Hybrid downscaling of wind climates over the eastern USA

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Abstract

Weibull distribution parameters (scale and shape) of wind speeds at 85 stations over the eastern USA are downscaled from distribution parameters of large-scale climate variables drawn from both global and regional models. A probabilistic statistical downscaling approach when applied in hybrid downscaling (combining dynamical and statistical downscaling), exhibits skill in reproducing the macro-scale variability in wind climates in independent data. However, use of predictors from a regional climate model (RCM) run at 50 km resolution does not substantially improve the downscaling results over those obtained when direct output from the parent atmosphere ocean general circulation model (AOGCM) run at approximately 200 km resolution is used for the predictors. The technique is applied to develop projections of mean and 90th percentile wind speeds based on output from six sets of RCM simulations. Projected differences in the mean and 90th percentile wind speeds based on output from six sets of RCM simulations, Projected differences in the mean and 90th percentile wind speeds based on output from six sets of RCM simulations, Projected differences in the mean and 90th percentile wind speeds based on output from six sets of RCM simulations, Projected differences in the mean and 90th percentile wind speeds based on output from six sets of RCM simulations, Projected differences in the mean and 90th percentile wind speeds based on output from six sets of RCM simulations.

Keywords: climate change, wind speeds, regional, downscaling

1. Introduction and objectives

There is interest in assessing how regional wind climates may evolve under a non-stationary climate because possible changes in wind regimes and intense wind events are of importance to a variety of potential climate change feedbacks (e.g. emissions of sea spray (Latham and Smith 1990), and erosion of sea-ice (Ogi and Rigor 2013)), ecological impacts (e.g. seed dispersal (Bullock et al 2012), and forest health and primary productivity (Blennow et al 2010, Peltola et al 2010)), and a number of other socio-economic sectors (e.g. transportation infrastructure and operation, electricity generation and distribution, structural design codes for buildings) (Della-Marta et al 2010, Kunz et al 2010, Pryor and Barthelmie 2013).

Prior research has sought to downscale wind climates from coarse grid-scale output from Atmosphere-Ocean General Circulation Models (AOGCMs) using a variety of empirical or/and dynamical approaches (Pryor et al 2005, 2006, Pinto et al 2010, Salameh et al 2009, Rockel and Woth 2007, Pryor et al 2012b, 2012a, Della-Marta and Pinto 2009). Here we adopt a hybrid approach in which AOGCM output is dynamically downscaled via application of Regional Climate Models (RCMs) and the resulting RCM output is further downscaled to the local (station) scale using an empirical probabilistic approach.

The research objectives are:

1) Quantify the skill of a probabilistic downscaling approach developed and previously applied over northern Europe (Pryor et al 2005, 2006) in reproducing the contemporary near-surface wind speed climate over the eastern United States of America (USA). This analysis is somewhat
analogous to transferability experiments in dynamical downscaling (Jacob et al 2012, Takle et al 2007).

(2) Quantify the degree to which hybrid downscaling (i.e. application of RCMs to generate higher resolution fields of the predictors) enhances the probabilistic downscaling skill relative to direct use of lower-resolution output from AOGCMs. This analysis is thus an assessment of ‘value-added’ to the downscaling by dynamical downscaling to 50 km resolution to produce predictors for the empirical downscaling (see Castro et al 2005, Chen et al 2012, Elguindí and Grundstein 2013 for discussion of the value-added by downscaling).

(3) Contingent on the findings relative to objectives 1 and 2, to quantify possible changes in wind climates over the eastern USA by mid-century and determine the degree to which any changes in the mean and 90th percentile wind speeds are consistent across the suite of RCMs used to derive the downscaling predictors. The 90th percentile wind speed (p90) is used here as an index of intense wind speeds, and because of the strong association between p90 end-user relevant metrics such as the wind energy density (Pryor and Barthelmie 2010). We further evaluate the degree of consistency in projected changes in wind speed regimes (2041–2060 versus 1981–1998) relative to those determined by direct output from these RCMs (presented in Pryor et al (2012b)).

