Development and prospects of the regional MiKlip decadal prediction system over Europe: Predictive skill, added value of regionalization and ensemble size dependency

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Abstract. The current state of development and prospects of the regional MiKlip decadal prediction system for Europe are analysed. The Miklip regional system consists of two 10-member hindcast ensembles computed with the global coupled model MPI-ESM-LR downscaled for the European region with COSMO-CLM to a horizontal resolution of 0.22° (~25km). Prediction skills are computed for temperature, precipitation, and wind speed using E-OBS and an ERA-Interim driven COSMO-CLM simulation as verification datasets. Focus is given to the eight European PRUDENCE regions and to lead years 1-5 after initialization. Evidence of the general potential for regional decadal predictability for all three variables is provided. For example, the initialized hindcasts outperform the uninitialized historical runs for some key regions in Europe, particularly in Southern Europe, and for some variables both in terms of accuracy and reliability. However, forecast skill is not detected in all cases, but it depends on the variable, the region, and the hindcast generation. A comparison of the downscaled hindcasts with the global MPI-ESM-LR runs reveals that the MiKlip prediction system may distinctly benefit from regionalization, in particular for parts of Southern Europe and for Scandinavia. The forecast accuracy and the reliability of the MiKlip ensemble is systematically enhanced when the ensemble size is stepwise increased, and a number of 10 members is found to be suitable for decadal predictions. This result is valid for all variables and European regions in both the global and regional MiKlip ensemble. The present results are encouraging towards the development of a regional decadal prediction system.

1. Introduction

In recent years, the interest in climate predictions on time-scales from one year up to a decade has increased in the climate science community, since this time span falls within the planning horizon for a wide variety of decision makers (Meehl et al., 2009; 2014). A large ensemble of initialised decadal hindcasts has been consolidated in a component of the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012), and the number of studies aiming at decadal predictions has strongly increased in recent years (for a review see Meehl et al., 2014). Typically, the North Atlantic is a key region for decadal predictions and forecast skill is found for various quantities such as heat content and SST (e.g. Kröger et al, 2012; Yeager et al., 2012), CO_2 uptake (Li et al., 2016) and integrated quantities such as the AMOC (Pohlmann et al., 2013a) and the sub-polar gyre (Matei et al., 2012; Yeager et al., 2012; Robson et al., 2013). Other studies focus on primary meteorological parameters on the global scale, in particular surface temperature (e.g Chikamoto et al., 2012; Doblas-Reyes et al., 2013; Ho et al., 2013; Corti et al., 2015). Comparatively few studies analyse storm tracks (Kruschke et al., 2014, 2016), Atlantic tropical cyclones (Dunestone et al., 2011), intense or extreme events (e.g. Benestad and Mezghani, 2015) or zoom into a certain region of the world (e.g. Guemas et al., 2015).

In the German research consortium MiKlip (http://www.fona-miklip.de), a global decadal prediction system was developed based on the Max-Planck-Institute Earth System Model (MPI-ESM) (for an overview see Marotzke et al., 2016). Within the the project, several hindcast generations were produced. The first two are discussed in this paper. The skill of the MiKlip System for decadal predictions was analysed in a wide variety of recent studies. For example, Müller et al. (2012) investigated global surface air temperature in the first generation of the global MiKlip system (baseline0, which was a contribution to CMIP5) and found that the initialized hindcasts have predictive skill over the North-Atlantic region, while negative skill scores are identified for the tropics. A modified initialization in the second global MiKlip system generation (baseline1) considerably improves the performance in the tropics, but brings only limited skill improvement over the North Atlantic and Europe (Pohlmann et al., 2013b). Kruschke et al. (2014) identified significant positive skill scores for cyclone frequencies over the central North Atlantic in the global baseline0 and baseline1 generations, while no significant skill was detected over the eastern North Atlantic and Europe. Furthermore, Kadow et al. (2016) evaluated the global MiKlip system with respect to temperature and precipitation, giving evidence that an enlargement of the hindcast ensemble generally leads to an improvement of the prediction system.

The MiKlip consortium is to our best knowledge the first institution worldwide which has established a decadal prediction system for the regional scale. With this aim, considerable efforts were made to downscale the global MPI-ESM hindcasts by developing and/or employing different regionalisation techniques. Previous experiences reveal that a skill for regional decadal predictions exists but that the interpretation of the results is quite complex due to the non-linear relationship to the global prediction skill. For example, Mieruch et al. (2014) found rather heterogeneous predictive skill for precipitation and temperature over Europe in the baseline0 generation. The skill differs over space, season, variable, and lead time after initialisation. However, a general feature is an improved model spread for precipitation in the downscaled hindcasts when

compared to their global counterparts. A potential for predicting regional peak winds and wind energy potentials over Central Europe several years ahead was identified in Haas et al. (2016) and Moemken et al. (2016). Particularly, they found highest skill scores for the first years after initialisation. All the individual studies analysing the MiKlip prediction system consider different ensembles, variables, lead times, skill metrics, and/or downscaling and data pre-processing methods.

5   Therefore it is difficult to draw general conclusions for the decadal predictability over Europe in the MiKlip decadal prediction system. In particular, an overall statement for the benefit of regionalisation and thus for the prospects of a regional decadal prediction system is hardly possible so far. This motivated us to analyse both the global and the downscaled MiKlip ensemble with respect to different issues.

In this study, the decadal predictive skill for temperature, precipitation, and wind speed over Europe is analysed for the
10   baseline0 and baseline1 generation of the MiKlip system. With this aim, we used the same methodologies for all three variables to ensure comparability. Global MPI-ESM and downscaled hindcast ensembles are considered to address the following four key questions:

- Is there a potential for skilful regional decadal predictions in Europe?
- Does regional downscaling provide an added value for decadal predictions?
15   - Does the regional decadal predictive skill depend on the ensemble size?
- How does the sample size affect the skill estimates?

The datasets used in this study are described in section 2, followed by the methodologies for data pre-processing and skill analysis in section 3. The results for the four key questions are shown in section 4. A summary and discussion, as well as an outlook for future work are given in section 5.

20   **2. Data**

The analysed global hindcasts were simulated with the coupled model MPI-ESM in low-resolution (MPI-ESM-LR; Giorgetta et al., 2013). Its atmospheric component is based on the ECHAM6 model (Stevens et al., 2013) with a horizontal resolution of T63 and 47 vertical levels, which is coupled to the MPI-OM ocean model (Jungclaus et al., 2013) with a horizontal resolution of 1.5° and 40 vertical levels. Two hindcast generations are considered here, both computed with the
25   MPI-ESM-LR but with different initialisation strategies. The first generation (baseline0; Müller et al., 2012) is initialised with oceanic conditions from a coupled experiment, where ocean temperature and salinity anomalies from the NCEP/NOAA reanalysis (Kalnay et al., 1996) were assimilated into the ocean model MPI-OM. For the second generation (baseline1; Pohlmann et al., 2013b), temperature and salinity anomalies from the ocean reanalysis system 4 (ORAS4; Balmaseda et al., 2013) are used instead, together with a full-field 3-D atmospheric initialisation using fields from ERA40 (Uppala et al.,
30   2005) and ERA-Interim (Dee et al., 2011). For both generations, yearly initialised hindcasts are available, each of them comprising a 10-year period. For each starting date, an ensemble was generated using a 1-day lagged initialisation from the assimilation experiments (cf. Marotzke et al., 2016 for more details). For baseline0 there are 10 members for each fifth year

and three members for the other years, whereas baseline1 provides 10 members for each starting year. The downscaling experiment was performed with the global forcing from hindcasts of five starting dates are used (1 January 1961, 1971, 1981, 1991, and 2001; hereafter referred to as dec1960, dec1970, dec1980, dec1990, and dec2000) to cover the whole period from 1961-2010. This resulted in an ensemble of 50 global hindcasts per generation (baseline0 and baseline1; hereafter MPI_b0 and MPI_b1).

The global hindcasts are dynamically downscaled to the EURO-CORDEX domain (Giorgi et al., 2006; cf Figure 1) at a horizontal grid resolution of 0.22° using the mesoscale non-hydrostatic regional climate model COSMO-CLM (CCLM; Rockel et al., 2008) on a rotated grid. The model version COSMO4.8-clm17 is employed. By using the MPI-ESM-LR ensemble as driving data, the global "initial condition" perturbation strategy is simply passed to the regional model. The downscaling experiment includes hindcasts for dec1960, dec1970, dec1980, dec1990, and dec2000, with ten members per decade (hereafter CCLM_b0 and CCLM_b1). The regional ensembles therefore consist of the same time series like the global ensembles MPI_b0 and MPI_b1.

