Decadal predictability of regional-scale peak winds over Europe
using the Earth System Model of the Max-Planck-Institute for Meteorology

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The predictability of high impact weather events on multiple time scales is a crucial issue both in scientific and socio-economic terms. In this study, a statistical-dynamical downscaling (SDD) approach is applied to an ensemble of decadal hindcasts obtained with the Max-Planck-Institute Earth System Model (MPI-ESM) to estimate the decadal predictability of peak wind speeds (as a proxy for gusts) over Europe. Yearly initialized decadal ensemble simulations with ten members are investigated for the period 1979 - 2005. The SDD approach is trained with COSMO-CLM regional climate model simulations and ERA-Interim reanalysis data and applied to the MPI-ESM hindcasts. The simulations for the period 1990 - 1993, which was characterized by several windstorm clusters, are analyzed in detail. The anomalies of the 95 % peak wind quantile of the MPI-ESM hindcasts are in line with the positive anomalies in reanalysis data for this period. To evaluate both the skill of the decadal predictability system and the added value of the downscaling approach, quantile verification skill scores are calculated for both the MPI-ESM large-scale wind speeds and the SDD simulated regional peak winds. Skill scores are predominantly positive for the decadal predictability system, with the highest values for short lead times and for (peak) wind speeds equal or above the 75 % quantile. This provides evidence that the analyzed hindcasts and the downscaling technique are suitable for estimating wind and peak wind speeds over Central Europe on decadal time scales. The skill scores for SDD simulated peak winds are slightly lower than those for large-scale wind speeds. This behavior can be largely attributed to the fact that peak winds are a proxy for gusts, and thus have a higher variability than wind speeds. The introduced cost-efficient downscaling technique has the advantage of estimating not only wind speeds but also estimates peak winds (a proxy for gusts) and can be easily applied to large ensemble datasets like operational decadal prediction systems.
Keywords: decadal predictability, downscaling, wind gusts, MPI-ESM-LR, COSMO-CLM;

MiKlip decadal prediction system.
1. Introduction

The IPCC Fifth Assessment Report (IPCC, 2013) states that the last three decades have been the warmest since 1850 on global average and for many regions of the globe. The long-term trend of increasing temperature in recent decades is expected to intensify during the present century. For other variables, like precipitation and wind, identified and projected long-term trends are comparatively small, and hidden within the natural variability on interannual to decadal time scales. Short-term climate projections to assess such decadal variations are crucial for decision makers to help developing adaptation strategies for the next decade. This points out the necessity of reliable predictions on interannual to decadal timescales, which should represent both natural climate variability and changes occurring due to increasing greenhouse gas concentrations (e.g. SOLomon et al., 2011). So-called decadal hindcasts are commonly used to assess decadal predictability (e.g. Smith et al., 2007). These hindcasts are initialized from an assimilation run, which takes into account sea surface temperatures and salinity anomalies in order to represent the oceans states over the historical period. The hindcasts are used to simulate the development of the atmospheric, oceanic and surface fields within the next decade. For comparison, so-called uninitialized historical runs are used. These runs are started from randomly chosen states of a pre-industrial control simulation and only use observed aerosol and greenhouse gas concentrations as external forcing.

A set of decadal hindcasts (for recent decades) and predictions (for future decades) has been released within the Coupled Model Intercomparison Project Phase 5 (CMIP5; Taylor et al., 2012). Commonly, these experiments are conducted using earth system models. A set of ensemble members is created by initializing the simulations at slightly different times of an assimilation run (e.g. MüLler et al., 2012). Assimilation runs use observed states of the ocean (e.g. sea surface temperature and salinity), and in some cases information on the states of the atmosphere. The hindcast experiments are usually validated against observations and
reanalysis datasets to identify any bias and to estimate their predictive skill. Analyses of CMIP5 models showed that the range of ensemble members is not appropriate to represent the uncertainty arising from the initialization inaccuracies (TAYLOR et al., 2012). A lack of observations and too short time series turned out to be challenging for validation. Another difficulty is the differentiation between naturally occurring and anthropogenically induced decadal variability (e.g. SOLOMON et al., 2011).

Even though decadal prediction is a fairly recent field of research, the number of studies dealing with the validation or the application of decadal hindcasts has increased in recent years. Most publications focus on (sea) surface temperature (e.g. SMITH et al., 2007; MÜLLER et al., 2012; SMITH et al., 2013), circulation patterns (e.g. MSADEK et al., 2010; TENG et al., 2011) or precipitation (e.g. BOER et al., 2008; VAN OLDENBORGH et al., 2012). Focusing on Central Europe, MIERUCH et al. (2014) for example found the highest predictive skill for temperature, while the results for precipitation are less skillful. On the contrary, studies on wind and/or related parameters are rare. KRUSCHKE et al. (2014) evaluated the predictive skill of cyclone activity over the Northern Hemisphere based on decadal hindcasts of the MPI-ESM. They identified distinct areas over the North Atlantic and the North Pacific with positive skill for intense cyclones. MÜLLER et al. (2012) identified the North Atlantic as “a key region for decadal climate predictions”, and they found a predictive skill for different parameters (e.g., mean sea level pressure, sea surface temperature) over this area for all lead times up to 9 years. At present, most investigations focus on features on a very large scale (i.e. global), whereas for stakeholders and planning strategies, information on the regional and local scale is more important.

