Supporting Information for "Role of Soil Moisture vs. Recent Climate Change for the 2010 Heat Wave in Western Russia"

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Introduction

In the supplementary material we include more details concerning the trend detection in annual maximum temperatures (Text S1). A more thorough explanation of the the model validation can be found in Text S2 and Figure S1 to Figure S3. Additional information is given for the estimation of the influence of climate change on soil moisture in the study region (Text S3 and Figure S4). Figure S5 displays the probability density function (pdf) and their uncertainty for simulations *R1960s* and *R2000s* as well as the best-estimate pdf for all five simulations. Finally, Figure S6 shows quantile-quantile plots for all five simulations as well as the HadGHCND data.

Text S1: Trend Detection in Annual Maximum Temperatures

To test if climate change has increased TXx in western Russia we investigate trends in the HadGHCND dataset. For this purpose we introduce a covariate in the GEV location parameter, that is, we split the location parameter into a constant (intercept) plus a time-varying (explanatory variable times a slope) part. Using time as explanatory variable (a linear trend) results in a non-significant increase of the location parameter of $0.020^{+0.044}_{-0.005}$ K per year (best estimate and $95\,\%$ confidence interval). This is in line with mean July temperatures of the last 130 years which also exhibit a non-significant linear trend (*Dole et al.*, 2011). In contrast, regressing mean July temperatures after 1950 against global mean temperature (smoothed with a 3-year running mean) results in a significant trend of 1.9 times the global mean (*Otto et al.*, 2012). Following this methodology, we use global mean temperatures (from GISTEMP-1200) as explanatory variable. This results in a significant trend of $1.90^{+3.62}_{+0.14}$ K/K in the location parameter. Thus, TXx and mean July temperatures have the same trend over the last 50 years in this region.

Text S2: Model Validation

We validate the CESM simulations against observations by fitting a GEV distribution to *R1960s* and *R2000s*. The resulting parameters are compared with the HadGHCND fit (Figure S1). While the shape and scale parameters compare well, the location parameter of the observation and the model are significantly different. This median bias of 1.75 °C can be corrected by subtracting it from all five simulations.

It is important that the SM climatologies of the online simulations do not show a large bias with respect to *CLM-ERA* as this could influence the temperature in the simulations. Annual mean daily precipitation estimates are similar across ERA-Interim, *R1960s* and *R2000s* (Figure S2(a)). During the summer months June, July and August (JJA), however, ERA-Interim has higher daily mean precipitation (not shown). To validate the soil moisture (SM) output of the coupled simulations we compare top 1 m SM between the offline and coupled simulations. The annual cycle of *CLM-ERA* and *R2000s* is shown in Figure S3. The most prominent feature, is the large SM anomaly in 2010. It was unprecedented in the ERA-Interim period and not reproduced in the interactive model simulations. On average SM is higher in *CLM-ERA* than *R1960s* and *R2000s* for both, the annual mean (not shown), and JJA (Figure S2(b)). Had *R1960s* and *R2000s* been as wet as *CLM-ERA* (in the mean) we would expect: (i) a (slightly) larger SM difference between "dry 2010" and "climatological" conditions, thus, (ii) lower TXx (for *R1960s* and *R2000s*) and (iii) consequently, higher risk ratios for the SM influence in simulations with prescribed 2010 SM than reported in Section 3.4. Therefore, the estimates of the SM influence reported in that section are rather conservative.

While the model represents the distribution of TXx and SM well, it has deficiencies capturing blocking frequency. In the study region it exhibits approximately half the *Tibaldi and Molteni* (1990) blocking frequency compared to ERA-Interim (not shown). This is a known problem of global climate models (*Brunet et al.*, 2010; *Scaife et al.*, 2010). The underestimation of blockings may be the reason why the coupled model does not reach SM values as low as in *CLM-ERA*. This is an additional motivation to prescribe SM to 2010 levels and investigate the atmospheric response.

