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# Comparing internal variabilities in three regional single model initial-condition large ensembles (SMILE) over Europe

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**Abstract**

Single model large ensembles are widely used model experiments to estimate internal climate variability. The underlying assumption is that the internal variability (here: inter-annual variability) of the chosen model is a good approximation of the observed natural (inter-annual) variability. In this study, we test this assumption based on three regional climate model large ensembles (16 members of an EC-EARTH-RACMO ensemble, 21 members of a CESM-CCLM ensemble, 50 members of a CanESM-CRCM ensemble) for four European domains (British Isles, France, Mid-Europe, Alps). Simulated inter-annual variability is evaluated against E-OBS and the inter-annunal variability and its future change are compared across the ensembles. To the knowledge of the authors, this is the first comparison of regional large ensembles over Europe. Analysis comprises seasonal temperature and precipitation, as well as indicators for dry periods and heat waves.

Results show a large consistency of all three ensembles with E-OBS data for most indicators and regions, validating the abilities of these ensembles to represent natural variability on the annual scale. EC-EARTH-RACMO shows the highest inter-annual variability for winter temperature and precipitation, whereas CESM-CCLM shows the highest variability for summer temperature and precipitation, as well as for heatwaves and dry periods. Despite these model differences, the sign of the future changes in internal variability is largely the same in all models: for summer temperature, summer precipitation and the number of heat waves, the internal variability increases, while it decreases for winter temperature. Changes of winter precipitation and dry periods are a bit unclear, with a tendency to increase for dry periods.

The overall consistency across single model large ensembles and observations strengthens the concept of large ensembles, and underlines their great potential for understanding and quantifying the role of internal climate variability.

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## 1 Introduction

The variability of the climate system is subject to various drivers. Variability can be caused by natural forcings like changes in solar radiation or volcanic eruptions at different time scales. Variability of single components of the climate system can also be caused by the redistribution of heat and momentum between and within different components (e.g. ocean and atmosphere) of the coupled climate system. Next to these variations, anthropogenic changes in greenhouse gas concentrations contribute to a changing climate state.

Uncertainty of climate model simulations can stem from three sources (Hawkins and Sutton, 2009): emission scenario, model response to a selected forcing and internal variability of the climate system. Internal variability is often referred to as "irreducible uncertainty" at time scales beyond seasons to decades. While scenario and model response uncertainty have been referred to in many climate simulation experiments (CMIP and CORDEX), future changes in uncertainty due to the internal variability component had received less attention for many years. In recent years, a new tool for the assessment of internal variability has become quite popular: single model initial-condition large ensembles (SMILEs), where the same model is forced with the same emission scenario several times – with the runs (members) just differing in their initial conditions. This setup is able to isolate the internal variability component from the scenario and model response uncertainty for the respective model. Based on SMILEs, it has been shown that the contribution of internal variability to total uncertainty of multi-model ensembles (CMIP, CORDEX) can be large, especially for mid-term projections and precipitation (Kumar and Ganguly, 2018; von Trentini et al., 2019). Terminology in this context is not always clear in the literature, as the terms natural variability, internal variability, inter-annual variability and inter-member variability are often used synonymously or mixed up. Here, the term internal variability is used to describe the variability at timescales from seconds up to multiple decades caused by unforced internal effects of a model or the real world due to the chaotic nature of the climate system only, without incorporating naturally forced variability due to volcanic eruptions and solar forcing. On the one hand, the anthropogenic changes in greenhouse gas concentrations can cause changes in the mean climate state that are superimposed by internal variability. On the other hand, higher greenhouse gas concentrations can cause changes in the internal variability itself in the future as well – adding another component to climate change effects.

Here we are interested in quantifying changes in variability at the annual timescale in seasonal temperature and precipitation, the number of heat waves and the duration of dry periods. To assess changes in inter-annual variability (IAV) with global warming in transient simulations, it is convenient to use the inter-member variability (IMV) in a SMILE for each year as an approximation of the inter-annual variability. As long as long-term variations are small compared to the inter-annual variability, as seems to be the case for seasonal mean and heavy precipitation in Europe (Aalbers et al., 2018, supplement) this approximation holds. Inter-member variability samples the variability per time period from different members of one model, therewith assuming no temporal autocorrelation for the respective timescale.

Early studies with regional climate models from PRUDENCE showed a distinct increase in inter-annual variability in summer temperatures (Fischer and Schär, 2009; Fischer and Schär, 2010; Vidale et al., 2007), traced back to land-

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atmosphere interactions (Seneviratne et al., 2006; Fischer et al., 2011), as well as decreasing winter temperature variability (Vidale et al., 2007). Later work with ENSEMBLES models revealed a less pronounced increase in summer temperature variability (Fischer et al., 2012). However, analysis of SMILEs showed increasing variability of European summer temperatures with increasing global warming (Suarez-Gutierrez et al., 2018; Yettella et al., 2018). Holmes et al. (2016) also find increasing temperature variability in summer and decreasing variability in winter, and point to the role of thermal advection as a reason for these changes. European winter temperature variability decreased since the pre-industrial era in another large climate model ensemble (Bengtsson and Hodges, 2019). Analysis of observations shows that more than half of summer temperature variability in the Mediterranean can be explained by large-scale atmospheric circulations and sea surface temperatures (Xoplaki et al., 2003).

For large areas of the globe, including Europe, an increase in precipitation variability from daily to multi-decadal time scales is expected due to higher temperatures (Pendergrass et al., 2017). However, Ferguson et al. (2018) only find significant changes in a small fraction of CMIP5 models' inter-annual variability in monthly precipitation for a western European domain until the end of the 21$^{st}$ century. Earlier analysis with regional climate models revealed summer increases and winter decreases in precipitation inter-annual variability over similar domains as used in this study (Giorgi et al., 2004).

Up to now, a number of large ensembles have been produced and some of them are publicly available. The terms large ensemble (LE) and SMILE are usually describing the same, but we prefer SMILE as it incorporates the type of large ensemble, which is built by different initial conditions. The National Center for Atmospheric Research (NCAR) has produced a 40-member CESM large ensemble (CESM-LE, Kay et al., 2015) forced by the representative concentration pathway (RCP) 8.5, and a 15-member "Medium Ensemble" (CESM-ME, a comparison of the two can be found in Sanderson et al., 2018) forced by RCP4.5 for the robust detection of diverging signals. The Geophysical Fluid Dynamics Laboratory large ensemble is built by 30 members (2006-2100, RCP8.5, Rodgers et al., 2015; von Känel et al., 2017). A new dimension in terms of size and scenario coverage was introduced by the Max Planck Institute Grand Ensemble (MPI-GE) with 100 members each for different forcings: historical, RCP2.6, RCP4.5, RCP8.5 and 1 % $CO_2$ increase per year (Maher et al., 2019).

However, most studies only use one SMILE for their analysis and the rare comparisons are usually just between two ensembles: similar patterns of inter-member variability of temperature and precipitation trends for the middle of the 21$^{st}$ century were found for a CCSM3 and an ECHAM5 ensemble over North America by Deser et al. (2014). Martel et al. (2018) showed a consensus of the inter-annual variability of annual mean and extreme precipitation in a CanESM2 large ensemble (which is also used for boundary conditions of the CRCM5 in this study, see Data section) and CESM-LE with two global observational data sets.

All these simulations are performed with global climate models (GCM), and only a few were dynamically downscaled with regional climate models (RCM). Here, we compare three dynamically downscaled large ensembles (all RCP8.5) for Europe. It is the first time that regional large ensembles are compared with respect to forced changes and their internal variability. The added value of RCM simulations is well documented for EURO-CORDEX (Giorgi et al., 2009; Torma et al., 2015;

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Sørland et al., 2018). Downscaled climate data is also a necessity for impact modelling at regional to local scales (e.g. for hydrology, agriculture, biodiversity research), where inter-annual variability is a critical parameter.