Within the BMBF-funded project MiKlip (“Mittelfristige Klimaprognosen”, decadal predictions), the goal is to create a model system based on the Max-Planck-Institute Earth System Model (MPI-ESM), which enables to meet the above mentioned demands on decadal
hindcasts (cf. MüLLER et al., 2012; MIERUCH et al., 2014). It is important to analyze the skill of such a model system both on the large scale and in particular on the regional scale. This study consists of two parts: First, a statistical-dynamical downscaling approach, which is trained with gust speeds of a regional climate model and estimates regional daily peak winds as a proxy for gusts, is validated. Second, the approach is applied to decadal hindcasts of the MPI-ESM and its predictive skill is evaluated. The decadal predictability is assessed using quantile verification skill scores, which are calculated by comparing initialized simulations and uninitialized historical runs. For the regionalization of large ensembles of decadal hindcasts and predictions, a cost-efficient downscaling approach is required. The combination of statistical and dynamical downscaling generally offers a good alternative to pure dynamical downscaling (e.g. FUENTES and HEIMANN, 2000; PINTO et al., 2010) and can be easily applied for decadal prediction systems. HAAS and PINTO (2012) recently provided evidence that such a combined statistical and dynamical approach is suitable to downscale large-scale footprints of European windstorms using ERA-Interim wind data as predictors. The general concept of the approach is to relate large-scale predictors (explanatory variable) and regional-scale predictands (dependent variable) by transfer functions based on multiple linear regression. The approach has been validated by reproducing purely dynamically downscaled gust speeds for a selection of historical storms. Both downscaling approaches have similar prediction skills in comparison to observed wind gusts (cf. HAAS and PINTO, 2012; their Fig. 3).

In the present study, the downscaling approach is applied to the decadal hindcasts and predictions of MPI-ESM in a low-resolution configuration (MPI-ESM-LR). As the main objective is to analyze changes in the wind speed statistics on interannual to decadal timescales, we have not selected specific extreme events (like in HAAS and PINTO, 2012) but we have considered the whole climatology and thus all daily values of the MPI-ESM-LR ensemble for the period 1979 - 2005. In order to capture the wind and gust speeds ranges and
distributions, selected quantiles are considered (mainly 5 %, 50 % and 90 % - 99 %). The
decadal predictability of these quantiles is quantified using a suitable skill score.

The structure of the paper is as follows. The used datasets are introduced in Section 2. In
Section 3, the method to estimate a transfer function between regional gust speeds and large-
scale wind speeds, the used skill score, and the cyclone tracking methodology are explained.
The characteristics of the peak winds predicted by the SDD are compared to gust
characteristics as derived from regional climate model (RCM) simulations in Section 4. The
results of the application of the SDD method to the decadal hindcasts and the quantification of
the added value of initialization are described in Section 5. The paper concludes with a
summary and conclusions section.

2. Data

A statistical-dynamical downscaling approach (SDD, see section 3.1) is used to determine
regional peak winds as a proxy for wind gusts from the hindcasts of the MPI-ESM-LR. In
order to assess the quality of the hindcasts, the predictive skill of large-scale MPI-ESM-LR
wind speeds is quantified. Further, the peak winds predicted by the SDD are compared to
gusts as derived from RCM simulations. The used datasets for these analyses are introduced
in following subsections.

2.1. MPI-ESM-LR

The decadal hindcasts and predictions evaluated in this study have been conducted within the
MiKlip project with the MPI-ESM-LR. The MPI-ESM-LR includes the ECHAM6 general
circulation model (European Centre Hamburg model generation 6; STEVENS et al., 2013) for
the atmospheric part and the MPIOM model (Max-Planck-Institute Ocean Model; JUNGCLAUS
et al., 2013) for the ocean component. This earth system model has already been used with a different configuration for CMIP5 (MÜLLER et al., 2012). In this study, the 2nd generation hindcasts (denoted “baseline1” within the MiKlip consortium) are considered. These hindcasts and predictions are initialized yearly on 1st January by nudging the model towards atmospheric and oceanic fields from the reanalysis data. Each of those simulations is named after its initialization time and covers a period of 10 years (e.g. dec1960 is valid from January 1961 to December 1970). The atmospheric and oceanic conditions for initializing the ensemble of hindcasts are taken from different time steps of an assimilation run to represent uncertainties in the initial states of the climate system. The 2nd generation ensemble of yearly initialized hindcasts comprises ten members each. Sea surface temperatures and salinity anomalies necessary for the assimilation run are taken from the ocean reanalysis system (ORAs4, BALMASEDA et al., 2012) of the European Centre for Medium-Range Weather Forecasts (ECMWF). Technical details as well as a comparison between the results from the 1st and 2nd generation of the ensembles can be found in POHLMANN et al. (2013). In order to identify the added value of initialization for decadal predictability, we additionally consider three ensemble members of the so-called uninitialized historical run for the period 1960 - 2005. These simulations are initialized from randomly chosen states of a pre-industrial control simulation and are, unlike the initialized runs, not tuned to the observed ocean and atmospheric states, but use only the observed aerosol and greenhouse gas concentrations as external forcing (1850 - 2005; cf. MÜLLER et al., 2012).

In this study, the MPI-ESM-LR ensemble simulations of large-scale wind speeds are used as predictor (explanatory variable) in the SDD (see section 3.1). These wind speeds are available as 6-hourly output from MPI-ESM simulations on a 1.875° x 1.875° grid (T63).