Text S3: Influence of Climate Change on 2010 Soil Moisture

Two approaches are applied to estimate the influence of recent climate change on the 2010 soil moisture. The first builds upon the temperature difference (*CLM-ERA_TEMP*) and the second on the longwave downward radiation (LWdown) difference (*CLM-ERA_RAD*) between the 1960s and the 2000s (see Figure S4).

In *CLM-ERA_TEMP* we first estimate the mean temperature change between 1960 to 1969 and 2000 to 2009 (1.4 °C). This difference is subtracted from the ERA-Interim forcing temperature for every time step in 2010. Thus no difference is made between day and night or between different seasons/ months. All other forcings (wind, relative humidity, precipitation, short wave downward radiation) are kept constant. Then the year 2010 is simulated again, starting from the same initial conditions as *CLM-ERA*.

LWdown is not a (necessary) forcing in CLM 4.0. For *CLM-ERA_RAD* we thus try to estimate how much less water would have evaporated due to decreased LWdown in the 1960s (thus resulting in smaller LWdown). Thereby, we use the LWdown difference from *R1960s* and *R2000s*. We assume that the influence of less greenhouse gases manifests itself mainly on cloud free days and that the effect is only important in the months April, May, June and July (AMJJ). Because, cloud cover was not in the daily output of the model, it is estimated as the ratio of shortwave downward radiation (from the model) and direct clear-sky radiation of the sun (theoretical value; *Masters*, 2013) and using days with a cloud fraction lower than approximately 0.35.

Then, the change in LWdown is determined between *R1960s* and *R2000s* on days with low cloud cover during AMJJ. It is found that on cloud free days LWdown is about $4.7\,\mathrm{Wm}^{-1}$ smaller in *R1960s* than in *R2000s*. Additionally, we compute the linear relationship between ET and LWdown in the study region, which is 0.018 mm per Wm^{-2} (R-squared of 0.8). Thus, according to this methodology on every cloud-free day 0.08 mm would not have evaporated in the 1960s. Finally, ET (soil moisture) is decreased (increased) by this value for every low-cloud day in *CLM-ERA*.

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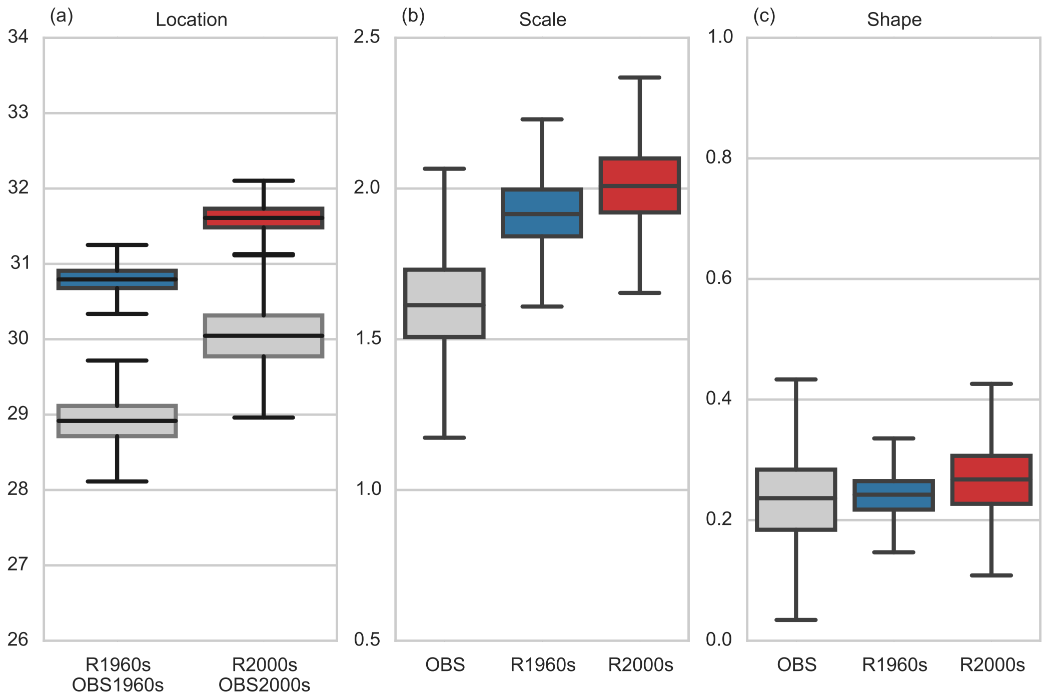