We evaluate the performance of both the global MPI-ESM and the regional CCLM hindcasts with the following datasets: For temperature and precipitation we consider the observational dataset E-OBS (Haylock et al., 2008) based on the ECA&D (European Climate Assessment & Dataset; http://eca.knml.nl/) at a regular 0.25°x0.25° grid. As no gridded dataset is available for wind, a CCLM simulation forced with boundary conditions from ERA40 and ERA-Interim is employed as verification dataset for wind speed. For this reanalysis driven simulation, CCLM is applied in the same model setup as for the regionalisation of the global hindcast ensemble (see above).

In this study, we want to quantify if the initialisation with observed climate states improves the performance of decadal predictions. To address this issue, uninitialised historical CMIP5 runs are usually considered as reference dataset (see also section 3.2). With this aim, a 10-member ensemble of uninitialised MPI-ESM-LR historical runs started from a pre-industrial control simulation are used, which are only forced by the aerosol and greenhouse gas concentrations for the period 1850-2005 (e.g. Müller et al., 2012).

3. Methods

3.1 Data processing

All datasets considered in this study are pre-processed in an analogous manner to enable a direct comparison. First, all data are interpolated to the same regular 0.25°x0.25° grid, which corresponds to the resolution of the E-OBS data. At each grid point, monthly anomaly time series are computed by subtracting the long-term means for the period 1961-2010 from the interpolated raw datasets. Finally, annual values are derived and multi-annual means for lead years 1-5 are built for further evaluation.

Following the suggestion of Goddard et al. (2013), the skill analysis is mainly performed for spatial means. Spatial averaging of the anomaly time series is performed for eight PRUDENCE regions over Europe (see Fig. 1; Christensen and Christensen,

2007). Note that we only used grid points over land surfaces for the spatial means, as E-OBS data are not available over the oceans. Additionally, we calculated the predictive skill on the basis of all individual grid points for specific analysis.

3.2 Skill metrics

The following three metrics are used to evaluate the performance of the global and regional hindcast ensembles and to
5   address the four key questions: the continuous ranked probability skill score (CRPSS), the mean squared error skill score (MSESS), and the anomaly correlation coefficient (ACC). The skill metrics are applied to the pre-processed time series described in section 3.1 and are computed for multi-annual means for lead time years 1-5 after initialisation. Recent studies analysing the MiKlip decadal prediction system demonstrated that the MiKlip ensemble performs best for the first years after initialisation for a wide range of variables, while the skill diminishes for longer forecast periods. For example, Müller et al.
10   (2012) found highest skill scores for years 1-4 and 2-5 for annual mean surface temperature both for the North Atlantic region and global means. The same is true for annual wind speed and wind energy potentials over Central Europe, for which skilful predictions are mainly restricted to the first years after initialisation (years 1-4), while negative skill scores are found for longer lead time periods (Moemken et al., 2016). Kruschke et al. (2014) provided evidence that the prediction skill for winter cyclones over the North Atlantic region is best for years 2-5 and reduced for longer time periods. Following the
15   recommendation by Goddard et al. (2013), we focus in the following on the lead time years 1-5 after initialisation.

The CRPSS (e.g. Goddard et al., 2013) is often used to assess the reliability of probabilistic forecast models and defined as

$$CRPSS = 1 - \frac{CRPS_{hind}}{CRPS_{ref}}$$

with

$$CRPS = \int_{-\infty}^{\infty} [F(y) - F_o(y)]^2 \, dy$$

The CRPS is the continuous ranked probability score (Wilks, 2011) and is defined as the quadratic measure of the discrepancy between the forecast cumulative density function (F) and the observed cumulative density function (F_o) of a
20   variable y. The cumulative density function (CDF) of a real-valued variable y is defined as:

CDF(y) = P(y ≤ t),

where P is the probability that the variable y has a value of less than or equal to t. $CRPS_{hind}$ is the CRPS of the initialised hindcasts, and $CRPS_{ref}$ is the CRPS of a reference dataset, which are in this study the uninitialized MPI-ESM-LR historical simulations. In case of a positive CRPSS the reliability in terms of the probabilistic quality of the forecast spread is higher in
25   the initialised hindcasts than in the reference dataset. It can thus be used to test if the model ensemble spread adequately represents the forecast uncertainty.

The deterministic MSESS (Goddard, 2013) is defined as

$$MSESS = 1 - \frac{MSE_{hind}}{MSE_{ref}}$$

with

$$MSE = \frac{1}{N} \sum_{n}^{N} (\overline{X_\iota} - O_i)^2$$

where MSE_{hind} is the mean squared error (MSE) between the ensemble mean of the initialised hindcasts (X_i) and the verification data, and MSE_{ref} is the mean squared error of a reference dataset (here: uninitialised historical simulations) versus the verification data (O_i). A positive MSESS means that the hindcasts are closer to the verification dataset than the uninitialised runs, indicating that the initialisation leads to higher accuracy in predicting observed values. In a sensitivity study we additionally choose the climatology as reference dataset. Note that independently from the ensemble size of the hindcast ensembles, the same historical 10-member ensemble is always used as reference dataset for the computation of CRPSS and MSESS.

The ACC (e.g. Wilks, 2011) is computed as the Pearson correlation between the ensemble mean of the hindcasts at a certain location i and the corresponding observations (Obs):

$$ACC_i = \frac{1}{N} \frac{\sum_t hind_t \, Obs_t}{\sigma_{hind} \, \sigma_{Obs}}$$

where $t = 1, \dots, N$ is the time index. The ACC quantifies the accuracy of the predictions only in terms of the temporal course, while it is independent from the mean bias. To compare the performance of the hindcasts and of the uninitialized historical runs, we compute the difference of the ACC of the hindcasts minus the ACC of the historicals for several issues (hereafter delta_ACC).

4. Results

4.1 Is there a potential for skilful regional decadal predictions in Europe?

In this section we address the first key question and analyze the general potential for skilful regional decadal predictions over Europe. Fig. 2 shows MSESS plots for temperature, precipitation and surface wind speed in CCLM_b0 and CCLM_b1 with the un-initialized simulations as reference. For temperature (Fig. 2a and 2b), positive skill scores are found in both ensembles over Scandinavia and for South-eastern Europe, while a stripe of negative values occurs over the British Isles and Central Europe. The analysis of the time series for Mid-Europe (spatial mean over Prudence region 4) reveals that this negative skill mainly results from a strong temperature increase from dec1960 to dec1970 in the observations, while CCLM_b0 and CCLM_b1 depict a decrease in temperature (not shown), which in fact was observed in Southern Europe for instance. As a consequence, the temperature in the hindcasts has a larger bias than the uni-initialized simulations compared to the observations during the first half of the considered period, but agree well to the observations from dec1980 onwards. The largest deviations between CCLM_b0 and CCLM_b1 are found for Iberia, parts of southern France and Italy, where the MSESS is positive for CCLM_b1 but neutral to negative for CCLM_b0.

Deviations between both ensembles are larger for precipitation (Fig. 2c and 2d), where the MSESS fields are distinctly patchier when compared to temperature (Fig. 2a and 2b), reflecting the local character of rainfall. Both ensembles show positive MSESS values for regions in Scandinavia and Eastern Europe, and to a lesser extent for Iberia and the British Isles (Fig. 2c and 2d). In CCLM_b1, predictive skill is also identified over Western Central Europe. Thus for CCLM_b1 positive

5   skill is found for larger areas indicating an added value of the improved initialization procedure in baseline1 compared to baseline0.

Regarding wind speed, the predictive skill in CCLM_b0 (Fig. 2e) shows high MSESS values over Scandinavia, Iberia, southern Italy and along the coasts of the North and the Baltic Sea, while negative values are found e.g. over parts of France, southern Germany and the Alpine region. In CCLM_b1, the MSESS depicts positive values over most of Western and

10 Central Europe, while negative values are now identified along the eastern coast of the Baltic Sea (Fig. 2f). Overall the predictive skill of CCLM_b0 is slightly higher and affects a larger area, indicating that the changes in the initialization method do not improve the results for wind speed.