The remaining manuscript is structured as follows: First, the data and methods are presented. Then, the mean temperature and precipitation changes together with the inter-member spread of projected changes for each ensemble is analysed. The inter-annual variability of three regional large ensembles is compared against E-OBS afterwards to assess the abilities of the models to represent observed variability for the selected indicators. Finally, differences in present climate and future changes in inter-member variability are compared between the SMILEs.

## 2 Data

We compare three data sets – each consisting of a GCM single model initial-condition large ensemble, which has been dynamically downscaled over Europe with a single regional climate model: a 50-member CanESM2-CRCM5 ensemble (Fyfe et al., 2017; Leduc et al., 2019), a 21-member CESM-CCLM ensemble (Fischer et al., 2013; Addor and Fischer, 2015; Brönnimann et al., 2018) and a 16-member EC-EARTH-RACMO ensemble (Aalbers et al., 2018), all forced with the RCP8.5 scenario, resolved on different spatial resolutions (Table 1). Hereafter we indicate the GCM-RCM combinations with the RCM names only (CRCM, RACMO, and CCLM). This setup with a shared scenario, but different models, enables us to analyze differences in internal variability in the three ensembles. Next to the differences in resolution, the different internal variabilities stem from the different models, differences in aerosol forcing in the RCM simulations (constant in CCLM and CRCM, transient in RACMO) and in the application of an ocean slab model in the EC-EARTH-RACMO ensemble. RACMO also uses slightly different grid specifications. These climate model data sets will be inter-compared, but will also be compared to observations: the observational E-OBS data set has daily precipitation and temperature available for Europe (version v12.0, spatial resolution of 0.22° on a rotated pole grid). We use the E-OBS data set for its availability on a European scale and a similar spatial resolution to the regional climate models under consideration. We accept the known weaknesses of the data set (Hofstra et al., 2009), and assume that it is suitable for the purpose of this study.

## 3 Methods

Daily data are used to calculate seasonal mean surface temperatures (tas), the number of heatwaves per year (tas-HW-Nr), seasonal precipitation sums (pr) and the maximum length of dry periods per year (pr-DP-MAX), see Table 2 for definitions. These indicators give an insight not only into the variability of seasonal climatology, but also into the variability of extremes with high societal impact. Heat waves are known to cause an increase of health problems and even fatalities among the population, as well as damages in infrastructure (e.g. highways) and ecological problems. Long dry periods can have major impacts on ecology, forestry, agriculture, drinking water supply, power plant cooling outages, transport on rivers and many more.

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The indicators are calculated on a grid basis for each ensemble. For comparison, the indicators are spatially aggregated to four regions in Europe, for which all three RCM domains overlap (Figure 1): British Isles (BI), France (FR), Mid-Europe (ME) and the Alps (AL). These regions are well known from other European climate model studies (Lenderink, 2010; Lorenz and Jacob, 2010; Kotlarski et al., 2014; von Trentini et al., 2019), and were introduced by Christensen and Christensen (2007). The procedure of calculating the indicators on the grid level and spatially aggregating them afterwards has the advantage that no regridding of data is needed. However, the different spatial resolutions of the models alone can lead to higher variability in the 0.11° data (CRCM and RACMO), compared to the 0.22° (E-OBS) and 0.44° (CCLM) data. This is especially the case for spatially heterogeneous variables and indicators. The indicators in this study however have relatively low spatial heterogeneity (seasonal temperature and precipitation, heatwaves and dry periods are rather large-scale phenomena), where the range of spatial resolutions of the data used here (0.11° and 0.44°) is not expected to be significantly sensitive. The effect of regridding before the calculation of indicators is shown by a short experimental analysis, where one year of five members of the 0.11° CRCM data is regridded to 0.44° (simply averaging 4x4 grid cells each), before the indicators are calculated. The results show that the effect of regridding on the inter-member variability is indeed minor for the indicators considered (Supplementary Material, Figure S1). The approach of direct regional aggregation of the indicators calculated on the grid level is therefore applied for the further analysis of this study.

For the comparison of inter-annual variability against E-OBS, we apply an approach as proposed by Suarez-Gutierrez et al. (2018) and Maher et al. (2019). For the observations and for each model and member separately, the anomalies (with respect to each member individually) from a reference period (here 1980-2009) are calculated for the years 1957-2015. Model biases in the mean state of the indicators are therewith neglected. For each year, we then plot the ensemble minimum and maximum member, the area between the 12.5$^{th}$ and 87.5$^{th}$ percentile, within which 75 % of the members are situated, and the E-OBS data. For a perfect model, the E-OBS data is expected to occur randomly distributed within the range spanned by the ensemble, concentrated in the inner 75 %, several years in between the minimum and maximum of members, but also outside this range from time to time. If the E-OBS data concentrates too much inside the total range or even the 75 % area, the variability of the ensemble overestimates the observational variability. Contrary, if too many E-OBS data points exceed the ensemble spread, the SMILE underestimates observational variability. To quantify this further, the probability density function of the anomalies in the period 1957-2015 are plotted for each member and E-OBS separately. The functions are estimated probability densities based on a normal kernel function, similar to an approach by Lehner et al. (2018).

The analysis of future changes in variability on the annual time scale will be based on the inter-member spread, if the assumption holds that the inter-member spread is a good estimate for the inter-annual variability. This assumption is tested here. Inter-annual variability is calculated as the standard deviation within one member (or the one E-OBS timeline) between years; inter-member variability as the standard deviation between members of one ensemble, for a given year. The comparison of inter-annual and inter-member variability in each ensemble is carried out by comparing the means and standard deviations of these two variability metrics. The inter-annual variability is calculated for each member during the 30-year reference period (1980-2009) and mean and standard deviation of these 50/21/16 values is calculated. In advance, the

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time series of each member is detrended with the multi-member ensemble mean. The inter-member variability is calculated for each of the 30 years of the reference period between the 50/21/16 members, leading to a mean and standard deviation, calculated from these 30 values. The mean and standard deviation of IAV and IMV are very similar for all indicators and regions (exemplary shown for winter temperature in Figure 2), and a two-sample Kolmogorov-Smirnov test on equal distributions ($\alpha$=0.05) only fails for CCLM for winter temperature in the Alps and summer temperature in Mid-Europe. The IMV has the advantage that it is insensitive to inflation effects of the variability due to an existing trend and forced effects like cooling after volcanic eruptions for example. The spread between members is thus a well suited metric to examine projected changes of inter-annual variability.

The temporal development of the variability is important information along with the underlying forced response (change in the multi-member mean) for a better understanding of changing climatic conditions. The inter-member variability is calculated based on anomalies to the multi-member mean for each year, resulting in detrended time series. These anomalies are absolute for seasonal mean temperature [°C] and number of heatwaves [number/year], due to their values close to zero in some cases, but relative [%] to the multi-member mean in the respective year for seasonal precipitation sums and maximum length of dry periods (in contrast to the previous evaluation against E-OBS, where they were absolute anomalies). The standard deviation of these anomalies is calculated per year, and smoothed with a moving average window of ±10 years (21 years in total at each time step). Relative anomalies thus give information on how much the standard deviation changes with respect to changes in the multi-member mean. For example, a stable inter-member variability in absolute terms will result in a decrease of the relative inter-member variability when the multi-member mean increases. Increasing inter-member variability, together with an increasing multi-member mean on the other hand means that the variability is increasing even more than the mean.

