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**Regional Climate Models Add Value to Global Model Data:
A Review and Selected Examples**

REGIONAL CLIMATE MODELS ADD VALUE TO GLOBAL MODEL DATA
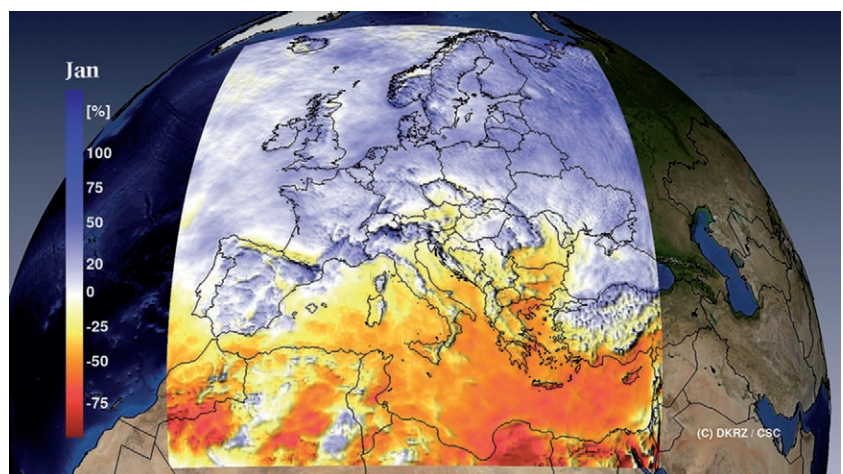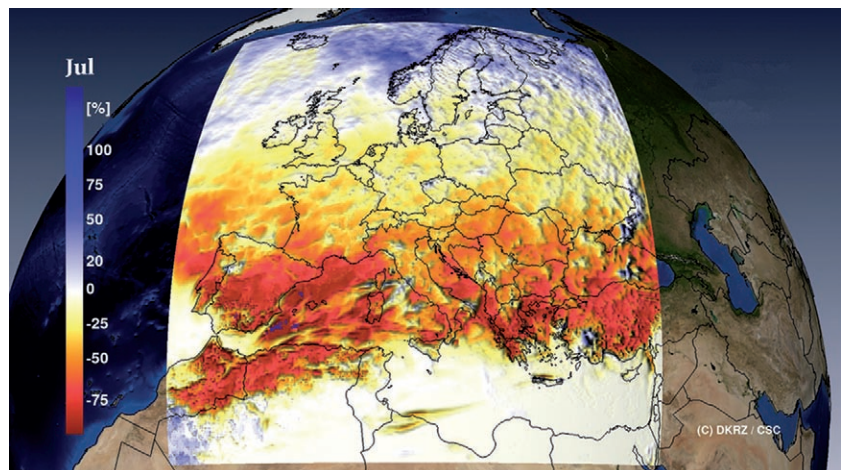
A Review and Selected Examples

by Frauke Feser, Burkhardt Rockel, Hans von Storch, Jörg Winterfeldt, and Matthias Zahn

Regional models may add value to global model results, but improvements depend essentially on the kind of application, experimental setup, analyzed model variable, and location.

HIGH-RESOLUTION CLIMATE MODELING. *Background information.* Atmospheric regional climate models (RCMs) serve a variety of purposes in climate research, such as process studies, weather forecasting, or long-term simulations. Such models include an atmospheric limited-area model combined with a description of the thermodynamics of the upper soil levels (Giorgi et al. 2001) and possibly other components of the Earth system (such as marginal seas and lakes). Reviews on regional climate modeling can be found in Foley (2010), Giorgi and Mearns (1999), Rummukainen (2010), and Wang et al. (2004).

RCMs are forced by time-variable conditions along the lateral atmospheric boundaries, sometimes also with large-scale constraints in the interior (von Storch et al. 2000; Miguez-Macho et al. 2004; Castro et al. 2005). These constraints are taken either from global model scenarios (Christensen and Christensen 2003) or from global reanalysis (Feser et al. 2001; Sotillo et al. 2005). They use high-resolution topographic details and can provide ▶

(TOP) Precipitation change in percentage 2070–2100 (IPCC scenario A1B) vs. 1961–1990, simulated with the RCM CCLM for summer. (BOTTOM) Precipitation change in percentage 2070–2100 (IPCC scenario A1B) vs. 1961–1990, simulated with the RCM CCLM for winter. Images courtesy of Michael Böttinger, DKRZ (visualization) / CSC (simulation).

multiyear to multidecadal weather information for past or future scenarios (Jones et al. 1995, 1997; Salathé et al. 2008). An important utility of such multidecadal model data is to quantitatively describe hazards and changing conditions in the regional Earth system, such as ocean currents, sea level, storm surges, or ocean wave conditions and related threats [e.g., compilaton of coastal analyses and scenarios for the future obtained from numerical models (CoastDat); see Weisse et al. 2009].