We conclude that in terms of the MSESS accuracy there generally is a potential for skilful decadal predictions over Europe in the regional MiKlip ensembles. However, the skill pattern depends on the region and the variable. For individual regions,

15 the initialisation of the hindcasts and decadal predictions lead to an added value for accurate (retrospective) forecasts several years ahead, while for some regions the uninitialized historical runs deliver more reliable predictions. Also the discrepancies between the two hindcast generations (CCLM_b0 and CCLM_b1) are rather heterogeneous. While for temperature we only found a slight shift in the pattern due to the different initialization methods, discrepancies can be large for precipitation and wind speed depending on the region.

20 A different picture is revealed when using the climatology as reference dataset for the MSESS computation (Fig. 3). Not surprisingly, for temperature the MSESS strongly increases to positive values for most of Europe (Fig. 3a and 3b). This is due to the strong positive trend in the observed temperature, which is predicted by the hindcasts but not captured by the climatology. Contrastingly, the MSESS with the climatology as reference generally decreases for wind speed in both CCLM_b0 and CCLM_b1 (Fig. 3e and 3f). The positive MSESS is maintained only for Northern Europe and CCLM_b0.

25 Hence, the climatology is generally closer to the observations than both the hindcasts and the historical runs. We have analysed the respective spatial mean wind speed time series for the Iberian Peninsula (Prudence region 2) and CCLM_b0, where this effect is strongest. The wind speed shows a slight negative trend in both, CCLM_b0 and the historicals, while the trend is slightly positive for the observational dataset (not shown). At the same time, the decadal variability for wind speed is quite small over this region in all datasets (it ranges from 0.05 to -0.05 in the historicals, and from 0.02 to -0.02 in CCLM_b0

30 and E-OBS). Hence, the deviation of the climatology to the observations and thus its MSE are generally small in this region, resulting in a negative MSESS when using the climatology as reference (see also equation for MSESS in section 3.2). Rather robust results are found for precipitation, independently from the choice of the reference dataset for CCLM_b0 and CCLM_b1 (cf. Fig 3e and 3f with Fig. 2e and 2f).

For a better understanding of the skill scores and their relation, the different skill metrics are compared in scatter plots. Fig. 4a and 4c show scatter diagrams of CRPSS vs MSESS for temperature and wind speed, respectively, on individual grid point basis for CCLM_b0. Generally, the accuracy and the reliability can vary highly with geographical position. However, for the majority of the individual land grid points over Europe, positive MSESS are concurrent with positive CRPSS values for both displayed variables (upper right quadrant). Both skill scores are linked to each other, showing a quasi-linear dependency between CRPSS and MSESS. This is identified for both CCLM_b0 (Fig. 4a and 4c) and MPI_b0 (Fig. 4b and 4d). In particular, we found that positive values for CRPSS often accompany with a high accuracy of the decadal predictions. This is generally true for all variables and both ensembles considered here (not shown).

On the other hand, no such linear relationship is detected between ACC and MSESS (see Fig. 4e for wind speed in CCLM_b0). The ACC vs MSESS combination is clearly more strongly scattered than CRPSS vs MSESS, both in terms of the general spread and the peak values of the number of grid points with a given skill score combination. Hence, a low mean bias of decadal predictions (resulting in positive MSESS values) does not necessarily imply a realistic temporal evolution. Still, positive MSESS values correspond to positive ACC values for most of the individual grid points, indicating a high potential for skilful regional decadal predictions over Europe.

4.2 Does regional downscaling provide an added value for decadal predictions?

Recent studies document that the application of regional climate models may improve climate simulations, in particular over complex terrain (Berg et al., 2013; Feldmann et al., 2013; Hackenbruch et al., 2016). This is mainly due to a more realistic representation of the topography (e.g. mountain ranges or coast lines) in the RCMs compared to global-scale GCMs. In this section, we analyse whether the downscaling with a regional climate model also leads to an added value for decadal predictions over Europe.

Figure 4 indicates a shift of the overall distribution of skill scores towards higher values for the regionalised hindcasts compared to the global ones in the baseline0 ensemble. For temperature and wind speed, the core area of the skill values from the regional hindcasts (Fig 4a and 4c) is more confined to the upper right quadrant compared to the global ensemble (Fig 4b and 4d). This indicates an added value of downscaling for the accuracy as well as for the reliability. For the wind speed correlation the patterns are quite similar, as there is a clear shift towards an improved correlation and for a higher MSESS from the downscaling (Fig. 4e and 4f). In contrast, no added value on grid point scale is detected for precipitation in CCLM_b0, neither for the accuracy skill scores (MSESS and ACC) nor for CRPSS (not shown). With respect to the baseline1 ensemble, only the prediction skill for temperature is improved by the downscaling, while no or only a marginal added value of regionalization is found for precipitation and wind speed (not shown). Note that results may be different when spatial means over the Prudence regions are analysed (see below).

Ideally, an added value of downscaling should be accompanied by a positive absolute skill. Figure 5 depicts these two aspects for the three variables (2m temperature, precipitation, near-surface wind), the three verification metrics (MSESS,

ACC, CRPSS) and additionally delta_ACC (see section 3.2), and the two ensemble generations (b0 and b1), as derived for the spatial means over the eight PRUDENCE regions (cf. Fig. 1). Green dots indicate higher skill scores for the CCLM ensembles compared to MPI-ESM-LR and thus an added value of downscaling. Red dots mean that the skill scores are lower in the CCLM ensembles, while in case of yellow dots the skill scores are equal in MPI-ESM-LR and CCLM. Red

5   background color indicates a negative skill score and green color a positive skill for the respective metric. Thus, this figure can be interpreted along several dimensions: (i) the skill of the different climate variables (background color), (ii) the improvement by downscaling (dot color), (iii) the improvement from b0 to b1, (iv) the skill for different regions, (v) and the different skill metrics.

For temperature, CCLM_b1 mostly shows an added value compared to MPI_b1 as well as compared to CCLM_b0. For most

10   regions, this is particularly expressed in all displayed metrics. For instance, with respect to the accuracy (MSESS, ACC, and delta_ACC) CCLM_b1 has higher skill in six or seven of eight PRUDENCE regions compared to MPI_b1. Only for the Alps (AL, Prudence region 6), no added value of downscaling is found in both ensemble generations for ACC and delta_ACC. Additionally, no benefit from downscaling could be detected for CCLM_b0 for the British Isles (BI – 1), France (FR – 3), Mid-Europe (ME - 4) and the Mediterranean Area (MD - 7), where CCLM_b1 performs better. In general, in CCLM_b1

15   there are more regions with positive skill scores in Southern Europe (IP - 2, AL - 6). In the Mediterranean region both ensemble generations depict only positive skill scores.

For precipitation, an improvement from downscaling is detected particularly for CCLM_b1 for the majority of metrics and regions. In addition, CCLM_b1 is clearly superior to CCLM_b0 with respect to both skill and added value. This indicates a positive effect of the improved initialization procedures in b1 compared to b0 (Pohlmann, 2013b). However, this

20   improvement does not affect all regions. CCLM_b0 performs better than its successor for the Iberian Peninsula, whereas skill and/or added value are higher in CCLM_b1 for the regions in the North-West (BI, FR, ME) and North (SC). With respect to reliability, CCLM_b0 slightly outperforms CCLM_b1 for precipitation (CCLM_b0: seven regions with positive CRPSS, CCLM_b1: six regions with positive CRPSS), while for temperature a contrary result is found (three regions with positive CRPSS in CCLM_b0 and four in CCLM_b1).

25   For near surface wind, Fig. 5 shows heterogeneous results. CCLM_b0 has an added value of downscaling in more regions than CCLM_b1. Further, CCLM_b0 provides an added value for the CRPSS in eight regions, while for CCLM_b1 an improvement by downscaling is restricted to four regions with respect to the reliability. CCLM_b0 has a positive skill in the northern parts of the domain (BI, SC), whereas positive skill scores are found for CCLM_b1 over most other PRUDENCE regions at least for one skill metric.

30   The detected shift in the skill patterns between CCLM_b0 and CCLM_b1 can be expected due to the different initialization procedures of the two generations. However, there also seem to be regions with more stable skill properties for the CCLM ensembles: The Mediterranean area shows positive skill for all variables and metrics (except wind in CCLM_b0), though this high prediction skill is not necessarily accompanied by an improvement of the skill scores compared to the MPI-ESM-LR ensembles.

An added value of regionalization for the majority of variables and metrics can be found for Southern Europe (MD, IP) and Scandinavia. As these areas have complex coastlines and orography, this result may be indicative of a better representation of small-scale processes in the CCLM. On the other hand, for the Alps (AL) an added value of downscaling for all skill scores is only revealed for wind in CCLM_b0. The PRUDENCE region AL is the smallest of the regions, with the steepest orography. It might be that for the Alps an even higher resolution for the downscaling would be advantageous to improve the accuracy and reliability of the hindcasts.

