Approximate estimation of an upper limit to changes in future precipitation return-values

Rasmus E. Benestad, Abdelkader Mezghani, Kajsa M. Parding, Anita V. Dyrrdal
The Norwegian Meteorological institute

Supporting Material

This supporting material provides additional analysis that addresses some of the assumptions made in the main paper. It also explains the strategy that we chose and to emphasise this has been structured as questions and answers. The analysis presented here was carried out with the open source R-package 'esd`[21].

What does "upper limit" refer to?

Precipitation is expected to respond to changes in the rate of evaporation and the atmospheric moisture. Assuming a link between the vapour saturation pressure, e_s (a function of temperature), and the wet-day mean precipitation, μ, the maximum systematic influence of the temperature on μ can be estimated based on the linear relationship between the mean seasonal variations in both. It is, however, possible that there are other factors which play a role in precipitation and also exhibit a seasonal cycle. This would mean that the effect of the temperature change on μ is weaker than estimated based solely on the seasonal cycles of μ and e_s. In other words, other factors that influence the seasonal cycle of precipitation may interfere with the regression analysis so that the coefficient is weaker than the true influence of temperature on precipitation

Why use the 100°W-30°E/0°N-40°N region of the North Atlantic as predictor?

The choice of predictor region in this study was motivated by the idea that the North Atlantic ocean is an important moisture source for precipitation over Europe and prevailing winds suggest that the moisture is transported from the west. Also, the sea surface temperature is highest at low latitudes, which suggest highest evaporation closer to the equator. The analysis presented here suggests a good match between the seasonal variations of the temperature averaged over this region and the local wet-day mean (Figure 1). The predictor was defined as the area mean saturation vapour pressure and the domain was set after some trials for some test stations, but this crude trial did not involve any systematic study nor any type of fitting/tuning.

Why use the wet-day mean rather than the mean precipitation?

A traditional approach for modelling and analysing precipitation involves monthly mean precipitation[1-5], however, this is not the optimal quantity for describing precipitation statistics. It doesn't rain every day in most places, and the proportion of wet days to total number of days in a monthly sample may have implications for the statistical parameters describing the distribution. A central question is whether the dry and wet days should be blended or kept apart, as different physical processes are present during days with and without precipitation.

A reductionist approach can involve splitting the precipitation data into two categories: one for zero-precipitation with a trivial non-distribution (dry days) and one for non-zero precipitation (wet days). For all intents and purposes, a threshold of 1mm/day can be used to make this distinction. One implication of the categorisation of precipitation is that each month has about 10 data points for a location if only 30% of the days have non-zero precipitation. A single month of rain gauge data corresponds to a small statistical sample subject to large sampling fluctuations, and mean estimates based on small samples are not well-constrained and do not conform to the central limit theorem[6]. To avoid problems associated with small sample sizes, we analyse the seasonal cycle rather than monthly mean values of the wet-day mean precipitation.

How does the wet-day mean relate to the more traditional mean and total precipitation amounts?

The traditional mean precipitation can be expressed as the product of the wet-day frequency and the wet-day mean precipitation according to

$$x = f_w \mu \qquad \text{(SM1).}$$

The distinction between the two categories f_w and μ is clearer for rain gauge data that samples spatially heterogeneous precipitation accumulated over 24 hours at smaller spatial scales compared to satellite-borne instruments which measure precipitation as a snapshot and with coarser spatial resolution.

While the case could be made for a distinction between wet and dry days based on different physical conditions, the approach is also supported by empirical observations. A simple demonstration of this point is the seasonal variation in the wet-day mean and the monthly mean respectively (Figure SM13): there is a more pronounced seasonal response in μ than in x, which according to equation SM1 is a product of two different factors. The seasonal variations constitute some of the most pronounced and systematic climate variability that takes place on earth with reasonably well-understood causes. Hence we have made use of the hypothesis that precipitation involves two categories: wet and dry days is supported by a more pronounced seasonal cycle.

What are the implications of changes in the wet-day frequency?

Changes in the wet-day frequency affect the probability for heavy precipitation amounts in the future according to $Pr(X > x) = f_w e^{-x/\mu'}$, and hence influences future return-values according to $x_{1year} = \mu' ln(365.25*f_w)$. This goes for both long-term changes (trends) as well as interannual-to-decadal variations. Historical precipitation observations can be used to estimate the interannual variability of f_w and its effect on x_{1year}, but short records (limited sample size) may preclude a complete account of the effect of decadal f_w changes.

Is the wet-day frequency stationary?