In addition to prevailing large-scale conditions, local climate is influenced by regional aspects, such as local orography, land–sea contrast, and small-scale atmospheric features such as convective cells, which are not well represented in global climate models. Limited computer resources prevent the practical use of high-resolution models for global simulations of long time periods. An alternative is a global climate model with regional refinements (e.g., Déqué et al. 1994; Côté et al. 1998; McGregor and Dix 2008). The computer resources required to run such models are less than those for high-resolution global climate models, but are still considerable.

RCMs are therefore constructed for limited areas with a considerably higher resolution to describe regional-scale climate variability and change. During the simulations these RCMs are controlled by the global climate driving data via various mathematical routines. This technique is called dynamical downscaling. Denis et al. (2002) developed a rather idealized way of testing the downscaling ability of nested RCMs called the Big-Brother Experiment. Instead of using data from global reanalyses, forecasts, or climate models as forcing for the RCMs, this method computes a high-resolution reference climate and

then degrades it by low-pass filtering. This filtered data is then used to drive the same limited-area model. Another method of downscaling, known as statistical downscaling, uses statistical relationships between observed small- and large-scale variables to derive climate at the regional scale from global climate model results. For a comparison of both methods we refer the reader to the work of Murphy (1999), for example.

Article objectives. One main purpose of regional climate modeling is to provide additional detail beyond the resolution of global reanalyses or global climate simulations. RCMs are also used for process studies or sensitivity experiments at the regional scale. In this article we will focus on the dynamical downscaling aspect. A large number of studies demonstrate that RCMs can realistically simulate weather and its statistics in comparison to observations (e.g., Früh et al. 2010; Kunz et al. 2010; Semmler and Jacob 2004). Other studies use dynamical downscaling of global climate model datasets with increasing greenhouse gas concentrations (e.g., Frei et al. 1998; Leung and Qian 2009; Rauscher et al. 2008). All of these studies implicitly assume a superiority of the RCM output over the driving global data, but usually do not explicitly prove this. The additional knowledge gained by the RCM is commonly termed "added value," but so far it has not been well explored and efforts in determining this added value are rare. There are even fewer studies on comparisons of RCM simulations with a geostatistical postprocessing of global model input data (e.g., Lo et al. 2008; Wood et al. 2004). Therefore, in this paper we will focus on direct RCM–global climate model comparisons.

In this article, efforts to determine such added value in case studies as well as in multidecadal simulations with different RCMs are summarized and evaluated. The simulations presented here mostly comprise "reconstructions," for example, simulations of the weather dynamics since 1948 until today of western Europe or the northwestern Pacific. Most of these simulations use a grid distance of about 50 km, have been constrained with spectral nudging (von Storch et al. 2000), and use global National Centers for Environmental Prediction–National Center for Atmospheric Research (NCEP–NCAR) reanalysis (hereafter the NCEP reanalysis; Kalnay et al. 1996) as forcing data.

The spectral nudging technique was used because in some cases RCMs can also deteriorate those scales for which they were not designed, namely, the global scales (e.g., Castro et al. 2005; Kanamitsu et al. 2010;

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CORRESPONDING AUTHOR: Frauke Feser, Max-Planck-Str. 1, Institute for Coastal Research, Helmholtz-Zentrum Geesthacht, 21502 Geesthacht, Germany
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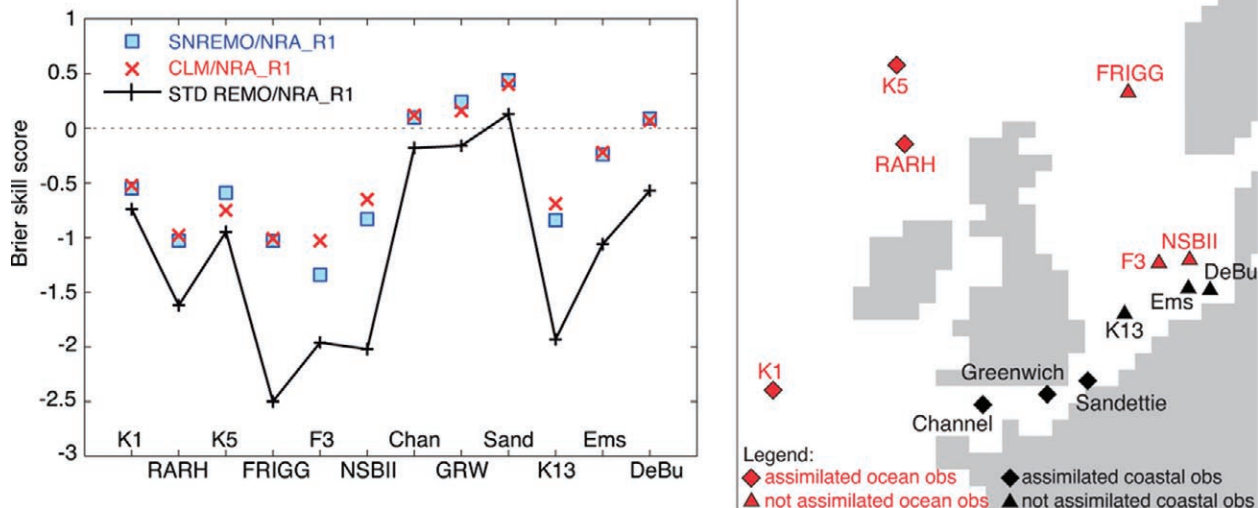Fɪɢ. 1. (left) BSSs, using buoy/in situ data as the truth; NCEP reanalysis (NRA_R1) time series as the reference forecast; and SN-REMO, STD-REMO (forced only via lateral boundaries), and CCLM time series are the forecasts, after Winterfeldt and Weisse (2009). (right) Locations of wind speed observations (obs) over the land–sea mask of the regional model.