We conclude that regional downscaling indeed may provide an added value for decadal predictions over Europe. However, while for some complex regions like MD, IP or SC this added value is to some extent systematic, for other areas in Europe the analysis reveals a mixed picture for the different variables and the skill metrics.

4.3 Does the regional decadal predictive skill depend on the ensemble size?

Past studies suggest that the ensemble size of a prediction system has an impact on the forecast skill of a model (Richardson, 2001; Ferro et al., 2008). Generally, there is consensus that the prediction skill for both seasonal and decadal predictions is enhanced when the number of ensemble members is increased. Kadow et al. (2014) analysed the global MiKlip baseline1 generation and concluded that the forecast accuracy for surface temperature for lead years 1 and 2-9 is improved for nearly the whole globe when the ensemble size is increased from 3 to 10 members. This is in line with the findings of Sienz et al. (2016), who examined the prediction skill for North Atlantic sea surface temperature in the same hindcast ensemble. Also for seasonal predictions of the North Atlantic Oscillation a forecast system profits from increasing size (e.g. Scaife et al., 2014). However, it is still open how a regional decadal forecast system does depend on the quantity of ensemble members. With this aim, we analysed the impact of the ensemble size on the predictive skill for the eight PRUDENCE regions in Europe in both the regional and the global MiKlip ensembles. In the following, results are only shown for the Iberian Peninsula (IP), as the findings are similar for the other PRUDENCE regions. Figure 6 exhibits the dependency of CRPSS, MSESS, and delta_ACC for lead years 1-5 (y-axis) on the ensemble size (x-axis) for all three variables spatially averaged over IP. For each ensemble size n (n varying between 2 and 10), the solid coloured lines depict the averaged skill scores for all permutations of n-member ensemble combinations for each of the four individual hindcast ensembles (MPI_b0, MPI_b1, CCLM_b0, and CCLM_b1). Ranked probability skill scores like the CRPSS may be negatively biased for small ensembles sizes (e.g. Ahrens and Walser, 2008), and different bias correction methods exist to overcome this issue. However, as this correction would only affect the CRPSS, a direct comparability with the MSESS and the ACC would not be warranted anymore after such a correction. To ensure the comparability of the results for the three skill metrics we therefore decided not to use a de-biased version of the CRPSS in this study.

Enhanced predictive skill can be observed when the number of members is stepwise increased for both the global and the regional hindcast ensembles. MSESS and CRPSS show a rather logarithmic relationship with increasing n, depicting the highest skill scores for the 10 member ensembles for all three variables (Figure 6a-c and 6g-i). On the other hand, the lowest

skill scores (often with negative values for CRPSS and MSESS) are always found for the 2-member ensembles. This ensemble size dependency of MSESS and CRPSS is systematic and is detected in both hindcast generations for all variables over all eight PRUDENCE regions (not shown), regardless whether the skill scores are negative or positive. In some cases, the ensemble size increase even leads to a shift from negative MSESS and CRPSS values to positive values in one or more

5   of the ensembles (e.g. Fig. 6a, 6g, and 6i). In contrast, no systematic conclusion can be stated for the delta_ACC, as the ensemble size dependency of the predictive skill depends on the variable and the considered MiKlip ensemble (Fig. 6d-f). But even here a larger ensemble size is advantageous, as negative skill scores become more robust (cf. MPI_b0 in Fig. 6f). Nevertheless, there are also examples for delta_ACC where the ensemble size dependency is similar to that of MSESS and CRPSS, like e.g. for temperature (Fig. 6d). These results suggest that a decadal prediction system generally benefits from

10   larger ensemble sizes, either in terms of more skilful and reliable decadal forecasts or at least of a reduction of the bias or the uncertainty, depending on the variable and the hindcast generation. Note that for most variables and skill scores the hindcast generation is more important for the skill than the resolution. In addition, most diagrams indicate an added value of downscaling. For temperature and wind speed, both generations of CCLM surpass their MPI counterparts for all skill scores, indicating a systematic added value of downscaling. This is particularly visible for wind in the b0 ensemble, where the

15   prediction skill of CCLM is distinctly better than for MPI-ESM-LR (Fig. 6c, 6f, and 6i). This is mainly due to higher skill scores over orographic structured terrains of IP in CLM_b0 compared to MPI_b0 (not shown).

For ensembles with less than 10 members, the skill scores of all possible n-member ensemble combinations are averaged. This is illustrated for the MSESS for precipitation in the CCLM_b0 ensemble (see box-whisker plots in Fig. 6b). Given that we are doing permutations without replacement, the spread between the individual n-member ensembles declines with an

20   increasing number of members n, and this decline should therefore not be over-interpreted. Nevertheless, the spread is quite large not only for small ensemble sizes but also for ensembles with $n>5$: For instance, the MSESS varies between -2.6 and +0.7 for the 2-member ensembles (Fig. 6b), and even for the 7-member ensemble quite different results can be found depending on the selection of the ensemble members, ranging from high positive MSESS values to zero. These results clearly demonstrate the necessity of using large ensembles to reduce uncertainties.

25   We conclude that the predictive skill with respect to both accuracy and model spread is generally improved when the size of the hindcast ensembles increases. This is valid for all variables, regions, and hindcast ensembles considered in this study. The skill scores converge towards a certain value in most cases for MSESS and CRPSS in all hindcasts (see Fig. 6a-c and 6g-i). The increments in added value by increasing the number of ensemble members decrease for more than 5 members. Nevertheless, it is recommended to use ten members or more for the skill assessment of decadal predictions on the regional

30   scale.

4.4 How does the sample size affect the skill estimates?

A lesson learned from the CMIP5 decadal experiments is that more starting years and thus a larger sample size is beneficial to establish robust skill estimates (Boer et al., 2016). This has been reflected in the progress from the first global MiKlip hindcast generation baseline0 to the second generation baseline1. Whereas baseline0 provides ten ensemble members every fifth year (compliant with the CMIP5 experimental protocol), baseline1 provides this ensemble size for each starting year of the hindcast period. To assess the impact of the small sample size with five starting years (used elsewhere in the paper) on the robustness of our main conclusions we performed a sensitivity analysis with the global baseline1 ensemble, for which the largest sample is available. For this, we compared the sample with ten-yearly starting dates with the full yearly initialized MPI-ESM-LR baseline1 ensemble over the same period from 1960 to 2000.

Fig. 7 presents a comparison between the ACC scores for the small (left; 5 starting years) and the large sample size (right; 41 starting years). For all three variables. the score maps show in general comparable spatial distributions. The skill maps for the larger sample size usually depict a smoother spatial distribution with less extreme skill values. The regional averages over most of the PRUDENCE regions are comparable. However, in some regions larger differences can occur: For temperature over Ireland and Scotland, for precipitation over parts of France and Eastern Europe and for wind from north-eastern Spain towards the Alps. Similar results are found for MSESS (not shown), for which not only the sample of MPI_b1 is increased but also of the uninitialized historical runs.

It is obvious that a larger sample size increases the robustness of the skill assessment, especially with respect to quantitative estimates. Therefore, this work supports the recommendations made for CMIP6 by Boer et al. (2016) to generate hindcast ensembles with yearly starting dates. Nevertheless, using the smaller sample size already represents the general features of the regional distribution. Therefore, the qualitative findings from chapter 4.1 are confirmed by the analysis of the larger sample size. The results regarding the added value and the ensemble size dependence are less affected by the sample size. Given the above findings, we conclude that the results obtained here for a limited sample size are qualitatively comparable to those which would be obtained for a larger sample size.

5. Summary and discussion

In this study, the decadal predictability in the regional MiKlip decadal prediction system is analysed for temperature, precipitation, and wind speed over Europe and compared to the forecast skill of the global ensemble. The goal is to assess the prospect of such a system for the application in forecasts on decadal timescales. Focus is given to years 1-5 after initialization. Three skill scores are used to quantify the accuracy and the reliability of the two different MiKlip hindcast generations. The main findings of our study can be summarized as follows:

- There is a potential for regional decadal predictability over Europe for temperature, precipitation, and wind speed in the MiKlip system, but the predictive skill depends on the variable, the region, and the hindcast generation.