## 4 Results

### 4.1 Ensemble spread of projected mean climate change

Before inter-annual and inter-member spread on annual timescales are analysed, simple scatter plots of the changes in mean temperature and precipitation for summer and winter between 1980-2009 and 2070-2099 give a first impression on the spread of projected changes between the members of the SMILEs and on the differences in the mean changes between models. In summer in Mid-Europe (ME), all models show decreasing precipitation; between -3 and -16 % for RACMO, and -14 to -35 % for CRCM and CCLM (Figure 3). Increases in temperature between 3 and 5 °C are projected by RACMO and CCLM, while CRCM shows much higher changes between 5 and more than 6 °C. Thus, RACMO and CCLM show similar changes in temperature, while CCLM and CRCM show similar changes in precipitation. The spread of changes for both temperature and precipitation of RACMO and CRCM are similar, both in terms of standard deviation and total range, while CCLM shows higher standard deviation and total range (Table 3). Similar results as discussed here for Mid-Europe (mean changes and spread) can also be found in France and the Alps (not shown), with the largest decrease in summer precipitation

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over France and the strongest warming over the Alps. The British Isles region shows less pronounced changes (although consistent in sign) with CRCM showing closer similarity of precipitation decreases to RACMO rather than to CCLM as in ME, FR and AL.

In winter, all models show increasing precipitation (1-32 %) and temperature increases between 1.4 and 5 °C by the end of the 21st century (Figure 4). RACMO and CRCM show similar standard deviation and range again, together with similar mean changes as well. CCLM shows distinctly smaller changes in combination with a smaller spread of changes (Table 3). Similar results also appear for FR, AL, and BI, although some members also project a slight decrease in precipitation in these regions.

### 4.2 Inter-annual variability of SMILEs and E-OBS

The comparison of E-OBS and the three SMILEs during the historical period from 1957-2015 in Mid-Europe (ME) shows largely good representations of inter-annual variability in the ensembles, as seen by well distributed E-OBS points within the 75 % range (12.5-87.5% quantile) and minimum and maximum range of the ensembles (years 1957-2015 in Figure 5). However, a too strong clustering of the E-OBS points in the 75 % area can be seen for winter precipitation in CRCM (97 % fall inside) or number of heatwaves in CCLM (90 %), meaning the simulated inter-annual variability is slightly too high. On the other hand, too many outliers beyond the minimum and maximum members appear in winter temperature in CCLM (22 % outside of total range), winter precipitation in RACMO (17 %) or maximum duration of dry periods in CRCM (10 %), i.e. for these models and indicators the inter-annual variability is (slightly) too low. These effects can be seen even better when comparing the probability density functions of the annual anomalies for each member and E-OBS (Figure 6). Note that probability density functions could also be somewhat inflated by the underlying mean trend but we expect this effect to be small because trends are small and largely consistent between models and observations. To evaluate the ability of the SMILEs in representing inter-annual variability, we test whether the E-OBS distribution looks like a possible member of the respective ensemble. The observations should not be expected to fall near the ensemble median, but rather should be ideally indistinguishable from a random additional member of the ensemble, since E-OBS only represents one possible realization of historical climate. Significant differences can be seen for the already mentioned examples: the distribution of CRCM in winter precipitation is much broader than the E-OBS distribution, whereas the winter temperature distribution for CCLM is too concentrated in the middle compared to E-OBS. Similar results can be found in the other three regions as well (Figures S2-S4), with only several cases where the E-OBS distributions show a distinctly different shape than all members of the ensembles (Figures 7, S5 and S6), especially maximum duration of dry periods of CCLM in France. This is not too surprising, as the maximum duration of dry periods is an extremely sensitive indicator, because of its potentially extreme differences in magnitude between (model) years/members (one wet day can make a huge difference). The other two SMILEs are able to represent the E-OBS variability for this indicator in France though. Other remarkable features are the underestimation of variability in RACMO for all six indicators in the British Isles region (Figure S5), as well as the relatively good performance of the models for the Alps (Figure 7), the probably most difficult region for a model to represent

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correctly due to the strong spatial heterogeneity. However, the Alps show some distinct "outlier-members" in the ensembles (e.g. winter precipitation in CRCM), which cannot be found in the other regions – at least not this pronounced. These outliers demonstrate how large the influence of internal variability can be in a single realization of climate, and that new members can still add information, even at the scale of 50 members.

### 4.3 Variability and projected changes in the SMILEs

The inter-member variability of deviations from the multi-member mean in every year is an important measure to quantify the internal variability on the annual time scale in historical periods and future climate projections of the SMILEs. While CRCM and RACMO usually show similar variabilities during historical periods, CCLM shows distinctly smaller variability in winter temperature and precipitation (Figure 8), and higher variability for the other four indicators for the summer season (tas-HW-Nr and pr-DP-MAX are expected to mostly occur during the summer in Europe).

For the future, all ensembles show increasing internal variability in summer temperature and precipitation in ME, while they all show decreasing variability in winter temperature. The variability in winter precipitation decreases in CRCM, while the other two ensembles show relatively stable or slightly decreasing variabilities. The variability in the number of heatwaves increases until about 2010-2030, reaches a plateau for about 30-40 years and then decreases again. This behaviour can be explained by the forced response of the indicator, which shows strong increases until around 2060, when the number of heatwaves stabilizes around 6 (and even decreases afterwards in CRCM), because the heatwaves get so long that their number per year cannot increase anymore (see Figure 5). This is especially true for CRCM, where the mean duration of heatwaves is about 20 days (not shown), leading to a rough estimate of 6*20=120 heatwave-days per year, equal to about four months. Since heatwaves are defined by the 95$^{th}$ percentile of temperature in the reference period (thus describing extreme conditions), the former extreme heat becomes a regular condition during the summer months at the end of the 21$^{st}$ century. The maximum duration of dry periods shows stable to slightly decreasing variability for RACMO, moderate increases in CRCM and strong increases in CCLM.

The above mentioned results are mostly valid for the other regions as well. Differences on the magnitudes of variability and its changes are shortly discussed now (see Figures S7-S9): lower levels of variability compared to the other regions occur over the British Isles for summer and winter temperature and winter precipitation. The Alps show a smaller variability for the number of heatwaves than the other regions. The variability of pr-DP-MAX for all three ensembles is similar in AL, while increases in BI and FR are rather small (CRCM even shows decreases in BI). If all regions are considered, RACMO generally has the highest internal variability in winter and the lowest variability in summer for temperature and precipitation, while CCLM has the highest internal variability for summer temperature and precipitation as well as for heatwaves and dry periods.

The ensemble mean changes are also shown for all six indicators in Figure 5: all three models agree on the strong increases in the three temperature driven indicators, as expected under the RCP8.5 scenario. Small increases in winter precipitation in

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all models are projected (largest for CRCM), while summer precipitation is projected to decrease in all ensembles. RACMO does not show the marked increase in the maximum length of dry periods as the other two ensembles.

The relation between changes of the ensemble mean and changes in the variability are often quite linear for all models: increasing ensemble means for summer temperature and heatwaves are accompanied by increasing variability in summer temperature and heatwaves (positive correlation, Figure S10) and decreasing variability in winter temperature (negative correlation). Summer precipitation ensemble means decrease, while the variability both relative to the ensemble mean (see Figure 8) and in absolute terms (Figure S11) increases. The increases of winter precipitation ensemble means co-occur with stable variabilities in RACMO and CCLM and decreasing variability in CRCM (in relative terms). In absolute terms, in winter, the change in variability thus follows the change in mean precipitation or is slightly smaller. This behaviour in both summer and winter has also been detected by Pendergrass et al. (2017) for CMIP5 and CESM-LE precipitation data in extratropical regions. Linear relations between the ensemble mean and variability can be found for dry periods as well for CRCM and CCLM, while RACMO shows hardly any changes in both metrics.

