ii) a scenario based on a counterfactual ensemble forced with greenhouse gas concentrations representative of 2014 had the anthropogenic greenhouse gas emissions not been released (Figure 2). For the estimation of the return times under current climatological conditions, a third scenario with the climatology between 2000-2010 is simulated. The regional results we provide are with reference to the observed climate of 2014 rather than the 2000-2010 climatology.

We are using the distributed computing framework - weather@home (Massey et al. 2014) - where members of the public facilitate multi-thousand-member ensemble weather simulation experiments at 1.25 x 1.875 degrees resolution globally and 0.44 degrees resolution for the regional model via the volunteer computing network.

For the "as observed" and the "as climatology" ensemble the model is forced with observed sea surface temperatures (SSTs) and sea ice extent using the OSTIA data set (Stark et al., 2007). The ensemble of possible temperatures in 2014 in "the world that might have been" is obtained by forcing the model with greenhouse gas concentrations of pre-industrial levels and removing the fingerprint of the anthropogenic warming from the SSTs.

Because we do not know the exact pattern of anthropogenic warming to remove from the SSTs several equally likely patterns of warming are obtained by calculating the difference between nonindustrial and present day simulations for available CMIP5 models (Taylor et al. 2012). As a result there are several different initial conditions ensembles ("natural") representing the analogous year in the counterfactual experiment. These are forced with preindustrial atmospheric gas composition, the SSTs obtained by subtracting the CMIP5-estimates of the human influence on SST from the observed OSTIA SST values and the sea ice extent that correspond to the year of maximum sea ice extent in each hemisphere of the OSTIA record.

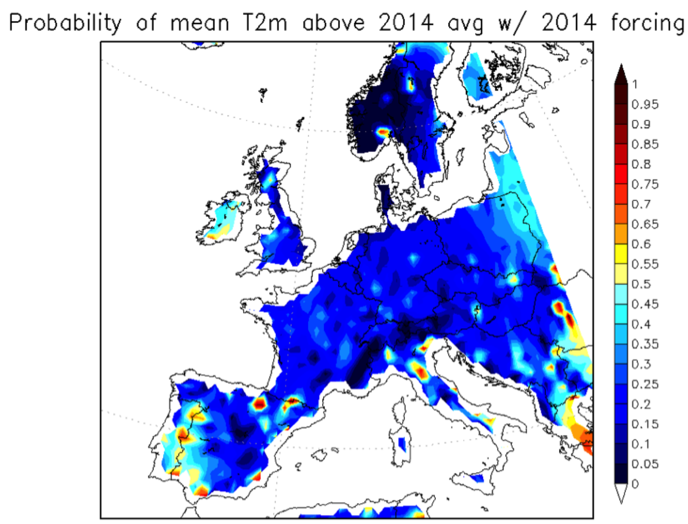

Figure 1: Spatial distribution of the probability of the mean 2m temperature to be above the observed 2014 (Dec-Nov) average, with the model ensemble driven with observed SSTs in 2014. The higher the observed temperature anomalies, the lower the likelihood for these temperatures to occur. Note that it is the grid point specific probability, representative of the climate variability at the smallest possible scale.

For the analysis of the fraction of attributable risk (FAR) (Allen 2003) and the return time with respect to the observed values of 2014, the HadCRU-TS-3.22 (Harris et al. 2014) dataset and the CRUTEM4 temperature anomalies (Jones et al. 2012) for the Dec 2013 to Nov

2014 period were used. CRUTEM4 was regridded to the HadCRU-TS-3.22 resolution and interpolated over ocean grid points.

In order for the team to compute the analysis in time the missing CRUTEM4 Nov 2014 anomalies were filled with Global Forecast System (GFS) analysis (EMC, 2003) data. They were bias corrected with respect to CRUTEM4 in order to ensure consistency. Furthermore, the

last days of November were missing in the OSTIA SST observations. These few missing days were filled by extrapolating the last available set of daily OSTIA SST data until the end of the month. Both, the "as-observed" and the counterfactual model ensembles were bias corrected using hindcast ensemble runs for the 1961-1990 period (Massey et al. 2014).

The ensembles generated in this experiment included ~500 members for the "as-observed" simulations and ~1500 members in the counterfactual experiments. While this is an ensemble size providing robust results for individual countries with respect to the observed thresholds in these countries the ensemble size is too small to allow for robust estimates of the return time of the observed 2014 temperatures in the "world that might have been" over the whole European domain.