2. Data and methods used

The probabilistic downscaling approach used here is predicated on the concept that the probability distribution of observations of a geophysical variable conforms to a known distribution type, and down scales the distribution parameters of a near-surface variable using distribution parameters of large-scale climate variables as predictors. This probabilistic framework is thus fundamentally different to approaches that seek to downscale a time series, and has been used previously to downscale wind (Pryor et al 2006) and precipitation (Schoof et al 2010) climates. In this research, wind speed observations (U) are described using a Weibull distribution:

\[ p(U) = \frac{k}{A} \left( \frac{U}{A} \right)^{k-1} \exp \left[ -\left( \frac{U}{A} \right)^k \right] . \]  

Thus the downscaling predictands at each station are the shape (k) and scale (A) parameters.

The downscaling predictors are moments of the probability distribution of the mean sea level pressure gradient (PG) and relative vorticity at 500 hPa (ζ). Time series of 3-hourly ζ are computed from u and v components of the wind speed fields at 500 hPa, and PG is computed as the maximum between adjacent grid points (in any of eight directions) and then the mean and standard deviation of the time series of ζ and PG are used as downscaling predictors. These predictors are used; (i) to assure consistency with prior research (and thus allow assessment of transferability), (ii) because they have been used previously to characterize winter storms (Della-Marta and Pinto 2009, Long et al 2009), (iii) because wind climates are strongly linked to the intensity of transient synoptic scale phenomena and vertical coupling as represented by PG and ζ (Pryor et al 2005) and (iv) because they have been demonstrated to be robustly reproduced by AOGCMs relative to reanalysis data sets (Pryor et al 2005).

The downscaling equations are:

\[ A_i = c_1 \cdot PG_i + c_2 \cdot J_i + c_3 \cdot \sigma(\xi_J) \]  
\[ k_i = c_4 \cdot PG_i + c_5 \cdot \sigma(PG_J) + c_6 \cdot J_i + c_7 \cdot \sigma(\xi_J) + c_8 \]

where i is the station, J is predictor from the model grid-cell containing the station, the overbar and \( \sigma \) indicate the mean and standard deviation of the probability distributions of the specified variable (PG and ζ), and \( c_1,2,3,4,5,6,7,8 \) are regression coefficients fitted using ordinary least-squares (OLS) regression.

Once the downscaling equations (2a) and (2b) are conditioned, they are applied to model-derived values of the mean and standard deviation of PG and ζ for 1981–1998 and 2041–2060 to determine the Weibull A and k from which the mean (\( \bar{U} \)) and p90 wind speeds at each station are derived:

\[ \bar{U} = A \Gamma \left( 1 + \frac{1}{k} \right) \]  
\[ U_X = A \left( 1 - 0.1 \cdot \ln \left( 1 - X \right) \right)^{1/k} \]

where \( \Gamma \) is the gamma function, and \( X = 0.9 \) for the 90th percentile.

Hourly wind speed observations (at 3 h time step) are drawn from the quality controlled and homogenized NCDC 6421 data set (Groisman 2002) (see figure 1). These 85 stations were selected based on two criteria; the wind speed time series (1981–1998) of 3-hourly observations must be ≥98% complete and the data must conform to a Weibull distribution (i.e. that the fitted Weibull distributions retrieve the second moment of the distribution (variance) to within 5% of the value computed from the time series).