- The MiKlip prediction system may distinctly benefit from regional downscaling. An added value in terms of accuracy and reliability is particularly revealed for temperature over the British Isles (BI), Scandinavia (SC), the Iberian Peninsula (IP), and for precipitation over the British Isles (BI), Scandinavia (SC), Mid-Europe (ME), and France (FR) for the b1 generation. Most of these regions are characterized by complex coastlines and orography, which indicates that the better representation of topographic structures in the regionalised hindcasts may improve the predictive skill.

- The improvement of the initialization procedure from baseline0 to baseline1 as described in Pohlmann et al. (2013b) increases the overall predictive skill in the downscaled MiKlip hindcasts over Europe, at least for precipitation and temperature. But improvement of the skill varies between variable and region. The skill for temperature increases around the Mediterranean Sea and parts of Scandinavia from b0 to b1. For precipitation the skill of b1 compared to b0 is higher in all regions but the Iberian Peninsula and Eastern Europe. Only for wind speed there is mostly no benefit from the improved initialization.

- A systematic enhancement of MSESS and CRPSS skill scores is found with increasing ensemble size, and a number of 10 members is found to be suitable for decadal predictions. This is valid for all variables and European regions in the global and regional MiKlip ensembles.

- As tested for the MPI_b1 data, which offer a full ten member ensemble for each starting year, a larger sample size would lead to similar results as presented here, Nevertheless, such an increase would improve the robustness of the skill maps.

Müller et al. (2012) and Pohlmann et al. (2013b) had found systematic prediction skills for surface temperature over large parts of the North-Atlantic and Europe in both global generations (baseline0, baseline1). From the results of our study, it is apparent that the Mediterranean Area and the Iberian Peninsula seem to be key European regions for decadal predictability with the regional prediction system. This is in line with findings from Guemas et al. (2015) and may be related to skilful predictions of the AMO (Garcia-Serrano et al., 2012; Guemas et al., 2015). Due to the rather non-linear relationship of these large-scale North Atlantic features to regional atmospheric conditions over Europe, the mechanisms steering the decadal variability and predictability of climate variables in European regions are thus more complex. The decadal variability of regional precipitation, temperature, and wind speed over most parts of Europe is largely affected by the North Atlantic oscillation, but its skilful decadal predictability over the continent is still under debate. With this respect, a better understanding of the mechanisms relevant for the regional climate over Europe on the decadal time scale is required, as was for example obtained for the tropical Atlantic (Dunstone et al., 2011). This is an objective of the ongoing second phase of the MiKlip project.

The skill scores may strongly vary between neighbouring grid points. Comparable results were found by e.g. Guemas et al. (2015), who detected a rather diffuse pattern for the accuracy of decadal predictions over Europe for seasonal temperature and precipitation. This might at least partly be due to spatial and temporal inhomogeneity of the gridded observational references. A more realistic assessment of the prediction skill can be made by considering spatial means (Goddard et al.,

2013) which was mostly considered in this study. In line with e.g. Kadow et al. (2016), we could show that an enlargement of the ensemble size up to 10 members results in an improvement of the prediction skill over Europe. However, prediction skill could further benefit from even larger ensemble sizes, especially in areas with low signal-to-noise ratio (cf. Sienz et al., 2016).

5   Bias and drift adjustment (e.g., Boer et al., 2016) provides prospect in skill improvement not only for GCMs but also for RCMs. This is particularly the case for ensemble simulations run with full-field initialization (like the third MiKlip generation prototype, not analysed here; cf. Marotzke et al., 2016). While bias and drift adjustment methods have improved the forecast skill of near-term climate prediction (e.g., Kruschke et al., 2016), such corrections are less important for the baseline0 and baseline1 ensembles analysed here as they were generated with anomaly initialisation (Marotzke et al., 2016).

10   Nevertheless, bias correction and calibration are an important topic in the second phase of MiKlip.

Due to the high computational costs of dynamical downscaling, only five starting dates (one per decade) are available for the regional MiKlip ensemble (see section 2). This is a shortcoming regarding the statistical significance of the results and some of the statements presented in this study. However, we could show that the qualitative findings are only partly influenced by the limited number of available hindcasts and that the main conclusions can be regarded as robust. The statistical

15   significance will be easier to quantify when the regional simulations for the newest Miklip ensemble generation are available with annual starting dates over more than 50 years. On the other hand, regional decadal forecasts may have advantages beyond the examples discussed in this paper. For example, RCMs enable the integration of improved components of the hydrological cycle or climate-system components with memory on multi-year time-scales like soil moisture (Khodaya et al., 2014; Sein et al., 2015). Kothe et al. (2016) has shown that extracting the initial state of the deep soil in the RCMs from

20   regional data assimilation schemes may improve decadal predictions. Further, Akhtar et al. (2017) demonstrated that the regional feedback between large water bodies and the atmosphere play a major in the regional climate system. This feedback can only be captured in regionalized climate predictions by a dynamic RCM-ocean coupling. Most of the approaches mentioned above are ongoing within the second phase of MiKlip and are expected to enhance the decadal predictability over Europe. We thus conclude that a decadal prediction system would clearly benefit from a regional forecast ensemble.

25   The regional decadal prediction system generated by the MiKlip consortium comprises altogether 1000 years (two hindcast generations, each of them comprising ten hindcast members for five starting years) of simulations with 0.22° for the entire EURO-CORDEX region, which is a to our best knowledge unprecedented. Hence, this ensemble enabled us to gain important insights into different aspects and the prospects of regional downscaling for decadal predictions, and serve as a good basis for future studies. In the ongoing second phase of MiKlip it is planned to downscale a complete ensemble

30   hindcast generation with ten members for more than 50 starting years, giving altogether more than 5000 years.

Author Contributions

MR, HF, SM and MU developed the concept of the paper; MR, HF and JGP wrote the first manuscript draft. MR, HF, SM, MU, NL and JM contributed with data analysis and analysis tools. HF, SM, MR, BA, BF contributed with RCM simulations. MK and WM contributed with the global MPI-ESM-LR simulations and prepared boundary conditions for RCM simulations. CK leads the MiKlip-C consortium, with CO-Is BA, BF, JGP, GS. All authors contributed with ideas, interpretation of the results and manuscript revisions.