von Storch et al. 2000). The technique makes sure that the global scales are not altered too much by the regional model, while allowing the regional scales to be developed exclusively by the regional model. Applications of spectral nudging led to encouraging results, which was also the case for ensemble studies (Weisse and Feser 2003).

ADDED VALUE. Global analysis or model data are assumed to reliably describe the dynamics of large-scale weather phenomena. Features resolved in numerical data are typically on the order of four grid boxes or above (Pielke 2002). For global reanalysis products, this means that phenomena smaller than about 500–800 km are not represented well. An RCM should give more realistic results at medium spatial scales, for example, at 600 km and less (e.g., an RCM with a maximum grid distance of 100 km, which can resolve weather phenomena with at least four to six grid points extension). Therefore, an added value of regional climate modeling is to be expected mainly at these regional dimensions (Laprise 2003). A new concept to define potential added value (regional climate statistics have to contain some fine spatial-scale variability that would be absent on a coarser grid as a necessary condition for added value) was recently introduced by Di Luca et al. (2011). RCMs are very sensitive to the physical parameterizations that are chosen (Christensen et al. 2007), which will also influence the ability of the RCM to add value. For the sake of brevity this point is not addressed in this

paper. In the following we will discuss some examples of studies in which the RCM is shown to add value compared to the forcing global climate model.

Near-surface wind speed. Winterfeldt and Weisse (2009) compared near-surface wind speeds of two regional models—the regional climate model (REMO; Jacob and Podzun 1997) and the Consortium for Small-Scale Modelling (COSMO) model in Climate Mode (CLM) (CCLM; see clm-community.eu; Rockel et al. 2008b; Steppeler et al. 2003)—and a global reanalysis (which served as input for the RCMs) of buoy data close to the coast and further off the coast in the North Sea. REMO was run with spectral nudging (SN-REMO) and without (STD-REMO), and CCLM was run with spectral nudging only. The nudged RCM was forced to simulate the large-scale features (which are assumed to be well resolved) of the driving fields correctly, while the dynamics at smaller scales were simulated solely by the RCM. The nudging method was applied only to horizontal wind components above 850 hPa (with increasing strengths toward higher model levels), where regional features become less important.

Figure 1 (right part) shows the location of the buoys used for the comparisons. Some of them were also used (assimilated) for the global reanalysis. The left part depicts the statistical measure of the Brier skill score (BSS) as a means of assessing the quality of model data compared to measurements. Positive values demonstrate an added value of the regional
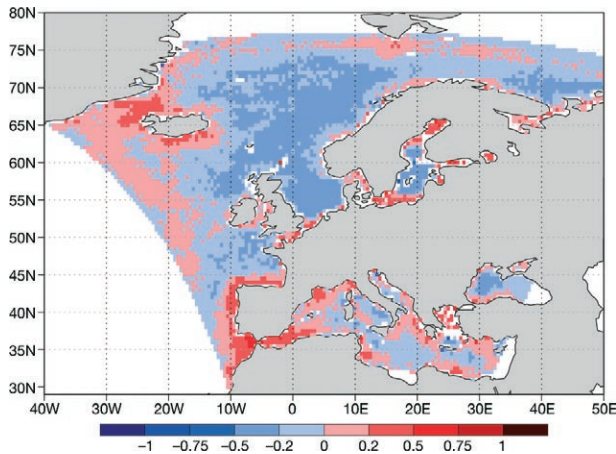
FIG. 2. Brier skill score using QuikSCAT level 2B12 as the truth, global reanalysis (NCEP reanalysis) as the reference forecast, and a regional model (SN-REMO) as the forecast, after Winterfeldt et al. (2010).