Figure 9 gives a summary of significant linear trends in the inter-member variability for all indicators and regions to visualize agreement of the three ensembles on the sign of change. As discussed before, model disagreement only occurs for winter precipitation and dry periods.

## 5 Discussion

### 5.1 Critical discussion on the methodology

The sampling of SMILEs for the quantification of internal variability is still relatively small – we only used three GCM-RCM combinations, because of the availability of these data sets (to the knowledge of the authors these three ensembles are the only regionally downscaled SMILEs over Europe). Despite the relatively good agreement between the models in many cases, pointing to rather robust results, more simulations with regionally downscaled SMILEs could help to make results even more robust – especially for winter precipitation and dry periods, where the three ensembles did not agree on the sign of change in variability.

The effect of regional aggregation after the calculation of indicators on the grid level, and the potential effects of the original resolution of different data sets on the internal variability seem to be minor, as seen in the experimental analysis conducted on a subset of the data (see methods section). This estimate of sensitivity to differing spatial resolutions might be conservative, however. Nevertheless, the methodology seems to be suitable for the selected indicators of this study.

The general problem of biases in climate model simulations is also important in the context of evaluating internal variability against observations and among the SMILEs. Therefore, methods based on anomalies are chosen to be able to compare results despite different biases in historical and future climate states. It can however not be ruled out that differences in the variability may originate from different biases of the models. CRCM for example shows much higher precipitation sums than the other two ensembles, leading to higher variability in absolute terms. The normalization with the ensemble mean is

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covering these differences in absolute amounts. In the end it largely depends on the definition of variability: is one interested in absolute deviations [mm] or in the fluctuations in relative terms [%]? Results can look totally different when changing from a relative to an absolute definition or vice versa. Another closely related metric used in this context is the coefficient of variation as recently applied by Giorgi et al. (2019).

### 5.2 Critical discussion on the results

The scatter plots of projected changes for seasonal temperature and precipitation show both agreement and dissent, but usually at least two of the three models show similar ranges for one variable. An even better agreement might be possible when comparing the data sets not for a fixed time period, but for time periods with the same global warming level in each driving GCM.

There is a general ability of large ensembles to represent inter-annual variability correctly, but care needs to be taken during the analysis for specific regions and indicators. Both cases of many individual members showing higher and lower variability compared to observational inter-annual variability can be found for all ensembles for specific indicators and regions. However, the single observed realization of historical climate makes it difficult to evaluate systematic errors of the ensembles, as the E-OBS distribution is not necessarily representative for the “real” inter-annual variability. It would be interesting to compare large ensembles against an observational large ensemble as proposed by McKinnon and Deser (2018) to better see systematic deficiencies of large ensembles compared to observations.

The increase of internal variability in almost all indicators is challenging the assumptions of Thompson et al. (2015), who showed that an analytical model based on the statistics of a historical period could be as good as a SMILE for predicting future variability of trends up to 2060. We here show that the assumptions that the internal variability will not change significantly in the future is for several regions and variables violated particularly in the second half of the 21$^{st}$ century. The increase in precipitation variability might be caused by a reduction in the number of wet days (>1mm) that exists in all three ensembles (not shown), as already discussed by Räisänen (2002). Decreases in the winter temperature variability can be explained by arctic amplification and sea ice loss (Screen, 2014; Sun et al., 2015).

There are quite distinct multi-decadal oscillations in the inter-member variability, especially for RACMO and CCLM (see Figure 8). The similarity of these oscillations over different regions (within one ensemble) indicates phenomena like the Atlantic meridional overturning circulation (AMOC) as a driver. As Hawkins et al. (2016) showed, there is at least a connection between near term trends in European climate and AMOC states during the initialisation for each member of a SMILE.

Land-atmosphere feedback mechanisms are not yet fully understood, and there are still improvements needed in their implementation in earth system models and regional climate models (Vogel et al., 2018). Uncertainties in the future development of heatwaves and dry periods could be rather large therefore (Miralles et al., 2019). Nevertheless, increasing frequency, intensity and variability in the number of heat waves and length of dry periods as projected by the SMILEs in this study seem plausible, although the magnitudes might be uncertain.

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## 6 Conclusions

There is an increasing interest of the scientific community to use single model initial-condition large ensembles in a wide variety of applications, ranging from deeper levels of understanding of natural climate variability to impact assessments in different fields. The rich data basis which these ensembles provide for the analysis of internal variability is very valuable and enables new insights into this critical part of the climate system. Especially future changes can be set into context much better. Only a few comparisons of different SMILEs have been undertaken so far (Deser et al., 2014; Martel et al., 2018; Rondeau-Genesse and Braun, 2019), all of them on the GCM level. The effects of dynamical downscaling of GCM large ensembles with regional climate models are not yet sufficiently explored. Further research is needed in this direction to see how much the internal variability is resembled or changed in the RCM simulations of a respective GCM large ensemble. However, downscaling is an important step to make climate simulation information attractive for local adaptation research and impact modellers.

The evaluation and comparison of the three RCM large ensembles in this study gives a first overview on the (dis)agreement of the SMILEs with observations and among each other. The moderate agreements in both cases suggest that the internal variabilities of RCM-SMILEs at the regional scale are good approximations of the inter-annual variability of the climate system. The direction of changes in internal variability is also mostly the same between the ensembles, suggesting a relatively robust signal. While the "summer indicators" all show increasing variability in the future, winter temperature and precipitation show decreasing variability or no change. The summer increases imply that the internal variability component of overall uncertainty of climate projections will be even larger for later time horizons. Furthermore, the change in variability is directly impact-relevant as it suggests that the most extreme summers and winters may warm stronger than the corresponding mean.

One limitation of many of the recent publications using SMILEs is the use of only one model, and thereby one estimate of internal variability, leaving it unclear how representative the results are. Although the respective SMILE is usually evaluated against observations in these studies, the uncertainty in future changes of internal variability cannot be quantified in the same way as in this study. A further challenge is also the fact that low frequency variability at decadal and multi-decadal time scales remains uncertain and cannot be rigorously evaluated due to the relatively short observational record and the difficulty of separating forced changes from unforced internal variability.

So, do we need to go the way CMIP and CORDEX went and apply a multi-model-multi-member ensemble in all studies? This would certainly be an ideal way to better understand and quantify sources of uncertainties, yet does not seem feasible for two reasons: (a) the computational resources to perform these experiments on regional scale are limited and the CORDEX matrix of scenario, GCM and RCM could already not be filled for this same reason, and b) the use of hundreds of simulations would also be very challenging for analysis and impact modellers. This study is therefore also meant to strengthen confidence in the overall concept of large ensembles, and to set the results of studies which only use one large ensemble into a more robust context. For example, findings of a previous study (von Trentini et al., 2019), quantifying the

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internal variability component of the overall uncertainty (model response uncertainty plus internal variability) in a EURO-CORDEX ensemble with the CRCM ensemble, seem to be more robust given the fact that the internal variability components of the RACMO and CCLM ensembles show high similarities with the CRCM ensemble.

Although beyond the scope of this paper, which only analysed the manifestations of internal model variability in surface variables, there is need for a better understanding of the mechanisms leading to the model-inherent characteristics of internal variability, and why differences between the models appear. Overall our results underline the great potential of SMILEs in quantifying the uncertainty due to internal variability, the time-of-emergence of climate changes signals, for extreme event attribution and for detection and attribution of trends also at the regional scale.