2.2. ERA-Interim
The ERA-Interim reanalysis data (Dee et al., 2011) from the ECMWF is considered for several purposes: first, it is employed as large-scale forcing for the dynamical downscaling (see section 2.3), and the resulting dataset is used to assess the predictive skill of the baseline hindcasts on the regional scale. Second, daily wind speeds serve as explanatory variables to train the statistical-dynamical approach (see section 3). Wind speeds are considered instead of wind gusts since the reanalysis or climate model datasets do not generally provide a wind gust variable derived with a sophisticated gust parameterization (cf. discussion in Rockel and Woth, 2007; Born et al., 2012). This is also the case for the ERA-interim data (IFS Documentation CY40R1, 2013). Third, mean sea level pressure data is used as input for the cyclone tracking method (see section 3.3). The ECMWF data has a horizontal resolution of 0.7 ° x 0.7 ° and is available in 6-hourly time steps from 1979 until present. For consistency reasons, the ERA-Interim wind speeds are bilinearly interpolated to the target grid (MPI-ESM-LR) before the transfer function to the RCM data is built.

2.3. COSMO-CLM

The regional-scale wind gust speeds are simulated with the COSMO-CLM (RCM of the Consortium for Small-scale MOdelling in CLimate Mode version 4.8., hereafter CCLM [Rockel et al., 2008]). This dynamical downscaling (DD) approach uses ERA-Interim reanalysis data as initial and boundary conditions for simulations with a horizontal resolution of 25km x 25km (0.22 ° x 0.22 °). The simulation area covers Europe including most of the East Atlantic sector. For the following investigations, we consider a section of this area containing all grid points between 13 °W, 40 °E, 25 °N and 71 °N (Figure 1a).

For the calculation of gusts, different parameterizations are available in the CCLM (Born et al., 2012). In this study, we consider wind gusts estimated with the approach from the German Weather Service (DWD), where gusts are computed at 10 m height using friction velocity as
estimator for turbulence (SCHULZ, 2008). The DWD gust parameterization distinguishes between convective and dynamical gusts. Here, the maximum of both convective and dynamical is used. BORN et al. (2012) found that wind gust estimates obtained with the DWD-approach correspond well with both other schemes and observations. Further, they concluded that the method is well calibrated for Germany. The wind gust estimation is computed at each step of the RCM and the largest value of the preceding 60 minutes is stored at every hour. Within the context of the present paper, we use the daily maximum of gust speed for every grid point.

3. Methods

3.1. Estimation of a Transfer Function between Regional and Large Scale

To estimate a transfer function between regional-scale gust data and large-scale wind data, we follow the statistical-dynamical downscaling (SDD) methodology introduced in HAAS and PINTO (2012), which is based on multiple linear regression. In general, the SDD is trained by linking daily maximum wind gusts simulated by the CCLM (regional scale) to ERA-Interim reanalysis daily 10m wind speeds (large scale). Hence, the resulting values from the application of the regression model can be seen as a proxy for wind gusts, but should not be named wind gusts as they were obtained without using an explicit wind gust parameterization like in the CCLM. Therefore, the downscaled wind values derived from the SDD approach are hereafter referred to as peak wind speeds, and are a proxy for gust speeds.

As the transfer function is designed for an application on large-scale MPI-ESM-LR runs, which are simulated on a different grid from that of ERA-Interim, the ERA-Interim data (0.75 ° x 0.75 °) is initially bilinearly interpolated to the MPI-ESM-LR grid (1.875 ° x
1.875 °). The regional-scale daily peak wind speed at each CCLM grid point (predictand $y$) is estimated by the 10m wind speeds ($x_k$) of the 16 surrounding grid points of the large-scale model. That involves the estimation of one regression model per CCLM grid point:

$$y_i = c_0 + c_1 x_{i1} + \ldots + c_k x_{ik} + \epsilon_i \quad i = 1, \ldots, e \quad k = 1, \ldots, 16$$  \hspace{1cm} (1)

where $e$ is the number of included daily values. The regression coefficients $c_k = \hat{c}$ are estimated by the method of least squares:

$$\hat{c} = (X^T X)^{-1} X^T y$$  \hspace{1cm} (2)

where $X$ is the matrix of large-scale predictors $x_{ik}$ and $y$ is the vector of predictands $y_i$. As only the DD includes an explicit gust parameterization, the definitions “DD gust speeds” and “SDD peak wind speeds” are used hereafter.

HAAS and PINTO (2012) demonstrated that the SDD methodology is capable of reproducing DD footprints of extreme windstorms over Europe. Furthermore, a validation against observations provided evidence that the skills of DD and SDD are similar. In section 4, we test how the methodology performs when using not only extreme events but the whole climatology.