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Figures
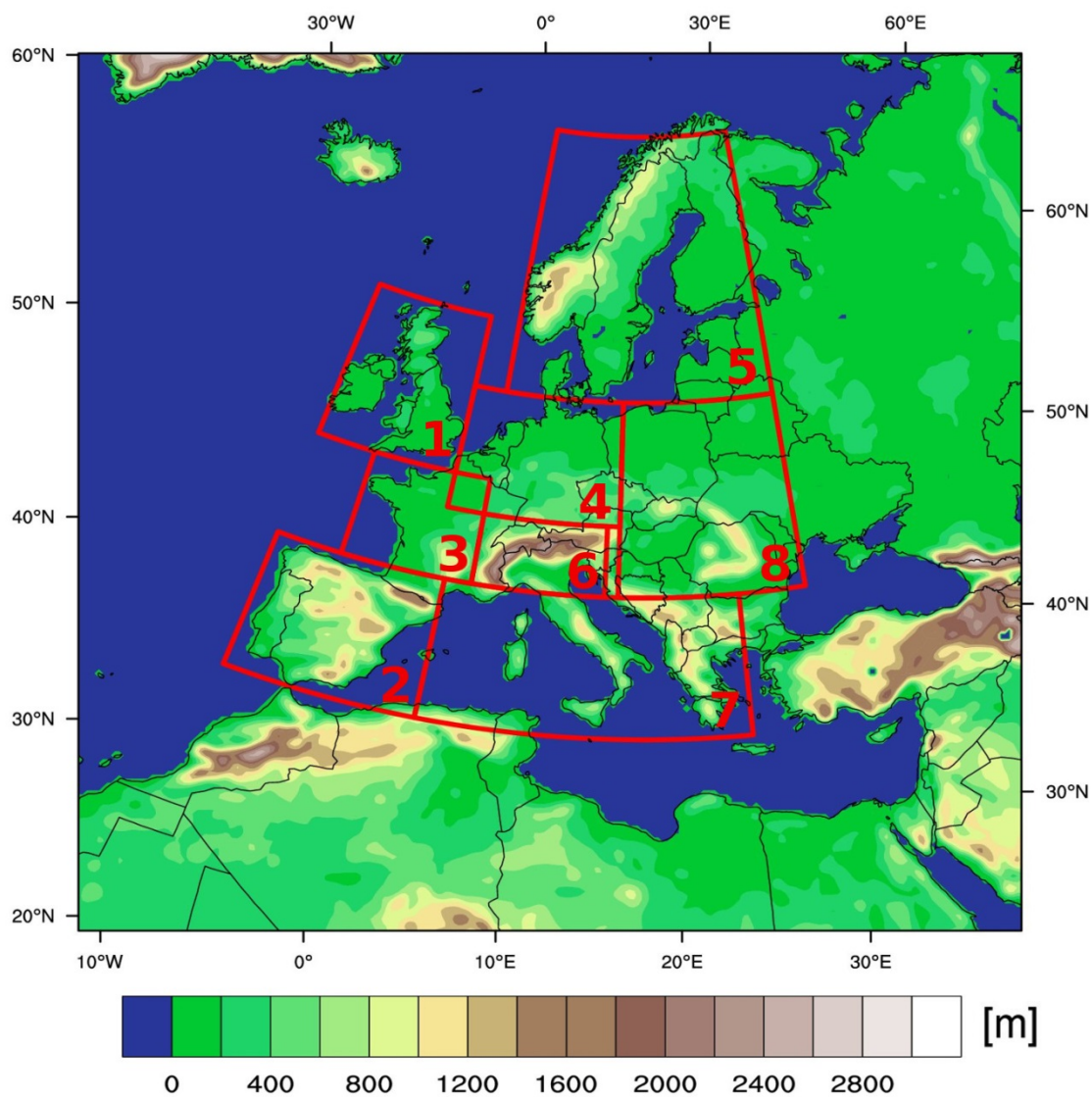
Figure 1: CCLM modelling domain (= EURO-CORDEX domain): Modell orography and PRUDENCE regions. 1: British Isles BI; 2: Iberian Peninsula IP; 3: France FR; 4: Mid-Europe ME; 5: Scandinavia SC; 6: Alps AL; 7: Mediterranean MD; 8: Eastern Europe EA.
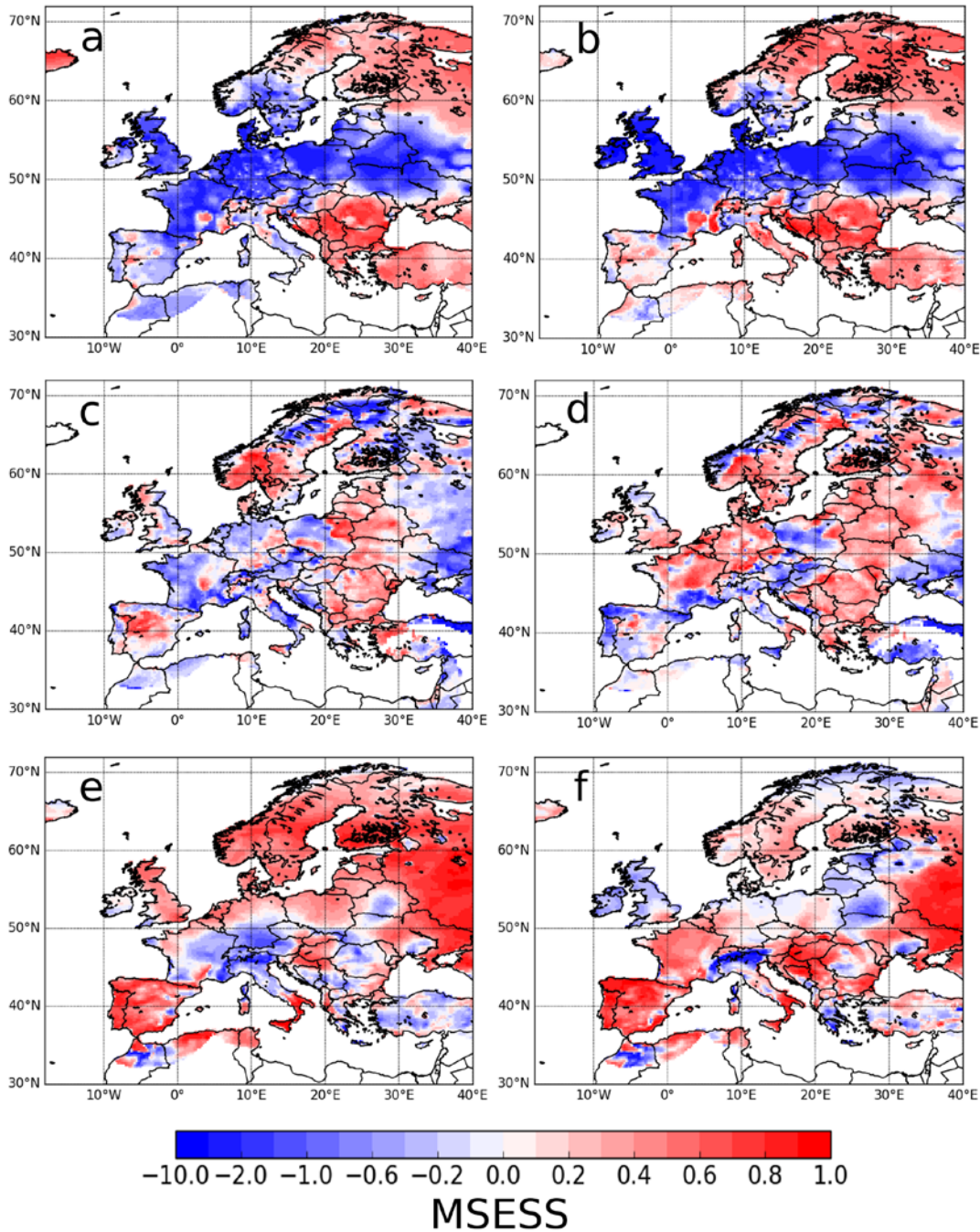
Figure 2: Spatial distribution of the MSESS for the multi-annual mean anomalies of lead years 1-5 for (a) temperature in CCLM_b0, (b) temperature in CCLM_b1, (c) precipitation in CCLM_b0, (d) precipitation in CCLM_b1, (e) wind speed in CCLM_b0, and (f) wind speed in CCLM_b1. As reference dataset we have used the uninitialized historical ensemble.
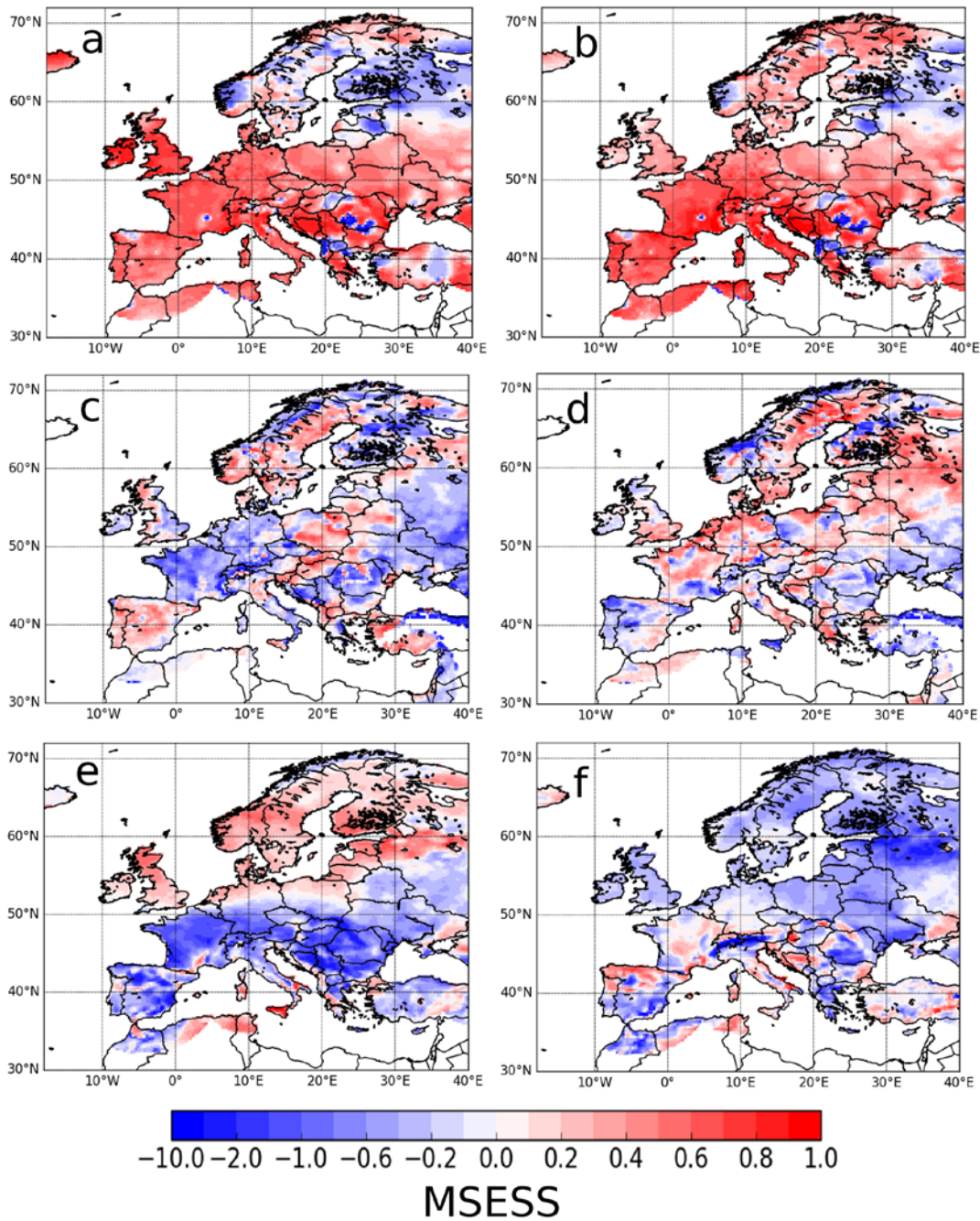
Figure 3: Spatial distribution of the MSESS for the multi-annual mean anomalies of lead years 1-5 for (a) temperature in CCLM_b0, (b) temperature in CCLM_b1, (c) precipitation in CCLM_b0, (d) precipitation in CCLM_b1, (e) wind speed in CCLM_b0, and (f) wind speed in CCLM_b1. As reference dataset we have used the climatology.
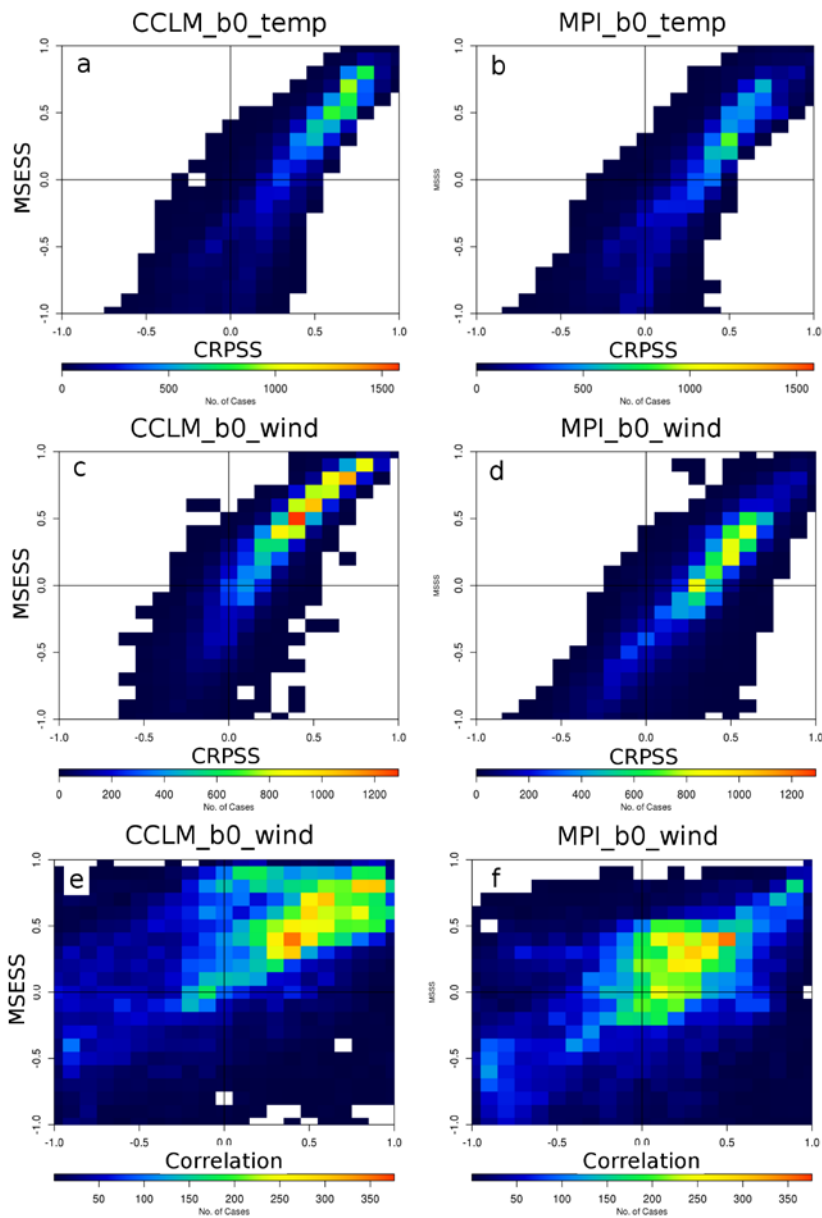