The wet-day frequency responds weakly to the seasonally varying conditions (Figure SM13; grey curve), which suggests that it is not as sensitive to systematic changes in the state of the local environment. We can also make use of some information from past trends in the wet-day frequency, as climate change is already happening (Figures SM6-SM7). Historical data suggest different tendencies in different regions (Figure SM7), but previous analysis indicates that the wet-day frequency f_w is strongly influenced by the circulation patterns[7]. Overall, there is little trend when taking the mean over all locations (Figure SM6).

One explanation for the weak historical trends is slow natural variations such as the North Atlantic Oscillation (NAO). Such natural variations are difficult to predict and there is little evidence of a systematic shift in the frequency of different circulation patterns.

Why use the seasonal cycle for model calibration?

Precipitation is generated by different atmospheric processes and depends on many factors. Hence the signal-to-noise ratio is often low for traditional model calibration based on chronological matching between the amount and some large-scale variable such as regional temperature. One technique commonly used in physics and electronics for optimising the information from systems and measurements with low signal-to-noise ratio involves cycles with well-established frequencies (eg. FM in radio, phase-locking), and in meteorology/climatology seasonal variations is the most pronounced cycle.

There has also been some analysis of tropical cyclone frequencies based on the seasonal variations[8], but there is an important caveat associated with such studies: the seasonal variations in the local insolation may affect both the large-scale conditions and the local variable under investigation, and their correlation may reflect the common dependency on this forcing rather than common link. Thus, the assumption that the seasonal cycle in the temperature over the North Atlantic is linked with the seasonal precipitation statistics is the weakest point of this study if one interprets the results as the most likely estimate of the wet-day mean precipitation. Nevertheless, from a physics perspective, it is expected that higher temperatures result in higher evaporation and higher humidity, hence, an increased capacity for greater rainfall amounts. The link is also assessed by extending the analysis to the spatial as well as the temporal dimension. Another important point is that we use this link to estimate an *upper limit* of the effect of a change in temperature on the precipitation, rather than the *most likely estimate* of the wet-day mean precipitation itself.

Is there other information indicating a connection between temperature and the wet-day mean precipitation?

There is a link between the wet-day mean and temperature found both in time and space. The fact that this relationship exists in two different dimensions is a stronger indicator of a physical link than if it were to be limited to only one.

Figure SM8 shows a scatter plot between the saturation vapour pressure e_s calculated based on the local mean daily maximum temperature and the wet-day mean precipitation μ. The fitted line shows the regression between the local seasonal cycles of μ and the temperature for 1420 locations (CLARIS data) in South america, Europe (stations selected for the

COST-VALUE experiment 1), and the US (GDCN). The analysis indicates that the wet-day mean (y) increases by 0.4 mm/day per degree C (x) increase of the local temperature if the elevation is accounted for:

```
Call:
lm(formula = y ~ x, data = calmu, weights = fw)

Weighted Residuals:
     Min      1Q  Median      3Q     Max
-3.4489 -0.9975 -0.0333  0.6501  7.6932

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept)  2.88501    0.24159   11.94   <2e-16 ***
x            0.40359    0.01261   32.01   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.215 on 1418 degrees of freedom
Multiple R-squared:  0.4195,    Adjusted R-squared:  0.419
F-statistic:  1025 on 1 and 1418 DF,  p-value: < 2.2e-16
```

Why not use year-by-year correlation in temperature and wet-day mean?

A correlation analysis of the annual mean time series of temperature and wet-day mean gives close-to-zero correlations:

summary(cor)

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
-0.2891	0.1177	0.2163	0.2020	0.3021	0.5728	

summary(f_w)

Min.	1st Qu.	Median	Mean	3rd Qu.	Max.	NA's
0.0943	0.1766	0.2545	0.2345	0.2790	0.3439	1204

There may be other factors influencing the precipitation statistics on shorter time scales, such as the track of cyclones, fronts, and high-pressure systems. The effect of temperature is expected to be more pronounced on the longer time scales[9] both for physical reasons as well as statistical ones: (a) the temperature influences the surface evaporation and atmospheric moisture and hence a background level for precipitation mechanisms; (b) for about half of the locations, the number of rainy days in a year was less than 100, implying a limited sample size. Furthermore, the proposed downscaling approach based on the relationship between the wet-day mean and saturation vapour pressure represents an upper limit to the wet-day mean precipitation, and it is not clear whether the upper limit should be expected to correlate on an annual basis. Figure SM3 presents the correlation between long-term trends predicted for the upper limit in μ and actual trends in μ derived from the observations. The observed values are scattered over a wider range, as other factors play a role and affect the trends over the observed intervals, however, the predicted upper limits are roughly of similar magnitude. The discrepancies can be interpreted as that the upper limit linked to temperature changes explain part of the long-term change in μ and that contributions from other conditions may come on top of that.