models over the global reanalysis. The spectrally nudged simulations always have a higher BSS than STD-REMO, and thus CCLM and SN-REMO reflect the measurements better than the regional model run the conventional way. While STD-REMO has negative BSS values at all stations apart from the coastal light ship *Sandettie*, SN-REMO and CCLM have positive BSS values for the four coastal light ships [*Channel*, *Greenwich*, *Sandettie*, and *Deutsche Bucht* (*DeBu*)]. Thus, global reanalysis wind speed time series are closer to the observations at all open-ocean stations (independent of their assimilation status), and even at the two coastal stations of K13 and Ems. The assimilation status of the coastal stations is of minor importance, because SN-REMO has positive BSS values for all three assimilated light ships in the English Channel, and one unassimilated coastal station only, namely Deutsche Bucht.

Winterfeldt et al. (2010) used satellite data to detect added value in dynamically downscaled wind speed fields. Quick Scatterometer (QuikSCAT) satellite data over northern Europe were compared to RCM (SN-REMO) near-surface wind speed. The BSS is displayed in Fig. 2. In large areas of the North Atlantic, the BSS is negative, indicating that dynamical downscaling does not add value there. The same holds for the interior of the Mediterranean, Baltic, and Black Seas.

Most mesoscale features such as land–sea wind circulation, or other orographically induced wind systems, do not occur over the open ocean but rather close to the coasts. Because these are some of the phenomena that a regional model may simulate more realistically than a global model, they can possibly

show some added value of RCMs. The regional model does not add value over the open ocean because of the lack of orographic details and infrequent mesoscale phenomena there. It may even be worse than the reanalyses, which is reflected by the negative BSSs. While the reanalysis assimilates near-surface winds, Winterfeldt and Weisse (2009) showed that the negative BSS in the open ocean was independent of the assimilation of near-surface wind observations. It is instead caused by the inferior representation of large-scale features, especially in time, combined with the low frequency of mesoscale features that drive the negative BSS scores in the open ocean. As indicated by positive BSS values, SN-REMO is able to add value in coastal areas, mainly for those with complex coastlines or topography. This is especially the case around the Iberian Peninsula, in the Mediterranean, English Channel, and Irish Sea; between Iceland and Greenland; and close to the coastlines of the Baltic and Black Seas. In these regions, where mesoscale phenomena are more common, the added value of the RCM is also clear (e.g., the mistral area can be identified by positive BSS values).

Sea level pressure, temperature, kinetic energy, and moisture flux. Regional models are mainly assumed to add detail at the specific scale for which they were constructed, which means that for added-value detection a scale separation may provide clearer results. By using spatial filters, model data can be separated into wavenumber ranges that should give the best improvement by either the global or the limited-area model. Scale-separated atmospheric model fields can be used to evaluate model variability, analyze comparisons or process studies, and locate added value.

The scale separation discussed here was performed using the digital filter described in Feser and von Storch (2005). The scale-dependent skill of a state-of-the-art RCM was examined by computing pattern correlation coefficients between spatially filtered global reanalyses, RCM simulations (with and without nudging of large scales), and an operational regional weather analysis as a reference. The operational analysis was provided by the German Weather Service [Deutscher Wetterdienst (DWD); 0.5 ° × 0.5 ° grid distance], and in the following it is regarded as the "truth," even though the analysis is a blending of available observation data as well as model forecasts.

Figure 3 shows the time series of pattern correlation coefficients (PCCs; which are to be interpreted as a conventional correlation coefficient, but across space instead of time) for two sample seasons for

near-surface pressure and temperature (Feser 2006). Shown are PCCs for full fields, low-pass-filtered (global scale), and bandpass-filtered (regional scale) fields. The dependency of the RCM results on the large-scale forcing is apparent in the pressure PCC; large differences between NCEP reanalyses and DWD analyses coincide with even greater differences between the RCM simulations and the DWD analyses for the unfiltered and low-pass-filtered fields. Thus, not surprisingly, both differences are reduced by applying the nudging technique. An improvement in the representation of large scales, as enforced by the nudging, is associated with an improvement of the simulation at the medium scales.

FIG. 3. (left) Six-hourly time series of SLP PCCs between DWD analyses and reanalyses or regional model data after Feser (2006) for winter 1998/99. (right) Time series of 2-m temperature anomaly PCC for summer 1998 for (top) full fields, (middle) low-pass-filtered, and (bottom) medium-pass-filtered fields.