The 3-hourly downscaling predictors are drawn from RCM simulations conducted under the North American Regional Climate Change Assessment Program (NARCCAP) (Mearns et al 2012). The AOGCM-RCM pairings used to supply the predictors (table 1) include three RCMs each of which is nested in two different AOGCMs, and all of which have one run nested within a common driving AOGCM. Further they include an AOGCM-RCM pairing for which daily data for the AOGCM are available from the CMIP3 data archive (http://pcmdi3.llnl.gov/ipcc/about_ipcc.php) (i.e. GFDL CM2.1). This model suite thus allows investigation of whether the hybrid downscaling adds value relative to direct downscaling from the AOGCM (objective (2)) and to assess the consistency of climate change signals across a range of AOGCM-RCM combinations (objective (3)). AOGCMs simulate plausible time sequences of conditions rather than reproducing conditions on a specific calendar date, and may thus be out of phase with observations, leading to a bias in the skill analysis conducted using independent observations. Thus, in the analysis of downscaling skill we also include a simulation with RCM3 nested within the NCEP-NCAR reanalysis (Kalnay et al 1996).
Table 1. Skill metrics (correlation coefficient \(r\), root mean square error (RMSE) and mean absolute error (MAE)) for the mean and 90th percentile wind speeds (during 1981, 1986, 1991 and 1996) across the 85 sites as determined from the Weibull \(A\) and \(k\) derived from the direct observations, and the Weibull \(A\) and \(k\) as downscaled using predictors from each of the models specified. Recall data from these years were withheld from the conditioning of the downsampling algorithms. The correlation coefficient \(r\), RMSE and MAE represent values computed for a sample size of 85 (i.e. one value of mean wind speed or p90 wind speed from each site). (Notes: The AOGCMs are; CCSM = community climate system model version 3 (Collins et al 2006), CGCM3 = canadian general circulation model (Scinocca et al 2008), GFDL = geophysical fluid dynamics laboratory model (CM2.1) (Delworth et al 2006). The RCMs are; CRCM = canadian regional climate model (de Elia and Cote 2010), RCM3 = regional climate model 3 used by UC-Santa Cruz (Pal et al 2007), WRFG = weather research and forecasting model (with the Grell cumulus parameterization) (Skamarock et al 2005). NCEP refers to the NCEP-NCAR reanalysis data set (Kalnay et al 1996).)

| AOGCM:RCM | Mean wind speed | 90th percentile wind speed |
|-----------|----------------|---------------------------|
|           | \(r\)          | RMSE (m s\(^{-1}\))     | MAE (m s\(^{-1}\)) | \(r\) | RMSE (m s\(^{-1}\)) | MAE (m s\(^{-1}\)) |
| GFDDL     | 0.83           | 0.48                      | 0.30               | 0.70 | 1.19               | 0.90               |
| CCSM:CRCCM| 0.86           | 0.45                      | 0.31               | 0.68 | 1.21               | 0.89               |
| CGCM3:CRCCM| 0.85         | 0.48                      | 0.33               | 0.71 | 1.15               | 0.87               |
| CGCM3:RCM3| 0.84           | 0.49                      | 0.35               | 0.72 | 1.18               | 0.92               |
| GFDDL:RCM3| 0.81           | 0.54                      | 0.34               | 0.67 | 1.29               | 1.05               |
| NCEP:RCM3 | 0.84           | 0.48                      | 0.34               | 0.72 | 1.13               | 0.85               |
| CCSM:WRFG | 0.71           | 0.67                      | 0.52               | 0.48 | 1.71               | 1.25               |
| CGCM3:WRFG| 0.75           | 0.61                      | 0.46               | 0.57 | 1.46               | 1.15               |

Figure 1. 10 m a.g.l. mean wind speeds (m s\(^{-1}\)) during 1981–1998 at the 85 stations used in the downsampling. The wind speed data are drawn from the NCDC 6421 data set and are recorded at a 3 h interval.

3. Results

Downscaling algorithms for the Weibull \(A\) and \(k\) at each station from each set of model output were independently developed using OLS regression of values from calendar month (i.e. January for all years, February for all years...) of the predictors and predictands computed for 1981–1998, but excluding 1981, 1986, 1991, 1996.