Why include the CLARIS and GDCN only in supporting analysis?

The point of this exercise is to demonstrate a link between the temperature and the wet-day mean that is not a result of a common external factor influencing both. It is expected that the analysis of the match in seasonal cycle will not give the same results for Latin America and the US, as there will be different dependencies to ocean temperature in different regions. For instance, precipitation falling over parts of the US is linked to the El Niño southern Oscillation and sea surface temperatures in the North Pacific[10]. Furthermore, the supporting analysis on the local climatological mean precipitation and temperature is limited to sites where both temperature and precipitation are measured. There are many more sites with rain gauges than thermometers, and hence, the analysis of the seasonal cycle can provide results to more sites within a region than an analysis that also requires local temperatures.

These results suggest that it may be possible to get a rough and approximate estimate for the change in the wet-day mean precipitation for locations where good rain gauge records are lacking but where it is possible to downscale the temperature.

How well do the dependencies with local temperature and large-scale maritime temperature correspond?

The saturation vapour pressure $e_s(\underline{\mathbf{r}})$ was estimated from the local mean climatological temperature for location with both temperature and precipitation data, based on the Clausius-Clapeyron equation. Here the vector $\underline{\mathbf{r}}$ refers to the location of the station data. A regression analysis was applied to $\mu(\underline{\mathbf{r}})$ and $e_s(\underline{\mathbf{r}})$ and the regression coefficients were compared with those derived from the mean annual cycle in equation 1:

```
Call:
lm(formula = y ~ x, data = calmu, weights = fw)

Weighted Residuals:
     Min      1Q  Median      3Q     Max
-4.3565 -1.0354 -0.0751  0.7310  6.0004

Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 4.038e+00  2.094e-01   19.28   <2e-16 ***
x           2.783e-03  8.788e-05   31.67   <2e-16 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 1.22 on 1418 degrees of freedom
Multiple R-squared:  0.4142,    Adjusted R-squared:  0.4138
F-statistic:  1003 on 1 and 1418 DF,  p-value: < 2.2e-16
```

It is not expected that the results should be identical, as the climatological temperature involves the mean of the local daily maximum temperature from the stations, whereas the seasonal temperatures were taken from a large region of the ocean and represented daily mean temperature. Nevertheless, similar values for the scaling factor (regression coefficients) between the saturation vapour pressure and the wet-day mean precipitation μ supports the hypothesis that the precipitation amounts are linked to temperature in a way that gives similar changes through the seasonal variations as in spatial variations. The results of this comparison are shown in Figure SM12, where the results shown in blue are based on the seasonal cycle and the grey the regression over space. The two approaches give results which overlap within the estimated error bars, except for a group of stations with poor match in the seasonal cycle (low R^2 from the regression). The stations with diverging results are located in regions where convective precipitation is less dominant (Figure 2).

Why use mean maximum temperature for the climatological analysis and mean daily mean temperature for the seasonal cycle?

Maximum temperature was available in all of the data sets used here, GDCN, CLARIS and ECA&D, and to obtain an estimate for the daily mean temperature, it would have to involve a crude calculation taking *mean=(min + max)/2*. However, the daily mean temperature was not estimated in this analysis because the geometrical distribution of mean daily maximum temperature was expected to be similar to mean daily maximum.

Is the model ensemble spread a good proxy for probabilities?

Model ensembles do not provide estimates of probabilities because they cannot be considered as a random sample of data and because they do not give a perfect reproduction of the observed quantities. According to the IPCC "*Ensemble members may not represent estimates of the climate system behaviour (trajectory) entirely independent of one another. This is likely true of members that simply represent different versions of the same model or use the same initial conditions. But even different models may share components and choices of parameterizations of processes and may have been calibrated using the same data sets. There is currently no 'best practice' approach to the characterization and combination of inter-dependent ensemble members, in fact there is no straight-forward or unique way to characterize model dependence*"[11].

Nevertheless, the spread of downscaled annual mean temperature from ensemble experiments such as CMIP5 is often comparable to the magnitude of the observed year-to-year temperature variations, and the 95-percentile has been used as an approximate estimate of one-in-twenty year hot summer season[12].