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**Table 1: Specifications of the three ensembles used in this study**

| | 'CRCM' | 'CCLM' | 'RACMO' |
|---|---|---|---|
| Scenario | RCP8.5 | RCP8.5 | RCP8.5 |
| GCM | CanESM2 | CESM 1.0.4 | EC-EARTH 2.3 |
| GCM Resolution | 2.8° | 2.0° | 1.0° |
| RCM | CRCM5 | CCLM4-18-7 | RACMO22E |
| RCM Resolution | 0.11° | 0.44° | 0.11° |
| No. of members | 50 | 21 | 16 |

**Table 2: Indicators and their definitions**

| Indicator | Used variable | Definition |
|---|---|---|
| tas-JJA | tas | Summer mean temperature (June-August) |
| tas-DJF | tas | Winter mean temperature (December-February) |
| tas-HW-Nr | tas | Number of heatwaves per year; a heatwave is defined as a minimum of three days above the 95$^{th}$ percentile of daily mean temperature of the reference period; no filtering on summer months is applied at any stage |
| pr-JJA | pr | Summer precipitation sum (June-August) |
| pr-DJF | pr | Winter precipitation sum (December-February) |
| pr-DP-MAX | pr | Maximum length of a dry period per year; dry periods are a minimum of 11 consecutive days with every day showing less than 1 mm of precipitation; no filtering on summer months is applied at any stage, the periods can thus also occur in winter (but this is rather unlikely in Europe) |

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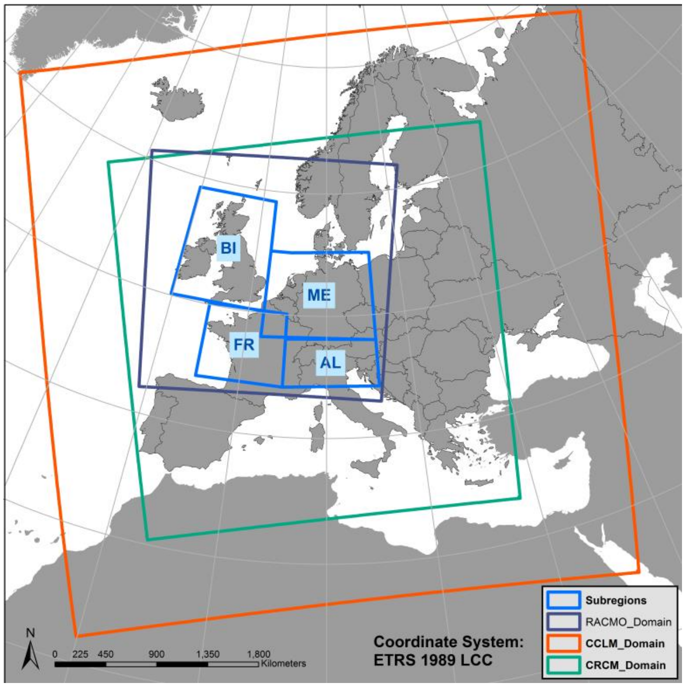


370 **Figure 1: Domains of the three RCMs and the boundaries of the four analysis regions; BI=British Isles, FR=France, ME=Mid-Europe, AL=Alps; the CCLM domain matches the EURO-CORDEX domain**

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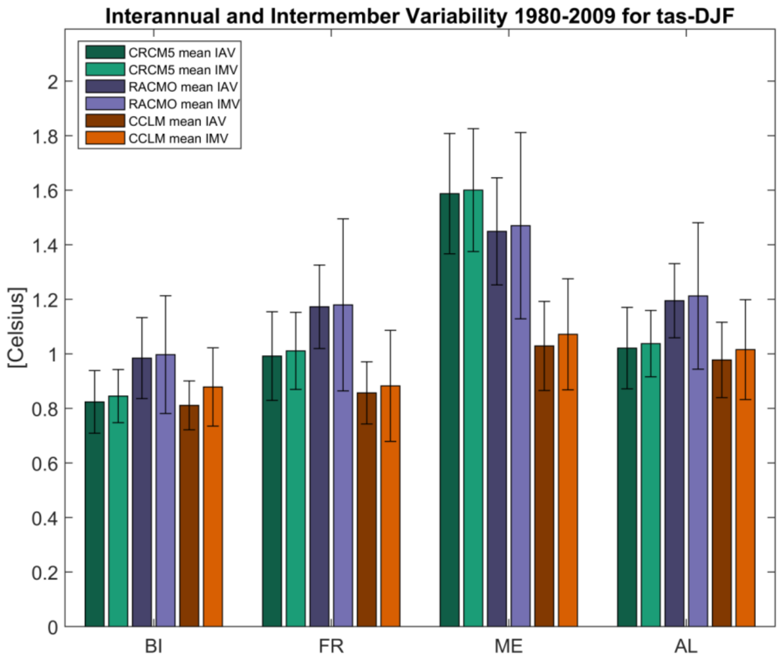


375 **Figure 2: Inter-annual variability (IAV) and Inter-member variability (IMV) of winter temperature in the three ensembles for the reference period 1980-2009 in all four regions. Bars: mean over the variability of each member (IAV) or year (IMV), Error bars: ± standard deviation (members or years); IMV: 16/21/50 members; IAV: 30 years of the reference period**

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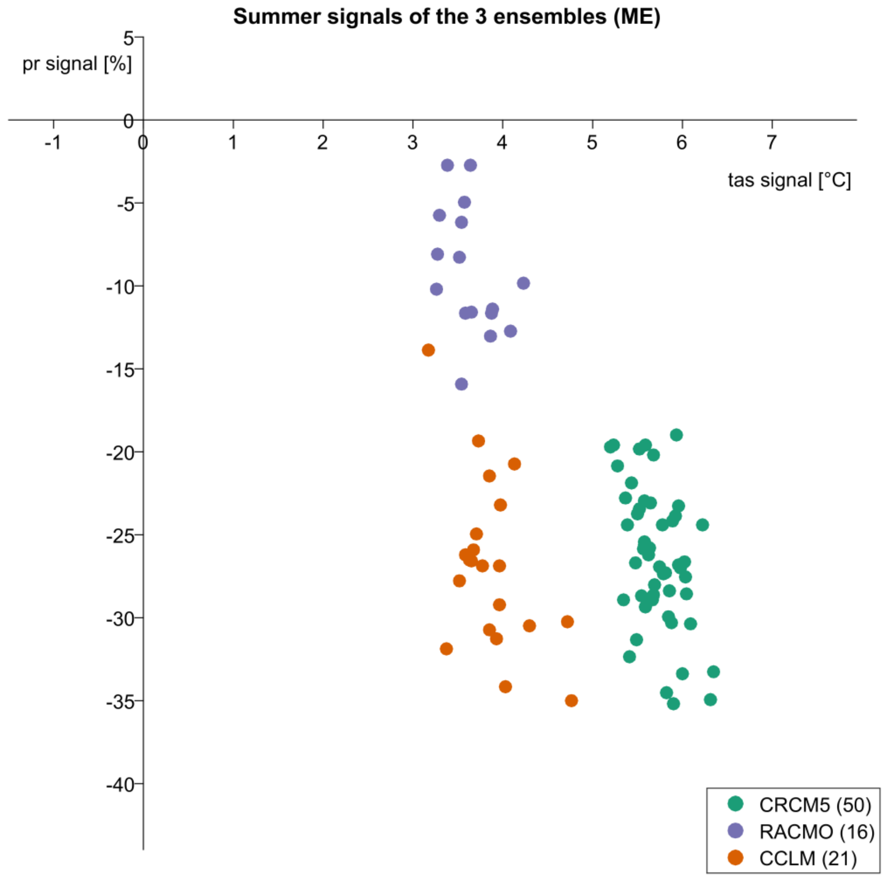


**Figure 3: Change in summer temperature and precipitation for every member of the three ensembles in Mid-Europe (2070-2099 against 1980-2009)**