Figure 4: Scatter diagrams for CRPSS (x-axis) vs MSESS (y-axis) for temperature at all individual EURO-CORDEX grid points for the multi-annual mean anomalies of lead years 1-5 in (a) CCLM_b0 and (b) MPI_b0. (c), (d) as (a), (b) but for CRPSS vs MSESS for wind. (e), (f) as (a), (b) but for ACC vs MSESS for wind. Colours denote the number of grid points over Europe with a given skill score combination. For MSESS and CRPSS we have used the uninitialized historical ensemble as reference dataset. Note the different scaling of the colour bars.
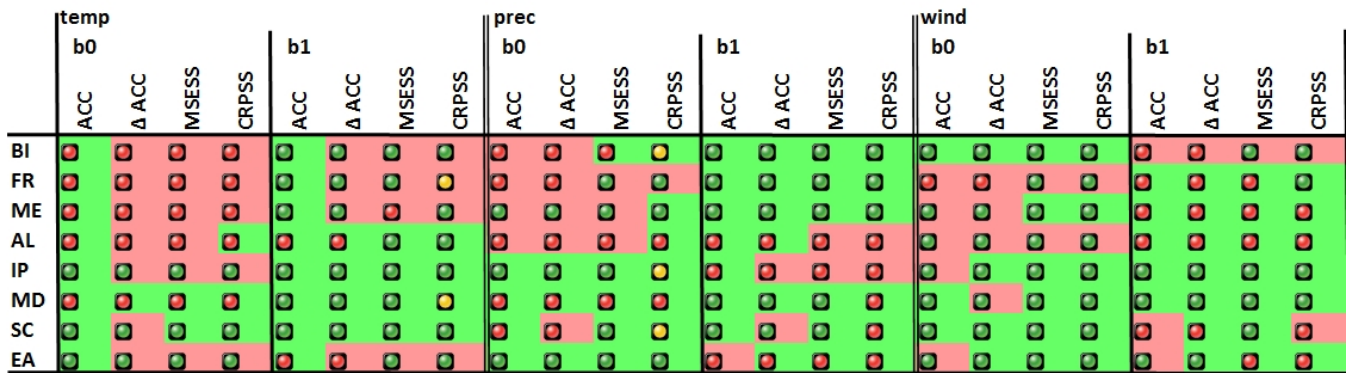
Figure 5: Predictive skill (MSESS, ACC, delta_ACC and CRPSS) and added value of the regional MiKlip ensembles (CCLM_b0 and CCLM_b1) over the eight PRUDENCE regions (cf. Fig. 1) for temperature (left columns), precipitation (middle), and 10m-wind (right) for the multi-annual mean anomalies of lead years 1-5. Red filled boxes indicate negative skill scores, green filled boxes positive skill scores. Green dots denote an added value compared to the global forcing by MPI-ESM-LR, red dots indicate no added value by regionalization, and yellow dots indicate skillscores which are equal in CCLM and MPI-ESM-LR. For MSESS, delta_ACC, and CRPSS we have used the uninitialized historical ensemble as reference dataset.