To assess the skill of the downsampling equations in reproducing historical wind climates, the downsampling models for each station and AOGCM-RCM combination were applied to independent data from 1981, 1986, 1991 and 1996 to derived downscaled values of the Weibull \(A\) and \(k\). \(A\) and \(k\) were then used to compute the mean and p90 wind speeds and the results compared to values derived from the Weibull \(A\) and \(k\) determined directly from the observations. The results indicate that the large-scale variability of both mean and p90 wind speeds across the eastern USA are relatively well captured (table 1 and figure 2), and thus indicate some degree of transferability of the downsampling approach. Downscaling results from all six AOGCM-RCM pairings indicate correlation coefficients \(r \geq 0.71\) with observed mean wind speeds and \(\geq 0.48\) for p90. Results from five of the six AOGCM-RCM pairings indicate correlation coefficients with the independent data of \(\geq 0.75\) for the mean and \(\geq 0.57\) for p90. These correlation coefficients are statistically different from 0 at \(>95\%\) confidence level according to a two-tail \(t\)-test (for a sample size of 85) (table 1). The MAE in downsampling results from five of the six AOGCM-RCM pairings when expressed as a percent of the mean observed value are \(<8\%\) for mean wind speed, and \(<12\%\) for p90. The downsampling skill is nevertheless lower than in prior application of the technique to northern Europe (Pryor et al 2006), which maybe attributable to the weaker synoptic forcing of wind climates (e.g. fewer cyclone passages) over parts of the eastern USA relative to northern Europe and the proportionally greater importance of mesoscale phenomena (e.g. mesoscale convective clusters) to wind regimes. Results from downsampling of the RCM3 output from a simulation conducted using NCEP lateral boundary conditions exhibits similar skill to that for AOGCM nested simulations (table 1). This implies that the conditions within the training period are similar to those in the four-year testing period (1981, 1986, 1991 and 1996). It may also indicate that either the RCMs are generating synoptic scale climates over eastern North America that are, to some degree, independent of the lateral boundary conditions or that the AOGCM-nested RCMs are generating similar storm climates to those manifest in reanalysis-nested runs (Long et al 2009). It does not preclude the possibility that relationships between the predictors and the surface wind speeds may alter as result of, for example, internal climate variability. The skill metrics presented in table 1 indicate...
Figure 2. Scatterplots of the (a) mean and (b) 90th percentile (p90) wind speeds for 1981, 1986, 1991 and 1996 at the 85 sites as determined from the Weibull A and k derived from the direct observations, and the Weibull A and k as downscaled using predictors from each of the AOGCM-RCM output specified. Frames (c) and (d) show the same variables but for direct downscaling from GFDL CM2.1, and using predictors drawn from the CRCM simulations with lateral boundary conditions from both the GFDL AOGCM and NCEP-NCAR reanalysis. To improve legibility one data point is excluded from frame (b), the observational estimate is 8.3 m s$^{-1}$, while the value derived from downscaling of CCSM-WRFG is 16.2 m s$^{-1}$.

The highest skill of downscaling based on output from CRCM (nested in either CCSM or CGCM3), and poorest performance for downscaling of output from CCSM-WRFG due mainly to higher variance in the downscaling predictors during the four validation years than during the years during which the transfer functions were conditioned. A relatively low-level of skill in simulated 10 m wind speeds from this model combination was also observed when the North American Regional Reanalysis was used as the target (Pryor et al 2012b).

As described above, the probabilistic downscaling approach was also applied to daily output of GFDL CM2.1. The results indicate comparable skill to use of the GFDL-RCM3 output (table 1 and figure 2), and thus there is little ‘value-added’ to the downscaling skill by use of predictors drawn from 3-hourly output from CRCM3 applied at a spatial resolution of $0.5^\circ \times 0.5^\circ$, relative to use of daily output from the parent AOGCM applied at a resolution of $2^\circ \times 2.5^\circ$. This finding is likely specific to this application, but is also consistent with the following first order reasoning: in the absence of strong thermo-topographic forcing, wind speed regimes respond to forcing at the synoptic scale (via transient weather systems), mesoscale phenomena, and at a local/site scale (via, e.g. roughness length and sheltering). Thus if the synoptic scale climate is relatively well-reproduced by the AOGCM, application of an RCM at $0.5^\circ \times 0.5^\circ$ may not substantially improve the probability distribution of the predictors (relative vorticity at 500 hPa and the mean sea-level pressure gradients). This finding illustrates both a possible limitation of empirical downscaling for wind speeds (the inability to capture changes in mesoscale/microscale effects), and offers a possible justification for dynamical downscaling at higher resolution.