Figure S1: Boxplots of the estimated GEV parameters for *R1960*, *R2000* and the HadGHCND dataset ('OBS'). (a) Location, (b) scale and (c) shape.

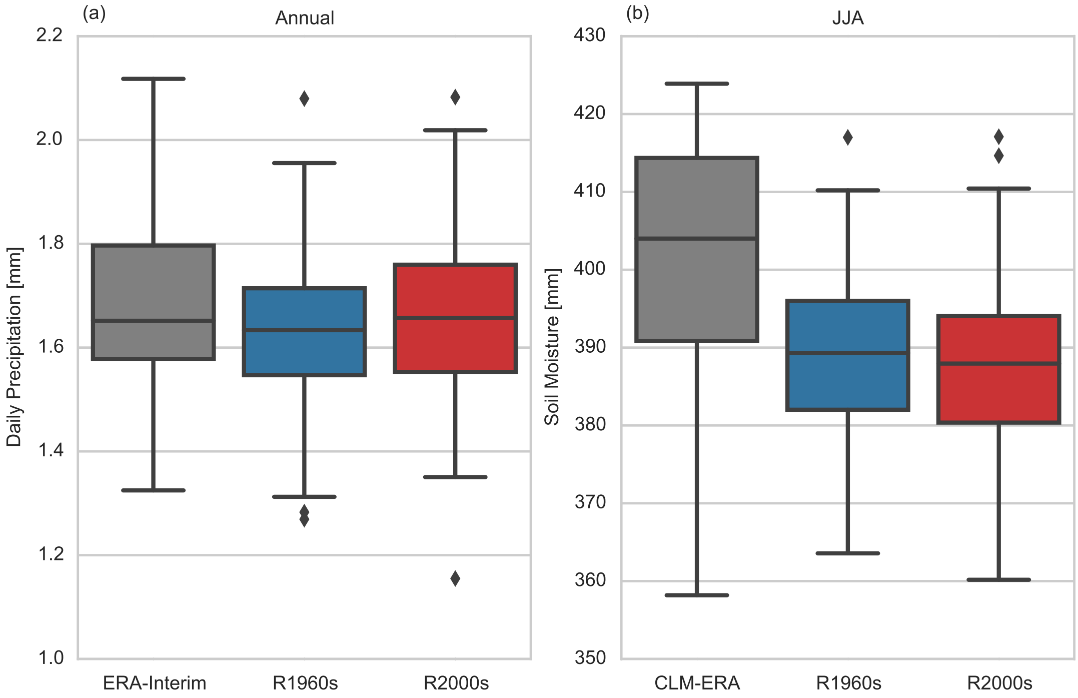

Figure S2: (a) Annual mean of daily precipitation for ERA-Interim, *R1960s* and *R2000s*. (b) Mean absolute soil moisture in the top 1 m for CLM-ERA, R1960s and R2000s for JJA. Note the time periods: 1981 to 2010 for ERA-Interim and *CLM-ERA* and 1960 to 1969 and 2000 to 2009 for *R1960s* and *R2000s*, respectively.

