Preparing local climate change scenarios for the Netherlands using resampling of climate model output.

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Supplementary Material
1. Details on the selection of the re-samples

Selection of the re-samples is done in a three-step procedure. We start with all possible re-combinations of the eight ensemble members, using blocks of 5-year periods, which amount to $8^6 \sim 2.6 \times 10^5$ re-samples for a 30-year period.

1. We select 1000 samples based on changes in seasonal mean winter precipitation. The changes are with respect to the mean winter precipitation for the control period, 1981-2010, over the eight members contained in ENS-EC. For the “L” scenarios the target percentage change of mean winter precipitation is $4\Delta T_{\text{glob}}$, whereas for the “H” scenarios this is $8\Delta T_{\text{glob}}$. This selection criterion, scaling the change with the global temperature change $\Delta T_{\text{glob}}$, has also been used in the previous set of scenarios for the Netherlands (Lenderink et al. 2007), but with slightly lower values of $3\Delta T_{\text{glob}}$ and $7\Delta T_{\text{glob}}$. The reason to take these higher values is related to the fact that it turns out that the criterion discussed in step 3 is easier to satisfy with the new higher values – noting that the results of the un-resampled ensemble, ENS-EC, as shown in Figure 1 of the main text are on average close to $6\Delta T_{\text{glob}}$. Another reason is that changes in ENS-EC are relatively large for dry months (P05 and P10) in winter and relatively small in wet months (P90 and P95), and by resampling this characteristic is mostly retained. As we value to represent the CMIP5 range for the wet months more, we decided to take somewhat higher values.

For the control period this implies that these samples have the same mean winter precipitation as the mean of the eight ensemble members. There are many samples that are very close to the two targets above; for instance, for the $W_H$ scenario for 2050 the global temperature rise $\Delta T_{\text{glob}}$ is 2 °C; the target DJF winter precipitation change is therefore 16 %, and the top 1000 samples deviate less than 0.1 % from the target value. Thus, this is a very weak constraint, and this finding is a reflection of the fact that the natural variability in winter precipitation is large. After this step, we have for each 30-year period and each scenario a selection of 1000 samples; these selected sets which will be referred to in the following as $S_1$.

2. From set $S_1$ (out of 1000) we select samples based on other seasonal mean characteristics. We compute the distribution of seasonal mean temperature and precipitation of each set $S_1$, and select a percentile range from that distribution. For instance, for the $W_H$ scenario, we aim to construct a scenario that is characterized by a strong decrease in summer precipitation and a relatively strong temperature increase in summer. This is achieved by selecting relatively cold and wet samples for the control period and relatively warm and dry samples for the future period. Selection in this way has been done three times with rather broad percentiles ranges, at least covering 30 % of the remaining data. Each selection is done successively, using the selected sampled from the previous step. The selected percentile ranges are shown in Supplementary Table 1. The selection of these percentile ranges has been done iteratively, checking the results of seasonal mean changes with the required representation of the CMIP5 uncertainty range. At the end of this step, we arrive for each scenario at a selection of ~50 samples. This is set $S_2$.

3. From set $S_2$ we select a set of eight samples that have the smallest possible duplication in using the same RACMO/EcEarth ensemble member for the same period. The number of ways 8 samples can be selected from ~50 samples is very large and increases strongly with sample
size. Thus, here a simple Monte-Carlo method is used. We randomly select a set of 8 samples, and count the number of overlaps of 3 (same ensemble member for a 5-year period is used 3 times) and 4 in this set, giving each occurrence of an overlap of 3 a penalty of 1, and an overlap of 4 a penalty of 5. Repeating this procedure 10,000 times, we chose the set with the lowest penalty. It turns out that for all scenarios the maximum size of the overlap is 3, and those occur between 3 and 7 times in a selected set for the control and future period.