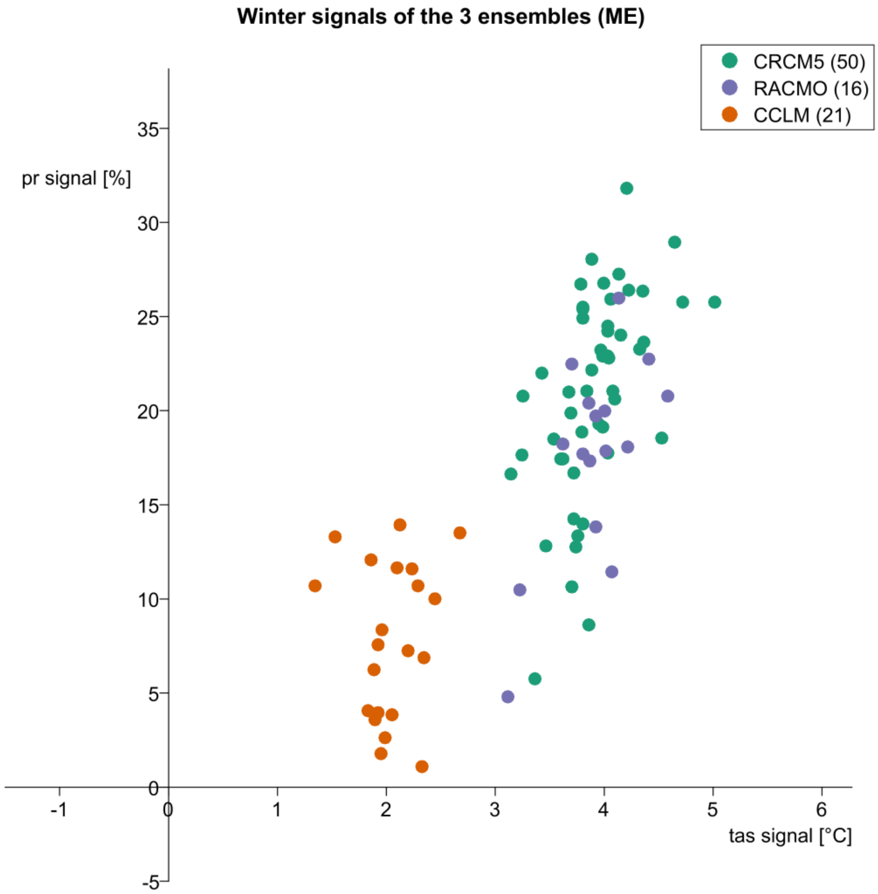


**Figure 4: Change in winter temperature and precipitation for every member of the three ensembles in Mid-Europe (2070-2099 against 1980-2009)**

**Table 3: Standard deviation and total range for changes in Figure 3 and Figure 4**

| | tas [°C] | | | pr [%] | | |
|---|---|---|---|---|---|---|
| | CRCM | RACMO | CCLM | CRCM | RACMO | CCLM |
| summer std | 0.27 | 0.28 | 0.39 | 4.2 | 3.8 | 5.1 |
| summer range | 1.16 | 0.96 | 1.59 | 16.2 | 13.2 | 21.1 |
| winter std | 0.37 | 0.38 | 0.30 | 5.5 | 5.3 | 4.2 |
| winter range | 1.87 | 1.47 | 1.33 | 26.1 | 21.2 | 12.9 |

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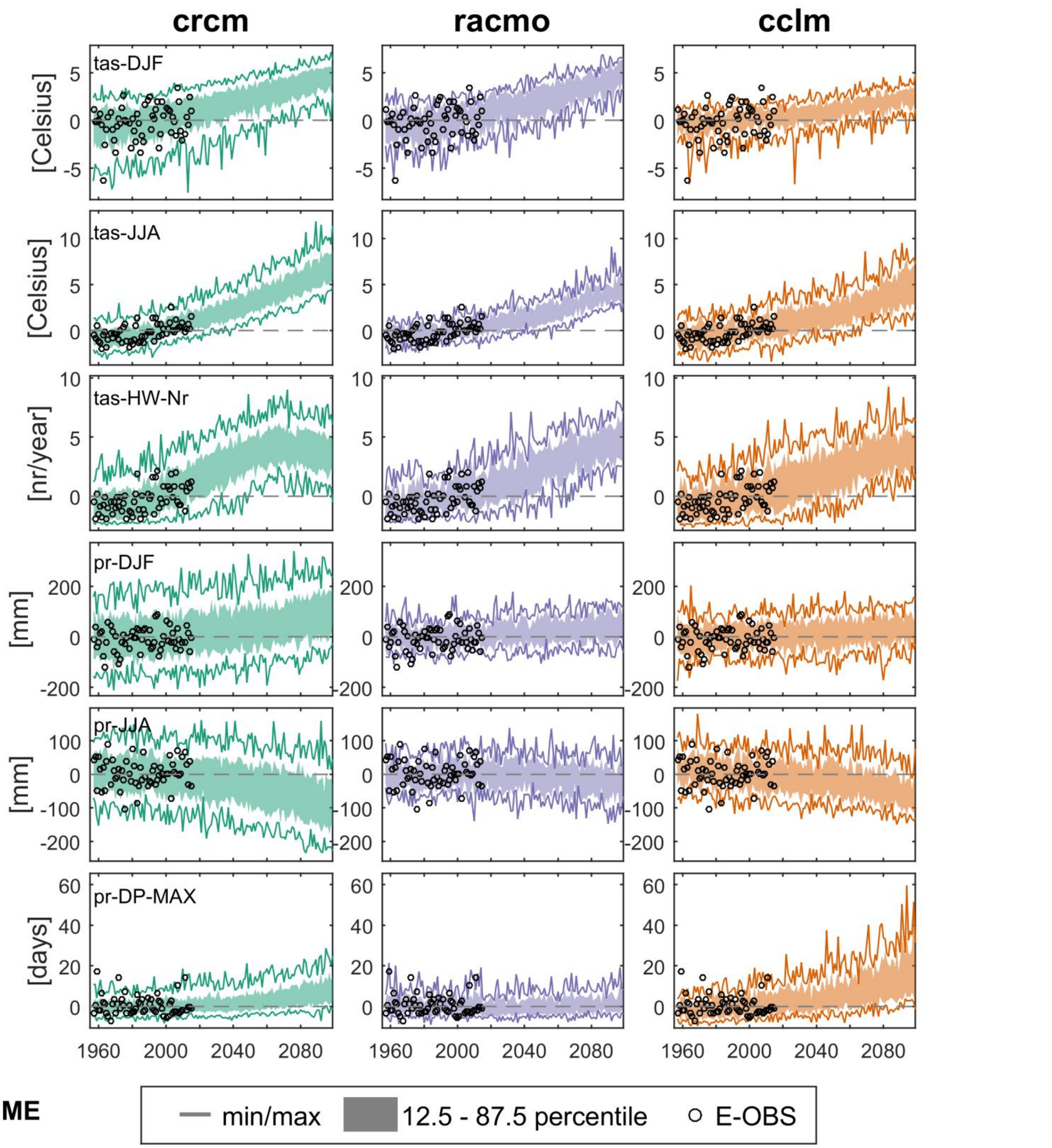


390 **Figure 5: Anomalies from 1980-2009 of the 6 indicators in Mid-Europe (ME) for E-OBS (circles 1957-2015) and the three ensembles (1957-2099), represented by the minimum/maximum (solid lines) of the ensemble and an area from the 12.5th and 87.5th percentile, spanning the range of the inner 75 % of the members (shadings)**