### 3.2. Quantile Verification Skill Scores

In order to assess the benefit of the initialization of the hindcasts for decadal predictability, both the hindcasts and the uninitialized historical runs are verified against ERA-Interim with the quantile verification score (QVS). For this purpose, all ten ensemble members are used to determine the ensemble mean quantiles per decade. The quantiles are calculated for different lead times after the initialization and cover the period 1979 - 2005, where all datasets are available. The quantiles of the simulated wind speeds in the original MPI-ESM-LR resolution...
(\(q_{\text{MPI}}\)) are evaluated against the ERA-Interim wind speed quantiles (\(q_{\text{ERA}}\)) resulting in the following quantile verification score (QVS, cf. FRIEDERICHS and HENSE, 2007):

\[
QVSM_{\text{MPI}}(\tau) = \sum_{i=1}^{n} \rho_{\tau}(q_{\text{MPI},i} - q_{\text{ERA},i})
\]

(3)

The parameter \(q\) indicates the ensemble mean \(\tau\)-quantile, with \(\tau\) equal to \{0.01, 0.05, 0.1, 0.25, 0.5, 0.75, 0.9, 0.95, 0.98, 0.99\}, specifying the associated probability. The index \(\text{MPI}\) is equal to \(\text{hist}\) for the historical runs or to \(\text{dec}\) for the decadal hindcasts. The index \(i\) refers to the initialized hindcasts and depends on the considered lead time (e.g. hindcast initialized in 1979 to hindcast initialized in 2005 for lead year 1). \(\rho_{\tau}\) is the check function for the \(\tau\)-quantiles where

\[
\rho_{\tau}(x) = \begin{cases} 
\tau \cdot x & \text{if } x \geq 0 \\
(\tau - 1) \cdot x & \text{if } x < 0 
\end{cases}
\]

(4)

for \(x\) equal to the difference between the MPI quantiles and the ERA quantiles. As a consequence, the overestimation (\(x > 0\)) of high quantiles by the MPI is more penalized than the overestimation of low quantiles, and vice versa in case of an underestimation (\(x < 0\)).

The quantiles of the peak winds obtained from the SDD approach applied to the MPI-ESM-LR wind speeds (\(q_{\text{MPI, SDD}}\)) are compared against gust quantiles downscaled by DD from the ERA-Interim wind speeds (\(q_{\text{ERA, DD}}\)), resulting in the following QVS:

\[
QVSM_{\text{MPI, SDD}}(\tau) = \sum_{i=1}^{n} \rho_{\tau}(q_{\text{MPI, SDD},i} - q_{\text{ERA, DD},i})
\]

(5)

Following FRIEDERICHS and HENSE (2007), we calculate the quantile verification skill scores (QVSS) based on the above-introduced QVS. For this purpose, the QVS of initialized decadal hindcasts (\(\text{dec}\)) are compared to the QVS of the uninitialized historical runs (\(\text{hist}\)) as follows:
The same equation is used for the downscaled historical runs \((\text{hist,SDD})\) and hindcasts \((\text{dec,SDD})\). A QVSS value of zero indicates that no added value is gained from initialization with observed atmospheric and oceanic states. In case of a positive QVSS the skill of the initialized hindcasts is higher than the skill of the uninitialized historical runs, meaning that the initialization leads to an enhanced decadal predictability.

### 3.3. Cyclone tracking

A cyclone identification and tracking method (Murray and Simmons, 1991; Pinto et al., 2005) is applied to 6-hourly ERA-Interim data to obtain complete cyclone life cycles. The Laplacian of the mean sea level pressure is used for cyclone identification as a proxy for the relative geostrophic vorticity (cf. Murray and Simmons, 1991). Trajectories are then built using the tracking algorithm and taking into account the most likely trajectory of a cyclone under the given state of the large-scale circulation. The resulting cyclone tracks include information of the basic properties of the cyclone (e.g. core pressure, propagating velocity) and its changes over time. In this study, the approach is used to quantify cyclone activity in certain time periods.

### 4. Validation: estimated peak winds versus simulated gusts

In order to analyze whether the SDD approach is suitable to quantify the whole range of wind speeds from which the peak wind speeds are recalculated, the estimated transfer function is reapplied to the ERA-Interim data. The SDD transfer function is applied on each calendar day.
between 1979 and 2010. The resulting peak wind speeds are then compared to the wind gust speeds simulated by CCLM (DD).

The differences between DD gust speeds and SDD peak wind speeds (proxy for gusts) are accumulated over the investigation period to calculate the RMSE shown in Figure 1b. At most grid points, the RMSE ranges between 2 ms\(^{-1}\) and 3 ms\(^{-1}\), with the lowest values over Eastern Scandinavia. This leads to an overall RMSE of 2.98 ms\(^{-1}\) for the entire investigation area. The highest deviations occur over the Mediterranean at the southeastern coast of France and over the North Sea near the Norwegian coast. While the generally high discrepancies over the North Sea and the North Atlantic are likely related to the variable roughness length over sea surfaces (due to temporal variable wave heights), it is unclear what leads to the particular large deviations near the Norwegian coast. The differences over the Mediterranean are presumably caused by local wind phenomena like the Mistral (canalized wind in the Rhone valley), which are not well reproduced by the SDD approach.