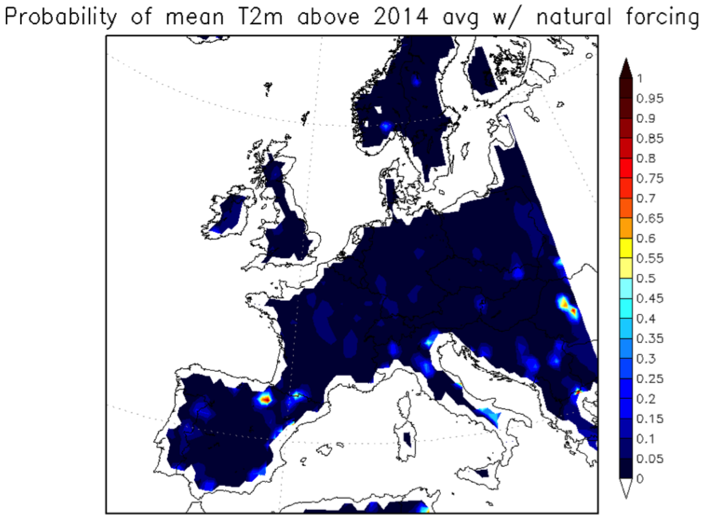

Figure 2: As Fig 1, but with the model ensemble driven with SSTs in a world that might have been without anthropogenic greenhouse gas and aerosol emissions. Note the strong reduction in likelihood for 2014 temperatures to have occurred under such "natural" conditions.

References

Environmental Modeling Center (2003): The GFS Atmospheric Model. NCEP Office Note 442, Global Climate and Weather Modeling Branch, EMC, Camp Springs, Maryland

Allen (2003): Liability for climate change. Nature, 421:891-892. doi:10.1038/421891a

Harris, I., Jones, P.D., Osborn, T.J., and Lister, D.H. (2014), Updated high-resolution grids of monthly climatic observations - the CRU TS3.10 Dataset. Int. J. Climatology 34: 623-642. doi:10.1002/joc.3711

Jones P.D., Lister D.H., Osborn T.J., Harpham C., Salmon M. and Morice C.P. (2012): Hemispheric and large-scale land surface air temperature variations: an extensive revision and an update to 2010. Journal of Geophysical Research 117, D05127. doi: 10.1029/2011JD017139

Massey, N., R. Jones, F.E.L. Otto, T. Aina, S. Wilson, J. Murphy, D. Hassell, Y. Yamazaki and M.Allen (2014) weather@home- development and validation of a very large ensemble modelling system for probabilistic event attribution. Quart. J. Roy. Met. Soc. DOI:10.1002/qj.2455

Stark, J. D., C. J. Donlon, M. J. Martin, and M. E. McCulloch (2007): OSTIA: An operational, high resolution, real time, global sea surface temperature analysis system. Oceans 2007 - Europe, Aberdeen, Scotland, IEEE, Vols. 1–3, 331–334, doi:10.1109/OCEANSE.2007.4302251.

Karl E. Taylor, Ronald J. Stouffer, and Gerald A. Meeh (2012): An Overview of CMIP5 and the Experiment Design. Bull. Amer. Meteor. Soc., 93, 485–498. doi:10.1175/BAMS-D-11-00094.1

3. KNMI:
EUROPEAN RECORD 2014 TEMPERATURES USING CLIMATE EXPLORER

Contacts: Harry Geurts - persvoorlichting@knmi.nl; Geert Jan van Oldenborgh - oldenborgh@knmi.nl; Gerard van der Schrier - schrier@knmi.nl

The KNMI used empirical event attribution using historical data records following the methodology pioneered in van Oldenborgh (2007) and made more rigorous in van Oldenborgh et al (2012). In essence, the KNMI team perform a two-step attribution process:

1. Compute the observed trend in the phenomenon under consideration (excluding the event itself).

2. Relate the event quantitatively by physical and observational arguments to a quantity for which a model-based attribution study has been performed.

For the first step we first constructed a long time series based on the E-OBS gridded daily mean temperature dataset (Haylock et al, 2008) at 0.5º. This dataset was extended back to 1901 by merging in the CRU TS 3.22 dataset, using a linear regression on the overlap period 1950-2013 to bias-correct the CRU TS 3.22, this also compensates for the different orography between the two datasets. Grid points that had a regression coefficient less than 0.67 or larger than 1.5 were discarded. The area with data in 30º-76ºN, 25ºW-45ºE was taken to be the European temperature series.