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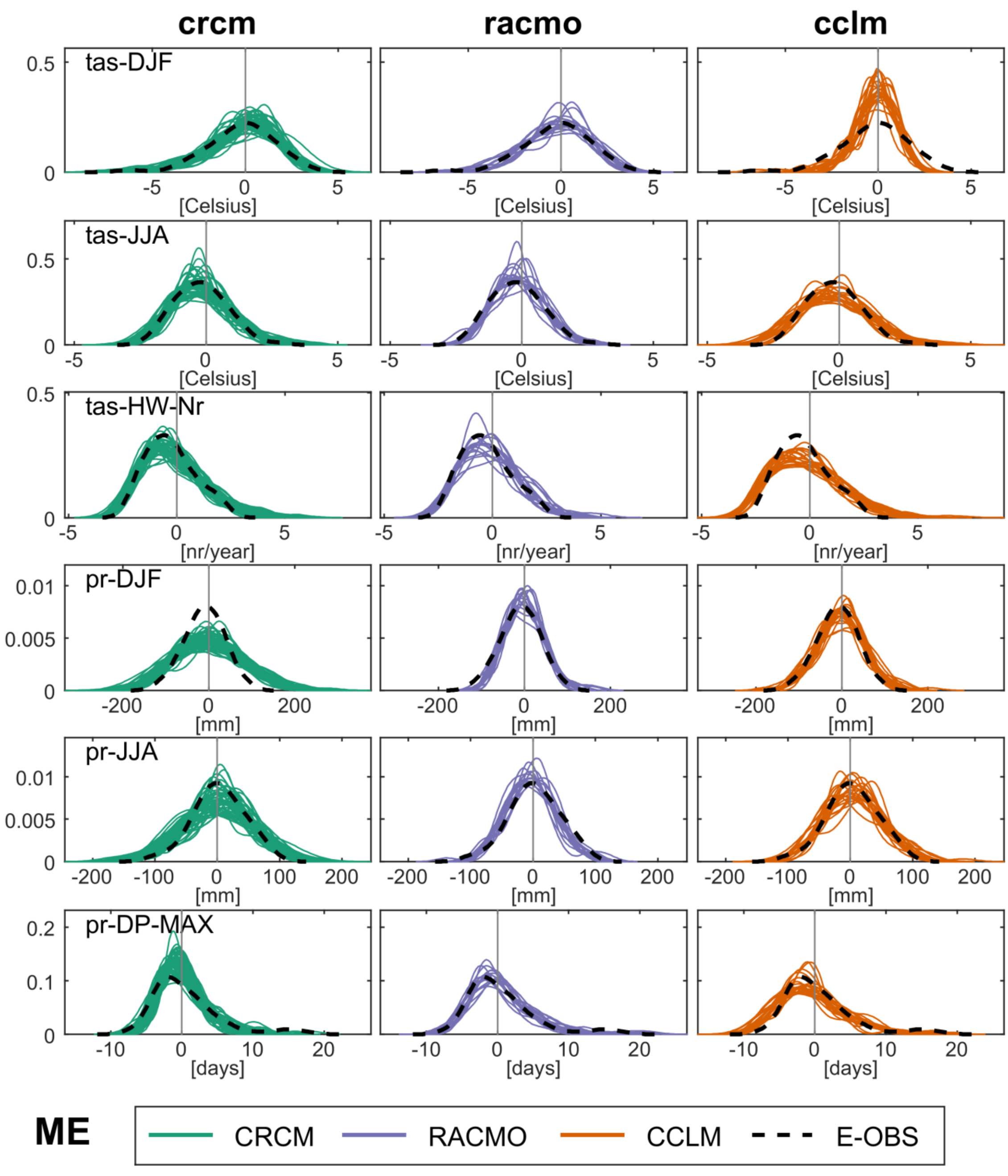


**Figure 6: Probability density functions of the annual anomalies in the period 1957-2015 in E-OBS and each ensemble member for all 6 indicators in Mid-Europe (ME)**

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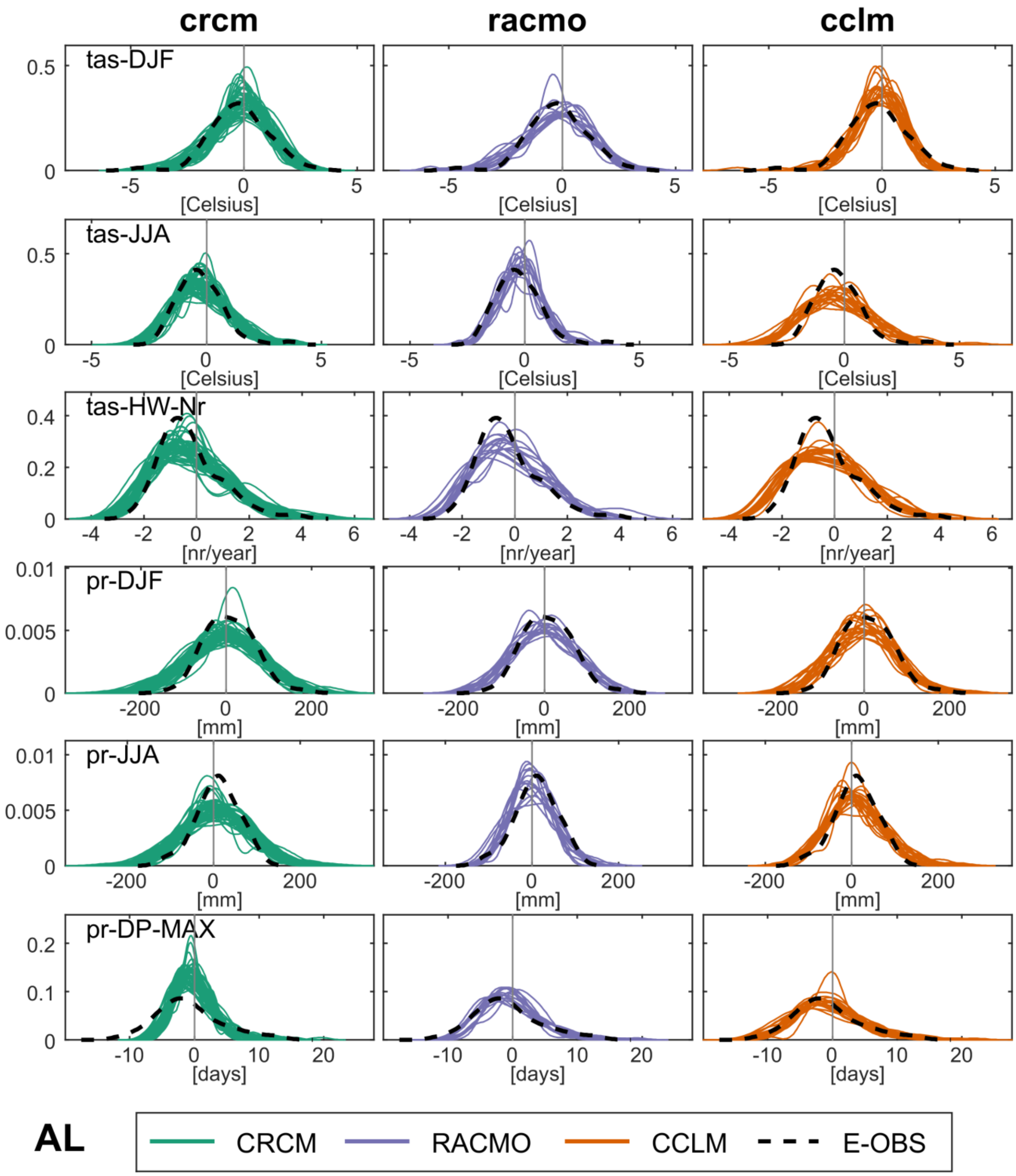


395 **Figure 7: Probability density functions of the annual anomalies for all 6 indicators in the Alps (AL). For details see Figure 6**