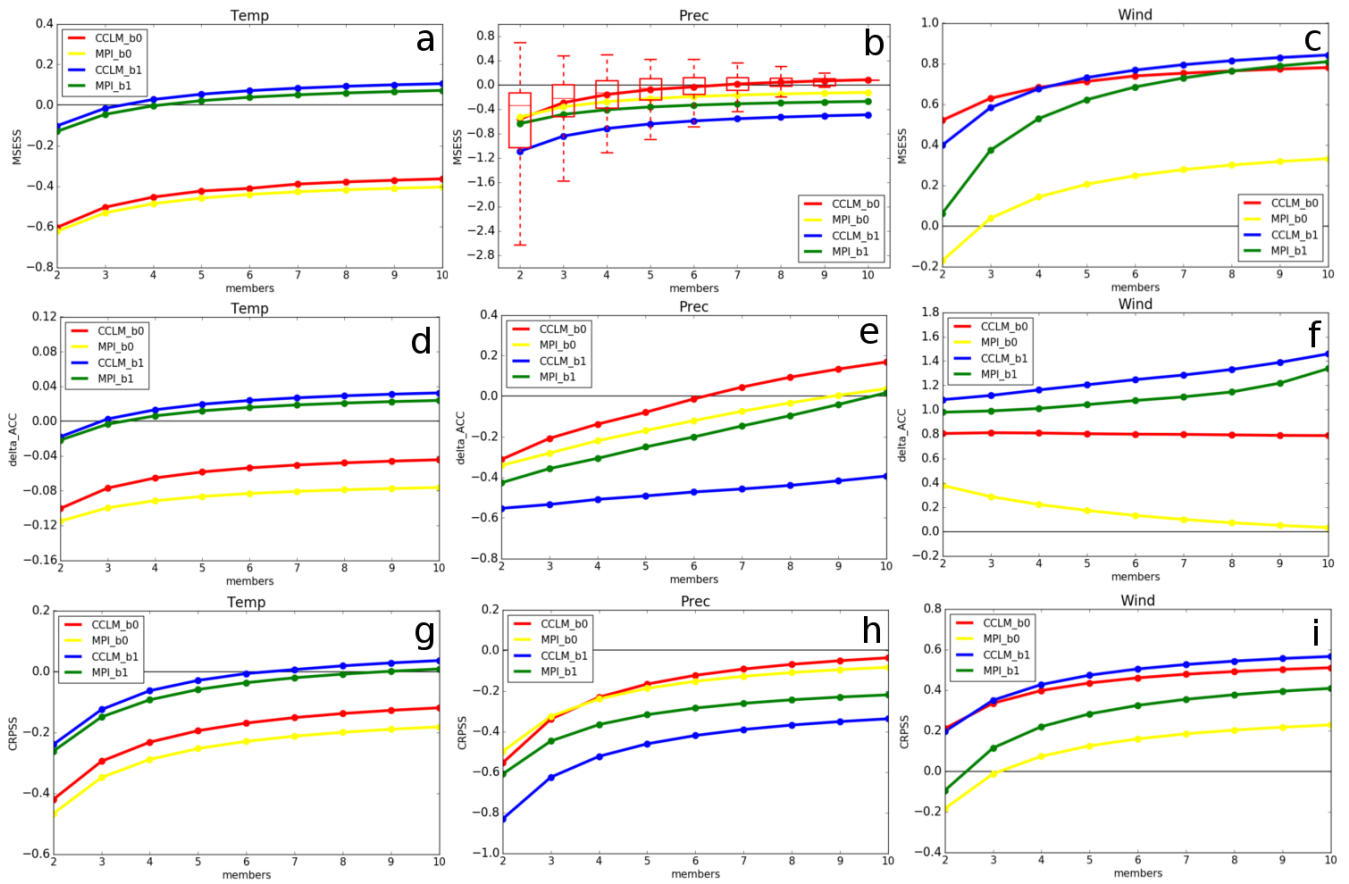
Figure 6: Skill scores for the multi-annual mean anomalies of lead years 1-5 of the CCLM_b0 (red), MPI_b0 (yellow), CCLM_b1 (blue), and MPI_b1 (green) ensembles depending on the ensemble size (x-axis, ranging from 2 to 10 members) over IP (cf. Fig. 1). MSESS for (a) temperature, (b) precipitation, and (c) wind speed; delta_ACC for (d) temperature, (e) precipitation, and (f) wind speed; CRPSS for (g) temperature, (h) precipitation, and (i) wind speed. In (b) box-whisker plots for the skill scores of all n-member combinations are shown. For MSESS, delta_ACC, and CRPSS we have used the uninitialized historical ensemble as reference dataset. Note the different scaling of the y-axis. For details please refer to main text.
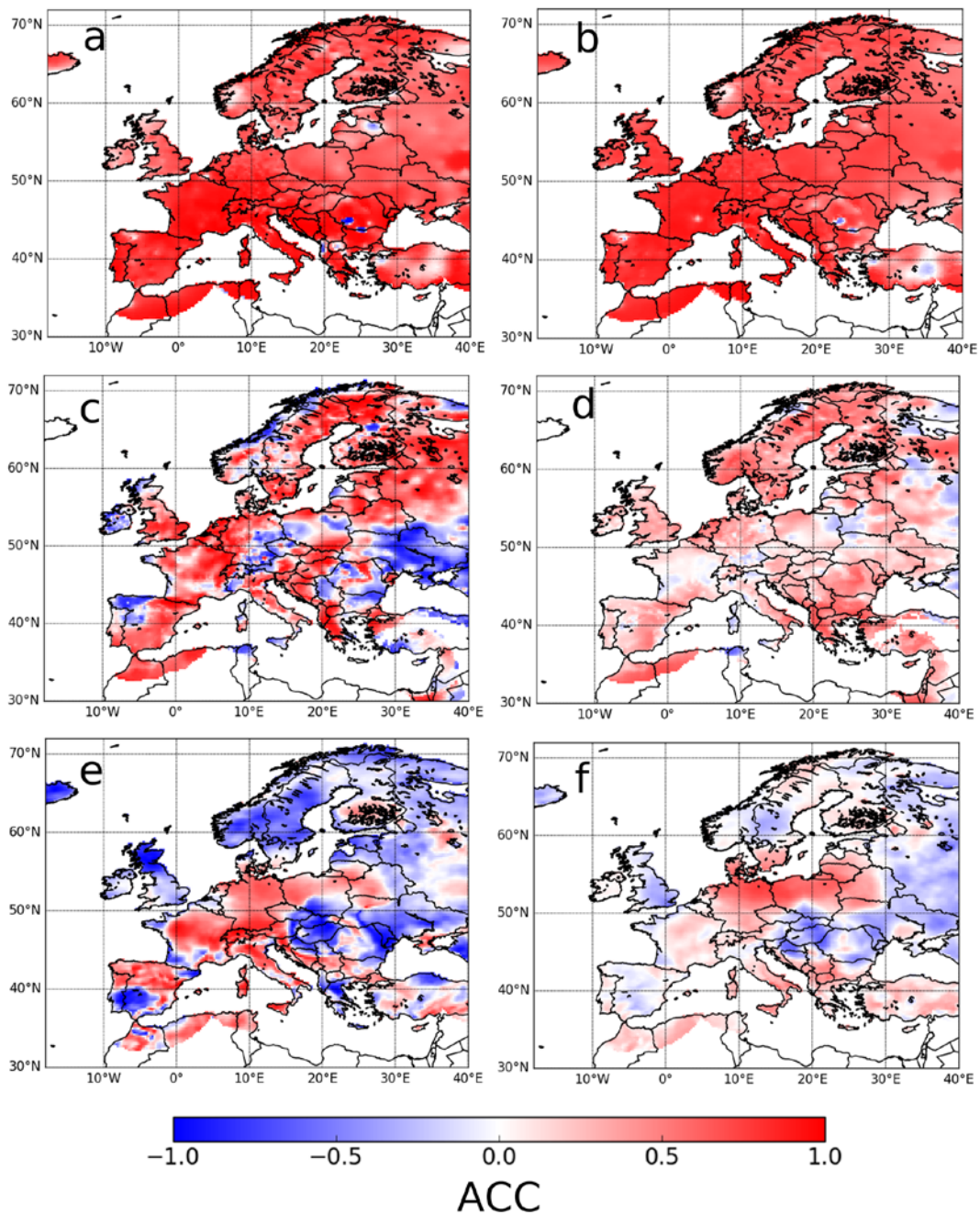
Figure 7: Spatial distribution of the ACC for the multi-annual mean anomalies of lead years 1-5 in MPI_b1 for (a,b) temperature, (c,d) precipitation, and (e,f) wind speed. For the left panels five start years (dec1960, dec1970, dec1980, dec1990, dec2000) have been used, while for the right panels all start years from dec1960 to dec2000 are taken into account. For more detaols see main text.