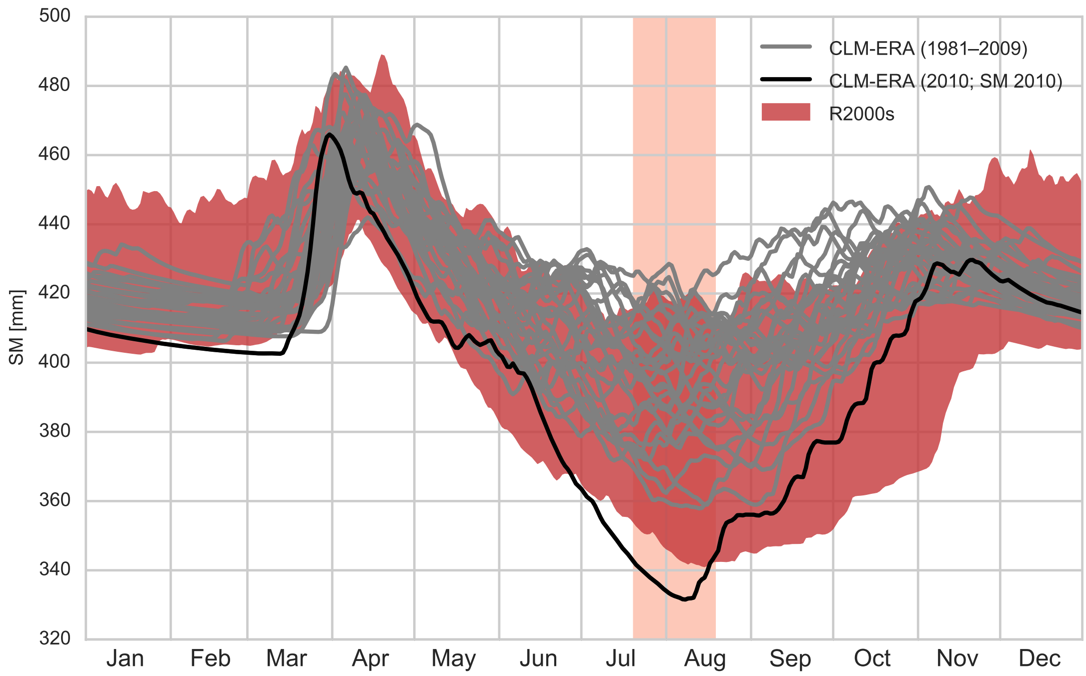

Figure S3: Absolute soil moisture in top 1 m for *R2000s* and *CLM-ERA*. The black line shows soil moisture conditions in 2010 and indicates the prescribed soil moisture in *R1960s+SM2010* and *R2000s+SM2010*. The light red shading indicates the approximate duration of the heat wave in 2010. *R1960s* and *R2010* are not shown but have a similar range as *R2000s*.