Can the comparison between two single years represent the mean change?

The comparisons shown here were made using the entire ensemble. Hence, for RCP4.5, the difference between years 2100 and 2010 involved comparing two data samples with the size *n=108*. The ensemble for RCP8.5 was smallest of the ones examined (*n=65*), however, nevertheless taken to be sufficient for such analysis (Table 1). The estimates of the differences between the data samples corresponding to 2100 and 2010 would of course be more accurate with more years since the sameple size would be increasing, but it could also be misleading as it would be much smaller than the uncertainties associated with the GCMs' ability to project the future.

What do the leading PCs represent?

The PCs derived through principal component analysis (PCA) describe the most prominent features in the data. They can be viewed as a set of components which together can mimic the original data if each is given an appropriate weight, just like sinusoids can make up a time series in a Fourier transform (FT). In FT, a spectrum tells which frequency is strongly present through a comparison between the weight for each sinusoid (spectral coefficient), and in the same way, the weight associated with each PC provides information about how strongly present they are. The main difference between FT and PCA is that the former is restricted to having sinusoidal shapes whereas PCs can have any shape.

For the seasonal cycle in precipitation, the leading PC tends to describe higher values during summer and lower values in winter. The second PC provides an additional feature, with more heavy precipitation during the autumn.

Does variation in the wet-day mean precipitation really correspond to changing probabilities?

The probability framework adopted here can be formulated as $Pr(X < x \mid \mu)$, meaning that it is conditional on the sample mean of μ and that the distribution is exponential. Previous studies have found that the wet-day daily precipitation is approximately exponentially distributed[7,13,14,15], albeit with a systematic bias connected to the location. The assumption can be assessed by comparing the actual percentiles with quantiles estimated for different samples with different μ (annual mean wet-day precipitation) using the formula for exponentially distributed data $q_p = -ln(1-p)\mu$ (Figure SM1). The exponential distribution implies a similar proportional change for all percentiles, which is roughly consistent a near-constant ratio of increase in daily precipitation percentiles above the 90th percentage[16]. The two quantities should be similar (as Figure SM indicates) and the data scattered along the diagonal in a scatter plot, indicating that a high percentile associated with a low wet-day mean μ is consistent with a more moderate percentile for a sample with a higher wet-day mean value.

Why calculate the saturation vapour pressure?

It is often wise to make use of terms with similar physical dimensions when calibrating statistical models[17]. The saturation vapour pressure is proportional to its density (ideal gas law: $e_s = \rho\, R_{specific}\, T$), and the total mass is the product between volume and density. The saturation vapour pressure is expected to be more linearly related to the wet-day mean than temperature because their physical dimensions both involve a measure of the water mass. If temperature was used, on the other hand, then the relationship would be expected to be nonlinear due to the Clausius-Clapeyron equation ($e_s=10^{(11.40–2353/T)}$ where T is temperature in degree Kelvin).

What is the connection between the mean seasonal cycle and long time scales?

The mean seasonal cycle is estimated by taking the mean value over all January months, then over all February months and so on until one mean value is found for each of the 12 calendar months. This type of aggregation gives a larger sample size compared to analyses applied on individual years, and gives a value that is based on a sample stretching over longer time periods. Calibration on larger sample sizes stretching over longer time periods puts more weight on slow processes with long time scales.

What are the error bars?

The error bars in Figures SM3 and SM9 were estimated as a part of the regression analysis. These are different from the error bars in Figure 1 which show the year-to-year variations (two standard deviations) about the seasonal mean. In some of the figures the error bars from the regression analysis are not explicitly shown because there was already too much to show (too cluttered graphics).

Supporting figures

Figure SM1. Test for assessing the consistency between the percentiles taken from observations and estimated values using q_p=-$ln(1-p)$μ where the value for the values for q_p is estimated using different value for p to compensate for variations in annual mean μ. A critical threshold x can correspond to different percentiles p according to $x = q_{p1}=-ln(1-p_1)\mu_2 = q_{p2}=-ln(1-p_2)\mu_2$ and if x is exponentially distributed and $p_1 = (p_2 - 1)\ exp\{\mu_2 - \mu_1\} - 1$.

Figure SM2. The statistics of the R^2 from the regression between the seasonal cycle in the saturation water vapour, estimated from the temperature over the seasonal cycles in the saturation water vapor from the surface temperature over 100°W-30°E/0°N-40°N, and the local wet-day mean μ. There is a portion of stations with very low variance explained by this regression, but most stations suggest a variance exceeding 60%.