When a higher spatial resolution is less important, as is the case for the more uniform variable air pressure, the overall added value is small. The RCM stands little chance to improve the large-scale field because the only relevant factor available is the driving analysis. The situation is different for air temperature because the regional dynamics of this variable depend strongly on the high-resolution detail. Therefore, the RCM is capable of improving the simulation not only of the medium-scale temperature fields, but also of the full field. The PCCs of the medium-pass-filtered and unfiltered fields are always higher for the RCM

simulations than for the global reanalyses. The largest added values are at the medium scales, where the regional models were expected to give the best results. For the PCC of the low-pass-filtered fields the conventional RCM simulation shows a deterioration compared to that of the NCEP reanalyses. In contrast, when nudging is applied to the large scales a small added value is obtained (note that the nudging is toward the global reanalyses, not toward the DWD analyses).

These findings are substantiated by Table 1, which lists the mean PCC P_{DWD}(NCEP) for the full and anomaly fields (with deviations from the time mean fields) as well as mean differences between PCCs of the regional simulations and P_{DWD}(NCEP). The table shows an improvement or deterioration by the RCMs over the global reanalyses. The mean improvement in sea level pressure (SLP) for the regional model is 1.4% for winter and 4.1% for summer with nudging of the large scales. No added value is provided for the standard RCM simulation. A similar result is obtained for the SLP anomalies (deviations from the long-term mean). The result is improved for air temperature. Simulations with the nudging of large scales give significant added value in both seasons for all spatial scales. These values are even larger for the anomalies. Without the nudging of large scales, no added value is obtained for large scales, but there is a significant increase for the medium-scale PCC.

Another example of improved temperatures in the RCM results was given by Prömmel et al. (2010), who showed that regionally simulated near-surface alpine temperatures display the largest added value over the forcing global reanalyses in regions with the most complex topography. Feldmann et al. (2008) compared precipitation fields over complex orographic terrain in southwest Germany, simulated by regional and global models, to the observations. The regional models added value to monthly climatological precipitation, especially during the summer months. The improvement was smaller in winter because of an overestimation of winter precipitation by the forcing global model and by the stronger coupling between the global and regional model arising because of more frequent baroclinic conditions with stronger cross-boundary flow.

Evidence for the added value of RCMs is also given in a dynamical downscaling study by Castro et al. (2005), who examined the value that was retained and added by a regional model in comparison to global NCEP data. The regional model successfully resolved the smaller-scale features, but on the large scales kinetic energy was lost, and therefore the value of the global reanalysis was not retained. This loss was reduced by applying an internal grid nudging (four-dimensional data assimilation), but at the same time the variability of kinetic energy for the regional scales was reduced.

A follow-up paper by Rockel et al. (2008a) repeated the experiments of Castro et al. (2005), but used another regional model (CCLM) with different resolutions and in addition to a spectral nudging technique. The change in kinetic energy (KE) and moisture flux convergence (MFC) was analyzed both on a large and
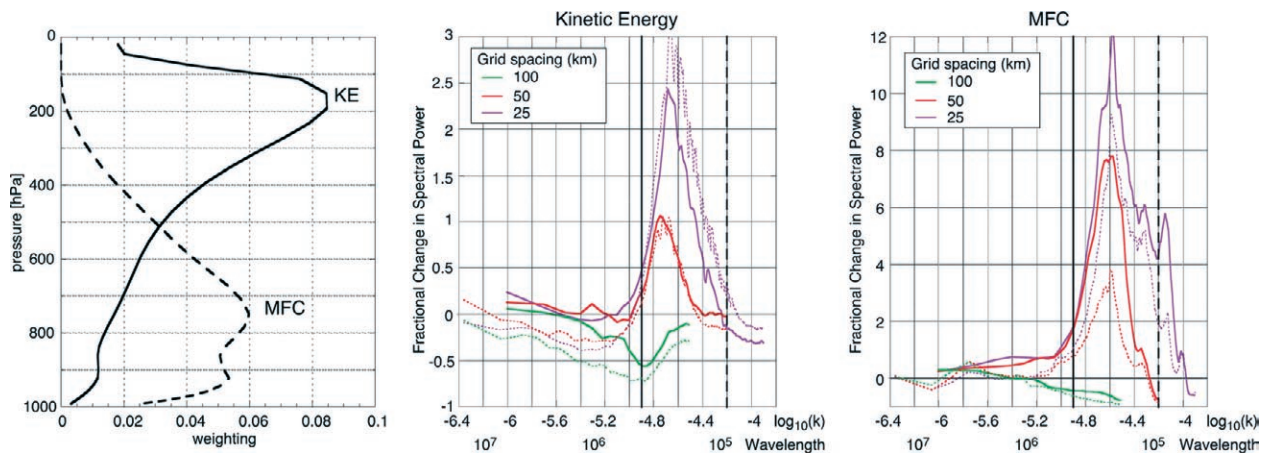