Detailed results of the SDD simulated peak winds, the DD simulated gusts and the differences of both downscaling methods are presented for selected quantiles (5 %, 50 %, and 95 %) in Figure 2. To a first order, the wind values for the low quantiles are overestimated by the SDD (Figure 2c, 5 %), those for the middle quantiles are well reproduced (Figure 2f, 50 %) and those for the high quantiles are underestimated (Figure 2i, 95 %). For the lower quantiles (Figure 2a-c) DD wind gusts are conspicuously higher than for SDD peak wind speeds and the highest differences are apparent in areas close to high orography. For higher quantiles, the deviations between SDD and DD are most pronounced near the Norwegian coast, Mediterranean and Southeastern Europe (Figure 2g-i). Figure 2g documents the good agreement between areas with enhanced cyclone activity and those with high gust speeds, in particular over the North Atlantic and to a lower extent over the Mediterranean Sea, where the area with maximum wind speeds is slightly shifted westwards.
The overestimation (underestimation) of low (high) wind quantiles by the SDD approach leads to steeper cumulative density functions (CDFs) for the SDD values than those for the DD gusts, yielding narrower probability density functions (PDFs). As an example, the CDFs and PDFs for a grid point next to Cologne (Germany; 6.894547 °E, 50.88583 °N are fitted by a Weibull distribution (Figure 3). The figure also reveals that the PDF of the SDD values is not only narrower, but also a bit skewed to the right: the range of gust speeds above the median is wider than the one below the median. This explains the slight tendency to lower SSD medians compared to DD medians (cf. Figure 2f).

Such discrepancies are systematic, and they appear in both the initialized hindcasts and the uninitialized historical runs. As our aim is to compare both simulations to assess the benefit of the initialization for decadal predictability, the impact of the systematic bias on the computed QVSS is assumed to be negligible. Therefore, the transfer function can be applied to the full ensemble of MPI-ESM-LR without any adjustments. Nevertheless, for specific applications, e.g. for an operational MiKlip prediction system, a bias correction might be appropriate to rescale the peak wind speeds to the range of simulated wind gust speeds and/or observed wind gusts in order to prevent under- or overestimations.

5. Application: Decadal hindcasts on global and regional scale

The aim of this section is to assess the decadal predictability of the 2nd generation decadal hindcast ensemble of the MPI-ESM-LR in terms of global and regional wind characteristics. For this assessment, we first examine whether the hindcasts are able to capture (peak) wind speed quantiles during the extraordinary stormy period 1990 - 1993. Further, the predictive skill of the initialized hindcasts compared to the historical uninitialized runs is determined for different wind quantiles. The dependency of the skill on the forecast time, as well as the
spread within the MPI-ESM-LR ensemble is quantified. Most analyses are performed for both MPI-ESM-LR large-scale wind speeds and SDD regional-scale peak wind speeds.

The early 1990s are characterized by winters with above-average storminess over Europe (e.g., ALEXANDERSSON et al., 2000; FESER et al., 2014). In particular, the 1990 and 1993 seasons featured clusters of windstorms reaching over Western Europe in rapid succession, embedded in an intensified and extended eddy driven jet (PINTO et al., 2014). The following analyses focus on the period 1990 - 1993, which are compared to the climatology of the years 1979 - 2005. Figure 4a depicts the 95 % quantiles of ERA-Interim wind speeds for 1990 - 1993, whose positive anomalies are in agreement with the observed enhanced windstorm activity, especially over the North Atlantic, the North Sea and Central Europe. For other regions like the Mediterranean, the 95 % quantiles of the ERA-Interim wind speeds are lower during 1990 - 1993 compared to the climatology (negative deviation, blue colors). A similar picture is found for SDD simulated regional-scale peak wind speeds (Figure 4e). Only the differences in the south of the investigation area are around zero over land. Both positive and negative deviations are in agreement with the anomalies of the number of cyclone tracks per year (green lines in Figure 4e). The positive anomalies of the 95 % quantiles are in line with the enhanced number of cyclones over the northern and central parts of the investigation area, as the most intense near surface wind speeds associated with a cyclone crossing over this area are typically located a few hundreds of kilometers south of the cyclone core (e.g. PFAHL, 2014, their Figure 8a). Further, the negative deviations over Southern Europe agree with weak cyclone anomalies (around zero) over this area.

In order to verify whether the hindcasts are able to capture the wind characteristics of this anomalous stormy period, the 95 % quantiles of daily maximum wind speeds are calculated for the initialized MPI-ESM-LR runs for the period 1990 - 1993. This four-year period is taken from hindcasts with different initializing dates to analyze the dependency on the lead
time after initialization. We consider the ensemble means of all ten realizations for the years
1-4 of the hindcast ensemble valid from January 1990, years 2-5 of the ensemble valid from
January 1989, and years 6-9 of the ensemble valid from January 1985. The quantiles for
1990 - 1993 are compared to the quantiles of the climatology (1979 - 2005) derived from the
uninitialized historical runs. Figure 4b-d shows that the large-scale wind anomalies in the
hindcasts for this period (1990 - 1993) are similar to those in ERA-Interim in terms of the
sign of the anomalies, although characterised by a smaller magnitude (Figure 4a). Only for
years 6-9 (Figure 4d), some discrepancies against ERA-Interim are noticeable. The same
results can be found for the SDD regional-scale peak winds (Figure 4f-h). For years 1-4, the
patterns of the downscaled MPI-ESM-LR runs agree best with the downscaled ERA-Interim
quantiles, in spite of the different magnitudes (Figure 4e,f). This result suggests that the
initialization enhances the predictive skill mainly for short lead times.