Figure SM3. A comparison between the long-term linear trends estimated from the annual mean μ and μ^* estimated using equation 1, taking the saturation water vapor from the surface temperature over 100°W-30°E/0°N-40°N. The scatter in the observed trends is greater than in the predicted ones, which is consistent with the wet-day mean also being affected by factors other than e_s. The historical trends have furthermore been weak compared to interannual-to-decadal variations, and the skill assessment is limited due to low signal-to-noise ratio. The error bars were estimated through linear regression, taking two times the standard error estimate, were wider for the observations than projections owing to the stronger presence of natural variability in the observations.

Figure SM4. Map of the geographical distribution in the historical trends in the wet-day mean μ. The trend is generally increasing, but there are some outliers showing a decrease. These outliers are probably spurious, as they do not match the bulk of the data.

Figure SM5. The wet-day percentile that corresponds a one-year return-value x_{1year} given the observed mean wet-day frequency. In this case, a one-year precipitation return-value corresponds roughly to the 99-percentile for the wet-day 24-hr precipitation if the wet-day frequency is accounted for [$Pr(X > x) = 1/365.25 = f_w*(1-p)$; $p = 1 - 1/(365.25*f_w)$]. The comparison between the 99-percentile and the exponential distribution suggests a good match if geographical biases are accounted for[7].

Figure SM6. Trend estimates in the wet-day frequency f_w for the 1032 locations suggests values scattered around zero. A general zero-trend is consistent with the annual wet-day frequency being stationary.

Figure SM7. The geographical distribution in the historical trends in the wet-day frequency f_w. There has been a general increase in the number of wet days in southern scandinavia and regions exposed to the sea.

Figure SM8. Scatter plot showing the correlation between the climatological mean daily maximum temperature (converted to saturation vapour pressure) and the wet-day mean μ. The size of the symbols is proportional to the number of rainy days. Insert map shows locations of stations used to compare the climatological mean wet-day mean against the mean surface temperature. The colours of symbols in the scatter plot match those in the map. The data included CLARIS data set from South America, a subset of the ECA&D in Europe used in the COST-VALUE experiment 1[w] and a subset of station data from GDCN as in reference [10] but selecting the stations with the longest records. The selection of location was also limited to sites where both temperature and precipitation had been recorded.

Figure SM9. Comparison between the regression coefficients estimated for each location based on the seasonal cycles in μ and e_s (blue) and based on the regression analysis of spatially varying mean climatology as in Fig SM11 (grey). Error bars represent two standard errors. The size of the symbols is proportional to the R^2-statistics from the regression analysis between the two mean seasonal cycles. The comparison between the results from the two types of analyses suggests a consistency within the margin of error for those locations where the mean seasonal cycle in μ matched that of the predictor from 100°W-30°E/0°N-40°N.

Figure SM10. Map showing the actual return-values estimated for 2100 for an RCP4.5 emissions scenario. The results here were estimated according to $x_{20year} = \mu_{95} \ln(365.25\, \overline{f_w})$, where μ_{95} was the 95-percentile of the values for μ downscaled from the CMIP5 RCP4.5 simulations (108 runs). Here $\overline{f_w}$ was the mean wet-day frequency, assuming that the number of rainy days is stationary. The downscaling of μ was based on statistical models calibrated on the mean seasonal cycle (Figure 1).

Figure SM11. An example of projected annual wet-day mean precipitation μ for the three different emission scenarios RCP 4.5 (grey), RCP2.6 (green) and RCP8.0 (red) as the percentage of the 2010 values (see Table 1).

Figure SM12. The mean temperature over the chosen predictor area 100°W-30°E/0°N-40°N.

Figure SM13. A comparison between the seasonal cycle in the mean precipitation, the wet-day mean precipitation, the wet-day frequency, as well as the wet and dry spell lengths. The most pronounced seasonal variations tends to be associated with the wet-day mean rather than the mean precipitation or the wet-day frequency.

References

[1] Adler, Robert F., George J. Huffman, Alfred Chang, Ralph Ferraro, Ping-Ping Xie, John Janowiak, Bruno Rudolf, et al. "The Version-2 Global Precipitation Climatology Project (GPCP) Monthly Precipitation Analysis (1979–Present)." *Journal of Hydrometeorology* 4, no. 6 (December 1, 2003): 1147–67. doi:10.1175/1525-7541(2003)004<1147:TVGPCP>2.0.CO;2.