FIG. 4. (left) Vertical contribution of kinetic energy and moisture flux convergence to total vertically integrated values (e.g., the mean over the large-scale domain of 50-km control simulation). Fractional change in spectral power for (middle) column-averaged total kinetic energy and (right) integrated moisture flux convergence as a mean over the last 15 days of May 1993. Results are for Δx = 100 km, 50 km, and 25 km on the small RCM domain. The results on the large domain are shown (dotted lines); k (m^{-1}) and wavelength (m) are given. The wavenumber of physically resolved waves for the course grid model (vertical solid lines) and the 25-km RCM (vertical dashed lines) are shown. Figure is reproduced after Rockel et al. (2008a).

small model domain and was compared to the global forcing model [40-yr European Centre for Medium-Range Weather Forecasts (ECMWF) Re-Analysis (ERA-40); see Uppala et al. 2005]. Figure 4 (left) depicts the vertical distributions of KE and MFC. It shows the great influence of the upper troposphere to the column-integrated KE and also shows that the largest contribution to the MFC comes from the planetary boundary layer because of the high moisture fluxes close to the surface.

The KE variability added by the RCM, compared with that from the global reanalyses, is presented in Fig. 4 (middle). Solid (global) and dashed (regional, 25-km grid distance) lines denote the wavenumbers of the physically resolved waves of the models according to the assumed $4 \times \Delta x$ (4 × grid distance) limit between resolvable and nonresolvable spatial scales (Pielke 2002). For low wavenumbers the RCM retains approximately the same variability as the global reanalysis, and for higher resolutions larger added variability appears.

For the MFC (Fig. 4, right) the regional simulations show comparable results to the KE, but the variability for wavenumbers larger than the wavenumber of the physically resolved waves is highly enhanced. The dotted curves in Fig. 4 (middle and right) describe the variability added by the RCM for the large domain for both KE and MFC. The results differ in that the KE is less retained at the large scales on the large domain, while increased variability is visible for smaller scales. For MFC the opposite is true. Large-scale variability of the global reanalysis is retained almost completely, while added variability is reduced for smaller wave lengths. This result is valid for RCM simulations with a resolution of 25, 50, and 100 km. The small RCM domain includes mostly land points, whereas for the large domain mainly ocean grid points were added. Therefore, in the large domain the SST is more important, influencing humidity, and thus the MFC,

and leading to the different behavior of the KE and MFC for large and small RCM areas. In this study, the added variability of RCM simulations compared to global reanalyses, especially for those spatial scales that are primarily resolved by the RCM, indicates an added value from the regional model.

Rockel et al. (2008a) also found that, depending on the model area and the degree of exchange via the lateral boundaries, success in simulating the "right" features at the observed time and location may depend on the constraint of the large-scale dynamics. This is in agreement with the results of Rinke and Dethloff (2000), who showed that in the circumpolar Arctic domain the lateral boundary control is weaker than that in model areas of similar domain sizes in midlatitude areas, which experience regular exchange (flushing) via the lateral boundaries of the prevalent eastward circulation. Another conclusion is that RCMs may develop systematic errors in the simulation of the large-scale flow if the boundary forcing is weak.

Polar lows and typhoons. RCMs allow for a more realistic description of mesoscale phenomena such as North Atlantic polar lows and East Asian typhoons (Zahn and von Storch 2008; Feser and von Storch 2008). Polar lows are mesoscale (200–1000 km) maritime, gale-producing storms in polar regions. In Fig. 5 mean sea level pressure (MSLP) and wind speed fields from analysis, reanalysis, and RCM data are shown at a time when a polar low has evolved in the North Atlantic. In the DWD analysis, the polar low is visible with closed isobars off the Norwegian coast, whereas in the NCEP field only a weak pressure trough exists. In the NCEP-driven climate mode RCM simulation, the polar low does develop more distinctly, but is shifted a bit in space and with a too-high core pressure (Zahn et al. 2008).

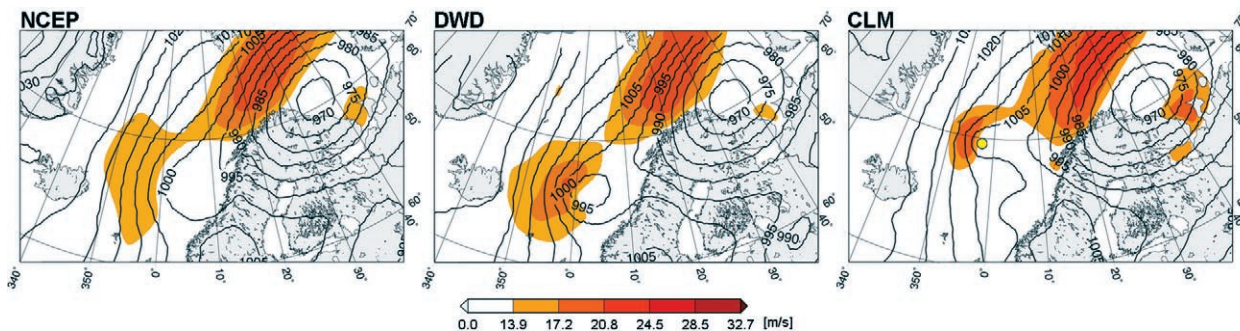In Fig. 6 the sea level pressure (isobars) and 10-m wind speed fields (colored patterns) were spatially