The weaker predictive skill for later years after the initialization can be explained by an
increasing ensemble spread with increasing forecast time, quantified by the standard deviation
of the ten ensemble members. The corresponding standard deviations of the 10 realizations
are shown in Figure 5 for the years 1-4, 2-5 and 6-9. For all lead times, the standard deviation
and thus the spread of the ensemble is highest over the sea, probably caused by higher
offshore wind speeds. This is valid for both the large-scale MPI-ESM-LR wind speeds
(Figure 5a-c) and SDD simulated peak wind speeds (Figure 5d-f). Over land, the standard
deviation is similar for the years 1-4 (Figure 5a,d) and the years 2-5 (Figure 5b,e), and
increases considerably for the years 6-9 (Figure 5c,f). The higher the variation between the
ensemble members, the wider the range of wind speeds, making the identification of outliers
less probable. This leads to comparatively smaller deviations between this period and the
climatology.
To quantify the predictive skill of the MPI-ESM-LR before and after applying the
downscaling technique, quantile verification skill scores are calculated (QVSS, see Section
3.2.). For this purpose, all the hindcasts initialized in the period 1979 - 2005 are taken into
account to calculate ensemble mean quantiles for different lead times. In Figure 6, the QVSS
of the 95 % quantiles is shown for both the large-scale MPI-ESM-LR wind speeds and the
SDD regional-scale peak winds for four different lead times. The highest positive skill scores
(averaged over all grid points) are found for year 1 after initialization, revealing that the
initialization of the hindcasts enhances the predictability for short forecast periods (Figures 6a
and 6e). Skill scores are highest over Central Europe. While the negative skill score in the
south of the investigation area increase, the positive skill score over Central Europe decreases
with increasing time after the initialization and turns negative over parts of the North Sea.
Over land, the QVSS decreases slightly with increasing forecast time, but the values are still
positive except for parts of the Alpine region. Overall, these results indicate that the decadal
hindcasts are closer to the reanalysis than the uninitialized historical runs and that the
initialization with realistic boundary conditions improves the predictive skill over Central
Europe, in particular for short lead times. This is valid for both MPI-ESM-LR wind speeds
and SDD regional-scale peak winds speeds.

The QVSS is subsequently determined for different quantiles of the SDD peak wind speeds.
This is shown in Figure 7 for year 1-4 after the initialization for the quantiles 5 %, 50 %,
75 %, 90 %, 98 %, and 99 %. For all quantiles equal or above 75 %, the spatial QVSS
patterns are quite similar, exhibiting the highest skills along a belt extending from the UK to
the Baltic Sea (Figure 7c-f). Although a similar pattern is also observable for the 50 %
quantile (Figure 7b), there are some negative values within the areas of positive QVSS. For
quantiles below 50 %, the structure of positive and negative skill scores is quite diffuse. A
very heterogeneous QVSS for example is found for the 5 % quantile (Figure 7a), which
indicates that it is generally difficult to predict weak wind periods. While this is probably
associated with the large-scale weak pressure gradients during these periods, it is unclear why
the distribution of the QVSS for this percentile is quite patchy, with high values over e.g.
Central Europe and low values over Scandinavia.

The observed structure for the high quantiles over Northern and Central Europe corresponds
well to the climatology of cyclones per year determined from ERA-Interim, which shows a
North-South gradient over this area (green lines in Figure 7c). This implies that the best
performance can be found for strong wind speeds associated with extratropical cyclones.

However, the agreement between cyclone activity and the QVSS is less tight for Southern
Europe. With increasing quantiles, the magnitude of the skill score decreases. Nevertheless,
for the highest quantile (99 %, Figure 7f) QVSS is predominantly positive over land, which
means that the initialization provides an added value with respect to the decadal predictability.

Finally, the QVSS is determined for quantiles of spatially accumulated wind speeds. This is
done for all grid points within the investigation area (Figure 1a) and within a smaller domain
including Germany and parts of its neighboring countries (see grey rectangle in Figure 6).
Table 1 summarizes the skill scores for large-scale wind speeds in the original MPI-ESM-LR
resolution. If only quantiles greater than or equal 50 % are considered, the highest skill scores
are obtained for the first year after initialization. For quantiles greater than or equal to 90 %
the skill scores typically decrease with increasing lead time. While this finding is valid for
both investigation areas, better values are found for the smaller area, which includes primarily
onshore areas. The results for all lead times and both regions indicate that the enhancement of
the decadal predictability by initialization of the hindcasts is highest for upper wind quantiles.

The results are less clear for the SDD simulated regional-scale peak wind speeds (Table 2).
For high quantiles (90 % or higher) the skill scores are higher for the smaller domain than for
the large European sector across all lead times except for year 1 after the initialization. The
differences between the maxima of the QVSS of the MPI-ESM-LR wind speeds and of SDD
simulated peak winds may be induced by a stronger influence of the SDD underestimation of
the high quantiles on either the hindcasts or the historical runs. Tables 1 and 2 cannot be
directly compared as the first includes results of the large-scale wind speed quantiles, while
the second summarizes the regional-scale peak wind speed results. The generally lower skill
scores for the latter can be attributed to the higher variability of gust / peak wind speeds
compared to wind speeds (e.g. BORN et al., 2012; HAAS et al., 2014). Therefore, it is not
unexpected to find lower skill for regional scale peak winds than for global scale winds.
Nevertheless, the results clearly indicate an improvement of the predictive skill for both the
MPI-ESM-LR large-scale wind speeds and the SDD regional-scale peak wind speeds in the
initialized hindcasts compared to the uninitialized historical runs. Additionally to the
identified predictive skill of the MPI-ESM-LR wind speeds, the SDD allows for the
estimation of peak wind speeds as a proxy for gusts.