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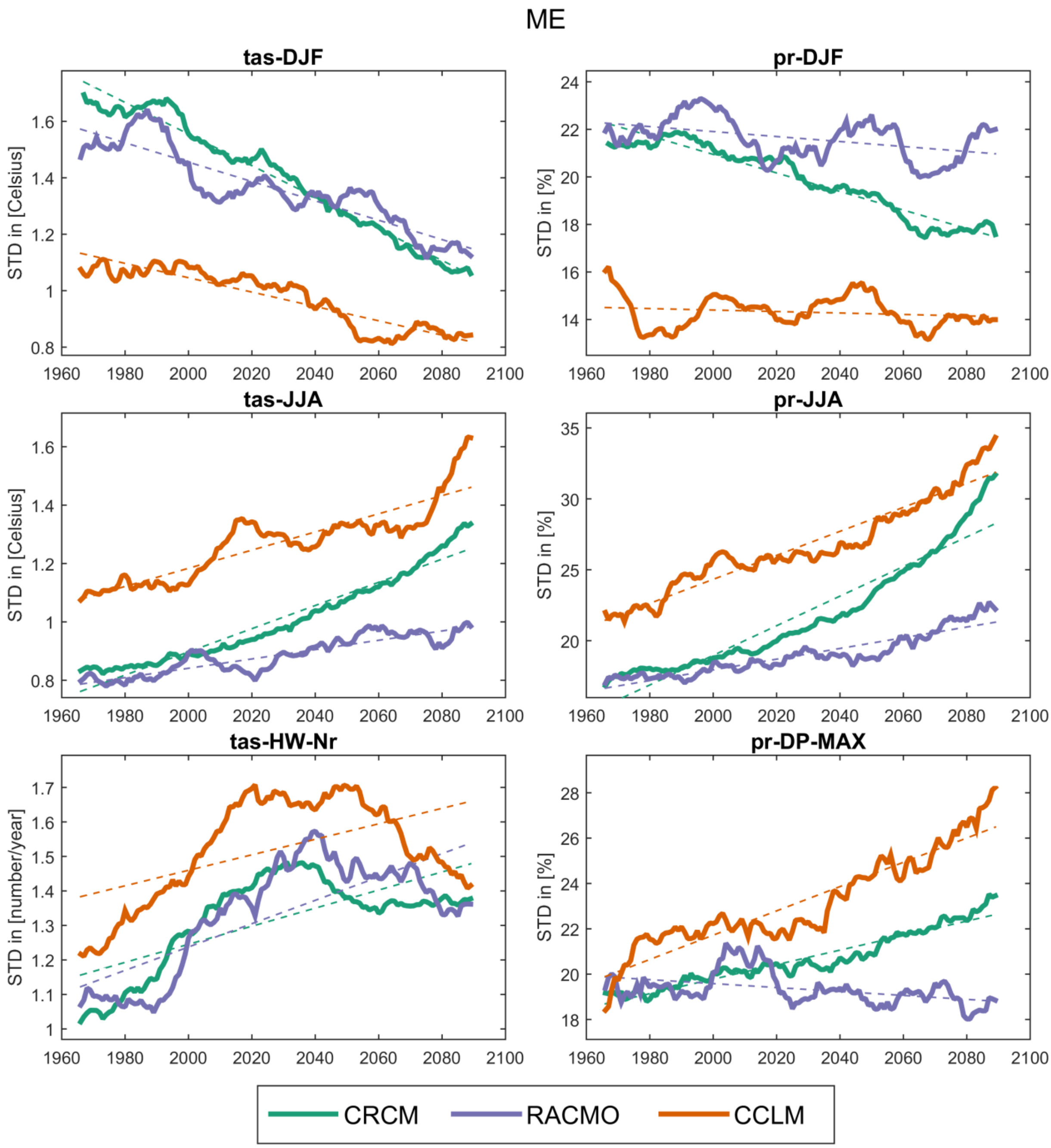


**Figure 8: Projected change of inter-member variability (IMV) for Mid-Europe (ME). IMV is sampled as the standard deviation over each ensemble for each year and is smoothed with a moving average of ± 10 years**

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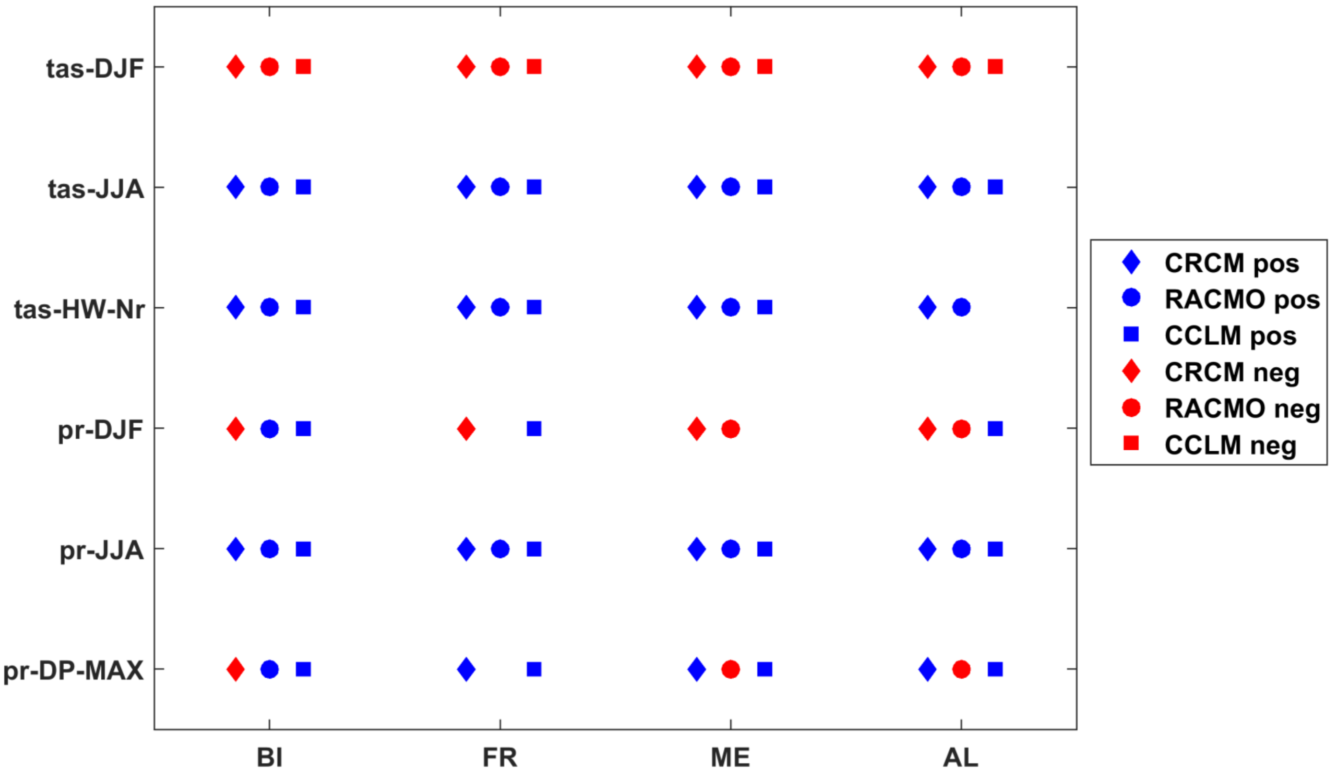


**Figure 9: Significant linear trends over the smoothed time series of inter-member variability; red: significant negative trends; blue: significant positive trends; missing symbols relate to no significant trend**

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**Author contribution**

FvT designed the concept of the study, performed the analysis and created all figures. EA and EF provided the RACMO and CCLM data and helped improving the concept and analysis. FvT led the manuscript writing with input from all authors.

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