| ΔTglob | Resampling Period | ΔPrecip (DJF) | ΔPrecip (JJA) | Δt2m (DJF) | Δt2m (JJA) |
|--------|------------------|--------------|--------------|-----------|-----------|
| WEOC   | 3.0 2066-2095    | 24 %         | control: 60-100 % future: 0-40 % | control: 20-50 % future: 50-80 % | control: 10-50 % future: 60-100 % |
| WMOC   | 2.0 2046-2075    | 16 %         | control: 70-100 % future: 0-30 % | control: 10-40 % future: 60-90 % | control: 10-50 % future: 60-100 % |
| GEOC   | 1.5 2031-2060    | 12 %         | control: 70-100 % future: 0-30 % | control: 10-40 % future: 60-90 % | control: 10-50 % future: 60-100 % |
| GOMC   | 1.0 2021-2050    | 8 %          | control: 65-100 % future: 0-35 % | control: 10-40 % future: 60-90 % | control: 10-50 % future: 60-100 % |
| WEOC   | 3.0 2066-2095    | 12 %         | control: 0-30 % future: 70-100 % | control: 50-80 % future: 10-50 % | control: 0-100 % future: 50-0 % |
| WMOC   | 2.0 2046-2075    | 8 %          | control: 0-30 % future: 70-100 % | control: 50-80 % future: 20-50 % | control: 0-100 % future: 50-0 % |
| GEOC   | 1.5 2031-2060    | 6 %          | control: 10-40 % future: 60-90 % | control: 50-80 % future: 20-50 % | control: 0-100 % future: 50-0 % |
| GOMC   | 1.0 2021-2050    | 4 %          | control: 25-55 % future: 45-75 % | control: 50-80 % future: 20-50 % | control: 0-100 % future: 50-0 % |

Supplementary Table 1. Summary of the selection criteria using in the resampling procedure. EOC refers to scenarios for the end of the century (2085), and MOC for the middle of the century (2050).

While developing the selection procedure, we first omitted the 3rd step, and selected 10 samples (instead of 8) for each scenario by taking 10% percentile ranges in step 2, and using two selection criteria in that step. In that case, the number of reoccurring 5 year data blocks was much larger, and amounted up to 5 times. Despite this, derived seasonal changes for many variables were rather similar.

Finally, we note that the resulting changes derived from the scenarios are not very dependent on details of the selection procedure. As long as samples have similar changes in seasonal means the other derived statistics are similar too. As an example, we show in Supplementary Figure 1 results of a different set in which instead of 4 and 8 % per degree a dependency of 3 and 7 % per degree is assumed in step 1, and small differences in the percentile ranges in step 2. Differences with Figure 6 of the main text are small.
Supplementary Figure 1. As Figure 6 of the main paper, but now for a different set (see text for details)
2. Results for spring and autumn

The procedure has been optimized to reproduce the spread in CMIP5 in summer and winter. Although, in principle, the procedure could be extended to spring and autumn as well, we have not done this. We note that for a number of statistics changes within the season are substantial, for instance with relatively large decreases in precipitation early autumn and increases late autumn in many of the simulations in CMIP5. Partly, this behavior is affected by memory effects. Within CMIP5 there are models that have a (much) larger tendency to exhibit large scale soil drying in summer, and these models also tend to continue the period of drying into autumn. In our single model approach we cannot reproduce this. Some experiments were performed with modifications in the soil scheme in our model to mimic the behavior of those CMIP5 models, but so far these have only been partly successful.

Results for spring and autumn are shown in Supplementary Figure 2 for 2050 and Supplementary Figure 3 for 2085.
Supplementary Figure 2. As Figure 5 of the main paper, but now for spring and autumn and 2050.
Supplementary Figure 3. Figure 5 of the main paper, but now for spring and autumn and 2085.
3. The circulation response

The scenarios have been constructed making use of natural variability within the EcEarth ensemble. As the major part of the natural variations are contained in the large scale atmospheric circulation, we will evaluate the mean sea level pressure response in the scenarios here. Supplementary Figure 4 shows the pressure response in winter and summer in the un-resampled ensemble at the 2 degrees warming period (2046-2075 compared to 1981-2010). In winter there is no clear large scale pattern in the change in mean sea level pressure. In contrast, in summer a clear increase in mean sea level pressure is seen just west of the British Isles. This pattern is also obtained in the mean pressure response to warming in CMIP5 (Van den Hurk et al. 2013b).

As explained above, two scenarios for 2050 are constructed from the 2-degrees warming period, that is $W_H$ and $W_L$. The pressure response in these two scenarios deviates from the pressure response of the un-resampled ensemble. In general, the deviations for the two scenarios are almost symmetric, and therefore we will only show the difference in pressure response between the $W_H$ and $W_L$ scenario. The total pressure response (future period minus control period) in $W_H$ ($W_L$) is approximately equal to the pressure response in the un-resampled ensemble plus (minus) half of the difference pattern. In winter the $W_H$ scenario is characterized by a stronger south westerly flow, whereas in summer there is an anomalous easterly flow. This causes warmer and wetter weather in winter and warmer and drier weather in summer. For the $W_L$ scenario the situation is reversed.