6. Summary and Conclusion

In this study, the decadal predictability of large-scale wind speeds from MPI-ESM-LR
hindcasts and of SDD simulated regional-scale peak wind speeds over Europe is evaluated.
The SDD model uses a linear transfer function to derive the peak wind speeds from large-
scale MPI-ESM-LR wind speeds. The transfer function is trained with the ERA-Interim
reanalysis data and CCLM wind gust speeds. In HAAS and PINTO (2012), this approach has
already been applied on a selection of severe windstorms. Here, we showed that the SDD
approach is also able to provide a good estimate for the complete range of peak wind speeds.
Still, the SDD shows an overestimation for the low quantiles and an underestimation for the high quantiles, which leads to a narrower PDF of the peak wind speeds.

The period 1990 - 1993 is characterized by a strong windstorm activity. In order to evaluate the skill of our methodology, we have compared the 95% quantiles of this period to the value of the whole climatology (1979 - 2005). As already found for reanalysis data, the large-scale MPI-ESM-LR wind speeds as well as the downscaled regional-scale peak wind speeds show a positive anomaly of the 95% quantile during this time period over the North Atlantic, the North Sea and Central Europe. The magnitudes of the anomalies in the hindcasts for the period 1990 - 1993 are generally smaller than for ERA-Interim and depend on the forecast time. In particular, the positive anomalies of the 95% quantile are best captured by the MPI-ESM-LR hindcast simulations for short lead times (years 1-4). This may be due to the enhanced ensemble spread with increasing forecast times.

To analyze the performance of the decadal hindcasts both in its original MPI-ESM-LR resolution and in the high resolution after the application of the SDD, quantile verification skill scores are calculated. These skill scores are key for the quantification of the added value of the initialized simulations compared to uninitialized historical runs. Regarding different lead times, we achieved the best QVSS for the first years after the initialization. The skill score values typically decrease with increasing time after the initialization, sometimes becoming negative, especially over offshore regions. Nevertheless, the results suggest that the observations used for initialization still play an important role at forecast times up to year 6-9 after the initialization. If different quantiles are considered, the QVSS patterns are almost unchanged for quantiles equal to or above 75%, but the magnitude slightly decreases for higher quantiles.
The accumulated QVSS has been considered over two investigation areas (Europe versus Germany) and confirms the above results, especially for the MPI-ESM-LR wind speeds. The skill scores of the downscaled regional-scale peak wind speeds are generally smaller compared to the MPI-ESM-LR wind speeds. These differences can be partially attributed to the fact that peak wind speeds estimated by the SDD approach are a proxy for gust speeds, which have a higher variability than wind speeds and are thus more difficult to predict (i.e. smaller QVSS). Nevertheless, the added value is given before and after the downscaling when considering the initialized hindcasts and predictions instead of the uninitialized historical runs. This is the case particularly for quantiles equal and above 75%.

The predominantly positive skill scores over Europe and the Eastern North Atlantic are in line with the results of MÜLLER et al. (2012), who compared surface temperatures of MPI-ESM-LR decadal hindcasts (1st generation ensemble) with observed surface temperatures. MIERUCH et al. (2014) obtained good results using these hindcasts for the prediction of decadal anomalies of temperature over Central Europe, while the results for precipitation were less promising.

Our results indicate that the predictive skill for large-scale MPI-ESM-LR wind speeds and regional-scale SDD simulated peak winds over Europe in the 2nd generation MiKlip ensemble runs is particularly promising for the 1-4 years lead time. This result is in line with the findings of KRUSCHKE et al. (2014), who analyzed the predictive skill of cyclone tracks over the Northern Hemisphere in the same simulations, and with REYERS et al. (2015), who identified a positive skill for wind energy applications over Europe, particularly for Northern and Western Germany. Such results suggest further applications of the SDD method to additional parameters to evaluate the skill of decadal hindcasts for Europe.
While providing an adequate method to obtain regional-scale peak winds from large-scale wind speeds, the SDD method leads to overestimated low quantiles and underestimated high quantiles. For further applications, a bias correction should be applied to adjust the peak wind speed results towards realistic wind gust distributions. For this study, the over- and underestimations were neglected, as they are systematic and concern the downscaling of all datasets used for comparisons, i.e. the initialized and uninitialized simulations. Our analyses showed that the initialized runs are appropriate for decadal predictions of wind and peak wind speeds. For predictions on the regional scale, our methodology is beneficial as it allows for the estimation of peak wind speeds as a proxy for gusts. Furthermore, it enables to quantify whether the probability of occurrence of strong wind events is above or below average for specific periods (an example is shown for the period 1990 - 1993 in this study). The proposed cost-efficient downscaling technique is therefore adequate for an application to large ensemble datasets and thus also for an implementation to operational decadal prediction systems.

Acknowledgments

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STEVENS, B., M. A. GIORGETTA, M. ESCH, T. MAURITSEN, T. CRUEGER, S. RAST, M.