FIG. 5. Isolines of air pressure (hPa; at mean sea level) and shaded 10-m wind speed (≥13.9 m s⁻¹) at 0600 UTC 15 Oct 1993: NCEP analysis after interpolation onto the CCLM grid, DWD analysis data, and CCLM simulation (after Zahn et al. 2008). The position of the polar low's pressure minimum in the CCLM simulation is shown (yellow dot).
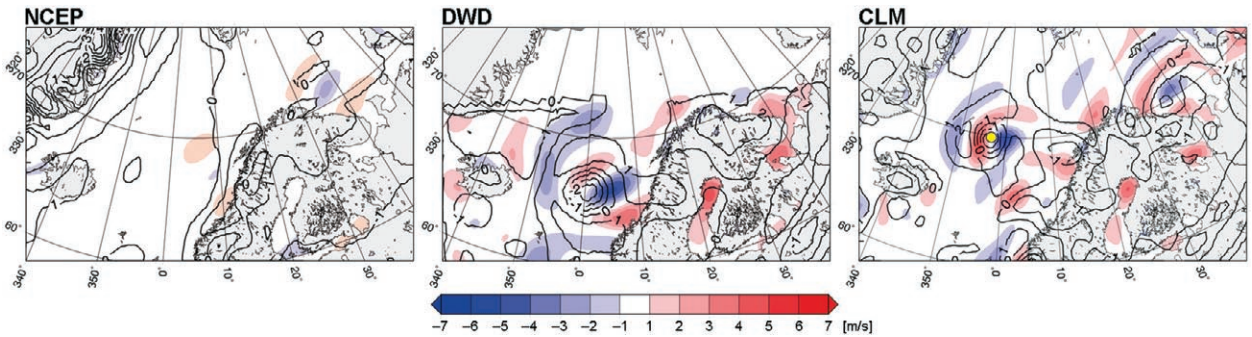
FIG. 6. Bandpass-filtered MSLP (isolines; hPa) and 10-m wind speed anomalies (shaded) at 0600 UTC 15 Oct 1993: NCEP analysis, DWD analysis data, and CCLM simulation (after Zahn et al. 2008). The position of the polar low's pressure minimum in the CCLM simulation is indicated (yellow dot).

filtered to analyze the polar low of Fig. 5 in more detail. A digital bandpass filter was used (Feser and von Storch 2005), which let weather phenomena sized between 200 and 600 km pass. This is the expected spatial scale of polar lows and therefore gives an indication whether the polar low appears in the data or not. In the filtered NCEP fields the bandpass filter shows some artificial sea level pressure isolines over the mountainous coast of Greenland, which is probably a result of orographic effects (note that MSLP needs to be extrapolated from model levels over mountainous regions). There is no anomaly over the ocean. For the DWD and CCLM data, however, the filter clearly visualizes the mesoscale anomalies as distinct minima in the filtered MSLP fields.

Although the RCM resolution still is too coarse to reproduce every dynamical detail of the polar low correctly, its added value is still large enough to allow for the development of a polar low climatology (Zahn and von Storch 2008) as well as a future projection of polar low frequency (Zahn and von Storch 2010). Such studies, which aim to assess long-term changes in polar low frequency, do not require every single case to be simulated correctly, but rather need their statistics to be realistically reproduced. Because the global data are too coarse to resolve polar lows in many cases, the RCM adds substantial value here in enabling an analysis of the polar low frequency on decadal time scales.