For the $W_H$ and $W_L$ scenarios at 2085 results are very similar. In winter the difference is now a east-west flow. In summer, the pressure pattern is more aligned with the mean pressure response from the un-resampled ensemble.

In term of the strength of the (south) westerly flow in winter, estimated from the geostrophic approximation using mean sea level pressure, the difference in response between $W_H$ and $W_L$ is approximately 1.4 m s$^{-1}$ for 2050 and 2.2 m s$^{-1}$ for 2085. In summer, the difference is typically 1 m s$^{-1}$ with a weaker westerly flow in the $W_H$ scenarios compared to the $W_L$ scenario. These numbers are comparable to the previous set of climate scenarios.
The scenarios are characterized by differences in the circulation response as shown in Supplementary Figure 4. One might question whether these patterns are similar in CMIP5. In order to investigate this we computed the pressure response anomaly for each CMIP5 model with respect to the multi-model mean response. In order to estimate the typical inter-model patterns of the response in mean sea level pressure we compute the first two EOFs. These EOF patterns should then be comparable to the pressure anomaly between the two scenarios, $W_H$ and $W_L$. It is shown that the first EOF (Explained Variance 42%) in winter is characterized by a dipole structure with high pressure centered over Spain and low pressure in northern Europe, with a westerly flow over the Netherland in between. The second EOF (EV 28%) characterizes a (weaker) south-south-westerly flow. In summer, the first EOF (EV 50%) is a relatively weak but elongated high pressure system centered over the North Sea, whereas the second EOF (EV 19%) is more a dipole structure with a high pressure system band centered over the north of the British Isles and low pressure in southeastern Europe. The inter scenario pattern of the change in mean sea level pressure and the EOFs reveal many similarities. Thus, we conclude that the difference in pressure response between the scenarios are within the range spanned by CMIP5.
Supplementary Figure 5. First and second EOF the inter-model differences in the pressure response between 1981-2010 and 2071-2100 for the CMIP5 RCP4.5. Each EOF has been multiplied with 1.5 times the standard deviation of the time series of the EOF magnitude and the color shaded is same as in Supplementary Figure 4.

The pressure response in the RACMO2 simulations is almost identical to the pressure response in EcEarth. Taking the same resampling period for each scenario will therefore result in virtually identical differences in the pressure response as shown in Supplementary Figure 4. In this respect, we also note that both RACMO2 and EcEarth share large part of the physics as both models are based on ECMWF physics.
4. Check on inter-annual variability

Here, we show results for year-to-year variability, and investigate whether this is affected by resampling. It turns out that resampling only has minor effect on year-to-year variability, which was expected given the 5-year blocks used for the resampling. As an example, we show results in Supplementary Figure 6 for seasonal mean winter temperature and precipitation for the W_H scenario compared to the original (un-resampled) model data. For temperature, there is a marginal decrease in year-to-year variability, but for precipitation it is unaffected over the Netherlands.

Supplementary Figure 6. Comparison of mean standard deviation of year-to-year variations in seasonal mean temperature (upper panels) and seasonal mean precipitation (lower panels) for un-resampled (left) and resampled (right) results for the W_H scenario.
5. Natural variability between the ensemble members

Here, we show the standard deviation of the 8 ensemble members in the resampled scenarios, compared to the standard deviation between the 8 members in the un-resampled data (ENS-RA). We first computed the statistics for the Netherlands from 30-year periods, then compute the climate change signal from the change between the future period with the control period. The standard deviation from the 8 climate change signals are then plotted (see Supplementary Figure 8).
Supplementary Figure 8. Examples of the (natural) variability between the 8 members of resampled and un-resampled model output. Shown is the standard deviation in the climate change response between the 8 members, derived from the model output at 2 degrees warming (W scenario for 2050) compared to the reference period. Statistics are derived for months. Upper panels: monthly average; middle panels, 1st and 99th percentile of daily temperature; lower panels, wet-day frequency and 99th percentile of daily precipitation. Blue and red are the resampled model output; black is the un-resampled output.