<table>
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<tr>
<th>Abbreviation</th>
<th>Description</th>
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<tr>
<td>BMBF</td>
<td>Federal Ministry of Education and Research (BundesMinisterium für Bildung und Forschung)</td>
</tr>
<tr>
<td>CCLM</td>
<td>RCM of the COsortium for Small-scale MOdelling in CLimate Mode (COSMO-CLM)</td>
</tr>
<tr>
<td>CDF</td>
<td>Cumulative Density Function</td>
</tr>
<tr>
<td>CMIP5</td>
<td>Coupled Model Intercomparison Project Phase 5</td>
</tr>
<tr>
<td>DD</td>
<td>Dynamical Downscaling</td>
</tr>
<tr>
<td>ECHAM</td>
<td>ECMWF HAMburg</td>
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<tr>
<td>ECMWF</td>
<td>European Centre for Medium-Range Weather Forecasts</td>
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<tr>
<td>EURO-CORDEX</td>
<td>COordinated Regional climate Downscaling EXperiment - EUROpean Domain</td>
</tr>
<tr>
<td>MiKlip</td>
<td>Decadal predictions (Mittelfristige Klimaprognosen)</td>
</tr>
<tr>
<td>MPI-ESM-LR</td>
<td>Max-Planck-Institute Earth System Model in its Lower Resolution</td>
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<tr>
<td>MPIOM</td>
<td>Max-Planck-Institute Ocean Model</td>
</tr>
<tr>
<td>ORAs4</td>
<td>Ocean Re-Analysis System of the ECMWF</td>
</tr>
<tr>
<td>PDF</td>
<td>Probabilistic Density Function</td>
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<tr>
<td>PRODEF</td>
<td>PRObabilistic DEcadal Forecast for Central and Western Europe</td>
</tr>
<tr>
<td>QVSS</td>
<td>Quantile Verification Skill Score</td>
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<tr>
<td>RCM</td>
<td>Regional Climate Model</td>
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<tr>
<td>RMSE</td>
<td>Root Mean Squared Error</td>
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<td>SDD</td>
<td>Statistical-Dynamical Downscaling</td>
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Table 1: QVSS for MPI-ESM-LR large-scale wind speeds. The QVSS values are spatially
accumulated over all grid points within the investigation area (EU, Figure 1) and within a
smaller domain including Germany (DE, Figure 6) for selected quantiles and different lead
times (years).

<table>
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<tr>
<th>Lead times</th>
<th>Quantiles</th>
<th>1 %</th>
<th>5 %</th>
<th>10 %</th>
<th>25 %</th>
<th>50 %</th>
<th>75 %</th>
<th>90 %</th>
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<td>-0.044</td>
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<td>0.038</td>
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<td>0.060</td>
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<td>-0.018</td>
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<td>0.050</td>
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Table 2: Same as Table 1 but for SDD simulated regional-scale peak wind speeds.

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<th>Lead times</th>
<th>Quantiles</th>
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</table>
Figure 1: a) Investigation area and topography. b) RMSE between DD gust speeds and SDD peak wind speeds.
Figure 2: From top to bottom: 5%, 50%, and 95% quantiles of dynamically downscaled gust speeds (left) and statistical-dynamically downscaled peak wind speeds (middle) for years 1979 - 2010 of ERA-Interim. Note the different labeling of color bars. Right: Differences between the quantiles of statistical-dynamical and dynamical downscaling (SDD-DD). Green lines: cyclone track density per year per (deg. lat.)² for 1979 - 2010 (based on ERA-Interim).
Figure 3: Example cumulative density functions (solid lines) and probabilistic density functions (dashed lines) fitted with a theoretical Weibull distribution at a grid point next to Cologne (Germany; 6.894547 °E, 50.88583 °N). Red denotes dynamically downscaled values and blue statistical-dynamically downscaled values. The box-and-whisker plots show the 5 %, 25 %, 50 %, 75 %, and 95 % quantiles.
Figure 4: Deviations of the years 1990 - 1993 from the climatology 1979 - 2005. Top: 95 % quantiles of large-scale wind speed for (a) ERA-Interim data, (b) years 1-4 from dec1989, (c) years 2-5 from dec1988, and (d) years 6-9 from dec1984. (b) – (d) are deviations from uninitialized MPI-ESM-LR simulations of the years 1979 - 2005. All MPI-ESM-LR simulations are ensemble means of ten realizations (initialized) or three realizations (uninitialized). Bottom: same as top row but for statistical-dynamically downscaled peak wind values. (e) Green: cyclone track density per year (deg. lat.)² for the period 1990 to 1993 minus 1979 to 2005 (based on ERA-Interim).
Figure 5: Ensemble spread of the 95% wind speed quantiles of the ten initialized MPI-ESM-LR realizations quantified as its standard deviation. Top: (a) years 1-4 from decade starting in January 1990, (b) years 2-5 from decade starting in January 1989, and (c) years 6-9 from starting in January 1985 of large-scale wind speeds. Bottom: as (a) – (c), but for regional-scale SDD simulated peak winds.
Figure 6: Quantile verification skill scores of the 95% wind speed and peak wind speed quantiles for different lead times. Top: (a) year 1, (b) years 1-4, (c) years 2-5, and (d) years 6-9 for large-scale MPI-ESM-LR winds speeds. Bottom: same as top but SDD simulated regional-scale peak wind speeds. Grey rectangle: Smaller investigation area (cf. Tables 1 and 2).
Figure 7: Quantile verification skill scores for SDD simulated regional-scale peak winds for years 1-4 after initialization and for different quantiles: (a) 5 %, (b) 50 %, (c) 75 %, (d) 90 %, (e) 98 %, and (f) 99 %. Green lines: cyclone track density per year (deg. lat.)$^2$ for the period 1979 to 2005 (based on ERA-Interim).