[2] Arkin, Phillip A., Robert Joyce, and John E. Janowiak. "The Estimation of Global Monthly Mean Rainfall Using Infrared Satellite Data: The GOES Precipitation Index (GPI)." *Remote Sensing Reviews* 11, no. 1–4 (October 1, 1994): 107–24. doi:10.1080/02757259409532261.

[3] Jaeger, L. "Monthly and Areal Patterns of Mean Global Precipitation." In *Variations in the Global Water Budget*, edited by Alayne Street-Perrott, Max Beran, and Robert Ratcliffe, 129–40. Springer Netherlands, 1983. http://link.springer.com/chapter/10.1007/978-94-009-6954-4_9.

[4] Wang, Yuqing, and Li Zhou. "Observed Trends in Extreme Precipitation Events in China during 1961–2001 and the Associated Changes in Large-Scale Circulation." *Geophysical Research Letters* 32, no. 9 (May 1, 2005): L09707. doi:10.1029/2005GL022574.

[5] Benestad, R. E., I. Hanssen-Bauer, and E. J. Førland. "An Evaluation of Statistical Models for Downscaling Precipitation and Their Ability to Capture Long-Term Trends." *International Journal of Climatology* 27, no. 5 (April 1, 2007): 649–65. doi:10.1002/joc.1421.

[6] Wheelan, Charles, and Jonathan Davis. *Naked Statistics: Stripping the Dread from the Data*. MP3 edition. Brilliance Audio, 2014.

[7] Benestad, R. E., and A. Mezghani. "On Downscaling Probabilities for Heavy 24-Hour Precipitation Events at Seasonal-to-Decadal Scales." *Tellus A* 67, no. 0 (March 30, 2015). doi:10.3402/tellusa.v67.25954.

[8] Benestad, R. E. "An Explanation for the Lack of Trend in the Hurricane Frequency." *arXiv:physics/0603195*, March 2006. http://arxiv.org/abs/physics/0603195.

[9] Benestad, R. E. "Association between Trends in Daily Rainfall Percentiles and the Global Mean Temperature." *Journal of Geophysical Research: Atmospheres* 118, no. 19 (2013): 10,802–10,810. doi:10.1002/jgrd.50814.

[10] Kimberly Smith, Courtenay Strong, and Shih-Yu Wang, 2015: Connectivity between Historical Great Basin Precipitation and Pacific Ocean Variability: A CMIP5 Model Evaluation. *J. Climate*, **28**, 6096–6112. doi: http://dx.doi.org/10.1175/JCLI-D-14-00488.1

[11] Knutti, R., G. Abramowitz, M. Collins, V. Eyring, P. J. Gleckler, B. Hewitson, and L. Mearns, 2010: Good Practice Guidance Paper on Assessing and Combining Multi Model Climate Projections. In: Meeting Report of the Intergovernmental Panel on Climate Change Expert Meeting on Assessing and Combining Multi Model Climate Projections [Stocker, T.F., D. Qin, G.-K. Plattner, M. Tignor, and P.M. Midgley (eds.)]. IPCC Working Group I Technical Support Unit, University of Bern, Bern, Switzerland

[12] Benestad, Rasmus E. "A New Global Set of Downscaled Temperature Scenarios." *Journal of Climate* 24, no. 8 (2011): 2080–98.

[13] Benestad, R.E., D. Nychka, and L. O. Mearns. "Specification of Wet-Day Daily Rainfall Quantiles from the Mean Value." *Tellus A* 64, no. 14981 (2012a). doi:10.3402/tellusa.v64i0.14981.

[14] Benestad, R.E. "Novel Methods for Inferring Future Changes in Extreme Rainfall over Northern Europe." *Climate Research* 34, no. doi: 10.3354/cr00693 (2007): 195–210.

[15] Benestad, R.E., D. Nychka, and L. O. Mearns. "Spatially and Temporally Consistent Prediction of Heavy Precipitation from Mean Values." *Nature Climate Change* 2, no. doi: 10.1038/NCLIMATE1497 (2012b).

[16] Pall, P., M. R. Allen, and D. A. Stone. "Testing the Clausius–Clapeyron Constraint on Changes in Extreme Precipitation under CO2 Warming." *Climate Dynamics* 28, no. 4 (January 16, 2007): 351–63. doi:10.1007/s00382-006-0180-2.

[17] Benestad, R. E., D. Chen, and I. Hanssen-Bauer. *Empirical-Statistical Downscaling*. Singapore: World Scientific Publishing, 2008.

Appendix

Figures

R-script (Rmarkdown) used to produce the plots