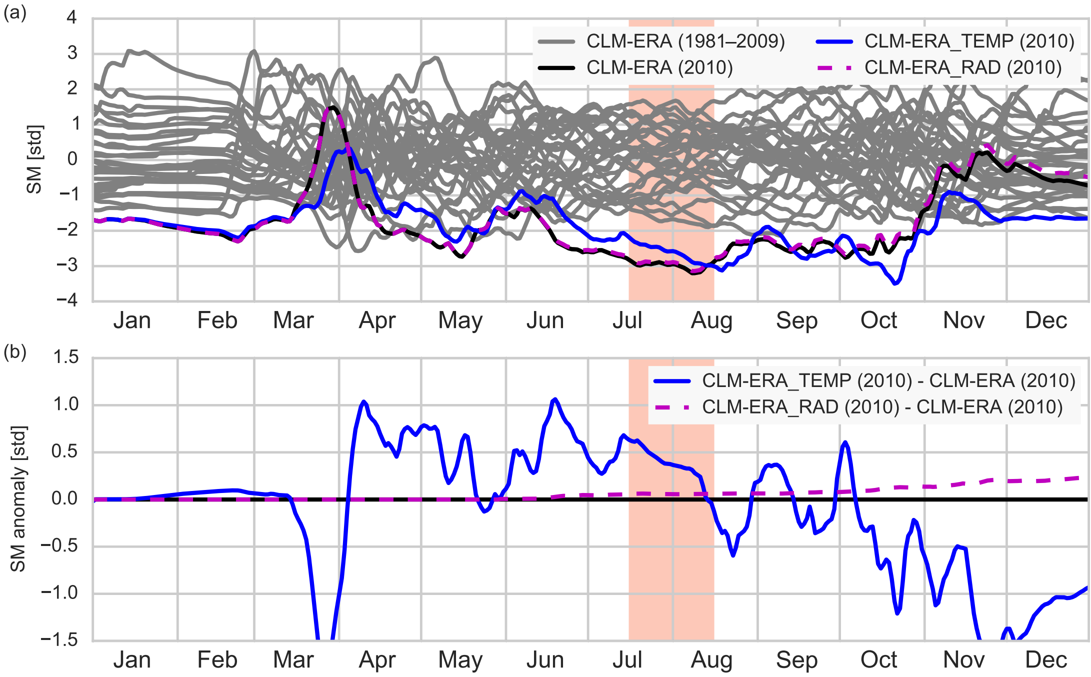

Figure S4: Absolute soil moisture in top 1 m. Light red shading indicates the approximate duration of the heat wave in 2010. (a) Gray (1981-2009) and black (2010) lines represent the best estimate soil moisture conditions in western Russia (as in Figure 2(b)). Blue and magenta line is the estimated soil moisture without recent climate change influence (see Text S1). (b) Difference between *CLM-ERA_TEMP*, *CLM-ERA_RAD* and *CLM-ERA*.