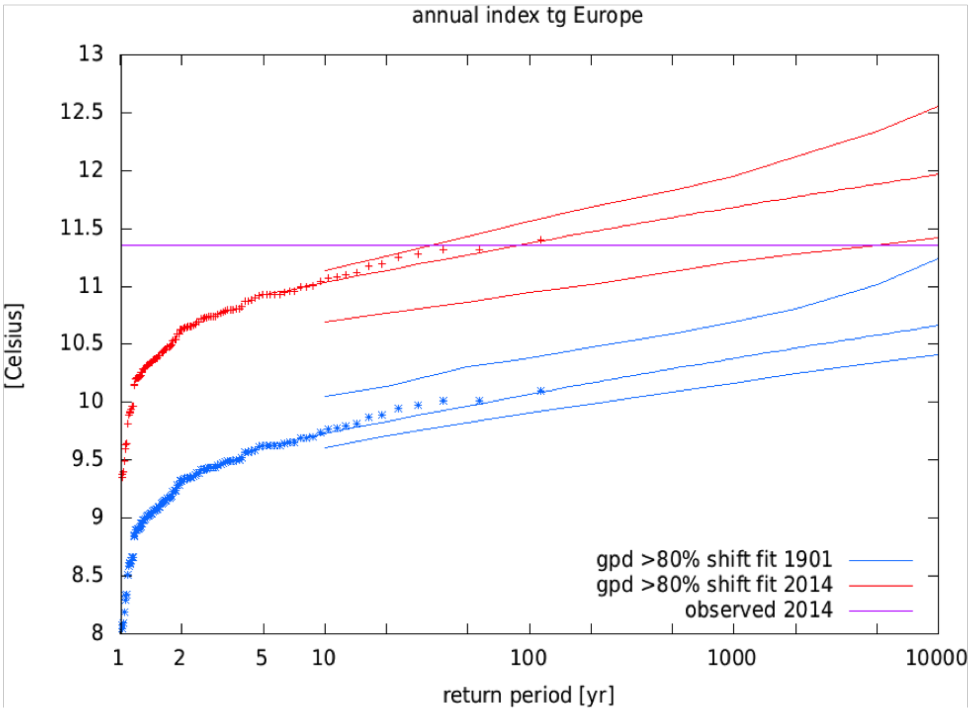

Figure 1: GPD fit to the top 20% of exceedances above a threshold that varies linearly with teh low-pass filtered global mean temperature. The blue curves show the fit in the climate of 1901, the blue ones the climate of 2014. The observations have been drawn twice, once shifted down with the fitted trend to the climate of 1901, once shifted up to 2014. The horizontal line represents the observed value in 2014. The upper and lower lines denote the 95% confidence intervals estimated with a 1000-memeber non-parametric bootstrap.

The trend in extremes was determined by fitting a Generalised Pareto Distribution (GPD) to the top 20% of the distribution above a threshold that varies linearly with the low-pass filtered global mean temperature as a measure of global warming. The fit is constrained by a penalty term of a Gaussian with σ=0.2 in the shape parameter ξ. A non-parametric bootstrap of 1000 samples gives an estimate of the uncertainties, we quote the 10th percentile as lower bound. The inverse GPD gives the return times in 1901, 2014 and hence the ratio of teh two. These can also be read off Figure 1 as the point were the blue and red curves intersect the horizontal line representing the observed value in 2014. The Cumulative Distribution Function of the ratio from the bootstrap is shown in Figure 2.

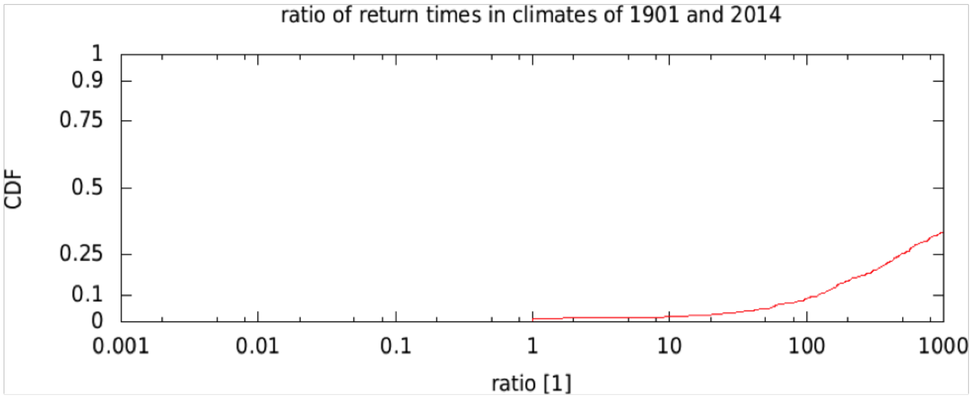

Figure 2: Cumulative distribution function of the ratio of the return times in the climate of 1901 and 2014 estimated with a 1000-member non-parametric bootstrap. The CDF crosses 0.1 at 80 years, the number quoted in the text.

The second step, attribution, is done by referring to Bindoff and Stott (2013), who find good agreement between the CMIP5 modelled trend in mean temperature over Europe and the observed trend, but not with the results of simulations using only natural forcings.

These routines are being developed as part of the KNMI Climate Explorer - a research tool built by van Oldenborgh to investigate climate variability and change.

References

Stott, P. A.: Attribution of regional-scale temperature changes to anthropogenic and natural causes. Geophys. Res. Lett., 30, 1728, doi:1029/2003GL017324, 2003.

van Oldenborgh, G. J.: How unusual was autumn 2006 in Europe?, Clim. Past, 3, 659-668, doi:10.5194/cp-3-659-2007, 2007.

Haylock, M. R. et al, A European daily high-resolution gridded data set of surface temperature and precipitation for 1950–2006. J. Geophys. Res. A 113, D20119, doi:10.1029/2008JD010201, 2008.

van Oldenborgh, G. J., van Urk, A. and Allen, M. R., The absence of a role of climate change in the 2011 Thailand floods. Bull. Amer. Met. Soc., 9, 1047–1049, doi:10.1175/BAMS-D-12-00021.1, 2012