Another example of a mesoscale phenomenon is a typhoon. Feser and von Storch (2008) performed a feasibility study of regional typhoon modeling for a typhoon season in the western Pacific in which 12 typhoons were analyzed. Ten of those could be simulated both by the forcing global reanalysis as well as by a regional model. These individual typhoons were compared to the Japan Meteorological Agency (JMA) best-track data. These best-track data include all sorts

of observational data, including satellites, and they are considered the truth for this comparison. The regional model was run with two resolutions, first with about 50 km × 50 km (0.5°), and in a double-nesting approach with about 18 km × 18 km (0.165°). Both simulations were spectrally nudged. The BSS was computed for SLP and for near-surface wind speeds. Positive values indicate that the regional model is closer to the best-track data than the global reanalysis,
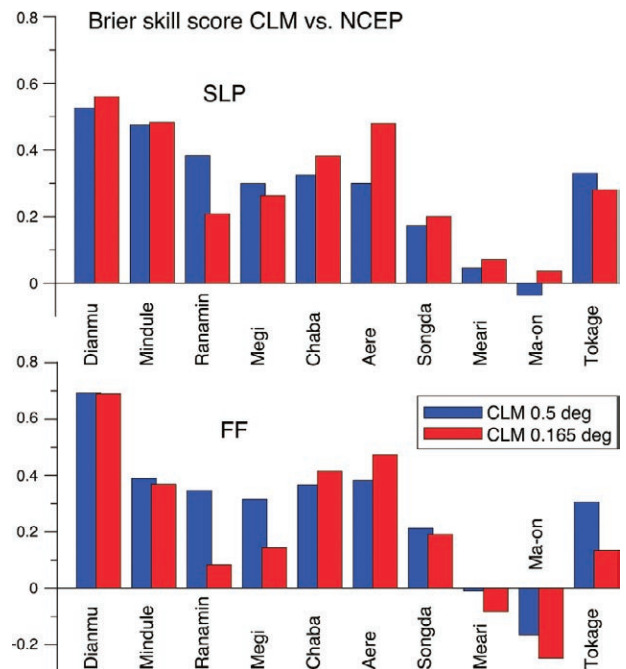

FIG. 7. Brier skill score between JMA best-track data and NCEP, CCLM at 0.5°, and CCLM at 0.165° for (top) SLP and (bottom) 10-m wind speed for analyzed typhoons (after Feser and von Storch 2008). For values larger than 0 the CCLM is closer to the best track than NCEP reanalysis, for 0 CCLM is equally close to the best track as NCEP reanalysis, and for values smaller than 0 NCEP is closer to the best track than CCLM.

while negative values indicate more realistic values for the reanalysis.

In all typhoon cases, except for one named Ma-On (200422), the SLP development is better described by the regional model (CCLM) than by the reanalysis (NCEP). In 7 out of the 10 cases, the high-resolution (0.165°) CCLM performs better than the coarse (0.5°) CCLM. In three cases the improved resolution does not lead to results closer to best-track data in terms of SLP (Fig. 7 shows the BSS of CCLM versus NCEP). The result is not as good for wind speed (see Fig. 7). In terms of this variable, CCLM shows larger discrepancies compared to the best-track data than NCEP in 2 out of 10 cases. Usage of 0.165° grid sizes leads to results closer to the best track than the 0.5° grid sizes in only 2 out of 10 cases. In 8 of the 10 cases, the 0.5° CCLM performs better than the 0.165° CCLM.

The examples given above highlight some variables and features of regional models that were expected to provide added value compared to the forcing global model. There may be other RCM properties that also lead to added value and other regional model characteristics might also lead to a deterioration of global model results.

SUMMARY AND CONCLUSIONS. Regional atmospheric models are tools used to achieve high-resolution climate data from coarsely resolved global models. Regional models show higher detail for mountain ranges or coastal zones, more numerous and differing vegetation and soil characteristics, and a description of smaller-scale atmospheric processes, which lead to the formation of mesoscale weather phenomena. These RCM characteristics are believed to produce model output that is closer to reality than the more coarsely resolved global model data, both for reanalyses for hindcast studies, and for global scenario simulations.

It has been shown in this paper that dynamical downscaling does not add value to global reanalysis wind speed in open ocean areas, while it does for complex coastal areas. The regional model needs the higher-resolved orography or coastlines to achieve more realistic results than the already well-described global reanalyses for near-surface wind speed. Regional models show an added value in describing mesoscale variability compared to the driving global reanalysis, in particular, when the RCM is constrained at the large spatial scales. This is more obvious for variables, such as near-surface temperature, that are more heterogeneous than sea level pressure. A comparison of column-averaged KE and integrated MFC revealed enhanced variability for RCM simulations compared to a coarser global reanalysis. This added variability occurred mainly on those spatial scales that are best resolved by the regional model, indicating added value from the RCM. The location of mesoscale phenomena such as polar lows can be described realistically in RCM simulations, but not all polar lows can be found in the global reanalysis. Regional modeled typhoon core pressure values and the corresponding near-surface wind speed values were, in general, closer to the reference best-track data than the forcing reanalyses.

We conclude that RCMs do indeed add value to global models for a number of applications, variables, and areas. If examined only at the regional scale, added value emerges very distinctly for many model variables, justifying the additional computational effort of RCM simulations.

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