The probabilistic downscaling equations (2a) and (2b) were applied to predictors derived from the RCMs for a future period (2041–2060) and for 1991–1998. Consistent with analyses of 10 m wind speeds as simulated by the RCMs (Pryor et al 2012b), the results indicate only very modest differences in mean and 90th percentile wind speed between
the two periods (figure 3). There is some consistent evidence of slightly lower future values of mean and p90 in the majority of the six independently downscaled distributions at stations in a swath extending across the lower Great Lakes (figure 3). This might be evidence that the primary storm track that extends across this area (Coleman and Klink 2009), may be displaced slightly poleward in the future (Ulbrich et al 2008, Long et al 2009). However, the ensemble mean change in either the mean or p90 wind speed has a maximum value of 5%, and thus is considerably smaller than the uncertainty associated with the downsampling approach (as indicated by figure 2 and table 1).

4. Concluding remarks

Returning to the original research objectives, results presented herein indicate:

(1) The probabilistic downsampling approach in which the Weibull $A$ and $k$ parameters of the wind speed probability distribution at a given site are downscaled from the mean and standard deviation of the probability distribution of mean sea-level pressure gradients and 500 hPa relative vorticity, exhibits some skill over eastern North America and thus some transferability. Evaluation of the downsampling skill indicates the macro-scale variability in wind climates is well-reproduced. Correlation coefficients for the mean and 90th percentile wind speeds from downscaled Weibull $A$ and $k$ and that from observations at 85 stations are $\geq 0.71$ and $\geq 0.48$ for all six AOGCM-RCM pairings that were downscaled, and are $\geq 0.75$ and 0.57 for five of the six. Further, MAE are an average of $<8\%$ and $<12\%$ of the downscaled mean and p90 wind speed, respectively, for five of the six AOGCM-RCM pairings (table 1).

(2) Prior research has shown that dynamical downsampling with RCMs almost uniformly ‘adds value’ to depiction of the wind climate over the contiguous USA (Pryor et al 2012b). However, the skill of the empirical downsampling is not substantially enhanced by use of 3-hourly predictors from an RCM run at 50 km resolution relative to once daily output from the parent AOGCM run at approximately 200 km resolution (table 1, figure 2).
(3) Differences in the mean and 90th percentile wind speeds over the eastern USA for 2041–2060 relative to 1981–1998 are of very modest magnitude (i.e. <5% of the value during 1981–1998). Thus while there is some evidence of consistent small magnitude (2–5%) declines in a region extended from Iowa to New York state, the differences are less than the uncertainty inherent in the downscaling procedure. The finding of very small magnitude changes in mean and 90th percentile wind speeds is consistent with analyses of possible future wind speed regimes over eastern USA as determined by direct output from the NARCCAP RCMs (Pryor et al 2012b). The validity of the implied near-term stability of wind climates is; (i) at least partly a function of the specific time windows used (i.e. the difference is a function of the precise normalization period (1981–1998) and may not be symptomatic of a tendency but rather long-term variability (Pryor et al 2012a)), and (ii) critically contingent on the ability of the RCMs to represent possible changes in the synoptic-scale flow regimes (and hence the probability distributions of PG and $\xi$). These results do not preclude the possibility of continued (even amplified) interannual variability, and/or changes in local/regional wind regimes due to changes in the frequency of mesoscale phenomena (that are not to captured at 50 km $\times$ 50 km resolution) or changes in surface roughness lengths due to altered land-use/land-cover (Vautard et al 2010).

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