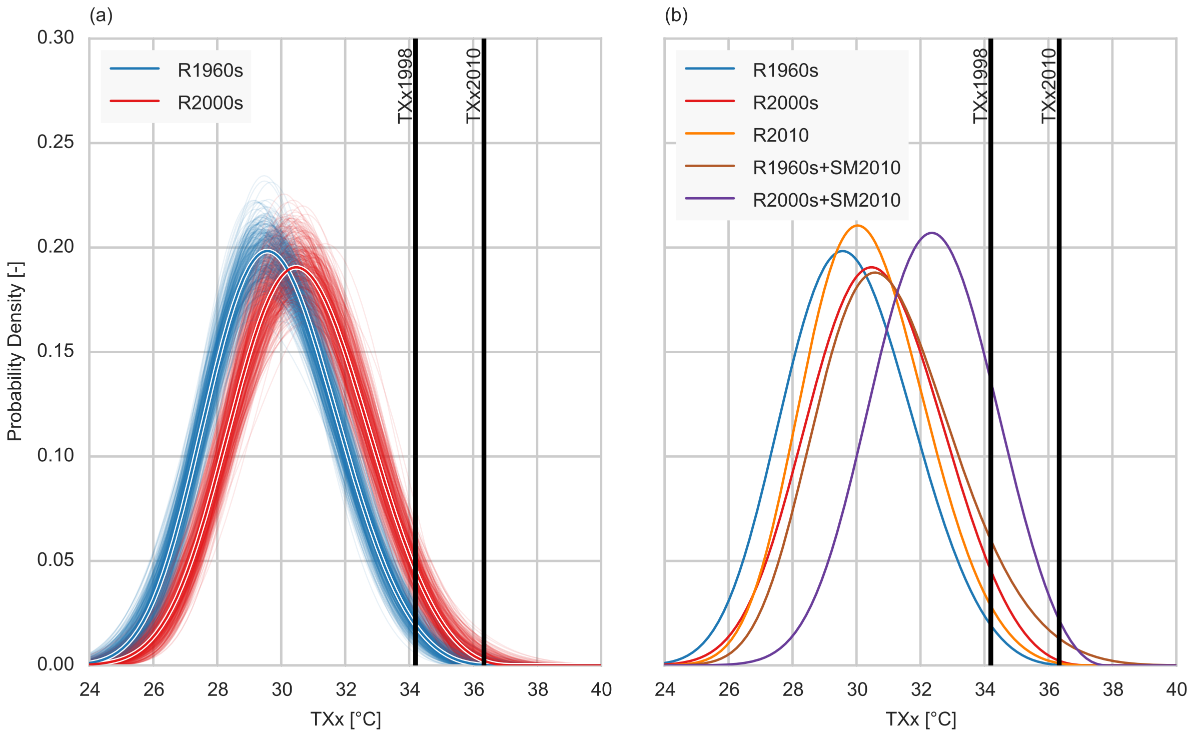

Figure S5: Probability density function for the four simulations. The vertical black lines indicate the warmest (TXx2010) and second warmest (TXx1998) event on the observational record. (a) Best estimate (white shading) and 400 random parameter sets of the Markov Chain Monte Carlo estimation to illustrate the uncertainty for *R1960s* and *R2000s*. (b) Only best estimate, including *R2010*, *R1960s+SM2010* and *R2000s+SM2010*. The heat wave probability p is given as the area under the curve to the right of TXx1998.

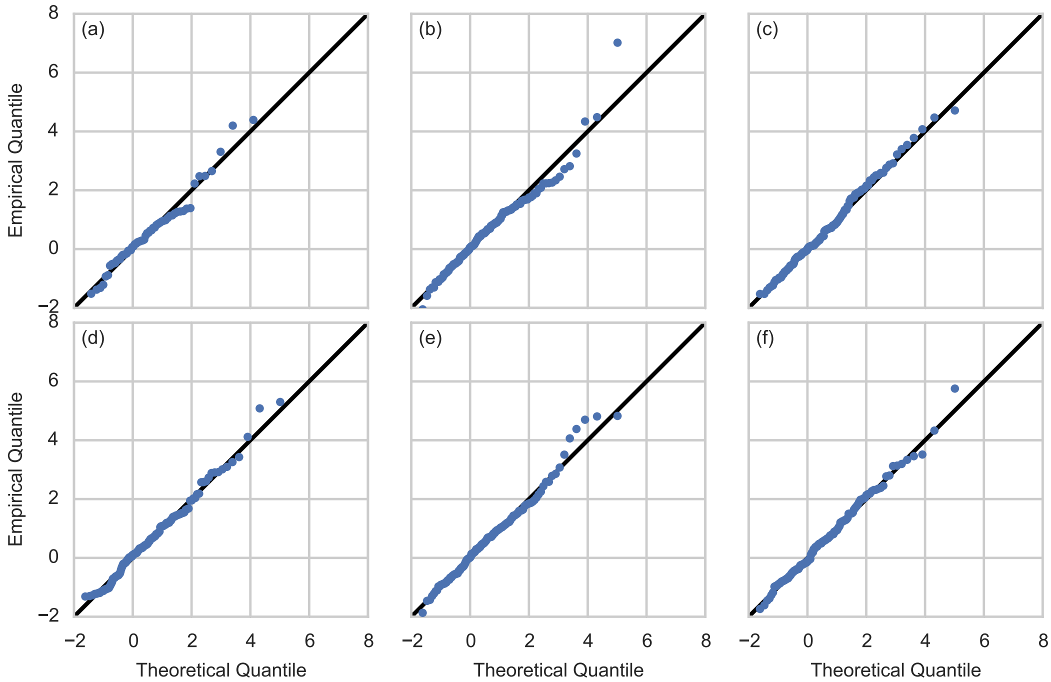

Figure S6: Quantile-quantile (QQ) plot for the fitted GEV distributions. From (a) to (f): HadGHCND with GISTEMP as covariate, *R1960s*, *R2000s*, *R2010*, *R1960s+SM2010* and *R1960s+SM2010*